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1 Appendices

1.1 Python code for return predictions

```
In [1]: import numpy as np # NUMPY
import pandas as pd # pandas
import cufflinks as cf # cufflinks
from sklearn.svm import SVC # scikit-learn
import warnings; warnings.simplefilter('ignore')
from statsmodels.tsa.stattools import adfuller
import configparser as cp
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn import metrics
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import mean_squared_error
from math import sqrt
import talib
from functools import partial

In [2]: dataset = "C:/Users/Lenovo/Downloads/Memoire/Database/cut/Close/ADA.xlsx"
data = pd.read_excel(dataset, index_col=0, parse_dates=True).dropna()

In [3]: data.head()
Out[3]:
      Date  ADA
2017-11-09  0.020053
2017-11-10  0.027119
2017-11-11  0.027437
2017-11-12  0.023977
2017-11-13  0.026808

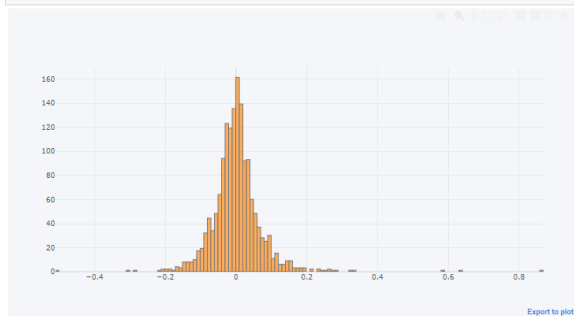
In [4]: data.dropna(inplace=True)

Calculating log returns

In [5]: rets = np.log(data / data.shift(1)).dropna() # Log returns
In [6]: rets.head()
Out[6]:
      Date  ADA
2017-11-10 -0.187168
2017-11-11  0.011058
2017-11-12 -0.134707
2017-11-13  0.073589
2017-11-14  0.018219

In [7]: adfuller(rets['ADA']) # stationarity test of time series
Out[7]: (-7.094393221849563,
4.206935587423704e-10,
18,
1558,
{'1X': -3.438504103755704,
'5X': -2.863398689546276,
'10X': -2.567758576991337},
-0.95.2906275952337)
```

Figure 1: Python code for return predictions of ADA - part 1

```
In [8]: cf.go_offline() #force Cufflinks to use offline Plotly mode (bug otherwise)
In [9]: rets.iplot(kind='histogram', subplots=True)

Export to plotly >

Add features

In [10]: rets['std14'] = rets['ADA'].rolling(14).std()
feature_names = ['std14'] #empty list to hold the feature names.
for n in [14, 30, 50]:
    rets['ma' + str(n)] = talib.SMA(rets['ADA'].values, timeperiod=n)
    rets['rsi' + str(n)] = talib.RSI(rets['ADA'].values, timeperiod=n) #SMA and RSI methods to calculate the SMA and RSI: 14, 30, 50.
    feature_names = feature_names + ['ma' + str(n), 'rsi' + str(n)] #Add the ma and rsi variable names to the feature_names list.

In [11]: feature_names
Out[11]: ['std14', 'ma14', 'rsi14', 'ma30', 'rsi30', 'ma50', 'rsi50']

In [12]: rets
Out[12]:
      Date  ADA  std14  ma14  rsi14  ma30  rsi30  ma50  rsi50
2017-11-10 -0.187168  NaN  NaN  NaN  NaN  NaN  NaN  NaN
2017-11-11  0.011058  NaN  NaN  NaN  NaN  NaN  NaN  NaN
2017-11-12 -0.134707  NaN  NaN  NaN  NaN  NaN  NaN  NaN
2017-11-13  0.073589  NaN  NaN  NaN  NaN  NaN  NaN  NaN
2017-11-14  0.018219  NaN  NaN  NaN  NaN  NaN  NaN  NaN
```

Figure 2: Python code for return predictions of ADA - part 2

```

... ..
2022-03-01 0.002620 0.050592 -0.010040 50.315504 -0.002506 50.219308 -0.003177 50.134551
2022-03-02 -0.024919 0.050675 -0.010347 48.557390 -0.003809 49.384944 -0.004663 49.636410
2022-03-03 -0.039111 0.049240 -0.008722 47.633657 -0.006244 48.951358 -0.007365 49.378405
2022-03-04 -0.068510 0.051702 -0.012002 45.694435 -0.006647 48.047372 -0.007610 48.841766
2022-03-05 0.026671 0.052652 -0.010139 52.444587 -0.006639 51.073451 -0.007992 50.614855

```

1577 rows x 8 columns

Add the lags

```
df = rets
```

```

col_list = ['ADA', 'std14', 'ma14', 'rsi14', 'ma30', 'rsi30', 'ma50', 'rsi50']
for col in col_list:
    for x in range(1,8):
        df[col+'__lag(x)'] = df[col].copy().shift(x)

```

```
rets
```

Date	ADA	std14	ma14	rsi14	ma30	rsi30	ma50	rsi50	ADA_lag1	std14_lag1	...	ma50_lag6	rsi50_lag6	ADA_lag7	std14
2017-11-10	-0.167156	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN
2017-11-11	0.011658	NaN	NaN	NaN	NaN	NaN	NaN	NaN	-0.167156	NaN	...	NaN	NaN	NaN	NaN
2017-11-12	-0.134797	NaN	NaN	NaN	NaN	NaN	NaN	NaN	0.011658	NaN	...	NaN	NaN	NaN	NaN
2017-11-13	0.073589	NaN	NaN	NaN	NaN	NaN	NaN	NaN	-0.134797	NaN	...	NaN	NaN	NaN	NaN
2017-11-14	0.016219	NaN	NaN	NaN	NaN	NaN	NaN	NaN	0.073589	NaN	...	NaN	NaN	NaN	NaN
...
2022-03-01	0.002620	0.050592	-0.010040	50.315504	-0.002506	50.219308	-0.003177	50.134551	0.111760	0.053294	...	-0.008230	49.718370	0.035237	0.04
2022-03-02	-0.024919	0.050675	-0.010347	48.557390	-0.003809	49.384944	-0.004663	49.636410	0.002620	0.050592	...	-0.007408	49.799644	-0.022579	0.02

Figure 3: Python code for return predictions of ADA - part 3

```

2022-03-03 -0.039111 0.049240 -0.008722 47.633657 -0.006244 48.951358 -0.007365 49.378405 -0.024919 0.050675 ... -0.007085 51.069412 -0.018280 0.02
2022-03-04 -0.068510 0.051702 -0.012002 45.694435 -0.006647 48.047372 -0.007610 48.841766 -0.039111 0.049240 ... -0.008215 49.913192 0.050042 0.04
2022-03-05 0.026671 0.052652 -0.010139 52.444587 -0.006639 51.073451 -0.007992 50.614855 -0.068510 0.051702 ... -0.008492 48.488709 -0.011321 0.04

```

1577 rows x 64 columns

```

In [16]: rets.columns
Out[16]: Index(['ADA', 'std14', 'ma14', 'rsi14', 'ma30', 'rsi30', 'ma50', 'rsi50',
            'ADA_lag1', 'std14_lag1', 'ma14_lag1', 'rsi14_lag1', 'ma30_lag1',
            'rsi30_lag1', 'ma50_lag1', 'rsi50_lag1', 'ADA_lag2', 'std14_lag2',
            'ma14_lag2', 'rsi14_lag2', 'ma30_lag2', 'rsi30_lag2', 'ma50_lag2',
            'rsi50_lag2', 'ADA_lag3', 'std14_lag3', 'ma14_lag3', 'rsi14_lag3',
            'ma30_lag3', 'rsi30_lag3', 'ma50_lag3', 'rsi50_lag3', 'ADA_lag4',
            'std14_lag4', 'ma14_lag4', 'rsi14_lag4', 'ma30_lag4', 'rsi30_lag4',
            'ma50_lag4', 'rsi50_lag4', 'ADA_lag5', 'std14_lag5', 'ma14_lag5',
            'rsi14_lag5', 'ma30_lag5', 'rsi30_lag5', 'ma50_lag5', 'rsi50_lag5',
            'ADA_lag6', 'std14_lag6', 'ma14_lag6', 'rsi14_lag6', 'ma30_lag6',
            'rsi30_lag6', 'ma50_lag6', 'rsi50_lag6', 'ADA_lag7', 'std14_lag7',
            'ma14_lag7', 'rsi14_lag7', 'ma30_lag7', 'rsi30_lag7', 'ma50_lag7',
            'rsi50_lag7'],
           dtype='object')
In [17]: rets.dropna(inplace=True) #remove all the null values from the dataframe
X = rets.drop(['ADA', 'std14', 'ma14', 'rsi14', 'ma30', 'rsi30', 'ma50', 'rsi50'],axis=1) #use the feature_names list to extract
all the predictor variable columns from the rets dataframe
Y = rets['ADA'] #Extract the log returns column
In [18]: X_train,X_test,Y_train,Y_test = train_test_split(X,Y,test_size=0.1,shuffle = False,random_state=0)

Random Forest

In [19]: regressor = RandomForestRegressor(n_estimators=100)
In [20]: regressor.fit(X_train,Y_train)
Out[20]: RandomForestRegressor()
In [21]: test_data_prediction = regressor.predict(X_test)
In [22]: print(test_data_prediction)
[-0.01255964 -0.01445449 -0.0059128  0.00543303  0.00195952 -0.00056808
 -0.01232149  0.00300497 -0.00556694 -0.0044533  -0.005352  -0.0024822
 -0.00979736  0.00577399 -0.00617741  0.01078323  0.00683644  0.00343425
 -0.01090256  0.00769217  0.00281217  0.00174251  0.00811192  -0.00119303
 -0.00156469 -0.00566876 -0.01273436 -0.01822796  0.01335807 -0.00235392
 -0.00547829 -0.00187899 -0.01093952  0.00864234 -0.00231129 -0.00076996
 0.00741569 -0.00753069 -0.00529194 -0.00167714  0.01854581  0.00623304
 -0.00019689  0.01460563  0.00382801  0.00520729  0.00410018  0.00420438
 0.00130909 -0.00644224 -0.00153871  0.0021580  -0.00135574  0.02207736
 0.0027689  -0.00863292  0.00138584 -0.00542623 -0.0073762  -0.01801816
 0.01508424  0.01904636  0.00216382 -0.01867802  0.00176899 -0.00298455
 0.00595253  0.00723267  0.00475706  0.00541288 -0.0002623 -0.00975924
 -0.0154563  0.00579782  0.00229187 -0.01907302 -0.00310787 -0.0063227
 -0.00364609 -0.00022903 -0.00358341  0.00150482  0.00451123  0.003193
 -0.00025555  0.0014004  -0.0022671  -0.00387652  0.003237  0.00195385
 -0.00632248  0.01868759  0.01804195  0.00371986 -0.00373891  0.00117694
 0.00436831 -0.00707202 -0.01367839 -0.00543172 -0.00194701 -0.00254358

```

Figure 4: Python code for return predictions of ADA - part 4

```

0.00438831 -0.00707202 -0.01387039 -0.00543172 -0.00194701 -0.00254358
0.00094595 0.00059086 -0.02121541 0.01074551 0.0140905 0.00192708
0.01786346 0.04061149 0.02400669 0.00831144 -0.00678203 0.00479369
-0.00423002 0.0055574 -0.01527992 0.0114958 0.00315659 -0.00963466
0.00396179 -0.00282234 -0.01181548 -0.0045577 -0.00790118 -0.00985311
-0.00324783 0.00067268 -0.00379452 0.00151016 0.01412454 0.00230975
-0.00345018 -0.00445758 -0.0071621 -0.00232111 0.00052674 -0.00587078
-0.00391361 0.01467411 0.00824506 -0.01956686 0.00540248 -0.00706651
-0.02404717 -0.00770565 -0.01205554 0.01668465 -0.00011533 0.00115243
0.00457974 0.00748179]

In [23]: Comparison_ADA_RF = pd.DataFrame({'Actual returns': Y_test, 'Predicted returns': test_data_prediction})

In [24]: Comparison_ADA_RF

Out[24]:
      Actual returns  Predicted returns
Date
2021-10-05      0.010840      -0.012680
2021-10-06     -0.000434      -0.014454
2021-10-07      0.028889     -0.005913
2021-10-08     -0.017042      0.005433
2021-10-09      0.013073      0.001980
...
2022-03-01      0.002030      0.018885
2022-03-02     -0.024919     -0.000115
2022-03-03     -0.030111      0.001152
2022-03-04     -0.008810      0.004980
2022-03-05      0.020871      0.007482

152 rows x 2 columns

In [25]: #Performance indicators
r_score_RF=metrics.r2_score(Y_test,test_data_prediction)
print("R squared value_RF :",r_score_RF)
print("MAE_RF:", mean_absolute_error(Y_test, test_data_prediction))
meanSquaredError_RF=mean_squared_error(Y_test, test_data_prediction)
print("MSE_RF:", meanSquaredError_RF)
rootMeanSquaredError_RF = sqrt(meanSquaredError_RF)
print("RMSE_RF:", rootMeanSquaredError_RF)

R squared Value_RF : -0.14929238034822445
MAE_RF: 0.037690393814650744
MSE_RF: 0.0024271168048556637
RMSE_RF: 0.049265769910310955

```

Figure 5: Python code for return predictions of ADA - part 5

```

In [26]: Comparison_ADA_RF.plot(kind='lines', title="ADA : Actual returns VS Predicted returns(Random Forest)", xtitle='Date', ytitle='R
returns'),

ADA : Actual returns VS Predicted returns(Random Forest)
Returns
0.1
0.05
0
-0.05
-0.1
Oct 10 2021 Oct 24 Nov 7 Nov 21 Dec 5 Dec 19 Jan 2 2022 Jan 16 Jan 30 Feb 13 Feb 27
Date
Export to plotly >

Out[26]: (None,)

In [ ]:

Linear Regression

In [27]: from sklearn.linear_model import LinearRegression
# Creation of the Regression Model
model = LinearRegression()

In [28]: # Train the model
model.fit(X_train, y_train)

Out[28]: LinearRegression()

In [29]: # Make predictions
y_pred_LR= model.predict(X_test)

In [30]: print(y_pred_LR)

[ 0.00326675  0.00584835 -0.01716241 -0.00175104 -0.01149544  0.01525241
 0.00309906 -0.00177968 -0.00680764  0.00559074 -0.00238105  0.02238099
-0.02247806  0.00260187 -0.00105222  0.0135486 -0.0119036 -0.00026533
 0.01779384 -0.01405123 -0.01175404  0.00473791  0.00462659  0.01005536
-0.00689797 -0.01318789  0.01680655 -0.01544413 -0.00816071  0.00371117
 0.00791305  0.00425344  0.00500868 -0.00083901  0.00363509  0.00141332
 0.01997127  0.00628787 -0.00647271 -0.00198178  0.00281815 -0.01454521
 0.01099526  0.00592712 -0.00265268  0.0023588 -0.00190447 -0.0099700
 0.01256722  0.00076177  0.00630975 -0.01623059 -0.00832442 -0.00898952
 0.00421697 -0.00294609 -0.00252832 -0.01593162  0.01912894 -0.00589619
 0.01170448  0.00156973  0.02380256 -0.00607054 -0.02253352 -0.00019578]

```

Figure 6: Python code for return predictions of ADA - part 6

```

0.02286217 -0.009827 -0.00514012 0.01966778 0.00043414 0.01303792
0.0137161 -0.01594671 0.00251935 0.01776116 -0.01712647 -0.00024794
0.00896741 0.00229929 0.0098718 0.02465734 -0.01019683 0.02134989
-0.01579293 0.0065253 0.00601145 0.00701811 0.0122464 -0.00078309
0.01321228 0.00402895 0.0172084 0.02862445 -0.03161463 0.00632745
-0.00316998 0.00207871 0.01458435 -0.00256645 -0.01544842 0.01404637
0.02822321 0.00065863 -0.02757046 0.00877247 0.02345493 0.00762818
0.02094084 -0.00752085 -0.01152959 0.00292328 0.01440811 0.00218129
0.01644677 0.00306812 0.00020946 0.01289724 0.00691365 -0.02180781
0.0185846 -0.00739723 -0.02087438 0.01504246 0.00247515 -0.01542343
-0.00517289 0.00307056 -0.00339735 -0.00035087 0.00771252 -0.00943516
-0.0029254 0.01421655 0.00062749 0.00699096 0.01166341 -0.01671291
0.01953166 0.00215561 -0.02074048 0.00590591 -0.00462363 -0.01120653
0.00578942 0.00827344 -0.01009688 0.00874766 0.00067992 -0.00154374
0.00683874 -0.00029486]

In [31]: Comparison_ADA_LR = pd.DataFrame({'Actual returns': Y_test, 'Predicted returns': y_pred_LR})

In [32]: Comparison_ADA_LR

Out[32]:
      Actual returns  Predicted returns
Date
2021-10-05      0.010840      0.002287
2021-10-06     -0.004434      0.005848
2021-10-07      0.028880     -0.017162
2021-10-08     -0.017842     -0.001761
2021-10-09      0.013073     -0.011495
...
2022-03-01      0.002820      0.008748
2022-03-02     -0.024919      0.000880
2022-03-03     -0.039111     -0.001844
2022-03-04     -0.088510      0.008831
2022-03-05      0.028871     -0.000294

152 rows x 2 columns

In [33]: #Performance indicators
r_score_LR=metrics.r2_score(Y_test,y_pred_LR)
print("R squared value_LR :",r_score_LR)
print("MAE_LR:", mean_absolute_error(Y_test, y_pred_LR))
print("MSE_LR:", mean_squared_error(Y_test, y_pred_LR))
print("MSE_LR:", mean_squared_error_LR)
rootMeanSquaredError_LR = sqrt(meanSquaredError_LR)
print("RMSE_LR:", rootMeanSquaredError_LR)

R squared value_LR : -0.18483064914061265
MAE_LR: 0.038244834310511816
MSE_LR: 0.002502167051249259
RMSE_LR: 0.05002166581841572

```

Figure 7: Python code for return predictions of ADA - part 7

```

In [34]: Comparison_ADA_LR.iplot(kind='lines', title="ADA : Actual returns VS Predicted returns(Linear Regression)", xtitle='Date', ytitle='Returns'),

ADA : Actual returns VS Predicted returns(Linear Regression)
Returns
Date
Export to plotly >

Out[34]: (None,)

In [ ]:

Decision Tree

In [35]: from sklearn.tree import DecisionTreeRegressor
# Create Decision Tree regressor
dtrree_regressor = DecisionTreeRegressor(random_state=0)

In [36]: # Train the model
dtrree_regressor.fit(X_train,y_train)

Out[36]: DecisionTreeRegressor(random_state=0)

In [37]: # Make predictions
pred_dtrree = dtrree_regressor.predict(X_test)

In [38]: print(pred_dtrree)

[-0.0078387  0.00182365 0.0002872 -0.01939624 -0.02967803 -0.06401654
 0.02351348  0.04194073  0.00226563  0.0121443  0.00578526  0.01121443
 0.0140677  -0.05340819 -0.05340819  0.07089768 -0.02031129  0.04032645
 0.07867047  0.00660054  0.00589353  0.00660054  0.01171565  0.00039098
-0.02577249 -0.00901189  0.04315227 -0.03008474  0.00620054 -0.03505798
-0.00978664  0.004931684 -0.0322271  0.01833012  0.00739882 -0.02645074
-0.06672755  0.02431261  0.02049827  0.01406493 -0.05258316  0.01061224
-0.04977072  0.0140677  0.00031334  0.01141772 -0.01875128  0.01033012
 0.0537742  0.02856484  0.03555773  0.00886186 -0.04580721 -0.01609023
-0.01280979  0.02786596 -0.10054275  0.09731253 -0.05951597 -0.02523102
-0.01481717  0.02412025  0.03220113  0.05942601  0.0013282  0.0185214
-0.12561608  0.02762366  0.05071465 -0.0120925 -0.0549177 -0.04936053]

```

Figure 8: Python code for return predictions of ADA - part 8

```

-0.00614003 -0.0549177 -0.02930047 -0.04936053 0.0034639 -0.03858825
-0.04936053 -0.01027155 -0.03440804 0.01063201 0.07590938 0.00693466
-0.00319547 -0.00967664 -0.02067807 0.07890933 0.00311062 -0.02036854
-0.05756971 0.03475336 0.07890383 -0.01249814 0.02476542 -0.05340819
0.0537742 -0.0332271 -0.01286079 -0.03577243 -0.02135742 -0.02481763
0.01361216 0.00762893 0.01206849 0.05740226 -0.05103911 0.07590938
0.01406493 -0.00765074 -0.02069356 0.00772028 0.12570542 0.03244394
0.00953942 0.03244394 -0.02052009 -0.00616236 0.02762366 0.0411964
-0.01057815 0.00619266 -0.00049521 -0.01419506 -0.02100914 -0.02523103
-0.05965197 -0.1333144 -0.01665753 -0.03107465 0.09064327 0.03093612
-0.07095728 -0.00629565 0.02276103 -0.05340819 0.02431261 0.01349139
0.00185342 0.0561094 0.0561094 -0.06299199 -0.10054275 0.00471144
-0.00857185 0.01090203 0.02412025 0.00762893 -0.00134794 -0.02481763
0.03220113 0.00227719]

In [39]: Comparison_ADA_DT = pd.DataFrame({'Actual returns': Y_test, 'Predicted returns': pred_dtree})

In [40]: Comparison_ADA_DT

Out[40]:
Actual returns Predicted returns
Date
2021-10-05 0.010040 -0.007840
2021-10-06 -0.000434 0.001030
2021-10-07 0.028889 0.000287
2021-10-08 -0.017842 -0.010298
2021-10-09 0.013073 -0.020667
...
2022-03-01 0.002020 0.007829
2022-03-02 -0.024919 -0.081348
2022-03-03 -0.030111 -0.024818
2022-03-04 -0.008510 0.032201
2022-03-05 0.020971 0.002277

152 rows x 2 columns

In [41]: #Performance indicators
r_score_DT=metric.r2_score(Y_test,pred_dtree)
print("R squared value_DT :",r_score_DT)
print("MAE_DT:", mean_absolute_error(Y_test, pred_dtree))
meanSquaredError_DT=mean_squared_error(Y_test, pred_dtree)
print("MSE_DT:", meanSquaredError_DT)
rootMeanSquaredError_DT = sort(meanSquaredError_DT)
print("RMSE_DT:", rootMeanSquaredError_DT)

R squared value_DT : -0.8157110036902249
MAE_DT : 0.05003303705550765
MSE_DT : 0.00383444040999036304
RMSE_DT : 0.0619232110761678

```

Figure 9: Python code for return predictions of ADA - part 9

```

In [42]: Comparison_ADA_DT.plot(kind='lines', title="ADA : Actual returns VS Predicted returns(Decision Tree)", xTitle='Date', yTitle='R
returns' ),

ADA : Actual returns VS Predicted returns(Decision Tree)

Returns
Date
Oct 10 2021
Oct 24
Nov 7
Nov 21
Dec 5
Dec 19
Jan 2 2022
Jan 16
Jan 30
Feb 13
Feb 27

Actual returns
Predicted returns

Out[42]: (None,)

In [ ]:

Gradient Boosting Regressor

In [43]: from sklearn.ensemble import GradientBoostingRegressor
# Create Gradient Boosting Regressor
GB_regressor=GradientBoostingRegressor(n_estimators=100)

In [44]: # Train the model
GB_regressor.fit(X_train,Y_train)

Out[44]: GradientBoostingRegressor()

In [45]: # Make the predictions
GB_predict=GB_regressor.predict(X_test)

In [46]: print(GB_predict)

[-0.00643337 -0.00643337 -0.00540177 -0.00515164 0.00131681 -0.0156906
-0.00530525 -0.0004993 -0.00643337 -0.0004993 -0.00314233 -0.00560311
0.00110095 -0.00305538 -0.00793167 -0.0004993 -0.01126757 -0.00032154
0.01034598 0.01369288 -0.00626999 -0.00925906 0.01474951 0.02466203
0.02397389 0.01053928 -0.03300956 -0.04670482 -0.02812546 -0.00449771
-0.00384047 0.00130958 -0.00778634 -0.00305538 -0.00387729 -0.00384047
0.00470231 0.00533945 -0.00053917 -0.00050976 0.00644915 0.00041081
0.00213091 0.01062084 0.00050073 0.00424229 -0.00255694 -0.00433332
-0.00430785 -0.00292894 -0.00314002 -0.00387729 0.00251864 0.00717826
0.00209011 -0.00231815 0.00013442 -0.00145931 -0.02690932 -0.00591404
0.01052360 0.01007702 0.0013945 0.00000463 0.00000502 -0.00050402
-0.00015 0.00412149 0.02001647 0.00097996 0.01514963 -0.01143286

```

Figure 10: Python code for return predictions of ADA - part 10

```

-0.00848469 -0.00192618 0.00122561 -0.01209831 -0.00089805 -0.00704207
-0.00597729 -0.00752834 -0.00275532 -0.00324886 -0.00768687 0.00063042
-0.00415931 -0.01258874 -0.00954744 0.00029114 0.01062682 -0.00421414
0.00084799 0.00470498 0.00736124 0.00768235 0.00035557 0.00430514
-0.00015854 -0.00184289 -0.00483767 -0.00311729 0.00463561 0.00526411
-0.00395126 0.00202457 -0.00075319 0.02616131 0.0152741 0.01106418
0.00393916 0.03206638 0.01010187 0.00141292 0.01823384 -0.01178144
-0.00801931 0.00044686 -0.00762068 0.0060327 -0.0004993 -0.00216469
-0.0020141 -0.00452274 -0.01111865 -0.00568814 -0.0006134 -0.03277544
-0.00736159 -0.00221704 -0.01111865 0.00109726 0.00694231 0.00688161
0.01406424 -0.00206517 0.00194983 0.00330542 0.001753 -0.00395338
0.00170936 0.00427799 0.00886677 -0.00289615 0.00397356 -0.01120815
0.01225948 -0.00634522 -0.01014156 0.00083068 0.0044111 0.0037734
0.01463651 0.00351999]

In [47]: Comparison_ADA_GB = pd.DataFrame({'Actual returns': Y_test, 'Predicted returns': GB_predict})
In [48]: Comparison_ADA_GB
Out[48]:
      Actual returns  Predicted returns
Date
2021-10-05    0.010849    -0.008433
2021-10-06   -0.000434    -0.008433
2021-10-07    0.028889    -0.005402
2021-10-08   -0.017842    0.005152
2021-10-09    0.013073    0.001317
--
2022-03-01    0.002620    0.000031
2022-03-02   -0.024919    0.004441
2022-03-03   -0.030111    0.003773
2022-03-04   -0.088510    0.014837
2022-03-05    0.028871    0.003520

152 rows x 2 columns

In [49]: #Performance indicators
r_score_GB=metrics.r2_score(Y_test,GB_predict)
print("R squared value_GB :",r_score_GB)
print("MAE_GB:", mean_absolute_error(Y_test, GB_predict))
meanSquaredError_GB=mean_squared_error(Y_test, GB_predict)
print("MSE_GB:", meanSquaredError_GB)
rootMeanSquaredError_GB = sqrt(meanSquaredError_GB)
print("RMSE_GB:", rootMeanSquaredError_GB)

R squared value_GB : -0.20023024506044473
MAE_GB: 0.038995178727995475
MSE_GB: 0.002534688459723208
RMSE_GB: 0.050345689584344835

```

Figure 11: Python code for return predictions of ADA - part 11

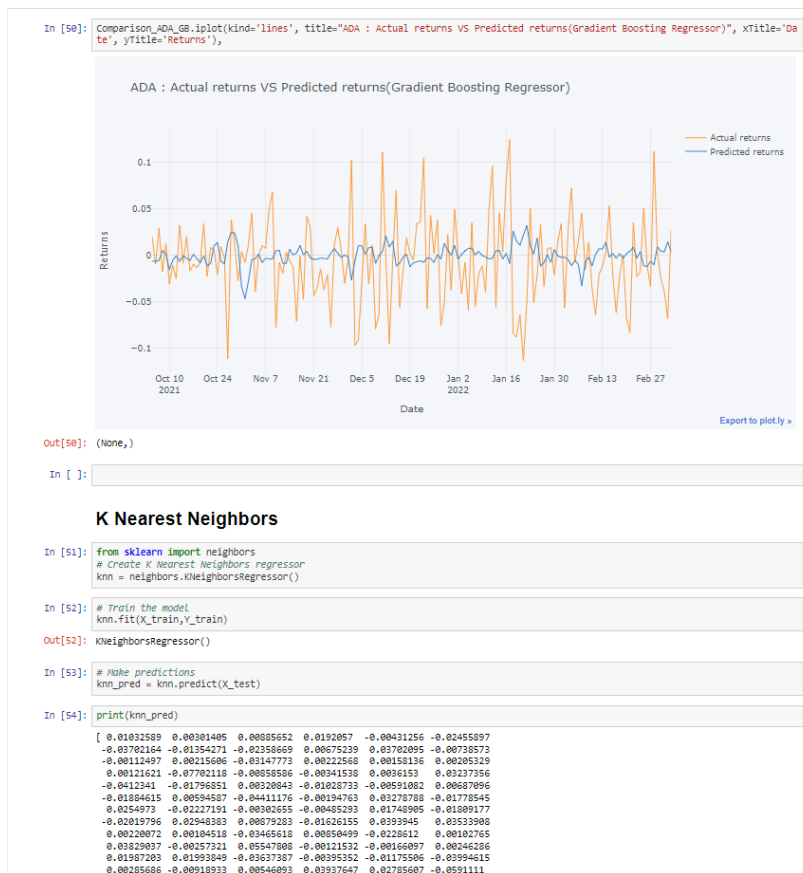


Figure 12: Python code for return predictions of ADA - part 12

```

-----
-0.06011489 -0.00896977 -0.00385812 -0.04586409 -0.00162838 -0.02520287
-0.00517485 0.07538272 0.02777895 -0.01404818 -0.01178335 0.01517752
-0.00743785 0.005342 -0.0012541 -0.01704258 0.00214369 0.00347031
-0.01368816 -0.00458987 -0.01019673 -0.01343527 0.00651879 -0.01419481
0.00945656 0.01202888 -0.04567178 -0.03959124 -0.02318263 0.0199783
0.00814119 0.02237003 0.01442628 0.01701314 0.01796781 -0.00872732
-0.01740087 -0.04354427 -0.01729776 -0.0417783 -0.02235793 0.02200391
-0.02926179 -0.01137861 0.00719558 -0.03412518 -0.00174559 -0.00997759
0.01402943 -0.03446986 0.01902169 0.04066416 -0.00227549 -0.01121638
-0.07521627 -0.00756925 0.01426713 -0.00856192 0.01024362 -0.00234652
-0.00695588 -0.0201647 0.01554772 0.01199937 -0.03655064 -0.02313176
0.0073974 -0.00601628 0.01319561 -0.04213602 0.02735237 -0.00354017
-0.04174744 -0.01752692 -0.03686894 -0.01574635 0.02484818 -0.00288569
-0.01701473 -0.0142895 ]

In [55]: Comparison_ADA_KNN = pd.DataFrame({'Actual returns': Y_test, 'Predicted returns': knn_pred})

In [56]: Comparison_ADA_KNN

Out[56]:
      Date  Actual returns  Predicted returns
2021-10-05  0.019849      0.010328
2021-10-06 -0.000434      0.003014
2021-10-07  0.028889      0.008857
2021-10-08 -0.017042      0.010208
2021-10-09  0.013073     -0.004313
...
2022-03-01  0.002020     -0.016748
2022-03-02 -0.024919      0.024840
2022-03-03 -0.030111     -0.002888
2022-03-04 -0.008510     -0.017015
2022-03-05  0.020871     -0.014290

152 rows x 2 columns

In [57]: #Performance indicators
r_score_KNN=metrics.r2_score(Y_test,knn_pred)
print("R squared value_KNN :",r_score_KNN)
print("MAE_KNN:", mean_absolute_error(Y_test, knn_pred))
meanSquaredError_KNN=mean_squared_error(Y_test, knn_pred)
print("MSE_KNN:", mean_squared_error(Y_test, knn_pred))
rootMeanSquaredError_KNN = sqrt(mean_squared_error(Y_test, knn_pred))
print("RMSE_KNN:", rootMeanSquaredError_KNN)

R squared value_KNN : -0.25283869598567164
MAE_KNN: 0.039080740742423935
MSE_KNN: 0.0026457888369521856
RMSE_KNN: 0.05143723201898777

```

Figure 13: Python code for return predictions of ADA - part 13

```

In [58]: Comparison_ADA_KNN.plot(kind='lines', title="ADA : Actual returns VS Predicted returns(K Nearest Neighbors)", xtitle='Date', ytitle='Returns'),

ADA : Actual returns VS Predicted returns(K Nearest Neighbors)

Returns
Date
Oct 10 2021
Oct 24
Nov 7
Nov 21
Dec 5
Dec 19
Jan 2 2022
Jan 16
Jan 30
Feb 13
Feb 27

Actual returns
Predicted returns

Export to plot.ly

Out[58]: (None,)

In [ ]:

Multilayer Perceptron

In [59]: from sklearn.neural_network import MLPRegressor
from sklearn.datasets import make_regression
# Create MLP Regressor
MLP = MLPRegressor()

In [60]: # Train the model
MLP.fit(X_train, Y_train)

Out[60]: MLPRegressor()

In [61]: # Make predictions
MLP_pred = MLP.predict(X_test)

In [62]: MLP_pred

Out[62]: array([[ 0.02761331,  0.00584564,  0.0565452 , -0.02381472,  0.00720952,
-0.05760871,  0.03421961,  0.01496444,  0.07325969,  0.00649307,
-0.00220143, -0.03368106, -0.01048956, -0.05337279,  0.04742616,
 0.01056228, -0.01253301,  0.01440653, -0.14573476,  0.04669354,
-0.05810828,  0.03773296,  0.14238758,  0.01511027,  0.11759954,
 0.13040044, -0.17218865, -0.02194661, -0.06370035, -0.27072067,
 0.00262953, -0.02313229, -0.13528307,  0.08151747, -0.04759037,
-0.00970404, -0.09798776, -0.11895577, -0.1788883 ,  0.18083367,
 0.03319364,  0.09080469,  0.02468655,  0.01085436,  0.05855939,
 0.12084688, -0.00416914, -0.06911367, -0.08001643, -0.06925188,
 0.0471183 ,  0.00300076,  0.02370001,  0.05520033, -0.01919133,

```

Figure 14: Python code for return predictions of ADA - part 14

```

0.04713182, 0.00208627, 0.02279903, 0.00220668, -0.05171815,
-0.05658817, -0.15303777, -0.1803392, -0.04130568, -0.15002151,
0.0418285, -0.23171099, 0.07481136, -0.14084833, -0.0436826,
-0.09525903, 0.02429178, 0.03222845, -0.03092195, -0.0734289,
0.00800669, -0.0225093, -0.25121526, -0.02495082, -0.14781579,
-0.07243345, -0.04533309, 0.00170066, -0.07767164, -0.06606031,
-0.10107775, 0.01227746, -0.05162903, -0.05697366, -0.02220531,
0.01039647, -0.10143577, -0.00199899, -0.0675521, -0.01585696,
-0.01650645, 0.00426029, 0.0306529, -0.0052233, -0.05953706,
-0.01374867, 0.00026996, -0.02380419, -0.02039479, -0.02979345,
-0.10195894, 0.013613, -0.00045237, -0.04954658, -0.06697488,
0.01739923, 0.07570151, -0.03406929, -0.14412714, -0.00355645,
-0.11667601, -0.07520931, 0.00909036, 0.00399006, -0.01702535,
-0.05117047, 0.00646434, -0.02347136, -0.01706872, -0.02950114,
-0.06315496, -0.01176136, -0.03606759, -0.03858934, -0.049406,
-0.03095332, 0.01000099, -0.05926435, -0.02812291, 0.02461065,
0.03670926, 0.04375254, 0.03626963, -0.06971434, -0.07194428,
-0.0950285, -0.00118377, 0.07520299, 0.01756603, 0.06536643,
-0.09589319, 0.04907097, -0.0694786, -0.07744855, 0.03232909,
-0.15340236, -0.09910959, 0.11091255, -0.06656956, -0.02551156,
-0.01053032, 0.02662303]

In [63]: Comparison_ADA_MLP = pd.DataFrame({'Actual returns': Y_test, 'Predicted returns': MLP_pred})

In [64]: Comparison_ADA_MLP

Out[64]:
      Date  Actual returns  Predicted returns
2021-10-05  0.010849      0.027013
2021-10-06 -0.00434      0.005848
2021-10-07  0.028889      0.005645
2021-10-08 -0.017842     -0.023816
2021-10-09  0.013073      0.007204
...
2022-03-01  0.002020      0.110913
2022-03-02 -0.024919     -0.008570
2022-03-03 -0.030111     -0.028512
2022-03-04 -0.008510     -0.010530
2022-03-05  0.020671      0.020623

152 rows x 2 columns

In [65]: #Performance Indicators
r_score_MLP=metrics.r2_score(Y_test,MLP_pred)
print("R squared value_MLP :",r_score_MLP)
print("MAE_MLP:", mean_absolute_error(Y_test, MLP_pred))
meanSquaredError_MLP=mean_squared_error(Y_test, MLP_pred)
print("MSE_MLP:", meanSquaredError_MLP)
rootMeanSquaredError_MLP = sqrt(meanSquaredError_MLP)
print("RMSE_MLP:", rootMeanSquaredError_MLP)

R squared value_MLP : -2.843705695866146
MAE_MLP : 0.07090627361120528
MSE_MLP : 0.00311727923241188
RMSE_MLP : 0.0090959095810747

In [66]: Comparison_ADA_MLP.plot(kind='lines', title="ADA : Actual returns VS Predicted returns(Multilayer Perceptron)", xtitle='Date',
ytitle='Returns'),

```

Figure 15: Python code for return predictions of ADA - part 15

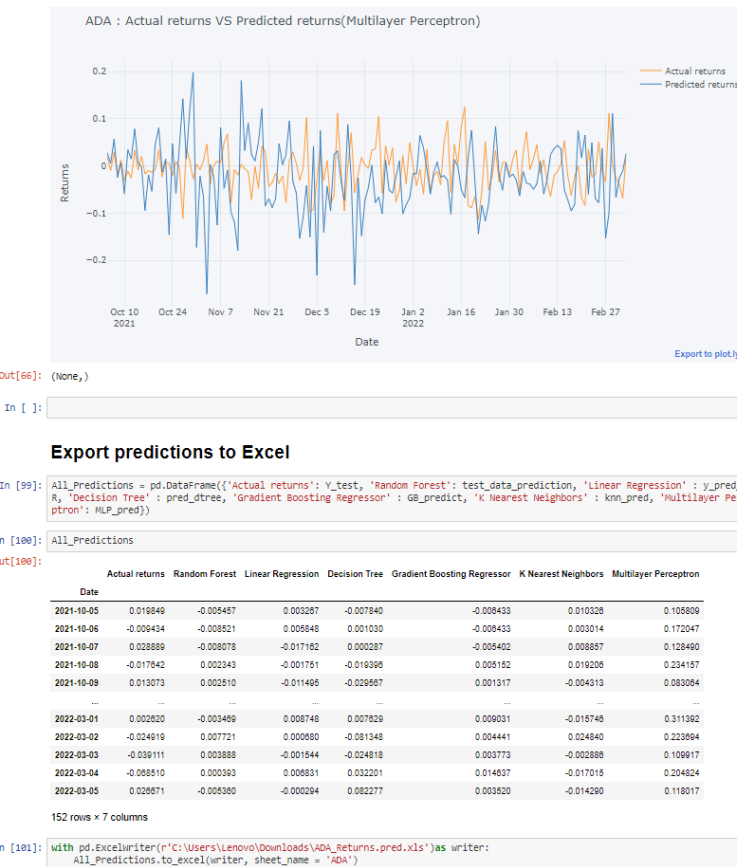


Figure 16: Python code for return predictions of ADA - part 16

1.2 Python code for price predictions

```

In [1]: import numpy as np # NumPy
import pandas as pd # pandas
import cufflinks as cf # Cufflinks
from sklearn.svm import SVC # scikit-learn
import warnings; warnings.simplefilter('ignore')
from statsmodels.tsa.stattools import adfuller
import configparser as cp
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn import metrics
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import mean_squared_error
from math import sqrt
import talib

In [2]: dataset = 'C:/Users/Lenovo/Downloads/Mémoire/Database/cut/Close/ADA.xlsx'
data = pd.read_excel(dataset, index_col=0, parse_dates=True).dropna()

In [3]: data.head()

Out[3]:
      ADA
Date
2017-11-09  0.032053
2017-11-10  0.027119
2017-11-11  0.027437
2017-11-12  0.023977
2017-11-13  0.025808

In [4]: data.dropna(inplace=True)

In [5]: adfuller(data['ADA']) # stationarity test of time series --> not stationary

Out[5]: (-1.7099796688541458,
0.4259781251889812,
22,
1555,
{'1%': -3.4345623007753496,
'5%': -2.8634004754918296,
'10%': -2.56719846450713},
-4835.609840993338)

In [6]: cf.go_offline() #force Cufflinks to use offline Plotly mode (bug otherwise)

Add features

In [8]: data['std14'] = data['ADA'].rolling(14).std()
feature_names = ['std14'] #empty list to hold the feature names.
for n in [14, 30, 50]:
    data['ma' + str(n)] = talib.SMA(data['ADA'].values, timeperiod=n)
    data['rsi' + str(n)] = talib.RSI(data['ADA'].values, timeperiod=n) #SMA and RSI methods to calculate the SMA and RSI: 14, 30, 50.
    feature_names = feature_names + ['ma' + str(n), 'rsi' + str(n)] #add the ma and rsi variable names to the feature_names list.

In [9]: feature_names

Out[9]: ['std14', 'ma14', 'rsi14', 'ma30', 'rsi30', 'ma50', 'rsi50']

```

Figure 17: Python code for price predictions of ADA - part 1

```

data
      ADA  std14  ma14  rsi14  ma30  rsi30  ma50  rsi50
Date
2017-11-09  0.032053  NaN  NaN  NaN  NaN  NaN  NaN
2017-11-10  0.027119  NaN  NaN  NaN  NaN  NaN  NaN
2017-11-11  0.027437  NaN  NaN  NaN  NaN  NaN  NaN
2017-11-12  0.023977  NaN  NaN  NaN  NaN  NaN  NaN
2017-11-13  0.025808  NaN  NaN  NaN  NaN  NaN  NaN
...
2022-03-01  0.962346  0.071943  0.933493  46.389854  1.025607  43.784198  1.096753  43.767441
2022-03-02  0.938662  0.057401  0.923041  44.217555  1.021819  42.961125  1.091824  43.340832
2022-03-03  0.902659  0.050296  0.914667  41.094906  1.015620  41.756189  1.083787  42.895303
2022-03-04  0.842889  0.047670  0.903651  36.488015  1.009420  39.837317  1.075982  41.644563
2022-03-05  0.865672  0.040090  0.894220  39.282158  1.003061  40.906106  1.067476  42.197863

1578 rows x 8 columns

Add the lags

df = data

col_list = ['ADA', 'std14', 'ma14', 'rsi14', 'ma30', 'rsi30', 'ma50', 'rsi50']
for col in col_list:
    for x in range(1,8):
        df[col+f'__lag{x}'] = df[col].copy().shift(x)

data
      ADA  std14  ma14  rsi14  ma30  rsi30  ma50  rsi50  ADA_lag1  std14_lag1  ...  ma50_lag6  rsi50_lag6  ADA_lag7  std14_la
Date
2017-11-09  0.032053  NaN  NaN  NaN  NaN  NaN  NaN  NaN  NaN  NaN  ...  NaN  NaN  NaN  NaN
2017-11-10  0.027119  NaN  NaN  NaN  NaN  NaN  NaN  NaN  NaN  0.032053  NaN  ...  NaN  NaN  NaN  NaN

```

Figure 18: Python code for price predictions of ADA - part 2

```

2017-11-09 0.027119 NaN NaN NaN NaN NaN NaN NaN NaN 0.032053 NaN ... NaN NaN NaN NaN N
2017-11-11 0.027437 NaN NaN NaN NaN NaN NaN NaN NaN NaN 0.027119 NaN ... NaN NaN NaN NaN N
2017-11-12 0.022977 NaN NaN NaN NaN NaN NaN NaN NaN NaN 0.027437 NaN ... NaN NaN NaN NaN N
2017-11-13 0.022608 NaN NaN NaN NaN NaN NaN NaN NaN NaN 0.022977 NaN ... NaN NaN NaN NaN N
...
2022-03-01 0.982348 0.071943 0.932493 48.398854 1.025807 43.784188 1.008753 43.787441 0.959828 0.085699 ... 1.132591 41.216423 0.889017 0.0944
2022-03-02 0.938862 0.057401 0.923041 44.217556 1.021819 42.961125 1.091824 43.340832 0.982348 0.071943 ... 1.125039 40.958503 0.869199 0.0617
2022-03-03 0.902859 0.050298 0.914887 41.094906 1.015820 41.758189 1.083787 42.898303 0.938862 0.057401 ... 1.117404 42.007561 0.853425 0.0908
2022-03-04 0.842889 0.047070 0.903851 38.488015 1.009420 39.837317 1.075682 41.844563 0.902859 0.050298 ... 1.110932 41.833545 0.868027 0.0888
2022-03-05 0.885872 0.040090 0.894220 39.282158 1.003061 40.908106 1.067476 42.197883 0.842889 0.047070 ... 1.104548 41.330556 0.887918 0.0893
1578 rows x 64 columns

```

In [64]: `data.dropna(inplace=True) #remove all the null values from the dataframe`

```

X = data.drop(['ADA', 'std14', 'ma14', 'rsi14', 'ma30', 'rsi30', 'ma50', 'rsi50'],axis=1) #use the feature_names list to extract
all the predictor variable columns from the "data" dataframe
Y = data['ADA'] #Extract the price column

```

In [15]: `X_train,X_test,Y_train,Y_test = train_test_split(X,Y,test_size=0.1,shuffle = False,random_state=0)`

Random Forest

In [16]: `# Create Random Forest regressor`
`regressor = RandomForestRegressor(n_estimators=100)`

In [17]: `# Train the model`
`regressor.fit(X_train,Y_train)`

Out[17]: `RandomForestRegressor()`

In [18]: `test_data_prediction = regressor.predict(X_test)`

In [19]: `print(test_data_prediction)`

```

[2.21721946 2.20593208 2.15283078 2.15767463 2.17670093 2.20528276
2.17891819 2.16715412 2.16550292 2.15303117 2.17419164 2.20723328
2.22830913 2.21886267 2.16532742 2.18862502 2.16941775 2.18736688
2.2235824 2.22823859 2.21394673 2.15679852 2.20755933 2.18774718
2.82435161 2.86965499 2.12821997 2.87247662 2.87981391 2.86532139
2.06135718 2.1834344 2.87750139 2.85740822 2.13865231 2.14398854
2.22171083 2.23261352 2.19738898 2.1597649 2.13243558 2.12967168
2.15368705 2.11841951 1.92230877 1.91466836 1.68148502 1.8921597
2.86955756 1.89658596 1.59783553 1.57213328 1.56454927 1.56849836
1.47438071 1.58757325 1.54385886 1.5349637 1.52887069 1.48442328
1.54625736 1.53611999 1.38664474 1.35939249 1.33740353 1.34115147
1.32721592 1.33817851 1.16670476 1.30793174 1.30182685 1.21421714
1.28262284 1.31710544 1.30837816 1.21577538 1.30684402 1.3892152
1.38979515 1.38844738 1.29515409 1.43912722 1.25136782 1.36655317
1.39179304 1.45247571 1.37375812 1.3321857 1.30818587 1.31602468
1.32110865 1.3319848 1.31898807 1.29471733 1.2781108 1.28807225
1.16989924 1.167721 1.15342374 1.11171137 1.14479711 1.28589438
1.24168188 1.28358147 1.28689849 1.38489812 1.62536583 1.44354494

```

Figure 19: Python code for price predictions of ADA - part 3

```

1.35741779 1.29385782 1.16657399 1.15939458 1.13982613 1.12212445
1.13874902 1.11986654 1.12125459 1.12802153 1.1213499 1.1285448
1.12262479 1.13945881 1.12767921 1.13585684 1.13681179 1.13748581
1.16182724 1.20737387 1.1918879 1.19588463 1.18614365 1.16428044
1.17164758 1.17931819 1.17283149 1.16946674 1.15710564 1.16367198
1.19516246 1.14439285 1.14849847 0.98975824 1.08463251 0.91491978
0.91889486 1.01736875 1.08119886 0.98987248 1.13665592 1.12757676
1.1389482 1.08328614 0.88406325]

```

In [20]: `Comparison_ADA_RF = pd.DataFrame({'Actual prices': Y_test, 'Predicted prices': test_data_prediction})`

In [21]: `Comparison_ADA_RF`

Out[21]:

Date	Actual prices	Predicted prices
2021-10-04	2.189235	2.217219
2021-10-05	2.233124	2.205932
2021-10-06	2.212165	2.152831
2021-10-07	2.278965	2.157875
2021-10-08	2.237178	2.178700
...
2022-03-01	0.982348	1.138858
2022-03-02	0.938862	1.127677
2022-03-03	0.902859	1.138948
2022-03-04	0.842889	1.003288
2022-03-05	0.885872	0.884063

153 rows x 2 columns

In [22]: `#Performance indicators`
`r_score_RF=metrics.r2_score(Y_test,test_data_prediction)`
`print("R squared value_RF :",r_score_RF)`
`print("MAE_RF:", mean_absolute_error(Y_test, test_data_prediction))`
`meanSquaredError_RF=mean_squared_error(Y_test, test_data_prediction)`
`print("MSE_RF:", meanSquaredError_RF)`
`rootMeanSquaredError_RF = sqrt(meanSquaredError_RF)`
`print("RMSE_RF:", rootMeanSquaredError_RF)`

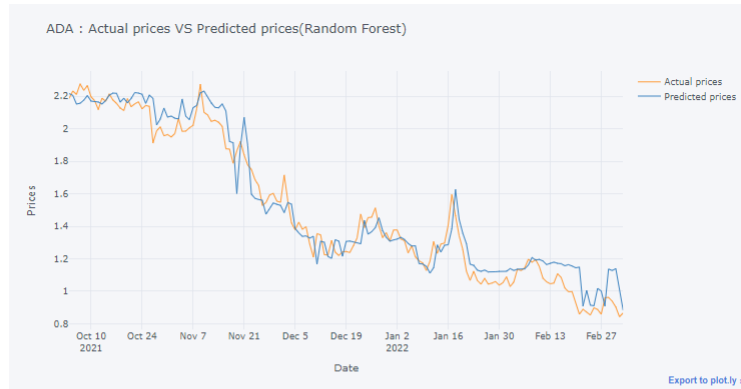
```

R squared value_RF : 0.9461487674859356
MAE_RF : 0.08117687988392156
MSE_RF : 0.018581136165624786
RMSE_RF : 0.10247585143021293

```

In [23]: `Comparison_ADA_RF.plot(kind='lines', title="ADA : Actual prices VS Predicted prices(Random Forest)", xtitle="Date", ytitle="Prices")`

Figure 20: Python code for price predictions of ADA - part 4



Out[23]: (None,)

In []:

Linear Regression

In [24]: `from sklearn.linear_model import LinearRegression`

```
# Creation of the Regression Model
model = LinearRegression()
```

In [25]: `# Train the model
model.fit(X_train, Y_train)`

Out[25]: `LinearRegression()`

In [26]: `# Make predictions
y_pred_LR = model.predict(X_test)`

In [27]: `print(y_pred_LR)`

```
[2.18811896 2.20959389 2.24542197 2.2321494 2.24567716 2.27429828
2.29366026 2.17410814 2.15952628 2.13474389 2.21853831 2.2888351
2.25220862 2.16764865 2.15226731 2.19189476 2.12513127 2.17896287
2.164922 2.1769551 2.13779157 2.07374451 2.1873875 2.18642126
1.98354949 1.98672342 2.03785553 1.98281968 2.0832762 1.92364768
1.98724262 2.0711946 2.08178129 1.95482371 2.08619619 1.95439186
2.13884179 2.20396896 2.11795841 2.18987583 2.09876799 2.02488185
2.03612683 2.02838881 1.93528725 1.89845892 1.84811511 1.89633886
1.94855845 1.86153687 1.78922258 1.73146893 1.70129726 1.70927035
1.56181338 1.59228212 1.62891349 1.59728824 1.57369289 1.59251972
1.71388619 1.59511226 1.42316179 1.443888138 1.45881871 1.41752668
1.43874852 1.36293523 1.23724469 1.3963261 1.38868314 1.26883785
1.2138318 1.38418277 1.22675252 1.26239685 1.38528373 1.26368646
1.2468237 1.3288868 1.37358652 1.51983583 1.4244125 1.45841361
1.48866944 1.53822268 1.43725334 1.35821132 1.38312775 1.36718724
```

Figure 21: Python code for price predictions of ADA - part 5

```
1.00758444 1.08433672 1.06539529 1.05242436 1.18349986 1.16922844
1.13788845 1.231955 1.19958874 1.19988917 1.1678764 1.09879716
1.06887882 1.07278892 1.06973482 1.13958289 1.08485396 1.02939157
1.02224373 1.02921888 0.95917538 0.84526397 0.87852951 0.85474975
0.85518313 0.94418124 0.91248382 0.87846817 0.98936859 0.97817855
0.94738829 0.94983516 0.8587895 ]
```

In [28]: `Comparison_ADA_LR = pd.DataFrame({'Actual prices': Y_test, 'Predicted prices': y_pred_LR})`

In [29]: `Comparison_ADA_LR`

Out[29]:

Date	Actual prices	Predicted prices
2021-10-04	2.18811896	2.188118
2021-10-05	2.231124	2.209594
2021-10-06	2.212155	2.249422
2021-10-07	2.278965	2.232149
2021-10-08	2.237178	2.248877
...
2022-03-01	0.982348	0.988288
2022-03-02	0.938882	0.978179
2022-03-03	0.902858	0.947388
2022-03-04	0.842889	0.949035
2022-03-05	0.888972	0.888790

153 rows x 2 columns

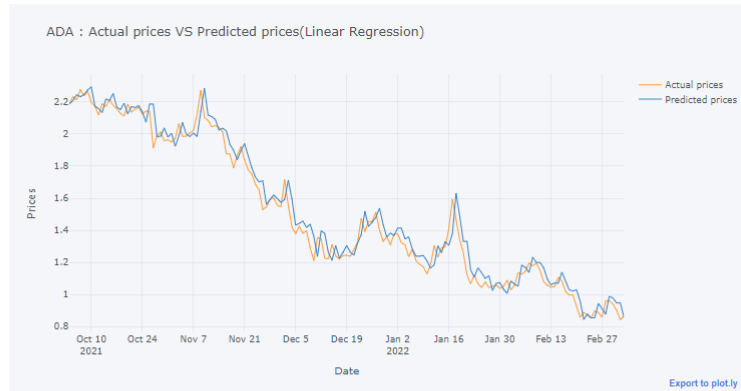
In [30]: `#Performance indicators`

```
r_score_LR=metrics.r2_score(Y_test,y_pred_LR)
print("R squared value_LR :",r_score_LR)
print("MAE_LR:", mean_absolute_error(Y_test, y_pred_LR))
meanSquaredError_LR=mean_squared_error(Y_test, y_pred_LR)
print("MSE_LR:", meanSquaredError_LR)
rootMeanSquaredError_LR = sqrt(meanSquaredError_LR)
print("RMSE_LR:", rootMeanSquaredError_LR)

R squared value_LR : 0.969852168694799
MAE_LR: 0.05932861328871536
MSE_LR: 0.0868849124681394985
RMSE_LR: 0.0776846998813241
```

In [31]: `Comparison_ADA_LR.plot(kind='lines', title="ADA : Actual prices VS Predicted prices(Linear Regression)", xtitle='Date', ytitle='Prices')`

Figure 22: Python code for price predictions of ADA - part 6



```

Out[31]: (None,)

In [ ]:

Decision Tree

In [32]: from sklearn.tree import DecisionTreeRegressor
# Create Decision Tree regressor
dtree_regressor = DecisionTreeRegressor(random_state=0)

In [33]: # Train the model
dtree_regressor.fit(X_train,Y_train)

Out[33]: DecisionTreeRegressor(random_state=0)

In [34]: # Make predictions
pred_dtree = dtree_regressor.predict(X_test)

In [35]: print(pred_dtree)

[2.135905 2.135905 2.114452 2.114452 2.114452 2.301541 2.114452 2.114452
2.114452 2.114452 2.114452 2.252873 2.252873 2.252873 2.114452 2.252873
2.114452 2.114452 2.252873 2.135905 2.135905 2.135905 2.135905 2.135905
2.135905 2.135905 2.135905 2.114452 2.114452 2.135905 2.135905
2.135905 2.114452 2.114452 2.114452 2.114452 2.114452 1.482573
2.135905 2.135905 1.482573 1.482573 1.482573 1.482573 1.17748
1.17748 1.482573 1.482573 1.482573 1.17748 1.659009 1.659009
1.17748 1.228501 1.17748 1.228501 1.056291 1.228501 1.228501
1.056291 1.356007 1.228501 1.228501 1.056291 1.228501 1.228501
1.228501 1.17748 1.17748 1.17748 1.17748 1.17748 1.17748
1.228501 1.228501 1.228501 1.228501 1.228501 1.228501 1.228501
1.152254 1.162690 1.166009 1.056291 1.056291 1.228501 1.228501
1.228501 1.330146 1.790898 1.384069 1.262258 1.262258 1.186161
1.155702 1.233497 1.234019 1.234019 1.234019 1.234019 1.234019
1.234019 1.234019 1.234019 1.234019 1.233497 1.218758
1.218758 1.218758

```

Figure 23: Python code for price predictions of ADA - part 7

```

1.218758 1.233497 1.233497 1.234019 1.234019 1.234019 1.234019 1.234019 1.234019
1.234019 1.234019 1.234019 1.234019 1.234019 1.234019 1.234019 1.234019
1.234019 1.234019 1.234019 1.234019 1.234019 1.234019 0.802262
0.802262]

In [36]: Comparison_ADA_DT = pd.DataFrame({'Actual prices': Y_test, 'Predicted prices': pred_dtree})

In [37]: Comparison_ADA_DT

Out[37]:
      Actual prices  Predicted prices
Date
2021-10-04      2.189235      2.135905
2021-10-05      2.233124      2.135905
2021-10-06      2.212165      2.114452
2021-10-07      2.270965      2.114452
2021-10-08      2.237178      2.114452
...
2022-03-01      0.902345      1.234019
2022-03-02      0.930802      1.234019
2022-03-03      0.902850      1.234019
2022-03-04      0.842889      0.802262
2022-03-05      0.805672      0.802262

153 rows x 2 columns

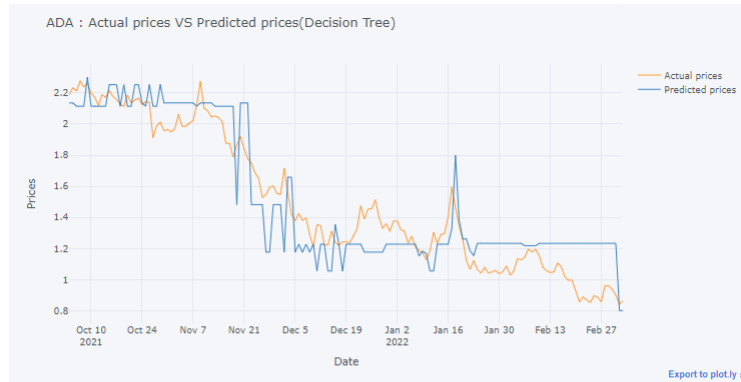
In [38]: #Performance indicators
r_score_DT=metrics.r2_score(Y_test,pred_dtree)
print("R squared value_DT :",r_score_DT)
print("MAE_DT:", mean_absolute_error(Y_test, pred_dtree))
meanSquaredError_DT=mean_squared_error(Y_test, pred_dtree)
print("MSE_DT:", meanSquaredError_DT)
rootMeanSquaredError_DT = sqrt(meanSquaredError_DT)
print("RMSE_DT:", rootMeanSquaredError_DT)

R squared value_DT : 0.8209887325542852
MAE_DT: 0.15264198039215685
MSE_DT: 0.034907681850084964
RMSE_DT: 0.18683997579182915

In [39]: Comparison_ADA_DT.plot(kind='lines', title="ADA : Actual prices VS Predicted prices(Decision Tree)", xtitle="Date", ytitle="Prices"),

```

Figure 24: Python code for price predictions of ADA - part 8



```

Out[39]: (None,)

In [ ]:

Gradient Boosting Regressor

In [40]: from sklearn.ensemble import GradientBoostingRegressor
# Create Gradient Boosting Regressor
GB_regressor=GradientBoostingRegressor(n_estimators=100)

In [41]: # Train the model
GB_regressor.fit(X_train,Y_train)

Out[41]: GradientBoostingRegressor()

In [42]: # Make the predictions
GB_predict=GB_regressor.predict(X_test)

In [43]: print(GB_predict)

[2.17133322 2.17133322 2.16349301 2.16349301 2.19004651 2.19130545
2.16008567 2.15183982 2.161481 2.14165282 2.13846557 2.139724
2.15266322 2.13390167 2.1311547 2.11284505 2.11741505 2.10776811
2.12525526 2.1360485 2.11560832 2.08674593 2.09967938 2.1233619
1.94369327 1.96821862 2.01430395 1.92533351 1.91772156 1.91772156
1.90349355 1.86445729 1.90349355 1.90349355 1.86445729 1.89042899
2.08027095 2.09748537 2.07907731 1.96291744 1.99552223 1.99042899
2.02811846 2.02633119 1.88490098 1.88490098 1.71484469 1.8926088
1.94238565 1.8785275 1.67714698 1.67479169 1.70471493 1.70471493
1.57413122 1.55940851 1.60809351 1.65791416 1.65791416 1.56992416
1.62040809 1.65016993 1.42497895 1.33667294 1.38235568 1.31971964
1.39768095 1.29352406 1.21895984 1.3227083 1.3090776 1.21128185
1.20241919 1.30396233 1.26639706 1.20048944 1.26304384 1.26304384
1.26304384 1.2835366 1.28872167 1.444405104 1.36984257 1.38155536
1.37231905 1.4635359 1.35956587 1.33260277 1.32436546 1.2135307
1.32146793 1.32704515 1.32146793 1.3135307 1.28624657 1.28522588

```

Figure 25: Python code for price predictions of ADA - part 9

```

1.22759751 1.1864838 1.1864838 1.16004212 1.18307343 1.27957517
1.25125635 1.27957517 1.29079313 1.392146 1.62141652 1.44669735
1.33997866 1.30030295 1.14841819 1.17627328 1.19983996 1.19753297
1.17928788 1.17928788 1.19815494 1.20078818 1.19149459 1.20130262
1.1691314 1.14850592 1.10320832 1.13298539 1.14604572 1.14368133
1.18719873 1.18819884 1.16811332 1.18468024 1.16921283 1.13619459
1.1386197 1.13179998 1.13984334 1.12710007 1.09307668 1.04943978
1.02083371 1.02083371 1.02083371 0.871808092 0.90533523 0.86909498
0.88583175 0.90578515 0.90578515 0.8415597 0.9913125 0.96994596
0.96994596 0.83623359 0.80157936]

In [44]: Comparison_ADA_GB = pd.DataFrame({'Actual prices': Y_test, 'Predicted prices': GB_predict})

In [45]: Comparison_ADA_GB

Out[45]:
   Actual prices  Predicted prices
Date
2021-10-04      2.180235      2.171333
2021-10-05      2.233124      2.171333
2021-10-06      2.212155      2.163493
2021-10-07      2.270995      2.163493
2021-10-08      2.237170      2.190049
...
2022-03-01      0.982348      0.991312
2022-03-02      0.938802      0.969048
2022-03-03      0.902859      0.969048
2022-03-04      0.842889      0.830284
2022-03-05      0.885972      0.801579

153 rows x 2 columns

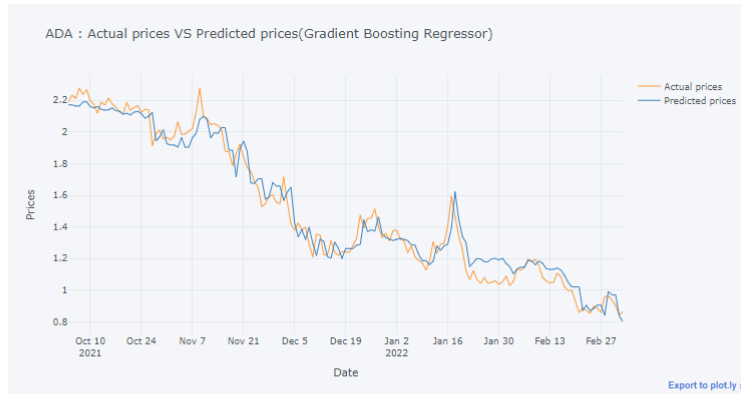
In [46]: #Performance Indicators
r_score_GB=metrics.r2_score(Y_test,GB_predict)
print("R squared value_GB :",r_score_GB)
print("MAE_GB:", mean_absolute_error(Y_test, GB_predict))
meanSquaredError_GB=mean_squared_error(Y_test, GB_predict)
print("MSE_GB:", meanSquaredError_GB)
rootMeanSquaredError_GB = sqrt(meanSquaredError_GB)
print("RMSE_GB:", rootMeanSquaredError_GB)

R squared value_GB : 0.964000158512029
MAE_GB: 0.0633864527250814
MSE_GB: 0.007809866564703725
RMSE_GB: 0.088378683749528154

In [47]: Comparison_ADA_GB.iplot(kind='lines', title="ADA : Actual prices VS Predicted prices(Gradient Boosting Regressor)", xTitle="Date", yTitle="Prices"),

```

Figure 26: Python code for price predictions of ADA - part 10



Out[47]: (None,)

In []:

K Nearest Neighbors

```
In [48]: from sklearn import neighbors
# Create K Nearest Neighbors regressor
knn = neighbors.KNeighborsRegressor()
```

```
In [49]: # Train the model
knn.fit(X_train, Y_train)
```

Out[49]: KNeighborsRegressor()

```
In [50]: # Make predictions
knn_pred = knn.predict(X_test)
```

```
In [51]: print(knn_pred)
```

```
[1.734714 1.5669456 1.695894 1.4617956 1.5300352 1.4833908 1.4743746
1.439117 1.4388038 1.584805 1.4118472 1.3861056 1.6443994 1.487752
1.4281482 1.5521368 1.6354756 1.4189266 1.3861056 1.428941 1.4330796
1.4281482 1.392117 1.4342282 1.3755214 1.3873114 1.6149366 1.3814618
1.0131782 0.6795878 0.572685 0.955576 0.519674 0.9684716 1.161763
1.3589124 1.3387014 1.1152898 1.1045216 1.1091944 1.4180826 1.172262
1.428675 1.3592538 1.2915856 1.2168726 1.2277396 1.2013836 1.2336638
0.85801 0.3841214 0.1737188 0.3687224 0.5507478 0.3270658 0.1469798
0.1271792 0.1171634 0.153799 0.1658852 0.0781418 0.0934414 0.120611
0.1354392 0.12499 0.1214412 0.0739386 0.1286398 0.092333 0.1111578
0.0971774 0.0996348 0.0731532 0.0807488 0.0599922 0.0843256 0.0868062
0.0756514 0.0684024 0.0501384 0.067104 0.1179092 0.105438 0.0777938
0.0589086 0.0561244 0.064384 0.0888856 0.0624776 0.0821826 0.0641162
0.0631434 0.0685912 0.0678356 0.059389 0.0800794 0.0737922 0.0754778
0.0956698 0.0786192 0.0761682 0.066517 0.0841896 0.059458 0.045134
0.0776636 0.071839 0.0561074 0.0889848 0.04559 0.0458482 0.0862112
```

Figure 27: Python code for price predictions of ADA - part 11

```
0.0671118 0.0638758 0.0443106 0.0430482 0.0394648 0.0356756 0.0350494
0.0316218 0.031858 0.022044 0.022125 0.0236148 0.0348246 0.0354988
0.036807 0.0408742 0.29585 0.308049 0.0566628 0.0571222 0.0746518
0.0755948 0.0568946 0.0381646 0.0533354 0.0612044 0.0396624 0.0554886
0.0647812 0.0887634 0.0689564 0.0579584 0.0797244 0.0862756 0.086254
0.0722856 0.0658994 0.1804846 0.0733344 0.0759092 0.0788352]
```

```
In [52]: Comparison_ADA_KNN = pd.DataFrame({'Actual prices': Y_test, 'Predicted prices': knn_pred})
```

In [53]: Comparison_ADA_KNN

Out[53]:

Date	Actual prices	Predicted prices
2021-10-04	2.189236	1.734714
2021-10-05	2.23124	1.566946
2021-10-06	2.212155	1.695894
2021-10-07	2.270905	1.461796
2021-10-08	2.237178	1.530035
...
2022-03-01	0.062346	0.085099
2022-03-02	0.938802	0.100405
2022-03-03	0.902850	0.073334
2022-03-04	0.842889	0.075909
2022-03-05	0.885872	0.078035

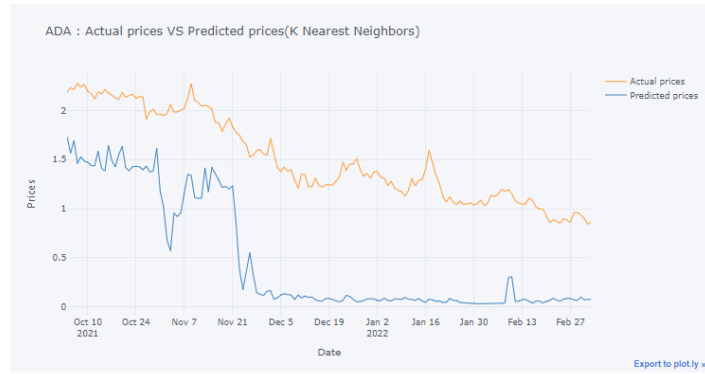
153 rows x 2 columns

```
In [54]: #Performance indicators
r_score_KNN=metrics.r2_score(Y_test,knn_pred)
print("R squared value_KNN :",r_score_KNN)
print("MAE_KNN:", mean_absolute_error(Y_test, knn_pred))
meansquaredError_KNN=mean_squared_error(Y_test, knn_pred)
print("MSE_KNN:", meansquaredError_KNN)
rootMeansquaredError_KNN = sqrt(meansquaredError_KNN)
print("RMSE_KNN:", rootMeansquaredError_KNN)
```

```
R squared value_KNN : -4.5775319193697835
MAE_KNN: 1.007904677124183
MSE_KNN: 1.0876338262288883
RMSE_KNN: 1.0428968435223152
```

```
In [55]: Comparison_ADA_KNN.plot(kind='lines', title="ADA : Actual prices VS Predicted prices(K Nearest Neighbors)", xTitle="Date", yTit
le="Prices"),
```

Figure 28: Python code for price predictions of ADA - part 12



```

Out[55]: (None,)

In [ ]:

Multilayer Perceptron

In [56]: from sklearn.neural_network import MLPRegressor
         from sklearn.datasets import make_regression
         # Create MLP Regressor
         MLP = MLPRegressor()

In [57]: # Train the model
         MLP.fit(X_train, Y_train)

Out[57]: MLPRegressor()

In [58]: # Make predictions
         MLP_pred = MLP.predict(X_test)

In [59]: MLP_pred

Out[59]: array([2.22410205, 2.16292555, 2.32124003, 2.19096081, 2.35970991,
                2.18530336, 2.3277437 , 2.11553266, 2.1953039 , 2.06113303,
                2.34004666, 2.11073654, 2.25502375, 2.05871014, 2.13876626,
                2.01900851, 2.08922216, 2.3659719 , 2.01477677, 2.0976608 ,
                2.1002379 , 2.04071079, 2.0331134 , 2.09001414, 1.66327655,
                2.09336549, 1.99189146, 1.63054307, 1.7682154 , 1.8931638 ,
                1.45676453, 2.19769964, 1.78796182, 1.80045988, 1.99618349,
                1.9780039 , 2.23606517, 2.4024842 , 1.8731132 , 2.04615599,
                2.20893362, 2.21011244, 1.87906916, 2.04120095, 1.75457481,
                1.87958085, 1.69073232, 1.96499646, 1.86663129, 1.77875153,
                1.70277076, 1.62258947, 1.20376467, 1.61163384, 1.67653368,
                1.40520619, 1.37240223, 1.29935557, 1.43119228, 1.17361088,
                1.53193683, 1.10820911, 1.52066412, 1.45463006, 0.98023344,
                1.36686844, 1.40896571, 1.42407228, 1.02886527, 1.29688769,
                1.06969017, 1.42204859, 1.32529533, 1.2080353 , 0.95132571,

```

Figure 29: Python code for price predictions of ADA - part 13

```

1.28959916, 1.33429166, 1.16448249, 1.20853022, 1.38876202,
1.45277772, 1.60810215, 1.39170349, 1.54079156, 1.50825027,
1.77811869, 1.26914075, 1.55837381, 1.54740943, 1.48227411,
1.51311402, 1.51139079, 1.46038662, 1.30859065, 1.33866798,
1.4343585 , 1.19405239, 1.26016212, 1.15870914, 1.17426685,
1.20030811, 1.49709424, 1.21272509, 1.30432115, 1.38392176,
1.60351421, 1.29454353, 1.52928105, 1.39627514, 1.50474123,
1.40447039, 1.13215235, 1.2178177 , 1.1569251 , 1.17802775,
1.2420277 , 1.17862206, 1.15811967, 1.18390471, 1.1580521 ,
1.15568026, 1.24414035, 1.04902016, 1.10252105, 1.34024072,
1.24276962, 1.1534442 , 1.28340977, 1.27877489, 1.19709428,
1.1433369 , 1.14380252, 1.14193418, 1.18312329, 1.12651211,
1.32400755, 1.13715817, 0.96676021, 1.03233818, 1.1396553 ,
0.94837913, 0.76778071, 0.96089496, 0.91571594, 0.83834397,
0.9952851 , 0.76317249, 0.69950412, 1.25341681, 1.1269454 ,
0.92758786, 0.7201256 , 0.97275422])

In [60]: Comparison_ADA_MLP = pd.DataFrame({'Actual prices': Y_test, 'Predicted prices': MLP_pred})

In [61]: Comparison_ADA_MLP

Out[61]:
      Actual prices  Predicted prices
Date
2021-10-04    2.180295    2.224103
2021-10-05    2.233124    2.182028
2021-10-06    2.212155    2.321240
2021-10-07    2.270965    2.190968
2021-10-08    2.237178    2.359710
...
2022-03-01    0.002348    1.253417
2022-03-02    0.038802    1.126945
2022-03-03    0.002850    0.927588
2022-03-04    0.842800    0.720128
2022-03-05    0.865872    0.972754

153 rows x 2 columns

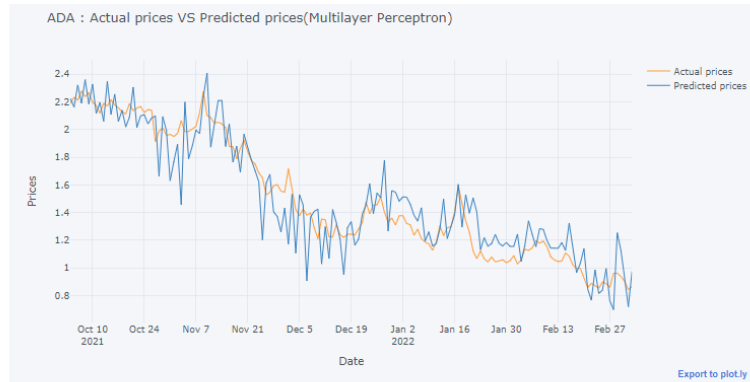
In [62]: #Performance indicators
         r_score_MLP=metrics.r2_score(Y_test, MLP_pred)
         print("R squared value_MLP :", r_score_MLP)
         print("MAE_MLP:", mean_absolute_error(Y_test, MLP_pred))
         meanSquaredError_MLP=mean_squared_error(Y_test, MLP_pred)
         print("MSE_MLP:", meanSquaredError_MLP)
         rootMeanSquaredError_MLP = sqrt(meanSquaredError_MLP)
         print("RMSE_MLP:", rootMeanSquaredError_MLP)

R squared value_MLP : 0.8562252176066499
MAE_MLP : 0.1287885293346291
MSE_MLP : 0.0208936471857137292
RMSE_MLP : 0.1674409503598364

In [63]: Comparison_ADA_MLP.iplot(kind='lines', title="ADA : Actual prices VS Predicted prices(Multilayer Perceptron)", xTitle="Date", yT
         itle="Prices"),

```

Figure 30: Python code for price predictions of ADA - part 14



Out[63]: (None,)

In []:

Export predictions to Excel

```
In [65]: All_Predictions = pd.DataFrame({'Actual prices': y_test, 'Random Forest': test_data_prediction, 'Linear Regression': y_pred_LR,
'Decision Tree': pred_dtree, 'Gradient Boosting Regressor': GB_predict, 'K Nearest Neighbors': knn_pred, 'Multilayer Perceptron': MLP_pred})
```

In [66]: All_Predictions

Out[66]:

Date	Actual prices	Random Forest	Linear Regression	Decision Tree	Gradient Boosting Regressor	K Nearest Neighbors	Multilayer Perceptron
2021-10-04	2.186235	2.217219	2.188118	2.135605	2.171333	1.734714	2.224103
2021-10-05	2.233124	2.205932	2.209594	2.135905	2.171333	1.506946	2.162926
2021-10-06	2.212155	2.152831	2.245422	2.114452	2.183463	1.895894	2.321240
2021-10-07	2.278995	2.157875	2.232149	2.114452	2.183463	1.481798	2.190988
2021-10-08	2.237178	2.178700	2.245877	2.114452	2.190049	1.530035	2.359710
...
2022-03-01	0.952348	1.138688	0.989399	1.234019	0.991312	0.085099	1.253417
2022-03-02	0.938882	1.127577	0.978179	1.234019	0.989948	0.100405	1.128945
2022-03-03	0.902859	1.138948	0.947380	1.234019	0.989948	0.073334	0.927888
2022-03-04	0.842889	1.003288	0.949035	0.802282	0.838284	0.075909	0.720126
2022-03-05	0.859872	0.884063	0.858790	0.802282	0.801579	0.078035	0.972754

153 rows x 7 columns

```
In [67]: with pd.ExcelWriter(r'C:\Users\Lenovo\Downloads\ADA_Prices_pred.xls') as writer:
All_Predictions.to_excel(writer, sheet_name = 'ADA')
```

Figure 31: Python code for price predictions of ADA - part 15

1.3 Price predictions with each algorithm

Date	Actual prices	Random Forest	Linear Regression	Decision Tree	Gradient Boosting Regressor	K Nearest Neighbors	Multilayer Perceptron
2021-10-04 00:00:00	2,189235	2,21721946	2,188118059	2,135905	2,171333222	1,734714	2,224102647
2021-10-05 00:00:00	2,233124	2,20593208	2,20959389	2,135905	2,171333222	1,5669456	2,162925553
2021-10-06 00:00:00	2,212155	2,15283078	2,245421972	2,114452	2,163493011	1,695894	2,321240034
2021-10-07 00:00:00	2,276995	2,15767463	2,232149399	2,114452	2,163493011	1,4617956	2,190968102
2021-10-08 00:00:00	2,237176	2,17670003	2,245677157	2,114452	2,190048513	1,5300352	2,359709914
2021-10-09 00:00:00	2,268615	2,20528276	2,274298281	2,301541	2,191305448	1,4833908	2,185303601
2021-10-10 00:00:00	2,197214	2,17091019	2,293660258	2,114452	2,160085667	1,4743746	2,327743704
2021-10-11 00:00:00	2,173389	2,16715412	2,174108138	2,114452	2,151839824	1,439117	2,115532659
2021-10-12 00:00:00	2,11919	2,16550292	2,158526283	2,114452	2,161481	1,4388038	2,195303898
2021-10-13 00:00:00	2,189053	2,15303117	2,134743892	2,114452	2,141652815	1,584805	2,061133026
2021-10-14 00:00:00	2,170363	2,17419164	2,218538307	2,114452	2,138465575	1,4110472	2,348046662
2021-10-15 00:00:00	2,214651	2,20723328	2,208835103	2,252873	2,139724	1,3861056	2,2110736542
2021-10-16 00:00:00	2,177713	2,22030913	2,252200616	2,252873	2,152663218	1,6443994	2,255023748
2021-10-17 00:00:00	2,156963	2,21886267	2,167648655	2,252873	2,133901674	1,487752	2,058710143
2021-10-18 00:00:00	2,128263	2,16532742	2,152267308	2,114452	2,131154705	1,4281482	2,138766257
2021-10-19 00:00:00	2,112962	2,18862502	2,191894763	2,252873	2,112845046	1,5521368	2,019008511
2021-10-20 00:00:00	2,18595	2,16041775	2,125131267	2,114452	2,117415052	1,6354756	2,089922156
2021-10-21 00:00:00	2,136591	2,18736688	2,170962874	2,114452	2,107768112	1,4189266	2,305971896
2021-10-22 00:00:00	2,154199	2,2235824	2,164922002	2,252873	2,125255263	1,3861056	2,014776773
2021-10-23 00:00:00	2,166815	2,22023869	2,176955104	2,252873	2,130348505	1,428541	2,097660502
2021-10-24 00:00:00	2,123435	2,21304673	2,137791575	2,135905	2,115608323	1,4330796	2,108025793
2021-10-25 00:00:00	2,144066	2,15679852	2,073744508	2,114452	2,086745931	1,4281482	2,040718789
2021-10-26 00:00:00	2,138777	2,20755933	2,187387498	2,252873	2,099679384	1,397217	2,083311344
2021-10-27 00:00:00	1,913237	2,18774718	2,186421257	2,114452	2,123361902	1,4342282	2,098014135
2021-10-28 00:00:00	1,988219	2,02435161	1,983549429	2,114452	1,943693269	1,3756214	1,663276548
2021-10-29 00:00:00	2,012187	2,06065499	1,986723422	2,252873	1,968210617	1,3873114	2,093365491
2021-10-30 00:00:00	1,957422	2,12821997	2,037855526	2,135905	2,014303951	1,6149366	1,991891485
2021-10-31 00:00:00	1,965026	2,07247662	1,982019676	2,135905	1,92538361	1,1814618	1,630543071
2021-11-01 00:00:00	1,950002	2,07901301	2,003276199	2,135905	1,917721564	1,10131782	1,768215405
2021-11-02 00:00:00	1,971377	2,06532139	1,923647678	2,135905	1,917721564	0,6795878	1,893016378
2021-11-03 00:00:00	2,063701	2,06135718	1,987242621	2,135905	1,903493546	0,572685	1,456764525
2021-11-04 00:00:00	1,984882	2,1834344	2,071194599	2,135905	1,964457289	0,955576	2,197699639
2021-11-05 00:00:00	1,986206	2,07750139	2,001781294	2,135905	1,903493546	0,919674	1,787961823
2021-11-06 00:00:00	2,006609	2,05740822	1,984023712	2,135905	1,903493546	0,9604716	1,880459884
2021-11-07 00:00:00	2,021872	2,13065231	2,006196185	2,135905	1,964457289	1,161763	1,99618349
2021-11-08 00:00:00	2,124419	2,14398854	1,984391058	2,114452	1,990428993	1,3509124	1,970803896
2021-11-09 00:00:00	2,273483	2,22171003	2,13884179	2,135905	2,080270949	1,3387014	2,236065169
2021-11-10 00:00:00	2,101802	2,23261352	2,285960957	2,135905	2,097485368	1,1152098	2,408248422
2021-11-11 00:00:00	2,085524	2,19736898	2,117950411	2,135905	2,079077307	1,1045216	1,873113196

Figure 32: Price predictions with each algorithm for ADA - part 1

2021-11-12 00:00:00	2,045766	2,1597649	2,10907593	2,135905	1,962917436	1,1091944	2,046155927
2021-11-13 00:00:00	2,053104	2,13243558	2,09076799	2,114452	1,995522234	1,4150826	2,208933623
2021-11-14 00:00:00	2,040853	2,12967168	2,024891052	2,114452	1,990428993	1,172262	2,210112436
2021-11-15 00:00:00	2,015587	2,15360705	2,036126829	2,114452	2,028118461	1,420875	1,879069183
2021-11-16 00:00:00	1,877235	2,11041951	2,02038081	2,114452	2,026331189	1,3592538	2,041200923
2021-11-17 00:00:00	1,87554	1,92230077	1,935207253	2,114452	1,884900979	1,2915856	1,764574013
2021-11-18 00:00:00	1,788331	1,91466036	1,898450916	2,114452	1,884900979	1,2168726	1,879580852
2021-11-19 00:00:00	1,864793	1,60140502	1,840115112	1,482573	1,71484469	1,227396	1,690732316
2021-11-20 00:00:00	1,921736	1,8921597	1,896338062	2,135905	1,892608796	1,2013836	1,964996463
2021-11-21 00:00:00	1,839763	2,06955756	1,940550448	2,135905	1,942385651	1,2335638	1,866631293
2021-11-22 00:00:00	1,776555	1,89658596	1,861536067	2,135905	1,878527498	0,85801	1,778751528
2021-11-23 00:00:00	1,750503	1,59768553	1,789222582	1,482573	1,677146984	0,3841314	1,702770763
2021-11-24 00:00:00	1,686423	1,57213328	1,731468933	1,482573	1,674791687	0,1737188	1,622509474
2021-11-25 00:00:00	1,651345	1,56454927	1,701297256	1,482573	1,704714929	0,3607224	1,203764668
2021-11-26 00:00:00	1,52842	1,56040536	1,70927035	1,482573	1,704714929	0,5507478	1,611633839
2021-11-27 00:00:00	1,546118	1,47430271	1,561013382	1,17748	1,574181218	0,3270658	1,676533685
2021-11-28 00:00:00	1,592855	1,50757325	1,592282121	1,17748	1,589402506	0,1469798	1,405206145
2021-11-29 00:00:00	1,602508	1,54385886	1,620313486	1,482573	1,68039251	0,1271792	1,372248226
2021-11-30 00:00:00	1,554903	1,5349637	1,597200241	1,482573	1,65791416	0,1171634	1,25933557
2021-12-01 00:00:00	1,547713	1,52887069	1,573692089	1,482573	1,65791416	0,1593798	1,431192277
2021-12-02 00:00:00	1,715366	1,48442238	1,592519722	1,17748	1,566924155	0,1658852	1,173610884
2021-12-03 00:00:00	1,556555	1,54625736	1,713006186	1,659009	1,62040809	0,0781418	1,531936832
2021-12-04 00:00:00	1,420706	1,53611999	1,595113262	1,659009	1,650169927	0,0934414	1,108820111
2021-12-05 00:00:00	1,378105	1,38664474	1,432161789	1,17748	1,424978947	0,120611	1,528684119
2021-12-06 00:00:00	1,425393	1,35939249	1,44308138	1,228501	1,336672939	0,1354392	1,454630059
2021-12-07 00:00:00	1,381941	1,33740353	1,458019709	1,17748	1,382355676	0,12499	0,908283443
2021-12-08 00:00:00	1,397074	1,34115147	1,417526684	1,228501	1,31971964	0,1214412	1,366868444
2021-12-09 00:00:00	1,29044	1,32721592	1,438740523	1,17748	1,397680951	0,0739386	1,408965711
2021-12-10 00:00:00	1,211689	1,33817851	1,36293523	1,228501	1,293524061	0,1206398	1,424072281
2021-12-11 00:00:00	1,354248	1,16670476	1,237244689	1,056291	1,218959839	0,092333	1,028865273
2021-12-12 00:00:00	1,347282	1,30793174	1,396326099	1,228501	1,322708296	0,1111578	1,296887689
2021-12-13 00:00:00	1,225348	1,30182605	1,380693139	1,228501	1,309077604	0,0971774	1,069690169
2021-12-14 00:00:00	1,222835	1,21421714	1,260037049	1,056291	1,211281847	0,0996348	1,422048585
2021-12-15 00:00:00	1,311847	1,20262284	1,213831801	1,056291	1,202419187	0,0731532	1,325295333
2021-12-16 00:00:00	1,240534	1,31710544	1,304182772	1,356087	1,303962334	0,0607488	1,208035298
2021-12-17 00:00:00	1,219892	1,30837016	1,226752521	1,228501	1,266397059	0,0599922	0,95132571
2021-12-18 00:00:00	1,242534	1,21577538	1,26239605	1,056291	1,200489437	0,0843256	1,289599163
2021-12-19 00:00:00	1,244661	1,30684402	1,305283731	1,228501	1,26304384	0,086062	1,334291659
2021-12-20 00:00:00	1,23824	1,3092152	1,263696458	1,228501	1,26304384	0,0756514	1,16448243
2021-12-21 00:00:00	1,280859	1,30307515	1,246023702	1,228501	1,26304384	0,0604024	1,208530224

Figure 33: Price predictions with each algorithm for ADA - part 2

2021-12-22 00:00:00	1,328041	1,30044738	1,320806799	1,228501	1,283536596	0,0501384	1,388762018
2021-12-23 00:00:00	1,474691	1,29251403	1,373506523	1,228501	1,288721674	0,0671104	1,452778719
2021-12-24 00:00:00	1,392367	1,43512722	1,519035834	1,17748	1,444051041	0,1179092	1,608103152
2021-12-25 00:00:00	1,453495	1,35136782	1,4244125	1,17748	1,369842572	0,105438	1,391783486
2021-12-26 00:00:00	1,456045	1,3665517	1,450413615	1,17748	1,381555365	0,0777938	1,540751561
2021-12-27 00:00:00	1,512913	1,39179304	1,480669442	1,17748	1,373318052	0,0508006	1,508350266
2021-12-28 00:00:00	1,402264	1,45247571	1,538222681	1,17748	1,462535903	0,0561244	1,778118888
2021-12-29 00:00:00	1,330814	1,37375012	1,437253336	1,17748	1,355658868	0,064304	1,269140748
2021-12-30 00:00:00	1,360415	1,3321897	1,358211317	1,228501	1,33260277	0,0808856	1,558373812
2021-12-31 00:00:00	1,310209	1,30818997	1,383127746	1,228501	1,324365457	0,0824776	1,547409434
2022-01-01 00:00:00	1,376975	1,31602468	1,367187237	1,228501	1,313530697	0,0821026	1,482274111
2022-01-02 00:00:00	1,377584	1,32110065	1,414605639	1,228501	1,321487926	0,0641162	1,513114024
2022-01-03 00:00:00	1,321637	1,3319848	1,413767283	1,228501	1,327045154	0,0651434	1,511398786
2022-01-04 00:00:00	1,311658	1,31890807	1,346725573	1,228501	1,321487926	0,0885912	1,460386625
2022-01-05 00:00:00	1,236002	1,29471733	1,359295092	1,228501	1,313530697	0,0670356	1,380590652
2022-01-06 00:00:00	1,279782	1,27811108	1,283650531	1,228501	1,286246572	0,059898	1,338667977
2022-01-07 00:00:00	1,211547	1,28007225	1,238673165	1,228501	1,285225879	0,080784	1,43458496
2022-01-08 00:00:00	1,187512	1,16989924	1,238945694	1,153254	1,227507508	0,0797922	1,194052387
2022-01-09 00:00:00	1,17386	1,167721	1,243401843	1,183698	1,186483798	0,0764778	1,26016213
2022-01-10 00:00:00	1,128052	1,15342374	1,210842024	1,168098	1,186483798	0,0956698	1,158709141
2022-01-11 00:00:00	1,18511	1,11171137	1,164691641	1,056291	1,160842117	0,0786192	1,174266848
2022-01-12 00:00:00	1,304535	1,14479711	1,184322355	1,056291	1,183073426	0,0761602	1,280938813
2022-01-13 00:00:00	1,233161	1,28509436	1,303177312	1,228501	1,279575172	0,066517	1,497094239
2022-01-14 00:00:00	1,290926	1,24160108	1,261428228	1,228501	1,25125635	0,0841896	1,212735086
2022-01-15 00:00:00	1,296263	1,28358147	1,329767096	1,228501	1,279575172	0,059458	1,304331153
2022-01-16 00:00:00	1,407251	1,28609849	1,306354663	1,228501	1,290793129	0,045134	1,383931764
2022-01-17 00:00:00	1,594131	1,38489012	1,379006336	1,330146	1,392145999	0,0776636	1,60351421
2022-01-18 00:00:00	1,465541	1,62536583	1,631747228	1,798038	1,621416517	0,071839	1,294543535
2022-01-19 00:00:00	1,341757	1,44354494	1,487460403	1,384869	1,448697352	0,0561074	1,529281046
2022-01-20 00:00:00	1,258055	1,35741779	1,330992465	1,262258	1,339978663	0,0609848	1,39627514
2022-01-21 00:00:00	1,123233	1,29305782	1,331741558	1,262258	1,300302951	0,04559	1,504741229
2022-01-22 00:00:00	1,066716	1,16657399	1,153294446	1,186161	1,148418192	0,0458402	1,40470392
2022-01-23 00:00:00	1,122371	1,15939458	1,108731078	1,155702	1,176273282	0,0862112	1,132152355
2022-01-24 00:00:00	1,066598	1,13002613	1,166324658	1,233497	1,199839558	0,0671118	1,217817699
2022-01-25 00:00:00	1,043574	1,12212445	1,136005196	1,234019	1,197532968	0,0630758	1,156925104
2022-01-26 00:00:00	1,079047	1,13074402	1,100457963	1,234019	1,179287876	0,0443106	1,176027753
2022-01-27 00:00:00	1,043533	1,11906664	1,117374811	1,234019	1,179287876	0,0430482	1,242027701
2022-01-28 00:00:00	1,050606	1,12125469	1,025602024	1,234019	1,198154941	0,0394648	1,178622063
2022-01-29 00:00:00	1,05957	1,12002153	1,069099145	1,234019	1,200788178	0,0356756	1,158119673
2022-01-30 00:00:00	1,037473	1,1219493	1,075227076	1,234019	1,191494591	0,0350494	1,183904706

Figure 34: Price predictions with each algorithm for ADA - part 3

2022-01-31 00:00:00	1,052303	1,12065468	1,033231237	1,234019	1,201302616	0,0316218	1,155052103
2022-02-01 00:00:00	1,088624	1,12262479	1,007584444	1,234019	1,169131395	0,031858	1,155568264
2022-02-02 00:00:00	1,028906	1,13945801	1,08433672	1,234019	1,148585017	0,032044	1,244148351
2022-02-03 00:00:00	1,056444	1,12767921	1,06535529	1,234019	1,103208822	0,032125	1,049028156
2022-02-04 00:00:00	1,135624	1,13585684	1,052424364	1,234019	1,132985394	0,0336148	1,162521031
2022-02-05 00:00:00	1,127345	1,13681179	1,183499857	1,233497	1,146845722	0,0348246	1,340246716
2022-02-06 00:00:00	1,144547	1,13740501	1,169220441	1,218758	1,143681833	0,0354508	1,242769617
2022-02-07 00:00:00	1,197307	1,16182724	1,137686453	1,218758	1,187190734	0,036807	1,153444197
2022-02-08 00:00:00	1,17872	1,20737387	1,231955004	1,218758	1,186198841	0,0406742	1,283409766
2022-02-09 00:00:00	1,19481	1,1918879	1,199568735	1,218758	1,160118321	0,29505	1,278774886
2022-02-10 00:00:00	1,152478	1,19586463	1,19968917	1,233497	1,184800238	0,308849	1,197094281
2022-02-11 00:00:00	1,080347	1,18614365	1,167576403	1,233497	1,169212835	0,0566638	1,143336901
2022-02-12 00:00:00	1,058199	1,16420044	1,096737164	1,234019	1,136194586	0,0571222	1,14302852
2022-02-13 00:00:00	1,045819	1,17164758	1,060076825	1,234019	1,1306197	0,0746518	1,141934182
2022-02-14 00:00:00	1,050267	1,17931019	1,072706916	1,234019	1,131799981	0,0755948	1,183123286
2022-02-15 00:00:00	1,107586	1,17203149	1,069734017	1,234019	1,139943343	0,0568946	1,126512115
2022-02-16 00:00:00	1,084981	1,16946674	1,139502893	1,233497	1,127100072	0,0381646	1,324007549
2022-02-17 00:00:00	1,019895	1,15710564	1,084053964	1,234019	1,093076684	0,0583354	1,137158172
2022-02-18 00:00:00	0,997113	1,16367198	1,029391568	1,234019	1,049439784	0,0612044	0,966760206
2022-02-19 00:00:00	0,997703	1,15516246	1,022243726	1,234019	1,020833713	0,0396624	1,032338184
2022-02-20 00:00:00	0,932902	1,14439265	1,029210092	1,234019	1,020833713	0,0554806	1,1396553
2022-02-21 00:00:00	0,858236	1,14849647	0,959175382	1,234019	1,020833713	0,0647812	0,848879127
2022-02-22 00:00:00	0,889017	0,90975824	0,845263972	1,234019	0,871080919	0,0887634	0,767788712
2022-02-23 00:00:00	0,869169	1,00463251	0,878529507	1,234019	0,905335226	0,0869564	0,986094982
2022-02-24 00:00:00	0,853425	0,91419783	0,85474975	1,234019	0,869094981	0,0579584	0,815719395
2022-02-25 00:00:00	0,898027	0,91060406	0,85518313	1,234019	0,885031749	0,0797344	0,838343369
2022-02-26 00:00:00	0,887918	1,01736675	0,944101241	1,234019	0,905785145	0,0862756	0,995285096
2022-02-27 00:00:00	0,858335	1,00119806	0,912403817	1,234019	0,905785145	0,086254	0,763172493
2022-02-28 00:00:00	0,959828	0,90987248	0,878460173	1,234019	0,841559704	0,0722056	0,699504124
2022-03-01 00:00:00	0,962346	1,13665592	0,989368589	1,234019	0,991312498	0,0850994	1,25341681
2022-03-02 00:00:00	0,938662	1,12757676	0,978178554	1,234019	0,969945959	0,1004046	1,126945401
2022-03-03 00:00:00	0,902659	1,1389482	0,947380285	1,234019	0,969945959	0,0733344	0,927587861
2022-03-04 00:00:00	0,842889	1,00328614	0,949035163	0,802262	0,83628359	0,0759092	0,720125597
2022-03-05 00:00:00	0,865672	0,88406325	0,858789504	0,802262	0,801579363	0,0780352	0,972754217

Figure 35: Price predictions with each algorithm for ADA - part 4

1.4 Performance indicators of each cryptoassets

R squared value_RF : 0.9461487674059356 MAE_RF : 0.08117687980392156 MSE_RF : 0.010501136165624786 RMSE_RF : 0.10247505143021293	R squared value_LR : 0.969052160694799 MAE_LR : 0.059325061320871536 MSE_LR : 0.0060349124601394985 RMSE_LR : 0.07768469900913241	R squared value_DT : 0.8209887325542852 MAE_DT : 0.15264198039215685 MSE_DT : 0.034907681980084964 RMSE_DT : 0.18683597579182915	R squared value_GB : 0.964000158512029 MAE_GB : 0.06638864527256014 MSE_GB : 0.00720066564785725 RMSE_GB : 0.08378583749528154	R squared value_KNN : -4.577519193697035 MAE_KNN : 1.00790467124183 MSE_KNN : 1.087638262288083 RMSE_KNN : 1.042986435223152	R squared value_MLP : 0.8562252176066499 MAE_MLP : 0.1287885293346291 MSE_MLP : 0.028036471857137292 RMSE_MLP : 0.16744089539590364
Comparison_ADA_RF.iplot(kind='lines', t)	Comparison_ADA_LR.iplot(kind='lines', t)	Comparison_ADA_DT.iplot(kind='lines', t)	Comparison_ADA_GB.iplot(kind='lines', t)	Comparison_ADA_KNN.iplot(kind='lines', t)	Comparison_ADA_MLP.iplot(kind='lines', t)
R squared value_RF : 0.6992046124174158 MAE_RF : 36.391694440784406 MSE_RF : 2116.9601949038017 RMSE_RF : 46.018522269358922	R squared value_LR : 0.9318336227724231 MAE_LR : 17.60382268045843 MSE_LR : 479.7482148717451 RMSE_LR : 21.903155363365915	R squared value_DT : -0.2355616060040263 MAE_DT : 67.627618248366 MSE_DT : 1315426.29055355 RMSE_DT : 03.2510693207951	R squared value_GB : 0.544887886305489 MAE_GB : 42.7210823444107 MSE_GB : 3203.03404068134 RMSE_GB : 56.59535352544304	R squared value_KNN : 0.244184451521196 MAE_KNN : 58.81283764052288 MSE_KNN : 5319.376164076809 RMSE_KNN : 72.93405352835401	R squared value_MLP : 0.9250288860860804 MAE_MLP : 18.264739585014667 MSE_MLP : 527.6392776644002 RMSE_MLP : 22.97040003340038
Comparison_BNB_RF.iplot(kind='lines', t)	Comparison_BNB_LR.iplot(kind='lines', t)	Comparison_BNB_DT.iplot(kind='lines', t)	Comparison_BNB_GB.iplot(kind='lines', t)	Comparison_BNB_KNN.iplot(kind='lines', t)	Comparison_BNB_MLP.iplot(kind='lines', t)
R squared value_RF : 0.9078260532952012 MAE_RF : 2181.9148016833315 MSE_RF : 7503396.427925985 RMSE_RF : 2739.232817401541	R squared value_LR : 0.9635420627803799 MAE_LR : 1254.593945897528 MSE_LR : 2987849.8003971135 RMSE_LR : 1722.7446136301264	R squared value_DT : 0.8382718766565242 MAE_DT : 2878.931704409196 MSE_DT : 1315426.29055355 RMSE_DT : 3628.420633078882	R squared value_GB : 0.9208305350881046 MAE_GB : 1942.952057818182 MSE_GB : 6444784.584681798 RMSE_GB : 2538.65802830586	R squared value_KNN : 0.6751322596430722 MAE_KNN : 4292.43717834789 MSE_KNN : 26445774.800336073 RMSE_KNN : 5142.545562300452	R squared value_MLP : 0.946064065055593 MAE_MLP : 1631.1304195896412 MSE_MLP : 4390860.913912776 RMSE_MLP : 2095.3856241543645
Comparison_BTC_RF.iplot(kind='lines', t)	Comparison_BTC_LR.iplot(kind='lines', t)	Comparison_BTC_DT.iplot(kind='lines', t)	Comparison_BTC_GB.iplot(kind='lines', t)	Comparison_BTC_KNN.iplot(kind='lines', t)	Comparison_BTC_MLP.iplot(kind='lines', t)
R squared value_RF : 0.9559549163932443 MAE_RF : 6.331510732314106 MSE_RF : 74.60650380057452 RMSE_RF : 8.64213526444183	R squared value_LR : 0.9622247790240248 MAE_LR : 5.956939558830908 MSE_LR : 64.05480930719503 RMSE_LR : 8.003244256300255	R squared value_DT : 0.914372975102621 MAE_DT : 8.684457965925629 MSE_DT : 145.19629725364082 RMSE_DT : 0.924974261258848	R squared value_GB : 0.9601327673523101 MAE_GB : 6.1561396320369917 MSE_GB : 67.6021912123633 RMSE_GB : 8.22205296652186	R squared value_KNN : 0.8558836937923051 MAE_KNN : 12.217079411924276 MSE_KNN : 244.3755818949517 RMSE_KNN : 15.63251681259808	R squared value_MLP : 0.9446471023613238 MAE_MLP : 7.28585143406645 MSE_MLP : 93.88067191894974 RMSE_MLP : 9.688187235954644
Comparison_DASH_RF.iplot(kind='lines', t)	Comparison_DASH_LR.iplot(kind='lines', t)	Comparison_DASH_DT.iplot(kind='lines', t)	Comparison_DASH_GB.iplot(kind='lines', t)	Comparison_DASH_KNN.iplot(kind='lines', t)	Comparison_DASH_MLP.iplot(kind='lines', t)
R squared value_RF : 0.5254471497563848 MAE_RF : 0.026197863520411846 MSE_RF : 0.0010881152657838187 RMSE_RF : 0.03298659221234523	R squared value_LR : 0.9485248587811035 MAE_LR : 0.007844516183543156 MSE_LR : 0.00011802876527698985 RMSE_LR : 0.0186410439289706	R squared value_DT : 0.7059123354174249 MAE_DT : 0.01972298046973203 MSE_DT : 0.0006763853191176473 RMSE_DT : 12.40874261212344	R squared value_GB : 0.6875474326760458 MAE_GB : 0.016089704373533655 MSE_GB : 0.0004422882103125926 RMSE_GB : 0.01213064930812116	R squared value_KNN : -12.639166299877937 MAE_KNN : 0.17051837385620916 MSE_KNN : 0.03172991162866474 RMSE_KNN : 0.178128918563297	R squared value_MLP : 0.947821487248963 MAE_MLP : 0.09926075653976013 MSE_MLP : 0.0212507845134548 RMSE_MLP : 0.14739429587554848
Comparison_DOGE_RF.iplot(kind='lines', t)	Comparison_DOGE_LR.iplot(kind='lines', t)	Comparison_DOGE_DT.iplot(kind='lines', t)	Comparison_DOGE_GB.iplot(kind='lines', t)	Comparison_DOGE_KNN.iplot(kind='lines', t)	Comparison_DOGE_MLP.iplot(kind='lines', t)
R squared value_RF : 0.38064151294499105 MAE_RF : 402.1976256380395 MSE_RF : 28059.45431817643 RMSE_RF : 529.5842277845672	R squared value_LR : 0.9470387636877368 MAE_LR : 121.62914134018943 MSE_LR : 23982.03907204087 RMSE_LR : 154.8615435298527	R squared value_DT : 0.10691739432574554 MAE_DT : 531.701364989281 MSE_DT : 404047.892171518 RMSE_DT : 635.9397290668678	R squared value_GB : -0.6875474326760458 MAE_GB : 656.893620518677 MSE_GB : 764159.4359266894 RMSE_GB : 874.1621336609642	R squared value_KNN : -0.36924313492162764 MAE_KNN : 683.169012309804 MSE_KNN : 62004.090208232 RMSE_KNN : 787.4182891503139	R squared value_MLP : 0.9458750921152969 MAE_MLP : 121.01551007012246 MSE_MLP : 24508.97573478668 RMSE_MLP : 156.5534273274731
Comparison_ETH_RF.iplot(kind='lines', t)	Comparison_ETH_LR.iplot(kind='lines', t)	Comparison_ETH_DT.iplot(kind='lines', t)	Comparison_ETH_GB.iplot(kind='lines', t)	Comparison_ETH_KNN.iplot(kind='lines', t)	Comparison_ETH_MLP.iplot(kind='lines', t)

Figure 36: Performance indicator scores - part 1

R squared value_RF : 0.939193654040105 MAE_RF : 1.1377674437908494 MSE_RF : 2.127662317176555 RMSE_RF : 1.4586508551317396	R squared value_LR : 0.9488357057139962 MAE_LR : 0.14046037132519472 MSE_LR : 1.7902793147746916 RMSE_LR : 1.3380131967864486	R squared value_DT : 0.8813972997942005 MAE_DT : 1.5583007777777778 MSE_DT : 4.150002727838881 RMSE_DT : 2.0371555482679473	R squared value_GB : 0.93757884603242686 MAE_GB : 1.1193418809563624 MSE_GB : 2.184165780232119 RMSE_GB : 1.477892343924996	R squared value_KNN : 0.8376819596602761 MAE_KNN : 1.8856883869281043 MSE_KNN : 5.679637217520757 RMSE_KNN : 2.383198946273843	R squared value_MLP : 0.9519982742209901 MAE_MLP : 1.0377305332112883 MSE_MLP : 1.6796185295798503 RMSE_MLP : 1.2960009759177846
Comparison_LINK_RF.iplot(kind='lines', t)	Comparison_LINK_LR.iplot(kind='lines', t)	Comparison_LINK_DT.iplot(kind='lines', t)	Comparison_LINK_GB.iplot(kind='lines', t)	Comparison_LINK_KNN.iplot(kind='lines', t)	Comparison_LINK_MLP.iplot(kind='lines', t)
R squared value_RF : 0.9454664853540824 MAE_RF : 7.314559649934637 MSE_RF : 93.7107763789529 RMSE_RF : 9.680432654533211	R squared value_LR : 0.9576443796597712 MAE_LR : 6.1303404518877025 MSE_LR : 72.78419687171478 RMSE_LR : 8.531365475216425	R squared value_DT : 0.826599416423369 MAE_DT : 13.54770890392157 MSE_DT : 292.71355827288016 RMSE_DT : 17.108873670492752	R squared value_GB : 0.9538424577243382 MAE_GB : 6.392424419286523 MSE_GB : 79.31744635352271 RMSE_GB : 8.906034266356867	R squared value_KNN : 0.7963664916511528 MAE_KNN : 14.055211848366014 MSE_KNN : 349.92525767031225 RMSE_KNN : 18.706289254427567	R squared value_MLP : 0.9471450521809076 MAE_MLP : 6.581259436062449 MSE_MLP : 90.82631529906322 RMSE_MLP : 9.530284114288683
Comparison_LTC_RF.iplot(kind='lines', t)	Comparison_LTC_LR.iplot(kind='lines', t)	Comparison_LTC_DT.iplot(kind='lines', t)	Comparison_LTC_GB.iplot(kind='lines', t)	Comparison_LTC_KNN.iplot(kind='lines', t)	Comparison_LTC_MLP.iplot(kind='lines', t)
R squared value_RF : 0.9553699644054112 MAE_RF : 0.005455297234599915 MSE_RF : 5.3612383678295604e-05 RMSE_RF : 0.007322804779022997	R squared value_LR : 0.9564973380358311 MAE_LR : 0.00535189062468223 MSE_LR : 5.223811212512324e-05 RMSE_LR : 0.00722897253050554	R squared value_DT : 0.8843937927439289 MAE_DT : 0.009105078583838993 MSE_DT : 0.00013887339000367112 RMSE_DT : 0.011784455439419809	R squared value_GB : 0.9634676674532282 MAE_GB : 0.00487599382523145 MSE_GB : 4.3804917479162625e-05 RMSE_GB : 0.00624569229705629	R squared value_KNN : -2.9571169985006924 MAE_KNN : 0.0556450485341775 MSE_KNN : 0.00475355863396157 RMSE_KNN : 0.0689458908376428	R squared value_MLP : -9.210003853535877 MAE_MLP : 0.08803198811861582 MSE_MLP : 0.0122648937400645 RMSE_MLP : 0.1107469807033398
Comparison_XLM_RF.iplot(kind='lines', t)	Comparison_XLM_LR.iplot(kind='lines', t)	Comparison_XLM_DT.iplot(kind='lines', t)	Comparison_XLM_GB.iplot(kind='lines', t)	Comparison_XLM_KNN.iplot(kind='lines', t)	Comparison_XLM_MLP.iplot(kind='lines', t)
R squared value_RF : 0.9285412818479349 MAE_RF : 0.03847404228261438 MSE_RF : 0.0023132325744486 RMSE_RF : 0.048896114974854884	R squared value_LR : 0.95138683330483 MAE_LR : 0.030212280439229012 MSE_LR : 0.001576279186276686 RMSE_LR : 0.03970236666280322	R squared value_DT : 0.7578931699871663 MAE_DT : 0.070962679738562 MSE_DT : 0.00783396411261436 RMSE_DT : 0.08852907104031667	R squared value_GB : 0.9148478238920132 MAE_GB : 0.04061839634400606 MSE_GB : 0.00275516039162045 RMSE_GB : 0.0525053364516845	R squared value_KNN : -6.746251519838874 MAE_KNN : 0.46896562875816983 MSE_KNN : 0.250759063928596 RMSE_KNN : 0.500758313264589	R squared value_MLP : 0.5987138190962153 MAE_MLP : 0.0861711841933239 MSE_MLP : 0.01299029390184122 RMSE_MLP : 0.11397497050244901
Comparison_XRP_RF.iplot(kind='lines', t)	Comparison_XRP_LR.iplot(kind='lines', t)	Comparison_XRP_DT.iplot(kind='lines', t)	Comparison_XRP_GB.iplot(kind='lines', t)	Comparison_XRP_KNN.iplot(kind='lines', t)	Comparison_XRP_MLP.iplot(kind='lines', t)

Figure 37: Performance indicator scores - part 2

1.6 Active investing portfolios

1.6.1 Using linear regression

1.6.1.1 Absolute momentum portfolio

Ab														
	ADA		BNB		BTC		DASH		DOGE		ETH		LINK	
	Returns	Weight	Returns	Weight	Returns	Weight	Returns	Weight	Returns	Weight	Returns	Weight	Returns	Weight
2021-10-04	-2.87%	0.00%	-0.84%	0.00%	0.30%	33.33%	-0.60%	0.00%	-0.44%	0.00%	0.83%	33.33%	-0.81%	0.00%
2021-10-05	0.98%	20.00%	-0.18%	0.00%	2.12%	20.00%	-0.99%	0.00%	6.40%	20.00%	-0.55%	0.00%	-1.09%	0.00%
2021-10-06	1.62%	11.11%	2.13%	11.11%	8.89%	11.11%	5.34%	11.11%	3.98%	11.11%	3.13%	11.11%	-2.91%	0.00%
2021-10-07	-0.59%	0.00%	1.34%	14.29%	7.27%	14.29%	-2.79%	0.00%	4.63%	14.29%	0.80%	14.29%	-2.63%	0.00%
2021-10-08	0.61%	14.29%	0.53%	14.29%	-2.99%	0.00%	1.95%	14.29%	-2.17%	0.00%	0.48%	14.29%	4.80%	14.29%
2021-10-09	1.27%	14.29%	-0.01%	0.00%	3.37%	14.29%	4.70%	14.29%	-6.87%	0.00%	2.84%	14.29%	4.39%	14.29%
2021-10-10	0.85%	25.00%	-3.45%	0.00%	-1.48%	0.00%	1.92%	25.00%	3.36%	25.00%	-3.07%	0.00%	-4.32%	0.00%
2021-10-11	-5.21%	0.00%	-6.37%	0.00%	-1.37%	0.00%	-6.77%	0.00%	-0.65%	0.00%	-3.63%	0.00%	-6.87%	0.00%
2021-10-12	-0.72%	0.00%	1.55%	12.50%	7.78%	12.50%	0.45%	12.50%	-2.81%	0.00%	2.79%	12.50%	1.16%	12.50%
2021-10-13	-0.72%	0.00%	11.37%	100.00%	-2.38%	0.00%	-1.32%	0.00%	-4.18%	0.00%	-1.24%	0.00%	-2.37%	0.00%
2021-10-14	3.93%	11.11%	4.64%	11.11%	1.59%	11.11%	-3.74%	0.00%	0.86%	11.11%	1.92%	11.11%	2.66%	11.11%
2021-10-15	-0.44%	0.00%	0.54%	11.11%	0.28%	11.11%	3.75%	11.11%	3.20%	11.11%	6.04%	11.11%	5.09%	11.11%
2021-10-16	1.96%	14.29%	-0.64%	0.00%	6.21%	14.29%	4.44%	14.29%	-0.57%	0.00%	0.53%	14.29%	-0.51%	0.00%
2021-10-17	-3.75%	0.00%	-3.81%	0.00%	-0.09%	0.00%	1.33%	33.33%	2.58%	33.33%	-0.68%	0.00%	2.49%	33.33%
2021-10-18	-0.71%	0.00%	2.10%	20.00%	1.23%	20.00%	-1.58%	0.00%	0.99%	20.00%	0.98%	20.00%	-2.06%	0.00%
2021-10-19	1.84%	25.00%	5.99%	25.00%	-0.05%	0.00%	-3.84%	0.00%	1.90%	25.00%	-1.57%	0.00%	-3.55%	0.00%
2021-10-20	-3.05%	0.00%	-1.05%	0.00%	2.14%	14.29%	4.77%	14.29%	2.39%	14.29%	3.44%	14.29%	-1.31%	0.00%
2021-10-21	2.16%	11.11%	2.69%	11.11%	4.88%	11.11%	5.23%	11.11%	1.33%	11.11%	7.10%	11.11%	8.07%	11.11%
2021-10-22	-0.28%	0.00%	-2.79%	0.00%	-5.29%	0.00%	-0.27%	0.00%	-1.35%	0.00%	0.77%	33.33%	4.86%	33.33%
2021-10-23	0.56%	100.00%	-1.29%	0.00%	-3.05%	0.00%	-1.77%	0.00%	-2.27%	0.00%	-2.74%	0.00%	-1.03%	0.00%
2021-10-24	-1.80%	0.00%	-2.38%	0.00%	-1.63%	0.00%	2.19%	16.67%	3.21%	16.67%	1.47%	16.67%	6.71%	16.67%
2021-10-25	-3.00%	0.00%	0.89%	14.29%	1.06%	14.29%	3.54%	14.29%	7.97%	14.29%	0.39%	14.29%	0.03%	14.29%
2021-10-26	5.48%	11.11%	7.20%	11.11%	6.01%	11.11%	1.32%	11.11%	-0.99%	0.00%	6.33%	11.11%	8.01%	11.11%
2021-10-27	-0.04%	0.00%	-5.45%	0.00%	-5.37%	0.00%	-7.29%	0.00%	-3.37%	0.00%	-4.20%	0.00%	-0.28%	0.00%
2021-10-28	-9.28%	0.00%	-7.92%	0.00%	-2.71%	0.00%	-13.99%	0.00%	-9.97%	0.00%	-4.57%	0.00%	-7.57%	0.00%
2021-10-29	0.16%	11.11%	7.57%	11.11%	2.60%	11.11%	5.38%	11.11%	17.14%	11.11%	6.90%	11.11%	4.78%	11.11%
2021-10-30	2.57%	10.00%	10.48%	10.00%	2.61%	10.00%	2.20%	10.00%	7.53%	10.00%	3.55%	10.00%	0.16%	10.00%
2021-10-31	-2.74%	0.00%	1.86%	33.33%	0.01%	33.33%	-0.30%	0.00%	-4.07%	0.00%	-0.60%	0.00%	-2.65%	0.00%
2021-11-01	1.07%	20.00%	-0.65%	0.00%	-1.52%	0.00%	5.72%	20.00%	-0.52%	0.00%	-2.35%	0.00%	-0.65%	0.00%
2021-11-02	-3.97%	0.00%	0.60%	25.00%	-1.20%	0.00%	-1.30%	0.00%	-8.79%	0.00%	-0.60%	0.00%	1.78%	25.00%
2021-11-03	3.31%	10.00%	4.52%	10.00%	4.64%	10.00%	1.98%	10.00%	2.17%	10.00%	9.77%	10.00%	4.03%	10.00%
2021-11-04	4.22%	14.29%	2.78%	14.29%	-0.15%	0.00%	2.08%	14.29%	6.15%	14.29%	0.33%	14.29%	-0.88%	0.00%
2021-11-05	-3.35%	0.00%	-1.02%	0.00%	-1.94%	0.00%	-1.94%	100.00%	-6.77%	0.00%	-1.74%	0.00%	-3.12%	0.00%
2021-11-06	-0.89%	0.00%	4.62%	33.33%	-1.11%	0.00%	-2.01%	0.00%	-1.94%	0.00%	-1.32%	0.00%	4.31%	33.33%
2021-11-07	1.12%	25.00%	4.90%	25.00%	-0.39%	0.00%	-2.65%	0.00%	0.57%	25.00%	-0.19%	0.00%	-0.80%	0.00%
2021-11-08	-1.09%	0.00%	4.34%	12.50%	4.94%	12.50%	0.15%	12.50%	2.04%	12.50%	2.57%	12.50%	0.49%	12.50%

Figure 50: Absolute momentum portfolio using linear regression - part 1

Absolute momentum													
LTC		XLM		XRP		sum of weights	nb assets	Portfolio returns without transac. cost	Number of transactions	Transaction cost	Portfolio returns with transac. cost	1r	Cumulative return
Returns	Weight	Returns	Weight	Returns	Weight								
0.41%	33.33%	-5.42%	0.00%	-1.41%	0.00%	100.00%	7	0.51%	10	1.0%	-0.5%	0.995	-0.49%
0.09%	20.00%	1.21%	20.00%	-1.22%	0.00%	100.00%	5	2.16%	6	0.6%	1.6%	1.016	1.06%
3.43%	11.11%	10.13%	11.11%	2.31%	11.11%	100.00%	1	4.00%	9	0.9%	3.1%	1.031	4.19%
1.87%	14.29%	0.64%	14.29%	0.79%	14.29%	100.00%	3	2.48%	9	0.9%	1.6%	1.016	5.84%
-1.14%	0.00%	3.15%	14.29%	2.70%	14.29%	100.00%	3	2.03%	6	0.6%	1.4%	1.014	7.35%
-0.05%	0.00%	5.20%	14.29%	3.58%	14.29%	100.00%	3	3.62%	2	0.2%	3.4%	1.034	11.02%
-0.33%	0.00%	-2.34%	0.00%	1.00%	25.00%	100.00%	6	1.78%	8	0.8%	1.0%	1.010	12.11%
-1.81%	0.00%	-7.70%	0.00%	-2.16%	0.00%	0.00%	10	0.00%	4	0.4%	-0.4%	0.996	11.66%
3.68%	12.50%	3.08%	12.50%	0.45%	12.50%	100.00%	2	2.62%	8	0.8%	1.8%	1.018	13.70%
-4.19%	0.00%	-3.93%	0.00%	-3.62%	0.00%	100.00%	9	11.37%	8	0.8%	10.6%	1.106	25.71%
2.67%	11.11%	1.53%	11.11%	1.81%	11.11%	100.00%	1	2.40%	9	0.9%	1.5%	1.015	27.60%
2.65%	11.11%	0.47%	11.11%	2.36%	11.11%	100.00%	1	2.71%	2	0.2%	2.5%	1.025	30.80%
3.56%	14.29%	0.09%	14.29%	3.48%	14.29%	100.00%	3	2.50%	10	1.0%	1.9%	1.019	33.28%
-0.97%	0.00%	-2.26%	0.00%	-1.57%	0.00%	100.00%	7	2.14%	9	0.9%	1.2%	1.012	34.92%
-1.33%	0.00%	0.38%	20.00%	-4.43%	0.00%	100.00%	5	1.14%	7	0.7%	0.4%	1.004	35.51%
2.90%	25.00%	-2.24%	0.00%	-2.66%	0.00%	100.00%	6	3.16%	7	0.7%	2.5%	1.025	38.84%
1.27%	14.29%	4.33%	14.29%	1.66%	14.29%	100.00%	3	2.86%	9	0.9%	2.0%	1.020	41.56%
10.13%	11.11%	-3.77%	0.00%	4.94%	11.11%	100.00%	1	5.17%	10	1.0%	4.2%	1.042	47.46%
5.68%	0.00%	0.35%	33.33%	-2.87%	0.00%	100.00%	7	2.99%	10	1.0%	2.0%	1.020	50.40%
-3.22%	0.00%	-3.38%	0.00%	-2.55%	0.00%	100.00%	9	0.56%	4	0.4%	0.2%	1.002	50.33%
4.01%	16.67%	0.70%	16.67%	-0.28%	0.00%	100.00%	4	3.05%	7	0.7%	2.3%	1.023	54.77%
-3.81%	0.00%	-4.25%	0.00%	0.05%	14.29%	100.00%	3	1.99%	9	0.9%	1.1%	1.011	55.85%
4.93%	11.11%	2.54%	11.11%	4.17%	11.11%	100.00%	1	5.11%	10	1.0%	4.1%	1.041	62.26%
-0.87%	0.00%	0.02%	100.00%	-2.34%	0.00%	100.00%	9	0.02%	9	0.9%	-0.9%	0.991	60.84%
-9.98%	0.00%	-7.19%	0.00%	-8.99%	0.00%	0.00%	10	0.00%	1	0.1%	-0.1%	0.999	60.68%
3.21%	11.11%	-0.66%	0.00%	5.45%	11.11%	100.00%	1	1.78%	9	0.9%	5.1%	1.011	68.85%
1.98%	10.00%	9.98%	10.00%	2.42%	10.00%	100.00%	0	4.95%	10	1.0%	3.3%	1.033	74.50%
-3.46%	0.00%	5.09%	33.33%	-1.23%	0.00%	100.00%	7	2.32%	10	1.0%	1.3%	1.013	76.81%
1.42%	20.00%	2.24%	20.00%	3.95%	20.00%	100.00%	5	2.88%	7	0.7%	2.2%	1.022	80.66%
2.60%	25.00%	3.06%	25.00%	-3.71%	0.00%	100.00%	6	2.01%	7	0.7%	1.3%	1.013	83.03%
2.14%	10.00%	11.29%	10.00%	4.87%	10.00%	100.00%	0	4.87%	10	1.0%	3.9%	1.039	90.11%
3.14%	14.29%	-2.79%	0.00%	8.04%	14.29%	100.00%	3	3.82%	10	1.0%	2.8%	1.028	95.48%
-0.95%	0.00%	-0.66%	0.00%	-1.37%	0.00%	100.00%	9	1.78%	7	0.7%	1.1%	1.011	97.60%
-1.64%	0.00%	8.92%	33.33%	-3.40%	0.00%	100.00%	7	5.95%	4	0.4%	5.5%	1.055	108.56%
-0.18%	0.00%	1.54%	25.00%	-1.82%	0.00%	100.00%	6	2.03%	5	0.5%	1.5%	1.015	111.75%
1.46%	12.50%	-3.59%	0.00%	5.62%	12.50%	100.00%	2	2.70%	10	1.0%	1.7%	1.017	115.95%

Figure 51: Absolute momentum portfolio using linear regression - part 2

2022-02-07	-2.70%	0,00%	3,31%	16,67%	1,63%	16,67%	3,10%	16,67%	4,51%	16,67%	-0,93%	0,00%	-0,93%	0,00%
2022-02-08	8,29%	10,00%	0,67%	10,00%	3,94%	10,00%	9,49%	10,00%	7,33%	10,00%	2,12%	10,00%	5,07%	10,00%
2022-02-09	-2,63%	0,00%	-3,74%	0,00%	-0,08%	0,00%	-0,40%	0,00%	-2,09%	0,00%	2,40%	50,00%	-1,75%	0,00%
2022-02-10	0,01%	20,00%	2,03%	20,00%	0,75%	20,00%	-2,39%	0,00%	-0,17%	0,00%	1,98%	20,00%	-1,45%	0,00%
2022-02-11	-2,68%	0,00%	1,17%	100,00%	-1,67%	0,00%	-3,60%	0,00%	-4,52%	0,00%	-3,34%	0,00%	-1,96%	0,00%
2022-02-12	-6,07%	0,00%	-3,82%	0,00%	-3,32%	0,00%	-5,74%	0,00%	-7,80%	0,00%	-5,18%	0,00%	-8,54%	0,00%
2022-02-13	-3,34%	0,00%	1,26%	16,67%	0,14%	16,67%	-1,37%	0,00%	1,11%	16,67%	-1,40%	0,00%	-2,83%	0,00%
2022-02-14	1,19%	12,50%	-1,58%	0,00%	1,50%	12,50%	1,12%	12,50%	1,98%	12,50%	0,64%	12,50%	-2,62%	0,00%
2022-02-15	-0,28%	0,00%	1,72%	33,33%	-0,53%	0,00%	1,01%	33,33%	-2,18%	0,00%	0,23%	33,33%	-1,68%	0,00%
2022-02-16	6,52%	10,00%	3,98%	10,00%	4,84%	10,00%	4,25%	10,00%	3,18%	10,00%	6,99%	10,00%	12,09%	10,00%
2022-02-17	-4,87%	0,00%	-1,21%	0,00%	-0,72%	0,00%	6,18%	50,00%	-1,94%	0,00%	-1,02%	0,00%	1,81%	50,00%
2022-02-18	-5,04%	0,00%	-3,89%	0,00%	-7,69%	0,00%	-9,11%	0,00%	-8,84%	0,00%	-5,87%	0,00%	-6,93%	0,00%
2022-02-19	-0,69%	0,00%	-5,02%	0,00%	-3,16%	0,00%	-0,17%	0,00%	0,89%	50,00%	-5,99%	0,00%	-6,04%	0,00%
2022-02-20	0,68%	16,67%	-0,02%	0,00%	0,31%	16,67%	-2,77%	0,00%	3,17%	16,67%	-1,62%	0,00%	1,51%	16,67%
2022-02-21	-6,80%	0,00%	-1,92%	0,00%	-2,34%	0,00%	-2,71%	0,00%	-0,56%	0,00%	-0,23%	0,00%	-2,06%	0,00%
2022-02-22	-11,88%	0,00%	-4,05%	0,00%	-3,80%	0,00%	-11,34%	0,00%	-2,06%	0,00%	-2,61%	0,00%	-5,93%	0,00%
2022-02-23	3,94%	14,29%	-1,03%	0,00%	0,90%	14,29%	6,06%	14,29%	-1,52%	0,00%	0,77%	14,29%	-1,58%	0,00%
2022-02-24	-2,71%	0,00%	-4,19%	0,00%	-1,55%	0,00%	-3,92%	0,00%	-4,18%	0,00%	-2,14%	0,00%	-1,45%	0,00%
2022-02-25	0,05%	20,00%	3,33%	20,00%	3,49%	20,00%	-2,17%	0,00%	-2,30%	0,00%	1,98%	20,00%	1,89%	20,00%
2022-02-26	10,40%	10,00%	6,57%	10,00%	3,17%	10,00%	4,38%	10,00%	2,31%	10,00%	6,40%	10,00%	9,04%	10,00%
2022-02-27	-3,36%	0,00%	-1,44%	0,00%	-0,48%	0,00%	3,92%	25,00%	-1,65%	0,00%	-0,50%	0,00%	1,50%	25,00%
2022-02-28	-3,72%	0,00%	-2,51%	0,00%	-3,57%	0,00%	-7,01%	0,00%	-3,44%	0,00%	-4,89%	0,00%	-6,27%	0,00%
2022-03-01	12,63%	10,00%	7,40%	10,00%	12,95%	10,00%	14,84%	10,00%	6,32%	10,00%	8,87%	10,00%	7,38%	10,00%
2022-03-02	-1,13%	0,00%	5,28%	16,67%	4,29%	16,67%	-1,29%	0,00%	2,73%	16,67%	2,96%	16,67%	1,83%	16,67%
2022-03-03	-3,15%	0,00%	1,39%	33,33%	-1,02%	0,00%	-1,16%	0,00%	-0,20%	0,00%	0,73%	33,33%	2,11%	33,33%
2022-03-04	0,17%	33,33%	-0,42%	0,00%	-2,63%	0,00%	-0,11%	0,00%	-0,23%	0,00%	-1,76%	0,00%	3,53%	33,33%
2022-03-05	-9,51%	0,00%	-9,31%	0,00%	-8,83%	0,00%	-5,72%	0,00%	-3,69%	0,00%	-9,26%	0,00%	-8,64%	0,00%

Figure 56: Absolute momentum portfolio using linear regression - part 7

1,42%	16,67%	-3,63%	0,00%	2,97%	16,67%	100,00%	4	2,82%	4	0,4%	2,4%	1,024	1118,38%
8,73%	10,00%	8,33%	10,00%	23,95%	10,00%	100,00%	0	7,79%	10	1,0%	6,8%	1,068	1201,10%
-2,37%	0,00%	-1,50%	0,00%	4,62%	50,00%	100,00%	8	3,51%	10	1,0%	2,5%	1,025	1233,74%
5,24%	20,00%	-1,30%	0,00%	-1,51%	0,00%	100,00%	5	2,00%	6	0,6%	1,4%	1,014	1252,44%
-2,94%	0,00%	-5,13%	0,00%	-2,45%	0,00%	100,00%	9	1,17%	5	0,5%	0,7%	1,007	1261,45%
-7,70%	0,00%	-3,04%	0,00%	-9,76%	0,00%	0,00%	10	0,00%	1	0,1%	-0,1%	0,999	1260,09%
1,76%	16,67%	0,20%	16,67%	6,23%	16,67%	100,00%	4	1,78%	6	0,6%	1,2%	1,012	1276,20%
0,30%	12,50%	1,36%	12,50%	1,00%	12,50%	100,00%	2	1,14%	9	0,9%	0,2%	1,002	1279,45%
-2,66%	0,00%	-0,82%	0,00%	-0,76%	0,00%	100,00%	7	0,99%	9	0,9%	0,1%	1,001	1280,63%
5,64%	10,00%	6,54%	10,00%	5,99%	10,00%	100,00%	0	6,00%	10	1,0%	5,0%	1,050	1349,71%
-2,63%	0,00%	-0,89%	0,00%	-4,40%	0,00%	100,00%	8	3,99%	10	1,0%	3,0%	1,030	1393,09%
8,83%	0,00%	4,08%	0,00%	-9,07%	0,00%	0,00%	10	0,00%	2	0,2%	-0,2%	0,998	1390,11%
-1,48%	0,00%	-2,77%	0,00%	3,73%	50,00%	100,00%	8	2,31%	2	0,2%	2,1%	1,021	1421,56%
-0,89%	0,00%	0,17%	16,67%	4,22%	16,67%	100,00%	4	1,68%	6	0,6%	1,1%	1,011	1437,94%
-3,75%	0,00%	-2,53%	0,00%	-5,25%	0,00%	0,00%	10	0,00%	6	0,6%	-0,6%	0,994	1428,71%
-6,94%	0,00%	-4,85%	0,00%	-2,56%	0,00%	0,00%	10	0,00%	0	0,0%	0,0%	1,000	1428,71%
3,67%	14,29%	3,51%	14,29%	0,59%	14,29%	100,00%	3	2,78%	7	0,7%	2,1%	1,021	1460,46%
0,55%	100,00%	-2,60%	0,00%	-4,17%	0,00%	100,00%	9	0,55%	7	0,7%	-0,2%	0,998	1458,11%
-0,58%	0,00%	-7,84%	0,00%	-6,95%	0,00%	100,00%	5	2,15%	6	0,6%	1,5%	1,015	1482,22%
6,67%	10,00%	9,45%	10,00%	10,11%	10,00%	100,00%	0	6,85%	10	1,0%	5,8%	1,058	1574,76%
-2,54%	0,00%	1,05%	25,00%	2,29%	25,00%	100,00%	6	2,19%	10	1,0%	1,2%	1,012	1594,66%
-4,57%	0,00%	0,08%	100,00%	-3,36%	0,00%	100,00%	9	0,08%	4	0,4%	-0,3%	0,997	1589,21%
8,80%	10,00%	8,48%	10,00%	11,03%	10,00%	100,00%	0	9,87%	10	1,0%	8,9%	1,089	1739,04%
-0,52%	0,00%	1,43%	16,67%	-3,05%	0,00%	100,00%	4	3,09%	10	1,0%	2,1%	1,021	1777,39%
-2,47%	0,00%	-4,28%	0,00%	-1,71%	0,00%	100,00%	7	1,41%	6	0,6%	0,8%	1,008	1792,61%
2,12%	33,33%	-0,44%	0,00%	-0,83%	0,00%	100,00%	7	1,94%	4	0,4%	1,5%	1,015	1821,74%
-9,44%	0,00%	-6,77%	0,00%	-6,60%	0,00%	0,00%	10	0,00%	3	0,3%	-0,3%	0,997	1815,97%

Figure 57: Absolute momentum portfolio using linear regression - part 8

2022-02-07	-2.70%	0,00%	3,31%	50,00%	1,63%	0,00%	3,10%	0,00%	4,51%	50,00%	-0,93%	0,00%	-0,93%	0,00%
2022-02-08	8,29%	0,00%	0,67%	0,00%	3,94%	0,00%	9,49%	50,00%	7,33%	0,00%	2,12%	0,00%	5,07%	0,00%
2022-02-09	-2,63%	0,00%	-3,74%	0,00%	-0,08%	0,00%	-0,40%	0,00%	-2,09%	0,00%	2,40%	50,00%	-1,75%	0,00%
2022-02-10	0,01%	0,00%	2,03%	50,00%	0,75%	0,00%	-2,39%	0,00%	-0,17%	0,00%	1,98%	0,00%	-1,45%	0,00%
2022-02-11	-2,68%	0,00%	1,17%	50,00%	-1,67%	50,00%	-3,60%	0,00%	-4,52%	0,00%	-3,34%	0,00%	-1,96%	0,00%
2022-02-12	-6,07%	0,00%	-3,82%	0,00%	-3,32%	50,00%	-5,74%	0,00%	-7,80%	0,00%	-5,18%	0,00%	-8,54%	0,00%
2022-02-13	-3,34%	0,00%	1,26%	0,00%	0,14%	0,00%	-1,37%	0,00%	1,11%	0,00%	-1,40%	0,00%	-2,83%	0,00%
2022-02-14	1,19%	0,00%	-1,58%	0,00%	1,50%	50,00%	1,12%	0,00%	1,98%	50,00%	0,64%	0,00%	-2,62%	0,00%
2022-02-15	-0,28%	0,00%	1,72%	50,00%	-0,53%	0,00%	1,01%	50,00%	-2,18%	0,00%	0,23%	0,00%	-1,68%	0,00%
2022-02-16	6,52%	0,00%	3,98%	0,00%	4,84%	0,00%	4,25%	0,00%	3,18%	0,00%	6,99%	50,00%	12,09%	50,00%
2022-02-17	-4,87%	0,00%	-1,21%	0,00%	-0,72%	0,00%	6,18%	50,00%	-1,94%	0,00%	-1,02%	0,00%	1,81%	50,00%
2022-02-18	-5,04%	50,00%	-3,89%	50,00%	-7,69%	0,00%	-9,11%	0,00%	-8,84%	0,00%	-5,87%	0,00%	-6,93%	0,00%
2022-02-19	-0,69%	0,00%	-5,02%	0,00%	-3,16%	0,00%	-0,17%	0,00%	0,89%	50,00%	-5,99%	0,00%	-6,04%	0,00%
2022-02-20	0,68%	0,00%	-0,02%	0,00%	0,31%	0,00%	-2,77%	0,00%	3,17%	50,00%	-1,62%	0,00%	1,51%	0,00%
2022-02-21	-6,80%	0,00%	-1,92%	0,00%	-2,34%	0,00%	-2,71%	0,00%	-0,56%	50,00%	-0,23%	50,00%	-2,06%	0,00%
2022-02-22	-11,88%	0,00%	-4,05%	0,00%	-3,80%	0,00%	-11,34%	0,00%	-2,06%	50,00%	-2,61%	0,00%	-5,93%	0,00%
2022-02-23	3,94%	50,00%	-1,03%	0,00%	0,90%	0,00%	6,06%	50,00%	-1,52%	0,00%	0,77%	0,00%	-1,58%	0,00%
2022-02-24	-2,71%	0,00%	-4,19%	0,00%	-1,55%	0,00%	-3,92%	0,00%	-4,18%	0,00%	-2,14%	0,00%	-1,45%	50,00%
2022-02-25	0,05%	0,00%	3,33%	50,00%	3,49%	50,00%	-2,17%	0,00%	-2,30%	0,00%	1,98%	0,00%	1,89%	0,00%
2022-02-26	10,40%	50,00%	6,57%	0,00%	3,17%	0,00%	4,38%	0,00%	2,31%	0,00%	6,40%	0,00%	9,04%	0,00%
2022-02-27	-3,36%	0,00%	-1,44%	0,00%	-0,48%	0,00%	3,92%	50,00%	-1,65%	0,00%	-0,50%	0,00%	1,50%	0,00%
2022-02-28	-3,72%	0,00%	-2,51%	50,00%	-3,57%	0,00%	-7,01%	0,00%	-3,44%	0,00%	-4,89%	0,00%	-6,27%	0,00%
2022-03-01	12,63%	0,00%	7,40%	0,00%	12,95%	50,00%	14,84%	50,00%	6,32%	0,00%	8,87%	0,00%	7,38%	0,00%
2022-03-02	-1,13%	0,00%	5,28%	50,00%	4,29%	50,00%	-1,29%	0,00%	2,73%	0,00%	2,96%	0,00%	1,83%	0,00%
2022-03-03	-3,15%	0,00%	1,39%	50,00%	-1,02%	0,00%	-1,16%	0,00%	-0,20%	0,00%	0,73%	0,00%	2,11%	50,00%
2022-03-04	0,17%	0,00%	-0,42%	0,00%	-2,63%	0,00%	-0,11%	0,00%	-0,23%	0,00%	-1,76%	0,00%	3,53%	50,00%
2022-03-05	-9,51%	0,00%	-9,31%	0,00%	-8,83%	0,00%	-5,72%	50,00%	-3,69%	50,00%	-9,26%	0,00%	-8,64%	0,00%

Figure 64: Dual momentum portfolio using linear regression - part 7

1,42%	0,00%	-3,63%	0,00%	2,97%	0,00%	100,00%	DOGE	0,0451073	BNB	0,0331407	3,91%	4	0,40%	3,51%	1,035123977	6993,47%
8,73%	0,00%	8,33%	0,00%	23,95%	50,00%	100,00%	XRP	0,2394607	DASH	0,0948664	16,72%	4	0,40%	16,32%	1,163163567	8150,87%
-2,37%	0,00%	-1,50%	0,00%	4,62%	50,00%	100,00%	XRP	0,0461533	ETH	0,0240186	3,51%	2	0,20%	3,31%	1,033085949	8423,86%
5,24%	50,00%	-1,30%	0,00%	-1,51%	0,00%	100,00%	LTC	0,0524165	BNB	0,0203291	3,64%	4	0,40%	3,24%	1,032372798	8699,80%
-2,94%	0,00%	-5,13%	0,00%	-2,45%	0,00%	100,00%	BNB	0,0116625	BTC	-0,0166577	-0,25%	2	0,20%	-0,45%	0,995502391	8660,22%
-7,70%	0,00%	-3,04%	50,00%	-9,76%	0,00%	100,00%	XLM	-0,0303861	BTC	-0,0332305	-3,18%	2	0,20%	-3,38%	0,966191657	8364,05%
1,76%	50,00%	0,20%	0,00%	6,23%	50,00%	100,00%	XRP	0,0623046	LTC	0,0175798	3,99%	4	0,40%	3,59%	1,035942158	8668,27%
0,30%	0,00%	1,36%	0,00%	1,00%	0,00%	100,00%	DOGE	0,0197519	BTC	0,0150215	1,74%	4	0,40%	1,34%	1,013386674	8785,64%
-2,66%	0,00%	-0,82%	0,00%	-0,76%	0,00%	100,00%	BNB	0,0171972	DASH	0,0101258	1,37%	4	0,40%	0,97%	1,009661486	8871,49%
5,64%	0,00%	6,54%	0,00%	5,99%	0,00%	100,00%	LINK	0,1208557	ETH	0,0699248	9,54%	4	0,40%	9,14%	1,091390252	9691,40%
-2,63%	0,00%	-0,89%	0,00%	-4,40%	0,00%	100,00%	DASH	0,0617544	LINK	0,0181003	3,99%	2	0,20%	3,79%	1,037927341	10062,76%
-8,83%	0,00%	-8,08%	0,00%	-9,07%	0,00%	100,00%	BNB	-0,0389468	ADA	-0,0504241	-4,47%	4	0,40%	-4,87%	0,951314582	9567,98%
-1,48%	0,00%	-2,77%	0,00%	3,73%	50,00%	100,00%	XRP	0,037312	DOGE	0,0089079	2,31%	4	0,40%	1,91%	1,019109977	9752,74%
-0,89%	0,00%	0,17%	0,00%	4,22%	50,00%	100,00%	XRP	0,0421549	DOGE	0,0316946	3,69%	0	0,00%	3,69%	1,036924751	10116,55%
-3,75%	0,00%	-2,53%	0,00%	-5,25%	0,00%	100,00%	ETH	-0,002342	DOGE	-0,0056173	-0,40%	2	0,20%	-0,60%	0,994020353	10055,46%
-6,94%	0,00%	-4,85%	0,00%	-2,56%	50,00%	100,00%	DOGE	-0,0206426	XRP	-0,0256121	-2,31%	2	0,20%	-2,51%	0,974872658	9800,28%
3,67%	0,00%	3,51%	0,00%	0,59%	0,00%	100,00%	DASH	0,0606299	ADA	0,0393552	5,00%	4	0,40%	4,60%	1,045992529	10255,62%
0,55%	50,00%	-2,60%	0,00%	-4,17%	0,00%	100,00%	LTC	0,0054913	LINK	-0,0145427	-0,45%	4	0,40%	-0,85%	0,991474323	10167,33%
-0,58%	0,00%	-7,84%	0,00%	-6,95%	0,00%	100,00%	BTC	0,0348673	BNB	0,0333205	3,41%	4	0,40%	3,01%	1,03009386	10476,31%
6,67%	0,00%	9,45%	0,00%	10,11%	50,00%	100,00%	ADA	0,1039755	XRP	0,1010674	10,25%	4	0,40%	9,85%	1,098521471	11518,31%
-2,54%	0,00%	1,05%	0,00%	2,29%	50,00%	100,00%	DASH	0,0391713	XRP	0,022867	3,10%	2	0,20%	2,90%	1,029019146	11855,46%
-4,57%	0,00%	0,08%	50,00%	-3,36%	0,00%	100,00%	XLM	0,0007821	BNB	-0,0251331	-1,22%	4	0,40%	-1,62%	0,983824512	11662,07%
8,80%	0,00%	8,48%	0,00%	11,03%	0,00%	100,00%	DASH	0,1484316	BTC	0,1295143	13,90%	4	0,40%	13,50%	1,134972936	13249,63%
-0,52%	0,00%	1,43%	0,00%	-3,05%	0,00%	100,00%	BNB	0,0527663	BTC	0,0429162	4,78%	2	0,20%	4,58%	1,045841203	13861,60%
-2,47%	0,00%	-4,28%	0,00%	-1,71%	0,00%	100,00%	LINK	0,0211086	BNB	0,0139237	1,75%	2	0,20%	1,55%	1,015516171	14078,23%
2,12%	50,00%	-0,44%	0,00%	-0,83%	0,00%	100,00%	LINK	0,035275	LTC	0,0211502	2,82%	2	0,20%	2,62%	1,026212571	14449,88%
-9,44%	0,00%	-6,77%	0,00%	-6,60%	0,00%	100,00%	DOGE	-0,0368536	DASH	-0,0571639	-4,70%	4	0,40%	-5,10%	0,948991232	13707,71%

Figure 65: Dual momentum portfolio using linear regression - part 8

1.6.2 Using gradient boosting regression

1.6.2.1 Absolute momentum portfolio

Ab														
	ADA		BNB		BTC		DASH		DOGE		ETH		LINK	
	Returns	Weight	Returns	Weight	Returns	Weight	Returns	Weight	Returns	Weight	Returns	Weight	Returns	Weight
	10%		10%		10%		10%		10%		10%		10%	
2021-10-04	-3.62%	0,00%	2,52%	50,00%	-0,44%	0,00%	-1,95%	0,00%	-3,41%	0,00%	-0,50%	0,00%	-2,16%	0,00%
2021-10-05	0,00%	0,00%	-5,06%	0,00%	1,94%	50,00%	0,00%	0,00%	7,84%	50,00%	-4,39%	0,00%	-3,98%	0,00%
2021-10-06	-0,36%	0,00%	8,22%	11,11%	5,96%	11,11%	4,62%	11,11%	3,12%	11,11%	7,70%	11,11%	8,12%	11,11%
2021-10-07	0,00%	0,00%	2,15%	14,29%	6,99%	14,29%	0,93%	14,29%	6,31%	14,29%	0,33%	14,29%	-0,09%	0,00%
2021-10-08	1,23%	25,00%	-4,98%	0,00%	-2,80%	0,00%	0,18%	25,00%	-2,73%	0,00%	0,10%	25,00%	0,00%	0,00%
2021-10-09	0,06%	100,00%	-6,13%	0,00%	0,00%	0,00%	0,00%	0,00%	-2,87%	0,00%	-2,30%	0,00%	-4,77%	0,00%
2021-10-10	-1,42%	0,00%	0,63%	14,29%	0,77%	14,29%	4,16%	14,29%	-2,81%	0,00%	0,00%	0,00%	5,01%	14,29%
2021-10-11	-0,38%	0,00%	-1,97%	0,00%	-1,86%	0,00%	-3,99%	0,00%	-0,54%	0,00%	-2,55%	0,00%	-6,52%	0,00%
2021-10-12	0,45%	14,29%	1,85%	14,29%	5,36%	14,29%	0,17%	14,29%	0,00%	0,00%	6,51%	14,29%	-1,56%	0,00%
2021-10-13	-0,92%	0,00%	6,83%	33,33%	0,05%	33,33%	-0,53%	0,00%	0,00%	0,00%	0,13%	33,33%	-1,72%	0,00%
2021-10-14	-0,15%	0,00%	5,00%	33,33%	0,49%	33,33%	-0,11%	0,00%	0,00%	0,00%	-0,92%	0,00%	1,62%	33,33%
2021-10-15	0,06%	14,29%	0,69%	14,29%	-0,20%	0,00%	1,31%	14,29%	0,20%	14,29%	4,24%	14,29%	5,53%	14,29%
2021-10-16	0,60%	14,29%	2,98%	14,29%	3,63%	14,29%	3,16%	14,29%	0,00%	0,00%	0,27%	14,29%	0,27%	14,29%
2021-10-17	-0,87%	0,00%	-0,68%	0,00%	0,82%	25,00%	-1,17%	0,00%	-0,90%	0,00%	0,42%	25,00%	0,09%	25,00%
2021-10-18	-0,13%	0,00%	-1,06%	0,00%	2,65%	25,00%	-3,56%	0,00%	0,56%	25,00%	1,34%	25,00%	-4,03%	0,00%
2021-10-19	-0,86%	0,00%	1,25%	25,00%	-0,84%	0,00%	-0,01%	0,00%	2,97%	25,00%	0,54%	25,00%	-2,91%	0,00%
2021-10-20	0,22%	25,00%	0,23%	25,00%	0,45%	25,00%	4,48%	25,00%	-2,89%	0,00%	-2,60%	0,00%	-0,48%	0,00%
2021-10-21	-0,46%	0,00%	0,78%	14,29%	1,60%	14,29%	5,57%	14,29%	2,97%	14,29%	-2,63%	0,00%	7,90%	14,29%
2021-10-22	0,83%	25,00%	-0,88%	0,00%	-1,79%	0,00%	-1,70%	0,00%	3,39%	25,00%	-7,69%	0,00%	2,05%	25,00%
2021-10-23	0,24%	50,00%	-0,13%	0,00%	-1,23%	0,00%	-0,22%	0,00%	-2,86%	0,00%	-7,99%	0,00%	1,01%	50,00%
2021-10-24	-0,69%	0,00%	0,08%	16,67%	-1,45%	0,00%	0,31%	16,67%	-1,55%	0,00%	-3,17%	0,00%	5,26%	16,67%
2021-10-25	-1,36%	0,00%	0,07%	14,29%	0,93%	14,29%	1,65%	14,29%	8,09%	14,29%	0,17%	14,29%	0,97%	14,29%
2021-10-26	0,62%	12,50%	-4,06%	0,00%	2,16%	12,50%	1,51%	12,50%	3,23%	12,50%	0,59%	12,50%	6,78%	12,50%
2021-10-27	1,13%	20,00%	0,69%	20,00%	-1,28%	0,00%	-1,64%	0,00%	0,90%	20,00%	-1,73%	0,00%	1,71%	20,00%
2021-10-28	-8,46%	0,00%	-3,65%	0,00%	-2,47%	0,00%	-13,09%	0,00%	-1,92%	0,00%	2,69%	100,00%	-10,25%	0,00%
2021-10-29	1,26%	10,00%	0,94%	10,00%	2,40%	10,00%	5,15%	10,00%	3,26%	10,00%	3,45%	10,00%	4,88%	10,00%
2021-10-30	2,34%	16,67%	10,08%	16,67%	-1,18%	0,00%	0,26%	16,67%	-0,43%	0,00%	-4,84%	0,00%	-1,06%	0,00%
2021-10-31	-4,41%	0,00%	0,53%	20,00%	2,16%	20,00%	0,18%	20,00%	-0,17%	0,00%	1,40%	20,00%	-1,35%	0,00%
2021-11-01	-0,40%	0,00%	-0,24%	0,00%	-1,93%	0,00%	4,15%	14,29%	1,57%	14,29%	0,44%	14,29%	1,09%	14,29%
2021-11-02	0,00%	0,00%	3,51%	14,29%	0,48%	14,29%	-5,02%	0,00%	0,42%	14,29%	-1,82%	0,00%	5,05%	14,29%
2021-11-03	-0,74%	0,00%	-1,94%	0,00%	1,56%	16,67%	8,16%	16,67%	0,26%	16,67%	-0,13%	0,00%	0,81%	16,67%
2021-11-04	3,20%	11,11%	6,02%	11,11%	0,35%	11,11%	0,22%	11,11%	0,01%	11,11%	0,55%	11,11%	-0,86%	0,00%
2021-11-05	-3,10%	0,00%	0,99%	16,67%	-1,84%	0,00%	0,01%	16,67%	0,34%	16,67%	0,85%	16,67%	-3,22%	0,00%
2021-11-06	0,00%	0,00%	9,38%	16,67%	0,18%	16,67%	0,89%	16,67%	-0,34%	0,00%	0,00%	0,00%	6,19%	16,67%
2021-11-07	3,20%	25,00%	-0,89%	0,00%	1,01%	25,00%	-4,73%	0,00%	0,09%	25,00%	0,00%	0,00%	-3,43%	0,00%
2021-11-08	1,32%	14,29%	3,38%	14,29%	1,10%	14,29%	1,41%	14,29%	0,00%	0,00%	-0,84%	0,00%	4,28%	14,29%

Figure 74: Absolute momentum portfolio using gradient boosting regression - part 1

Absolute momentum																					
LTC		XLM		XRP		sum of weights		nb assets returns<0		Portfolio returns without transac. Cost		Number of transactions		Transaction cost		Portfolio returns with transac. cost		1+r		Cumulative return	
Returns	Weight	Returns	Weight	Returns	Weight																
10%		10%		10%																	
-0,16%	0,00%	-1,69%	0,00%	0,93%	50,00%	100,00%	8	1,72%	10	1,0%	0,72%	1,01	0,72%								
-0,76%	0,00%	-3,36%	0,00%	-0,93%	0,00%	100,00%	8	4,89%	4	0,4%	4,49%	1,04	5,25%								
8,30%	11,11%	7,88%	11,11%	1,57%	11,11%	100,00%	1	6,17%	9	0,9%	5,27%	1,05	10,79%								
-3,14%	0,00%	5,57%	14,29%	1,38%	14,29%	100,00%	3	3,38%	9	0,9%	2,48%	1,02	13,53%								
0,97%	25,00%	0,00%	0,00%	-1,66%	0,00%	100,00%	6	0,62%	9	0,9%	-0,28%	1,00	13,21%								
3,27%	0,00%	0,00%	0,00%	-3,98%	0,00%	100,00%	9	0,06%	4	0,4%	-0,34%	1,00	12,83%								
1,72%	14,29%	1,30%	14,29%	3,27%	14,29%	100,00%	3	2,41%	8	0,8%	1,61%	1,02	14,64%								
-1,76%	0,00%	-0,69%	0,00%	3,60%	100,00%	100,00%	9	3,60%	7	0,7%	2,90%	1,03	17,96%								
0,95%	14,29%	-0,35%	0,00%	3,28%	14,29%	100,00%	3	2,65%	7	0,7%	1,95%	1,02	20,27%								
-1,35%	0,00%	0,00%	0,00%	0,00%	0,00%	100,00%	7	2,34%	7	0,7%	1,64%	1,02	22,24%								
-0,52%	0,00%	0,00%	0,00%	-0,34%	0,00%	100,00%	7	2,37%	2	0,2%	2,17%	1,02	24,89%								
1,90%	14,29%	0,00%	0,00%	-3,94%	0,00%	100,00%	3	1,99%	8	0,8%	1,19%	1,01	26,37%								
6,55%	14,29%	-0,35%	0,00%	0,00%	0,00%	100,00%	3	2,50%	2	0,2%	2,30%	1,02	29,28%								
0,16%	25,00%	-0,33%	0,00%	0,00%	0,00%	100,00%	6	0,37%	7	0,7%	-0,33%	1,00	28,85%								
-0,86%	0,00%	-5,84%	0,00%	3,32%	25,00%	100,00%	6	1,97%	4	0,4%	1,57%	1,02	30,87%								
0,58%	25,00%	0,00%	0,00%	-6,59%	0,00%	100,00%	6	1,34%	4	0,4%	0,94%	1,01	32,10%								
-0,48%	0,00%	0,00%	0,00%	-2,66%	0,00%	100,00%	6	1,34%	6	0,6%	0,74%	1,01	33,08%								
9,99%	14,29%	6,01%	14,29%	0,00%	0,00%	100,00%	3	4,97%	8	0,8%	4,17%	1,04	38,63%								
-5,26%	0,00%	0,00%	0,00%	2,86%	25,00%	100,00%	6	2,28%	9	0,9%	1,38%	1,01	40,55%								
-5,54%	0,00%	-6,13%	0,00%	-3,04%	0,00%	100,00%	8	0,62%	4	0,4%	0,22%	1,00	40,87%								
1,87%	16,67%	0,13%	16,67%	0,59%	16,67%	100,00%	4	1,54%	7	0,7%	0,84%	1,01	42,05%								
-2,61%	0,00%	1,87%	14,29%	-0,24%	0,00%	100,00%	3	1,96%	9	0,9%	1,06%	1,01	43,56%								
3,24%	12,50%	-2,17%	0,00%	0,24%	12,50%	100,00%	2	2,30%	10	1,0%	1,30%	1,01	45,24%								
3,87%	20,00%	0,00%	0,00%	0,00%	0,00%	100,00%	5	1,66%	9	0,9%	0,76%	1,01	46,52%								
-13,00%	0,00%	-12,01%	0,00%	-5,72%	0,00%	100,00%	9	2,69%	6	0,6%	2,09%	1,02	49,58%								
4,99%	10,00%	6,61%	10,00%	4,83%	10,00%	100,00%	4	3,78%	10	1,0%	2,78%	1,03	53,74%								
3,96%	16,67%	6,32%	16,67%	0,57%	16,67%	100,00%	4	3,92%	10	1,0%	2,92%	1,03	58,23%								
-2,63%	0,00%	1,59%	20,00%	0,00%	0,00%	100,00%	5	1,19%	8	0,8%	0,39%	1,00	58,85%								
0,36%	14,29%	6,30%	14,29%	0,59%	14,29%	100,00%	3	2,07%	9	0,9%	1,17%	1,01	60,71%								
6,78%	14,29%	3,17%	14,29%	1,43%	14,29%	100,00%	3	2,98%	4	0,4%	2,58%	1,03	64,85%								
1,40%	16,67%	6,33%	16,67%	-3,99%	0,00%	100,00%	4	3,09%	8	0,8%	2,29%	1,02	68,62%								
0,40%	11,11%	2,33%	11,11%	2,82%	11,11%	100,00%	1	1,77%	10	1,0%	0,77%	1,01	69,92%								
0,79%	16,67%	-6,07%	0,00%	0,81%	16,67%	100,00%	4	0,63%	9	0,9%	-0,27%	1,00	69,77%								
2,38%	0,00%	4,78%	16,67%	4,06%	16,67%	100,00%	4	4,25%	6	0,6%	3,65%	1,04	75,55%								
-0,37%	0,00%	2,10%	25,00%	0,00%	0,00%	100,00%	6	1,60%	8	0,8%	0,80%	1,01	77,05%								
1,10%	14,29%	-0,78%	0,00%	2,35%	14,29%	100,00%	3	2,14%	9	0,9%	1,24%	1,01	79,24%								

Figure 75: Absolute momentum portfolio using gradient boosting regression - part 2

2022-02-07	3,80%	11,11%	4,25%	11,11%	0,17%	11,11%	3,29%	11,11%	2,71%	11,11%	0,87%	11,11%	0,53%	11,11%
2022-02-08	-0,08%	0,00%	8,09%	14,29%	10,71%	14,29%	8,42%	14,29%	0,00%	0,00%	2,76%	14,29%	-0,62%	0,00%
2022-02-09	-2,20%	0,00%	-4,44%	0,00%	0,16%	50,00%	-3,73%	0,00%	0,00%	0,00%	-0,84%	0,00%	0,00%	0,00%
2022-02-10	2,13%	20,00%	-0,30%	0,00%	0,95%	20,00%	0,29%	20,00%	0,00%	0,00%	-0,16%	0,00%	-0,52%	0,00%
2022-02-11	-1,32%	0,00%	-2,44%	0,00%	-1,77%	0,00%	1,30%	100,00%	0,00%	0,00%	-4,70%	0,00%	-7,64%	0,00%
2022-02-12	-2,82%	0,00%	0,20%	100,00%	-8,78%	0,00%	-6,89%	0,00%	-1,48%	0,00%	-2,11%	0,00%	-10,02%	0,00%
2022-02-13	-0,49%	0,00%	0,19%	50,00%	0,00%	0,00%	-0,71%	0,00%	0,00%	0,00%	-1,15%	0,00%	0,00%	0,00%
2022-02-14	0,10%	33,33%	-1,44%	0,00%	-0,54%	0,00%	-0,62%	0,00%	1,51%	33,33%	-5,29%	0,00%	-0,25%	0,00%
2022-02-15	0,72%	20,00%	1,00%	20,00%	0,27%	20,00%	-0,11%	0,00%	-1,46%	0,00%	4,20%	20,00%	0,63%	20,00%
2022-02-16	-1,13%	0,00%	6,98%	11,11%	10,59%	11,11%	2,58%	11,11%	1,51%	11,11%	8,20%	11,11%	10,46%	11,11%
2022-02-17	-3,02%	0,00%	-5,06%	0,00%	-0,24%	0,00%	4,39%	50,00%	0,00%	0,00%	-3,23%	0,00%	0,24%	50,00%
2022-02-18	-3,99%	0,00%	-10,03%	0,00%	-11,28%	0,00%	-6,43%	0,00%	-1,48%	0,00%	-7,70%	0,00%	-8,87%	0,00%
2022-02-19	-2,73%	0,00%	-1,27%	0,00%	-0,23%	0,00%	1,25%	50,00%	0,00%	0,00%	-1,16%	0,00%	-3,30%	0,00%
2022-02-20	0,00%	0,00%	-3,09%	0,00%	-0,65%	0,00%	-1,32%	0,00%	0,00%	0,00%	0,00%	0,00%	1,85%	50,00%
2022-02-21	0,00%	0,00%	6,15%	100,00%	-5,42%	0,00%	-8,44%	0,00%	0,00%	0,00%	-6,08%	0,00%	-4,79%	0,00%
2022-02-22	-14,67%	0,00%	-2,95%	0,00%	-1,57%	0,00%	-8,60%	0,00%	0,67%	100,00%	-1,18%	0,00%	-2,15%	0,00%
2022-02-23	3,95%	12,50%	4,46%	12,50%	0,27%	12,50%	5,31%	12,50%	-0,46%	0,00%	3,67%	12,50%	2,98%	12,50%
2022-02-24	-4,00%	0,00%	-1,77%	0,00%	0,26%	100,00%	-1,35%	0,00%	-0,50%	0,00%	-7,58%	0,00%	-4,92%	0,00%
2022-02-25	1,83%	25,00%	-1,76%	0,00%	-1,07%	0,00%	-4,71%	0,00%	1,18%	25,00%	-0,56%	0,00%	0,74%	25,00%
2022-02-26	2,34%	11,11%	4,28%	11,11%	5,35%	11,11%	5,61%	11,11%	-1,16%	0,00%	9,60%	11,11%	0,57%	11,11%
2022-02-27	0,00%	0,00%	0,00%	0,00%	1,59%	20,00%	0,43%	20,00%	0,00%	0,00%	1,29%	20,00%	0,58%	20,00%
2022-02-28	-7,09%	0,00%	-5,22%	0,00%	-4,04%	0,00%	-6,47%	0,00%	0,00%	0,00%	-3,59%	0,00%	-0,90%	0,00%
2022-03-01	17,79%	11,11%	6,61%	11,11%	9,25%	11,11%	13,61%	11,11%	-0,68%	0,00%	12,91%	11,11%	5,85%	11,11%
2022-03-02	-2,16%	0,00%	4,80%	16,67%	10,60%	16,67%	0,21%	16,67%	-0,21%	0,00%	3,13%	16,67%	3,73%	16,67%
2022-03-03	0,00%	0,00%	3,47%	25,00%	-0,22%	0,00%	0,59%	25,00%	1,19%	25,00%	-0,70%	0,00%	0,81%	25,00%
2022-03-04	-13,78%	0,00%	-1,92%	0,00%	-8,42%	0,00%	-3,17%	0,00%	0,00%	0,00%	-5,65%	0,00%	-6,39%	0,00%
2022-03-05	-4,15%	0,00%	-7,40%	0,00%	-4,85%	0,00%	-4,83%	0,00%	0,67%	100,00%	-10,08%	0,00%	-0,28%	0,00%

Figure 80: Absolute momentum portfolio using gradient boosting regression - part 7

3,49%	11,11%	0,00%	0,00%	3,35%	11,11%	100,00%	1	2,50%	10	1,0%	1,50%	1,01	985,68%
10,11%	14,29%	2,50%	14,29%	23,49%	14,29%	100,00%	3	9,44%	10	1,0%	8,44%	1,08	1077,32%
-2,43%	0,00%	-1,41%	0,00%	6,09%	50,00%	100,00%	8	3,13%	7	0,7%	2,43%	1,02	1105,90%
4,71%	20,00%	2,68%	20,00%	-2,35%	0,00%	100,00%	5	2,15%	6	0,6%	1,55%	1,02	1124,63%
-3,16%	0,00%	-1,91%	0,00%	-3,62%	0,00%	100,00%	9	1,30%	5	0,5%	0,80%	1,01	1134,47%
-4,92%	0,00%	-4,11%	0,00%	-12,01%	0,00%	100,00%	9	0,20%	2	0,2%	0,00%	1,00	1134,50%
-0,31%	0,00%	-0,75%	0,00%	12,57%	50,00%	100,00%	8	6,38%	2	0,2%	6,18%	1,06	1210,81%
0,00%	0,00%	0,00%	0,00%	0,38%	33,33%	100,00%	7	0,66%	4	0,4%	0,26%	1,00	1214,24%
-1,97%	0,00%	0,00%	0,00%	0,00%	0,00%	100,00%	5	1,36%	7	0,7%	0,66%	1,01	1222,95%
5,77%	11,11%	3,23%	11,11%	4,39%	11,11%	100,00%	1	5,97%	10	1,0%	4,97%	1,05	1288,68%
-3,36%	0,00%	0,00%	0,00%	-3,47%	0,00%	100,00%	8	2,31%	9	0,9%	1,41%	1,01	1308,31%
-8,97%	0,00%	-7,82%	0,00%	-11,81%	0,00%	0,00%	10	0,00%	2	0,2%	-0,20%	1,00	1305,49%
-0,99%	0,00%	-1,16%	0,00%	3,28%	50,00%	100,00%	8	2,27%	2	0,2%	2,07%	1,02	1334,55%
-1,96%	0,00%	-0,80%	0,00%	8,83%	50,00%	100,00%	8	5,34%	2	0,2%	5,14%	1,05	1408,35%
-0,82%	0,00%	-6,78%	0,00%	-8,79%	0,00%	100,00%	9	6,15%	3	0,3%	5,85%	1,06	1496,61%
-5,82%	0,00%	-2,64%	0,00%	-9,66%	0,00%	100,00%	9	0,67%	2	0,2%	0,47%	1,00	1504,19%
0,00%	0,00%	2,71%	12,50%	6,09%	12,50%	100,00%	2	3,68%	9	0,9%	2,78%	1,03	1548,74%
0,00%	0,00%	-2,99%	0,00%	-5,26%	0,00%	100,00%	9	0,26%	8	0,8%	-0,54%	0,99	1539,77%
0,00%	0,00%	0,37%	25,00%	0,00%	0,00%	100,00%	6	1,03%	5	0,5%	0,53%	1,01	1548,46%
6,20%	11,11%	2,34%	11,11%	7,24%	11,11%	100,00%	1	4,84%	10	1,0%	3,84%	1,04	1611,70%
-5,83%	0,00%	7,45%	20,00%	0,00%	0,00%	100,00%	5	2,27%	9	0,9%	1,37%	1,01	1635,12%
0,00%	0,00%	-1,82%	0,00%	-1,58%	0,00%	0,00%	10	0,00%	5	0,5%	-0,50%	1,00	1626,44%
6,72%	11,11%	4,82%	11,11%	4,94%	11,11%	100,00%	1	9,17%	9	0,9%	8,27%	1,08	1769,18%
0,00%	0,00%	4,92%	16,67%	-0,58%	0,00%	100,00%	4	4,57%	9	0,9%	3,67%	1,04	1837,69%
-0,24%	0,00%	-5,23%	0,00%	-3,20%	0,00%	100,00%	6	1,51%	7	0,7%	0,81%	1,01	1853,45%
0,18%	100,00%	-1,95%	0,00%	-1,03%	0,00%	100,00%	9	0,18%	5	0,5%	-0,32%	1,00	1847,11%
-13,64%	0,00%	-6,91%	0,00%	-3,49%	0,00%	100,00%	9	0,67%	2	0,2%	0,47%	1,00	1856,36%

Figure 81: Absolute momentum portfolio using gradient boosting regression - part 8

2022-02-07	3,80%	50,00%	4,25%	50,00%	0,17%	0,00%	3,29%	0,00%	2,71%	0,00%	0,87%	0,00%	0,53%	0,00%
2022-02-08	-0,08%	0,00%	8,09%	0,00%	10,71%	50,00%	8,42%	0,00%	0,00%	0,00%	2,76%	0,00%	-0,62%	0,00%
2022-02-09	-2,20%	0,00%	-4,44%	0,00%	0,16%	50,00%	-3,73%	0,00%	0,00%	0,00%	-0,84%	0,00%	0,00%	0,00%
2022-02-10	2,13%	0,00%	-0,30%	0,00%	0,95%	0,00%	0,29%	0,00%	0,00%	0,00%	-0,16%	0,00%	-0,52%	0,00%
2022-02-11	-1,32%	0,00%	-2,44%	0,00%	-1,77%	0,00%	1,30%	50,00%	0,00%	50,00%	-4,70%	0,00%	-7,64%	0,00%
2022-02-12	-2,82%	0,00%	0,20%	50,00%	-8,78%	0,00%	-6,89%	0,00%	-1,48%	50,00%	-2,11%	0,00%	-10,02%	0,00%
2022-02-13	-0,49%	0,00%	0,19%	50,00%	0,00%	0,00%	-0,71%	0,00%	0,00%	0,00%	-1,15%	0,00%	0,00%	0,00%
2022-02-14	0,10%	0,00%	-1,44%	0,00%	-0,54%	0,00%	-0,62%	0,00%	1,51%	50,00%	-5,29%	0,00%	-0,25%	0,00%
2022-02-15	0,72%	0,00%	1,00%	50,00%	0,27%	0,00%	-0,11%	0,00%	-1,48%	0,00%	4,20%	50,00%	0,63%	0,00%
2022-02-16	-1,13%	0,00%	6,98%	0,00%	10,59%	50,00%	2,58%	0,00%	1,51%	0,00%	8,20%	0,00%	10,46%	50,00%
2022-02-17	-3,02%	0,00%	-5,06%	0,00%	-0,24%	0,00%	4,39%	50,00%	0,00%	0,00%	-3,23%	0,00%	0,24%	50,00%
2022-02-18	-3,99%	50,00%	-10,03%	0,00%	-11,28%	0,00%	-6,43%	0,00%	-1,48%	50,00%	-7,70%	0,00%	-8,87%	0,00%
2022-02-19	-2,73%	0,00%	-1,27%	0,00%	-0,23%	0,00%	1,25%	50,00%	0,00%	0,00%	-1,16%	0,00%	-3,30%	0,00%
2022-02-20	0,00%	0,00%	-3,09%	0,00%	-0,65%	0,00%	-1,32%	0,00%	0,00%	0,00%	0,00%	0,00%	1,85%	50,00%
2022-02-21	0,00%	50,00%	6,15%	50,00%	-5,42%	0,00%	-8,44%	0,00%	0,00%	0,00%	-6,08%	0,00%	-4,79%	0,00%
2022-02-22	-14,67%	0,00%	-2,95%	0,00%	-1,57%	0,00%	-8,60%	0,00%	0,67%	50,00%	-1,18%	50,00%	-2,15%	0,00%
2022-02-23	3,93%	0,00%	4,46%	0,00%	0,27%	0,00%	5,31%	50,00%	-0,46%	0,00%	3,67%	0,00%	2,98%	0,00%
2022-02-24	-4,00%	0,00%	-1,77%	0,00%	0,26%	50,00%	-1,35%	0,00%	-0,50%	0,00%	-7,58%	0,00%	-4,92%	0,00%
2022-02-25	1,83%	50,00%	-1,76%	0,00%	-1,07%	0,00%	-4,71%	0,00%	1,18%	50,00%	-0,56%	0,00%	0,74%	0,00%
2022-02-26	2,34%	0,00%	4,28%	0,00%	5,35%	0,00%	5,61%	0,00%	-1,16%	0,00%	9,60%	50,00%	0,57%	0,00%
2022-02-27	0,00%	0,00%	0,00%	0,00%	1,59%	50,00%	0,43%	0,00%	0,00%	0,00%	1,29%	0,00%	0,58%	0,00%
2022-02-28	-7,09%	0,00%	-5,22%	0,00%	-4,04%	0,00%	-6,47%	0,00%	0,00%	50,00%	-3,59%	0,00%	-0,90%	0,00%
2022-03-01	17,79%	50,00%	6,61%	0,00%	9,25%	0,00%	13,61%	50,00%	-0,68%	0,00%	12,91%	0,00%	5,85%	0,00%
2022-03-02	-2,16%	0,00%	4,80%	0,00%	10,60%	50,00%	0,21%	0,00%	-0,21%	0,00%	3,13%	0,00%	3,73%	0,00%
2022-03-03	0,00%	0,00%	3,47%	50,00%	-0,22%	0,00%	0,59%	0,00%	1,19%	50,00%	-0,70%	0,00%	0,81%	0,00%
2022-03-04	-13,78%	0,00%	-1,92%	0,00%	-8,42%	0,00%	-3,17%	0,00%	0,00%	50,00%	-5,65%	0,00%	-6,39%	0,00%
2022-03-05	-4,15%	0,00%	-7,40%	0,00%	-4,85%	0,00%	-4,83%	0,00%	0,67%	50,00%	-10,08%	0,00%	-0,28%	50,00%

Figure 88: Dual momentum portfolio using gradient boosting regression - part 7

3,49%	0,00%	0,00%	0,00%	3,35%	0,00%	100,00%	BNB	0,0425299	ADA	0,0380428	4,03%	2	0,20%	3,83%	1,038286371	10383,70%
10,11%	0,00%	2,50%	0,00%	23,49%	50,00%	100,00%	XRP	0,2348768	BTC	0,1071059	17,10%	4	0,40%	16,70%	1,166991323	12134,39%
-2,43%	0,00%	-1,41%	0,00%	6,09%	50,00%	100,00%	XRP	0,0609458	BTC	0,0016076	3,13%	-	0,00%	3,13%	1,0312767	12517,04%
4,71%	50,00%	2,68%	50,00%	-2,35%	0,00%	100,00%	LTC	0,0471027	XLM	0,0268288	3,70%	4	0,40%	3,30%	1,032965766	12932,97%
-3,16%	0,00%	-1,91%	0,00%	-8,62%	0,00%	100,00%	DASH	0,0130299	DOGE	0	0,65%	4	0,40%	0,25%	1,002514974	12965,75%
-4,92%	0,00%	-4,11%	0,00%	-12,01%	0,00%	100,00%	BNB	0,0020265	DOGE	-0,0148367	-0,64%	2	0,20%	-0,84%	0,991594881	12855,93%
-0,31%	0,00%	-0,75%	0,00%	12,57%	50,00%	100,00%	XRP	0,1256922	BNB	0,0019393	6,38%	2	0,20%	6,18%	1,061815747	13656,81%
0,00%	0,00%	0,00%	0,00%	0,38%	50,00%	100,00%	DOGE	0,0150602	XRP	0,0037504	0,94%	2	0,20%	0,74%	1,007405513	13758,68%
-1,97%	0,00%	0,00%	0,00%	0,00%	0,00%	100,00%	ETH	0,0420365	BNB	0,0099899	2,60%	4	0,40%	2,20%	1,022013232	14063,76%
5,77%	0,00%	3,23%	0,00%	4,39%	0,00%	100,00%	BTC	0,1059361	LINK	0,1045967	10,53%	4	0,40%	10,13%	1,101266358	15498,07%
-3,36%	0,00%	0,00%	0,00%	-3,47%	0,00%	100,00%	DASH	0,0438822	LINK	0,0023791	2,31%	2	0,20%	2,11%	1,02113069	15827,67%
-8,97%	0,00%	-7,82%	0,00%	-11,81%	0,00%	100,00%	DOGE	-0,0148367	ADA	-0,0399212	-2,74%	4	0,40%	-3,14%	0,968621046	15327,88%
-0,99%	0,00%	-1,16%	0,00%	3,28%	50,00%	100,00%	XRP	0,0328459	DASH	0,0125133	2,27%	4	0,40%	1,87%	1,018679626	15616,06%
-1,96%	0,00%	-0,80%	0,00%	8,83%	50,00%	100,00%	XRP	0,08833	LINK	0,0185491	5,34%	2	0,20%	5,14%	1,051439572	16424,49%
-0,82%	0,00%	-6,78%	0,00%	-8,79%	0,00%	100,00%	BNB	0,0615163	ADA	0	3,08%	4	0,40%	2,68%	1,026758149	16866,66%
-5,82%	0,00%	-2,64%	0,00%	-9,66%	0,00%	100,00%	DOGE	0,0067477	ETH	-0,0118117	-0,25%	4	0,40%	-0,65%	0,993467986	16755,83%
0,00%	0,00%	2,71%	0,00%	6,09%	50,00%	100,00%	XRP	0,0609159	DASH	0,0531404	5,70%	4	0,40%	5,30%	1,053028172	17649,66%
0,00%	50,00%	-2,99%	0,00%	-5,26%	0,00%	100,00%	BTC	0,0025579	LTC	0	0,13%	4	0,40%	-0,27%	0,997278962	17601,36%
0,00%	0,00%	0,37%	0,00%	0,20%	0,00%	100,00%	ADA	0,0183372	DOGE	0,0117628	1,50%	4	0,40%	1,10%	1,011049984	17796,96%
6,20%	0,00%	2,34%	0,00%	7,24%	50,00%	100,00%	ETH	0,0960257	XRP	0,072379	8,42%	4	0,40%	8,02%	1,080202354	19232,34%
-5,83%	0,00%	7,45%	50,00%	0,00%	0,00%	100,00%	XLM	0,0744773	BTC	0,0159306	4,52%	4	0,40%	4,12%	1,041203952	20028,91%
0,00%	0,00%	-1,82%	0,00%	-1,58%	0,00%	50,00%	DOGE	0	DOGE	0	0,00%	3	0,30%	-0,30%	0,997	19968,53%
6,72%	0,00%	4,82%	0,00%	4,94%	0,00%	100,00%	ADA	0,1779467	DASH	0,1360668	15,70%	3	0,30%	15,40%	1,154006762	23059,21%
0,00%	0,00%	4,92%	50,00%	-0,58%	0,00%	100,00%	BTC	0,1059837	XLM	0,0491515	7,76%	4	0,40%	7,36%	1,073567594	24762,98%
-0,24%	0,00%	-5,23%	0,00%	-3,20%	0,00%	100,00%	BNB	0,0346856	DOGE	0,0118683	2,33%	4	0,40%	1,93%	1,019276945	25242,26%
0,18%	50,00%	-1,95%	0,00%	-1,03%	0,00%	100,00%	LTC	0,001757	DOGE	0	0,09%	2	0,20%	-0,11%	0,998878491	25213,84%
-13,64%	0,00%	-6,91%	0,00%	-3,49%	0,00%	100,00%	DOGE	0,0067477	LINK	-0,0027705	0,20%	2	0,20%	0,00%	0,999988597	25213,55%

Figure 89: Dual momentum portfolio using gradient boosting regression - part 8

2022-02-07	2,15%	12,50%	2,14%	12,50%	0,95%	12,50%	3,47%	12,50%	1,81%	12,50%	1,74%	12,50%	3,21%	12,50%
2022-02-08	3,92%	12,50%	4,77%	12,50%	13,85%	12,50%	8,90%	12,50%	0,77%	12,50%	-0,32%	0,00%	-0,21%	0,00%
2022-02-09	-1,28%	0,00%	-6,80%	0,00%	-0,06%	0,00%	-1,64%	0,00%	0,52%	33,33%	-0,09%	0,00%	-0,63%	0,00%
2022-02-10	0,33%	20,00%	1,06%	20,00%	-0,88%	0,00%	-0,98%	0,00%	-1,23%	0,00%	3,22%	20,00%	-0,46%	0,00%
2022-02-11	-0,81%	0,00%	-2,43%	0,00%	-2,38%	0,00%	-0,01%	0,00%	-1,35%	0,00%	-3,13%	0,00%	-10,36%	0,00%
2022-02-12	-1,85%	0,00%	-0,24%	0,00%	-5,71%	0,00%	-9,83%	0,00%	-0,93%	0,00%	-5,99%	0,00%	-7,39%	0,00%
2022-02-13	0,64%	12,50%	0,20%	12,50%	0,18%	12,50%	1,30%	12,50%	0,24%	12,50%	0,19%	12,50%	-1,23%	0,00%
2022-02-14	0,65%	25,00%	-0,15%	0,00%	-0,38%	0,00%	-1,44%	0,00%	1,70%	25,00%	-2,16%	0,00%	-0,08%	0,00%
2022-02-15	-0,62%	0,00%	-0,05%	0,00%	-0,16%	0,00%	2,29%	50,00%	-1,82%	0,00%	2,23%	50,00%	-0,54%	0,00%
2022-02-16	-0,22%	0,00%	9,79%	11,11%	8,20%	11,11%	1,66%	11,11%	1,93%	11,11%	8,45%	11,11%	11,64%	11,11%
2022-02-17	-1,06%	0,00%	-5,13%	0,00%	0,56%	25,00%	6,35%	25,00%	-0,12%	0,00%	-1,98%	0,00%	-0,64%	0,00%
2022-02-18	0,57%	100,00%	-4,85%	0,00%	-10,57%	0,00%	-8,36%	0,00%	-2,69%	0,00%	-8,38%	0,00%	-9,44%	0,00%
2022-02-19	-0,73%	0,00%	-0,51%	0,00%	-0,59%	0,00%	-0,58%	0,00%	0,05%	33,33%	-2,49%	0,00%	-0,73%	0,00%
2022-02-20	-0,93%	0,00%	-0,39%	0,00%	-0,57%	0,00%	-3,06%	0,00%	0,05%	25,00%	-0,49%	0,00%	1,10%	25,00%
2022-02-21	0,36%	100,00%	-2,61%	0,00%	-4,23%	0,00%	-5,02%	0,00%	-0,10%	0,00%	-5,21%	0,00%	-5,82%	0,00%
2022-02-22	-20,79%	0,00%	-3,24%	0,00%	-2,26%	0,00%	-14,81%	0,00%	0,88%	100,00%	-6,42%	0,00%	-5,13%	0,00%
2022-02-23	10,43%	11,11%	2,72%	11,11%	3,73%	11,11%	12,84%	11,11%	0,15%	11,11%	4,32%	11,11%	3,38%	11,11%
2022-02-24	-9,00%	0,00%	-0,87%	0,00%	-1,04%	0,00%	-2,77%	0,00%	-0,69%	0,00%	-4,54%	0,00%	-3,68%	0,00%
2022-02-25	-0,39%	0,00%	-0,63%	0,00%	-1,58%	0,00%	-5,82%	0,00%	-0,93%	0,00%	-0,80%	0,00%	0,60%	100,00%
2022-02-26	11,72%	10,00%	3,00%	10,00%	0,14%	10,00%	10,04%	10,00%	0,17%	10,00%	10,80%	10,00%	2,28%	10,00%
2022-02-27	-1,59%	0,00%	0,12%	16,67%	1,30%	16,67%	-2,53%	0,00%	0,78%	16,67%	3,04%	16,67%	2,52%	16,67%
2022-02-28	-9,12%	0,00%	-3,29%	0,00%	-4,46%	0,00%	-8,39%	0,00%	-0,69%	0,00%	-6,20%	0,00%	-4,42%	0,00%
2022-03-01	24,92%	10,00%	7,24%	10,00%	10,51%	10,00%	19,00%	10,00%	0,09%	10,00%	9,99%	10,00%	12,70%	10,00%
2022-03-02	-0,80%	0,00%	2,92%	14,29%	12,45%	14,29%	-1,31%	0,00%	0,14%	14,29%	4,82%	14,29%	0,82%	14,29%
2022-03-03	1,01%	25,00%	-0,33%	0,00%	0,42%	25,00%	-0,23%	0,00%	0,04%	25,00%	0,18%	25,00%	-2,66%	0,00%
2022-03-04	-11,91%	0,00%	-0,66%	0,00%	-9,48%	0,00%	0,13%	33,33%	0,12%	33,33%	-5,46%	0,00%	-6,11%	0,00%
2022-03-05	-11,88%	0,00%	-6,01%	0,00%	-5,05%	0,00%	-7,78%	0,00%	0,09%	100,00%	-12,66%	0,00%	-4,33%	0,00%

Figure 104: Absolute momentum portfolio using random forest - part 7

4,47%	12,50%	-2,86%	0,00%	-0,17%	0,00%	100,00%	2	2,49%	4	0,4%	2,09%	1,02	483,64%
10,37%	12,50%	5,18%	12,50%	23,81%	12,50%	100,00%	2	8,95%	4	0,4%	8,55%	1,09	533,52%
-4,67%	0,00%	0,75%	33,33%	6,70%	33,33%	100,00%	7	2,66%	8	0,8%	1,86%	1,02	545,30%
6,58%	20,00%	2,17%	20,00%	-2,66%	0,00%	100,00%	5	2,67%	7	0,7%	1,97%	1,02	558,03%
-4,09%	0,00%	-1,39%	0,00%	-0,46%	0,00%	0,00%	10	0,00%	5	0,5%	-0,50%	1,00	554,74%
-4,83%	0,00%	-9,33%	0,00%	-15,30%	0,00%	0,00%	10	0,00%	0	0,0%	0,00%	1,00	554,74%
2,58%	12,50%	-0,98%	0,00%	17,24%	12,50%	100,00%	2	2,82%	8	0,8%	2,02%	1,02	567,98%
-1,87%	0,00%	1,01%	25,00%	0,43%	25,00%	100,00%	6	0,95%	9	0,9%	0,05%	1,00	568,31%
-3,74%	0,00%	-0,97%	0,00%	-1,65%	0,00%	100,00%	8	2,26%	6	0,6%	1,66%	1,02	579,40%
6,29%	11,11%	6,92%	11,11%	2,57%	11,11%	100,00%	1	6,38%	9	0,9%	5,48%	1,05	616,65%
-1,78%	0,00%	1,27%	25,00%	0,84%	25,00%	100,00%	6	2,26%	9	0,9%	1,36%	1,01	626,36%
-11,25%	0,00%	-9,21%	0,00%	-14,98%	0,00%	100,00%	9	0,57%	5	0,5%	0,07%	1,00	626,85%
0,45%	33,33%	-2,64%	0,00%	5,11%	33,33%	100,00%	7	1,87%	4	0,4%	1,47%	1,01	637,55%
0,11%	25,00%	-0,89%	0,00%	10,77%	25,00%	100,00%	6	3,01%	4	0,4%	2,61%	1,03	656,78%
-1,66%	0,00%	-5,80%	0,00%	-10,79%	0,00%	100,00%	9	0,36%	5	0,5%	-0,14%	1,00	655,71%
-7,98%	0,00%	-5,72%	0,00%	-10,28%	0,00%	100,00%	9	0,88%	2	0,2%	0,68%	1,01	660,84%
-0,05%	0,00%	0,29%	11,11%	3,12%	11,11%	100,00%	1	4,55%	9	0,9%	3,65%	1,04	688,64%
0,34%	50,00%	2,92%	50,00%	-4,13%	0,00%	100,00%	8	1,63%	10	1,0%	0,63%	1,01	693,61%
-0,71%	0,00%	-1,42%	0,00%	-0,84%	0,00%	100,00%	9	0,60%	3	0,3%	0,30%	1,00	696,01%
7,01%	10,00%	1,42%	10,00%	6,26%	10,00%	100,00%	0	5,28%	10	1,0%	4,28%	1,04	730,12%
-4,37%	0,00%	10,56%	16,67%	-0,76%	0,00%	100,00%	4	3,05%	10	1,0%	2,05%	1,02	747,15%
-1,88%	0,00%	-6,05%	0,00%	-0,53%	0,00%	0,00%	10	0,00%	6	0,6%	-0,60%	0,99	742,07%
8,84%	10,00%	6,61%	10,00%	5,14%	10,00%	100,00%	0	10,51%	10	1,0%	9,51%	1,10	822,11%
-0,11%	0,00%	1,84%	14,29%	1,53%	14,29%	100,00%	3	3,50%	10	1,0%	2,50%	1,03	845,21%
-0,06%	0,00%	-3,11%	0,00%	-5,70%	0,00%	100,00%	6	0,41%	8	0,8%	-0,39%	1,00	841,54%
0,14%	33,33%	-0,86%	0,00%	-1,11%	0,00%	100,00%	7	0,13%	6	0,6%	-0,47%	1,00	837,13%
-15,79%	0,00%	-6,00%	0,00%	-3,53%	0,00%	100,00%	9	0,09%	3	0,3%	-0,21%	1,00	835,20%

Figure 105: Absolute momentum portfolio using random forest - part 8

1.6.3.2 Dual momentum portfolio

	ADA		BNB		BTC		DASH		DOGE		ETH		LINK	
	Returns	Weight	Returns	Weight	Returns	Weight	Returns	Weight	Returns	Weight	Returns	Weight	Returns	Weight
	10%	10%	10%	10%	10%	10%	10%	10%	10%	10%	10%	10%	10%	10%
2021-10-04	-1.58%	0.00%	-0.29%	0.00%	-0.56%	0.00%	-0.77%	0.00%	-1.28%	0.00%	-0.42%	0.00%	1.34%	50.00%
2021-10-05	-0.51%	0.00%	-4.82%	0.00%	2.58%	50.00%	-2.26%	0.00%	11.84%	50.00%	-3.33%	0.00%	-4.75%	0.00%
2021-10-06	-2.41%	0.00%	8.43%	50.00%	5.82%	0.00%	5.92%	0.00%	4.87%	0.00%	7.37%	0.00%	5.95%	0.00%
2021-10-07	0.22%	0.00%	-4.28%	0.00%	8.72%	50.00%	1.35%	0.00%	2.61%	0.00%	0.35%	0.00%	-0.11%	0.00%
2021-10-08	0.88%	0.00%	1.38%	50.00%	-2.27%	0.00%	-0.48%	0.00%	-0.09%	0.00%	0.10%	0.00%	1.86%	50.00%
2021-10-09	1.31%	50.00%	-4.76%	0.00%	0.90%	0.00%	1.86%	50.00%	-2.12%	0.00%	0.41%	0.00%	-5.96%	0.00%
2021-10-10	-1.56%	0.00%	0.54%	0.00%	1.17%	0.00%	3.58%	0.00%	-0.46%	0.00%	-0.29%	0.00%	5.30%	50.00%
2021-10-11	-0.17%	50.00%	-1.81%	0.00%	-0.51%	0.00%	-4.74%	0.00%	-2.69%	0.00%	-4.19%	0.00%	-6.92%	0.00%
2021-10-12	-0.08%	0.00%	0.97%	0.00%	1.53%	0.00%	0.92%	0.00%	-1.84%	0.00%	3.80%	50.00%	-0.96%	0.00%
2021-10-13	-0.58%	0.00%	11.04%	50.00%	0.04%	0.00%	-0.67%	0.00%	-3.18%	0.00%	0.22%	0.00%	-1.06%	0.00%
2021-10-14	0.98%	0.00%	0.93%	0.00%	0.11%	0.00%	0.45%	0.00%	1.16%	50.00%	0.71%	0.00%	0.00%	0.00%
2021-10-15	1.52%	0.00%	-0.87%	0.00%	-0.33%	0.00%	-0.17%	0.00%	0.19%	0.00%	1.08%	0.00%	7.68%	50.00%
2021-10-16	0.59%	0.00%	0.73%	0.00%	1.07%	0.00%	6.93%	50.00%	0.27%	0.00%	-0.89%	0.00%	0.91%	0.00%
2021-10-17	-0.07%	0.00%	-0.12%	0.00%	-0.12%	0.00%	-2.70%	0.00%	1.93%	50.00%	1.05%	0.00%	-0.16%	0.00%
2021-10-18	-2.41%	0.00%	-0.84%	0.00%	0.08%	0.00%	-3.63%	0.00%	0.58%	50.00%	-0.66%	0.00%	-4.78%	0.00%
2021-10-19	1.08%	50.00%	-1.46%	0.00%	0.12%	0.00%	-0.82%	0.00%	1.36%	50.00%	-0.45%	0.00%	-2.86%	0.00%
2021-10-20	-1.29%	0.00%	1.70%	50.00%	0.12%	0.00%	7.08%	50.00%	0.30%	0.00%	0.48%	0.00%	-0.44%	0.00%
2021-10-21	1.25%	0.00%	-0.19%	0.00%	-0.01%	0.00%	2.28%	0.00%	1.83%	0.00%	0.05%	0.00%	9.17%	50.00%
2021-10-22	1.66%	50.00%	0.80%	0.00%	-0.28%	0.00%	0.50%	0.00%	1.30%	0.00%	-0.28%	0.00%	0.10%	0.00%
2021-10-23	-0.15%	0.00%	-1.26%	0.00%	-0.25%	0.00%	-0.59%	0.00%	-2.25%	0.00%	-1.03%	0.00%	0.27%	50.00%
2021-10-24	-0.32%	0.00%	0.37%	0.00%	-0.11%	0.00%	-1.30%	0.00%	1.48%	0.00%	-0.20%	0.00%	8.33%	50.00%
2021-10-25	-2.54%	0.00%	-0.65%	0.00%	0.07%	0.00%	0.47%	50.00%	5.22%	50.00%	0.04%	0.00%	-2.50%	0.00%
2021-10-26	2.35%	0.00%	-0.23%	0.00%	0.12%	0.00%	0.99%	0.00%	0.70%	0.00%	-0.23%	0.00%	9.56%	50.00%
2021-10-27	-0.90%	0.00%	2.29%	50.00%	0.09%	0.00%	-0.47%	0.00%	-2.57%	0.00%	0.02%	0.00%	-1.50%	0.00%
2021-10-28	-7.47%	0.00%	-1.69%	0.00%	-0.75%	50.00%	-12.29%	0.00%	-1.80%	0.00%	-0.59%	50.00%	-14.30%	0.00%
2021-10-29	1.79%	0.00%	0.34%	0.00%	0.87%	0.00%	2.81%	0.00%	5.61%	0.00%	0.63%	0.00%	10.12%	50.00%
2021-10-30	3.28%	0.00%	4.97%	50.00%	0.86%	0.00%	0.82%	0.00%	1.81%	0.00%	-0.12%	0.00%	0.94%	0.00%
2021-10-31	-2.62%	0.00%	0.21%	0.00%	0.43%	0.00%	0.08%	0.00%	-0.68%	0.00%	0.14%	0.00%	-7.21%	0.00%
2021-11-01	0.32%	0.00%	1.54%	0.00%	0.60%	0.00%	6.45%	50.00%	2.00%	0.00%	-0.11%	0.00%	4.37%	0.00%
2021-11-02	-0.66%	0.00%	5.37%	50.00%	1.30%	0.00%	-4.51%	0.00%	-0.22%	0.00%	-0.07%	0.00%	4.38%	0.00%
2021-11-03	-0.19%	0.00%	0.26%	0.00%	0.83%	0.00%	7.44%	50.00%	-1.00%	0.00%	0.69%	0.00%	1.74%	0.00%
2021-11-04	5.92%	50.00%	8.07%	50.00%	-0.18%	0.00%	0.85%	0.00%	0.02%	0.00%	0.17%	0.00%	0.32%	0.00%
2021-11-05	-4.85%	0.00%	-3.88%	0.00%	-0.87%	0.00%	-0.65%	0.00%	-2.67%	0.00%	-0.39%	50.00%	-1.88%	0.00%
2021-11-06	-0.97%	0.00%	9.45%	50.00%	1.29%	0.00%	-0.20%	0.00%	-0.47%	0.00%	-0.19%	0.00%	4.32%	50.00%
2021-11-07	3.56%	50.00%	3.89%	50.00%	1.71%	0.00%	-4.34%	0.00%	-0.59%	0.00%	-0.23%	0.00%	-0.95%	0.00%
2021-11-08	0.63%	0.00%	1.37%	0.00%	0.83%	0.00%	2.37%	0.00%	1.14%	0.00%	0.40%	0.00%	2.64%	50.00%

Figure 106: Dual momentum portfolio using random forest - part 1

MENTUM														
XLM		XRP		50%		50%		Portfolio returns without transac. Cost	Number of transactions	Transaction cost	Portfolio returns with transac. cost	1+r	Cumulative return	
Returns	Weight	Returns	Weight	MAX		2e MAX								
				asset	returns	asset	returns							
0.67%	50.00%	0.32%	0.00%	100.00%	LINK	0.013445	XLM	0.0066881	1.01%	10	1.00%	0.01%	1.00006659	0.01%
-5.42%	0.00%	0.79%	0.00%	100.00%	DOGE	0.118423	BTC	0.0237601	7.21%	4	0.40%	6.81%	1.06891573	6.82%
12.40%	50.00%	1.63%	0.00%	100.00%	XLM	0.133972	BNB	0.0843014	10.41%	4	0.40%	10.01%	1.00138764	17.51%
0.24%	0.00%	1.02%	0.00%	100.00%	BTC	0.0872413	LTC	0.0304865	5.89%	4	0.40%	5.49%	1.05466399	23.96%
-1.38%	0.00%	-0.41%	0.00%	100.00%	LINK	0.0186136	BNB	0.013787	1.62%	4	0.40%	1.22%	1.01220029	25.47%
-0.92%	0.00%	-0.43%	0.00%	100.00%	DASH	0.0185504	ADA	0.0131312	1.58%	4	0.40%	1.18%	1.011840819	26.96%
2.10%	0.00%	1.99%	0.00%	100.00%	LINK	0.0530104	LTC	0.0447295	4.89%	4	0.40%	4.49%	1.04468994	32.65%
-2.65%	0.00%	2.98%	50.00%	100.00%	XRP	0.0298246	ADA	-0.0017302	1.40%	4	0.40%	1.00%	1.010047207	33.99%
0.83%	0.00%	0.38%	0.00%	100.00%	LTC	0.0426264	ETH	0.0380096	4.03%	4	0.40%	3.63%	1.036317971	38.85%
0.70%	50.00%	0.03%	0.00%	100.00%	BNB	0.1104105	XLM	0.0070461	5.87%	4	0.40%	5.47%	1.054728302	46.45%
1.53%	50.00%	-1.68%	0.00%	100.00%	XLM	0.0152762	DOGE	0.0115805	1.34%	2	0.20%	1.14%	1.01142836	48.13%
0.05%	0.00%	-0.22%	0.00%	100.00%	LINK	0.0767617	LTC	0.0473086	6.20%	4	0.40%	5.80%	1.058035184	56.72%
0.02%	0.00%	1.08%	0.00%	100.00%	DASH	0.0693991	LTC	0.0595236	6.44%	2	0.20%	6.24%	1.062431355	66.51%
-2.68%	0.00%	2.13%	50.00%	100.00%	XRP	0.0211849	DOGE	0.019256	2.03%	4	0.40%	1.63%	1.016270423	69.22%
-0.78%	0.00%	-1.13%	0.00%	100.00%	LTC	0.0146672	DOGE	0.0058454	1.03%	2	0.20%	0.83%	1.008256273	70.51%
-1.39%	0.00%	-0.04%	0.00%	100.00%	DOGE	0.0135923	ADA	0.0107594	1.22%	2	0.20%	1.02%	1.010175867	72.35%
-0.08%	0.00%	-0.35%	0.00%	100.00%	DASH	0.0707915	BNB	0.0170462	4.39%	4	0.40%	3.99%	1.039918853	79.23%
2.86%	0.00%	2.01%	0.00%	100.00%	LINK	0.0917263	LTC	0.0732253	8.25%	4	0.40%	7.85%	1.07847584	93.30%
-0.87%	0.00%	1.55%	50.00%	100.00%	ADA	0.0165567	XRP	0.0154667	1.60%	4	0.40%	1.20%	1.012011686	95.62%
-0.73%	50.00%	-2.70%	0.00%	100.00%	XLM	0.0072695	LINK	0.0027464	0.50%	4	0.40%	0.10%	1.001007954	95.81%
0.47%	0.00%	0.13%	0.00%	100.00%	LINK	0.0833432	LTC	0.0454889	6.44%	2	0.20%	6.24%	1.062416053	108.04%
-1.83%	0.00%	-1.88%	0.00%	100.00%	DOGE	0.0521867	DASH	0.0047478	2.85%	4	0.40%	2.45%	1.024467293	113.13%
2.19%	0.00%	0.67%	0.00%	100.00%	LINK	0.0956423	LTC	0.0574051	7.65%	4	0.40%	7.25%	1.072523721	128.58%
0.24%	0.00%	1.35%	0.00%	100.00%	LTC	0.0444675	BNB	0.0229131	3.37%	2	0.20%	3.17%	1.031690292	135.83%
-12.21%	0.00%	-13.00%	0.00%	100.00%	ETH	-0.0059052	BTC	-0.0074979	-0.67%	4	0.40%	-1.07%	0.989298464	133.30%
7.77%	0.00%	8.62%	50.00%	100.00%	LINK	0.101217	XRP	0.0861865	9.37%	4	0.40%	8.97%	1.089701755	154.23%
3.69%	0.00%	2.08%	0.00%	100.00%	LTC	0.0511625	BNB	0.0497416	5.05%	4	0.40%	4.65%	1.046452076	166.04%
5.27%	50.00%	1.43%	50.00%	100.00%	XLM	0.052712	XRP	0.0142157	3.35%	4	0.40%	2.95%	1.02446382	173.88%
7.88%	50.00%	2.17%	0.00%	100.00%	XLM	0.0787508	DASH	0.064446	7.16%	2	0.20%	6.96%	1.069605405	192.94%
2.92%	0.00%	0.85%	0.00%	100.00%	LTC	0.0544798	BNB	0.0537054	5.41%	4	0.40%	5.01%	1.050092592	207.62%
6.88%	50.00%	0.55%	0.00%	100.00%	DASH	0.0743636	XLM	0.068765	7.16%	4	0.40%	6.76%	1.067564317	228.40%
0.72%	0.00%	3.88%	0.00%	100.00%	BNB	0.0807091	ADA	0.0592218	7.00%	4	0.40%	6.60%	1.065965448	250.06%
-4.11%	0.00%	1.51%	50.00%	100.00%	XRP	0.0150812	ETH	-0.0039419	0.56%	4	0.40%	0.16%	1.001569654	250.61%
2.72%	0.00%	-0.75%	0.00%	100.00%	BNB	0.0944631	LINK	0.0431887	6.88%	4	0.40%	6.48%	1.064825919	273.24%
2.83%	0.00%	-0.60%	0.00%	100.00%	BNB	0.0389329	ADA	0.0356002	3.73%	2	0.20%	3.53%	1.035266694	286.51%
-2.77%	0.00%	4.79%	50.00%	100.00%	XRP	0.0478795	LINK	0.0264113	3.71%	4	0.40%	3.31%	1.033145399	299.32%

Figure 107: Dual momentum portfolio using random forest - part 2

2022-02-07	2,15%	0,00%	2,14%	0,00%	0,95%	0,00%	3,47%	50,00%	1,81%	0,00%	1,74%	0,00%	3,21%	0,00%
2022-02-08	3,92%	0,00%	4,77%	0,00%	13,85%	50,00%	8,90%	0,00%	0,77%	0,00%	-0,32%	0,00%	-0,21%	0,00%
2022-02-09	-1,28%	0,00%	-6,80%	0,00%	-0,06%	0,00%	-1,64%	0,00%	0,52%	0,00%	-0,09%	0,00%	-0,63%	0,00%
2022-02-10	0,33%	0,00%	1,06%	0,00%	-0,88%	0,00%	-0,98%	0,00%	-1,23%	0,00%	3,22%	50,00%	-0,46%	0,00%
2022-02-11	-0,81%	0,00%	-2,43%	0,00%	-2,38%	0,00%	-0,01%	50,00%	-1,35%	0,00%	-3,13%	0,00%	-10,36%	0,00%
2022-02-12	-1,85%	0,00%	-0,24%	50,00%	-5,71%	0,00%	-9,83%	0,00%	-0,93%	50,00%	-5,99%	0,00%	-7,39%	0,00%
2022-02-13	0,64%	0,00%	0,20%	0,00%	0,18%	0,00%	1,30%	0,00%	0,24%	0,00%	0,19%	0,00%	-1,23%	0,00%
2022-02-14	0,65%	0,00%	-0,15%	0,00%	-0,38%	0,00%	-1,44%	0,00%	1,70%	50,00%	-2,16%	0,00%	-0,08%	0,00%
2022-02-15	-0,62%	0,00%	-0,05%	0,00%	-0,16%	0,00%	2,29%	50,00%	-1,82%	0,00%	2,23%	50,00%	-0,54%	0,00%
2022-02-16	-0,22%	0,00%	9,79%	50,00%	8,20%	0,00%	1,66%	0,00%	1,93%	0,00%	8,45%	0,00%	11,64%	50,00%
2022-02-17	-1,06%	0,00%	-5,13%	0,00%	0,56%	0,00%	6,35%	50,00%	-0,12%	0,00%	-1,98%	0,00%	-0,64%	0,00%
2022-02-18	0,57%	50,00%	-4,85%	0,00%	-10,57%	0,00%	-8,36%	0,00%	-2,69%	50,00%	-8,38%	0,00%	-9,44%	0,00%
2022-02-19	-0,73%	0,00%	-0,51%	0,00%	-0,59%	0,00%	-0,58%	0,00%	0,05%	0,00%	-2,49%	0,00%	-0,73%	0,00%
2022-02-20	-0,93%	0,00%	-0,39%	0,00%	-0,57%	0,00%	-3,06%	0,00%	0,05%	0,00%	-0,49%	0,00%	1,10%	50,00%
2022-02-21	0,36%	50,00%	-2,61%	0,00%	-4,23%	0,00%	-5,02%	0,00%	-0,10%	50,00%	-5,21%	0,00%	-5,82%	0,00%
2022-02-22	-20,79%	0,00%	-3,24%	0,00%	-2,26%	50,00%	-14,81%	0,00%	0,88%	50,00%	-6,42%	0,00%	-5,13%	0,00%
2022-02-23	10,43%	50,00%	2,72%	0,00%	3,73%	0,00%	12,84%	50,00%	0,15%	0,00%	4,32%	0,00%	3,38%	0,00%
2022-02-24	-9,00%	0,00%	-0,87%	0,00%	-1,04%	0,00%	-2,77%	0,00%	-0,69%	0,00%	-4,54%	0,00%	-3,68%	0,00%
2022-02-25	-0,39%	50,00%	-0,63%	0,00%	-1,68%	0,00%	-5,82%	0,00%	-0,93%	0,00%	-0,80%	0,00%	0,60%	50,00%
2022-02-26	11,72%	50,00%	3,00%	0,00%	0,14%	0,00%	10,04%	0,00%	0,17%	0,00%	10,80%	50,00%	2,28%	0,00%
2022-02-27	-1,59%	0,00%	0,12%	0,00%	1,30%	0,00%	-2,53%	0,00%	0,78%	0,00%	3,04%	50,00%	2,52%	0,00%
2022-02-28	-9,12%	0,00%	-3,29%	0,00%	-4,46%	0,00%	-8,39%	0,00%	-0,69%	50,00%	-6,20%	0,00%	-4,42%	0,00%
2022-03-01	24,92%	50,00%	7,24%	0,00%	10,51%	0,00%	19,00%	50,00%	0,09%	0,00%	9,99%	0,00%	12,70%	0,00%
2022-03-02	-0,80%	0,00%	2,92%	0,00%	12,45%	50,00%	-1,31%	0,00%	0,14%	0,00%	4,82%	50,00%	0,82%	0,00%
2022-03-03	1,01%	50,00%	-0,33%	0,00%	0,42%	50,00%	-0,23%	0,00%	0,04%	0,00%	0,18%	0,00%	-2,66%	0,00%
2022-03-04	-11,91%	0,00%	-0,66%	0,00%	-9,48%	0,00%	0,13%	50,00%	0,12%	0,00%	-5,46%	0,00%	-6,11%	0,00%
2022-03-05	-11,88%	0,00%	-6,01%	0,00%	-5,05%	0,00%	-7,78%	0,00%	0,09%	50,00%	-12,66%	0,00%	-4,33%	0,00%

Figure 112: Dual momentum portfolio using random forest - part 7

4,47%	50,00%	-2,36%	0,00%	-0,17%	0,00%	100,00%	LTC	0,0446648	DASH	0,0346557	3,97%	4	0,40%	3,57%	1,035660273	9021,83%
10,37%	0,00%	5,18%	0,00%	23,81%	50,00%	100,00%	XRP	0,2381085	BTC	0,1385476	18,83%	4	0,40%	18,43%	1,184328027	10703,23%
-4,67%	0,00%	0,75%	50,00%	6,70%	50,00%	100,00%	XRP	0,0670403	XLM	0,0075247	3,73%	2	0,20%	3,53%	1,035282522	11084,40%
6,58%	50,00%	2,17%	0,00%	-2,66%	0,00%	100,00%	LTC	0,0658192	ETH	0,0321938	4,90%	4	0,40%	4,50%	1,045006468	11587,77%
-4,09%	0,00%	-1,39%	0,00%	-0,46%	50,00%	100,00%	DASH	-8,911E-05	XRP	-0,0046264	-0,24%	4	0,40%	-0,64%	0,993642255	11513,46%
-4,83%	0,00%	-9,33%	0,00%	-15,30%	0,00%	100,00%	BNB	-0,0024199	DOGE	-0,0092999	-0,59%	4	0,40%	-0,99%	0,990140099	11398,95%
2,58%	50,00%	-0,98%	0,00%	17,24%	50,00%	100,00%	XRP	0,1723699	LTC	0,0258496	9,91%	4	0,40%	9,51%	1,095109773	12492,62%
-1,87%	0,00%	1,01%	50,00%	0,43%	0,00%	100,00%	DOGE	0,0169987	XLM	0,0101383	1,36%	4	0,40%	0,96%	1,009568486	12613,11%
-3,74%	0,00%	-0,97%	0,00%	-1,65%	0,00%	100,00%	DASH	0,0229071	ETH	0,0222734	2,26%	4	0,40%	1,86%	1,018590252	12849,45%
6,29%	0,00%	6,92%	0,00%	2,57%	0,00%	100,00%	LINK	0,1163661	BNB	0,097915	10,71%	4	0,40%	10,31%	1,103140554	14185,06%
-1,78%	0,00%	1,27%	50,00%	0,84%	0,00%	100,00%	DASH	0,0635285	XLM	0,0127484	3,81%	4	0,40%	3,41%	1,034138417	14672,73%
-11,25%	0,00%	-9,21%	0,00%	-14,98%	0,00%	100,00%	ADA	0,0056748	DOGE	-0,0268779	-1,06%	4	0,40%	-1,46%	0,985398452	14457,03%
0,45%	50,00%	-2,64%	0,00%	5,11%	50,00%	100,00%	XRP	0,0511447	LTC	0,0045183	2,78%	4	0,40%	2,38%	1,023831542	14803,94%
0,11%	0,00%	-0,89%	0,00%	10,77%	50,00%	100,00%	XRP	0,1076815	LINK	0,0109591	5,93%	2	0,20%	5,73%	1,057320313	15658,24%
-1,66%	0,00%	-5,80%	0,00%	-10,79%	0,00%	100,00%	ADA	0,003586	DOGE	-0,000981	0,13%	4	0,40%	-0,27%	0,997302525	15615,74%
-7,98%	0,00%	-3,72%	0,00%	-10,28%	0,00%	100,00%	DOGE	0,008795	BTC	-0,022584	-0,69%	2	0,20%	-0,89%	0,991105511	15475,95%
-0,05%	0,00%	0,29%	0,00%	3,12%	0,00%	100,00%	DASH	0,1284007	ADA	0,1042851	11,63%	4	0,40%	11,23%	1,112342937	17225,80%
0,34%	50,00%	2,92%	50,00%	-4,13%	0,00%	100,00%	XLM	0,0291718	LTC	0,00344	1,63%	4	0,40%	1,23%	1,012305898	17439,01%
-0,71%	0,00%	-1,42%	0,00%	-0,84%	0,00%	100,00%	LINK	0,006023	ADA	-0,0039311	0,10%	4	0,40%	-0,30%	0,997045947	17387,20%
7,01%	0,00%	1,42%	0,00%	6,26%	0,00%	100,00%	ADA	0,1172438	ETH	0,1079615	11,26%	2	0,20%	11,06%	1,110602661	19321,33%
-4,37%	0,00%	10,56%	50,00%	-0,76%	0,00%	100,00%	XLM	0,1056006	ETH	0,0303804	6,80%	2	0,20%	6,60%	1,065990495	20602,95%
-1,88%	0,00%	-6,05%	0,00%	-0,53%	50,00%	100,00%	XRP	-0,0053165	DOGE	-0,0069009	-0,61%	4	0,40%	-1,01%	0,989891319	20393,67%
8,84%	0,00%	6,61%	0,00%	5,14%	0,00%	100,00%	ADA	0,2492475	DASH	0,1899843	21,96%	4	0,40%	21,56%	1,215615903	24812,43%
-0,11%	0,00%	1,84%	0,00%	1,53%	0,00%	100,00%	BTC	0,1244915	ETH	0,0481793	8,63%	4	0,40%	8,23%	1,082335397	26863,61%
-0,06%	0,00%	-3,11%	0,00%	-5,70%	0,00%	100,00%	ADA	0,0100848	BTC	0,0041771	0,71%	2	0,20%	0,51%	1,00513099	27001,96%
0,14%	50,00%	-0,86%	0,00%	-1,11%	0,00%	100,00%	LTC	0,0014412	DASH	0,0012774	0,14%	4	0,40%	-0,26%	0,997359336	26930,39%
-15,79%	0,00%	-6,00%	0,00%	-3,53%	50,00%	100,00%	DOGE	0,0009407	XRP	-0,0352576	-1,72%	4	0,40%	-2,12%	0,978841515	26358,47%

Figure 113: Dual momentum portfolio using random forest - part 8

1.6.3.3 Naive portfolio

	+2% winner & -2% loser																				sum of weights	asset	returns
	ADA		BNB		BTC		DASH		DOGE		ETH		LINK		LTC		XLM		XRP				
	Returns	Weight	Returns	Weight	Returns	Weight	Returns	Weight	Returns	Weight	Returns	Weight	Returns	Weight	Returns	Weight	Returns	Weight	Returns	Weight			
2021-10-04	-1.00%	8.00%	-0.29%	10.00%	-0.56%	10.00%	-0.77%	10.00%	-1.28%	8.00%	-0.42%	10.00%	1.31%	10.00%	-0.53%	10.00%	0.67%	12.00%	0.32%	10.00%	100.00%	LINK	0.013445
2021-11-08	0.63%	2.00%	1.37%	16.00%	0.83%	8.00%	2.37%	8.00%	1.14%	8.00%	0.46%	6.00%	2.64%	8.00%	0.05%	18.00%	2.97%	12.00%	0.98%	14.00%	100.00%	XRP	0.0478795

Figure 114: Naive portfolio using random forest - part 1

	2e MAX										Portfolio returns without transac. cost	Number of transactions	Transaction cost	Portfolio returns with transac. cost	1+	Cumulative return	
	asset	returns	asset	returns	asset	returns	asset	returns	asset	returns							
XLM	0.006681	ADA	-0.0158258	DOGE	-0.0128095	DASH	-0.0077019	BTC	-0.0056309	LTC	-0.0052459	-0.21%	4	0.4%	-0.61%	0.99	-0.61%
XLM	0.0264118	XLM	-0.0276745	LTC	0.0004953	ETH	0.0004479	BTC	0.0004479	BTC	0.0004479	1.6%	4	0.4%	0.7%	1.01	11.17%

Figure 115: Naive portfolio using random forest - part 2

2022-01-13	8,16%	4,38%	8,85%	-0,20%	-0,68%	2,38%	0,01%	4,49%	1,77%	13,13%	4,23%	4,24%
2022-01-14	-2,21%	1,35%	-8,84%	-0,02%	1,31%	0,86%	-6,62%	-3,06%	-2,45%	-11,58%	-3,13%	-2,94%
2022-01-15	2,26%	0,49%	1,19%	0,00%	12,86%	0,00%	-0,60%	7,84%	3,37%	-0,03%	2,74%	2,90%
2022-01-16	0,88%	-0,47%	-0,28%	0,00%	1,10%	-0,28%	0,35%	0,54%	-0,83%	5,07%	0,61%	0,56%
2022-01-17	7,85%	0,17%	0,59%	-6,58%	-6,25%	0,36%	-0,19%	0,82%	0,84%	0,00%	-0,24%	-0,26%
2022-01-18	16,47%	-1,54%	-0,64%	-0,15%	-5,43%	-0,24%	-2,22%	3,62%	-2,55%	-3,27%	0,40%	0,26%
2022-01-19	-10,65%	0,15%	0,17%	-6,36%	-1,48%	-3,61%	-8,40%	-6,85%	0,00%	0,00%	-3,70%	-3,41%
2022-01-20	-7,50%	-0,61%	0,19%	0,00%	0,00%	0,00%	-0,98%	-1,10%	-0,73%	0,00%	-1,07%	-1,03%
2022-01-21	-2,96%	-3,51%	-1,63%	-7,12%	0,00%	-0,12%	0,19%	-7,71%	-2,62%	0,00%	-2,55%	-2,36%
2022-01-22	-11,68%	-15,75%	-5,74%	-9,29%	0,85%	-13,75%	-19,19%	-9,25%	-12,91%	-13,45%	-11,02%	-10,66%
2022-01-23	2,43%	-3,90%	-5,10%	-8,00%	0,21%	-5,47%	-11,76%	-6,92%	-2,64%	-2,38%	-4,35%	-4,08%
2022-01-24	2,00%	-0,16%	-1,73%	-1,21%	-1,16%	7,42%	-2,04%	4,96%	2,34%	3,59%	1,40%	1,43%
2022-01-25	-0,19%	0,21%	0,71%	-4,56%	0,00%	-4,78%	-6,90%	-0,33%	0,00%	-2,31%	-1,82%	-1,66%
2022-01-26	-1,52%	3,83%	6,72%	-0,15%	0,72%	-2,79%	1,20%	-6,03%	0,36%	0,94%	0,33%	0,50%
2022-01-27	0,00%	-0,72%	-2,24%	-0,87%	-0,67%	2,22%	-3,74%	0,00%	0,00%	0,00%	-0,60%	-0,53%
2022-01-28	1,60%	3,43%	0,29%	0,36%	1,85%	-3,23%	-4,23%	0,00%	-0,36%	-3,22%	-0,35%	-0,24%
2022-01-29	0,22%	0,00%	0,54%	3,60%	-0,70%	5,64%	1,99%	7,78%	5,35%	1,86%	2,63%	2,48%
2022-01-30	-0,77%	-0,16%	-0,54%	0,45%	-1,83%	0,00%	0,00%	0,13%	4,23%	1,47%	0,30%	0,22%
2022-01-31	0,82%	-1,38%	0,34%	-2,58%	0,50%	0,00%	22,26%	0,00%	-1,95%	-3,70%	1,43%	1,10%
2022-02-01	-2,68%	-0,59%	1,37%	3,55%	0,50%	3,63%	-5,11%	-0,37%	0,00%	3,65%	0,40%	0,50%
2022-02-02	-1,76%	2,00%	-0,55%	-1,18%	-1,17%	4,33%	7,83%	0,52%	1,99%	-0,52%	1,15%	1,08%
2022-02-03	-3,95%	-4,05%	2,39%	-2,50%	1,87%	-5,60%	-11,02%	-6,92%	-1,95%	-3,73%	-3,55%	-3,21%
2022-02-04	2,70%	-2,71%	-3,14%	3,24%	0,00%	-1,13%	1,97%	6,08%	0,00%	0,47%	0,75%	0,46%
2022-02-05	1,22%	3,25%	7,77%	8,10%	-1,83%	15,89%	4,68%	5,01%	7,77%	10,12%	6,20%	6,20%
2022-02-06	-0,28%	2,90%	1,62%	0,60%	-0,21%	0,60%	9,49%	0,00%	2,67%	0,00%	1,74%	1,61%
2022-02-07	3,80%	4,25%	0,17%	3,29%	2,71%	0,87%	0,53%	3,49%	0,00%	3,35%	2,25%	2,20%
2022-02-08	-0,08%	8,09%	10,71%	8,42%	0,00%	2,76%	-0,62%	10,11%	2,50%	23,49%	6,54%	6,34%
2022-02-09	-2,20%	-4,44%	0,16%	-3,73%	0,00%	-0,84%	0,00%	-2,43%	-1,41%	6,09%	-0,88%	-0,87%
2022-02-10	2,13%	-0,30%	0,95%	0,29%	0,00%	-0,16%	-0,52%	4,71%	2,68%	-2,35%	0,74%	0,70%
2022-02-11	-1,32%	-2,44%	-1,77%	1,30%	0,00%	-4,70%	-7,64%	-3,16%	-1,91%	-3,62%	-2,53%	-2,45%
2022-02-12	-2,82%	0,20%	-8,78%	-6,89%	-1,48%	-2,11%	-10,02%	-4,92%	-4,11%	-12,01%	-5,29%	-5,01%
2022-02-13	-0,49%	0,19%	0,00%	-0,71%	0,00%	-1,15%	0,00%	-0,31%	-0,75%	12,57%	0,94%	0,83%
2022-02-14	0,10%	-1,44%	-0,54%	-0,62%	1,51%	-5,29%	-0,25%	0,00%	0,38%	0,00%	-0,62%	-0,69%
2022-02-15	0,72%	1,00%	0,27%	-0,11%	-1,48%	4,20%	0,63%	-1,97%	0,00%	0,00%	0,32%	0,40%
2022-02-16	-1,13%	6,98%	10,59%	2,58%	1,51%	8,20%	10,46%	5,77%	3,23%	4,39%	5,26%	5,30%
2022-02-17	-3,02%	-5,06%	-0,24%	4,99%	0,00%	-3,23%	0,24%	-3,36%	0,00%	-3,47%	-1,37%	-1,47%
2022-02-18	-3,99%	-10,03%	-11,28%	-6,43%	-1,48%	-7,70%	-8,87%	-8,97%	-7,82%	-11,81%	-7,84%	-7,74%
2022-02-19	-2,73%	-1,27%	-0,23%	1,25%	0,00%	-1,16%	-3,30%	-0,99%	-1,16%	3,28%	-0,63%	-0,63%
2022-02-20	0,00%	-3,09%	-0,65%	-1,32%	0,00%	0,00%	1,85%	-1,96%	-0,80%	8,83%	0,29%	0,20%
2022-02-21	0,00%	6,15%	-5,42%	-8,44%	0,00%	-6,08%	-4,79%	-0,82%	-6,78%	-8,79%	-3,50%	-3,31%
2022-02-22	-14,67%	-2,95%	-1,57%	-8,60%	0,67%	-1,18%	-2,15%	-5,82%	-2,64%	-9,66%	-4,86%	-4,53%
2022-02-23	3,93%	4,46%	0,27%	5,31%	-0,46%	3,67%	2,98%	0,00%	2,71%	6,09%	2,90%	2,79%
2022-02-24	-4,00%	-1,77%	0,26%	-1,35%	-0,50%	-7,58%	-4,92%	0,00%	-2,99%	-5,26%	-2,81%	-2,80%
2022-02-25	1,83%	-1,76%	-1,07%	-4,71%	1,18%	-0,56%	0,74%	0,00%	0,37%	0,00%	-0,40%	-0,35%
2022-02-26	2,34%	4,28%	5,35%	5,61%	-1,16%	9,60%	0,57%	6,20%	2,34%	7,24%	4,24%	4,24%
2022-02-27	0,00%	0,00%	1,59%	0,43%	0,00%	1,29%	0,58%	-5,83%	7,45%	0,00%	0,55%	0,66%
2022-02-28	-7,09%	-5,22%	-4,04%	-6,47%	0,00%	-3,59%	-0,90%	0,00%	-1,82%	-1,58%	-3,07%	-3,09%
2022-03-01	17,79%	6,61%	9,25%	13,61%	-0,68%	12,91%	5,85%	6,72%	4,82%	4,94%	8,18%	8,08%
2022-03-02	-2,16%	4,80%	10,60%	0,21%	-0,21%	3,13%	3,73%	0,00%	4,92%	-0,58%	2,44%	2,63%
2022-03-03	0,00%	3,47%	-0,22%	0,59%	1,19%	-0,70%	0,81%	-0,24%	-5,23%	-3,20%	-0,35%	-0,30%
2022-03-04	-13,78%	-1,92%	-8,42%	-3,17%	0,00%	-5,65%	-6,39%	0,18%	-1,95%	-1,03%	-4,21%	-4,26%
2022-03-05	-4,15%	-7,40%	-4,85%	-4,83%	0,67%	-10,08%	-0,28%	-13,64%	-6,91%	-3,49%	-5,49%	-5,45%

Figure 128: Equal weight and risk parity portfolios using gradient boosting regression - part 3

Covariance matrix										Risk parity																						
	1	2	3	4	5	6	7	8	9	10	Portfolio 3/10					Portfolio risk parity																
1	ADA	BNB	BTC	DASH	DOGE	ETH	LINK	LTC	XLM	XRP	Avg return	-0,21%	Avg return	-0,20%																		
2	ADA	0,2908	0,2413	0,3761	0,1477	0,1936	0,3408	0,4296	0,3185	0,2777	Volatility	0,0292169	Volatility	0,0283353																		
3	ADA	0,2413	0,2406	0,4552	0,2900	0,0845	0,2283	0,3214	0,2876	0,2522	0,3338	Sharpe ratio	-0,072419	Sharpe ratio	-0,070512																	
4	ADA	0,3761	0,3061	0,2900	0,8565	0,1626	0,2387	0,4163	0,5220	0,3512	0,4014																					
5	ADA	0,1477	0,1098	0,0845	0,1626	0,3709	-0,0056	0,1078	0,1206	0,1700	0,0699																					
6	ADA	0,1936	0,2044	0,2283	0,2387	-0,0056	0,5425	0,2341	0,2502	0,1926	0,2919																					
7	ADA	0,3408	0,3020	0,3214	0,4163	0,1078	0,2341	1,0093	0,4417	0,3619	0,2683																					
8	ADA	0,4296	0,3507	0,2876	0,5220	0,1206	0,2502	0,4417	0,8011	0,3394	0,3737																					
9	ADA	0,3185	0,2986	0,2522	0,3512	0,1700	0,1926	0,3619	0,3394	0,6053	0,2829																					
10	ADA	0,2777	0,3023	0,3338	0,4014	0,0699	0,2919	0,2683	0,3737	0,2829	0,8000																					
		Asset weights										Covariance weights										Risk contributions										
Portfolio	Ann Volatility	Ann Variance	ADA	BNB	BTC	DASH	DOGE	ETH	LINK	LTC	XLM	XRP	ADA	BNB	BTC	DASH	DOGE	ETH	LINK	LTC	XLM	XRP	ADA	BNB	BTC	DASH	DOGE	ETH	LINK	LTC	XLM	XRP
Equal-weight	0,558187359	0,311573	10%	10%	10%	10%	10%	10%	10%	10%	10%	10%	0,3413703	0,3058475	0,2758826	0,3920864	0,1337885	0,2370781	0,3824591	0,3916457	0,317281	0,3401921	10,96%	9,82%	8,79%	12,58%	4,25%	7,61%	12,28%	12,57%	10,18%	10,92%
Risk parity	0,541844589	0,293054	9,82%	10,85%	11,60%	8,33%	12,03%	11,80%	8,15%	8,44%	9,82%	9,16%	0,3305703	0,3015044	0,2701154	0,3720844	0,1357549	0,2367625	0,3601023	0,3722643	0,3088669	0,3295524	11,08%	11,17%	10,69%	10,57%	5,57%	9,54%	10,01%	10,72%	10,35%	10,30%
Solver	Risk parity	0,521260453	0,271712	9%	10%	11%	8%	18%	12%	8%	8%	9%	0,3142665	0,2852829	0,2570011	0,3560788	0,1502987	0,2240755	0,3436356	0,3529668	0,2980896	0,312162	Deviation	10,00%	10,00%	10,00%	10,00%	10,00%	10,00%	10,00%	10,00%	10,00%
	Number of assets	10																														
	Deviation from parity	0%																														
	Sum of weights	100%																														
	With gradient boosting regressor																															
	Returns for equal weight	-0,212%																														
	Returns for RP portfolio	-0,200%																														

Figure 129: Equal weight and risk parity portfolios using gradient boosting regression - part 4

2022-01-13	12.26%	0.56%	12.87%	0.19%	-0.68%	2.35%	0.35%	10.62%	4.04%	14.44%		5.70%	5.61%
2022-01-14	-3.38%	4.48%	-11.41%	-0.03%	2.02%	1.87%	-7.04%	-6.34%	-2.62%	-13.09%		-3.55%	-3.27%
2022-01-15	3.38%	0.31%	-0.06%	1.07%	1.15%	0.43%	0.39%	8.43%	1.79%	-0.72%		1.62%	1.49%
2022-01-16	0.20%	0.96%	0.25%	0.07%	2.72%	-0.37%	-0.01%	-0.82%	1.43%	3.05%		0.75%	0.79%
2022-01-17	7.68%	-0.08%	-0.05%	-5.07%	-0.58%	-0.02%	-0.55%	2.45%	-0.98%	0.83%		0.36%	0.39%
2022-01-18	17.36%	-0.13%	-0.15%	-1.67%	-1.34%	-0.50%	-0.83%	3.67%	-2.22%	-3.36%		1.08%	1.03%
2022-01-19	-11.19%	-0.46%	-0.10%	-4.03%	-3.61%	-2.35%	-10.89%	-7.81%	0.08%	-1.00%		-4.14%	-3.84%
2022-01-20	-5.97%	0.00%	0.04%	-1.45%	0.87%	-0.03%	0.99%	-2.47%	-3.71%	0.78%		-1.10%	-1.02%
2022-01-21	-4.74%	-5.19%	-1.13%	-6.66%	-0.35%	-0.17%	-1.28%	-5.67%	-3.68%	-0.48%		-2.94%	-2.77%
2022-01-22	-9.78%	-12.30%	-10.16%	-9.46%	-0.08%	-16.47%	-22.61%	-9.40%	-10.57%	-8.67%		-10.95%	-10.68%
2022-01-23	-0.62%	-2.53%	-1.70%	-7.54%	0.12%	-4.14%	-8.80%	-6.03%	-3.64%	-5.22%		-4.01%	-3.70%
2022-01-24	-2.53%	2.81%	0.76%	0.52%	2.26%	3.62%	4.82%	0.91%	5.71%	1.96%		1.96%	1.85%
2022-01-25	-0.70%	0.10%	5.31%	-7.32%	-1.38%	-1.12%	-5.06%	-0.38%	0.44%	-2.28%		-1.24%	-0.96%
2022-01-26	0.77%	1.22%	2.81%	-0.48%	-0.32%	1.38%	0.38%	-5.41%	-0.89%	1.10%		0.06%	0.21%
2022-01-27	-1.03%	-0.67%	-2.47%	-0.01%	-0.20%	-0.17%	-0.58%	0.72%	0.99%	0.76%		-0.27%	-0.33%
2022-01-28	0.20%	1.48%	-0.29%	-0.29%	0.01%	-2.36%	-2.19%	-0.22%	1.85%	-2.82%		-0.46%	-0.43%
2022-01-29	-0.11%	1.07%	0.62%	2.34%	0.75%	3.98%	2.81%	5.75%	0.46%	2.17%		1.98%	1.89%
2022-01-30	0.17%	-0.51%	0.08%	2.14%	-0.05%	-0.12%	0.36%	0.95%	7.15%	1.07%		1.12%	1.04%
2022-01-31	-0.12%	-1.82%	-1.02%	-4.56%	0.32%	0.01%	14.82%	-2.77%	-2.74%	-3.26%		-0.11%	-0.26%
2022-02-01	0.18%	-0.50%	0.14%	2.20%	0.34%	5.74%	-4.75%	1.48%	0.84%	2.27%		0.79%	0.91%
2022-02-02	1.50%	3.21%	1.40%	0.56%	0.13%	1.84%	0.61%	3.27%	2.37%	0.86%		1.58%	1.57%
2022-02-03	-1.03%	-3.62%	-2.00%	-3.68%	-0.09%	-1.72%	-9.31%	-8.19%	-1.91%	-3.54%		-3.51%	-3.21%
2022-02-04	0.73%	-3.31%	0.22%	5.52%	0.09%	-0.40%	-2.48%	6.90%	1.62%	0.54%		0.94%	0.75%
2022-02-05	0.08%	8.37%	7.03%	7.70%	1.53%	15.60%	13.35%	5.93%	4.34%	10.57%		7.45%	7.38%
2022-02-06	0.05%	1.45%	0.81%	2.14%	-0.44%	1.66%	4.65%	-1.08%	4.65%	0.20%		1.41%	1.34%
2022-02-07	2.15%	2.14%	0.95%	3.47%	1.81%	1.74%	3.21%	4.47%	-2.36%	-0.17%		1.74%	1.66%
2022-02-08	3.92%	4.77%	13.85%	8.90%	0.77%	-0.32%	-0.21%	10.37%	5.18%	23.81%		7.10%	6.85%
2022-02-09	-1.28%	-6.80%	-0.06%	-1.64%	0.52%	-0.09%	-0.63%	-4.67%	0.75%	6.70%		-0.72%	-0.71%
2022-02-10	0.33%	1.06%	-0.88%	-0.98%	-1.23%	3.22%	-0.46%	6.58%	2.17%	-2.66%		0.71%	0.68%
2022-02-11	-0.81%	-2.43%	-2.38%	-0.01%	-1.35%	-3.13%	-10.36%	-4.09%	-1.39%	-0.46%		-2.64%	-2.52%
2022-02-12	-1.85%	-0.24%	-5.71%	-9.83%	-0.93%	-5.99%	-7.39%	-4.83%	-9.33%	-15.30%		-6.14%	-5.84%
2022-02-13	0.64%	0.20%	0.18%	1.30%	0.24%	0.19%	-1.23%	2.58%	-0.98%	17.24%		2.04%	1.87%
2022-02-14	0.65%	-0.15%	-0.38%	-1.44%	1.70%	-2.16%	-0.08%	-1.87%	1.01%	0.43%		-0.23%	-0.19%
2022-02-15	-0.62%	-0.05%	-0.16%	2.29%	-1.82%	2.23%	-0.54%	-3.74%	-0.97%	-1.65%		-0.50%	-0.45%
2022-02-16	-0.22%	9.79%	8.20%	1.66%	1.93%	8.45%	11.64%	6.29%	6.92%	2.57%		5.72%	5.75%
2022-02-17	-1.06%	-5.13%	0.56%	6.35%	-0.12%	-1.98%	-0.64%	-1.78%	1.27%	0.84%		-0.17%	-0.31%
2022-02-18	0.57%	-4.85%	-10.57%	-8.36%	-2.69%	-8.38%	-9.44%	-11.25%	-9.21%	-14.98%		-7.92%	-7.70%
2022-02-19	-0.73%	-0.51%	-0.59%	-0.58%	0.05%	-2.49%	-0.73%	0.45%	-2.64%	5.11%		-0.26%	-0.34%
2022-02-20	-0.93%	-0.39%	-0.57%	-3.06%	0.05%	-0.49%	1.10%	0.11%	-0.89%	10.77%		0.57%	0.49%
2022-02-21	0.36%	-2.61%	-4.23%	-5.02%	-0.10%	-5.21%	-5.82%	-1.66%	-5.80%	-10.79%		-4.09%	-3.96%
2022-02-22	-20.79%	-3.24%	-2.26%	-14.81%	0.88%	-6.42%	-5.13%	-7.98%	-3.72%	-10.28%		-7.38%	-6.94%
2022-02-23	10.43%	2.72%	3.73%	12.84%	0.15%	4.32%	3.38%	-0.05%	0.29%	3.12%		4.09%	3.93%
2022-02-24	-9.00%	-0.87%	-1.04%	-1.04%	-0.69%	-4.54%	-3.68%	0.34%	2.92%	-4.13%		-2.35%	-2.31%
2022-02-25	-0.39%	-0.63%	-1.68%	-5.82%	-0.93%	-0.80%	0.60%	-0.71%	-1.42%	-0.84%		-1.26%	-1.22%
2022-02-26	11.72%	3.00%	0.14%	10.04%	0.17%	10.80%	2.28%	7.01%	1.42%	6.26%		5.28%	5.12%
2022-02-27	-1.59%	0.12%	1.30%	-2.53%	0.78%	3.04%	2.52%	-4.37%	10.56%	-0.76%		0.91%	1.05%
2022-02-28	-9.12%	-3.29%	-4.46%	-8.39%	-0.69%	-6.20%	-4.42%	-1.88%	-6.05%	-0.53%		-4.50%	-4.45%
2022-03-01	24.92%	7.24%	10.51%	19.00%	0.09%	9.99%	12.70%	8.84%	6.61%	5.14%		10.51%	10.13%
2022-03-02	-0.80%	2.92%	12.45%	-1.31%	0.14%	4.82%	0.82%	-0.11%	1.84%	1.53%		2.23%	2.54%
2022-03-03	1.01%	-0.33%	0.42%	-0.23%	0.04%	0.18%	-2.66%	-0.06%	-3.11%	-5.70%		-1.04%	-0.93%
2022-03-04	-11.91%	-0.66%	-9.48%	0.13%	0.12%	-5.46%	-6.11%	0.14%	-0.86%	-1.11%		-3.52%	-3.63%
2022-03-05	-11.88%	-6.01%	-5.05%	-7.78%	0.09%	-12.66%	-4.33%	-15.79%	-6.00%	-3.53%		-7.29%	-7.13%

Figure 132: Equal weight and risk parity portfolios using random forest - part 3

Covariance matrix														Risk parity																							
	1	2	3	4	5	6	7	8	9	10	Portfolio 1/10							Portfolio risk parity																			
	ADA	BNB	BTC	DASH	DOGE	ETH	LINK	LTC	XLM	XRP	Avg return	Volatility	Sharpe ratio	Avg return	Volatility	Sharpe ratio	Risk contributions																				
1	ADA	1.1845	0.4556	0.3759	0.5588	0.1201	0.2729	0.4555	0.6290	0.4246	0.4299	0.4906887	0.3604251	0.3270482	0.4779039	0.1023332	0.2514778	0.463762	0.5135858	0.4053027	0.4542716	12.82%	9.42%	8.85%	12.49%	2.67%	6.57%	12.12%	13.42%	10.59%	11.35%						
2	BNB	0.4556	0.6812	0.3010	0.3766	0.0559	0.2252	0.4419	0.4155	0.3739	0.2776	0.473866	0.3514565	0.3214443	0.4504902	0.1010836	0.2471022	0.4382609	0.4862915	0.3917306	0.4157001	13.15%	10.77%	10.53%	10.60%	3.43%	6.24%	10.08%	11.59%	10.86%	10.75%						
3	BTC	0.3759	0.3010	0.5134	0.3137	0.0558	0.2391	0.3167	0.3920	0.3341	0.4186																										
4	DASH	0.5588	0.3766	0.3137	0.2421	0.1365	0.2862	0.5395	0.3350	0.4297	0.5181																										
5	DOGE	0.1201	0.0559	0.0658	0.1066	0.1846	0.0197	0.0990	0.1238	0.1218	0.1202																										
6	ETH	0.2729	0.2252	0.2391	0.2862	0.0257	0.4016	0.3364	0.2629	0.2320	0.2429																										
7	LINK	0.4555	0.4419	0.3167	0.5295	0.0990	0.3264	1.0765	0.5515	0.4639	0.3767																										
8	LTC	0.6290	0.4155	0.3920	0.8338	0.1238	0.2629	0.5315	1.0885	0.4802	0.5769																										
9	XLM	0.4246	0.3739	0.3341	0.4297	0.1218	0.2320	0.4639	0.4802	0.6021	0.3890																										
10	XRP	0.4299	0.2776	0.4186	0.5181	0.1202	0.2429	0.3767	0.5768	0.3890	0.9928																										
Asset weights	ADA	BNB	BTC	DASH	DOGE	ETH	LINK	LTC	XLM	XRP	Covariance * weights							Risk contributions																			
Equal-weight	10%	10%	10%	10%	10%	10%	10%	10%	10%	10%	0.4906887	0.3604251	0.3270482	0.4779039	0.1023332	0.2514778	0.463762	0.5135858	0.4053027	0.4542716	12.82%	9.42%	8.85%	12.49%	2.67%	6.57%	12.12%	13.42%	10.59%	11.35%							
Risk parity	7%	9%	10%	7%	25%	13%	7%	7%	8%	8%	0.4048369	0.3025718	0.2801177	0.39216192	0.1108917	0.2183095	0.3858888	0.4211856	0.3445442	0.3652194	10.00%	10.00%	10.00%	10.00%	10.00%	10.00%	10.00%	10.00%	10.00%	10.00%	10.00%	10.00%	10.00%	10.00%	10.00%	10.00%	10.00%
Solver	Number of assets	10	Deviation from parity	0%	Sum of weights	100%	With random forest																														
Returns for equal weight	-0.192%	Returns for RP portfolio	-0.180%	Deviation																																	

Figure 133: Equal weight and risk parity portfolios using random forest - part 4