Give Me Some Credit – EDA, Logistic Regression, WOE

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The ADS & the Data

```
Int64Index: 150000 entries, 1 to 150000
Data columns (total 11 columns):
 #   Column                                Non-Null Count   Dtype
---  ------                                --------------   -----
 0   SeriousDlqin2yrs                      150000 non-null  int64
 1   RevolvingUtilizationOfUnsecuredLines  150000 non-null  float64
 2   age                                   150000 non-null  int64
 3   NumberOfTime30-59DaysPastDueNotWorse  150000 non-null  int64
 4   DebtRatio                             150000 non-null  float64
 5   MonthlyIncome                         120269 non-null  float64
 6   NumberOfOpenCreditLinesAndLoans       150000 non-null  int64
 7   NumberOfTimes90DaysLate               150000 non-null  int64
 8   NumberRealEstateLoansOrLines          150000 non-null  int64
 9   NumberOfTime60-89DaysPastDueNotWorse  150000 non-null  int64
 10  NumberOfDependents                    146076 non-null  float64
```

- Dataset provided: 1 target and 10 predictors
  - Age is the only sensitive feature
- Objective: predict the likelihood of a customer not paying a loan back in 2 years
- ADS: performed exploratory data analysis, utilized logistic regression model with weight of evidence coursing, random forest model
- Our goal: Assess ADS for fairness and make it easier to interpret its decisions

Statistical Parity and Disparate Impact

```
Statistical Parity:  4.7097065459703045e-06
Disparate Impact:  1.001058527563299
```

```
Statistical Parity:  [ 7.60615532e-06  6.26484269e-05  1.89448780e-03 -2.70147112e-04
 -1.67104674e-03]
```

```
Disparate Impact:  [1.00034473 1.00284164 1.08825299 0.98780521 0.92604806]
```

- Performed one adjustment to the code due to runtime issues
- Statistical parity is negligibly small
- Disparate Impact decreases over the iterations
- Decided to be an acceptable amount of disparate impact
  - Objective of the ADS is predict whether or not someone is able to pay back a loan, regardless of fairness
- Considering the results, the notion that younger people are less likely to be approved for a loan is not supported by the disparate impact measure

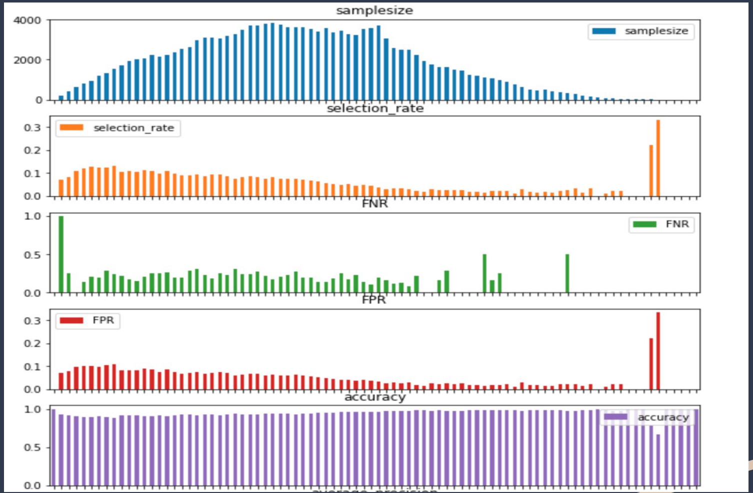
Fairlearn

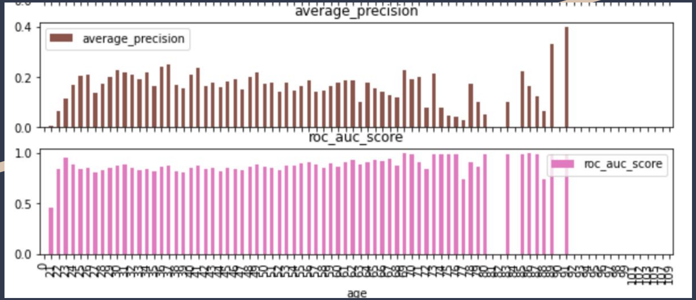
```
samplesize                150000
selection_rate           0.06684
FNR                     0.216235
FPR                     0.053099
accuracy                0.943833
average_precision       0.176908
roc_auc_score           0.865333
dtype: object
```

This is the result of running the fairlearn metric frame on the model predictions and a test set with a sensitive feature of age.

- The false negative rate is higher than the false positive rate, meaning that this test is more specific and less sensitive
- Although accuracy is high, the precision is not, meaning that the model grouped predictions together but does not necessarily mean that those predictions were correct
- The ROC AUC Score is relatively high showing its proficiency at separating different classes within the model.

Fairlearn Cont.





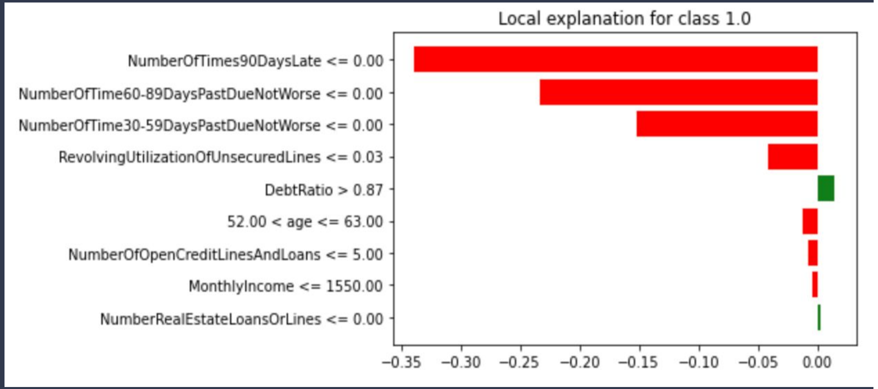
- X axis at the bottom being age
- Majority of the people are in their 40s with very few people in their 90s
- For the false negative and positive rates, they are opposites of one another
    - False negative rate has a peak during the early 20s and then is level after to be around 0.25. The false positive rate decreases starting at 0.1 then a major spike around 98 and 99 years old.
    - This can tell us that the two age extremes are predicted incorrectly by the model more than any other age group
- The accuracy is almost uniform for all age groups with a slight decrease around 97 years old. The average precision hovers around 0.2 and 0.1 with it being lower at early ages like 21 and 22 while increasing in the late 80s and early 90s.
- The ROC AUC score stays high throughout age groups except for 21 year olds at around 0.4 while every other age group is around 0.8 or 0.9.

Fairlearn Cont.

```
samplesize                149999
selection_rate          0.266493
FNR                     0.783765
FPR                     0.280235
accuracy                0.277167
average_precision       0.223092
roc_auc_score           0.401047
dtype: object
```

- This shows the difference for the overall values of the metric
- We can see how a few values such as the false negative rate and false positive rates increased while ROC AUC score and accuracy has decreased.
- This shows the variability between all the different age groups in the dataset.
- Many extremes in this dataset because lack of samples

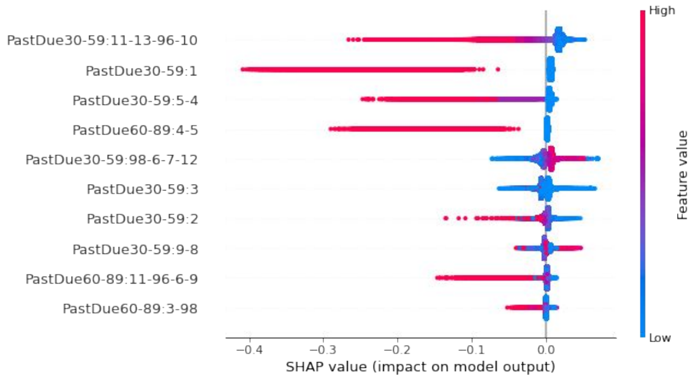
Lime

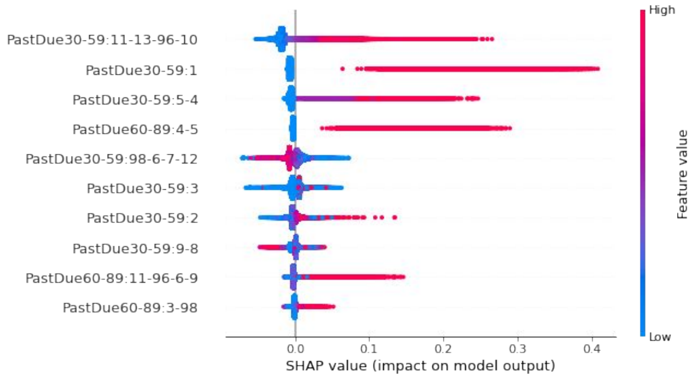


- Best predictors are if someone has a history of not paying back their debts.
  - If they have this history, the model is more likely to predict them to have financial distress in the next two years
- Debt ratio and number of real estate loans or lines deter model from predicting to financial distress
  - Number or real estate loans is ambiguous because it could be from a real estate investor rather than someone that is finding an initial place to live
  - For the debt ratio, if someone has a debt ratio lower than 0.87, they are less likely to face default on a loan The weights of the variables are explained later in the report with SHAP values.

SHAP

- SHAP values for the most impactful features on the ADS
- Both show the impact these predictors have on positive or negative decisions
- The same weight for both on predictions
- Smaller values result in an increase in likelihood of positive prediction, and larger values result in a decrease in likelihood of a positive prediction





ADS Link and Citation

- https://www.kaggle.com/code/sarboldipo/givemesomecredit-eda-logistic-regression-woe/notebook#EXPLORATORY-DATA-ANALYSIS
- https://www.kaggle.com/competitions/GiveMeSomeCredit/data?select=cs-test.csv