DATA6550 – Bias Project – Hiring & Employment Bias

Title: Hiring & Employment Bias

Step 1: Dataset Description & Known Bias

We have chosen a publicly available human resources dataset (HR Employee Attrition Dataset) that consists of employee demographic, job and pay-related characteristics, as well as attrition result. The data sets contain variables (age, gender, branch, job description, monthly salary, years of stay at company, work satisfaction, and attrition variable that indicates whether the employee left the organization or not).

The dataset can be used to examine bias within the employment and organization-decision making process since one can study how various groups of employees can have disparate results. Biases that can be known in this dataset are gender bias, income-based bias and departmental and job-role bias, selection bias in which a particular group of people may have a systematically higher attrition rate caused by organisational practices, pay structure, or working conditions. Such differences cause some ethical issues regarding fairness, equity in the workplace, and transparency in managing and retaining employees.

Step 2: Group Communication Plan

Group discussions were conducted in person at the University Library. so during those Meetings. The groups discussed dataset selection, bias identification, task division and analysis strategies. So the notes have been collected and summarized into the document as weeks A and B.

Step 3: Project Setup (GitHub & Documentation)

To become the final report in this project, a common Google Document was created. The document was circulated among the group members and the instructor (jfwallin@gmail.com) with permission to make changes in the document and this enabled the tracking of the contribution through the version history of Google Docs. The final report will be presented as a single group submission through D2L by providing a link to the document and a PDF version of the final report.

Moreover, a common GitHub repository called DATA6550-Bias was established to store datasets, code, collaboration products and analysis products. The access to the repository was provided to every member of the group to allow joint development and version control. The repository is arranged in a hierarchical directory structure between individual code contributions, datasets, collaboration summaries and the final report. Members of the groups take the initiative to make and commit changes regularly so as to keep a clear record of contributions.

Step 4: Methodology

This research paper has adopted a systematic approach of data analysis in the investigation of the possible bias in the employee attrition results through the HR Employee Attrition Dataset. To start the analysis, the data was prepared, and the dataset was loaded, its structure was inspected, the type of data and the absence or inconsistency of data were checked.

Exploratory Data Analysis (EDA) was performed to get to know how the employees are distributed in terms of their demographic and job-related features like age, gender, department, job role, monthly income, and the years of employment in the company. Patterns and trends used to find out patterns and trends associated with employee attrition were identified using summary statistics and visualization.

Comparative analysis among the various groups of employees was done to measure possible bias through the comparison of attrition rate. The comparisons were aimed at determining differences that can be signs of gender bias, income-based bias, or job-role and departmental bias. These categories of differences based on group-wise comparisons and visualizations were highlighted by differences in attrition outcomes.

All the analyses were performed in Python, mainly with the help of such libraries as pandas, matplotlib, and seaborn. Every member of the group performed his/her analysis answering different bias-related questions and submitted his/her code to a certain directory in the common GitHub repository to maintain the transparency, reproducibility, and transparent attribution of the contributions.

Step 5: Analysis & Findings

Mahendra Potla - MonthlyIncome → Attrition (economic bias).

Because employee turnover is costly, many businesses utilize predictive algorithms to find potential departing employees. According to this data, more attrition is associated with lower monthly income. Income, however, is more than simply a figure; it also represents organizational influence, job level, career advancement, and opportunity availability. Although income frequently indicates greater structural difficulties rather than directly pushing employees to quit, the statistical link is true.

The greater problem is economic prejudice. Other models with excessive focus on income can make the lower-paid workers be considered high risk simply because of their position in the hierarchy. This can quietly shift the responsibility of the organizational structures to individuals. Predictive systems could be able to balance inequality over time by converting structural disadvantages into judgments grounded on data.

To use data fairly and predictively, organizations have to find a balance between fairness and prediction. Income should be perceived as a clue and not a conclusion. Companies could use analytics to uncover the root causes and make workplaces fairer by combining payroll information with engagement, happiness, and progress indicators. In this manner, models contribute to people and do not make the already existent discrepancies even greater.

To summarize, though monthly income and turnover of the employees have a statistical correlation, the correlation is more of a symptom of pre-existing organizational and structural imbalances than a causative factor. The reliance of predictive models on income can be counterintuitive in the sense that it can contribute to the actuality of inequalities as well as introduce economic bias. Businesses need to prioritize fairness, understanding context, and systematic betterment to use data appropriately. Equity should be encouraged and workplace outcomes improved through predictive analytics instead of being used to mechanize discrepancies.

