Importing Library

In [1]:
```python
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```python
import datetime as dt
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

import scipy.cluster.hierarchy as sch
from scipy.cluster.hierarchy import dendrogram, linkage

from sklearn.metrics import confusion_matrix, classification_report
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split
from sklearn.mixture import GaussianMixture
from sklearn.cluster import KMeans, AgglomerativeClustering, AffinityPropagation
from sklearn.svm import SVR

from yellowbrick.cluster import KElbowVisualizer
```

Loading Data

In [3]:
```python
data = pd.read_csv('data.csv', encoding='latin-1')
data.dropna()
data.head()
```

Out[3]:

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
0	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	12/1/2010 8:26	2.55	17850.0	United Kingdom
1	536365	71053	WHITE METAL LANTERN	6	12/1/2010 8:26	3.39	17850.0	United Kingdom
2	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	12/1/2010 8:26	2.75	17850.0	United Kingdom
3	536365	84029G	KNITTED UNION FLAG HOT WATER BOTTLE	6	12/1/2010 8:26	3.39	17850.0	United Kingdom
4	536365	84029E	RED WOOLLY HOTTIE WHITE HEART.	6	12/1/2010 8:26	3.39	17850.0	United Kingdom

In [4]:
```python
data.info()
```

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

In [5]:
```python
data['Revenue'] = data.apply(lambda i: i['Quantity'] * i['UnitPrice'], axis=1)
```

In [56]:
```python
data['InvoiceDate'] = pd.to_datetime(data['InvoiceDate'])
data['Month'] = data['InvoiceDate'].dt.month
data['Year'] = data['InvoiceDate'].dt.year
```

Exploring Data

To knew more about data, we need to answer the follwing questions:

1. What was the total revenue?
2. Which months had the higher sales?
3. What products are in the top 10 in sales and revenue?
4. Which products were returned more frequently?
5. What are the top 10 countries that purchased the most?
6. How much is the share of the revenue for each cluster?

Total revenue

In [7]:
```python
total_revenue = data['Revenue'].sum()
total_revenue
```

Out[7]:
```
9747747.933999998
```

Months` sales

In [8]:
```python
total_per_month = data.groupby(['Year','Month'])['Revenue'].sum()
```

In [9]:
```python
total_per_month.plot(kind='bar', color='#63b3c0',figsize=(8,5))
```

Out[9]:
```
<AxesSubplot:xlabel='Year,Month'>
```

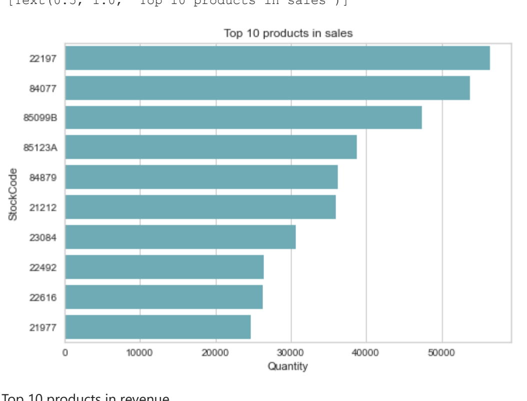
Products Sales

Top `n` products in sales

In [10]:
```python
most_popular_products = data[['StockCode','Description','Quantity','Revenue']].groupby('StockCode', as_index=Fa
```

In [11]:
```python
sns.barplot(x='Quantity', y='StockCode', data=most_popular_products.head(10), color='#63b3c0').set(title='Top 1
```

Out[11]:
```
[Text(0.5, 1.0, 'Top 10 products in sales')]
```

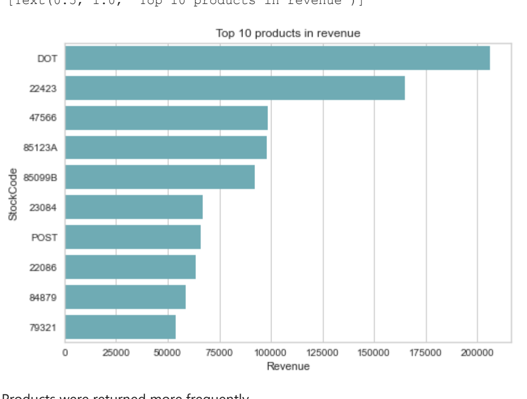


Top 10 products in revenue

In [12]:
```python
most_revenue = most_popular_products.sort_values(by='Revenue', ascending=False)
```

In [13]:
```python
sns.barplot(x='Revenue', y='StockCode', data=most_revenue.head(10), color='#63b3c0').set(title='Top 10 products
```

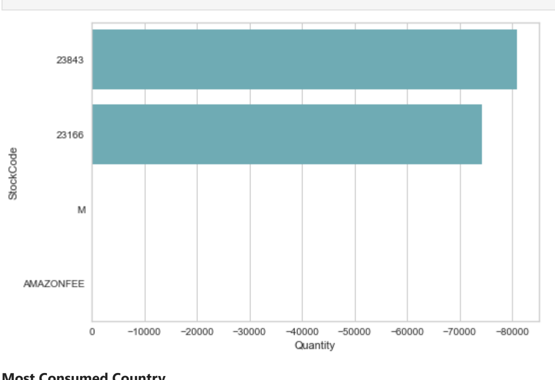
Out[13]:
```
[Text(0.5, 1.0, 'Top 10 products in revenue')]
```



Products were returned more frequently

In [14]:
```python
most_returned_products = data[
                                ['StockCode','Description','Quantity','Revenue']
                                ].loc[data['Revenue'] < 0].sort_values(by='Revenue', ascending=True)
```

In [15]:
```python
sns.barplot(x='Quantity',y='StockCode', data=most_returned_products.head(10), color='#63b3c0')
plt.gca().invert_xaxis()
```

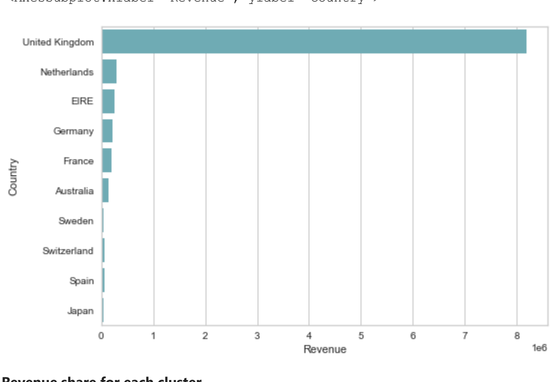


Most Consumed Country

In [16]:
```python
most_countries = data[['Country','Quantity','Revenue']].groupby(['Country'], as_index=False).sum().sort_values
```

In [17]:
```python
sns.barplot(y='Country', x='Revenue', data=most_countries.head(10), color='#63b3c0')
```

Out[17]:
```
<AxesSubplot:xlabel='Revenue', ylabel='Country'>
```



Revenue share for each cluster

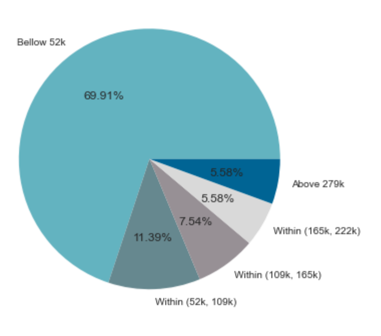
In [18]:
```python
customers = pd.DataFrame(data.groupby('CustomerID')['Revenue'].sum()).sort_values('Revenue', ascending=False)
```

In [19]:
```python
revenues = customers['Revenue']
minn = revenues.min()
maxx = revenues.max()
n = (maxx - minn) // 5
```

In [20]:
```python
g1 = customers[revenues < minn + n ]
g2 = customers[(revenues >= minn + n) & (revenues >= minn + 2*n)]
g3 = customers[(revenues >= minn + 2*n) & (revenues >= minn + 3*n)]
g4 = customers[(revenues >= minn + 3*n) & (revenues >= minn + 4*n)]
g5 = customers[(revenues >= minn + 4*n)]
```

In [21]:
```python
def custom_labels(b, inc, n):
  lst = []
  prepare_num = lambda number: int((b + number * inc) / 1000)
  for i in range(1, n):
    num = prepare_num(i)
    if i == 1:
      lst.append(f'Bellow {num}k')
    elif i == n-1:
      lst.append(f'Above {num}k')
    else:
      lst.append(f'Within ({prepare_num(i-1)}k, {num}k)')
  return lst
```

In [22]:
```python
labels = custom_labels(minn, n, 6)
sns.set_palette(sns.color_palette(['#63b3c0','#66888f','#979095','#d9d9d9', '#006494']))
plt.figure(figsize =(10, 6))
pie_data = [i['Revenue'].sum() for i in (g1, g2, g3, g4, g5)]
plt.pie(pie_data, labels = labels, autopct='%1.2f%%')
plt.show()
```



Correlation od data coulmns

Preparing Data

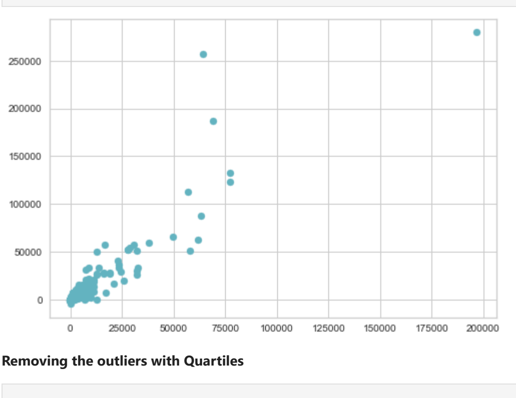
1. Setup the data with required columns
2. Removing the outliers
3. Correlation betwween the selected featuers
4. Split data into train set & test set
5. Scaling using minmax scaler

In [23]:
```python
customers = pd.DataFrame(data.groupby('CustomerID')['Revenue'].sum()).sort_values('Revenue', ascending=False)
customers['Purchases'] = data.groupby('CustomerID')['InvoiceNo'].count()
customers['Quantity'] = data.groupby('CustomerID')['Quantity'].sum()
customers['RevenuePercentage'] = customers.apply(lambda i: i['Revenue'] / total_revenue, axis=1)

subset = customers.copy()
subset.reset_index(inplace=True)
subset.head()
```

Out[23]:

	CustomerID	Revenue	Purchases	Quantity	RevenuePercentage
0	14646.0	279489.02	2085	196719	0.028672
1	18102.0	256438.49	433	64122	0.026307
2	17450.0	187482.17	351	69029	0.019233
3	14911.0	132572.62	5903	77180	0.013600
4	12415.0	123725.45	778	77242	0.012693

In [24]:
```python
plt.scatter(subset['Quantity'], subset['Revenue'])
plt.show()
```

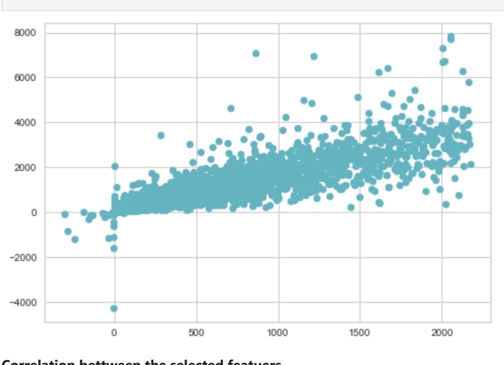


Removing the outliers with Quartiles

In [25]:
```python
Q1 = np.percentile(subset['Quantity'], 25, interpolation = 'midpoint')
Q3 = np.percentile(subset['Quantity'], 75, interpolation = 'midpoint')

IQR = Q3 - Q1
```

In [26]:
```python
upper = np.where(subset['Quantity'] >= (Q3 + 1.5*IQR))
lower = np.where(subset['Quantity'] <= (Q1 - 1.5*IQR))

subset.drop(upper[0], inplace = True)
subset.drop(lower[0], inplace = True)
```

In [27]:
```python
plt.scatter(subset['Quantity'], subset['Revenue'])
plt.show()
```

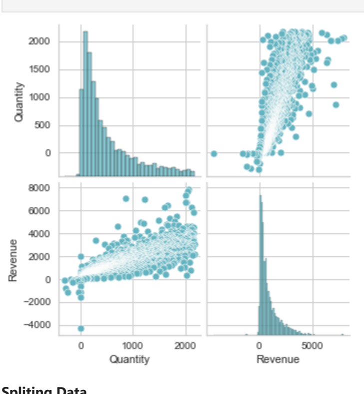


Correlation betwween the selected featuers

In [28]:
```python
subset['Quantity'].corr(subset['Revenue'])
```

Out[28]:
```
0.8664743082485633
```

In [29]:
```python
sns.pairplot(subset[['Quantity', 'Revenue']])
plt.show()
```



Spliting Data

In [30]:
```python
x = subset[['Revenue', 'Quantity']]
x_train, x_test = train_test_split(x, test_size=0.33, random_state=42)
```

Scaling using minmax scaler

In [31]:
```python
# Quantity
revenue_scaler = MinMaxScaler()
revenue_scaler.fit(x_train[['Revenue']])
x_train['RevenueScaled'] = revenue_scaler.transform(x_train[['Revenue']])
x_test['RevenueScaled'] = revenue_scaler.transform(x_test[['Revenue']])

# Revenue
quantity_scaler = MinMaxScaler()
quantity_scaler.fit(x_train[['Quantity']])
x_train['QuantityScaled'] = quantity_scaler.transform(x_train[['Quantity']])
x_test['QuantityScaled'] = quantity_scaler.transform(x_test[['Quantity']])
```

In [32]:
```python
x_train.head()
```

Out[32]:

	Revenue	Quantity	RevenueScaled	QuantityScaled
2621	465.68	305	0.396142	0.245657
2061	702.79	898	0.415903	0.485253
797	2166.38	1401	0.537879	0.688485
4150	101.34	106	0.365778	0.165253
3153	316.68	185	0.383724	0.197172

In [33]:
```python
x_test.head()
```

Out[33]:

	Revenue	Quantity	RevenueScaled	QuantityScaled
511	3102.42	1116	0.615888	0.573333
2173	653.13	261	0.411764	0.227879
4047	120.90	198	0.367408	0.202424
1119	1558.72	631	0.487236	0.377374
710	2398.86	1560	0.557253	0.752727

In [34]:
```python
train_points = x_train[['RevenueScaled', 'QuantityScaled']].to_numpy()
test_points = x_test[['RevenueScaled', 'QuantityScaled']].to_numpy()
```

KMeans clustering

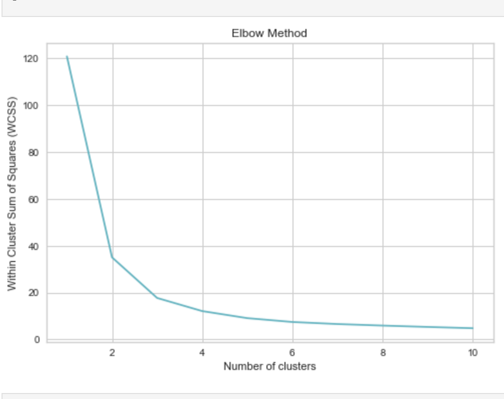
1. Determine optimal cluster number with Elbow method
2. Fiting KMeans Model
3. Plotting the Result

Determine optimal cluster number with Elbow method

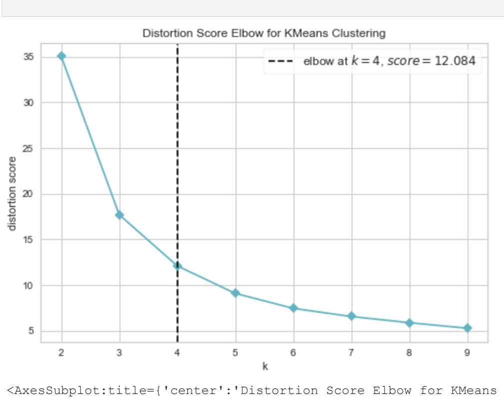
Given inertia formula:

$$\sum_{i=1}^{N}(x_i - C_k)^2$$

In [35]:
```python
WCSS = []

for i in range(1, 11):
    model = KMeans(n_clusters = i,
                   init = 'k-means++',                 # Initialization method for kmeans
                   max_iter = 300,                     # Maximum number of iterations
                   n_init = 10,                        # Choose how often algorithm will run with different ce
                   random_state = 0)                   # Choose random state for reproducibility
    model.fit(train_points)
    WCSS.append(model.inertia_)                        # Kmeans inertia_ :  Sum of squared distances of sample

plt.plot(range(1, 11), WCSS)
plt.title('Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('Within Cluster Sum of Squares (WCSS)')
plt.show()
```



In [36]:
```python
visualizer = KElbowVisualizer(KMeans(), k=(2, 10), timings=False)
visualizer.fit(train_points)
visualizer.show()
```



Out[36]:
```
<AxesSubplot:title={'center':'Distortion Score Elbow for KMeans Clustering'}, xlabel='k', ylabel='distortion sc
ore'>
```

Fiting KMeans Model

Given the formula

number of clusters   number of cases   case i centroid for cluster j

$$\text{objective function} \leftarrow J = \sum_{j=1}^{k}\sum_{i=1}^{n}\underbrace{\left\|x_i^{(j)} - c_j\right\|^2}_{\text{Distance function}}$$

In [37]:
```python
K = 4
KMeansModel = KMeans(n_clusters=K, init='k-means++', random_state=0)
KMeansModel.fit(train_points)
```

Out[37]:
```
KMeans
KMeans(n_clusters=4, random_state=0)
```

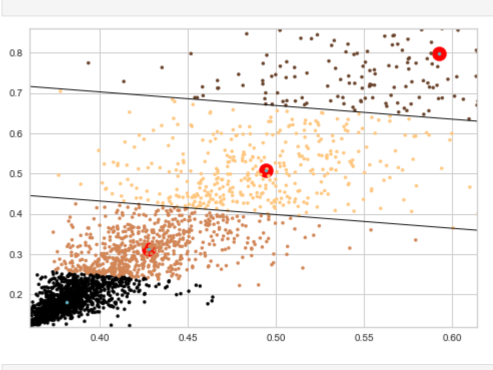
In [38]:
```python
kmeans_predicted = KMeansModel.predict(test_points)
```

In [39]:
```python
centers = KMeansModel.cluster_centers_
centers
```

Out[39]:
```
array([[0.38145145, 0.18101653],
       [0.59256913, 0.79888929],
       [0.42772828, 0.31293894],
       [0.49420702, 0.50918886]])
```

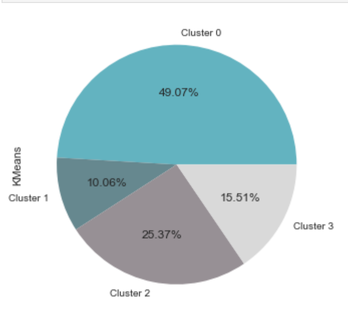
In [40]:
```python
f, (ax1, ax2) = plt.subplots(1, 2, sharey=True, figsize=(20, 6))

ax1.set_title('Train Data')
ax1.scatter(train_points[:, 0], train_points[:, 1], c=KMeansModel.labels_, cmap='Set2')
ax1.scatter(centers[:, 0], centers[:, 1], c='red')

ax2.set_title('Test Data')
ax2.scatter(test_points[:, 0], test_points[:, 1], c=kmeans_predicted, cmap='Set2')
ax2.scatter(centers[:, 0], centers[:, 1], c='red')

plt.xlabel('Total Qunatity')
plt.ylabel('Total Revenue')
plt.show()
```

In [41]:
```python
from scipy.spatial import Voronoi, voronoi_plot_2d

vor = Voronoi(centers)
voronoi_plot_2d(vor)
plt.scatter(centers[:, 0],centers[:, 1], s=200, c='red')
plt.scatter(train_points[:, 0], train_points[:, 1], c=KMeansModel.labels_,  s=10, cmap='copper')
plt.show()
```



In [42]:
```python
kmeans_points = pd.DataFrame(
    x_train['QuantityScaled'].append(x_test['QuantityScaled']),
    columns=['QuantityScaled',]
    )
kmeans_points['RevenueyScaled'] = x_train['QuantityScaled'].append(x_test['QuantityScaled'])
kmeans_points['KMeans'] = np.concatenate((KMeansModel.labels_, kmeans_predicted))
```

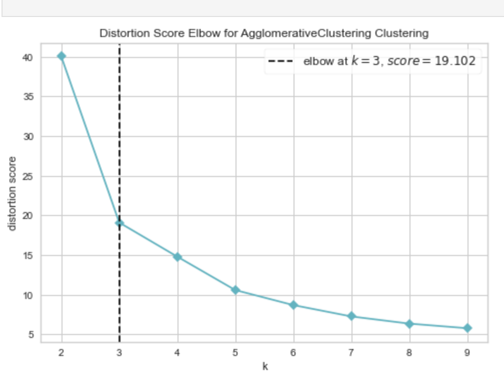
In [43]:
```python
kmeans_points.groupby('KMeans')['KMeans'].count().plot.pie(labels=[f'Cluster {i}' for i in range(K)], autopct='
plt.show()
```



Agglomerative Clustering

1. Determine optimal cluster number with Elbow method
2. Fiting Agglomerative Model Model
3. Plotting the result

In [57]:
```python
visualizer = KElbowVisualizer(AgglomerativeClustering(), k=(2, 10), timings=False)
visualizer.fit(train_points)
visualizer.show()
```



Out[57]:
```
<AxesSubplot:title={'center':'Distortion Score Elbow for AgglomerativeClustering Clustering'}, xlabel='k', ylab
el='distortion score'>
```

In [58]:
```python
K = 3
AggModel_train = AgglomerativeClustering(n_clusters=K, affinity = 'euclidean', linkage = 'ward', compute_distar
AggModel_train.fit(train_points)
```

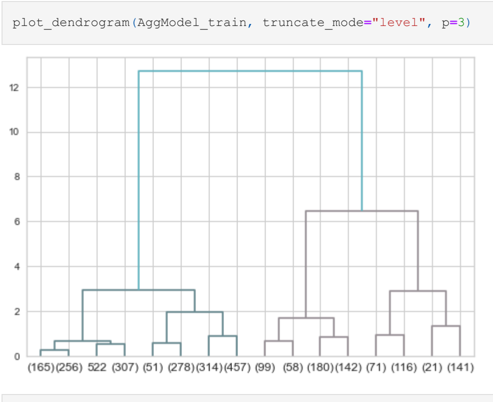
Out[58]:
```
AgglomerativeClustering
AgglomerativeClustering(compute_distances=True, n_clusters=3)
```

In [59]:
```python
plt.scatter(train_points[:, 0], train_points[:, 1], c=AggModel_train.labels_, cmap='Set2')
plt.title('Train Data')
plt.xlabel('Total Qunatity')
plt.ylabel('Total Revenue')
plt.show()
```

The following function is quoted form official site

In [60]:
```python
def plot_dendrogram(model, **kwargs):
    # Create linkage matrix and then plot the dendrogram

    # create the counts of samples under each node
    counts = np.zeros(model.children_.shape[0])
    n_samples = len(model.labels_)
    for i, merge in enumerate(model.children_):
        current_count = 0
        for child_idx in merge:
            if child_idx < n_samples:
                current_count += 1  # leaf node
            else:
                current_count += counts[child_idx - n_samples]
        counts[i] = current_count

    linkage_matrix = np.column_stack(
        [model.children_, model.distances_, counts]
    ).astype(float)

    # Plot the corresponding dendrogram
    dendrogram(linkage_matrix, **kwargs)
    plt.show()
```

In [61]:
```python
plot_dendrogram(AggModel_train, truncate_mode="level", p=3)
```



In [62]:
```python
visualizer_test = KElbowVisualizer(AgglomerativeClustering(), k=(2, 10), timings=False)
visualizer_test.fit(test_points)
visualizer_test.show()
```

Out[62]: <AxesSubplot:title={'center':'Distortion Score Elbow for AgglomerativeClustering Clustering'}, xlabel='k', ylab el='distortion score'>

In [63]:
```
K = 4
AggModel_test = AgglomerativeClustering(n_clusters=K, affinity = 'euclidean', linkage = 'ward', compute_distanc
AggModel_test.fit(test_points)
```

Out[63]:
```
AgglomerativeClustering
AgglomerativeClustering(compute_distances=True, n_clusters=4)
```

In [64]:
```
plt.scatter(test_points[:, 0], test_points[:, 1], c=AggModel_test.labels_, cmap='Set2')
plt.title('Train Data')
plt.xlabel('Total Qunatity')
plt.ylabel('Total Revenue')
plt.show()
```

In [52]:
```
plot_dendrogram(AggModel_test, truncate_mode="level", p=4)
```


Evaluate Kmeans

In [53]:
```
from sklearn.metrics.cluster import (adjusted_mutual_info_score, normalized_mutual_info_score, adjusted_rand_sc
    contingency_matrix, expected_mutual_information, homogeneity_completeness_v_measure, homogeneity_score, mut
    fowlkes_mallows_score, entropy, silhouette_samples, silhouette_score, calinski_harabasz_score, davies_bould

print("The Completeness score is %0.12f" % completeness_score(x_test['QuantityScaled'], kmeans_predicted))
print("Random score is %0.12f " % rand_score(x_test['QuantityScaled'], kmeans_predicted))
print("The normalized Mutual info score is %0.12f" %normalized_mutual_info_score( x_test['QuantityScaled'],kmea
```

```
The Completeness score is 0.990829231077
Random score is 0.674134374350
The normalized Mutual info score is 0.317479196890
```

In [65]:
```
from sklearn.metrics.cluster import contingency_matrix
kmean_con = contingency_matrix(x_test['RevenueScaled'], kmeans_predicted)
sns.heatmap(kmean_con)
plt.show()
```


Refrences

link 1

link 2

link 3

link 4

link 5

link 6