```
1 from google.colab import drive
2 drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

Business Understanding

A. Topic

How an e-commerce company can utilize customer's behavioral data to improve Customer Relationship Management (CRM)

B. Problem Statement

Today CRM and Cohort Analysis is the must have knowledge for any Data Scientist or Data Analyst. The company uses CRM to improve customer service relationships and assist in customer retention and drive sales growth. Company would like to analyze and gather information about customer's behavior.

C. Objectives

- Improve customer service relationships
- Assist in customer retention
- Drive sales growth

D. Mission

- Analyze and gather information about customer's behavior
- Create Cluster based on customer's behavior
- Make or apply marketing strategy recommendation for customer

E. About the Dataset

The dataset contains the information about customer's purchases across the United States. There are about 9800 observations and their purchases during the year period from 2015 to 2018.

a. Features Description

Row ID:ID number row Order ID:ID Order Order Date:Order Date Ship Date:Ship Date Ship mode:Ship mode Customer ID:Customer ID Customer Name:Customer Name Segment:Segment Country:Country City:City Product Name:Product Name Sales:Sales Sub-Category: Sub-Category Category:Category Product ID:Product ID Region:Region Postal Code:Postal Code State:State

b. Dataset Source

dataset: customer_segmentation.csv

G. Add Information

Terminology:

- Cohort - group of people (users, individuals and etc.) who have a common characteristic(s) during a period of time

- Cohort - group of people (users, individuals and etc.) who have a common characteristic(-s) during a period of time.
- Cohort Analysis - a subset of behavioral analytics that researches groups of people who have taken a common action during a selected period of time.
- Retention - the continued possession, use, or control something.

Type of cohorts as:

- Time Cohorts (So called Retention)
- Behavior Cohorts (RFM, LFL and other variations of analysis)
- Size Cohorts (Clustering, Behavior Patterns Segmentation and etc.)

Import Library

```
!pip install yellowbrick
!pip install scikit-learn-extra
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Requirement already satisfied: yellowbrick in /usr/local/lib/python3.8/dist-packages (1.5)
Requirement already satisfied: scikit-learn>=1.0.0 in /usr/local/lib/python3.8/dist-packages (from yellowbrick) (1.0.2)
Requirement already satisfied: numpy>=1.16.0 in /usr/local/lib/python3.8/dist-packages (from yellowbrick) (1.21.6)
Requirement already satisfied: cycler>=0.10.0 in /usr/local/lib/python3.8/dist-packages (from yellowbrick) (0.11.0)
Requirement already satisfied: scipy>=1.0.0 in /usr/local/lib/python3.8/dist-packages (from yellowbrick) (1.7.3)
Requirement already satisfied: matplotlib!=3.0.0,>=2.0.2 in /usr/local/lib/python3.8/dist-packages (from yellowbrick) (3.2.2)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.8/dist-packages (from matplotlib!=3.0.0,>=2.0.2->yellowbrick
Requirement already satisfied: python-dateutil>=2.1 in /usr/local/lib/python3.8/dist-packages (from matplotlib!=3.0.0,>=2.0.2->yellowbr
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in /usr/local/lib/python3.8/dist-packages (from matplotlib!=3.0
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.8/dist-packages (from scikit-learn>=1.0.0->yellowbrick) (1.2.0)
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.8/dist-packages (from scikit-learn>=1.0.0->yellowbrick) (
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.8/dist-packages (from python-dateutil>=2.1->matplotlib!=3.0.0,>=2.0.2
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Collecting scikit-learn-extra
  Downloading scikit_learn_extra-0.2.0-cp38-cp38-manylinux2010_x86_64.whl (1.9 MB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 1.9/1.9 MB 44.3 MB/s eta 0:00:00
Requirement already satisfied: scikit-learn>=0.23.0 in /usr/local/lib/python3.8/dist-packages (from scikit-learn-extra) (1.0.2)
Requirement already satisfied: numpy>=1.13.3 in /usr/local/lib/python3.8/dist-packages (from scikit-learn-extra) (1.21.6)
Requirement already satisfied: scipy>=0.19.1 in /usr/local/lib/python3.8/dist-packages (from scikit-learn-extra) (1.7.3)
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.8/dist-packages (from scikit-learn>=0.23.0->scikit-learn-extra) (
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.8/dist-packages (from scikit-learn>=0.23.0->scikit-learn-
Installing collected packages: scikit-learn-extra
Successfully installed scikit-learn-extra-0.2.0
```

```
# Basic Understanding
import pandas as pd
import numpy as np
import io

# Warning ignore
import warnings

# Plotting
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
warnings.filterwarnings('ignore')
import plotly.express as px

# Preprocessing
from sklearn.preprocessing import LabelEncoder, OneHotEncoder, OrdinalEncoder
from sklearn.preprocessing import MinMaxScaler, StandardScaler
from sklearn.decomposition import PCA

# Clustering
from sklearn.cluster import KMeans
from sklearn_extra.cluster import KMedoids
from yellowbrick.cluster import KElbowVisualizer, SilhouetteVisualizer
```

Import Data

```
# from google.colab import files
# uploaded = files.upload()
```

EDA

A. Read Data

```
# dataset = pd.read_csv('https://drive.google.com/file/d/1CYLEq-I6UNDzUEGpUgGH0vx4Bfa9wVb_/view')
# dataset = pd.read_csv(io.BytesIO(uploaded['customer-segmentation.csv']))
# dataset = pd.read_csv('customer-segmentation.csv')
dataset = pd.read_csv("/content/drive/MyDrive/Colab Notebooks/customer-segmentation.csv")
df_copy = dataset.copy()
```

```
df_copy.head()
```

	Row ID	Order ID	Order Date	Ship Date	Ship Mode	Customer ID	Customer Name	Segment	Coun
0	1	CA-2017-152156	08/11/2017	11/11/2017	Second Class	CG-12520	Claire Gute	Consumer	Uni Sta
1	2	CA-2017-152156	08/11/2017	11/11/2017	Second Class	CG-12520	Claire Gute	Consumer	Uni Sta
2	3	CA-2017-138688	12/06/2017	16/06/2017	Second Class	DV-13045	Darrin Van Huff	Corporate	Uni Sta

a. Rename Columns

```
df_copy.columns = ['row_id', 'order_id', 'order_date', 'ship_date', 'ship_mode',
                   'customer_id', 'customer_name', 'segment', 'country', 'city', 'state',
                   'postal_code', 'region', 'product_id', 'category',
                   'sub_category', 'product_name', 'sales']
```

```
# Copy after rename, untuk berjaga2 apabila file data awal dibutuhkan
df = df_copy.copy()
```

```
df.head()
```

	row_id	order_id	order_date	ship_date	ship_mode	customer_id	customer_name
0	1	CA-2017-152156	08/11/2017	11/11/2017	Second Class	CG-12520	Claire Gute

```
1 df.shape
```

```
(9800, 18)
```

Catatan:

- dataset terdiri dari 9800 baris dan 18 fitur/kolom
- **'row_id'** sama seperti index sehingga tidak dibutuhkan dan harus didrop agar duplicate data dapat lebih terlihat. **NOTED**
- 'order_id' mungkin menggambarkan tahun order karena tidak ada keterangan lebih lanjut. sehingga untuk sekarang dibiarkan
- 'order_date' dan ' ship_date' isinya berupa tanggal. perlu dicek tipe datanya. **NOTED**
- 'customer_id' dan 'customer_name' perlu dicek apakah nama yang sama memiliki id yang sama atau terdapat kesalahan. **NOTED**
- dipilih salah satu antara 'customer_id' dengan 'customer_name'. **NOTED**
- dari semua tipe data string atau object perlu dicek apakah ada kata yang sama tapi tulisannya labil. **NOTED**
- **'postal_code'** tidak dibutuhkan karena sudah terdapat fitur demografi lain yang lebih spesifik sehingga lebih baik didrop. **NOTED**
- 'product_id' merupakan kode terkait barang. dengan kata lain, menggambarkan kolom category, sub category dan product name. sehingga lebih baik didrop. **NOTED**
- 'product_name' merupakan fitur nama produk yang terlalu mendetail sehingga untuk customer segmentation/clustering terlalu banyak. oleh karena itu, lebih baik didrop. **NOTED**
- perlu visualisasi untuk melihat hubungan semua fitur pada sales dan customer
- pastikan sales > 0

```
1 df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9800 entries, 0 to 9799
Data columns (total 18 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   row_id         9800 non-null   int64  
 1   order_id       9800 non-null   object 
 2   order_date     9800 non-null   object 
 3   ship_date      9800 non-null   object 
 4   ship_mode      9800 non-null   object 
 5   customer_id    9800 non-null   object 
 6   customer_name  9800 non-null   object 
 7   segment        9800 non-null   object 
 8   country        9800 non-null   object 
 9   city           9800 non-null   object 
 10  state          9800 non-null   object 
 11  postal_code    9789 non-null   float64
 12  region         9800 non-null   object 
 13  product_id     9800 non-null   object 
 14  category       9800 non-null   object 
 15  sub_category   9800 non-null   object 
 16  product_name   9800 non-null   object 
 17  sales          9800 non-null   float64
dtypes: float64(2), int64(1), object(15)
memory usage: 1.3+ MB
```

Catatan:

- dari info dataset terdapat 3 fitur numerik dan 15 fitur kategorikal
- fitur yang mengandung tanggal masih dalam tipe data object sehingga perlu diubah ke datetime. **NOTED**
- terlihat ada missing value pada fitur postal code, namun karena postal code tidak digunakan maka fitur akan dirop. **NOTED**

```
1 df.describe(include=['O'])
```

	order_id	order_date	ship_date	ship_mode	customer_id	customer_name	s
count	9800	9800	9800	9800	9800	9800	
unique	4922	1230	1326	4	793	793	

```
df.drop(columns=['row_id', 'postal_code']).describe()
```

	sales
count	9800.000000
mean	230.769059
std	626.651875
min	0.444000
25%	17.248000
50%	54.490000
75%	210.605000
max	22638.480000

Catatan:

- min sales = 0.444
- mean sales = 54.489
- max sales = 22638.48

```
df.nunique()
```

```
row_id           9800
order_id         4922
order_date       1230
ship_date        1326
ship_mode           4
customer_id       793
customer_name     793
segment             3
country             1
city              529
state              49
postal_code       626
region              4
product_id       1861
category            3
sub_category       17
product_name     1849
sales            5757
dtype: int64
```

Catatan:

- dari 9800 observasi ternyata hanya terdapat 793 customer.
- dari 9800 observasi ternyata terdapat 4922 transaksi. berarti dari 4922 transaksi dilakukan oleh 793 customer.

b. Some Feature Engineering

```
# Drop 'row_id' dan 'postal_code'
df.drop(columns=['row_id', 'postal_code'], inplace=True)
```

```
df.head()
```

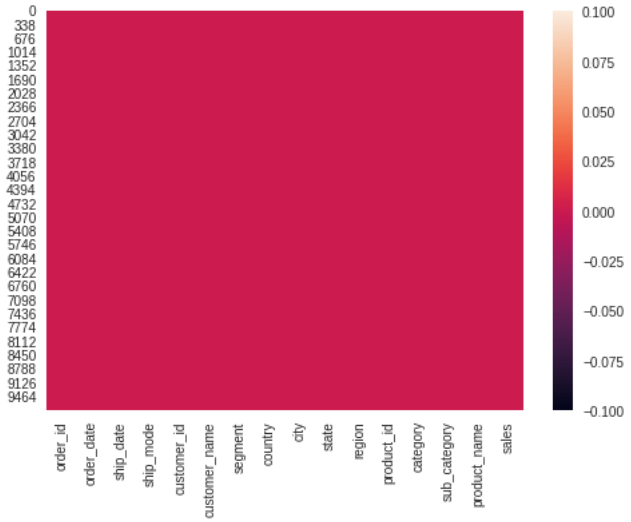
	order_id	order_date	ship_date	ship_mode	customer_id	customer_name	segmer
0	CA-2017-152156	08/11/2017	11/11/2017	Second Class	CG-12520	Claire Gute	Consum
1	CA-2017-152156	08/11/2017	11/11/2017	Second Class	CG-12520	Claire Gute	Consum

B. Missing Value

	138688			Class			

Check

```
1 sns.heatmap(df.isna());
```




```
1 df.isna().sum()
```

```
order_id         0
order_date       0
ship_date        0
ship_mode        0
customer_id      0
customer_name    0
segment          0
country          0
city             0
state            0
region           0
product_id       0
category         0
sub_category     0
product_name     0
sales            0
dtype: int64
```

Catatan:

- Tidak ada missing value karena sebelumnya 'postal_code' telah didrop

C. Duplicated Data

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

```
1
```

```
1 df[df.duplicated(keep=False)]
```

	order_id	order_date	ship_date	ship_mode	customer_id	customer_name	segm
3405	US-2015-150119	23/04/2015	27/04/2015	Standard Class	LB-16795	Laurel Beltran	H O
3406	US-2015-150119	23/04/2015	27/04/2015	Standard Class	LB-16795	Laurel Beltran	H O

```
1 df['order_id'].count()
```

```
9800
```

```
1 df.drop_duplicates(inplace=True);
```

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

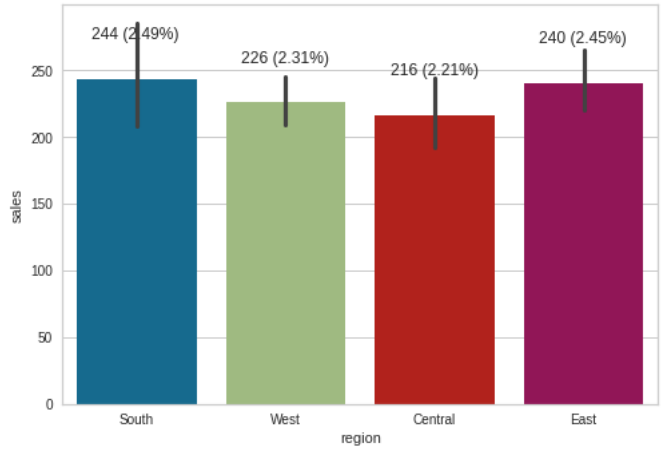
```
0
```

```
1 df['order_id'].count()
```

```
9799
```

D. Visualization

```
1 # temp = df.groupby('region')['sales'].mean().reset_index()
2 ax = sns.barplot(data = df, x='region',y='sales')
3 for p in ax.patches:
4   ax.annotate('{:.0f} ({:.2f}%)'.format(p.get_height(), p.get_height()*100/len(df)), \
5                 (p.get_x()+0.1, p.get_height()+30))
6 plt.show()
```



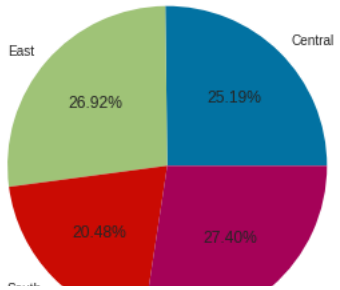
Catatan:

- dari visualisasi barplot region terhadap sales dan modus pada region, region west merupakan modus namun **rata-rata sales** pada region west tidak yang tertinggi (ketiga tertinggi) sehingga
- dapat diasumsikan bahwa region west banyak membeli produk-produk dengan harga rendah.

- Apa yang mempengaruhi penjualan di setiap region? a. banyak customer ?

```
1 temp = df.groupby('region')['customer_id'].nunique()
2 plt.pie(temp, labels=temp.index, autopct='%.2f%%')
```

```
([<matplotlib.patches.Wedge at 0x7f9191541dc0>,
  <matplotlib.patches.Wedge at 0x7f919154e2b0>,
  <matplotlib.patches.Wedge at 0x7f919154e940>,
  <matplotlib.patches.Wedge at 0x7f919154efd0>],
 [Text(0.773132643738409, 0.7824742265314932, 'Central'),
  Text(-0.8320277939379772, 0.7195343981455669, 'East'),
  Text(-0.7849139174036318, -0.770655657389268, 'South'),
  Text(0.7169010581875779, -0.8342978321735777, 'West')],
 [Text(0.4217087147664048, 0.42680412356263264, '25.19%'),
  Text(-0.45383334214798754, 0.39247330807940006, '26.92%'),
  Text(-0.42813486403834455, -0.42035763130323706, '20.48%'),
  Text(0.3910369408295879, -0.4550715448219514, '27.40%')])
```




```
1 df.groupby('region')['customer_id'].nunique().mean()
```

```
621.25
```

```
1 df['sales'].mean()
```

```
230.76389536687415
```

- Dari segi banyak customer. a. south memiliki jumlah customer yang paling sedikit, namun memiliki penjualan yang paling banyak. b. west memiliki jumlah customer yang paling banyak, namun memiliki penjualan yang lebih sedikit daripada south. c. central memiliki jumlah customer mendekati rata-rata, namun memiliki penjualan dibawah rata-rata d. east memiliki jumlah customer diatas rata-rata dan memiliki penjualan yang cukup tinggi.

Di asumsikan bahwa, a. customer south lebih sering membeli barang yang lebih mahal daripada west. b. Customer di west membeli barang yang cenderung lebih murah daripada customer south. c. Customer central cenderung membeli barang murah. d. Customer east cenderung membeli harga standard

Apa barang yang sering dibeli oleh customer south dan west ?

```
1 df.groupby('region')['category', 'product_name'].describe()
```

	category				product_name			
	count	unique	top	freq	count	unique	top	freq
region								
Central	2277	3	Office Supplies	1399	2277	1283	Staple envelope	13
East	2784	3	Office Supplies	1667	2784	1402	Staple envelope	17
South	1598	3	Office Supplies	983	1598	1035	Staples	9
West	3140	3	Office Supplies	1860	3140	1493	Staples	13

```
1 df[df['region'] == 'South']['category'].describe()
```

```
count               1598
unique                 3
top       Office Supplies
freq                 983
Name: category, dtype: object
```

```
1 df[df['region'] == 'South']['product_name'].describe()
```

```
count        1598
unique       1035
top       Staples
freq            9
Name: product_name, dtype: object
```

```
1 df[df['region'] == 'West']['category'].describe()
```

```
count               3140
unique                 3
top       Office Supplies
freq                1860
Name: category, dtype: object
```

```
1 df[df['region'] == 'West']['product_name'].describe()
```

```
count        3140
unique       1493
top       Staples
freq           13
Name: product_name, dtype: object
```

```
1 df[df['region'] == 'South'][['product_name','sales']].max()
```

```
product_name    iOttie XL Car Mount
sales                       22638.48
dtype: object
```

```
1 df[df['region'] == 'South'][['sales']].sum()
```

```
sales    389151.459
dtype: float64
```

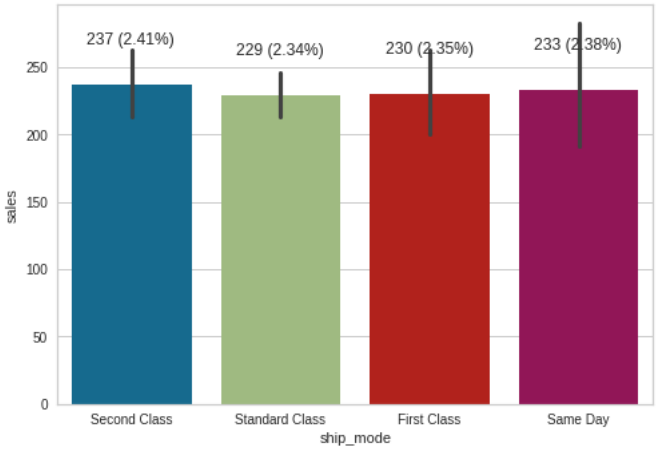
```
1 df[df['region'] == 'West'][['product_name','sales']].max()
```

```
product_name    netTALK DUO VoIP Telephone Service
sales                                      13999.96
dtype: object
```

```
1 df[df['region'] == 'West'][['sales']].sum()
```

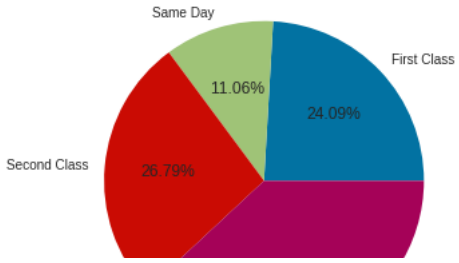
```
sales    710219.6845
dtype: float64
```

```
1 # temp = df.groupby('ship_mode')['sales'].mean().reset_index()
2 ax = sns.barplot(data = df, x='ship_mode',y='sales')
3 for p in ax.patches:
4   ax.annotate('{:.0f} ({:.2f}%)'.format(p.get_height(), p.get_height()*100/len(df)), \
5               (p.get_x()+0.1, p.get_height()+30))
6 plt.show()
```




```
1 temp = df.groupby('ship_mode')['customer_id'].nunique()
2 plt.pie(temp, labels=temp.index, autopct='%.2f%%')
```

```
([<matplotlib.patches.Wedge at 0x7f919141a100>,
  <matplotlib.patches.Wedge at 0x7f919141a5b0>,
  <matplotlib.patches.Wedge at 0x7f919141ac40>,
  <matplotlib.patches.Wedge at 0x7f9191424310>],
 [Text(0.7997222766369717, 0.7552776179992222, 'First Class'),
  Text(-0.31494093275500545, 1.0539507620735455, 'Same Day'),
  Text(-1.0954358021759087, 0.10010196457224689, 'Second Class'),
  Text(0.4032303554700173, -1.0234281999376036, 'Standard Class')],
 [Text(0.4362121508928936, 0.41196960981775754, '24.09%'),
  Text(-0.17178596332091203, 0.5748822338582975, '11.06%'),
  Text(-0.5975104375504956, 0.05460107158486193, '26.79%'),
  Text(0.21994383025637307, -0.5582335636023292, '38.05%')])
```



Catatan:

- Dapat diasumikan bahwa Customer yang membeli produk dengan harga rata-rata cukup tinggi lebih memilih Same Day pada 'ship_mode'
- Dapat diasumsikan bahwa Customer yang membeli produk dengan harga rata-rata rendah lebih memilih standard class pada 'ship_mode'

Some Feature Engineering

```
# Data Conversion
df_viz = df.copy()
df_viz["order_date"] = pd.to_datetime(df_viz["order_date"])
df_viz["ship_date"] = pd.to_datetime(df_viz["ship_date"])
```

```
## Extract Order Date
df_viz['year'] = df_viz['order_date'].dt.year.apply(str)
df_viz['month'] = df_viz['order_date'].dt.month.apply(int)
df_viz['year_month'] = df_viz['order_date'].dt.strftime('%Y-%m')
df_viz['month_date'] = df_viz['order_date'].dt.strftime('%m-%d')
```

```
temp = df_viz.groupby('year_month')['sales'].sum().reset_index()
plt.figure(figsize=(15,5))
px.line(x= temp['year_month'],y = temp['sales'])
plt.show()
```

```
<Figure size 1080x360 with 0 Axes>
```

Catatan:

- pada bulan September tahun 2015 ke bulan Februari tahun 2016 terjadi penurunan sales yang cukup tinggi/drastis. Setelah dicek event pada bulan Desember 2015, Januari 2016, dan Februari tahun 2016 terdapat event ***xxx*** sehingga penjualan/sales mengalami penurunan.
- pada bulan Maret ke bulan April tahun 2018 terjadi penurunan sales yang cukup tinggi/drastis. Setelah dicek event pada bulan Maret dan April tahun 2018 terdapat event ***xxx*** sehingga penjualan/sales mengalami penurunan.
- Maka direkomendasikan....

RFM (Recency, Frequency, Monetary)(Optional)

A. Create RFM DataFrame (Optional)

```
df_rfm = df_viz[['order_id', 'customer_id', 'order_date', 'sales']].copy()
df_rfm['order_date'] = pd.to_datetime(df_rfm['order_date'])
df_rfm
```

	order_id	customer_id	order_date	sales
0	CA-2017-152156	CG-12520	2017-08-11	261.9600
1	CA-2017-152156	CG-12520	2017-08-11	731.9400
2	CA-2017-138688	DV-13045	2017-12-06	14.6200
3	US-2016-108966	SO-20335	2016-11-10	957.5775
4	US-2016-108966	SO-20335	2016-11-10	22.3680
...	...	...	...	...
9795	CA-2017-125920	SH-19975	2017-05-21	3.7980
9796	CA-2016-128608	CS-12490	2016-12-01	10.3680
9797	CA-2016-128608	CS-12490	2016-12-01	235.1880
9798	CA-2016-128608	CS-12490	2016-12-01	26.3760
9799	CA-2016-128608	CS-12490	2016-12-01	10.3840

```
df_customers = pd.DataFrame(df_rfm['customer_id'].unique())
df_customers.columns = ['customer_id']
df_customers.head()
```

	customer_id
0	CG-12520
1	DV-13045
2	SO-20335
3	BH-11710
4	AA-10480

```
df_recency = df_rfm.groupby(by='customer_id')['order_date'].max().reset_index()
df_recency.columns = ['customer_id', 'recency_date']
recent_date = df_recency['recency_date'].max()
df_customers = df_customers.merge(df_recency, on='customer_id')
df_customers['recency'] = round((recent_date - df_customers['recency_date'])\
/ np.timedelta64(1, 'D')).astype(int)
```

```
# df_recency = df_rfm.groupby('customer_id')['order_date'].max().reset_index()
# df_recency.columns = ['customer_id','recency_date']
# df_customers = df_customers.merge(df_recency, on='customer_id')
# df_customers['recency'] = round((pd.to_datetime('today') - df_customers['recency_date'])\
#                                 / np.timedelta64(1, 'D')).astype(int)
```

```
df_frequency = df_rfm.groupby('customer_id')['order_id'].nunique().reset_index()
df_frequency.columns = ['customer_id','frequency']
df_customers = df_customers.merge(df_frequency, on='customer_id')
```

```
df_monetary = df_rfm.groupby('customer_id')['sales'].sum().reset_index()
df_monetary.columns = ['customer_id','monetary']
df_customers = df_customers.merge(df_monetary, on='customer_id')
```

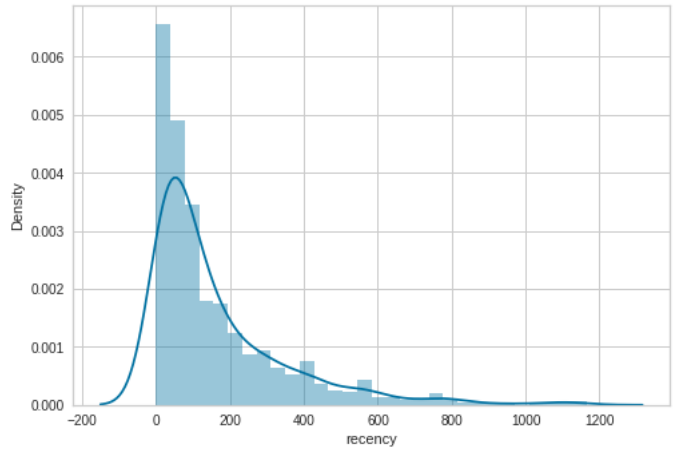
```
df_customers.head()
```

	customer_id	recency_date	recency	frequency	monetary
0	CG-12520	2018-01-26	338	3	1148.7800
1	DV-13045	2018-11-12	48	5	1119.4830
2	SO-20335	2018-09-09	112	6	2602.5755
3	BH-11710	2018-07-12	171	8	6255.3510
4	AA-10480	2018-04-15	259	4	1790.5120

B. Plot Statistical Distribution (Optional)

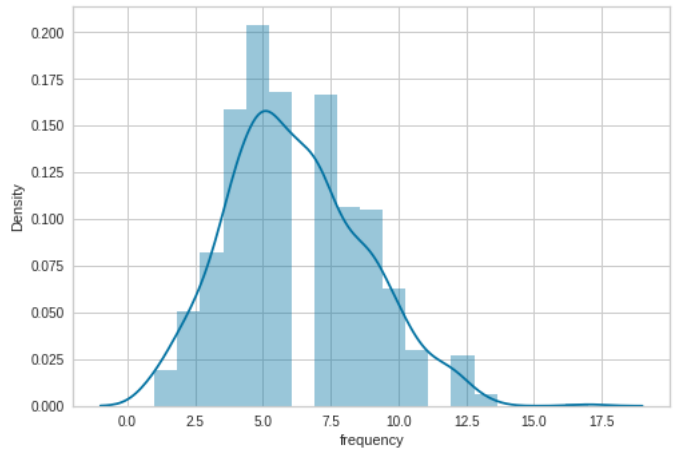
```
1 sns.distplot(df_customers['recency'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f9190a8f5b0>
```



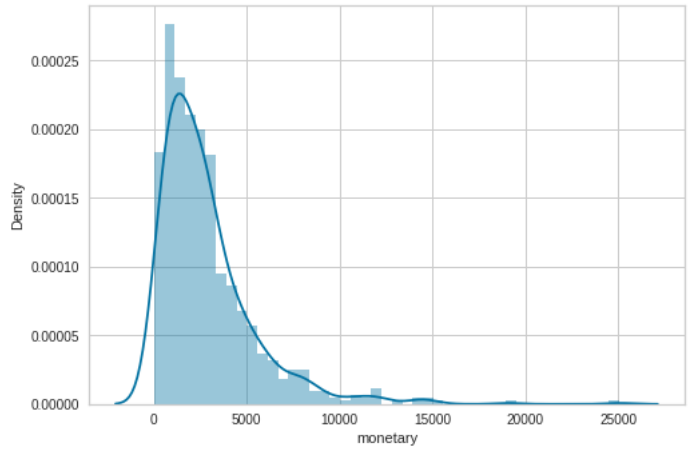

```
1 sns.distplot(df_customers['frequency'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f918e9c03a0>
```




```
1 sns.distplot(df_customers['monetary'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f918e914400>
```

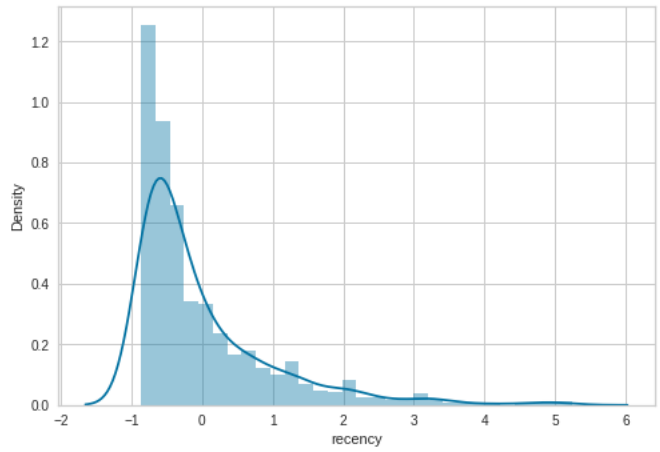


- secara distribusi, terlihat recency dan monetary skew positive, sedangkan frekuensi skew sedikit rendah, sehingga nanti diperlukan stardardization atau log transformation untuk menghandle skew data.

```
1 sc = StandardScaler()
2 rfm_sc = sc.fit_transform(df_customers[['recency', 'frequency', 'monetary']])
3 rfm_sc = pd.DataFrame(rfm_sc, columns=['recency', 'frequency', 'monetary'])
```

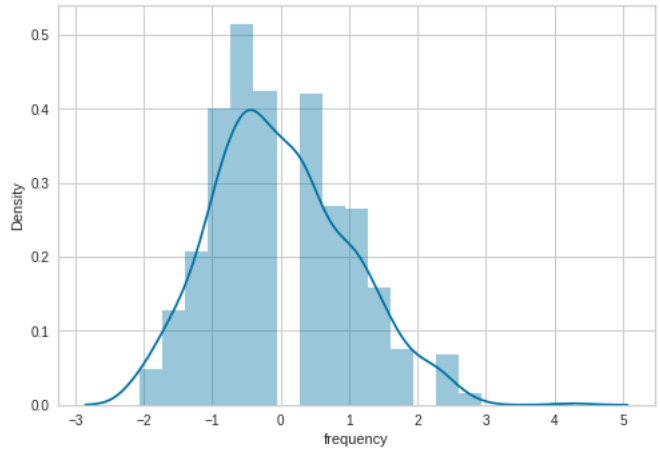
```
1 sns.distplot(rfm_sc['recency'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f918e8b9df0>
```



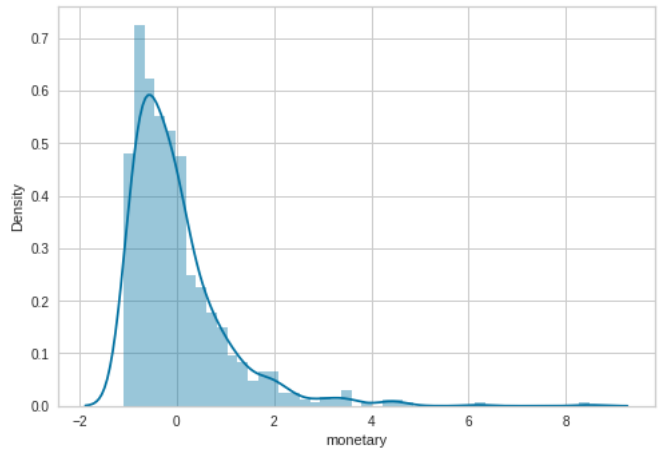

```
1 sns.distplot(rfm_sc['frequency'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f918e801fd0>
```




```
1 sns.distplot(rfm_sc['monetary'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f9190bb3550>
```



C. Calculate RFM Scores (Optional)

Using quantile-based discretization

```
1 df_customers['r'] = pd.qcut(df_customers['recency'], q=5, labels=[5, 4, 3, 2, 1])
2 df_customers['f'] = pd.qcut(df_customers['frequency'].rank(method='first'), q=5, labels=[5, 4, 3, 2, 1])
```

```
3 df_customers['m'] = pd.qcut(df_customers['monetary'], q=5, labels=[5, 4, 3, 2, 1])
```

```
1 df_customers.head()
```

	customer_id	recency_date	recency	frequency	monetary	r	f	m
0	CG-12520	2018-01-26	338	3	1148.7800	1	5	4
1	DV-13045	2018-11-12	48	5	1119.4830	4	4	4
2	SO-20335	2018-09-09	112	6	2602.5755	3	3	3
3	BH-11710	2018-07-12	171	8	6255.3510	2	2	1
4	AA-10480	2018-04-15	259	4	1790.5120	2	5	3

```
1 df_customers.groupby('r').agg(
2     count=('customer_id', 'count'),
3     min_recency=('recency', min),
4     max_recency=('recency', max),
5     std_recency=('recency', 'std'),
6     avg_recency=('recency', 'mean')
7 ).sort_values(by='avg_recency')
```

	count	min_recency	max_recency	std_recency	avg_recency
r					
5	160	0	32	8.966375	13.581250
4	162	33	69	10.549404	46.802469
3	154	70	128	16.354008	95.616883
2	158	130	277	40.647778	190.012658
1	159	278	1165	197.402866	479.031447

Dari hasil aggregasi by recency quantile:

- q5 memiliki recency paling baru antara 0-32 hari yang lalu
- q1 memiliki recency paling lama antara 278-1165 hari yang lalu
- dari keseluruhan banyak customer yang melakukan transaksi baru-baru ini. dapat diasumsikan perusahaan cukup bisa mengakuisisi customer retention. namun, butuh diimprove lagi karena cukup banyak pula customer yang sudah lama tidak melakukan transaksi.

```
1 df_customers.groupby('f').agg(
2     count=('customer_id', 'count'),
3     min_frequency=('frequency', min),
4     max_frequency=('frequency', max),
5     std_frequency=('frequency', 'std'),
6     avg_frequency=('frequency', 'mean')
7 ).sort_values(by='avg_frequency')
```

	count	min_frequency	max_frequency	std_frequency	avg_frequency
f					
5	159	1	4	0.951160	2.981132
4	158	4	5	0.464016	4.689873
3	159	5	7	0.543616	5.955975
2	158	7	8	0.495769	7.424051
1	159	8	17	1.290038	9.981132

Dari hasil aggregasi by frequency quantile:

- secara keseluruhan merata dari 1-17 transaksi.
- q1 memiliki sedikit customer yang melakukan transaksi hingga 17 kali. hal ini dilihat dari banyaknya customer, min freq, high freq, dan rata-rata frequency yang dekat dengan min freq.
- dapat diasumsikan bahwa customer jarang melakukan transaksi dilihat dari q5, q3, dan q1 dimana rata-rata frekuensi cenderung mendekati min freq.

```
df_customers.groupby('m').agg(
    count=('customer_id', 'count'),
    min_monetary=('monetary', min),
    max_monetary=('monetary', max),
    std_monetary=('monetary', 'std'),
    avg_monetary=('monetary', 'mean')
).sort_values(by='avg_monetary')
```

m	count	min_monetary	max_monetary	std_monetary	avg_monetary
5	159	4.833	933.704	280.046196	511.524475
4	158	937.039	1707.286	227.177631	1297.693241
3	159	1707.710	2697.248	275.435829	2209.927448
2	158	2716.412	4260.784	434.244062	3337.792584
1	159	4262.292	25043.050	3001.072843	6893.948393

Dari hasil aggregrasi by monetary quantile:

- q5 memiliki min mon lebih dari 0, sehingga dapat diasumsikan tidak ada customer yang mereturn/tidak jadi membeli produk.
- q1 memiliki anomali dimana max mon mencapai 25043.05 tetapi rata-rata hanya 6893. Sehingga dapat diasumsikan ada beberapa / sedikit customer yang melakukan transaksi dengan harga cukup tinggi atau jumlah barang yang banyak.
- secara keseluruhan terllihat bahwa terjadi skew positive

```
df_customers['rfm'] = df_customers['r'].astype(str) +\
                      df_customers['f'].astype(str) +\
                      df_customers['m'].astype(str)

df_customers['rfm_score'] = df_customers['r'].astype(int) +\
                            df_customers['f'].astype(int) +\
                            df_customers['m'].astype(int)
```

```
df_customers.head()
```

	customer_id	recency_date	recency	frequency	monetary	r	f	m	rfm	rfm_score
0	CG-12520	2018-01-26	338	3	1148.7800	1	5	4	154	10
1	DV-13045	2018-11-12	48	5	1119.4830	4	4	4	444	12
2	SO-20335	2018-09-09	112	6	2602.5755	3	3	3	333	9
3	BH-11710	2018-07-12	171	8	6255.3510	2	2	1	221	5
4	AA-10480	2018-04-15	259	4	1790.5120	2	5	3	253	10

```
df_customers.groupby('rfm_score').agg(
    customers=('customer_id', 'count'),
    mean_recency=('recency', 'mean'),
    mean_frequency=('frequency', 'mean'),
    mean_monetary=('monetary', 'mean'),
).sort_values(by='rfm_score')
```

rfm_score	customers	mean_recency	mean_frequency	mean_monetary
3	6	354.333333	10.500000	8787.693667
4	13	218.000000	9.384615	5569.481385
5	48	224.062500	8.395833	5384.860702

D. Clustering Bases On RFM Scores (Optional)

```
# kmeans atau kmedoids in another file
df_customers.to_csv("/content/customer_rfm.csv")
```

```
1
```

11	93	245.935484	4.193548	1135.826680

```
1
```

Data Preprocessing

A. Feature Engineering

```
df.head()
```

	order_id	order_date	ship_date	ship_mode	customer_id	customer_name	segment	co
0	CA-2017-152156	08/11/2017	11/11/2017	Second Class	CG-12520	Claire Gute	Consumer	
1	CA-2017-152156	08/11/2017	11/11/2017	Second Class	CG-12520	Claire Gute	Consumer	
2	CA-2017-138688	12/06/2017	16/06/2017	Second Class	DV-13045	Darrin Van Huff	Corporate	

```
df.describe(include=['O'])
```

	order_id	order_date	ship_date	ship_mode	customer_id	customer_name	segment	country	city	state	region	product_id	c
count	9799	9799	9799	9799	9799	9799	9799	9799	9799	9799	9799	9799	
unique	4922	1230	1326	4	793	793	3	1	529	49	4	1861	
top	CA-2018-100111	05/09/2017	26/09/2018	Standard Class	WB-21850	William Brown	Consumer	United States	New York City	California	West	OFF-PA-10001970	

```
df.groupby('customer_id')['customer_name'].nunique().reset_index().sort_values('customer_name',ascending=0)
```

	customer_id	customer_name
0	AA-10315	1
521	ML-17755	1
523	ML-18265	1
524	MM-17260	1
525	MM-17920	1

Catatan:

- 'product_name' merupakan fitur nama produk yang terlalu mendetail sehingga untuk customer segmentation/clustering terlalu banyak. oleh karena itu, lebih baik didrop. **NOTED**
- 'sub_category' tidak dibutuhkan untuk clustering saat ini karena memiliki banyak value untuk di cluster sehingga butuh didrop. **NOTED**
- 'city' tidak dibutuhkan untuk clustering saat ini karena memiliki banyak value untuk di cluster sehingga butuh didrop. **NOTED**
- 'state' tidak dibutuhkan untuk clustering saat ini karena memiliki banyak value untuk di cluster sehingga butuh didrop. **NOTED**
- dipertimbangkan mengambil 'customer_id' saja
- country di **drop**
- product name **drop**
- order id di **drop**
- date di **drop**, kecuali diextrax misal bulannya aja
- order_to_ship: jarak hari dari order ke pengiriman

```
df_fe = df.copy()
df_fe["order_date"] = pd.to_datetime(df_fe["order_date"])
df_fe["ship_date"] = pd.to_datetime(df_fe["ship_date"])
```

```
df_fe.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 9799 entries, 0 to 9799
Data columns (total 16 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   order_id       9799 non-null   object
 1   order_date     9799 non-null   datetime64[ns]
 2   ship_date      9799 non-null   datetime64[ns]
 3   ship_mode      9799 non-null   object
 4   customer_id    9799 non-null   object
 5   customer_name  9799 non-null   object
 6   segment        9799 non-null   object
 7   country        9799 non-null   object
 8   city           9799 non-null   object
 9   state          9799 non-null   object
 10  region         9799 non-null   object
 11  product_id     9799 non-null   object
 12  category       9799 non-null   object
 13  sub_category   9799 non-null   object
 14  product_name   9799 non-null   object
 15  sales          9799 non-null   float64
dtypes: datetime64[ns](2), float64(1), object(13)
memory usage: 1.5+ MB
```

```
df_fe.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 9799 entries, 0 to 9799
Data columns (total 16 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   order_id       9799 non-null   object
 1   order_date     9799 non-null   datetime64[ns]
 2   ship_date      9799 non-null   datetime64[ns]
 3   ship_mode      9799 non-null   object
 4   customer_id    9799 non-null   object
 5   customer_name  9799 non-null   object
 6   segment        9799 non-null   object
 7   country        9799 non-null   object
 8   city           9799 non-null   object
 9   state          9799 non-null   object
 10  region         9799 non-null   object
 11  product_id     9799 non-null   object
 12  category       9799 non-null   object
 13  sub_category   9799 non-null   object
```

```
 14  product_name   9799 non-null   object
 15  sales          9799 non-null   float64
dtypes: datetime64[ns](2), float64(1), object(13)
memory usage: 1.5+ MB
```

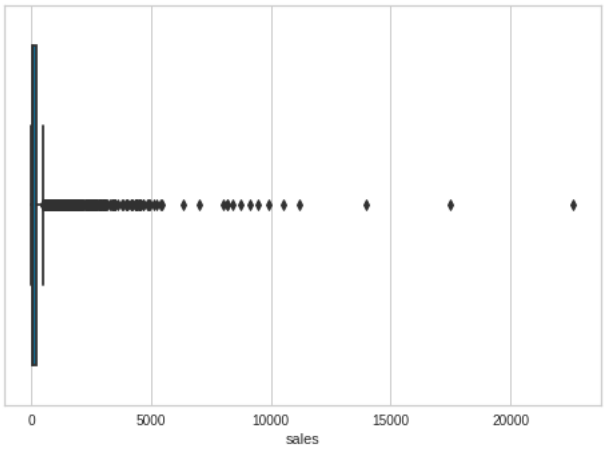
```
df_fe.drop(columns=['order_id', 'order_date', 'ship_date', 'customer_id', 'product_id', \
'sub_category', 'city', 'state', 'customer_name', 'country',  'product_name'], inplace=True)
```

```
df_fe.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 9799 entries, 0 to 9799
Data columns (total 5 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   ship_mode  9799 non-null   object
 1   segment    9799 non-null   object
 2   region     9799 non-null   object
 3   category   9799 non-null   object
 4   sales      9799 non-null   float64
dtypes: float64(1), object(4)
memory usage: 717.4+ KB
```

```
sns.boxplot(df_fe['sales'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7ff4d853a3d0>
```




```
df_fe['sales'].describe().T
```

```
count     9799.000000
mean       230.763895
std        626.683644
min          0.444000
25%         17.248000
50%         54.480000
75%        210.572000
max      22638.480000
Name: sales, dtype: float64
```

```
iqr = df_fe['sales'].quantile(0.75) - df_fe['sales'].quantile(0.25)
upper = df_fe['sales'] >= (df_fe['sales'].quantile(0.75) + 1.5*iqr)
lower = df_fe['sales'] <= (df_fe['sales'].quantile(0.25) - 1.5*iqr)
df_fe.loc[upper, ['sales']].count()
```

```
sales    1145
dtype: int64
```

```
df_fe.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 9799 entries, 0 to 9799
Data columns (total 5 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   ship_mode  9799 non-null   object
 1   segment    9799 non-null   object
 2   region     9799 non-null   object
 3   category   9799 non-null   object
```

```
 4   sales      9799 non-null   float64
dtypes: float64(1), object(4)
memory usage: 717.4+ KB
```

B. Encoding

- region one hot
- category one hot
- segment one hot
- ship_mode label

```
df_encode = df_fe.copy()
ohe = OneHotEncoder(handle_unknown='ignore')
le = LabelEncoder()

# Label Encoding
le_temp = le.fit(df_encode['ship_mode'])
le_temp.classes_ = np.array(['Same Day', 'First Class', 'Second Class', 'Standard Class'])
df_encode['ship_mode'] = le_temp.transform(df_encode['ship_mode'])

# One Hot Encoding (ada error, dimana memunculkan missing value)
# ohe_temp = ohe.fit_transform(df_encode[['region', 'category', 'segment']])
# ohe_temp = pd.DataFrame(ohe_temp.toarray(), columns = ohe.get_feature_names_out())
# df_encode = pd.concat([df_encode, ohe_temp], axis=1)
# df_encode.drop(['region', 'category', 'segment'], axis=1, inplace=True)

# One Hot Encoding 2
ohe_temp = pd.get_dummies(df_encode[['region', 'category', 'segment']])
df_encode = df_encode.join(ohe_temp)
df_encode.drop(['region', 'category', 'segment'], axis=1, inplace=True)


df_encode
```

	ship_mode	sales	region_Central	region_East	region_South	region_West	category_Furniture	category_Office Supplies	category_Technol
0	2	261.9600	0	0	1	0	1	0	
1	2	731.9400	0	0	1	0	1	0	
2	2	14.6200	0	0	0	1	0	1	
3	3	957.5775	0	0	1	0	1	0	
4	3	22.3680	0	0	1	0	0	1	
...	...	...	...	...	...	...	...	...	
9795	3	3.7980	1	0	0	0	0	1	
9796	3	10.3680	0	1	0	0	0	1	
9797	3	235.1880	0	1	0	0	0	0	
9798	3	26.3760	0	1	0	0	0	0	
9799	3	10.3840	0	1	0	0	0	0	

9799 rows × 12 columns

```
df_encode.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 9799 entries, 0 to 9799
Data columns (total 12 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   ship_mode                9799 non-null   int64
 1   sales                    9799 non-null   float64
 2   region_Central           9799 non-null   uint8
 3   region_East              9799 non-null   uint8
 4   region_South             9799 non-null   uint8
 5   region_West              9799 non-null   uint8
```

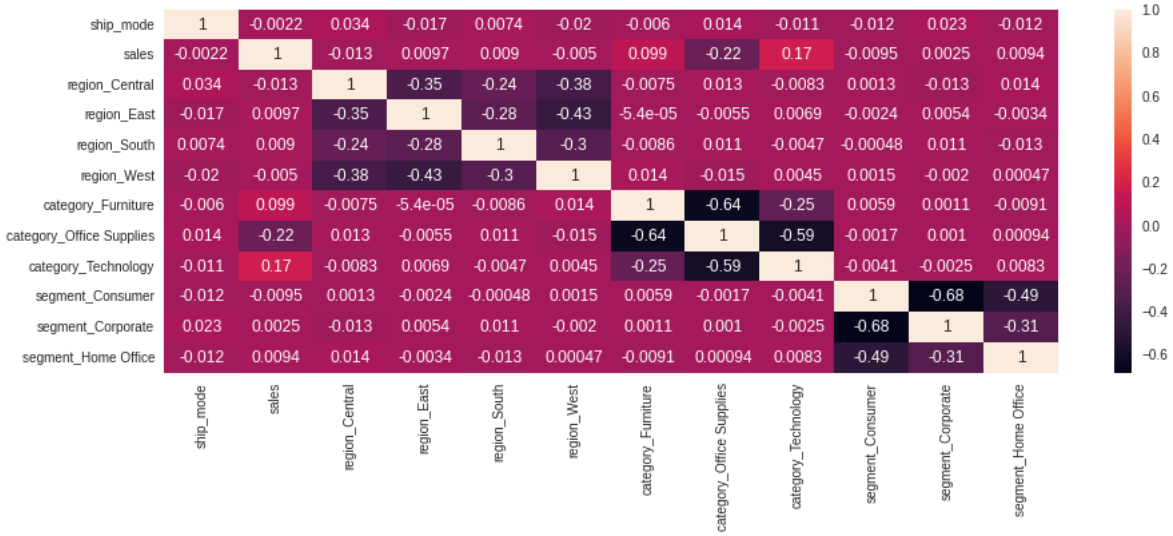
```
 6   category_Furniture        9799 non-null   uint8
 7   category_Office Supplies  9799 non-null   uint8
 8   category_Technology       9799 non-null   uint8
 9   segment_Consumer          9799 non-null   uint8
 10  segment_Corporate         9799 non-null   uint8
 11  segment_Home Office       9799 non-null   uint8
dtypes: float64(1), int64(1), uint8(10)
memory usage: 583.4 KB
```

```
1 df_encode.isna().sum()
```

```
ship_mode                   0
sales                       0
region_Central              0
region_East                 0
region_South                0
region_West                 0
category_Furniture          0
category_Office Supplies    0
category_Technology         0
segment_Consumer            0
segment_Corporate           0
segment_Home Office         0
dtype: int64
```

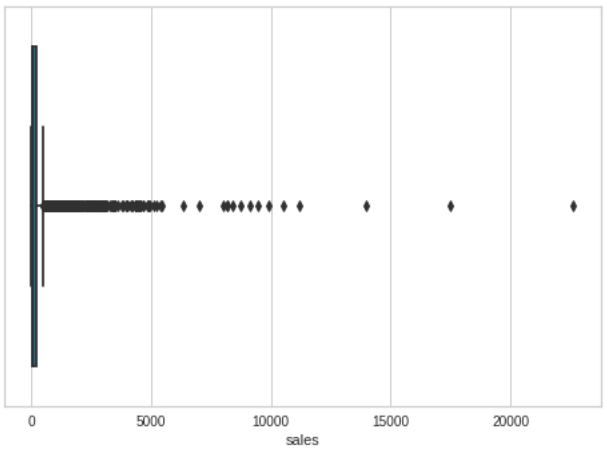
Correlation

```
1 plt.figure(figsize=(15,5))
2 sns.heatmap(df_encode.corr(), annot=True)
3 plt.show()
```




```
1 sns.boxplot(df_encode['sales'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7ff4d56014f0>
```



```
q1 = df_encode['sales'].quantile(0.25)
q3 = df_encode['sales'].quantile(0.75)
iqr = q3 - q1
upper = q3 + (1.5 * iqr)
lower = q1 - (1.5 * iqr)

# df_outlier = df_encode[(df_encode['sales'] >= upper) | (df_encode['sales'] <= lower)]
# df_outlier.info()

df_encode2 = df_encode[(df_encode['sales'] <= upper) & (df_encode['sales'] >= lower)]
df_encode2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 8654 entries, 0 to 9799
Data columns (total 12 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   ship_mode                8654 non-null   int64
 1   sales                    8654 non-null   float64
 2   region_Central           8654 non-null   uint8
 3   region_East              8654 non-null   uint8
 4   region_South             8654 non-null   uint8
 5   region_West              8654 non-null   uint8
 6   category_Furniture       8654 non-null   uint8
 7   category_Office Supplies 8654 non-null   uint8
 8   category_Technology      8654 non-null   uint8
 9   segment_Consumer         8654 non-null   uint8
 10  segment_Corporate        8654 non-null   uint8
 11  segment_Home Office      8654 non-null   uint8
dtypes: float64(1), int64(1), uint8(10)
memory usage: 287.3 KB
```

C. Scaling

```
# mms = MinMaxScaler()
# X_mms = mms.fit_transform(df_encode)
# X_mms = pd.DataFrame(X_mms, columns=df_encode.columns)

mms = MinMaxScaler()
X_mms = mms.fit_transform(df_encode2)
X_mms = pd.DataFrame(X_mms, columns=df_encode2.columns)
```

```
# Reduce with PCA
# print('Number of features before PCA: {}'.format(len(X_mms[0])))
# pca = PCA()
# X_pca = pca.fit_transform(X_mms)
# print('Number of features after PCA: {}'.format(len(X_pca[0])))
```

```
# pd.DataFrame(X_pca)
```

Modeling

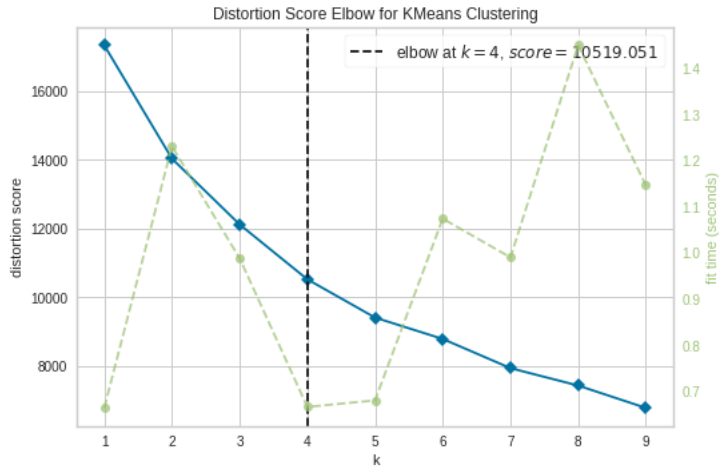
A. K-Means

```
X_mms.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8654 entries, 0 to 8653
Data columns (total 12 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   ship_mode                8654 non-null   float64
 1   sales                    8654 non-null   float64
 2   region_Central           8654 non-null   float64
 3   region_East              8654 non-null   float64
 4   region_South             8654 non-null   float64
 5   region_West              8654 non-null   float64
 6   category_Furniture       8654 non-null   float64
 7   category_Office Supplies 8654 non-null   float64
 8   category_Technology      8654 non-null   float64
```

```
 9   segment_Consumer          8654 non-null   float64
 10  segment_Corporate         8654 non-null   float64
 11  segment_Home Office       8654 non-null   float64
dtypes: float64(12)
memory usage: 811.4 KB
```

```
# create a kmeans model
model = KMeans(random_state=42)

# use the KElbowVisualizer to calculate distortion for different numbers of clusters
visualizer = KElbowVisualizer(model, k=(1,10))
visualizer.fit(X_mms)
visualizer.show()
```




```
<matplotlib.axes._subplots.AxesSubplot at 0x7ff4d3bd95b0>
```

```
fig, ax = plt.subplots(2, 2, figsize=(15,8))
for i in [3, 4, 5, 6]:
    '''
    Create KMeans instance for different number of clusters
    '''
    km = KMeans(n_clusters=i, init='k-means++', random_state=42)
    q, mod = divmod(i, 2)
    '''
    Create SilhouetteVisualizer instance with KMeans instance
    Fit the visualizer
    '''
    visualizer = SilhouetteVisualizer(km, colors='yellowbrick', ax=ax[q-2][mod])
    visualizer.fit(X_mms)
    print(f'Silhouette Score cluster={i}: {visualizer.silhouette_score_}\n')
```

```
Silhouette Score cluster=3: 0.2694973264960649

Silhouette Score cluster=4: 0.26105034563482526

Silhouette Score cluster=5: 0.2882678269799616
```

Predict / clustering

```
1 kmeans = KMeans(n_clusters=5, random_state=42)
2 y = kmeans.fit_predict(X_mms)
```

```
1 y
```

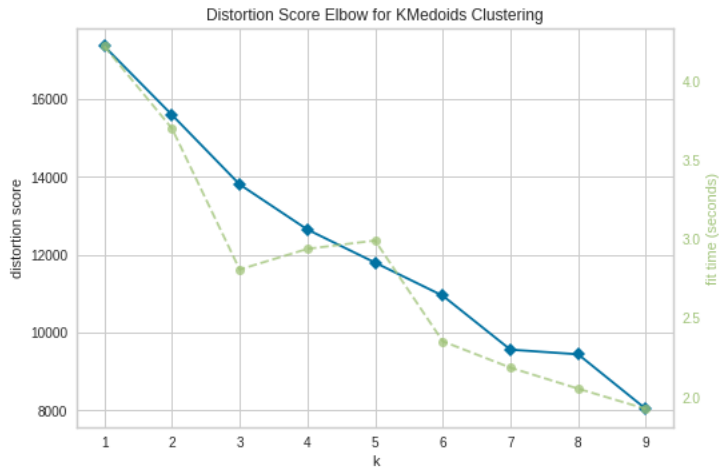
```
array([4, 2, 0, ..., 3, 3, 3], dtype=int32)
```

B. K-Medoids

```
1 X_mms.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8654 entries, 0 to 8653
Data columns (total 12 columns):
 #   Column                    Non-Null Count  Dtype  
---  ------                    --------------  -----  
 0   ship_mode                 8654 non-null   float64
 1   sales                     8654 non-null   float64
 2   region_Central            8654 non-null   float64
 3   region_East               8654 non-null   float64
 4   region_South              8654 non-null   float64
 5   region_West               8654 non-null   float64
 6   category_Furniture        8654 non-null   float64
 7   category_Office Supplies  8654 non-null   float64
 8   category_Technology       8654 non-null   float64
 9   segment_Consumer          8654 non-null   float64
 10  segment_Corporate         8654 non-null   float64
 11  segment_Home Office       8654 non-null   float64
dtypes: float64(12)
memory usage: 811.4 KB
```

```
1 kmedoids = KMedoids(init='k-medoids++', random_state=42)
2
3 # use the KElbowVisualizer to calculate distortion for different numbers of clusters
4 visualizer = KElbowVisualizer(kmedoids, k=(1,10))
5 visualizer.fit(X_mms)
6 visualizer.show()
```

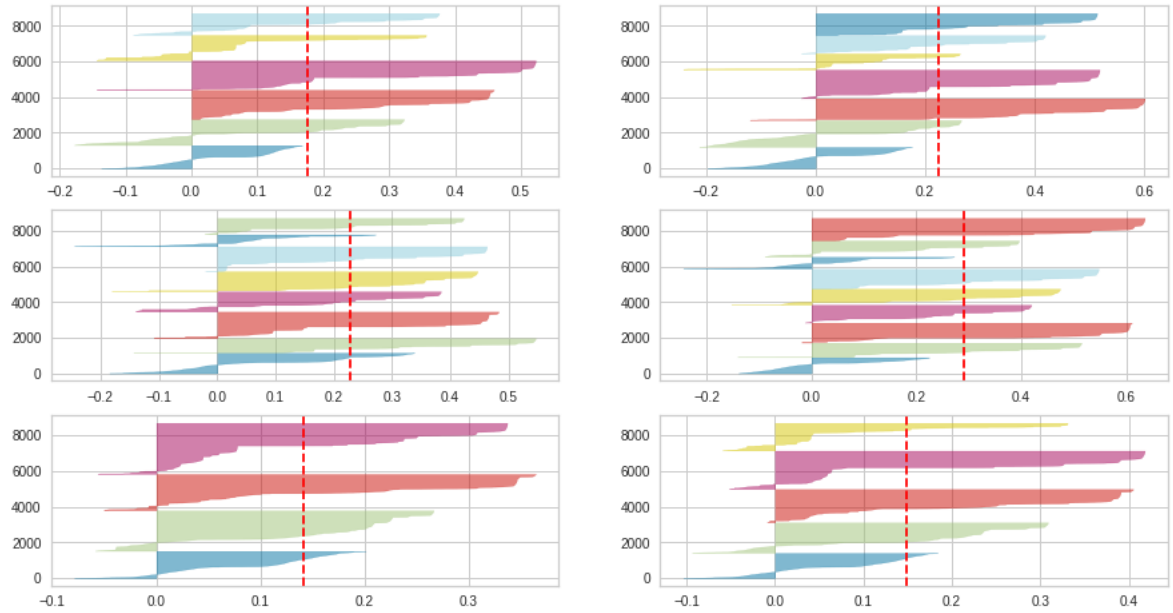



```
<matplotlib.axes._subplots.AxesSubplot at 0x7ff4bc2b7dc0>
```

```
1 fig, ax = plt.subplots(3, 2, figsize=(15,8))
2 for i in [4, 5, 6, 7, 8, 9]:
3     '''
4     Create KMedoids instance for different number of clusters
5     '''
```

```
    km = KMedoids(n_clusters=i, init='k-medoids++', random_state=42)
    q, mod = divmod(i, 2)
    '''
    Create SilhouetteVisualizer instance with KMedoids instance
    Fit the visualizer
    '''
    visualizer = SilhouetteVisualizer(km, colors='yellowbrick', ax=ax[q-3][mod])
    visualizer.fit(X_mms)
    print(f'Silhouette Score cluster={i}: {visualizer.silhouette_score_}\n')
```

```
Silhouette Score cluster=4: 0.14119025951776737

Silhouette Score cluster=5: 0.14948076720579598

Silhouette Score cluster=6: 0.17661105481764344

Silhouette Score cluster=7: 0.22499528142221434

Silhouette Score cluster=8: 0.22801971197490492

Silhouette Score cluster=9: 0.2907087484993553
```



Predict / clustering

```
# kmedoids = KMedoids(n_clusters=4, random_state=42)
# y_med = kmedoids.fit_predict(X_mms)
```

```
# y_med
```

- dikarenakan kelbow tidak memiliki nilai k yang pasti dan silhoutte juga memiliki skor yang sangat rendah (init='k-medoids++), maka sulit mendapatkan cluster pasti menggunakan data awal sebagai clustering. sehingga digunakan RFM

Evaluation

```
df_tes = df_fe[(df_fe['sales'] <= upper) & (df_fe['sales'] >= lower)].copy()
df_tes['cluster'] = y
df_tes
```

	ship_mode	segment	region	category	sales	cluster
0	Second Class	Consumer	South	Furniture	261.960	4
2	Second Class	Corporate	West	Office Supplies	14.620	2
4	Standard Class	Consumer	South	Office Supplies	22.368	0
5	Standard Class	Consumer	West	Furniture	48.860	4
6	Standard Class	Consumer	West	Office Supplies	7.280	0
...	...	...	...	...	...	...
9795	Standard Class	Corporate	Central	Office Supplies	3.798	2
9796	Standard Class	Corporate	East	Office Supplies	10.368	2

```
# df_med = df_fe.copy()
# df_med['cluster'] = y_med
# df_med
```

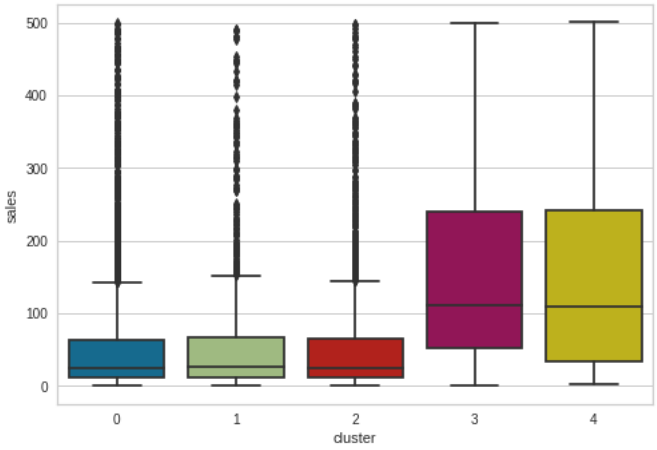
```
# df_med2 = df_fe.drop(columns=['order_to_ship']).copy()
# df_med2['cluster'] = y_med2
# df_med2
```

A. K-Means

Visualization / Interpretation

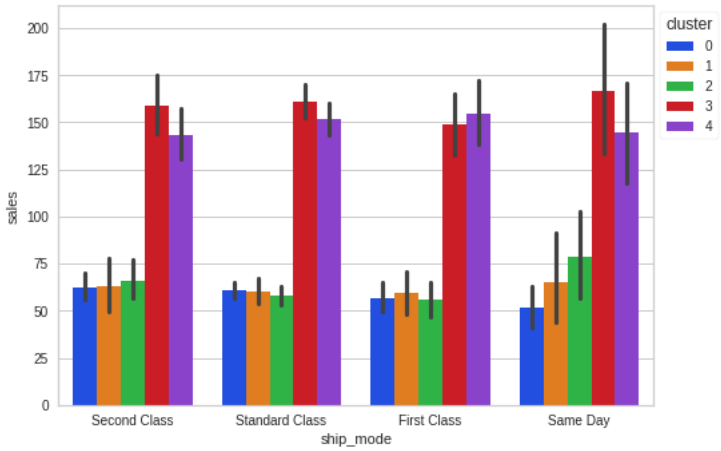
```
sns.boxplot(data=df_tes, x='cluster', y='sales')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7ff4bc069310>
```

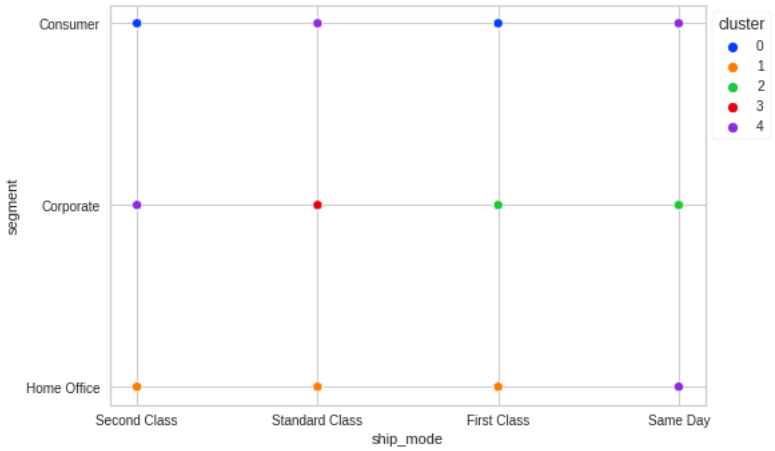



```
ax =sns.scatterplot(data=df_tes, x='ship_mode', y='sales', hue=df_tes['cluster'], palette='bright')
plt.xlabel('ship_mode')
plt.ylabel('sales')
sns.move_legend(ax, 'upper left',bbox_to_anchor=(1, 1))
plt.show()
```


```
ax =sns.barplot(data=df_tes, x='ship_mode', y='sales', hue='cluster', palette='bright')
plt.xlabel('ship_mode')
plt.ylabel('sales')
sns.move_legend(ax, 'upper left',bbox_to_anchor=(1, 1))
plt.show()
```

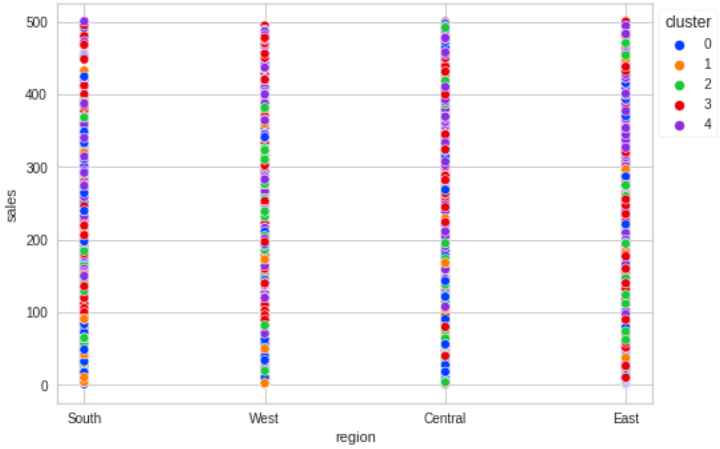



```
ax = sns.scatterplot(data=df_tes, x='ship_mode', y='segment', hue=df_tes['cluster'], palette='bright')
plt.xlabel('ship_mode')
plt.ylabel('segment')
sns.move_legend(ax, 'upper left',bbox_to_anchor=(1, 1))
plt.show()
```

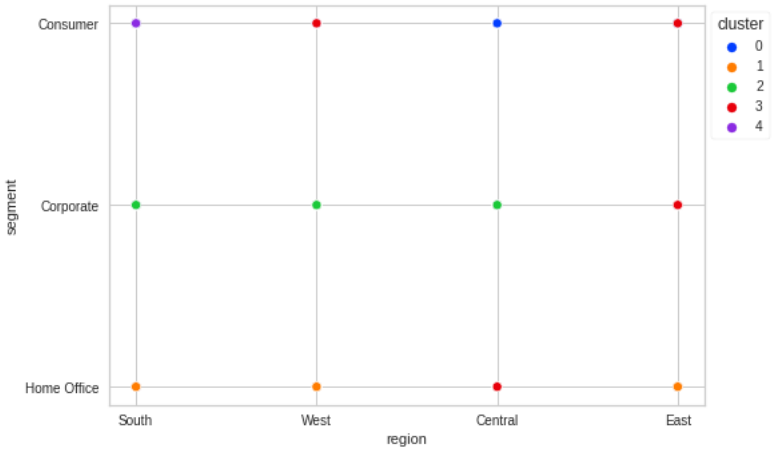



```
ax = sns.scatterplot(data=df_tes, x='category', y='segment', hue=df_tes['cluster'], palette='bright')
plt.xlabel('category')
plt.ylabel('segment')
sns.move_legend(ax, "upper left", bbox_to_anchor=(1, 1))
plt.show()
```


```
1 ax = sns.scatterplot(data=df_tes, x='region', y='sales', hue=df_tes['cluster'], palette='bright')
2 plt.xlabel('region')
3 plt.ylabel('sales')
4 sns.move_legend(ax, "upper left", bbox_to_anchor=(1, 1))
5 plt.show()
```




```
1 ax = sns.scatterplot(data=df_tes, x='region', y='segment', hue=df_tes['cluster'], palette='bright')
2 plt.xlabel('region')
3 plt.ylabel('segment')
4 sns.move_legend(ax, "upper left", bbox_to_anchor=(1, 1))
5 plt.show()
```



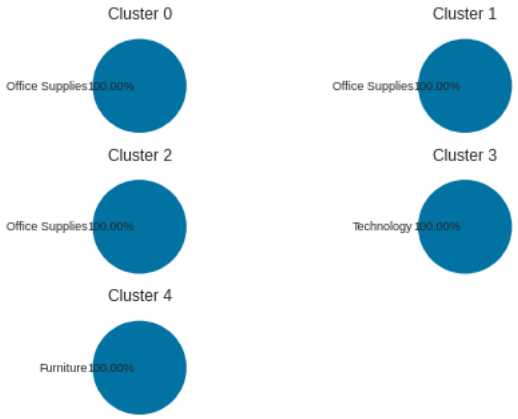

```
1 df_tes.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 8654 entries, 0 to 9799
Data columns (total 6 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   ship_mode  8654 non-null   object
 1   segment    8654 non-null   object
 2   region     8654 non-null   object
 3   category   8654 non-null   object
 4   sales      8654 non-null   float64
 5   cluster    8654 non-null   int32
dtypes: float64(1), int32(1), object(4)
memory usage: 697.5+ KB
```

```
1 # create a function to generate pie charts for a given categorical feature
2 def cluster_demographic(var):
3
4     # Create subsets for each cluster
5     df_0 = df_tes[df_tes['cluster']==0]
6     df_1 = df_tes[df_tes['cluster']==1]
7     df_2 = df_tes[df_tes['cluster']==2]
```

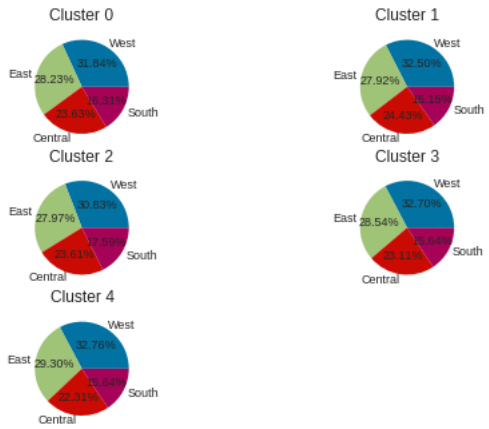
```
    df_3 = df_tes[df_tes['cluster']==3]
    df_4 = df_tes[df_tes['cluster']==4]

    fig, ax = plt.subplots(3, 2)
    plt.figure(figsize=(15,7))


    ax[0,0].pie(df_0[var].value_counts(), labels=df_0[var].value_counts().index, \
                    autopct="%.2f%%", textprops={'fontsize': 9})
    ax[0,0].title.set_text('Cluster 0')
    ax[0,1].pie(df_1[var].value_counts(), labels=df_1[var].value_counts().index, \
                    autopct="%.2f%%", textprops={'fontsize': 9})
    ax[0,1].title.set_text('Cluster 1')
    ax[1,0].pie(df_2[var].value_counts(), labels=df_2[var].value_counts().index, \
                    autopct="%.2f%%", textprops={'fontsize': 9})
    ax[1,0].title.set_text('Cluster 2')
    ax[1,1].pie(df_3[var].value_counts(), labels=df_3[var].value_counts().index, \
                    autopct="%.2f%%", textprops={'fontsize': 9})
    ax[1,1].title.set_text('Cluster 3')
    ax[2,0].pie(df_4[var].value_counts(), labels=df_4[var].value_counts().index, \
                    autopct="%.2f%%", textprops={'fontsize': 9})
    ax[2,0].title.set_text('Cluster 4')
    df_4.head()


    fig.delaxes(ax[2][1])
    plt.suptitle(var)

    plt.show()
```

```
cluster_demographic('category')
```



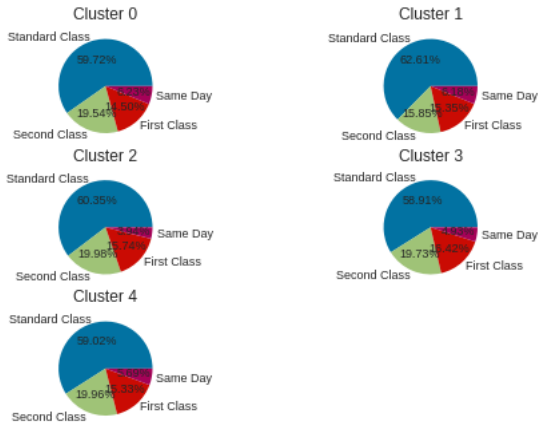

```
<Figure size 1080x504 with 0 Axes>
```

```
cluster_demographic('region')
```




```
<Figure size 1080x504 with 0 Axes>
```

```
cluster_demographic('ship_mode')
```




```
1 cluster_demographic('segment')
```


```
<Figure size 1080x504 with 0 Axes>
```

B. K-Medoids (Not Used)

Visualization / Interpretation

```
1
```

Conclusion

A. Customer Segmentation

What a definition of a cluster group.

a. K-Means

- **Cluster 0** : Mayoritas Consumer dari berbagai macam region yang membeli kategori office supplies dengan tingkat daya beli cukup rendah.
- **Cluster 1** : Mayoritas Home Office dari berbagai macam region yang membeli kategori office supplies dengan tingkat daya beli cukup rendah.
- **Cluster 2** : Mayoritas Corporate dari berbagai macam region yang membeli kategori Office Supplies dengan tingkat daya beli cukup rendah.
- **Cluster 3** : Berbagai jenis customer dari berbagai macam region yang membeli kategori Technology dengan tingkat daya beli cukup tinggi.
- **Cluster 4** : Berbagai jenis customer dari berbagai macam region yang membeli kategori furniture dengan tingkat daya beli cukup tinggi.

b. K-Medoids (Not Used)

- **Cluster 0** :
- **Cluster 1** :
- **Cluster 2** :
- **Cluster 3** :
- **Cluster 4** :

B. Marketing Strategy Recommendation

a. K-Means

- **Cluster 0**: Dapat direkomendasikan barang-barang terkait office supplies yang digunakan perorangan dengan harga rendah dipasaran, juga bisa diberikan diskon-diskon terkait barang tersebut.
- **Cluster 1**: Dapat direkomendasikan barang-barang terkait office supplies yang memiliki dimensi cukup kecil dan paket-paket yang memiliki potongan harga daripada membeli satuan.
- **Cluster 2**: Dapat direkomendasikan barang-barang terkait office supplies dengan potongan harga untuk barang yang lebih banyak. (semakin banyak barang dibeli semakin besar potongan harga). Dengan kata lain, menerapkan harga grosir pada cluster ini.
- **Cluster 3**: Bisa menjadi target utama pemasaran dalam barang-barang terkait teknologi yang baru.
- **Cluster 4**: Bisa menjadi target utama pemasaran dalam barang-barang terkait furniture yang baru.