Group9_Notebook

December 10, 2023

[ ]:
```
# import warnings
# warnings.filterwarnings("ignore", category=SettingWithCopyWarning)
import os
import pandas as pd
pd.options.mode.chained_assignment = None
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import TimeSeriesSplit, GridSearchCV,␣
 ↪train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import mean_absolute_error
from sklearn.linear_model import LinearRegression
from sklearn.svm import SVR
from catboost import CatBoostRegressor
from sklearn.neural_network import MLPRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.pipeline import Pipeline
import xgboost as xgb
from pmdarima import auto_arima
import joblib
```

[ ]:
```
#df =pd.read_csv("drive/My Drive/Optiver_Data/train.csv")
df = pd.read_csv('train.csv')
```

[ ]:
```
df
```

[ ]:
```
         stock_id  date_id  seconds_in_bucket  imbalance_size  \
0               0        0                  0      3180602.69
1               1        0                  0       166603.91
2               2        0                  0       302879.87
3               3        0                  0     11917682.27
4               4        0                  0       447549.96
…             …       …                  …             …
5237975       195      480                540      2440722.89
5237976       196      480                540       349510.47
5237977       197      480                540            0.00
```

```
5237978       198      480                540      1000898.84
5237979       199      480                540      1884285.71

         imbalance_buy_sell_flag  reference_price  matched_size  far_price  \
0                              1         0.999812   13380276.64        NaN
1                             -1         0.999896    1642214.25        NaN
2                             -1         0.999561    1819368.03        NaN
3                             -1         1.000171   18389745.62        NaN
4                             -1         0.999532   17860614.95        NaN
…                            …              …            …          …
5237975                       -1         1.000317   28280361.74   0.999734
5237976                       -1         1.000643    9187699.11   1.000129
5237977                        0         0.995789   12725436.10   0.995789
5237978                        1         0.999210   94773271.05   0.999210
5237979                       -1         1.002129   24073677.32   1.000859

         near_price  bid_price   bid_size  ask_price   ask_size       wap  \
0               NaN   0.999812   60651.50   1.000026    8493.03  1.000000
1               NaN   0.999896    3233.04   1.000660   20605.09  1.000000
2               NaN   0.999403   37956.00   1.000298   18995.00  1.000000
3               NaN   0.999999    2324.90   1.000214  479032.40  1.000000
4               NaN   0.999394   16485.54   1.000016     434.10  1.000000
…              …          …          …         …          …        …
5237975    0.999734   1.000317   32257.04   1.000434  319862.40  1.000328
5237976    1.000386   1.000643  205108.40   1.000900   93393.07  1.000819
5237977    0.995789   0.995789   16790.66   0.995883  180038.32  0.995797
5237978    0.999210   0.998970  125631.72   0.999210  669893.00  0.999008
5237979    1.001494   1.002129  250081.44   1.002447  300167.56  1.002274

           target  time_id       row_id
0       -3.029704        0        0_0_0
1       -5.519986        0        0_0_1
2       -8.389950        0        0_0_2
3       -4.010200        0        0_0_3
4       -7.349849        0        0_0_4
…             …       …            …
5237975  2.310276    26454  480_540_195
5237976 -8.220077    26454  480_540_196
5237977  1.169443    26454  480_540_197
5237978 -1.540184    26454  480_540_198
5237979 -6.530285    26454  480_540_199

[5237980 rows x 17 columns]
```

[ ]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5237980 entries, 0 to 5237979
```

```
Data columns (total 17 columns):
 #   Column                   Dtype  
---  ------                   -----  
 0   stock_id                 int64  
 1   date_id                  int64  
 2   seconds_in_bucket        int64  
 3   imbalance_size           float64
 4   imbalance_buy_sell_flag  int64  
 5   reference_price          float64
 6   matched_size             float64
 7   far_price                float64
 8   near_price               float64
 9   bid_price                float64
 10  bid_size                 float64
 11  ask_price                float64
 12  ask_size                 float64
 13  wap                      float64
 14  target                   float64
 15  time_id                  int64  
 16  row_id                   object 
dtypes: float64(11), int64(5), object(1)
memory usage: 679.4+ MB
```

Features Description:

stock_id - A unique identifier for the stock. Not all stock IDs exist in every time bucket.

date_id - A unique identifier for the date. Date IDs are sequential & consistent across all stocks.

imbalance_size - The amount unmatched at the current reference price (in USD).

imbalance_buy_sell_flag - An indicator reflecting the direction of auction imbalance.

```
buy-side imbalance; 1
sell-side imbalance; -1
no imbalance; 0
```

reference_price - The price at which paired shares are maximized, the imbalance is minimized and the distance from the bid-ask midpoint is minimized, in that order. Can also be thought of as being equal to the near price bounded between the best bid and ask price.

matched_size - The amount that can be matched at the current reference price (in USD).

far_price - The crossing price that will maximize the number of shares matched based on auction interest only. This calculation excludes continuous market orders.

near_price - The crossing price that will maximize the number of shares matched based auction and continuous market orders.

[bid/ask]_price - Price of the most competitive buy/sell level in the non-auction book.

[bid/ask]_size - The dollar notional amount on the most competitive buy/sell level in the non-auction book.

wap - The weighted average price in the non-auction book.

seconds_in_bucket - The number of seconds elapsed since the beginning of the day's closing auction, always starting from 0.

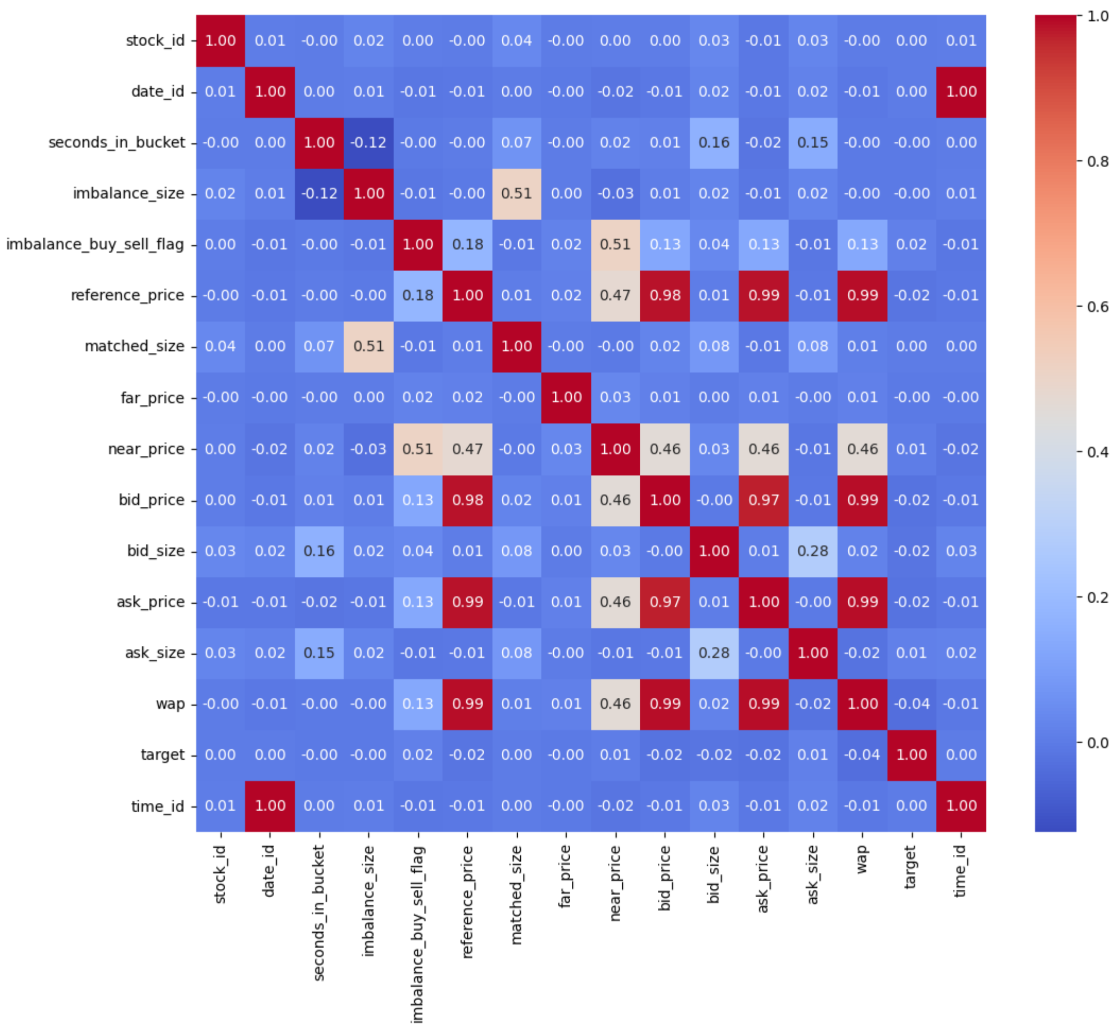
target - The 60 second future move in the wap of the stock, less the 60 second future move of the synthetic index. Only provided for the train set.

[ ]:
```
df.describe()
```

[ ]:
```
           stock_id       date_id  seconds_in_bucket  imbalance_size  \
count  5.237980e+06  5.237980e+06       5.237980e+06    5.237760e+06
mean   9.928856e+01  2.415100e+02       2.700000e+02    5.715293e+06
std    5.787176e+01  1.385319e+02       1.587451e+02    2.051591e+07
min    0.000000e+00  0.000000e+00       0.000000e+00    0.000000e+00
25%    4.900000e+01  1.220000e+02       1.300000e+02    8.453415e+04
50%    9.900000e+01  2.420000e+02       2.700000e+02    1.113604e+06
75%    1.490000e+02  3.610000e+02       4.100000e+02    4.190951e+06
max    1.990000e+02  4.800000e+02       5.400000e+02    2.982028e+09

       imbalance_buy_sell_flag  reference_price  matched_size     far_price  \
count             5.237980e+06     5.237760e+06  5.237760e+06  2.343638e+06
mean             -1.189619e-02     9.999955e-01  4.510025e+07  1.001713e+00
std               8.853374e-01     2.532497e-03  1.398413e+08  7.214705e-01
min              -1.000000e+00     9.352850e-01  4.316610e+03  7.700000e-05
25%              -1.000000e+00     9.987630e-01  5.279575e+06  9.963320e-01
50%               0.000000e+00     9.999670e-01  1.288264e+07  9.998830e-01
75%               1.000000e+00     1.001174e+00  3.270013e+07  1.003318e+00
max               1.000000e+00     1.077488e+00  7.713682e+09  4.379531e+02

         near_price     bid_price      bid_size     ask_price      ask_size  \
count  2.380800e+06  5.237760e+06  5.237980e+06  5.237760e+06  5.237980e+06
mean   9.996601e-01  9.997263e-01  5.181359e+04  1.000264e+00  5.357568e+04
std    1.216920e-02  2.499345e-03  1.114214e+05  2.510042e-03  1.293554e+05
min    7.869880e-01  9.349150e-01  0.000000e+00  9.398270e-01  0.000000e+00
25%    9.971000e-01  9.985290e-01  7.374720e+03  9.990290e-01  7.823700e+03
50%    9.998890e-01  9.997280e-01  2.196900e+04  1.000207e+00  2.301792e+04
75%    1.002590e+00  1.000905e+00  5.583168e+04  1.001414e+00  5.787841e+04
max    1.309732e+00  1.077488e+00  3.028784e+07  1.077836e+00  5.440500e+07

                wap        target       time_id
count  5.237760e+06  5.237892e+06  5.237980e+06
mean   9.999920e-01 -4.756125e-02  1.331005e+04
std    2.497509e-03  9.452860e+00  7.619271e+03
min    9.380080e-01 -3.852898e+02  0.000000e+00
25%    9.987810e-01 -4.559755e+00  6.729000e+03
50%    9.999970e-01 -6.020069e-02  1.334500e+04
75%    1.001149e+00  4.409552e+00  1.990700e+04
```

```
max     1.077675e+00  4.460704e+02  2.645400e+04
```

[ ]:
```python
df_corr = df.drop('row_id', axis=1)
correlation_matrix = df_corr.corr()
plt.figure(figsize=(12, 10))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f")
# plt.show()
plt.savefig('heatmap.png')
```



Also, `time_id` is highly correlated to `date_id`. Therefore we can drop `time_id`

[ ]:
```python
stocks = df['stock_id'].sort_values(ascending=True).unique()
stocks
```

```
[ ]: array([  0,   1,   2,   3,   4,   5,   6,   7,   8,   9,  10,  11,  12,
        13,  14,  15,  16,  17,  18,  19,  20,  21,  22,  23,  24,  25,
        26,  27,  28,  29,  30,  31,  32,  33,  34,  35,  36,  37,  38,
        39,  40,  41,  42,  43,  44,  45,  46,  47,  48,  49,  50,  51,
        52,  53,  54,  55,  56,  57,  58,  59,  60,  61,  62,  63,  64,
        65,  66,  67,  68,  69,  70,  71,  72,  73,  74,  75,  76,  77,
        78,  79,  80,  81,  82,  83,  84,  85,  86,  87,  88,  89,  90,
        91,  92,  93,  94,  95,  96,  97,  98,  99, 100, 101, 102, 103,
       104, 105, 106, 107, 108, 109, 110, 111, 112, 113, 114, 115, 116,
       117, 118, 119, 120, 121, 122, 123, 124, 125, 126, 127, 128, 129,
       130, 131, 132, 133, 134, 135, 136, 137, 138, 139, 140, 141, 142,
       143, 144, 145, 146, 147, 148, 149, 150, 151, 152, 153, 154, 155,
       156, 157, 158, 159, 160, 161, 162, 163, 164, 165, 166, 167, 168,
       169, 170, 171, 172, 173, 174, 175, 176, 177, 178, 179, 180, 181,
       182, 183, 184, 185, 186, 187, 188, 189, 190, 191, 192, 193, 194,
       195, 196, 197, 198, 199], dtype=int64)
```

there are a total of 200 stocks

```
[ ]: records_per_stock = pd.DataFrame(df['stock_id'].value_counts().
      ↪sort_index(ascending=True)).reset_index()
     records_per_stock.columns = ['stock_id','count']
     print(records_per_stock)
```

```
     stock_id  count
0           0  26455
1           1  26455
2           2  26455
3           3  26455
4           4  26455
..        …      …
195       195  26455
196       196  26455
197       197  26455
198       198  26455
199       199  21615

[200 rows x 2 columns]
```

```
[ ]: pd.DataFrame(df.groupby('stock_id')['date_id'].value_counts())
```

```
[ ]:                    count
     stock_id date_id
     0        0           55
              1           55
              244         55
              253         55
              252         55
```

```
…                 …
199       231           55
          230           55
          229           55
          228           55
          480           55

[95236 rows x 1 columns]
```

There are total of 481 dates with almost all have around 55 records or instances.

