Time Series Forecasting with Python (ARIMA, LSTM, Prophet)

Double-click (or enter) to edit

```
import numpy as np
import pandas as pd
import os
from statsmodels.tsa.statespace.sarimax import SARIMAX
from statsmodels.graphics.tsaplots import plot_acf,plot_pacf
from statsmodels.tsa.seasonal import seasonal_decompose
#from pmdarima import auto_arima
from sklearn.metrics import mean_squared_error
from statsmodels.tools.eval_measures import rmse
import warnings
warnings.filterwarnings("ignore")
import matplotlib.pyplot as plt
%matplotlib inline
```

In this article we will try to forecast a time series data basically. We'll build three different model with Python and inspect their results. Models we will use are ARIMA (Autoregressive Integrated Moving Average), LSTM (Long Short Term Memory Neural Network) and Facebook Prophet. Let's jump in and start with ARIMA.

ARIMA (Autoregressive Integrated Moving Average)

ARIMA is a model which is used for predicting future trends on a time series data. It is model that form of regression analysis.

- **AR (Autoregression) :** Model that shows a changing variable that regresses on its own lagged/prior values.
- **I (Integrated) :** Differencing of raw observations to allow for the time series to become stationary
- **MA (Moving average) :** Dependency between an observation and a residual error from a moving average model

For ARIMA models, a standard notation would be ARIMA with p, d, and q, where integer values substitute for the parameters to indicate the type of ARIMA model used.

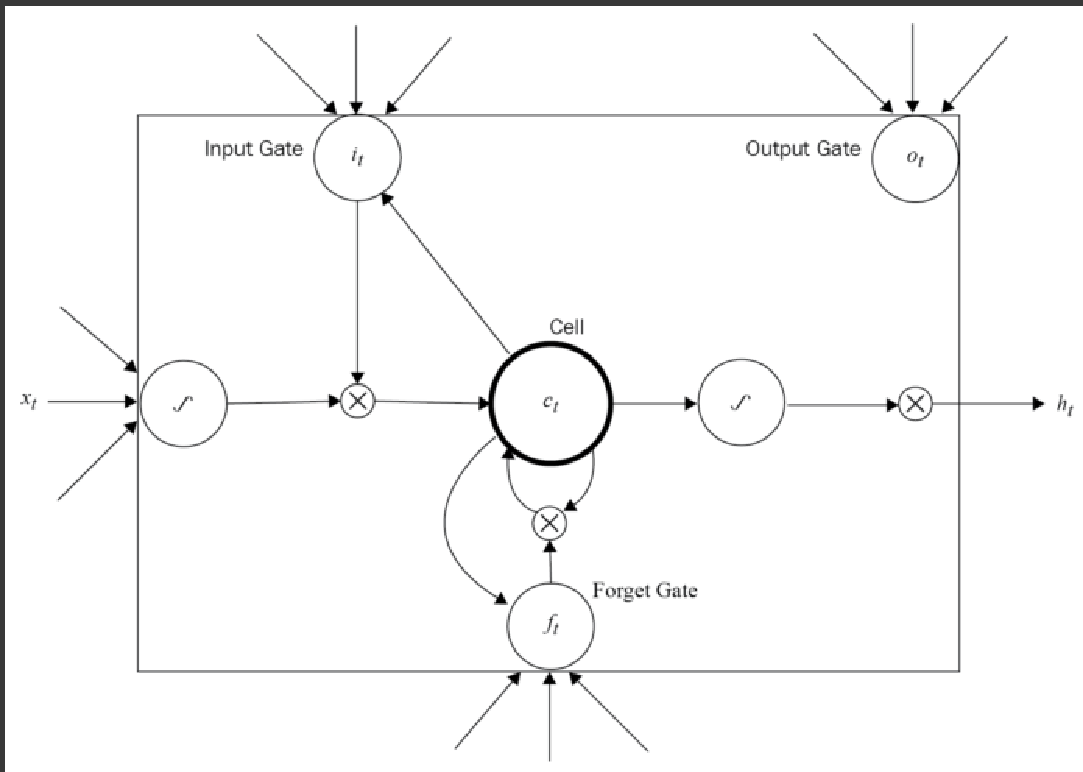
- **p:** the number of lag observations in the model; also known as the lag order.
- **d:** the number of times that the raw observations are differenced; also known as the degree of differencing.
- **q:** the size of the moving average window; also known as the order of the moving average.

For more information about ARIMA you can check:
[What is ARIMA]
[Autoregressive Integrated Moving Average (ARIMA)]

LSTM Neural Network

> LSTM stands for long short term memory. It is a model or architecture that extends the memory of recurrent neural networks. Typically, recurrent neural networks have 'short term memory' in that they use persistent previous information to be used in the current neural network. Essentially, the previous information is used in the present task. That means we do not have a list of all of the previous information available for the neural node. LSTM introduces long-term memory into recurrent neural networks. It mitigates the vanishing gradient problem, which is where the neural network stops learning because the updates to the various weights within a given neural network

> become smaller and smaller. It does this by using a series of 'gates'. These are contained in memory blocks which are connected through layers, like this:



> LSTM work There are three types of gates within a unit: Input Gate: Scales input to cell (write) Output Gate: Scales output to cell (read) Forget Gate: Scales old cell value (reset) Each gate is like a switch that controls the read/write, thus incorporating the long-term memory function into the model.

For more detail:
[What is LSTM?]
[What is LSTM? - Quora]
[Wikipedia]

Prophet

> Prophet is a procedure for forecasting time series data based on an additive model where non-linear trends are fit with yearly, weekly, and daily seasonality, plus holiday effects. It works best with time series that have strong seasonal effects and several seasons of historical data. Prophet is robust to missing data and shifts in the trend, and typically handles outliers well.

[Facebook's Prophet Web Page]
[Forecasting at Scale]

FORECAST

Read Dataset

```
df = pd.read_csv('data/monthly-beer-production-in-austr.csv')
```

```
df.head()
```

	Month	Monthly beer production
0	1956-01	93.2
1	1956-02	96.0
2	1956-03	95.2
3	1956-04	77.1
4	1956-05	70.9

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 476 entries, 0 to 475
Data columns (total 2 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   Month                    476 non-null    object
 1   Monthly beer production  476 non-null    float64
dtypes: float64(1), object(1)
memory usage: 7.6+ KB
```

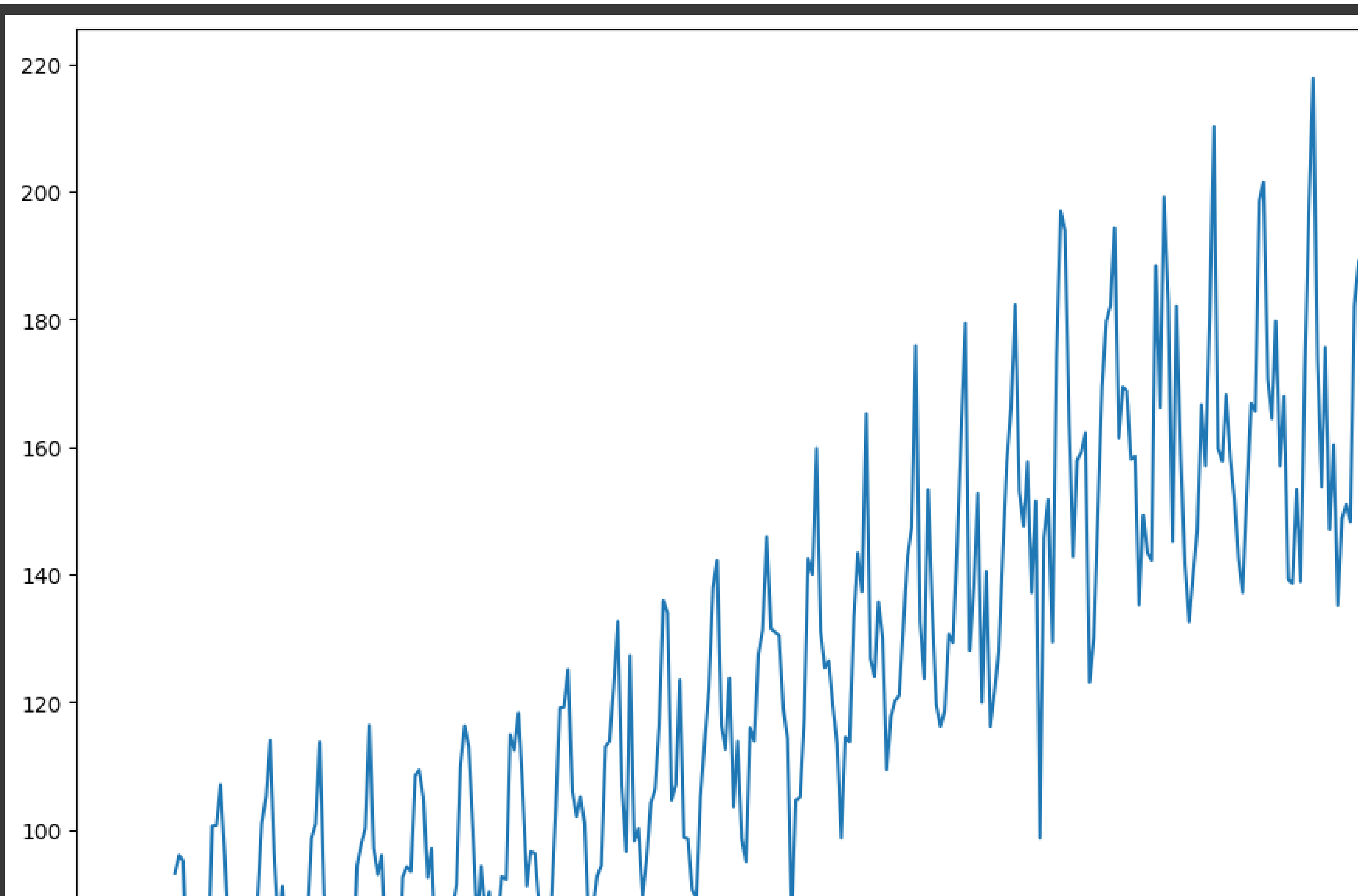
```
df.Month = pd.to_datetime(df.Month)
```

```
df = df.set_index("Month")
df.head()
```

Month	Monthly beer production
1956-01-01	93.2
1956-02-01	96.0
1956-03-01	95.2
1956-04-01	77.1
1956-05-01	70.9

```
df.index.freq = 'MS'
```

```
plt.figure(figsize=(18,9))
plt.plot(df.index, df["Monthly beer production"], linestyle="-")
plt.xlabel=('Dates')
plt.ylabel=('Total Production')
plt.show();
```

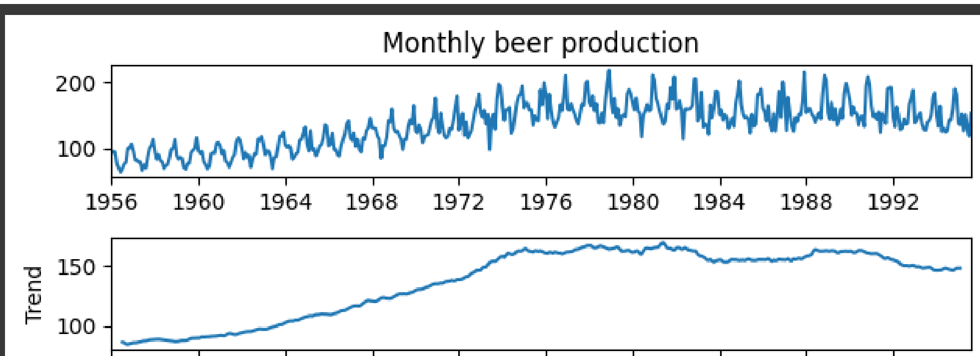


When we look at plot we can sey there is a seasonality in data. That's why we will use SARIMA (Seasonal ARIMA) instead of ARIMA.

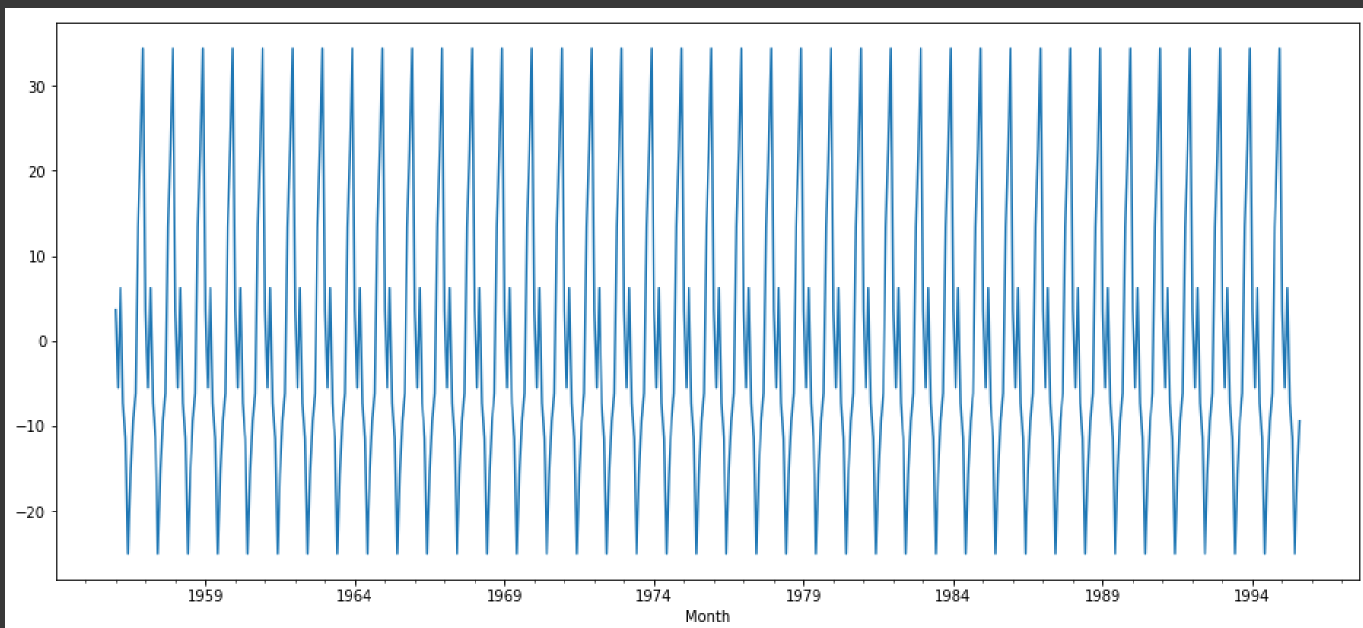
> Seasonal ARIMA, is an extension of ARIMA that explicitly supports univariate time series data with a seasonal component. It adds three new hyperparameters to specify the autoregression (AR), differencing (I) and moving average (MA) for the seasonal component of the series, as well as an additional parameter for the period of the seasonality.

> There are four seasonal elements that are not part of ARIMA that must be configured; they are:
> **P:** Seasonal autoregressive order.
> **D:** Seasonal difference order.
> **Q:** Seasonal moving average order.
> **m:** The number of time steps for a single seasonal period.

```
a = seasonal_decompose(df["Monthly beer production"], model = "add")
a.plot();
```




```
import matplotlib.pyplot as plt
plt.figure(figsize = (16,7))
a.seasonal.plot();
```



ARIMA Forecast

Let's split the data into train and test set

```
train_data = df[:len(df)-12]
test_data = df[len(df)-12:]
```

```
arima_model = SARIMAX(train_data['Monthly beer production'], order = (2,1,1), seasonal_order = (4,0,3,12))
arima_result = arima_model.fit()
arima_result.summary()
```

Statespace Model Results

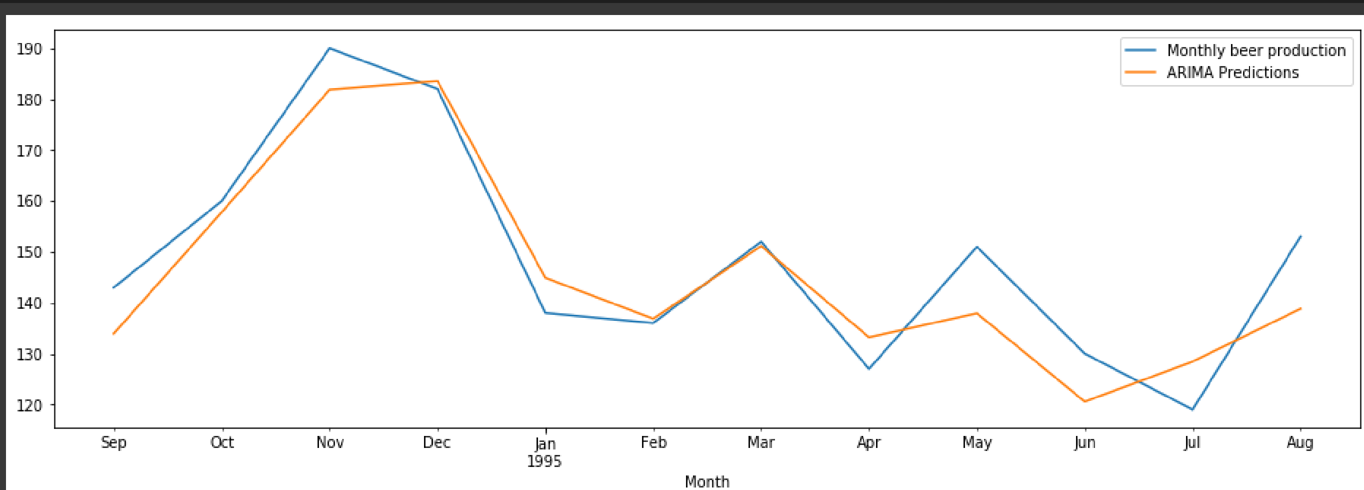
Dep. Variable:	Monthly beer production	**No. Observations:**	464
Model:	SARIMAX(2, 1, 1)x(4, 0, 3, 12)	**Log Likelihood**	-1708.067
Date:	Fri, 31 Mar 2023	**AIC**	3438.135
Time:	05:23:56	**BIC**	3483.650
Sample:	01-01-1956	**HQIC**	3456.053
	- 08-01-1994		
Covariance Type:	opg		

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
ar.L1	-0.1259	0.039	-3.270	0.001	-0.201	-0.050
ar.L2	-0.1737	0.047	-3.722	0.000	-0.265	-0.082
ma.L1	-0.8436	0.028	-30.241	0.000	-0.898	-0.789
ar.S.L12	1.7500	0.107	16.291	0.000	1.539	1.961
ar.S.L24	-1.5989	0.201	-7.954	0.000	-1.993	-1.205
ar.S.L36	0.7794	0.156	4.982	0.000	0.473	1.086
ar.S.L48	0.0683	0.058	1.174	0.241	-0.046	0.182
ma.S.L12	-1.5499	0.118	-13.122	0.000	-1.781	-1.318
ma.S.L24	1.3816	0.193	7.161	0.000	1.003	1.760

```
arima_pred = arima_result.predict(start = len(train_data), end = len(df)-1, typ="levels").rename("ARIMA Predic
arima_pred
```

```
1994-09-01    133.943955
1994-10-01    157.814451
1994-11-01    181.865146
1994-12-01    183.541331
1995-01-01    144.902539
1995-02-01    136.857294
1995-03-01    151.136283
1995-04-01    133.214691
1995-05-01    137.923012
1995-06-01    120.564847
1995-07-01    128.439705
1995-08-01    138.819035
Freq: MS, Name: ARIMA Predictions, dtype: float64
```

```
test_data['Monthly beer production'].plot(figsize = (16,5), legend=True)
arima_pred.plot(legend = True);
```




```
arima_rmse_error = rmse(test_data['Monthly beer production'], arima_pred)
arima_mse_error = arima_rmse_error**2
mean_value = df['Monthly beer production'].mean()

print(f'MSE Error: {arima_mse_error}\nRMSE Error: {arima_rmse_error}\nMean: {mean_value}')
```

```
MSE Error: 66.11050409066426
RMSE Error: 8.13083661689646
Mean: 136.39537815126045
```

```
test_data['ARIMA_Predictions'] = arima_pred
```

LSTM Forecast

First we'll scale our train and test data with MinMaxScaler

```
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
```

```
scaler.fit(train_data)
scaled_train_data = scaler.transform(train_data)
scaled_test_data = scaler.transform(test_data)
```

Before creating LSTM model we should create a Time Series Generator object.

```
from keras.preprocessing.sequence import TimeseriesGenerator

n_input = 12
n_features= 1
generator = TimeseriesGenerator(scaled_train_data, scaled_train_data, length=n_input, batch_size=1)
```

```
Using TensorFlow backend.
```

```
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import LSTM

lstm_model = Sequential()
lstm_model.add(LSTM(200, activation='relu', input_shape=(n_input, n_features)))
lstm_model.add(Dense(1))
lstm_model.compile(optimizer='adam', loss='mse')

lstm_model.summary()
```

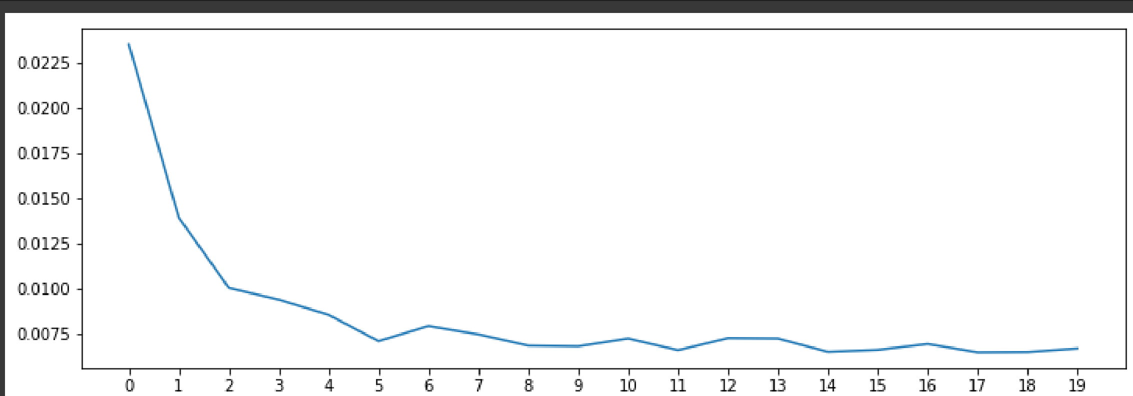
```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm_1 (LSTM)                (None, 200)               161600
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 201
=================================================================
Total params: 161,801
Trainable params: 161,801
Non-trainable params: 0
_________________________________________________________________
```

```
lstm_model.fit_generator(generator,epochs=20)
```

```
Epoch 1/20
452/452 [==============================] - 7s 16ms/step - loss: 0.0235
Epoch 2/20
452/452 [==============================] - 7s 15ms/step - loss: 0.0139
Epoch 3/20
452/452 [==============================] - 7s 15ms/step - loss: 0.0100
Epoch 4/20
452/452 [==============================] - 7s 15ms/step - loss: 0.0094
```

```
Epoch 5/20
452/452 [==============================] - 7s 15ms/step - loss: 0.0085
Epoch 6/20
452/452 [==============================] - 6s 14ms/step - loss: 0.0071
Epoch 7/20
452/452 [==============================] - 7s 15ms/step - loss: 0.0079
Epoch 8/20
452/452 [==============================] - 7s 15ms/step - loss: 0.0075
Epoch 9/20
452/452 [==============================] - 7s 15ms/step - loss: 0.0068
Epoch 10/20
452/452 [==============================] - 7s 14ms/step - loss: 0.0068
Epoch 11/20
452/452 [==============================] - 7s 14ms/step - loss: 0.0072
Epoch 12/20
452/452 [==============================] - 7s 15ms/step - loss: 0.0066
Epoch 13/20
452/452 [==============================] - 7s 15ms/step - loss: 0.0073
Epoch 14/20
452/452 [==============================] - 7s 15ms/step - loss: 0.0072
Epoch 15/20
452/452 [==============================] - 7s 15ms/step - loss: 0.0065
Epoch 16/20
452/452 [==============================] - 7s 15ms/step - loss: 0.0066
Epoch 17/20
452/452 [==============================] - 7s 15ms/step - loss: 0.0069
Epoch 18/20
452/452 [==============================] - 7s 15ms/step - loss: 0.0065
Epoch 19/20
452/452 [==============================] - 7s 15ms/step - loss: 0.0065
Epoch 20/20
452/452 [==============================] - 7s 15ms/step - loss: 0.0067
<keras.callbacks.History at 0x7feb0fb1bb00>
```

```
losses_lstm = lstm_model.history.history['loss']
plt.figure(figsize=(12,4))
plt.xticks(np.arange(0,21,1))
plt.plot(range(len(losses_lstm)),losses_lstm);
```




```
lstm_predictions_scaled = list()

batch = scaled_train_data[-n_input:]
current_batch = batch.reshape((1, n_input, n_features))

for i in range(len(test_data)):
    lstm_pred = lstm_model.predict(current_batch)[0]
    lstm_predictions_scaled.append(lstm_pred)
    current_batch = np.append(current_batch[:,1:,:],[[lstm_pred]],axis=1)
```

As you know we scaled our data that's why we have to inverse it to see true predictions.

```
lstm_predictions_scaled
```

```
[array([0.5463722], dtype=float32),
 array([0.61506224], dtype=float32),
 array([0.7296704], dtype=float32),
 array([0.7273484], dtype=float32),
 array([0.57843447], dtype=float32),
 array([0.54464334], dtype=float32),
 array([0.6067966], dtype=float32),
 array([0.47749722], dtype=float32),
 array([0.4800045], dtype=float32),
 array([0.46057016], dtype=float32),
 array([0.47920656], dtype=float32),
 array([0.5383399], dtype=float32)]
```

```
lstm_predictions = scaler.inverse_transform(lstm_predictions_scaled)
```

```
lstm_predictions
```

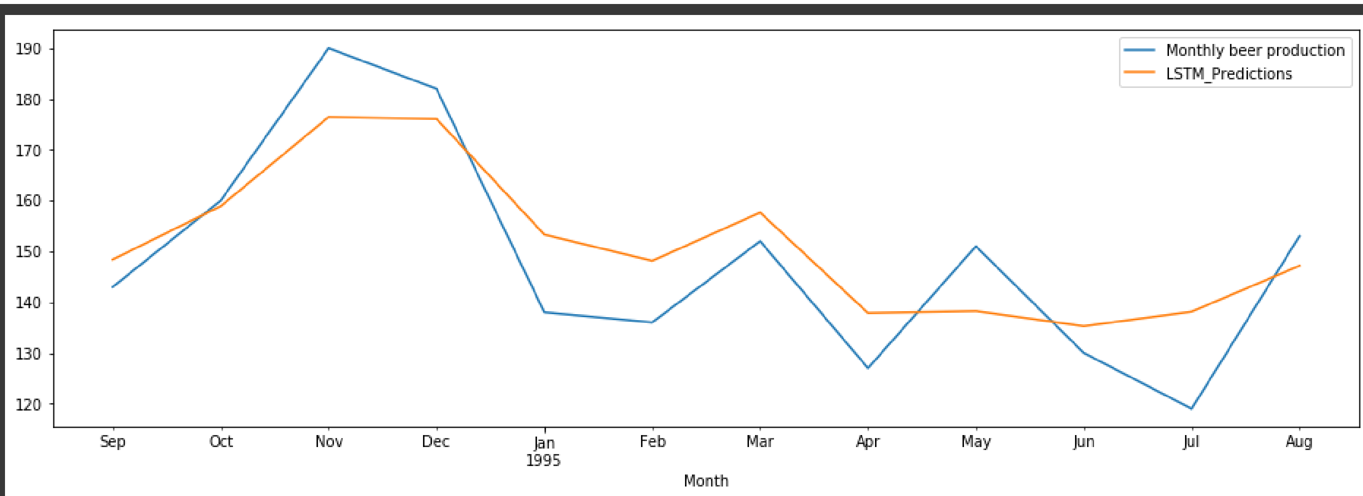
```
array([[148.39494281],
       [158.90452223],
       [176.43957202],
       [176.08430325],
       [153.3004735 ],
       [148.1304314 ],
       [157.63988321],
       [137.85707467],
       [138.24068688],
       [135.26723396],
       [138.11860399],
       [147.16600667]])
```

```
test_data['LSTM_Predictions'] = lstm_predictions
```

```
test_data
```

Month	Monthly beer production	ARIMA_Predictions	LSTM_Predictions
1994-09-01	143.0	133.943955	148.394943
1994-10-01	160.0	157.814451	158.904522
1994-11-01	190.0	181.865146	176.439572
1994-12-01	182.0	183.541331	176.084303
1995-01-01	138.0	144.902539	153.300473
1995-02-01	136.0	136.857294	148.130431
1995-03-01	152.0	151.136283	157.639883
1995-04-01	127.0	133.214691	137.857075
1995-05-01	151.0	137.923012	138.240687
1995-06-01	130.0	120.564847	135.267234
1995-07-01	119.0	128.439705	138.118604
1995-08-01	153.0	138.819035	147.166007

```
test_data['Monthly beer production'].plot(figsize = (16,5), legend=True)
test_data['LSTM_Predictions'].plot(legend = True);
```




```
lstm_rmse_error = rmse(test_data['Monthly beer production'], test_data["LSTM_Predictions"])
lstm_mse_error = lstm_rmse_error**2
mean_value = df['Monthly beer production'].mean()

print(f'MSE Error: {lstm_mse_error}\nRMSE Error: {lstm_rmse_error}\nMean: {mean_value}')
```

```
MSE Error: 114.18522368052443
RMSE Error: 10.685748625179446
Mean: 136.39537815126045
```

Prophet Forecast

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 476 entries, 1956-01-01 to 1995-08-01
Freq: MS
Data columns (total 1 columns):
Monthly beer production    476 non-null float64
dtypes: float64(1)
memory usage: 7.4 KB
```

```
df_pr = df.copy()
df_pr = df.reset_index()
```

```
df_pr.columns = ['ds','y'] # To use prophet column names should be like that
```

```
train_data_pr = df_pr.iloc[:len(df)-12]
test_data_pr = df_pr.iloc[len(df)-12:]
```

```
from fbprophet import Prophet
```

```
m = Prophet()
m.fit(train_data_pr)
future = m.make_future_dataframe(periods=12,freq='MS')
prophet_pred = m.predict(future)
```

```
prophet_pred.tail()
```

	ds	trend	yhat_lower	yhat_upper	trend_lower	trend_upper	additive_terms	additive_terms_lowe
471	1995-04-01	151.068031	130.647918	155.542987	151.004482	151.126144	-7.935845	-7.9358
472	1995-05-01	151.003711	127.299626	151.905075	150.919475	151.086627	-11.400874	-11.4008
473	1995-06-01	150.937247	114.386775	139.600597	150.827205	151.035387	-23.933819	-23.9338
474	1995-07-01	150.872927	121.592724	148.391044	150.736676	150.995624	-15.749936	-15.7499

```
prophet_pred = pd.DataFrame({"Date" : prophet_pred[-12:]['ds'], "Pred" : prophet_pred[-12:]["yhat"]})
```

```
prophet_pred = prophet_pred.set_index("Date")
```

```
prophet_pred.index.freq = "MS"
```

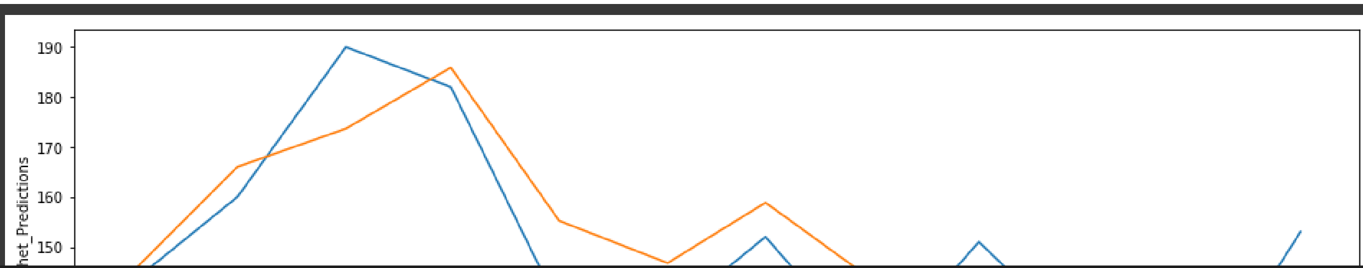
```
prophet_pred
```

	Pred
Date	
1994-09-01	145.014244
1994-10-01	166.010984
1994-11-01	173.651126
1994-12-01	185.899777
1995-01-01	155.190582
1995-02-01	146.743233
1995-03-01	158.839055
1995-04-01	143.132187
1995-05-01	139.602837
1995-06-01	127.003428
1995-07-01	135.122992
1995-08-01	141.582905

```
test_data["Prophet_Predictions"] = prophet_pred['Pred'].values
```

```
import seaborn as sns
```

```
plt.figure(figsize=(16,5))
ax = sns.lineplot(x= test_data.index, y=test_data["Monthly beer production"])
sns.lineplot(x=test_data.index, y = test_data["Prophet_Predictions"]);
```



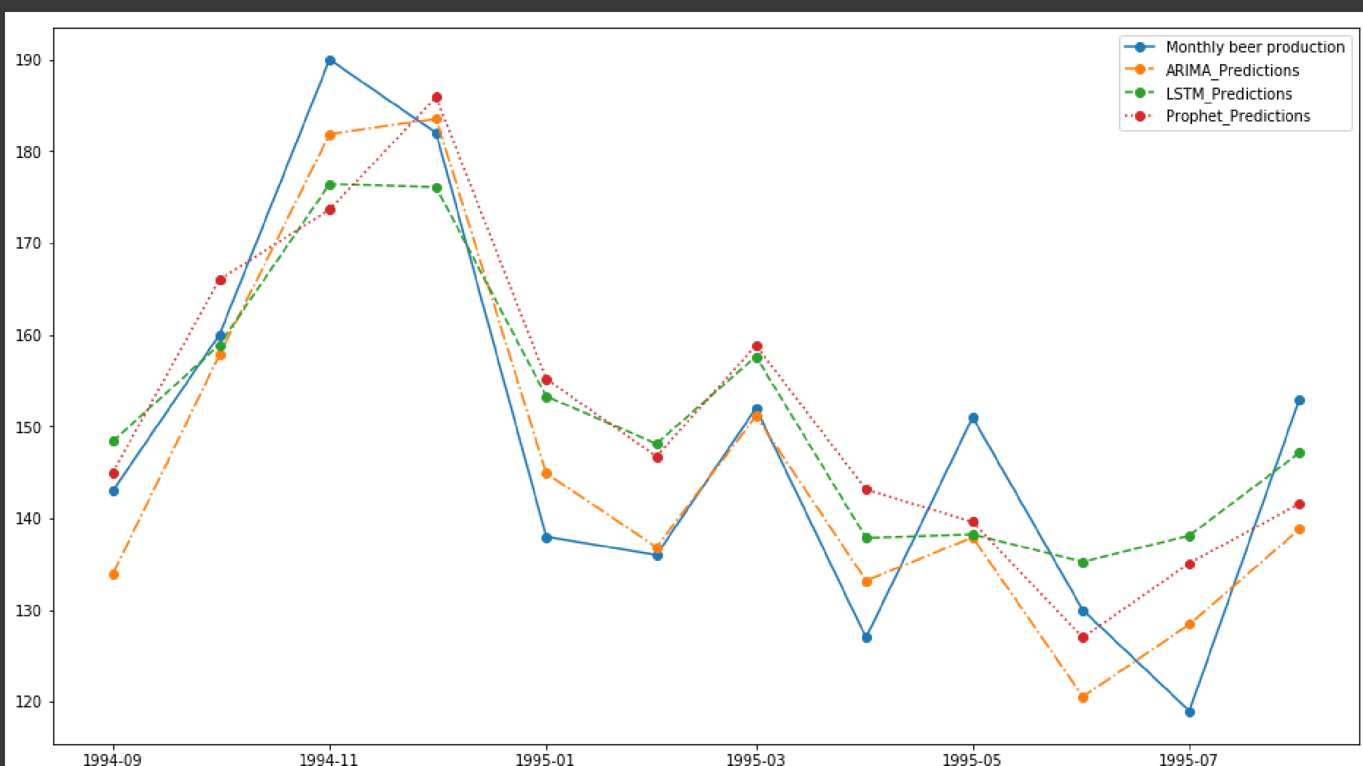
```
prophet_rmse_error = rmse(test_data['Monthly beer production'], test_data["Prophet_Predictions"])
prophet_mse_error = prophet_rmse_error**2
mean_value = df['Monthly beer production'].mean()

print(f'MSE Error: {prophet_mse_error}\nRMSE Error: {prophet_rmse_error}\nMean: {mean_value}')
```

```
MSE Error: 130.81766824441812
RMSE Error: 11.437555169021836
Mean: 136.39537815126045
```

```
rmse_errors = [arima_rmse_error, lstm_rmse_error, prophet_rmse_error]
mse_errors = [arima_mse_error, lstm_mse_error, prophet_mse_error]
errors = pd.DataFrame({"Models" : ["ARIMA", "LSTM", "Prophet"],"RMSE Errors" : rmse_errors, "MSE Errors" : mse
```

```
plt.figure(figsize=(16,9))
plt.plot_date(test_data.index, test_data["Monthly beer production"], linestyle="-")
plt.plot_date(test_data.index, test_data["ARIMA_Predictions"], linestyle="-.")
plt.plot_date(test_data.index, test_data["LSTM_Predictions"], linestyle="--")
plt.plot_date(test_data.index, test_data["Prophet_Predictions"], linestyle=":")
plt.legend()
plt.show()
```




```
print(f"Mean: {test_data['Monthly beer production'].mean()}")
errors
```

```
Mean: 148.41666666666666
```

	Models	RMSE Errors	MSE Errors
0	ARIMA	8.130837	66.110504
1	LSTM	10.685749	114.185224
2	Prophet	11.437555	130.817668

```
test_data
```

Month	Monthly beer production	ARIMA_Predictions	LSTM_Predictions	Prophet_Predictions
1994-09-01	143.0	133.943955	148.394943	145.014244
1994-10-01	160.0	157.814451	158.904522	166.010984
1994-11-01	190.0	181.865146	176.439572	173.651126
1994-12-01	182.0	183.541331	176.084303	185.899777
1995-01-01	138.0	144.902539	153.300473	155.190582
1995-02-01	136.0	136.857294	148.130431	146.743233
1995-03-01	152.0	151.136283	157.639883	158.839055
1995-	127.0	133.214691	137.857075	143.132187