Sprint 1

Straddle screening tool

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Research Question

What is the highest reachable consistency in screening stocks that will exhibit abnormal price volatility at a foreseeable market or stock event (dividends announcement…)?

Candidate stocks should have their at-the-money options tree premiums exhibiting high correlation (positive for calls and/or negative for puts) with their underlying stocks' prices.

Data sources

- S&P 100 list of symbols - Wikipedia
- S&P 100 Stock historical (12 years) – API from Quantmod; QuantTools
- S&P 100 stock historical events – API from Quantmod
- Option Tree historical data (call on select stocks in sprint 2) – Quantmod; QuantTools
- Greeks historical data (call on select stocks in sprint 2) – API from fOptions

Update summary

To make sure I can meet all deadlines – I have taken the path of leveraging Rattle package in R Studio for clustering, modeling…

Rattle is a popup interface that calls upon 100s of other packages in the background. It offers all phases of modeling from exploration/transformation/clustering/modeling/testing/validating.

For my data to be ready for raddle and to avoid transformation within Rattle, I went back and added a key field – HLPPC – High Low Percentage Change - that measures the percentage price gap within each day's high and low price points.

Below is a bird eye view of what was done in Sprint 2:

- ✓ Pre-raddle transformation – adding HLPPC
- ✓ Principal component review of the aggregated data set S&P100Full
- ✓ Splitting the data into training, validation & testing.
- ✓ Clustering the data set S&P100Full (K means, EWKM…)
- ✓ Modeling the data for HLPPC (using decision tree, neural network & linear)
- ✓ Validating & testing all 3 models.

R Studio Libraries

library(quandl)

library(QuantTools)

library(quantmod)

library(derivmkts)

library(RND)

setDefaults(getSymbols.av, api.key="V7YC53BOMBUB28FJ")

library(rattle)

Pre-Rattle Transformation

Comment: I noticed that I will need percent price change as a variable in any of my clustering & models - adding that to the merged full SnP100 file might be tricky

I added % closing price change column to the consolidated data frame

SnP100full$PerChange <- c(-diff(SnP100full$Close)/SnP100full$Close[-1]*100,0)

Challenges

Did a dry run on a test sample and have 2 challenges in running Clustering functions:

1. there are still NAs in relatively newer stocks (e.g. Netflix...) that were not existent throughout the 2007-2019 sample period.
2. Preset library functions for measuring percentage price change (Overnight & intra-day) do not seem to be compatible with various clustering functions.

Solutions

Go back to the individual stock data frames and do couple of clean-ups:

1. Transform all remaining NAs in individual data sets into nill value
2. add overnight and same day percentage price change
3. remerge the individual 100 stock data frames into a new large data frame

Transform all remaining NAs in individual data sets into nil value

AAPLfull[is.na(AAPLfull)] <-0

ABBVfull[is.na(ABBVfull)] <-0

… replicate for all stocks

Add overnight and same day percentage price change

 # start with overnight (difference between close of the day and the previous day)

AAPLfull$ON_PPC<- c(-diff(AAPLfull$Close)/AAPLfull$Close[-1]*100,0)

ABBVfull$ON_PPC<- c(-diff(ABBVfull$Close)/ABBVfull$Close[-1]*100,0)

… replicate for all 100 stocks

Measure percent change between a day's high & low

AAPLfull$HLppc<- c((AAPLfull$High - AAPLfull$Low)/AAPLfull$Low*100)

ABBVfull$HLppc<- c((ABBVfull$High - ABBVfull$Low)/ABBVfull$Low*100)

… replicate for all 100 stocks

Removing NAs

There seems to be few NAs in few stocks - this applies to period where a stock was not yet listed

Clean-up - another round of cleaning NAs in the percentage change fields

AAPLfull[is.na(AAPLfull)] <-0

ABBVfull[is.na(ABBVfull)] <-0

… replicate for all 100 stocks

Re-merging all 100 files after adding overnight and high/close percentage change

SnP100full<- rbind(AAPLfull, ABBVfull, ABTfull, ACNfull, ADBEfull, AGNfull, AIGfull, ALLfull, AMGNfull, AMZNfull, AXPfull, BAfull, BACfull, BIIBfull, BKfull, BKNGfull, BLKfull, BMYfull, Cfull, CATfull, CELGfull, CHTRfull, CLfull, CMCSAfull, COFfull, COPfull, COSTfull, CSCOfull, CVSfull, CVXfull, DDfull, DHRfull, DISfull, DOWfull, DUKfull, EMRfull, EXCfull, Ffull, FBfull, FDXfull, GDfull, GEfull, GILDfull, GMfull, GOOGfull, GOOGLfull, GSfull, HDfull, HONfull, IBMfull, INTCfull, JNJfull, JPMfull, KHCfull, KMIfull, KOfull, LLYfull, LMTfull, LOWfull, MAfull, MCDfull, MDLZfull, MDTfull, METfull, MMMfull, MOfull, MRKfull, MSfull, MSFTfull, NEEfull, NFLXfull, NKEfull, NVDAfull, ORCLfull, OXYfull, PEPfull, PFEfull, PGfull, PMfull, PYPLfull, QCOMfull, RTNfull, SBUXfull, SLBfull, SOfull, SPGfull, Tfull, TGTfull, TXNfull, UNHfull, UNPfull, UPSfull, USBfull, UTXfull, Vfull, VZfull, WBAfull, WFCfull, WMTfull, XOMfull)

Explore % change by stock vs stock volatility (outside Rattle)

<u>Comment</u>: Obviously new stocks like Netflix and stocks that witnessed turmoil during the 2008 global economic crisis (e.g. AIG) top the list when sorted by average daily percentage price change.

I wanted to explore a summarized table by stock of key metrics

```
SnPSummary <- group_by(SnP100full, SnP100full$Symbol)

SnPSummary = summarise(SnPSummary,

                avg_vlty = mean(Volatility),

                min_vlty = min(Volatility),

                max_vlty = max(Volatility),

                avg_ON_ppc = mean(ON_PPC),

                min_On_ppc = min(ON_PPC),
```

max_on_ppc = max(ON_PPC),

avg_HL_ppc = mean(HLppc),

min_HL_ppc = min(HLppc),

max_HL_ppc = max(HLppc))

SnPSummary

Filter

	SnP100full$Symbol	avg_vlty	min_vlty	max_vlty	avg_ON_ppc	min_On_ppc	max_on_ppc	avg_HL_ppc	min_HL_ppc	max_HL_ppc
100	NFLX	0.4582624	0	2.5101368	-0.08265853809	-29.688136	53.599581	3.808675	0.61086947	29.595746
99	AIG	0.4156295	0	7.0795822	0.21284567693	-39.759036	155.042028	3.639627	0.31728341	309.600008
98	NVDA	0.4155334	0	1.9600368	-0.01218033521	-22.962378	44.355492	3.550914	0.66979236	33.146067
97	MS	0.3868942	0	4.7694282	0.07635247392	-46.519337	34.939751	3.405129	0.48515410	111.282043
96	C	0.3832878	0	4.2090489	0.13016364372	-36.638654	64.000000	3.248808	0.42153862	81.311472
95	F	0.3324752	0	2.5995613	0.02972956565	-22.790698	33.333333	3.133792	0.50000000	160.476190
94	BAC	0.3793326	0	3.1143036	0.07719676457	-26.073298	40.784314	3.111502	0.39318480	61.660079
93	COF	0.3545884	0	2.4113365	0.04054039161	-20.904921	33.408072	3.105245	0.32330516	33.410138
92	MET	0.3391642	0	2.7983662	0.04699267873	-21.874999	36.555554	2.852607	0.43948903	31.444098

Rattle

INSTALL.PACKAGES("RATTLE")

INSTALL.PACKAGES("RATTLE", DEPENDENCIES=C("DEPENDS", "SUGGESTS"))

LIBRARY(RATTLE)

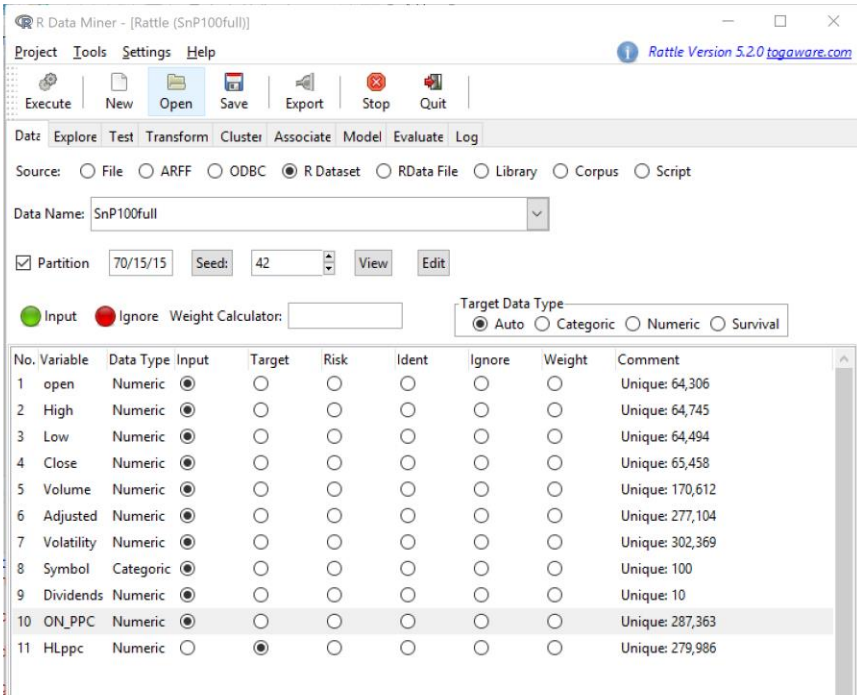
RATTLE()

https://cran.r-project.org/src/contrib/Archive/RGtk2/RGtk2_2.20.35.tar.gz

Select in case of a difficulty to open .rattle file in RGtk2 – please use the above link to download the earlier 2.20.35 version of RGtk2 library – that should solve the issue

Re-Explore data within Rattle

Select file SnP100full with High Low percentage change as a target variable.



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Below is a description of the dataset.

The data is limited to the training dataset.

crs$dataset[crs$train, c(crs$input, crs$risk, crs$target)]

11 Variables 212352 Observations

The data was few pages and couldn't clearly move it from text to clean tables – I summarized in the table below

Rattle timestamp: 2019-08-09 09:33:06 bassa

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Basic statistics for key numeric variable of the dataset.

metric	$Volatility	$ON_PPC	$HLppc	$Dividends
nobs	212352	212352	212352	212352
NAs	0	0	0	0

Minimum	0	-100	0	0
Maximum	7.079582	155.04203	309.6	0.77
1 Quartile	0.140928	-0.845982	1.203861	0
3 Quartile	0.29334	0.761575	2.55102	0
Mean	0.250731	**-0.012775**	**2.207995**	0.005104
Median	0.200953	-0.046004	1.712853	0
Sum	53243.1645	-2712.801	468872.2	1083.78137
SE Mean	0.00044	0.004421	0.004533	0.000116
LCL Mean	0.249868	-0.02144	2.199111	0.004876
UCL Mean	0.251593	-0.00411	2.216879	0.005332
Variance	0.041118	4.150226	4.362836	0.002871
Stdev	0.202775	2.03721	2.08874	0.053586
Skewness	5.600613	1.686744	23.2184	10.91106
Kurtosis	79.753947	287.57577	2484.471	121.978523

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Kurtosis for each numeric variable of the dataset.

