Case Type: B2B Demand forecasting of a particular product

Use and context of the data

The dataset contains historical product demand for a manufacturing company with footprints globally. The company provides thousands of products within dozens of product categories. There are four central warehouses to ship products within the region it is responsible for. Since the products are manufactured in different locations all over the world, it normally takes more than one month to ship products via ocean to different central warehouses. If forecasts for each product in different central with reasonable accuracy for the monthly demand for month after next can be achieved, it would be beneficial to the company in multiple ways.

Import modules and data

In [24]:
```
import math
from sklearn.metrics import mean_squared_error
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
dataframe = pd.read_csv("Historical Product Demand.csv")
dataframe.head()
```

Out[24]:

	Product_Code	Warehouse	Product_Category	Date	Order_Demand
0	Product_0993	Whse_J	Category_028	2012/7/27	100
1	Product_0979	Whse_J	Category_028	2012/1/19	500
2	Product_0979	Whse_J	Category_028	2012/2/3	500
3	Product_0979	Whse_J	Category_028	2012/2/9	500
4	Product_0979	Whse_J	Category_028	2012/3/2	500

Count of Products by grouping

In [25]:
```
dataframe_grouped = dataframe.groupby(['Product_Code']).size().rese
t_index(name='counts').sort_values(['counts'],ascending=False)
dataframe_grouped.head()
```

Out[25]:

	Product_Code	counts
1348	Product_1359	16936
1284	Product_1295	10575
1367	Product_1378	9770
619	Product_0620	9428
1275	Product_1286	8888

Select a product to work on this project

We will be working on demand forecasting of product 1359 as it has the highest count. There is no particular way of choosing a product and any of the above products can be worked upon for its demand forecasting

We do not need the details of 'Warehouse', 'Product Code' and 'Product Category' for demand forecasting. All we need is the demand and time(date)

In [26]:
```
dataframe_for_product1359 = dataframe.loc[dataframe['Product_Code']
== 'Product_1359'].sort_values(['Date'],ascending=False)
dataframe_for_product1359=dataframe_for_product1359.drop(columns=['
Warehouse','Product_Code','Product_Category'])
dataframe_for_product1359.head()
```

Out[26]:

	Date	Order_Demand
921328	2017/1/6	100000
863636	2016/9/9	9000
893829	2016/9/9	40000
1013066	2016/9/9	2000
863593	2016/9/9	1000

Creating the major axis-that is Time. All the data will now be indexed in terms of time.

In [27]:
```
dataframe_for_product1359.index=pd.to_datetime(dataframe_for_product1359.Date,format='%Y/%m/%d')
dataframe_for_product1359.drop(columns=['Date'],inplace=True)
dataframe_for_product1359.head(2)
```

Out[27]:

	Order_Demand
Date	
2017-01-06	100000
2016-09-09	9000

Formatting

In [28]:
```
dataframe_for_product1359['Order_Demand'] = dataframe_for_product1359['Order_Demand'].astype(str)
dataframe_for_product1359['Order_Demand'] = dataframe_for_product1359['Order_Demand'].map(lambda x: x.lstrip('(').rstrip(')'))
dataframe_for_product1359['Order_Demand'] = dataframe_for_product1359['Order_Demand'].astype(int)
dataframe_for_product1359.head()
```

Out[28]:

	Order_Demand
Date	
2017-01-06	100000
2016-09-09	9000
2016-09-09	40000
2016-09-09	2000
2016-09-09	1000

