



# Machine learning for Pairs Trading in Utilities

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# Motivation

## Machine learning for pairs trading

### Assets Price & Return

- High dimensional
- Non-linear

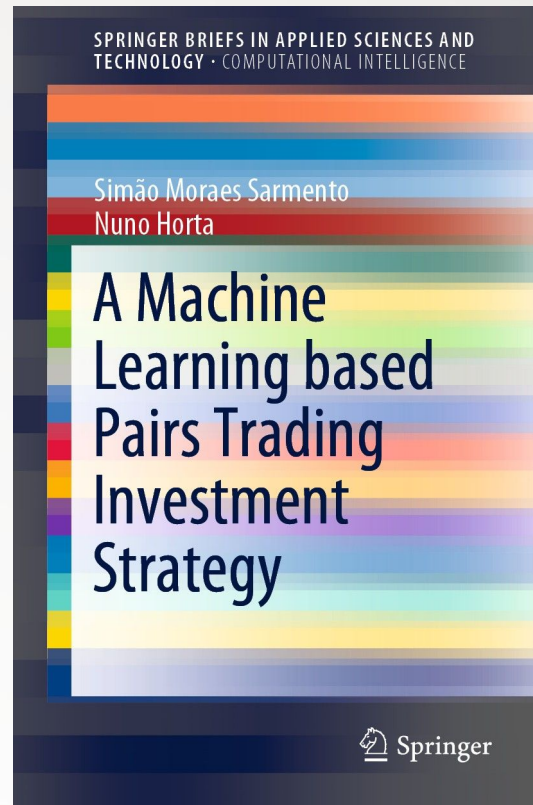
Can Unsupervised Learning find more promising pairs?

### Purpose:

- finding the appropriate candidate pairs
- selecting the most promising ones.

### Compare with traditional method

- OPTICS
- Correlation



# Data

Data: Yahoo finance API (yahooquery)

- US market: 9502 asset
- Stock: 6010 (exclude ETF)
- Sector Utilities: 82 stocks
- Pairs:  $(82*81)/2 = 3321$

Daily data

Train period 2023/03 – 2023/12

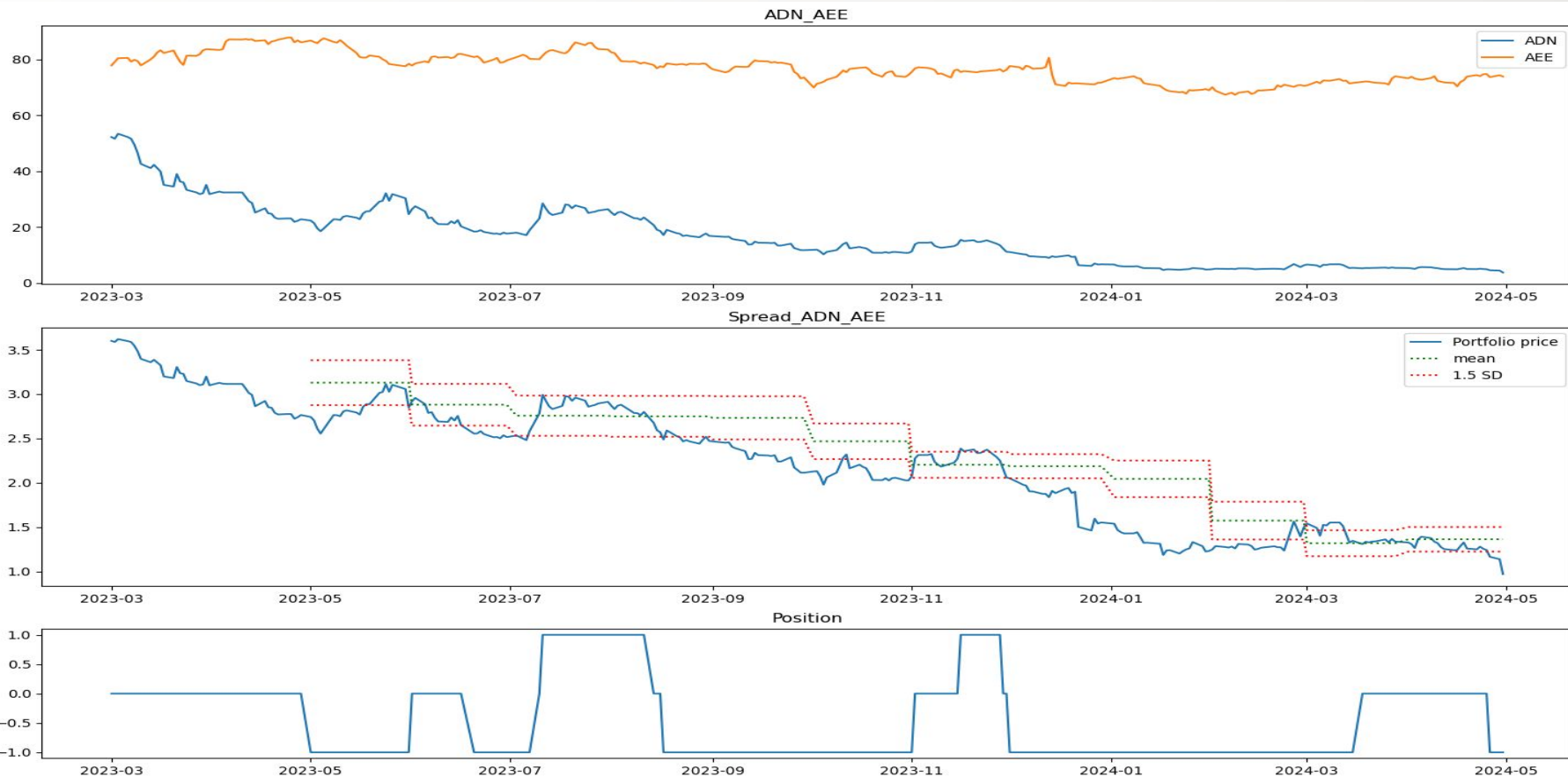
Test period 2023/01–2023/04

Ticker	Company	Sector	Industry	Country	Market Cap	P/E	Price	Change	Volume
ADN	Advent Technologies Holdings Inc	Utilities	Utilities - Renewable	USA	11.42M	0.00	0.15	-2.97%	848185.0
AEE	Ameren Corp.	Utilities	Utilities - Regulated Electric	USA	19.82B	17.00	74.36	0.96%	691501.0
AEP	American Electric Power Company Inc.	Utilities	Utilities - Regulated Electric	USA	45.60B	20.40	86.67	1.65%	1900397.0
AES	AES Corp.	Utilities	Utilities - Diversified	USA	12.66B	54.37	17.81	3.46%	5798232.0
AGR	Avangrid Inc	Utilities	Utilities - Regulated Electric	USA	14.15B	15.88	36.58	0.54%	334536.0
...	...	...	...	...	...	...	...	...	...
VST	Vistra Corp	Utilities	Utilities - Independent Power Producers	USA	27.04B	22.28	77.74	6.93%	3862044.0
WEC	WEC Energy Group Inc	Utilities	Utilities - Regulated Electric	USA	26.07B	19.60	82.63	1.40%	1160992.0
WTRG	Essential Utilities Inc	Utilities	Utilities - Regulated Water	USA	9.98B	19.58	36.47	1.05%	703016.0
XEL	Xcel Energy, Inc.	Utilities	Utilities - Regulated Electric	USA	30.27B	16.38	54.49	0.99%	2732624.0
YORW	York Water Co.	Utilities	Utilities - Regulated Water	USA	509.10M	21.39	35.53	0.44%	28265.0

# Trading Execution Threshold-Based Trading Model

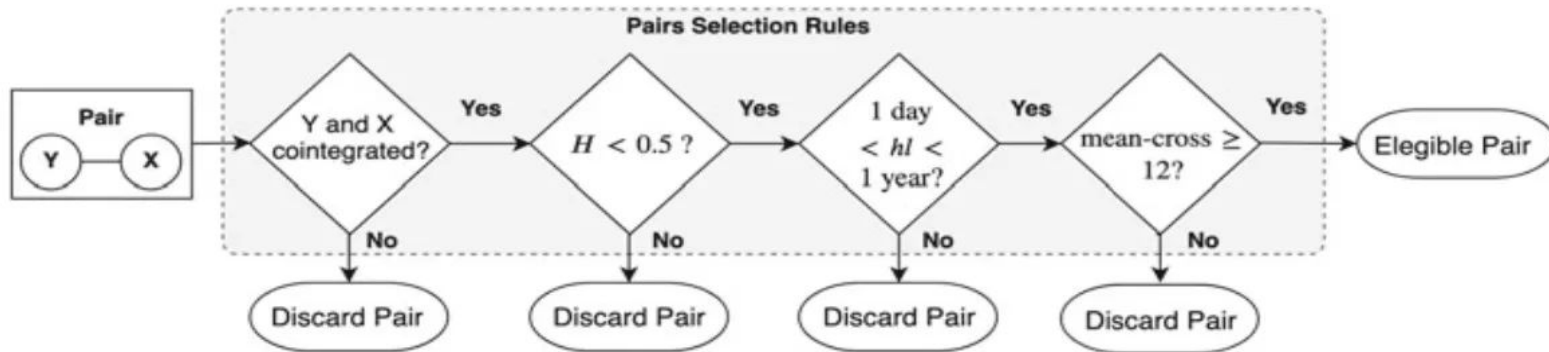
1. Calculate the spread's ( $S_t = Y_t - X_t$ ) mean  $\mu$ , and standard deviation  $\sigma$  during the pair's formation period.
2. Define the model thresholds: the threshold that triggers a long position  $L$ , the threshold that triggers a short position  $S$ , and the exit threshold  $exit$  that defines the level at which a position should be exited.
3. Monitor the evolution of the spread,  $S_t$  and control if any **threshold is crossed**.
4. In case  $L$  is crossed, go long the spread by **buying  $Y$  and selling  $X$** . If  $S$  is triggered, short the spread by **selling  $Y$  and buying  $X$** . Exit position when  $exit$  is triggered and a position was being held.