Larger values mean sharper peaks and flatter tails.

Positive values indicate an acute peak around the mean.

Negative values indicate a smaller peak around the mean.

Open	High	Low	Close	Volume	Adjusted	Volatility	ON_PPC	HLppc	Dividends
55.91057	55.84031	55.97522	55.86483	140.44138	57.52392	79.75395	287.57577	2484.47069	55.91057

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Skewness for each numeric variable of the dataset.

Positive means the right tail is longer.

Open	High	Low	Close	Volume	Adjusted	Volatility	ON_PPC	HLppc	Dividends
6.709407	6.706561	6.712658	6.707722	8.901054	6.784499	5.600613	1.686744	23.218403	10.911060

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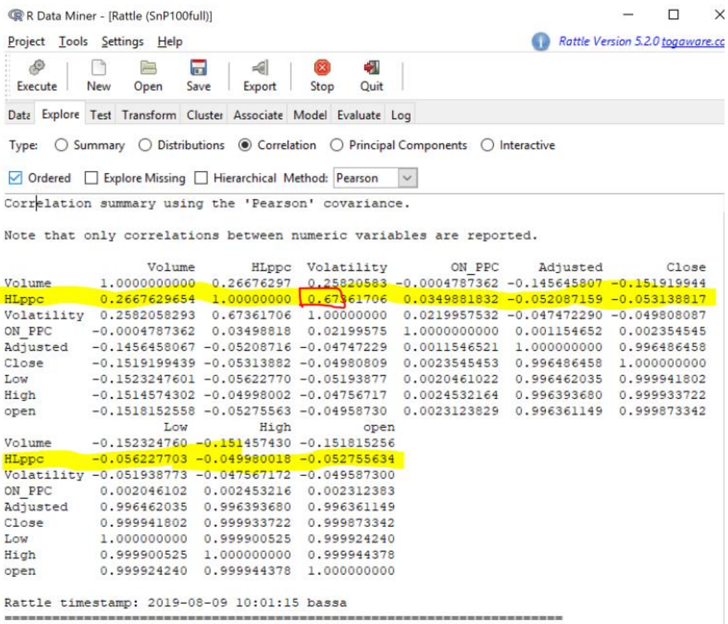
Explore Correlation Between Key Variables

Take away: ***Its very obvious that HLPPC High low percentage price change per day has a high correlation with stock volatility at 67%***

