Python for Data Analysis Final Project

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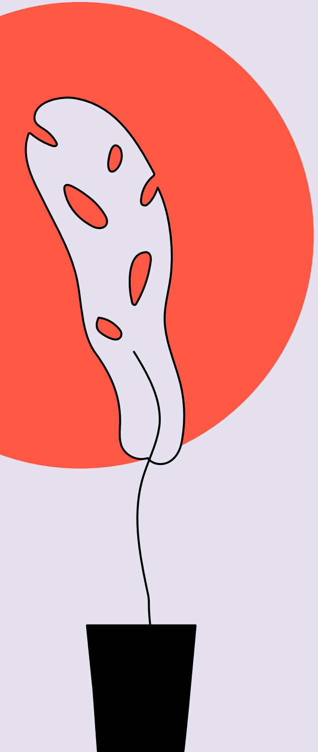

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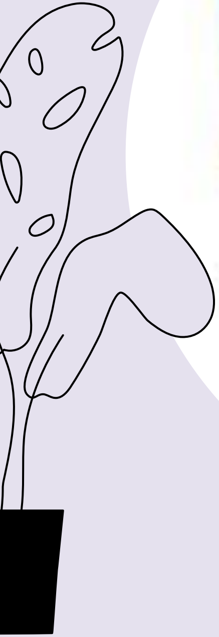
Introduction

Of our subject and dataset

Taiwanese Company Bankruptcy Prediction



TEJ Ratings ◦ Risk ◦ Index ◦ Databank

A company faces bankruptcy when they are unable to pay off their debts. The Taiwan Economic Journal for the years 1999 to 2009 has listed the details of company bankruptcy based on the business regulations of the Taiwan Stock Exchange. Our dataset to analyze will be this data.

Dataset :
https://archive.ics.uci.edu/ml/datasets/Taiwanese+Bankruptcy+Prediction

We may wonder to what extent parameters such as those studied in the dataset (the profit, the sales, the revenue...) have an influence on the bankruptcy of a company, and therefore how they can help predict the bankruptcy?

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General informations

About the dataset

Dataset :

Size	6819 x 96
Values Type	Int and Float
Missing values ?	No
Duplicated Values ?	No
Unique values ?	1
Standardized data ?	NO

A quick look at the data

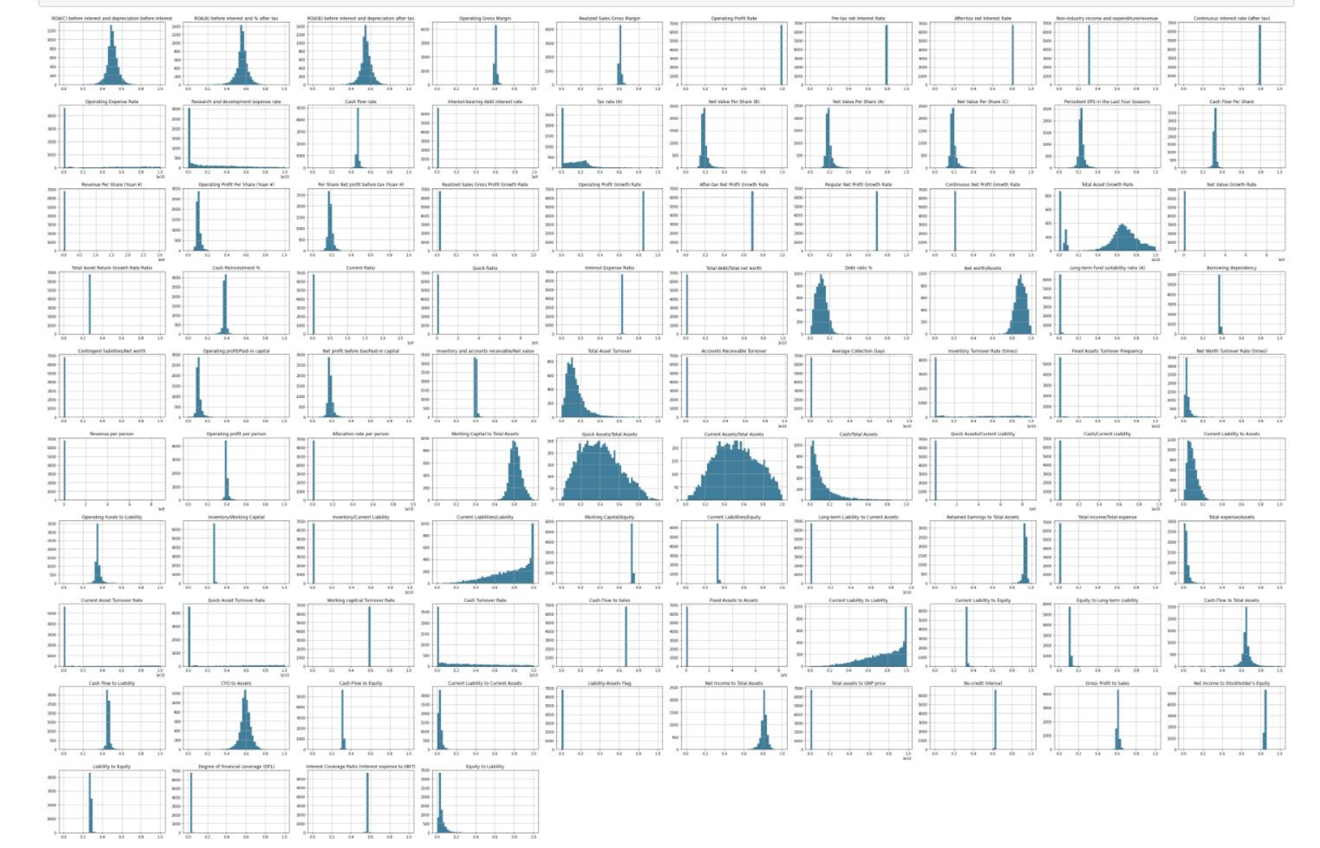


Fig1: general view of the distribution of the variables

A quick look at the data

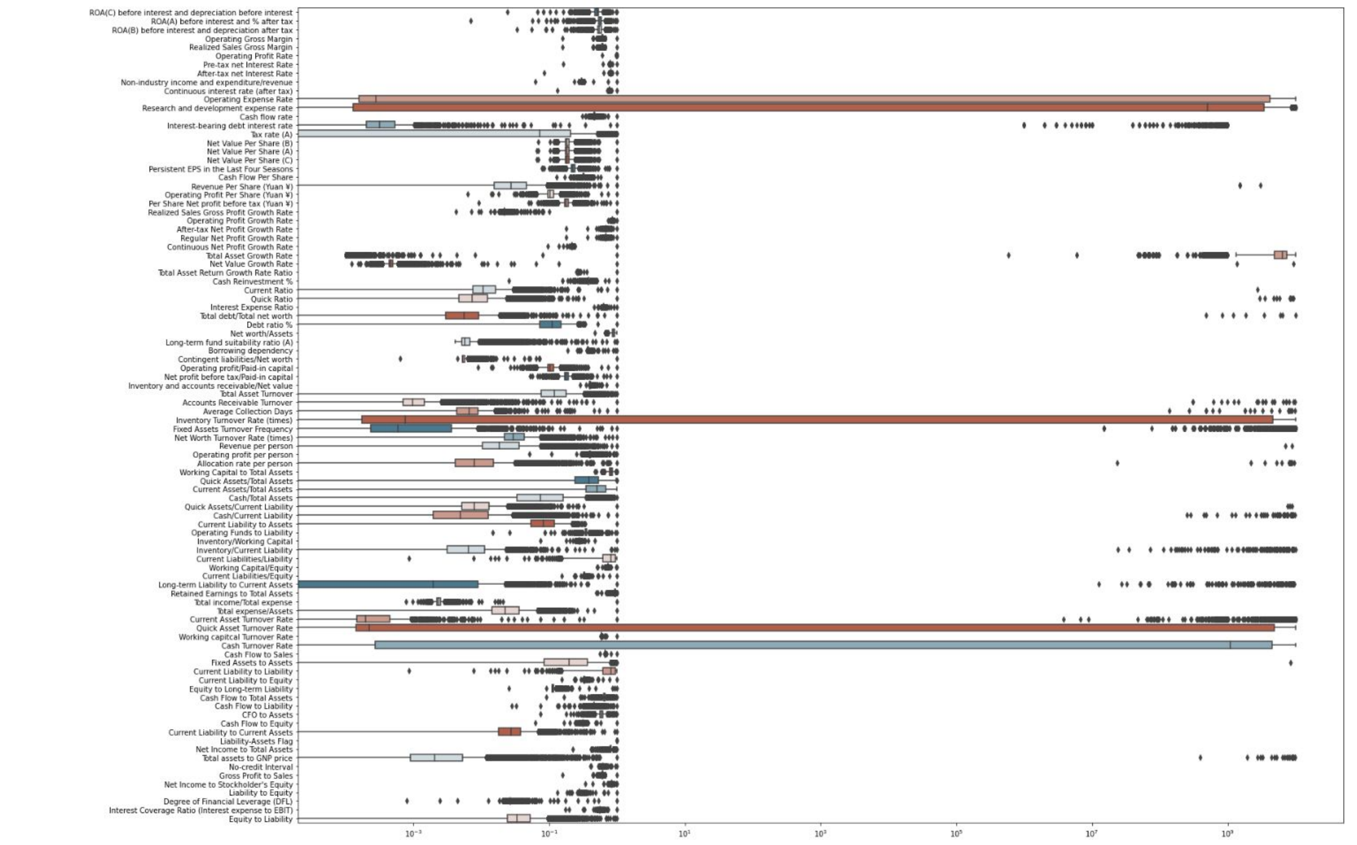


Fig2: boxplot graph of the distribution of the variables

Comments :

- The data isn't standardized
- Values are very disparates and broad

Our target

- We want to predict bankrupt
- Let’s look at the repartition of the values for this column
- 2 values for this column :

1 if the company is bankrupt, 0 if it isn’t.

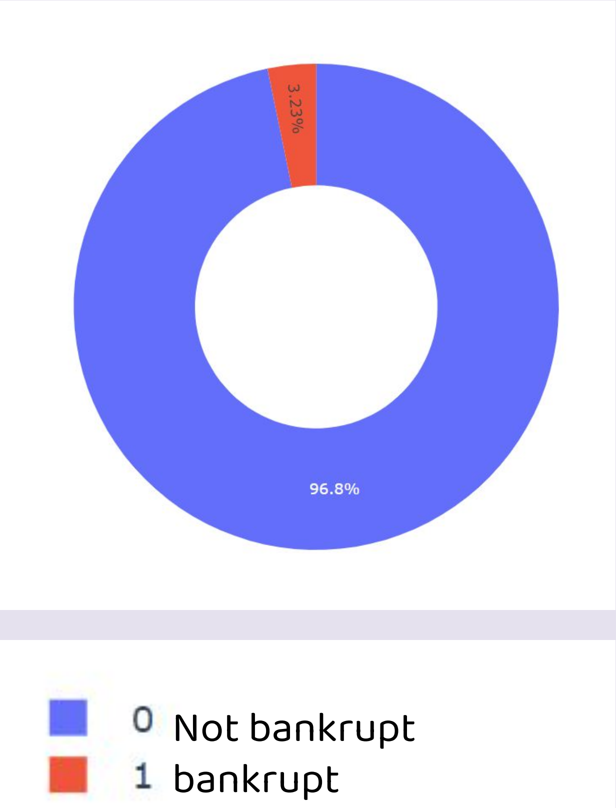
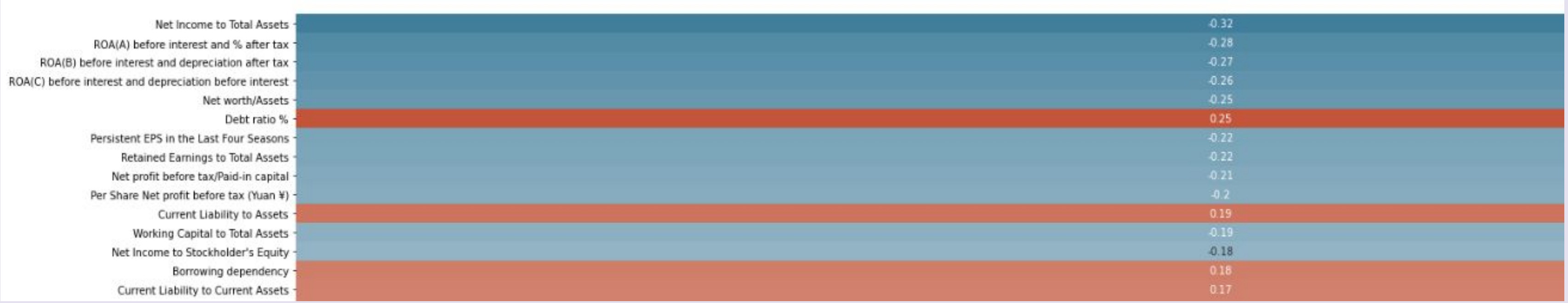


Fig3: Values repartition for bankrupt

Comments :

- classification strongly imbalanced.
- nearly 97% of 0

Correlation with the target



Net Income to Total Assets	-0.32
ROA(A) before interest and % after tax	-0.28
ROA(B) before interest and depreciation after tax	-0.27
ROA(C) before interest and depreciation before interest	-0.26
Net worth/Assets	-0.25
Debt ratio %	0.25
Persistent EPS in the Last Four Seasons	-0.22
Retained Earnings to Total Assets	-0.22
Net profit before tax/Paid-in capital	-0.21
Per Share Net profit before tax (Yuan ¥)	-0.2
Current Liability to Assets	0.19
Working Capital to Total Assets	-0.19
Net Income to Stockholder's Equity	-0.18
Borrowing dependency	0.18
Current Liability to Current Assets	0.17

Fig3: Zoom on the heatmap showing the correlation of the variables with the target to better see the 15 more correlated parameters with the target

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Preliminary Analysis

Summary and analysis

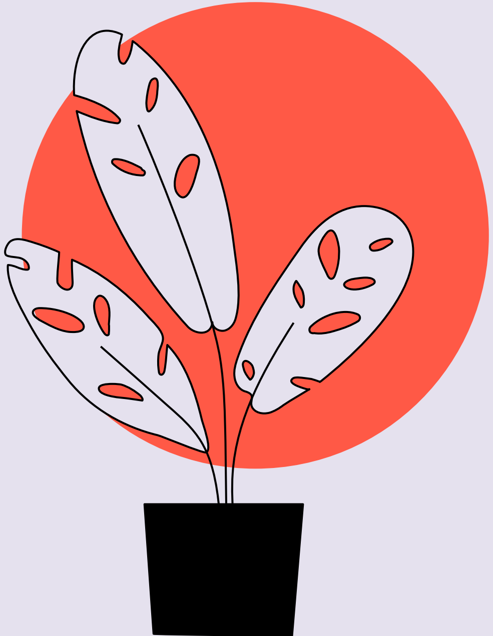
- Too much features (96) so we will have to do a selection

- We have one unique value so we can delete it (data cleaning)

- For our work, we will have to standardize the values

- Strongly imbalanced classification, we need to take this Into account because for example, predicting 0 every time Will give us a good result, but the model will be bad

- Among the features that seem to be the more correlated With bankrupt, we can find net income to total assets, debt ratio and features about ROA for example. This seems rather coherent.



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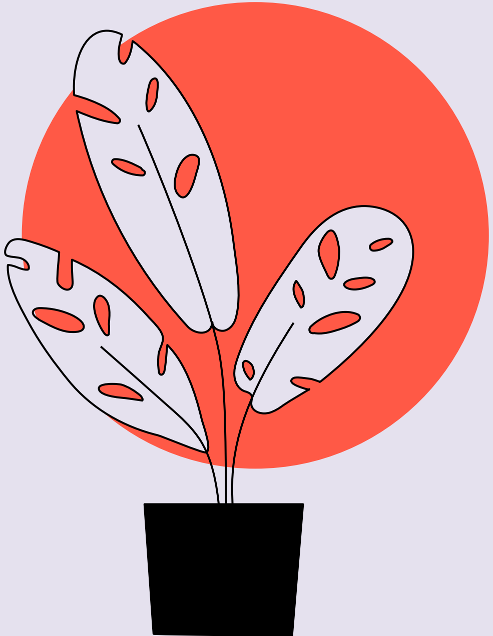
Preprocessing and PCA

Preprocessing

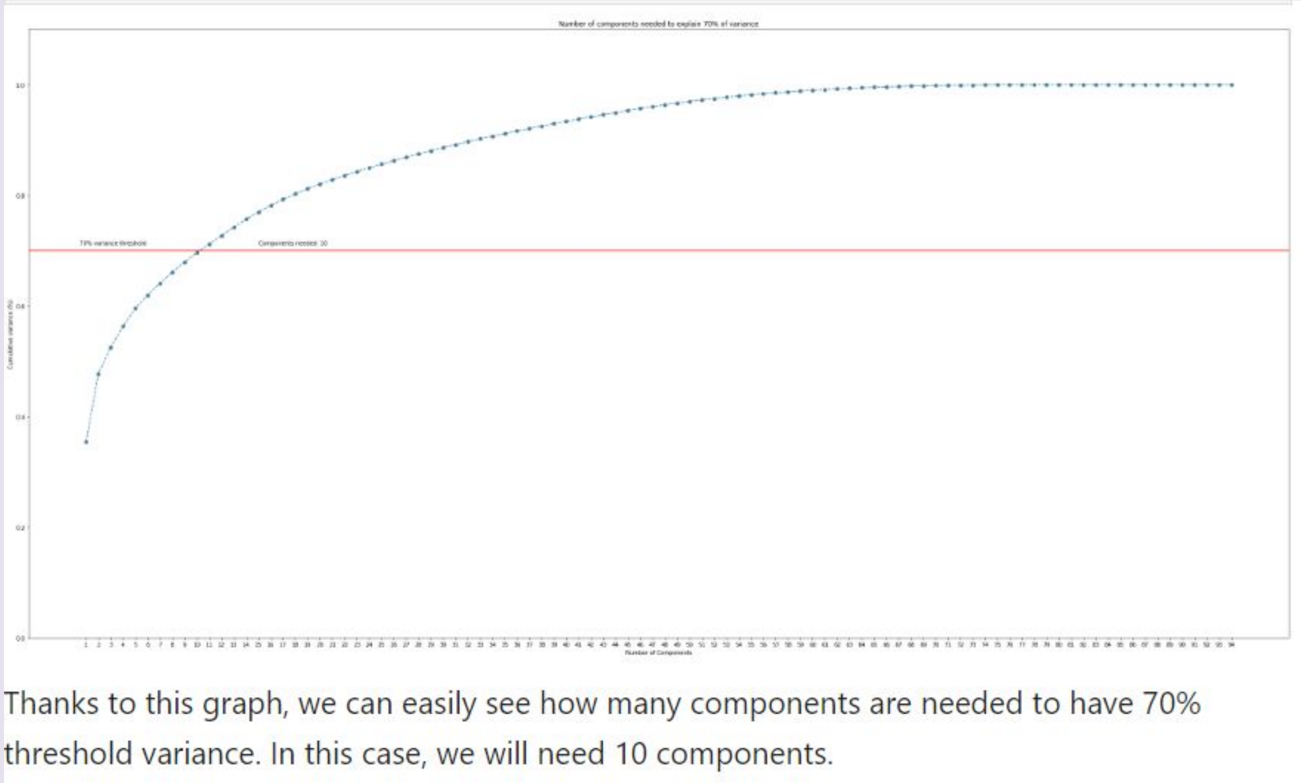
Before starting our work we :

- split features and target
- split our dataset into train and test set
- standardize the numeric features
- oversample the under represented classes to avoid making mistakes

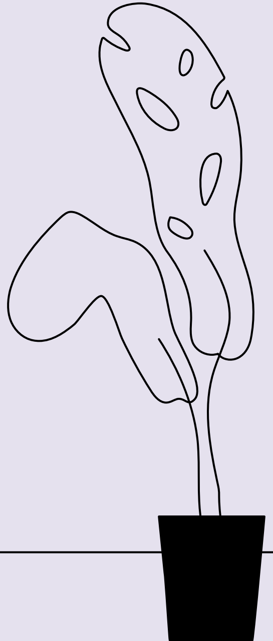


PCA

We need to reduce the number of features so we will do a PCA.



Thanks to this graph, we can easily see how many components are needed to have 70% threshold variance. In this case, we will need 10 components.



PCA

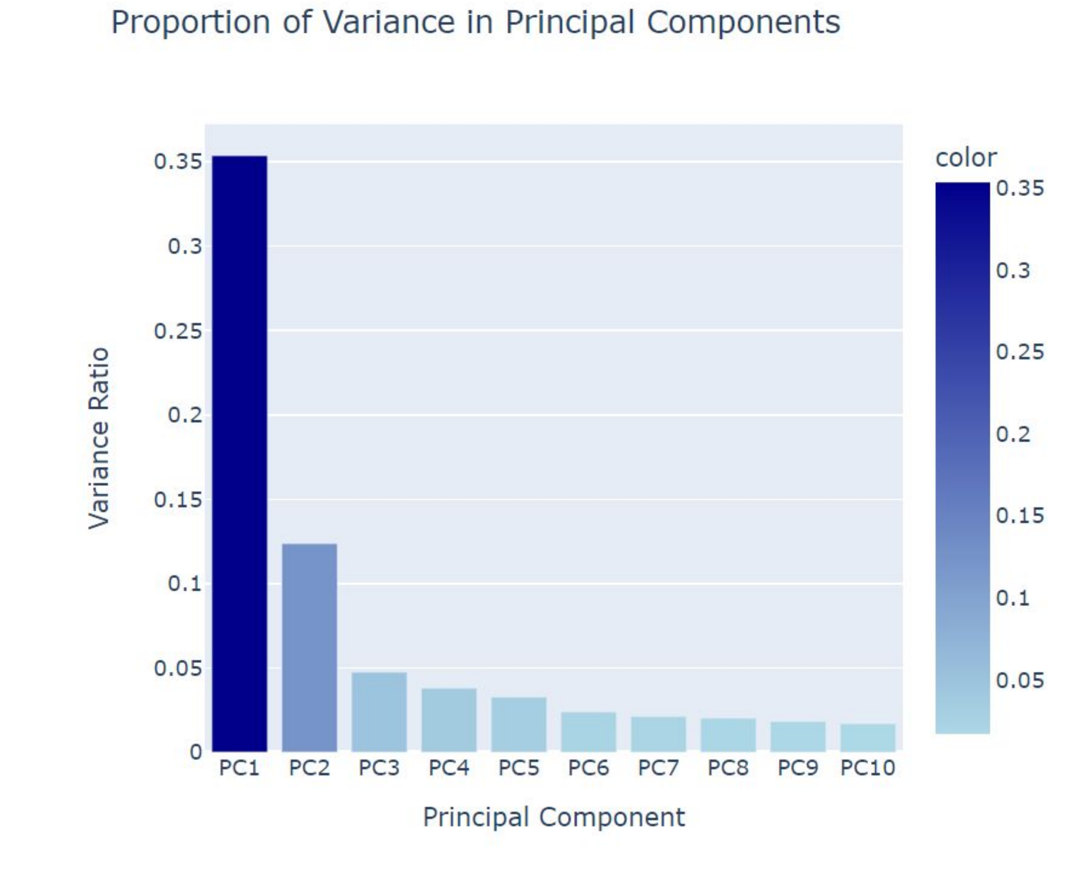


Fig5 : The proportion of variance for the 10 principal components

PCA

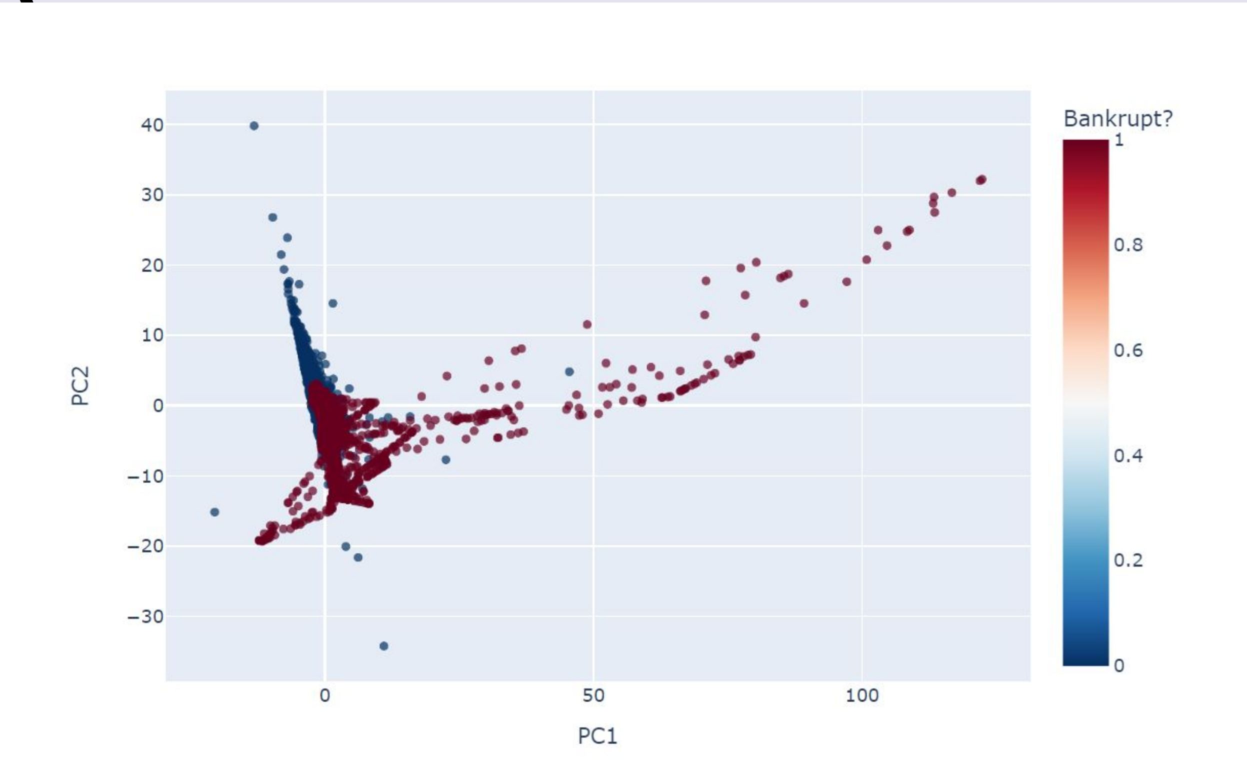


Fig6 : Observation on the 2 first components

PCA

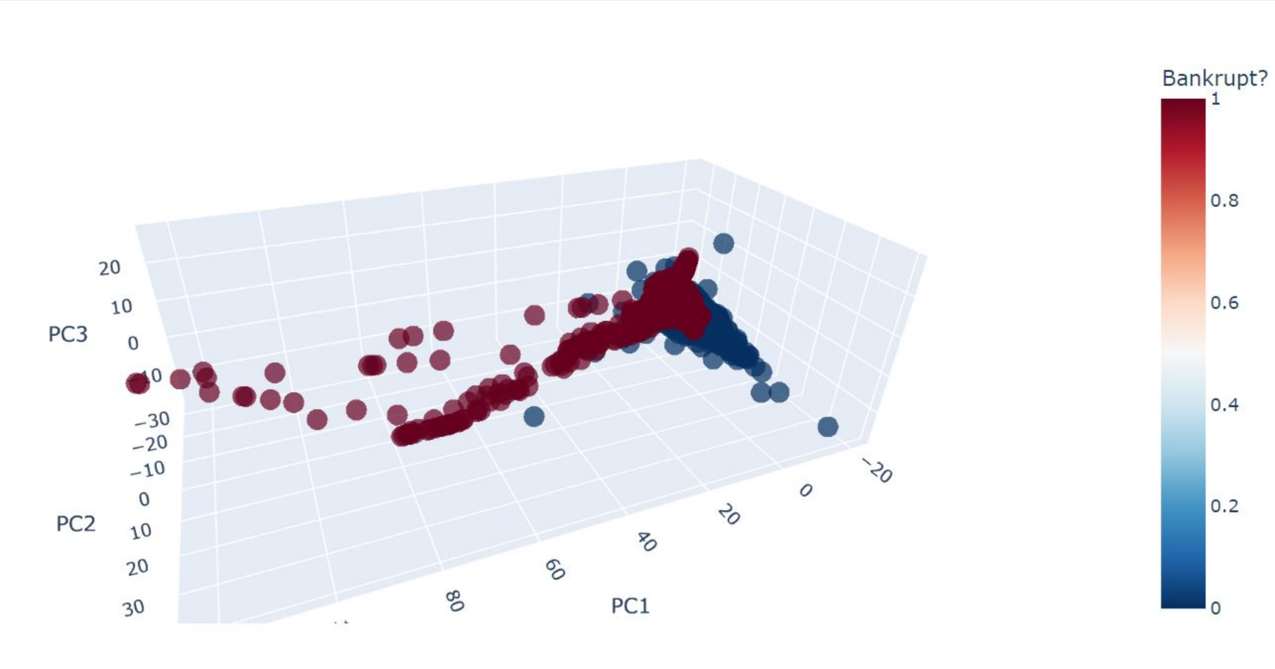


Fig7 : Observation on the 3 first components

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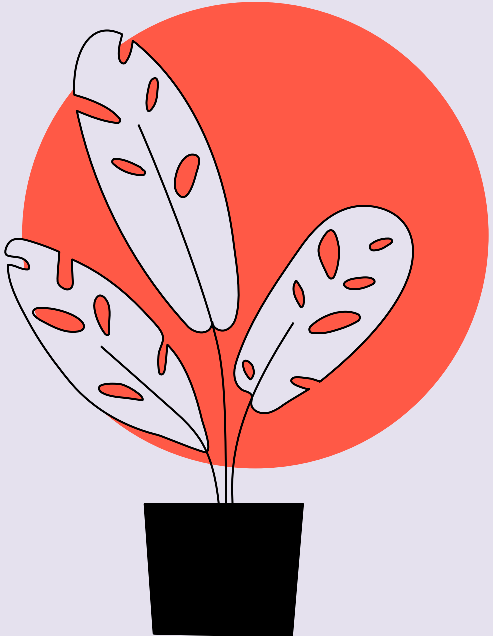
Modeling

For modeling :

- We choose f2-score because it seemed more appropriate

We tried :

- Logistic regression
- Support vector machine (Linear Kernel)
- K – nearest neighbors
- Support Vector Machine (RBF Kernel)
- Decision Tree
- Bagging
- Random Forest
- Gradient Boosting



Evaluation

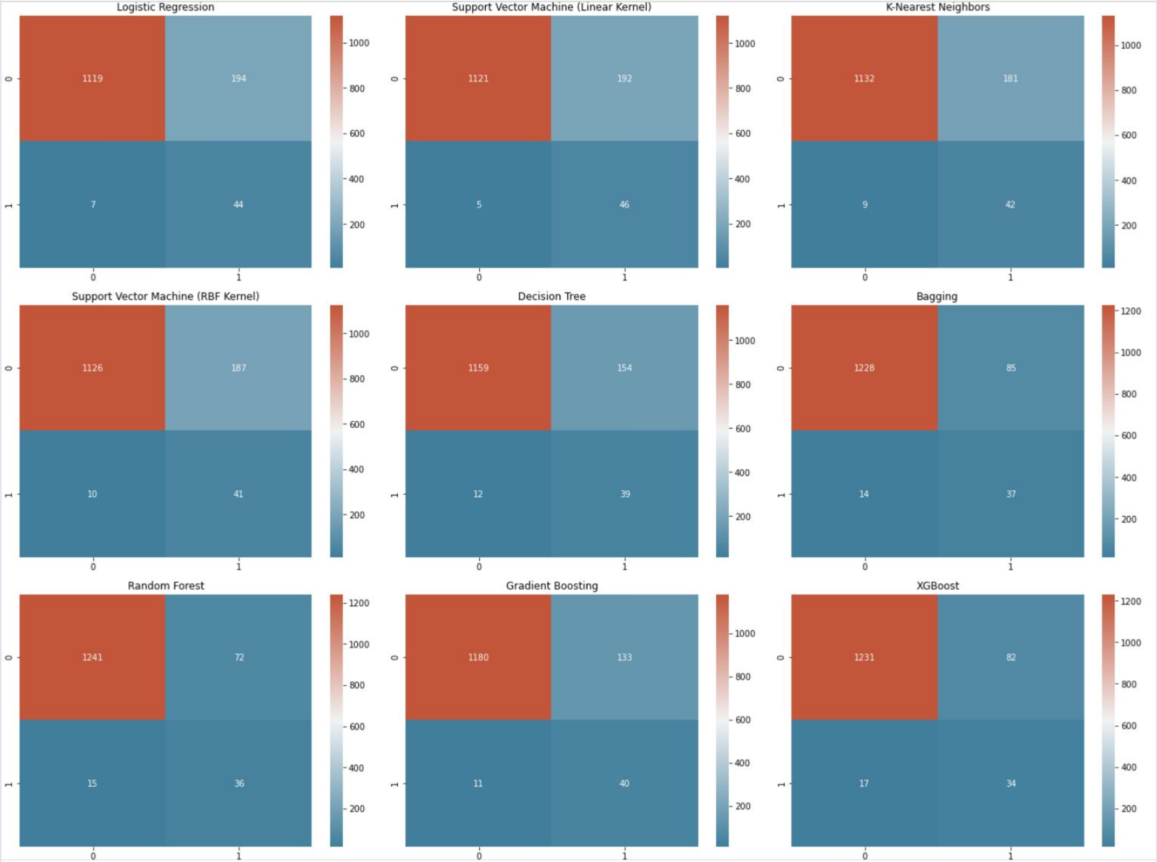
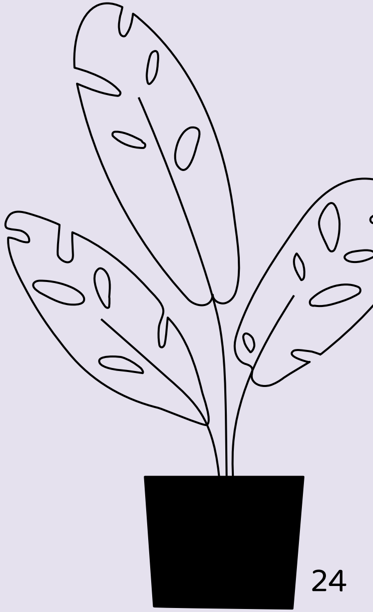


Fig8: Confusion matrix



Evaluation

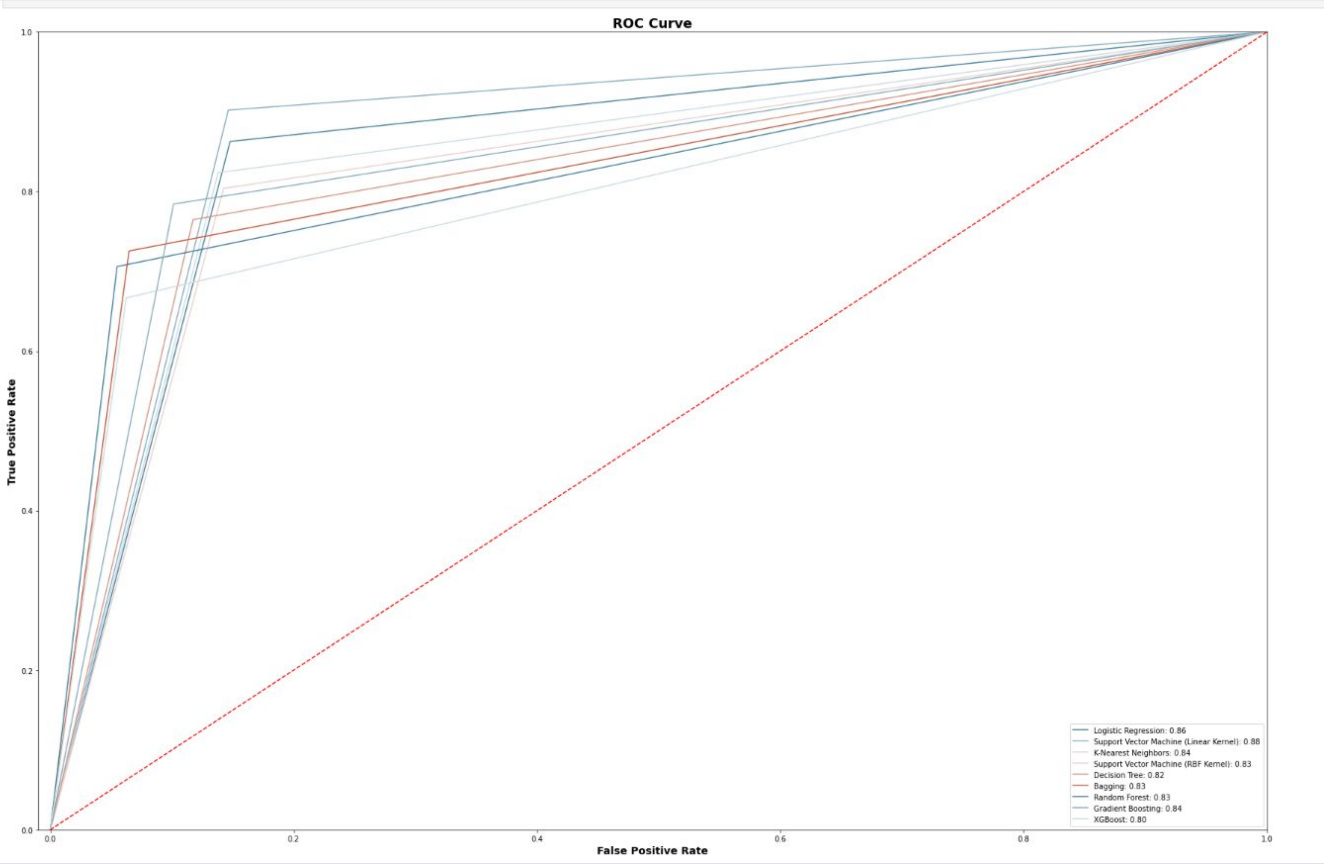
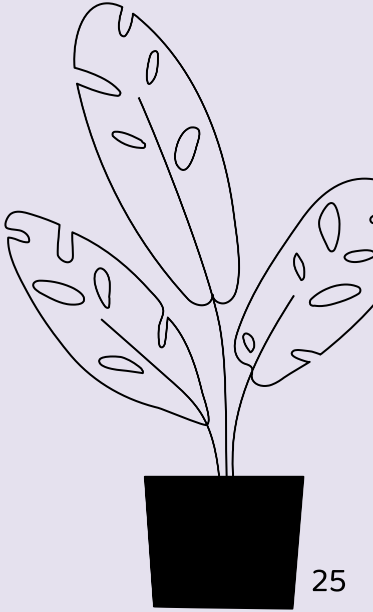
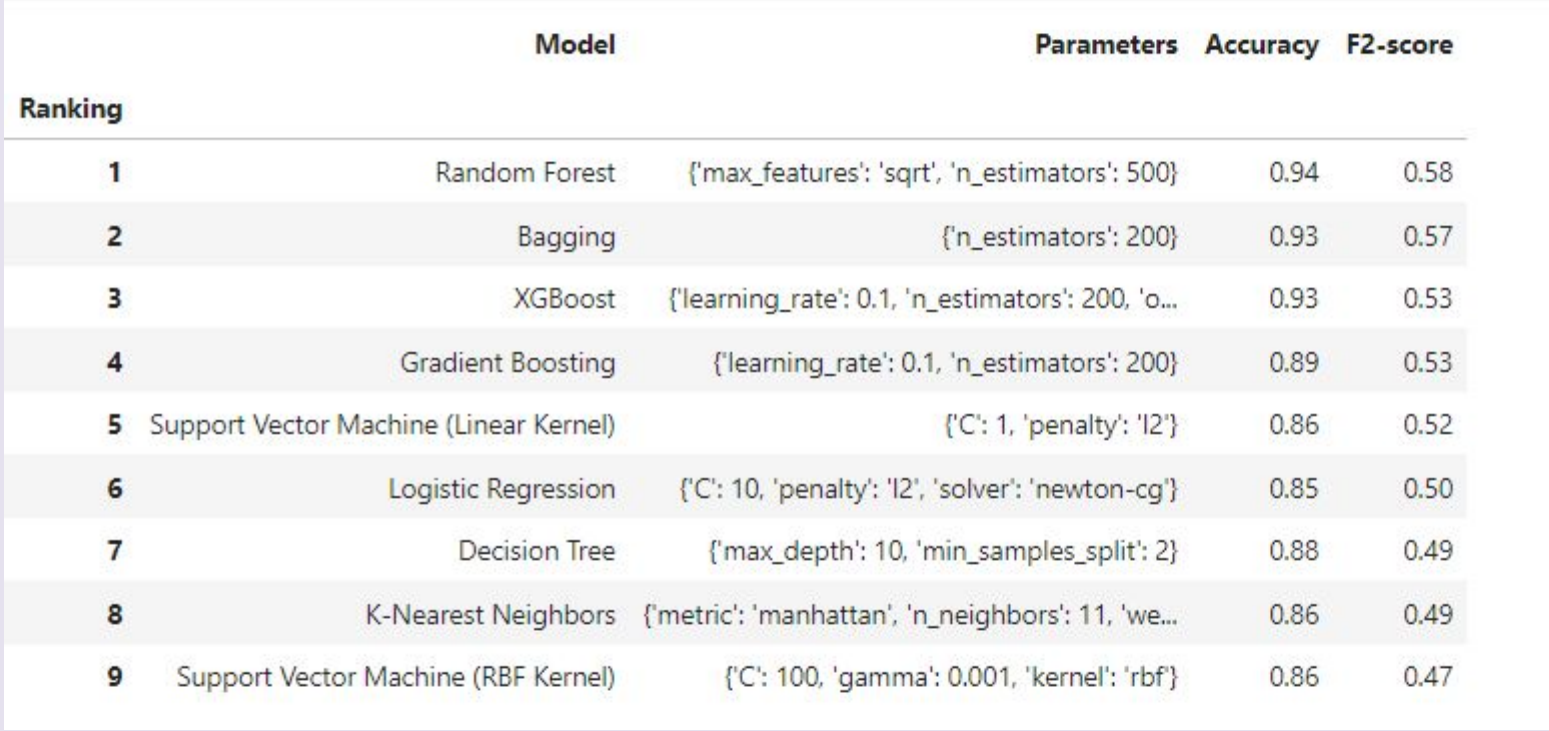


Fig9: ROC curves

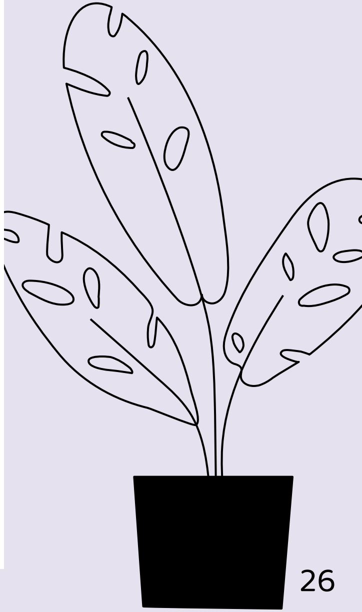


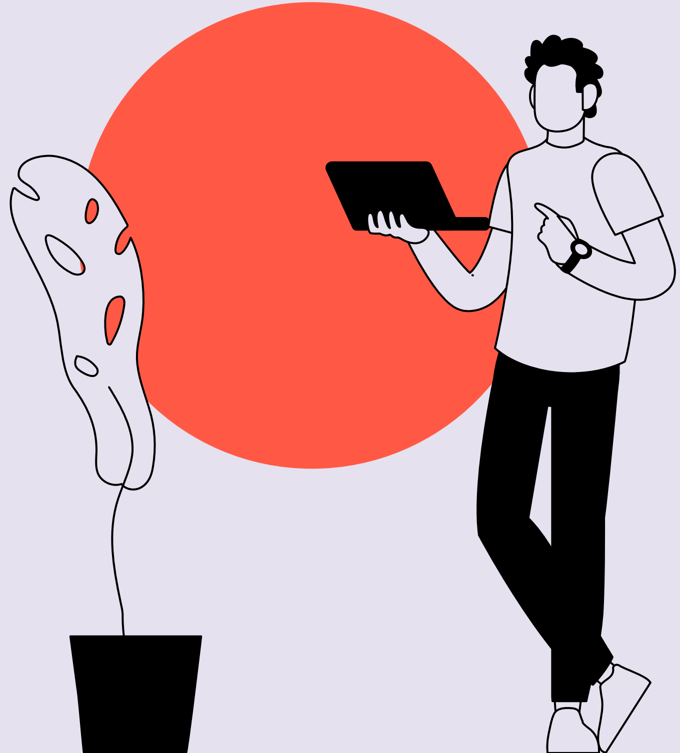
Summary

Fig10: Summary and Accuracy



	Model	Parameters	Accuracy	F2-score
Ranking				
1	Random Forest	{'max_features': 'sqrt', 'n_estimators': 500}	0.94	0.58
2	Bagging	{'n_estimators': 200}	0.93	0.57
3	XGBoost	{'learning_rate': 0.1, 'n_estimators': 200, 'o...	0.93	0.53
4	Gradient Boosting	{'learning_rate': 0.1, 'n_estimators': 200}	0.89	0.53
5	Support Vector Machine (Linear Kernel)	{'C': 1, 'penalty': 'l2'}	0.86	0.52
6	Logistic Regression	{'C': 10, 'penalty': 'l2', 'solver': 'newton-cg'}	0.85	0.50
7	Decision Tree	{'max_depth': 10, 'min_samples_split': 2}	0.88	0.49
8	K-Nearest Neighbors	{'metric': 'manhattan', 'n_neighbors': 11, 'we...	0.86	0.49
9	Support Vector Machine (RBF Kernel)	{'C': 100, 'gamma': 0.001, 'kernel': 'rbf'}	0.86	0.47





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Conclusion

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Conclusion

To conclude we can say that the parameters studied during this study are good indicators of the bankruptcy or not of a company.
With the precautions we took to make our models as accurate as possible and usable on other similar datasets, we obtained rather good predictions with for the random forest model, an accuracy of 94%.