# Microsoft Stock price prediction using Neural Networks (LSTM)

Dataset: https://www.kaggle.com/datasets/borismarjanovic/price-volume-data-for-all-us-stocks-etfs

```
# Importing libraries
import pandas as pd
from datetime import timedelta
import numpy as np
import tensorflow as tf
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import mean_absolute_error
from matplotlib import pyplot as plt
from typing import List
```

```
# Read Microsoft Stock prices Dataset
df = pd.read_csv('msft.us.txt', parse_dates = ['Date'])
```

```
# 10 first entries
df.head(10)
```

| | Date | Open | High | Low | Close | Volume | OpenInt |
|---|---|---|---|---|---|---|---|
| **0** | 1986-03-13 | 0.06720 | 0.07533 | 0.06720 | 0.07533 | 1371330506 | 0 |
| **1** | 1986-03-14 | 0.07533 | 0.07533 | 0.07533 | 0.07533 | 409569463 | 0 |
| **2** | 1986-03-17 | 0.07533 | 0.07533 | 0.07533 | 0.07533 | 176995245 | 0 |
| **3** | 1986-03-18 | 0.07533 | 0.07533 | 0.07533 | 0.07533 | 90067008 | 0 |
| **4** | 1986-03-19 | 0.07533 | 0.07533 | 0.07533 | 0.07533 | 63655515 | 0 |
| **5** | 1986-03-20 | 0.07533 | 0.07533 | 0.06720 | 0.07533 | 77665088 | 0 |
| **6** | 1986-03-21 | 0.07533 | 0.07533 | 0.06720 | 0.06720 | 79732075 | 0 |
| **7** | 1986-03-24 | 0.06720 | 0.06720 | 0.06720 | 0.06720 | 86775144 | 0 |
| **8** | 1986-03-25 | 0.06720 | 0.06720 | 0.06720 | 0.06720 | 42641156 | 0 |
| **9** | 1986-03-26 | 0.06720 | 0.07533 | 0.06720 | 0.06720 | 30239240 | 0 |

```
df.shape
```

```
(7983, 7)
```

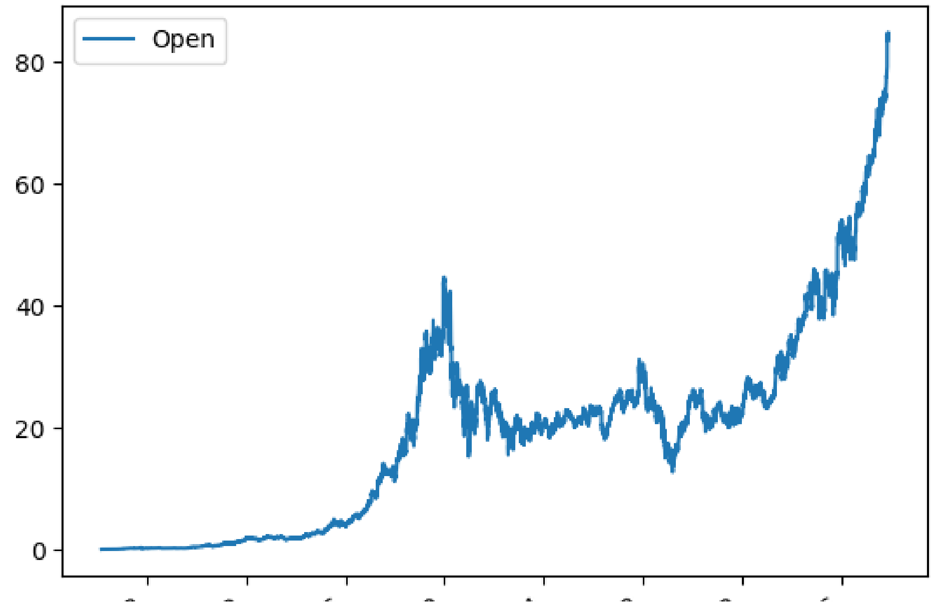
7983 rows 7 columns

```
df['Date'].min()
```

```
Timestamp('1986-03-13 00:00:00')
```

```
# Microsoft stocks by Date
df.plot(x='Date', y='Open')
```

```
<Axes: xlabel='Date'>
```




```
# Correlation
df[['Open', 'High', 'Low', 'Close']].corr()
```

| | Open | High | Low | Close |
|---|---|---|---|---|
| **Open** | 1.000000 | 0.999886 | 0.999879 | 0.999782 |
| **High** | 0.999886 | 1.000000 | 0.999820 | 0.999886 |
| **Low** | 0.999879 | 0.999820 | 1.000000 | 0.999882 |
| **Close** | 0.999782 | 0.999886 | 0.999882 | 1.000000 |

```
# Dataframe for 5 years:
df_5_years = df[df['Date'] > df['Date'].max() - timedelta(days=365*5)]
```

```
df_5_years
```

| | Date | Open | High | Low | Close | Volume | OpenInt |
|---|---|---|---|---|---|---|---|
| **6723** | 2012-11-12 | 25.259 | 25.321 | 24.6240 | 24.630 | 70004599 | 0 |
| **6724** | 2012-11-13 | 23.778 | 24.026 | 23.5400 | 23.840 | 149637406 | 0 |
| **6725** | 2012-11-14 | 23.970 | 24.016 | 23.5820 | 23.620 | 86466650 | 0 |
| **6726** | 2012-11-15 | 23.655 | 23.735 | 23.4320 | 23.461 | 57895114 | 0 |
| **6727** | 2012-11-16 | 23.470 | 23.497 | 23.1790 | 23.339 | 72827220 | 0 |
| **...** | ... | ... | ... | ... | ... | ... | ... |
| **7978** | 2017-11-06 | 84.200 | 84.700 | 84.0825 | 84.470 | 19852151 | 0 |
| **7979** | 2017-11-07 | 84.770 | 84.900 | 83.9300 | 84.260 | 17927878 | 0 |
| **7980** | 2017-11-08 | 84.140 | 84.610 | 83.8300 | 84.560 | 18029584 | 0 |
| **7981** | 2017-11-09 | 84.110 | 84.270 | 82.9000 | 84.090 | 21175384 | 0 |
| **7982** | 2017-11-10 | 83.790 | 84.095 | 83.2300 | 83.870 | 19396301 | 0 |

1260 rows × 7 columns

```
df_5_years.shape[0]
```

```
1260
```

```
# 80% of Data = train
# 20% of Data = test (validation)
train_size = int(df_5_years.shape[0] * 0.8)
train_df = df_5_years.iloc[:train_size]
val_df = df_5_years.iloc[train_size:]
```

```
print('Train dataframe shape is ', train_df.shape, '\nTest dataframe shape is ', val_df.shape,
```

```
Train dataframe shape is (1008, 7)
Test dataframe shape is (252, 7)
```

```
print('Min Date for train Dataset is', train_df['Date'].min())
print('Max Date for train Dataset is', train_df['Date'].max())
```

```
Min Date for train Dataset is 2012-11-12 00:00:00
Max Date for train Dataset is 2016-11-10 00:00:00
```

```
print('Min Date for test Dataset is', val_df['Date'].min())
print('Max Date for test Dataset is', val_df['Date'].max())
```

```
Min Date for test Dataset is 2016-11-11 00:00:00
Max Date for test Dataset is 2017-11-10 00:00:00
```

```
# Normalization
scaler = StandardScaler()
scaler.fit(train_df[['Low']])
```

```
▾ StandardScaler
StandardScaler()
```

```
def make_dataset(
    # Dataframe
    df,
    # Number of elements of time series used to make a prediction
    window_size,
    # Number of elements in batch
    batch_size,
    # Use scaler for Normalization
    use_scaler = True,
    # Mix elements or not
    shuffle = True):
  # To predict the n+1 element n previous elements will be used as features
  # That is why n elements should be subtracted from features
  features = df[['Low']].iloc[:-window_size]
  # Applying Normalization:
  if use_scaler:
    features = scaler.transform(features)
  # Converting Data to type float32
  data = np.array(features, dtype=np.float32)
  ds = tf.keras.preprocessing.timeseries_dataset_from_array(
      data = data,
      targets = df['Low'].iloc[window_size:],
      sequence_length = window_size,
      # Number of elements traversed per stride
      sequence_stride = 1,
```

```
      shuffle = shuffle,
      batch_size = batch_size)
  return ds
```

```
example_ds = make_dataset(df=train_df, window_size=3, batch_size=2, use_scaler=False, shuffle=F
```

```
example_feature, example_label = next(example_ds.as_numpy_iterator())
```

```
# Features shape
example_feature.shape
# batch size, number of elements in the sequence, feature size
```

```
(2, 3, 1)
```

```
example_label.shape
# batch size (number of labels)
```

```
(2,)
```

```
# First 6 elements of the Dataset
train_df['Low'].iloc[:6]
```

```
6723    24.624
6724    23.540
6725    23.582
6726    23.432
6727    23.179
6728    23.292
Name: Low, dtype: float64
```

```
print(example_feature[0])
# 3 first elements of the batch
```

```
[[24.624]
 [23.54 ]
 [23.582]]
```

```
print(example_label[0])
# the 4th element of the Dataset is the label
```

```
23.432
```

```
print(example_feature[1])
```

```
[[23.54 ]
 [23.582]
 [23.432]]
```

```
print(example_label[1])
```

```
23.179
```

```
window_size = 10
batch_size = 8
train_ds = make_dataset(df=train_df, window_size=window_size, batch_size=batch_size, use_scaler
val_ds = make_dataset(df=val_df, window_size=window_size, batch_size=batch_size, use_scaler=Tru
```

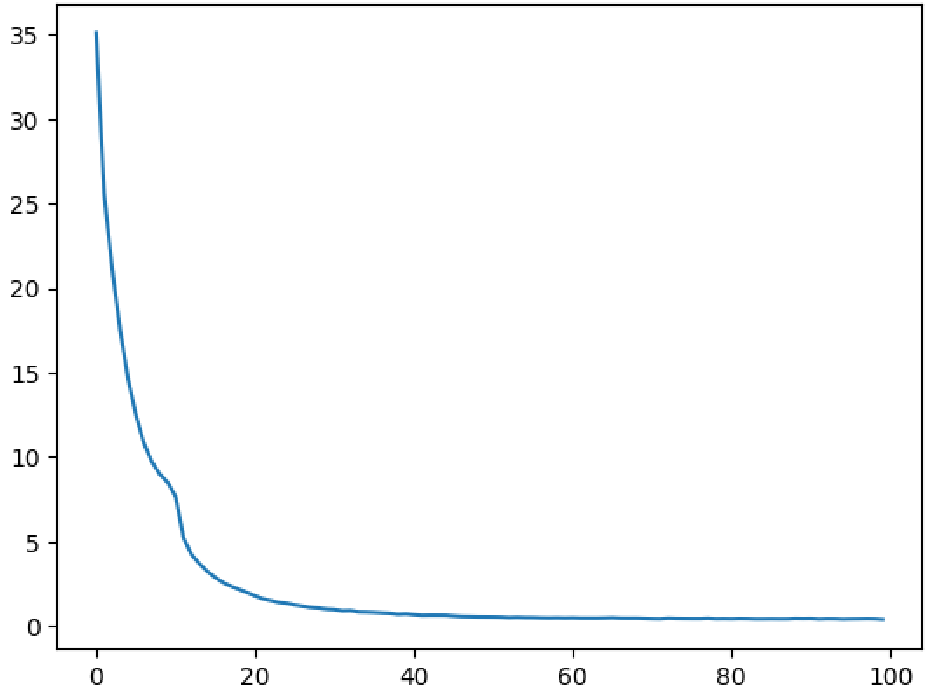
```
# In Sequential Class the layers are executed sequentiall.
# In this case, first LSTM (RNN), then Dense
lstm_model = tf.keras.models.Sequential([
    tf.keras.layers.LSTM(32, return_sequences=False),
    tf.keras.layers.Dense(1)
])
```

```
def compile_and_fit(model, train_ds, val_ds, num_epochs: int = 20):
  model.compile(
      loss = tf.losses.MeanSquaredError(),
      optimizer = tf.optimizers.Adam(),
      metrics = [tf.metrics.MeanAbsoluteError()]
  )
  history = model.fit(
      train_ds,
      #num epochs = number of times train dataset samples are used
      epochs = num_epochs,
      validation_data = val_ds,
      verbose = 0
  )
  return history
```

```
history = compile_and_fit(lstm_model, train_ds, val_ds, num_epochs = 100)
```

```
plt.plot(history.history['mean_absolute_error'])
```

```
[<matplotlib.lines.Line2D at 0x7fe777701cf0>]
```




```
plt.plot(history.history['val_mean_absolute_error'])
```

```
[<matplotlib.lines.Line2D at 0x7fe7774eb730>]
```


```
lstm_model.evaluate(train_ds)
```

```
124/124 [==============================] - 0s 4ms/step - loss: 0.4271 - mean_absolute_errc
[0.42710080742836, 0.44977810978889465]
```

```
lstm_model.evaluate(val_ds)
```

```
30/30 [==============================] - 0s 3ms/step - loss: 95.0061 - mean_absolute_error
[95.00608825683594, 8.288752555847168]
```

The values are very different. That means the model is retraining itself

```
# Different number of epochs
lstm_model = tf.keras.models.Sequential([
    tf.keras.layers.LSTM(32, return_sequences=False),
    tf.keras.layers.Dense(1)
])

history = compile_and_fit(lstm_model, train_ds, val_ds, num_epochs = 200)
```

```
lstm_model.evaluate(train_ds)
```

```
124/124 [==============================] - 1s 4ms/step - loss: 0.3803 - mean_absolute_errc
[0.3802919387817383, 0.428501158952713]
```

```
lstm_model.evaluate(val_ds)
```

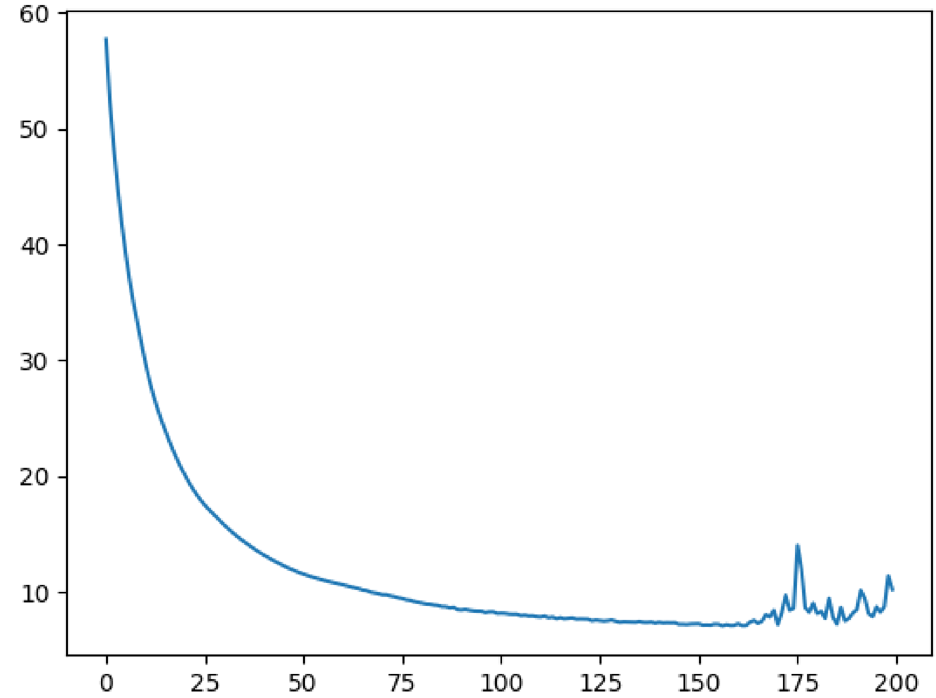
```
30/30 [==============================] - 0s 4ms/step - loss: 189.0219 - mean_absolute_errc
[189.02188110351562, 10.219088554382324]
```

```
plt.plot(history.history['mean_absolute_error'])
```

```
[<matplotlib.lines.Line2D at 0x7fe775623160>]
```


```
plt.plot(history.history['val_mean_absolute_error'])
```

```
[<matplotlib.lines.Line2D at 0x7fe7756c8970>]
```




The difference in the plots is the process of retraining

```
# Applying Drop-out method
# Different number of epochs
lstm_model = tf.keras.models.Sequential([
    tf.keras.layers.LSTM(32, return_sequences=False),
    tf.keras.layers.Dropout(0.2),
    tf.keras.layers.Dense(1)
])

history = compile_and_fit(lstm_model, train_ds, val_ds, num_epochs = 200)
```

```
lstm_model.evaluate(train_ds)
```

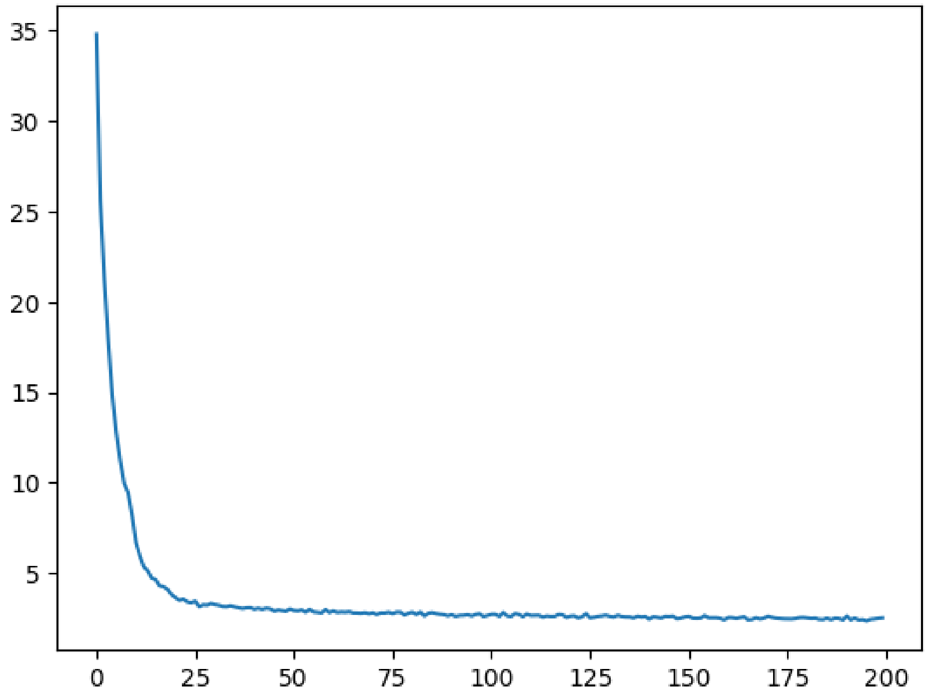
```
124/124 [==============================] - 0s 4ms/step - loss: 0.7548 - mean_absolute_errc
[0.7548012137413025, 0.687798023223877]
```

```
lstm_model.evaluate(val_ds)
```

```
30/30 [==============================] - 0s 4ms/step - loss: 43.2630 - mean_absolute_error
[43.26302719116211, 5.591761112213135]
```

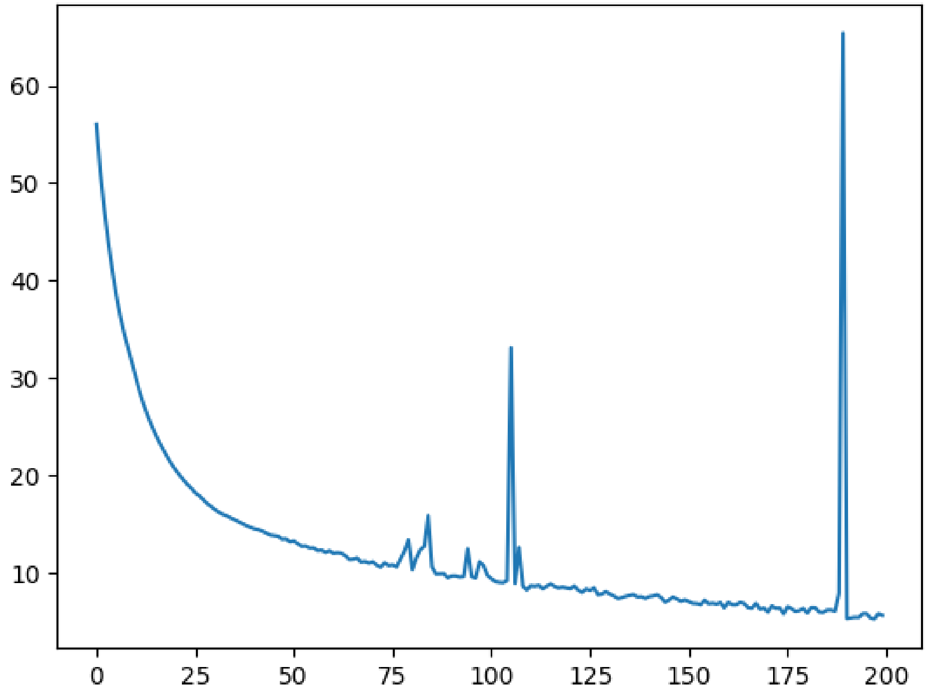
```
plt.plot(history.history['mean_absolute_error'])
```

```
[<matplotlib.lines.Line2D at 0x7fe774ef97b0>]
```




```
plt.plot(history.history['val_mean_absolute_error'])
```

```
[<matplotlib.lines.Line2D at 0x7fe774d563b0>]
```



0s completed at 14:48