Group 8

OPTIMIZING TRADING STRATEGIES WITH ML

A CASE STUDY ON HSI INDEX

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PRESENTATION

CONTENT

01
INTRODUCTION

Introduction

Research Object

HSI includes the top 50 companies with the highest market value among the stocks listed on the **Hong Kong Stock Exchange**.

Hong Kong dollar maintained its peg to the U.S. dollar even in the currency crisis wave

Method Originality

Regressor Algorithms

Classifier Algorithms

Batch DTW

Quantitative Trading

Macro Research

References

- Fleiss, A., Liu, C., Eom, G., Yu, S., & Zhang, W. (2021). Dynamic Time Warping: S&P 500 Sector ETF Pattern Matching Trading Strategy. *The Journal of Financial Data Science*, *3*(1), 93-110.
- So, R. W., & Tse, Y. (2004). Price discovery in the Hang Seng index markets: index, futures, and the tracker fund. *Journal of Futures Markets: Futures, Options, and Other Derivative Products*, *24*(9), 887-907.

Introduction

Assumption 1

Frictionless transactions

Assumption 2

Liquid market

REASONS

Trading size related
Too early to decide in the train/test set
(Need to consider actual deployment)

Assumption 3

No slippage

Quite related to IT infrastructures, and the crowdedness of the trading strategy.

Assumption 4

Short selling allowed but no borrowing costs

Borrowing costs depend on investors' credit ratings.

Assumption 5

Returns calculated daily basis,
but annualized in reporting

Convenient to report and compare across different models.

Introduction

Metric	Formula
CAGR	$\frac{Cumulative\ Portfolio\ Value}{Capital}\hat{}\left(\frac{365}{Number\ of\ Strategy\ Exercised\ Day}\right) * 100\%$
Sharpe Ratio	$\sqrt{252} \times \frac{\text{Average Value}\ of\ Daily\ Return}{Standard\ Deviation\ of\ Daily\ Return}$
Sortino Ratio	$\sqrt{252} \times \frac{\text{Average value}\ of\ daily\ return}{\frac{\sum Daily\ Return^2}{\sqrt{Number\ of\ Days}}}$
Max Drawdown ($)	$Maximum\ absolute\ value\ of\ drawdown$
Max Drawdown (%)	$\max\left(\frac{Maximum\ Drawdown\ (\$)}{Cumulative\ Maximum\ portfolio\ value} \times 100\%\right)$
Max Drawdown (Days)	$The\ longest\ drawdown\ period$
Multiples of Invested Capital	$\frac{Porfolio\ Performance\ in\ Return}{Initial\ Capital}$
Win Rate	$\frac{Number\ of\ Win\ Days}{Number\ of\ Trade\ Days} \times 100\%$

For our results

Not just consider the prediction accuracy, instead we pay more attention to the final return.

For the performance

The final returns depend on two aspects:

- Win/Loss
- Risk/Reward

02
DATA DESCRIPTION

2.1 Data Pre-processing

Historical price data for Hang Seng Index (HSI) from Yahoo Finance

November 2001	October 2011	October 2013	October 2023
Training Set	Testing Set	Deployment Set	

Regressor	Classifier	DTW
Daily Log Returns	Sign of Daily Log Return	Daily Price Percentage Change
	Negative value as -1 Positive value as 1	Normalization transformation between -1 and 1

2.2 Feature Engineering

Self-correlation Features: Log Return & Technical Indicator

- **Lag features** lagged daily log returns to capture the price change in HSI.
- **Moving averages** of HSI in 21 days, 63 days, and 252 days.
- **Exponential moving averages** of HSI in 10 days, 30 days, and 200 days.

Selective Correlation Features: Correlated Assets

- Leading stocks representing different industries

0005.HK	HSBC Holdings plc	**0293.HK**	Cathay Pacific Airways Limited
0001.HK	CK Hutchison Holdings Limited	**0003.HK**	The Hong Kong and China Gas Company Limited

2.2 Feature Engineering

Effective Correlation Features: Indices & Currency Exchange Rates

- Indices related to the global economic environment

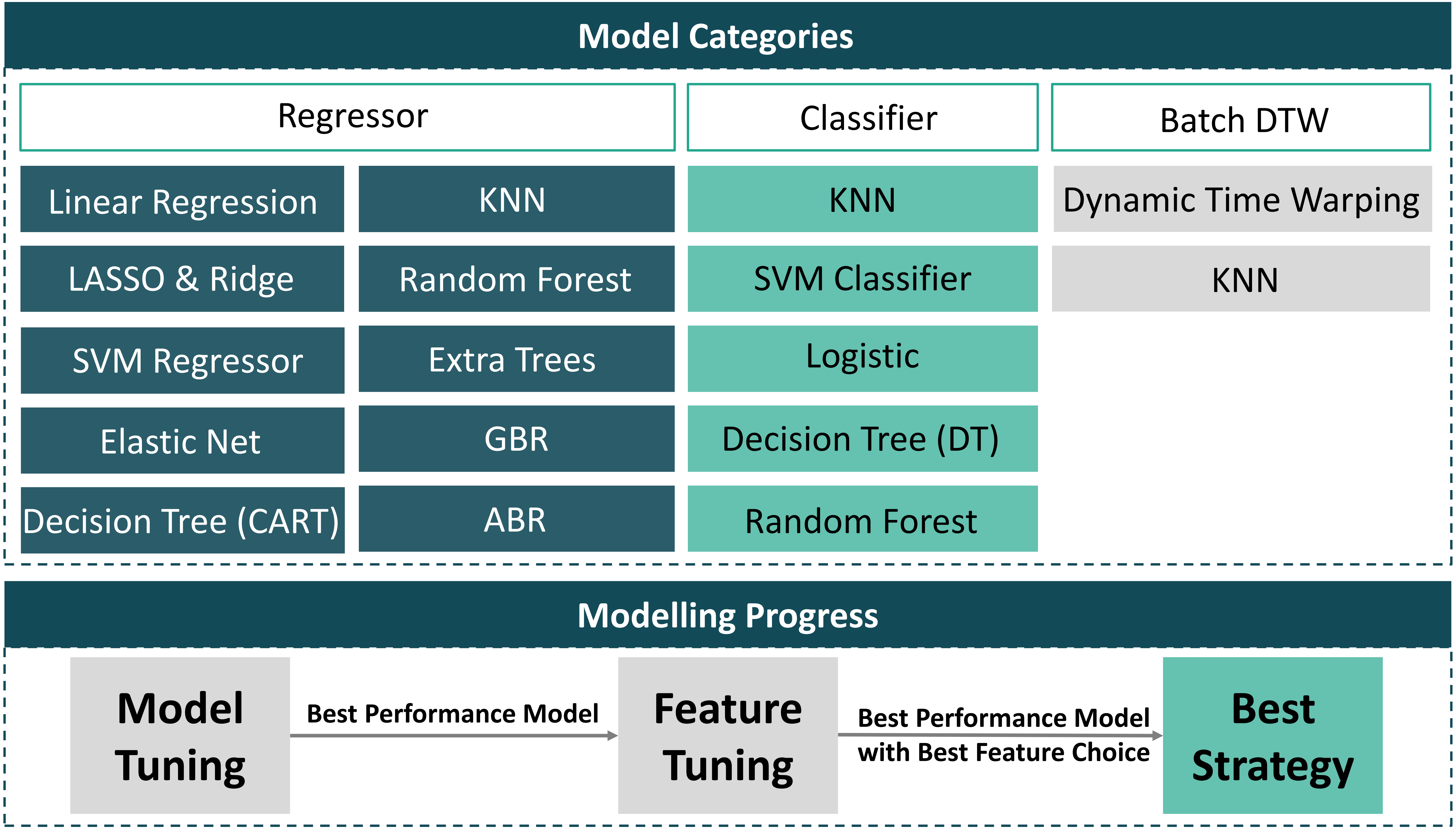
VIX	CBOE Volatility Index
JP225	Nikkei 225
T-bill	10-Year Treasury Constant Maturity Rate
SPX	S&P 500
SCI	Shanghai Composite Index

- Exchange rates exhibiting global monetary policies

USD/JPY	U.S. Dollar to Japanese Yen
GBP/USD	British Pound to U.S. Dollar

03
METHODOLOGY

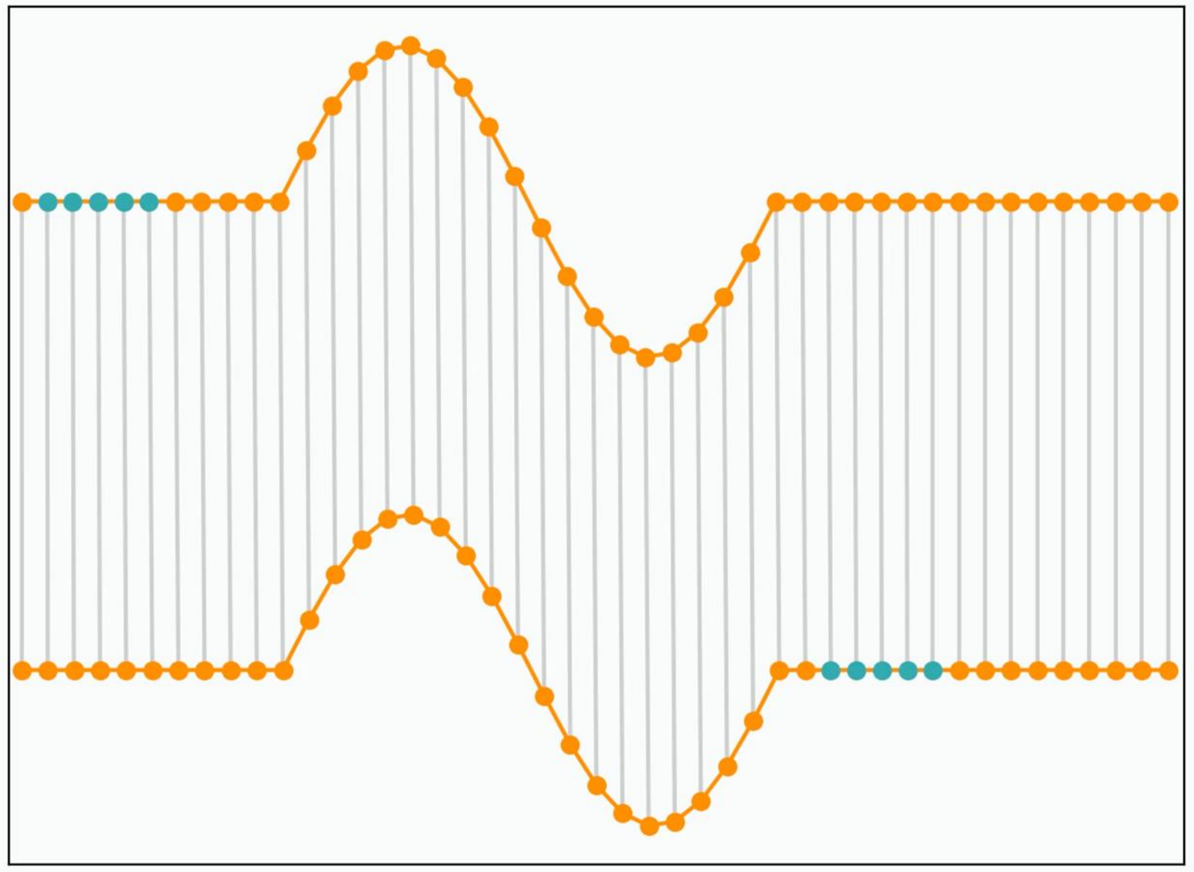
3.1 Methodology outline



3.1.1 DTW

Introduction to DTW Method

Consider two time series, X and Y, how to measure the similarity between them?



Warping Window Width: Number of data points of X to compare with Y at once.

Dynamic Time Warping: The minimum Euclidean distance between time sequences under all admissible alignments.

The smaller the distance, the more similar they are.

