

W U T I S

Stock Chart Pattern Recognition

Can future stock movements be predicted by locating patterns in historical data?



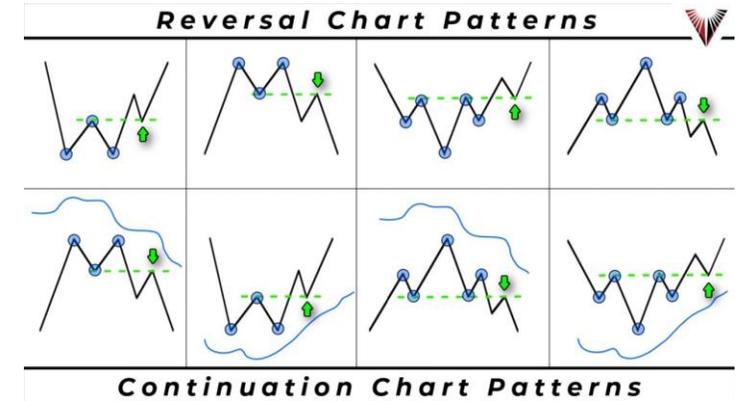
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FOUNDATIONS OF TECHNICAL ANALYSIS:
COMPUTATIONAL ALGORITHMS, STATISTICAL
INFERENCE, AND EMPIRICAL IMPLEMENTATION

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Harry Mamaysky
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◦ Introduction: Pattern Types

[Head and Shoulders]

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Head and Shoulders (HS) and Inverse Head and Shoulders (IHS)

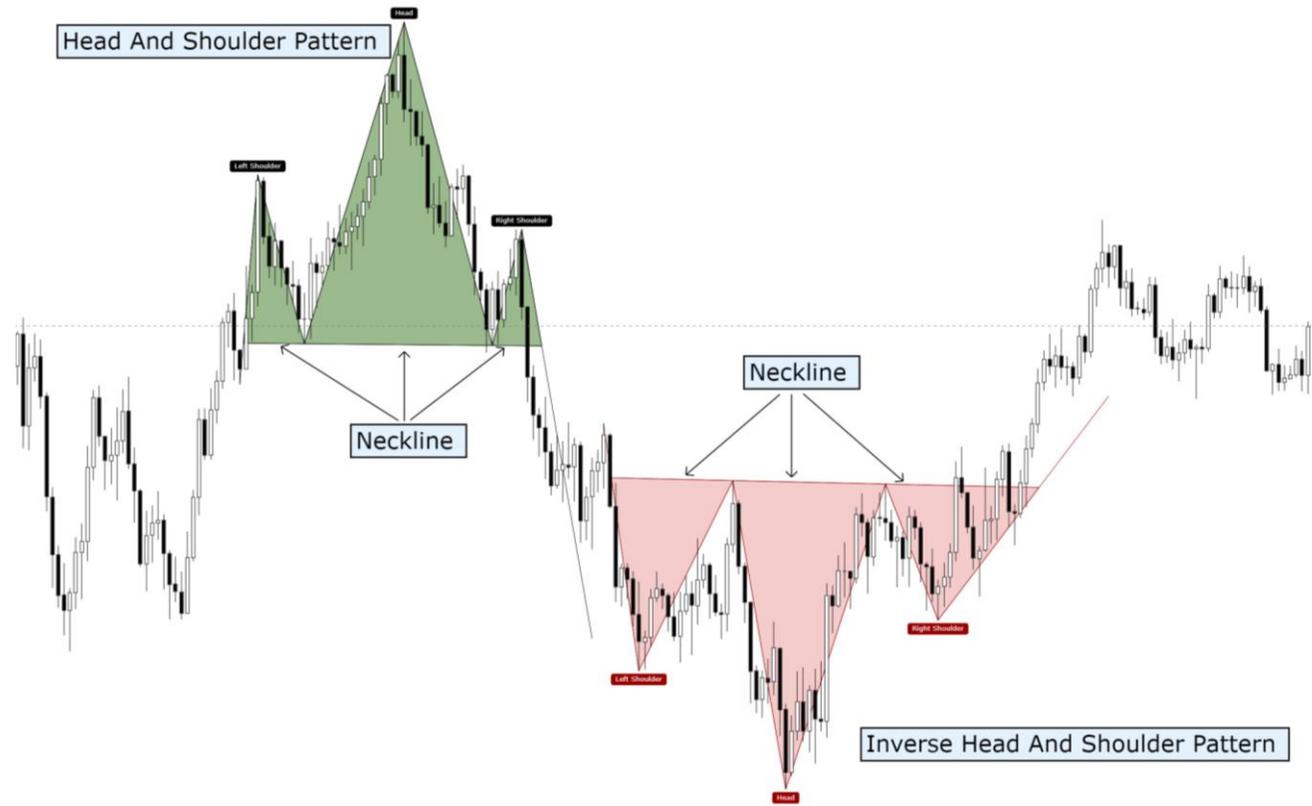
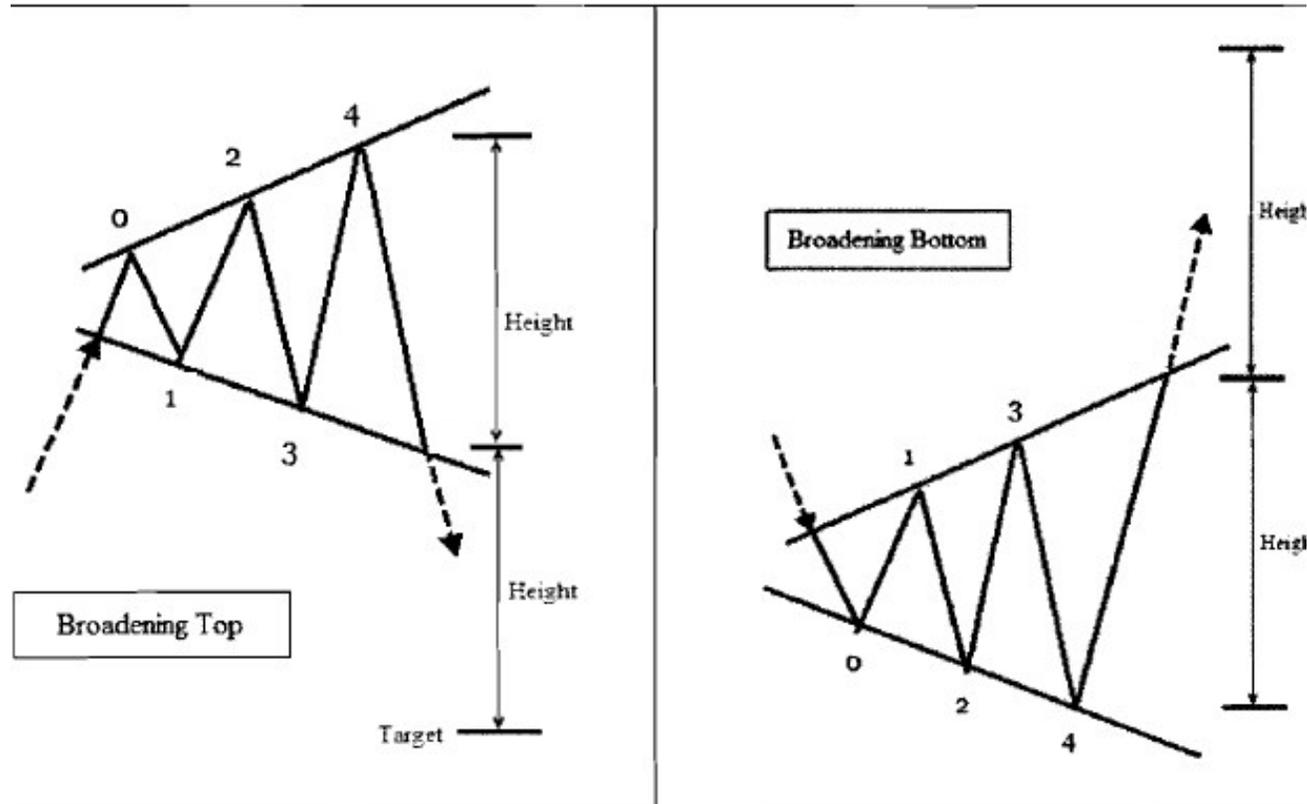


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Broadening Tops (BTOP) and Broadening Bottoms (BBOT)

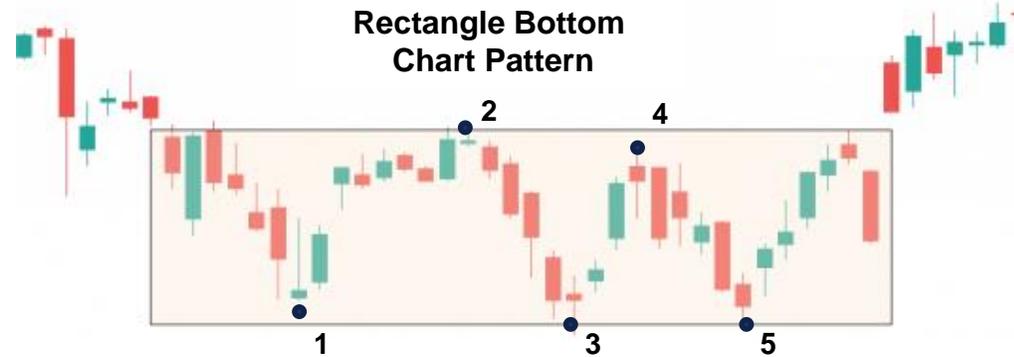


◦ Introduction: Pattern Types

[Other Patterns]

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- **Rectangle Tops (RTOP) and Bottoms (RBOT)**
- **Triangle Tops (TTOP) and Bottoms (TBOT)**
- **Double Tops (DTOP) and Bottoms (DBOT)**

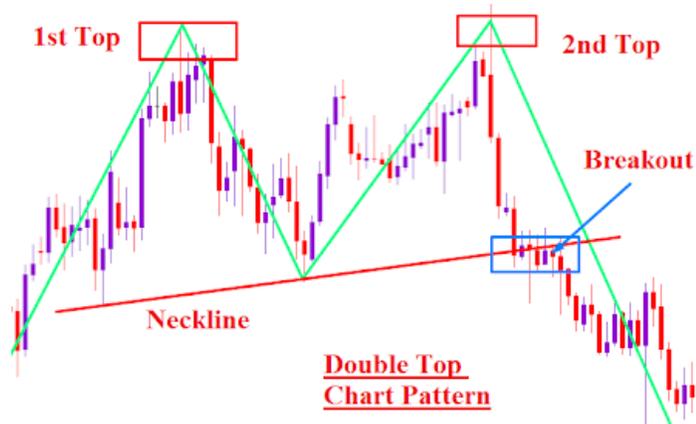
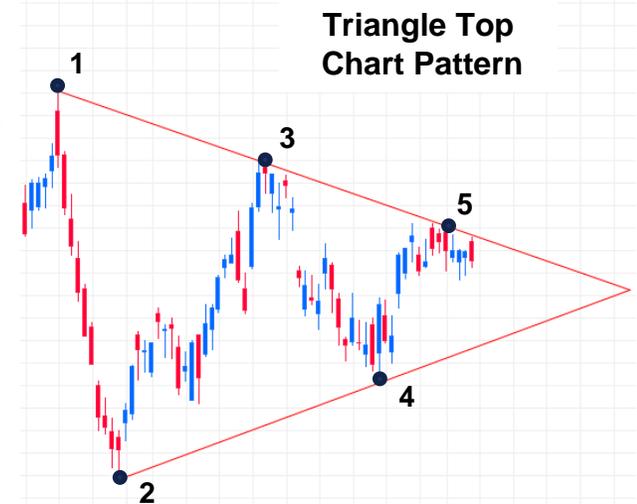


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Algorithm Structure

Step 1. Use smoothing estimators to draw non-linear relationship in the data: Kernel Regression (incl. bandwidth gamma)

Step 2. Locate local optima based on kernel regression estimates and categorize them (maxima or minima)

Step 3. Define technical pattern-types and indicate matches of consecutive optima in the data

Step 4. Calculate post-pattern returns (3-day, 5-day, and 15-day) for each located pattern-type

Step 5. Check if any pattern-type has a significant effect on the returns of the stock or index

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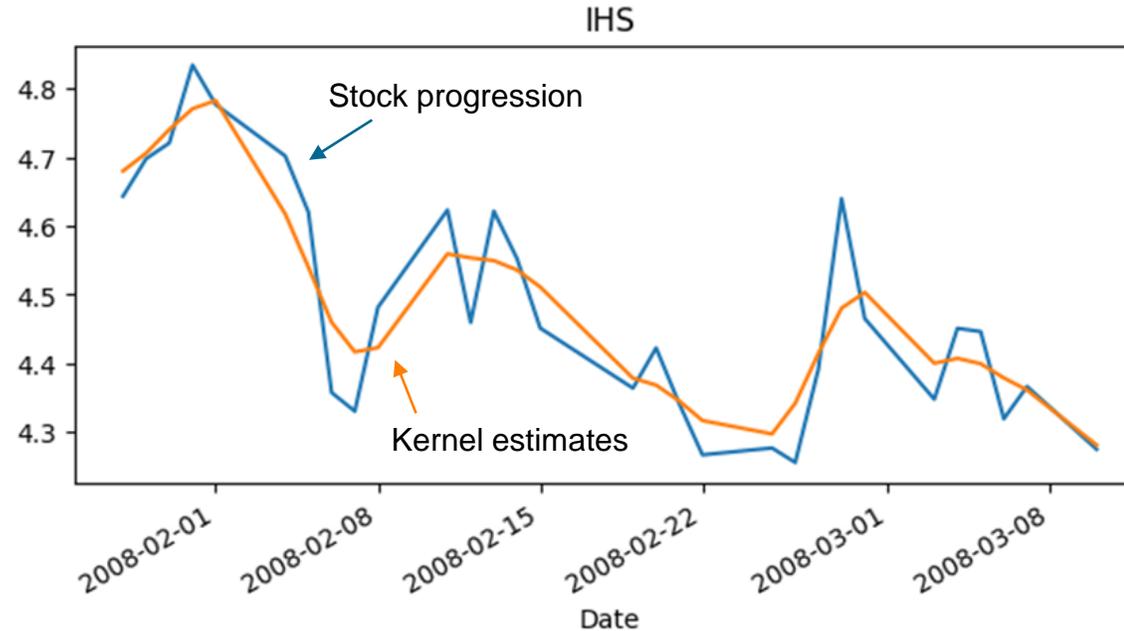


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Step 2. Locate local optima based on kernel regression estimates and categorize them (maxima or minima)

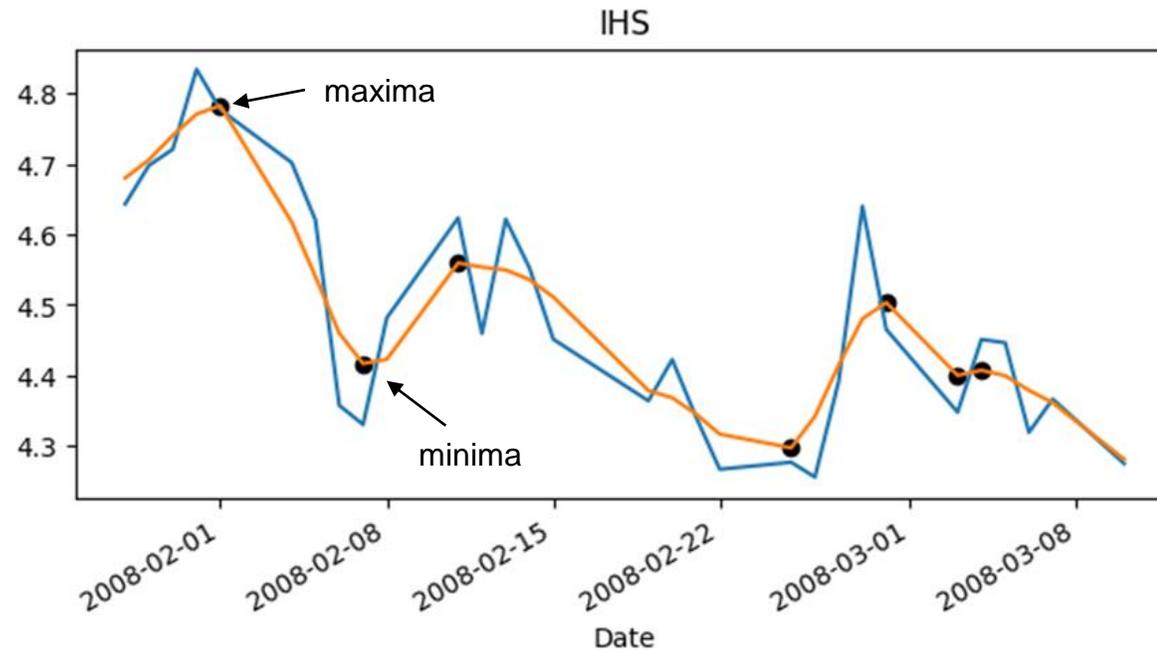


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Step 3. Define technical pattern-types and indicate matches of consecutive optima in the data

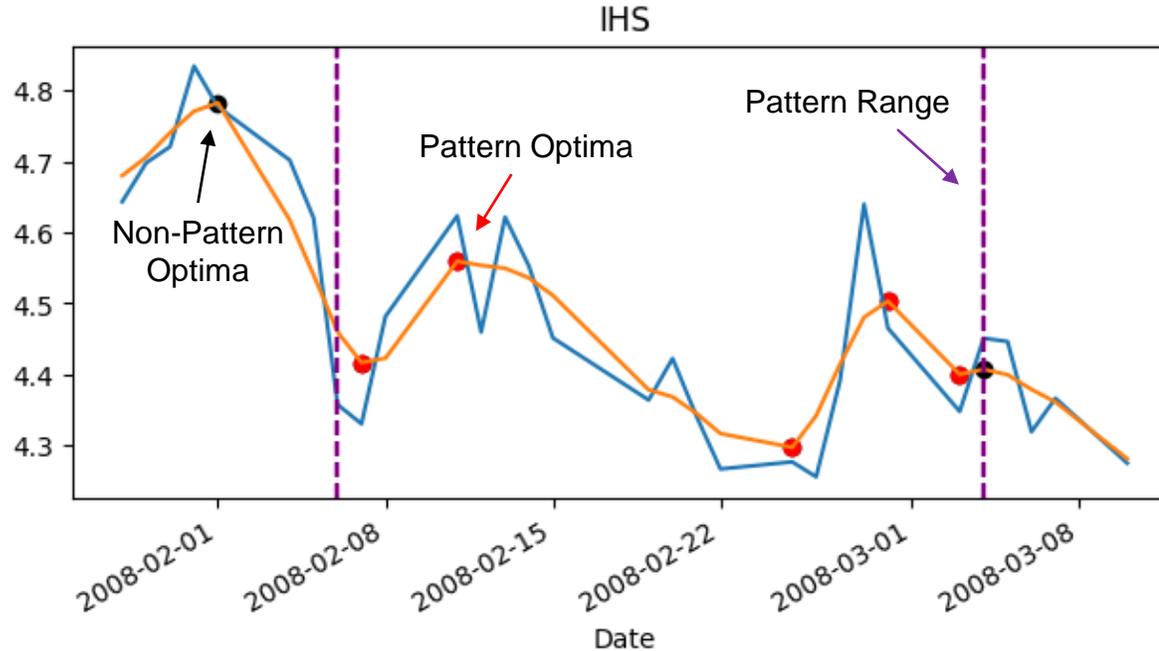


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Stocks/Indices:

- **Apple (AAPL):** 15 years (2008-2023)
- **Bitcoin USD (BTC-USD):** 6 years (2017-2023)
- **Nasdaq (^IXIC):** 40 years (1983-2023)
- **Gold (GC=F):** 22 years (2001-2023)
- **Walmart (WMT):** 35 years (1988-2023)
- **Crude Oil (CL=F):** 22 years (2001-2023)
- **Exxon Mobil (XOM):** 50 years (1973-2023)
- **Solar Edge (SEDG):** 8 years (2015-2023)

Parameters

[Tuning the Algorithm: Data Frequency I]

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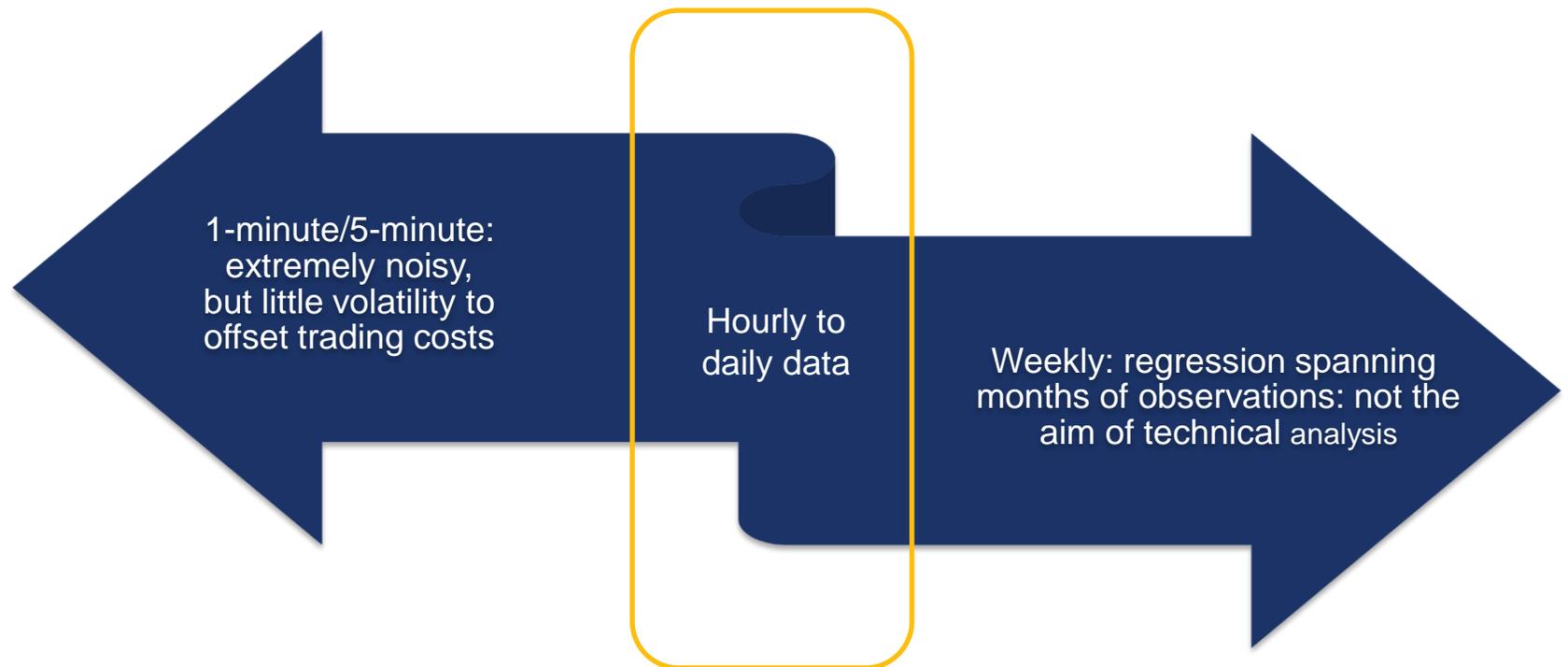
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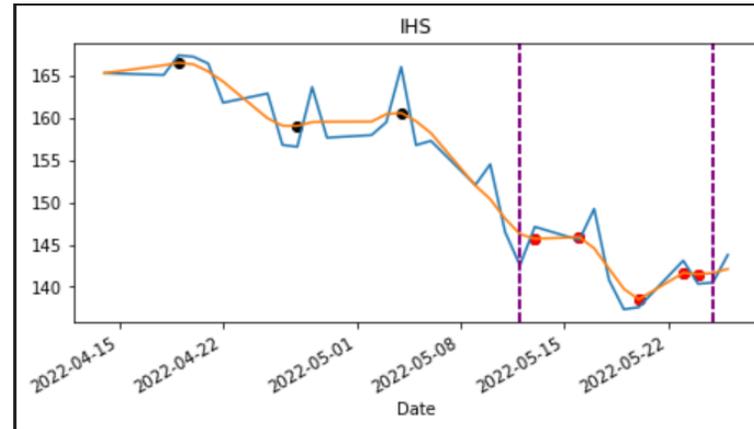


Parameters

[Tuning the Algorithm: Data Frequency II]

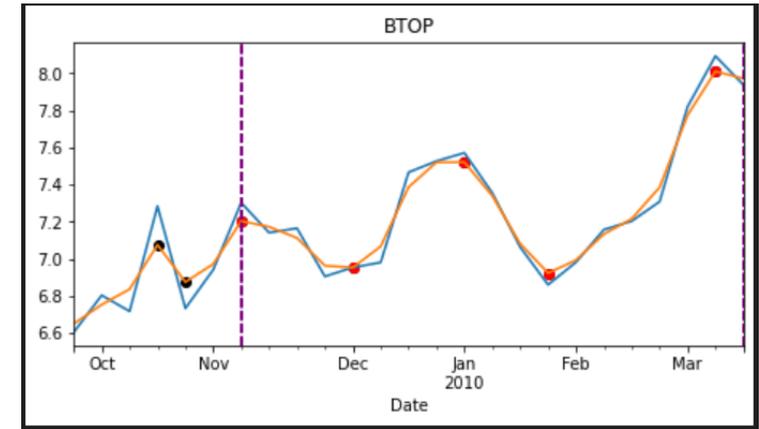
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Hourly/daily: reasonable fit with appropriate gamma value and window size

Frequency = daily
Gamma = 0.3
Window size = 30 days



5min/weekly: too noisy/too general, not in the focus of technical analysis

Frequency = weekly
Gamma = 0.025
Window size = 25

Frequency used: daily

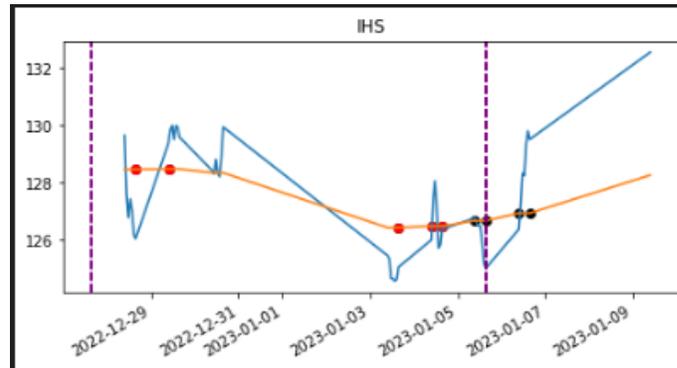
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[Tuning the Algorithm: Gamma]

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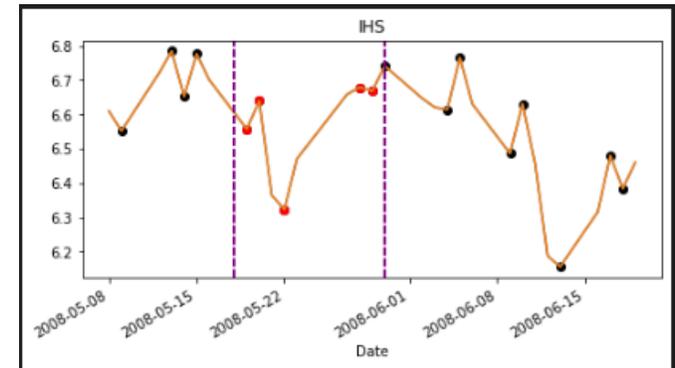
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Changing the hyperparameter regulating the flexibility of the kernel regression, we can decide on the right fit for our purposes: trying to capture more than the long-term trend while finding a point where noise is not too much either.



Underfitting: lack of local information

Frequency = hourly
Gamma = 0.1
Window size = 50 days



Overfitting: capturing the noise, resulting in too many extrema

Frequency = daily
Gamma = 15
Window size = 30 days

Gammas used:
0.1, 0.3, 1.0

Parameters

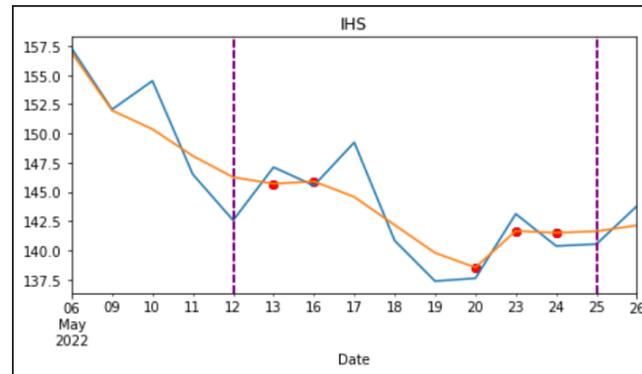
[Tuning the algorithm: window size]

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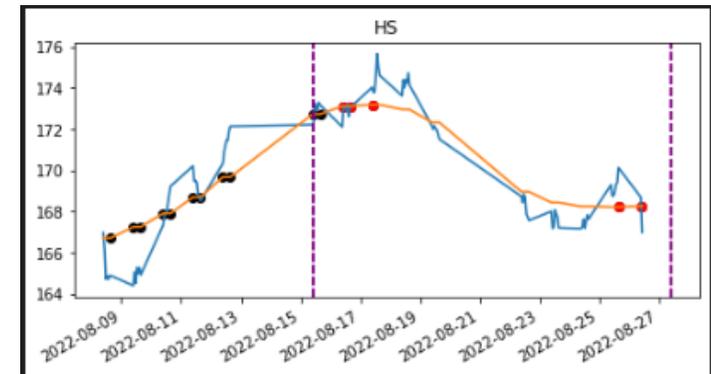


Window size controls the number of optima included and the sample on which we estimate the kernel regression. Since 5 extrema are required for patterns, we should choose windows which contain at least 5 but not many more (effect of older movements is less and less defined, only 5 points are used in these patterns, skipping intermediates is not implemented)



Small windows yield fewer patterns as each set of 5 points is assessed only once

Frequency = daily
Gamma = 0.3
Window size = 15d



Large windows allow for many optima even if the curve is underfitted

Frequency = hourly
Gamma = 0.1
Window size = 100h

Windows used:
20d, 30d, 45d

◦ Interpreting Results

[Results I – Tally of significant patterns by type]

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of significant post-pattern avg. returns by stock and pattern

Pattern	Apple	Bitcoin	Nasdaq	Gold	Walmart	Crude Oil	Exxon	Solar Edge
IHS	24	9	26	27	27	22	27	0
HS	9	5	20	20	21	16	27	5
BTOP	2	3	11	12	18	13	23	1
BBOT	4	0	12	17	21	4	25	3

of significant post-pattern avg. returns by stock and return-type

Return-Type	Apple	Bitcoin	Nasdaq	Gold	Walmart	Crude Oil	Exxon	Solar Edge
3day	17	12	29	32	33	26	35	6
5day	11	3	23	29	31	23	34	1
15day	11	2	17	15	23	6	33	2

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Avg. returns of patterns across all tickers

Pattern	3day	5day	15day
IHS	0.0148	0.0162	0.0227
HS	-0.0121	-0.0109	-0.0054
BTOP	-0.0128	-0.0105	-0.0064
BBOT	0.0116	0.0116	0.0179

Avg. positive
post-pattern
return



Avg. negative
post-pattern
return

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As a continuation of this project, further analysis could focus on:

- Comparing the outlined method with alternatives built upon mean-reversion
- Building signals generated by the framework into a larger ML model
- Backtesting long-term performance accounting for trading costs
- Optimizing parameters based on returns and the underlying asset
- Assessing the performance of other alternatives for smoothing

Appendix

◦ Interpreting Results

[Results II]

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Avg. returns of significant patterns across all tickers

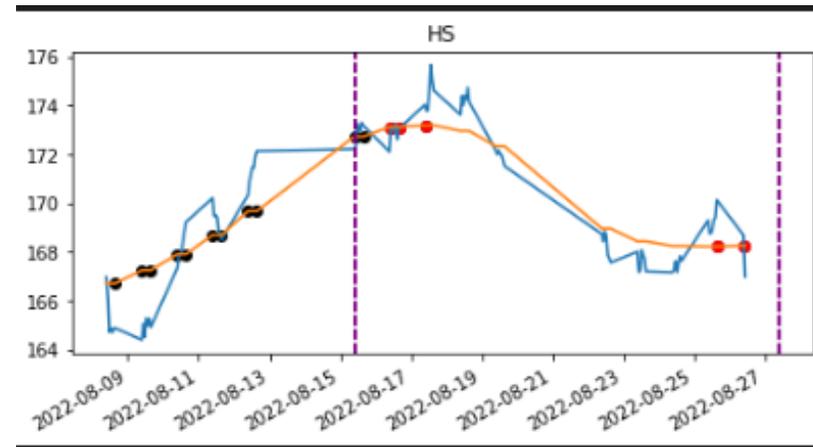
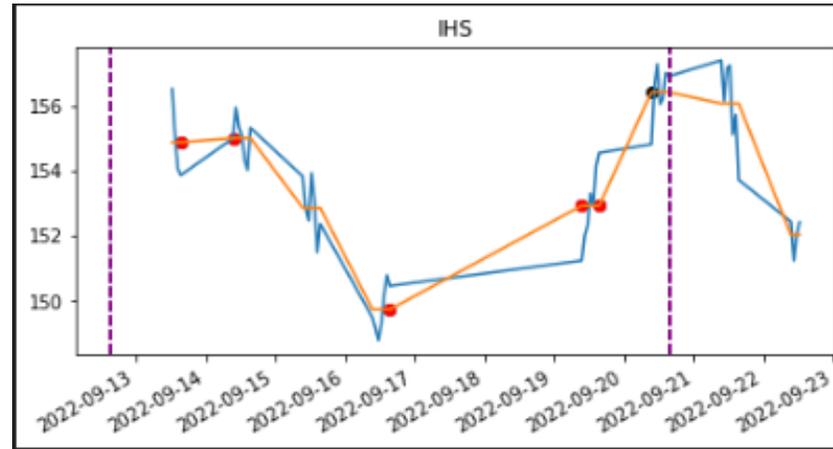
Pattern	3day	5day	15day
IHS	0.0148	0.0162	0.0225
HS	-0.0121	-0.0109	-0.0085
BTOP	-0.0128	-0.0135	-0.0148
BBOT	0.0158	0.0164	0.0238

Avg. positive
post-pattern
return



Avg. negative
post-pattern
return

Example: hourly data fit



Low gamma = 0.1 to avoid overfitting
May not be enough as the curve will have a lot of optima for large windows.
Window = 100
Frequency = 1h

Appendix: AAPL

[Significance of post-pattern returns] Code Output [Frequency: Daily]

➔ Gamma Input: ↑

➔ Gamma Input: ↑

Gamma: 0.1; Window Size: 20					
	Pattern	Freq	3days pval	5days pval	15days pval
0	IHS	4	0.2767797	0.5055845	0.09168277
1	HS	3	0.1688136	0.9593731	0.42807581
2	BTOP	3	0.7129389	0.4607928	0.93562472
3	BBOT	2	0.3048544	0.1134831	0.91129793

Gamma: 0.3; Window Size: 20					
	Pattern	Freq	3days pval	5days pval	15days pval
0	IHS	44	8.533E-05	0.048529	0.00067909
1	HS	27	0.101048	0.8390097	0.90748642
2	BTOP	16	0.2994309	0.619576	0.73858882
3	BBOT	14	0.1807897	0.356069	0.15024456

Gamma: 1.0; Window Size: 20					
	Pattern	Freq	3days pval	5days pval	15days pval
0	IHS	83	9.825E-07	1.623E-06	2.8632E-05
1	HS	88	2.52E-05	0.021807	0.71537913
2	BTOP	24	0.4153405	0.7100944	0.81498338
3	BBOT	15	0.1742634	0.4529007	0.33407722

↓ Window Size: ↑

Gamma: 0.1; Window Size: 30					
	Pattern	Freq	3days pval	5days pval	15days pval
0	IHS	27	1.336E-06	0.0001145	0.00022161
1	HS	16	0.0302318	0.120009	0.152203
2	BTOP	9	0.8803331	0.8443969	0.44071266
3	BBOT	8	0.0570611	0.8778699	0.90060688

Gamma: 0.3; Window Size: 30					
	Pattern	Freq	3days pval	5days pval	15days pval
0	IHS	55	1.586E-08	0.0001874	6.8433E-06
1	HS	39	0.0031571	0.233051	0.29391596
2	BTOP	29	0.1868557	0.8275097	0.05946954
3	BBOT	24	0.0522505	0.3113712	0.03915444

Gamma: 1.0; Window Size: 30					
	Pattern	Freq	3days pval	5days pval	15days pval
0	IHS	87	9.847E-08	4.677E-07	1.4183E-05
1	HS	97	3.244E-05	0.0445852	0.54169892
2	BTOP	30	0.3371644	0.5270511	0.35804742
3	BBOT	18	0.1114314	0.3275282	0.16739379

↓ Window Size: ↑

Gamma: 0.1; Window Size: 45					
	Pattern	Freq	3days pval	5days pval	15days pval
0	IHS	36	1.052E-08	2.277E-06	4.6562E-06
1	HS	23	0.0854756	0.0923114	0.25611653
2	BTOP	13	0.338364	0.4610382	0.32878613
3	BBOT	14	0.0376705	0.4914992	0.79277367

Gamma: 0.3; Window Size: 45					
	Pattern	Freq	3days pval	5days pval	15days pval
0	IHS	57	1.799E-09	8.388E-06	2.9078E-06
1	HS	38	0.000768	0.0856474	0.41497754
2	BTOP	36	0.04054	0.6511486	0.03448059
3	BBOT	27	0.0609054	0.1312845	0.00504009

Gamma: 1.0; Window Size: 45					
	Pattern	Freq	3days pval	5days pval	15days pval
0	IHS	87	9.709E-09	1.944E-07	5.8033E-06
1	HS	99	3.552E-06	0.0376284	0.7747698
2	BTOP	33	0.1559079	0.2234287	0.43532693
3	BBOT	21	0.0315337	0.2393283	0.39792602

Total sign. post-pattern return averages (by pattern) ➔

Total	17	11	11
IHS	8	8	8
HS	6	3	0
BTOP	1	0	1
BBOT	2	0	2

Freq.: number of times that pattern was detected by the algorithm

Note: p-values were calculated under the assumption that expected returns are equal to zero (for the 3days to 15days calculated)

Appendix: AAPL

[Average post-pattern returns] Code Output [Frequency: Daily]

Gamma: 0.1; Window Size: 20					
	Pattern	Freq	3days avg	5days avg	15days avg
0	IHS	4	0.007255	0.011711	0.0595657
1	HS	3	-0.015784	0.000741	-0.0053409
2	BTOP	3	-0.0101	-0.012869	-0.0037462
3	BBOT	2	0.035295	0.050939	0.0108759

Gamma: 0.3; Window Size: 20					
	Pattern	Freq	3days avg	5days avg	15days avg
0	IHS	44	0.012961	0.010098	0.0394542
1	HS	27	-0.010612	-0.001239	0.0016456
2	BTOP	16	-0.007638	-0.002894	0.0052237
3	BBOT	14	0.012321	0.010783	0.0286569

Gamma: 1.0; Window Size: 20					
	Pattern	Freq	3days avg	5days avg	15days avg
0	IHS	83	0.015577	0.02045	0.0306639
1	HS	88	-0.013441	-0.008691	0.0025315
2	BTOP	24	-0.004802	-0.00291	0.0037436
3	BBOT	15	0.015398	0.009734	0.0244076

Gamma: 0.1; Window Size: 30					
	Pattern	Freq	3days avg	5days avg	15days avg
0	IHS	27	0.016526	0.02661	0.0586358
1	HS	16	-0.010732	-0.011348	-0.012982
2	BTOP	9	-0.001649	-0.002992	0.0285402
3	BBOT	8	0.031077	0.004395	0.0051412

Gamma: 0.3; Window Size: 30					
	Pattern	Freq	3days avg	5days avg	15days avg
0	IHS	55	0.015184	0.016644	0.0450534
1	HS	39	-0.013026	-0.004959	-0.0109301
2	BTOP	29	-0.005758	-0.00083	0.0237028
3	BBOT	24	0.013438	0.008558	0.0273724

Gamma: 1.0; Window Size: 30					
	Pattern	Freq	3days avg	5days avg	15days avg
0	IHS	87	0.016101	0.020658	0.0309927
1	HS	97	-0.012388	-0.007316	0.0039688
2	BTOP	30	-0.004823	-0.004003	0.0125674
3	BBOT	18	0.015477	0.011647	0.0295987

Gamma: 0.1; Window Size: 45					
	Pattern	Freq	3days avg	5days avg	15days avg
0	IHS	36	0.019012	0.028528	0.0589354
1	HS	23	-0.008774	-0.012628	-0.0105741
2	BTOP	13	-0.008758	-0.007949	0.0252986
3	BBOT	14	0.022977	0.011725	0.0061085

Gamma: 0.3; Window Size: 45					
	Pattern	Freq	3days avg	5days avg	15days avg
0	IHS	57	0.015909	0.019761	0.0459241
1	HS	38	-0.015201	-0.007561	-0.008762
2	BTOP	36	-0.008575	-0.001505	0.0234339
3	BBOT	27	0.012142	0.011847	0.0343527

Gamma: 1.0; Window Size: 45					
	Pattern	Freq	3days avg	5days avg	15days avg
0	IHS	87	0.016749	0.021297	0.0324516
1	HS	99	-0.013363	-0.007444	0.0018195
2	BTOP	33	-0.006579	-0.007281	0.0103077
3	BBOT	21	0.017543	0.012095	0.0169584

Total post-pattern return averages (by pattern) 

Total avg.	3days	5days	15days
IHS	0.0159	0.0201	0.0392
HS	-0.0128	-0.0074	-0.0009
BTOP	-0.0064	-0.0037	0.0155
BBOT	0.0164	0.0111	0.0237

Freq.: number of times that pattern was detected by the algorithm

Total avg.: calculated by dividing absolute sum of returns by the sum of all pattern occurrences (of a given type)

Appendix: Nasdaq

[Significance of post-pattern returns] Code Output [Frequency: Daily]

➔ **Gamma Input: ↑**

➔ **Gamma Input: ↑**

Gamma: 0.1; Window Size: 20

	Pattern	Freq	3days pval	5days pval	15days pval
0	IHS	13	0.0057106	0.0032423	0.0203817
1	HS	20	0.0917031	0.4019819	0.78398588
2	BTOP	4	0.2063604	0.1142148	0.9030216
3	BBOT	5	0.1367723	0.0786976	0.30583565

Gamma: 0.3; Window Size: 20

	Pattern	Freq	3days pval	5days pval	15days pval
0	IHS	110	7.587E-12	5.591E-08	5.1017E-07
1	HS	125	1.675E-09	8.152E-05	0.30844333
2	BTOP	25	0.0877852	0.5930577	0.14265705
3	BBOT	21	0.0887111	0.6759689	0.13698014

Gamma: 1.0; Window Size: 20

	Pattern	Freq	3days pval	5days pval	15days pval
0	IHS	276	1.089E-28	8.102E-20	3.6785E-16
1	HS	273	2.083E-13	1.233E-05	0.38249254
2	BTOP	59	0.0003301	0.3196694	0.51283139
3	BBOT	52	0.3536955	0.8333632	0.13694126

↓ **Window Size: ↑**

Gamma: 0.1; Window Size: 30

	Pattern	Freq	3days pval	5days pval	15days pval
0	IHS	63	1.195E-07	1.736E-08	0.00089855
1	HS	95	7.115E-11	2.236E-07	0.0210689
2	BTOP	24	0.0009654	0.008399	0.6623081
3	BBOT	27	0.0005848	0.0075397	0.02521202

Gamma: 0.3; Window Size: 30

	Pattern	Freq	3days pval	5days pval	15days pval
0	IHS	189	6.043E-21	7.9E-16	1.2125E-10
1	HS	209	3.033E-20	1.013E-09	0.04975549
2	BTOP	57	0.0147047	0.1481504	0.63708282
3	BBOT	46	0.0024355	0.5681883	0.11989929

Gamma: 1.0; Window Size: 30

	Pattern	Freq	3days pval	5days pval	15days pval
0	IHS	296	1.034E-31	6.199E-22	7.4166E-17
1	HS	294	3.661E-18	6.223E-08	0.9804245
2	BTOP	75	5.848E-05	0.1496226	0.88433579
3	BBOT	61	0.092184	0.7177512	0.05627305

↓ **Window Size: ↑**

Gamma: 0.1; Window Size: 45

	Pattern	Freq	3days pval	5days pval	15days pval
0	IHS	122	1.026E-17	3.985E-17	na
1	HS	144	4.532E-24	2.496E-16	0.00030933
2	BTOP	52	5.041E-11	3.782E-06	0.03130211
3	BBOT	34	1.25E-05	0.0003349	0.00773443

Gamma: 0.3; Window Size: 45

	Pattern	Freq	3days pval	5days pval	15days pval
0	IHS	220	4.915E-25	6.431E-18	3.4295E-10
1	HS	221	5.006E-26	6.04E-13	0.00045777
2	BTOP	76	4E-06	0.0026705	0.71068022
3	BBOT	59	2.134E-06	0.019335	0.00361985

Gamma: 1.0; Window Size: 45

	Pattern	Freq	3days pval	5days pval	15days pval
0	IHS	315	3.663E-35	8.301E-26	2.1087E-18
1	HS	299	1.762E-21	8.047E-10	0.96857972
2	BTOP	86	2.705E-06	0.1132102	0.89457434
3	BBOT	61	0.0118823	0.0523394	0.0038598

Total sign. post-pattern return averages (by pattern) ➔

Total	29	23	17
IHS	9	9	8
HS	8	8	4
BTOP	7	3	1
BBOT	5	3	4

Freq.: number of times that pattern was detected by the algorithm

Note: p-values were calculated under the assumption that expected returns are equal to zero (for the 3days to 15days calculated)

Appendix: Nasdaq

[Average post-pattern returns] Code Output [Frequency: Daily]

Gamma: 0.1; Window Size: 20					
	Pattern	Freq	3days avg	5days avg	15days avg
0	IHS	13	0.018829	0.027473	0.0339388
1	HS	20	-0.006517	-0.003632	-0.0015512
2	BTOP	4	-0.013648	-0.025112	-0.0031676
3	BBOT	5	0.010204	0.013385	-0.0137414

Gamma: 0.3; Window Size: 20					
	Pattern	Freq	3days avg	5days avg	15days avg
0	IHS	110	0.01117	0.013987	0.0207514
1	HS	125	-0.009896	-0.008924	-0.0035118
2	BTOP	25	-0.004935	-0.002251	0.0120887
3	BBOT	21	0.011088	0.004747	0.0252703

Gamma: 1.0; Window Size: 20					
	Pattern	Freq	3days avg	5days avg	15days avg
0	IHS	276	0.011919	0.013722	0.0195148
1	HS	273	-0.008021	-0.006301	0.0019892
2	BTOP	59	-0.009002	-0.00327	0.0037384
3	BBOT	52	0.003412	-0.001263	0.0144351

Gamma: 0.1; Window Size: 30					
	Pattern	Freq	3days avg	5days avg	15days avg
0	IHS	63	0.011815	0.016767	0.0181946
1	HS	95	-0.011162	-0.012681	-0.0102928
2	BTOP	24	-0.007462	-0.012602	-0.0032235
3	BBOT	27	0.021416	0.016653	0.0303035

Gamma: 0.3; Window Size: 30					
	Pattern	Freq	3days avg	5days avg	15days avg
0	IHS	189	0.012918	0.014198	0.019581
1	HS	209	-0.011544	-0.010676	-0.0051586
2	BTOP	57	-0.004842	-0.003924	0.0024388
3	BBOT	46	0.012661	0.004227	0.0178941

Gamma: 1.0; Window Size: 30					
	Pattern	Freq	3days avg	5days avg	15days avg
0	IHS	296	0.011977	0.013768	0.0193625
1	HS	294	-0.009176	-0.007436	5.483E-05
2	BTOP	75	-0.008492	-0.003967	0.0007199
3	BBOT	61	0.005495	0.001895	0.0168472

Gamma: 0.1; Window Size: 45					
	Pattern	Freq	3days avg	5days avg	15days avg
0	IHS	122	0.01272	0.017343	0.0185582
1	HS	144	-0.013403	-0.016608	-0.0137348
2	BTOP	52	-0.008458	-0.012929	-0.0104625
3	BBOT	34	0.024773	0.022461	0.0304071

Gamma: 0.3; Window Size: 45					
	Pattern	Freq	3days avg	5days avg	15days avg
0	IHS	220	0.012552	0.013648	0.0178692
1	HS	221	-0.012113	-0.011556	-0.0088382
2	BTOP	76	-0.0074	-0.006461	-0.001596
3	BBOT	59	0.017311	0.012841	0.0248602

Gamma: 1.0; Window Size: 45					
	Pattern	Freq	3days avg	5days avg	15days avg
0	IHS	315	0.012005	0.014319	0.0195252
1	HS	299	-0.009989	-0.008207	-8.691E-05
2	BTOP	86	-0.008686	-0.003999	0.0005651
3	BBOT	61	0.00793	0.008069	0.0231221

Total post-pattern return averages (by pattern) 

Total avg.	3days	5days	15days
IHS	0.0122	0.0144	0.0193
HS	-0.0103	-0.0095	-0.0035
BTOP	-0.0078	-0.0059	0.0000
BBOT	0.0118	0.0079	0.0213

Freq.: number of times that pattern was detected by the algorithm

Total avg.: calculated by dividing absolute sum of returns by the sum of all pattern occurrences (of a given type)

Appendix: Crude Oil

[Significance of post-pattern returns] Code Output [Frequency: Daily]

➔ **Gamma Input: ↑**

➔ **Gamma Input: ↑**

Gamma: 0.1; Window Size: 20					
	Pattern	Freq	3days pval	5days pval	15days pval
0	IHS	15	5.558E-05	0.02381	0.74118988
1	HS	16	0.0661012	0.9116343	0.3958954
2	BTOP	1	na	na	na
3	BBOT	1	na	na	na

Gamma: 0.3; Window Size: 20					
	Pattern	Freq	3days pval	5days pval	15days pval
0	IHS	39	0.0371431	0.0282082	0.92744285
1	HS	56	7.668E-07	0.0010828	0.16349774
2	BTOP	15	0.0044616	0.0122553	0.99778684
3	BBOT	14	0.0072143	0.0003105	0.00559855

Gamma: 1.0; Window Size: 20					
	Pattern	Freq	3days pval	5days pval	15days pval
0	IHS	114	2.571E-14	1.203E-08	7.3225E-05
1	HS	118	4.769E-09	2.871E-05	0.60103019
2	BTOP	31	0.0049242	0.0028446	0.1352852
3	BBOT	35	0.0434886	0.6167591	0.84520262

↓ **Window Size: ↑**

Gamma: 0.1; Window Size: 30					
	Pattern	Freq	3days pval	5days pval	15days pval
0	IHS	33	1.304E-09	2.424E-06	0.10667819
1	HS	38	2.895E-05	0.0559929	0.84392812
2	BTOP	14	0.1490777	0.0603227	0.38838663
3	BBOT	11	0.5118571	0.4529004	0.311368

Gamma: 0.3; Window Size: 30					
	Pattern	Freq	3days pval	5days pval	15days pval
0	IHS	64	0.0001415	0.0003499	0.09246206
1	HS	64	5.868E-07	0.0006673	0.34862791
2	BTOP	32	0.0001292	0.0062212	0.78397689
3	BBOT	29	0.5724057	0.6945926	0.73603999

Gamma: 1.0; Window Size: 30					
	Pattern	Freq	3days pval	5days pval	15days pval
0	IHS	115	7.637E-17	1.439E-10	1.6678E-05
1	HS	119	1.421E-09	2.051E-05	0.56500056
2	BTOP	37	0.0019146	0.0024853	0.13631681
3	BBOT	45	0.6549082	0.660552	0.69061478

↓ **Window Size: ↑**

Gamma: 0.1; Window Size: 45					
	Pattern	Freq	3days pval	5days pval	15days pval
0	IHS	49	3.926E-14	2.615E-10	0.00774311
1	HS	57	2.036E-09	5.086E-05	0.02115707
2	BTOP	28	0.0041887	0.416582	0.20852443
3	BBOT	17	0.5979997	0.5417364	0.36571797

Gamma: 0.3; Window Size: 45					
	Pattern	Freq	3days pval	5days pval	15days pval
0	IHS	69	1.213E-05	5.972E-05	0.06471952
1	HS	73	2.469E-09	4.781E-05	0.18511561
2	BTOP	41	0.0004986	0.0175608	0.5742156
3	BBOT	34	0.6527613	0.830224	0.94394683

Gamma: 1.0; Window Size: 45					
	Pattern	Freq	3days pval	5days pval	15days pval
0	IHS	116	3.036E-17	1.016E-10	1.109E-05
1	HS	119	7.359E-11	7.166E-06	0.45659019
2	BTOP	41	0.0005178	0.0010782	0.10352233
3	BBOT	48	0.6458474	0.6964126	0.75751696

Total sign. post-pattern return averages (by pattern) ➔

Total	26	23	6
IHS	9	9	4
HS	8	7	1
BTOP	7	6	0
BBOT	2	1	1

Freq.: number of times that pattern was detected by the algorithm

Note: p-values were calculated under the assumption that expected returns are equal to zero (for the 3days to 15days calculated)

Appendix: Crude Oil

[Average post-pattern returns] Code Output [Frequency: Daily]

Gamma: 0.1; Window Size: 20					
	Pattern	Freq	3days avg	5days avg	15days avg
0	IHS	15	0.029041	0.024581	0.0089419
1	HS	16	-0.013927	0.001797	-0.0140813
2	BTOP	1	-0.048957	-0.032925	0.0505085
3	BBOT	1	0.044139	0.054682	0.0814868

Gamma: 0.3; Window Size: 20					
	Pattern	Freq	3days avg	5days avg	15days avg
0	IHS	39	0.014156	0.016173	0.0013049
1	HS	56	-0.025152	-0.024059	-0.0125351
2	BTOP	15	-0.023634	-0.028165	5.116E-05
3	BBOT	14	0.020697	0.032985	0.0784961

Gamma: 1.0; Window Size: 20					
	Pattern	Freq	3days avg	5days avg	15days avg
0	IHS	114	0.021293	0.022476	0.0296586
1	HS	118	-0.018472	-0.019224	-0.003645
2	BTOP	31	-0.018341	-0.031204	-0.030495
3	BBOT	35	0.012715	0.003742	0.0041814

Gamma: 0.1; Window Size: 30					
	Pattern	Freq	3days avg	5days avg	15days avg
0	IHS	33	0.034275	0.029271	0.0241225
1	HS	38	-0.018285	-0.016525	0.0020792
2	BTOP	14	-0.009744	0.015636	0.0176478
3	BBOT	11	-0.092363	-0.102072	-0.1660132

Gamma: 0.3; Window Size: 30					
	Pattern	Freq	3days avg	5days avg	15days avg
0	IHS	64	0.018588	0.019814	0.0174883
1	HS	64	-0.022335	-0.022132	-0.0080061
2	BTOP	32	-0.021371	-0.018211	0.0033906
3	BBOT	29	-0.028936	-0.018939	-0.021368

Gamma: 1.0; Window Size: 30					
	Pattern	Freq	3days avg	5days avg	15days avg
0	IHS	115	0.024176	0.024483	0.032321
1	HS	119	-0.019296	-0.019593	-0.0040019
2	BTOP	37	-0.017884	-0.027171	-0.0256278
3	BBOT	45	-0.014742	-0.01371	-0.0166131

Gamma: 0.1; Window Size: 45					
	Pattern	Freq	3days avg	5days avg	15days avg
0	IHS	49	0.030533	0.029635	0.0297638
1	HS	57	-0.019218	-0.026532	-0.0236057
2	BTOP	28	-0.015819	0.006648	-0.0153537
3	BBOT	17	-0.047187	-0.052957	-0.0951179

Gamma: 0.3; Window Size: 45					
	Pattern	Freq	3days avg	5days avg	15days avg
0	IHS	69	0.01987	0.020796	0.0183545
1	HS	73	-0.024507	-0.024537	-0.0112722
2	BTOP	41	-0.015435	-0.012345	0.0057891
3	BBOT	34	-0.019675	-0.008871	0.0038548

Gamma: 1.0; Window Size: 45					
	Pattern	Freq	3days avg	5days avg	15days avg
0	IHS	116	0.024179	0.024533	0.0328992
1	HS	119	-0.020573	-0.020814	-0.0052295
2	BTOP	41	-0.018482	-0.027516	-0.0251674
3	BBOT	48	-0.014201	-0.011515	-0.0121982

Total post-pattern return averages (by pattern) →

Total avg.	3days	5days	15days
IHS	0.0231	0.0234	0.0256
HS	-0.0206	-0.0208	-0.0077
BTOP	-0.0179	-0.0177	-0.0113
BBOT	-0.0166	-0.0145	-0.0168

Freq.: number of times that pattern was detected by the algorithm

Total avg.: calculated by dividing absolute sum of returns by the sum of all pattern occurrences (of a given type)