```
import numpy as np
import pandas as pd
import scipy.stats as stats
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, mean_absolute_error
from datetime import datetime
import calendar
import math
# Importing the most popular regression libraries.
from sklearn.linear_model import LinearRegression
from sklearn.neighbors import KNeighborsRegressor
from sklearn.linear_model import Ridge
from sklearn.linear_model import Lasso
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.ensemble import ExtraTreesRegressor
from xgboost import XGBRegressor
from pandas.util._decorators import Appender
#from pmdarima.arima import auto_arima
from statsmodels.tsa.arima_model import ARIMA
```

```
/usr/local/lib/python3.7/dist-packages/statsmodels/tools/_testing.py:19: FutureWarni
  import pandas.util.testing as tm
```

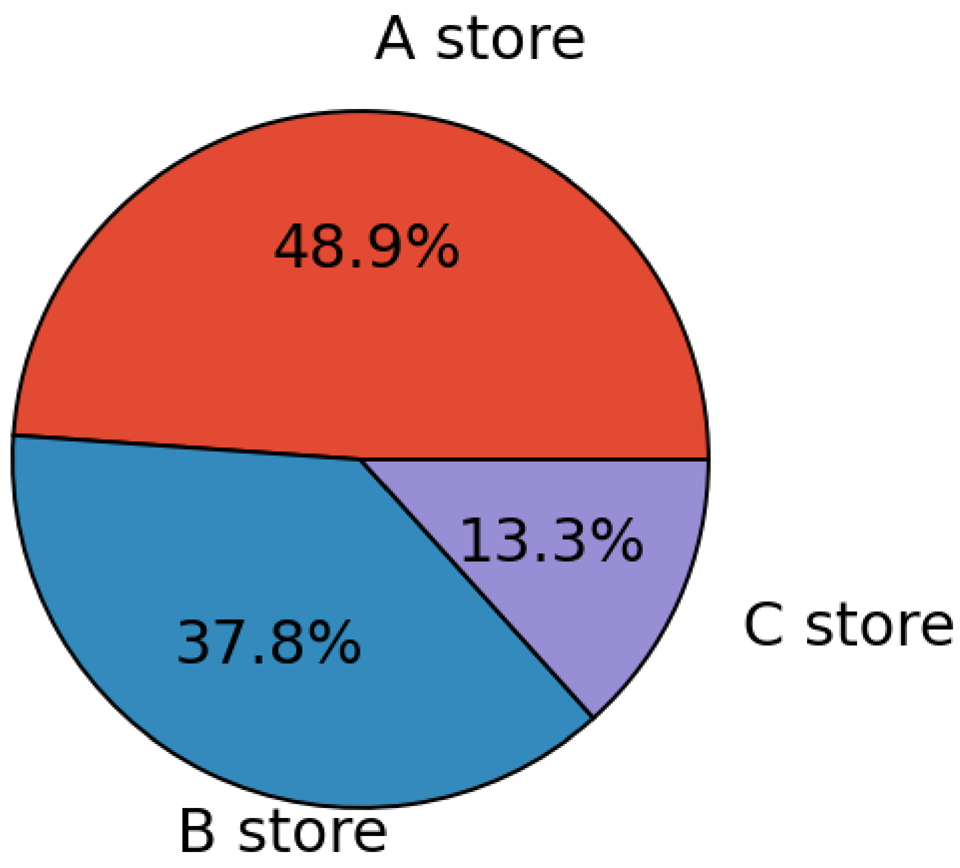
```
#Loading the data from csv files.
train=pd.read_csv('train.csv')
features=pd.read_csv('features.csv')
stores = pd.read_csv('stores.csv')
```

```
data = train.merge(features, on=['Store', 'Date'], how='inner').merge(stores, on=['Store']
print(data.shape)
```

```
(421570, 17)
```

```
#We came to know that Type A stores have their medians higher than any other medians in ot
#so the weekly sales for store type A is more than other store types.
sorted_type = stores.groupby('Type')
plt.style.use('ggplot')
labels=['A store','B store','C store']
sizes=sorted_type.describe()['Size'].round(1)
sizes=[(22/(17+6+22))*100,(17/(17+6+22))*100,(6/(17+6+22))*100] # convert to the proportic
fig, axes = plt.subplots(1,1, figsize=(10,10))
wprops={'edgecolor':'black',
      'linewidth':2}
tprops = {'fontsize':30}
axes.pie(sizes,
        labels=labels,
        explode=(0.0,0,0),
        autopct='%1.1f%%',
```

```
        pctdistance=0.6,
        labeldistance=1.2,
        wedgeprops=wprops,
        textprops=tprops,
        radius=0.8,
        center=(0.5,0.5))
plt.show()
```




```
print(data)
```

```
        Store  Dept        Date  ...  IsHoliday_y  Type    Size
0           1     1  2010-02-05  ...        False     A  151315
1           1     2  2010-02-05  ...        False     A  151315
2           1     3  2010-02-05  ...        False     A  151315
3           1     4  2010-02-05  ...        False     A  151315
4           1     5  2010-02-05  ...        False     A  151315
...       ...   ...         ...  ...          ...   ...     ...
421565     45    93  2012-10-26  ...        False     B  118221
421566     45    94  2012-10-26  ...        False     B  118221
421567     45    95  2012-10-26  ...        False     B  118221
421568     45    97  2012-10-26  ...        False     B  118221
421569     45    98  2012-10-26  ...        False     B  118221

[421570 rows x 17 columns]
```

```
data.shape
```

```
(421570, 17)
```

```
data.describe
```

```
<bound method NDFrame.describe of         Store  Dept        Date  ...  IsHoliday_y
0           1     1  2010-02-05  ...        False     A  151315
1           1     2  2010-02-05  ...        False     A  151315
2           1     3  2010-02-05  ...        False     A  151315
3           1     4  2010-02-05  ...        False     A  151315
4           1     5  2010-02-05  ...        False     A  151315
...       ...   ...         ...  ...          ...   ...     ...
421565     45    93  2012-10-26  ...        False     B  118221
421566     45    94  2012-10-26  ...        False     B  118221
421567     45    95  2012-10-26  ...        False     B  118221
421568     45    97  2012-10-26  ...        False     B  118221
421569     45    98  2012-10-26  ...        False     B  118221

[421570 rows x 17 columns]>
```

```
data.dtypes
```

```
Store             int64
Dept              int64
Date             object
Weekly_Sales    float64
IsHoliday_x        bool
Temperature     float64
Fuel_Price      float64
MarkDown1       float64
MarkDown2       float64
MarkDown3       float64
MarkDown4       float64
MarkDown5       float64
CPI             float64
Unemployment    float64
IsHoliday_y        bool
Type             object
Size              int64
dtype: object
```

```
master_df=data
```

```
master_df=master_df.fillna(0)
master_df.isna().sum()
master_df = master_df[master_df['Weekly_Sales'] >= 0]
# Cleaning holiday columns
master_df['IsHoliday'] = master_df['IsHoliday_x']
master_df = master_df.drop(columns=['IsHoliday_x', 'IsHoliday_y'])
```

```
master_df['Date'] = pd.to_datetime(master_df['Date'], format='%Y-%m-%d')
master_df['Week_Number'] = master_df['Date'].dt.week
master_df['Quarter'] = master_df['Date'].dt.quarter
```

```
master_df['Month'] = master_df['Date'].dt.month.apply(lambda x: calendar.month_abbr[x])
master_df["Year"] = master_df["Date"].dt.year
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:2: FutureWarning: Serie
```

```
master_df.dtypes
```

```
Store                    int64
Dept                     int64
Date            datetime64[ns]
Weekly_Sales           float64
Temperature            float64
Fuel_Price             float64
MarkDown1              float64
MarkDown2              float64
MarkDown3              float64
MarkDown4              float64
MarkDown5              float64
CPI                    float64
Unemployment           float64
Type                    object
Size                     int64
IsHoliday                 bool
Week_Number              int64
Quarter                  int64
Month                   object
Year                     int64
dtype: object
```

