Binance: BTC and ETH

MGSC: 310 Ryan Welte, Nathan Cuadros, and Ethan Leimel.

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https://www.binance.com/en

Motivation

- Understand correlations between cryptocurrencies
- Predict future price action of BTC and ETH
- Potential to be used for hyperactive trading algorithms

Source Image:
https://www.google.com/url?sa=i&url=https%3A%2F%2Fmarkets.businessinsider.com%2Fnews%2Fcurrencies%2Fbitcoin-vs-ethereum-expert

Sourcing & The Data

- We searched major cryptocurrency exchanges for their trading data
- Binance is a major, international exchange but also with a US version
- Exchange data is done in “pairs,” wherein different digital assets are exchanged
    - (Versus fiat onboarding)
- We had to clean the data to see the below, as a result of the unique format
- Column meanings, data is every minute for the past 4 year period

BTC_Open	BTC_High	BTC_Low	BTC_Close	BTC_Volume	BTC_QuoteAssetVolume	BTC_NumberOfTrades	BTC_TalkerBuyBaseAssetVolume	BTC_TalkerBuyQuoteAssetVolume	BTC_ETH_OpenTime	BTC_PriceDif
<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<int>	<dbl>	<dbl>	<S3: POSIXct>	<dbl>
33862.11	33862.12	33700.00	33783.78	285.00394	9623330.0	4527	54.372814	1837221.0	2021-07-07 17:00:00	-78.32812
33783.78	33900.00	33769.28	33900.00	129.55704	4382238.0	2303	62.745605	2123122.8	2021-07-07 17:01:00	116.21875
33899.99	33929.64	33821.53	33840.02	263.87085	8940190.0	2579	162.349670	5500115.0	2021-07-07 17:02:00	-59.96875
33840.01	33851.02	33756.94	33789.78	50.25749	1699258.1	1351	16.678175	564000.0	2021-07-07 17:03:00	-50.23047
33789.78	33824.70	33766.66	33816.53	44.73964	1512140.9	972	19.517048	659710.0	2021-07-07 17:04:00	26.75000
33818.56	33822.62	33770.00	33806.76	20.17600	681999.7	925	8.627949	291642.5	2021-07-07 17:05:00	-11.79688

Apache Arrow

Binance trading data came in Parquet files

- Parquet files used often at intersection of trading and data science,
  - "efficient as well as performant flat columnar storage format of data compared to row based files like CSV"
- Read into a dataframe using the Apache Arrow package in R
- Head of one initial dataframe appears below
  - (we used both ETH / USDT trading pair, and BTC / USDT trading pairs)

```
BTC_USDT = read_parquet(
  file <- (here::here("datasets", "BTC-USDT.parquet")),
  col_select = NULL,
  as_data_frame = TRUE,
  props = ParquetArrowReaderProperties$create()
)
ETH_USDT = read_parquet(
  file <- (here::here("datasets", "ETH-USDT.parquet")),
  col_select = NULL,
  as_data_frame = TRUE,
  props = ParquetArrowReaderProperties$create()
)
```

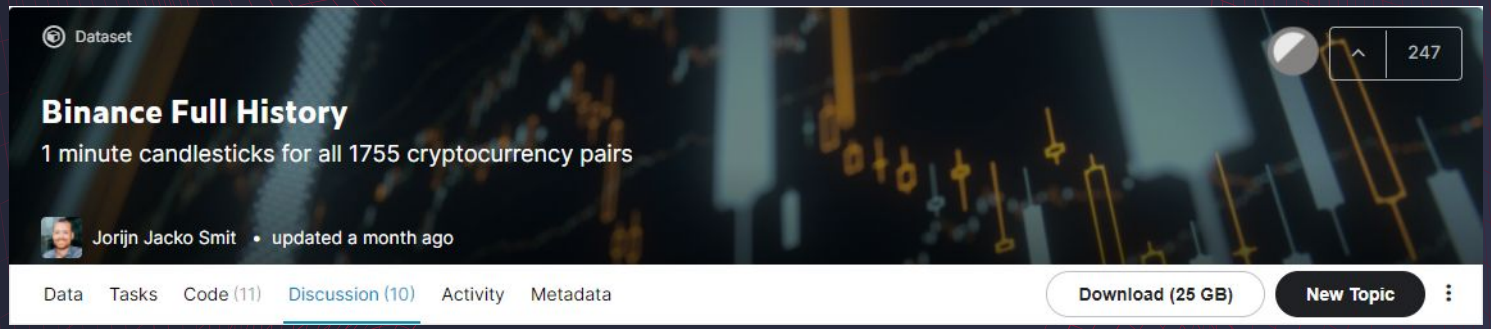
Data Cleaning

Original Dataset was massive (25gb in Apache format)

One observation for every minute for 4 years of data.

For each pair compared to each other. ~ 40 pairs compared to one another

So we decided to scale down...



Data Link: https://www.kaggle.com/jorijnsmit/binance-full-history/discussion/198669

Data Cleaning – Code

```r
#data cleaning:
BTC_USDT$BTC_PriceDif <-c(BTC_USDT$close - BTC_USDT$open)
shifted = lag(BTC_USDT$BTC_PriceDif, n = 1)
BTC_USDT$BTC_LastMinPriceDiff = shifted

BTC_USDT <- BTC_USDT %>% mutate(BTCBuy = BTC_LastMinPriceDiff > 0)

ETH_USDT$ETH_PriceDif <-c(ETH_USDT$close - ETH_USDT$open)
shifted = lag(ETH_USDT$ETH_PriceDif, n = 1)
ETH_USDT$ETH_LastMinPriceDiff = shifted

ETH_USDT <- ETH_USDT %>% mutate(ETHBuy = ETH_LastMinPriceDiff > 0)

names(BTC_USDT)[1:10] <-c("BTC_Open",
"BTC_High","BTC_Low","BTC_Close","BTC_Volume","BTC_QuoteAssetVolume","BTC_NumberOfTrades","BTC_TalkerBuyBase
AssetVolume","BTC_TalkerBuyQuoteAssetVolume","BTC_ETH_OpenTime")

names(ETH_USDT)[1:9] <-c("ETH_Open",
"ETH_High","ETH_Low","ETH_Close","ETH_Volume","ETH_QuoteAssetVolume","ETH_NumberOfTrades","ETH_TalkerBuyBase
AssetVolume","ETH_TalkerBuyQuoteAssetVolume")

BTC_USDT1month = slice_tail(BTC_USDT, n = 43200) #one month
ETH_USDT1month = slice_tail(ETH_USDT, n = 43200) #one month

BTC_USDT1year = slice_tail(BTC_USDT, n = 525600) #one year
ETH_USDT1year = slice_tail(ETH_USDT, n = 525600) #one year

BTC_USDT11month = slice_head(BTC_USDT1year, n = 482400) #11 months
ETH_USDT11month = slice_head(ETH_USDT1year, n = 482400) #11 months


ETH_BTC_USDT11month = cbind(BTC_USDT11month, ETH_USDT11month)
ETH_BTC_USDT11month = subset(ETH_BTC_USDT11month, select = -c(open_time))

ETH_BTC_USDT = cbind(BTC_USDT1month, ETH_USDT1month)
ETH_BTC_USDT = subset(ETH_BTC_USDT, select = -c(open_time))
```

Data Cleaning

Focus on two pairs:

BTC v USDT
ETH v USDT

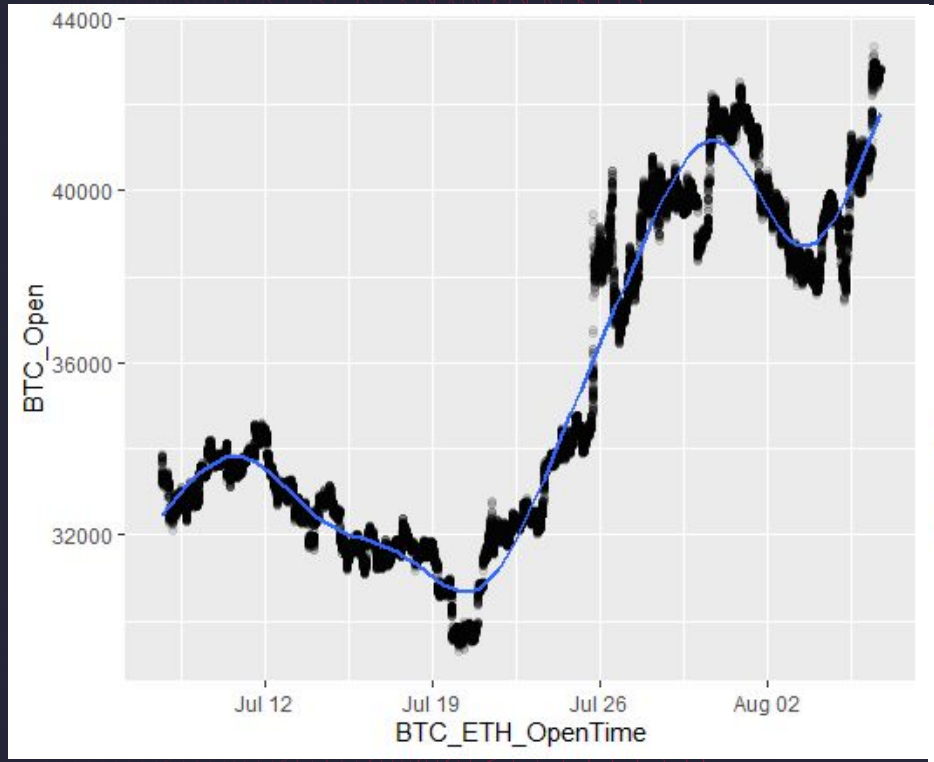
Full ~2,081,094 observations
One Year = 525,600 observations
One Month = 43,200 observations

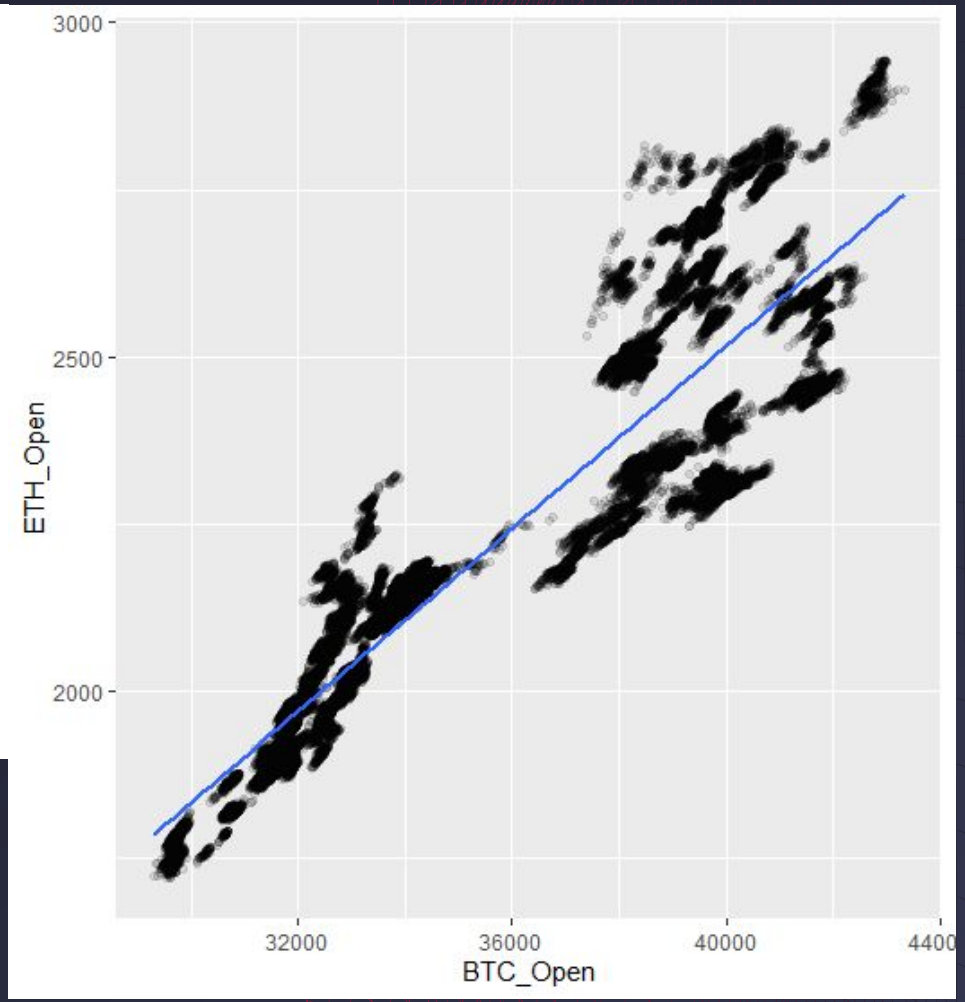
In addition to the variables on the right, we added a few features:

Price Difference (Open - Close)
Last Minute Price Difference
And a boolean variable called Buy:

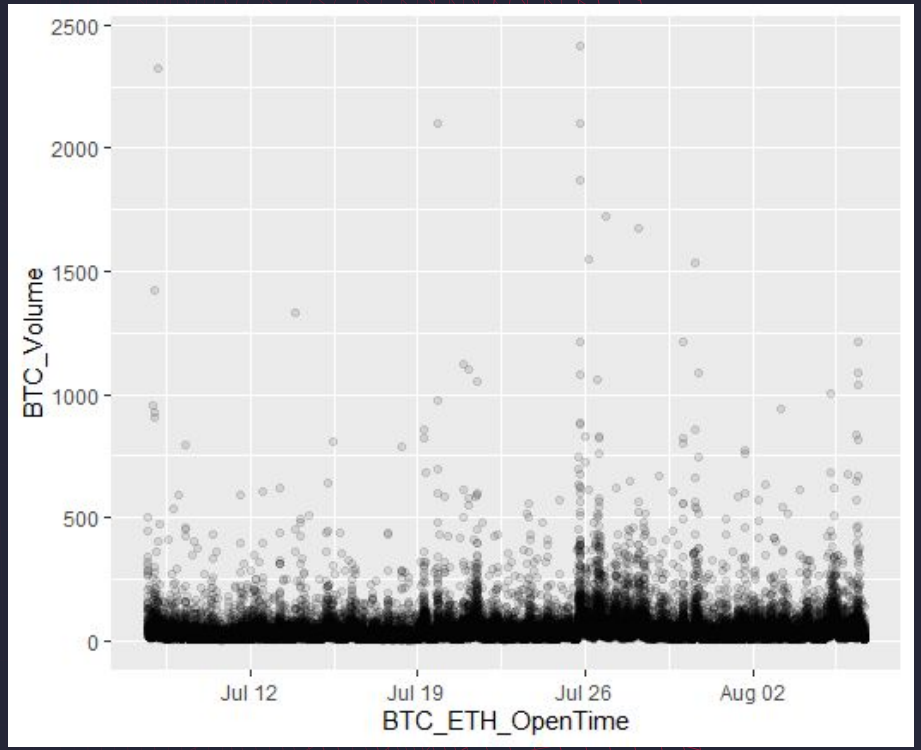
- marked as a true if the last minute price difference was positive
- marked as a false if the next minute price difference was negative

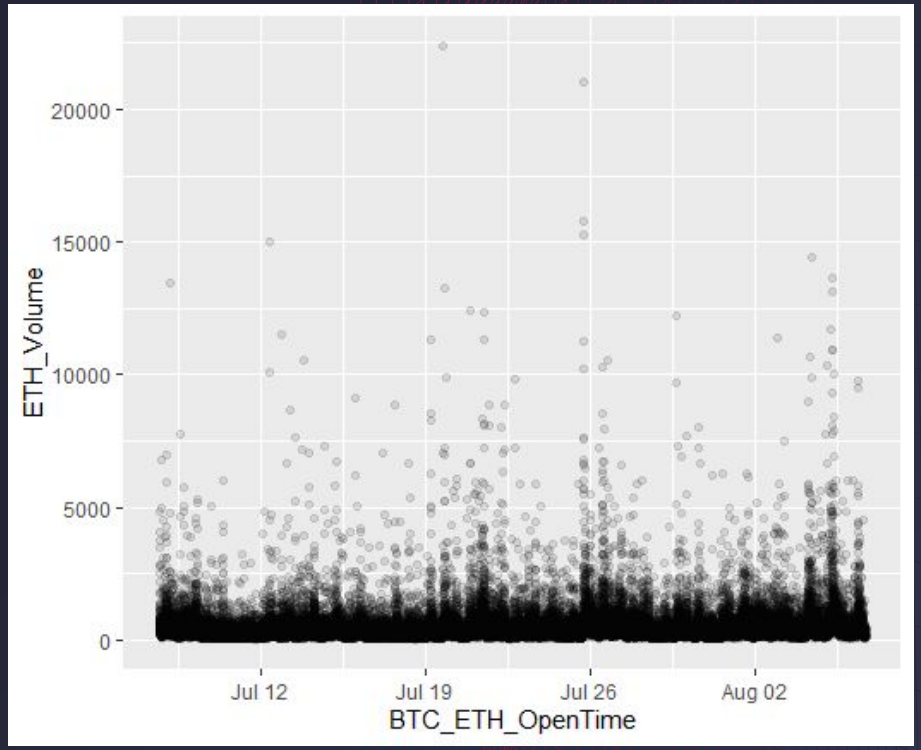
EACH PAIR HAS FOLLOWING INFO
Open Price
High Price
Low Price
Close Price
Volume Traded
Quote Asset Volume
Number of Trades
Taker Buy Base Asset Volume
Taker Buy Quote Asset Volume
Open Time



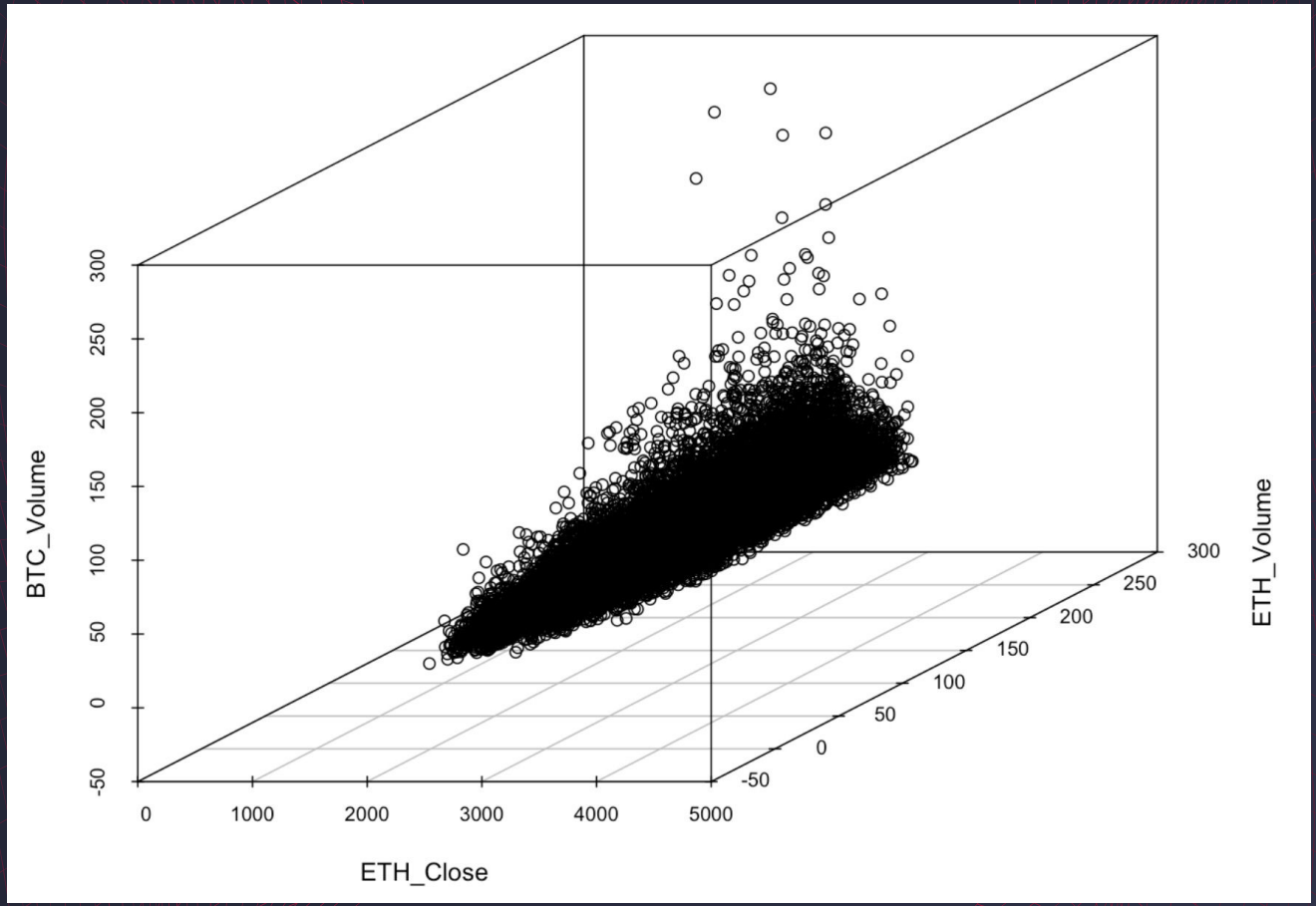


DATA VISUALIZED





DATA VISUALIZED



DATA VISUALIZED

Reasons for higher volume

Final Data

All of the previous Variables but for BTC and ETH:

11 Month Data = 482400 obs. 25 Variables wide

BTC_Open	BTC_High	BTC_Low	BTC_Close	BTC_Volume	BTC_QuoteAssetVolume	BTC_NumberOfTrades	BTC_TalkerBuyBaseAssetVolume	BTC_TalkerBuyQuoteAssetVolume	BTC_ETH_OpenTime	BTC_PriceDif	BTC_LastMinPriceDiff	BTCBuy
11632.08	11640.21	11631.89	11640.20	35.59820	414194.0	455	21.666656	252091.52	2020-08-06 01:04:00	8.12011719	3.13964844	TRUE
11640.20	11662.71	11640.19	11661.15	63.01425	734114.2	911	35.758518	416570.06	2020-08-06 01:05:00	20.95019531	8.12011719	TRUE
11661.15	11665.29	11658.41	11665.29	40.74549	475116.8	467	13.504595	157481.38	2020-08-06 01:06:00	4.13964844	20.95019531	TRUE
11665.29	11666.37	11660.34	11664.99	56.22023	655721.6	413	16.494774	192381.55	2020-08-06 01:07:00	-0.29980469	4.13964844	TRUE
11664.68	11670.00	11664.65	11667.44	57.79376	674305.8	531	34.298206	400172.16	2020-08-06 01:08:00	2.76074219	-0.29980469	FALSE
11667.45	11670.00	11663.30	11664.90	74.34583	867526.2	511	37.331669	435616.59	2020-08-06 01:09:00	-2.54980469	2.76074219	TRUE
11664.89	11670.00	11664.89	11669.40	41.16197	480262.9	426	19.480251	227298.58	2020-08-06 01:10:00	4.51074219	-2.54980469	FALSE
11669.41	11674.37	11669.40	11672.76	114.24286	1333247.5	516	96.457245	1125666.25	2020-08-06 01:11:00	3.34960938	4.51074219	TRUE

