

Predicting the Quarterly Gross Profit for Walmart

```
In [1]: 1 # Importing Packages
2 import itertools
3 import numpy as np
4 import pandas as pd
5 import matplotlib.pyplot as plt
6 import statsmodels.api as sm
7 import matplotlib
8 import itertools
9 import numpy as np
10 import pandas as pd
11 import matplotlib.pyplot as plt
12 import statsmodels.api as sm
13 import matplotlib
14 import sklearn.preprocessing
15 from sklearn.metrics import r2_score
16 import keras
17
18 from keras.layers import Dense,Dropout,SimpleRNN,GRU, Bidirectional,LSTM
19 from tensorflow.keras.optimizers import SGD
20 from keras.models import Sequential
21 from sklearn.preprocessing import MinMaxScaler, StandardScaler
22
23 plt.style.use('fivethirtyeight')
24 matplotlib.rcParams['axes.labelsize'] = 14
25 matplotlib.rcParams['xtick.labelsize'] = 12
26 matplotlib.rcParams['ytick.labelsize'] = 12
27 matplotlib.rcParams['text.color'] = 'k'
```

```
In [7]: 1 # Reading the Data
2 df=pd.read_excel('Walmart Quarterly Gross Profit.xlsx')
3 df.head()
```

```
Out[7]:   Date  Quartely Gross Profit
0 2009-01-31          26797
1 2009-04-30          23854
2 2009-07-31          25820
3 2009-10-31          25458
4 2010-01-31          28847
```

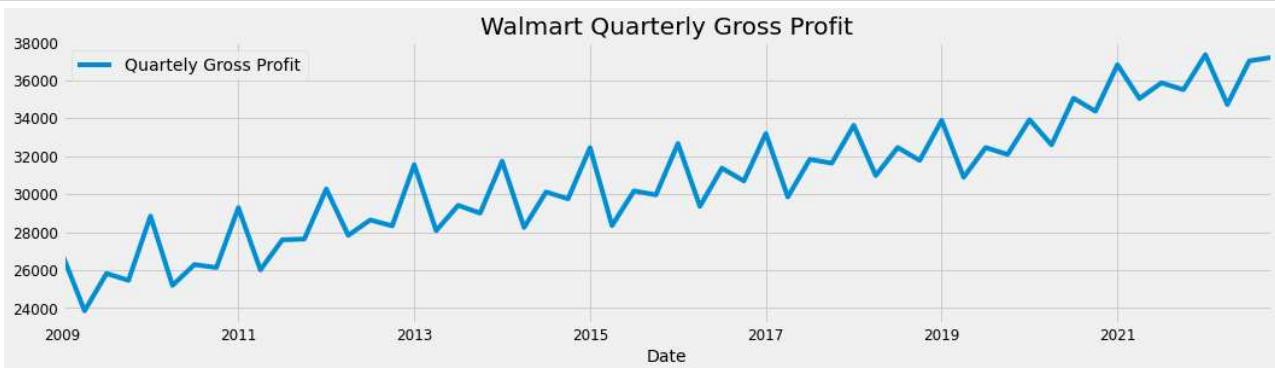
```
In [8]: 1 df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 56 entries, 0 to 55
Data columns (total 2 columns):
 #   Column           Non-Null Count  Dtype  
--- 
 0   Date             56 non-null    datetime64[ns]
 1   Quartely Gross Profit  56 non-null  int64  
dtypes: datetime64[ns](1), int64(1)
memory usage: 1.0 KB
```

```
In [9]: 1 # Setting Date as Index
2 df = df.set_index('Date')
3 df.head()
```

```
Out[9]:   Quartely Gross Profit
          Date
2009-01-31      26797
2009-04-30      23854
2009-07-31      25820
2009-10-31      25458
2010-01-31      28847
```

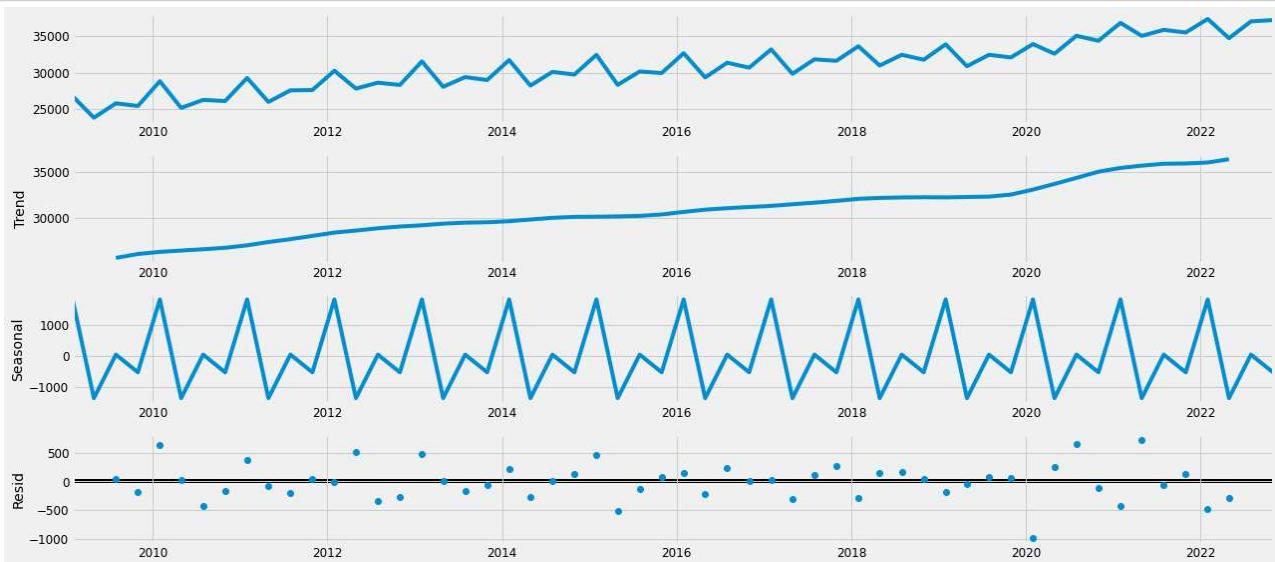
In [10]:

```
1 # Plotting the data
2 df.plot(figsize=(16,4),legend=True)
3 plt.title('Walmart Quarterly Gross Profit')
4 plt.show()
```



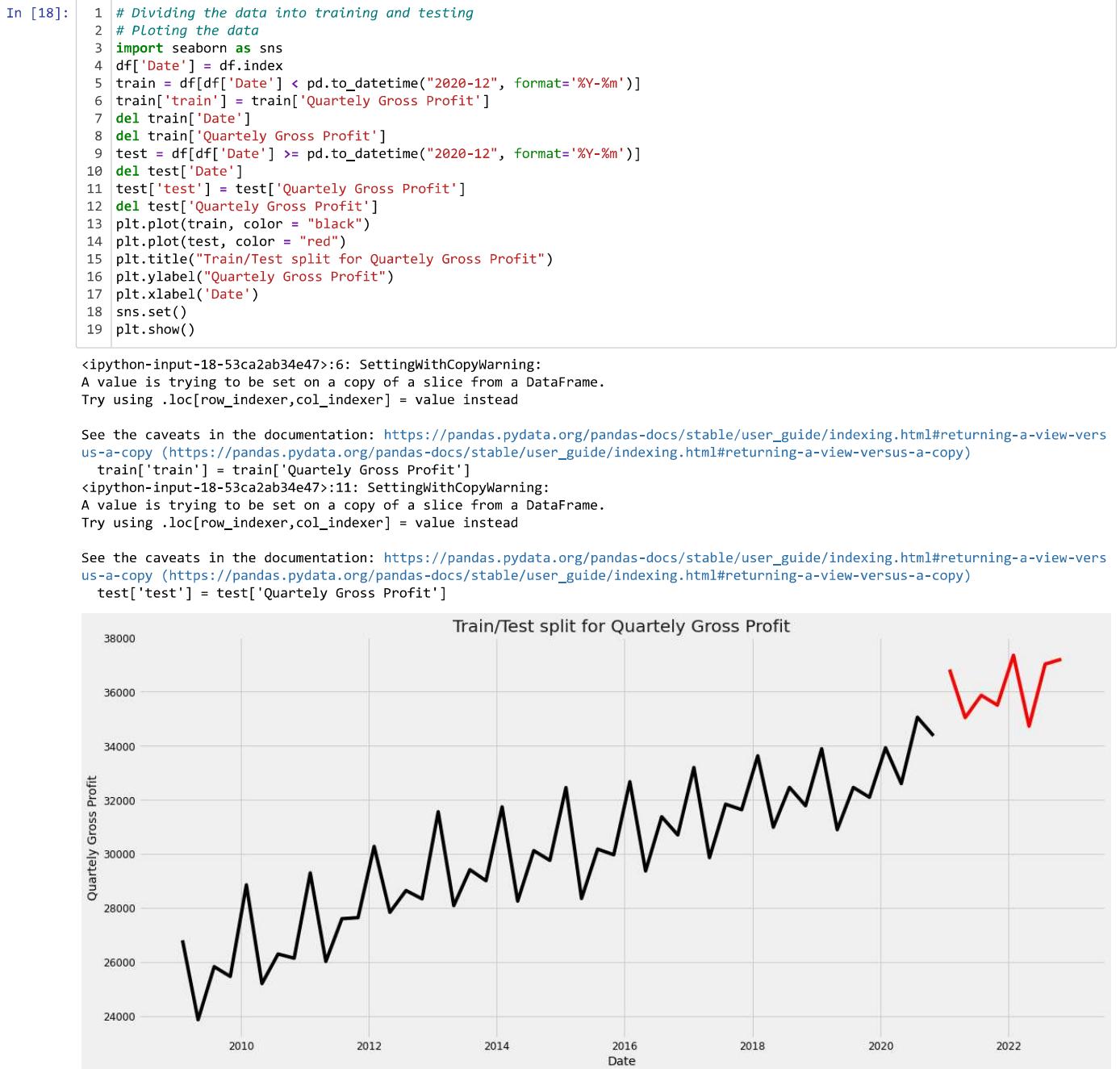
In [11]:

```
1 # Decomposition the data
2 from pylab import rcParams
3 rcParams['figure.figsize'] = 18, 8
4
5 decomposition = sm.tsa.seasonal_decompose(df, model = 'additive')
6 fig = decomposition.plot()
7 plt.show()
```



```
In [13]: 1 !pip install pmdarima

Looking in indexes: https://pypi.org/simple, (https://pypi.org/simple,), https://us-python.pkg.dev/colab-wheels/public/simple/ (https://us-python.pkg.dev/colab-wheels/public/simple/)
Collecting pmdarima
  Downloading pmdarima-2.0.2-cp38-cp38-manylinux_2_17_x86_64.manylinux2014_x86_64.manylinux_2_28_x86_64.whl (1.9 MB)
    |██████████| 1.9 MB 4.3 MB/s
Requirement already satisfied: urllib3 in /usr/local/lib/python3.8/dist-packages (from pmdarima) (1.24.3)
Collecting statsmodels>=0.13.2
  Downloading statsmodels-0.13.5-cp38-cp38-manylinux_2_17_x86_64.manylinux2014_x86_64.whl (9.9 MB)
    |██████████| 9.9 MB 52.4 MB/s
Requirement already satisfied: scikit-learn>=0.22 in /usr/local/lib/python3.8/dist-packages (from pmdarima) (1.0.2)
Requirement already satisfied: scipy>=1.3.2 in /usr/local/lib/python3.8/dist-packages (from pmdarima) (1.7.3)
Requirement already satisfied: pandas>=0.19 in /usr/local/lib/python3.8/dist-packages (from pmdarima) (1.3.5)
Requirement already satisfied: numpy>=1.21.2 in /usr/local/lib/python3.8/dist-packages (from pmdarima) (1.21.6)
Requirement already satisfied: Cython!=0.29.18,!>=0.29.31,>=0.29 in /usr/local/lib/python3.8/dist-packages (from pmdarima) (0.29.3)
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.8/dist-packages (from pmdarima) (1.2.0)
Requirement already satisfied: setuptools!=50.0.0,>=38.6.0 in /usr/local/lib/python3.8/dist-packages (from pmdarima) (57.4.0)
Requirement already satisfied: pytz>=2017.3 in /usr/local/lib/python3.8/dist-packages (from pandas>=0.19->pmdarima) (2022.6)
Requirement already satisfied: python-dateutil>=2.7.3 in /usr/local/lib/python3.8/dist-packages (from pandas>=0.19->pmdarima) (2.8.2)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.8/dist-packages (from python-dateutil>=2.7.3->pandas>=0.19->pmdarima) (1.15.0)
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.8/dist-packages (from scikit-learn>=0.22->pmdarima) (3.1.0)
Requirement already satisfied: patsy>=0.5.2 in /usr/local/lib/python3.8/dist-packages (from statsmodels>=0.13.2->pmdarima) (0.5.3)
Requirement already satisfied: packaging>=21.3 in /usr/local/lib/python3.8/dist-packages (from statsmodels>=0.13.2->pmdarima) (21.3)
Requirement already satisfied: pyparsing!=3.0.5,>=2.0.2 in /usr/local/lib/python3.8/dist-packages (from packaging>=21.3->statsmodels>=0.13.2->pmdarima) (3.0.9)
Installing collected packages: statsmodels, pmdarima
  Attempting uninstall: statsmodels
    Found existing installation: statsmodels 0.12.2
    Uninstalling statsmodels-0.12.2:
      Successfully uninstalled statsmodels-0.12.2
Successfully installed pmdarima-2.0.2 statsmodels-0.13.5
```

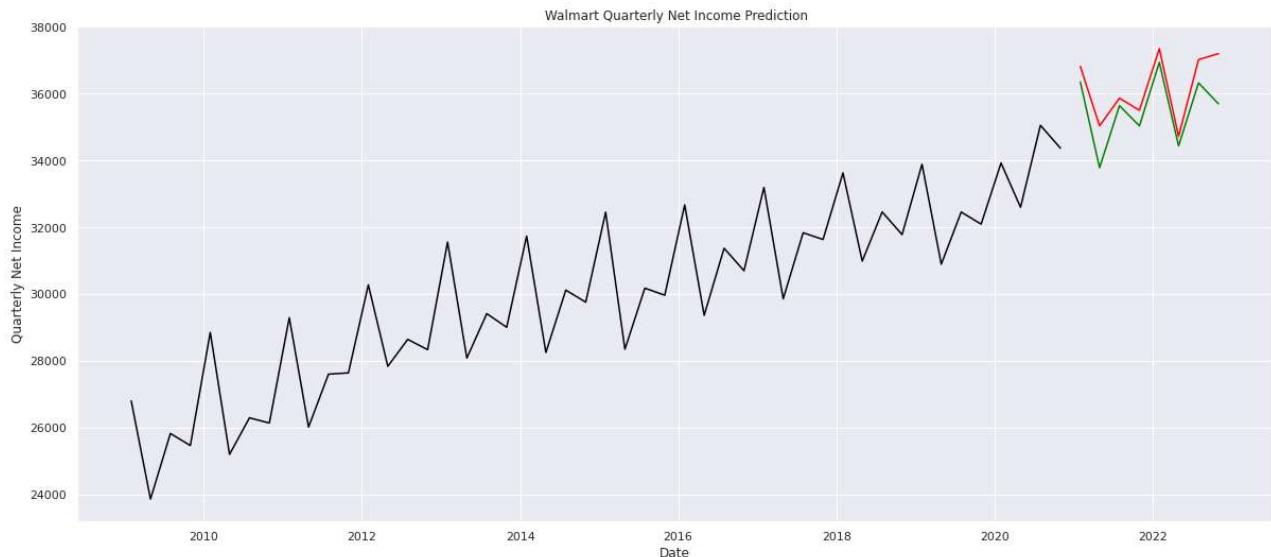


```
In [19]: 1 # Applying ARIMA Model
2 from pmldarima.arima import auto_arima
3 model = auto_arima(train, trace=True, error_action='ignore', suppress_warnings=True)
4 model.fit(train)
5 forecast = model.predict(n_periods=len(test))
6 forecast = pd.DataFrame(forecast, index = test.index, columns=['Prediction'])

Performing stepwise search to minimize aic
ARIMA(2,1,2)(0,0,0)[0] intercept : AIC=804.349, Time=0.32 sec
ARIMA(0,1,0)(0,0,0)[0] intercept : AIC=862.330, Time=0.03 sec
ARIMA(1,1,0)(0,0,0)[0] intercept : AIC=844.558, Time=0.04 sec
ARIMA(0,1,1)(0,0,0)[0] intercept : AIC=846.847, Time=0.09 sec
ARIMA(0,1,0)(0,0,0)[0] intercept : AIC=860.584, Time=0.02 sec
ARIMA(1,1,2)(0,0,0)[0] intercept : AIC=inf, Time=0.29 sec
ARIMA(2,1,1)(0,0,0)[0] intercept : AIC=805.513, Time=0.23 sec
ARIMA(3,1,2)(0,0,0)[0] intercept : AIC=792.556, Time=0.15 sec
ARIMA(3,1,1)(0,0,0)[0] intercept : AIC=790.184, Time=0.15 sec
ARIMA(3,1,0)(0,0,0)[0] intercept : AIC=838.276, Time=0.16 sec
ARIMA(4,1,1)(0,0,0)[0] intercept : AIC=776.234, Time=0.13 sec
ARIMA(4,1,0)(0,0,0)[0] intercept : AIC=778.402, Time=0.32 sec
ARIMA(5,1,1)(0,0,0)[0] intercept : AIC=771.630, Time=0.37 sec
ARIMA(5,1,0)(0,0,0)[0] intercept : AIC=776.029, Time=0.11 sec
ARIMA(5,1,2)(0,0,0)[0] intercept : AIC=766.964, Time=0.52 sec
ARIMA(4,1,2)(0,0,0)[0] intercept : AIC=777.558, Time=0.65 sec
ARIMA(5,1,3)(0,0,0)[0] intercept : AIC=740.335, Time=0.57 sec
ARIMA(4,1,3)(0,0,0)[0] intercept : AIC=738.945, Time=0.49 sec
ARIMA(3,1,3)(0,0,0)[0] intercept : AIC=738.149, Time=0.43 sec
ARIMA(2,1,3)(0,0,0)[0] intercept : AIC=801.268, Time=0.33 sec
ARIMA(3,1,4)(0,0,0)[0] intercept : AIC=742.050, Time=0.50 sec
ARIMA(2,1,4)(0,0,0)[0] intercept : AIC=799.565, Time=0.39 sec
ARIMA(4,1,4)(0,0,0)[0] intercept : AIC=741.146, Time=0.64 sec
ARIMA(3,1,3)(0,0,0)[0] : AIC=750.706, Time=0.32 sec

Best model: ARIMA(3,1,3)(0,0,0)[0] intercept
Total fit time: 7.321 seconds
```

```
In [20]: 1 # Plotting the prediction
2 plt.plot(train, color = "black")
3 plt.plot(test, color = "red")
4 plt.plot(forecast, color = "green")
5 plt.title("Walmart Quarterly Net Income Prediction")
6 plt.ylabel("Quarterly Net Income")
7 plt.xlabel('Date')
8 sns.set()
9 plt.show()
```



```
In [21]: 1 from math import sqrt
2 from sklearn.metrics import mean_squared_error
3 rms = sqrt(mean_squared_error(test,forecast))
4 print("RMSE: ", rms)
```

RMSE: 795.3660204459867

SARIMA Model

```
In [ ]: 1 df=pd.read_excel('Walmart Quarterly Gross Profit.xlsx')
2 df = df.set_index('Date')
```

```
In [ ]: 1 # set the typical ranges for p, d, q
2 p = d = q = range(0, 2)
3
4 #take all possible combination for p, d and q
5 pdq = list(itertools.product(p, d, q))
6 seasonal_pdq = [(x[0], x[1], x[2], 12) for x in list(itertools.product(p, d, q))]
7
8 print('Examples of parameter combinations for Seasonal ARIMA...')
9 print('SARIMAX: {} x {}'.format(pdq[1], seasonal_pdq[1]))
10 print('SARIMAX: {} x {}'.format(pdq[1], seasonal_pdq[2]))
11 print('SARIMAX: {} x {}'.format(pdq[2], seasonal_pdq[3]))
12 print('SARIMAX: {} x {}'.format(pdq[2], seasonal_pdq[4]))
```

Examples of parameter combinations for Seasonal ARIMA...
 SARIMAX: (0, 0, 1) x (0, 0, 1, 12)
 SARIMAX: (0, 0, 1) x (0, 1, 0, 12)
 SARIMAX: (0, 1, 0) x (0, 1, 1, 12)
 SARIMAX: (0, 1, 0) x (1, 0, 0, 12)

```
In [ ]: 1 # Using Grid Search find the optimal set of parameters that yields the best performance
2 for param in pdq:
3     for param_seasonal in seasonal_pdq:
4         try:
5             mod = sm.tsa.statespace.SARIMAX(df, order = param, seasonal_order = param_seasonal, enforce_stationary = False,enf
6             result = mod.fit()
7             print('SARIMA{}x{}12 - AIC:{}'.format(param, param_seasonal, result.aic))
8         except:
9             continue
```

```
/usr/local/lib/python3.8/dist-packages/statsmodels/tsa/base/tsa_model.py:524: ValueWarning: No frequency information was provided, so inferred frequency Q-OCT will be used.
warnings.warn('No frequency information was'
/usr/local/lib/python3.8/dist-packages/statsmodels/tsa/base/tsa_model.py:524: ValueWarning: No frequency information was provided, so inferred frequency Q-OCT will be used.
warnings.warn('No frequency information was'
/usr/local/lib/python3.8/dist-packages/statsmodels/tsa/base/tsa_model.py:524: ValueWarning: No frequency information was provided, so inferred frequency Q-OCT will be used.
warnings.warn('No frequency information was'
/usr/local/lib/python3.8/dist-packages/statsmodels/tsa/base/tsa_model.py:524: ValueWarning: No frequency information was provided, so inferred frequency Q-OCT will be used.
warnings.warn('No frequency information was'
SARIMA(0, 0, 0)x(0, 0, 12)12 - AIC:1319.260809022218
SARIMA(0, 0, 0)x(0, 0, 1, 12)12 - AIC:1299.3606413938437

/usr/local/lib/python3.8/dist-packages/statsmodels/tsa/base/tsa_model.py:524: ValueWarning: No frequency information was provided, so inferred frequency Q-OCT will be used.
warnings.warn('No frequency information was'
/usr/local/lib/python3.8/dist-packages/statsmodels/tsa/base/tsa_model.py:524: ValueWarning: No frequency information was provi
```

```
In [ ]: 1 #Fitting the SARIMA model using above optimal combination of p, d, q (optimal means combination at which we got lowest AIC score)
2
3 model = sm.tsa.statespace.SARIMAX(df, order = (1, 1, 1),
4                                     seasonal_order = (1, 1, 0, 12))
5
6 result = model.fit()
7 print(result.summary().tables[1])
```

```
/usr/local/lib/python3.8/dist-packages/statsmodels/tsa/base/tsa_model.py:524: ValueWarning: No frequency information was provided, so inferred frequency Q-OCT will be used.
warnings.warn('No frequency information was'
/usr/local/lib/python3.8/dist-packages/statsmodels/tsa/base/tsa_model.py:524: ValueWarning: No frequency information was provided, so inferred frequency Q-OCT will be used.
warnings.warn('No frequency information was'

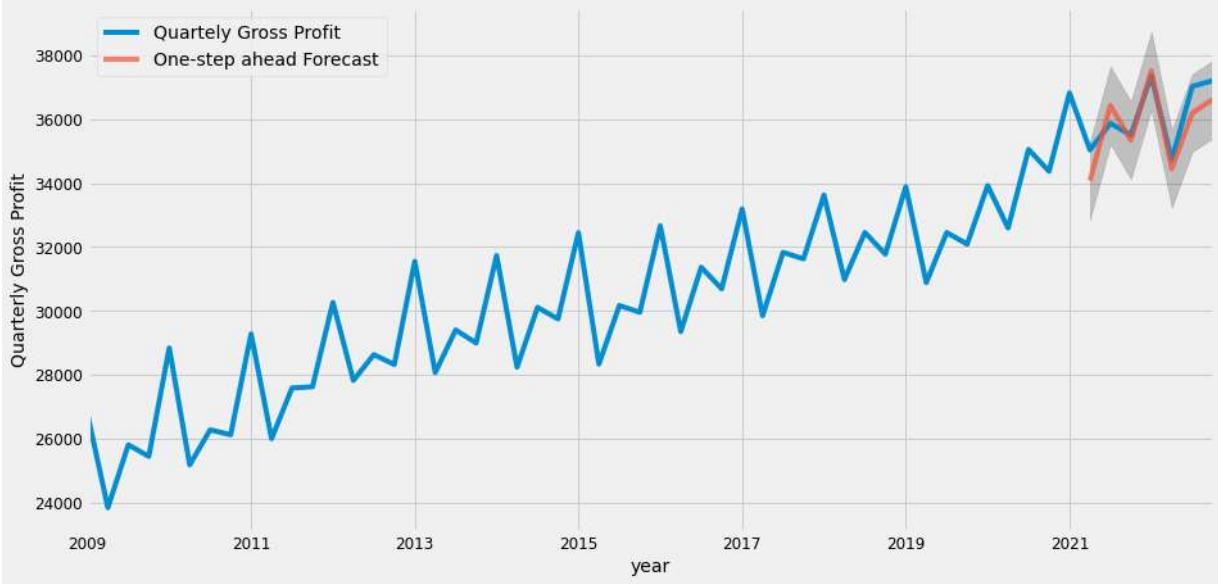
=====
      coef      std err        z      P>|z|      [0.025      0.975]
-----
ar.L1      -0.6932      0.576     -1.202      0.229     -1.823      0.437
ma.L1       0.5590      0.672      0.832      0.406     -0.758      1.876
ar.S.L12     -0.0334      0.162     -0.206      0.837     -0.351      0.284
sigma2      3.845e+05   7.61e+04      5.051      0.000     2.35e+05    5.34e+05
=====
```

```
In [ ]: 1 prediction = result.get_prediction(start = pd.to_datetime('2021-04-30'), dynamic = False)
2 prediction_ci = prediction.conf_int()
3 prediction_ci
```

Out[13]:

	lower Quartile Gross Profit	upper Quartile Gross Profit
2021-04-30	32857.872160	35288.511639
2021-07-31	35215.102362	37645.741841
2021-10-31	34126.986510	36557.625989
2022-01-31	36295.730420	38726.369899
2022-04-30	33232.407619	35663.047098
2022-07-31	34975.561730	37406.201209
2022-10-31	35396.471258	37827.110737

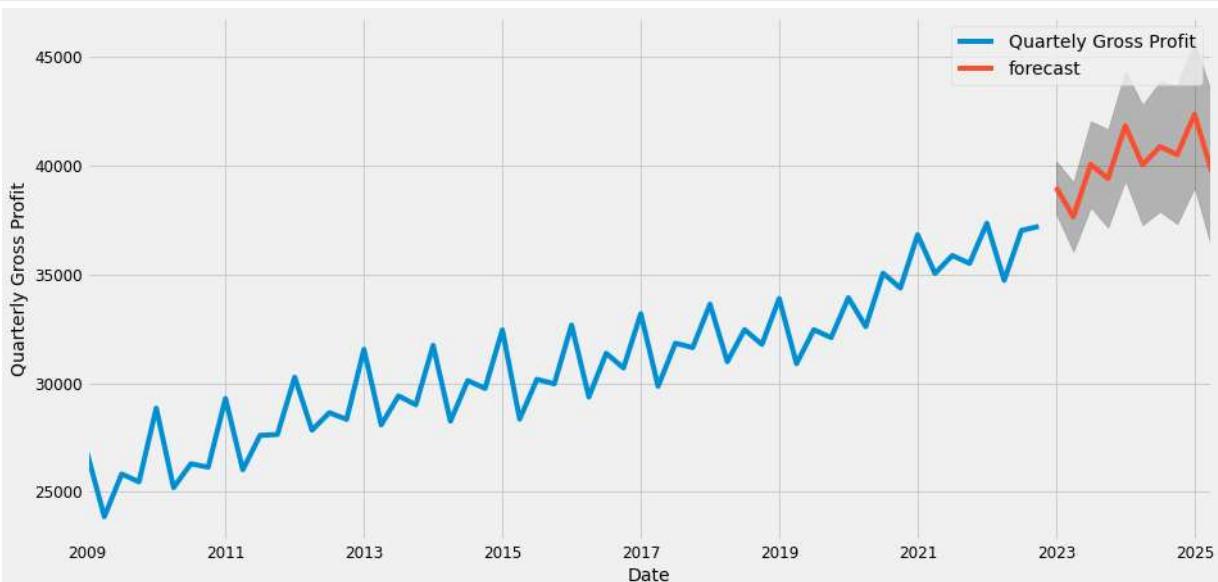
```
In [ ]: 1 #Visualize the forecasting
2 ax = df['2009:'].plot(label = 'observed')
3 prediction.predicted_mean.plot(ax = ax, label = 'One-step ahead Forecast', alpha = 0.7, figsize = (14, 7))
4 ax.fill_between(prediction_ci.index, prediction_ci.iloc[:, 0], prediction_ci.iloc[:, 1], color = 'k', alpha = 0.2)
5 ax.set_xlabel("year")
6 ax.set_ylabel('Quarterly Gross Profit')
7 plt.legend()
8 plt.show()
```



```
In [ ]: 1 # Evaluation metrics are Squared Mean Error(SME) and Root Mean Squared Error(RMSE)
2
3 from sklearn.metrics import mean_squared_error
4
5 y_hat = prediction.predicted_mean
6 y_truth = df['2021-03-31']
7 mse = mean_squared_error(y_truth,y_hat)
8 rmse = np.sqrt(mse)
9
10 print('The Mean Squared Error of our forecasts is', mse)
11 print('The Root Mean Squared Error of our forecasts is', rmse)
```

The Mean Squared Error of our forecasts is 344661.6083567878
The Root Mean Squared Error of our forecasts is 587.0788774575251

```
In [ ]: 1 # forecasting for out of sample data
2 pred_uc = result.get_forecast(steps = 10)
3 pred_ci = pred_uc.conf_int()
4
5 ax = df.plot(label = 'observed', figsize = (14, 7))
6 pred_uc.predicted_mean.plot(ax = ax, label = 'forecast')
7 ax.fill_between(pred_ci.index, pred_ci.iloc[:, 0], pred_ci.iloc[:, 1], color = 'k', alpha = 0.25)
8 ax.set_xlabel('Date')
9 ax.set_ylabel('Quarterly Gross Profit')
10
11 plt.legend()
12 plt.show()
13
```



DNN MODEL

```
In [ ]: 1 def convert2matrix(data_arr, look_back):
2     X, Y =[], []
3     for i in range(len(data_arr)-look_back):
4         d=i+look_back
5         X.append(data_arr[i:d,0])
6         Y.append(data_arr[d,0])
7     return np.array(X).astype('int'), np.array(Y).astype('int')
```

```
In [ ]: 1 df=pd.read_excel('Walmart Quarterly Gross Profit.xlsx')
2
3 df = df.set_index('Date')
4
```

```
In [ ]: 1 df1 = df
2 #Split data set into testing dataset and train dataset
3 train_size = 49
4 train, test =df1.values[0:train_size,:],df1.values[train_size:len(df1.values),:]
5 # setup Look_back window
6 look_back = 4
7 #convert dataset into right shape in order to input into the DNN
8 trainX, trainY = convert2matrix(train, look_back)
9 testX, testY = convert2matrix(test, look_back)
```

```
In [ ]: 1 from keras.models import Sequential
2 from keras.layers import Dense
3 def model_dnn(look_back):
4     model=Sequential()
5     model.add(Dense(units=32, input_dim=look_back, activation='relu'))
6     model.add(Dense(8, activation='relu'))
7     model.add(Dense(1))
8     model.compile(loss='mean_squared_error', optimizer='adam',metrics = ['mse', 'mae'])
9     return model
```

```
In [ ]: 1 model=model_dnn(look_back)
2 history=model.fit(trainX,trainY, epochs=500, batch_size=4, verbose=1, validation_data=(testX,testY),shuffle=False)
```

```
Epoch 1/500
12/12 [=====] - 1s 28ms/step - loss: 733065728.0000 - mse: 733065728.0000 - mae: 27035.9141 - val_loss: 674150592.0000 - val_mse: 674150592.0000 - val_mae: 25941.2969
Epoch 2/500
12/12 [=====] - 0s 5ms/step - loss: 326192384.0000 - mse: 326192384.0000 - mae: 17984.2949 - val_loss: 241177600.0000 - val_mse: 241177600.0000 - val_mae: 15491.7451
Epoch 3/500
12/12 [=====] - 0s 5ms/step - loss: 97188968.0000 - mse: 97188968.0000 - mae: 9684.1953 - val_loss: 42310372.0000 - val_mse: 42310372.0000 - val_mae: 6414.0586
Epoch 4/500
12/12 [=====] - 0s 6ms/step - loss: 12307298.0000 - mse: 12307298.0000 - mae: 3051.8325 - val_loss: 1188411.6250 - val_mse: 1188411.6250 - val_mae: 1065.2422
Epoch 5/500
12/12 [=====] - 0s 6ms/step - loss: 2697772.5000 - mse: 2697772.5000 - mae: 1361.0554 - val_loss: 614048.0000 - val_mse: 6140484.0000 - val_mae: 2232.1941
Epoch 6/500
12/12 [=====] - 0s 6ms/step - loss: 4224405.0000 - mse: 4224405.0000 - mae: 1774.1111 - val_loss: 4520942.5000 - val_mse: 4520942.5000 - val_mae: 1833.9037
Epoch 7/500
```

```
In [ ]: 1 def model_loss(history):
2     plt.figure(figsize=(8,4))
3     plt.plot(history.history['loss'], label='Train Loss')
4     plt.plot(history.history['val_loss'], label='Test Loss')
5     plt.title('model loss')
6     plt.ylabel('loss')
7     plt.xlabel('epochs')
8     plt.legend(loc='upper right')
9     plt.show();
```

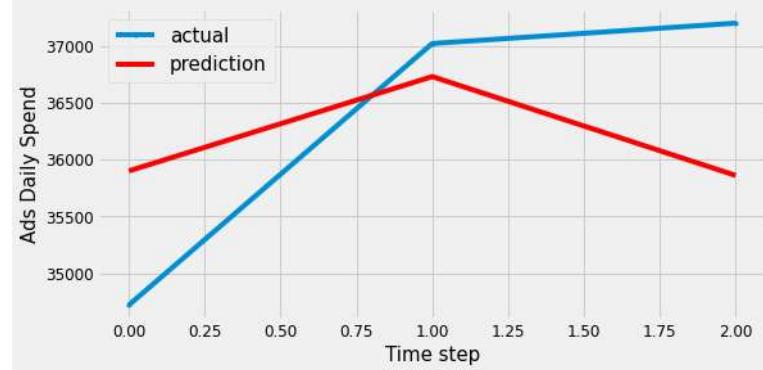
```
In [ ]: 1 train_score = model.evaluate(trainX, trainY, verbose=0)
2 print('Train Root Mean Squared Error(RMSE): %.2f; Train Mean Absolute Error(MAE) : %.2f '
3 % (np.sqrt(train_score[1]), train_score[2]))
4 test_score = model.evaluate(testX, testY, verbose=0)
5 print(train_score)
6 print(test_score)
7 print('Test Root Mean Squared Error(RMSE): %.2f; Test Mean Absolute Error(MAE) : %.2f '
8 % (np.sqrt(test_score[1]), test_score[2]))
```

```
Train Root Mean Squared Error(RMSE): 726.05; Train Mean Absolute Error(MAE) : 558.04
[527151.25, 527151.25, 558.036865234375]
[1088594.875, 1088594.875, 936.0260620117188]
Test Root Mean Squared Error(RMSE): 1043.36; Test Mean Absolute Error(MAE) : 936.03
```

```
In [ ]: 1 def prediction_plot(testY, test_predict):
2     len_prediction=[x for x in range(len(testY))]
3     plt.figure(figsize=(8,4))
4     plt.plot(len_prediction, testY[:8], marker='.', label="actual")
5     plt.plot(len_prediction, test_predict[:8], 'r', label="prediction")
6     plt.tight_layout()
7     #sns.despine(top=True)
8     plt.subplots_adjust(left=0.07)
9     plt.ylabel('Ads Daily Spend', size=15)
10    plt.xlabel('Time step', size=15)
11    plt.legend(fontsize=15)
12    plt.show();
```

```
In [ ]: 1 test_predict = model.predict(testX)
2 prediction_plot(testY, test_predict)
```

1/1 [=====] - 0s 20ms/step



GRU and BiLSTM Models

```
In [ ]: 1 df=pd.read_excel('Walmart Quarterly Gross Profit.xlsx')
2 df.head()
```

Out[33]:

	Date	Quarterly Gross Profit
0	2009-01-31	26797
1	2009-04-30	23854
2	2009-07-31	25820
3	2009-10-31	25458
4	2010-01-31	28847

```
In [ ]: 1 df = df.set_index('Date')
2 df.head()
```

Out[34]:

Date	Quarterly Gross Profit
2009-01-31	26797
2009-04-30	23854
2009-07-31	25820
2009-10-31	25458
2010-01-31	28847

```
In [ ]: 1 # Split train data and test data
2 train_size = int(len(df)*0.8)
3
4 train_data = df.iloc[:train_size]
5 test_data = df.iloc[train_size:]
```

```
In [ ]: 1 scaler = MinMaxScaler().fit(train_data)
2 train_scaled = scaler.transform(train_data)
3 test_scaled = scaler.transform(test_data)
```

```
In [ ]: 1 # Create input dataset
2 def create_dataset(X, look_back = 1):
3     Xs, ys = [], []
4
5     for i in range(len(X)-look_back):
6         v = X[i:i+look_back]
7         Xs.append(v)
8         ys.append(X[i+look_back])
9
10    return np.array(Xs), np.array(ys)
11 LOOK_BACK = 4
12 X_train, y_train = create_dataset(train_scaled,LOOK_BACK)
13 X_test, y_test = create_dataset(test_scaled,LOOK_BACK)
14 # Print data shape
15 print('X_train.shape: ', X_train.shape)
16 print('y_train.shape: ', y_train.shape)
17 print('X_test.shape: ', X_test.shape)
18 print('y_test.shape: ', y_test.shape)

X_train.shape: (40, 4, 1)
y_train.shape: (40, 1)
X_test.shape: (8, 4, 1)
y_test.shape: (8, 1)
```

```
In [ ]: 1 # Create BiLSTM model
2 def create_bilstm(units):
3     model = Sequential()
4     # Input Layer
5     model.add(Bidirectional(
6         LSTM(units = units, return_sequences=True),
7         input_shape=(X_train.shape[1], X_train.shape[2])))
8     # Hidden Layer
9     model.add(Bidirectional(LSTM(units = units)))
10    model.add(Dense(1))
11    #Compile model
12    model.compile(optimizer='adam',loss='mse')
13    return model
14 model_bilstm = create_bilstm(64)
15 # Create GRU model
16 def create_gru(units):
17     model = Sequential()
18     # Input Layer
19     model.add(GRU (units = units, return_sequences = True,
20     input_shape = [X_train.shape[1], X_train.shape[2]]))
21     model.add(Dropout(0.2))
22     # Hidden Layer
23     model.add(GRU(units = units))
24     model.add(Dropout(0.2))
25     model.add(Dense(units = 1))
26     #Compile model
27     model.compile(optimizer='adam',loss='mse')
28     return model
29 model_gru = create_gru(64)
```

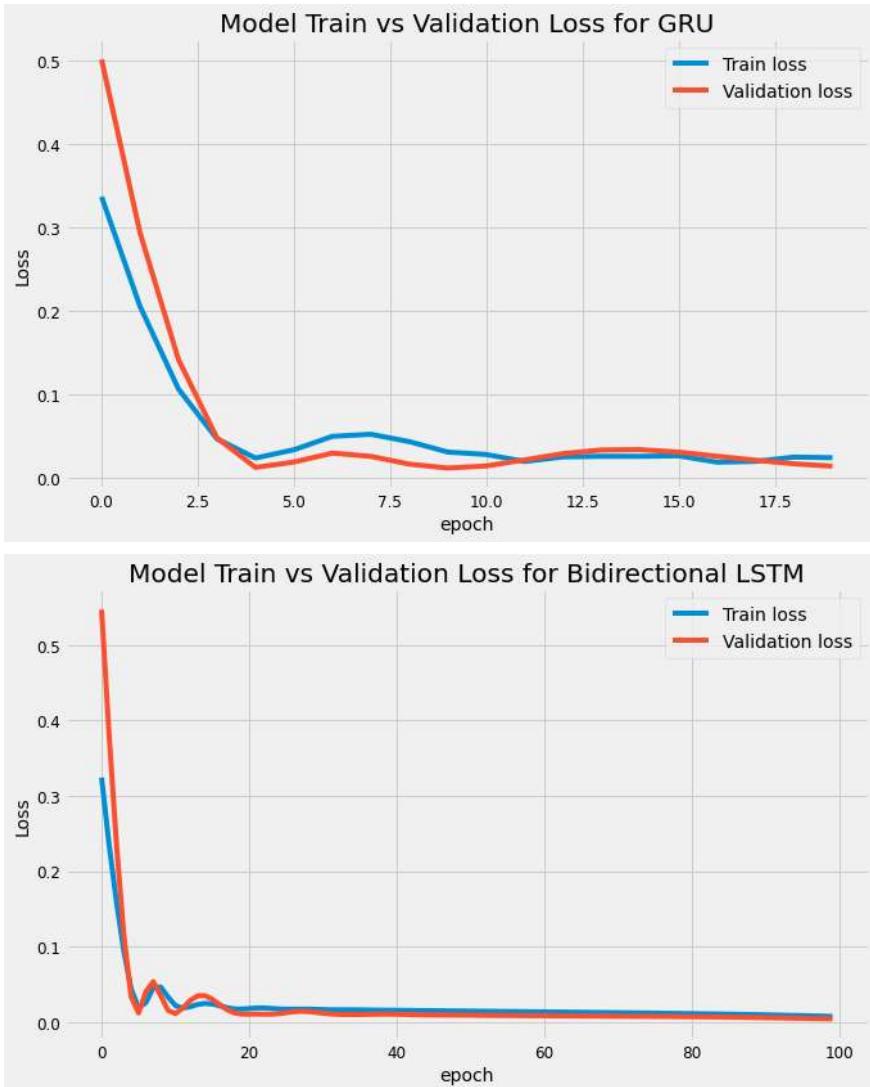
```
In [ ]: 1 def fit_model(model):
2     early_stop = keras.callbacks.EarlyStopping(monitor = 'val_loss',
3                                              patience = 10)
4     history = model.fit(X_train, y_train, epochs = 100,
5                          validation_split = 0.2,
6                          batch_size = 16, shuffle = False,
7                          callbacks = [early_stop])
8
9 history_gru = fit_model(model_gru)

Epoch 1/100
2/2 [=====] - 4s 849ms/step - loss: 0.3370 - val_loss: 0.5017
Epoch 2/100
2/2 [=====] - 0s 32ms/step - loss: 0.2054 - val_loss: 0.2937
Epoch 3/100
2/2 [=====] - 0s 32ms/step - loss: 0.1062 - val_loss: 0.1415
Epoch 4/100
2/2 [=====] - 0s 39ms/step - loss: 0.0464 - val_loss: 0.0476
Epoch 5/100
2/2 [=====] - 0s 33ms/step - loss: 0.0234 - val_loss: 0.0122
Epoch 6/100
2/2 [=====] - 0s 31ms/step - loss: 0.0334 - val_loss: 0.0186
Epoch 7/100
2/2 [=====] - 0s 30ms/step - loss: 0.0495 - val_loss: 0.0294
Epoch 8/100
2/2 [=====] - 0s 35ms/step - loss: 0.0520 - val_loss: 0.0254
Epoch 9/100
2/2 [=====] - 0s 31ms/step - loss: 0.0431 - val_loss: 0.0162
Epoch 10/100
2/2 [=====] - 0s 32ms/step - loss: 0.0306 - val_loss: 0.0115
Epoch 11/100
2/2 [=====] - 0s 49ms/step - loss: 0.0277 - val_loss: 0.0139
Epoch 12/100
2/2 [=====] - 0s 41ms/step - loss: 0.0194 - val_loss: 0.0212
Epoch 13/100
2/2 [=====] - 0s 59ms/step - loss: 0.0248 - val_loss: 0.0288
Epoch 14/100
2/2 [=====] - 0s 37ms/step - loss: 0.0255 - val_loss: 0.0331
Epoch 15/100
2/2 [=====] - 0s 39ms/step - loss: 0.0255 - val_loss: 0.0336
Epoch 16/100
2/2 [=====] - 0s 36ms/step - loss: 0.0261 - val_loss: 0.0305
Epoch 17/100
2/2 [=====] - 0s 40ms/step - loss: 0.0185 - val_loss: 0.0256
Epoch 18/100
2/2 [=====] - 0s 40ms/step - loss: 0.0195 - val_loss: 0.0208
Epoch 19/100
2/2 [=====] - 0s 41ms/step - loss: 0.0246 - val_loss: 0.0166
Epoch 20/100
2/2 [=====] - 0s 38ms/step - loss: 0.0239 - val_loss: 0.0137
```

```
In [ ]: 1 history_bilstm = fit_model(model_bilstm)

Epoch 1/100
2/2 [=====] - 9s 2s/step - loss: 0.3242 - val_loss: 0.5467
Epoch 2/100
2/2 [=====] - 0s 38ms/step - loss: 0.2366 - val_loss: 0.3836
Epoch 3/100
2/2 [=====] - 0s 35ms/step - loss: 0.1606 - val_loss: 0.2384
Epoch 4/100
2/2 [=====] - 0s 39ms/step - loss: 0.0950 - val_loss: 0.1166
Epoch 5/100
2/2 [=====] - 0s 37ms/step - loss: 0.0446 - val_loss: 0.0340
Epoch 6/100
2/2 [=====] - 0s 35ms/step - loss: 0.0190 - val_loss: 0.0122
Epoch 7/100
2/2 [=====] - 0s 36ms/step - loss: 0.0260 - val_loss: 0.0407
Epoch 8/100
2/2 [=====] - 0s 40ms/step - loss: 0.0457 - val_loss: 0.0538
Epoch 9/100
2/2 [=====] - 0s 70ms/step - loss: 0.0467 - val_loss: 0.0353
Epoch 10/100
2/2 [=====] - 0s 28ms/step - loss: 0.0224 - val_loss: 0.0158
```

```
In [ ]: 1 def plot_loss (history, model_name):
2     plt.figure(figsize = (10, 6))
3     plt.plot(history.history['loss'])
4     plt.plot(history.history['val_loss'])
5     plt.title('Model Train vs Validation Loss for ' + model_name)
6     plt.ylabel('Loss')
7     plt.xlabel('epoch')
8     plt.legend(['Train loss', 'Validation loss'], loc='upper right')
9
10    plot_loss (history_gru, 'GRU')
11    plot_loss (history_bilstm, 'Bidirectional LSTM')
```



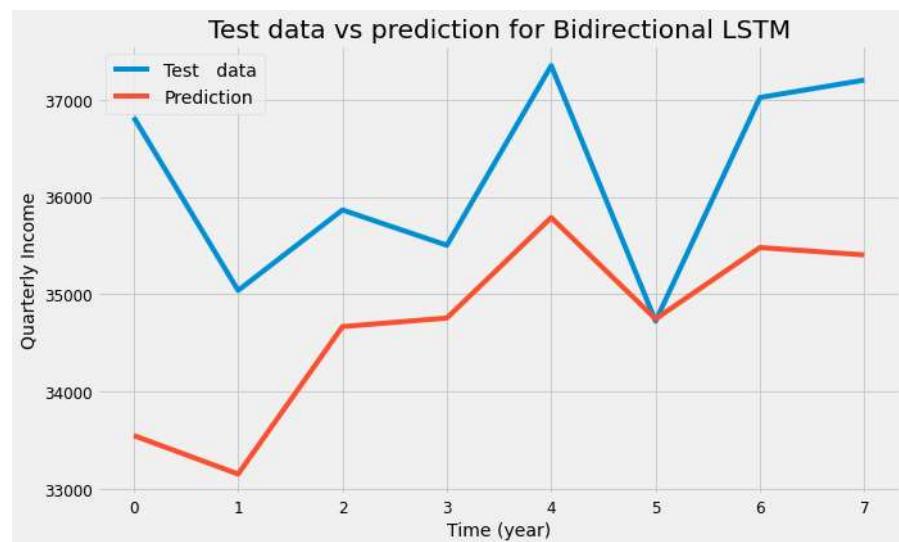
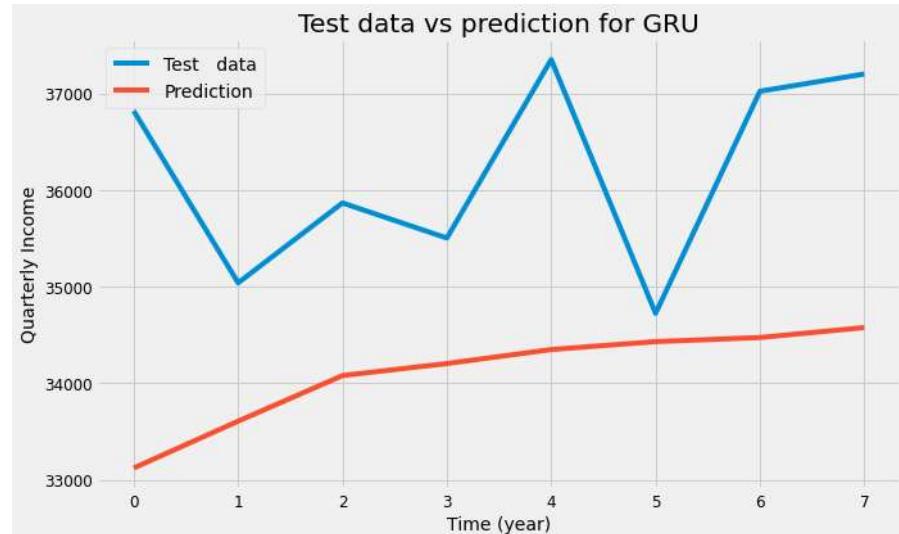
In []:

```

1 # Make prediction
2 def prediction(model):
3     prediction = model.predict(X_test)
4     prediction = scaler.inverse_transform(prediction)
5     return prediction
6 prediction_gru = prediction(model_gru)
7 prediction_bilstm = prediction(model_bilstm)
8 # Plot test data vs prediction
9 def plot_future(prediction, model_name, y_test):
10    plt.figure(figsize=(10, 6))
11    range_future = len(prediction)
12    plt.plot(np.arange(range_future), np.array(scaler.inverse_transform(y_test)),
13             label='Test data')
14    plt.plot(np.arange(range_future),
15             np.array(prediction), label='Prediction')
16    plt.title('Test data vs prediction for ' + model_name)
17    plt.legend(loc='upper left')
18    plt.xlabel('Time (year)')
19    plt.ylabel('Quarterly Income')
20
21 plot_future(prediction_gru, 'GRU', y_test)
22 plot_future(prediction_bilstm, 'Bidirectional LSTM', y_test)

```

1/1 [=====] - 1s 822ms/step
 1/1 [=====] - 2s 2s/step



```
In [ ]: 1 def evaluate_prediction(predictions, actual, model_name):  
2     errors = predictions - actual  
3     mse = np.square(errors).mean()  
4     rmse = np.sqrt(mse)  
5     mae = np.abs(errors).mean()  
6     print(model_name + ':')  
7     print('Mean Absolute Error: {:.4f}'.format(mae))  
8     print('Root Mean Square Error: {:.4f}'.format(rmse))  
9     print()  
10    evaluate_prediction(prediction_gru, scaler.inverse_transform(y_test), 'GRU')  
11    evaluate_prediction(prediction_bilstm, scaler.inverse_transform(y_test), 'Bidirectional LSTM')
```

```
GRU:  
Mean Absolute Error: 2085.2383  
Root Mean Square Error: 2320.4647  
  
Bidirectional LSTM:  
Mean Absolute Error: 1503.6255  
Root Mean Square Error: 1743.0772
```

```
In [ ]: 1 def evaluate_prediction(predictions, actual, model_name):  
2     errors = predictions - actual  
3     mse = np.square(errors).mean()  
4     rmse = np.sqrt(mse)  
5     mae = np.abs(errors).mean()  
6     print(model_name + ':')  
7     print('Mean Absolute Error: {:.4f}'.format(mae))  
8     print('Root Mean Square Error: {:.4f}'.format(rmse))  
9     print()  
10    evaluate_prediction(scaler.transform(prediction_gru), y_test, 'GRU')  
11    evaluate_prediction(scaler.transform(prediction_bilstm), y_test, 'Bidirectional LSTM')
```

```
GRU:  
Mean Absolute Error: 0.2079  
Root Mean Square Error: 0.2313  
  
Bidirectional LSTM:  
Mean Absolute Error: 0.1499  
Root Mean Square Error: 0.1738
```

```
/usr/local/lib/python3.8/dist-packages/sklearn/base.py:450: UserWarning: X does not have valid feature names, but MinMaxScaler wa  
s fitted with feature names  
    warnings.warn(  
/usr/local/lib/python3.8/dist-packages/sklearn/base.py:450: UserWarning: X does not have valid feature names, but MinMaxScaler wa  
s fitted with feature names  
    warnings.warn(
```