Week7_2_ARIMA_SARIMA

May 21, 2021

Time Series: ARIMA and SARIMA

Import Libraries

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

import datetime
# for interactive visualizations
import plotly.offline as py
import plotly.figure_factory as ff
import statsmodels.tsa.api as smt

from sklearn.preprocessing import MinMaxScaler
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
from sklearn.ensemble import (GradientBoostingRegressor,AdaBoostRegressor)
from sklearn.ensemble import RandomForestRegressor
from xgboost.sklearn import XGBRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.neighbors import KNeighborsRegressor
from sklearn.svm import SVR

import keras
from keras.layers import Dense
from keras.models import Sequential
from keras.optimizers import Adam
from keras.callbacks import EarlyStopping
from keras.utils import np_utils
from keras.layers import LSTM
from sklearn.model_selection import KFold, cross_val_score, train_test_split

import statsmodels.tsa.api as smt
import statsmodels.api as sm
from statsmodels.tools.eval_measures import rmse
```

```
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
import pickle

import warnings
warnings.filterwarnings("ignore")
```

[2]:
```
######  <span style="font-family: Arial; font-weight:bold;font-size:1.em;color:
↪#ea0ea1">Load dataset
```

[3]:
```
traindat = pd.read_csv("/home/jayanthikishore/Downloads/ML_classwork/Week7_srrt/
↪tseries_train.csv")
traindat.head()
```

[3]:
```
         date  store  item  sales
0  2013-01-01      1     1     13
1  2013-01-02      1     1     11
2  2013-01-03      1     1     14
3  2013-01-04      1     1     13
4  2013-01-05      1     1     10
```

[4]:
```
dat = ff.create_table(traindat.head())
py.iplot(dat)
```

How many stores in the dataset

[5]:
```
# check how many stores
traindat.store.unique()
```

[5]:
```
array([ 1,  2,  3,  4,  5,  6,  7,  8,  9, 10])
```

Monthly Sales at each store

[6]:
```
#Monthly Sales Sum
# %load monthly_sum.py
%run -i '~/Desktop/Analysis/Work/ML_EIT/Github/monthly_sum.py'
%run -i '~/Desktop/Analysis/Work/ML_EIT/Github/arange_supervised.py'
%run -i '~/Desktop/Analysis/Work/ML_EIT/Github/predict_df.py'

monthlysales = monthly_sum(traindat)
monthlysales.head()
```

[6]:
```
        date   sales
0 2013-01-31  454904
1 2013-02-28  459417
2 2013-03-31  617382
3 2013-04-30  682274
4 2013-05-31  763242
```

Yearly Sales at each store

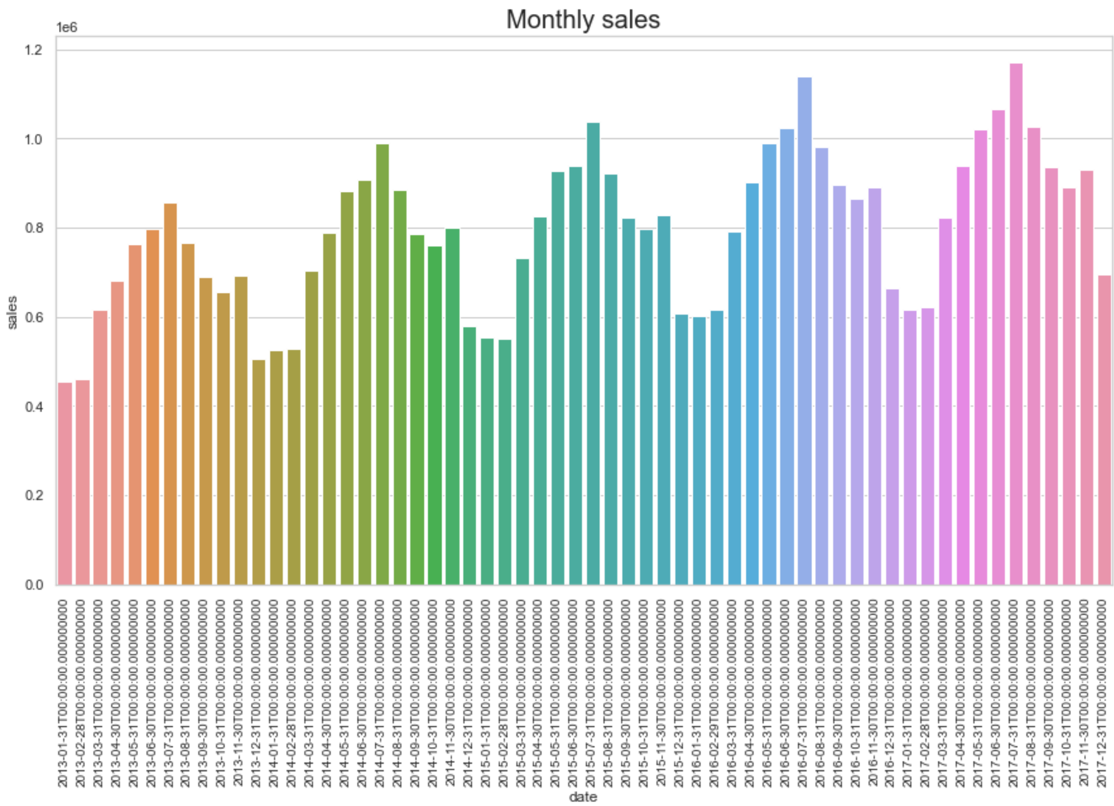
[7]:
```
#Yearly Sales Sum
%run -i '~/Desktop/Analysis/Work/ML_EIT/Github/yrly_sum.py'

yrlysales = yearly_sum(traindat)
yrlysales.head()
```

[7]:

	date	sales
0	2013-12-31	7941243
1	2014-12-31	9135482
2	2015-12-31	9536887
3	2016-12-31	10357160
4	2017-12-31	10733740

Exploratory Data Analysis (EDA)

[8]:
```
plt.rcParams['figure.figsize'] = (15, 8)

sns.set_theme(style="whitegrid")
sns.barplot(x="date", y="sales", data=monthlysales)
# sns.barplot(monthlysales['sales'], palette = 'hsv')
plt.title('Monthly sales', fontsize = 20)

# xx = monthlysales.index.values.astype('datetime64[D]')
xx = monthlysales['date']
yy = monthlysales['sales']
# ticks = np.arange(xx[0], xx[-1], (xx[-1] - xx[0]).astype('timedelta64[D]') /
↪20)
# plt.xticks(ticks, ticks)
plt.gca().tick_params('x', labelrotation=90, labelsize=10)
plt.show()
```



Days and Years count

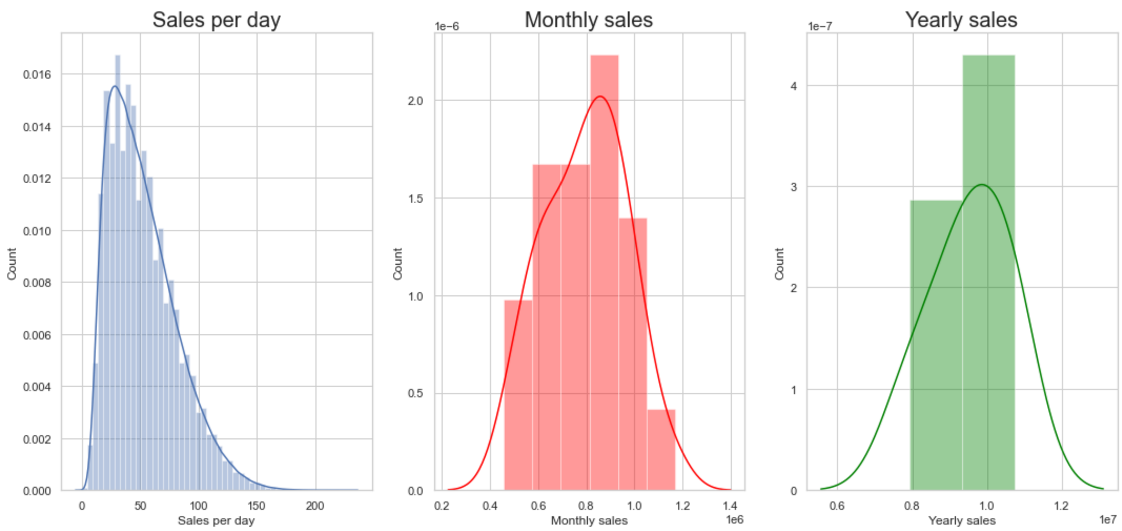
[9]:
```
#finding the number of days, and no. of years of dataset
def duration(data):
    data.date = pd.to_datetime(data.date)
    num_days = data.date.max() - data.date.min()
    num_years = num_days.days / 365
    print("Number of days: ",num_days.days,"days")
    print("Number of years: ",num_years,'years')

duration(traindat)
```

```
Number of days:  1825 days
Number of years:  5.0 years
```

Monthly sales

[10]:
```
#sales for each day and monthly
plt.rcParams['figure.figsize'] = (18, 8)

plt.subplot(1, 3, 1)
sns.set(style = 'whitegrid')
sns.distplot(traindat['sales'])
```

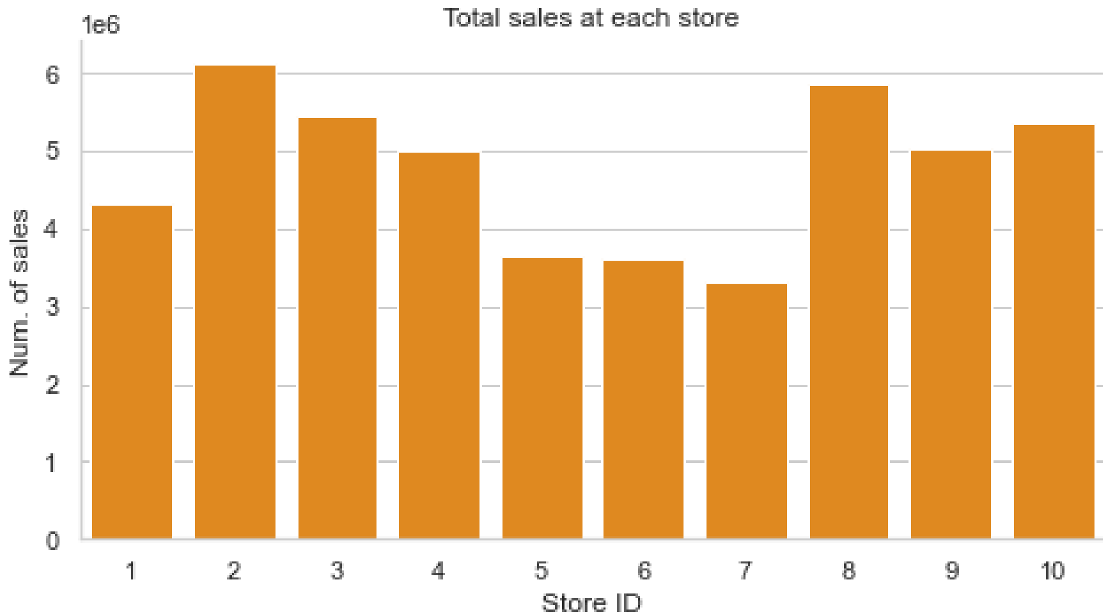
```
plt.title('Sales per day', fontsize = 20)
plt.xlabel('Sales per day')
plt.ylabel('Count')

plt.subplot(1, 3, 2)
sns.set(style = 'whitegrid')
sns.distplot(monthlysales['sales'], color = 'red')
plt.title('Monthly sales', fontsize = 20)
plt.xlabel('Monthly sales')
plt.ylabel('Count')

plt.subplot(1, 3, 3)
sns.set(style = 'whitegrid')
sns.distplot(yrlysales['sales'], color = 'green')
plt.title('Yearly sales', fontsize = 20)
plt.xlabel('Yearly sales')
plt.ylabel('Count')
plt.show()
```



Each Store Sales

[11]:
```
#sales per each store
def each_store_sales():
    ech_store = traindat.groupby('store')['sales'].sum().reset_index()

    fig, ax = plt.subplots(figsize=(8,4))
    sns.set(style = 'whitegrid')
    sns.barplot(ech_store.store,ech_store.sales,color='darkorange')
    ax.set(xlabel="Store ID",ylabel='Num. of sales',title='Total sales at each␣
 ↪store')
```

```
    sns.despine()

each_store_sales()
```

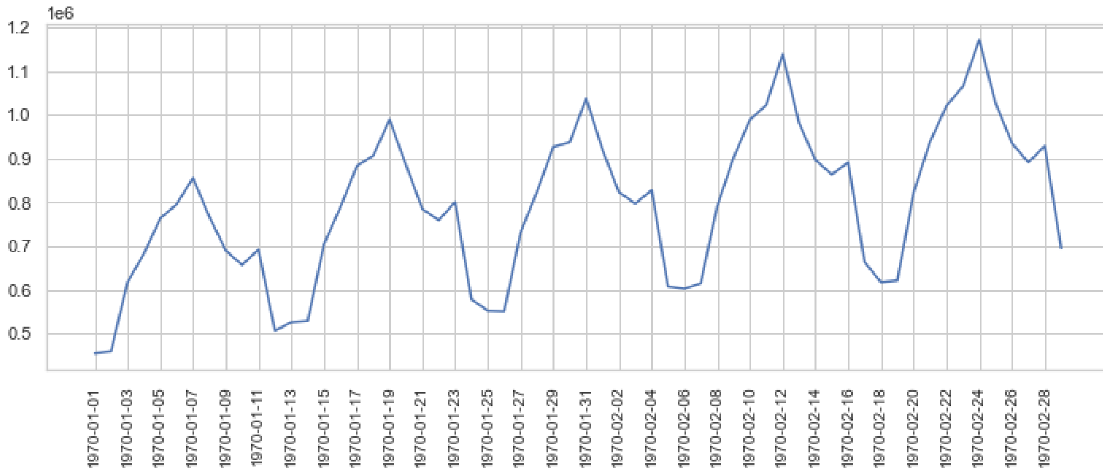


[12]:
```
# Average monthly sales
# Overall sales
avg_monthly_sales = monthlysales.sales.mean()
print(f"Overall average monthly sales: ${avg_monthly_sales}")

#last 12 months average
avg_last12months = monthlysales.sales[-12:].mean()
print(f"Last 12 months average sales: ${avg_last12months}")
```

```
Overall average monthly sales: $795075.2
Last 12 months average sales: $894478.3333333334
```

Stationary Calculations

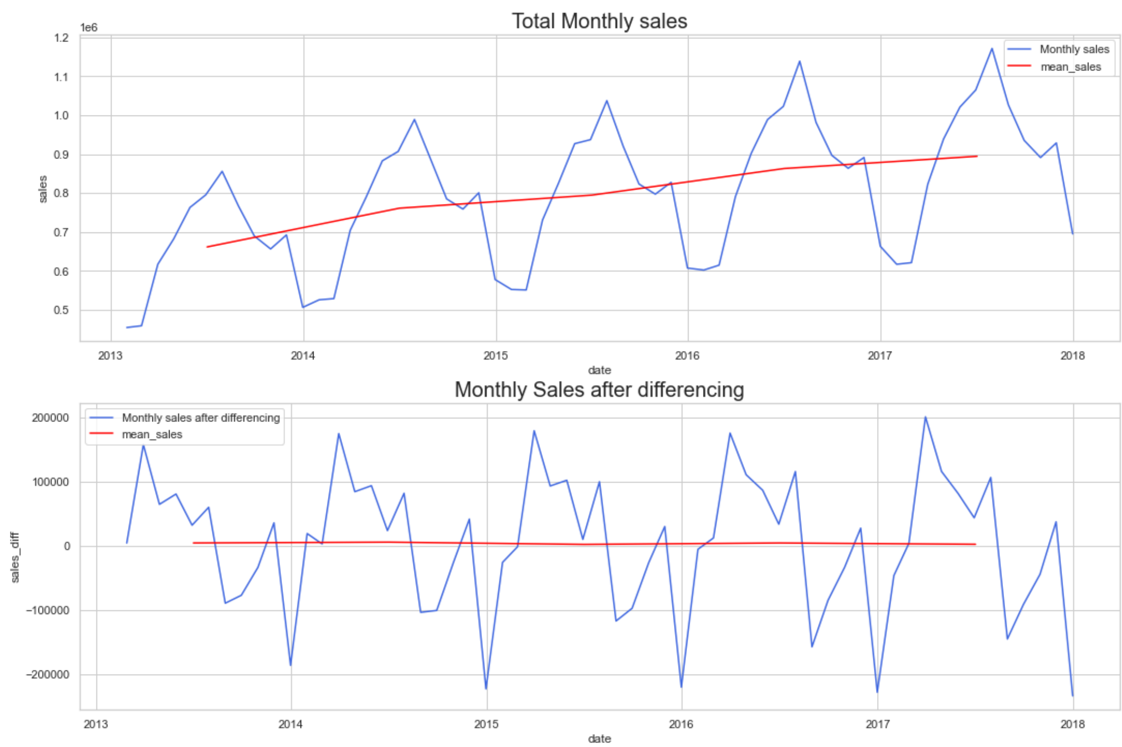
[13]:
```
#monthly line plot
x = monthlysales.index.values.astype('datetime64[D]')
y = monthlysales['sales']
plt.figure(figsize=(12,4))
plt.plot(x, y)
ticks = np.arange(x[0], x[-1], (x[-1] - x[0]).astype('timedelta64[D]') / 20)
plt.xticks(ticks, ticks)
plt.gca().tick_params('x', labelrotation=90, labelsize=10)
```



[14]:
```
def diff_sales(data):
    data['sales_diff'] = data.sales.diff()
    data = data.dropna()

    data.to_csv("/home/jayanthikishore/Downloads/sales_statinary_diff.csv")
    return data

stationary_df = diff_sales(monthlysales)

#sales for each day and monthly
plt.rcParams['figure.figsize'] = (18, 12)

plt.subplot(2,1,1)
sns.lineplot('date','sales',data=monthlysales,color='royalblue',label='Monthly␣
↪sales')
yrly_sales = monthlysales.groupby(monthlysales.date.dt.year)['sales'].mean().
↪reset_index()
yrly_sales.date = pd.to_datetime(yrly_sales.date,format='%Y')
sns.lineplot((yrly_sales.date+datetime.timedelta(6*365/12)),yrly_sales.
↪sales,data=yrly_sales,
            color='red',label="mean_sales")
plt.title('Total Monthly sales', fontsize = 20)


plt.subplot(2,1,2)
sns.
↪lineplot('date','sales_diff',data=stationary_df,color='royalblue',label='Monthly␣
↪sales after differencing')
yrly_sales = stationary_df.groupby(stationary_df.date.dt.year)['sales_diff'].
↪mean().reset_index()
```

```
yrly_sales.date = pd.to_datetime(yrly_sales.date,format='%Y')
sns.lineplot((yrly_sales.date+datetime.timedelta(6*365/12)),yrly_sales.
 ↪sales_diff,data=stationary_df,
            color='red',label="mean_sales")
plt.title('Monthly Sales after differencing', fontsize = 20)
```

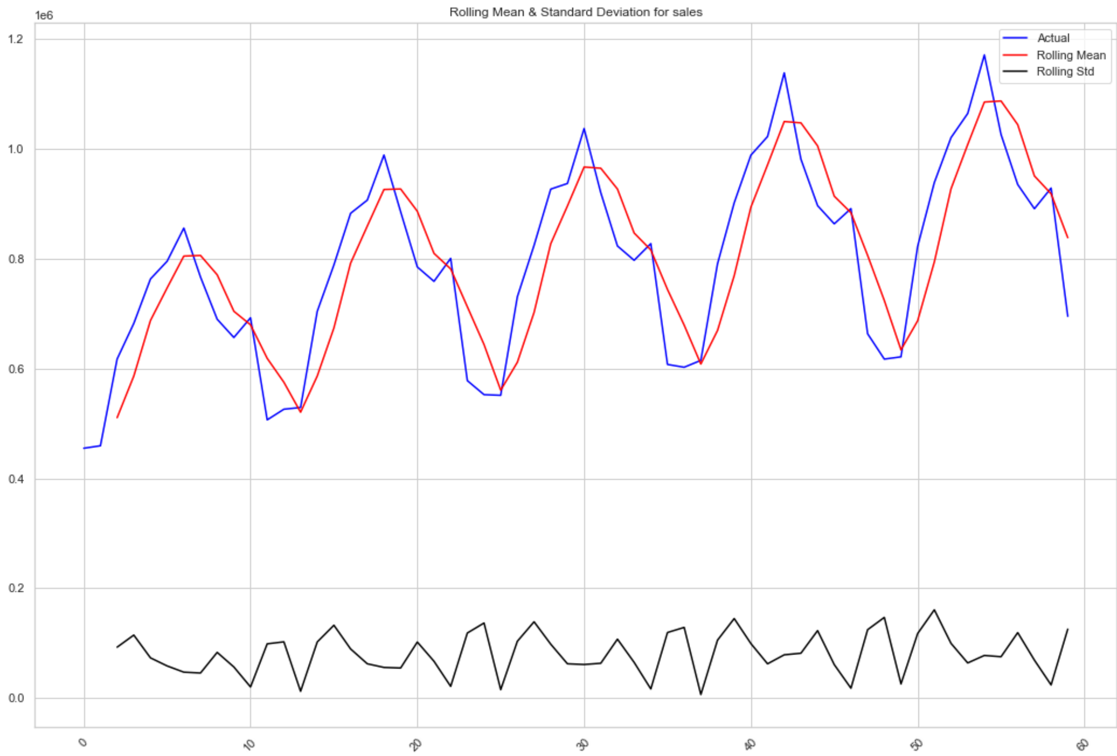
[14]: Text(0.5, 1.0, 'Monthly Sales after differencing')



Rolling mean and std

[15]:
```
from statsmodels.tsa.stattools import adfuller
def stationarity_check(df, ts):

    # Determing rolling statistics
    rolmean = df[ts].rolling(window = 3, center = False).mean()
    rolstd = df[ts].rolling(window = 3, center = False).std()

    # Plot rolling statistics:
    orig = plt.plot(df[ts],
                    color = 'blue',
                    label = 'Actual')
    mean = plt.plot(rolmean,
                    color = 'red',
```

```
                    label = 'Rolling Mean')
    std = plt.plot(rolstd,
                   color = 'black',
                   label = 'Rolling Std')
    plt.legend(loc = 'best')
    plt.title('Rolling Mean & Standard Deviation for %s' %(ts))
    plt.xticks(rotation = 45)
    plt.show(block = False)
    plt.close()

    # Perform Dickey-Fuller test:
    # Null Hypothesis (H_0): time series is not stationary
    # Alternate Hypothesis (H_1): time series is stationary
    print ('Results of Dickey-Fuller Test:')
    dftest = adfuller(df[ts],
                      autolag='AIC')
    dfoutput = pd.Series(dftest[0:4],
                         index = ['Test Statistic',
                                  'p-value',
                                  '# Lags Used',
                                  'Number of Observations Used'])
    for key, value in dftest[4].items():
        dfoutput['Critical Value (%s)'%key] = value
    print (dfoutput)

stationarity_check(monthlysales,"sales")
```

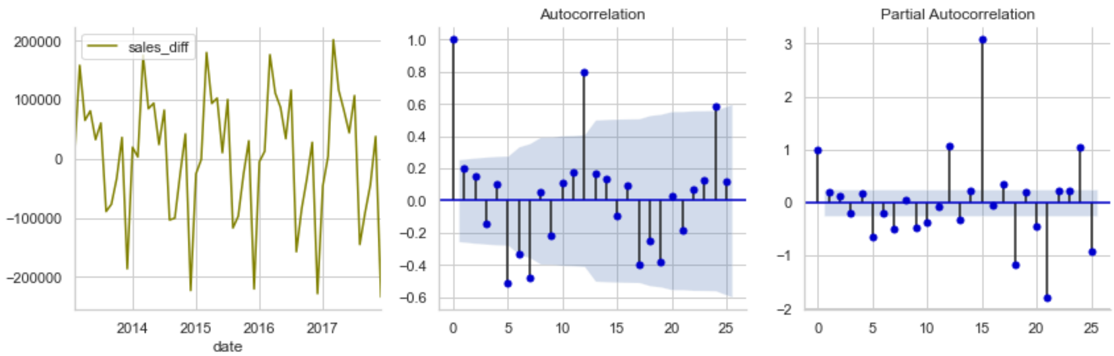



```
Results of Dickey-Fuller Test:
Test Statistic                 -5.247519
p-value                         0.000007
# Lags Used                    11.000000
Number of Observations Used    48.000000
Critical Value (1%)            -3.574589
Critical Value (5%)            -2.923954
Critical Value (10%)           -2.600039
dtype: float64
```

Auto Correlation Function (ACF) and Auto Correlation Function (PACF)

[16]:
```
#Auto correlation function (ACF) and Partial auto correlation function (PACF)
def acf_pacf(data, lags=None):
    #convert dataframe to datetime index
    dt_data = data.set_index('date').drop('sales',axis=1)
    dt_data.dropna(axis=0)

    layout = (1,3)
    raw = plt.subplot2grid(layout, (0,0))
    acf = plt.subplot2grid(layout, (0,1))
    pacf = plt.subplot2grid(layout, (0,2))

    dt_data.plot(ax=raw, figsize=(12,4), color='olive')
```

```
    smt.graphics.plot_acf(dt_data, lags=lags, ax=acf, color='mediumblue')
    smt.graphics.plot_pacf(dt_data, lags=lags, ax=pacf, color="mediumblue")

    sns.despine()
    plt.tight_layout()

acf_pacf(stationary_df,lags=25)
```



[17]:
```
model_df = arange_supervised(stationary_df)
model_df.head()
```

[17]:
```
         date   sales  sales_diff     lag_1      lag_2      lag_3      lag_4  \
0  2014-02-28  529117      3130.0   19380.0 -186036.0    36056.0   -33320.0
1  2014-03-31  704301    175184.0    3130.0    19380.0 -186036.0    36056.0
2  2014-04-30  788914     84613.0  175184.0     3130.0    19380.0 -186036.0
3  2014-05-31  882877     93963.0   84613.0   175184.0     3130.0    19380.0
4  2014-06-30  906842     23965.0   93963.0    84613.0   175184.0     3130.0

      lag_5      lag_6     lag_7     lag_8     lag_9    lag_10    lag_11    lag_12
0  -76854.0   -89161.0   60325.0   32355.0   80968.0   64892.0  157965.0    4513.0
1  -33320.0   -76854.0  -89161.0   60325.0   32355.0   80968.0   64892.0  157965.0
2   36056.0   -33320.0  -76854.0  -89161.0   60325.0   32355.0   80968.0   64892.0
3 -186036.0    36056.0  -33320.0  -76854.0  -89161.0   60325.0   32355.0   80968.0
4   19380.0  -186036.0   36056.0  -33320.0  -76854.0  -89161.0   60325.0   32355.0
```

Auto Regressive Integrated Moving Avearge (ARIMA)

[18]:
```
dt_dat = stationary_df.set_index('date')
dt_dat.dropna(axis=0)
dt_dat.head()
```

[18]:
```
             sales  sales_diff
date
2013-02-28  459417      4513.0
```

```
2013-03-31  617382    157965.0
2013-04-30  682274     64892.0
2013-05-31  763242     80968.0
2013-06-30  795597     32355.0
```

[19]:
```
dt_dat.index = pd.to_datetime(dt_dat.index)
dt_dat.head()
```

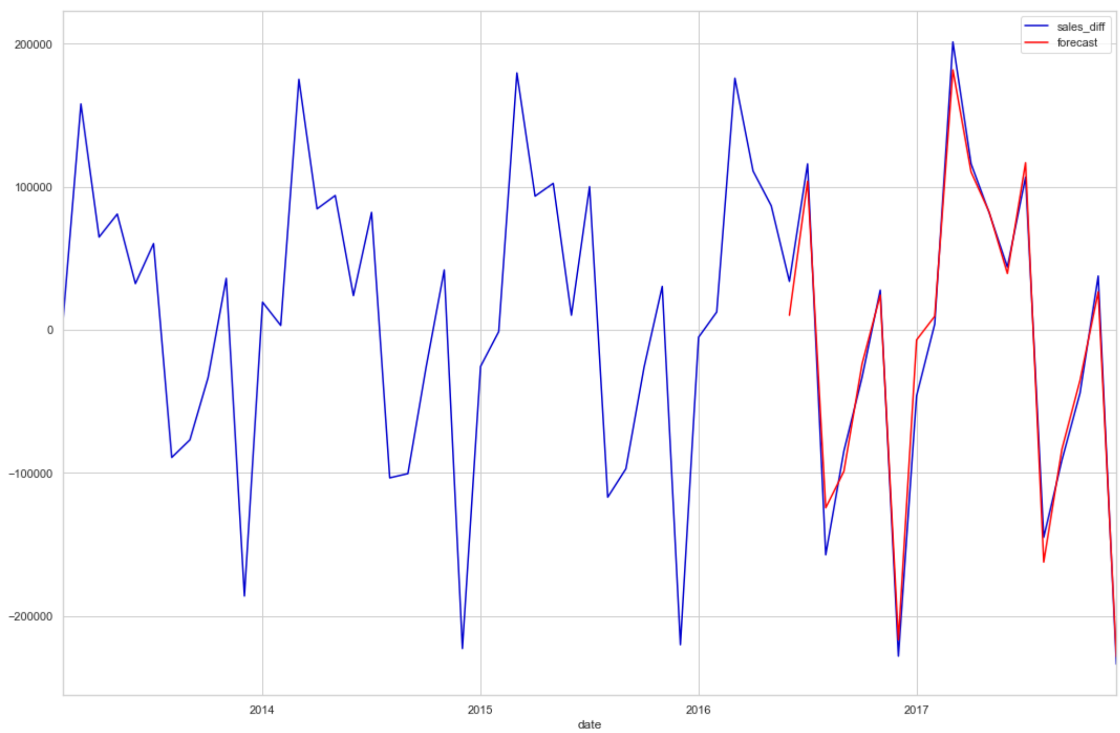
[19]:
```
             sales  sales_diff
date
2013-02-28  459417      4513.0
2013-03-31  617382    157965.0
2013-04-30  682274     64892.0
2013-05-31  763242     80968.0
2013-06-30  795597     32355.0
```

SARIMAX modeling

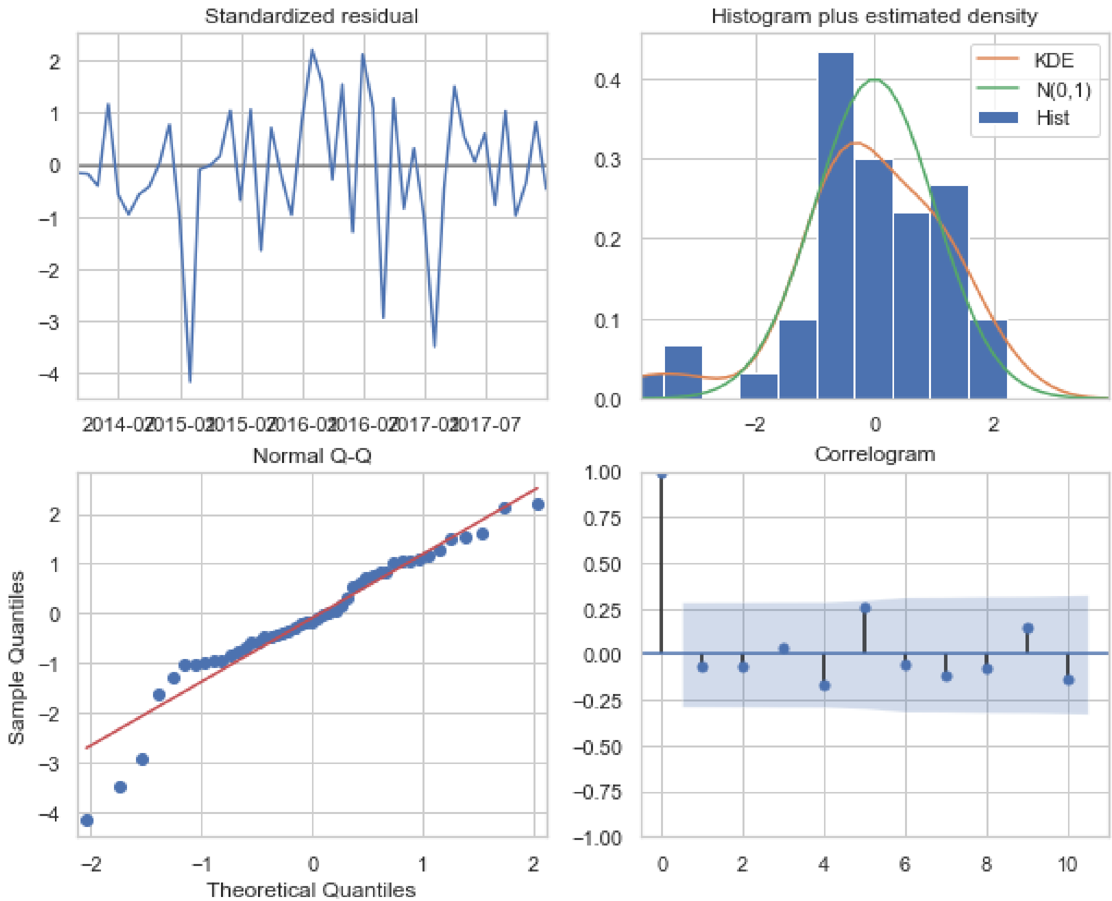
[20]:
```
model_scores = {}
def get_scores(data):

    #model_scores = {}

    rmse = np.sqrt(mean_squared_error(data.sales_diff[-12:], data.forecast[-12:
 ↪]))
    mae = mean_absolute_error(data.sales_diff[-12:], data.forecast[-12:])
    #calc. Mean Squared Error
    mse = mean_squared_error(data.sales_diff[-12:],data.forecast[-12:])
    r2 = r2_score(data.sales_diff[-12:], data.forecast[-12:])
    model_scores['ARIMA'] = [rmse, mae, mse, r2]

    print(f"RMSE: {rmse}")
    print(f"MAE: {mae}")
    print(f"MSE: {mse}")
    print(f"R2 Score: {r2}")

    pickle.dump(model_scores, open( "/home/jayanthikishore/Downloads/
 ↪arima_model_scores.pkl", "wb" ))

def sarimax_model(data):

    # Model
    sarmax = sm.tsa.statespace.SARIMAX(dt_dat.sales_diff, order=(12,0,0),␣
 ↪seasonal_order=(0,1,0,12), trend='c').fit()

    # Predictions
    start, end, dynamic = 40, 100, 7
```

```
    data['forecast'] = sarmax.predict(start=start, end=end, dynamic=dynamic)
    pred_df = data.forecast[start+dynamic:end]

    data[['sales_diff', 'forecast']].plot(color=['mediumblue', 'Red'])

    get_scores(data)

    return sarmax, data, pred_df

sarmax, dt_dat, predictions = sarimax_model(dt_dat)
```

```
RMSE: 14959.835978461171
MAE: 11265.441970463036
MSE: 223796692.5024613
R2 Score: 0.9835644139413118
```



[21]:
```
sarmax.plot_diagnostics(figsize=(10, 8));
```



[22]:
```python
def plot_results(results, original_df, model_name):

    fig, ax = plt.subplots(figsize=(15,5))
    sns.lineplot(original_df.date, original_df.sales, data=original_df, ax=ax,
                 label='Original', color='mediumblue')
    sns.lineplot(results.date, results.pred_value, data=results, ax=ax,
                  label='Predicted', color='Red')

    ax.set(xlabel = "Date",
           ylabel = "Sales",
           title = f"{model_name} Sales Forecasting Prediction")

    ax.legend()

    sns.despine()


    plt.savefig(f'/home/jayanthikishore/Downloads/{model_name}_forecast.png')
```

[23]:
```
original_df = pd.read_csv('/home/jayanthikishore/Downloads/ML_classwork/
↪Week7_srrt/tseries_train.csv')
prediction_df, original_df = predict_df(predictions)
# plot_results(prediction_df, original_df, 'arima')
```

[24]:
```
print(model_scores)
```

```
{'ARIMA': [14959.835978461171, 11265.441970463036, 223796692.5024613,
0.9835644139413118]}
```

[25]:
```
#store the model results for each model data frame for final comparison
rmse1 = list({model_scores['ARIMA'][0]})
mae1 = list({model_scores['ARIMA'][1]})
mse1 = list({model_scores['ARIMA'][2]})
r21 = list({model_scores['ARIMA'][3]})
results_temp = pd.DataFrame({'Method':['ARIMA'],'RMSE':rmse1,
                            'MAE':mae1,'MSE':mse1,'MSE':mse1,
                            'R_square':r21},index={'1'})
# resultsapp = pd.concat([results,results_temp])
results = results_temp[['Method','RMSE','MAE','MSE','R_square']]

results
```

[25]:

	Method	RMSE	MAE	MSE	R_square
1	ARIMA	14959.835978	11265.44197	2.237967e+08	0.983564

Models: Linear Reg (LReg), Random Forest (RF), XG Boost, and LSTM

[26]:
```
#Loading the model fit values
mdl_df = pd.read_csv('~/Downloads/model_df.csv')

#Train and Split the datasets
data = mdl_df.drop(['sales','date'],axis=1)
train, test = data[0:-12].values,data[-12:].values
train.shape,test.shape
```

[26]: ((35, 13), (12, 13))

[27]:
```
def scale_data(train_set, test_set):
    #apply Min Max Scaler
    scaler = MinMaxScaler(feature_range=(-1, 1))
    scaler = scaler.fit(train_set)

    # reshape training set
    train_set = train_set.reshape(train_set.shape[0], train_set.shape[1])
    train_set_scaled = scaler.transform(train_set)
```

```
    # reshape test set
    test_set = test_set.reshape(test_set.shape[0], test_set.shape[1])
    test_set_scaled = scaler.transform(test_set)

    X_train, y_train = train_set_scaled[:, 1:], train_set_scaled[:, 0:1].ravel()
    X_test, y_test = test_set_scaled[:, 1:], test_set_scaled[:, 0:1].ravel()

    return X_train, y_train, X_test, y_test, scaler

X_train, y_train, X_test, y_test, scaler_object = scale_data(train, test)

y_train.shape
```

[27]: (35,)

[28]:
```
# Modeling functions
def undo_scaling(y_pred, x_test, scaler_obj, lstm=False):
    #reshape y_pred
    y_pred = y_pred.reshape(y_pred.shape[0], 1, 1)

    if not lstm:
        x_test = x_test.reshape(x_test.shape[0], 1, x_test.shape[1])

    #rebuild test set for inverse transform
    pred_test_set = []
    for index in range(0,len(y_pred)):
        pred_test_set.append(np.
 ↪concatenate([y_pred[index],x_test[index]],axis=1))

    #reshape pred_test_set
    pred_test_set = np.array(pred_test_set)
    pred_test_set = pred_test_set.reshape(pred_test_set.shape[0], pred_test_set.
 ↪shape[2])

    #inverse transform
    pred_test_set_inverted = scaler_obj.inverse_transform(pred_test_set)

    return pred_test_set_inverted
```

[29]:
```
def load_original_df():
    #load in original dataframe without scaling applied
    original_df = pd.read_csv('/home/jayanthikishore/Downloads/ML_classwork/
 ↪Week7_srrt/tseries_train.csv')
    original_df.date = original_df.date.apply(lambda x: str(x)[:-3])
    original_df = original_df.groupby('date')['sales'].sum().reset_index()
    original_df.date = pd.to_datetime(original_df.date)
    return original_df
```

[30]:
```python
def predict_df(unscaled_predictions, original_df):
    #create dataframe that shows the predicted sales
    result_list = []
    sales_dates = list(original_df[-13:].date)
    act_sales = list(original_df[-13:].sales)

    for index in range(0,len(unscaled_predictions)):
        result_dict = {}
        result_dict['pred_value'] = int(unscaled_predictions[index][0] +␣
↪act_sales[index])
        result_dict['date'] = sales_dates[index+1]
        result_list.append(result_dict)

    df_result = pd.DataFrame(result_list)

    return df_result
```

[31]:
```python
model_scores = {}

def get_scores(unscaled_df, original_df, model_name):
    #calc. of Root Mean Squared Error
    rmse = np.sqrt(mean_squared_error(original_df.sales[-12:], unscaled_df.
↪pred_value[-12:]))
    #calc. of Mean Absolute Error
    mae = mean_absolute_error(original_df.sales[-12:], unscaled_df.
↪pred_value[-12:])
    #calc. Mean Squared Error
    mse = mean_squared_error(original_df.sales[-12:],unscaled_df.pred_value[-12:
↪])
    #calc. of R2 value
    r2 = r2_score(original_df.sales[-12:], unscaled_df.pred_value[-12:])
    model_scores[model_name] = [rmse, mae, mse, r2]

    print(f"RMSE: {rmse}")
    print(f"MAE: {mae}")
    print(f"MSE: {mse}")
    print(f"R2 Score: {r2}")
```

[32]:
```python
def plot_results(results, original_df, model_name):

    fig, ax = plt.subplots(figsize=(15,5))
    sns.lineplot(original_df.date, original_df.sales, data=original_df, ax=ax,
                 label='Original', color='mediumblue')
    sns.lineplot(results.date, results.pred_value, data=results, ax=ax,
                 label='Predicted', color='Red')
```

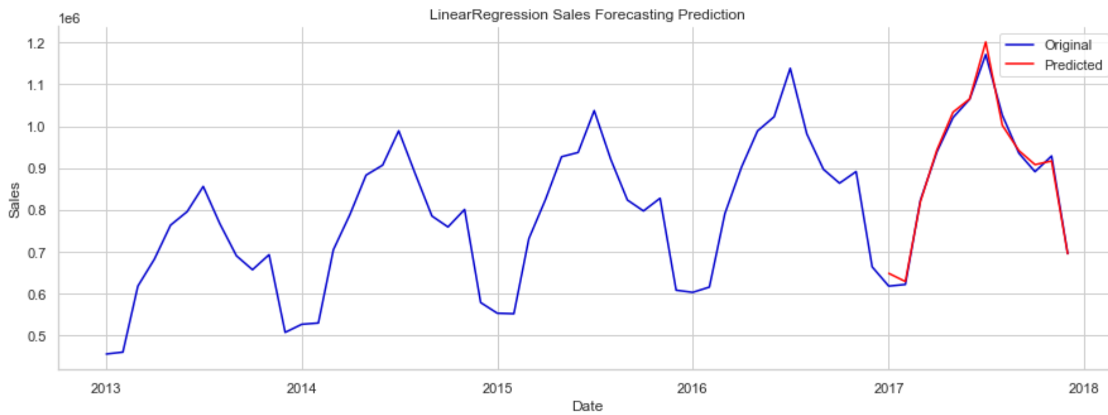
```
    ax.set(xlabel = "Date",
           ylabel = "Sales",
           title = f"{model_name} Sales Forecasting Prediction")

    ax.legend()

    sns.despine()

    plt.savefig(f'/home/jayanthikishore/Downloads/{model_name}_forecast.png')
```

[33]:
```
def run_model(train_data, test_data, model, model_name):

    X_train, y_train, X_test, y_test, scaler_object = scale_data(train_data,␣
 ↪test_data)

    mod = model
    mod.fit(X_train, y_train)
    predictions = mod.predict(X_test)

    # Undo scaling to compare predictions against original data
    original_df = load_original_df()
    unscaled = undo_scaling(predictions, X_test, scaler_object)
    unscaled_df = predict_df(unscaled, original_df)

    get_scores(unscaled_df, original_df, model_name)

    plot_results(unscaled_df, original_df, model_name)
```

Linear Regression (LR)

[34]:
```
run_model(train, test, LinearRegression(), 'LinearRegression')
```

```
RMSE: 16221.040790693221
MAE: 12433.0
MSE: 263122164.33333334
R2 Score: 0.9907155879704752
```




```
[35]: #store the model results for each model data frame for final comparison
rmse1 = list({model_scores['LinearRegression'][0]})
mae1 = list({model_scores['LinearRegression'][1]})
mse1 = list({model_scores['LinearRegression'][2]})
r21 = list({model_scores['LinearRegression'][3]})
results_temp = pd.DataFrame({'Method':['Linear Regression'],'RMSE':rmse1,
                            'MAE':mae1,'MSE':mse1,'MSE':mse1,
                            'R_square':r21},index={'2'})
results = pd.concat([results,results_temp])
results = results[['Method','RMSE','MAE','MSE','R_square']]

results
```

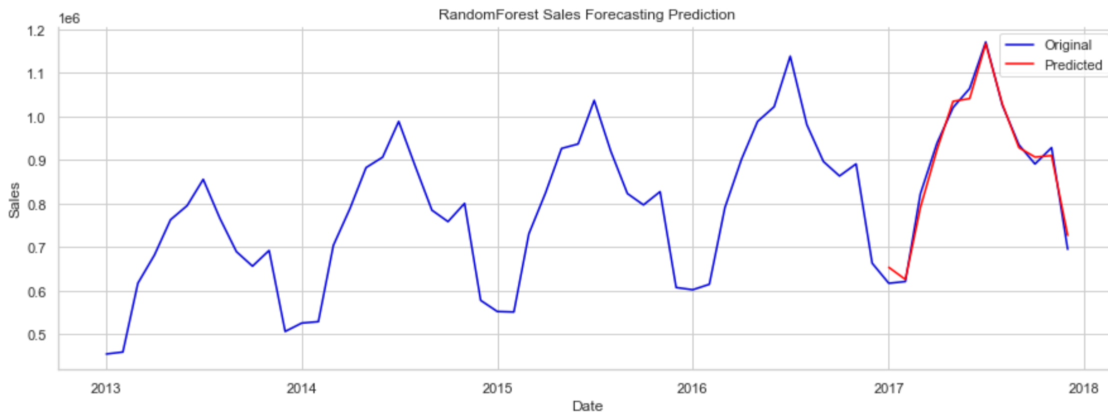
[35]:

	Method	RMSE	MAE	MSE	R_square
1	ARIMA	14959.835978	11265.44197	2.237967e+08	0.983564
2	Linear Regression	16221.040791	12433.00000	2.631222e+08	0.990716

Random Forest Regressor (RFR)

```
[36]: run_model(train, test, RandomForestRegressor(n_estimators=100, max_depth=20),
          'RandomForest')
```

```
RMSE: 20443.5992652142
MAE: 17072.916666666668
MSE: 417940750.9166667
R2 Score: 0.985252727966605
```



[37]:
```python
#store the model results for each model data frame for final comparison
rmse1 = list({model_scores['RandomForest'][0]})
mae1 = list({model_scores['RandomForest'][1]})
mse1 = list({model_scores['RandomForest'][2]})
r21 = list({model_scores['RandomForest'][3]})
results_temp = pd.DataFrame({'Method':['Random Forest'],'RMSE':rmse1,
                            'MAE':mae1,'MSE':mse1,'MSE':mse1,
                            'R_square':r21},index={'3'})
results = pd.concat([results,results_temp])
results = results[['Method','RMSE','MAE','MSE','R_square']]

results
```

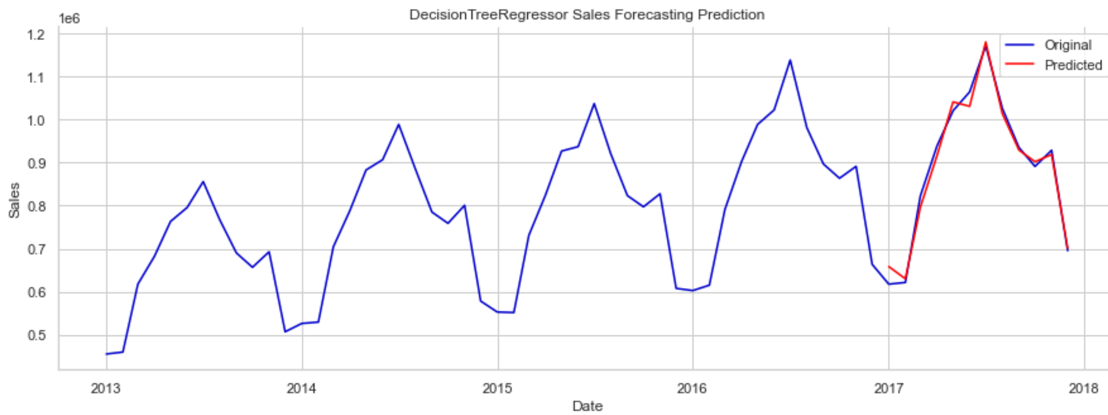
[37]:

	Method	RMSE	MAE	MSE	R_square
1	ARIMA	14959.835978	11265.441970	2.237967e+08	0.983564
2	Linear Regression	16221.040791	12433.000000	2.631222e+08	0.990716
3	Random Forest	20443.599265	17072.916667	4.179408e+08	0.985253

DecisionTree Regressor (DTR)

[38]:
```python
run_model(train, test, DecisionTreeRegressor(), 'DecisionTreeRegressor')
```

```
RMSE: 20459.483664876134
MAE: 17195.0
MSE: 418590471.8333333
R2 Score: 0.9852298022024079
```



[39]:
```
#store the model results for each model data frame for final comparison
rmse1 = list({model_scores['DecisionTreeRegressor'][0]})
mae1 = list({model_scores['DecisionTreeRegressor'][1]})
mse1 = list({model_scores['DecisionTreeRegressor'][2]})
r21 = list({model_scores['DecisionTreeRegressor'][3]})
results_temp = pd.DataFrame({'Method':['DecisionTreeRegressor'],'RMSE':rmse1,
                            'MAE':mae1,'MSE':mse1,'MSE':mse1,
                            'R_square':r21},index={'4'})
results = pd.concat([results,results_temp])
results = results[['Method','RMSE','MAE','MSE','R_square']]

results
```

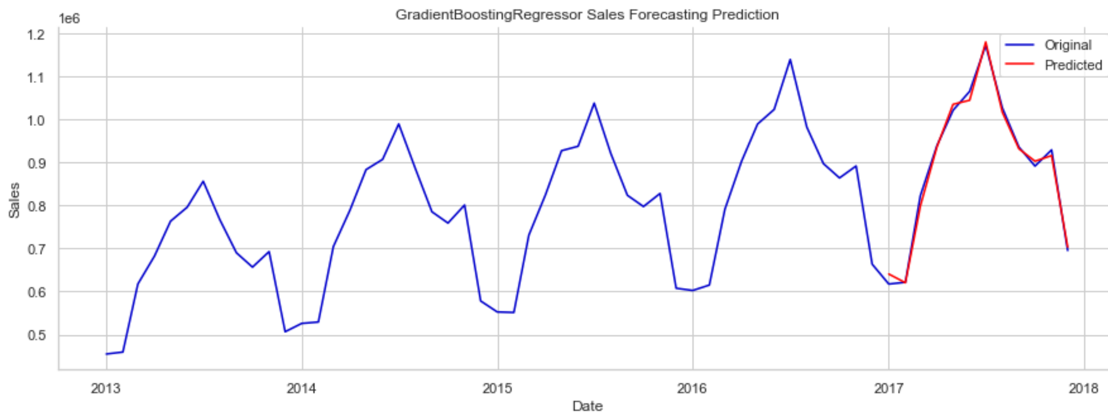
[39]:

	Method	RMSE	MAE	MSE	R_square
1	ARIMA	14959.835978	11265.441970	2.237967e+08	0.983564
2	Linear Regression	16221.040791	12433.000000	2.631222e+08	0.990716
3	Random Forest	20443.599265	17072.916667	4.179408e+08	0.985253
4	DecisionTreeRegressor	20459.483665	17195.000000	4.185905e+08	0.985230

Gradient Boost Regressor (GBR)

[40]:
```
run_model(train, test, GradientBoostingRegressor(), 'GradientBoostingRegressor')
```

```
RMSE: 13798.242382033059
MAE: 11655.333333333334
MSE: 190391492.83333334
R2 Score: 0.993281930198242
```



[41]:
```
#store the model results for each model data frame for final comparison
rmse1 = list({model_scores['GradientBoostingRegressor'][0]})
mae1 = list({model_scores['GradientBoostingRegressor'][1]})
mse1 = list({model_scores['GradientBoostingRegressor'][2]})
r21 = list({model_scores['GradientBoostingRegressor'][3]})
results_temp = pd.DataFrame({'Method':['GradientBoostingRegressor'],'RMSE':
 ↪rmse1,
                             'MAE':mae1,'MSE':mse1,'MSE':mse1,
                             'R_square':r21},index={'5'})
results = pd.concat([results,results_temp])
results = results[['Method','RMSE','MAE','MSE','R_square']]

results
```

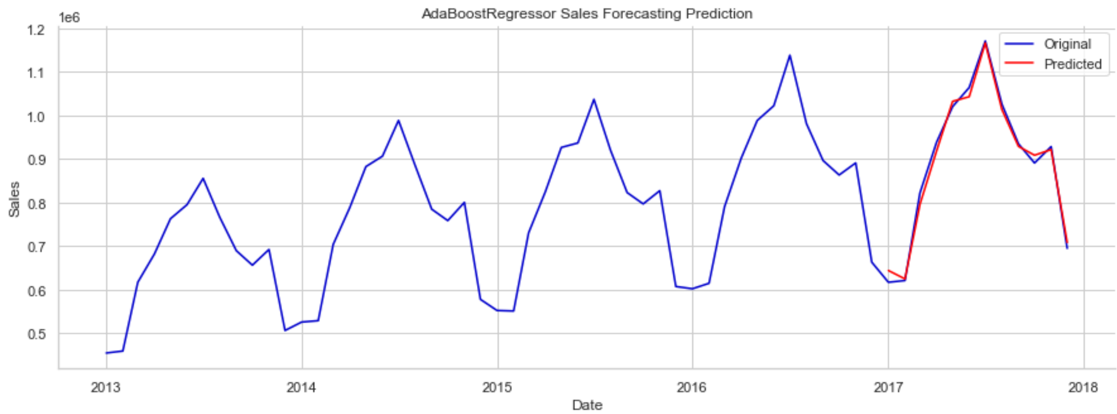
[41]:
```
                      Method          RMSE           MAE           MSE  \
1                      ARIMA  14959.835978  11265.441970  2.237967e+08
2          Linear Regression  16221.040791  12433.000000  2.631222e+08
3              Random Forest  20443.599265  17072.916667  4.179408e+08
4      DecisionTreeRegressor  20459.483665  17195.000000  4.185905e+08
5  GradientBoostingRegressor  13798.242382  11655.333333  1.903915e+08

   R_square
1  0.983564
2  0.990716
3  0.985253
4  0.985230
5  0.993282
```

Ada Boost Regressor (ABR)

[42]:
```
run_model(train, test, AdaBoostRegressor(), 'AdaBoostRegressor')
```

```
RMSE: 16290.581312525344
```

MAE: 14259.833333333334
MSE: 265383039.5
R2 Score: 0.9906358117317541



[43]:

```python
#store the model results for each model data frame for final comparison
rmse1 = list({model_scores['AdaBoostRegressor'][0]})
mae1 = list({model_scores['AdaBoostRegressor'][1]})
mse1 = list({model_scores['AdaBoostRegressor'][2]})
r21 = list({model_scores['AdaBoostRegressor'][3]})
results_temp = pd.DataFrame({'Method':['AdaBoostRegressor'],'RMSE':rmse1,
                            'MAE':mae1,'MSE':mse1,'MSE':mse1,
                            'R_square':r21},index={'6'})
results = pd.concat([results,results_temp])
results = results[['Method','RMSE','MAE','MSE','R_square']]

results
```

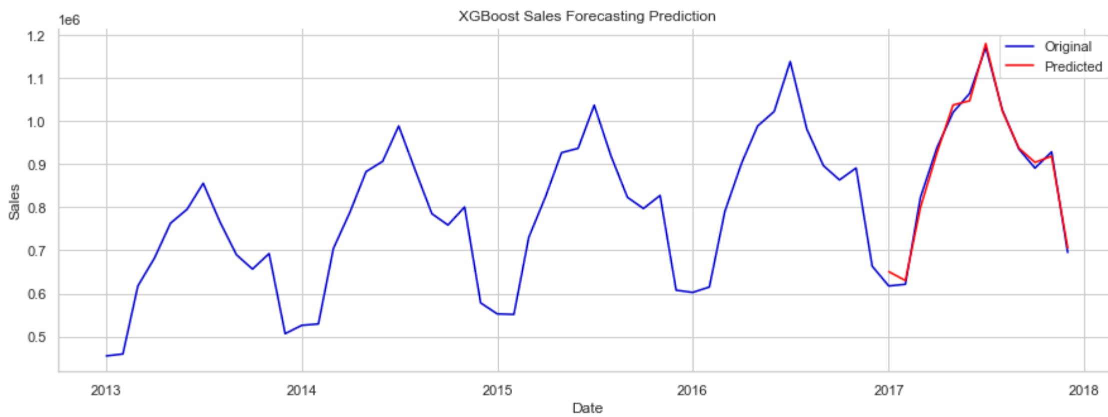
[43]:

```
                     Method          RMSE           MAE           MSE  \
1                     ARIMA  14959.835978  11265.441970  2.237967e+08
2         Linear Regression  16221.040791  12433.000000  2.631222e+08
3             Random Forest  20443.599265  17072.916667  4.179408e+08
4     DecisionTreeRegressor  20459.483665  17195.000000  4.185905e+08
5 GradientBoostingRegressor  13798.242382  11655.333333  1.903915e+08
6         AdaBoostRegressor  16290.581313  14259.833333  2.653830e+08

   R_square
1  0.983564
2  0.990716
3  0.985253
4  0.985230
5  0.993282
6  0.990636
```

XG Boost Regressor XGBR)

[44]:
```
run_model(train, test, XGBRegressor( n_estimators=100,
                                    learning_rate=0.2,
                                    objective='reg:squarederror'), 'XGBoost')
```

```
RMSE: 15701.003359658262
MAE: 13342.666666666666
MSE: 246521506.5
R2 Score: 0.9913013514225064
```



[45]:
```
#store the model results for each model data frame for final comparison
rmse1 = list({model_scores['XGBoost'][0]})
mae1 = list({model_scores['XGBoost'][1]})
mse1 = list({model_scores['XGBoost'][2]})
r21 = list({model_scores['XGBoost'][3]})
results_temp = pd.DataFrame({'Method':['XGBoost'],'RMSE':rmse1,
                            'MAE':mae1,'MSE':mse1,'MSE':mse1,
                            'R_square':r21},index={'7'})
results = pd.concat([results,results_temp])
results = results[['Method','RMSE','MAE','MSE','R_square']]

results
```

[45]:

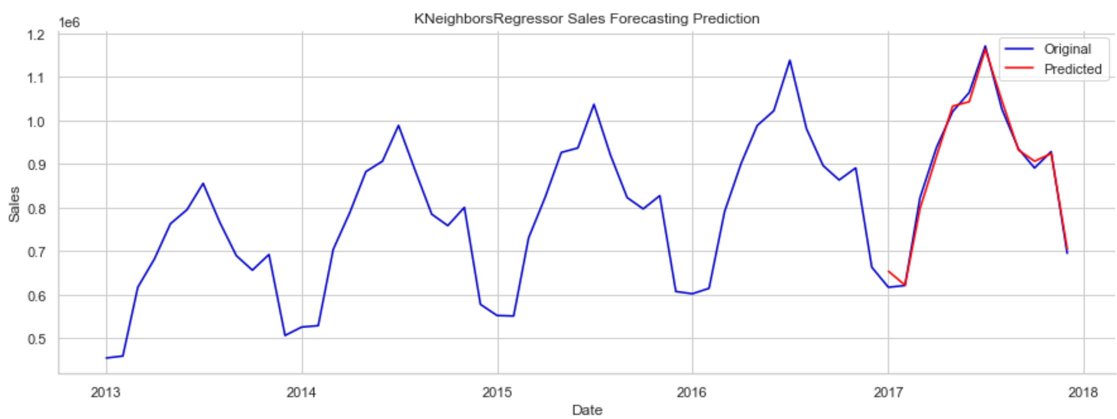
	Method	RMSE	MAE	MSE \
1	ARIMA	14959.835978	11265.441970	2.237967e+08
2	Linear Regression	16221.040791	12433.000000	2.631222e+08
3	Random Forest	20443.599265	17072.916667	4.179408e+08
4	DecisionTreeRegressor	20459.483665	17195.000000	4.185905e+08
5	GradientBoostingRegressor	13798.242382	11655.333333	1.903915e+08
6	AdaBoostRegressor	16290.581313	14259.833333	2.653830e+08
7	XGBoost	15701.003360	13342.666667	2.465215e+08

```
   R_square
1  0.983564
2  0.990716
3  0.985253
4  0.985230
5  0.993282
6  0.990636
7  0.991301
```

KNearest Neighbors Regressor (KNN Regressor)

[46]:
```
run_model(train, test, KNeighborsRegressor(n_neighbors=3),␣
 ↪'KNeighborsRegressor')
```

```
RMSE: 17675.47813591851
MAE: 14580.0
MSE: 312422527.3333333
R2 Score: 0.9889759972200841
```



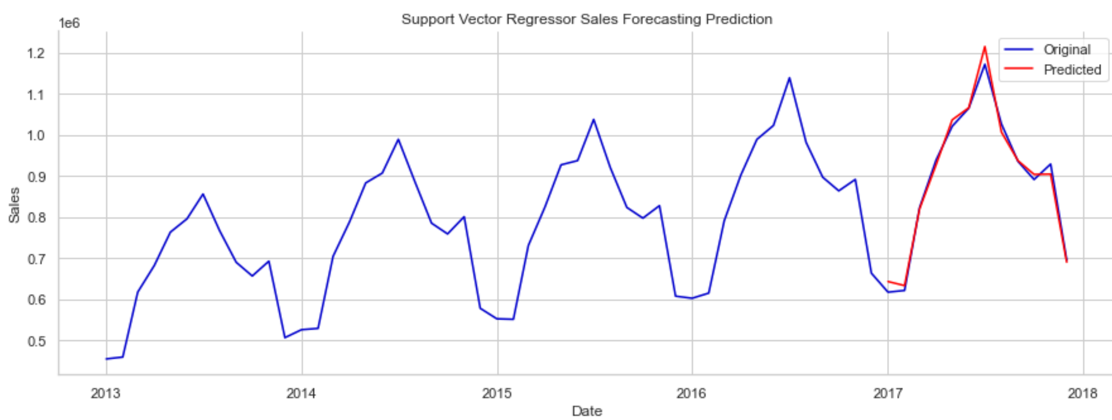
[47]:
```
#store the model results for each model data frame for final comparison
rmse1 = list({model_scores['KNeighborsRegressor'][0]})
mae1 = list({model_scores['KNeighborsRegressor'][1]})
mse1 = list({model_scores['KNeighborsRegressor'][2]})
r21 = list({model_scores['KNeighborsRegressor'][3]})
results_temp = pd.DataFrame({'Method':['KNeighborsRegressor'],'RMSE':rmse1,
                            'MAE':mae1,'MSE':mse1,'MSE':mse1,
                            'R_square':r21},index={'8'})
results = pd.concat([results,results_temp])
results = results[['Method','RMSE','MAE','MSE','R_square']]

results
```

```
[47]:                        Method          RMSE           MAE           MSE  \
      1                       ARIMA  14959.835978  11265.441970  2.237967e+08
      2           Linear Regression  16221.040791  12433.000000  2.631222e+08
      3               Random Forest  20443.599265  17072.916667  4.179408e+08
      4       DecisionTreeRegressor  20459.483665  17195.000000  4.185905e+08
      5   GradientBoostingRegressor  13798.242382  11655.333333  1.903915e+08
      6           AdaBoostRegressor  16290.581313  14259.833333  2.653830e+08
      7                     XGBoost  15701.003360  13342.666667  2.465215e+08
      8        KNeighborsRegressor  17675.478136  14580.000000  3.124225e+08

         R_square
      1  0.983564
      2  0.990716
      3  0.985253
      4  0.985230
      5  0.993282
      6  0.990636
      7  0.991301
      8  0.988976
```

Support Vector Regressor (SVR)

```
[48]: run_model(train, test, SVR(kernel='linear'), 'Support Vector Regressor')
```

```
RMSE: 18781.218768138202
MAE: 14618.916666666666
MSE: 352734178.4166667
R2 Score: 0.9875535781730366
```




```
[49]: #store the model results for each model data frame for final comparison
rmse1 = list({model_scores['Support Vector Regressor'][0]})
mae1 = list({model_scores['Support Vector Regressor'][1]})
mse1 = list({model_scores['Support Vector Regressor'][2]})
```

```
r21 = list({model_scores['Support Vector Regressor'][3]})
results_temp = pd.DataFrame({'Method':['Support Vector Regressor'],'RMSE':rmse1,
                            'MAE':mae1,'MSE':mse1,'MSE':mse1,
                            'R_square':r21},index={'9'})
results = pd.concat([results,results_temp])
results = results[['Method','RMSE','MAE','MSE','R_square']]

results
```

[49]:

```
                     Method          RMSE           MAE           MSE  \
1                     ARIMA  14959.835978  11265.441970  2.237967e+08
2         Linear Regression  16221.040791  12433.000000  2.631222e+08
3             Random Forest  20443.599265  17072.916667  4.179408e+08
4     DecisionTreeRegressor  20459.483665  17195.000000  4.185905e+08
5 GradientBoostingRegressor  13798.242382  11655.333333  1.903915e+08
6         AdaBoostRegressor  16290.581313  14259.833333  2.653830e+08
7                   XGBoost  15701.003360  13342.666667  2.465215e+08
8       KNeighborsRegressor  17675.478136  14580.000000  3.124225e+08
9  Support Vector Regressor  18781.218768  14618.916667  3.527342e+08

   R_square
1  0.983564
2  0.990716
3  0.985253
4  0.985230
5  0.993282
6  0.990636
7  0.991301
8  0.988976
9  0.987554
```

Long Short Term Memory Model (LSTM)

[50]:

```
def lstm_model(train_data, test_data):

    X_train, y_train, X_test, y_test, scaler_object = scale_data(train_data,␣
 ↪test_data)

    X_train = X_train.reshape(X_train.shape[0], 1, X_train.shape[1])
    X_test = X_test.reshape(X_test.shape[0], 1, X_test.shape[1])

    model = Sequential()
    model.add(LSTM(4, batch_input_shape=(1, X_train.shape[1], X_train.shape[2]),
                   stateful=True))
    model.add(Dense(1))
    model.add(Dense(1))
    model.compile(loss='mean_squared_error', optimizer='adam')
```

```python
    model.fit(X_train, y_train, epochs=200, batch_size=1, verbose=1,
              shuffle=False)
    predictions = model.predict(X_test,batch_size=1)

    original_df = load_original_df()
    unscaled = undo_scaling(predictions, X_test, scaler_object, lstm=True)
    unscaled_df = predict_df(unscaled, original_df)

    get_scores(unscaled_df, original_df, 'LSTM')

    plot_results(unscaled_df, original_df, 'LSTM')
```

[51]:
```python
lstm_model(train, test)
```

```
Epoch 1/200
35/35 [==============================] - 1s 842us/step - loss: 0.2790
Epoch 2/200
35/35 [==============================] - 0s 943us/step - loss: 0.2694
Epoch 3/200
35/35 [==============================] - 0s 900us/step - loss: 0.2577
Epoch 4/200
35/35 [==============================] - 0s 913us/step - loss: 0.2470
Epoch 5/200
35/35 [==============================] - 0s 878us/step - loss: 0.2366
Epoch 6/200
35/35 [==============================] - 0s 1ms/step - loss: 0.2261
Epoch 7/200
35/35 [==============================] - 0s 937us/step - loss: 0.2151
Epoch 8/200
35/35 [==============================] - 0s 917us/step - loss: 0.2037
Epoch 9/200
35/35 [==============================] - 0s 991us/step - loss: 0.1917
Epoch 10/200
35/35 [==============================] - 0s 936us/step - loss: 0.1793
Epoch 11/200
35/35 [==============================] - 0s 912us/step - loss: 0.1666
Epoch 12/200
35/35 [==============================] - 0s 892us/step - loss: 0.1536
Epoch 13/200
35/35 [==============================] - 0s 873us/step - loss: 0.1406
Epoch 14/200
35/35 [==============================] - 0s 878us/step - loss: 0.1279
Epoch 15/200
35/35 [==============================] - 0s 889us/step - loss: 0.1158
Epoch 16/200
35/35 [==============================] - 0s 906us/step - loss: 0.1043
Epoch 17/200
```

```
35/35 [==============================] - 0s 914us/step - loss: 0.0938
Epoch 18/200
35/35 [==============================] - 0s 891us/step - loss: 0.0841
Epoch 19/200
35/35 [==============================] - 0s 929us/step - loss: 0.0754
Epoch 20/200
35/35 [==============================] - 0s 1ms/step - loss: 0.0674
Epoch 21/200
35/35 [==============================] - 0s 921us/step - loss: 0.0602
Epoch 22/200
35/35 [==============================] - 0s 860us/step - loss: 0.0535
Epoch 23/200
35/35 [==============================] - 0s 908us/step - loss: 0.0475
Epoch 24/200
35/35 [==============================] - 0s 849us/step - loss: 0.0421
Epoch 25/200
35/35 [==============================] - 0s 902us/step - loss: 0.0372
Epoch 26/200
35/35 [==============================] - 0s 847us/step - loss: 0.0329
Epoch 27/200
35/35 [==============================] - 0s 846us/step - loss: 0.0291
Epoch 28/200
35/35 [==============================] - 0s 919us/step - loss: 0.0259
Epoch 29/200
35/35 [==============================] - 0s 984us/step - loss: 0.0231
Epoch 30/200
35/35 [==============================] - 0s 878us/step - loss: 0.0208
Epoch 31/200
35/35 [==============================] - 0s 907us/step - loss: 0.0189
Epoch 32/200
35/35 [==============================] - 0s 910us/step - loss: 0.0174
Epoch 33/200
35/35 [==============================] - 0s 964us/step - loss: 0.0161
Epoch 34/200
35/35 [==============================] - 0s 1ms/step - loss: 0.0150
Epoch 35/200
35/35 [==============================] - 0s 912us/step - loss: 0.0141
Epoch 36/200
35/35 [==============================] - 0s 865us/step - loss: 0.0133
Epoch 37/200
35/35 [==============================] - 0s 920us/step - loss: 0.0126
Epoch 38/200
35/35 [==============================] - 0s 902us/step - loss: 0.0121
Epoch 39/200
35/35 [==============================] - 0s 864us/step - loss: 0.0115
Epoch 40/200
35/35 [==============================] - 0s 986us/step - loss: 0.0110
Epoch 41/200
```

```
35/35 [==============================] - 0s 899us/step - loss: 0.0106
Epoch 42/200
35/35 [==============================] - 0s 885us/step - loss: 0.0102
Epoch 43/200
35/35 [==============================] - 0s 847us/step - loss: 0.0098
Epoch 44/200
35/35 [==============================] - 0s 811us/step - loss: 0.0095
Epoch 45/200
35/35 [==============================] - 0s 833us/step - loss: 0.0092
Epoch 46/200
35/35 [==============================] - 0s 869us/step - loss: 0.0088
Epoch 47/200
35/35 [==============================] - 0s 888us/step - loss: 0.0086
Epoch 48/200
35/35 [==============================] - 0s 946us/step - loss: 0.0083
Epoch 49/200
35/35 [==============================] - 0s 898us/step - loss: 0.0080
Epoch 50/200
35/35 [==============================] - 0s 1ms/step - loss: 0.0078
Epoch 51/200
35/35 [==============================] - 0s 887us/step - loss: 0.0075
Epoch 52/200
35/35 [==============================] - 0s 860us/step - loss: 0.0073
Epoch 53/200
35/35 [==============================] - 0s 884us/step - loss: 0.0071
Epoch 54/200
35/35 [==============================] - 0s 859us/step - loss: 0.0069
Epoch 55/200
35/35 [==============================] - 0s 861us/step - loss: 0.0067
Epoch 56/200
35/35 [==============================] - 0s 917us/step - loss: 0.0065
Epoch 57/200
35/35 [==============================] - 0s 858us/step - loss: 0.0064
Epoch 58/200
35/35 [==============================] - 0s 875us/step - loss: 0.0062
Epoch 59/200
35/35 [==============================] - 0s 917us/step - loss: 0.0060
Epoch 60/200
35/35 [==============================] - 0s 831us/step - loss: 0.0059
Epoch 61/200
35/35 [==============================] - 0s 828us/step - loss: 0.0057
Epoch 62/200
35/35 [==============================] - 0s 825us/step - loss: 0.0056
Epoch 63/200
35/35 [==============================] - 0s 826us/step - loss: 0.0055
Epoch 64/200
35/35 [==============================] - 0s 944us/step - loss: 0.0053
Epoch 65/200
```

```
35/35 [==============================] - 0s 930us/step - loss: 0.0052
Epoch 66/200
35/35 [==============================] - 0s 905us/step - loss: 0.0051
Epoch 67/200
35/35 [==============================] - 0s 869us/step - loss: 0.0050
Epoch 68/200
35/35 [==============================] - 0s 908us/step - loss: 0.0049
Epoch 69/200
35/35 [==============================] - 0s 981us/step - loss: 0.0048
Epoch 70/200
35/35 [==============================] - 0s 975us/step - loss: 0.0047
Epoch 71/200
35/35 [==============================] - 0s 903us/step - loss: 0.0046
Epoch 72/200
35/35 [==============================] - 0s 884us/step - loss: 0.0045
Epoch 73/200
35/35 [==============================] - 0s 884us/step - loss: 0.0044
Epoch 74/200
35/35 [==============================] - 0s 908us/step - loss: 0.0043
Epoch 75/200
35/35 [==============================] - 0s 860us/step - loss: 0.0042
Epoch 76/200
35/35 [==============================] - 0s 972us/step - loss: 0.0041
Epoch 77/200
35/35 [==============================] - 0s 1ms/step - loss: 0.0040
Epoch 78/200
35/35 [==============================] - 0s 951us/step - loss: 0.0040
Epoch 79/200
35/35 [==============================] - 0s 951us/step - loss: 0.0039
Epoch 80/200
35/35 [==============================] - 0s 1ms/step - loss: 0.0038
Epoch 81/200
35/35 [==============================] - 0s 855us/step - loss: 0.0038
Epoch 82/200
35/35 [==============================] - 0s 944us/step - loss: 0.0037
Epoch 83/200
35/35 [==============================] - 0s 880us/step - loss: 0.0036
Epoch 84/200
35/35 [==============================] - 0s 870us/step - loss: 0.0036
Epoch 85/200
35/35 [==============================] - 0s 958us/step - loss: 0.0035
Epoch 86/200
35/35 [==============================] - 0s 756us/step - loss: 0.0035
Epoch 87/200
35/35 [==============================] - 0s 723us/step - loss: 0.0034
Epoch 88/200
35/35 [==============================] - 0s 855us/step - loss: 0.0034
Epoch 89/200
```

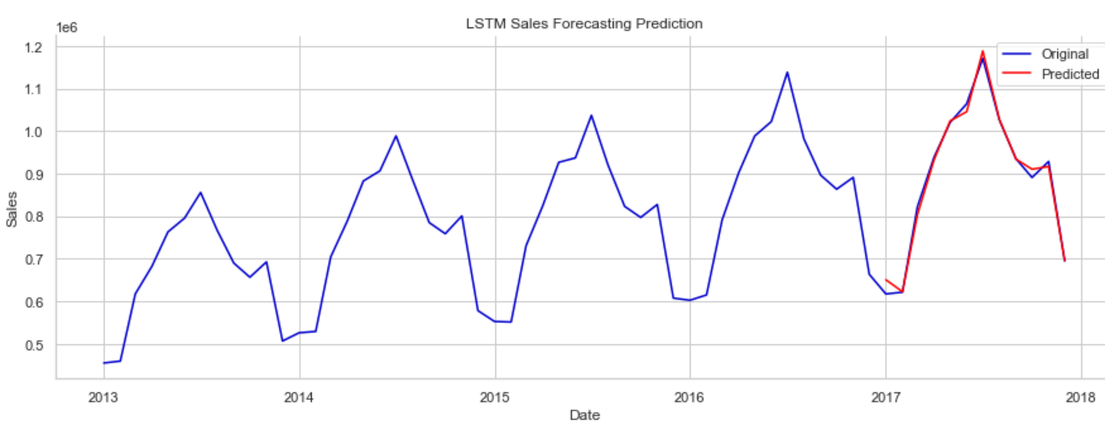
```
35/35 [==============================] - 0s 1ms/step - loss: 0.0033
Epoch 90/200
35/35 [==============================] - 0s 802us/step - loss: 0.0033
Epoch 91/200
35/35 [==============================] - 0s 917us/step - loss: 0.0032
Epoch 92/200
35/35 [==============================] - 0s 876us/step - loss: 0.0032
Epoch 93/200
35/35 [==============================] - 0s 1ms/step - loss: 0.0031
Epoch 94/200
35/35 [==============================] - 0s 950us/step - loss: 0.0031
Epoch 95/200
35/35 [==============================] - 0s 951us/step - loss: 0.0031
Epoch 96/200
35/35 [==============================] - 0s 1ms/step - loss: 0.0030
Epoch 97/200
35/35 [==============================] - 0s 910us/step - loss: 0.0030
Epoch 98/200
35/35 [==============================] - 0s 965us/step - loss: 0.0029
Epoch 99/200
35/35 [==============================] - 0s 901us/step - loss: 0.0029
Epoch 100/200
35/35 [==============================] - 0s 962us/step - loss: 0.0029
Epoch 101/200
35/35 [==============================] - 0s 933us/step - loss: 0.0028
Epoch 102/200
35/35 [==============================] - 0s 900us/step - loss: 0.0028
Epoch 103/200
35/35 [==============================] - 0s 970us/step - loss: 0.0028
Epoch 104/200
35/35 [==============================] - 0s 962us/step - loss: 0.0027
Epoch 105/200
35/35 [==============================] - 0s 939us/step - loss: 0.0027
Epoch 106/200
35/35 [==============================] - 0s 1ms/step - loss: 0.0027
Epoch 107/200
35/35 [==============================] - 0s 940us/step - loss: 0.0027
Epoch 108/200
35/35 [==============================] - 0s 997us/step - loss: 0.0026
Epoch 109/200
35/35 [==============================] - 0s 940us/step - loss: 0.0026
Epoch 110/200
35/35 [==============================] - 0s 967us/step - loss: 0.0026
Epoch 111/200
35/35 [==============================] - 0s 901us/step - loss: 0.0026
Epoch 112/200
35/35 [==============================] - 0s 937us/step - loss: 0.0025
Epoch 113/200
```

```
35/35 [==============================] - 0s 944us/step - loss: 0.0025
Epoch 114/200
35/35 [==============================] - 0s 1ms/step - loss: 0.0025
Epoch 115/200
35/35 [==============================] - 0s 985us/step - loss: 0.0025
Epoch 116/200
35/35 [==============================] - 0s 941us/step - loss: 0.0024
Epoch 117/200
35/35 [==============================] - 0s 919us/step - loss: 0.0024
Epoch 118/200
35/35 [==============================] - 0s 879us/step - loss: 0.0024
Epoch 119/200
35/35 [==============================] - 0s 909us/step - loss: 0.0024
Epoch 120/200
35/35 [==============================] - 0s 901us/step - loss: 0.0024
Epoch 121/200
35/35 [==============================] - 0s 937us/step - loss: 0.0023
Epoch 122/200
35/35 [==============================] - 0s 937us/step - loss: 0.0023
Epoch 123/200
35/35 [==============================] - 0s 974us/step - loss: 0.0023
Epoch 124/200
35/35 [==============================] - 0s 869us/step - loss: 0.0023
Epoch 125/200
35/35 [==============================] - 0s 908us/step - loss: 0.0023
Epoch 126/200
35/35 [==============================] - 0s 892us/step - loss: 0.0023
Epoch 127/200
35/35 [==============================] - 0s 946us/step - loss: 0.0022
Epoch 128/200
35/35 [==============================] - 0s 936us/step - loss: 0.0022
Epoch 129/200
35/35 [==============================] - 0s 856us/step - loss: 0.0022
Epoch 130/200
35/35 [==============================] - 0s 930us/step - loss: 0.0022
Epoch 131/200
35/35 [==============================] - 0s 903us/step - loss: 0.0022
Epoch 132/200
35/35 [==============================] - 0s 854us/step - loss: 0.0022
Epoch 133/200
35/35 [==============================] - 0s 864us/step - loss: 0.0022
Epoch 134/200
35/35 [==============================] - 0s 900us/step - loss: 0.0021
Epoch 135/200
35/35 [==============================] - 0s 907us/step - loss: 0.0021
Epoch 136/200
35/35 [==============================] - 0s 876us/step - loss: 0.0021
Epoch 137/200
```

```
35/35 [==============================] - 0s 902us/step - loss: 0.0021
Epoch 138/200
35/35 [==============================] - 0s 924us/step - loss: 0.0021
Epoch 139/200
35/35 [==============================] - 0s 903us/step - loss: 0.0021
Epoch 140/200
35/35 [==============================] - 0s 844us/step - loss: 0.0021
Epoch 141/200
35/35 [==============================] - 0s 918us/step - loss: 0.0021
Epoch 142/200
35/35 [==============================] - 0s 894us/step - loss: 0.0020
Epoch 143/200
35/35 [==============================] - 0s 927us/step - loss: 0.0020
Epoch 144/200
35/35 [==============================] - 0s 847us/step - loss: 0.0020
Epoch 145/200
35/35 [==============================] - 0s 898us/step - loss: 0.0020
Epoch 146/200
35/35 [==============================] - 0s 870us/step - loss: 0.0020
Epoch 147/200
35/35 [==============================] - 0s 888us/step - loss: 0.0020
Epoch 148/200
35/35 [==============================] - 0s 1ms/step - loss: 0.0020
Epoch 149/200
35/35 [==============================] - 0s 924us/step - loss: 0.0020
Epoch 150/200
35/35 [==============================] - 0s 886us/step - loss: 0.0019
Epoch 151/200
35/35 [==============================] - 0s 904us/step - loss: 0.0019
Epoch 152/200
35/35 [==============================] - 0s 907us/step - loss: 0.0019
Epoch 153/200
35/35 [==============================] - 0s 907us/step - loss: 0.0019
Epoch 154/200
35/35 [==============================] - 0s 944us/step - loss: 0.0019
Epoch 155/200
35/35 [==============================] - 0s 878us/step - loss: 0.0019
Epoch 156/200
35/35 [==============================] - 0s 930us/step - loss: 0.0019
Epoch 157/200
35/35 [==============================] - 0s 906us/step - loss: 0.0019
Epoch 158/200
35/35 [==============================] - 0s 921us/step - loss: 0.0019
Epoch 159/200
35/35 [==============================] - 0s 873us/step - loss: 0.0019
Epoch 160/200
35/35 [==============================] - 0s 947us/step - loss: 0.0018
Epoch 161/200
```

```
35/35 [==============================] - 0s 938us/step - loss: 0.0018
Epoch 162/200
35/35 [==============================] - 0s 844us/step - loss: 0.0018
Epoch 163/200
35/35 [==============================] - 0s 866us/step - loss: 0.0018
Epoch 164/200
35/35 [==============================] - 0s 917us/step - loss: 0.0018
Epoch 165/200
35/35 [==============================] - 0s 849us/step - loss: 0.0018
Epoch 166/200
35/35 [==============================] - 0s 989us/step - loss: 0.0018
Epoch 167/200
35/35 [==============================] - 0s 879us/step - loss: 0.0018
Epoch 168/200
35/35 [==============================] - 0s 983us/step - loss: 0.0018
Epoch 169/200
35/35 [==============================] - 0s 846us/step - loss: 0.0018
Epoch 170/200
35/35 [==============================] - 0s 830us/step - loss: 0.0018
Epoch 171/200
35/35 [==============================] - 0s 955us/step - loss: 0.0017
Epoch 172/200
35/35 [==============================] - 0s 889us/step - loss: 0.0017
Epoch 173/200
35/35 [==============================] - 0s 935us/step - loss: 0.0017
Epoch 174/200
35/35 [==============================] - 0s 932us/step - loss: 0.0017
Epoch 175/200
35/35 [==============================] - 0s 902us/step - loss: 0.0017
Epoch 176/200
35/35 [==============================] - 0s 889us/step - loss: 0.0017
Epoch 177/200
35/35 [==============================] - 0s 903us/step - loss: 0.0017
Epoch 178/200
35/35 [==============================] - 0s 965us/step - loss: 0.0017
Epoch 179/200
35/35 [==============================] - 0s 867us/step - loss: 0.0017
Epoch 180/200
35/35 [==============================] - 0s 876us/step - loss: 0.0017
Epoch 181/200
35/35 [==============================] - 0s 827us/step - loss: 0.0017
Epoch 182/200
35/35 [==============================] - 0s 881us/step - loss: 0.0017
Epoch 183/200
35/35 [==============================] - 0s 910us/step - loss: 0.0016
Epoch 184/200
35/35 [==============================] - 0s 996us/step - loss: 0.0016
Epoch 185/200
```

```
35/35 [==============================] - 0s 976us/step - loss: 0.0016
Epoch 186/200
35/35 [==============================] - 0s 840us/step - loss: 0.0016
Epoch 187/200
35/35 [==============================] - 0s 879us/step - loss: 0.0016
Epoch 188/200
35/35 [==============================] - 0s 913us/step - loss: 0.0016
Epoch 189/200
35/35 [==============================] - 0s 871us/step - loss: 0.0016
Epoch 190/200
35/35 [==============================] - 0s 928us/step - loss: 0.0016
Epoch 191/200
35/35 [==============================] - 0s 996us/step - loss: 0.0016
Epoch 192/200
35/35 [==============================] - 0s 844us/step - loss: 0.0016
Epoch 193/200
35/35 [==============================] - 0s 898us/step - loss: 0.0016
Epoch 194/200
35/35 [==============================] - 0s 994us/step - loss: 0.0016
Epoch 195/200
35/35 [==============================] - 0s 810us/step - loss: 0.0015
Epoch 196/200
35/35 [==============================] - 0s 947us/step - loss: 0.0015
Epoch 197/200
35/35 [==============================] - 0s 909us/step - loss: 0.0015
Epoch 198/200
35/35 [==============================] - 0s 882us/step - loss: 0.0015
Epoch 199/200
35/35 [==============================] - 0s 941us/step - loss: 0.0015
Epoch 200/200
35/35 [==============================] - 0s 988us/step - loss: 0.0015
RMSE: 14898.670930656868
MAE: 11001.166666666666
MSE: 221970395.5
R2 Score: 0.9921676510399641
```



Metrics for all models

[52]:
```python
#store the model results for each model data frame for final comparison
rmse1 = list({model_scores['LSTM'][0]})
mae1 = list({model_scores['LSTM'][1]})
mse1 = list({model_scores['LSTM'][2]})
r21 = list({model_scores['LSTM'][3]})
results_temp = pd.DataFrame({'Method':['LSTM'],'RMSE':rmse1,
                            'MAE':mae1,'MSE':mse1,'MSE':mse1,
                            'R_square':r21},index={'10'})
results = pd.concat([results,results_temp])
results = results[['Method','RMSE','MAE','MSE','R_square']]

results
```

[52]:
```
                        Method          RMSE           MAE           MSE  \
1                        ARIMA  14959.835978  11265.441970  2.237967e+08
2            Linear Regression  16221.040791  12433.000000  2.631222e+08
3                Random Forest  20443.599265  17072.916667  4.179408e+08
4        DecisionTreeRegressor  20459.483665  17195.000000  4.185905e+08
5    GradientBoostingRegressor  13798.242382  11655.333333  1.903915e+08
6            AdaBoostRegressor  16290.581313  14259.833333  2.653830e+08
7                      XGBoost  15701.003360  13342.666667  2.465215e+08
8          KNeighborsRegressor  17675.478136  14580.000000  3.124225e+08
9     Support Vector Regressor  18781.218768  14618.916667  3.527342e+08
10                        LSTM  14898.670931  11001.166667  2.219704e+08

    R_square
1   0.983564
2   0.990716
3   0.985253
4   0.985230
5   0.993282
6   0.990636
7   0.991301
8   0.988976
9   0.987554
10  0.992168
```

[ ]:
```python

```