

Forecasting Crude Price

Capstone Project

INTRODUCTION

- There are different types of crude oil in the market– the thick, unprocessed liquid that drillers extract below the earth – and others are more desirable than others.
 - There are **two kinds** of Brent, WTI and Dubai/Oman.
 - we need benchmarks to value the commodity based on its quality and location, In our case WTI (West Texas Intermediate) would be used.
 - **“Brent”** actually refers to oil from four different fields in the North Sea: Brent, Forties, Oseberg and Ekofisk. Crude from this region is light and sweet, making them ideal for the refining of diesel fuel, gasoline.
- ★ My Goal is to build a **Time Series model** to predict bunker price using Brent Crude. With the aid of **Brent Crude** Datasets. I would explore the commodities prices and determine the best model.

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01

Data Exploration

Datasets:

- Brent Crude Price

Source: Energy Information Administration

Data Cleaning

Overview

dataframe shape
(8815, 2)

dataframe types
Date object
Price float64
dtype: object

Missing Values

missing values
Date 0
Price 0
dtype: int64

duplicate values
0

As shown Data has no Missing values and Duplicates , but note there is no data on weekends.

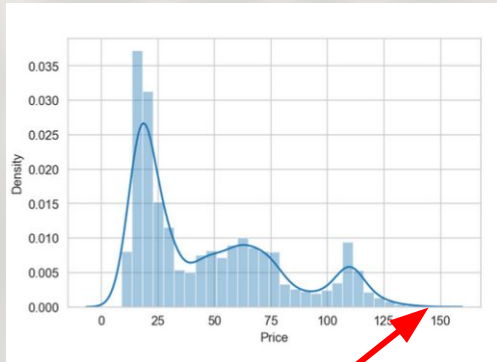
Describe Data

dataframe describe
Price
count 8815.000000
mean 47.157345
std 32.052617
min 9.100000
25% 18.950000
50% 35.720000
75% 68.415000
max 143.950000

Max value being
priced at 144

Data Transformation

Distribution plot



Our Outlier , 144 is very small in term of Density. This would not affect our analysis

Convert date to datetime

	<u>Date</u>	Price
0	05/20/1987	18.63
1	05/21/1987	18.45
2	05/22/1987	18.55
3	05/25/1987	18.60
4	05/26/1987	18.63

Before

Convert to date column to index

	<u>Date</u>	Price
0	1987-05-20	18.63
1	1987-05-21	18.45
2	1987-05-22	18.55
3	1987-05-25	18.60
4	1987-05-26	18.63

After

	<u>Date</u>	Price
	1987-05-20	18.63
	1987-05-21	18.45
	1987-05-22	18.55

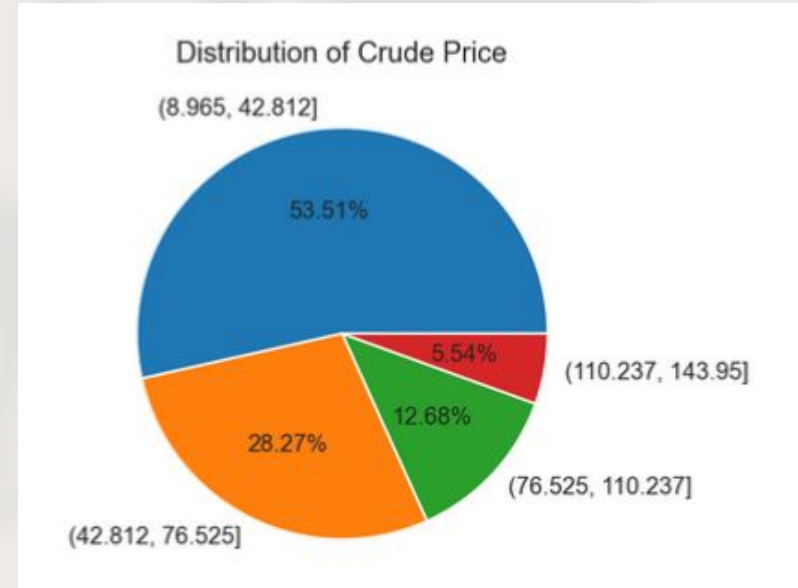
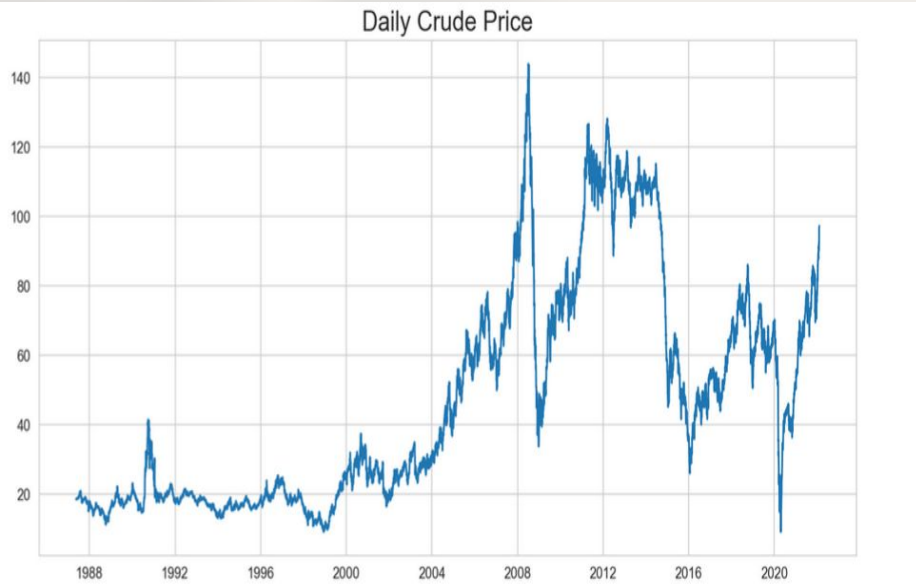
EDA

Exploratory Data analysis

- Pie Chart
- Pairplots

Visualize Data

Plotting Data

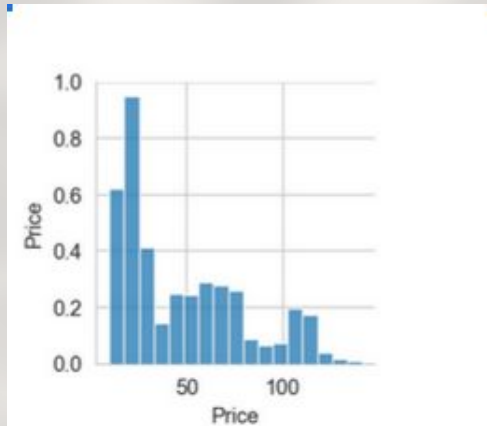
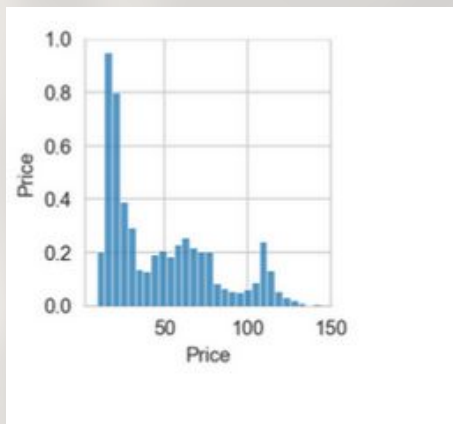


Pie chart

- 53.51% - 8.9 to 43
- 5.54% 110 to 144

Pairplots of Prices

Degree of Granularity



Daily avg

Weekly avg

Monthly avg

Yearly avg

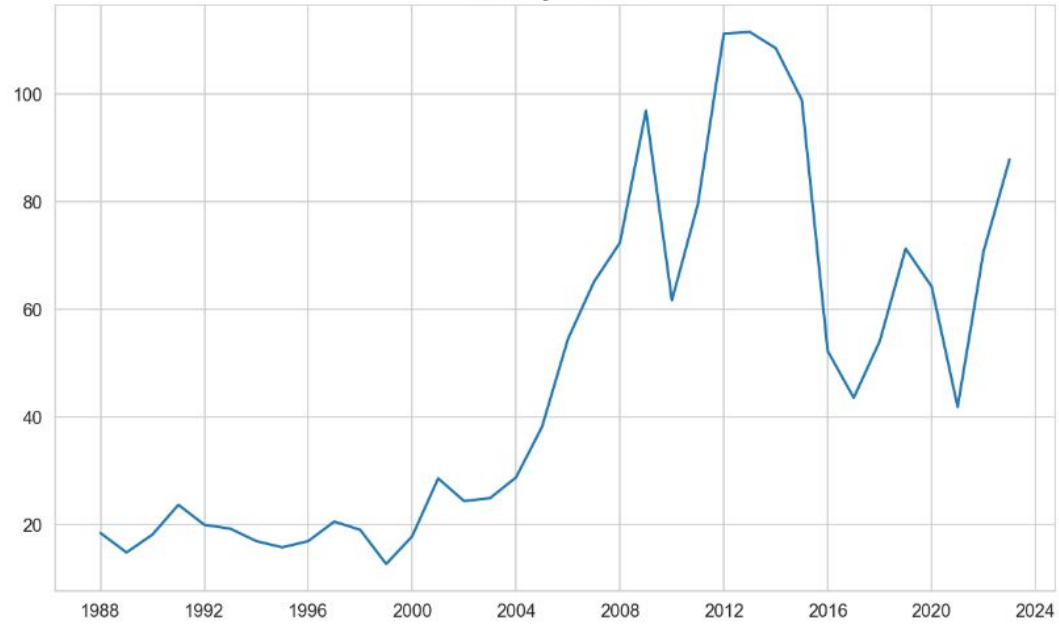
Date	Price
1987-05-20	18.63
1987-05-21	18.45
1987-05-22	18.55
1987-05-25	18.60
1987-05-26	18.63

Date	Price
1987-05-24	18.543333
1987-05-31	18.602000
1987-06-07	18.702000
1987-06-14	18.754000
1987-06-21	19.007500

Date	Price
1987-05-31	18.580000
1987-06-30	18.860476
1987-07-31	19.856522
1987-08-31	18.979524
1987-09-30	18.313182

Date	Price
1987-12-31	18.525813
1988-12-31	14.905412
1989-12-31	18.228228
1990-12-31	23.761445
1991-12-31	20.041128

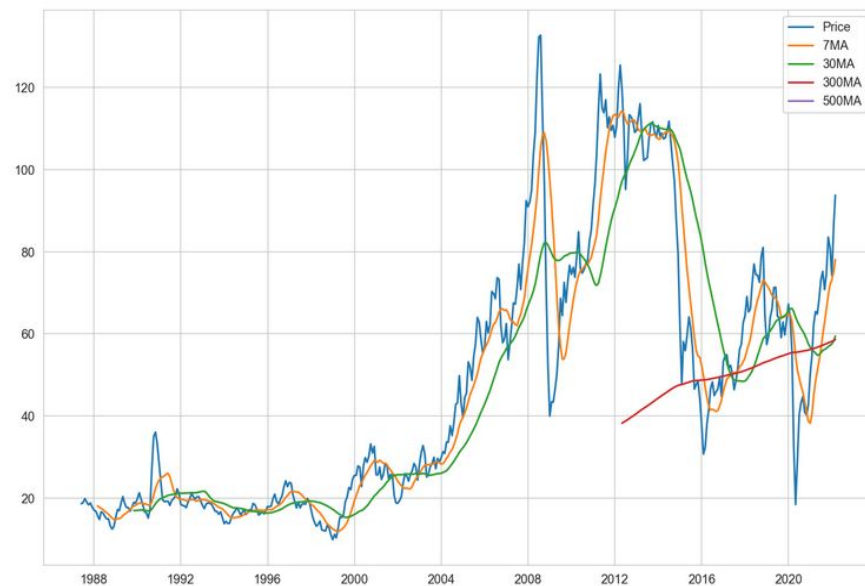
Yearly Price



Moving Average

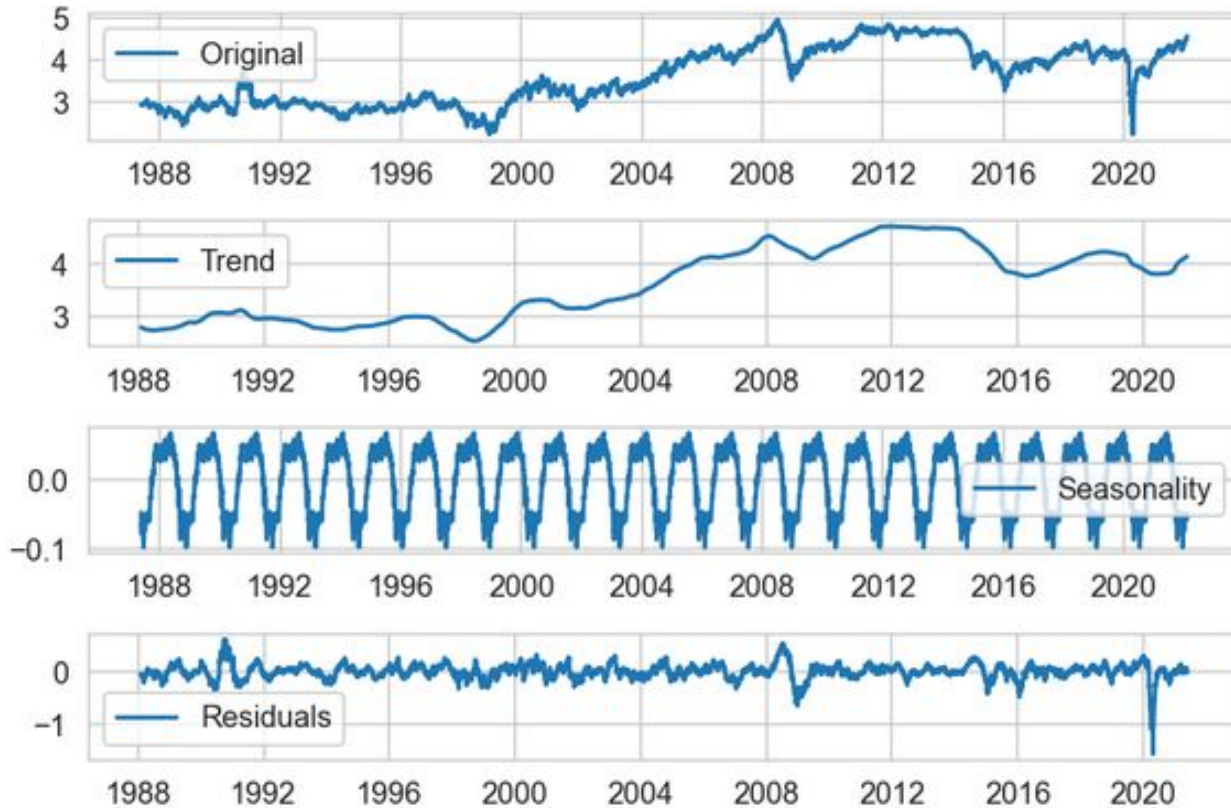


Daily



Monthly

Seasonal Decompose

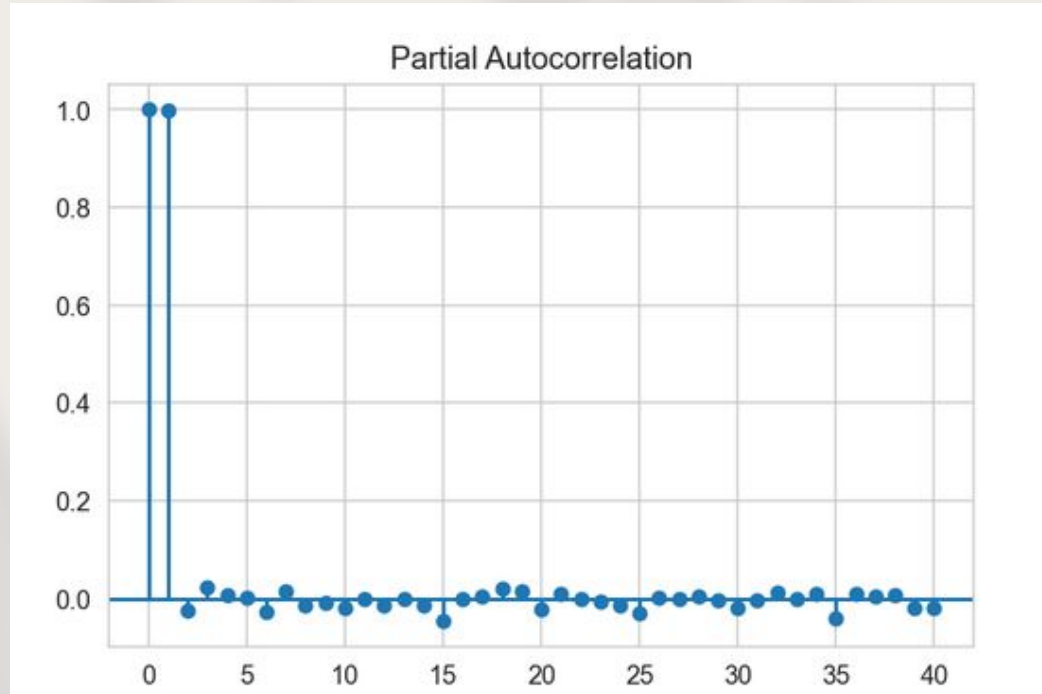


Data increasing Trend

Data pattern

Residuals is the Noise
which will affect our model

Partial AutoCorrelation function



- PACF is apply to determine what order of model
- We know our model is strongly correlated between 0 and 1 lags as diagram shows a 1.0

Augmented Dickey–Fuller test

ADF: -1.8997715641726658

P-value: 0.33216858177501096

Number of lags: 35

Number of Observation used for ADF Regression & Critical value

Calculation: 8779

Critical value:

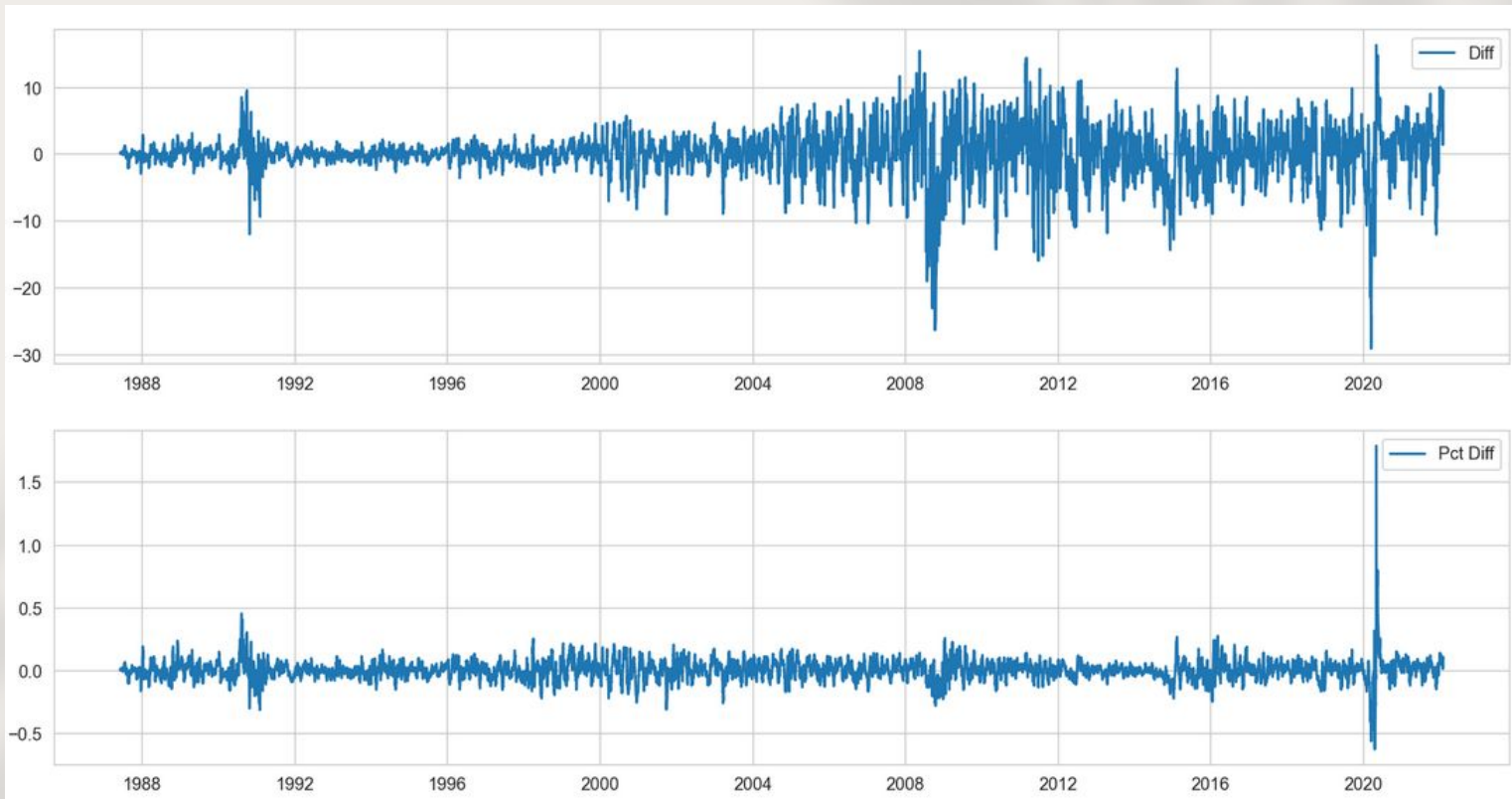
1% : -3.43109509774388

5% : -2.8618692838372026

10% : -2.566945272806482

P-value = 0.3 > 0.05, means dataset is not stationary

Differencing Data



Train -Test Split

Train test sets

- y_train : 2000 to 2007
- y_test : 2008

(8815, 1)

(2046, 1) (253, 1)

- Why 2000 to 2007?

Auto ARIMA

Performing stepwise search to minimize aic

```
ARIMA(0,1,0)(0,0,0)[12] intercept : AIC=5546.136, Time=0.30 sec
ARIMA(1,1,0)(1,0,0)[12] intercept : AIC=5548.524, Time=0.30 sec
ARIMA(0,1,1)(0,0,1)[12] intercept : AIC=5548.614, Time=0.35 sec
ARIMA(0,1,0)(0,0,0)[12]          : AIC=5546.836, Time=0.04 sec
ARIMA(0,1,0)(1,0,0)[12] intercept : AIC=5546.554, Time=0.25 sec
ARIMA(0,1,0)(0,0,1)[12] intercept : AIC=5546.644, Time=0.26 sec
ARIMA(0,1,0)(1,0,1)[12] intercept : AIC=5548.051, Time=0.87 sec
ARIMA(1,1,0)(0,0,0)[12] intercept : AIC=5548.096, Time=0.19 sec
ARIMA(0,1,1)(0,0,0)[12] intercept : AIC=5548.098, Time=0.24 sec
ARIMA(1,1,1)(0,0,0)[12] intercept : AIC=5542.902, Time=0.86 sec
ARIMA(1,1,1)(1,0,0)[12] intercept : AIC=5549.737, Time=1.07 sec
ARIMA(1,1,1)(0,0,1)[12] intercept : AIC=5549.818, Time=1.04 sec
ARIMA(1,1,1)(1,0,1)[12] intercept : AIC=5551.305, Time=1.62 sec
ARIMA(2,1,1)(0,0,0)[12] intercept : AIC=5550.518, Time=0.58 sec
ARIMA(1,1,2)(0,0,0)[12] intercept : AIC=5550.523, Time=0.28 sec
ARIMA(0,1,2)(0,0,0)[12] intercept : AIC=5548.832, Time=0.22 sec
ARIMA(2,1,0)(0,0,0)[12] intercept : AIC=5548.795, Time=0.20 sec
ARIMA(2,1,2)(0,0,0)[12] intercept : AIC=5552.509, Time=0.68 sec
ARIMA(1,1,1)(0,0,0)[12]          : AIC=5543.626, Time=0.42 sec
```

Best model: ARIMA(1,1,1)(0,0,0)[12] intercept

Auto ARIMA Plot



- Making prediction on Test set

LSTM (Long short-term memory)

	Target Date	Target-3	Target-2	Target-1	Target
0	1987-05-25	18.63	18.45	18.55	18.60
1	1987-05-26	18.45	18.55	18.60	18.63
2	1987-05-27	18.55	18.60	18.63	18.60
3	1987-05-28	18.60	18.63	18.60	18.60
4	1987-05-29	18.63	18.60	18.60	18.58
...
8807	2022-02-01	90.70	91.47	92.35	90.24
8808	2022-02-02	91.47	92.35	90.24	91.43
8809	2022-02-03	92.35	90.24	91.43	92.99
8810	2022-02-04	90.24	91.43	92.99	96.86
8811	2022-02-07	91.43	92.99	96.86	97.28

8812 rows × 5 columns

Years includes: 1987-05-25 to 2022-02-07

Converting to shifting 3 days back for the price label as Target-3 ,2,1

Converting to array

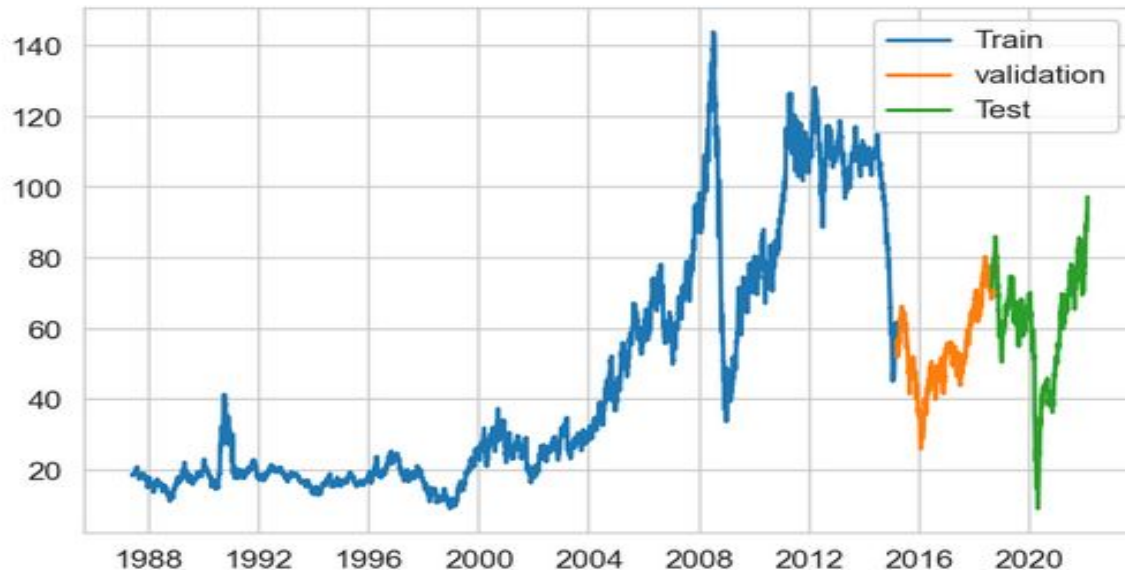
```
def win_df_date_X_y(win_dataframe):  
    df_as_np = win_dataframe.to_numpy()  
    dates= df_as_np[:,0]  
    middle_matrix=df_as_np[:,1:-1]  
    X=middle_matrix.reshape((len(dates),middle_matrix.shape[1],1))  
  
    Y=df_as_np[:, -1]  
    return dates, X.astype(np.float32),Y.astype(np.float32)
```



```
((8812,), (8812, 3, 1), (8812,))
```

Train-Test sets

```
q_80 = int(len(dates) *.8)  
q_90 = int(len(dates) *.9)
```



```
dates_train, X_train, y_train = dates[:q_80], X[:q_80], y[:q_80]  
dates_val, X_val, y_val = dates[q_80:q_90], X[q_80:q_90], y[q_80:q_90]  
dates_test, X_test, y_test = dates[q_90:], X[q_90:], y[q_90:]
```

Modeling LSTM

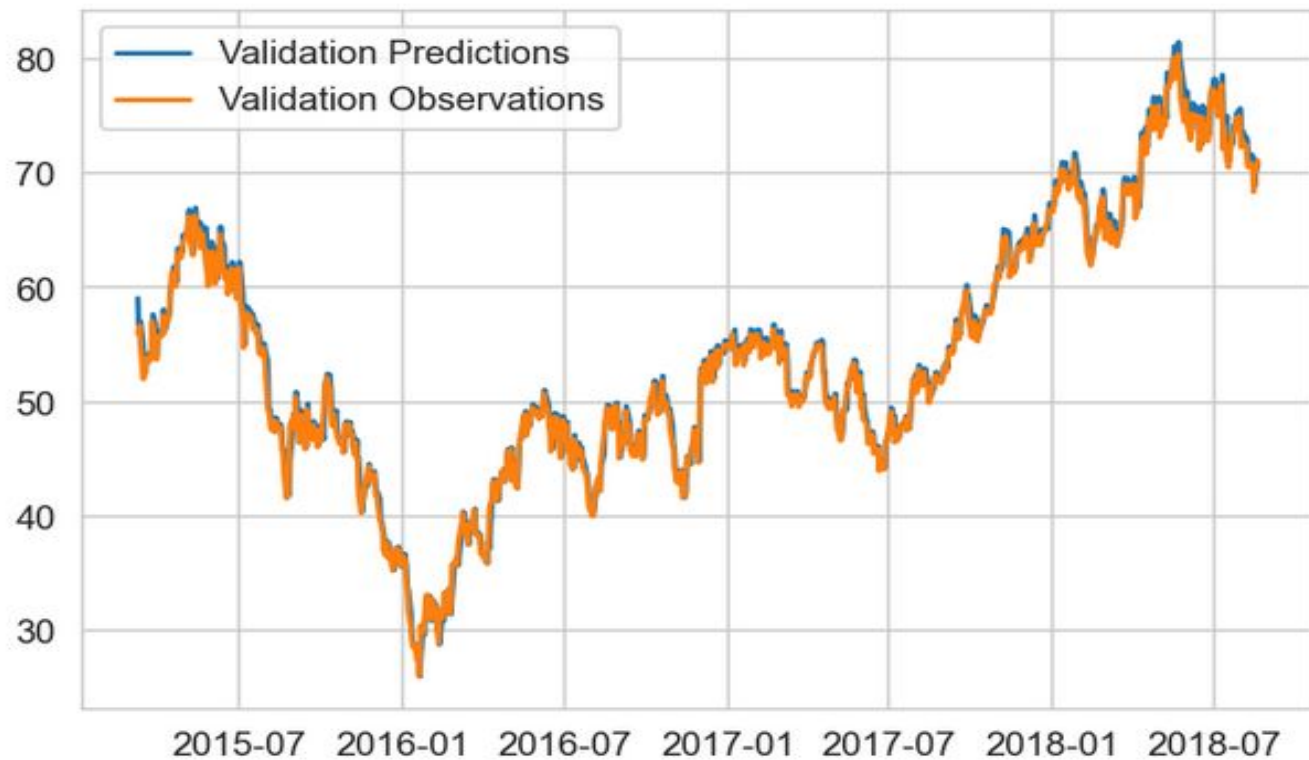
```
from keras.models import Sequential
from tensorflow.keras.optimizers import Adam
from tensorflow.keras import layers
```

```
model= Sequential([layers.Input((3,1)),
                    layers.LSTM(60),
                    layers.Dense(32,activation ='relu'),
                    layers.Dense(32,activation ='relu'),
                    layers.Dense(1)])
model.compile(loss='mse',
              optimizer=Adam(learning_rate=0.001),
              metrics=['mean_absolute_error'])
```

```
model.fit(X_train, y_train, validation_data=(X_val,y_val), epochs=100, )
```

```
Epoch 69/100
221/221 [=====] -
absolute_error: 0.8969
Epoch 70/100
221/221 [=====] -
absolute_error: 0.8785
Epoch 71/100
221/221 [=====] -
absolute_error: 0.8848
Epoch 72/100
221/221 [=====] -
absolute_error: 0.8849
Epoch 73/100
221/221 [=====] -
```

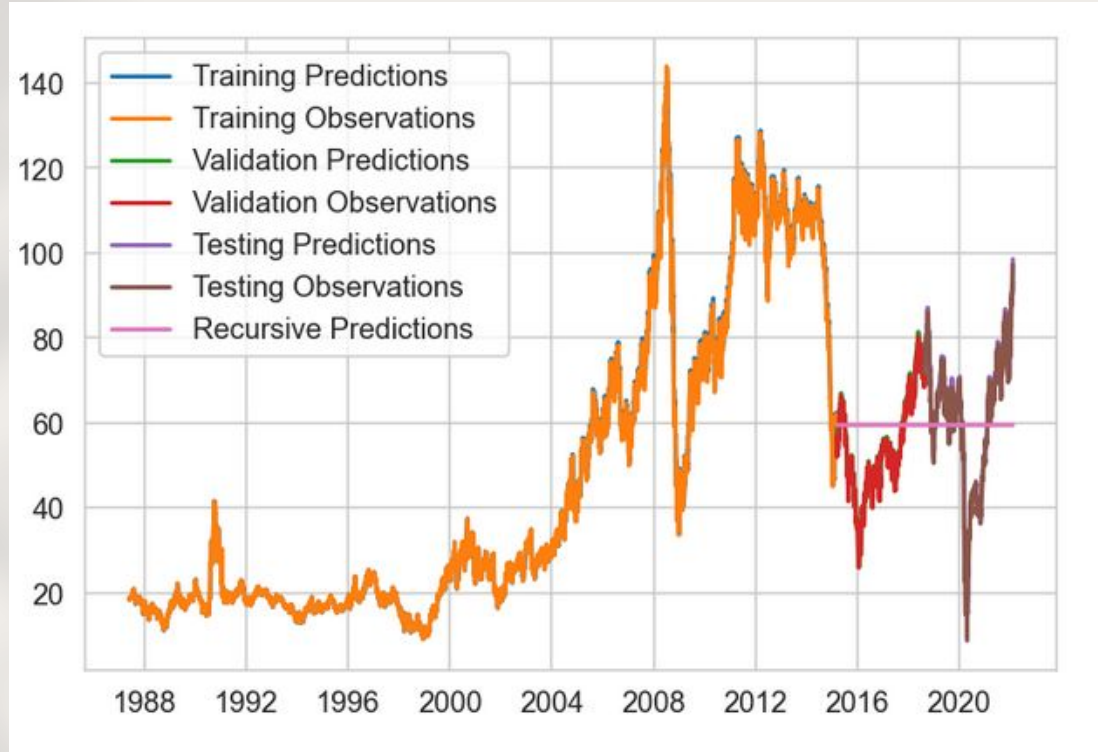






Recursive Prediction

```
recursive_predictions = []  
recursive_dates =  
np.concatenate([dates_val, dates_test])  
  
for target_date in recursive_dates:  
    last_window = deepcopy(X_train[-1])  
    next_prediction =  
    model.predict(np.array([last_window])).flatten()  
  
    recursive_predictions.append(next_prediction)  
    last_window[-1] = next_prediction
```



Conclusion

- Explore Model used with **Generative adversarial network GAN**
- Explore Project in a Classification point of view
- Include other variables like stock of Oil and Gas companies to do multivariate analysis

THANKS!