stock-ml

May 12, 2023

0.1 The Setting Up

[ ]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np

from keras.layers import LSTM, Dense, Dropout
from sklearn.model_selection import TimeSeriesSplit
from sklearn.metrics import mean_squared_error
from sklearn.linear_model import LinearRegression
from keras.models import Sequential, load_model
from keras.optimizers import Adam
from sklearn.model_selection import train_test_split

train = pd.read_csv("train.csv")
train.drop(columns = ["dates"], inplace = True, axis = 1)
testing = pd.read_csv("test.csv")
df = pd.read_csv("BTC-USD.csv")
train

#Factor F -> Most probably VOLUMES
```

[ ]:
```
        Factor A  Factor B  Factor C  Factor D  Factor E   Factor F  \
0         502.52    498.78    493.98     947.6    505.24    79050.0
1         503.33    495.09    496.93     928.6    506.21    31082.0
2         500.62    493.71    504.75     935.5    505.51    19375.0
3         502.08    492.98    502.20     923.5    505.25    22010.0
4         502.81    493.23    499.57     918.1    504.86    26533.0
…            …         …         …         …         …          …
161763  10499.99  10499.99  10499.99  100499.9   1499.99  10000500.0
161764  10499.99  10499.99  10499.99  100499.9   1499.99  10000500.0
161765  10499.99  10499.99  10499.99  100499.9   1499.99  10000500.0
161766  10499.99  10499.99  10499.99  100499.9   1499.99  10000500.0
161767  10499.99  10499.99  10499.99  100499.9   1499.99  10000500.0

        Factor G  Factor H  Factor I  Factor J  Factor K  Factor L  Factor M  \
0         502.10    502.73    630.41    496.60    508.95    512.01    499.20
```

```
1         502.28    501.96    630.61    496.76    508.97    512.45    500.14
2         502.09    499.17    630.81    496.91    508.99    513.31    499.96
3         501.88    500.43    631.01    497.06    509.01    513.49    500.05
4         501.70    501.46    631.21    497.21    509.03    513.59    500.31
…           …        …        …        …        …        …        …
161763    599.99   1499.99  10499.99  10499.99  10499.99  10499.99  10499.99
161764    599.99   1499.99  10499.99  10499.99  10499.99  10499.99  10499.99
161765    599.99   1499.99  10499.99  10499.99  10499.99  10499.99  10499.99
161766    599.99   1499.99  10499.99  10499.99  10499.99  10499.99  10499.99
161767    599.99   1499.99  10499.99  10499.99  10499.99  10499.99  10499.99

        Factor N  TGD Consultancy Share price  TGD Automobiles Share price  \
0         501.94                        519.0                        420.0
1         501.51                        518.0                        420.0
2         501.00                        523.0                        437.0
3         501.04                        522.0                        437.0
4         501.10                        522.0                        437.0
…           …                           …                            …
161763  10499.99                        498.0                        420.0
161764  10499.99                        502.0                        420.0
161765  10499.99                        508.0                        420.0
161766  10499.99                        507.0                        420.0
161767  10499.99                        499.0                        420.0

        TGD Power Share price
0                       507.0
1                       507.0
2                       522.0
3                       522.0
4                       522.0
…                       …
161763                  507.0
161764                  507.0
161765                  507.0
161766                  507.0
161767                  507.0

[161768 rows x 17 columns]
```

0.1.1 Features DataFrame

[ ]:
```
features = train.drop(columns = ["TGD Consultancy Share price", "TGD␣
↪Automobiles Share price", "TGD Power Share price"], axis = 1)
features = features.to_numpy()
features
```

```
[ ]: array([[  502.52,   498.78,   493.98, …,   512.01,   499.2 ,   501.94],
       [  503.33,   495.09,   496.93, …,   512.45,   500.14,   501.51],
       [  500.62,   493.71,   504.75, …,   513.31,   499.96,   501.  ],
       …,
       [10499.99, 10499.99, 10499.99, …, 10499.99, 10499.99, 10499.99],
       [10499.99, 10499.99, 10499.99, …, 10499.99, 10499.99, 10499.99],
       [10499.99, 10499.99, 10499.99, …, 10499.99, 10499.99, 10499.99]])
```

0.1.2 Targets

```
[ ]: target = train[["TGD Consultancy Share price", "TGD Automobiles Share price",␣
      ↪"TGD Power Share price"]]
     target = target.to_numpy()
     print(target)
     consul = target[:, 0]
     auto = target[:, 1]
     power = target[:, 2]
     print(consul)
```

```
[[519. 420. 507.]
 [518. 420. 507.]
 [523. 437. 522.]
 …
 [508. 420. 507.]
 [507. 420. 507.]
 [499. 420. 507.]]
[519. 518. 523. … 508. 507. 499.]
```

0.2 Sequential Model

```
[ ]: model = Sequential()
     model.add(Dense(1, input_shape = (14, ), activation = "linear"))

     model.compile(loss = "mse", optimizer = "adam", metrics = ["mae"])
     history = model.fit(features, consul, batch_size = 32, epochs = 100,␣
      ↪validation_data = (features, consul))
     test_loss, test_mae = model.evaluate(features, consul)
```

```
Epoch 1/100
5056/5056 [==============================] - 20s 4ms/step - loss:
65594298368.0000 - mae: 30102.4785 - val_loss: 21943796.0000 - val_mae:
3117.6562
Epoch 2/100
5056/5056 [==============================] - 19s 4ms/step - loss: 9277739.0000 -
mae: 1771.8094 - val_loss: 496257.3125 - val_mae: 341.5976
Epoch 3/100
5056/5056 [==============================] - 18s 4ms/step - loss: 315567.3750 -
```

```
mae: 190.6971 - val_loss: 75479.8516 - val_mae: 90.8694
Epoch 4/100
5056/5056 [==============================] - 18s 4ms/step - loss: 556924.6875 -
mae: 126.9680 - val_loss: 36687.1875 - val_mae: 80.8977
Epoch 5/100
5056/5056 [==============================] - 19s 4ms/step - loss: 212762.7031 -
mae: 82.2480 - val_loss: 17427.7207 - val_mae: 56.9141
Epoch 6/100
5056/5056 [==============================] - 14s 3ms/step - loss: 264758.7188 -
mae: 73.6811 - val_loss: 1847.4258 - val_mae: 26.9438
Epoch 7/100
5056/5056 [==============================] - 13s 3ms/step - loss: 371066.1562 -
mae: 71.7879 - val_loss: 23369.6133 - val_mae: 62.0651
Epoch 8/100
5056/5056 [==============================] - 18s 4ms/step - loss: 182873.7656 -
mae: 57.0945 - val_loss: 4959.1064 - val_mae: 37.5257
Epoch 9/100
5056/5056 [==============================] - 18s 4ms/step - loss: 289597.7500 -
mae: 70.0762 - val_loss: 7644154.0000 - val_mae: 810.8555
Epoch 10/100
5056/5056 [==============================] - 18s 4ms/step - loss: 187374.5938 -
mae: 60.0326 - val_loss: 2643.0029 - val_mae: 31.0357
Epoch 11/100
5056/5056 [==============================] - 13s 3ms/step - loss: 300414.9688 -
mae: 61.7911 - val_loss: 11336.8828 - val_mae: 48.1649
Epoch 12/100
5056/5056 [==============================] - 18s 4ms/step - loss: 225669.2031 -
mae: 62.5659 - val_loss: 2200.1392 - val_mae: 29.6672
Epoch 13/100
5056/5056 [==============================] - 14s 3ms/step - loss: 171194.0156 -
mae: 69.9958 - val_loss: 1445.8398 - val_mae: 25.8996
Epoch 14/100
5056/5056 [==============================] - 13s 3ms/step - loss: 124861.8750 -
mae: 70.7358 - val_loss: 226278.8125 - val_mae: 153.9160
Epoch 15/100
5056/5056 [==============================] - 19s 4ms/step - loss: 251173.2812 -
mae: 58.6591 - val_loss: 54975.9336 - val_mae: 81.7366
Epoch 16/100
5056/5056 [==============================] - 18s 4ms/step - loss: 509285.3125 -
mae: 68.5634 - val_loss: 1076.9318 - val_mae: 23.6200
Epoch 17/100
5056/5056 [==============================] - 13s 3ms/step - loss: 219382.1875 -
mae: 49.9215 - val_loss: 954.8101 - val_mae: 22.5538
Epoch 18/100
5056/5056 [==============================] - 13s 3ms/step - loss: 147235.1250 -
mae: 56.7252 - val_loss: 2319.3015 - val_mae: 29.7741
Epoch 19/100
5056/5056 [==============================] - 18s 4ms/step - loss: 248115.9219 -
```

```
mae: 62.0425 - val_loss: 1299.3257 - val_mae: 25.0584
Epoch 20/100
5056/5056 [==============================] - 18s 4ms/step - loss: 139975.6406 -
mae: 64.5621 - val_loss: 1064.0327 - val_mae: 23.8111
Epoch 21/100
5056/5056 [==============================] - 13s 3ms/step - loss: 328233.5625 -
mae: 64.5210 - val_loss: 258880.4219 - val_mae: 175.0932
Epoch 22/100
5056/5056 [==============================] - 14s 3ms/step - loss: 142123.1406 -
mae: 55.1743 - val_loss: 139320.3594 - val_mae: 121.8099
Epoch 23/100
5056/5056 [==============================] - 19s 4ms/step - loss: 136604.7344 -
mae: 60.1236 - val_loss: 4244.3604 - val_mae: 34.1760
Epoch 24/100
5056/5056 [==============================] - 14s 3ms/step - loss: 280991.5938 -
mae: 57.6002 - val_loss: 3399.7266 - val_mae: 32.6218
Epoch 25/100
5056/5056 [==============================] - 13s 3ms/step - loss: 241118.7500 -
mae: 53.9373 - val_loss: 3463.4307 - val_mae: 32.4759
Epoch 26/100
5056/5056 [==============================] - 13s 3ms/step - loss: 198043.0938 -
mae: 65.2141 - val_loss: 758.9670 - val_mae: 19.9491
Epoch 27/100
5056/5056 [==============================] - 18s 3ms/step - loss: 212897.9375 -
mae: 56.2265 - val_loss: 933.7592 - val_mae: 22.4241
Epoch 28/100
5056/5056 [==============================] - 19s 4ms/step - loss: 161216.6406 -
mae: 53.4148 - val_loss: 5067.1445 - val_mae: 35.5278
Epoch 29/100
5056/5056 [==============================] - 14s 3ms/step - loss: 222909.2656 -
mae: 55.0396 - val_loss: 433799.6875 - val_mae: 202.8564
Epoch 30/100
5056/5056 [==============================] - 13s 3ms/step - loss: 282923.2812 -
mae: 70.6662 - val_loss: 4230.0044 - val_mae: 31.2496
Epoch 31/100
5056/5056 [==============================] - 13s 3ms/step - loss: 329864.2500 -
mae: 52.1515 - val_loss: 689.2288 - val_mae: 18.9539
Epoch 32/100
5056/5056 [==============================] - 15s 3ms/step - loss: 184035.5625 -
mae: 52.1356 - val_loss: 731.1476 - val_mae: 19.8768
Epoch 33/100
5056/5056 [==============================] - 14s 3ms/step - loss: 177036.2969 -
mae: 56.3071 - val_loss: 1680.7600 - val_mae: 25.9912
Epoch 34/100
5056/5056 [==============================] - 14s 3ms/step - loss: 336286.3438 -
mae: 52.4380 - val_loss: 18163.6777 - val_mae: 52.4938
Epoch 35/100
5056/5056 [==============================] - 14s 3ms/step - loss: 157352.6250 -
```

```
mae: 54.4865 - val_loss: 654.6801 - val_mae: 18.3941
Epoch 36/100
5056/5056 [==============================] - 19s 4ms/step - loss: 270537.9375 -
mae: 57.7442 - val_loss: 16014.7461 - val_mae: 50.5597
Epoch 37/100
5056/5056 [==============================] - 13s 3ms/step - loss: 258979.1562 -
mae: 62.2688 - val_loss: 47348.4102 - val_mae: 81.1073
Epoch 38/100
5056/5056 [==============================] - 14s 3ms/step - loss: 103321.5234 -
mae: 50.8816 - val_loss: 12155.9072 - val_mae: 46.1140
Epoch 39/100
5056/5056 [==============================] - 14s 3ms/step - loss: 173140.0938 -
mae: 61.8370 - val_loss: 3505.6355 - val_mae: 31.1665
Epoch 40/100
5056/5056 [==============================] - 13s 3ms/step - loss: 358866.9688 -
mae: 72.6261 - val_loss: 633.9193 - val_mae: 18.0836
Epoch 41/100
5056/5056 [==============================] - 19s 4ms/step - loss: 155385.4219 -
mae: 51.6564 - val_loss: 1910.4373 - val_mae: 26.2711
Epoch 42/100
5056/5056 [==============================] - 18s 4ms/step - loss: 168595.3125 -
mae: 54.7640 - val_loss: 1199.8976 - val_mae: 22.9455
Epoch 43/100
5056/5056 [==============================] - 13s 3ms/step - loss: 188273.7188 -
mae: 53.1175 - val_loss: 4118.0278 - val_mae: 32.4044
Epoch 44/100
5056/5056 [==============================] - 19s 4ms/step - loss: 150469.9062 -
mae: 67.7830 - val_loss: 165369.5312 - val_mae: 130.1904
Epoch 45/100
5056/5056 [==============================] - 14s 3ms/step - loss: 279218.8125 -
mae: 59.3911 - val_loss: 845.4066 - val_mae: 20.5700
Epoch 46/100
5056/5056 [==============================] - 18s 4ms/step - loss: 132977.2031 -
mae: 44.9718 - val_loss: 984.2792 - val_mae: 21.6097
Epoch 47/100
5056/5056 [==============================] - 18s 4ms/step - loss: 276941.1875 -
mae: 53.8375 - val_loss: 614.4174 - val_mae: 17.6776
Epoch 48/100
5056/5056 [==============================] - 18s 4ms/step - loss: 240610.5000 -
mae: 70.4250 - val_loss: 1573.1031 - val_mae: 24.1192
Epoch 49/100
5056/5056 [==============================] - 13s 3ms/step - loss: 94920.8750 -
mae: 54.4786 - val_loss: 3792.9583 - val_mae: 31.4724
Epoch 50/100
5056/5056 [==============================] - 18s 4ms/step - loss: 290924.1562 -
mae: 51.6540 - val_loss: 206671.9844 - val_mae: 140.5921
Epoch 51/100
5056/5056 [==============================] - 13s 3ms/step - loss: 205788.4844 -
```

```
mae: 61.8342 - val_loss: 669.5153 - val_mae: 19.1084
Epoch 52/100
5056/5056 [==============================] - 19s 4ms/step - loss: 206944.7812 -
mae: 61.4186 - val_loss: 34052.3438 - val_mae: 64.2011
Epoch 53/100
5056/5056 [==============================] - 18s 4ms/step - loss: 163369.0938 -
mae: 57.5873 - val_loss: 604.0778 - val_mae: 17.5682
Epoch 54/100
5056/5056 [==============================] - 13s 3ms/step - loss: 186228.1250 -
mae: 60.8094 - val_loss: 176430.5156 - val_mae: 127.3252
Epoch 55/100
5056/5056 [==============================] - 18s 4ms/step - loss: 110362.3047 -
mae: 48.1331 - val_loss: 568.3551 - val_mae: 16.9285
Epoch 56/100
5056/5056 [==============================] - 13s 3ms/step - loss: 189585.8281 -
mae: 61.1817 - val_loss: 569.7248 - val_mae: 17.0028
Epoch 57/100
5056/5056 [==============================] - 13s 3ms/step - loss: 243862.4219 -
mae: 58.8256 - val_loss: 640.3350 - val_mae: 18.1908
Epoch 58/100
5056/5056 [==============================] - 18s 4ms/step - loss: 416917.0938 -
mae: 50.5750 - val_loss: 29516.0332 - val_mae: 63.7390
Epoch 59/100
5056/5056 [==============================] - 18s 4ms/step - loss: 539250.7500 -
mae: 65.0116 - val_loss: 746.3959 - val_mae: 19.1331
Epoch 60/100
5056/5056 [==============================] - 14s 3ms/step - loss: 206543.0000 -
mae: 47.6995 - val_loss: 631.7553 - val_mae: 17.8596
Epoch 61/100
5056/5056 [==============================] - 18s 4ms/step - loss: 179552.7812 -
mae: 63.8664 - val_loss: 853.8471 - val_mae: 19.7640
Epoch 62/100
5056/5056 [==============================] - 18s 4ms/step - loss: 166353.7812 -
mae: 50.3135 - val_loss: 80311.6875 - val_mae: 93.2775
Epoch 63/100
5056/5056 [==============================] - 14s 3ms/step - loss: 303187.1250 -
mae: 68.7271 - val_loss: 606.7645 - val_mae: 17.5718
Epoch 64/100
5056/5056 [==============================] - 18s 4ms/step - loss: 242333.9531 -
mae: 55.7357 - val_loss: 536.8682 - val_mae: 16.1680
Epoch 65/100
5056/5056 [==============================] - 18s 4ms/step - loss: 224571.3438 -
mae: 60.1762 - val_loss: 121178.8516 - val_mae: 109.4055
Epoch 66/100
5056/5056 [==============================] - 18s 4ms/step - loss: 312739.5938 -
mae: 64.3808 - val_loss: 553.6360 - val_mae: 16.6387
Epoch 67/100
5056/5056 [==============================] - 18s 4ms/step - loss: 443497.3750 -
```

```
mae: 44.6440 - val_loss: 1999.7167 - val_mae: 25.0293
Epoch 68/100
5056/5056 [==============================] - 13s 3ms/step - loss: 166960.4219 -
mae: 48.7354 - val_loss: 1122.6351 - val_mae: 20.8231
Epoch 69/100
5056/5056 [==============================] - 18s 4ms/step - loss: 104130.2422 -
mae: 51.0252 - val_loss: 2878.8176 - val_mae: 26.2473
Epoch 70/100
5056/5056 [==============================] - 18s 4ms/step - loss: 231266.0781 -
mae: 63.6947 - val_loss: 569.6965 - val_mae: 16.5532
Epoch 71/100
5056/5056 [==============================] - 14s 3ms/step - loss: 154557.2812 -
mae: 46.0869 - val_loss: 21371.1914 - val_mae: 53.6287
Epoch 72/100
5056/5056 [==============================] - 18s 4ms/step - loss: 280625.8438 -
mae: 66.4204 - val_loss: 691.2181 - val_mae: 18.1429
Epoch 73/100
5056/5056 [==============================] - 14s 3ms/step - loss: 134864.2969 -
mae: 40.6779 - val_loss: 3503.7888 - val_mae: 29.0380
Epoch 74/100
5056/5056 [==============================] - 19s 4ms/step - loss: 510529.5625 -
mae: 50.9646 - val_loss: 1091.7936 - val_mae: 21.3934
Epoch 75/100
5056/5056 [==============================] - 18s 4ms/step - loss: 153795.0312 -
mae: 42.6905 - val_loss: 500.9304 - val_mae: 15.5161
Epoch 76/100
5056/5056 [==============================] - 19s 4ms/step - loss: 156610.8906 -
mae: 53.3920 - val_loss: 674.9383 - val_mae: 18.2067
Epoch 77/100
5056/5056 [==============================] - 14s 3ms/step - loss: 155597.9219 -
mae: 49.6674 - val_loss: 1284.4065 - val_mae: 21.7417
Epoch 78/100
5056/5056 [==============================] - 13s 3ms/step - loss: 228603.2500 -
mae: 54.7085 - val_loss: 493.6328 - val_mae: 15.3520
Epoch 79/100
5056/5056 [==============================] - 14s 3ms/step - loss: 603007.2500 -
mae: 71.0250 - val_loss: 499.4172 - val_mae: 15.5013
Epoch 80/100
5056/5056 [==============================] - 14s 3ms/step - loss: 160751.0781 -
mae: 51.8655 - val_loss: 1005.8172 - val_mae: 20.7066
Epoch 81/100
5056/5056 [==============================] - 13s 3ms/step - loss: 353808.5000 -
mae: 61.5506 - val_loss: 1453.1213 - val_mae: 22.2524
Epoch 82/100
5056/5056 [==============================] - 19s 4ms/step - loss: 67614.3828 -
mae: 40.2642 - val_loss: 982.4613 - val_mae: 19.9773
Epoch 83/100
5056/5056 [==============================] - 18s 4ms/step - loss: 530585.3750 -
```

```
mae: 55.7013 - val_loss: 114997.6641 - val_mae: 111.3419
Epoch 84/100
5056/5056 [==============================] - 13s 3ms/step - loss: 562966.6250 -
mae: 63.0988 - val_loss: 572.0912 - val_mae: 16.5106
Epoch 85/100
5056/5056 [==============================] - 19s 4ms/step - loss: 157480.3906 -
mae: 44.3841 - val_loss: 557.1979 - val_mae: 16.6844
Epoch 86/100
5056/5056 [==============================] - 18s 4ms/step - loss: 676183.0000 -
mae: 53.8899 - val_loss: 8222.9219 - val_mae: 36.8841
Epoch 87/100
5056/5056 [==============================] - 14s 3ms/step - loss: 237316.3125 -
mae: 55.6906 - val_loss: 16959968.0000 - val_mae: 1252.6908
Epoch 88/100
5056/5056 [==============================] - 14s 3ms/step - loss: 256684.2344 -
mae: 62.0075 - val_loss: 565.9066 - val_mae: 15.9171
Epoch 89/100
5056/5056 [==============================] - 14s 3ms/step - loss: 96717.8438 -
mae: 52.6639 - val_loss: 1200.7699 - val_mae: 21.0669
Epoch 90/100
5056/5056 [==============================] - 14s 3ms/step - loss: 303068.7812 -
mae: 60.7837 - val_loss: 1061.3591 - val_mae: 20.5522
Epoch 91/100
5056/5056 [==============================] - 19s 4ms/step - loss: 202744.6250 -
mae: 48.6825 - val_loss: 763.9022 - val_mae: 18.4322
Epoch 92/100
5056/5056 [==============================] - 18s 3ms/step - loss: 149962.4062 -
mae: 54.7543 - val_loss: 562.6147 - val_mae: 16.4179
Epoch 93/100
5056/5056 [==============================] - 19s 4ms/step - loss: 209370.9688 -
mae: 54.5471 - val_loss: 471.9667 - val_mae: 14.8823
Epoch 94/100
5056/5056 [==============================] - 14s 3ms/step - loss: 515346.9688 -
mae: 41.6148 - val_loss: 505.1797 - val_mae: 15.6883
Epoch 95/100
5056/5056 [==============================] - 18s 3ms/step - loss: 375187.8125 -
mae: 55.3153 - val_loss: 534.9887 - val_mae: 15.8874
Epoch 96/100
5056/5056 [==============================] - 19s 4ms/step - loss: 156233.1875 -
mae: 47.6353 - val_loss: 1844.9520 - val_mae: 23.6583
Epoch 97/100
5056/5056 [==============================] - 14s 3ms/step - loss: 320946.5000 -
mae: 53.7118 - val_loss: 1202.6537 - val_mae: 20.6933
Epoch 98/100
5056/5056 [==============================] - 18s 4ms/step - loss: 228008.1562 -
mae: 54.4995 - val_loss: 2457.7366 - val_mae: 25.6870
Epoch 99/100
5056/5056 [==============================] - 14s 3ms/step - loss: 276141.5938 -
```

```
mae: 50.8632 - val_loss: 563.4454 - val_mae: 16.4556
Epoch 100/100
5056/5056 [==============================] - 14s 3ms/step - loss: 203987.4531 -
mae: 55.8594 - val_loss: 8272.0791 - val_mae: 38.9757
5056/5056 [==============================] - 8s 2ms/step - loss: 8272.0791 -
mae: 38.9757
```

[ ]:
```
model.layers[0].weights
```

[ ]:
```
[<tf.Variable 'dense_1/kernel:0' shape=(14, 1) dtype=float32, numpy=
 array([[ 1.8425053e-01],
        [-2.7889353e-03],
        [ 2.5527823e-01],
        [-1.7407632e-02],
        [ 6.2402081e-01],
        [-5.1219191e-05],
        [ 3.4917164e-01],
        [-1.6837765e-02],
        [-6.1093658e-02],
        [ 1.4051086e-01],
        [ 2.6643597e-02],
        [-7.7480391e-02],
        [ 5.2235629e-03],
        [-3.0684316e-01]], dtype=float32)>,
 <tf.Variable 'dense_1/bias:0' shape=(1,) dtype=float32,
numpy=array([0.3548912], dtype=float32)>]
```

[ ]:
```
display(testing)
testing.drop(columns = ["dates"], axis = 1, inplace = True)
testing = testing.to_numpy()
print(testing)
```

```
            dates  Factor A  Factor B  Factor C  Factor D  Factor E  \
0      2142-11-28  10499.99  10499.99  10499.99  100499.9   1499.99
1      2142-11-29  10499.99  10499.99  10499.99  100499.9   1499.99
2      2142-11-30  10499.99  10499.99  10499.99  100499.9   1499.99
3      2142-12-01  10499.99  10499.99  10499.99  100499.9   1499.99
4      2142-12-02    503.94    497.55    499.63     894.7    502.82
…             …       …       …       …        …        …
29995  2225-01-12    500.82    506.68    500.90     893.7    504.21
29996  2225-01-13    499.46    503.79    505.45     913.4    504.21
29997  2225-01-14    501.84    504.53    505.15     903.9    503.90
29998  2225-01-15    496.40    505.25    500.41     929.0    503.16
29999  2225-01-16    496.94    506.88    495.79     895.7    503.98

         Factor F  Factor G  Factor H  Factor I  Factor J  Factor K  Factor L  \
0      10000500.0    599.99   1499.99  10499.99  10499.99  10499.99  10499.99
1      10000500.0    599.99   1499.99  10499.99  10499.99  10499.99  10499.99
```

```
2      10000500.0    599.99   1499.99  10499.99  10499.99  10499.99  10499.99
3      10000500.0    599.99   1499.99  10499.99  10499.99  10499.99  10499.99
4         94705.0    500.88    499.93    736.35    596.33    498.68    514.90
…             …         …        …         …         …         …         …
29995    233367.0    501.30    499.24    736.27    586.38    507.95    514.26
29996    180508.0    501.44    497.56    736.31    586.31    507.96    514.11
29997    193973.0    501.27    497.46    736.38    586.23    507.98    514.49
29998    167564.0    501.16    499.57    736.41    586.19    507.98    514.53
29999    159933.0    501.25    501.03    736.47    586.11    508.00    513.87

       Factor M  Factor N
0      10499.99  10499.99
1      10499.99  10499.99
2      10499.99  10499.99
3      10499.99  10499.99
4        499.69    500.44
…          …         …
29995    496.98    500.78
29996    498.10    501.06
29997    497.65    500.21
29998    498.27    501.61
29999    498.56    501.32

[30000 rows x 15 columns]

[[10499.99 10499.99 10499.99 … 10499.99 10499.99 10499.99]
 [10499.99 10499.99 10499.99 … 10499.99 10499.99 10499.99]
 [10499.99 10499.99 10499.99 … 10499.99 10499.99 10499.99]
 …
 [  501.84    504.53    505.15 …   514.49    497.65    500.21]
 [  496.4     505.25    500.41 …   514.53    498.27    501.61]
 [  496.94    506.88    495.79 …   513.87    498.56    501.32]]
```

[ ]:
```python
y_model = model.predict(testing)
y_model
```

```
938/938 [==============================] - 1s 1ms/step
```

[ ]:
```
array([[577.7951],
       [577.7951],
       [577.7951],
       …,
       [535.9618],
       [533.6906],
       [534.2224]], dtype=float32)
```

[ ]:
```python
regModel = LinearRegression(fit_intercept = True)
regModel.fit(features, consul)
```

```
y_model = regModel.predict(testing)
y_model
```

[ ]:
```
array([511.50642871, 511.50642871, 511.50642871, …, 508.34586616,
       508.38211539, 509.15862322])
```

[ ]:
```

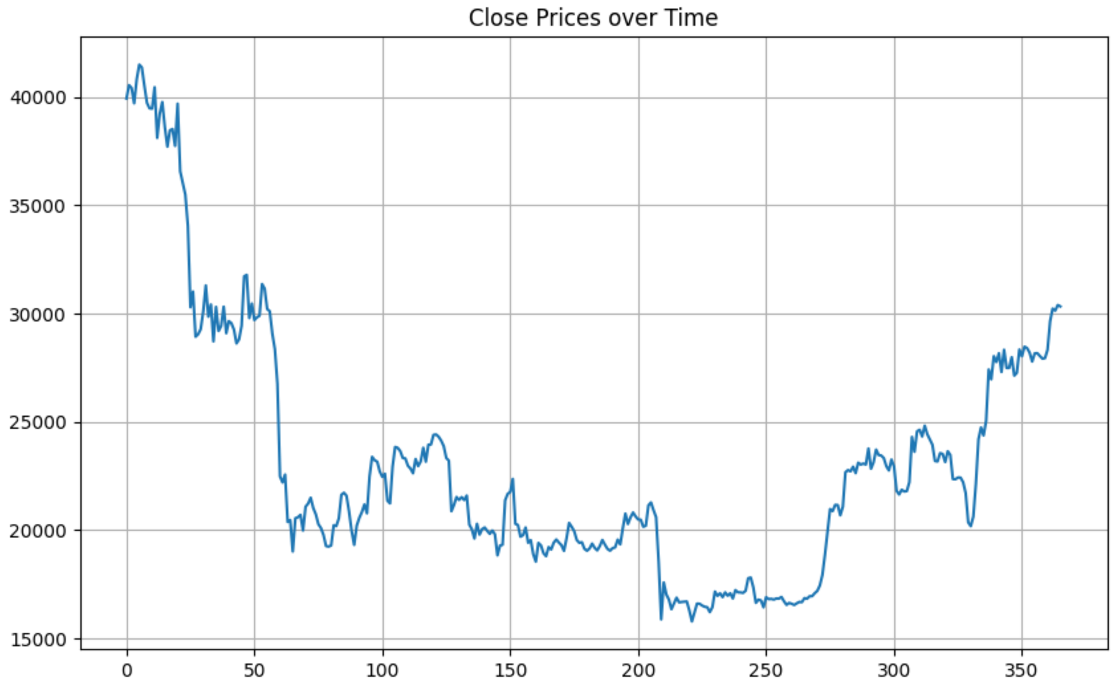
```

0.2.1 The Plot

[ ]:
```
plt.figure(figsize = (10, 6))
for i in range(len(df["Close"][:50])):
  plt.vlines(x = i, ymax = df["High"][i], ymin = df["Low"][i], color = "black")
  if df["Open"][i] <= df["Close"][i]:
    plt.vlines(x = i, ymax = df["Close"][i], ymin = df["Open"][i], color =␣
 ↪"green", linewidth = 8)
  else:
    plt.vlines(x = i, ymax = df["Open"][i], ymin = df["Close"][i], color =␣
 ↪"red", linewidth = 8)
plt.plot(df["Close"][:50], color = "cyan")
plt.grid()
plt.show()
```

[ ]:
```
plt.figure(figsize = (10, 6))
plt.plot(df["Close"])
```

```
plt.grid()
plt.title("Close Prices over Time")
plt.show()
```



[ ]:
```
means = []
for i in range(len(df["Close"])):
  means.append(df["Close"][:i+1].mean())
print(means)
```

```
[39935.515625, 40244.4902345, 40304.48828133333, 40157.60449225, 40291.3265626,
40493.23046883333, 40619.108817, 40607.640625, 40511.27170144444, 40408.8175782,
40323.40625009091, 40334.648112083334, 40164.095252538464, 40098.16852692857,
40076.54583346667, 39984.875732562505, 39851.34627770589, 39774.55447061112,
39709.016241894744, 39611.088086050004, 39615.24441976191, 39477.05788363637,
39327.660665869575, 39168.256185, 38963.8965626, 38630.55258423077,
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37186.63709687097, 37002.839477625, 36786.47821978788, 36599.401137500005,
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35701.81881015383, 35536.7460938, 35393.30316317073, 35254.471214714285,
35115.232921558134, 34967.786132863635, 34831.055338599996, 34713.987984086954,
34650.422082829784, 34590.878092499996, 34493.08629628571, 34412.574335979996,
34320.257008313725, 34233.961951673075, 34152.31478483018, 34100.80287909258,
34047.25152703636, 33978.80695457143, 33910.968201807016, 33827.74124467241,
33735.08140233898, 33618.874186266665, 33436.39081718033, 33255.268271241934,
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```

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23089.599458779616, 23108.96608865659, 23128.938966238355, 23148.629994934425]
```

[ ]:
```
plt.figure(figsize = (10, 6))
plt.plot(means)
plt.grid()
plt.title("Mean of close prices over time")
plt.show()
```


Mean of close prices over time
40000
37500
35000
32500
30000
27500
25000
22500
0
50
100
150
200
250
300
350

[ ]: