A benchmark study on methods to ensure fair algorithmic decisions for credit scoring

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ABSTRACT

The utility of machine learning in evaluating the creditworthiness of loan applicants has been proofed since decades ago. However, automatic decisions may lead to different treatments over groups or individuals, potentially causing discrimination. This paper benchmarks 12 top bias mitigation methods discussing their performance based on 5 different fairness metrics, accuracy achieved and potential profits for the financial institutions. Our findings show the difficulties in achieving fairness while preserving accuracy and profits. Additionally, it highlights some of the best and worst performers and helps bridging the gap between experimental machine learning and its industrial application.

INTRODUCTION

Credit scoring applications are playing an important role in the modern society, the approval process of loans increasingly migrating from human decision towards complex algorithmic decision. Agarwal et al. (2021) mention important benefits of the automated decision process for the financial institutions such as building the business while lowering costs, the ability to increase approval rates without increasing credit risks and generally a smoother experience for the client in the application process. Meanwhile, this business reality raises questions over the supervision of such automated decisions. Blattner et al. (2021) discuss how algorithmic governance faces the trade-off between complexity (read: performance) and oversight (read: capacity to audit). The interpretability of the models, and particularly of the credit scoring methods has been a recurring preoccupation of the industry regulators (e.g. national banks, financial authorities, government). Their interest was related to the capability of a human to understand how the decision was taken, in order to supervise, mitigate risks and prevent misconducts of financial institutions. An automatic decision, even if interpretable, may lead to different treatments over groups or individuals, defined by some specific attributes, eventually causing discrimination (Hurlin et al., 2021).

While the laws explicitly cover some discrimination factors (such as gender, race, nationality), other not restricted information may be used to discriminate vulnerable groups (e.g. based on behavior, wealth). More, information from external public sources, like social networks may be used as correlated information possibly leading to traits of race or gender (Ferretti, 2017).

There is a certain concern (among researchers, but also at government level) on the use of AI in decision making and several reports (Commission, 2020; Council, 2021) are indicating the future regulatory guidelines for this field. Both interpretability and fairness are addressed, together with privacy (already regulated by GDPR in the EU), technical robustness and accountability (with specific requirements in force through Basel III and IFRS9 regulations).
Our paper addresses the problem of ensuring fairness in the process of automatic decision of credit scoring using machine learning algorithms. We benchmark the state of the art methods in this field considering different fairness definitions from the literature. Our empirical findings were obtained by applying these methods on two datasets containing retail credit applications, one of them being a novel real-world dataset relating to the Romanian consumer loans market.

The main contributions of our work are as follows:

1. We help to bridge the gap between lab development and industrialized machine learning by identifying the strengths and weaknesses of 12 bias mitigation methods with the help of a real-world data environment implementation, being at the moment the most inclusive comparison of this type.

2. We show empirical evidence from a case study indicating how bias mitigation methods perform from three different perspectives: the amelioration of fairness metrics, the balanced accuracy of the models and the expected profit for the financial institutions.

3. The paper makes publicly available a new dataset in the area of credit scoring, facilitating the reproduction of our results and developing novel experiments in this field, where real data is limited.

4. Last but not least, we review in depth the fairness metrics found in the machine learning fairness literature together with the most prominent fairness processors emerged in the last decade.

The remainder of the paper is structured as follows. The Literature review section describes the state of the art in the area of fairness in machine learning, with a special section dedicated to credit scoring fairness developments. The Methodology describes the general framework for applying fairness processors to data, based on the three routes found in the literature: pre-processing, in-processing and post-processing. The fairness metrics used in the experiments are also described in this section. Next, the paper presents the experimental setup, including data pre-processing. The Results section presents and discusses the outcomes of the case study. The last section concludes the paper and provides insights for future developments.

**LITERATURE REVIEW**

**Fairness in machine learning**

Research interest on the fairness of machine learning has increased in the last decade, several fairness measures arising in the literature. As Paaßen et al. (2019) note, the different measures are based on the intuitions regarding fairness. *Individual fairness* advocates for similar treatment of similar cases, while *looking for accuracy fairness* implies different treatment for different cases. Most views concern equal treatment in general over different groups, defined by protected attributes (also called sensitive attributes) like gender, nationality and race (*statistical parity*) or, more specific, equal treatment based on some constraints, like *predictive parity* and *threshold fairness*.

Generally, the literature sources agree that not all the fairness criteria can be used simultaneously to evaluate the fairness of a ML process (Paaßen et al., 2019; Bono et al., 2021; Parkes et al., 2019), as some of them are in contradiction with others. Therefore, although we review all the criteria suggested by the literature in this field from a credit scoring perspective, we do not expect to identify a method that can satisfy all the fairness criteria at the same time.

Three fairness criteria have emerged as industry standards in the field: separation, independence and sufficiency.

The *separation* criterion evaluates the classification in such way that false positive rate (FP - clients wrongly associated with a high risk of not repaying debt) equal the false negative rate (FN - clients wrongly associated with a low risk of not repaying debt) for each subgroup (protected and unprivileged), this being guaranteed for any cutoff used. Kozodoi et al. (2022) suggest a way of measuring the separation as the average absolute difference between the group-wise FP and FN rates (FPR and FNR):

\[
SP = \frac{1}{2} \left| (FPR_{D=\text{unprivileged}} - FPR_{D=\text{privileged}}) + (FNR_{D=\text{unprivileged}} - FNR_{D=\text{privileged}}) \right|
\]

in their financial statements.
were out-passed by machine learning techniques in terms of profitability for the financial institutions, will result in only trivial improvements. While fairness of algorithmic decision-making is becoming a hot topic for debates and research, we noticed credit scoring being one of the favourite examples to be given by the literature when referring to possible discrimination caused by machine learning methods. Barocas et al. (Barocas et al., 2019) note that, based on practical experiments sufficiency is already satisfied at some degree due to machine learning inner mechanisms and trying to impose sufficiency when training a model will result in only trivial improvements. While fairness of algorithmic decision-making is becoming a hot topic for debates and research, we noticed credit scoring being one of the favourite examples to be given by the literature when referring to possible discrimination caused by machine learning methods.

Another trend in the AI fairness literature is to observe the individual fairness in the data, which tries to offset the limitations of the group fairness assessment methods discussed above. One problem with the group fairness is the propagation of an error (e.g. from a small group), leading to discrimination in subgroups, even if the group fairness might still be achieved (Kearns et al., 2018). By focusing on the statistical fairness, this leads to the impossibility of achieving the desired protection for individuals. In other words, the fairness achieved by considering individual attributes will not be translated into achieving fairness for the combination of two or more of those attributes. Speicher et al. (2018) employed inequality indices from economics in order to measure the outcomes of an algorithm towards individuals or groups. Their findings also suggest that eliminating the unfairness of treatment between groups may lead to increasing the unfairness within a group (at individual level).

**Credit scoring application fairness**

The research community studying modern machine learning techniques for credit scoring has recently turned their attention towards the implications of the distributional impact of algorithmic decisions on sensitive/vulnerable groups. While traditional methods for credit scoring (e.g. human application analysis) were out-passed by machine learning techniques in terms of profitability for the financial institutions, evidence showing how the later are producing predictions with greater variance (Fuster et al., 2022).

In their work, Zarsky (2016) try to create an analytic framework for an orderly debate on the subject of algorithmic decision making, focusing on credit scoring to substantiate the proposal. Two dimensions are considered as main triggers for concerns: the problems generated by machine learning reasoning and the attributes that exacerbate these problems. The two problems identified as debatable are the efficiency (or inefficiency) of the automated decision making and the second is, obviously, the fairness...
of the process. One attribute involved in the debate is the automation of the process, which can show solid results at an aggregated level but it is still prone to errors because of inaccuracies in the training data or specific algorithm settings (also identified by Hurley and Adebayo (2016) to be a possible burden for the consumer). The alternative human approach is also subject to biased decisions. Transparency is considered to be a solution to improve automated processing, by giving the opportunity to improve/correct the data, but may also lead to increasing costs.

Kozodoi et al. (2022) are looking to assess the feasibility of a fair credit scoring system in a profit-driven environment. They deal with strong inverse proportionality between fairness and profitability and show how the possibility of reducing discrimination can be achieved at very reasonable costs for the financial institutions. However, a totally fair scoring system seems utopian, as the profitability is suppressed by too strict conditions and increasing risk of default.

Another question addressed by the fair credit scoring literature challenges the efficiency in time of imposing protection to specific groups. Liu et al. (2018) try to quantify over time the impact of fairness constrained classification. They assume the lender will always try to maximize the utility of the models (profit), irrespective of the fairness constraints. In other words, applying fairness criteria could have unwanted effects over time, both for a protected group (a defaulted client will worsen their credit worthiness) and for the financial institution (credit defaults are considerably impacting the profitability of the business). Therefore, a dynamic and temporal modeling of fairness criteria could improve the overall process. Creager et al. (2020) propose a framework for causal modeling having the lending business as a fundament. They demonstrate the utility of such approach in simulating different scenarios in a profit-driven, but policy-constrained environment. The long term vision for evaluating the implications of fairness on the financial institutions and individuals seems to become a pursuit for researchers, in a not yet charted territory.

An auditor model is used to evaluate the classification fairness giving some constraints, also taking into account the explicability factor (Hickey et al., 2020). However, even if the framework was tested on a credit risk dataset, the authors do not discuss the feasibility of the method in real-world terms, where the profitability of the lending business needs to be demonstrated along fairness implementation.

The bias embedded in data could go unobserved in an exclusively mathematical approach. Lee and Floridi (2021) argue for an approach where the context-dependency of the data is exploited. They compare different algorithms in terms of fairness capability showing how some of the algorithms are not successful because of making associations between the protected attributes and other features in the dataset (which are a proxy for the loan outcome). However, the study makes a not realistic assumption by considering the intention of the lender to maximize the value of the loans. In practice, the overall profitability of the lending business should be considered (see Petrides et al. (2022) for a profit-driven approach in credit scoring). In the same line of work, Kilbertus et al. (2020) discuss on the difficulties of achieving perfect fairness and maximizing profits in the context of potentially biased previous decisions. The credit scoring models are trained based on previous lending data, leading to sub-optimal performance. The authors are proposing a stochastic decision rules system, attempting to improve the decisions in terms of utility and fairness.

A group unfairness index was introduced by Szepannek and Lübke (2021) to easily quantifying and comparing the fairness of models. The index is based on the group fairness by acceptance rate, a relevant fairness definition in the context of credit scoring.

METHODOLOGY
From the literature on machine learning fairness, a pipeline with three different approaches can be depicted. The general consensus is to first measure the bias in the algorithmic decisions by using one or several assessment metrics, then to mitigate the unfairness by employing a specific mitigation method. Finally, the results are compared in terms of bias evaluation and performance metrics after and before the mitigation method was applied. We show in Figure 1 the fairness pipeline used in our research. Next, we present the bias assessment metrics used in evaluating the fairness of the classification throughout our experiments and the bias mitigation algorithms tested in our benchmarking environment.

Bias assessment metrics
As shown in the Literature review section, different criteria for evaluating the fairness of a classifier were developed recently. Initially, they were built intuitively to tackle the unfairness of ML algorithms in
various classification problems. Subsequently, optimizations and new visions have risen (like using the economic inequality indexes \cite{Speicher18}), resulting in a set of measures generally accepted as a standard in the field.

**Separation metrics**

*Average odds difference* is a measure of classification fairness introduced by \cite{Hardt16} which computes the difference between FPR for protected and unprotected groups and adding to it the difference between TPR for protected and unprotected groups. This is especially useful in the credit scoring context, since the TPR (clients classified as goods and indeed repaying their debt) and FPR (clients wrongly classified as goods, not repaying their debt) are influencing the profitability of the business model.

\[
SP = \frac{1}{2} \left| (\text{FPR}_{D=\text{unprivileged}} - \text{FPR}_{D=\text{privileged}}) + (\text{TPR}_{D=\text{unprivileged}} - \text{TPR}_{D=\text{privileged}}) \right| \tag{4}
\]

A value close to 0 is obtained in the case of a fair classification. For practical reasons we consider the fairness to be inside the interval \((-0.1, 0.1)\).
Equal opportunity difference is a relaxed version of the Average odds difference, taking into account only the difference between TPR for protected and unprotected groups. In the credit scoring context, this means the classifier should have the same error rate when suggesting acceptance for loans in both protected and unprotected groups. The requirement of equalized errors puts pressure on the decision makers to improve the misclassification rates by optimizing models and increasing the quality of data (Barocas et al., 2019). The fairness interval considered for this metric is (-0.1, 0.1).

\[
EOD = TPR(D=unprivileged) - TPR(D=privileged)
\]

(5)

Independence metrics
The statistical parity difference measures the difference between probabilities of acceptance in the protected and unprotected groups. A value close to zero would imply same acceptance rate in both groups (Dwork et al., 2012). The fairness range for this metric is considered in the interval (-0.1, 0.1).

\[
SPD = Pr(\hat{Y} = 1|D = unprivileged) - Pr(\hat{Y} = 1|D = privileged)
\]

(6)

Disparate impact starts from the idea of independence and calculates the ratio between the probability of acceptance for the unprivileged group and the privileged group. A value close to 1 would imply an ideal degree of fairness, while values lower than 1 are indicating an advantage for the privileged group and values higher than 1, an advantage for the unprivileged group (Feldman et al., 2015). In a more flexible approach, the interval (0.8, 1.25) is considered as acceptable for a classifier to be considered fair.

\[
DI = \frac{Pr(\hat{Y} = 1|D = unprivileged)}{Pr(\hat{Y} = 1|D = privileged)}
\]

(7)

Individual fairness metric
Theil index lies in the category of metrics measuring inequality in economics, being a special case of the generalized entropy index \((\alpha=1)\). This allows in the context of fairness to observe the inequalities both at group level (between groups) and individual level (within group) (Speicher et al., 2018).

\[
Theil = \frac{1}{n} \sum_{i=1}^{n} b_i \ln \frac{b_i}{\mu}, \text{where } b_i = \hat{y}_i - y_i + 1
\]

(8)

In formula (8) \(n\) represents the number of instances in the dataset, \(\mu\) is the mean value of the benefits within a group, while \(\hat{y}\) and \(y\) are the individual predicted outcome and true outcome, respectively. A value close to 0 is the proxy for fair learning.

Bias mitigation methods
The bias mitigation methods are classified in three categories, based on their position in the fair AI process (see Figure 1). The pre-processing methods are tackling fairness issues before applying the classification method, and therefore are independent of the classification algorithm. The in-processing methods are developed within the classification method in order to ensure fairness. The post-processing bias mitigation methods are placed at the end of the fair processing pipeline. They are making adjustments after the model was trained, considering protected attributes restrictions. Post-processing methods, like pre-processing methods are independent of the classification algorithm used, permitting a classifier agnostic approach in mitigating the bias. The following methods were selected among those introduced by highly cited papers on this topic.

Pre-processing mitigation methods
Reweighing is one of the early-stages techniques in the fair AI area for mitigating bias. It is centered around the idea of reweighing the data without relabeling, in order to remove discrimination (Calders et al., 2009; Kamiran and Calders, 2012). The algorithm tries to achieve fairness by assigning lower weights to attributes that have been favored.
The weights will be assigned as a ratio between expected and observed probability to see an instance with its protected attribute in a class:

\[
W(X) = \frac{P_{\text{exp}}(S = X(S) \land \text{Class} = X(\text{Class}))}{P_{\text{obs}}(S = X(S) \land \text{Class} = X(\text{Class}))},
\]

where \( X \) is the entire dataset, \( S \) is a binary variable stating whether an individual is a member of a protected group. In this way, the resulting dataset will carry a fair representation of the protected instances.

Learning fair representations is a pre-processing technique that encodes the data while obfuscates the information about protected groups (Zemel et al., 2013). The method acts like a clustering model, building prototypes based on the requirement that one element from a protected group to be mapped to a certain prototype with the same probability as an element from an unprotected group (using the statistical parity criterion described in Subsection Bias assessment metrics). Formally, this is represented by:

\[
P(Z = k|x^+ \in X^+) = P(Z = k|x^- \in X^-), \forall k,
\]

where \( Z \) is a random attribute with \( k \) classes, each representing a prototype in the context of the clustering model, \( x^+ \) represents an individual from a protected group \( (X^+) \), and \( x^- \) represents an individual from an unprotected group \( (X^-) \).

Another method, developed by Feldman et al. (2015), is the Disparate Impact Remover. The algorithm detects the disparate impact (described in subsection Bias assessment metrics) and tries to repair the data in order to achieve fairness. The repair is done in a way to preserve the predictability of the target variable and to preserve the relative per-attribute ordering (ranking). The synthetic dataset will keep the original values for the protected attribute(s) and target variable. A more relaxed version of the algorithm considers a trade-off between fairness and utility (accuracy), performing a partial repair. Depending on the problem addressed and on the classifier’s performance, a compromise can be achieved.

In-processing mitigation methods
By adding adversarial learning to the predictor, Zhang et al. (2018) introduced a framework where the target is to increase the chances of the predictor for classifying, while minimizing the adversary’s chances to predict the protected feature. The method uses the equality of odds as fairness metric.

The term gerrymandering in the context of AI fairness questions the ability of a fairness constraint applied to a certain protected group to ensure the fairness at individual level. This means that an apparent fair classification at group level will not necessarily imply fairness for all the individuals. The Gerryfair method (Kearns et al., 2018) consists of two algorithms working as a learner and an auditor, working as a cost-sensitive classification oracle using linear methods. The fairness metrics used are false positive rates, false negative rates and statistical parity.

Another cost-sensitive method for mitigating bias is the Exponentiated gradient reduction (Agarwal et al., 2018). The algorithm consists of a sequence of two reductions aiming at yielding the classifier with the lowest error in the context of the defined constraints. The metrics considered for fairness optimization are the statistical parity and equalized odds. The method was designed only for binary classification.

Building on the work of Agarwal et al. (2018), the Grid search reduction was developed for predicting continuous outcomes instead of the discrete classification (Agarwal et al., 2019). The reason for choosing this direction was the practical need for numerical prediction (e.g. quantifying the risk of default in the credit scoring setting). The fairness metrics used by the method are the statistical parity and the bounded group loss, which is essentially the control of the prediction error for the protected group. For each metric a separate optimization algorithm was built.

An approach trying to satisfy several fairness metrics is the so called Meta classifier (Celis et al., 2019). The central idea of the method consists in developing an algorithm for a large family of classification problems. The current implementation supports only two metrics: the false discovery rate and the disparate impact. A very practical feature is the possibility to vary the constraint parameter \( \tau \) in order to achieve a reasonable trade-off between fairness and accuracy.

Prejudice remover is one of the methods developed in the early stages of AI fairness evolution, proposing a regularization approach applied to logistic regression (Kamishima et al., 2012). It defines prejudice as the statistical dependence between protected attributes and other information. Further, it
regularizes the learner’s behavior regarding the sensitive attributes by enforcing independence. The regularization parameter can be adjusted based on the accuracy-fairness trade-off.

**Post-processing mitigation methods**

One of the first methods developed for fairness post-processing is the Reject Option Classification, developed by Kamiran et al. (2012). The method uses posterior probabilities from a classifier to label instances with the aim of neutralizing discrimination. Rejected instances situated in a so called critical region are given special labels depending on the protected group membership. They are considered to be easy to influence by biases. The method relabels the instances using two cost-sensitive matrices for deprived and favored groups, by optimizing loss functions \( L \) for the two categories, according to a discrimination-accuracy trade-off coefficient \( \theta \) (Eq. 11).

\[
L_{+, -}^d = L_{+, +}^f = \theta / (1 - \theta)
\]

Calibrated equalized odds postprocessing is another method that changes output labels after classification to preserve fairness. Introduced by Pleiss et al. (2017), the method builds upon the work of Hardt et al. (2016) which introduced the equalized odds fairness measure. The calibration is added to the method of mitigating bias, by giving the possibility to ensure fairness for both protected and unprotected groups without leaving the option of incentivizing the algorithm when taking into account the sensitive feature. The method gives the practitioner the freedom of choosing the level of fairness constraint, an adjustment needed when classification accuracy suffers after the calibration.

**EXPERIMENTS**

In order to benchmark the different mitigation methods described above and evaluate them according to the classification performance indicators and bias assessment metrics, we used two datasets. The first is the well-known german credit dataset, available from the UCI Machine Learning Repository (Dua and Graff, 2017). The other dataset is a private dataset containing information on customers applying for personal loans, obtained from a romanian bank. We have run our experiments according to the pipeline described in Figure 1 using the framework from AI Fairness 360 (Bellamy et al., 2019).

**Data**

We used the german credit dataset as it is one of the most popular datasets used for benchmarking in the field and was also included in other research on fair AI, like the works of Kozodoi et al. (2022); Szepannek and Lübke (2021); Le Quy et al. (2022). Since real-world datasets in the field of credit scoring are rather rare and imply business specific challenges (like class imbalance and profit ratios) as shown by Petrides et al. (2022), we considered useful to bring to the attention of the community a novel dataset containing consumer loans data. We provide a summary of the statistics for both datasets in Table 1.

| Dataset             | Instances | Cat/Num/Bin attributes | Default Ratio | Protected attributes | Protected group ratio |
|---------------------|-----------|------------------------|---------------|----------------------|-----------------------|
| German credit       | 1000      | 32/7/1                 | 30%           | Age                  | 19%                   |
| Consumer loans      | 21568     | 8/7/9                  | 5.7%          | Age                  | 4.09%                 |

**Table 1.** Summary statistics for the datasets

Both datasets consist of samples of loan application, with the target attribute being the outcome of the loan: good or bad. In the industry standard the clients repaying their loans are named goods, while those not reimbursing the debt are called bads.

The independent attributes in the datasets can be divided into 3 categories: sociodemographic attributes, including information about age, education, profession; customer history providing information regarding the relationship between the customer and the bank (e.g. other products owned, previous loans); and economic information like client’s income or loan amount.

A detailed view on the attributes for the consumer loans dataset is provided in Table 6 in Appendix A.

We considered as protected attribute the age of the applicant, as suggested in other studies on this topic Zhou et al. (2021); Kozodoi et al. (2022); Le Quy et al. (2022). A threshold at the age of 25 was implemented for the aforementioned dataset. A copy of this dataset will be uploaded to a free data repository upon acceptance of this paper.
considered to differentiate between the vulnerable group (under 25) and the invulnerable group (25 and over) (Kamiran and Calders, 2009). More, when testing the variables importance in relation with the target variable (Default Flag) for the consumer loans dataset, age had the highest score, $-\log(p) = 73.736$. The weight of evidence for this score suggest a split in the data at $age = 23$. However, we kept the threshold at 25 for comparability reasons with other research studies. Another possible vulnerable attribute, marital status, followed the age in terms of importance, with a score of 56.937.

Even if other works (Hurlin et al., 2021) suggest the use of gender as protected attribute, we consider it inappropriate, since the use of attributes like gender and race is explicitly prohibited by the laws worldwide, ensuring fairness through unawareness.

**Experiments design**
We conducted our experiments starting with data prepossessing. As expected, the workload for cleaning the data was high in the case of consumer loans dataset, while the german credit dataset was already curated.

**Curating the consumer loans dataset**
We started by dropping some irrelevant attributes like ID, birth place and profession, the later having too many different classes and making the attributes more noisy than useful.

For the categorical attributes with missing values we added the class missing. The behavior of attributes with missing values can be interesting to observe when the missing value can have a certain significance itself. For example, a missing value for an attribute like workplace seniority can be explained if the loan applicant is already retired. Obviously, other missing information can be related to data collection issues. The preprocessing of categorical attributes was finalized with a one hot encoding for the transformation into numerical values, a condition for being able to run all the algorithms in the benchmarking phase.

Missing data for the numerical attributes was imputed with the median value for each of them. This method was adopted as the distributions were rather skewed.

**Experiments setup**
Next, for the consumer loans, data was partitioned randomly into training set (70%), validation set (15%) and test set (15%), considering a stratification that assigns the instances to each set based on the target variable distribution. Because the german credit data is rather small (1000 instances) we partitioned the data into training (70%) and test (30%).

After splitting the data we verified how the split affected the difference in mean outcomes (statistical parity) between protected and unprotected groups. A large difference would mean significantly different conditions between training and testing environments. Table 2 shows these values for the two datasets splits.

| Dataset          | Training | Validation | Test   |
|------------------|----------|------------|--------|
| German credit    | -0.1260  | N/A        | -0.1335|
| Consumer loans   | -0.1971  | -0.2050    | -0.1997|

**Table 2.** Statistical parity differences for the training/validation/test datasets

The protected group was defined considering the values of the attribute age, with values under 25. The favorable label for the target variable was set to represent the good behavior of the loan applicants. Note that the real-world consumer loans dataset encodes the target variable as Default Flag, meaning the favorable label would be in this case 0.

Next, we developed the experiments in accordance with the pipeline presented in Figure 1. For each bias mitigation method we chose the corresponding path, according to the class it belonged (pre-processing, in-processing, post-processing).

For the pre-processing and post-processing methods we used the logistic regression as the non-sensitive classifier to be trained. In the case of in-processing methods, we used the same classifiers for initially testing the fairness as the ones used by the methods themselves. This is one of the disadvantages of the in-processing debiasing methods. As mentioned in the Methodology section, this type of bias mitigation algorithms do not usually allow the user to select different classifiers for trainings, as the methods are built
around certain classifiers, not permitting the same independence as the pre-processing and post-processing methods. As we will see in the Results section, the outcomes may be quite different between the three categories.

For evaluating the performance of the different bias mitigation metrics we used fairness specific metrics, a general classification metric and a profit metric (for a synthetic view see Table 3). The fairness specific metrics were described in more detail in the Methodology section. The general classification metric employed was the balanced accuracy, which represents the average of Sensitivity and Specificity (see eq. 12). This method is particularly useful in the case of imbalanced datasets. Even if simple accuracy rate was used by most of the papers introducing fairness processing methods, we considered it to be insufficient in our context.

\[
Balanced\ accuracy = \frac{1}{2} \left( \frac{TP}{TP+FN} + \frac{TN}{TN+FP} \right) = \frac{1}{2} (TPR + TNR) \quad (12)
\]

For profit calculations we used the ROI measure (Verbraken et al., 2014) to estimate the outcome for a correct classification of a good client. The values used in the experiments are ROI=0.34, while the loss is accounted considering a 0.9 rate. We determined these values taking into account the specifics of the Romanian market during on-site discussions with the bank representatives. The ROI estimation follows the same process as reported by Petrides et al. (2022), by observing the behaviour of clients fully reimbursing their loans. Some of the loans are reimbursed earlier than scheduled initially, causing a lower than anticipated ROI. Therefore, ROI has been computed by multiplying the interest rate with the loan term and adjusted by an early repayment coefficient (ERC) (eq. 13).

\[
ROI = \text{Interest rate} \times \#\text{years} \times \text{ERC} \quad (13)
\]

The loss incurred by loans not re-paid (false positives in the context of our experimental setup) do not necessarily mean a total loss, as the clients made some payments before defaulting. Note that most application scorecards are built considering a probability of default during a one year time horizon, after failing to repay for 90 consecutive days. The loss coefficient (LC) was set to 0.9. The model’s profit was computed by adjusting the TPR with ROI and subtracting the losses caused by FP missclassification.

\[
Profit = TPR \times ROI - FPR \times LC \quad (14)
\]

Since the german credit dataset does not have any information regarding the ROI, we used the same values for calculating profits for both datasets, a practice also observed in the work of Kozodoi et al. (2022).

| Metric                          | Fairness interval | Description          |
|---------------------------------|-------------------|----------------------|
| Average odds difference         | (-0.1, 0.1)       | Separation metric    |
| Equal opportunity difference    | (-0.1, 0.1)       | Separation metric    |
| Statistical parity difference   | (-0.1, 0.1)       | Independence metric  |
| Disparate impact                | (0.8, 1.25)       | Independence metric  |
| Theil index                     | ≈ 0               | Individual fairness  |
| Balanced accuracy               | N/A               | Classification metric|
| Profit                          | N/A               | Model’s profit (%)   |

Table 3. Performance metrics

RESULTS

This section presents the results obtained after running our experiments on the two datasets, the best values for each criterion being underlined (see Tables 4 and 5).

By analyzing the results we can denote an overall loss of accuracy and profit when bias is mitigated for all fairness processors.
| Fairness processor                      | Pre/In/Post processing | DI      | SP      | AOD     | EOD     | TI      | BAcc    | P       |
|----------------------------------------|------------------------|---------|---------|---------|---------|---------|---------|---------|
| Reweighing                             | Pre                    | 0.818   | -0.127  | -0.026  | -0.148  | 0.303   | 0.764   | 0.319   |
| Learning Fair Representations           | Pre                    | 0.850   | -0.044  | -0.009  | -0.050  | 0.087   | 0.578   | 0.283   |
| Disparate impact remover                | Pre                    | 0.964   | -0.035  | -0.059  | -0.011  | 0.019   | 0.507   | 0.270   |
| Optimized preprocessing                 | Pre                    | 0.000   | -0.335  | -0.284  | -0.344  | 0.962   | 0.566   | 0.278   |
| Adversarial Debiasing                   | In                     | 0.868   | -0.128  | -0.054  | -0.086  | 0.025   | 0.645   | 0.289   |
| GerryFair                               | In                     | 0.830   | -0.169  | -0.205  | -0.131  | 0.022   | 0.522   | 0.272   |
| Meta Classifier*                        | In                     | 0.762   | -0.048  | -0.004  | -0.010  | 0.075   | 0.619   | 0.288   |
| Exponentiated Gradient Red.            | In                     | 0.918   | -0.077  | -0.0027 | -0.0077 | 0.058   | 0.559   | 0.277   |
| Grid Search Reduction                   | In                     | 1.036   | 0.029   | 0.117   | 0.04    | 0.205   | 0.560   | 0.279   |
| Prejudice Remover*                      | In                     | N/A     | N/A     | N/A     | N/A     | 0.058   | 0.500   | 0.269   |
| Reject Option Classification            | Post                   | 0.984   | -0.010  | 0.153   | 0.030   | 0.313   | 0.714   | 0.313   |
| Calibrated Odds-Equalizing              | Post                   | 1.036   | 0.029   | 0.117   | 0.04    | 0.205   | 0.560   | 0.279   |
| No bias mitigation                      | N/A                    | 0.184   | -0.591  | -0.395  | -0.574  | 0.290   | 0.776   | 0.321   |

Abreviations: DI = Disparate impact; SP = Statistical parity; AOD = Average odds difference; EOD = Equal opportunity difference; TI = Theil Index; SEDF = Smoothed empirical differential fairness; BAcc = Ballanced Accuracy; P = Profit; * = Unstable results

Table 4. Benchmark results (Consumer loans dataset)

Contrary to our expectations (set by the literature review), that all fairness constraints cannot be satisfied at the same time, our results demonstrate the opposite in several cases. Methods like, Learning Fair Representations, Disparate impact remover, and Exponentiated Gradient reduction managed to achieve fairness for all 5 metrics in the case of the consumer loan dataset. For the german credit data, Grid Search Reduction achieved a comparable performance.

Two of the methods failed to achieve consistent results on each dataset tested. As will be later shown, this might be caused by bias in the methods.

The mixed results obtained after applying the methods on the two datasets show a relevant connection between method and data quality. For example, only one method managed to reduce the Theil index significantly in the case of the german credit dataset, which could be a consequence of small data (1000 instances). The consumer loans dataset was instead very imbalanced (5.7% defaulted loans), causing accuracy classification problems. In this context, the use of Ballanced Accuracy was particularly important in the context of the imbalanced data in differentiating the classification performance.

Next, we review the performances of each fairness processor, also mentioning the difficulties and special processing required during the experiments.

The pre-processing method of Reweighing the examples in each group clearly performs well for most of the bias indicators. The classification performance is not affected too much, this being an advantage over other more sophisticated methods, but a higher than recommended value of the Theil index might suggest unfairness at individual level. In the case of the german dataset, although the algorithm is improving without any doubt the fairness metrics, the results are very volatile due to the small data...
| Fairness processor                  | Pre/In/Post processing | DI     | SP      | AOD     | EOD     | TI      | BAcc    | P      |
|------------------------------------|------------------------|--------|---------|---------|---------|---------|---------|--------|
| Reweighing                         | Pre                    | 0.756  | -0.14   | -0.095  | -0.053  | 0.288   | 0.704   | 0.160  |
| Learning Fair Representations      | Pre                    | 0.801  | -0.048  | -0.075  | -0.127  | 0.277   | 0.553   | 0.004  |
| Disparate impact remover           | Pre                    | 0.819  | -0.148  | -0.103  | -0.103  | 0.114   | 0.674   | 0.081  |
| Optimized preprocessing            | Pre                    | 0.542  | 0.168   | 0.1044  | 0.002   | 0.221   | 0.642   | 0.067  |
| Adversarial Debiasing              | In                     | 0.994  | -0.003  | 0.071   | -0.039  | 0.139   | 0.681   | 0.076  |
| GerryFair                          | In                     | 0.811  | -0.156  | -0.121  | -0.097  | 0.12    | 0.655   | 0.068  |
| Meta Classifier*                   | In                     | 0.648  | 0.145   | 0.083   | 0.029   | 0.182   | 0.689   | 0.107  |
| Exponentiated Gradient Red.        | In                     | 0.8335 | -0.139  | -0.101  | -0.071  | 0.108   | 0.668   | 0.075  |
| Grid Search Reduction              | In                     | 0.937  | -0.052  | -0.027  | 0.076   | 0.094   | 0.677   | 0.080  |
| Prejudice Remover*                 | In                     | 0.719  | -0.237  | -0.196  | -0.193  | 0.112   | 0.454   | 0.074  |
| Reject Option Classification       | Post                   | 0.944  | -0.040  | 0.022   | -0.006  | 0.145   | 0.711   | 0.119  |
| Calibrated Odds-Equalizing         | Post                   | 0.478  | -0.474  | -0.483  | -0.321  | 0.115   | 0.621   | 0.043  |
| No bias mitigation                 | N/A                    | 0.590  | -0.256  | -0.195  | -0.224  | 0.255   | 0.712   | 0.157  |

Abreviations: DI = Disparate impact; SP = Statistical parity; AOD = Average odds difference; EOD = Equal opportunity difference; TI = Theil Index; SEDF = Smoothed empirical differential fairness; BAcc = Ballanced Accuracy; P = Profit ; * = Unstable results

Table 5. Benchmark results (German credit dataset)

sample.

While Learning Fair Representations method might seem difficult to setup because of various values and combinations of the parameters (two fairness parameters, classification threshold, loss tolerance), the results were promising on both our datasets. Since this is a pre-processing bias mitigation method, the operator has the freedom to choose more powerful classifiers.

When applying the Disparate impact remover, the algorithm indeed optimises the value of the disparate impact, but with a high cost for accuracy and profits, leaving no room for compromise between fairness and accuracy or profits.

The Optimized Preprocessing algorithm was found to be very slow when dealing with a large number of attributes. We had to reduce the number of attributes by selecting only the top 5 attributes considering information value, along the protected attribute and the target attribute, in order to create a testing environment similar to the one described by Calmon et al. (2017). Some of the fairness metrics remained at unwanted levels, while the accuracy has significantly decreased.

Adversarial debiasing is implementing using a tensor flow for the classification, employing a predictor and adversary model to achieve fairness. The method achieves fairness at almost all chapters, with a loss in the accuracy. The slightly better results over other methods might be due to the use of tensor flow instead of the logistic regression.

GerryFair algorithm is an in-processing method for mitigating bias in datasets which takes into account the individual level of unfairness. The dataset needs to be specially pre-processed in order to fit its requirements, in a similar manner with the optimized preprocessing method. It also has several
hyper-parameters to be tuned before being able to perform a suitable job for the dataset. These parameters include the fairness target ($\gamma$), maximum number of iterations, the maximum L1-Norm to be used for dual variables and the learner to be used. The learner is required to be a regressor. Our typical logistic regression used as a classifier in the experiments is not supported by this method, therefore we tried the learners recommended by Kearns et al. (2018). We found it quite difficult to tune the parameters in order to obtain a reasonable trade-off between fairness and balanced accuracy. The method tends to overfit when dealing with the german dataset because of its small size.

When using the Meta Fair Classifier, the user defines the importance of the fairness metric (false discovery ratio or disparate impact) as one of the inputs for the algorithm. The classifier showed promising results, but not enough stable. When running the algorithm for multiple times on both datasets, the stability issue makes unusable the option of averaging the results, as sometimes the fairness constraints are not achieved. The problem of stabilization has been discussed also by Huang and Vishnoi (2019) and Friedler et al. (2019) in their work.

When testing the Exponentiated Gradient Reduction algorithm, several fairness constraints were considered as a parameter (Equalized odds, True Positive Rate Difference, Demographic Parity and Error Rate Ratio). Among these, the True Positive Rate Difference was associated with the best balanced accuracy and profit, while the fairness metrics achieved the targeted values for each constraint used in the case of the consumer loans dataset. For the german credit dataset however, the best results considering the constraints were obtained when using the Demographic Parity as a parameter. This shows how tied the results are to the data quality and stresses the importance of experimenting when adopting a solution.

Grid Search Reduction allows the user (along with the fairness constraint) to define the constraint weight in order to achieve a reasonable compromise between accuracy and fairness. This proves to be a convenient feature for an in-processing algorithm, leaving the practitioner to experiment and decide on the most convenient solution. Yet, the transition from unfair to fair classification seems not smooth enough to have many options of compromise between accuracy and fairness. The results show a significant penalty in accuracy when fairness is achieved.

The last tested in-processing method, Prejudice remover failed to achieve fairness on both datasets or became overfit. None of the variations in the fairness parameter of the algorithm ameliorated the results. A possible cause was reported by Kamishima et al. (2013) to be in the design of the method, which models on a hypothetical distribution.

The post-processing method Reject Option Classification showed some of the best results in terms of balanced accuracy and profit in a fairness constrained context. The fairness constraints allowed include the statistical parity difference, average odds difference and the equal opportunity difference. The relatively high values of the Theil index show unfairness still persist perhaps at individual level.

The Calibrated Odds-Equalizing post-processing algorithm has been struggling in mitigating bias with the consumer loans dataset. It was tested with full and reduced data (feature selection applied), but the fairness metrics did not show significant improvements over the unrestricted setup. However, the balanced accuracy was reduced after the post-processing, in the case of consumer loans, from $0.755$ to about $0.56$, depending on the parameters applied to the algorithm (e.g. cost constraint can be chosen from FNR, TNR or weighted).

CONCLUSIONS

The paper adds to the literature of fair AI decision making by benchmarking twelve bias mitigation methods against five fairness metrics and evaluating them in the context of credit scoring data, both in terms of balanced accuracy and profits. We based our experiments on two datasets, the classical german credit dataset and a novel consumer loans dataset from a Romanian bank, in order to show the challenges in implementing these methods in a real-world setup.

Almost every bias mitigation method benchmarked in our study has managed to increase the overall fairness in the context of a potentially automated decision context. Considering the 5 fairness metrics covering (virtually) the entire spectre of fairness definitions, we managed to identify the strengths and weaknesses of each method. None of the fairness processors can be considered a leader in this area or a universal panacea for treating unfairness while satisfying at the same time the accuracy and profit criteria. For this reason, for a practitioner willing to mitigate bias in their decision, a group of methods should be employed and choose at a later stage the most convenient one, based on costs limitations.
However, contrary to our expectations raised by the literature review that a fairness processor cannot satisfy all the fairness criteria, we have found several methods that were able to reduce unfairness at each chapter, but incurred significant costs.

When tested on the real-world consumer loans dataset, some of the bias mitigation methods underperformed in accuracy compared to the results reported by the papers introducing them. We also noted that the vast majority of these papers considered simple accuracy as the performance criteria, which in our case was unusable because of the highly class imbalanced data. This shows the difficulty in implementing fairness constraints in a real-world environment with highly imbalanced data (the typical scenario for credit risk analysis), where the loss in accuracy can translate to severely increased costs or diminished profits.

Our methodology describes the differences in the way input data needs to be prepared before feeding the different methods: different encoding of the sensitive attributes, the necessity to transform categorical features by hot-encoding them or the importance of reducing the number of features in the dataset because of convergence time.

One of the limitations of our work is that the paper is observational and limited to the case studies, not being able to give answers regarding the causes that may generate the fairness gaps. This could be the object of a qualitative (rather than quantitative) study of the lending business, that would look outside the statistical definitions of fairness.

The accuracy results provided in the study might be optimized by employing different classifiers in a case by case manner. This optimization, however, was not included in our scope, the focus being on the bias processors and fairness metrics. We used the logistic regression in order for the methods to be truly comparable, as most of the in-processing models use this algorithm for classification, and which is also widely known as the industry standard [Xiao et al., 2021; Gunnarsson et al., 2021]. Where possible, after choosing one or several bias mitigation methods, a practitioner should test several classifiers to achieve best results.

In the wake of cost-sensitive classification methods [Verbeke et al., 2022] aiming to improve the effectiveness of different processes, among which the lending business, the addition of fairness constraints to a cost sensitive framework for credit scoring could be a possible solution to the still open challenge of managing the trade-off between profit, risk and fairness.

Since some of the bias mitigation methods are computationally-intensive, one may consider benchmarking them by calculating the associated energy and carbon footprint, information which is becoming of interest in the data science area [Patterson et al., 2022]. In conjunction with the other results this may be used as a criterion for deciding on the bias processor to be used in practice.

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**APPENDIX A**

Table 6 lists and describes the features of the consumer loans dataset.

| #   | Name                    | Type          | Domain | Description                                                                 |
|-----|-------------------------|---------------|--------|-----------------------------------------------------------------------------|
| 1   | Product                 | Categorical   | #6     | Different consumer loan types                                              |
| 2   | Age                     | Numerical     | R+     | Age of the applicant                                                        |
| 3   | Area                    | Categorical   | #4     | Urban/ Rural area                                                           |
| 4   | Residential Status      | Categorical   | #5     | Residence type (e.g. property, rented)                                     |
| 5   | Education               | Categorical   | #10    | Level of education                                                          |
| 6   | Marital status          | Categorical   | #4     | Personal status                                                             |
| 7   | Household members       | Numerical     | R+     | Number of family members in the household                                 |
| 8   | No. of dependents       | Numerical     | R+     | Number of dependents in the household                                       |
| 9   | Income                  | Numerical     | R+     | Monthly income of the applicant                                             |
| 10  | Work seniority          | Numerical     | R+     | Work seniority in # of years                                               |
| 11  | Business age            | Numerical     | R+     | Years active for the employer                                               |
| 12  | Legal form              | Categorical   | #15    | Different types of business of the employer                                 |
| 13  | Economic sector         | Categorical   | #18    | Activity sector of the employer                                             |
| 14  | Employees no            | Categorical   | #9     | Company size for the employer                                               |
| 15  | Length relationship     | Numerical     | R+     | Relationship length between the applicant and the financial institution    |
| 16  | Debit card              | Binary        | #2     | Other products with the financial institution                              |
| 17  | Current account         | Binary        | #2     | Other products with the financial institution                              |
| 18  | Savings account         | Binary        | #2     | Other products with the financial institution                              |
| 19  | Salary account          | Binary        | #2     | Other products with the financial institution                              |
| 20  | Foreign account         | Binary        | #2     | Other products with the financial institution                              |
| 21  | Deposit                 | Binary        | #2     | Marker if the applicant has a deposit with the fin. institution            |
| 22  | Finalized loan          | Binary        | #2     | Marker if the applicant has previously finalized a loan                   |
| 23  | Pension funds           | Binary        | #2     | Pension funds subscriptions                                                |
| 24  | Default flag            | Binary        | #2     | 1 - Defaulted loan; 0 - Non-defaulted loan                                |

*Table 6.* Description of features for the consumer loans dataset