Tarush Gupta
DATS 6103 Project: Predicting Bankruptcy
Individual Final Report

1. Introduction

As part of our Data Mining project this semester, our group set out to use the methods learned during this course and solve a challenge that we collectively found interesting. As students in the Masters in Applied Economics program, we share an economic intuition, which we combined with our data mining skills, to explore bankruptcy prediction using a dataset with publicly-traded firms in Taiwan, between 1999 and 2009.

Recent financial collapses have highlighted the importance of regulating large firms and increasing oversight. Consequently, firms audit their financial health annually by reporting their financial ratios and corporate governance indicators (Shailer, 2004). Finance literature, and more recently, machine learning literature has used these indicators to assess the probability of a firm declaring bankruptcy (Altman, 1968; Lee and Yeh, 2004; Lin et al., 2011).

For the purposes of the project, we use a dataset from Kaggle, that was originally collected from the Taiwan Economic Journal between 1999 and 2009 (accessible at: https://www.finasia.biz). The Kaggle data were obtained from the University of California, Irvine, Machine Learning Repository (Liang et al., 2016). We begin by inspecting and preprocessing this data, over which we run inferential and predictive models to ascertain the determinants of bankruptcy.

During our Exploratory Data Analysis, we removed any feature variables with high multicollinearity--|95%| or greater. We still faced some collinearity related issues, which we address using Variance Inflation Factor. The data is well-organized and complete and did not require much attention. We fix the moderate imbalance problem in our binary Boolean target class variable, Bankruptcy (1, if a firm went bankrupt; 0, otherwise), wherein only 3.2% of the observations fall in the minority class, using the Synthetic Minority Oversampling Technique, or SMOTE, as developed by Chawla et al. (2002). We Winsorize any outliers and use the standardize our data before running any models.

Collectively, we run seven statistical models on our data to understand the impact of the feature variables Bankruptcy. To reduce dimensionality and understand the importance of the features within our data, we run the Principal Component Analysis. On this classification data with a binary target variable, we run the Logistic regression, and its capped-extension, the Probit regression. Additionally, we run four tree-based shallow machine learning models: Decision Tree Classifier, Multi-Layer Perceptron Classifier, Histogram-based Gradient Boosting Regressor, and the Linear Probability Model.

Our models indicate that debt-based measures, intuitively, had the most significant statistical impact on increasing the probability of a firm declaring bankruptcy. This is visible in our Linear Probability Model results, which show that a 1% increase in the (Total Debt)/(Total Net Worth) ratio increases the chance of bankruptcy by nearly 5.7 percentage points. Our PCA results show that just 8 components can explain a majority of the data. From our predictive methods, we observe that based on the F1-score, the Decision Tree Classifier fits and explains this data best (75% model accuracy).

We plot and tabulate our results, which we present interactively using a GUI. The GUI enables users to explore the data, its characteristics, and use it to run our statistical models. Our findings are important for investors and financial lenders who want to invest in firms, and use our indicators to assess the financial health of the firms. The results are also useful for building and training other machine learning models.

2. Description of the Individual Work

In the project, I contributed to the coding aspect, writing the report, and making the presentation. In coding, my contribution was two-fold: assisting with the exploratory data analysis, and building the GUI. Within the group report, I contributed the text for the first two sections with additions and edits from my group mates. For the presentation, I added my slides on the exploratory data analysis and the respective references, as well as some formatting changes.

Within the exploratory data analysis, I explored the properties of the data, added figures, and handled multicollinearity and class imbalance. For the GUI, I learned how to use QT Designer and the PyQt5 libraries to implement the interactive aspect. In the report, I led the research and literature review to complete the first section, and explored the properties of our data to complete the second section. I further explain these contributions in the next section.

