Hands-on Activity 5.2: Build and Apply Multilayer Perceptron

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CPE 019 - CPE32S9

Problem:

Based on the dataset that I used, I am trying to forecast or predict the number of car sales every 6 months and the following years by using MLP.

Dataset used: https://drive.google.com/file/d/17j7CPYUPuGcfxBSSOUrhCOHx41o80q9E/view?usp=sharing

```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import seaborn as sns
import matplotlib.pyplot as plt;
from statsmodels.tsa.seasonal import seasonal_decompose
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, InputLayer
import warnings
warnings.filterwarnings('ignore')
```

```
path=('/content/drive/MyDrive/CPE 019 Emerging Technologies 3/HOA 5.2/sales-cars.csv')
df_cars = pd.read_csv(path)
```

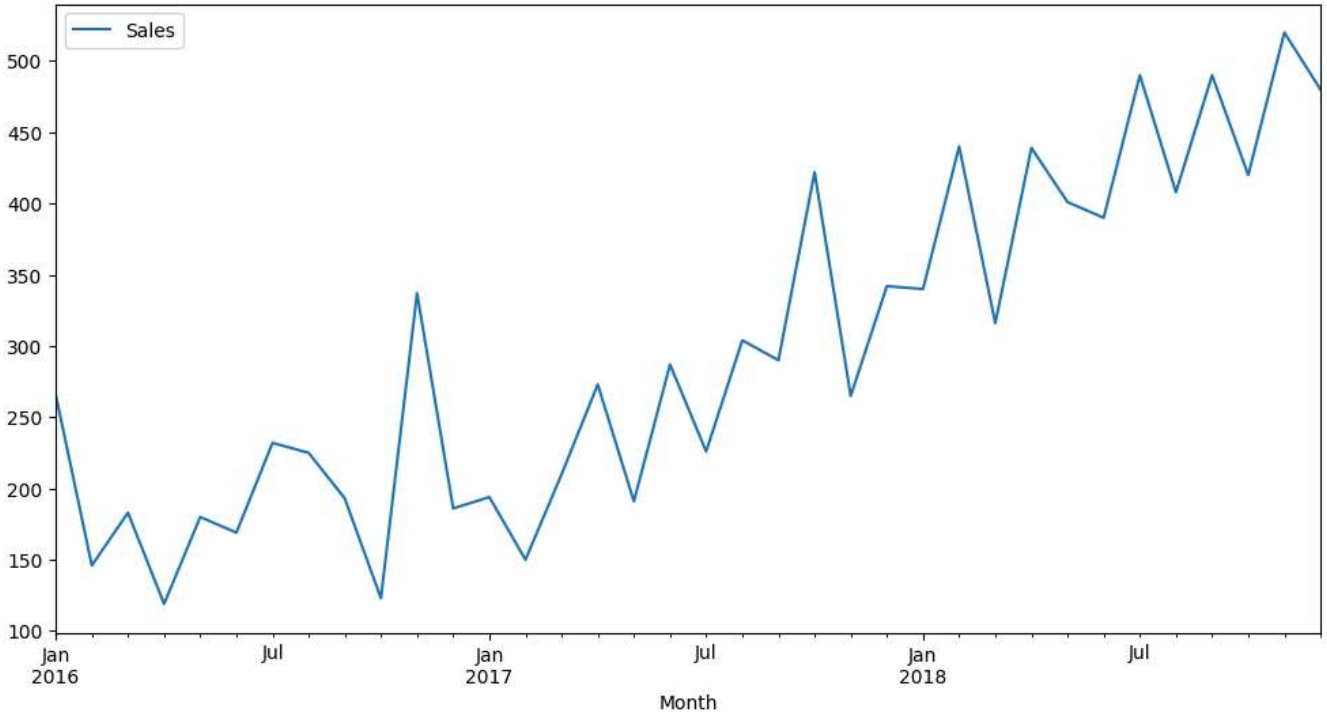
```
df_cars.head()
```

	Month	Sales
0	2016-01	266
1	2016-02	146
2	2016-03	183
3	2016-04	119
4	2016-05	180

```
df_cars.index = pd.to_datetime(df_cars.Month, format='%Y-%m')


df_cars = df_cars.resample("M").sum()


df_cars.plot(figsize=(12,6)); #cell 8 and 9 was for tidying up the appearance of months par
```




```
# Train Test Split
train = df_cars[:-6]
test = df_cars[-6:]


train.head()
```

Month	Sales
2016-01-31	266
2016-02-29	146
2016-03-31	183
2016-04-30	119
2016-05-31	180

```
test.head()
```

Month	Sales
2018-07-31	490
2018-08-31	408
2018-09-30	490
2018-10-31	420
2018-11-30	520

```
#generate lags
def generate_lag(df, n):
    X, y = [], []
    for i in range(len(df) - n):
        X.append(df[i:i+n])
        y.append(df[n+i])

    return np.array(X), np.array(y), np.array(y[-n:]).reshape(1,n)


X, y, last_batch_values = generate_lag(train.Sales.values, 12)


X
```

```
array([[266, 146, 183, 119, 180, 169, 232, 225, 193, 123, 337, 186],
       [146, 183, 119, 180, 169, 232, 225, 193, 123, 337, 186, 194],
       [183, 119, 180, 169, 232, 225, 193, 123, 337, 186, 194, 150],
       [119, 180, 169, 232, 225, 193, 123, 337, 186, 194, 150, 210],
       [180, 169, 232, 225, 193, 123, 337, 186, 194, 150, 210, 273],
       [169, 232, 225, 193, 123, 337, 186, 194, 150, 210, 273, 191],
       [232, 225, 193, 123, 337, 186, 194, 150, 210, 273, 191, 287],
       [225, 193, 123, 337, 186, 194, 150, 210, 273, 191, 287, 226],
       [193, 123, 337, 186, 194, 150, 210, 273, 191, 287, 226, 304],
       [123, 337, 186, 194, 150, 210, 273, 191, 287, 226, 304, 290],
       [337, 186, 194, 150, 210, 273, 191, 287, 226, 304, 290, 422],
       [186, 194, 150, 210, 273, 191, 287, 226, 304, 290, 422, 265],
       [194, 150, 210, 273, 191, 287, 226, 304, 290, 422, 265, 342],
       [150, 210, 273, 191, 287, 226, 304, 290, 422, 265, 342, 340],
       [210, 273, 191, 287, 226, 304, 290, 422, 265, 342, 340, 440],
       [273, 191, 287, 226, 304, 290, 422, 265, 342, 340, 440, 316],
       [191, 287, 226, 304, 290, 422, 265, 342, 340, 440, 316, 439],
       [287, 226, 304, 290, 422, 265, 342, 340, 440, 316, 439, 401]])
```

```
y
```

```
array([194, 150, 210, 273, 191, 287, 226, 304, 290, 422, 265, 342, 340,
       440, 316, 439, 401, 390])
```

```
last_batch_values
```

```
array([[226, 304, 290, 422, 265, 342, 340, 440, 316, 439, 401, 390]])
```

Creating the model

```
def mlp_model(input_, y_, epochs=1000):
    model = Sequential()
    model.add(Dense(100, activation='relu', input_dim=input_.shape[1]))
    model.add(Dense(1))
    model.compile(optimizer='adam', loss='mse')
    print(model.fit(input_, y_, epochs=epochs))
    return model


model = mlp_model(X,y, epochs=370)
model
```

```
Epoch 1/370
1/1 [==============================] - 1s 570ms/step - loss: 91195.3906
Epoch 2/370
1/1 [==============================] - 0s 11ms/step - loss: 78907.2188
Epoch 3/370
1/1 [==============================] - 0s 10ms/step - loss: 67474.3516
Epoch 4/370
1/1 [==============================] - 0s 13ms/step - loss: 56977.9219
Epoch 5/370
1/1 [==============================] - 0s 14ms/step - loss: 47440.3516
Epoch 6/370
1/1 [==============================] - 0s 11ms/step - loss: 38920.6250
Epoch 7/370
1/1 [==============================] - 0s 10ms/step - loss: 31385.3789
Epoch 8/370
1/1 [==============================] - 0s 12ms/step - loss: 24796.7852
Epoch 9/370
1/1 [==============================] - 0s 11ms/step - loss: 19208.9531
Epoch 10/370
1/1 [==============================] - 0s 11ms/step - loss: 14578.6338
Epoch 11/370
1/1 [==============================] - 0s 13ms/step - loss: 10862.2695
Epoch 12/370
1/1 [==============================] - 0s 10ms/step - loss: 8035.8369
Epoch 13/370
1/1 [==============================] - 0s 10ms/step - loss: 6031.0396
Epoch 14/370
1/1 [==============================] - 0s 10ms/step - loss: 4776.9614
Epoch 15/370
1/1 [==============================] - 0s 10ms/step - loss: 4180.6797
Epoch 16/370
```

```
1/1 [==============================] - 0s 10ms/step - loss: 4115.1880
Epoch 17/370
1/1 [==============================] - 0s 10ms/step - loss: 4449.8633
Epoch 18/370
1/1 [==============================] - 0s 11ms/step - loss: 5049.6650
Epoch 19/370
1/1 [==============================] - 0s 10ms/step - loss: 5778.8896
Epoch 20/370
1/1 [==============================] - 0s 12ms/step - loss: 6515.3677
Epoch 21/370
1/1 [==============================] - 0s 11ms/step - loss: 7157.9722
Epoch 22/370
1/1 [==============================] - 0s 11ms/step - loss: 7643.0522
Epoch 23/370
1/1 [==============================] - 0s 10ms/step - loss: 7933.8491
Epoch 24/370
1/1 [==============================] - 0s 11ms/step - loss: 8017.6240
Epoch 25/370
1/1 [==============================] - 0s 11ms/step - loss: 7906.3887
Epoch 26/370
1/1 [==============================] - 0s 11ms/step - loss: 7631.7949
Epoch 27/370
1/1 [==============================] - 0s 12ms/step - loss: 7236.3574
Epoch 28/370
1/1 [==============================] - 0s 11ms/step - loss: 6758.4502
Epoch 29/370
1/1 [==============================] - 0s 11ms/step - loss: 6239.1406
```

```
#forecast
def forecast_function(model, last_batch, n):
    in_value = last_batch.copy()
    preds = []
    for i in range(n):
        p = model.predict(in_value)
        preds.append(p.ravel())
        in_value = np.append(in_value, p)[1:].reshape(last_batch.shape)
    return np.array(preds).ravel()


pred = forecast_function(model, last_batch_values, 6)
```

```
1/1 [==============================] - 0s 86ms/step
1/1 [==============================] - 0s 140ms/step
1/1 [==============================] - 0s 38ms/step
1/1 [==============================] - 0s 37ms/step
1/1 [==============================] - 0s 37ms/step
1/1 [==============================] - 0s 35ms/step
```

```
pred
```

```
array([446.093  , 468.80255, 507.66254, 452.39258, 545.29425, 534.06464],
      dtype=float32)
```

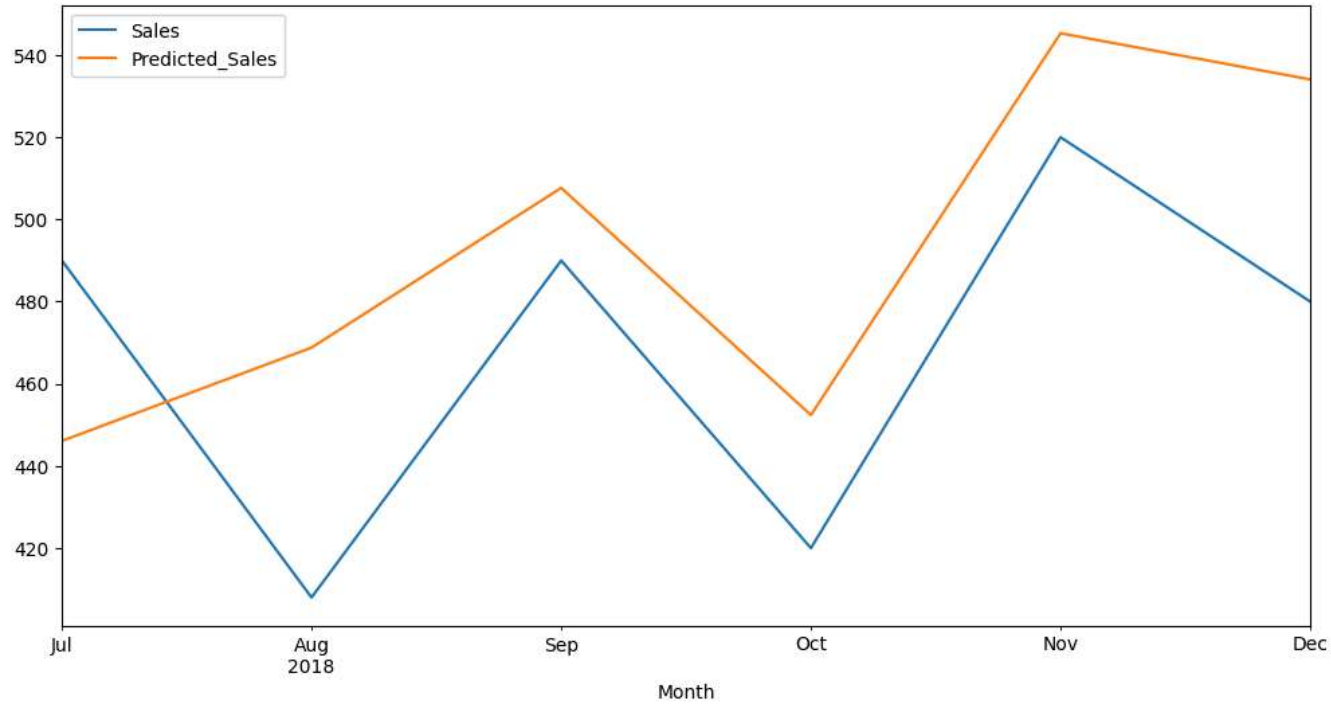
```
test['Predicted_Sales']=pred
```

```
test.head()
```

Month	Sales	Predicted_Sales
2018-07-31	490	446.092987
2018-08-31	408	468.802551
2018-09-30	490	507.662537
2018-10-31	420	452.392578
2018-11-30	520	545.294250

```
#shows the difference between the Sales and Predicted Sales
test.plot(figsize=(12,6))
```

```
<Axes: xlabel='Month'>
```



Accuracy

```
def error_function(df,column_1,column_2):
    data = df.copy()
    my_list = []
    for i in range(len(data)):
        x = (data[column_2][i]*100)/data[column_1][i]
        if x >= 100:
            error = x-100
            #data['error_percentage'][i] = error
            my_list.append(error)
        else:
            error = 100-x
            my_list.append(error)
            #data['error_percentage'][i] = error
    data['error_percentage'] = my_list
    return data


column_1 = 'Sales'
column_2 = 'Predicted_Sales'
df_new = error_function(test,column_1,column_2)


df_new
```

Month	Sales	Predicted_Sales	error_percentage
2018-07-31	490	446.092987	8.960615
2018-08-31	408	468.802551	14.902586
2018-09-30	490	507.662537	3.604599
2018-10-31	420	452.392578	7.712519
2018-11-30	520	545.294250	4.864279
2018-12-31	480	534.064636	11.263466

```
def mean_error(df,error_column):
    total = 0
    for i in range(len(df)):
        total += df[error_column][i]
    mean_error_ = total/(len(df))
    return mean_error_


error_rate = mean_error(df_new,'error_percentage')


error_rate
```

```
8.551343952349256
```

```
sum_of_actual_sales = sum(df_new.Sales.values)
```

```
sum_of_actual_sales
```

```
2808
```

```
sum_of_predicted_sales = sum(df_new.Predicted_Sales.values)
```

```
sum_of_predicted_sales
```

```
2954.309539794922
```

```
rate_of_actual_and_predict_sums = (sum_of_predicted_sales*100)/sum_of_actual_sales
```

```
if rate_of_actual_and_predict_sums >= 100:
    total_percentage = rate_of_actual_and_predict_sums - 100
else:
    total_percentage = 100-rate_of_actual_and_predict_sums
```

```
print('Percentage error: ',total_percentage)
```

```
Percentage error:  5.21045369640035
```