

# Predicting the direction of the DAX by using indicators

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#### How does the data of a stock market look?

- The typical representation of market prices is the candlestick chart
- Each candle represents a period (in this example, one day)
- Each candle contains four prices (open, high, low, close)
- The direction can be defined by the difference between the close and open prices
- When the difference is positive, the direction is upward; when the difference is negative, the direction is downward



#### How is the DAX calculated?

- The DAX is calculated from the price of the 30 largest German companies
- The price development of individual companies is generally influenced by supply and demand
- There are many different factors that influence the market behaviors



#### **Data Collection**

- I have collected data from 1987 to the present by using the yfinance library
- The data includes open, high, low, close (OHLC) prices and the volume of the market
- The target variable is the direction, calculated by the difference between close-price and openprice
- As input variables, I have calculated multiple indicators across different timeframes

#### **Indicators**

- Use 10 different types of indicators
  - Simple Moving Average
  - Relative Strength Index
  - Average True Range
  - Bollinger Bands
- Each indicator was calculated for three different time periods
- For each indicator that returns a market price, i created a categorical column
  - 1 if the price is above the indicator price
  - 0 if the price is lover then the indicator price



### **Data Cleaning**

- Before 2000 there are missing Values for the volume of the market
  - started from 2000
- By computing an Indicator with a timeperiod of 14 day, the first 13 rows has missing values
  - I dropped the first 13 days

# Time Dependency

		open	low	high close		moving average	direction
	01.01.2024	5975	6048	5974	6048	6050	Up
	02.01.2024	6843	6068	60 5	6082	6042	Down
$\longrightarrow$	03.01.2024	6032	6047	5997	6034	6040	Up

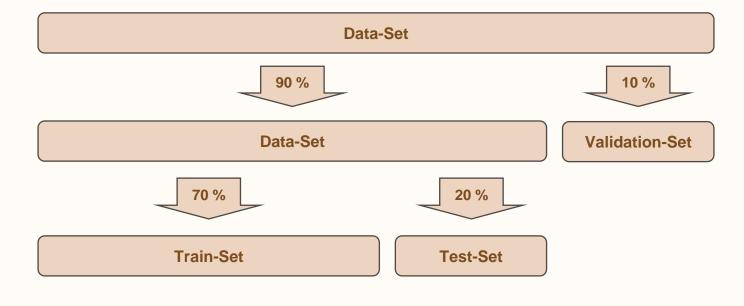
#### Feature Selection

- Varianace Threshold to drop features with a variance less then 0.02
- Correlation Matrix to identify multicorrelarity with a threshold = 0.99
- End up with 43 features

## Transforming, Scaling and Sampling

- Power Transformer
- Min Max Scaler for X
- My target is allready in a range between 0 and 1
- Class Imbalance: Train-Set = 0.045 Test-Set = 0.044 -> So I did not use any sampling method

# X-y Split

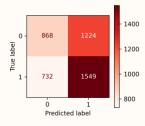


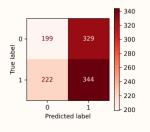
# Logistic - Regression

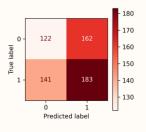


**Test-Set** 

**Validation-Set** 







Accuracy

Карра

0.552

0.094

0.496

-0.015

0.501

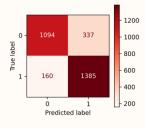
0.005

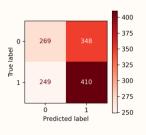
#### Random Forest with GridSearchCV

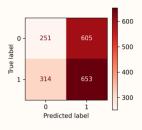


Test-Set

Validation-Set







Accuracy Kappa 0.833

0.532

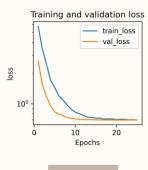
-0.032

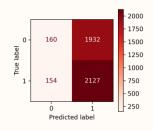
#### **Neural Network**

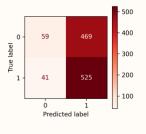


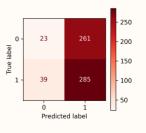
**Test-Set** 

**Validation-Set** 

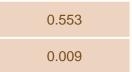


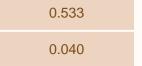


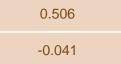








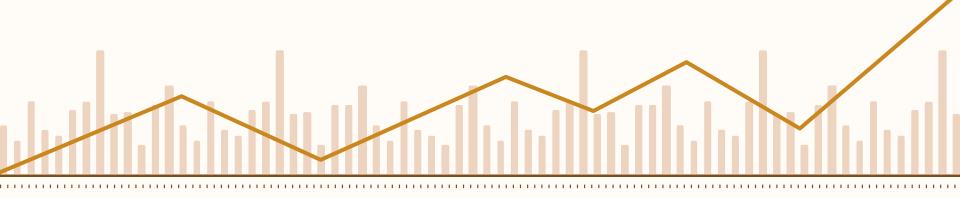




#### Final Results

Validation Set	Accuracy	F1	Recall	Precission	Kappa
Logistic Regression	0.502	0.547	0.565	0.530	-0.006
Random Forest	0.498	0.593	0.685	0.522	-0.030
Neural Network	0.506	0.655	0.879	0.522	-0.041

- The performance of all models is realy bad -> they are not practical for actual use
- Financial markets are known for their unpredictability and constant changes
- The performance of a model heavely relies on the input
- Next Steps: Is there an improvement, if I add features from different sources like more pattern related indicators and fundamental data from the companies?



# Thank you for your attention!

- Better trust a goldfish then my model! -