Quantitative Trading Strategy

Group 7

Objective

- Implement two broad types of trading strategy – mean reversion and momentum
- Explore the performance of both strategies
- Mean-reversion strategies: **pairs trading** strategies on HK equities

Data sources: Bloomberg, Hong Kong Exchange (via Nasdaq Datalink), Yahoo Finance

Data period: 5 years historical – 22 May 2018 – 22 May 2023 (80-20 train-test split)

Pairwise correlation?
Sortino ratio?

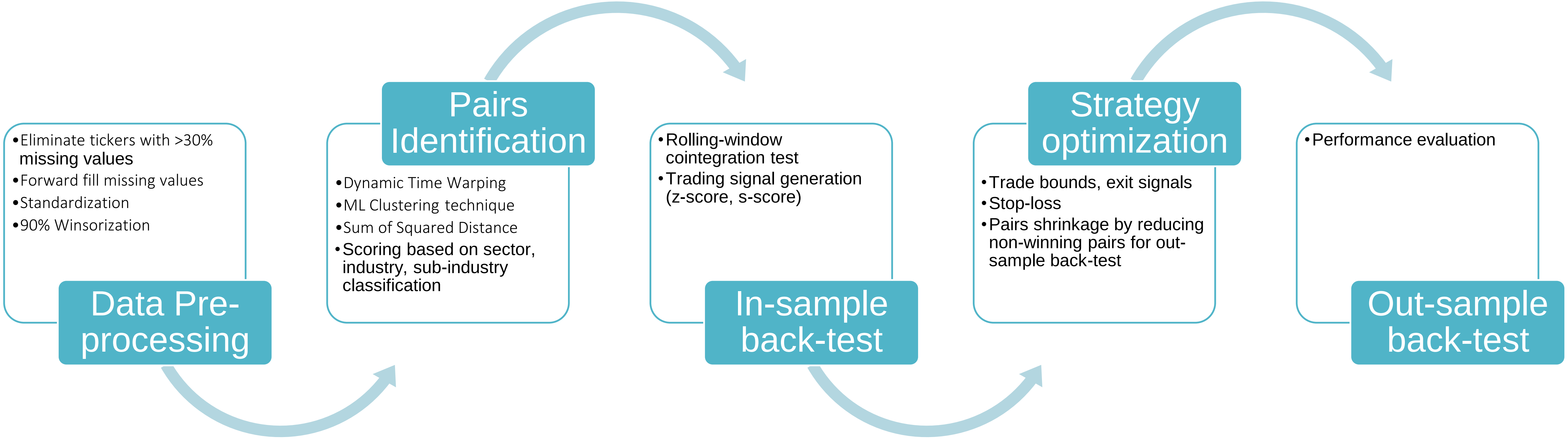
Pairs Trading

Economic Justifications of pairs trading strategies

Mean reverting behaviour between related stocks

- Market inefficiencies: Related assets may not react on the same stimulus at the same time, resulting in transient dislocation of spread; this is expected to be corrected in the long run
- Diversification: Running multiple pairs from different sectors concurrently may achieve diversification due to low correlation
- Risk Management: Strive for market neutrality through pairs of long and short trade

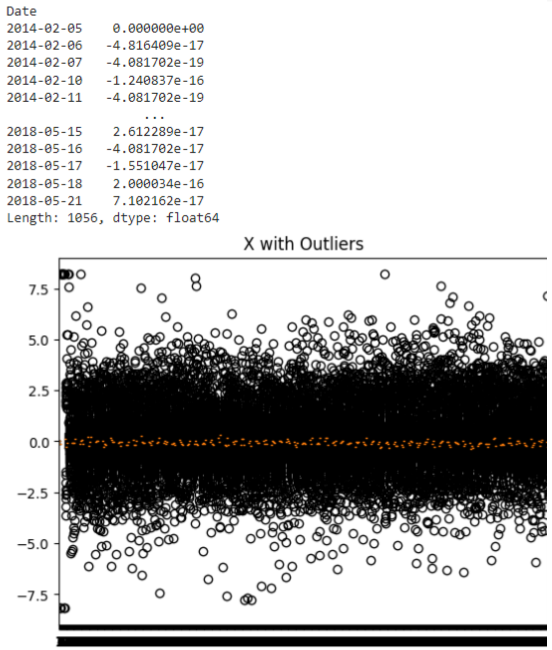
Trading Strategy - Pipeline

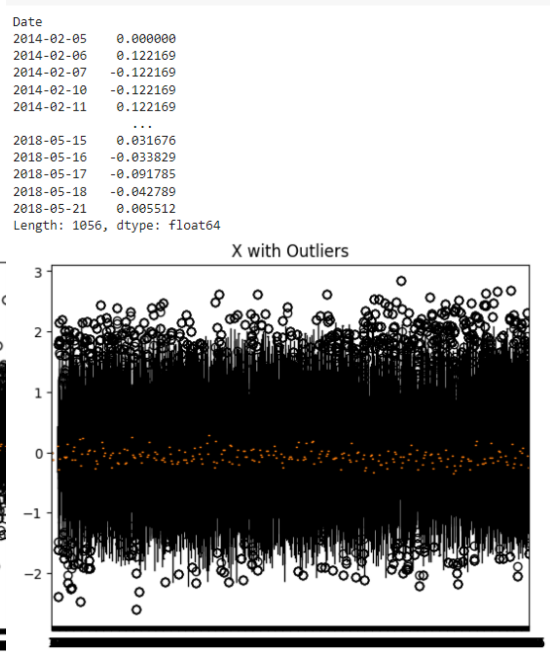


Data Pre-processing

Handling missing prices

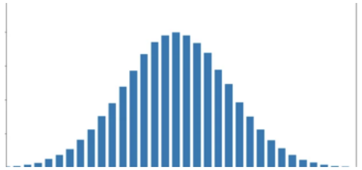
- Only trades assets that are listed on or before the training start date
- Forward fill remaining missing values to account for missing values due to trading holidays





Processing for machine learning techniques

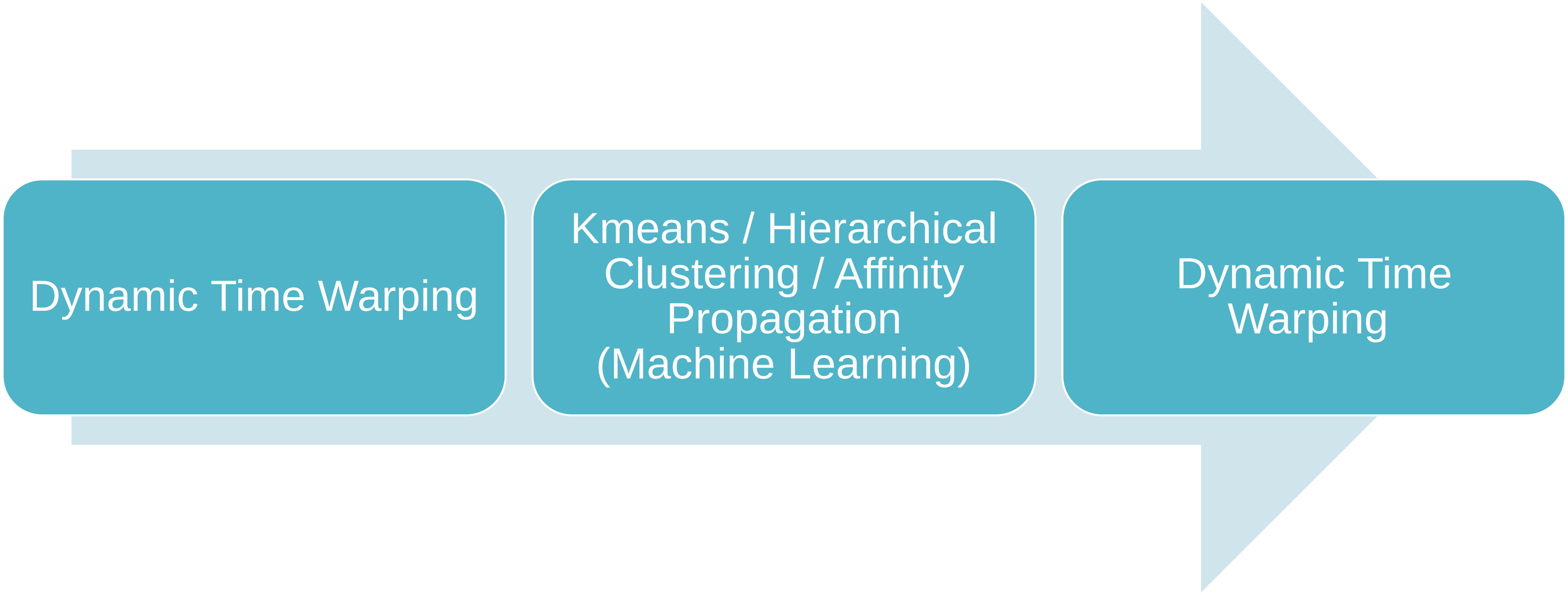
- Standardization of values
- Winsorization – 90% of mean

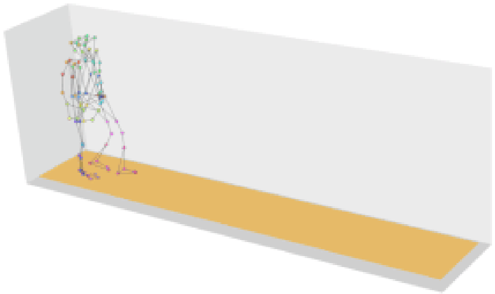


Reference:

1. *Nakagawa, K., Imamura, M., & Yoshida, K. (2019). Stock price prediction using k-medoids clustering with indexing dynamic time warping. Electronics and Communications in Japan, 102(2), 3-8.* https://doi.org/10.1002/ecj.12140

Flow-chart of pairs identification





1. Dynamic Time Warping

Package Used: Implemented **DtwParallel** python package (***Escudero Arnanz et. al. (2023)***)

Why DTW?

- Manage varying time series length, speed, and distortions
- DTW warps time sequence to enhance alignment
- Allows DTW to compare intricate distance that are out of phase or different in length time
- Superior method to Euclidean distance but computationally expensive

Implementation

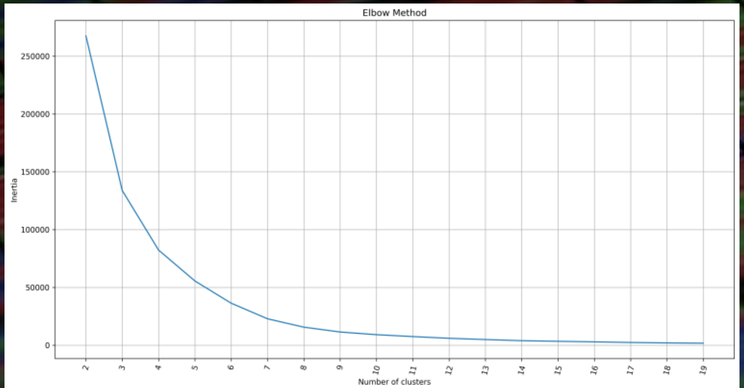
- Set "Sakoe Chiba" global constraint to lower computational cost (known for lower error rate)
- DTW => Clustering Algorithm => DTW

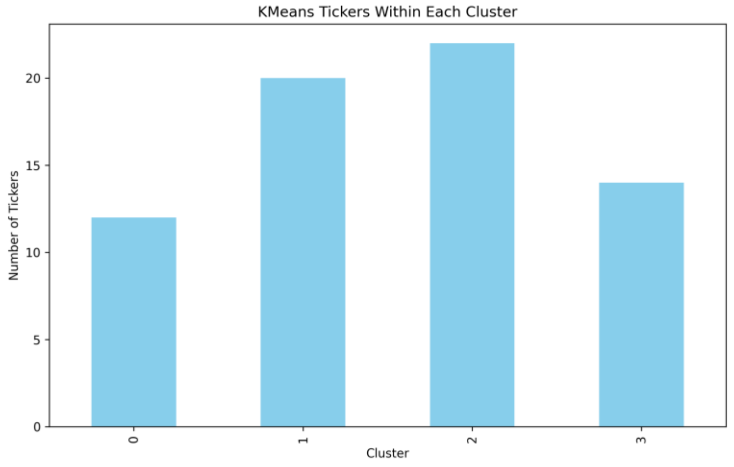
Reference:

1. *Escudero Arnanz, O., G Marques, A., Soguero-Ruiz, C., Mora-Jiménez, I., & Robles, G.(2023) Dtwparallel: A Python Package to Efficiently Compute Dynamic Time Warping. Original Software Publication, Software X. Volume 22, 101364.* https://doi.org/10.1016/j.softx.2023.101364
2. *Nakagawa, K., Imamura, M., & Yoshida, K. (2019). Stock price prediction using k-medoids clustering with indexing dynamic time warping. Electronics and Communications in Japan, 102(2), 3-8.*
3. *Geler, Z., Kurbalija, V., Ivanović, M., & Radovanović, M. (2022). Elastic distances for time-series classification: Itakura versus Sakoe-Chiba constraints. Knowledge and Information Systems, 64(10), 2797-2832.*

Clustering Algorithms

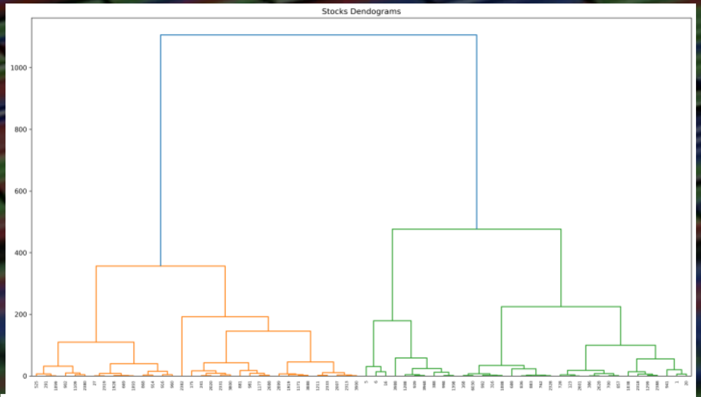
K Means

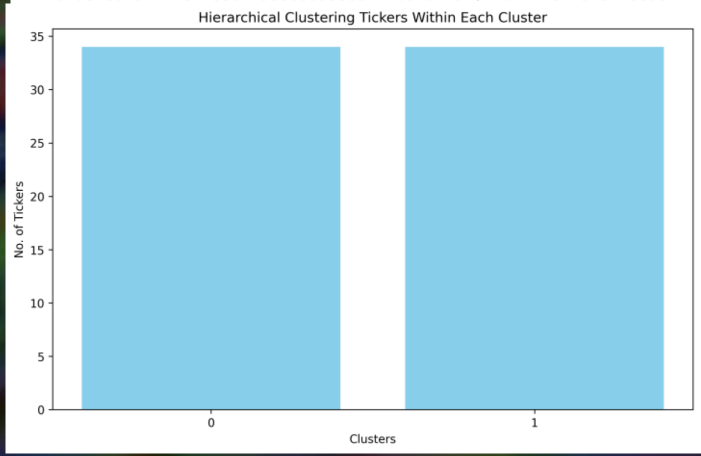




(4 clusters of 12, 20, 22, 14 Tickers)

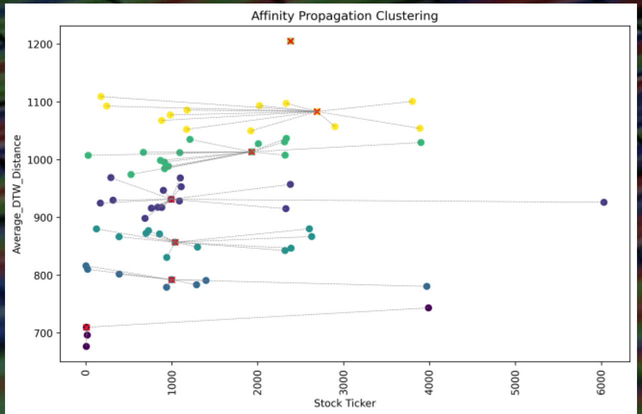
Hierarchical Clustering

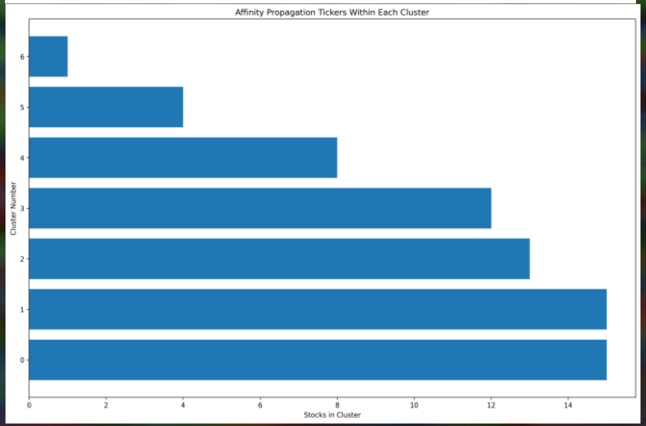




(2 clusters of 34, 34 tickers)

Affinity Propagation





(6 clusters of 4, 15, 8, 12, 15, 1, 13 tickers)

Clustering Score Metrics

K Means algorithm performs well in Calinski Harabasz and Davies Bouldin index but did worse in Silhouette Score than Agglomerative Clustering and Affinity Propagation, albeit all three models have similar score

K-Means showed consistent performance across all three performance metrics

K-Means cluster stocks will be best technique to perform clustering

```
----------Silhoulette Score----------

K-Means : 0.5844500087935521
Agglomerative Hierarchical : 0.5917165679497547
Affinity Propagation : 0.5848175076184303

----------Calinski-Harabasz Index----------

K-Means : 1366.1156610109422
Agglomerative Hierarchical : 150.93934799095928
Affinity Propagation : 378.2074401165306

----------Davies-Bouldin Index----------

K-Means : 0.35311695678482397
Agglomerative Hierarchical : 0.5333106401926954
Affinity Propagation : 0.38443711213277304
```

	Ticker_1	Ticker_2	DTW_Distance
0	1288	3988	335.33
1	998	1398	453.44
2	939	1398	923.47
3	939	998	1024.79
4	902	916	1077.47
5	525	2380	1198.53
6	857	992	1216.54
7	386	857	1291.75
8	2899	3800	1305.89
9	1919	2899	1339.13

Stanley

Sector Scoring

- Sector scoring ensures that selected pairs have fundamental similarities
- Assess the sector, industry and sub-industry classifications using data from Bloomberg. With each similarity, 1 score is added to the pair.
- Pairs that are common across all three classifications will have a max score of 3. These are the pairs that are selected for the trading strategies.
- **<u>Results: 38 pairs have been identified with DTW distance less than 100,000</u>**

Trading Strategy

T+0: Cointegration test → **Trading window** → **T+20: Cointegration test**

T+0: Cointegration test

- Run first cointegration test on the pairs to check for stationarity
- Use **past 100 days price series**
- **Significance level = 5%**
- Only pairs that met the criterion can be traded

Trading window

- Trading signals generated **based on 'z' or 's' score**
- Exit signals can be symmetrical or vary with long and short position

T+20: Cointegration test

- Run second cointegration test on all pairs to check for stationarity
- If an existing pair failed the test, this implies pair-breakage, position to be closed
- Act as **natural 'time-based' stop-loss**
- Process repeats

Trading Signals

1

Z-score based signals

$$spread_t = X_{2,t} - \beta X_{1,t}$$

$$z = \frac{spread_t - \overline{spread}_{60ma}}{\sigma(Spread_{60ma})}$$

Long if $z < -trade\_bound$
Short if $z > trade\_bound$
Exit if $|z| < exit\_bound$

Trade bound = 1.4
Exit bound = 1

2

S-score based signals

Modelling the spread as an Orstein-Uhlenbeck Process

If speed of mean-reversion is greater than 8.4, there is a strong mean-reverting strength, implying short-term mean reversion tendencies. Then we calculate the s-score.

$$s = \frac{spread_t - m}{\sigma_{equilibirum}}$$

Long if $s < -trade\_bound$
Short if $s > trade\_bound$
Exit long if $s > long\_exit\_bound$
Exit short if s $> short\_exit\_bound$

Trade bound = 0.8
Long Exit bound = -0.4
Short Exit bound = 0.6

Marco Avellaneda & Jeong-Hyun Lee (2010) Statistical arbitrage in the US equities market, Quantitative Finance, 10:7, 761-782, DOI: 10.1080/14697680903124632

Trading Strategy

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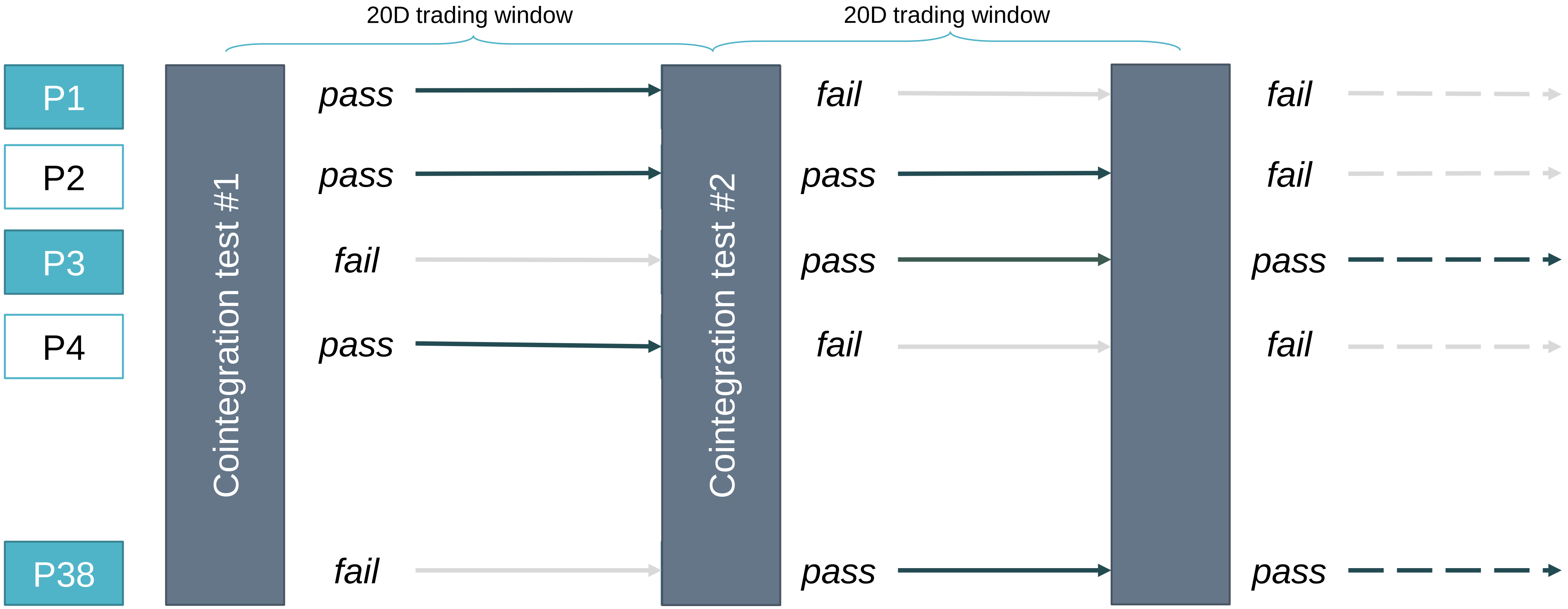
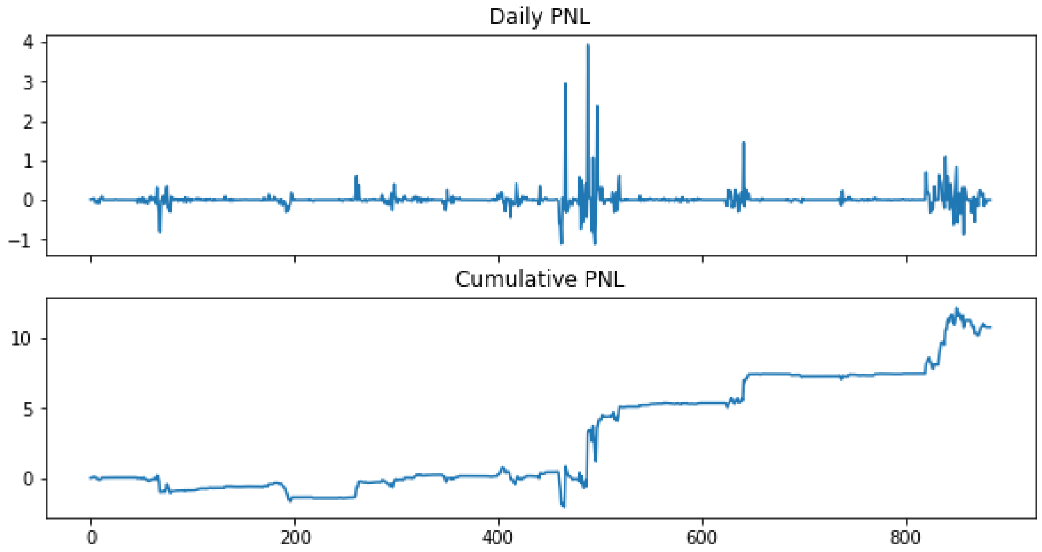
Illustration: Pairs trading lifecycle



