In [1]:

```
# Get Libraries
import pandas as pd
import plotly.express as px
from matplotlib import pyplot as plt
import numpy as np
import xgboost as xgb
from sklearn.model_selection import GridSearchCV
```

In [2]:

```
# GET DATA
df = pd.read_csv("C://Users/Joe/Desktop/GC_Traffic.txt")
df.columns  = ['temp']

# Sales Data
df['Sales'] = df.temp.apply(lambda x: int(x.split('\t')[-1]))

# Date Data
df['Date' ] = df.temp.apply(lambda x: x.split(' ')[0])
df.Date     = pd.to_datetime(df.Date,format='%d/%m/%y')
df['year' ] = df.Date.apply(lambda x: str(x).split('-')[0])
df['month'] = df.Date.apply(lambda x: str(x).split('-')[1])
df['date' ] = df.Date.apply(lambda x: str(x).split('-')[2].split(' ')[0])

df.year  = df.year.apply(lambda  x: int(x))
df.month = df.month.apply(lambda x: int(x))
df.date  = df.date.apply(lambda  x: int(x))

df.drop(columns=['Date','temp'], axis=1, inplace=True)

df.head()
```

Out[2]:

	Sales	year	month	date
0	2093576	2016	1	1
1	2397260	2016	1	2
2	2173039	2016	1	3
3	2051240	2016	1	4
4	1954117	2016	1	5

In [3]:

```
index_2017 = df.query('year==2017 and month==1 and date==1').index[0] # Leap-Year
index_2018 = df.query('year==2018 and month==1 and date==1').index[0]
index_2019 = df.query('year==2019 and month==1 and date==1').index[0]

print('Indexes are :', index_2017, index_2018, index_2019)
```

```
Indexes are : 366 731 1096
```

In [4]:
```
# Create Data for Supervised Learning

def prepare_data(dfs, starting_index, lags):

    sl_df = pd.DataFrame()
    for i in range(starting_index,df.shape[0]):
        a = pd.Series([dfs.Sales[i], dfs.date[i], dfs.month[i], dfs.year[i]])
        b = pd.Series(dfs.Sales[i-lags:i].values)
        c = a.append(b, ignore_index = True)
        sl_df = sl_df.append(c, ignore_index=True)

    sl_df.columns = ['target', 'date', 'month', 'year']+['D'+str(i+1) for i in ra
    return sl_df



def define_window(window='annually', days=365):
    if window=='annually':
        return index_2017, 365
    elif window=='semi-annually':
        return 183, 182          # 183 due to Leap year - 2016
    elif window=='monthly':
        return 31, 30
    elif window=='weekly':
        return 7, 7
    else:
        return days, days


starting_index, lag_days = define_window('annually', 10)
sl_df = prepare_data(df, starting_index, lag_days)
sl_df.date, sl_df.month, sl_df.year = sl_df.date.apply(lambda x: int(x)), sl_df.r

sl_df.head(3)
```

Out[4]:

	target	date	month	year	D1	D2	D3	D4	D5	D6
0	2002787.0	1	1	2017	2397260.0	2173039.0	2051240.0	1954117.0	1923592.0	1927622.0
1	2308711.0	2	1	2017	2173039.0	2051240.0	1954117.0	1923592.0	1927622.0	2074300.0
2	2274992.0	3	1	2017	2051240.0	1954117.0	1923592.0	1927622.0	2074300.0	2121106.0

3 rows × 369 columns

In [5]:
```
sl_df.describe().transpose()
```

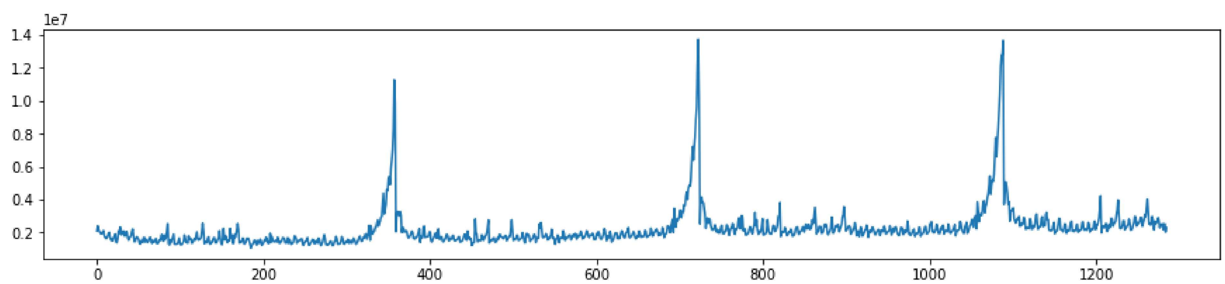
Out[5]:

	count	mean	std	min	25%	50%	75%	max
target	919.0	2.395257e+06	1.287029e+06	1216615.0	1841189.0	2117926.0	2469712.5	13714689.0
date	919.0	1.559956e+01	8.815010e+00	1.0	8.0	16.0	23.0	31.0
month	919.0	5.935800e+00	3.387985e+00	1.0	3.0	6.0	9.0	12.0
year	919.0	2.017808e+03	7.528405e-01	2017.0	2017.0	2018.0	2018.0	2019.0
D1	919.0	2.034454e+06	1.086932e+06	1061345.0	1559747.0	1792616.0	2115539.5	13714689.0
...	...	...	...	...	...	...	...	...
D361	919.0	2.399833e+06	1.288152e+06	1216615.0	1841189.0	2117978.0	2473142.0	13714689.0
D362	919.0	2.398643e+06	1.287855e+06	1216615.0	1841189.0	2117978.0	2472663.0	13714689.0
D363	919.0	2.397962e+06	1.287619e+06	1216615.0	1841189.0	2117978.0	2472663.0	13714689.0
D364	919.0	2.397419e+06	1.287466e+06	1216615.0	1841189.0	2117978.0	2472663.0	13714689.0
D365	919.0	2.396082e+06	1.287205e+06	1216615.0	1841189.0	2117926.0	2471643.0	13714689.0

369 rows × 8 columns

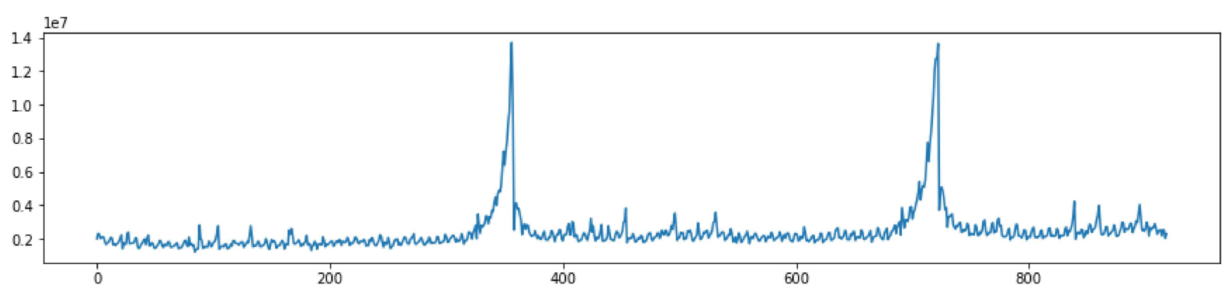
In [6]:
```
df.Sales.plot(figsize=(15,3))
```

Out[6]: <matplotlib.axes._subplots.AxesSubplot at 0x15af7beecd0>



In [7]:
```
sl_df.target.plot(figsize=(15,3))
```

Out[7]: <matplotlib.axes._subplots.AxesSubplot at 0x15af7581670>



In [8]:
```
sl_df.head(3)
```

Out[8]:

	target	date	month	year	D1	D2	D3	D4	D5	
0	2002787.0	1	1	2017	2397260.0	2173039.0	2051240.0	1954117.0	1923592.0	192762
1	2308711.0	2	1	2017	2173039.0	2051240.0	1954117.0	1923592.0	1927622.0	207430
2	2274992.0	3	1	2017	2051240.0	1954117.0	1923592.0	1927622.0	2074300.0	212110

3 rows × 369 columns

Parameter Tuning for XGBoost

- Train Test Data Split

In [9]:
```
from sklearn.model_selection import train_test_split
X, y = sl_df.iloc[:,1:], sl_df.iloc[:,0:1]
print('X-y dimension = ', X.shape, y.shape)

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_s
print('Dimension',
      '\nX train =',X_train.shape,
      '\nX_test  =',X_test.shape ,
      '\ny_train =',y_train.shape,
      '\ny_test  =',y_test.shape)
```

```
X-y dimension =  (919, 368) (919, 1)
Dimension
X train = (735, 368)
X_test  = (184, 368)
y_train = (735, 1)
y_test  = (184, 1)
```

- Metric Definition

In [10]:
```
def get_score(actual, predict, metric=4):
    if metric == 1:
        return abs(actual - predict).mean()              # Mean Absolute Error
    if metric == 2:
        return ((actual - predict)**2).mean()            # Mean Squared Error
    if metric == 3:
        return np.sqrt(((actual - predict)**2).mean())   # Root Mean Squared Err
    if metric == 4:
        return abs((actual - predict)/actual*100).mean()  # Mean Absolute Percent
```

- HyperParameter Setting using GridSearchCV

In [43]:
```
parameters = {
              'learning_rate'   : [0.2, 0.3],
              'max_depth'       : [3,5,8],
              'n_estimators'    : [100, 500]
             }

XGB_MDL_01  = xgb.XGBRegressor()
XGB_Grid_01 = GridSearchCV(XGB_MDL_01, parameters, cv = 5, n_jobs = -1)
XGB_Grid_01.fit(X_train, y_train)

print('\n Best Grid Score        =', XGB_Grid_01.best_score_,
      '\n Best Parameter Setting =', XGB_Grid_01.best_params_ )

# Best Grid Score        = 0.9375800030649412
# Best Parameter Setting = {'learning_rate': 0.2, 'max_depth': 8, 'n_estimators':
```

```
 Best Grid Score        = 0.9375800030649412
 Best Parameter Setting = {'learning_rate': 0.2, 'max_depth': 8, 'n_estimator
s': 500}
```

In [44]:
```
parameters = {
              'learning_rate'   : [0.15, 0.2, 0.25],
              'max_depth'       : [6, 8, 10],
              'n_estimators'    : [500, 1000]
             }

XGB_MDL_02  = xgb.XGBRegressor()
XGB_Grid_02 = GridSearchCV(XGB_MDL_02, parameters, cv = 5, n_jobs = -1)
XGB_Grid_02.fit(X_train, y_train)

print('\n Best Grid Score        =', XGB_Grid_02.best_score_,
      '\n Best Parameter Setting =', XGB_Grid_02.best_params_ )

# Best Grid Score        = 0.9382100019763087
# Best Parameter Setting = {'learning_rate': 0.2, 'max_depth': 10, 'n_estimators
```

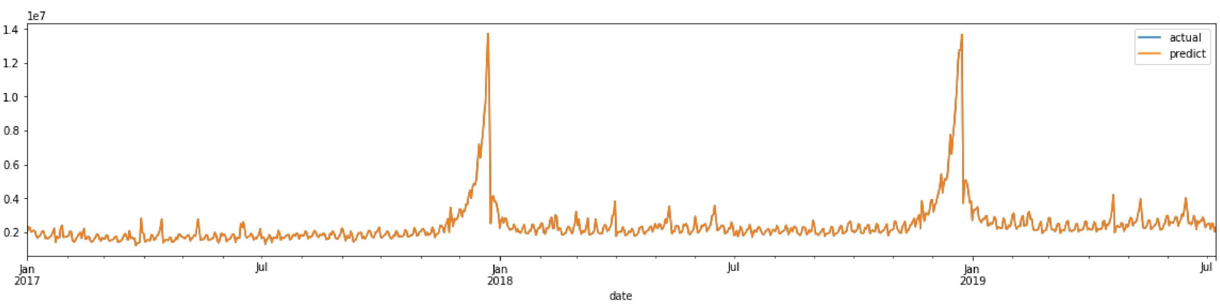
```
 Best Grid Score        = 0.9382100019763087
 Best Parameter Setting = {'learning_rate': 0.2, 'max_depth': 10, 'n_estimator
s': 1000}
```

In [11]:
```
# Assign Best Parameter Setting

X_train, y_train = sl_df.drop(columns='target', axis=1), sl_df['target']

XGB_Model_Final = xgb.XGBRegressor(learning_rate = 0.2, max_depth = 5, n_estimatc
XGB_Model_Final.fit(X_train,y_train)
XGB_Model_Final_pred = XGB_Model_Final.predict(X_train)

print('Mean Absolute Percentage Error = ', get_score(y_train, XGB_Model_Final_pre
```

```
Mean Absolute Percentage Error =  0.0024573902435886426
```

Plot XGBoost Prediction

In [12]:
```
def plot_actual_predict(actual, predict, date, month, year):

    temp_df = pd.DataFrame()
    temp_df['actual']  = actual
    temp_df['predict'] = predict

    temp_df['date']    = date.astype(str) + '/' + month.astype(str) + '/' + year.
    temp_df.date       = pd.to_datetime(temp_df.date,format='%d/%m/%Y')
    temp_df.set_index('date', inplace=True)

    temp_df[['actual','predict']].plot(figsize=(20,4))


X_train.date  = X_train.date.apply(lambda x: int(x))
X_train.month = X_train.month.apply(lambda x: int(x))
X_train.year  = X_train.year.apply(lambda x: int(x))

plot_actual_predict(y_train, XGB_Model_Final_pred, X_train.date, X_train.month, X
```



Use Previous Year Data to Predict Current Year Sales

Year-wise Training and Prediction

In [13]:
```
def iterative_train_test(dfs, target_year):

    X_train = dfs[dfs.year <  target_year].drop(columns=['target'], axis=1)
    X_test  = dfs[dfs.year == target_year].drop(columns=['target'], axis=1)
    y_train = dfs[dfs.year <  target_year].target
    y_test  = dfs[dfs.year == target_year].target

    XGB_Annual_Model = xgb.XGBRegressor(objective ='reg:squarederror', learning_r
                                        max_depth = 5, n_estimators = 500)
    XGB_Annual_Model.fit(X_train,y_train)
    return XGB_Annual_Model.predict(X_test)
```

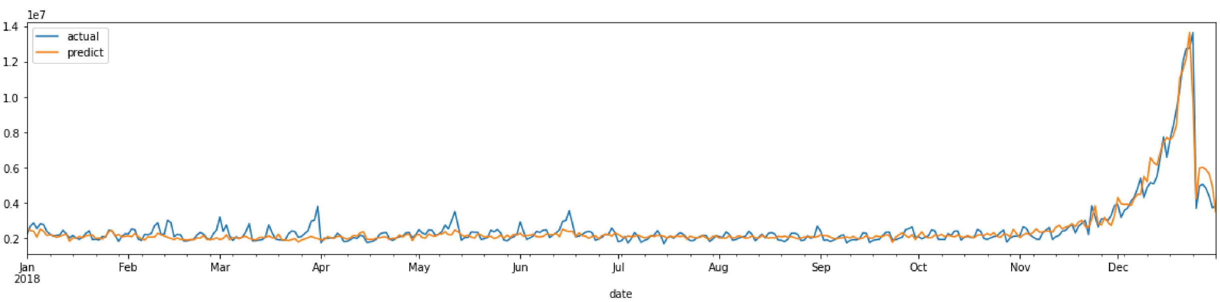
Result Output

In [14]:
```
def plot_actual_predict(actual, predict, date, month, year):

    temp_df = pd.DataFrame()
    temp_df['actual']  = actual
    temp_df['predict'] = predict

    temp_df['date']    = date.astype(str) + '/' + month.astype(str) + '/' + year.
    temp_df.date       = pd.to_datetime(temp_df.date,format='%d/%m/%Y')
    temp_df.set_index('date', inplace=True)

    temp_df[['actual','predict']].plot(figsize=(20,4))
```

Prediction of 2018 based on 2016-2017 Data

In [15]:
```
pred_2018 = iterative_train_test(sl_df, 2018)
print('MAPE of 2018 Prediction is ', get_score(sl_df.query('year==2018').target,

plot_actual_predict(sl_df.query('year==2018').target, pred_2018, sl_df.date, sl_d
```

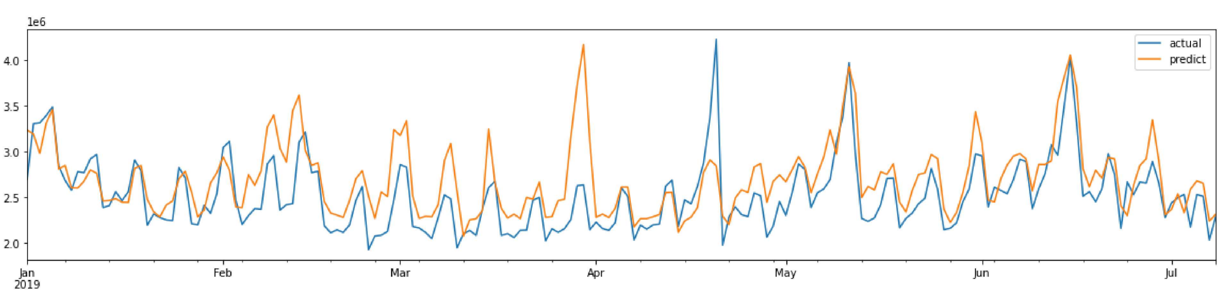
```
MAPE of 2018 Prediction is  9.580226403054203 %
```



Prediction of 2019 based on 2016-2018 Data

In [16]:
```
pred_2019 = iterative_train_test(sl_df, 2019)
print('MAPE of 2019 Prediction is ', get_score(sl_df.query('year==2019').target,

plot_actual_predict(sl_df.query('year==2019').target, pred_2019, sl_df.date, sl_d
```

```
MAPE of 2019 Prediction is  9.970565442057168 %
```



Future Predictions

- User Defined Functions

In [17]:
```
from pandas.tseries.offsets import DateOffset

def predict_one_day(temp_df):

    XGB = xgb.XGBRegressor(objective ='reg:squarederror', learning_rate = 0.2,
                                    max_depth = 5, n_estimators = 500)

    X_train, y_train = temp_df.drop(columns='target', axis=1).iloc[:-1,], temp_df
    X_test           = temp_df.drop(columns='target', axis=1).iloc[-1:,]

    XGB.fit(X_train, y_train)

    return XGB.predict(X_test)



def add_record(temp_df, date, month, year, past_values):
    temp_df = temp_df.append(temp_df.iloc[-1,:], ignore_index=True)
    temp_df.iloc[-1,:] = [0] + [date] + [month] + [year] + past_values
    return temp_df


def update_record(temp_df, window, date):
    year  = int(str(date).split('-')[0])
    month = int(str(date).split('-')[1])
    date  = int(str(date).split('-')[2].split(' ')[0])

    temp_df = add_record(temp_df, date, month, year, list(temp_df.target[-window:
    temp_df.target.iloc[-1,] = predict_one_day(temp_df)

    return temp_df


def generate_new_date_dataframe(store_df, n_days):
    temp_var        = str(store_df.date.iloc[-1,]) + '/' + str(store_df.month.il
    current_date    = pd.to_datetime(temp_var, format='%d/%m/%Y')
    return pd.DataFrame([current_date + DateOffset(days=x) for x in range(1,1+n_c


def predict_future_dates(store_df, new_date_df, window):
    for i in range(new_date_df.shape[0]):
        store_df = update_record(store_df, window, new_date_df.date.iloc[i])
    return store_df
```

- Perform Prediction

In [22]:

```
store_df = sl_df.copy()

n_days      = 179
new_date_df = generate_new_date_dataframe(store_df, n_days)
store_df    = predict_future_dates(sl_df, new_date_df, 365)

store_df.tail(10)
```

Out[22]:

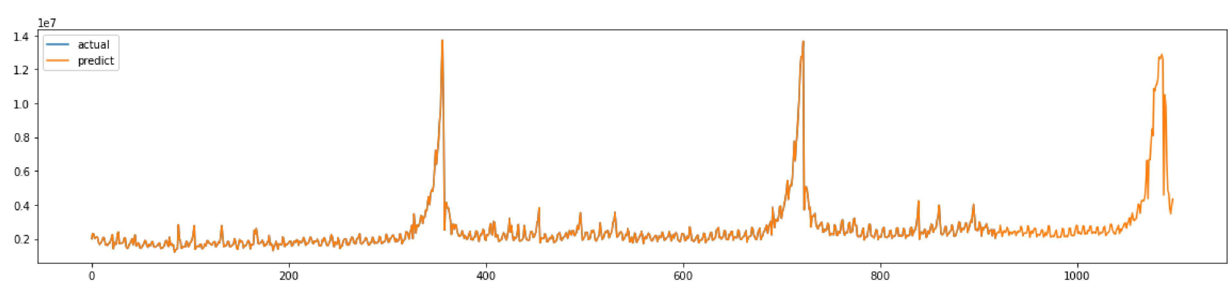
	target	date	month	year	D1	D2	D3	D4	D5
1088	4571631.0	25.0	12.0	2019.0	3710950.0	4979283.0	5070313.0	4838417.0	4397841.0
1089	10504838.0	26.0	12.0	2019.0	4979283.0	5070313.0	4838417.0	4397841.0	3736114.0
1090	9822598.0	27.0	12.0	2019.0	5070313.0	4838417.0	4397841.0	3736114.0	3849566.0
1091	6513446.0	28.0	12.0	2019.0	4838417.0	4397841.0	3736114.0	3849566.0	2696421.0
1092	4863807.5	29.0	12.0	2019.0	4397841.0	3736114.0	3849566.0	2696421.0	3305187.0
1093	4654674.5	30.0	12.0	2019.0	3736114.0	3849566.0	2696421.0	3305187.0	3313575.0
1094	3813959.0	31.0	12.0	2019.0	3849566.0	2696421.0	3305187.0	3313575.0	3393393.0
1095	3468875.0	1.0	1.0	2020.0	2696421.0	3305187.0	3313575.0	3393393.0	3486347.0
1096	3962469.0	2.0	1.0	2020.0	3305187.0	3313575.0	3393393.0	3486347.0	2841354.0
1097	4339146.5	3.0	1.0	2020.0	3313575.0	3393393.0	3486347.0	2841354.0	2685121.0

- Display Future Projection

In [23]:

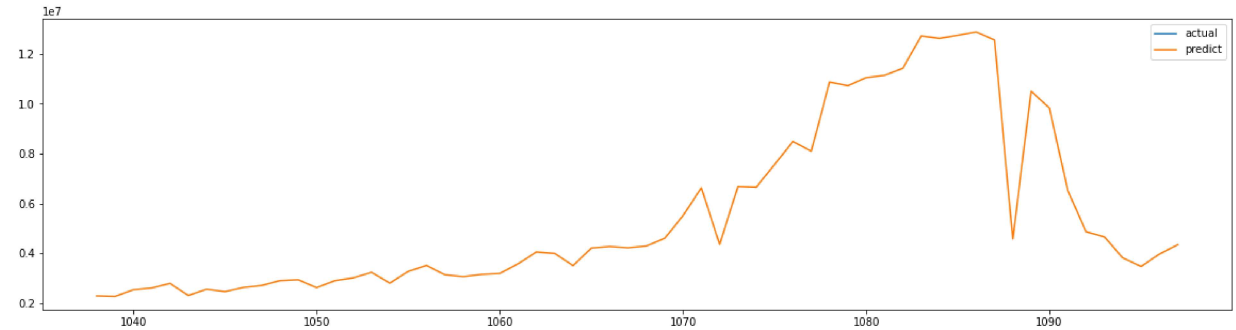
```
from numpy import asarray

XGB_output = pd.DataFrame()

predict = list(XGB_Model_Final_pred) + list(store_df.target.iloc[-n_days:,])
actual  = list(store_df.target.iloc[:-n_days,]) + [np.nan]*n_days

XGB_output['actual']  = actual
XGB_output['predict'] = predict

# Save as Excel - Use Actual Dates

XGB_output[['actual','predict']].plot(figsize=(20,4))
```

Out[23]: <matplotlib.axes._subplots.AxesSubplot at 0x15a81ffe250>



In [24]:
```
#print(Zoom_Last.tail(5))

Zoom_Last = XGB_output.iloc[-60:,]
Zoom_Last[['actual','predict']].plot(figsize=(20,5))
```

Out[24]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x15a825f1a60>
```



In [25]:
```
XGB_output.to_excel('output_xgb_large.xlsx')
```

In [ ]:

In [128]:

In [ ]:

In [ ]:

In [ ]:

In [ ]: