



# **Bankruptcy**

## **How to pick a winning investment**

By the Three Wolf Moon of Wall Street  
Binita, Juan, and Faye

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Compare various modeling strategies and future efforts

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Model that handles time-series data well

# 01 Objective

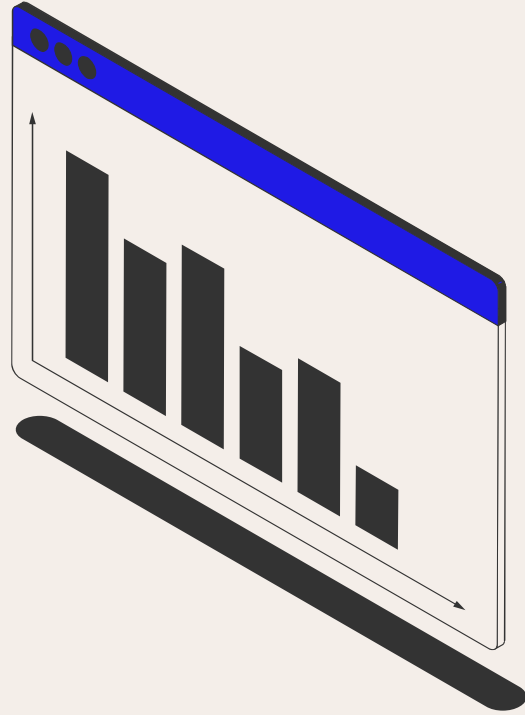
We have been contracted to advise a hedge fund looking to add prudent investments to their portfolio. The client is risk-averse.

We will build a classification model that predicts whether a company will succeed or go bankrupt in order to better advise our client which companies to invest with and which to avoid.



**02**

# **Exploratory data analysis of bankruptcy**



# The dataset

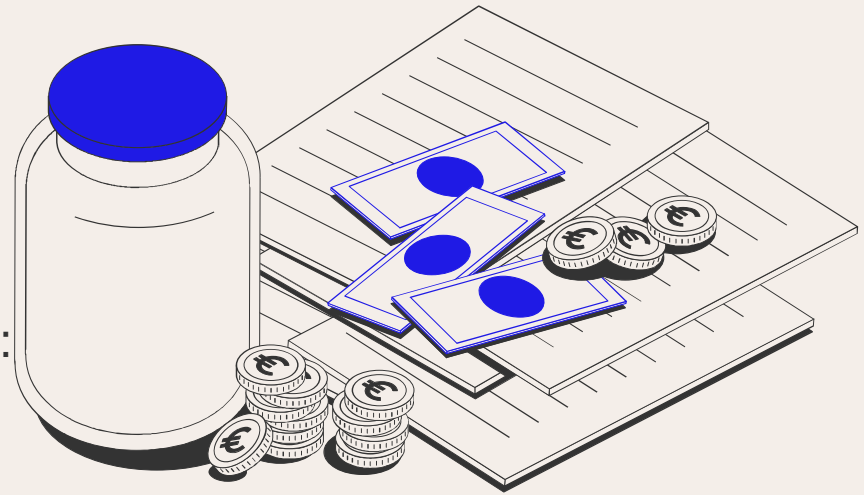
## US Company Bankruptcy Prediction Dataset ( 1999 - 2018)

- 8,971 distinct companies:
  - 8,362 are in business “alive”
  - 609 are bankrupt
- 18 financial health features such as:

Total assets

Earnings before interest and taxes

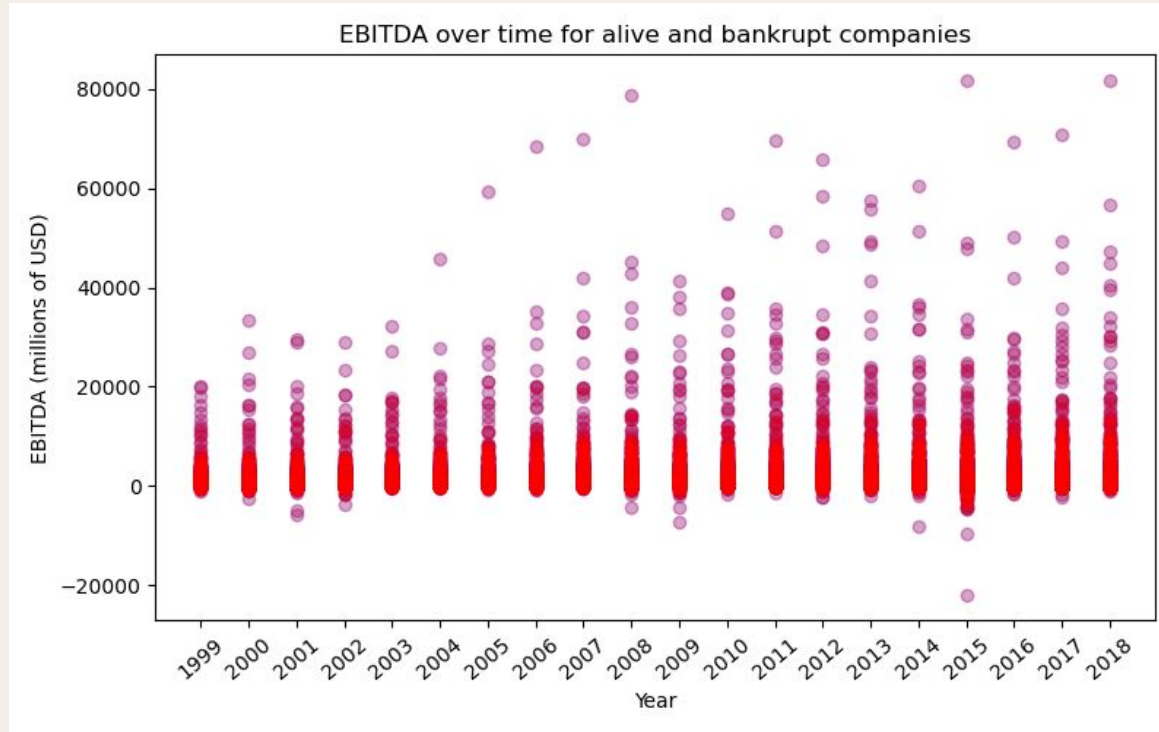
Total long-term debt



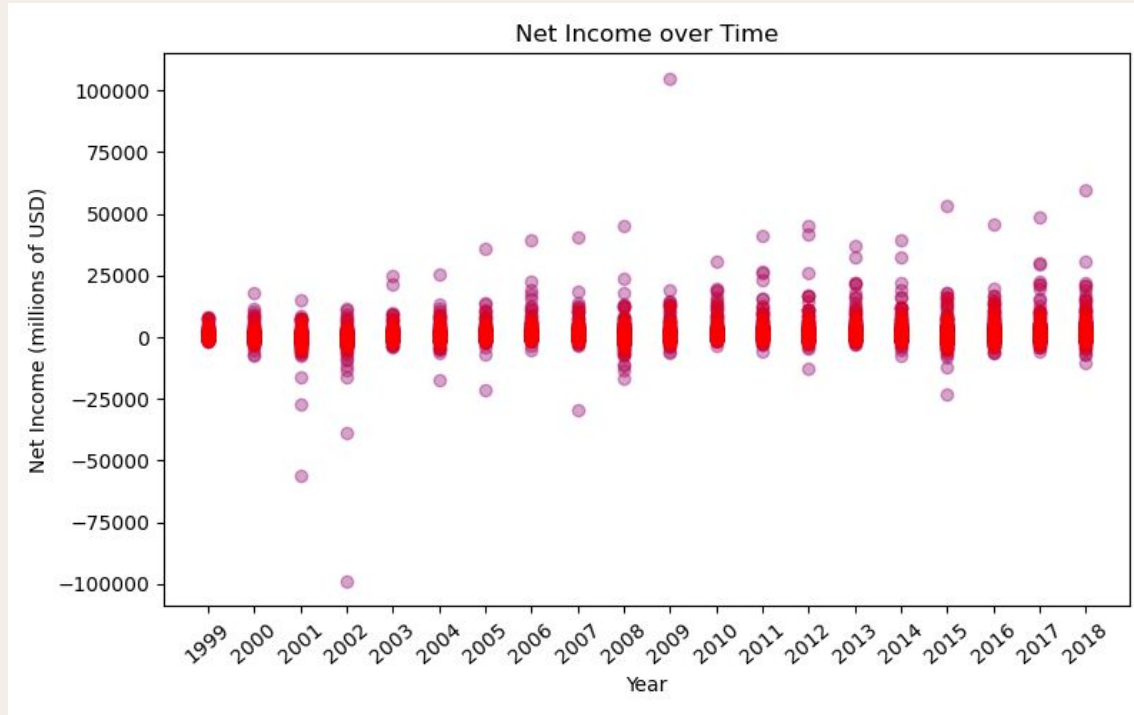
Link to dataset:

<https://www.kaggle.com/datasets/utkarshx27/american-companies-bankruptcy-prediction-dataset>

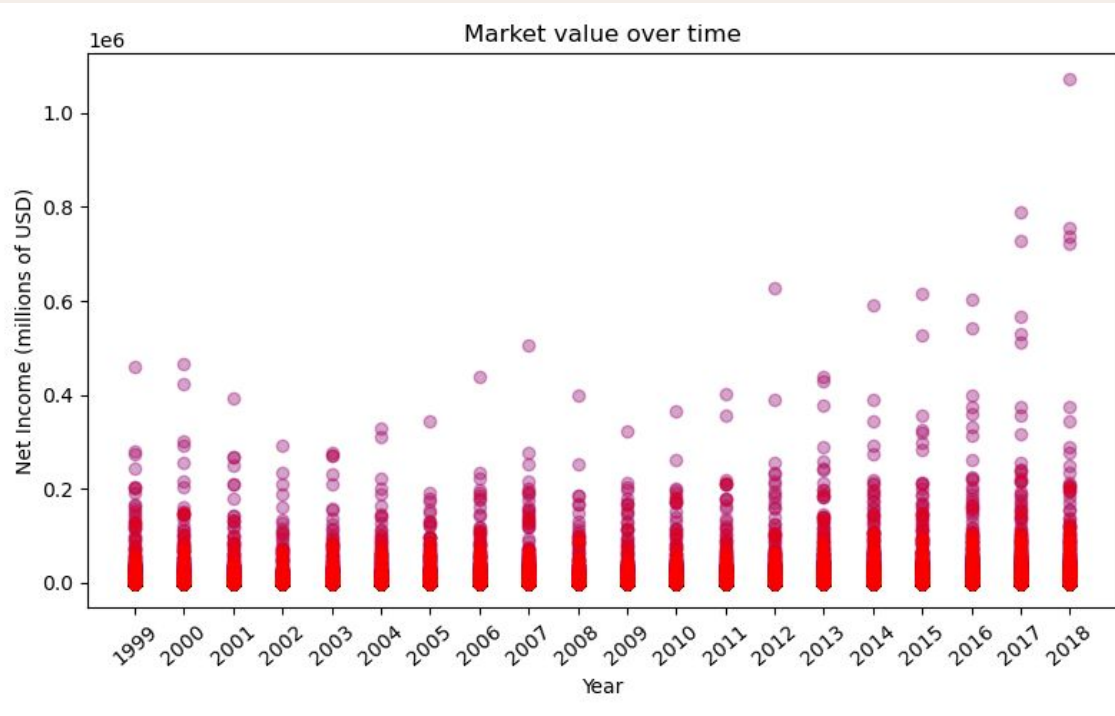
# The relationship between **EBITDA** and bankruptcy



# The relationship between **Net income** and bankruptcy

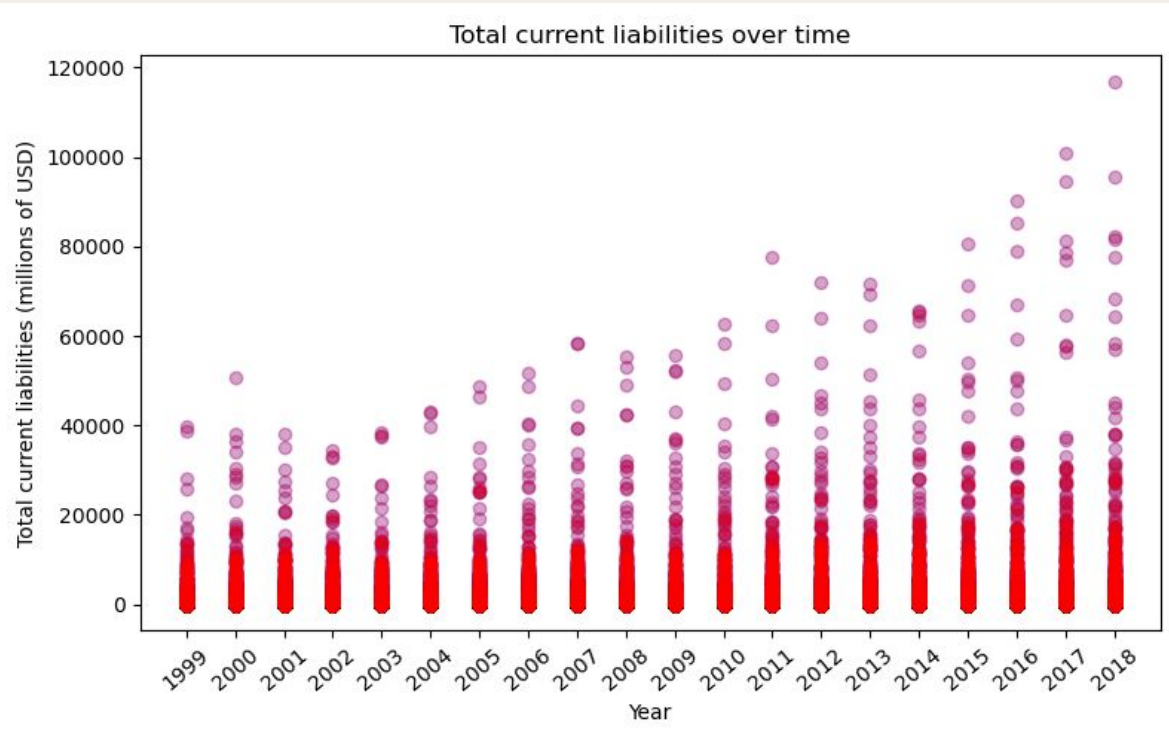


# The relationship between market value and bankruptcy

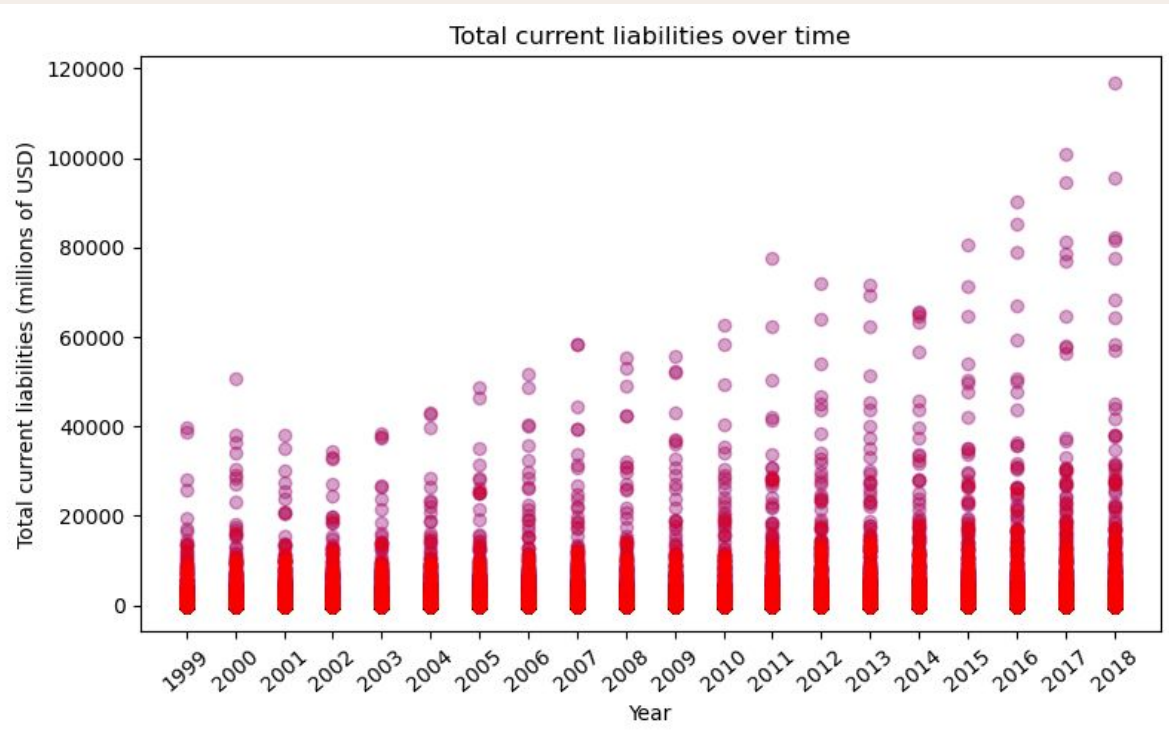




# The relationship between **total liabilities** and bankruptcy

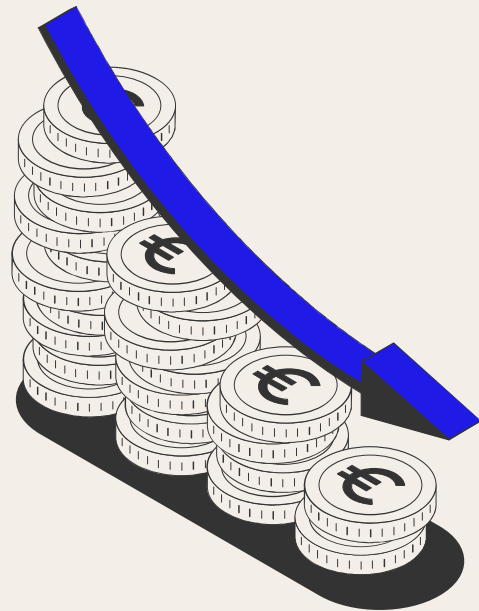


# The relationship between operating costs and bankruptcy



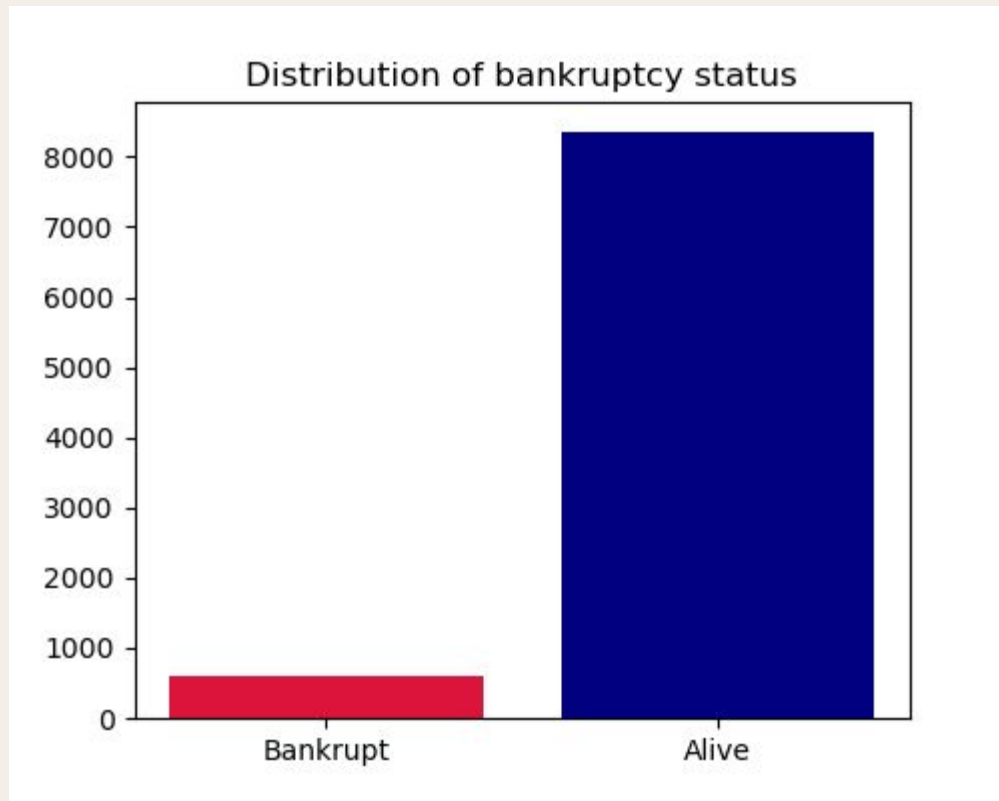
**03**

# Tree models for classification



# Handling imbalanced classes

Correcting class imbalances before training a model is important to reduce bias, improve generalization, ensure accurate performance metrics, and facilitate better decision-making.



# Random Forest + RandomSearchCV

**Test set accuracy: 0.9407**

**Precision ( $TP / (TP + FP)$ ):  
23%**

**Recall ( $TP / (TP + FN)$ ):  
64%**

True Positive	False Positive
310	995
172	18194
False Negative	True Negative

# Random Forest

## Feature Importances:

X8 Market value	0.092
X15 Retained Earnings	0.073
X6 Net Income	0.071
X3 Depreciation and amortization	0.067
X7 Total Receivables	0.063

# XGBoost

**Test set accuracy XGBoost: 0.9395**

**Precision ( $TP / (TP + FP)$ ):  
35%**

**Recall ( $TP / (TP + FN)$ ): 57%**

True Positive	False Positive
459	846
345	18021
False Negative	True Negative

# XGBoost

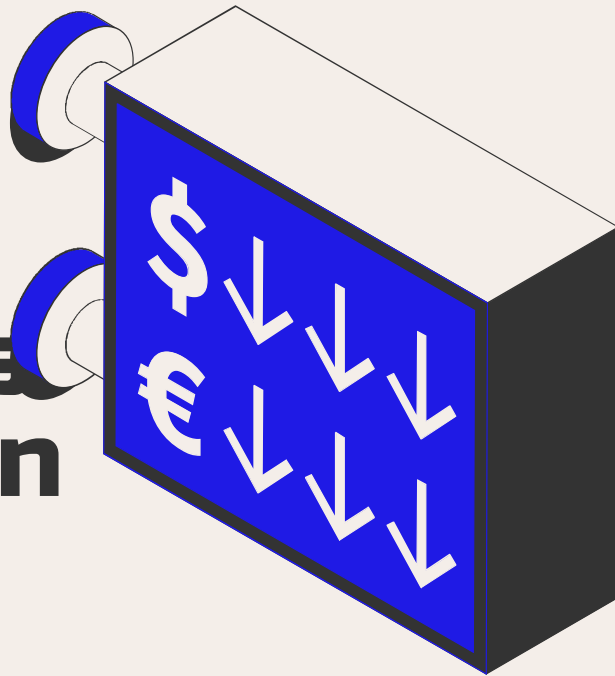
## Feature Importances:

X15 Retained Earnings	2771
X8 Market value	2459
X3 Depreciation and amortization	2397



**04**

# Neural networks for classification



# Neural Network model

**Test set accuracy: 0.8343**

**Precision ( $TP / (TP + FP)$ ):  
45%**

**Recall ( $TP / (TP + FN)$ ):  
19%**

True Positive	False Positive
594	711
2549	15817
False Negative	True Negative

# **Recurrent Neural Network model**

**Explored LSTM, Dense, Dropout, BatchNormalization,  
and EarlyStopping to optimize**

**Only achieved Test set accuracy: 0.9025**

**05**

# Key Findings



# Accuracy over baseline