In-sample test results

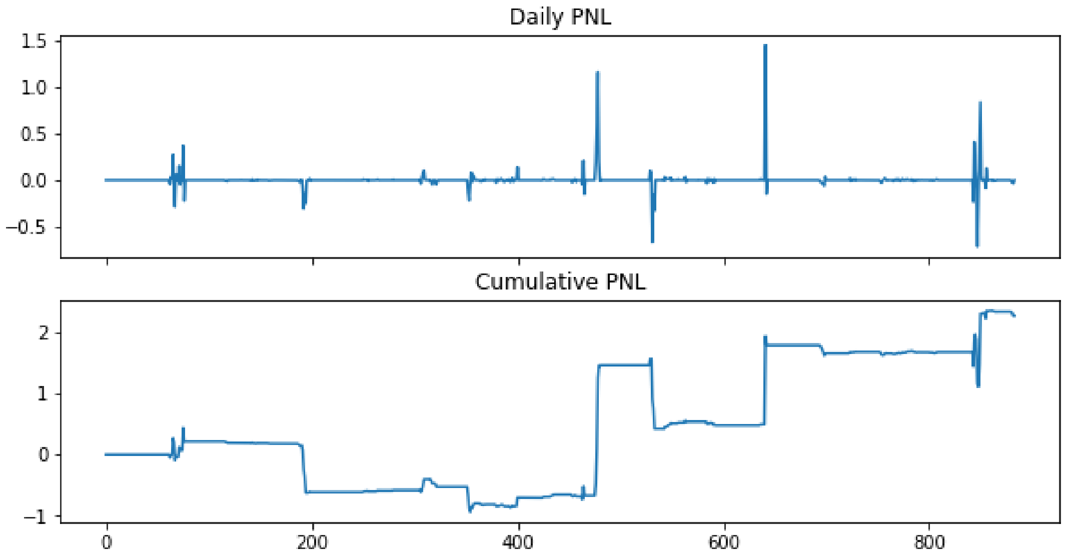
Z-score based trading strategy

```
PERFORMANCE STATISTICS FOR PORTFOLIO
Trading days:884
Daily annualized sharpe: 0.7947286994811176
Average annual returns: 307.2657423219267%
Total returns: 1077.8687151292984%
Max drawdown: -287.5915572820258%
```



S-score based trading strategy

```
PERFORMANCE STATISTICS FOR PORTFOLIO
Trading days:884
Daily annualized sharpe: 0.4651348335616768
Average annual returns: 64.80354660054081%
Total returns: 227.32672696380186%
Max drawdown: -137.71211928650376%
```



Strategy Optimization

Some optimization of the trading strategies include tuning the trade bounds, exit bounds, trading window, number of datapoint for cointegration tests.

After the optimization, the following parameters are used:

Z-score: (trade_bound = 1.4, exit_bound = 1.0, window = 20, look_back = 100)

S-score: (trade_bound = 0.8, exit_bound = (-0.40, 0.60), window = 20, look_back = 100)

