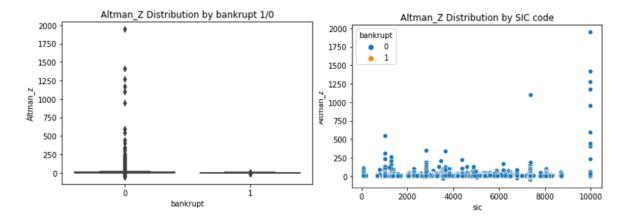


# BT4016 ASSIGNMENT 2

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#### **EDA**



From the charts, it is clear that there are some SIC's which exhibit higher bankruptcy rates. The statistical distribution of Altman's Z-score is also very different for companies which went bankrupt, versus those that didn't.

Digging deeper, the mean Altman's z-score for bankrupt=1 is 0.565, and the median is 0.773, whereas for bankrupt=0, the mean and median are 6.554 and 3.678 respectively - clearly, Altman's is a decent guage of predicting bankruptcy.

However, I foresee that there will be many false positives just by using Altman's Z-score, since there are many good companies (bankrupt=0) with a low score - as can be seen by the 25th percentile at 2.07, which is below our threshold cutoff of 2.675.

#### Question 1

```
Confusion Matrix:
[[16946 9692]
[ 21 160]]
True negative: 16946, False positive: 9692, False negative: 21, True positive: 160

Accuracy: 0.6378313881949365
Recall: 0.8839779005524862
Precision: 0.016240357287860333
MCC: 0.08833705585350643
F1: 0.03189474733379846
```

## Question 2

#### **LOGISTIC REGRESSION**

```
accuracy: 0.9932510533576941
precision: 0.5
recall: 0.04419889502762431
MCC: 0.14719355521340557
F1: 0.08121827411167512
array([[26630, 8], [173, 8]], dtype=int64)
```

#### **CART**

```
accuracy: 0.9876207166561021
precision: 0.12437810945273632
recall: 0.13812154696132597
MCC: 0.12484691347193112
F1: 0.13089005235602091
array([[26462, 176], [156, 25]], dtype=int64)
```

#### **XGBOOST**

```
accuracy: 0.9925053133972184
precision: 0.22222222222222
recall: 0.04419889502762431
MCC: 0.09648671909706168
F1: 0.07373271889400922
array([[26610, 28], [173, 8]], dtype=int64)
```

## Question 3

#### **CART, SMOTE ONLY**

#### **CART, SMOTE + ENN**

#### **CART, OVERWEIGHT CLASS WEIGHT**

```
accuracy: 0.988142734628435
precision: 0.14871794871794872
recall: 0.16022099447513813
MCC: 0.14839752868376088
F1: 0.15425531914893617
array([[26472, 166], [152, 29]], dtype=int64)
```

Smote is not that good at improving the F1 score, since the plain CART model had a score of 0.131, as opposed to 0.101 and 0.110 for SMOTE and SMOTE+ENN respectively. Overweighting the class weight within the CART as a hyperparameter, however, did improve the F1 score to 0.154.

## Question 4

For this question, I built 2 models.

The first model was with feature engineering – I added in the following columns:

- 1) Boolean for dividend paid or not
- 2) Ratio of dividend to earnings ratio for each security
- 3) Ratio of operating expenses to revenue for each security

The rationale for including these was that they are not addressed in the Altman's Score. I also included the one-hot-encoded first SIC (first digit only, since the EDA tells us only first digits make a difference).

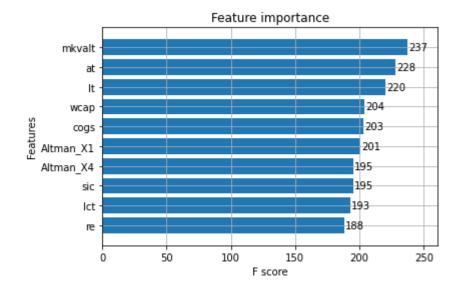
The second model was a plain vanilla one with all the features, and one-hot-encoded first digit of SIC score. (since based on EDA, only the first digit makes a significant difference). I used pos\_scale\_weight to balance the classes. This model was primarily to comply with the grading criteria of not being allowed to do feature engineering.

To tune the hyperparameters, I first visualized the ROC\_AUC across different folds, and from this I arrived at a narrow range of values for which to tune. For tuning, I used Bayesian Hyperparameter Optimization, with 5 folds. The ROC AUC score achieved during cross val on training set was 0.939.

The test predictions are attached in a csv file.

It is also worth mentioning that in a real credit investment scenario, the consequence of a false negative (i.e. predict bankrupt = 0 but it actually goes bankrupt and we lose all out money), is much more severe than the consequence of a false positive, where we predict that a company is going to go bankrupt, and avoid investing in it. Hence, we aim for a high recall, but can be more lenient in our precision metric.

## Question 5



None of the top 5 are Altman's ratios. Rather, the top 5 comprise of the market value, total assets, total liabilities, working capital and cost of goods sold. These figures generally increase as the size of the firm increases → the model presumably is picking up the trend that larger companies tend to default less frequently than smaller ones.

The 6<sup>th</sup> and 7<sup>th</sup> most important features, however, are the X1 and X4 ratios.