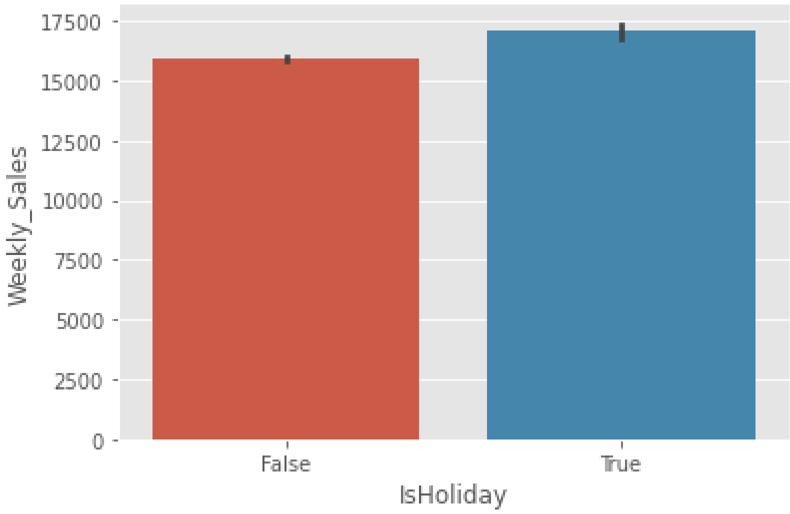
```
master_df.isna().sum()
```

```
Store           0
Dept            0
Date            0
Weekly_Sales    0
Temperature     0
Fuel_Price      0
MarkDown1       0
MarkDown2       0
MarkDown3       0
MarkDown4       0
MarkDown5       0
CPI             0
Unemployment    0
Type            0
Size            0
IsHoliday       0
Week_Number     0
Quarter         0
Month           0
Year            0
dtype: int64
```

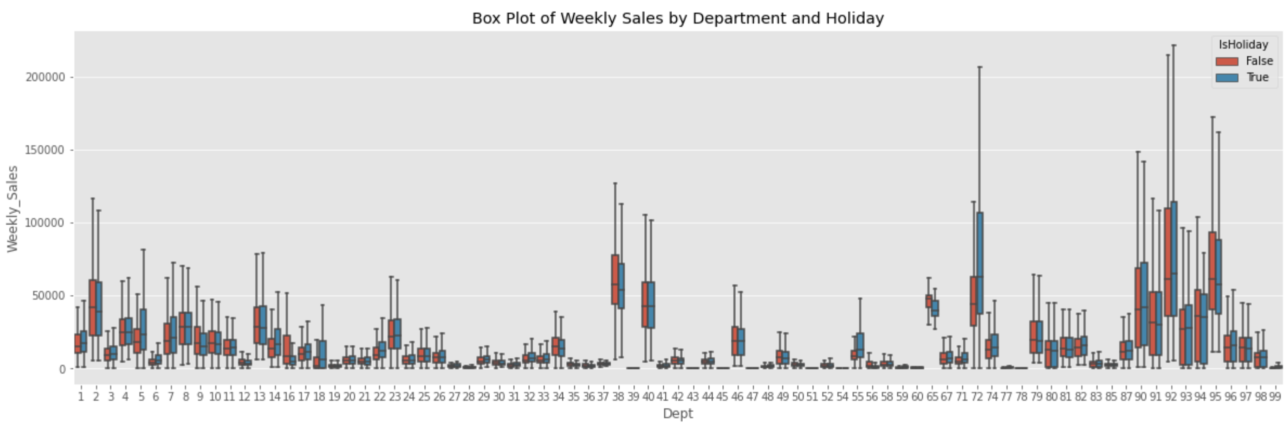
```
holiday = master_df['Weekly_Sales'].loc[master_df['IsHoliday']== True] # Weekly Sales in H
non_holiday = master_df['Weekly_Sales'].loc[master_df['IsHoliday']== False] #Weekly Sales
sns.barplot(x='IsHoliday', y='Weekly_Sales', data=master_df)
```

```
sns.barplot(x='IsHoliday', y='Weekly_Sales', data=master_df)
```

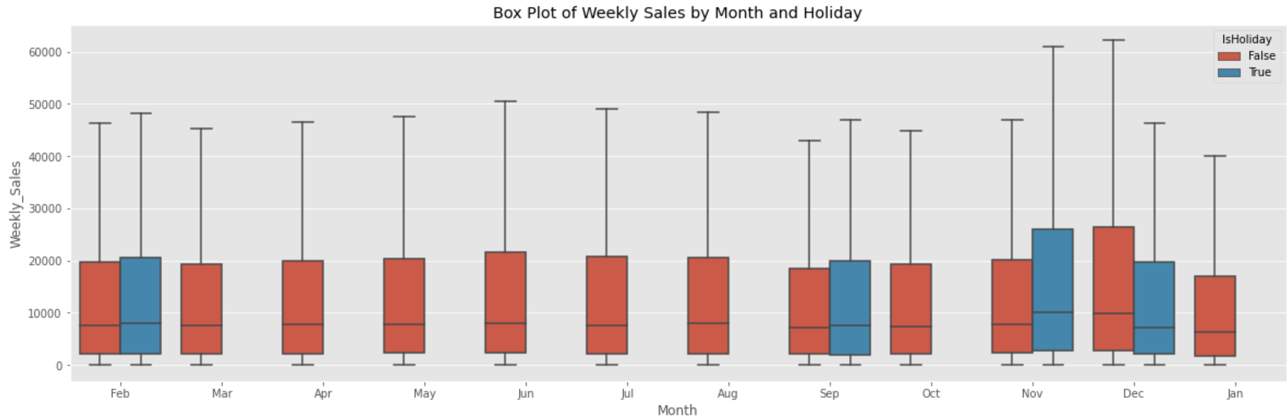
<matplotlib.axes._subplots.AxesSubplot at 0x7fb65ab01890>




```
data_11= pd.concat([master_df['Dept'], master_df['Weekly_Sales'], master_df['IsHoliday']],
plt.figure(figsize=(20,6))
plt.title('Box Plot of Weekly Sales by Department and Holiday')
fig = sns.boxplot(x='Dept', y='Weekly_Sales', data=data_11, showfliers=False, hue="IsHolic
```

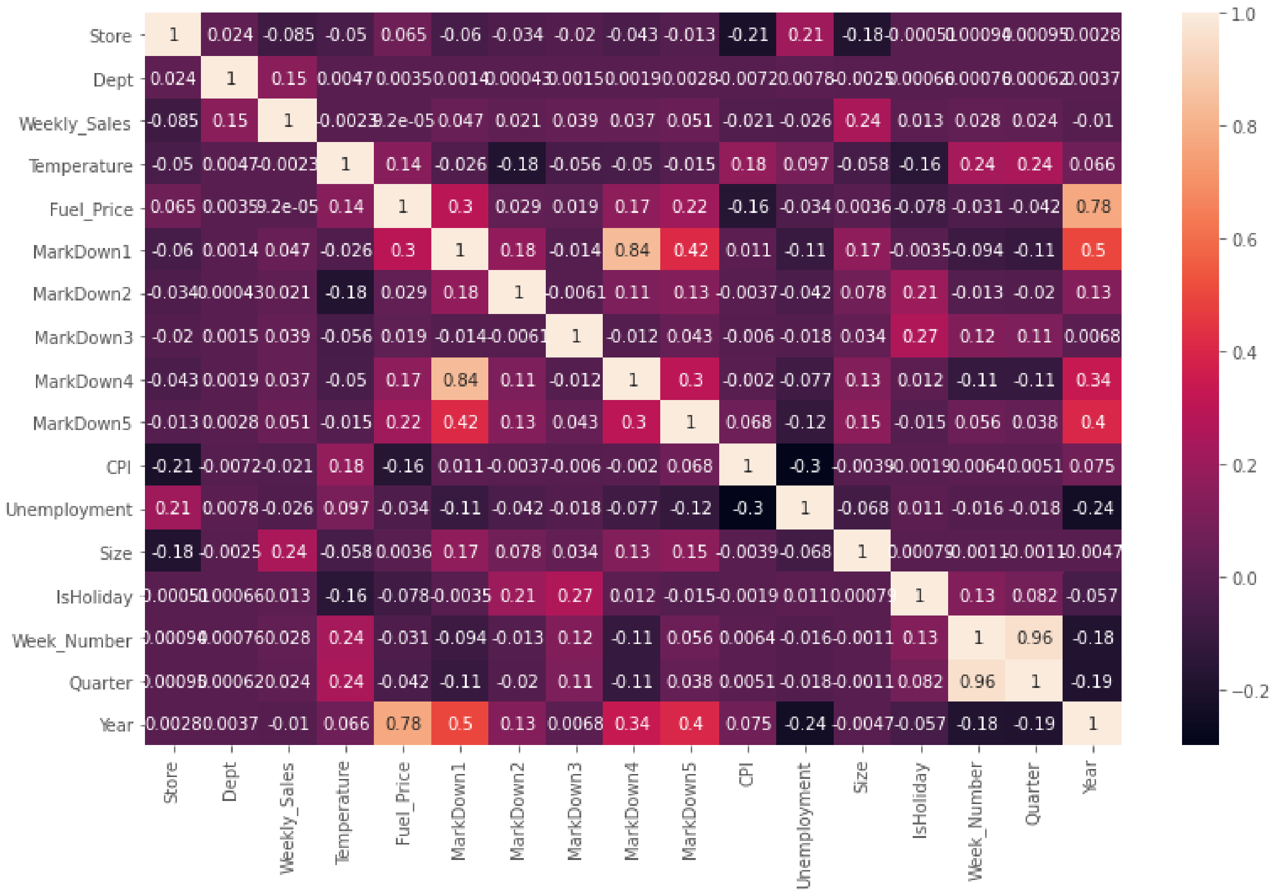



```
data_14 = pd.concat([master_df['Month'], master_df['Weekly_Sales'], master_df['IsHoliday']
plt.figure(figsize=(20,6))
plt.title('Box Plot of Weekly Sales by Month and Holiday')
fig = sns.boxplot(x='Month', y='Weekly_Sales', data=data_14, showfliers=False, hue='IsHoli
```




```
plt.figure(figsize=(13,8))
sns.heatmap(master_df.corr('pearson'), annot = True)
```

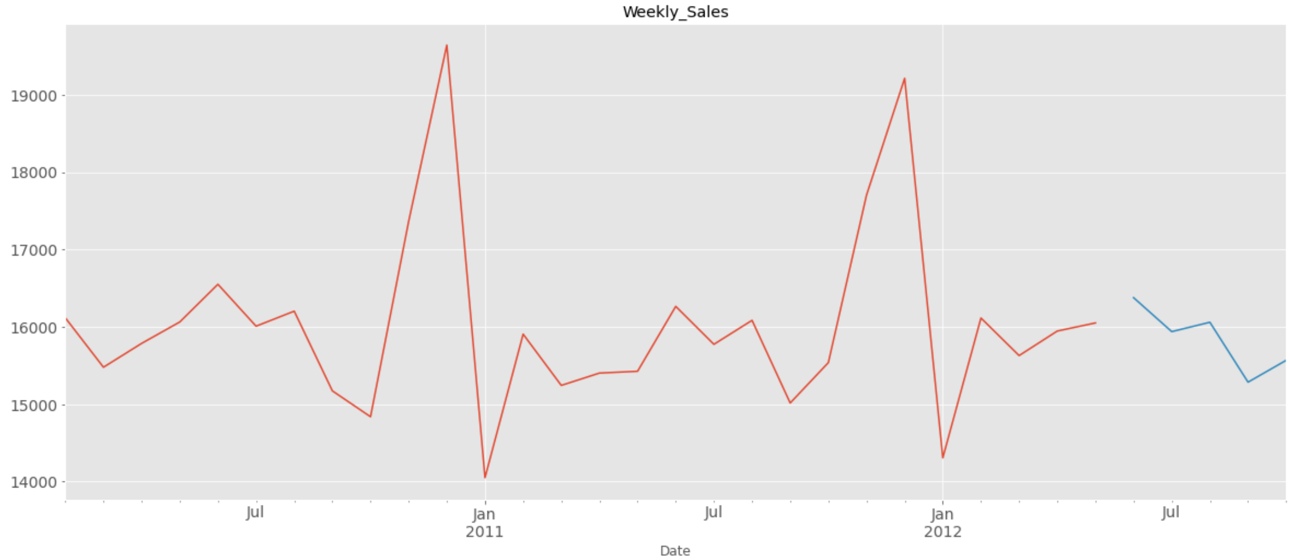
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fb65ab011d0>
```




```
master_df2=master_df.copy()
```

```
master_df.Date = pd.to_datetime(master_df.Date,format='%Y-%m-%d')
master_df.index = master_df.Date
master_df = master_df.drop('Date', axis=1)
master_df = master_df.resample('MS').mean() # Resmapling the time series data with month s
```

```
# -Test splitting of time series data
_data = master_df[:int(0.85*(len(master_df)))]
test_data = master_df[int(0.85*(len(master_df))):]
# ARIMA takes univariate data.
_data = _data['Weekly_Sales']
test_data = test_data['Weekly_Sales']
# Plot of Weekly_Sales with respect to years in  and test.
_data.plot(figsize=(20,8), title= 'Weekly_Sales', fontsize=14)
test_data.plot(figsize=(20,8), title= 'Weekly_Sales', fontsize=14)
plt.show()
```




```
from statsmodels.tsa.stattools import adfuller
result = adfuller(master_df['Weekly_Sales'])
print('ADF Statistic: {}'.format(result[0]))
print('p-value: {}'.format(result[1]))
print('Critical Values:')
for key, value in result[4].items():
    print('\t{}: {}'.format(key, value))
```

```
ADF Statistic: -4.173916935101529
p-value: 0.0007291844915316654
Critical Values:
        1%: -3.769732625845229
        5%: -3.005425537190083
        10%: -2.6425009917355373
```

```
#https://stackoverflow.com/questions/24316935/python-statsmodel-arima-start-stationarity
fig = plt.figure(figsize=(20,8))
```

```
model = ARIMA(master_df['Weekly_Sales'], order=(2,0,1))
ax = plt.gca()
results = model.fit()
plt.plot(master_df['Weekly_Sales'])
plt.plot(results.fittedvalues, color='blue')
ax.legend(['Weekly_Sales', 'Forecast'])

results.summary()
```

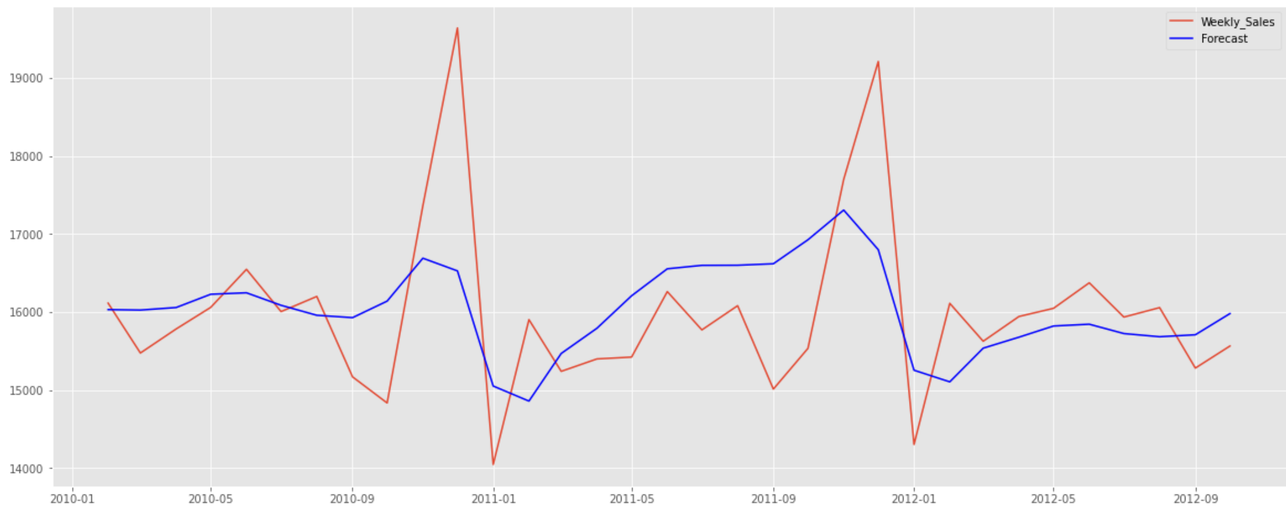
ARMA Model Results

Dep. Variable:	Weekly_Sales	**No. Observations:**	33
Model:	ARMA(2, 1)	**Log Likelihood**	-273.765
Method:	css-mle	**S.D. of innovations**	926.244
Date:	Sun, 27 Jun 2021	**AIC**	557.531
Time:	12:30:48	**BIC**	565.013
Sample:	02-01-2010	**HQIC**	560.048
	- 10-01-2012		

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
const	1.603e+04	25.263	634.625	0.000	1.6e+04	1.61e+04
ar.L1.Weekly_Sales	0.6123	0.168	3.653	0.001	0.284	0.941
ar.L2.Weekly_Sales	-0.2458	0.165	-1.488	0.148	-0.570	0.078
ma.L1.Weekly_Sales	-1.0000	0.087	-11.477	0.000	-1.171	-0.829

Roots

	Real	**Imaginary**	**Modulus**	**Frequency**
AR.1	1.2453	-1.5865j	2.0169	-0.1441
AR.2	1.2453	+1.5865j	2.0169	0.1441
MA.1	1.0000	+0.0000j	1.0000	0.0000

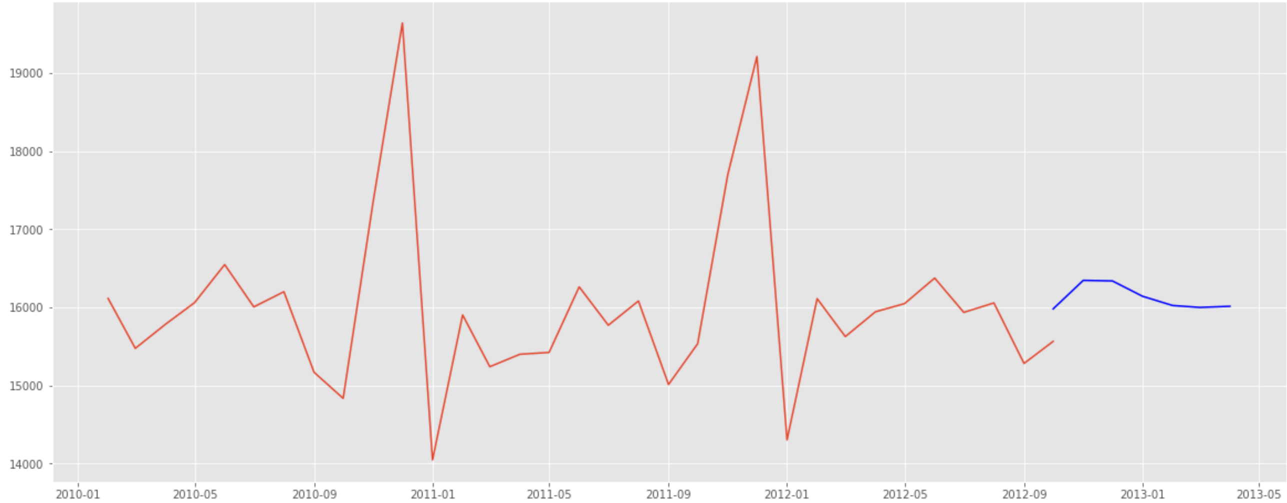



```
master_df.index
```

```
DatetimeIndex(['2010-02-01', '2010-03-01', '2010-04-01', '2010-05-01',
               '2010-06-01', '2010-07-01', '2010-08-01', '2010-09-01',
               '2010-10-01', '2010-11-01', '2010-12-01', '2011-01-01',
               '2011-02-01', '2011-03-01', '2011-04-01', '2011-05-01',
               '2011-06-01', '2011-07-01', '2011-08-01', '2011-09-01',
               '2011-10-01', '2011-11-01', '2011-12-01', '2012-01-01',
               '2012-02-01', '2012-03-01', '2012-04-01', '2012-05-01',
               '2012-06-01', '2012-07-01', '2012-08-01', '2012-09-01',
               '2012-10-01'],
              dtype='datetime64[ns]', name='Date', freq='MS')
```

```
fig = plt.figure(figsize=(20,8))
#num_points = len(clear_data['car.count'])
x = results.predict(start=("2012-10-01"), end=("2013-04-01"), dynamic=False)

plt.plot(master_df["Weekly_Sales"])
plt.plot(x, color='b')
```

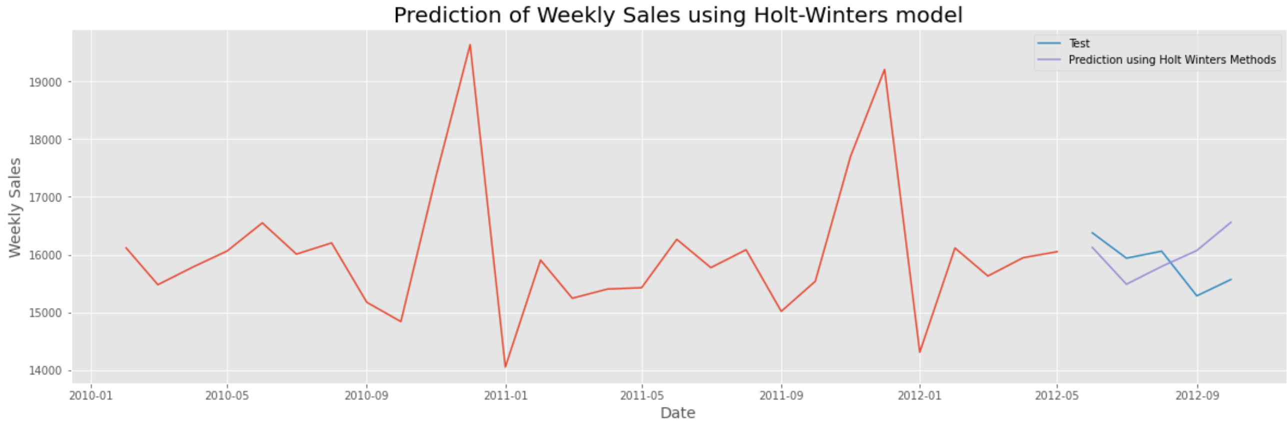
```
[<matplotlib.lines.Line2D at 0x7fb64f821910>]
```




```
# # Applying auto_arima model on  data.
# model_auto_arima = auto_arima(_data, trace=True, error_action='ignore', suppress_warning
# model_auto_arima = auto_arima(_data, trace=True,start_p=0, start_q=0, start_P=0, start_(
# model_auto_arima.fit(_data)


# # Predicting the test values using predict function.
# forecast = model_auto_arima.predict(n_periods=len(test_data))
# forecast = pd.DataFrame(forecast,index = test_data.index,columns=['Prediction'])
# plt.figure(figsize=(20,6))
```

```
# plt.title('Prediction of Weekly Sales using Auto ARIMA model', fontsize=20)
# plt.plot(_data, label='')
# plt.plot(test_data, label='Test')
# plt.plot(forecast, label='Prediction using ARIMA Model')
# plt.legend(loc='best')
# plt.xlabel('Date', fontsize=14)
# plt.ylabel('Weekly Sales', fontsize=14)
# plt.show()


# # Performance metric for ARIMA model -MSE/RMSE
# print('Mean Squared Error (MSE) of ARIMA: ', mean_squared_error(test_data, forecast))
# print('Root Mean Squared Error (RMSE) of ARIMA: ', math.sqrt(mean_squared_error(test_dat
# print('Mean Absolute Deviation (MAD) of ARIMA: ', mean_absolute_error(test_data, forecas


# Fitting the Holt-Winters method for Weekly Sales.
from statsmodels.tsa.api import ExponentialSmoothing
model_holt_winters = ExponentialSmoothing(_data, seasonal_periods=7, trend='additive', sea
pred = model_holt_winters.forecast(len(test_data))# Predict the test data
#Visualize , test and predicted data.
plt.figure(figsize=(20,6))
plt.title('Prediction of Weekly Sales using Holt-Winters model', fontsize=20)
plt.plot(_data, label='')
plt.plot(test_data, label='Test')
plt.plot(pred, label='Prediction using Holt Winters Methods')
plt.legend(loc='best')
plt.xlabel('Date', fontsize=14)
plt.ylabel('Weekly Sales', fontsize=14)
plt.show()
```

```
/usr/local/lib/python3.7/dist-packages/statsmodels/tsa/holtwinters.py:712: Convergen
  ConvergenceWarning)
```




```
print('Mean Squared Error (MSE) of Holt-Winters: ', mean_squared_error(test_data, pred))
```

```
print('Mean Squared Error (MSE) of Holt-Winters: ', mean_squared_error(test_data, pred))
print('Root Mean Squared Error (RMSE) of Holt-Winters: ', math.sqrt(mean_squared_error(tes
print('Mean Absolute Deviation (MAD) of Holt-Winters: ', mean_absolute_error(test_data, pr
```

```
Mean Squared Error (MSE) of Holt-Winters:  388409.6112769923
Root Mean Squared Error (RMSE) of Holt-Winters:  623.2251690015354
Mean Absolute Deviation (MAD) of Holt-Winters:  549.8500311065163
```

```
# df=master_df2[['Store','Dept','Date','Weekly_Sales','Size','IsHoliday']]
# df
```

```
# # Converting Categorical Variable 'IsHoliday' into Numerical Variables.
# type_mapping = {False: 0, True: 1}
# df['IsHoliday'] = df['IsHoliday'].map(type_mapping)
# df
```

```
# df['Super_Bowl'] = np.where(
# (df['Date']==datetime(2010,2,10))|
# (df['Date'] == datetime(2011,2,11))|
# (df['Date'] == datetime(2012,2,10))|
# (df['Date'] == datetime(2013,2,8)), 1, 0)
# df['Labor_day'] = np.where(
# (df['Date'] == datetime(2010,9,10))|
# (df['Date'] == datetime(2011,9,9))|
# (df['Date'] == datetime(2012,9,7))|
# (df['Date'] == datetime(2013,9,6)), 1, 0)
# df['Thanksgiving'] = np.where(
# (df['Date']==datetime(2010, 11, 26)) | (df['Date']==datetime(2011, 11, 25)) |
# (df['Date']==datetime(2012, 11, 23)) | (df['Date']==datetime(2013, 11, 29)),1,0)
# df['Christmas'] = np.where(
# (df['Date']==datetime(2010, 12, 31))| (df['Date']==datetime(2011, 12, 30))|
# (df['Date']==datetime(2012, 12, 28))| (df['Date']==datetime(2013, 12, 27)),1,0)

# df
```

```
# df = df.sort_values(by='Date', ascending=True) # Sorting the data in increasing order of
# y = df['Weekly_Sales']
# X = df.drop(['Weekly_Sales'], axis=1)
# X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3) # Train:Test =
# X_train, X_cv, y_train, y_cv = train_test_split(X_train, y_train, test_size=0.3) #Train:
```

```
# def wmae_train(test, pred):
#   weights = X_train['IsHoliday'].apply(lambda is_holiday:5 if   is_holiday else 1)
#   error = np.sum(weights * np.abs(test - pred), axis=0) / np.sum(weights)
#   return error
# def wmae_cv(test, pred): # WMAE for CV
#   weights = X_cv['IsHoliday'].apply(lambda is_holiday:5 if is_holiday else 1)
#   error = np.sum(weights * np.abs(test - pred), axis=0) / np.sum(weights)
#   return error
# def wmae_test(test, pred): # WMAE for test
#   weights = X_test['IsHoliday'].apply(lambda is_holiday:5 if is_holiday else 1)
```

```
#   weights = X_test['IsHoliday'].apply(lambda is_holiday:5 if is_holiday else 1)
#   error = np.sum(weights * np.abs(test - pred), axis=0) / np.sum(weights)
#   return error


# X_train['Date']=X_train['Date'].map(datetime.toordinal)
# # X_test.columns = ["Date"]
# # X_test['Date'] = pd.to_datetime(X_test['Date'])
# # X_test['Date']=X_test['Date'].map(dt.datetime.toordinal)
# X_cv['Date']=X_cv['Date'].map(datetime.toordinal)
# X_test['Date']=X_test['Date'].map(datetime.toordinal)


# X_cv.dtypes


# # Define the list of errors and list of hyper parameters.
# error_cv_rf = []
# error_train_rf = []
# max_depth = [1,5,10,15,20,25,30,35]
# n_estimators = [10]
# rf_hyperparams = []
# """Calculating train and CV errors for maximum depth and number of estimators parameters
# for i in max_depth:
#     for j in n_estimators:
#         rf = RandomForestRegressor(max_depth=i, n_estimators=j)
#         rf.fit(X_train, y_train)
#         y_pred_cv_rf = rf.predict(X_cv)
#         y_pred_train_rf = rf.predict(X_train)
#         error_cv_rf.append(wmae_cv(y_cv, y_pred_cv_rf))
#         error_train_rf.append(wmae_train(y_train, y_pred_train_rf))
#         rf_hyperparams.append({'Maximum Depth':i, 'No. of Estimators':j})


# rf_dataframe = pd.DataFrame(rf_hyperparams)
# rf_dataframe['Train Error']=error_train_rf
# rf_dataframe['CV Error']=error_cv_rf
# rf_dataframe.sort_values(by=['CV Error'], ascending=True)
# rf_dataframe.head()


# sns.set(font_scale=1.0)
# train_rf = pd.pivot_table(rf_dataframe,'Train Error','Maximum Depth','No. of Estimators'
# cv_rf = pd.pivot_table(rf_dataframe, 'CV Error','Maximum Depth','No. of Estimators') # P
# fig, ax = plt.subplots(1,2, figsize=(20,6))
# ax_train = sns.heatmap(train_rf, annot=True, fmt='2g', ax=ax[0], linewidths=0.01)
# ax_cv = sns.heatmap(cv_rf, annot=True, fmt='4g', ax=ax[1], linewidths=0.01)
# bottom_train, top_train = ax_train.get_ylim()
# ax_train.set_ylim(bottom_train + 0.5, top_train - 0.5)
# bottom_cv, top_cv = ax_cv.get_ylim()
# ax_cv.set_ylim(bottom_cv + 0.5, top_cv - 0.5)
# ax[0].set_title('Training set')
# ax[1].set_title('CV set')
# plt.show()


# model_rf = RandomForestRegressor(max_depth= 35, n_estimators=80).fit(X_train, y_train) #
# y_pred = model_rf.predict(X_test) # Predict the test data
```

```
# y_pred = model_rf.predict(X_test) # Predict the test data.
# print('Weighted Mean Absolute Error (WMAE) for Random Forest Regression:', wmae_test(y_t


# models = pd.DataFrame({
# 'Model Name':
# ['Linear Regression','KNN Regression','Ridge Regression','Lasso Regression','Decision Tr

# 'WMAE Score':
# ['14904.66', '11887.99', '14824.52', '14810.89', '2134.17', '1785.20', '1986.29', '2765.
#  })
# Index = pd.Series([1, 2, 3, 4, 5, 6, 7, 8])
# models.set_index(Index, inplace=True)
# models


# https://medium.com/analytics-vidhya/walmart-recruiting-store-sales-forecasting-kaggle-cc
```

```
#Joining the train data with store and features data using inner join.
train = train.merge(features, on=['Store', 'Date'], how='inner').merge(stores, on=['Store'
print(train.shape)
```

```
(421570, 17)
```

```
# Make one IsHoliday column instead of two.
train = train.drop(['IsHoliday_y'], axis=1)
train = train.rename(columns={'IsHoliday_x':'IsHoliday'})
print('Train columns:\n', train.columns)
```

```
Train columns:
 Index(['Store', 'Dept', 'Date', 'Weekly_Sales', 'IsHoliday', 'Temperature',
       'Fuel_Price', 'MarkDown1', 'MarkDown2', 'MarkDown3', 'MarkDown4',
       'MarkDown5', 'CPI', 'Unemployment', 'Type', 'Size'],
      dtype='object')
```

```
# Converting Date to datetime
train['Date'] = pd.to_datetime(train['Date'])

# Extract date features
train['Date_dayofweek'] =train['Date'].dt.dayofweek
train['Date_month'] =train['Date'].dt.month
train['Date_year'] =train['Date'].dt.year
train['Date_day'] =train['Date'].dt.day
```

```
train_data = [train]

# Converting Categorical Variable 'Type' into Numerical Variables.
type_mapping = {"A": 1, "B": 2, "C": 3}
for dataset in train_data:
    dataset['Type'] = dataset['Type'].map(type_mapping)

# Converting Categorical Variable 'IsHoliday' into Numerical Variables.
type_mapping = {False: 0, True: 1}
for dataset in train_data:
```

```
    dataset['IsHoliday'] = dataset['IsHoliday'].map(type_mapping)
```

```
(aggle has provided some dates to be allocated to special holidays. We have taken the spec:
iin['Super_Bowl'] = np.where((train['Date'] == datetime(2010,2,10)) | (train['Date'] == da
                             (train['Date'] == datetime(2012,2,10)) | (train['Date'] == da
iin['Labor_day'] = np.where((train['Date'] == datetime(2010,9,10)) | (train['Date'] == dat
                            (train['Date'] == datetime(2012,9,7)) | (train['Date'] == date
iin['Thanksgiving'] = np.where((train['Date']==datetime(2010, 11, 26)) | (train['Date']==d
                               (train['Date']==datetime(2012, 11, 23)) | (train['Date']==d
iin['Christmas'] = np.where((train['Date']==datetime(2010, 12, 31)) | (train['Date']==date
                            (train['Date']==datetime(2012, 12, 28)) | (train['Date']==date
```

```
print('Train holidays:\n')
print ('Christmas:\n', train.Christmas.value_counts(),'\n')
print ('Super Bowl:\n', train.Super_Bowl.value_counts(),'\n')
print ('Thanksgiving:\n', train.Thanksgiving.value_counts(),'\n')
print ('Labor Day:\n', train.Labor_day.value_counts(),'\n')
```

```
Train holidays:

Christmas:
 0    415624
1      5946
Name: Christmas, dtype: int64

Super Bowl:
 0    415631
1      5939
Name: Super_Bowl, dtype: int64

Thanksgiving:
 0    415611
1      5959
Name: Thanksgiving, dtype: int64

Labor Day:
 0    412709
1      8861
Name: Labor_day, dtype: int64
```

```
# Since we have Imputed IsHoliday according to Extra holidays..These extra holiday variabl
# Droping the Extra holiday variables because its redundant.
dp = ['Super_Bowl','Labor_day','Thanksgiving','Christmas']
train.drop(dp, axis=1, inplace=True)
```

```
train = train.fillna(0)
#Remove negative values as sales cannot be negative.
train = train[train['Weekly_Sales'] >= 0]
train.shape
```

```
(420285, 20)
```

```
train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 420285 entries, 0 to 421569
Data columns (total 20 columns):
 #   Column          Non-Null Count   Dtype
---  ------          --------------   -----
 0   Store           420285 non-null  int64
 1   Dept            420285 non-null  int64
 2   Date            420285 non-null  datetime64[ns]
 3   Weekly_Sales    420285 non-null  float64
 4   IsHoliday       420285 non-null  int64
 5   Temperature     420285 non-null  float64
 6   Fuel_Price      420285 non-null  float64
 7   MarkDown1       420285 non-null  float64
 8   MarkDown2       420285 non-null  float64
 9   MarkDown3       420285 non-null  float64
 10  MarkDown4       420285 non-null  float64
 11  MarkDown5       420285 non-null  float64
 12  CPI             420285 non-null  float64
 13  Unemployment    420285 non-null  float64
 14  Type            420285 non-null  int64
 15  Size            420285 non-null  int64
 16  Date_dayofweek  420285 non-null  int64
 17  Date_month      420285 non-null  int64
 18  Date_year       420285 non-null  int64
 19  Date_day        420285 non-null  int64
dtypes: datetime64[ns](1), float64(10), int64(9)
memory usage: 67.3 MB
```

```
# Not so important features.
features_drop=['Unemployment','CPI','MarkDown5']
train=train.drop(features_drop, axis=1)

print('Final train shape:', train.shape)
train.head(2)
```

```
in shape: (420285, 17)
```

Dept	Date	Weekly_Sales	IsHoliday	Temperature	Fuel_Price	MarkDown1	MarkDown2
1	2010-02-05	24924.50	0	42.31	2.572	0.0	0.0
2	2010-02-05	50605.27	0	42.31	2.572	0.0	0.0

```
train = train.sort_values(by='Date', ascending=True) # Sorting the data in increasing orde
y = train['Weekly_Sales']
X = train.drop(['Weekly_Sales'], axis=1)

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3) # Train:Test = 70
X_train, X_cv, y_train, y_cv = train_test_split(X_train, y_train, test_size=0.3) #Train:CV
```

```
# Remove Date column as it does not allow the models to fit on the data.
X_train = X_train.drop(['Date'], axis=1)
X_cv = X_cv.drop(['Date'], axis=1)
```

```
X_test = X_test.drop(['Date'], axis=1)


# Final shapes.
print('Train:', X_train.shape, y_train.shape)
print('CV:', X_cv.shape, y_cv.shape)
print('Test', X_test.shape, y_test.shape)
```

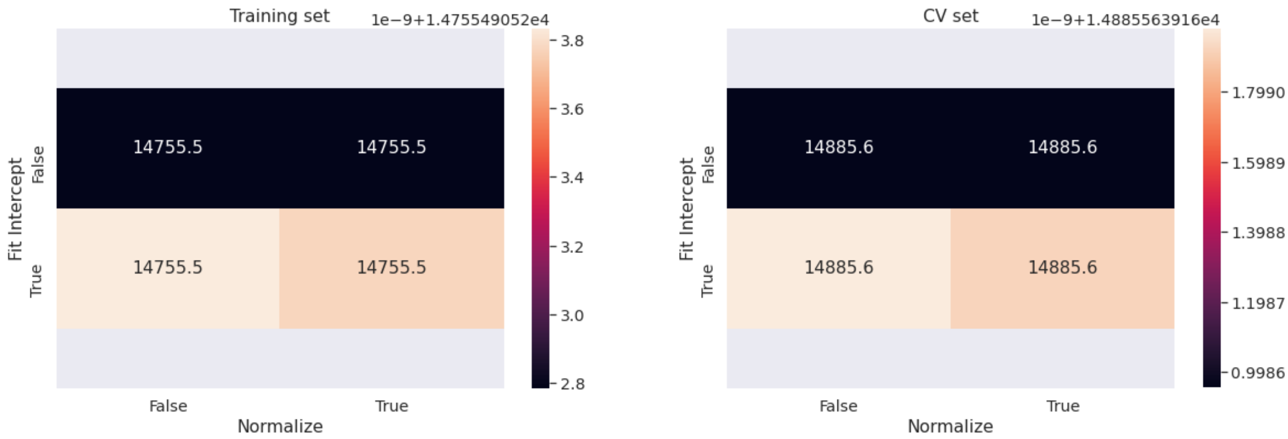
```
Train: (205939, 15) (205939,)
CV: (88260, 15) (88260,)
Test (126086, 15) (126086,)
```

```
"""Define Performance metric - Weighted Mean Absolute Error (WMAE)"""

def wmae_train(test, pred): # WMAE for train
  weights = X_train['IsHoliday'].apply(lambda is_holiday:5 if is_holiday else 1)
  error = np.sum(weights * np.abs(test - pred), axis=0) / np.sum(weights)
  return error

def wmae_cv(test, pred): # WMAE for CV
  weights = X_cv['IsHoliday'].apply(lambda is_holiday:5 if is_holiday else 1)
  error = np.sum(weights * np.abs(test - pred), axis=0) / np.sum(weights)
  return error

def wmae_test(test, pred): # WMAE for test
  weights = X_test['IsHoliday'].apply(lambda is_holiday:5 if is_holiday else 1)
  error = np.sum(weights * np.abs(test - pred), axis=0) / np.sum(weights)
  return error


# Define list of empty train error and cv error.
error_cv_lr = []
error_train_lr = []
fit_intercept = [True,False]
normalize = [True,False]
lr_hyperparams = []

"""Calculating train and CV errors for Fit Intercept and Normalize parameters."""

for i in fit_intercept:
    for j in normalize:
        lr = LinearRegression(fit_intercept=i, normalize=j) # Apply Linear Regression.
        lr.fit(X_train, y_train) # Fit the model.
        y_pred_cv_lr = lr.predict(X_cv) # Predict CV data.
        y_pred_train_lr = lr.predict(X_train) # Predict Train data.
        error_cv_lr.append(wmae_cv(y_cv, y_pred_cv_lr)) # Get CV error.
        error_train_lr.append(wmae_train(y_train, y_pred_train_lr)) # Get Train error.
        lr_hyperparams.append({'Fit Intercept':i, 'Normalize':j}) # Hyperparameters.


"""Making dataframe containing values of hyper parameters with train and cv errors for the

lr_dataframe = pd.DataFrame(lr_hyperparams)
lr_dataframe['Train Error'] = error_train_lr
lr_dataframe['CV Error'] = error_cv_lr
lr_dataframe.sort_values(by=['CV Error'], ascending=True)
```

```
lr_dataframe
```

	Fit Intercept	Normalize	Train Error	CV Error
0	True	True	14755.49052	14885.563916
1	True	False	14755.49052	14885.563916
2	False	True	14755.49052	14885.563916
3	False	False	14755.49052	14885.563916

```
"""Creating heatmaps for Train loss and CV loss."""

sns.set(font_scale=1.3)
train_lr = pd.pivot_table(lr_dataframe,'Train Error','Fit Intercept','Normalize') # Train
cv_lr = pd.pivot_table(lr_dataframe, 'CV Error','Fit Intercept','Normalize') # CV Pivot ta
fig, ax = plt.subplots(1,2, figsize=(20,6))
ax_train = sns.heatmap(train_lr, annot=True, fmt='4g', ax=ax[0]) # Train heatmap.
ax_cv = sns.heatmap(cv_lr, annot=True, fmt='4g', ax=ax[1]) # CV heatmap.

bottom_train, top_train = ax_train.get_ylim()
ax_train.set_ylim(bottom_train + 0.5, top_train - 0.5)

bottom_cv, top_cv = ax_cv.get_ylim()
ax_cv.set_ylim(bottom_cv + 0.5, top_cv - 0.5)

ax[0].set_title('Training set')
ax[1].set_title('CV set')
plt.show()
```




```
"""Calculate Prediction and WMAE score."""

model_linear_reg = LinearRegression(fit_intercept=True,normalize=True).fit(X_train,y_trair
```

```
y_pred = model_linear_reg.predict(X_test) # Predict test data.
print('Weighted Mean Absolute Error (WMAE) for Linear Regression:', wmae_test(y_test, y_pr
```

```
Weighted Mean Absolute Error (WMAE) for Linear Regression: 14781.35040615615
```

```
# # Define the list of errors and list of hyper parameters.
# error_cv_rf = []
# error_train_rf = []
# max_depth = [1,5,10,15,20,25,30,35]
# n_estimators = [10,20,30,40,50,60,70,80]
# rf_hyperparams = []

# """Calculating train and CV errors for maximum depth and number of estimators parameters

# for i in max_depth: # Loop over max_depth.
#     for j in n_estimators: # Loop over n_estimators.
#         rf = RandomForestRegressor(max_depth=i, n_estimators=j) # Apply Random Forest Re
#         rf.fit(X_train, y_train) # Fit the model.
#         y_pred_cv_rf = rf.predict(X_cv) # Predict CV data.
#         y_pred_train_rf = rf.predict(X_train) # Predict Train data.
#         error_cv_rf.append(wmae_cv(y_cv, y_pred_cv_rf)) # Get CV error.
#         error_train_rf.append(wmae_train(y_train, y_pred_train_rf)) # Get Train error.
#         rf_hyperparams.append({'Maximum Depth':i, 'No. of Estimators':j}) # Get list of


"""Calculate Prediction and  WMAE score."""

model_rf = RandomForestRegressor(max_depth= 35, n_estimators=80).fit(X_train, y_train) # F
y_pred = model_rf.predict(X_test) # Predict the test data.
print('Weighted Mean Absolute Error (WMAE) for Random Forest Regression:', wmae_test(y_tes
```

```
Weighted Mean Absolute Error (WMAE) for Random Forest Regression: 1787.0114520444897
```

```
#Reading kaggle provided test file for which the prediction is needed.
test_kaggle = pd.read_csv('test.csv')
test_kaggle.head()
```

	Store	Dept	Date	IsHoliday
0	1	1	2012-11-02	False
1	1	1	2012-11-09	False
2	1	1	2012-11-16	False
3	1	1	2012-11-23	True
4	1	1	2012-11-30	False

```
le.merge(features, on=['Store', 'Date'], how='inner').merge(stores, on=['Store'], how='inn
)

ne column.
```

```
le.drop(['IsHoliday_y'], axis=1)
le.rename(columns={'IsHoliday_x':'IsHoliday'})
mns:\n', test_kaggle.columns)

tetime
d.to_datetime(test_kaggle['Date'])


week'] = test_kaggle['Date'].dt.dayofweek
'] = test_kaggle['Date'].dt.month
] = test_kaggle['Date'].dt.year
 = test_kaggle['Date'].dt.day
```

```
(115064, 16)
Test_Kaggle columns:
 Index(['Store', 'Dept', 'Date', 'IsHoliday', 'Temperature', 'Fuel_Price',
       'MarkDown1', 'MarkDown2', 'MarkDown3', 'MarkDown4', 'MarkDown5', 'CPI',
       'Unemployment', 'Type', 'Size'],
      dtype='object')
```

```
test_kaggle_data = [test_kaggle]

# Converting Categorical Variable 'Type' into Numerical Variables.
type_mapping = {"A": 1, "B": 2, "C": 3}
for dataset in test_kaggle_data:
    dataset['Type'] = dataset['Type'].map(type_mapping)

# Converting Categorical Variable 'IsHoliday' into Numerical Variables.
type_mapping = {False: 0, True: 1}
for dataset in test_kaggle_data:
    dataset['IsHoliday'] = dataset['IsHoliday'].map(type_mapping)
#test = test.drop(['Date'], axis=1)
```

```
# Special holidays.
test_kaggle['Super_Bowl'] = np.where((test_kaggle['Date'] == datetime(2010,2,10)) | (test_
                               (test_kaggle['Date'] == datetime(2012,2,10)) | (test_kaggle
test_kaggle['Labor_day'] = np.where((test_kaggle['Date'] == datetime(2010,9,10)) | (test_k
                              (test_kaggle['Date'] == datetime(2012,9,7)) | (test_kaggle['
test_kaggle['Thanksgiving'] = np.where((test_kaggle['Date']==datetime(2010, 11, 26)) | (te
                                 (test_kaggle['Date']==datetime(2012, 11, 23)) | (test_kag
test_kaggle['Christmas'] = np.where((test_kaggle['Date']==datetime(2010, 12, 31)) | (test_
                              (test_kaggle['Date']==datetime(2012, 12, 28)) | (test_kaggle
```

```
# Since we have Imputed IsHoliday according to Extra holidays..These extra holiday variabl
# Dropping the Extra holiday variables because its redundant.
dp = ['Super_Bowl','Labor_day','Thanksgiving','Christmas']
test_kaggle.drop(dp, axis=1, inplace=True)
```

```
test_kaggle = test_kaggle.fillna(0) # Filling null values with 0.
```

```
test_kaggle.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 115064 entries, 0 to 115063
Data columns (total 19 columns):
 #   Column          Non-Null Count   Dtype
---  ------          --------------   -----
 0   Store           115064 non-null  int64
 1   Dept            115064 non-null  int64
 2   Date            115064 non-null  datetime64[ns]
 3   IsHoliday       115064 non-null  int64
 4   Temperature     115064 non-null  float64
 5   Fuel_Price      115064 non-null  float64
 6   MarkDown1       115064 non-null  float64
 7   MarkDown2       115064 non-null  float64
 8   MarkDown3       115064 non-null  float64
 9   MarkDown4       115064 non-null  float64
 10  MarkDown5       115064 non-null  float64
 11  CPI             115064 non-null  float64
 12  Unemployment    115064 non-null  float64
 13  Type            115064 non-null  int64
 14  Size            115064 non-null  int64
 15  Date_dayofweek  115064 non-null  int64
 16  Date_month      115064 non-null  int64
 17  Date_year       115064 non-null  int64
 18  Date_day        115064 non-null  int64
dtypes: datetime64[ns](1), float64(9), int64(9)
memory usage: 17.6 MB
```

```
# Removing unimportant features.
features_drop=['Unemployment','CPI','MarkDown5']
test_kaggle = test_kaggle.drop(features_drop, axis=1)
```

```
#Excluding Date as it throws error while making prediction.
test_kaggle = test_kaggle.loc[:, test_kaggle.columns != 'Date']
```

```
print('Final test_kaggle shape:', test_kaggle.shape)
test_kaggle.head(2)
```

Final test_kaggle shape: (115064, 15)

	Store	Dept	IsHoliday	Temperature	Fuel_Price	MarkDown1	MarkDown2	MarkDown3
0	1	1	0	55.32	3.386	6766.44	5147.7	50.82
1	1	2	0	55.32	3.386	6766.44	5147.7	50.82

```
y=train["Weekly_Sales"]
y
```

```
0         24924.50
330761    14612.19
330762    26323.15
330763    36414.63
330764    11437.81
            ...
```

```
330702     8930.71
330703     4841.81
330704     7035.13
330706     2124.60
421569     1076.80
Name: Weekly_Sales, Length: 420285, dtype: float64
```

```
traincopy=train.copy()
traincopy
```

ales	IsHoliday	Temperature	Fuel_Price	MarkDown1	MarkDown2	MarkDown3	MarkDown4
24.50	0	42.31	2.572	0.00	0.00	0.0	0.00
12.19	0	27.19	2.784	0.00	0.00	0.0	0.00
23.15	0	27.19	2.784	0.00	0.00	0.0	0.00
14.63	0	27.19	2.784	0.00	0.00	0.0	0.00
37.81	0	27.19	2.784	0.00	0.00	0.0	0.00
...	...	...	...	...	...	...	...
30.71	0	57.95	3.514	1151.88	68.01	3.0	392.12
41.81	0	57.95	3.514	1151.88	68.01	3.0	392.12
35.13	0	57.95	3.514	1151.88	68.01	3.0	392.12
24.60	0	57.95	3.514	1151.88	68.01	3.0	392.12
76.80	0	58.85	3.882	4018.91	58.08	100.0	211.94

```
traincopy=traincopy.drop(['Weekly_Sales'],axis=1)
traincopy
```

	Store	Dept	Date	IsHoliday	Temperature	Fuel_Price	MarkDown1	MarkDown2
0	1	1	2010-02-05	0	42.31	2.572	0.00	0.00
330761	35	3	2010-02-05	0	27.19	2.784	0.00	0.00
330762	35	4	2010-02-05	0	27.19	2.784	0.00	0.00
330763	35	5	2010-02-05	0	27.19	2.784	0.00	0.00
330764	35	6	2010-02-05	0	27.19	2.784	0.00	0.00
...	...	...	...	...	...	...	...	...
330702	34	14	2012-10-26	0	57.95	3.514	1151.88	68.01
330703	34	16	2012-10-26	0	57.95	3.514	1151.88	68.01
330704	34	17	2012-	0	57.95	3.514	1151.88	68.01

```
#traincopy['Date']=traincopy['Date'].map(datetime.toordinal)
traincopy=traincopy.drop(["Date"],axis=1)
traincopy.dtypes
```

```
Store                int64
Dept                 int64
IsHoliday            int64
Temperature        float64
Fuel_Price         float64
MarkDown1          float64
MarkDown2          float64
MarkDown3          float64
MarkDown4          float64
Type                 int64
Size                 int64
Date_dayofweek       int64
Date_month           int64
Date_year            int64
Date_day             int64
dtype: object
```

```
test_kaggle.dtypes
```

```
Store                int64
Dept                 int64
IsHoliday            int64
Temperature        float64
Fuel_Price         float64
MarkDown1          float64
MarkDown2          float64
MarkDown3          float64
MarkDown4          float64
Type                 int64
Size                 int64
```

```
Date_dayofweek      int64
Date_month          int64
Date_year           int64
Date_day            int64
dtype: object
```

```
# Applying Random Forest to kaggle provided test file with the best hyper parameter values
model_rf = RandomForestRegressor(max_depth= 35, n_estimators=80).fit(traincopy,y) # Fit th
y_pred = model_rf.predict(test_kaggle) # Predict the final test data that Kaggle has provi
```

```
y_pred
```

```
array([32948.22075 , 47799.968625, 11268.084125, ..., 59429.562   ,
        6617.98075 ,   734.398125])
```

```
test_kaggle_final=pd.read_csv('test.csv')
test_kaggle_final
```

	Store	Dept	Date	IsHoliday
0	1	1	2012-11-02	False
1	1	1	2012-11-09	False
2	1	1	2012-11-16	False
3	1	1	2012-11-23	True
4	1	1	2012-11-30	False
...	...	...	...	...
115059	45	98	2013-06-28	False
115060	45	98	2013-07-05	False
115061	45	98	2013-07-12	False
115062	45	98	2013-07-19	False
115063	45	98	2013-07-26	False

115064 rows × 4 columns

```
finalpred = pd.DataFrame({
        "Store_Dept_Date": test_kaggle_final.Store.astype(str)+'_'+test_kaggle_final.Dept.
        "Weekly_Sales": y_pred # This is predicetd Weekly Sales on final test data using F
    })

finalpred.to_csv('Weekly Sales Prediction.csv', index=False)
```

```
finalpred
```

	Store_Dept_Date	Weekly_Sales
0	1_1_2012-11-02	32948.220750
1	1_1_2012-11-09	47799.968625
2	1_1_2012-11-16	11268.084125
3	1_1_2012-11-23	39139.680375
4	1_1_2012-11-30	31703.801500
...	...	...
115059	45_98_2013-06-28	3839.315500
115060	45_98_2013-07-05	4314.053625
115061	45_98_2013-07-12	59429.562000
115062	45_98_2013-07-19	6617.980750
115063	45_98_2013-07-26	734.398125

115064 rows × 2 columns

✓ 0s completed at 6:46 PM