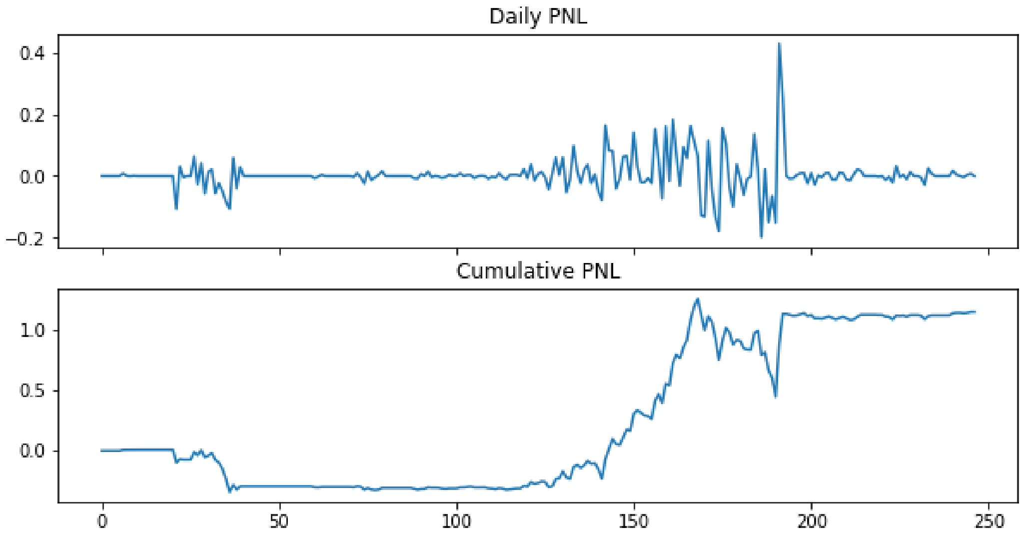
Once the optimization has been completed, we run in-sample test again. Here, we will exclude pairs that performed poorly, i.e. achieved negative Sharpe ratio.

The idea is that if the pairs failed to perform during in-sample testing, the likelihood that these pairs will perform in out-sample test will be low.

Out-sample test results

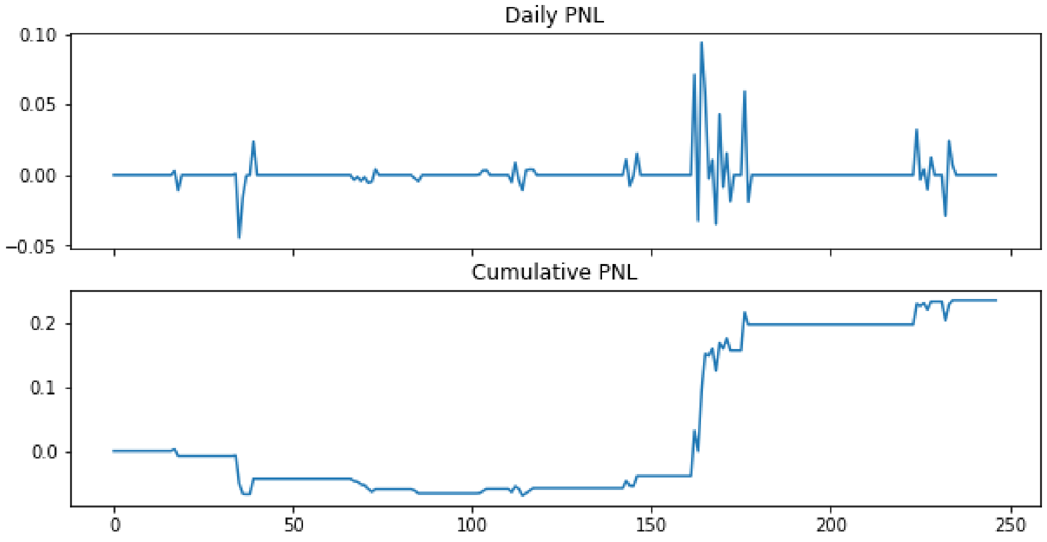
Z-score based trading strategy

```
PERFORMANCE STATISTICS FOR PORTFOLIO
Trading days:247
Daily annualized sharpe: 1.2700436580023897
Average annual returns: 116.40831551214876%
Total returns: 114.09862671230454%
Max drawdown: -80.516082241705%
```



S-score based trading strategy

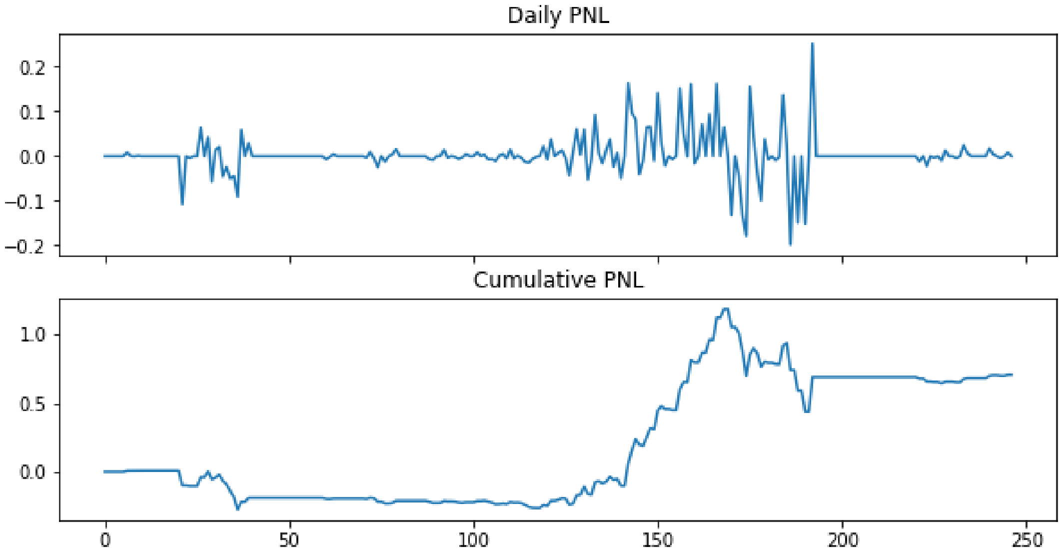
```
PERFORMANCE STATISTICS FOR PORTFOLIO
Trading days:247
Daily annualized sharpe: 1.3210873328181705
Average annual returns: 23.991989546695244%
Total returns: 23.51595800807035%
Max drawdown: -7.220146896730542%
```



Implementation of Stop-loss

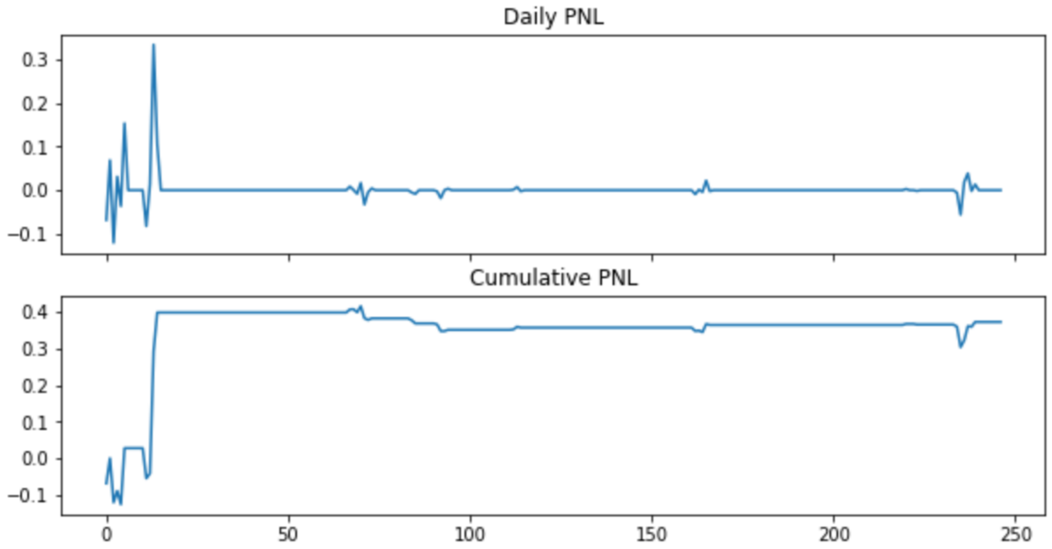
Z-score based strategy (stop-loss = +/-1.9)

```
PERFORMANCE STATISTICS FOR PORTFOLIO
Trading days:247
Daily annualized sharpe: 0.9951717529153895
Average annual returns: 72.13712300896333%
Total returns: 70.7058308857696%
Max drawdown: -74.66441584301113%
```



S-score based strategy (stop-loss = +/-1.6)

```
PERFORMANCE STATISTICS FOR PORTFOLIO
Trading days:247
Daily annualized sharpe: 0.8717752057419755
Average annual returns: 38.052418485632764%
Total returns: 37.297410182346404%
Max drawdown: -12.599695277706715%
```



Further Analysis – summary of Out-sample test

	Z-score strategy			**S-score strategy**		
	Sharpe Ratio	MDD (%)	Annualized return (%)	Sharpe Ratio	MDD (%)	Annualized return (%)
Without stop loss	1.27	81	116	1.32	7.22	24
With stop loss	0.99	75	72	0.87	12.6	38
With stop loss + trxn cost (30 bps)	0.46	77	32	0.58	14.1	25

Challenges encountered and overcame

Due to computational time constraint, static window for cointegration test was used which led to poor detection of pair breakage. Also led to wrong trades being placed right before pair breakages.

S-score – using s-score as signals can be difficult as it needs to meet conditions: 1) speed of mean reversion must be fast enough, 2) trade bounds must be met; this led to much lesser trades

Data-sorting and classification

Difficulty at identifying pairs with positive sharpe ratio

Stop-loss (based on PnL & drawdown) – Most of our strategies faced huge negative pnl before going into positive. Max Drawdown is also high. Stop-losses implemented cannot effectively manage drawdowns as such.

On hindsight, we should have heed to the Principle of Parsimony and kept model simple.

Areas of Improvement

- Survivor bias
- Handling of missing values
- Inclusion of transaction cost
- Inclusion of market impact
- Apply effective stop-losses
- Implement capital allocation