



Not So Creative
We see the future

Stock Recommendation Engine

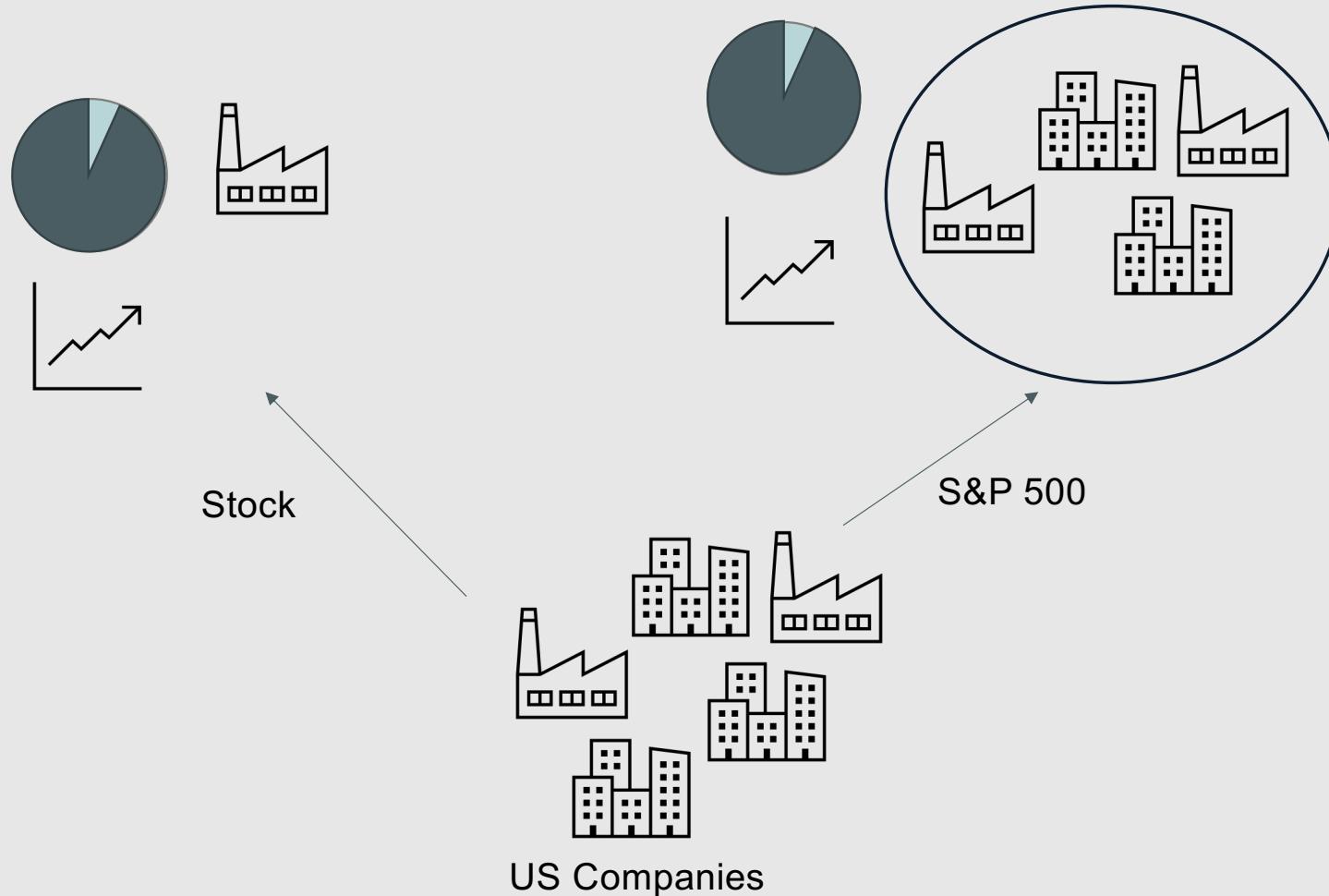
NotSoCreative

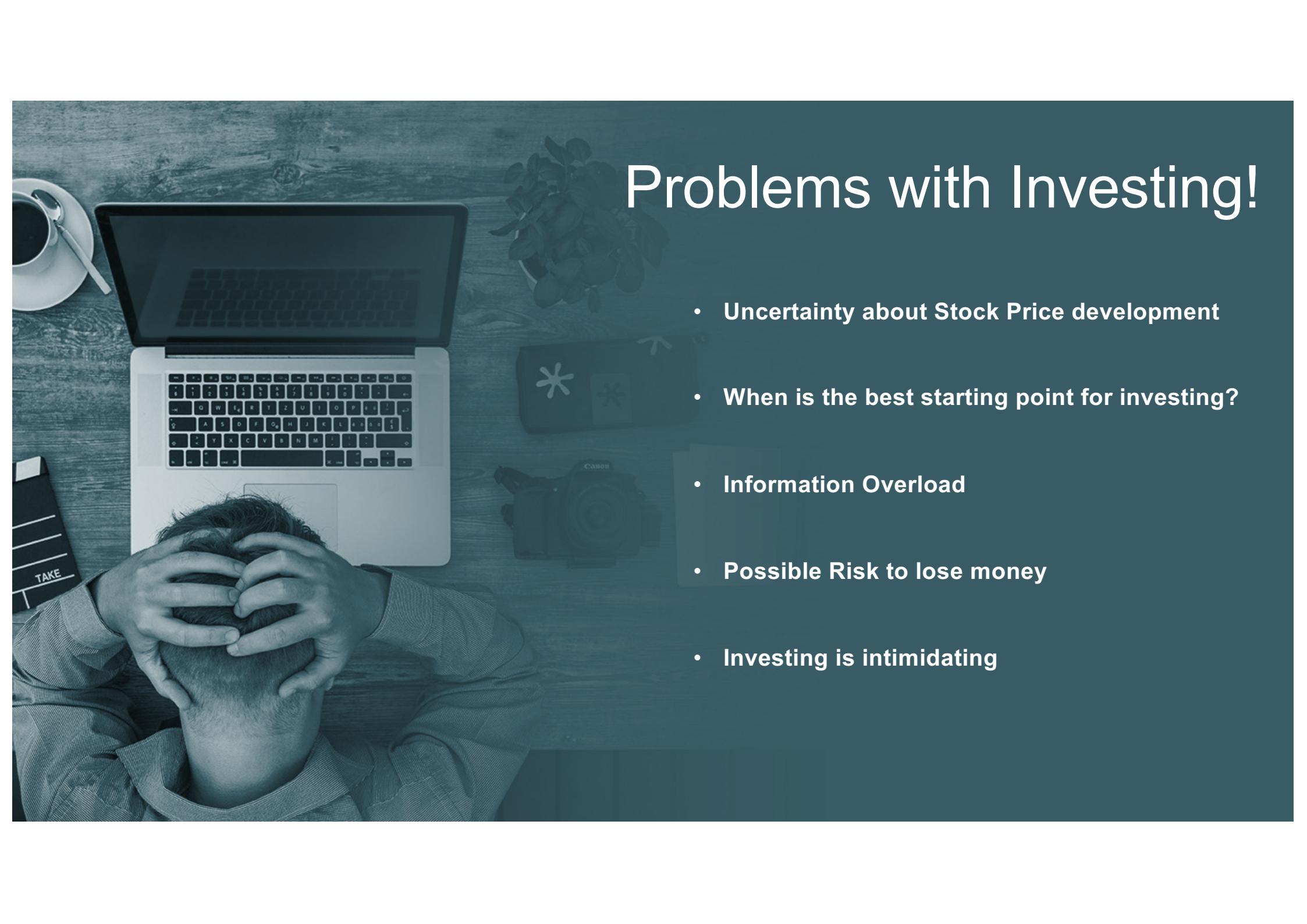


Why should we invest ?



Stocks & The S&P 500



A photograph of a man sitting at a wooden desk. He is leaning forward with his hands clasped behind his head, looking down with a weary or stressed expression. On the desk in front of him is an open laptop. To the left, there's a white coffee cup with a saucer and a small plant. In the background, there's a green plant and a camera. The overall atmosphere is one of stress or frustration.

Problems with Investing!

- **Uncertainty about Stock Price development**
- **When is the best starting point for investing?**
- **Information Overload**
- **Possible Risk to lose money**
- **Investing is intimidating**

Possible Investment Solutions

- Do Nothing
- Random Investment
- Buy and Hold (BaH)
- Cost Average (CA)

Boundaries:

- Worst Investment Action (WIA)
- Best Investment Action (BIA)

➤ We use these as a Benchmark



Our Solution

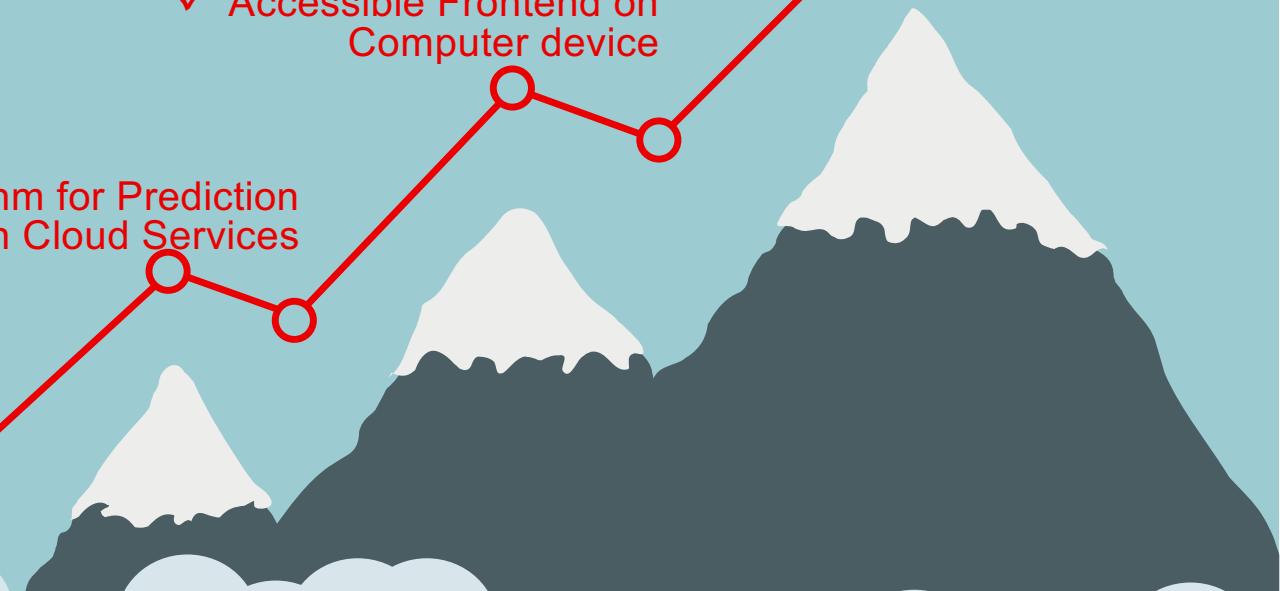
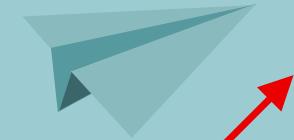
Stock Recommendation System

Automate investment actions for a two week time span for the S&P 500

✓ Stock Market Data

✓ Algorithm for Prediction on Cloud Services

✓ Accessible Frontend on Computer device



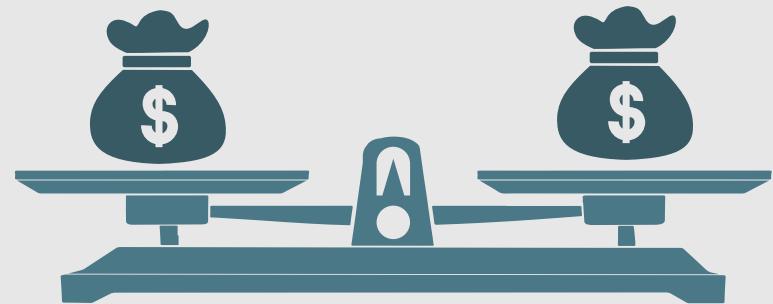
Metrics for Success



➤ Easy Answer? : “Of course the amount of Money we made is the most important Metric!”

2 most important Metrics:

1. Mean Portfolio Value (MPV)
2. Gain (percentage, absolute)



How to analyze the Stock Market

1. Fundamental Analysis
2. Technical Analysis



-O Technical Analysis to analyze Stocks O-

- **Technical analysis** = Analysis considering patterns & price trends
- **Tools** = Technical Indicators
- **Types** indicators:
 - Trend
 - Momentum
 - Volatility
 - Volume



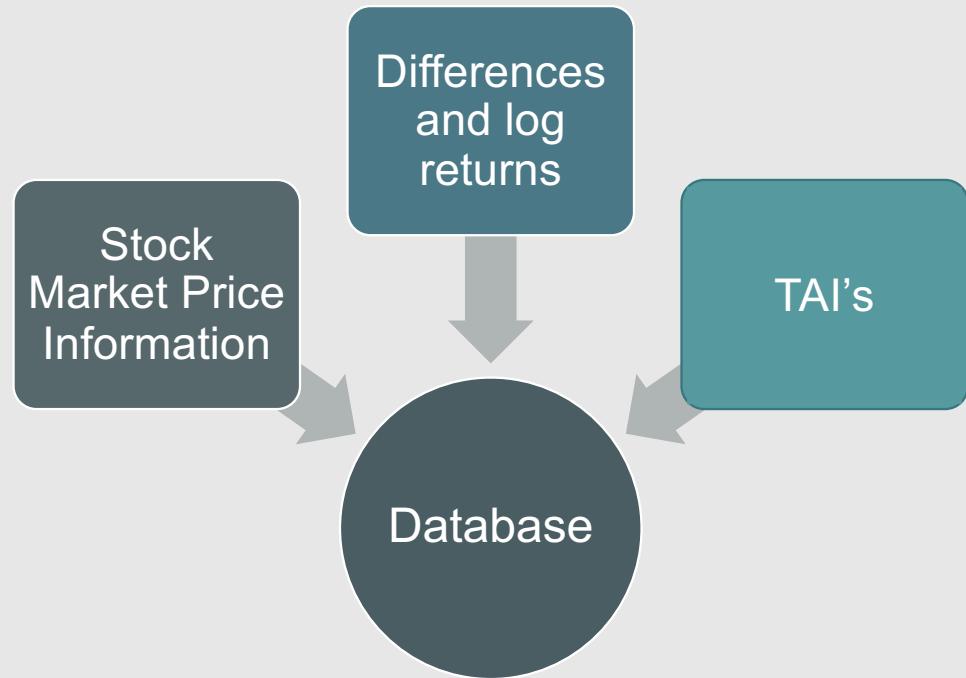


Designing our Algorithm



Data Collection & Feature Extraction

- Stock Market Price information
Open, Close, Volume, High and Low
- Differences and Logarithmic Returns
 - i.e. $\text{open}(t) - \text{open}(t-1)$
 - i.e. $\log[\text{open}(t)] - \log[\text{open}(t-1)]$
- Technical Analysis Indicators



Feature Selection

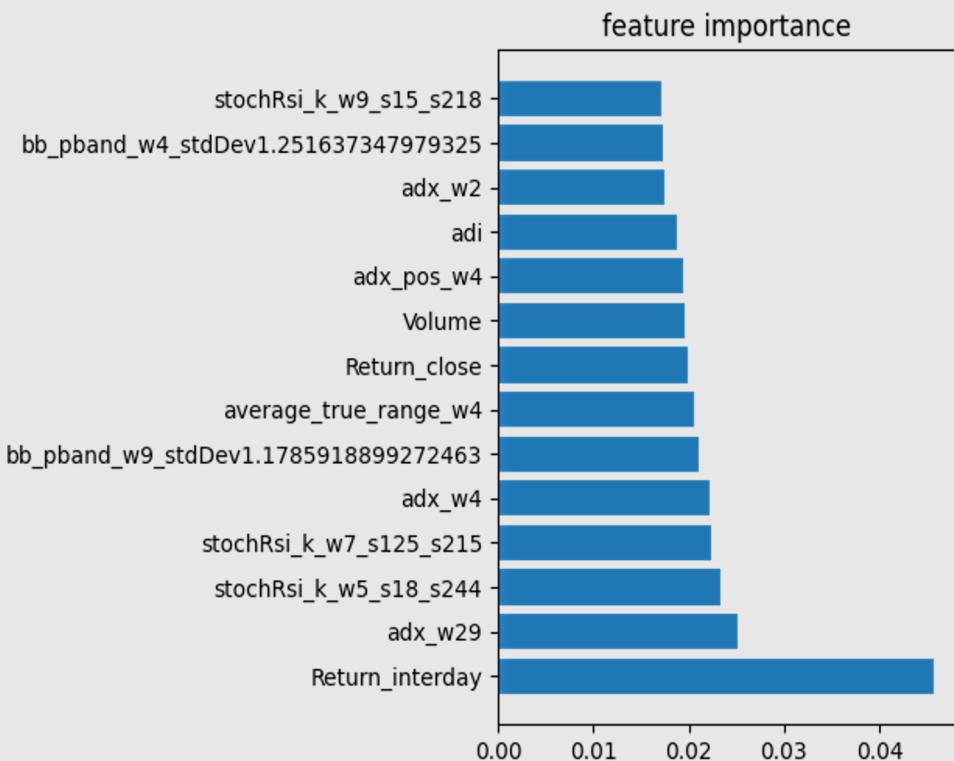


➤ Correlation Analysis

Neglect correlated features
From 425 to 100 features

➤ Decision Tree Regressor

Order the remaining features given
their importance



Designing our Algorithm



Data Scaling



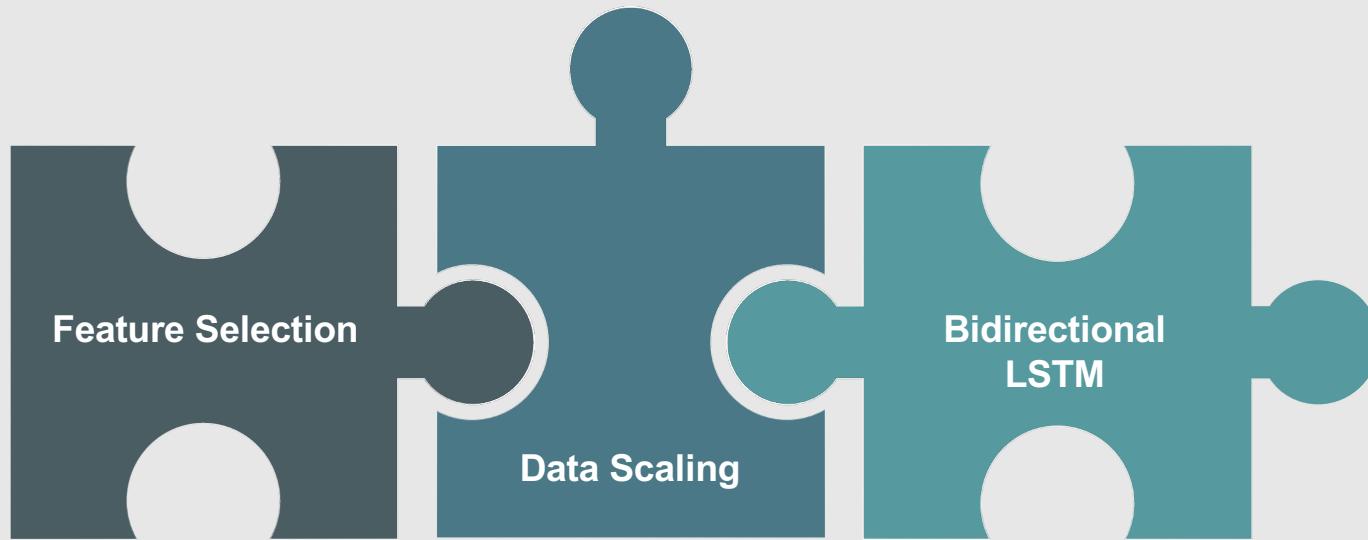
01 Robust Scaler

This scaler removes the median and scales the data according to the quantile range.

02 MinMax Scaler and Robust Scaler

Performs the best compared to other combinations

Designing our Algorithm



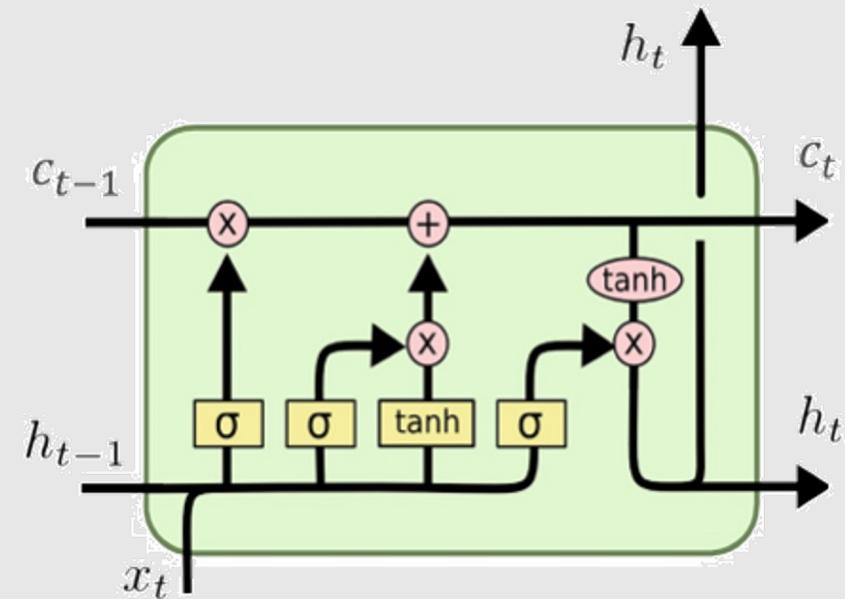
Error Metrics



Model	MAE train	RMSE train	MAPE train	MAE test	RMSE test	MAPE test
XGBOOST	38.519	61.335	0.0138	374.531	465.743	0.0736
Random Forest	50.786	81.912	0.0171	204.864	258.227	0.0512
LSTM	18.702	28.728	0.0063	43.572	55.644	0.0112
Bi-LSTM	15.085	25.298	0.0051	42.524	53.582	0.01098

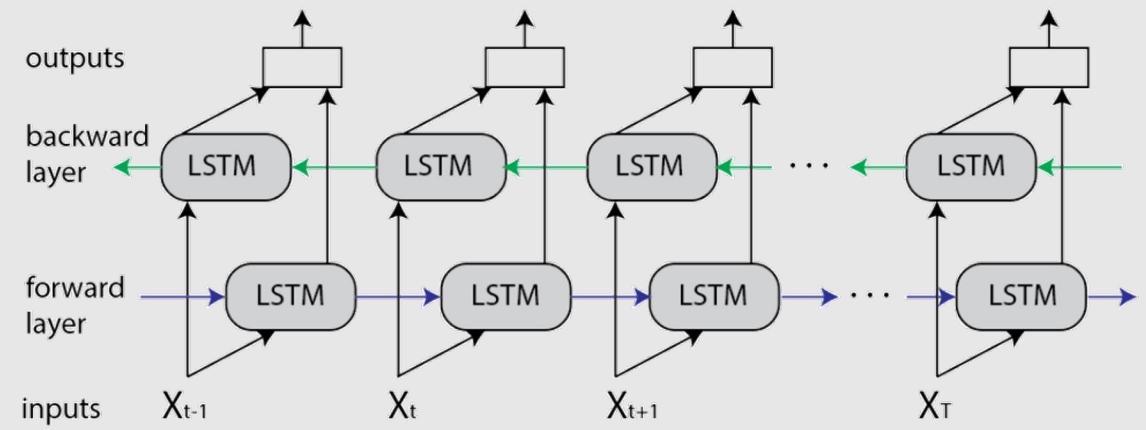
What is a LSTM?

- Due to its capability of storing past information, LSTM is very useful for predicting stock prices
- LSTM combats RNN's vanishing gradients or long-term dependence issue



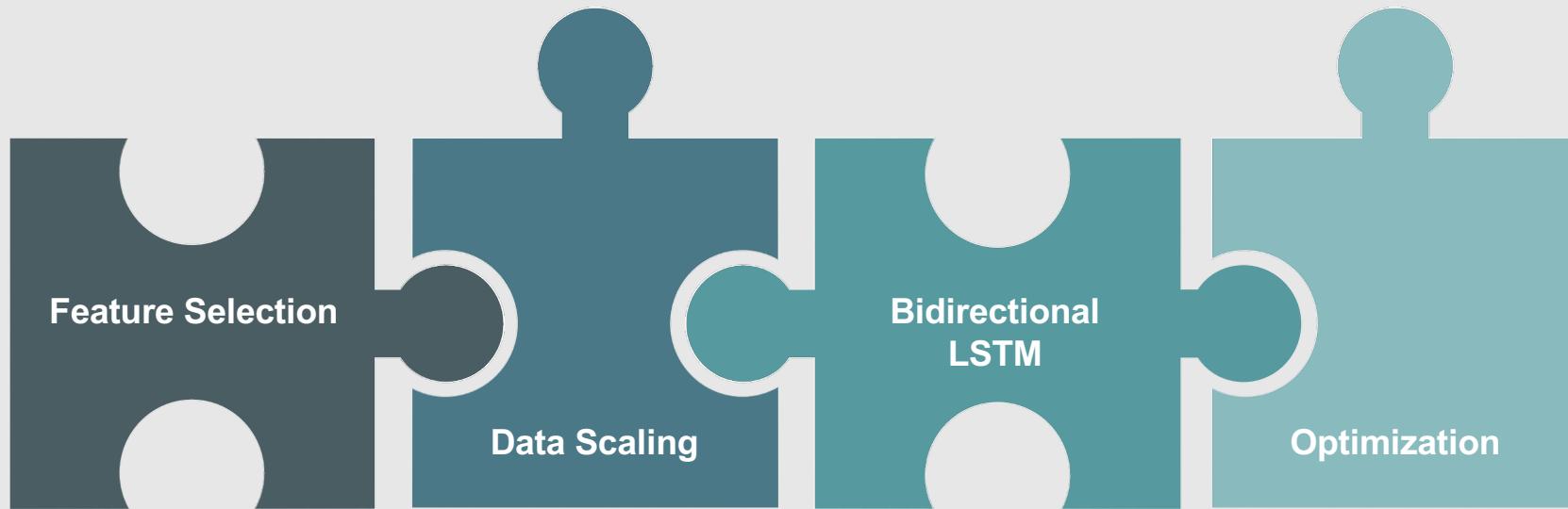
Our Solution: Bidirectional LSTM

- Input in both directions and is capable of utilizing information from both sides
- Bi-LSTMs with additional training outperforms regular unidirectional LSTMs





Designing our Algorithm



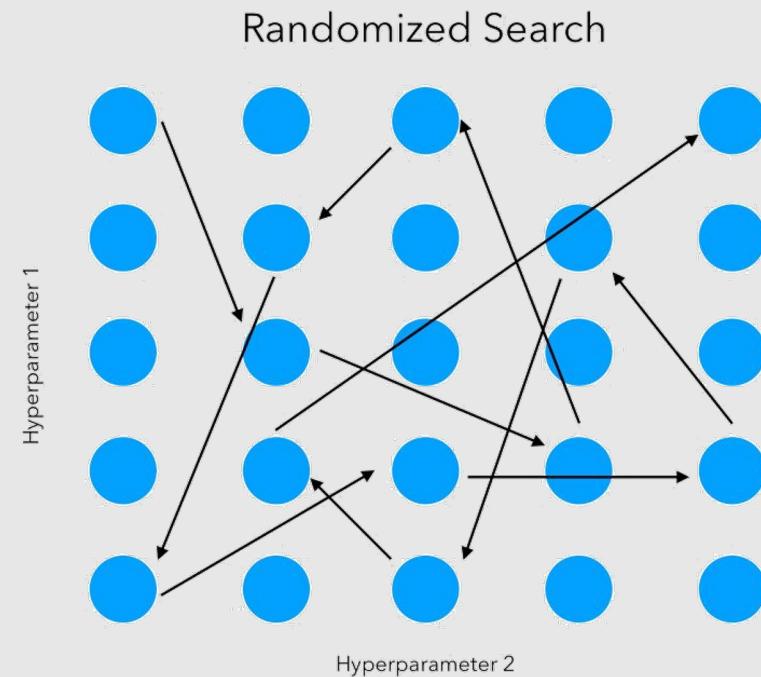
Hyperparameter Optimization

Random Search

Tries a random combination of parameter values

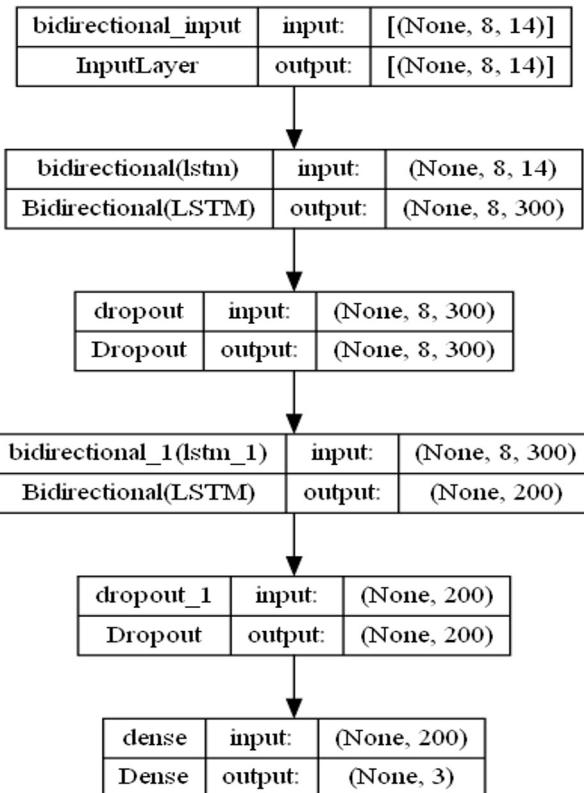
Advantages

- Good results (*Bergstra Bengio 2012*)
- Parallelizable
- Easy implementation



Model Architecture

Structure



Hyperparameter

Batch size: 32

Epochs: 36

Number of layer: 2

Number neurons: 150, 100

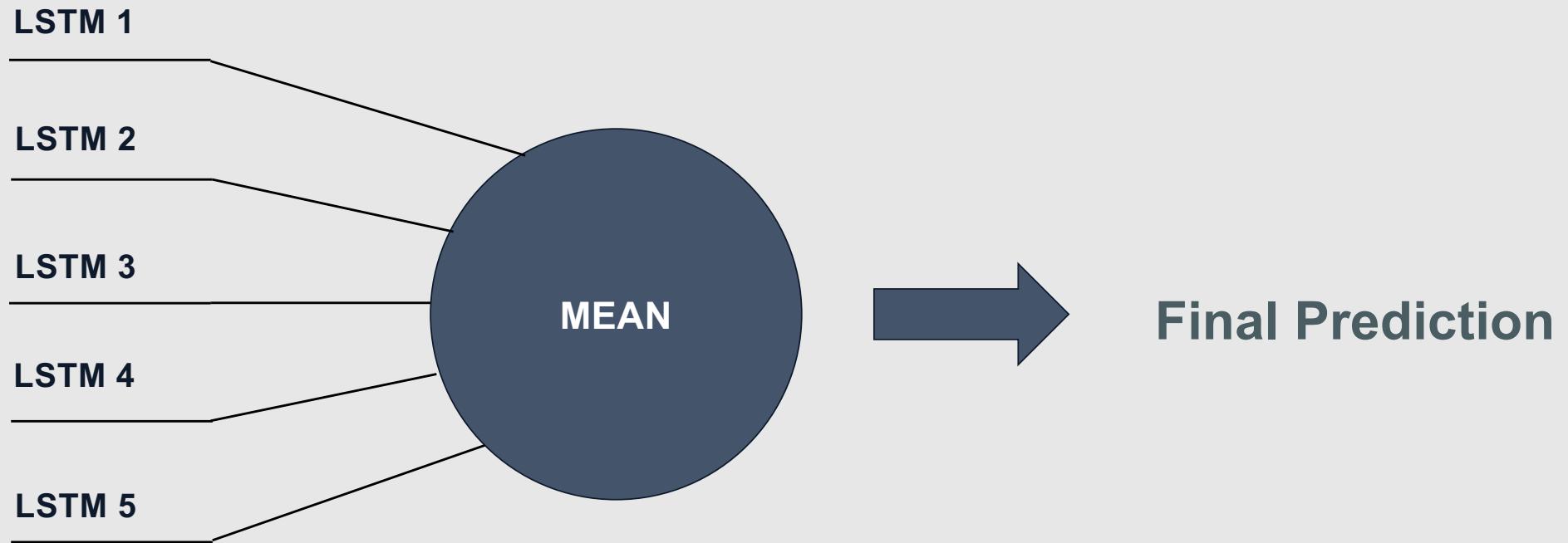
Learning rate: 0,00224

Dropout rate: 0,2

Optimizer: Adam

Initializer: He_uniform

Tackling Randomness



BUY!



Deciding to Buy, Sell or Hold

Decision Rule & Amount of Money invested depending on:

- Open Price
- Predicted Value of day after tomorrow
- Predicted Value of day after after tomorrow

SELL!

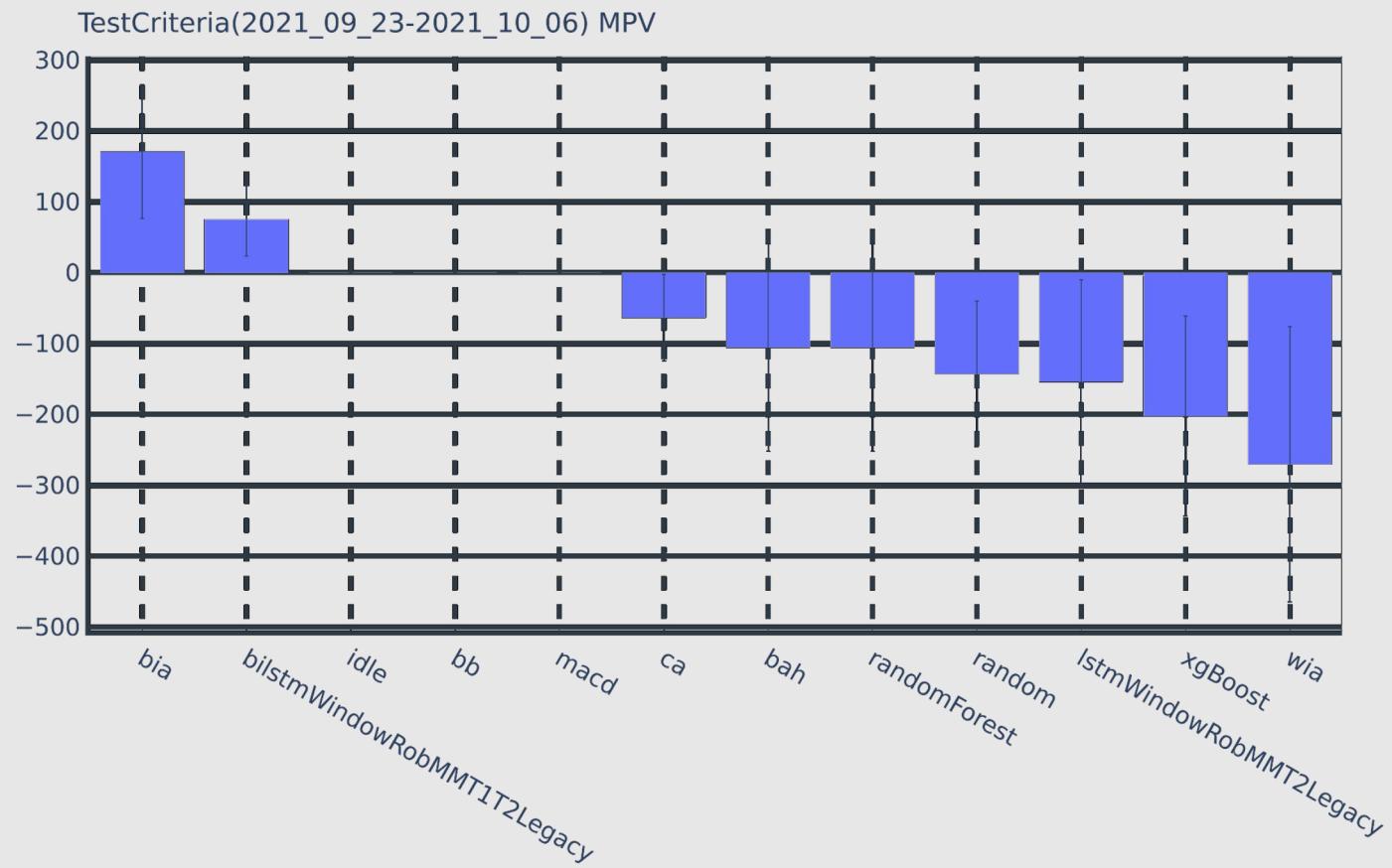


Example:

$\text{Open}(t) < \text{Predicted}(t+2) < \text{Predicted}(t+3)$

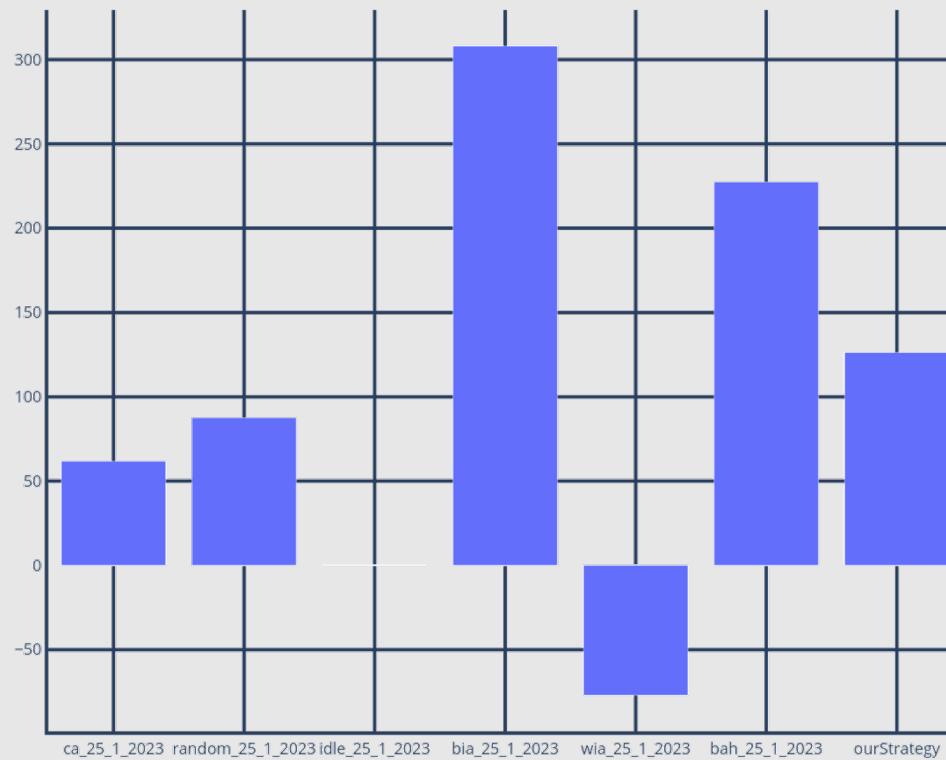
→ We Buy the Maximum

Performance of our Algorithmn

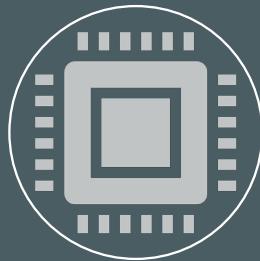


Results after 2 weeks test period

Mean Portfolio Value Comparison (10,000\$ offset)



Communication with Frontend



Backend

- Computing power
- Strategy logic



Frontend

- User-friendly GUI

User expectations

Resource Utilization

- × Huge local CPU requirements
- × Unusable device during calculation

Excessive Waits

- × Long hours until recommendation
- × Need of device turned on

Local Storage Utilization

- × Peril of deleting critical files
- × Inaccessibility from other devices

UIX

Alternatives apart from GUI

- × Access to data only through frontend
- × Daily time allocation to examine data

Backend Evolution



-O Cloud Backend to reduce Local Computing Power



Google Cloud



No user's device
Cloud-based solution



Reduced time
Possibility of powerful resources



No local docs
Data access from anywhere



Daily digest
Email service enabled

Google Cloud's Google Storage

Bucket that keeps the strategy data and the description of the strategy

Instance Selection

Roughly 10 min calculation.
4 VCPU's with 16GB

Google Cloud's Computer Engine

Cloud-based Debian 11 VM running the script
SSH and Crontab



Frontend Dashboard



Dashboard

Dashboard for your important informations, current and last recommendations



Overview over all
important Metrics with
real Time Updates



Different Options for
Aesthetics and
Colorblindness



Available E-Mail
Subscription



Available Version for
Windows and MacOs
soon

Frontend Live Demo



Future Work

01 Include fundamental analysis

02 Frontend application on every device

03 Increasing the number of operations per day

04 Include tax & transaction fees



Product Summary



- Recommendation Engine for S&P 500
- Mean Portfolio Value = 10,144.59\$ in a two-week time window with starting capital of 10,000\$
- Accessible frontend
- Backend hosted on Google Cloud
- Full stack product