3.1.1 DTW

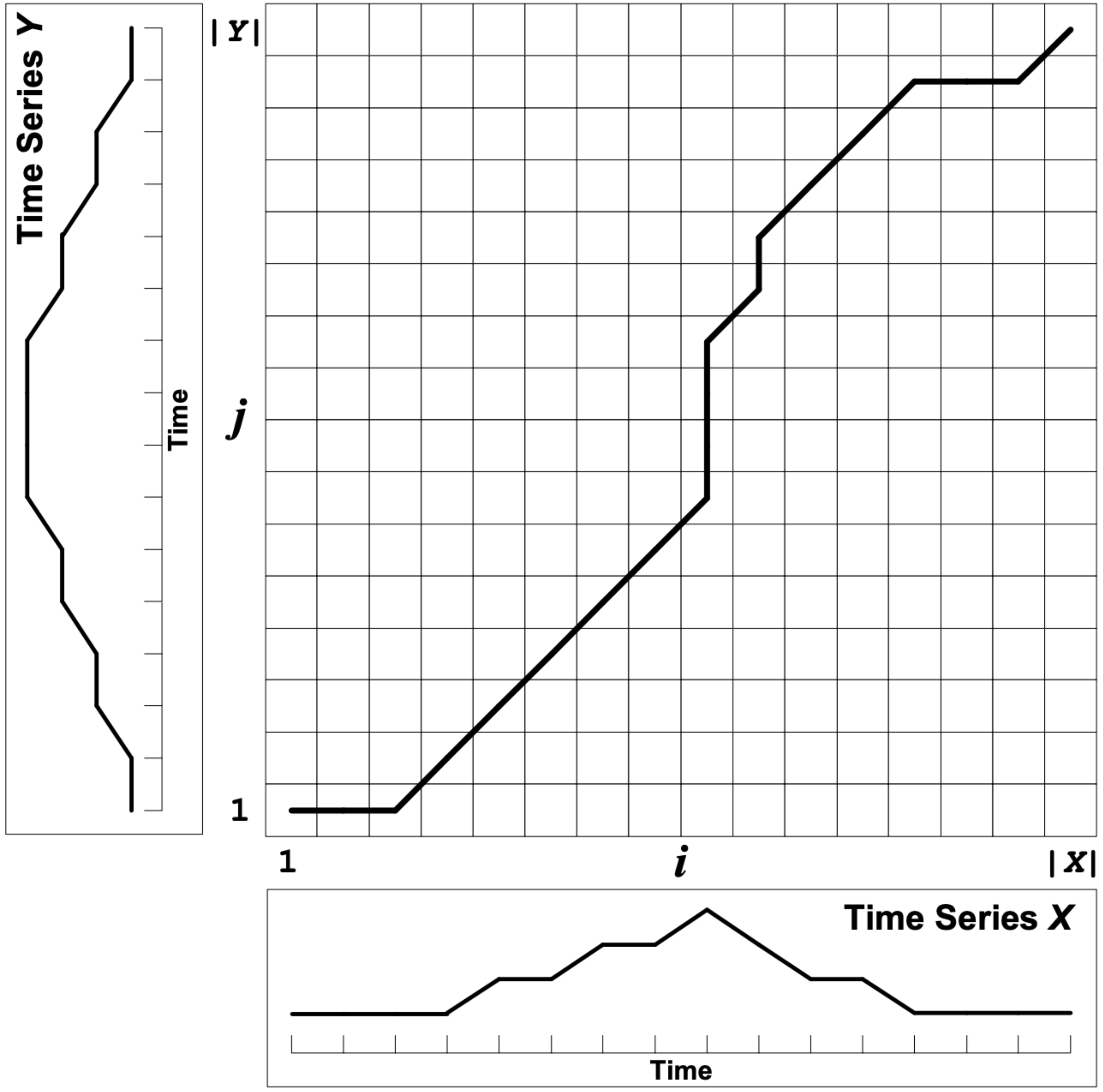
Introduction to DTW Method

Warping path: The path through a lattice of grid points to align two sequences computationally.

Objective: Find the path that minimizes the dynamic time warping distance.

$$DTW(Q,C) = min\left\{\frac{\sqrt{\sum_{k=1}^{K} W_k}}{K}\right\}$$

$W_k = (i,j)_k$ - the k^{th} element of path,
K – lengths of different warping paths

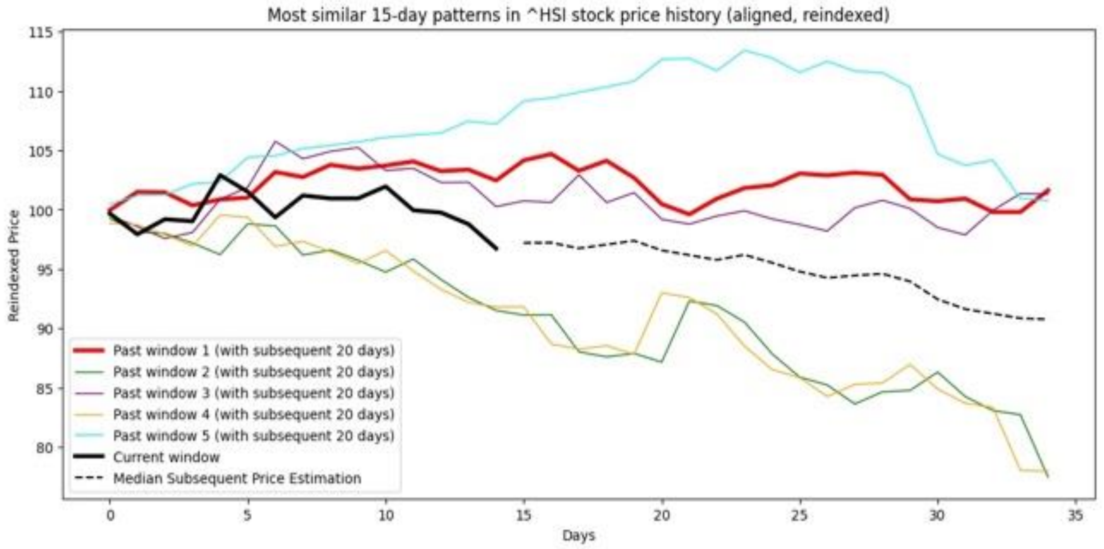


3.1.2 KNN-DTW

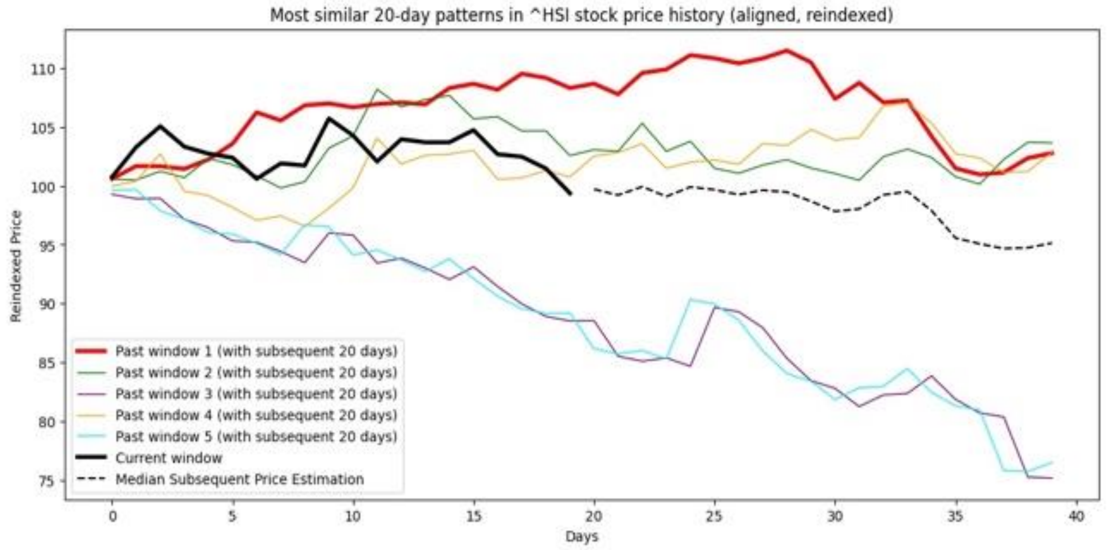
KNN-DTW Performance in Stock Market

Identify patterns with different windows from January 1, 2000 to November 30, 2023 to predict potential market trends

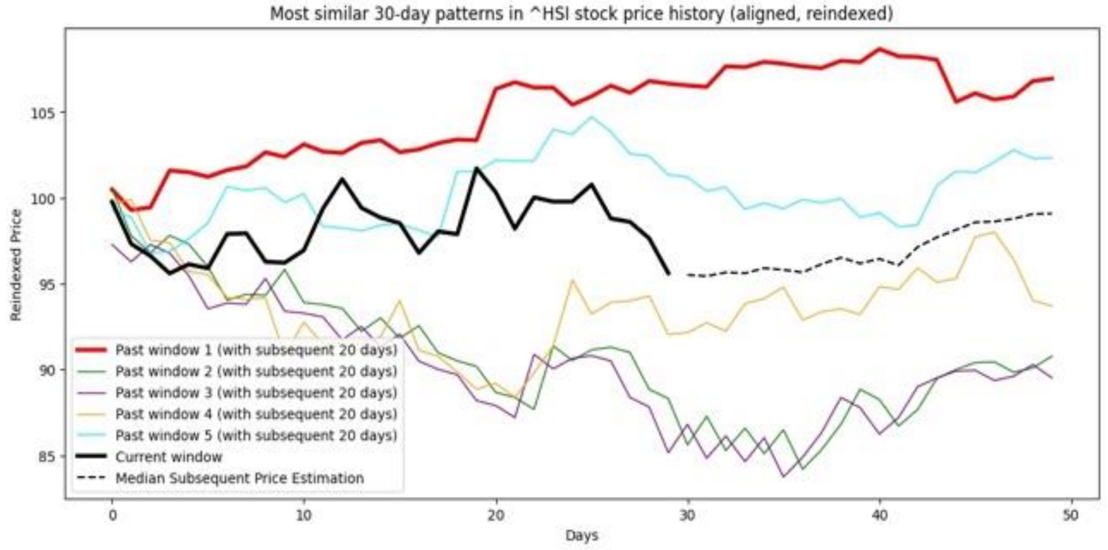
15 days



20 days



30 days



04
METHODOLOGY COMPARISON

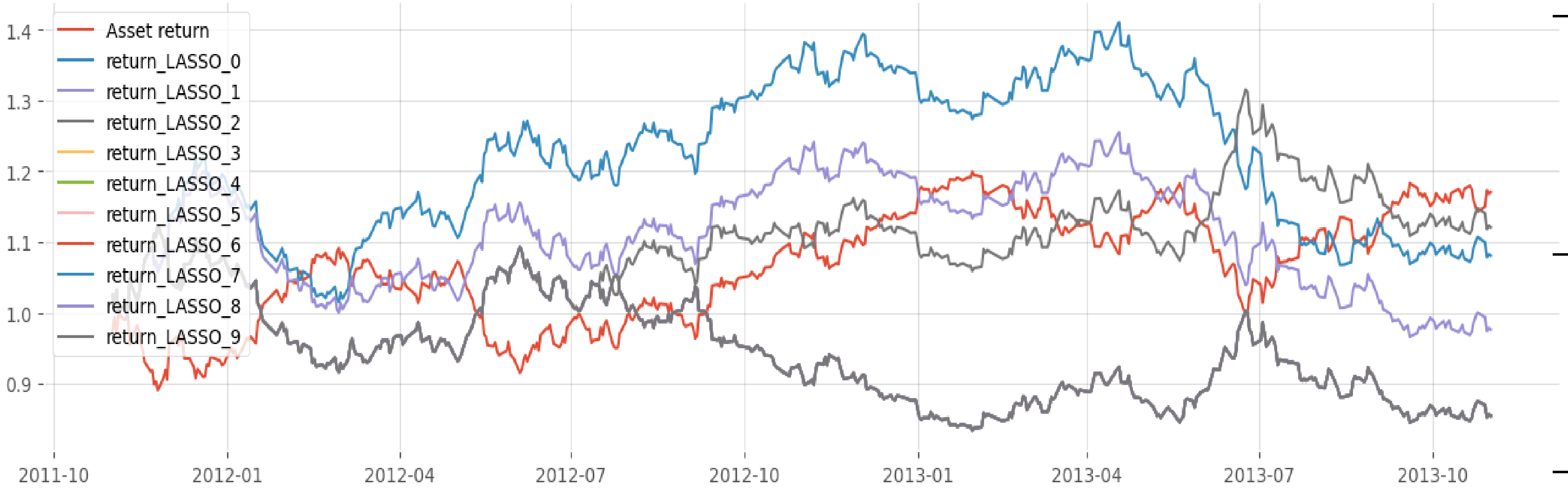
4.1 Regressor Algorithms

4.1.1 LASSO and RIDGE

Lasso Regression

$$\sum_{k=1}^{n}\left(Y_k-\sum_{j=0}^{p} b_j X_{jk}\right)^2+\alpha\sum_{j=0}^{p}\left|b_j\right|.$$

Hyperparameter Tuning: α

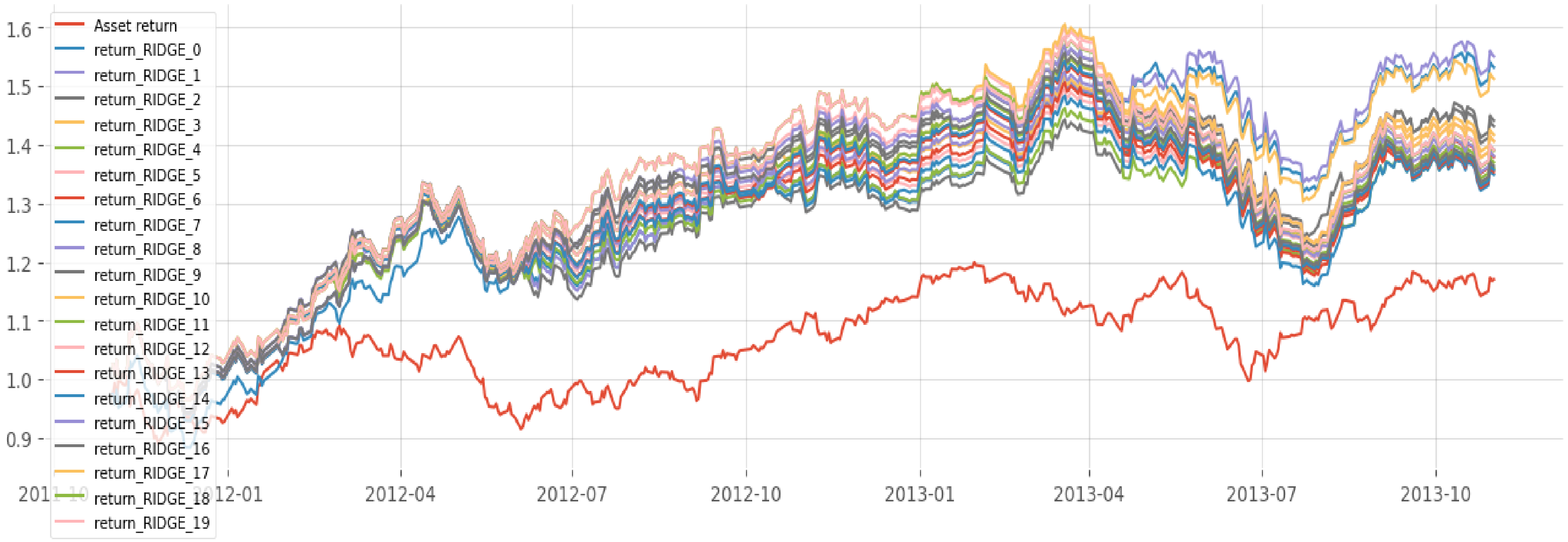


	CAGR (%)	Sharpe Ratio	Sortino Ratio	Maximum Drawdown (%)	Maximum Drawdown (days)	Multiples of Invested Capital	Win Rates (%)
$\alpha = 0.03$	5.8528	0.3443	0.5031	-18.4068	303	1.1207	50.8130
$\alpha = 0.01$	3.9534	0.2394	0.3515	-24.2791	196	1.0807	53.2520
$\alpha = 0.02$	-1.1831	-0.0527	-0.0768	-23.0297	308	0.9764	51.8293

Ridge Regression

$$\sum_{k=1}^{n}\left(Y_k-\sum_{j=0}^{p} b_j X_{jk}\right)^2+\alpha\sum_{j=0}^{p} {b_j}^2$$

Hyperparameter Tuning: α



	CAGR (%)	Sharpe Ratio	Sortino Ratio	Maximum Drawdown (%)	Maximum Drawdown (days)	Multiples of Invested Capital	Win Rates (%)
$\alpha = 0.01$	23.7315	1.3954	2.1120	-15.0839	157	1.5318	53.6585
$\alpha = 0.02$	24.4946	1.2845	1.9339	-15.0839	149	1.5508	53.8618
$\alpha = 0.04$	22.9429	1.2113	1.8295	-15.0839	121	1.5124	53.0488
$\alpha = 0.03$	20.0191	1.0715	1.6023	-15.0839	149	1.4412	53.0488
$\alpha = 0.10$	19.6114	1.0517	1.5723	-21.8294	226	1.4314	53.2520

4.1.2 Support Vector Machine

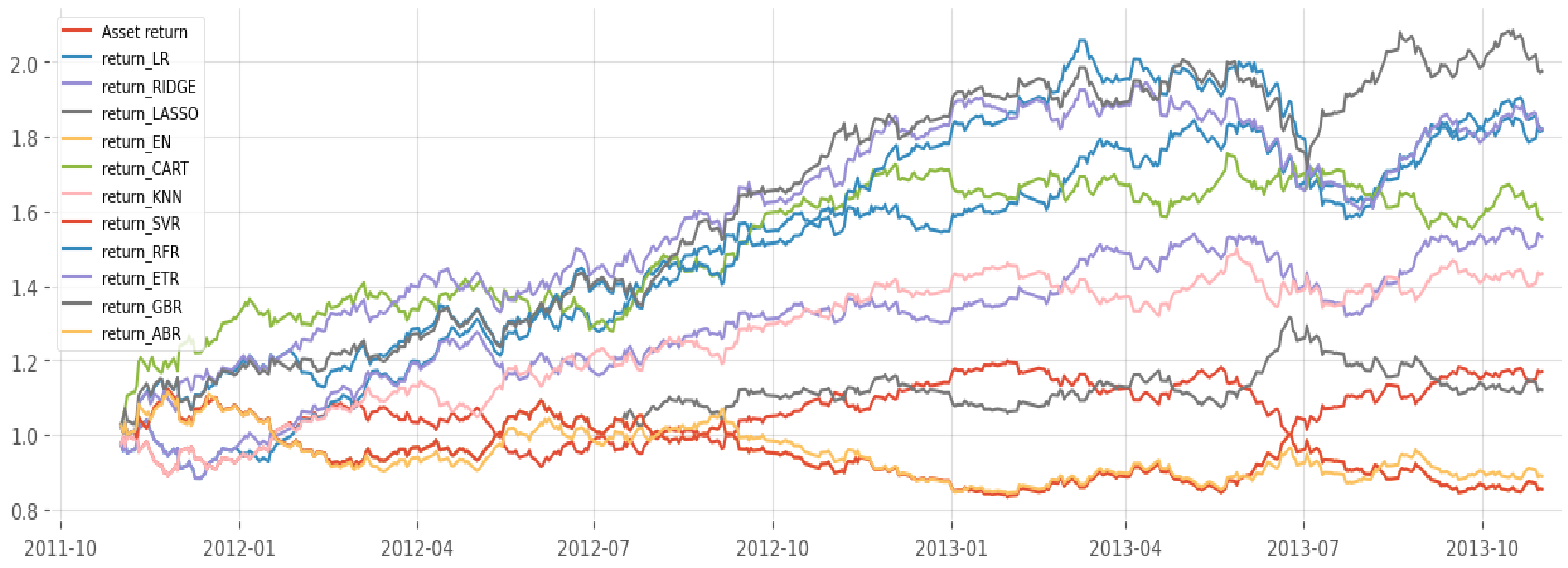
Hyperparameters Considered

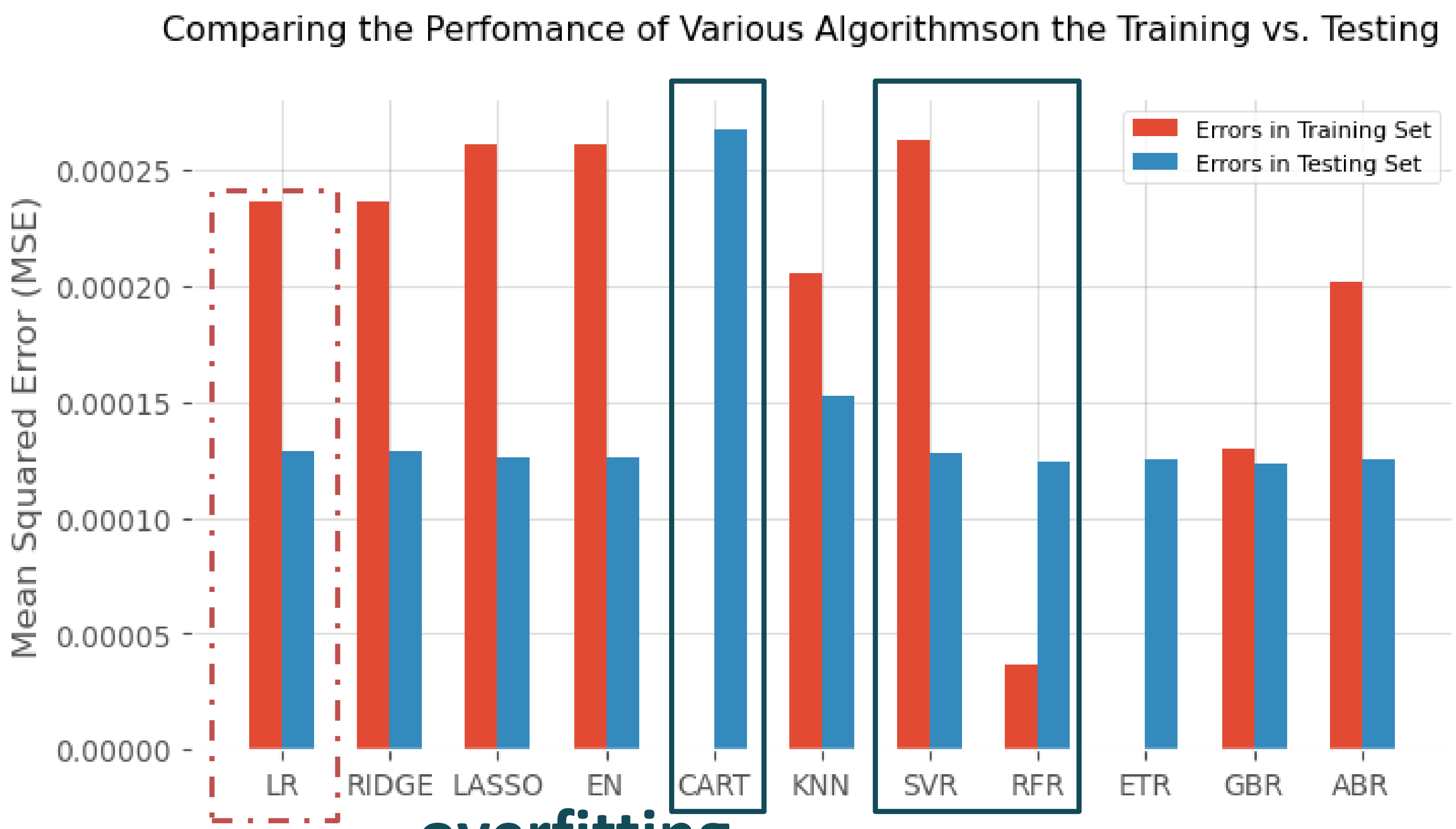
- Kernel types
- Degree (Degree of the polynomial kernel function)
- α
- C (Regularization parameter)

Kernel Type	CAGR (%)	Sharpe Ratio	Sortino Ratio	Maximum Drawdown (%)	Maximum Drawdown (days)	Multiples of Invested Capital	Win Rates (%)
Linear	-7.5557	-0.4382	-0.6156	-7.5557	704	0.8544	48.9837
Polynomial	-7.5557	-0.4382	-0.6156	-7.5557	704	0.8544	48.9837
Sigmoid	-7.5557	-0.4382	-0.6156	-7.5557	704	0.8544	48.9837

4.1.3 Summary of Regressor Methods

Summary of Regressor Algorithms Results in Test Set





overfitting

Method	CAGR (%)	Sharpe Ratio	Sortino Ratio	Maximum Drawdown (%)	Maximum Drawdown (days)	Multiples of Invested Capital	Win Rates (%)
LR	34.9200	1.9015	2.9782	-15.0839	161	1.8218	54.6748
GBR	40.5046	1.9921	3.1040	-14.5883	103	1.9760	57.9268
RIDGE	23.7315	1.3954	2.1120	-15.0839	157	1.5318	53.6585
LASSO	5.8528	0.3443	0.5031	-18.4068	303	1.1207	50.8130
KNN	19.6643	1.1994	1.8491	-11.6164	156	1.4327	51.6260

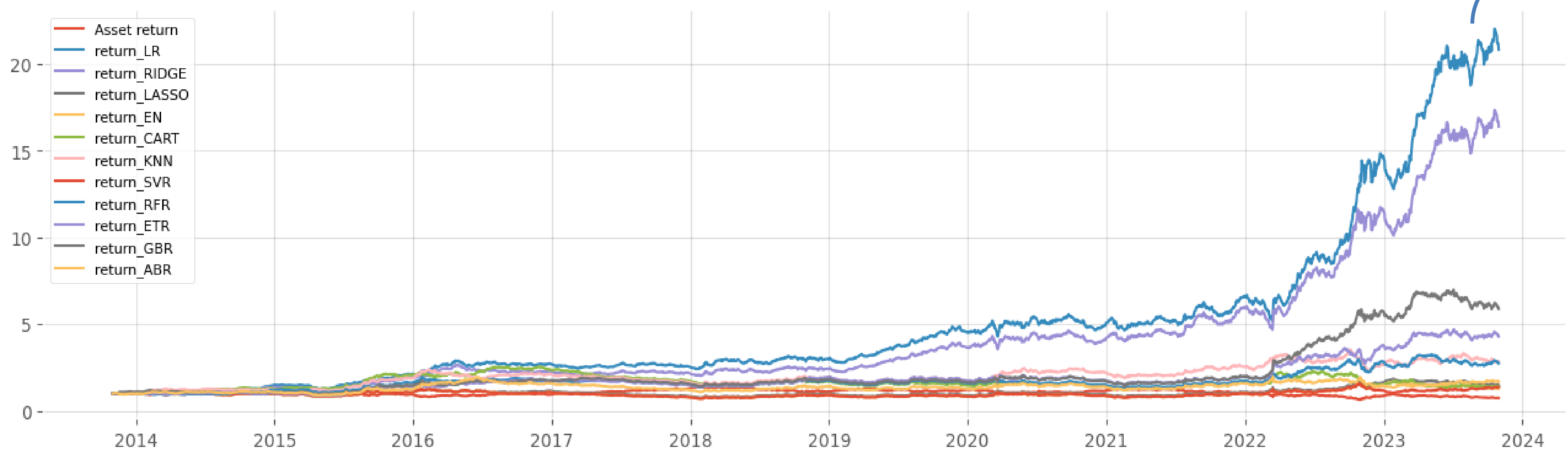
Tips:

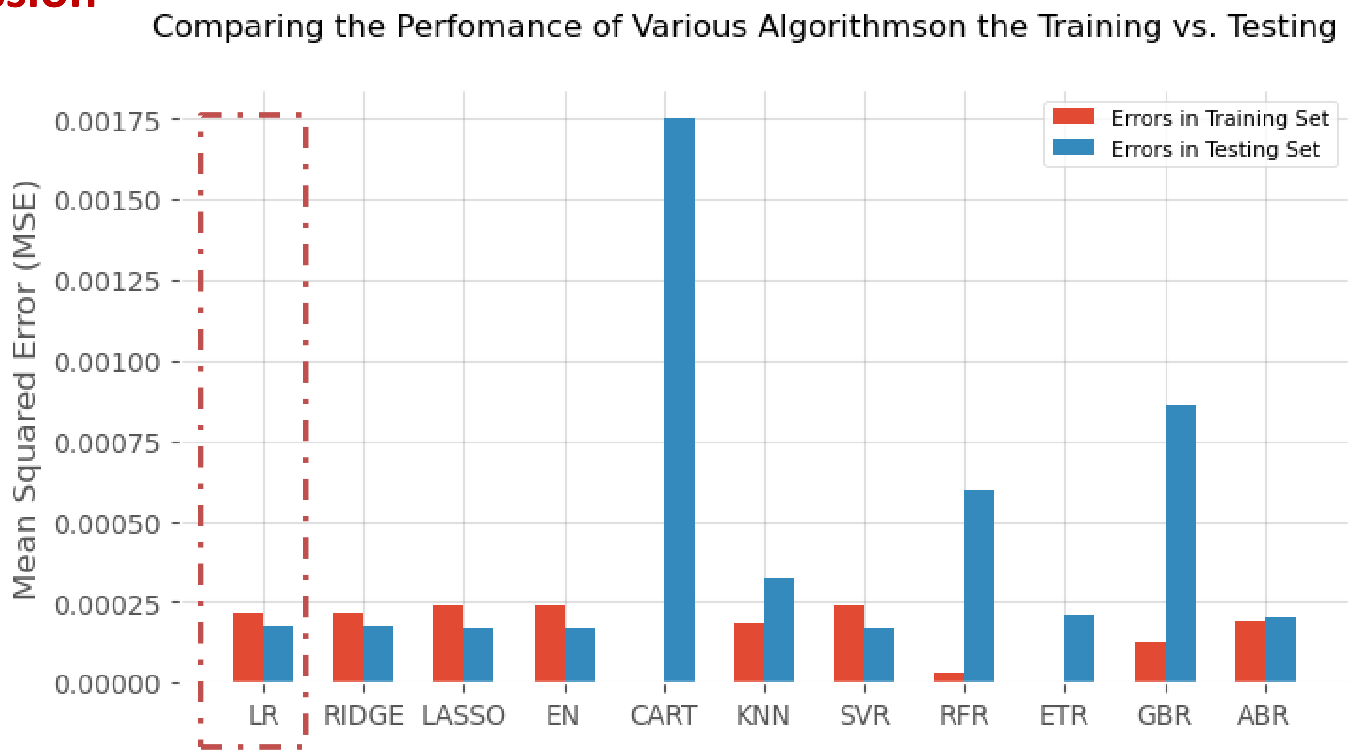
- The results of GBR strongly depend on the selection of the **random state factor.**
- It brings significant **randomness** to the construction of strategies

4.1.3 Summary of Regressor Methods

Deployment of Regressor Algorithms

Linear Regression





Method	CAGR (%)	Sharpe Ratio	Sortino Ratio	Maximum Drawdown (%)	Maximum Drawdown (days)	Multiples of Invested Capital	Win Rates (%)
LR	35.462483	1.621746	2.568857	-22.549792	686	20.8234	53.8805
GBR	19.362806	0.983552	1.545012	-26.452799	1086	5.8736	49.9797
RIDGE	32.266810	1.501322	2.366920	-23.786484	1098	16.3999	53.5961
LASSO	3.954199	0.296885	0.439844	-40.411751	2219	1.4739	48.3950
KNN	10.908397	0.617543	0.938929	-38.161941	1562	2.8169	49.4514

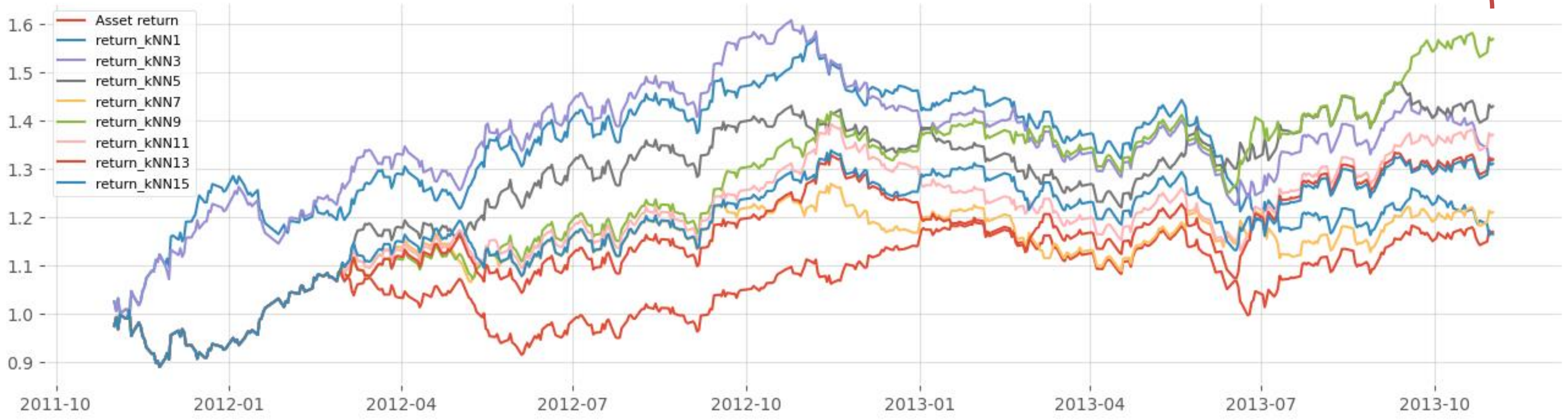
4.2 Classifier Algorithms

4.2.1 K-Nearest Neighbors Algorithm

Hyperparameters Considered

- Number of neighbors (k=1,…,15)
- Distance metrics
- Weights
- Algorithm types

K = 9



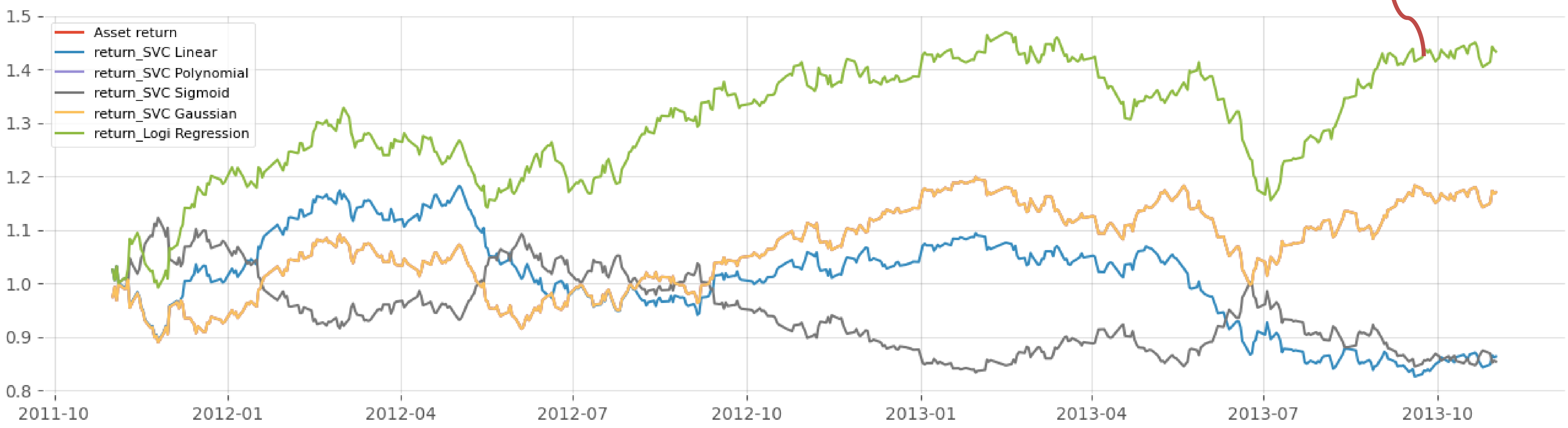
Number of K	CAGR (%)	Sharpe Ratio	Sortino Ratio	Maximum Drawdown (%)	Maximum Drawdown (days)	Multiples of Invested Capital	Win Rates (%)
K = 9	25.2268	1.4645	2.2542	-11.8462	258	1.5691	54.0650
K = 5	19.5498	1.1935	1.8616	-14.7101	290	1.4299	51.4228
K = 11	17.0698	1.0728	1.6192	-18.7695	350	1.3711	52.4390
K = 13	14.8533	0.9617	1.4526	-19.2080	298	1.3196	52.6423
K = 15	14.4932	0.9435	1.4246	-15.4123	350	1.3113	52.4390

4.2.2 SVC and Logistic Regression

Hyperparameters Considered

- Kernel types
- Degree (Degree of the polynomial kernel function)
- α
- C (Regularization parameter)

Logistic Regression



Kernel	CAGR (%)	Sharpe Ratio	Sortino Ratio	Maximum Drawdown (%)	Maximum Drawdown (days)	Multiples of Invested Capital	Win Rates (%)
Logistic Regression	19.6925	1.0529	1.6592	-21.3615	256	1.4333	52.4390
Polynomial	8.1733	0.6154	0.8970	-16.8251	274	1.1704	51.0163
Gaussian	8.1733	0.6154	0.8970	-16.8251	274	1.1704	51.0163
Linear	-7.0362	-0.4061	-0.5586	-30.1168	547	0.8641	50.0000
Sigmoid	-7.5557	-0.4382	-0.6156	-25.7433	704	0.8544	48.9837

4.2.3 Decision Tree

Hyperarameters Considered

- Maximum Depth
- Splitting Strategy
- Maximum Number of Features
- Minimum Number of Samples
  - Internal Node
  - Leaf Node

Depth = 4

Maximum Depth	CAGR (%)	Sharpe Ratio	Sortino Ratio	Maximum Drawdown (%)	Maximum Drawdown (days)	Multiples of Invested Capital	Win Rates (%)
Depth = 4	42.9619	2.0901	3.4125	-14.8205	110	2.0458	54.0650
Depth = 11	29.0849	1.4945	2.2476	-12.5453	217	1.6675	53.8618
Depth = 2	24.8364	1.2976	2.0247	-19.7886	246	1.5594	52.6423
Depth = 3	24.7504	1.2936	2.0252	-21.4576	274	1.5572	50.4065
Depth = 5	23.6572	1.2426	1.9259	-17.1378	183	1.5300	52.0325

4.2.4 Random Forest

Summary of Random Forest Fine Tuning

Hyperarameters Considered

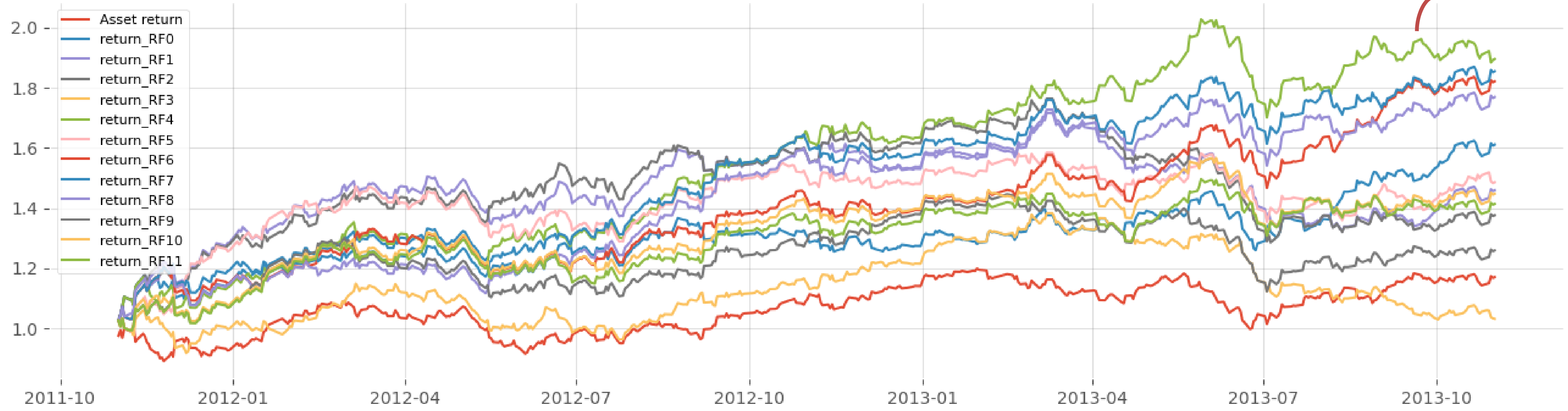
- Number of Estimators
- Maximum Features
- Maximum Depth
- Random State

Model Number	Maximum Number of Features	Maximum Depth	Random State
4	5	None	1
7	None	3	1
6	None	2	1
8	None	4	1
0	None	None	1

** The number of estimators was initially considered but did not yield satisfactory results.

4.2.4 Random Forest

Model 4

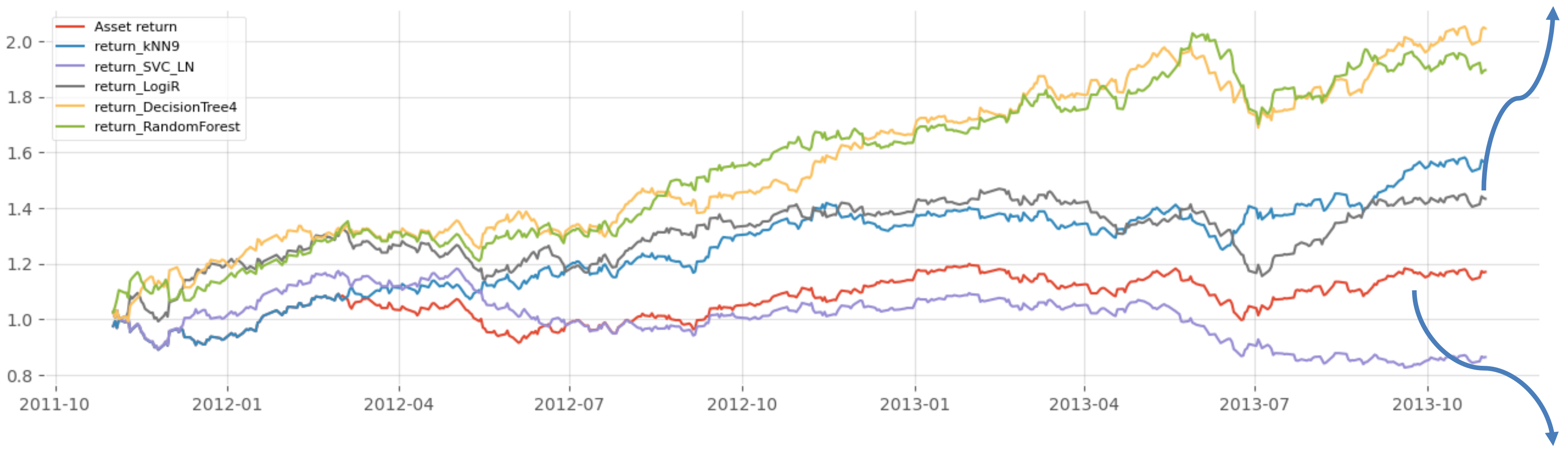


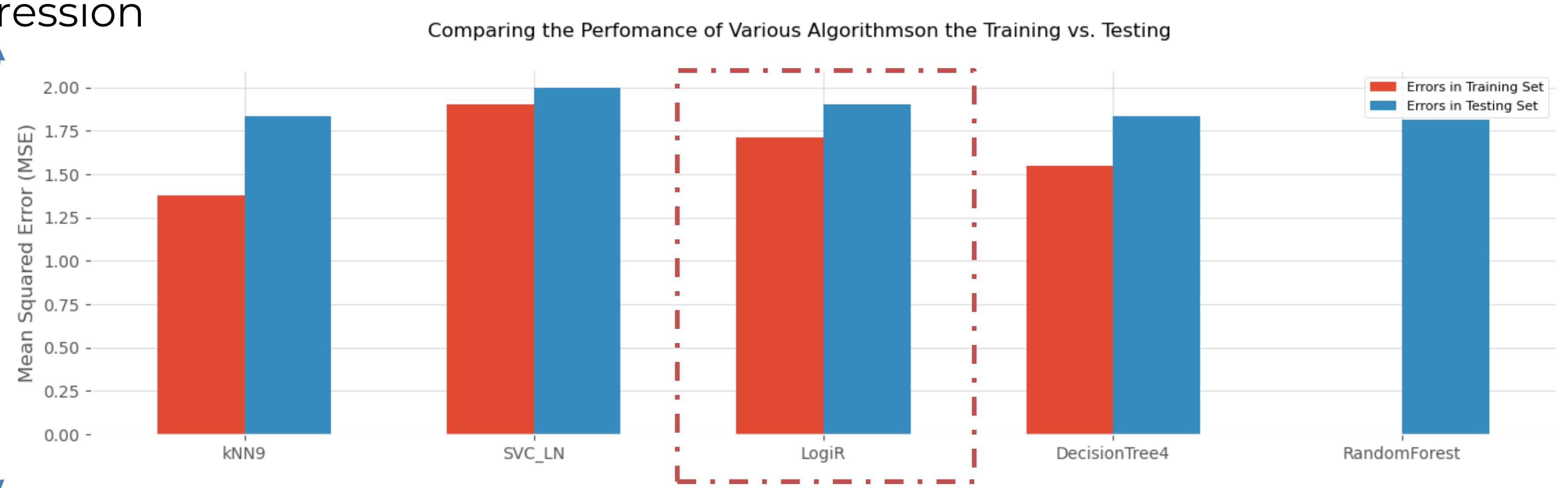
Model Number	CAGR (%)	Sharpe Ratio	Sortino Ratio	Maximum Drawdown (%)	Maximum Drawdown (days)	Multiples of Invested Capital	Win Rates (%)
4	37.6403	1.8703	2.9395	-16.1001	155	1.8961	54.6748
7	36.1510	1.8076	2.7798	-12.1017	123	1.8553	54.6748
6	34.9200	1.7543	2.7075	-12.4709	161	1.8218	53.8618
8	32.9764	1.6692	2.5491	-12.6202	134	1.7697	54.6748
0	26.8971	1.3959	2.1012	-13.4632	185	1.6113	53.4553

** Model 4: maximum number of features = 5, random state = 1

4.2.5 Summary of Classifier Methods

Summary of Classifier Algorithms Results in Test Set

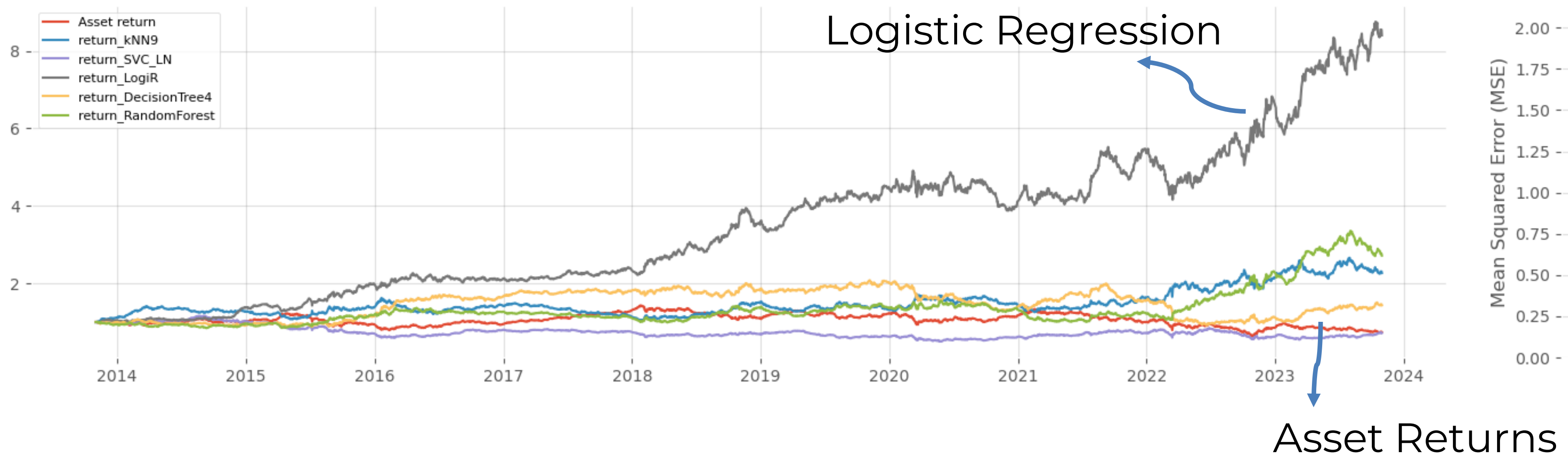


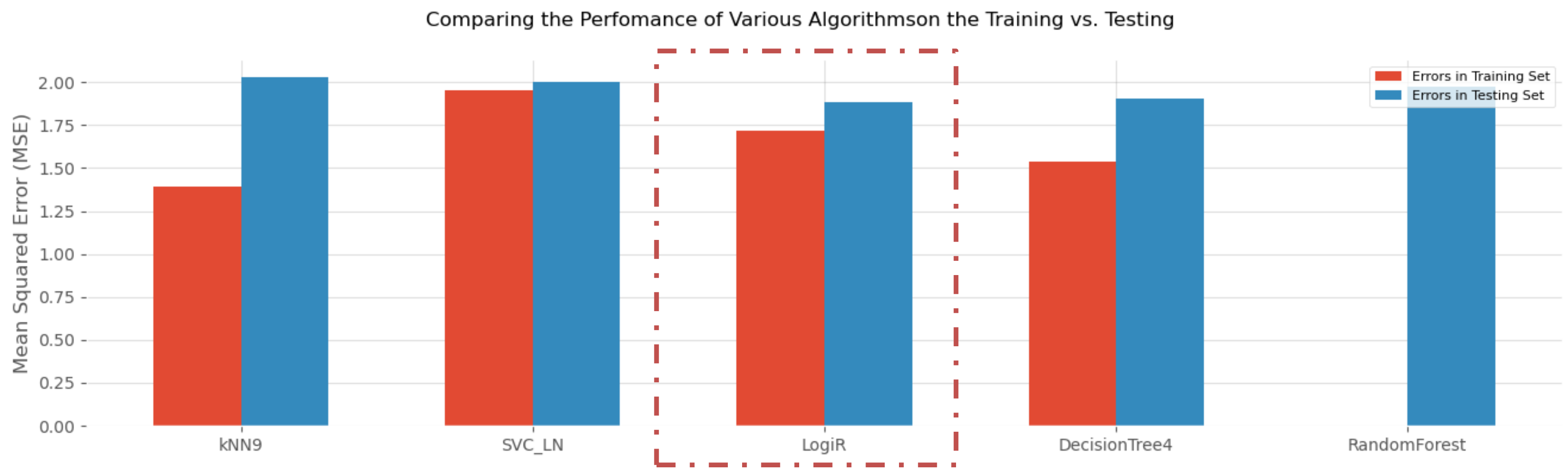


Machine Learning Model	CAGR (%)	Sharpe Ratio	Sortino Ratio	Maximum Drawdown (%)	Maximum Drawdown (days)	Multiples of Invested Capital	Win Rates (%)
Asset Return	**8.1733**	**0.6154**	**0.8970**	**-16.8251**	**274**	**1.1704**	**51.0163**
Decision Tree (Depth = 4)	42.9619	2.0901	3.4125	-14.8205	110	2.0458	54.0650
Random Forest (Model 4)	37.6403	1.8703	2.9395	-16.1001	155	1.8961	54.6748
KNN (k = 9)	25.2268	1.4645	2.2542	-11.8462	258	1.5691	54.0650
Logistic Regression	19.6925	1.0529	1.6592	-21.3615	256	1.4333	52.4390
SVC (Linear)	-7.0362	-0.4061	-0.5586	-30.1168	547	0.8641	50.0000

4.2.5 Summary of Classifier Methods

Deployment of Classifier Algorithms





Machine Learning Model	CAGR (%)	Sharpe Ratio	Sortino Ratio	Maximum Drawdown (%)	Maximum Drawdown (days)	Multiples of Invested Capital	Win Rates (%)
Asset Return	**-2.9994**	**-0.0504**	**-0.0713**	**-55.7008**	**2101**	**0.7374**	**51.3206**
Logistic Regression	23.7113	1.1679	1.7574	-24.6399	518	8.4013	52.8647
Random Forest (Model 4)	10.5054	0.5993	0.9071	-34.9102	954	2.7162	50.6705
KNN (k = 9)	8.5271	0.5111	0.7736	-35.9702	1517	2.2671	49.2076
Decision Tree (Depth = 4)	5.2265	0.3565	0.5019	-54.3402	1453	1.6646	52.6615
SVC (Linear)	-3.2534	-0.0636	-0.0895	-57.0879	3344	0.7183	49.9797

4.3 Batch DTW

4.3.1 KNN-DTW

Hyperparameters	
Days of Warping Window (W)	10, 13, 15, 17
K in K-Nearest-Neighbor (K)	1, 2, 3
Days of Prediction (F)	1, 2, 3
Threshold of prediction movements (10^{-4}) (TH)	4, 8, 10, 12, 14

Best Performance

Add

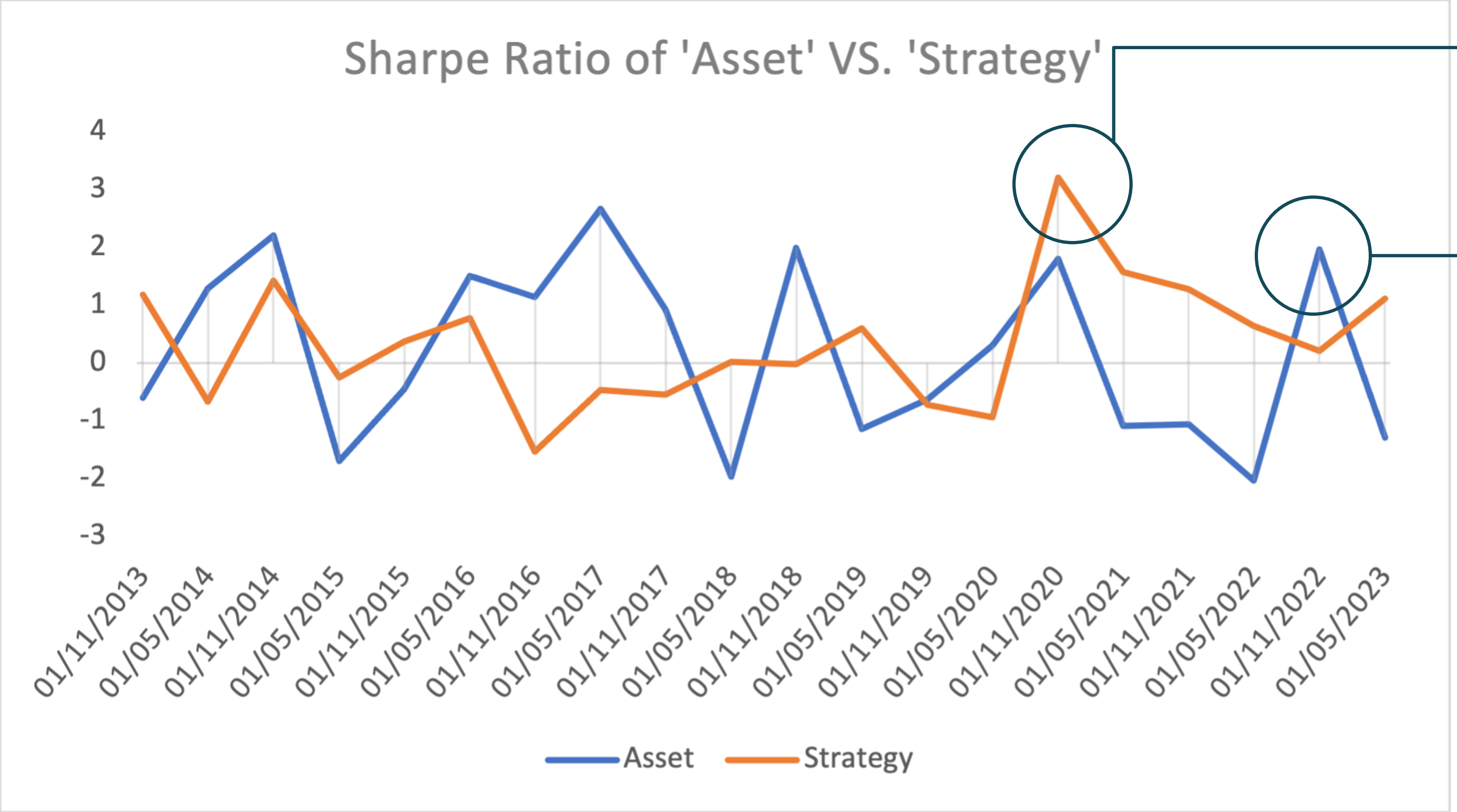
Testing* Performance

Hyperparameter Combination	CAGR (%)	Sharpe Ratio	Sortino Ratio	Maximum Drawdown (%)	Maximum Drawdown (days)	Multiples of Invested Capital	Win Rates (%)
Asset Return	**-9.6893**	**0.8831**	**1.3399**	**-11.6164**	**71**	**1.0236**	**50.8197**
{W=17, K=2, F=1}	79.7368	3.1360	6.7218	-4.3174	12	1.1593	50.9804
Best Combination with Different Thresholds (TH)							
TH = 0.0004	79.7854	3.2777	7.1956	-3.5414	11	1.1593	58.5366

* Due to the time complexity, only the first 3 months of testing period has been used.

4.3.1 KNN-DTW

Deployment Performance



The strategy only achieved a **50%** success rate.

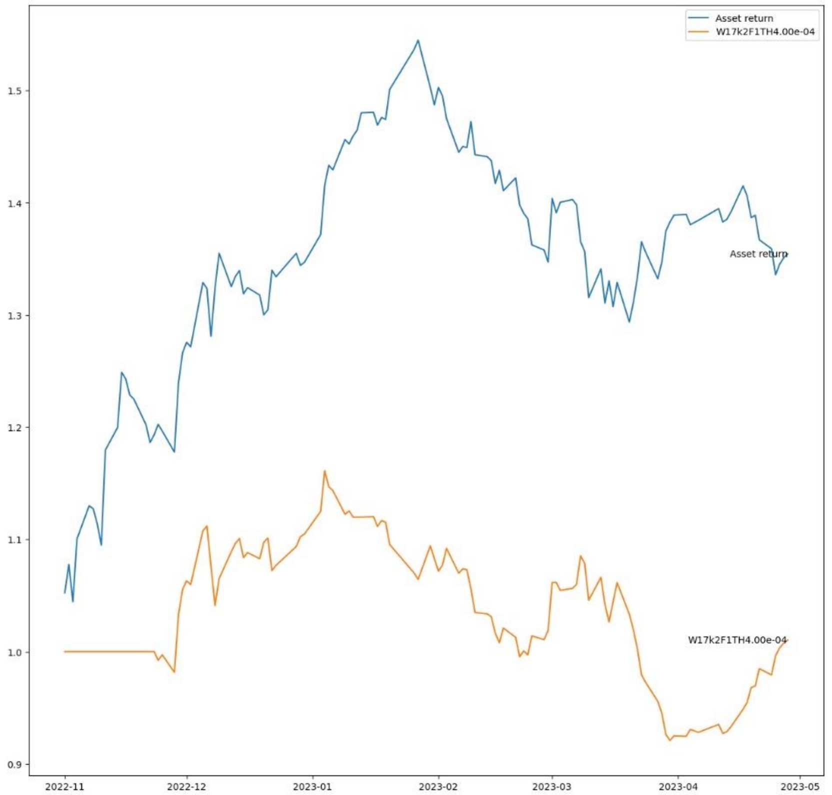
Example

Win

2021/11 – 2022/05

Lose

2022/11 – 2023/05



4.3.2 KNN-DTW Upgrading

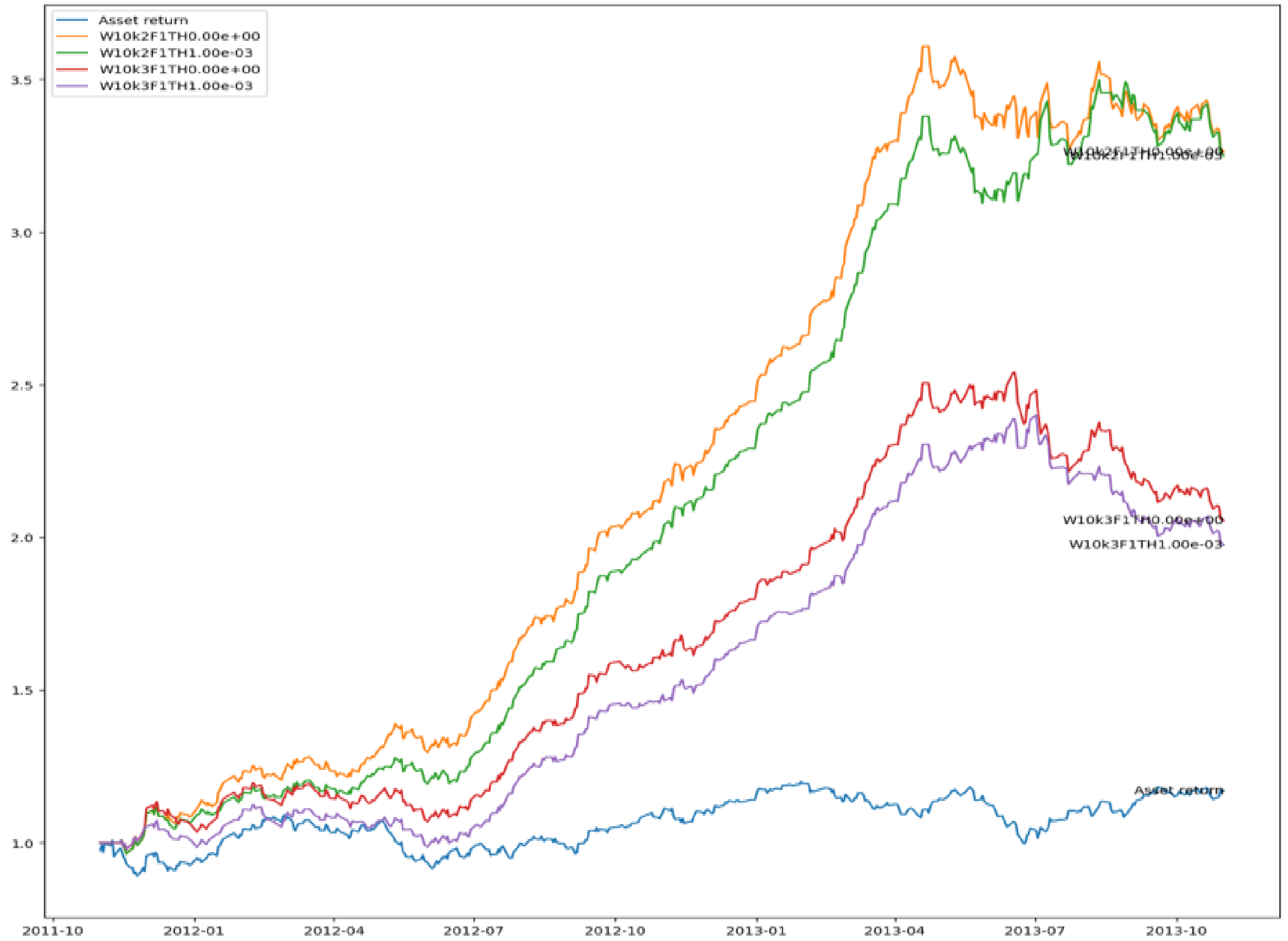
A strong trending interval from **5th June 2012** to **19th April 2013**.

Consider a wider range of training windows.

Hyperparameters	
Days of Warping Window (W)	**5 - 25**
K in K-Nearest-Neighbor (K)	1, 2, 3
Days of Prediction (F)	1, 2, 3
Threshold of prediction movements (10^{-4}) (TH)	0,10

4.3.2 KNN-DTW Upgrading

Testing & Deployment Performance



{W=10,K=2,F=1,TH=0.001}

Deployment

Testing Performance	CAGR (%)	Sharpe Ratio	Sortino Ratio	Maximum Drawdown (%)	Maximum Drawdown (days)	Multiples of Invested Capital	Win Rates (%)
Strategy	80.1242	3.9536	7.0305	-8.4474	80	3.2497	61.8267
Deployment Performance							
Asset Return	**-2.9995**	**-0.0504**	**-0.0713**	**-55.7008**	**2101**	**0.7374**	**51.3206**
Strategy	6.6159	0.4450	0.6513	-46.6614	1425	1.8980	51.4908

4.4 Final Model: Linear Regression

Comparison Among All Methods

Method	CAGR (%)	Sharpe Ratio	Sortino Ratio	Maximum Drawdown (%)	Maximum Drawdown (days)	Multiples of Invested Capital	Win Rates (%)
Best Strategy **LR**	34.9200	1.9015	2.9782	-15.0839	161	1.8218	54.6748
Logistic Regression	19.6925	1.0529	1.6592	-21.3615	256	1.4333	52.4390
Too good to be true **KNN-DTW**	80.1242	3.9536	7.0305	-8.4474	80	3.2497	61.8267
Asset Return *Benchmark*	8.1733	0.6154	0.8970	-16.8251	274	1.1704	51.0163

4.4 Final Model: Linear Regression

Feature Selecting

Only Autocorrelated Variables

- **Choice0:** 'lag_1', 'lag_2', 'lag_3', 'lag_4', 'lag_5', 'lag_6', 'Const'

Step 1: Add Other Variables

- **Choice1**: 'lag_4', '0005.HK', '0001.HK', '0293.HK', '^N225', '^TNX', 'Const'
- **Choice2**: 'lag_4', 'lag_6', '0005.HK', '0001.HK', '0293.HK', '^N225', '^TNX', 'Const'
- **Choice3**: 'lag_4', 'lag_6', '0005.HK', '0001.HK', '0293.HK', '0003.HK', '^TNX', 'Const'
- **Choice4**: 'lag_1', 'lag_2', 'lag_4', 'lag_6', '0005.HK', '0001.HK', '0293.HK', '0003.HK', '^N225', '^TNX', 'Const'

Step 2: Add Exchange Rate Indicators

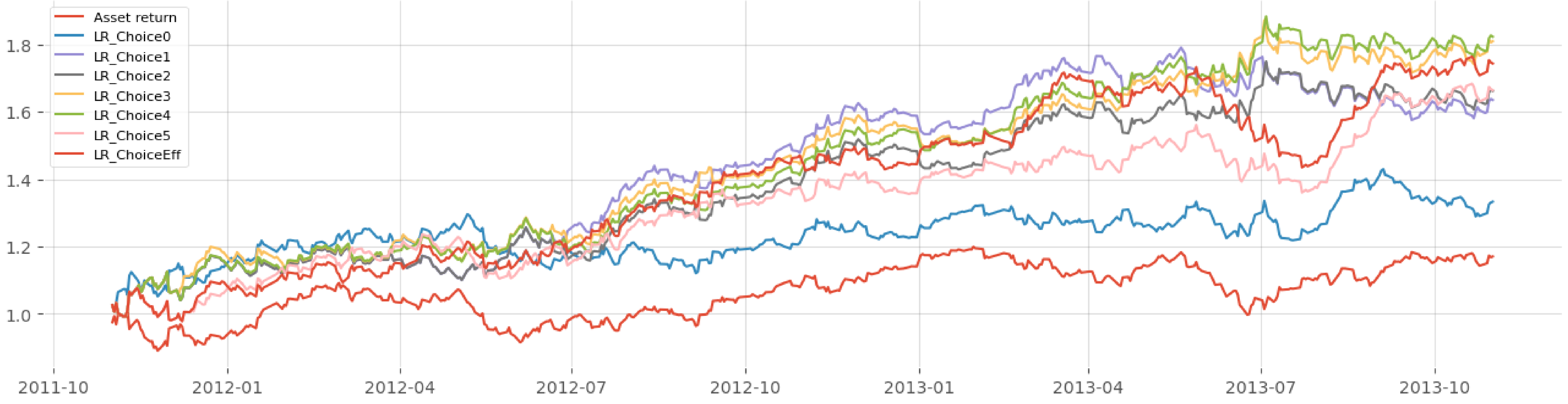
- **Choice5**: 'lag_3‘, '0005.HK_6DT‘, '0003.HK_6DT', '0005.HK_12DT', '0003.HK_12DT', 'DEXJPUS', 'DEXUSUK', '^VIX', '^SPX', '^VIX_3DT', '^N225_3DT', '^TNX_3DT', '^SPX_3DT', '000001.SS_3DT', '^VIX_6DT', '^SPX_6DT', '^VIX_12DT', '^SPX_12DT', 'Const'

Step 3: Add Technical Indicators

- **ChoiceEff**: lag_3', '0005.HK_6DT', '0003.HK_6DT', '0005.HK_12DT', '0003.HK_12DT', 'DEXJPUS', 'DEXUSUK', '^VIX', '^SPX', '^VIX_3DT', '^N225_3DT', '^TNX_3DT', '^SPX_3DT', '000001.SS_3DT', '^VIX_6DT', '^SPX_6DT', '^VIX_12DT', '^SPX_12DT', 'HSI_MA21', 'HSI_MA63', 'HSI_MA252', 'HSI_EMA10', 'HSI_EMA30', 'HSI_EMA200'

4.4 Final Model: Linear Regression

Feature Tuning of Linear Regression



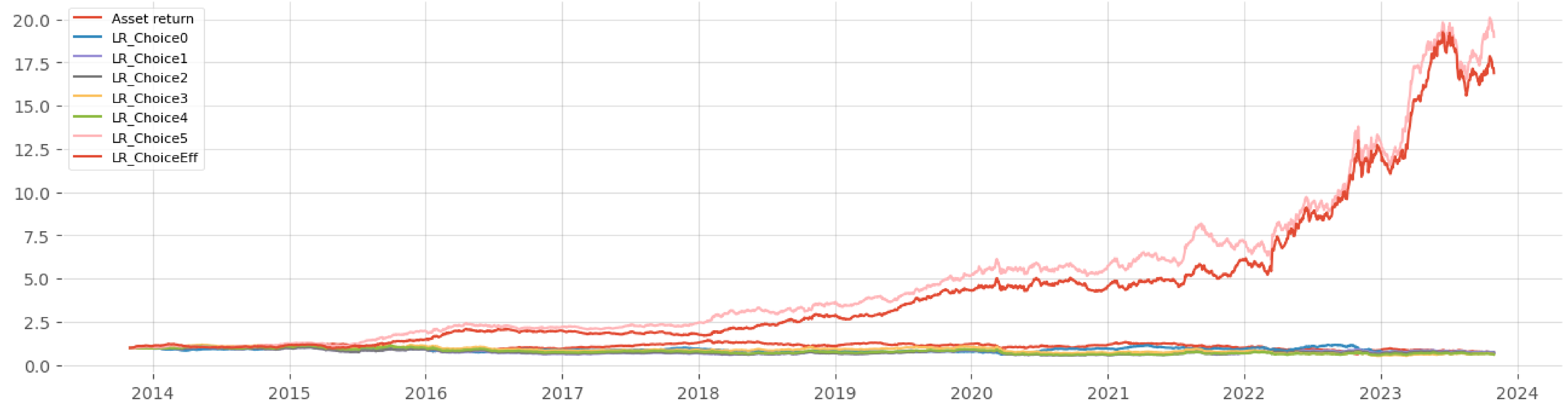
Feature Group	CAGR (%)	Sharpe Ratio	Sortino Ratio	Maximum Drawdown (%)	Maximum Drawdown (days)	Multiples of Invested Capital	Win Rates (%)
ChoiceEff	31.9771	1.6251	2.4829	-17.2123	99	1.7431	54.4715
Choice4	34.9644	1.7559	2.7154	-7.8315	119	1.8230	54.6748
Choice3	34.4681	1.7341	2.6913	-8.2871	120	1.8096	53.4553
Choice5	28.9482	1.4887	2.2981	-12.8502	95	1.6639	53.6585
Choice2	28.8767	1.4858	2.2728	-8.3278	119	1.6621	53.4553

Why Exchange Rate Indicators

- Many companies listed on the HSI have significant international operations and trade globally.
- Hong Kong is a major international financial center with close economic ties with various countries.

4.4 Final Model: Linear Regression

Deployment of Linear Regression with Different Features



Feature Group	CAGR (%)	Sharpe Ratio	Sortino Ratio	Maximum Drawdown (%)	Maximum Drawdown (days)	Multiples of Invested Capital	Win Rates (%)
ChoiceEff	32.6501	1.5157	2.4133	-20.6281	702	16.8815	52.6615
Choice4	-4.7576	-0.1399	-0.1990	-49.9190	2951	0.6141	48.5981
Choice3	-4.6419	-0.1357	-0.1926	-55.9962	3168	0.6216	48.7607
Choice5	34.2188	1.5738	2.4719	-25.4967	617	18.9882	53.7180
Choice2	-4.2112	-0.1131	-0.1623	-47.3741	3457	0.6503	48.3950

4.4 Final Model: Linear Regression

Threshold Setting

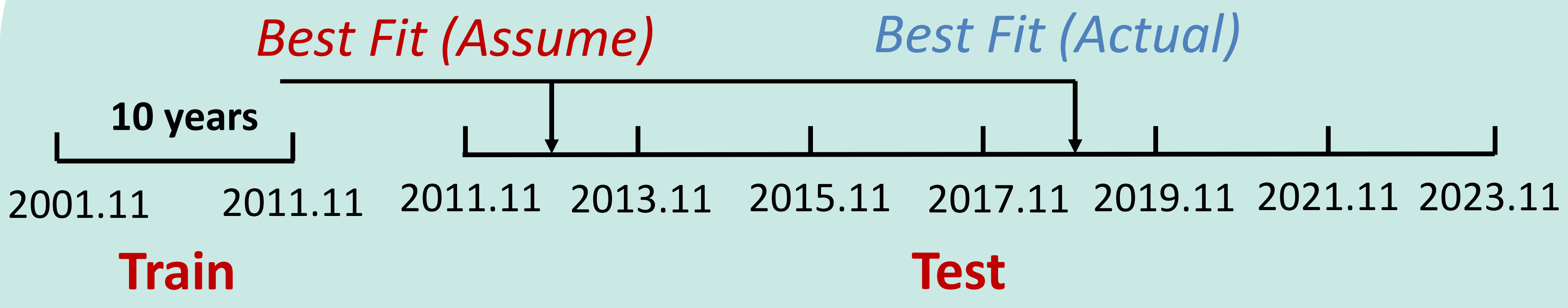
	t=0	t=1	Action
Slim Fluctuation	100	100.1	Not Buy
Real Uptrend	100	120	Buy

Long the asset only when the increase in stock price is greater than the threshold.

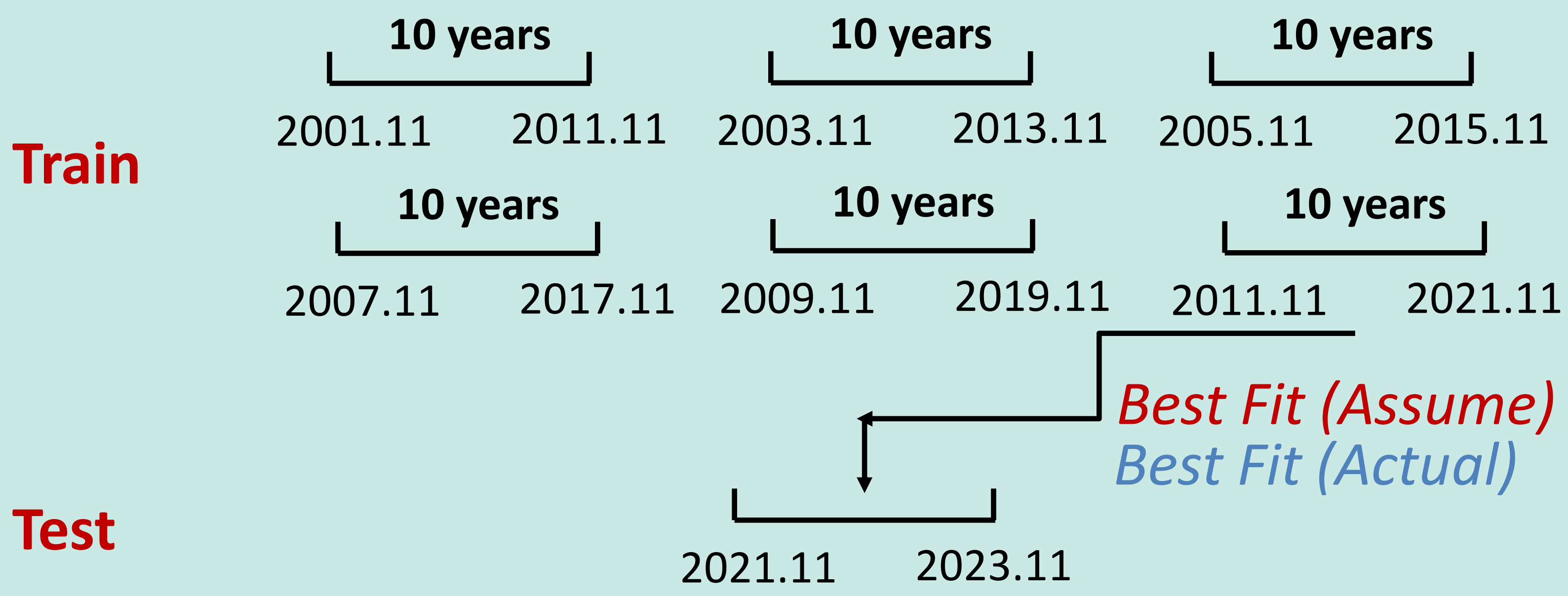
After fine-tuning, the strategy beats the market well and performs better when setting thresholds as 0.12%, 0.13%, 0.14%, and 0.18%.

Rolling Method

- **Training set is fixed, but testing set is rolling**



- **Testing set is fixed, but training set is rolling**



Deploy the model in the deploy set, and the results are better than the original deployment.

If a fixed training and testing set is used, it is easy to generate survivorship bias.

4.4 Final Model: Linear Regression

Final Deployment of Linear Regression

Feature Group	Threshold	CAGR (%)	Sharpe Ratio	Sortino Ratio	Max Drawdown (%)	Max Drawdown (days)	Multiples of Invested Capital	Win Rates (%)
ChoiceEff	0.12%	37.3668	1.9039	3.1759	-15.4786	687	23.9440	54.5241
	0.13%	35.5867	1.8463	3.0647	-15.4786	687	21.0152	54.5894
	0.14%	35.7875	1.8778	3.1141	-15.4786	687	21.3286	55.0995
	0.18%	30.1927	1.7111	2.8363	-17.3076	692	14.0017	55.0683
Choice5	*Recommend* **0.12%**	**30.7481**	**1.6207**	**2.6135**	**-22.9378**	**647**	**14.6108**	**54.9941**
	0.13%	28.3977	1.5306	2.4670	-23.3552	653	12.1862	54.7472
	0.14%	26.2745	1.4524	2.3321	-23.3552	653	10.3142	54.5629
	0.18%	27.5912	1.5795	2.5729	-21.0715	425	11.4419	55.5311
Asset (Benchmark)		**-2.9994**	**-0.0504**	**-0.0713**	**-55.7008**	**2101**	**0.7374**	**51.3206**

Why did we choose Choice5 instead of ChoiceEff?

ChoiceEff includes features like SMA and EMA. Lots of individual investors in the market will use these indicators as their trading signal, which may cause the strategy crowded.

05
DISCUSSION

5.1 Limitations

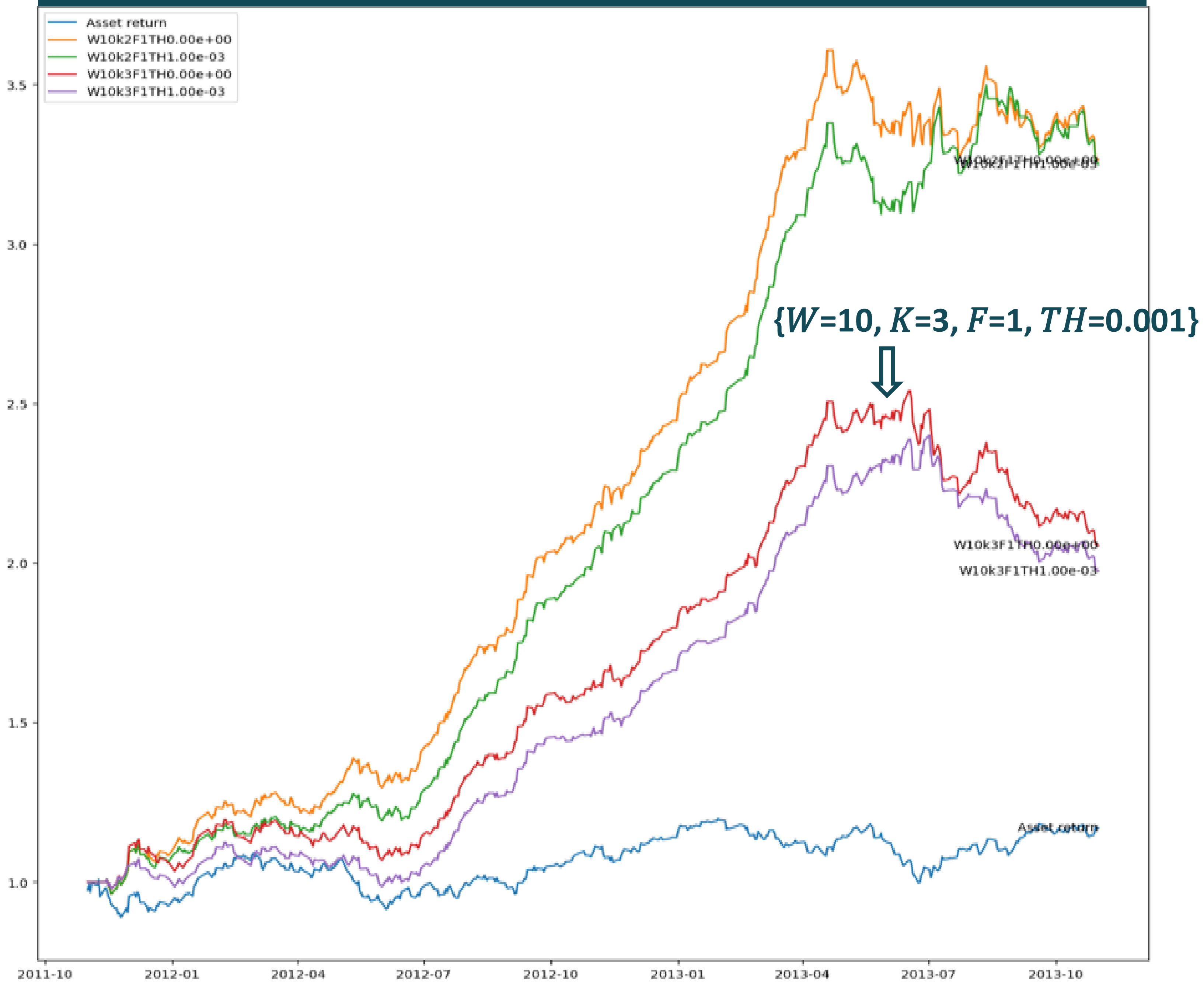
LIMITATIONS

1. Survivorship Bias
2. Computational Limits

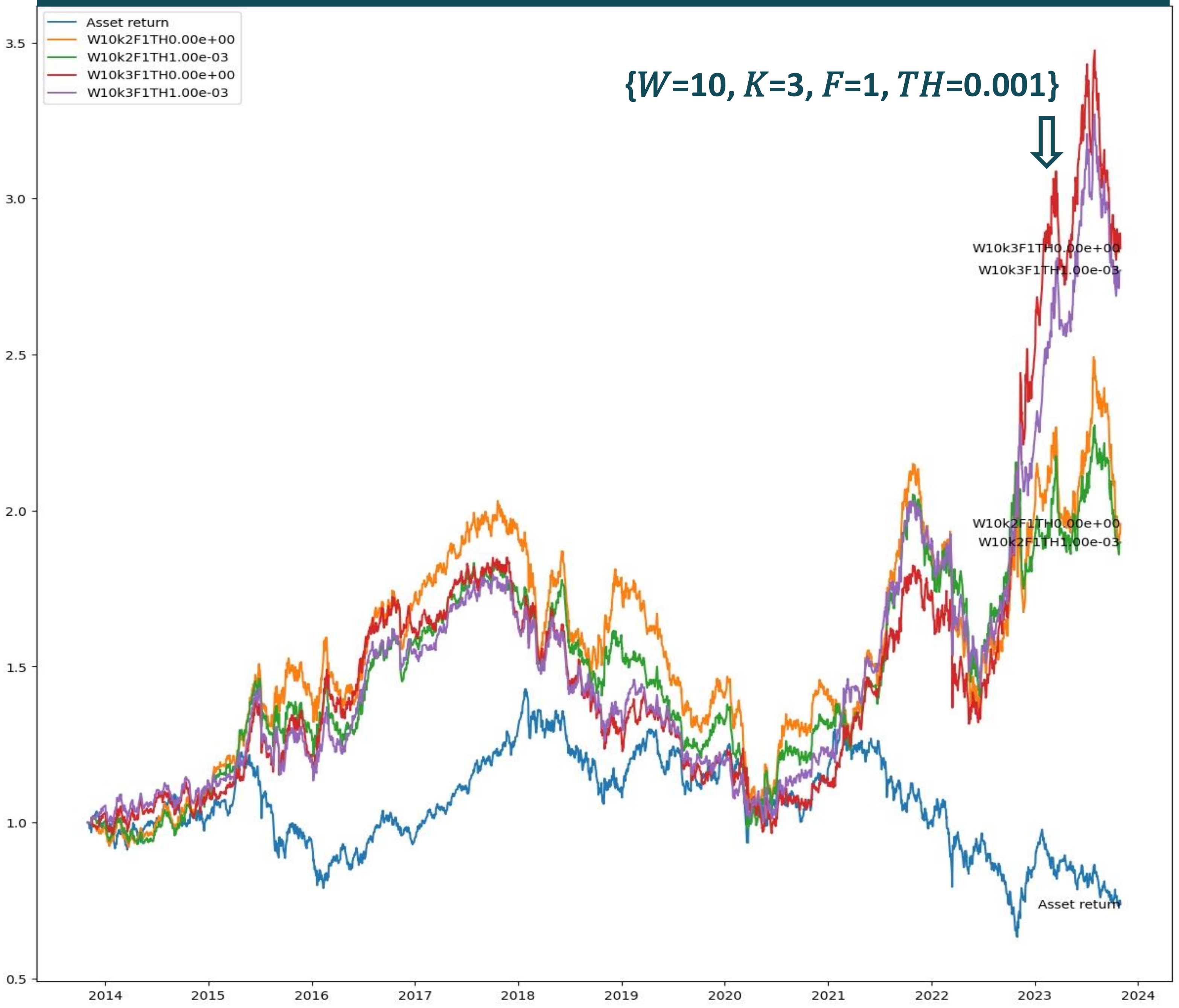
5.1.1 Limitation in DTW

Performance in Deployment Period

Testing Performance



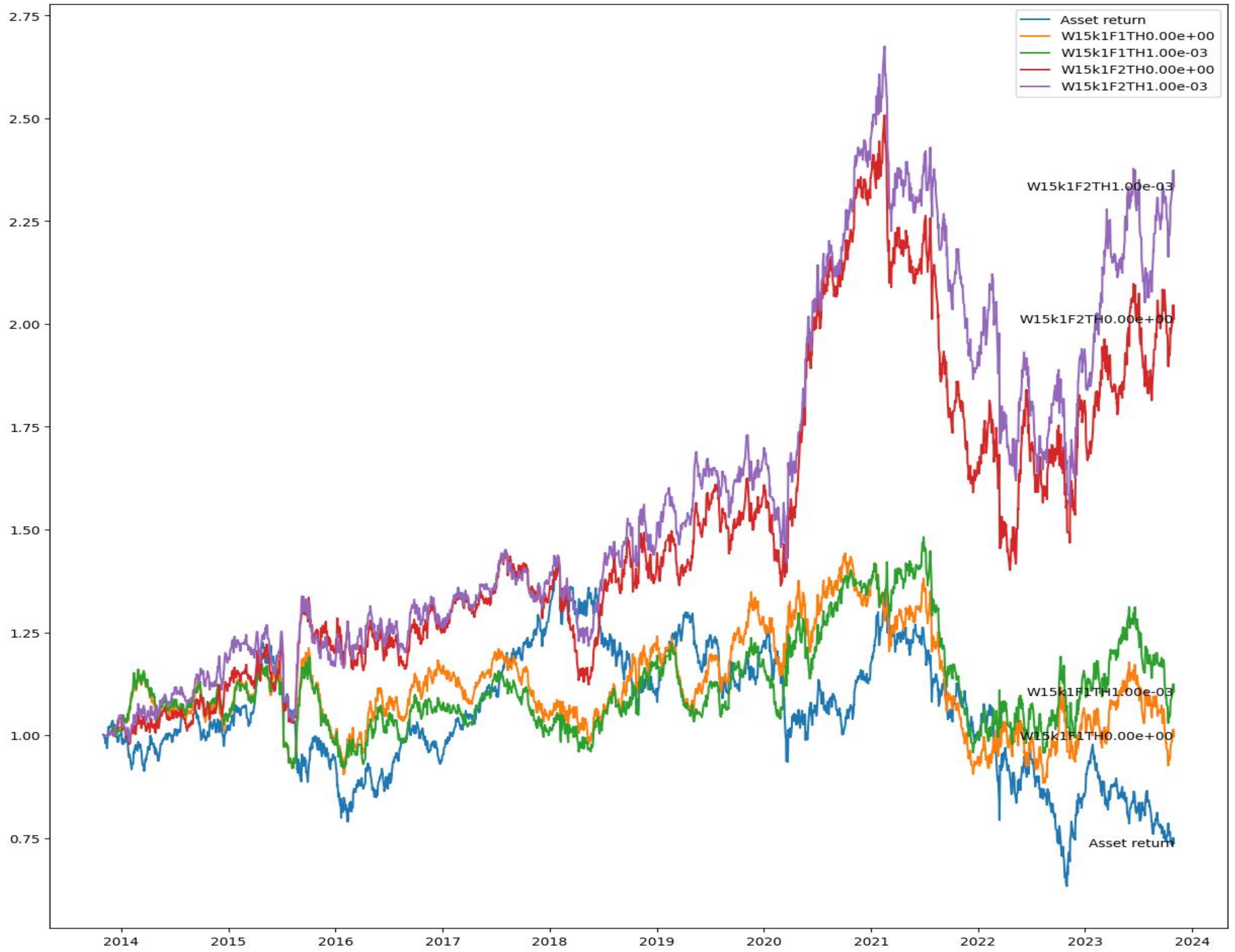
Deployment Performance



Best strategy in the training dataset is also likely to be beaten by other strategies in the future.

5.1.1 Limitation in DTW

Further Exploration in Deployment Period



The best combination is

{W=15, K=2, F=1, TH=0.001}

Hyperparameters	
Days of Warping Window (W)	10, 15
K in K-Nearest-Neighbor (K)	1, 2
Days of Prediction (F)	1, 2
Threshold of prediction movements (10^{-4}) (TH)	0,10

Hyperparameter Combination	CAGR (%)	Sharpe Ratio	Sortino Ratio	Maximum Drawdown (%)	Maximum Drawdown (days)	Multiples of Invested Capital	Win Rates (%)
Asset Return	**-2.9994**	**-0.0504**	**-0.0713**	**-55.7008**	**-2.9994**	**-0.0504**	**51.3206**
{W=15,K=2,F=1,TH=0.001}	8.8413	0.5617	0.8225	-41.7549	986	8.8413	51.5196

5.2 Improvements

IMPROVEMENTS

1. Rolling Methods Application
2. Threshold Optimization Focus
3. DTW Parameter Enhancement
4. DTW and PCA Integration

06
CONCLUSION

CONCLUSION

Some Machine Learning Approach

RF & DT ⇨ Involve random state

Non-parametric ML ⇨ Lazy training

Trading Strategy Goal: Stable

Best Strategy: Linear Regression

- Stability highlight: able to capture a comprehensive set of features

Thank You for Listening