INSAID

INTERNATIONAL SCHOOL OF AI AND DATA SCIENCE

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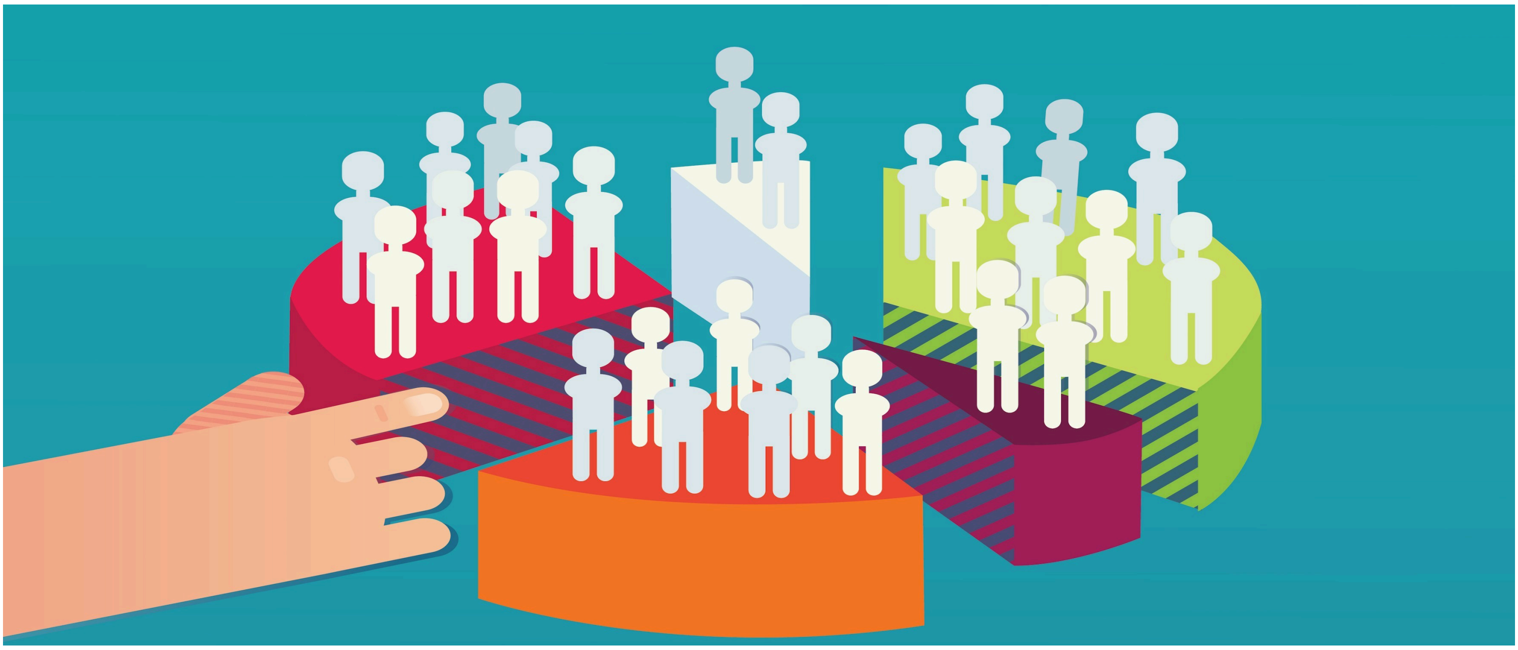
1. Introduction

Segmenting customers is the **process** of **dividing** up mass **consumers** into **groups** with **similar needs** and **wants**. It can **help companies** to **focus** on **marketing** efforts, so that **customer satisfaction** and **overall profit** could be achieved at higher rates. **Segmentation exists** to **mitigate** the **inevitable problems** that evolve from a "**One size fits all**" approach. Best in class **suppliers develops different** types of

segmentation to **understand** how to **create**, **position**, and **communicate** the value of their offering to **address** the different **needs** required in different customer segments.



Many **companies adopts different segmentation schemes**, that is often **develop best but static** (snapshot of consumer's preferences at the moment). Market **trends evolve** over time. **It** may **grow**, **decline** or **disappear within** certain **time** period due to number of **reasons** like **demographics trend**, **technological advancement**, **economic cycles** etc.

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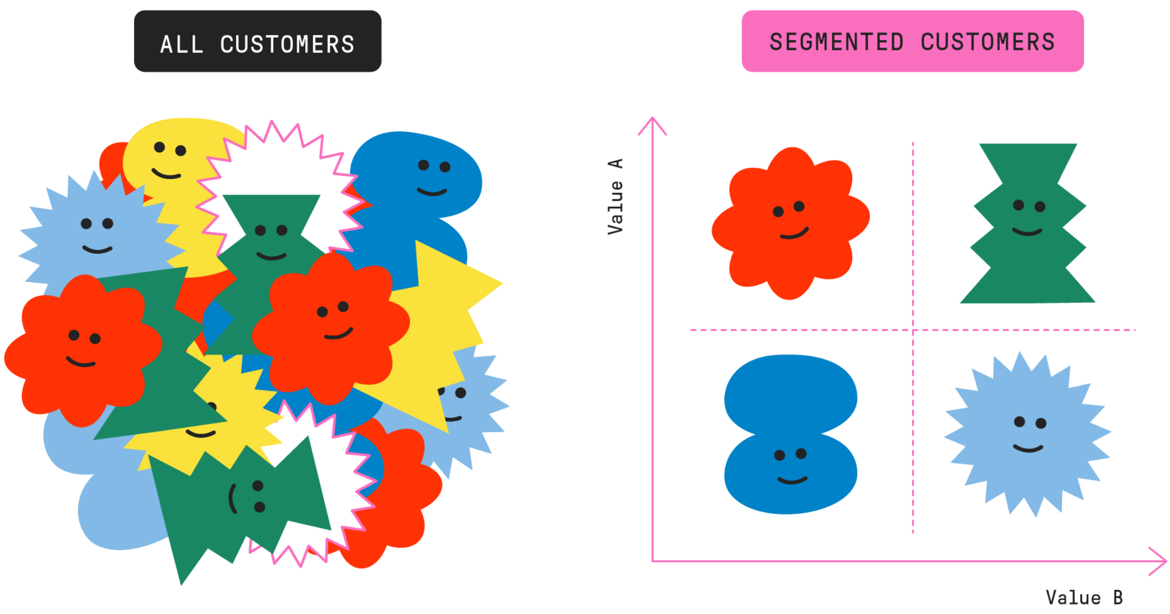
2. Problem Statement

At some point, it becomes **impossible** to **focus** on an **individual customer** and **sometimes** the **communication** between customers **become complex**. We **need a way** out to **understand** our **customers** in **structured** and **shared manner**.



Scenario:

Knack Grant is a UK based non-store **online retail company** started in 2009. The company mainly **sells** unique **all-occasion gift-ware**. Many customers of the company are wholesalers. The **company** is **growing** at **rapid speed**. At the **same time** they are **unable** to **catch up** the **customer expectation** and **maintain healthy relationship** i.e failing in Customer Relationship Management(CRM).

In order **to tackle this problem**, they **hired a team of data scientists**. They **need** an **automated solution** to **identify** the **customers expectations** and the **future trends** so that they can **engage** with customers in **more structured and shared manner** leading their company to future endavours.

Note:

- This **problem** is a type of **unsupervised learning**, i.e. there is no target present in our data.
- We will **clusters customers based on their behavior**.
- It will **give** us an **approximation** about the **customer purchasing behavior leading** to **better marketing**.

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3. Installing & Importing Libraries

3.1 Installing Libraries

```
!pip install -q datascience                       # Package that is required by pandas profiling
!pip install -q pandas-profiling                  # Toolbox for Generating Statistics Report
```

3.2 Upgrading Libraries

Note: After upgrading, you need to restart the runtime. Make sure not to execute the cell above (3.1) and below (3.2) again after restarting the runtime.

```
!pip install -q --upgrade pandas-profiling
!pip install -q --upgrade yellowbrick
```

3.3 Importing Libraries

```
# For Panel Data Analysis
import pandas as pd
#from pandas_profiling import ProfileReport
import pandas.util.testing as tm
pd.set_option('display.max_columns', None)
pd.set_option('display.max_colwidth', -1)
pd.set_option('display.max_rows', None)
pd.set_option('mode.chained_assignment', None)

# For Numerical Python
import numpy as np
```

```
# For Random seed values
from random import randint

# For Scientifc Python
from scipy import stats

# For datetime
import datetime
from datetime import datetime as dt


# For Data Visualization
import matplotlib.pyplot as plt
import matplotlib.cm as cm
%matplotlib inline
from pandas_profiling import ProfileReport
import seaborn as sns
import plotly.express as px
from plotly.offline import plot
import plotly.graph_objects as go
from plotly.subplots import make_subplots

# For Data Modeling
from sklearn.cluster import KMeans

# To Disable Warnings
import warnings
warnings.filterwarnings(action = "ignore")
```

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4. Data Acquisition & Wrangling

This data set is based on online transactions occurring between 01/12/2017 and 09/12/2019 and is accessible here.

Records	Features	Dataset Size
1067371	8	90.4 MB

Id	Features	Description
01	**Invoice**	Invoice number. A 6-digit integral number uniquely assigned to each transaction. If this code starts with the letter 'c', it indic
02	**StockCode**	Product item code. A 5-digit integral number along with letters uniquely assigned to each distinct product.
03	**Description**	Product item name.
04	**Quantity**	The quantities of each product item per transaction. Some values are negative due error while tracking data under process
05	**InvoiceDate**	Invice date and time. The day and time when a transaction was generated.
06	**Price**	Product price per unit in sterling (£).
07	**Customer ID**	Customer number. A 5-digit integral number uniquely assigned to each customer.
08	**Country**	Country name. The name of the country where a customer resides.

```
LINK = 'https://storage.googleapis.com/retail-analytics-data/OnlineRetailV3.csv'

def load_cust_seg_data(link = LINK):
  return pd.read_csv(filepath_or_buffer = link)
```

```
data = load_cust_seg_data()
print('Data Shape:', data.shape)
data.head()
```

```
Data Shape: (1067371, 8)
```

	Invoice	StockCode	Description	Quantity	InvoiceDate	Price	Customer ID	Country
0	489434	85048	15CM CHRISTMAS GLASS BALL 20 LIGHTS	12	2017-12-1	6.95	13085.0	United Kingdom
1	489434	79323P	PINK CHERRY LIGHTS	12	2017-12-1	6.75	13085.0	United Kingdom
2	489434	79323W	WHITE CHERRY LIGHTS	12	2017-12-1	6.75	13085.0	United Kingdom

4.1 Data Description

- In this section we will get **information about the data** and see some observations.

```
print('Described Column Length:', len(data.describe().columns))
data.describe()
```

```
Described Column Length: 3
```

	Quantity	Price	Customer ID
count	1.067371e+06	1.067371e+06	824364.000000
mean	9.938898e+00	4.649388e+00	15324.638504
std	1.727058e+02	1.235531e+02	1697.464450
min	-8.099500e+04	-5.359436e+04	12346.000000
25%	1.000000e+00	1.250000e+00	13975.000000
50%	3.000000e+00	2.100000e+00	15255.000000
75%	1.000000e+01	4.150000e+00	16797.000000
max	8.099500e+04	3.897000e+04	18287.000000

Observation:

- On **average** customer had **bought** around **quantity** of **10** of **each** product **item**.
- **25%** of customers **bought** product **items** with <= **unit quantity**, while **50%** and **75%** of customers **bought** product **item** with **quantity <= 3 and 10**.
- **Average price** of all the **transacted items** was **£4.64 pounds**.

- **25%** of product **items** had **price of £1.25 pounds**, while **50% and 75%** of **items** had **price of £2.1 pounds** and **£4.15 pounds**.

4.2 Pre Profiling Report

- For quick analysis pandas profiling is very handy.
- Generates profile reports from a pandas DataFrame.
- For each column statistics are presented in an interactive HTML report.

```
#profile = ProfileReport(df = data)
#profile.to_file(output_file = 'Pre Profiling Report.html')
#print('Accomplished!')
```

```
#from google.colab import files                   # Use only if you are using Google Colab, otherwi
#files.download('Pre Profiling Report.html')      # Use only if you are using Google Colab, otherwi
```

Observation:

- According to the report there are **total 8 variables** out which **5 are categorical and 3 are numerical**.
- Around **2.9% of data is missing** i.e. 247389 cells.
- Around **3.2% of rows are duplicate** i.e. 34335 rows.
- **Invoice, StockCode, Description, InvoiceDate** features have **high cardinalities**.
- There is **absence of correlation among features** with each others

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5. Data Pre-Processing

5.1 Identification & Handling of Missing Data

5.1.1 Null Data Identification & Handling

Before Handling Null Data

```
null_frame = pd.DataFrame(index = data.columns.values)
null_frame['Null Frequency'] = data.isnull().sum().values
percent = data.isnull().sum().values/data.shape[0]
null_frame['Missing %age'] = np.round(percent, decimals = 4) * 100
null_frame.transpose()
```

	Invoice	StockCode	Description	Quantity	InvoiceDate	Price	Customer ID	Country
Null Frequency	0.0	0.0	4382.00	0.0	0.0	0.0	243007.00	0.0

Observation:

- **Feature:**
  - Problem → Action Required {Reason}
- **Description:**
  - Missing information (4382) → Drop records {Ratio is very less, won't affect the results}
- **Customer ID:**
  - Missing information (243007) → Drop records {Ratio is not high enough, as we still have around 80% info to retain}

Performing Operations

```
print('Data Shape [Before]:', data.shape)
data.dropna(axis = 0, subset = ['Description', 'Customer ID'], inplace = True)
print('Data Shape [After]:', data.shape)
```

```
Data Shape [Before]: (1067371, 8)
Data Shape [After]: (824364, 8)
```

After Handling Null Data

- Now that we have performed the operations, let's verify whether the null data has been eliminated or not.

```
null_frame = pd.DataFrame(index = data.columns.values)
null_frame['Null Frequency'] = data.isnull().sum().values
percent = data.isnull().sum().values/data.shape[0]
null_frame['Missing %age'] = np.round(percent, decimals = 4) * 100
null_frame.transpose()
```

	Invoice	StockCode	Description	Quantity	InvoiceDate	Price	Customer ID	Country
Null Frequency	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

Observation:

- We can see that we have **eliminated null data successfully**.

5.1.2 Zero Data Identification & Handling

```
zero_frame = pd.DataFrame(index = data.columns.values)
zero_frame['Null Frequency'] = data[data == 0].count().values
percent = data[data == 0].count().values / data.shape[0]
zero_frame['Missing %age'] = np.round(percent, decimals = 4) * 100
zero_frame.transpose()
```

	Invoice	StockCode	Description	Quantity	InvoiceDate	Price	Customer ID	Country
Null Frequency	0.0	0.0	0.0	0.0	0.0	71.00	0.0	0.0

Observation:

- **Feature:**
  - Problem → Action Required {Reason}
- **Price:**
  - Identified 71 zeros → Drop records {Price of product item cannot be zero. Some orders were cancelled so price = 0}

Performing Operations

```
data = data[data['Price'] != 0]
```

After Handling Zero Data

- Now that we have performed the operations, let's verify whether the zero data has been eliminated or not.

```
zero_frame = pd.DataFrame(index = data.columns.values)
zero_frame['Null Frequency'] = data[data == 0].count().values
percent = data[data == 0].count().values / data.shape[0]
zero_frame['Missing %age'] = np.round(percent, decimals = 4) * 100
zero_frame.transpose()
```

	Invoice	StockCode	Description	Quantity	InvoiceDate	Price	Customer ID	Country
Null Frequency	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

Observation:

- We can see that we have **eliminated zero data successfully**.

5.2 Identification & Handling of Redundant Data

- In this section **we will identify redundant rows and columns** in our data if present.
- **Before** we will **make a copy of our data** and **analyze** the **effect**.

- **Later down**, all the **changes** will be **introduced** in the **original data**.

5.2.1 Identfication & Handling of Redundant Records

```
data_copy = data.copy()
```

Before Handling Duplicate Rows

```
print('Contains Redundant Records?:', data_copy.duplicated().any())
print('Duplicate Count:', data_copy.duplicated().sum())
print('Data Shape:', data_copy.shape)
```

```
Contains Redundant Records?: True
Duplicate Count: 26480
Data Shape: (824293, 8)
```

Observation:

- It turns out that there are **26479 duplicate** rows **present** in our data.
- We will **drop** these **records** as they are **not useful** for our analysis and model development.

Performing Operations

```
before_shape = data_copy.shape
print('Data Shape [Before]:', before_shape)

data_copy.drop_duplicates(inplace = True)

after_shape = data_copy.shape
print('Data Shape [After]:', after_shape)

drop_percent = after_shape[0] / before_shape[0]
print('Drop Ratio:', np.round(drop_percent, decimals = 2))
```

```
Data Shape [Before]: (824293, 8)
Data Shape [After]: (797813, 8)
Drop Ratio: 0.97
```

After Handling Duplicate Rows

```
print('Contains Redundant Records?:', data_copy.duplicated().any())
print('Duplicate Count:', data_copy.duplicated().sum())
print('Data Shape:', data_copy.shape)
```

```
Contains Redundant Records?: False
Duplicate Count: 0
Data Shape: (797813, 8)
```

Applying Above Operations on Original Data

```
before_shape = data.shape
print('Data Shape [Before]:', before_shape)

data.drop_duplicates(inplace = True)

after_shape = data.shape
print('Data Shape [After]:', after_shape)

drop_percent = after_shape[0] / before_shape[0]
print('Drop Ratio:', np.round(drop_percent, decimals = 2))

print('Contains Redundant Records?:', data.duplicated().any())
```

```
Data Shape [Before]: (824293, 8)
Data Shape [After]: (797813, 8)
Drop Ratio: 0.97
Contains Redundant Records?: False
```

5.2.2 Identfication & Handling of Redundant Features

- For handling duplicate features we have created a custom function to identify duplicacy in features with different name but similar values below.

```
def duplicate_cols(dataframe):
  ls1 = []
  ls2 = []

  columns = dataframe.columns.values
  for i in range(0, len(columns)):
    for j in range(i+1, len(columns)):
      if (np.where(dataframe[columns[i]] == dataframe[columns[j]], True, False).all() == True):
        ls1.append(columns[i])
        ls2.append(columns[j])

  if ((len(ls1) == 0) & (len(ls2) == 0)):
    return None
  else:
    duplicate_frame = pd.DataFrame()
    duplicate_frame['Feature 1'] = ls1
    duplicate_frame['Feature 2'] = ls2
    return duplicate_frame
```

Before Handling Redundant Columns

```
print(duplicate_cols(data_copy))
```

```
None
```

Observation:

- It turns out that there are **no duplicate columns present** in our data.

5.3 Identification & Handling of Inconsistent Data Types

Before changes: Respective Data Type per Feature

```
type_frame = pd.DataFrame(data = data.dtypes, columns = ['Type'])
type_frame.transpose()
```

	Invoice	StockCode	Description	Quantity	InvoiceDate	Price	Customer ID	Country
Type	object	object	object	int64	object	float64	float64	object

Observation:

- **Inconsistent Feature:**
  - Actual Type → Desired Type
- **InvoideDate:**
  - Object → Datetime
- **Customer ID:**
  - Float → Integer

Performing Operations

```
data['Customer ID'] = data['Customer ID'].astype(np.int64)

# Removing Time Factor (Example: 2017-12-01 07:45:00 --> 2017-12-01)
data['InvoiceDate'] = pd.to_datetime(data['InvoiceDate']).apply(dt.date)

# Transforming Object Type to Datetime
data['InvoiceDate'] = pd.to_datetime(data['InvoiceDate'])
```

After changes: Respective Data Type per Feature

```
type_frame = pd.DataFrame(data = data.dtypes, columns = ['Type'])
type_frame.transpose()
```

	Invoice	StockCode	Description	Quantity	InvoiceDate	Price	Customer ID	Country
Type	object	object	object	int64	datetime64[ns]	float64	int64	object

5.4 Looking at the Final Dataset

```
# Shape
print('The final shape of the data: Rows: {} | Columns: {}\n'.format(data.shape[0], data.shape[1]))
```

```
# Data
data.head()
```

```
The final shape of the data: Rows: 797813 | Columns: 8
```

	Invoice	StockCode	Description	Quantity	InvoiceDate	Price	Customer ID	Country
0	489434	85048	15CM CHRISTMAS GLASS BALL 20 LIGHTS	12	2017-12-01	6.95	13085	United Kingdom
1	489434	79323P	PINK CHERRY LIGHTS	12	2017-12-01	6.75	13085	United Kingdom
2	489434	79323W	WHITE CHERRY LIGHTS	12	2017-12-01	6.75	13085	United Kingdom

6. Exploratory Data Analysis

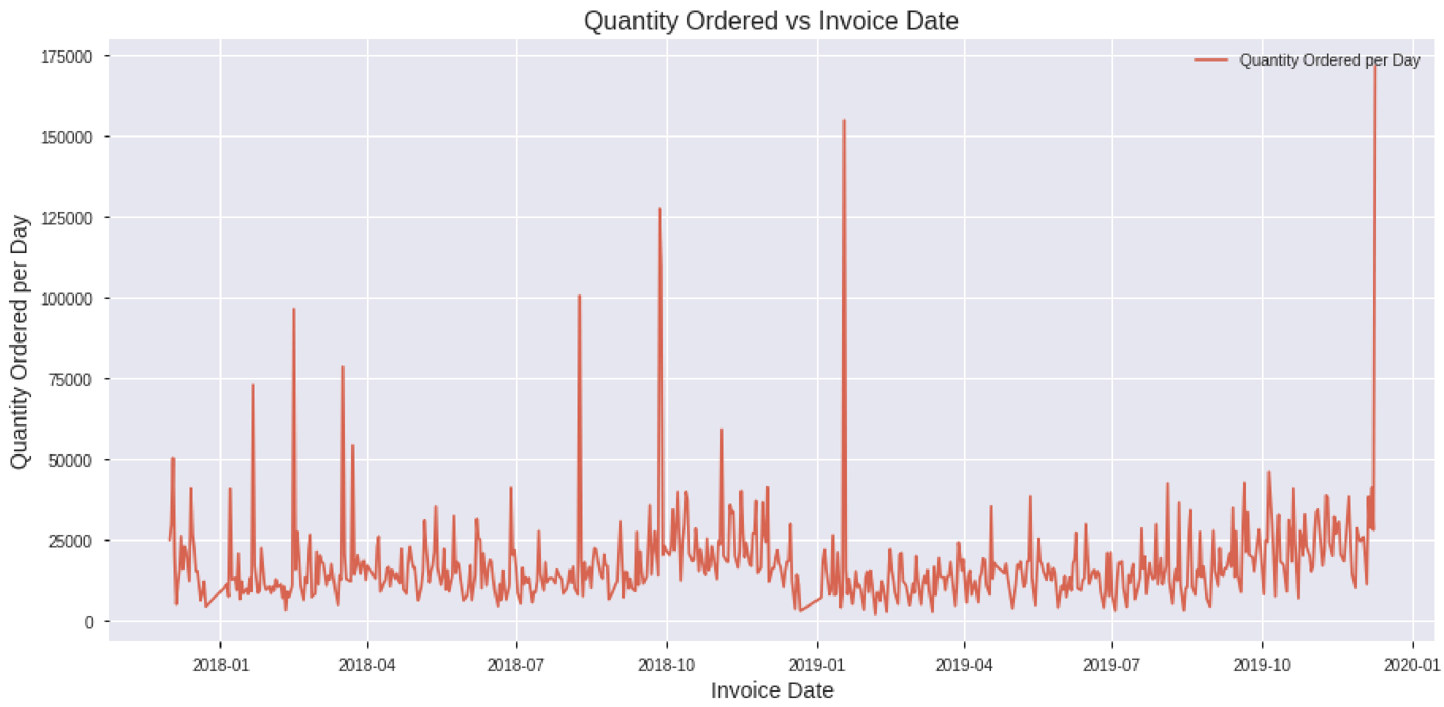
- **Before moving further** into analysis, we **will create** a **new feature** that will **show** the **total amount spend** by customer **on** that **product**.
- Another thing is while accumulating data by machine, the error was introduced in **Quantity** feature, **having** some **negative values**.
- We **need** to **change** this **feature** with **absolute** value.

```
# Converting negative values to positive
data['Quantity'] = np.abs(data['Quantity'])

# Creating a new feature
data['TotalSpend'] = data['Quantity'] * data['Price']
```

Question 1: What is the ordered quantity of product items per day by the customer?

```
dx = data.groupby(by = 'InvoiceDate', as_index = False).agg('sum')
```

```
figure = plt.figure(figsize = [15, 7])
sns.lineplot(x = 'InvoiceDate', y = 'Quantity', data = dx, color = '#D96552')

plt.xlabel('Invoice Date', size = 14)
plt.ylabel('Quantity Ordered per Day', size = 14)
plt.legend(labels = ['Quantity Ordered per Day'], loc = 'upper right', frameon = False)
plt.title('Quantity Ordered vs Invoice Date', size = 16)
plt.grid(b = True, axis = 'y')
plt.show()
```



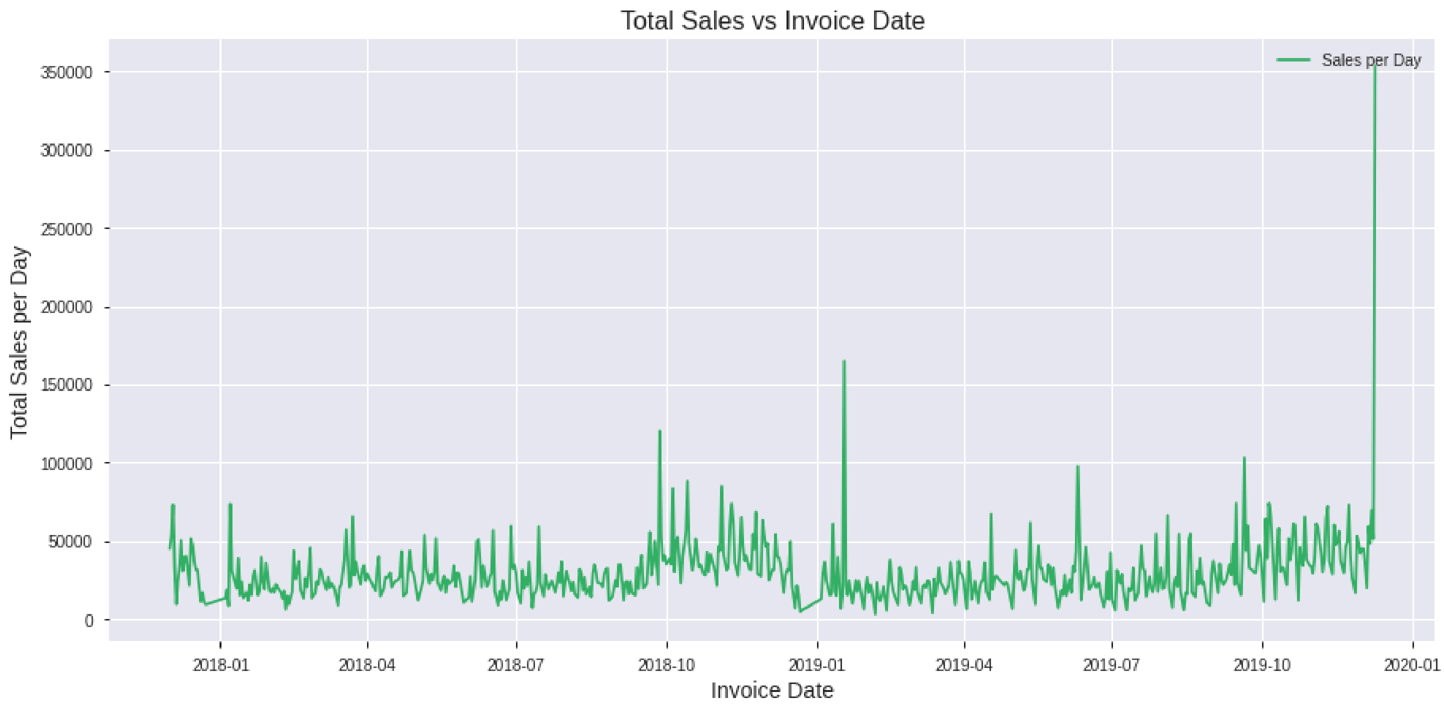
Observation:

We can see high quantity ordered around the month of,

- September/October-2018 (~130000),
- January-2019 (~160000)and
- January-2020 (~175000).

Question 2: What is the total sales of product items per day by the customer?

```
figure = plt.figure(figsize = [15, 7])
sns.lineplot(x = 'InvoiceDate', y = 'TotalSpend', data = dx, color = '#32B165')

plt.xlabel('Invoice Date', size = 14)
plt.ylabel('Total Sales per Day', size = 14)
plt.legend(labels = ['Sales per Day'], loc = 'upper right', frameon = False)
plt.title('Total Sales vs Invoice Date', size = 16)
plt.grid(b = True, axis = 'y')
plt.show()
```



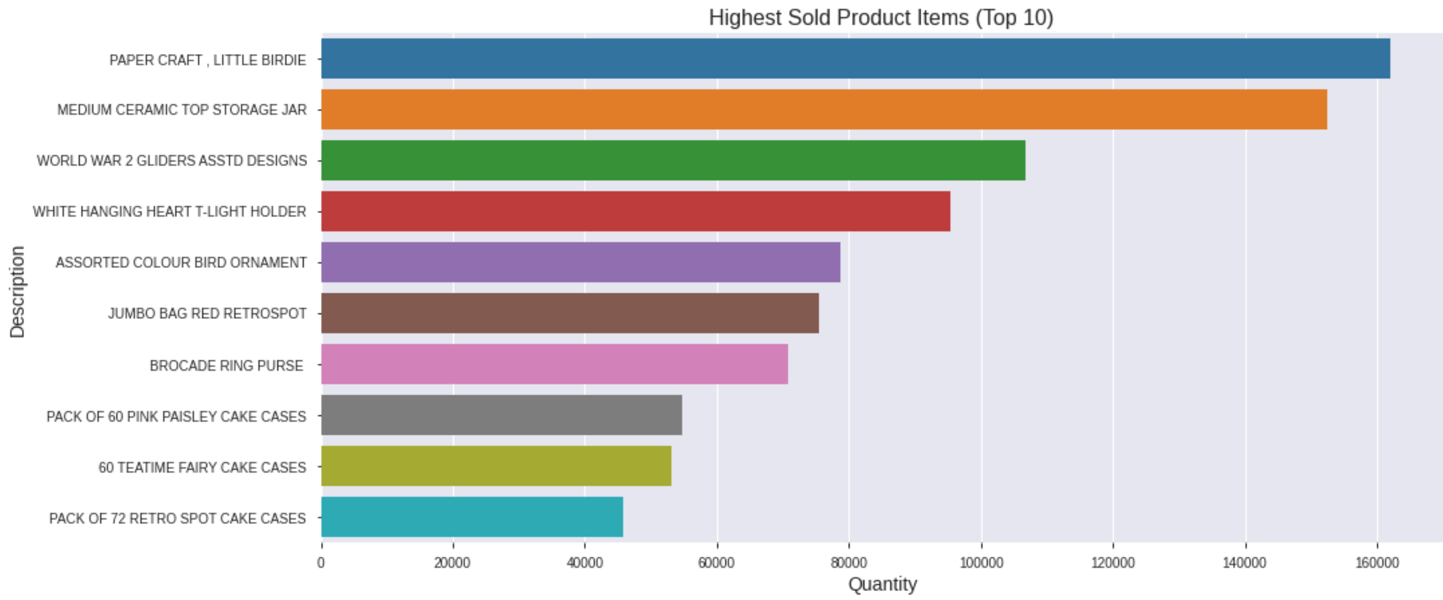
Observation:

- **Sales** around the month of **January, 2019** was pretty **high** (**~£165000 pounds**).
- **Sales** around the month of **December, 2019** was pretty **high** (**~£360000 pounds**).

Question 3: Which are the top 10 product that were sold at high quantity to the customer?

```
dx = data.groupby(by = 'Description', as_index = False).agg('sum').sort_values(by ='Quantity', asce
# Selecting top 10 products
top_ = dx[0:10]
```

```
figure = plt.figure(figsize = [15, 7])
sns.barplot(x = 'Quantity', y ='Description', data = top_)
plt.xlabel(xlabel = 'Quantity', size = 14)
plt.ylabel(ylabel = 'Description', size = 14)
plt.title(label = 'Highest Sold Product Items (Top 10)', size = 16)
plt.grid(b = True, axis = 'x')
plt.show()
```



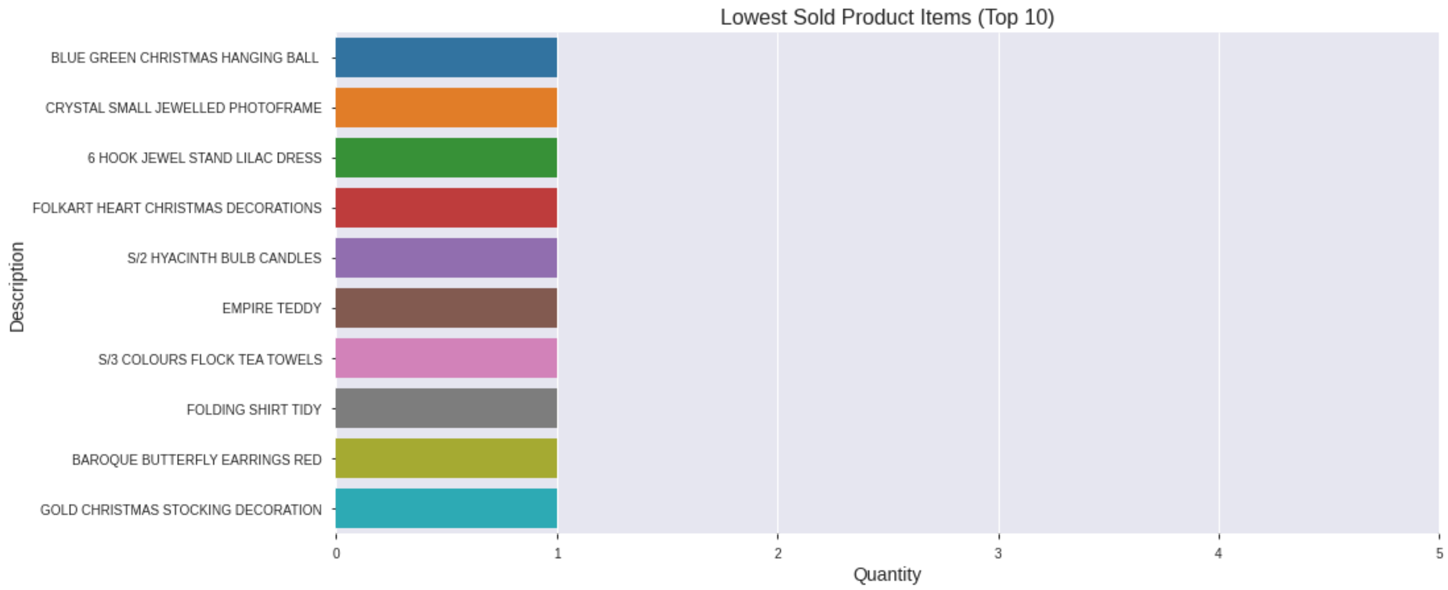
Observation:

- **Paper craft, little birdie** has been **sold** at **highest amount** of **quantity** than any other product item.

Question 4: Which are the top 10 product items that were sold at low quantity to the customer?

```
dx = data.groupby(by = 'Description', as_index = False).agg('sum').sort_values(by ='Quantity', asce
# Selecting top 10 products
top_ = dx[0:10]
```

```
figure = plt.figure(figsize = [15, 7])
sns.barplot(x = 'Quantity', y ='Description', data = top_)
plt.xticks(ticks = range(0, 6))
plt.xlabel(xlabel = 'Quantity', size = 14)
plt.ylabel(ylabel = 'Description', size = 14)
plt.title(label = 'Lowest Sold Product Items (Top 10)', size = 16)
plt.grid(b = True, axis = 'x')
plt.show()
```



Observation:

- The **items** displayed **above** have been **sold** at only **unit quantity**.

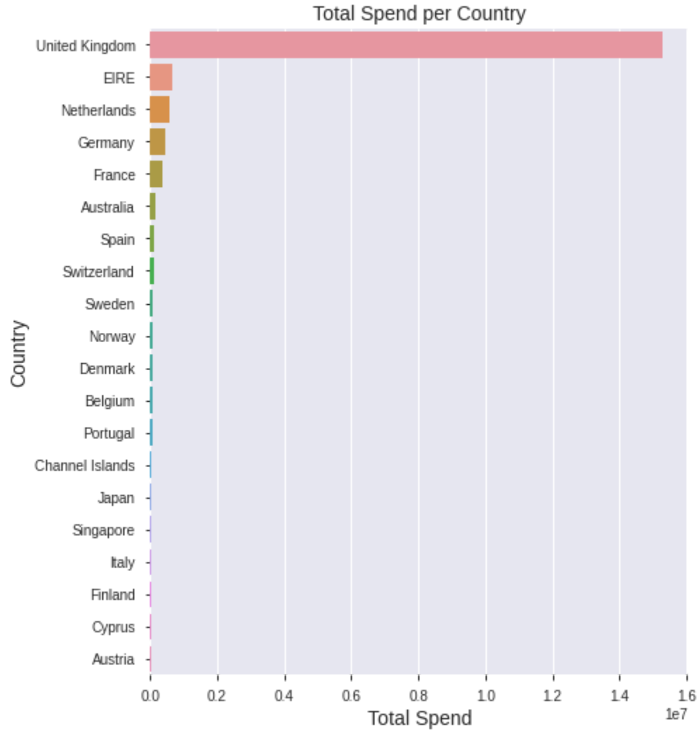
Question 5: What is the total amount that was spend by per country?

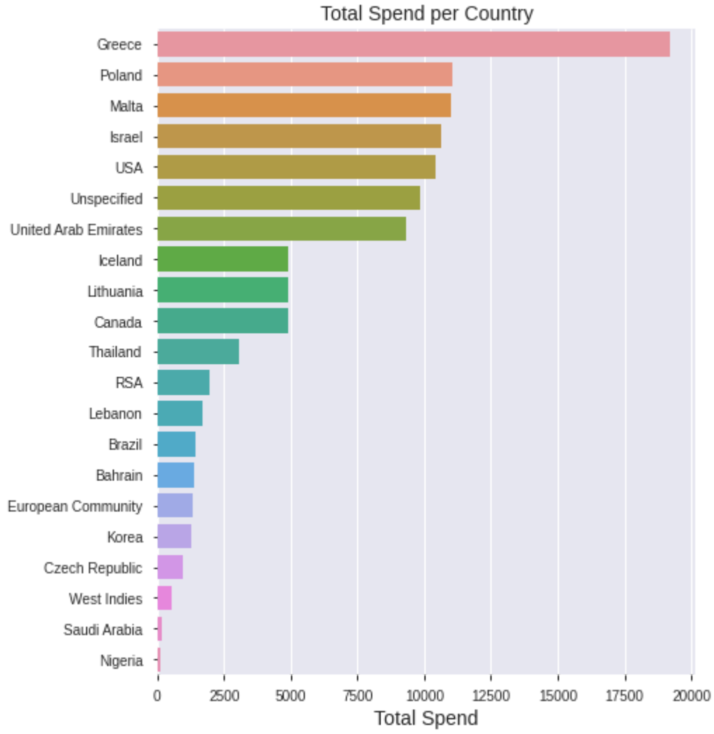
- **Note:** There are total 41 countries, plotting all of these in one go is complex, instead we will divide the plot.

```
dx = data.groupby(by = 'Country', as_index = False).agg('sum').sort_values(by ='TotalSpend', ascenc
```

```
print('Note: Below X scale is different for both the plots')
fig, (ax1, ax2) = plt.subplots(1, 2, figsize = [15, 8])
ax1 = sns.barplot(x = 'TotalSpend', y = 'Country', data = dx[0:20], ci = None, ax = ax1)
ax1.set_xlabel(xlabel = 'Total Spend', size = 14)
ax1.set_ylabel(ylabel = 'Country', size = 14)
ax1.set_title(label = 'Total Spend per Country', size = 14)
ax1.grid(b = True, axis = 'x')

ax2 = sns.barplot(x = 'TotalSpend', y = 'Country', data = dx[20:], ci = None, ax = ax2)
ax2.set_xlabel(xlabel = 'Total Spend', size = 14)
ax2.set_ylabel(ylabel = '')
ax2.set_title(label = 'Total Spend per Country', size = 14)
ax2.grid(b = True, axis = 'x')
plt.tight_layout(pad=3.0)
plt.show()
```

Note: Below X scale is different for both the plots





Observation:

- **United Kingdom spent highest** than any other country on buying items while **Nigeria spent lowest** than any other country.

Note: These are few question, from here if you would like to explore further, you are most welcome.

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7. Customer Segmentation Techniques

- In this section we will explore two techniques of clustering customer i.e. using K-Means and RFM(Recency Frequency Monetary).

7.1 Segmentation using K-Means

- We will be **segmenting customers based on** their **behaviour** i.e the **quantity ordered** and **total amount** on that product.
- **Firstly**, we will **run K-means** at **default setting**. Then we will **tune** it over **multiple K values**, **finding optimal K**.

- But **before** that we will **normalized two features** that are important for clustering i.e. **Quantity and TotalSpend**.

```
data['LogQuantity'] = np.log1p(data['Quantity'])
data['LogTotalSpend'] = np.log1p(data['TotalSpend'])
```

```
kmeans = KMeans(n_clusters = 8, max_iter = 500, random_state = 42)
kmeans.fit(data[['LogQuantity', 'LogTotalSpend']])
print('Within Sum of Square Variation (Inertia):', kmeans.inertia_)
```

```
Within Sum of Square Variation (Inertia): 193550.2050761361
```

7.1.1 Hyperparameter Tuning: Finding Optimal K

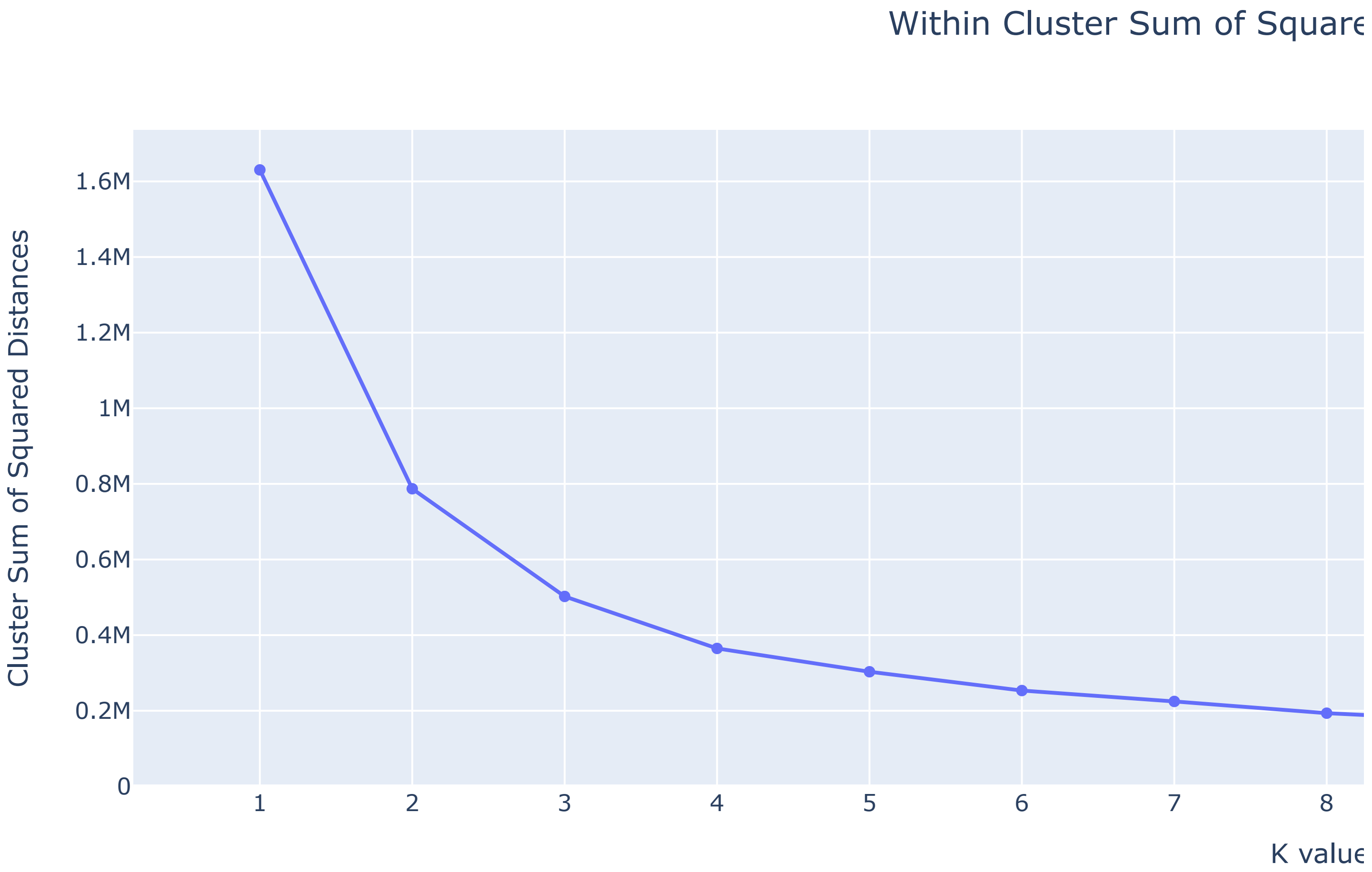
- We **will iterate** our model **over some iterations**, finding optimal K value for clustering.
- We **check inertia**, defined as the mean squared distance between each instance and its closest centroid. Logically, as per the definition **lower** the **inertia better** the **model**.
- We will **use Elbow rule** in order to **find** the **optimal number** of **clusters**.

```
# Have some patience, may take some time :)
inertia_vals = []
K_vals = [x for x in range(1, 16)]

for i in K_vals:
  k_model = KMeans(n_clusters = i, max_iter = 500, random_state = 42)
  k_model.fit(data[['LogQuantity', 'LogTotalSpend']])
  inertia_vals.append(k_model.inertia_)
  print('Iteration', i, 'completed')
```

```
Iteration 1 completed
Iteration 2 completed
Iteration 3 completed
Iteration 4 completed
Iteration 5 completed
Iteration 6 completed
Iteration 7 completed
Iteration 8 completed
Iteration 9 completed
Iteration 10 completed
Iteration 11 completed
Iteration 12 completed
Iteration 13 completed
Iteration 14 completed
Iteration 15 completed
```

```
# Visualzing the Inertia vs K Values
fig = go.Figure()

fig.add_trace(go.Scatter(x = K_vals, y = inertia_vals, mode = 'lines+markers'))
fig.update_layout(xaxis = dict(tickmode = 'linear', tick0 = 1, dtick = 1),
                  title_text = 'Within Cluster Sum of Squared Distances VS K Values',
                  title_x = 0.5,
                  xaxis_title = 'K values',
```

```
                   yaxis_title = 'Cluster Sum of Squared Distances')
fig.show()
```



Observation:

- As we can see that the **cluster sum of squared distances values** are **pretty high**.
- We can see that **after K = 5**, there is **significant drop** in **inertia**.
- So **K = 5 is optimal** for our **solution**.

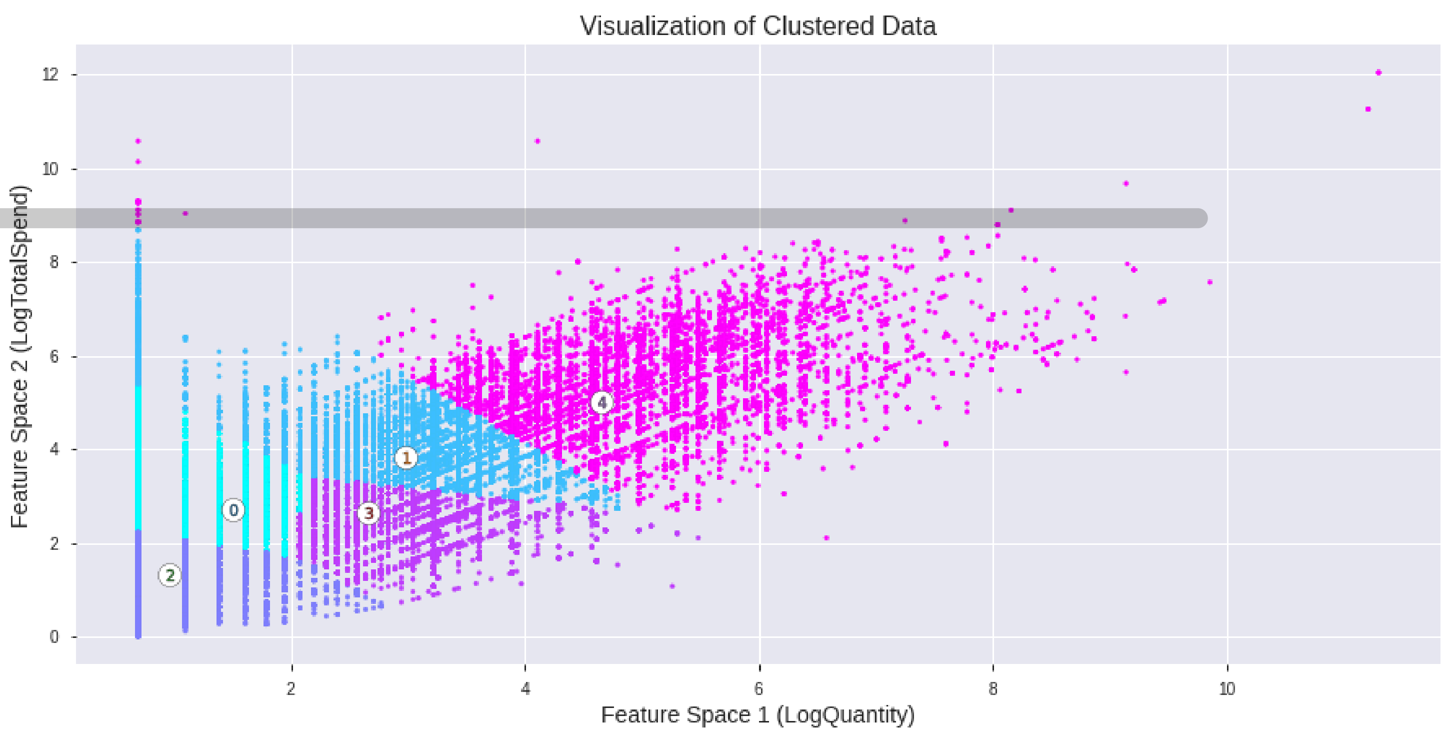
7.1.2 Final Model

```
kmeans = KMeans(n_clusters = 5, max_iter = 500, random_state = 42)
kmeans.fit(X = data[['LogQuantity', 'LogTotalSpend']])
data['Labels'] = kmeans.labels_
centers = kmeans.cluster_centers_
```

7.1.3 Visualization of Clusters

```
fig, ax1 = plt.subplots(1, 1, figsize = [15, 7])
ax1.scatter(x = data['LogQuantity'], y = data['LogTotalSpend'], marker='.', s = 30, c = data['Label
ax1.scatter(x = centers[:, 0], y = centers[:, 1], marker = 'o', c = "white", alpha = 1, s = 200, ec
for i, c in enumerate(centers):
  ax1.scatter(x = c[0], y = c[1], marker = '$%d$' % i, alpha = 1, s = 50, edgecolor = 'k')
plt.xlabel(xlabel = 'Feature Space 1 (LogQuantity)', size = 14)
```

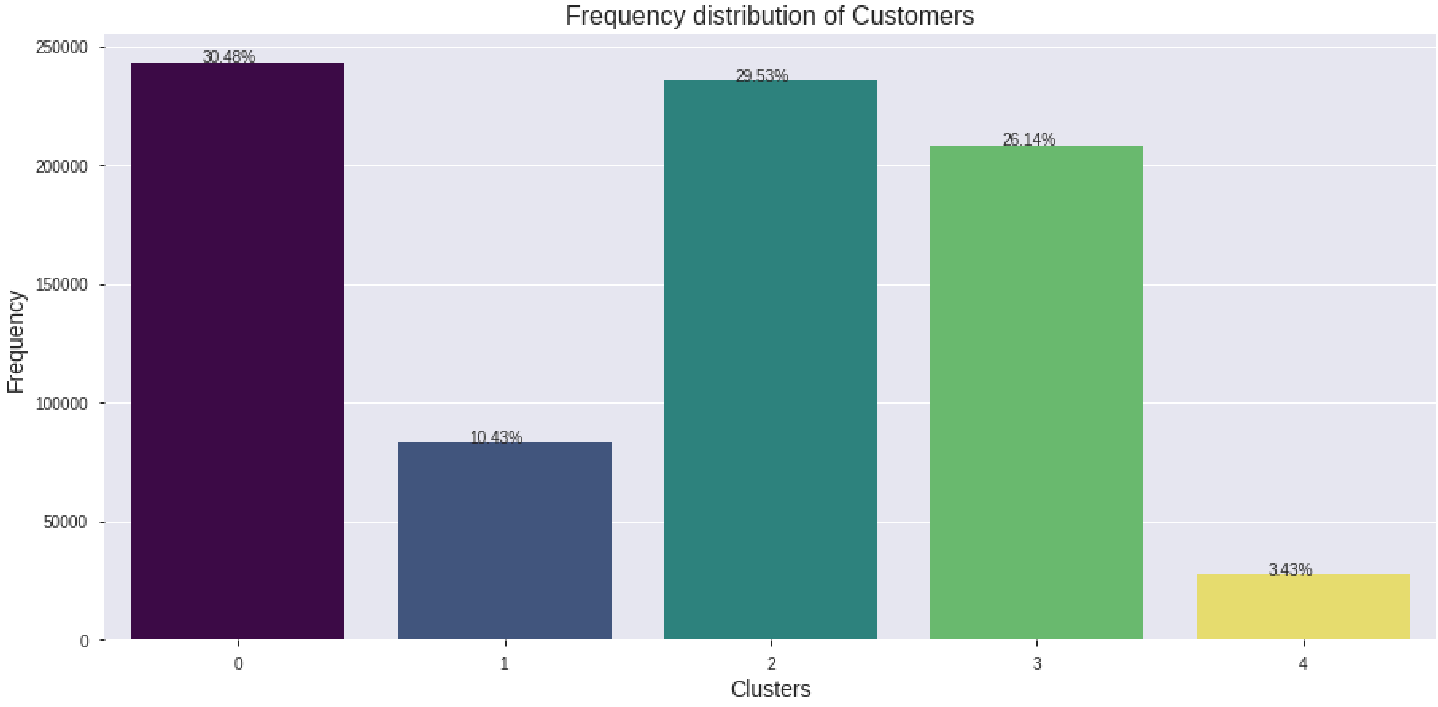
```
plt.ylabel(ylabel = 'Feature Space 2 (LogTotalSpend)', size = 14)
plt.title(label = 'Visualization of Clustered Data', size = 16)
plt.show()
```



Observation:

- We can see **clusters** and their **respective centroids** are very **dense**.
- **To understand better** we will **look** at the **count** of each **cluster label**.

```
figure = plt.figure(figsize = [15, 7])
flatui = ["#440154", "#3B528B", "#21918C", "#5EC962", "#FDEB5E"]
ax = sns.countplot(x = 'Labels', data = data, palette = sns.color_palette(flatui))

total = data.shape[0]
for p in ax.patches:
  percentage = '{:.2f}%'.format(100*p.get_height()/ total)
  x = p.get_x() + p.get_width() / 3
  y = p.get_y() + p.get_height()
  ax.annotate(percentage, (x, y))

plt.xlabel('Clusters', size = 14)
plt.ylabel('Frequency', size = 14)
plt.title(label = 'Frequency distribution of Customers', size = 16)
plt.show()
```



Observation:

- We can see that **clusters 1 and 4 are more profitable because** they seem to **order more quantity** as well as have **high purchase** values.
- For the **cluster 2**, both the **quantity and purchase** value is **less**.
- For the **cluster 0**, though the **quantity** ordered is **less**, the **purchase** value is **greater** than the cluster 3.
- On the other hand, the **cluster 3** has **higher quantity** ordered **than cluster 0** but the **purchase** value is **lesser**.

Having identified the charactersitics of each cluster, we can roll out targeted advertising, promotion offers, etc.

7.2 Segmentation using RFM

- RFM stands for **Recency**, **Frequency** and **Monetary**.
  - **RECENCY (R):** Days since last purchase. If score value is high it signifies that customer recently visited the shop.
  - **FREQUENCY (F):** Total number of purchases. If score value is high it signifies that customer buying frequency is high.
  - **MONETARY (M):** Total money customer spent. If score value is high it signifies that customer spending habit is high.
- It is a very **old technique** to **segment** the **customers** and it **works very well**.

Working:

- Firstly, we will calculate the RFM metrics for each customer.

#	Customer	Recency	Frequency	Monetary
01	A	53 days	3 transactions	£230
02	B	120 days	10 transactions	£900
03	C	10 days	8 transactions	£200

- Secondly, we will add segment numbers to RFM table.

#	Customer	Recency	Frequency	Monetary	R	F	M
01	A	53 days	3 transactions	£230	2	2	2
02	B	120 days	10 transactions	£900	1	1	2
03	C	10 days	8 transactions	£200	3	3	3

- Finally, Sort according to the RFM scores from the best customers (score 444).

#	Segment	RFM	Description	Marketing
01	Best Customers	444	Bought most recently and most often, and spend the most	No price incentives, new
02	Loyal Customers	X4X	Buys most frequently	Use R and F to further s
03	Big Spenders	XX4	Spends the most	Market your most exper
04	Almost Lost	244	Haven't purchased for sometime, but purchased frequently and spend the most	Aggresive price incentiv
05	Lost Customers	144	Haven't puchased for some time, but purchased frequently and spend the most	Aggressive price incenti
06	Lost Cheap Customers	111	Last purchase long ago, purchased few, and spent little.	Don't spend too much tr

```
print('Last Date:', data['InvoiceDate'].max())
```

```
Last Date: 2019-12-09 00:00:00
```

```
NOW = datetime.datetime(2019,12,10)
```

```
rmf_table = data.groupby(by = 'Customer ID', as_index = False).agg({'InvoiceDate': lambda x: (NOW -
                                                     'Invoice': lambda x: len(x),
                                                     'TotalSpend': lambda x: x.sum()
rmf_table.rename(columns = {'InvoiceDate':'Recency', 'Invoice':'Frequency', 'TotalSpend':'Monetary'
rmf_table.head()
```

	Customer ID	Recency	Frequency	Monetary
0	12346	326	47	155164.66
1	12347	3	222	4921.53
2	12348	76	51	2019.40
3	12349	19	180	4452.84
4	12350	311	17	334.40

Next we will segment the data according to the percentile i.e. 25%, 50% and 75%.

```
quantiles = rmf_table.quantile(q = [0.25, 0.5, 0.75])
quantiles = quantiles.to_dict()
```

```
quantiles
```

```
{'Customer ID': {0.25: 13831.5, 0.5: 15318.0, 0.75: 16802.5},
 'Recency': {0.25: 25.0, 0.5: 96.0, 0.75: 382.0},
 'Frequency': {0.25: 20.0, 0.5: 52.0, 0.75: 140.0},
 'Monetary': {0.25: 342.32, 0.5: 880.8100000000002, 0.75: 2316.635}}
```

Below we have created two functions that will help in achieving R, F and M values.

```
def calRecency(x, y, z):
  if x <= z[y][0.25]:
    return 4
  elif x <= z[y][0.50]:
    return 3
  elif x <= z[y][0.75]:
    return 2
  else:
    return 1

def calFrequencyMonetary(x, y, z):
  if x <= z[y][0.25]:
    return 1
  elif x <= z[y][0.50]:
    return 2
  elif x <= z[y][0.75]:
    return 3
  else:
    return 4
```

```
rmf_table['R Value'] = rmf_table['Recency'].apply(calRecency, args = ('Recency', quantiles))
rmf_table['F Value'] = rmf_table['Frequency'].apply(calFrequencyMonetary, args = ('Frequency', quar
rmf_table['M Value'] = rmf_table['Monetary'].apply(calFrequencyMonetary, args = ('Monetary', quanti
```

```
rmf_table.head()
```

	Customer ID	Recency	Frequency	Monetary	R Value	F Value	M Value
0	12346	326	47	155164.66	2	2	4
1	12347	3	222	4921.53	4	4	4
2	12348	76	51	2019.40	3	2	3
3	12349	19	180	4452.84	4	4	4
4	12350	311	17	334.40	2	1	1

Now we will append R, F and M score to a single feature.

```
rmf_table['RFM Score'] = rmf_table['R Value'].map(str) + rmf_table['F Value'].map(str) + rmf_table|
rmf_table.head()
```

	Customer ID	Recency	Frequency	Monetary	R Value	F Value	M Value	RFM Score
0	12346	326	47	155164.66	2	2	4	224
1	12347	3	222	4921.53	4	4	4	444
2	12348	76	51	2019.40	3	2	3	323
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]