## Importing Required Libraries

In [78]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn import preprocessing
from sklearn.cluster import KMeans
from pandas.plotting import parallel_coordinates
from sklearn.metrics import silhouette_samples, silhouette_score
from scipy.cluster.hierarchy import linkage, dendrogram
from sklearn.neighbors import NearestNeighbors
from sklearn import cluster
from sklearn import metrics
```

Loading the dataset into a variable

In [2]:
```
customer = pd.read_csv('Wholesale customers data.csv')
customer.head()
```

Out[2]:

| | Channel | Region | Fresh | Milk | Grocery | Frozen | Detergents_Paper | Delicassen |
|---|---|---|---|---|---|---|---|---|
| **0** | 2 | 3 | 12669 | 9656 | 7561 | 214 | 2674 | 1338 |
| **1** | 2 | 3 | 7057 | 9810 | 9568 | 1762 | 3293 | 1776 |
| **2** | 2 | 3 | 6353 | 8808 | 7684 | 2405 | 3516 | 7844 |
| **3** | 1 | 3 | 13265 | 1196 | 4221 | 6404 | 507 | 1788 |
| **4** | 2 | 3 | 22615 | 5410 | 7198 | 3915 | 1777 | 5185 |

The data set refers to clients of a wholesale distributor. It includes the annual spending in monetary units (m.u.) on diverse product categories. Let's explore the wholesale customers data

### Data Preprocessing

In [3]:
```
customer.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 440 entries, 0 to 439
Data columns (total 8 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   Channel           440 non-null    int64
 1   Region            440 non-null    int64
 2   Fresh             440 non-null    int64
 3   Milk              440 non-null    int64
 4   Grocery           440 non-null    int64
 5   Frozen            440 non-null    int64
 6   Detergents_Paper  440 non-null    int64
 7   Delicassen        440 non-null    int64
dtypes: int64(8)
memory usage: 27.6 KB
```

The data contains 8 attributes with 440 rows, all of integer data type.

In [4]:
```
customer.isnull().sum()
```

Out[4]:
```
Channel             0
Region              0
Fresh               0
Milk                0
Grocery             0
Frozen              0
Detergents_Paper    0
Delicassen          0
dtype: int64
```

There are no null values is our data!

In [5]:
```
customer.duplicated().sum()
```

Out[5]:
```
0
```

There are no duplicates in the data!

Let's see the summary statistics for wholesale customer data

```
In [6]: customer.describe()
```

Out[6]:

| | Channel | Region | Fresh | Milk | Grocery | Frozen | Deterg |
|---|---|---|---|---|---|---|---|
| **count** | 440.000000 | 440.000000 | 440.000000 | 440.000000 | 440.000000 | 440.000000 | |
| **mean** | 1.322727 | 2.543182 | 12000.297727 | 5796.265909 | 7951.277273 | 3071.931818 | 2 |
| **std** | 0.468052 | 0.774272 | 12647.328865 | 7380.377175 | 9503.162829 | 4854.673333 | 4 |
| **min** | 1.000000 | 1.000000 | 3.000000 | 55.000000 | 3.000000 | 25.000000 | |
| **25%** | 1.000000 | 2.000000 | 3127.750000 | 1533.000000 | 2153.000000 | 742.250000 | |
| **50%** | 1.000000 | 3.000000 | 8504.000000 | 3627.000000 | 4755.500000 | 1526.000000 | |
| **75%** | 2.000000 | 3.000000 | 16933.750000 | 7190.250000 | 10655.750000 | 3554.250000 | 3 |
| **max** | 2.000000 | 3.000000 | 112151.000000 | 73498.000000 | 92780.000000 | 60869.000000 | 40 |

We can observe that attributes have high variability

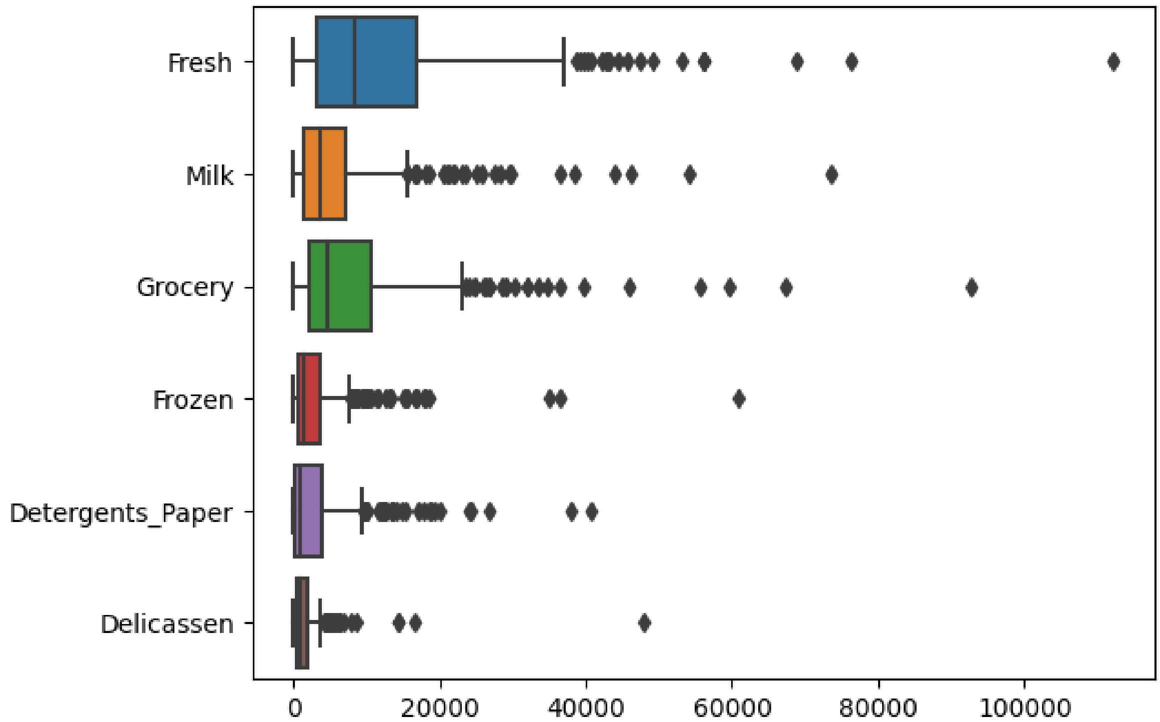
Let's remove the channel and region columns from our data for better analysis of numerical values only.

```
In [7]: customer = customer.drop('Channel', axis=1)
        customer = customer.drop('Region', axis=1)
```

Let's visualize our data using box plot and histogram to learn the distribution of data

In [8]:
```
sns.boxplot(data = customer, orient = 'h')
```

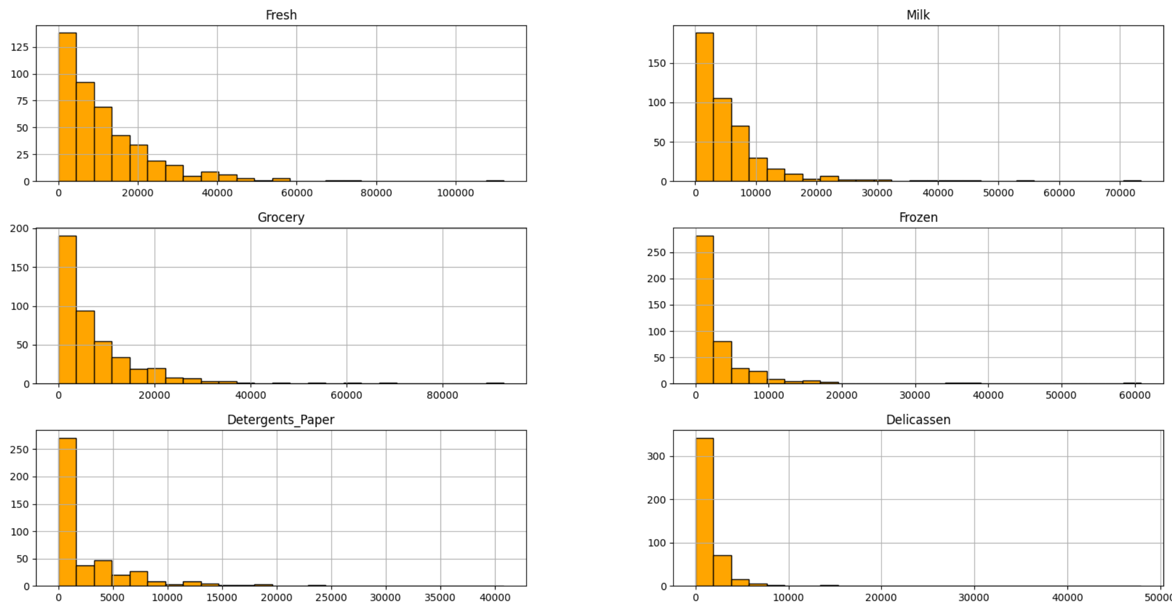
Out[8]: <Axes: >




Let's check the distribution of attributes

In [9]:
```python
customer.hist(figsize = (20,10), bins = 25, color='orange', edgecolor='black')
```

Out[9]:
```
array([[<Axes: title={'center': 'Fresh'}>,
        <Axes: title={'center': 'Milk'}>],
       [<Axes: title={'center': 'Grocery'}>,
        <Axes: title={'center': 'Frozen'}>],
       [<Axes: title={'center': 'Detergents_Paper'}>,
        <Axes: title={'center': 'Delicassen'}>]], dtype=object)
```



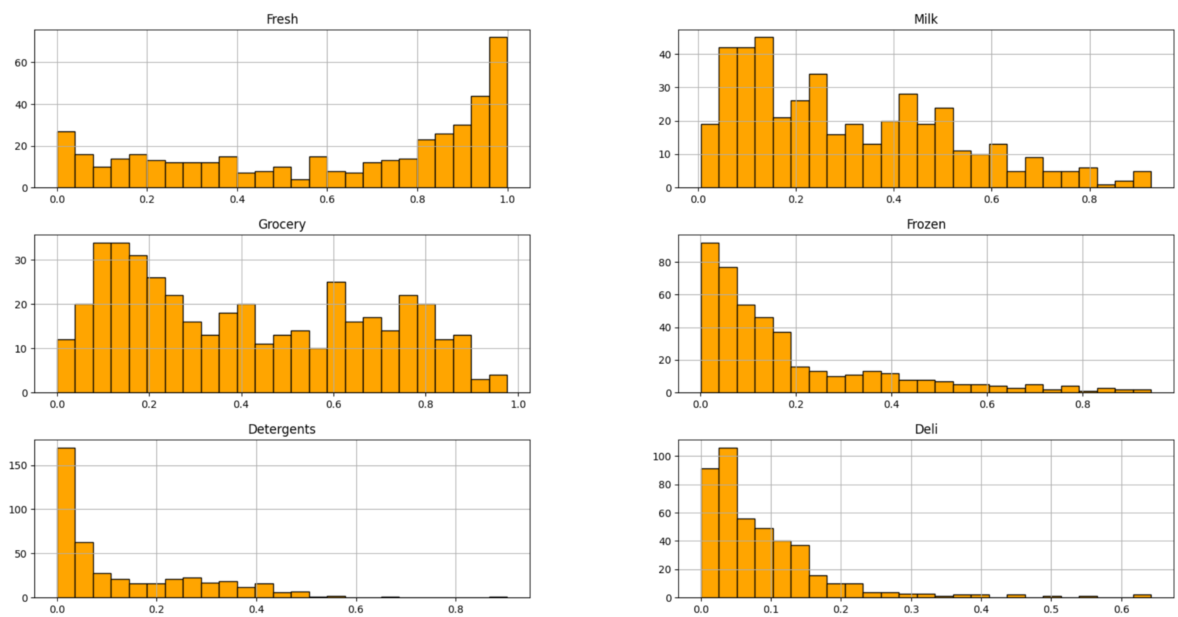

From the histogram we can observe that the data is not normally distributed. Thus, we will normalize the wholesale customers data.

We will use sci-kit learn library to normalize the data.

In [10]:
```
cust_norm = preprocessing.normalize(customer)
cust_norm = pd.DataFrame(cust_norm)
cust_norm.rename(columns = {0:'Fresh',1:'Milk',2:'Grocery',3:'Frozen',4:'Deter
cust_norm.info()
cust_norm.hist(figsize = (20,10), bins = 25, color='orange', edgecolor='black'
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 440 entries, 0 to 439
Data columns (total 6 columns):
 #   Column      Non-Null Count  Dtype  
---  ------      --------------  -----  
 0   Fresh       440 non-null    float64
 1   Milk        440 non-null    float64
 2   Grocery     440 non-null    float64
 3   Frozen      440 non-null    float64
 4   Detergents  440 non-null    float64
 5   Deli        440 non-null    float64
dtypes: float64(6)
memory usage: 20.8 KB
```

Out[10]:
```
array([[<Axes: title={'center': 'Fresh'}>,
        <Axes: title={'center': 'Milk'}>],
       [<Axes: title={'center': 'Grocery'}>,
        <Axes: title={'center': 'Frozen'}>],
       [<Axes: title={'center': 'Detergents'}>,
        <Axes: title={'center': 'Deli'}>]], dtype=object)
```




This doesn't look like a normal distribution but its an improvement from what we had before. We have completed the preprocessing steps. Now let's apply the K-means clustering algorithm

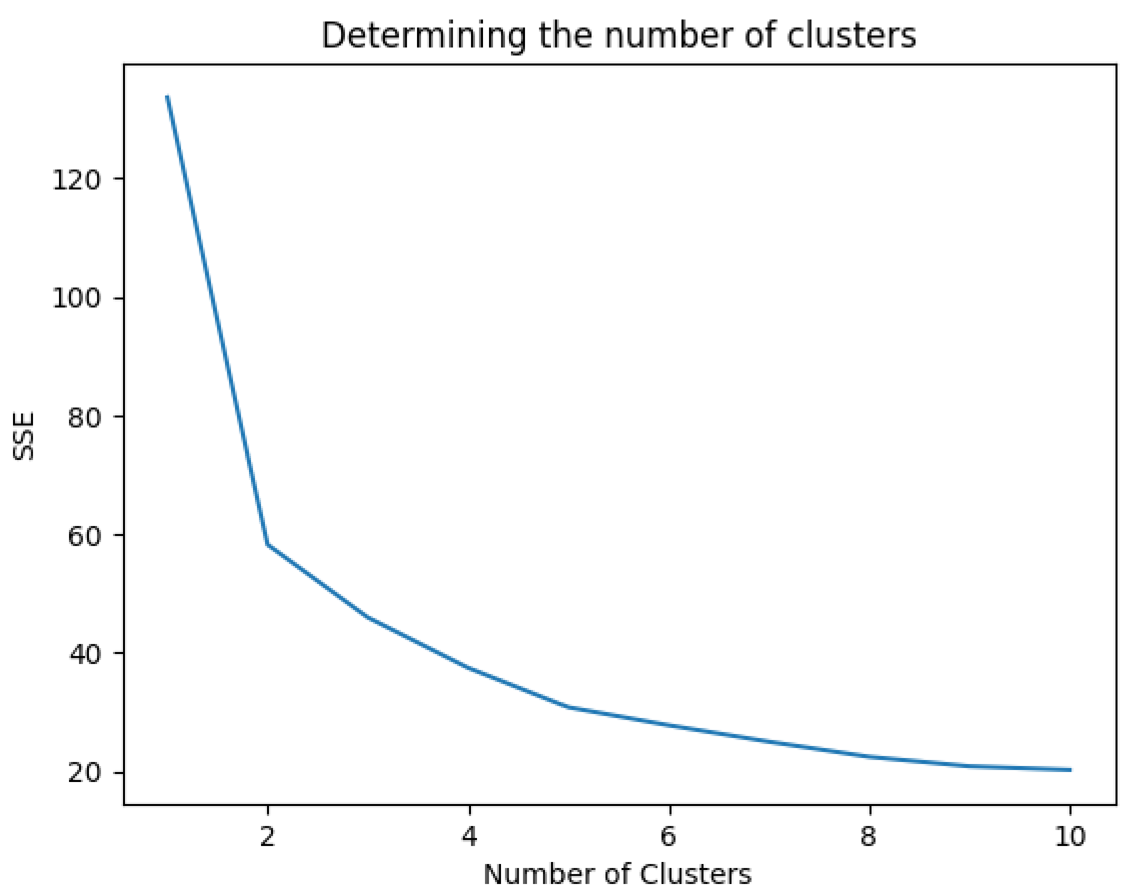
## K-means Clustering

We will apply kmeans clustering from sci-kit learn library. We will apply the number of clusters ranging from 1 to 10 and then select the most appropriate number of clusters using the elbow method

In [11]:
```
SSE = []
clusters = [1,2,3,4,5,6,7,8,9,10]
for k in clusters:
    kmeans = KMeans(n_clusters = k, n_init='auto')
    kmeans.fit(cust_norm)
    SSE.append(kmeans.inertia_)

plt.plot(clusters, SSE)
plt.xlabel('Number of Clusters')
plt.ylabel('SSE')
plt.title('Determining the number of clusters')
```

Out[11]:
```
Text(0.5, 1.0, 'Determining the number of clusters')
```




Looking at the elbow plot, we can see that 2 number of clusters seems to be the ideal choice for this dataset. So let's fit the algorithm again for 2 clusters.

In [12]:
```
kmeans1 = KMeans(n_clusters=2, n_init='auto')
customer_kmeans = kmeans1.fit_predict(cust_norm)
```

Now, let's obtain the labels from our model and check if every data point has been assigned a label or not

In [13]:
```
len(cust_norm) == len(kmeans1.labels_)
```

Out[13]:
```
True
```

We have labels for every record. Now let's concat labels field to our data and rename the columns

In [14]:
```
labels = pd.DataFrame(kmeans1.labels_)
labels.rename(columns = {0:'label'}, inplace = True)
data = pd.concat([cust_norm, labels], axis=1)
```

In [15]:
```
data.head()
```

Out[15]:

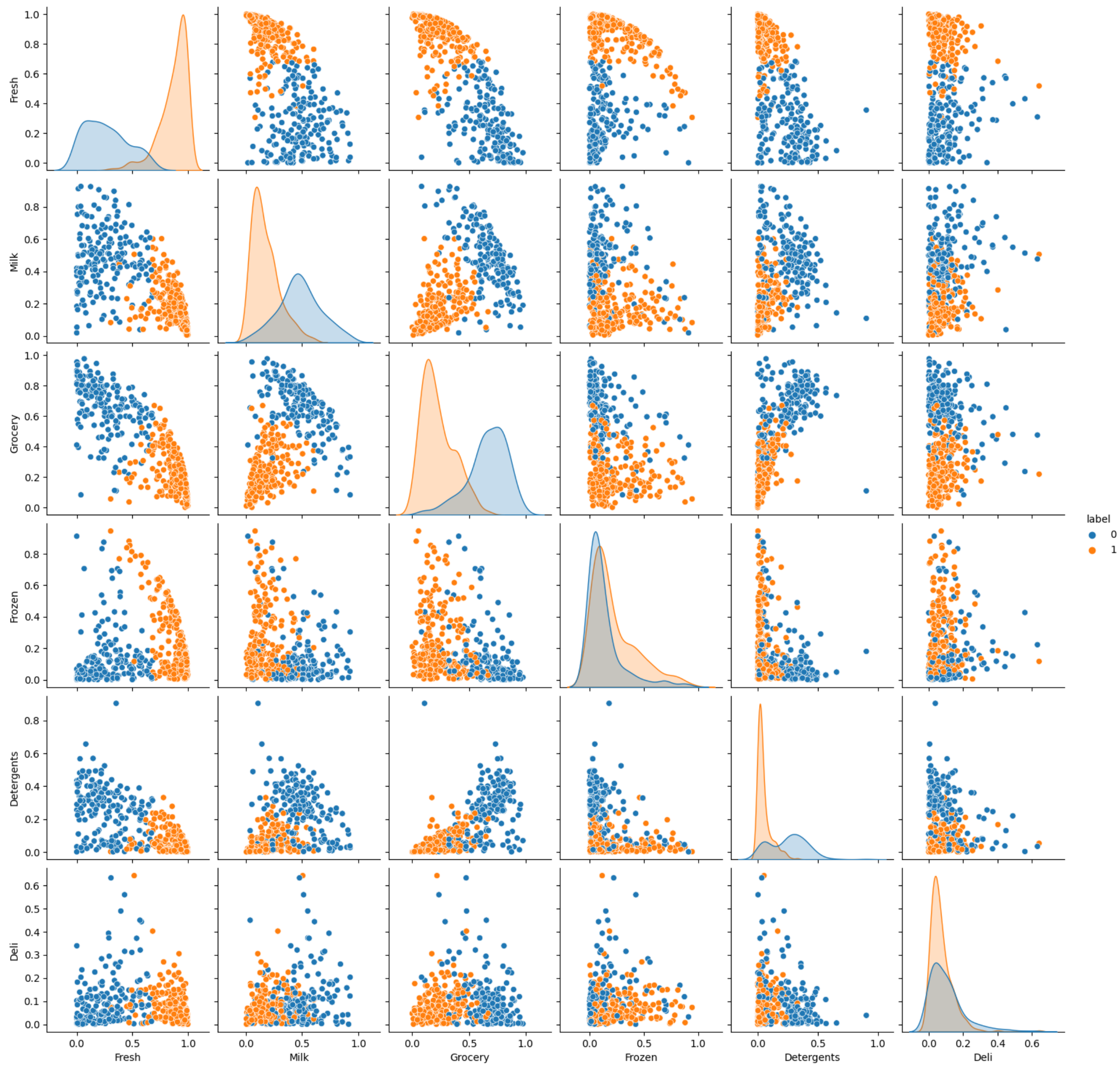
| | Fresh | Milk | Grocery | Frozen | Detergents | Deli | label |
|---|---|---|---|---|---|---|---|
| **0** | 0.708333 | 0.539874 | 0.422741 | 0.011965 | 0.149505 | 0.074809 | 1 |
| **1** | 0.442198 | 0.614704 | 0.599540 | 0.110409 | 0.206342 | 0.111286 | 0 |
| **2** | 0.396552 | 0.549792 | 0.479632 | 0.150119 | 0.219467 | 0.489619 | 0 |
| **3** | 0.856837 | 0.077254 | 0.272650 | 0.413659 | 0.032749 | 0.115494 | 1 |
| **4** | 0.895416 | 0.214203 | 0.284997 | 0.155010 | 0.070358 | 0.205294 | 1 |

## Visualizing Clusters

Finally, let's visualize our clustering model using scatterplots

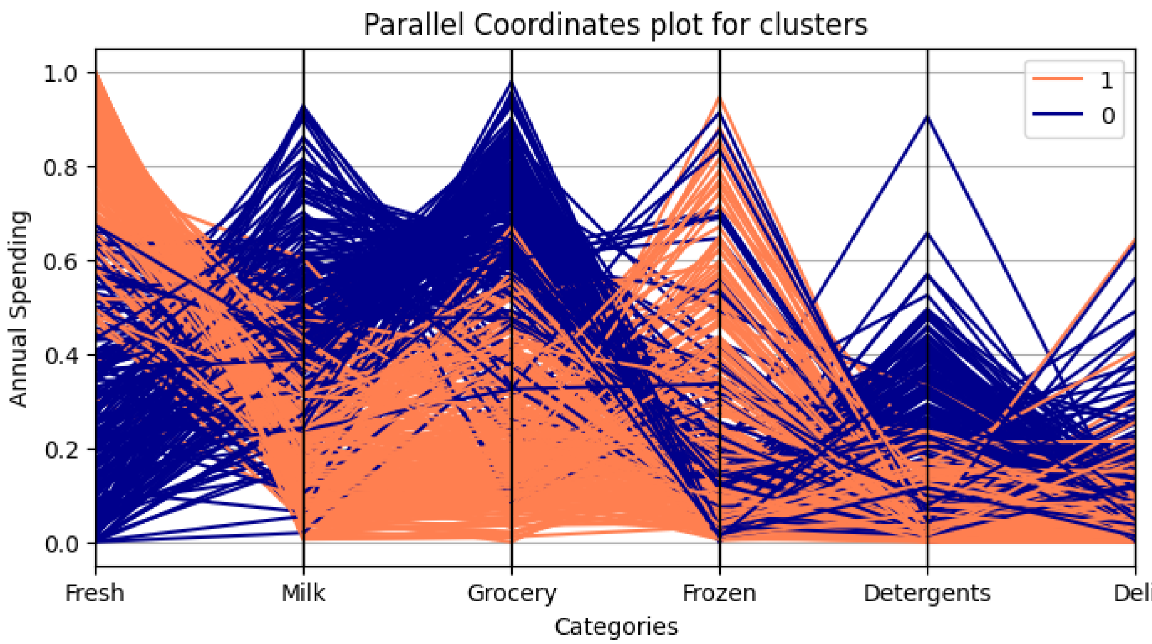
```
In [16]: sns.pairplot(data, hue = 'label')
```

```
Out[16]: <seaborn.axisgrid.PairGrid at 0x1e326451950>
```




This is bit difficult to interpret, let's plot a parallel coordinates plot for the clusters to obtain better understanding of results.

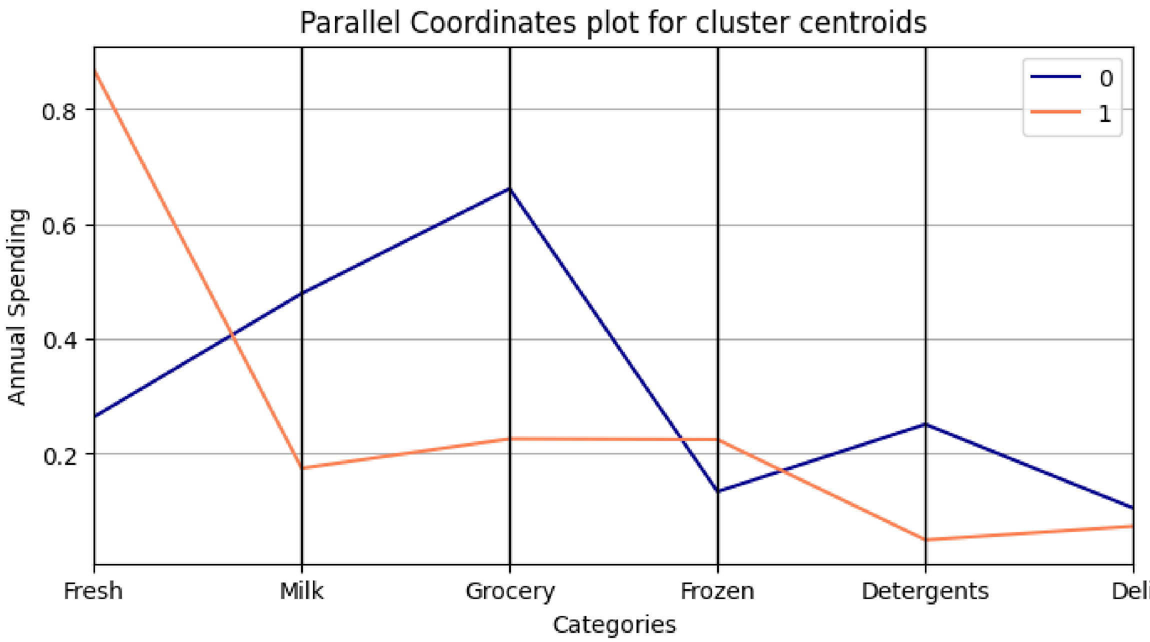
In [17]:
```
plt.figure(figsize=(8,4))
parallel_coordinates(data, 'label', color=('coral','darkblue'))
plt.title('Parallel Coordinates plot for clusters')
plt.ylabel('Annual Spending')
plt.xlabel('Categories')
plt.show()
```




We will also plot the parallel coordinates plot for the centroids of the clustering result.

In [18]:
```
# Create a dataframe containing centroids value from clustering output
centroids = pd.DataFrame(kmeans1.cluster_centers_, columns = data.columns[0:6]
centroids['cluster'] = centroids.index
```

In [109]:
```
plt.figure(figsize=(8,4))
parallel_coordinates(centroids, 'cluster', color=('darkblue','coral'))
plt.title('Parallel Coordinates plot for cluster centroids')
plt.ylabel('Annual Spending')
plt.xlabel('Categories')
plt.show()
```




## Silhouette Analysis

In [20]:
```
n_clusters = [2,3,4,5,6,7,8,9,10]
for k in n_clusters:
    sil_kmeans = KMeans(n_clusters = k, n_init='auto')
    cluster_labels = sil_kmeans.fit_predict(cust_norm)

    #The silhouette score gives the average value for all the samples
    sil_avg = silhouette_score(cust_norm,cluster_labels)
    print("For n_cluster =",k,"The average silhouette score is: ",sil_avg)
```

```
For n_cluster = 2 The average silhouette score is:  0.5002248259665941
For n_cluster = 3 The average silhouette score is:  0.4365632328906848
For n_cluster = 4 The average silhouette score is:  0.3798290278483874
For n_cluster = 5 The average silhouette score is:  0.3747453809922325
For n_cluster = 6 The average silhouette score is:  0.3643696320545916
For n_cluster = 7 The average silhouette score is:  0.3195688089575444
For n_cluster = 8 The average silhouette score is:  0.3329818912816675
For n_cluster = 9 The average silhouette score is:  0.2680799795960205
For n_cluster = 10 The average silhouette score is:  0.3141539002326934
```

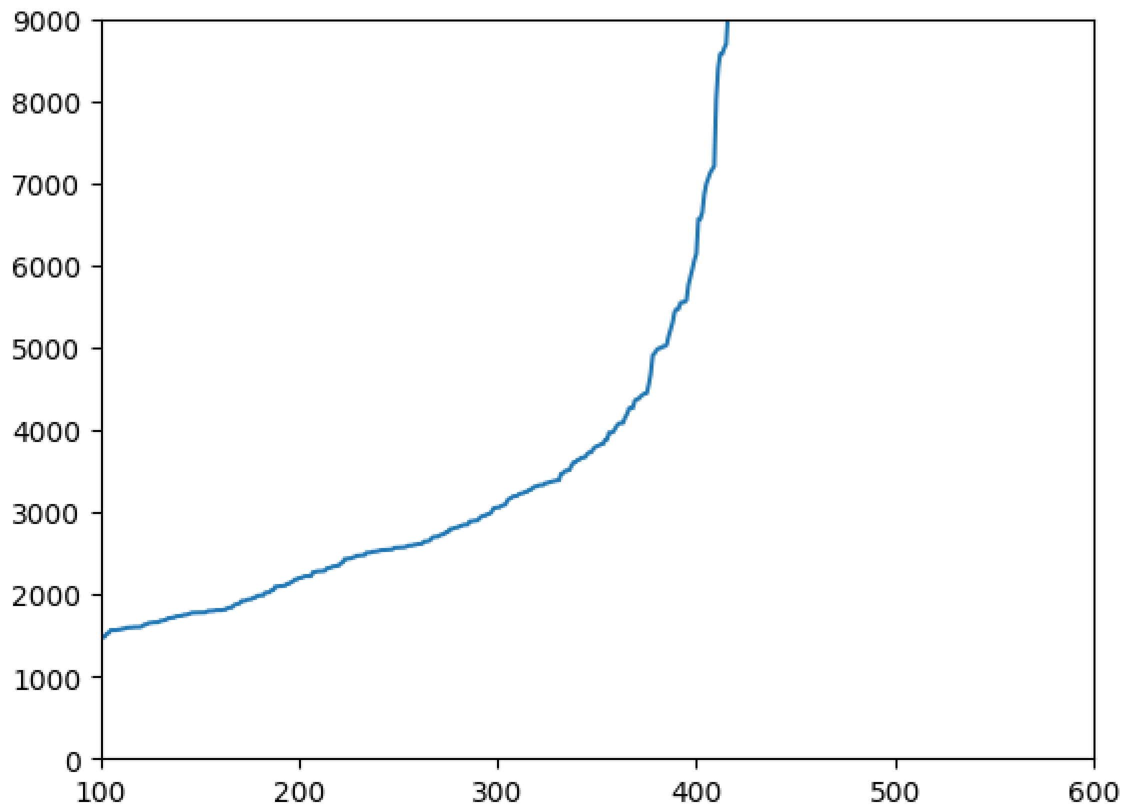
Thus, the highest silhouette score is obtained for n_clusters = 2.

## DBSCAN

Let's pick min_samples = 20 and We will determine the eps value using knn

In [110]:
```
neighbors = NearestNeighbors(n_neighbors=20)
neighbors_fit = neighbors.fit(customer)
distances, indices = neighbors_fit.kneighbors(customer) #will find k neighbors
```

In [111]:
```
distances = np.sort(distances, axis=0)
distances = distances[:,1]
plt.plot(distances)
plt.ylim(0,9000)
plt.xlim(100,600)
plt.show()
```

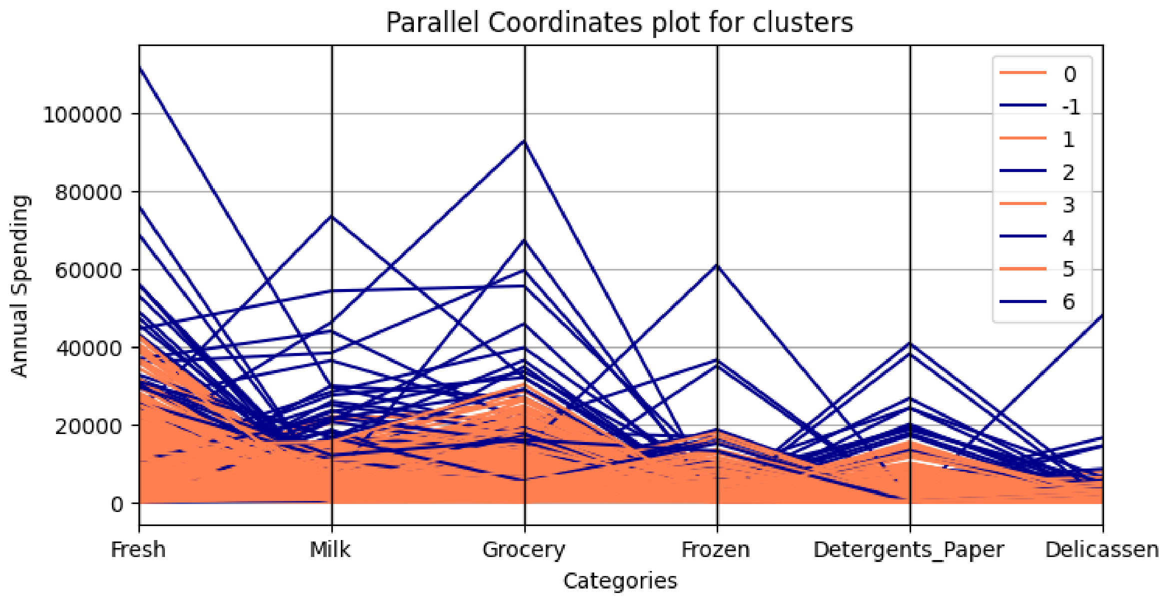



We determine for minimum 20 samples in a cluster the eps value to be 5000

In [112]:
```
dbscan = cluster.DBSCAN(eps=6000, min_samples=2)
clustering_labels = dbscan.fit_predict(customer.to_numpy())
```

In [113]:
```
customer['db_label'] = clustering_labels
```

In [114]:
```
plt.figure(figsize=(8,4))
parallel_coordinates(customer, 'db_label', color=('coral','darkblue'))
plt.title('Parallel Coordinates plot for clusters')
plt.ylabel('Annual Spending')
plt.xlabel('Categories')
plt.show()
```




In [115]:
```
metrics.silhouette_score(customer, customer['db_label'])
```

Out[115]: 0.14647081024822362

In [ ]: