COLLEGE OF ENGINEERING - Fall 2019

INDUSTRIAL ENGINEERING AND OPERATIONS RESEARCH DEPARTMENT - DATA SCIENCE (INDENG242)

COURSE PROJECT:

Machine Learning For The Prediction Of The Success Of Altcoins

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1 Motivation

Altcoins are alternative cryptocurrencies launched after the success of bitcoin. While the success of altcoins primarily depends on a number of factors such as the tech use case, funding, community and competition, general volume movement surges after they get listed on a major exchange.

Figure 1: Value of $100 of IOTA invested at the time of ICO

With the thousands of Initial Coin Offerings (ICOs), airdrops and obscure offerings that altcoins end up going through, we want to predict the likelihood of a particular set of altcoins gaining in value over a period of time. For instance, Fig. 1 represents the value of 100$ invested in IOTA at the time of ICO till date. The all time high was equivalent to $910,170 and $35,080 at the time of this report. Even if some of the portfolio of altcoins selected lose its value, the large growth rates of a small number would relate to profitability. This calculation has been considered for determination of portfolio value.

Identifying what makes an altcoin successful or unsuccessful has been hypothesized to be dependent on features not limited to the existence of a white paper, team credibility, Github activity, market cap etc. The data collection and modelling has been done to test these hypotheses.

2 Data

Historical altcoin data is not easily available publicly as a result of a variety of coins constantly being added and removed. We determined that Coinmarketcap.com and Coincheckup.com provided sufficient resources for data collection pertaining to our problem statement. In order to evaluate the change in altcoin performance, we decided to consider a 10-month gap between our prediction estimation. All required data for this time frame was scrapped from the HTML from a historical snapshot from The Wayback Machine.

The data from Feb 2019 had 1761 observations, while the data from Dec 2019 had 1916 observations. The count of common coins between these data sets was found to be 1460. Fields that were considered to provide no value to the contribution of features was removed. Fields that had a large number of "NAs" were also dropped. As a consequence of altcoins purchases being done in exchange for BTC or ETH, all prices were converted to BTC, tied to the USD value of BTC on

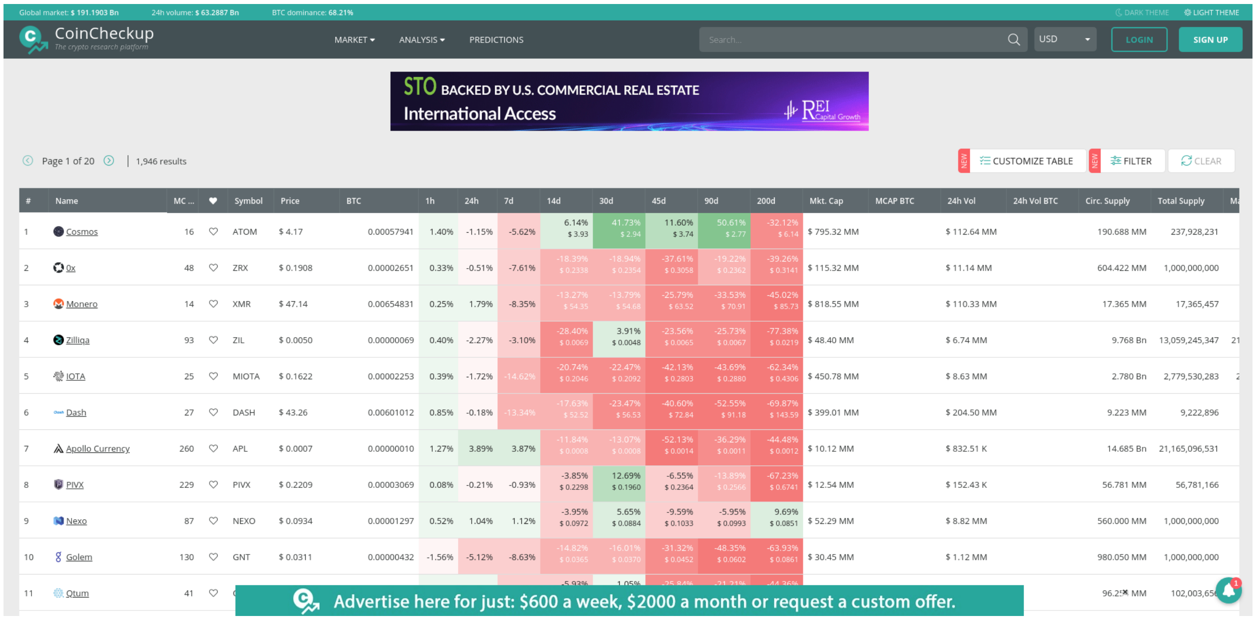


Figure 2: Fundamental analysis page of coincheckup.com

the day of the data snapshot. An assumption taken was that the market cap change would be of considerable importance. For cryptocurrencies, market cap is defined as the product of price and number of coins in circulation. However, it turns out the number of coins in circulation is modified or adjusted for a number of reasons. For instance, when it is discovered that some coins are lost forever (wallet seed is lost or destroyed) or the developers decide to "drop" privately held coins into circulation. As a result, this field was determined to be unreliable and removed from consideration for model building.

For the creation of a test and training set, the percentage change in price was calculated for each coin based on the December and February data. This value was plotted and based on the number of coins, a growth of greater than 30% was defined to be a successful outcome. A zoomed in plot of percentage change in price can be seen in Fig. 3. The red horizontal line marks the 30% cut-off of the price change. This was used to create a column in the data frame to set a binary value for said outcome.

Python files used to generate the dataset are attached in annex. We used *parse.py*, *parse_ia.py* and *parse_fa.py* to parse the HTMl from 3 different pages of CoinCheckup.com, namely the fundamental analysis page (fa) and the investment analysis page (ia). It needs to be done for the version of the website in March and in December. Then we can merge all the data from March in *merge_fixed_data.py*.

Then in *add_performance_to_merged_data.py* we can read data from December and create 5 columns:

1. label_Price: price in December

2. label_growth_rate_Price: (label_Price - Price)/Price

3. label_Mkt. Cap: Market Cap in December

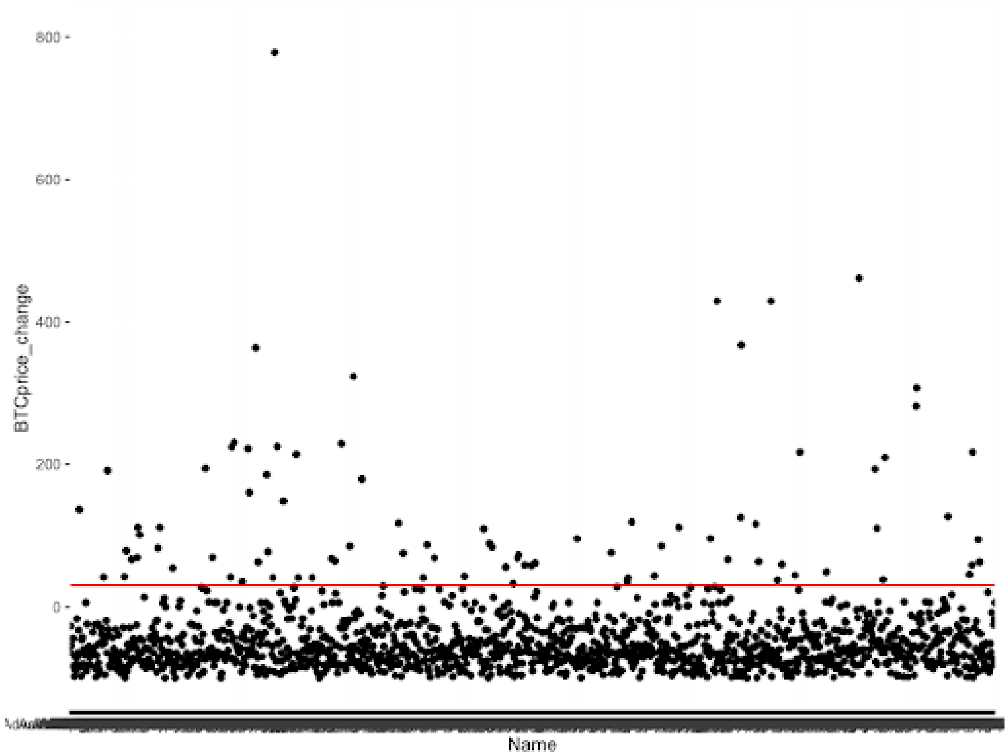


Figure 3: Plot of BTC Price Change for all coins

4. label_growth_rate_Mkt. Cap: (label_Mkt. Cap - Mkt. Cap)/Mkt. Cap

5. label_disappeared: whether a coin is listed in March but not in December

3 Dead coin prediction

3.1 Logistic regression

The list of coins on Coincheckup.com is different between 10 months ago and now. Some have been added (new coins) and others have been removed. We label the removed coins as dead coins and the remaining coins as still alive. We want to predict the death of a coin over those 10 months based on the data that we had in March. As a result, we created a column "label_disappeared" in the March dataset to tell whether the coin is dead or not. We split the dataset in 70% training and 30% testing (with fair distribution of dead coins in both parts).

#	Alive	Dead
Train	1025	208
Test	439	89

We begin with a logistic regression on the features which are numeric and have a very low rate of NAs. We check that our VIF is correct. Then we reduce the range of features to the relevant ones and make a final logistic model, that we compare to the baseline We do a logistic regression with an arbitrary threshold $p = 0.2$ and with an AIC of 1015.9 we get:

$$\hat{Y}_{dead} = sigmoid(-0.004X_{X45d} - 0.032X_{Social})$$

with $sigmoid : x \to \dfrac{1}{1+e^{-x}}$. See appendix for feature descriptions.

We can make predictions on the test set and compare with the result 10 months later. The proportion of dead coins is around 20% and when we predict that if a coin is dead, it is true more or less half of the time, so the model is not too bad!

Real Pred	Alive	Dead
Alive	320	117
Dead	37	52

Model	Accuracy	TPR	FPR
Baseline	83.1%	0	0
Logistic reg.	70.5%	58.4%	26.8%

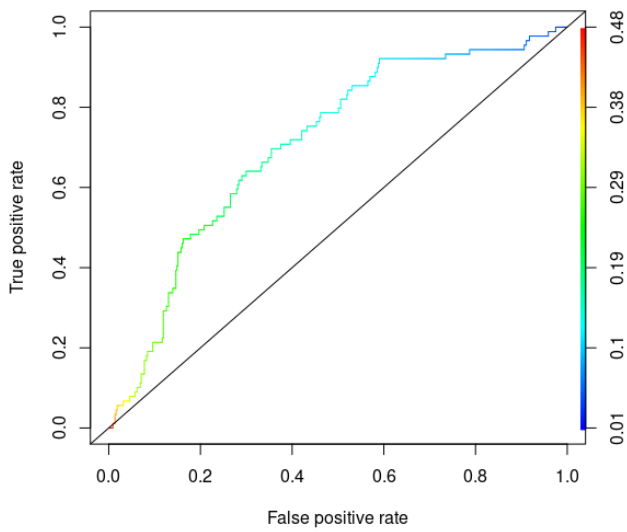


Figure 4: ROC of the logistic regression (dead coin prediction)

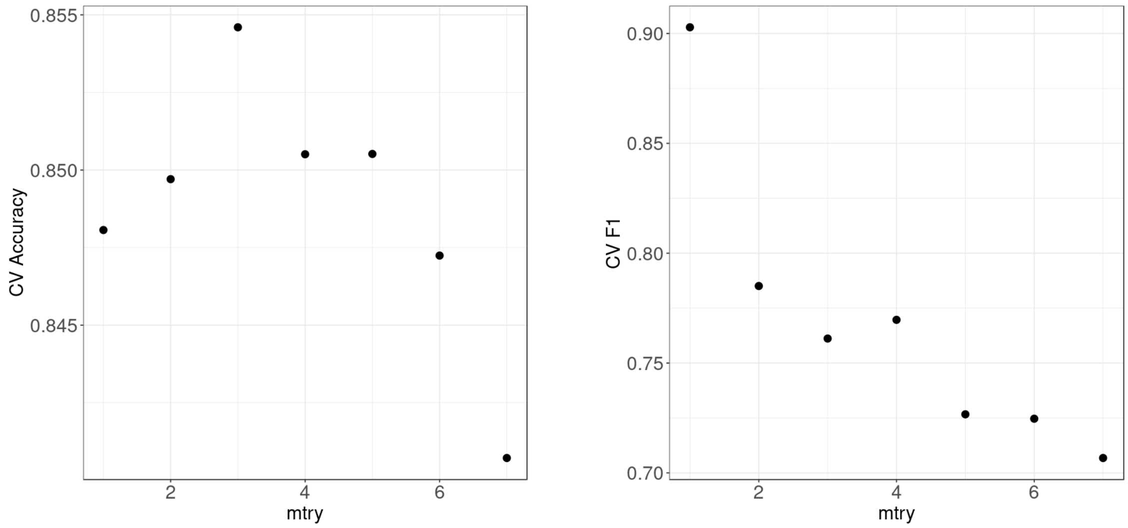
3.2 Random forest

We began checking the number of NAs in each column to select the features. We choose: X_{X24h}, X_{X14d}, X_{X45d}, X_{Social}, $X_{Mkt.Cap}$, $X_{Age.mo.}$ and $X_{Business}$. Then we try a random forest with cross-validation. We try a cross-validation measured with Accuracy and then F1-score as Accuracy is less relevant for unbalanced data.