3. Detailed Description of Individual Work

My additions to the exploratory data analysis include setting up my requirement in the initialization section, adding the 'nan checker', checking for multicollinearity using the Pearson and the Spearman Correlation matrices, dropping the multicollinear columns and any other variables without any information ('Net Income Flag'). Here, I also contribute the income-to-bankruptcy graph. Next, I split the data into training, testing and validation subsets. I further split each of these into their respective target vector and feature matrices. I then standardize this data using the Standard Scaler. On this data, I use a scatter plot to visually inspect the imbalance in our target variable. I implement the solution to this using SMOTE, and once again plot the new target class. Over this data, I run a two-component Principal Component Analysis. My code for this part is as follows:

```
path = os.path.abspath(os.getcwd())
bankrupt = pd.read csv("data.csv", sep=',',header=0, index col=None)
def nan checker(df):
df nan = nan checker(bankrupt)
                multicoll mat.append(corr mat.columns[j])
                multicoll mtx.append(corr mtx.columns[j])
mcm diff = [ele for ele in multicoll mat if ele not in multicoll mtx]
bankrupt = bankrupt.drop(multicoll mtx,axis=1)
```

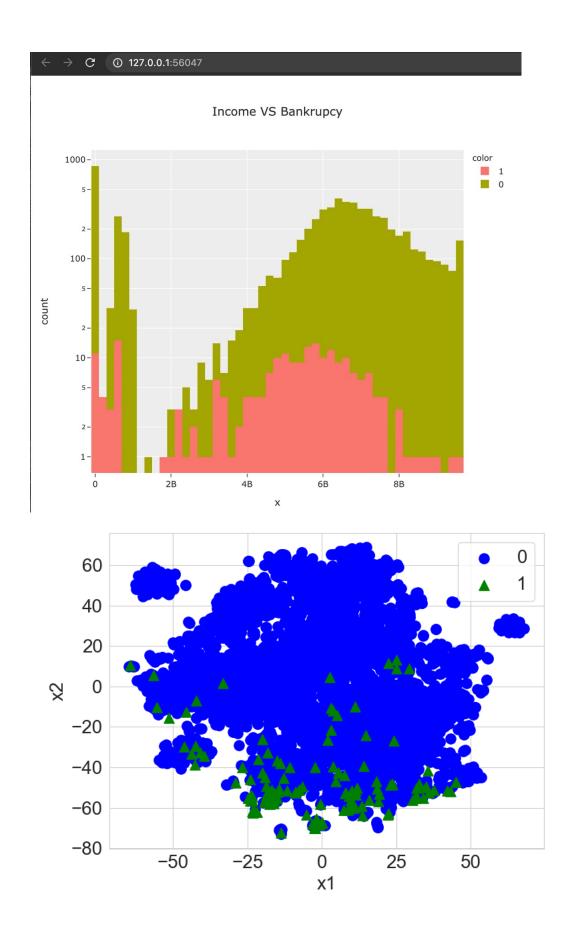
```
bankrupt['NetIncomeFlag'].value counts()
itob.show()
df train, df test = train test split(bankrupt,
df val, df test = train test split(df test,
df train, df val, df test = df train.reset index(drop=True),
df val.reset index(drop=True), df test.reset index(drop=True)
pd.DataFrame([[df test.shape[0], df test.shape[1]]], columns=['# rows', '#
X train = df train[np.setdiff1d(df train.columns, ['Bankrupt'])].values
X test = df test[np.setdiff1d(df test.columns, ['Bankrupt'])].values
y test = df test['Bankrupt'].values
```

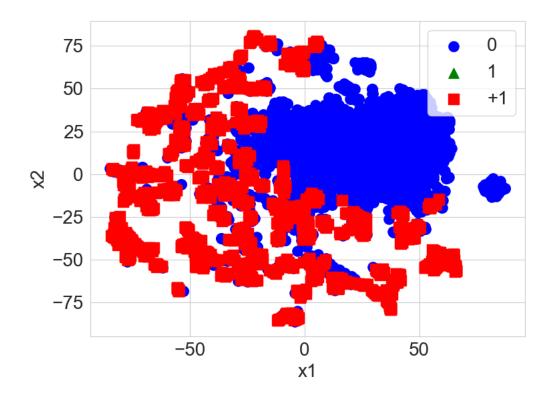
```
def plot scatter tsne(X, y, classes, labels, colors, markers, loc, dir name,
   tsne df = pd.DataFrame(np.column stack((X embedded, y)), columns=['x1',
       plt.scatter(data x1, data x2, c=color, marker=marker, s=120,
   plt.savefig(dir name + fig name)
plot scatter tsne(X train,
```

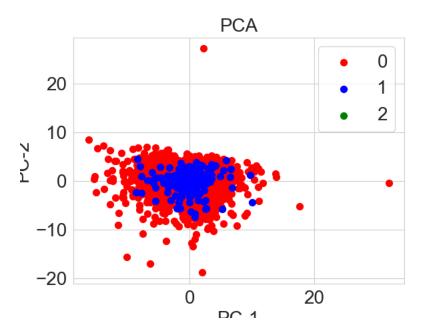
```
pd.Series(y smote train).value counts()
def separate generate original (X aug train, y aug train, X train, y train,
minor class):
    y aug gen ori train = np.array(y aug train)
```

```
y val = ss.fit transform(y val.reshape(-1, 1)).reshape(-1)
y test = ss.fit transform(y test.reshape(-1, 1)).reshape(-1)
bank = pd.DataFrame(data=X train, columns=['PC-1', 'PC-2'])
plt.figure()
plt.xlabel("PC-1")
plt.ylabel("PC-2")
plt.show()
```

The resulting figures from this code are:







For the GUI, I learned how to use QT Designer to build our application. This created a .ui file, which we converted to a .py file, which I use to connect our code with the GUI. The code from the .ui converted to the .py file is as follows:

-*- coding: uti-8 -*# Form implementation generated from reading ui file
'C:\Users\Amar\BR_GUI.ui'

```
from PyQt5 import QtCore, QtGui, QtWidgets
   def setupUi(self, MainWindow):
        self.centralwidget = QtWidgets.QWidget(MainWindow)
        self.widget = QtWidgets.QWidget(self.centralwidget)
        self.widget.setGeometry(QtCore.QRect(30, 10, 537, 161))
        self.widget.setObjectName("widget")
        self.gridLayout = QtWidgets.QGridLayout(self.widget)
        self.pushButton 4 = QtWidgets.QPushButton(self.widget)
        self.pushButton 2 = QtWidgets.QPushButton(self.widget)
        self.pushButton = QtWidgets.QPushButton(self.widget)
        self.pushButton.setObjectName("pushButton")
        self.label 2.setObjectName("label 2")
        self.gridLayout.addWidget(self.label 2, 6, 0, 1, 1)
        self.label = QtWidgets.QLabel(self.widget)
        spacerItem = QtWidgets.QSpacerItem(20, 48,
QtWidgets.QSizePolicy.Minimum, QtWidgets.QSizePolicy.Expanding)
        spacerItem1 = QtWidgets.QSpacerItem(20, 48,
QtWidgets.QSizePolicy.Minimum, QtWidgets.QSizePolicy.Expanding)
        spacerItem3 = QtWidgets.QSpacerItem(568, 20,
QtWidgets.QSizePolicy.Expanding, QtWidgets.QSizePolicy.Minimum)
        self.menubar = QtWidgets.QMenuBar(MainWindow)
```

```
self.menubar.setGeometry(QtCore.QRect(0, 0, 667, 24))
        self.menubar.setObjectName("menubar")
        self.menuStart.setObjectName("menuStart")
        self.menuImport Data.setObjectName("menuImport Data")
        self.menuPlot = QtWidgets.QMenu(self.menubar)
        self.menuPlot.setObjectName("menuPlot")
        self.menuCorrelation Matrix = QtWidgets.QMenu(self.menuPlot)
        self.menuProperties = QtWidgets.QMenu(self.menubar)
        self.menuProperties.setObjectName("menuProperties")
        self.menuTablulate.setObjectName("menuTablulate")
        self.statusbar = QtWidgets.QStatusBar(MainWindow)
        self.toolBar = QtWidgets.QToolBar(MainWindow)
        self.toolBar.setObjectName("toolBar")
        self.actionVariables = QtWidgets.QAction(MainWindow)
        self.actionROA C beforeinterestanddepreceiationbeforeinterest =
QtWidgets.QAction (MainWindow)
self.actionROA C beforeinterestanddepreceiationbeforeinterest.setObjectName("
        self.actionROA A beforeinterestsnd aftertax =
QtWidgets.QAction(MainWindow)
        self.actionROA B beforeinterestanddespreciationaftertax =
QtWidgets.QAction(MainWindow)
self.actionROA B beforeinterestanddespreciationaftertax.setObjectName("action
        self.actionOperating Gross Margin = QtWidgets.QAction(MainWindow)
QtWidgets.QAction (MainWindow)
self.actionRealized Sales Gross Margin.setObjectName("actionRealized Sales Gr
```

```
self.actionOperating Profit Rate = QtWidgets.QAction(MainWindow)
        self.actionPre tax Net Interest rate = QtWidgets.QAction(MainWindow)
self.actionPre tax Net Interest rate.setObjectName("actionPre tax Net Interes
        self.actionAfter tax Net Interest Rate =
QtWidgets.QAction(MainWindow)
QtWidgets.QAction(MainWindow)
self.actionNon industry Income and Expenditure Revenue.setObjectName("actionN
        self.actionContinuous Interest Rate After Tax =
QtWidgets.QAction(MainWindow)
        self.actionOperating Expense Rate = QtWidgets.QAction(MainWindow)
self.actionOperating Expense Rate.setObjectName("actionOperating Expense Rate
        self.actionResearch and Development Expense Rate =
QtWidgets.QAction (MainWindow)
self.actionResearch and Development Expense Rate.setObjectName("actionResearc
        self.actionCash Flow Rate = QtWidgets.QAction(MainWindow)
        self.actionTax Rate A = QtWidgets.QAction(MainWindow)
        self.actionTax Rate A.setObjectName("actionTax Rate A")
        self.actionNet Value Per Share A = QtWidgets.QAction(MainWindow)
self.actionNet Value Per Share A.setObjectName("actionNet Value Per Share A")
       self.actionNet Value Per Share B = QtWidgets.QAction(MainWindow)
self.actionNet Value Per Share B.setObjectName("actionNet Value Per Share B")
        self.actionNet Value Per Share C = QtWidgets.QAction(MainWindow)
QtWidgets.QAction(MainWindow)
        self.actionCash Flow Per Share = QtWidgets.QAction(MainWindow)
        self.actionRevenue Per Share YuanY = QtWidgets.QAction(MainWindow)
self.actionRevenue Per Share YuanY.setObjectName("actionRevenue Per Share Yua
        self.actionOperating Profit Per Share YuanY =
```

```
QtWidgets.QAction(MainWindow)
self.actionOperating    Profit Per Share YuanY.setObjectName("actionOperating Pr
        self.actionPer SHare Net Profit Before Tax YuanY =
QtWidgets.QAction(MainWindow)
QtWidgets.QAction(MainWindow)
QtWidgets.QAction(MainWindow)
self.actionOperating    Profit Growth Rate.setObjectName("actionOperating Profit
QtWidgets.QAction(MainWindow)
QtWidgets.QAction (MainWindow)
self.actionRegular Net Profit Growth Rate.setObjectName("actionRegular Net Pr
        self.actionContinuous Net Profit Growth Rate =
QtWidgets.QAction(MainWindow)
self.actionTotal Asset Growth Rate.setObjectName("actionTotal Asset Growth Ra
        self.actionNet Value Growth Rate = QtWidgets.QAction(MainWindow)
self.actionNet Value Growth Rate.setObjectName("actionNet Value Growth Rate")
QtWidgets.QAction(MainWindow)
        self.actionCash Reinvestment = QtWidgets.QAction(MainWindow)
        self.actionCurrent Ratio = QtWidgets.QAction(MainWindow)
        self.actionQuick Ratio = QtWidgets.QAction(MainWindow)
        self.actionInterest Expense Ratio = QtWidgets.QAction(MainWindow)
self.actionInterest Expense Ratio.setObjectName("actionInterest Expense Ratio
        self.actionTotal Debt Total net Worth = QtWidgets.QAction(MainWindow)
```

```
self.actionTotal Debt Total net Worth.setObjectName("actionTotal Debt Total n
        self.actionDebt Ratio = QtWidgets.QAction(MainWindow)
        self.actionNet Worth Assets = QtWidgets.QAction(MainWindow)
        self.actionShape = QtWidgets.QAction(MainWindow)
        self.actionList = QtWidgets.QAction(MainWindow)
        self.actionSummary Statistics = QtWidgets.QAction(MainWindow)
        self.actionSize = QtWidgets.QAction(MainWindow)
        self.actionComplete = QtWidgets.QAction(MainWindow)
        self.actionComplete.setObjectName("actionComplete")
        self.actionPositive = QtWidgets.QAction(MainWindow)
        self.actionPositive.setObjectName("actionPositive")
        self.actionNegative = QtWidgets.QAction(MainWindow)
        self.actionPCA Feature Composition = QtWidgets.QAction(MainWindow)
self.actionPCA Feature Composition.setObjectName("actionPCA Feature Compositi
        self.actionClass Imbalance = QtWidgets.QAction(MainWindow)
        self.actionClass Imbalance.setObjectName("actionClass Imbalance")
        self.actionDebt Ratio to Bankruptcy = QtWidgets.QAction(MainWindow)
QtWidgets.QAction(MainWindow)
self.actionDebt Ratio vs Asset Turnover.setObjectName("actionDebt Ratio vs As
        self.actionGrouped Means = QtWidgets.QAction(MainWindow)
        self.actionGrouped Means.setObjectName("actionGrouped Means")
        self.actionLPM Results = QtWidgets.QAction(MainWindow)
        self.actionLPM Results.setObjectName("actionLPM Results")
        self.actionProbit Results = QtWidgets.QAction(MainWindow)
        self.actionRaw Data = QtWidgets.QAction(MainWindow)
        self.actionClean Data 2 = QtWidgets.QAction(MainWindow)
        self.actionClean Data 2.setObjectName("actionClean Data 2")
        self.actionView GitHub Repository = QtWidgets.QAction(MainWindow)
        self.actionView Project Report = QtWidgets.QAction(MainWindow)
self.actionView Project Report.setObjectName("actionView Project Report")
```

```
self.menuStart.addSeparator()
self.menuStart.addAction(self.actionView GitHub Repository)
self.menuStart.addAction(self.actionView Project Report)
self.menuCorrelation Matrix.addAction(self.actionPositive)
self.menuCorrelation Matrix.addAction(self.actionNegative)
self.menuInferential Plots.addSeparator()
self.menuInferential Plots.addAction(self.actionGrouped Means)
self.menuDataset.addAction(self.actionShape)
self.menuProperties.addAction(self.menuDataset.menuAction())
self.menuProperties.addAction(self.menuVariables 2.menuAction())
self.menuTablulate.addSeparator()
self.menubar.addAction(self.menuPlot.menuAction())
self.retranslateUi(MainWindow)
self.pushButton 4.clicked.connect(MainWindow.pushButton click)
QtCore.QMetaObject.connectSlotsByName(MainWindow)
 translate = QtCore.QCoreApplication.translate
MainWindow.setWindowTitle(_translate("MainWindow", "MainWindow"))
self.pushButton_4.setText(_translate("MainWindow", "PCA Results"))
self.pushButton_2.setText(_translate("MainWindow", "LPM Results"))
self.menuStart.setTitle( translate("MainWindow", "Start"))
```

```
self.menuInferential Plots.setTitle( translate("MainWindow",
       self.menuProperties.setTitle( translate("MainWindow", "Properties"))
self.actionROA B beforeinterestanddespreciationaftertax.setText( translate("M
self.actionAfter tax    Net Interest Rate.setText( translate("MainWindow",
       self.actionNet Value Per Share A.setText( translate("MainWindow",
       self.actionNet Value Per Share B.setText( translate("MainWindow",
```

```
self.actionCash Flow Per Share.setText( translate("MainWindow", "Cash
self.actionPer SHare Net Profit Before Tax YuanY.setText( translate("MainWind
self.actionOperating Profit Growth Rate.setText( translate("MainWindow",
       self.actionTotal Asset Growth Rate.setText( translate("MainWindow",
       self.actionCash Reinvestment.setText( translate("MainWindow", "Cash
       self.actionQuick Ratio.setText( translate("MainWindow", "Quick
```

Additionally, I used the PyQt5 library to connect this GUI with our code. The code for this is as follows:

```
PCA Var Weight.set index('Variables', inplace=True)
        self.pushButton click()
        self.aktions()
        self.data r()
    def pushButton click(self):
        self.pB Probit.clicked.connect(dpro)
        self.pB CHMap.clicked.connect(dchm)
   def aktions(self):
        self.actionCM Complete.triggered.connect(dchm)
        self.actionCM Positive.triggered.connect(acmp)
        self.actionIP PCA FComp.triggered.connect(ippc)
        self.actionIP Debt Ratio to Bankruptcy.triggered.connect(ipdb)
        self.actionView Git.triggered.connect(vgit)
   def data c(self):
```

```
PCA Results Viewer
def dpca():
   PCA Var Weight.set index('Variables', inplace=True)
def dpro():
   Probit Results = pd.read csv('Probit Results.csv', index col=0)
   plt.show()
def dpre():
def draw():
def raw dial():
```

```
def dcle():
   print(raw.shape)
def acmp():
   corrPos = corr mat.iloc[:, 0].sort values(ascending=False).iloc[0:18]
   print(corrPos)
```

```
print("*" * 75)
def ipci():
    plt.show()
def ipgm():
   bankrupt means = pd.melt(bankrupt means, id vars='Bankrupt',
def ipdb():
   plt.show()
def ipda():
def vrep():
```

```
# Redirect to Kaggle Competition
def vkag():
    webbrowser.open("https://www.kaggle.com/fedesoriano/company-bankruptcy-
prediction/code")

# GUI RUNNER
if __name__ == '__main__':
    app = QApplication(sys.argv)
    my_pyqt_form = MyBR_GUI()
    my_pyqt_form.show()
    sys.exit(app.exec_())
```

4. Results

Below, I report the results from our seven statistical models., which are the Principal Component Analysis, the Logistic regression, the Probit regression, Decision Tree Classifier, Multi-Layer Perceptron Classifier, Histogram-based Gradient Boosting Regressor, and the Linear Probability Model.

The LPM results are below, sorted by magnitude:

Variable	Beta	Standar	T-Stat	P-values
		d Error		
Totaldebt/Totalnetworth	0.05692	0.00652	8.72506	2.66E-
	8514	4709	6282	18
Constant	0.03226	0.00193	16.6714	2.11E-
	2795	5207	9746	62
Operatingprofit/Paid-incapital	0.03149	0.00615	5.11695	3.11E-
	7086	543	9648	07
TotalAssetTurnover	0.02066	0.00588	3.51311	0.00044
	1977	1382	5917	2884
Totalexpense/Assets	0.01997	0.00595	3.35420	0.00079
	927	6478	888	5923
Cash/CurrentLiability	0.01849	0.00730	2.53099	0.01137
	0886	577	7459	3867
NetValuePerShare(C)	0.01761	0.00385	4.57534	4.75E-
	8261	0694	6833	06
Revenueperperson	0.01413	0.00459	3.07688	0.00209
	3286	3376	3962	1767
Liability-AssetsFlag	0.01002	0.00426	2.34788	0.01888
	2477	8733	1013	0552
Contingentliabilities/Networth	0.00931	0.00113	8.19818	2.44E-
	4309	6143	0515	16
CurrentLiabilitytoLiability	0.00620	0.00270	2.29475	0.02174
·	577	4328	4419	7202
Totalincome/Totalexpense	0.00179	0.00076	2.33390	0.01960
	0716	7261	6765	0604

TotalAssetGrowthRate	-	0.00183	-	0.00329
	0.00539	532	2.93900	2656
	4018		705	
Taxrate(A)	-	0.00196	_	0.00112
	0.00638	1173	3.25736	4521
	8254		4168	
NetValueGrowthRate	-	0.00227	-	0.00049
	0.00790	0913	3.48224	722
	7885		9769	
AccountsReceivableTurnover	-	0.00269	-	7.81E-
	0.01065	6245	3.95005	05
	0307		2333	
Operatingprofitperperson	-	0.00399	-	0.00020
	0.01484	5807	3.71413	3898
	0975		7545	
Netprofitbeforetax/Paid-	-	0.00745	-	0.00378
incapital	0.02157	2767	2.89532	7632
	8202		7463	
ROA(B)beforeinterestanddeprec	-	0.00740	-	0.00043
iationaftertax	0.02604	5364	3.51675	6856
	2856		5642	
RevenuePerShare(Yuan¥)	-	0.00682	-	6.83E-
	0.04901	3678	7.18286	13
	3524		0249	

The results from the LPM in the table are for variables that are standardized, which allows us to compare the magnitudes against each other. However, it is important to note that none of our variables are insignificant at the 95% significance level (alpha = 5%) are included here. Explaining the most impactful variable here, a one-standard deviation increase in the (Total Debt)/(Total Net Worth) increases the possibility if a firm declaring bankruptcy by nearly 5.7 percentage points. he other coefficients have the same interpretation. We see that in general, debt and liability ratios increase the probability of bankruptcy, while value/profitability metrics decrease the probability of bankruptcy, which is logical. However, there are some curious results from this estimation – we see that Net Value per Share and Asset Turnover have positive coefficients, implying that as they increase, the probability of bankruptcy increases. This may be the result of omitted variables bias – indeed, it is easy to reason that an intangible omitted variable such as 'Executive Competence' would surely influence the probability of bankruptcy.

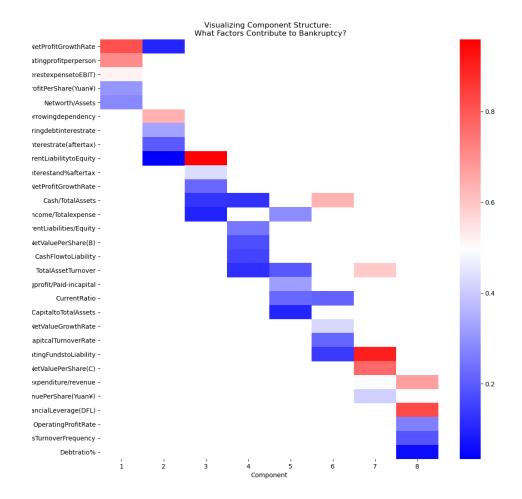
Our Probit Model results are as follows:

Variable	Parameters	T-Stat	P-values
Operatingprofit/Paid-incapital	0.467751671	3.192098992	0.001412429
Totaldebt/Totalnetworth	0.374387096	7.561067932	4.00E-14
Revenueperperson	0.185454735	3.111594243	0.001860801
GrossProfittoSales	0.097805344	2.107706823	0.035056357
AverageCollectionDays	0.087668754	2.009843246	0.044447782

Cash/CurrentLiability	0.079282144	2.459584177	0.013909807
Cashflowrate	-0.16056375	-	0.010096499
		2.572506752	
QuickRatio	-	-	0.00832482
	0.212959966	2.638603834	
Cash/TotalAssets	-0.23139262	-	0.031382021
		2.152194726	
AccountsReceivableTurnover	-0.24360273	-4.33921339	1.43E-05
RevenuePerShare(Yuan¥)	-	-	0.029304919
	0.302684324	2.179360221	
ROA(B)beforeinterestanddepreciationaftertax	-	-	0.000142947
_	0.323479296	3.803013532	
Netprofitbeforetax/Paid-incapital	-	-	0.000833619
	0.529058932	3.341383889	
Constant	-	-	7.65E-136
	2.797022563	24.80639267	

We see that the most important determinant of bankruptcy in the Probit is (Operating Profit)/(Paid-in Capital), with a coefficient of approximately 0.467. This means that a one standard deviation increase in (Operating Profit/Paid-in Capital) is estimated to increase the Z-score by 0.467. As the Probit is a nonlinear model, the actual partial effect of this increase will change depending on where in the distribution the initial Z-score falls. Unfortunately, interpretation is further complicated by omitted variable bias, more severe in the probit than in the LPM. This is evidenced by variables such Revenue per Person having a positive coefficient, implying an increased probability of bankruptcy as Revenue per Person increases, which is nonsensical. The reason for this increased bias is that, unlike in OLS regression with the LPM, omitting features which are correlated with the outcome but not with the other predictors leads to bias in coefficient estimates of the predictors.

Our Principal Component Analysis suggests that without standardizing the data, just eight components alone can explain 97% of the variation in the data. The deconstruction of the components is as follows:



We see that each component is mostly comprised of a group of related variables. The first component is comprised of profitability metrics, the fifth component is mostly comprised of liquidity metrics, and so on. While the PCA did not feature heavily into our analysis, it provides an intriguing path for future analysis.

The results of our four machine learning models are as follows:

F1 Score	Estimator
0.75	Decision Tree Classifier
0.74	MLP Classifier
0.74	Histogram Gradient Boosting Classifier
0.61	Logistic Regression

We find that the decision tree classifier had the best performance, closely followed by the MLP classifier and the Histogram Gradient Boosting Classifier. Logistic Regression performed notably worse than the other models. All model parameters were tuned using Grid SearchCV.

5. Conclusion

The results of our inferential and predictive models suggest that debt indicators tend to increase the probability of a firm declaring bankruptcy, and these effects are stronger than the negative effects of the probability indices on bankruptcy. It is important to note that our inferential models suffer from an omitted variable bias, which may lead to spurious results.

Our predictive models show that a Random tree Classifier explains our data with 75% accuracy, and can be further trained to understand the determinants of bankruptcy in similar datasets. This data also suffers from two collection problems: high multicollinearity and class imbalance. We try to address these issues, but find high collinearity still persists in our data.

Future models can build on these results, and use our findings to hyper-tune the parameters of their predictive models to better build models that gauge bankruptcy based on these factors.

6. Code Percentage

Total code lines without blank lines or comments: 674 Total lines of code found on internet, other sources: 76 Total lines of code modified (that were found): 8 Total lines of code added (own): 598 Percentage: (76-8)*100 = 9.79%. (76+598)

7. References

Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The journal of finance*, 23(4), 589-609.

Chawla, Nitesh V., Kevin W. Bowyer, Lawrence O. Hall, and W. Philip Kegelmeyer. "SMOTE: synthetic minority over-sampling technique." *Journal of artificial intelligence research* 16 (2002): 321-357.

Lee, Tsun-Siou, and Yin-Hua Yeh. "Corporate governance and financial distress: Evidence from Taiwan." (2004): 378-388.

Liang, Deron, Chia-Chi Lu, Chih-Fong Tsai, and Guan-An Shih. "Financial ratios and corporate governance indicators in bankruptcy prediction: A comprehensive study." *European Journal of Operational Research* 252, no. 2 (2016): 561-572.

Lin, Wei-Yang, Ya-Han Hu, and Chih-Fong Tsai. "Machine learning in financial crisis prediction: a survey." *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)* 42, no. 4 (2011): 421-436.

Shailer, Gregory EP. *An introduction to corporate governance in Australia*. Pearson Education Australia, 2004.