Also a significant variable with high correlation to High/Low ppc is the traded volume at 26%




```
Correlation summary using the 'Pearson' covariance.

Note that only correlations between numeric variables are reported.

                  Volume       HLppc  Volatility        ON_PPC     Adjusted        Close
Volume      1.0000000000  0.26676297  0.25820583 -0.0004787362 -0.145645807 -0.151919944
HLppc       0.2667629654  1.00000000  0.67361706  0.0349881832 -0.052087159 -0.053138817
Volatility  0.2582058293  0.67361706  1.00000000  0.0219957532 -0.047472290 -0.049808087
ON_PPC     -0.0004787362  0.03498818  0.02199575  1.0000000000  0.001154652  0.002354545
Adjusted   -0.1456458067 -0.05208716 -0.04747229  0.0011546521  1.000000000  0.996486458
Close      -0.1519199439 -0.05313882 -0.04980809  0.0023545453  0.996486458  1.000000000
Low        -0.1523247601 -0.05622770 -0.05193877  0.0020461022  0.996462035  0.999941802
High       -0.1514574302 -0.04998002 -0.04756717  0.0024532164  0.996393680  0.999933722
open       -0.1518152558 -0.05275563 -0.04958730  0.0023123829  0.996361149  0.999873342
                   Low         High         open
Volume     -0.152324760 -0.151457430 -0.151815256
HLppc      -0.056227703 -0.049980018 -0.052755634
Volatility -0.051938773 -0.047567172 -0.049587300
ON_PPC      0.002046102  0.002453216  0.002312383
Adjusted    0.996462035  0.996393680  0.996361149
Close       0.999941802  0.999933722  0.999873342
Low         1.000000000  0.999900525  0.999924240
High        0.999900525  1.000000000  0.999944378
open        0.999924240  0.999944378  1.000000000

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======================================================================
```
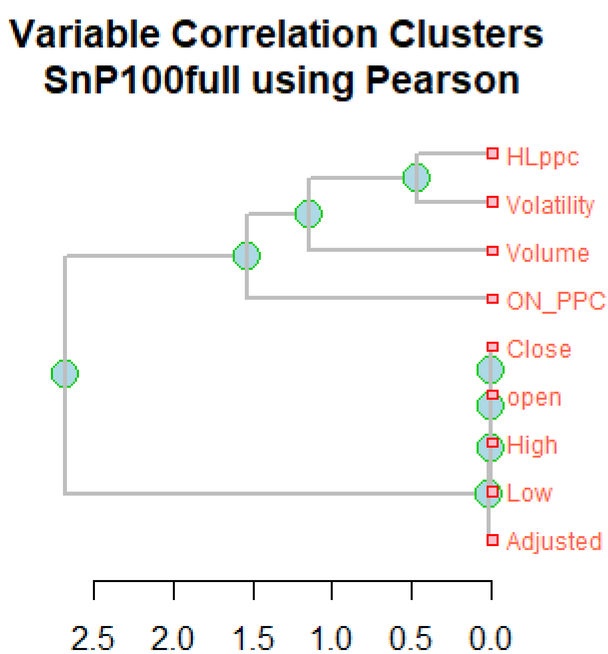
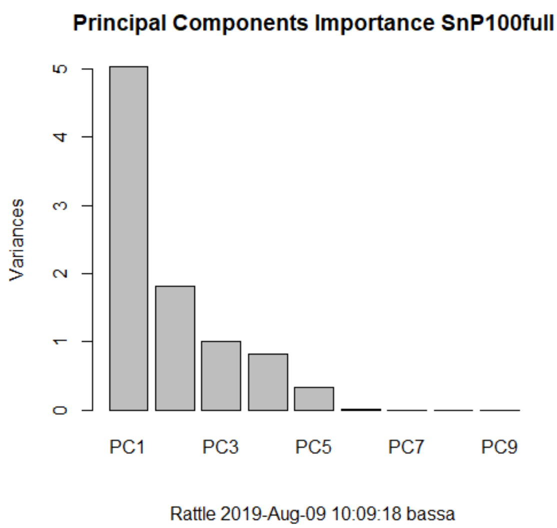
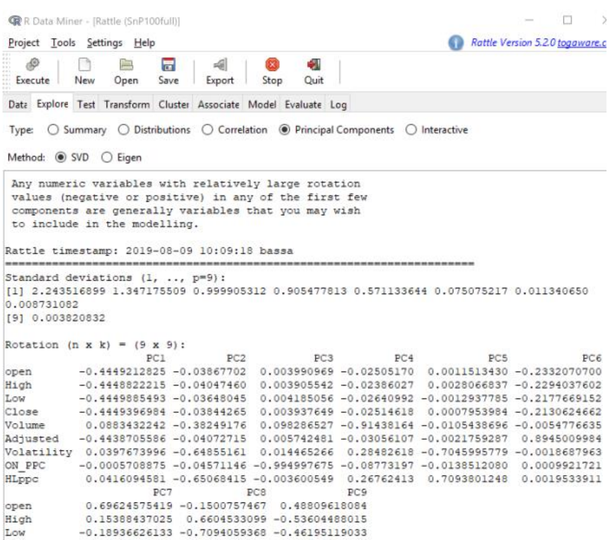



Principal component

***Take-away*: PC 1 and 2 provide the most significant results – interestingly:**

- ***PC1 is driven relatively more by other variables than volatility and HLPPC.***
- ***PC2 is mostly driven by volatility and HLPPC***





Clustering

In clustering we used 2 methods Kmeans and EWKM

K means

***Take-away*: Very obvious from the data means that volatility & ON_PPC (overnight volatility) have the highest "Data means" vs our target variable HLPPC.**

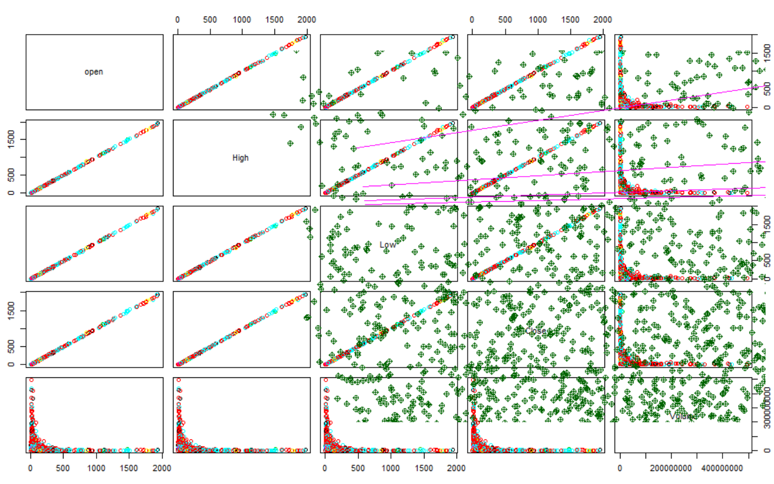
<u>Limitation</u>: It was challenging to map more than 5 variables in a clustering chart – the key variables (volatility & ON_PPC) could not be captured in the chart below – which made the chart plot less useful.


```
Cluster sizes:

[1] "8098 102386 2331 1927 65683 737 6802 2168 1754 20466"

Data means:

       open        High         Low       Close      Volume    Adjusted
0.043698124 0.043764123 0.043987077 0.043792787 0.011390931 0.040135184
 Volatility   Dividends      ON_PPC
0.035416030 0.006628185 0.392042150

Cluster centers:

         open       High        Low      Close      Volume    Adjusted
1  0.01609991 0.01648120 0.01581672 0.01611960 0.023074059 0.013373868
2  0.01710462 0.01713751 0.01721555 0.01714485 0.013391147 0.014307049
3  0.01050156 0.01059775 0.01045047 0.01050034 0.164794708 0.009164876
4  0.04395180 0.04395646 0.04424581 0.04403101 0.008290425 0.041285596
5  0.03860041 0.03861447 0.03891687 0.03869412 0.005413192 0.034162415
6  0.82010688 0.82098539 0.82587030 0.82155784 0.001577265 0.821557842
7  0.14571484 0.14600334 0.14651397 0.14597216 0.002997334 0.143084923
8  0.29287297 0.29315104 0.29483071 0.29342391 0.001742851 0.289259846
9  0.51976416 0.52043452 0.52314435 0.52090077 0.001217580 0.501276113
10 0.07871503 0.07881348 0.07926253 0.07888660 0.003803185 0.074256202
   Volatility     Dividends    ON_PPC
1  0.13244210 0.00000000000 0.3928479
2  0.03305692 0.00005254951 0.3919905
3  0.06702872 0.00000000000 0.3924286
4  0.02973600 0.70943998814 0.3916255
5  0.02753662 0.00009038747 0.3920493
6  0.03317629 0.01348041375 0.3919954
7  0.03594380 0.00005455124 0.3920990
8  0.03398906 0.00053912706 0.3919984
9  0.03373692 0.00962548471 0.3921376
10 0.03124923 0.00003626087 0.3919332

Within cluster sum of squares:
```

Within cluster sum of squares:

[1] 46.34335 70.02040 23.55418 62.58690 40.09805 29.81370 25.71628

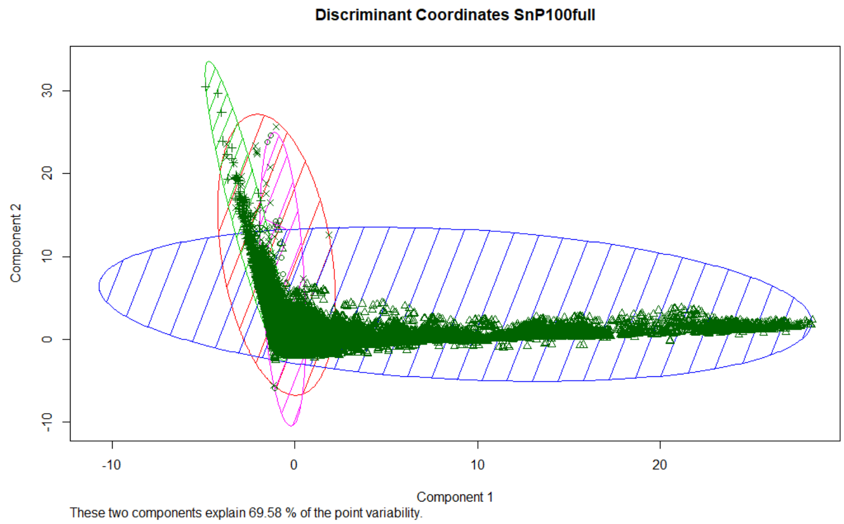
[8] 30.84591 50.33915 29.06806



EWKM

***<u>Take-away</u>*: Because of the limitations in charting Kmeans cluster – I tried using the EWKM - Entropy Weighted K-Means which is more useful for high dimensional data.**

Below is summarized version of the findings.



4 clusters, 1 iterations, 0 restarts, 2 total iterations.

Cluster sizes:

[1] "27464 122157 34997 27734"

Data means:

open	High	Low
0.043698124	0.043764123	0.043987077
Close	Volume	Adjusted
0.043792787	0.011390931	0.040135184
Volatility	Dividends	ON_PPC
0.035416030	0.006628185	0.392042150

Cluster centers:

	open	High	Low
1	0.022540517	0.022620328	0.022644125
2	0.064403462	0.064470034	0.064862211
3	0.009875018	0.009922726	0.009907357

4	0.016131883	0.016204758	0.016180303

	Close	Volume	Adjusted
1	0.022589408	0.009935015	0.019211047
2	0.064544478	0.004567639	0.060118188
3	0.009897513	0.031075741	0.008027256
4	0.016158773	0.018046617	0.013354978

	Volatility	Dividends	ON_PPC
1	0.03710539	0.00798676223	0.3924519
2	0.03002261	0.00844149761	0.3919591
3	0.04609568	0.00444670015	0.3917770
4	0.04402251	0.00004870013	0.3923368

Cluster weights:

	open	High	Low	Close	Volume	Adjusted
1	0.18	0.18	0.19	0.19	0.05	0.18
2	0.00	0.00	0.00	0.00	0.77	0.00
3	0.19	0.19	0.19	0.19	0.00	0.21
4	0.18	0.18	0.18	0.18	0.00	0.18

	Volatility	Dividends	ON_PPC
1	0	0.0	0.02
2	0	0.0	0.23
3	0	0.0	0.03
4	0	0.1	0.00

Within cluster sum of squares:

[1] 0 0 0 0

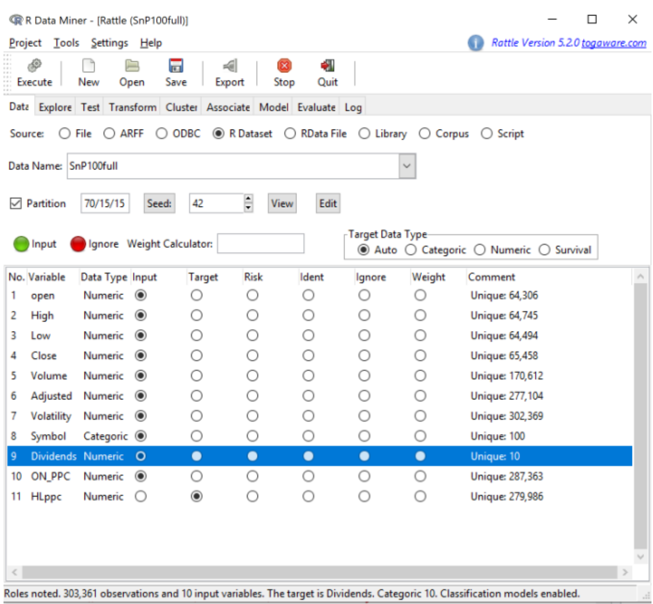
Comments: ONPPC – Overnight percentage price change seem to be the most determinant in the EWKM clustering – on the other hand Volatility seems to be at par with other variables.

Modeling

Testing & Training

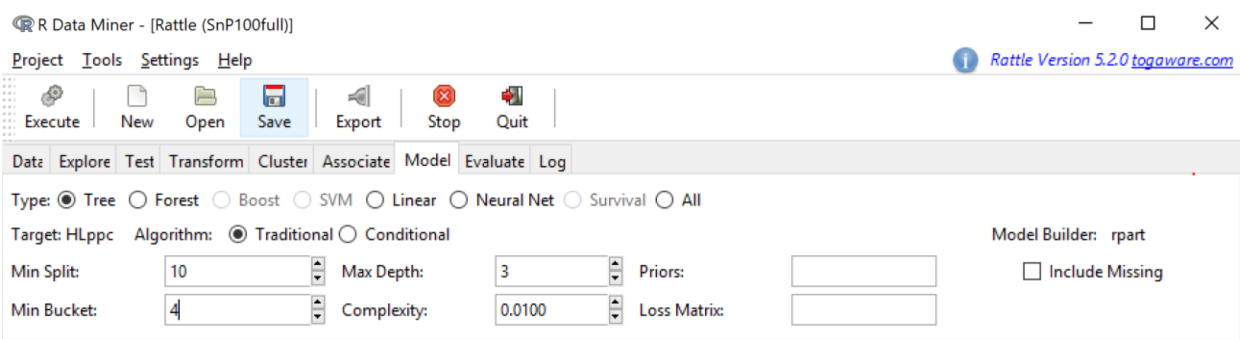
Take-aways:

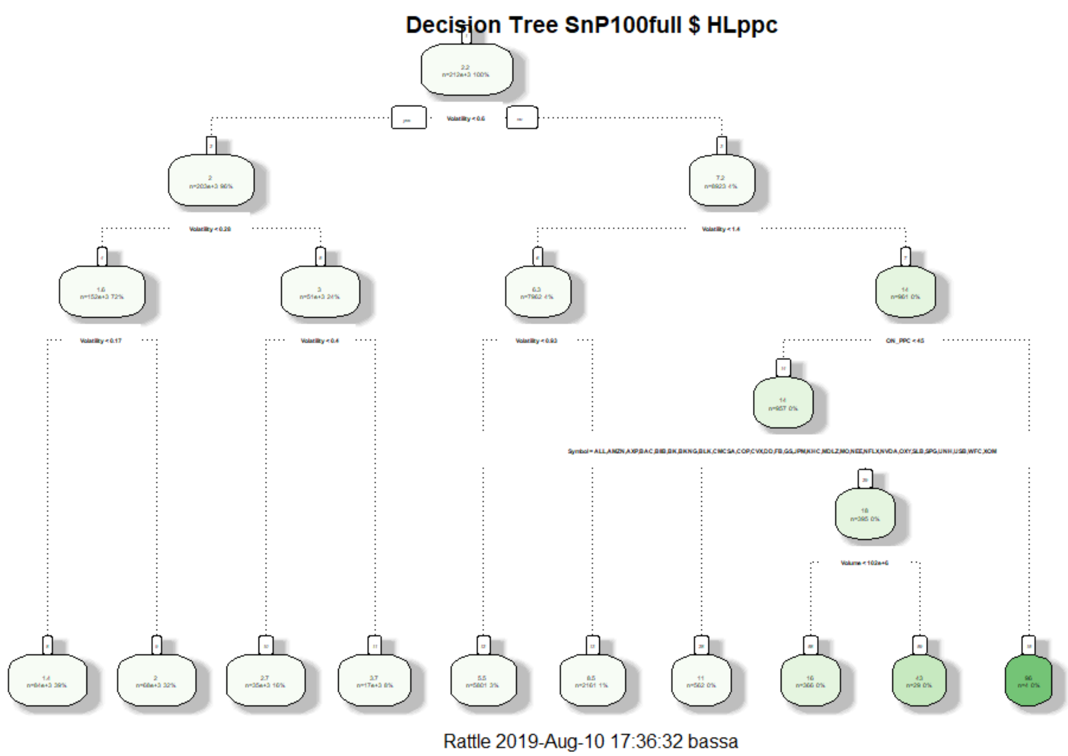
- ***Data was split in a 70% training, 15% validation & 15% testing format.***
- ***We are trying to predict a stock's percentage change to screen the highest for a straddle strategy.***
- ***3 models were compatible with the nature our data frame.***
    1. ***Decision trees***
    2. ***Neural Networks***
    3. ***Linear regression***
- ***Testing and validation came back with very similar results – so only one was reported to save on real estate.***
- ***Also to save on real estate – the bulk of coefficient tables, nodes tables were removed.***
- ***Predict & Observe method was used to compare prediction capability of all 3 models with Pseudo R-Square score used as a benchmark.***



Decision trees

Take-away: Driven by volatility & volume variables – decision tree were able to predict at 0.476 R-square.





Summary of the Decision Tree model for Classification (built using 'rpart'):

n= 212352 node), split, n, deviance, yval

* denotes terminal node

1) root 212352 926452.60 2.207995

2) Volatility< 0.6044209 203429 322549.00 1.990545

4) Volatility< 0.2761405 152209 103667.00 1.637718

8) Volatility< 0.1741081 83749 31857.02 1.366199 *

9) Volatility>=0.1741081 68460 58082.70 1.969875 *

5) Volatility>=0.2761405 51220 143626.70 3.039031

10) Volatility< 0.4033684 34670 66522.50 2.708230 *

11) Volatility>=0.4033684 16550 65362.53 3.732015 *

3) Volatility>=0.6044209 8923 374988.00 7.165469

6) Volatility< 1.378729 7962 120587.00 6.334969

12) Volatility< 0.9283672 5801 54583.42 5.541613 *

13) Volatility>=0.9283672 2161 52551.00 8.464659 *

7) Volatility>=1.378729 961 203410.40 14.046260

14) ON_PPC< 44.62153 957 115484.80 13.704970

28)
Symbol=ALL,AMZN,AXP,BAC,BIIB,BK,BKNG,BLK,CMCSA,COP,CVX,DD,FB,GS,JPM,KHC,MDLZ,MO,NEE,NFLX,NVDA,OXY,SLB,SPG,UNH,USB,WFC,XOM 562 22652.93 10.935450 *

29) Symbol=AIG,C,COF,F,GE,MET,MS 395 82388.08 17.645390

58) Volume< 1.019247e+08 366 32205.36 15.597690 *

59) Volume>=1.019247e+08 29 29279.57 43.488750 *

15) ON_PPC>=44.62153 4 61144.00 95.701280 *

Regression tree:

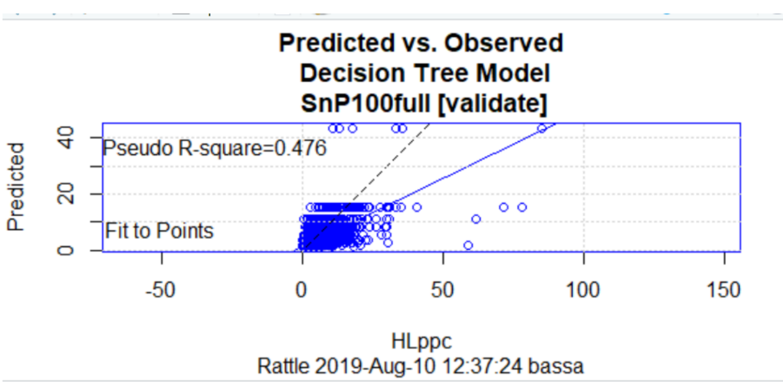
rpart(formula = HLppc ~ ., data = crs$dataset[crs$train, c(crs$input,

crs$target)], method = "anova", model = TRUE, parms = list(split = "information"),

control = rpart.control(minsplit = 10, minbucket = 4, usesurrogate = 0,

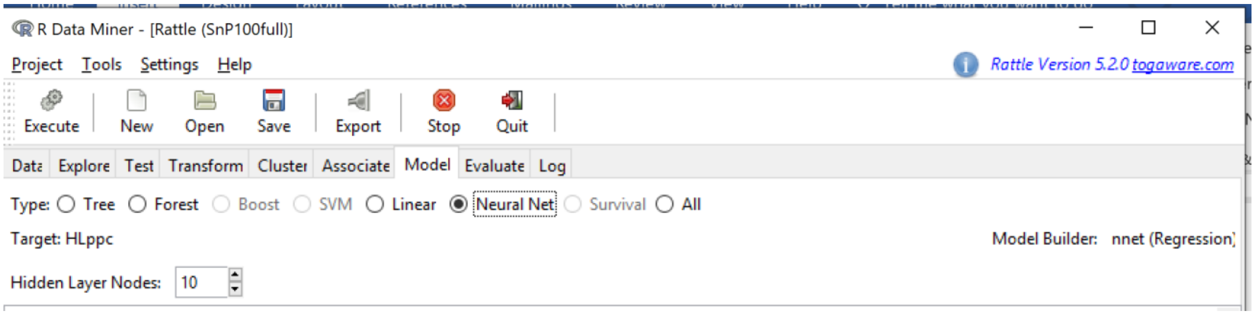
maxsurrogate = 0))

Test – validation test came back with very similar results



Neural Networks

Take-away: Neural Network was able to predict at 0.36 R-square (vs. 0.47 for decision trees)



Summary of the Neural Net model (built using nnet):

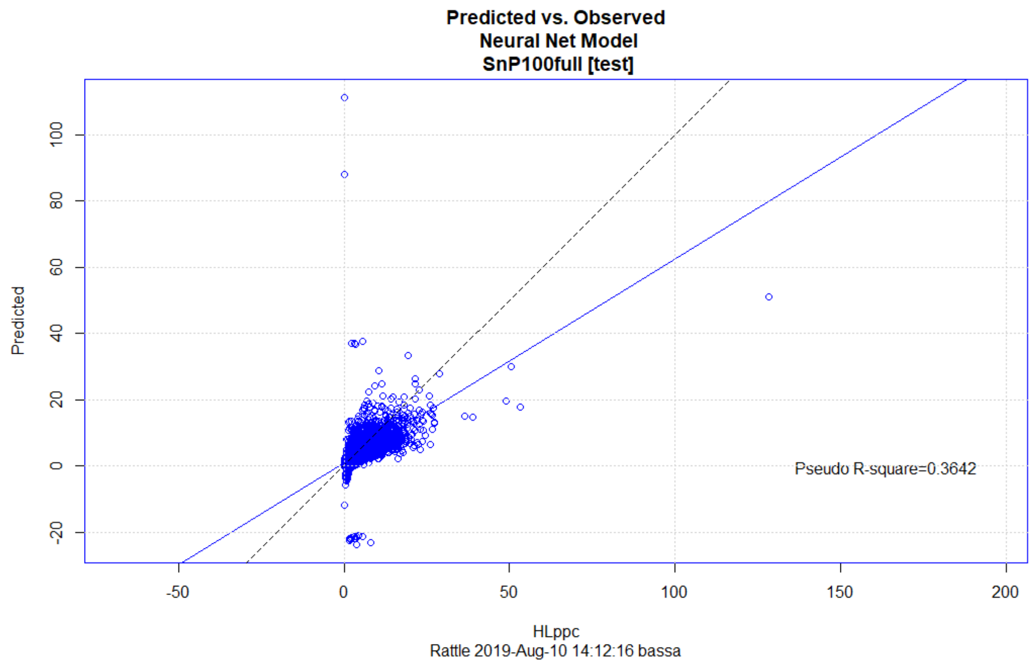
A 108-10-1 network with 1209 weights.

Inputs: open, High, Low, Close, Volume, Adjusted, Volatility, SymbolABBV, SymbolABT, SymbolACN, SymbolADBE, SymbolAGN, SymbolAIG, SymbolALL, SymbolAMGN, SymbolAMZN, SymbolAXP, SymbolBA, SymbolBAC, SymbolBIIB, SymbolBK, SymbolBKNG, SymbolBLK, SymbolBMY, SymbolC, SymbolCAT, SymbolCELG, SymbolCHTR, SymbolCL, SymbolCMCSA, SymbolCOF, SymbolCOP, SymbolCOST, SymbolCSCO, SymbolCVS, SymbolCVX, SymbolDD, SymbolDHR, SymbolDIS, SymbolDOW, SymbolDUK, SymbolEMR, SymbolEXC, SymbolF, SymbolFB, SymbolFDX, SymbolGD, SymbolGE, SymbolGILD, SymbolGM, SymbolGOOG, SymbolGOOGL, SymbolGS, SymbolHD, SymbolHON, SymbolIBM, SymbolINTC, SymbolJNJ, SymbolJPM, SymbolKHC, SymbolKMI, SymbolKO, SymbolLLY, SymbolLMT, SymbolLOW, SymbolMA, SymbolMCD, SymbolMDLZ, SymbolMDT, SymbolMET, SymbolMMM, SymbolMO, SymbolMRK, SymbolMS, SymbolMSFT, SymbolNEE, SymbolNFLX, SymbolNKE, SymbolNVDA, SymbolORCL, SymbolOXY, SymbolPEP, SymbolPFE, SymbolPG, SymbolPM, SymbolPYPL, SymbolQCOM, SymbolRTN, SymbolSBUX, SymbolSLB, SymbolSO, SymbolSPG, SymbolT, SymbolTGT, SymbolTXN, SymbolUNH, SymbolUNP, SymbolUPS, SymbolUSB, SymbolUTX, SymbolV, SymbolVZ, SymbolWBA, SymbolWFC, SymbolWMT, SymbolXOM, Dividends, ON_PPC.

Output: HLppc.

Sum of Squares Residuals: 228870081711185948.0000.

Neural Network build options: skip-layer connections; linear output units.

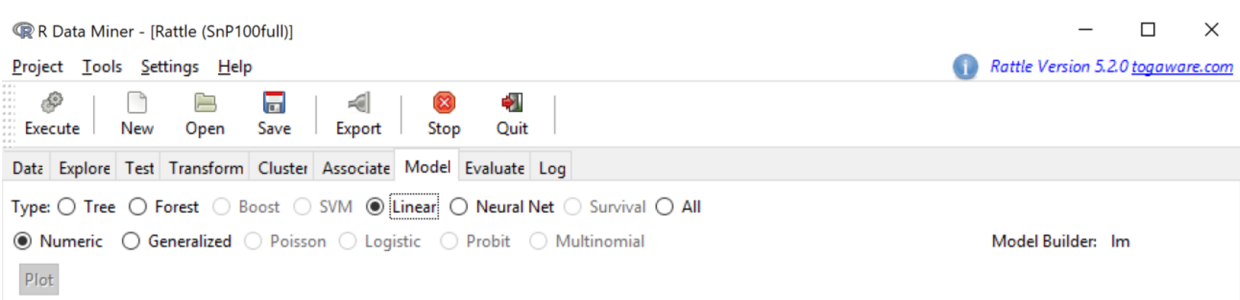


Linear

Take-away: Compared with decision trees and neural network, Linear regression was able to produce the highest R-square of 0.58.

Linear model also produced a clear list of predicted percentage change:

	Estimate	*Std. Error*	*t value*
SymbolABBV	*1.734e+00*	*5.441e-02*	*31.869*
SymbolABT	*1.573e+00*	*4.605e-02*	*34.162*



Summary of the Linear Regression model (built using lm):

Call:

lm(formula = HLppc ~ ., data = crs$dataset[crs$train, c(crs$input,

crs$target)])

Residuals:

Min 1Q Median 3Q Max

-35.298 -0.478 -0.089   0.336 260.503

Test