clustering_titanic

November 11, 2025

[41]:
```python
import math
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler, MinMaxScaler
from scipy.cluster.hierarchy import linkage, dendrogram, fcluster
import seaborn as sns
from scipy.spatial.distance import pdist, squareform
```

[42]:
```python
df = pd.read_csv("data/titanic.csv")
df.head()
```

[42]:
```
   PassengerId  Survived  Pclass  \
0            1         0       3
1            2         1       1
2            3         1       3
3            4         1       1
4            5         0       3

                                                Name     Sex   Age  SibSp  \
0                            Braund, Mr. Owen Harris    male  22.0      1
1  Cumings, Mrs. John Bradley (Florence Briggs Th…  female  38.0      1
2                             Heikkinen, Miss. Laina  female  26.0      0
3       Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0      1
4                           Allen, Mr. William Henry    male  35.0      0

   Parch            Ticket     Fare Cabin Embarked
0      0         A/5 21171   7.2500   NaN        S
1      0          PC 17599  71.2833   C85        C
2      0  STON/O2. 3101282   7.9250   NaN        S
3      0            113803  53.1000  C123        S
4      0            373450   8.0500   NaN        S
```

0.0.1 Preprocessing

[43]:
```
#from google.colab import drive
#drive.mount('/content/drive')
```

Fill missing values and convert to numerical (where possible)

[44]:
```
sexes = sorted(df['Sex'].unique())
sexes_mapping = dict(zip(sexes, range(0, len(sexes) + 1)))
df['Sex_Val'] = df['Sex'].map(sexes_mapping).astype(int)
```

[45]:
```
df['Embarked'] = df['Embarked'].fillna(df['Embarked'].mode()[0])
embarked_locs = sorted(df['Embarked'].unique())
embarked_locs_mapping = dict(zip(embarked_locs, range(0, len(embarked_locs) +␣
↪1)))
df['Embarked_Val'] = df['Embarked'].map(embarked_locs_mapping).astype(int)
```

[46]:
```
df['AgeFill'] = df.groupby(['Sex', 'Pclass'])['Age'].transform(lambda x: x.
↪fillna(x.median()))
```

[47]:
```
df['FamilySize'] = df['SibSp'] + df['Parch']
```

[48]:
```
df.head()
```

[48]:
```
   PassengerId  Survived  Pclass  \
0            1         0       3
1            2         1       1
2            3         1       3
3            4         1       1
4            5         0       3

                                                Name     Sex   Age  SibSp  \
0                            Braund, Mr. Owen Harris    male  22.0      1
1  Cumings, Mrs. John Bradley (Florence Briggs Th…  female  38.0      1
2                             Heikkinen, Miss. Laina  female  26.0      0
3       Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0      1
4                           Allen, Mr. William Henry    male  35.0      0

   Parch            Ticket     Fare Cabin Embarked  Sex_Val  Embarked_Val  \
0      0         A/5 21171   7.2500   NaN        S        1             2
1      0          PC 17599  71.2833   C85        C        0             0
2      0  STON/O2. 3101282   7.9250   NaN        S        0             2
3      0            113803  53.1000  C123        S        0             2
4      0            373450   8.0500   NaN        S        1             2

   AgeFill  FamilySize
0     22.0           1
1     38.0           1
```

```
2      26.0           0
3      35.0           1
4      35.0           0
```

Check categorical variables

[49]:
```
df.dtypes[df.dtypes.map(lambda x: x == 'object')]
```

[49]:
```
Name        object
Sex         object
Ticket      object
Cabin       object
Embarked    object
dtype: object
```

[50]:
```
df_train = df.drop(['Name', 'Sex', 'Ticket', 'Cabin', 'Embarked'], axis=1)
df_train.drop(['Survived', 'Age', 'SibSp', 'Parch', 'PassengerId',␣
 ↪'Embarked_Val', 'Sex_Val'], axis=1, inplace=True)
df_train.dtypes
```

[50]:
```
Pclass           int64
Fare           float64
AgeFill        float64
FamilySize       int64
dtype: object
```

[51]:
```
df_train.head()
```

[51]:
```
   Pclass     Fare  AgeFill  FamilySize
0       3   7.2500     22.0           1
1       1  71.2833     38.0           1
2       3   7.9250     26.0           0
3       1  53.1000     35.0           1
4       3   8.0500     35.0           0
```

[52]:
```
scaler = MinMaxScaler()
train_data = scaler.fit_transform(df_train)
```

0.0.2 Clustering

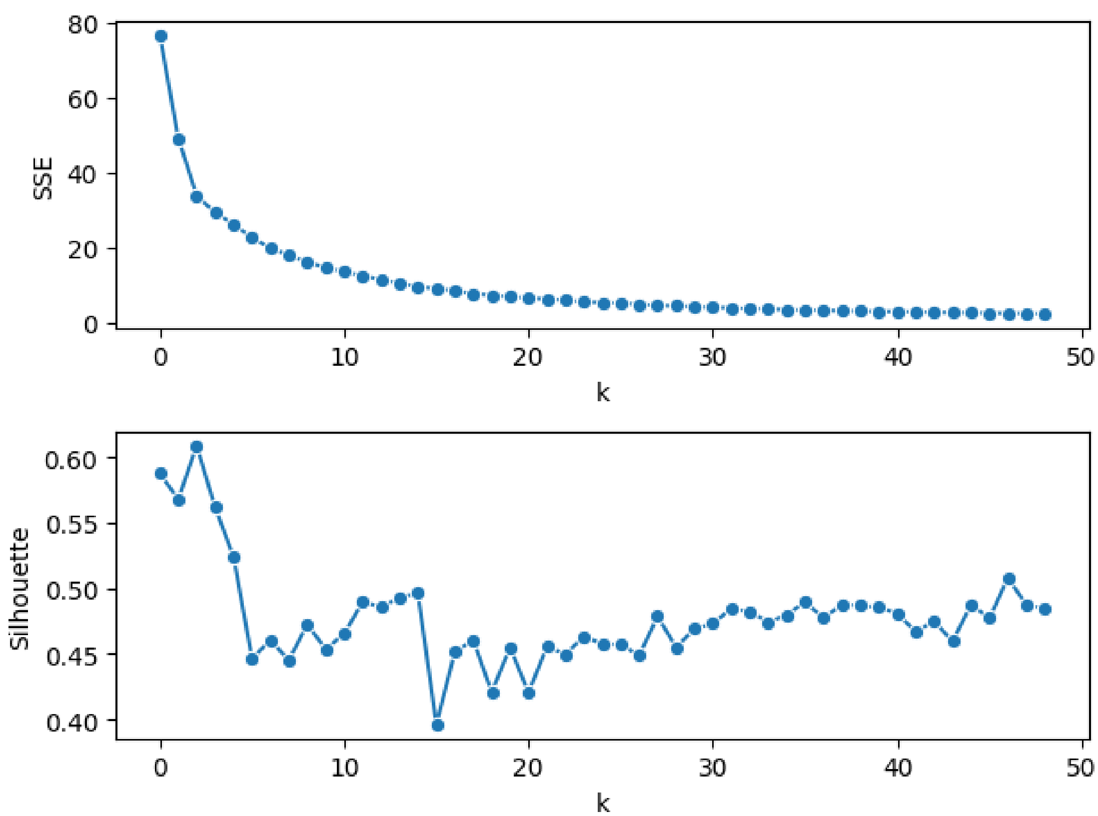
[53]:
```
from sklearn.metrics import *
from sklearn.cluster import KMeans, DBSCAN, AgglomerativeClustering
from sklearn.neighbors import kneighbors_graph
```

[17]:
```
%%time
sse_list = []
sil_list = []
```

```
for k in range(2, 51):
    kmeans = KMeans(init='k-means++', n_clusters=k, n_init=10, max_iter=100)
    kmeans.fit(train_data)
    sse_list.append(kmeans.inertia_)
    sil_list.append(silhouette_score(train_data, kmeans.labels_))
```

```
CPU times: user 9.45 s, sys: 44.5 ms, total: 9.5 s
Wall time: 5.31 s
```

[18]:
```
fig, axs = plt.subplots(2) # 1 row, 2 columns

sns.lineplot(x=range(len(sse_list)), y=sse_list, marker='o', ax=axs[0])
axs[0].set(xlabel='k', ylabel='SSE')
sns.lineplot(x=range(len(sil_list)), y=sil_list, marker='o', ax=axs[1])
axs[1].set(xlabel='k', ylabel='Silhouette')

plt.tight_layout() # Adjust the padding between and around subplots
```



[22]:
```
kmeans = KMeans(init='k-means++', n_clusters=5, n_init=10, max_iter=100)
kmeans.fit(train_data)
```

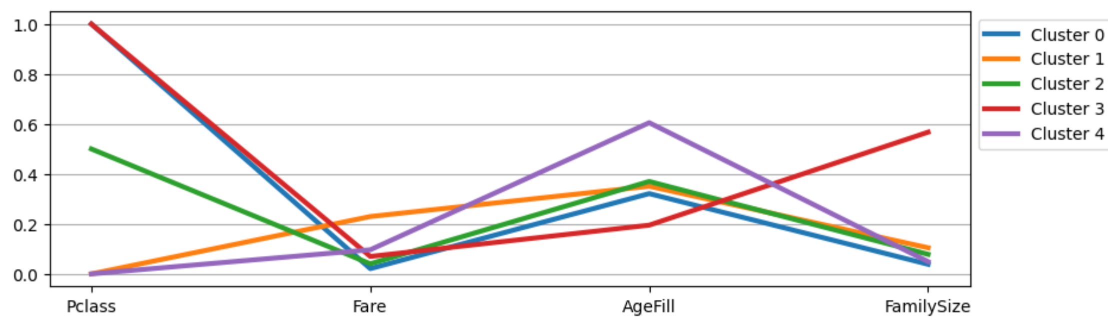
[22]: KMeans(max_iter=100, n_clusters=5, n_init=10)

[23]:
```
print('labels', np.unique(kmeans.labels_, return_counts=True))
print('sse', kmeans.inertia_)
print('silhouette', silhouette_score(train_data, kmeans.labels_))
```

```
labels (array([0, 1, 2, 3, 4], dtype=int32), array([433, 109, 184,  58, 107]))
sse 29.169946054563958
silhouette 0.5614640538880703
```

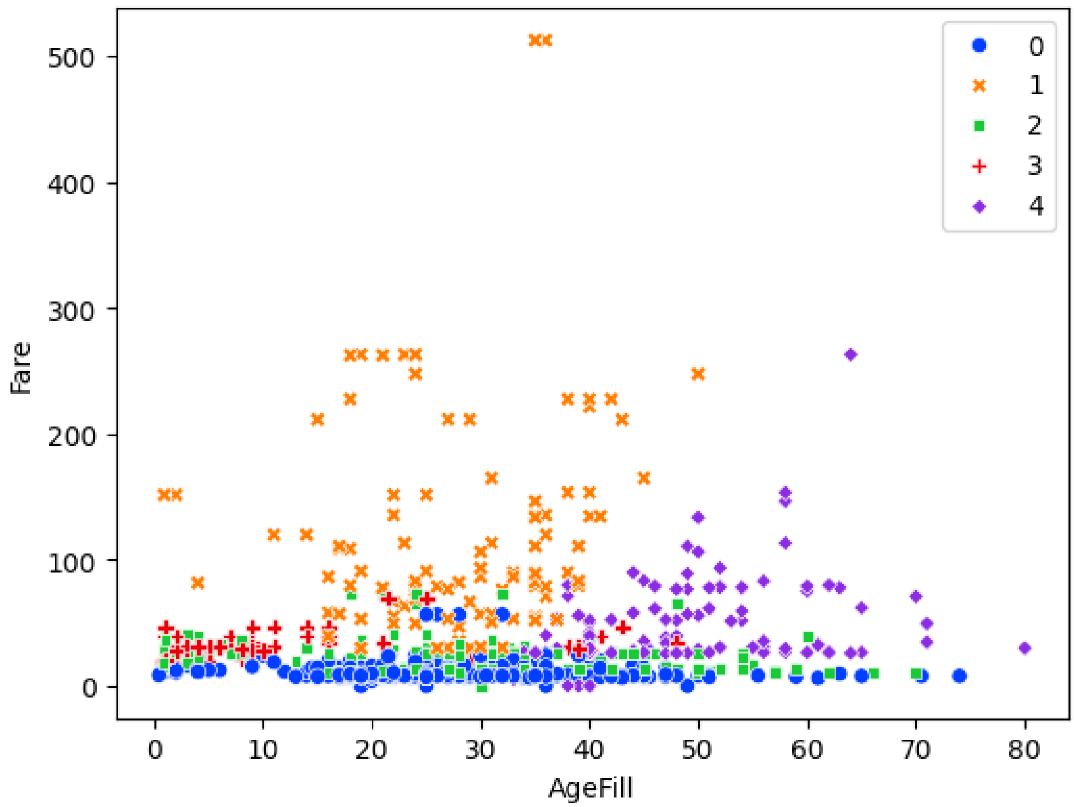
[23]:
```

```

[24]:
```
plt.figure(figsize=(10, 3))

for i in range(len(kmeans.cluster_centers_)):
    plt.plot(range(0, 4), kmeans.cluster_centers_[i], label='Cluster %s' % i,␣
 ↪linewidth=3)
plt.xticks(range(0, 4), list(df_train.columns))
plt.legend(bbox_to_anchor=(1,1))
plt.grid(axis='y')
plt.show()
```



[25]:
```
df_clusters = df_train.copy()
df_clusters['Labels'] = kmeans.labels_
```

[26]:
```
sns.scatterplot(data=df_clusters,
                x="AgeFill",
                y="Fare",
                hue=kmeans.labels_,
                style=kmeans.labels_,
                palette="bright")
plt.show()
```



[27]:
```
df_clusters.head()
```

[27]:

	Pclass	Fare	AgeFill	FamilySize	Labels
0	3	7.2500	22.0	1	0
1	1	71.2833	38.0	1	4
2	3	7.9250	26.0	0	0
3	1	53.1000	35.0	1	1
4	3	8.0500	35.0	0	0

[28]:
```
pclass_xt = pd.crosstab(df_clusters['Pclass'], df_clusters['Labels'])
pclass_xt
```

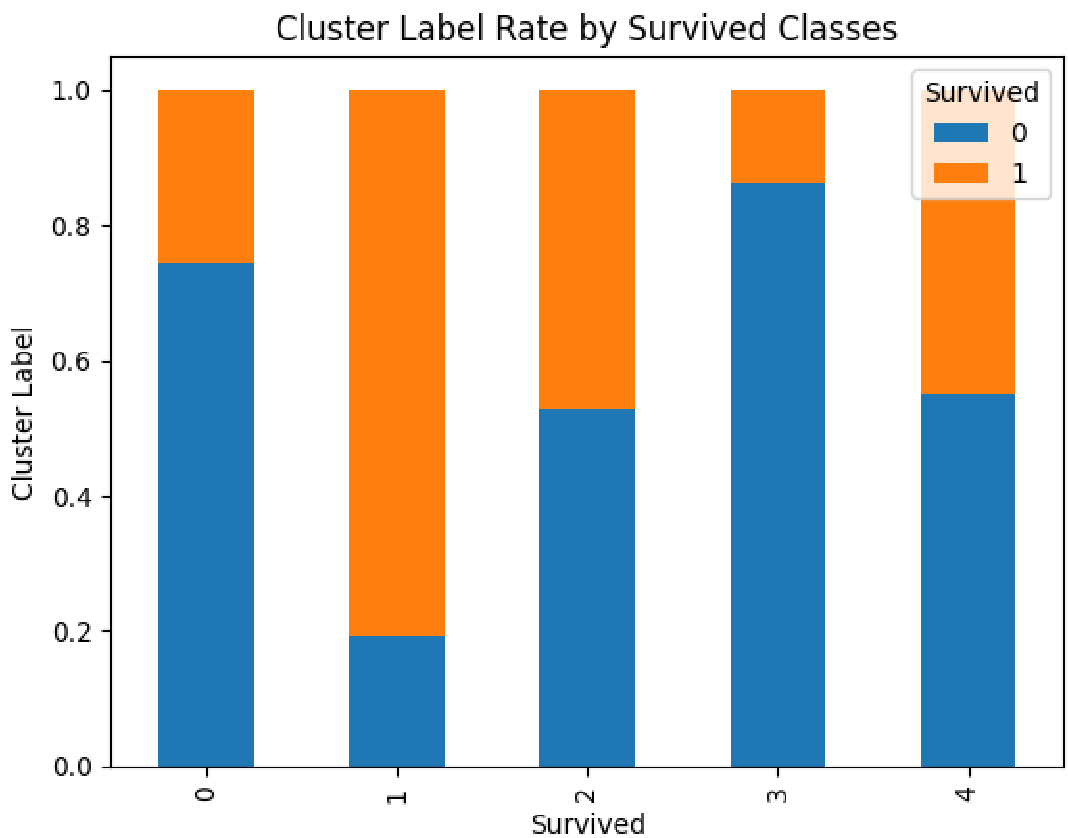
[28]:

Labels	0	1	2	3	4
Pclass					
1	0	109	0	0	107
2	0	0	184	0	0
3	433	0	0	58	0

[29]:
```
psurv_xt = pd.crosstab(df_clusters['Labels'], df['Survived'])
psurv_xt
```

[29]:
```
Survived    0    1
Labels
0         322  111
1          21   88
2          97   87
3          50    8
4          59   48
```

[30]:
```
psurv_xt_pct = psurv_xt.div(psurv_xt.sum(1).astype(float), axis=0)
psurv_xt_pct.plot(kind='bar', stacked=True, title='Cluster Label Rate by␣
 ↪Survived Classes')
plt.xlabel('Survived')
plt.ylabel('Cluster Label')
plt.show()
```

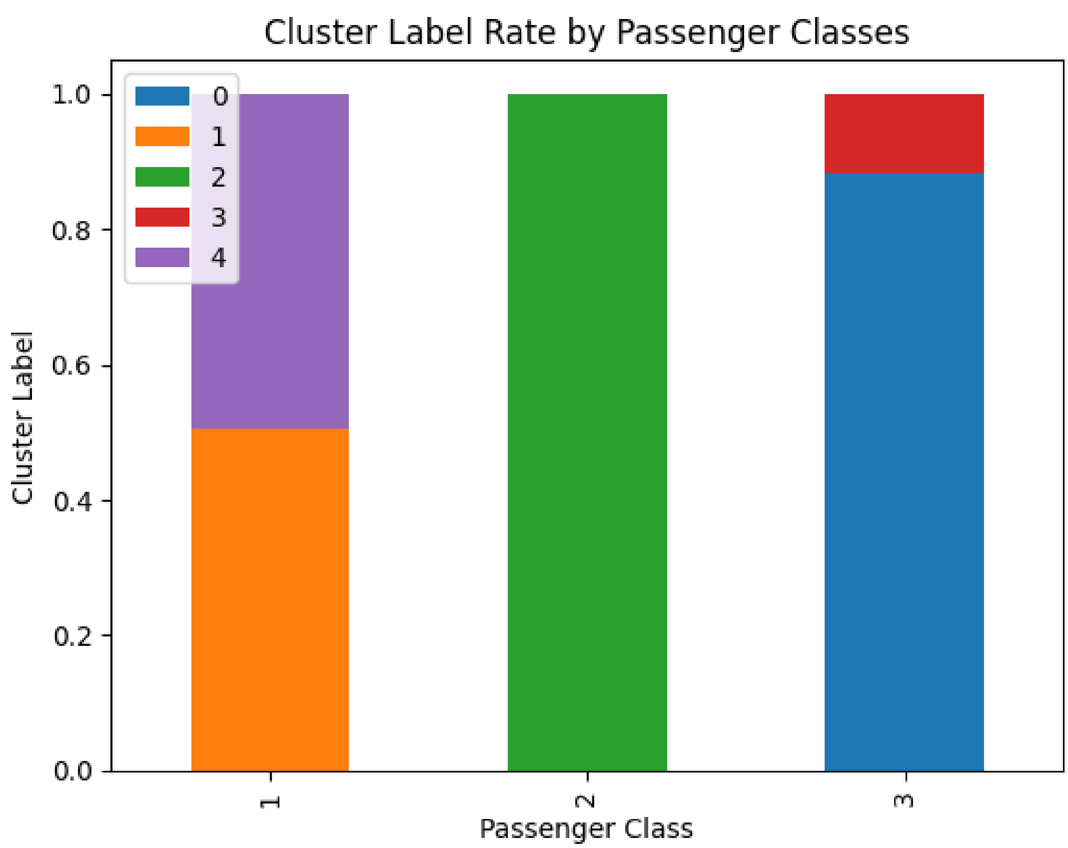


[31]:
```
df_clusters[df_clusters['Labels']==1].describe()
```

[31]:
```
       Pclass        Fare     AgeFill  FamilySize  Labels
count   109.0  109.000000  109.000000  109.000000   109.0
mean      1.0  118.044533   28.256147    1.045872     1.0
```

std	0.0	92.682510	9.034489	1.173672	0.0
min	1.0	26.283300	0.920000	0.000000	1.0
25%	1.0	56.929200	22.000000	0.000000	1.0
50%	1.0	86.500000	29.000000	1.000000	1.0
75%	1.0	146.520800	35.000000	1.000000	1.0
max	1.0	512.329200	50.000000	5.000000	1.0

[32]:
```
pclass_xt_pct = pclass_xt.div(pclass_xt.sum(1).astype(float), axis=0)
pclass_xt_pct.plot(kind='bar', stacked=True, title='Cluster Label Rate by␣
↪Passenger Classes')
plt.xlabel('Passenger Class')
plt.ylabel('Cluster Label')
plt.legend(loc='best')
plt.show()
```

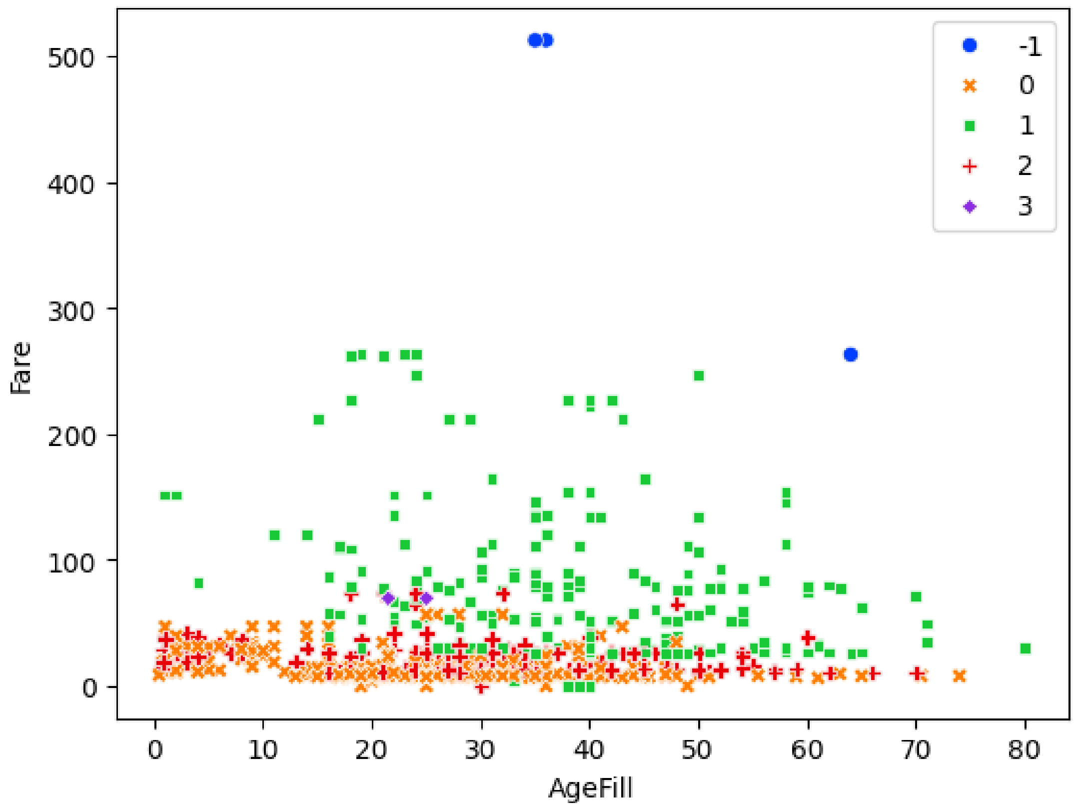


0.0.3 DBScan

[34]:
```
# density based clustering
print('dbscan')

dbscan = DBSCAN(eps=0.3, min_samples=5, metric='euclidean')
dbscan.fit(train_data)

hist, bins = np.histogram(dbscan.labels_, bins=range(-1, len(set(dbscan.
 ↪labels_)) + 1))
print('labels', dict(zip(bins, hist)))
print('silhouette', silhouette_score(train_data[dbscan.labels_ != -1], dbscan.
 ↪labels_[dbscan.labels_ != -1]))
```

```
dbscan
labels {np.int64(-1): np.int64(4), np.int64(0): np.int64(484), np.int64(1):
np.int64(212), np.int64(2): np.int64(184), np.int64(3): np.int64(7),
np.int64(4): np.int64(0)}
silhouette 0.5728928528267885
```

[35]:
```
sns.scatterplot(data=df_clusters,
                x="AgeFill",
                y="Fare",
                hue=dbscan.labels_,
                style=dbscan.labels_,
                palette="bright")
plt.show()
```



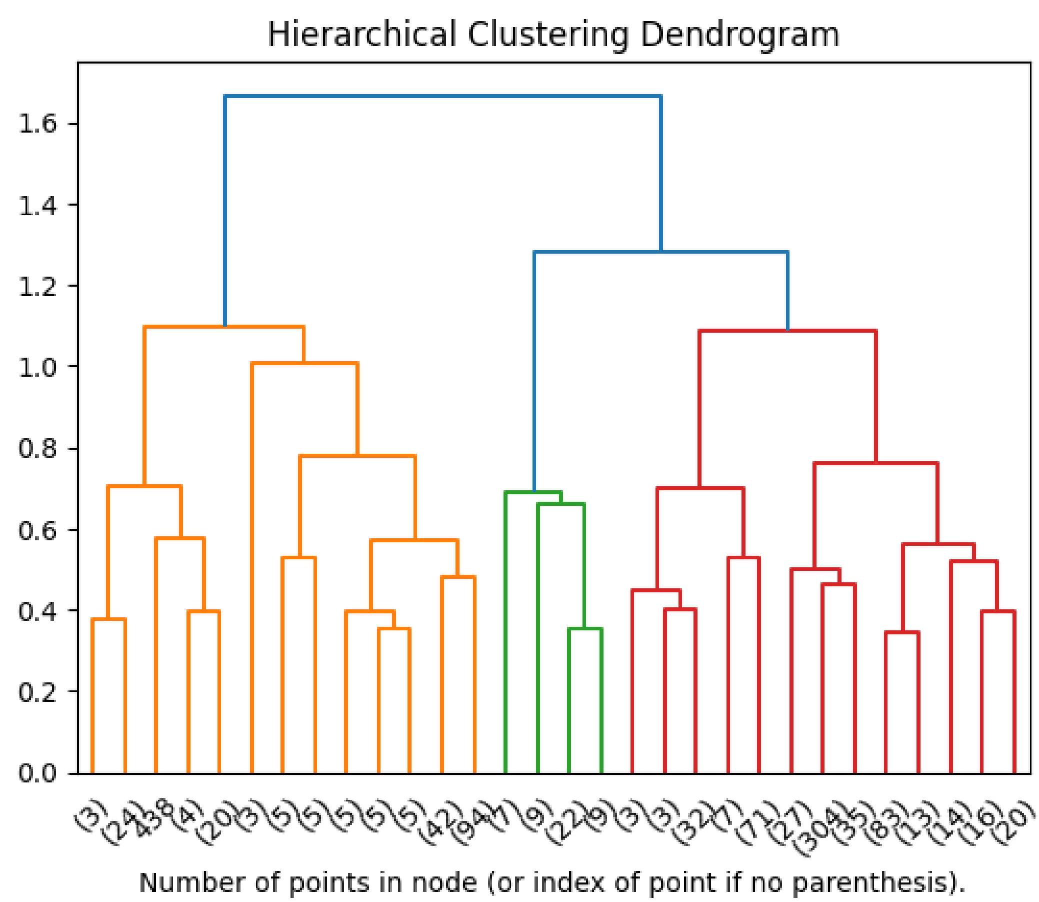
0.0.4 Hierarchical

[36]:
```
def get_linkage_matrix(model):
    # Create linkage matrix

    # 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)
```

```
    return linkage_matrix

def plot_dendrogram(model, **kwargs):
    linkage_matrix = get_linkage_matrix(model)
    dendrogram(linkage_matrix, **kwargs)
```

[37]:
```
# setting distance_threshold=0 ensures we compute the full tree.
model = AgglomerativeClustering(distance_threshold=0, n_clusters=None,␣
↪metric='euclidean', linkage='complete')
model = model.fit(train_data)
```

[38]:
```
plt.title("Hierarchical Clustering Dendrogram")
plot_dendrogram(model, truncate_mode="lastp", color_threshold=1.2)
plt.xlabel("Number of points in node (or index of point if no parenthesis).")
plt.show()
```



[39]:
```
# get the labels according to a specific threshold value cut
Z = get_linkage_matrix(model)
```

```python
labels = fcluster(Z, t=1.2, criterion='distance')
```

[40]:
```python
labels
```

[40]:
```
array([3, 1, 3, 1, 3, 3, 1, 2, 3, 3, 3, 1, 3, 2, 3, 3, 2, 3, 3, 3, 3, 3,
       3, 1, 2, 2, 3, 1, 3, 3, 1, 1, 3, 3, 1, 1, 3, 3, 3, 3, 3, 3, 3, 3,
       3, 3, 3, 3, 3, 3, 2, 3, 1, 3, 1, 1, 3, 3, 3, 2, 3, 1, 1, 2, 1, 3,
       3, 3, 2, 3, 3, 2, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 1, 3, 3, 3, 3,
       1, 3, 3, 3, 1, 3, 3, 3, 1, 1, 3, 3, 3, 3, 1, 3, 3, 3, 3, 3, 3, 3,
       1, 3, 3, 3, 3, 3, 3, 3, 1, 2, 3, 3, 3, 3, 1, 3, 3, 3, 3, 3, 3, 3,
       3, 3, 3, 3, 1, 1, 3, 1, 3, 3, 3, 3, 3, 3, 3, 2, 3, 3, 3, 1, 3, 3,
       3, 1, 3, 3, 3, 2, 3, 3, 3, 3, 2, 3, 1, 2, 1, 3, 1, 2, 3, 3, 1, 3,
       3, 1, 3, 3, 2, 3, 2, 3, 3, 1, 3, 1, 3, 3, 3, 3, 3, 3, 1, 1, 3, 3,
       3, 3, 3, 2, 3, 3, 3, 3, 3, 3, 3, 1, 3, 3, 3, 3, 3, 1, 3, 3, 1, 3,
       3, 3, 3, 3, 1, 3, 3, 3, 3, 3, 1, 3, 3, 2, 3, 3, 3, 3, 3, 3, 3, 3,
       3, 3, 3, 1, 3, 3, 1, 3, 3, 3, 1, 3, 3, 3, 1, 1, 1, 3, 3, 2, 1, 1,
       3, 3, 2, 3, 1, 1, 1, 3, 3, 1, 3, 1, 3, 3, 2, 3, 3, 3, 3, 3, 1, 3,
       3, 3, 3, 3, 1, 1, 3, 3, 3, 1, 3, 1, 1, 1, 3, 3, 3, 3, 3, 1, 1, 1,
       3, 1, 1, 1, 3, 3, 3, 3, 3, 3, 1, 1, 3, 3, 3, 3, 2, 1, 3, 3, 3, 1,
       3, 1, 1, 3, 1, 3, 1, 1, 3, 1, 3, 1, 3, 3, 3, 3, 3, 3, 3, 3, 3, 1,
       3, 3, 3, 3, 1, 3, 3, 3, 2, 3, 3, 3, 3, 3, 1, 3, 3, 1, 1, 3, 3, 1,
       2, 1, 3, 1, 3, 3, 1, 3, 3, 1, 3, 3, 2, 3, 3, 3, 1, 3, 3, 1, 3, 3,
       3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 1, 3, 3, 3, 3, 3,
       3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 1, 3, 3, 3, 1, 1, 3, 3, 1, 3,
       3, 3, 3, 3, 3, 1, 3, 1, 3, 1, 3, 3, 1, 1, 3, 3, 1, 1, 3, 3, 1, 3,
       1, 3, 3, 3, 3, 1, 3, 3, 3, 3, 3, 3, 3, 1, 3, 3, 3, 3, 2, 3, 3, 3,
       1, 3, 1, 1, 3, 3, 3, 3, 1, 1, 3, 3, 1, 3, 1, 3, 3, 3, 3, 3, 1, 1,
       3, 1, 3, 3, 3, 3, 1, 1, 3, 1, 3, 3, 3, 3, 1, 3, 3, 1, 3, 3, 3, 1,
       3, 3, 3, 3, 3, 3, 3, 3, 1, 1, 3, 1, 1, 2, 2, 3, 1, 1, 3, 3, 3, 3,
       1, 3, 3, 3, 3, 1, 1, 1, 1, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 1,
       1, 3, 3, 3, 3, 1, 3, 3, 3, 1, 3, 1, 3, 1, 3, 1, 3, 3, 3, 1, 3, 3,
       3, 3, 3, 3, 3, 1, 3, 3, 1, 3, 1, 3, 3, 1, 3, 1, 2, 3, 3, 3, 3, 3,
       3, 3, 3, 3, 3, 1, 3, 3, 3, 1, 3, 1, 3, 3, 1, 3, 1, 1, 2, 3, 3, 3,
       2, 3, 3, 1, 2, 3, 3, 1, 3, 1, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 1,
       1, 3, 1, 3, 3, 3, 3, 3, 3, 1, 3, 1, 3, 3, 3, 3, 3, 3, 2, 1, 3, 1,
       3, 2, 3, 3, 2, 3, 3, 1, 1, 3, 3, 3, 1, 3, 3, 3, 1, 3, 1, 1, 3, 3,
       3, 3, 3, 1, 1, 3, 1, 1, 1, 3, 3, 3, 1, 3, 3, 3, 3, 3, 3, 3, 1, 3,
       3, 3, 3, 3, 1, 3, 3, 3, 3, 3, 2, 1, 3, 3, 1, 1, 1, 3, 3, 1, 3, 3,
       1, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 1, 3, 3, 3, 1, 3, 1, 1, 3, 3, 3,
       3, 3, 3, 3, 3, 3, 3, 3, 3, 1, 3, 1, 1, 3, 3, 3, 3, 2, 3, 1, 3, 3,
       2, 1, 3, 3, 1, 3, 3, 3, 3, 3, 1, 3, 3, 3, 1, 3, 3, 1, 3, 3, 3, 2,
       3, 1, 3, 3, 3, 2, 1, 3, 1, 3, 2, 3, 3, 3, 3, 1, 3, 3, 3, 3, 3, 1,
       3, 3, 3, 1, 3, 3, 1, 3, 3, 3, 2, 3, 3, 1, 2, 3, 3, 1, 3, 3, 1, 1,
       3, 3, 3, 3, 1, 2, 3, 3, 3, 1, 3, 3, 3, 1, 1, 3, 3, 3, 3, 3, 3, 1,
       3, 3, 3, 3, 3, 2, 3, 1, 3, 1, 3], dtype=int32)
```

[ ]:
```python
print('Silhouette', silhouette_score(train_data, labels))
```

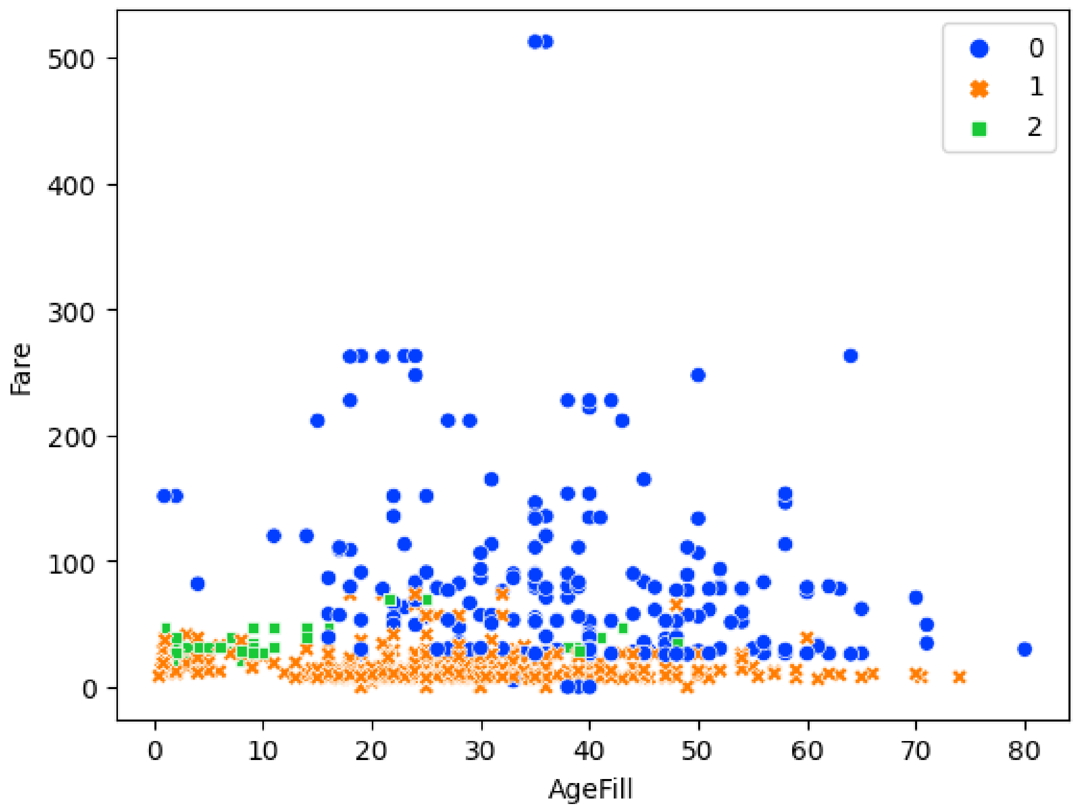
Silhouette 0.5026555448852588

0.0.5 Choosing the number of clusters

[ ]:
```
hier = AgglomerativeClustering(n_clusters=3, metric='euclidean',␣
↪linkage='complete')
hier.fit(train_data)
```

[ ]: AgglomerativeClustering(linkage='complete', n_clusters=3)

[ ]:
```
sns.scatterplot(data=df_clusters,
                x="AgeFill",
                y="Fare",
                hue=hier.labels_,
                style=hier.labels_,
                palette="bright")
plt.show()
```



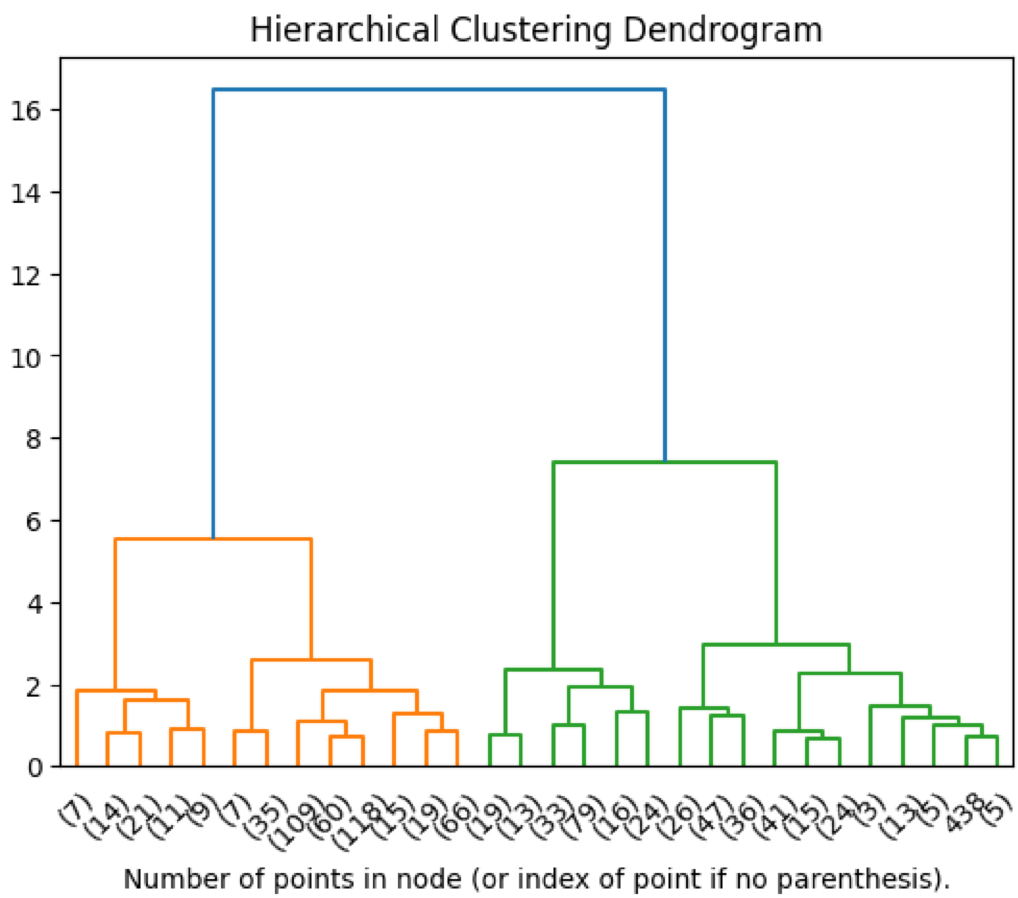
connectivity constraint

[ ]:
```
# hierarchical clustering
# Compute the (weighted) graph of k-Neighbors for points in X
```

```
connectivity = kneighbors_graph(train_data, n_neighbors=100, include_self=False)
```

[ ]:
```
# setting distance_threshold=0 ensures we compute the full tree.
model = AgglomerativeClustering(distance_threshold=0,
                                n_clusters=None,
                                metric='euclidean',
                                linkage='ward',
                                connectivity=connectivity)

# connecet: Defines for each sample the neighboring
# samples following a given structure of the data.

model = model.fit(train_data)
```

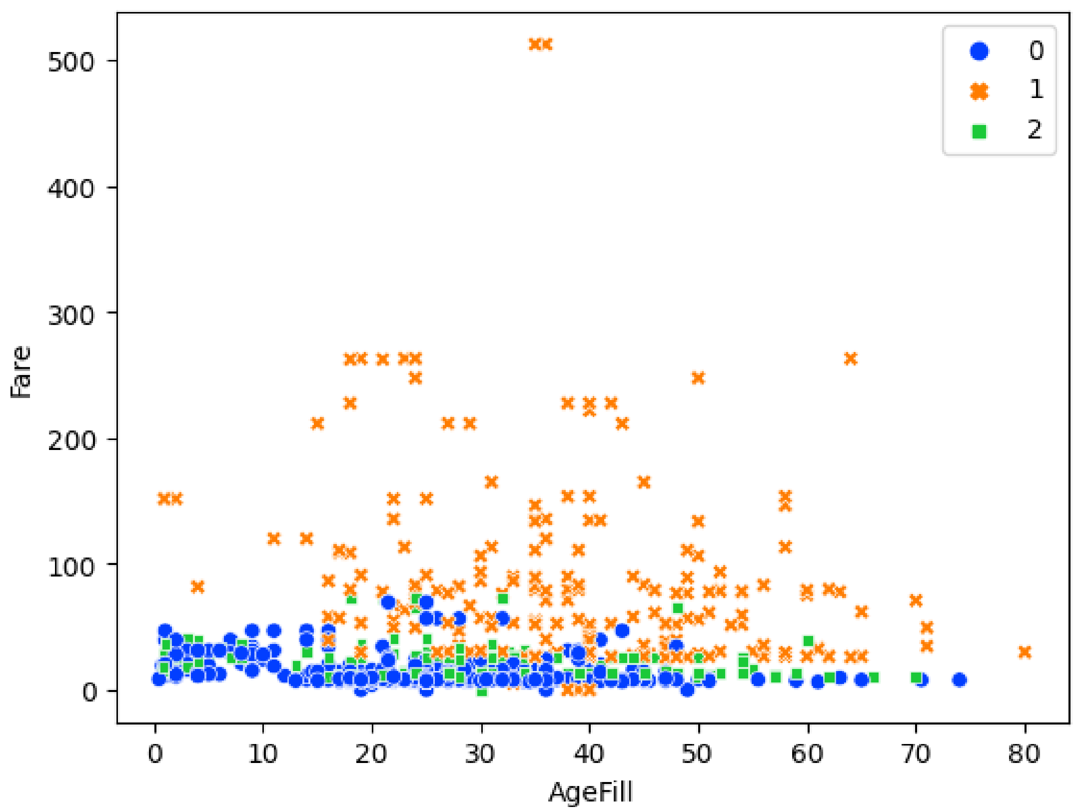
[ ]:
```
plt.title("Hierarchical Clustering Dendrogram")
plot_dendrogram(model, truncate_mode="lastp")
plt.xlabel("Number of points in node (or index of point if no parenthesis).")
plt.show()
```



[ ]:
```
ward = AgglomerativeClustering(n_clusters=3,
                               linkage='ward',
                               metric='euclidean',
                               connectivity=connectivity)
ward.fit(train_data)

hist, bins = np.histogram(ward.labels_, bins=range(0, len(set(ward.labels_)) +
 ↪1))
print('labels', dict(zip(bins, hist)))
print('silhouette', silhouette_score(train_data, ward.labels_))
```

```
labels {0: 491, 1: 216, 2: 184}
silhouette 0.5676262875725462
```

[ ]:
```
sns.scatterplot(data=df_clusters,
                x="AgeFill",
                y="Fare",
                hue=ward.labels_,
                style=ward.labels_,
                palette="bright")
plt.show()
```



[ ]:
```python
print('average linkage')
average_linkage = AgglomerativeClustering(n_clusters=3, linkage='average',␣
 ↪metric='manhattan',  connectivity=connectivity)
average_linkage.fit(train_data)

hist, bins = np.histogram(average_linkage.labels_,
                          bins=range(0, len(set(average_linkage.labels_)) + 1))

print('labels', dict(zip(bins, hist)))
print('silhouette', silhouette_score(train_data, average_linkage.labels_))
```

```
average linkage
labels {0: 881, 1: 7, 2: 3}
silhouette 0.37132365914471405
```

[ ]:
```python
print('complete linkage')
complete_linkage = AgglomerativeClustering(n_clusters=3, linkage='complete',␣
 ↪metric='l1', connectivity=connectivity)
complete_linkage.fit(train_data)

hist, bins = np.histogram(complete_linkage.labels_,
                          bins=range(0, len(set(complete_linkage.labels_)) + 1))

print('labels', dict(zip(bins, hist)))
print('silhouette', silhouette_score(train_data, complete_linkage.labels_))
```

```
complete linkage
labels {0: 882, 1: 3, 2: 6}
silhouette 0.35741232675404144
```

[ ]:
```python

```

Categorical & Mixed distances

[54]:
```python
cols2drop = ['PassengerId', 'Name', 'Cabin', 'Ticket', 'FamilySize', 'Sex_Val',␣
 ↪'Embarked_Val', 'Age']
df_xm = df.drop(cols2drop, axis=1)
df_xm['Pclass'] = df_xm['Pclass'].map({1: '1st', 2: '2nd', 3: '3rd'})
df_xm.head()
```

[54]:

	Survived	Pclass	Sex	SibSp	Parch	Fare	Embarked	AgeFill
0	0	3rd	male	1	0	7.2500	S	22.0
1	1	1st	female	1	0	71.2833	C	38.0
2	1	3rd	female	0	0	7.9250	S	26.0
3	1	1st	female	1	0	53.1000	S	35.0
4	0	3rd	male	0	0	8.0500	S	35.0

[55]:
```
df_xm2 = pd.get_dummies(df_xm[[c for c in df_xm.columns if c != 'Survived']],
    prefix_sep='=')
df_xm2
```

[55]:
```
     SibSp  Parch     Fare  AgeFill  Pclass=1st  Pclass=2nd  Pclass=3rd  \
0        1      0   7.2500     22.0       False       False        True
1        1      0  71.2833     38.0        True       False       False
2        0      0   7.9250     26.0       False       False        True
3        1      0  53.1000     35.0        True       False       False
4        0      0   8.0500     35.0       False       False        True
..     …    …      …      …         …         …         …
886      0      0  13.0000     27.0       False        True       False
887      0      0  30.0000     19.0        True       False       False
888      1      2  23.4500     21.5       False       False        True
889      0      0  30.0000     26.0        True       False       False
890      0      0   7.7500     32.0       False       False        True

     Sex=female  Sex=male  Embarked=C  Embarked=Q  Embarked=S
0         False      True       False       False        True
1          True     False        True       False       False
2          True     False       False       False        True
3          True     False       False       False        True
4         False      True       False       False        True
..          …       …         …         …         …
886       False      True       False       False        True
887        True     False       False       False        True
888        True     False       False       False        True
889       False      True        True       False       False
890       False      True       False        True       False

[891 rows x 12 columns]
```

[56]:
```
X = df_xm2[['Pclass=1st', 'Pclass=2nd',         'Pclass=3rd',
    'Sex=female',         'Sex=male',         'Embarked=C',
    'Embarked=Q',         'Embarked=S']].values
```

[57]:
```
X[:5]
```

[57]:
```
array([[False, False,  True, False,  True, False, False,  True],
       [ True, False, False,  True, False,  True, False, False],
       [False, False,  True,  True, False, False, False,  True],
       [ True, False, False,  True, False, False, False,  True],
       [False, False,  True, False,  True, False, False,  True]])
```

[58]:
```
D = pdist(X, 'jaccard')
D = squareform(D)
```

[59]:
```
D
```

[59]:
```
array([[0. , 1. , 0.5, …, 0.5, 0.8, 0.5],
       [1. , 0. , 0.8, …, 0.8, 0.5, 1. ],
       [0.5, 0.8, 0. , …, 0. , 1. , 0.8],
       …,
       [0.5, 0.8, 0. , …, 0. , 1. , 0.8],
       [0.8, 0.5, 1. , …, 1. , 0. , 0.8],
       [0.5, 1. , 0.8, …, 0.8, 0.8, 0. ]])
```

[59]:
```

```

[60]:
```
# Mixed custom distance
```

[61]:
```
from scipy.spatial.distance import seuclidean, jaccard
```

[ ]:
```
def mixed(a, b):
    index = 4
    d_con = seuclidean(a[:index], b[:index], V=np.ones(index))
    w_con = index/len(a)
    d_cat = jaccard(a[index:], b[index:])
    w_cat = (len(a)-index)/len(a)
    d = w_con * d_con + w_cat * d_cat
    return d
```

[ ]:
```
df_xm2.head()
```

[ ]:
```
   SibSp  Parch     Fare  AgeFill  Pclass=1st  Pclass=2nd  Pclass=3rd  \
0      1      0   7.2500     22.0       False       False        True
1      1      0  71.2833     38.0        True       False       False
2      0      0   7.9250     26.0       False       False        True
3      1      0  53.1000     35.0        True       False       False
4      0      0   8.0500     35.0       False       False        True

   Sex=female  Sex=male  Embarked=C  Embarked=Q  Embarked=S
0       False      True       False       False        True
1        True     False        True       False       False
2        True     False       False       False        True
3        True     False       False       False        True
4       False      True       False       False        True
```

[ ]:
```
X = df_xm2.values
```

[ ]:
```
X[:5]
```

[ ]:
```
array([[1, 0, 7.25, 22.0, False, False, True, False, True, False, False,
        True],
       [1, 0, 71.2833, 38.0, True, False, False, True, False, True,
```

```
         False, False],
        [0, 0, 7.925, 26.0, False, False, True, True, False, False, False,
         True],
        [1, 0, 53.1, 35.0, True, False, False, True, False, False, False,
         True],
        [0, 0, 8.05, 35.0, False, False, True, False, True, False, False,
         True]], dtype=object)
```

[ ]:
```
mixed(X[0], X[10])
```

[ ]:
```
7.118140707983781
```

[ ]:
```
D = pdist(X, mixed)
D = squareform(D)
```

[ ]:
```
D
```

[ ]:
```
array([[ 0.        , 22.66733208,  1.72599765, …,  5.77688201,
         8.24020256,  3.6874353 ],
       [22.66733208,  0.        , 22.03081168, …, 17.41288898,
        14.6678715 , 21.94127388],
       [ 1.72599765, 22.03081168,  0.        , …,  5.43931802,
         8.025     ,  2.53418385],
       …,
       [ 5.77688201, 17.41288898,  5.43931802, …,  0.        ,
         3.41848425,  6.87315457],
       [ 8.24020256, 14.6678715 ,  8.025     , …,  3.41848425,
         0.        ,  8.21493111],
       [ 3.6874353 , 21.94127388,  2.53418385, …,  6.87315457,
         8.21493111,  0.        ]])
```

[ ]:
```

```

0.0.6 K-Mode

https://github.com/nicodv/kmodes

[62]:
```
!pip install kmodes
```

```
Collecting kmodes
  Downloading kmodes-0.12.2-py2.py3-none-any.whl.metadata (8.1 kB)
Requirement already satisfied: numpy>=1.10.4 in /usr/local/lib/python3.12/dist-
packages (from kmodes) (2.0.2)
Requirement already satisfied: scikit-learn>=0.22.0 in
/usr/local/lib/python3.12/dist-packages (from kmodes) (1.6.1)
Requirement already satisfied: scipy>=0.13.3 in /usr/local/lib/python3.12/dist-
packages (from kmodes) (1.16.3)
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.12/dist-
packages (from kmodes) (1.5.2)
```

```
Requirement already satisfied: threadpoolctl>=3.1.0 in
/usr/local/lib/python3.12/dist-packages (from scikit-learn>=0.22.0->kmodes)
(3.6.0)
Downloading kmodes-0.12.2-py2.py3-none-any.whl (20 kB)
Installing collected packages: kmodes
Successfully installed kmodes-0.12.2
```

[ ]:
```python
from kmodes.kmodes import KModes
```

[ ]:
```python
X = df[['Pclass', 'Sex', 'Embarked']].values
```

[ ]:
```python
X[:5]
```

[ ]:
```
array([[3, 'male', 'S'],
       [1, 'female', 'C'],
       [3, 'female', 'S'],
       [1, 'female', 'S'],
       [3, 'male', 'S']], dtype=object)
```

[ ]:
```python
km = KModes(n_clusters=4, init='Huang', n_init=5, verbose=0)
clusters = km.fit_predict(X)
```

[ ]:
```python
km.cluster_centroids_
```

[ ]:
```
array([['3', 'female', 'S'],
       ['1', 'male', 'C'],
       ['3', 'male', 'S'],
       ['2', 'male', 'S']], dtype='<U21')
```

[ ]:
```python
km.labels_
```

[ ]:
```
array([2, 1, 0, 0, 2, 2, 1, 2, 0, 0, 0, 0, 2, 2, 0, 0, 2, 3, 0, 0, 3, 3,
       0, 1, 0, 0, 1, 1, 0, 2, 1, 1, 0, 3, 1, 1, 1, 2, 0, 0, 0, 0, 1, 0,
       0, 2, 2, 0, 1, 0, 2, 2, 1, 0, 1, 1, 0, 1, 0, 2, 1, 0, 1, 2, 1, 1,
       0, 2, 0, 2, 3, 0, 3, 1, 2, 2, 2, 2, 3, 0, 2, 2, 0, 1, 0, 0, 2, 2,
       0, 2, 2, 2, 1, 2, 2, 2, 1, 1, 0, 3, 0, 2, 1, 2, 2, 2, 0, 2, 2, 0,
       1, 0, 2, 0, 0, 2, 2, 3, 1, 0, 3, 2, 1, 0, 1, 1, 2, 2, 0, 2, 1, 2,
       0, 0, 3, 1, 0, 1, 2, 1, 0, 0, 0, 2, 3, 3, 2, 0, 3, 3, 3, 0, 2, 2,
       2, 1, 0, 2, 2, 2, 2, 0, 2, 2, 2, 2, 0, 0, 1, 2, 1, 2, 0, 2, 1, 2,
       2, 1, 3, 2, 0, 1, 2, 3, 0, 1, 0, 1, 2, 2, 0, 3, 0, 3, 1, 1, 2, 2,
       0, 0, 2, 2, 2, 1, 2, 0, 2, 1, 0, 1, 2, 0, 2, 3, 2, 1, 0, 3, 1, 3,
       2, 3, 2, 2, 1, 2, 3, 2, 3, 0, 0, 2, 3, 0, 3, 0, 3, 0, 3, 3, 0, 0,
       3, 2, 1, 1, 0, 0, 1, 3, 2, 0, 1, 2, 0, 0, 1, 0, 1, 0, 2, 2, 1, 1,
       0, 3, 2, 2, 0, 0, 1, 2, 0, 1, 0, 0, 0, 3, 2, 0, 2, 2, 2, 2, 1, 1,
       2, 2, 3, 0, 0, 1, 1, 0, 2, 1, 1, 0, 1, 1, 0, 2, 2, 0, 2, 1, 1, 1,
       1, 1, 1, 1, 0, 2, 3, 0, 0, 3, 0, 1, 2, 2, 0, 0, 2, 1, 2, 0, 0, 1,
       0, 1, 1, 2, 0, 2, 1, 1, 2, 1, 3, 0, 3, 3, 3, 0, 0, 0, 2, 2, 2, 1,
       1, 2, 1, 2, 0, 0, 0, 0, 2, 1, 0, 2, 2, 2, 1, 0, 0, 1, 1, 2, 2, 1,
```

```
0, 1, 0, 1, 1, 2, 1, 0, 2, 0, 2, 3, 2, 0, 2, 0, 1, 2, 2, 1, 0, 2,
0, 3, 3, 0, 2, 2, 0, 2, 0, 3, 2, 3, 2, 0, 2, 2, 0, 3, 2, 0, 0, 0,
3, 0, 1, 2, 2, 0, 2, 2, 0, 0, 2, 2, 1, 0, 0, 2, 1, 0, 0, 0, 1, 3,
0, 2, 2, 0, 2, 1, 0, 1, 0, 1, 3, 2, 1, 1, 2, 1, 1, 0, 0, 2, 1, 2,
1, 3, 2, 2, 3, 1, 2, 0, 2, 2, 0, 0, 0, 1, 3, 2, 2, 0, 2, 3, 2, 0,
1, 0, 0, 1, 2, 2, 2, 2, 1, 1, 2, 1, 1, 2, 0, 2, 2, 0, 0, 0, 0, 1,
0, 1, 2, 2, 2, 2, 1, 1, 2, 1, 0, 2, 0, 2, 0, 2, 1, 1, 1, 2, 0, 1,
2, 3, 0, 1, 1, 0, 0, 0, 1, 1, 2, 1, 0, 0, 0, 3, 1, 1, 0, 1, 2, 3,
1, 3, 2, 1, 0, 1, 1, 1, 0, 0, 2, 2, 3, 2, 0, 2, 2, 0, 1, 2, 3, 0,
1, 0, 2, 2, 0, 0, 0, 2, 0, 1, 3, 1, 1, 0, 3, 1, 2, 2, 2, 1, 2, 0,
3, 2, 0, 2, 1, 1, 0, 2, 1, 2, 1, 2, 2, 1, 0, 0, 0, 2, 0, 2, 2, 0,
2, 0, 0, 3, 1, 1, 1, 2, 2, 1, 3, 0, 2, 2, 1, 2, 1, 1, 0, 0, 2, 3,
0, 2, 2, 1, 0, 2, 0, 1, 2, 1, 2, 0, 2, 0, 2, 0, 0, 3, 2, 0, 3, 1,
1, 1, 1, 2, 2, 3, 3, 2, 2, 0, 0, 1, 3, 3, 3, 2, 2, 0, 0, 1, 0, 1,
2, 2, 3, 1, 2, 2, 2, 0, 1, 0, 2, 1, 1, 3, 2, 0, 1, 2, 1, 1, 0, 2,
2, 3, 0, 1, 0, 1, 1, 1, 1, 2, 3, 2, 1, 0, 2, 2, 0, 2, 3, 3, 1, 2,
0, 0, 3, 0, 0, 1, 3, 3, 3, 2, 0, 1, 2, 2, 1, 1, 1, 2, 2, 1, 2, 0,
1, 2, 0, 2, 2, 2, 0, 3, 2, 3, 2, 0, 2, 2, 1, 0, 2, 0, 1, 0, 2, 2,
2, 2, 0, 1, 0, 2, 2, 0, 2, 0, 0, 0, 1, 2, 2, 2, 0, 2, 2, 1, 2, 3,
0, 1, 2, 3, 0, 0, 1, 0, 3, 0, 1, 1, 2, 2, 1, 0, 3, 0, 2, 2, 3, 0,
2, 1, 0, 1, 2, 2, 0, 2, 1, 0, 2, 2, 2, 1, 2, 0, 0, 3, 1, 2, 2, 1,
2, 2, 2, 1, 2, 3, 1, 1, 2, 2, 2, 1, 3, 1, 2, 2, 0, 0, 0, 0, 0, 1,
0, 1, 2, 3, 0, 0, 3, 0, 0, 1, 2, 2, 2, 0, 1, 2, 0, 0, 2, 2, 2, 1,
0, 2, 0, 3, 2, 0, 3, 0, 0, 1, 2], dtype=uint16)
```

[ ]: