[SL]ACHATHON
Optimize Supply Chain Inventory

Effectively manage and optimize inventory by capturing variables such as lead times, manufac- turing frequency, batch size, and ordering policies from across the supply chain. Using algo- rithms, exception-based forecasts, and real-time downstream demand signals, suggest and

adjust inventories to optimal levels. Maintain the right amount of inventory required to meet

demand, keep logistics costs low, and avoid common inventory issues such as stockouts, over- stocking, and backorders.

Librarys for necessary tasks

```
import numpy as np

import pandas as pd

import seaborn as sns

import matplotlib.pyplot as plt

import plotly.express as ps

import statistics as stc

from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
```

Read data using pandas

```
df = pd.read_csv('supply chain.csv')

df.head(5)
```

```
      RegionName               CountryName  State       City
PostalCode  \
0  South America  United States of America  Texas  Southlake
26192
1  South America  United States of America  Texas  Southlake
26192
2  South America  United States of America  Texas  Southlake
26192
3  South America  United States of America  Texas  Southlake
26192
4  South America  United States of America  Texas  Southlake
26192

      WarehouseAddress    WarehouseName    EmployeeName  \
0  2014 Jabberwocky Rd  Southlake Texas    Summer Payne
1  2014 Jabberwocky Rd  Southlake Texas   Rose Stephens
```

```
2  2014 Jabberwocky Rd  Southlake Texas  Annabelle Dunn
3  2014 Jabberwocky Rd  Southlake Texas    Tommy Bailey
4  2014 Jabberwocky Rd  Southlake Texas    Blake Cooper

                EmployeeEmail  EmployeePhone  ...    CustomerName  \
0    summer.payne@example.com     5151238181  ...      Flor Stone
1   rose.stephens@example.com     5151238080  ...  Lavera Emerson
2  annabelle.dunn@example.com     5151234444  ...       Fern Head
3    tommy.bailey@example.com     5151234567  ...     Shyla Ortiz
4    blake.cooper@example.com     5151234569  ...       Jeni Levy

                    CustomerAddress CustomerCreditLimit  \
0                  2904 S Salina St                5000
1  5344 Haverford Ave, Philadelphia                5000
2      1795 Wu Meng, Muang Chonburi                1200
3           Walpurgisstr 69, Munich                2400
4             Via Frenzy 6903, Roma                1200

                          CustomerEmail CustomerPhone    Status
OrderDate  \
0               flor.stone@raytheon.com   13171234104   Shipped  17-
Nov-16
1  lavera.emerson@plainsallamerican.com   13171234111   Shipped  20-
Feb-17
2                fern.head@usfoods.com   18121234115  Canceled  03-
Jan-17
3               shyla.ortiz@abbvie.com   13171234126   Pending  15-
Oct-17
4                jeni.levy@centene.com   18121214129   Shipped  09-
Apr-17

   OrderItemQuantity PerUnitPrice TotalItemQuantity
0                132       469.99                122
1                124       519.99                123
2                 92       800.74                123
3                128       849.99                124
4                106       109.99                125

[5 rows x 28 columns]
```

```
df.tail(5)
```

```
    RegionName CountryName        State    City PostalCode  \
395       Asia       India  Maharashtra  Bombay     490231
396       Asia       India  Maharashtra  Bombay     490231
397       Asia       India  Maharashtra  Bombay     490231
398       Asia       India  Maharashtra  Bombay     490231
399       Asia       India  Maharashtra  Bombay     490231

       WarehouseAddress WarehouseName     EmployeeName  \
```

```
395  1298 Vileparle (E)        Bombay   Veera Abdellah
396  1298 Vileparle (E)        Bombay     Vega Vincent
397  1298 Vileparle (E)        Bombay  Villanueva Noah
398  1298 Vileparle (E)        Bombay     Zima Colleen
399  1298 Vileparle (E)        Bombay     Volk Colleen

                EmployeeEmail  EmployeePhone  ...     CustomerName  \
395   VeeraAbdellah@gmail.com     8788092231  ...     Vega Vincent
396     VegaVincent@gmail.com     6700989921  ...  Villanueva Noah
397  VillanuevaNoah@gmail.com     7890991231  ...   Voldemort Lord
398     ZimaColleen@gmail.com     8690991436  ...   Lucy Cechtelar
399      VolkCollen@gmail.com     9426826971  ...         John Snow

          CustomerAddress CustomerCreditLimit
CustomerEmail  \
395        4284 Dorigo Ln                4900
VegaVincent@gmail.com
396        6794 Lake Dr E                5000
VillanuevaNoah@gmail.com
397  31 Douglas Blvd #950                4000
VoldemortLord@gmail.com
398           44 W 4th St                3000
LucyCechtelar@gmail.com
399       11279 Loytan St                2000
JohnSnow@gmail.com

    CustomerPhone    Status  OrderDate  OrderItemQuantity PerUnitPrice
\
395     787879874   Shipped  27-Sep-17                 32       725.99

396     785811219   Pending  16-Aug-16                 66       798.26

397     789243757  Canceled  27-May-16                 82       849.99

398     964940981   Shipped  27-May-17                157       821.99

399     567897474  Canceled  27-May-17                 32       579.59


    TotalItemQuantity
395               107
396               118
397               118
398                95
399                92

[5 rows x 28 columns]

df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 400 entries, 0 to 399
Data columns (total 28 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   RegionName           400 non-null    object
 1   CountryName          400 non-null    object
 2   State                400 non-null    object
 3   City                 400 non-null    object
 4   PostalCode           400 non-null    object
 5   WarehouseAddress     400 non-null    object
 6   WarehouseName        400 non-null    object
 7   EmployeeName         400 non-null    object
 8   EmployeeEmail        400 non-null    object
 9   EmployeePhone        400 non-null    int64
 10  EmployeeHireDate     400 non-null    object
 11  EmployeeJobTitle     400 non-null    object
 12  CategoryName         400 non-null    object
 13  ProductName          400 non-null    object
 14  ProductDescription   400 non-null    object
 15  ProductStandardCost  400 non-null    float64
 16  Profit               400 non-null    float64
 17  ProductListPrice     400 non-null    float64
 18  CustomerName         400 non-null    object
 19  CustomerAddress      400 non-null    object
 20  CustomerCreditLimit  400 non-null    int64
 21  CustomerEmail        400 non-null    object
 22  CustomerPhone        400 non-null    int64
 23  Status               400 non-null    object
 24  OrderDate            400 non-null    object
 25  OrderItemQuantity    400 non-null    int64
 26  PerUnitPrice         400 non-null    float64
 27  TotalItemQuantity    400 non-null    int64
dtypes: float64(4), int64(5), object(19)
memory usage: 87.6+ KB

df.describe()

       EmployeePhone  ProductStandardCost       Profit
ProductListPrice  \
count   4.000000e+02           400.000000   400.000000
400.000000
mean    1.300551e+12          1812.654525   189.743700
2002.398800
std     3.546655e+12          4297.988742   254.318871
4432.591249
min     1.856490e+07            12.630000     0.000000
15.550000
25%     9.716165e+08           414.160000    59.972500
502.982500
50%     1.168870e+10           698.320000   134.200000
```

```
849.990000
75%     2.651186e+10          1671.950000   229.520000
1999.890000
max     1.144164e+13         75410.000000  2770.000000
78180.000000

       CustomerCreditLimit  CustomerPhone  OrderItemQuantity
PerUnitPrice  \
count           400.000000   4.000000e+02         400.000000
400.000000
mean           2033.617500   6.422348e+10          89.240000
839.253100
std            1534.488065   1.871854e+11          34.064253
706.449917
min             100.000000   4.538500e+04          32.000000
16.990000
25%             700.000000   3.545837e+09          61.000000
352.982500
50%            1500.000000   9.800588e+09          85.500000
686.990000
75%            3500.000000   1.812122e+10         118.000000
1055.990000
max            5000.000000   9.138593e+11         157.000000
4139.000000

       TotalItemQuantity
count         400.000000
mean          123.695000
std            67.438876
min             0.000000
25%            92.750000
50%           123.000000
75%           178.000000
max           353.000000
```

```
df.duplicated().sum()
```

```
0
```

This data does not have any duplicates

```
df.isnull().sum()
```

```
RegionName             0
CountryName            0
State                  0
City                   0
PostalCode             0
WarehouseAddress       0
WarehouseName          0
EmployeeName           0
```

```
EmployeeEmail          0
EmployeePhone          0
EmployeeHireDate       0
EmployeeJobTitle       0
CategoryName           0
ProductName            0
ProductDescription     0
ProductStandardCost    0
Profit                 0
ProductListPrice       0
CustomerName           0
CustomerAddress        0
CustomerCreditLimit    0
CustomerEmail          0
CustomerPhone          0
Status                 0
OrderDate              0
OrderItemQuantity      0
PerUnitPrice           0
TotalItemQuantity      0
dtype: int64
```

No null values found

```
df['WarehouseName'].unique()
```

```
array(['Southlake Texas', 'San Francisco', 'New Jersy',
       'Seattle Washington', 'Toronto', 'Sydney', 'Mexico City',
       'Beijing', 'Bombay'], dtype=object)
```

```
df2['CountryName'].unique()
```

```
array(['United States of America', 'Canada', 'Australia', 'Mexico',
       'China', 'India'], dtype=object)
```

```
df['RegionName'].unique()
```

```
array(['South America', 'North  America', 'North America',
'Australia',
       'Asia'], dtype=object)
```

Regionname,CountryName these columns are almost same.The only difference is factor levels.

Outlier deteaction

```
df.Profit.describe()
```

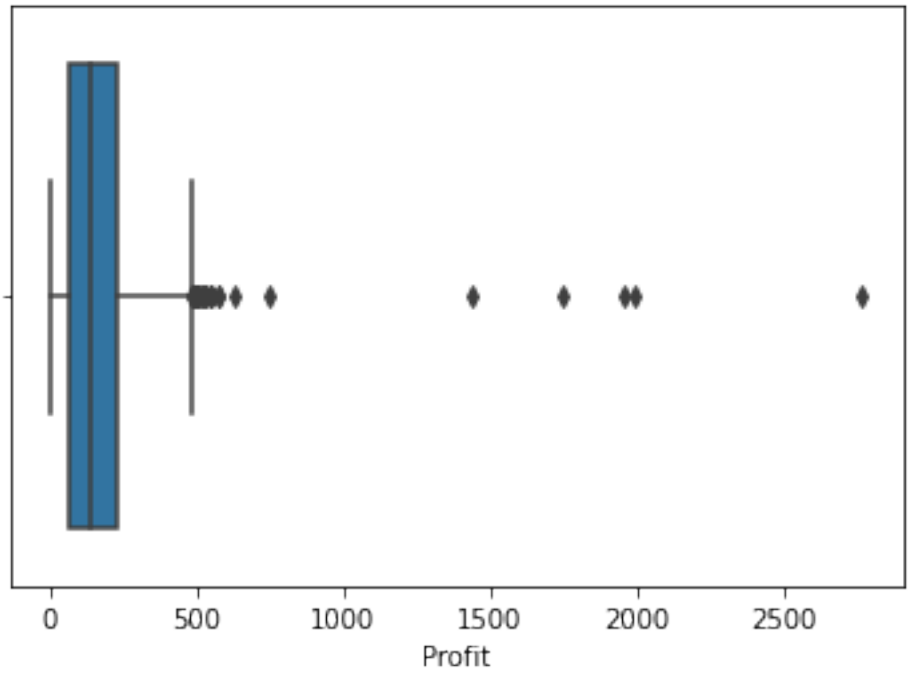
```
count     400.000000
mean      189.743700
std       254.318871
min         0.000000
```

```
25%        59.972500
50%       134.200000
75%       229.520000
max      2770.000000
Name: Profit, dtype: float64
```

```
sns.boxplot(df['Profit'])
```

```
/usr/local/lib/python3.7/site-packages/seaborn/_decorators.py:43:
FutureWarning: Pass the following variable as a keyword arg: x. From
version 0.12, the only valid positional argument will be `data`, and
passing other arguments without an explicit keyword will result in an
error or misinterpretation.
  FutureWarning
```

```
<AxesSubplot:xlabel='Profit'>
```




```
mean_profit = stc.mean(df['Profit'])
print(mean_profit)
```

```
189.7437
```

```
std_profit = stc.stdev(df['Profit'])
print(std_profit)
```

```
254.318870645152
```

```
profit_upper  = mean_profit+3*std_profit
print(profit_upper)
```

```
952.700311935456
```

```
len(df[df.Profit>profit_upper])
```

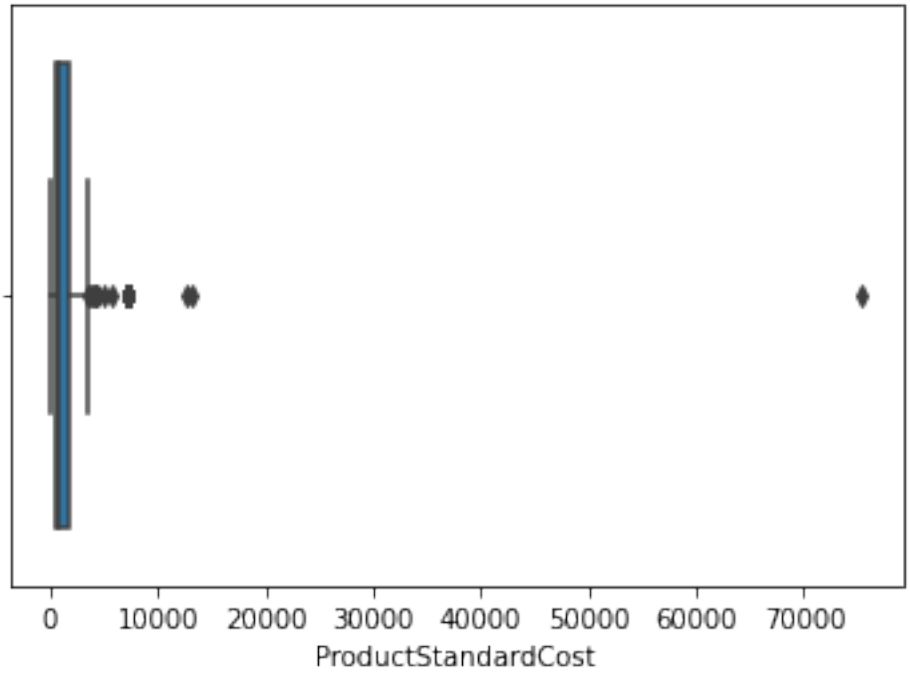
```
5
```

The count of outliers are very less

```
sns.boxplot(df['ProductStandardCost'])
```

```
/usr/local/lib/python3.7/site-packages/seaborn/_decorators.py:43:
FutureWarning: Pass the following variable as a keyword arg: x. From
version 0.12, the only valid positional argument will be `data`, and
passing other arguments without an explicit keyword will result in an
error or misinterpretation.
  FutureWarning
```

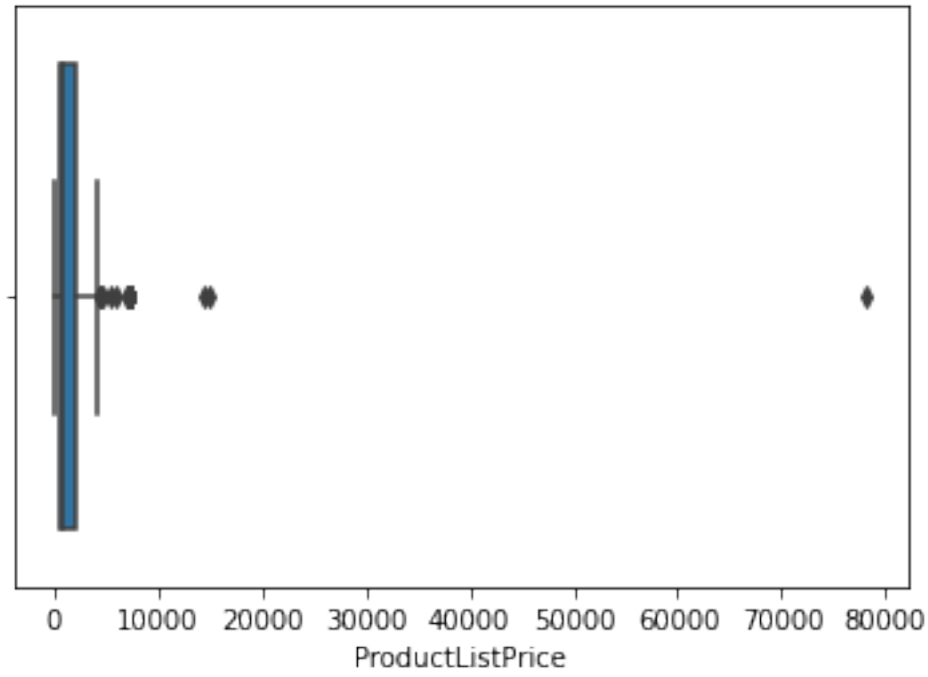
```
<AxesSubplot:xlabel='ProductStandardCost'>
```




```
sns.boxplot(df2['ProductListPrice'])
```

```
/usr/local/lib/python3.7/site-packages/seaborn/_decorators.py:43:
FutureWarning: Pass the following variable as a keyword arg: x. From
version 0.12, the only valid positional argument will be `data`, and
passing other arguments without an explicit keyword will result in an
error or misinterpretation.
  FutureWarning
```

```
<AxesSubplot:xlabel='ProductListPrice'>
```



Outliers considerably very low

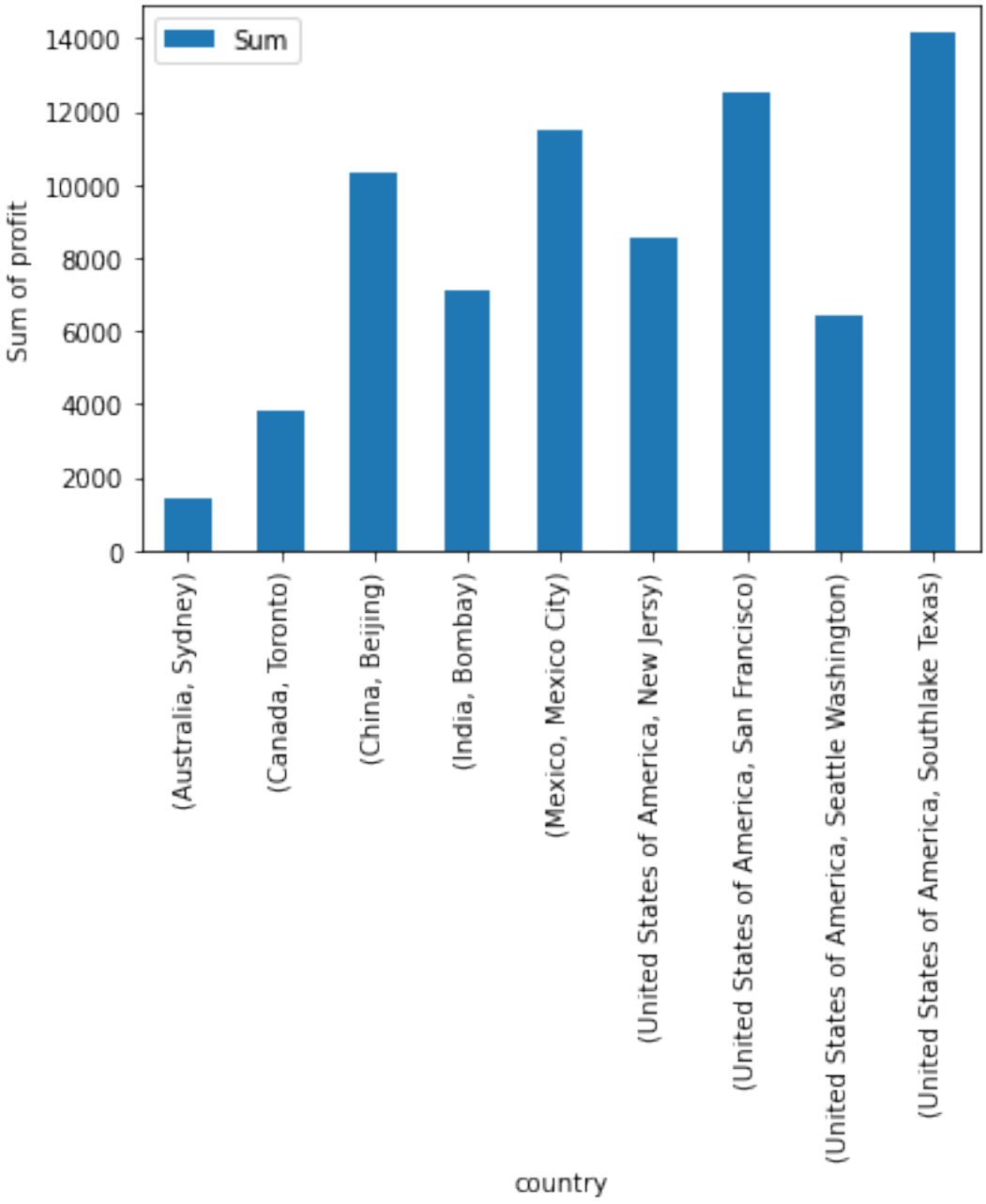
Here tring to find the high profitable warehouse and the country

```
country_pro =
df.groupby(['CountryName','WarehouseName']).agg(Sum=('Profit','sum'))
country_pro.sort_values(by='Sum',ascending=False)
```

		Sum
CountryName	WarehouseName	
United States of America	Southlake Texas	14181.44
	San Francisco	12539.70
Mexico	Mexico City	11498.05
China	Beijing	10348.09
United States of America	New Jersy	8524.89
India	Bombay	7138.22
United States of America	Seattle Washington	6406.94
Canada	Toronto	3817.83
Australia	Sydney	1442.32

```
country_pro.plot(kind = 'bar',xlabel='country',ylabel='Sum of profit')
```

```
<AxesSubplot:xlabel='country', ylabel='Sum of profit'>
```

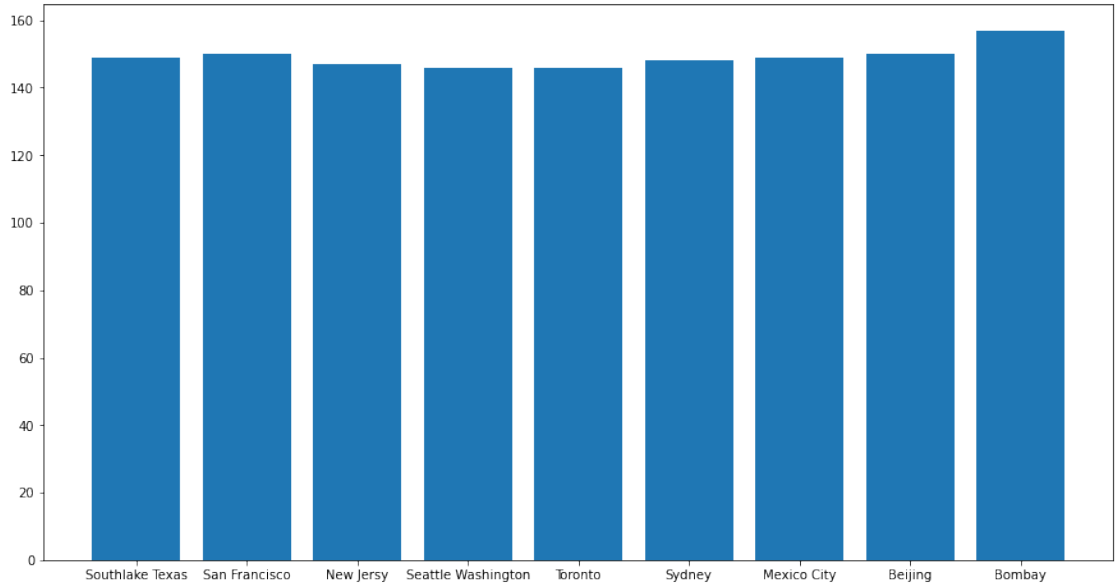


Most profitable ware houses are united states of america(Southlake Texas,San Francisco),mexico(Mexico City),China(Beijing)...

Find the Warehouse which received more orders

```
x = df['WarehouseName']
y = df['OrderItemQuantity']
plt.figure(figsize = (15,8))
plt.bar(x,y)
```

```
<BarContainer object of 400 artists>
```



Ware houses are having almost equal number of orders

Depict Category wise orders

```
df['CategoryName'].unique()
```

```
array(['CPU', 'Video Card', 'Storage', 'Mother Board', 'RAM'],
      dtype=object)
```

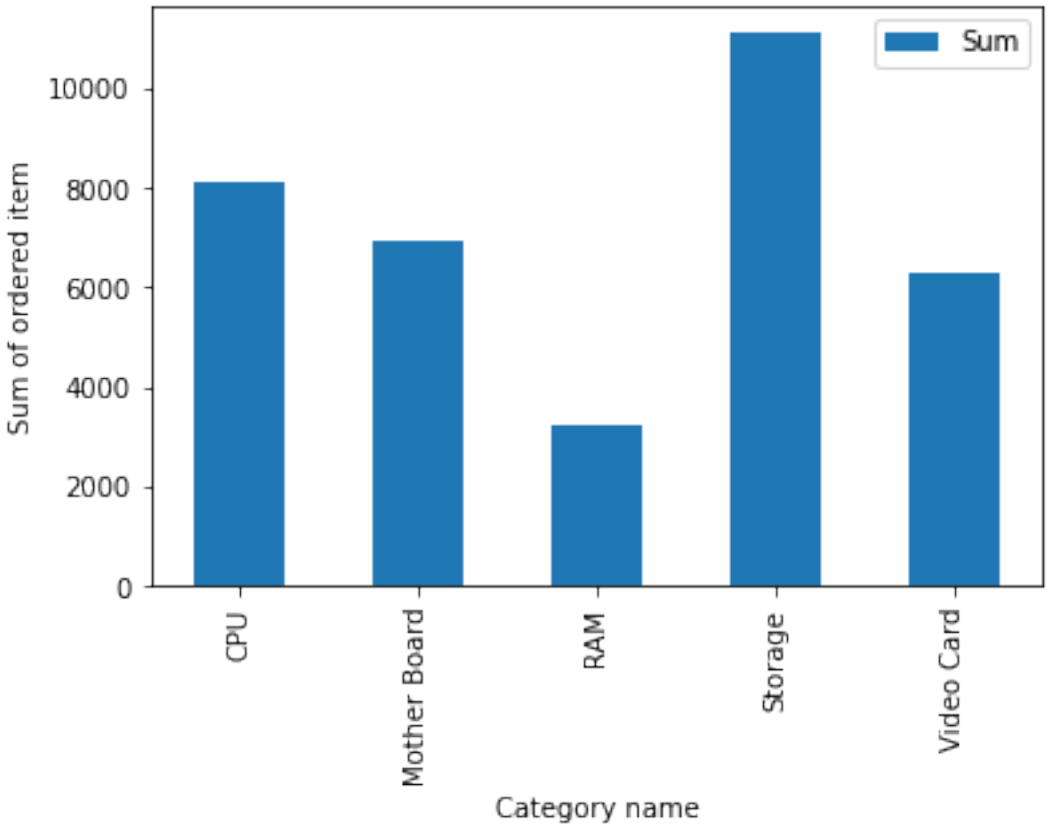
```
category=df.groupby(['CategoryName']).agg(Sum=('OrderItemQuantity','sum'))
```

```
category.sort_values(by='Sum',ascending=False)
```

CategoryName	Sum
Storage	11116
CPU	8127
Mother Board	6931
Video Card	6311
RAM	3211

```
category.plot(kind='bar',xlabel='Category name',ylabel='Sum of ordered item')
```

```
<AxesSubplot:xlabel='Category name', ylabel='Sum of ordered item'>
```



Storage has in the top position with high variance.Cpu and mother board are having the next two positions.

Find out the percentage of cancelled,pending and shipped orders

```
df['Status'].unique()
```

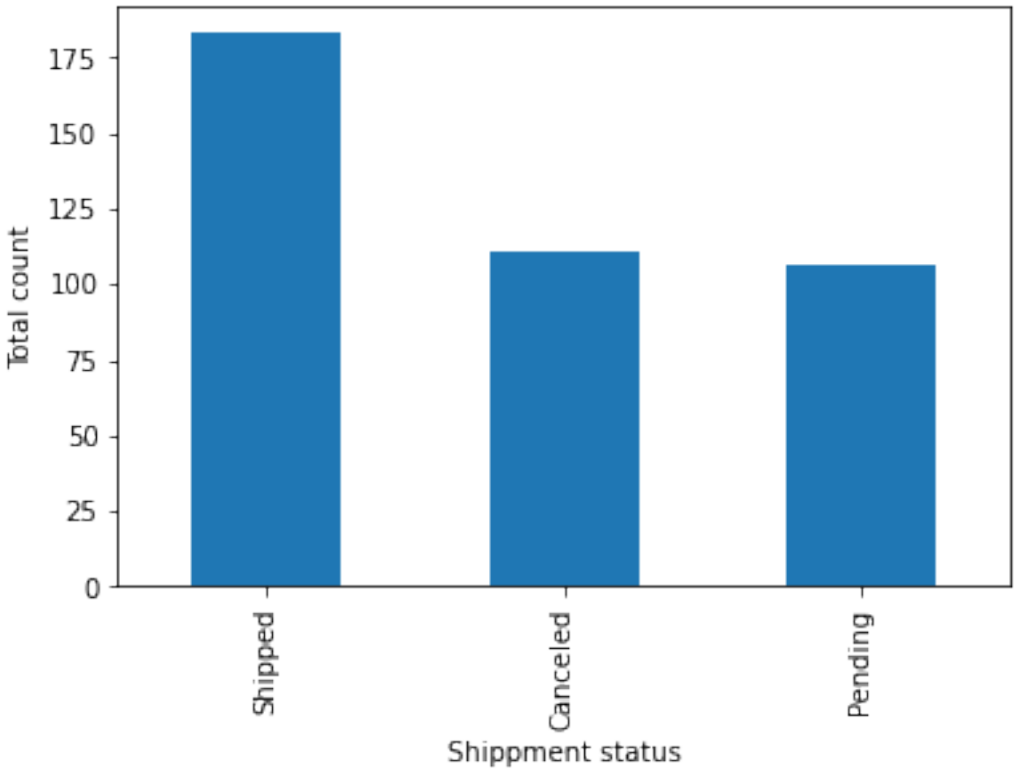
```
array(['Shipped', 'Canceled', 'Pending'], dtype=object)
```

```
status = df['Status'].value_counts()
print(status)
```

```
Shipped     183
Canceled    111
Pending     106
Name: Status, dtype: int64
```

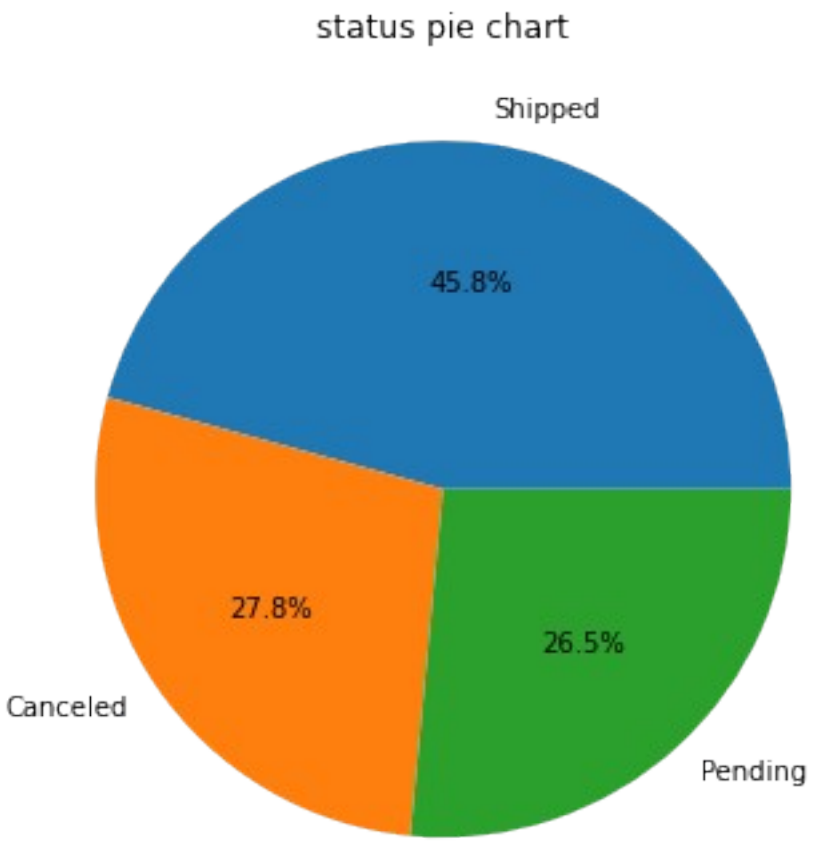
```
status.plot(kind='bar',xlabel =  'Shippment status',ylabel = 'Total count')
```

```
<AxesSubplot:xlabel='Shippment status', ylabel='Total count'>
```




```
plt.figure(figsize = (12,6))
plt.pie(status,labels=status.index,autopct='%1.1f%%')
plt.title("status pie chart")
```

```
Text(0.5, 1.0, 'status pie chart')
```



canceled orders and pending orders are almost equal.This will effect the profit as negatively. shipped orders are only 45% of whole data.

Have a look at couuntry and ware house wise status.

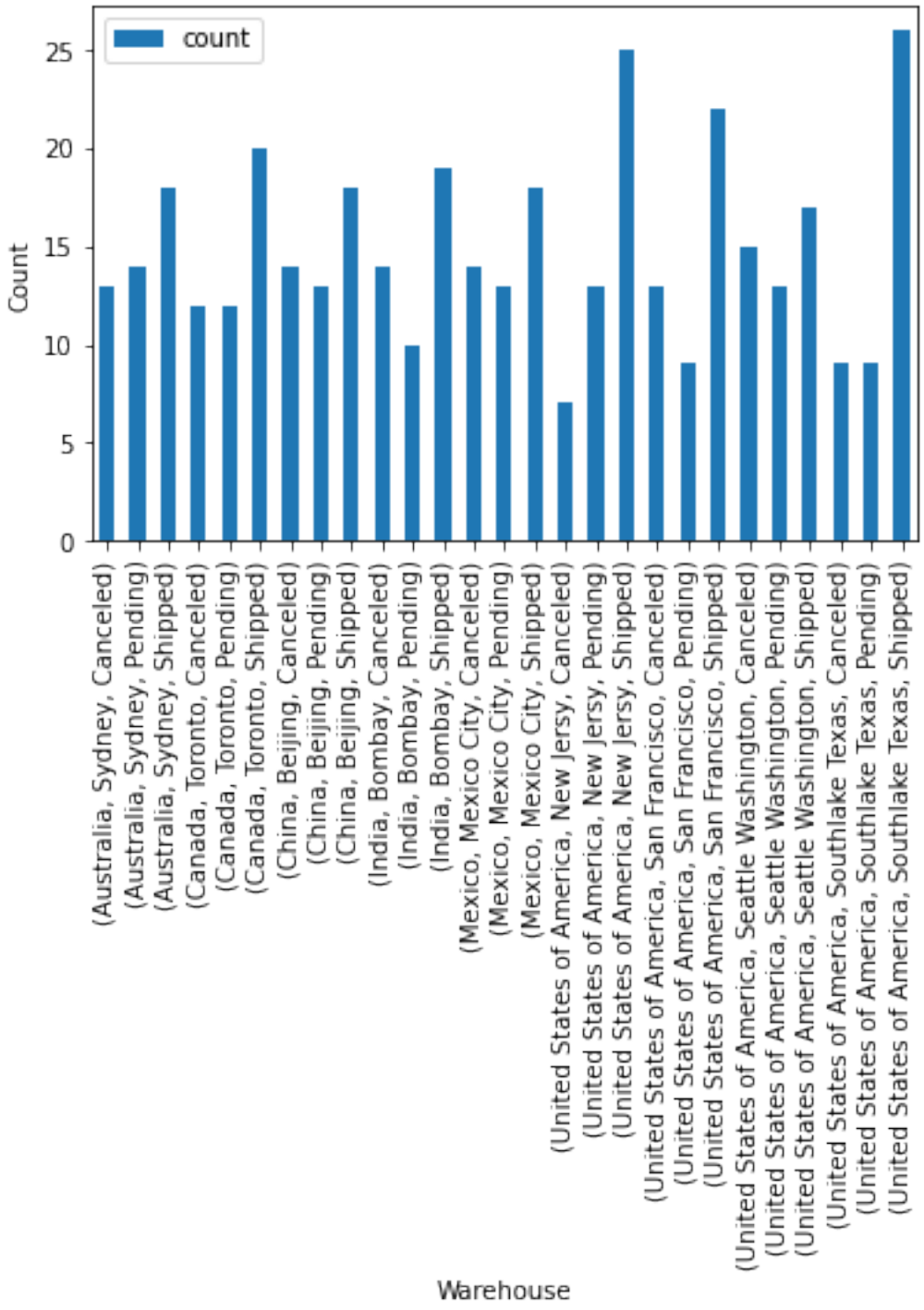
```
order_status =
df.groupby(['CountryName','WarehouseName','Status']).agg(count=('Count
ryName','count'))

order_status.sort_values(by='CountryName',ascending = False)
```

			count
CountryName	WarehouseName	Status	
United States of America	Southlake Texas	Shipped	26
		Pending	9
		Canceled	9
	Seattle Washington	Shipped	17
		Pending	13
		Canceled	15
	San Francisco	Shipped	22
		Pending	9
		Canceled	13

```
                        New Jersy          Shipped      25
                                           Pending      13
                                           Canceled      7
Mexico                  Mexico City        Shipped      18
                                           Pending      13
                                           Canceled     14
India                   Bombay             Shipped      19
                                           Pending      10
                                           Canceled     14
China                   Beijing            Shipped      18
                                           Pending      13
                                           Canceled     14
Canada                  Toronto            Shipped      20
                                           Pending      12
                                           Canceled     12
Australia               Sydney             Pending      14
                                           Shipped      18
                                           Canceled     13
```

```
order_status.plot(kind='bar',xlabel = 'Warehouse',ylabel = 'Count')
```

```
<AxesSubplot:xlabel='Warehouse', ylabel='Count'>
```




```
canceled_order = df[df['Status']=='Canceled']
['WarehouseName'].value_counts()

print(canceled_order)
```

```
Seattle Washington    15
Mexico City           14
```

```
Bombay                14
Beijing               14
Sydney                13
San Francisco         13
Toronto               12
Southlake Texas        9
New Jersy              7
Name: WarehouseName, dtype: int64
```

```
pending_orders = df[df['Status']=='Pending']
['WarehouseName'].value_counts()

print(pending_orders)
```

```
Sydney                14
Beijing               13
New Jersy             13
Seattle Washington    13
Mexico City           13
Toronto               12
Bombay                10
San Francisco          9
Southlake Texas        9
Name: WarehouseName, dtype: int64
```

```
shipped_orders = df[df['Status']=='Shipped']
['WarehouseName'].value_counts()

print(shipped_orders)
```

```
Southlake Texas       26
New Jersy             25
San Francisco         22
Toronto               20
Bombay                19
Sydney                18
Mexico City           18
Beijing               18
Seattle Washington    17
Name: WarehouseName, dtype: int64
```

Seattle washingtone,Mexico city,Beijing these warehouse performace are very poor.Need to improve.

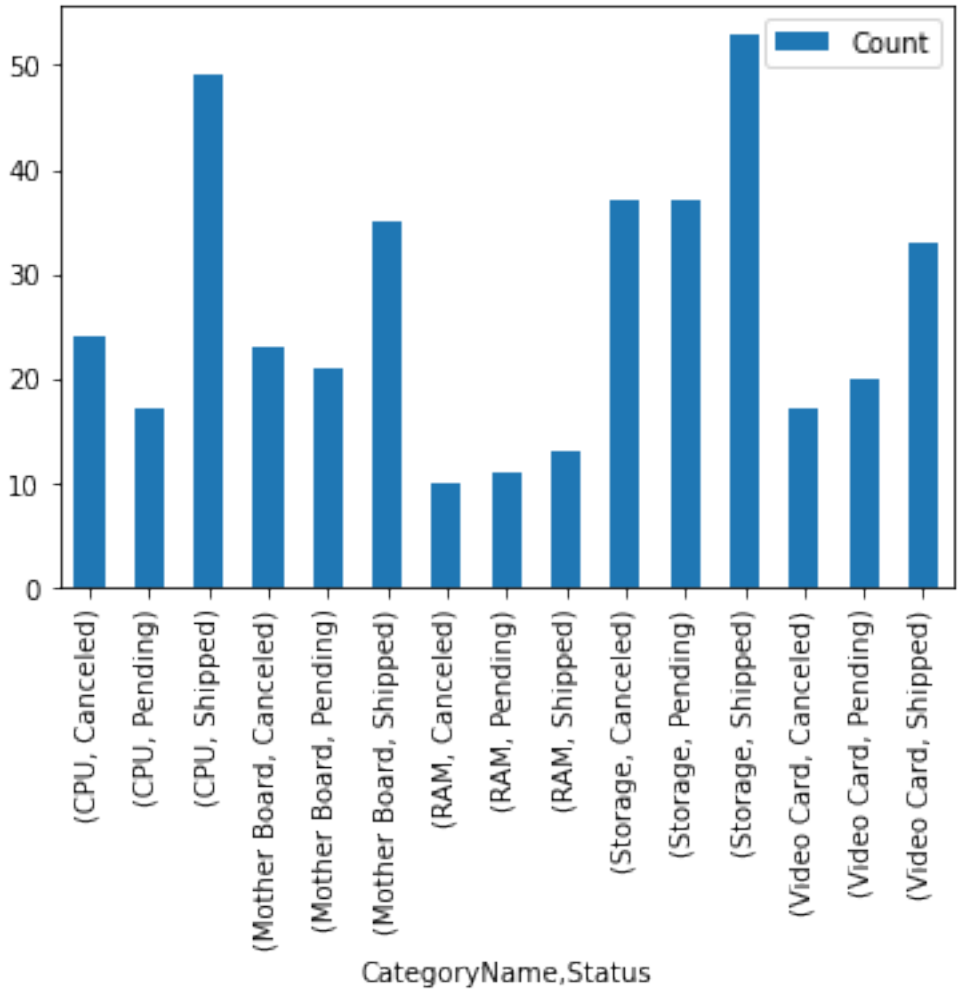
Category wise status

```
status_cat =
df.groupby(['CategoryName','Status']).agg(Count=('CategoryName','count
'))

status_cat.sort_values(by='CategoryName',ascending = False)
```

```
                       Count
CategoryName Status
Video Card   Canceled     17
             Pending      20
             Shipped      33
Storage      Canceled     37
             Pending      37
             Shipped      53
RAM          Canceled     10
             Pending      11
             Shipped      13
Mother Board Canceled     23
             Pending      21
             Shipped      35
CPU          Canceled     24
             Pending      17
             Shipped      49
```

```
status_cat.plot(kind = 'bar')
```

```
<AxesSubplot:xlabel='CategoryName,Status'>
```



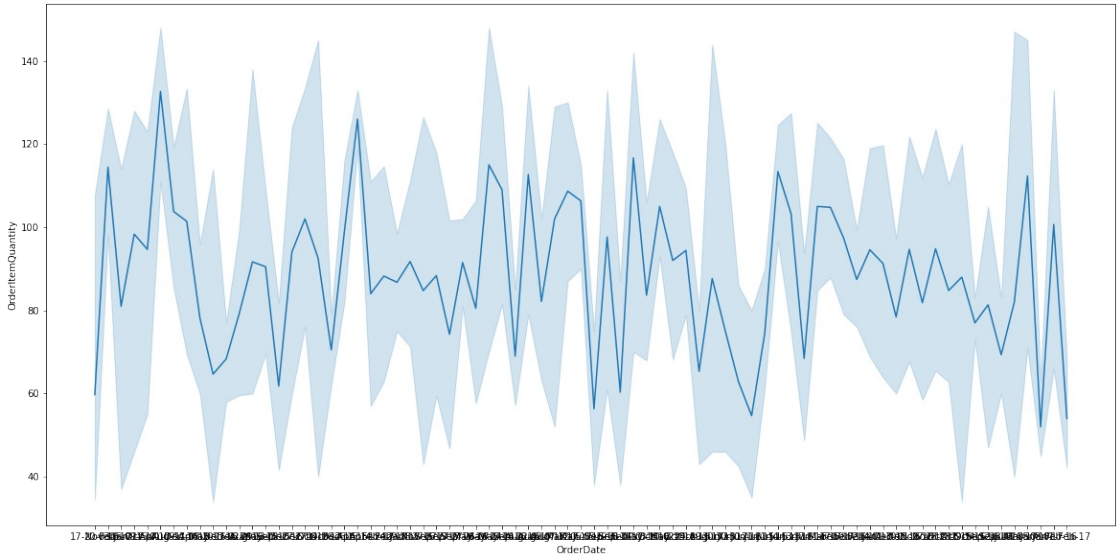
It gives a wired view of status.category Ram,storage are affected more that others.

Plot a time order graph.

```
plt.subplots(figsize=(20,10))
```

```
sns.lineplot(data=df,x='OrderDate',y='OrderItemQuantity')
```

```
<AxesSubplot:xlabel='OrderDate', ylabel='OrderItemQuantity'>
```



Is there any stock issue.find out the stock check.

```
order_quantity = df['OrderItemQuantity'].sum()

print(order_quantity)
```

```
35696
```

```
total_quantity = df['TotalItemQuantity'].sum()

print(total_quantity)
```

```
49478
```

```
df1 =
pd.DataFrame(df,columns=['WarehouseName','CategoryName','OrderItemQuan
tity','TotalItemQuantity'])

df1['StockItemDiffer'] = df1['TotalItemQuantity'] -
df1['OrderItemQuantity']

df1
```

```
       WarehouseName CategoryName  OrderItemQuantity
TotalItemQuantity  \
0    Southlake Texas          CPU                132
122
1    Southlake Texas          CPU                124
123
2    Southlake Texas          CPU                 92
123
3    Southlake Texas          CPU                128
124
4    Southlake Texas          CPU                106
```

```
125
..               ...          ...                 ...                 ..
.
395           Bombay   Video Card                32
107
396           Bombay   Video Card                66
118
397           Bombay   Video Card                82
118
398           Bombay   Video Card               157
95
399           Bombay   Video Card                32
92

     StockItemDiffer
0                -10
1                 -1
2                 31
3                 -4
4                 19
..               ...
395               75
396               52
397               36
398              -62
399               60

[400 rows x 5 columns]
```

```
df1.sort_values(by ='StockItemDiffer', ascending = False)
```

```
     WarehouseName  CategoryName  OrderItemQuantity  TotalItemQuantity
\
382         Bombay    Video Card                103                353

384         Bombay    Video Card                 34                267

383         Bombay    Video Card                 68                267

366         Bombay  Mother Board                 37                227

363         Bombay  Mother Board                 37                226

..             ...           ...                ...                ...

106      New Jersy    Video Card                137                  9

110      New Jersy    Video Card                139                 11

101      New Jersy    Video Card                145                  6
```

```
100      New Jersy    Video Card                147                    6

59   San Francisco           CPU                150                    3


     StockItemDiffer
382              250
384              233
383              199
366              190
363              189
..               ...
106             -128
110             -128
101             -139
100             -141
59              -147

[400 rows x 5 columns]
```

Here have a look at the over stock.video card and mother board are less selling or over stock either of one.bombay ware houe has huge amout of stock.

```
short_Total.sort_values(by = 'StockItemDiffer',ascending = True )
```

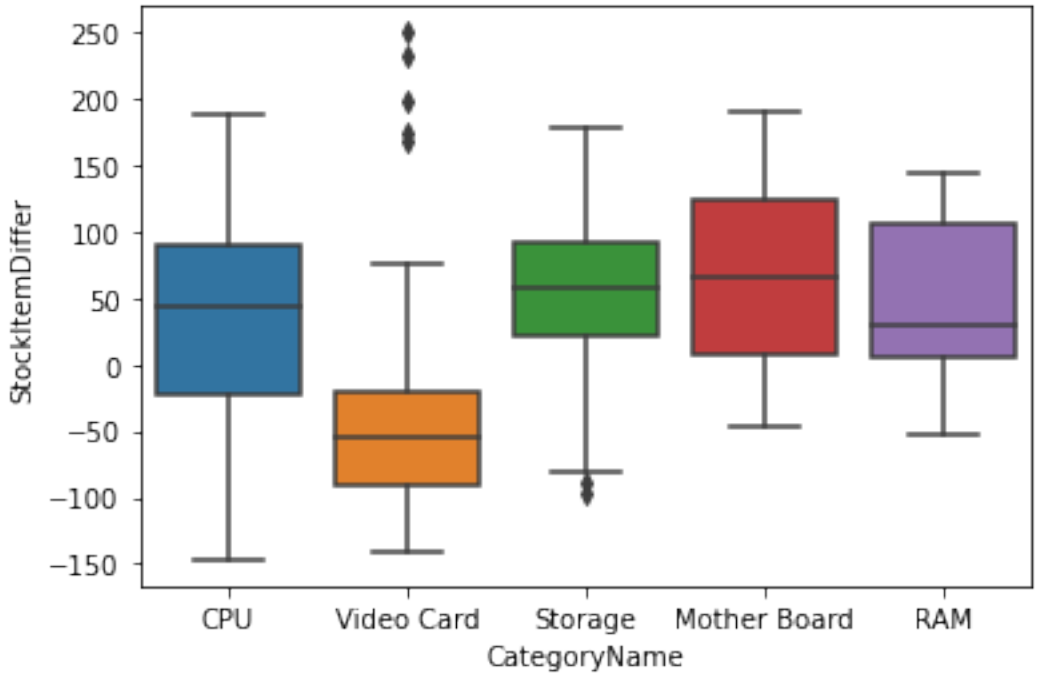
```
       WarehouseName  CategoryName  OrderItemQuantity
TotalItemQuantity  \
59     San Francisco           CPU                150
3
100        New Jersy    Video Card                147
6
101        New Jersy    Video Card                145
6
110        New Jersy    Video Card                139
11
106        New Jersy    Video Card                137
9
..               ...           ...                ...                .
..
233           Sydney  Mother Board                119
117
392           Bombay    Video Card                114
112
192          Toronto  Mother Board                134
132
6    Southlake Texas           CPU                127
126
1    Southlake Texas           CPU                124
123
```

```
     StockItemDiffer
59              -147
100             -141
101             -139
110             -128
106             -128
..               ...
233               -2
392               -2
192               -2
6                 -1
1                 -1

[139 rows x 5 columns]
```

San francisco and new jersy are having huge amout of unavailability of cpu,video card.

```
sns.boxplot(x = df1['CategoryName'],y = df1['StockItemDiffer'])
```

```
<AxesSubplot:xlabel='CategoryName', ylabel='StockItemDiffer'>
```

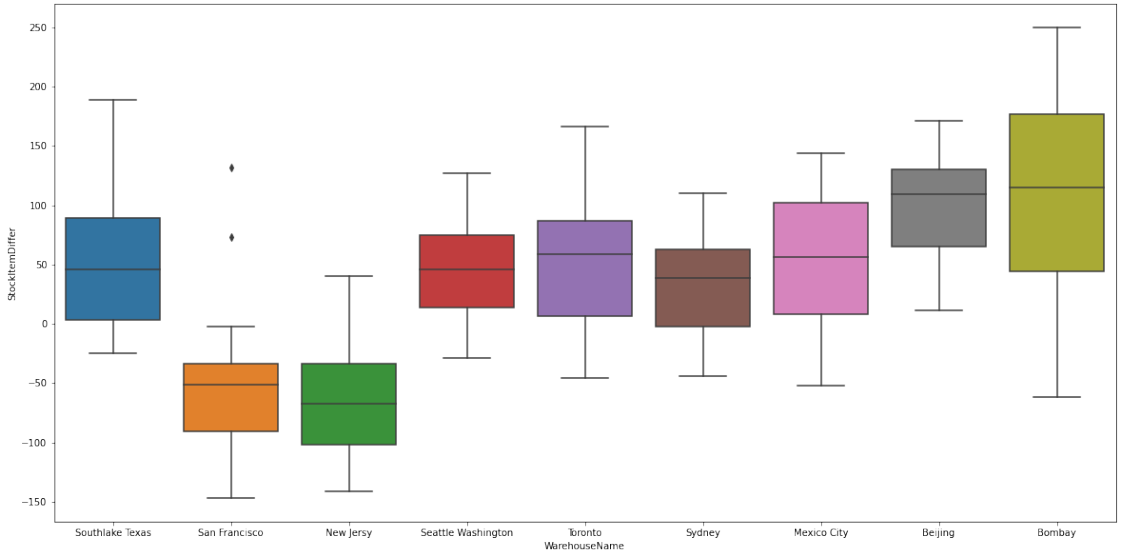


In the boxplot convey the shortage of video card.

```
plt.figure(figsize=(20,10))
```

```
sns.boxplot(x = df1['WarehouseName'], y = df1['StockItemDiffer'])
```

```
<AxesSubplot:xlabel='WarehouseName', ylabel='StockItemDiffer'>
```



San fransisco,new jersy unavailability and bombay's overstock dumbing.We have to focus on these place for the improvement.

Add a column to the data to show the orderpercost.

```
df3 =
pd.DataFrame(df,columns=['WarehouseName','CategoryName','PerUnitPrice'
,'OrderItemQuantity'])

df3['Orderpercost'] = df3['PerUnitPrice'] * df3['OrderItemQuantity']

df3.sort_values(by = 'Orderpercost' ,ascending =False)
```

	WarehouseName	CategoryName	PerUnitPrice	OrderItemQuantity
358	Bombay	Storage	4139.00	145
245	Sydney	Storage	4139.00	133
303	Mexico City	RAM	2998.89	130
272	Mexico City	Storage	2998.89	115
266	Sydney	Storage	2377.09	138
..	...	...	...	...
200	Toronto	Mother Board	41.99	56
298	Mexico City	RAM	41.99	45
163	Seattle Washington	Storage	16.99	75

```
129           New Jersy       Storage         16.99                 65

335             Beijing           CPU         16.99                 43


     Orderpercost
358     600155.00
245     550487.00
303     389855.70
272     344872.35
266     328038.42
..            ...
200       2351.44
298       1889.55
163       1274.25
129       1104.35
335        730.57

[400 rows x 5 columns]
```

```
x = df3['CategoryName']
```

```
y = df3['Orderpercost']
```

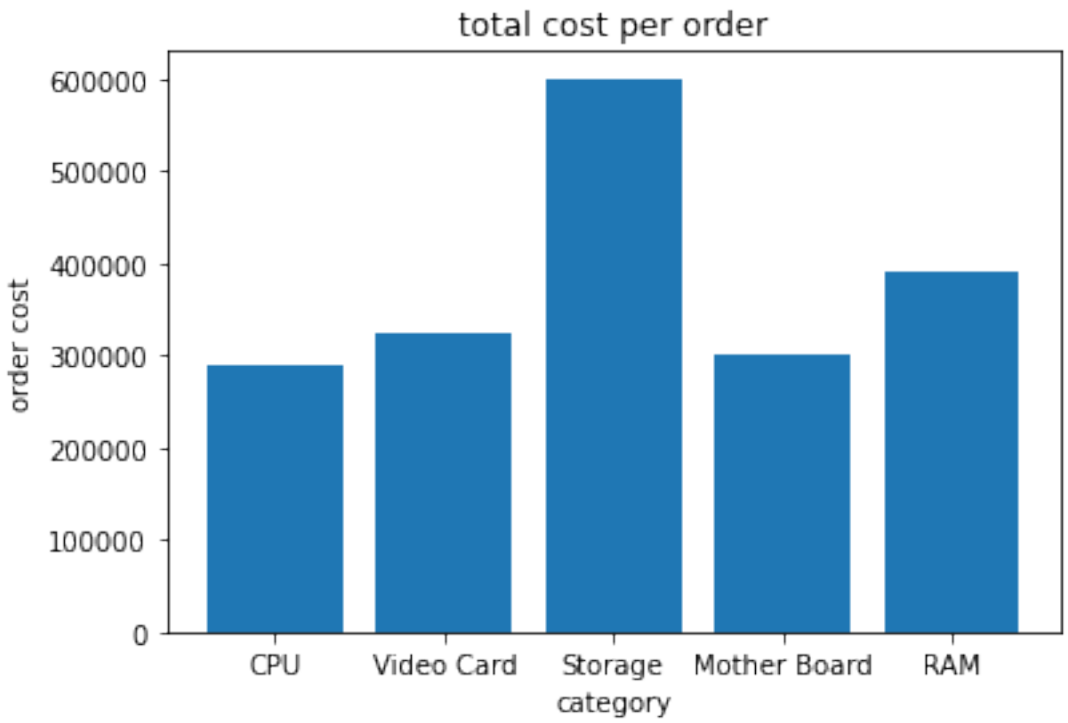
```
plt.bar(x,y)
```

```
plt.ylabel('order cost')
```

```
plt.xlabel('category')
```

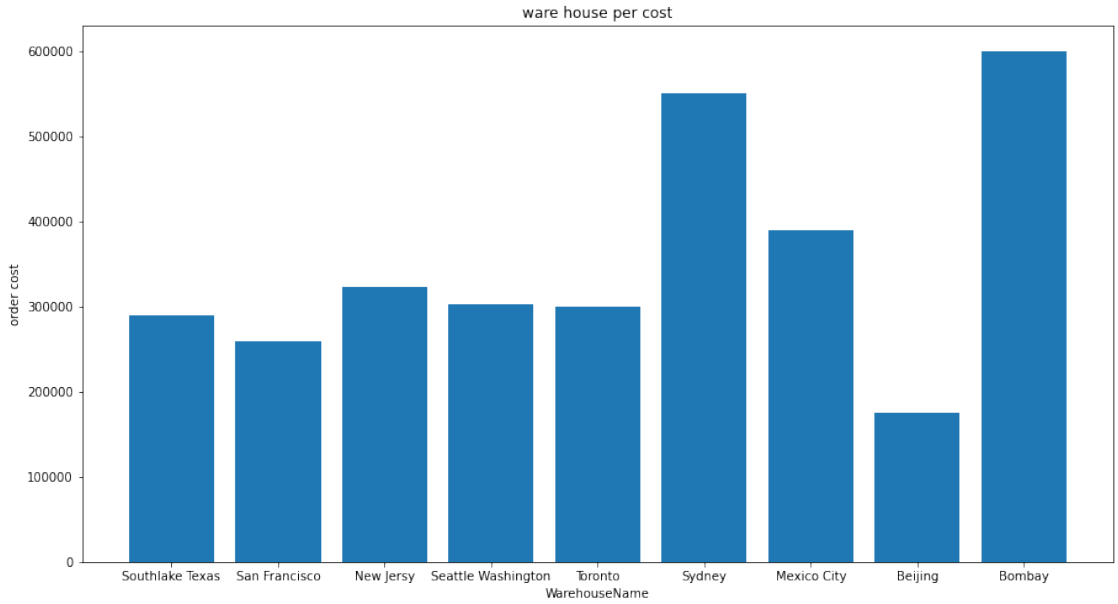
```
plt.title('total cost per order')
```

```
Text(0.5, 1.0, 'total cost per order')
```




```
x = df3['WarehouseName']

y = df3['Orderpercost']

plt.figure(figsize=(15,8))

plt.bar(x,y)

plt.ylabel('order cost')

plt.xlabel('WarehouseName')

plt.title('ware house per cost')
```

```
Text(0.5, 1.0, 'ware house per cost')
```

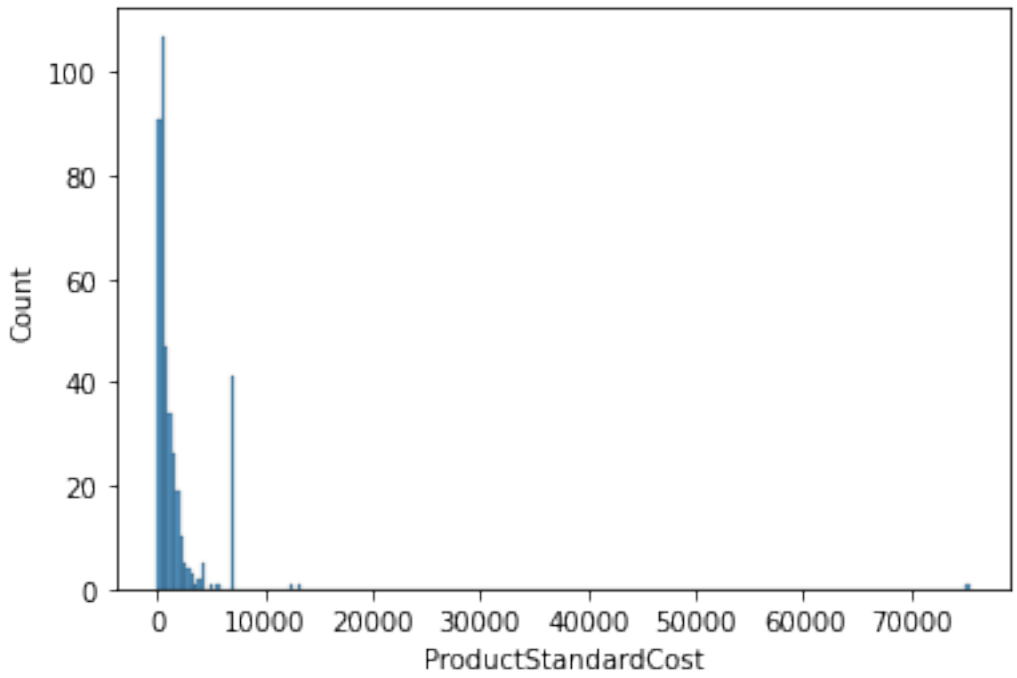


In the criteria of Per order cost bombay,sydeny are in first row.storage and ram are the product.

Trying check the variable distribution for mechine learning.

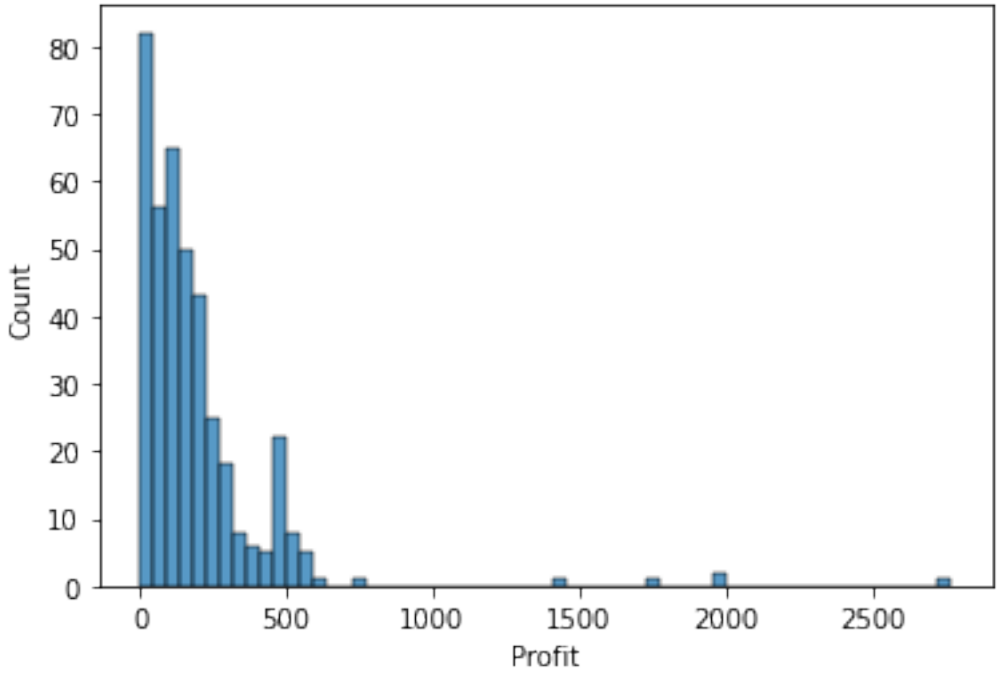
```
sns.histplot(df['ProductStandardCost'])
```

```
<AxesSubplot:xlabel='ProductStandardCost', ylabel='Count'>
```



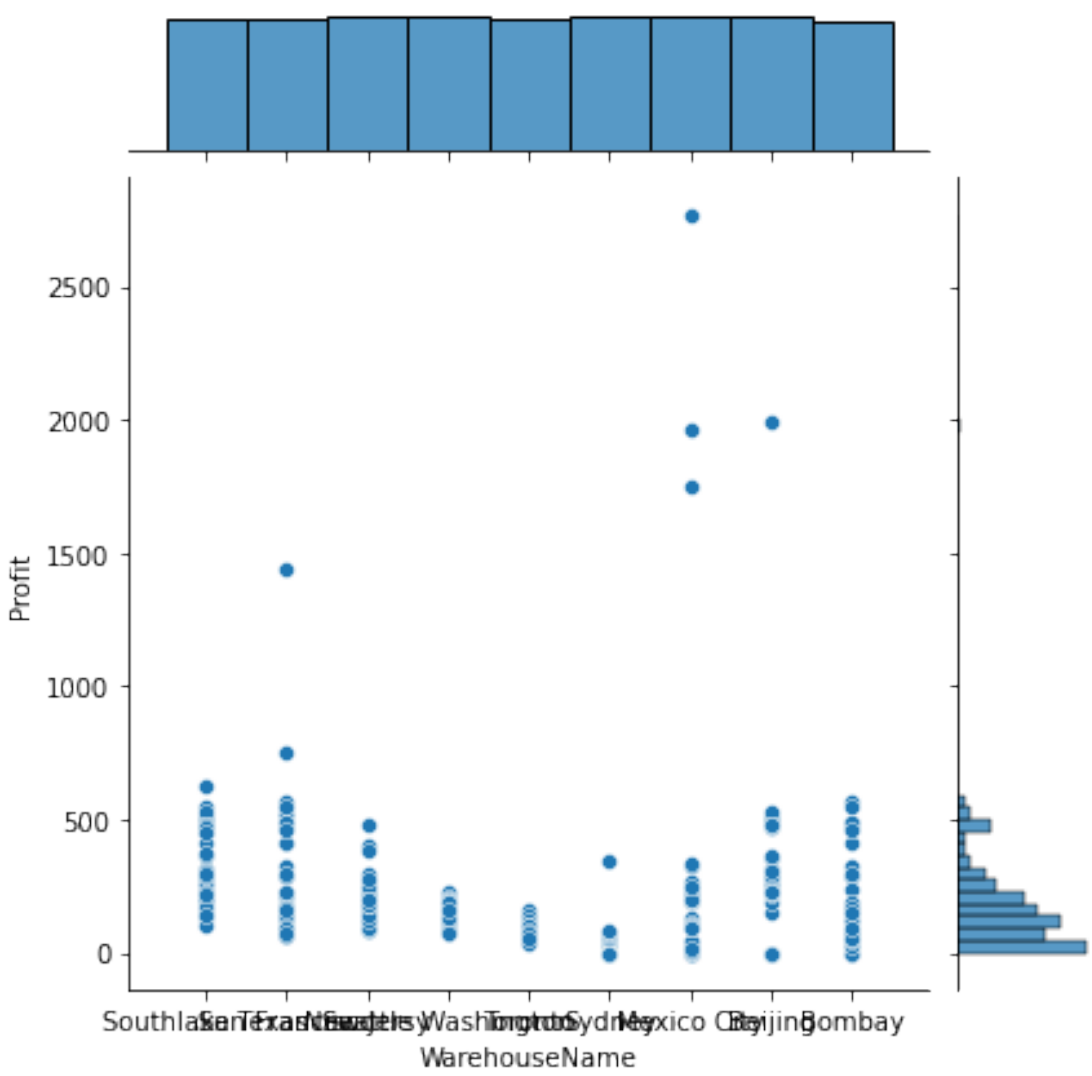

```
sns.histplot(df['Profit'])
```

```
<AxesSubplot:xlabel='Profit', ylabel='Count'>
```



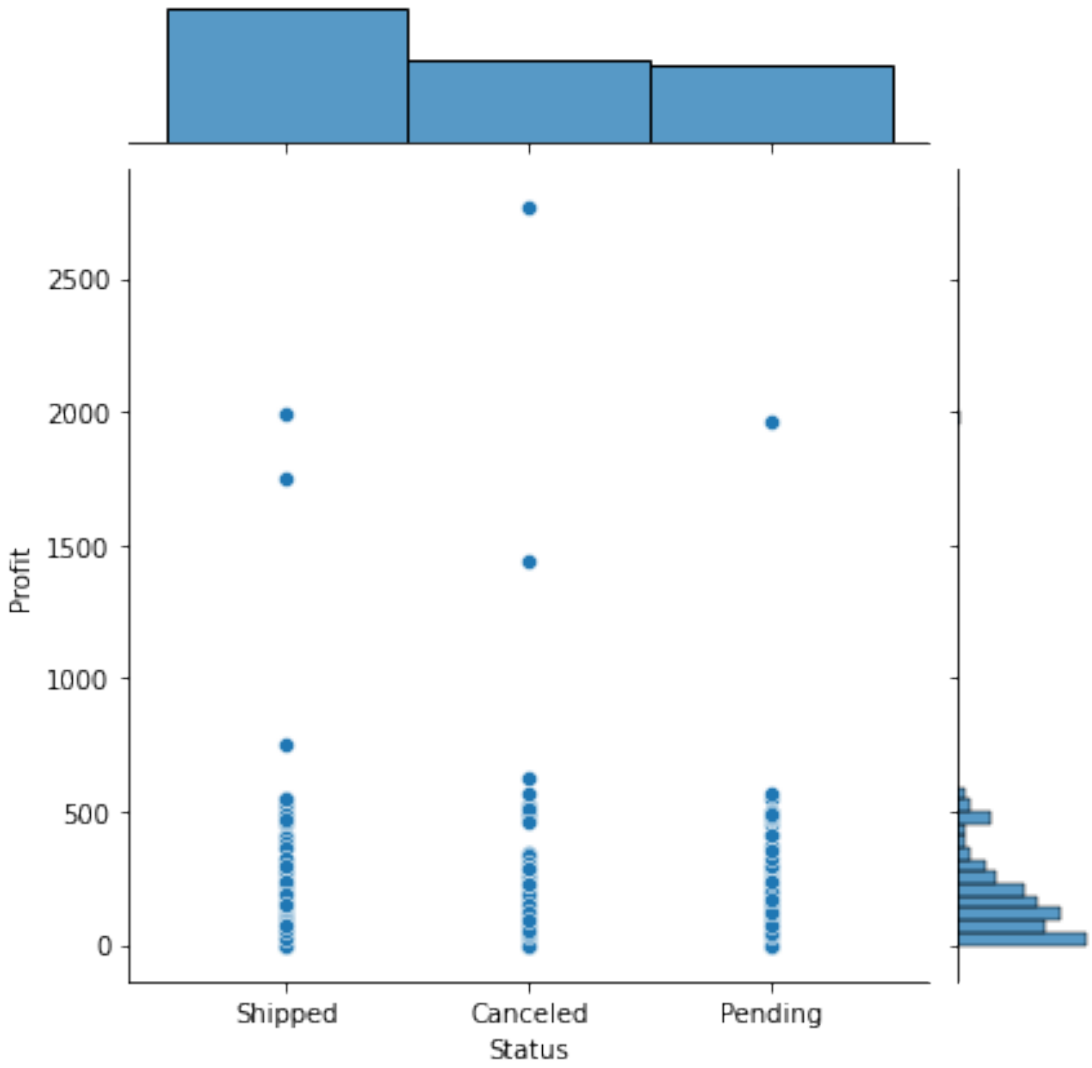

```
sns.jointplot(data=df,x='WarehouseName',y='Profit')
```

```
<seaborn.axisgrid.JointGrid at 0x7f62e5af47d0>
```




```
sns.jointplot(data=df,x='Status',y='Profit')
```

```
<seaborn.axisgrid.JointGrid at 0x7f62789d6150>
```




```
plot =
ps.scatter(data_frame=df,x='Profit',y='ProductListPrice',trendline='ol
s',
                  title = 'Relation between profit and product list
price')
plot.show()
```


```
plot2 =
ps.scatter(data_frame=df,x='Profit',y='ProductStandardCost',trendline=
'ols',
                  title = 'Relation between profit and product list
price')
plot2.show()
```


```
sns.pairplot(df)
```

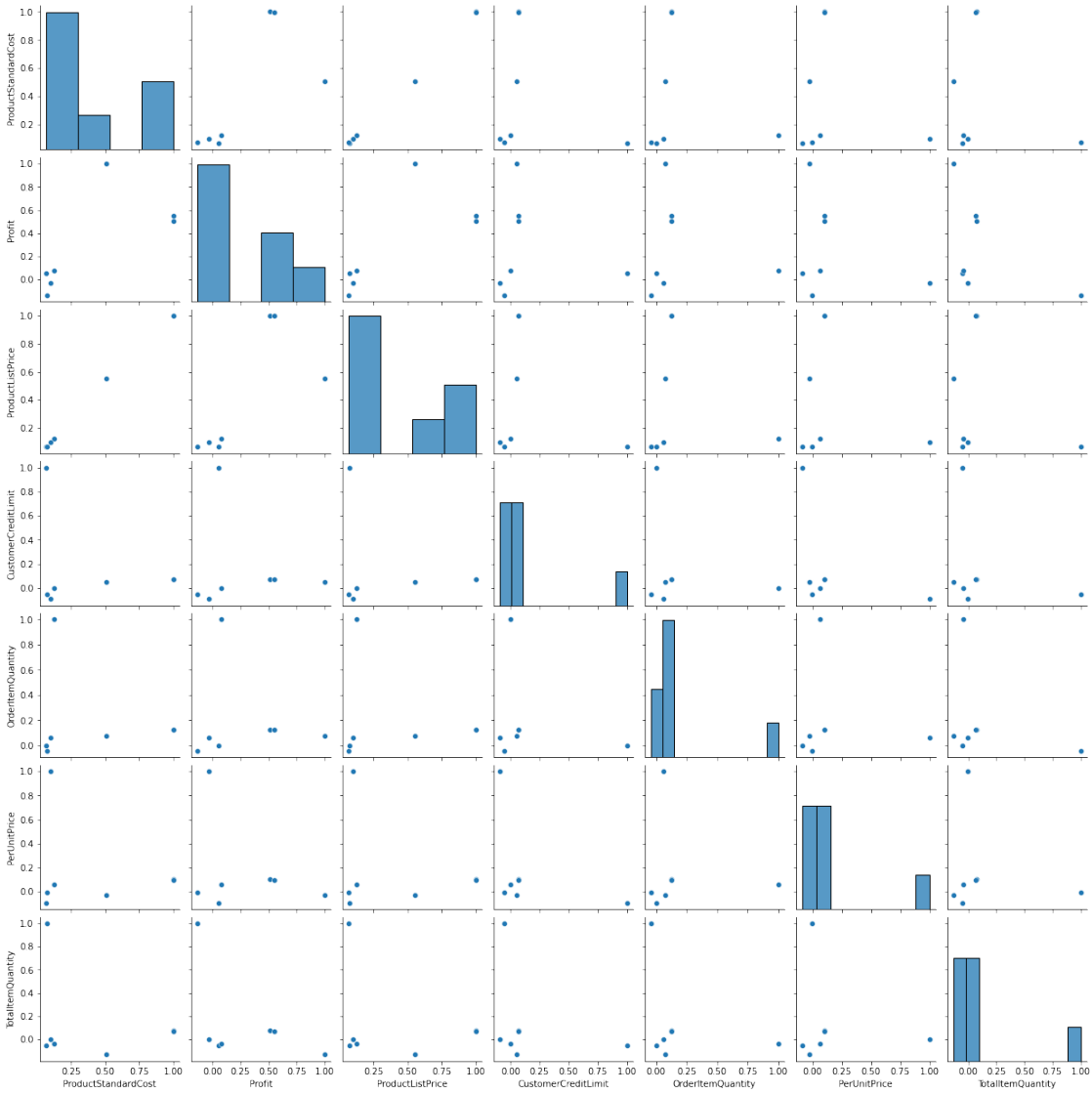
```
<seaborn.axisgrid.PairGrid at 0x7fbb96bbbbd0>
```


```
cor = df.corr()
print(cor['Profit'].sort_values(ascending = False))
```

```
Profit                 1.000000
ProductListPrice       0.549919
ProductStandardCost    0.507970
OrderItemQuantity      0.075729
CustomerCreditLimit    0.052779
PerUnitPrice          -0.029464
EmployeePhone         -0.056564
CustomerPhone         -0.122882
TotalItemQuantity     -0.133516
Name: Profit, dtype: float64
```

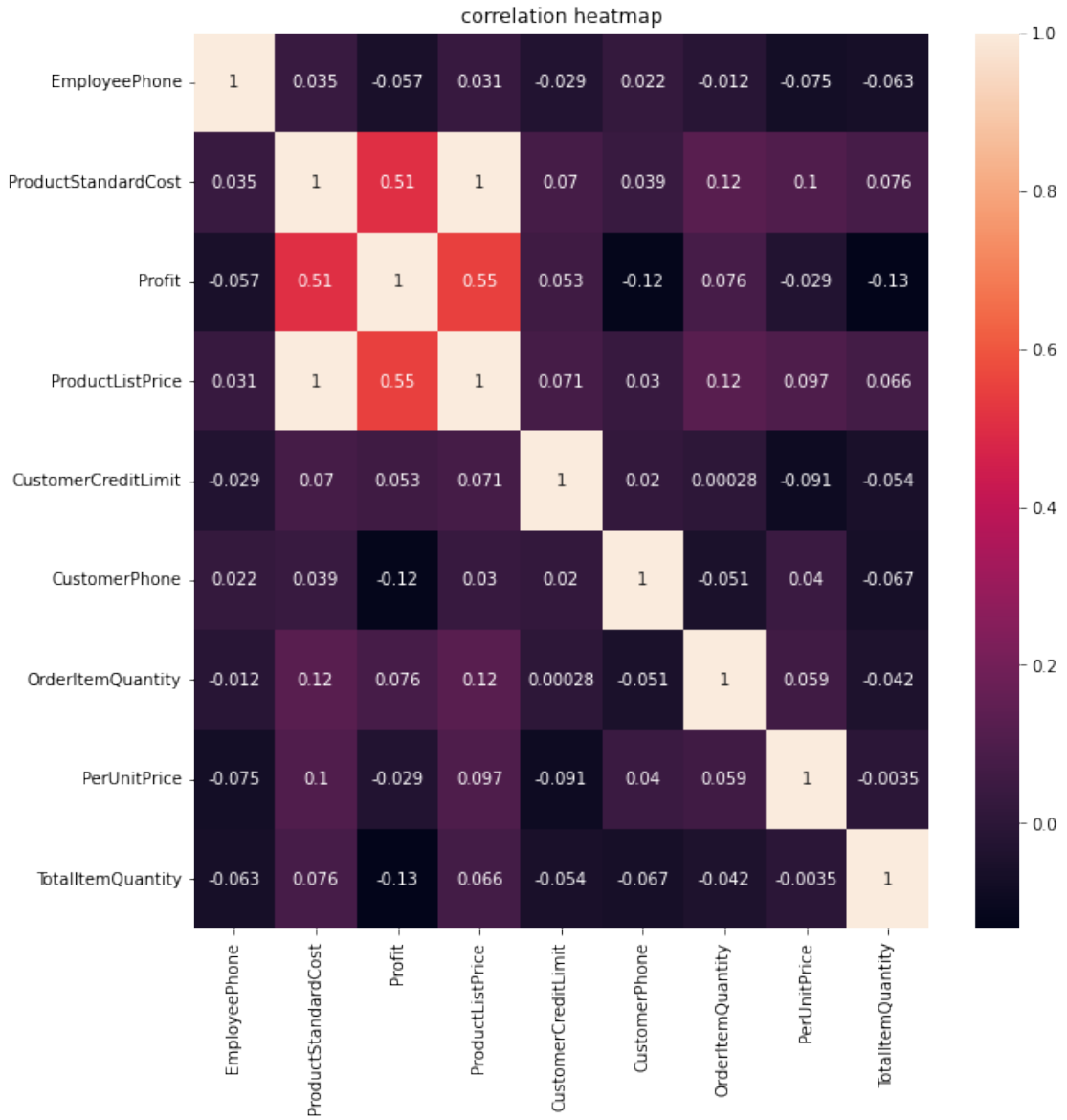
```
sns.pairplot(cor)
```

```
<seaborn.axisgrid.PairGrid at 0x7f368455c750>
```




```
plt.figure(figsize=(10,10))
sns.heatmap(cor,annot=True)
plt.title('correlation heatmap')
```

```
Text(0.5, 1.0, 'correlation heatmap')
```



Profit,ProductListPrice , ProductStandardCost , OrderItemQuantity , CustomerCreditLimit thes columns are significant to predict.

Make a model with the variables

```
x =
np.array(df[['ProductStandardCost','ProductListPrice','OrderItemQuanti
ty','CustomerCreditLimit']])

y = np.array(df[['Profit']])

x_train,x_test,y_train,y_test = train_test_split(x,y,test_size = 0.30,
                                                 random_state = 32)

print('x_train = ',x_train.shape)
```

```
print('x_test = ',x_test.shape)
print('y_train = ',y_train.shape)
print('y_test = ',y_test.shape)
```

```
x_train =  (280, 4)
x_test =  (120, 4)
y_train =  (280, 1)
y_test =  (120, 1)
```

```
model1 = LinearRegression()
```

```
model1.fit(x_train , y_train)
```

```
model1.score(x_test , y_test)
```

```
0.999999999970977
```

```
The model score is 0.999
```