NagaKarthik Kamidi - Overtime × Attrition (Workload Bias)

There is a sharp correlation between overtime needs and employee attrition in the analysis of HR data, indicating that excessive workloads are a major motivation factor for employee attrition. The staff who work overtime are almost three times more likely to exit the company in terms of employees with regular hours; namely, the attrition rates increase by about 10.4% and more than 30.5% when overtime is added. The statistics represent a tipping point in employee tolerance, in which a workload imbalance, the excessive allocation of additional hours, has a direct adverse impact on the work-life balance. This is the most notable among employees who have the lowest work-life balance score of 1 and have a massive attrition spike at 31.25, which is the highest among all balance levels measured.

Further discussion on departmental measures points out that not the entire amount of workload exists evenly in the organization. It has been analyzed that certain departments are worse affected by the overtime-attrition loop, such that the pressure of the department on the extended hours of work makes it a volatile retention environment. Although an average score of 2 and 3 indicates moderate work-life balance, which is associated with the lowest attrition rates, even the highest balance score (4) indicates a slightly higher rate of 17.65% attrition. Such implication indicates that retention strategy should be multi-fold as much as burnout prevention.

Steps are recommended:

Introduce Workload Capping: Have a cap on the amount of overtime so that the expectations of the organization do not serve to force workers into burnout.

The Leading Indicator to be monitored is Overtime: Overtime frequency as a leading indicator in retention models has the potential to predict when employees are at the brink of turning over.

Mounika varma - Distance Home and Attrition of Employees(Proxy Bias)

This discussion has investigated the relationship between commuting distance and employee attrition using the HR Employee Attrition dataset. The four distance categories (Very Close, Close, Moderate, and Far) were used to group the employees and the data analysis in terms of Exploratory data analysis and percentage comparisons showed an evident upward trend on the attrition with the commuting distance.

The initial category of employees was the Very Close category, which had a rate of attrition of about 13.8, and the Far category whose rate of attrition was about 22.1. This steady growth in the distance group indicates that employees who have higher commuting distance within an organization have higher chances of leaving the organization. A further analysis of Boxplot revealed that the median commuting distance of workers who had left was a little higher than that of those who stayed.

Though the causation between the two is not pronounced, the trend shows that the burden of commuting can affect the retention results. These results emphasize the need to look at non-noticed structural aspects when comparing workforce data.

Venu Desireddy - Gender and Age Differences in employee attrition(Demographic Outcome Bias)

This discussion explored the gender and age variation in employee attrition based on the HR Employee Attrition data. The primary objective of the analysis was to compare the rate of attrition between both male and female employees and then further on the analysis by grouping the employees into the age group to gain a better insight on how career stage can affect the retention trend. The analysis of the data was performed with exploratory data analysis and comparisons of percentages to find significant trends in the data.

The findings demonstrate that the attrition rate does not precisely match between genders, which implies that retention could be different among the employees of both genders. Even though the difference is not a drastic one, it is still substantial enough to indicate that the phenomena of turnover might be related to the demographic factors. Variation in the attrition rates was also found to occur across the age groups when they were analyzed. There was a relatively higher attrition in certain age groups than others, and this could be the difference in career mobility, level of experience, or professional priority at some point of employment.

Although this analysis does not prove that gender, age, and attrition are directly linked, the patterns observed confirm the possibility of the workforce report providing different results across demographic lines. These results highlight the need to analyze the structural and demographic variables in assessing employee retention and work-related fairness generally. Although the dataset is not real, the methodology shows how data analysis can be employed to detect any possible differences in organizational contexts.

Step 6: Ethical Implications

According to this experiment, it is very unethical to retain employees using predictive analytics. The data used is not real; however, the statistical relationships suggested show how the apparently neutral work-related variables can be biased in automated decision-making systems.

Economic Prejudice in Monthly Income.

The monthly income and attrition studies showed that the rate of turnover among the low-paid staff is high. Although such a correlation may be a true representation of organizational trend, the presence of structural inequality may be further exaggerated by the high level of dependency on income in predictive designs. Income is a key determinant of promotions and job levels, in addition to the organization structure in which skills and dedication of a person are not the main determinants. By placing low-income workers in high-risk categories which are predictive systems, the companies will be discriminating against certain groups of workers and attribute structural problems, i.e., wage equity and opportunities to advance professionally.

This also brings the issue of fairness and distributive justice as an ethical issue. Organizations must learn that inequality in income is not caused by the performance of an individual; moreover, the use of income as a criterion in intervention is also not advisable.

Inequality in workload (attrition and overtime)

A correlation of overtime revealed that there was a close relationship that existed between workload being too high and workers quitting their jobs. The rate of turnover among employees who worked extra hours was very high. This observation poses ethical concerns on the welfare of the workers and the organization.

The use of overtime by predictive systems is considered a cue of retention and not correction of the underlying issues that cause overtime, i.e. they tolerate burnout rather than correct it. With the data in an ethical manner, it is important to understand that overtime may be an indication that the organization is inefficient, it does not have sufficient numbers of workers or the working environment is unfavorable. With the use of overtime as a predictive risk flag but structural adjustments not taking place, it is possible that management would be the reactive rather than the proactive type.

This comes into more ethical concerns regarding equity in the workplace, the health of the employees, and the efficiency of the organizations in operation.

proxy bias (Distance From Home)

The commuting distance analysis showed that there was a progressive trend in the commuting distance of the sample which was one of the factors that lead to attrition. The distance to work may not be important but it may be an indicator of the level of socialness. Workers with the inability to balance work and family (as well, those who work in distant areas) might experience difficulty in getting a place to stay, commuting to work, or facing undue treatment.

The most common mistake that organizations are likely to make is to introduce socioeconomic injustices to automated decision systems without considering the background where predictive models employ commuting distance as a direct risk factor. This is a proxy bias that implies that the non-sensitive variables are a measure of structural inequality.

The moral issue in this case is that foretelling technologies will punish employees because of something that is outside their reach and therefore the furtherance of the already pervasive social inequalities.

Demographic Inequalities (Gender and Age).

Gender and age analysis showed that there were differences in the rate of attrition by the various demographic groups. Though the differences may not be very vast, they should at least be handled with sensitivity on the ethical aspect.

Demographic information can be considered when estimating the way to create a biased and inequality-advocating atmosphere at the workplace. This may influence judgments concerning promotions, training or retention opportunities, which are not good in that group, when models repeatedly indicate that such a group is more likely to leave.

In modeling it is important to consider the possibility of inclusion, exclusion or involvement of demographic factors with the aim of inclusion on the basis of fairness auditing and not simply forecasting.

More General Ethical Ideas
There are certain significant ethical themes of all the analyses:

- Correlation is not necessarily causal. It should not be understood that predictive relations express individual behavior.

- The indirect variables may render the structural inequality. Systemic losses can be depicted by statistics that appear to be objective.

- Justice and precision ought to be hand in hand. A morally questionable model will be a good predictor of attrition and will increase inequality.

- The context is important. The decisions made on the basis of data should be made with the help of knowledge, interpretation of data by the organization and human judgment.

Responsibility in data science: Ethics.

Evidence provided by this experiment shows that the idea of data bias is not isolated to the attributes that are explicitly sensitive like race or gender. Subtle bias may be brought about by correlated variables that tend to be pointers to deeper-rooted social or organizational patterns.

Thus, data scientists and data analysts must:

- Consider carefully the choice of features.

- Consider the influence of fairness.

- Make the rules clear.

- Learn not to be too predictive.

The ethics should accompany all data analysis life cycle, including exploration, modeling and reporting.

Step 7: Bias Mitigation Strategies

- Normalize income within job roles
- Bias Mitigation Strategies
- Equalize earnings in occupations.
- Include performance variables, satisfaction, and experience.
- Assess equality in income groups.
- Add the variables of satisfaction, tenure, performance, and engagement, so as not to rely on the salary too much.
- Supervise overtime working as one of the biggest burnout factors, and implement workload restriction.
- Add variables to lessen over-dependence on salary in models. Incorporate the variables of satisfaction, tenure, performance, and engagement in order to eliminate structural work load imbalances across departments before the use of overtime.
- Watch the overtime as one of the major burnout markers and set workload limits.
- Prior to the use of overtime in models, normalize workloads and structural imbalances between departments.

Conclusion

In this project, the question was investigated on whether there could be bias in employee attrition in the HR Employee Attrition dataset. We as a group examined the relationship between structural and demographic variables as income, overtime, commuting distance, gender, and age, and employee turnover. These findings demonstrated that attrition is not uniform and it can be different among various groups of employees.

The results do not cause the direct cases, but they demonstrate that workplace conditions and demographic factors can be connected to their retention. Certain factors, like income or distance to home, might be a manifestation of more structural problems, and not individual behavior. Equally, the differences between the genders and the ages ought to be viewed cautiously and fairly.

In general, this project highlights the necessity of integrating data analysis and ethical consciousness. Pattern recognition is just a starting point, organizations should be able to think about the context, equity, and overarching effects of data-driven decisions.

References

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