Income Category Prediction

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***Abstract*—Income inequality is present in the United States and it is a major concern. People with certain set of features seem to be earning more compared to other people. Through various Machine Learning techniques, this study aims to show the attributes that best explain the income inequality that is present in the United States. The dataset used here is obtained from Kaggle.com which in turn was provided by the U.S. Census Bureau.**

***Index Terms*—income inequality, classification, Support Vector Machine, Gradient Boosting Classifier, Naïve Bayesian, XGBoost, ANN**

I. Introduction

A. How does income inequality affect our lives?

The big question is "is income inequality good or bad for the society and economy?". To put it in another way, does people like Mark Zuckerberg getting richer affect the life of a typical citizen? Some argue that it does in a bad way and some argue that it does in a good way. Let us look at both points of view.

B. How is it good?

One very obvious way is how it allows entrepreneurs to take bigger risks. For example, Steve Jobs and others like him wouldn't have taken the risk of starting a company and running it if it was not worth it. It allowed him to accumulate tremendous amount of wealth. If there was no permission for him, or others for that matter, to accumulate such massive amounts of capital, then very few people would have started a company. Which would mean lesser jobs and lesser economic growth. So some people argue that income inequality is necessary for economic growth.

C. How is it bad?

Numerous studies have shown that excessive inequality is bad for growth. One study points out that low-earning families invest less in education and skills. This means that there is reduced number of skilled workers which results in slow economic growth as less productive work is being done. It is also observed that people that go to universities tend to earn more than the people who do not. Now, this is a serious issue because the rich stay rich by sending their kids to universities and the poor stay poor because they cannot do so. This widening gap results in other serious problems. Some of the issues can be explained by how different economic groups behave and interact with each other as the income gap widens.

How income inequality affects the way different groups behave:
a. The poor invest less in education and health. This causes problems to the economy if they are more in number.
b. If inequality squeezes the middle class then it reduces their demand for goods and services.
c. The rich may use their economic power to lobby against the rules that are against their interests at the expense of greater social good.

How income inequality affects the way different groups interact:
a. Trust is lowered between the groups leading to high transaction costs. For example, if a customer trusts the business owner and vice versa, then they may agree to a deal without any legal advice or contracts.
b. People's network of social relationships might not extend beyond their own income group. Hence, the elite groups might use their network to exclude outsiders from economic opportunities.
c. Social unrest and volatility may be caused because high levels of inequality leads to societies not coming to a political consensus.

As can be inferred from the above explanations, extreme income inequality on a large scale is definitely not good. Our study is focused on finding the factors that cause this inequality with the dataset we have. Before taking a look at our approach, we study what others have done with this dataset.

II. Previous Work

The first study has used various classification algorithms like Naïve Bayesian, K Star, Random Forest and Zero R. They have used the first 100 instances of the dataset and the instances with missing values are removed. The less sensitive attributes like final weight, capital gain, capital loss, hours per week are removed. They have used Weka, which is a collection of machine learning algorithms for data mining tasks. After running all the classification algorithms, they conclude that Naïve Bayesian is the best with an accuracy of 84.31%. Though Naïve Bayesian is followed by Zero R then Random Forest and K Star, these three algorithms remain in the same range.[3]

The second study uses Principal Component Analysis, PCA and Support Vector Machine, SVM for the classification. Scaling of the features in the range of [-1,1] is done because large values can cause computational problems and may also lead to wrong results. As SVM deals very well with real numbers, it is inferred that scaling is a much better approach than discretization. Accuracy of 84.92% is obtained.[4]

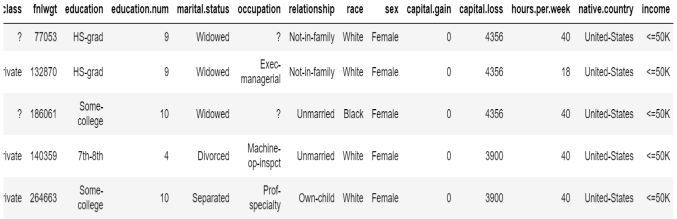
The third study used random forest classifier to predict income levels of an individual. Random forest is preferred to decision tree since using results from many decision trees will avoid the overfitting problem associated with using a decision tree classifier. Results from the fitted classifier model show that marital status, capital gain, education, age and work hours determine much of the difference between low and high income levels. Though the model accuracy is 85%, the model is weak in predicting high income individuals.[1]

The fourth study has used various data pre-processing techniques like label encoding, one-hot encoding, and shuffling. Based on the scores of the Extra Tree Classifier for different attributes the most relevant features have been selected. The learning algorithm, used to build the predictive model is an Ensemble Learning and Boosting Algorithm known as Gradient Boosting Classifier. The model was deployed which clocked the highest accuracy of 88.16%, eventually breaking the benchmark accuracy of existing works.[2]

III. Problem statement

To analyze the dataset to find the attributes that cause higher income in some individuals and to classify income level as $\leq 50k$ or $> 50k$ from the dataset using the relevant attributes.

Our dataset is taken from Kaggle.com which was provided by the U.S. Census Bureau. It contains 15 attributes and 32561 observations. The target variable is income which is binary, is either $\leq 50k$ or $> 50k$. “Fig. 1” shows a snapshot of the dataset being used.



:lass	fnlwgt	education	education.num	marital.status	occupation	relationship	race	sex	capital.gain	capital.loss	hours.per.week	native.country	income
?	77053	HS-grad	9	Widowed	?	Not-in-family	White	Female	0	4356	40	United-States	<=50K
ivate	132870	HS-grad	9	Widowed	Exec-managerial	Not-in-family	White	Female	0	4356	18	United-States	<=50K
?	186061	Some-college	10	Widowed	?	Unmarried	Black	Female	0	4356	40	United-States	<=50K
ivate	140359	7th-8th	4	Divorced	Machine-op-inspct	Unmarried	White	Female	0	3900	40	United-States	<=50K
ivate	264663	Some-college	10	Separated	Prof-specialty	Own-child	White	Female	0	3900	40	United-States	<=50K

Fig. 1. Snapshot of the dataset

IV. Proposed Solution

“Fig. 2” shows the workflow of our proposed solution. The solution involves 5 steps- Data Extraction, EDA, Preprocessing, Model Building and Results.

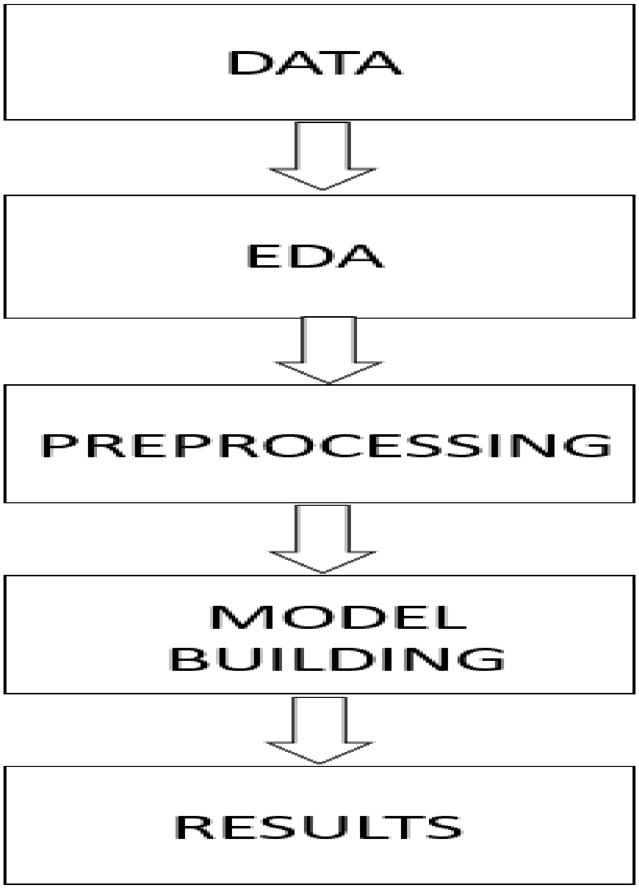


Fig. 2. Proposed Steps

A. Data

Our dataset is taken from Kaggle.com which was provided by the U.S. Census Bureau. It contains 15 attributes and 32561 observations. The dataset is mostly clean but needs some preprocessing which is done in the next steps. The target variable is income which is binary, is either $\leq 50k$ or $> 50k$. “Fig. 1” shows a snapshot of the dataset.

B. EDA

Exploratory Data Analysis is done to find the attributes that most contribute to the income inequality. It also shows the attributes which have very little influence over income.

“Fig. 3” shows the influence of workclass over income. Self employed people and the people who work for the Federal Government earn more compared to other income classes.

“Fig. 4” shows the influence of education over income. People with doctorate degree earn the highest followed by professional school degree and masters degree. As expected, having only high school education will lead to significantly lesser income than others with higher educational levels.

“Fig. 5” shows the influence of marital status over income income. As expected, married people have a higher probability of earning an income greater than 50k whereas, people who are

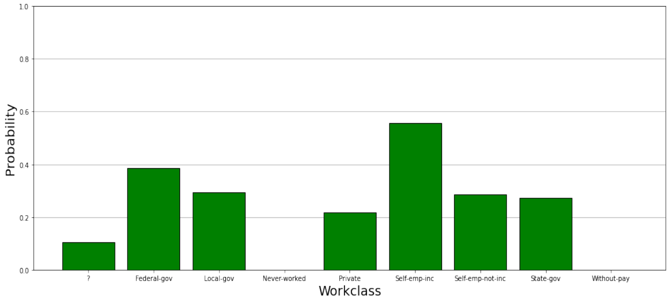


Fig. 3. Work Class vs Income probability

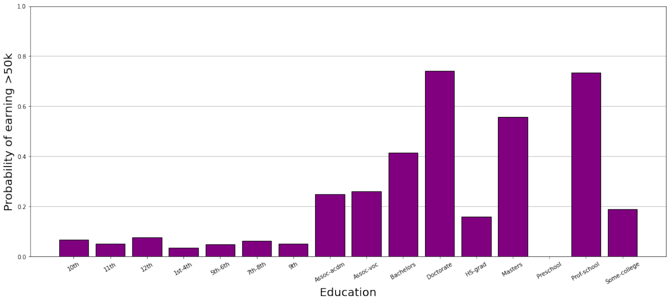


Fig. 4. Education vs Income probability

never married have the least probability. The reason might be because married people are generally older and need a stable source of income to provide for their family.

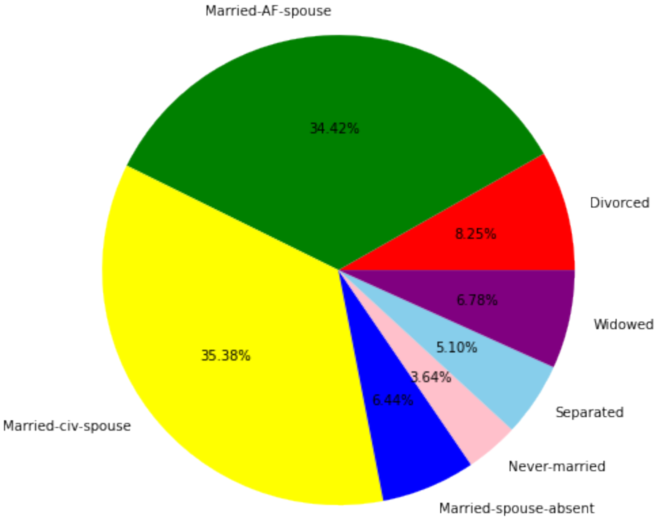


Fig. 5. Marital Status vs Income probability

"Fig. 6" shows the people's occupation vs the probability that they earn more than 50k. Executives with managerial responsibilities earn the highest followed by people of professional speciality and protective servants.

"Fig. 7" shows that race does have influnce over income although it is quite less. White people have a higher probability of earning more followed by Asian people.

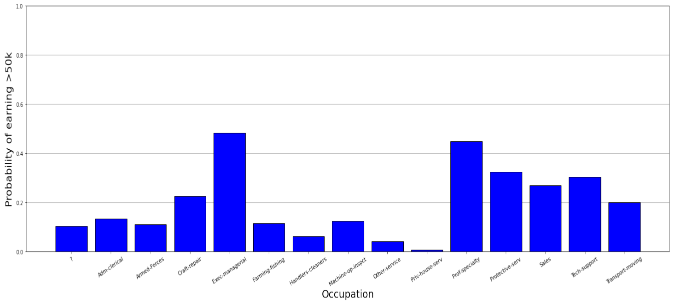


Fig. 6. Occupation vs Income probability

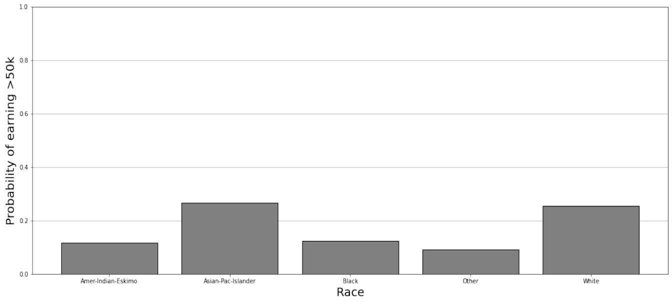


Fig. 7. Race vs Income probability

"Fig. 8" shows the positive correlation between education number and income. Higher education leads to higher income.

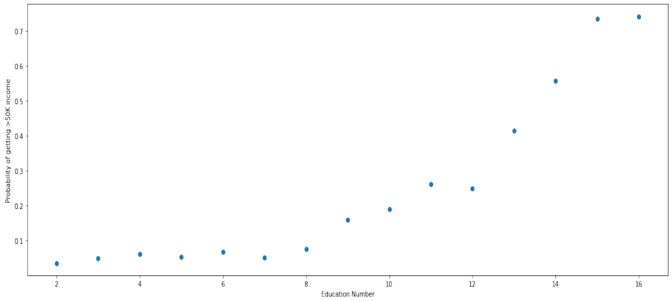


Fig. 8. Education number vs Income probability

"Fig. 9" shows an interesting insight. People who earn more generally tend to work longer hours compared to those who earn less. These people belong to the category of executives who, contrary to popular belief, work more than the employees at the entry level jobs.

"Fig. 10" shows that people in their 40s to 60s earn more than young people and old people. This is as expected because income level increases with more experience.

Finally "Fig. 11" is a correlation matrix showing the correlation between all the attributes.

C. *Preprocessing*

In the preprocessing step, we convert the $\leq 50k$ to 0 and $> 50k$ to 1 as the category to be predicted. Next, we drop the variable fnlwgt because it has very little correlation with the

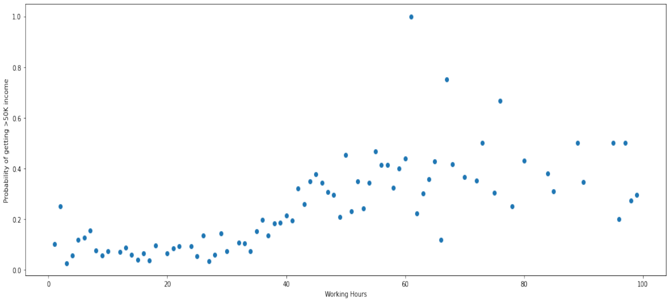


Fig. 9. Working Hours vs Income probability

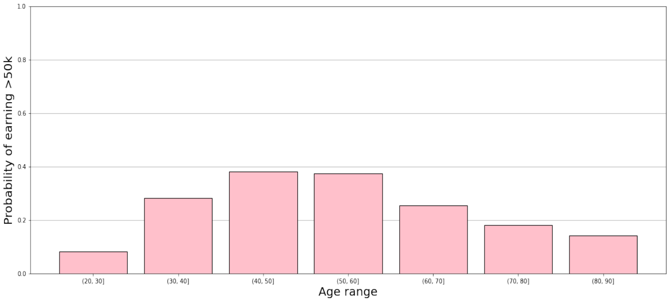


Fig. 10. Age range vs Income probability

target variable. We also drop the education num variable as it may cause multicollinearity problem with education.
Since we have only few rows with missing values, we drop those rows.
Next, we split the data into dependent and independent variables, and then we split the dependent variables into continuous variables and categorical variables.

D. Model Building

We have used 5 models for the predictions. Naive Bayes model, Random Forest, XGBoost, ANN and an ensemble of XGBoost and ANN. The data has been stratified for better model building and results.

In the Naive Bayes model, we have used 3 split cross-validation to validate the model.

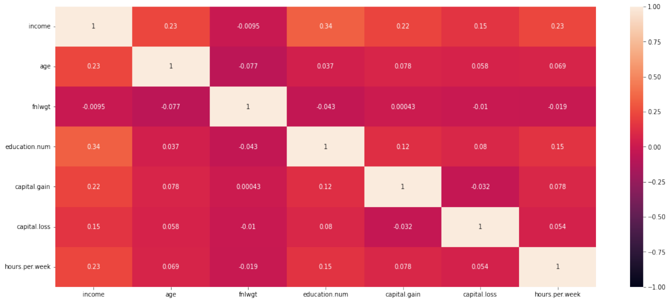


Fig. 11. Correlation Matrix

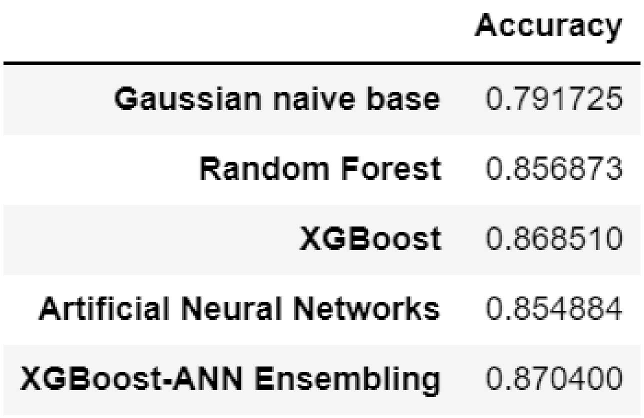
The next model is Random forest. The number of estimators is set to 200 with max depth as 16. Grid Search is used to find the optimal parameters.

The third model is XGBoost. Grid Search is used to find the best parameters. Cross-validation is done to validate the model. The predictions are saved for ensembling which is done later.

The fourth model is ANN. Hyperparameter optimization is done. The best parameters are found out using Grid Search. Cross-validation is done for validation.

The last model is an ensemble model with XGBoost and ANN models. Higher weight is given to XGBoost and predictions are made.

E. Results



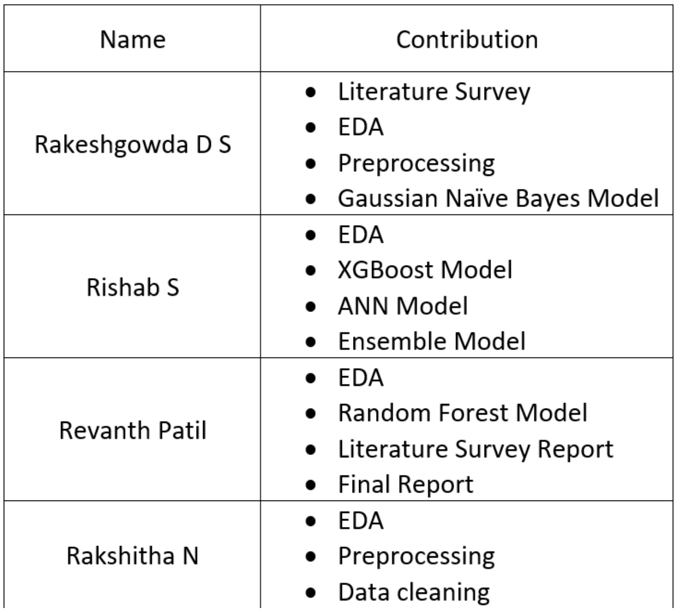
	Accuracy
Gaussian naive base	0.791725
Random Forest	0.856873
XGBoost	0.868510
Artificial Neural Networks	0.854884
XGBoost-ANN Ensembling	0.870400

Fig. 12. Final accuracies of all the models

The results are shown in “Fig. 12”. The ensemble model gives the highest accuracy of 86.97%. The XGBoost model gives the next best accuracy of 86.85%.

V. Conclusion

Through this project, we came to know the problem of income inequality in the United States of America. We learnt how income inequality affects the lives of all the people. We got to know that income inequality is required for the growth of economy and the reason for why it is so. But too much income inequality is also bad for the society and harmony.
We learnt about different ways of analysing the data and cleaning it. We gained a lot of knowledge about different Machine Learning Classification models, tuning the parameters of the model, cross validation and prediction of results with the models. Through this project, we have hopefully shed light on the various factors which are responsible for income inequality, its pros and cons.



Name	Contribution
Rakeshgowda D S	• Literature Survey • EDA • Preprocessing • Gaussian Naïve Bayes Model
Rishab S	• EDA • XGBoost Model • ANN Model • Ensemble Model
Revanth Patil	• EDA • Random Forest Model • Literature Survey Report • Final Report
Rakshitha N	• EDA • Preprocessing • Data cleaning

Fig. 13. Final accuracies of all the models

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