PREDICTING CRUDE OIL PRICE

DATA GATHERING

import packages

```
# import packages
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split, cross_val_score, KFold, GridSearchCV
from sklearn.linear_model import LinearRegression, Ridge
from sklearn.pipeline import make_pipeline
from sklearn.metrics import mean_absolute_error, mean_squared_error as MSE, r2_score
from keras.models import Sequential
import tensorflow as tf
from keras.layers import LSTM, Dense, Dropout, Embedding, Masking
from sklearn.preprocessing import MinMaxScaler

from pandas.plotting import register_matplotlib_converters
import warnings
```

```
register_matplotlib_converters()
%matplotlib inline
warnings.filterwarnings('ignore')
plt.style.use('seaborn-deep')
plt.rcParams['figure.figsize'] = (16,9)
plt.rcParams['axes.labelsize'] = 16
plt.rcParams['axes.titlesize'] = 18
plt.rcParams['legend.fontsize'] = 14
plt.rcParams['xtick.labelsize'] = 14
plt.rcParams['ytick.labelsize'] = 14
```

```
2023-01-01 14:51:12.771884: W tensorflow/stream_executor/platform/default/dso_loader.cc:64] Could not load dynamic library 'libcudart.sc
2023-01-01 14:51:12.771906: I tensorflow/stream_executor/cuda/cudart_stub.cc:29] Ignore above cudart dlerror if you do not have a GPU se
```

read data

```
# read data and print first few rows
brent = pd.read_csv('Brent.csv', parse_dates = ['Date'])
```

DATA WRANGLING

make a copy of the data

```
# make a copy of the data
brent_oil = brent.copy()
```

check for data errors

Data type is correct and there is absence of missing values

```
# check data information
brent_oil.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8216 entries, 0 to 8215
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
```

```
 0   Date    8216 non-null   datetime64[ns]
 1   Price   8216 non-null   float64
dtypes: datetime64[ns](1), float64(1)
memory usage: 128.5 KB
```

```
brent_oil.tail()
```

Date	Price	Year
2019-09-24	64.13	2019
2019-09-25	62.41	2019
2019-09-26	62.08	2019
2019-09-27	62.48	2019
2019-09-30	60.99	2019

we can see a minimum price of 9 dollars and a maximum of 143 dollars. There is no way to tell if they are outliers or inconsistent until we carry out further analysis. Looking at the law of demand, price generally increases as demand increases which is the case for this scenario of oil prices.

```
# check summary statistics
brent_oil.describe()
```

	Price
count	8216.000000
mean	46.332605
std	32.704113
min	9.100000
25%	18.730000
50%	31.260000
75%	67.432500
max	143.950000

EXPLORATORY ANALYSIS

The following blocks of code show the forensic tools prepared to aid in the hunt for major incidents:

- create a year column
- set date as index to enable resampling in pandas
- data subset based on 20 year period
- plot line graph

```
# create a year column
brent_oil['Year'] = brent_oil.Date.dt.year

# Set date as index so can do resampling using pandas
brent_oil.set_index('Date', inplace=True)
```

we want to plot a time series graph of the Crude oil prices for the last 20 years with reference to the dataset provided. This will span between 1999 to present (2019). We will create a new subset containing data from 1999 to 2019.

```
# create subset on a 20-year period
brent_99_19 = brent_oil[brent_oil['Year']>= 1999]
```

Brent Crude oil prices prices Between Jan 4 1999 - September 30, 2019

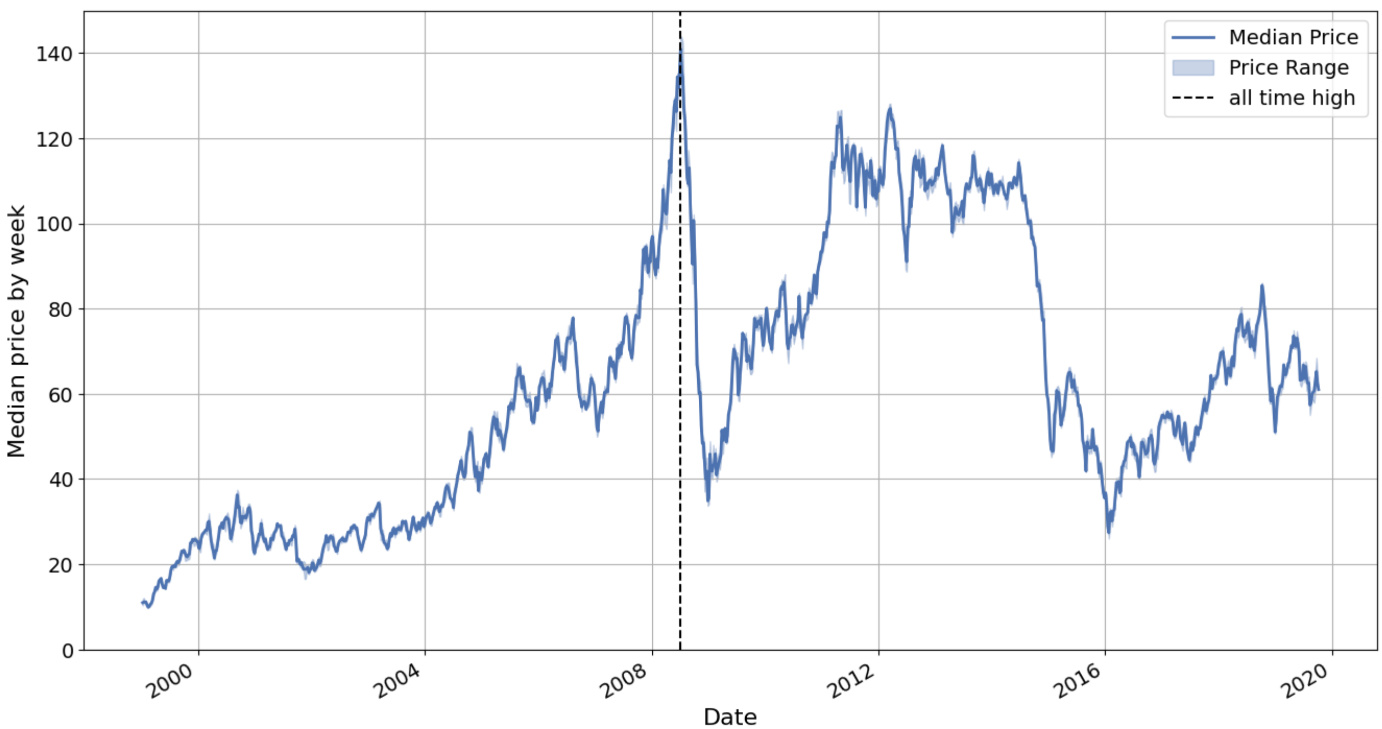
```
fig, ax =  plt.subplots()

# calculate weekly statistics of price
weekly_median_price = brent_99_19.resample('1W').Price.median()
weekly_max_price = brent_99_19.resample('1W').Price.max()
weekly_min_price = brent_99_19.resample('1W').Price.min()

# plot the time series filling it with some
# calculated statistics
ax.plot(weekly_median_price.index, weekly_median_price, lw = 2, label = 'Median Price')
ax.fill_between(weekly_median_price.index, weekly_max_price,\
                weekly_median_price, alpha = 0.3,\
                color = 'C0', label = 'Price Range')
ax.fill_between(weekly_median_price.index, weekly_min_price,\
                weekly_median_price, alpha = 0.3,\
                color = 'C0')

# annotate the plot to show significant events
# that led to variation in price
ax.axvline(pd.Timestamp('2008-7-01'), ls = '--', c = 'k', label = 'all time high')

# set axis labels and titles
ax.set_ylabel('Median price by week')
ax.set_xlabel('Date')
ax.set_ylim([0, 150])
ax.legend()
ax.grid()
fig.autofmt_xdate()
```



Feature Engineering for Machine learning

Looking at the data of the brent crude oil prices, only one column(Price) which is the traget variable is present apart from the date column. We will need to engineer new features from the available price column to use as our independent variable. Here, we will create 3-day and 9-day moving averages from the price column. According to [Investopedia](), One purpose of computing the moving average of a stock is to create a continuously updated average price that can smooth out the price data. This can help reduce the effect of short-term, random price fluctuations on the stock over a given period of time.

```
# create a function to calculate 3 day and 9 day
# moving average
def compute_rolling(df, horizon, col):
    label = f'moving_{horizon}_day_avg_{col}'
    df[label] = df[col].rolling(horizon).mean()
    return df


# set the rolling horizon to 3 and 9
rolling_horizon = [3, 9]

# iterate using for loop
for horizon in rolling_horizon:
    for col in ['Price']:
        brent_99_19 = compute_rolling(brent_99_19, horizon, col)
```

Looking at the new dataframe created, we can see that we have missing values. These row will have to be dropped as maxhine learning models can work with missing values

```
# lets print head of the new dataframe
brent_99_19.head(10)
```

	Price	Year	moving_3_day_avg_Price	moving_9_day_avg_Price
Date				
1999-01-04	10.94	1999	NaN	NaN
1999-01-05	10.30	1999	NaN	NaN
1999-01-06	10.67	1999	10.636667	NaN
1999-01-07	11.08	1999	10.683333	NaN
1999-01-08	11.70	1999	11.150000	NaN
1999-01-11	12.07	1999	11.616667	NaN
1999-01-12	11.78	1999	11.850000	NaN
1999-01-13	10.90	1999	11.583333	NaN
1999-01-14	11.10	1999	11.260000	11.171111
1999-01-15	10.97	1999	10.990000	11.174444

```
# drop rows wih missing values
brent_99_19 = brent_99_19.loc['1999-01-14':]
```

Variance of the two features are similar so no need to for any transformation

```
# check variance of the features
brent_99_19[['moving_3_day_avg_Price', 'moving_9_day_avg_Price']].var()
```

```
moving_3_day_avg_Price    960.218232
moving_9_day_avg_Price    959.877391
dtype: float64
```

Predicting oil price using linear regression

Linear regression is a statistical technique used in data science and machine learning for making predictions about future events. It does this by identifying a linear relationship between an independent variable and a dependent variable. This allows it to use the data it has been given to predict the outcome of future events with a certain level of accuracy. It is a powerful tool that is widely used in a variety of fields, including finance, marketing, and economics.

Linear regression is a type of supervised learning algorithm that can be used to make predictions about continuous or numeric variables, such as sales, salary, age, or product price. It does this by identifying a mathematical relationship between an independent variable and a dependent variable, which is the response or outcome being analyzed or studied. In other words, the regression model uses the data it has been given to predict the value of the dependent variable. This is a useful tool for predicting future events or understanding the relationships between different variables.

There are different types of linear Regression but we will be using the Multiple linear regression with scikit learn.

In multiple linear regression, the equation for predicting the value of a dependent variable is similar to the equation used in simple linear regression, but with additional weights and inputs for the different features being considered. The equation for multiple linear regression looks like this:

y(x) = p0 + p1x1 + p2x2 + … + p(n)x(n)

The machine learning model uses this equation and various weight values to draw lines that best fit the data, and determines the combination of weights that creates the strongest relationship between the variables. To optimize the weights (pi), the regression model uses a cost function called the root mean squared error (MSE) or mean squared error (MSE). This cost function measures the average squared difference between the actual and predicted values of the observations, and produces a single number representing the cost or score associated with the current set of weights. The goal is to minimize the MSE in order to improve the accuracy of the regression model.

SPLIT DATA INTO TRAINING AND TEST SET

We will be splitting the data into 70% train set and 30% test set

```
# create the feature and target variables
X = brent_99_19.drop(['Year','Price'], axis = 1)
y = brent_99_19.Price


# use train_test_split to split the data into
# train and test set
X_train, X_test, y_train, y_test = train_test_split( X, y,\
                                                    test_size = 0.3, random_state = 42,\
                                                    shuffle = False)
```

Visualize the train and test set ranges

```
fig, ax = plt.subplots()
ax.plot(X_train.index, y_train, c='r')
ax.plot(X_test.index, y_test, c='b')
plt.legend(['Train', 'Test'])
```

```
<matplotlib.legend.Legend at 0x7f453ff32e80>
```

BUILD A LINEAR REGRESSION MODEL

```
# instantiate LinearRegression
linear_reg = LinearRegression()

# fit model on train set
linear_reg.fit(X_train, y_train)
```

```
▾ LinearRegression
LinearRegression()
```

PREDICT ON THE TEST SET

```
# predict on test set
y_pred_linear = linear_reg.predict(X_test)
```

The Mean Squared Error measures how close a regression line is to a set of data points. It is a risk function corresponding to the expected value of the squared error loss. A smaller MSE is preferred because it indicates that your data points are dispersed closely around its central moment (mean). It reflects the centralized distribution of your data values, [hrer]

We use the following method to measure accuracy of our model

- mean squared error
- mean absolute error
- root mean squared error

```
# https://stackabuse.com/linear-regression-in-python-with-scikit-learn/
mae = mean_absolute_error(y_test, y_pred_linear)
mse = MSE(y_test, y_pred_linear)
rmse = np.sqrt(mse)

print(f'Mean absolute error: {mae:.2f}')
print(f'Mean squared error: {mse:.2f}')
print(f'Root mean squared error: {rmse:.2f}')
```

```
Mean absolute error: 0.63
Mean squared error: 0.69
Root mean squared error: 0.83
```

CROSS-VALIDATION WITH LINEAR REGRESSION

The previous code block used Linear regression without cross-validation. Lets see if using cross-validation will yield better accuracy

```
# create a KFold object with 5 splits
folds = KFold(n_splits = 5, shuffle = False)
scores = cross_val_score(linear_reg, X,\
                         y, scoring='neg_mean_squared_error',\
                         cv=folds, n_jobs = -1)
# print the MSE
print('MSE: {}'.format(-scores.mean()))
```

```
MSE: 0.838006138281464
```

The RMSE is slightly higher than that obtained without cross validation but nonetheless, both method indicate that our model fits quite well with the data

```
# view the RMSE
print('RMSE using cross val is: {}'.format(np.sqrt((-scores).mean())))
```

```
RMSE using cross val is: 0.915426752002291
```

VISUALIZE THE PREDICTED PRICE AND THE ACTUAL PRICE FOR THE SPECIFIC TIME PERIOD

```
fig, ax = plt.subplots()
ax.plot(X_test.index, y_test, c='k')
ax.plot(X_test.index, y_pred_linear, c='b')
plt.legend(['actual price', 'predicted price'])
```

```
<matplotlib.legend.Legend at 0x7f2d4045beb0>
```

Get the beta values

```
# https://stackabuse.com/linear-regression-in-python-with-scikit-learn/
# get feature names and the coefficients
feature_names = X.columns
model_coefficients = linear_reg.coef_

# create  dataframe of features with
# the corresponding coefficients
coefficients_df = pd.DataFrame(data = np.round(model_coefficients, 3),
                              index = feature_names, \
                              columns = ['Coefficient value'])
# Print coefficient
print(coefficients_df)
```

```
                       Coefficient value
moving_3_day_avg_Price             1.216
moving_9_day_avg_Price            -0.217
```

Get the alpha value

```
# get the intercept
intercept = linear_reg.intercept_
print(np.round(intercept, 3))
```

```
0.041
```

The linear regression equation is

y = 0.041 + 1.216Xa - 0.217Xb

Prediction Oil Prices Using Long short-term Memory

With deep learning models, we know that we have to scale our data for optimal performance. We use MinMaxScaler to scale the values between zero and one and then use the fit_transform method to fit the scaler and transform the model.

```
##We need 2 scalers per model -Train and Test require different scalers
sc1 = MinMaxScaler(feature_range=(0,1))
sc2 = MinMaxScaler(feature_range=(0,1))
```

DEFINE TRAIN AND TEST SET

STEP 1

LSTM requires values to be a numpy array and since we are dealing with a time series, the time should sequential as we will be trying to predict future prices based on past prices. we first create our train and test data by subsetting the orignal data.

In order to make predictions based on past data, we need to create a specific data structure that includes information from the previous time stamp since we will be using the moving averages. Therefore, the training data, X_train, is a list of lists containing the prices from the previous time stamp, and the training labels, y_train, are the stock prices for the following day, corresponding to each list in X_train.

We will reshape the data as LSTM works with 3D array

```
##Function to Prepare Training Data for LSTM
def prepare_train_data_lstm(scaler,train_data,n_dim):
  input_data = scaler.fit_transform(train_data.values)
  print('Shape of Input Data Initially',input_data.shape)
  timesteps = 1
  global X1
  X1 = []
  global y1
  y1=[]
  for i in range(len(input_data)-timesteps-1):
    t=[]
    for j in range(0,timesteps):

        t.append(input_data[[(i+j)], :])
    X1.append(t)
    y1.append(input_data[i+ timesteps,0])

  X1, y1= np.array(X1), np.array(y1)
  print('Shape of Train Part after transformation',X1.shape)
  print('Shape of Test Part after transformation ',y1.shape)

  X1 = X1.reshape(X1.shape[0],timesteps, n_dim)
  print('Final Shape ',X1.shape)
  return X1,y1
```

BUILD LSTM MODEL

According to inte Fundamentally, we are building a Neural network regressor for continuous value prediction using LSTM. We instantiate the model and Then, add the 1st LSTM layer with the Dropout layer followed. We will add 3 more layers to the neural network. Finally, add the output layer. To compile the RNN, we will select an SGD algorithm and a loss function. Adam is a commonly used optimizer, so it is a good choice to begin with. The loss function will be the average of the squares of the differences between the predicted values and the actual values.

```
##LSTM Model Function
def lstm_model(scaler,train_data,n_dim):
#initialize model
  prepare_train_data_lstm(scaler,train_data,n_dim)

  global model
  model = Sequential()

#layer 1 of LSTM
  model.add(LSTM(units=30,return_sequences=True,input_shape=(X1.shape[1],n_dim)))
  model.add(Dropout(0.2))

#layer 2 of LSTM
  model.add(LSTM(units=30,return_sequences=True))
  model.add(Dropout(0.2))

#layer 3 of LSTM
  model.add(LSTM(units=30,return_sequences=True))
  model.add(Dropout(0.2))


#layer 4 of LSTM
  model.add(LSTM(units=30))
  model.add(Dropout(0.2))

#Output layer of model
  model.add(Dense(units=1))

  optimizer = tf.keras.optimizers.Adam(lr=2e-5)
#compiling the model
  model.compile(optimizer=optimizer,loss='mean_squared_error')
  model.fit(X1, y1, epochs=50, batch_size=32)


##Function to Prepare Test Data
def prepare_test_data_lstm(scaler,test_data,n_dim):
  inputs = scaler.transform(test_data.values)
  global X1_test
  X1_test = []
  timesteps = 1
  for i in range(len(inputs)-timesteps-1):
      t=[]
      for j in range(0,timesteps):

          t.append(inputs[[(i+j)], :])
      X1_test.append(t)
  X1_test = np.array(X1_test)
  X1_test = np.reshape(X1_test, (X1_test.shape[0], X1_test.shape[1], n_dim))
  print('Shape of Test Dataset',X1_test.shape)



def predict_data(model_name,scaler_pred,test_data,X1_test,n_dim):

  pred = model_name.predict(X1_test)
  print(len(test_data[1:]))
  set_scale = scaler_pred.fit_transform(test_data.iloc[1:,0].values.reshape(-1,1))
  pred_descale = scaler_pred.inverse_transform(pred)
  global pred_df
  pred_df = pd.DataFrame(pred_descale,columns=['Predicted'])
  return pred_df


##Function to Calculate Result Metrics
def result_metrics_forecast(test_series,forecast_series,model_name):
  print('Result Metrics for ' +  str(model_name))
  print('R2 Score : ',round(r2_score(test_series,forecast_series),3))
  print('Mean Squared Error : ',round(MSE(test_series,forecast_series),3))
  print('Root Mean Squared Error : ',np.sqrt(round(MSE(test_series,forecast_series),3)))
  print('Mean Absolute Error : ',round(mean_absolute_error(test_series,forecast_series),3))
  fig = plt.figure(figsize=(10,10))
  plt.plot(test_series.index,test_series,label='Actual')
  plt.plot(test_series.index,forecast_series,label='Predicted')
  plt.title(str(model_name) + ' -Forecasting')
  plt.ylabel('Price')
  plt.legend()
```

```
X1,y1 = prepare_train_data_lstm(sc1,X_train,2)
```

```
Shape of Input Data Initially (3679, 2)
Shape of Train Part after transformation (3677, 1, 1, 2)
Shape of Test Part after transformation  (3677,)
Final Shape  (3677, 1, 2)
```

```
prepare_test_data_lstm(sc1,X_test,2)
```

```
Shape of Test Dataset (1576, 1, 2)
```

```
lstm_model(sc1,X_train,2)
```

```
Shape of Input Data Initially (3679, 2)
Shape of Train Part after transformation (3677, 1, 1, 2)
Shape of Test Part after transformation  (3677,)
Final Shape  (3677, 1, 2)
Epoch 1/50
115/115 [==============================] - 6s 9ms/step - loss: 0.2063
Epoch 2/50
115/115 [==============================] - 1s 7ms/step - loss: 0.2006
Epoch 3/50
115/115 [==============================] - 1s 6ms/step - loss: 0.1946
Epoch 4/50
115/115 [==============================] - 1s 7ms/step - loss: 0.1882
Epoch 5/50
115/115 [==============================] - 1s 7ms/step - loss: 0.1813
Epoch 6/50
115/115 [==============================] - 1s 7ms/step - loss: 0.1737
Epoch 7/50
115/115 [==============================] - 1s 7ms/step - loss: 0.1655
Epoch 8/50
115/115 [==============================] - 1s 6ms/step - loss: 0.1564
Epoch 9/50
115/115 [==============================] - 1s 7ms/step - loss: 0.1466
Epoch 10/50
115/115 [==============================] - 1s 6ms/step - loss: 0.1358
Epoch 11/50
115/115 [==============================] - 1s 7ms/step - loss: 0.1243
Epoch 12/50
115/115 [==============================] - 1s 7ms/step - loss: 0.1120
Epoch 13/50
115/115 [==============================] - 1s 6ms/step - loss: 0.0991
Epoch 14/50
115/115 [==============================] - 1s 6ms/step - loss: 0.0861
Epoch 15/50
115/115 [==============================] - 1s 6ms/step - loss: 0.0729
Epoch 16/50
115/115 [==============================] - 1s 7ms/step - loss: 0.0616
Epoch 17/50
115/115 [==============================] - 1s 6ms/step - loss: 0.0523
Epoch 18/50
115/115 [==============================] - 1s 7ms/step - loss: 0.0444
Epoch 19/50
115/115 [==============================] - 1s 6ms/step - loss: 0.0399
Epoch 20/50
115/115 [==============================] - 1s 7ms/step - loss: 0.0364
Epoch 21/50
115/115 [==============================] - 1s 6ms/step - loss: 0.0340
Epoch 22/50
115/115 [==============================] - 1s 7ms/step - loss: 0.0334
Epoch 23/50
115/115 [==============================] - 1s 6ms/step - loss: 0.0312
Epoch 24/50
115/115 [==============================] - 1s 8ms/step - loss: 0.0299
Epoch 25/50
115/115 [==============================] - 1s 7ms/step - loss: 0.0285
Epoch 26/50
115/115 [==============================] - 1s 7ms/step - loss: 0.0265
Epoch 27/50
115/115 [==============================] - 1s 7ms/step - loss: 0.0256
```

```
predict_data(model,sc2,X_test,X1_test,2)
```

```
50/50 [==============================] - 1s 2ms/step
1577
```

	Predicted
0	89.291924
1	89.271988
2	89.130928
3	88.997383
4	88.713951
...	...
1571	59.968620
1572	60.000504

```
data_out_pred = pred_df.copy()
data_out_actual = X_test.iloc[2:,0].copy()
```

Visualize the actual price and the predicted price

```
result_metrics_forecast(data_out_actual,data_out_pred,'LSTM')
```

```
Result Metrics for LSTM
R2 Score :  0.796
Mean Squared Error :  105.612
Root Mean Squared Error :  10.27676992055383
Mean Absolute Error :  7.949
```