Based on the results of figure 5, an mtry of 3 looks good. We can try sampling stratification to handle the imbalance of the data.

Real Pred	Alive	Dead
Alive	427	10
Dead	70	19

Model	Accuracy	TPR	FPR
Baseline	83.1%	0	0
Logistic reg.	70.5%	58.4%	26.8%
Random forest	84.47%	21.35%	2.29%



(a) Accuracy (b) F1-score

Figure 5: Cross validation of the random forest (dead coin prediction)

3.3 Gradient Boosting

Finally we can try a gradient boosting method with cross-validation.

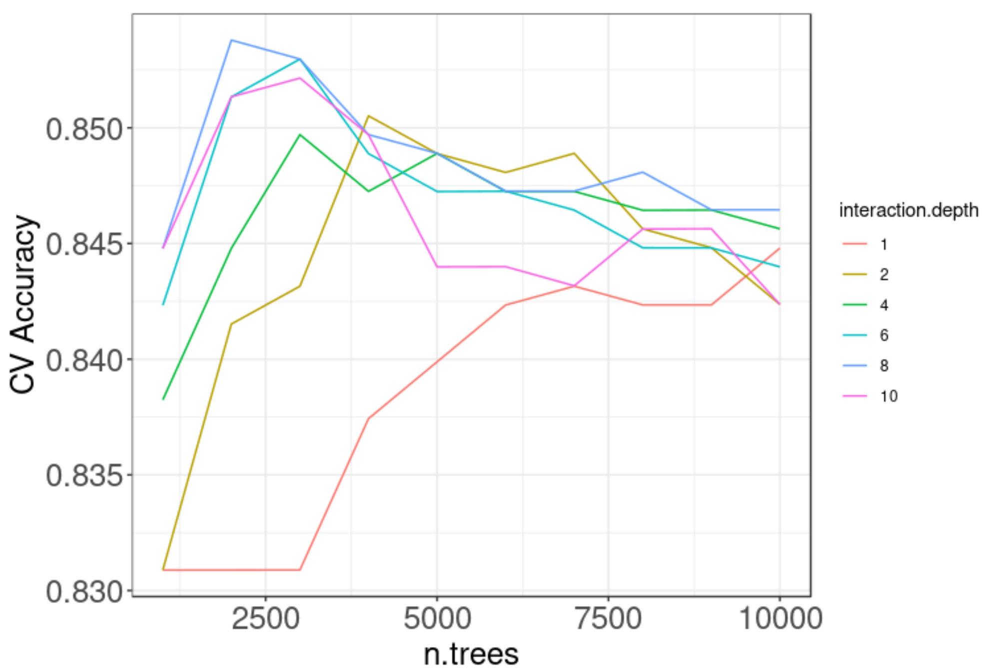


Figure 6: Cross validation of the gradient boosting (dead coin prediction)

Real Pred	Alive	Dead
Alive	221	218
Dead	70	19

Model	Accuracy	TPR	FPR
Baseline	83.1%	0	0
Logistic reg.	70.5%	58.4%	26.8%
Random forest	84.47%	21.35%	2.29%
Gradient boosting	45.45%	21.35%	49.66%

Based on results from figure 6, we choose n.trees = 2000, interaction.depth = 8.

3.4 Conclusion

Our random forest reaches the best accuracy, beating the baseline, while having a positive TPR and a low FPR.

Our gradient boosting model is very bad while the logistic regression threshold has been chosen to get the highest TPR, but it is at the expense of the accuracy and FPR.

4 Portfolio determination based on naive growth rates

Now let's tackle serious matters, we want to make money! To do that we need to establish a portfolio of assets. For now we assume that there is no opportunity cost for each asset to be in the portfolio. In practice there are fees to enter a position for each coin.

We want to naively predict $Y = label\_rate\_Price = \frac{p_T - p_0}{p_0}$ over a period T of 10 months. After trying a linear regression on a lot of features, we stumble upon a multi-colinearity problem. So we remove the guilty features and then keep the few significant features:

$$Y = -2.53 \times 10^{-3} X_{Circ.Supply} + 9.58 \times 10^{-12} X_{Total.Supply} + \epsilon$$

Model	MSE	MAE	OSR^2
Baseline	N/A	N/A	N/A
Linear reg.	547.6	1.94	-166.77

It looks bad. We can compare it to the baseline (predicting negative all the time). We assume that we invest the same amount of money in each coin (ignoring fees) if we follow the baseline while we invest sizes $s_i = \frac{Y_i}{p_{0,i}}$ if we follow our regression strategy. We can thus compute the result growth rate of both portfolios:

1. Linear regression: $R = \frac{\sum_{i=1}^{N} s_i p_T^i - \sum_{i=1}^{N} s_i p_0^i}{\sum_{i=1}^{N} s_i p_0^i} = \frac{\sum_{i=1}^{N} Y_i r_i}{\sum_{i=1}^{N} Y_i} = 0.142$

2. Baseline: $R_b = \frac{\sum_{i=1}^{N} r_i}{N} = -0.342$

Surprisingly we still beat the baseline on the test set and even earn money. We are lucky.

5 Portfolio determination in a log normal stock model

5.1 Linear regression

We often assume that the price of a stock follows a log-normal distribution, that is to say that for S_t the price of an asset at time t, $log(S_t) \sim \mathcal{N}(\mu, \sigma^2)$. Let's B_t be a standard Brownian motion ($\forall s < t, B_t - B_s \sim \mathcal{N}(0, t-s)$). We can write $S_t = S_0 e^{\mu t + \sigma B_t}$. Then for a time $T > 0$ being our 10 months, $Y^{log} = log(S_T) - log(S_0) = \mu T + \sigma B_T$ where $B_T \sim \mathcal{N}(0, T)$.

Thus performing a linear regression $\forall 1 \leq i \leq n, Y_i^{log} = \beta_0 + \sum_{j=1}^{p} \beta_j X_{ij} + \epsilon_i$, we can try, assuming our parameters constant, to estimate $\mu = \frac{1}{T}(\beta_0 + \sum_{j=1}^{p} \beta_j X_{ij})$. However estimating σ from ϵ would require us to assume that each coin has the same constant volatility which is too strong.

We need to do a new split of the data. We come across a big multi-colinearity issue which forces us to remove some features. Making particular choices we find:

$$\hat{Y^{log}} = \mu T = -1.06 - 0.00169 X_{X7d} - 0.00033 X_{MarketCap} + 0.00412 X_{Age} + \epsilon$$

Model	MSE	MAE	OSR^2	R
Baseline	1.35	0.774	0	0.413
Linear reg.	1.332	0.766	0.0152	0.50

We can create a portfolio with sizes $s_i = exp(\hat{Y^{log}}_i)$. Then our return is $R_{log} = \frac{\sum_{i=1}^{N} s_i p_T^i - \sum_{i=1}^{N} s_i p_0^i}{\sum_{i=1}^{N} s_i p_0^i} = \frac{\sum_{i=1}^{N} s_i r_i}{\sum_{i=1}^{N} s_i} = 0.500$ against $R_b = \frac{\sum_{i=1}^{N} r_i}{N} = 0.413$ for the baseline.

Much better already! We see that filtering out coins where information is missing, our portfolio behaves already better! That's because trustworthy coins get all their information filled.

5.2 Random forest

We take the features from the 2 previous models and we try it out on a random forest.
The best value is 1 for mtry.

Model	MSE	MAE	OSR^2	R
Baseline	1.35	0.774	0	0.413
Linear reg.	1.332	0.766	0.0152	0.50
Random forest	1.343	0.768	0.005	0.318

Unfortunately this model does not beat the baseline in term of financial gain.

5.3 Gradient boosting

We use the same features as for the random forest. After cross-validation (figure 8, we conclude that the best parameters are the biggest ones.

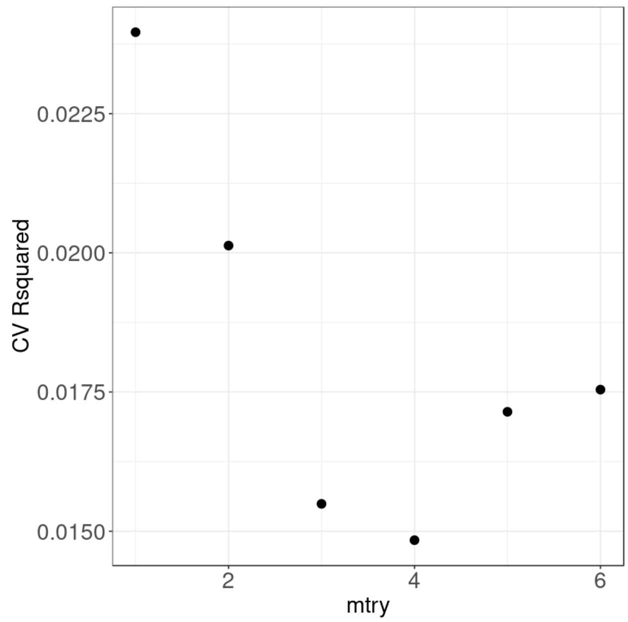


Figure 7: Cross validation of the random forest (log-normal model)

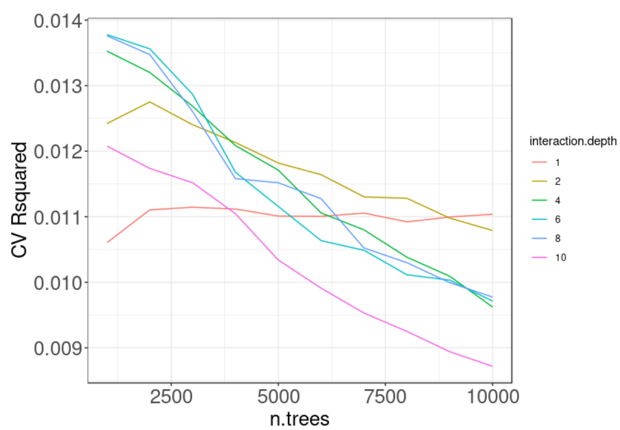


Figure 8: Cross validation of the gradient boosting (log-normal model)

Model	MSE	MAE	OSR^2	R
Baseline	1.35	0.774	0	0.413
Linear reg.	1.332	0.766	0.0152	0.50
Random forest	1.343	0.768	0.005	0.318
Gradient boosting	1.418	0.785	-0.050	0.290

This is also very bad compared to the baseline in term of porfolio return R.

5.4 Conclusion

The linear regression stays the best fit on the test set. The other model seem to overfit the data. Complicated models on low quality data makes bad results.

6 Portfolio determination in real-world

In reality there is an opportunity cost in choosing more coins in a portfolio. This cost comes form the fees to enter and exit the position: buy and sell fees plus withdraw fee (blockchain mining reward). Using the model from previous section. If we choose the coin with the best predicted μ according to the linear regression, we get a growth rate $r = 2.067$ for CannabisCoin, which outperforms R_{log}.

The top 5 includes: CannabisCoin, GlobalBoost-Y, Quebecoin, SolarCoin, Curecoin.

7 Appendix

7.1 Column Definitions

Column Name	Description
MC.._past	Position of the coin the time of snapshot
Symbol_past	Trading symbol for each coin
Price_past	Price in USD at the time of snapshot
BTC_past	Price in BTC at the time of snapshot
X30d_past	Percentage change in price over 30 days
X45d_past	Percentage change in price over 45 days
X90d_past	Percentage change in price over 90 days
X200d_past	Percentage change in price over 200 days
Mkt..Cap_past	Market Cap in USD
MCAP.BTC_past	Market Cap in BTC
Circ..Supply_past	No of circulating coins in supply
Total.Supply_past	Total supply of coins
Max..Supply_past	Maximum supply of coins possible
Team_past	Confidence value of the team based on past performance of leadership, developers etc, in percentage.
Advisors_past	Confidence value of the advisors, whether they have been successful historically and confirmed to be associated with said coin, in percentage.
Brand.Buzz_past	How large and active is the community as compared to the rest of the market, in percentage
Product_past	Is the coin an idea or a product at this stage, does it have a roadmap and available, confidence in percentage
Coin_past	Confidence in ability to transact high volumes and availabilty, in percentage
Social_past	Confidence in activity over social media, in percentage
Communication_past	Confidence of accessibility and activity over slack, telegram, email etc, in percentage
Business_past	Confidence in investors behind project, publishing of revenue reports etc, in percentage
GitHub_past	Confidence in activity on Github, in percentage
Age..mo._past	Age of the coins, in number of months
Winning.months_past	No of successful months with positive growth over 12 months, in percentage
Start.price_past	ICO start price
CMGR....3mo_past	Compound Monthly Growth Rate trailing 3 months
Cum..ROI_past	Cumulative ROI, the ROI in % from start trading price till the current price
Avg..volume_past	Average volume of coins traded
ATH_past	All time high of coin in USD

X..fm..ATH_past	Change in USD price from ATH, in percentage
ATH..BTC._past	All time high of coin in BTC
X..fm..ATH..BTC._past	Change in BTC price from ATH, in percentage
Name	Name of the coin
Mkt.BTC_c	Market cap converstion from USD to BTC
growth8mth	Price change over month duration
BTCprice_change	Percentage change in BTC compared to December
BTCmcap_change	Market cap change of in BTC compared to December snapshot
success	Binary value where 1 equals greater than 30% increase in price

7.2 Python Code

parse.py

```
# URL = "https://web.archive.org/web/20190208144932/https://coincheckup.com/predictions"

import re
from bs4 import BeautifulSoup
import csv


datas = []
for tab_idx in range(1, 22):
    with open(f"html/20190208/predictions/Predictions Overview -
        CoinCheckup{tab_idx}.html") as file:
        soup = BeautifulSoup(file.read(), 'html.parser')

        cryptos = [link.string for link in soup.find_all('a') if link.get("href") and "coins"
            in link.get("href")]

        divs = [row for row in soup.find_all(attrs={"class": re.compile("ag-row
            ag-row-no-focus ag-row-\w* ag-row-level-0")}) if
                row.div is not None and row.div.span is None]
        data = [[cryptos[idx]] + [ cell.string.strip("$ ").replace(',', '') for cell in
            div.children] for idx, div in enumerate(divs)]

        datas.append(data)


with open('coincheckup_10_months_predictions.csv', 'w', newline='') as csvfile:
    writer = csv.writer(csvfile, delimiter=',')
    writer.writerow([span.string for span in soup.find_all(role="columnheader")])
    for data in datas:
        for row in data:
            writer.writerow(row)
```

parse_fa.py

```
# URL = "https://web.archive.org/web/20190208144932/https://coincheckup.com/analysis"

import re
from bs4 import BeautifulSoup
import csv


def current():
    datas = []
    for tab_idx in range(1, 21):
        with open(f"html/20191205/fundamental_analysis/Analysis Overview -
            CoinCheckup{tab_idx}.html") as file:
            soup = BeautifulSoup(file.read(), 'html.parser')

            cryptos = [link.string for link in soup.find_all('a') if link.get("href") and
                "coins" in link.get("href")]

            divs = [row for row in soup.find_all(attrs={"class": re.compile("ag-row
                ag-row-no-focus ag-row-\w* ag-row-level-0")}) if
                    row.div is not None and row.contents[1].img is None]
            data = [[cryptos[idx]] + [div.contents[i].string if div.contents[i].div is None
                else div.contents[i].div.string for i in range(len(div.contents)-1) if i != 1]
                for idx, div in enumerate(divs)]
            for d in data:
                #print(d)
                for i in range(len(d)):
                    if d[i] is not None: # Some 200d values are None
                        d[i] = d[i].strip("$% ")    # MM and K units should be handled here
            datas.append(data)


    with open('coincheckup_current_fa.csv', 'w', newline='') as csvfile:
        writer = csv.writer(csvfile, delimiter=',')
        ### WARNING: Problem with order in the column, FIXED HEADER
        header=['Name', 'MC #', 'Symbol', 'Price', 'BTC', '1h', '24h', '7d', '14d', '30d',
            '45d', '90d', '200d', 'Mkt. Cap', 'MCAP BTC', '24h Vol', '24h Vol BTC', 'Circ.
            Supply', 'Total Supply', 'Max. Supply', 'Team', 'Advisors', 'Brand/Buzz',
            'Product', 'Coin', 'Social', 'Communication', 'Business', 'GitHub','GitHub', 'Avg.
            volume', 'Age (mo)', 'Winning months']
        #writer.writerow([span.string for span in soup.find_all(role="columnheader")[1:-1] if
            span.string is not None])
        writer.writerow(header)
        for data in datas:
            for row in data:
```

```
            writer.writerow(row)


def ten_months():
    datas = []
    for tab_idx in range(1, 19):
        with open(f"html/20190208/fundamental_analysis/Analysis Overview -
            CoinCheckup{tab_idx}.html") as file:
            soup = BeautifulSoup(file.read(), 'html.parser')

            cryptos = [link.string for link in soup.find_all('a') if link.get("href") and
                "coins" in link.get("href")]

            divs = [row for row in
                    soup.find_all(attrs={"class": re.compile("ag-row ag-row-no-focus
                        ag-row-\w* ag-row-level-0")}) if
                    row.div is not None and row.contents[1].img is None]
            data = [
                [cryptos[idx]] + [div.contents[i].string if div.contents[i].div is None else
                    div.contents[i].div.string
                                for i in range(len(div.contents) - 2)] for idx, div in
                                    enumerate(divs)]

            for d in data:
                print(d)
                for i in range(len(d)):
                    ### WARNING: I modify this part because there is a column that is
                        useless
                    if i <=2 :
                        if i == 2 :
                            continue
                        if d[i] is not None: # Some 200d values are None
                            d[i] = d[i].strip("$% ")

                    else :
                        if d[i] is not None: # Some 200d values are None
                            d[i-1] = d[i].strip("$% ")

            datas.append(data)

    with open('coincheckup_10_months_fa.csv', 'w', newline='') as csvfile :
        writer = csv.writer( csvfile , delimiter=',')

        ### WARNING: Problem with order in the column, FIXED HEADER
        header=['Name', 'MC #', 'Symbol', 'Price', 'BTC', '1h', '24h', '7d', '14d', '30d',
```

```
        '45d', '90d', '200d', 'Mkt. Cap', 'MCAP BTC', '24h Vol', '24h Vol BTC', 'Circ.
        Supply', 'Total Supply', 'Max. Supply', 'Team', 'Advisors', 'Brand/Buzz',
        'Product', 'Coin', 'Social', 'Communication', 'Business', 'GitHub','GitHub', 'Avg.
        volume', 'Age (mo)', 'Winning months']
    #writer.writerow([span.string for span in soup.find_all(role="columnheader")[1:-1] if
        span.string is not None])
    writer.writerow(header)
    for data in datas:
        for row in data:
            writer.writerow(row)

current()
ten_months()
```

parse_ia.py

```
# URL = "https://web.archive.org/web/20190208144932/https://coincheckup.com/analysis"

import re
from bs4 import BeautifulSoup
import csv


def current():
    datas = []
    numeration=1
    for tab_idx in range(1, 25):
        with open(f"html/20191205/investment_analysis/Investment Overview -
            CoinCheckup{tab_idx}.html") as file:
            soup = BeautifulSoup(file.read(), 'html.parser')

            cryptos = [link.string for link in soup.find_all('a') if link.get("href") and
                "coins" in link.get("href")]

            divs = [row for row in soup.find_all(attrs={"class": re.compile("ag-row
                ag-row-no-focus ag-row-\w* ag-row-level-0")}) if
                    row.div is not None and row.contents[1].img is None]

            data = [[cryptos[idx]] + [ cell.string.strip("$% ").replace(',', '') for cell in
                div.children] for idx, div in enumerate(divs)]

            datas.append(data)



    with open('coincheckup_current_ia.csv', 'w', newline='') as csvfile:
        writer = csv.writer(csvfile, delimiter=',')
        writer.writerow([span.string for span in soup.find_all(role="columnheader")[1:] if
            span.string is not None])
        for data in datas:
            for row in data:
                data.insert
                writer.writerow(row)


def ten_months():
    datas = []
    for tab_idx in range(1, 22):
        with open(f"html/20190208/investment_analysis/Investment Overview -
            CoinCheckup{tab_idx}.html") as file:
```

```
            soup = BeautifulSoup(file.read(), 'html.parser')

            cryptos = [link.string for link in soup.find_all('a') if link.get("href") and
                "coins" in link.get("href")]

            divs = [row for row in
                    soup.find_all(attrs={"class": re.compile("ag-row ag-row-no-focus
                        ag-row-\w* ag-row-level-0")}) if
                    row.div is not None and row.contents[1].img is None]
            if len(cryptos) == 0:
                print("WARNING: File of idx {} is ignored because it contains no
                    data".format(tab_idx))
                continue
            data = [[cryptos[idx]] + [ cell.string.strip("$% ").replace(',', '') for cell in
                div.children] for idx, div in enumerate(divs)]

            datas.append(data)

    with open('coincheckup_10_months_ia.csv', 'w', newline='') as csvfile:
        writer = csv.writer(csvfile, delimiter=',')
        writer.writerow([span.string for span in soup.find_all(role="columnheader")[1:] if
            span.string is not None])
        for data in datas:
            for row in data:
                writer.writerow(row)
current()
ten_months()
```

merge_fixed_data.py

```
import csv

num_fields = ['MC #', 'Price', 'BTC', '1h', '24h', '7d', '14d', '30d', '45d', '90d', '200d',
    'Mkt. Cap', 'MCAP BTC', '24h Vol', '24h Vol BTC', 'Circ. Supply', 'Total Supply', 'Max.
    Supply', 'Team', 'Advisors', 'Brand/Buzz', 'Product', 'Coin', 'Social', 'Communication',
    'Business', 'GitHub', 'Avg. volume', 'Age (mo)', 'Winning months']

with open("fixed_data/coincheckup_10_months_fa.csv", 'r', newline='') as old_fa,
    open("fixed_data/coincheckup_10_months_fa.csv", 'r', newline='') as old_ia:
    fa_reader = csv.DictReader(old_fa, delimiter=',')
    ia_reader = csv.DictReader(old_ia, delimiter=',')

    fields = set(fa_reader.fieldnames).union(set(ia_reader.fieldnames))
    #data = pd.DataFrame({field: [] for field in fields})
    data = {row["Name"]: row for row in fa_reader}
    for row in ia_reader:
        for key, value in row.items():
            data[row["Name"]][key] = value

    for name, row in data.items():
        for field in num_fields:
            if row[field] in {'--', '---', '', 'N/A'}:
                row[field] = ''
            else:
                row[field] = float(row[field].strip("$% ").replace(',', '').replace(' ',
                    '').replace('K', '000').replace('MM', '000000').replace('Bn',
                    '000000000').replace('Tn', '000000000000'))

with open("merged_10months_data.csv", 'w', newline='') as output:
    writer = csv.DictWriter(output, delimiter=',', fieldnames=fields)
    writer.writeheader()
    for row in data.values():
        writer.writerow(row)
```

7.3 Annotated R Code

7.3.1 Dead coin prediction

```
In [2]: library(caret)
        library(MASS)
        library(caTools)
        library(randomForest)
        library(ggplot2)
        library(GGally)
        library(car)
        library(rpart)
        library(rattle)
        library(boot)
        library(dplyr)
        library(ROCR)

        mean_squared_error <- function(responses, predictions) {
          MSE <- mean(((responses - predictions))^2)
          return(MSE)
        }

        mean_absolute_error <- function(responses, predictions) {
          MAE <- mean(abs(responses - predictions))
          return(MAE)
        }

        OS_R_squared <- function(responses, predictions, train_responses) {
          baseline <- mean(train_responses)
          SSE <- sum((responses - predictions)^2)
          SST <- sum((responses - baseline)^2)
          r2 <- 1 - SSE/SST
          return(r2)
        }

        all_metrics <- function(responses, predictions, train_responses) {
          filter_vec = !is.na(responses) & !is.na(predictions)
          responses <- responses[filter_vec]
          predictions <- predictions[filter_vec]
          train_responses <- train_responses[filter_vec]
          mse <- mean_squared_error(responses, predictions)
          mae <- mean_absolute_error(responses, predictions)
          OSR2 <- OS_R_squared(responses, predictions, train_responses)
          return(c(mse, mae, OSR2))
        }

        tableAccuracy <- function(label, pred) {
          t = table(label, pred)
```

```
  a = sum(diag(t))/length(label)
  return(a)
}

tableTPR <- function(label, pred) {
  t = table(label, pred)
  return(t[2,2]/(t[2,1] + t[2,2]))
}

tableFPR <- function(label, pred) {
  t = table(label, pred)
  return(t[1,2]/(t[1,1] + t[1,2]))
}
```

We load the preprocessed data:

```
In [3]: df <- read.csv("../python/coincheckup/dataset.csv", stringsAsFactors=FALSE, na="")
        df$label_disappeared = as.factor(df$label_disappeared)
        # name and Symbol are the only strings
```

a) Logistic regression

We begin with a logistic regression on the features which are numeric and nhave a very low rate of NAs:

```
In [4]: set.seed(42)
        split = sample.split(df$label_disappeared, SplitRatio = 0.7)
        train_data <- filter(df, split== TRUE)
        test_data <- filter(df, split== FALSE)

        table(train_data$label_disappeared)
        table(test_data$label_disappeared)

        #LOGISTIC
        logistic <- glm(label_disappeared ~ Price + X1h + X24h + X7d + X14d + X30d + X45d +
                        X90d + X200d + Mkt..Cap + X24h.Vol + Circ..Supply + Total.Supply +
                        Team + Product + Coin + Social + Communication + Business +
                        Avg..volume + Age..mo., data = train_data, family="binomial")
        summary(logistic)

        pred = predict(logistic, newdata = test_data, type="response")

        table(test_data$label_disappeared, pred>0.2)

        tableAccuracy(test_data$label_disappeared, pred>0.2)
        tableTPR(test_data$label_disappeared, pred>0.2)
        tableFPR(test_data$label_disappeared, pred>0.2)

        vif(logistic)
```

```
FALSE  TRUE
 1025   208
```

```
FALSE  TRUE
  439    89
```

```
Warning message:
“glm.fit: fitted probabilities numerically 0 or 1 occurred”
```

```
Call:
glm(formula = label_disappeared ~ Price + X1h + X24h + X7d +
    X14d + X30d + X45d + X90d + X200d + Mkt..Cap + X24h.Vol +
    Circ..Supply + Total.Supply + Team + Product + Coin + Social +
    Communication + Business + Avg..volume + Age..mo., family = "binomial",
    data = train_data)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.4129  -0.6457  -0.4438  -0.2806   2.6774

Coefficients:
                Estimate Std. Error z value Pr(>|z|)
(Intercept)    4.904e-02  4.592e-01   0.107  0.91494
Price         -5.873e-03  1.089e-02  -0.539  0.58957
X1h            7.936e-05  5.658e-03   0.014  0.98881
X24h           4.684e-04  2.211e-03   0.212  0.83221
X7d            2.764e-03  1.811e-03   1.526  0.12690
X14d          -5.093e-04  1.361e-03  -0.374  0.70821
X30d           5.891e-04  2.114e-03   0.279  0.78049
X45d          -6.051e-03  2.321e-03  -2.608  0.00912 **
X90d           2.879e-03  1.871e-03   1.539  0.12384
X200d         -2.364e-03  2.256e-03  -1.048  0.29464
Mkt..Cap      -5.270e-05  3.726e-04  -0.141  0.88753
X24h.Vol      -4.836e-04  4.349e-04  -1.112  0.26623
Circ..Supply   5.619e-05  4.204e-04   0.134  0.89366
Total.Supply   2.683e-14  4.072e-14   0.659  0.51002
Team          -2.397e-02  1.576e-02  -1.520  0.12847
Product       -4.131e-03  4.869e-03  -0.848  0.39625
Coin           7.949e-03  5.937e-03   1.339  0.18066
Social        -1.858e-02  8.662e-03  -2.145  0.03199 *
Communication -3.273e-03  3.600e-03  -0.909  0.36335
Business      -3.909e-04  3.243e-03  -0.121  0.90407
Avg..volume   -8.158e-11  8.827e-10  -0.092  0.92636
```

```
Age..mo.       7.262e-03  5.277e-03   1.376  0.16878
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 1087.97  on 1191  degrees of freedom
Residual deviance:  954.15  on 1170  degrees of freedom
  (41 observations deleted due to missingness)
AIC: 998.15

Number of Fisher Scoring iterations: 11
```

```
        FALSE TRUE
  FALSE   307  117
  TRUE     31   55
```

0.685606060606061
0.63953488372093
0.275943396226415

Price 1.02584781560209 **X1h** 1.15769836383294 **X24h** 2.96033449373743 **X7d** 2.95185035557887 **X14d** 3.24090275717362 **X30d** 4.91817668782566 **X45d** 4.59783289757329 **X90d** 2.61198284261179 **X200d** 1.91331591388318 **Mkt..Cap** 1.03647241353168 **X24h.Vol** 1.03491142934378 **Circ..Supply** 1.05018223690908 **Total.Supply** 1.03860840602233 **Team** 7.10648538827917 **Product** 1.81658646390026 **Coin** 2.19831931567567 **Social** 3.19603310898613 **Communication** 1.46875216267816 **Business** 1.5922862721872 **Avg..volume** 1.0164595410715 **Age..mo.** 1.3693268345375

Then we reduce the range of features to the relevant ones and make a final logistic model, that we compare to the baseline:

```
In [5]: logistic <- glm(label_disappeared ~ X45d + Social + 0, data = train_data,
                family="binomial")
        summary(logistic)

        pred = predict(logistic, newdata = test_data, type="response")

        table(test_data$label_disappeared, pred>0.2)

        tableAccuracy(test_data$label_disappeared, pred>0.2)
        tableTPR(test_data$label_disappeared, pred>0.2)
        tableFPR(test_data$label_disappeared, pred>0.2)

        # Baseline accuracy:
        t_ <- table(test_data$label_disappeared)
```

```
t_[1]/sum(t_)

rocr.pred <- prediction(pred, test_data$label_disappeared)
perf <- performance(rocr.pred, "tpr", "fpr")
plot(perf, colorize = TRUE)
abline(0, 1)
as.numeric(performance(rocr.pred, "auc")@y.values)
```

```
Warning message:
“glm.fit: fitted probabilities numerically 0 or 1 occurred”


Call:
glm(formula = label_disappeared ~ X45d + Social + 0, family = "binomial",
    data = train_data)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.1773  -0.6347  -0.4854  -0.3496   2.7011

Coefficients:
        Estimate Std. Error z value Pr(>|z|)
X45d   -0.004062   0.001108  -3.667 0.000245 ***
Social -0.032039   0.001607 -19.935  < 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: 1696.8  on 1224  degrees of freedom
Residual deviance: 1011.9  on 1222  degrees of freedom
  (9 observations deleted due to missingness)
AIC: 1015.9

Number of Fisher Scoring iterations: 8
```

```
        FALSE TRUE
  FALSE   320  117
  TRUE     37   52
```

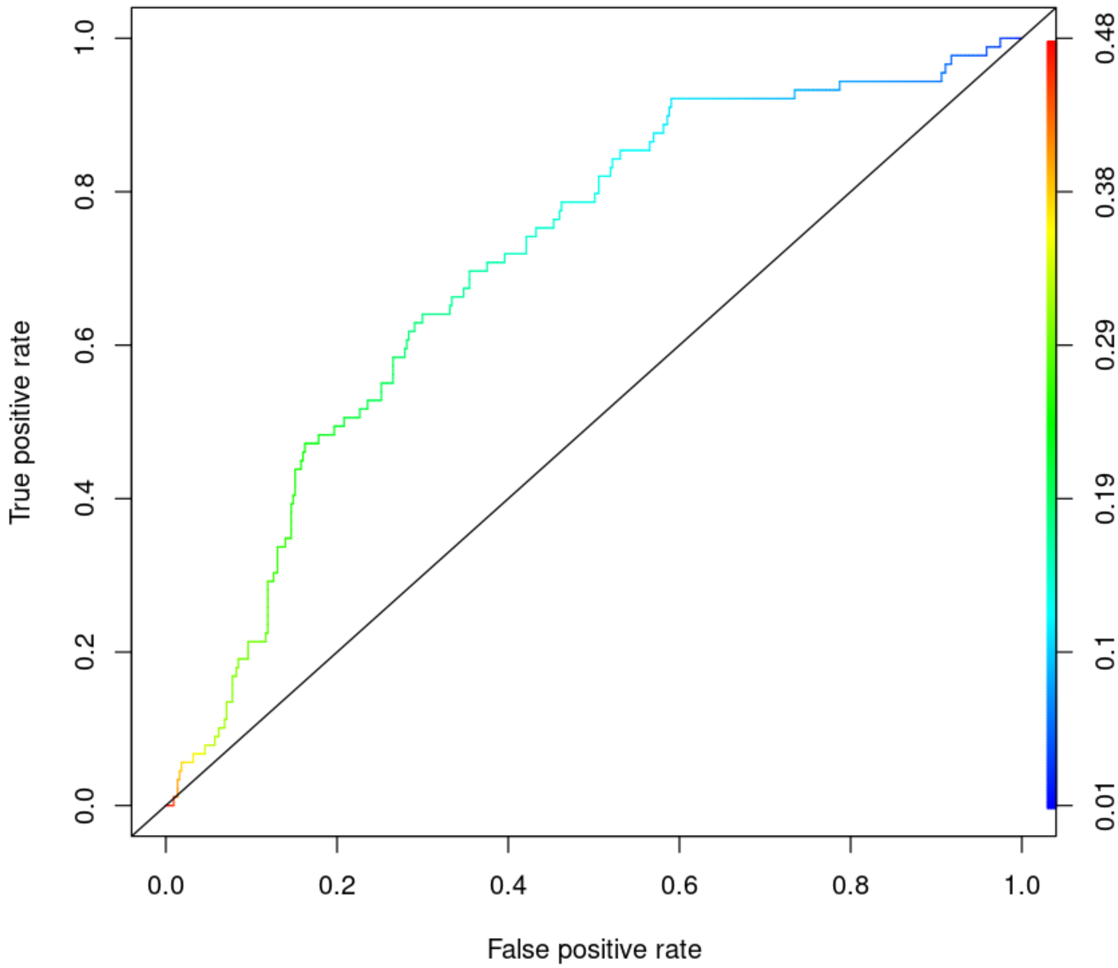
0.704545454545455

0.584269662921348

0.267734553775744

FALSE: 0.831439393939394

0.708919342812334



b) Random Forest

Let's begin checking the number of NAs in each column to select the features.

```
In [10]: sapply(df, function(x){ sum(is.na(x)) })
```

Name 0 **MC..** 0 **Symbol** 0 **Price** 0 **BTC** 0 **X1h** 0 **X24h** 0 **X7d** 0 **X14d** 0 **X30d** 4 **X45d** 11 **X90d** 22 **X200d** 48 **Mkt..Cap** 0 **MCAP.BTC** 0 **X24h.Vol** 0 **X24h.Vol.BTC** 0 **Circ..Supply** 0 **Total.Supply** 9 **Max..Supply** 1394 **Team** 0 **Advisors** 566 **Brand.Buzz** 566 **Product** 0 **Coin** 0 **Social** 0 **Communication** 0 **Business** 0 **GitHub** 697 **GitHub.1** 697 **Avg..volume** 0 **Age..mo.** 1 **Winning.months** 1 **label_Price** 297 **label_Mkt..Cap** 297 **label_growth_rate_Price** 297 **label_growth_rate_Mkt..Cap** 297 **label_disappeared** 0

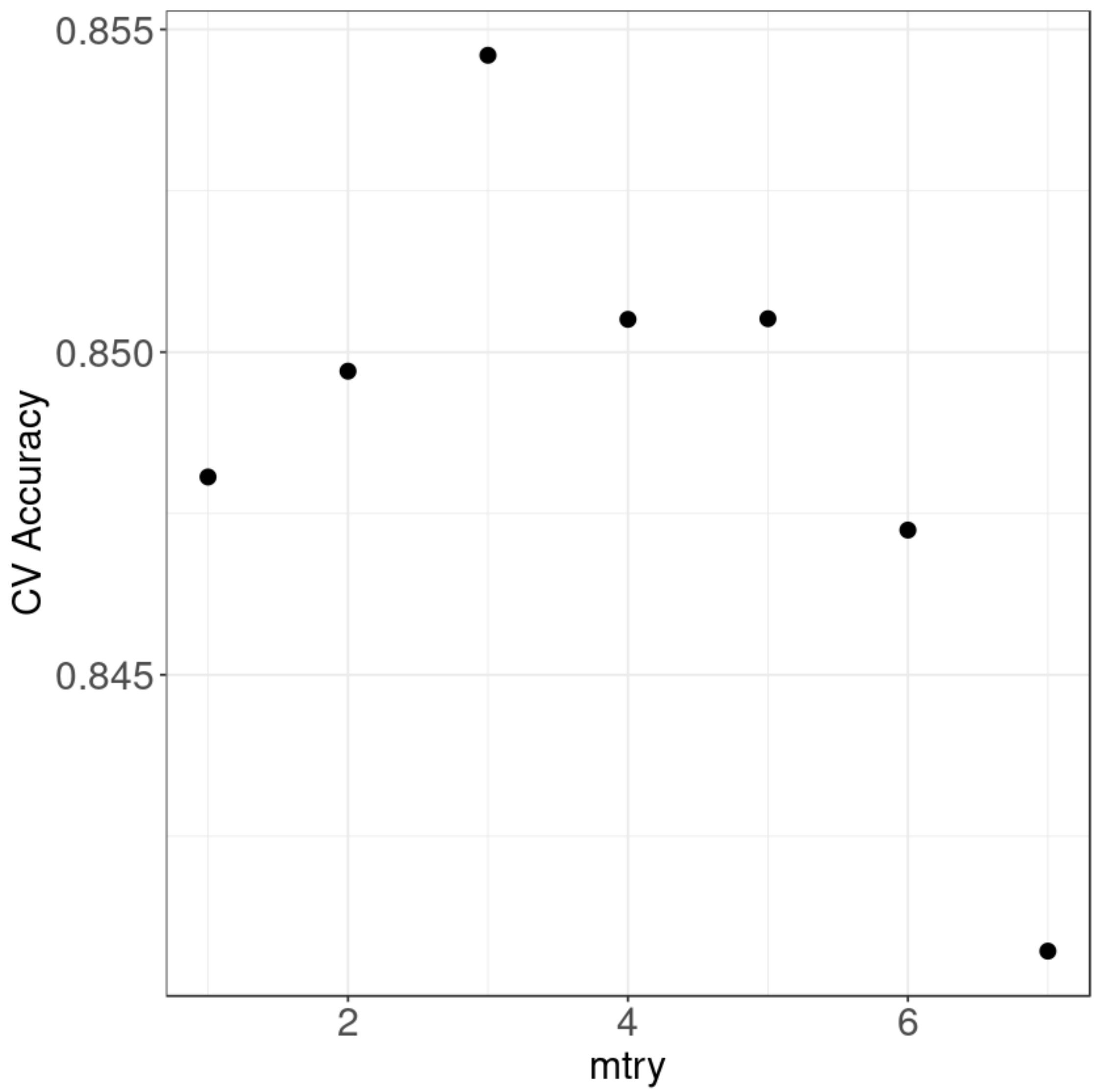
Now let's try a random forest with cross-validation. The dataset is not balanced so we try a cross-validation measured with Accuracy and then F1-score as Accuracy is less relevant in this case.

```
In [11]: set.seed(42)
         test_data_filled_with_0 <- test_data
         test_data_filled_with_0[is.na(test_data_filled_with_0)] <- 0
         train_data.mm = as.data.frame(model.matrix(label_disappeared ~ X24h + X14d + X45d +
                 Social + Mkt..Cap + Age..mo. + Business, data = train_data))
         test_data.mm = as.data.frame(model.matrix(label_disappeared ~ X24h + X14d + X45d +
                 Social + Mkt..Cap + Age..mo. + Business, data = test_data_filled_with_0))

         train.rf <- train(label_disappeared ~ X24h + X14d + X45d + Social + Mkt..Cap +
                           Age..mo. + Business,
                           data = train_data,
                           method = "rf",
                           na.action  = na.omit,
                           tuneGrid = data.frame(mtry=1:7),
                           trControl = trainControl(method="cv", number=5),
                           metric = "Accuracy")
         train.rf$results
         train.rf
         best.rf <- train.rf$finalModel
         pred.rf <- predict(best.rf, newdata = test_data.mm) # can use same model matrix

         ggplot(train.rf$results, aes(x = mtry, y = Accuracy)) + geom_point(size = 3) +
           ylab("CV Accuracy") + theme_bw() + theme(axis.title=element_text(size=18),
                           axis.text=element_text(size=18))
```

