```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.cluster import KMeans
from sklearn.decomposition import PCA
```

#### Load the data





#### data.info()

<<class 'pandas.core.frame.DataFrame'>
 RangeIndex: 1453 entries, 0 to 1452
 Data columns (total 15 columns):

#	Column	Non-Null Count	Dtype
0	yummy	1453 non-null	object
1	convenient	1453 non-null	object
2	spicy	1453 non-null	object
3	fattening	1453 non-null	object
4	greasy	1453 non-null	object
5	fast	1453 non-null	object
6	cheap	1453 non-null	object
7	tasty	1453 non-null	object
8	expensive	1453 non-null	object
9	healthy	1453 non-null	object
10	disgusting	1453 non-null	object
11	Like	1453 non-null	object
12	Age	1453 non-null	int64
13	VisitFrequency	1453 non-null	object
14	Gender	1453 non-null	object

dtypes: int64(1), object(14)
memory usage: 170.4+ KB

data.describe()



Age I

ılı

count	1453.000000
mean	44.604955
std	14.221178
min	18.000000
25%	33.000000
50%	45.000000
75%	57.000000
max	71.000000

#### data.columns

### data.shape

**→** (1453, 15)

### data.isnull()

 $\overline{\Rightarrow}$ 

							_			
	yummy	convenient	spicy	fattening	greasy	fast	cheap	tasty	expensive	hea
0	False	False	False	False	False	False	False	False	False	F
1	False	False	False	False	False	False	False	False	False	F
2	False	False	False	False	False	False	False	False	False	F
3	False	False	False	False	False	False	False	False	False	F
4	False	False	False	False	False	False	False	False	False	F
1448	False	False	False	False	False	False	False	False	False	F
1449	False	False	False	False	False	False	False	False	False	F
1450	False	False	False	False	False	False	False	False	False	F
1451	False	False	False	False	False	False	False	False	False	F
1452	False	False	False	False	False	False	False	False	False	F
1453 rows × 15 columns										

data.isnull().sum()

```
\overline{\Rightarrow}
```

0 0 yummy convenient 0 spicy 0 fattening 0 greasy 0 0 fast cheap tasty 0 expensive 0 healthy disgusting 0 0 Like Age 0

dtype: int64

VisitFrequency 0

Gender

```
data.replace({'Yes': 1, 'No': 0}, inplace=True)
```

0

data.dropna(subset=['VisitFrequency', 'Like'], inplace=True)

data

<b>→</b>		yummy	convenient	spicy	fattening	greasy	fast	cheap	tasty	expensive	hea]
	0	0	1	0	1	0	1	1	0	1	
	1	1	1	0	1	1	1	1	1	1	
	2	0	1	1	1	1	1	0	1	1	
	3	1	1	0	1	1	1	1	1	0	
	4	0	1	0	1	1	1	1	0	0	
	1448	0	1	0	1	1	0	0	0	1	
	1449	1	1	0	1	0	0	1	1	0	
	1450	1	1	0	1	0	1	0	1	1	
Next step		Ge	nerate code with	data	Vie	ew recomi			New	interactive sheet	

# Mapping VisitFrequency to numeric values

```
visit_freq_mapping = {
   'More than once a week': 5,
   'Once a week': 4,
   'Once a month': 3,
   'Every three months': 2,
   'Once a year': 1,
   'Never': 0
}
data['VisitFrequency'] = data['VisitFrequency'].map(visit_freq_mapping)

data['Like'] = pd.to_numeric(data['Like'], errors='coerce')
```

### **Encode categorical variables**

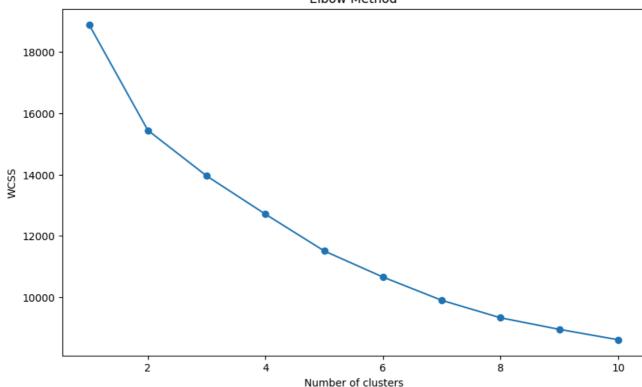
```
le = LabelEncoder()
for col in ['yummy', 'convenient', 'spicy', 'fattening', 'greasy', 'fast', 'cheap', 'tast
    data[col] = le.fit_transform(data[col])

from sklearn.impute import SimpleImputer
imputer = SimpleImputer(strategy='mean')
data_imputed = imputer.fit_transform(data[['yummy', 'convenient', 'spicy', 'fattening', '
```

```
scaler = StandardScaler()
data scaled = scaler.fit transform(data imputed)
wcss = []
for i in range(1, 11):
    kmeans = KMeans(n_clusters=i, random_state=0)
    kmeans.fit(data_scaled)
    wcss.append(kmeans.inertia_)
→ /usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:1416: FutureWarnin
       super()._check_params_vs_input(X, default_n_init=10)
     /usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:1416: FutureWarnin
       super()._check_params_vs_input(X, default_n_init=10)
     /usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:1416: FutureWarnin
       super(). check params vs input(X, default n init=10)
     /usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:1416: FutureWarnin
       super()._check_params_vs_input(X, default_n_init=10)
     /usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:1416: FutureWarnin
       super()._check_params_vs_input(X, default_n_init=10)
     /usr/local/lib/python3.10/dist-packages/sklearn/cluster/ kmeans.py:1416: FutureWarnin
       super()._check_params_vs_input(X, default_n_init=10)
     /usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:1416: FutureWarnin
       super()._check_params_vs_input(X, default_n_init=10)
     /usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:1416: FutureWarnin
       super()._check_params_vs_input(X, default_n_init=10)
     /usr/local/lib/python3.10/dist-packages/sklearn/cluster/ kmeans.py:1416: FutureWarnin
       super()._check_params_vs_input(X, default_n_init=10)
     /usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:1416: FutureWarnin
       super()._check_params_vs_input(X, default_n_init=10)
plt.figure(figsize=(10, 6))
plt.plot(range(1, 11), wcss, marker='o')
plt.title('Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS')
plt.show()
```

 $\overline{\mathbf{T}}$ 

#### Elbow Method



```
optimal_clusters = 4
kmeans = KMeans(n_clusters=optimal_clusters, random_state=0)
data['Cluster'] = kmeans.fit_predict(data_scaled)

/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:1416: FutureWarnin super()._check_params_vs_input(X, default_n_init=10)

cluster_centers = pd.DataFrame(scaler.inverse_transform(kmeans.cluster_centers_), columns

plt.figure(figsize=(10, 6))
sns.scatterplot(x='Age', y='Like', hue='Cluster', data=data, palette='Set1')
plt.title('Customer Segments')
plt.show()
```

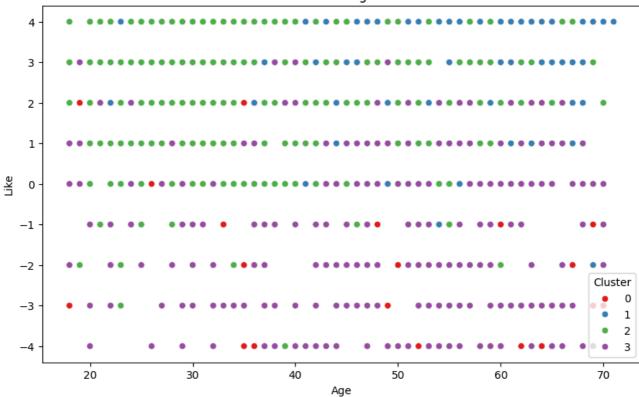
 $\overline{2}$ 

0

0.074380

0.840336

#### **Customer Segments**



```
print("Cluster Centers:")
print(cluster_centers)
→ Cluster Centers:
                                    spicy
                                          fattening
                                                                     fast
                                                                              cheap
           yummy
                    convenient
                                                        greasy
     0 0.074380 -1.332268e-15
                                0.074380
                                            0.859504
                                                      0.735537
                                                                0.636364
                                                                           0.338843
       0.840336
                 9.705882e-01
                                0.130252
                                            0.352941
                                                      0.046218
                                                                0.928571
                                                                           0.739496
     2 0.941272
                 9.902121e-01
                                0.076672
                                            0.991843
                                                      0.575856
                                                                0.938010
                                                                           0.619902
        0.035343 1.000000e+00
                                0.101871
                                            0.964657
                                                      0.648649
                                                                0.904366
                                                                           0.567568
                  expensive
                              healthy
                                       disgusting
           tasty
                                                        Like
                                                                     Age
     0 0.123967
                   0.644628
                             0.057851
                                           0.77686 -0.223298
                                                              48.504132
     1
       0.920168
                   0.189076
                             0.789916
                                                    2.066450
                                           0.02521
                                                              49.407563
     2
        0.957586
                   0.355628
                             0.106036
                                           0.08646
                                                    2.076979
                                                               38.181077
        0.239085
                   0.372141
                             0.060291
                                           0.41580 -0.550745
                                                              49.434511
print("\nCluster Analysis:")
print(data.groupby('Cluster').mean())
\rightarrow
     Cluster Analysis:
                                        spicy fattening
                 yummy
                        convenient
                                                            greasy
                                                                         fast
     Cluster
```

0.074380

0.130252

0.859504

0.352941

0.735537

0.046218

0.636364

0.928571

0.000000

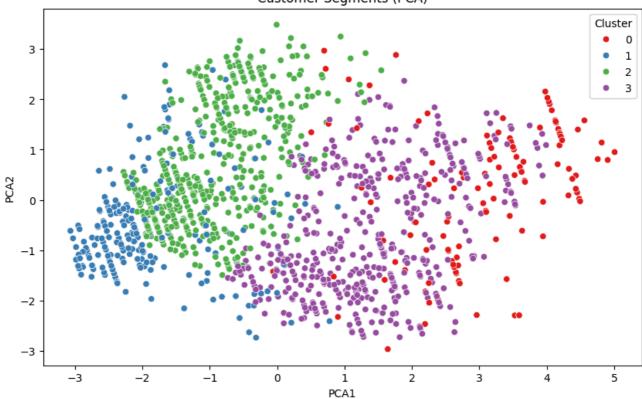
0.970588

```
2
            0.941272 0.990212 0.076672 0.991843 0.575856 0.938010
    3
            0.035343 1.000000 0.101871 0.964657 0.648649 0.904366
               cheap
                       tasty expensive healthy disgusting
                                                                 Like \
    Cluster
            0.338843 0.123967 0.644628 0.057851
                                                     0.77686 -1.980000
    1
            0.739496 0.920168 0.189076 0.789916
                                                     0.02521 2.413408
    2
            0.619902 0.957586
                                0.355628 0.106036
                                                     0.08646 2.250474
    3
            0.567568 0.239085 0.372141 0.060291
                                                     0.41580 -0.858209
                  Age VisitFrequency
                                       Gender
    Cluster
            48.504132
                            0.942149 0.545455
    1
            49.407563
                            2.987395 0.432773
    2
            38.181077
                            2.941272 0.432300
    3
            49.434511
                            1.735967 0.480249
pca = PCA(n_components=2)
data_pca = pca.fit_transform(data_scaled)
data['PCA1'] = data_pca[:, 0]
data['PCA2'] = data_pca[:, 1]
```

```
plt.figure(figsize=(10, 6))
sns.scatterplot(x='PCA1', y='PCA2', hue='Cluster', data=data, palette='Set1')
plt.title('Customer Segments (PCA)')
plt.show()
```

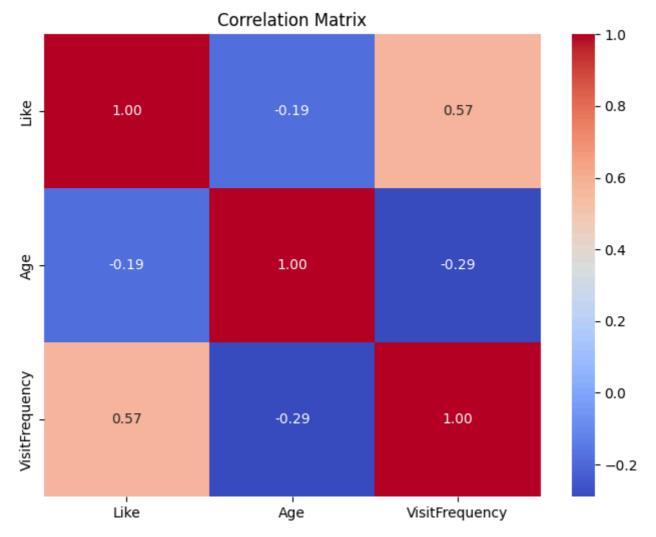
**₹** 

# Customer Segments (PCA)



```
corr_matrix = data[['Like', 'Age', 'VisitFrequency']].corr()
plt.figure(figsize=(8, 6))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt='.2f')
plt.title('Correlation Matrix')
plt.show()
```





```
print(data[['Like', 'Age']].describe())
print("\nGender distribution:\n", data['Gender'].value_counts())
print("\nVisit Frequency distribution:\n", data['VisitFrequency'].value_counts())
```

$\overline{\Rightarrow}$		Like	Age
	count	1158.000000	1453.000000
	mean	1.013817	44.604955
	std	2.355189	14.221178
	min	-4.000000	18.000000
	25%	0.000000	33.000000
	50%	1.000000	45.000000
	75%	3.000000	57.000000
	max	4.000000	71.000000

Gender distribution:

Gender

0 788

1 665

Name: count, dtype: int64

## Visit Frequency distribution:

VisitFrequency

- 3 439
- 2 342
- 1 252
- 4 235
- 0 131

5 54

Name: count, dtype: int64

```
numeric_columns = data.select_dtypes(include=['number']).columns
segment_means = data[numeric_columns].groupby('Cluster').mean()
print("\nSegment Means:\n", segment_means)
```

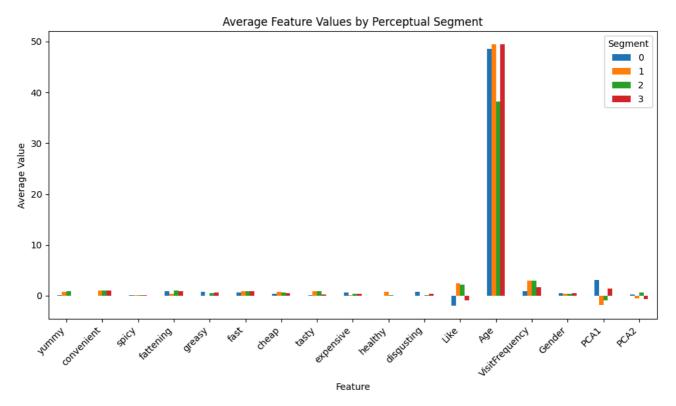
 $\overline{2}$ 

```
Segment Means:
```

```
spicy fattening
                                                             fast \
           yummy convenient
                                                  greasy
Cluster
0
        0.074380
                   0.000000 0.074380
                                      0.859504 0.735537 0.636364
1
                                      0.352941 0.046218 0.928571
        0.840336
                   0.970588 0.130252
2
        0.941272
                   0.990212 0.076672
                                      0.991843 0.575856
                                                        0.938010
3
        0.035343
                  1.000000 0.101871
                                      0.964657 0.648649 0.904366
           cheap
                   tasty expensive healthy disgusting
                                                            Like
Cluster
0
        0.338843 0.123967
                           0.644628 0.057851
                                                0.77686 -1.980000
1
        0.739496 0.920168
                           0.189076 0.789916
                                                0.02521
                                                       2.413408
2
        0.619902 0.957586
                           0.355628 0.106036
                                                0.08646 2.250474
3
        0.567568 0.239085
                           0.372141 0.060291
                                                0.41580 -0.858209
             Age VisitFrequency
                                  Gender
                                             PCA1
                                                      PCA2
Cluster
0
        48.504132
                       0.942149 0.545455 3.045976 0.202149
1
        49.407563
                       2
        38.181077
                       2.941272
                                0.432300 -0.961170 0.685318
3
                                0.480249 1.384262 -0.686590
        49.434511
                       1.735967
```

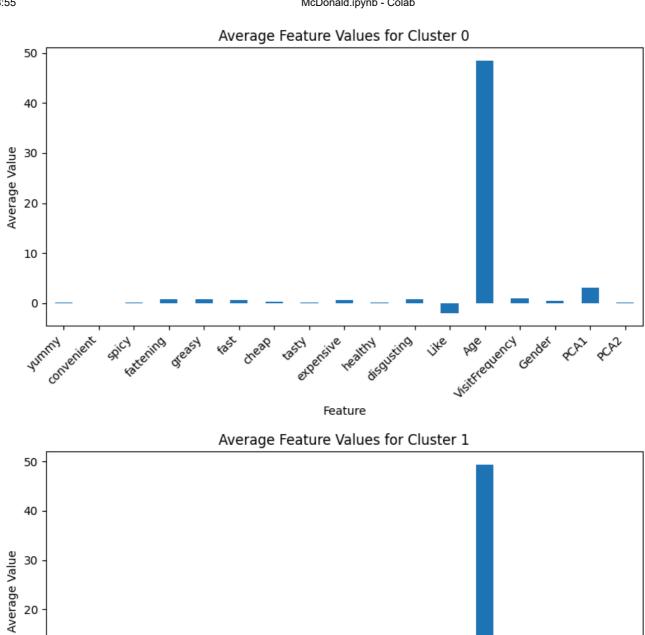
```
segment_means_t = segment_means.transpose()
segment_means_t.plot(kind='bar', figsize=(10, 6))
plt.title('Average Feature Values by Perceptual Segment')
plt.ylabel('Average Value')
plt.xlabel('Feature')
plt.xticks(rotation=45, ha='right')
plt.legend(title='Segment')
plt.tight_layout()
plt.show()
```

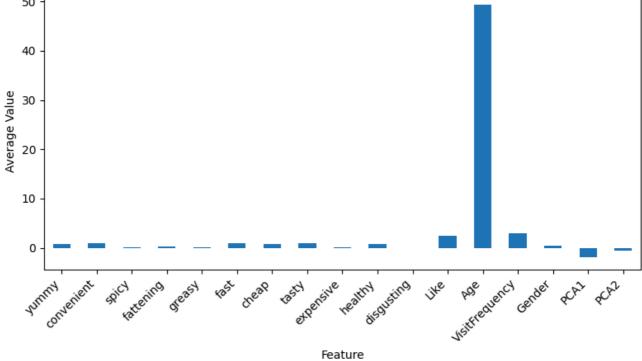


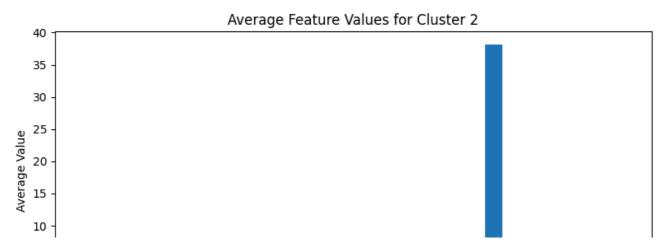


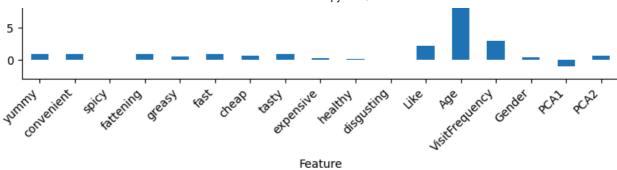
```
for cluster in segment_means.index:
    cluster_data = segment_means.loc[cluster]
    # A bar chart for the current cluster
    plt.figure()
    cluster_data.plot(kind='bar', figsize=(8, 5))
    plt.title(f'Average Feature Values for Cluster {cluster}')
    plt.ylabel('Average Value')
    plt.xlabel('Feature')
    plt.xticks(rotation=45, ha='right')
    plt.tight_layout()
    plt.show()
```

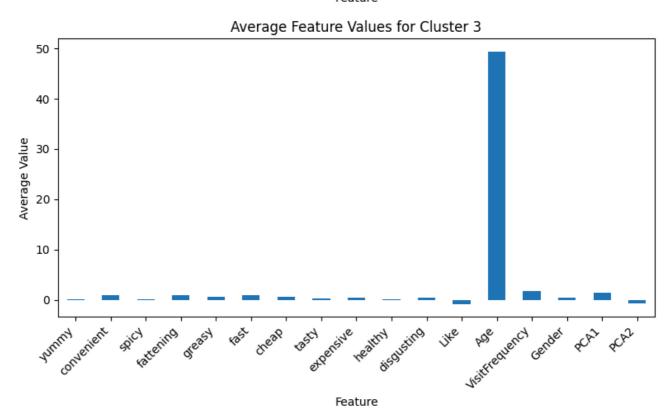
 $\overline{2}$ 







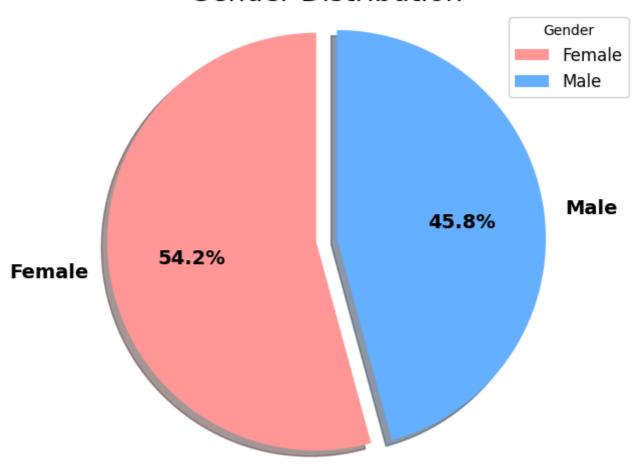




```
labels = ['Female', 'Male']
size = data['Gender'].value_counts()
colors = ['#ff9999','#66b3ff']
explode = [0, 0.1]
```



# Gender Distribution



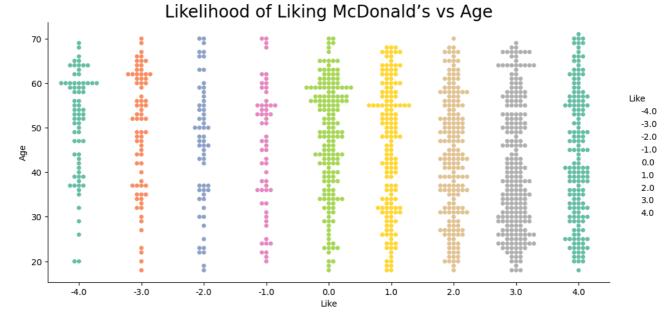
```
sns.catplot(data=data, x="Like", y="Age", orient="v", height=5, aspect=2, palette="Set2",
plt.title('Likelihood of Liking McDonald's vs Age', fontsize=20)
plt.xlabel('Like')
plt.ylabel('Age')
plt.show()
```



<ipython-input-43-2536c07e6668>:1: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.

 $sns.catplot(data=data,\ x="Like",\ y="Age",\ orient="v",\ height=5,\ aspect=2,\ palette="v",\ height=5,\ aspect=2,\ palette="v",\ height=5,\ aspect=2,\ palette="v",\ height=5,\ height=5$ 

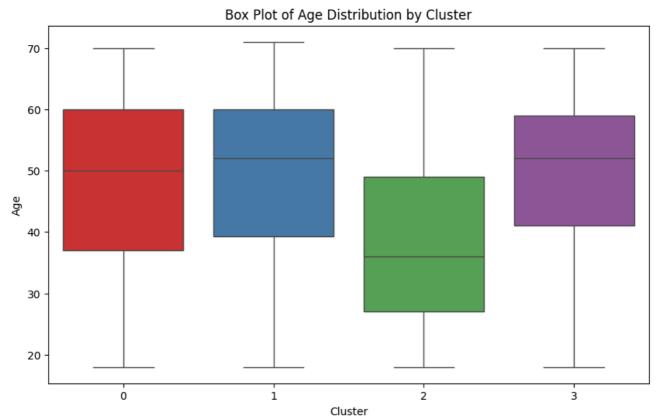


```
plt.figure(figsize=(10, 6))
sns.boxplot(x='Cluster', y='Age', data=data, palette='Set1')
plt.title('Box Plot of Age Distribution by Cluster')
plt.xlabel('Cluster')
plt.ylabel('Age')
plt.show()
```

<ipython-input-44-144ae284e3e5>:2: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.

sns.boxplot(x='Cluster', y='Age', data=data, palette='Set1')



# Categorize sentiment based on the "Like" column

```
def categorize_sentiment(like_score):
    if like_score <= 0:
        return 'Negative'
    elif 1 <= like_score <= 3:
        return 'Neutral'
    else:
        return 'Positive'

data['Sentiment'] = data['Like'].apply(categorize_sentiment)</pre>
```

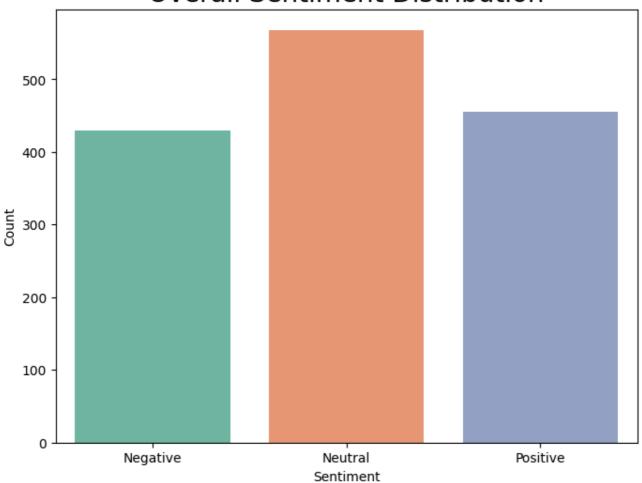
#### Overall sentiment distribution

```
plt.figure(figsize=(8, 6))
sns.countplot(x='Sentiment', data=data, palette='Set2')
plt.title('Overall Sentiment Distribution', fontsize=20)
plt.xlabel('Sentiment')
plt.ylabel('Count')
plt.show()
```

<ipython-input-47-9eed0a076eab>:2: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14. sns.countplot(x='Sentiment', data=data, palette='Set2')

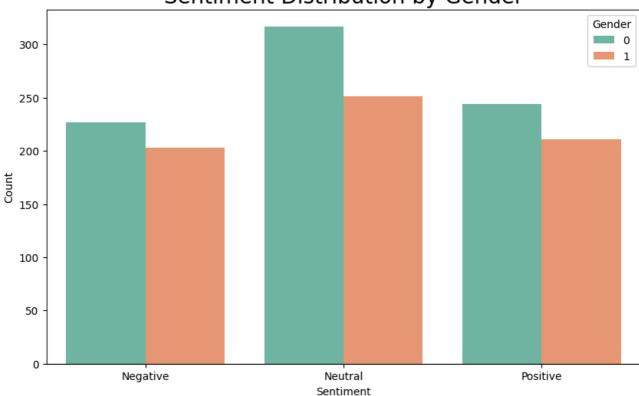
# **Overall Sentiment Distribution**



```
plt.figure(figsize=(10, 6))
sns.countplot(x='Sentiment', hue='Gender', data=data, palette='Set2')
plt.title('Sentiment Distribution by Gender', fontsize=20)
plt.xlabel('Sentiment')
plt.ylabel('Count')
plt.legend(title='Gender')
plt.show()
```



# Sentiment Distribution by Gender



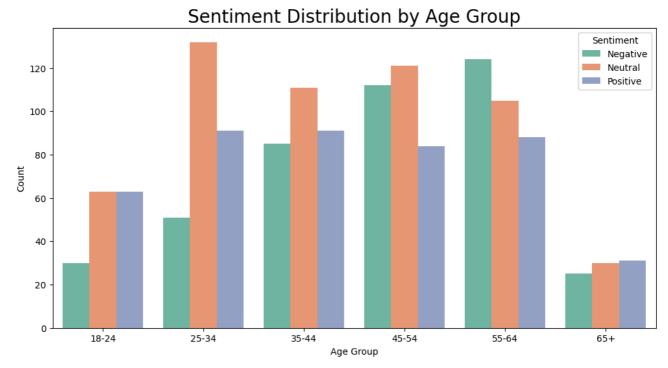
```
age_bins = [18, 25, 35, 45, 55, 65, 75]
age_labels = ['18-24', '25-34', '35-44', '45-54', '55-64', '65+']
data['AgeGroup'] = pd.cut(data['Age'], bins=age_bins, labels=age_labels)

plt.figure(figsize=(12, 6))
sns.countplot(x='AgeGroup', hue='Sentiment', data=data, palette='Set2')
plt.title('Sentiment Distribution by Age Group', fontsize=20)
plt.xlabel('Age Group')
plt.ylabel('Count')
```

plt.legend(title='Sentiment')

plt.show()





```
plt.figure(figsize=(12, 6))
sns.countplot(x='VisitFrequency', hue='Sentiment', data=data, palette='Set2')
plt.title('Sentiment Distribution by Visit Frequency', fontsize=20)
plt.xlabel('Visit Frequency')
plt.ylabel('Count')
plt.legend(title='Sentiment')
plt.show()
```