Importing Libraries

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import plotly.express as px
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_absolute_percentage_error
import tensorflow as tf
from keras import Model
from keras.layers import Input, Dense, Dropout
from keras.layers import LSTM
```

Reading Dataset

```
df = pd.read_csv('Gold Price (2013-2023).csv')
```

Dataset Overview

```
df
```

	Date	Price	Open	High	Low	Vol.	Change %
0	12/30/2022	1,826.20	1,821.80	1,832.40	1,819.80	107.50K	0.01%
1	12/29/2022	1,826.00	1,812.30	1,827.30	1,811.20	105.99K	0.56%
2	12/28/2022	1,815.80	1,822.40	1,822.80	1,804.20	118.08K	-0.40%
3	12/27/2022	1,823.10	1,808.20	1,841.90	1,808.00	159.62K	0.74%
4	12/26/2022	1,809.70	1,805.80	1,811.95	1,805.55	NaN	0.30%
...	...	...	...	...	...	...	...
2578	01/08/2013	1,663.20	1,651.50	1,662.60	1,648.80	0.13K	0.97%
2579	01/07/2013	1,647.20	1,657.30	1,663.80	1,645.30	0.09K	-0.16%
2580	01/04/2013	1,649.90	1,664.40	1,664.40	1,630.00	0.31K	-1.53%
2581	01/03/2013	1,675.60	1,688.00	1,689.30	1,664.30	0.19K	-0.85%
2582	01/02/2013	1,689.90	1,675.80	1,695.00	1,672.10	0.06K	0.78%

2583 rows × 7 columns

As you can see, the data set includes daily gold price information including daily Open, High and Low prices and the final price of each day (Price) along with the volume of transactions and price changes in each day.

Dataset Basic Information:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2583 entries, 0 to 2582
Data columns (total 7 columns):
 #   Column    Non-Null Count  Dtype 
---  ------    --------------  ----- 
 0   Date      2583 non-null   object
 1   Price     2583 non-null   object
 2   Open      2583 non-null   object
 3   High      2583 non-null   object
 4   Low       2583 non-null   object
 5   Vol.      2578 non-null   object
 6   Change %  2583 non-null   object
dtypes: object(7)
memory usage: 141.4+ KB
```

All variables are stored as object.

Data Preparation

Feature Subset Selection Since we will not use Vol. and Change % features to predict Price, we will drop these two features:

```
df.drop(['Vol.', 'Change %'], axis=1, inplace=True)
```

Transforming Data Date feature is stored as object in the data frame. To increase the speed of calculations, we convert it's data type to datetime and then sort this feature in ascending order:

```
df['Date'] = pd.to_datetime(df['Date'])
df.sort_values(by='Date', ascending=True, inplace=True)
df.reset_index(drop=True, inplace=True)
```

The " , " sign is redundant in the dataset. First, we remove it from the entire dataset and then change the data type of the numerical variables to float:

```
NumCols = df.columns.drop(['Date'])
df[NumCols] = df[NumCols].replace({',': ''}, regex=True)
df[NumCols] = df[NumCols].astype('float64')
```

RESULT

```
df.head()
```

	Date	Price	Open	High	Low
0	2013-01-02	1689.9	1675.8	1695.0	1672.1
1	2013-01-03	1675.6	1688.0	1689.3	1664.3
2	2013-01-04	1649.9	1664.4	1664.4	1630.0
3	2013-01-07	1647.2	1657.3	1663.8	1645.3
4	2013-01-08	1663.2	1651.5	1662.6	1648.8

Checking Duplicates

There are no duplicate samples in Date feature:

```
df.duplicated().sum()
```

```
0
```

Checking Missing Values

There are no missing values in the dataset:

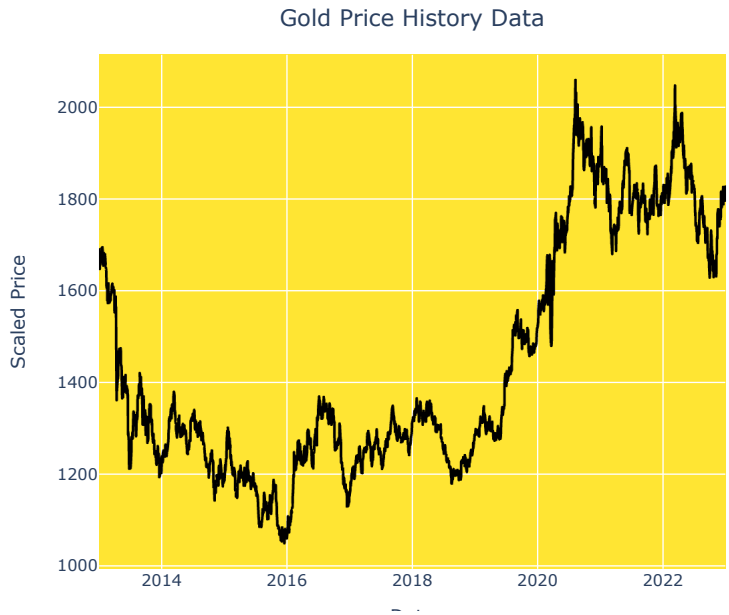
```
df.isnull().sum().sum()
```

```
0
```

Visualizing Gold Price History Data

Interactive Gold Price Chart:

```
fig = px.line(y=df.Price, x=df.Date)
fig.update_traces(line_color='black')
fig.update_layout(xaxis_title="Date",
                  yaxis_title="Scaled Price",
                  title={'text': "Gold Price History Data", 'y':0.95, 'x':0.5, 'xanchor':'center', 'yanchor':'top'},
                  plot_bgcolor='rgba(255,223,0,0.8)')
```



Splitting Data to Training & Test Sets

Since we cannot train on future data in time series data, we should not divide the time series data randomly. In time series splitting, testing set is always later than training set. We consider the last year for testing and everything else for training:

```
test_size = df[df.Date.dt.year==2022].shape[0]
test_size
```

```
260
```

Gold Price Training and Test Sets Plot:

```
plt.figure(figsize=(15, 6), dpi=150)
plt.rcParams['axes.facecolor'] = 'yellow'
plt.rc('axes',edgecolor='white')
plt.plot(df.Date[:-test_size], df.Price[:-test_size], color='black', lw=2)
plt.plot(df.Date[-test_size:], df.Price[-test_size:], color='blue', lw=2)
plt.title('Gold Price Training and Test Sets', fontsize=15)
plt.xlabel('Date', fontsize=12)
plt.ylabel('Price', fontsize=12)
plt.legend(['Training set', 'Test set'], loc='upper left', prop={'size': 15})
plt.grid(color='white')
plt.show()
```

Data Scaling

Since we aim to predict Price only based on its historical data, we scale Price using MinMaxScaler to avoid intensive computations:

```
scaler = MinMaxScaler()
scaler.fit(df.Price.values.reshape(-1,1))
```

```
MinMaxScaler()
```

Restructure Data & Create Sliding Window

The use of prior time steps to predict the next time step is called sliding window. In this way, time series data can be expressed as supervised learning. We can do this by using previous time steps as input variables and use the next time step as the output variable. The number of previous time steps is called the window width. Here we set window width to 60. Therefore, X_train and X_test will be nested lists containing lists of 60 time-stamp prices. y_train and y_test are also lists of gold prices containing the next day's gold price corresponds to each list in X_train and X_test respectively:


```
window_size = 60
```

Training Set:

```
train_data = df.Price[:-test_size]
train_data = scaler.transform(train_data.values.reshape(-1,1))
```

```
X_train = []
y_train = []

for i in range(window_size, len(train_data)):
    X_train.append(train_data[i-60:i, 0])
    y_train.append(train_data[i, 0])
```

Test Set:

```
test_data = df.Price[-test_size-60:]
test_data = scaler.transform(test_data.values.reshape(-1,1))
```

```
X_test = []
y_test = []

for i in range(window_size, len(test_data)):
    X_test.append(test_data[i-60:i, 0])
    y_test.append(test_data[i, 0])
```

Converting Data to Numpy Arrays

Now X_train and X_test are nested lists (two-dimensional lists) and y_train is a one-dimensional list. We need to convert them to numpy arrays with a higher dimension, which is the data format accepted by TensorFlow when training the neural network:

```
X_train = np.array(X_train)
X_test  = np.array(X_test)
y_train = np.array(y_train)
y_test  = np.array(y_test)
```

```
X_train = np.reshape(X_train, (X_train.shape[0], X_train.shape[1], 1))
X_test  = np.reshape(X_test, (X_test.shape[0], X_test.shape[1], 1))
y_train = np.reshape(y_train, (-1,1))
y_test  = np.reshape(y_test, (-1,1))
```

```
print('X_train Shape: ', X_train.shape)
print('y_train Shape: ', y_train.shape)
print('X_test Shape:  ', X_test.shape)
print('y_test Shape:  ', y_test.shape)
```

```
X_train Shape:  (2263, 60, 1)
y_train Shape:  (2263, 1)
X_test Shape:   (260, 60, 1)
y_test Shape:   (260, 1)
```

#Creating an LSTM Network

We build an LSTM network, which is a type of Recurrent Neural Networks designed to solve vanishing gradient problem:

Model Definition:

```
def define_model():
    input1 = Input(shape=(window_size,1))
    x = LSTM(units = 64, return_sequences=True)(input1)
    x = Dropout(0.2)(x)
    x = LSTM(units = 64, return_sequences=True)(x)
    x = Dropout(0.2)(x)
    x = LSTM(units = 64)(x)
    x = Dropout(0.2)(x)
    x = Dense(32, activation='softmax')(x)
    dnn_output = Dense(1)(x)

    model = Model(inputs=input1, outputs=[dnn_output])
    model.compile(loss='mean_squared_error', optimizer='Nadam')
    model.summary()

    return model
```

Model Training:

```
model = define_model()
history = model.fit(X_train, y_train, epochs=150, batch_size=32, validation_split=0.1, verbose=1)
```

```
Model: "model"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_1 (InputLayer)        [(None, 60, 1)]           0

 lstm (LSTM)                 (None, 60, 64)            16896

 dropout (Dropout)           (None, 60, 64)            0

 lstm_1 (LSTM)               (None, 60, 64)            33024

 dropout_1 (Dropout)         (None, 60, 64)            0

 lstm_2 (LSTM)               (None, 64)                33024

 dropout_2 (Dropout)         (None, 64)                0

 dense (Dense)               (None, 32)                2080

 dense_1 (Dense)             (None, 1)                 33

=================================================================
Total params: 85,057
Trainable params: 85,057
Non-trainable params: 0
_________________________________________________________________
Epoch 1/150
64/64 [==============================] - 26s 269ms/step - loss: 0.0411 - val_loss: 0.0725
Epoch 2/150
64/64 [==============================] - 8s 131ms/step - loss: 0.0113 - val_loss: 0.0360
Epoch 3/150
64/64 [==============================] - 7s 110ms/step - loss: 0.0072 - val_loss: 0.0168
Epoch 4/150
64/64 [==============================] - 10s 149ms/step - loss: 0.0049 - val_loss: 0.0069
Epoch 5/150
64/64 [==============================] - 8s 130ms/step - loss: 0.0035 - val_loss: 0.0030
Epoch 6/150
64/64 [==============================] - 7s 110ms/step - loss: 0.0027 - val_loss: 0.0022
Epoch 7/150
64/64 [==============================] - 8s 129ms/step - loss: 0.0021 - val_loss: 0.0028
Epoch 8/150
64/64 [==============================] - 8s 124ms/step - loss: 0.0018 - val_loss: 0.0042
Epoch 9/150
64/64 [==============================] - 9s 137ms/step - loss: 0.0016 - val_loss: 0.0061
Epoch 10/150
64/64 [==============================] - 8s 131ms/step - loss: 0.0013 - val_loss: 0.0055
Epoch 11/150
64/64 [==============================] - 7s 117ms/step - loss: 0.0014 - val_loss: 0.0085
Epoch 12/150
64/64 [==============================] - 10s 145ms/step - loss: 0.0013 - val_loss: 0.0049
Epoch 13/150
64/64 [==============================] - 8s 131ms/step - loss: 0.0013 - val_loss: 0.0085
Epoch 14/150
64/64 [==============================] - 7s 111ms/step - loss: 0.0012 - val_loss: 0.0052
Epoch 15/150
64/64 [==============================] - 8s 131ms/step - loss: 0.0011 - val_loss: 0.0036
Epoch 16/150
```

Model Evaluation

Next, we evaluate our time series forecast using MAPE (Mean Absolute Percentage Error) metric:

```
result = model.evaluate(X_test, y_test)
y_pred = model.predict(X_test)
```

```
9/9 [==============================] - 0s 30ms/step - loss: 0.0016
9/9 [==============================] - 2s 31ms/step
```

```
MAPE = mean_absolute_percentage_error(y_test, y_pred)
Accuracy = 1 - MAPE
print("Test Loss:", result)
print("Test MAPE:", MAPE)
print("Test Accuracy:", Accuracy)
```

```
Test Loss: 0.001582730794325471
Test MAPE: 0.047808953086504964
Test Accuracy: 0.952191046913495
```

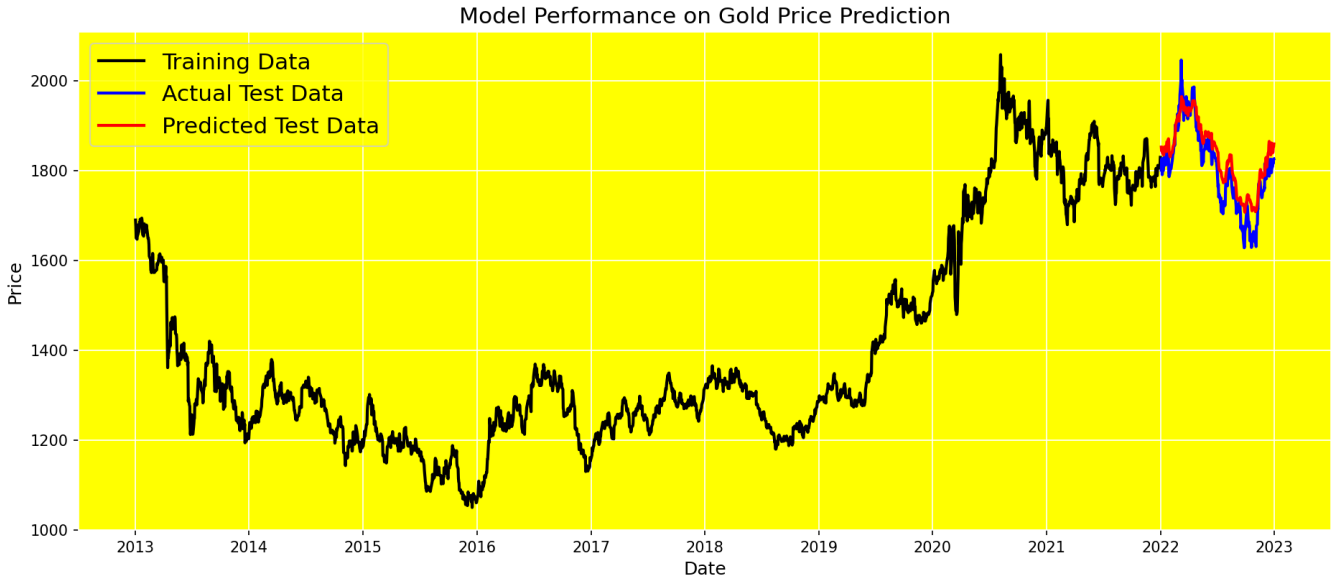
Visualizing Results

Returning the actual and predicted Price values to their primary scale:

```
y_test_true = scaler.inverse_transform(y_test)
y_test_pred = scaler.inverse_transform(y_pred)
```

Investigating the closeness of the prices predicted by the model to the actual prices:

```
plt.figure(figsize=(15, 6), dpi=150)
plt.rcParams['axes.facecolor'] = 'yellow'
plt.rc('axes',edgecolor='white')
plt.plot(df['Date'].iloc[:-test_size], scaler.inverse_transform(train_data), color='black', lw=2)
plt.plot(df['Date'].iloc[-test_size:], y_test_true, color='blue', lw=2)
plt.plot(df['Date'].iloc[-test_size:], y_test_pred, color='red', lw=2)
plt.title('Model Performance on Gold Price Prediction', fontsize=15)
plt.xlabel('Date', fontsize=12)
plt.ylabel('Price', fontsize=12)
plt.legend(['Training Data', 'Actual Test Data', 'Predicted Test Data'], loc='upper left', prop={'size': 15})
plt.grid(color='white')
plt.show()
```



Conclusion:

As can be seen, the price predicted by the LSTM model follows the actual prices greatly! The value of Loss and Accuracy (1-MAPE) obtained on the test data also confirm the great performance of the model:¶ **Loss: 0.001 Accuracy: 95%**