Final Paper

Professor: Johanna Devaney

Student: Ethan Lo

CUNY Graduate Center
Data Analysis and Visualization
DATA 71200 Advanced Data Analysis Methods (Summer 2022)

Contents

1) Describe your data set, why you chose it, and what you are trying to predict with it

My data set is "Company Bankruptcy Prediction" from Kaggle.com (https://www.kaggle.com/datasets/fedesoriano/company-bankruptcy-prediction). There are three reasons why I have chosen the data set; first, The data were collected from the Taiwan Economic Journal for the years 1999 to 2009. Company bankruptcy was defined based on the business regulations of the Taiwan Stock Exchange. As a Taiwanese I have to honor their hard work. Second, Since the data set has only binary labels, and it will be used for predicting both supervised and unsupervised experiments. It will be more convenient for my processed. Last but not least, it has 95 features and 6819 rows, perfect amounts for both supervised and unsupervised learning; A large enough number of features to training effectively, but there won't be too many rows causing training to take too much time.

The goal of predicting is a company will Bankruptcy or not.

2) Detail what you did to clean your data and any changes in the data representation that you applied. Discuss any challenges that arose during this process.

General Description

Use scikitlearn to divide the data set into training and testing sets. Make sure that the testing and training sets are balanced in terms of target classes. The dataset is composed of a combination of 6819 observations per each of our 96 features. All of the features are numerical (int64 or float64). There are no missing values (Nan) among the data. The Class label is "Bankrupt?", 0 is fine, 1 is bankrupt. The detail of the data set is in the Annexs.

Value Counts

Looking at the result, it is clear to see how the labels are strongly unbalanced. We got 6599 rows are Financially stable, only 220 rows are Financially unstable.

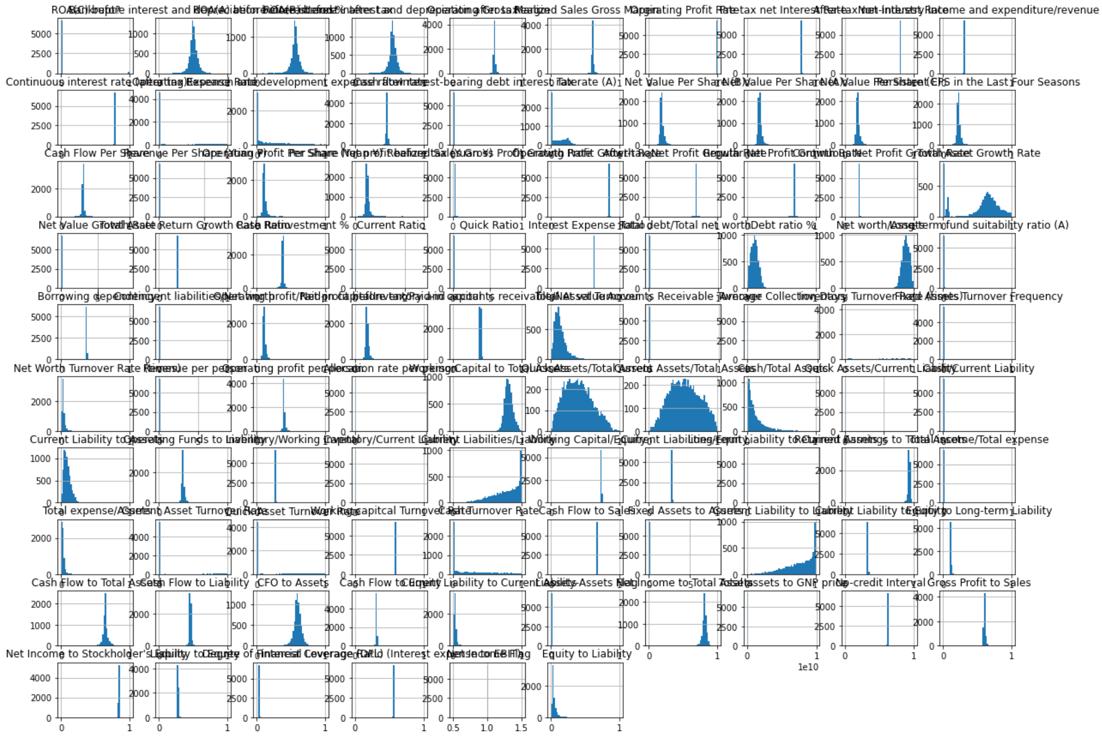
```
[ ] print('Target Value_counts:')
    print(bank_data['Bankrupt?'].value_counts())
    print('-'* 30)
    print('Financially stable: ', round(bank_data['Bankrupt?'].value_counts()[0]/len(bank_data) * 100,2), '% of th
    print('Financially unstable: ', round(bank_data['Bankrupt?'].value_counts()[1]/len(bank_data) * 100,2), '% of

    Target Value_counts:
    0    6599
    1     220
    Name: Bankrupt?, dtype: int64
    ------------------------------
    Financially stable:  96.77 % of the dataset
    Financially unstable:  3.23 % of the dataset
```

Data Cleaning

Although we already know that there are no missing values, it is important to computationally check that this is true. I used DataFrame.dropna() function to make sure no missing values in my data set. In the end, used DataFrame.duplicated().sum() to make sure there has no duplicated in the data set.

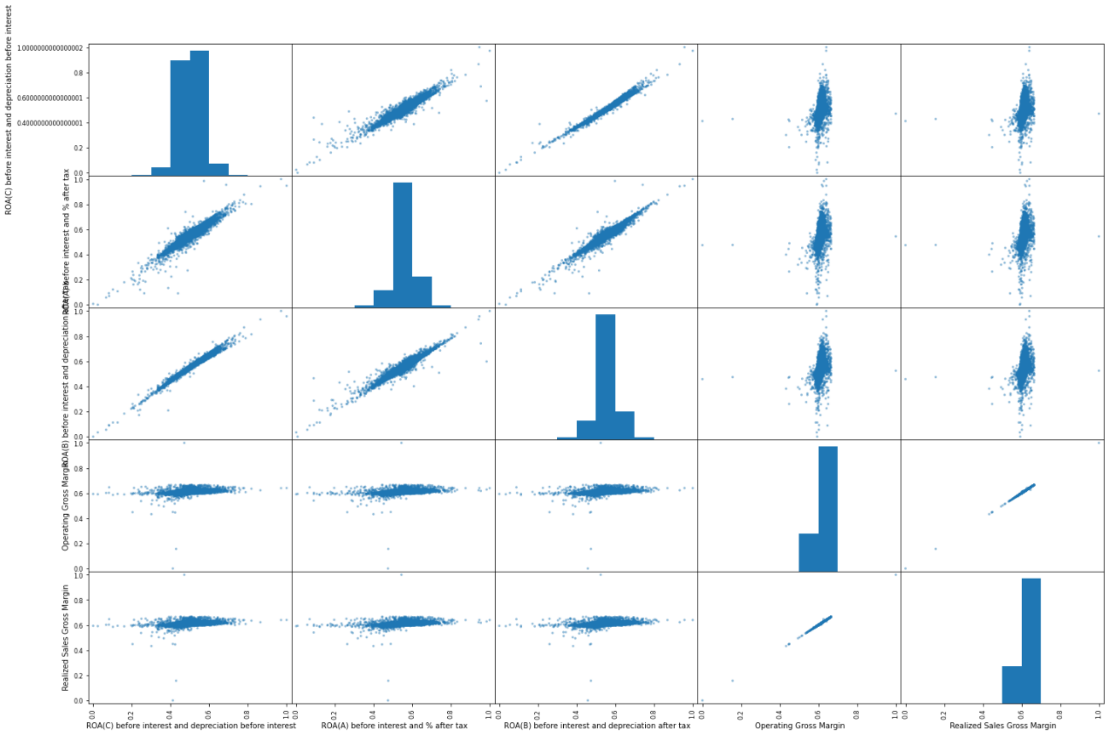
3) Discuss what you learned by visualizing your data

DataFrame.hist



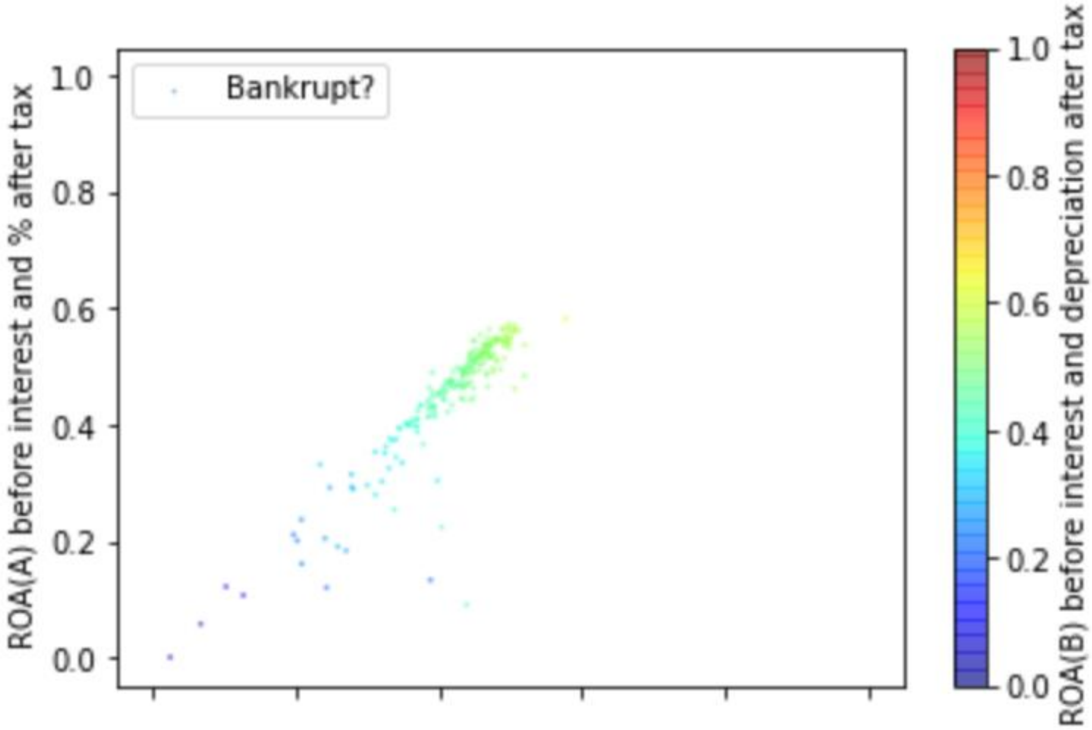
The features in the dataset have significant similarities, probably related to me not standardizing beforehand.

plotting.scatter_matrix()



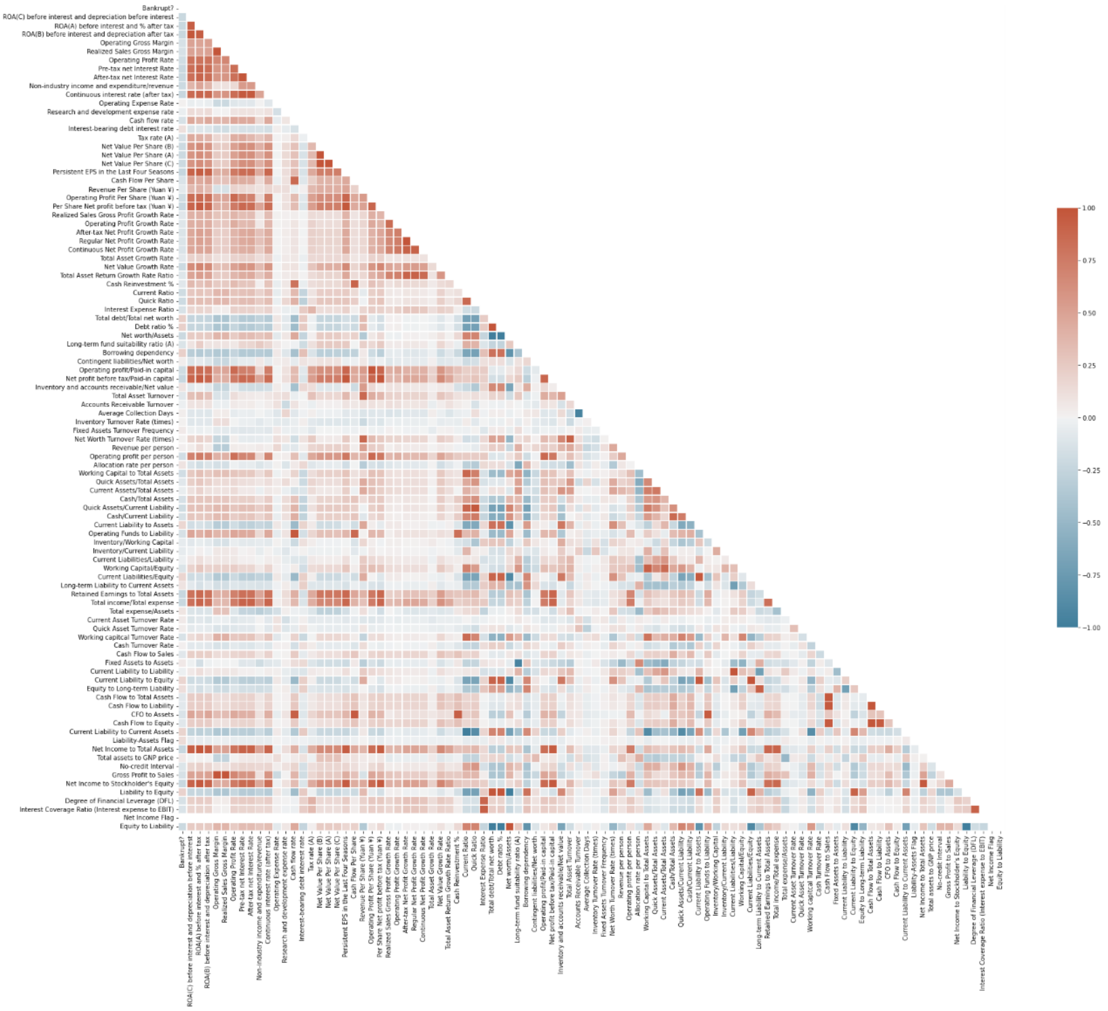
Only do plotting.scatter_matrix() in the first 5 columns, because use all 96 columns will take forever. Most of the data are normally distributed, so using standardization would be a good preprocessing method.

Scatter Plot



The features be selected are x=' ROA(C) before interest and depreciation before interest', y=' ROA(A) before interest and % after tax' There is a strong positive correlation between the two. But for the prediction of the model, it doesn't seem to be very helpful.

Heatmap



According to the heat map, it can be intuitively found that about half of the data does not have a strong correlation for prediction. The evidence is we only requered 53 features in PCA () to acchive 95% of Variance Explained.

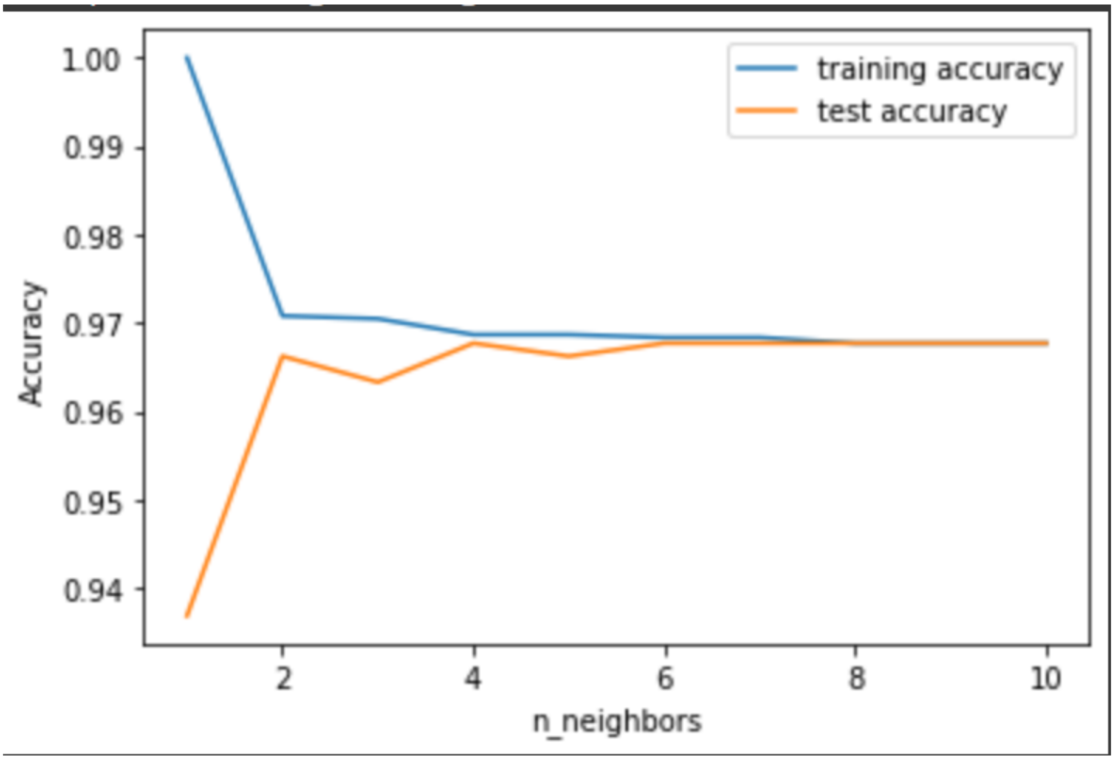
4) Describe your experiments with the two supervised learning algorithms you chose. This should include a brief description, in your own words, of what the

algorithms do and the parameters that you adjusted. You should also report the relative performance of the algorithms on predicting your target attribute, reflecting on the reasons for any differences in performance between models and parameter settings.

the two supervised learning algorithms has chosen were k-Nearest Neigbors Classification and Support Vector Machines.

k-Nearest Neigbors

The reseon why I chosen k-Nearest Neigbors was because that the data set is base on binery claissfattion. As far I know, k-Nearest Neigbors usesuly has well performance in those kind of subject. First, I compared different values for k. As the result, after k >= 4, it has not too much impovement for my model.



So I used Cross Validation to test the comment. When “n_neighbors=4” in 5-fold of Cross Validation, the mean accuracy is 0.9675 which is closs with my 假說. The second think I did is to optimize my model; Used GridSearchCV to find the best params. As the result, when {'metric': 'chebyshev', 'n_neighbors': 9, 'weights': 'distance'} the model has the bast performance. In the test data set, the model got accuracy of best performing params 0.9679.

For Evaluation Metrics:

In KNN model:

Test set R^2: 0.96

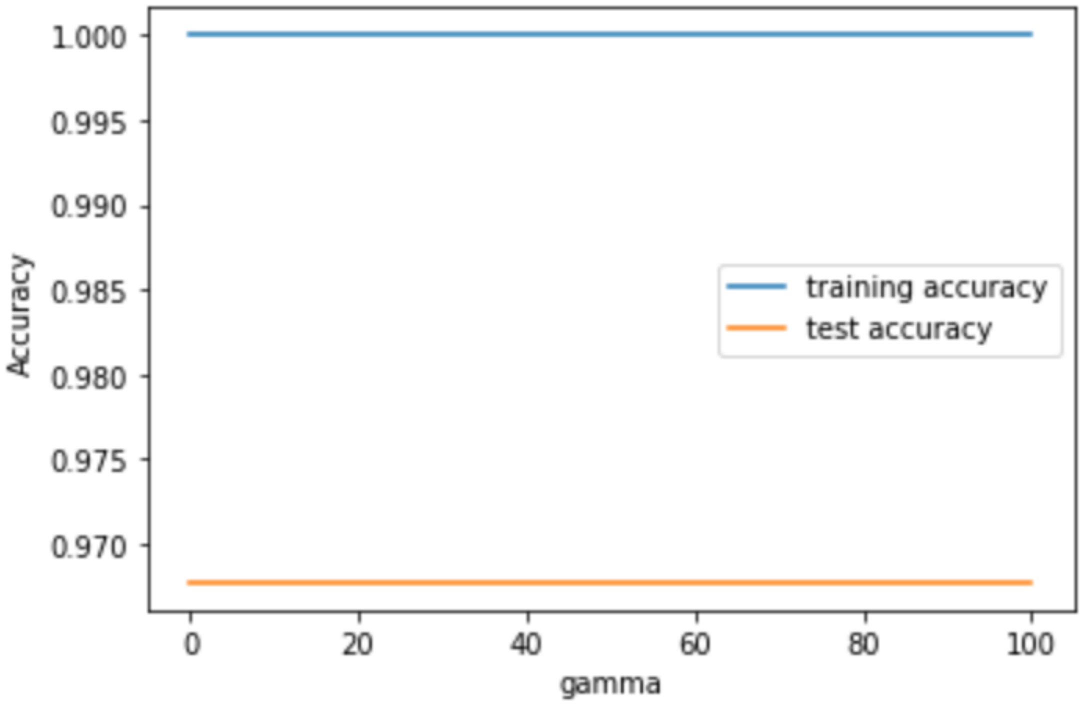
Test set RMSE: 0.04

Test set MSE: 0.04

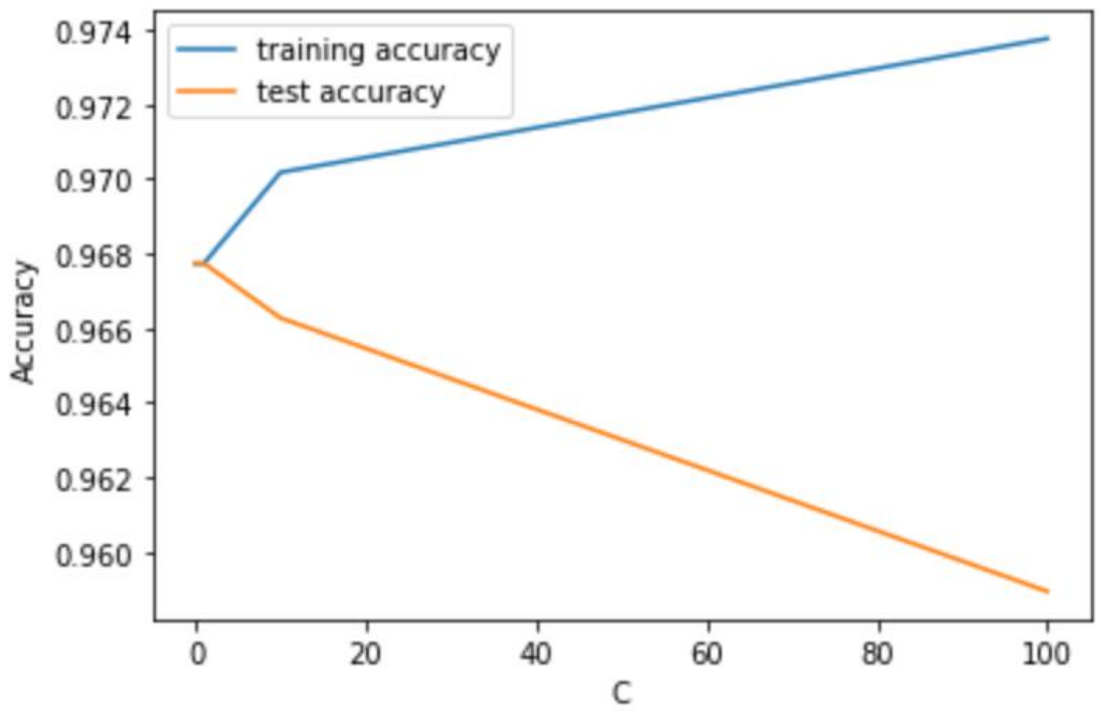
Test set F1: 0.00

Support Vector Machines

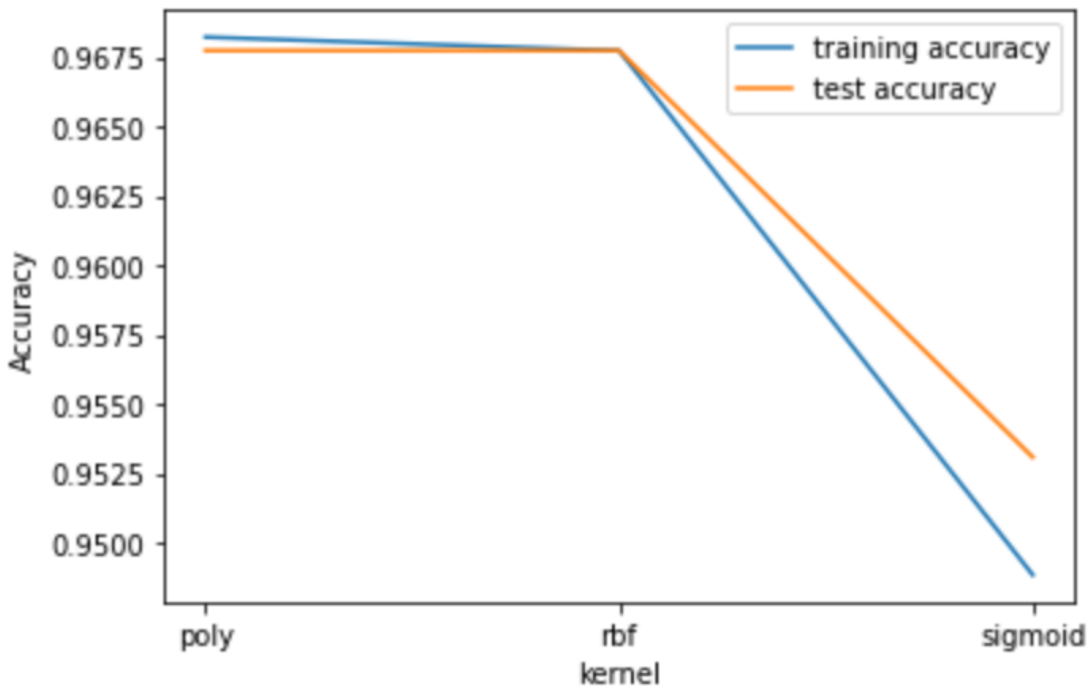
The reseon why I chosen Support Vector Machines was because that the data set has 95 features whick is a high dimaintion data set. In the high dimaintion 維度 situation, Support Vector Machines is the perfect way to solve the problem. Fisrt, I compared different values for gamma, I tried gamma = [0.001, 0.01, 0.1, 1, 10, 100], not much difference in this case.



Second I compared different values for C, C_settings = [0.001, 0.01, 0.1, 1, 10, 100], By the result, when C was growing, the accuracy getting worse.



Finely, I compared different values for kernel, In the kernel, if used linear couldn't run. In the plot, it's easy to see “poly” and “rbf” have better performance than sigmoid in this data set.



For optimized my model; Used GridSearchCV to find the best params. As the result, when {'C': 0.01, 'gamma': 0.01, 'kernel': 'rbf'} the model has the bast performance, The best accuracy is 0.968 in the test data set. In evaluation metrics:

In SVC model:

Test set R^2: 0.97

Test set RMSE: 0.03

Test set MSE: 0.03

Test set F1: 0.00

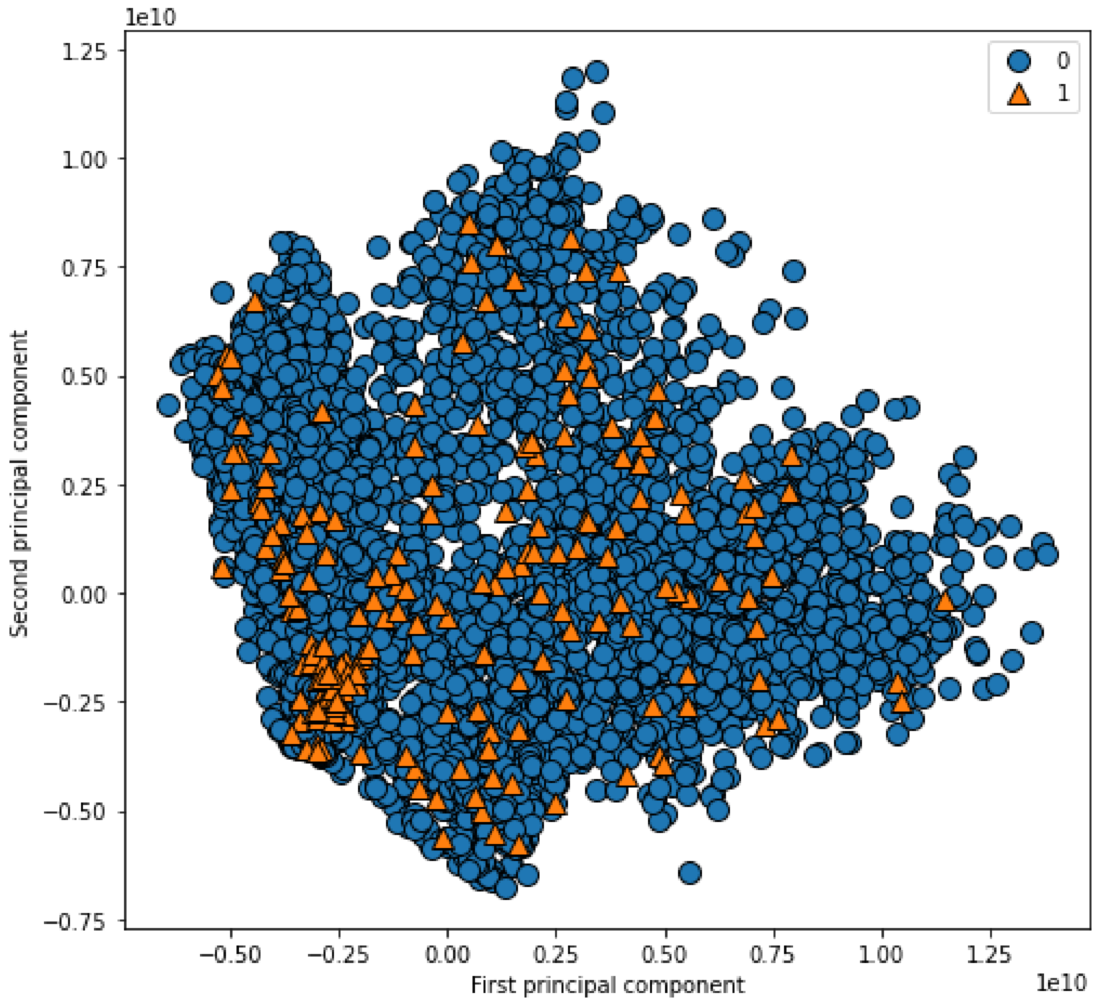
Since the data set has the 95 dimestion(維度), Support Vector Machines has better performance than k-Nearest Neigbors Classification was totally be excepted.

5) Describe your experiments using PCA for feature selection, discussing whether it improved any of your results with your best-performing supervised learning algorithm.

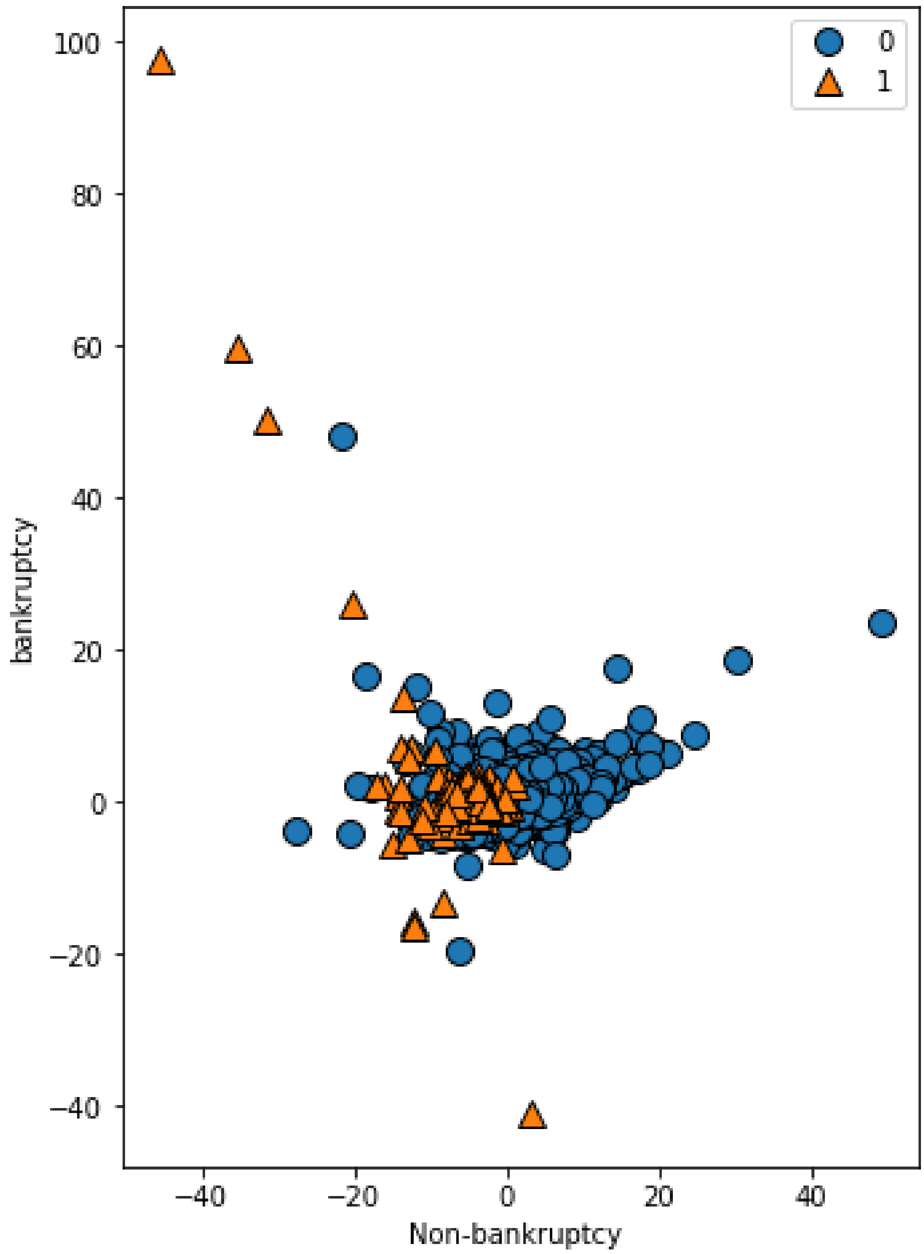
PCA() doing the great job to save my time. To retain to capture 95% of the variance, only required 53 features which are almost half of the whole 95 features. This can be seen in my k-Nearest Neigbors model. We can intuitively see that after passing through PCA(), when using the same hyperparameters, the accuracy of the model has indeed been improved, from 0.9675 to 0.9677. However, in Support Vector Machines, PCA() has no effect, the reason is because Support Vector Machines it already contains the function of dimensionality reduction.

6) Discuss the results of using PCA as a pre-processing step for clustering. This should include a brief description, in your own words, of what the algorithms do. If you used the Wine dataset for this, briefly explain why your original dataset wasn't appropriate.

PCA effectively reduces the complexity of the model, and taking half of the features in my dataset can explain almost 95% of the dataset. In addition to improving the speed of training, this also reduces the interference of noise. And scaled data or unscaled data has very significant difference. This graph is unscaled data and is basically completely unclassifiable.



This graph is scaled data and it looks good on classifiable.



7) Summarize what you learned across the three projects, including what you think worked and what you would do differently if you had to do it over.

I wasn't fine-tuned enough in the data processing this time, although the data it has been processed, but next time I hope to remove the deviation from the mean. Then I want to standardize the data and then visualize it, maybe I can observe more interesting results. This time, I only used k-Nearest Neighbors and Support Vector Machines. Next time, I will want to add random forest to see if it can be better than the current model. And since I didn't expect PCA to have no effect on Support Vector Machines, I'll try to replace Support Vector Machines with another model next time.

Appendix

	Column	Dtype
0	Bankrupt?	int64
1	ROA(C) before interest and depreciation before interest	float64
2	ROA(A) before interest and % after tax	float64
3	ROA(B) before interest and depreciation after tax	float64
4	Operating Gross Margin	float64
5	Realized Sales Gross Margin	float64
6	Operating Profit Rate	float64
7	Pre-tax net Interest Rate	float64
8	After-tax net Interest Rate	float64
9	Non-industry income and expenditure/revenue	float64
10	Continuous interest rate (after tax)	float64
11	Operating Expense Rate	float64
12	Research and development expense rate	float64
13	Cash flow rate	float64
14	Interest-bearing debt interest rate	float64
15	Tax rate (A)	float64
16	Net Value Per Share (B)	float64
17	Net Value Per Share (A)	float64
18	Net Value Per Share (C)	float64
19	Persistent EPS in the Last Four Seasons	float64
20	Cash Flow Per Share	float64
21	Revenue Per Share (Yuan ¥)	float64
22	Operating Profit Per Share (Yuan ¥)	float64
23	Per Share Net profit before tax (Yuan ¥)	float64

24 Realized Sales Gross Profit Growth Rate	float64
25 Operating Profit Growth Rate	float64
26 After-tax Net Profit Growth Rate	float64
27 Regular Net Profit Growth Rate	float64
28 Continuous Net Profit Growth Rate	float64
29 Total Asset Growth Rate	float64
30 Net Value Growth Rate	float64
31 Total Asset Return Growth Rate Ratio	float64
32 Cash Reinvestment %	float64
33 Current Ratio	float64
34 Quick Ratio	float64
35 Interest Expense Ratio	float64
36 Total debt/Total net worth	float64
37 Debt ratio %	float64
38 Net worth/Assets	float64
39 Long-term fund suitability ratio (A)	float64
40 Borrowing dependency	float64
41 Contingent liabilities/Net worth	float64
42 Operating profit/Paid-in capital	float64
43 Net profit before tax/Paid-in capital	float64
44 Inventory and accounts receivable/Net value	float64
45 Total Asset Turnover	float64
46 Accounts Receivable Turnover	float64
47 Average Collection Days	float64
48 Inventory Turnover Rate (times)	float64
49 Fixed Assets Turnover Frequency	float64
50 Net Worth Turnover Rate (times)	float64
51 Revenue per person	float64
52 Operating profit per person	float64
53 Allocation rate per person	float64
54 Working Capital to Total Assets	float64
55 Quick Assets/Total Assets	float64
56 Current Assets/Total Assets	float64
57 Cash/Total Assets	float64
58 Quick Assets/Current Liability	float64
59 Cash/Current Liability	float64
60 Current Liability to Assets	float64
61 Operating Funds to Liability	float64

```
 62 Inventory/Working Capital                            float64
 63 Inventory/Current Liability                          float64
 64 Current Liabilities/Liability                        float64
 65 Working Capital/Equity                               float64
 66 Current Liabilities/Equity                           float64
 67 Long-term Liability to Current Assets                float64
 68 Retained Earnings to Total Assets                    float64
 69 Total income/Total expense                           float64
 70 Total expense/Assets                                 float64
 71 Current Asset Turnover Rate                          float64
 72 Quick Asset Turnover Rate                            float64
 73 Working capitcal Turnover Rate                       float64
 74 Cash Turnover Rate                                   float64
 75 Cash Flow to Sales                                   float64
 76 Fixed Assets to Assets                               float64
 77 Current Liability to Liability                       float64
 78 Current Liability to Equity                          float64
 79 Equity to Long-term Liability                        float64
 80 Cash Flow to Total Assets                            float64
 81 Cash Flow to Liability                               float64
 82 CFO to Assets                                        float64
 83 Cash Flow to Equity                                  float64
 84 Current Liability to Current Assets                  float64
 85 Liability-Assets Flag                                int64
 86 Net Income to Total Assets                           float64
 87 Total assets to GNP price                            float64
 88 No-credit Interval                                   float64
 89 Gross Profit to Sales                                float64
 90 Net Income to Stockholder's Equity                   float64
 91 Liability to Equity                                  float64
 92 Degree of Financial Leverage (DFL)                   float64
 93 Interest Coverage Ratio (Interest expense to EBIT)   float64
 94 Net Income Flag                                      int64
 95 Equity to Liability                                  float64
dtypes: float64(93), int64(3)
```