TrendCalculus, defined.

How to execute a data science of trends.

2017-05-01

Andrew Morgan.

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Part 1. Calculating Trends
Part 2. Predicting Trend Change
Part 3. Co-Trending

Calculuating Trends

How I do the math.

Studying Trends

My focus is broad patterns; big flock behaviours, and my objective is long range predictions.

Trends are a natural way to think, explain, and forecast.

Yet we lack tools to study Trends effectively.

This project seeks to rectify that.

Studying Trends

In these slides I will

- Set out a revised definition of a trend
- Set out an equation for finding trends, reversals.
- Explain some of my data formats, charting etc.
- Explain how to handle special cases
- Show how to identify trend reversals on streams

Studying Trends

before we begin

A comparative study of billions of time series demands methods that are quick, simple, elegant.

Don't shrug off the difficulty of achieving simplicity. "Obvious" is the toughest goal of invention.

Studying Trends

Let’s start from scratch.

Studying Trends

I define a trend as:

Rising = Higher Highs, Higher Lows
Falling = Lower Highs, Lower Lows

Studying Trends

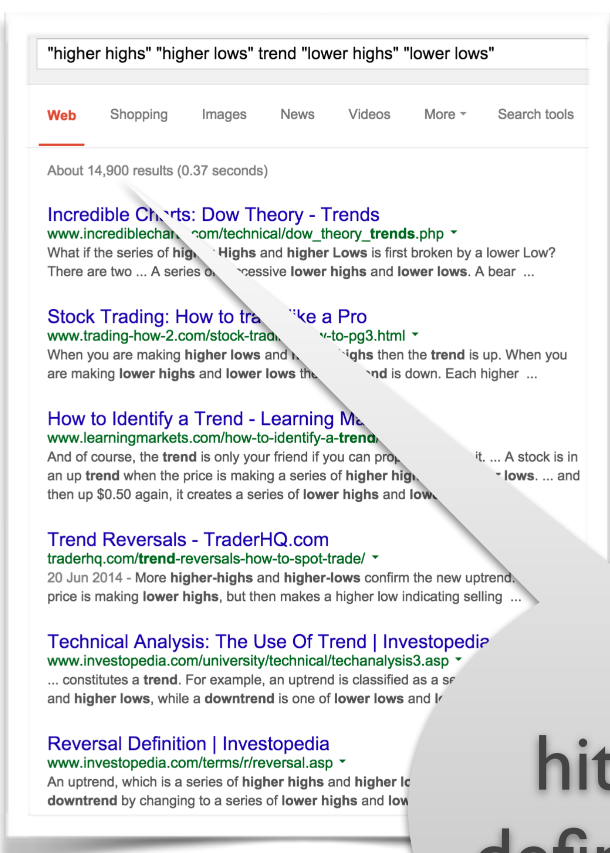
It's an established market definition.

Rising = Higher Highs, Higher Lows
Falling = Lower Highs, Lower Lows

This definition comes from market traders
right back to W. D. Gann (1923)

Studying Trends

Market practitioners really use it.



= Higher Highs, Higher Lows

= Lower Highs, Lower Lows

n comes from market traders back to W. D. Gann (1923)

~15k google hits reference this definition, so it's quite well known.

Studying Trends

I wish to *calculate* this definition as:

Rising	= +1	Higher Highs, Higher Lows
Falling	= -1	Lower Highs, Lower Lows

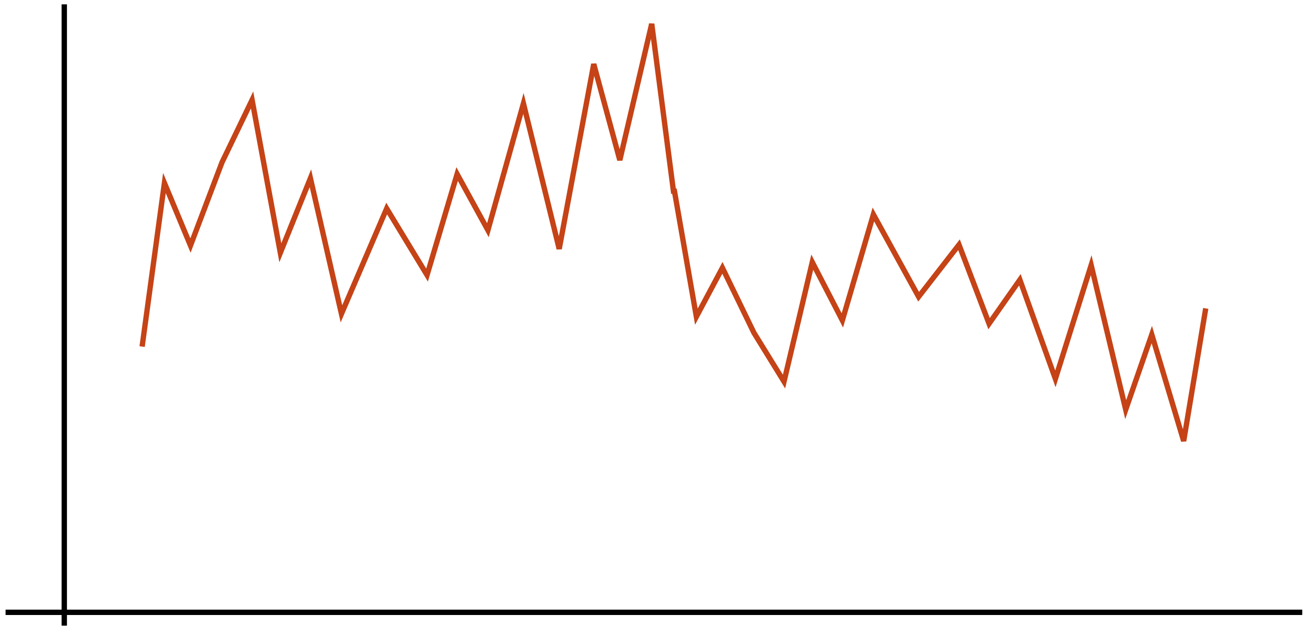
Studying Trends

So I must create a way to do so.

Studying Trends

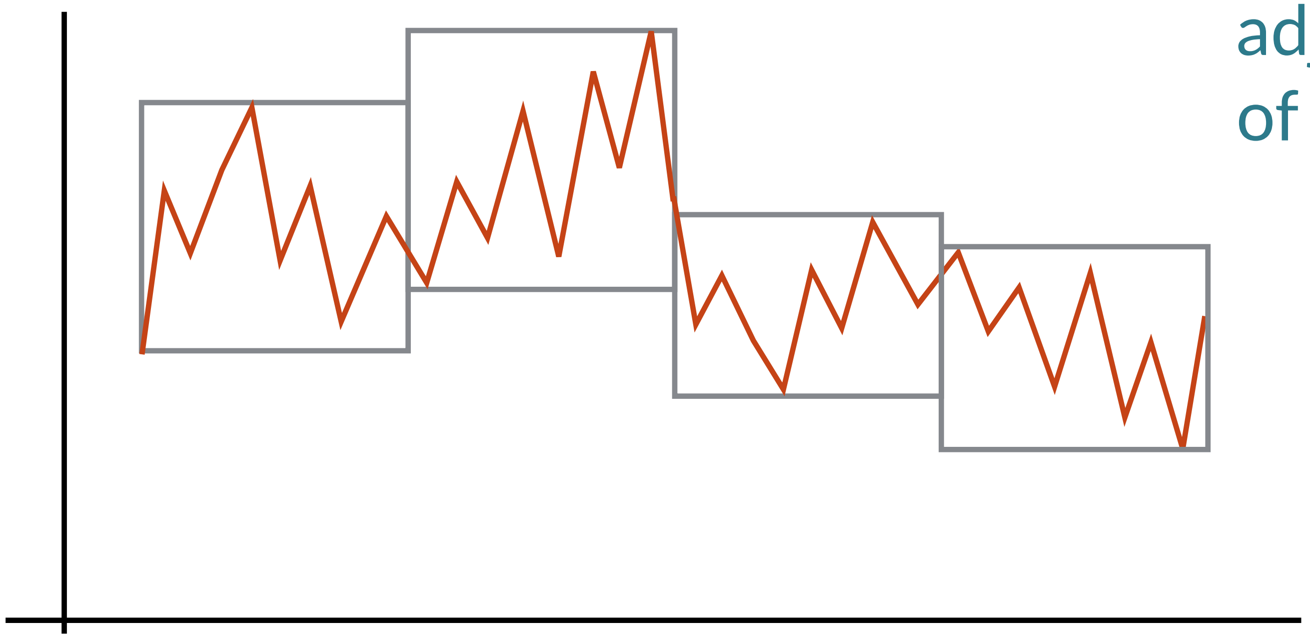
So I must create a way to do so.
But how?

I'll illustrate.



Studying Trends

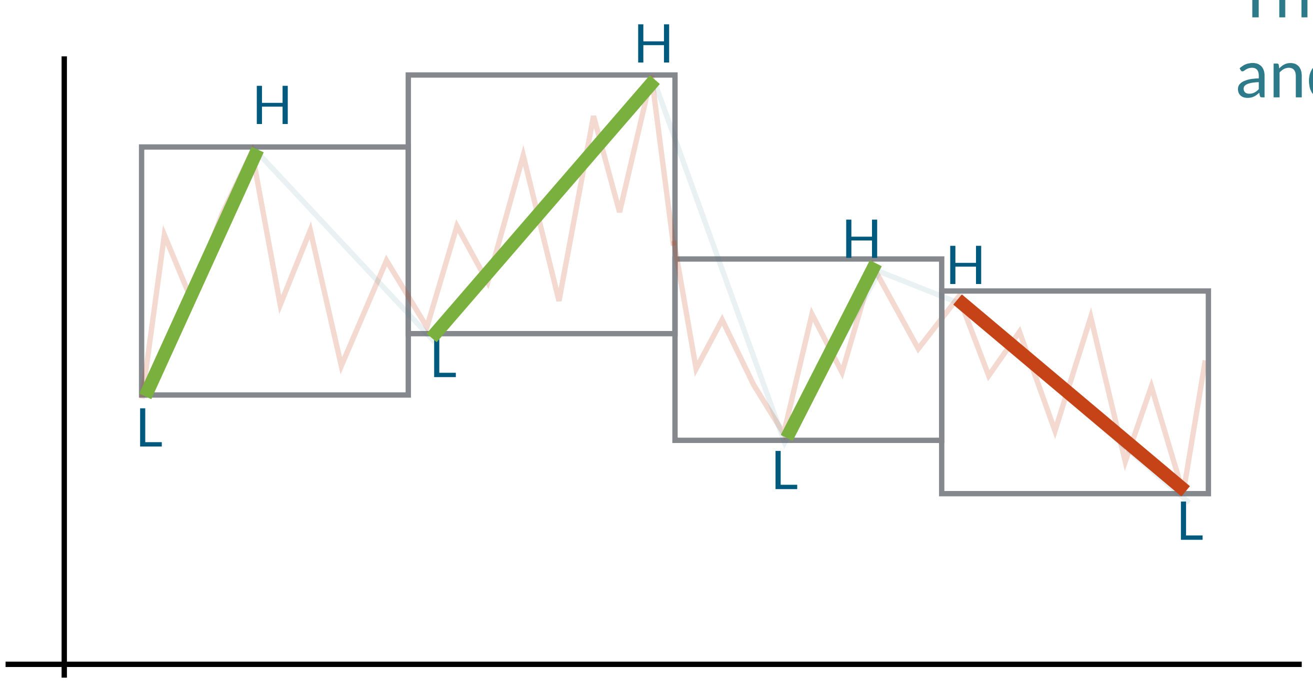
Stream data across fixed window size of N.



Selecting N will adjusts our Scale of investigation

Studying Trends

Calculate a summary for each window
Find dated Highs and Lows for them.

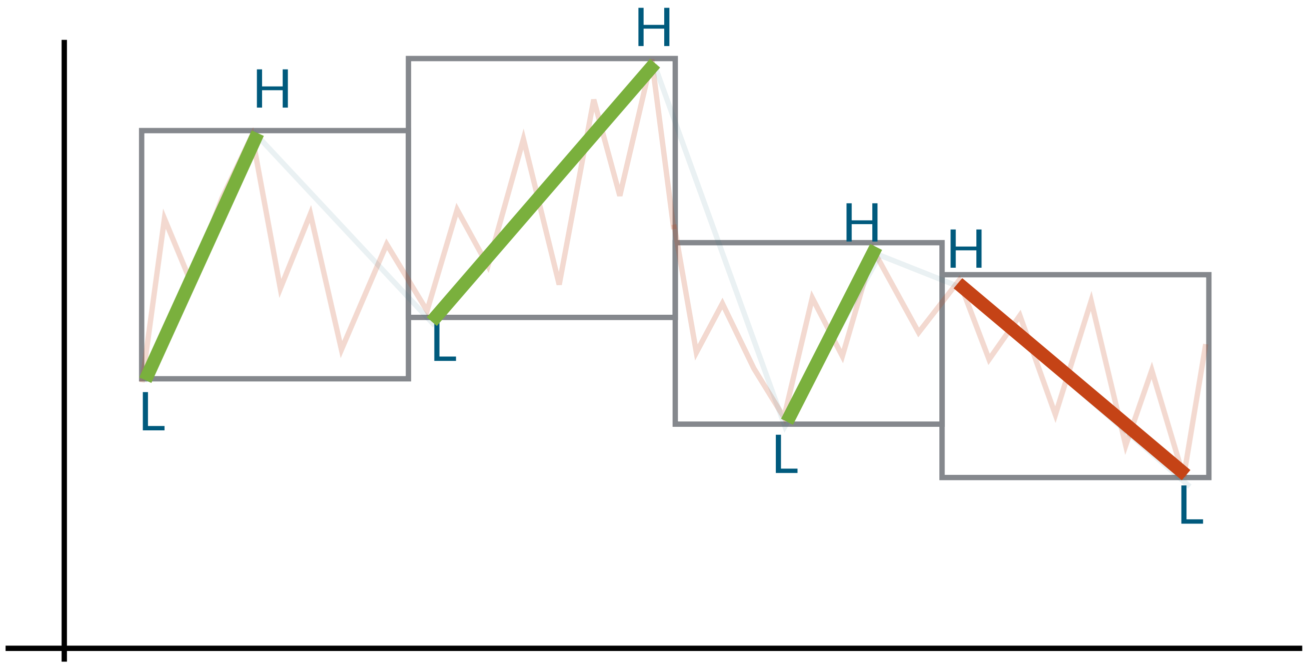


The time of the Highs and Lows is critical later.

Studying Trends

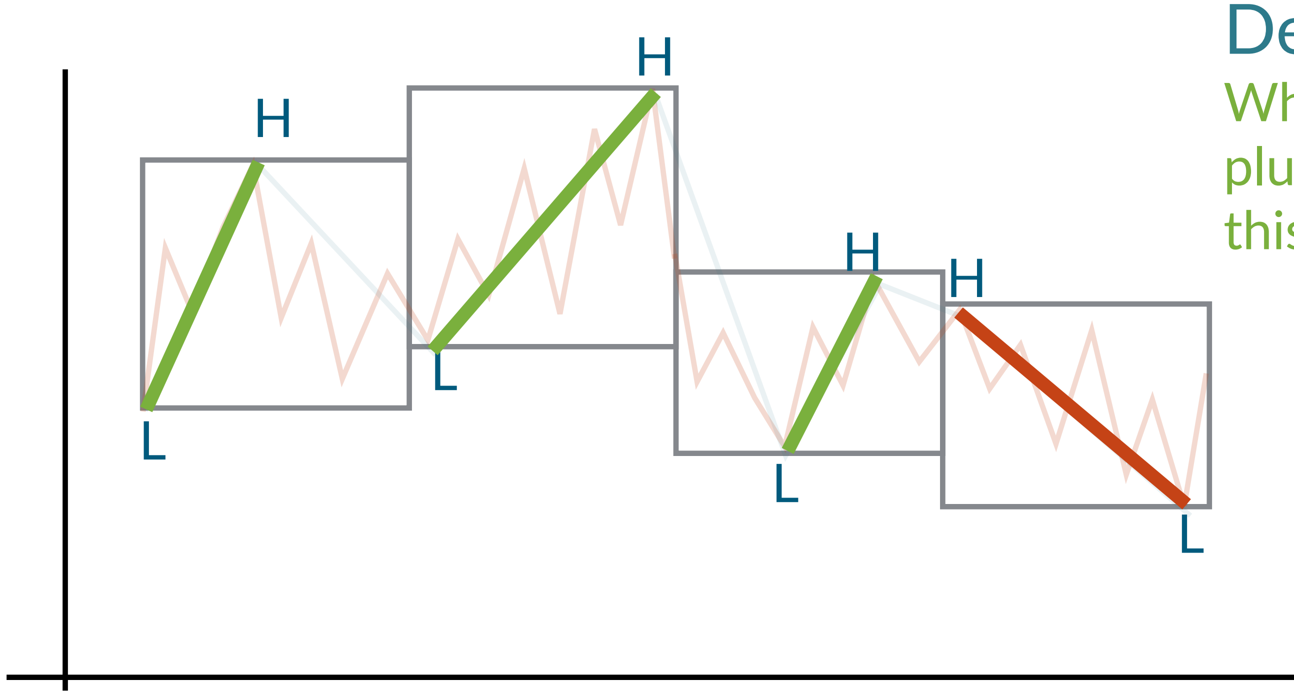
Examine summaries across windows.

Compare the leading window against the previous



Studying Trends

We now need some math, to generate +1 or -1 values for each window.



Develop a Calculation

What equation can emit plus and minuses from this input data?

Studying Trends

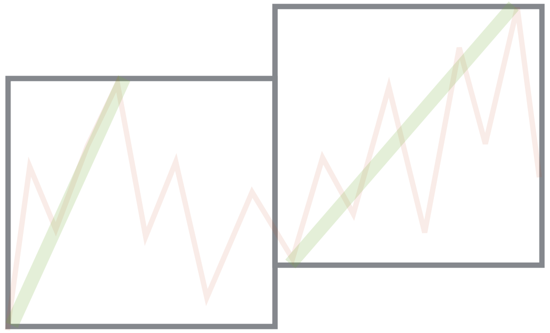
the TrendCalculus equation is:

$$\begin{aligned}&where\\&H, L = High, Low\\&p_i = CurrentWindow\\&p_{i-1} = PreviousWindow\end{aligned}$$

Studying Trends

the TrendCalculus equation is:

$$sign(sign(H_{p_i} - H_{p_{i-1}}) + sign(L_{p_i} - L_{p_{i-1}}))$$



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Studying Trends

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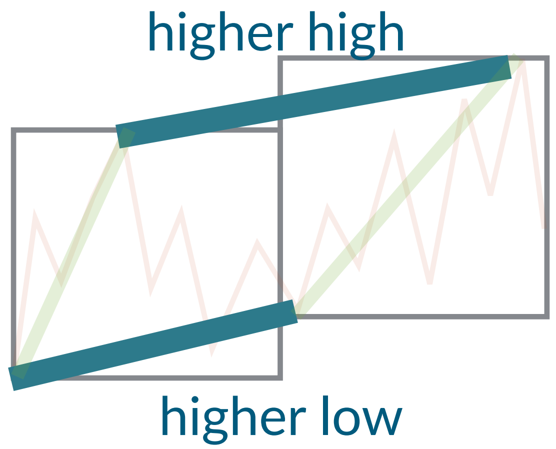

$$
\begin{aligned}
&where \\
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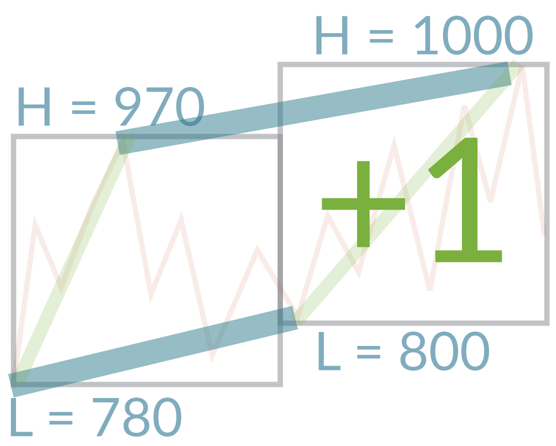
&p_{i-1} = PreviousWindow
\end{aligned}
$$

Studying Trends

Calculate trends as (+1, -1) for a window=

$$sign(sign(H_{p_i} - H_{p_{i-1}}) + sign(L_{p_i} - L_{p_{i-1}}))$$



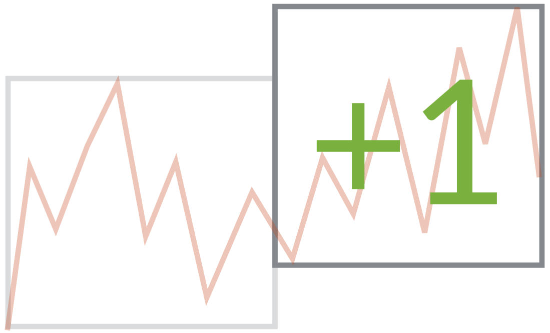
for example:

Simple Trend = Sign(sign(HighDiff) + sign(LowDiff))
Simple Trend = Sign(sign(1000-970) + sign(800-780))
Simple Trend = Sign(sign(30) + sign(20))
Simple Trend = Sign(1 + 1)
Simple Trend = Sign(2)
Simple Trend = +1

Studying Trends

Calculate trends as (+1, -1) for a window=

$$sign(sign(H_{p_i} - H_{p_{i-1}}) + sign(L_{p_i} - L_{p_{i-1}}))$$



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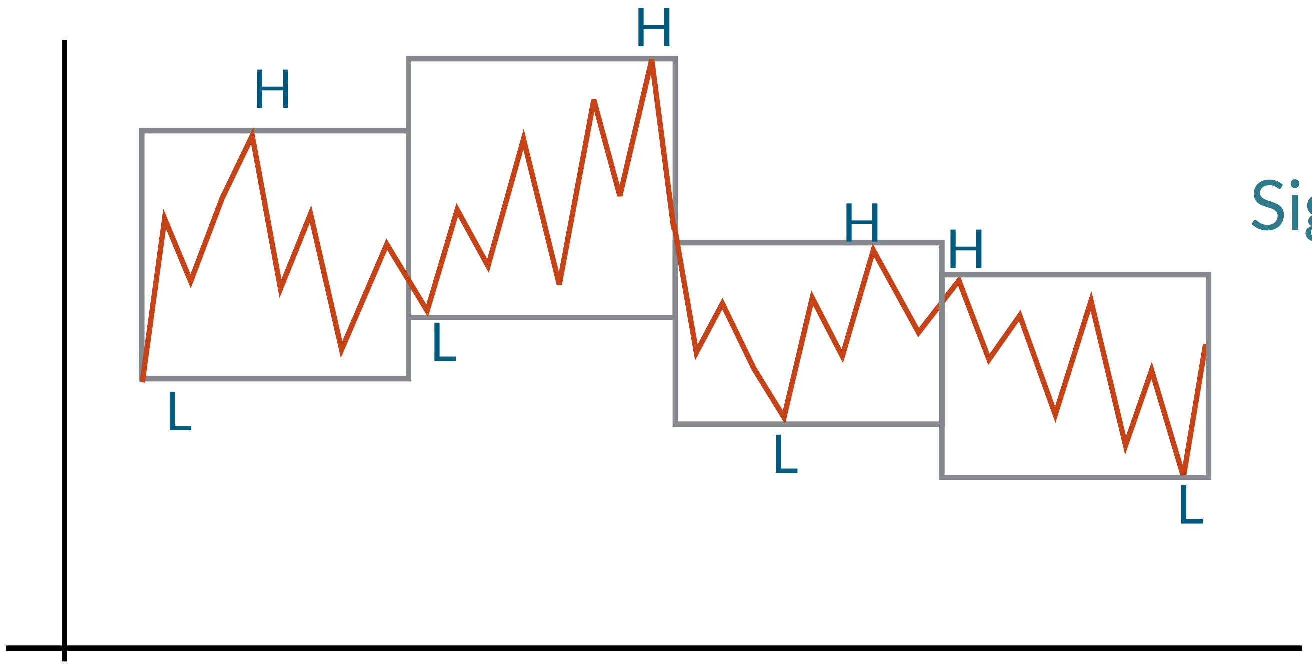
Simple Trend = +1

Studying Trends

More detailed example

$$sign(sign(H_{p_i} - H_{p_{i-1}}) + sign(L_{p_i} - L_{p_{i-1}}))$$

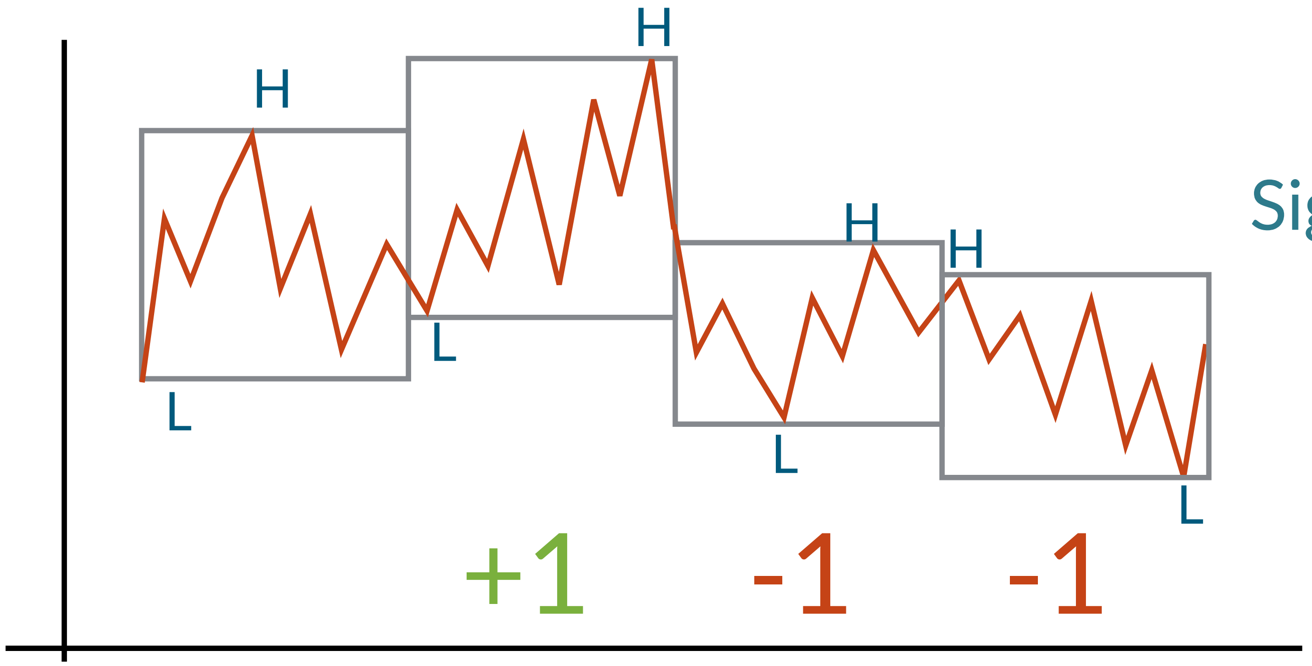


Sign each window.

Studying Trends

...where we identify a reversal.

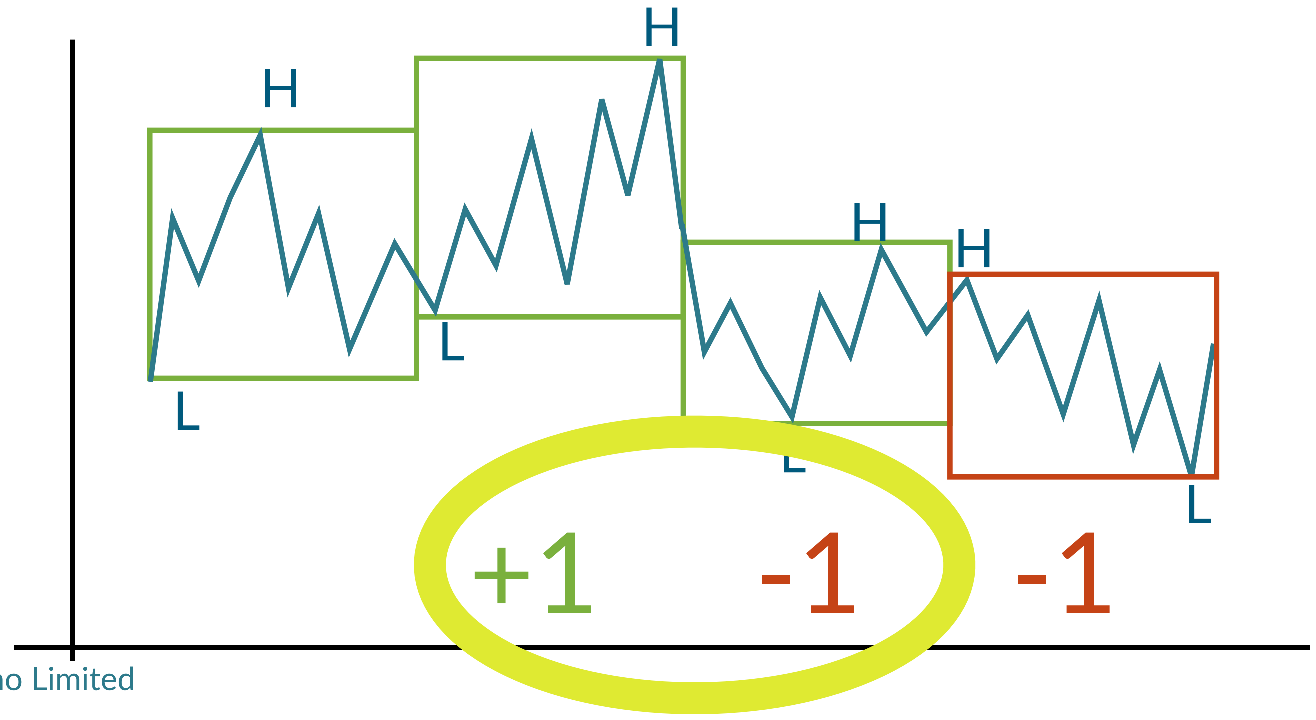
$$sign(sign(H_{p_i} - H_{p_{i-1}}) + sign(L_{p_i} - L_{p_{i-1}}))$$



Sign each window.

Studying Trends

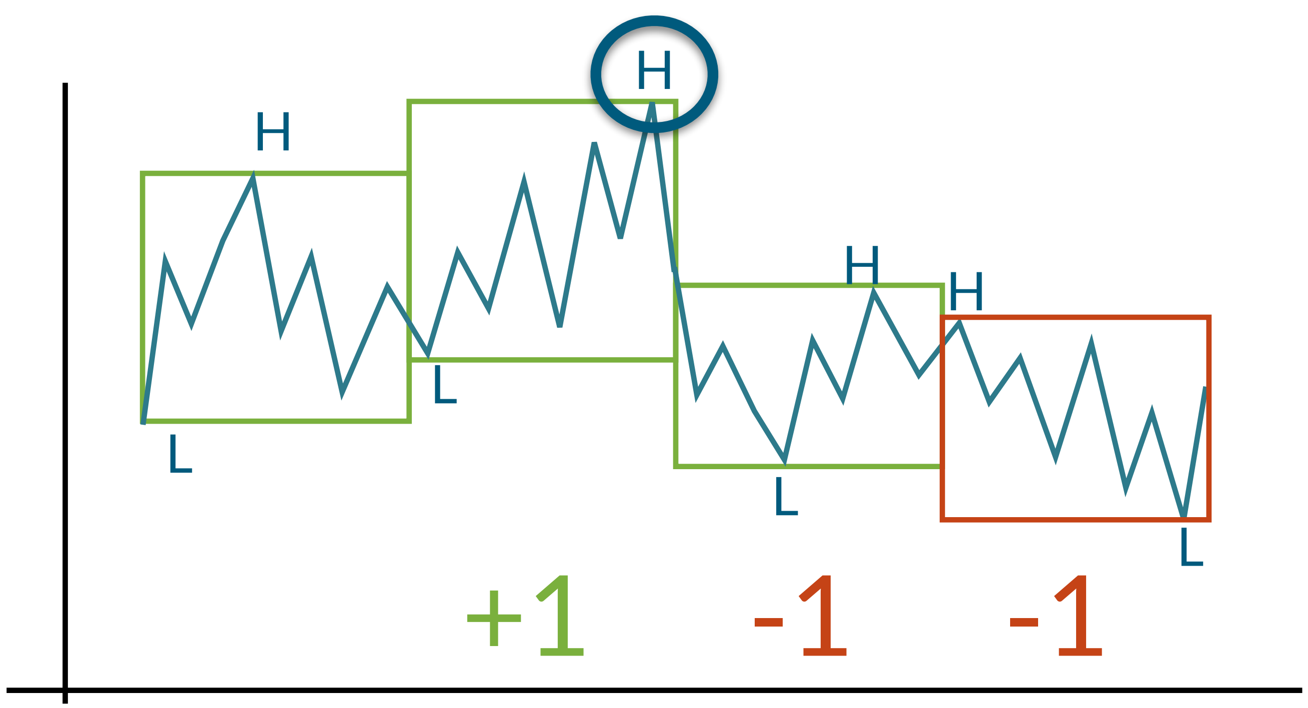
When the trend values flip, we find
a change in trend on the previous window.



Studying Trends

Reversal finding rule:

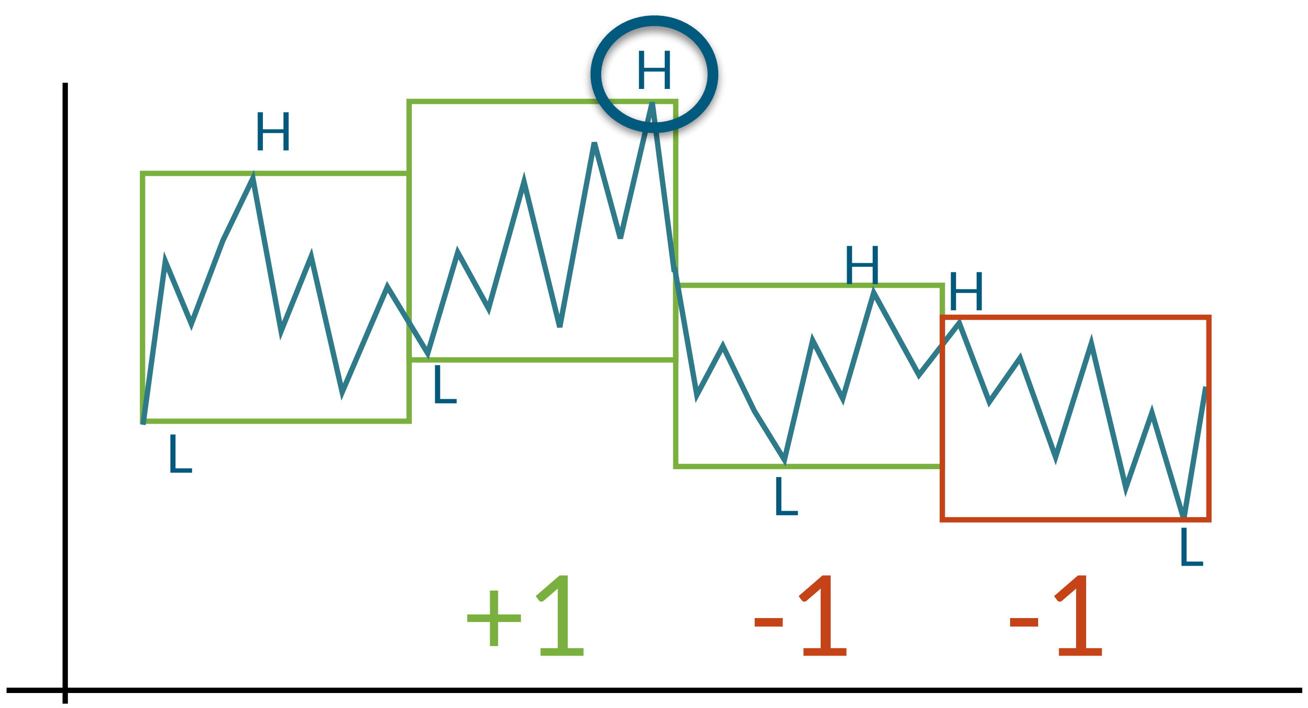
If trend moves from +1 to -1, previous **high** is reversal.
If trend moves from -1 to +1, previous **low** is reversal.



Studying Trends

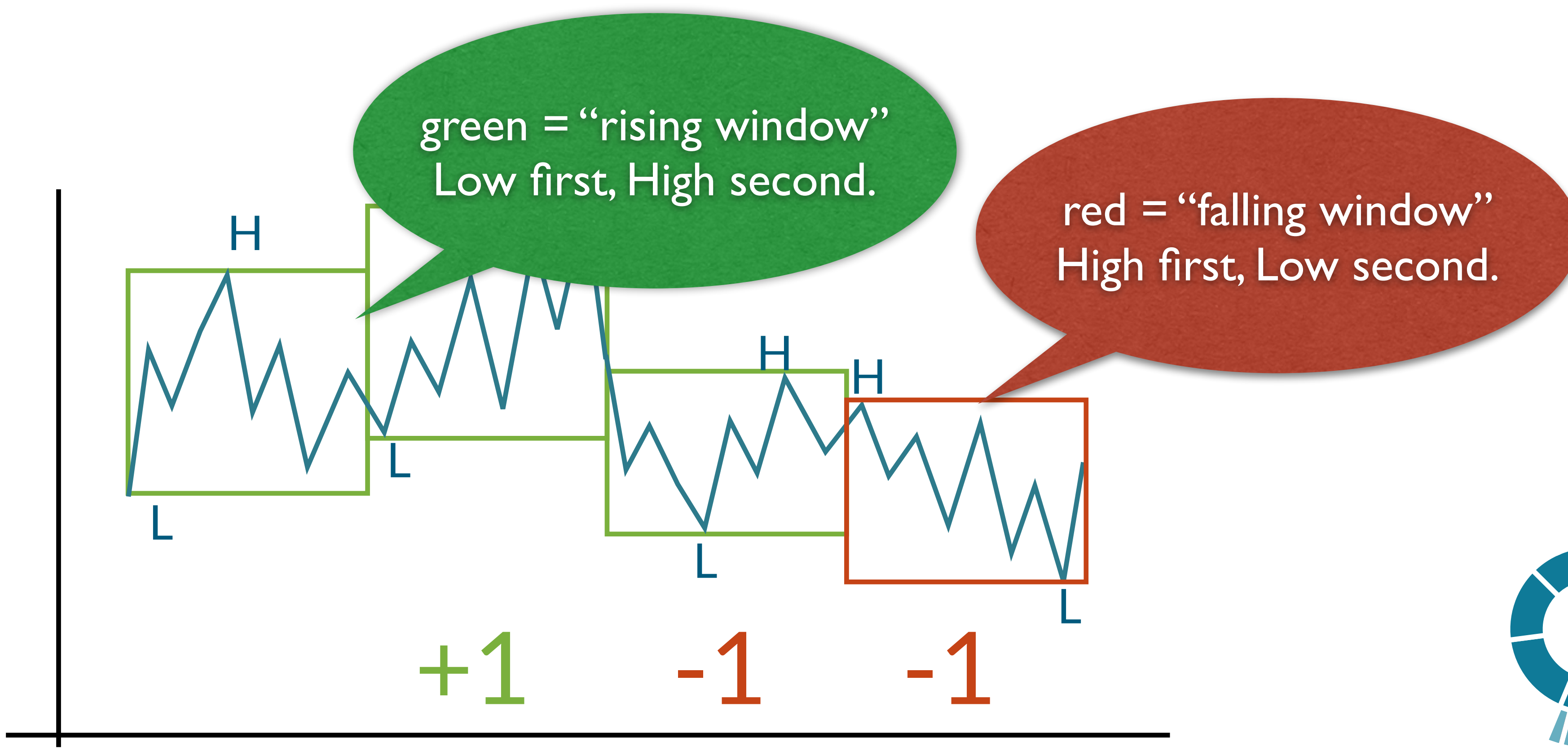
Reversal outputs

Using these simple rules we output a new time series that includes just the reversal points found on this scale, N. Output is the dated value found: Date, Value



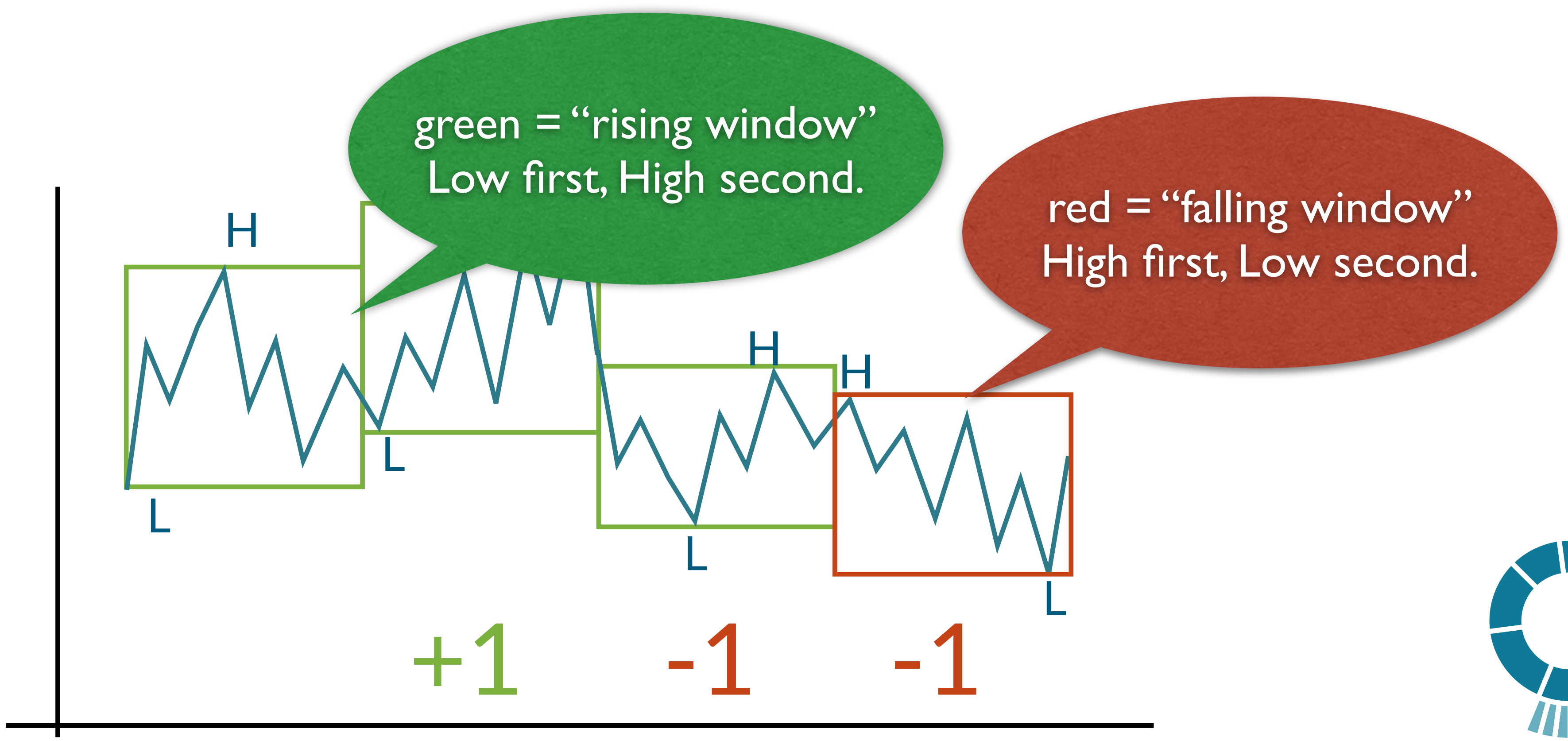
Studying Trends

just a note, on charting the windows:



Studying Trends

How should we summarise our windows?



Studying Trends

I create a "FHLS bar" data structure

The FHLS data format is:

1. Time Series Id
2. OpenDate (of bar)
3. First of H/L
4. High
5. Low
6. Second of H/L
7. High Date
8. Low Date
9. First Date
10. Second Date
11. CloseDate

I replace the Open with the value of which ever came FIRST, the high or the low.

I replace the Close with the value of which ever came SECOND, the high or the low.

Studying Trends

I create a "FHLS bar" data structure

The FHLS data format is:

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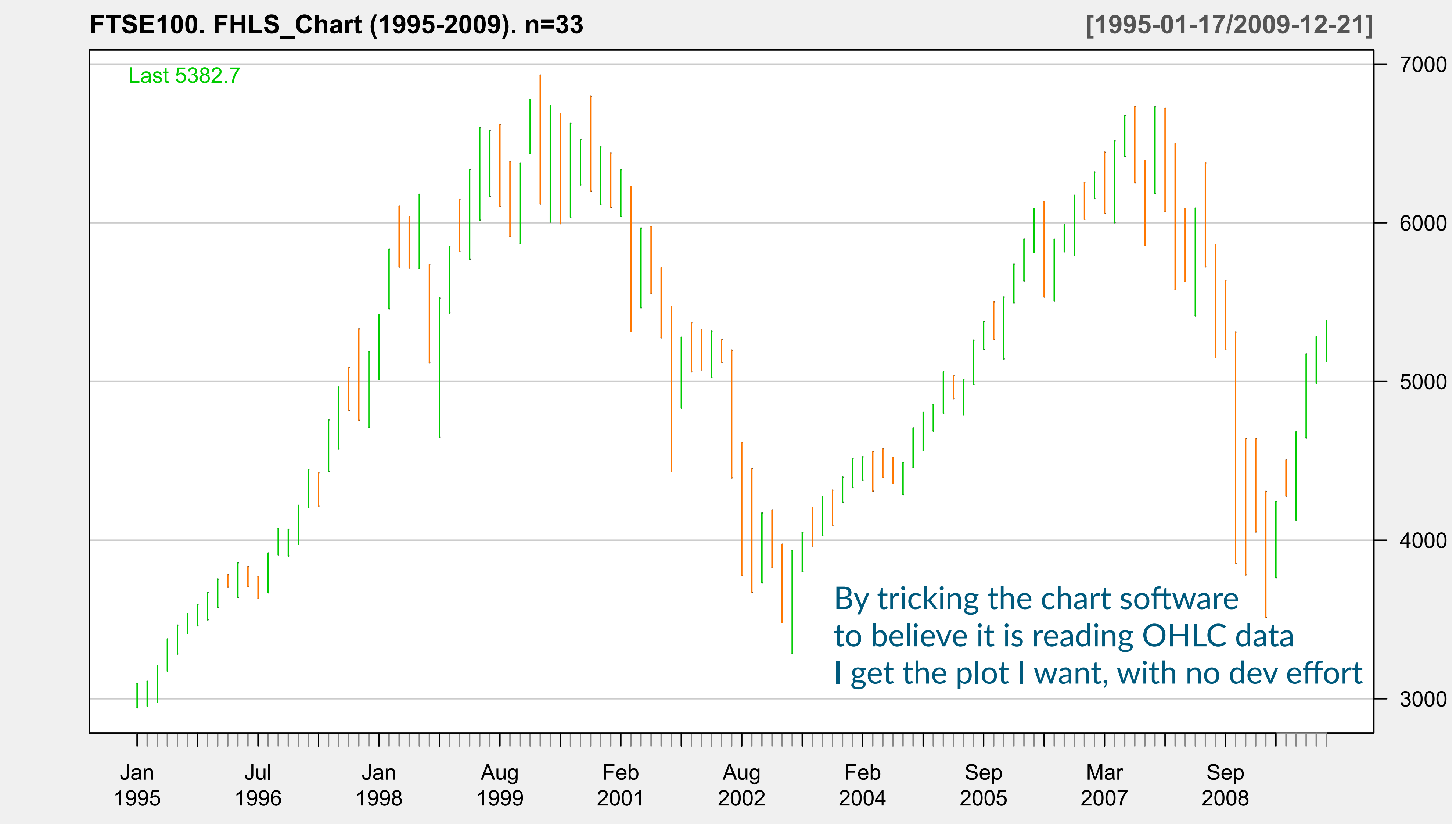
5. Low
6. Second of H/L
7. High Date
8. Low Date
9. First Date
10. Second Date
11. Close Date

This format may look very simple, but was constructed carefully.

The dated first and second values are very important to our calculations downstream.

Studying Trends

We can draw charts this way, a FHLS chart:



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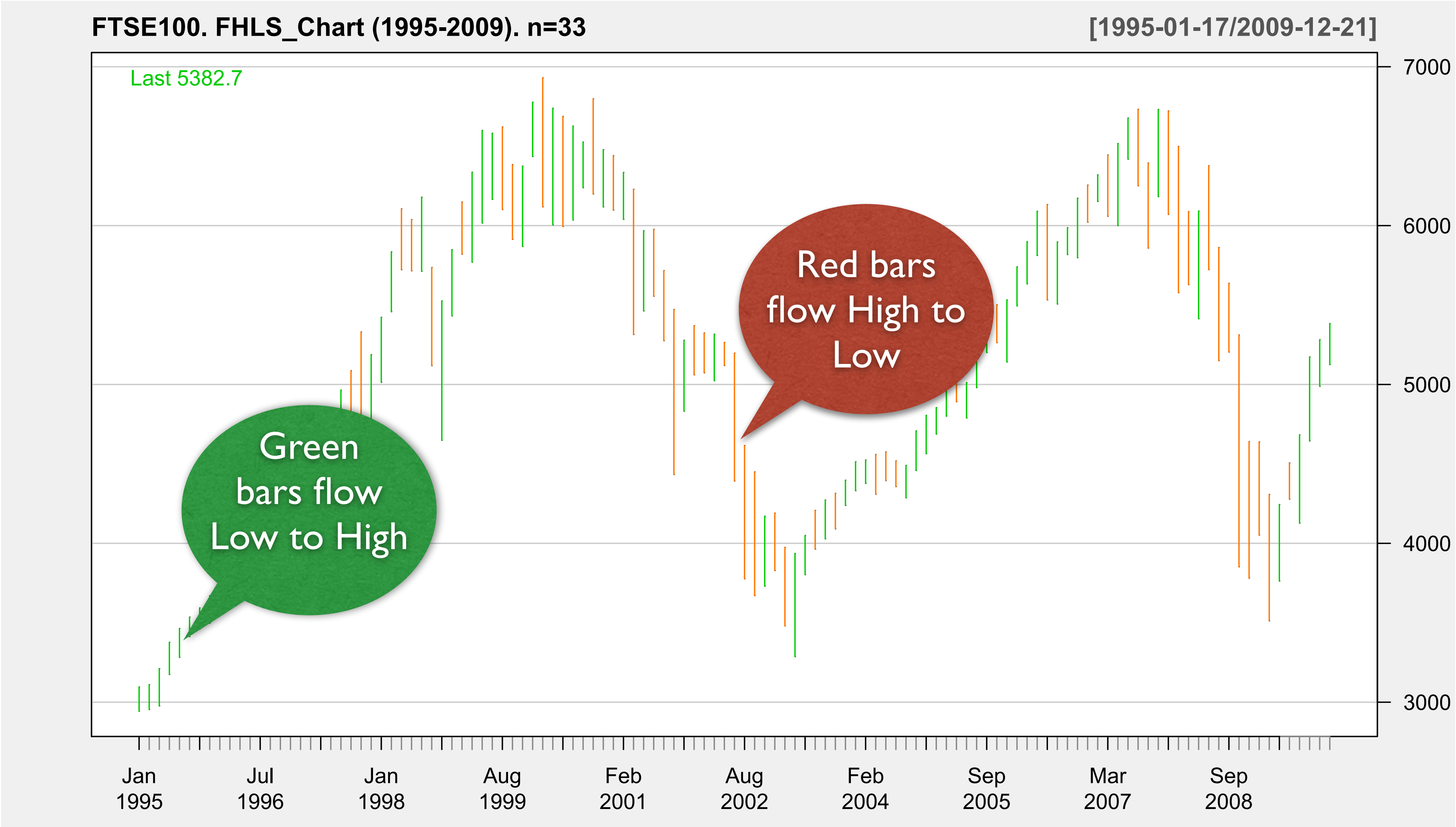
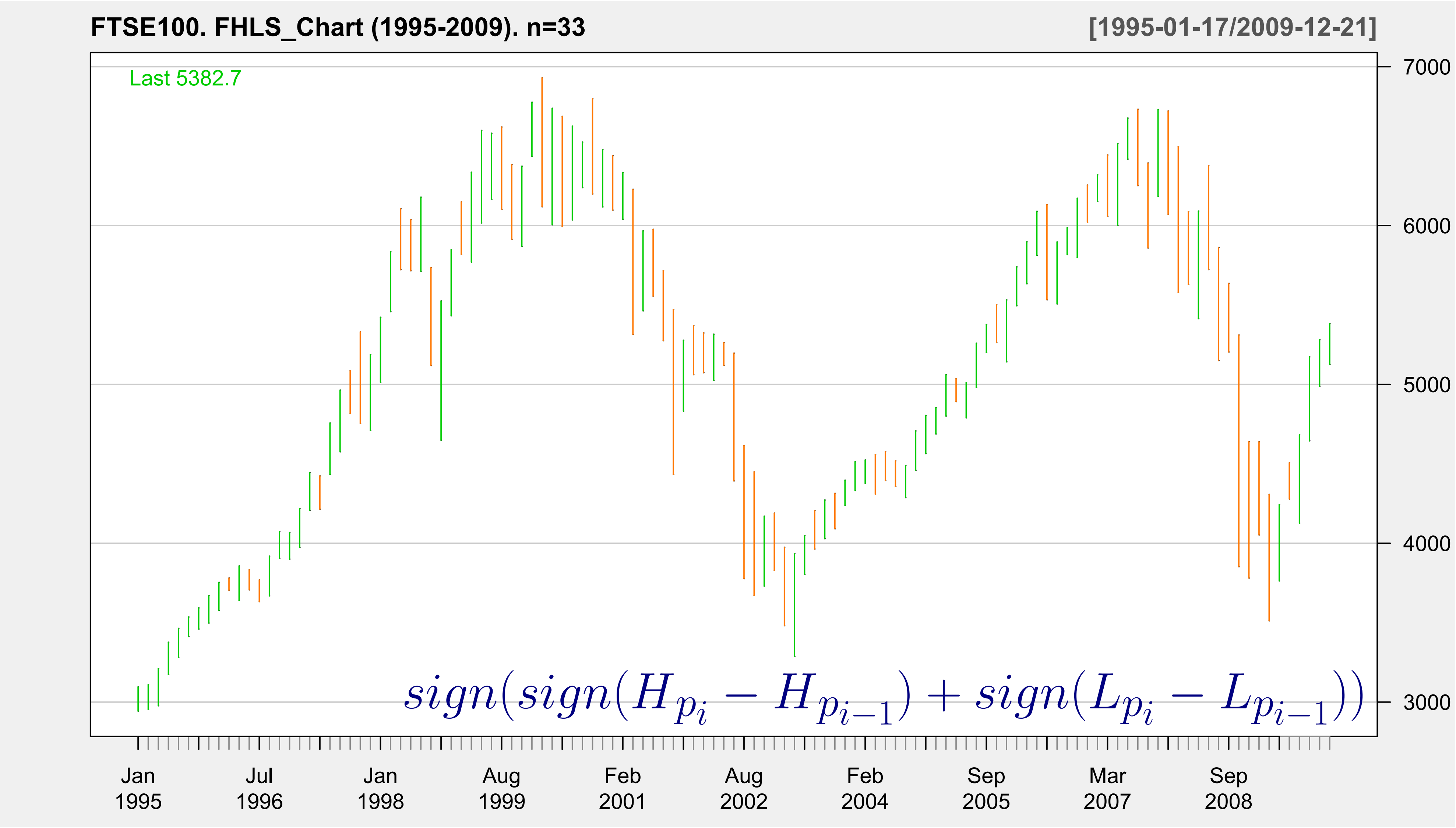


Studying Trends

We draw reversals as dots, on the FHLS chart.



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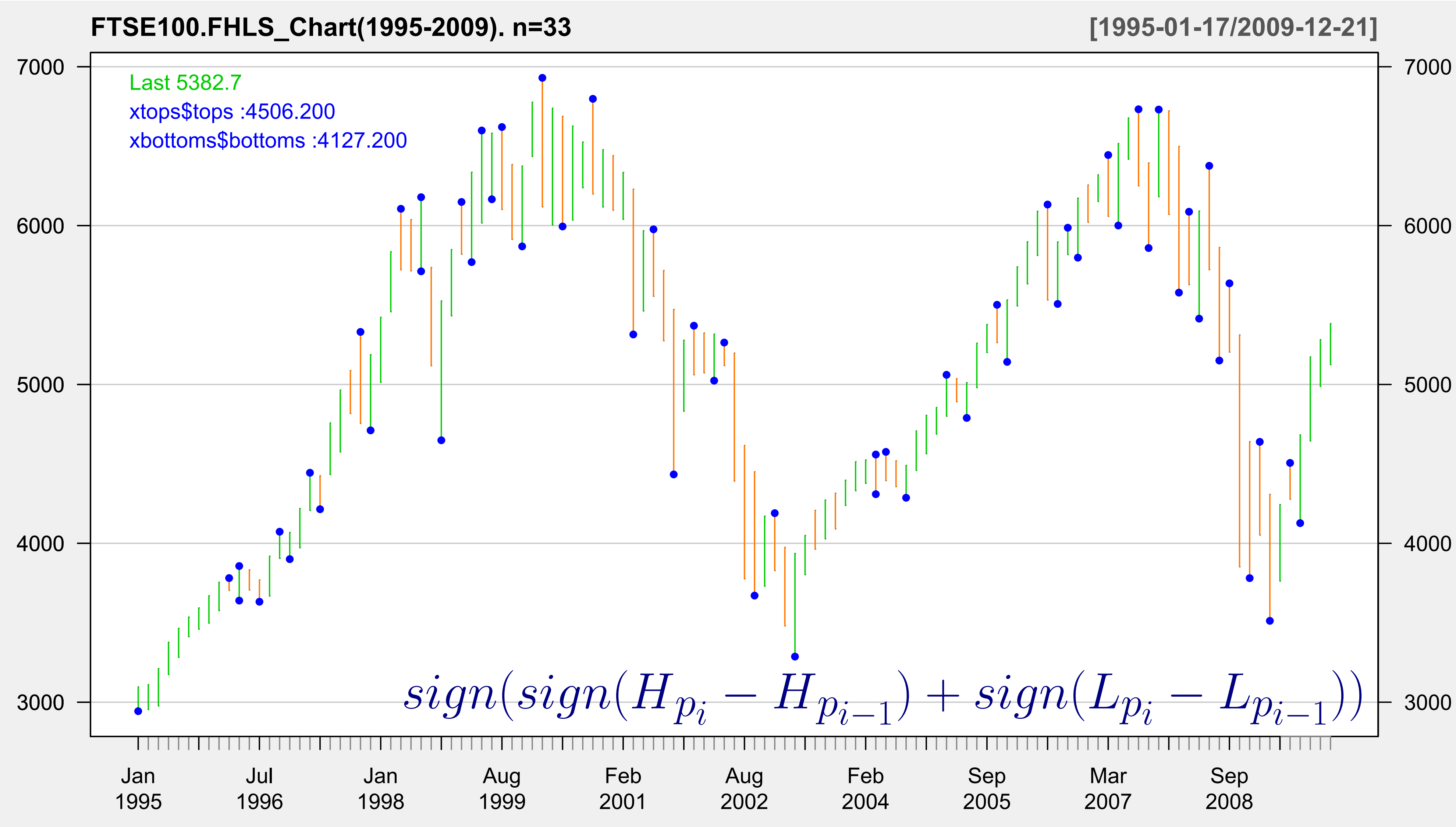

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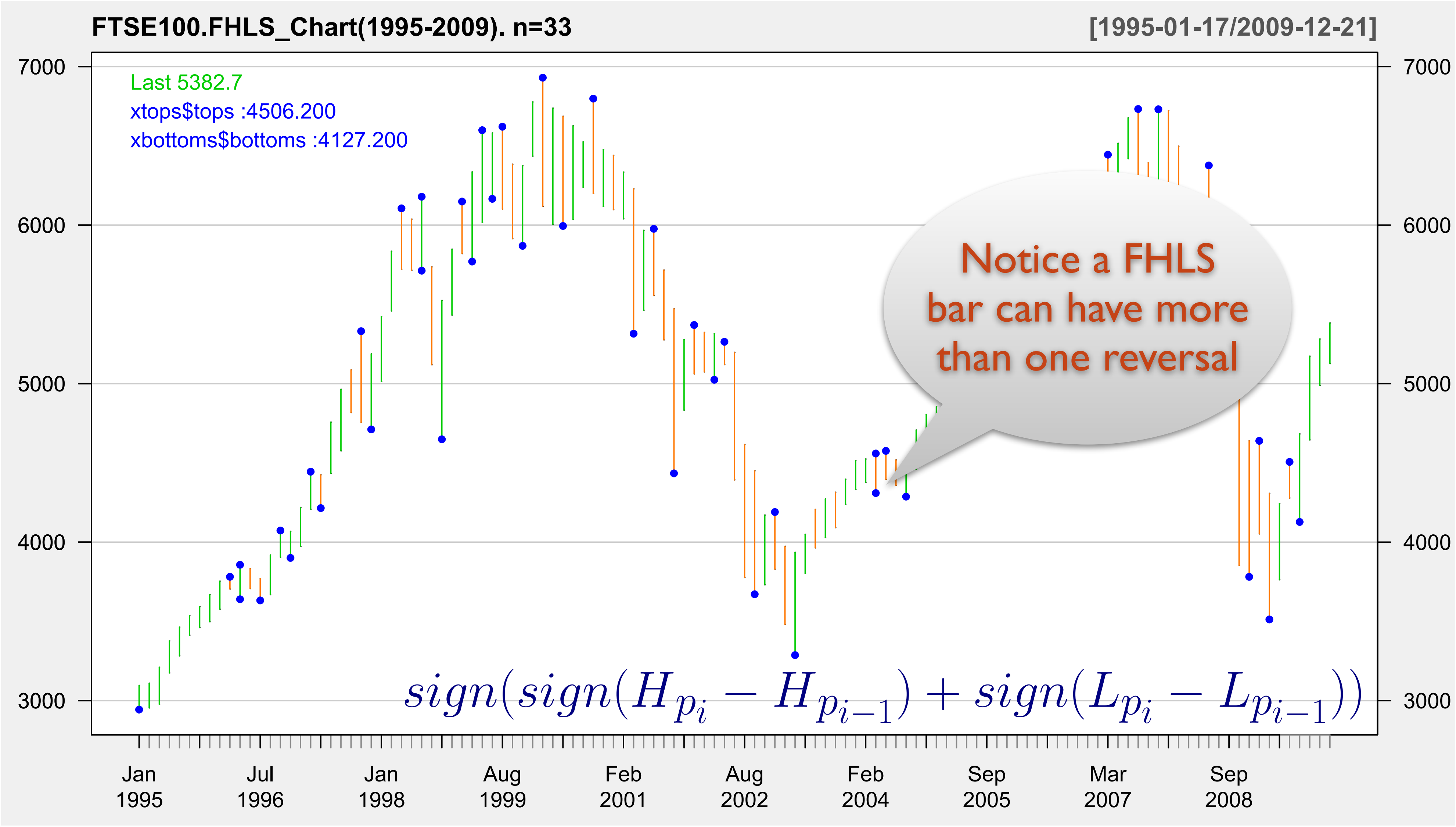

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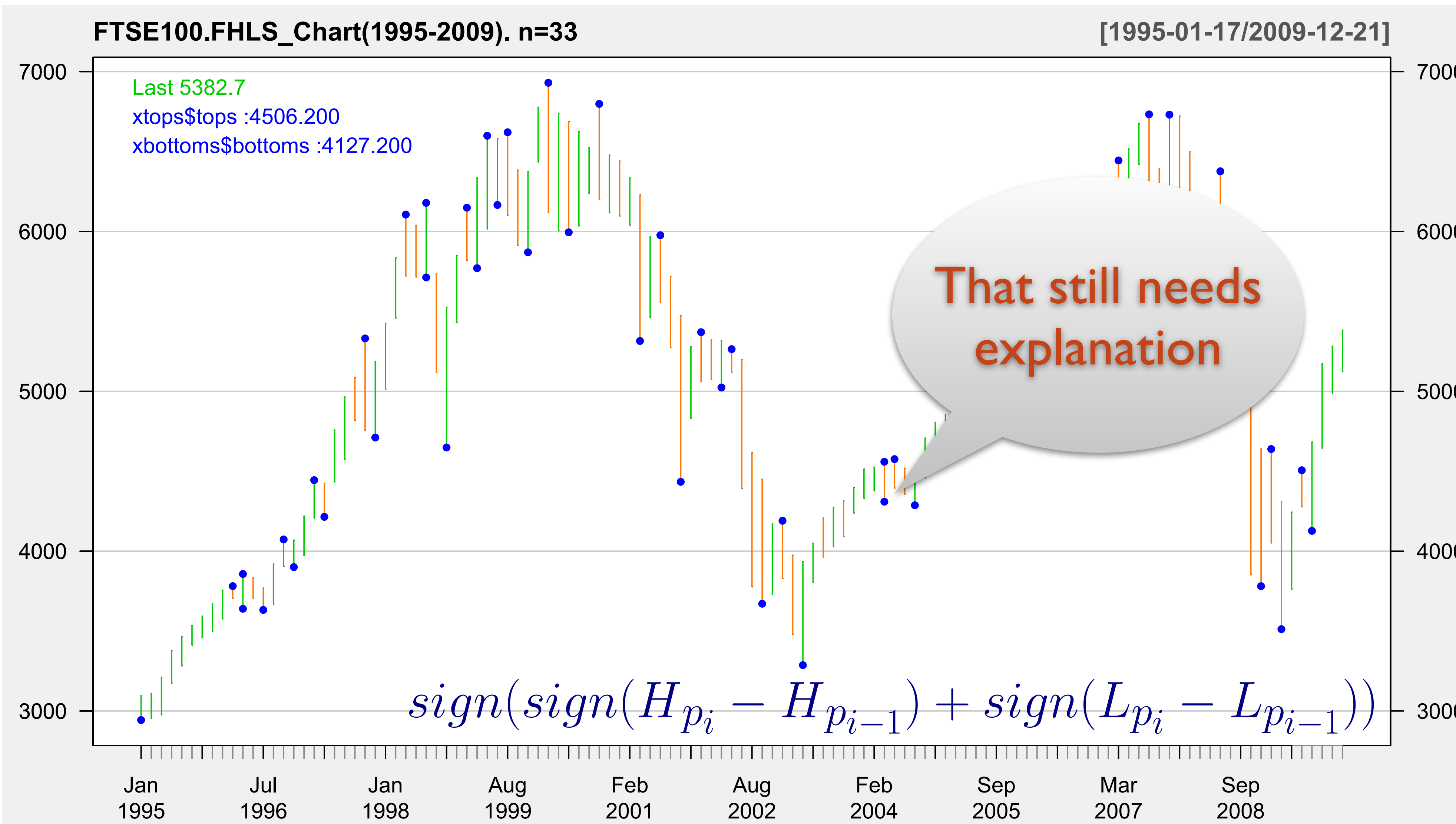

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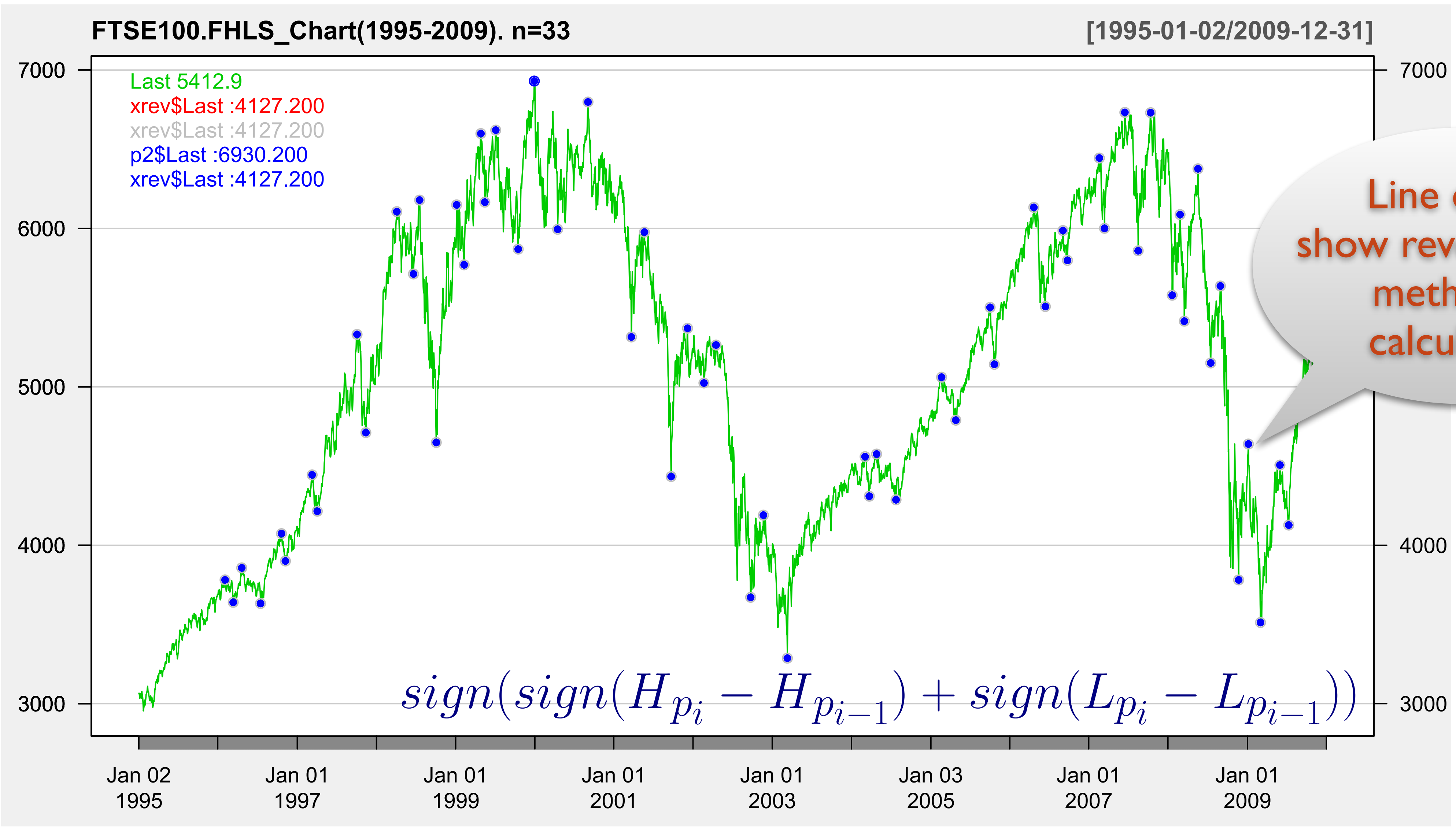


Line charts show reversals, not method of calculation.

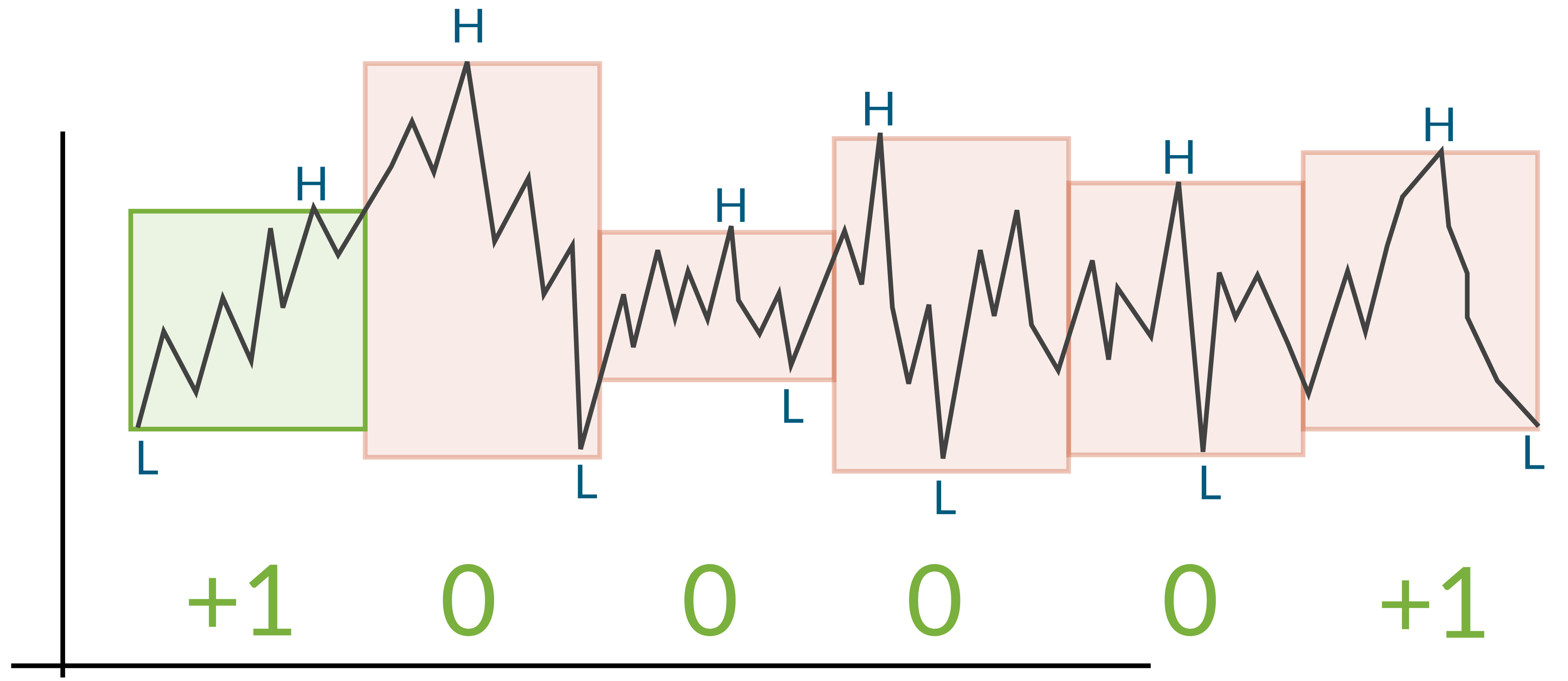
Special Cases

I skirted over some special cases to handle

Special Cases

The equation also finds 0 values.

$$sign(sign(H_{p_i} - H_{p_{i-1}}) + sign(L_{p_i} - L_{p_{i-1}}))$$

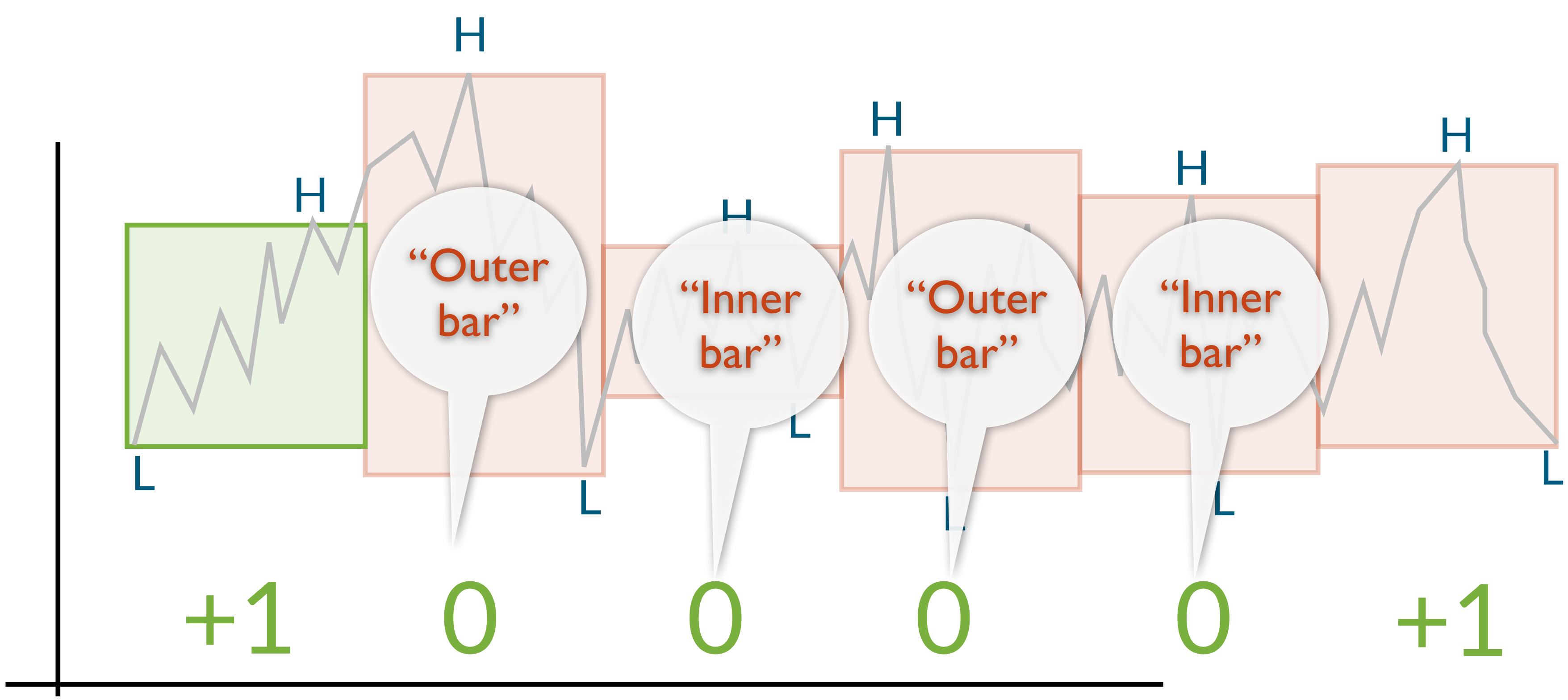


Special Cases

The equation also finds 0 values.

$$sign(sign(H_{p_i} - H_{p_{i-1}}) + sign(L_{p_i} - L_{p_{i-1}}))$$

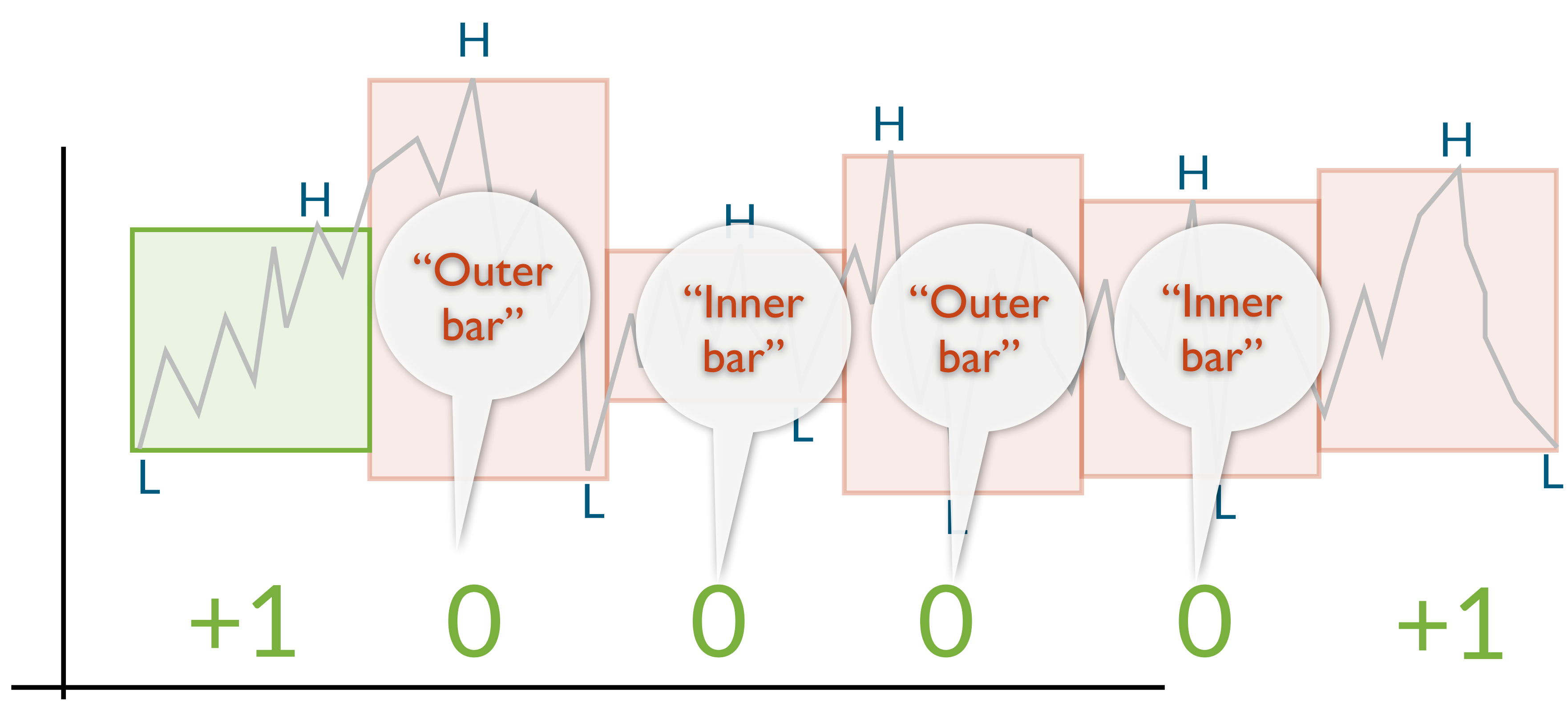
“Inner” “Outer” is trader language for these cases.



Special Cases

The equation also finds 0 values.

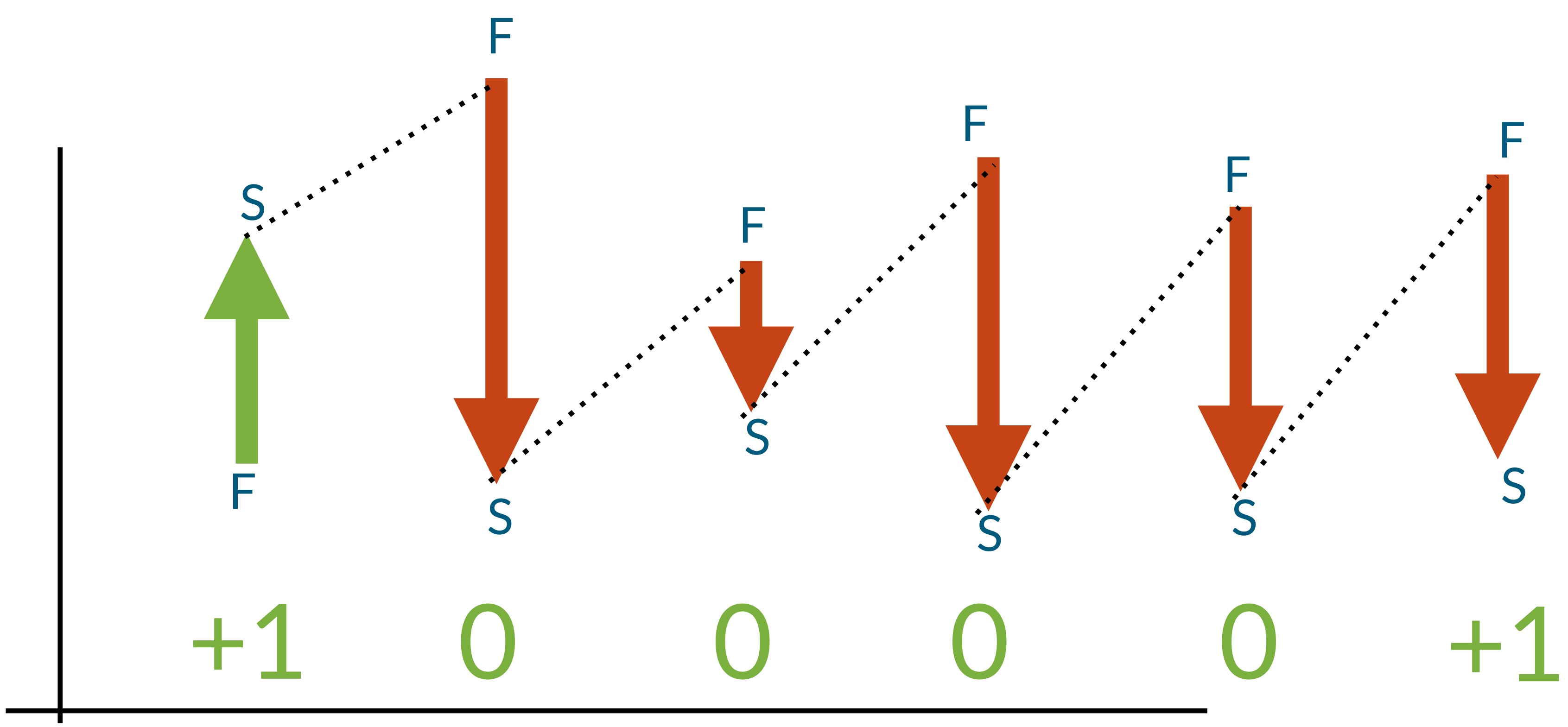
This sort of breaks our algo, no?



Special Cases

The equation also finds 0 values.

Nope, there is an efficient solution…



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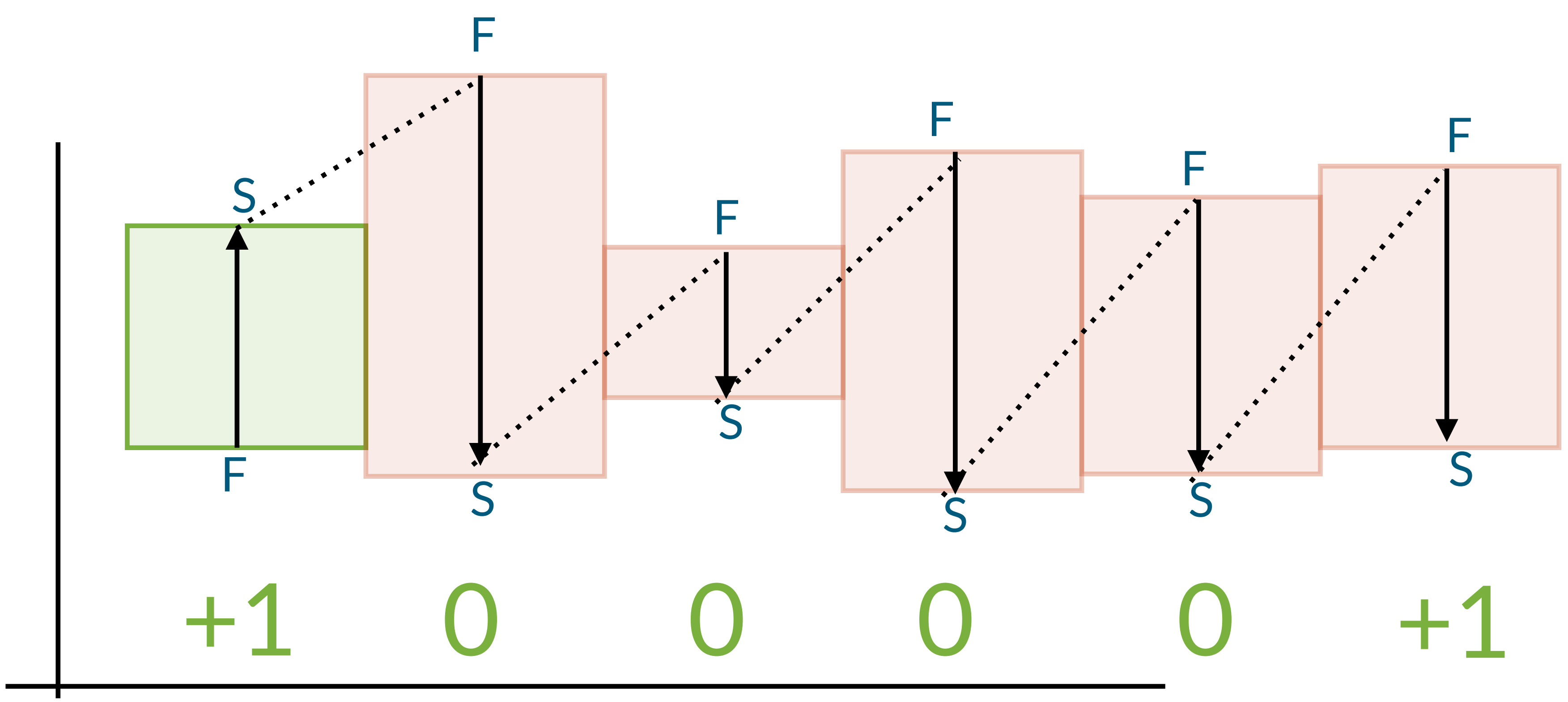
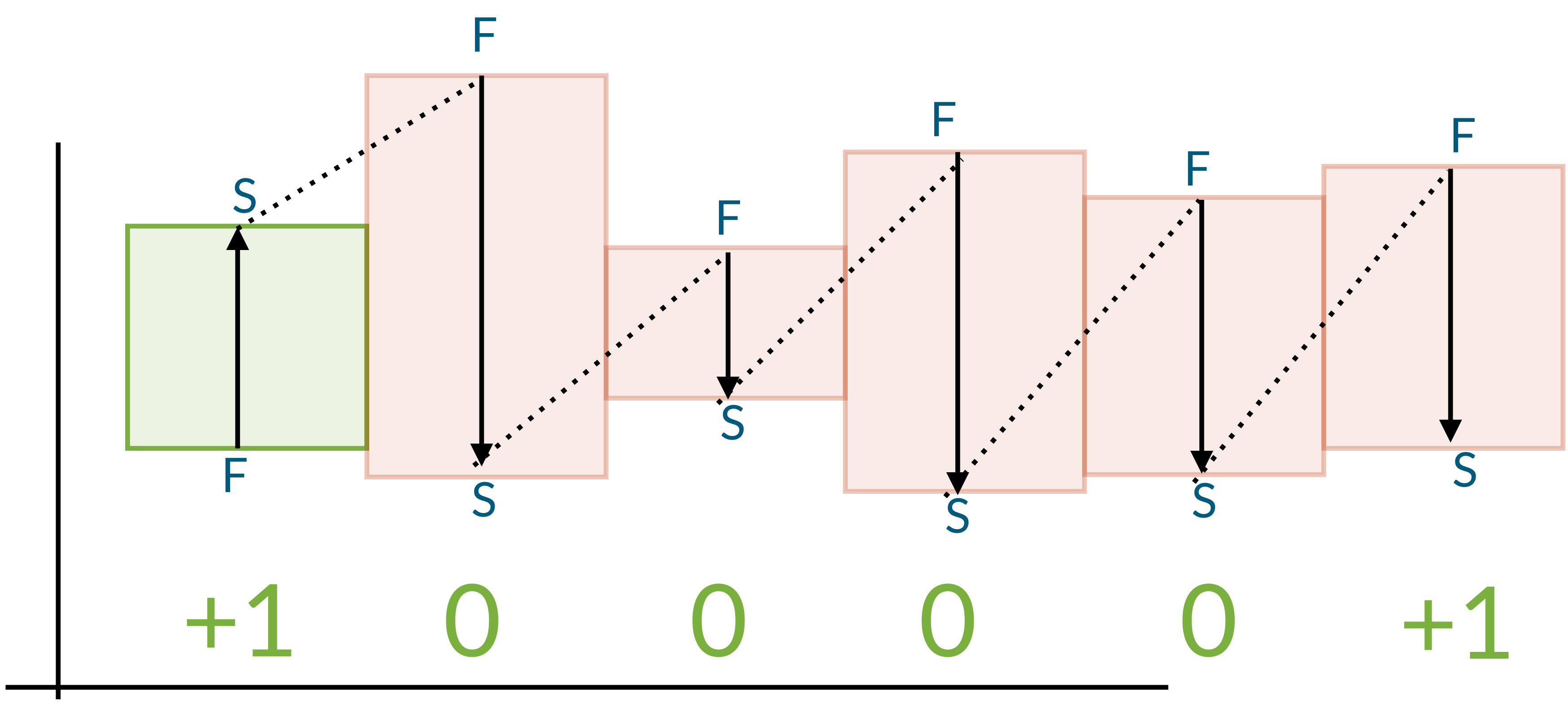


Special Cases

The equation also finds 0 values.

Our eyes imagine the path taken across FHLS bars.

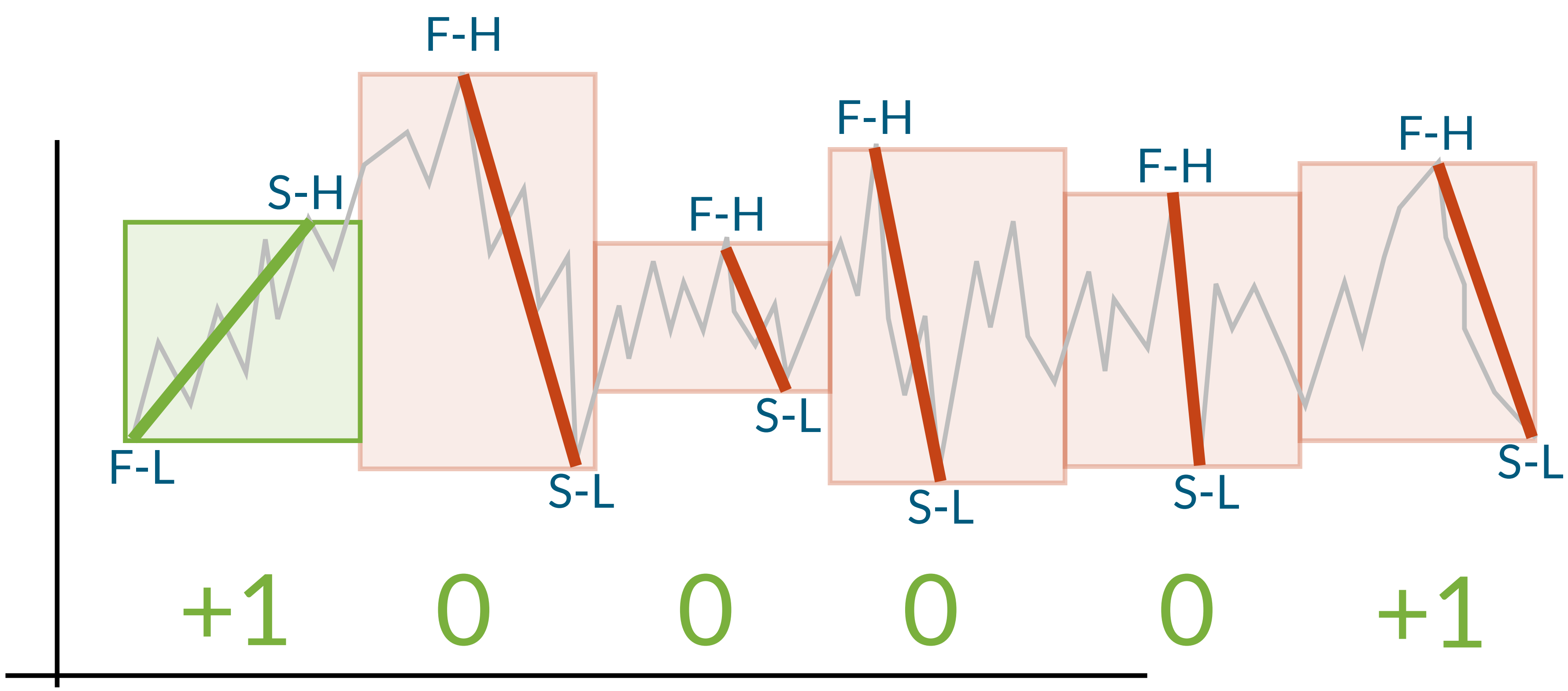
But these points are all dated in time… hence we have First and Second values in our summary to indicate the “flow”



Special Cases

The equation also finds 0 values.

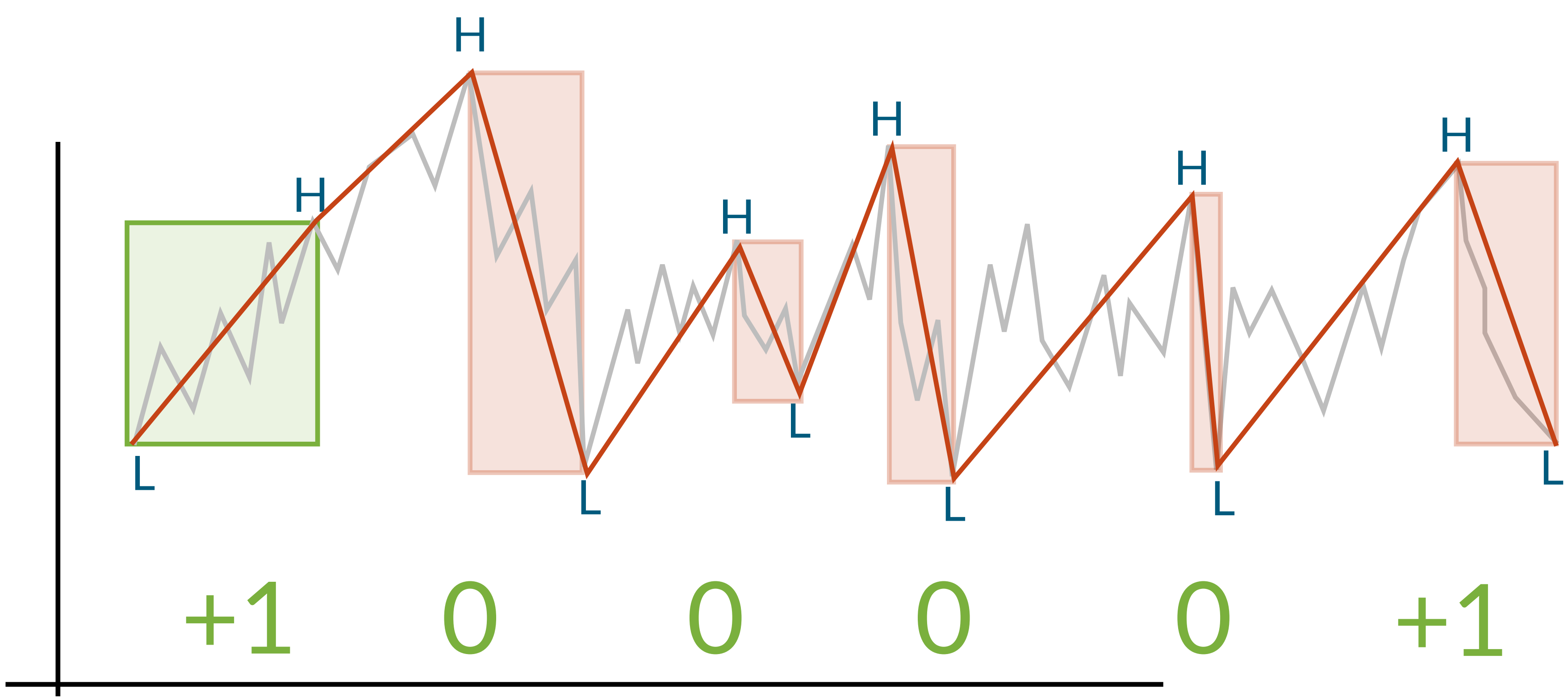
… and that dotted line is in fact really there not just implied.



Special Cases

The equation also finds 0 values.

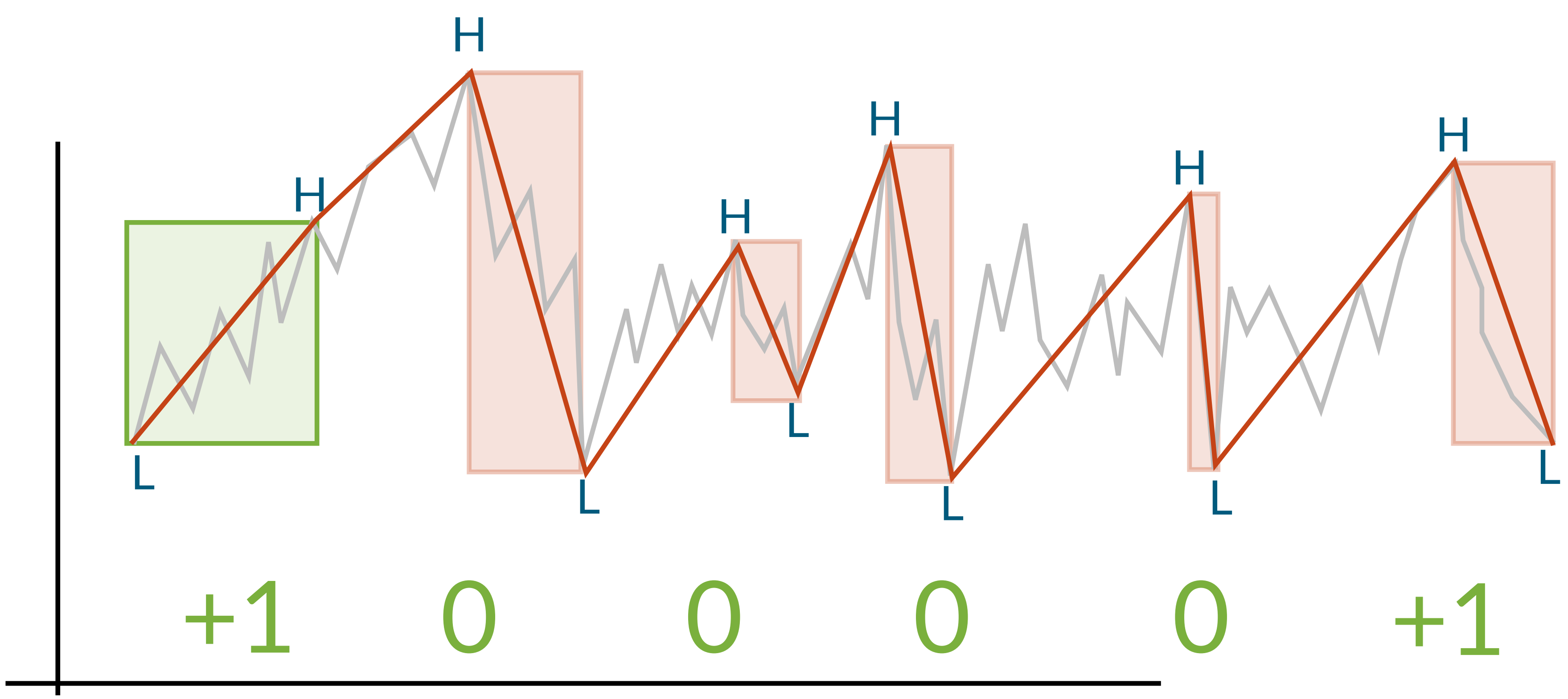
the dated highs / lows have gaps between them!



Special Cases

The equation also finds 0 values.

Let's make use of this property for special cases, for handling those 0 values.



Special Cases

I’ll illustrate, from the beginning:

Special Cases

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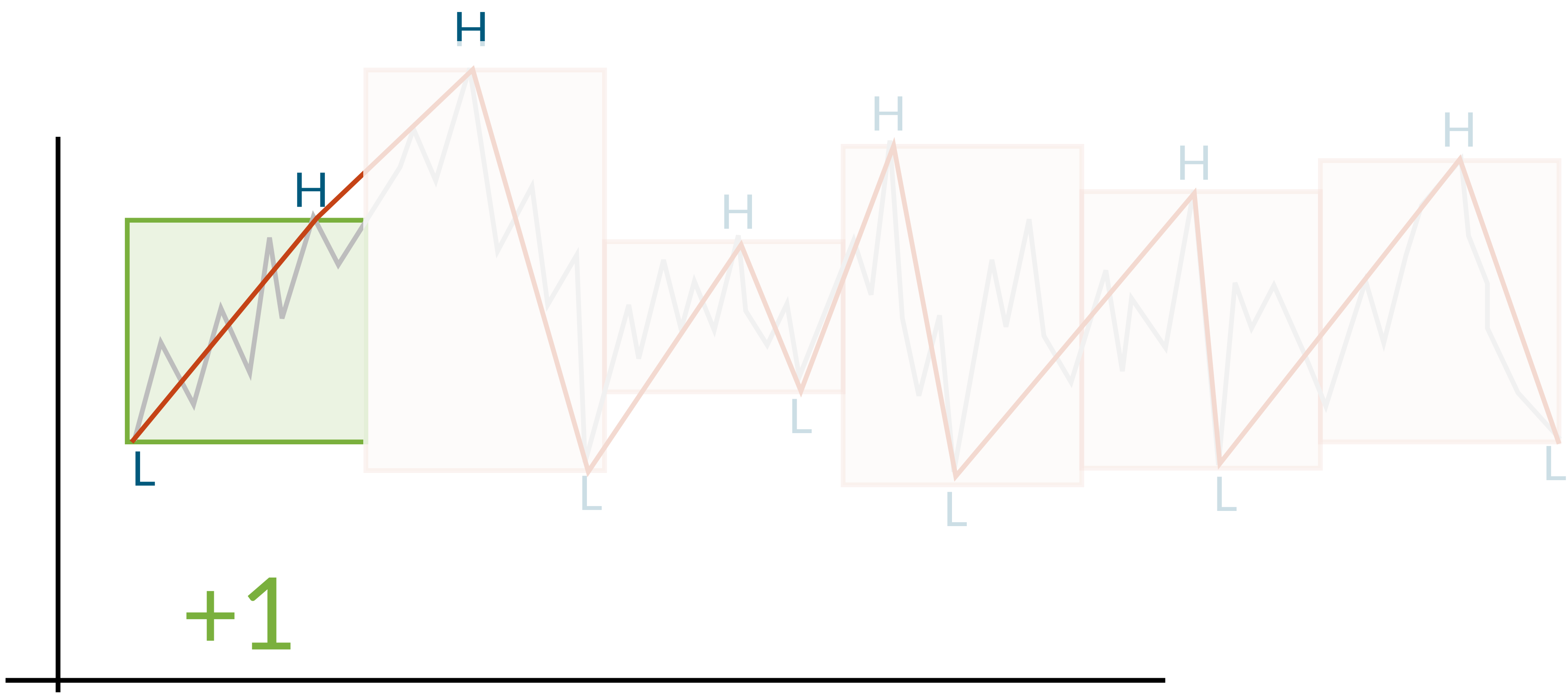
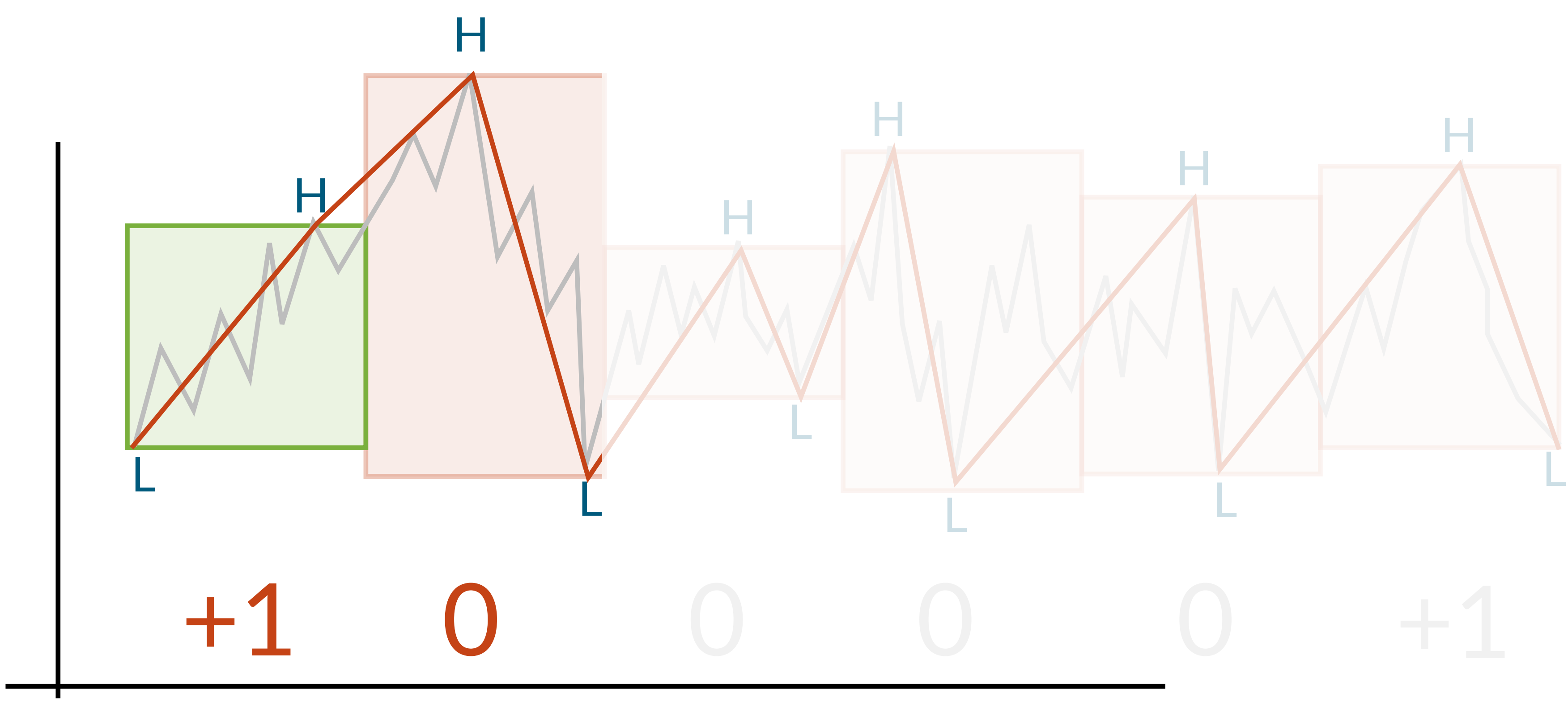


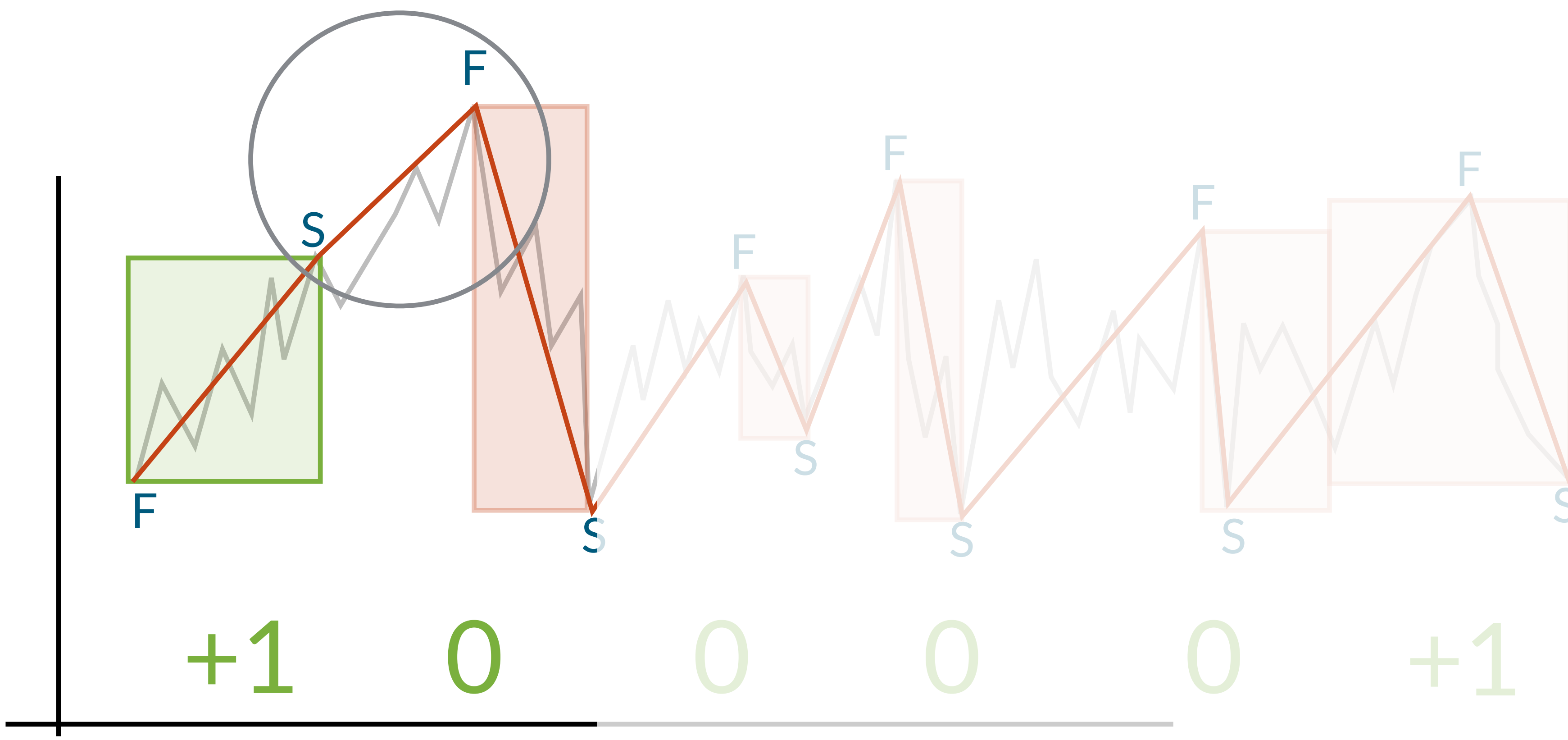
Special Cases

Find a 0 Trend (inner / outer bar)



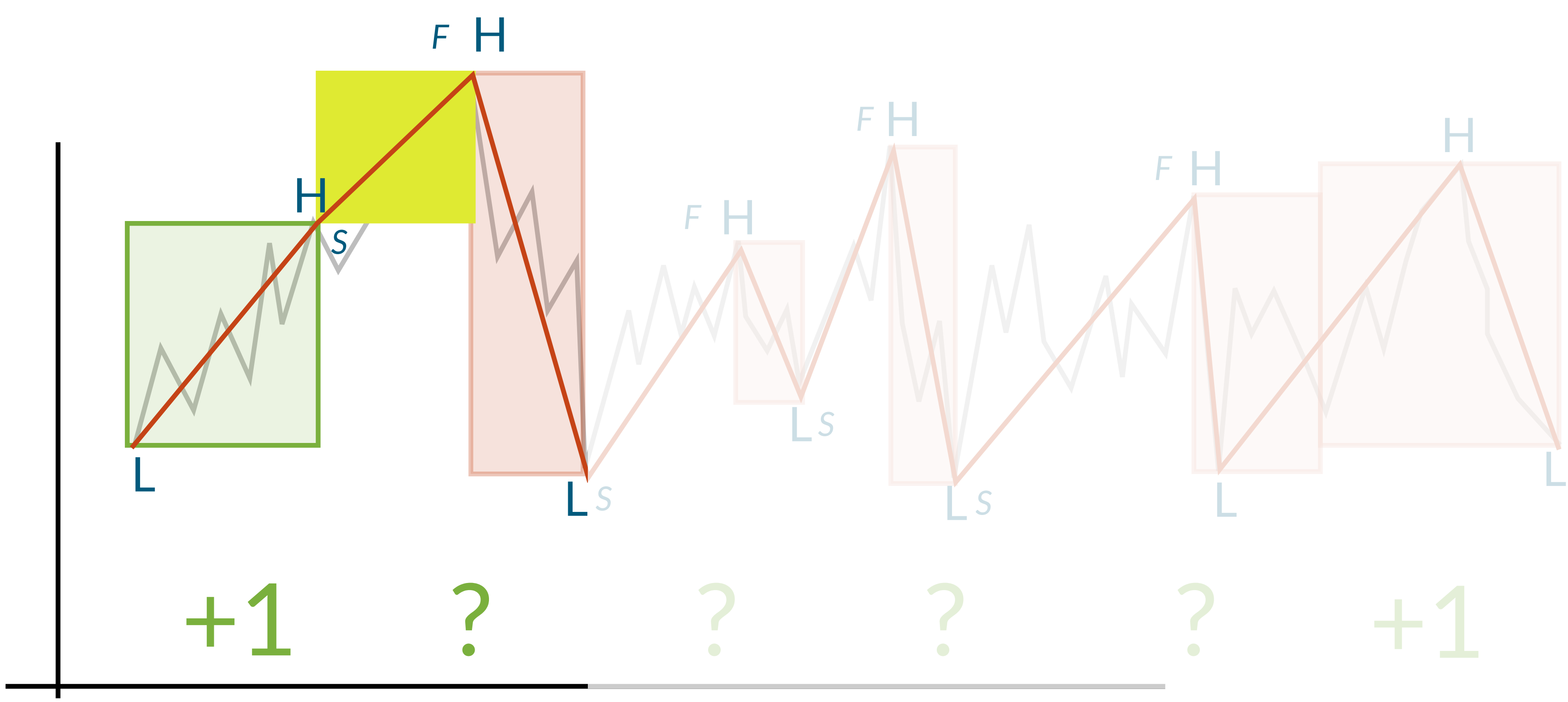
Special Cases

insert a new FHLS summary for the gap implied, by “borrowing” adjacent Second/First values.



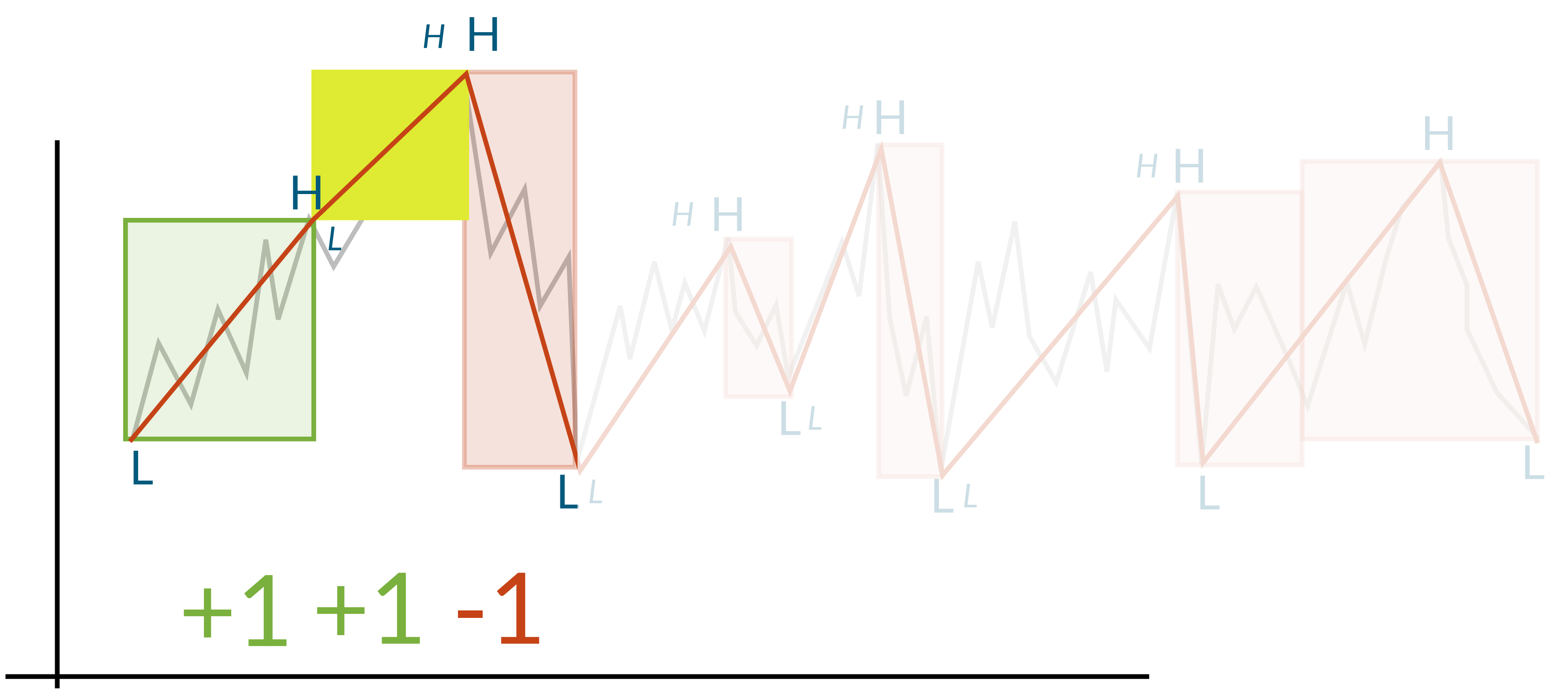
Special Cases

insert a new FHLS summary for the gap implied,
by "borrowing" adjacent Second/First values.
(ie, of "Second" of previous window and "First" of current window)



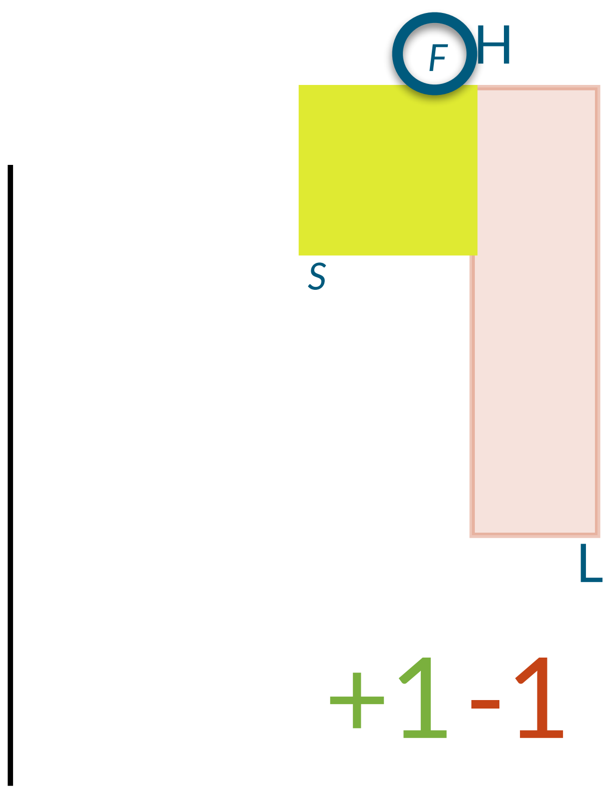
Special Cases

Emit these “special bars” during FHLS construction, format them like a regular window of highs/lows. Use them to find the trend changes



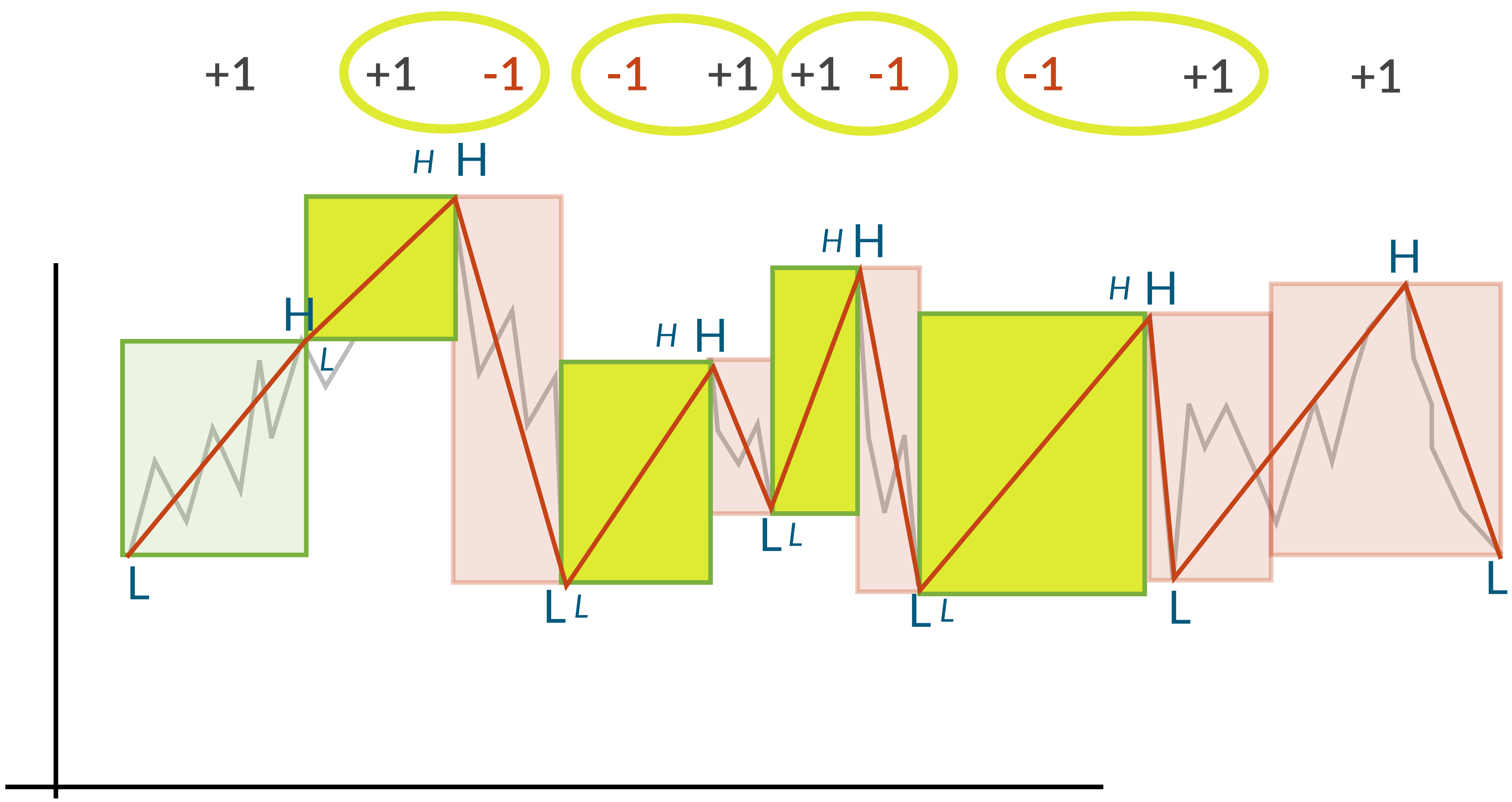
Special Cases

Then … compare the current bar against the “split bar”:
One of the signs (hdiff or ldiff) will have a value of zero
but the other will be a +1 or -1, so we never get a zero.
Then find reversals as usual…
i.e. we see here we find a lower low, so the last high is reversal.



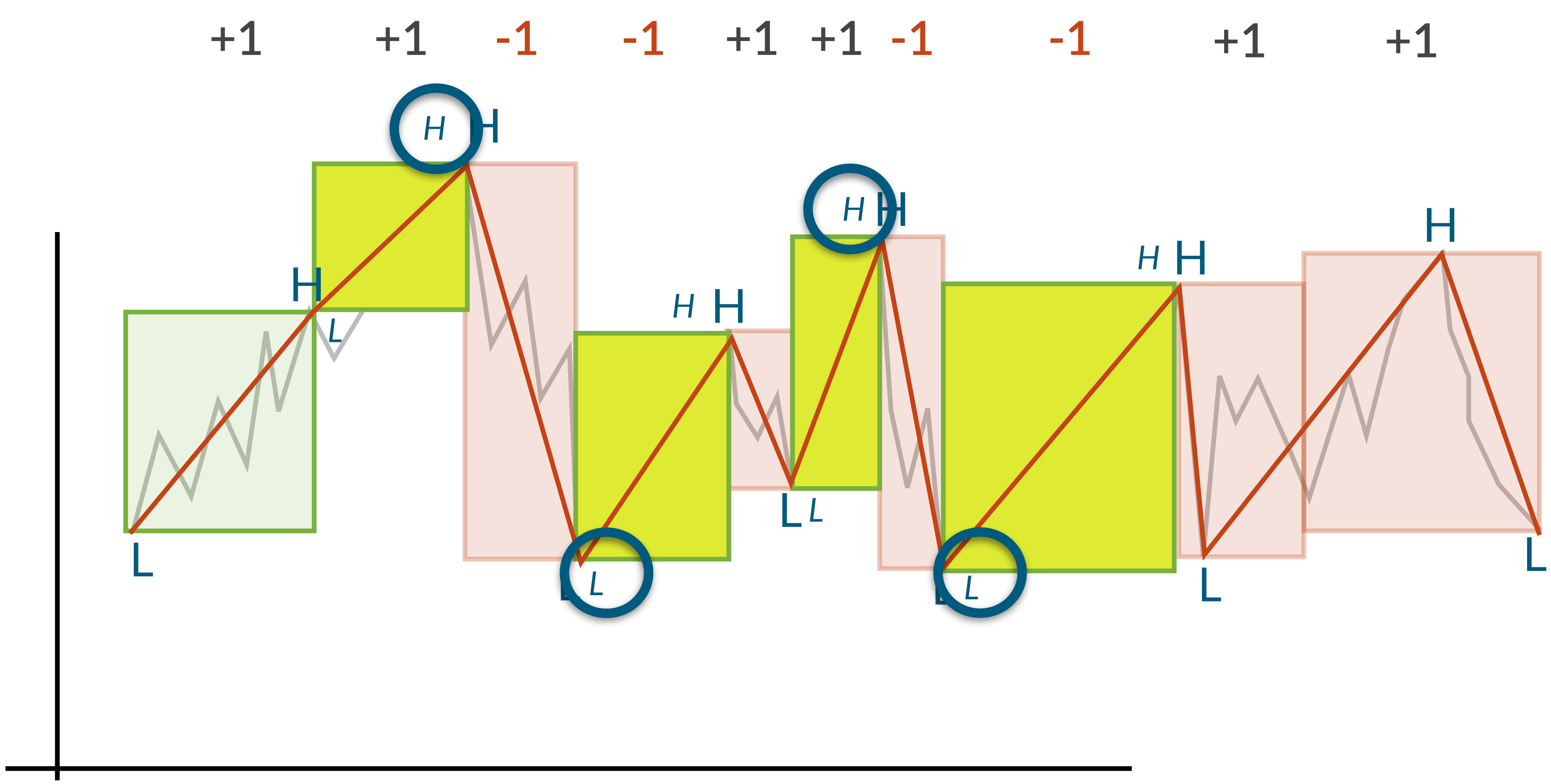
Special Cases

continue to find trends over this modified stream.



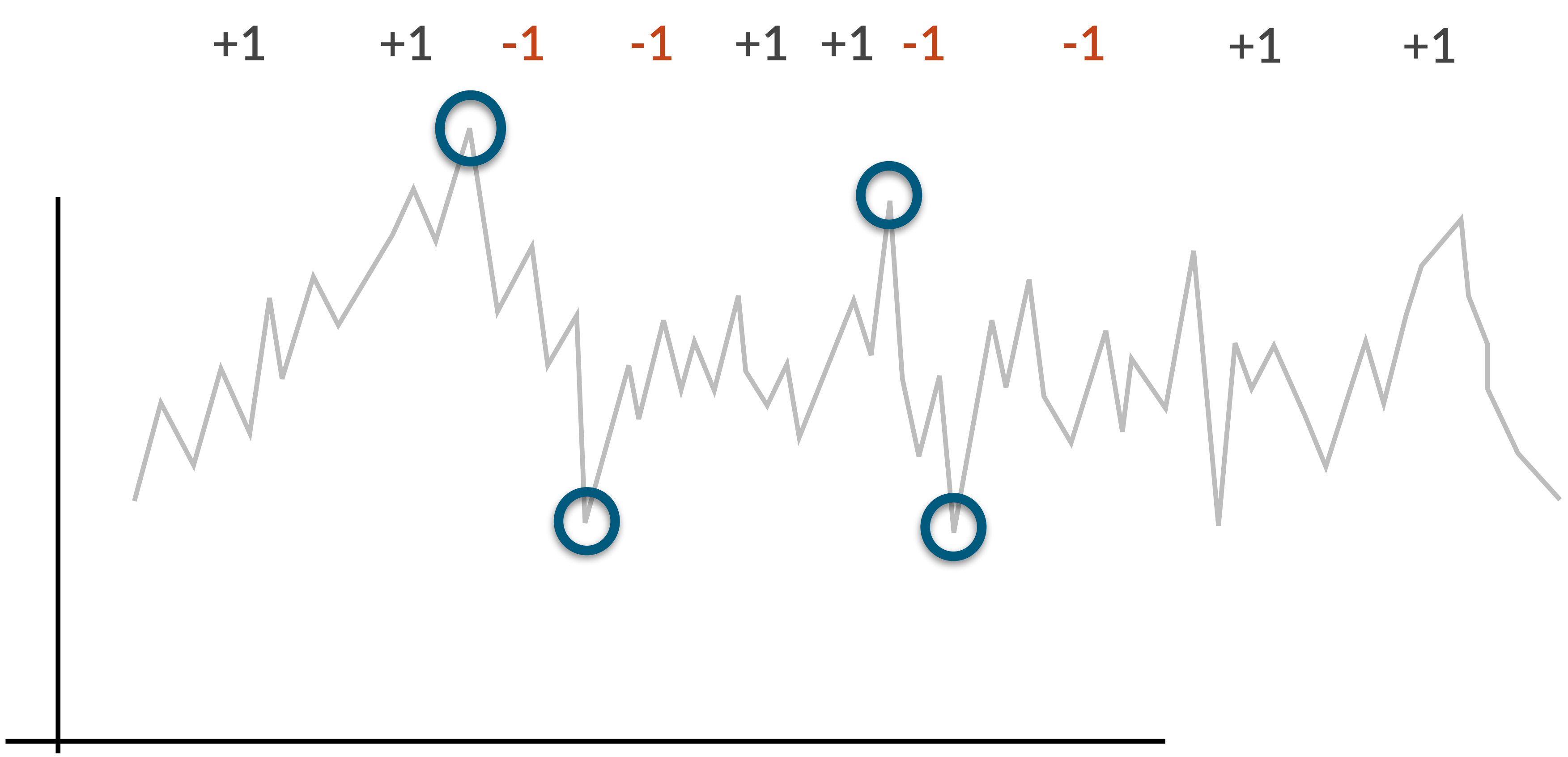
Special Cases

we're not seeing zeros now...



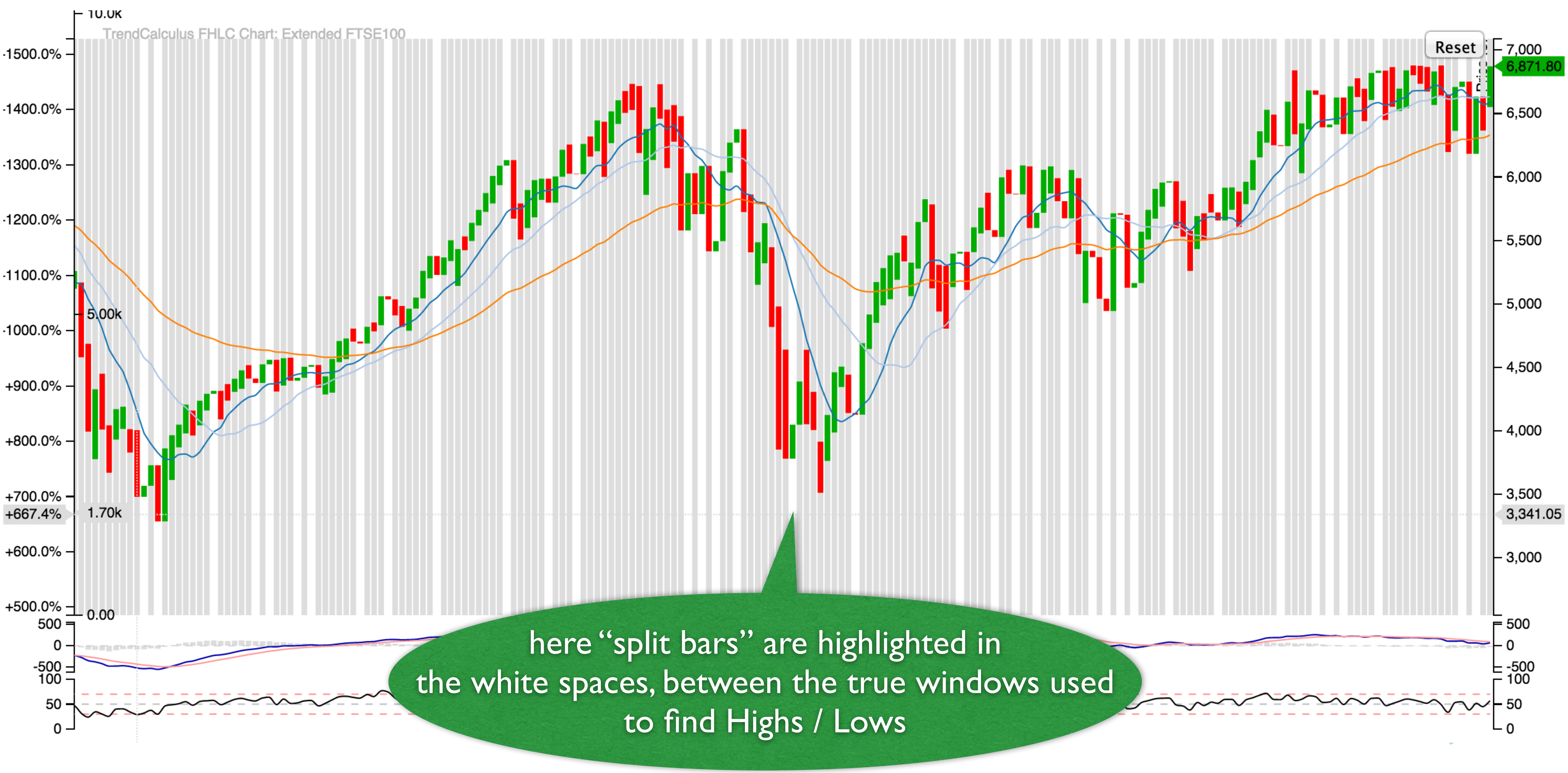
Special Cases

and when we find reversals, the results are good, and **Very** fast to compute.



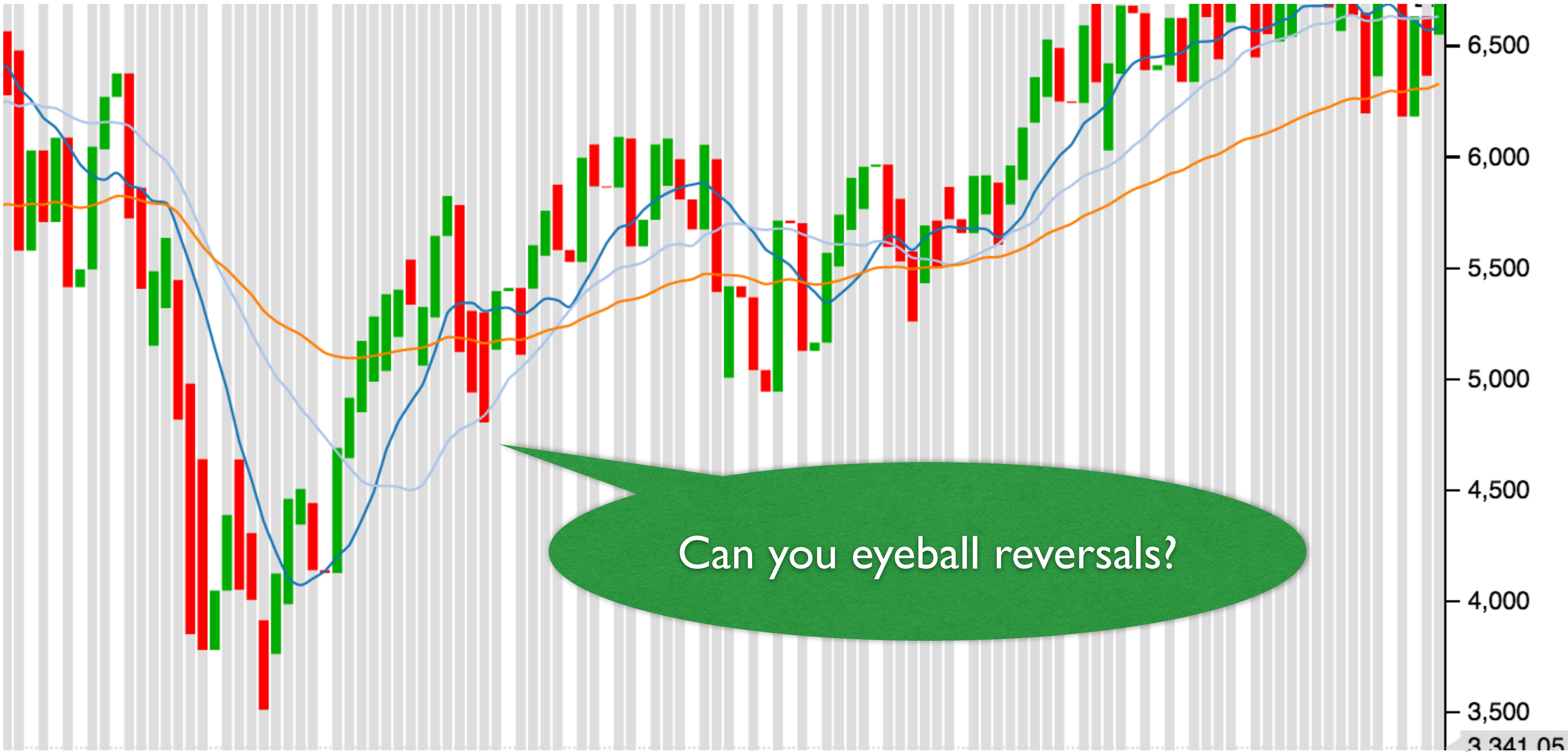
FHLS data charted

FHLS chart, with split bars in white spaces to solve Inner/Outer cases



FHLS data charted

The results are so intuitive you can “eyeball” the results.



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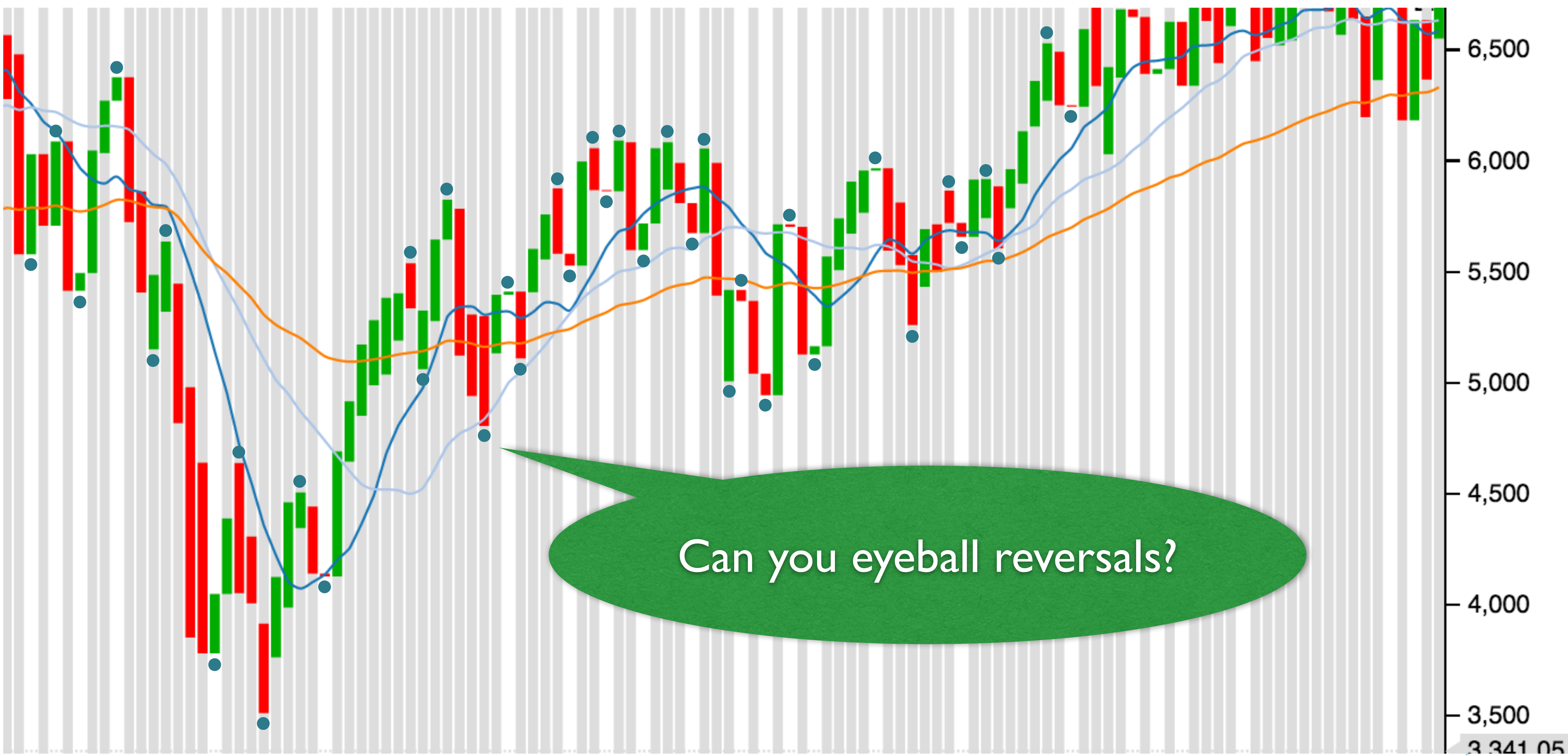


Stackable Processing

The final output is a stream of trend reversals

The output is a time series of trend *change points*.

You can run this output through the algo again, to "stack" TrendCalculus. This creates a multi-scale reversal finder. Processing data in several passes is a highly efficient process due to the data reduction on later passes.

In this case, N is not fixed windows of time, but a number of change points to summarise over.

Stackable Processing

This is what “stacking” means:

14 stacks

```
time cat db_output.csv |  luajit trendcalculus.lua -F "," -OFS "," -p 1 -h -H -n $z -r \
        | tee out/rev01.csv |  luajit trendcalculus.lua -F "," -OFS "," -p 2 -h -H -n $p -r \
        | tee out/rev02.csv | luajit trendcalculus.lua -F "," -OFS "," -p 3 -h -H -n $p -r  \
        | tee out/rev03.csv | luajit trendcalculus.lua -F "," -OFS "," -p 4 -h -H -n $p -r  \
        | tee out/rev04.csv | luajit trendcalculus.lua -F "," -OFS "," -p 5 -h -H -n $p -r  \
        | tee out/rev05.csv | luajit trendcalculus.lua -F "," -OFS "," -p 6 -h -H -n $p -r  \
        | tee out/rev06.csv | luajit trendcalculus.lua -F "," -OFS "," -p 7 -h -H -n $p -r  \
        | tee out/rev07.csv | luajit trendcalculus.lua -F "," -OFS "," -p 8 -h -H -n $p -r  \
        | tee out/rev08.csv | luajit trendcalculus.lua -F "," -OFS "," -p 9 -h -H -n $p -r  \
        | tee out/rev09.csv | luajit trendcalculus.lua -F "," -OFS "," -p 10 -h -H -n $p -r  \
        | tee out/rev10.csv | luajit trendcalculus.lua -F "," -OFS "," -p 11 -h -H -n $p -r  \
        | tee out/rev11.csv | luajit trendcalculus.lua -F "," -OFS "," -p 12 -h -H -n $p -r  \
        | tee out/rev12.csv | luajit trendcalculus.lua -F "," -OFS "," -p 13 -h -H -n $p -r  \
        | tee out/rev13.csv | luajit trendcalculus.lua -F "," -OFS "," -p 14 -h -H -n $p -r > out/rev14.csv
```

We feed the output of each pass back into the algorithm. We set the -p option to indicate the “pass number” in output. We fix n to a fixed increment (n=3) in the stack. Each further run, p, additionally reduces noise and filters down the number of change points further. Below is a count of change points created.

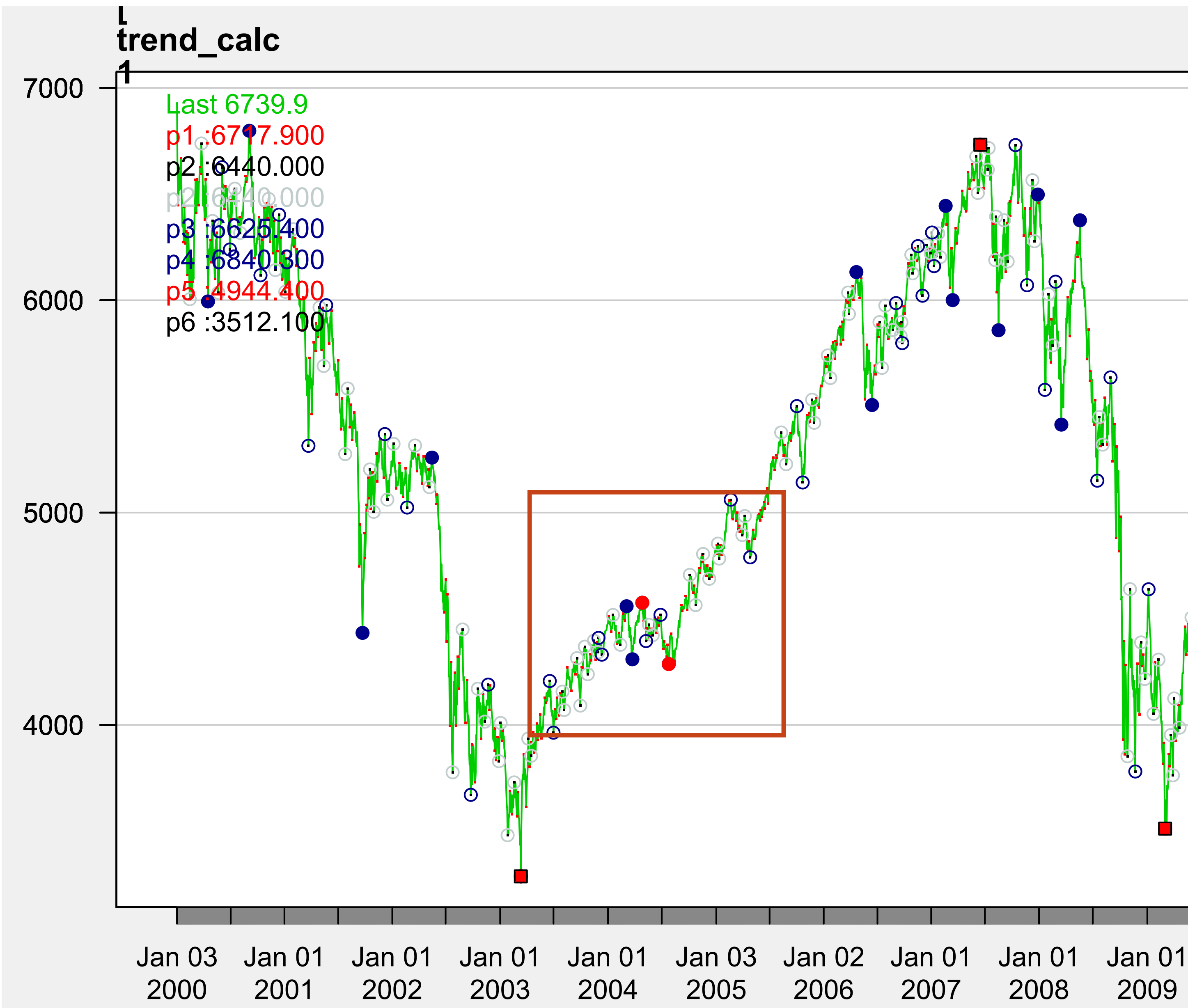
```
Andrews-MacBook-Pro-2:trendcalculus-public andrewmorgan$ wc -l out/*.csv
   33936 out/db_output.csv
    3625 out/rev01.csv
    1247 out/rev02.csv
     475 out/rev03.csv
     166 out/rev04.csv
      59 out/rev05.csv
      26 out/rev06.csv
      10 out/rev07.csv
       4 out/rev08.csv
       1 out/rev09.csv
       1 out/rev10.csv
       1 out/rev11.csv
       1 out/rev12.csv
       1 out/rev13.csv
       1 out/rev14.csv
```

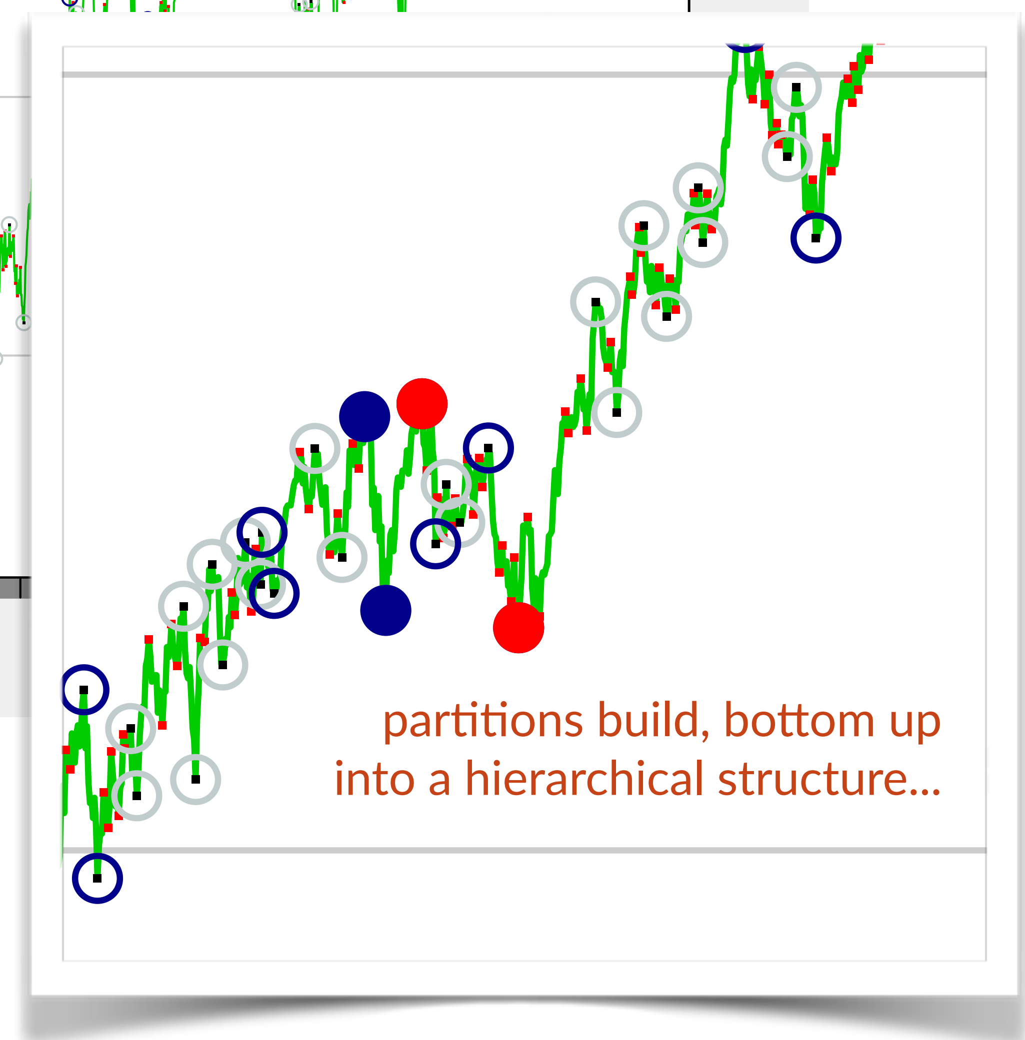
I fed in 33936 raw values, representing the daily close of the Dow Junes Industrial Average

The trend turning points on the first pass reduce the time series to 3625 rows. Subsequent passes summarise further.

The summarisation rate looks geometric to me. What does this mean? ... apart from it being a fantastic way to compress the information and to index the partitions of time?

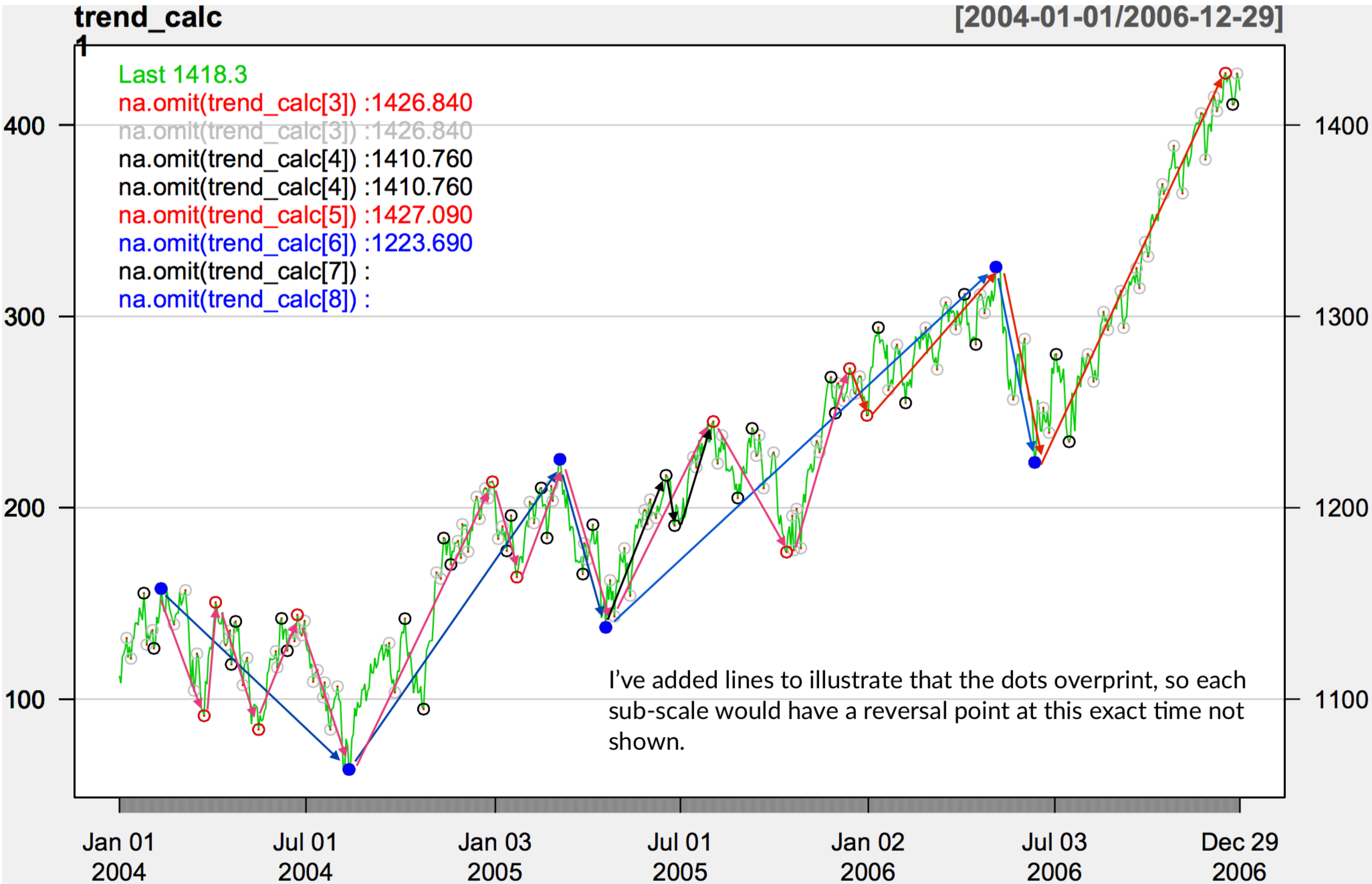
MultiScale Trends, Visualised





multiple stacked timeframes
build up into long term structures

MultiScale Trends, Visualised



Importance of Multi-Scale

All branching and circulatory systems in nature are said to observe **“Horton’s Law of Stream Order”**

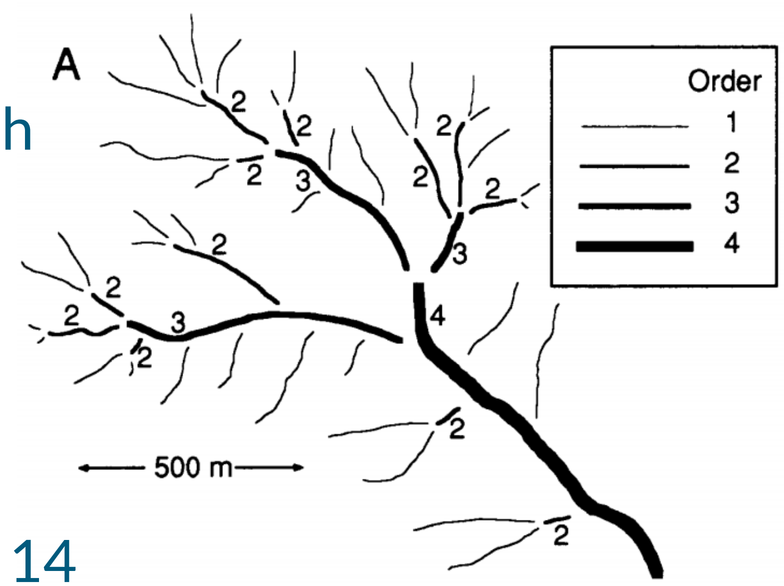
What about TrendCalculus induced multi-scale trend partitions?

Each pass of my algorithm, I simplify trends further. This “Pass number” is a “Stream Order” of the broader trend which branches into sequences of smaller trends on lower scales.

“Stream Order” frequency diminishes geometrically (says Horton). So, how about my stacked trend outputs?

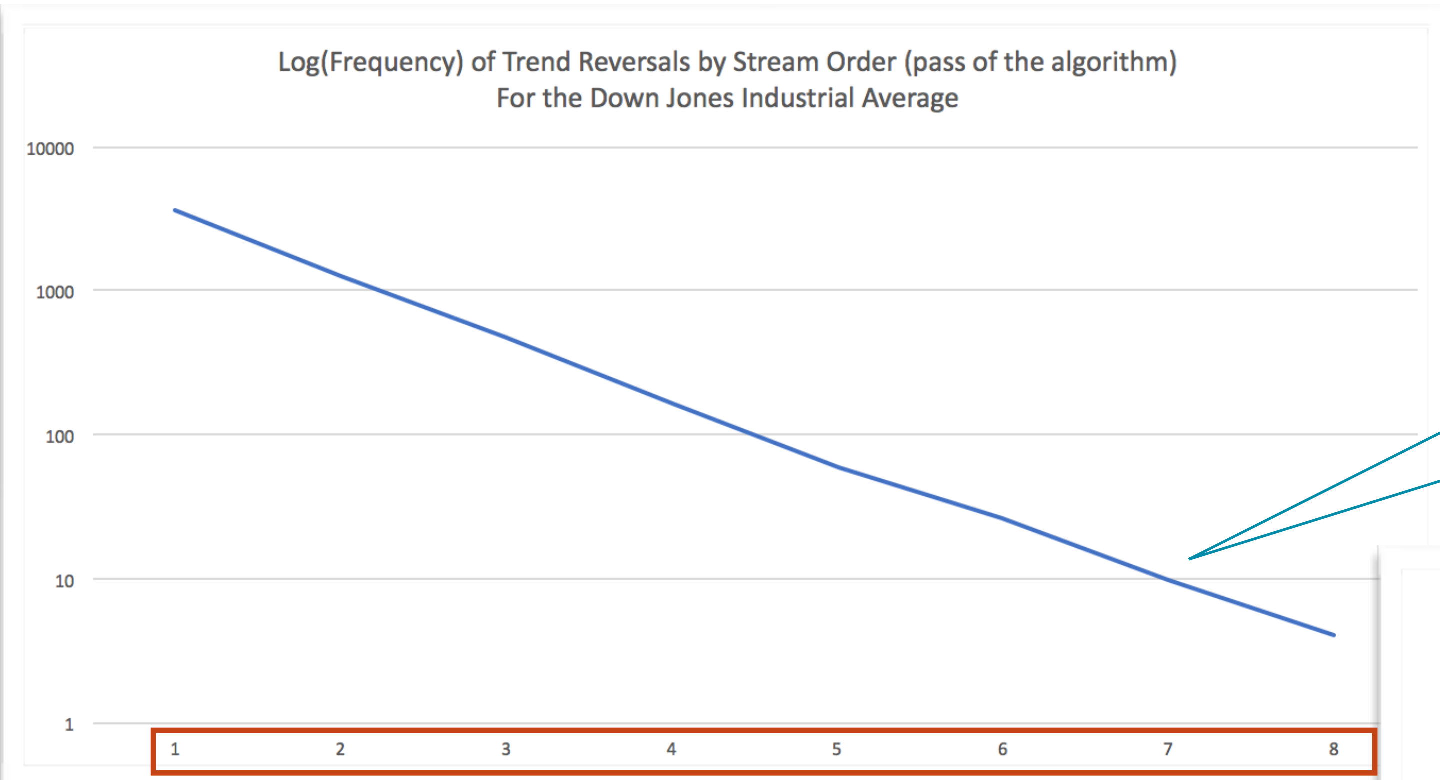
My test script, (included in repo for trendcalculus) calculates 14 passes of the algorithm (aka Stream Orders) for the DJI index.

Does my output follow Horton’s Law?
(Yes it does!)



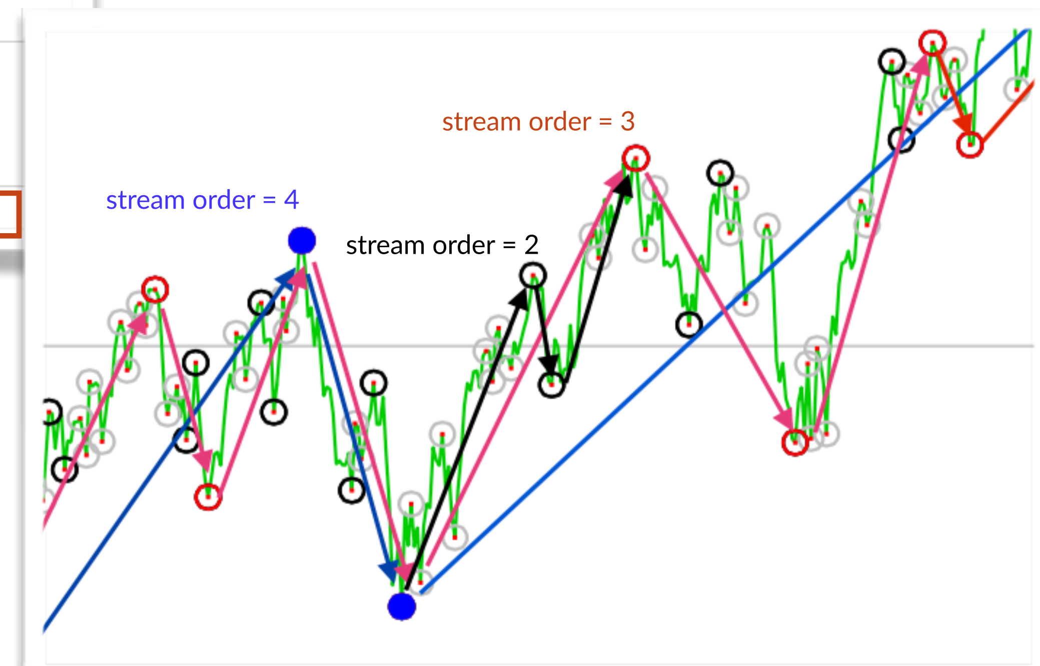
Stream Order

Trend Branching: Horton's Law



This shows us the DJI trends subdivide and "branch" according to power laws governing many natural phenomena, like rivers, blood vessels, trees. Horton's Law of Stream Order is true for trends on the the Stock Market !

```
Andrews-MacBook-Pro-2:trendcalculus-public andrewmorgan$ wc -l out/*.csv
   33936 out/db_output.csv
    3625 out/rev01.csv
    1247 out/rev02.csv
     475 out/rev03.csv
     166 out/rev04.csv
      59 out/rev05.csv
      26 out/rev06.csv
      10 out/rev07.csv
       4 out/rev08.csv
       1 out/rev09.csv
       1 out/rev10.csv
       1 out/rev11.csv
       1 out/rev12.csv
       1 out/rev13.csv
       1 out/rev14.csv
```



Studying Trends

In summary, TrendCalculus:

Pros:

- stream based
- simple, fast
- visual, interpretable
- stackable, multi-scale (fractal?)

Cons:

The trend reversal finding method is

- a lagging indicator.
- the lags accumulate for higher scales.

Studying Trends

Now I have explained how it works:

to do:

Get implementation right.
Describe why we need it.
Do great things.

5 minute break

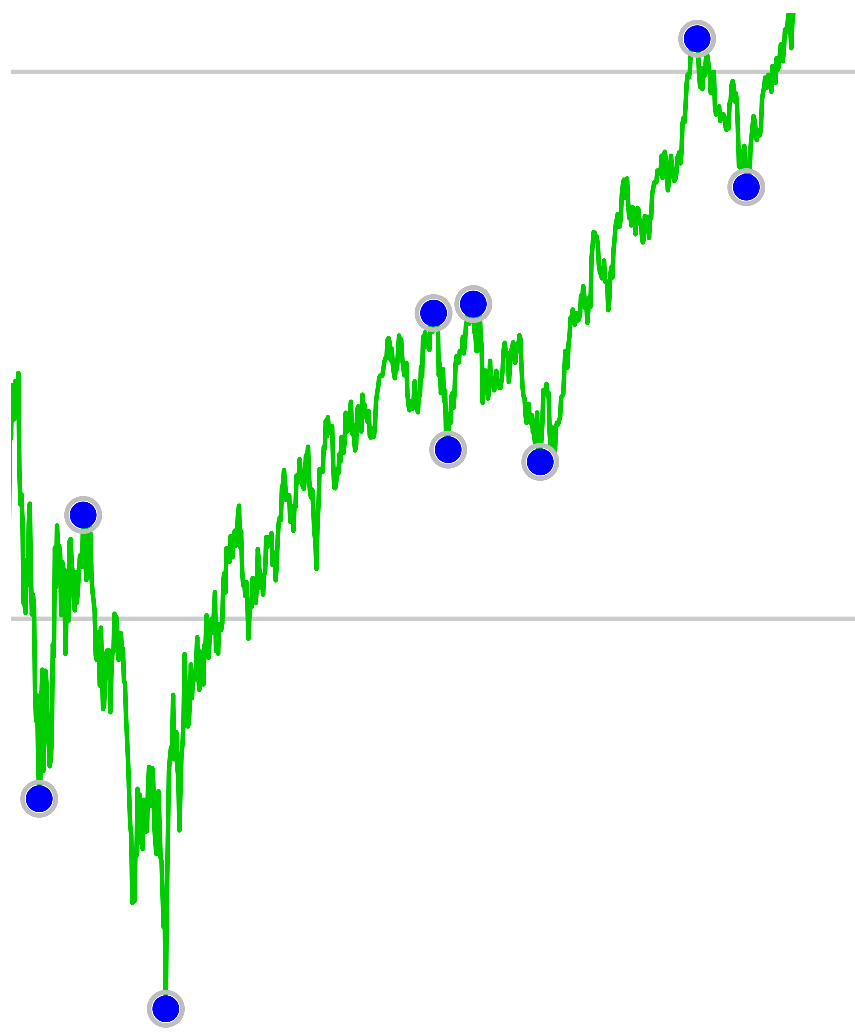
Predicting Trend Change

Experimental Approach

A Holy Grail of Predicting

Can we predict tops and bottoms in the stock market?

For example, predict turning points AS THEY HAPPEN?



This would seem to be impossible right?

But putting that aside :-) how might we design experiments to at least try?

I will explain my approach to an experimental design…
… show early results.

How would we start?

With a Hypothesis !

Hypothesis:

With TrendCalculus generated trend reversals
data as training labels,
merged with realtime rolling trend "features",
I can machine-learn realtime "predicted trend" (+1, -1)
over stock market indices data
that helps beats the "lag" inherent in straight TrendCalculus.

Experimental Design

The goal demands designing great supporting data.

We need Labels! *We need great Features!*

Use trend calculus change points to build LABELS.
Use internal rolling trend calculus arrays to build FEATURES.

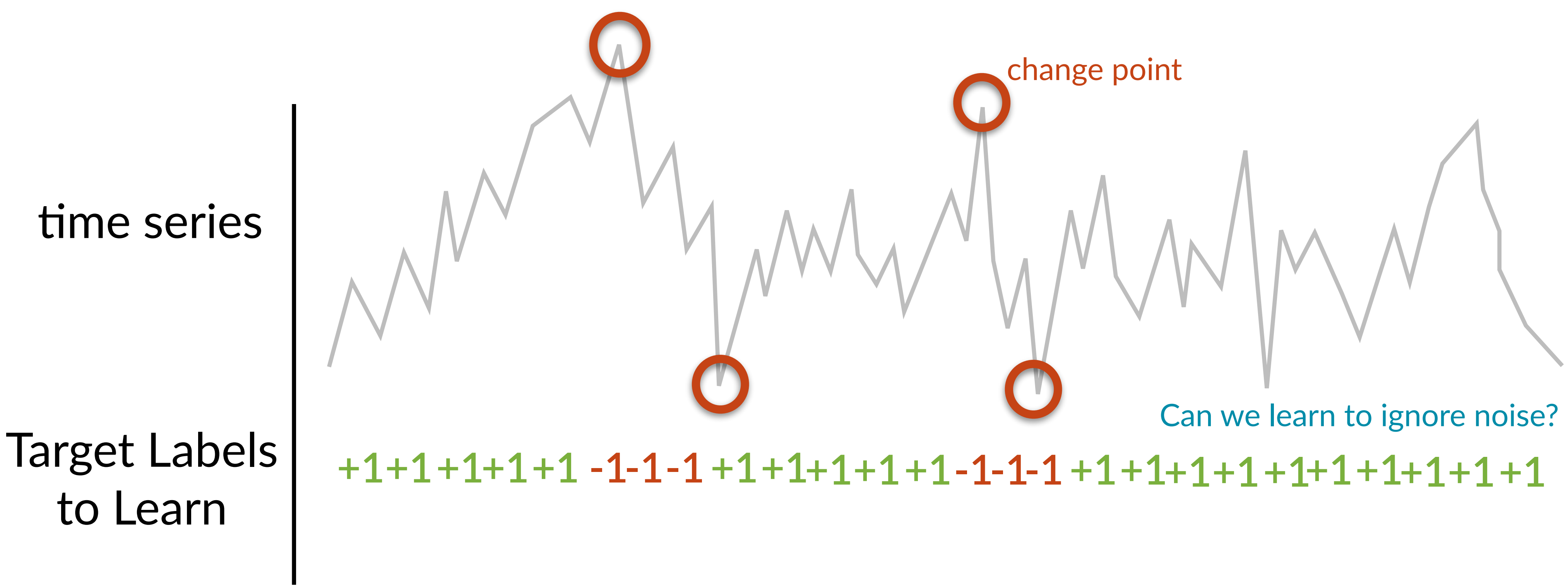
Experiment Approach

a) find Trend change points for timeframe, n, as targets

b) "tag" my time-series with rolling trend signals, per "tick"

c) merge the rolling features against actual trend change points.

d) try and machine learn the trend labels, at tick level.



Introducing "TCFG"

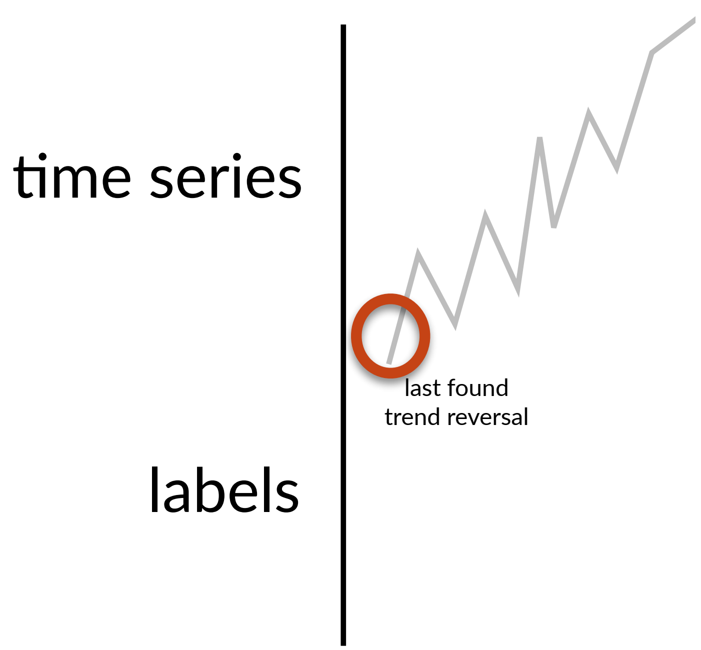
a "TrendCalculus Feature Generator"

(1) "Rewind" and "Hindsight" produces training targets:

Introducing “TCFG”

a “TrendCalculus Feature Generator”

(1) “Rewind” and “Hindsight” produces training targets:



Introducing “TCFG”

“TrendCalculus Feature Generator”

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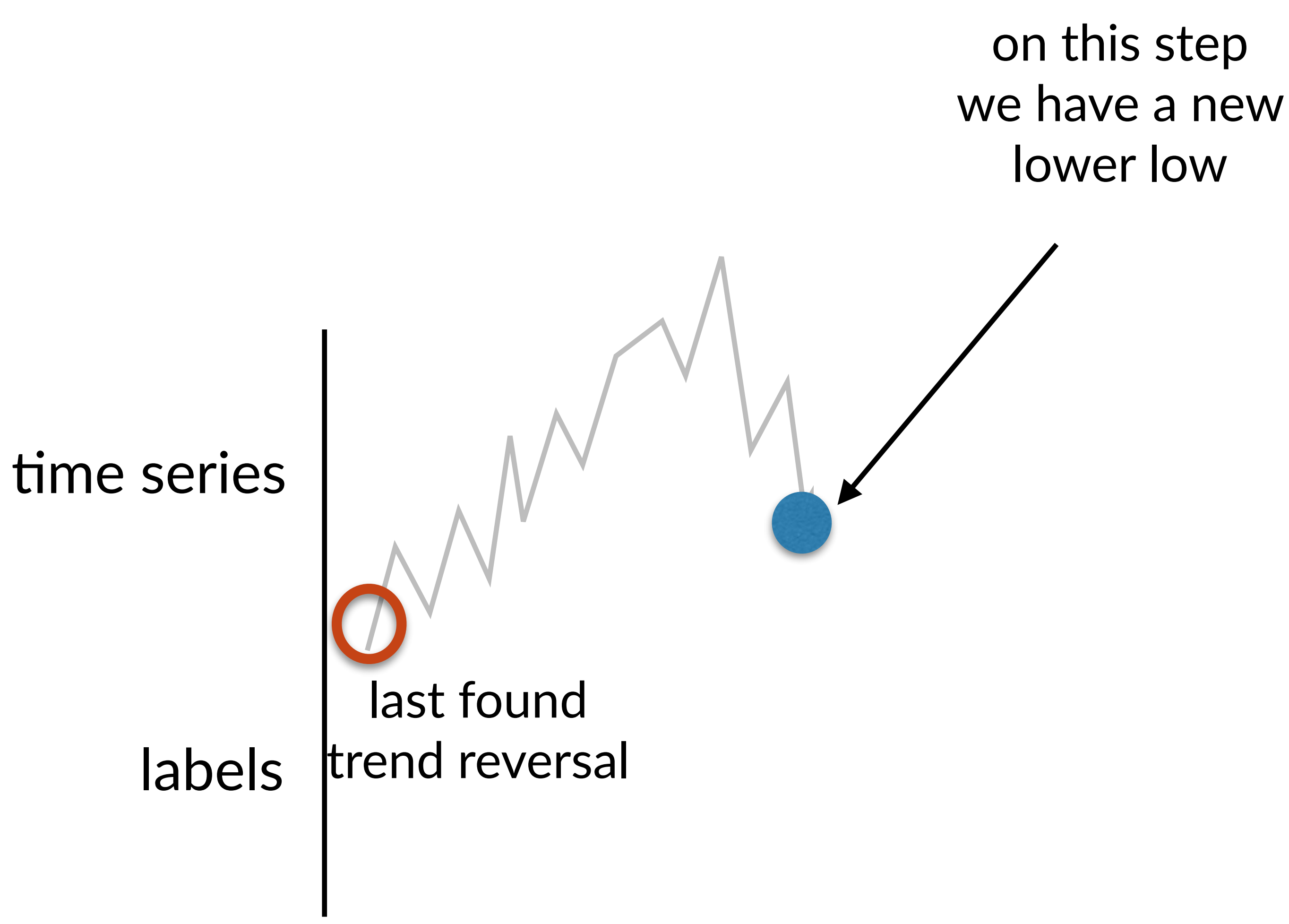
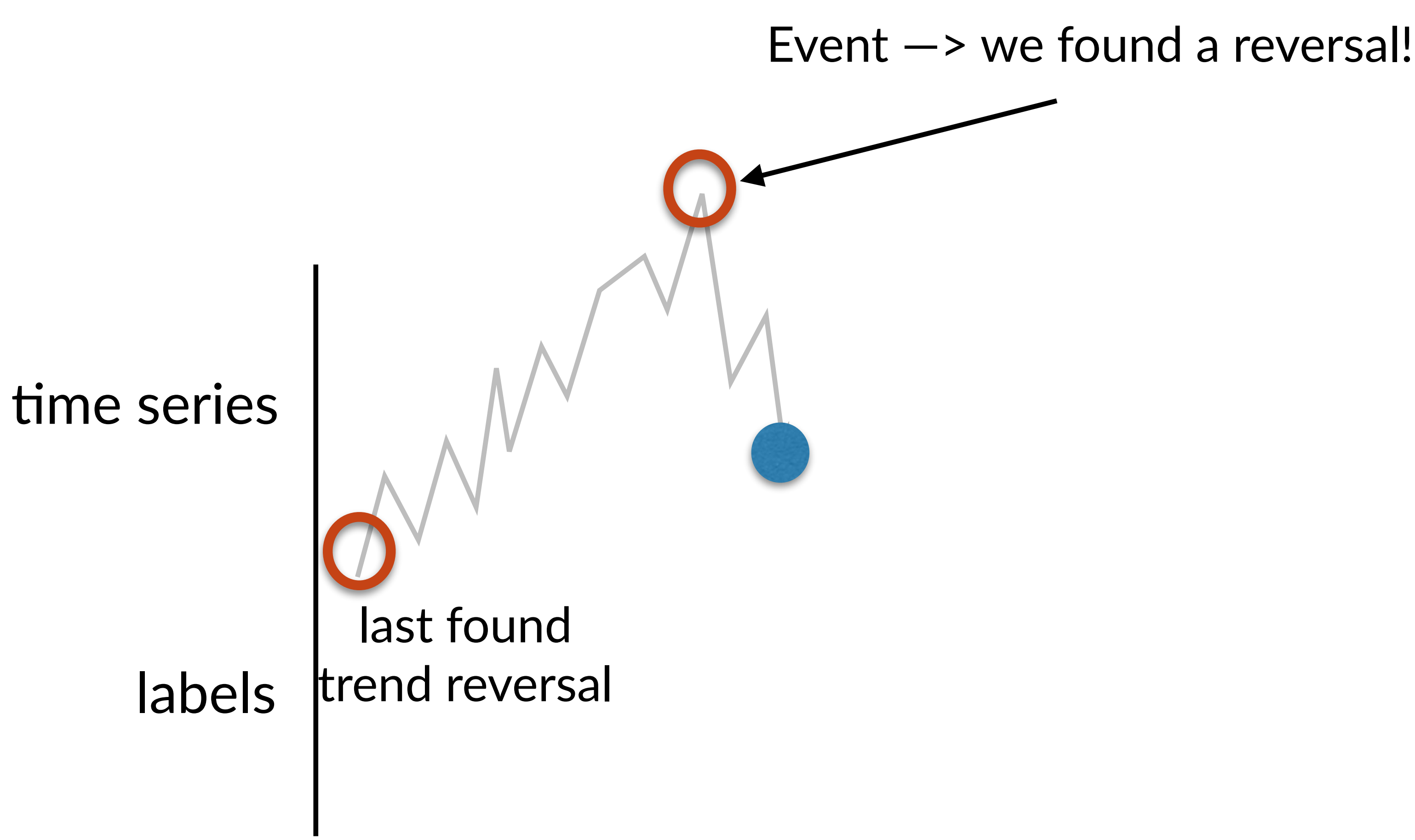


Introducing “TCFG”

“TrendCalculus Feature Generator”

(1) “Rewind” and “Hindsight” produces training targets:

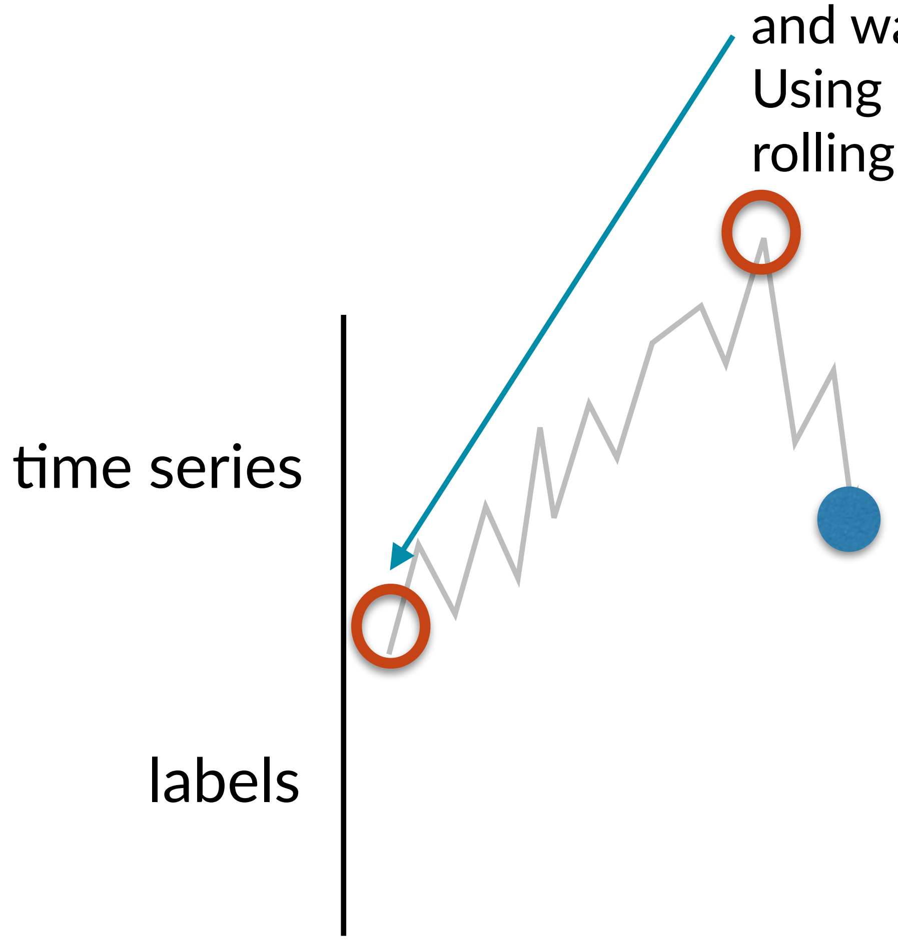


Introducing “TCFG”

“TrendCalculus Feature Generator”

(1) “Rewind” and “Hindsight” produces training targets:

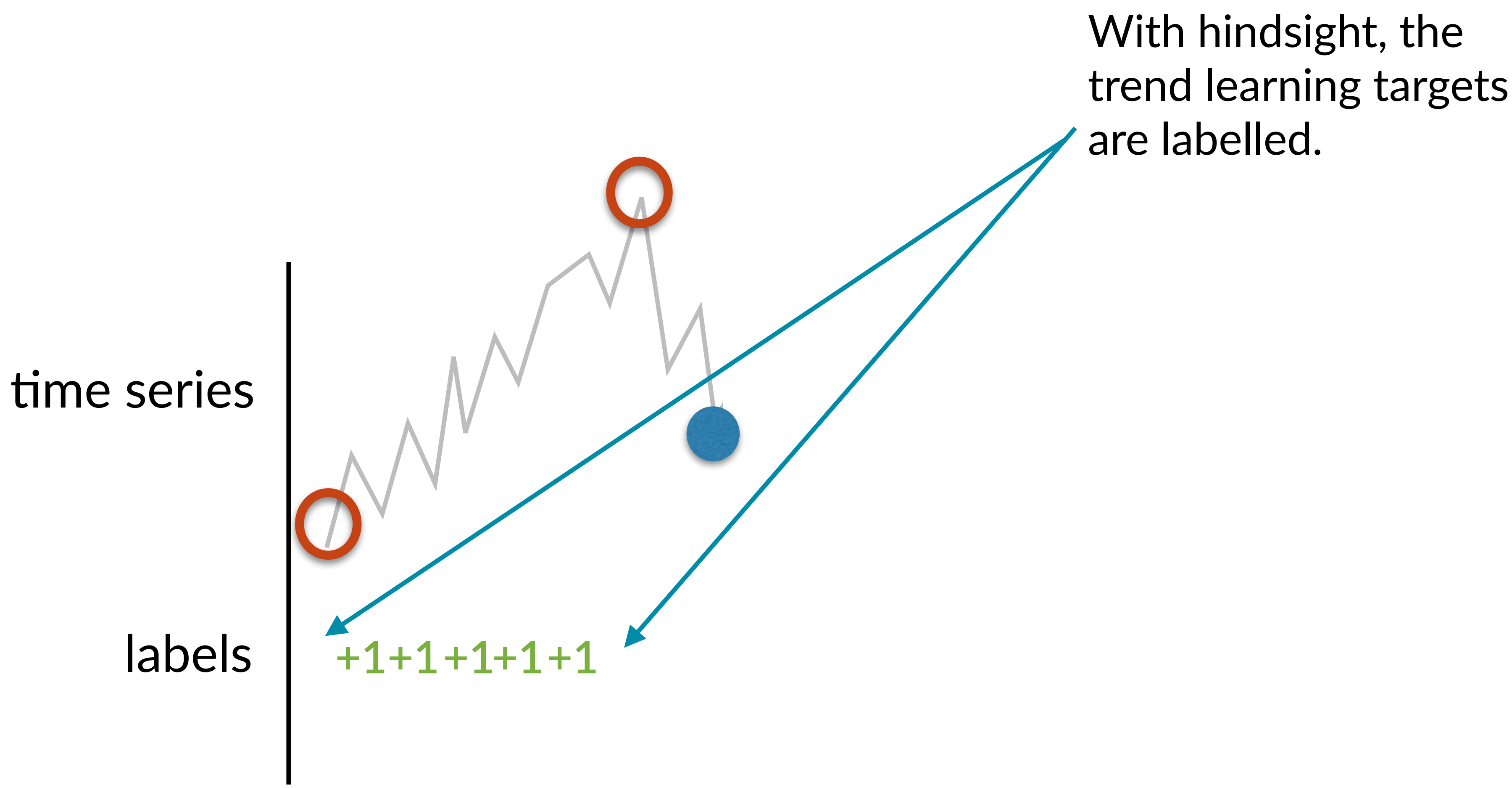
We rewind back to the Start of the trend
and walk forward over the time series until the trend’s End.
Using “hindsight” we label up trend targets and print them against the rolling trend features - to build the machine learning training dataset.



Introducing "TCFG"

"TrendCalculus Feature Generator"

(1) "Rewind" and "Hindsight" produces training targets:

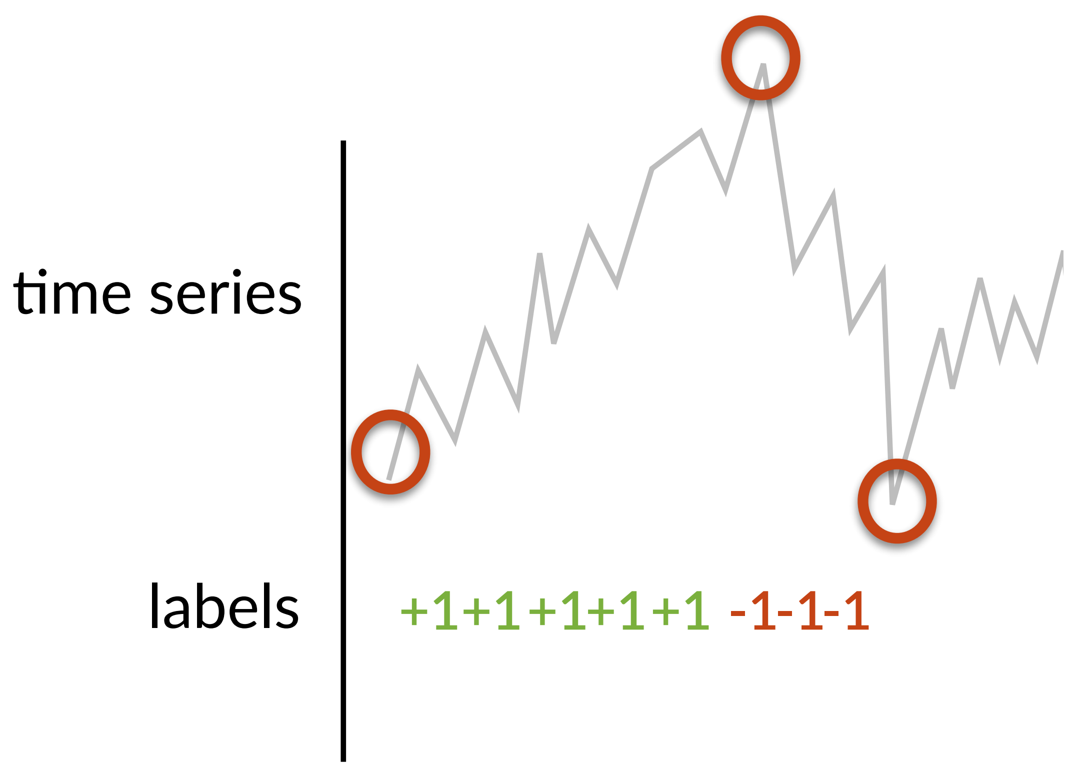


Introducing “TCFG”

“TrendCalculus Feature Generator”

(1) “Rewind” and “Hindsight” produces training targets:

and we continue to label through time… as a lagging labeller

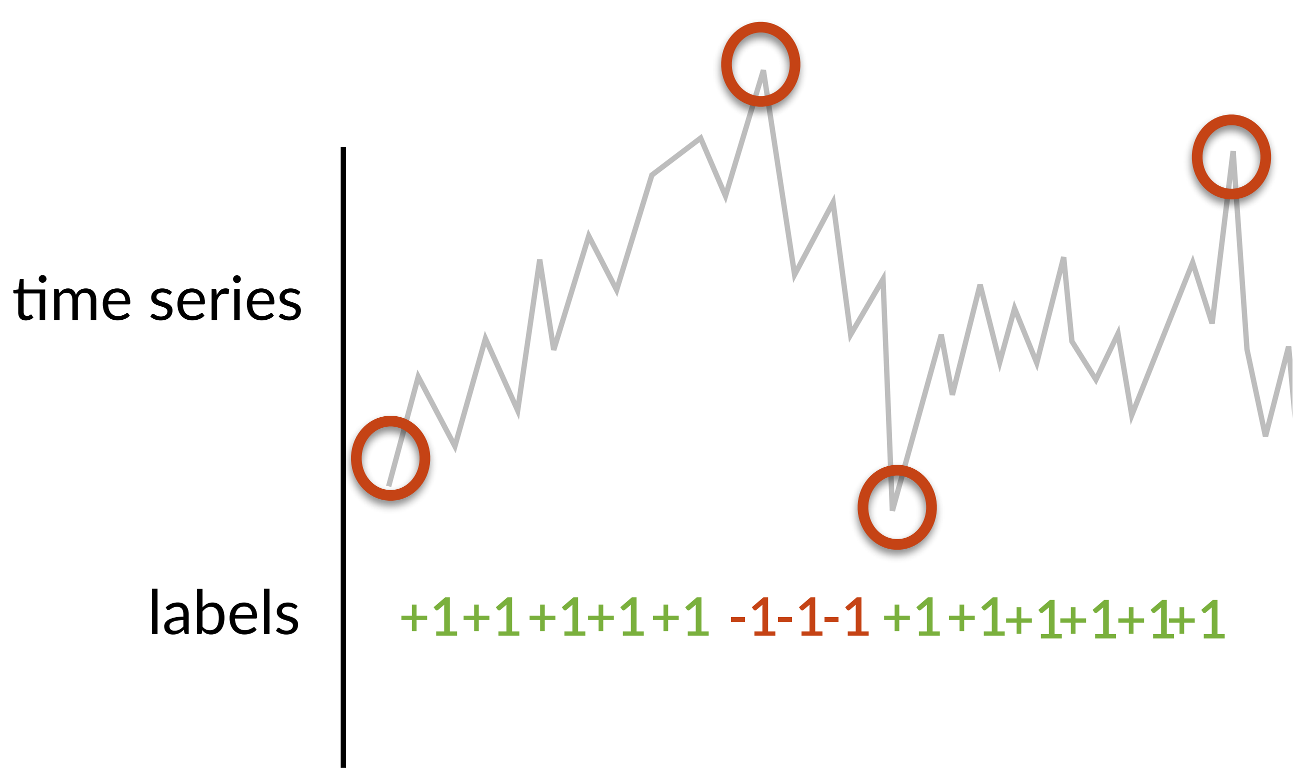


Introducing "TCFG"

"TrendCalculus Feature Generator"

(1) "Rewind" and "Hindsight" produces training targets:

And we populate our training target labels in this way
in an incremental batch process as reversals are found.
So — how about features?



= "Lagging Labels"

Introducing “TCFG”

“TrendCalculus Feature Generator”

(1) “Rewind” and “Hindsight” produces training targets:

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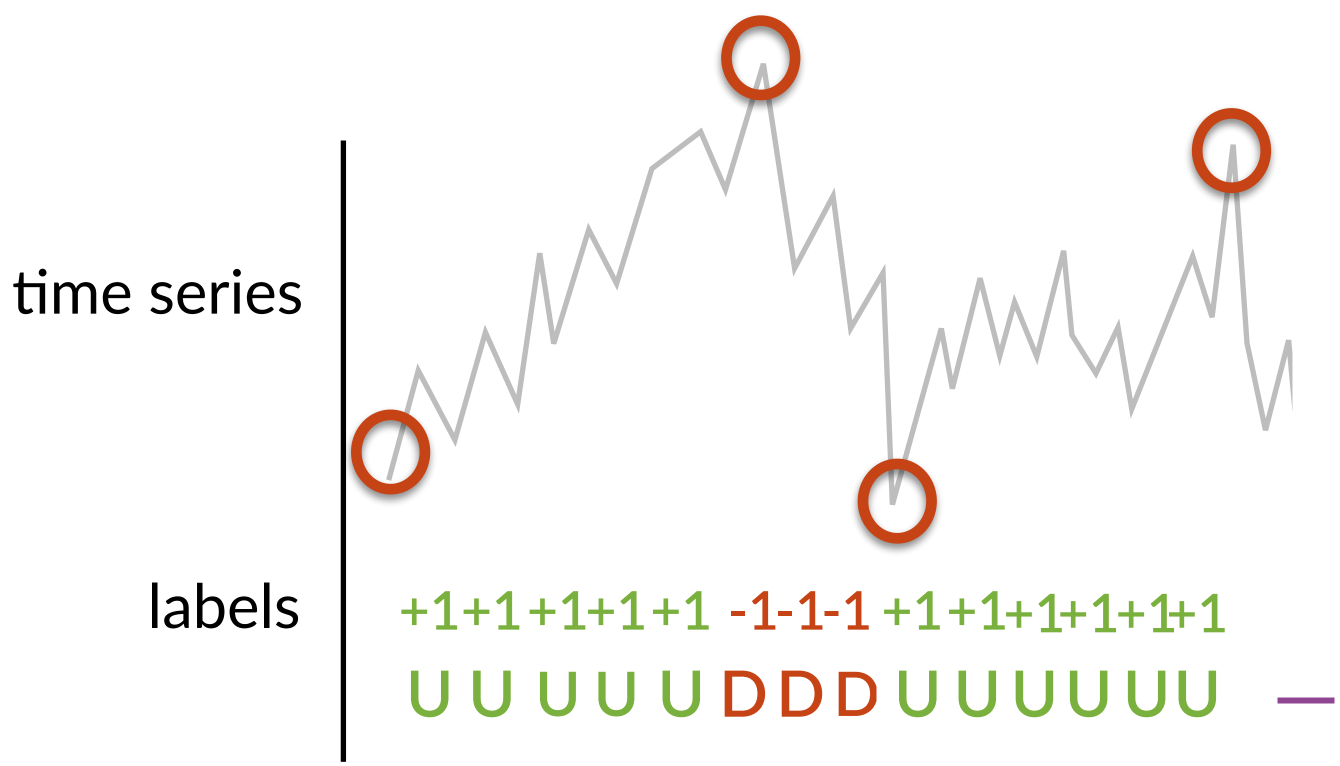


= “Lagging Labels”

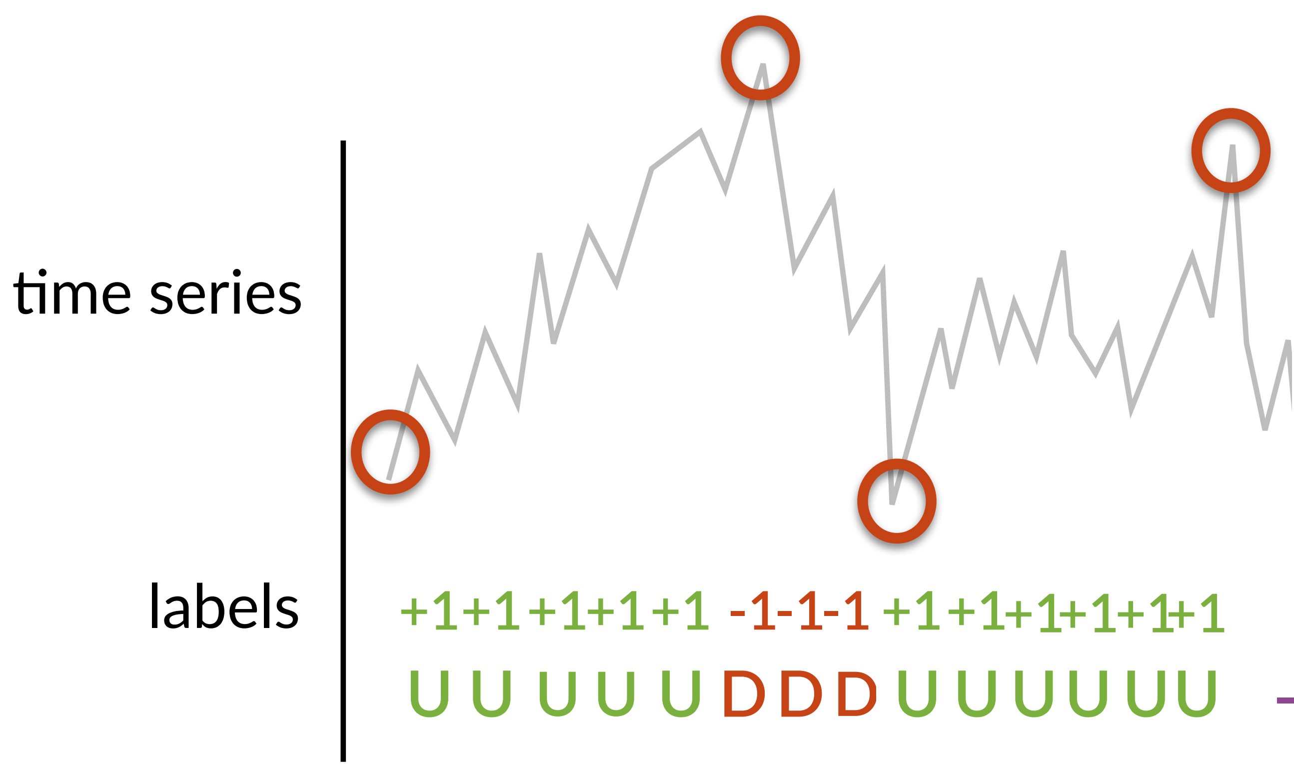
—> as “Categorical Labels”

Introducing “TCFG”

“TrendCalculus Feature Generator” - feature builder code

(1) “Rewind” and “Hindsight” produces training targets:

Why a lagging labeller?
Incremental training can be organised over time.
The model can then be updated as new trends end



= “Lagging Labels”

—> as “Categorical Labels”

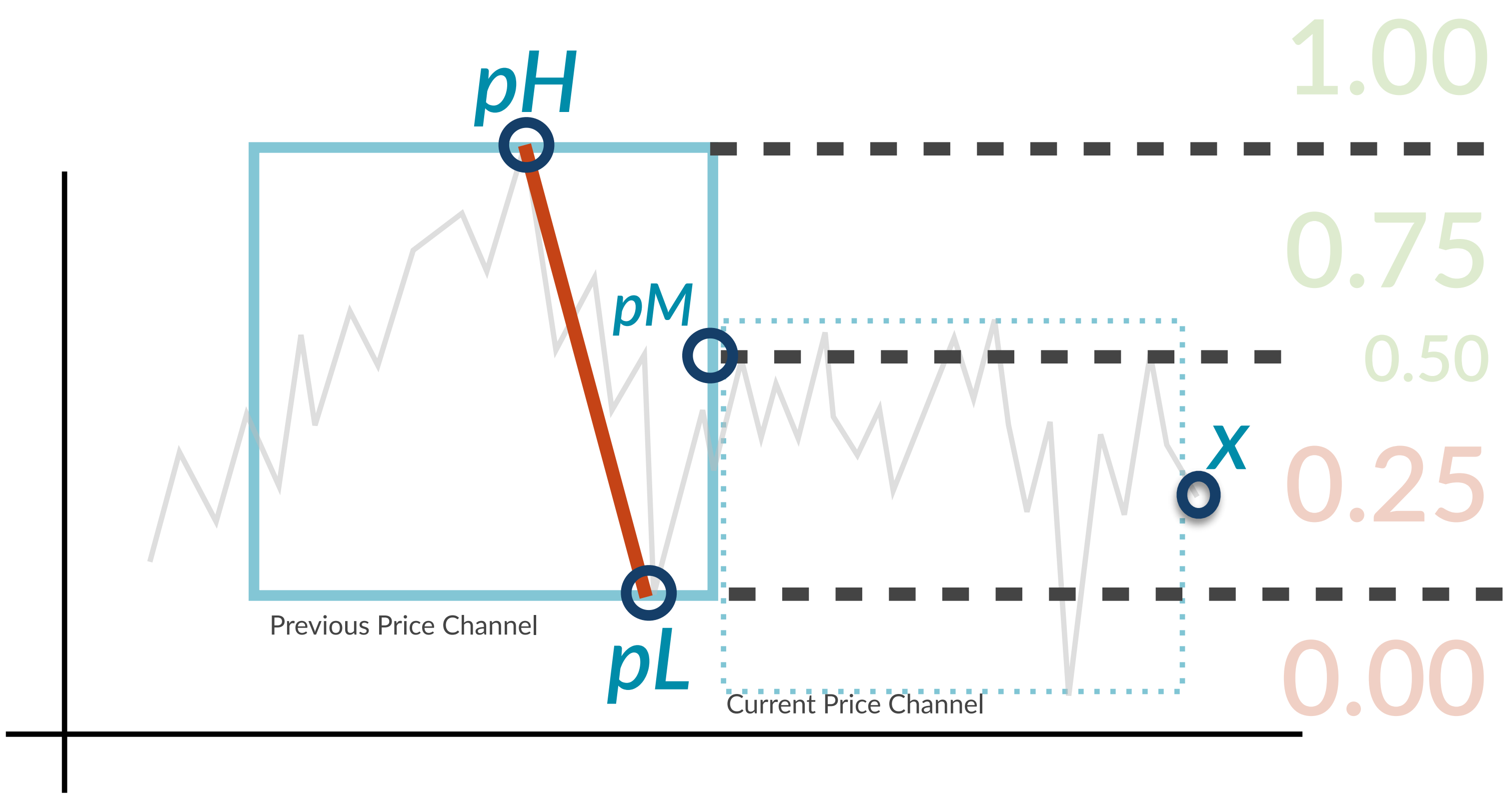
Introducing "TCFG"

a "TrendCalculus Feature Generator"

(2) Let's merge Labels with normalised Features.

What might they be?

I'm trialling a simple rolling trend indicator over all timeframes:



Rolling Trend Feature, Tz

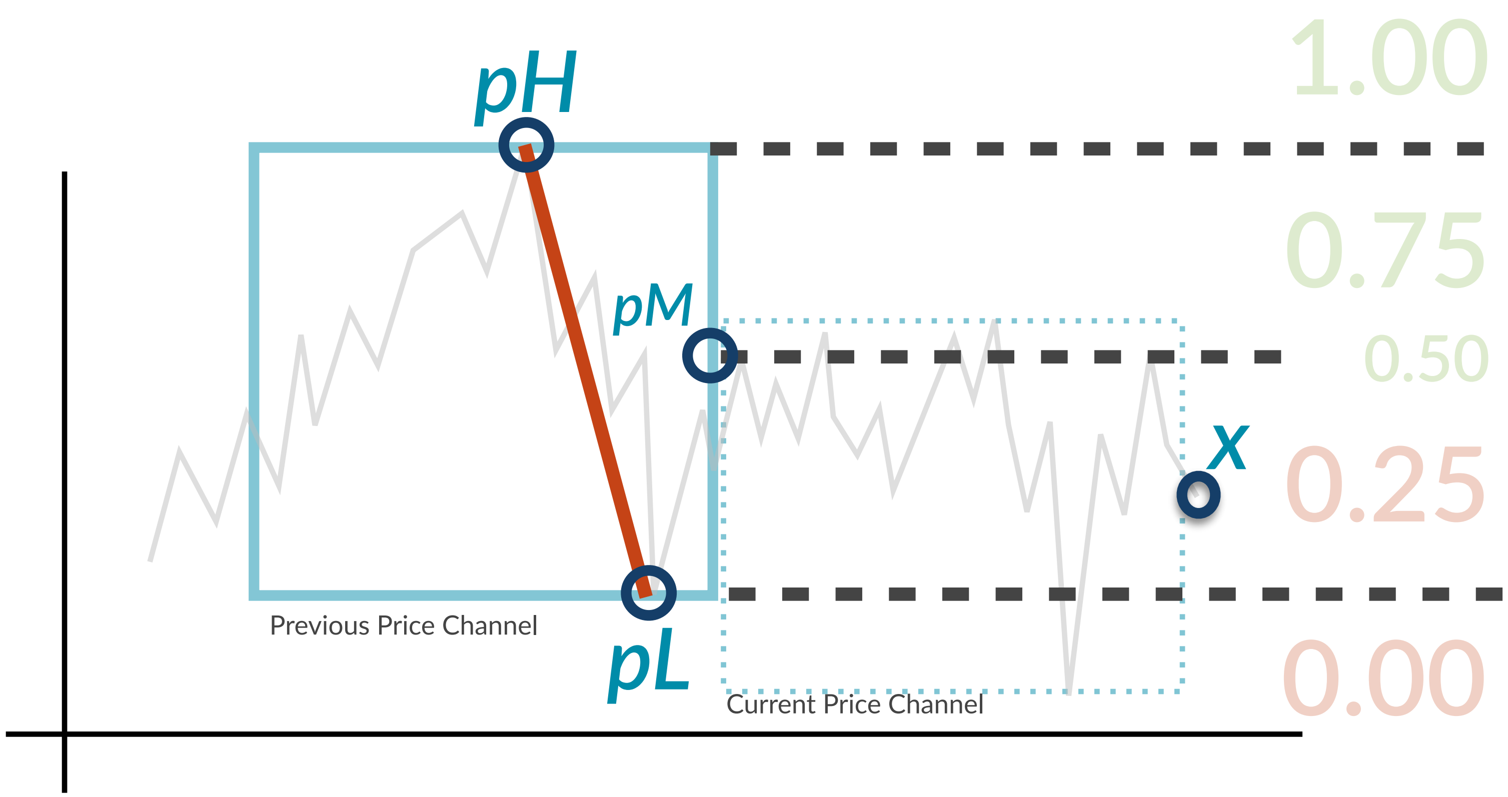
```
preTz = sign(sign(x - pH) - sign(x-pL))
# edge case
if  preTz = 0 then
      if x > pM then Tz = 0.75
      elseif x < pM then Tz = 0.5
      else Tz =0.5
end if
```

Introducing “TCFG”

Using this feature to build “Trendmaps”, I’m inspecting trends on all timeframes visually. They show Tz on ALL timeframes from 1 to N. They are generated in real time and do not have look ahead bias.

They reveal rich multi-scale trend structures.

Lets see them…



Rolling Trend Feature, Tz

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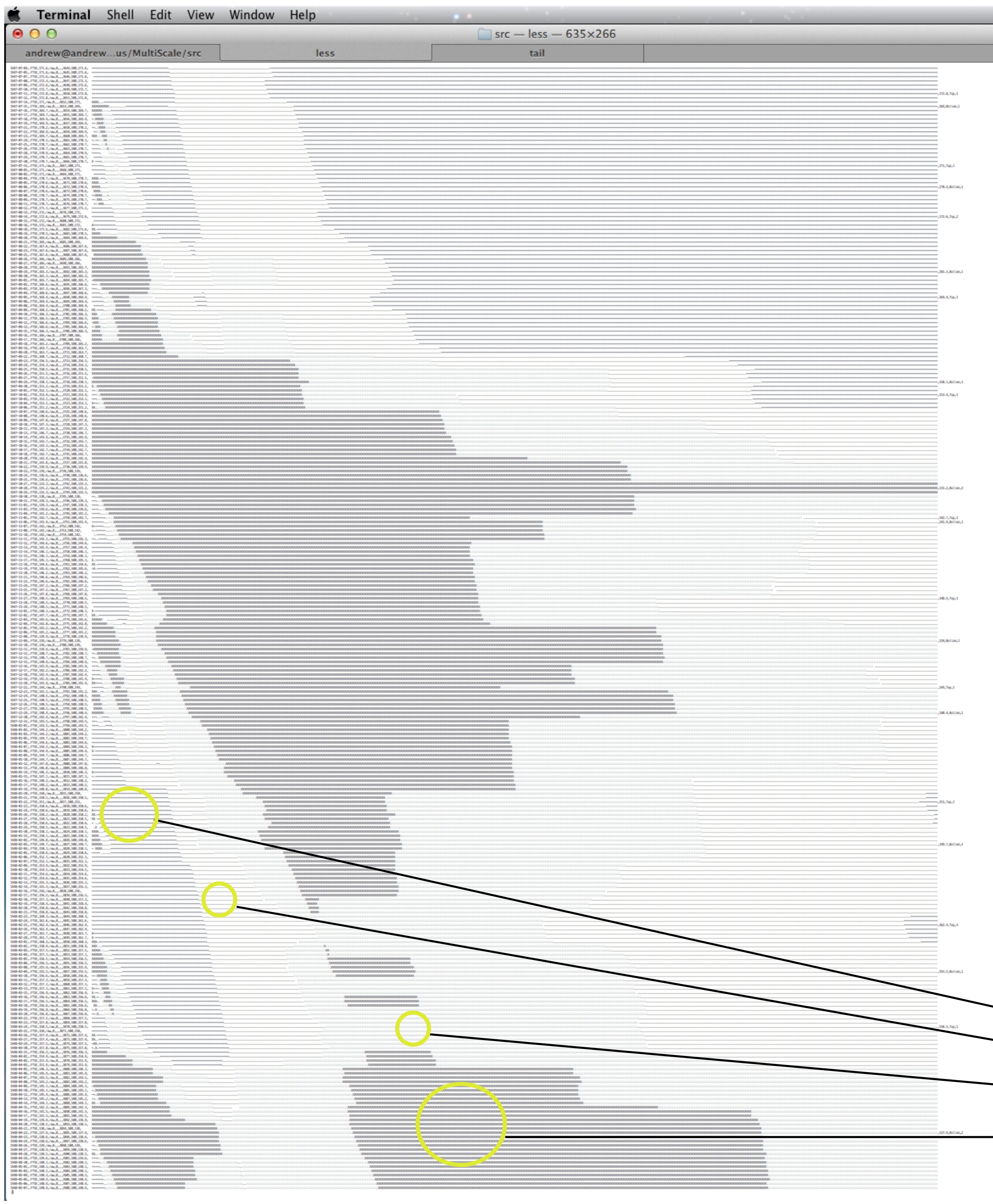
      else Tz =0.5
end if
```

“TrendMap” features



A Tz rolling trend feature is taken for all timeframes from 2 to N*multiplier.

I present Tz as symbols, for quick visualisation.
Rich structures seen across time scales / time!

Can Neural Nets learn the patterns? Cycles?
Can it learn trends and beat the lag?

Can it ignore NOISE, find true SIGNAL?

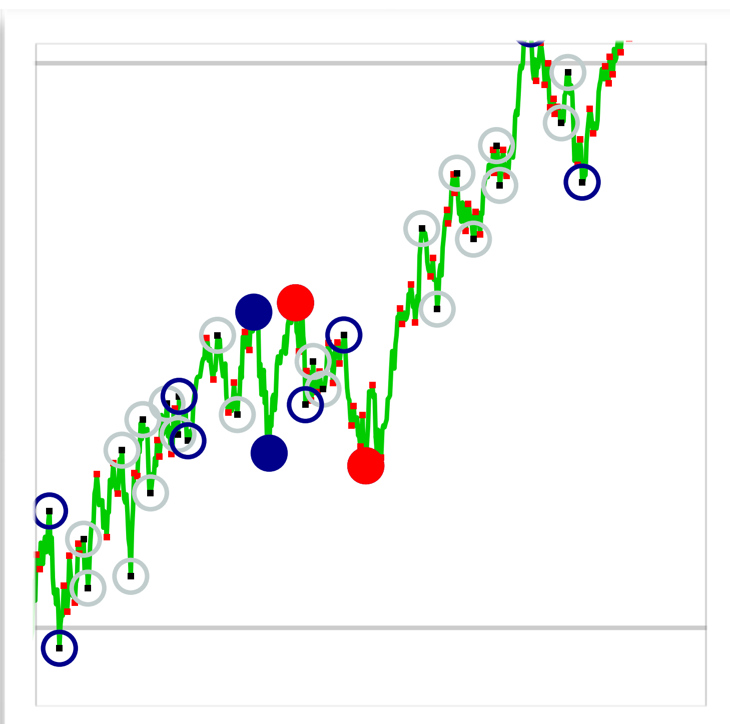
These are hard problems.
And, why the experiment is so much fun.

- * Uptrend
- . Neutral - Bullish
- : Neutral - Bearish
- # Downtrend

Experiment Approach

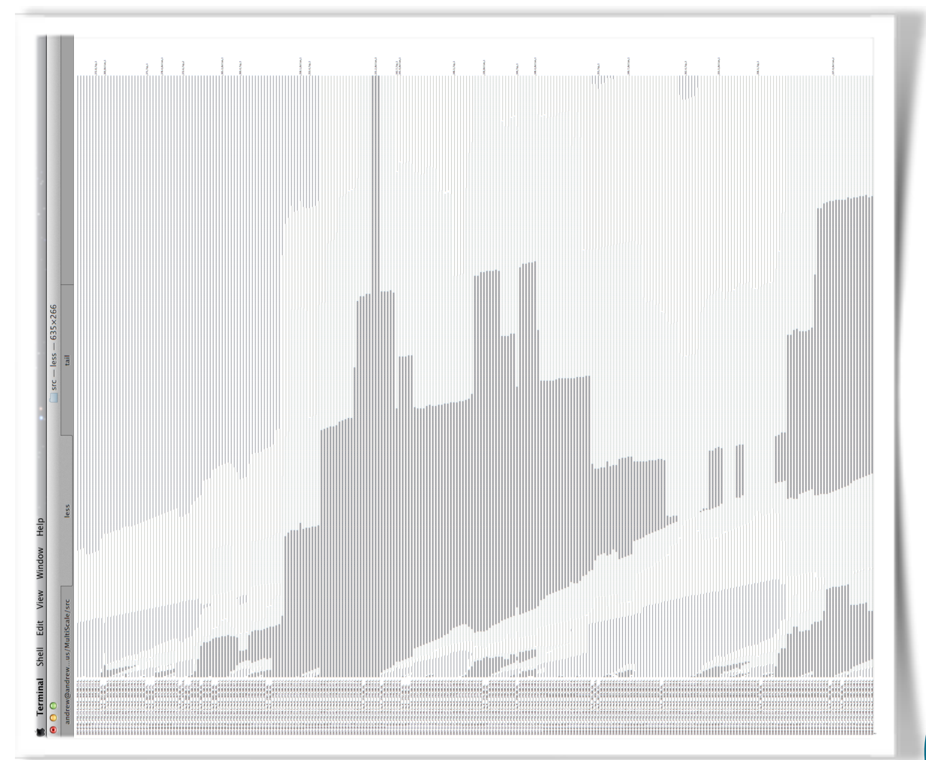
(2) Let's merge trend Labels with these trend Features.

Source of
Trend Labels



trend reversals

Source of
Trend Features

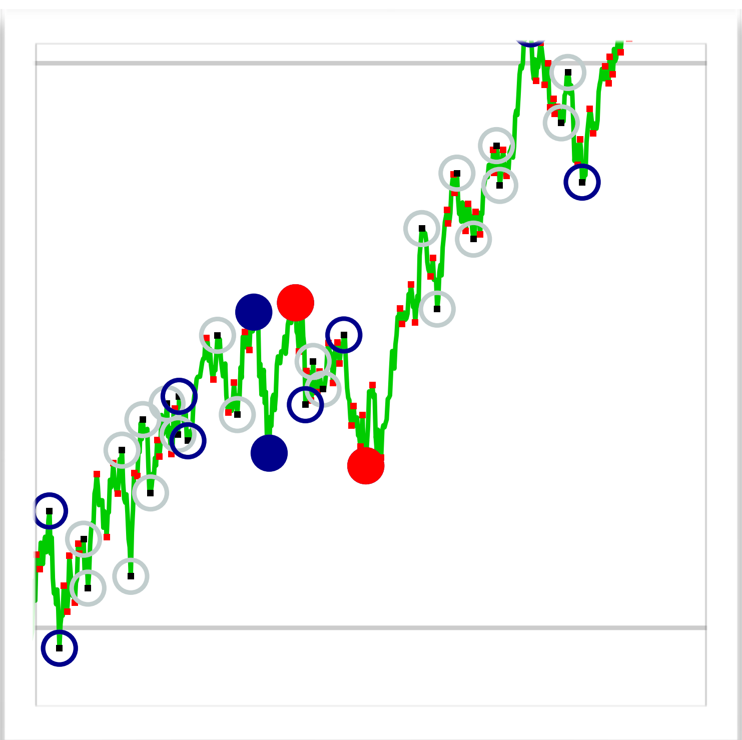


"rolling" trend features

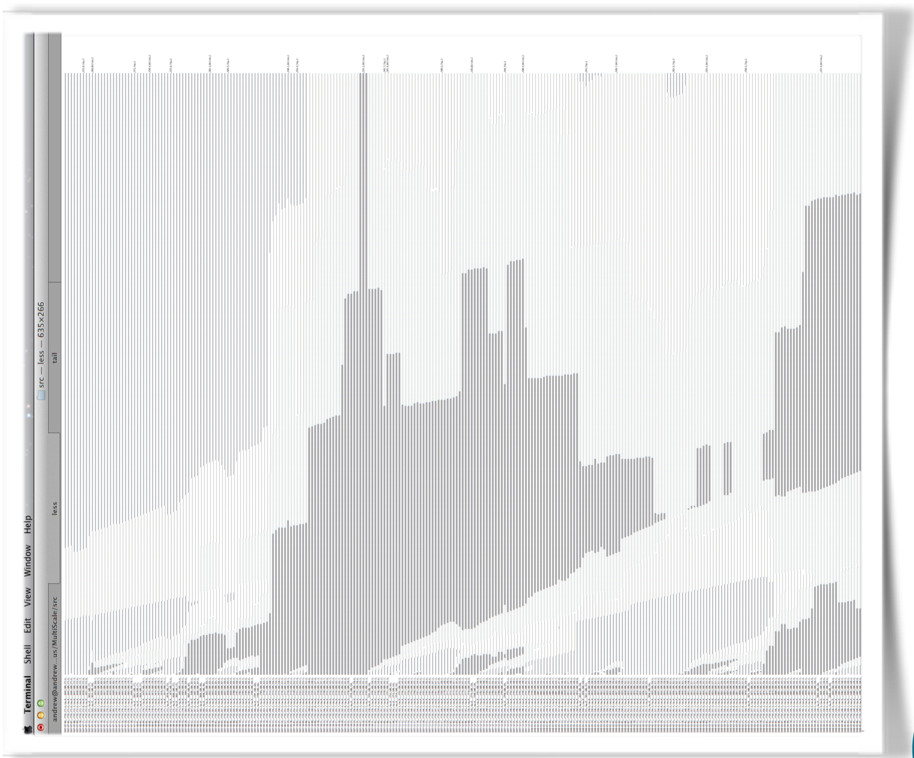
Experiment Approach

(2) Let's merge trend Labels with these trend Features.

Create a machine learning dataset this way.
Objective is to predict Trend Reversals.



trend reversals



"rolling" trend features

Experiment Approach

(2) Let's merge trend Labels with simple trend Features.

Here's an example of labelled training data:

Row	TCFG	UserDate	Value	trend	change	dummy	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12	T13	T14
1	tcfg BARC.L	1070841600000	496.0	D	-0.4613	·	0	0	0	0	0	0.2500	0.2500	0.7500	0.7500	0.7500	0.7500	0.7500	0.7500	0.7500
2	tcfg BARC.L	1070928000000	495.0	D	-0.1005	·	0	0	0	0	0	0.2500	0.2500	0.2500	0.2500	0.7500	0.7500	0.7500	0.7500	0.7500
3	tcfg BARC.L	1071014400000	487.0	D	-0.6685	·	0	0	0	0	0	0	0.2500	0.2500	0.2500	0.2500	0.2500	0.2500	0.2500	0.2500
4	tcfg BARC.L	1071100800000	479.2500	D	-0.6616	·	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	tcfg BARC.L	1071187200000	476.2500	D	-0.3032	·	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	tcfg BARC.L	1071446400000	480.2500	D	0.3969	·	1.0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	tcfg BARC.L	1071532800000	476.0	D	-0.4157	·	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	tcfg BARC.L	1071619200000	487.7500	U	0.8438	·	1.0	1.0	0.7500	0.2500	0	0	0	0	0.2500	0.2500	0.2500	0.2500	0.2500	0.2500
9	tcfg BARC.L	1071705600000	491.2500	U	0.3441	·	1.0	1.0	1.0	0.7500	0.2500	0	0	0	0	0.2500	0.2500	0.2500	0.2500	0.2500
10	tcfg BARC.L	1071792000000	494.0	U	0.2728	·	1.0	1.0	1.0	0.7500	0.7500	0.2500	0	0	0	0.2500	0.2500	0.2500	0.2500	0.2500
11	tcfg BARC.L	1072051200000	492.7500	U	-0.1258	·	1.0	1.0	1.0	1.0	0.7500	0.7500	0.2500	0	0	0	0.2500	0.2500	0.2500	0.2500
12	tcfg BARC.L	1072137600000	490.0	U	-0.2720	·	0	0.7500	1.0	1.0	0.7500	0.7500	0.2500	0.2500	0	0	0.2500	0.2500	0.2500	0.2500
13	tcfg BARC.L	1072224000000	491.2500	U	0.1269	·	0	0	1.0	1.0	1.0	0.7500	0.7500	0.2500	0.2500	0	0	0.2500	0.2500	0.2500
14	tcfg BARC.L	1072310400000	491.2500	U	0	·	1.0	0	0.7500	1.0	1.0	0.7500	0.7500	0.2500	0.2500	0.2500	0	0.2500	0.2500	0.2500
15	tcfg BARC.L	1072396800000	491.2500	U	0	·	0.5000	0.2500	0	0.7500	1.0	1.0	0.7500	0.7500	0.2500	0.2500	0.2500	0	0.2500	0.2500
16	tcfg BARC.L	1072656000000	493.0	U	0.1763	·	1.0	1.0	0.7500	0.7500	0.7500	1.0	0.7500	0.7500	0.7500	0.2500	0.2500	0.2500	0.2500	0.2500
17	tcfg BARC.L	1072742400000	496.2500	U	0.3182	·	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.7500	0.7500	0.7500	0.5000	0.2500	0.2500
18	tcfg BARC.L	1072828800000	498.2500	U	0.1988	·	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.7500	0.7500	0.7500	0.7500	0.7500	0.2500
19	tcfg BARC.L	1072915200000	498.2500	U	0	·	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.7500	0.7500	0.7500	0.7500	0.7500
20	tcfg BARC.L	1073001600000	504.0	U	0.5205	·	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.7500	0.7500	0.7500	0.7500
21	tcfg BARC.L	1073260800000	506.0	U	0.1958	·	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.7500	0.7500	0.7500
22	tcfg BARC.L	1073347200000	513.0	U	0.5991	·	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.7500	0.7500
23	tcfg BARC.L	1073433600000	510.7500	U	-0.2158	·	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.7500
24	tcfg BARC.L	1073520000000	510.5000	U	-0.0245	·	0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.7500
25	tcfg BARC.L	1073606400000	514.0	U	0.3300	·	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
26	tcfg BARC.L	1073865600000	508.5000	U	-0.4892	·	0	0	0.5000	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
27	tcfg BARC.L	1073952000000	511.2500	U	0.2640	·	0	1.0	0.7500	0.7500	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
28	tcfg BARC.L	1074038400000	521.5000	U	0.7626	·	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
29	tcfg BARC.L	1074124800000	527.7500	U	0.5365	·	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
30	tcfg BARC.L	1074211200000	536.0	U	0.6536	·	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
31	tcfg BARC.L	1074470400000	530.7500	D	-0.4540	·	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
32	tcfg BARC.L	1074556800000	520.7500	D	-0.7362	·	0	0	0.7500	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
33	tcfg BARC.L	1074643200000	517.5000	D	-0.3023	·	0	0	0.2500	0.7500	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
34	tcfg BARC.L	1074729600000	517.0	D	-0.0483	·	0	0	0	0.2500	0.7500	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
35	tcfg BARC.L	1074816000000	507.5000	D	-0.7253	·	0	0	0	0	0	0	0.2500	0.7500	0.7500	0.7500	0.7500	0.7500	1.0	1.0
36	tcfg BARC.L	1075075200000	508.0	D	0.0492	·	0	0	0	0	0	0	0	0.2500	0.7500	0.7500	0.7500	0.7500	0.7500	1.0
37	tcfg BARC.L	1075161600000	500.0	D	-0.6569	·	0	0	0	0	0	0	0	0	0.2500	0.2500	0.2500	0.2500	0.2500	0.2500
38	tcfg BARC.L	1075248000000	511.0	D	0.8005	·	1.0	0.2500	0	0	0	0.2500	0.2500	0.2500	0.2500	0.7500	0.7500	0.7500	0.7500	0.7500

Experiment Approach

(2) Let’s merge trend Labels with trend Features.

Row	TCFG	UserDate	Value	trend	change	dummy	T1	T2	T3											
1	tcfg BARC.L	1070841600000	496.0	D	-0.4613	·	0	0	0											
2	tcfg BARC.L	1070928000000	495.0	D	-0.1005	·	0	0	0											
3	tcfg BARC.L	1071014400000	487.0	D	-0.6685	·	0	0	0											
4	tcfg BARC.L	1071100800000	479.2500	D	-0.6616	·	0	0	0											
5	tcfg BARC.L	1071187200000	476.2500	D	-0.3032	·	0	0	0											
6	tcfg BARC.L	1071446400000	480.2500	D	0.3969	·	1.0	0	0											
7	tcfg BARC.L	1071532800000	476.0	D	-0.4157	·	0	0	0											
8	tcfg BARC.L	1071619200000	487.7500	U	0.8438	·	1.0	1.0	0.7500	0.25										
9	tcfg BARC.L	1071705600000	491.2500	U	0.3441	·	1.0	1.0	1.0	0.75										
10	tcfg BARC.L	1071792000000	494.0	U	0.2728	·	1.0	1.0	1.0	0.75										
11	tcfg BARC.L	1072051200000	492.7500	U	-0.1258	·	1.0	1.0	1.0	1										
12	tcfg BARC.L	1072137600000	490.0	U	-0.2720	·	0	0.7500	1.0	1										
13	tcfg BARC.L	1072224000000	491.2500	U	0.1269	·	0	0	1.0	1										
14	tcfg BARC.L	1072310400000	491.2500	U	0	·	1.0	0	0.7500	1										
15	tcfg BARC.L	1072396800000	491.2500	U	0	·	0.5000	0.2500	0	0.75										
16	tcfg BARC.L	1072656000000	493.0	U	0.1763	·	1.0	1.0	0.7500	0.75										
17	tcfg BARC.L	1072742400000	496.2500	U	0.3182	·	1.0	1.0	1.0	1										
18	tcfg BARC.L	1072828800000	498.2500	U	0.1988	·	1.0	1.0	1.0	1										
19	tcfg BARC.L	1072915200000	498.2500	U	0	·	1.0	1.0	1.0	1										
20	tcfg BARC.L	1073001600000	504.0	U	0.5205	·	1.0	1.0	1.0	1										
21	tcfg BARC.L	1073260800000	506.0	U	0.1958	·	1.0	1.0	1.0	1										
22	tcfg BARC.L	1073347200000	513.0	U	0.5991	·	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.7500	0.7500
23	tcfg BARC.L	1073433600000	510.7500	U	-0.2158	·	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.7500
24	tcfg BARC.L	1073520000000	510.5000	U	-0.0245	·	0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.7500
25	tcfg BARC.L	1073606400000	514.0	U	0.3300	·	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
26	tcfg BARC.L	1073865600000	508.5000	U	-0.4892	·	0	0	0.5000	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
27	tcfg BARC.L	1073952000000	511.2500	U	0.2640	·	0	1.0	0.7500	0.7500	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
28	tcfg BARC.L	1074038400000	521.5000	U	0.7626	·	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
29	tcfg BARC.L	1074124800000	527.7500	U	0.5365	·	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
30	tcfg BARC.L	1074211200000	536.0	U	0.6536	·	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
31	tcfg BARC.L	1074470400000	530.7500	D	-0.4540	·	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
32	tcfg BARC.L	1074556800000	520.7500	D	-0.7362	·	0	0	0.7500	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
33	tcfg BARC.L	1074643200000	517.5000	D	-0.3023	·	0	0	0.2500	0.7500	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
34	tcfg BARC.L	1074729600000	517.0	D	-0.0483	·	0	0	0	0.2500	0.7500	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
35	tcfg BARC.L	1074816000000	507.5000	D	-0.7253	·	0	0	0	0	0	0	0.2500	0.7500	0.7500	0.7500	0.7500	0.7500	1.0	1.0
36	tcfg BARC.L	1075075200000	508.0	D	0.0492	·	0	0	0	0	0	0	0	0.2500	0.7500	0.7500	0.7500	0.7500	0.7500	1.0
37	tcfg BARC.L	1075161600000	500.0	D	-0.6569	·	0	0	0	0	0	0	0	0	0.2500	0.2500	0.2500	0.2500	0.2500	0.2500
38	tcfg BARC.L	1075248000000	511.0	D	0.8005	·	1.0	0.2500	0	0	0	0.2500	0.2500	0.2500	0.2500	0.7500	0.7500	0.7500	0.7500	0.7500

Value	trend	change	dummy	T1	T2	T3	
496.0	D	-0.4613	·	0	0	0	
495.0	D	-0.1005	·	0	0	0	
487.0	D	-0.6685	·	0	0	0	
479.2500	D	-0.6616	·	0	0	0	
476.2500	D	-0.3032	·	0	0	0	
480.2500	D	0.3969	·	1.0	0	0	
476.0	D	-0.4157	·	0	0	0	
487.7500	U	0.8438	·	1.0	1.0	0.7500	0.
491.2500	U	0.3441	·	1.0	1.0	1.0	0.
494.0	U	0.2728	·	1.0	1.0	1.0	0.
492.7500	U	-0.1258	·	1.0	1.0	1.0	
490.0	U	-0.2720	·	0	0.7500	1.0	

Experiment Approach

(2) Let's merge trend Labels with trend Features.

“30day Trend” Labels [Up, Down]

Row	TCFG	UserDate	Value	trend	change	dummy	T1	T2	T3											
1	tcfg BARC.L	1070841600000	496.0	D	-0.4613	·	0	0	0											
2	tcfg BARC.L	1070928000000	495.0	D	-0.1005	·	0	0	0											
3	tcfg BARC.L	1071014400000	487.0	D	-0.6685	·	0	0	0											
4	tcfg BARC.L	1071100800000	479.2500	D	-0.6616	·	0	0	0											
5	tcfg BARC.L	1071187200000	476.2500	D	-0.3032	·	0	0	0											
6	tcfg BARC.L	1071446400000	480.2500	D	0.3969	·	1.0	0	0											
7	tcfg BARC.L	1071532800000	476.0	D	-0.4157	·	0	0	0											
8	tcfg BARC.L	1071619200000	487.7500	U	0.8438	·	1.0	1.0	0.7500	0.25										
9	tcfg BARC.L	1071705600000	491.2500	U	0.3441	·	1.0	1.0	1.0	0.75										
10	tcfg BARC.L	1071792000000	494.0	U	0.2728	·	1.0	1.0	1.0	0.75										
11	tcfg BARC.L	1072051200000	492.7500	U	-0.1258	·	1.0	1.0	1.0	1										
12	tcfg BARC.L	1072137600000	490.0	U	-0.2720	·	0	0.7500	1.0	1										
13	tcfg BARC.L	1072224000000	491.2500	U	0.1269	·	0	0	1.0	1										
14	tcfg BARC.L	1072310400000	491.2500	U	0	·	1.0	0	0.7500	1										
15	tcfg BARC.L	1072396800000	491.2500	U	0	·	0.5000	0.2500	0	0.75										
16	tcfg BARC.L	1072656000000	493.0	U	0.1763	·	1.0	1.0	0.7500	0.75										
17	tcfg BARC.L	1072742400000	496.2500	U	0.3182	·	1.0	1.0	1.0	1										
18	tcfg BARC.L	1072828800000	498.2500	U	0.1988	·	1.0	1.0	1.0	1										
19	tcfg BARC.L	1072915200000	498.2500	U	0	·	1.0	1.0	1.0	1										
20	tcfg BARC.L	1073001600000	504.0	U	0.5205	·	1.0	1.0	1.0	1										
21	tcfg BARC.L	1073260800000	506.0	U	0.1958	·	1.0	1.0	1.0	1										
22	tcfg BARC.L	1073347200000	513.0	U	0.5991	·	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.7500	0.7500
23	tcfg BARC.L	1073433600000	510.7500	U	-0.2158	·	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.7500
24	tcfg BARC.L	1073520000000	510.5000	U	-0.0245	·	0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.7500
25	tcfg BARC.L	1073606400000	514.0	U	0.3300	·	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
26	tcfg BARC.L	1073865600000	508.5000	U	-0.4892	·	0	0	0.5000	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
27	tcfg BARC.L	1073952000000	511.2500	U	0.2640	·	0	1.0	0.7500	0.7500	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
28	tcfg BARC.L	1074038400000	521.5000	U	0.7626	·	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
29	tcfg BARC.L	1074124800000	527.7500	U	0.5365	·	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
30	tcfg BARC.L	1074211200000	536.0	U	0.6536	·	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
31	tcfg BARC.L	1074470400000	530.7500	D	-0.4540	·	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
32	tcfg BARC.L	1074556800000	520.7500	D	-0.7362	·	0	0	0.7500	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
33	tcfg BARC.L	1074643200000	517.5000	D	-0.3023	·	0	0	0.2500	0.7500	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
34	tcfg BARC.L	1074729600000	517.0	D	-0.0483	·	0	0	0	0.2500	0.7500	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
35	tcfg BARC.L	1074816000000	507.5000	D	-0.7253	·	0	0	0	0	0	0	0.2500	0.7500	0.7500	0.7500	0.7500	0.7500	1.0	1.0
36	tcfg BARC.L	1075075200000	508.0	D	0.0492	·	0	0	0	0	0	0	0	0.2500	0.7500	0.7500	0.7500	0.7500	0.7500	1.0
37	tcfg BARC.L	1075161600000	500.0	D	-0.6569	·	0	0	0	0	0	0	0	0	0.2500	0.2500	0.2500	0.2500	0.2500	0.2500
38	tcfg BARC.L	1075248000000	511.0	D	0.8005	·	1.0	0.2500	0	0	0	0.2500	0.2500	0.2500	0.2500	0.7500	0.7500	0.7500	0.7500	0.7500

Value	trend	change	dummy	T1	T2	T3	
496.0	D	-0.4613	·	0	0	0	
495.0	D	-0.1005	·	0	0	0	
487.0	D	-0.6685	·	0	0	0	
479.2500	D	-0.6616	·	0	0	0	
476.2500	D	-0.3032	·	0	0	0	
480.2500	D	0.3969	·	1.0	0	0	
476.0	D	-0.4157	·	0	0	0	
487.7500	U	0.8438	·	1.0	1.0	0.7500	0.
491.2500	U	0.3441	·	1.0	1.0	1.0	0.
494.0	U	0.2728	·	1.0	1.0	1.0	0.
492.7500	U	-0.1258	·	1.0	1.0	1.0	
490.0	U	-0.2720	·	0	0.7500	1.0	

Experiment Approach

(2) Let's merge trend Labels with trend Features.

Tz Trend Features

Value	trend	change	dummy	T1	T2	T3
496.0	D	-0.4613	·	0	0	0
495.0	D	-0.1005	·	0	0	0
487.0	D	-0.6685	·	0	0	0
479.2500	D	-0.6616	·	0	0	0
476.2500	D	-0.3032	·	0	0	0
480.2500	D	0.3969	·	1.0	0	0
476.0	D	-0.4157	·	0	0	0
487.7500	U	0.8438	·	1.0	1.0	0.7500
491.2500	U	0.3441	·	1.0	1.0	1.0
494.0	U	0.2728	·	1.0	1.0	1.0
492.7500	U	-0.1258	·	1.0	1.0	1.0
490.0	U	-0.2720	·	0	0.7500	1.0

Row	TCFG	UserDate	Value	trend	change	dummy	T1	T2	T3											
1	tcfg BARC.L	1070841600000	496.0	D	-0.4613	·	0	0	0											
2	tcfg BARC.L	1070928000000	495.0	D	-0.1005	·	0	0	0											
3	tcfg BARC.L	1071014400000	487.0	D	-0.6685	·	0	0	0											
4	tcfg BARC.L	1071100800000	479.2500	D	-0.6616	·	0	0	0											
5	tcfg BARC.L	1071187200000	476.2500	D	-0.3032	·	0	0	0											
6	tcfg BARC.L	1071446400000	480.2500	D	0.3969	·	1.0	0	0											
7	tcfg BARC.L	1071532800000	476.0	D	-0.4157	·	0	0	0											
8	tcfg BARC.L	1071619200000	487.7500	U	0.8438	·	1.0	1.0	0.7500	0.25										
9	tcfg BARC.L	1071705600000	491.2500	U	0.3441	·	1.0	1.0	1.0	0.75										
10	tcfg BARC.L	1071792000000	494.0	U	0.2728	·	1.0	1.0	1.0	0.75										
11	tcfg BARC.L	1072051200000	492.7500	U	-0.1258	·	1.0	1.0	1.0	1										
12	tcfg BARC.L	1072137600000	490.0	U	-0.2720	·	0	0.7500	1.0	1										
13	tcfg BARC.L	1072224000000	491.2500	U	0.1269	·	0	0	1.0	1										
14	tcfg BARC.L	1072310400000	491.2500	U	0	·	1.0	0	0.7500	1										
15	tcfg BARC.L	1072396800000	491.2500	U	0	·	0.5000	0.2500	0	0.75										
16	tcfg BARC.L	1072656000000	493.0	U	0.1763	·	1.0	1.0	0.7500	0.75										
17	tcfg BARC.L	1072742400000	496.2500	U	0.3182	·	1.0	1.0	1.0	1										
18	tcfg BARC.L	1072828800000	498.2500	U	0.1988	·	1.0	1.0	1.0	1										
19	tcfg BARC.L	1072915200000	498.2500	U	0	·	1.0	1.0	1.0	1										
20	tcfg BARC.L	1073001600000	504.0	U	0.5205	·	1.0	1.0	1.0	1										
21	tcfg BARC.L	1073260800000	506.0	U	0.1958	·	1.0	1.0	1.0	1										
22	tcfg BARC.L	1073347200000	513.0	U	0.5991	·	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.7500	0.7500
23	tcfg BARC.L	1073433600000	510.7500	U	-0.2158	·	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.7500
24	tcfg BARC.L	1073520000000	510.5000	U	-0.0245	·	0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.7500
25	tcfg BARC.L	1073606400000	514.0	U	0.3300	·	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
26	tcfg BARC.L	1073865600000	508.5000	U	-0.4892	·	0	0	0.5000	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
27	tcfg BARC.L	1073952000000	511.2500	U	0.2640	·	0	1.0	0.7500	0.7500	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
28	tcfg BARC.L	1074038400000	521.5000	U	0.7626	·	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
29	tcfg BARC.L	1074124800000	527.7500	U	0.5365	·	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
30	tcfg BARC.L	1074211200000	536.0	U	0.6536	·	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
31	tcfg BARC.L	1074470400000	530.7500	D	-0.4540	·	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
32	tcfg BARC.L	1074556800000	520.7500	D	-0.7362	·	0	0	0.7500	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
33	tcfg BARC.L	1074643200000	517.5000	D	-0.3023	·	0	0	0.2500	0.7500	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
34	tcfg BARC.L	1074729600000	517.0	D	-0.0483	·	0	0	0	0.2500	0.7500	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
35	tcfg BARC.L	1074816000000	507.5000	D	-0.7253	·	0	0	0	0	0	0	0.2500	0.7500	0.7500	0.7500	0.7500	0.7500	1.0	1.0
36	tcfg BARC.L	1075075200000	508.0	D	0.0492	·	0	0	0	0	0	0	0	0.2500	0.7500	0.7500	0.7500	0.7500	0.7500	1.0
37	tcfg BARC.L	1075161600000	500.0	D	-0.6569	·	0	0	0	0	0	0	0	0	0.2500	0.2500	0.2500	0.2500	0.2500	0.2500
38	tcfg BARC.L	1075248000000	511.0	D	0.8005	·	1.0	0.2500	0	0	0	0.2500	0.2500	0.2500	0.2500	0.7500	0.7500	0.7500	0.7500	0.7500

ML Experiments tried:

Non-Temporal Models

1. Gradient Boosted Trees
2. Random Forest
3. Feed Forward Neural Nets

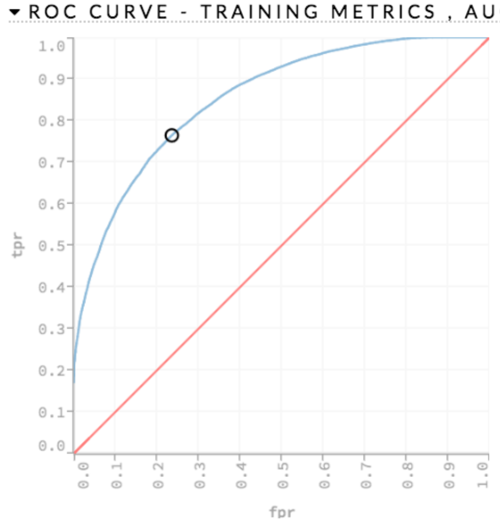
Temporal Models

a. LSTM Recurrent Neural Nets
b. Echo State Machines

Experiment Results:

Gradient Boosted Trees: AUC = 0.837767

ROC CURVE - TRAINING METRICS , AUC = 0.854982



Selected mark(s):

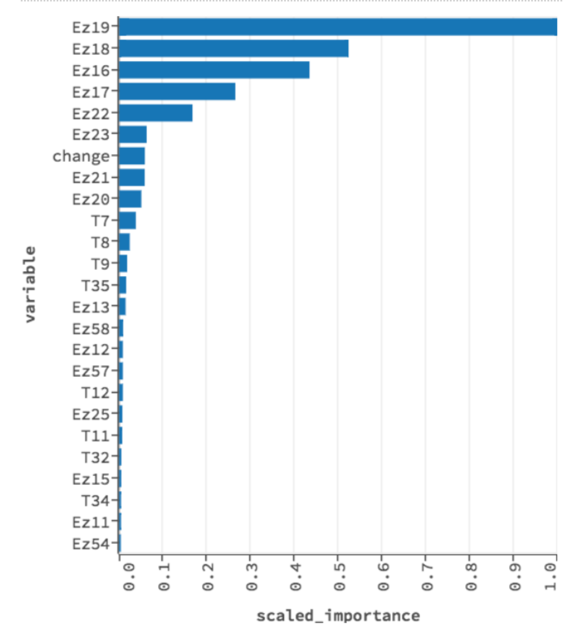
threshold	0.5775
f1	0.7643
f2	0.7643
f0point5	0.7642
accuracy	0.7643
precision	0.7642
absolute_MCC	0.5287
min_per_class_accuracy	0.7643
tns	51138
fns	15754
fps	15770
tps	51109
tnr	0.7643
fnr	0.2356
fpr	0.2357
tpr	0.7644
idx	179

CM	51138	15770
	15754	51109

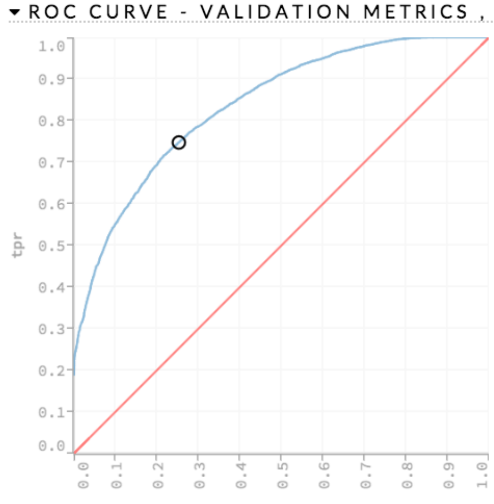
Threshold: 0.5775345625648151

Criterion: max min_per_class_accuracy

VARIABLE IMPORTANCES



ROC CURVE - VALIDATION METRICS , AUC = 0.837767



Selected mark(s):

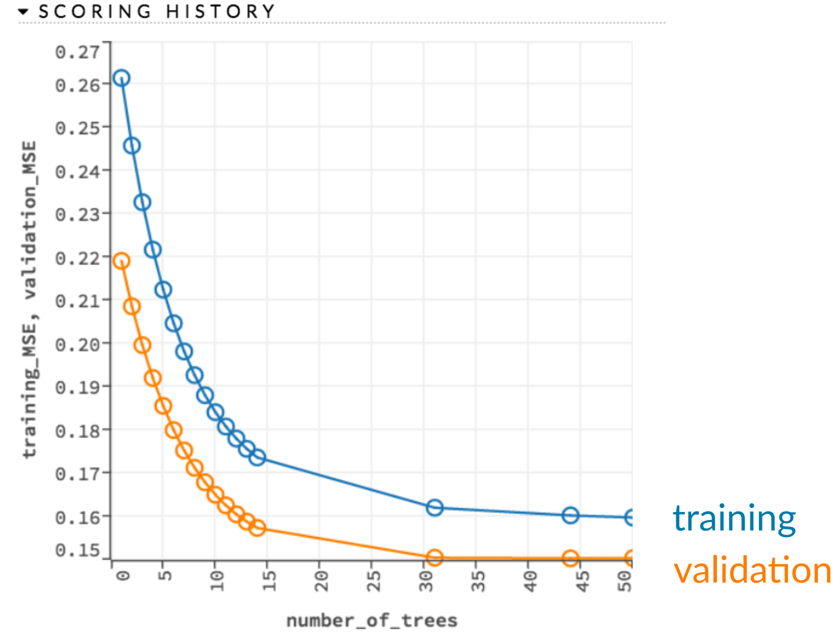
threshold	0.6692
f1	0.7963
f2	0.7662
f0point5	0.8289
accuracy	0.7472
precision	0.8521
absolute_MCC	0.4741
min_per_class_accuracy	0.7470
tns	4095
fns	2701
fps	1387
tps	7991
tnr	0.7470
fnr	0.2526
fpr	0.2530
tpr	0.7474
idx	164

CM	4095	1387
	2701	7991

Threshold: 0.669218899873452

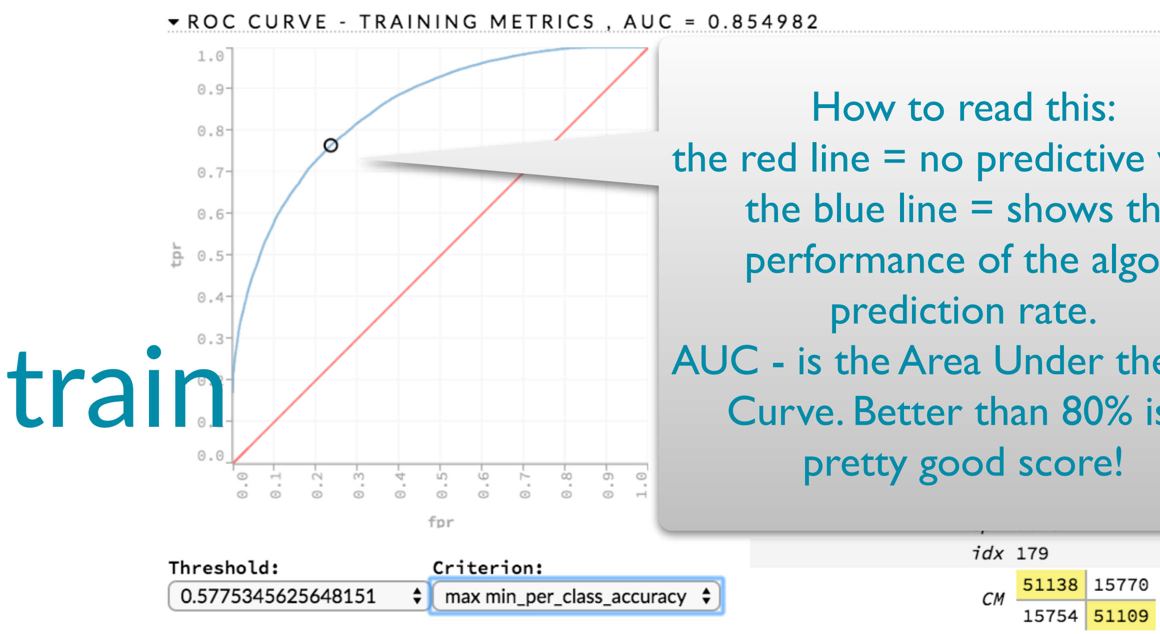
Criterion: max min_per_class_accuracy

SCORING HISTORY

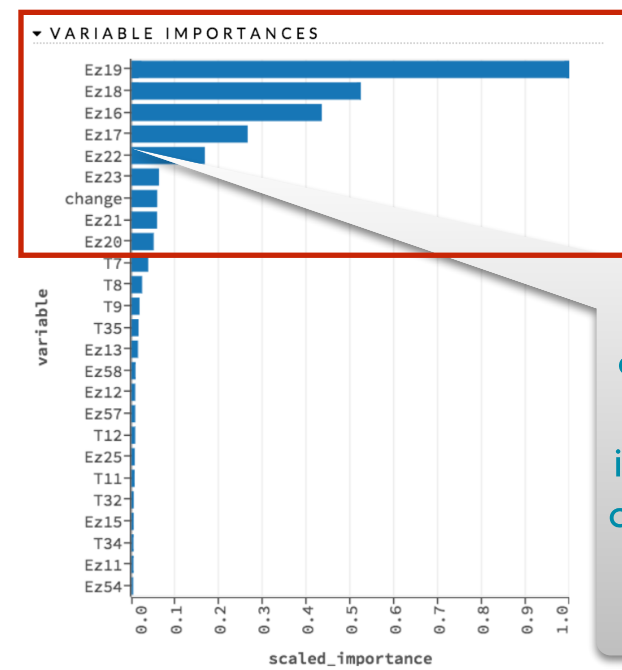


Experiment Results:

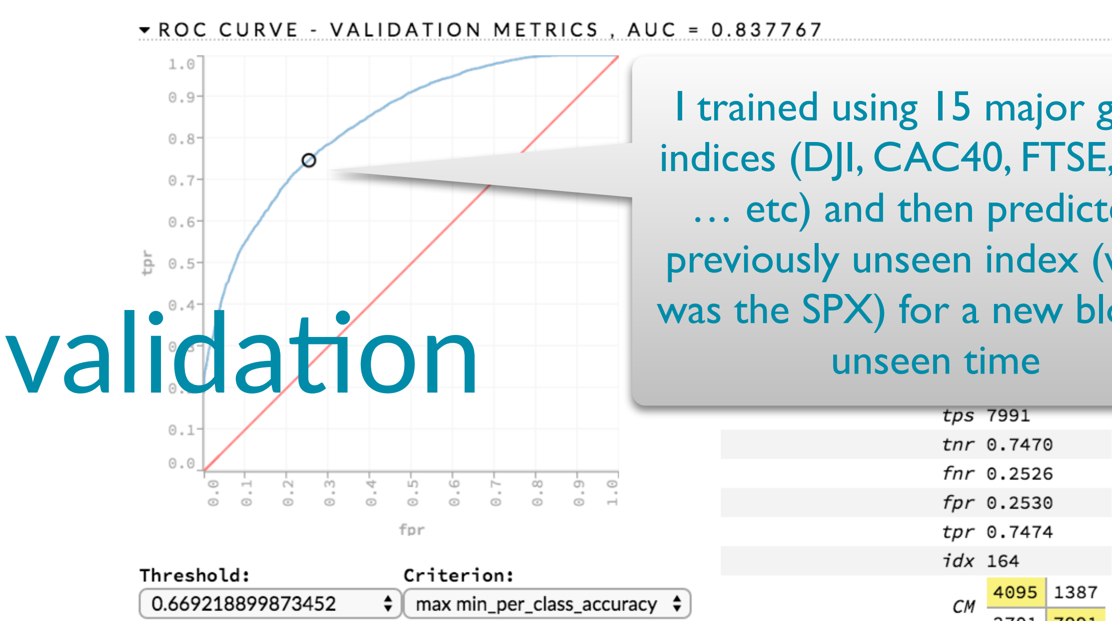
Gradient Boosted Trees: AUC = 0.837767



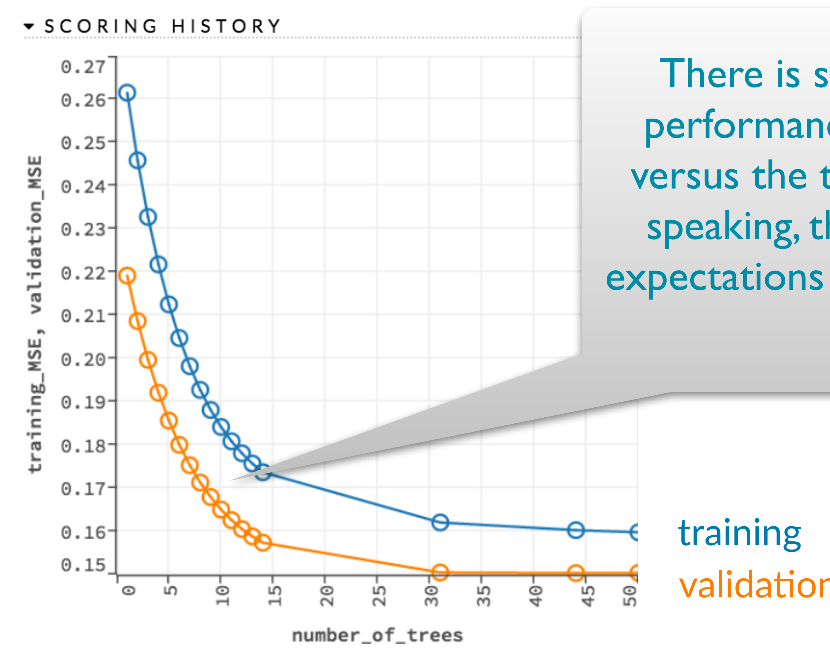
How to read this:
the red line = no predictive value.
the blue line = shows the performance of the algo's prediction rate.
AUC - is the Area Under the blue Curve. Better than 80% is a pretty good score!



I am testing another bespoke feature over my raw trend maps, that I call Ez, not described here. It significantly improved ML over Tz alone & strongly outperforms the raw Tz trend features. 16 - 23 day timeframes drive how the model predicts 30 day trends.



I trained using 15 major global indices (DJI, CAC40, FTSE, DAX … etc) and then predicted a previously unseen index (which was the SPX) for a new block of unseen time



There is still a gap between the performance on the training data versus the test data - but generally speaking, the approach exceeded expectations and the experiment was a success.

What are my other results?

The results so far are pretty good, but there's lots to do:

Major point of learning:

My "temporal features" trained **non-temporal** algorithms!

To Do: I should generate Sharpe Ratios to evaluate performance properly, which is still to do.

I tested out some other algorithms too, including:

Non-Temporal Models

1. Gradient Boosted Trees — AUC 0.8377 - best score
2. Random Forest — *(slightly worse than GBT, but didn't grid search much)*
3. Feed Forward Neural Nets — AUC 0.7803 *(perhaps my poor tuning? Needs rerunning)*

Temporal Models - unfinished work in progress

a. LSTM Recurrent Neural Nets — (see my github for Torch7 code - basic coding done)
b. Echo State Machines — (i did this too, it's an amazing story, for later)

Next Steps. As these tests were all done 2 years ago, I should refactor to latest Keras + Tensorflow, formalise the methods, results evaluation, and documentation.

Next steps

The results so far are pretty good, but there's lots to do.

For example, I developed a trend feature that has *really* improved the quality of the predictions beyond what I've described here … so lots of things to try out including more advanced feature building.

The future: as public interest in RNNs catches up with me, some great new RNN methods coming available outside of Torch7 which could be helpful.

Note: My torch7 code for my LSTM experiments is now online here:
https://github.com/bytesumo/LSTM-Experiments

Summary

My experiments have much to do with a new way of thinking about trends in time series and how we learn about them.

I'm proposing through my work that trends in society and economics exists, irrespective of their measurement.

How we sense these, and build methods to understand them, is a challenge we've not yet tackled well.

My experiments demonstrate the research is fruitful, and full of new ground to explore.

Co-Trending

Taking things even further.

New Directions

So far we have examined a single Time Series on its own.

But - there are lots of time series. Billions of them?

How do we look at co-trending across these series?

How might we better predict, through understanding co-trending, and potentially do causation discovery?

We are moving into a new area, the study of Causality Discovery through the lens of Co-trending.

What is co-trending?

Trend reversals define *time periods*, on a time scale, having a consistent “trend” - a tendency up or down.

Trends can thus be viewed as a partitioning of time. Turning points, when trends change, are important.

Co-trending - is when times series “tend” to change their trend directions, in concert.

A +1+1+1+1+1 -1-1-1 +1+1+1+1+1+1+1+1+1+1+1 -1-1-1 +1+1+1+1+1+1

B +1+1+1+1+1 -1-1-1-1 +1+1+1+1+1+1+1+1+1+1 -1-1-1 +1+1+1+1+1+1

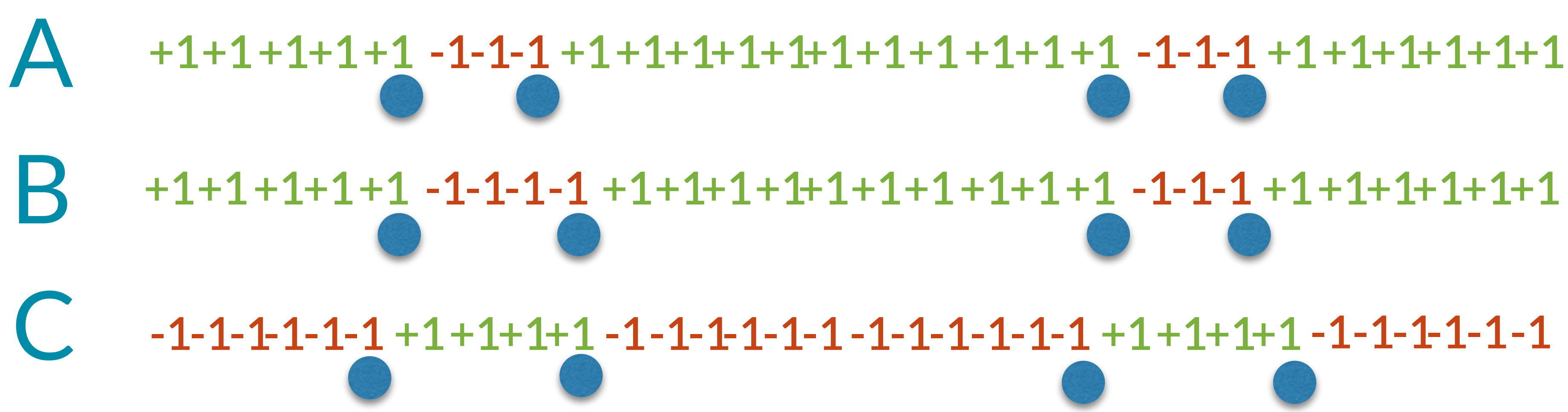
C -1-1-1-1-1-1 +1+1+1+1 -1-1-1-1-1-1 -1-1-1-1-1-1 +1+1+1+1 -1-1-1-1-1-1

What is co-trending?

Distance metrics are an obvious approach to finding similarity - and several methods exist.

But what about finding leading indicators?

For prediction, we need methods for finding these.



Process discovery?

If we consider “leading indicator discovery” as a **process discovery task**, that could be useful too.

It would seek to discover “unseen process couplings” of trend effects seen across our time series, to suggest relations between trends (rather than shock propagation)

A +1+1+1+1+1 -1-1-1 +1+1+1+1+1+1+1+1+1+1+1 -1-1-1 +1+1+1+1+1+1

B +1+1+1+1+1 -1-1-1-1 +1+1+1+1+1+1+1+1+1+1 -1-1-1 +1+1+1+1+1+1

C -1-1-1-1-1-1 +1+1+1+1 -1-1-1-1-1-1 -1-1-1-1-1-1 +1+1+1+1 -1-1-1-1-1-1

Shoulders to stand on.

Several approaches to measuring Co-Trending come to mind, and the best paper is here:

http://wolfweb.unr.edu/~zal/pubs/MTA.pdf

But before we proceed with methods that are Available, perhaps we need to ask, what is Needed?

By defining a target “causal Model”, we may better define the requirements for “Co-Trending” methods we’ll develop.

Next Steps

I have a ton more research and have enlisted some help from some amazing people … but that work is not ready for public distribution just yet.

If you are interested in learning more, or helping, do reach out.

< More details coming soon! >

andrew@bytesumo.com

Data Science, Data Architecture, Big Data Engineering.

Andrew Morgan is the Head of Data Science for a top 4 audit firm client. He is also the CEO of ByteSumo Ltd., a data science consultancy. He's been excited about "big data" since 1993.

He is a specialist in data processing languages, data platform design, emerging data technologies, exotic data structures, data science methods, technical architecture, and data security systems.

He founded ByteSumo to build a data science led consultancy that has the experts and tools needed to transform and disrupt traditional enterprises.

(curr. client role)	*2014 - present*	*Head of Data Science*
ByteSumo	2013 - present	CEO
Capgemini	2010 - 2013	Senior Enterprise Architect, BIM
Thomson Reuters	2006 - 2010	Architect, Senior Technologist
Aprimo (now Teradata)	2005 - 2006	Senior Consultant
Acxiom Corporation	2000 - 2005	Business Solutions Architect
dunnhumby	1999 - 2000	Database Consultant
Elf Gas & Power UK	1995 - 1999	Operational Dev. Executive
Gov't of Ontario	1994 - 1994	Jnr. Planner, GIS systems.

Bachelor of Arts, Geography. University of Toronto. 1994
Specialism in Geostatistics, and Geographic Information Systems.

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