Bias mitigation for automated decision-making systems

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Summary

The increasingly widespread availability and use of digital data - including personal data or relating to sensitive information - has inevitably contributed to the development of automated decision systems, such as ranking systems, recommendations systems, matching systems etc. The application of AI and ML brings definitely many advantages, particularly due to simplification and speeding-up of human complex tasks. Nonetheless, it should not be overlooked the fact that these systems lead as well to a wide range of critical aspects, such as data availability, data quality and features selection: indeed, the outcomes of ML algorithms will surely reflects the input. Hence, that is why data preparation is a crucial factor for an automated model building process and it requires relevant amount of time and resources.

Previous research has made progress in identifying various types of bias that can lead to discrimination in machine learning. Bias are data imbalance, which may enclose cultural/historical stereotypes, sampling or collecting issues, inaccurate labeling etc. Namely sources of possible harmful information, that will be encoded by learning algorithms in the same way they gain and use helpful insights. Historical or cultural prejudices against some social groups are the kind of noxious information that we would not embed in automated processes, but at the same time we cannot help it, since they are inner part of data. For this reason and for the fact that nowadays ML and AI pervades many aspects of our society, it has been promoted the integration of ethical principles in the implementation of automated decision systems that may affect people's lives.

The contribution of our research to the delicate subject of fairness in ML lies in having structured an introductory synthesis of the principles of fairness, of bias types and tools needed to reduce discrimination in the use of data within these systems. Then we performed experiments on two known datasets in the ML fairness field: the COMPAS dataset (for criminal recidivism score attribution) and a dataset with information related to drug consumption. Based on these data, we focused on the study of the fairness metrics and how we could improve fairness by means of *data balancing*, which can be considered a bias mitigation technique. Our results confirm the findings of previous research and highlight a possible process to maximize fairness, or at least to direct towards the choice of the most suitable metric for the evaluation of fairness in these two specific cases. The approach of bias mitigation acts as countermeasure for social inequalities, addressing to a less discriminatory outcome.

Last but not least, this research also aims to achieve a noble goal, specifically to advocate for the moral integrity of every person of science, who must bear in mind to have powerful tools to deal with, which could both build defenses and destroy as weapons, even when these are intangible.

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Introduction

1.1 | Motivation

In the era of big data, it is vitally important to take into consideration the social implications of the scientific research. The idea behind good science is the more discoveries made and more research done, the closer we will be to healing ourselves and the world. Hence, sometimes we are all so smitten by reaching results that we overlook the fact that progress could have consequences on the social sphere. In particular, it happens when science and technology deal with human sensitive data.

It is a fact that we live in a world of pervasive technology and we score a goal when we manage to replace human wearing efforts by automating tasks. However, the results of Artificial Intelligence and Machine Learning can bring us on the one hand to easier solutions, but on the other, to possible unequal conditions.

There are several well known cases - that became real scandals - of the combined use of data and technology, such as the Cambridge Analytica case in early 2018, for political advertising purposes [4]. Or the COMPAS software [5], used as a decision support tool by U.S. courts to determine criminal recidivism. Or again, the AI Amazon recruiting tool, biased against women [45].

In some cases, the outcomes were not intentionally discriminating categories of people, but they did, due to either data feedback loops or initial databases that reflected inner social prejudices.

Hence, when it comes to human factor, it is important to face the ethics implications of data analysis.

How we should implement algorithms for automated decisions or machine learning? Which data and which types of data should we take into account? Sometimes the legal, regulated aspects give us the answers (e.g. GDPR for data privacy), but in other circumstances, scientists should play a leading role in proper data usage and algorithms implementation, by using common sense.

We might think not to have any responsibility and treat data in the same way we treat any other bare ingredient of our work, as big black boxes, but this should not be the right approach towards sensitive data. What motivated us the most, is in fact the awareness that data are not only the “oil of the 21st century” [31], but also the identity of billions of human beings, on which we cannot speculate.

1.2 | Aims and Objectives

The aim of this thesis is to research cases of possible social inequalities, arose due to data usage in web platforms.
The objective is to give examples of bad data usage, in order to find some guidelines for avoiding idirect use of sensitive information in algorithms.

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Background & Literature Overview

2.1 | Fairness in Machine Learning

Nowadays, artificial intelligence is getting more and more involved in fields that uses sensitive data, such as health care, hiring criminal justice, hence there has been a wider focus on the connections of bias and unfairness embedded in it. Some people may claim that using artificial intelligence for decision-making could get choices fairer, but this is a wrong assumption: indeed using massive data in automated systems has a double-edge. It may avoid procedural mistakes, but it reflects and amplify as well societal bias embedded in training datasets. In addiction, it has to take into consideration the human decisions made during the machine learning development process, and the complex feedback loops that arise when a machine learning model is used in a real context.
Fairness is an articulated concept that depends on social context, legal aspects, different stakeholders, thus culture. It is impossible to determine a single and unique definition of fairness and it is difficult to formalize and quantify fairness principles mathematically. Nevertheless table 2.1 summarize 13 statistical measures for fairness, other formal definitions and 2 possible other context for fairness research (rows 23 and 24), which focus on different aspects of fairness and can produce entirely different outcomes. [44] proposes another classification of these fairness policies into:

- **Group fairness**: similar predictions within different groups.
- **Individual fairness**: similar predictions to similar individuals.
- **Subgroup fairness**: obtain the optimal trade-off between best properties of the group and individual notions of fairness. It selects a group fairness constraint like true positive rate parity and asks whether this constraint holds over a large collection of subgroups.

We will treat more in detail and technically some of these fairness definitions (statistical measures) in 4, while other main fairness concepts (similarity-base measures and causal reasoning)

are explained in the current chapter.
In Machine Learning, there are three main ways to improve fairness, as described in [55]: the first one examines methods to improve fairness by **optimizing algorithms**, at different phases of machine learning pipeline; the second one is about using **interactive systems**, such as HypDB (understand causality and the Simpson paradox) or Northstar, or AnchorViz (for interactive visualization, advanced analytics, classification etc. without the need for technical tasks); the third one involves **hybrid automatic and interactive systems**, such as IBM AI Fairness 360 or Google's What-If tool. In the latter case though, certain mechanisms implies assumptions that may not be appropriate in all data and model contexts. However, tools such as IBM AI Fairness 360 benefits from an open source library that can be used an customized for many different purposes.

2.1.1 | Sensitive data

The General Data Protection Regulation (GDPR) [1] is a regulation in EU law on data protection and privacy in the European Union (EU) and the European Economic Area (EEA), adopted on 14 April 2016, become enforceable on 25 May 2018.
The need of having a unified regulation for sensitive data in Europe takes its origin from the massive usage and request of personal or identifying data in online platforms. These data are commonly treated then with machine learning, artificial intelligence or big data tools.
A common sense is to quantify fairness via an associative relationship between the sensitive attributes and the outcomes of a classifier/predictor. For instance, in the United States, the Equal Employment Opportunity Commission defined the **four-fifths rule** [3] as a guideline (a good practice, not a legal definition) for comparing predicted positive outcome rates based on sensitive features (e.g. total number of hired people in a protected group, over total number of hired).
In GDPR we have a distinction between personal data and personal sensitive data. The first term is defined in Art. 4 and includes any information related to an identified or identifiable natural person, by means of which they can be directly or indirectly identified (name, identification number, location data, address, credit card, telephone number...). Sensitive personal data are instead defined in Art. 9 and they include genetic, biometric and health data, as well as personal data revealing racial and ethnic origin, political opinions, religious or ideological convictions or trade union membership. This kind of data are subject to higher level of protection.
In particular, according to the Italian privacy code [2], a narrow and closed list of data types was considered sensitive data:

- racial and ethnic origin
- religious, philosophical or other beliefs

Table 2.1: Overview of fairness definitions, adapted from [51] and [23].
Yellow color stands for independence; pink color for sufficiency; green color for separation. Darkest colors for equivalence; lightest colors for relaxed version. See chapter 4 for details.

1	Group fairness / Statistical parity / Equal acceptance rate / Bench-marking / Demographic parity	Based on predicted outcome	Statistical measures
2	Conditional statistical parity		
3	Predictive parity / Outcome test	Based on predicted and actual outcome	
4	False positive error rate balance / Predictive equality		
5	False negative error rate balance / Equal opportunity		
6	Equalized odds / Conditional procedure / Accuracy equality / Disparate mistreatment		
7	Conditional use accuracy equality		
8	Overall accuracy equality		
9	Treatment equality		
10	Test-fairness / Calibration / Matching conditional frequencies	Based on predicted probabilities and actual outcome	
11	Balance for positive class		
12	Balance for negative class		
13	Well-calibration		
14	Casual discrimination		Similarity-base measures
15	Fairness through unawareness	Individual fairness	
16	Fairness through awareness		
17	Counterfactual fairness		Causal reasoning
18	No unresolved discrimination		
19	No proxy discrimination		
20	Fair Inference		
21	Preferred impact		Preference-base measures
22	Preferred treatment		
23	Equality of resources $\leftrightarrow$ equity		
24	Equality of capability of functioning		

- political opinions
- membership of parties, trade unions, associations or organizations of a religious, philosophical, political or trade union nature
- the state of health and sexual life

For example, it has been clarified that social status, social benefits received, educational qualifications, training and work experience, the debtor's solvency, income received or assets owned are not included in the strict treatment reserved for sensitive data (but they are still protected by the privacy law).

2.1.2 | Similarity-base measures

On the account of table 2.1, we define the following similarity-base measures:

- **Causal discrimination**: a classifier satisfies this definition if it produces the same classification for any two individual with the exact same set of attributes.
- **Fairness through unawareness**: a classifier is said to achieve fairness through unawareness if sensitive attributes are not explicitly used in the prediction process.
  Satisfying this principle is not sufficient to avoid discrimination if other connected data are available, for instance in [20] is shown an heuristic method to retrieve ethnicity attribute given surname and geolocalization.
- **Fairness through awareness**: a classifier satisfy this definition if it relies on the principle that similar subjects should have similar classification. In particular, the similarity is defined by a distance metric: for a set of subjects V , a distance metric between applicants $d_1 : V \times V \longrightarrow \mathbb{R}$. We can formalize the awareness guideline by using the *Lipschitz condition* on the classifier, as in [18]: if we consider a classifier as a mapping from subjects to distributions D over outcomes with its own metric $d_2 : D \times D \longrightarrow \mathbb{R}$, the *Lipschitz condition* requires that for any two individuals x, y that are at distance $d_1(x, y) \in [0, 1]$ mapped to distributions $D(x)$ and $D(y)$, respectively, holds the inequality $d_2(D(x), D(y)) \leq K \cdot d_1(x, y)$, for a certain constant value K. In other words, the distributions over outcomes observed by x and y are indistinguishable up to their respective space distances d_1 and d_2.

2.1.3 | Causal reasoning

Causal reasoning is the process of research for causality that leads to an effect. This process has a leading role in discrimination avoidance, because it covers all the non-observational fairness concepts (i.e. the ones that do not depend only on the joint distribution of predictor, protected attribute, features and outcome, as defined in [38]), which can allow us to resolve

fairness conclusively, overcoming the inherent limitations of observational criteria. However, some researches proved that counterfactual reasoning may generate hindsight bias ad outcome bias [8], [48]. On the account of table 2.1, we define the following causal reasoning principles:

- **Counterfactual fairness**: this concept is strictly bounded to individual fairness, because it requires modeling counterfactuals on an individual level (e.g. answer to questions such as "What would have happened to me, if I had belonged to another subgroup?"). The formal definition of a counterfactually fair classifier is the following (adapted from [39]):
  The classifier C is **counterfactually fair** if under any context attribute $X = x$, sensitive attribute $A = a$ and actual outcome $Y = y$

  $$\mathbb{P}(C_{A=a} = y | X = x, A = a) = \mathbb{P}(C_{A=a'} = y | X = x, A = a) \quad \forall y \in Y \text{ and } a' \neq a \in A.$$

  where the $C_{A=a}$ has to be interpreted as the outcome of the classifier C if A had taken value a.

- **No unresolved discrimination**: it means avoiding discriminatory influences between variables and sensitive attributes.
  A **resolving variable** is a variable influenced by the sensitive attribute, in a manner that we accept as non-discriminatory. This implies that in a causal graph, any variable directly connected to the sensitive attribute should be non-resolving and any other variable should only be indirectly connected to the sensitive attribute by non-resolving variables.

- **No proxy discrimination**: it means avoiding proxy variables interference between possible sensitive attribute and predicted outcome connections. A **proxy variable** is a variable whose value can be used to derive a value of another variable. If there is no a direct connection between a proxy to a feature, unawareness can avoid proxy discrimination.

- **Fair inference**: it means avoiding illegitimate paths between sensitive attribute and predicted outcome.
  An **illegitimate path** is a connection between sensitive attribute and predicted outcome through another variable, that does not make a logic sense.

2.1.4 | Preference-base measures

In [6] are defined two distinct notions concerning unfairness in a decision-making process: **disparate treatment** if the decisions are somehow based on the individual's sensitive attributes and **disparate impact** if the decision process outcomes unequally treat people with certain sensitive attribute values. Hence, we introduce preference-base measures as a relaxation of

two statistical measures: preferred treatment is the relaxed version for treatment equality and preferred impact is a relaxed version for demographic parity (or better, proportional parity). Accordingly to [56], if we denotes with B_a as the fraction of benefits received by users sharing a certain value of the sensitive attribute $a \in A$, then we can define classifiers that satisfy these two fairness concepts as follow:

- **Preferred treatment**: a classifier C offers preferred treatment when $B_a(C_a) \geq B_a(C_{a'})$, $\forall a, a' \in A$. This means that the preferred condition is preserved if each group gets more benefits from its own group-conditional classifier than any other classifier. In this way no group members would feel treated better by switching their group membership. Note that, if a classifier C does not make group-base distinctions (i.e. $C_z = C$, $\forall a \in A$), as a group-conditional classifiers does, it by default satisfies preferred treatment.
- **Preferred impact**: a classifier C offers preferred impact over a classifier C' if it achieves higher group benefit for each sensitive attribute subgroup, namely $B_a(C) \geq B_a(C')$, $\forall a \in A$.

2.2 | Social discrimination in the digital context

How is it possible to have social discrimination in a digital context? It is a fact that when we use personal and sensitive data we may incur in discrimination. In particular, this issue occurs when data are mined and then processed by algorithms, which should relieve and speed up the manual human workload, as for artificial intelligence and, to be more specific, machine learning. In [7] Barocas and Selbst lists five mechanisms by which data mining may lead to disproportional outcomes; the sixth one is a human factor; the seventh one is a type that does not exclude the co-occurrence of the others:

1. Defining target variable, class labels and a model: indeed some of them could have a greater or lesser adverse impact on unprivileged groups For instance, if we choose "arrive at work on time" as a label to predict if my employees are good, then people in disadvantaged economic conditions might be mistreated because they have to take public transports if they cannot afford a car. Besides, functional misspecification, such as choosing a linear model on a variable that depends quadratically on the inputs, could infer discrimination on the whole process.
2. Labelling examples for the training data: when data are labelled (as for spam emails identification), the labels might be given on a biased base or, if they are given manually, humans can make mistakes that can lead to deviated predictions.
3. Collecting training data: if we train our model on biased dataset, namely if we collected and used biased data, we may learn from a bias sample and reproduce the bias.

4. Feature selection: when we process data in AI, we have to make decisions about which attributes observe and involve in our analyses. This may have consequences on the protected groups if they are not well represented in the selected features.

5. Proxies: this is equivalent to the proxy discrimination in case of proxy variables, already described in this chapter.

6. Intentional discrimination: in some cases, it may happen that discrimination takes its origins from a malicious intent by the AI developers and this is not an aspect to be overlooked. For instance, if an organization wants to discriminate against pregnant women, it is pretty accurate a prediction of pregnancy based on women shopping purchases.

7. Feedback loops: a possible cause of unfair predictions, generated by the outcomes of a system, used again as inputs. If the first outputs are biased due to an algorithm systematic error or to one of the previous discrimination causes, then the second outputs will be biased at a higher rate. This cycle could be performed several times and increase exponentially the discrimination.

In [36], Kamiran et al. formalize a model of discrimination in decision making. We adapted it by using the same notation as in 4.2.2.
Kamiran claims that a classifier consists of three main parts:

1. A score function $r = R(X)$, where X does not include the sensitive attribute.

2. A discrimination **bias function**:

$$B(A) = \begin{cases} b & A = privileged \\ -b & A = unprivileged \end{cases}$$

3. The final decision function $Y = C(R(X) + B(A))$.

Therefore, he final score to which we submit the classifier will be $r^* = r \pm b$ and the final decision will be given by $C(r^*)$. The classifier C has to define a decision acceptance threshold θ and accept individuals for which $r^* \geq \theta$.
This discrimination model has a serious implications: the bias is more likely to affect subjects that are already close to the decision threshold by their individual score r. Then, if an subject is far from the decision boundary, it may lead to deceptive conclusions, because adding or subtracting the discriminatory bias b will not change the final decision.
We will focus on bias in the next chapter.

2.2.1 | Automated Decision-making Systems (ADS or ADM)

Many companies have sought to automate their processes to achieve greater responsiveness and lower costs. Anyway, processes that involve high-level decision-making are usually left

to managers who make decisions based on the interpretation of the data itself. They are procedures in which initial decisions (in whole or in part) are delegated to a person or corporate organization, then they would use automatically enforced decision-making models to perform an action. The aim of ADS is to minimize human intervention in ongoing decision-making. Their aim is to sense situations, use codified knowledge, and react properly in the presence of people. Existing systems are derived from both artificial intelligence and decision-support tools, where they often involve both business rule processing and statistical analysis or algorithms. The Automated decision making systems are mainly used in business analytics and informatics to make decisions, such as:

- Recommending a decision to the ultimate decision maker responsible.
- Guiding a user through facts, legislation, policy etc.
- Supporting decision systems, providing useful information for the ultimate decision maker, on the whole decision process.
- Providing preliminary assessment for individuals, as a self-assessment tool.
- Entirely substituting a decision process, by fully automatizing it.

The last case is, by far, the most critical one: decision making by machines can lead to discrimination of certain groups of people or negatively impact the consumer market by triggering lock-in effects. A major challenge is indeed how to protect people's rights, especially with regard to data protection, and whether existing specific protection rules for the ones who use the ADS. Lastly, it should be discussed who is responsible if something does not work (algorithmic accountability) and who has the responsibility for supervising those who create and implement the algorithms (ADS auditing and control).

2.2.2 | Examples

The following table 2.2 summarizes cases of possible discrimination, related to direct or indirect use of sensitive data. For each ground, are listed known studies regarding cases of discrimination that actually happened and a brief description of them.

Table 2.2: Table of possible discrimination grounds.

Ground	Type of discrimination	Description	Ref.
Search engines	Political orientation	A study on 4,556 undecided voters with different demographic characteristics in United States and India. It demonstrates that biased search rankings can shift the voting preferences of undecided voters by 20% or more.	[21]
	Gender	Gender unequal distribution in photos retrieved by Bing for the query "person" and for queries based on 68 character traits (e.g., "intelligent person") in four regional markets.	[47]
	Language	A research that shows that cultural stereotyped biases from textual data propagate to artificial intelligence (AI) technologies in widespread use.	[12]
Freelance marketplaces	Gender and Race	Gender and race are significantly correlated with worker evaluations on TaskRabbit and Fiverr. This study is on 13,500 worker profiles: It gathers information about workers' gender, race, customer reviews, ratings, and positions in search rankings.	[26]

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Table 2.2 – continued from previous page

Ground	Type of discrimination	Description	Ref.
Resume search engines	Gender	Indeed, Monster, and CareerBuilder are tools that allow recruiters to proactively search for candidates based on keywords and filters. This study shows gender indirect discrimination that leads to disadvantage rankings for some candidates.	[14]
Ad delivery systems	Race	This study concerns the problem of raising questions as to whether Google's advertising technology exposes racial bias in society and how ad and search technology can develop to assure racial fairness.	[50]
Intimate platforms	Sexual orientation	Despite the fact that that romantic and sexual choices are understood as intensely personal, this article aims to analyse if intimate platform designers (such as Tinder, OkCupid or Grindr) can help alter troubling patterns of social interaction, without unduly interfering with individual intimate choices.	[32]

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Table 2.2 – continued from previous page

Ground	**Type of discrimination**	**Description**	**Ref.**
Social networks	Race	Twitter's automatic cropping tool algorithm appeared to be systematically favoring white faces. There have not been conducted formal studies yet about this issue, but Twitter company declared to have checked the absence of algorithmic biases before using the tool. This discovery was made fortuitously by Twitter users.	[29]
Language translation tools	Race	This simple experiment is based on translating 11 occupation titles from one gender-inflected language to another, taking into consideration German, Italian, Polish, Spanish and French. It shows that Google Translate systematically changes the gender of translations when they do not fit with stereotypes, especially when it comes to single-words translations, not placed in a context.	[37]

3

Bias & Fairness

In chapter 2 we introduced the bias function to depict how bias can affect discrimination in a decision-making process. The bias function is a formal concept that we find in every estimator or decision rule and it is an objective property of the estimator. However, there is a distinction between the statistical formalization of bias and bias that we find for decision systems. We could deeply analyse bias in the statistical sphere, but this is not the aim of our research: we will limited the mention of the statistical bias to show how it is related to the decision process in machine learning.
As written in [17], "The bias of a learning algorithm - if it can be formulated explicitly - provides a specification for the desired behavior of the algorithm and clarifies the design and implementation of machine learning algorithms. [...] The bias of a learning algorithm is the persistent or systematic error that the learning algorithm is expected to make when trained on training sets". In [24] is demonstrated that, given a learning algorithm L, its average error at a point x on a sample of size m is equal to the squared statistical bias plus the variance:

$$Error(L, m, x) = Bias(L, m, x)^2 + Variance(L, m, x)$$

Therefore, a bias in a learning algorithm is an error and the objective should be to reduce it as much as possible. In the same paper, Dietterich an Kong distinguish betweeen two types of ML algorithm bias:

- **Absolute bias**: an assumption by the learning algorithm that the target function to be learned is definitely a member of some designated set of functions (such as the set of linear discriminate functions or the set of boolean conjunctions).
- **Relative bias**: an assumption that the function to learned is more likely to be from one set of functions than from another (e.g. the decision tree algorithms consider small trees before larger ones).

There is a relationship between ML absolute-relative bias and statistical bias: if the relative bias is strong, then the algorithm will have low variance; on the opposite, if it is weak, the

algorithm will have high variance. If the absolute bias is inappropriate (it does not contain any good approximations to the target function), the algorithm will have high statistical bias. However, we cannot properly analyse discrimination and fairness in ML by focusing on statistical bias or algorithmic ML bias: even though they might have an impact on sensitive data and personal information, usually they are not the main cause of discrimination, then we have to move further, on other more specific biases that we find in previous ML fairness studies.

In this chapter, we will analyse where and when errors and bias can occur during a decision process in machine learning. We will research for the causes and we will try to give a schematic taxonomy of the types of bias we may encounter in our following experiments, based on past research.

3.1 | Bias taxonomy - past research

3.1.1 | A Framework for Understanding Unintended Consequences of Machine Learning [49]

In this paper are described 6 sources of bias that may be incurred at different steps of the ML process:

1. **Historical bias**: when there is a misalignment between real world expectations and model outcomes. It requires understanding and studying the application and generation of data over time. Even if we have perfectly-measured features, they might still reflect historical factors, for instance conditions that we find only in poorer neighborhoods. Accordingly to this, we can even reflect the world perfectly, but still inflict harm on a population.

2. **Representation bias**: when defining and sampling a population still under development, then certain part of the input space are underrepresented and others are overrepresented. This bias may be due to two main reasons: (1) the sampling methods reach only a part of the population and (2) the target population has changed or is anyway different from the original training population.

3. **Measurement bias**: when measuring features and labels in a prediction problem, we add random noise. This might be caused by three main reasons: (1) different measurement process for different groups or (2) different data quality for different groups and (3) oversimplification of the classification model (e.g. selecting or having available too few features for a good prediction).

4. **Aggregation bias**: when a single model is used for all groups, which require in fact different specific models, due to different conditional distributions, backgrounds, cultures

etc. Usually with this kind of bias the model will be optimal only for the dominant population.

5. **Evaluation bias**: when the evaluation and/or test data for an algorithm does not represent the target population. Misrepresented test data lead to the development of models that are optimized only for a subset of the population.

6. **Deployment bias**: when there is a misalignment between the problem a model is intended to solve and the way in which it is actually carried out after deployment (e.g. when we adapt a specific model to a generic task).

3.1.2 | On Simpson's Paradox and the Sure Thing Principle [11] - Berkson's Bias, Selection Bias, and Missing Data [53]

There are two well-known paradoxes in fairness theories that may introduce bias, due to wrong data interpretation:

1. **Simpson's bias**: it is derived from Simpson's paradox, which claims that it is possible to have $\mathbb{P}(A|B) < \mathbb{P}(A|B')$ and at the same time $\mathbb{P}(A|BC) \geq \mathbb{P}(A|B'C)$, $\mathbb{P}(A|BC') \geq \mathbb{P}(A|B'C')$, where C and C' are two distinct groups.
   To be more clear, in table 3.1 are shown data regarding a new medical treatment on local patients (C) and patients from Chicago (C'). If we look at the overall treatment data, we are prone to say that it is a bad treatment compared to the standard one (Table a: 11% vs 46% alive people), but if we look at data divided per groups, we would notice that the treatment seems paradoxically good (Table b: higher rate of alive people in both groups).

2. **Berkson's bias**: this is based on the Berkson's paradox, which says that given two independent events, if you take into account only outcomes where at least one occurs, then they become negatively dependent. In terms of probability it becomes: $0 < \mathbb{P}(A) < 1$, $0 < \mathbb{P}(B) < 1$ and $\mathbb{P}(A|B) = \mathbb{P}(A)$, then $\mathbb{P}(A|B, A \cup B) < \mathbb{P}(A|A \cup B)$.
   In general, Berkson says that if we only focus on a portion of data, we will be falsely tempted to say that there is a negative correlation between two attributes (e.g. the assumption that all Hollywood movies are bad, compared to their books, is due to the fact that we are just considering books and movies that overcome a certain "goodness" threshold, overlooking all bad movies and bad books).

Table 3.1: Simpson's paradox example - extract from [11]

(a)

Treatment	*Standard*	*New*
Dead:	*5950*	*9005*
Alive:	*5050 (46%)*	*1095 (11%)*

(b)

Treatment	*C patients only*		*C' patients only*	
	Standard	*New*	*Standard*	*New*
Dead:	*950*	*9000*	*5000*	*5*
Alive:	*50 (5%)*	*1000 (10%)*	*5000 (50%)*	*95 (95%)*

3.1.3 | Social Data: Biases, Methodological Pitfalls, and Ethical Boundaries [46]

This paper defines biases that can be encountered when analyzing social data, in particular taken from social platforms. From 1 to 6 are listed biases of selection phase (**selection bias**), depending for instance on the choice of the social platform from which to collect data. We report here the exact definitions of the paper:

1. **Population bias**: differences in demographics or other user characteristics between a population of users represented in a dataset or platform and a target population.
    - Different socio-demographic groups behave differently on social platforms -> we cannot generalize the behavior of a group for the whole of society.
    - Some studies use proxy for prediction, but proxies for personal traits have different reliability across different demographic groups (e.g. if we use political twitter posts to understand political orientation, politicians will get much higher accuracy than normal users).
2. **Behavioral bias**: differences in user behavior across platforms or contexts, or across users represented in different datasets.
    - **Interaction biases**: concern the different ways users interact with each other in social platforms, due to different personalities and different generations.

- **Content consumption biases**: regard different kind of contents interactions for different users, due to disparate interests and pool of contents. They may be expressed as well as lexical, syntactic, semantic, and structural differences in the contents generated by users.
- **Linking biases**: behavioral biases that are expressed as differences in the attributes of networks obtained from user connections, interactions or activity. They regards external factors and attributes that may influence and change users' behaviour.
- **Response biases**: are due to "missing" reports, inaccurate self-reports made by users. Most of the time, people lie about themselves or are not accurate regarding the information they provide.

3. **Temporal variations**: differences in populations or behaviors over time. This concept is similar to the historical bias. It is connected as well to behavioral biases, because over time users' behavior change rapidly on social platforms.

4. **Functional biases**: biases that are a result of platform-specific mechanisms or affordances, that is, the possible actions within each system or environment. They are strictly related to behaviour or population, but through the social platform design.

   - introducing a new feature, or changing an existing feature on a platform, impacts usage patterns.
   - users react and behave in different ways, based on what they see and how they see, namely not only the contents, but also the order and disposition of the information they access (e.g. ranking algorithms).

5. **Normative biases**: biases that are a result of written norms or expectations about unwritten norms describing acceptable patterns of behavior on a given platform.

   - on different platforms we may face different terms and conditions and simply different codes of conduct, hence people have to act in different ways.
   - users might be influence by other users' impact.
   - herding effect (influence of previous ratings and reviews), friendship paradox (popular individual can steer the behaviour of common users), anchoring effect (tendency to conform), male names for users and organizations could have a stronger an more positive impact...

6. **External biases**: biases resulting from factors outside the social platform, including considerations of socioeconomic status, ideological/religious/political leaning, education, social pressure, privacy concerns, topical interests, language, personality, and culture.

   - socio-cultural elements that are reflected on social platform data.

- elements with high social impact (e.g. media communications, disasters, global pandemics...) are reflected and have a strong influence on social media.
- different kind of contents are spread in different ways throughout social platforms, both due to automated mechanisms and human curation.

7. **Data collection biases**: biases introduced due to the selection of data sources, or by the way in which data from these sources are acquired and prepared.
   - data acquisition.
   - data querying (APIs).
   - data filtering.
8. **Data processing biases**: biases introduced by data processing operations such as cleaning, enrichment, and aggregation.
   - normalization of geographical references.
   - inserting default options.
   - automatic processes for data enrichment (e.g. made with machine learning).

3.1.4 | Search Bias, Language Bias and Genetic Programming [54]

As we already said at the beginning of this chapter, when bias regards ML sphere, it is a matter of choice an hypothesis over many other: we have to address a system towards a solution, even if we do not know whether it exists or not. This is called *heuristic knowledge* and it aims to reach reasonable generalisation, with limited information.
This paper defines three major kind of biases, with reference to the hypothesis choice:

1. **Selection bias**: it generates when we have to choose an hypothesis over another. For instance, in terms of evolutionary biology, this type of bias is the result of a fitness selection. Besides, every parameter and measure that we choose to represent an individual is a selection bias.
2. **Language bias**: in the article, Whigham claims that if we have an exiguous language pool, the hypothesis we can create might be restricted as well. By language here we mean all the descriptive tools we need to formulate a decision process.
3. **Search bias**: it consists in the process of turning one hypothesis into another, in order to search for the best one. It can be represented by the crossover during a random forest algorithm and the maximum depth of any created tree.

3.1.5 | Bias amplification in Artificial intelligent systems [42]

This paper divides bias in 5 main categories. We report here the exact definition the authors gave for each or them:

- **dataset bias**: it refers to bias that results from a too-small or too homogenous dataset, which then perpetuates inaccurate generalizations. This kind of bias concerns any preliminary issue related to the dataset.
- **association bias**: it occurs when data used to train an algorithm reinforces and multiplies cultural bias, when applied to a larger problem. (e.g. even due to unintentional discrimination, made by feedback loops based on cultural inference, it may be possible that some job advertisements are more likely to be shown to males than females).
- **automation bias**: describes situations in which the AI fails to take social or cultural factors into consideration (e.g. some machines may enforce the European stereotype of beauty by selecting greatly light skin rather than dark-skinned subjects).
- **interaction bias**: occurs when machines are empowered to learn without safeguards in place to identify and exclude harmful or pernicious beliefs (e.g. a bot that learns what to say by its users, may end up learning offensive or dangerous language if not controlled).
- **confirmation bias**: occurs when information is oversimplified or personified and makes improper generalizations or assumptions about a group or individual (e.g. in online purchasing there are often suggestion such as "you may also like these products...", but it is not rare that they mispredict what we like).

4

Methodology background

4.1 | Metrics

4.1.1 | Diversity

The diversity indicates abundance or lack of different species in a community (dataset) and we chose the **Shannon index** as a measure for it.
The Shannon index takes its origin from ecology, where it is also known as Shannon's diversity or Shannon's entropy. The idea beyond this index is that the more different individuals there are and the more equal their proportional abundances (number of individuals per species) in the category/cluster of interest, the more difficult it is to correctly predict the next individual in the category. The aim of this index is indeed to quantify the entropy associated with this prediction.
The Shannon index takes into consideration both the species richness (number of species present) and species abundance.

$$H' = -\sum_{i=1}^{R} p_i \ln p_i$$

where p_i is the proportion n/N of n individuals of one particular species i, divided by the total number of individuals found N; ln is the natural logarithm, is the sum of the calculations, and s is the number of species.
With this index we quantifies the uncertainty in predicting the species identity of an individual chosen randomly from the community.

The greater is the difference between the abundances of the types, the smaller is the corresponding Shannon index value. If hypothetically there is only one species in the dataset, Shannon diversity exactly equals zero (no uncertainty in predicting the type of the next randomly chosen individual). An important notice is that if the true diversity doubles between two experiments, it does not mean that the index doubles as well: we can only evaluate a comparative measure, indeed whether an experiment gets more or less diversity than another.

4.2 | Fairness

In this section we will give an outlook of the main fairness metrics we used in order to evaluate the fairness level of our classification algorithm. It is important to stress that fairness in ML could be evaluate in many different ways and it also depends on anti-discrimination laws that states in different countries, concerning the usage of sensitive attributes. In our case, we focused on the fairness metrics in "fairness" CRAN package.

4.2.1 | Fairness - R library

The fairness R package provides the calculation and comparison of commonly used fairness measures across population subgroups.
By using this library we could assessed our predictive model whether its results reinforce existing social biases. We identified the sensitive attribute that gave the highest disparate impact on the subjects of each dataset, then we evaluated and compared the fairness metrics values for this attribute.
In the below section 4.2.3 we listed all the fairness metrics offered in R Fairness package that are the ones we relied on for our research. For all the metrics, the ideal goal is to reach an equal value (parity) in each subcategory, which represents a perfect fairness situation. Since we are not virtually able to reach exactly the same values, we quantify how much a dataset lacks of fairness towards the sensitive attribute, by calculating the **mean signed deviation** of the subcategories values from the objective fair value.

4.2.2 | Statistical metrics

Sometimes it happens that, in order to avoid disparate treatment, we might be led to use a classifier with a distribution that does not take into account the sensitive attributes (this is called **unawareness**, i.e. $C = c(x, A) = c(X)$), but it has been proved that this strategy does not avoid discrimination. In fact, there could be variables strictly related or correlated to the sensitive ones (e.g. postal code related to ethnicity), that serves as **proxies** for the sensitive attributes.

All the following definitions refers to a binary classification under these assumptions:

- $X \in R^d$: quantified features of the individual (e.g. number of priors, misdemeanor...).
- $A \in \{unprotected, protected\}$: a binary sensitive attribute (e.g. Male/Female).
- $C := c(X, A) \in \{negative, positive\}$: binary predicted outcome (e.g. rejected or hired, which makes decision based on a score $R := r(x, a) \in [0, 1]$.
- $Y \in \{negative, positive\}$: target variable with the actual outcome (e.g. if the individual truly rejected or hired).

- ◇ X, A, Y generated from an elemental distribution D, namely $(X, A, Y) \sim D$.
- ◇ The best accuracy is gotten with $C(X, A) = Y \in (X, A, Y) \sim D$.
- ◇ We use the notation $\mathbb{P}_{protected}[c] := \mathbb{P}[C = c | A = protected]$ for the conditional probability of being classified as c, given that .

When we want to describe the performance of supervised learning classification model, we usually rely on a **confusion matrix**, which is a particular contingency table with rows and columns that represent respectively the instances of the predicted and actual classes. Predictive and actual classes can assume *positive* or *negative* value if we are using a binary classifier. On the main diagonal in the confusion matrix, we find the correct predictions, whereas on the secondary diagonal the prediction errors.
In the confusion matrix cells we find the following data, that will help understanding the fairness metrics:

- TP - **true positive**: both predicted and actual outcome are in the positive class.
- FP - **false positive**: predicted is in the positive class, but actual outcome is in the negative.
- FN - **false negative**: predicted is in the negative class, but actual outcome is in the positive.
- TN - **true negative**: both predicted and actual outcome are in the negative class.

From these four cases, we can derive the following metrics:

- PPV - **positive predictive value**: it is the probability of an individual with a positive prediction to truly belong to the positive class $\mathbb{P}(Y = positive \mid C = positive)$.
  Alternatively, it is the fraction of correctly predicted positive cases, out of all predicted positive cases $\frac{TP}{TP+FP}$.
  It is also named **precision**.
- FDR - **false discovery rate**: it is a false acceptance, namely a wrong prediction of a truly negative case to be in the positive class $\mathbb{P}(Y = negative \mid C = positive)$.
  Alternatively, it is the fraction of incorrectly predicted negative cases (that truly belong to the positive class) out of all predicted positive cases: $\frac{FP}{TP+FP}$.
- FOR - **false omission rate**: it is an incorrect rejection, namely wrong prediction of a truly positive case to be in the negative class $\mathbb{P}(Y = positive \mid C = negative)$.
  Alternatively, it is the fraction of incorrectly predicted positive cases (that truly belong to the negative class), out of all predicted negative cases: $\frac{FN}{TN+FN}$.

- NPV - **negative predictive value**: it is the probability of an individual with a negative prediction to truly belong to the negative class $\mathbb{P}(Y = negative \mid C = negative)$.
  Alternatively, it is the fraction of correctly predicted negative cases, out of all predicted negative cases $\frac{TN}{TN+FN}$.
- TPR - **true positive rate**: it is the probability of truly positive cases to be predicted correctly $\mathbb{P}(C = positive \mid Y = positive)$.
  Alternatively, it is the fraction of correctly predicted positive cases, out of all actual positive cases $\frac{TP}{TP+FN}$.
  It is also named **sensitivity** or **recall**.
- FPR - **false positive rate**: it is a false alarm, namely wrong positive prediction of an actual negative case $\mathbb{P}(C = positive \mid Y = negative)$.
  Alternatively, it is the fraction of incorrectly predicted negative cases, out of all actual negative cases $\frac{FP}{FP+TN}$.
- FNR - **false negative rate**: it is the probability of truly positive cases to be predicted incorrectly as negative $\mathbb{P}(C = negative \mid Y = positive)$.
  Alternatively, it is the fraction of incorrectly predicted positive cases out of all actual positive cases $\frac{FN}{TP+FN}$.
- TNR - **true negative rate**: it is the probability of a truly negative case to be predicted as negative $\mathbb{P}(C = negative \mid Y = negative)$.
  Alternatively, it is the fraction of correctly predicted negative cases, out of all actual negative cases $\frac{TN}{FP+TN}$.

4.2.3 | Fairness metrics

4.2.3.1 | Demographic parity

Demographic parity (also known as Independence or Statistical parity) is achieved when the percentages or rates of the positive outcomes are equal for each group.
This metric only relies on the predicted outcome, not the actual one. In terms of probability, it means that the classifier C is independent from the sensitive attribute A. We can get demographic fairness simply by equalize the number of classified positive (negative) outcomes for each subcategory of the protected attribute:

$$\#_{protected}[C = c] = \#_{unprotected}[C = c] \quad \forall\, c \in \{negative, positive\}$$

Usually both demographic parity and proportional parity are formulated in terms of $positive$ predictions. However, since we do not have a comparison between actual and predicted outcome, the equality of positive predicted is equivalent to the equality of negative predicted.
We can not formulate this principle in terms of statistical metrics (confusion matrix), because

it does not take into consideration a comparison between predicted and actual outcome.

In `fairness` package:

this metric is evaluated by counting the sum of positive outcomes for each subcategory: the base category will get 1 as default value for positive outcomes, whereas all the other categories will be compared to this one, namely $\frac{\#positive\ outcomes\ for\ category}{\#number\ of\ positive\ outcome\ for\ base\ category}$. In this case, the different number of individuals per category has not been taken into account, then it makes sense to use this metric only when we have a perfectly balanced dataset in terms of the sensitive attribute. In `fairness` package, for all the following described metrics we will consider a base subcategory (e.g. 'Caucasian' for ethnicity attribute or 'Male' for gender attribute) and this base category will always get 1 as fairness metric value. All the other categories will get lower of higher values: this R package will give us both the absolute value of the different metrics and the comparative value towards the base category, but it only gives a ready-plot with the comparative measures.

4.2.3.2 | Proportional parity

Proportional parity is similar to demographic parity (or another way to indicate demographic parity) because for both metrics we do not compare the predicted outcomes to the actual outcomes. The difference is that this metric is much more useful when we have an unbalanced dataset towards the sensitive attribute.
In fact, for this metric we consider also the number of individuals for each population. In terms of probability, we can formulate it as follow:

$$P_{protected}[C = c] = P_{unprotected}[C = c] \quad \forall\, c \in \{negative, positive\}$$

In `fairness` package:

instead of using the `sum()` function (as it is used for the demographic parity), the `mean()` function gives the metric value, so that the less populated subcategories could anyway reach the same metric value as the highest populated ones.

Differently from the previous two metrics, all the following ones take into account both the actual and the predicted values.

4.2.3.3 | Equalized odds

This metric is also known as Separation and it is achieved if the **sensitivities** (true positives divided by all positives) in the subgroups are close one another.

With a formal definition [27], we say that a predictor C satisfies *equalized odds* with respect to protected attribute A and outcome Y, if C and A are independent conditional on Y. That means equalized odds may allow C to depend on A but only through the target variable Y.
In terms of probability:

$$P_{protected,Y=y}[C = positive] = P_{unprotected,Y=y}[C = positive] \quad \forall\, y \in \{negative, positive\}$$

Since we introduce dependency on the sensitive attribute, it goes without saying that we can not both satisfy equalized odds and demographic parity at the same time. Depending on the y value, we equalize *true positive rates* or *false positive rates*, hence this metric is quite restrictive because it requires that both rates should be equal in order to get fairness.
In terms of statistical measures (confusion matrix), we can formulate this metric as follow:

$$TPR_{protected} = TPR_{unprotected} \ and \ FPR_{protected} = FPR_{unprotected}$$

4.2.3.4 | Equality of opportunity

This metric is a weaker version of the Equalized odds.

4.2.3.5 | Predictive rate parity

This parity is also known as **Sufficiency** and it checks if the **precision rates** are equivalent for all subgroups under consideration [51], so that the fraction of correct positive predictions should be the same for each sensitive attribute value.
In terms of probability, this means:

$$P_{protected,C=positive}[Y = y] = P_{unprotected,C=positive}[Y = y] \quad \forall\, y \in \{negative, positive\}$$

A classifier with equal PPV has also equal FDR, that is why we can use indistinctly all y values to equalize the probabilities. Ineed, in terms of statistical measures (confusion matrix), we can formulate this metric as follow:

$$PPV_{protected} = PPV_{unprotected} \ or \ FDR_{protected} = FDR_{unprotected}$$

4.2.3.6 | Accuracy parity

The accuracy represents the fraction of predictions that a classifier gets correctly, therefore accuracy parity is obtained when all the sensitive attribute groups have equal prediction accuracy. The accuracy is the probability of a subject -in either positive or negative class - to be assigned to its respective class: namely, true negatives are as desirable as true positives for this fairness metric.

$$P[C = Y, protected] = P[C = Y, unprotected]$$

In terms of statistical measures (confusion matrix), we can formulate this metric as follow:

$$(\frac{TP + TN}{\#\, of\, predictions})_{protected} = (\frac{TP + TN}{\#\, of\, predictions})_{unprotected}$$

4.2.3.7 | False negative rate parity

This is also known as **Equality of opportunity** and it is considered as a weaker version of Equalized odds.
This metric is satisfied if all the sensitive attribute groups have equal FNR (the probability of a subject in a positive class to have a negative predictive value). Since a classifier with equal FNR will get also equal TPR, we can use both indistinctly.
In terms of probability, we can formulate it as follow:

$$P_{protected,Y=positive}[C = c] = P_{unprotected,Y=positive}[C = c] \quad \forall\, c \in \{negative, positive\}$$

In terms of statistical measures (confusion matrix), we can formulate this metric as follow:

$$FNR_{protected} = FNR_{unprotected} \ or \ TPR_{protected} = TPR_{unprotected}$$

If the prevalence of positive outcome for both subcategories of the sensitive attribute is the same in the entire population and does not depend on the sensitive attribute itself, this definition becomes equivalent to the demographic or proportional parity.

4.2.3.8 | Specificity parity or False positive rate parity

This metric is also known as **Predictive equality**.
In Equalized odds we already introduced the FPR, but in that case it required to satisfy both TPR *and* FPR equality at the same time, then FPR parity is less restrictive.
This metric is satisfied if all the sensitive attribute groups have equal FPR (the probability of a subject in the negative class to have a positive predictive value). Since a classifier with equal FPR will get also equal TNR, we can use both indistinctly.
In terms of probability, we can formulate it as follow:

$$P_{protected,Y=negative}[C = c] = P_{unprotected,Y=negative}[C = c] \quad \forall\, c \in \{negative, positive\}$$

In terms of statistical measures (confusion matrix), we can formulate this metric as follow:

$$FPR_{protected} = FPR_{unprotected} \ or \ TNR_{protected} = TNR_{unprotected}$$

Specificity is also known as TNR (true negatives divided by all negatives), therefore it represents the probability of a subject in the actual negative class to be predicted as negative. This metric could be useful as it is ideally the opposite of Equalized odds.

4.2.3.9 | Negative predictive value parity

Negative predictive value parity is satisfied when the negative predictive values in the subgroups are equal. This metric could be useful as it is ideally the opposite of the Predictive rate

parity.
In terms of probability, this means:

$$P_{protected,C=negative}[Y = y] = P_{unprotected,C=negative}[Y = y] \quad \forall\, y \in \{negative, positive\}$$

A classifier with equal NPV has also equal FOR, that is why we can use indistinctly all y values to equalize the probabilities. Indeed, in terms of statistical measures (confusion matrix), we can formulate this metric as follow:

$$NPV_{protected} = NPV_{unprotected} \; or \; FOR_{protected} = FOR_{unprotected}$$

In `fairness` package:

Negative predictive value parity and Predictive rate parity are only treated individually, but if we would require both to be satisfied, then the metric is called **Conditional use accuracy equality** [10] and it implies equivalent accuracy for sensitive attribute subcategories, from both positive and negative predicted classes.

4.2.3.10 | Matthews correlation coefficient comparison

Matthews correlation coefficient is a scalar metric used in binary classification, such as accuracy, precision, recall or F1-score.
Unfortunately, these mentioned metrics are subject to some flaws: for instance, precision and accuracy are sensitive to class imbalance [35]. Instead, recall and F1-score only depend on the positive groups and do not consider the number of negative samples misclassified as positive (otherwise it could have been an issue in problems containing class imbalanced data with many negative samples), yet they are still not utterly effective when comparing performance between classifiers [28].
Then, according to Davide Chicco and Giuseppe Jurman [15], the most informative metric to evaluate a binary classifier is the Matthews correlation coefficient (MCC):

$$MCC = \frac{TP \cdot TN - FP \cdot FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}$$

or equivalently, in terms of rates

$$MCC = \sqrt{TPR \cdot TNR \cdot PPV \cdot NPV} - \sqrt{FPR \cdot FNR \cdot FDR \cdot FOR}$$

MCC is a more reliable statistical measure because it produces a high score only if the prediction obtained good results in every confusion matrix category (true positives, false negatives, true negatives, and false positives), in proportion to both the size of the positive and negative classes. It ranges from -1 to 1.
Despite of these positive aspects, some studies claims as well that MCC is not suitable for imbalanced datasets: indeed, according to a recently published research paper, if we are working

on imbalanced dataset (in terms of target class) MCC value deteriorates seriously compared to a balanced dataset [57].

4.2.3.11 | ROC and AUC comparison

The **receiver operating characteristics** (ROC) curve is a popular valuation that plots true positive rate over false positive rate, in order to provide a visualization of the offset between correctly classified positive samples and incorrectly classified negative samples.
If the dataset we are working on is highly skewed (not equally distributed on both sides of the distribution, hence not symmetrical distributed), ROC curves can present overly optimistic results and we should use instead **Precision–Recall** (PR) curves [16].
The **area under the ROC curve** (AUC) can be used as a metric to to compare classifiers performance: it is both scale-invariant and threshold invariant, which means respectively that it is independent from the predicted absolute values and from the classification cutoff. An excellent model has AUC near to the 1 which means it has good measure of (separability); on the other hand, an area of 0.5 corresponds to random guessing.

4.2.4 | Fairness criteria

The three main following fairness criteria [6] are based on the concept of statistical independence and they have been already mentioned in the previous fairness metric section 4.2.3.
This definition will be helpful in the comprehension: definition *[section]

Definition 1 (Conditional independence) *Given X, Y, Z three discrete random variables. If, when Z is known, the value of Y does not add any additional information about X, namely*

$$\mathbb{P}(X \leq x, Y \leq y | Z = z) = \mathbb{P}(X \leq x | Z = z) \cdot \mathbb{P}(Y \leq y | Z = z) \; \forall x, y, z.$$

we say that X and Y are conditionally independent given Z and it is written

$$X \perp Y \mid Z$$

In particular, if X and Y are conditionally independent given Z, then

$$\mathbb{P}(X = x | Y = y, Z = z) = \mathbb{P}(X = x | Z = z)$$

4.2.4.1 | Independence

It requires the sensitive attribute A to be independent from the classifier C, then we could say $R \perp A$, where R is the score variable we use for the prediction of our classifier C.
We have already formally defined this as demographic parity or proportional parity in the previous section.
This principle is quite popular in data fairness, mainly due to the fact that in some realistic situations, such as hiring processes, we want to stress that human performance or qualifications

are totally independent from certain other innate attributes, such as gender or ethnicity.
Anyway there is a drawback: it may happen that if we choose randomly people from a subcategory and qualified people from another subcategory, we can still satisfy independence, even though the random subjects might be people with far lower qualifications.

4.2.4.2 | Separation

Since in practical contexts we often have a correlation between the target variable and the sensitive attribute (e.g. one age category may have lower or higher probability to get a loan, due to banks business reasons), then there could be allowed a correlation between the prediction and the sensitive attribute, conditionally to the target variable Y. Namely, $R \perp A \mid Y$.
This principle implies both true positive rate parity and false positive rate parity and in some situations it is considered more helpful than independence because it aims to reduce errors uniformly in all subgroups.
However, the main ethical compromise in achieving this principle is that it may arise gaps between subgroups: for instance, if we have high qualified subjects in one group and low qualified subjects in another, while satisfying separation, we will give better outcomes to the first group. This might lead to amplify social gaps between the two groups, because the first one could result in have more disposable income, which would be transferred to their children, who will reinforce the population of their parents' group as adults. This is a sort of *echo chamber* that may lead to amplify social discrepancies.

4.2.4.3 | Sufficiency

This principle is achieved if the target variable is independent from the sensitive attribute, conditionally to the prediction $Y \perp A \mid R$. In particular, when we work with a binary classification, we satisfy this condition by requiring a of positive/negative predictive value parity across all subgroups.
Even sufficiency, as separation, may not help reducing the gap between two different groups, for similar reasons.

In a perfect situation, the best goal would be reaching all the three criteria at the same time, but they imposes complex constraints on the distribution D, therefore they are mutual exclusive, as we show below.
But if all the criteria cannot be satisfied at the same time, how can we get fairness? The proper answer will be reaching an optimal trade-off between these three principles.
We analyse pairwise the relationships between the criteria:

4.2.4.4 | Independence $\longleftrightarrow$ Sufficiency

These two criteria cannot both hold, under the assumption that A and Y are not independent, hence $A \not\perp Y$. We have to bear in mind that this is not a restrictive assumption, but the most common situation in real cases: usually the sensitive attribute is related to the target, that means having higher positive outcomes in a subgroup than in another.
By this assumption, it is trivial the implication:

$$A \not\perp Y \implies A \not\perp R \mid Y \; or \; A \not\perp R.$$

That means: if A depends on the target Y, then either A depends on the classifier conditionally to the target *or* it does not depend on the classifier at all (target and classifier are obviously always dependant).
$proof$: we can demonstrate it by reducing to absurd. Let assume that both sufficiency and independence holds, then

$$A \perp Y \mid R \; and \; A \perp R \implies A \perp (Y, R) \implies A \perp Y$$

which is absurd due to our original hypothesis.

4.2.4.5 | Independence $\longleftrightarrow$ Separation

Also in this case, Independence and Separation cannot both hold, but besides the previous assumption of $A \not\perp Y$ we have to add that Y is binary to prove the mutual exclusion. As before, it is also taken for granted that $R \not\perp Y$, like in realistic classification problems.
$proof$: let assume instead that both independence and separation holds

$$A \perp R \, and \, A \perp R \mid Y$$

For the theorem of total probability,

$$\mathbb{P}(R = r \mid A = a) = \sum_y \mathbb{P}(R = r \mid A = a, Y = y) \cdot \mathbb{P}(Y = y \mid A = a)$$

then by the assumption of independence and separation, it becomes

$$\mathbb{P}(R = r) = \sum_y \mathbb{P}(R = r \mid Y = y) \cdot \mathbb{P}(Y = y \mid A = a)$$

As well for the theorem of total probabilities we can say

$$\mathbb{P}(R = r) = \sum_y \mathbb{P}(R = r \mid Y = y) \cdot \mathbb{P}(Y = y)$$

Hence, we can equalize the summations

$$\sum_y \mathbb{P}(R = r \mid Y = y) \cdot \mathbb{P}(Y = y \mid A = a) = \sum_y \mathbb{P}(R = r \mid Y = y) \cdot \mathbb{P}(Y = y) \tag{4.1}$$

but in case of a binary target, this equation is satisfied if $A \perp Y$ or $R \perp Y$ (this is not an exclusive or).
Indeed, on the one hand,

$$\mathbb{P}(Y = y \mid A = a) = \frac{\mathbb{P}(A = a \mid Y = y) \cdot \mathbb{P}(Y = y)}{\mathbb{P}(A = a)}$$

then the equation

$$\sum_y \mathbb{P}(R = r \mid Y = y) \cdot \frac{\mathbb{P}(A = a \mid Y = y) \cdot \mathbb{P}(Y = y)}{\mathbb{P}(A = a)} = \sum_y \mathbb{P}(R = r \mid Y = y) \cdot \mathbb{P}(Y = y)$$

holds if and only if

$$\frac{\mathbb{P}(A = a \mid Y = y)}{\mathbb{P}(A = a)} = 1$$

that means

$$\mathbb{P}(A = a \mid Y = y) = \mathbb{P}(A = a) \cdot \mathbb{P}(Y = y)$$

namely $A \perp Y$.
On the other hand, since we considered Y as binary, we can develop the summation for $y = 0$ and $y = 1$. The left term will be

$$\mathbb{P}(R = r \mid Y = 1) \cdot \mathbb{P}(Y = 1 \mid A = a) + \mathbb{P}(R = r \mid Y = 0) \cdot (1 - \mathbb{P}(Y = 1 \mid A = a))$$

and the right

$$\mathbb{P}(R = r \mid Y = 1) \cdot \mathbb{P}(Y = 1) + \mathbb{P}(R = r \mid Y = 1) \cdot (1 - \mathbb{P}(Y = 1))$$

Then if we equalize these two terms as in 4.1, we get

$$\mathbb{P}(Y = 1) \cdot k = \mathbb{P}(Y = 1 \mid A = a) \cdot k$$

where $k = \mathbb{P}(R = r \mid Y = 1) - \mathbb{P}(R = r \mid Y = 0)$.
This equation can be satisfied if $A \perp Y$ (as we already said), because $\mathbb{P}(Y = 1 \mid A = a) = \mathbb{P}(Y = 1)$, or if $k = 0$, that is $R \perp Y$.
In both case, this result is absurd, since it denies the hypothesis, then it is not possible to assume both $A \perp R \; and \; A \perp R \mid Y$.

4.2.4.6 | Separation $\longleftrightarrow$ Sufficiency

Both Separation and sufficiency implies non-trivial restrictions for A, R and Y. If all the restrictions hold, we end up in a degenerate solution space.
$proof$: we already proved that, if either sufficiency or separation holds, then independence cannot hold, therefore $A \not\perp R$.
When both sufficiency and separation hold, the following property of conditional independence should be valid

$$A \perp R \;\; Y \; and \; A \perp Y \;\; R \Longrightarrow A \perp (R, Y)$$

under the assumption that all events have positive probabilities, as it is showed in [52].
It is then trivial the implication

$$A \perp (R, Y) \implies A \perp R \, and \, A \perp Y$$

but it cannot be possible due to implausible independence principle.

4.3 | Bias mitigation techniques

We have already analyzed in previous chapters the significance of biases, their types and how can they affect fairness in data science. In this section we will focus on some bias mitigation techniques: in particular, these are usually divided in three main groups, based on where in the machine learning pipeline they are exploited. Then we have **pre-processing** techniques when we apply the bias mitigation algorithm on the training data; **in-processing** techniques if we want to modify the model during its training and get a fairer machine learning algorithm; **post-processing** techniques to mitigate bias on the already predicted labels.
Another way to classify the bias mitigation methods could be based on which fairness criterion or fairness metric they are trying to satisfy, but this might result in an categorization overlay.
In addiction, we will not depict all the existing state-of-the-art techniques, so the following list will not be exhaustive, but we will mainly focus on **balancing data** and other methods that are implemented and available in IBM AIF360 R package.
There is a principle in information theory called **data processing inequality** that declares any data process as a possible source of loss of information. In no cases there is the possibility to get new information from a data processing. Moreover, in the best situation, you can only equalize the amount of information throughout the process. Thus, for all the following techniques we cannot expect not to lose *information*, by meaning with this term all the data characteristics that they had before the technique application.
On account of the high evolution rate of new algorithm and resources for big data, and due to the already remarkable quantity of possible techniques combinations, how can we optimally chose a bias mitigation strategy? First of all, we have to focus on the step of ML process where we can take action, since most of the time we can only modify our data in post-processing. However, if we have *carte blanche*, it might be a good strategy to combine different types of processing algorithms together, as for the Fairway method [13], which proposes a combination of pre-processing and in-processing bias mitigation.
Although we may think that the more strategies we put together, the highest fairness we get, this is a deceptive conjecture. Indeed, we have to bear in mind that some algorithms focus on different fairness criteria (e.g. $reweighing$ algorithm is based on the independence criterion, whereas $disparateinpactremover$ on separation) and we already showed how independence, sufficiency and separation are mutually incompatible. When we used multiple algorithms, we

should check their cumulative performance, compared to the individual one, because it could be possible they interfere one another.
As a rule of thumb, we should deal with post-processing algorithms only in case we are not allowed to interfere with the ML process in advance (the earliest intervention, the best results).
In conclusion, there are no unique effective strategies to be applied in terms of fairness: for each dataset we have to make specific and different considerations in order to take into account all the possible case limitations.

4.3.1 | Pre-processing

4.3.1.1 | Balancing

Providing unbalanced data to a classifier can make them biased towards the majority class, basically because the classifier does not have enough data to learn more about the minority. Since it is quite frequent to have an imbalanced dataset, we can many research in literature about this problem. Specifically, some studies [40] [41] have shown that for some classifiers a balanced dataset provides an enhancement in classification performance, rather than the imbalanced one. However, some other studies [9] [33] on the contrary, studies have also proved that classifiers modelled on some imbalanced datasets do not show performance differences (not even relevant performance decrease) to classifiers modelled on the same balanced data. Consequently, previous research suggests always to rebalance data when they are highly skewed, by using one of the several available resampling techniques, such as random sampling methods, cost-sensitive methods, kernel-based methods, and active learning methods [28]. In fact, these methods can be divided into two groups: (1) based on re-sampling or combinations and (2) based on algorithmic strategies, as cost-sensitive and boosting.
In particular, in our experiment we used two basic sampling methods, with no algorithmic approach: random sampling and **synthetic minority oversampling technique** (SMOTE), which include both undersampling and oversampling.

- **Random sampling**: it consists in the random removal or addiction of instances of the majority or minority class to achieve the exact number of individual for each group. alternatively, it is possible as well to decide a specific and different proportion of subjects for each group, so that data will be amplified or reduced accordingly.
  Basing on add or subtract instances, we call it upsampling/oversamling or downsampling/undersampling respectively.
  This technique might have relevant side effects: downsampling can potentially lead to loss of information, while oversampling can result in overfitting, due to the fact that it exactly replicates the minority samples and it introduces redundancy.

- **SMOTE**: it is an re-sampling approach in which the minority class is oversampled by

creating synthetic examples instead of random over-sampling with replacement.
The oversampling rests on generating synthetic examples by using k minority class nearest neighbors, in the following way:

1. Take the current feature vector (sample) and evaluate the difference between it and its k nearest neighbors.
2. Multiply these differences by a random number between 0 and 1, and add it to the current feature vector. This step can be interpreted as a selection of a random point along the line segment between two specific features.

Figure 4.1 offers a visualisation of how it works.

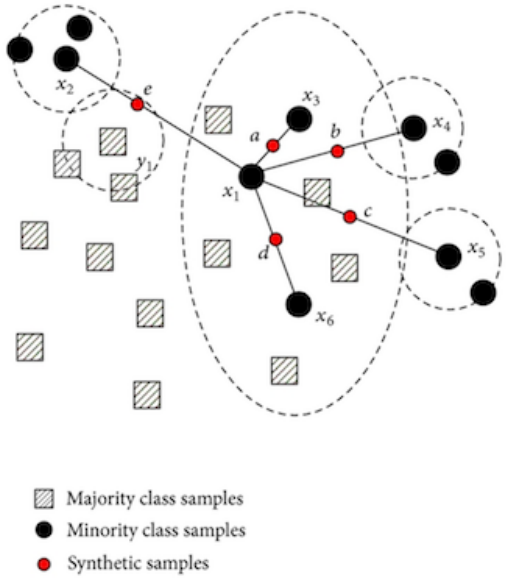


Figure 4.1: SMOTE visualisation - extract from [30]

See algorithm 1 for a SMOTE pseudo-implementation.

Algorithm 1 SMOTE algorithm

Require: n = number of minority class samples
$perc$ = amount of SMOTE oversampling/undersamplig % between 0 and 100
k = number of nearest neighbours
Ensure: $(perc/100) \cdot n$ synthetic minority class samples
▷ If $perc$ is less than 1, select randomly only a percentage of samples in the minority class
if $n < 100$ **then**
  $n = (N/100) \cdot n$
  $perc = 100$
else
  $numAttributes$ = number of attributes
  $Sample[\,][\,]$: array for original minority class samples
  $index$: index for counting the number of new synthetic samples, initialized to 0
  $Synthetic[\,][\,]$: array for new synthetic samples
▷ Compute k nearest neighbors for each minority class sample
  for $i = 1$ **to** n **do** ▷ Compute k nearest neighbors for i; save the indices in $nnArray$
    Populate$(perc, i, nnArray)$ ▷ See procedure below
  end for
end if
▷ Procedure to generate the synthetic samples:
procedure Populate($perc, i, nnArray$)
  while $n \neq 0$ **do**
▷ Choose a random number between 1 and k, call it nn, to randmly select one of the k nearest neighbors of i
    for $j = 1$ **to** $numAttributes$ **do**
      $diff = Sample[nnArray[nn]][j] - Sample[i][j]$
      gap = random number between 0 and 1
      $Synthetic[index][j] = Sample[i][j] + gap \cdot diff$
    end for
    $index++$
    $perc = perc - 1$
  end while
return
end procedure

5

Case studies

The experiment is based on two datasets and its aim is to research on bias and bias mitigation. For each dataset we proceed in the following parallel way:

1. **Data exploration**: we firstly made data exploration for each dataset, then we used logistic regression to model the prediction on the binary attributes we were interested into (crime recidivism or drug consumption).
2. **Fairness metrics**: after classification, we analysed and compared the fairness metrics available in R `fairness` package. By means of this evaluation, we identified the sensitive attribute that got the mean worst performance in terms of fairness.
3. **Bias mitigation**: we performed on the dataset one or more bias mitigation techniques describes in chapter 4 and we evaluate again the fairness metrics, focusing on the identified attributed at step 2. Then we compared them to the ones of the original dataset.
4. **Comparisons**: we drew our comparative conclusions between the different types of mitigation and the different datasets.

5.1 | Datasets

5.1.1 | COMPAS

5.1.1.1 | Context description

The COMPAS case is a scandalous case of software discrimination, which owns its notoriety to ProPublica, an independent no-profit organization that aims to produce investigative journalism in the public interest.
In 2016 ProPublica collected the risk scores assigned to more than 7,000 people arrested in Broward County, Florida, between 2013 and 2014. They conducted an accurate study [34] in order to prove that the software used to evaluate risk assessment by the law enforcement

was biased against black people. Their analysis showed that scores for white court defendants were skewed toward lower-risk categories, while Scores for black defendants were not. Risk assessments are quite common yardsticks in U.S.A. courtrooms: they can have a relevant role in decisions about whether or not a criminal (or alleged criminal) can be set free in the criminal justice system, by giving the assessments results to judges during sentences. It is also frequent in many jurisdictions to adopt a risk assessment software before rigorously testing whether it works.
The risk assessment tool was developed by a for-profit company, Northpointe, which never made available to the public the algorithm source code or the calculations used to get defendants' risk scores, hence it was impossible for the people involved in the case to assess what might have drawn the disparity.It assigns risk scores between 1 and 10, which indicate their likelihood of committing a violent crime based on more than 100 factors, including age, gender, and criminal history. In particular, ProPublica revealed that blacks were almost twice as likely as whites to be labeled as higher risk subjects, without in fact re-offend. On the other hand their research stand also that whites were much more likely than blacks to be labeled lower risk, with actual recidivism.
This tool had then a high impact on several people's lives: some judges preferred to evaluate the cases without relying on it, but some other totally reckon on this automated tool, sentencing people for longer prison detention or releasing other in advance, regardless of fairness.

5.1.1.2 | Data exploration and classification:

We took an already cleaned COMPAS dataset, available in the package `fairness` for R.
The dataset has 6172 entries and the following 9 variables:

- **Two_yr_Recidivism**: yes/no for recidivism or no recidivism. This is the outcome or target in this dataset.
- **Number_of_Priors**: number of priors, normalized to mean 0 and standard deviation 1.
- **Age_Above_FourtyFive**: yes/no for age above 45 years or not.
- **Age_Below_TwentyFive**: yes/no for age below 25 years or not.
- **Female**: female/male for gender.
- **Misdemeanor**: yes/no for having recorded misdemeanor(s) or not.
- **ethnicity**: Caucasian, African American, Asian, Hispanic, Native American or Other.
- **probability**: predicted probabilities for recidivism, results from a classification made by the authors of the `fairness` package, ranges from 0 to 1.
- **predicted** binary predicted values for recidivism, 0/1 for no/yes.

Since the aim of this research is not to study Northpointe software fairness, nor any other already-existing algorithms fairness, we firstly deleted the columns 'predicted' and 'probability', because we want to use our own classification results.
Then, we merge the two age variables into one single column made of three options: under25/over45/between25_45.
We also substituted 'yes/no' in 'Two_yr_Recidivism' with 'Yes_recidivism' and 'No_recidivism' to be more clear: indeed, 'Yes_recidivism' will be our *unfavorable* outcome, and 'No_recidivism' the *favorable* one.
Now the dataset appears as in table 5.1.

Table 5.1: COMPAS dataset first rows

	Two_yr_Recidivism	Number_of_Priors	Female	Misdemeanor	ethnicity	Age
4	No_recidivism	-0.68	Male	yes	Other	between25_45
5	Yes_recidivism	2.27	Male	no	Caucasian	between25_45
7	No_recidivism	-0.68	Female	yes	Caucasian	between25_45
11	No_recidivism	-0.68	Male	no	African_American	between25_45
14	No_recidivism	-0.68	Male	yes	Hispanic	between25_45
24	No_recidivism	-0.68	Male	yes	Other	between25_45

There are three sensitive attributes to work on: Female, ethnicity and Age.
In addiction, we can visualise the subgroups distributions with the following pie charts (figure 5.1) we see how these attributes are balanced or imbalanced in the dataset. As we can notice, the dataset is imbalanced: there are evidently more male than female, more subjects between 25 and 45 years old and some ethnicity categories are underrepresented, such as Asian, compared to African American or Caucasian.
However, our target variable seems quite balanced: we have nearly the same amount of recidivists and non-recidivists in our data.
We would like to find the most common combination of the three attributes, both in terms of recidivism and non-recidivism. Hence, we prepared an ordered table in figure 5.2 for combinations on recidivists and another one 5.3 for combination on non-recidivists.

In these two tables we can read an absolute count of the rows with that specific sensitive attribute combination, but we still do not know which is the relative weight that the combination has on the entire dataset, or among all the recidivists/non-recidivsts, yet the percentage of incidence of yes (respectively no) recidivism on that specific combination.
Therefore, we plotted, for each combination of these attributes, the percentages of recidivists and non-recidivists on the whole dataset (figure 5.2a and 5.2b), then on the total number of

Table 5.2: COMPAS dataset Yes_recidivism frequent combinations (first rows)

	Age	ethnicity	Female	count
24	between25_45	African_American	Male	855
14	below25	African_American	Male	427
27	between25_45	Caucasian	Male	371
2	above45	African_American	Male	176
17	below25	Caucasian	Male	146
6	above45	Caucasian	Male	135
23	between25_45	African_American	Female	123
26	between25_45	Caucasian	Female	112
29	between25_45	Hispanic	Male	91
13	below25	African_American	Female	64

Table 5.3: COMPAS dataset No_recidivism frequent combinations (first rows)

	Age	ethnicity	Female	count
20	between25_45	African_American	Male	708
24	between25_45	Caucasian	Male	490
5	above45	Caucasian	Male	351
11	below25	African_American	Male	237
2	above45	African_American	Male	223
19	between25_45	African_American	Female	212
23	between25_45	Caucasian	Female	155
26	between25_45	Hispanic	Male	148
14	below25	Caucasian	Male	128
4	above45	Caucasian	Female	107

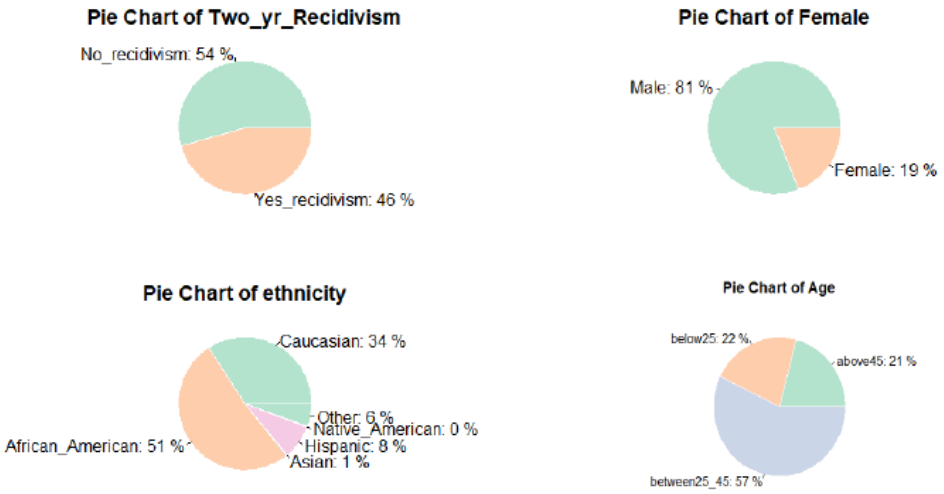
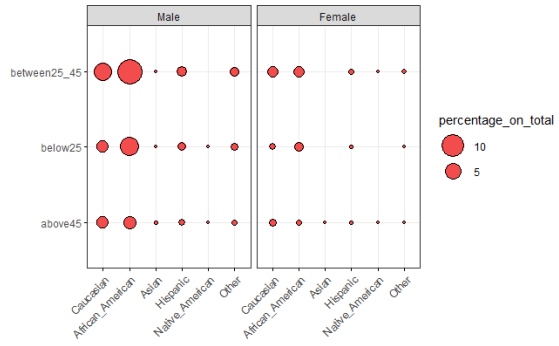
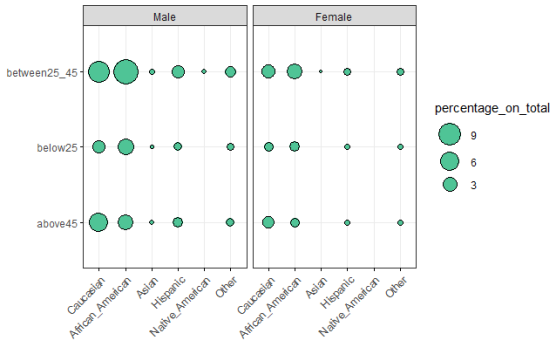


Figure 5.1: COMPAS categorical variables distributions

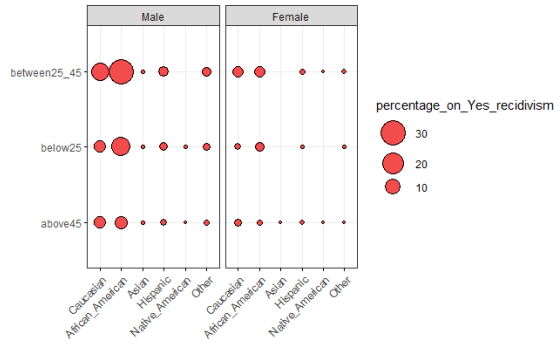
recidivists or non-recidivists of the dataset (figure 5.2c and 5.2d) and on the total amount of subjects for each combination(figure 5.2e and 5.2f). In the graphs we used always red color for the recidivists and green color for non-recidivists. We can notice that the first couple and the second couple of graphs show almost the same trend: this is due to the fact that the first couple of graphs plots the percentage on the whole data, while the second couple plots the percentage on all the recidivists 5.2c and on all the non-recidivists 5.2d, but we have already noticed that there is nearly the same number of recidivists and non-recidivists in the dataset. Morover, as confirmation of the unbalancing, in the first two couple of graphs we see higher percentages for males, in particular Caucasian and African-American.
The most interesting visualisation is given by the last couple of graphs: here we see, for instance, that the Caucasian males under 25 are more commonly recidivists than non-recidivists, but it is also evident that the African-American males under 25 have far more tendency to recidivism than no-recidivism. Indeed, it is quite remarkable the overall higher percentage of recidivism for the below 25 age category, while, concerning to males and females in-within each graph, we do not have any considerable difference.
Anyway, the differences between recidivism and no-recidivism on the ethnicity lines are what drew our attention the most: if we compare the two graphs, all in all we have truly different balloon sizes for male African-Americans, for male and female Native-Americans or for all Asians. On the contrary, all the Caucasians seem to have approximately the same percentages for each of them combinations (both for recidivism and no-recidivism).
Accordingly to these reports, we may expect some degrees of unfairness for our classifier, whatever model we will choose. Indeed, if we train our model on skewed sensitive data, it is highly probable to get unfairness.



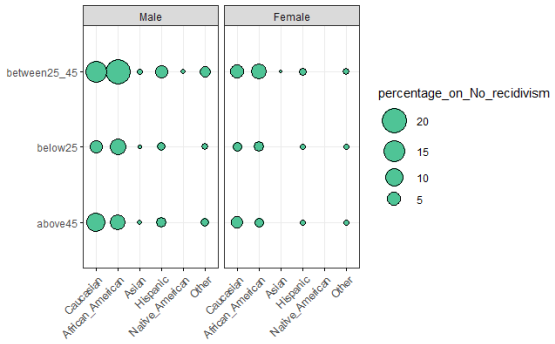
(a) % of Yes_recidivism on all data for each combination



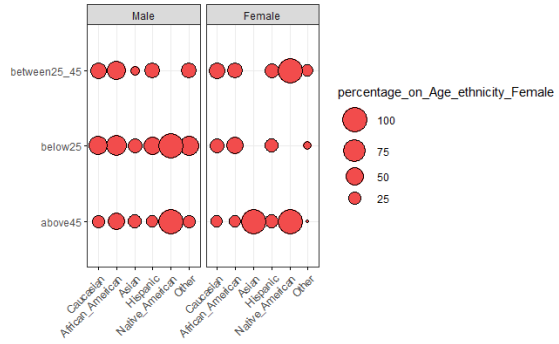
(b) % of No_recidivism on all data for each combination



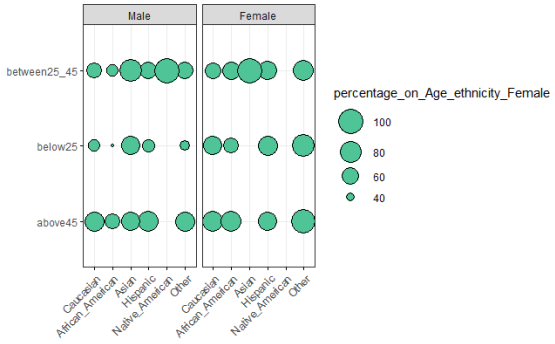
(c) % on Yes_recidivism for each combination



(d) % on No_recidivism for each combination



(e) % of Yes_recidivism on each combination



(f) % of No_recidivism on each combination

Figure 5.2: IMAGE RECIDIVISM ON DIFFERENT COMBINATIONS

Since we have only categorical data, except for the number of priors, we will focus our interest on the possible relationships among the sensitive categorical attributes. We performed the Pearson's Chi-square test and we plotted the residuals in a corrplot, for different attribute combinations. We reported here in figure 5.3 the resulting Pearson's Chi-square test graphs, to understand how the three sensitive attributes are related to the target.

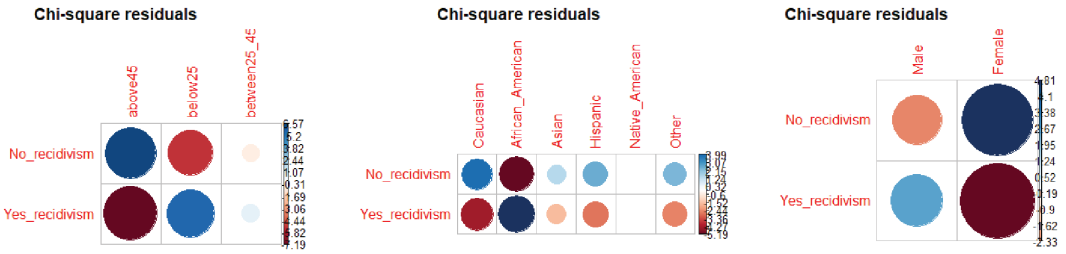


Figure 5.3: COMPAS Pearson's Chi-square test

Positive residuals are in blue: these values in cells specify an attraction (positive association) between the corresponding row and column variables. Negative residuals are in red: this implies a repulsion (negative association) between the corresponding row and column variables.
As we already noticed previously, there is a strong association between Age below 25 and recidivism and between African-American and recidivism. Now, we can also observe that there is a relevant positive correlation also for females and no-recidivism as for other age or ethnic categories.
In our test we got $p - value < 2.2 \cdot 10^{-16}$ for both Age category and ethnicity; $p - value = 2.898 \cdot 10^{-15}$ for gender attribute, namely all significantly low values, so that we could reject the null hypothesis of independence among variables.

5.1.1.3 | Classification

As we already mentioned in chapter 4, we used logistic regression to make our own predictions. We randomly sampled our data: 70% as training test and 30% as test set. We used R `seed()` function to make the experiment repeatable, so that we have the same results at each run time.
We chose to use an optimal cutoff for the predicted probabilities: locating the cut-off point requires a compromise between sensitivity (TNR) and specificity (TPR) and we found it by equalizing their two curves, as in figure 5.4. In fact, there are several approaches to this problem, but this is one of the most frequently used criterion for determination of the test cutoff value: this point of the curve is where the product of these two indices ($Sensitivity \cdot Specificty$) is maximum (see [25]).

Once we found the optimal cutoff we defined the predictions and the resulting confusion matrix was the one in figure 5.5.

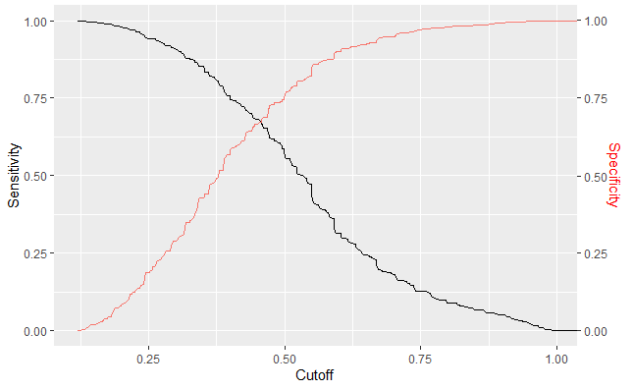


Figure 5.4: COMPAS sensitivity and specificity curves

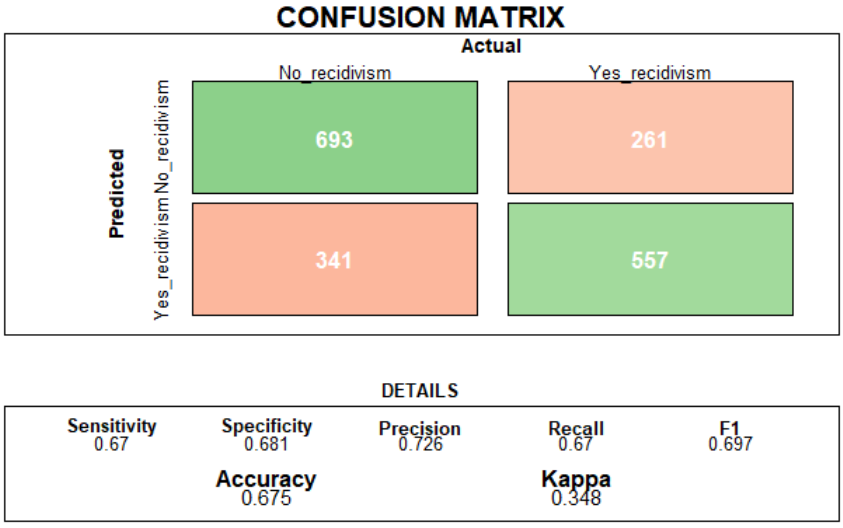


Figure 5.5: COMPAS linear regression confusion matrix

Choen's Kappa is quite good, we can consider it as 'fair' regarding Choen's suggestions. The accuracy is the ratio of correct predictions to total predictions made and it is close to 70%, then it is acceptable. Among the other measures, we see F1 score, which is more explicating than the others, but also not so useful, since our target was quite balanced from the beginning. An F1 score reaches its best value at 1 and worst value at 0, then in this case is similar to accuracy and we can take it as acceptable.
Lastly, we plotted the density of the predicted probabilities for each sensitive attribute (figure 5.6).
The vertical line represents the optimized cutoff: we can clearly notice that some subcategories are more likely classified as recidivists, such as age below 25, while some others are predominantly classified as non-recidivists, like Asians.
In the following section we will try to understand which is the most mistreated sensitive attribute, hence the one for which we have highest unsatisfied fairness metrics parity.

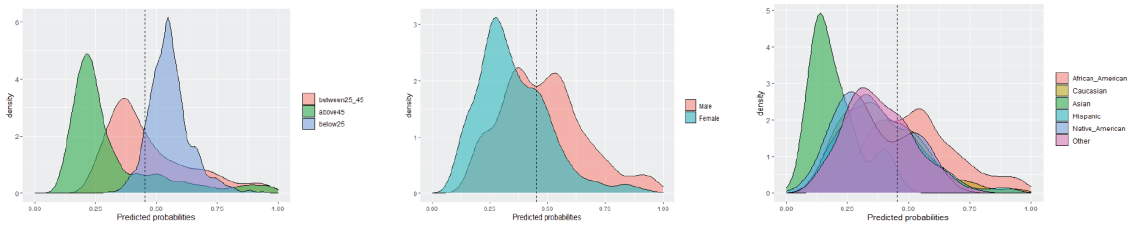


Figure 5.6: COMPAS predicted probabilities' densities

5.1.1.4 | Fairness metrics

For fairness analysis we took advantage of the `fairness` package in CRAN for R language. This library gives the possibility to have absolute and relative values for each of the fairness metrics described in chapter **??**. The relatives values are compared to a base subcategory, that can be chosen indistinctly, since it will be given the value to this base subcategory and a comparative value to all the others. The objective of the parity metrics will be having approximately the same values for each subcategory (figures 5.7, 5.8, 5.9), therefore when we plot the relative values for each subcategory, for each metric, we desire to have all of them as close as possible to value 1. However, this goal is evidently not reached and there are subcategories for which barplots are even missing in some metrics, probably due to under-representation in the dataset. In fact, later we will see that when we balance these sensitive attributes, we will not get this kind of issue.
All the fairness metrics numerical values are available in appendix B.

Come this far, how can we detect the sensitive attribute in which we have the most mistreated subcategories in terms of fairness? We compared the delta-percentages for each fairness metric pairwise with respect to the sensitive attributes, then the worst results are the ones we obtained by comparing ethnicity to the other two sensitive attributes, as in figures 5.10a and 5.10b. In order to make this comparisons we attributed a value for each fairness metric plot in figures 5.7-5.8-5.9 by calculating the mean signed deviation for each subcategory to the value 1. Then we compared these values of one attribute to the ones of the others.
In table 5.4 there are the values of ethnicity compared to Female and in table 5.5 there are the ones of ethnicity compared to Age. We reported here only these two, as the most significant ones.
In both cases there are few ethnicity fairness values that are better than the ones for the other sensitive attributes. We can observe in particular that the NPV parity is extreamly lower for ethnicity than the other attributes (even nearly 1500% less). How is it possible? If we look at the single fairness metrics plots for ethnicity, we can see that Native Americans have an almost doubled value than Caucasian and Asians are considered as 0 value, even though, to be more precise, there were not enough Asians to get this metric value for this subcategory: indeed, the actual calculated value is 'NaN' (see numerical values in appendix B, that means

Figure 5.7: COMPAS fairness metrics Age

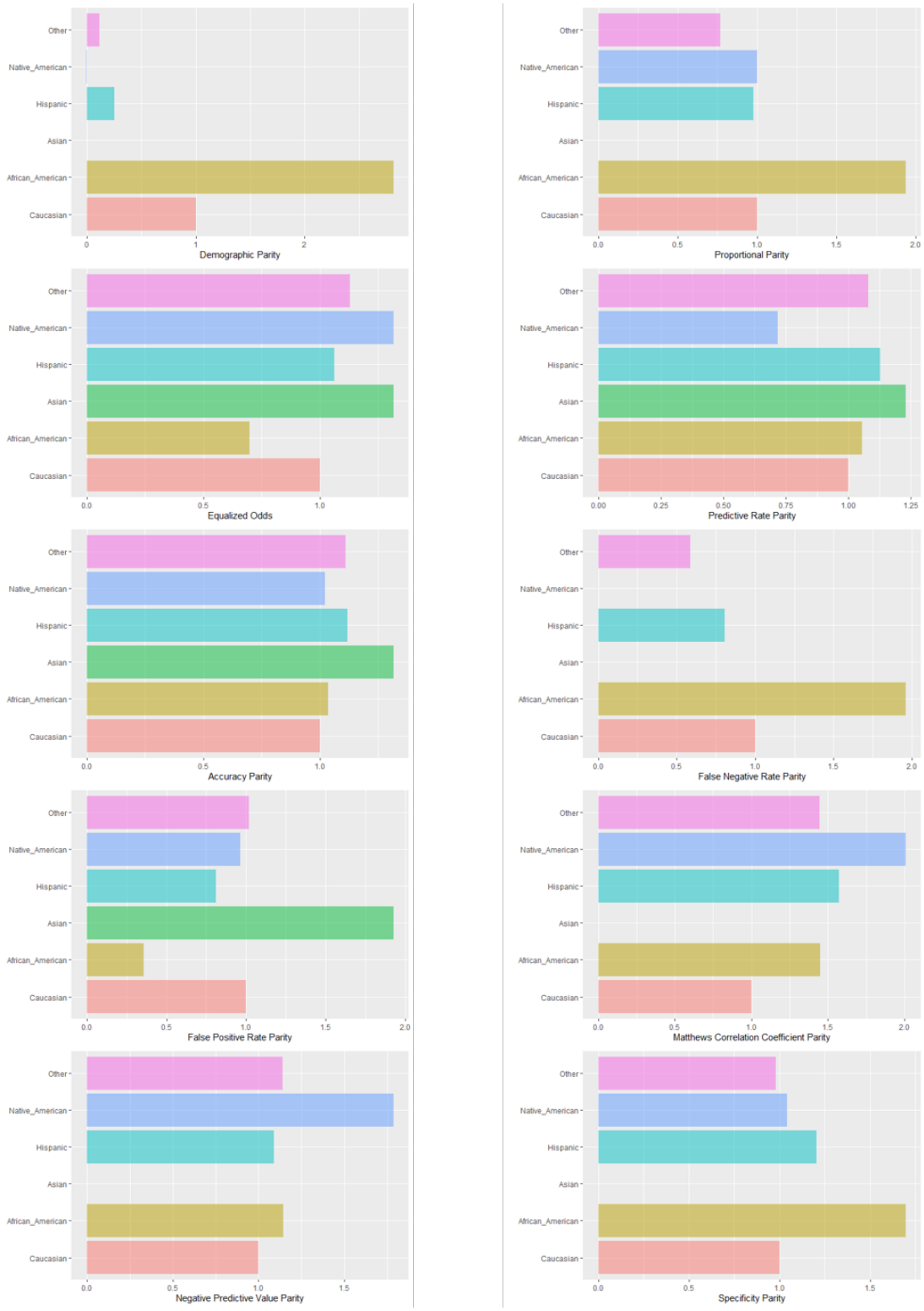


Figure 5.8: COMPAS fairness metrics ethnicity

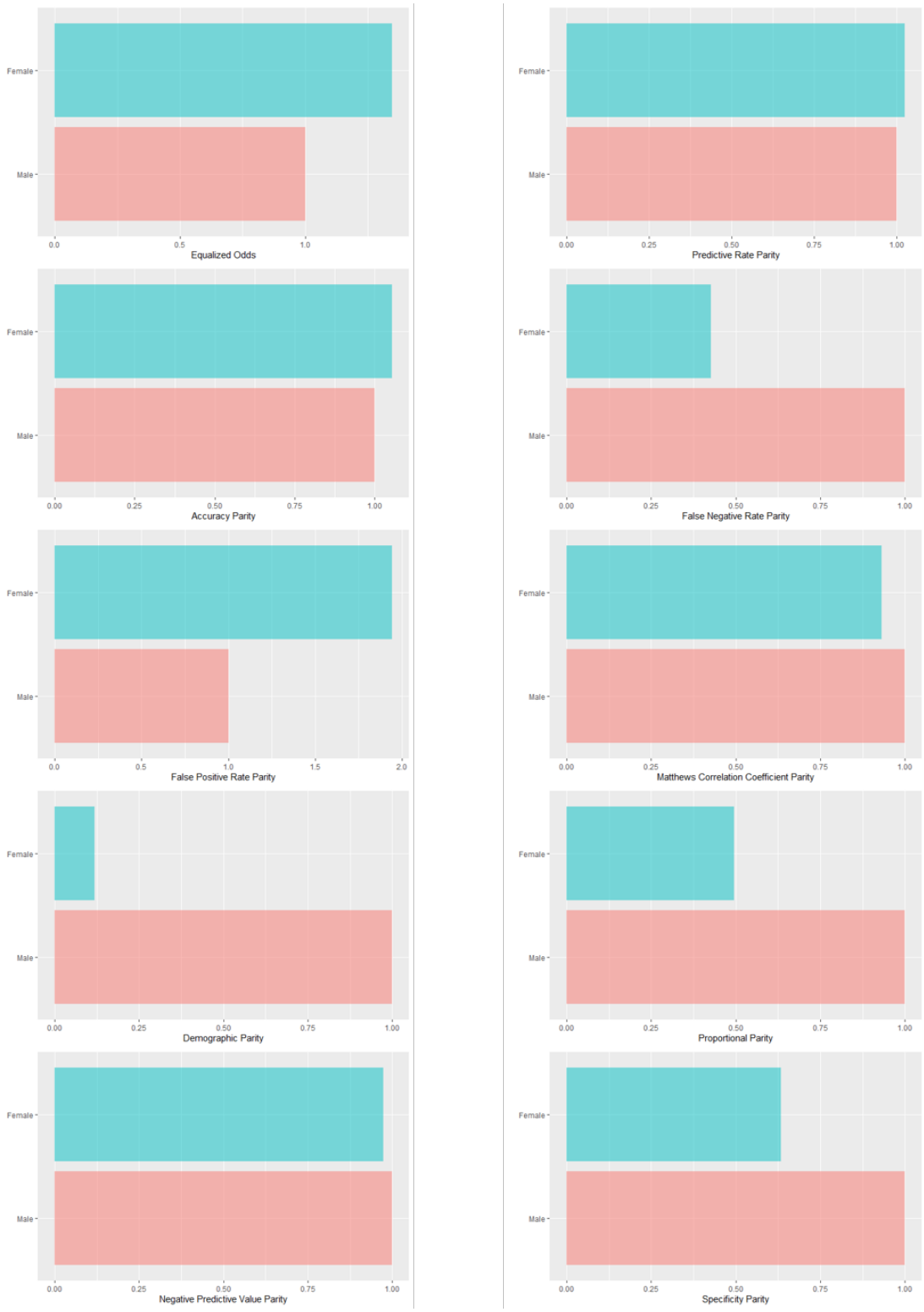


Figure 5.9: COMPAS fairness metrics Female

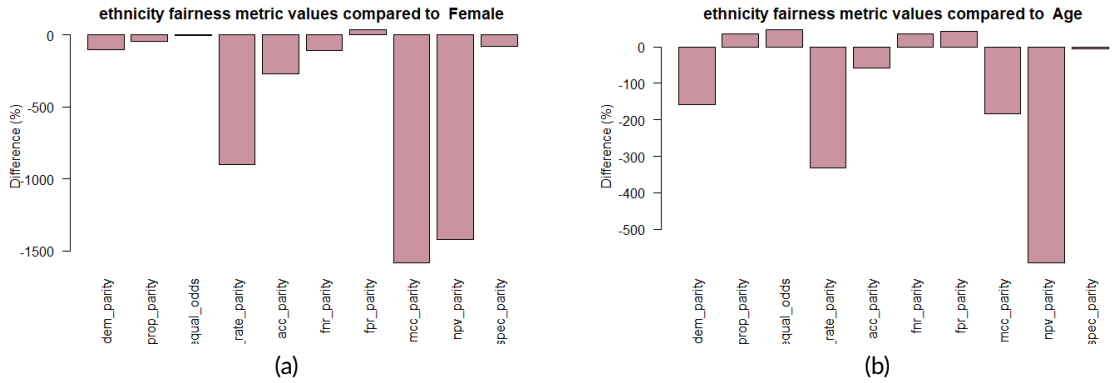


Figure 5.10: Fairness metric values of ethnicity compared to: (a) Female and (b) Age.

Table 5.4: COMPAS ethnicity VS Female fairness metrics mean signed deviations (% values)

dem_parity	prop_parity	equal_odds	pred_rate_parity	acc_parity
-105.38	-44.48	-7.79	-902.96	-271.60
fnr_parity	**fpr_parity**	**mcc_parity**	**npv_parity**	**spec_parity**
-107.37	35.93	-1580.76	-1418.87	-78.52

Table 5.5: COMPAS ethnicity VS Age fairness metrics mean signed deviations (% values)

dem_parity	prop_parity	equal_odds	pred_rate_parity	acc_parity
-158.48	35.96	47.52	-332.90	-58.14
fnr_parity	**fpr_parity**	**mcc_parity**	**npv_parity**	**spec_parity**
36.50	41.76	-184.33	-591.03	-5.64

there were no Asians subjects predicted recidivists (negative class) that were truly recidivists. Overall, this comparison for NPV parities means that there is much more disparity in predicted recidivists that are actual recidivists among ethnic groups than among age/gender categories. Namely if we take randomly an Asian and a Native-American, is much more likely to have an Asian both predicted and actual recidivist and, at the same time, a Native-American predicted recidivist but actually non-recidivists, than a randomly selected male-female couple with the respective same predicted characteristics of the two ethnic subcategories.
Another sensibly low metric difference, especially regarding the comparison to Female, is the mcc-parity: we know that for imbalanced dataset this metric might be not reliable, but our dataset is quite balanced for the recidivism target class, hence we cannot consider MCC as not indicative from the outset. In addiction, MCC takes into account NPV for its calculation, then we could expect it reflects the same trend of NPV parity. This low percentage difference

in MCC parity explains that the classifier (in terms of all TP, FP, TN and FN) could work in much more different ways for the ethnicity subgroups than for the gender subgroups.
The last visibly low metric comparison is the predictive rate parity, that we analysed better under the name of sufficiency: compared to Female in particular, it reaches the 903% less. No improvements for equalized-odds (separation) or for demographic/proportional parity (independence) goes along with this comparative sufficiency decrease. Sufficiency constrains having equal PPV (or equivalently FDR). This relates to the idea of *calibration*, the notion that, between two subgroups, the rate of actual recidivists subjects in the predicted-recidivist-portion (all the predicted recidivists in the dataset) are equal across any two sensitive groups. However, in both graphs, we see a slightly better FPR parity for ethnicity than for the other two attributes: it might reflects as well in a mildly better performance for equalized-odds in ethnicity-Age graph, since it requires both FPR parity and TPR parity. Whereas despite of this fact, in ethnicity-Female graph we have anyway a comparative reduction of equalized-odds metric, probably due to a worse satisfaction of TPR parity for ethnicity than for Female.
In conclusion, for COMPAS dataset we chose to focus on the ethnicity sensitive attributes for further fairness analysis.

5.1.1.5 | Bias mitigation

The first bias mitigation technique that we apply for every dataset is resampling, for rebalancing. We used Shannon index as a metric for detecting changes among our data, bearing in mind that it increases as both the richness and the evenness of the community increase. As we are not modifying the number of species (subcategories), all the Shannon index changes are based on subgroups evenness. Of course, when we balance the data towards an attribute, we will see Shannon index changes within that attribute, but we performed this analysis specifically to observe if these shifts may influence on the others as well.
For COMPAS we created 7 fully balanced datasets and we report for each of them the Shannon index comparison to the original data (see the corresponding references):

- balanced_data0: balanced for Two_yr_recidivism. No relevant improvements in diversity 5.11a, as we expected, since the target was already almost fully balanced.

- balanced_data1: balanced for Female. Of course higher Shannon index value for Female, namely less diversity in this category and higher evenness 5.11b .

- balanced_data2: balanced for ethnicity. Great increase of Shannon index for ethnicity, concurrent with an exceptional raising for Number_of_Priors 5.11c, that reflects in a change of distribution, with slightly lower standard deviation (0.8469448). In this case, we would accept the compromise to lose Number_of_Priors diversity in favor of ethnicity balancing.

- balanced_data3: balanced for Age. Soft increment for Age Shannon index, that goes along with an even higher increment for Number_of_Priors 5.11d.

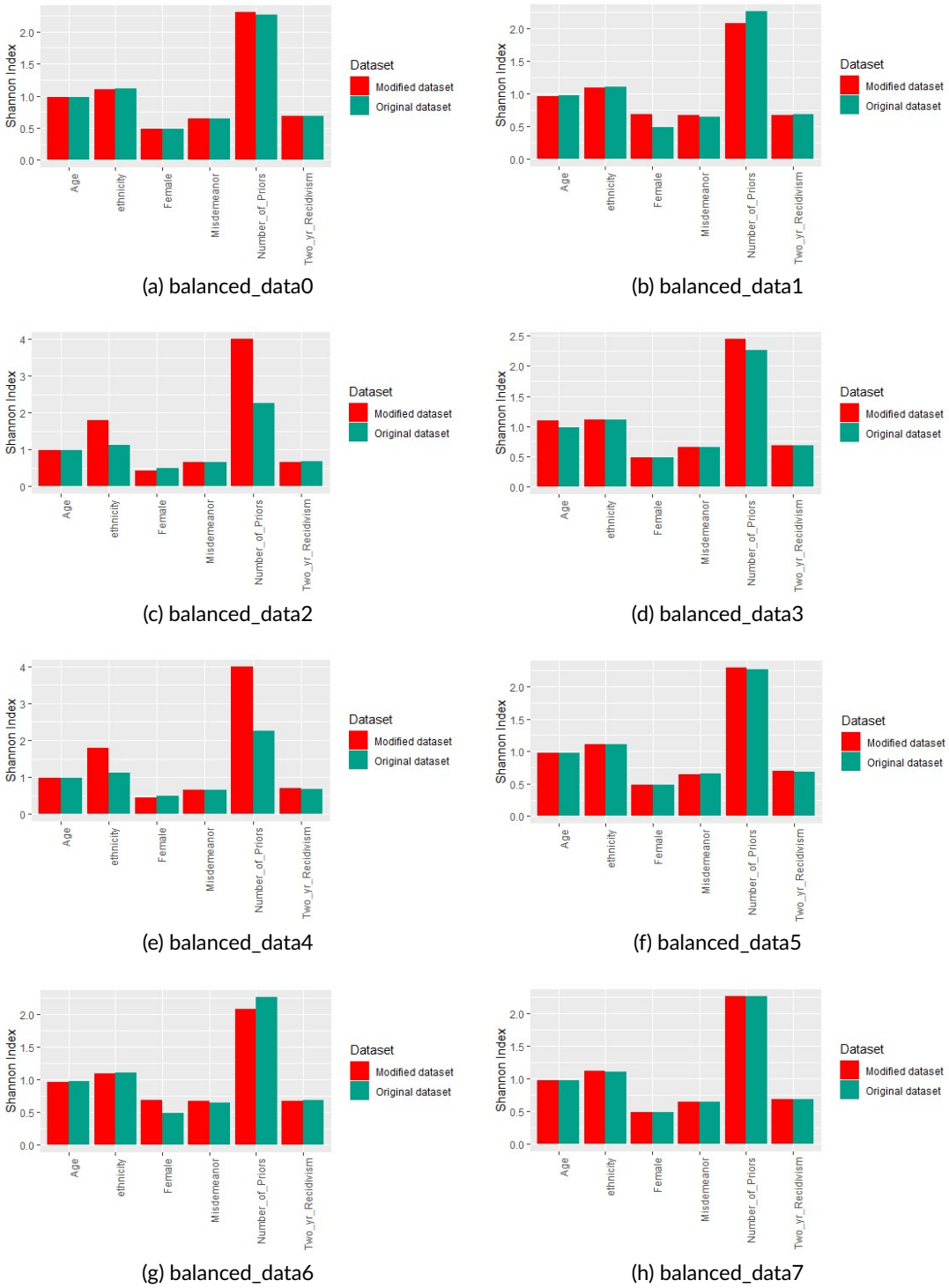
- balanced_data4: balanced for Two_yr_recidivism within each fully balanced subcategory of ethnicity $[Two\_yr\_recidivism|ethnicity]$. We tried this combination to see if we could get better improvements compared to balanced_data2. In fact, the Shannon index results are pretty much the same, except for a very light improvement for Two_yr_Recidivism, but, for instance, no other evident changes for Number_of_Priors or others 5.11e.

- balanced_data5: balanced for Two_yr_recidivism within each unbalanced subcategory of ethnicity. In this case we wanted to assure that the results were pretty much the same as balanced_data0 and indeed it is what we got in terms of Shannon index 5.11f.

- balanced_data6: balanced for ethnicity within each balanced subcategory of Female $[ethnicity|Female]$. Since apart from ethnicity, the second most unbalanced sensitive attribute was Female (as we can notice from balanced_data1), we balanced both female and ethnicity 5.11g. We could have chosen to invert the balancing orders: firstly balancing for ethnicity and then for Female within each already balanced subcategory of ethnicity and we did this in balanced_data7. We decided not to modify the original data with more than two balancing at the same time, because it could have strayed too far from the characteristics of the initial population.

- balanced_data7: balanced for Female within each balanced subcategory of ethnicity $[Female|ethnicity]$. In this case, there is practically no changing for Shannon index 5.11h.

How can we select the balanced dataset for which we get the best fairness performance? For each of them, we performed again classification with logistic regression and then we compared the fairness metrics between the original and balanced datasets. This is not a standard work: actually, we can never say in a deterministic way if a dataset is fairer than another. As we already stressed in the previous chapters, we have to accept compromises, because there is no way to get each kind of fairness equally satisfied at the same time, not even for a single sensitive attribute, not mention all of them. Hence, we decided to focus on ethnicity and we should consider which fairness metric is more relevant for us, depending on the study case we are dealing with. For recidivism classification is it better to lend more weight to independence, sufficiency or separation? This is the question we have to make when we face a data fairness analysis. However, since we have no legal expertise in this sector and this is not the aim of this research, we have addressed our approach to not let prevaricate one fairness criterion on the others. We simply analysed the different fairness metrics and tried to select the balanced dataset which gave us the overall better outcomes.



(a) balanced_data0 (b) balanced_data1

(c) balanced_data2 (d) balanced_data3

(e) balanced_data4 (f) balanced_data5

(g) balanced_data6 (h) balanced_data7

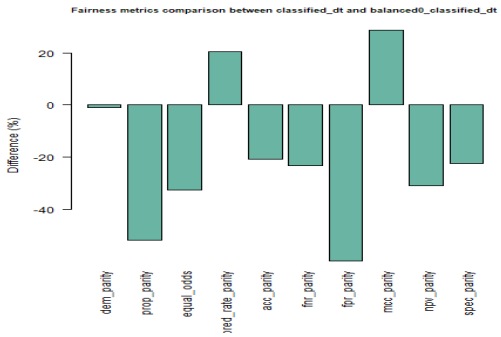
Figure 5.11: Shannon index comparison between original dataset and balances datasets.

5.1.1.6 | Comparisons

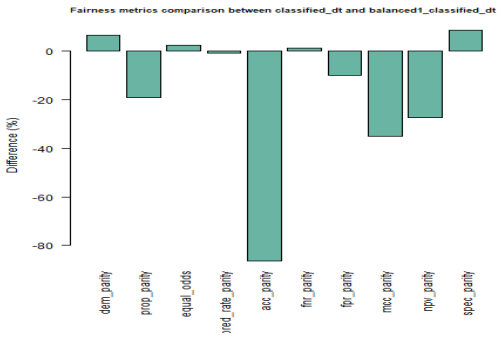
- **Observations on balanced datasets VS original data**:
  In figures 5.12a÷5.12h are reported the most relevant comparisons between different classified datasets, only regarding the ethnicity variable, which is the one we chose as most mistreated.
  As a matter of fact, we get much better results for almost every fairness metric when there is ethnicity fully balanced (figures 5.12c and 5.12e). If we look further, we notice that for 5.12e we lose accuracy parity in favor of higher proportional parity. In this case, both Two_yr_Recidivism and ethnicity are balanced. Keep in mind that these two are both comparisons to the original classified dataset: we get much better values for demographic parity in 5.12e than in 5.12c, but this is not as indicative as proportional parity. Indeed, it is much better to get higher proportional parity values than demographic parity values in terms of fairness, as we explained in 4.
  However, it is noticeable the fact that when Two_yr_Recidivism is fully balanced, the new dataset gives an overall worse fairness performance 5.12a than when Female is fully balanced 5.12b. That is another reason why a balancing combination of Female and ethnicity 5.12g or 5.12h might be more interesting than a combination of ethnicity and recidivism 5.12e.
  The plausible assumption of having similar fairness performance when balancing an attribute such as Two_yr_Recidivism on its own 5.12a and within the subcategories of ethnicity 5.12f is evidently deceptive: in spite of having worse results for some metrics, we got widely different metric values in two cases. Another proof of evidence for this is the comparison between the last two plots 5.12g and 5.12h, both balanced for ethnicity and Female, but in different ways.

- **Observations on selected balanced datasets**:
  After our previous observations, we retrieve indeed that when we focus on ethnicity fairness, the best fairness metrics performances are obtained of course on ethnicity balanced datasets. Hence, we compared the four ethnicity balanced datasets and we report in figure 5.13a÷5.13b the most relevant comparative graphs.
  The immediate deduction is that balanced_data2 does not satisfy Independence for ethnicity groups as much as balanced_data4 does and balanced_data7 does not satisfy Separation as much as balanced_data6 does.

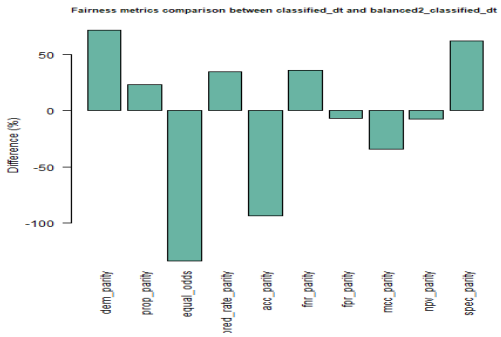
Lastly, in figure 5.14 we have a useful overview of all balanced datasets metric values, split in different graphs for each metric. In this way, it could be immediate the choice of one dataset over another, depending on which metric we want to satisfy the most. For instance, if we need to have false negative rates as similar as possible for each subcategory, it is better to use balanced_data4.
In these graphs we have plotted the mean deviations from perfect fairness for each fairness



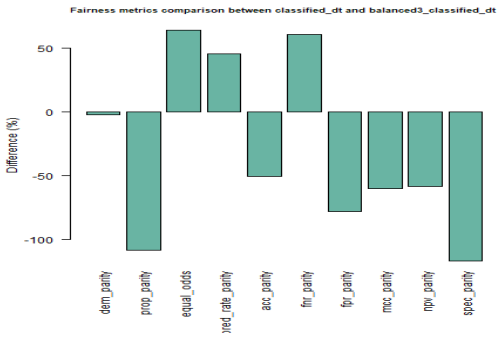
(a) balanced_data0



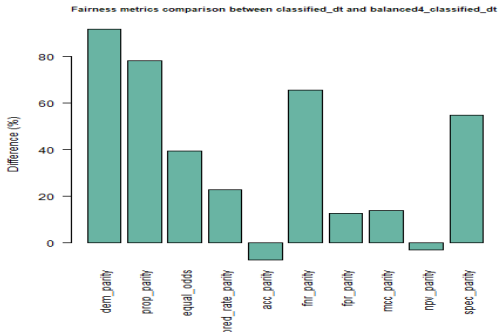
(b) balanced_data1



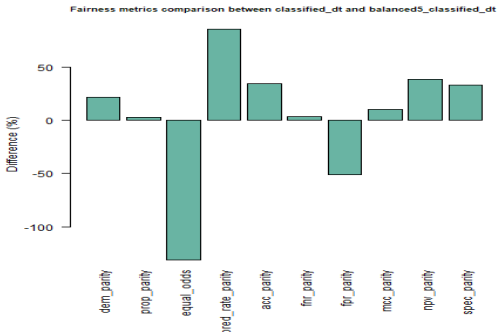
(c) balanced_data2



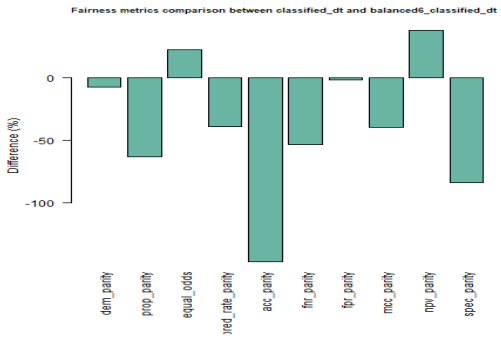
(d) balanced_data3



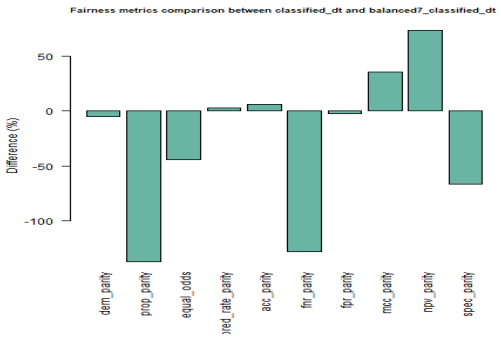
(e) balanced_data4



(f) balanced_data5



(g) balanced_data6



(h) balanced_data7

Figure 5.12: COMPAS fairness metric comparison between balanced datasets and original data.

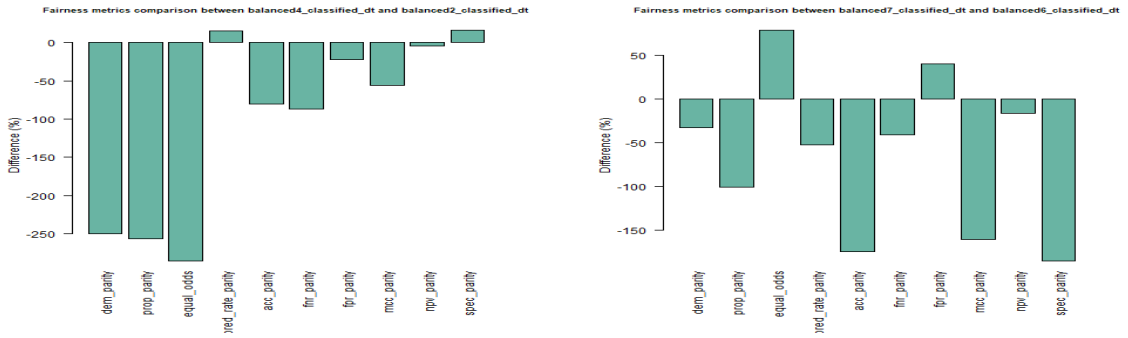


Figure 5.13: COMPAS fairness metric comparison between: (a) balanced_data2-balanced_data4 and (b) balanced_data6-balanced_data7.

metric (all subgroups with value 1), for balanced classified datasets and original classified dataset (Classified_dt). Notice that we do not have comparative values here and the optimal value is 0 (no deviation, namely all subgroups with the same fairness metric value).

Figure 5.14: Mean deviations from complete fairness, for each fairness metric, for balanced classified datasets and original classified dataset

5.1.2 | Drugs

For Drugs dataset we will not explain all the analysis steps as it was done for COMPAS data. Instead, we will report the significant results that will be used for the last comparative analysis among the different datasets. For any further detail, the R code for all datasets analysis is available in appendix A.

5.1.2.1 | Context description

The database was collected by Elaine Fehrman between March 2011 and March 2012 for research proposal, by means of an online survey tool from Survey Gizmo was employed to gather data.
The study recruited 2051 participants over a 12-month recruitment period and the data were collected maximising anonymity. Every participant has been categorized in a different level of of 'drug user' based on the recency of use, for each drug. The drugs evaluation regards
In the original research [22], two isolated categories ('Never used' and 'Used over a decade ago') are set into the class of non-users and all other categories form the class of users; whereas, we decided to categorize only 'Never used' individuals as non-users. The aim of the original study was to evaluate the individual drug consumption risk separately, for each drug (18 different) and group of drugs. However, our main interest in this case lies in the fact that usually, for clinical cohorts, data are biased when compared with the general population and in fact [22] research showed that this dataset truly is biased when compared to the data published by Egan, et al [19] and Costa Jr & McCrae [43]. The 5 scores, the impulsiveness and the sensation seeing are the results of the so-called NEO Five-Factor Inventory (NEO-FFI-R) questionnaire, which is a highly reliable measure of basic personality traits.

5.1.2.2 | Data exploration

This is a cleaned data frame with 1885 rows and 12 variables, available on UCI repository. Among the variables there are sensitive attributes and some continuous scores: we will not analyse the scores because they brings information we are not interested to the aim of our research. However, we will not perform any feature selection for classification and we will involve them in the logistic regression model. Here is the list of variables:

- **Age**: is age of participant.
- **Gender**: is gender of participant.
- **Education**: is level of education of participant.
- **Country**: is country of current residence of participant.
- **Ethnicity**: is ethnicity of participant.

- **Nscore**: is NEO-FFI-R Neuroticism.
- **Escore**: is NEO-FFI-R Extraversion.
- **Oscore**: is NEO-FFI-R Openness to experience.
- **Ascore**: is NEO-FFI-R Agreeableness.
- **Cscore**: is NEO-FFI-R Conscientiousness.
- **Impulsive**: is impulsiveness measured by BIS-11.
- **SS**: is sensation seeing measured by ImpSS.

  Other columns list several types of drugs. We'll select only two of them for which predicting the consumption: **Coke** and **Crack**.

At first, we only had real values, then we mutated them to categorical, to get more data readability. After that, the data are presented as in table 5.6.

Data are highly skewed (except for Gender, which is fully balanced), as we can observe in figure 5.15.

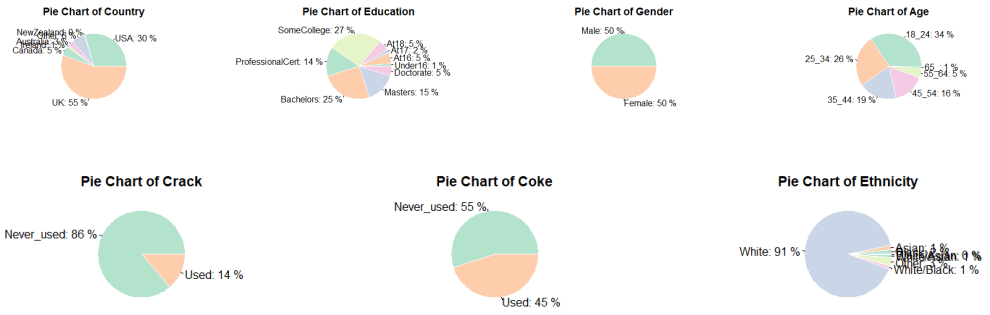


Figure 5.15: Drug dataset categorical variable distributions

Likewise COMPAS case, there are three sensitive attributes in our data (Gender, Ethnicity and Age) and a bunch of other variables that might be even proxies for the sensitive ones.
Since we are interested into two different drug consumption predictions, in the following analysis we will proceed in parallel for Coke and Crack.
In figure 5.16 is shown the Coke percentage consumption distribution on the whole dataset and on each single combination of sensitive attributes. Whereas, in figure 5.17 there are the same plots for Crack consumption. These data regards only subjects who used the corresponding drug. Moreover, we did not perform any cross evaluation for the two drugs consumption: we limited the research on an individual separated consumption analysis.
In figure 5.18 and 5.19 are reported the Chi-square residuals of Pearson's Chi-square test (respectively for Coke and Crack variables), in order to see any possible relationship or causal

Table 5.6: Drug dataset first rows

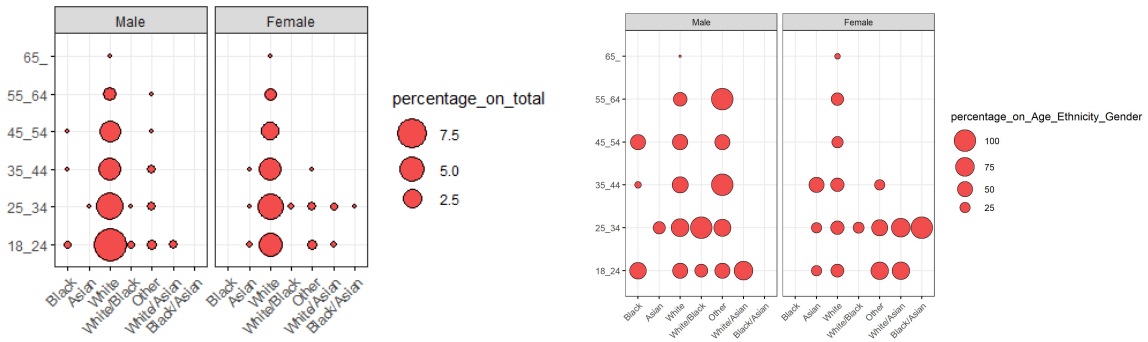
Age	Gender	Education	Country	Ethnicity	Nscore	Escore
25_34	Male	Doctorate	UK	White	-0.68	1.94
35_44	Male	ProfessionalCert	UK	White	-0.47	0.81
18_24	Female	Masters	UK	White	-0.15	-0.81
35_44	Female	Doctorate	UK	White	0.74	-1.63
65_	Female	At18	Canada	White	-0.68	-0.30
45_54	Male	Masters	USA	White	-0.47	-1.09

Oscore	Ascore	Cscore	Impulsive	SS	Coke	Crack
1.44	0.76	-0.14	-0.71	-0.22	Used	Never_used
-0.85	-1.62	-1.01	-1.38	0.40	Never_used	Never_used
-0.02	0.59	0.58	-1.38	-1.18	Used	Never_used
-0.45	-0.30	1.31	-0.22	-0.22	Never_used	Never_used
-1.56	2.04	1.63	-1.38	-1.55	Never_used	Never_used
-0.45	-0.30	0.94	-0.22	0.08	Never_used	Never_used

inference between consumption and sensitive attributes. Regarding both Coke and Crack, Chi-squared approximation may be incorrect, since one Chi-squared test assumption is broken: there are indeed less then 5 subjects over 65 years old who have used the drug. We have also a similar borderline situation for Ethnicity variable. However, we can rely on the Gender Chi-square test: there is a strong association between male and both drugs consumption.

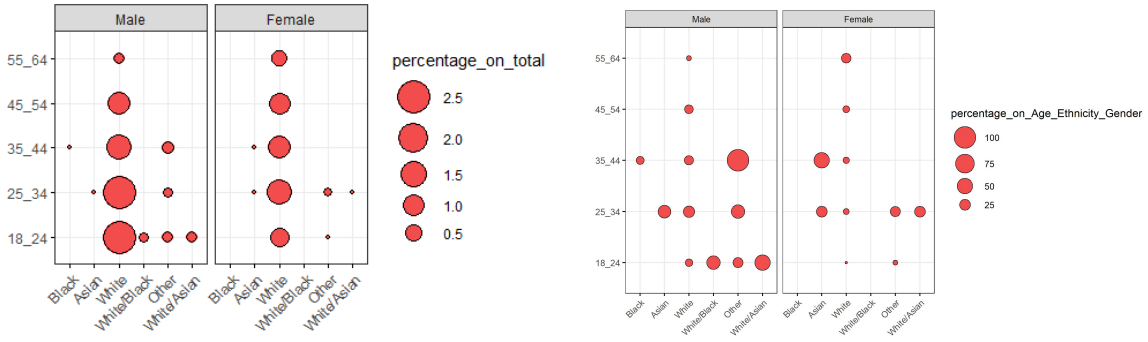
5.1.2.3 | Data classification

We modelled again a logistic regression, which involved all features as predictors. The positive class is "Never_used" and the negative is "Used". The confusion matrix is quite different for Coke (figure 5.20) and Crack (figure 5.21): we can notice a really high TPR for Crack (actual non-consumers predicted as non-consumers) that is not so surprising, since 86% of subjects are crack non-consumers. In figure 5.22 are represented the density plots for Coke consumption probability, with the relative optimal cutoff. It is relevant that in Crack case the optimized cutoff is surprisingly low (0.1829116), probably due to high unbalanced data for Crack consumption variable (only 14% of subjects used this drug), which also leads to issues for fairness



(a) (b)

Figure 5.16: % of coke consumption on: (a) total and (b) each sensitive attribute combination.



(a) (b)

Figure 5.17: % of crack consumption on: (a) total and (b) each sensitive attribute combination.

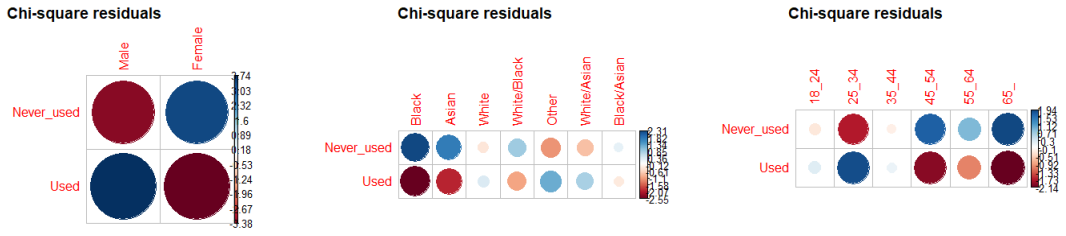


Figure 5.18: Drug dataset Pearson's Chi-square test for Coke

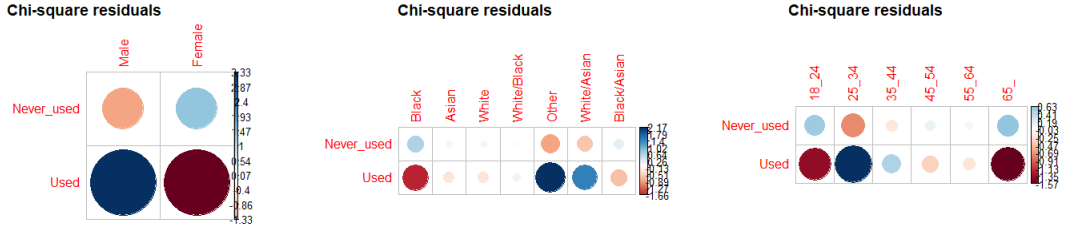


Figure 5.19: Drug dataset Pearson's Chi-square test for Crack

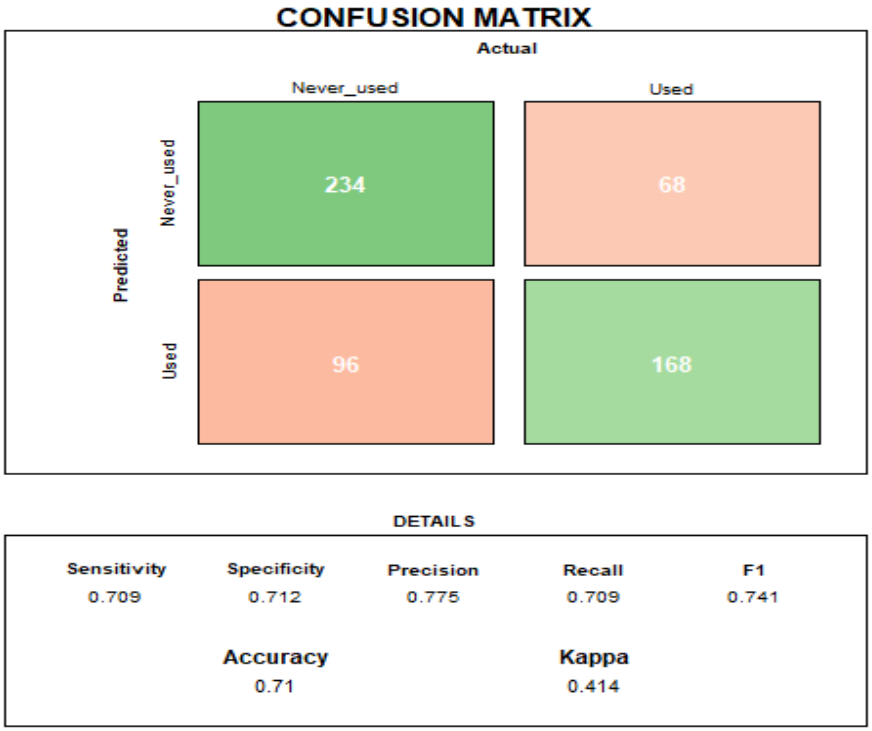


Figure 5.20: Drug dataset Coke classification confusion matrix

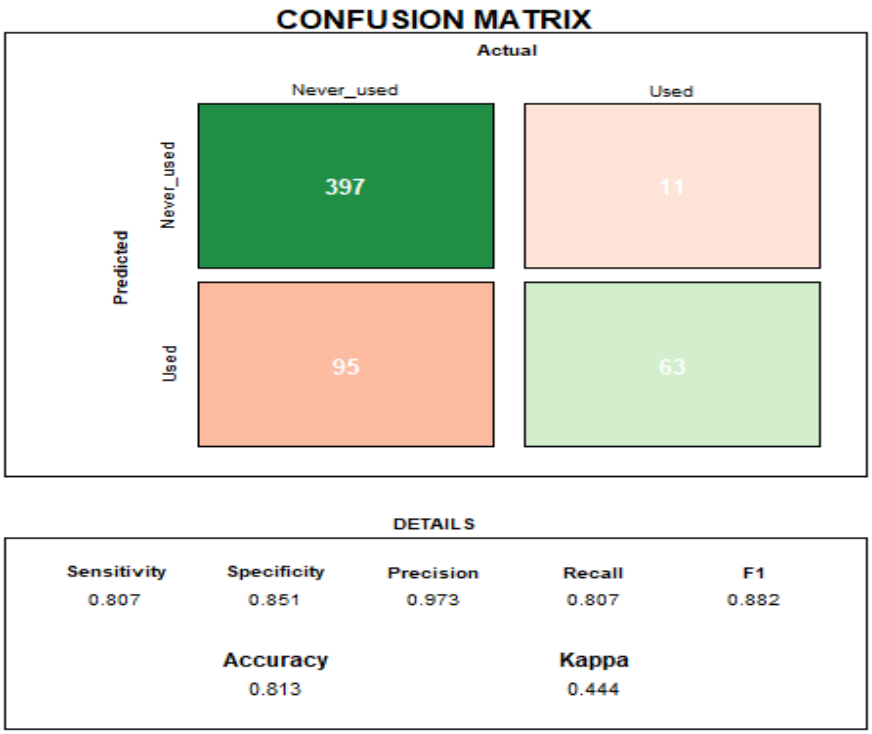


Figure 5.21: Drug dataset Crack classification confusion matrix

metrics and density probabilities plots (hence, we will not report them here for Crack case).

5.1.2.4 | Fairness metrics

We tried several sensitive attributes fairness metrics comparisons and, as well as for COMPAS, it results that for both Coke (figures 5.23a and 5.23b) and Crack (figures 5.24a and 5.24b) the most critic sensitive attribute is Ethnicity. For all the fairness metrics plots and values, please refer to the attached code in appendix B.

5.1.2.5 | Bias mitigation

Taking into account that Gender is already balanced in the original dataset, we created 3 balanced datasets for Coke as follow:

- balanced_data0: balanced for Ethnicity.
- balanced_data1: balanced for Country. In this way, we wanted to see if there could be any improvement in Ethnicity fairness metrics, since Country may be a proxy for Ethnicity.
- balanced_data2: balanced for Ethnicity and Age. For each already balanced ethnic subcategory, we balanced on Age. Here we got some issues in using SMOTE: since there are too few examples in some subcategories, replicas are introduced by the algorithm. It was indeed impossible to balance Ethnicity for each balanced Age subcategory (opposite order), but this combination was still acceptable for metrics evaluation.

And 3 balanced datasets for Crack:

- balanced_data0: balanced for Crack.
- balanced_data1: balanced for Crack and Ethnicity.
- balanced_data2: balanced for Crack and Age. In this case, SMOTE could not perform Age balancing within each balanced subcategory of Crack, due to few examples in subcategories, then we simply run SMOTE for Age on the whole balanced_data0.

For this dataset we faced dimension problems: when we classify the datasets we get a little more than 500 rows and the fairness metric computation does not work properly on such small datasets, especially when there are underrepresented subcategories in some attributes. In particular in Crack case, we had too few samples for Crack consumers and we had to create balanced datasets always balanced towards Crack in order to get fairness metrics values. Anyway, even if all these balanced datasets are balanced towards Crack, it is not surprising to see that some metrics have better mean deviations in case we *only* balance Crack. Indeed,

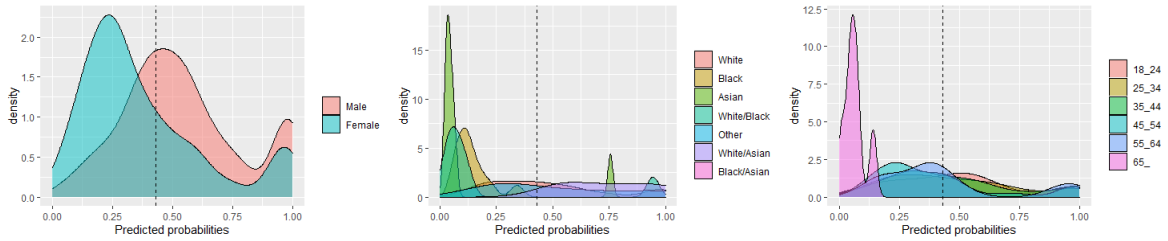


Figure 5.22: Drug dataset Coke density probabilities

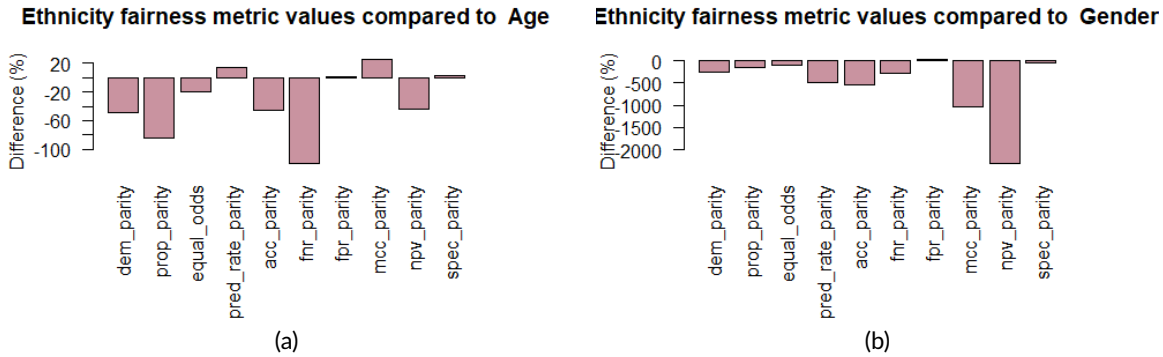


Figure 5.23: Drug dataset Coke fairness metrics comparisons between Ethnicity VS (a) Age and (b) Gender.

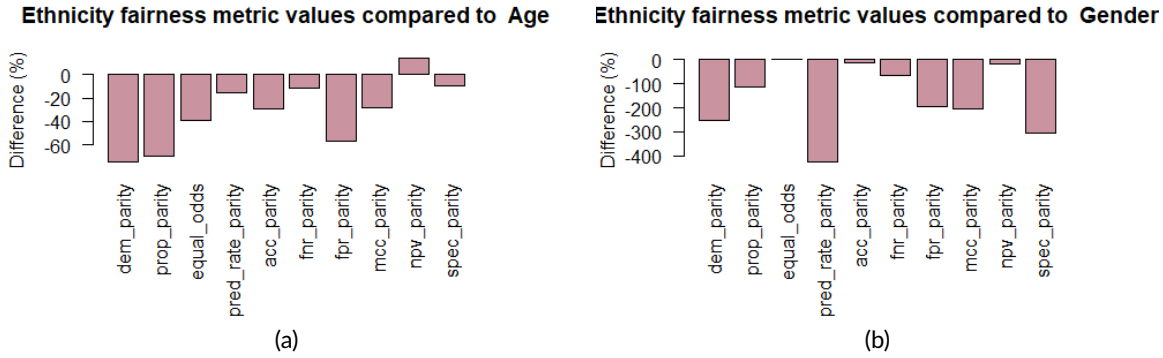


Figure 5.24: Drug dataset Crack fairness metrics comparisons between Ethnicity VS (a) Age and (b) Gender.

when we try to balance a couple of attributes with SMOTE or ROSE, it does not guarantees to reach a fully balancing for both attributes if we cannot perform the algorithm within each balanced subcategory of Crack. Then, for balanced_data1 and balanced_data2 we do not get a 50-50 proportions for Crack subcategories and this can influence the fairness metric outcomes.
We reported here in figure 5.25 and 5.26 the Mean deviations from complete fairness of balanced classified datasets and original classified dataset (Classified_dt).

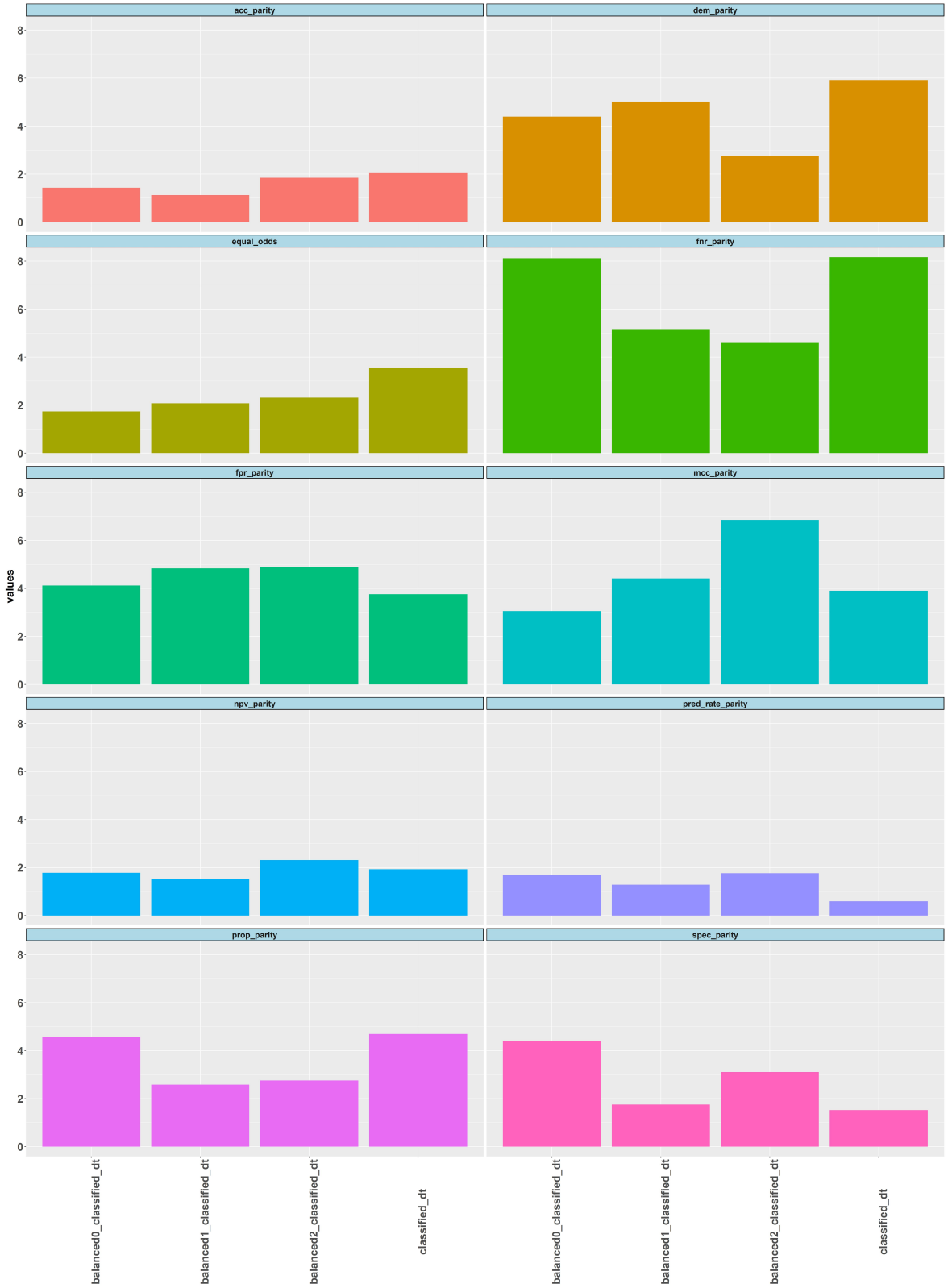


Figure 5.25: Mean deviations from complete fairness, for each fairness metric in Coke case, for balanced classified datasets and original classified datasets

Figure 5.26: Mean deviations from complete fairness, for each fairness metric in Crack case, for balanced classified datasets and original classified datasets

6

Conclusions

Automated decision systems are likely to be used more and more in every process of our ordinary everyday life. Our first initial analysis - concerning how these systems are being used in the past and the kind of bias and discrimination they may lead to - brings evidence of different and crucial influence of the decisions issued by such systems on different groups of population. In addition, lack of transparency and accountability caused the developing organizations to be criticized and exposed to further investigation. Discriminating behaviors may arise for many reasons, hence before deployment of such tools it is necessary a risks assessment and evaluation of their impact on the society. Thus, it has an ethical importance to investigate whether such algorithms provide outcomes that can declass, demerit, or exclude individuals belonging to disadvantaged groups.

6.1 | Achieved Aims and Objectives

With this research we intended to carry out a comparative analysis of the various known fairness metrics, for the evaluation of classification systems, which are actually a small part of all the automatic decision systems that we can deal with today. In particular, we observed how the metrics varied based on the balance of the datasets, which is reflected in an alteration of the bias present in the data.
We also made our contribution to research on fairness in machine learning by focusing in particular on the balancing of sensitive attributes, which leads to the reduction of selection and population bias.

6.2 | Critique and Limitations

Surely a great limitation in the field of fairness in machine learning lies in the fact that every situation that interfaces with human and / or social variables requires an *ad hoc* study, dedicated only to particular circumstances and situations. It is not possible to recreate automated

tools for the removal of absolute discrimination, in any context. Furthermore, even the fact that each sensitive attribute must be analyzed in its own right, did not allow us to carry out a cross or aggregate analysis of all the attributes, for an overall assessment of discrimination.
Another limitation is certainly due to the innumerable presence of types of bias (here we have created a taxonomy of the best known, but it is constantly evolving), which therefore could not be analyzed all, specifically for our datasets.
A last one also concerns the difficulty in actually being able to quantize a data such as fairness: numerous researches have now been conducted, but it is not possible - and it would certainly not be ethically correct - to establish (only) numerically whether a process is more or less discriminating than a other.

6.3 | Future Work

This research can be deepened with various analyzes of other bias mitigation techniques, such as those provided by the IBM AIF360 tool. Besides, it is possible to create a tool for comparing fairness metrics that takes into account other factors, such as the type of attribute being analyzed or parameters relating to the context of application (e.g. legal context, recruiting systems etc.), perhaps through benchmarks obtained from previous analyzes.
A further point of study is the combination and comparison of the various techniques of debias, to study whether there could be a link between certain social contexts and more marked improvements by means of certain specific techniques.

A

R code

R code for COMPAS dataset:

```
## ------------------------------------------------------------------------------------
#prendo il dataset dalla libreria fairness di CRAN
library(fairness)
library(knitr)
library(recipes)
library(skimr)
library(modeldata)
library(RColorBrewer)
library(tangram)
library(dplyr)
library(vegan)
library(diverse)
library(randomForest)
library(caret)
library(varhandle)
library(MASS)
library(dostats) #per %contains%
library(graphics) #per mosaicplot
library(corrplot)
library(wesanderson)
library(Amelia)
library(ROCR) #per ROC function
library(ROSE)#binary balancing
library("UBL")#multiclass balancing
library(ggplot2)
library(ggpubr)
library(xtable)
library(tidyr)

#carico il file util con le altre funzioni
source("util.R")

```

```
33
34 ## ------------------------------------------------------------------------------------
35 knitr::purl('COMPAS.Rmd')
36
37
38 ## ------------------------------------------------------------------------------------
39 #load data
40 raw_data = fairness::compas
41 write.csv(raw_data,'COMPAS.csv')
42 #in questo dataset  gi stato fatto del lavoro rispetto al dataset originale. Tra l'altro: nel
       ds originale c'era anche il marital status, che qui viene eliminato (probabilmente perch
       si tratta di un dato personale e non sensibile?), poi lo score nel ds originale
      presentato in modo diverso (raw score, decile score, text score...)
43 h = head(raw_data)
44 #print(xtable(h, type = "latex"), file = "COMPAShead.tex")
45 #probability e predicted per ora non ci interessano, perci eliminiamo le due colonne
46 raw_data$predicted = NULL
47 raw_data$probability = NULL
48
49 #sostituisci yes\no di 2yrRecidivism con Recidivism\No recidivism
50 levels(raw_data$Two_yr_Recidivism)[levels(raw_data$Two_yr_Recidivism)=="yes"] <- "Yes_
       recidivism"
51 levels(raw_data$Two_yr_Recidivism)[levels(raw_data$Two_yr_Recidivism)=="no"] <- "No_
       recidivism"
52
53 #crea una sola colonna di age, con under25/over45/between25_45
54 raw_data$Age <- mapply(create_Age, raw_data$Age_Below_TwentyFive, raw_data$Age_Above_
       FourtyFive)
55 raw_data$Age = as.factor(raw_data$Age)
56
57 h = head(raw_data)
58 print(xtable(h, type = "latex"), file = "COMPAShead.tex")
59 summary(raw_data)
60 #
61
62 #data visualization CATEGORICAL
63
64 #Filter out categorical columns
65 cat_data <- raw_data[, sapply(raw_data, is.categorical)]
66 cat_names <- names(cat_data)
67
68 #pie print per ogni colonna categorica
69 for ( i in seq(1,length( cat_data ),1) ){
70   pie_print(cat_data,cat_names[i])
71 }
72 a = table(raw_data)
73 a = as.data.frame(a)
74 #a$Number_of_Priors = NULL
```

```
ggballoonplot(a, x = "ethnicity", y = "Age", size = "Freq",
              color = "#8591C2", fill = "#8591C2", facet.by = "Female",
              ggtheme = theme_bw()) #+
  #scale_fill_gradientn(colors = wes_palette(2, name="GrandBudapest"))

#seleziono yes_recidivism e plotto la stessa cosa
raw_data_copy = raw_data
a = subset(raw_data_copy, Two_yr_Recidivism =="Yes_recidivism")
a = table(a)
a = as.data.frame(a)
ggballoonplot(a, x = "ethnicity", y = "Age", size = "Freq",
              color = "#F24D4D", fill = "#F24D4D", facet.by = "Female",
              ggtheme = theme_bw())

#seleziono no_recidivism e plotto la stessa cosa
a = subset(raw_data_copy, Two_yr_Recidivism =="No_recidivism")
a = table(a)
a = as.data.frame(a)
ggballoonplot(a, x = "ethnicity", y = "Age", size = "Freq",
              color = "#50C395", fill = "#50C395", facet.by = "Female",
              ggtheme = theme_bw())

## ------------------------------------------------------------------------------------
#missing values
missmap(raw_data, main = "Missing values vs observed")
#no missing values

# Create a boxplot using base R
boxplot(Number_of_Priors~Female,data=raw_data)
boxplot(Number_of_Priors~Age,data=raw_data)
boxplot(Number_of_Priors~ethnicity,data=raw_data)

#sembra che ci siano parecchi outlier del numero dei precedenti in funzione degli attributi
    sensibili, che potrebbero quindi non essere outlier o alcuni essere dovuti ad errori di
    registrazione

boxplot(Number_of_Priors~Misdemeanor,data=raw_data)
#ci sono anche degli outlier del numero dei precedenti in funzione del fatto che il crimine
    sia stato (o meno) registrato

## ------------------------------------------------------------------------------------
#plotto lo Two_yr_recidivism al variare di Female
####################Female
d = group_by_feature_sensitive(raw_data,  "Two_yr_Recidivism", "Female")
bar(dv = count_val,
    factors = c("Two_yr_Recidivism", "Female"), #non riesco a risolvere il problema di
    passare in questa lista una variabile contente la stringa, invece della stringa stessa.
    dataframe = as.data.frame(d),
```

```
    errbar = FALSE,
    ylim=c(0, as.numeric(d[4])+0.1*as.numeric(d[4])),
    col = c("#50C395","#F24D4D")
    )  #I increased the upper y-limit to accommodate the legend.

####################ethnicity
d = group_by_feature_sensitive(raw_data, "Two_yr_Recidivism", "ethnicity")
bar(dv = count_val,
    factors = c("Two_yr_Recidivism", "ethnicity"), #non riesco a risolvere il problema di passare in questa lista una variabile contente la stringa, invece della stringa stessa.
    dataframe = as.data.frame(d),
    errbar = FALSE,
    ylim=c(0, as.numeric(d[4])+0.1*as.numeric(d[4])),
    col = c("#50C395","#F24D4D")
    )  #I increased the upper y-limit to accommodate the legend.
########################Misdemeanor
d = group_by_feature_sensitive(raw_data, "Two_yr_Recidivism", "Misdemeanor")
bar(dv = count_val,
    factors = c("Two_yr_Recidivism", "Misdemeanor"), #non riesco a risolvere il problema di passare in questa lista una variabile contente la stringa, invece della stringa stessa.
    dataframe = as.data.frame(d),
    errbar = FALSE,
    ylim=c(0, as.numeric(d[4])+0.1*as.numeric(d[4])),
    col = c("#50C395","#F24D4D")
    )  #I increased the upper y-limit to accommodate the legend.
########################Age
d = group_by_feature_sensitive(raw_data, "Two_yr_Recidivism", "Age")
bar(dv = count_val,
    factors = c("Two_yr_Recidivism", "Age"), #non riesco a risolvere il problema di passare in questa lista una variabile contente la stringa, invece della stringa stessa.
    dataframe = as.data.frame(d),
    errbar = FALSE,
    ylim=c(0, as.numeric(d[4])+0.1*as.numeric(d[4])),
    col = c("#50C395","#F24D4D")
    )  #I increased the upper y-limit to accommodate the legend.



## ------------------------------------------------------------------------------------
#NUMERICAL COLUMN
#Number_of_Priors come lo visualizzo/interpreto? essendo normalized to mean = 0 and standard deviation = 1


## ------------------------------------------------------------------------------------
#con frquent_comb1 non devo dividere "manualmente" tra i due valori di Two_yr_Recidivism (cio yes_recidivism e no_recidivism), ma lo fa in automatico, restituendomi poi due tabelle.
```

```
    Per capire quale sia riferita a yes e quale a no, occorre guardare le colonne: in una
    tabella  presente la colonna "percentage_on_yes_recidivism" e nell'altra "percentage_on_
    no_recidivism" e le due tabelle sono quindi riferite rispettivamente a "yes_recidivism" e
     "no_recidivism"
frquent_comb1(raw_data, filter = "Two_yr_Recidivism", c("Age", "ethnicity"))
frquent_comb1(raw_data, filter = "Two_yr_Recidivism", c("Age", "ethnicity", "Female"))

#plotto la distribuzione delle combinazioni (in proporzione )

frquent_comb1(raw_data, filter = "Two_yr_Recidivism", c("Age", "Female"))
frquent_comb1(raw_data, filter = "Two_yr_Recidivism", c("ethnicity", "Female"))
frquent_comb1(raw_data, filter = "Two_yr_Recidivism", c("ethnicity"))
##
#COME SI LEGGE LA TABELLA?
#esempio con frquent_comb(raw_data, data_good, c("Marital", "ageR"))
#dataset originale: raw_data
#dataset filtrato: data_good (filtro su status=good)
#attributi che mi interessano: c("Marital", "ageR") -> pu essere una lista di lunghezza
    variabile
#-Percentage_on_partition rappresenta la probabilit  condizionata: es. P(marital=x,ageR=y|
    status=good).
#-percentage_on_total  la percentuale della coppia selezionata (qui ad esempio data dalle
    combinazioni di marital e ageR) sul totale delle righe del dataset originale. p = #(
    status=good, marital=x, ageR=y)/#(numero righe dataset originale)
#-numrows_filter_on_col  un parametro che non mi interessa in output, ma non riesco ad
    eliminarlo dallpa funzione
#-percentage_on_Marital_ageR  la probabilit condizionata p(good| marital=x, ageR=y) = #(
    status=good, marital=x, ageR=y)/#(marital=x, ageR=y)
########
#esempio: dato Status="good"  probabile al 25,81% cheo si tratti di  una persona sposata, tra
     i 30 e 40 anni.
#esempio: dato Status="bad"  probabile al 14.49% che si tratti di un single sotto i 25 anni.
########



## ------------------------------------------------------------------------------------
#########################
#plotto la distribuzione delle combinazioni (conteggio casi)
a = frquent_comb1(raw_data, filter = "Two_yr_Recidivism", c("Age", "ethnicity", "Female"))

a1 = as.data.frame(a[1]) #la tabella 1 ha sempre no_recidivism
a2 = as.data.frame(a[2]) #la tabella 2 ha sempre yes_recidivism

ggballoonplot(a1, x = "ethnicity", y = "Age", size = "percentage_on_No_recidivism",
              color = "black", fill = "#50C395", facet.by = "Female", ggtheme = theme_bw())
#percentage_on_Age_ethnicity_Female

```

```
ggballoonplot(a2, x = "ethnicity", y = "Age", size = "percentage_on_Yes_recidivism",
              color = "black", fill = "#F24D4D", facet.by = "Female", ggtheme = theme_bw())

ggballoonplot(a1, x = "ethnicity", y = "Age", size = "percentage_on_total",
              color = "black", fill = "#50C395", facet.by = "Female", ggtheme = theme_bw())
#percentage_on_Age_ethnicity_Female

ggballoonplot(a2, x = "ethnicity", y = "Age", size = "percentage_on_Age_ethnicity_Female",
              color = "black", fill = "#F24D4D", facet.by = "Female", ggtheme = theme_bw())

ggballoonplot(a1, x = "ethnicity", y = "Age", size = "percentage_on_Age_ethnicity_Female",
              color = "black", fill = "#50C395", facet.by = "Female", ggtheme = theme_bw())
#percentage_on_Age_ethnicity_Female

ggballoonplot(a2, x = "ethnicity", y = "Age", size = "percentage_on_total",
              color = "black", fill = "#F24D4D", facet.by = "Female", ggtheme = theme_bw())

a1$percentage_on_No_recidivism = NULL
a1$percentage_on_total = NULL
a1$percentage_on_Age_ethnicity_Female = NULL
a2$percentage_on_Yes_recidivism = NULL
a2$percentage_on_total = NULL
a2$percentage_on_Age_ethnicity_Female = NULL
print(xtable(a1, type = "latex"), file = "No_recFreqComb.tex")
print(xtable(a2, type = "latex"), file = "Yes_recFreqComb.tex")
####################

## ------------------------------------------------------------------------------------
###OCCHIO: qui il bad e good del valore target (in questo caso recidivism) devono avere un
    certo ordine
#source("util.R")
mosaicp(raw_data, c("Two_yr_Recidivism", "Age"))
mosaicp(raw_data, c("Two_yr_Recidivism", "ethnicity"))
mosaicp(raw_data, c("Two_yr_Recidivism", "Female"))

#Il blu indica che il valore osservato  pi alto del valore atteso se i dati fossero random
#Il rosso indica che il valore osservato  pi basso del valore atteso se i dati fossero random

#gi da questo mosaicplot possiamo capire cosa aspettarci per le metriche di fairness. es.
    attributo Female:  evidente che per gli uomini ci sar pi disparit, perch verranno
    categorizzati Yes_recid pi delle donne. Anche per gli african-american o per quelli
    sottoi 25 anni.

## ------------------------------------------------------------------------------------
#chi squared test (consideriamo le colonne come categoriche)
source("util.R")
chisq_fun(raw_data, "Two_yr_Recidivism", "Age")
chisq_fun(raw_data, "Two_yr_Recidivism", "ethnicity")
```

```
chisq_fun(raw_data, "Two_yr_Recidivism", "Female")
#In console possiamo osservare la differenza tra i valori osservati (prima tabella) e i
    valori attesi (seconda tabella).


## ------------------------------------------------------------------------------------
#SHANNON INDEX
#uso funzioni create nella libreria
source("util.R")
shannon_diversity(raw_data)
print_shannon(raw_data)
#print_cmp_shannon(raw_data, raw_data)

## ------------------------------------------------------------------------------------
#sostituisco i livelli con valori numerici
levels(raw_data$Two_yr_Recidivism)[levels(raw_data$Two_yr_Recidivism)=="yes"] <- 1
levels(raw_data$Two_yr_Recidivism)[levels(raw_data$Two_yr_Recidivism)=="no"] <- 0
#rimuovo da raw_data le colonne age_above e age_below
cols_to_drop <- names(raw_data) %in% c("Age_Above_FourtyFive", "Age_Below_TwentyFive")
raw_data <- raw_data[, !cols_to_drop, drop = FALSE]

#split into train and test set
sample_size = floor(0.7*nrow(raw_data))
#set a random seed per rendere l'esperimento ripetibile
set.seed(42)

# randomly split data
picked = sample(seq_len(nrow(raw_data)),size = sample_size)
training_set =raw_data[picked,]
test_set =raw_data[-picked,]

#as.factor mi serve per fare una classificazione binaria
raw_data$Two_yr_Recidivism = as.factor(raw_data$Two_yr_Recidivism)
#devo anche eliminare recidivismo dal training_set
cols_to_drop <- names(training_set) %in% c("Two_yr_Recidivism")
#training e test set senza variabile target
training_set_data <- training_set[, !cols_to_drop, drop = FALSE]
#anche sui dati di test
test_set_data <- test_set[, !cols_to_drop, drop = FALSE]

## ------------------------------------------------------------------------------------
#REGRESSIONE LOGISTICA
#in questo caso ho bisogno del dataset numerico
#training_set = as.data.frame(lapply(unclass(training_set), as.numeric))
levels(training_set$Two_yr_Recidivism)[levels(training_set$Two_yr_Recidivism)=="Yes_
    recidivism"] <- 1
levels(training_set$Two_yr_Recidivism)[levels(training_set$Two_yr_Recidivism)=="No_recidivism
    "] <- 0
```

```
levels(training_set$Two_yr_Recidivism)

levels(test_set$Two_yr_Recidivism)[levels(test_set$Two_yr_Recidivism)=="Yes_recidivism"] <- 1
levels(test_set$Two_yr_Recidivism)[levels(test_set$Two_yr_Recidivism)=="No_recidivism"] <- 0
levels(test_set$Two_yr_Recidivism)
################################
#poi commento le righe in cui calcola il modello perch ci potrebbe mettere troppo (
    sufficiente salvarlo e ricaricarlo)
logitMod <- glm(Two_yr_Recidivism ~ ., data = training_set, family=binomial(link="logit"))
logitMod #capire cosa significano questi dati

pred = predict(logitMod, test_set_data, type = "response") #se non metto il type = response,
    mi restituisce una predizione tra -1 e 1, altrimenti me la restituisce tra 0 e 1. Scelgo
    tra -1 e 1 perc poi ottengo il cutoff ottimizzato anch'esso tra -1 e 1 e mi  pi facile
    fare la predizione
classified_dt = cbind(test_set, pred) #questo  quello che uso per la libreria fairness
classified_dt2 = cbind(test_set_data, pred)


## ------------------------------------------------------------------------------------
#ROC
pred1 <- prediction(pred, test_set$Two_yr_Recidivism) #pred1  un oggetto pred.obj di ROCR
perf <- performance(pred1, measure = "tpr", x.measure = "fpr")
plot(perf)
#posso anche fare una ROC comparison per le categorie di un attributo sensibile, tipo Female,
     con la libreria fairness:
roc_fairness <- roc_parity(data         = classified_dt,
                      outcome      = 'Two_yr_Recidivism',
                      group        = 'Female',
                      probs        = 'pred',
                      preds_levels = c('No_recidivism','Yes_recidivism'),
                      base         = 'Male')
roc_fairness$Metric
roc_fairness$ROCAUC_plot

#AUC
auc.perf = performance(pred1, measure = "auc")
auc.perf@y.values #stampa a video il valore di AUC
###############
#plotto sensitivity e specificity in modo da individuare il cutoff ottimizzato
sens <- data.frame(x=unlist(performance(pred1, "sens")@x.values),
                   y=unlist(performance(pred1, "sens")@y.values))
spec <- data.frame(x=unlist(performance(pred1, "spec")@x.values),
                   y=unlist(performance(pred1, "spec")@y.values))

sens %>% ggplot(aes(x,y)) +
  geom_line() +
  geom_line(data=spec, aes(x,y,col="red")) +
```

```
  scale_y_continuous(sec.axis = sec_axis(~., name = "Specificity")) +
  labs(x='Cutoff', y="Sensitivity") +
  theme(axis.title.y.right = element_text(colour = "red"), legend.position="none")
################


## ------------------------------------------------------------------------------------
#troviamo l'optimal cutoff, cio l'optimal score che minimizza il misclassification error del modello di regressione logistica
#The best threshold (or cutoff) point to be used in glm models is the point which maximises the specificity and the sensitivity. This threshold point might not give the highest prediction in your model, but it wouldn't be biased towards positives or negatives.
optimized_cutoff = opt.cut(perf, pred1)#il cutoff ottimale  leggermente pii basso di quello standard, che sarebbe invece 0.5

#converto la colonna pred di classified_dt2 in yes/no recidivism usando il cutoff ottimizzato
#yes era 1, quindi ho recidivismo se  maggiore del cutoff
classified_dt2$pred = ifelse(classified_dt2$pred<optimized_cutoff,"No_recidivism","Yes_recidivism")
#sostituisco i valori dei livelli per poter plottare la matrice di confusione
levels(test_set$Two_yr_Recidivism)[levels(test_set$Two_yr_Recidivism)==1] <- "Yes_recidivism"
levels(test_set$Two_yr_Recidivism)[levels(test_set$Two_yr_Recidivism)==0] <- "No_recidivism"
levels(test_set$Two_yr_Recidivism)
#anche per classified_dt2
classified_dt2$pred <- factor(classified_dt2$pred, levels = c("Yes_recidivism", "No_recidivism"))


## ------------------------------------------------------------------------------------
#matrice di confusione
cm <- confusionMatrix(data = as.factor(classified_dt2$pred), reference = as.factor(test_set$Two_yr_Recidivism))
#plotto la matrice di confusione
draw_confusion_matrix(cm)

## ------------------------------------------------------------------------------------
#ci occupiamo di group fairness: indipendenza, separazione e sufficienza

#lo facciamo per tutti i sensitive attribute

#ripristino di nuovo i livelli yes/no per renderlo pi leggibile
levels(classified_dt$Two_yr_Recidivism)[levels(classified_dt$Two_yr_Recidivism)==1] <- "Yes_recidivism"
levels(classified_dt$Two_yr_Recidivism)[levels(classified_dt$Two_yr_Recidivism)==0] <- "No_recidivism"

#per scegliere la categoria "base" per cui confrontare tutte le altre, per ogni attributo sensibile, ci conviene guardare le tabelle delle frequenze plottate in precedenza:
```

```
369
370
371 ## ------------------------------------------------------------------------------------
372 fair_metrics(data         = classified_dt,
373                       outcome      = 'Two_yr_Recidivism',
374                       group        = 'Age',
375                       probs =       'pred',
376                       preds_levels = c('No_recidivism','Yes_recidivism'),
377                       cutoff       = optimized_cutoff,
378                       base         = 'between25_45')
379
380 fair_metrics(data         = classified_dt,
381                       outcome      = 'Two_yr_Recidivism',
382                       group        = 'ethnicity',
383                       probs =       'pred',
384                       preds_levels = c('No_recidivism','Yes_recidivism'),
385                       cutoff       = optimized_cutoff,
386                       base         = 'Caucasian')
387
388 fair_metrics(data         = classified_dt,
389                       outcome      = 'Two_yr_Recidivism',
390                       group        = 'Female',
391                       probs =       'pred',
392                       preds_levels = c('No_recidivism','Yes_recidivism'),
393                       cutoff       = optimized_cutoff,
394                       base         = 'Male')
395 source("util.R")
396 fair_metrics_cmp_graph2(data         = classified_dt,
397                       outcome      = 'Two_yr_Recidivism',
398                       group1        = 'Female',
399                       group2 = 'ethnicity',
400                       probs =       'pred',
401                       preds_levels = c('No_recidivism','Yes_recidivism'),
402                       cutoff       = optimized_cutoff,
403                       base1         = 'Male',
404                       base2        = 'Caucasian')
405 fair_metrics_cmp_graph2(data         = classified_dt,
406                       outcome      = 'Two_yr_Recidivism',
407                       group1        = 'Age',
408                       group2 = 'ethnicity',
409                       probs =       'pred',
410                       preds_levels = c('No_recidivism','Yes_recidivism'),
411                       cutoff       = optimized_cutoff,
412                       base1         = 'between25_45',
413                       base2        = 'Caucasian')
414
415
416 ## ------------------------------------------------------------------------------------
```

```
#la libreria ROSE si pu usare soltanto per bilanciare attributi binari (nasce per bilanciare classificazione binaria)
library("ROSE")
balanced_data = ovun.sample(Female~., data = raw_data, method="both", N = nrow(raw_data), p=0.5, seed = 42)$data
print_cmp_shannon(raw_data, balanced_data)

#library(imbalance)
#plotComparison(balanced_data, raw_data,  attrs = c("ethnicity", "Number_of_Priors"), cols = 2, classAttr = "Two_yr_Recidivism")

#Filter out categorical columns
cat_data <- balanced_data[, sapply(balanced_data, is.categorical)]
cat_names <- names(cat_data)
#pie print per ogni colonna categorica
for ( i in seq(1,length( cat_data ),1) ){
  pie_print(cat_data,cat_names[i])
}
library("UBL")
#questo per il multiclass con la libreria UBL
source("util.R")
sample_size = floor(nrow(raw_data)/3)
  #set a random seed per rendere l'esperimento ripetibile
  set.seed(10)
  data_reduced = raw_data[sample(nrow(raw_data), sample_size), ]
  balanced_data = AdasynClassif(ethnicity~., data_reduced, beta = 1, dist = "HEOM", k=1)
  C.perc = list(Caucasian = 0.1, Asian = 0.1, Other=0.1, African_American=0.1, Hispanic=0.1, Native_American=0.1)

#balanced_data = adasyn_mod(ethnicity~., data_reduced, beta = 1, dist = "HEOM", k=1) #NON POSSO FARLO COS: Error in class.freq(dat, tgt) : non trovo la funzione "class.freq"
#Filter out categorical columns
cat_data <- balanced_data[, sapply(balanced_data, is.categorical)]
cat_names <- names(cat_data)
#pie print per ogni colonna categorica
for ( i in seq(1,length( cat_data ),1) ){
  pie_print(cat_data,cat_names[i])
}
#print_cmp_shannon(raw_data, balanced_data1)



## ------------------------------------------------------------------------------------
#ora provo a riplottare le metriche di fairness per ethnicity
#quindi prima faccio di nuovo sampling, regressione e trovo dataset classificato
source("util.R")
#sostituisco i livelli con valori numerici
levels(balanced_data$Two_yr_Recidivism)[levels(balanced_data$Two_yr_Recidivism)=="yes"] <- 1
```

```
460 levels(balanced_data$Two_yr_Recidivism)[levels(balanced_data$Two_yr_Recidivism)=="no"] <- 0
461 #rimuovo da balanced_data le colonne age_above e age_below
462 cols_to_drop <- names(balanced_data) %in% c("Age_Above_FourtyFive", "Age_Below_TwentyFive")
463 balanced_data <- balanced_data[, !cols_to_drop, drop = FALSE]
464
465 #split into train and test set
466 sample_size = floor(0.7*nrow(balanced_data))
467 #set a random seed per rendere l'esperimento ripetibile
468 set.seed(42)
469
470 # randomly split data
471 picked = sample(seq_len(nrow(balanced_data)),size = sample_size)
472 training_set =balanced_data[picked,]
473 test_set =balanced_data[-picked,]
474
475 #as.factor mi serve per fare una classificazione binaria
476 balanced_data$Two_yr_Recidivism = as.factor(balanced_data$Two_yr_Recidivism)
477 #devo anche eliminare recidivismo dal training_set
478 cols_to_drop <- names(training_set) %in% c("Two_yr_Recidivism")
479 #training e test set senza variabile target
480 training_set_data <- training_set[, !cols_to_drop, drop = FALSE]
481 #anche sui dati di test
482 test_set_data <- test_set[, !cols_to_drop, drop = FALSE]
483
484
485
486
487 levels(training_set$Two_yr_Recidivism)[levels(training_set$Two_yr_Recidivism)=="Yes_
        recidivism"] <- 1
488 levels(training_set$Two_yr_Recidivism)[levels(training_set$Two_yr_Recidivism)=="No_recidivism
        "] <- 0
489 levels(training_set$Two_yr_Recidivism)
490
491 levels(test_set$Two_yr_Recidivism)[levels(test_set$Two_yr_Recidivism)=="Yes_recidivism"] <- 1
492 levels(test_set$Two_yr_Recidivism)[levels(test_set$Two_yr_Recidivism)=="No_recidivism"] <- 0
493 levels(test_set$Two_yr_Recidivism)
494 ################################
495 #poi commento le righe in cui calcola il modello perch ci potrebbe mettere troppo (
        sufficiente salvarlo e ricaricarlo)
496 logitMod <- glm(Two_yr_Recidivism ~ ., data = training_set, family=binomial(link="logit"))
497 logitMod #capire cosa significano questi dati
498
499 pred = predict(logitMod, test_set_data, type = "response") #se non metto il type = response,
        mi restituisce una predizione tra -1 e 1, altrimenti me la restituisce tra 0 e 1. Scelgo
        tra -1 e 1 perc poi ottengo il cutoff ottimizzato anch'esso tra -1 e 1 e mi  pi facile
        fare la predizione
500 balanced_classified_dt = cbind(test_set, pred) #questo  quello che uso per la libreria
        fairness
```

```
501 classified_dt2 = cbind(test_set_data, pred)
502 #classified_dt = rbind(classified_dt1, classified_dt2)
503
504 pred1 <- prediction(pred, test_set$Two_yr_Recidivism) #pred1  un oggetto pred.obj di ROCR
505 perf <- performance(pred1, measure = "tpr", x.measure = "fpr")
506 optimized_cutoff_prova = opt.cut(perf, pred1)#il cutoff ottimale  leggermente pii basso di
    quello standard, che sarebbe invece 0.5
507
508 #ripristino di nuovo i livelli yes/no per renderlo pi leggibile
509 levels(balanced_classified_dt$Two_yr_Recidivism)[levels(balanced_classified_dt$Two_yr_
    Recidivism)==1] <- "Yes_recidivism"
510 levels(balanced_classified_dt$Two_yr_Recidivism)[levels(balanced_classified_dt$Two_yr_
    Recidivism)==0] <- "No_recidivism"
511
512 #plotto shannon compare per vedere come cambia l'indice rispetto al dataset originale per l'
    attributo ethnicity
513
514 #voglio provare a calcolare il valore medio delle predizioni per tutti i caucasian: PER
    PROPORTIONAL PARITY FA PROPRIO QUESTO!!!!
515 cdt_caucasian = classified_dt
516 cdt_caucasian = classified_dt[classified_dt$ethnicity=="Caucasian",]
517 cdt_caucasian$pred=ifelse(cdt_caucasian$pred<optimized_cutoff,0,1)
518 m = mean(cdt_caucasian$pred)
519 m #questa m  quella che io avrei chiamato percentage on ethnicity nella mia funzione frquent_
    comb1, cio percentage_on_ethnicity  la probabilit condizionata p(good| ethnicity=x) = #(
    status=good, ethnicity=x)/#(ethnicity=x)
520
521 cdt_caucasian = classified_dt
522 cdt_caucasian$pred=ifelse(cdt_caucasian$pred<optimized_cutoff,0,1)
523 frquent_comb1(cdt_caucasian, filter = "pred", c("ethnicity"))
524 ###################
525 levels(classified_dt$Two_yr_Recidivism)
526
527 ############################################################
528
529 fair_metrics_cmp(data1         = classified_dt,
530                  data2 = balanced_classified_dt,
531                  outcome      = 'Two_yr_Recidivism',
532                  outcome_base = 'No_recidivism',
533                  group        = 'ethnicity',
534                  probs =       'pred',
535                  preds_levels = c('No_recidivism','Yes_recidivism'),
536                  cutoff1       = optimized_cutoff,
537                  cutoff2       = optimized_cutoff_prova,
538                  base         = 'Caucasian')
539
540 # fair_metrics(data         = classified_dt,
541 #                       outcome      = 'Two_yr_Recidivism',
```

```
#                       group        = 'ethnicity',
#                       probs =       'pred',
#                       preds_levels = c('No_recidivism','Yes_recidivism'),
#                       cutoff       = optimized_cutoff,
#                       base         = 'Caucasian')


## ------------------------------------------------------------------------------
#CREO I SEGUENTI DATASET BILANCIATI:
#balanced_data0: bilanciato per Two_yr_recidivism
#balanced_data1: bilanciato per Female
#balanced_data2: bilanciato per ethnicity
#balanced_data3: bilanciato per Age
#balanced_data4: bilanciato per Two_yr_recidivism|ethnicity

#i due successivi li scarterei:
#balanced_data5: bilanciato per Female|ethnicity
#balanced_data6: bilanciato per Age|ethnicity

#balanced_data0: bilanciato per Two_yr_recidivism
balanced_data0=NULL
balanced_data0 = ovun.sample(Two_yr_Recidivism~., data = raw_data, method="both", N = nrow(
    raw_data), p=0.5, seed = 42)$data
print_cmp_shannon(raw_data, balanced_data0)
#shannon index praticamente uguale per Two_yr, perci questo potrebbe essere inutile (non ho
    cambiato il grado diversit in questo attributo, perci dovrei avere la stessa proporzione
    di individui yes/no recidivism)

######################
#balanced_data1: bilanciato per Female
#la libreria ROSE si pu usare soltanto per bilanciare attributi binari (nasce per bilanciare
    classificazione binaria)
balanced_data1 = NULL
balanced_data1 = ovun.sample(Female~., data = raw_data, method="both", N = nrow(raw_data), p
    =0.5, seed = 42)$data
print_cmp_shannon(raw_data, balanced_data1)
#shannon index migliorato per Female (cio riduzione di diversit)

##################
#balanced_data2: bilanciato per ethnicity con un random balance che ho creato io
#balanced_data2 = rebalance_multiclass(raw_data, "ethnicity")

#questo invece ha ethnicity bilanciato con smote ed  meglio usare questo!
balanced_data2 = SmoteClassif(ethnicity ~ ., raw_data, dist = "HEOM")

print_cmp_shannon(raw_data, balanced_data2)
#shannon index aumentato per ethnicity
```

```
585
586 ###################
587 #balanced_data3: bilanciato per Age
588 #balanced_data3 = rebalance_multiclass(raw_data, "Age")
589
590 #questo invece ha ethnicity bilanciato con smote ed  meglio usare questo!
591 balanced_data3 = SmoteClassif(Age ~ ., raw_data, dist = "HEOM")
592
593 print_cmp_shannon(raw_data, balanced_data3)
594 #shannon index leggermente aumentato per Age
595
596
597 ######################
598 #balanced_data4: bilanciato per Two_yr_recidivism|ethnicity (cio voglio ogni sottocategoria
      di ethnicity, gi precedentemente bilanciato (balanced_data2), bilanciata anche rispetto
      al recidivismo )
599 balanced_data4 = NULL
600 for(i in levels(balanced_data2$ethnicity)){
601   #faccio il rebalancing di Two_yr_Recidivism per ogni categoria di ethnicity
602   temp_dt = balanced_data2[balanced_data2$ethnicity==i, ]
603   s = ovun.sample(Two_yr_Recidivism~., data = temp_dt, method="both", N = nrow(temp_dt), p
      =0.5, seed = 42)$data
604   #metto poi insieme i vari piccoli dataset bilanciati
605   balanced_data4 = rbind(balanced_data4, s)
606 }
607
608 #plotto entrambi i confronti dello shannon index
609 print_cmp_shannon(raw_data, balanced_data4) #ethnicity aumentato di molto (ma c'era da
      aspettarsel, visto che  il confronto con il dataset originale)
610 print_cmp_shannon(balanced_data2, balanced_data4)#non  cambiato quasi nulla, quindi sembra
      sia sufficiente fare un rebalancing anche solo su ethnicity per migliorare la situazione
611
612 ###################
613 #balanced_data5: bilanciato per Two_yr_recidivism|ethnicity (cio voglio ogni sottocategoria
      di ethnicity bilanciata rispetto a Two_yr_recidivism)
614 #rispetto al dataset precedente, qui non abbiamo entrambi gli attributi contemporaneamente
      bilanicati vicendevolmente: ethniciy non  affatto bilanciato qui!
615 balanced_data5 = NULL
616 for(i in levels(raw_data$ethnicity)){
617   #faccio il rebalancing di Two_yr_Recidivism per ogni categoria di ethnicity
618   temp_dt = raw_data[raw_data$ethnicity==i, ]
619   s = ovun.sample(Two_yr_Recidivism~., data = temp_dt, method="both", N = nrow(temp_dt), p
      =0.5, seed = 42)$data
620   #metto poi insieme i vari piccoli dataset bilanciati
621   balanced_data5 = rbind(balanced_data5, s)
622 }
623 print_cmp_shannon(raw_data, balanced_data5) #shannon praticamente uguali
624 print_cmp_shannon(balanced_data4, balanced_data5)
```

```
625
626 #################
627 #bilancio ethnicity in ogni sottocategoria bilanciata di Female
628 balanced_data6 = NULL
629 for(i in levels(balanced_data1$ethnicity)){
630   #faccio il rebalancing di Two_yr_Recidivism per ogni categoria di ethnicity
631   temp_dt = balanced_data1[balanced_data1$ethnicity==i, ]
632   s = SmoteClassif(ethnicity ~ ., temp_dt, dist = "HEOM")
633   #metto poi insieme i vari piccoli dataset bilanciati
634   balanced_data6 = rbind(balanced_data6, s)
635 }
636 print_cmp_shannon(raw_data, balanced_data6) #molto meglio per ethnicity e un po' meglio per
      female
637
638 #confronto con bilanciato solo su female
639 print_cmp_shannon(balanced_data1, balanced_data6)#meglio per ethnicity
640
641 #confronto con bilanciato solo su ethnicity
642 print_cmp_shannon(balanced_data2, balanced_data6)#meglio per Female
643
644 ###############################
645 balanced_data7 = NULL
646 #bilancio il gender in ogni sottocategoria bilanciata di ethnicity
647 for(i in levels(balanced_data2$Female)){
648   temp_dt = raw_data[raw_data$Female==i, ]
649   s = ovun.sample(Two_yr_Recidivism~., data = temp_dt, method="both", N = nrow(temp_dt), p
        =0.5, seed = 42)$data
650   #metto poi insieme i vari piccoli dataset bilanciati
651   balanced_data7 = rbind(balanced_data7, s)
652 }
653 print_cmp_shannon(raw_data, balanced_data7) #molto meglio per ethnicity e un po' meglio per
      female
654
655
656 summary(raw_data$Number_of_Priors)
657 summary(balanced_data2$Number_of_Priors)
658 sd(raw_data$Number_of_Priors)
659 sd(balanced_data2$Number_of_Priors)
660
661
662
663 ## ------------------------------------------------------------------------------------
664 #balanced_data0: bilanciato per Two_yr_recidivism
665 #balanced_data1: bilanciato per Female
666 #balanced_data2: bilanciato per ethnicity
667 #balanced_data3: bilanciato per Age
668 #balanced_data4: bilanciato per Two_yr_recidivism|ethnicity
669
```

```
#otteniamo tutti i balanced dataset classificati:
source("util.R")

#balanced_data0

#sostituisco i livelli con valori numerici
levels(balanced_data0$Two_yr_Recidivism)[levels(balanced_data0$Two_yr_Recidivism)=="yes"] <-
    1
levels(balanced_data0$Two_yr_Recidivism)[levels(balanced_data0$Two_yr_Recidivism)=="no"] <- 0
#rimuovo da balanced_data0 le colonne age_above e age_below
cols_to_drop <- names(balanced_data0) %in% c("Age_Above_FourtyFive", "Age_Below_TwentyFive")
balanced_data0 <- balanced_data0[, !cols_to_drop, drop = FALSE]

#split into train and test set
sample_size = floor(0.7*nrow(balanced_data0))
#set a random seed per rendere l'esperimento ripetibile
set.seed(42)

# randomly split data
picked = sample(seq_len(nrow(balanced_data0)),size = sample_size)
training_set =balanced_data0[picked,]
test_set =balanced_data0[-picked,]

#as.factor mi serve per fare una classificazione binaria
balanced_data0$Two_yr_Recidivism = as.factor(balanced_data0$Two_yr_Recidivism)
#devo anche eliminare recidivismo dal training_set
cols_to_drop <- names(training_set) %in% c("Two_yr_Recidivism")
#training e test set senza variabile target
training_set_data <- training_set[, !cols_to_drop, drop = FALSE]
#anche sui dati di test
test_set_data <- test_set[, !cols_to_drop, drop = FALSE]

levels(training_set$Two_yr_Recidivism)[levels(training_set$Two_yr_Recidivism)=="Yes_
    recidivism"] <- 1
levels(training_set$Two_yr_Recidivism)[levels(training_set$Two_yr_Recidivism)=="No_recidivism
    "] <- 0
levels(training_set$Two_yr_Recidivism)

levels(test_set$Two_yr_Recidivism)[levels(test_set$Two_yr_Recidivism)=="Yes_recidivism"] <- 1
levels(test_set$Two_yr_Recidivism)[levels(test_set$Two_yr_Recidivism)=="No_recidivism"] <- 0
levels(test_set$Two_yr_Recidivism)
################################
#poi commento le righe in cui calcola il modello perch ci potrebbe mettere troppo (
    sufficiente salvarlo e ricaricarlo)
logitMod <- glm(Two_yr_Recidivism ~ ., data = training_set, family=binomial(link="logit"))
logitMod #capire cosa significano questi dati

```

```
713 pred = predict(logitMod, test_set_data, type = "response") #se non metto il type = response,
        mi restituisce una predizione tra -1 e 1, altrimenti me la restituisce tra 0 e 1. Scelgo
        tra -1 e 1 perc poi ottengo il cutoff ottimizzato anch'esso tra -1 e 1 e mi  pi facile
        fare la predizione
714 balanced0_classified_dt = cbind(test_set, pred) #questo  quello che uso per la libreria
        fairness
715 classified_dt2 = cbind(test_set_data, pred)
716 #classified_dt = rbind(classified_dt1, classified_dt2)
717 pred1 <- prediction(pred, test_set$Two_yr_Recidivism) #pred1  un oggetto pred.obj di ROCR
718 perf <- performance(pred1, measure = "tpr", x.measure = "fpr")
719 optimized_cutoff0 = opt.cut(perf, pred1)#il cutoff ottimale  leggermente pii basso di quello
        standard, che sarebbe invece 0.5
720
721 #ripristino di nuovo i livelli yes/no per renderlo pi leggibile
722 levels(balanced0_classified_dt$Two_yr_Recidivism)[levels(balanced0_classified_dt$Two_yr_
        Recidivism)==1] <- "Yes_recidivism"
723 levels(balanced0_classified_dt$Two_yr_Recidivism)[levels(balanced0_classified_dt$Two_yr_
        Recidivism)==0] <- "No_recidivism"
724
725 ##########################
726
727
728 ## ------------------------------------------------------------------------------------
729 #balanced_data1
730
731 #sostituisco i livelli con valori numerici
732 levels(balanced_data1$Two_yr_Recidivism)[levels(balanced_data1$Two_yr_Recidivism)=="yes"] <-
        1
733 levels(balanced_data1$Two_yr_Recidivism)[levels(balanced_data1$Two_yr_Recidivism)=="no"] <- 0
734 #rimuovo da balanced_data1 le colonne age_above e age_below
735 cols_to_drop <- names(balanced_data1) %in% c("Age_Above_FourtyFive", "Age_Below_TwentyFive")
736 balanced_data1 <- balanced_data1[, !cols_to_drop, drop = FALSE]
737
738 #split into train and test set
739 sample_size = floor(0.7*nrow(balanced_data1))
740 #set a random seed per rendere l'esperimento ripetibile
741 set.seed(42)
742
743 # randomly split data
744 picked = sample(seq_len(nrow(balanced_data1)),size = sample_size)
745 training_set =balanced_data1[picked,]
746 test_set =balanced_data1[-picked,]
747
748 #as.factor mi serve per fare una classificazione binaria
749 balanced_data1$Two_yr_Recidivism = as.factor(balanced_data1$Two_yr_Recidivism)
750 #devo anche eliminare recidivismo dal training_set
751 cols_to_drop <- names(training_set) %in% c("Two_yr_Recidivism")
752 #training e test set senza variabile target
```

```
753 training_set_data <- training_set[, !cols_to_drop, drop = FALSE]
754 #anche sui dati di test
755 test_set_data <- test_set[, !cols_to_drop, drop = FALSE]
756
757 levels(training_set$Two_yr_Recidivism)[levels(training_set$Two_yr_Recidivism)=="Yes_
        recidivism"] <- 1
758 levels(training_set$Two_yr_Recidivism)[levels(training_set$Two_yr_Recidivism)=="No_recidivism
        "] <- 0
759 levels(training_set$Two_yr_Recidivism)
760
761 levels(test_set$Two_yr_Recidivism)[levels(test_set$Two_yr_Recidivism)=="Yes_recidivism"] <- 1
762 levels(test_set$Two_yr_Recidivism)[levels(test_set$Two_yr_Recidivism)=="No_recidivism"] <- 0
763 levels(test_set$Two_yr_Recidivism)
764 ################################
765 #poi commento le righe in cui calcola il modello perch ci potrebbe mettere troppo (
        sufficiente salvarlo e ricaricarlo)
766 logitMod <- glm(Two_yr_Recidivism ~ ., data = training_set, family=binomial(link="logit"))
767 logitMod #capire cosa significano questi dati
768
769 pred = predict(logitMod, test_set_data, type = "response") #se non metto il type = response,
        mi restituisce una predizione tra -1 e 1, altrimenti me la restituisce tra 0 e 1. Scelgo
        tra -1 e 1 perc poi ottengo il cutoff ottimizzato anch'esso tra -1 e 1 e mi  pi facile
        fare la predizione
770 balanced1_classified_dt = cbind(test_set, pred) #questo  quello che uso per la libreria
        fairness
771 classified_dt2 = cbind(test_set_data, pred)
772 #classified_dt = rbind(classified_dt1, classified_dt2)
773 pred1 <- prediction(pred, test_set$Two_yr_Recidivism) #pred1  un oggetto pred.obj di ROCR
774 perf <- performance(pred1, measure = "tpr", x.measure = "fpr")
775 optimized_cutoff1 = opt.cut(perf, pred1)#il cutoff ottimale  leggermente pii basso di quello
        standard, che sarebbe invece 0.5
776
777 #ripristino di nuovo i livelli yes/no per renderlo pi leggibile
778 levels(balanced1_classified_dt$Two_yr_Recidivism)[levels(balanced1_classified_dt$Two_yr_
        Recidivism)==1] <- "Yes_recidivism"
779 levels(balanced1_classified_dt$Two_yr_Recidivism)[levels(balanced1_classified_dt$Two_yr_
        Recidivism)==0] <- "No_recidivism"
780
781 ################################
782
783
784 ## ------------------------------------------------------------------------------------
785 #balanced_data2
786
787 #sostituisco i livelli con valori numerici
788 levels(balanced_data2$Two_yr_Recidivism)[levels(balanced_data2$Two_yr_Recidivism)=="yes"] <-
        1
789 levels(balanced_data2$Two_yr_Recidivism)[levels(balanced_data2$Two_yr_Recidivism)=="no"] <- 0
```

```
790 #rimuovo da balanced_data2 le colonne age_above e age_below
791 cols_to_drop <- names(balanced_data2) %in% c("Age_Above_FourtyFive", "Age_Below_TwentyFive")
792 balanced_data2 <- balanced_data2[, !cols_to_drop, drop = FALSE]
793
794 #split into train and test set
795 sample_size = floor(0.7*nrow(balanced_data2))
796 #set a random seed per rendere l'esperimento ripetibile
797 set.seed(42)
798
799 # randomly split data
800 picked = sample(seq_len(nrow(balanced_data2)),size = sample_size)
801 training_set =balanced_data2[picked,]
802 test_set =balanced_data2[-picked,]
803
804 #as.factor mi serve per fare una classificazione binaria
805 balanced_data2$Two_yr_Recidivism = as.factor(balanced_data2$Two_yr_Recidivism)
806 #devo anche eliminare recidivismo dal training_set
807 cols_to_drop <- names(training_set) %in% c("Two_yr_Recidivism")
808 #training e test set senza variabile target
809 training_set_data <- training_set[, !cols_to_drop, drop = FALSE]
810 #anche sui dati di test
811 test_set_data <- test_set[, !cols_to_drop, drop = FALSE]
812
813 levels(training_set$Two_yr_Recidivism)[levels(training_set$Two_yr_Recidivism)=="Yes_
        recidivism"] <- 1
814 levels(training_set$Two_yr_Recidivism)[levels(training_set$Two_yr_Recidivism)=="No_recidivism
        "] <- 0
815 levels(training_set$Two_yr_Recidivism)
816
817 levels(test_set$Two_yr_Recidivism)[levels(test_set$Two_yr_Recidivism)=="Yes_recidivism"] <- 1
818 levels(test_set$Two_yr_Recidivism)[levels(test_set$Two_yr_Recidivism)=="No_recidivism"] <- 0
819 levels(test_set$Two_yr_Recidivism)
820 ################################
821 #poi commento le righe in cui calcola il modello perch ci potrebbe mettere troppo (
        sufficiente salvarlo e ricaricarlo)
822 logitMod <- glm(Two_yr_Recidivism ~ ., data = training_set, family=binomial(link="logit"))
823 logitMod #capire cosa significano questi dati
824
825 pred = predict(logitMod, test_set_data, type = "response") #se non metto il type = response,
        mi restituisce una predizione tra -1 e 1, altrimenti me la restituisce tra 0 e 1. Scelgo
        tra -1 e 1 perc poi ottengo il cutoff ottimizzato anch'esso tra -1 e 1 e mi  pi facile
        fare la predizione
826 balanced2_classified_dt = cbind(test_set, pred) #questo  quello che uso per la libreria
        fairness
827 classified_dt2 = cbind(test_set_data, pred)
828 #classified_dt = rbind(classified_dt1, classified_dt2)
829 pred1 <- prediction(pred, test_set$Two_yr_Recidivism) #pred1  un oggetto pred.obj di ROCR
830 perf <- performance(pred1, measure = "tpr", x.measure = "fpr")
```

```
831 optimized_cutoff2 = opt.cut(perf, pred1)#il cutoff ottimale  leggermente pii basso di quello
        standard, che sarebbe invece 0.5
832
833 #ripristino di nuovo i livelli yes/no per renderlo pi leggibile
834 levels(balanced2_classified_dt$Two_yr_Recidivism)[levels(balanced2_classified_dt$Two_yr_
        Recidivism)==1] <- "Yes_recidivism"
835 levels(balanced2_classified_dt$Two_yr_Recidivism)[levels(balanced2_classified_dt$Two_yr_
        Recidivism)==0] <- "No_recidivism"
836
837 ##############################
838
839
840 ## ------------------------------------------------------------------------------------
841 #balanced_data3
842
843 #sostituisco i livelli con valori numerici
844 levels(balanced_data3$Two_yr_Recidivism)[levels(balanced_data3$Two_yr_Recidivism)=="yes"] <-
        1
845 levels(balanced_data3$Two_yr_Recidivism)[levels(balanced_data3$Two_yr_Recidivism)=="no"] <- 0
846 #rimuovo da balanced_data3 le colonne age_above e age_below
847 cols_to_drop <- names(balanced_data3) %in% c("Age_Above_FourtyFive", "Age_Below_TwentyFive")
848 balanced_data3 <- balanced_data3[, !cols_to_drop, drop = FALSE]
849
850 #split into train and test set
851 sample_size = floor(0.7*nrow(balanced_data3))
852 #set a random seed per rendere l'esperimento ripetibile
853 set.seed(42)
854
855 # randomly split data
856 picked = sample(seq_len(nrow(balanced_data3)),size = sample_size)
857 training_set =balanced_data3[picked,]
858 test_set =balanced_data3[-picked,]
859
860 #as.factor mi serve per fare una classificazione binaria
861 balanced_data3$Two_yr_Recidivism = as.factor(balanced_data3$Two_yr_Recidivism)
862 #devo anche eliminare recidivismo dal training_set
863 cols_to_drop <- names(training_set) %in% c("Two_yr_Recidivism")
864 #training e test set senza variabile target
865 training_set_data <- training_set[, !cols_to_drop, drop = FALSE]
866 #anche sui dati di test
867 test_set_data <- test_set[, !cols_to_drop, drop = FALSE]
868
869 levels(training_set$Two_yr_Recidivism)[levels(training_set$Two_yr_Recidivism)=="Yes_
        recidivism"] <- 1
870 levels(training_set$Two_yr_Recidivism)[levels(training_set$Two_yr_Recidivism)=="No_recidivism
        "] <- 0
871 levels(training_set$Two_yr_Recidivism)
872
```

```
873 levels(test_set$Two_yr_Recidivism)[levels(test_set$Two_yr_Recidivism)=="Yes_recidivism"] <- 1
874 levels(test_set$Two_yr_Recidivism)[levels(test_set$Two_yr_Recidivism)=="No_recidivism"] <- 0
875 levels(test_set$Two_yr_Recidivism)
876 ################################
877 #poi commento le righe in cui calcola il modello perch ci potrebbe mettere troppo (
        sufficiente salvarlo e ricaricarlo)
878 logitMod <- glm(Two_yr_Recidivism ~ ., data = training_set, family=binomial(link="logit"))
879 logitMod #capire cosa significano questi dati
880
881 pred = predict(logitMod, test_set_data, type = "response") #se non metto il type = response,
        mi restituisce una predizione tra -1 e 1, altrimenti me la restituisce tra 0 e 1. Scelgo
        tra -1 e 1 perc poi ottengo il cutoff ottimizzato anch'esso tra -1 e 1 e mi  pi facile
        fare la predizione
882 balanced3_classified_dt = cbind(test_set, pred) #questo  quello che uso per la libreria
        fairness
883 classified_dt2 = cbind(test_set_data, pred)
884 #classified_dt = rbind(classified_dt1, classified_dt2)
885 pred1 <- prediction(pred, test_set$Two_yr_Recidivism) #pred1  un oggetto pred.obj di ROCR
886 perf <- performance(pred1, measure = "tpr", x.measure = "fpr")
887 optimized_cutoff3 = opt.cut(perf, pred1)#il cutoff ottimale  leggermente pii basso di quello
        standard, che sarebbe invece 0.5
888
889 #ripristino di nuovo i livelli yes/no per renderlo pi leggibile
890 levels(balanced3_classified_dt$Two_yr_Recidivism)[levels(balanced3_classified_dt$Two_yr_
        Recidivism)==1] <- "Yes_recidivism"
891 levels(balanced3_classified_dt$Two_yr_Recidivism)[levels(balanced3_classified_dt$Two_yr_
        Recidivism)==0] <- "No_recidivism"
892 ##################
893
894
895 ## ------------------------------------------------------------------------------------
896 #balanced_data4
897
898 #sostituisco i livelli con valori numerici
899 levels(balanced_data4$Two_yr_Recidivism)[levels(balanced_data4$Two_yr_Recidivism)=="yes"] <-
        1
900 levels(balanced_data4$Two_yr_Recidivism)[levels(balanced_data4$Two_yr_Recidivism)=="no"] <- 0
901 #rimuovo da balanced_data4 le colonne age_above e age_below
902 cols_to_drop <- names(balanced_data4) %in% c("Age_Above_FourtyFive", "Age_Below_TwentyFive")
903 balanced_data4 <- balanced_data4[, !cols_to_drop, drop = FALSE]
904
905 #split into train and test set
906 sample_size = floor(0.7*nrow(balanced_data4))
907 #set a random seed per rendere l'esperimento ripetibile
908 set.seed(42)
909
910 # randomly split data
911 picked = sample(seq_len(nrow(balanced_data4)),size = sample_size)
```

```
912 training_set =balanced_data4[picked,]
913 test_set =balanced_data4[-picked,]
914
915 #as.factor mi serve per fare una classificazione binaria
916 balanced_data4$Two_yr_Recidivism = as.factor(balanced_data4$Two_yr_Recidivism)
917 #devo anche eliminare recidivismo dal training_set
918 cols_to_drop <- names(training_set) %in% c("Two_yr_Recidivism")
919 #training e test set senza variabile target
920 training_set_data <- training_set[, !cols_to_drop, drop = FALSE]
921 #anche sui dati di test
922 test_set_data <- test_set[, !cols_to_drop, drop = FALSE]
923
924 levels(training_set$Two_yr_Recidivism)[levels(training_set$Two_yr_Recidivism)=="Yes_
    recidivism"] <- 1
925 levels(training_set$Two_yr_Recidivism)[levels(training_set$Two_yr_Recidivism)=="No_recidivism
    "] <- 0
926 levels(training_set$Two_yr_Recidivism)
927
928 levels(test_set$Two_yr_Recidivism)[levels(test_set$Two_yr_Recidivism)=="Yes_recidivism"] <- 1
929 levels(test_set$Two_yr_Recidivism)[levels(test_set$Two_yr_Recidivism)=="No_recidivism"] <- 0
930 levels(test_set$Two_yr_Recidivism)
931 ################################
932 #poi commento le righe in cui calcola il modello perch ci potrebbe mettere troppo (
    sufficiente salvarlo e ricaricarlo)
933 logitMod <- glm(Two_yr_Recidivism ~ ., data = training_set, family=binomial(link="logit"))
934 logitMod #capire cosa significano questi dati
935
936 pred = predict(logitMod, test_set_data, type = "response") #se non metto il type = response,
    mi restituisce una predizione tra -1 e 1, altrimenti me la restituisce tra 0 e 1. Scelgo
    tra -1 e 1 perc poi ottengo il cutoff ottimizzato anch'esso tra -1 e 1 e mi  pi facile
    fare la predizione
937 balanced4_classified_dt = cbind(test_set, pred) #questo  quello che uso per la libreria
    fairness
938 classified_dt2 = cbind(test_set_data, pred)
939 #classified_dt = rbind(classified_dt1, classified_dt2)
940 pred1 <- prediction(pred, test_set$Two_yr_Recidivism) #pred1  un oggetto pred.obj di ROCR
941 perf <- performance(pred1, measure = "tpr", x.measure = "fpr")
942 optimized_cutoff4 = opt.cut(perf, pred1)#il cutoff ottimale  leggermente pii basso di quello
    standard, che sarebbe invece 0.5
943
944 #ripristino di nuovo i livelli yes/no per renderlo pi leggibile
945 levels(balanced4_classified_dt$Two_yr_Recidivism)[levels(balanced4_classified_dt$Two_yr_
    Recidivism)==1] <- "Yes_recidivism"
946 levels(balanced4_classified_dt$Two_yr_Recidivism)[levels(balanced4_classified_dt$Two_yr_
    Recidivism)==0] <- "No_recidivism"
947
948
949 ## ------------------------------------------------------------------------
```

```
950 ##############################
951
952 #balanced_data5
953
954 #sostituisco i livelli con valori numerici
955 levels(balanced_data5$Two_yr_Recidivism)[levels(balanced_data5$Two_yr_Recidivism)=="yes"] <-
        1
956 levels(balanced_data5$Two_yr_Recidivism)[levels(balanced_data5$Two_yr_Recidivism)=="no"] <- 0
957 #rimuovo da balanced_data5 le colonne age_above e age_below
958 cols_to_drop <- names(balanced_data5) %in% c("Age_Above_FourtyFive", "Age_Below_TwentyFive")
959 balanced_data5 <- balanced_data5[, !cols_to_drop, drop = FALSE]
960
961 #split into train and test set
962 sample_size = floor(0.7*nrow(balanced_data5))
963 #set a random seed per rendere l'esperimento ripetibile
964 set.seed(42)
965
966 # randomly split data
967 picked = sample(seq_len(nrow(balanced_data5)),size = sample_size)
968 training_set =balanced_data5[picked,]
969 test_set =balanced_data5[-picked,]
970
971 #as.factor mi serve per fare una classificazione binaria
972 balanced_data5$Two_yr_Recidivism = as.factor(balanced_data5$Two_yr_Recidivism)
973 #devo anche eliminare recidivismo dal training_set
974 cols_to_drop <- names(training_set) %in% c("Two_yr_Recidivism")
975 #training e test set senza variabile target
976 training_set_data <- training_set[, !cols_to_drop, drop = FALSE]
977 #anche sui dati di test
978 test_set_data <- test_set[, !cols_to_drop, drop = FALSE]
979
980 levels(training_set$Two_yr_Recidivism)[levels(training_set$Two_yr_Recidivism)=="Yes_
        recidivism"] <- 1
981 levels(training_set$Two_yr_Recidivism)[levels(training_set$Two_yr_Recidivism)=="No_recidivism
        "] <- 0
982 levels(training_set$Two_yr_Recidivism)
983
984 levels(test_set$Two_yr_Recidivism)[levels(test_set$Two_yr_Recidivism)=="Yes_recidivism"] <- 1
985 levels(test_set$Two_yr_Recidivism)[levels(test_set$Two_yr_Recidivism)=="No_recidivism"] <- 0
986 levels(test_set$Two_yr_Recidivism)
987 ##############################
988 #poi commento le righe in cui calcola il modello perch ci potrebbe mettere troppo (
        sufficiente salvarlo e ricaricarlo)
989 logitMod <- glm(Two_yr_Recidivism ~ ., data = training_set, family=binomial(link="logit"))
990 logitMod #capire cosa significano questi dati
991
992 pred = predict(logitMod, test_set_data, type = "response") #se non metto il type = response,
        mi restituisce una predizione tra -1 e 1, altrimenti me la restituisce tra 0 e 1. Scelgo
```

```
    tra -1 e 1 perc poi ottengo il cutoff ottimizzato anch'esso tra -1 e 1 e mi  pi facile
    fare la predizione
balanced5_classified_dt = cbind(test_set, pred) #questo  quello che uso per la libreria
    fairness
classified_dt2 = cbind(test_set_data, pred)
#classified_dt = rbind(classified_dt1, classified_dt2)
pred1 <- prediction(pred, test_set$Two_yr_Recidivism) #pred1  un oggetto pred.obj di ROCR
perf <- performance(pred1, measure = "tpr", x.measure = "fpr")
optimized_cutoff5 = opt.cut(perf, pred1)#il cutoff ottimale  leggermente pii basso di quello
    standard, che sarebbe invece 0.5

#ripristino di nuovo i livelli yes/no per renderlo pi leggibile
levels(balanced5_classified_dt$Two_yr_Recidivism)[levels(balanced5_classified_dt$Two_yr_
    Recidivism)==1] <- "Yes_recidivism"
levels(balanced5_classified_dt$Two_yr_Recidivism)[levels(balanced5_classified_dt$Two_yr_
    Recidivism)==0] <- "No_recidivism"

## ------------------------------------------------------------------------------------
##############################

#balanced_data6

#sostituisco i livelli con valori numerici
levels(balanced_data6$Two_yr_Recidivism)[levels(balanced_data6$Two_yr_Recidivism)=="yes"] <-
    1
levels(balanced_data6$Two_yr_Recidivism)[levels(balanced_data6$Two_yr_Recidivism)=="no"] <- 0
#rimuovo da balanced_data6 le colonne age_above e age_below
cols_to_drop <- names(balanced_data6) %in% c("Age_Above_FourtyFive", "Age_Below_TwentyFive")
balanced_data6 <- balanced_data6[, !cols_to_drop, drop = FALSE]

#split into train and test set
sample_size = floor(0.7*nrow(balanced_data6))
#set a random seed per rendere l'esperimento ripetibile
set.seed(42)

# randomly split data
picked = sample(seq_len(nrow(balanced_data6)),size = sample_size)
training_set =balanced_data6[picked,]
test_set =balanced_data6[-picked,]

#as.factor mi serve per fare una classificazione binaria
balanced_data6$Two_yr_Recidivism = as.factor(balanced_data6$Two_yr_Recidivism)
#devo anche eliminare recidivismo dal training_set
cols_to_drop <- names(training_set) %in% c("Two_yr_Recidivism")
#training e test set senza variabile target
training_set_data <- training_set[, !cols_to_drop, drop = FALSE]
#anche sui dati di test
test_set_data <- test_set[, !cols_to_drop, drop = FALSE]
```

```
1034
1035 levels(training_set$Two_yr_Recidivism)[levels(training_set$Two_yr_Recidivism)=="Yes_
         recidivism"] <- 1
1036 levels(training_set$Two_yr_Recidivism)[levels(training_set$Two_yr_Recidivism)=="No_recidivism
         "] <- 0
1037 levels(training_set$Two_yr_Recidivism)
1038
1039 levels(test_set$Two_yr_Recidivism)[levels(test_set$Two_yr_Recidivism)=="Yes_recidivism"] <- 1
1040 levels(test_set$Two_yr_Recidivism)[levels(test_set$Two_yr_Recidivism)=="No_recidivism"] <- 0
1041 levels(test_set$Two_yr_Recidivism)
1042 ################################
1043 #poi commento le righe in cui calcola il modello perch ci potrebbe mettere troppo (
         sufficiente salvarlo e ricaricarlo)
1044 logitMod <- glm(Two_yr_Recidivism ~ ., data = training_set, family=binomial(link="logit"))
1045 logitMod #capire cosa significano questi dati
1046
1047 pred = predict(logitMod, test_set_data, type = "response") #se non metto il type = response,
         mi restituisce una predizione tra -1 e 1, altrimenti me la restituisce tra 0 e 1. Scelgo
         tra -1 e 1 perc poi ottengo il cutoff ottimizzato anch'esso tra -1 e 1 e mi  pi facile
         fare la predizione
1048 balanced6_classified_dt = cbind(test_set, pred) #questo  quello che uso per la libreria
         fairness
1049 classified_dt2 = cbind(test_set_data, pred)
1050 #classified_dt = rbind(classified_dt1, classified_dt2)
1051 pred1 <- prediction(pred, test_set$Two_yr_Recidivism) #pred1  un oggetto pred.obj di ROCR
1052 perf <- performance(pred1, measure = "tpr", x.measure = "fpr")
1053 optimized_cutoff6 = opt.cut(perf, pred1)#il cutoff ottimale  leggermente pii basso di quello
         standard, che sarebbe invece 0.5
1054
1055 #ripristino di nuovo i livelli yes/no per renderlo pi leggibile
1056 levels(balanced6_classified_dt$Two_yr_Recidivism)[levels(balanced6_classified_dt$Two_yr_
         Recidivism)==1] <- "Yes_recidivism"
1057 levels(balanced6_classified_dt$Two_yr_Recidivism)[levels(balanced6_classified_dt$Two_yr_
         Recidivism)==0] <- "No_recidivism"
1058
1059
1060
1061 ## ------------------------------------------------------------------------------------
1062 ################################
1063
1064 #balanced_data7
1065
1066 #sostituisco i livelli con valori numerici
1067 levels(balanced_data7$Two_yr_Recidivism)[levels(balanced_data7$Two_yr_Recidivism)=="yes"] <-
         1
1068 levels(balanced_data7$Two_yr_Recidivism)[levels(balanced_data7$Two_yr_Recidivism)=="no"] <- 0
1069 #rimuovo da balanced_data7 le colonne age_above e age_below
1070 cols_to_drop <- names(balanced_data7) %in% c("Age_Above_FourtyFive", "Age_Below_TwentyFive")
```

```
balanced_data7 <- balanced_data7[, !cols_to_drop, drop = FALSE]

#split into train and test set
sample_size = floor(0.7*nrow(balanced_data7))
#set a random seed per rendere l'esperimento ripetibile
set.seed(42)

# randomly split data
picked = sample(seq_len(nrow(balanced_data7)),size = sample_size)
training_set =balanced_data7[picked,]
test_set =balanced_data7[-picked,]

#as.factor mi serve per fare una classificazione binaria
balanced_data7$Two_yr_Recidivism = as.factor(balanced_data7$Two_yr_Recidivism)
#devo anche eliminare recidivismo dal training_set
cols_to_drop <- names(training_set) %in% c("Two_yr_Recidivism")
#training e test set senza variabile target
training_set_data <- training_set[, !cols_to_drop, drop = FALSE]
#anche sui dati di test
test_set_data <- test_set[, !cols_to_drop, drop = FALSE]

levels(training_set$Two_yr_Recidivism)[levels(training_set$Two_yr_Recidivism)=="Yes_
    recidivism"] <- 1
levels(training_set$Two_yr_Recidivism)[levels(training_set$Two_yr_Recidivism)=="No_recidivism
    "] <- 0
levels(training_set$Two_yr_Recidivism)

levels(test_set$Two_yr_Recidivism)[levels(test_set$Two_yr_Recidivism)=="Yes_recidivism"] <- 1
levels(test_set$Two_yr_Recidivism)[levels(test_set$Two_yr_Recidivism)=="No_recidivism"] <- 0
levels(test_set$Two_yr_Recidivism)
################################
#poi commento le righe in cui calcola il modello perch ci potrebbe mettere troppo (
    sufficiente salvarlo e ricaricarlo)
logitMod <- glm(Two_yr_Recidivism ~ ., data = training_set, family=binomial(link="logit"))
logitMod #capire cosa significano questi dati

pred = predict(logitMod, test_set_data, type = "response") #se non metto il type = response,
    mi restituisce una predizione tra -1 e 1, altrimenti me la restituisce tra 0 e 1. Scelgo
    tra -1 e 1 perc poi ottengo il cutoff ottimizzato anch'esso tra -1 e 1 e mi  pi facile
    fare la predizione
balanced7_classified_dt = cbind(test_set, pred) #questo  quello che uso per la libreria
    fairness
classified_dt2 = cbind(test_set_data, pred)
#classified_dt = rbind(classified_dt1, classified_dt2)
pred1 <- prediction(pred, test_set$Two_yr_Recidivism) #pred1  un oggetto pred.obj di ROCR
perf <- performance(pred1, measure = "tpr", x.measure = "fpr")
optimized_cutoff7 = opt.cut(perf, pred1)#il cutoff ottimale  leggermente pii basso di quello
    standard, che sarebbe invece 0.5
```

```
1111
1112 #ripristino di nuovo i livelli yes/no per renderlo pi leggibile
1113 levels(balanced7_classified_dt$Two_yr_Recidivism)[levels(balanced7_classified_dt$Two_yr_
     Recidivism)==1] <- "Yes_recidivism"
1114 levels(balanced7_classified_dt$Two_yr_Recidivism)[levels(balanced7_classified_dt$Two_yr_
     Recidivism)==0] <- "No_recidivism"
1115
1116
1117
1118 ## ------------------------------------------------------------------------------------
1119 #ora confronto ciascun dataset bilanciato con quello orignale
1120 #poi seleziono quelli che sembrano effettivamente migliori del dataset originale
1121 #poi confronto tra loro questi dataset bilanciati rimanenti e scelgo il migliore
1122
1123 #balanced_data0: bilanciato per Two_yr_recidivism
1124 #balanced_data1: bilanciato per Female
1125 #balanced_data2: bilanciato per ethnicity
1126 #balanced_data3: bilanciato per Age
1127 #balanced_data4: bilanciato per Two_yr_recidivism|ethnicity
1128
1129 #creo anche un dataset con i valori delle mean deviation per ogni dataset bilanciato, per
     ogni metrica
1130 msd_balanced=NULL
1131
1132 source("util.R")
1133 png("COMPASb0rdComp.png")
1134 p = fair_metrics_cmp_graph(data1         = classified_dt,
1135                 data2 = balanced0_classified_dt,
1136                 outcome      = 'Two_yr_Recidivism',
1137                 outcome_base = 'No_recidivism',
1138                 group        = 'ethnicity',
1139                 probs1 =       'pred',
1140                 probs2 =       'pred',
1141                 preds_levels = c('No_recidivism','Yes_recidivism'),
1142                 cutoff1       = optimized_cutoff,
1143                 cutoff2      = optimized_cutoff0,
1144                 base         = 'Caucasian')
1145 dev.off()
1146 #praticamente solo peggioramenti
1147 msd_balanced=p[[1]]
1148 msd_balanced= rbind(msd_balanced, p[[2]])
1149
1150 png("COMPASb1rdComp.png")
1151 p = fair_metrics_cmp_graph(data1         = classified_dt,
1152                 data2 = balanced1_classified_dt,
1153                 outcome      = 'Two_yr_Recidivism',
1154                 outcome_base = 'No_recidivism',
1155                 group        = 'ethnicity',
```

```
                probs1 =       'pred',
                probs2 =       'pred',
                preds_levels = c('No_recidivism','Yes_recidivism'),
                cutoff1       = optimized_cutoff,
                cutoff2      = optimized_cutoff1,
                base         = 'Caucasian')
dev.off()
msd_balanced= rbind(msd_balanced, p[[2]])
#in questo caso abbiamo dei miglioramenti abbastanza notevoli: dal momento che questo sembra
    il miglioramento pi notevole per le metriche di fairness, proviamo a migliorarlo
    ulteriormente mettendo lo stesso numero di individui per ogni etnia tra i maschi e tra le
     femmine, quindi avremo un doppio bilanciamento (lo chiamo balanced6_classified_dt)

png("COMPASb2rdComp.png")
p = fair_metrics_cmp_graph(data1         = classified_dt,
                data2 = balanced2_classified_dt,
                outcome      = 'Two_yr_Recidivism',
                outcome_base = 'No_recidivism',
                group        = 'ethnicity',
                probs1 =       'pred',
                probs2 =       'pred',
                preds_levels = c('No_recidivism','Yes_recidivism'),
                cutoff1       = optimized_cutoff,
                cutoff2      = optimized_cutoff2,
                base         = 'Caucasian')
dev.off()
msd_balanced= rbind(msd_balanced, p[[2]])
#questo era il dataset bilanciato per ethnicity: abbiamo qualche miglioramento, ma anche
    qualche peggioramento

png("COMPASb3rdComp.png")
p = fair_metrics_cmp_graph(data1         = classified_dt,
                data2 = balanced3_classified_dt,
                outcome      = 'Two_yr_Recidivism',
                outcome_base = 'No_recidivism',
                group        = 'ethnicity',
                probs1 =       'pred',
                probs2 =       'pred',
                preds_levels = c('No_recidivism','Yes_recidivism'),
                cutoff1       = optimized_cutoff,
                cutoff2      = optimized_cutoff3,
                base         = 'Caucasian')
dev.off()
msd_balanced= rbind(msd_balanced, p[[2]])
#qualche miglioramento e peggioramento

png("COMPASb4rdComp.png")
p = fair_metrics_cmp_graph(data1         = classified_dt,
```

```
                data2 = balanced4_classified_dt,
                outcome      = 'Two_yr_Recidivism',
                outcome_base = 'No_recidivism',
                group        = 'ethnicity',
                probs1 =       'pred',
                probs2 =       'pred',
                preds_levels = c('No_recidivism','Yes_recidivism'),
                cutoff1       = optimized_cutoff,
                cutoff2      = optimized_cutoff4,
                base         = 'Caucasian')
dev.off()
msd_balanced= rbind(msd_balanced, p[[2]])
#in questo caso abbiamo ponderato sia l'etnia sia il recidivismo: stesso numero di individui per ciascuna etnia e, all'interno della singola etnia, stesso numero di recidivi e non recidivi

###################
#balanced balanced5_classified_dt
#re avessimo invece ponderato il recidivismo in funzione dell'etnia, cio ugual numero di recidivi per ogni etnia, ma con l'attributo etnia non equilibrato? proviamo (vedi chunck precedente e poi qui sotto)

png("COMPASb5rdComp.png")
p = fair_metrics_cmp_graph(data1         = classified_dt,
                data2 = balanced5_classified_dt,
                outcome      = 'Two_yr_Recidivism',
                outcome_base = 'No_recidivism',
                group        = 'ethnicity',
                probs1 =       'pred',
                probs2 =       'pred',
                preds_levels = c('No_recidivism','Yes_recidivism'),
                cutoff1       = optimized_cutoff,
                cutoff2      = optimized_cutoff5,
                base         = 'Caucasian')
dev.off()
msd_balanced= rbind(msd_balanced, p[[2]])
#alcune metriche sono migliori, ma altre decisamente peggiori

####################
#balanced6_classified_dt

png("COMPASb6b1Comp.png")
#NOTARE CHE QUESTA NON  UNA COMPARISON RISPETTO AL DATASET ORIGINALE
fair_metrics_cmp_graph(data1         = balanced1_classified_dt,
                data2 = balanced6_classified_dt,
                outcome      = 'Two_yr_Recidivism',
                outcome_base = 'No_recidivism',
                group        = 'ethnicity',
```

```
                probs1 =       'pred',
                probs2 =       'pred',
                preds_levels = c('No_recidivism','Yes_recidivism'),
                cutoff1       = optimized_cutoff1,
                cutoff2      = optimized_cutoff6,
                base         = 'Caucasian')
dev.off()

png("COMPASb6rdComp.png")
p = fair_metrics_cmp_graph(data1         = classified_dt,
                data2 = balanced6_classified_dt,
                outcome      = 'Two_yr_Recidivism',
                outcome_base = 'No_recidivism',
                group        = 'ethnicity',
                probs1 =       'pred',
                probs2 =       'pred',
                preds_levels = c('No_recidivism','Yes_recidivism'),
                cutoff1       = optimized_cutoff1,
                cutoff2      = optimized_cutoff6,
                base         = 'Caucasian')
dev.off()
msd_balanced= rbind(msd_balanced, p[[2]])
#a quanto pare il balanced6_classified_dt NON  meglio del #1

png("COMPASb7rdComp.png")
p = fair_metrics_cmp_graph(data1         = classified_dt,
                data2 = balanced7_classified_dt,
                outcome      = 'Two_yr_Recidivism',
                outcome_base = 'No_recidivism',
                group        = 'ethnicity',
                probs1 =       'pred',
                probs2 =       'pred',
                preds_levels = c('No_recidivism','Yes_recidivism'),
                cutoff1       = optimized_cutoff1,
                cutoff2      = optimized_cutoff7,
                base         = 'Caucasian')
dev.off()
msd_balanced= rbind(msd_balanced, p[[2]])

#CONFRONTO TRA LORO BALANCED DATASETS
######################
png("COMPASb2b4Comp.png")
fair_metrics_cmp_graph(data1         = balanced4_classified_dt,
                data2 = balanced2_classified_dt,
                outcome      = 'Two_yr_Recidivism',
                outcome_base = 'No_recidivism',
                group        = 'ethnicity',
                probs1 =       'pred',
```

```
                probs2 =       'pred',
                preds_levels = c('No_recidivism','Yes_recidivism'),
                cutoff1       = optimized_cutoff4,
                cutoff2      = optimized_cutoff2,
                base         = 'Caucasian')
dev.off()

png("COMPASb7b6Comp.png")
fair_metrics_cmp_graph(data1         = balanced7_classified_dt,
                data2 = balanced6_classified_dt,
                outcome      = 'Two_yr_Recidivism',
                outcome_base = 'No_recidivism',
                group        = 'ethnicity',
                probs1 =       'pred',
                probs2 =       'pred',
                preds_levels = c('No_recidivism','Yes_recidivism'),
                cutoff1       = optimized_cutoff6,
                cutoff2      = optimized_cutoff7,
                base         = 'Caucasian')
dev.off()
fair_metrics_cmp_graph(data1         = balanced7_classified_dt,
                data2 = balanced6_classified_dt,
                outcome      = 'Two_yr_Recidivism',
                outcome_base = 'No_recidivism',
                group        = 'ethnicity',
                probs1 =       'pred',
                probs2 =       'pred',
                preds_levels = c('No_recidivism','Yes_recidivism'),
                cutoff1       = optimized_cutoff7,
                cutoff2      = optimized_cutoff6,
                base         = 'Caucasian')
#dev.off()

msd_balanced
long_msd_balanced <- msd_balanced %>% gather(metrics, values, dem_parity:spec_parity)
 xlab("")

g = ggplot(long_msd_balanced, aes(fill=metrics, y=values, x=datasets)) +
    geom_bar(position="dodge", stat="identity") +
    #ggtitle("Studying 4 species..") +
    facet_wrap(~metrics, ncol=2) +
    #facet_grid(metrics ~ datasets)
    theme(legend.position="none",
          strip.text = element_text(face="bold", size=15,lineheight=5.0),
strip.background = element_rect(fill="lightblue", colour="black",
size=1,),axis.text.x = element_text(angle = 90),
axis.text=element_text(size=20, face="bold"),
        axis.title=element_text(size=20,face="bold")) +
```

```
1340     xlab("")
1341 ggsave("MetricsValuesForbd.jpg", plot = g, width = 24, height = 33, units = "in")
1342
1343
1344 ## ------------------------------------------------------------------------------
1345 #USO DI AIF360
1346 library(aif360)
1347 #load_aif360_lib()
1348
1349
1350 ## ------------------------------------------------------------------------------
1351 ##########################
1352 #converto dataset in binario
1353 #qua devo usare il balanced non ancora classificato, NON quello classificato!!!
1354 #OCCHIO: fai il run di queste righe di conversione 0-1 solo se il dataset non  ancora stato
      convertito!!! ad esempio fai prima un check is.numeric
1355
1356 levels(balanced_data1$Two_yr_Recidivism)[levels(balanced_data1$Two_yr_Recidivism)=="Yes_
      recidivism"] <- 1
1357 levels(balanced_data1$Two_yr_Recidivism)[levels(balanced_data1$Two_yr_Recidivism)=="No_
      recidivism"] <- 0
1358 #prendo caucasian come riferiemnto perch il confronto tra le metrich di fairness lo far poi
      con caucasian come base
1359 #I caucasian sono codificati con 1 (privilegiati)
1360 levels(balanced_data1$ethnicity)[levels(balanced_data1$ethnicity)!="Caucasian"] <- 0
1361 levels(balanced_data1$ethnicity)[levels(balanced_data1$ethnicity)=="Caucasian"] <- 1
1362 levels(balanced_data1$Female)[levels(balanced_data1$Female)=="Female"] <- 0
1363 levels(balanced_data1$Female)[levels(balanced_data1$Female)=="Male"] <- 1
1364 levels(balanced_data1$Misdemeanor)[levels(balanced_data1$Misdemeanor)=="yes"] <- 0
1365 levels(balanced_data1$Misdemeanor)[levels(balanced_data1$Misdemeanor)=="no"] <- 1
1366 levels(balanced_data1$Age)[levels(balanced_data1$Age)!="between25_45"] <- 0
1367 levels(balanced_data1$Age)[levels(balanced_data1$Age)=="between25_45"] <- 1
1368 # #trasformo colonne categoriche in numeriche
1369 # must_convert<-sapply(balanced_data1,is.factor)       # logical vector telling if a variable
       needs to be displayed as numeric
1370 # balanced_data1<-sapply(balanced_data1[,must_convert],unclass)    # data.frame of all
      categorical variables now displayed as numeric
1371
1372
1373 ## ------------------------------------------------------------------------------
1374 #i favoriti sono gli adulti-1
1375 formatted_dataset <- aif360::aif_dataset(data_path = balanced_data1, favor_label = 0,
1376 unfavor_label = 1, #label favorita per la variabile target: 0 corrisponde a good
1377 unprivileged_protected_attribute = 0, # 0-young-unprivileged
1378 privileged_protected_attribute = 1, #se non lo scrivo, per il valore privilegiato viene
      considerato il valore pi alto
1379 target_column = "Two_yr_Recidivism", #qua prima avevo pred.rescaled
1380 protected_attribute = "ethnicity")
```

```
formatted_dataset

#tecnica di debias preprocessing
di <- disparate_impact_remover(repair_level = 0.8, sensitive_attribute = "ethnicity")
rp <- di$fit_transform(formatted_dataset)

#reweighing (tecnica preprocessing)
pri <- list("ethnicity", 1)
unpri <- list("ethnicity", 0)
rw <- reweighing(unpri,pri)
#rw$fit(formatted_dataset)
#ad_transformed <- rw$transform(formatted_dataset)
ad_fit_transformed <- rw$fit_transform(rp) #questo lo faccio su rp, cos analizzo entrambe le tecniche in una volta sola (altrimenti dovrei fare mille classificazioni e mille casi)


## ------------------------------------------------------------------------------------
#ora torniamo a un dataset in formato data frame (non aif360)
col_names <- c(ad_fit_transformed$feature_names, "Two_yr_Recidivism")
col_names
new_data <- data.frame(ad_fit_transformed$features, ad_fit_transformed$labels)
colnames(new_data) <- col_names



#quindi new_data  un dataset su cui ho fatto rebalancing per Female, disparate impact remover e reweighing


## ------------------------------------------------------------------------------------
#sostituisco i livelli con valori numerici
levels(new_data$Two_yr_Recidivism)[levels(new_data$Two_yr_Recidivism)=="yes"] <- 1
levels(new_data$Two_yr_Recidivism)[levels(new_data$Two_yr_Recidivism)=="no"] <- 0
#rimuovo da new_data le colonne age_above e age_below
cols_to_drop <- names(new_data) %in% c("Age_Above_FourtyFive", "Age_Below_TwentyFive")
new_data <- new_data[, !cols_to_drop, drop = FALSE]

#split into train and test set
sample_size = floor(0.7*nrow(new_data))
#set a random seed per rendere l'esperimento ripetibile
set.seed(42)

# randomly split data
picked = sample(seq_len(nrow(new_data)),size = sample_size)
training_set =new_data[picked,]
test_set =new_data[-picked,]

#as.factor mi serve per fare una classificazione binaria
```

```
1427 new_data$Two_yr_Recidivism = as.factor(new_data$Two_yr_Recidivism)
1428 #devo anche eliminare recidivismo dal training_set
1429 cols_to_drop <- names(training_set) %in% c("Two_yr_Recidivism")
1430 #training e test set senza variabile target
1431 training_set_data <- training_set[, !cols_to_drop, drop = FALSE]
1432 #anche sui dati di test
1433 test_set_data <- test_set[, !cols_to_drop, drop = FALSE]
1434
1435 levels(training_set$Two_yr_Recidivism)[levels(training_set$Two_yr_Recidivism)=="Yes_
         recidivism"] <- 1
1436 levels(training_set$Two_yr_Recidivism)[levels(training_set$Two_yr_Recidivism)=="No_recidivism
         "] <- 0
1437 levels(training_set$Two_yr_Recidivism)
1438
1439 levels(test_set$Two_yr_Recidivism)[levels(test_set$Two_yr_Recidivism)=="Yes_recidivism"] <- 1
1440 levels(test_set$Two_yr_Recidivism)[levels(test_set$Two_yr_Recidivism)=="No_recidivism"] <- 0
1441 levels(test_set$Two_yr_Recidivism)
1442 ################################
1443 #poi commento le righe in cui calcola il modello perch ci potrebbe mettere troppo (
         sufficiente salvarlo e ricaricarlo)
1444 logitMod <- glm(Two_yr_Recidivism ~ ., data = training_set, family=binomial(link="logit"))
1445 logitMod #capire cosa significano questi dati
1446
1447 pred = predict(logitMod, test_set_data, type = "response")
1448 new_data_classified_dt = cbind(test_set, pred) #questo  quello che uso per la libreria
         fairness
1449 classified_dt2 = cbind(test_set_data, pred)
1450 #classified_dt = rbind(classified_dt1, classified_dt2)
1451 optimized_cutoff_new = opt.cut(perf, pred1)#il cutoff ottimale  leggermente pii basso di
         quello standard, che sarebbe invece 0.5
1452
1453
1454 ## ------------------------------------------------------------------------------------
1455 #ripristino di nuovo TUTTI i livelli categorici per renderlo pi leggibile
1456 new_data_classified_dt$Two_yr_Recidivism = ifelse(new_data_classified_dt$Two_yr_Recidivism
         ==1,"Yes_recidivism", "No_recidivism")
1457
1458 new_data_classified_dt$ethnicity = ifelse(new_data_classified_dt$ethnicity==1,"Caucasian", "
         Not_caucasian")
1459
1460
1461 new_data_classified_dt$Female = ifelse(new_data_classified_dt$Female==1,"Male", "Female")
1462
1463
1464 new_data_classified_dt$Misdemeanor = ifelse(new_data_classified_dt$Misdemeanor==1,"no", "yes"
         )
1465
1466
```

```
1467 new_data_classified_dt$Age = ifelse(new_data_classified_dt$Age==1,"between25_45", "Not_
         between25_45")
1468
1469
1470
1471 ## ------------------------------------------------------------------------------------
1472 #confronto con il dataset bilanciato su female
1473 fair_metrics_cmp_graph(data1         = balanced1_classified_dt,
1474                 data2 = new_data_classified_dt,
1475                 outcome      = 'Two_yr_Recidivism',
1476                 outcome_base = 'No_recidivism',
1477                 group        = 'ethnicity',
1478                 probs1 =       'pred',
1479                 probs2 =       'pred',
1480                 preds_levels = c('No_recidivism','Yes_recidivism'),
1481                 cutoff1       = optimized_cutoff1,
1482                 cutoff2      = optimized_cutoff_new,
1483                 base         = 'Caucasian')
1484
1485 #confronto con il dataset originale
1486 fair_metrics_cmp_graph(data1         = classified_dt,
1487                 data2 = new_data_classified_dt,
1488                 outcome      = 'Two_yr_Recidivism',
1489                 outcome_base = 'No_recidivism',
1490                 group        = 'ethnicity',
1491                 probs1 =       'pred',
1492                 probs2 =       'pred',
1493                 preds_levels = c('No_recidivism','Yes_recidivism'),
1494                 cutoff1       = optimized_cutoff,
1495                 cutoff2      = optimized_cutoff_new,
1496                 base         = 'Caucasian')
1497
1498
1499 ## ------------------------------------------------------------------------------------
1500 #converto di nuovo il dataset in binario
1501 levels(new_data$Two_yr_Recidivism)[levels(new_data$Two_yr_Recidivism)=="Yes_recidivism"] <- 1
1502 levels(new_data$Two_yr_Recidivism)[levels(new_data$Two_yr_Recidivism)=="No_recidivism"] <- 0
1503 #prendo caucasian come riferiemnto perch il confronto tra le metrich di fairness lo far poi
         con caucasian come base
1504 #I caucasian sono codificati con 1 (privilegiati)
1505 levels(new_data$ethnicity)[levels(new_data$ethnicity)!="Caucasian"] <- 0
1506 levels(new_data$ethnicity)[levels(new_data$ethnicity)=="Caucasian"] <- 1
1507 levels(new_data$Female)[levels(new_data$Female)=="Female"] <- 0
1508 levels(new_data$Female)[levels(new_data$Female)=="Male"] <- 1
1509 levels(new_data$Misdemeanor)[levels(new_data$Misdemeanor)=="yes"] <- 0
1510 levels(new_data$Misdemeanor)[levels(new_data$Misdemeanor)=="no"] <- 1
1511 levels(new_data$Age)[levels(new_data$Age)!="between25_45"] <- 0
1512 levels(new_data$Age)[levels(new_data$Age)=="between25_45"] <- 1
```

```
# #trasformo colonne categoriche in numeriche
# must_convert<-sapply(new_data,is.factor)       # logical vector telling if a variable needs to be displayed as numeric
# new_data<-sapply(new_data[,must_convert],unclass)    # data.frame of all categorical variables now displayed as numeric


## ------------------------------------------------------------------------------------
#creo dataset formattato per aif360
#NOTA BENE: formatted_dataset  la versione di raw_data per aif360. formatted_dataset sar SEMPRE quello che uso per il fit dei metodidi debias e far la predizione sul formatted_dataset di new_data
#creo quindi il formatted dataset di new_data e lo chiamo
formatted_dataset_forPred <- aif360::aif_dataset(data_path = new_data, favor_label = 0,
unfavor_label = 1, #label favorita per la variabile target: 0 corrisponde a good
unprivileged_protected_attribute = 0, # 0-young-unprivileged
privileged_protected_attribute = 1, #se non lo scrivo, per il valore privilegiato viene considerato il valore pi alto
target_column = "Two_yr_Recidivism", #qua prima avevo pred.rescaled
protected_attribute = "ethnicity")


## ------------------------------------------------------------------------------------
#applico tecniche di debias inprocessing: adversarial debiasing and prejudice remover
#prejudice remover
model <- prejudice_remover(class_attr = "Two_yr_Recidivism", sensitive_attr = "ethnicity")
model$fit(formatted_dataset_forPred)
formatted_dataset_pr <- model$predict(formatted_dataset_forPred) #FUNZIONA ma devi fare questo come prima tecnica in assoluto
#in formatted_dataset_pr ho quindi IL NUOVO DATASET FORMATTATO con le predizioni del recidivismo fatto con prejudice remover


## ------------------------------------------------------------------------------------
#ora torniamo a un dataset in formato data frame (non aif360)
col_names <- c(formatted_dataset_pr$feature_names, "preds")#questa colonna contiene le predizioni sul recidivismo appena fatte dall'algoritmo
col_names
new_data_pr <- data.frame(formatted_dataset_pr$features, formatted_dataset_pr$labels)
colnames(new_data_pr) <- col_names
#new_data_pr in questo caso  gi classificato!!!


## ------------------------------------------------------------------------------------
new_data_pr$Two_yr_Recidivism = new_data$Two_yr_Recidivism


```

```
## ------------------------------------------------------------------------------------
#ripristino di nuovo TUTTI i livelli categorici per renderlo pi leggibile
 new_data_pr$Two_yr_Recidivism = ifelse(new_data_pr$Two_yr_Recidivism==1,"Yes_recidivism", "
    No_recidivism")

new_data_pr$ethnicity = ifelse(new_data_pr$ethnicity==1,"Caucasian", "Not_caucasian")


new_data_pr$Female = ifelse(new_data_pr$Female==1,"Male", "Female")


new_data_pr$Misdemeanor = ifelse(new_data_pr$Misdemeanor==1,"no", "yes")


new_data_pr$Age = ifelse(new_data_pr$Age==1,"between25_45", "Not_between25_45")



## ------------------------------------------------------------------------------------
#confronto le metriche con quelle di
#new_data_pr
#source("util.R")

#NOTA BENE: in questo caso abbiamo solo due sottocategorie (caucasian e non caucasian) per un
     dataset e ancora tutte le etnie nell'altro, quindi non possiamo usare la funzione di
    confronto delle metriche usata fino ad ora, perch teneva conto soltanto delle somme dei
    valori assoluti, allora la modifichiamo con una media.
#confronto con il dataset bilanciato su female
fair_metrics_cmp_graph(data1         = new_data_classified_dt,
                data2 = new_data_pr,
                outcome      = 'Two_yr_Recidivism',
                outcome_base = 'No_recidivism',
                group        = 'ethnicity',
                probs1 =       'pred',
                preds2 = 'preds', #per il secondo dataset non c' una colonna pred/prob, ma le
     previsioni sono gi messe in Two_yr_rec
                preds_levels = c('No_recidivism','Yes_recidivism'),
                cutoff1       = optimized_cutoff_new,
                cutoff2      = 0.5,
                base         = 'Caucasian')

#confronto con il dataset originale
fair_metrics_cmp_graph(data1         = classified_dt,
                data2 = new_data_pr,
                outcome      = 'Two_yr_Recidivism',
                outcome_base = 'No_recidivism',
                group        = 'ethnicity',
                probs1 =       'pred',
```

```
                probs2 =       'preds',
                preds_levels = c('No_recidivism','Yes_recidivism'),
                cutoff1       = optimized_cutoff,
                cutoff2      = 0.5,
                base         = 'Caucasian')



## ------------------------------------------------------------------------------------
#adversarial debiasing
tf$reset_default_graph() #questo serve per non avere problemi con tensorflow
sess = tf$compat$v1$Session()
plain_model = adversarial_debiasing(privileged_groups = pri,
unprivileged_groups = unpri,
scope_name='plain_classifier',
debias=TRUE, #CAPIRE BENE LA DIFFERENZA TRA QUESTO TRUE/FALSE
sess=sess)
plain_model$fit(formatted_dataset_forPred)
formatted_dataset_ADVdebiasing <- plain_model$predict(formatted_dataset_forPred)


## ------------------------------------------------------------------------------------
#ora torniamo a un dataset in formato data frame (non aif360)
col_names <- c(formatted_dataset_ADVdebiasing$feature_names, "preds")
col_names
new_data_ADVdebiasing <- data.frame(formatted_dataset_ADVdebiasing$features, formatted_
    dataset_ADVdebiasing$labels)
colnames(new_data_ADVdebiasing) <- col_names
#new_data_ADVdebiasing  gi classificato

## ------------------------------------------------------------------------------------
new_data_ADVdebiasing$Two_yr_Recidivism = new_data$Two_yr_Recidivism


## ------------------------------------------------------------------------------------
#ripristino di nuovo TUTTI i livelli categorici per renderlo pi leggibile
 new_data_ADVdebiasing$Two_yr_Recidivism = ifelse(new_data_ADVdebiasing$Two_yr_Recidivism==1,
    "Yes_recidivism", "No_recidivism")

new_data_ADVdebiasing$ethnicity = ifelse(new_data_ADVdebiasing$ethnicity==1,"Caucasian", "Not
    _caucasian")


new_data_ADVdebiasing$Female = ifelse(new_data_ADVdebiasing$Female==1,"Male", "Female")


new_data_ADVdebiasing$Misdemeanor = ifelse(new_data_ADVdebiasing$Misdemeanor==1,"no", "yes")
```

```
1641
1642
1643 new_data_ADVdebiasing$Age = ifelse(new_data_ADVdebiasing$Age==1,"between25_45", "Not_
     between25_45")
1644
1645
1646
1647 ## -------------------------------------------------------------------------------------
1648 #confronto le metriche di fairness: vedo se ci sono stati miglioramenti rispetto alle
     tecniche di preprocessing debias.
1649 #per questi due nuovi dataset non ho l'optimal cutoff quindi prendo 0.5 di default
1650 #confronto con il dataset bilanciato su female
1651 fair_metrics_cmp_graph(data1         = new_data_classified_dt,
1652                 data2 = new_data_ADVdebiasing,
1653                 outcome      = 'Two_yr_Recidivism',
1654                 outcome_base = 'No_recidivism',
1655                 group        = 'ethnicity',
1656                 probs1 =       'pred',
1657                 probs2 =       'preds',
1658                 preds_levels = c('No_recidivism','Yes_recidivism'),
1659                 cutoff1       = optimized_cutoff_new,
1660                 cutoff2      = 0.5,
1661                 base         = 'Caucasian')
1662
1663 #confronto con il dataset originale
1664 fair_metrics_cmp_graph(data1         = classified_dt,
1665                 data2 = new_data_ADVdebiasing,
1666                 outcome      = 'Two_yr_Recidivism',
1667                 outcome_base = 'No_recidivism',
1668                 group        = 'ethnicity',
1669                 probs1 =       'pred',
1670                 probs2 =       'preds',
1671                 preds_levels = c('No_recidivism','Yes_recidivism'),
1672                 cutoff1       = optimized_cutoff,
1673                 cutoff2      = 0.5,
1674                 base         = 'Caucasian')
1675
1676
1677
1678 ## -------------------------------------------------------------------------------------
1679 #formatted_dataset_ADVdebiasing  quello predetto e new_data  quello vero
1680 #la versione di new_data formattata per aif360 esiste gi (creata qualche chunck prima) e si
     chiama ad_fit_transformed, ma non posso usarlo qui perch contiene weights diversi dal
     dataset originale, allora uso formatted_dataset_forPred
1681 true_label_dt = formatted_dataset_forPred
1682 #il dataset che scelgo con le predizioni  quello uscito dall'adversarial debiasing e ha le
     predizioni di tipo 0-1
1683 pred_label_dt = formatted_dataset_ADVdebiasing
```

```
1684
1685
1686
1687 ## ------------------------------------------------------------------------------------
1688 roc <- reject_option_classification(unprivileged_groups = unpri,
1689 privileged_groups = pri,
1690 low_class_thresh = 0.01,
1691 high_class_thresh = 0.99,
1692 num_class_thresh = as.integer(100),
1693 num_ROC_margin = as.integer(50),
1694 metric_name = "Statistical parity difference",
1695 metric_ub = 0.05,
1696 metric_lb = -0.05)
1697 roc <- roc$fit_predict(true_label_dt, pred_label_dt) #il primo  il dataset contenente le
     label vere e il secondo contiene le predizioni
1698
1699
1700
1701
1702 ## ------------------------------------------------------------------------------------
1703 #ora torniamo a un dataset in formato data frame (non aif360)
1704 col_names <- c(roc$feature_names, "preds")
1705 col_names
1706 new_data_roc <- data.frame(roc$features, roc$labels)
1707 colnames(new_data_roc) <- col_names
1708 #new_data_ADVdebiasing  gi classificato
1709
1710 ## ------------------------------------------------------------------------------------
1711 new_data_roc$Two_yr_Recidivism = new_data$Two_yr_Recidivism
1712
1713
1714 ## ------------------------------------------------------------------------------------
1715 #ripristino di nuovo TUTTI i livelli categorici per renderlo pi leggibile
1716  new_data_roc$Two_yr_Recidivism = ifelse(new_data_roc$Two_yr_Recidivism==1,"Yes_recidivism",
     "No_recidivism")
1717
1718 new_data_roc$ethnicity = ifelse(new_data_roc$ethnicity==1,"Caucasian", "Not_caucasian")
1719
1720
1721 new_data_roc$Female = ifelse(new_data_roc$Female==1,"Male", "Female")
1722
1723
1724 new_data_roc$Misdemeanor = ifelse(new_data_roc$Misdemeanor==1,"no", "yes")
1725
1726
1727 new_data_roc$Age = ifelse(new_data_roc$Age==1,"between25_45", "Not_between25_45")
1728
1729
```

```

## ------------------------------------------------------------------------------------
#confronto le metriche di fairness: vedo se ci sono stati miglioramenti rispetto alle
    tecniche di preprocessing debias.
#per questi due nuovi dataset non ho l'optimal cutoff quindi prendo 0.5 di default
#confronto con il dataset classificato con adv debiasing
fair_metrics_cmp_graph(data1         = new_data_ADVdebiasing,
                data2 = new_data_roc,
                outcome      = 'Two_yr_Recidivism',
                outcome_base = 'No_recidivism',
                group        = 'ethnicity',
                probs1 =       'preds',
                probs2 =       'preds',
                preds_levels = c('No_recidivism','Yes_recidivism'),
                cutoff1       = 0.5,
                cutoff2      = 0.5,
                base         = 'Caucasian')

#confronto con il dataset originale
fair_metrics_cmp_graph(data1         = classified_dt,
                data2 = new_data_roc,
                outcome      = 'Two_yr_Recidivism',
                outcome_base = 'No_recidivism',
                group        = 'ethnicity',
                probs1 =       'pred',
                probs2 =       'preds',
                preds_levels = c('No_recidivism','Yes_recidivism'),
                cutoff1       = optimized_cutoff,
                cutoff2      = 0.5,
                base         = 'Caucasian')



## ------------------------------------------------------------------------------------
#TENTATIVO DI USO DI AIF360
library(aif360)
#load_aif360_lib()


## ------------------------------------------------------------------------------------
############################
#converto dataset in binario
#qua devo usare il balanced non ancora classificato, NON quello classificato!!!
#OCCHIO: fai il run di queste righe di conversione 0-1 solo se il dataset non  ancora stato
    convertito!!! ad esempio fai prima un check is.numeric

levels(balanced_data1$Two_yr_Recidivism)[levels(balanced_data1$Two_yr_Recidivism)=="Yes_
    recidivism"] <- 1
```

```
levels(balanced_data1$Two_yr_Recidivism)[levels(balanced_data1$Two_yr_Recidivism)=="No_recidivism"] <- 0
#prendo caucasian come riferiemnto perch il confronto tra le metrich di fairness lo far poi con caucasian come base
#I caucasian sono codificati con 1 (privilegiati)
levels(balanced_data1$ethnicity)[levels(balanced_data1$ethnicity)!="Caucasian"] <- 0
levels(balanced_data1$ethnicity)[levels(balanced_data1$ethnicity)=="Caucasian"] <- 1
levels(balanced_data1$Female)[levels(balanced_data1$Female)=="Female"] <- 0
levels(balanced_data1$Female)[levels(balanced_data1$Female)=="Male"] <- 1
levels(balanced_data1$Misdemeanor)[levels(balanced_data1$Misdemeanor)=="yes"] <- 0
levels(balanced_data1$Misdemeanor)[levels(balanced_data1$Misdemeanor)=="no"] <- 1
levels(balanced_data1$Age)[levels(balanced_data1$Age)!="between25_45"] <- 0
levels(balanced_data1$Age)[levels(balanced_data1$Age)=="between25_45"] <- 1
# #trasformo colonne categoriche in numeriche
# must_convert<-sapply(balanced_data1,is.factor)       # logical vector telling if a variable needs to be displayed as numeric
# balanced_data1<-sapply(balanced_data1[,must_convert],unclass)    # data.frame of all categorical variables now displayed as numeric


## ------------------------------------------------------------------------------------
#i favoriti sono gli adulti-1
formatted_dataset <- aif360::aif_dataset(data_path = balanced_data1, favor_label = 0,
unfavor_label = 1, #label favorita per la variabile target: 0 corrisponde a good
unprivileged_protected_attribute = 0, # 0-young-unprivileged
privileged_protected_attribute = 1, #se non lo scrivo, per il valore privilegiato viene considerato il valore pi alto
target_column = "Two_yr_Recidivism", #qua prima avevo pred.rescaled
protected_attribute = "ethnicity")
formatted_dataset

#tecnica di debias preprocessing
di <- disparate_impact_remover(repair_level = 0.8, sensitive_attribute = "ethnicity")
rp <- di$fit_transform(formatted_dataset)

#reweighing (tecnica preprocessing)
pri <- list("ethnicity", 1)
unpri <- list("ethnicity", 0)
rw <- reweighing(unpri,pri)
#rw$fit(formatted_dataset)
#ad_transformed <- rw$transform(formatted_dataset)
ad_fit_transformed <- rw$fit_transform(rp) #questo lo faccio su rp, cos analizzo entrambe le tecniche in una volta sola (altrimenti dovrei fare mille classificazioni e mille casi)


## ------------------------------------------------------------------------------------
#ora torniamo a un dataset in formato data frame (non aif360)
col_names <- c(ad_fit_transformed$feature_names, "Two_yr_Recidivism")
```

```
col_names
new_data <- data.frame(ad_fit_transformed$features, ad_fit_transformed$labels)
colnames(new_data) <- col_names



#quindi new_data  un dataset su cui ho fatto rebalancing per Female, disparate impact remover e reweighing


## ------------------------------------------------------------------------------------
#sostituisco i livelli con valori numerici
levels(new_data$Two_yr_Recidivism)[levels(new_data$Two_yr_Recidivism)=="yes"] <- 1
levels(new_data$Two_yr_Recidivism)[levels(new_data$Two_yr_Recidivism)=="no"] <- 0
#rimuovo da new_data le colonne age_above e age_below
cols_to_drop <- names(new_data) %in% c("Age_Above_FourtyFive", "Age_Below_TwentyFive")
new_data <- new_data[, !cols_to_drop, drop = FALSE]

#split into train and test set
sample_size = floor(0.7*nrow(new_data))
#set a random seed per rendere l'esperimento ripetibile
set.seed(42)

# randomly split data
picked = sample(seq_len(nrow(new_data)),size = sample_size)
training_set =new_data[picked,]
test_set =new_data[-picked,]

#as.factor mi serve per fare una classificazione binaria
new_data$Two_yr_Recidivism = as.factor(new_data$Two_yr_Recidivism)
#devo anche eliminare recidivismo dal training_set
cols_to_drop <- names(training_set) %in% c("Two_yr_Recidivism")
#training e test set senza variabile target
training_set_data <- training_set[, !cols_to_drop, drop = FALSE]
#anche sui dati di test
test_set_data <- test_set[, !cols_to_drop, drop = FALSE]

levels(training_set$Two_yr_Recidivism)[levels(training_set$Two_yr_Recidivism)=="Yes_recidivism"] <- 1
levels(training_set$Two_yr_Recidivism)[levels(training_set$Two_yr_Recidivism)=="No_recidivism"] <- 0
levels(training_set$Two_yr_Recidivism)

levels(test_set$Two_yr_Recidivism)[levels(test_set$Two_yr_Recidivism)=="Yes_recidivism"] <- 1
levels(test_set$Two_yr_Recidivism)[levels(test_set$Two_yr_Recidivism)=="No_recidivism"] <- 0
levels(test_set$Two_yr_Recidivism)
################################
```

```
#poi commento le righe in cui calcola il modello perch ci potrebbe mettere troppo (sufficiente salvarlo e ricaricarlo)
logitMod <- glm(Two_yr_Recidivism ~ ., data = training_set, family=binomial(link="logit"))
logitMod #capire cosa significano questi dati

pred = predict(logitMod, test_set, type = "response")
new_data_classified_dt = cbind(test_set, pred) #questo  quello che uso per la libreria fairness
classified_dt2 = cbind(test_set_data, pred)
#classified_dt = rbind(classified_dt1, classified_dt2)
optimized_cutoff_new = opt.cut(perf, pred1)#il cutoff ottimale  leggermente pii basso di quello standard, che sarebbe invece 0.5


## ------------------------------------------------------------------------------------
#ripristino di nuovo TUTTI i livelli categorici per renderlo pi leggibile
new_data_classified_dt$Two_yr_Recidivism = ifelse(new_data_classified_dt$Two_yr_Recidivism==1,"Yes_recidivism", "No_recidivism")

new_data_classified_dt$ethnicity = ifelse(new_data_classified_dt$ethnicity==1,"Caucasian", "Not_caucasian")


new_data_classified_dt$Female = ifelse(new_data_classified_dt$Female==1,"Male", "Female")


new_data_classified_dt$Misdemeanor = ifelse(new_data_classified_dt$Misdemeanor==1,"no", "yes")


new_data_classified_dt$Age = ifelse(new_data_classified_dt$Age==1,"between25_45", "Not_between25_45")



## ------------------------------------------------------------------------------------
#confronto con il dataset bilanciato su female
fair_metrics_cmp_graph(data1         = balanced1_classified_dt,
                data2 = new_data_classified_dt,
                outcome      = 'Two_yr_Recidivism',
                outcome_base = 'No_recidivism',
                group        = 'ethnicity',
                probs1 =       'pred',
                probs2 =       'pred',
                preds_levels = c('No_recidivism','Yes_recidivism'),
                cutoff1       = optimized_cutoff1,
                cutoff2      = optimized_cutoff_new,
                base         = 'Caucasian')
```

```
1902
1903 #confronto con il dataset originale
1904 fair_metrics_cmp_graph(data1         = classified_dt,
1905                 data2 = new_data_classified_dt,
1906                 outcome      = 'Two_yr_Recidivism',
1907                 outcome_base = 'No_recidivism',
1908                 group        = 'ethnicity',
1909                 probs1 =       'pred',
1910                 probs2 =       'pred',
1911                 preds_levels = c('No_recidivism','Yes_recidivism'),
1912                 cutoff1       = optimized_cutoff,
1913                 cutoff2      = optimized_cutoff_new,
1914                 base         = 'Caucasian')
1915
1916
1917 ## ------------------------------------------------------------------------------
1918 #converto di nuovo il dataset in binario
1919 levels(new_data$Two_yr_Recidivism)[levels(new_data$Two_yr_Recidivism)=="Yes_recidivism"] <- 1
1920 levels(new_data$Two_yr_Recidivism)[levels(new_data$Two_yr_Recidivism)=="No_recidivism"] <- 0
1921 #prendo caucasian come riferiemnto perch il confronto tra le metrich di fairness lo far poi
     con caucasian come base
1922 #I caucasian sono codificati con 1 (privilegiati)
1923 levels(new_data$ethnicity)[levels(new_data$ethnicity)!="Caucasian"] <- 0
1924 levels(new_data$ethnicity)[levels(new_data$ethnicity)=="Caucasian"] <- 1
1925 levels(new_data$Female)[levels(new_data$Female)=="Female"] <- 0
1926 levels(new_data$Female)[levels(new_data$Female)=="Male"] <- 1
1927 levels(new_data$Misdemeanor)[levels(new_data$Misdemeanor)=="yes"] <- 0
1928 levels(new_data$Misdemeanor)[levels(new_data$Misdemeanor)=="no"] <- 1
1929 levels(new_data$Age)[levels(new_data$Age)!="between25_45"] <- 0
1930 levels(new_data$Age)[levels(new_data$Age)=="between25_45"] <- 1
1931 # #trasformo colonne categoriche in numeriche
1932 # must_convert<-sapply(new_data,is.factor)       # logical vector telling if a variable needs
      to be displayed as numeric
1933 # new_data<-sapply(new_data[,must_convert],unclass)    # data.frame of all categorical
     variables now displayed as numeric
1934
1935
1936 ## ------------------------------------------------------------------------------
1937 #creo dataset formattato per aif360
1938 #NOTA BENE: formatted_dataset  la versione di raw_data per aif360. formatted_dataset sar
     SEMPRE quello che uso per il fit dei metodidi debias e far la predizione sul formatted_
     dataset di new_data
1939 #creo quindi il formatted dataset di new_data e lo chiamo
1940 formatted_dataset_forPred <- aif360::aif_dataset(data_path = new_data, favor_label = 0,
1941 unfavor_label = 1, #label favorita per la variabile target: 0 corrisponde a good
1942 unprivileged_protected_attribute = 0, # 0-young-unprivileged
1943 privileged_protected_attribute = 1, #se non lo scrivo, per il valore privilegiato viene
     considerato il valore pi alto
```

```
target_column = "Two_yr_Recidivism", #qua prima avevo pred.rescaled
protected_attribute = "ethnicity")


## ------------------------------------------------------------------------------------
#applico tecniche di debias inprocessing: adversarial debiasing and prejudice remover
#prejudice remover
model <- prejudice_remover(class_attr = "Two_yr_Recidivism", sensitive_attr = "ethnicity")
model$fit(formatted_dataset_forPred)
formatted_dataset_pr <- model$predict(formatted_dataset_forPred) #FUNZIONA ma devi fare
    questo come prima tecnica in assoluto
#in formatted_dataset_pr ho quindi IL NUOVO DATASET FORMATTATO con le predizioni del
    recidivismo fatto con prejudice remover



## ------------------------------------------------------------------------------------
#ora torniamo a un dataset in formato data frame (non aif360)
col_names <- c(formatted_dataset_pr$feature_names, "preds")#questa colonna contiene le
    predizioni sul recidivismo appena fatte dall'algoritmo
col_names
new_data_pr <- data.frame(formatted_dataset_pr$features, formatted_dataset_pr$labels)
colnames(new_data_pr) <- col_names
#new_data_pr in questo caso  gi classificato!!!


## ------------------------------------------------------------------------------------
new_data_pr$Two_yr_Recidivism = new_data$Two_yr_Recidivism


## ------------------------------------------------------------------------------------
#ripristino di nuovo TUTTI i livelli categorici per renderlo pi leggibile
 new_data_pr$Two_yr_Recidivism = ifelse(new_data_pr$Two_yr_Recidivism==1,"Yes_recidivism", "
    No_recidivism")

new_data_pr$ethnicity = ifelse(new_data_pr$ethnicity==1,"Caucasian", "Not_caucasian")


new_data_pr$Female = ifelse(new_data_pr$Female==1,"Male", "Female")


new_data_pr$Misdemeanor = ifelse(new_data_pr$Misdemeanor==1,"no", "yes")


new_data_pr$Age = ifelse(new_data_pr$Age==1,"between25_45", "Not_between25_45")


```

```
## ------------------------------------------------------------------------------------
#confronto le metriche con quelle di
#new_data_pr
#source("util.R")

#NOTA BENE: in questo caso abbiamo solo due sottocategorie (caucasian e non caucasian) per un dataset e ancora tutte le etnie nell'altro, quindi non possiamo usare la funzione di confronto delle metriche usata fino ad ora, perch teneva conto soltanto delle somme dei valori assoluti, allora la modifichiamo con una media.
#confronto con il dataset bilanciato su female
fair_metrics_cmp_graph(data1         = new_data_classified_dt,
                data2 = new_data_pr,
                outcome      = 'Two_yr_Recidivism',
                outcome_base = 'No_recidivism',
                group        = 'ethnicity',
                probs1 =       'pred',
                preds2 = 'preds', #per il secondo dataset non c' una colonna pred/prob, ma le previsioni sono gi messe in Two_yr_rec
                preds_levels = c('No_recidivism','Yes_recidivism'),
                cutoff1       = optimized_cutoff_new,
                cutoff2      = 0.5,
                base         = 'Caucasian')

#confronto con il dataset originale
fair_metrics_cmp_graph(data1         = classified_dt,
                data2 = new_data_pr,
                outcome      = 'Two_yr_Recidivism',
                outcome_base = 'No_recidivism',
                group        = 'ethnicity',
                probs1 =       'pred',
                probs2 =       'preds',
                preds_levels = c('No_recidivism','Yes_recidivism'),
                cutoff1       = optimized_cutoff,
                cutoff2      = 0.5,
                base         = 'Caucasian')



## ------------------------------------------------------------------------------------
#adversarial debiasing
tf$reset_default_graph() #questo serve per non avere problemi con tensorflow
sess = tf$compat$v1$Session()
plain_model = adversarial_debiasing(privileged_groups = pri,
unprivileged_groups = unpri,
scope_name='plain_classifier',
debias=TRUE, #CAPIRE BENE LA DIFFERENZA TRA QUESTO TRUE/FALSE
sess=sess)
```

```
plain_model$fit(formatted_dataset_forPred)
formatted_dataset_ADVdebiasing <- plain_model$predict(formatted_dataset_forPred)


## ------------------------------------------------------------------------------------
#ora torniamo a un dataset in formato data frame (non aif360)
col_names <- c(formatted_dataset_ADVdebiasing$feature_names, "preds")
col_names
new_data_ADVdebiasing <- data.frame(formatted_dataset_ADVdebiasing$features, formatted_
    dataset_ADVdebiasing$labels)
colnames(new_data_ADVdebiasing) <- col_names
#new_data_ADVdebiasing  gi classificato

## ------------------------------------------------------------------------------------
new_data_ADVdebiasing$Two_yr_Recidivism = new_data$Two_yr_Recidivism


## ------------------------------------------------------------------------------------
#ripristino di nuovo TUTTI i livelli categorici per renderlo pi leggibile
 new_data_ADVdebiasing$Two_yr_Recidivism = ifelse(new_data_ADVdebiasing$Two_yr_Recidivism==1,
    "Yes_recidivism", "No_recidivism")

new_data_ADVdebiasing$ethnicity = ifelse(new_data_ADVdebiasing$ethnicity==1,"Caucasian", "Not
    _caucasian")


new_data_ADVdebiasing$Female = ifelse(new_data_ADVdebiasing$Female==1,"Male", "Female")


new_data_ADVdebiasing$Misdemeanor = ifelse(new_data_ADVdebiasing$Misdemeanor==1,"no", "yes")


new_data_ADVdebiasing$Age = ifelse(new_data_ADVdebiasing$Age==1,"between25_45", "Not_
    between25_45")



## ------------------------------------------------------------------------------------
#confronto le metriche di fairness: vedo se ci sono stati miglioramenti rispetto alle
    tecniche di preprocessing debias.
#per questi due nuovi dataset non ho l'optimal cutoff quindi prendo 0.5 di default
#confronto con il dataset bilanciato su female
fair_metrics_cmp_graph(data1         = new_data_classified_dt,
                data2 = new_data_ADVdebiasing,
                outcome      = 'Two_yr_Recidivism',
                outcome_base = 'No_recidivism',
                group        = 'ethnicity',
                probs1 =       'pred',
```

```
                probs2 =       'preds',
                preds_levels = c('No_recidivism','Yes_recidivism'),
                cutoff1       = optimized_cutoff_new,
                cutoff2      = 0.5,
                base         = 'Caucasian')

#confronto con il dataset originale
fair_metrics_cmp_graph(data1         = classified_dt,
                data2 = new_data_ADVdebiasing,
                outcome      = 'Two_yr_Recidivism',
                outcome_base = 'No_recidivism',
                group        = 'ethnicity',
                probs1 =       'pred',
                probs2 =       'preds',
                preds_levels = c('No_recidivism','Yes_recidivism'),
                cutoff1       = optimized_cutoff,
                cutoff2      = 0.5,
                base         = 'Caucasian')



## ------------------------------------------------------------------------------------
#formatted_dataset_ADVdebiasing  quello predetto e new_data  quello vero
#la versione di new_data formattata per aif360 esiste gi (creata qualche chunck prima) e si chiama ad_fit_transformed, ma non posso usarlo qui perch contiene weights diversi dal dataset originale, allora uso formatted_dataset_forPred
true_label_dt = formatted_dataset_forPred
#il dataset che scelgo con le predizioni  quello uscito dall'adversarial debiasing e ha le predizioni di tipo 0-1
pred_label_dt = formatted_dataset_ADVdebiasing



## ------------------------------------------------------------------------------------
roc <- reject_option_classification(unprivileged_groups = unpri,
privileged_groups = pri,
low_class_thresh = 0.01,
high_class_thresh = 0.99,
num_class_thresh = as.integer(100),
num_ROC_margin = as.integer(50),
metric_name = "Statistical parity difference",
metric_ub = 0.05,
metric_lb = -0.05)
roc <- roc$fit_predict(true_label_dt, pred_label_dt) #il primo  il dataset contenente le label vere e il secondo contiene le predizioni

## ------------------------------------------------------------------------------------
#ora torniamo a un dataset in formato data frame (non aif360)
```

```
col_names <- c(roc$feature_names, "preds")
col_names
new_data_roc <- data.frame(roc$features, roc$labels)
colnames(new_data_roc) <- col_names
#new_data_ADVdebiasing  gi classificato

## ------------------------------------------------------------------------------------
new_data_roc$Two_yr_Recidivism = new_data$Two_yr_Recidivism


## ------------------------------------------------------------------------------------
#ripristino di nuovo TUTTI i livelli categorici per renderlo pi leggibile
 new_data_roc$Two_yr_Recidivism = ifelse(new_data_roc$Two_yr_Recidivism==1,"Yes_recidivism",
    "No_recidivism")

new_data_roc$ethnicity = ifelse(new_data_roc$ethnicity==1,"Caucasian", "Not_caucasian")


new_data_roc$Female = ifelse(new_data_roc$Female==1,"Male", "Female")


new_data_roc$Misdemeanor = ifelse(new_data_roc$Misdemeanor==1,"no", "yes")


new_data_roc$Age = ifelse(new_data_roc$Age==1,"between25_45", "Not_between25_45")


## ------------------------------------------------------------------------------------
#confronto le metriche di fairness: vedo se ci sono stati miglioramenti rispetto alle
    tecniche di preprocessing debias.
#per questi due nuovi dataset non ho l'optimal cutoff quindi prendo 0.5 di default
#confronto con il dataset classificato con adv debiasing
fair_metrics_cmp_graph(data1         = new_data_ADVdebiasing,
                data2 = new_data_roc,
                outcome      = 'Two_yr_Recidivism',
                outcome_base = 'No_recidivism',
                group        = 'ethnicity',
                probs1 =       'preds',
                probs2 =       'preds',
                preds_levels = c('No_recidivism','Yes_recidivism'),
                cutoff1       = 0.5,
                cutoff2      = 0.5,
                base         = 'Caucasian')

#confronto con il dataset originale
fair_metrics_cmp_graph(data1         = classified_dt,
                data2 = new_data_roc,
                outcome      = 'Two_yr_Recidivism',
```

```
                outcome_base = 'No_recidivism',
                group        = 'ethnicity',
                probs1 =       'pred',
                probs2 =       'preds',
                preds_levels = c('No_recidivism','Yes_recidivism'),
                cutoff1       = optimized_cutoff,
                cutoff2      = 0.5,
                base         = 'Caucasian')
```

R code for Drug dataset:

```
## ----echo=FALSE, warning=FALSE-----------------------------------------------------
library(fairness)
library(knitr)
library(recipes)
library(skimr)
library(modeldata)
library(RColorBrewer)
library(tangram)
library(dplyr)
library(vegan)
library(diverse)
library(randomForest)
library(caret)
library(varhandle)
library(MASS)
library(dostats) #per %contains%
library(graphics) #per mosaicplot
library(corrplot)
library(wesanderson)
library(Amelia)
library(ROCR) #per ROC function
library(ROSE)#binary balancing
library(UBL)#multiclass balancing
library(ggplot2)
library(ggpubr)
library(xtable)
library(tidyr)
library(formatR)

#carico il file util con le altre funzioni
source("util.R")


## ---- echo = F--------------------------------------------------------------------
library(knitr)
opts_chunk$set(tidy.opts=list(width.cutoff=60),tidy=TRUE)

```

```
## ---- echo=FALSE-------------------------------------------------------------
#Load data
raw_data <- read.csv(file = "drug_consumption.data")


## ----------------------------------------------------------------------------
knitr::purl('Drug.Rmd')


## ----------------------------------------------------------------------------
#Data preparation
column.names <- c("ID", "Age", "Gender", "Education", "Country", "Ethnicity", "Nscore", "
    Escore", "Oscore", "Ascore", "Cscore", "Impulsive", "SS", "Alcohol", "Amphet", "Amyl", "
    Benzos", "Caff", "Cannabis", "Choc", "Coke", "Crack", "Ecstasy", "Heroin", "Ketamine", "
    Legalh", "LSD", "Meth", "Mushrooms", "Nicotine", "Semer", "VSA")
raw_data = setNames(raw_data, column.names)

head(raw_data)



## ----------------------------------------------------------------------------
#encode from numerical to categorical
#potrei anche considerare "usata pi di 10 anni fa" come Never used
#Qui devo mettere stringhe e non valori numerici, oppure cambiarli dopo in stringhe,
    altrimenti poi fa regressione invece di classificazione
raw_data[raw_data == "CL0"]<- "Never_used" #never used
raw_data[raw_data == "CL1"]<- "Used" #used more than a decade ago
raw_data[raw_data == "CL2"]<- "Used" #used within the last decade
raw_data[raw_data == "CL3"]<- "Used"
raw_data[raw_data == "CL4"]<- "Used"
raw_data[raw_data == "CL5"]<- "Used"
raw_data[raw_data == "CL6"]<- "Used"

#elimino la colonna ID perch non mi interessa
raw_data$ID = NULL

require(dplyr)
require(magrittr)
raw_data = raw_data %>%
  as_tibble %>%
  mutate_at(.vars= vars(Age:Ethnicity), .funs = funs(as.factor)) %>%         mutate(Age =
    factor(Age, labels = c("18_24", "25_34", "35_44", "45_54", "55_64", "65_"))) %>%
            mutate(Gender = factor(Gender, labels = c("Male", "Female"))) %>%
            mutate(Education = factor(Education, labels = c("Under16", "At16", "At17", "At18
    ", "SomeCollege","ProfessionalCert", "Bachelors", "Masters", "Doctorate"))) %>%
            mutate(Country = factor(Country, labels = c("USA", "NewZealand", "Other", "
    Australia", "Ireland","Canada","UK"))) %>%
```

```
80              mutate(Ethnicity = factor(Ethnicity, labels = c("Black", "Asian", "White", "
    White/Black", "Other", "White/Asian", "Black/Asian"))) %>%
81             mutate(Coke = factor(Coke, labels = c("Never_used", "Used"))) %>%
82             mutate(Crack = factor(Crack, labels = c("Never_used", "Used")))
83
84 #%>%   mutate_at(vars(Alcohol:VSA), funs(as.numeric))
85
86 # data.table(raw_data, options = list(scrollX = TRUE, searching = FALSE, pageLength = 5),
    caption = 'Table 2: Clean Drug Use Data')
87
88 #seleziono due colonne di droghe che mi interessano
89 #scelgo Crack e Coke (cocaina)
90 #elimino tutte le altre colonne che non mi interessano
91 raw_data = subset(raw_data, select=-c(Alcohol, Amphet, Amyl, Benzos, Caff, Cannabis, Choc,
    Ecstasy, Heroin, Ketamine, Legalh, LSD, Meth, Mushrooms, Nicotine, Semer, VSA) )
92
93 h = head(raw_data)
94 print(xtable(h, type = "latex"), file = "DRUGShead.tex")
95 summary(raw_data)
96
97
98
99 ## ------------------------------------------------------------------------------------
100
101 #data visualization CATEGORICAL
102
103 #Filter out categorical columns
104 cat_data <- raw_data[, sapply(raw_data, is.categorical)]
105 cat_names <- names(cat_data)
106
107 #pie print per ogni colonna categorica
108 for ( i in seq(1,length( cat_data ),1) ){
109   pie_print(cat_data,cat_names[i])
110 }
111
112 ###################
113 a = table(cat_data) #lo faccio solo sui categorici
114 a = as.data.frame(a)
115 #a$Number_of_Priors = NULL
116 ggballoonplot(a, x = "Ethnicity", y = "Age", size = "Freq",
117               color = "#8591C2", fill = "#8591C2", facet.by = "Gender",
118               ggtheme = theme_bw()) #+
119   #scale_fill_gradientn(colors = wes_palette(2, name="GrandBudapest"))
120
121 ## ------------------------------------------------------------------------------------
122 #giusto per farci un'idea, quanti hanno consumato cocaina e quanti hanno consumato crack nel
    nostro dataset
123 table(raw_data$Coke) #847
```

```
124 table(raw_data$Crack) #258
125
126
127 ## -----------------------------------------------------------------------------
128 #missing values
129 missmap(raw_data, main = "Missing values vs observed")
130 #no missing values
131
132
133 ## -----------------------------------------------------------------------------
134 # Create a boxplot using base R
135 #posso provare a farlo con gli score, ma dovrei capire se davvero questi score (o anche solo
        uno) mi interessano
136 boxplot(Nscore~Ethnicity,data=raw_data)
137 boxplot(Nscore~Age,data=raw_data)
138 boxplot(Nscore~Gender,data=raw_data)
139
140
141 ## -----------------------------------------------------------------------------
142 ##COKE
143
144 #plotto lo Coke consumption al variare di Gender
145 ####################Gender
146 d = group_by_feature_sensitive(raw_data,  "Coke", "Gender")
147 bar(dv = count_val,
148     factors = c("Coke", "Gender"), #non riesco a risolvere il problema di passare in questa
        lista una variabile contente la stringa, invece della stringa stessa.
149     dataframe = as.data.frame(d),
150     errbar = FALSE,
151     ylim=c(0, as.numeric(d[4])+0.1*as.numeric(d[4]))
152     )  #I increased the upper y-limit to accommodate the legend.
153
154 ####################Ethnicity
155 d = group_by_feature_sensitive(raw_data, "Coke", "Ethnicity")
156 bar(dv = count_val,
157     factors = c("Coke", "Ethnicity"), #non riesco a risolvere il problema di passare in
        questa lista una variabile contente la stringa, invece della stringa stessa.
158     dataframe = as.data.frame(d),
159     errbar = FALSE,
160     ylim=c(0, as.numeric(d[4])+0.1*as.numeric(d[4]))
161     )  #I increased the upper y-limit to accommodate the legend.
162 ########################Education
163 d = group_by_feature_sensitive(raw_data, "Coke", "Education")
164 bar(dv = count_val,
165     factors = c("Coke", "Education"), #non riesco a risolvere il problema di passare in
        questa lista una variabile contente la stringa, invece della stringa stessa.
166     dataframe = as.data.frame(d),
167     errbar = FALSE,
```

```
    ylim=c(0, as.numeric(d[4])+0.1*as.numeric(d[4]))
    )  #I increased the upper y-limit to accommodate the legend.
##########################Age
d = group_by_feature_sensitive(raw_data, "Coke", "Age")
bar(dv = count_val,
    factors = c("Coke", "Age"), #non riesco a risolvere il problema di passare in questa lista una variabile contente la stringa, invece della stringa stessa.
    dataframe = as.data.frame(d),
    errbar = FALSE,
    ylim=c(0, as.numeric(d[4])+0.1*as.numeric(d[4]))
    )  #I increased the upper y-limit to accommodate the legend.
##########################Country
d = group_by_feature_sensitive(raw_data, "Coke", "Country")
bar(dv = count_val,
    factors = c("Coke", "Country"), #non riesco a risolvere il problema di passare in questa lista una variabile contente la stringa, invece della stringa stessa.
    dataframe = as.data.frame(d),
    errbar = FALSE,
    ylim=c(0, as.numeric(d[4])+0.1*as.numeric(d[4]))
    )  #I increased the upper y-limit to accommodate the legend.

## ------------------------------------------------------------------------------------
##Crack

#plotto lo Crack consumption al variare di Gender
#####################Gender
d = group_by_feature_sensitive(raw_data,  "Crack", "Gender")
bar(dv = count_val,
    factors = c("Crack", "Gender"), #non riesco a risolvere il problema di passare in questa lista una variabile contente la stringa, invece della stringa stessa.
    dataframe = as.data.frame(d),
    errbar = FALSE,
    ylim=c(0, as.numeric(d[4])+0.1*as.numeric(d[4]))
    )  #I increased the upper y-limit to accommodate the legend.

####################Ethnicity
d = group_by_feature_sensitive(raw_data, "Crack", "Ethnicity")
bar(dv = count_val,
    factors = c("Crack", "Ethnicity"), #non riesco a risolvere il problema di passare in questa lista una variabile contente la stringa, invece della stringa stessa.
    dataframe = as.data.frame(d),
    errbar = FALSE,
    ylim=c(0, as.numeric(d[4])+0.1*as.numeric(d[4]))
    )  #I increased the upper y-limit to accommodate the legend.
########################Education
d = group_by_feature_sensitive(raw_data, "Crack", "Education")
bar(dv = count_val,
    factors = c("Crack", "Education"), #non riesco a risolvere il problema di passare in
```

```
    questa lista una variabile contente la stringa, invece della stringa stessa.
212     dataframe = as.data.frame(d),
213     errbar = FALSE,
214     ylim=c(0, as.numeric(d[4])+0.1*as.numeric(d[4]))
215     )  #I increased the upper y-limit to accommodate the legend.
216 ##########################Age
217 d = group_by_feature_sensitive(raw_data, "Crack", "Age")
218 bar(dv = count_val,
219     factors = c("Crack", "Age"), #non riesco a risolvere il problema di passare in questa
    lista una variabile contente la stringa, invece della stringa stessa.
220     dataframe = as.data.frame(d),
221     errbar = FALSE,
222     ylim=c(0, as.numeric(d[4])+0.1*as.numeric(d[4]))
223     )  #I increased the upper y-limit to accommodate the legend.
224 ##########################Country
225 d = group_by_feature_sensitive(raw_data, "Crack", "Country")
226 bar(dv = count_val,
227     factors = c("Crack", "Country"), #non riesco a risolvere il problema di passare in questa
     lista una variabile contente la stringa, invece della stringa stessa.
228     dataframe = as.data.frame(d),
229     errbar = FALSE,
230     ylim=c(0, as.numeric(d[4])+0.1*as.numeric(d[4]))
231     )  #I increased the upper y-limit to accommodate the legend.
232
233 ## ------------------------------------------------------------------------------------
234 #Coke
235 frquent_comb1(raw_data, filter = "Coke", "Age")
236 frquent_comb1(raw_data, filter = "Coke", c("Age", "Ethnicity"))
237 frquent_comb1(raw_data, filter = "Coke", c("Age", "Ethnicity", "Gender"))
238 frquent_comb1(raw_data, filter = "Coke", c("Age", "Ethnicity", "Gender", "Education"))
239
240 ## ------------------------------------------------------------------------------------
241 ############################
242 #plotto la distribuzione delle combinazioni (conteggio casi)
243 a = frquent_comb1(raw_data, filter = "Coke", c("Age", "Ethnicity", "Gender"))
244
245 a1 = as.data.frame(a[1]) #la tabella 1 ha sempre Used
246 a2 = as.data.frame(a[2]) #la tabella 2 ha sempre Never_Used
247
248 #Coloro sempre Used di rosso
249
250 ggballoonplot(a1, x = "Ethnicity", y = "Age", size = "percentage_on_Used",
251               color = "black", fill = "#F24D4D", facet.by = "Gender", ggtheme = theme_bw())
252 #percentage_on_Age_ethnicity_Female
253
254 ggballoonplot(a2, x = "Ethnicity", y = "Age", size = "percentage_on_Never_used",
255               color = "black", fill = "#50C395", facet.by = "Gender", ggtheme = theme_bw())
256
```

```
ggballoonplot(a1, x = "Ethnicity", y = "Age", size = "percentage_on_total",
              color = "black", fill = "#F24D4D", facet.by = "Gender", ggtheme = theme_bw())
#percentage_on_Age_ethnicity_Female

ggballoonplot(a2, x = "Ethnicity", y = "Age", size = "percentage_on_Age_Ethnicity_Gender",
              color = "black", fill = "#50C395", facet.by = "Gender", ggtheme = theme_bw())


g = ggballoonplot(a1, x = "Ethnicity", y = "Age", size = "percentage_on_Age_Ethnicity_Gender"
    ,
              color = "black", fill = "#F24D4D", facet.by = "Gender", ggtheme = theme_bw())
#percentage_on_Age_ethnicity_Female
ggsave("DRUGSCokeperOnComb.jpg", plot = g, width = 20, height = 12, units = "cm")

ggballoonplot(a2, x = "Ethnicity", y = "Age", size = "percentage_on_total",
              color = "black", fill = "#50C395", facet.by = "Gender", ggtheme = theme_bw())



## ------------------------------------------------------------------------------------
#Crack
frquent_comb1(raw_data, filter = "Crack", "Age")
frquent_comb1(raw_data, filter = "Crack", c("Age", "Ethnicity"))
frquent_comb1(raw_data, filter = "Crack", c("Age", "Ethnicity", "Gender"))
frquent_comb1(raw_data, filter = "Crack", c("Age", "Ethnicity", "Gender", "Education"))
#non posso fare tutte le combinazioni. C' un modo per capire a priori quali attributi possono
     essere i pi interessanti da valutare?


## ------------------------------------------------------------------------------------

##########################
#plotto la distribuzione delle combinazioni (conteggio casi)
a = frquent_comb1(raw_data, filter = "Crack", c("Age", "Ethnicity", "Gender"))

a1 = as.data.frame(a[2]) #la tabella 1 ha sempre Used
a2 = as.data.frame(a[1]) #la tabella 2 ha sempre Never_Used

#Coloro sempre Used di rosso

ggballoonplot(a1, x = "Ethnicity", y = "Age", size = "percentage_on_Used",
              color = "black", fill = "#F24D4D", facet.by = "Gender", ggtheme = theme_bw())
#percentage_on_Age_ethnicity_Female

ggballoonplot(a2, x = "Ethnicity", y = "Age", size = "percentage_on_Never_used",
              color = "black", fill = "#50C395", facet.by = "Gender", ggtheme = theme_bw())

ggballoonplot(a1, x = "Ethnicity", y = "Age", size = "percentage_on_total",
```

```
303               color = "black", fill = "#F24D4D", facet.by = "Gender", ggtheme = theme_bw())
304 #percentage_on_Age_ethnicity_Female
305
306 ggballoonplot(a2, x = "Ethnicity", y = "Age", size = "percentage_on_Age_Ethnicity_Gender",
307               color = "black", fill = "#50C395", facet.by = "Gender", ggtheme = theme_bw())
308
309
310 g = ggballoonplot(a1, x = "Ethnicity", y = "Age", size = "percentage_on_Age_Ethnicity_Gender"
        ,
311               color = "black", fill = "#F24D4D", facet.by = "Gender", ggtheme = theme_bw())
312 #percentage_on_Age_ethnicity_Female
313 ggsave("DRUGSCrackPerOnComb.jpg", plot = g, width = 20, height = 12, units = "cm")
314
315 ggballoonplot(a2, x = "Ethnicity", y = "Age", size = "percentage_on_total",
316               color = "black", fill = "#50C395", facet.by = "Gender", ggtheme = theme_bw())
317
318
319 ## ------------------------------------------------------------------------------------
320 #chi squared test (consideriamo le colonne come categoriche)
321 source("util.R")
322 chisq_fun(raw_data, "Coke", "Age")
323 chisq_fun(raw_data, "Coke", "Ethnicity")
324 chisq_fun(raw_data, "Coke", "Gender")
325
326
327 ## ------------------------------------------------------------------------------------
328 chisq_fun(raw_data, "Crack", "Age")
329 chisq_fun(raw_data, "Crack", "Ethnicity")
330 chisq_fun(raw_data, "Crack", "Gender")
331 #In console possiamo osservare la differenza tra i valori osservati (prima tabella) e i
        valori attesi (seconda tabella).
332
333
334 ## ------------------------------------------------------------------------------------
335 #SHANNON INDEX
336 #uso funzioni create nella libreria
337 shannon_diversity(raw_data)
338 print_shannon(raw_data)
339 #print_cmp_shannon(raw_data, raw_data)
340
341
342 ## ------------------------------------------------------------------------------------
343 #sostituisco i livelli con valori numerici
344 raw_data$Coke = as.factor(raw_data$Coke)
345 levels(raw_data$Coke)[levels(raw_data$Coke)=="Used"] <- 1
346 levels(raw_data$Coke)[levels(raw_data$Coke)=="Never_used"] <- 0
347
348 #split into train and test set
```

```r
sample_size = floor(0.7*nrow(raw_data))
#set a random seed per rendere l'esperimento ripetibile
set.seed(42)
# randomly split data
picked = sample(seq_len(nrow(raw_data)),size = sample_size)
training_set =raw_data[picked,]
test_set =raw_data[-picked,]

#as.factor mi serve per fare una classificazione binaria
raw_data$Coke = as.factor(raw_data$Coke)
#devo anche eliminare Coke dal training_set
cols_to_drop <- names(training_set) %in% c("Coke")
#training e test set senza variabile target
training_set_data <- training_set[, !cols_to_drop, drop = FALSE]
#anche sui dati di test
test_set_data <- test_set[, !cols_to_drop, drop = FALSE]


## ------------------------------------------------------------------------------------
#REGRESSIONE LOGISTICA
#elimino colonna crack
cols_to_drop <- names(raw_data) %in% c("Crack")
raw_data_copy = raw_data
raw_data <- raw_data[, !cols_to_drop, drop = FALSE]

################################
#poi commento le righe in cui calcola il modello perch ci potrebbe mettere troppo (
    sufficiente salvarlo e ricaricarlo)
logitMod <- glm(Coke ~ ., data = training_set, family=binomial(link="logit"))
logitMod #capire cosa significano questi dati
#saveRDS(model, "./logitMod_compas_rf.rds") #commento perch l'ho gi salvato
##########################################
#logitMod = readRDS(file = "./model_compas_rf.rds")
#logitMod

#faccio la predizione su entrambi training e test set, perch per le metriche di
    classificazione mi servono dataset originale e dataset classificato *della stessa
    dimensione*
#pred = predict(logitMod, training_set_data)
#classified_dt1 = cbind(training_set_data, pred)
pred = predict(logitMod, test_set_data, type = "response") #se non metto il type = response,
    mi restituisce una predizione tra -1 e 1, altrimenti me la restituisce tra 0 e 1. Scelgo
    tra -1 e 1 perc poi ottengo il cutoff ottimizzato anch'esso tra -1 e 1 e mi  pi facile
    fare la predizione
classified_dt = cbind(test_set, pred) #questo  quello che uso per la libreria fairness
classified_dt2 = cbind(test_set_data, pred)
#classified_dt = rbind(classified_dt1, classified_dt2)

```

```
391
392
393 ## ------------------------------------------------------------------------------
394 #ROC
395 pred1 <- prediction(pred, test_set$Coke) #pred1  un oggetto pred.obj di ROCR
396 perf <- performance(pred1, measure = "tpr", x.measure = "fpr")
397 plot(perf)
398 #posso anche fare una ROC comparison per le categorie di un attributo sensibile, tipo Female,
      con la libreria fairness:
399 roc_fairness <- roc_parity(data         = classified_dt,
400                       outcome      = 'Coke',
401                       group        = 'Gender',
402                       probs        = 'pred',
403                       preds_levels = c('Used','Never_used'),
404                       base         = 'Male')
405 roc_fairness$Metric
406 roc_fairness$ROCAUC_plot
407
408 #AUC
409 auc.perf = performance(pred1, measure = "auc")
410 auc.perf@y.values #stampa a video il valore di AUC
411 ###############
412 #plotto sensitivity e specificity in modo da individuare il cutoff ottimizzato
413 sens <- data.frame(x=unlist(performance(pred1, "sens")@x.values),
414                    y=unlist(performance(pred1, "sens")@y.values))
415 spec <- data.frame(x=unlist(performance(pred1, "spec")@x.values),
416                    y=unlist(performance(pred1, "spec")@y.values))
417
418 sens %>% ggplot(aes(x,y)) +
419   geom_line() +
420   geom_line(data=spec, aes(x,y,col="red")) +
421   scale_y_continuous(sec.axis = sec_axis(~., name = "Specificity")) +
422   labs(x='Cutoff', y="Sensitivity") +
423   theme(axis.title.y.right = element_text(colour = "red"), legend.position="none")
424 #################
425
426 ## ------------------------------------------------------------------------------
427 #troviamo l'optimal cutoff, cio l'optimal score che minimizza il misclassification error del
      modello di regressione logistica
428 #The best threshold (or cutoff) point to be used in glm models is the point which maximises
      the specificity and the sensitivity. This threshold point might not give the highest
      prediction in your model, but it wouldn't be biased towards positives or negatives.
429 optimized_cutoff = opt.cut(perf, pred1)#il cutoff ottimale  leggermente pii basso di quello
      standard, che sarebbe invece 0.5
430
431 #converto la colonna pred di classified_dt2 in yes/no recidivism usando il cutoff ottimizzato
432 #yes era 1, quindi ho recidivismo se  maggiore del cutoff
433 classified_dt2$pred = ifelse(classified_dt2$pred<optimized_cutoff,"Never_used","Used")
```

```
#sostituisco i valori dei livelli per poter plottare la matrice di confusione
levels(test_set$Coke)[levels(test_set$Coke)==1] <- "Used"
levels(test_set$Coke)[levels(test_set$Coke)==0] <- "Never_used"
#levels(test_set$Coke)
#anche per classified_dt2
classified_dt2$pred <- factor(classified_dt2$pred, levels = c("Used", "Never_used"))

## ----message=FALSE, warning=FALSE----------------------------------------------------
#matrice di confusione
cm <- confusionMatrix(data = as.factor(classified_dt2$pred), reference = as.factor(test_set$
    Coke))
#plotto la matrice di confusione
png("DRUGSCokeCM.png")
draw_confusion_matrix(cm)
dev.off()

## ------------------------------------------------------------------------------------
#ci occupiamo di group fairness: indipendenza, separazione e sufficienza

#lo facciamo per tutti i sensitive attribute (Marital, ageR)

#ripristino di nuovo i livelli yes/no per renderlo pi leggibile
levels(classified_dt$Coke)[levels(classified_dt$Coke)==1] <- "Used"
levels(classified_dt$Coke)[levels(classified_dt$Coke)==0] <- "Never_used"

#per scegliere la categoria "base" per cui confrontare tutte le altre, per ogni attributo
    sensibile, ci conviene guardare le tabelle delle frequenze plottate in precedenza:


## ------------------------------------------------------------------------------------
fair_metrics(data         = classified_dt,
                      outcome      = 'Coke',
                      group        = 'Age',
                      probs =       'pred',
                      preds_levels = c('Never_used','Used'),
                      cutoff       = optimized_cutoff,
                      base         = '18_24')

fair_metrics(data         = classified_dt,
                      outcome      = 'Coke',
                      group        = 'Ethnicity',
                      probs =       'pred',
                      preds_levels = c('Never_used','Used'),
                      cutoff       = optimized_cutoff,
                      base         = 'White')

fair_metrics(data         = classified_dt,
                      outcome      = 'Coke',
```

```
                      group        = 'Gender',
                      probs =       'pred',
                      preds_levels = c('Never_used','Used'),
                      cutoff       = optimized_cutoff,
                      base         = 'Male')

fair_metrics_cmp_graph2(data         = classified_dt,
                      outcome      = 'Coke',
                      group1        = 'Gender',
                      group2 = 'Ethnicity',
                      probs =       'pred',
                      preds_levels = c('Never_used','Used'),
                      cutoff       = optimized_cutoff,
                      base1         = 'Male',
                      base2        = 'White')
fair_metrics_cmp_graph2(data         = classified_dt,
                      outcome      = 'Coke',
                      group1        = 'Age',
                      group2 = 'Ethnicity',
                      probs =       'pred',
                      preds_levels = c('Never_used','Used'),
                      cutoff       = optimized_cutoff,
                      base1         = '18_24',
                      base2        = 'White')
fair_metrics_cmp_graph2(data         = classified_dt,
                      outcome      = 'Coke',
                      group1        = 'Ethnicity',
                      group2 = 'Age',
                      probs =       'pred',
                      preds_levels = c('Never_used','Used'),
                      cutoff       = optimized_cutoff,
                      base1         = 'White',
                      base2        = '18_24')
fair_metrics_cmp_graph2(data         = classified_dt,
                      outcome      = 'Coke',
                      group1        = 'Gender',
                      group2 = 'Age',
                      probs =       'pred',
                      preds_levels = c('Never_used','Used'),
                      cutoff       = optimized_cutoff,
                      base1         = 'Male',
                      base2        = '18_24')


## ------------------------------------------------------------------------------------
#CREO I SEGUENTI DATASET BILANCIATI PER COKE:
#balanced_data0: bilanciato per Ethnicity
#balanced_data1: bilanciato per Country
```

```
#balanced_data2: bilanciato per Ethnicity and Age

#balanced_data0: bilanciato per Ethnicity
#questo invece ha ethnicity bilanciato con smote ed  meglio usare questo!
raw_data = as.data.frame(raw_data)
balanced_data0 = SmoteClassif(Ethnicity ~ ., raw_data, dist = "HEOM", k=2)

#balanced_data1: bilanciato per Country
raw_data = as.data.frame(raw_data)
balanced_data = SmoteClassif(Country ~ ., raw_data, dist = "HEOM", k=2)
balanced_data1 = NULL
for(i in levels(balanced_data$Country)){
  #faccio il rebalancing di Two_yr_Recidivism per ogni categoria di ethnicity
  temp_dt = balanced_data[balanced_data$Country==i, ]
  s = SmoteClassif(Ethnicity ~ ., temp_dt, dist = "HEOM", k=2)
  #metto poi insieme i vari piccoli dataset bilanciati
  balanced_data1 = rbind(balanced_data1, s)
}

balanced_data2 = NULL
for(i in levels(balanced_data0$Ethnicity)){
  #faccio il rebalancing di Two_yr_Recidivism per ogni categoria di ethnicity
  temp_dt = balanced_data0[balanced_data0$Ethnicity==i, ]
  s = SmoteClassif(Age ~ ., temp_dt, dist = "HEOM")
  #metto poi insieme i vari piccoli dataset bilanciati
  balanced_data2 = rbind(balanced_data2, s)
}

cat_data <- balanced_data1[, sapply(balanced_data1, is.categorical)]
cat_names <- names(cat_data)
for ( i in seq(1,length( cat_data ),1) ){
  pie_print(cat_data,cat_names[i])
}

## ------------------------------------------------------------------------------
#balanced_data0
#split into train and test set
sample_size = floor(0.7*nrow(balanced_data0))
#set a random seed per rendere l'esperimento ripetibile
set.seed(42)
# randomly split data
picked = sample(seq_len(nrow(balanced_data0)),size = sample_size)
training_set =balanced_data0[picked,]
test_set =balanced_data0[-picked,]

#as.factor mi serve per fare una classificazione binaria
balanced_data0$Coke = as.factor(balanced_data0$Coke)
#devo anche eliminare Coke dal training_set
```

```
cols_to_drop <- names(training_set) %in% c("Coke")
#training e test set senza variabile target
training_set_data <- training_set[, !cols_to_drop, drop = FALSE]
#anche sui dati di test
test_set_data <- test_set[, !cols_to_drop, drop = FALSE]


#REGRESSIONE LOGISTICA
#elimino colonna crack
cols_to_drop <- names(balanced_data0) %in% c("Crack")
balanced_data0_copy = balanced_data0
balanced_data0 <- balanced_data0[, !cols_to_drop, drop = FALSE]

################################
#poi commento le righe in cui calcola il modello perch ci potrebbe mettere troppo (sufficiente salvarlo e ricaricarlo)
logitMod <- glm(Coke ~ ., data = training_set, family=binomial(link="logit"))
logitMod #capire cosa significano questi dati
#saveRDS(model, "./logitMod_compas_rf.rds") #commento perch l'ho gi salvato
##########################################
#logitMod = readRDS(file = "./model_compas_rf.rds")
#logitMod


#devo fare queste due righe altrimenti non riconosce i livelli di country
logitMod$xlevels[["Country"]] <- union(logitMod$xlevels[["Country"]], levels(raw_data$Country))
pred = predict(logitMod, test_set_data, type = "response") #se non metto il type = response, mi restituisce una predizione tra -1 e 1, altrimenti me la restituisce tra 0 e 1. Scelgo tra -1 e 1 perc poi ottengo il cutoff ottimizzato anch'esso tra -1 e 1 e mi  pi facile fare la predizione
balanced0_classified_dt = cbind(test_set, pred) #questo  quello che uso per la libreria fairness
#classified_dt2 = cbind(test_set_data, pred)
#classified_dt = rbind(classified_dt1, classified_dt2)
pred1 <- prediction(pred, test_set$Coke) #pred1  un oggetto pred.obj di ROCR
perf <- performance(pred1, measure = "tpr", x.measure = "fpr")
optimized_cutoff0 = opt.cut(perf, pred1)

## ----------------------------------------------------------------------------------
#balanced_data1
#split into train and test set
sample_size = floor(0.7*nrow(balanced_data1))
#set a random seed per rendere l'esperimento ripetibile
set.seed(42)
# randomly split data
picked = sample(seq_len(nrow(balanced_data1)),size = sample_size)
training_set =balanced_data1[picked,]
```

```
618 test_set =balanced_data1[-picked,]
619
620 #as.factor mi serve per fare una classificazione binaria
621 balanced_data1$Coke = as.factor(balanced_data1$Coke)
622 #devo anche eliminare Coke dal training_set
623 cols_to_drop <- names(training_set) %in% c("Coke")
624 #training e test set senza variabile target
625 training_set_data <- training_set[, !cols_to_drop, drop = FALSE]
626 #anche sui dati di test
627 test_set_data <- test_set[, !cols_to_drop, drop = FALSE]
628
629
630 #REGRESSIONE LOGISTICA
631 #elimino colonna crack
632 cols_to_drop <- names(balanced_data1) %in% c("Crack")
633 balanced_data1_copy = balanced_data1
634 balanced_data1 <- balanced_data1[, !cols_to_drop, drop = FALSE]
635
636 ################################
637 #poi commento le righe in cui calcola il modello perch ci potrebbe mettere troppo (
      sufficiente salvarlo e ricaricarlo)
638 logitMod <- glm(Coke ~ ., data = training_set, family=binomial(link="logit"))
639 logitMod #capire cosa significano questi dati
640 #saveRDS(model, "./logitMod_compas_rf.rds") #commento perch l'ho gi salvato
641 ############################################
642 #logitMod = readRDS(file = "./model_compas_rf.rds")
643 #logitMod
644
645 #devo fare queste due righe altrimenti non riconosce i livelli di country
646 logitMod$xlevels[["Country"]] <- union(logitMod$xlevels[["Country"]], levels(raw_data$Country
      ))
647 pred = predict(logitMod, test_set_data, type = "response") #se non metto il type = response,
      mi restituisce una predizione tra -1 e 1, altrimenti me la restituisce tra 0 e 1. Scelgo
      tra -1 e 1 perc poi ottengo il cutoff ottimizzato anch'esso tra -1 e 1 e mi  pi facile
      fare la predizione
648 balanced1_classified_dt = cbind(test_set, pred) #questo  quello che uso per la libreria
      fairness
649 #classified_dt2 = cbind(test_set_data, pred)
650 #classified_dt = rbind(classified_dt1, classified_dt2)
651 pred1 <- prediction(pred, test_set$Coke) #pred1  un oggetto pred.obj di ROCR
652 perf <- performance(pred1, measure = "tpr", x.measure = "fpr")
653 optimized_cutoff1 = opt.cut(perf, pred1)
654
655
656
657 ## ----------------------------------------------------------------------------------
658 #balanced_data2
659 #split into train and test set
```

```
660 sample_size = floor(0.7*nrow(balanced_data2))
661 #set a random seed per rendere l'esperimento ripetibile
662 set.seed(42)
663 # randomly split data
664 picked = sample(seq_len(nrow(balanced_data2)),size = sample_size)
665 training_set =balanced_data2[picked,]
666 test_set =balanced_data2[-picked,]
667
668 #as.factor mi serve per fare una classificazione binaria
669 balanced_data2$Coke = as.factor(balanced_data2$Coke)
670 #devo anche eliminare Coke dal training_set
671 cols_to_drop <- names(training_set) %in% c("Coke")
672 #training e test set senza variabile target
673 training_set_data <- training_set[, !cols_to_drop, drop = FALSE]
674 #anche sui dati di test
675 test_set_data <- test_set[, !cols_to_drop, drop = FALSE]
676
677
678 #REGRESSIONE LOGISTICA
679 #elimino colonna crack
680 cols_to_drop <- names(balanced_data2) %in% c("Crack")
681 balanced_data2_copy = balanced_data2
682 balanced_data2 <- balanced_data2[, !cols_to_drop, drop = FALSE]
683
684 ################################
685 #poi commento le righe in cui calcola il modello perch ci potrebbe mettere troppo (
      sufficiente salvarlo e ricaricarlo)
686 logitMod <- glm(Coke ~ ., data = training_set, family=binomial(link="logit"))
687 logitMod #capire cosa significano questi dati
688 #saveRDS(model, "./logitMod_compas_rf.rds") #commento perch l'ho gi salvato
689 ############################################
690 #logitMod = readRDS(file = "./model_compas_rf.rds")
691 #logitMod
692
693
694 #devo fare queste due righe altrimenti non riconosce i livelli di country
695 logitMod$xlevels[["Country"]] <- union(logitMod$xlevels[["Country"]], levels(raw_data$Country
      ))
696 pred = predict(logitMod, test_set_data, type = "response") #se non metto il type = response,
      mi restituisce una predizione tra -1 e 1, altrimenti me la restituisce tra 0 e 1. Scelgo
      tra -1 e 1 perc poi ottengo il cutoff ottimizzato anch'esso tra -1 e 1 e mi  pi facile
      fare la predizione
697 balanced2_classified_dt = cbind(test_set, pred) #questo  quello che uso per la libreria
      fairness
698 #classified_dt2 = cbind(test_set_data, pred)
699 #classified_dt = rbind(classified_dt1, classified_dt2)
700 pred1 <- prediction(pred, test_set$Coke) #pred1  un oggetto pred.obj di ROCR
701 perf <- performance(pred1, measure = "tpr", x.measure = "fpr")
```

```
optimized_cutoff2 = opt.cut(perf, pred1)



## ------------------------------------------------------------------------------
#ora confronto ciascun dataset bilanciato con quello orignale
#poi seleziono quelli che sembrano effettivamente migliori del dataset originale
#poi confronto tra loro questi dataset bilanciati rimanenti e scelgo il migliore
levels(balanced0_classified_dt$Coke)[levels(balanced0_classified_dt$Coke)==1] <- "Used"
levels(balanced0_classified_dt$Coke)[levels(balanced0_classified_dt$Coke)==0] <- "Never_used"
levels(balanced1_classified_dt$Coke)[levels(balanced1_classified_dt$Coke)==1] <- "Used"
levels(balanced1_classified_dt$Coke)[levels(balanced1_classified_dt$Coke)==0] <- "Never_used"
levels(balanced2_classified_dt$Coke)[levels(balanced2_classified_dt$Coke)==1] <- "Used"
levels(balanced2_classified_dt$Coke)[levels(balanced2_classified_dt$Coke)==0] <- "Never_used"

fair_metrics(data         = balanced2_classified_dt,
                      outcome      = 'Coke',
                      group        = 'Ethnicity',
                      probs =       'pred',
                      preds_levels = c('Never_used','Used'),
                      cutoff       = optimized_cutoff,
                      base         = 'White')

#creo anche un dataset con i valori delle mean deviation per ogni dataset bilanciato, per
    ogni metrica
msd_balanced=NULL

source("util.R")
png("DRUGSb0rdComp.png")
p = fair_metrics_cmp_graph(data1         = classified_dt,
                data2 = balanced0_classified_dt,
                outcome      = 'Coke',
                outcome_base = 'Never_used',
                group        = 'Ethnicity',
                probs1 =       'pred',
                probs2 =       'pred',
                preds_levels = c('Never_used','Used'),
                cutoff1       = optimized_cutoff,
                cutoff2      = optimized_cutoff0,
                base         = 'White')
dev.off()
#praticamente solo peggioramenti
msd_balanced=p[[1]]
msd_balanced= rbind(msd_balanced, p[[2]])

png("DRUGSb1rdComp.png")
p = fair_metrics_cmp_graph(data1         = classified_dt,
                data2 = balanced1_classified_dt,
```

```
749                 outcome      = 'Coke',
750                 outcome_base = 'Never_used',
751                 group        = 'Ethnicity',
752                 probs1 =       'pred',
753                 probs2 =       'pred',
754                 preds_levels = c('Never_used','Used'),
755                 cutoff1       = optimized_cutoff,
756                 cutoff2      = optimized_cutoff1,
757                 base         = 'White')
758 dev.off()
759 msd_balanced= rbind(msd_balanced, p[[2]])
760
761 png("DRUGSb2rdComp.png")
762 p = fair_metrics_cmp_graph(data1         = classified_dt,
763                 data2 = balanced2_classified_dt,
764                 outcome      = 'Coke',
765                 outcome_base = 'Never_used',
766                 group        = 'Ethnicity',
767                 probs1 =       'pred',
768                 probs2 =       'pred',
769                 preds_levels = c('Never_used','Used'),
770                 cutoff1       = optimized_cutoff,
771                 cutoff2      = optimized_cutoff2,
772                 base         = 'White')
773 dev.off()
774 msd_balanced= rbind(msd_balanced, p[[2]])
775
776
777
778
779 #CONFRONTO TRA LORO BALANCED DATASETS
780 ######################
781 png("DRUGSb0b1Comp.png")
782 fair_metrics_cmp_graph(data1         = balanced0_classified_dt,
783                 data2 = balanced1_classified_dt,
784                 outcome      = 'Coke',
785                 outcome_base = 'Never_used',
786                 group        = 'Ethnicity',
787                 probs1 =       'pred',
788                 probs2 =       'pred',
789                 preds_levels = c('Never_used','Used'),
790                 cutoff1       = optimized_cutoff0,
791                 cutoff2      = optimized_cutoff1,
792                 base         = 'White')
793 dev.off()
794
795 png("DRUGSb0b2Comp.png")
796 fair_metrics_cmp_graph(data1         = balanced0_classified_dt,
```

```
                data2 = balanced2_classified_dt,
                outcome      = 'Coke',
                outcome_base = 'Never_used',
                group        = 'Ethnicity',
                probs1 =       'pred',
                probs2 =       'pred',
                preds_levels = c('Never_used','Used'),
                cutoff1       = optimized_cutoff0,
                cutoff2      = optimized_cutoff2,
                base         = 'White')
dev.off()



msd_balanced
long_msd_balanced <- msd_balanced %>% gather(metrics, values, dem_parity:spec_parity)


g = ggplot(long_msd_balanced, aes(fill=metrics, y=values, x=datasets)) +
    geom_bar(position="dodge", stat="identity") +
    #ggtitle("Studying 4 species..") +
    facet_wrap(~metrics, ncol=2) +
    #facet_grid(metrics ~ datasets)
    theme(legend.position="none",
          strip.text = element_text(face="bold", size=15,lineheight=5.0),
strip.background = element_rect(fill="lightblue", colour="black",
size=1,),axis.text.x = element_text(angle = 90),
axis.text=element_text(size=20, face="bold"),
        axis.title=element_text(size=20,face="bold")) +
    xlab("")
ggsave("OverallCoke.jpg", plot = g, width = 24, height = 33, units = "in")

## ------------------------------------------------------------------------------------
raw_data = raw_data_copy
#sostituisco i livelli con valori numerici
raw_data$Crack = as.factor(raw_data$Crack)
levels(raw_data$Crack)[levels(raw_data$Crack)=="Used"] <- 1
levels(raw_data$Crack)[levels(raw_data$Crack)=="Never_used"] <- 0

#split into train and test set
sample_size = floor(0.7*nrow(raw_data))
#set a random seed per rendere l'esperimento ripetibile
set.seed(42)
# randomly split data
picked = sample(seq_len(nrow(raw_data)),size = sample_size)
training_set =raw_data[picked,]
test_set =raw_data[-picked,]

```

```
#as.factor mi serve per fare una classificazione binaria
raw_data$Crack = as.factor(raw_data$Crack)
#devo anche eliminare Crack dal training_set
cols_to_drop <- names(training_set) %in% c("Crack")
#training e test set senza variabile target
training_set_data <- training_set[, !cols_to_drop, drop = FALSE]
#anche sui dati di test
test_set_data <- test_set[, !cols_to_drop, drop = FALSE]

## ------------------------------------------------------------------------------------
#REGRESSIONE LOGISTICA
#elimino colonna coke
cols_to_drop <- names(raw_data) %in% c("Coke")
raw_data_copy = raw_data
raw_data <- raw_data[, !cols_to_drop, drop = FALSE]

################################
#poi commento le righe in cui calcola il modello perch ci potrebbe mettere troppo (
    sufficiente salvarlo e ricaricarlo)
logitMod <- glm(Crack ~ ., data = training_set, family=binomial(link="logit"))
logitMod #capire cosa significano questi dati
#saveRDS(model, "./logitMod_compas_rf.rds") #commento perch l'ho gi salvato
##########################################
#logitMod = readRDS(file = "./model_compas_rf.rds")
#logitMod


pred = predict(logitMod, test_set_data, type = "response") #se non metto il type = response,
    mi restituisce una predizione tra -1 e 1, altrimenti me la restituisce tra 0 e 1. Scelgo
    tra -1 e 1 perc poi ottengo il cutoff ottimizzato anch'esso tra -1 e 1 e mi  pi facile
    fare la predizione
classified_dt = cbind(test_set, pred) #questo  quello che uso per la libreria fairness
classified_dt2 = cbind(test_set_data, pred)
#classified_dt = rbind(classified_dt1, classified_dt2)


## ------------------------------------------------------------------------------------
#ROC
pred1 <- prediction(pred, test_set$Crack) #pred1  un oggetto pred.obj di ROCR
perf <- performance(pred1, measure = "tpr", x.measure = "fpr")
plot(perf)
#posso anche fare una ROC comparison per le categorie di un attributo sensibile, tipo Female,
     con la libreria fairness:
roc_fairness <- roc_parity(data         = classified_dt,
                      outcome      = 'Crack',
                      group        = 'Gender',
                      probs        = 'pred',
                      preds_levels = c('Never_used','Used'),
```

```
                      base         = 'Male')
roc_fairness$Metric
roc_fairness$ROCAUC_plot

#AUC
auc.perf = performance(pred1, measure = "auc")
auc.perf@y.values #stampa a video il valore di AUC
###############
#plotto sensitivity e specificity in modo da individuare il cutoff ottimizzato
sens <- data.frame(x=unlist(performance(pred1, "sens")@x.values),
                   y=unlist(performance(pred1, "sens")@y.values))
spec <- data.frame(x=unlist(performance(pred1, "spec")@x.values),
                   y=unlist(performance(pred1, "spec")@y.values))

sens %>% ggplot(aes(x,y)) +
  geom_line() +
  geom_line(data=spec, aes(x,y,col="red")) +
  scale_y_continuous(sec.axis = sec_axis(~., name = "Specificity")) +
  labs(x='Cutoff', y="Sensitivity") +
  theme(axis.title.y.right = element_text(colour = "red"), legend.position="none")
#################

## ------------------------------------------------------------------------------------
#troviamo l'optimal cutoff, cio l'optimal score che minimizza il misclassification error del
    modello di regressione logistica
#The best threshold (or cutoff) point to be used in glm models is the point which maximises
    the specificity and the sensitivity. This threshold point might not give the highest
    prediction in your model, but it wouldn't be biased towards positives or negatives.
optimized_cutoff = opt.cut(perf, pred1)#il cutoff ottimale  leggermente pii basso di quello
    standard, che sarebbe invece 0.5
optimized_cutoff

#converto la colonna pred di classified_dt2 in yes/no recidivism usando il cutoff ottimizzato
#yes era 1, quindi ho recidivismo se  maggiore del cutoff
classified_dt2$pred = ifelse(classified_dt2$pred<optimized_cutoff,"Never_used","Used")
#sostituisco i valori dei livelli per poter plottare la matrice di confusione
levels(test_set$Crack)[levels(test_set$Crack)==1] <- "Used"
levels(test_set$Crack)[levels(test_set$Crack)==0] <- "Never_used"
levels(test_set$Crack)
#anche per classified_dt2
classified_dt2$pred <- factor(classified_dt2$pred, levels = c("Used", "Never_used"))

## ------------------------------------------------------------------------------------
#matrice di confusione
cm <- confusionMatrix(data = as.factor(classified_dt2$pred), reference = as.factor(test_set$
    Crack))
#plotto la matrice di confusione
png("DRUGSCrackCM.png")
```

```
931 draw_confusion_matrix(cm)
932 dev.off()
933
934 ## ----------------------------------------------------------------------------------
935 #ci occupiamo di group fairness: indipendenza, separazione e sufficienza
936
937 #lo facciamo per tutti i sensitive attribute (Marital, ageR)
938
939 #ripristino di nuovo i livelli yes/no per renderlo pi leggibile
940 levels(classified_dt$Crack)[levels(classified_dt$Crack)==1] <- "Used"
941 levels(classified_dt$Crack)[levels(classified_dt$Crack)==0] <- "Never_used"
942
943 #per scegliere la categoria "base" per cui confrontare tutte le altre, per ogni attributo
        sensibile, ci conviene guardare le tabelle delle frequenze plottate in precedenza:
944
945
946 ## ----------------------------------------------------------------------------------
947 source("util.R")
948 levels(classified_dt$Crack) #se non metto un outcome_base, la libreria fairness prende il
        primo di questi valori come valore positivo ---- qui va bene perch il primo  never used
949 fair_metrics(data         = classified_dt,
950                       outcome      = 'Crack',
951                       group        = 'Age',
952                       probs =       'pred',
953                       preds_levels = c('Never_used','Used'),
954                       cutoff       = optimized_cutoff,
955                       base         = '18_24')
956
957 fair_metrics(data         = classified_dt,
958                       outcome      = 'Crack',
959                       group        = 'Ethnicity',
960                       probs =       'pred',
961                       preds_levels = c('Never_used','Used'),
962                       cutoff       = optimized_cutoff,
963                       base         = 'White')
964
965 fair_metrics(data         = classified_dt,
966                       outcome      = 'Crack',
967                       group        = 'Gender',
968                       probs =       'pred',
969                       preds_levels = c('Never_used','Used'),
970                       cutoff       = optimized_cutoff,
971                       base         = 'Male')
972 fair_metrics_cmp_graph2(data         = classified_dt,
973                       outcome      = 'Crack',
974                       group1        = 'Gender',
975                       group2 = 'Ethnicity',
976                       probs =       'pred',
```

```
                      preds_levels = c('Never_used','Used'),
                      cutoff       = optimized_cutoff,
                      base1         = 'Male',
                      base2        = 'White')
fair_metrics_cmp_graph2(data         = classified_dt,
                      outcome      = 'Crack',
                      group1        = 'Age',
                      group2 = 'Ethnicity',
                      probs =       'pred',
                      preds_levels = c('Never_used','Used'),
                      cutoff       = optimized_cutoff,
                      base1         = '18_24',
                      base2        = 'White')
fair_metrics_cmp_graph2(data         = classified_dt,
                      outcome      = 'Crack',
                      group1        = 'Ethnicity',
                      group2 = 'Age',
                      probs =       'pred',
                      preds_levels = c('Never_used','Used'),
                      cutoff       = optimized_cutoff,
                      base1         = 'White',
                      base2        = '18_24')
fair_metrics_cmp_graph2(data         = classified_dt,
                      outcome      = 'Crack',
                      group1        = 'Gender',
                      group2 = 'Age',
                      probs =       'pred',
                      preds_levels = c('Never_used','Used'),
                      cutoff       = optimized_cutoff,
                      base1         = 'Male',
                      base2        = '18_24')


## ------------------------------------------------------------------------------------
#CREO I SEGUENTI DATASET BILANCIATI PER CRACK:
#balanced_data0: bilanciato per Crack
#balanced_data1: bilanciato per Crack and Ethnicity
#balanced_data2: bilanciato per Crack, Ethnicity and Age

#balanced_data0: bilanciato per Ethnicity
#questo invece ha ethnicity bilanciato con smote ed  meglio usare questo!
raw_data = raw_data_copy
raw_data = as.data.frame(raw_data)
balanced_data0 = ovun.sample(Crack~., data = raw_data, method="both", N = nrow(raw_data), p
    =0.5, seed = 42)$data
#balanced_data0 = SmoteClassif(Age ~ ., balanced_data0, dist = "HEOM")


```

```
#balanced_data1 = SmoteClassif(Country ~ ., raw_data, dist = "HEOM", k=2)
balanced_data1 = SmoteClassif(Ethnicity ~ ., balanced_data0, dist = "HEOM", k=2)


balanced_data2 = NULL
balanced_data2 = SmoteClassif(Age ~ ., balanced_data0, dist = "HEOM", k=2)
# for(i in levels(balanced_data0$Ethnicity)){
#   #faccio il rebalancing di Two_yr_Recidivism per ogni categoria di ethnicity
#   temp_dt = balanced_data0[balanced_data0$Ethnicity==i, ]
#   s = SmoteClassif(Age ~ ., temp_dt, dist = "HEOM")
#   #metto poi insieme i vari piccoli dataset bilanciati
#   balanced_data2 = rbind(balanced_data2, s)
# }

cat_data <- balanced_data0[, sapply(balanced_data0, is.categorical)]
cat_names <- names(cat_data)
for ( i in seq(1,length( cat_data ),1) ){
  pie_print(cat_data,cat_names[i])
}

## ------------------------------------------------------------------------------------
#balanced_data0
#split into train and test set
sample_size = floor(0.7*nrow(balanced_data0))
#set a random seed per rendere l'esperimento ripetibile
set.seed(42)
# randomly split data
picked = sample(seq_len(nrow(balanced_data0)),size = sample_size)
training_set =balanced_data0[picked,]
test_set =balanced_data0[-picked,]

#as.factor mi serve per fare una classificazione binaria
balanced_data0$Crack = as.factor(balanced_data0$Crack)
#devo anche eliminare Coke dal training_set
cols_to_drop <- names(training_set) %in% c("Crack")
#training e test set senza variabile target
training_set_data <- training_set[, !cols_to_drop, drop = FALSE]
#anche sui dati di test
test_set_data <- test_set[, !cols_to_drop, drop = FALSE]


#REGRESSIONE LOGISTICA
#elimino colonna crack
cols_to_drop <- names(balanced_data0) %in% c("Crack")
balanced_data0_copy = balanced_data0
balanced_data0 <- balanced_data0[, !cols_to_drop, drop = FALSE]

################################
```

```
#poi commento le righe in cui calcola il modello perch ci potrebbe mettere troppo (
    sufficiente salvarlo e ricaricarlo)
logitMod <- glm(Crack ~ ., data = training_set, family=binomial(link="logit"))
logitMod #capire cosa significano questi dati
#saveRDS(model, "./logitMod_compas_rf.rds") #commento perch l'ho gi salvato
##############################################
#logitMod = readRDS(file = "./model_compas_rf.rds")
#logitMod

#devo fare queste due righe altrimenti non riconosce i livelli di country
logitMod$xlevels[["Country"]] <- union(logitMod$xlevels[["Country"]], levels(raw_data$Country
    ))
logitMod$xlevels[["Ethnicity"]] <- union(logitMod$xlevels[["Ethnicity"]], levels(raw_data$
    Ethnicity))
pred = predict(logitMod, test_set_data, type = "response") #se non metto il type = response,
    mi restituisce una predizione tra -1 e 1, altrimenti me la restituisce tra 0 e 1. Scelgo
    tra -1 e 1 perc poi ottengo il cutoff ottimizzato anch'esso tra -1 e 1 e mi  pi facile
    fare la predizione
balanced0_classified_dt = cbind(test_set, pred) #questo  quello che uso per la libreria
    fairness
#classified_dt2 = cbind(test_set_data, pred)
#classified_dt = rbind(classified_dt1, classified_dt2)
pred1 <- prediction(pred, test_set$Crack) #pred1  un oggetto pred.obj di ROCR
perf <- performance(pred1, measure = "tpr", x.measure = "fpr")
optimized_cutoff0 = opt.cut(perf, pred1)



## -----------------------------------------------------------------------------------
#balanced_data1
#split into train and test set
sample_size = floor(0.7*nrow(balanced_data1))
#set a random seed per rendere l'esperimento ripetibile
set.seed(42)
# randomly split data
picked = sample(seq_len(nrow(balanced_data1)),size = sample_size)
training_set =balanced_data1[picked,]
test_set =balanced_data1[-picked,]

#as.factor mi serve per fare una classificazione binaria
balanced_data1$Crack = as.factor(balanced_data1$Crack)
#devo anche eliminare Crack dal training_set
cols_to_drop <- names(training_set) %in% c("Crack")
#training e test set senza variabile target
training_set_data <- training_set[, !cols_to_drop, drop = FALSE]
#anche sui dati di test
test_set_data <- test_set[, !cols_to_drop, drop = FALSE]

```

```
1113
1114 #REGRESSIONE LOGISTICA
1115 #elimino colonna crack
1116 cols_to_drop <- names(balanced_data1) %in% c("Coke")
1117 balanced_data1_copy = balanced_data1
1118 balanced_data1 <- balanced_data1[, !cols_to_drop, drop = FALSE]
1119
1120 ################################
1121 #poi commento le righe in cui calcola il modello perch ci potrebbe mettere troppo (
         sufficiente salvarlo e ricaricarlo)
1122 logitMod <- glm(Crack ~ ., data = training_set, family=binomial(link="logit"))
1123 logitMod #capire cosa significano questi dati
1124 #saveRDS(model, "./logitMod_compas_rf.rds") #commento perch l'ho gi salvato
1125 ############################################
1126 #logitMod = readRDS(file = "./model_compas_rf.rds")
1127 #logitMod
1128
1129 #devo fare queste due righe altrimenti non riconosce i livelli di country
1130 logitMod$xlevels[["Country"]] <- union(logitMod$xlevels[["Country"]], levels(raw_data$Country
         ))
1131 logitMod$xlevels[["Age"]] <- union(logitMod$xlevels[["Age"]], levels(raw_data$Age))
1132 pred = predict(logitMod, test_set_data, type = "response") #se non metto il type = response,
         mi restituisce una predizione tra -1 e 1, altrimenti me la restituisce tra 0 e 1. Scelgo
         tra -1 e 1 perc poi ottengo il cutoff ottimizzato anch'esso tra -1 e 1 e mi  pi facile
         fare la predizione
1133 balanced1_classified_dt = cbind(test_set, pred) #questo  quello che uso per la libreria
         fairness
1134 #classified_dt2 = cbind(test_set_data, pred)
1135 #classified_dt = rbind(classified_dt1, classified_dt2)
1136 pred1 <- prediction(pred, test_set$Crack) #pred1  un oggetto pred.obj di ROCR
1137 perf <- performance(pred1, measure = "tpr", x.measure = "fpr")
1138 optimized_cutoff1 = opt.cut(perf, pred1)
1139
1140
1141
1142 ## ----------------------------------------------------------------------------------
1143 #balanced_data2
1144 #split into train and test set
1145 sample_size = floor(0.7*nrow(balanced_data2))
1146 #set a random seed per rendere l'esperimento ripetibile
1147 set.seed(42)
1148 # randomly split data
1149 picked = sample(seq_len(nrow(balanced_data2)),size = sample_size)
1150 training_set =balanced_data2[picked,]
1151 test_set =balanced_data2[-picked,]
1152
1153 #as.factor mi serve per fare una classificazione binaria
1154 balanced_data2$Crack = as.factor(balanced_data2$Crack)
```

```r
#devo anche eliminare Coke dal training_set
cols_to_drop <- names(training_set) %in% c("Crack")
#training e test set senza variabile target
training_set_data <- training_set[, !cols_to_drop, drop = FALSE]
#anche sui dati di test
test_set_data <- test_set[, !cols_to_drop, drop = FALSE]


#REGRESSIONE LOGISTICA
#elimino colonna crack
cols_to_drop <- names(balanced_data2) %in% c("Coke")
balanced_data2_copy = balanced_data2
balanced_data2 <- balanced_data2[, !cols_to_drop, drop = FALSE]

################################
#poi commento le righe in cui calcola il modello perch ci potrebbe mettere troppo ( sufficiente salvarlo e ricaricarlo)
logitMod <- glm(Crack ~ ., data = training_set, family=binomial(link="logit"))
logitMod #capire cosa significano questi dati
#saveRDS(model, "./logitMod_compas_rf.rds") #commento perch l'ho gi salvato
##########################################
#logitMod = readRDS(file = "./model_compas_rf.rds")
#logitMod

#devo fare queste due righe altrimenti non riconosce i livelli di country
logitMod$xlevels[["Country"]] <- union(logitMod$xlevels[["Country"]], levels(raw_data$Country))
pred = predict(logitMod, test_set_data, type = "response") #se non metto il type = response, mi restituisce una predizione tra -1 e 1, altrimenti me la restituisce tra 0 e 1. Scelgo tra -1 e 1 perc poi ottengo il cutoff ottimizzato anch'esso tra -1 e 1 e mi  pi facile fare la predizione
balanced2_classified_dt = cbind(test_set, pred) #questo  quello che uso per la libreria fairness
#classified_dt2 = cbind(test_set_data, pred)
#classified_dt = rbind(classified_dt1, classified_dt2)
pred1 <- prediction(pred, test_set$Crack) #pred1  un oggetto pred.obj di ROCR
perf <- performance(pred1, measure = "tpr", x.measure = "fpr")
optimized_cutoff2 = opt.cut(perf, pred1)

## -----------------------------------------------------------------------------
summary(balanced1_classified_dt)


## -----------------------------------------------------------------------------
#ora confronto ciascun dataset bilanciato con quello orignale
#poi seleziono quelli che sembrano effettivamente migliori del dataset originale
#poi confronto tra loro questi dataset bilanciati rimanenti e scelgo il migliore
levels(balanced0_classified_dt$Crack)[levels(balanced0_classified_dt$Crack)==1] <- "Used"
```

```
levels(balanced0_classified_dt$Crack)[levels(balanced0_classified_dt$Crack)==0] <- "Never_
    used"
levels(balanced1_classified_dt$Crack)[levels(balanced1_classified_dt$Crack)==1] <- "Used"
levels(balanced1_classified_dt$Crack)[levels(balanced1_classified_dt$Crack)==0] <- "Never_
    used"
levels(balanced2_classified_dt$Crack)[levels(balanced2_classified_dt$Crack)==1] <- "Used"
levels(balanced2_classified_dt$Crack)[levels(balanced2_classified_dt$Crack)==0] <- "Never_
    used"

fair_metrics(data         = balanced1_classified_dt,
                      outcome      = 'Crack',
                      group        = 'Ethnicity',
                      probs =       'pred',
                      preds_levels = c('Never_used','Used'),
                      cutoff       = optimized_cutoff1,
                      base         = 'White')

#creo anche un dataset con i valori delle mean deviation per ogni dataset bilanciato, per
    ogni metrica
msd_balanced=NULL

source("util.R")
png("DRUGSb0rdComp.png")
p = fair_metrics_cmp_graph(data1         = classified_dt,
                data2 = balanced0_classified_dt,
                outcome      = 'Crack',
                outcome_base = 'Never_used',
                group        = 'Ethnicity',
                probs1 =       'pred',
                probs2 =       'pred',
                preds_levels = c('Never_used','Used'),
                cutoff1       = optimized_cutoff,
                cutoff2      = optimized_cutoff0,
                base         = 'White')
dev.off()
#praticamente solo peggioramenti
msd_balanced=p[[1]]
msd_balanced= rbind(msd_balanced, p[[2]])

png("DRUGSb1rdComp.png")
p = fair_metrics_cmp_graph(data1         = classified_dt,
                data2 = balanced1_classified_dt,
                outcome      = 'Crack',
                outcome_base = 'Never_used',
                group        = 'Ethnicity',
                probs1 =       'pred',
                probs2 =       'pred',
                preds_levels = c('Never_used','Used'),
```

```
                cutoff1       = optimized_cutoff,
                cutoff2      = optimized_cutoff1,
                base         = 'White')
dev.off()
msd_balanced= rbind(msd_balanced, p[[2]])

png("DRUGSb2rdComp.png")
p = fair_metrics_cmp_graph(data1         = classified_dt,
                data2 = balanced2_classified_dt,
                outcome      = 'Crack',
                outcome_base = 'Never_used',
                group        = 'Ethnicity',
                probs1 =       'pred',
                probs2 =       'pred',
                preds_levels = c('Never_used','Used'),
                cutoff1       = optimized_cutoff,
                cutoff2      = optimized_cutoff2,
                base         = 'White')
dev.off()
msd_balanced= rbind(msd_balanced, p[[2]])

#CONFRONTO TRA LORO BALANCED DATASETS
######################
png("DRUGSb0b1Comp.png")
fair_metrics_cmp_graph(data1         = balanced0_classified_dt,
                data2 = balanced1_classified_dt,
                outcome      = 'Crack',
                outcome_base = 'Never_used',
                group        = 'Ethnicity',
                probs1 =       'pred',
                probs2 =       'pred',
                preds_levels = c('Never_used','Used'),
                cutoff1       = optimized_cutoff0,
                cutoff2      = optimized_cutoff1,
                base         = 'White')
dev.off()

png("DRUGSb0b2Comp.png")
fair_metrics_cmp_graph(data1         = balanced0_classified_dt,
                data2 = balanced2_classified_dt,
                outcome      = 'Crack',
                outcome_base = 'Never_used',
                group        = 'Ethnicity',
                probs1 =       'pred',
                probs2 =       'pred',
                preds_levels = c('Never_used','Used'),
                cutoff1       = optimized_cutoff0,
                cutoff2      = optimized_cutoff2,
```

```
                base         = 'White')
dev.off()

msd_balanced
long_msd_balanced <- msd_balanced %>% gather(metrics, values, dem_parity:spec_parity)


g = ggplot(long_msd_balanced, aes(fill=metrics, y=values, x=datasets)) +
    geom_bar(position="dodge", stat="identity") +
    #ggtitle("Studying 4 species..") +
    facet_wrap(~metrics, ncol=2) +
    #facet_grid(metrics ~ datasets)
    theme(legend.position="none",
          strip.text = element_text(face="bold", size=15,lineheight=5.0),
strip.background = element_rect(fill="lightblue", colour="black",
size=1,),axis.text.x = element_text(angle = 90),
axis.text=element_text(size=20, face="bold"),
        axis.title=element_text(size=20,face="bold")) +
    xlab("")
ggsave("OverallCrack.jpg", plot = g, width = 24, height = 33, units = "in")
```

B

Data files

COMPAS fairness metrics data

	between25_45	above45	below25
Positively classified	460	71.0000000	365.0000000
Demographic Parity	1	0.1543478	0.7934783

	between25_45	above45	below25
Proportion	0.4283054	0.1863517	0.9193955
Proportional Parity	1.0000000	0.4350907	2.1465885

	between25_45	above45	below25
Sensitivity	0.7244224	0.9031008	0.1294118
Equalized odds	1.0000000	1.2466494	0.1786413

	between25_45	above45	below25
Precision	0.7149837	0.7516129	0.6875000
Predictive Rate Parity	1.0000000	1.0512308	0.9615604

	between25_45	above45	below25
Accuracy	0.6815642	0.7322835	0.6020151
Accuracy Parity	1.0000000	1.0744159	0.8832845

	between25_45	above45	below25
FNR	0.2755776	0.09689922	0.8705882
FNR Parity	1.0000000	0.35162234	3.1591405

	between25_45	above45	below25
FPR	0.3739316	0.6260163	0.04405286
FPR Parity	1.0000000	1.6741463	0.11780994

	between25_45	above45	below25
MCC	0.3512148	0.3327091	0.1551546
MCC Parity	1.0000000	0.9473094	0.4417657

```
           between25_45   above45   below25
NPV           0.6369565 0.6478873 0.5945205
NPV Parity    1.0000000 1.0171610 0.9333770

                  between25_45   above45   below25
Specificity           0.6260684 0.3739837 0.9559471
Specificity Parity    1.0000000 0.5973529 1.5269053

                     Caucasian African_American Asian   Hispanic
Positively classified       214       602.000000     0 54.0000000
Demographic Parity            1         2.813084     0  0.2523364

                     Native_American      Other
Positively classified     1.000000000 25.0000000
Demographic Parity        0.004672897  0.1168224

                   Caucasian African_American Asian  Hispanic Native_American         Other
Proportion          0.3328149        0.6438503     0 0.3253012       0.3333333         0.2551020
Proportional Parity 1.0000000        1.9345594     0 0.9774237       1.0015576         0.7664982

               Caucasian African_American    Asian  Hispanic Native_American  Other
Sensitivity    0.7608142        0.5314534 1.000000 0.8073394        1.000000  0.859375
Equalized odds 1.0000000        0.6985323 1.314381 1.0611519        1.314381  1.129546

                      Caucasian African_American     Asian  Hispanic  Native_American  Other
Precision             0.6969697        0.7357357 0.8571429 0.7857143  0.5000000        0.7534247
Predictive Rate Parity 1.0000000        1.0556208 1.2298137 1.1273292  0.7173913        1.0810006

                Caucasian African_American     Asian  Hispanic Native_American  Other
Accuracy         0.651633        0.6748663 0.8571429 0.7289157       0.6666667  0.7244898
Accuracy Parity  1.000000        1.0356540 1.3153767 1.1185985       1.0230708  1.1118065

           Caucasian African_American Asian  Hispanic Native_American     Other
FNR        0.2391858        0.4685466     0 0.1926606               0 0.1406250
FNR Parity 1.0000000        1.9589237     0 0.8054851               0 0.5879322

           Caucasian African_American    Asian  Hispanic Native_American  Other
FPR             0.52        0.1856540 1.000000 0.4210526       0.5000000  0.5294118
FPR Parity      1.00        0.3570269 1.923077 0.8097166       0.9615385  1.0180995

           Caucasian African_American Asian  Hispanic Native_American     Other
MCC        0.2491225        0.3610301     0 0.3915207        0.500000 0.3602994
MCC Parity 1.0000000        1.4492073     0 1.5715990        2.007045 1.4462742
           Caucasian African_American Asian  Hispanic Native_American    Other
NPV        0.5607477         0.641196   NaN 0.6111111        1.000000 0.640000
NPV Parity 1.0000000         1.143466   NaN 1.0898148        1.783333 1.141333
                  Caucasian African_American Asian  Hispanic Native_American  Other
Specificity             0.48         0.814346     0 0.5789474        0.500000  0.4705882
```

```
Specificity Parity      1.00         1.696554     0 1.2061404        1.041667  0.9803922

                      Male    Female
Positively classified  802 94.000000
Demographic Parity       1  0.117207
                         Male    Female
Proportion          0.5357381 0.2647887
Proportional Parity 1.0000000 0.4942503
                    Male    Female
Sensitivity    0.6231343 0.8391304
Equalized odds 1.0000000 1.3466285
                           Male    Female
Precision              0.7208633 0.7394636
Predictive Rate Parity 1.0000000 1.0258028
                     Male    Female
Accuracy        0.6680027 0.7042254
Accuracy Parity 1.0000000 1.0542254
                Male    Female
FNR        0.3768657 0.1608696
FNR Parity 1.0000000 0.4268618
                Male   Female
FPR        0.2799423 0.544000
FPR Parity 1.0000000 1.943258
                Male    Female
MCC        0.3431249 0.3194837
MCC Parity 1.0000000 0.9311003
                Male    Female
NPV        0.6221945 0.6063830
NPV Parity 1.0000000 0.9745875
                        Male    Female
Specificity        0.7200577 0.4560000
Specificity Parity 1.0000000 0.6332826
```

References

[1] 2018 reform of eu data protection rules. https://ec.europa.eu/commission/sites/beta-political/files/data-protection-factsheet-changes_en.pdf.

[2] Codice in materia di protezione dei dati personali. https://www.agid.gov.it/sites/default/files/repository_files/leggi_decreti_direttive/decreto_legislativo_196_2003.pdf.

[3] Part 1607 - uniform guidelines on employee selection procedures. https://www.govinfo.gov/content/pkg/CFR-2011-title29-vol4/xml/CFR-2011-title29-vol4-part1607.xml.

[4] Wikipedia:facebook–cambridge analytica data scandal. https://en.wikipedia.org/wiki/Facebook-Cambridge_Analytica_data_scandal.

[5] Julia Angwin, Jeff Larson, Surya Mattu, and Lauren Kirchner. Machine bias. https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing.

[6] Solon Barocas, Moritz Hardt, and Arvind Narayanan. *Fairness and Machine Learning*. fairmlbook.org, 2019. http://www.fairmlbook.org.

[7] Solon Barocas and Andrew D. Selbst. Big Data's Disparate Impact. *SSRN eLibrary*, 2014.

[8] Jonathan Baron and John Hershey. Outcome bias in decision evaluation. *Journal of personality and social psychology*, 54:569–79, 05 1988.

[9] Gustavo Batista, Ronaldo Prati, and Maria-Carolina Monard. A study of the behavior of several methods for balancing machine learning training data. *SIGKDD Explorations*, 6:20–29, 06 2004.

[10] Richard Berk, Hoda Heidari, Shahin Jabbari, Michael Kearns, and Aaron Roth. Fairness in criminal justice risk assessments: The state of the art. *Sociological Methods & Research*, 0(0):0049124118782533, 0.

[11] Colin R. Blyth. On simpson's paradox and the sure-thing principle. *Journal of the American Statistical Association*, 67(338):364–366, 1972.

[12] Aylin Caliskan, Joanna J. Bryson, and Arvind Narayanan. Semantics derived automatically from language corpora contain human-like biases. *Science*, 356(6334):183–186, 2017.

[13] Joymallya Chakraborty, Suvodeep Majumder, Zhe Yu, and Tim Menzies. Fairway: a way to build fair ml software. *Proceedings of the 28th ACM Joint Meeting on European Software Engineering Conference and Symposium on the Foundations of Software Engineering*, Nov 2020.

[14] Le Chen, Ruijun Ma, Anikó Hannák, and Christo Wilson. Investigating the impact of gender on rank in resume search engines. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, CHI '18, New York, NY, USA, 2018. Association for Computing Machinery.

[15] Davide Chicco and Giuseppe Jurman. The advantages of the matthews correlation coefficient (mcc) over f1 score and accuracy in binary classification evaluation. *BMC Genomics*, 21, 12 2020.

[16] Jesse Davis and Mark Goadrich. The relationship between precision-recall and roc curves. volume 06, 06 2006.

[17] Thomas G Dietterich and Eun Bae Kong. Machine learning bias, statistical bias, and statistical variance of decision tree algorithms. Technical report, Technical report, Department of Computer Science, Oregon State University, 1995.

[18] Cynthia Dwork, Moritz Hardt, Toniann Pitassi, Omer Reingold, and Rich Zemel. Fairness through awareness. 2011.

[19] Vincent Egan, Ian Deary, and Elizabeth Austin. The neo-ffi: Emerging british norms and an item-level analysis suggest n, a and c are more reliable than o and e. *Personality and Individual Differences*, 29:907–920, 11 2000.

[20] Marc Elliott, Allen Fremont, Peter Morrison, Philip Pantoja, and Nicole Lurie. A new method for estimating race/ethnicity and associated disparities where administrative records lack self-reported race/ethnicity. *Health services research*, 43:1722–36, 05 2008.

[21] Robert Epstein and Ronald E. Robertson. The search engine manipulation effect (seme) and its possible impact on the outcomes of elections. *Proceedings of the National Academy of Sciences*, 112(33):E4512–E4521, 2015.

[22] E. Fehrman, A. K. Muhammad, E. M. Mirkes, V. Egan, and A. N. Gorban. The five factor model of personality and evaluation of drug consumption risk, 2017.

[23] Pratik Gajane and Mykola Pechenizkiy. On formalizing fairness in prediction with machine learning. 2018.

[24] Stuart Geman, Elie Bienenstock, and René Doursat. Neural networks and the bias/variance dilemma. *Neural Computation*, 4:1–58, 01 1992.

[25] Farrokh Habibzadeh, Parham Habibzadeh, and Mahboobeh Yadollahie. On determining the most appropriate test cut-off value: The case of tests with continuous results. *Biochemia Medica*, 26:297–307, 10 2016.

[26] Anikó Hannák, Claudia Wagner, David Garcia, Alan Mislove, Markus Strohmaier, and Christo Wilson. Bias in online freelance marketplaces: Evidence from taskrabbit and fiverr. In *Proceedings of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing*, CSCW '17, page 1914–1933, New York, NY, USA, 2017. Association for Computing Machinery.

[27] Moritz Hardt, Eric Price, and Nathan Srebro. Equality of opportunity in supervised learning. *CoRR*, abs/1610.02413, 2016.

[28] H. He and E. A. Garcia. Learning from imbalanced data. *IEEE Transactions on Knowledge and Data Engineering*, 21(9):1263–1284, 2009.

[29] Alex Hern. Twitter apologises for 'racist' image-cropping algorithm, 2020. Available on line.

[30] Feng Hu and Hang Li. A novel boundary oversampling algorithm based on neighborhood rough set model: Nrsboundary-smote. *Mathematical Problems in Engineering*, 2013, 11 2013.

[31] Clive Humby. *British mathematician and entrepreneur*. 2006.

[32] Jevan A. Hutson, Jessie G. Taft, Solon Barocas, and Karen Levy. Debiasing desire: Addressing bias discrimination on intimate platforms. *Proc. ACM Hum.-Comput. Interact.*, 2(CSCW), November 2018.

[33] Nathalie Japkowicz and Shaju Stephen. The class imbalance problem: A systematic study. *Intell. Data Anal.*, 6:429–449, 11 2002.

[34] Lauren Kirchner Julia Angwin Jeff Larson, Surya Mattu. Propublica/compas-analysis. https://github.com/propublica/compas-analysis, 2016.

[35] Justin Johnson and Taghi Khoshgoftaar. Survey on deep learning with class imbalance. *Journal of Big Data*, 6:27, 03 2019.

[36] Faysal Kamiran, Indre Zliobaite, and Toon Calders. Quantifying explainable discrimination and removing illegal discrimination in automated decision making. *Knowledge and Information Systems*, 35(3):613–644, 2013.

[37] Nicolas Kayser-Bril. Female historians and male nurses do not exist, google translate tells its european users, 2020. Available on line.

[38] Niki Kilbertus, Mateo Rojas-Carulla, Giambattista Parascandolo, Moritz Hardt, Dominik Janzing, and Bernhard Schölkopf. Avoiding discrimination through causal reasoning. 2018.

[39] Matt J. Kusner, Joshua R. Loftus, Chris Russell, and Ricardo Silva. Counterfactual fairness. 2018.

[40] Jorma Laurikkala. Improving identification of difficult small classes by balancing class distribution. In *Proceedings of the 8th Conference on AI in Medicine in Europe: Artificial Intelligence Medicine*, AIME '01, page 63–66, Berlin, Heidelberg, 2001. Springer-Verlag.

[41] X. Liu and Z. Zhou. The influence of class imbalance on cost-sensitive learning: An empirical study. In *Sixth International Conference on Data Mining (ICDM'06)*, pages 970–974, 2006.

[42] Kirsten Lloyd. Bias amplification in artificial intelligence systems. 09 2018.

[43] Robert McCrae and Paul Costa. A contemplated revision of the neo five-factor inventory. *Personality and Individual Differences*, 36:587–596, 02 2004.

[44] Ninareh Mehrabi, Fred Morstatter, Nripsuta Saxena, Kristina Lerman, and Aram Galstyan. A survey on bias and fairness in machine learning, 2019.

[45] David Meyer. Amazon reportedly killed an ai recruitment system because it couldn't stop the tool from discriminating against women. https://fortune.com/2018/10/10/amazon-ai-recruitment-bias-women-sexist/.

[46] Alexandra Olteanu, Carlos Castillo, Fernando Diaz, and Emre Kiciman. Social data: Biases, methodological pitfalls, and ethical boundaries. *SSRN Electronic Journal*, 01 2016.

[47] Jahna Otterbacher, Jo Bates, and Paul Clough. Competent men and warm women: Gender stereotypes and backlash in image search results. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*, CHI '17, page 6620–6631, New York, NY, USA, 2017. Association for Computing Machinery.

[48] Neal J. Roese and James M. Olson. Counterfactuals, causal attributions, and the hindsight bias: A conceptual integration. *Journal of Experimental Social Psychology*, 32(3):197 – 227, 1996.

[49] Harini Suresh and John V. Guttag. A framework for understanding unintended consequences of machine learning. 2020.

[50] Latanya Sweeney. Discrimination in online ad delivery. *Commun. ACM*, 56(5):44–54, May 2013.

[51] S. Verma and J. Rubin. Fairness definitions explained. In *2018 IEEE/ACM International Workshop on Software Fairness (FairWare)*, pages 1–7, 2018.

[52] Larry Wasserman. *All of Statistics: A Concise Course in Statistical Inference*. Springer Texts in Statistics. Springer, New York, 2004.

[53] Daniel Westreich. Berkson's bias, selection bias, and missing data. *Epidemiology (Cambridge, Mass.)*, 23:159–64, 11 2011.

[54] P.A. Whigham. Search bias, language bias and genetic programming. 02 1970.

[55] Jing Nathan Yan, Ziwei Gu, Hubert Lin, and Jeffrey M. Rzeszotarski. Silva: Interactively assessing machine learning fairness using causality. page 1–13, 2020.

[56] Muhammad Zafar, Isabel Valera, Manuel Rodriguez, Krishna P. Gummadi, and Adrian Weller. From parity to preference-based notions of fairness in classification. 06 2017.

[57] Qiuming Zhu. On the performance of matthews correlation coefficient (mcc) for imbalanced dataset. *Pattern Recognition Letters*, 136, 05 2020.