Unit sales Predictions

Capstone 1 Report

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https://github.com/Mokonzi4n/Springboard/tree/master/Capstone_Project_1

Background: Solar Industry Fuse requirement

- The solar industry has grown exponentially from 40GW in 2010 - 531GW in 2018 cumulatively. It is projected to reach 1.27 TW in 2022
- The energy produced by the sun is converted to electrical energy by solar panels. These are connected in series to attain the required voltage and in parallel to provide the required current.
- At the levels of parallel connections fuses are used to protect the panels. Additionally, fuses are needed to protect wire that is used to carry current from the points of parallel connection to the inverter where this current is converted from direct current (DC) to alternating current (AC).
- This implies Utility scale solar installations would require thousands of fuses per installation. For instance a 1MW installation will require approximate 1300 fuses.

Problem

- The solar industry is project based, seasonal and policy driven. Slight changes in policy like increase in tariffs or changes in Federal Incentive Tax Credits completely change the annual expectations of the market. Making it very erratic and unpredictable.
- Additionally the project length and time to fuse requirement varies greatly from one project to another. And for most projects, by the time the fuses are needed in the field, the fuse manufacturers are required to respond within 2-4 weeks else would lose tens of thousands of dollars to competition having fuses on the shelve.
- The normal lead time for 5000 fuses is 3-4 weeks if there are no raw materials already purchased or finished goods on the shelf. This makes planning and manufacturing of fuses to meet customer needs highly dependent on customer input and forecasts.

Project Motivation: Forecasting Demand

- Planners and Production Managers of Manufacturing companies are faced with the difficulty year in year out to plan and budget for raw materials to be used to build finished goods for the following year.
- They have to estimate or plan according to forecasts provided by the sales teams, volume done in the previous year and market data.
- Inaccurate estimates or information from the sales teams lead to situations where demand cannot be met in a timely manner due to under-stocking of finished goods and low inventory of raw materials. In other cases there could be demand drop-off for a part and hence an overstock on raw materials. This leads to scrapping finished goods and increased operating costs.
- Demand forecasting is the estimation of the probable demand of a product or service in the future and it is based on the analysis of passed demand and aspects of the market for the specific product or service.
- This is useful in making business decisions related to sales, production, staff requirement etc. in especially new and emergent markets which are usually competitive and hard to predict.
- The effectiveness of business decisions is highly dependent on the accuracy of the information gathered with respect to the market and business. This accuracy is dependent on that of the demand forecasts especially when related to sales, production etc.
- Having accurate forecasts in the solar industry for fuse manufacturers will be very important in helping with production planning, process selection, capacity planning, inventory management, facility layout planning. It will provide reasonable data for the organization's capital investment and expansion decision.
- Using Data Science techniques to implement models that analyze sales data and provide accurate or close to accurate predictions of monthly sales will be an invaluable tool in the hands of different functional teams within any business organization
- The main clients would be sales, production and planning teams of manufacturing industries that want to be leaner in their budgeting and planning for production, to minimize risks and losses due to under or over estimating annual product sales

Data Science Approach

- Export data from the SAP business operations software in an excel format.
- Wrangle the data in pandas to eliminate any bad and irrelevant data or outliers.
- Do an EDA on the data to determine if there are any trends by year, month, by region, and by SKU.
- Use 4 years (2014 - 2017) of data as the training data set in the ARIMA model
- Test the ARIMA model on the 5th year (2018).
- Refine the model as needed until predicted sales data by the model is as close as possible to the actual 2018 sales

Data Set

- Fives years (2014 - 2018) of global sales units data by month, by quarter and by region of all product SKUs sold into the renewable energy industry specifically PV solar.

Data Wrangling

- Tidy Data Format:
  Before pulling the data into a .csv file, features of the business operating software were used to arrange the data in a tidy format where columns represent separate variables and each row represents individual observations.

	Quote	End Customer	Product Hierarchy	Product Family	Geographic Region	Sold-to party	Distributor	Part Number	Month of Year	Quarter of Year	Day	Net Inv Qty	Net Inv-$
0	D05013	*SANMINA/ARROW YRLY 2013	PPF650NA09 ZZ	Midgit KLKD	US/CAN	306110	ARROW PEMCO GROUP	KLKD030.T	Period 01 2014	20141	2014-01-01 00:00:00	NaN	-25086.51
1	JPIS012	SUN-WA TECHNOS(DAIHEN)	PPF650NA09 ZZ	Midgit KLKD	ASIA	405253	FUJIX CO., LTD.	KLKD005.T	Period 01 2014	20141	2014-01-01 00:00:00	200.0	558.93

- Inconsistent Column Names: Converted “Month of Year” rows into date time format and renamed it “Month” and “Quarter of Year” into “Quarter” with alphanumeric representations (i.e. Q1, Q2, Q3, Q4).

	End Customer	Product Hierarchy	Product Family	Geographic Region	Sold-to party	Distributor	Part Number	Month	Year	Quarter	Day	Net Inv Qty	Net Inv-$
0	*SANMINA/ARROW YRLY 2013	PPF650NA09 ZZ	Midgit KLKD	US/CAN	306110	ARROW PEMCO GROUP	KLKD030.T	1	2014	Q1	2014-01-01 00:00:00	NaN	-25086.51
1	SUN-WA TECHNOS(DAIHEN)	PPF650NA09 ZZ	Midgit KLKD	ASIA	405253	FUJIX CO., LTD.	KLKD005.T	1	2014	Q1	2014-01-01 00:00:00	200.0	558.93

Data Wrangling

- Missing data:

  Ran the .info() attribute and realized the "Net Inv Qty column had some missing data. There are 3764 missing values on the Qty column. We apply the dropna() method to drop all missing value rows

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 29916 entries, 0 to 29915
Data columns (total 13 columns):
End Customer          29916 non-null object
Product Hierarchy     29916 non-null object
Product Family        29916 non-null object
Geographic Region     29916 non-null object
Sold-to party         29916 non-null int64
Distributor           29916 non-null object
Part Number           29916 non-null object
Month                 29916 non-null int64
Year                  29916 non-null int64
Quarter               29916 non-null object
Day                   29916 non-null object
Net Inv Qty           26152 non-null float64
Net Inv-$             29916 non-null float64
dtypes: float64(2), int64(3), object(8)
memory usage: 3.0+ MB
```

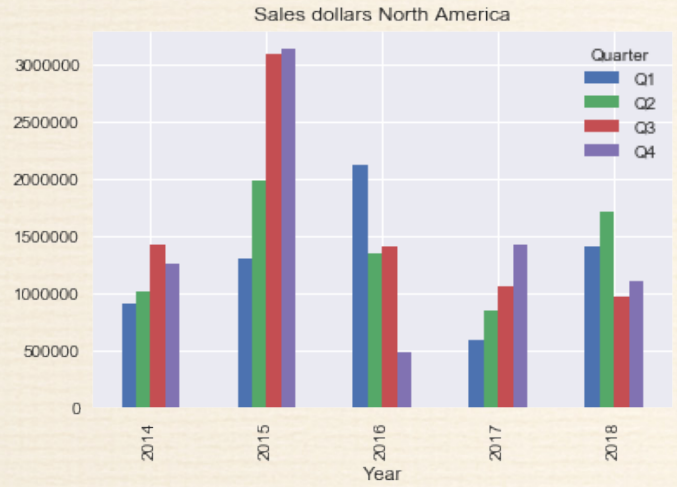
```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 26152 entries, 1 to 29915
Data columns (total 13 columns):
End Customer          26152 non-null object
Product Hierarchy     26152 non-null object
Product Family        26152 non-null object
Geographic Region     26152 non-null object
Sold-to party         26152 non-null int64
Distributor           26152 non-null object
Part Number           26152 non-null object
Month                 26152 non-null int64
Year                  26152 non-null int64
Quarter               26152 non-null object
Day                   26152 non-null object
Net Inv Qty           26152 non-null float64
Net Inv-$             26152 non-null float64
dtypes: float64(2), int64(3), object(8)
memory usage: 2.8+ MB
```

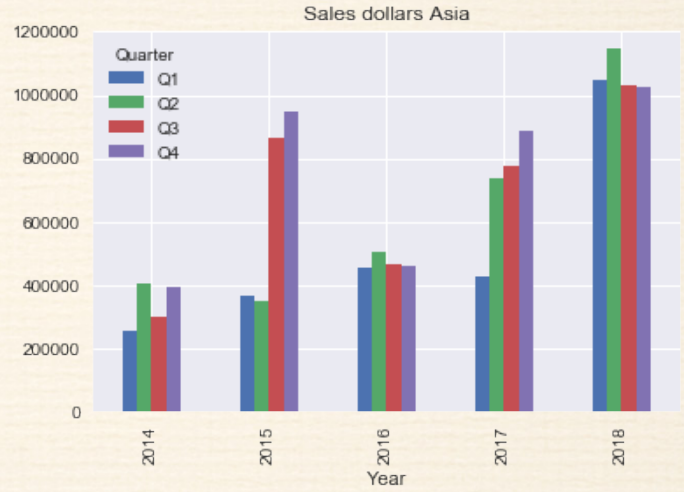
```
 10.0     5342
NaN       3764
 20.0     2377
 100.0    2101
 30.0     1163
Name: Net Inv Qty, dtype: int64
```

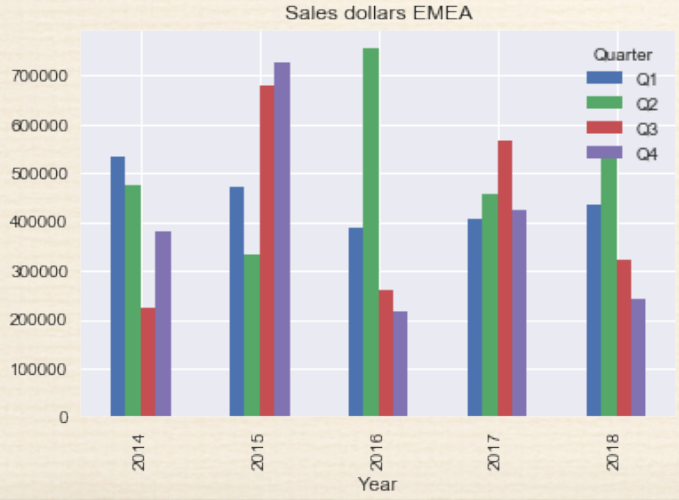
```
10.0     5342
20.0     2377
100.0    2101
30.0     1163
50.0     1134
Name: Net Inv Qty, dtype: int64
```

Data Story Telling

- Regional Comparisons by Quarter:
  - The strongest markets are the US and Asia followed by Europe and then Latin America
  - 2015 was a great year for both US and Asia markets but 2016 saw a steep decline in these markets
  - Since 2014 Europe has been on a consistent decline in units sold while Latin America has been growing slowly having a remarkable quarter in Q3 of 2018

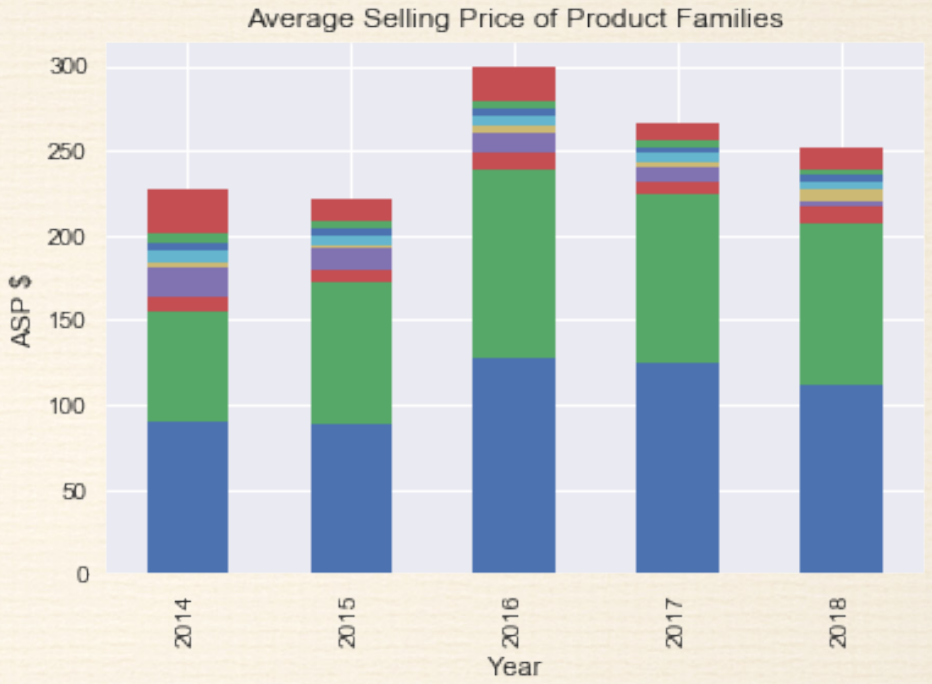






Data Story Telling

- Product Family Comparison:
  - The average selling prices overall have fluctuated but have seen a drop over the years.
  - Comparing only product families sold across the 5 years we have that 2016 was the highest year of ASPs but has seen a decline across all product families since then

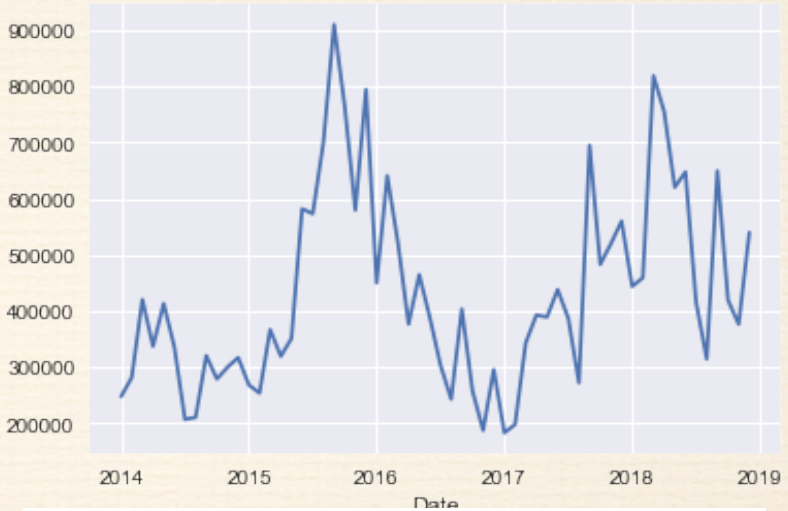


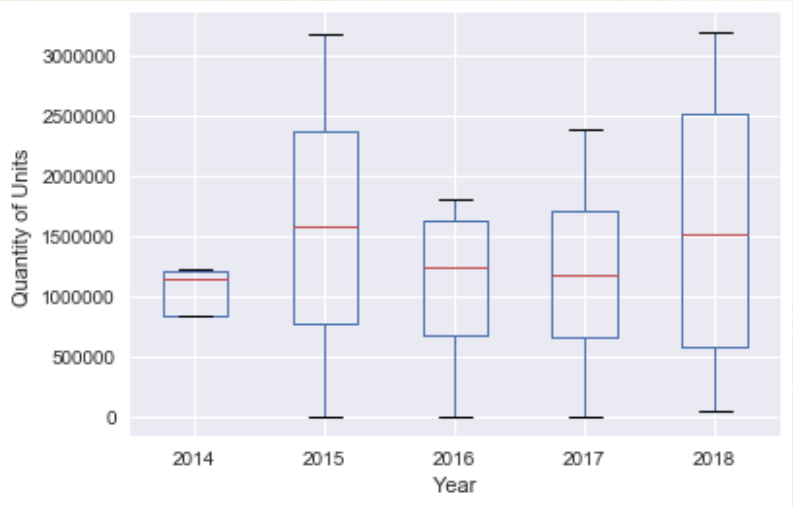
Exploratory Data Analysis

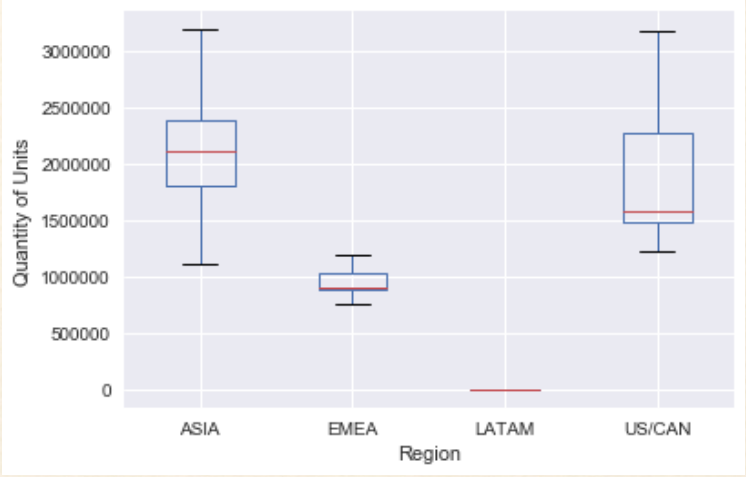
- The main objective is to analyze the data to understand any trends and patterns and to be able to use the first four years to forecast the fifth year.

- Looking at the figure it is clear that the best years so far have been 2015 and 2018. The most variability in terms of quantity sold across the 4 regions is in 2018. The biggest markets have been Asia and the US

	Net Inv Qty				
Year	**2014**	**2015**	**2016**	**2017**	**2018**
count	4.000000e+00	4.000000e+00	4.000000e+00	4.000000e+00	4.000000e+00
mean	8.824770e+05	1.582397e+06	1.070201e+06	1.188924e+06	1.566689e+06
std	5.887321e+05	1.369326e+06	8.072041e+05	1.002952e+06	1.426316e+06
min	2.512000e+03	2.460000e+03	3.296000e+03	6.870000e+03	4.747500e+04
25%	8.312208e+05	7.788308e+05	6.765260e+05	6.623700e+05	5.764935e+05
50%	1.152010e+06	1.573098e+06	1.240136e+06	1.179558e+06	1.516326e+06
75%	1.203266e+06	2.376664e+06	1.633811e+06	1.706111e+06	2.506521e+06
max	1.223376e+06	3.180932e+06	1.797236e+06	2.389709e+06	3.186628e+06

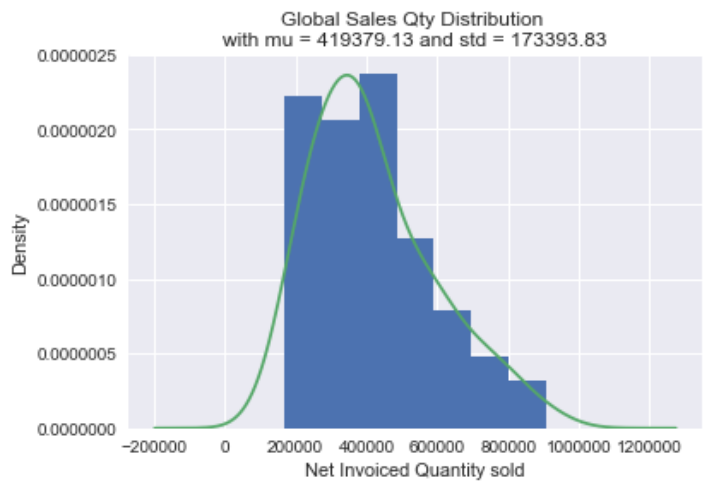


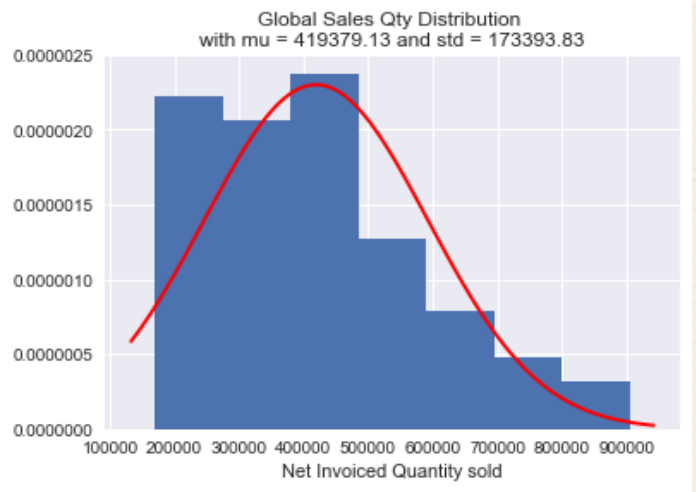


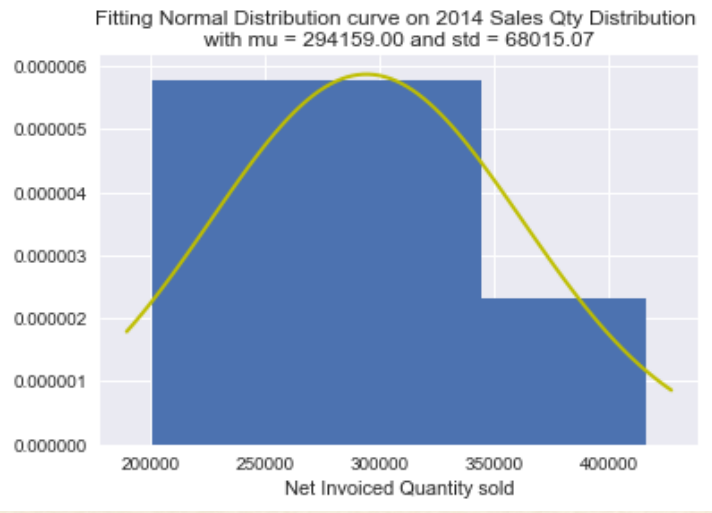


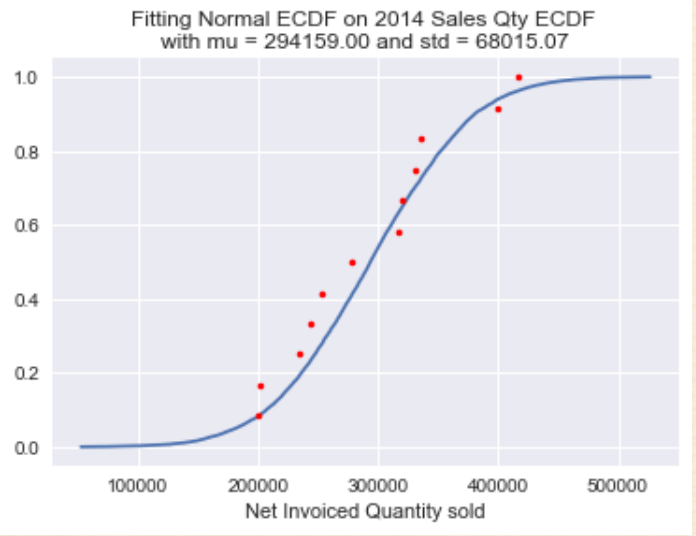
Exploratory Data Analysis

- Global Quantity Sales Distribution: Doing a normality test and plotting the distribution of the total quantity sold globally for the 5 years of data, it gives a right skewed distribution. Which indicates that there are fewer months in which the very high quantities were bought.



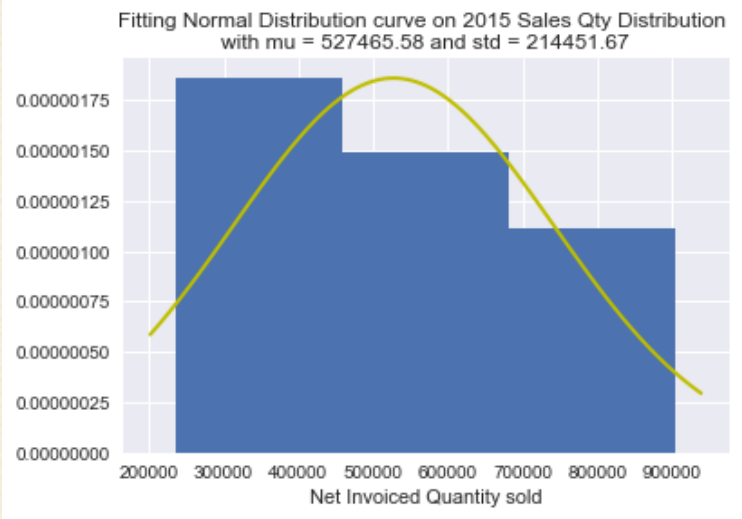


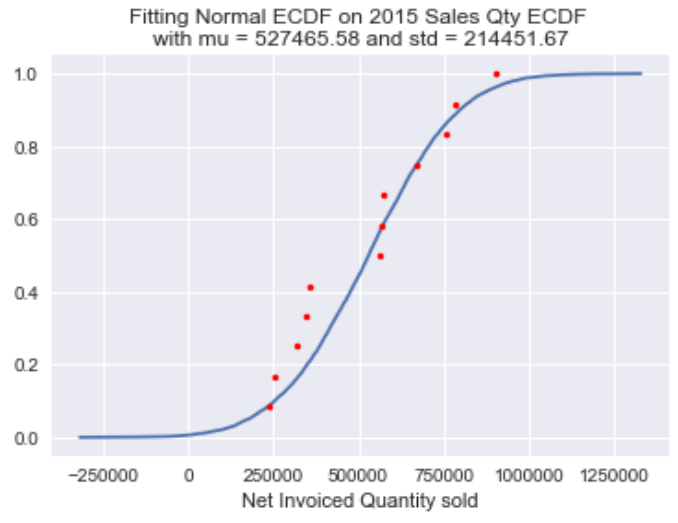


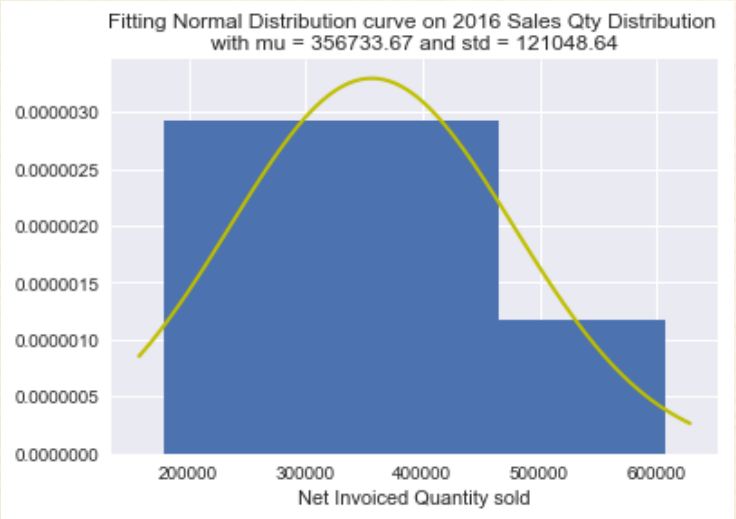


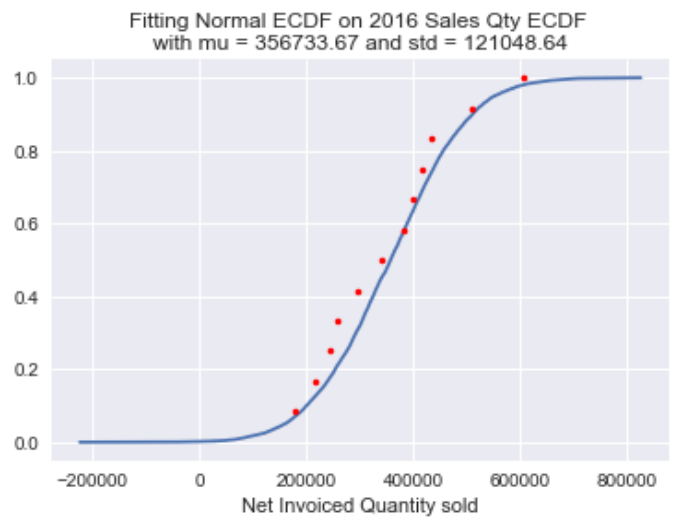
Exploratory Data Analysis

- The data varies greatly from year to year and there does not seem to be a specific trend in the sales quantities. The distribution of the sales quantity by year also is not normal..

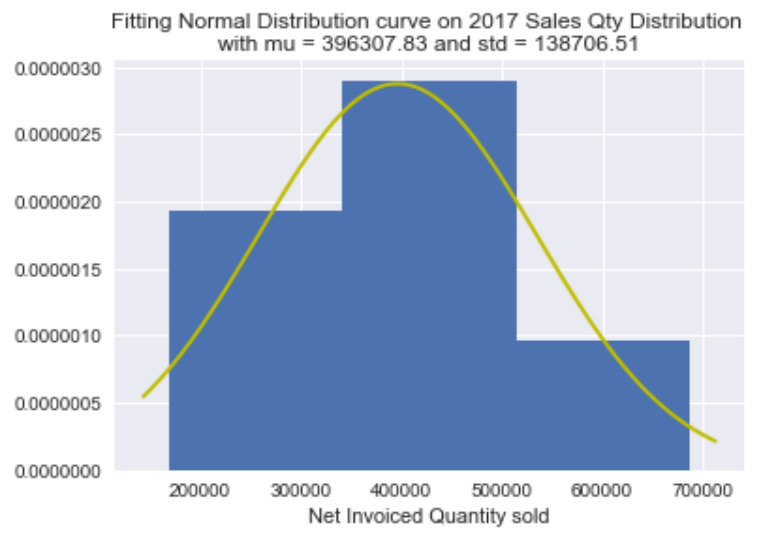


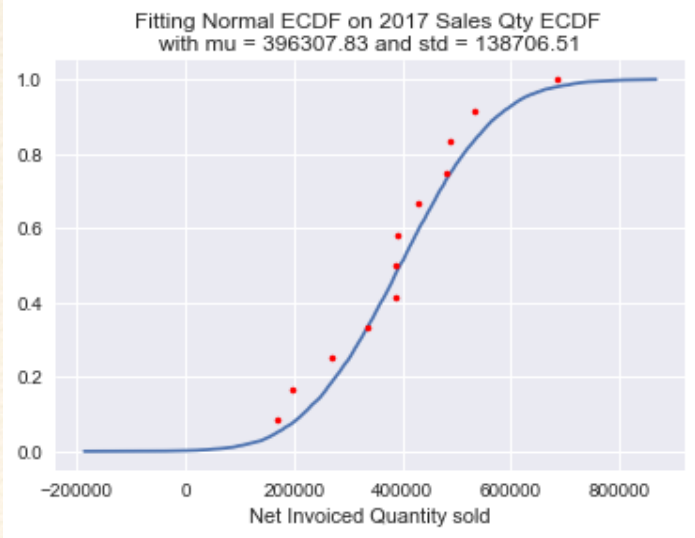


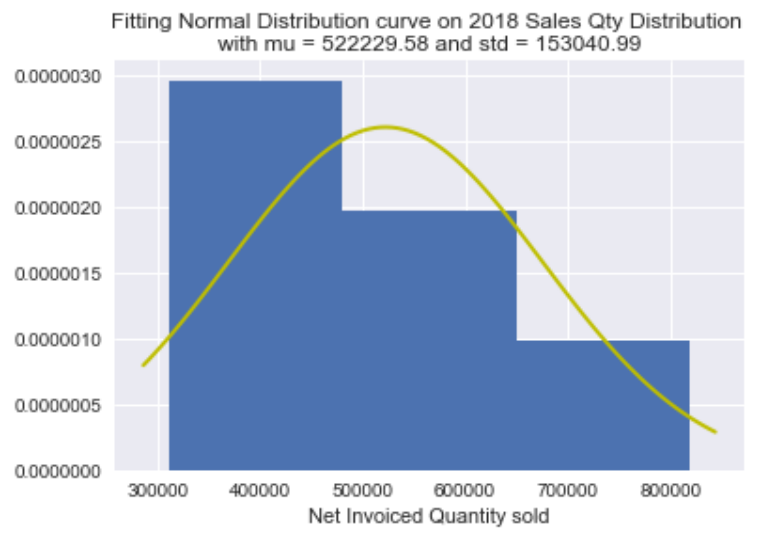


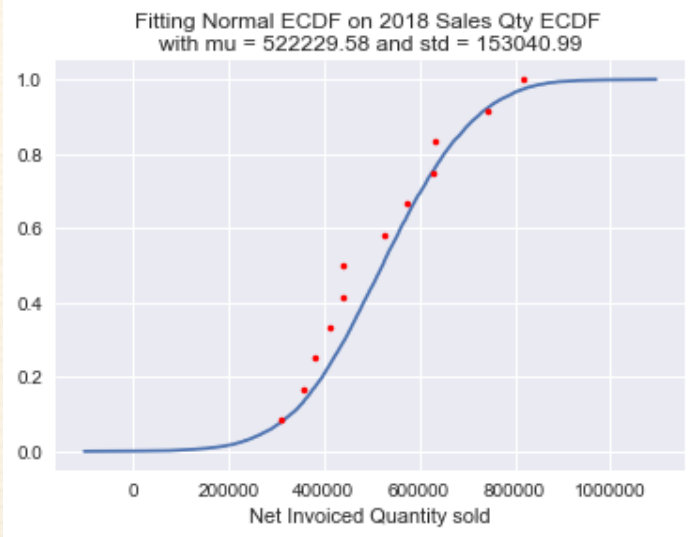


Exploratory Data Analysis









- To better forecast the sales quantities, we will need to account for the variability and seasonality of the data. One of the ways to do this is to use an ARIMA model.