Supply_Chain_Analytics (1)

May 10, 2025

[ ]:
```
# Load all the modules we need
# For plotting
import matplotlib.pyplot as plt
import matplotlib
import seaborn as sns
import datetime

# For ML
import sklearn

# For data manipulation
import numpy as np
import pandas as pd

# This makes all the plots to be shown within jupyter
%matplotlib inline
# Setting the default plot size
matplotlib.rcParams['figure.figsize'] = (20.0, 10.0)
```

First load the Excel sheet using pandas and then load each page into a new data frame

[ ]:
```
xlsx = pd.ExcelFile('Project.xlsx')
```

[ ]:
```
customer_order = xlsx.parse('customer order')
material_master = xlsx.parse('Material Master')
sales_past_demand = xlsx.parse('sales past demand')
customer_master = xlsx.parse('Customer Master')
invoice = xlsx.parse('Invoice')
stock_master = xlsx.parse('stock master')
delivery_data = xlsx.parse('Delivery data')
booking_data = xlsx.parse('Booking details')
```

1 Pre-processing of data

1.1 customer order

[ ]:
```
pd.isnull(customer_order).describe()
```

[ ]:
```
         SONO   ITEM   PTNO   DESC   DATE ORD_QTY   CUST   PLNT  Price  \
count   39398  39398  39398  39398  39398   39398  39398  39398  39398
unique      1      1      1      1      1       1      1      2      1
top     False  False  False  False  False   False  False  False  False
freq    39398  39398  39398  39398  39398   39398  39398  39388  39398

       customer PO ref PO date
count            39398   39398
unique               1       1
top              False   False
freq             39398   39398
```

There is some missing data in PLNT. Lets see what they are.

Since there are only 10 values missing, lets fill it with the most common PLNT values.

[ ]:
```
customer_order.PLNT.describe()
```

[ ]:
```
count    39388.000000
mean       861.837869
std        196.784207
min        130.000000
25%        930.000000
50%        930.000000
75%        930.000000
max        930.000000
Name: PLNT, dtype: float64
```

[ ]:
```
customer_order.PLNT.fillna(930, inplace=True)
```

[ ]:
```
pd.isnull(customer_order).describe()
```

[ ]:
```
         SONO   ITEM   PTNO   DESC   DATE ORD_QTY   CUST   PLNT  Price  \
count   39398  39398  39398  39398  39398   39398  39398  39398  39398
unique      1      1      1      1      1       1      1      1      1
top     False  False  False  False  False   False  False  False  False
freq    39398  39398  39398  39398  39398   39398  39398  39398  39398

       customer PO ref PO date
count            39398   39398
unique               1       1
top              False   False
freq             39398   39398
```

pd.to_datetime(customer_order['PO date']) gives an error due to some strings which are set to 00:00:00. So we need to remove these first, we do this by setting PO date to the DATE

[ ]:
```
customer_order[customer_order['PO date'] == datetime.time(0)].count()
```

[ ]:
```
SONO               397
ITEM               397
PTNO               397
DESC               397
DATE               397
ORD_QTY            397
CUST               397
PLNT               397
Price              397
customer PO ref    397
PO date            397
dtype: int64
```

1.1.1 Check date format

[ ]:
```
customer_order['DATE'][:2]
```

[ ]:
```
0    23-08-2016
1    23-08-2016
Name: DATE, dtype: object
```

[ ]:
```
customer_order['PO date'][:2]
```

[ ]:
```
0    2016-08-23 00:00:00
1    2206-08-19 00:00:00
Name: PO date, dtype: object
```

Fill in the missing 'PO date' with the corresponding values from 'DATE'. To do this, first get the month and day from each corresponding 'DATE' value. and using this and the year (2016) create a datetime.date and assign it to 'PO DATE'

[ ]:
```
tmp = customer_order[customer_order['PO date'] == datetime.time(0)]
day, month = [], []
for i in tmp['DATE'].str.split('-').values:
    day.append(int(i[0]))
    month.append(int(i[1]))
customer_order.loc[customer_order['PO date'] == datetime.time(0), 'PO date'] =␣
 ↪[datetime.date(2016, m, d) for m, d in zip(month, day)]
```

[ ]:
```
customer_order['PO date'] = pd.to_datetime(customer_order['PO date'],␣
 ↪format='%Y/%m/%d')
```

```
customer_order['DATE'] = pd.to_datetime(customer_order['DATE'],␣
↪format='%d-%m-%Y')
```

[ ]:
```
x = (customer_order['DATE'] - customer_order['PO date'])
customer_order[x.dt.days < 0]
```

[ ]:
```
            SONO  ITEM             PTNO  \
1      101195540    10     6114-80-7101I.
3091   101196033    10     21M-939-2261I.
3092   101196033    20     209-939-7120I.
3093   101196033    30     209-939-7110I.
3094   101196033    40      07155-01125I.
3095   101196033    50     195-30-18271I.
3096   101196033    60      04064-08530I.
3097   101196033    70     707-99-56220I.
3098   101196033    80     707-99-77160I.
3099   101196033    90     707-99-67830I.
3100   101196033   100     707-99-69700I.
9547   103122797    20      202-63-N1140.
9549   103122801    30      07000-13025I.
9550   103122801    40       07000-13032.
10288  103124522    20      WL10430C4381.
10523  103124893    10          C0010010.
10524  103124893    20      S290AFA27005.
10525  103124893    30      S290AFA27055.
10526  103124893    40      WL10675C2267.
10987  103125462    10         V30641148.
10988  103125462    20     207-60-71183I.
10989  103125462    30     6736-51-5142I.
12827  101190460    10     207-60-71183I.
12828  101190460    20     600-185-4100I.
12829  101190460    30     600-181-6740I.
12830  101190460    40      04120-21746I.
12831  101190461    10     20Y-26-22270I.
12832  101190461    20     6217-71-6640I.
12833  101190461    30     6217-71-6650I.
12834  101190461    40     209-38-12460I.
…            …     …                 …
31380  101193919   140         M30441178.
31381  101193920    10     21W-06-22120I.
31382  101193920    30         M30441178.
31383  101193920    40     600-319-5611I.
31384  101193920    50     6736-51-5142I.
31385  101193920    60     707-98-45280I.
31386  101193920    70     600-319-5611I.
31387  101193920    80     600-319-3610I.
31388  101193920    90     600-181-6740I.
```

31389	101193920	110	707-52-15430I.
31390	101193920	120	07000-13032.
31391	101193920	130	20Y-27-11561I.
31392	101193920	140	09244-02496.
31393	101193920	150	207-60-71183I.
31394	101193920	160	04121-21744I.
31395	101193920	170	600-311-9733I.
31396	101193920	180	6732-81-3380I.
31397	101193920	190	600-185-4100I.
31398	101193920	200	D205-70-19570RCI.
31399	101193920	210	04121-21744I.
31400	101193920	220	7834-27-3003I.
31401	101193920	230	H30441174.
31402	101193920	240	K30441176.
31403	101193920	250	6736-51-5142I.
31404	101193920	260	M30741167.
31405	101193920	270	707-99-25870I.
31406	101193920	280	V30541167.
31407	101193920	290	600-319-3610I.
31408	101193920	300	206-06-61130I.
34644	101194455	10	7834-41-2003I.

	DESC	DATE	ORD_QTY	CUST	\
1	ELEMENT ASS'Y (GD623) ^$	2016-08-23	3	LUA1053	
3091	ADAPTER (PC600LC-8R)	2016-09-07	3	A1284	
3092	SHIM (PC1250-7)	2016-09-07	1	A1284	
3093	SHIM (PC1250-7)	2016-09-07	1	A1284	
3094	WEAR RING	2016-09-07	2	A1284	
3095	PACKING (D355A-1) 195-30-14210I	2016-09-07	2	A1284	
3096	SNAP RING (D275)	2016-09-07	2	A1284	
3097	SERVICE KIT (PC600LC-6)	2016-09-07	2	A1284	
3098	SERVICE KIT (PC600-6)	2016-09-07	2	A1284	
3099	SERVICE KIT (PC600LC-6)	2016-09-07	2	A1284	
3100	SERVICE KIT (PC600)	2016-09-07	2	A1284	
9547	TUBE (PC130-7)	2016-05-26	1	BHP0025	
9549	O RING	2016-05-26	5	BHM0072	
9550	O RING (PC71)	2016-05-26	5	BHM0072	
10288	HEX.HEAD BOLT M24X365-CL10.9-ZNC	2016-07-15	1	AHS0170	
10523	CONNECTION BELLOW WL2010	2016-07-28	1	CGN0054	
10524	O-RING FACE SEAL -12	2016-07-28	1	CGN0054	
10525	O-RING BOSS END -12	2016-07-28	1	CGN0054	
10526	HOSE	2016-07-28	1	CGN0054	
10987	1000 Hrs FILTER KIT (PC210-8MO) (KGO)	2016-08-26	2	DES0418	
10988	ELEMENT (PC210-8MO) ^$	2016-08-26	2	DES0418	
10989	ENGINE OIL FILTER (PC210-8) ^$	2016-08-26	5	DES0418	
12827	ELEMENT (PC210-8MO) ^$	2016-04-05	4	LUA1051	
12828	FILTER ASSY (PC210LC-8) ^$	2016-04-05	2	LUA1051	

12829	AIR CLEANER ELEMENT ASSY (PC200-6) ^$	2016-04-05	4	LUA1051
12830	V-BELT (PC210-8)	2016-04-05	2	LUA1051
12831	RING (PC200-6)	2016-04-05	2	LUA1053
12832	CLAMP (PC600)	2016-04-05	2	LUA1053
12833	CLAMP (PC600)	2016-04-05	2	LUA1053
12834	FILTER (PC600) (209-38-12550I)	2016-04-05	1	LUA1053
…	…	… …	…	
31380	KOMATSU Powtr TO 30 (20 LTR)	2016-07-07	8	DEI0089
31381	LAMP ASSY (PC130-7)	2016-07-07	1	DEI0067
31382	KOMATSU Powtr TO 30 (20 LTR)	2016-07-07	6	DEI0067
31383	CARTRIDGE (PC210-8MO) ^$	2016-07-07	6	DEI0067
31384	ENGINE OIL FILTER (PC210-8) ^$	2016-07-07	8	DEI0067
31385	BUCKET CYLINDER SEAL KIT (PC200-6)	2016-07-07	2	DEI0067
31386	CARTRIDGE (PC210-8MO) ^$	2016-07-07	8	DEI0067
31387	FUEL PRE FILTER (PC210LC-8) ^$	2016-07-07	8	DEI0067
31388	AIR CLEANER ELEMENT ASSY (PC200-6) ^$	2016-07-07	4	DEI0067
31389	BUSHING (07177-07030I)	2016-07-07	4	DEI0067
31390	O RING (PC71)	2016-07-07	20	DEI0067
31391	BOLT (PC200-6)	2016-07-07	20	DEI0067
31392	PIN ASSY (PC200-6)	2016-07-07	30	DEI0067
31393	ELEMENT (PC210-8MO) ^$	2016-07-07	2	DEI0067
31394	V-BELT (PC200-6)	2016-07-07	1	DEI0067
31395	SEPARATOR ASSY (PC200-6) ^$	2016-07-07	1	DEI0067
31396	V-BELT (PC200-6)	2016-07-07	2	DEI0067
31397	FILTER ASSY (PC210LC-8) ^$	2016-07-07	2	DEI0067
31398	TOOTH DURA RC (PC200-6) ^`	2016-07-07	10	DEI0067
31399	V-BELT (PC200-6)	2016-07-07	2	DEI0067
31400	PUMP CONTROLLER (LTK PC200-6)(PC300-6)	2016-07-07	1	DEI0067
31401	KOMATSU DEO 15W40 DH (20 LTR)	2016-07-07	8	DEI0067
31402	KOMATSU HO46-HM (20 LTR)	2016-07-07	2	DEI0067
31403	ENGINE OIL FILTER (PC210-8) ^$	2016-07-07	5	DEI0067
31404	1000 Hrs FILTER KIT (PC200-6)	2016-07-07	2	DEI0067
31405	BUCKET CYLINDER SEAL KIT (PC130-7)	2016-07-07	1	DEI0067
31406	TOOTH POINT SET 25 NOS (PC130,200, 210)	2016-07-07	3	DEI0067
31407	FUEL PRE FILTER (PC210LC-8) ^$	2016-07-07	5	DEI0067
31408	SWITCH (PC300SE-6)	2016-07-07	1	DEI0067
34644	GOVERNOR MOTER ASSY (PC200-6, PC130-7)	2016-07-22	1	CAS0500

	PLNT	Price	customer PO ref	PO date
1	930.0	6024	SPR 130_ Ms MONTE CA	2206-08-19
3091	930.0	36422	1200617997	2016-09-10
3092	930.0	366	1200617997	2016-09-10
3093	930.0	303	1200617997	2016-09-10
3094	930.0	1848	1200617997	2016-09-10
3095	930.0	1763	1200617997	2016-09-10
3096	930.0	375	1200617997	2016-09-10
3097	930.0	45217	1200617997	2016-09-10

