Impacts of Social Factors in Wage Definitions

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Abstract: Now more than ever, automated decision-making systems such as Artificial Intelligence models are being used to make decisions based on sensible/social data. For this reason, it is important to understand the impacts of social features in these models for salary predictions and wage classifications, avoiding to perpetuate unfairness that exists in society. In this study, publicly accessible data about job's and employee's information in Brazil was analyzed by descriptive and inferential statistical methods to measure social bias. The impact of social features on decision-making systems was also evaluated, with it varying depending on the model. This study concluded that, for a model with a complex approach to analyze the training data, social features are not able to define its predictions with an acceptable pattern, whereas for models with a simpler approach, they are. This means that, depending on the model used, an automated decision-making system can be more, or less, susceptible to social bias.

1 INTRODUCTION

Automated decision-making systems are being used more and more constantly in recent times for answering questions with underlying social factors (Ferrer et al., 2021). With the frequent use of Big Data for AI (Artificial Intelligence) models, it raises the "unavoidable" problem of data discrimination being part of these systems (Favaretto et al., 2019). Knowing this, there are multiple different studies that point to social discrimination and consequently wage discrimination being present in society, such as (Johnson and Lambrinos, 1985), (Neumark, 1988), (Blinder, 1973), and (Passos and Machado, 2022). Social discrimination can be explained as any form of segregation, denial/reduction of rights or unequal treatment directed to any person or group of society (United Nations (General Assembly), 1966), although discrimination does not have an objective definition (Altman, 2011). Because of all these factors, there is a need to analyze the impact of social factors and, consequently, social bias, in the matter of wage distribution not only in AI applications, but also in a more general setting for Big Data analysis.

There are a wide variety of decision-making systems for salary prediction, mostly based on features without explicit bias (although it is possible to have implicit bias), such as (Viroonluecha and Kaewkiriya, 2018), (Lothe et al., 2021), and (Kuo et al., 2021). However, regarding social features and salary prediction, there are few using AI models to understand wage distributions by social factors, together with evaluating social factors impact on wages via (or in) AI applications. Because of this, it lacks a study that evaluates social feature's impact on people's wages in both senses of wage discrimination and digital discrimination. For digital discrimination, that is, biased salary prediction models, it is possible to analyze data distribution and features impact based on how a specific AI model works, based on (Cabrera et al., 2023). Notice that, for this analysis to be made, there is need for model creation, but the priority is to analyze prediction distribution patterns only, therefore, its precision is not the focus of this study. The objectives of this study are to determine the impacts of features such as gender, handicap and race in wages both in a

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data analysis and salary prediction sense.

This study was made through multiple statistical methods and AI model results for different feature combinations to evaluate possible bias. First, the data set used, the Annual List of Social Information (RAIS), further explained in section 4.1, was analyzed based on descriptive and inferential statistical methods. Using insights obtained from these experiments, the application of these data in AI models of very different natures was made with multiple feature combinations with the objective of observing feature impacts in the model results. Having in mind its way of learning, and combining results from different models, it is possible to understand how each set of features impacts the model. With this, the features impact can be not only analyzed via statistical methods to measure and infer possible bias and discrimination, but also understand how it can impact an AI model.

About the features, they are separated into two types: the objective and the social features. RAIS does have both kinds of features. The objective features, such as education level and weekly workload, should help to point out the direct reason for a person's salary, even though not always does, and the social factors, such as gender, age and race, are the ones that, in an ideal world, should not affect the wages, even though they do. A decision-making system to predict salaries that uses features such as race, gender and handicap will likely be negatively affected by it in terms of prejudice and discrimination, although simply removing such factors will likely not fix the problem (Pelillo and Scantamburlo, 2021). For this reason, in this study, AI models were created to show the possible biased outcomes with respect to wage distribution based on social factors.

2 BACKGROUND

2.1 Statistical Tests

Descriptive statistics are used to present, organize and analyze data (Fisher and Marshall, 2009) (Conner and Johnson, 2017). Numerical methods such as mean, median, and standard deviation, together with measurements such as sample size and mode, for example, can be used to identify distribution patterns in data and determine starting points to inferential statistics. Also, visual methods can be used to verify the same information in a more compacted matter, for example, using histograms, to analyze frequency distribution in data, bar graphs to group up data sub-parts and compare it, box plots, to analyze most numerical methods in a single graph, between many other possibilities.

Inferential statistics are used, as the name suggests, to make inferences about an entire population based on a given sample (Marshall and Jonker, 2011). About the types used in this study, the hypothesis tests are used to expand the insights that come from the descriptive statistical methods to a bigger data range. There are multiple hypothesis tests available, each one has its particularities about how it should be used. There are the t-tests, z-tests, and multiple types of other parametric and non-parametric tests, and the tests used in this study are non-parametric, for reasons explained in section 5.2.2.

2.2 Machine Learning Models

2.2.1 General Terms

It is part of the context of supervised machine learning, the concepts of training and testing data. The model will use these data as part of the training process to make future predictions. This prediction is based on training and testing data, that is, pairs $\{X,Y\}$, X being the basis for getting the result, Y. The training is used only to learn, meanwhile, the testing data is used to determine whether the training was good for generalizing to new data or not.

This pair $\{X,Y\}$ is used in supervised and semi-supervised learning, meanwhile the unsupervised learning uses only X. The focus of this study is the supervised and semi-supervised methods, given the uses of the Random Forest and Label Propagation methods, explained later in this article. In the supervised learning method, the sample used to train and test is separated, usually in the proportion 80-20 for training-testing, and, for any new X collected, it is possible to apply it to get a predicted Y. In the semi-supervised method, this proportion is usually 10-90 for labeled-unlabeled data, with the goal being to obtain the label (Y) pattern from this 10% to the remaining 90%, meaning that the purpose of this method is to classify this 90%, but not receiving new data to predict afterward.

Given its similarities, the characteristics that make both learning methods differ from each other is its possible application. The supervised method is better when there is a lot of labeled data, that is, $\{X,Y\}$ pairs, with the possibility of classifying new isolated data. Meanwhile the semi-supervised method is better with fewer labeled data, using these few to propagate the pattern to new ones, with this being the reason for the "training data" for this method being usually low.

2.2.2 How Machines Learns

Machines learn by finding statistical patterns in training data and make inferences to reach a reliable output (Mitchell, 2006). The methods used by the machine to get these patterns will differ from model to model. Some examples of supervised methods are Decision Trees, Logistic Regression, Support Vector Machine and Gradient Tree Boosting.

2.2.3 Random Forest and Label Propagation

In this study, the two models used to analyze bias and make predictions are, as stated before, the Random Forest (Breiman, 2001) model, as a supervised method, and Label Propagation (Zhou et al., 2003), as semi-supervised. Random Forests are an ensemble of decision trees in which they themselves will "vote" for the best option. Often the feature selection for this model uses random factors with the concepts of bagging and boosting (Breiman, 2001). The divisions made for the classifications are defined by voting of each tree in the forest, defining the best outputs for each input X. The "questions" made at each node are heavily based on mathematical and statistical methods, not fully understood yet (Biau, 2012). In other internal tests, AI models other than Random Forest, the ones cited in section 2.2.2, were tested, but Random Forest was chosen as the main option because of its better overall precision. The Label Propagation model proposed is based on a definition of affinity between each point, and defining that a given point with a similar structure to another is likely to have the same label. In more simplified terms, the model works by creating geographical points using X and the labeled fraction's Y, and, based on proximity of these points, the unlabeled parts will be defined as part of a group (a class to predict). Supposing consistency in these data, the model will group similar data as a single class based on this 10% to all the data, including the labeled fraction (again).

2.3 Sociological Discrimination and Machine Learning Bias

In this study, there is a constant use of the terms discrimination and bias, which have different meanings depending on the application areas: sociology or machine learning. Although there is no formal definition for discrimination in sociological terms (Altman, 2011), discrimination towards or against any group means, ultimately, any kind of segregation or difference in the way of treatment, in favor or not, of any person or group, to any person or group, with different choices or characteristics regarding factors of self-determination such as race, color, gender, language, religion, political or other opinion (United Nations (General Assembly), 1966).

In terms of discrimination and bias in machine learning, there is a considerable difference compared to in sociology. In this case, the machine way of learning makes bias possible in AI: if the data have biased patterns, then the machine will replicate this discrimination, thus becoming discriminatory. Lastly, it is needed to reinforce that discrimination by itself, in both application areas, does not have a negative intent; it may be merely a way of separating groups that, without care, can have a charge of negative intent.

Also, it is important to understand that data can have an underlying biased information. Implicit bias can be defined as when people act on the basis of prejudice and stereotypes without intending to do so (Brownstein and Zalta, 2019). Similarly, people can have biased, that is, discriminatory behavior without actively thinking about it, and this can be based on a series of historical discrimination such as systemic racism (Payne and Hannay, 2021) and/or based on the person's personal experiences (Tversky and Kahneman, 1974). With this in mind, the possibility of this implicit bias being present in objectively defined information, such as someone's personal experience telling that different races have different work qualities ending up defining a certain job occupation as more common to a certain race than to another, can make Big Data data sets have this underlying prejudice, and it needs to be considered while making objective analysis.

2.4 Bias Analysis Using Machine Learning Models

Knowing how machines learn and the methods used by each model, it is possible to analyze bias and, in this study, discrimination. When a model learns with biased data, it can become biased, which means that the discrimination existing in the real world is propagated to the model. Using different approaches better explained in section 4, it is possible to measure this bias, also understanding which features discriminate against a group and by how much on average, similarly as in (Blinder, 1973).

3 RELATED WORK

Thinking about discrimination, that can be defined, as stated before, as a different way of treatment towards or against a certain group, with a detailed explanation defined in (Altman, 2011), and going further to exemplify such discrimination in society, as any type of disregard to self-determination factors such as race, color, gender and etc., defined in the International Covenant on Civil and Political Rights (United Nations (General Assembly), 1966), there is the purpose of this study, wage discrimination. Wage discrimination can be defined, based on the International Covenant, as a structural reduction on someone's salary "just because" of factors they do not have control over, e.g., race and gender, or they have the right of choice and not being discriminated because of it, e.g., religious or political opinion. This type of discrimination can be observed in many different studies of many different purposes, like bias against handicapped workers, presented in (Johnson and Lambrinos, 1985), discriminatory behavior by employers using Oaxaca-Blinder estimator in (Neumark, 1988), bias analysis comparing gender and color factors using a linear regression function in (Blinder, 1973) and comparing salary differential based on gender in public and private sectors in Brazil, presented in (Passos and Machado, 2022). But, as well as social factors being analyzed in wage structures, there is also purely (or mostly) objective factors being used in salary prediction automated decision-making systems, such as (Viroonluecha and Kaewkiriya, 2018), (Lothe et al., 2021) and (Kuo et al., 2021). Even then, these similar studies either do not analyse the full scope of wage discrimination (evaluating different AI models for predictions) or do not approach a detailed analysis of both objective and social feature's impact in wages.

With this in mind, it is important to also notice this discrimination and bias will likely be, at some point, stored in databases. Given the importance of data to create machine learning models, and the possibility of this biased data being used as a source of learning by the model, a problem starts: the use of Big Data for AI models. Since the model learns searching patterns in data, social features in Big Data being used, specially for financial problems, if not well handled, may perpetuate inequality in a workplace environment, as explained in (Kim, 2016) and (Favaretto et al., 2019). Data-driven solution to problems of financial nature, depending on how it is approached, may have implicit discrimination if the data available often rely on feature correlation and not cause-effect, as explained in (Gillis and Spiess, 2019).

These AI models will use this biased data to get statistical patterns of, for example, correlation between gender and salary, will find it, and will replicate it. To analyze the model and prove that it is not biased, it is necessary to a) show that the methods for the model assumptions and statistical analysis are not biased and b) show that the data used for the model training is not biased, according to (Ferrer et al., 2021). And based on this, it is possible to affirm the same, but with the opposite objective: if a) the model training method is biased or b) the data used for training is biased, then the model is also biased. The search for bias in data can be made with a combination of descriptive statistics, based in (Fisher and Marshall, 2009), and inferential statistics, based in (Marshall and Jonker, 2011).

Analyzing the model's results is important not only as a part of model tuning, but also to define its impacts when used: in this case, discrimination. This step of AI modeling is better described in (Cabrera et al., 2023), but, in a more objective description, this is making sense of model results, that is, understanding what kind of patterns the model replicate, through grouping data and analyzing the most repeated patterns in the results, for example, this can be made by getting the model predictions and analyzing them with multiple descriptive and inferential statistical approaches, similar to (Blinder, 1973), although this study simply made a descriptive analysis of the results based on the model's way of learning.

When analyzing the model's results, if it has gotten to the conclusion of bias being present in the model and, possibly, in data, it is needed to mitigate it. To reduce the bias, ultimately, it is necessary to handle the data used, especially regarding factors including sensitive data and Big Data previously discussed. There is also the possibility of the bias to be present only in the AI model, but not in data itself, being that, in this case, the change of algorithm would likely be needed. For data bias to be reduced, it is not as simple as removing social features from the data in hopes of the bias to disappear, since social discrimination might still be strongly linked to objective factors (Kamiran and Calders, 2009) (Pelillo and Scantamburlo, 2021). In other words, implicit bias, or "involuntary discrimination", can, and likely will, be present. Implicit bias is when, without noticing, someone ends up discriminating against a given social group (Brownstein and Zalta, 2019). This bias can happen based on personal experiences of an individual (Tversky and Kahneman, 1974) or a systemic, and historical, discrimination that makes an individual be biased without knowing (Payne and Hannay, 2021).

4 METHODOLOGY

A simple description of the methodology used is, as described in Figure 1: (1) descriptive analysis of the available data to display distribution patterns; (2) inferential analysis to confirm insights of step 1; (3) AI models are created to evaluate how they react to these different factors analyzed in steps 1 and 2. With this, it is possible reach the defined objectives finding bias in data and analysis its impacts in AI models.

Figure 1: Flowchart of the methodology.

4.1 Datasets

For this study, it was used, as the stated before, the Annual List of Social Information, RAIS, to make all the experiments and analysis. Being more specific, the data used was from the state of São Paulo (Brazil), in 2019. This Brazilian database contains over 60 different features describing job information from all the country totaling millions of samples. Among these features, the most important to this study were: employee's title (CBO), time in the company, education level, weekly workload, race, gender, handicap, age, monthly wage, and company's area (CNAE) and size.

In this data set, there are features from both the employee's and company's perspective. For the purpose of the further described experiments, these features will be separated into two types: social and objective. Social features are the ones regarding information that, in an ideal analysis, should not have a direct impact on the salary, such as race and gender. Meanwhile, the objective features are the ones that should, such as CBO and education level.

4.2 Pre-Processing

With all the available data, the statistical analysis scope was limited to CBO in Computer Science area and CNAE in Information and Communication area, with at least a bachelor degree, with salary between 1 and 12 minimum wages. For the Random Forest model, the only difference is that the lower interval of wages, for AI model training, is 1.5 minimum wages. Meanwhile, the scope of the Label Propagation was more open, due to no limitation by CNAE, but more limited by sample size, due to its high computational cost, without filtering by salary range, grouping all "defective races" as one, and "non-defective races" as another, the same being done for handicapped and non-handicapped groups, for the purpose of defining all "defects" as one, to simplify the proximity analysis for the Label Propagation.

4.3 Statistical Analysis

After this filtering, the remaining data were separated into eight social groups, based on Table 1.

Table 1: Data segregation for bias analysis.

#	Gender	Handicap	Race
A	0	0	0
B	0	0	1
C	0	1	0
D	0	1	1
E	1	0	0
F	1	0	1
G	1	1	0
H	1	1	1

This table covers all the social combinations considering gender, handicap, and race in a binary sense. For gender, 0 means male, 1, female; for handicap, 0 means not impaired, 1, impaired; and for race, 0 means white or yellow, 1, black, brown or indigenous.

With regard to all available data, it is important to understand how it is distributed. The descriptive analysis was made for the purposes of understanding the general distribution of the available sample for social factors, with a more detailed approach, and, also, to analyze the general impact of objective factors on employee's wages, for reasons explained in further detail in section 4.5. The inferential analysis is of the most importance for the bias analysis in the sense of discrimination, but not for an AI model turning biased, while the descriptive analysis is crucial for both senses of bias analysis in this study.

4.3.1 Descriptive Statistic

The data were first organized and analyzed using multiple methods, mainly visual, to understand the basic distribution patterns in the sample. These methods were applied in the same data with two different approaches: analyzing with exclusive segregation, as in Table 1, for social features; and without it, for objective features.

4.3.2 Inferential Statistic

The same is applied to the inferential statistics tests, Mann-Whitney U tests, specifically. There are tests for both exclusive and non-exclusive segregation data. The Mann-Whitney U test was chosen given the normality tests also performed, on top of the idea of the tests itself, between non-correlating groups.

4.4 Salary Predictions

Both the Random Forest and the Label Propagation algorithms were applied to create salary predictors using different feature combinations. The difference between these two is the application method and its reasoning. The Random Forest model was created using mainly the first configuration explained in section 4.2, and the Label Propagation model used a limited version of data, with a sample size of less than 10,000. Also, Random Forest is easily applied to any new data isolated, while Label Propagation is more of use to propagate a specific regions (or companies) pattern to new samples, being useful to, for example, add new employees in a company already with a desirable (fair) default salary distribution.

4.5 Bias Analysis

Given the results for both algorithms, it is possible to obtain the predictions and analyze the prediction patterns for each social aspect, based on (Cabrera et al., 2023). With different feature combinations, the impact of each social aspect to the person's final salary can be measured, thus analyzing the AI model's bias. However, to validate the label propagation method with only objective feature analysis, shown in section 5, it is essential to analyze if objective factors alone are important for the salary based on the sample, or if the data are not at all defined by objective factors.

5 RESULTS

5.1 Data

The filter limited the sample size to around 71,000 with a CBO and CNAE with 11 and 31 different areas, respectively. The salary ranges used for the classification and data analysis ranged from 0 to 11, which are the following, in minimum wages: (0) up to 0.5; (1) 0.51 to 1; (2) 1.01 to 1.5; (3) 1.51 to 2; (4) 2.01 to 3; (5) 3.01 to 4; (6) 4.01 to 5; (7) 5.01 to 7; (8) 7.01 to 10; (9) 10.01 to 15; (10) 15.01 to 20; and (11) 20 or more. Even then, with the filters, the sample's salary range was between 1 and 12 minimum wages, meaning that the ranges considered in the analysis were from 1 (only its top limit) and 9.

For the Random Forest models, the data used was the same as the statistical tests, with the difference that the smallest salary range was 3 instead of 1. For the Label Propagation, the smaller sample with differences explained in section 4.2 has around 6,000 lines.

5.2 Statistical Analysis

5.2.1 Descriptive Statistic

Analyzing the full sample it is noticeable, firstly, that the data does not have normal salary distribution between the salary ranges, as shown in Figure 2.

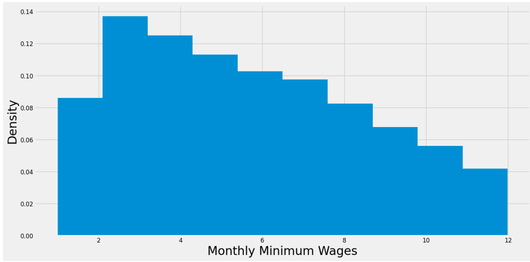


Figure 2: Wage distribution for the sample.

With the eight groups separated, the general wage analysis, comparing all of them between each other based only on the social factors described, ends up pointing, mostly, to the same insights shown by Johnson and Lambrinos, Blinder, and Passos: social bias is present in data and in salary distribution. Boxplots describing the general wage distribution by group from Table 1 are shown in Figure 3.

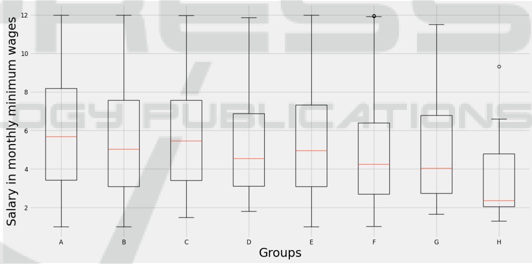


Figure 3: Wage distribution between social groups.

In Figure 3, it is possible to infer that, for this sample, there is a systematic wage reduction analyzing from group A to group H of Table 1, that is, as the social "defects" start to appear, the wage tends to be reduced by a certain rate. This rate can be observed in Table 2.

The purpose of this table is to show the impact on wages that social factors can have. In this case, the values for each group are, first, being measured independently, getting both mean and medians to confirm, in other terms, the non-normal data distribution shown in Figure 2 and further described in section 5.2.2. This asymmetric distribution of data shows a median smaller than the mean, that is, most people in this sample have a salary tending towards the lower end of the spectrum, with a few with a higher salary pushing the wage average up.

Table 2: Mean, median and average wage reduction by social group comparing to highest average earner.

#	Mean	Median	Ratio (median)
A	5.92	5.68	1.00
B	5.47	5.03	0.89
C	5.73	5.47	0.96
D	5.29	4.56	0.80
E	5.39	4.95	0.87
F	4.77	4.25	0.75
G	4.93	4.04	0.71
H	3.38	2.36	0.42

Based on Table 2, there is a metric for measuring the sample's bias for each social group in comparison to the biggest average earner, the group A. It is noticeable that any type of "defect" has some level of wage reduction, for example, it is shown that the "race" factor alone reduces the salary by around 11% on average for the group B, that is, a person with the social characteristics male and non-handicapped, if it has the "race" factor as black, brown or indigenous, will end up with a wage with an average of 11% less than the same group but with "race" as white or yellow. Another example is for the group with social characteristics of female, with handicap, and black, brown or indigenous, in comparison to its male counterparts, being that the female group will have an average of almost 50% wage reduction, from median equaling 4.56 in group D to equaling 2.36 in group H. The same insights can be observed in the inferential tests, showing that most of them can be expanded to the entire population, further explained in section 5.2.2.

Age as a social factor is not being included in these eight groups, given it would be too many main groups to compare. Even then, a simpler approach to analyze ages in general was chosen: evaluation of wage changes based on the person's age range, as a simple correlation analysis, being the same as for some objective factors also analyzed. This evaluation had results shown in Figure 4, with further tests in section 5.2.2.

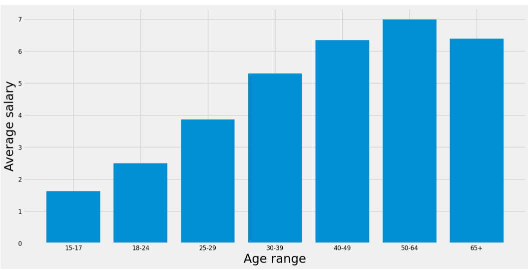


Figure 4: Wage distribution by age.

Some tests are essential to analyze prediction patterns from the AI models, specially to the feature variations shown in section 5.3. For this reason, it is needed to show that future results from combinations of objective features only should actually have reasonable differentiation in prediction. In figures 5, 6, 7, 8 and 9, the general difference in salary based on changes in objective features is displayed.

Figure 5: Wage distribution by job occupation.

The separation for CBO and CNAE segregation is based on each of the 11 and 31 different classifications respectively. The bars are sorted from the smallest to the biggest numerical codes with "212" prefixes - Computer Science area - for CBO.

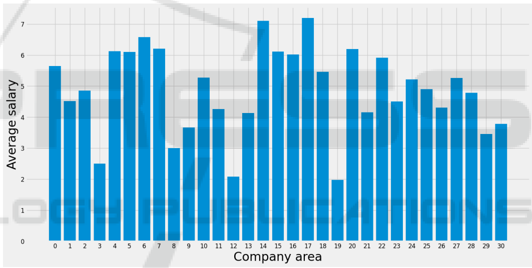


Figure 6: Wage distribution by company area.

With the same sorting method as for CBO, CNAE is being sorted by its numerical codes starting from any in the intervals [58, 63] - Information area - for CNAE.

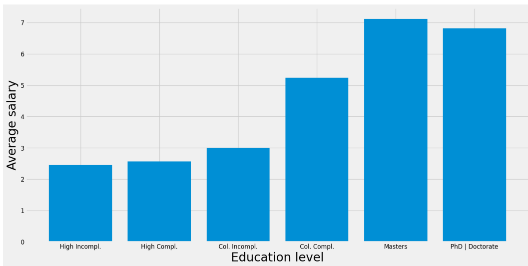


Figure 7: Wage distribution by education level.

Given the education level filter, it can also be observed that, as well as CBO and CNAE, education level also tends to follow a given structural change on wage distributions, meaning there is impact on people's wages.

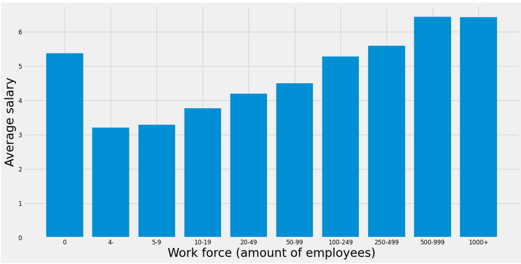


Figure 8: Wage distribution by company size.

The idea behind these analysis is not to observe the distribution patterns for each of these factors, but actually to understand that they do have an impact on wages, even if it ends up not being apparent in future tests. Together, all the main objective factors distribution in general segregation can be observed as somewhat impactful regarding salaries, that is, the employee's occupation, weekly workload and education level, together with the companies area and size does correlate with different salaries. This information is important to analyze results in section 5.3.

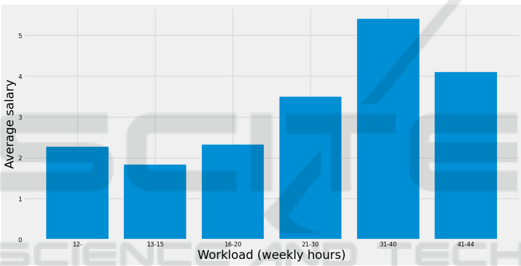


Figure 9: Wage distribution by weekly workload.

5.2.2 Inferential Statistic

Based on a descriptive analysis, it is possible to affirm there is a disparity in salary distribution, that is, discrimination against certain social groups, in the given sample. However, it is necessary to verify if the same happens to the entire population. For this to be achieved, many hypothesis tests were made, firstly, in the groups displayed in Table 1. The following results are for the non-parametric hypothesis test of Mann-Whitney U for all eight groups being compared with others with the same social characteristics, with the only difference being "gender", "handicap" and "race".

```
--- (1) Male x Female
A >= E: [stat.=77382722.0, p=1.000]
B >= F: [stat.=5886390.0, p=0.999]
C >= G: [stat.=5080.5, p=0.890]
D >= H: [stat.=700.0, p=0.994]
--- (2) Non-handicapped x Handicapped
A >= C: [stat.=56032.0, p=0.004]
B >= D: [stat.=2932.5, p=0.0791]
E >= G: [stat.=4020.0, p=0.0635]
F >= H: [stat.=649.0, p=0.968]
--- (3) White-Yellow x Black-Brown-Indigenous
A >= B: [stat.=93512304.0, p=0.999]
C >= D: [stat.=3388.0, p=0.535]
E >= F: [stat.=5795580.0, p=0.999]
G >= H: [stat.=676.5, p=0.987]
```

These tests are questioning "does the wage distribution of the four described male groups, non-handicapped groups, and white-yellow groups tend to be greater than or equal to its counterparts?", with the answer being yes for all of them in case of gender-based and race-based tests. More specifically, the null hypothesis is that the male wage distribution is greater than or equal to the female wage distribution, and the alternative is that it is lesser than, or, in other words, the female wage distribution is greater than the male wage distribution. This, in terms of the interpretation of the p value, for a significance level of 0.05, means: $p > 0.05$, accept null hypothesis; $p < 0.05$, reject null hypothesis. Realistically, any value "too close" to the determined significance level means it is not possible to infer the null hypothesis, even if it is slightly greater or smaller than the significance level, and this will be the interpretation taken for future tests.

About the other tests, they follow the same structure based on the analysis of the eight social groups, this includes fixing gender and race, changing handicap (part 2), analyzing the impact of handicap in these groups, and fixing gender and handicap, changing race (part 3), analyzing the impact of race in these groups, in the same idea as in part 1, fixing handicap and race, changing gender, analyzing the impact of gender in these groups.

For the handicapped groups, in part 2, it is not possible to infer, based on this sample, that the non-handicapped group has a wage distribution greater than or equal to the handicapped group for all but the "female and black, brown or indigenous" groups. All of these inferences are in accordance with the descriptive analysis made in Table 2, since the average difference on wages is close to none in all cases but in the group F x H, with a salary reduction of almost 50%. Meanwhile, for the racial analysis, in part 3, the results are similar to the ones portrayed in part 1: all groups without the "defect" have a wage distribution greater than or equal to the ones with.

For further tests with AI models in section 5.3, and to showcase that, based on data available, it should be possible to discriminate samples by objective features alone, not being necessary to include social features in the tests, there are some objective hypothesis made regarding figures 5, 6, 7, 8 and 9. Also, to complement inferences about the social factor "age", there is also a simple test made. The following results show that different objective factors have a different wage distribution between itself.

```
--- (1) CBO
0 == 4: [stat.=415029.0, p=4.038e-79]
0 == 9: [stat.=450288.0, p=1.893e-119]
2 == 5: [stat.=121963.5, p=6.348e-11]
2 == 7: [stat.=143555.5, p=1.828e-34]
3 == 9: [stat.=572897.5, p=2.938e-55]
2 == 10: [stat.=608907.0, p=4.792e-80]
--- (2) CNAE
17 == 3: [stat.=14.0, p=0.114]
17 == 12: [stat.=49.0, p=0.002]
0 == 13: [stat.=342.0, p=0.091]
0 == 21: [stat.=35981.0, p=5.462e-14]
9 == 3: [stat.=13.0, p=0.200]
9 == 8: [stat.=16.0, p=0.029]
--- (3) Education level
Masters+ == College-: [stat.=385488359.5,
p=0.000]
Masters == College: [stat.=208581.0,
p=8.7e-23]
College == High School: [stat.=116361099.5,
p=0.0]
--- (4) Company size (amount of employees)
0 or 250+ == 1-249: [stat.=905620232.5,
p=0.0]
500-999 == 250-499: [stat.=38279111.5,
p=6.216e-25]
500-999 == 250-499: [stat.=61481152.0,
p=2.079e-08]
--- (5) Weekly workload (in hours)
21+ == 20-: [stat.=7313.5, p=5.515e-07]
31-40 == 21-30: [stat.=27422.5, p=0.001]
31-40 == 16-20: [stat.=993.0, p=0.020]
--- (6) Age
40+ == 39-: [stat.=264942423.5, p=0.000]
40-49 == 25-29: [stat.=142423120.0, p=0.000]
50-64 == 40-49: [stat.=17405969.0,
p=1.562e-52]
```

These tests were also non-parametric hypothesis tests given that data is not normally distributed nor is directly related to each other. For this and all hypothesis tests with objective features, the alternative hypothesis was two-sided. Hypothesis tests results for job occupation, company area, education level, company size and employee's workload are displayed in parts 1, 2, 3, 4, and 5, respectively.

All these tests point out that most objective characteristics do have different wage distributions (based on $p < 0.05$). This imply that objective factors do have impact on people's wages given that, if not, they would not have these differences nor the descriptive discrepancies displayed in figures 5 to 9. This analysis lead to further tests made to analyze social factor's impacts on people's wages through different applications in AI models for salary predictors, but also to analyze social factor's impacts in salary predictors. Specifically about the approach for the tests, categories were selected to be tested regarding its distribution with other categories, with objectives of showing that, with different categories, there is a different wage distribution that, in a model application, should discriminate, that is, determine a person's wage.

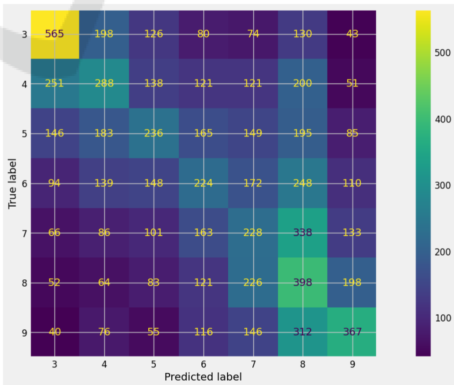
5.3 Salary Predictions

For the salary prediction, the main objective was not to create the best predictor possible, but to analyze how two very different AI models in specific act given multiple feature combinations. Mainly, how the models understand social factors, and how the wage distribution by social and objective factors are used to differentiate labels. To analyze social factor's impact on people's wages through AI model implementations.

Depending on the model's approach to get the data pattern, the results can vary from being completely dependent on social factors, to being simply complemented by these factors, but having as priority the objective factors.

5.3.1 Random Forest

Given that the Random Forest makes mathematical and statistical "questions" to build the trees in the forest, as explained in section 2.2.3, this AI model ends up not being majorly defined by social factors alone in the feature combinations made. This happens because, with these questions, the AI is able to understand the patterns shown in sections 5.2.1 and 5.2.2. For this reason, for the objective features only model, it is possible to get a viable wage distribution, even if not very precise. The objective factors only model's confusion matrix and cross-validation scores with 5 divisions are displayed in Figure 10.



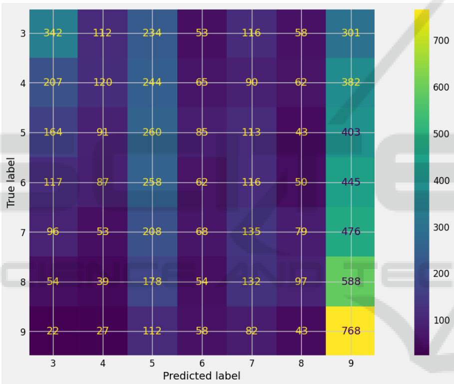

```
General score: 0.286.
5-fold: [0.249, 0.267, 0.249, 0.256, 0.274]
Mean: 0.259, Std: 0.010
```

Figure 10: Results for Random Forest model with objective factors only.

With around 26% precision and an overall regular distribution in miss-classifications, the Random Forest model does have, for these objectives, a satisfactory outcome. Now, for the classifications with only social features, in Figure 11, the model is not able to get the necessary patterns for a non-biased classification.

The Random Forest predictions with social factors were completely biased, meaning the model was not able to get wage distribution patterns based only on gender, handicap, race and age, thus, social factors alone have little impact on wages for Random Forest, based on this data. In Figure 12, are displayed the mixed features results. More evenly distributed and with a higher precision, social factors end up complementing the Random Forest model, even if alone they do not accomplish much.

Comparing Figure 10 with Figure 12, it is possible to infer that objective factors are complemented by social factors mainly in labels in both extremes. This means that social factors, in these experiments, are helping the model to reach a more precise outcome to both smaller and bigger wages.



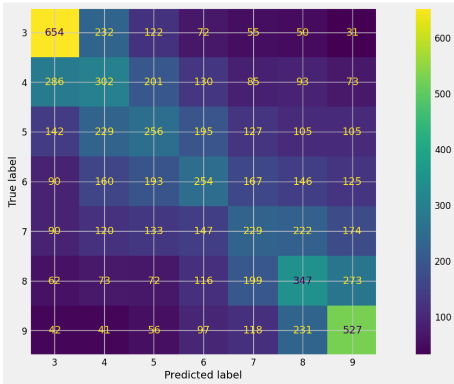

```
General score: 0.222.
5-fold: [0.194, 0.188, 0.194, 0.202, 0.197]
Mean: 0.195, Std: 0.005
```

Figure 11: Results for Random Forest model with social factors only.

5.3.2 Label Propagation

Given that the Label Propagation model basically suppose data consistency, that is, similar features have similar labels, building "geographical" points, with each coordinate being one feature, it is possible to group up data based on its similarity, simply put. Because of this, this model is more likely to replicate social patterns described in section 5.2. The figures 13, 14 and 15 display results for the different feature combinations for the Label Propagation model.

Based on Figure 13 it is possible to infer that, since objective features do not have a clear consistency, using only them to classify based on data similarity will not have good results given there will be




```
General score: 0.319.
5-fold: [0.287, 0.298, 0.292, 0.294, 0.298]
Mean: 0.294, Std: 0.004
```

Figure 12: Results for Random Forest model with mixed factors.

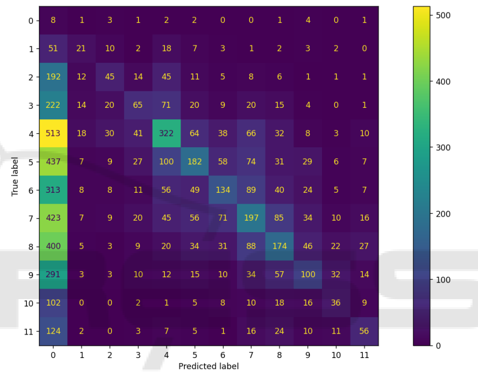


Figure 13: Results for Label Propagation model with objective factors only.

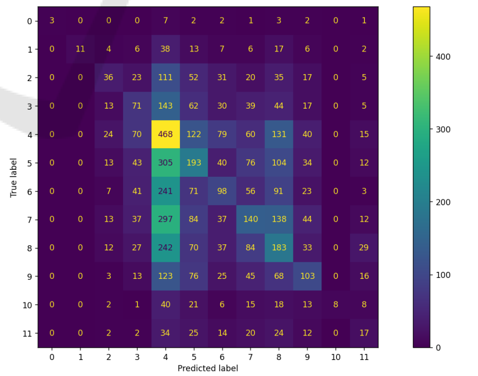


Figure 14: Results for Label Propagation model with social factors only.

multiple similar samples with very different salaries, with the model having a score around 20%. But, when based on social data only, in Figure 14, the data pattern is more clear for the model, given that, without brute mathematical and statistical tests to make a detailed data analysis, the rough proximity between samples will determine the salary, therefore, social factors will have bigger impact than for the Random Forest model, with the model having around 24% precision.

With both factors being used (Figure 15), it is possible to clear the results distribution, raising the score to around 28%. The miss-classification's range from the correct label is still higher than the Random Forest models.

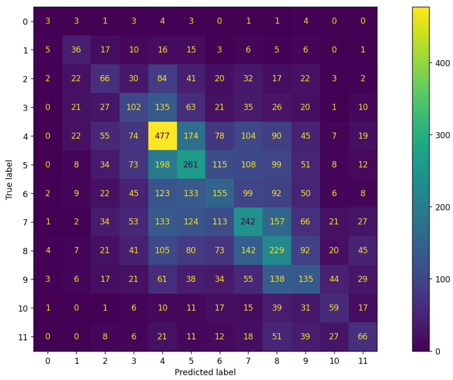


Figure 15: Results for Label Propagation model with mixed factors.

5.3.3 Impact Analysis

Given the salary prediction results, it is possible to infer that, for the Random Forest model, an almost purely based on inferential statistics algorithm, social factors alone do not have a clear impact on people's salary, but, when used together with objective data, they do have a bigger impact. For the Label Propagation algorithm, a simpler model using data proximity for label classifications, social factors do have a bigger impact, given that its samples will become "geographical" points and be grouped, and wages are, in RAIS, heavily socially oriented.

These tests point out that, for simpler statistical methods, social factors in data can end up defining a big part of people's salary, meaning that, if not carefully built, social discrimination can be perpetuated depending on which approaches are taken to use this data for automated decision-making systems. However, for more complex statistical methods, such as the ones applied in Random Forest, if objective factors have an underlying impact, it can be found, possibly reducing social factor's impact.

6 CONCLUSION AND FUTURE WORKS

The speed in which data is being collected makes it practically impossible to have quality control over what is collected and being continuously used for multiple purposes. Because of this, data sets such as RAIS will likely have continuous use for multiple objectives, and given that the data set does contain social information associated with finances, the likelihood of RAIS having multiple instances of discrimination being presented is high, having potential negative impact in social and wage discrimination. For this study's objective, RAIS was used for two purposes: bias analysis, purely applied to statistics; and salary prediction, to analyze social factors in AI models. This data set general analysis, representing social and financial information in Brazil, does point to the conclusion that social discrimination can be further analyzed, and there is a clear social discrimination pattern in it. Other than for bias analysis, it was found unlikely for the data set to be of good use for salary predictions, given its uneven wage distribution, on top of the fact that social features should not be part of wage determination, and they do, in fact, have a big impact in it.

It was also found clear the impact of different features in the salaries. Objective features did have impact in general and, without considering implicit social bias on objective features, they define the wages in an acceptable pattern, that is, the groups expected to receive higher salaries, do. Regarding social features alone, many types of social discrimination were observed in RAIS data. Mainly, wage discrimination by "gender" and "race" features were the clearest to visualize based on the descriptive and inferential experiments, with the "gender" factor having the biggest positive impact for the male group, and the biggest negative impact for the female group, followed by the "race" factor, with people with white or yellow races being positively affected, and black, brown or indigenous races being negatively affected. There is also some level of impact to observe on handicapped workers, mostly for female groups, but it is not possible to infer that the non-handicapped group is largely impacted by this social factor alone.

About the use of social factors for automated decision-making systems for salary prediction, in this study, the application of the Random Forest and Label Propagation models resulted in different outputs, that is because of the methods used to make the decisions: Random forest used complex mathematical and statistical tests to define the "flow" of questions to determine the output, meanwhile Label Propagation bases itself on proximity meaning similarity. The results show that, for more complex statistical methods, social factors alone will not have a decisive impact on wages, but will complement the objective factors to reduce error and make the classification distribution more even and the miss-classifications closer to the confusion matrix main diagonal. Since the model will be dependent on more complex hypothesis, it ends up not being able to classify wages only based on social factors, since it is less volatile to plain bias. Meanwhile, for models more volatile regarding patterns of bias, the opposite occurs. Label Propagation will not be able to get clear distribution patterns from objective factors alone, but will for social factors. Objective factors for Label Propagation are complementary to social factors, meaning that social factors are decisive for a general classification, having objective factors in second plan.

About next steps, now that social bias and wage discrimination was found in RAIS, it is needed to search for methods to mitigate it. Multiple methods for reducing bias can be explored, in this case, for both general data not being socially biased, and for automated decision-making systems, specially AI models not being affected by social discrimination stored in Big Data. Also, it is possible to analyze how other AI models interact with these feature combinations.

REFERENCES

Altman, A. (2011). Discrimination.

Biau, G. (2012). Analysis of a random forests model. *The Journal of Machine Learning Research*, 13:1063–1095.

Blinder, A. S. (1973). Wage discrimination: reduced form and structural estimates. *Journal of Human resources*, pages 436–455.

Breiman, L. (2001). Random forests. *Machine learning*, 45:5–32.

Brownstein, M. and Zalta, E. (2019). Implicit bias.

Cabrera, Á. A., Tulio Ribeiro, M., Lee, B., Deline, R., Perer, A., and Drucker, S. M. (2023). What did my ai learn? how data scientists make sense of model behavior. *ACM Transactions on Computer-Human Interaction*, 30(1):1–27.

Conner, B. and Johnson, E. (2017). Descriptive statistics. *American Nurse Today*, 12(11):52–55.

Favaretto, M., De Clercq, E., and Elger, B. S. (2019). Big data and discrimination: perils, promises and solutions. a systematic review. *Journal of Big Data*, 6(1):1–27.

Ferrer, X., van Nuenen, T., Such, J. M., Coté, M., and Criado, N. (2021). Bias and discrimination in ai: a cross-disciplinary perspective. *IEEE Technology and Society Magazine*, 40(2):72–80.

Fisher, M. J. and Marshall, A. P. (2009). Understanding descriptive statistics. *Australian critical care*, 22(2):93–97.

Gillis, T. B. and Spiess, J. L. (2019). Big data and discrimination. *The University of Chicago Law Review*, 86(2):459–488.

Johnson, W. G. and Lambrinos, J. (1985). Wage discrimination against handicapped men and women. *Journal of Human Resources*, pages 264–277.

Kamiran, F. and Calders, T. (2009). Classifying without discriminating. In *2009 2nd international conference on computer, control and communication*, pages 1–6. IEEE.

Kim, P. T. (2016). Data-driven discrimination at work. *Wm. & Mary L. Rev.*, 58:857.

Kuo, J.-Y., Lin, H.-C., and Liu, C.-H. (2021). Building graduate salary grading prediction model based on deep learning. *Intelligent Automation & Soft Computing*, 27(1).

Lothe, D., Tiwari, P., Patil, N., Patil, S., and Patil, V. (2021). Salary prediction using machine learning. *INTERNATIONAL JOURNAL*, 6(5).

Marshall, G. and Jonker, L. (2011). An introduction to inferential statistics: A review and practical guide. *Radiography*, 17(1):e1–e6.

Mitchell, T. M. (2006). *The discipline of machine learning*, volume 9. Carnegie Mellon University, School of Computer Science, Machine Learning ....

Neumark, D. (1988). Employers' discriminatory behavior and the estimation of wage discrimination. *Journal of Human resources*, pages 279–295.

Passos, L. and Machado, D. C. (2022). Diferenciais salariais de gênero no brasil: comparando os setores público e privado. *Revista de Economia Contemporânea*, 26.

Payne, B. K. and Hannay, J. W. (2021). Implicit bias reflects systemic racism. *Trends in cognitive sciences*, 25(11):927–936.

Pelillo, M. and Scantamburlo, T. (2021). *Machines We Trust: Perspectives on Dependable AI*. MIT Press.

Tversky, A. and Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases: Biases in judgments reveal some heuristics of thinking under uncertainty. *science*, 185(4157):1124–1131.

United Nations (General Assembly) (1966). International covenant on civil and political rights. *Treaty Series*, 999:171.

Viroonluecha, P. and Kaewkiriya, T. (2018). Salary predictor system for thailand labour workforce using deep learning. In *2018 18th International Symposium on Communications and Information Technologies (ISCIT)*, pages 473–478.

Zhou, D., Bousquet, O., Lal, T., Weston, J., and Schölkopf, B. (2003). Learning with local and global consistency. *Advances in neural information processing systems*, 16.

APPENDIX

Tests and source codes used in this study are available at https://github.com/Artxzyy/article1-src-code.