

## Group Members

1.Suthasinee Pojam 6220422065

2.Siraprapa Chunloy

3.Teremate Tangpatong

## Load Dependencies

!pip install pycaret



```

Downloading pydantic 1.9.2 cp37- cp37m-manylinux2014_x86_64.whl (10.1 MB)
| 10.1 MB 33.9 MB/s
Requirement already satisfied: tqdm>=4.48.2 in /usr/local/lib/python3.7/dist-packages (from pandas-profiling)
Collecting visions[type_image_path]==0.7.4
  Downloading visions-0.7.4-py3-none-any.whl (102 kB)
  | 102 kB 8.3 MB/s
Requirement already satisfied: attrs>=19.3.0 in /usr/local/lib/python3.7/dist-packages (from visions[type_
Requirement already satisfied: networkx>=2.4 in /usr/local/lib/python3.7/dist-packages (from visions[type_
Requirement already satisfied: Pillow in /usr/local/lib/python3.7/dist-packages (from visions[type_image_p
Collecting imagehash
  Downloading ImageHash-4.2.1.tar.gz (812 kB)
  | 812 kB 42.9 MB/s
Collecting scipy<=1.5.4
  Downloading scipy-1.5.4-cp37-cp37m-manylinux1_x86_64.whl (25.9 MB)
  | 25.9 MB 1.6 MB/s
Requirement already satisfied: retrying>=1.3.3 in /usr/local/lib/python3.7/dist-packages (from plotly>=4.
Requirement already satisfied: wcwidth in /usr/local/lib/python3.7/dist-packages (from prompt-toolkit<2.0
Requirement already satisfied: typing-extensions>=3.7.4.3 in /usr/local/lib/python3.7/dist-packages (from
Requirement already satisfied: urllib3<1.27,>=1.21.1 in /usr/local/lib/python3.7/dist-packages (from requi
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.7/dist-packages (from requests>=2
Requirement already satisfied: charset-normalizer~=2.0.0 in /usr/local/lib/python3.7/dist-packages (from
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.7/dist-packages (from requests
Requirement already satisfied: wasabi<1.1.0,>=0.4.0 in /usr/local/lib/python3.7/dist-packages (from spac
Requirement already satisfied: srsly<1.1.0,>=1.0.2 in /usr/local/lib/python3.7/dist-packages (from spacy<
Requirement already satisfied: cymem<2.1.0,>=2.0.2 in /usr/local/lib/python3.7/dist-packages (from spac
Requirement already satisfied: blis<0.5.0,>=0.4.0 in /usr/local/lib/python3.7/dist-packages (from spacy<2
Requirement already satisfied: plac<1.2.0,>=0.9.6 in /usr/local/lib/python3.7/dist-packages (from spacy<
Requirement already satisfied: murmurhash<1.1.0,>=0.28.0 in /usr/local/lib/python3.7/dist-packages (fro
Requirement already satisfied: thinc==7.4.0 in /usr/local/lib/python3.7/dist-packages (from spacy<2.4.0->
Requirement already satisfied: catalogue<1.1.0,>=0.0.7 in /usr/local/lib/python3.7/dist-packages (from sp
Requirement already satisfied: preshed<3.1.0,>=3.0.2 in /usr/local/lib/python3.7/dist-packages (from spa
Requirement already satisfied: importlib-metadata>=0.20 in /usr/local/lib/python3.7/dist-packages (from
Requirement already satisfied: zipp>=0.5 in /usr/local/lib/python3.7/dist-packages (from importlib-metada
Requirement already satisfied: notebook>=4.4.1 in /usr/local/lib/python3.7/dist-packages (from widgetsnt
Requirement already satisfied: nbconvert in /usr/local/lib/python3.7/dist-packages (from notebook>=4.4.1
Requirement already satisfied: terminado>=0.8.1 in /usr/local/lib/python3.7/dist-packages (from notebook
Requirement already satisfied: Send2Trash in /usr/local/lib/python3.7/dist-packages (from notebook>=4.4
Requirement already satisfied: pyzmq>=13 in /usr/local/lib/python3.7/dist-packages (from jupyter-client->
Requirement already satisfied: ptyprocess in /usr/local/lib/python3.7/dist-packages (from terminado>=0.8
Requirement already satisfied: PyWavelets in /usr/local/lib/python3.7/dist-packages (from imagehash->vis

```

Collecting databricks-cli&gt;=0.8.7

Downloading databricks-cli-0.16.2.tar.gz (58 kB)

58 kB 5.8 MB/s

Requirement already satisfied: click>=7.0 in /usr/local/lib/python3.7/dist-packages (from mlflow->pycaret

Requirement already satisfied: sqlparse>=0.3.1 in /usr/local/lib/python3.7/dist-packages (from mlflow->p

Collecting docker>=4.0.0

Downloading docker-5.0.3-py2.py3-none-any.whl (146 kB)

146 kB 49.0 MB/s

Collecting alembic&lt;=1.4.1

Downloading alembic-1.4.1.tar.gz (1.1 MB)

1.1 MB 45.6 MB/s

## Collecting prometheus-flask-exporter

Downloading prometheus\_flask\_exporter-0.18.7-py3-none-any.whl (17 kB)

Requirement already satisfied: packaging in /usr/local/lib/python3.7/dist-packages (from mlflow->pycaret)

Requirement already satisfied: entrypoints in /usr/local/lib/python3.7/dist-packages (from mlflow->pycaret)

Requirement already satisfied: cloudpickle in /usr/local/lib/python3.7/dist-packages (from mlflow->pycaret)

Collecting gitpython>=2.1.0

Downloading GitPython-3.1.24-py3-none-any.whl (180 kB)

```
import pandas as pd
from pycaret.clustering import *
```

## ▼ Load Data

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

Mounted at /content/drive

```
df = pd.read_csv('/content/drive/MyDrive/SupermarketData.csv')
```

df.shape

(956574, 22)

```
df.head()
```

SHOP\_WEEK SHOP\_DATE SHOP\_WEEKDAY SHOP\_HOUR QUANTITY SPEND PROD\_

```
df['SHOP_DATE'] = df['SHOP_DATE'].apply(lambda x: pd.to_datetime(str(x), format='%Y%m%d'))

1      200733      20071010      4      20      3      6.75  PRD0900001

df2=df

df.describe()
```

	SHOP_WEEK	SHOP_WEEKDAY	SHOP_HOUR	QUANTITY	SPEND	BAS
count	956574.000000	956574.000000	956574.000000	956574.000000	956574.000000	9.56574e+05
mean	200702.251671	3.996021	14.950665	1.514577	1.871697	9.94100e+01
std	65.857803	1.997058	3.636119	1.621021	2.767820	3.33200e+01
min	200607.000000	1.000000	8.000000	1.000000	0.010000	9.94100e+01
25%	200637.000000	2.000000	12.000000	1.000000	0.750000	9.94100e+01
50%	200713.000000	4.000000	15.000000	1.000000	1.200000	9.94100e+01
75%	200742.000000	6.000000	18.000000	1.000000	2.060000	9.94100e+01
max	200819.000000	7.000000	21.000000	129.000000	476.160000	9.94100e+01

```
df.info

...      ...      ...      ...      ...      ...
956569  200617 2006-06-22      5      12      3  3.96
956570  200633 2006-10-13      6      20      3  3.96
956571  200617 2006-06-22      5      18      3  3.96
956572  200619 2006-07-06      5      19      3  3.96
956573  200635 2006-10-23      2      21      3  3.96

PROD_CODE PROD_CODE_10 PROD_CODE_20 PROD_CODE_30 PROD_CODE_40 \
0  PRD0900001  CL00072  DEP00021  G00007  D00002
1  PRD0900001  CL00072  DEP00021  G00007  D00002
2  PRD0900001  CL00072  DEP00021  G00007  D00002
3  PRD0900001  CL00072  DEP00021  G00007  D00002
4  PRD0900001  CL00072  DEP00021  G00007  D00002

...      ...      ...      ...      ...      ...
956569  PRD0904997  CL00074  DEP00021  G00007  D00002
956570  PRD0904997  CL00074  DEP00021  G00007  D00002
956571  PRD0904997  CL00074  DEP00021  G00007  D00002
956572  PRD0904997  CL00074  DEP00021  G00007  D00002
956573  PRD0904997  CL00074  DEP00021  G00007  D00002

CUST_CODE CUST_PRICE_SENSITIVITY CUST_LIFESTAGE  BASKET_ID \
0  CUST0000583261      UM      YF 994107800547472
1  CUST0000537317      MM      OF 994107900512001
2  CUST0000472158      MM      YF 994108700468327
3  CUST0000099658      LA      OF 994107700237811
4  CUST0000000000      NA      NA 994100000000000
```

```

4          NaN          NaN          NaN 994108300002212
...
956569      NaN          NaN          NaN 994101100088778
956570      NaN          NaN          NaN 994102700099738
956571  CUST0000544241          LA          YA 994101100506174
956572  CUST0000423155          LA          YF 994101300433650
956573      NaN          NaN          NaN 994102900104676

BASKET_SIZE BASKET_PRICE_SENSITIVITY BASKET_TYPE \
0          L          MM    Top Up
1          L          MM    Full Shop
2          L          MM    Full Shop
3          L          LA    Full Shop
4          L          MM    Full Shop
...
956569      M          MM    Top Up
956570      L          LA    Top Up
956571      L          LA    Top Up
956572      L          LA    Full Shop
956573      L          MM    Top Up

BASKET_DOMINANT_MISSION STORE_CODE STORE_FORMAT STORE_REGION
0          Grocery STORE00001      LS      E02
1          Fresh  STORE00001      LS      E02
2          Grocery STORE00001      LS      E02
3          Mixed  STORE00001      LS      E02
4          Fresh  STORE00001      LS      E02
...
956569      Fresh STORE00002      LS      W01
956570      Fresh STORE00002      LS      W01
956571      Fresh STORE00002      LS      W01
956572      Fresh STORE00002      LS      W01

```

## Prepare customer single view

### ▼ Define features

Total visits = COUNT(DISTINCT BASKET ID)

Ticket size = SUM(SPEND)/COUNT(DISTINCT BASKET ID)

Total no. of SKUs

FirstDate min SHOP\_Date

LastDate max SHOP\_Date

## ▼ Calculate features

```
##prepare customer single view
```

```
df_csv = df_groupby = df[df['CUST_CODE'].notnull()].groupby(by=['CUST_CODE']).agg(TotalSpend=('SPEND', 'sum',
TotalVisits=('BASKET_ID', 'nunique'),
TotalSKUs=('PROD_CODE', 'nunique'),
TotalSKUs_10=('PROD_CODE_10', 'nunique'),
TotalSKUs_20=('PROD_CODE_20', 'nunique'),
TotalSKUs_30=('PROD_CODE_30', 'nunique'),
TotalSKUs_40=('PROD_CODE_40', 'nunique'),
FirstDate=('SHOP_DATE', 'min'),
LastDate=('SHOP_DATE', 'max'),

).reset_index()
```

```
##calculate ticket size
```

```
df_csv['TicketSize'] = df_csv['TotalSpend']/df_csv['TotalVisits']
```

```
##find max date in the dataset
```

```
max_date = df_csv['LastDate'].max()
```

```
##calculate total days of the relationship
```

```
df_csv['total_days'] = (df_csv['LastDate'] - df_csv['FirstDate']).dt.days + 1
```

```
##calculate recency days
```

```
df_csv['recency'] = (max_date - df_csv['LastDate']).dt.days
```

```
df_csv.head(5)
```

	CUST_CODE	TotalSpend	TotalVisits	TotalSKUs	TotalSKUs_10	TotalSKUs_20	Tot
0	CUST0000000181	2.44	1	1	1	1	
1	CUST0000000369	959.33	220	189	81	36	
2	CUST0000000689	328.57	16	116	73	41	
3	CUST0000000711	1.00	1	1	1	1	
4	CUST0000000712	1.00	1	1	1	1	

```
df_csv.shape
```

```
(6100, 13)
```

```
df2['attend']=1
```

```
df2.head()
```

	SHOP_WEEK	SHOP_DATE	SHOP_WEEKDAY	SHOP_HOUR	QUANTITY	SPEND	PROD_
0	200732	2007-10-05	6	17	3	6.75	PRD09
1	200733	2007-10-10	4	20	3	6.75	PRD09
2	200741	2007-12-09	1	11	1	2.25	PRD09
3	200731	2007-09-29	7	17	1	2.25	PRD09
4	200737	2007-11-10	7	14	3	6.75	PRD09

```
##prepare customer single view
df_csv2 = df2[df2['CUST_CODE'].notnull()].groupby(by=['CUST_CODE','SHOP_WEEK']).agg(TotalAtt=('attend', 'sum'))

df_csv3 = df_csv2[df_csv2['CUST_CODE'].notnull()].groupby(by=['CUST_CODE','SHOP_WEEK']).agg(TotalAttMin=('TotalAtt', 'min'),
TotalAttMax=('TotalAtt', 'max'))

df_csv3.head()
```

	CUST_CODE	SHOP_WEEK	TotalAttMin	TotalAttMax
0	CUST0000000181	200645	1	1
1	CUST0000000369	200607	4	4
2	CUST0000000369	200608	4	4
3	CUST0000000369	200609	3	3
4	CUST0000000369	200610	12	12

```
df_csv_final = pd.concat([df_csv3, df_csv], ignore_index=True)
```

```
df_csv.head()
```

	CUST_CODE	TotalSpend	TotalVisits	TotalSKUs	TotalSKUs_10	TotalSKUs_20	TotalSKUs_30
0	CUST0000000181	2.44	1	1	1	1	1
1	CUST0000000369	959.33	220	189	81	36	15
2	CUST0000000689	328.57	16	116	73	41	20
3	CUST0000000369	959.33	220	189	81	36	15
4	CUST0000000369	959.33	220	189	81	36	15

```
df_csv.dtypes
```

```

CUST_CODE      object
TotalSpend      float64
TotalVisits     int64
TotalSKUs       int64
TotalSKUs_10    int64
TotalSKUs_20    int64
TotalSKUs_30    int64
TotalSKUs_40    int64
FirstDate       datetime64[ns]
LastDate        datetime64[ns]
TicketSize      float64
total_days      int64
recency         int64
dtype: object

```

```
#df_final=df_csv.join(df_csv3,how='left',on='CUST_CODE',c)
```

```
#result = pd.concat([df_csv, df_csv3], axis=1, join="left",on='CUST_CODE')
```

```
merged = pd.merge(df_csv,df_csv3, on=['CUST_CODE'])
```

```
df_csv.shape
```

```
(6100, 13)
```

```
merged.shape
```

```
(78137, 16)
```

```
#df_csv=merged
```

```
df_csv.head()
```

	CUST_CODE	TotalSpend	TotalVisits	TotalSKUs	TotalSKUs_10	TotalSKUs_20	TotalSKUs_30	TotalSKUs_40
0	CUST0000000181	2.44	1	1	1	1	1	1
1	CUST0000000369	959.33	220	189	81	36	36	36
2	CUST0000000689	328.57	16	116	73	41	41	41

## ▼ Cluster customers

```
exp_clu = setup(data=df_csv, ignore_features=['CUST_CODE', 'FirstDate', 'LastDate'], normalize=True)
```



	Description	Value
<b>0</b>	session_id	3728
<b>1</b>	Original Data	(6100, 13)
<b>2</b>	Missing Values	False
<b>3</b>	Numeric Features	9
<b>4</b>	Categorical Features	1
<b>5</b>	Ordinal Features	False
<b>6</b>	High Cardinality Features	False
<b>7</b>	High Cardinality Method	None
<b>8</b>	Transformed Data	(6100, 18)
<b>9</b>	CPU Jobs	-1
<b>10</b>	Use GPU	False
<b>11</b>	Log Experiment	False
<b>12</b>	Experiment Name	cluster-default-name
<b>13</b>	USI	8620
<b>14</b>	Imputation Type	simple
<b>15</b>	Iterative Imputation Iteration	None
<b>16</b>	Numeric Imputer	mean
<b>17</b>	Iterative Imputation Numeric Model	None
<b>18</b>	Categorical Imputer	mode
<b>19</b>	Iterative Imputation Categorical Model	None
<b>20</b>	Unknown Categoricals Handling	least_frequent
<b>21</b>	Normalize	True
<b>22</b>	Normalize Method	zscore

models()

		Name	Reference
ID			
get_metrics()	kmeans	K-Means Clustering	sklearn.cluster._kmeans.KMeans
	ap	Affinity Propagation	sklearn.cluster._affinity_propagation.Affinity...
	meanshift	Mean Shift Clustering	sklearn.cluster._mean_shift.MeanShift
	sc	Spectral Clustering	sklearn.cluster._spectral.SpectralClustering
	hclust	Agglomerative Clustering	sklearn.cluster._agglomerative.AgglomerativeCl

		Name	Display Name	Score Function	Score
ID					
	silhouette	Silhouette	Silhouette	<function silhouette_score at 0x7fa001689d40>	make_scorer(silhouette_sco
	chs	Calinski-Harabasz	Calinski-Harabasz	<function calinski_harabasz_score at 0x7fa0016...	make_scorer(calinski_harabasz_sco
	db	Davies-	Davies-	<function davies_bouldin_score	make_scorer(davies_bouldin_sco

▼ Compare model performance

```
metrics = []
for model in models().index:
    if model in ['meanshift', 'optics']:
        continue
    create_model(model)
    metric_result = pull()
    metric_result['model'] = model
    metrics.append(metric_result)
```

	Silhouette	Calinski-Harabasz	Davies-Bouldin	Homogeneity	Rand Index	Completeness
0	-0.0878	290.8768	2.9148	0	0	0

```
cluster_metrics = pd.concat(metrics)
cluster_metrics.set_index("model", inplace=True)
```

	Silhouette	Calinski-Harabasz	Davies-Bouldin	Homogeneity	Rand Index	Completeness
model						
sc	0.672900	40.611800	0.247600	0	0	0
birch	0.457400	1768.474900	0.855000	0	0	0
kmeans	0.292500	3714.085100	1.172000	0	0	0
hclust	0.281800	3289.183500	1.256000	0	0	0
ap	0.000000	0.000000	0.000000	0	0	0
dbscan	-0.035400	219.369900	1.584800	0	0	0

▾ Spectral Clustering Clustering

```
sc = create_model('sc')
```

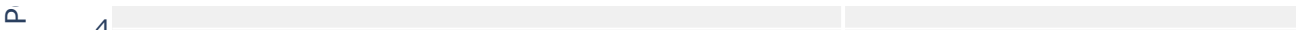
	Silhouette	Calinski-Harabasz	Davies-Bouldin	Homogeneity	Rand Index	Completeness
0	0.6729	40.6118	0.2476	0	0	0

```
plot_model(sc)
```

2D Cluster PCA Plot



▼ KMeans Clustering



```
kmeans = create_model('kmeans')
```

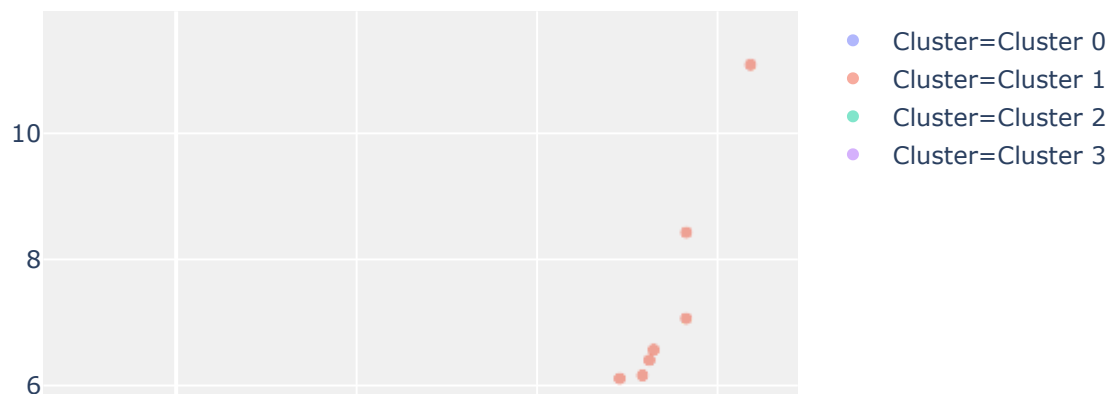
	Silhouette	Calinski-Harabasz	Davies-Bouldin	Homogeneity	Rand Index	Completeness
0	0.2925	3714.0851	1.172	0	0	0

```
print(kmeans)
```

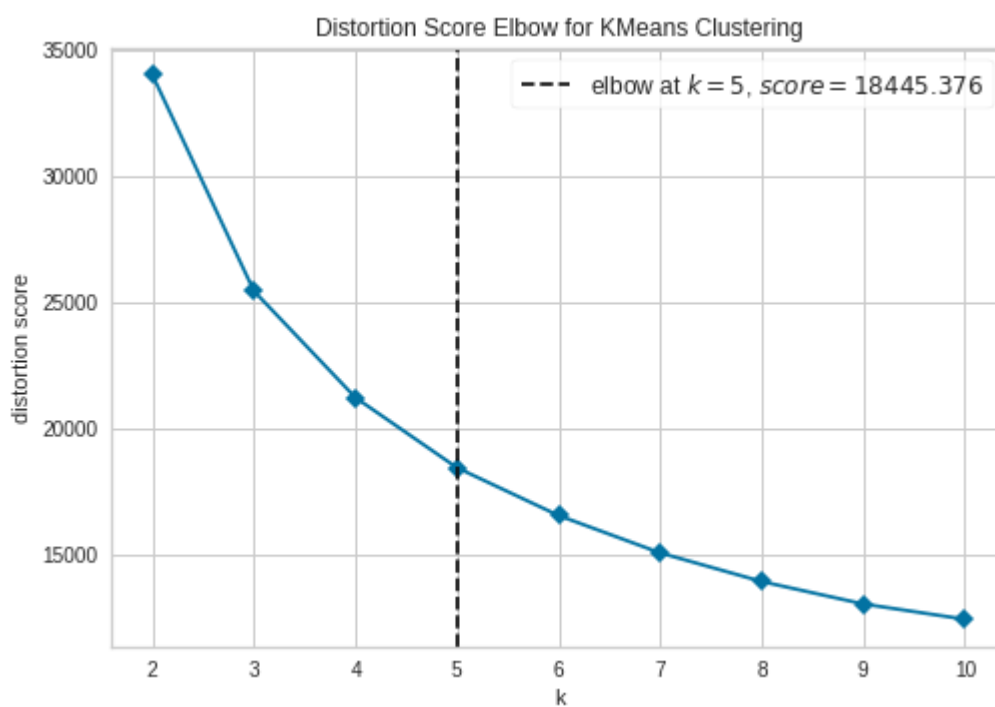
```
KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
        n_clusters=4, n_init=10, n_jobs=-1, precompute_distances='deprecated',
        random_state=3728, tol=0.0001, verbose=0)
```

```
plot_model(kmeans)
```

## 2D Cluster PCA Plot

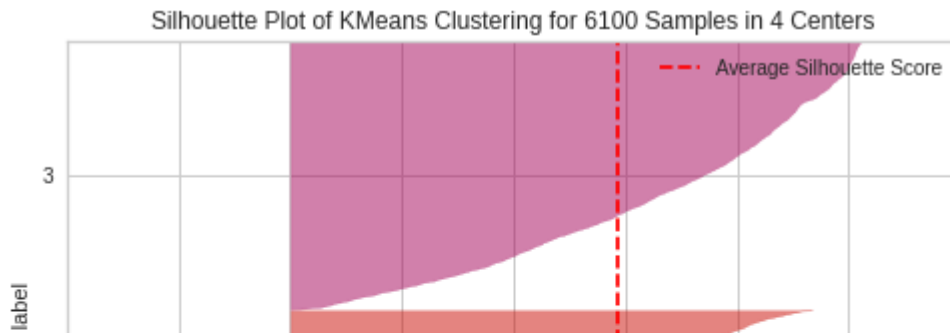


```
plot_model(kmeans, plot = 'elbow')
```



```
plot_model(kmeans, plot = 'silhouette')
```

## [https://scikit-learn.org/stable/auto\\_examples/cluster/plot\\_kmeans\\_silhouette\\_analysis.html](https://scikit-learn.org/stable/auto_examples/cluster/plot_kmeans_silhouette_analysis.html)



## ▼ Interpret results and plan for actions



```
kmeans_df = assign_model(kmeans)
kmeans_df
```

	CUST_CODE	TotalSpend	TotalVisits	TotalSKUs	TotalSKUs_10	TotalSKUs_20
<b>0</b>	CUST0000000181	2.44	1	1	1	1
<b>1</b>	CUST0000000369	959.33	220	189	81	36
<b>2</b>	CUST0000000689	328.57	16	116	73	41
<b>3</b>	CUST0000000998	5.95	3	4	4	4
<b>4</b>	CUST0000001163	39.74	4	24	21	15
...	...	...	...	...	...	...
<b>6095</b>	CUST0000999593	453.58	30	206	91	50
<b>6096</b>	CUST0000999645	105.11	11	46	36	27

```
final_df= kmeans_df.drop(columns=['CUST_CODE','FirstDate','LastDate'])
member_df = final_df[['Cluster']]
member_df['member_count'] = 1
member_df = member_df.groupby(by=['Cluster']).agg('sum').reset_index()
final_df = final_df.groupby(by=['Cluster']).agg('mean').reset_index()
final_df = final_df.merge(member_df,how='left',on='Cluster')
import seaborn as sns
pink = sns.light_palette('pink', as_cmap = True)
s = final_df.style.background_gradient(cmap=pink)
s
```

	Cluster	TotalSpend	TotalVisits	TotalSKUs	TotalSKUs_10	TotalSKUs_20	TotalSKUs_
0	Cluster_0	39.472479	7.125345	14.867477	11.889564	9.276091	6.4483
1	Cluster_1	2500.713525	173.713115	369.357923	120.882514	53.551913	22.3032
2	Cluster_2	412.896452	35.329372	107.172326	59.922750	34.348896	17.3446

Cluster	Character	Name	Action
Cluster 0	ซื้อสินค้าบ่อย มีการเข้ามาดูสินค้าบ่อย ไม่ค่อยมีความสนใจกับสินค้าของเรา	เพื่อนบ้านที่ห่างไกล	ยิง ads ให้ลูกค้ารู้จักสินค้าเรามากขึ้น , เพิ่ม promotion
Cluster 1	ซื้อสินค้าปริมาณค่อนข้างสูง มีการตอบสนองต่อ promotion ที่ดี	คนสนิทแต่ยังไม่ใช่แฟน	เพิ่ม promotion เพื่อให้การซื้อสูงขึ้น
Cluster 2	ซื้อสินค้าปานกลาง เข้าชมสินค้าปานกลาง	เพื่อนบ้านในหมู่บ้านเดียวกัน	ยิง ads ให้ลูกค้ารู้จักสินค้าเรามากขึ้น , เพิ่ม promotion
Cluster 3	ซื้อสินค้าในปริมาณที่สูง ตอบสนองต่อ promotion ดีมาก	คนที่รู้ใจ	พยายามเสนอ promotion ที่ถูกใจโดยพิจารณาความชอบของแต่ละบุคคล พยายามรักษาลูกค้า