3098	930.0	82255	1200617997	2016-09-10
3099	930.0	46875	1200617997	2016-09-10
3100	930.0	67645	1200617997	2016-09-10
9547	130.0	5646	ANKIT	2016-06-01
9549	130.0	542	Madanram	2016-06-01
9550	130.0	21	Madanram	2016-06-01
10288	930.0	764	Counter bolt	2016-07-16
10523	930.0	4481	3000602559	2016-08-22
10524	930.0	6	3000602559	2016-08-22
10525	930.0	6	3000602559	2016-08-22
10526	930.0	510	3000602559	2016-08-22
10987	930.0	0	FOC NS	2016-08-28
10988	930.0	0	FOC NS	2016-08-28
10989	930.0	0	FOC NS	2016-08-28
12827	930.0	6899	SPR_2 PNC Infratech	2016-05-04
12828	930.0	10023	SPR_2 PNC Infratech	2016-05-04
12829	930.0	7217	SPR_2 PNC Infratech	2016-05-04
12830	930.0	1610	SPR_2 PNC Infratech	2016-05-04
12831	930.0	276	SPR_1 JPA Amelia	2016-05-04
12832	930.0	808	SPR_1 JPA Amelia	2016-05-04
12833	930.0	744	SPR_1 JPA Amelia	2016-05-04
12834	930.0	11275	SPR_1 JPA Amelia	2016-05-04
…	…	…	…	…
31380	930.0	2908	July 1st Order Thru	2016-07-29
31381	930.0	9419	July 1st Order Thru	2016-07-29
31382	930.0	2908	July 1st Order Thru	2016-07-29
31383	930.0	3523	July 1st Order Thru	2016-07-29
31384	930.0	1754	July 1st Order Thru	2016-07-29
31385	930.0	7365	July 1st Order Thru	2016-07-29
31386	930.0	3523	July 1st Order Thru	2016-07-29
31387	930.0	3178	July 1st Order Thru	2016-07-29
31388	930.0	7465	July 1st Order Thru	2016-07-29
31389	930.0	1812	July 1st Order Thru	2016-07-29
31390	930.0	18	July 1st Order Thru	2016-07-29
31391	930.0	314	July 1st Order Thru	2016-07-29
31392	930.0	197	July 1st Order Thru	2016-07-29
31393	930.0	7136	July 1st Order Thru	2016-07-29
31394	930.0	4259	July 1st Order Thru	2016-07-29
31395	930.0	11869	July 1st Order Thru	2016-07-29
31396	930.0	4263	July 1st Order Thru	2016-07-29
31397	930.0	10367	July 1st Order Thru	2016-07-29
31398	930.0	887	July 1st Order Thru	2016-07-29
31399	930.0	4259	July 1st Order Thru	2016-07-29
31400	930.0	29277	July 1st Order Thru	2016-07-29
31401	930.0	3137	July 1st Order Thru	2016-07-29
31402	930.0	2658	July 1st Order Thru	2016-07-29
31403	930.0	1754	July 1st Order Thru	2016-07-29

```
31404  930.0  23786   July 1st Order Thru 2016-07-29
31405  930.0   5463   July 1st Order Thru 2016-07-29
31406  930.0  16292   July 1st Order Thru 2016-07-29
31407  930.0   3178   July 1st Order Thru 2016-07-29
31408  930.0   4017   July 1st Order Thru 2016-07-29
34644  930.0  59696  SRL/16-17/053 (Anand 2016-07-26

[83 rows x 11 columns]
```

As you can see above there are still ~80 rows which have date > po date, this could perhaps be deleted.

[ ]:
```
customer_order.drop(customer_order[x.dt.days < 0].index, inplace=True)
```

1.2 material_master

[ ]:
```
material_master.head()
```

[ ]:
```
  Material code`            Material Description Type Unit  Model  \
0  01010-61435I.              BOLT (01010-51435I)  ROH   EA  PC450
1  01010-61455I.  BOLT (D65E-12) (01010-31455I.)  ROH   EA    D65
2  01010-61635I.                     BOLT (GD511)  ROH   EA  GD511
3  01010-61645I.             BOLT (01010-81645I.)  ROH   EA   D475
4  01010-61650I.    BOLT (HD465) (01010-81650I.)  ROH   EA  HD465

  safety stock  Demand
0            8      30
1            1       2
2            1      12
3            8      32
4            5      18
```

[ ]:
```
pd.isnull(material_master).describe()
```

[ ]:
```
       Material code` Material Description   Type   Unit  Model safety stock  \
count            6022                 6022   6022   6022   6022         6022
unique              1                    1      1      1      1            1
top             False                False  False  False  False        False
freq             6022                 6022   6022   6022   6022         6022

       Demand
count    6022
unique      1
top     False
freq     6022
```

No null values here, lets just remove unwated columns: 1. Type 2. Unit

```
[ ]: material_master.drop(['Type', 'Unit'], axis=1, inplace=True)
```

```
[ ]: material_master.columns
```

```
[ ]: Index([u'Material code`', u'Material Description', u'Model', u'safety stock',
            u'Demand'],
           dtype='object')
```

```
[ ]: material_master.rename(columns={'Material code`': 'Material code'},␣
      ↪inplace=True)
```

1.3 sales past demand

```
[ ]: sales_past_demand.head()
```

```
[ ]:   Material code`  DEM36  DEM35  DEM34  DEM33  DEM32  DEM31  DEM30  DEM29  \
     0  01010-61435I.      6      0      0      0      0      0      5      0
     1  01010-61455I.      0      0      0      0      0      0      0      0
     2  01010-61635I.      0      0      0      0      0      0      0      0
     3  01010-61645I.      0      0      0      0      0      0      0      0
     4  01010-61650I.      0      0      0      0      0      0      0      0

        DEM28  …  DEM10  DEM9  DEM8  DEM7  DEM6  DEM5  DEM4  DEM3  DEM2  DEM1
     0      0  …      0     4     0     0    16    12     2     0     0     0
     1      0  …      0     0     0     0     0     0     0     2     0     0
     2      0  …      0     0     0     0     0     0     0     8     1     0
     3      0  …      0     0     0     0     0     0     0     0     2     0
     4      0  …      0     0     0     0     0     2     0     0     0     0

     [5 rows x 37 columns]
```

This holds the sales demands for given materials for the last 36months, this could be used to make predicitons for future demands. No pre-processing required here

```
[ ]: sales_past_demand.columns
```

```
[ ]: Index([u'Material code`', u'DEM36', u'DEM35', u'DEM34', u'DEM33', u'DEM32',
            u'DEM31', u'DEM30', u'DEM29', u'DEM28', u'DEM27', u'DEM26', u'DEM25',
            u'DEM24', u'DEM23', u'DEM22', u'DEM21', u'DEM20', u'DEM19', u'DEM18',
            u'DEM17', u'DEM16', u'DEM15', u'DEM14', u'DEM13', u'DEM12', u'DEM11',
            u'DEM10', u'DEM9', u'DEM8', u'DEM7', u'DEM6', u'DEM5', u'DEM4', u'DEM3',
            u'DEM2', u'DEM1'],
           dtype='object')
```

```
[ ]: sales_past_demand.rename(columns={'Material code`': 'Material code'},␣
      ↪inplace=True)
```

1.4 customer_master

[ ]:
```
pd.isnull(customer_master).describe()
```

[ ]:
```
        customer code   Name  Street   City PostalCode Region Industry
count             976    976     976    976        976    976      976
unique              1      1       1      1          1      1        1
top             False  False   False  False      False  False    False
freq              976    976     976    976        976    976      976
```

No null values here, lets remove the unwated columns: 1. Street, 2. City

[ ]:
```
customer_master.drop(['Street', 'City'], axis=1, inplace=True)
```

[ ]:
```
customer_master.columns
```

[ ]:
```
Index([u'customer code', u'Name ', u'PostalCode', u'Region', u'Industry'],
dtype='object')
```

[ ]:
```
customer_master.rename(columns={'Name ': 'Name'}, inplace=True)
```

1.5 invoice

[ ]:
```
pd.isnull(invoice).describe()
```

[ ]:
```
        Bill.Doc.   Item Material code Description Required quantity  \
count       39343  39343         39343       39343             39343
unique          1      1             1           1                 1
top         False  False         False       False             False
freq        39343  39343         39343       39343             39343

        Billed Quantity  Value delivery doc RefItm Sales ord so Item   Plnt  \
count             39343  39343        39343  39343     39343   39343  39343
unique                1      1            1      1         1       1      1
top               False  False        False  False     False   False  False
freq              39343  39343        39343  39343     39343   39343  39343

        Bill date
count       39343
unique          1
top         False
freq        39343
```

No null values here too. Lets remove unwanted columns: 1. Refitm 2. so item

[ ]:
```
invoice.drop(['so Item', 'RefItm'], axis=1, inplace=True)
```

Convert the date to pd_datetime

[ ]:
```
invoice['Bill date'] = pd.to_datetime(invoice['Bill date'], format='%Y/%m/%d')
```

[ ]:
```
invoice.columns
```

[ ]:
```
Index([u'Bill.Doc.', u'Item', u'Material code', u'Description',
       u'Required quantity', u'Billed Quantity', u'Value', u'delivery doc',
       u'Sales ord', u'Plnt', u'Bill date'],
      dtype='object')
```

1.6 stock_master

[ ]:
```
stock_master.head()
```

[ ]:
```
        Material  ValA  DocumentNo  Year  Itm    D/C  Amount    Quantity BUn  \
0  01010-61435I.   930   920006718  2016    2  Recpt  167.56           4  EA
1  01010-61435I.   930   920006757  2016   21   Issu  167.56           4  EA
2  01010-61435I.   930   920009004  2016    2  Recpt  502.68          12  EA
3  01010-61435I.   930   920009049  2016    1   Issu  502.68          12  EA
4  01010-61435I.   930   920011287  2016   13  Recpt  708.00          15  EA

  Pstng Date
0 2016-04-22
1 2016-04-22
2 2016-04-29
3 2016-04-29
4 2016-05-04
```

[ ]:
```
pd.isnull(stock_master).describe()
```

[ ]:
```
       Material   ValA DocumentNo   Year    Itm    D/C Amount    Quantity  \
count     68555  68555      68555  68555  68555  68555  68555       68555
unique        1      1          1      1      1      1      1           1
top       False  False      False  False  False  False  False       False
freq      68555  68555      68555  68555  68555  68555  68555       68555

          BUn Pstng Date
count   68555      68555
unique      1          1
top     False      False
freq    68555      68555
```

No null values here. Lets remove unwanted columns: 1. Year 2. ValA

[ ]:
```
stock_master.drop(['ValA', 'Year'], axis=1, inplace=True)
```

Convert date to pd_datetime

[ ]:
```
stock_master['Pstng Date'] = pd.to_datetime(stock_master['Pstng Date'],␣
↪format='%Y/%m/%d')
```

[ ]:
```
stock_master.columns
```

[ ]:
```
Index([u'Material', u'DocumentNo', u'Itm', u'D/C', u'Amount', u'   Quantity',
       u'BUn', u'Pstng Date'],
      dtype='object')
```

[ ]:
```
stock_master.rename(columns={'   Quantity': 'Quantity'}, inplace=True)
```

1.7 delivery data

[ ]:
```
delivery_data.head()
```

[ ]:
```
   Delivery no  delivery Item        Material  Plnt  Delivery quantity Unit  \
0     81211954             10  600-181-6740I.   299                  1   EA
1     81211955             10  600-181-6740I.   299                  1   EA
2     81211957             10  600-411-1151I.   299                  1   EA
3     81211967             10  600-411-1151I.   299                  1   EA
4     81212008             10   WL10670A2582.   930                  1   EA

        date                          Description  sales ord  \
0 2016-04-04   AIR CLEANER ELEMENT ASSY (PC200-6) ^$  103121287
1 2016-04-04   AIR CLEANER ELEMENT ASSY (PC200-6) ^$  103121288
2 2016-04-04  CORROSION RESISTOR FILTER (PC200-6) ^$  103121290
3 2016-04-04  CORROSION RESISTOR FILTER (PC200-6) ^$  103121289
4 2016-04-05                     TUBE-LIFT BORE SPOOL  103121296

   sale ord item
0             10
1             10
2             10
3             10
4             10
```

Dropping plant and unit, as its not needed

[ ]:
```
delivery_data.drop(['Plnt', 'Unit'], axis=1, inplace=True)
```

[ ]:
```
pd.isnull(delivery_data).describe()
```

[ ]:
```
       Delivery no delivery Item Material Delivery quantity   date  \
count        40356         40356    40356             40356  40356
unique           1             1        1                 1      1
top          False         False    False             False  False
freq         40356         40356    40356             40356  40356
```

```
       Description sales ord  sale ord item
count        40356     40356         40356
unique           1         1             1
top          False     False         False
freq         40356     40356         40356
```

No missing data here

[ ]:
```
delivery_data.columns
```

[ ]:
```
Index([u'Delivery no', u'delivery Item', u'Material', u'Delivery quantity',
       u'date', u'Description', u'sales ord ', u'sale ord item'],
      dtype='object')
```

[ ]:
```
delivery_data.rename(columns={'sales ord ': 'sales ord'}, inplace=True)
```

1.8 booking_data

[ ]:
```
booking_data.head()
```

[ ]:
```
   Delivery no Delivery date  ShPt SOrg.          Consignment details  \
0     81211954    2016-04-04   299    50  LOCAL COLLECTION - PRASHANT
1     81211955    2016-04-04   299    50  LOCAL COLLECTION - PRASHANT
2     81211957    2016-04-04   299    50  LOCAL COLLECTION - PRASHANT
3     81211967    2016-04-04   299    50  LOCAL COLLECTION - PRASHANT
4     81212008    2016-04-05   930    50     BYHAND RAKESH 05-04-2016

     GC date Recpt date
0 2016-04-11 2016-05-05
1 2016-04-11 2016-05-05
2 2016-04-11 2016-05-05
3 2016-04-11 2016-05-05
4 2016-04-05 2016-04-06
```

[ ]:
```
pd.isnull(booking_data).describe()
```

[ ]:
```
       Delivery no Delivery date   ShPt  SOrg. Consignment details GC date  \
count         8445          8445   8445   8445                8445    8445
unique           1             1      1      1                   2       2
top          False         False  False  False               False   False
freq          8445          8445   8445   8445                7559    8441

       Recpt date
count        8445
unique          2
top         False
```

```
freq          8443
```

There are null values in Consigment details, GC date and Recpt date, lets have a look

```
[ ]: booking_data.loc[pd.isnull(booking_data['Consignment details']), 'Consignment␣
      ↪details'] = "No details"
```

For GC date and Recpt date, we can only 3~4 rows are missing data, lets drop these rows

```
[ ]: booking_data.drop(booking_data[pd.isnull(booking_data['GC date'])].index,␣
      ↪inplace=True)
```

```
[ ]: booking_data[pd.isnull(booking_data['Recpt date'])]
```

```
[ ]: Empty DataFrame
     Columns: [Delivery no, Delivery date, ShPt, SOrg., Consignment details, GC date,
     Recpt date]
     Index: []
```

Luckily the fields which were missing the GC date and Recpt date, were overlapping. Lets drop unwanted rows: 1. ShPt 2. SOrg.

```
[ ]: booking_data.drop(['ShPt', 'SOrg.'], axis=1, inplace=True)
```

2 Merging the tables

Since there are multiple tables and there is a strong relation amongst these tables, we could merge the tables for easier access and manipulation

2.0.1 Customer Order and Master

```
[ ]: customer = pd.merge(customer_master, customer_order, left_on=['customer code'],␣
      ↪right_on=['CUST'])
```

```
[ ]: customer.drop(['CUST'], axis=1, inplace=True)
```

```
[ ]: print('Customer order:', len(customer_order))
     print('Customer master:', len(customer_master))
     print('Customer:', len(customer))
```

```
('Customer order:', 39315)
('Customer master:', 976)
('Customer:', 39315)
```

No data loss here

2.1 Bill

We can see that there is no unique key, lets try and find a combination of keys to get a unique key

Using ['Sales ord', 'Item', 'Billed Quantity'] from invoice and ['sales ord', 'sale ord item', 'Delivery quantity'] from delivery data, we can get the unique row for merging

```
[ ]: bill = pd.merge(invoice, delivery_data, left_on=['Sales ord', 'Item', 'Billed␣
     ↪Quantity'], right_on=['sales ord', 'sale ord item', 'Delivery quantity'])
```

```
[ ]: bill.drop(['sales ord', 'sale ord item', 'Delivery quantity'], axis=1,␣
     ↪inplace=True)
```

```
[ ]: bill.drop(['Description_x'], axis = 1, inplace=True)
     bill.rename(columns={'Description_y':'Description'}, inplace=True)
```

```
[ ]: bill.rename(columns={'date':'delivery date'}, inplace=True)
```

```
[ ]: (bill['delivery Item'] == bill['Item']).value_counts()
```

```
[ ]: True     40307
     dtype: int64
```

```
[ ]: bill.drop(['Item'], axis=1, inplace=True)
```

```
[ ]: len(bill.groupby(['Delivery no']).count())
```

```
[ ]: 7844
```

Now we can merge the booking data onto the bill

```
[ ]: bill = pd.merge(bill, booking_data, on='Delivery no', how='left')
```

3 Analysis of Duplicates

3.1 Bill

lets drop these duplicates

```
[ ]: bill.drop(bill[bill.duplicated(['Sales ord', 'Delivery no', 'Description',␣
     ↪'Consignment details', 'Value'])].index, inplace=True)
```

3.1.1 Customer

```
[ ]: customer[customer.duplicated(['PTNO', 'customer code', 'SONO', 'Price',␣
     ↪'ITEM'], keep=False)]
```

```
[ ]: Empty DataFrame
Columns: [customer code, Name, PostalCode, Region, Industry, SONO, ITEM, PTNO,
DESC, DATE, ORD_QTY, PLNT, Price, customer PO ref, PO date]
Index: []
```

3.1.2 material_master

```
[ ]: material_master[material_master.duplicated(['Material code'], keep=False)]
```

```
[ ]: Empty DataFrame
Columns: [Material code, Material Description, Model, safety stock, Demand]
Index: []
```

3.1.3 stock master

```
[ ]: stock_master.head(2)
```

```
[ ]:        Material  DocumentNo  Itm    D/C  Amount  Quantity BUn Pstng Date
     0  01010-61435I.   920006718    2  Recpt  167.56         4  EA 2016-04-22
     1  01010-61435I.   920006757   21   Issu  167.56         4  EA 2016-04-22
```

```
[ ]: stock_master[stock_master.duplicated(['Material', 'Itm', 'DocumentNo'],␣
      ↪keep=False)]
```

```
[ ]: Empty DataFrame
Columns: [Material, DocumentNo, Itm, D/C, Amount, Quantity, BUn, Pstng Date]
Index: []
```

3.1.4 sales_past_demand

```
[ ]: sales_past_demand.head(2)
```

```
[ ]:   Material code  DEM36  DEM35  DEM34  DEM33  DEM32  DEM31  DEM30  DEM29  \
     0  01010-61435I.      6      0      0      0      0      0      5      0
     1  01010-61455I.      0      0      0      0      0      0      0      0

        DEM28  …  DEM10  DEM9  DEM8  DEM7  DEM6  DEM5  DEM4  DEM3  DEM2  DEM1
     0      0  …      0     4     0     0    16    12     2     0     0     0
     1      0  …      0     0     0     0     0     0     0     2     0     0

     [2 rows x 37 columns]
```

```
[ ]: sales_past_demand[sales_past_demand.duplicated(['Material code'], keep=False)]
```

```
[ ]: Empty DataFrame
Columns: [Material code, DEM36, DEM35, DEM34, DEM33, DEM32, DEM31, DEM30, DEM29,
```

```
DEM28, DEM27, DEM26, DEM25, DEM24, DEM23, DEM22, DEM21, DEM20, DEM19, DEM18,
DEM17, DEM16, DEM15, DEM14, DEM13, DEM12, DEM11, DEM10, DEM9, DEM8, DEM7, DEM6,
DEM5, DEM4, DEM3, DEM2, DEM1]
Index: []

[0 rows x 37 columns]
```

4 End of Pre-Processing

Now the data has been cleaned up and duplicates have been removed. We've also merged relavant data together to get new df's.

Currently we have the following DF's: 1. bill 2. customer 3. sales_past_demand 4. stock_master 5. material master

5 Data Analysis

6 Order to Delivery reports

The order to delivery analysis comprises finding the following: 1. Order to delivery note generation 2. Delivery to invoice generation 3. Invoice to consignment 4. Consignment to reaching customers(Recpt date)

6.1 1.Order to delivery note generation

```
[ ]: # Bill is missing the PO Date, which we need, lets add that

     tmp = customer[['SONO', 'PO date', 'ITEM']]
     bill = bill.merge(tmp, how='left', left_on=['Sales ord', 'delivery Item'],␣
      ↪right_on=['SONO', 'ITEM'])
     bill.drop(['SONO', 'ITEM'], axis=1, inplace=True)
```

```
[ ]: order_to_delivery = bill[['PO date', 'Delivery date']]
     order_to_delivery.loc[:, 'ORD_to_DEL'] = order_to_delivery['Delivery date'] -␣
      ↪order_to_delivery['PO date']
```

```
/usr/lib/python2.7/site-packages/pandas/core/indexing.py:297:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/indexing.html#indexing-view-versus-copy
  self.obj[key] = _infer_fill_value(value)
/usr/lib/python2.7/site-packages/pandas/core/indexing.py:477:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
```

```
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/indexing.html#indexing-view-versus-copy
  self.obj[item] = s
```

[ ]:
```
order_to_delivery.head(2)
```

[ ]:

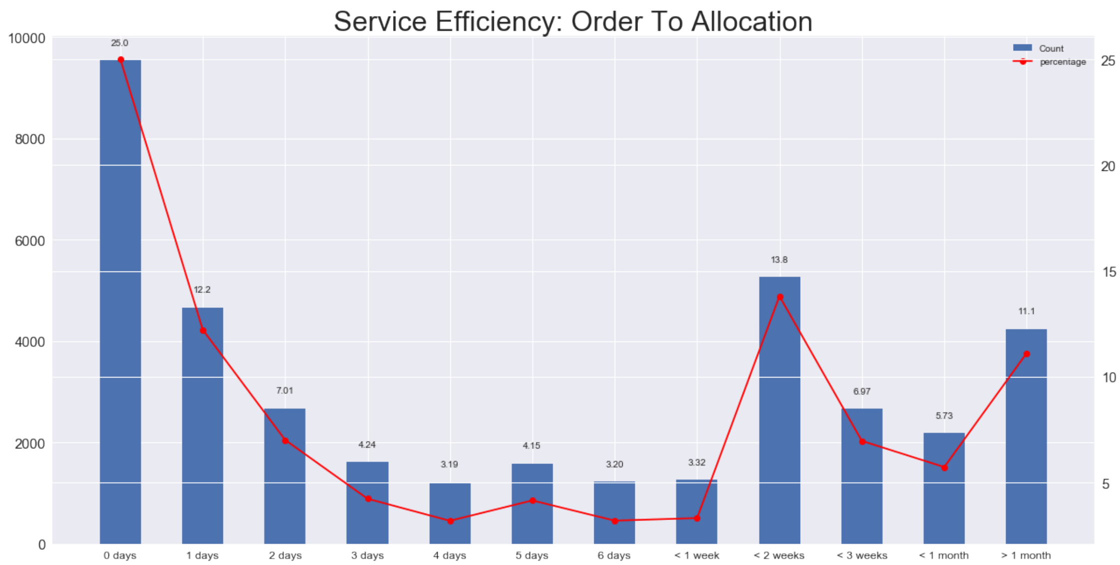
	PO date	Delivery date	ORD_to_DEL
0	2016-05-16	2016-06-06	21 days
1	2016-05-13	2016-06-08	26 days

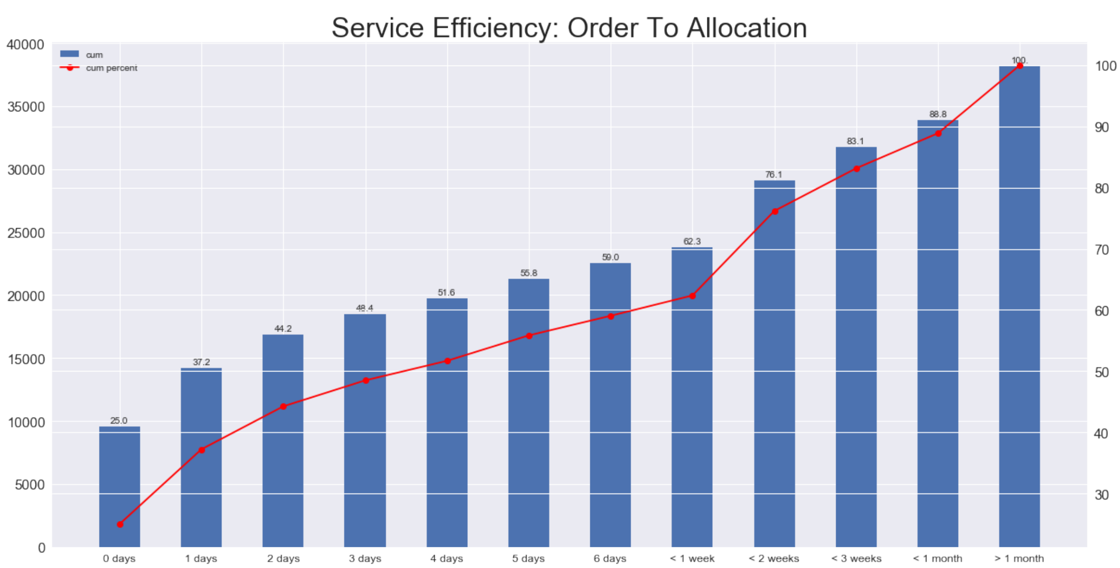
[ ]:
```
tmp = order_to_delivery['ORD_to_DEL'].value_counts().reset_index()
tmp.columns = ['Days', 'Count']
tmp['Days'] = tmp['Days'].apply(lambda x: x.days)
tmp.sort_values(by=['Days'], inplace=True)
tmp = tmp.reset_index().drop('index', axis=1)
```

[ ]:
```
def display_days_difference(tmp, title):

    df = pd.DataFrame(columns=['Days', 'cum'])
    for i in xrange(7):
        df.loc[i] = [str(i) + ' days', tmp[tmp['Days'] <= i]['Count'].sum()]
    df.loc[7] = ['< 1 week', tmp[tmp['Days'] <= 7]['Count'].sum()]
    df.loc[8] = ['< 2 weeks', tmp[tmp['Days'] <= 14]['Count'].sum()]
    df.loc[9] = ['< 3 weeks', tmp[tmp['Days'] <= 21]['Count'].sum()]
    df.loc[10] = ['< 1 month', tmp[tmp['Days'] <= 30]['Count'].sum()]
    df.loc[11] = ['> 1 month', tmp['Count'].sum()]

    df['Count'] = df['cum']
    for i in xrange(11, 0, -1):
        df.loc[i, 'Count'] = df.loc[i, 'Count'] - df.loc[i - 1, 'Count']

    df['percentage'] = 100*df.Count/df.Count.sum()
    df['cum percent'] = df.percentage.cumsum()

    #setting font size
    plt.rc('axes', titlesize=30)     # fontsize of the axes title
    plt.rc('axes', labelsize=15)    # fontsize of the x and y labels
    plt.rc('xtick', labelsize=12)    # fontsize of the tick labels
    plt.rc('ytick', labelsize=15)    # fontsize of the tick labels

    for (i, j) in [('Count', 'percentage'), ('cum', 'cum percent')]:
        fig, ax1 = plt.subplots()
        ax2 = ax1.twinx()
        ax1.bar([x for x in xrange(len(df))], df[i], width=.5, label=i)
        ax2.plot([x for x in xrange(len(df))], df[j], color='red', marker='o')
```

```
        for k in xrange(len(df)):
            ax1.text(k, df[i][k] + 300, str(float(df[j][k]))[:4],␣
↪horizontalalignment='center')
        plt.xticks([x for x in xrange(len(df))], df['Days'])
        h1, l1 = ax1.get_legend_handles_labels()
        h2, l2 = ax2.get_legend_handles_labels()
        ax1.legend(h1+h2, l1+l2, loc=0)
        plt.title(title)
        plt.show()
```

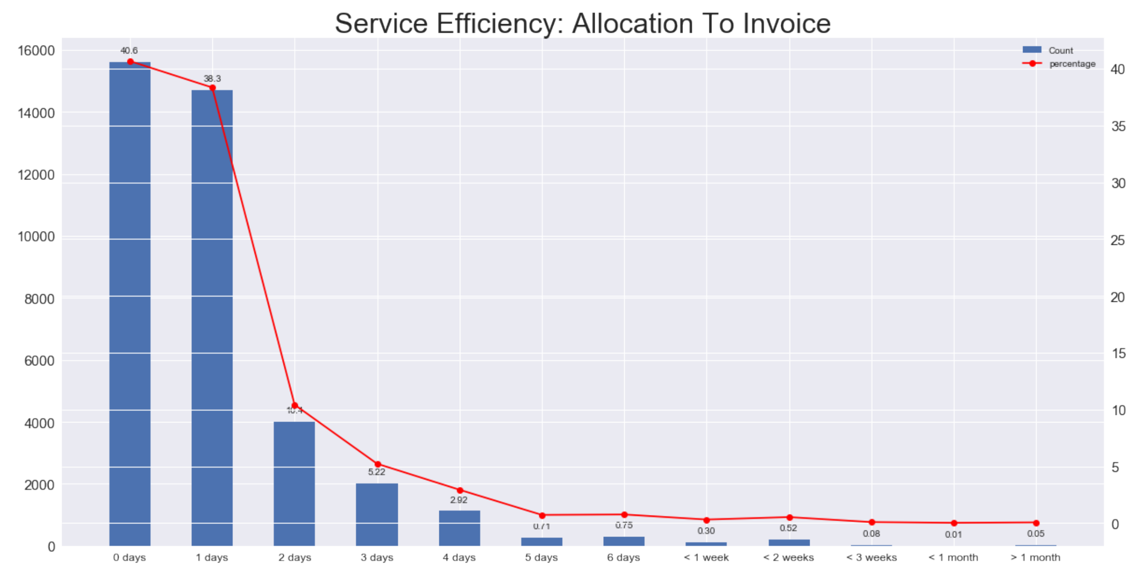
[ ]:
```
display_days_difference(tmp, 'Service Efficiency: Order To Allocation')
```

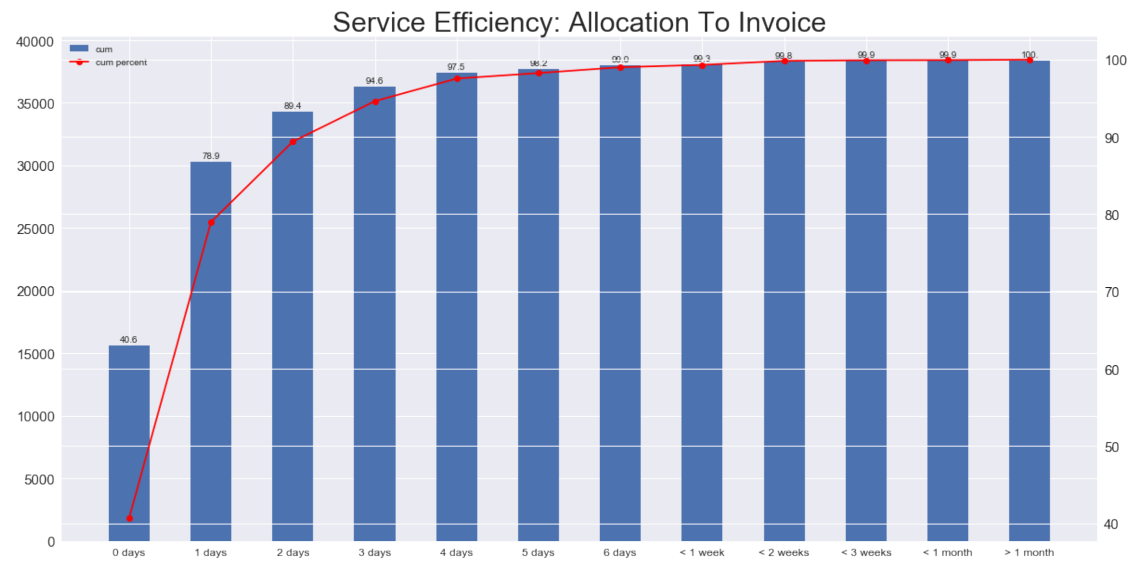




6.2 2. Delivery to invoice generation.

[ ]:
```
delivery_to_bill = bill[['Bill date', 'Delivery date']]
delivery_to_bill.loc[:, 'DEL_TO_BILL'] = delivery_to_bill['Bill date'] - delivery_to_bill['Delivery date']
tmp = delivery_to_bill['DEL_TO_BILL'].value_counts().reset_index()
tmp.columns = ['Days', 'Count']
tmp['Days'] = tmp['Days'].apply(lambda x: x.days)
tmp.sort_values(by=['Days'], inplace=True)
tmp = tmp.reset_index().drop('index', axis=1)
display_days_difference(tmp, 'Service Efficiency: Allocation To Invoice')
```





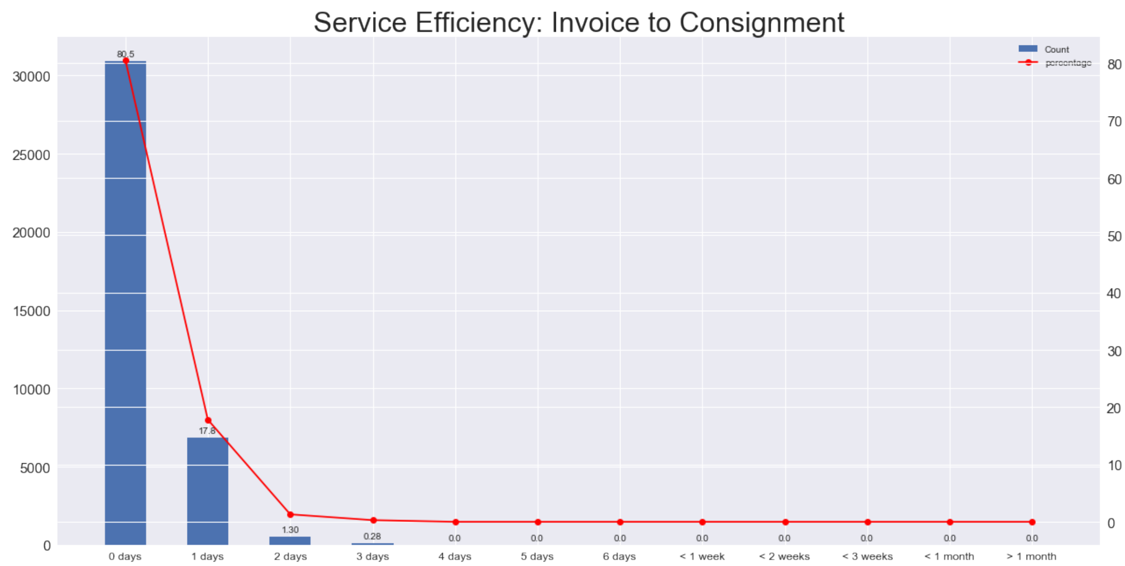
6.3 3. Invoice to consignment generation

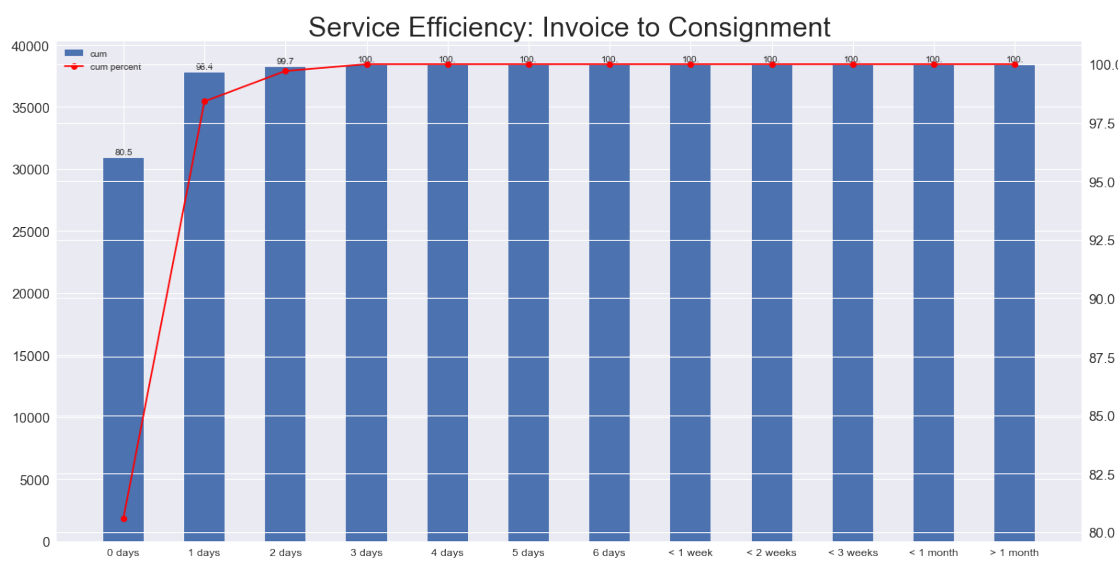
[ ]:
```
bill_to_GC = bill[['Bill date', 'GC date']]
bill_to_GC.loc[:, 'BILL_TO_GC'] = bill_to_GC['GC date'] - bill_to_GC['Bill␣
↪date']
bill_to_GC.loc[:, 'BILL_TO_GC'] = bill_to_GC['BILL_TO_GC'].dt.components.days
```

[ ]:
```
def test2 (row):
    if row['BILL_TO_GC'] < -10  :
        return 3
    if row['BILL_TO_GC'] < -5   :
        return 2
    if row['BILL_TO_GC'] < -1   :
        return 1

    return 0
```

[ ]:
```
bill_to_GC.loc[:, 'BILL_TO_GC'] = bill_to_GC.apply(lambda row: test2 (row),axis␣
↪=1)
bill_to_GC.loc[:, 'BILL_TO_GC'] = pd.to_timedelta(bill_to_GC['BILL_TO_GC'],␣
↪unit='D')
```

[ ]:
```
tmp = bill_to_GC['BILL_TO_GC'].value_counts().reset_index()
tmp.columns = ['Days', 'Count']
tmp['Days'] = tmp['Days'].apply(lambda x: x.days)
tmp.sort_values(by=['Days'], inplace=True)
tmp = tmp.reset_index().drop('index', axis=1)
display_days_difference(tmp, 'Service Efficiency: Invoice to Consignment')
```

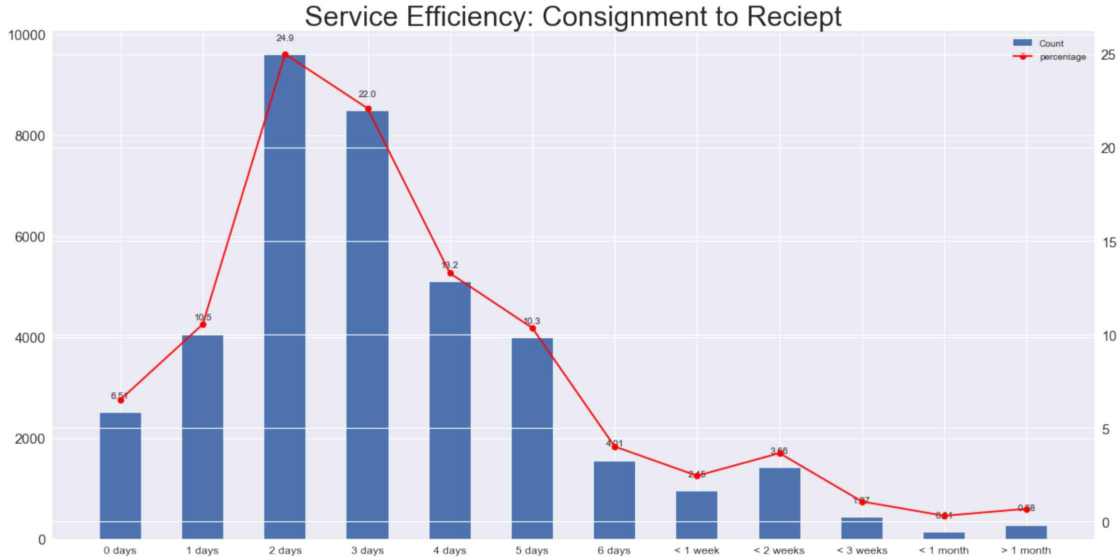


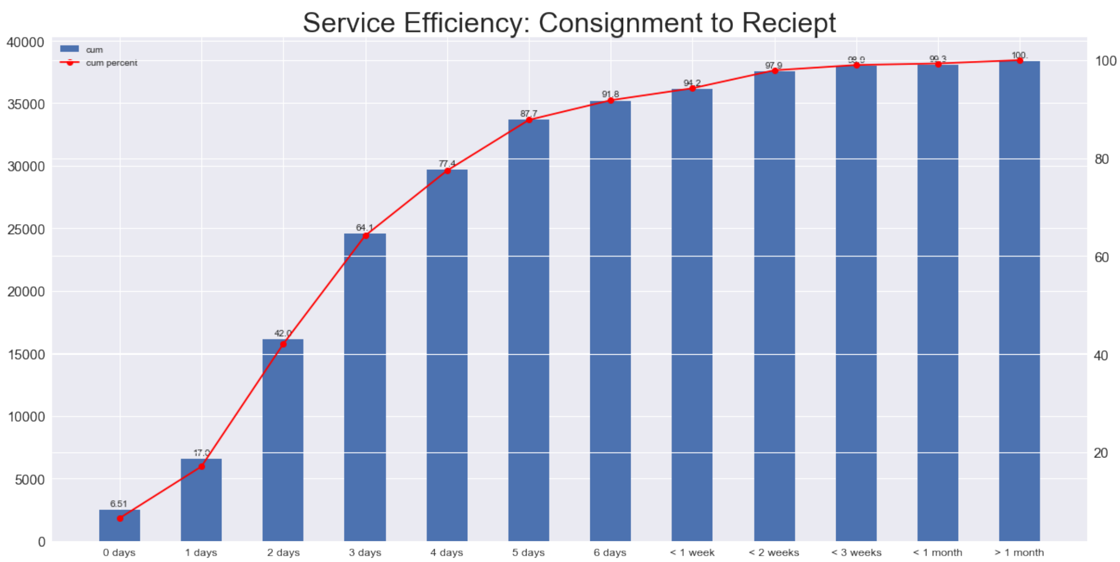


6.4 4. Consignment to receipt

[ ]:
```
GC_to_recpt = bill[['GC date', 'Recpt date']]
GC_to_recpt.loc[:, 'GC_TO_RECPT'] = GC_to_recpt['Recpt date'] - GC_to_recpt['GC date']
tmp = GC_to_recpt['GC_TO_RECPT'].value_counts().reset_index()
tmp.columns = ['Days', 'Count']
tmp['Days'] = tmp['Days'].apply(lambda x: x.days)
tmp.sort_values(by=['Days'], inplace=True)
tmp = tmp.reset_index().drop('index', axis=1)
```

```python
display_days_difference(tmp, 'Service Efficiency: Consignment to Reciept')
```

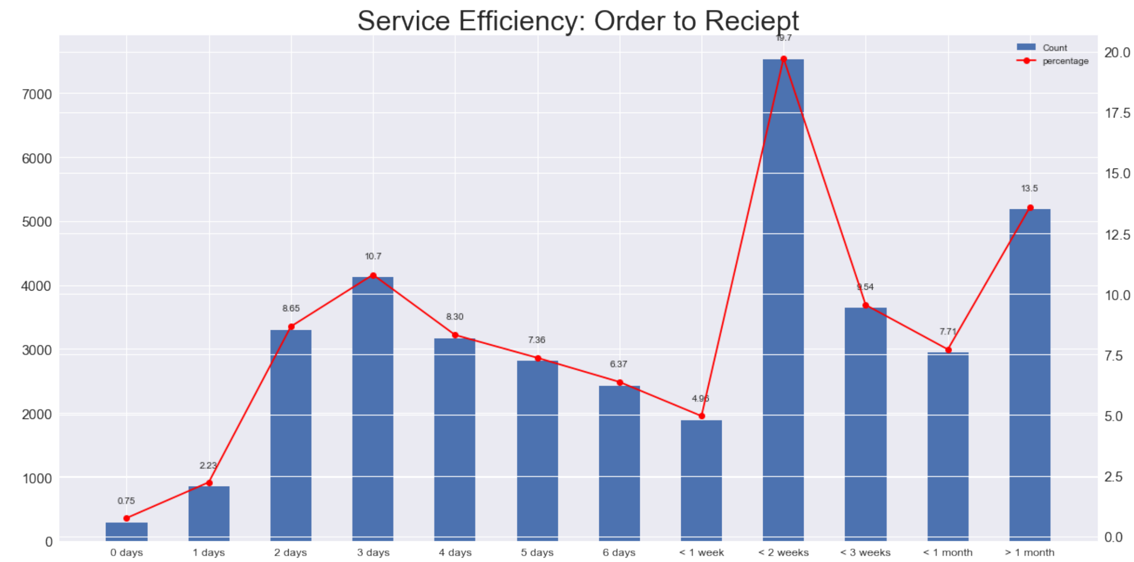


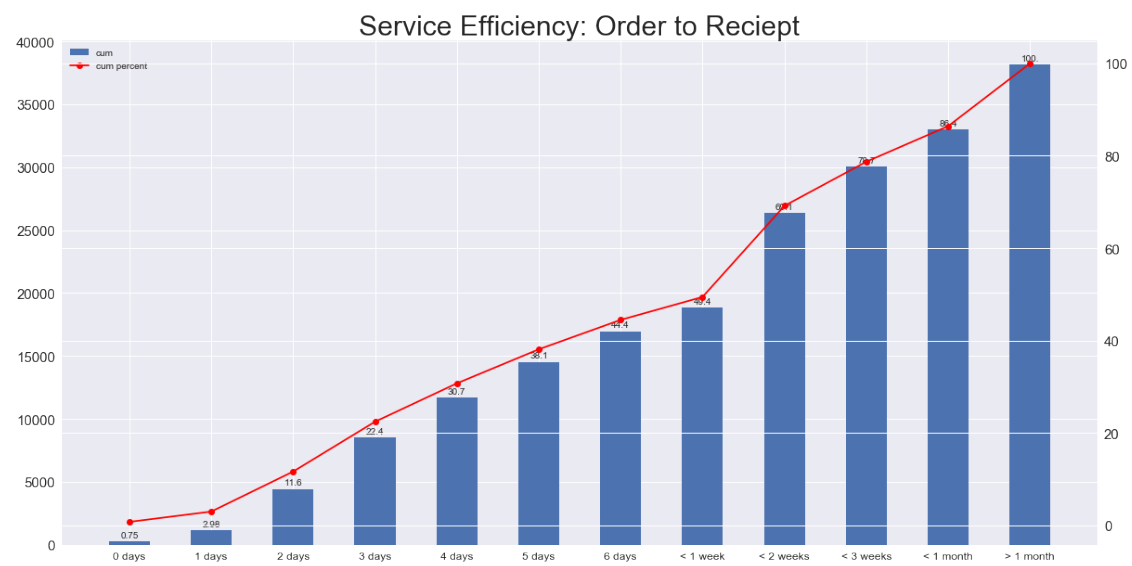


6.5 TOTAL TIME

[ ]:
```python
PO_to_recpt = bill[['PO date', 'Recpt date']]
PO_to_recpt.loc[:, 'PO_TO_RECPT'] = PO_to_recpt['Recpt date'] - PO_to_recpt['PO␣
↪date']
tmp = PO_to_recpt['PO_TO_RECPT'].value_counts().reset_index()
tmp.columns = ['Days', 'Count']
tmp['Days'] = tmp['Days'].apply(lambda x: x.days)
```

```
tmp.sort_values(by=['Days'], inplace=True)
tmp = tmp.reset_index().drop('index', axis=1)
display_days_difference(tmp, 'Service Efficiency: Order to Reciept')
```



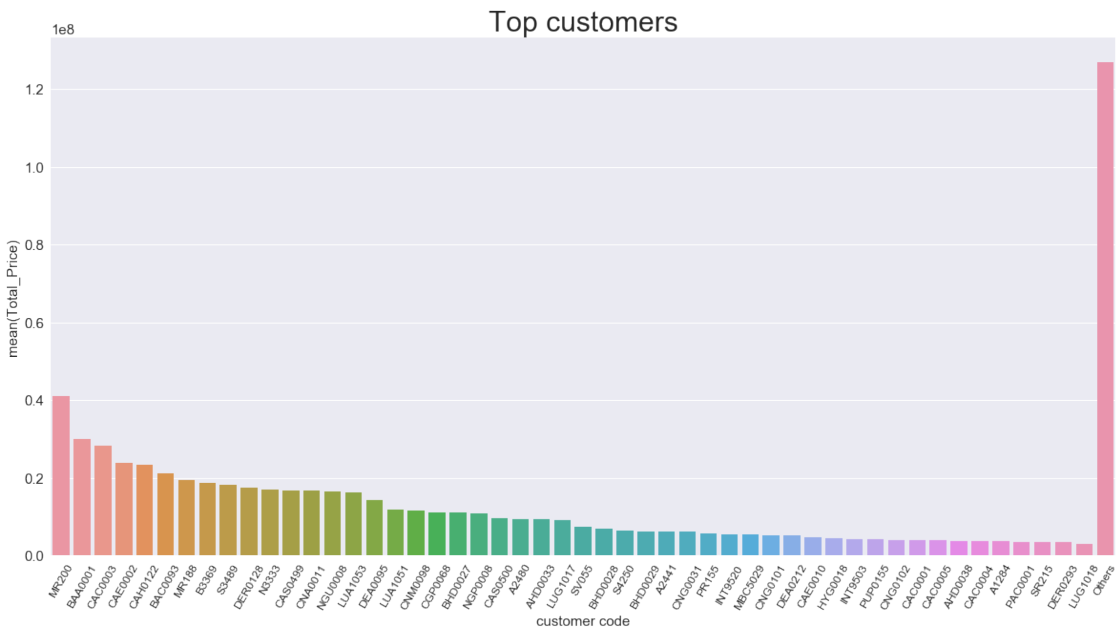


7 Customer wise sales

[ ]:
```python
tmp = customer[['customer code', 'Total_Price']]
tmp = tmp.groupby(['customer code']).sum().reset_index()
tmp.sort_values(by='Total_Price', ascending=False, inplace=True)
tmp = tmp.reset_index(drop=True)

tmp2 = tmp.loc[50:]
tmp = tmp.loc[:49]
tmp.loc[50] = ['Others', tmp2['Total_Price'].sum()]
```

[ ]:
```python
sns.barplot(x='customer code', y='Total_Price', data=tmp)
plt.xticks(rotation=60)
plt.title("Top customers")
plt.plot()
```

[ ]: []

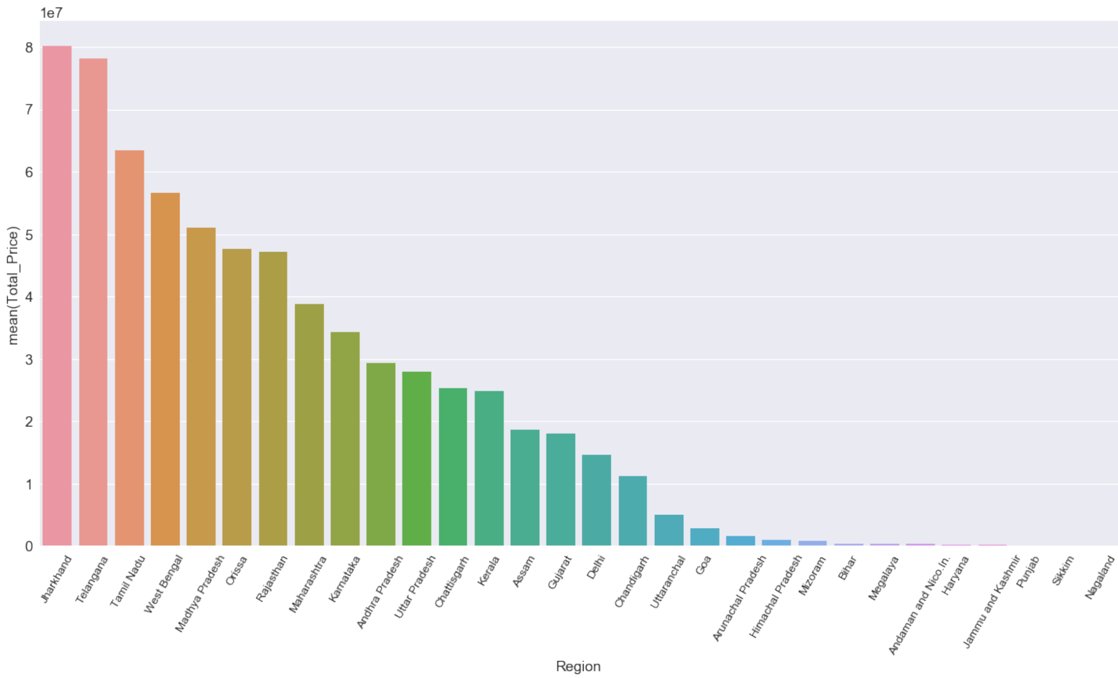


8 Region wise Sales

[ ]:
```python
df = customer.groupby('Region')['Total_Price'].sum().reset_index()
# sort by income
df = df.sort_values(by='Total_Price', ascending=False)
df = df.reset_index(drop=True)
```

```
[ ]: #Plotting the region wise profit graph

     sns.barplot(x = 'Region', y= 'Total_Price', data=df)
     plt.xticks(rotation=60)
     plt.plot()
```

```
[ ]: []
```

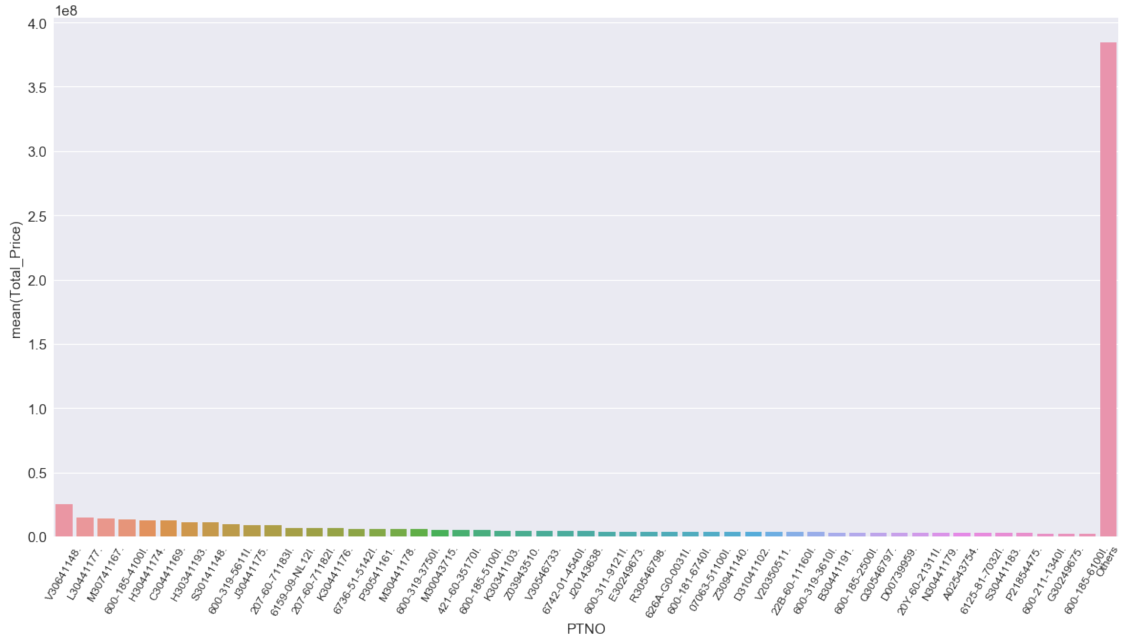


9 Material Wise Profit

```
[ ]: df = customer.groupby('PTNO')['Total_Price'].sum().reset_index()
     # sort by income
     df = df.sort_values(by='Total_Price', ascending=False)
     df = df.reset_index(drop=True)

     tmp = df.loc[50:]
     df = df.loc[:49]
     df.loc[50] = ['Others', tmp['Total_Price'].sum()]
```

```
[ ]: #Plotting the region wise profit graph

     sns.barplot(x = 'PTNO', y= 'Total_Price', data=df)
     plt.xticks(rotation=60)
     plt.plot()
```

[ ]: []



10 Model wise demand

[ ]:
```
model_demand = material_master
model_demand = model_demand.groupby('Model').sum().reset_index()
model_demand.drop(['safety stock'], axis=1, inplace=True)
model = model_demand.sort_values(by='Demand', ascending=False)
model = model.reset_index(drop=True)
```

[ ]:

	Model	Demand
0	PC200	129526
1	PC300	61608
2	PC71	44963
3	PC210	34785
4	D155	32093
5	300CK	29608
6	PC130	26286
7	PC450	21973
8	Others	14919
9	OTHER	13158
10	D475	9353
11	90CK	8794
12	GD511	7975
13	D65	6908

```
14    PC600    3769
```

[ ]:
```
# 8, 9 is others, lets combine and remove them
tmp = model.loc[8:9]
model = model.drop([8, 9])
tmp
```

[ ]:

	Model	Demand
8	Others	14919
9	OTHER	13158

[ ]:
```
model = model.reset_index(drop=True)
tmp = tmp.reset_index(drop=True)
```

[ ]:
```
tmp
```

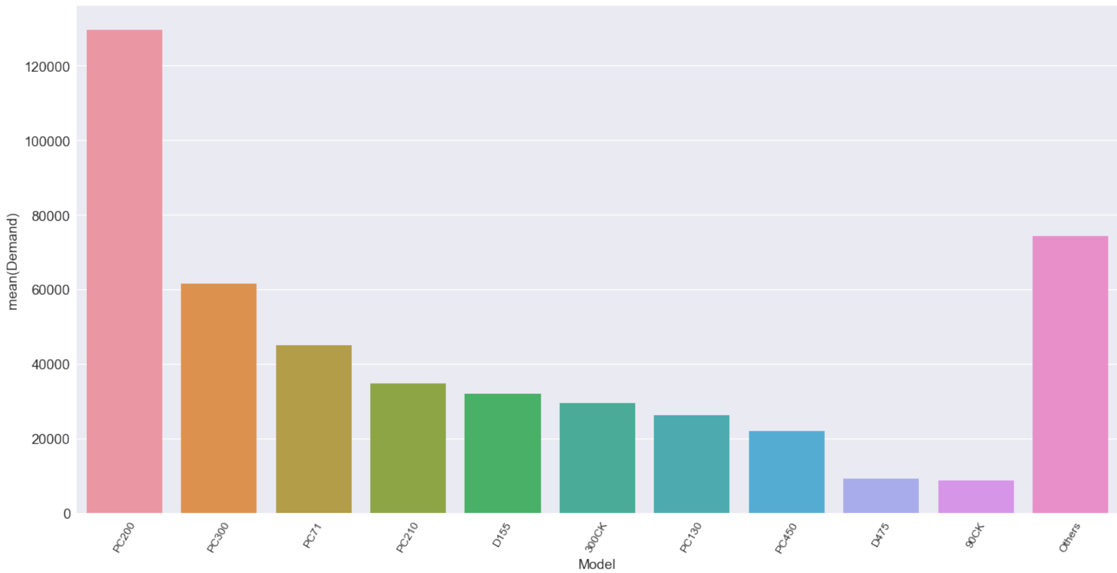
[ ]:

	Model	Demand
0	Others	14919
1	OTHER	13158

[ ]:
```
tmp = pd.concat([tmp, model.loc[10:]])
model = model.loc[:9]
model.loc[10] = ['Others', tmp['Demand'].sum()]
```

[ ]:
```
sns.barplot(x = 'Model', y= 'Demand', data=model)
plt.xticks(rotation=60)
plt.plot()
```

[ ]: []



11 Pie chart to be displayed : Out of stock or stocks needed immediately

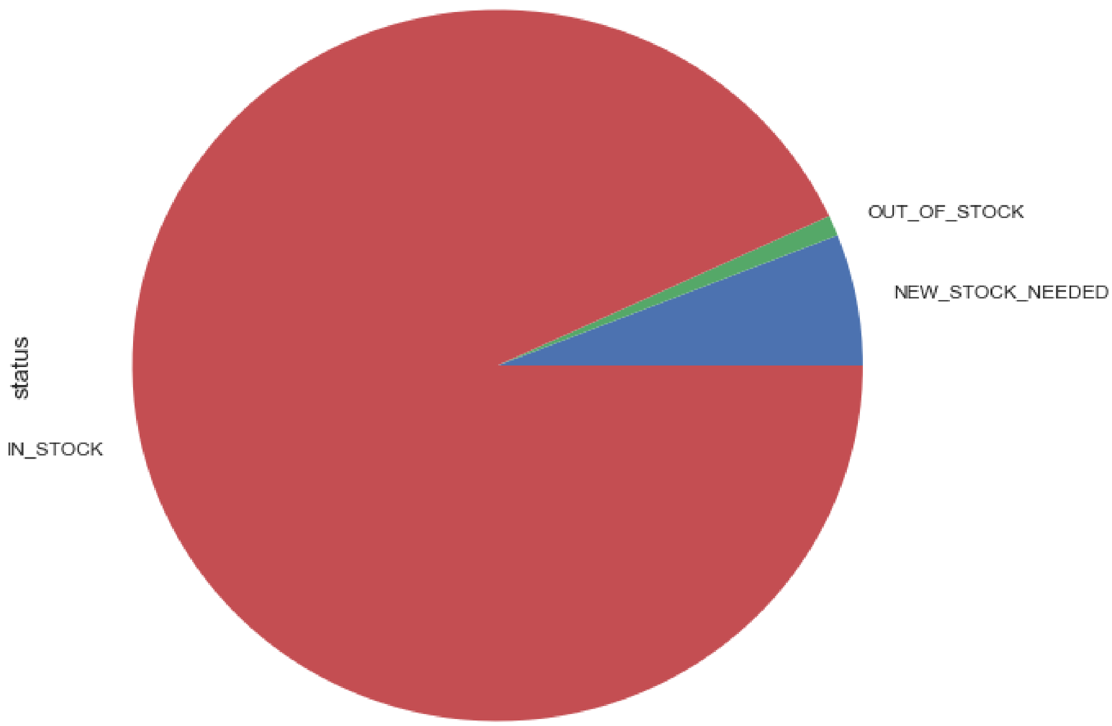
[ ]:
```
stock_df = material_master.merge(stock_master,left_on='Material code',right_on= 'Material')
stock_df.drop(['Material Description','DocumentNo','D/C','Amount','BUn','Pstng Date','Material'],axis=1, inplace=True)
```

[ ]:
```
stock_df = stock_df.groupby(['Material code','Model','safety stock'])['Quantity'].sum().reset_index()
```

[ ]:
```
# checking for various conditions
def test (row):
   if row['safety stock'] < row['Quantity']  :
      return 'IN_STOCK'
   if row['safety stock'] > row['Quantity']  :
      return 'OUT_OF_STOCK'
   if row['safety stock'] == row['Quantity']  :
      return 'NEW_STOCK_NEEDED'

   return 'Other'
```

[ ]:
```
stock_df['status'] = stock_df.apply (lambda row: test (row),axis=1)
```

[ ]:
```
#pie chart(using quantity and safety_stock)

plt.figure(figsize=(10, 10))
stock_df.status.value_counts(sort=False).plot(kind='pie')
plt.show()
```



12 Season wise demand forecast

Here we try to find out how the demand for various products in the company vary with the seasons

First we split the order dates for each material according to seasons We consider 5 seasons:
1. Winter - November to Feb (11,12,1,2) 2. Spring - March to April (3,4)
3. Summer - May to June (5,6) 4. Monsoon - July to August (7,8)
5. Autumn - September to October (9,10)

Lets get the month from 'PO date' and assign it to a new df

[ ]:
```
df = customer[['PO date', 'Total_Price']]
df.loc[:, 'month'] = df['PO date'].apply(lambda x: x.month)
df = df.drop(['PO date'], axis=1)
```

[ ]:
```
df = df.groupby(['month']).sum().reset_index()
```

[ ]:
```
# checking for various conditions
def test_s (row):
```

```
    if (row['month'] ==1)|(row['month']==2)   :
       return 'winter'

    if (row['month'] ==3)|(row['month'] ==4)   :
       return 'spring'
    if (row['month'] ==5)|(row['month'] ==6)  :
       return 'summer'
    if (row['month']==7)|(row['month']==8) :
       return 'mansoon'
    if (row['month'] ==9)|(row['month'] ==10)   :
       return 'autumn'
    if (row['month'] ==11)|(row['month'] ==12)   :
       return 'winter'
```

[ ]:
```
df['season'] = df.apply (lambda row: test_s (row),axis=1)
df = df.drop(['month'], axis=1)
```

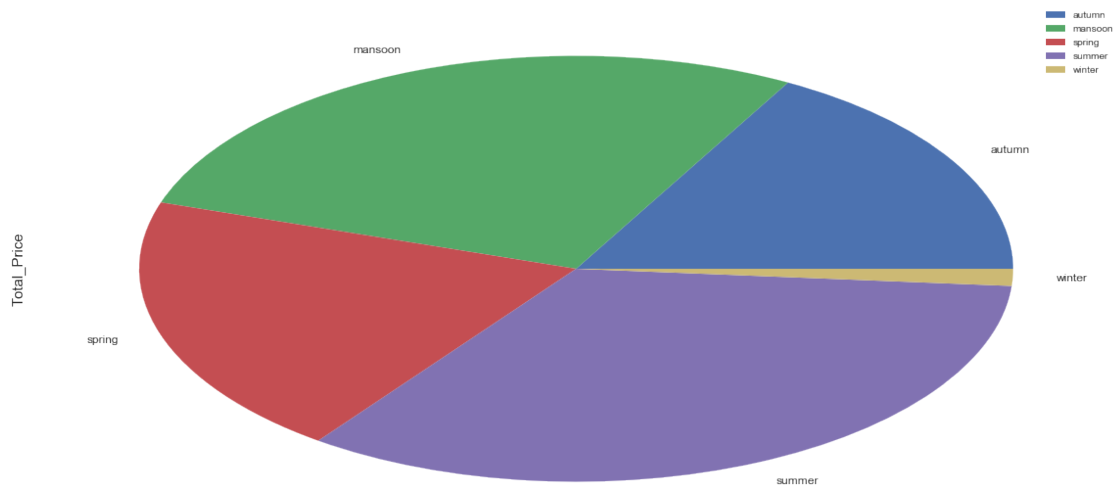
[ ]:
```
df = df.groupby('season').sum().reset_index()
df
```

[ ]:

	season	Total_Price
0	autumn	115282947
1	mansoon	190583361
2	spring	136098629
3	summer	229683886
4	winter	8753860

[ ]:
```
plt.figure(figsize=(10, 10))
df.plot(kind='pie', y='Total_Price', labels=df['season'])
plt.show()
```

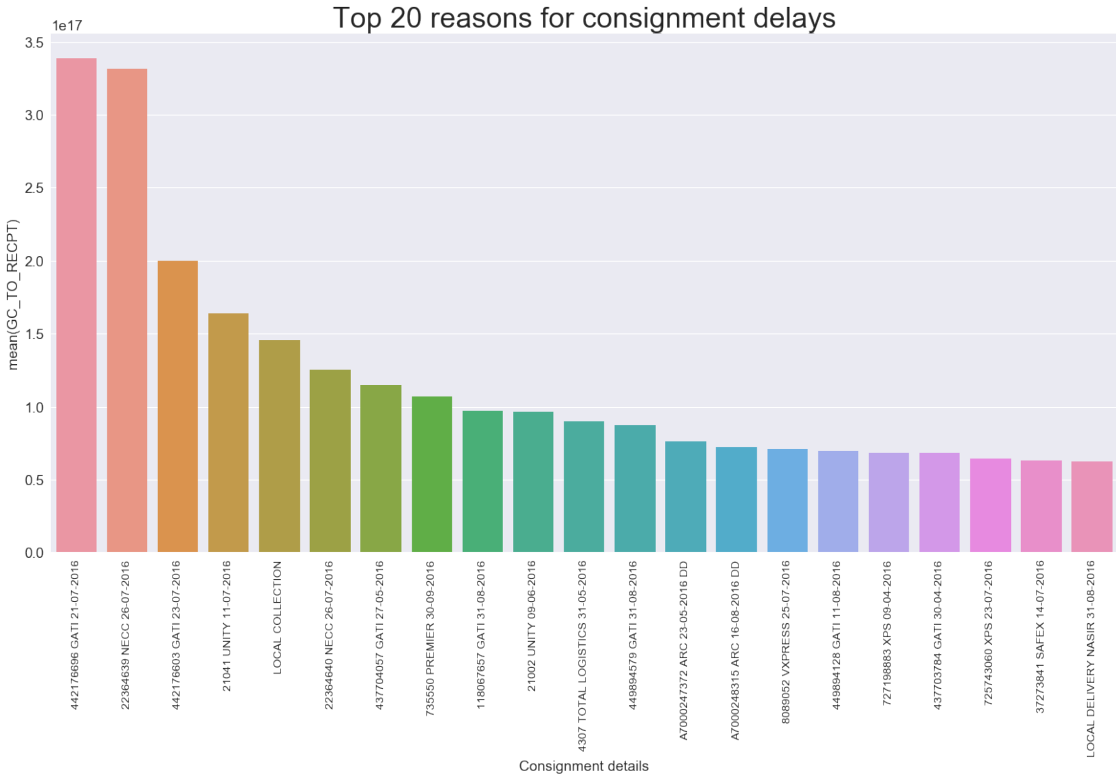
<matplotlib.figure.Figure at 0x7f557ec62ad0>



13 Checking possible reason for delay from consignment to delivery

[ ]:
```
GC_to_recpt = bill[['GC date', 'Recpt date', 'Consignment details']]
GC_to_recpt.loc[:, 'GC_TO_RECPT'] = GC_to_recpt['Recpt date'] - GC_to_recpt['GC␣
↪date']
GC_to_recpt = GC_to_recpt.sort_values(by='GC_TO_RECPT', ascending=False)
GC_to_recpt = GC_to_recpt.groupby('Consignment details').sum().reset_index().
↪sort_values(by='GC_TO_RECPT', ascending=False).reset_index(drop=True)
```

[ ]:
```
# Top 20 reasons for consignment delays

GC_to_recpt = GC_to_recpt.loc[:20]
sns.barplot(y = 'GC_TO_RECPT', x= 'Consignment details', data=GC_to_recpt)
plt.xticks(rotation=90)
plt.title('Top 20 reasons for consignment delays')
plt.show()
```

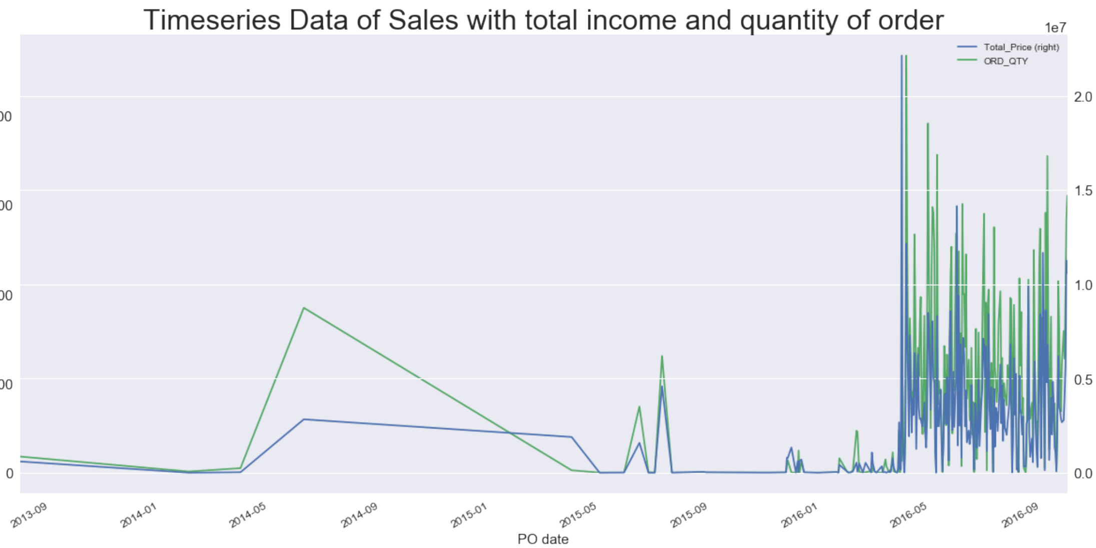


14 Query Drill down

[ ]:
```
# Lets see if the orders fluctuate as per the date, you know if there
# is a season for most orders. Maybe end of fiscal year or start of new
# fiscal year, this would show optimal time to pump up production of parts

# df is a new dataframe created using the customer_order table, we only need
# to put emphasis on the date of orders and the Price.
df = customer[['PO date', 'Total_Price', 'ORD_QTY']]
```

[ ]:
```
df = df.groupby(['PO date']).sum().reset_index()
df = df.sort_values(by=['PO date'])
df['PO date'] = pd.to_datetime(df['PO date'])
```

[ ]:
```
ax = df.plot(x='PO date', y='Total_Price', secondary_y=True)
df.plot(x='PO date', y='ORD_QTY', ax=ax)
plt.title('Timeseries Data of Sales with total income and quantity of order')
plt.show()
```



14.0.1 Month of the year

[ ]:
```
df = customer[['PO date', 'Total_Price', 'ORD_QTY']]
df.loc[:,'month'] = df['PO date'].apply(lambda x: x.month)
df = df.drop(['PO date'], axis=1)
df = df.groupby(['month']).sum().reset_index()
```

[ ]:
```
df
```

[ ]:

	month	Total_Price	ORD_QTY
0	1	534144	191
1	2	3298831	1099
2	3	27143439	1439
3	4	108955190	38685
4	5	120713266	38275
5	6	108970620	38315
6	7	104511662	34957
7	8	86071699	29733
8	9	115282947	35748
9	11	2934394	215
10	12	1986491	378

[ ]:
```
ax = df.plot(x='month', y='Total_Price', secondary_y=True, marker='o')
df.plot(x='month', y='ORD_QTY', marker='o', ax=ax)
plt.xticks([x for x in xrange(1, 13)], ['Jan', 'Feb', 'Mar', 'Apr', 'May',␣
 ↪'Jun', 'July', 'Aug', 'Sep', 'Oct', 'Nov', 'Dec'])
plt.title('Income and Order Quantity per month')
plt.show()
```

14.0.2 Day of the month

[ ]:
```
df = customer[['PO date', 'Total_Price', 'ORD_QTY']]
df.loc[:,'day'] = df['PO date'].apply(lambda x: x.day)
df = df.drop(['PO date'], axis=1)
df = df.groupby(['day']).sum().reset_index()
```

[ ]:
```
df.head()
```

[ ]:

	day	Total_Price	ORD_QTY
0	1	12893564	3604
1	2	30516498	8774
2	3	24459472	5732
3	4	26489072	7810
4	5	26719262	10069

[ ]:
```
ax = df.plot(x='day', y='Total_Price', secondary_y=True, marker='o')
df.plot(x='day', y='ORD_QTY', marker='o', ax=ax)
plt.title('Income and Order Quantity per day of the month')
plt.show()
```

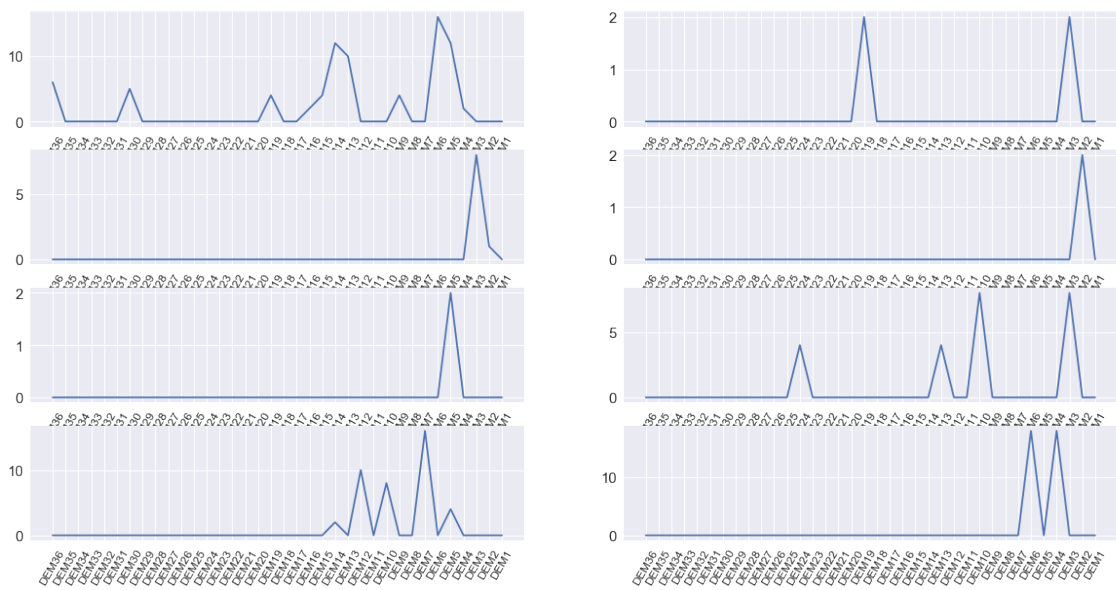
14.0.3 Machine Learning

[ ]:
```
sales_past_demand.head()
```

[ ]:
```
   Material code  DEM36  DEM35  DEM34  DEM33  DEM32  DEM31  DEM30  DEM29  \
0  01010-61435I.      6      0      0      0      0      0      5      0
1  01010-61455I.      0      0      0      0      0      0      0      0
2  01010-61635I.      0      0      0      0      0      0      0      0
3  01010-61645I.      0      0      0      0      0      0      0      0
4  01010-61650I.      0      0      0      0      0      0      0      0

   DEM28  …   DEM10  DEM9  DEM8  DEM7  DEM6  DEM5  DEM4  DEM3  DEM2  DEM1
0      0  …       0     4     0     0    16    12     2     0     0     0
1      0  …       0     0     0     0     0     0     0     2     0     0
2      0  …       0     0     0     0     0     0     0     8     1     0
3      0  …       0     0     0     0     0     0     0     0     2     0
4      0  …       0     0     0     0     0     2     0     0     0     0

[5 rows x 37 columns]
```

[ ]:
```
tmp = sales_past_demand.drop(['Material code'], axis=1)
```

[ ]:
```
for i in xrange(0, 8):
    plt.subplot(4, 2, i + 1)
    plt.plot([x for x in range(0, 36)], tmp.loc[i].values)
    plt.xticks([x for x in range(0, 36)], tmp.loc[i].index, rotation=60)
plt.show()
```

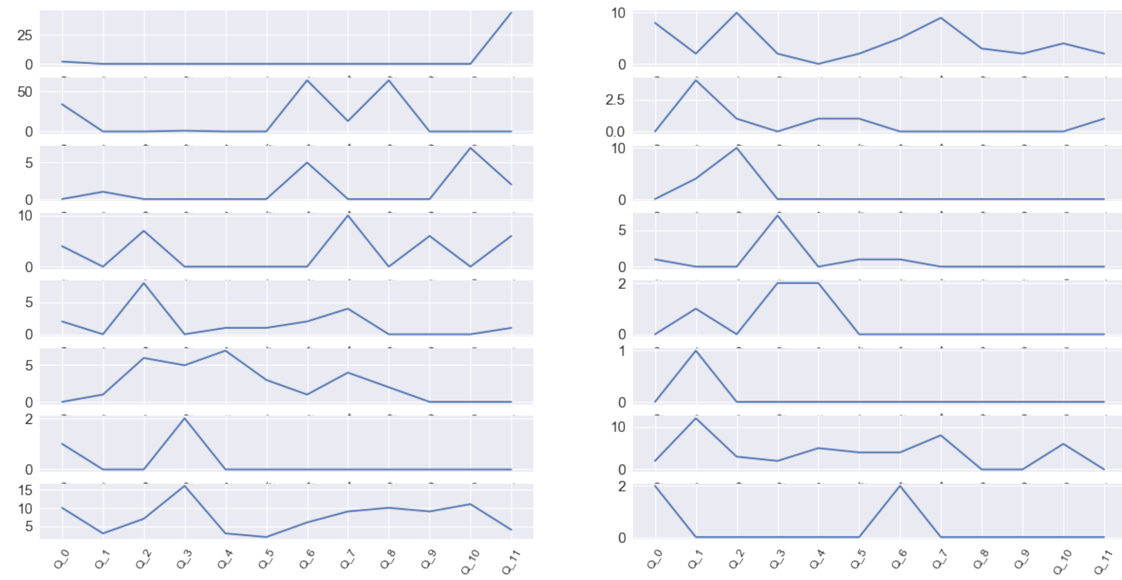


There is no periodicity in this whatsoever, perhaps we need to find other factors which influence these purchases? Or maybe we could try and represent data in some other form?

Instead of data per month, divide the data as to have data per 3 months. This allows us to predict the demand for the next three months which would be aggregated better than data per month.

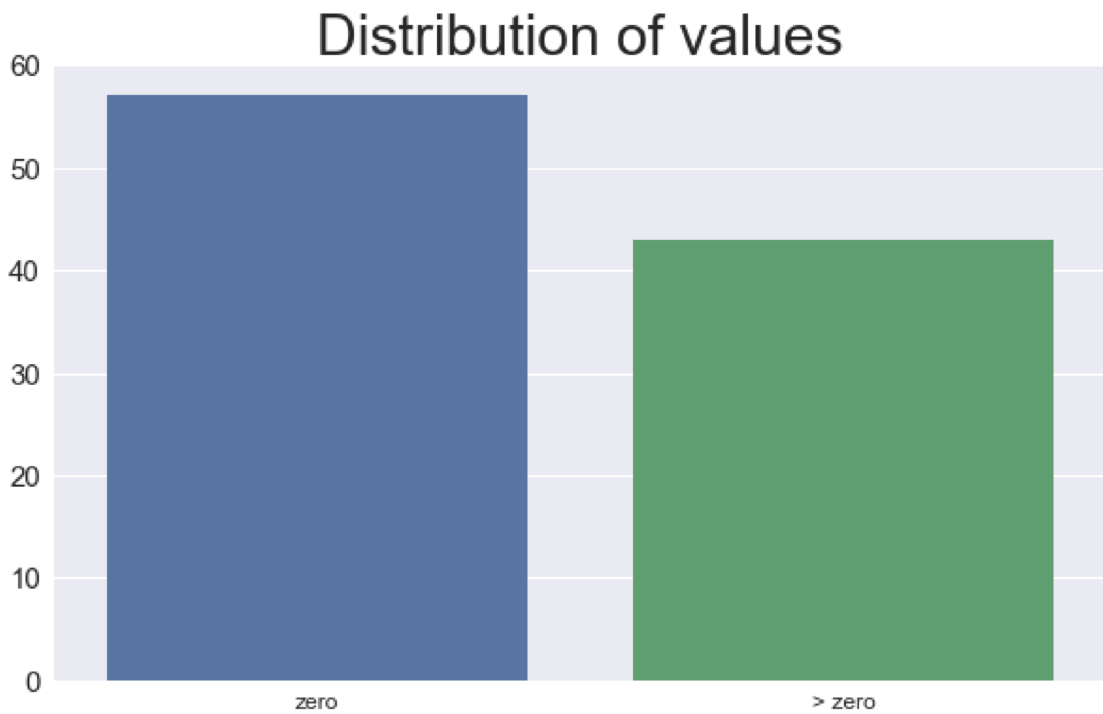
[ ]:
```
df = pd.DataFrame()
df['Material code'] = sales_past_demand['Material code']
for i in range(1, 37, 3):
    df['Q_' + str((i-1)/3)] = sales_past_demand[['DEM' + str(x) for x in␣
 ↪range(i, i + 3)]].sum(axis=1)
```

[ ]:
```
tmp = df.drop(['Material code'], axis=1)
for i in xrange(0, 16):
    plt.subplot(8, 2, i + 1)
    plt.plot([x for x in range(0, 12)], tmp.loc[i+100].values)
    plt.xticks([x for x in range(0, 12)], tmp.loc[i+100].index, rotation=60)
plt.show()
```



Here, we can some sort of patterns. this could be predicted well. First lets see the prediction value, if we predict 0 for Q__11 by default.

```
[ ]: x = len(tmp[tmp['Q_11'] == 0])/float(len(tmp))
y = 1 - x
x = x * 100
y = y * 100
plt.figure(figsize=(10, 6))
plt.title('Distribution of values')
sns.barplot(y = [x, y], x = ['zero', '> zero'])
plt.show()
print 'If we predict the demand to be zero every time, our accuracy would therefore be:', x, '%'
```




```
If we predict the demand to be zero every time, our accuracy would therefore be:
57.1072733311 %
```

So are prediction should at minimum perform better than 57%. Lets drop the 'Material code' since we're training our model to predict the demand for any given material Quaters.

So we've split the data into quarters (3 months). Since we have data of 36 months, this gives us 12 quarters. So the idea is to train the model on 11 quarters so that it is able to predict the 12th quarter.

```
[ ]: df = df.drop(['Material code'], axis=1)
     df.columns
```

```
[ ]: Index([u'Q_0', u'Q_1', u'Q_2', u'Q_3', u'Q_4', u'Q_5', u'Q_6', u'Q_7', u'Q_8',
            u'Q_9', u'Q_10', u'Q_11'],
           dtype='object')
```

14.1 Regression

Now we have our desired inputs and desired outputs. But it wouldn't make sense to train the machine learning algorithm and test it on the same data, so we'll now split our data into training and tests sets (70% - 30%).

```
[ ]: from sklearn.model_selection import train_test_split
```

```
X_train, X_test, y_train, y_test = train_test_split(df.drop('Q_11', axis=1), df.
 ↪Q_11, test_size=.3, random_state=42)
```

Now given the Training and testing set, we can use GridSearchCV to find best model for the given data.

ElasticNet

[ ]:
```
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import ElasticNet

param = {'alpha': [1.0, 2, 5, 10, 50, 100, 1000], 'normalize': [True, False]}
reg = GridSearchCV(ElasticNet(), param)
reg.fit(X_train, y_train)
reg.score(X_test, y_test)
```

[ ]: 0.86167075983978569

[ ]:
```
reg.best_params_
```

[ ]: {'alpha': 100, 'normalize': False}

Lasso

[ ]:
```
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import Lasso

param = {'alpha': [1.0, 2, 5, 10, 50, 100, 1000], 'normalize': [True, False]}
reg = GridSearchCV(Lasso(), param)
reg.fit(X_train, y_train)
reg.score(X_test, y_test)
```

[ ]: 0.84968164809059832

[ ]:
```
reg.best_params_
```

[ ]: {'alpha': 100, 'normalize': False}

Ridge

[ ]:
```
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import Ridge

param = {'alpha': [1.0, 10, 100], 'normalize': [True, False], 'solver' :␣
 ↪['auto', 'svd', 'cholesky', 'lsqr', 'sparse_cg', 'sag']}
reg = GridSearchCV(Ridge(), param)
reg.fit(X_train, y_train)
reg.score(X_test, y_test)
```

[ ]: 0.87287512860147776

```
reg.best_params_
```

[ ]: {'alpha': 100, 'normalize': False, 'solver': 'sag'}

AdaboostRegressor

```
from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import AdaBoostRegressor

param = {'n_estimators': [50, 100, 500], 'loss': ['linear', 'square',␣
 ↪'exponential']}
reg = GridSearchCV(AdaBoostRegressor(), param)
reg.fit(X_train, y_train)
reg.score(X_test, y_test)
```

[ ]: 0.74447372512362997

```
reg.best_params_
```

[ ]: {'loss': 'linear', 'n_estimators': 50}

14.1.1 Picking the best model

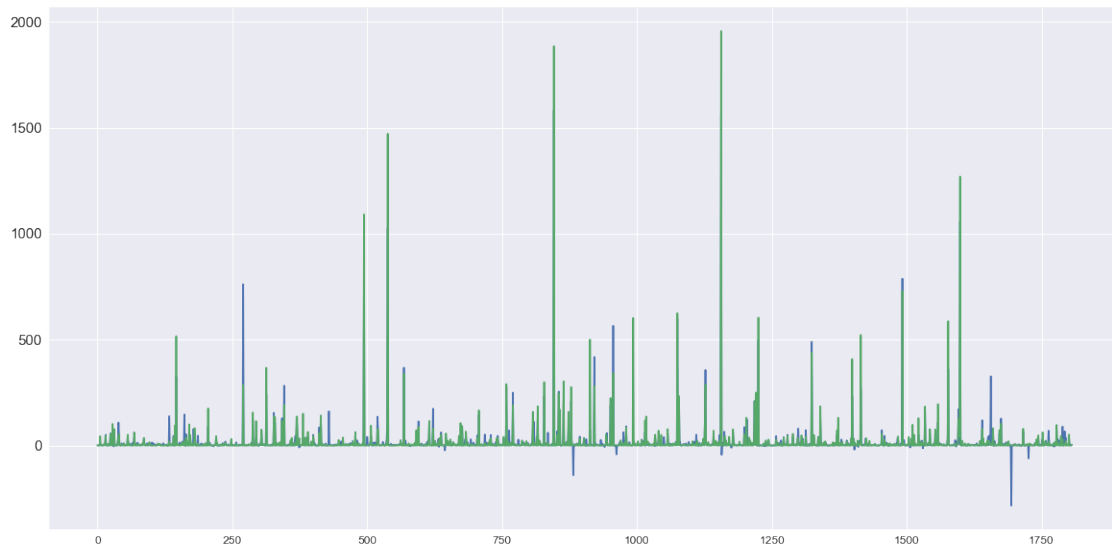
Since we got the highest score with the Ridge model, we'll use it to do our predictions.

```
from sklearn.linear_model import Ridge

reg = Ridge(alpha=100, normalize=False, solver='sag')
reg.fit(X_train, y_train)
reg.score(X_test, y_test)
```

[ ]: 0.87211240115639543

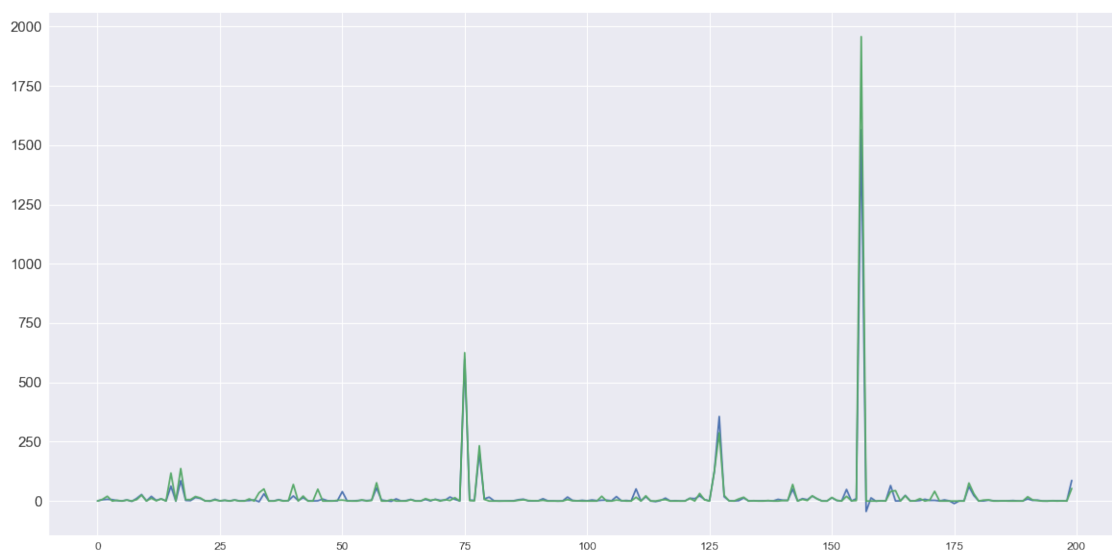
Lets compare the prediction with the actual values

```
pred = reg.predict(X_test)
plt.plot(pred)
plt.plot(y_test.values)
plt.show()
```

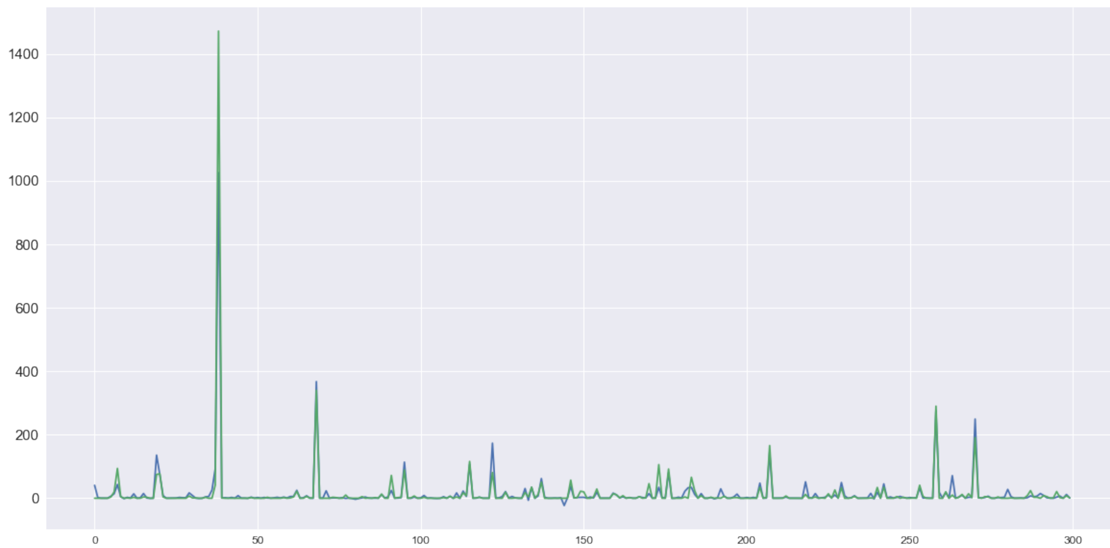


Zooming in a little:

[ ]:
```
plt.plot(pred[1000:1200])
plt.plot(y_test.values[1000:1200])
plt.show()
```



[ ]:
```
plt.plot(pred[500:800])
plt.plot(y_test.values[500:800])
plt.show()
```



1400
1200
1000
800
600
400
200
0
0
50
100
150
200
250
300