mtry <int>	Accuracy <dbl>	Kappa <dbl>	AccuracySD <dbl>	KappaSD <dbl>
1	0.8480651	0.1820981	0.01230487	0.07219353
2	0.8497045	0.2675792	0.01730529	0.08837830
3	0.8545991	0.3131013	0.01457905	0.07484737
4	0.8505074	0.2927120	0.01216925	0.05062367
5	0.8505175	0.3181606	0.01943042	0.07520890
6	0.8472421	0.2995333	0.01863631	0.06998712
7	0.8407181	0.2733978	0.02110235	0.08098173

```
Random Forest

1233 samples
   7 predictor
   2 classes: 'FALSE', 'TRUE'

No pre-processing
Resampling: Cross-Validated (5 fold)
Summary of sample sizes: 980, 978, 980, 979, 979
Resampling results across tuning parameters:

  mtry  Accuracy   Kappa
  1     0.8480651  0.1820981
  2     0.8497045  0.2675792
```

```
  3     0.8545991  0.3131013
  4     0.8505074  0.2927120
  5     0.8505175  0.3181606
  6     0.8472421  0.2995333
  7     0.8407181  0.2733978

Accuracy was used to select the optimal model using the largest value.
The final value used for the model was mtry = 3.
```



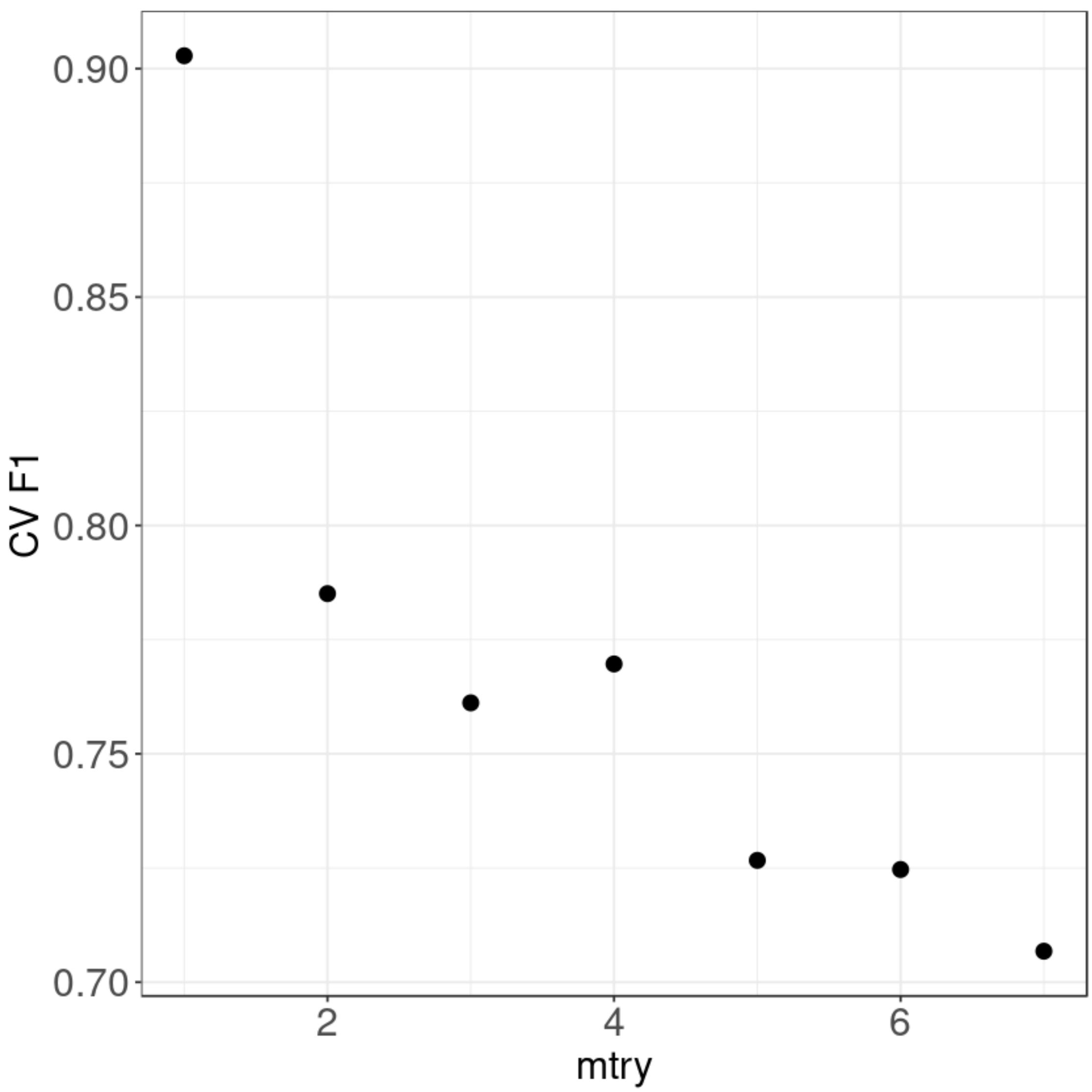

```
In [14]: f1 <- function (data, lev = NULL, model = NULL) {
           pred <- data$pred[!is.na(data$pred)&!is.na(data$obs)]
           obs <- data$obs[!is.na(data$pred)&!is.na(data$obs)]
```

```
    precision <- posPredValue(pred, obs, positive = lev[2])
    recall  <- sensitivity(pred, obs, postive = lev[1])
    f1_val <- (2 * precision * recall) / (precision + recall)
    names(f1_val) <- c("F1")
    #print(precision)
    #print(recall)
    #print(f1_val)
    f1_val
  }

  train.rf <- train(label_disappeared ~ X24h + X14d + X45d + Social + Mkt..Cap +
                    Age..mo. + Business,
                    data = train_data,
                    method = "rf",
                    na.action  = na.omit,
                    tuneGrid = data.frame(mtry=1:7),
                    trControl = trainControl(method="cv", number=5, summaryFunction = f1)
                    metric = PYl+s"F1")
  train.rf$results
  train.rf
  best.rf <- train.rf$finalModel
  pred.rf <- predict(best.rf, newdata = test_data.mm) # can use same model matrix

  ggplot(train.rf$results, aes(x = mtry, y = F1)) + geom_point(size = 3) +
    ylab("CV F1") + theme_bw() + theme(axis.title=element_text(size=18),
    axis.text=element_text(size=18))
```

mtry <int>	F1 <dbl>	F1SD <dbl>
1	0.9028305	0.08709772
2	0.7850726	0.07805387
3	0.7611599	0.11121317
4	0.7696718	0.06996851
5	0.7266709	0.10382716
6	0.7246719	0.11886381
7	0.7067876	0.12034424

```
Random Forest

1233 samples
   7 predictor
   2 classes: 'FALSE', 'TRUE'

No pre-processing
Resampling: Cross-Validated (5 fold)
Summary of sample sizes: 979, 980, 979, 978, 980
Resampling results across tuning parameters:

  mtry  F1
```

```
  1     0.9028305
  2     0.7850726
  3     0.7611599
  4     0.7696718
  5     0.7266709
  6     0.7246719
  7     0.7067876

F1 was used to select the optimal model using the largest value.
The final value used for the model was mtry = 1.
```



An mtry of 3 looks good. We can try sampling stratification to handle the imbalance of the data.

In [15]:
```
set.seed(42)
rare.class.prevalence = 0.2
nRareSamples = 1000 * rare.class.prevalence
mod.rf <- randomForest(label_disappeared ~ X24h + X14d + X45d + Social + Mkt..Cap +
        Age..mo. + Business, data = train_data, mtry = 3, nodesize = 5, ntree = 1000,
        strata=train_data$label_disappeared,
        sampsize=c(nRareSamples,nRareSamples), na.action = na.omit)
# print(mod.rf)

pred.rf <- predict(mod.rf, newdata = test_data)

table(test_data$label_disappeared, pred.rf)

tableAccuracy(test_data$label_disappeared, pred.rf)
tableTPR(test_data$label_disappeared, pred.rf)
tableFPR(test_data$label_disappeared, pred.rf)
```

```
       pred.rf
        FALSE TRUE
  FALSE   427   10
  TRUE     70   19
```

0.84469696969697
0.213483146067416
0.022883295194508

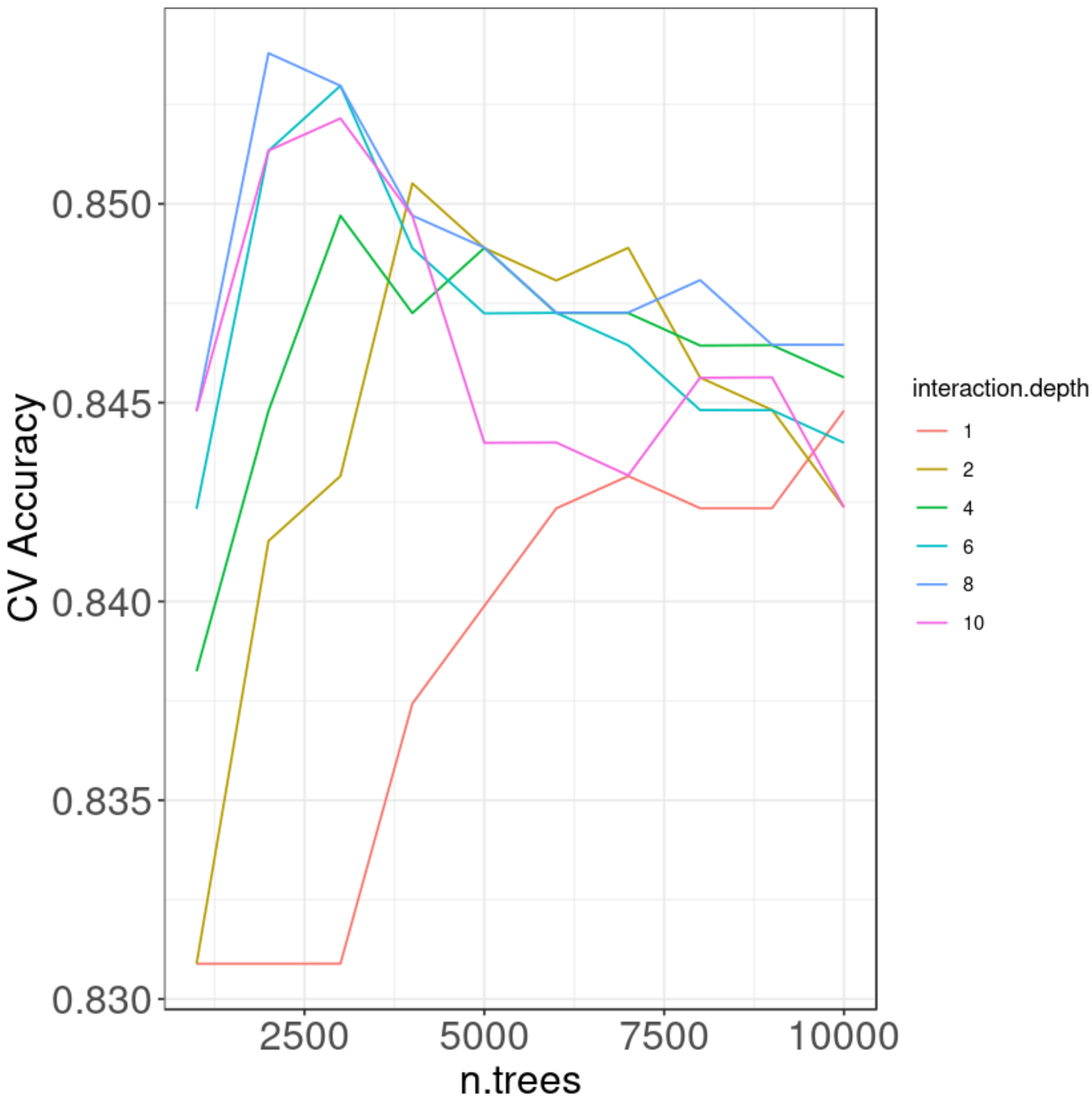
c) Boosting

Finally we can try a boosting method with cross-validation.

In [17]:
```
tGrid = expand.grid(n.trees = (1:10)*1000, interaction.depth = c(1,2,4,6,8,10),
                    shrinkage = 0.001, n.minobsinnode = 10)

set.seed(42)
train.boost <- train(label_disappeared ~ X24h + X14d + X45d + Social + Mkt..Cap +
                     Age..mo. + Business,
                     data = train_data,
                     method = "gbm",   ## gradient boosting machine
                     tuneGrid = tGrid,
                     trControl = trainControl(method="cv", number=5),
                     metric = "Accuracy",
                     na.action = na.omit)
train.boost
best.boost <- train.boost$finalModel

ggplot(train.boost$results, aes(x = n.trees, y = Accuracy, colour =
  as.factor(interaction.depth))) + geom_line() +
  ylab("CV Accuracy") + theme_bw() + theme(axis.title=element_text(size=18),
```

```
          axis.text=element_text(size=18)) +
          scale_color_discrete(name = "interaction.depth")
```

```
Stochastic Gradient Boosting

1233 samples
   7 predictor
   2 classes: 'FALSE', 'TRUE'

No pre-processing
Resampling: Cross-Validated (5 fold)
Summary of sample sizes: 980, 978, 980, 979, 979

Tuning parameter 'shrinkage' was held constant at a value of 0.001

Tuning parameter 'n.minobsinnode' was held constant at a value of 10
Accuracy was used to select the optimal model using the largest value.
The final values used for the model were n.trees = 2000, interaction.depth =
 8, shrinkage = 0.001 and n.minobsinnode = 10.
```



We choose n.trees = 2000, interaction.depth = 8.

In [18]:
```
pred.best.boost <- predict(best.boost, newdata = test_data.mm, n.trees = 2000,
interaction.depth = 8) # from CV plot

table(test_data$label_disappeared, pred.best.boost>0.7)

tableAccuracy(test_data$label_disappeared, pred.best.boost>0.7)
tableTPR(test_data$label_disappeared, pred.best.boost>0.7)
tableFPR(test_data$label_disappeared, pred.best.boost>0.7)
```

```
        FALSE TRUE
  FALSE   221  218
```

```
  TRUE     70   19
```

0.454545454545455
0.213483146067416
0.496583143507973

7.3.2 Portfolio determination based on naive growth rates

a) Regression

We try a linear model on a lot of features.

```
In [22]: set.seed(42)
         split = sample.split(df$label_growth_rate_Price, SplitRatio = 0.7)
         price_train_data <- filter(df, split== TRUE)
         price_test_data <- filter(df, split== FALSE)

         price_train_data = price_train_data %>% filter(as.integer(label_disappeared)==1)
                 # we keep label_disappeared = FALSE
         price_test_data = price_test_data %>% filter(as.integer(label_disappeared)==1)

         mod <- lm(label_growth_rate_Price ~ Price + X1h + X24h + X7d + X14d + X30d + X45d +
                         X90d + X200d + Mkt..Cap + X24h.Vol + Circ..Supply + Total.Supply +
                         Team + Product + Coin + Social + Communication + Business +
                         Avg..volume + Age..mo., data = price_train_data)

         summary(mod)

         pred_lm = predict(mod, newdata = price_test_data)

         all_metrics(price_test_data$label_growth_rate_Price, pred_lm,
                         price_train_data$label_growth_rate_Price)
```

```
Call:
lm(formula = label_growth_rate_Price ~ Price + X1h + X24h + X7d +
    X14d + X30d + X45d + X90d + X200d + Mkt..Cap + X24h.Vol +
    Circ..Supply + Total.Supply + Team + Product + Coin + Social +
    Communication + Business + Avg..volume + Age..mo., data = price_train_data)

Residuals:
    Min      1Q  Median      3Q     Max
-95.323  -0.448   0.006   0.504 157.521

Coefficients:
                Estimate Std. Error t value Pr(>|t|)
(Intercept)   -1.380e+00  1.463e+00  -0.943    0.346
Price         -1.363e-05  9.791e-04  -0.014    0.989
```

```
X1h            2.563e-02  2.873e-02   0.892    0.373
X24h          -1.096e-02  9.764e-03  -1.122    0.262
X7d           -3.442e-03  7.134e-03  -0.482    0.630
X14d           9.311e-04  3.500e-03   0.266    0.790
X30d           5.279e-04  4.867e-03   0.108    0.914
X45d          -2.804e-03  2.983e-03  -0.940    0.347
X90d           5.591e-03  5.494e-03   1.018    0.309
X200d         -2.616e-03  5.139e-03  -0.509    0.611
Mkt..Cap       4.964e-05  1.062e-03   0.047    0.963
X24h.Vol       9.059e-06  1.117e-03   0.008    0.994
Circ..Supply  -1.920e-03  1.103e-03  -1.741    0.082 .
Total.Supply   9.642e-12  3.189e-13  30.230   <2e-16 ***
Team           1.977e-02  4.204e-02   0.470    0.638
Product       -6.773e-03  1.328e-02  -0.510    0.610
Coin          -8.403e-03  1.685e-02  -0.499    0.618
Social         3.590e-03  2.370e-02   0.151    0.880
Communication -5.365e-03  8.557e-03  -0.627    0.531
Business       6.493e-03  1.123e-02   0.578    0.563
Avg..volume    2.020e-11  1.844e-09   0.011    0.991
Age..mo.       1.896e-02  1.633e-02   1.161    0.246
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 7.24 on 962 degrees of freedom
  (40 observations deleted due to missingness)
Multiple R-squared:  0.4896,Adjusted R-squared:  0.4785
F-statistic: 43.95 on 21 and 962 DF,  p-value: < 2.2e-16
```

1. 582.295129943916 2. 2.15332619393653 3. -173.530306079791

In [23]:
```
vif(mod)
```

Price 1.02423943344359 **X1h** 1.27695002473311 **X24h** 2.20857264825821 **X7d** 2.20262213596122 **X14d** 51.0399053125082 **X30d** 57.8341308908584 **X45d** 16.3502969281802 **X90d** 6.77458705855804 **X200d** 3.77206853766809 **Mkt..Cap** 1.02694209743189 **X24h.Vol** 1.02876014673704 **Circ..Supply** 1.07660848685341 **Total.Supply** 1.01072167422902 **Team** 6.49637787342385 **Product** 1.9710382752697 **Coin** 1.90590139973695 **Social** 3.14333047583439 **Communication** 1.53408207175482 **Business** 1.36185221776999 **Avg..volume** 1.02165670821974 **Age..mo.** 1.3028447664378

This is not good, there is some multicolinearity. Let's remove the guilty features.

In [26]:
```
mod <- lm(label_growth_rate_Price ~ Price + X1h + X24h + X7d + X30d + X90d + X200d +
          Mkt..Cap + X24h.Vol + Circ..Supply + Total.Supply + Team + Product +
          Coin + Social + Communication + Business + Avg..volume + Age..mo.,
          data = price_train_data)

summary(mod)
```

```r
pred_lm = predict(mod, newdata = price_test_data)

all_metrics(price_test_data$label_growth_rate_Price, pred_lm,
            price_train_data$label_growth_rate_Price)
```

```
Call:
lm(formula = label_growth_rate_Price ~ Price + X1h + X24h + X7d +
    X30d + X90d + X200d + Mkt..Cap + X24h.Vol + Circ..Supply +
    Total.Supply + Team + Product + Coin + Social + Communication +
    Business + Avg..volume + Age..mo., data = price_train_data)

Residuals:
    Min      1Q  Median      3Q     Max
-95.222  -0.426  -0.009   0.496 157.685

Coefficients:
                Estimate Std. Error t value Pr(>|t|)
(Intercept)   -1.506e+00  1.452e+00  -1.037   0.2999
Price         -1.311e-05  9.783e-04  -0.013   0.9893
X1h            2.299e-02  2.857e-02   0.805   0.4212
X24h          -9.303e-03  9.536e-03  -0.976   0.3295
X7d           -3.687e-03  7.124e-03  -0.517   0.6049
X30d          -8.050e-05  9.549e-04  -0.084   0.9328
X90d           1.554e-03  3.466e-03   0.448   0.6541
X200d         -4.926e-04  4.608e-03  -0.107   0.9149
Mkt..Cap       5.801e-05  1.061e-03   0.055   0.9564
X24h.Vol       7.150e-05  1.114e-03   0.064   0.9489
Circ..Supply  -1.902e-03  1.102e-03  -1.726   0.0846 .
Total.Supply   9.631e-12  3.186e-13  30.233   <2e-16 ***
Team           1.702e-02  4.190e-02   0.406   0.6847
Product       -6.461e-03  1.327e-02  -0.487   0.6263
Coin          -7.157e-03  1.676e-02  -0.427   0.6695
Social         5.232e-03  2.359e-02   0.222   0.8245
Communication -5.266e-03  8.549e-03  -0.616   0.5381
Business       6.734e-03  1.122e-02   0.600   0.5484
Avg..volume    1.029e-11  1.843e-09   0.006   0.9955
Age..mo.       2.052e-02  1.613e-02   1.272   0.2037
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 7.236 on 964 degrees of freedom
  (40 observations deleted due to missingness)
Multiple R-squared:  0.4891,Adjusted R-squared:  0.4791
F-statistic: 48.58 on 19 and 964 DF,  p-value: < 2.2e-16
```

1. 564.062942832866 2. 1.90025594030086 3. -168.065604361777

```
In [27]: vif(mod)
```

Price 1.02383458947674 **X1h** 1.26378621144891 **X24h** 2.10915904620629 **X7d** 2.1991343191775 **X30d** 2.22872902583279 **X90d** 2.69968306031107 **X200d** 3.03647959935625 **Mkt..Cap** 1.02665757634139 **X24h.Vol** 1.02508903973853 **Circ..Supply** 1.07610953486792 **Total.Supply** 1.00943241102529 **Team** 6.46108652227192 **Product** 1.96792266463445 **Coin** 1.88882024934975 **Social** 3.11853701685625 **Communication** 1.53321255914753 **Business** 1.36088711654353 **Avg..volume** 1.02158918501001 **Age..mo.** 1.27210148432654

This still does not look good. Let's narrow down the features.

```
In [20]: mod <- lm(label_growth_rate_Price ~ Circ..Supply + Total.Supply + 0,
                   data = price_train_data)

         summary(mod)

         pred_lm = predict(mod, newdata = price_test_data)

         all_metrics(price_test_data$label_growth_rate_Price, pred_lm,
         price_train_data$label_growth_rate_Price)
```

```
Call:
lm(formula = label_growth_rate_Price ~ Circ..Supply + Total.Supply +
    0, data = price_train_data)

Residuals:
    Min      1Q  Median      3Q     Max
-96.415  -0.701  -0.407   0.164 158.564

Coefficients:
               Estimate Std. Error t value Pr(>|t|)
Circ..Supply -2.534e-03  8.533e-04   -2.97  0.00305 **
Total.Supply  9.579e-12  3.097e-13   30.93  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 7.074 on 1017 degrees of freedom
  (5 observations deleted due to missingness)
Multiple R-squared:  0.485,Adjusted R-squared:  0.484
F-statistic: 478.9 on 2 and 1017 DF,  p-value: < 2.2e-16
```

1. 547.59691212069 2. 1.94101815834009 3. -166.769645220578

We can compare it to the baseline (predicting negative all the time). We assume that we invest the same amount of money in each coin, ignoring fees, and compute the result growth rate of our portfolio following our regression strategy and the baseline.

```
In [29]: filter_vec = !is.na(pred_lm)
         sum((pred_lm*price_test_data$label_growth_rate_Price)[filter_vec])
                         /sum(pred_lm[filter_vec])

         # Baseline
         sum(price_test_data$label_growth_rate_Price[filter_vec])
                         /length(price_test_data$label_growth_rate_Price[filter_vec])
```

0.142130885876864
-0.342125271527515
We beat it!

7.3.3 Portfolio determination in a log normal stock model

a) Regression

With our new log-normal assumption we can try to predict the difference of the logarithms of the price between March and December.

```
In [30]: df$price_log_diff = log(df$label_Price) - log(df$Price) # follow mu T + sigma B_T

         split = sample.split(df$price_log_diff, SplitRatio = 0.7)
         price_train_data <- filter(df, split== TRUE)
         price_test_data <- filter(df, split== FALSE)

         price_train_data = price_train_data %>% filter(as.integer(label_disappeared)==1)
         # we keep label_disappeared = FALSE
         price_test_data = price_test_data %>% filter(as.integer(label_disappeared)==1)

         mod_log <- lm(price_log_diff ~ Price + X1h + X24h + X7d + X14d + X30d + X45d + X90d +
                 X200d + Mkt..Cap + X24h.Vol + Circ..Supply + Total.Supply + Team +
                 Product + Coin + Social + Communication + Business + Avg..volume + Age..mo.,
                 data = price_train_data)

         summary(mod_log)

         pred_lm = predict(mod_log, newdata = price_test_data)

         all_metrics(price_test_data$price_log_diff, pred_lm, price_train_data$price_log_diff)
```

```
Call:
lm(formula = price_log_diff ~ Price + X1h + X24h + X7d + X14d +
    X30d + X45d + X90d + X200d + Mkt..Cap + X24h.Vol + Circ..Supply +
    Total.Supply + Team + Product + Coin + Social + Communication +
    Business + Avg..volume + Age..mo., data = price_train_data)

Residuals:
    Min      1Q  Median      3Q     Max
```

```
-6.2257 -0.4446  0.0628  0.5709  3.8110

Coefficients:
                Estimate Std. Error t value Pr(>|t|)
(Intercept)   -9.089e-01  1.915e-01  -4.747 2.37e-06 ***
Price          2.427e-05  3.484e-05   0.697   0.4861
X1h           -3.607e-03  5.843e-03  -0.617   0.5372
X24h          -3.514e-03  1.624e-03  -2.164   0.0307 *
X7d           -1.298e-03  1.028e-03  -1.262   0.2074
X14d          -6.971e-04  3.174e-04  -2.196   0.0283 *
X30d           5.989e-04  4.839e-04   1.238   0.2161
X45d           6.502e-05  2.585e-04   0.252   0.8014
X90d           5.886e-04  5.132e-04   1.147   0.2517
X200d         -9.859e-04  5.229e-04  -1.885   0.0597 .
Mkt..Cap      -2.969e-04  1.388e-04  -2.139   0.0327 *
X24h.Vol      -7.968e-07  1.410e-04  -0.006   0.9955
Circ..Supply   2.499e-04  1.455e-04   1.718   0.0862 .
Total.Supply   1.668e-14  1.874e-14   0.890   0.3738
Team           7.936e-03  5.567e-03   1.426   0.1543
Product       -1.076e-03  1.750e-03  -0.615   0.5385
Coin          -2.972e-03  2.195e-03  -1.354   0.1761
Social        -7.665e-04  3.138e-03  -0.244   0.8071
Communication  3.429e-04  1.144e-03   0.300   0.7645
Business      -3.736e-03  1.468e-03  -2.544   0.0111 *
Avg..volume    1.576e-10  1.418e-10   1.112   0.2665
Age..mo.       3.241e-03  2.212e-03   1.465   0.1433
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.9755 on 978 degrees of freedom
  (37 observations deleted due to missingness)
Multiple R-squared:  0.05583,Adjusted R-squared:  0.03555
F-statistic: 2.754 on 21 and 978 DF,  p-value: 3.95e-05
```

1. 1.37419565150063 2. 0.786600323768397 3. -0.0510270204478771

```
In [31]: vif(mod_log)
```

Price 1.06407441227154 **X1h** 1.07115978177007 **X24h** 1.22544188241185 **X7d** 1.31330264496053 **X14d** 753.264205918813 **X30d** 1730.32601194076 **X45d** 491.069203199915 **X90d** 10.6815410522711 **X200d** 3.59844428634785 **Mkt..Cap** 1.0247473315568 **X24h.Vol** 1.02517852100103 **Circ..Supply** 1.07871229383061 **Total.Supply** 1.01891666805316 **Team** 6.3719217947138 **Product** 1.92537905891746 **Coin** 1.86682147289798 **Social** 3.14543604788404 **Communication** 1.52506691080304 **Business** 1.3559062673666 **Avg..volume** 1.09292020780236 **Age..mo.** 1.31230648270897

```
In [34]: mod_log <- lm(price_log_diff ~ Price + X1h + X24h + X7d + X14d + X90d + X200d +
                  Mkt..Cap + X24h.Vol + Circ..Supply + Total.Supply + Team + Product +
```

```r
                 Coin + Social + Communication + Business + Avg..volume + Age..mo.,
                 data = price_train_data)

summary(mod_log)

pred_lm = predict(mod_log, newdata = price_test_data)

all_metrics(price_test_data$price_log_diff, pred_lm, price_train_data$price_log_diff)
```

```
Call:
lm(formula = price_log_diff ~ Price + X1h + X24h + X7d + X14d +
    X90d + X200d + Mkt..Cap + X24h.Vol + Circ..Supply + Total.Supply +
    Team + Product + Coin + Social + Communication + Business +
    Avg..volume + Age..mo., data = price_train_data)

Residuals:
    Min      1Q  Median      3Q     Max
-6.1966 -0.4454  0.0553  0.5753  3.7657

Coefficients:
                Estimate Std. Error t value Pr(>|t|)
(Intercept)   -9.555e-01  1.909e-01  -5.005 6.62e-07 ***
Price          2.525e-05  3.491e-05   0.723 0.469718
X1h           -3.627e-03  5.851e-03  -0.620 0.535459
X24h          -3.597e-03  1.626e-03  -2.212 0.027225 *
X7d           -1.328e-03  1.029e-03  -1.291 0.196887
X14d          -4.881e-05  2.479e-05  -1.969 0.049266 *
X90d           8.115e-04  4.038e-04   2.010 0.044752 *
X200d         -1.469e-03  4.261e-04  -3.448 0.000589 ***
Mkt..Cap      -2.973e-04  1.391e-04  -2.138 0.032777 *
X24h.Vol      -6.626e-06  1.412e-04  -0.047 0.962579
Circ..Supply   2.468e-04  1.458e-04   1.693 0.090731 .
Total.Supply   1.546e-14  1.874e-14   0.825 0.409431
Team           8.054e-03  5.568e-03   1.446 0.148377
Product       -1.288e-03  1.751e-03  -0.735 0.462238
Coin          -2.875e-03  2.198e-03  -1.308 0.191143
Social        -5.695e-04  3.138e-03  -0.181 0.856039
Communication  4.538e-04  1.145e-03   0.396 0.692061
Business      -3.784e-03  1.471e-03  -2.573 0.010242 *
Avg..volume    1.605e-10  1.420e-10   1.130 0.258656
Age..mo.       3.300e-03  2.204e-03   1.497 0.134725
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.9776 on 980 degrees of freedom
  (37 observations deleted due to missingness)
Multiple R-squared:  0.04984,Adjusted R-squared:  0.03142
```

```
F-statistic: 2.706 on 19 and 980 DF,  p-value: 0.0001092
```

1. 1.37718128083273 2. 0.789451576546088 3. -0.0533105214163541

```
In [35]: vif(mod_log)
```

Price 1.06389350752336 **X1h** 1.06954219074384 **X24h** 1.22325176284725 **X7d** 1.30815268834064 **X14d** 4.57576438585392 **X90d** 6.58402089382897 **X200d** 2.37953671288416 **Mkt..Cap** 1.02437219200182 **X24h.Vol** 1.02414192975333 **Circ..Supply** 1.07809508758456 **Total.Supply** 1.01415980805924 **Team** 6.34760662656953 **Product** 1.92036647546332 **Coin** 1.86268778843273 **Social** 3.13312064680212 **Communication** 1.52216803443362 **Business** 1.3550512673174 **Avg..volume** 1.09262600492207 **Age..mo.** 1.29729721274557

The VIF is okay now. Let's remove some features.

```
In [38]: mod_log <- lm(price_log_diff ~ X24h + X200d + Mkt..Cap + Business,
                       data = price_train_data)

         summary(mod_log)

         pred_lm_log = predict(mod_log, newdata = price_test_data)

         all_metrics(price_test_data$price_log_diff, pred_lm_log,
                        price_train_data$price_log_diff)
```

```
Call:
lm(formula = price_log_diff ~ X24h + X200d + Mkt..Cap + Business,
    data = price_train_data)

Residuals:
    Min      1Q  Median      3Q     Max
-6.2460 -0.4330  0.0580  0.5923  3.9618

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.7949174  0.1167271  -6.810 1.68e-11 ***
X24h        -0.0047998  0.0014715  -3.262  0.00114 **
X200d       -0.0008992  0.0002755  -3.265  0.00113 **
Mkt..Cap    -0.0003394  0.0001378  -2.464  0.01392 *
Business    -0.0027869  0.0012598  -2.212  0.02717 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.9794 on 1000 degrees of freedom
  (32 observations deleted due to missingness)
Multiple R-squared:  0.03057,Adjusted R-squared:  0.02669
```

```
F-statistic: 7.883 on 4 and 1000 DF,  p-value: 2.956e-06
```

1. 1.35643667936919 2. 0.784982884758303 3. -0.0401929076627052

```
In [39]: filter_vec = !is.na(pred_lm_log)
         sum((exp(pred_lm_log)*price_test_data$label_growth_rate_Price)[filter_vec])
                /sum(exp(pred_lm_log)[filter_vec])

         # Baseline
         sum(price_test_data$label_growth_rate_Price[filter_vec])
                /length(price_test_data$label_growth_rate_Price[filter_vec])
```

0.461436810190696
0.439390893108447
That's fine but not amazing, let's think a bit and try something else.

```
In [40]: mod_log <- lm(price_log_diff ~ X7d + Mkt..Cap + Age..mo., data = price_train_data)

         summary(mod_log)

         pred_lm_log = predict(mod_log, newdata = price_test_data)

         all_metrics(price_test_data$price_log_diff, pred_lm_log,
                           price_train_data$price_log_diff)
```

```
Call:
lm(formula = price_log_diff ~ X7d + Mkt..Cap + Age..mo., data = price_train_data)

Residuals:
    Min      1Q  Median      3Q     Max
-6.3005 -0.4493  0.0632  0.5849  3.9844

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -1.0571347  0.0505030 -20.932   <2e-16 ***
X7d         -0.0016871  0.0009027  -1.869   0.0619 .
Mkt..Cap    -0.0003295  0.0001397  -2.359   0.0185 *
Age..mo.     0.0041164  0.0019420   2.120   0.0343 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.9966 on 1033 degrees of freedom
Multiple R-squared:  0.01299,Adjusted R-squared:  0.01012
F-statistic: 4.531 on 3 and 1033 DF,  p-value: 0.003655
```

1. 1.3321906348193 2. 0.766205419022985 3. 0.0152780706337514

In [41]:
```
filter_vec = !is.na(pred_lm_log)
sum((exp(pred_lm_log)*price_test_data$label_growth_rate_Price)[filter_vec])
        /sum(exp(pred_lm_log)[filter_vec])

# Baseline
sum(price_test_data$label_growth_rate_Price[filter_vec])
        /length(price_test_data$label_growth_rate_Price[filter_vec])
```

0.500360688948723
0.412744498999508
Much better already! We see that filtering out coisn where informations are missing, our portfolio behaves already better! That's because trustworthy coins get all their information filled.

b) Random forest

We take the features from the 2 previous models and we try it out on a random forest.

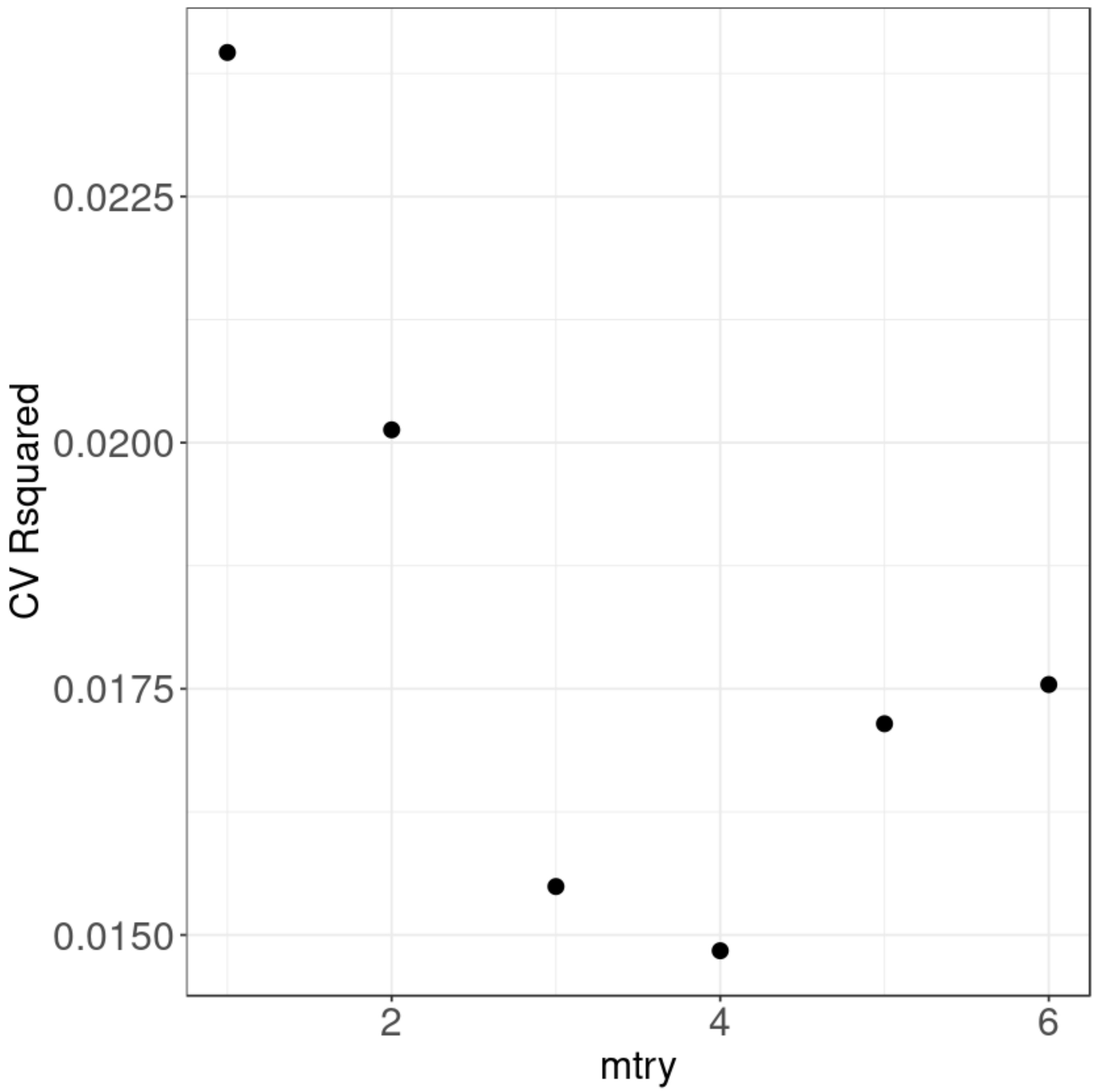
In [50]:
```
price_test_data_filled_with_0 <- price_test_data
price_test_data_filled_with_0[is.na(price_test_data_filled_with_0)] <- 0
price_test_data_log.mm = as.data.frame(model.matrix(price_log_diff ~ X24h + X7d +
        X200d + Mkt..Cap + Age..mo. + Business, data = price_test_data_filled_with_0))

train.rf <- train(price_log_diff ~ X24h + X7d + X200d + Mkt..Cap + Age..mo. +
                  Business,
                  data = price_train_data,
                  method = "rf",
                  na.action  = na.omit,
                  tuneGrid = data.frame(mtry=1:6),
                  trControl = trainControl(method="cv", number=5),
                  distribution="gaussian",
                  metric = "RMSE")
train.rf$results
train.rf
best.rf <- train.rf$finalModel
pred.rf <- predict(best.rf, newdata = price_test_data_log.mm)
all_metrics(price_test_data$price_log_diff, pred_lm_log,
        price_train_data$price_log_diff)
```

mtry <int>	RMSE <dbl>	Rsquared <dbl>	MAE <dbl>	RMSESD <dbl>	RsquaredSD <dbl>	MAESD <dbl>
1	0.9868626	0.02396270	0.7021205	0.09754761	0.03461219	0.04148504
2	1.0030523	0.02013034	0.7180743	0.09988699	0.03206543	0.03882143
3	1.0138758	0.01549198	0.7273112	0.10018572	0.02833747	0.03858953
4	1.0172491	0.01483976	0.7298685	0.09965039	0.02697329	0.04055537
5	1.0190250	0.01714539	0.7307562	0.10116483	0.03156220	0.03939837
6	1.0224764	0.01754349	0.7330653	0.10168716	0.03172612	0.04190727

```
Random Forest

1037 samples
   6 predictor

No pre-processing
Resampling: Cross-Validated (5 fold)
Summary of sample sizes: 804, 805, 805, 804, 802
Resampling results across tuning parameters:

  mtry  RMSE       Rsquared    MAE
  1     0.9868626  0.02396270  0.7021205
  2     1.0030523  0.02013034  0.7180743
  3     1.0138758  0.01549198  0.7273112
  4     1.0172491  0.01483976  0.7298685
  5     1.0190250  0.01714539  0.7307562
  6     1.0224764  0.01754349  0.7330653

RMSE was used to select the optimal model using the smallest value.
The final value used for the model was mtry = 1.
```

1. 1.3321906348193 2. 0.766205419022985 3. 0.0152780706337514

```
In [51]: ggplot(train.rf$results, aes(x = mtry, y = Rsquared)) + geom_point(size = 3) +
           ylab("CV Rsquared") + theme_bw() + theme(axis.title=element_text(size=18),
           axis.text=element_text(size=18))
```



The best value is 1 for mtry.

```
In [52]: filter_vec = !is.na(pred.rf)
         sum((exp(pred.rf)*price_test_data$label_growth_rate_Price)[filter_vec])
                 /sum(exp(pred.rf)[filter_vec])

         # Baseline
         sum(price_test_data$label_growth_rate_Price[filter_vec])
                 /length(price_test_data$label_growth_rate_Price[filter_vec])
```

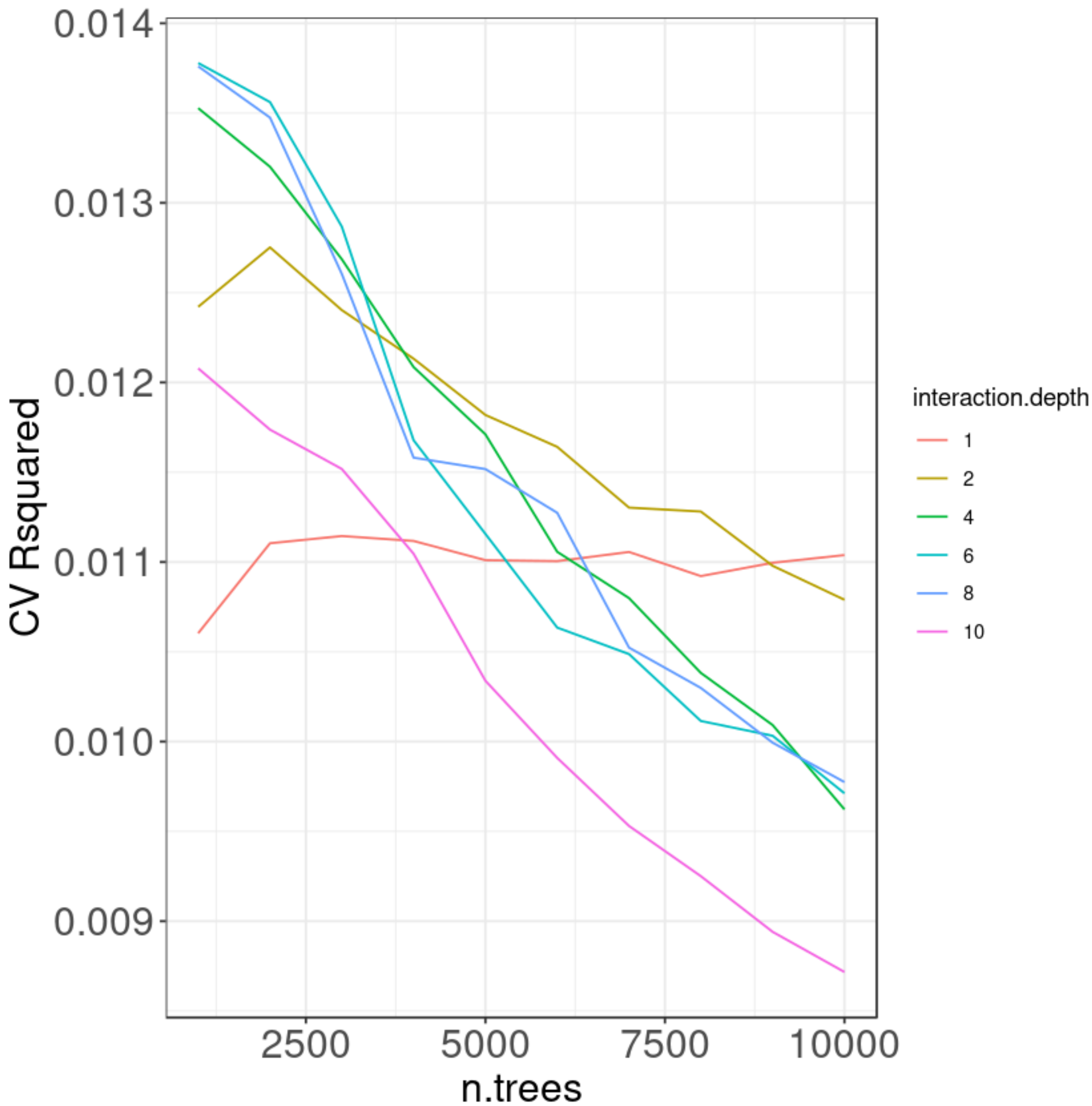
0.318126401502254
0.410949916909122
Unfortunately this model does not beat the baseline.

c) Boosting

We use the same features.

```
In [54]: tGrid = expand.grid(n.trees = (1:10)*1000, interaction.depth = c(1,2,4,6,8,10),
                             shrinkage = 0.001, n.minobsinnode = 10)

         set.seed(42)
         train.boost <- train(price_log_diff ~ X24h + X7d + X200d + Mkt..Cap + Age..mo. +
                              Business,
                              data = price_train_data,
                              method = "gbm",    ## gradient boosting machine
                              tuneGrid = tGrid,
                              trControl = trainControl(method="cv", number=5),
                              distribution = "gaussian",
                              metric = "RMSE",
                              na.action = na.omit)
         train.boost
         best.boost <- train.boost$finalModel

         ggplot(train.boost$results, aes(x = n.trees, y = Rsquared, colour =
           as.factor(interaction.depth))) + geom_line() +
           ylab("CV Rsquared") + theme_bw() + theme(axis.title=element_text(size=18),
           axis.text=element_text(size=18)) +
           scale_color_discrete(name = "interaction.depth")
```

```
Stochastic Gradient Boosting

1037 samples
   6 predictor

No pre-processing
Resampling: Cross-Validated (5 fold)
Summary of sample sizes: 803, 804, 805, 804, 804

Tuning parameter 'shrinkage' was held constant at a value of 0.001

Tuning parameter 'n.minobsinnode' was held constant at a value of 10
RMSE was used to select the optimal model using the smallest value.
The final values used for the model were n.trees = 1000, interaction.depth =
 6, shrinkage = 0.001 and n.minobsinnode = 10.
```



The best parameters are the biggest ones.

```
In [56]: pred.best.boost <- predict(best.boost, newdata = price_test_data_log.mm,
          n.trees = 10000, interaction.depth=10) # from CV plot
```

```
Warning message in predict.gbm(best.boost, newdata = price_test_data_log.mm, n.trees = 10000, :
"Number of trees not specified or exceeded number fit so far. Using 1000."
```

It does not want to do it so we need to do it ourselves.

```
In [63]: library(gbm)

         mod.boost <- gbm(price_log_diff ~ X24h + X7d + X200d + Mkt..Cap + Age..mo. + Business,
                          data = price_train_data,
```

```
                                distribution = "gaussian",
                                n.trees = 10000,
                                shrinkage = 0.001,
                                interaction.depth = 10)

        # NOTE: we need to specify number of trees to get a prediction for boosting
        pred.boost <- predict(mod.boost, newdata = price_test_data_log.mm, n.trees=10000)
```

In [64]:
```
filter_vec = !is.na(pred.boost)
sum((exp(pred.boost)*price_test_data$label_growth_rate_Price)[filter_vec])
        /sum(exp(pred.boost)[filter_vec])

# Baseline
sum(price_test_data$label_growth_rate_Price[filter_vec])
        /length(price_test_data$label_growth_rate_Price[filter_vec])
```

0.290123603135029
0.410949916909122
This is also very bad compared to the baseline. Too much overfitting!