

REAL-TIME TRADING SYSTEM

**Implementation of different trading
strategies in a real-time system**

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Agenda

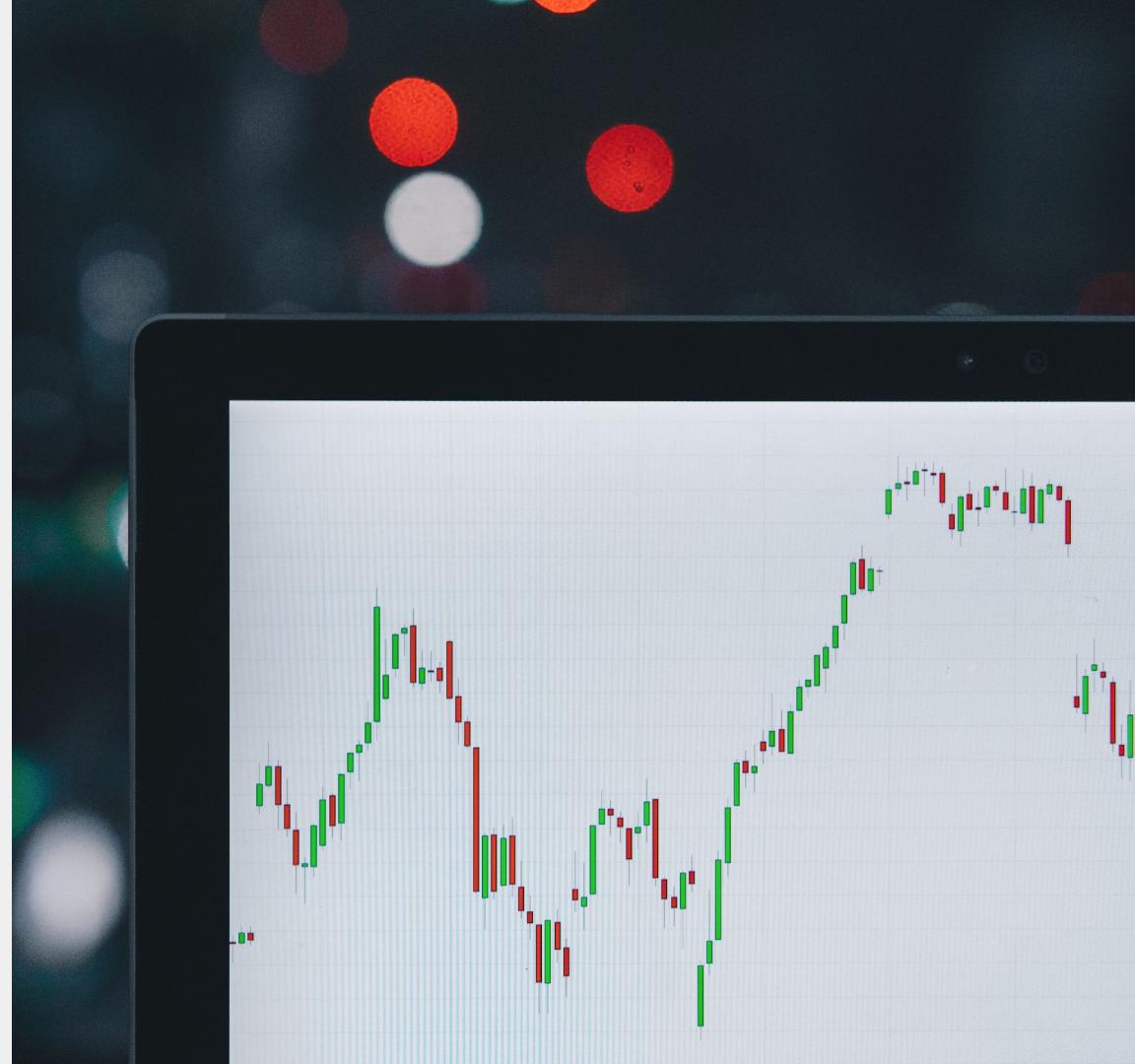
Project Introduction

System Design

Trading Strategies

Comparison of Results

Future Work





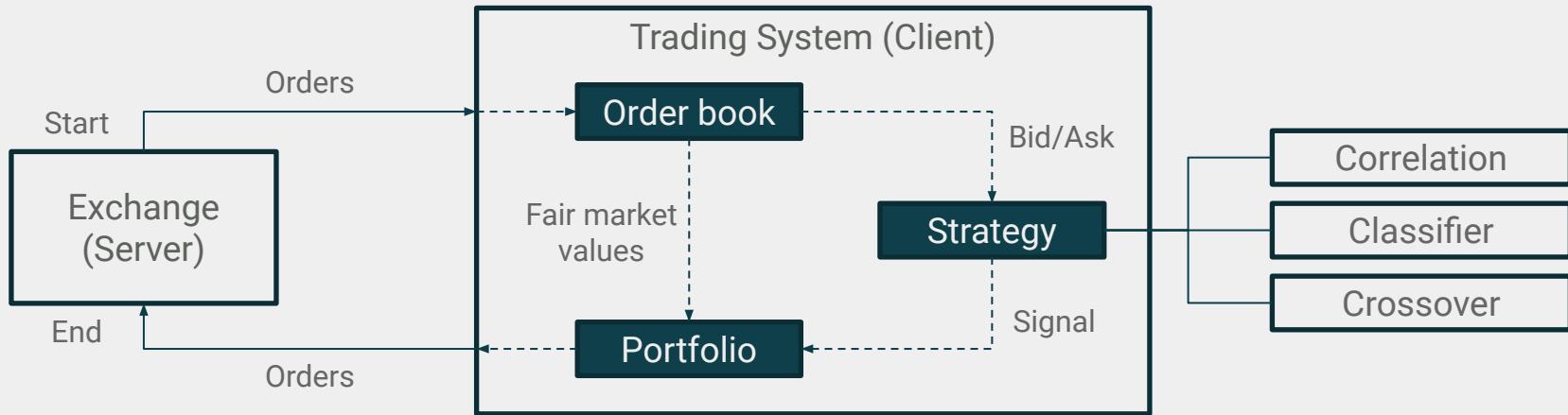
Business Problem

- Build a real-time trading system that is capable of interacting with a fictitious stock market
- Trading system receives market updates from a server and makes decisions based on the following different strategies
- The goal of each strategy is to maximize the return on the invested money

System Design



Overview



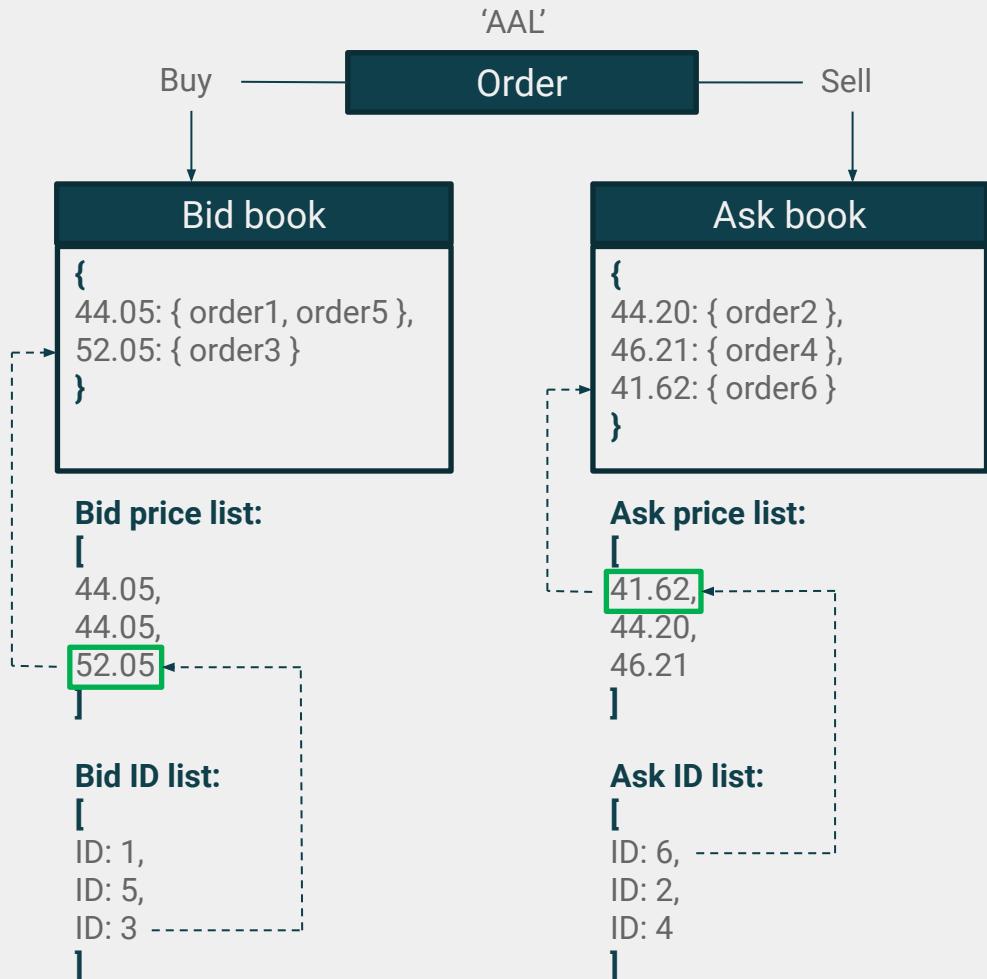
Execution time: ~ 0.601 sec from start to end

Order book: Dictionary where key equals symbol and item equals class object (bid/ask book)

Portfolio: Holdings with updated market values, quantity, cash position

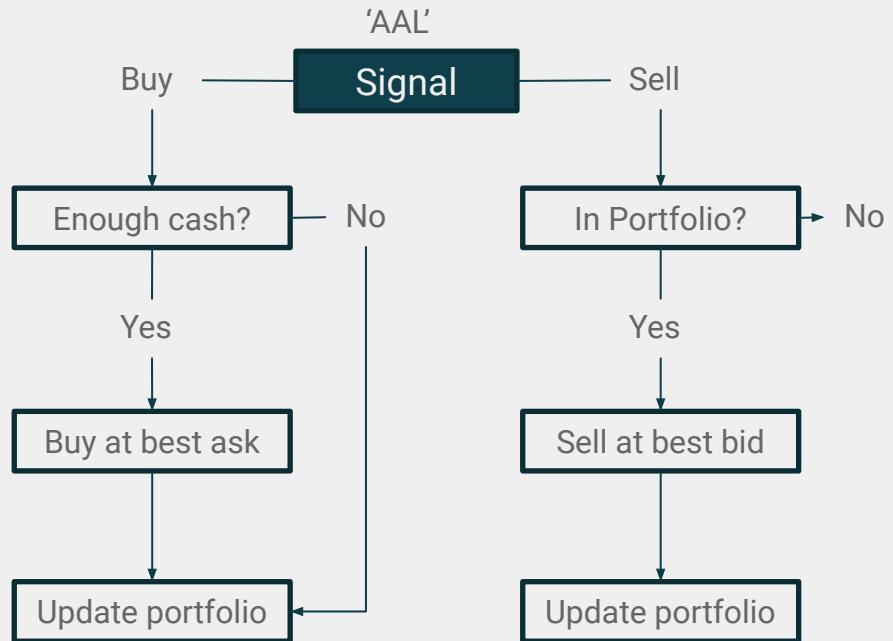
Order book

- New orders are stored in bid or ask book with price as key
- Sorted price lists are maintained as pointers to the dictionary
- ID lists are maintained as pointers to the price list
- ID lists are in same order as price lists, so books can be queried by ID also (i.e. for price modifications)



Portfolio

- Checks whether there is enough cash or stocks in the portfolio
- If yes, buys pre-determined amount of shares (Buy)
- If yes, sells all shares in portfolio (Sell)
- Updates quantity, cash position and market value of position (avg. best bid and best ask)
- If no, update market values, if in portfolio (Buy)
- If no, do nothing (Sell)



The background image shows an aerial view of the Frankfurt skyline. In the foreground, the historic Römerberg area is visible with its traditional half-timbered houses. Behind it, the modern financial district of Frankfurt am Main rises, dominated by the Commerzbank Tower and other skyscrapers. The River Main flows through the city on the left. The sky is filled with scattered clouds.

Trading Strategies

Feature Engineering

1. Create dataframe from each symbol
2. Extract features from each symbol
3. Recombine data from each symbol into single train dataset

Features:

Dummy:

- Action
- Side
- Exchange

With two windows, lengths 5 and 10, compute:

- Standard deviation
- Mean
- Difference

For:

- Quantity
- Price
- News

Classifier

1. Create dataframe for each symbol
2. Calculate response for each row
3. Combine with extracted features
4. Train classifier on first 80% of data, test on last 20%

Defining the response:

1. Calculate percent change on price for consecutive orders of the same stock, ignoring side/action
2. If change > 5%, correct prediction is "Buy"
3. If $-5\% < \text{change} < 5\%$, correct prediction is "Hold"
4. If change < -5%, correct prediction is "Sell"

Training the classifier:

1. Extract features from each symbol for every row after minimum window is met (10 rows)
2. Predict "Buy," "Hold," or "Sell" using those features as a multiclass problem
3. Best performance on gradient boosting classifier
 - a. 92% accuracy
 - b. 96% F1 score for "Hold"
 - c. 77% F1 score for "Buy" and "Sell"

Crossover Strategy

- Short (5 orders) and long (10 orders) rolling mean price
 - $\text{diff} = \text{short} - \text{long}$
- “Buy” when $\text{diff} > 5\%$
- “Hold” when $-5\% < \text{diff} < 5\%$
- “Sell” when $\text{diff} < -5\%$



<https://www.investopedia.com/articles/active-trading/052014/how-us-e-moving-average-buy-stocks.asp>

Rolling dataframe for classifier and crossover strategies

- Create dict with keys = symbols, values = empty dataframes
- Append new orders to dataframe corresponding to each symbol
- Hold before dataframe reaches length = 10
- Once length = 10, extract features
- Run classifier or crossover strategy on last row
- Make each trading strategy a class with a handle_market_order method and a rolling_df_dict instance attribute

Index	Symbol	Action	Price	Exchange	Side	Recommendation
1	'AAPL'	A	44.08	2	B	"Hold"



2	'AAPL'	A	47.45	1	B	"Hold"
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Index	Symbol	Action	Price	Exchange	Side	Recommendation
1	'AAPL'	A	44.08	2	B	"Hold"
...
10	'AAPL"	A	73.22	3	S	"Sell"



Index	Symbol	Action	Price	Exchange	Side	Recommendation
2	'AAPL'	A	47.45	1	B	"Hold"
...
11	'AAPL"	A	71.92	2	S	"Sell"

Correlation strategy

Pairs included in the strategy	Correlation coefficient
('BMRN', 'GOOGL')	0.657
('CSCO', 'ISRG')	0.475
('CTXS', 'INTC')	0.440
('CERN', 'CTRP')	0.436
('ADI', 'DISCK'),	0.427
('ALXN', 'FAST')	0.400

Initial exploration:

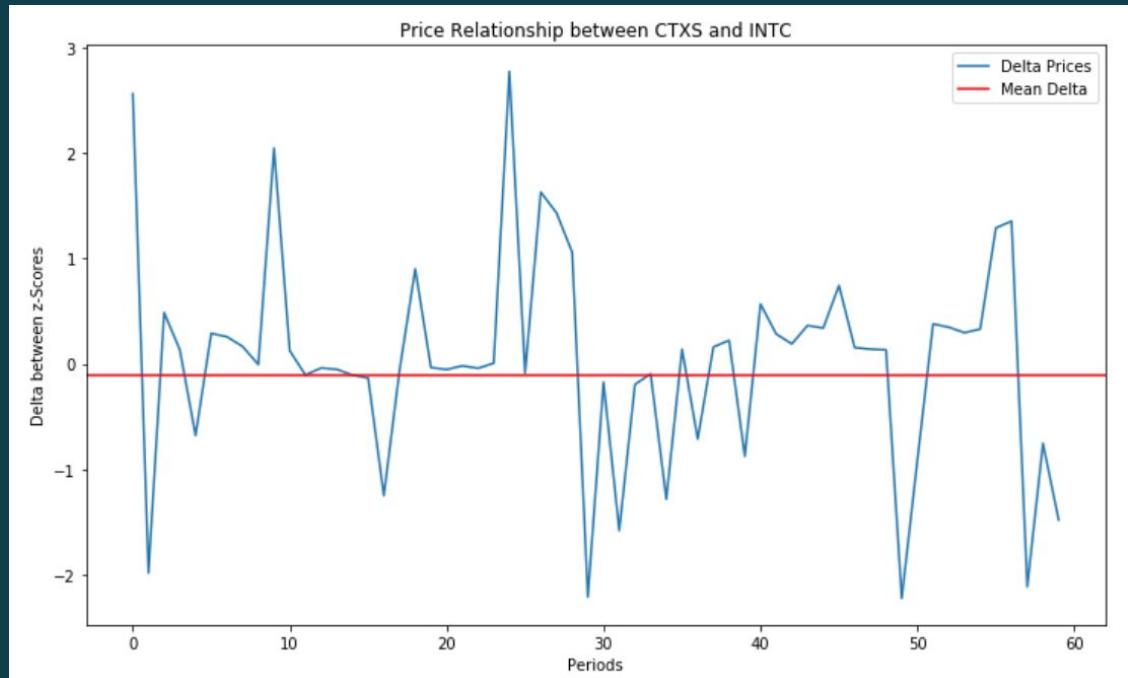
- Calculate returns for each stock for the given periods
- Determine correlation coefficients between the returns of the stocks
- Identify pairs with highest correlation

Real-time implementation:

- Use window of past 10 prices to calculate the z-score of the prices for the incoming stock and its partner
- Calculate delta between the z-score prices for the pair of the incoming stock
- Send buy/sell/hold signal based on a predefined threshold for the delta between the z-score prices

Fine-tuning of the correlation strategy

- Tested different thresholds and 1/-1 yields the best results
- Delta >1: “Buy” INTC and “Sell” CTXS as CTXS increases while INTC doesn’t or INTC decreases while CTXS doesn’t
- Delta <-1: Decreasing delta: “Sell” INTC and “Buy” CTXS as CTXS decreases while INTC doesn’t or INTC increases while CTXS doesn’t
- $1 > \text{delta} > -1$: “Hold”



Comparison of Results



Our strategies come with different pros and cons

Strategy	Return	Max frequency	Insights
Cross-Over	42.2% initial cash: \$100k trx amount: 15	10 order/sec	<ul style="list-style-type: none">• High frequency, low volume strategy• Data storage: pandas dataframes 10 rows
Classification	262.6% initial cash: \$100k trx amount: 10	3.3 order/sec	<ul style="list-style-type: none">• High frequency, low volume strategy• Data storage: 10 rows of 9 columns in pandas dataframe• Feature creation and prediction slows down execution time
Correlation	75.1% initial cash: \$100k trx amount: 200	100 order/sec	<ul style="list-style-type: none">• Low frequency, high volume strategy• Data storage: 10 prices in a dictionary of dequeues by symbol; no other data required

The background image shows a panoramic aerial view of the London skyline. In the foreground, the iconic red and white Tower Bridge spans the River Thames. To the right, the dense urban sprawl of the City of London and its skyscrapers, including the Gherkin and the Walkie-Talkie, are visible. Further along the riverbank, the residential and commercial areas of Southwark and Lambeth are shown, with numerous smaller buildings, parks, and waterfront developments. The River Thames curves through the city, with several bridges and ferries visible on the water.

Future Work

Moving forward we want to make a few improvements

- **Closed loop:** Create a feedback loop of the transactions made by our system back into our order book
- **Multiple exchanges:** Make the trading system more fine grained by acknowledging different exchanges and having separate order books for each
- **Transaction fees:** Consider transaction fees when calculating the return on investment of a strategy
- **Threading:** Implement threading to be able to process multiple incoming orders
- **Cloud computing:** Improve runtime using cloud technology