# Pairs





# Cointegration



## Mean-Reversion and Stationarity

- Mean-reversion is the tendency of a time series to return to its historical average over time.
- Stationarity implies that the statistical properties of a time series, such as mean and variance, do not change over time.
- **Cointegration Test p-value < 0.05**: Ensures a stable long-term relationship between the pair.
- **Hurst Exponent < 0.5**: Confirms mean-reverting behavior.
- **1 < Half-Life < 365**: Validates that the mean reversion occurs at a reasonable pace.
- **Mean-Cross  $\geq 12$** : Ensures sufficient trading opportunities through frequent mean reversion.

# Machine Learning

Identification of two securities, for example two stocks, for which the corresponding prices series display a similar behaviour, or simply seem to be **linked** to each other.

## Normalization & Dimensionality reduction

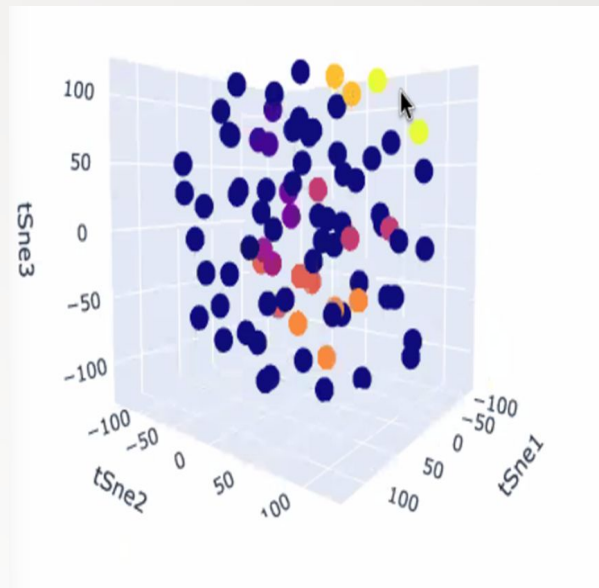
- We imported,adjusted, standardized these data and find a compact representation for each security
- T-SNE:Non-linear method.

Unsupervised Learning—apply an appropriate clustering algorithm;

- OPTICS : A density-based algorithm
- Handles Varying Densities
- Effectively with Noise
- Flexible Clustering

Select pairs—define a set of rules to select pairs for trading.

- Combined with Cointegration, we finally came up with 4 pairs that can meet all our requirements.





# Result & Beaktest

## 1. Correlation

Pair	correlation	pvalue	hurst_exponent	half_life	crossovers	Return	Std Dev	Max Drawdown	Sharpe Ratio	Omega
AGR_ES	0.977222	0.014088	0.371316	6.513701	26	-0.199022	0.084834	-0.075814	-2.346009	1.316523
BKH_POR	0.975519	0.03509	0.230085	36.62348	33	-0.047788	0.049497	-0.023879	-0.965465	1.186399
ES_WTRG	0.974181	0.021631	0.412536	38.71063	26	-0.136136	0.087945	-0.090848	-1.547979	1.34521
CPK_ORA	0.973617	0.001601	0.14878	7.060058	46	0.155662	0.101842	-0.026966	1.52847	1.443658

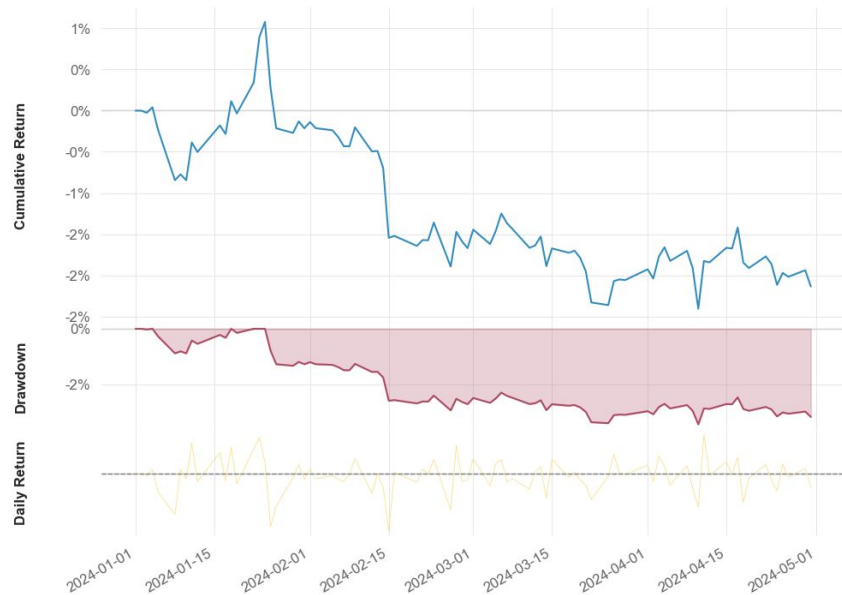
## 2. OPTICS

Pair	OPTICS	pvalue	hurst_exponent	half_life	crossovers	Return	Std Dev	Max Drawdown	Sharpe Ratio	Omega
AMPS_SWX	74.49906	0.001184	0.390763	319.1302	24	2.384911	0.286012	-0.049647	8.338499	2.583018
AES_D	44.41755	0.010932	0.361442	265.1005	26	-0.049624	0.154581	-0.105985	-0.321022	1.627348
ARTNA_NWN	49.96095	0.004631	0.349361	49.28517	34	0.093354	0.135373	-0.047971	0.689605	1.455371
NWN_UGI	58.28693	0.040827	0.326623	172.0943	18	-0.192875	0.103003	-0.068142	-1.872517	1.339657

# Result & Performance

correlation Performance (daily equal-weighted\*)

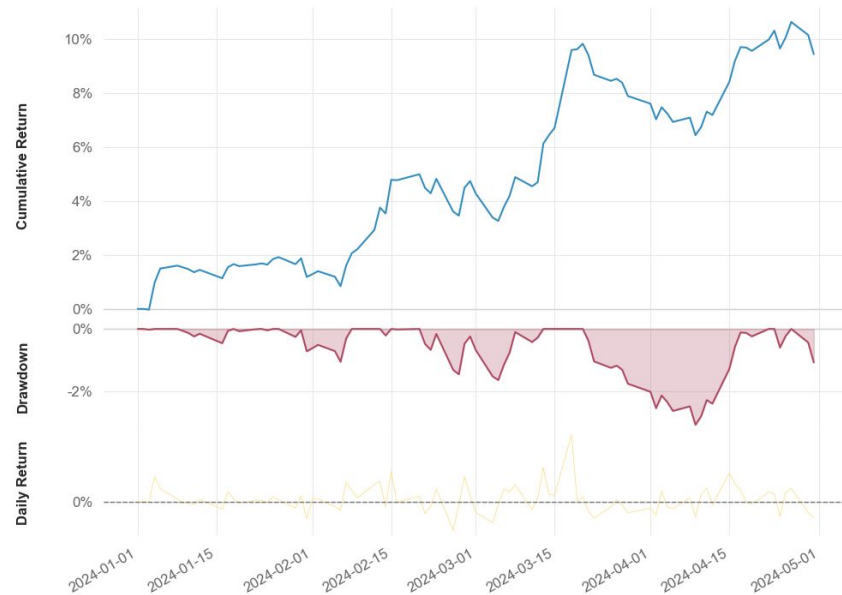
1 Jan '24 - 30 Apr '24 ; Sharpe: -1.52



\* When a multi-column DataFrame is passed, the mean of all columns will be used as returns.  
To change this behavior, use a pandas Series or pass the column name in the 'strategy\_col' parameter.

OPTICS Performance (daily equal-weighted\*)

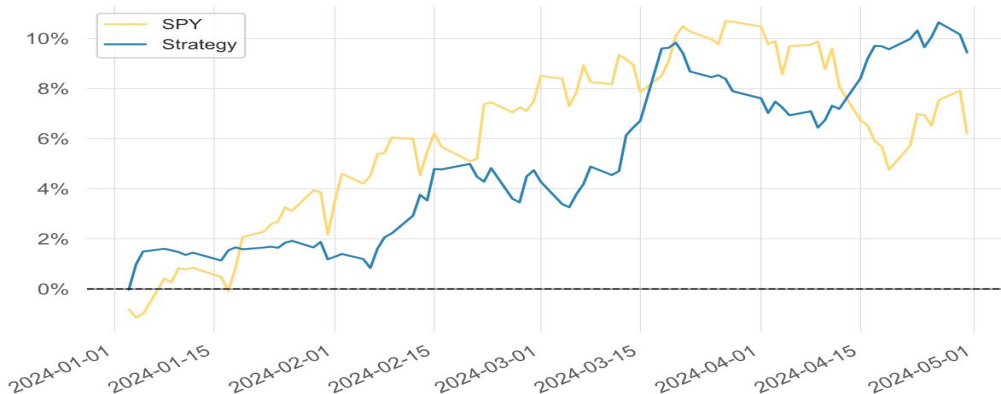
1 Jan '24 - 30 Apr '24 ; Sharpe: 3.15



\* When a multi-column DataFrame is passed, the mean of all columns will be used as returns.  
To change this behavior, use a pandas Series or pass the column name in the 'strategy\_col' parameter.

# Result & Performance

Cumulative Returns vs Benchmark



Cumulative Returns vs Benchmark (Log Scaled)



## Key Performance Metrics

Metric	SPY	Strategy
Risk-Free Rate	0.0%	0.0%
Time in Market	100.0%	100.0%
Cumulative Return	6.21%	9.44%
CAGR %	13.72%	21.25%
Sharpe	1.62	3.19
Prob. Sharpe Ratio	82.03%	98.0%
Smart Sharpe	1.49	2.94
Sortino	2.48	6.42
Smart Sortino	2.29	5.91
Sortino/√2	1.75	4.54
Smart Sortino/√2	1.62	4.18
Omega	1.77	1.77
Max Drawdown	-5.35%	-3.09%
Longest DD Days	34	30
Volatility (ann.)	11.84%	8.83%
R^2	0.01	0.01
Information Ratio	0.04	0.04
Calmar	2.56	6.89
Skew	-0.09	1.32
Kurtosis	-0.07	4.97
Expected Daily	0.07%	0.11%
Expected Monthly	1.52%	2.28%
Expected Yearly	6.21%	9.44%
Kelly Criterion	9.15%	15.86%
Risk of Ruin	0.0%	0.0%

# Future development

## Refining Entry Points

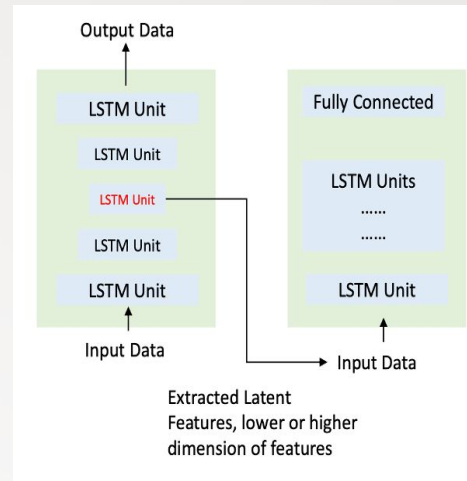
- Threshold-Based Trading Model: One limitation is the lack of precision in defining entry points.
- Deep Learning Model: Implementing Autoencoder LSTM for Time Series Forecasting could achieve more robust performance.

## Sentiment and Event Analysis

- News Impact: Analyzing how news events cause price jumps.
- Pair Selection: Selecting pairs based on mean-reversion speed and jump behavior to enhance performance.

## Empirical Research

- Sector and Asset Variability: Conducting research across different sectors and asset classes.
- Frequency Analysis: Investigating from different frequencies, including microstructure market data



Sarmiento, Simão Moraes, and Nuno Horta. *A machine learning based pairs trading investment strategy*. Springer, 2020.

Gu, Shihao, Bryan Kelly, and Dacheng Xiu. "Autoencoder asset pricing models." *Journal of Econometrics* 222, no. 1 (2021): 429-450.

Stübinger, Johannes, and Sylvia Endres. "Pairs trading with a mean-reverting jump-diffusion model on high-frequency data." *Quantitative Finance* 18, no. 10 (2018): 1735-1751.



**Thanks!**  
**Q&A**