Determining Monthly Demand

Get the demand in terms of January, February.....December

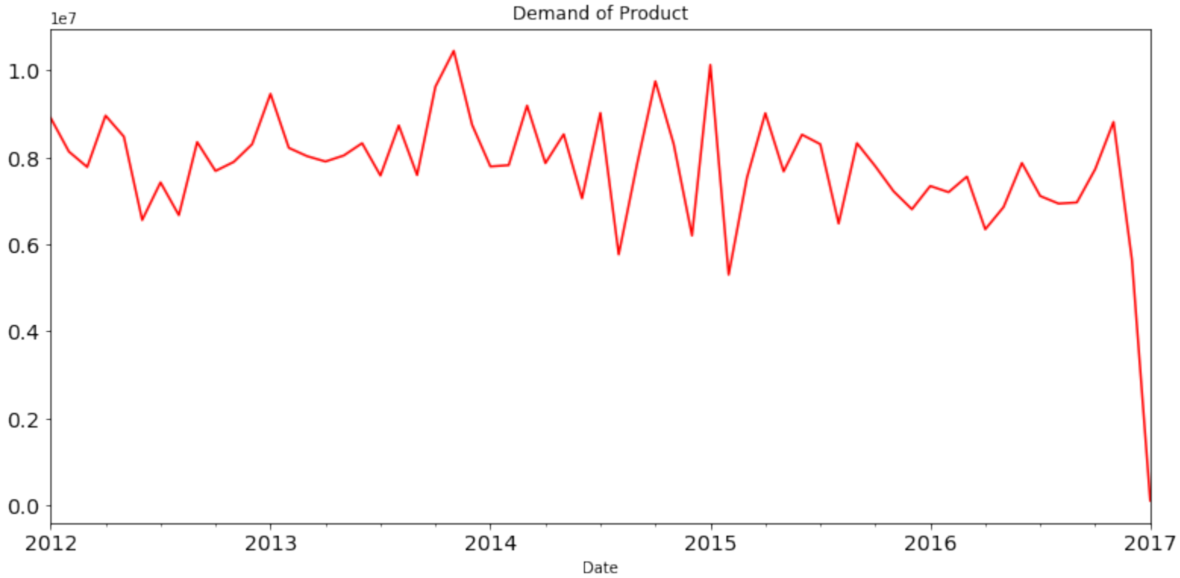
In [54]:
```
dataframe_for_product1359_Monthly= dataframe_for_product1359.resample('M').sum()
dataframe_for_product1359_Monthly.head()
```

Out[54]:

	Order_Demand
Date	
2012-01-31	8911000
2012-02-29	8131000
2012-03-31	7775000
2012-04-30	8960000
2012-05-31	8475000

Note that the sharp dip in 2017 is due to the data being incomplete in 2017

In [30]:
```
dataframe_for_product1359_Monthly.Order_Demand.plot(figsize=(13,6),
title= 'Demand of Product', fontsize=14,color="Red")
plt.show()
```



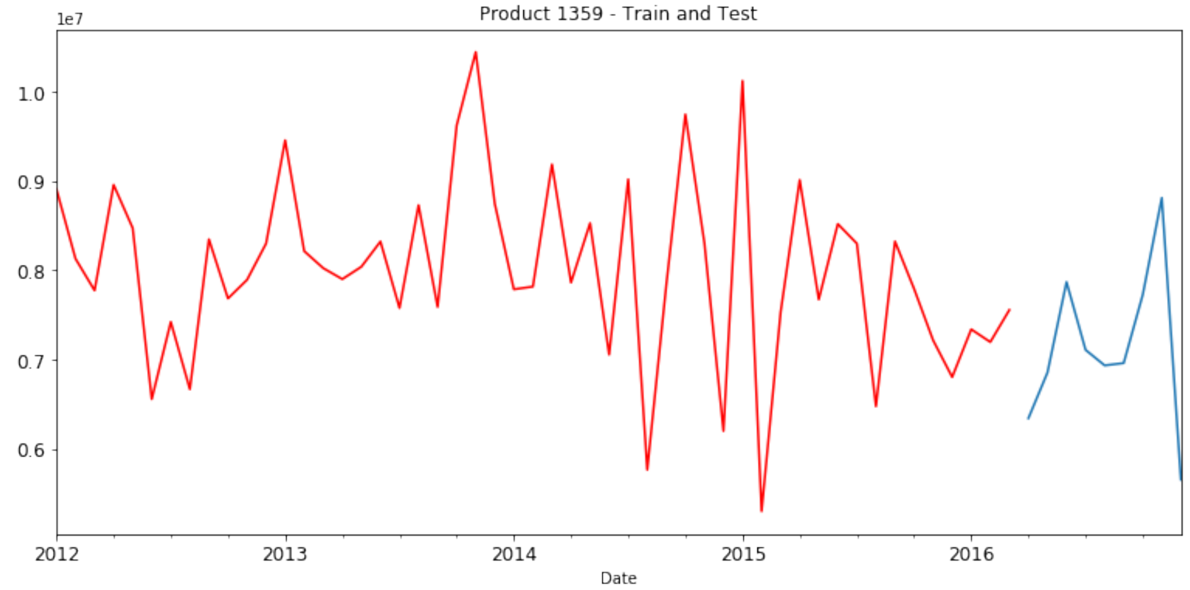
Create Train and Test Data

Last 10 months make up the test data

In [31]:
```
Demand_for_1359_Train = dataframe_for_product1359_Monthly[:'2016-03
-31']
Demand_for_1359Test = dataframe_for_product1359_Monthly['2016-04-30
':'2016-12-31']
```

Demand for product 1359

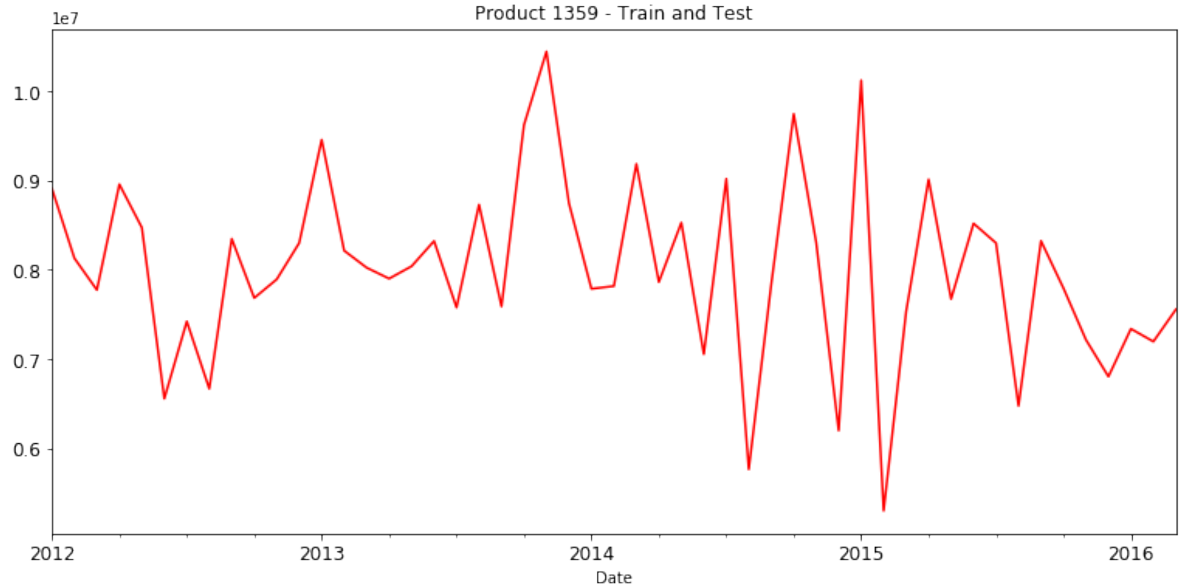
In [56]:
```
Demand_for_1359_Train.Order_Demand.plot(figsize=(13,6), title= 'Pro
duct 1359 - Train and Test', fontsize=12,color="Red")
Demand_for_1359Test.Order_Demand.plot(figsize=(13,6), title= 'Produ
ct 1359 - Train and Test', fontsize=12)
plt.show()
```



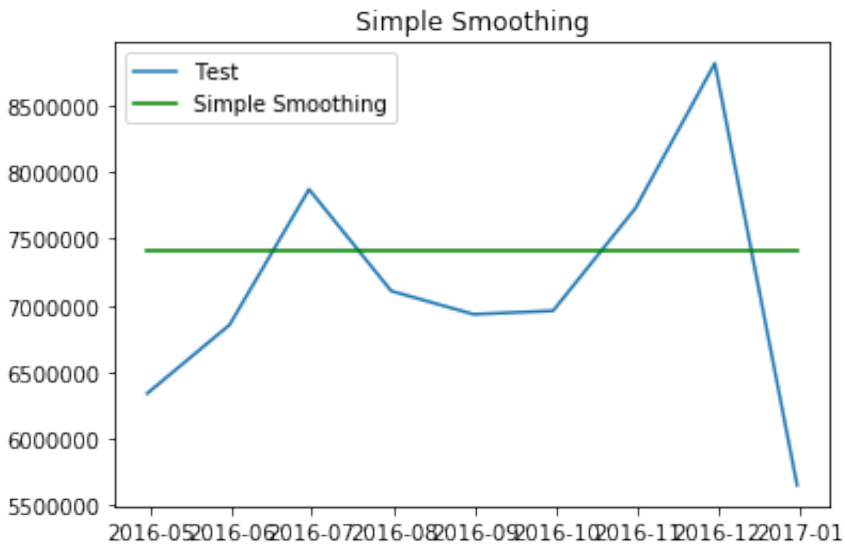
Simple Smoothing

In [49]:
```
from statsmodels.tsa.api import ExponentialSmoothing, SimpleExpSmoo
thing, Holt
y_hat_avg = Demand_for_1359Test.copy()
fit2 = SimpleExpSmoothing(np.asarray(Demand_for_1359_Train['Order_D
emand'])).fit(smoothing_level=0.6,optimized=False)
y_hat_avg['SES'] = fit2.forecast(len(Demand_for_1359Test))
```

In [50]:
```
Demand_for_1359_Train.Order_Demand.plot(figsize=(13,6), title= 'Pro
duct 1359 - Train and Test', fontsize=12,color="Red")
plt.plot(Demand_for_1359_Train['Order_Demand'], label='Train',color
="Red")
plt.show()
```



In [57]:
```
plt.plot(Demand_for_1359Test['Order_Demand'], label='Test')
plt.plot(y_hat_avg['SES'], label='Simple Smoothing',color="Green")
plt.title("Simple Smoothing")
plt.legend(loc='best')
plt.show()
```



Root mean square error calculation

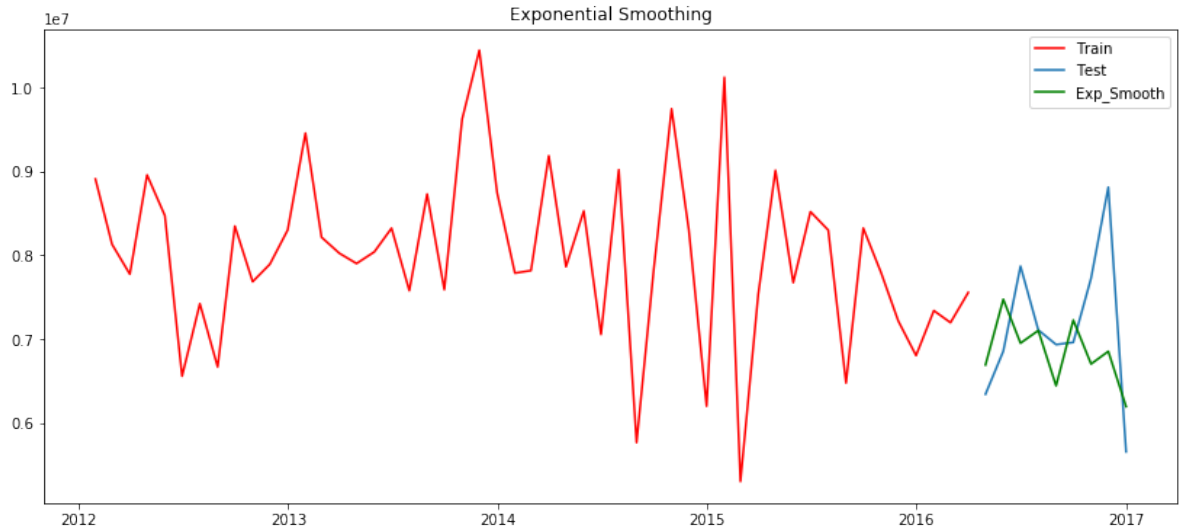
In [34]:
```
smooth_rms = math.sqrt(mean_squared_error(Demand_for_1359Test.Order
_Demand, y_hat_avg.SES))
print(smooth_rms)
```

```
905476.4628886498
```

Exponential Smoothing

Exponential smoothing uses the weighted average of previous observations where more weight is given to the most recent observations and the weight decreases as observations get older.

In [38]:
```
exp_hat_avg = Demand_for_1359Test.copy()
fit1 = ExponentialSmoothing(np.asarray(Demand_for_1359_Train['Order
_Demand']) ,seasonal_periods=4 ,trend='additive', seasonal='additiv
e',).fit()
exp_hat_avg['Exp_Smooth'] = fit1.forecast(len(Demand_for_1359Test))
plt.figure(figsize=(14,6))
plt.plot( Demand_for_1359_Train['Order_Demand'], label='Train',colo
r="Red")
plt.plot(Demand_for_1359Test['Order_Demand'], label='Test')
plt.plot(exp_hat_avg['Exp_Smooth'], label='Exp_Smooth',color="Green
")
plt.legend(loc='best')
plt.title("Exponential Smoothing");
plt.show()
```



Root mean square error calculation

In [58]:
```
exp_rms = math.sqrt(mean_squared_error(Demand_for_1359Test.Order_Demand, exp_hat_avg.Exp_Smooth))
print(exp_rms)
```

```
872760.1292784497
```

In [ ]: