Importing Libraries

In [294…

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
%matplotlib inline
```

In [295…

```
pd.options.mode.chained_assignment = None #turn off the SettingWithCopyWarning warning that is raised
#when assigning values to a slice of a DataFrame.
```

In [296…

```
#This code sets some default configurations for Matplotlib plots by updating the rcParams dictionary.
plt.rcParams.update(
    {"font.size": 10, "figure.facecolor": "w", "axes.facecolor": "w", "axes.spines.right": False,"axes.spines.t
        : False, "axes.spines.bottom": False,
        "xtick.top": False,
        "xtick.bottom": False,
        "ytick.right": False,
        "ytick.left": False,
    }
)
```

When i tried to read .CSV file, it throw an error, which basically occurs when the Python interpreter is unable to decode a byte sequence in the file using the UTF-8 character encoding.

so in that case i used following statement to figure out the type of encoding, and used that encoding to read data.csv file

In [12]:

```
import chardet
with open("data.csv", "rb") as f:
    result = chardet.detect(f.read())
    file_encoding = result["encoding"]

# read CSV file with detected encoding
df = pd.read_csv("data.csv", encoding=file_encoding)
```

Now in order to covert and create our .csv file into encoding of UTF-8, i have used : to_csv()

In [13]:

```
df.to_csv("ecommerce_data.csv", index=False, encoding="utf-8")
```

Now finally we are able to read our new .csv file having encoding : UTF-8

In [297…

```
data = pd.read_csv("ecommerce_data.csv")
```

Data Wrangling

In [298…

```
data.info() #overall view
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 541909 entries, 0 to 541908
Data columns (total 8 columns):
 #   Column       Non-Null Count   Dtype
---  ------       --------------   -----
 0   InvoiceNo    541909 non-null  object
 1   StockCode    541909 non-null  object
 2   Description  540455 non-null  object
 3   Quantity     541909 non-null  int64
 4   InvoiceDate  541909 non-null  object
 5   UnitPrice    541909 non-null  float64
 6   CustomerID   406829 non-null  float64
 7   Country      541909 non-null  object
dtypes: float64(2), int64(1), object(5)
memory usage: 33.1+ MB
```

In [299…

```
data.describe() #looking at numeric info
```

Out[299]:

	Quantity	UnitPrice	CustomerID
count	541909.000000	541909.000000	406829.000000
mean	9.552250	4.611114	15287.690570
std	218.081158	96.759853	1713.600303
min	-80995.000000	-11062.060000	12346.000000
25%	1.000000	1.250000	13953.000000
50%	3.000000	2.080000	15152.000000
75%	10.000000	4.130000	16791.000000
max	80995.000000	38970.000000	18287.000000

In [300…
```
data.shape #check Dimension
```
Out[300]:
```
(541909, 8)
```

Cleaning up the data!

check for dublicates

In [301…
```
data.duplicated().sum()
```
Out[301]:
```
5268
```

There are 5268 rows duplicated

In [302…
```
data = data.drop_duplicates()
```

In [303…
```
#check again
data.duplicated().sum()
```
Out[303]:
```
0
```

Missing Values

In [304…
```
#Checking Null Values
for col in data.columns:
    pct_missing = data[col].isnull().mean()
    print(f'{col} - {pct_missing :.1%}')
```
```
InvoiceNo - 0.0%
StockCode - 0.0%
Description - 0.3%
Quantity - 0.0%
InvoiceDate - 0.0%
UnitPrice - 0.0%
CustomerID - 25.2%
Country - 0.0%
```

This shows that there is missing values in columns : Description and Customer ID

Handling missing values

In [305…
```
#make a copy
copy = data.copy()
```

In [306…
```
#dealing with the missing value in our main data
data['Description'] = data['Description'].fillna("Unknown")
data['CustomerID'] = data['CustomerID'].fillna(0)
```

In [307…
```
data.isna().sum()
```
Out[307]:
```
InvoiceNo      0
StockCode      0
Description    0
Quantity       0
InvoiceDate    0
UnitPrice      0
CustomerID     0
Country        0
dtype: int64
```

Now we can proceed further as our data set is clean

DataType

Convert column with proper datatype

In [308…
```
data['InvoiceDate'] = pd.to_datetime(data['InvoiceDate'])
data['Quantity'] = pd.to_numeric(data['Quantity'])
data['UnitPrice'] = pd.to_numeric(data['UnitPrice'])
```

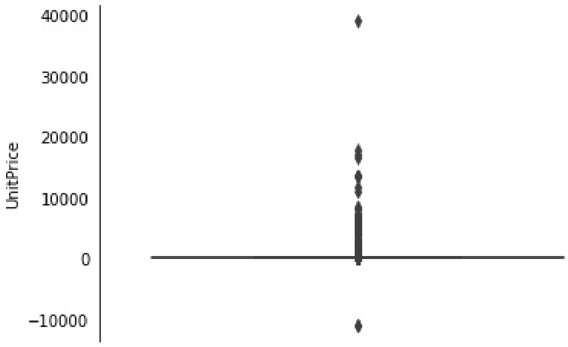
In [309…
```
#creating a separate column for time
data['Time'] = data['InvoiceDate'].dt.time
#creating a separate column for month
data['Month'] = data['InvoiceDate'].dt.month_name()
#creating a separate column for day name
data['Day'] = data['InvoiceDate'].dt.day_name()
#creating a column for year
data['Year']= data['InvoiceDate'].dt.year
```

In [310…
```
#creating a column for total
data['Total'] = data['Quantity']*data['UnitPrice']
```

Structuring

In [311…
```
#Check Unit Price `s Distribution
sns.boxplot( y= 'UnitPrice' ,data =data)
```

Out[311]: <AxesSubplot:ylabel='UnitPrice'>



It seems that there are values in UnitPrice column which are under 0

In [312…
```
data[data['UnitPrice'] < 0 ]
```

Out[312]:

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country	Time	Month	Day	Year	Total
299983	A563186	B	Adjust bad debt	1	2011-08-12 14:51:00	-11062.06	0.0	United Kingdom	14:51:00	August	Friday	2011	-11062.06
299984	A563187	B	Adjust bad debt	1	2011-08-12 14:52:00	-11062.06	0.0	United Kingdom	14:52:00	August	Friday	2011	-11062.06

These are debt which are not required, so we remove them

There are some invoices which are debt, which we don't need in our analysis, these invoices are associated with description having word "dept".

Now to remove rows that contains word "debt" or "DEBT" we can use below code

In [313…
```
mask = data['Description'].str.contains('debt', case=False)
# Invert mask and use boolean indexing to filter out rows
data = data[~mask]
```

In [314…
```
data = data[data['UnitPrice']>0] #filtering our data
```

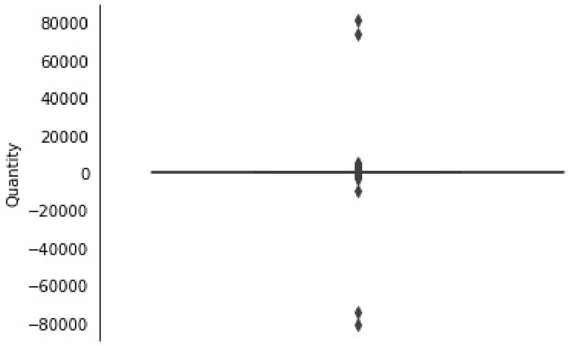
In [315…
```
#check the minimum
data['UnitPrice'].min()
```

Out[315]: 0.001

Now let us also check for Quantity's distribution

In [316…
```
#Check Quantity's Distribution
sns.boxplot( y= 'Quantity' ,data =data)
```

Out[316]: <AxesSubplot:ylabel='Quantity'>



This means that there are values in column Quantity which are under 0, which happens when there is a cancelled purchase

In [317…
```
data[data['Quantity'] < 0]
```

Out[317]:

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country	Time	Month	Day	Year
141	C536379	D	Discount	-1	2010-12-01 09:41:00	27.50	14527.0	United Kingdom	09:41:00	December	Wednesday	2010
154	C536383	35004C	SET OF 3 COLOURED FLYING DUCKS	-1	2010-12-01 09:49:00	4.65	15311.0	United Kingdom	09:49:00	December	Wednesday	2010
235	C536391	22556	PLASTERS IN TIN CIRCUS PARADE	-12	2010-12-01 10:24:00	1.65	17548.0	United Kingdom	10:24:00	December	Wednesday	2010
236	C536391	21984	PACK OF 12 PINK PAISLEY TISSUES	-24	2010-12-01 10:24:00	0.29	17548.0	United Kingdom	10:24:00	December	Wednesday	2010
237	C536391	21983	PACK OF 12 BLUE PAISLEY TISSUES	-24	2010-12-01 10:24:00	0.29	17548.0	United Kingdom	10:24:00	December	Wednesday	2010
...	...	...	...	...	...	...	...	...	...	...	...	...
540449	C581490	23144	ZINC T-LIGHT HOLDER STARS SMALL	-11	2011-12-09 09:57:00	0.83	14397.0	United Kingdom	09:57:00	December	Friday	2011
541541	C581499	M	Manual	-1	2011-12-09 10:28:00	224.69	15498.0	United Kingdom	10:28:00	December	Friday	2011
541715	C581568	21258	VICTORIAN SEWING BOX LARGE	-5	2011-12-09 11:57:00	10.95	15311.0	United Kingdom	11:57:00	December	Friday	2011
541716	C581569	84978	HANGING HEART JAR T-LIGHT HOLDER	-1	2011-12-09 11:58:00	1.25	17315.0	United Kingdom	11:58:00	December	Friday	2011
541717	C581569	20979	36 PENCILS TUBE RED RETROSPOT	-5	2011-12-09 11:58:00	1.25	17315.0	United Kingdom	11:58:00	December	Friday	2011

9251 rows × 13 columns

Now we can create a separate data frame for cancelled purchases

In [318…

```
cancelled_purchases = data[data['Quantity'] < 0]
```

Now let's remove the cancelled purchases from our dataframe

In [319…

```
data = data[data['Quantity'] > 0] #we modified our dataframe data to contain only purchased product
```

In [320…

```
data['Quantity'].min() # check min to confirm for positive quantity
```

Out[320]: 1

Analysis

1) What was the best month for sales?

In [321…

```
#[['Total']] means that it will sum up on Total field and display as Month | Total
sales_2010 = data[data['Year']== 2010].groupby('Month').sum()[['Total']].reset_index()
sales_2011 = data[data['Year']== 2011].groupby('Month').sum()[['Total']].reset_index()
```

In [322…

```
#let's get a list of years to know which years are present
years = data['Year'].unique()
```

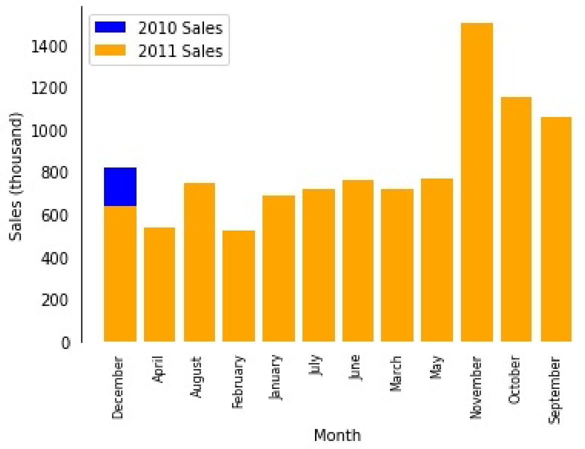
In [323…

```
print(years)
```

```
[2010 2011]
```

In [324…

```
plt.bar(sales_2010["Month"],sales_2010['Total']/1000, label='2010 Sales', color='blue')
plt.bar(sales_2011["Month"],sales_2011['Total']/1000, label='2011 Sales', color='orange')
plt.xticks(rotation = 'vertical',size = 8)
plt.ylabel("Sales (thousand)")
plt.xlabel("Month")
plt.legend()
plt.show()
#we can use plt.savefig('my_plot.png') to save the plot, but remove plt.show()
```



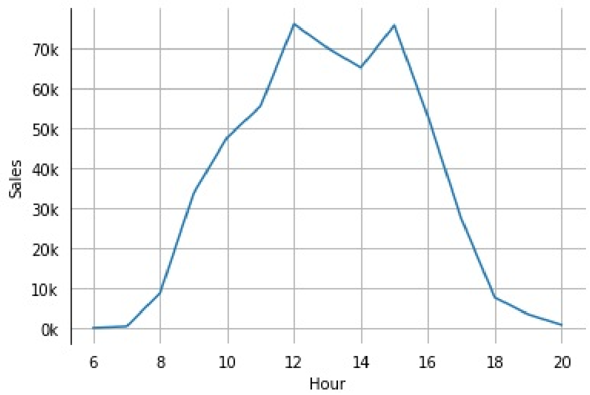
Based on the analysis, it was found that the month with the highest total sales in 2011 was November, followed by October and September, while April and February had the least total sales. As for the year 2010, data was only available for December.

2) What time should we display advertisements to maximize likelihood of customer's buying product?

In [325…
```
#lets create a new column for hours, fetched from InvoiceDate field
data['Hour']=data['InvoiceDate'].dt.hour
```

In [326…
```
BestTimeAdds = data.groupby('Hour').count().reset_index()
```

In [327…
```
from matplotlib.ticker import StrMethodFormatter
plt.plot(BestTimeAdds['Hour'],BestTimeAdds['InvoiceNo']/1000)
plt.xlabel('Hour')
plt.ylabel('Sales')
plt.grid()
formatter = StrMethodFormatter('{x:.0f}k')
plt.gca().yaxis.set_major_formatter(formatter)
plt.show()
```



According to the data, the ideal time for this e-commerce company to run ads is between 12PM and 3PM as this time period yields the highest sales.

It is possible that this is because customers are more likely to be available during their break times and are more likely to use their mobile devices or computers during these hours.

3) What Products are most often sold together

In [328…
```
soldTogether = data.groupby("InvoiceNo")['Description'].agg(lambda x : " , ".join(x)).reset_index()
```

In [329…
```
soldTogether #we got items that are sold together, separated by ","
```

Out[329]:

	InvoiceNo	Description
0	536365	WHITE HANGING HEART T-LIGHT HOLDER , WHITE MET...
1	536366	HAND WARMER UNION JACK , HAND WARMER RED POLKA...
2	536367	ASSORTED COLOUR BIRD ORNAMENT , POPPY'S PLAYHO...
3	536368	JAM MAKING SET WITH JARS , RED COAT RACK PARIS...
4	536369	BATH BUILDING BLOCK WORD
...	...	...
19954	581583	LUNCH BAG RED RETROSPOT , 6 CHOCOLATE LOVE HEA...
19955	581584	RED FLOCK LOVE HEART PHOTO FRAME , 6 CHOCOLATE...
19956	581585	BLACK TEA TOWEL CLASSIC DESIGN , ASSORTED BOTT...
19957	581586	LARGE CAKE STAND HANGING STRAWBERY , SET OF 3...
19958	581587	CIRCUS PARADE LUNCH BOX , PLASTERS IN TIN CIR...

19959 rows × 2 columns

In [330…

```
from itertools import combinations
from collections import Counter

count = Counter()
for row in soldTogether['Description']:
    row_list = row.split(",")
    #item mostly solved together , here it shows 2 items sold together,we can change it to 3
    #to show 3 items sold together and so on ...
    count.update(Counter(combinations(row_list,2)))

#most_common is method from collections
for key,value in count.most_common(10):
    print(key,value)
```

```
(' KEY FOB ', ' KEY FOB ') 743
(' KEY FOB ', ' BACK DOOR  ') 544
(' KEY FOB ', ' SHED ') 511
(' JUMBO BAG PINK POLKADOT ', ' JUMBO BAG RED RETROSPOT ') 477
(' KEY FOB ', ' FRONT  DOOR  ') 455
(' GREEN REGENCY TEACUP AND SAUCER ', ' ROSES REGENCY TEACUP AND SAUCER  ') 443
('COFFEE', 'SUGAR ') 432
(' JUMBO SHOPPER VINTAGE RED PAISLEY ', ' JUMBO BAG RED RETROSPOT ') 427
(' SET 3 RETROSPOT TEA', 'COFFEE') 426
(' SET 3 RETROSPOT TEA', 'SUGAR ') 414
```

Analysis (Pair Products) : we can see that Key Fob are mostly sold with extra pair of Key Fob or with Back Door or with Shed. And so on...

FeedBack : we can recommend our customer in buying these items while purchasing for one item, this way we can enhance sales.

4) What product sold the most ?

In [331…

```
soldMost = data.groupby('Description').sum()[['Quantity']].reset_index()
```

In [332…

```
soldMost = soldMost.sort_values('Quantity',ascending = False ).head(5) #the data was big for products so i have
#just got results for top 10
soldMost
```

Out[332]:

	Description	Quantity
2386	PAPER CRAFT , LITTLE BIRDIE	80995
2051	MEDIUM CERAMIC TOP STORAGE JAR	78033
3933	WORLD WAR 2 GLIDERS ASSTD DESIGNS	54951
1815	JUMBO BAG RED RETROSPOT	48371
3843	WHITE HANGING HEART T-LIGHT HOLDER	37872

In [333…

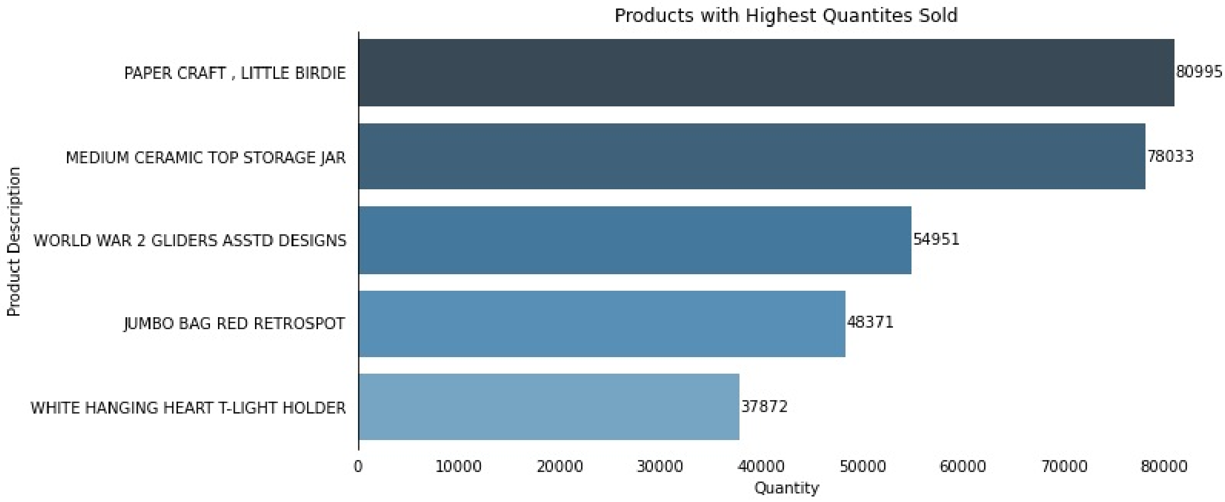
```
#Choosing Palette and reverse it
Palette = sns.color_palette('Blues_d')
Palette.reverse()

plt.figure(figsize = (10,5))
#Visualizing
ax =sns.barplot(y = 'Description' , x= 'Quantity' , data = soldMost, palette = Palette)

#Data labels
ax.bar_label(ax.containers[0])

#Setting Title
plt.title('Products with Highest Quantites Sold')
plt.ylabel('Product Description')
```

```
plt.show()
```

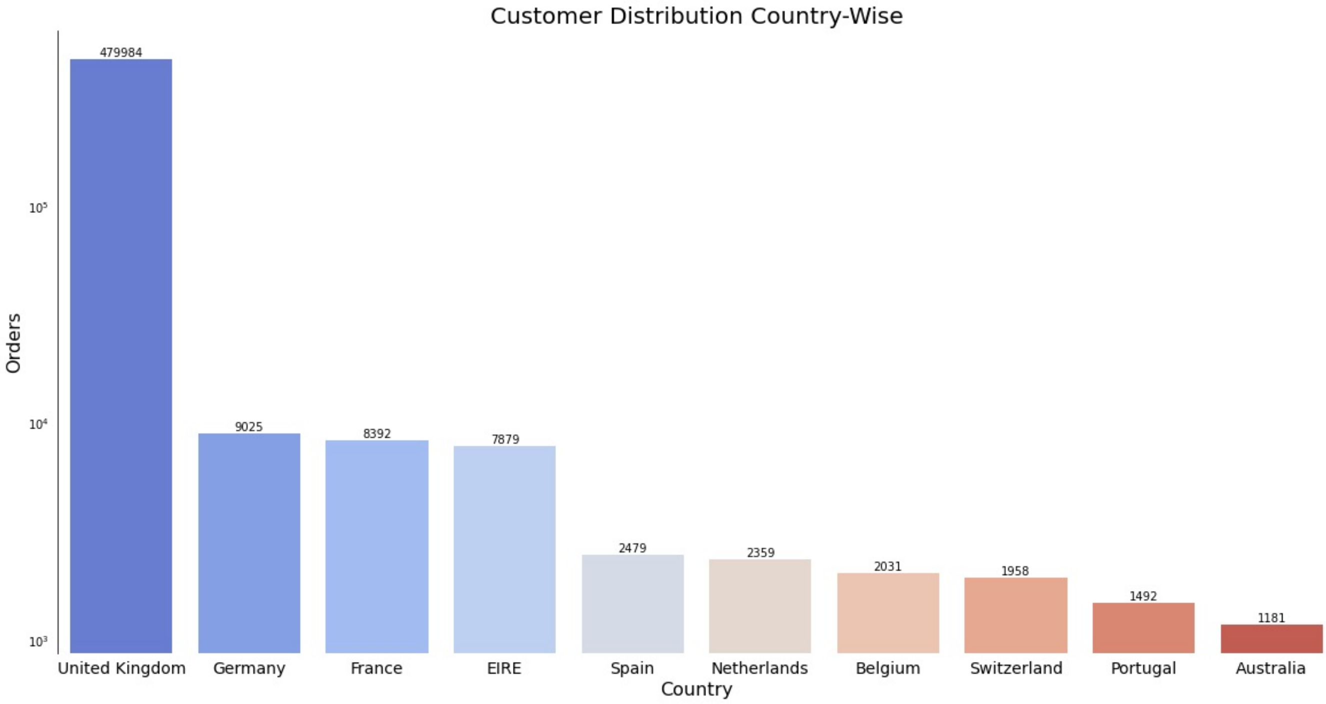


Analysis : We can see that these items are sold the most from the company's website, out of them Paper Craft are sold most with approx 81k quantity

4) Which countries have more customers?

In [334…
```
custCountry = data['Country'].value_counts().reset_index(drop = False).head(10)
custCountry.columns = ['Country','Counts'] # renaming the columns
```

In [335…
```
plt.figure(figsize = (20,10))
ax =sns.barplot(x= 'Country', y = 'Counts'  , data = custCountry, palette = 'coolwarm')
ax.bar_label(ax.containers[0])
plt.title("Customer Distribution Country-Wise",fontsize=20)
plt.ylabel("Orders",fontsize = 16)
plt.xlabel('Country',fontsize = 16)
plt.xticks(fontsize = 14)
plt.yscale('log')
```



4) which day has more number of sales?

In [336…
```
daySales = data.groupby('Day').count()[['InvoiceNo']].reset_index()
daySales.columns = ['Day','Sales']
daySales.sort_values(by='Day')
```

Out[336]:

	Day	Sales
0	Friday	79666
1	Monday	92466
2	Sunday	62339
3	Thursday	100213
4	Tuesday	98726
5	Wednesday	91467

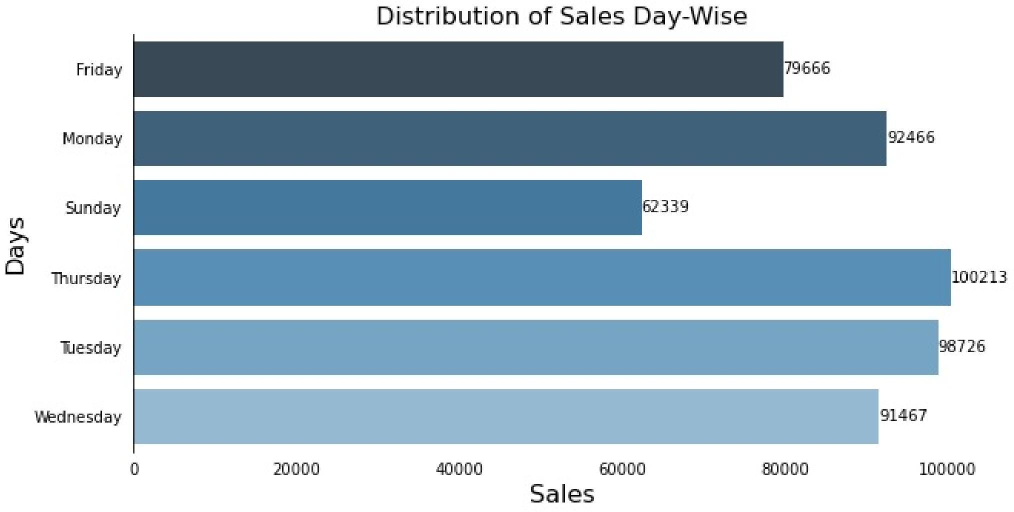
In [337…

```
#Choosing Palette and reverse it
Palette = sns.color_palette('Blues_d')
Palette.reverse()

plt.figure(figsize = (10,5))
#Visualizing
ax =sns.barplot(y = 'Day' , x= 'Sales' , data = daySales, palette = Palette)

#Data labels
ax.bar_label(ax.containers[0])

#Setting Title
plt.title('Distribution of Sales Day-Wise',fontsize = 16)
plt.ylabel('Days',fontsize = 16)
plt.xlabel('Sales',fontsize = 16)
plt.show()
```



RMF Analysis

As a algorithm the RFM was used, for being an easy-to-understand model.

The term RFM comes from the function of three acronyms: Recency, Frequency, and Monetary, seeking to better understand the customer and verify when was his last purchase, how many times he has bought and how much he has spent with the company.

Recency(R) Days since the customer's last purchase Frequency(F) Number of products bought by the customer Monetarity(M) Total spent on purchases

Customer Score:

The customer score ranges from 1 to 5, where the higher this number, the better. This score is assigned for each acronym independently:

The more recent the customer's purchase the higher the Recency (R) score.

The more purchases the customer makes, the higher the Frequency score (F)

The more the customer spends on purchases, the higher the score the customer will have Monetarity(M) This definition of each score can be given through inference, i.e. some business definition or by quintile.

In [338…

```
#Ignoring Cancel orders
copy[~copy['InvoiceNo'].str.contains('C' ,na = False)]

#Dropping Null values in Customer ID column
copy= copy.dropna(subset= ['CustomerID'])

#Make Checkoutprice Column
copy['CheckoutPrice'] = copy['UnitPrice'] * copy['Quantity']

#Ignoring Debts
copy =copy[copy['UnitPrice']>0]
```

```python
#Dealing with datatypes
copy['InvoiceDate'] = pd.to_datetime(copy['InvoiceDate'])
copy['CustomerID'] = copy['CustomerID'].astype('int64')
```

In [339…

```python
recent_date = copy['InvoiceDate'].max()
```

In [341…

```python
#Set our data to rfm Analysis
rfm = copy.groupby('CustomerID').agg({'InvoiceDate' : lambda date : (recent_date - date.max()).days ,
                                      'InvoiceNo' : lambda num :num.nunique() ,
                                      'CheckoutPrice' : lambda CheckoutPrice :CheckoutPrice.sum()} )
rfm
```

Out[341]:

	InvoiceDate	InvoiceNo	CheckoutPrice
CustomerID			
12346	325	2	0.00
12347	1	7	4310.00
12348	74	4	1797.24
12349	18	1	1757.55
12350	309	1	334.40
...	...	...	...
18280	277	1	180.60
18281	180	1	80.82
18282	7	3	176.60
18283	3	16	2045.53
18287	42	3	1837.28

4371 rows × 3 columns

In [342…

```python
rfm.columns = ['Recency' ,'Frequency' , 'Monetary']
```

In [343…

```python
#Ignore 0 in Monatery so we will not need those customers in our analysis
rfm = rfm[rfm['Monetary']>0]
```

In [344…

```python
#Set Recency Score
rfm['Recency_Score'] = pd.qcut(rfm['Recency'] ,5 , labels= [5,4,3,2,1])
```

In [345…

```python
#Set Frequency Score
rfm['Frequency_Score'] = pd.qcut(rfm['Frequency'].rank(method ='first') ,5 , labels= [1,2,3,4,5])
```

In [346…

```python
#Set Monatry Score
rfm['Monetary_Score'] = pd.qcut(rfm['Monetary'] ,5 , labels= [1,2,3,4,5])
```

In [347…

```python
#Set RFM Score
rfm['RFM_Score'] = (rfm['Recency_Score'].astype(str) + rfm['Frequency_Score'].astype(str) +
                    rfm['Monetary_Score'].astype(str) )
```

In [348…

```python
rfm
```

Out[348]:

	Recency	Frequency	Monetary	Recency_Score	Frequency_Score	Monetary_Score	RFM_Score
CustomerID							
12347	1	7	4310.00	5	4	5	545
12348	74	4	1797.24	2	3	4	234
12349	18	1	1757.55	4	1	4	414
12350	309	1	334.40	1	1	2	112
12352	35	11	1545.41	3	5	4	354
...	...	...	...	...	...	...	...
18280	277	1	180.60	1	2	1	121
18281	180	1	80.82	1	2	1	121
18282	7	3	176.60	5	3	1	531
18283	3	16	2045.53	5	5	5	555
18287	42	3	1837.28	3	3	4	334

4320 rows × 7 columns

Segmentation calculation:

The calculation to know which segmentation the customer is in is given by averaging the F and R scores

I see that Monetary could be deceptive , So i will segment our customers on Recency and Frequency Scores

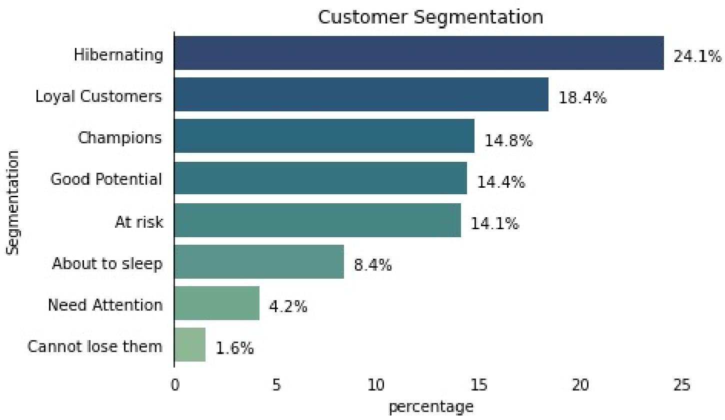
In [349…

```
#Our Customer Segmentation
seg_map = {
    r'[1-2][1-2][1-5]': 'Hibernating',
    r'[1-2][3-4][1-5]': 'At risk',
    r'[1-2]5[1-5]' :'Cannot lose them',
    r'3[1-2][1-5]' : 'About to sleep',
    r'33[1-5]' : 'Need Attention',
    r'[3-4][4-5][1-5]' : 'Loyal Customers',
    r'[4-5][1-3][1-5]' : 'Good Potential',
    r'5[4-5][1-5]' : 'Champions',

}
rfm['Segment'] = rfm['RFM_Score'] .replace(seg_map ,regex =True)
```

In [350…

```
#Bar Plot for Our segments
Segments = (rfm['Segment'].value_counts(normalize=True)* 100).reset_index(name='percentage')
Segments = Segments.round(1)
b =sns.barplot(y='index',x='percentage', data=Segments, palette = 'crest_r')
for i, v in enumerate(Segments['percentage']):
    b.text(v,i+0.20,"  {:.1f}".format(v)+"%", color='black', ha="left")
    b.set_ylabel('Segmentation')
    b.set_title('Customer Segmentation')
```



In [351…

```
rfm
```

Out[351]:

CustomerID	Recency	Frequency	Monetary	Recency_Score	Frequency_Score	Monetary_Score	RFM_Score	Segment
12347	1	7	4310.00	5	4	5	545	Champions
12348	74	4	1797.24	2	3	4	234	At risk
12349	18	1	1757.55	4	1	4	414	Good Potential
12350	309	1	334.40	1	1	2	112	Hibernating
12352	35	11	1545.41	3	5	4	354	Loyal Customers
...	...	...	...	...	...	...	...	...
18280	277	1	180.60	1	2	1	121	Hibernating
18281	180	1	80.82	1	2	1	121	Hibernating
18282	7	3	176.60	5	3	1	531	Good Potential
18283	3	16	2045.53	5	5	5	555	Champions
18287	42	3	1837.28	3	3	4	334	Need Attention

4320 rows × 8 columns

Findings

24.1% of our customers are in the hibernation segment and that for customers who have purchased from us a few times and the last time was a long time

18.4% of our customers are loyal and usually buys from us

14.8% of our customers are champions so we are their favourtie market

14.4% of our customers have good potential that refers to customers who have bought from us recently and have not buy many times

14.1% of our cutomeers are at risk segment so we must attract them again

8.4% of our customers are about to sleep and this segment of customers who last purchase from us for a fairly long time

4.2% of our customers are needing more attention to make them fall under Champions segment

1.6% of our customers can`t lost them and they purchased from us many times but last time was for a long time

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