ETH_Open	ETH_High	ETH_Low	ETH_Close	ETH_Volume	ETH_QuoteAssetVolume	ETH_NumberOfTrades	ETH_TalkerBuyBaseAssetVolume	ETH_TalkerBuyQuoteAssetVolume	ETH_PriceDif	ETH_LastMinPriceDiff	ETHBuy
394.54	394.73	394.40	394.67	1210.24048	477507.50	500	579.77637	228747.281	0.130004883	-0.059997559	FALSE
394.66	394.95	394.65	394.95	863.37103	340832.56	241	478.49503	188912.984	0.290008545	0.130004883	TRUE
394.94	395.49	394.92	395.41	542.61682	214412.58	230	392.28162	155002.266	0.470001221	0.290008545	TRUE
395.43	395.97	395.36	395.96	574.83020	227416.62	305	385.03357	152306.641	0.529998779	0.470001221	TRUE
395.96	396.00	395.56	395.90	326.35202	129171.44	201	168.64676	66746.117	-0.059997559	0.529998779	TRUE
395.90	396.38	395.90	396.26	1108.85950	439311.59	448	465.04163	184217.984	0.360015869	-0.059997559	FALSE
396.27	396.53	396.20	396.22	702.19690	278337.62	284	220.39751	87354.914	-0.049987793	0.360015869	TRUE
396.22	396.54	396.15	396.47	603.87799	239389.62	246	173.07681	68611.438	0.250000000	-0.049987793	FALSE
396.49	396.73	396.31	396.56	690.17590	273682.41	295	362.46872	143720.109	0.070007324	0.250000000	TRUE

We have the Data formatted... Now what?

We decided that our training set would be 11 months and our test set would be 1 month of data

This allows for plenty of training space for the model yet a large amount of test points due to the size of the dataset.

Dates of the sets:
Train: 08-06-2020 01:04:00-> 07-07-2021 16:59:00
Test: 07-07-21 17:00:00 -> 08-06-2021 16:59:00

Data Questions

Question 1:

Since we have split the dataset into an 11-month period followed by a 1-month, can we gain any valuable correlation or predictive insight from a simple regression analysis based on variables we think are relevant to price?

Question 2:

Is it possible to predict the minute change of the other crypto pair given information solely of the other? EX: Predict BTC based on only ETH data?

Question 3:

Can we predict whether or not to buy , hold, or sell Bitcoin or Ethereum based off the past minute of price action?

Model I: Linear Regression

Can we determine whether there is a correlation between closing price compared to the other columns we are given, or can they be used to make general predictions regarding price?

Linear Regression

- Used variables as predictors which seemed, intuitively, would have an impact on closing price, such as the closing price of the inverse currency
- BTC and ETH known to be highly correlated, but with ETH more volatile and often lagging behind BTC, reactionarily

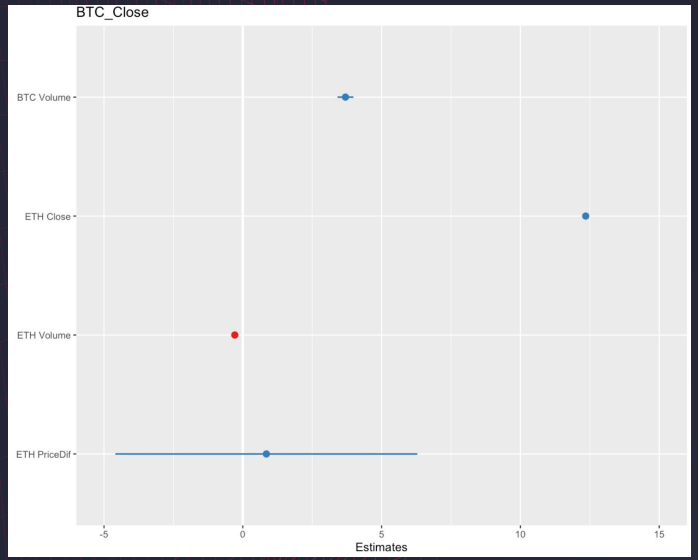
```
total_split <- initial_split(ETH_BTC_USDT, 0.9)
total_train <- training(total_split)
total_test <- testing(total_split)

lm_mod1 = lm(ETH_Close ~  BTC_Volume+  BTC_Close + ETH_Volume + BTC_PriceDif, data = total_train)
summary(lm_mod1)
lm_mod2 = lm(BTC_Close ~ BTC_Volume + ETH_Close + ETH_Volume + ETH_PriceDif, data = total_train)
summary(lm_mod2)

preds_train <- predict(lm_mod1, newdata = total_train)
preds_test <- predict(lm_mod1, newdata = total_test)

plot_model(lm_mod1)
plot_model(lm_mod2)
```

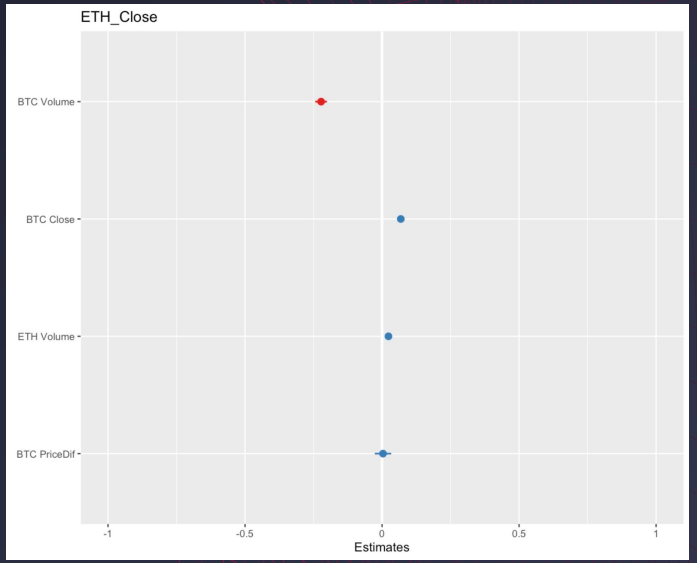
Linear Regression

Coefficient tables..

Show ETH Price Difference has a large impact on BTC_Close, but with a wide range

For ETH_Close, BTC_Volume seems to be strongest predictor, and it's a negative correlation





Linear Regression

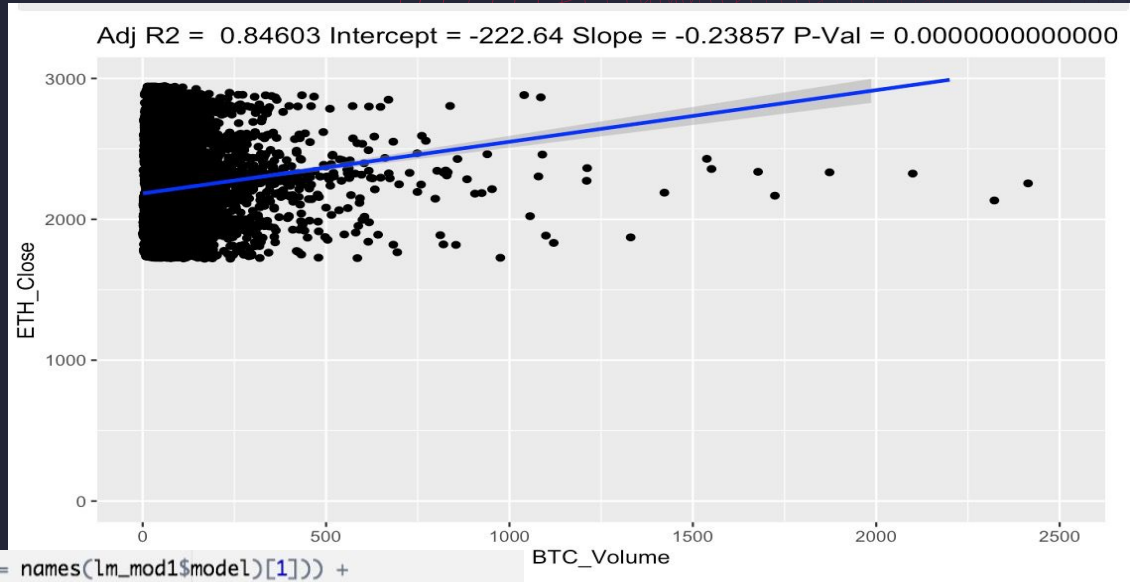
- sjPlot Tab Model

	ETH_Close		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	-221.36	-231.68 – -211.04	**<0.001**
BTC Volume	-0.22	-0.24 – -0.20	**<0.001**
BTC Close	0.07	0.07 – 0.07	**<0.001**
ETH Volume	0.02	0.02 – 0.03	**<0.001**
BTC PriceDif	0.00	-0.03 – 0.03	0.820
Observations	38880		
R^2 / R^2 adjusted	0.846 / 0.846		

	BTC_Close		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	8187.10	8070.93 – 8303.27	**<0.001**
BTC Volume	3.70	3.41 – 3.99	**<0.001**
ETH Close	12.35	12.30 – 12.41	**<0.001**
ETH Volume	-0.29	-0.31 – -0.26	**<0.001**
ETH PriceDif	0.85	-4.59 – 6.29	0.760
Observations	38880		
R^2 / R^2 adjusted	0.846 / 0.846		

Linear Regression

- Shows that BTC volume does not adequately explain the whole ETH model, because even though it has a coef of -0.24, there is still a positive linear correlation when incorporating all the variables




```
ggplot(lm_mod1$model, aes_string(x = names(lm_mod1$model)[2], y = names(lm_mod1$model)[1])) +
  geom_point() +
  stat_smooth(method = "lm", col = "blue") +
  labs(title = paste("Adj R2 = ",signif(summary(lm_mod1)$adj.r.squared, 5),
                     "Intercept =",signif(lm_mod1$coef[[1]],5 ),
                     "Slope =",signif(lm_mod1$coef[[2]], 5),
                     "P-Val =",signif(summary(lm_mod1)$coef[2,4], 5))) + xlim(20,15000) + ylim(1500, 3000)


#https://sejohnston.com/2012/08/09/a-quick-and-easy-function-to-plot-lm-results-in-r/
```

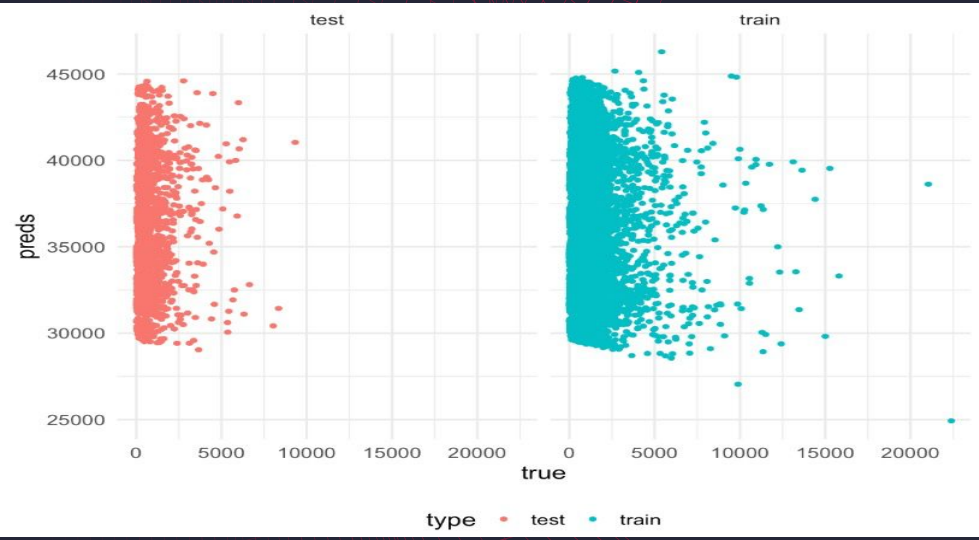
Linear Regression

```
Call:
lm(formula = ETH_Close ~ BTC_Volume + BTC_Close + ETH_Volume +
    BTC_PriceDif, data = total_train)

Residuals:
    Min      1Q  Median      3Q     Max
-536.11  -61.01  -10.64   58.27  565.99

Coefficients:
              Estimate   Std. Error t value            Pr(>|t|)
(Intercept) -221.3614343    5.2656771 -42.039 <0.0000000000000002 ***
BTC_Volume    -0.2224421    0.0109470 -20.320 <0.0000000000000002 ***
BTC_Close      0.0683782    0.0001487 459.780 <0.0000000000000002 ***
ETH_Volume     0.0233634    0.0009613  24.305 <0.0000000000000002 ***
BTC_PriceDif   0.0034745    0.0152495   0.228                 0.82
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 109.1 on 38875 degrees of freedom
Multiple R-squared:  0.8461,    Adjusted R-squared:  0.8461
F-statistic: 5.343e+04 on 4 and 38875 DF,  p-value: < 0.00000000000000022
```

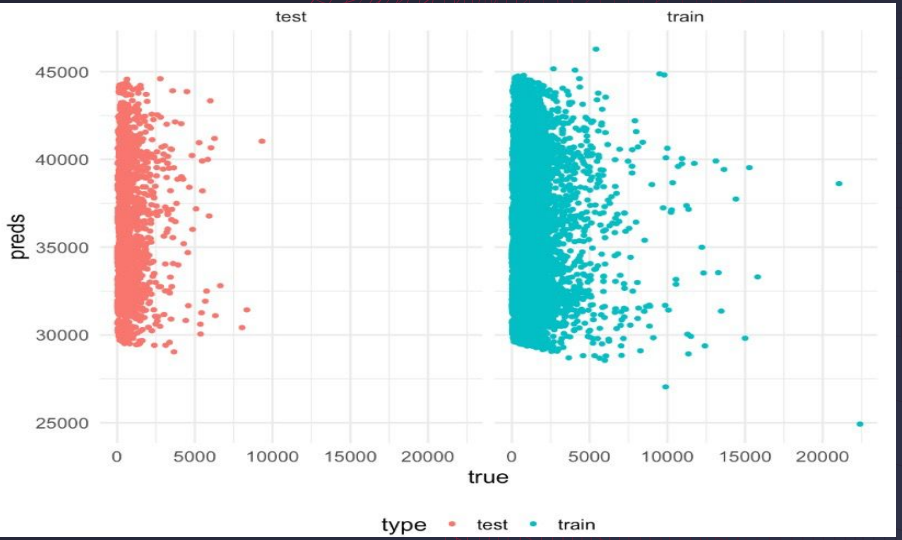
- Model Performance
- Explains nearly 84% of the price change for both BTC and ETH with the predictors selected: closing price of other, volume of other, volume, and volatility
- This means that we can easily predict price based on historical data,
- ETH MAE:
  Testing: 85.50178
  Training: 85.16782
  BTC MAE:
  Testing: 1107.509
  Training: 1099.556

```
Call:
lm(formula = BTC_Close ~ BTC_Volume + ETH_Close + ETH_Volume +
    ETH_PriceDif, data = total_train)

Residuals:
    Min      1Q  Median      3Q     Max
-9651.3  -839.8  -330.1   328.8  5664.0

Coefficients:
              Estimate Std. Error t value            Pr(>|t|)
(Intercept)  8187.10083   59.27049 138.131 <0.0000000000000002 ***
BTC_Volume      3.69794    0.14660  25.226 <0.0000000000000002 ***
ETH_Close      12.35282    0.02687 459.747 <0.0000000000000002 ***
ETH_Volume     -0.28877    0.01293 -22.327 <0.0000000000000002 ***
ETH_PriceDif    0.84882    2.77584   0.306                 0.76
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1467 on 38875 degrees of freedom
Multiple R-squared:  0.8464,    Adjusted R-squared:  0.8464
F-statistic: 5.355e+04 on 4 and 38875 DF,  p-value: < 0.00000000000000022
```

Linear Regression



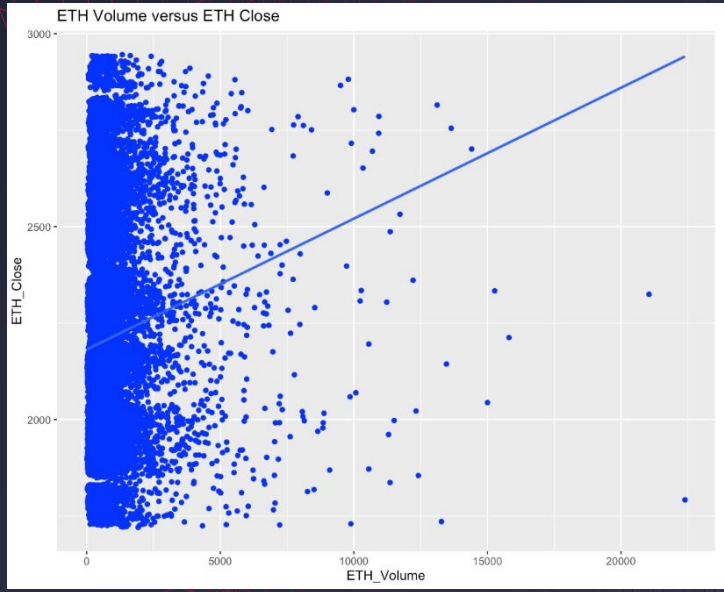
Model 1 (ETH)



Model 2 (BTC)

Linear Regression – Conclusion

- Linear Regression is most helpful for determining general trends related to how the changes in factors related to the variable on which we are predicting, but more importantly, attributes of the opposite currency, have on price.
- Helpful insight to build another model off of, but obviously you could not start with some of the information we had
- ETH is positively correlated with it's own volume, and BTC Price, with no correlation for BTC Price change. It is negatively correlated to BTC volume which may show a flow from Ether to Bitcoin
- BTC is positively correlated with it's own volume, and ETH Price, positively with price changes in ETH, and negatively with the opposite volume, similarly to ETH
- Strongest correlation to volume of other one (negative), and price of other one (positive)



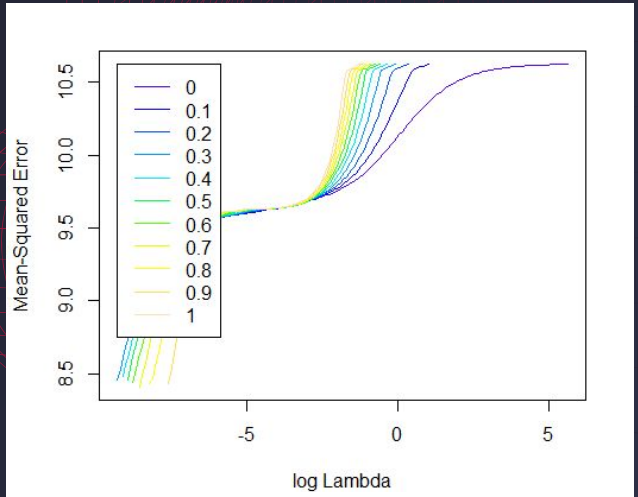
Model 2: Elastic Net

Is it possible to predict the minute change of the other crypto pair given information solely of the other? EX: Predict BTC based on only ETH data?

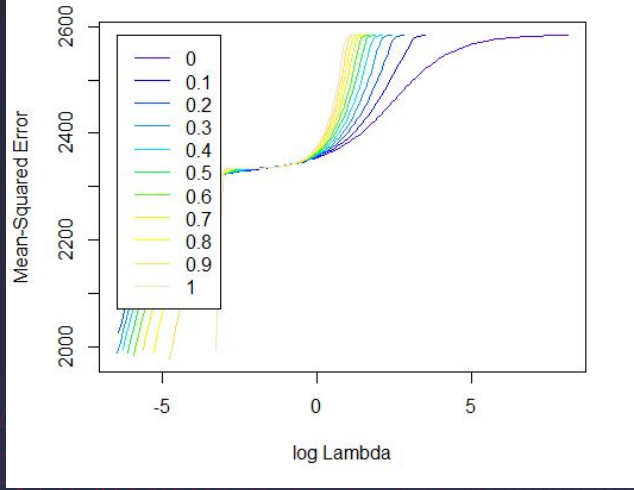
Elastic Net

```
enet_mod_ETH <- cva.glmnet(ETH_PriceDif ~ BTC_Open + BTC_High +
BTC_Low + BTC_Close + BTC_Volume + BTC_QuoteAssetVolume +
BTC_NumberOfTrades + BTC_TalkerBuyBaseAssetVolume +
BTC_TalkerBuyQuoteAssetVolume,
                        data = ETH_BTC_USDT11month,
                        alpha = seq(0,1, by = 0.1))

enet_mod_BTC <- cva.glmnet(BTC_PriceDif ~ ETH_Open + ETH_High +
ETH_Low + ETH_Close + ETH_Volume + ETH_QuoteAssetVolume +
ETH_NumberOfTrades + ETH_TalkerBuyBaseAssetVolume +
ETH_TalkerBuyQuoteAssetVolume,
                        data = ETH_BTC_USDT11month,
                        alpha = seq(0,1, by = 0.1))
```

Predicting ETH



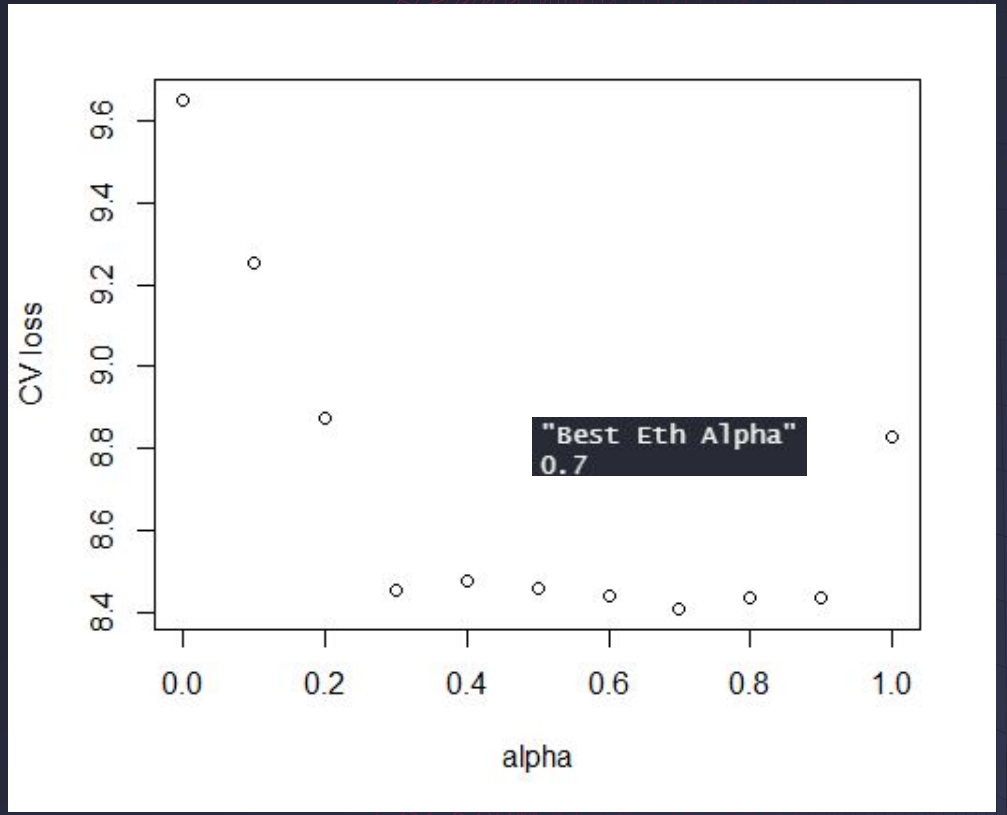
Predicting BTC



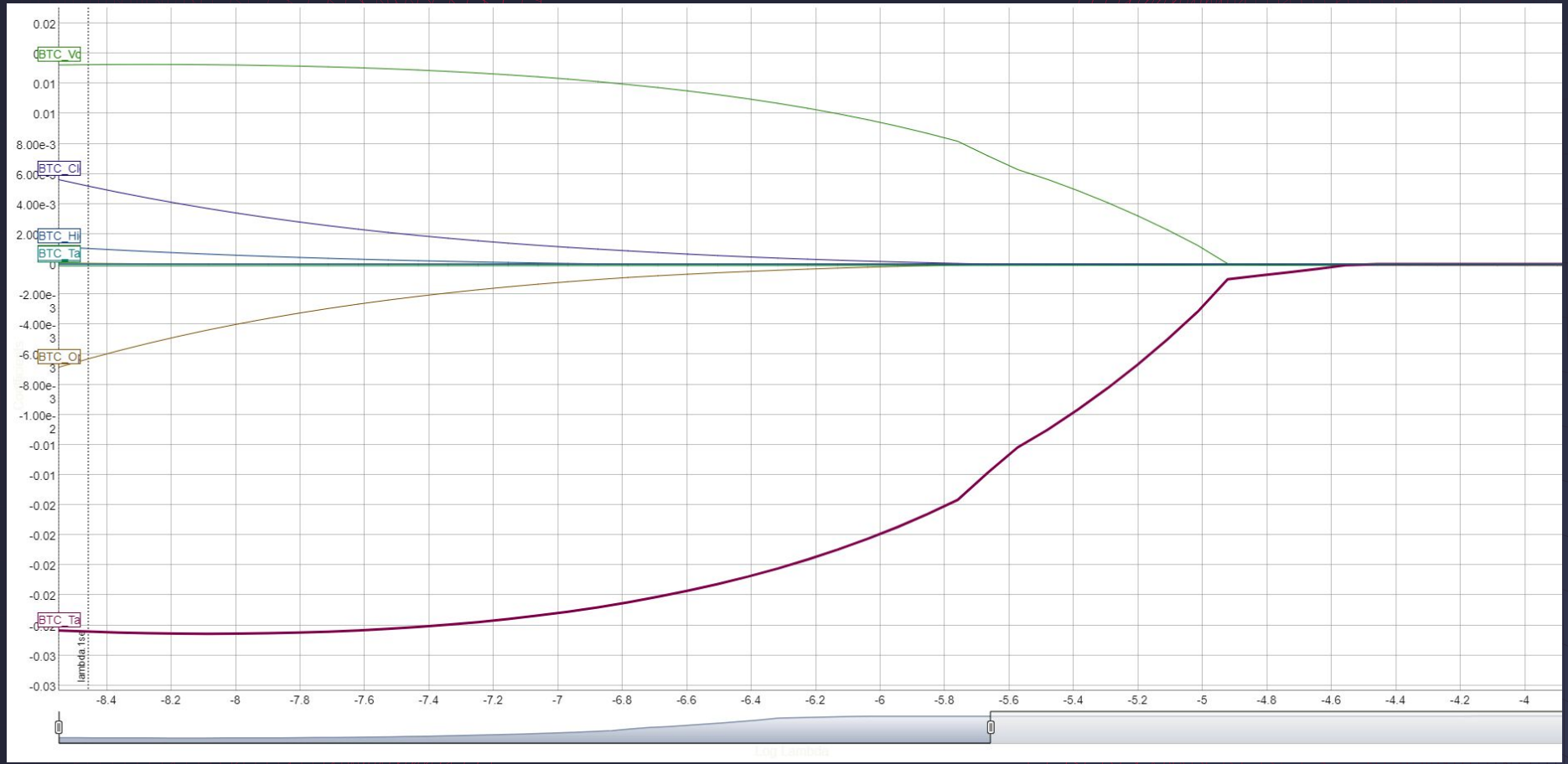
Elastic Net

Predicting ETH

```
[1] "Coefs For ETH"
10 x 1 sparse Matrix of class "dgCMatrix"
                                       s1
(Intercept)                  0.001080469336
BTC_Open                    -0.006286752650
BTC_High                     0.001041556294
BTC_Low                      0.000058624609
BTC_Close                    0.005189141334
BTC_Volume                   0.013257193272
BTC_QuoteAssetVolume        -0.000001258945
BTC_NumberOfTrades          -0.000114053769
BTC_TalkerBuyBaseAssetVolume -0.024411716492
BTC_TalkerBuyQuoteAssetVolume 0.000002516258
```

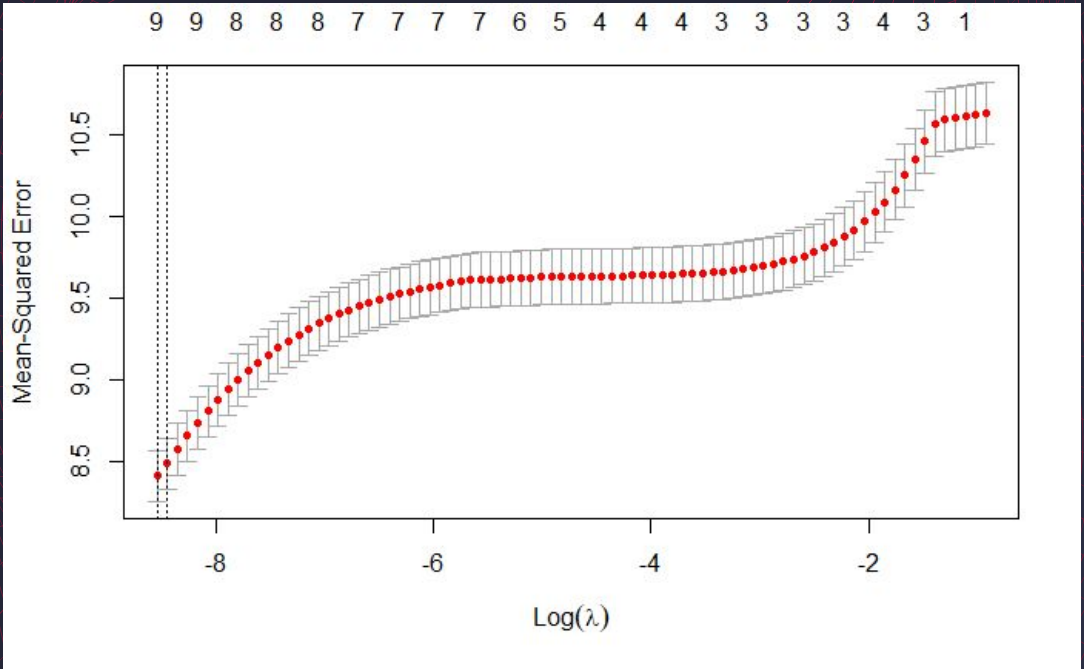


alpha <dbl>	lambdaMin <dbl>	lambdaSE <dbl>	eror <dbl>
0.7	0.0001937685	0.0002126607	8.40991


BTC_Vo
BTC_Cl
BTC_Hi
BTC_Ta
BTC_Op
BTC_Ta
lambda 1st
0.02
0.01
0.01
8.00e-3
4.00e-3
2.00
-2.00e-3
-4.00e-3
-6.0
-8.00e-3
-1.00e-2
-0.01
-0.01
-0.02
-0.02
-0.02
-0.02
-0.03
-0.03
-8.4
-8.2
-8
-7.8
-7.6
-7.4
-7.2
-7
-6.8
-6.6
-6.4
-6.2
-6
-5.8
-5.6
-5.4
-5.2
-5
-4.8
-4.6
-4.4
-4.2
-4

Elastic Net

Predicting ETH

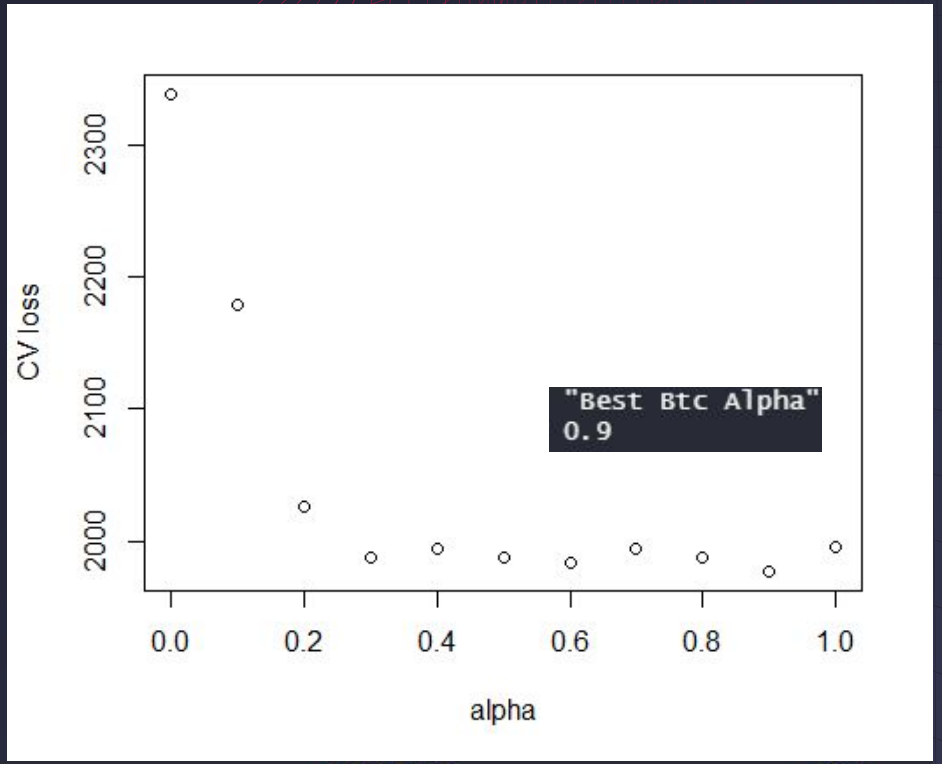


alpha <dbl>	lambdaMin <dbl>	lambdaSE <dbl>	eror <dbl>
0.7	0.0001937685	0.0002126607	8.40991

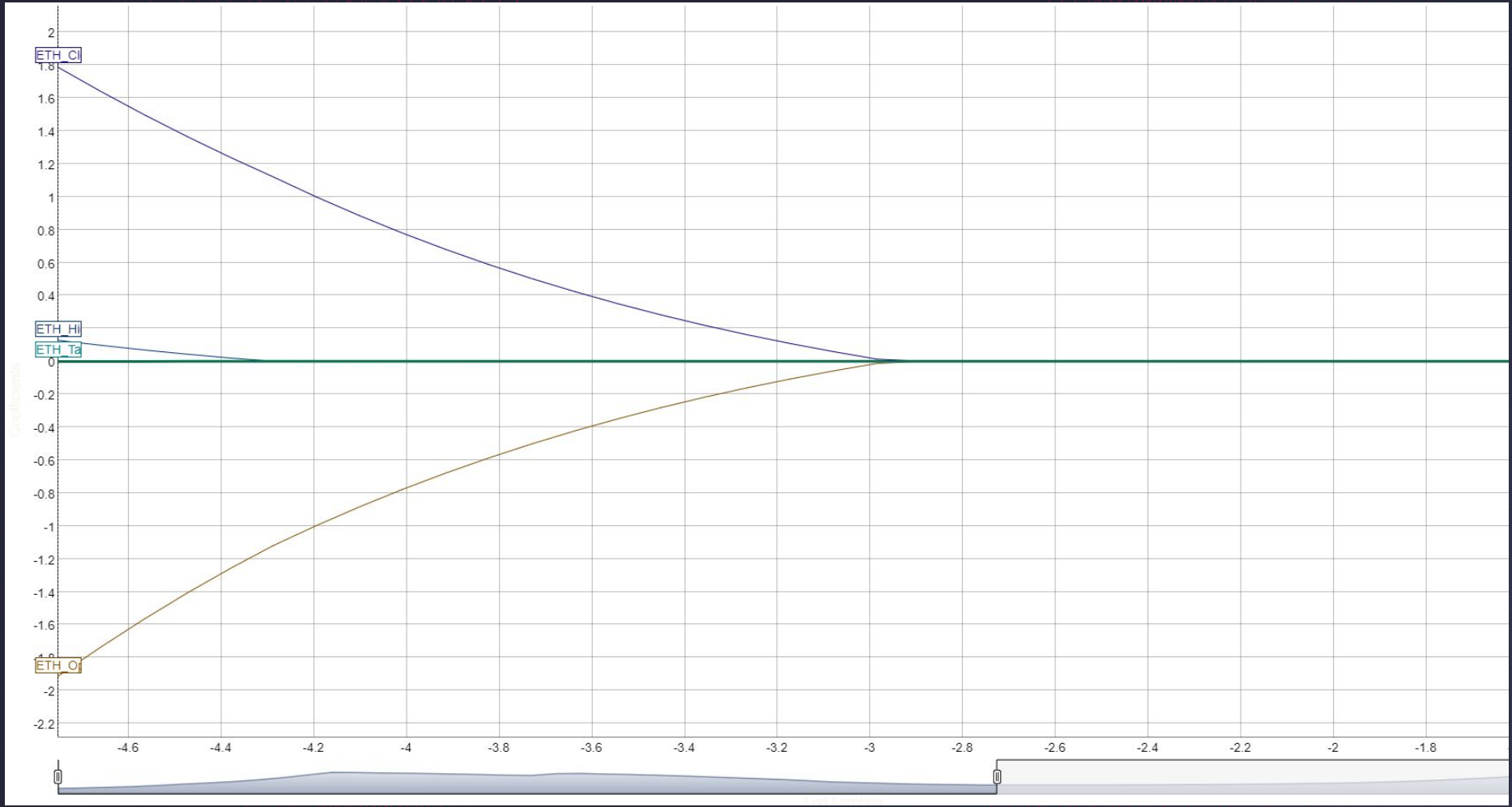
Elastic Net

Predicting BTC

```
[1] "Coefs For BTC"
10 x 1 sparse Matrix of class "dgCMatrix"
                                        s1
(Intercept)                   0.07052978029
ETH_Open                     -1.91581542700
ETH_High                      0.12789285855
ETH_Low                       .
ETH_Close                     1.78820788396
ETH_Volume                    0.00090799059
ETH_QuoteAssetVolume         -0.00002558075
ETH_NumberOfTrades           -0.00089071199
ETH_TalkerBuyBaseAssetVolume -0.00107270106
ETH_TalkerBuyQuoteAssetVolume 0.00005091806
```

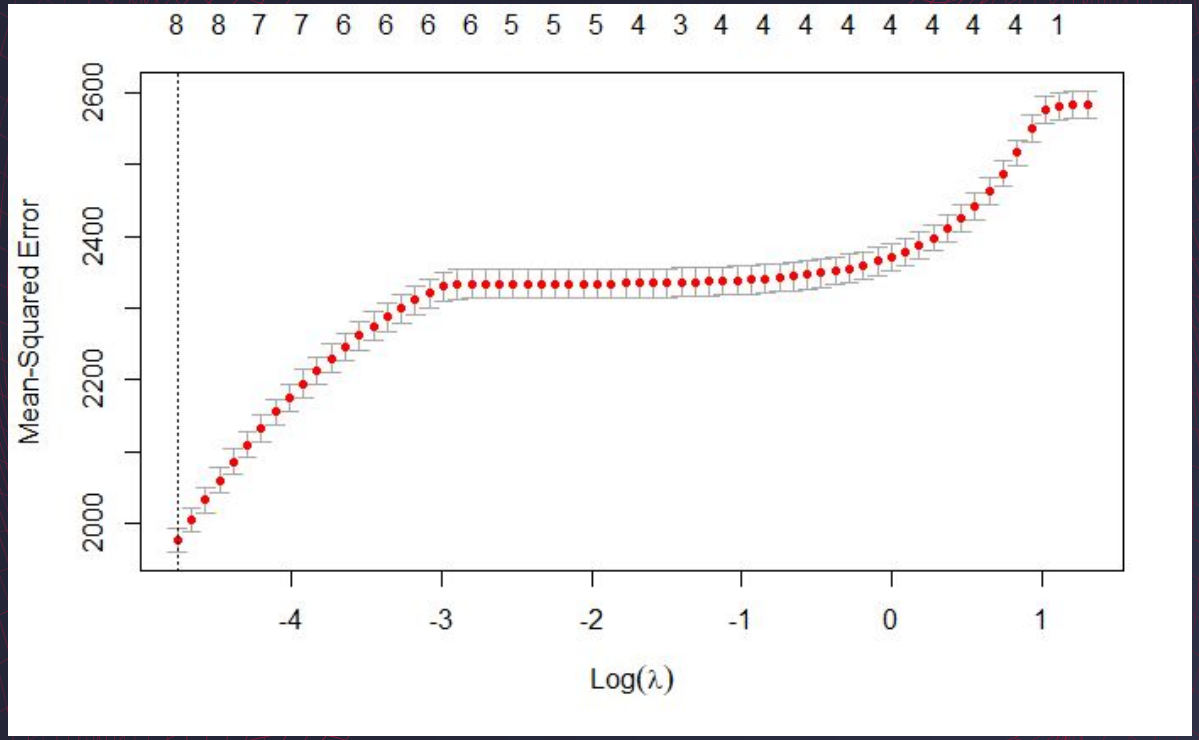


alpha <dbl>	lambdaMin <dbl>	lambdaSE <dbl>	eror <dbl>
0.9	0.008634273	0.008634273	1977.347


ETH_Cl
ETH_Hi
ETH_Ta
ETH_Op
2
1.8
1.6
1.4
1.2
1
0.8
0.6
0.4
0
-0.2
-0.4
-0.6
-0.8
-1
-1.2
-1.4
-1.6
-2
-2.2
-4.6
-4.4
-4.2
-4
-3.8
-3.6
-3.4
-3.2
-3
-2.8
-2.6
-2.4
-2.2
-2
-1.8

Elastic Net

Predicting BTC



alpha <dbl>	lambdaMin <dbl>	lambdaSE <dbl>	eror <dbl>
0.9	0.008634273	0.008634273	1977.347

Elastic Net: So, how did it do?

```
varsBTC <- c('BTC_Open', 'BTC_High', 'BTC_Low', 'BTC_Close', 'BTC_Volume', 'BTC_QuoteAssetVolume', 'BTC_NumberOfTrades','BTC_TalkerBuyBaseAssetVolume',
'BTC_TalkerBuyQuoteAssetVolume')
BTC_USDT1monthX = BTC_USDT1month[varsBTC]
BTC_USDT11monthX = BTC_USDT11month[varsBTC]
BTC_USDT1monthY = BTC_USDT1month['BTC_PriceDif']
BTC_USDT11monthY = BTC_USDT11month['BTC_PriceDif']


varsETH <- c('ETH_Open', 'ETH_High', 'ETH_Low', 'ETH_Close', 'ETH_Volume', 'ETH_QuoteAssetVolume', 'ETH_NumberOfTrades', 'ETH_TalkerBuyBaseAssetVolume',
'ETH_TalkerBuyQuoteAssetVolume')
ETH_USDT1monthX = ETH_USDT1month[varsETH]
ETH_USDT11monthX = ETH_USDT11month[varsETH]
ETH_USDT1monthY = ETH_USDT1month['ETH_PriceDif']
ETH_USDT11monthY = ETH_USDT11month['ETH_PriceDif']

#preds test
EthPreds1month = predict(enet_mod_ETH, BTC_USDT1monthX, alpha = best_alpha_ETH)
BtcPreds1month = predict(enet_mod_BTC, ETH_USDT1monthX, alpha = best_alpha_BTC)
#preds train
EthPreds11month = predict(enet_mod_ETH, BTC_USDT11monthX, alpha = best_alpha_ETH)
BtcPreds11month = predict(enet_mod_BTC, ETH_USDT11monthX, alpha = best_alpha_BTC)

BTC_USDT1monthY$pred <- BtcPreds1month
ETH_USDT1monthY$pred <- EthPreds1month

BTC_USDT11monthY$pred <- BtcPreds11month
ETH_USDT11monthY$pred <- EthPreds11month
```

Elastic Net: So, how did it do?

```
"Test MSE"
"BTC"
19.54091
"ETH"
1.656208
"Test RSQ"
"BTC"
0.2716237
"ETH"
0.2225512
```

```
"Train MSE"
"BTC"
25.83561
"ETH"
1.457341
"Train RSQ"
"BTC"
0.2728549
"ETH"
0.2255522
```

```
[1] "1 month"
[1] "BTC"
  BTC_PriceDif          pred.lambda.1se
 Min.   :-759.4102   Min.   :-610.2004
 1st Qu.: -16.1509   1st Qu.:  -5.2223
 Median :   0.1406   Median :   0.4253
 Mean   :   0.2143   Mean   :   0.2096
 3rd Qu.:  16.4102   3rd Qu.:   5.8609
 Max.   :1783.9023   Max.   : 724.5594
[1] "ETH"
  ETH_PriceDif          pred.lambda.1se
 Min.   :-33.00000   Min.   :-35.34904
 1st Qu.: -1.40002   1st Qu.: -0.20731
 Median :  0.01001   Median :  0.03939
 Mean   :  0.01290   Mean   :  0.03694
 3rd Qu.:  1.41016   3rd Qu.:  0.27604
 Max.   : 61.12012   Max.   : 37.23607
```

```
[1] "11 months"
[1] "BTC"
  BTC_PriceDif          pred.lambda.1se
 Min.   :-2157.9102   Min.   :-696.8154
 1st Qu.:  -14.1211   1st Qu.:  -2.7760
 Median :   -0.0195   Median :   0.1893
 Mean   :    0.0443   Mean   :   0.0443
 3rd Qu.:   13.9902   3rd Qu.:   3.3004
 Max.   : 1510.6797   Max.   : 529.6729
[1] "ETH"
  ETH_PriceDif          pred.lambda.1se
 Min.   :-215.46997   Min.   :-39.59875
 1st Qu.:  -0.64999   1st Qu.: -0.16782
 Median :   0.00000   Median :  0.00866
 Mean   :   0.00339   Mean   :  0.00339
 3rd Qu.:   0.65997   3rd Qu.:  0.19438
 Max.   : 168.91003   Max.   : 33.66883
```

Model Conclusions: Elastic Net

This model works well. It's not great at predicting extremes of the data.

Neither model was extremely overfit or underfit

MSE's were small in comparison to domain of dataset

Still not very applicable to a business money making method. (not accurate enough) and I did not apply any time series methodology so the model is not built for forecasting.

Still useful for analyzing past data.

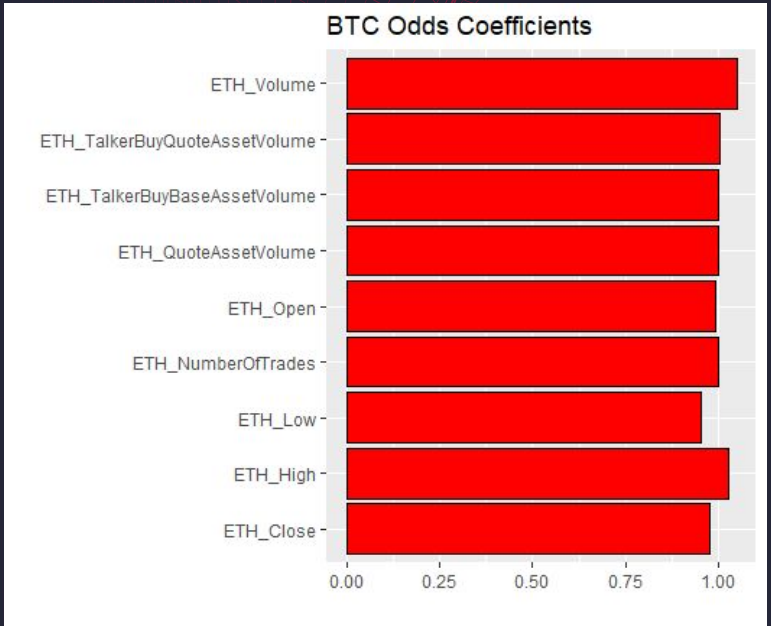
Verdict: semi-usable

Model 3: Logistic

Can we predict whether or not to buy or sell Bitcoin or Ethereum based off the past minute's price action?

Logistic: BTC Model

Exponentiated




```
plot <- ggplot(coeffs, aes(x = Coefficient.values, y = conditional))
+ geom_bar(stat="identity", color = "black", fill = "red")
+ ggtitle("BTC Odds Coefficients") + labs(x = "", y = "")

print(plot)
```

```
logit_fit_train <- glm(BTCBuy ~ ETH_Open + ETH_High + ETH_Low + ETH_Close
                       + ETH_Volume + ETH_QuoteAssetVolume + ETH_NumberOfTrades
                       + ETH_TalkerBuyBaseAssetVolume
                       + ETH_TalkerBuyQuoteAssetVolume,
                     family = binomial,
                     data = ETH_BTC_USDT11month)
```

Unexponentiated

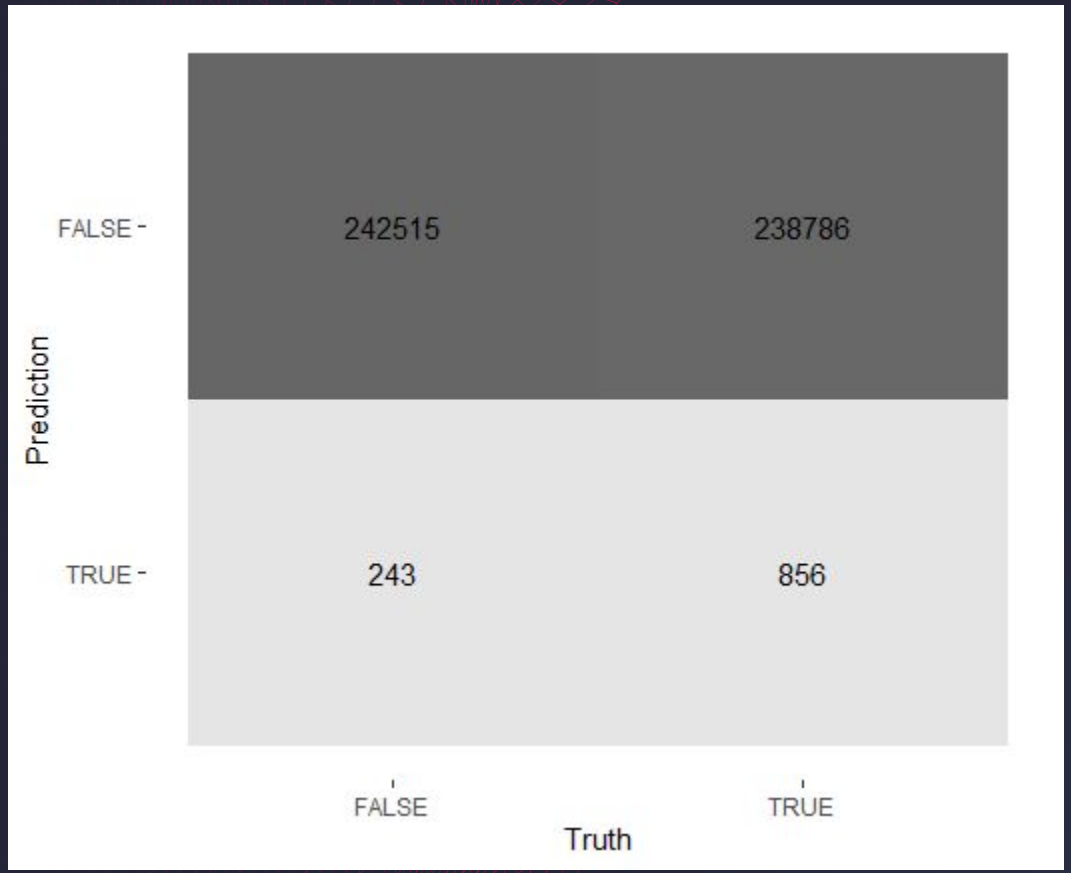
```
Deviance Residuals:
    Min       1Q   Median       3Q      Max
-6.2014  -1.1699  -0.5004   1.1671   4.6493

Coefficients:
                                 Estimate     Std. Error z value Pr(>|z|)
(Intercept)                -0.00749080551  0.00681254398  -1.100  0.27152
ETH_Open                    0.02475682392  0.00200516220  12.347  < 2e-16 ***
ETH_High                   -0.04753044083  0.00228497439 -20.801  < 2e-16 ***
ETH_Low                    -0.02410570019  0.00234362654 -10.286  < 2e-16 ***
ETH_Close                   0.04690118463  0.00217199293  21.594  < 2e-16 ***
ETH_Volume                 -0.00181868409  0.00002160060 -84.196  < 2e-16 ***
ETH_QuoteAssetVolume        0.00000057117  0.00000001305  43.769  < 2e-16 ***
ETH_NumberOfTrades          0.00003459287  0.00001057229   3.272  0.00107 **
ETH_TalkerBuyBaseAssetVolume  0.00360274403  0.00004121384  87.416  < 2e-16 ***
ETH_TalkerBuyQuoteAssetVolume -0.00000115869  0.00000002369 -48.905  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 668728  on 482399  degrees of freedom
Residual deviance: 655496  on 482390  degrees of freedom
AIC: 655516

Number of Fisher Scoring iterations: 4
```

Logistic: BTC Confusion Matrix


```
results_train <- data.frame(
  `truth` = ETH_BTC_USDT11month %>% select(BTCBuy),
  `Class1` =  BTCBuy_train_pred,
  `type` = rep("train",length(BTCBuy_train_pred))
)


results_test <- data.frame(
  `truth` = ETH_BTC_USDT %>% select(BTCBuy),
  `Class1` =  BTCBuy_test_pred,
  `type` = rep("test",length(BTCBuy_test_pred))
)

results <- bind_rows(results_train, results_test)
```

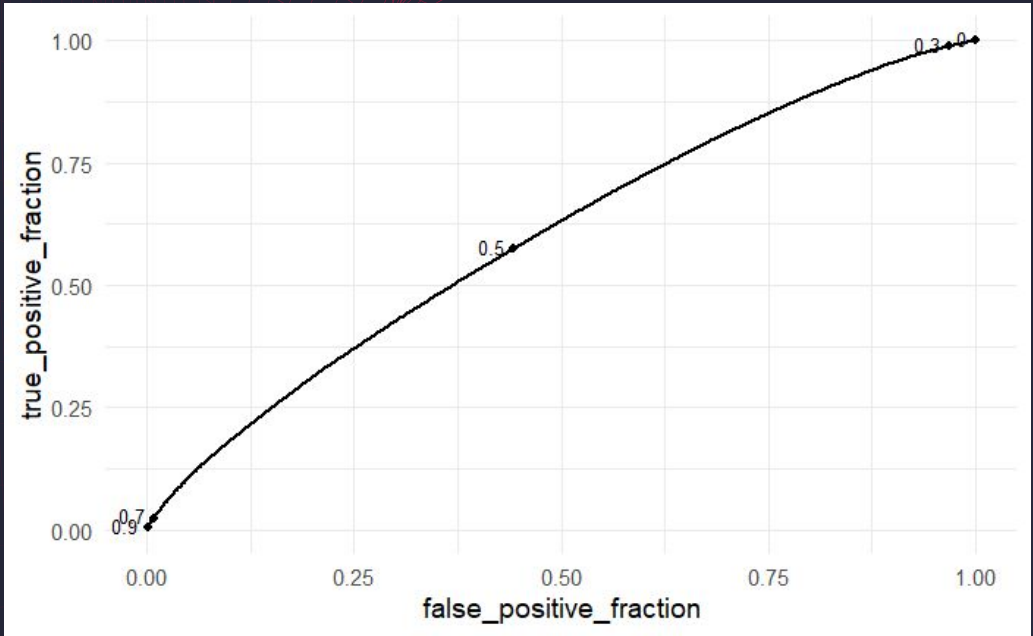
```
results_logit <- data.frame(
  `truth` = ETH_BTC_USDT11month$BTCBuy,
  `Class1` =  BTCBuy_train_pred,
  `Class2` = 1 - BTCBuy_train_pred,
  `predicted` = as.factor(ifelse(BTCBuy_train_pred > 0.5,
                                 "TRUE","FALSE"))
)

cm <- conf_mat(results_logit,
               truth = truth,
               estimate = predicted)

print(cm)
autoplot(cm, "heatmap")
```

Logistic: BTC Confusion Matrix w/ threshold of 0.9



- More conservative threshold
- Better at predicting when not to Buy
- AUC score is still poor

Logistic: BTC ROC Plot




```
p <- ggplot(results_logit,
            aes(m = Class1, d = truth)) +
  geom_roc(labelsize = 3.5,
           cutoffs.at =
             c(0.9,0.7,0.5,0.3,0)) +
  theme_minimal(base_size = 14)

print(p)
calc_auc(p)

roc_auc(results_logit,
        truth = truth,
        estimate = predicted)
```

PANEL <fctr>	group <int>	AUC <dbl>
1	-1	0.5984277

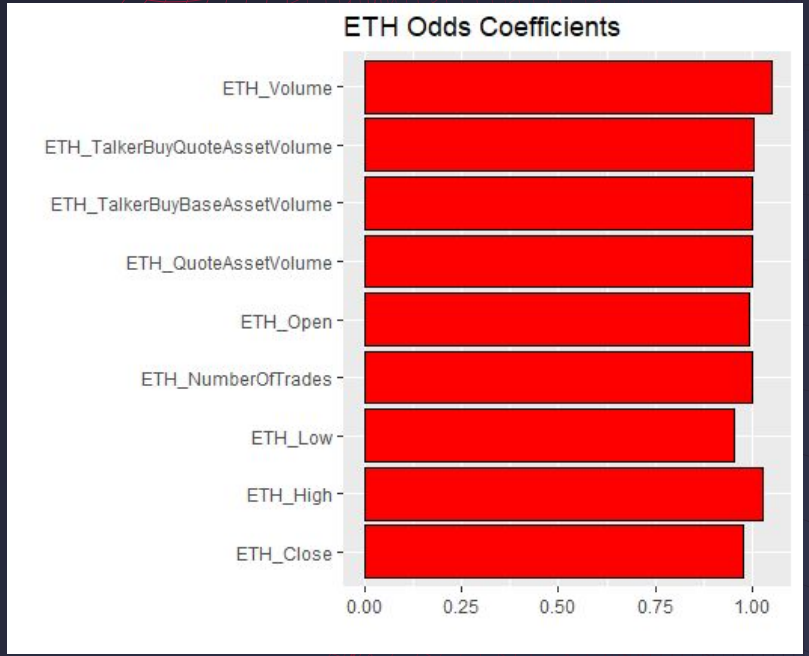
Logistic: ETH Model

```
logit_fit_train2 <- glm(ETHBuy ~ BTC_Open + BTC_High + BTC_Low
                        + BTC_Close + BTC_Volume + BTC_QuoteAssetVolume
                        + BTC_NumberOfTrades
                        + BTC_TalkerBuyBaseAssetVolume
                        + BTC_TalkerBuyQuoteAssetVolume,
                    family = binomial,
                    data = ETH_BTC_USDT11month)
```

Unexponentiated

```
Deviance Residuals:
    Min       1Q   Median       3Q      Max
-3.3557  -1.1644  -0.9681   1.1871   3.4945

Coefficients:
                                Estimate      Std. Error z value          Pr(>|z|)
(Intercept)                  -0.058072398386  0.008069928921  -7.196 0.000000000000619 ***
BTC_Open                      0.003076653563  0.000124858477  24.641           < 2e-16 ***
BTC_High                     -0.002653871939  0.000140607902 -18.874           < 2e-16 ***
BTC_Low                      -0.001373104357  0.000143627872  -9.560           < 2e-16 ***
BTC_Close                     0.000952782301  0.000133319363   7.147 0.000000000000889 ***
BTC_Volume                   -0.000198500216  0.000298735319  -0.664             0.506
BTC_QuoteAssetVolume         -0.000000164108  0.000000009388 -17.480           < 2e-16 ***
BTC_NumberOfTrades           -0.000011552409  0.000007976316  -1.448             0.148
BTC_TalkerBuyBaseAssetVolume  0.000465575471  0.000545438609   0.854             0.393
BTC_TalkerBuyQuoteAssetVolume 0.000000342080  0.000000017196  19.893           < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 668703  on 482399  degrees of freedom
Residual deviance: 666240  on 482390  degrees of freedom
AIC: 666260

Number of Fisher Scoring iterations: 3
```

Exponentiated



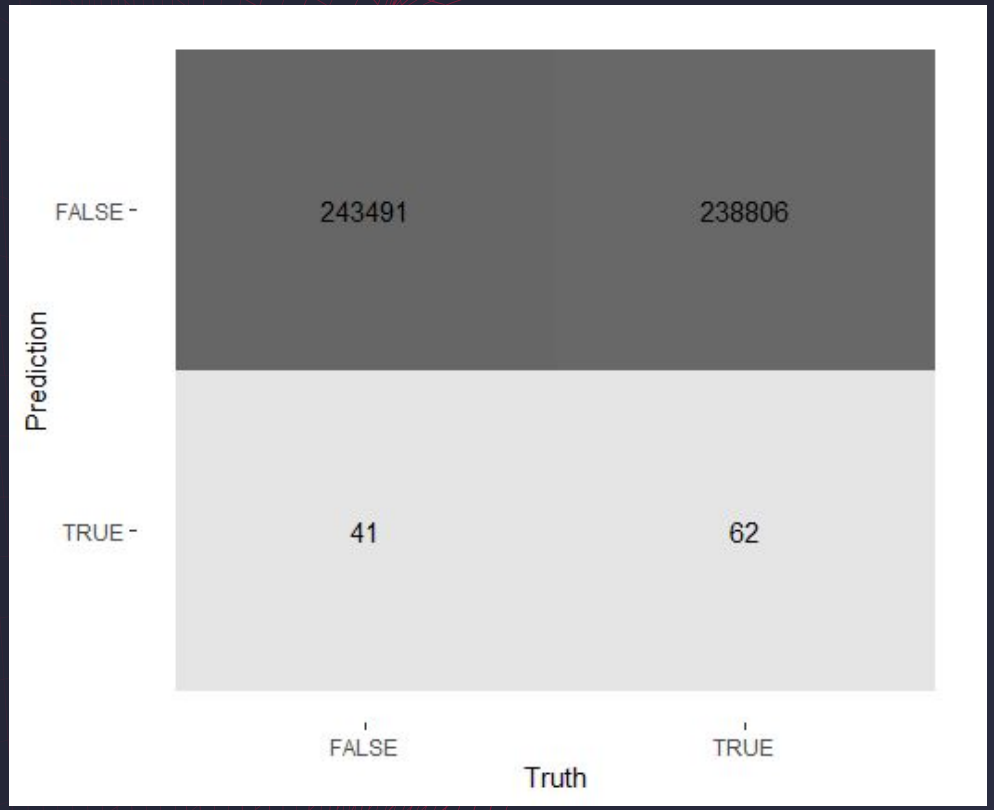

```
plot2 <- ggplot(coeffs2, aes(x = Coefficient.values, y = conditional))
+ geom_bar(stat="identity", color = "black", fill = "red")
+ ggtitle("ETH Odds Coefficients")
+ labs(x = "", y = "")

print(plot2)
```

Logistic: ETH Confusion Matrix


```
results_train2 <- data.frame(
  `truth` = ETH_BTC_USDT11month %>% select(ETHBuy),
  `Class1` =  ETHBuy_train_pred,
  `type` = rep("train",length(ETHBuy_train_pred))
)


results_test2 <- data.frame(
  `truth` = ETH_BTC_USDT %>% select(ETHBuy),
  `Class1` =  ETHBuy_test_pred,
  `type` = rep("test",length(ETHBuy_test_pred))
)

results2 <- bind_rows(results_train2, results_test2)
```

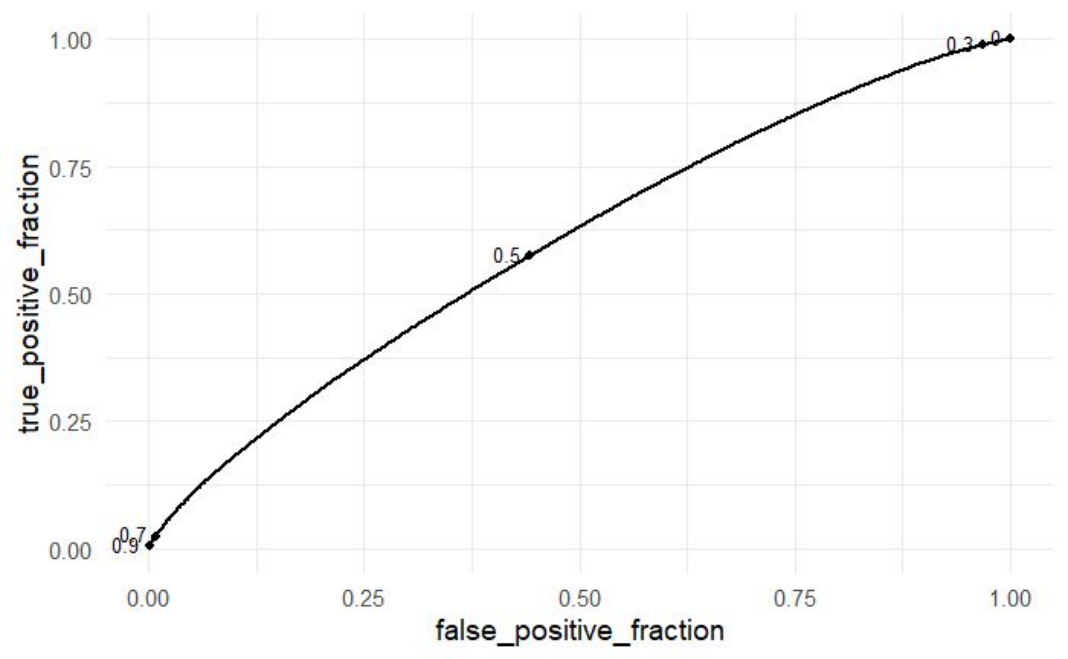
```
results_logit2 <- data.frame(
  `truth` = ETH_BTC_USDT11month$ETHBuy,
  `Class1` =  ETHBuy_train_pred,
  `Class2` = 1 - ETHBuy_train_pred,
  `predicted` = as.factor(ifelse(ETHBuy_train_pred > 0.49,
                                 "TRUE","FALSE"))
)

cm2 <- conf_mat(results_logit2,
                truth = truth,
                estimate = predicted)

print(cm2)
autoplot(cm2, "heatmap")
```

Logistic: ETH Confusion Matrix threshold of 0.9



- Not a powerful threshold
- Small opportunities for true positives
- AUC Score very poor

Logistic: ETH ROC Plot




```
p2 <- ggplot(results_logit2,
             aes(m = Class1, d = truth)) +
  geom_roc(labelsize = 3.5,
           cutoffs.at =
            c(0.99,0.9,0.7,0.5,0.3,0.1,0)) +
  theme_minimal(base_size = 14)
print(p2)
calc_auc(p2)


roc_auc(results_logit2,
        truth = truth,
        estimate = predicted)
```

PANEL <fctr>	group <int>	AUC <dbl>
1	-1	0.548675

Logistic: Conclusion

Model is not helpful

Too many false positives and true negatives

Trading Algorithm would do poor job

Low AUC scores

Model Comparisons

1. Linear Regression <- Useful
2. Elastic Net <- Useful
3. Logistic Regression <- Not Useful

But none are anything close to ready to apply to a commercial scale for current Crypto numbers.

Data Link: https://www.kaggle.com/jorijnsmit/binance-full-history/discussion/198669

THANKS!

Test Our Code!!!

RatFuryJunior/MGSC_310_Binance_Analysis

https://github.com/RatFuryJunior/MGSC_310_Binance_Analysis

Questions??

MGSC: 310 Ryan Welte, Nathan Cuadros, and Ethan Leimel.