```
[ ]: df.groupby('stock_id')['date_id'].nunique().value_counts()
```

```
[ ]: date_id
481    189
444      2
480      2
477      1
300      1
186      1
290      1
422      1
411      1
393      1
Name: count, dtype: int64
```

among which, 189 stocks have 481 date_ids and the rest of the stocks have lesser than 381 stocks.

```
[ ]: date_counts = df.groupby(['stock_id', 'date_id']).size().
      ↪reset_index(name='count')

     max_date_counts_per_stock = date_counts['count'].max()
     min_date_counts_per_stock = date_counts['count'].min()

     print(max_date_counts_per_stock, min_date_counts_per_stock)
```

```
55 55
```

Lets Consider a small sample of the data to visualize

```
[ ]: df_stock_id_1 = df[df['stock_id'] == 1].iloc[:2000,:].reset_index()
     df_stock_id_1
```

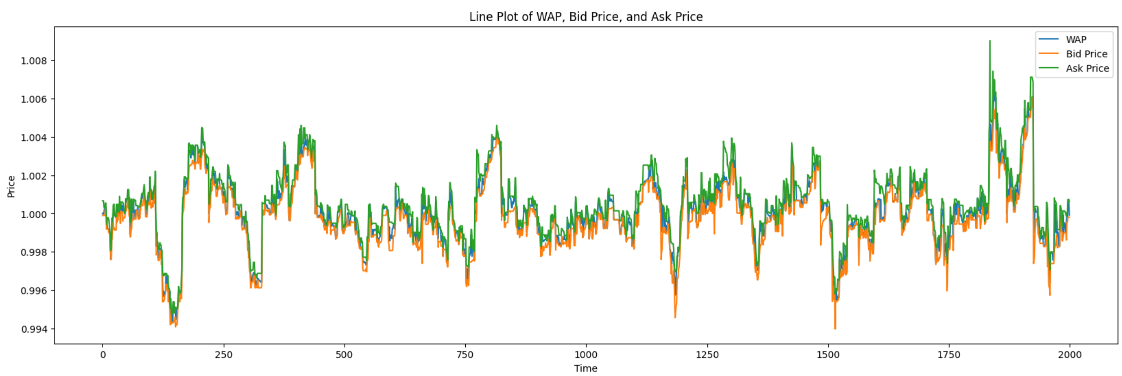
```
[ ]:        index  stock_id  date_id  seconds_in_bucket  imbalance_size  \
     0          1         1        0                  0       166603.91
     1        192         1        0                 10       165923.20
     2        383         1        0                 20       165923.20
     3        574         1        0                 30       165923.20
     4        765         1        0                 40       162349.47
```

```
…      …        …      …              …         …
1995  382821        1      36             150      811540.95
1996  383013        1      36             160      774266.90
1997  383205        1      36             170      754338.20
1998  383397        1      36             180      630521.93
1999  383589        1      36             190      622956.40

      imbalance_buy_sell_flag  reference_price  matched_size  far_price  \
0                          -1         0.999896    1642214.25        NaN
1                          -1         0.999955    1642894.96        NaN
2                          -1         0.999955    1642894.96        NaN
3                          -1         0.999896    1642894.96        NaN
4                          -1         0.999955    1646468.69        NaN
…                       …              …             …         …
1995                       -1         0.999539    1778082.90        NaN
1996                       -1         0.999919    1815356.95        NaN
1997                       -1         1.000379    1835285.65        NaN
1998                       -1         0.999919    1968881.75        NaN
1999                       -1         0.999810    1976447.28        NaN

      near_price  bid_price  bid_size  ask_price  ask_size       wap  \
0            NaN   0.999896   3233.04   1.000660  20605.09  1.000000
1            NaN   0.999896   3743.52   1.000660  33717.42  0.999973
2            NaN   0.999896   3743.52   1.000660  33717.42  0.999973
3            NaN   0.999896   4254.00   1.000308   3574.83  1.000120
4            NaN   0.999896  21270.00   1.000308   3574.83  1.000248
…          …         …         …        …         …        …
1995         NaN   0.999539    184.44   1.000027    922.65  0.999621
1996         NaN   0.999810   2582.86   1.000732    738.64  1.000527
1997         NaN   0.999810   9040.01   1.000732    738.64  1.000662
1998         NaN   0.999810  18449.00   1.000732   4431.84  1.000553
1999         NaN   0.999810    553.47   1.000623   3692.80  0.999916

        target  time_id    row_id
0    -5.519986        0     0_0_1
1    -1.620054        1    0_10_1
2    -6.459951        2    0_20_1
3    -5.149841        3    0_30_1
4    -6.750226        4    0_40_1
…          …       …        …
1995  0.330210     1995  36_150_1
1996 -5.639792     1996  36_160_1
1997 -5.850196     1997  36_170_1
1998  1.280308     1998  36_180_1
1999 -0.900030     1999  36_190_1

[2000 rows x 18 columns]
```

1 wap - Weighted Average Price

[ ]:
```
# df_long = pd.melt(df[['wap','bid_price','ask_price']], var_name='price type',␣
↪value_name='Price')

plt.figure(figsize=(20, 6))
sns.lineplot(x=df_stock_id_1['time_id'], y='wap',␣
↪data=df_stock_id_1,label='WAP')
sns.lineplot(x=df_stock_id_1['time_id'], y='bid_price', data =␣
↪df_stock_id_1,label='Bid Price')
sns.lineplot(x=df_stock_id_1['time_id'], y='ask_price',␣
↪data=df_stock_id_1,label='Ask Price')
plt.xlabel('Time')
plt.ylabel('Price')
plt.legend()
plt.title('Line Plot of WAP, Bid Price, and Ask Price')
```

[ ]:
```
Text(0.5, 1.0, 'Line Plot of WAP, Bid Price, and Ask Price')
```



As we can see, the bid_price, ask_price and wap follow the same pattern. That is because as provided with the feature description

WAP =(BidPrice$AskSize + AskPrice$ BidSize) / AskSize + BidSize

The higher the bid size,i.e. more buyers, the higher would be the MAP value

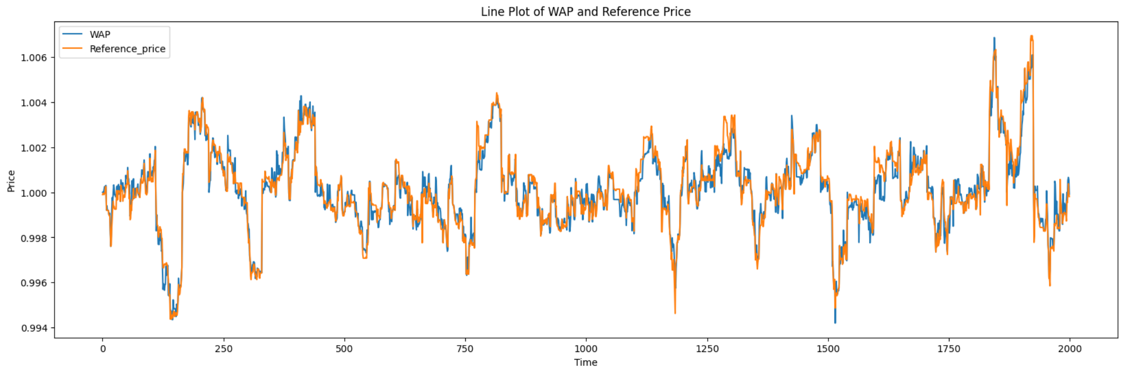
The higher be the ask size, i.e more sellers, the lower would be the MAP value

2 reference_price

The price at which paired shares are maximized, the imbalance is minimized and the distance from the bid-ask midpoint is minimized, in that order. Can also be thought of as being equal to the near price bounded between the best bid and ask price.

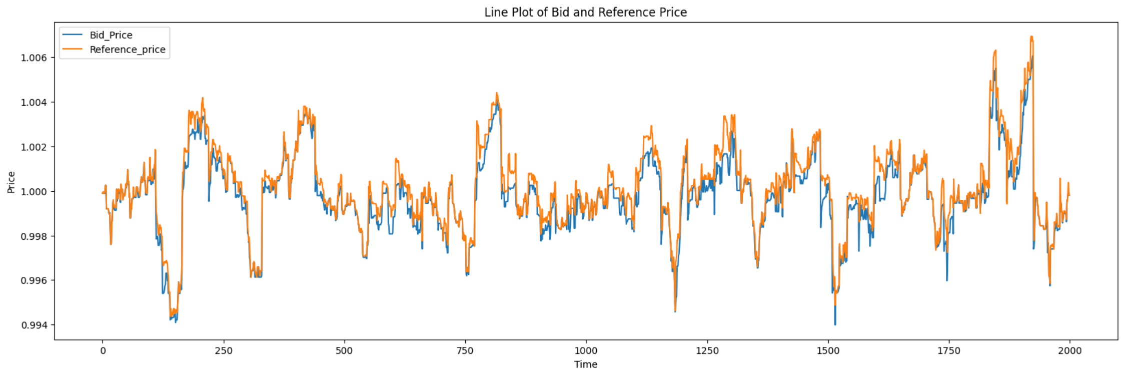
[ ]:
```
plt.figure(figsize=(20, 6))
sns.lineplot(x=df_stock_id_1['time_id'], y='wap',␣
 ↪data=df_stock_id_1,label='WAP')
sns.lineplot(x=df_stock_id_1['time_id'], y='reference_price', data =␣
 ↪df_stock_id_1,label='Reference_price')
plt.xlabel('Time')
plt.ylabel('Price')
plt.legend()
plt.title('Line Plot of WAP and Reference Price')
```

[ ]:
```
Text(0.5, 1.0, 'Line Plot of WAP and Reference Price')
```



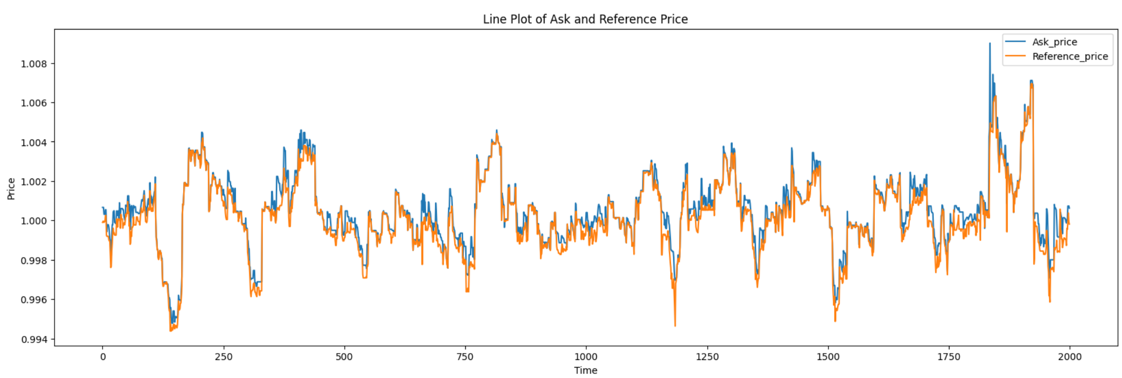
[ ]:
```
plt.figure(figsize=(20, 6))
sns.lineplot(x=df_stock_id_1['time_id'], y='bid_price',␣
 ↪data=df_stock_id_1,label='Bid_Price')
sns.lineplot(x=df_stock_id_1['time_id'], y='reference_price', data =␣
 ↪df_stock_id_1,label='Reference_price')
plt.xlabel('Time')
plt.ylabel('Price')
plt.legend()
plt.title('Line Plot of Bid and Reference Price')
```

[ ]:
```
Text(0.5, 1.0, 'Line Plot of Bid and Reference Price')
```




```
[ ]: plt.figure(figsize=(20, 6))
     sns.lineplot(x=df_stock_id_1['time_id'], y='ask_price',␣
      ↪data=df_stock_id_1,label='Ask_price')
     sns.lineplot(x=df_stock_id_1['time_id'], y='reference_price', data =␣
      ↪df_stock_id_1,label='Reference_price')
     plt.xlabel('Time')
     plt.ylabel('Price')
     plt.legend()
     plt.title('Line Plot of Ask and Reference Price')
```

```
[ ]: Text(0.5, 1.0, 'Line Plot of Ask and Reference Price')
```



From the graphs, we can see that there is a pattern between the ask price, near price

Also, from the correlation matrix, AskPrice, BidPrice and reference_price are highly correlated so, we can actually loose the AskPrice, BidPrice and reference_price for training and just use WAP

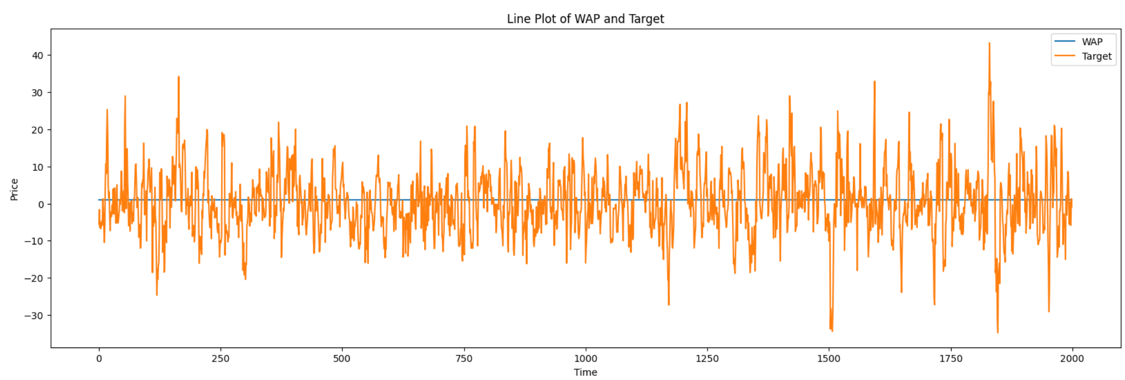
3 Target

The 60 second future move in the wap of the stock, minus the 60 second future move of the synthetic index. Only provided for the train set.

The synthetic index is a custom weighted index of Nasdaq-listed stocks constructed by Optiver for this competition.

[ ]:
```
plt.figure(figsize=(20, 6))
sns.lineplot(x=df_stock_id_1['time_id'], y='wap',␣
 ↪data=df_stock_id_1,label='WAP')
sns.lineplot(x=df_stock_id_1['time_id'], y='target', data =␣
 ↪df_stock_id_1,label='Target')
plt.xlabel('Time')
plt.ylabel('Price')
plt.legend()
plt.title('Line Plot of WAP and Target')
```

[ ]:
```
Text(0.5, 1.0, 'Line Plot of WAP and Target')
```



From the description of target variable, we can understand that the wap has significance over the target variable.

And basically, the current target is dependent on the future WAP value. Therefore, the previous target variable can be used as the feature to predict the current target when solving it as a timeseries problem.

4 Far Price and Near Price

When the continuous market orders are not considered, the `Far Price` is the price which results in the maximum number of matched shares based solely on the existing auction interest in the order book.

On the other hand, `Near Price` maximizes the number of shares based on both action interest and continuous market orders. This information is provided by Nasdaq 5 minutes before the closing cross.

Value of the reference price can be defined by the near price value:

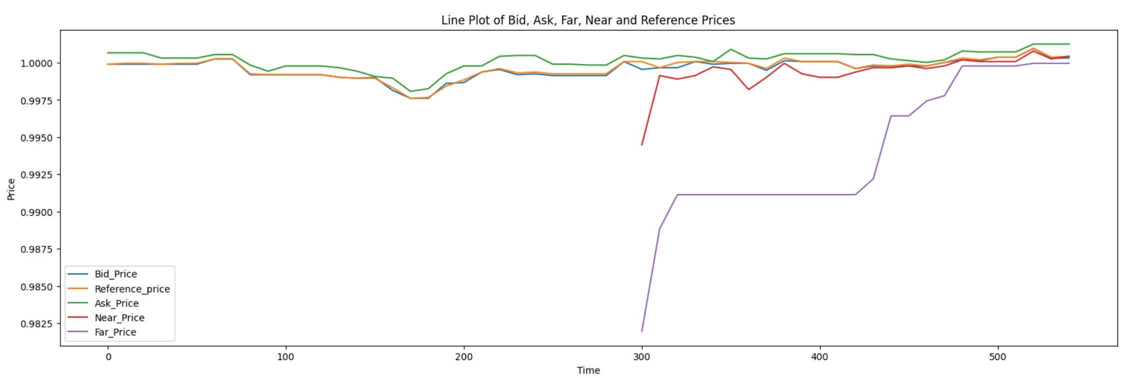
If Near Price lies between the ask price and bid price, the reference price would be close to the Near Price.

If Near Price is more than best ask price, reference price is set to the best ask

If Near Price is less than the best bid, reference price is set to the bid

[ ]:
```
## checking the relation of ask_price, bid_price, reference_price, near_price
↪and far_price
## on a particular day, as the far_price, near_price change on each day for
↪each seconds_in_bucket
df_stock_id_1_date_id_0 = df_stock_id_1[df_stock_id_1['date_id']==0]

plt.figure(figsize=(20, 6))
sns.lineplot(x=df_stock_id_1_date_id_0['seconds_in_bucket'], y='bid_price',
↪data=df_stock_id_1_date_id_0,label='Bid_Price')
sns.lineplot(x=df_stock_id_1_date_id_0['seconds_in_bucket'],
↪y='reference_price', data = df_stock_id_1_date_id_0,label='Reference_price')
sns.lineplot(x=df_stock_id_1_date_id_0['seconds_in_bucket'], y='ask_price',
↪data=df_stock_id_1_date_id_0,label='Ask_Price')
sns.lineplot(x=df_stock_id_1_date_id_0['seconds_in_bucket'], y='near_price',
↪data=df_stock_id_1_date_id_0,label='Near_Price')
sns.lineplot(x=df_stock_id_1_date_id_0['seconds_in_bucket'], y='far_price',
↪data=df_stock_id_1_date_id_0,label='Far_Price')
plt.xlabel('Time')
plt.ylabel('Price')
plt.legend()
plt.title('Line Plot of Bid, Ask, Far, Near and Reference Prices')
```

[ ]:
```
Text(0.5, 1.0, 'Line Plot of Bid, Ask, Far, Near and Reference Prices')
```

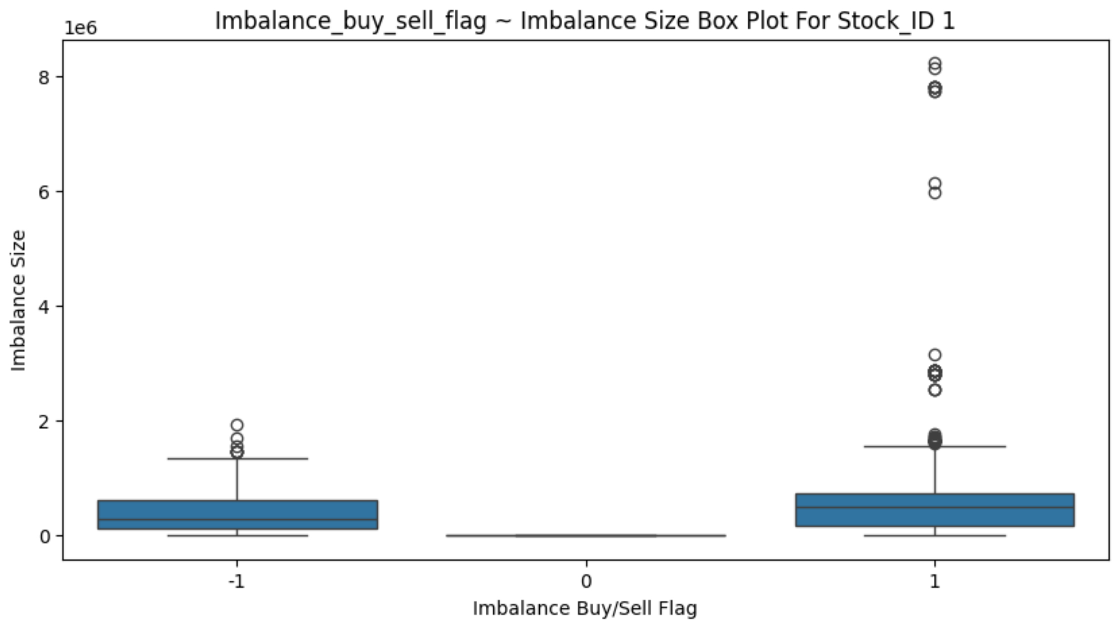


5 imbalance_size and imbalance_buy_sell_flag

Imbalance_size denotes the number of unmatched shares at the reference price and buy/sell flag indicates the direction of the market for the particular stock. Whether is towards buying side or towards selling size.

[ ]:
```
plt.figure(figsize=(10,5))
sns.boxplot(x='imbalance_buy_sell_flag', y = 'imbalance_size', data =␣
 ↪df_stock_id_1 )
plt.xlabel('Imbalance Buy/Sell Flag')
plt.ylabel('Imbalance Size')
plt.title('Imbalance_buy_sell_flag ~ Imbalance Size Box Plot For Stock_ID 1')
```

[ ]:
```
Text(0.5, 1.0, 'Imbalance_buy_sell_flag ~ Imbalance Size Box Plot For Stock_ID
1')
```

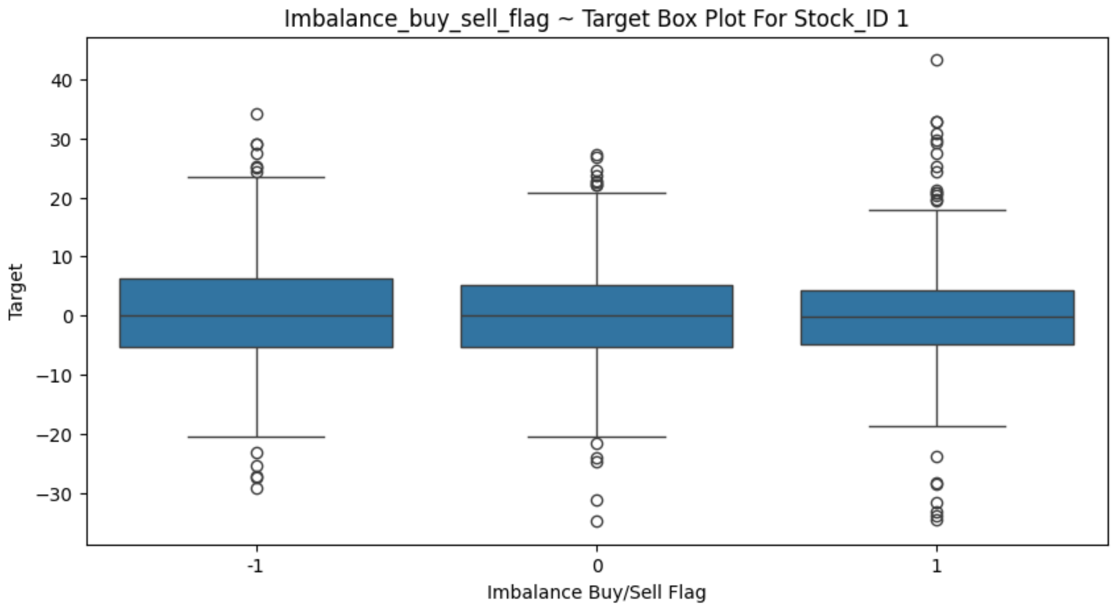


based on the box plot, both -1 and +1 flags have comparably close imbalance sizes but more that 0 flag have very less values - can be zero too.

and also have outliers

[ ]:
```
plt.figure(figsize=(10,5))
sns.boxplot(x='imbalance_buy_sell_flag', y = 'target', data = df_stock_id_1 )
plt.xlabel('Imbalance Buy/Sell Flag')
plt.ylabel('Target')
plt.title('Imbalance_buy_sell_flag ~ Target Box Plot For Stock_ID 1')
```

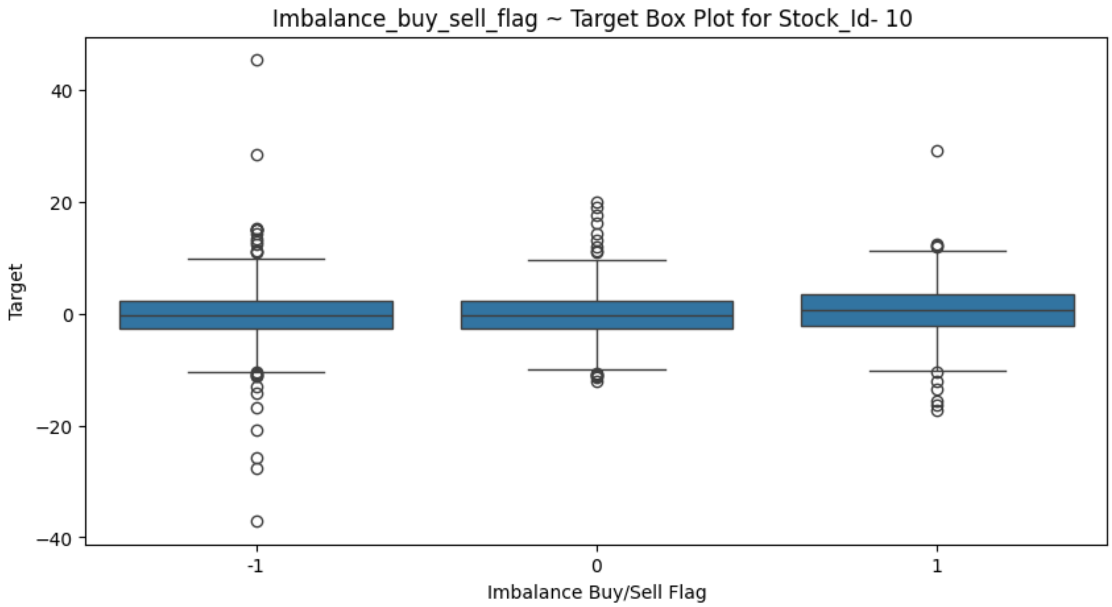
[ ]:
```
Text(0.5, 1.0, 'Imbalance_buy_sell_flag ~ Target Box Plot For Stock_ID 1')
```



For each of the flags, the median target is 0 and the distribution is also similar. Lets check the same with other stock _id

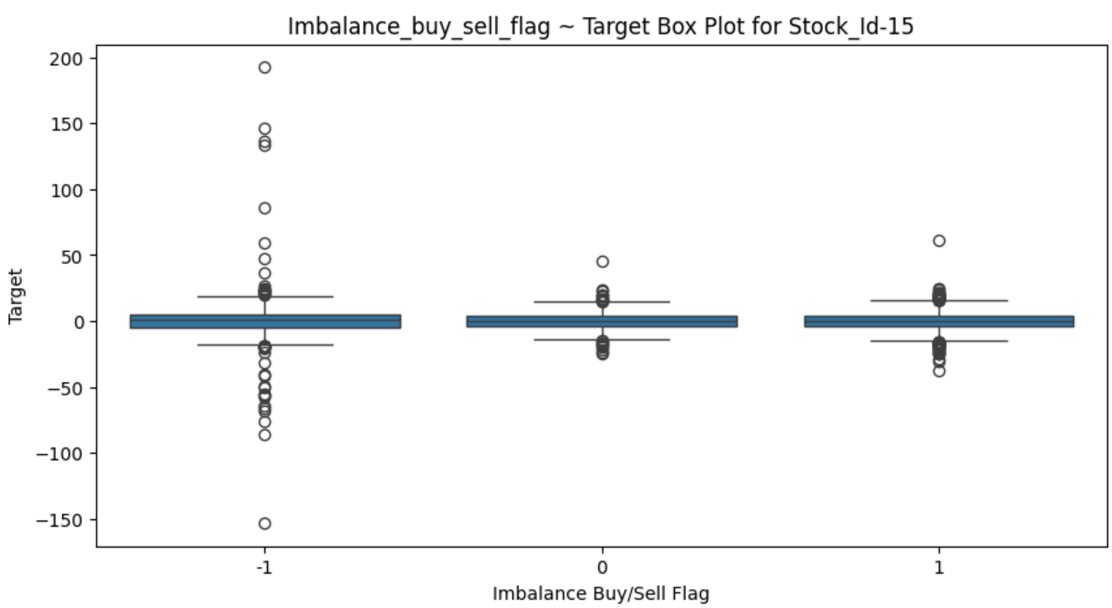
[ ]:
```
df_stock_id_10 = df[df['stock_id'] == 10].iloc[:2000,:].reset_index()

plt.figure(figsize=(10,5))
sns.boxplot(x='imbalance_buy_sell_flag', y = 'target', data = df_stock_id_10 )
plt.xlabel('Imbalance Buy/Sell Flag')
plt.ylabel('Target')
plt.title('Imbalance_buy_sell_flag ~ Target Box Plot for Stock_Id- 10 ')
```

[ ]:
```
Text(0.5, 1.0, 'Imbalance_buy_sell_flag ~ Target Box Plot for Stock_Id- 10 ')
```




```
[ ]: df_stock_id_15 = df[df['stock_id'] == 15].iloc[:2000,:].reset_index()

     plt.figure(figsize=(10,5))
     sns.boxplot(x='imbalance_buy_sell_flag', y = 'target', data = df_stock_id_15 )
     plt.xlabel('Imbalance Buy/Sell Flag')
     plt.ylabel('Target')
     plt.title('Imbalance_buy_sell_flag ~ Target Box Plot for Stock_Id-15')
```

```
[ ]: Text(0.5, 1.0, 'Imbalance_buy_sell_flag ~ Target Box Plot for Stock_Id-15')
```



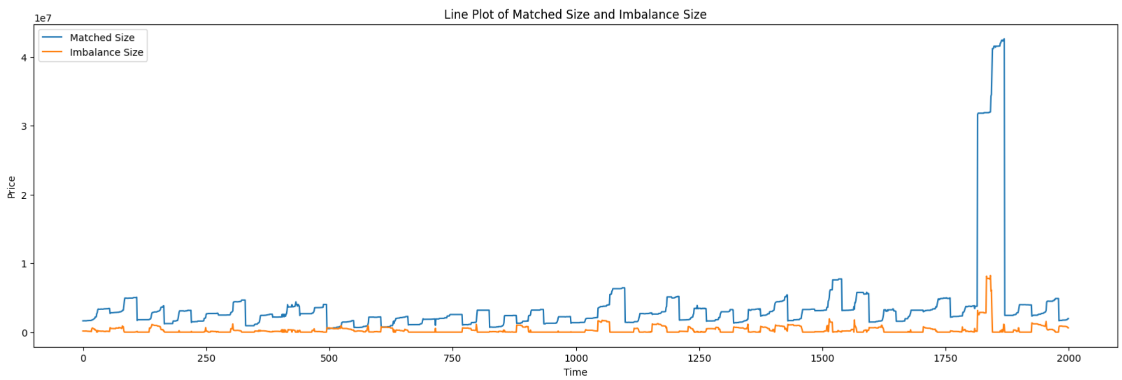
From the other 2 stock_id's box plot its safe to assume that, the imbalance_buy_sell_flag has no good significance over the target.

6 matched_size

The amount that can be matched at the current reference price (in USD).

[ ]:
```
plt.figure(figsize=(20, 6))
sns.lineplot(x=df_stock_id_1['time_id'], y='matched_size',␣
↪data=df_stock_id_1,label='Matched Size')
sns.lineplot(x=df_stock_id_1['time_id'], y='imbalance_size', data =␣
↪df_stock_id_1,label='Imbalance Size')
plt.xlabel('Time')
plt.ylabel('Price')
plt.legend()
plt.title('Line Plot of Matched Size and Imbalance Size')
```

[ ]:
```
Text(0.5, 1.0, 'Line Plot of Matched Size and Imbalance Size')
```



7 row_id

row id is the combination of date_id , stock_id, seconds_in_bucket

[ ]:
```
df[['date_id','seconds_in_bucket','stock_id','row_id']]
```

[ ]:

	date_id	seconds_in_bucket	stock_id	row_id
0	0	0	0	0_0_0
1	0	0	1	0_0_1
2	0	0	2	0_0_2
3	0	0	3	0_0_3

```
4              0                    0         4        0_0_4
…          …                    …        …          …
5237975      480                  540       195   480_540_195
5237976      480                  540       196   480_540_196
5237977      480                  540       197   480_540_197
5237978      480                  540       198   480_540_198
5237979      480                  540       199   480_540_199

[5237980 rows x 4 columns]
```

7.1 Kaggle Citation

https://www.kaggle.com/code/lukaszsztukiewicz/ml-in-timeseries-feature-engineering

This code is borrowed from one of the Kaggle Notebooks which helps reduce the size of the dataset once it's loaded into the memory. This helps speed up data processing and training tasks.

[ ]:
```
def reduce_mem_usage(df, verbose=0):
    start_mem = df.memory_usage().sum() / 1024**2

    for col in df.columns:
        col_type = df[col].dtype

        if col_type != object:
            c_min = df[col].min()
            c_max = df[col].max()
            if str(col_type)[:3] == "int":
                if c_min > np.iinfo(np.int8).min and c_max < np.iinfo(np.int8).
↪max:
                    df[col] = df[col].astype(np.int8)
                elif c_min > np.iinfo(np.int16).min and c_max < np.iinfo(np.
↪int16).max:
                    df[col] = df[col].astype(np.int16)
                elif c_min > np.iinfo(np.int32).min and c_max < np.iinfo(np.
↪int32).max:
                    df[col] = df[col].astype(np.int32)
                elif c_min > np.iinfo(np.int64).min and c_max < np.iinfo(np.
↪int64).max:
                    df[col] = df[col].astype(np.int64)
            else:
                if c_min > np.finfo(np.float16).min and c_max < np.finfo(np.
↪float16).max:
                    df[col] = df[col].astype(np.float16)
                else:
                    df[col] = df[col].astype(np.float32)

    print(f"Memory usage of dataframe is {start_mem:.2f} MB")
    end_mem = df.memory_usage().sum() / 1024**2
```

```
    print(f"Memory usage after optimization is: {end_mem:.2f} MB")
    decrease = 100 * (start_mem - end_mem) / start_mem
    print(f"Decreased by {decrease:.2f}%")

    return df

df = reduce_mem_usage(df, verbose=1)
```

```
Memory usage of dataframe is 679.36 MB
Memory usage after optimization is: 234.78 MB
Decreased by 65.44%
```

[ ]:
```
TOTAL_STOCKS = 200
TOTAL_DATES = 481
TOTAL_SECONDS_IN_BUCKET = 55


def handle_missing_date_and_seconds(org_df):

    ideal_index = pd.MultiIndex.
 ↪from_product([range(TOTAL_STOCKS),range(TOTAL_DATES), [ j * 10 for j in␣
 ↪range(TOTAL_SECONDS_IN_BUCKET)]]
        ,names = ['stock_id','date_id','seconds_in_bucket'])
    updated_small_df = org_df.
 ↪set_index(['stock_id','date_id','seconds_in_bucket']).reindex(ideal_index)
    updated_small_df = updated_small_df.reset_index()
    return updated_small_df

updated_df = handle_missing_date_and_seconds(df)
```

[ ]:
```
updated_df
```

[ ]:
```
         stock_id  date_id  seconds_in_bucket  imbalance_size  \
0               0        0                  0     3180602.750
1               0        0                 10     1299772.750
2               0        0                 20     1299772.750
3               0        0                 30     1299772.750
4               0        0                 40     1218204.375
…             …      …                  …             …
5290995       199      480                500     2661783.500
5290996       199      480                510     2658917.500
5290997       199      480                520     1352558.875
5290998       199      480                530     1352558.875
5290999       199      480                540     1884285.750

         imbalance_buy_sell_flag  reference_price  matched_size  far_price  \
0                            1.0         1.000000    13380277.0        NaN
```

```
1                          1.0        1.000000    15261107.0        NaN
2                          1.0        1.000000    15261107.0        NaN
3                          1.0        1.000000    15261107.0        NaN
4                          1.0        1.000000    15342675.0        NaN
…                          …             …            …           …
5290995                   -1.0        1.002930    23969216.0   1.000977
5290996                   -1.0        1.002930    23972082.0   1.000977
5290997                   -1.0        1.001953    23978380.0   1.000977
5290998                   -1.0        1.001953    23978380.0   1.000977
5290999                   -1.0        1.001953    24073678.0   1.000977

         near_price  bid_price       bid_size  ask_price       ask_size  \
0               NaN   1.000000   60651.500000   1.000000    8493.030273
1               NaN   1.000000   13996.500000   1.000000   23519.160156
2               NaN   1.000000    4665.500000   1.000000   12131.599609
3               NaN   1.000000   55998.000000   1.000000   46203.300781
4               NaN   1.000000   14655.950195   1.000000   26610.449219
…               …         …            …         …             …
5290995    1.001953   1.002930  122246.179688   1.002930  425296.156250
5290996    1.001953   1.002930  677012.062500   1.002930  347268.875000
5290997    1.001953   1.001953  225361.656250   1.001953  194630.515625
5290998    1.001953   1.001953  285559.062500   1.001953  214513.312500
5290999    1.001953   1.001953  250081.437500   1.002930  300167.562500

              wap    target  time_id       row_id
0        1.000000 -3.029297      0.0        0_0_0
1        1.000000  0.389893      1.0       0_10_0
2        1.000000  4.218750      2.0       0_20_0
3        1.000000  5.449219      3.0       0_30_0
4        1.000000  3.169922      4.0       0_40_0
…             …         …       …          …
5290995  1.002930 -7.210938  26450.0  480_500_199
5290996  1.002930 -9.750000  26451.0  480_510_199
5290997  1.001953  3.630859  26452.0  480_520_199
5290998  1.001953  4.761719  26453.0  480_530_199
5290999  1.001953 -6.531250  26454.0  480_540_199

[5291000 rows x 17 columns]
```

[ ]:
```
updated_df.isna().any()
```

[ ]:
```
stock_id                   False
date_id                    False
seconds_in_bucket          False
imbalance_size              True
imbalance_buy_sell_flag     True
reference_price             True
```

```
matched_size                 True
far_price                    True
near_price                   True
bid_price                    True
bid_size                     True
ask_price                    True
ask_size                     True
wap                          True
target                       True
time_id                      True
row_id                       True
dtype: bool
```

As from the results of EDA, we are removing the following features from the udpated dataframe

[ ]:
```
updated_df.
 ↪drop(['reference_price','bid_price','ask_price','time_id','row_id'],axis=1,inplace=True)
```

[ ]:
```
updated_df.shape,updated_df.columns
```

[ ]:
```
((5291000, 12),
 Index(['stock_id', 'date_id', 'seconds_in_bucket', 'imbalance_size',
        'imbalance_buy_sell_flag', 'matched_size', 'far_price', 'near_price',
        'bid_size', 'ask_size', 'wap', 'target'],
       dtype='object'))
```

[ ]:
```
updated_df = reduce_mem_usage(updated_df, verbose=1)
```

```
Memory usage of dataframe is 282.57 MB
Memory usage after optimization is: 161.47 MB
Decreased by 42.86%
```

As the dataset set is really huge, we will only consider data of stock_id 1 for the implementation of the models

[ ]:
```
updated_stock_1_df = updated_df[updated_df['stock_id'] == 1]
updated_stock_1_df = updated_stock_1_df.reset_index(drop=True)
updated_stock_1_df
```

[ ]:
```
       stock_id  date_id  seconds_in_bucket  imbalance_size  \
0             1        0                  0   166603.906250
1             1        0                 10   165923.203125
2             1        0                 20   165923.203125
3             1        0                 30   165923.203125
4             1        0                 40   162349.468750
…           …       …                 …             …
26450         1      480                500    88468.406250
26451         1      480                510   310778.500000
26452         1      480                520   310778.500000
```

```
26453          1      480                 530   310778.500000
26454          1      480                 540    43854.511719

       imbalance_buy_sell_flag  matched_size  far_price  near_price  \
0                         -1.0    1642214.25        NaN         NaN
1                         -1.0    1642895.00        NaN         NaN
2                         -1.0    1642895.00        NaN         NaN
3                         -1.0    1642895.00        NaN         NaN
4                         -1.0    1646468.75        NaN         NaN
…                        …           …          …          …
26450                     -1.0    7635810.50   0.996094    0.996582
26451                     -1.0    7413500.50   0.996094    0.996582
26452                     -1.0    7413500.50   0.996094    0.996582
26453                     -1.0    7413500.50   0.996094    0.996582
26454                     -1.0    7680424.50   0.996094    0.996582

            bid_size       ask_size       wap     target
0        3233.040039   20605.089844  1.000000  -5.519531
1        3743.520020   33717.421875  1.000000  -1.620117
2        3743.520020   33717.421875  1.000000  -6.460938
3        4254.000000    3574.830078  1.000000  -5.148438
4       21270.000000    3574.830078  1.000000  -6.750000
…              …              …         …         …
26450  176306.437500   64345.000000  0.996582   2.849609
26451    1324.329956   47135.699219  0.996582   3.169922
26452    3783.800049   85374.296875  0.996582   5.691406
26453    7567.600098  112065.601562  0.996582  10.648438
26454    5675.700195  167909.093750  0.996582  15.859375

[26455 rows x 12 columns]
```

[ ]:
```python
updated_stock_1_df.isnull().sum()
```

[ ]:
```
stock_id                       0
date_id                        0
seconds_in_bucket              0
imbalance_size                 0
imbalance_buy_sell_flag        0
matched_size                   0
far_price                  14671
near_price                 14430
bid_size                       0
ask_size                       0
wap                            0
target                         0
dtype: int64
```

[ ]:
```
updated_stock_1_df[updated_stock_1_df['far_price'].isnull()].index
```

[ ]:
```
Index([    0,     1,     2,     3,     4,     5,     6,     7,     8,     9,
       …
       26420, 26421, 26422, 26423, 26424, 26425, 26426, 26427, 26428, 26429],
      dtype='int64', length=14671)
```

[ ]:
```
updated_stock_1_df[updated_stock_1_df['near_price'].isnull()].index
```

[ ]:
```
Index([    0,     1,     2,     3,     4,     5,     6,     7,     8,     9,
       …
       26420, 26421, 26422, 26423, 26424, 26425, 26426, 26427, 26428, 26429],
      dtype='int64', length=14430)
```

Take the data from this (preprocessed). Input scaling. Dropping vs Imputing features. We can build mdoels for 2-3 stocks instead of the whole data. Use this same preprocessed data in the other models.

[ ]:
```
updated_stock_1_df.describe()
```

[ ]:
```
       stock_id       date_id  seconds_in_bucket  imbalance_size  \
count   26455.0  26455.000000       26455.000000    2.645500e+04
mean        1.0    240.000000         270.000000    5.185133e+05
std         0.0    138.855064         158.748079    9.908059e+05
min         1.0      0.000000           0.000000    0.000000e+00
25%         1.0    120.000000         130.000000    0.000000e+00
50%         1.0    240.000000         270.000000    1.615905e+05
75%         1.0    360.000000         410.000000    6.596827e+05
max         1.0    480.000000         540.000000    2.927485e+07

       imbalance_buy_sell_flag  matched_size     far_price    near_price  \
count             26455.000000  2.645500e+04  11784.000000  12025.000000
mean                 -0.032318  4.222393e+06      0.999512      1.000000
std                   0.803223  1.269290e+07      0.019318      0.010941
min                  -1.000000  4.490097e+05      0.893555      0.898926
25%                  -1.000000  1.746630e+06      0.996094      0.997070
50%                   0.000000  2.768589e+06      0.999512      0.999512
75%                   1.000000  4.467678e+06      1.002930      1.001953
max                   1.000000  3.122824e+08      1.247070      1.110352

           bid_size      ask_size           wap        target
count  26455.000000  26455.000000  26455.000000  26455.000000
mean   22565.740234  23091.035156      1.000000     -0.119934
std    33339.742188  33105.167969      0.002806     11.585938
min       68.839996     71.300003      0.986816    -80.812500
25%     2801.045044   2984.600098      0.998535     -6.832031
50%    12344.000000  13204.500000      1.000000     -0.110291
75%    28996.700195  31192.240234      1.000977      6.710938
```

```
max     693967.437500  748327.687500      1.016602     62.062500
```

[ ]:
```
# Fill Missing data
from sklearn.impute import SimpleImputer

# Impute missing values with the mean
imputer = SimpleImputer(strategy='mean')
updated_stock_1_df[['far_price', 'near_price']] = imputer.
 ↪fit_transform(updated_stock_1_df[['far_price', 'near_price']])

# Count the number of NaNs in each column
missing_values = updated_stock_1_df.isna().sum()

# Display the columns with missing values and their count
print(missing_values[missing_values > 0])

data = updated_stock_1_df
X = data.drop(['target'], axis=1)  # Exclude non-numeric or non-predictive␣
 ↪columns
y = data['target']
```

```
Series([], dtype: int64)
```

7.2 Utility Functions

[ ]:
```
def perform_grid_search(model, param_grid, X, y, cv_splits):

    grid_search = GridSearchCV(model, param_grid,␣
 ↪cv=TimeSeriesSplit(n_splits=cv_splits).split(X),␣
 ↪scoring='neg_mean_absolute_error', return_train_score=True, n_jobs=4)

    grid_search.fit(X, y)

    print(f"Best parameters for {type(model).__name__}: {grid_search.
 ↪best_params_}")

    return grid_search.best_estimator_, grid_search.best_params_, grid_search.
 ↪cv_results_, -grid_search.best_score_
```

[ ]:
```
## Graph grid scores
def plot_cv_results(model_name, dir, cv_results):
    test_scores = cv_results['mean_test_score'] * -1
    train_scores = cv_results['mean_train_score'] * -1
    # train_scores = cv_results['mean_train_score']
    min_test = np.min(test_scores)
    min_test_x = np.argmin(test_scores)
```

```
    min_train = np.min(train_scores)
    min_train_x = np.argmin(train_scores)
    plt.plot(test_scores, label='test mae scores')
    plt.plot(train_scores, label='train mae scores')
    plt.scatter([min_test_x, min_test_x], [min_test, train_scores[min_test_x]],␣
↪c='r', label=f'best (train, test) mae␣
↪({round(train_scores[min_test_x],3)},{round(min_test,3)})')
    plt.scatter(min_train_x, min_train, c='g', label=f'best train mae␣
↪{round(min_train,3)}')
    plt.xlabel('Iterations')
    plt.ylabel('Mean Absolute Error')
    plt.title(f'{model_name}: GridSearch MAE per iteration')
    plt.legend(loc='best', fontsize="8")
    # plt.legend(loc='upper right', fontsize="10")
    plt.savefig(dir+f'{model_name}_cvgraph.png')
    # plt.show()
```

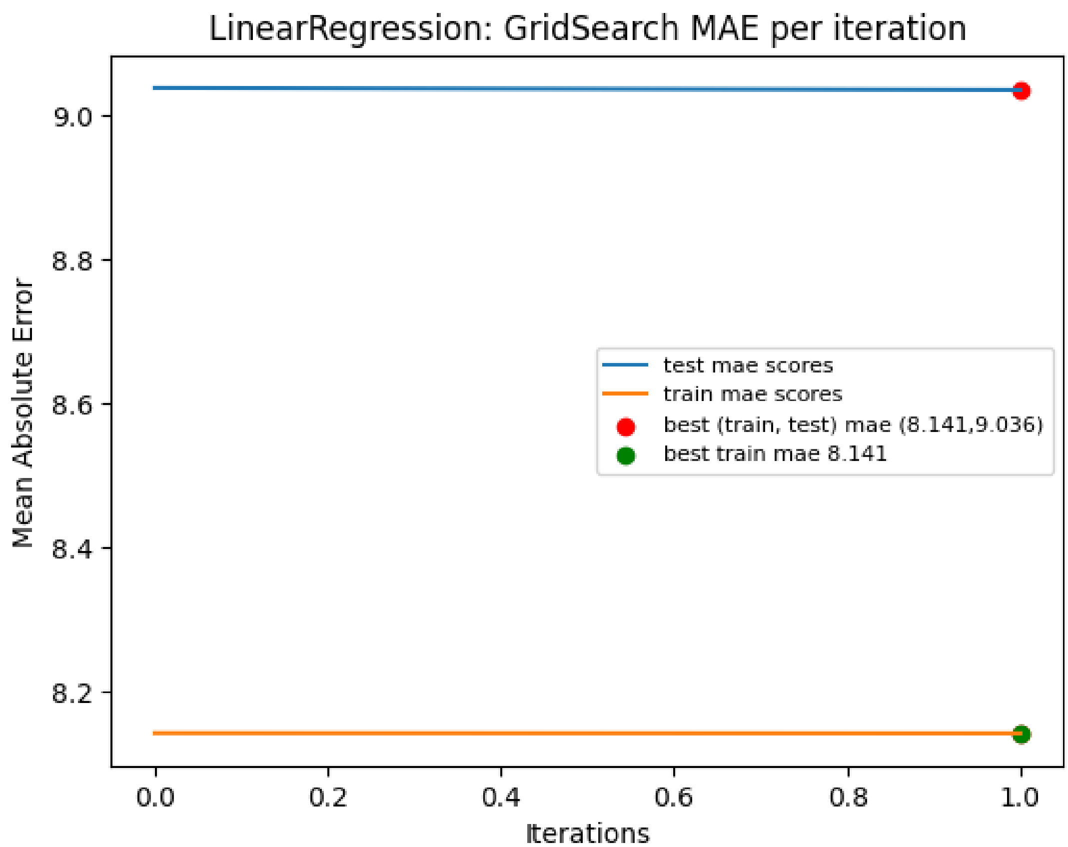
[ ]:
```
def save_model_data(model_name, model, params, cv_results, mae):
    dir = f'./results_new/{model_name}/'
    try:
        os.makedirs(dir)
    except Exception as e:
        pass
    # save model
    joblib.dump(model, dir+f'{model_name}_bestmodel.pkl')

    # save params, mae
    with open(dir+f'{model_name}_params_mae.txt', 'w') as file:
        file.write(str(params)+"\n"+str(mae))

    with open(dir+f'{model_name}_cvresults.txt', 'w') as file:
        file.write(str(cv_results))

    if not model_name == 'ARIMA':
        plot_cv_results(model_name, dir, cv_results)
```

[ ]:
```
# LR Grid search
lr_param_grid = {'linearregression__fit_intercept': [True, False]}
lr_pipeline = Pipeline([('scaler', StandardScaler()), ('linearregression',␣
↪LinearRegression())])
best_lr_model, lr_params, lr_cv_results, lr_mae =␣
↪perform_grid_search(lr_pipeline, lr_param_grid, X, y, 5)
```

```
Best parameters for Pipeline: {'linearregression__fit_intercept': False}
```

[ ]:
```
save_model_data('LinearRegression', best_lr_model, lr_params, lr_cv_results,␣
↪lr_mae)
```

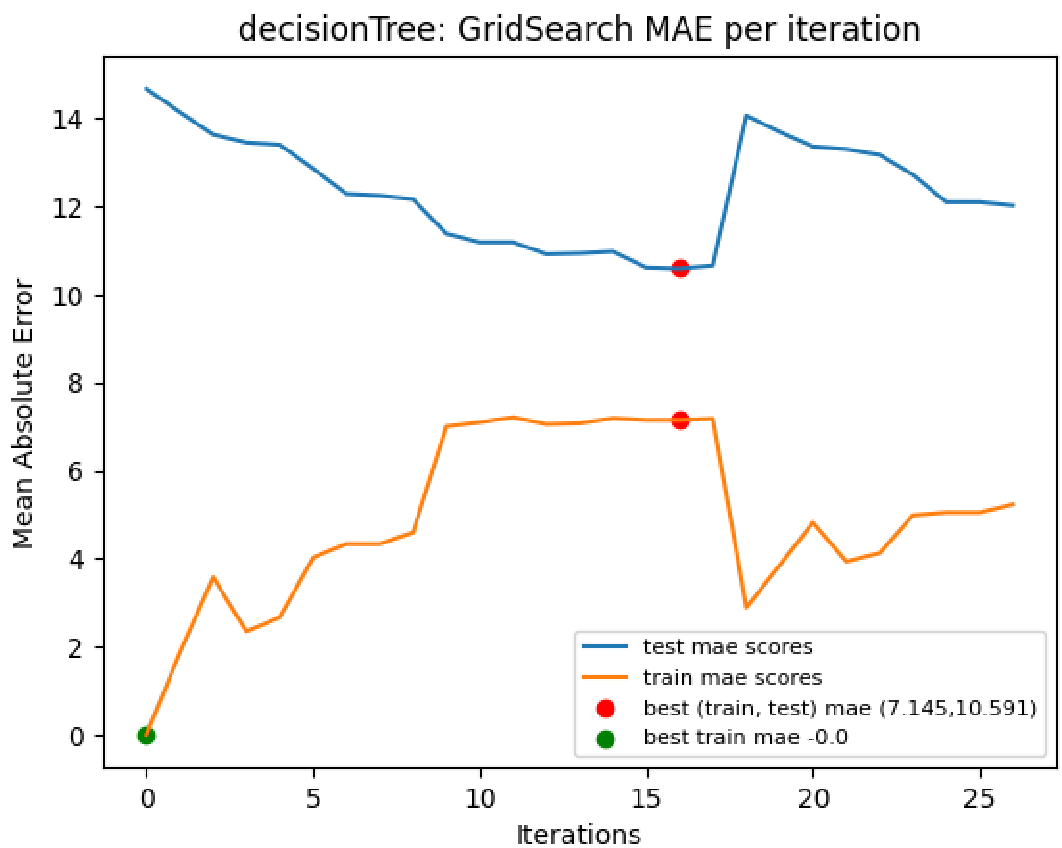
```python
# plot_cv_results('LinearRegression', lr_cv_results)
```



[ ]:
```python
# Decision Tree
dt_param_grid = {'max_depth': [None, 10, 20], 'min_samples_split': [2, 5, 10],␣
↪'min_samples_leaf': [1, 2, 4]}
best_dt_model, dt_params, dt_cv_results, dt_mae =␣
↪perform_grid_search(DecisionTreeRegressor(), dt_param_grid, X, y, 5)
```

```
Best parameters for DecisionTreeRegressor: {'max_depth': 10, 'min_samples_leaf':
4, 'min_samples_split': 5}
```

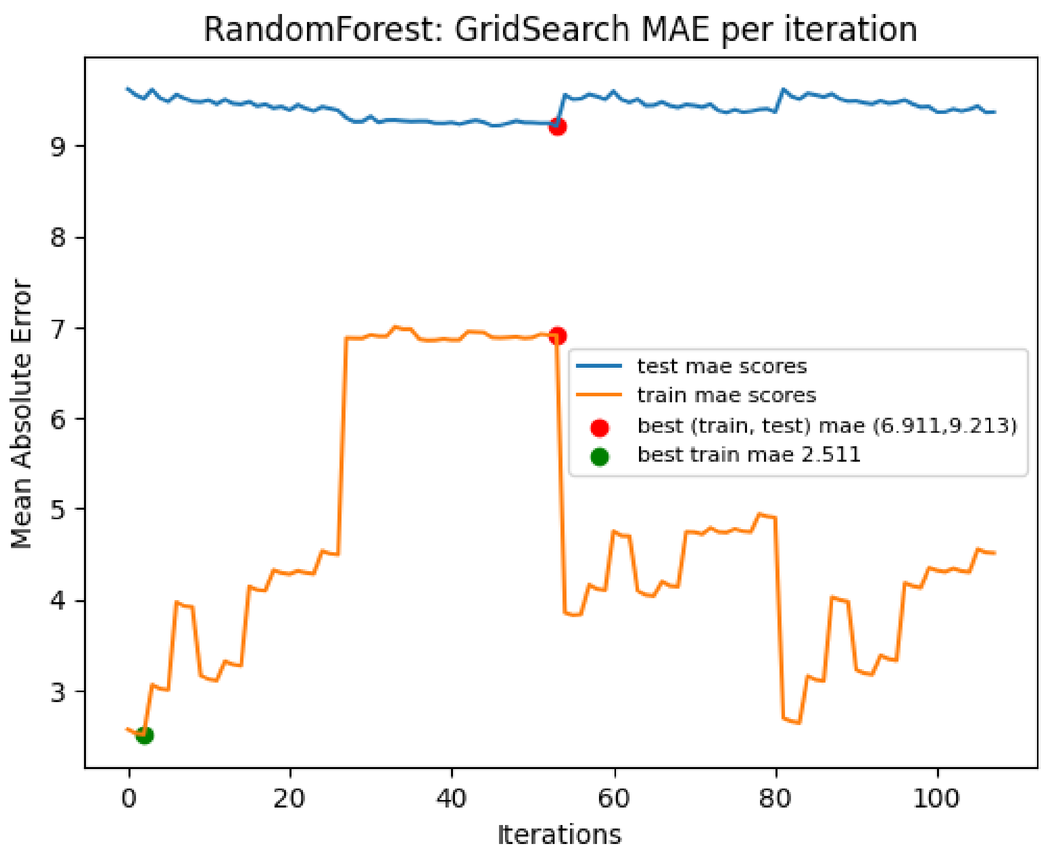
[ ]:
```python
save_model_data('decisionTree',best_dt_model, dt_params, dt_cv_results, dt_mae)
```




```
[ ]: # Random Forest
rf_param_grid = param_grid = {
    'n_estimators': [50, 100, 150],
    'max_depth': [None, 10, 20, 30],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4]
}
best_rf_model, rf_params, rf_cv_results, rf_mae =␣
 ↪perform_grid_search(RandomForestRegressor(), rf_param_grid, X, y, 5)
```

```
Best parameters for RandomForestRegressor: {'max_depth': 10, 'min_samples_leaf':
4, 'min_samples_split': 10, 'n_estimators': 150}
```

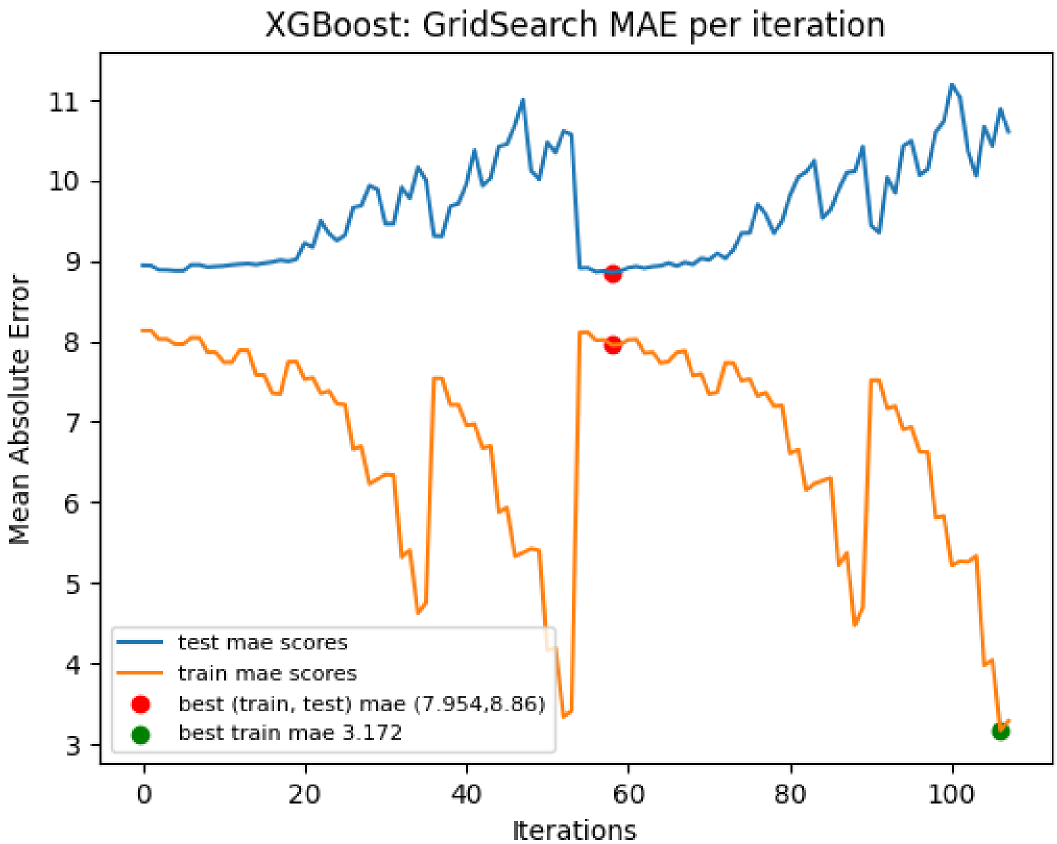
```
[ ]: save_model_data('RandomForest',best_rf_model, rf_params, rf_cv_results, rf_mae)
```



[ ]:
```
# XG Boost
xgb_param_grid = xgb_param_grid = param_grid = {
    'xgbregressor__n_estimators': [50, 100, 150],
    'xgbregressor__max_depth': [3, 5, 7],
    'xgbregressor__learning_rate': [0.01, 0.1, 0.2],
    'xgbregressor__subsample': [0.8, 1.0],
    'xgbregressor__colsample_bytree': [0.8, 1.0],
}
xgb_pipeline = Pipeline([('xgbregressor', xgb.XGBRegressor())])
best_xgb_model, xgb_params, xgb_cv_results, xgb_mae =␣
↪perform_grid_search(xgb_pipeline, xgb_param_grid, X, y, 5)
```

```
Best parameters for Pipeline: {'xgbregressor__colsample_bytree': 1.0,
'xgbregressor__learning_rate': 0.01, 'xgbregressor__max_depth': 3,
'xgbregressor__n_estimators': 150, 'xgbregressor__subsample': 0.8}
```

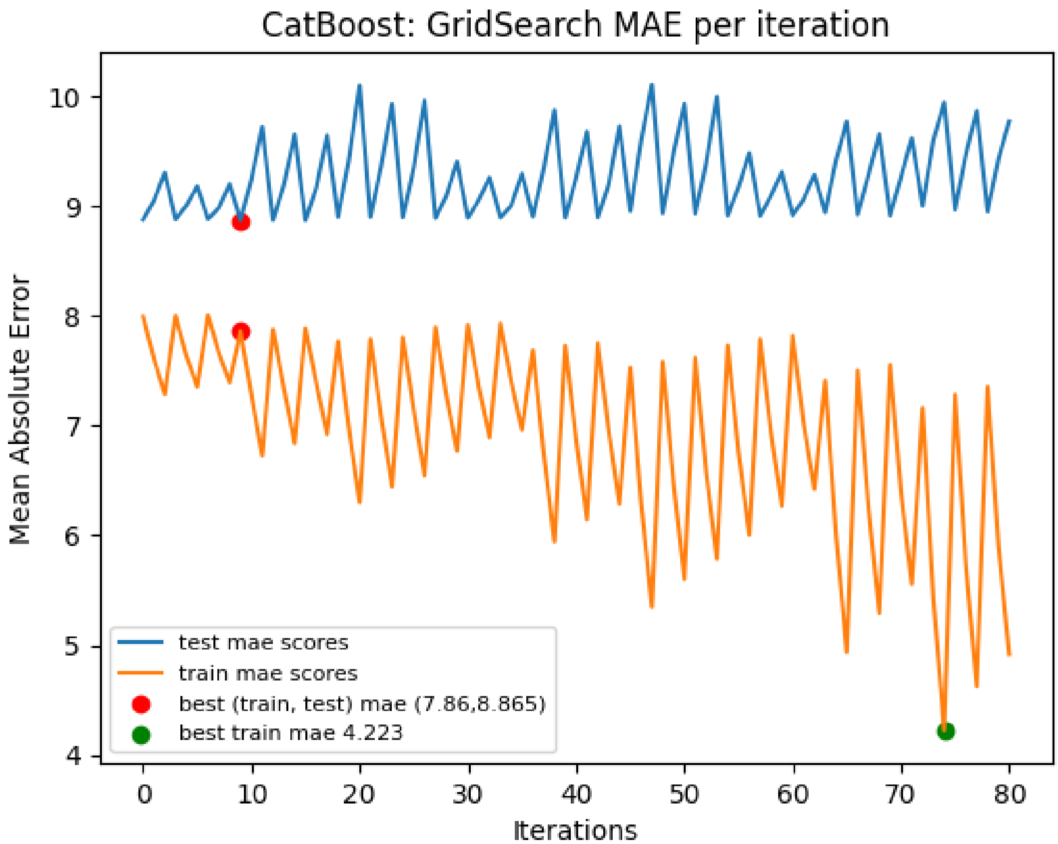
[ ]:
```
save_model_data('XGBoost',best_xgb_model, xgb_params,xgb_cv_results, xgb_mae)
```



[ ]:
```
# Cat Boost
catboost_grid_param_grid = {
    'catbreg__iterations': [100, 200, 300],
    'catbreg__learning_rate': [0.01, 0.05, 0.1],
    'catbreg__depth': [6, 8, 10],
    'catbreg__l2_leaf_reg': [1, 3, 5]
}

catboost_pipeline = Pipeline([('scaler', StandardScaler()), ('catbreg',␣
 ↪CatBoostRegressor(verbose=0))])
best_catboost_model, best_cb_params, cb_cv_results, cb_mae =␣
 ↪perform_grid_search(catboost_pipeline, catboost_grid_param_grid, X, y, 5)
```

```
Best parameters for Pipeline: {'catbreg__depth': 6, 'catbreg__iterations': 200,
'catbreg__l2_leaf_reg': 1, 'catbreg__learning_rate': 0.01}
```

[ ]:
```
save_model_data('CatBoost', best_catboost_model, best_cb_params, cb_cv_results,␣
 ↪cb_mae)
```

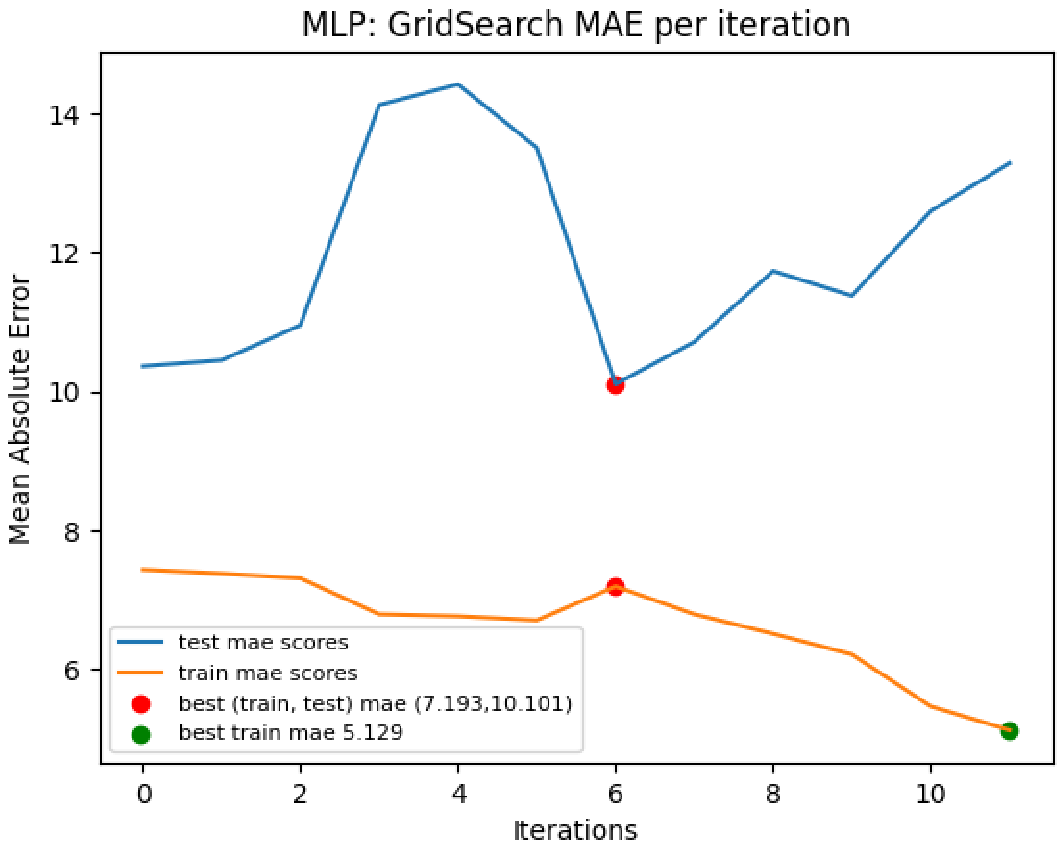


[ ]:
```
# Neural Network
nn_param_grid = {'mlpregressor__hidden_layer_sizes': [(100,), (50, 50)],␣
↪'mlpregressor__activation': ['relu', 'tanh'], 'mlpregressor__max_iter':␣
↪[500, 1000, 2000]}
nn_pipeline = Pipeline([('scaler', StandardScaler()), ('mlpregressor',␣
↪MLPRegressor())])
best_nn_model, nn_params, nn_cv_results, nn_mae =␣
↪perform_grid_search(nn_pipeline, nn_param_grid, X, y, 5)
```

```
Best parameters for Pipeline: {'mlpregressor__activation': 'tanh',
'mlpregressor__hidden_layer_sizes': (100,), 'mlpregressor__max_iter': 500}
```

```
c:\Users\saman\miniconda3\envs\mlproject_py3.9\lib\site-
packages\sklearn\neural_network\_multilayer_perceptron.py:691:
ConvergenceWarning: Stochastic Optimizer: Maximum iterations (500) reached and
the optimization hasn't converged yet.
  warnings.warn(
```

[ ]:
```
save_model_data('MLP',best_nn_model, nn_params, nn_cv_results, nn_mae)
```



[ ]:
```
# ARIMA
# Fine-tuning ARIMA Model

arima_model = auto_arima(y, seasonal=False, stepwise=True,␣
 ↪error_action='ignore', trace=True)

arima_mae = mean_absolute_error(y, arima_model.predict(n_periods=len(y)))
```

```
Performing stepwise search to minimize aic
 ARIMA(2,1,2)(0,0,0)[0] intercept   : AIC=inf, Time=12.06 sec
 ARIMA(0,1,0)(0,0,0)[0] intercept   : AIC=189182.204, Time=0.24 sec
 ARIMA(1,1,0)(0,0,0)[0] intercept   : AIC=188476.570, Time=0.30 sec
 ARIMA(0,1,1)(0,0,0)[0] intercept   : AIC=188369.853, Time=0.69 sec
 ARIMA(0,1,0)(0,0,0)[0]             : AIC=189180.204, Time=0.14 sec
 ARIMA(1,1,1)(0,0,0)[0] intercept   : AIC=inf, Time=7.92 sec
 ARIMA(0,1,2)(0,0,0)[0] intercept   : AIC=188263.665, Time=1.19 sec
 ARIMA(1,1,2)(0,0,0)[0] intercept   : AIC=187633.047, Time=4.17 sec
 ARIMA(1,1,3)(0,0,0)[0] intercept   : AIC=inf, Time=13.86 sec
 ARIMA(0,1,3)(0,0,0)[0] intercept   : AIC=inf, Time=9.38 sec
 ARIMA(2,1,1)(0,0,0)[0] intercept   : AIC=inf, Time=10.32 sec
```

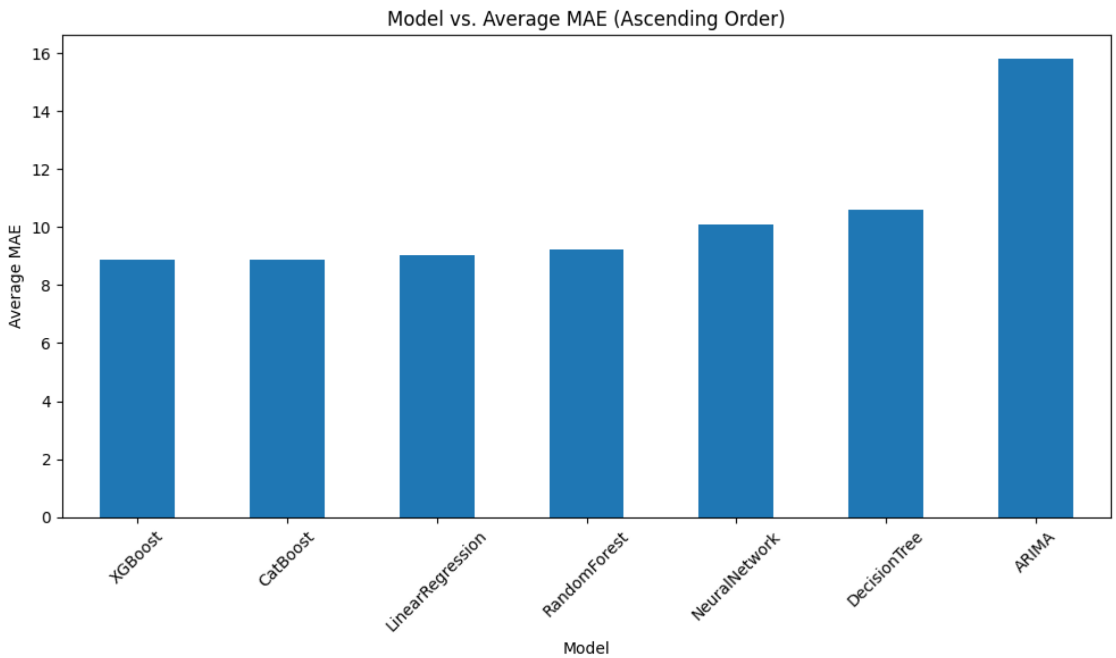
```
 ARIMA(2,1,3)(0,0,0)[0] intercept   : AIC=inf, Time=19.16 sec
 ARIMA(1,1,2)(0,0,0)[0]             : AIC=187631.047, Time=2.01 sec
 ARIMA(0,1,2)(0,0,0)[0]             : AIC=188261.665, Time=0.60 sec
 ARIMA(1,1,1)(0,0,0)[0]             : AIC=inf, Time=2.88 sec
 ARIMA(2,1,2)(0,0,0)[0]             : AIC=inf, Time=4.83 sec
 ARIMA(1,1,3)(0,0,0)[0]             : AIC=inf, Time=6.31 sec
 ARIMA(0,1,1)(0,0,0)[0]             : AIC=188367.854, Time=0.32 sec
 ARIMA(0,1,3)(0,0,0)[0]             : AIC=inf, Time=3.28 sec
 ARIMA(2,1,1)(0,0,0)[0]             : AIC=inf, Time=3.79 sec
 ARIMA(2,1,3)(0,0,0)[0]             : AIC=inf, Time=8.24 sec

Best model:  ARIMA(1,1,2)(0,0,0)[0]
Total fit time: 111.721 seconds
```

[ ]:
```
save_model_data('ARIMA', arima_model, None, None, arima_mae)
```

[ ]:
```
# Combine all reports
results = {

    'LinearRegression': lr_mae,

    'NeuralNetwork': nn_mae,

    'RandomForest': rf_mae,

    'DecisionTree': dt_mae,

    'XGBoost': xgb_mae,

    'CatBoost': cb_mae,

    'ARIMA': arima_mae

}

# Convert results to DataFrame

results_df = pd.DataFrame.from_dict(results, orient='index', columns=['Average␣
 ↪MAE'])

# Save the DataFrame to a CSV file

results_df.to_csv('model_cv_results.csv', index=True)
```

[ ]:
```
# Plotting Models vs Average MAE

plt.figure(figsize=(10, 6))
```

```
results_df['Average MAE'].sort_values().plot(kind='bar')

plt.xlabel('Model')

plt.ylabel('Average MAE')

plt.title('Model vs. Average MAE (Ascending Order)')

plt.xticks(rotation=45)

plt.tight_layout()

plt.savefig('final_model_comparisons.png')
```




```
[ ]: # Performing train test split
     X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
      ↪random_state=104, shuffle=False)
```

```
[ ]: X_train.index, y_train.shape, X_test.index, y_test.shape
```

```
[ ]: (Index([    0,     1,     2,     3,     4,     5,     6,     7,     8,     9,
             …
             21154, 21155, 21156, 21157, 21158, 21159, 21160, 21161, 21162, 21163],
            dtype='int64', length=21164),
```

```
(21164,),
Index([21164, 21165, 21166, 21167, 21168, 21169, 21170, 21171, 21172, 21173,
       …
       26445, 26446, 26447, 26448, 26449, 26450, 26451, 26452, 26453, 26454],
      dtype='int64', length=5291),
(5291,))
```

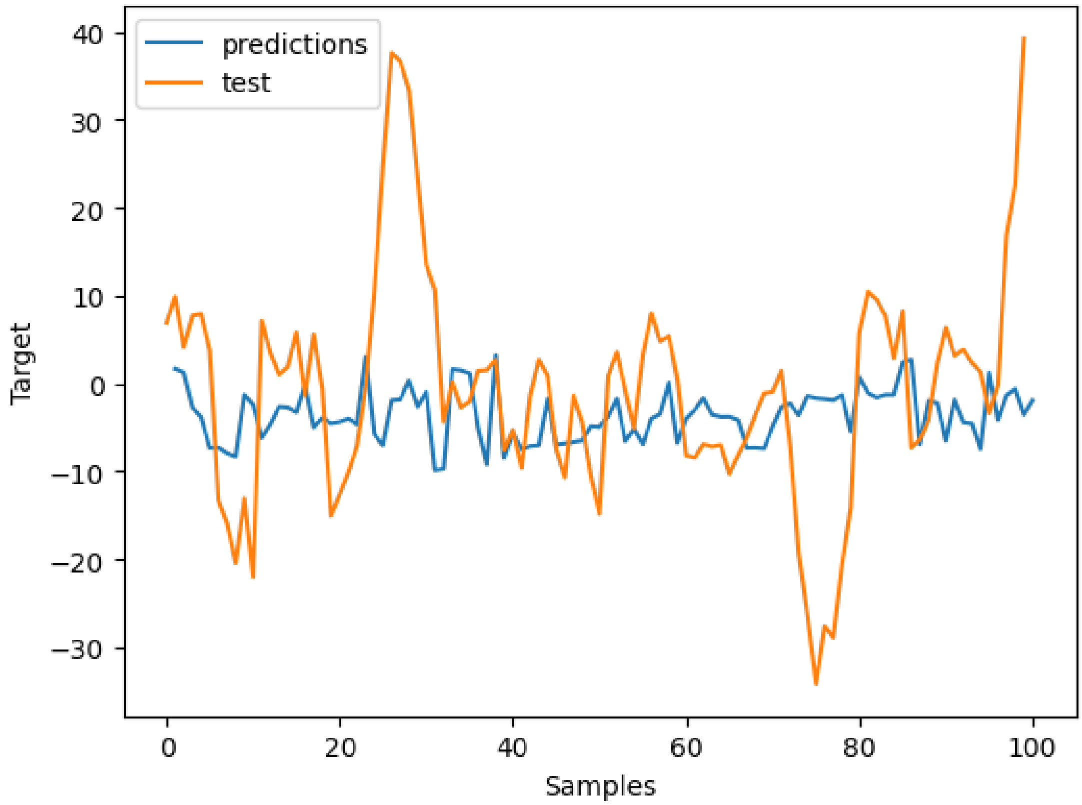
[ ]:
```
def plot_test_predictions(model_name, model):
    dir = f'./results_new/{model_name}/'
    try:
        os.makedirs(dir)
    except Exception as e:
        pass
    # save model
    joblib.dump(model, dir+f'{model_name}_fulltrain.pkl')
    predictions = model.predict(X_test)
    test_mae = mean_absolute_error(y_test, predictions)
    print(f"{model_name} MAE",test_mae)
# Reset index for predictions and y_test
    predictions = pd.Series(predictions, index=np.arange(1,len(predictions)+1))
    y_test_reset = y_test.reset_index(drop=True)
    plt.plot(predictions[:100], label='predictions')
    plt.plot(y_test_reset[:100], label='test')
    plt.legend()
    plt.xlabel('Samples')
    plt.ylabel('Target')
    plt.savefig(dir+'testvspred.png')
```

[ ]:
```
# Now let's train all the best models with the initial data
# Random Forest
randomForestModel = RandomForestRegressor(**rf_params, n_jobs=-1)
randomForestModel.fit(X_train, y_train)
```

[ ]:
```
RandomForestRegressor(max_depth=10, min_samples_leaf=4, min_samples_split=10,
                      n_estimators=150, n_jobs=-1)
```

[ ]:
```
plot_test_predictions('RandomForest', randomForestModel)
```

```
RandomForest MAE 9.037459692016114
```

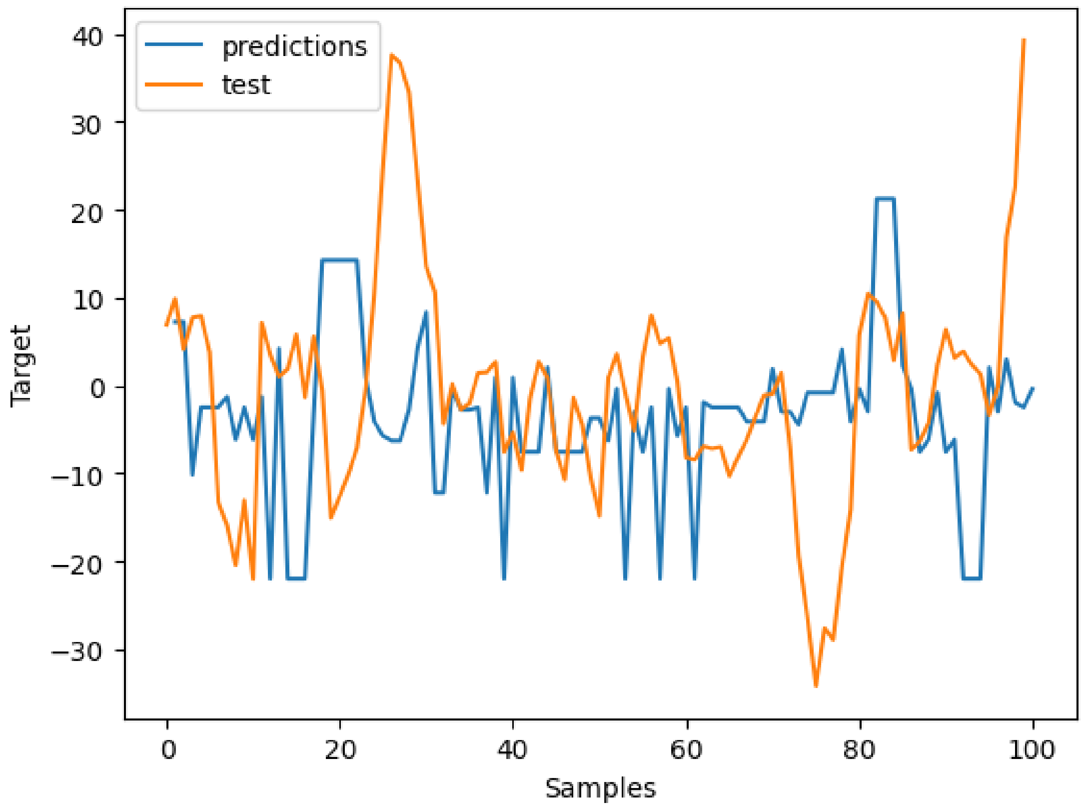


[ ]:
```
decision_tree_model = DecisionTreeRegressor(**dt_params)
decision_tree_model.fit(X_train, y_train)
```

[ ]: DecisionTreeRegressor(max_depth=10, min_samples_leaf=4, min_samples_split=5)

[ ]:
```
plot_test_predictions('decisionTree', decision_tree_model)
```

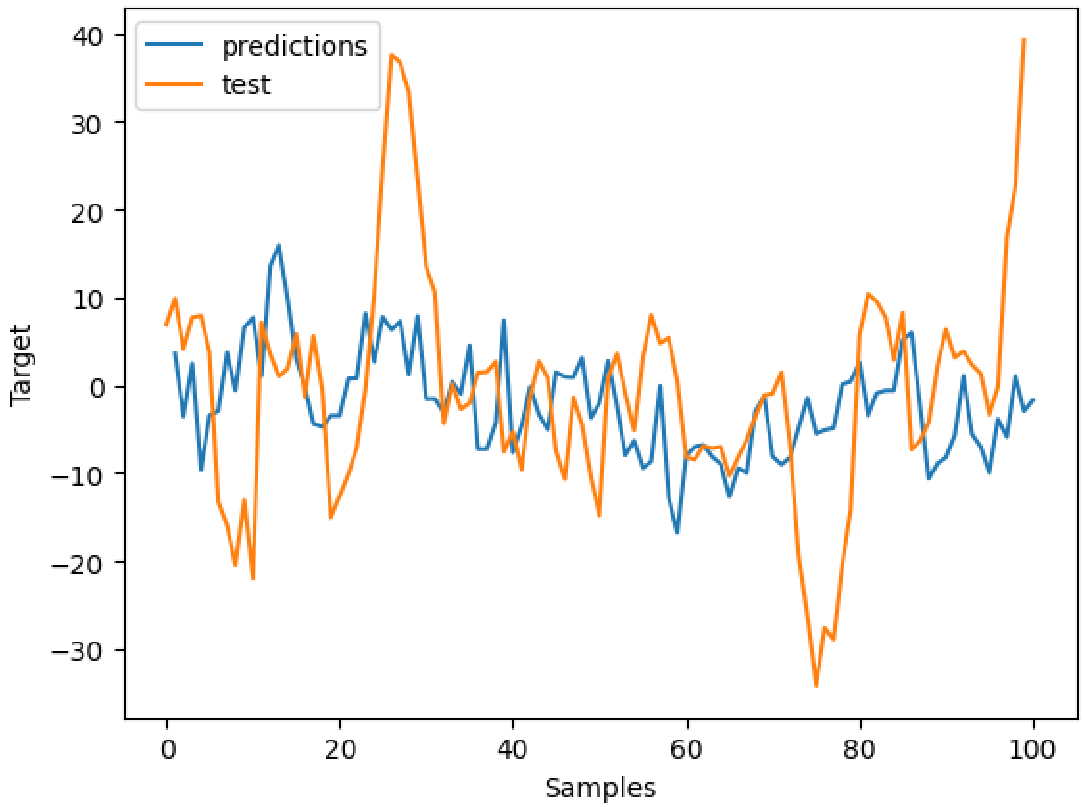
decisionTree MAE 12.064760747975175



[ ]:
```
xgboost_model = xgb.XGBRegressor(**xgb_params)
xgboost_model.fit(X_train, y_train)
plot_test_predictions('XGBoost', xgboost_model)
```

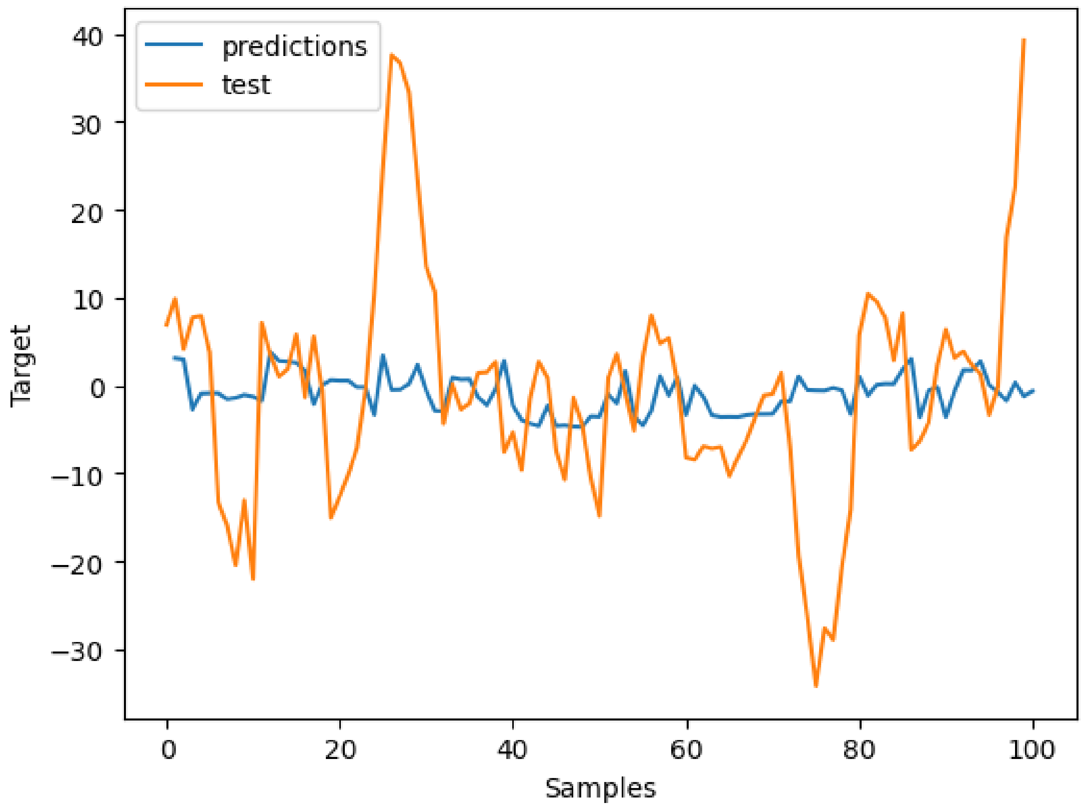
```
c:\Users\saman\miniconda3\envs\mlproject_py3.9\lib\site-
packages\xgboost\core.py:160: UserWarning: [15:28:13] WARNING: C:\buildkite-
agent\builds\buildkite-windows-cpu-autoscaling-
group-i-0750514818a16474a-1\xgboost\xgboost-ci-windows\src\learner.cc:742:
Parameters: { "xgbregressor__colsample_bytree", "xgbregressor__learning_rate",
"xgbregressor__max_depth", "xgbregressor__n_estimators",
"xgbregressor__subsample" } are not used.

  warnings.warn(smsg, UserWarning)
```

```
XGBoost MAE 9.953676
```



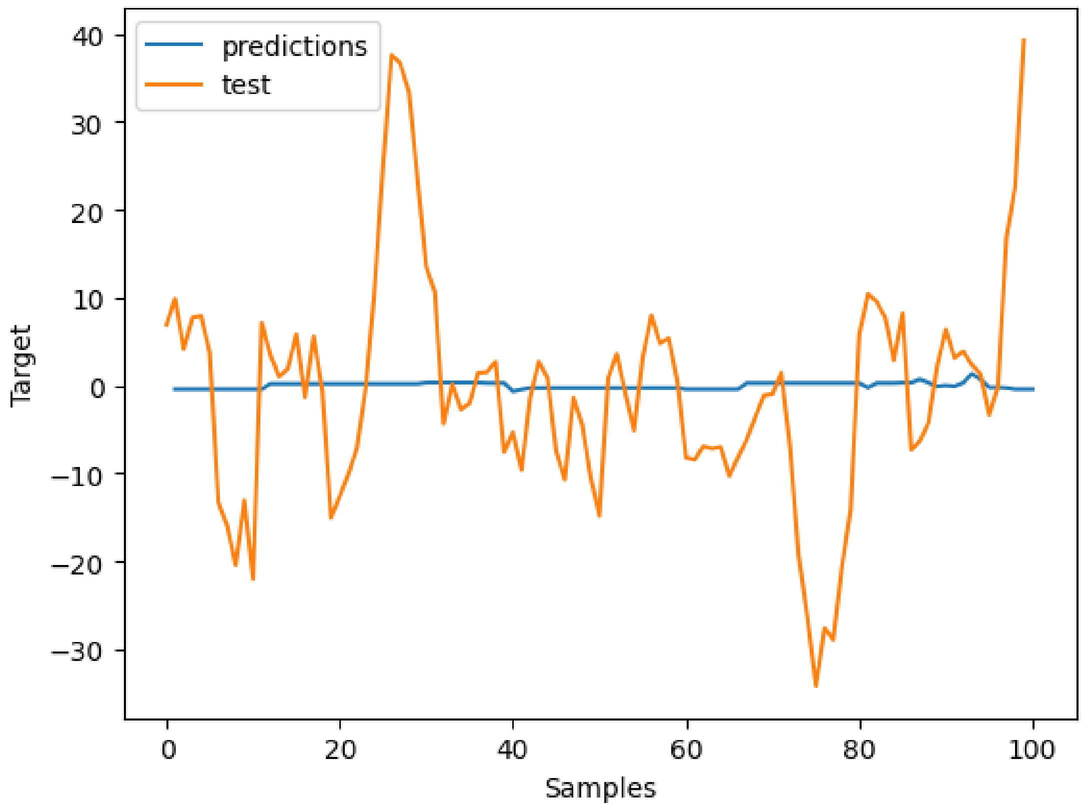

```
[ ]: best_cat_params = {'depth': 6, 'iterations': 200, 'l2_leaf_reg': 1,␣
      ↪'learning_rate': 0.01}
     cat_model = CatBoostRegressor(**best_cat_params, verbose=0)
     cat_model.fit(X_train, y_train)

     plot_test_predictions('CatBoost', cat_model)
```

```
CatBoost MAE 8.088586981079215
```



[ ]:
```
best_mlp = {'activation': 'tanh', 'hidden_layer_sizes': (100,), 'max_iter': 500}
mlpModel = MLPRegressor(**best_mlp)
mlpModel.fit(X_train, y_train)
plot_test_predictions('MLP', mlpModel)
```

```
MLP MAE 8.320367
```


predictions
test
Target
Samples
40
30
20
10
0
−10
−20
−30
0
20
40
60
80
100

```
[ ]:
```