Covid-19 has caused devistating problems with the country's economy. You have been assigned to forecast the unemployment rate for next month (June 2020). Using a Recurrent Neural Network forecast one month into the future of what the Unemployment Rate will be for next month.

Make sure to back test your model against one or two previous months

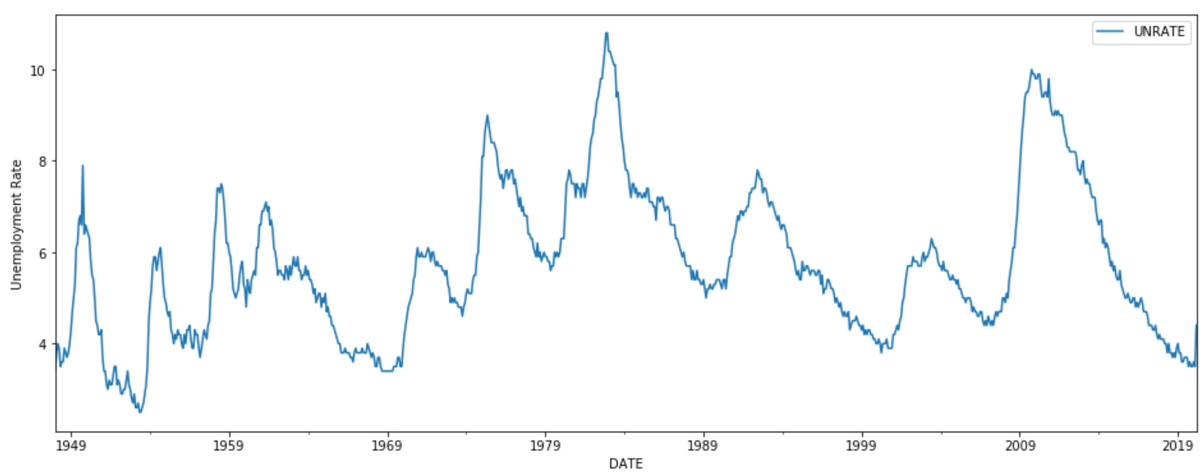
In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

import Data

- Data was collected from the Federal Reserve Economic Data Website
- https://fred.stlouisfed.org/series/UNRATE (https://fred.stlouisfed.org/series/UNRATE)
- Data begins Jan 1948 through march 2020

In [2]:
```
data = pd.read_csv("resources/unemployment_rate.csv", parse_dates = True
, index_col="DATE")
```

In [3]:
```
data.plot(figsize = (16,6))
plt.ylabel("Unemployment Rate");
```



Data Sample

- We wil take 5 years of data to test
- This will be 60 months in total
- This will give us enough data to test out model on

In [4]:
```
sample_size = 60
```

In [5]:
```
sample_index = len(data) - sample_size
```

In [6]:
```
sample_index
```

Out[6]:
```
807
```

In [7]:
```
len(data)
```

Out[7]:
```
867
```

Train Test Split

In [8]:
```
train = data.iloc[:sample_index]
```

In [9]:
```
test = data.iloc[sample_index:]
```

In [10]:
```
train.shape
```

Out[10]:
```
(807, 1)
```

In [11]:
```
test.shape
```

Out[11]:
```
(60, 1)
```

Scaling the data

- This will allow our model to consider the outliers and the behavior of the data better

In [12]:
```
from sklearn.preprocessing import MinMaxScaler
```

In [13]:
```
scalar = MinMaxScaler()
```

In [14]:
```
train_scaled = scalar.fit_transform(train)
```

In [15]:
```
test_scaled = scalar.transform(train)
```

Time Series Generator

- We will create the generator to train our model
- length will be 3 months- Our model will train to attampt to predict 3 months of Unemployment Rates

In [113]:
```
length = 2
```

In [114]:
```
from tensorflow.keras.preprocessing.sequence import TimeseriesGenerator
```

In [115]:
```
gen = TimeseriesGenerator(train_scaled,train_scaled,length=length, batch
_size=1)
```

Early Stopping

- THis will allow our model to train and stop when beginning to overtrain
- Also will allow us to set our epoch at a high value to train longer if possible

In [116]:
```
from tensorflow.keras.callbacks import EarlyStopping
```

In [117]:
```
stop = EarlyStopping(monitor="val_loss", mode = "min", patience=20)
```

Validation Generator

- Allows them model to compare the training data to. We will use our testing set

In [118]:
```
val_gen = TimeseriesGenerator(test_scaled,test_scaled, length=length, ba
tch_size=1)
```

Creating Model

- We will use a LSTM model to prevent gradient decay of our network

In [119]:
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense
```

In [120]:
```
n_features = 1
```

In [121]:
```
model = Sequential()
model.add(LSTM(units = 250, activation = "relu", input_shape = (length,n
_features)))
model.add(Dense(units = 1))
model.compile(optimizer = "adam", loss = "mse")
```

Fitting Model

- We will add all of our created parameters to to boost efficiency in training

In [122]:
```
model.fit_generator(generator=gen, validation_data=val_gen, epochs=40, c
allbacks=[stop])
```

```
Epoch 1/40
805/805 [==============================] - 21s 26ms/step - loss: 0.0100
- val_loss: 0.0012
Epoch 2/40
805/805 [==============================] - 21s 26ms/step - loss: 0.0014
- val_loss: 0.0011
Epoch 3/40
805/805 [==============================] - 21s 26ms/step - loss: 0.0014
- val_loss: 0.0010
Epoch 4/40
805/805 [==============================] - 21s 26ms/step - loss: 0.0014
- val_loss: 0.0015
Epoch 5/40
805/805 [==============================] - 21s 26ms/step - loss: 0.0013
- val_loss: 0.0011
Epoch 6/40
805/805 [==============================] - 21s 26ms/step - loss: 0.0012
- val_loss: 9.0027e-04
Epoch 7/40
805/805 [==============================] - 21s 26ms/step - loss: 0.0013
- val_loss: 9.9298e-04
Epoch 8/40
805/805 [==============================] - 21s 26ms/step - loss: 0.0010
- val_loss: 7.7924e-04
Epoch 9/40
805/805 [==============================] - 21s 26ms/step - loss: 0.0010
- val_loss: 8.1457e-04
Epoch 10/40
805/805 [==============================] - 21s 26ms/step - loss: 0.0011
- val_loss: 7.3941e-04
Epoch 11/40
805/805 [==============================] - 21s 26ms/step - loss: 9.2004
e-04 - val_loss: 6.9342e-04
Epoch 12/40
805/805 [==============================] - 21s 26ms/step - loss: 0.0010
- val_loss: 8.6859e-04
Epoch 13/40
805/805 [==============================] - 21s 26ms/step - loss: 8.7828
e-04 - val_loss: 9.6106e-04
Epoch 14/40
805/805 [==============================] - 21s 26ms/step - loss: 8.4787
e-04 - val_loss: 7.3521e-04
Epoch 15/40
805/805 [==============================] - 21s 26ms/step - loss: 7.9738
e-04 - val_loss: 7.9432e-04
Epoch 16/40
805/805 [==============================] - 21s 26ms/step - loss: 8.8170
e-04 - val_loss: 6.6762e-04
Epoch 17/40
805/805 [==============================] - 21s 26ms/step - loss: 8.8365
e-04 - val_loss: 6.9428e-04
Epoch 18/40
805/805 [==============================] - 21s 26ms/step - loss: 8.1471
e-04 - val_loss: 7.2798e-04
Epoch 19/40
805/805 [==============================] - 21s 26ms/step - loss: 8.3920
e-04 - val_loss: 8.3959e-04
```

```
Epoch 20/40
805/805 [==============================] - 21s 26ms/step - loss: 8.3831
e-04 - val_loss: 6.2917e-04
Epoch 21/40
805/805 [==============================] - 21s 26ms/step - loss: 8.3469
e-04 - val_loss: 6.5456e-04
Epoch 22/40
805/805 [==============================] - 21s 26ms/step - loss: 7.8537
e-04 - val_loss: 8.5316e-04
Epoch 23/40
805/805 [==============================] - 21s 26ms/step - loss: 7.9547
e-04 - val_loss: 8.0352e-04
Epoch 24/40
805/805 [==============================] - 21s 26ms/step - loss: 8.1381
e-04 - val_loss: 7.0247e-04
Epoch 25/40
805/805 [==============================] - 21s 26ms/step - loss: 8.0431
e-04 - val_loss: 6.3282e-04
Epoch 26/40
805/805 [==============================] - 21s 26ms/step - loss: 7.8246
e-04 - val_loss: 6.7598e-04
Epoch 27/40
805/805 [==============================] - 21s 26ms/step - loss: 7.7531
e-04 - val_loss: 0.0019
Epoch 28/40
805/805 [==============================] - 21s 26ms/step - loss: 8.1814
e-04 - val_loss: 9.9667e-04
Epoch 29/40
805/805 [==============================] - 21s 26ms/step - loss: 7.8402
e-04 - val_loss: 6.5742e-04
Epoch 30/40
805/805 [==============================] - 21s 26ms/step - loss: 7.4684
e-04 - val_loss: 6.4425e-04
Epoch 31/40
805/805 [==============================] - 21s 26ms/step - loss: 7.4811
e-04 - val_loss: 0.0014
Epoch 32/40
805/805 [==============================] - 21s 26ms/step - loss: 7.8432
e-04 - val_loss: 0.0010
Epoch 33/40
805/805 [==============================] - 21s 26ms/step - loss: 7.8852
e-04 - val_loss: 8.1593e-04
Epoch 34/40
805/805 [==============================] - 21s 26ms/step - loss: 7.7648
e-04 - val_loss: 9.1759e-04
Epoch 35/40
805/805 [==============================] - 21s 26ms/step - loss: 8.1643
e-04 - val_loss: 6.8340e-04
Epoch 36/40
805/805 [==============================] - 21s 26ms/step - loss: 8.1314
e-04 - val_loss: 6.7990e-04
Epoch 37/40
805/805 [==============================] - 21s 26ms/step - loss: 7.6006
e-04 - val_loss: 0.0010
Epoch 38/40
805/805 [==============================] - 21s 26ms/step - loss: 7.6761
e-04 - val_loss: 0.0012
```

```
Epoch 39/40
805/805 [==============================] - 21s 26ms/step - loss: 7.6807
e-04 - val_loss: 9.2922e-04
Epoch 40/40
805/805 [==============================] - 21s 26ms/step - loss: 8.2927
e-04 - val_loss: 6.6779e-04
```

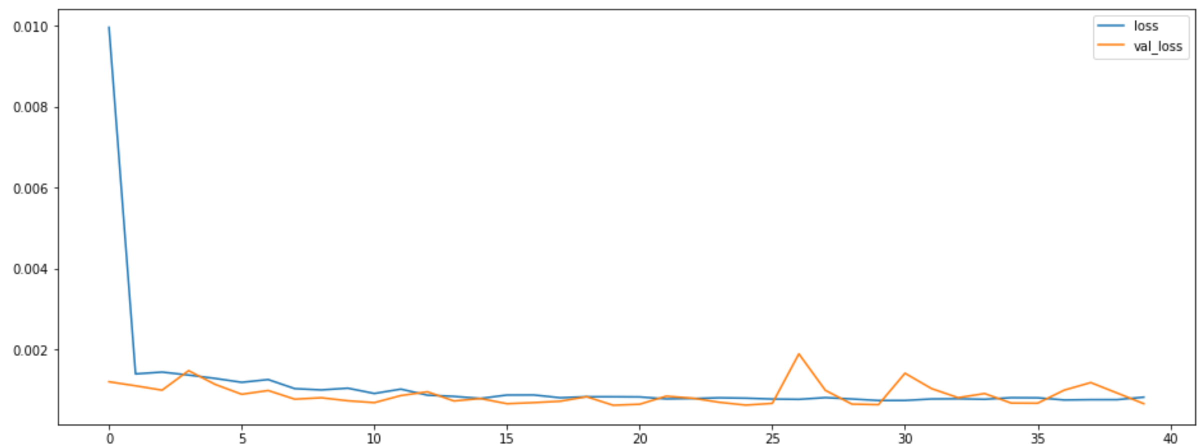
Out[122]: `<tensorflow.python.keras.callbacks.History at 0x7f287e0c5d50>`

Model Performance

- Lets take a look at how our model did training
- appears that our model trained very well and did not overtrain at the end
- We will test the the model by making soe predicitons

In [123]:
```
pd.DataFrame(model.history.history).plot(figsize = (16,6))
```

Out[123]: `<matplotlib.axes._subplots.AxesSubplot at 0x7f28803700d0>`



Predicitons

- We will test our model on predicting the test data before forecasting
- This will give us a better understanding of the model accuracy

In [124]:
```
test_predictions = []
batch = train_scaled[-length:]
current_batch = batch.reshape((1,length,n_features))
for x in range(len(test)):
    current_predictions = model.predict(current_batch)[0]
    test_predictions.append(current_predictions)
    current_batch = np.append(current_batch[:,1:,:], [[current_predictio
ns]], axis = 1)
```

inverse predicitons

- our model was trained on scaled data so we must inverse that process to get the true values

In [125]:
```
true_predicitons = scalar.inverse_transform(test_predictions)
```

Matching True and Test

In [126]:
```
test["predictions"] = true_predicitons
```

```
/home/ubuntu/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.p
y:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  """Entry point for launching an IPython kernel.
```

Plotting Test and Predictions

- Using the LSTM model the predicitons are mostly accurate for the first value forward. We will consider this for our forecast and take a close look at the first month forward.
- model prediciton on 2015 was 5.28 and the true value was 5.4. This was pretty close in prediction
- We will run our forecast below

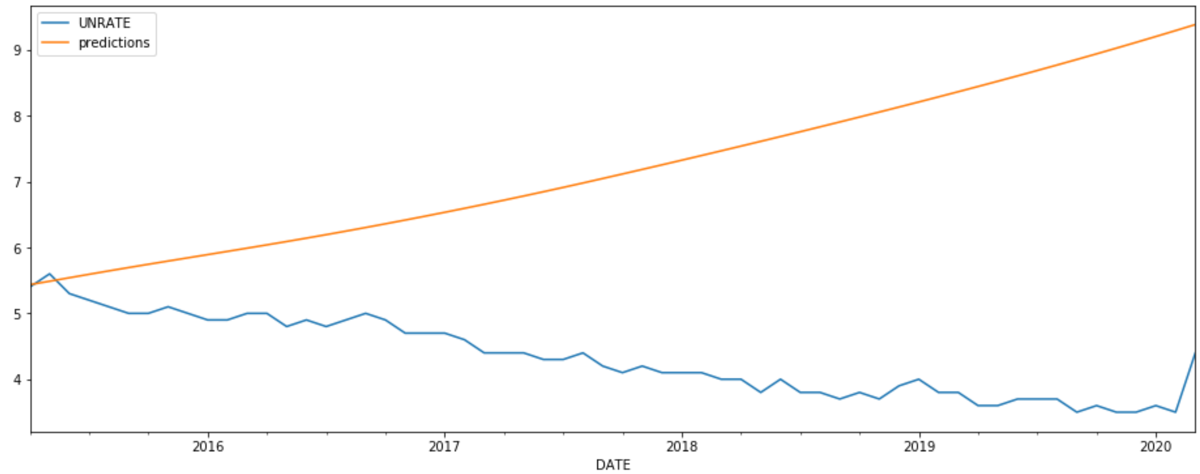
In [127]:
```
test.head()
```

Out[127]:

DATE	UNRATE	predictions
2015-04-01	5.4	5.435588
2015-05-01	5.6	5.487394
2015-06-01	5.3	5.540391
2015-07-01	5.2	5.592756
2015-08-01	5.1	5.644289

In [128]:
```
test.plot(figsize = (16,6))
```

Out[128]: <matplotlib.axes._subplots.AxesSubplot at 0x7f287b1a6890>



Forecasting with model

- Our forecast will be to predict the next month of May 2020

In [129]:
```
forecast  = []
periods = length
first_batch = train_scaled[-length:]
c_batch = first_batch.reshape((1,length,n_features))
for x in range(periods):
    pre = model.predict(c_batch)[0]
    forecast.append(pre)
    c_batch = np.append(c_batch[:,1:,:], [[pre]], axis=1)
```

Inverse Forecast

In [130]:
```
true_forecast = scalar.inverse_transform(forecast)
```

In [131]:
```
true_forecast
```

Out[131]:
```
array([[5.43558815],
       [5.48739359]])
```

Time Series creation for forecast

- must begin at the end of the data at month's start
- last day in data shown below

In [132]:
```
data.tail()[-1:]
```

Out[132]:

DATE	UNRATE
2020-03-01	4.4

In [133]:
```
time_index = pd.date_range(start="2020-4-1", periods=periods, freq="MS")
```

In [134]:
```
time_index
```

Out[134]:
```
DatetimeIndex(['2020-04-01', '2020-05-01'], dtype='datetime64[ns]', fre
q='MS')
```

In [135]:
```
forecast_data_frame = pd.DataFrame(true_forecast, index=time_index, colu
mns=["forecast"])
```

Model Predicts the unemployment rate for 4/2020 will be 5.28

- we will plot this on a graph below

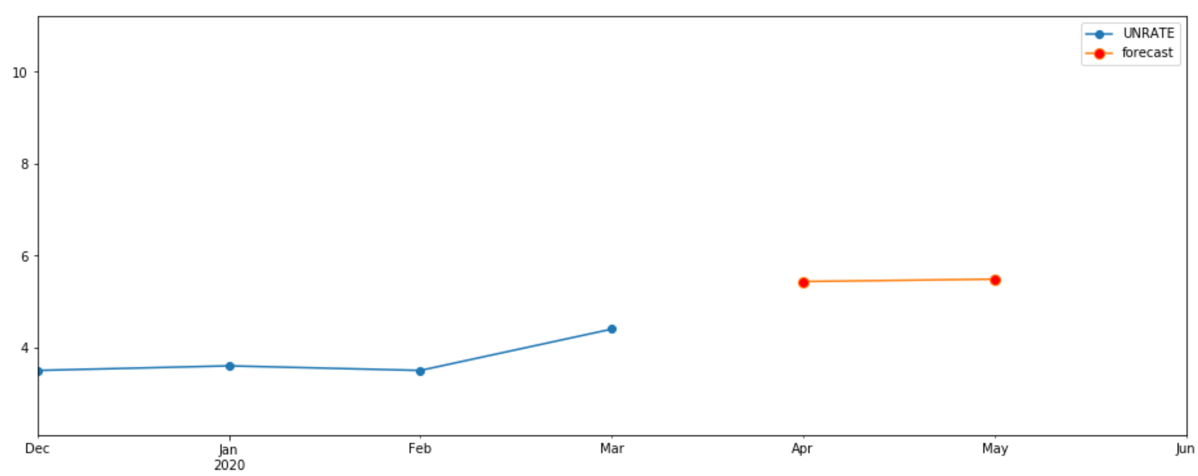
In [136]:
```
forecast_data_frame
```

Out[136]:

	forecast
2020-04-01	5.435588
2020-05-01	5.487394

In [137]:
```
ax = data.plot(figsize = (16,6), marker = 'o')
forecast_data_frame.plot(ax = ax, marker = "o", mfc = "r", ms = 8)
plt.xlim("2019-12-30","2020-6-1")
```

Out[137]:
```
(599, 605)
```



Saving Model

In [151]:
```
model.save("unemployment_Model.h5")
```

Back testing the model

- We will take the data up to year end 2018 and forecast for jan 1 2019
- THis will allow us to see how our model performed

In [ ]:
```
```

In [139]:
```
new_data = data.loc["1948-01-01": "2018-12-1"]
```

In [140]:
```
new_scalar = MinMaxScaler()
```

In [141]:
```
new_data_scaled = new_scalar.fit_transform(new_data)
```

Forecast and back testing

In [142]:
```
forecast = []
period = length
b = new_data_scaled[-length:]
curr_batch = b.reshape((1,length,n_features))
for x in range(period):
    predd = model.predict(curr_batch)[0]
    forecast.append(predd)
    curr_batch = np.append(curr_batch[:,1:,:], [[predd]], axis=1)
```

In [143]:
```
t_forecast = new_scalar.inverse_transform(forecast)
```

In [144]:
```
t_forecast
```

Out[144]:
```
array([[3.98228661],
       [4.04095157]])
```

In [145]:
```
new_data.tail()[-1:]
```

Out[145]:

	UNRATE
DATE	
2018-12-01	3.9

In [146]:
```
t_index = pd.date_range(start="2019-1-1", periods=period, freq='MS')
```

In [147]:
```
t_index
```

Out[147]:
```
DatetimeIndex(['2019-01-01', '2019-02-01'], dtype='datetime64[ns]', fre
q='MS')
```

In [148]:
```
fotecast_Df =pd.DataFrame(t_forecast,index=t_index, columns=["forecast"
])
```

In [ ]:

Model Predicts 3.98

- True value was 4.0
- Model is very Accurate in predictions of unemployment rate

In [149]:
```
fotecast_Df
```

Out[149]:

	forecast
2019-01-01	3.982287
2019-02-01	4.040952

In [150]:
```
data.loc["2019-1-1"]
```

Out[150]:
```
UNRATE    4.0
Name: 2019-01-01 00:00:00, dtype: float64
```

In [ ]:

In [ ]: