vl1ueptud

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1 Clustering

Importing Necessary Libraries

```
[]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
from sklearn.cluster import DBSCAN
from sklearn.decomposition import PCA
from sklearn.neighbors import NearestNeighbors
from sklearn.preprocessing import StandardScaler
```

Data Pre-processing

```
[]: dataset = pd.read csv('data.csv')
     dataset
[]:
               id
                       f_00
                                 f_01
                                           f_02
                                                     f_03
                                                                f_04
                                                                          f_05 \
     0
                0 -0.389420 -0.912791
                                      0.648951
                                                 0.589045 -0.830817
                                                                     0.733624
     1
                1 -0.689249 -0.453954
                                      0.654175
                                                 0.995248 -1.653020
                                                                     0.863810
     2
                2 0.809079 0.324568 -1.170602 -0.624491 0.105448
                                                                     0.783948
     3
                3 -0.500923 0.229049 0.264109 0.231520 0.415012 -1.221269
                4 -0.671268 -1.039533 -0.270155 -1.830264 -0.290108 -1.852809
           11778 -0.158279 1.858053 -0.921248 -1.429355 -0.764838 -1.589881
     11778
     11779
           11779 1.525135 -0.607098 -1.150169 0.097532 0.080528 -0.455163
           11780 -0.620387 -0.571274 -0.055193 -1.439184 0.453599
     11780
     11781
           11781 0.508547 -1.457904 -1.744796 -1.463034 -1.262898 -0.636495
     11782
           11782 0.650153 -0.082629 -1.447581 0.432188 0.882758 -0.525402
                f_06
                      f_07
                            f_08
                                         f_19
                                                   f_20
                                                             f 21
                                                                        f_22
     0
            2.258560
                         2
                                 ... -0.478412 -0.757002 -0.763635 -1.090369
                                 ... -0.428791 -0.089908 -1.784204 -0.839474
     1
           -0.090651
                         2
     2
            1.988301
                         5
                              11
                                 ... -0.413534 -1.602377
                                                         1.190984
                                                                   3.267116
     3
            0.138850
                         6
                                  ... 0.619283 1.287801
                                                         0.532837
                                                                    1.036631
     4
            0.781898
                         8
                                  ... -1.628830 -0.434948 0.322505
                                                                   0.284326
```

```
0 ... -0.348376 -0.869971 2.027264 3.412598
11778 -1.040811
                  10
                         8 ... 1.921439 -1.081978 0.755980 0.535688
11779 -0.789688
                   0
11780 -0.123739
                   1
                           11781 1.013085
                   2
                           ... 1.243519 1.027125 -0.031330 -3.912239
11782 0.241355
                  10
                         6 ...
                                    {\tt NaN}
                                             {\tt NaN}
                                                       {\tt NaN}
                                                                 NaN
                              f_25
          f_23
                    f_24
                                       f_26
                                                 f_27
                                                           f_28
      1.142641 -0.884274 1.137896 1.309073 1.463002 0.813527
0
1
      0.459685 1.759412 -0.275422 -0.852168 0.562457 -2.680541
2
     -0.088322 -2.168635 -0.974989 1.335763 -1.110655 -3.630723
3
     -2.041828 1.440490 -1.900191 -0.630771 -0.050641 0.238333
     -2.438365 1.473930 -1.044684 1.602686 -0.405263 -1.987263
11778 -0.064369 -2.231076 1.034084 0.973716 0.578975 0.961858
11779 -1.206252 1.457501 1.384902 0.079117 1.583883 -0.010434
11780 1.365082 -0.042190 -0.127365 -0.341521 -0.650510 2.074136
11781 0.804292 -0.280057 0.873512 -0.340227 0.699506 0.205752
11782
           {\tt NaN}
                     {\tt NaN}
                               {\tt NaN}
                                         NaN
                                                  {\tt NaN}
                                                            NaN
```

[11783 rows x 30 columns]

[]: dataset.isna().sum()

```
[]: id
             0
    f 00
             0
    f_01
    f_02
             0
    f_03
             0
    f_04
             0
    f_05
             0
    f_06
             0
    f 07
             0
    f_08
             0
    f_09
    f_10
             0
    f_11
             0
    f_12
             0
    f_13
             0
    f_14
             0
    f_15
             1
    f_16
             1
    f_17
             1
    f_18
             1
    f_19
             1
    f_20
             1
     f_21
```

```
f_22  1
f_23  1
f_24  1
f_25  1
f_26  1
f_27  1
f_28  1
dtype: int64
```

[]: dataset.shape

[]: (11783, 30)

[]: dataset.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11783 entries, 0 to 11782
Data columns (total 30 columns):

#	Column	Non-Null Count	Dtype
0	id	11783 non-null	 int64
1	f_00	11783 non-null	float64
2	f_01	11783 non-null	float64
3	f_02	11783 non-null	float64
4	f_03	11783 non-null	float64
5	f_04	11783 non-null	float64
6	f_05	11783 non-null	float64
7	f_06	11783 non-null	float64
8	f_07	11783 non-null	int64
9	f_08	11783 non-null	int64
10	f_09	11783 non-null	int64
11	f_10	11783 non-null	int64
12	f_11	11783 non-null	int64
13	f_12	11783 non-null	int64
14	f_13	11783 non-null	int64
15	f_14	11783 non-null	float64
16	f_15	11782 non-null	float64
17	f_16	11782 non-null	float64
18	f_17	11782 non-null	float64
19	f_18	11782 non-null	float64
20	f_19	11782 non-null	float64
21	f_20	11782 non-null	float64
22	f_21	11782 non-null	float64
23	f_22	11782 non-null	float64
24	f_23	11782 non-null	float64
25	f_24	11782 non-null	float64
26	f_25	11782 non-null	float64

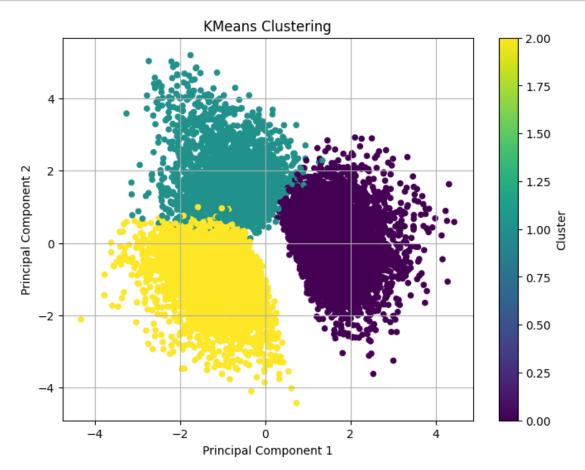
```
27 f_26
                11782 non-null float64
     28 f<sub>2</sub>7
                11782 non-null float64
     29 f_28
                11782 non-null float64
    dtypes: float64(22), int64(8)
    memory usage: 2.7 MB
[]: dataset.dropna(inplace=True)
[]: dataset.drop('id', axis=1, inplace=True)
[]: scaler = StandardScaler()
    scaled_df = scaler.fit_transform(dataset)
    df_scaled = pd.DataFrame(scaled_df, columns=dataset.columns)
    df_scaled.head()
[]:
           f_00
                     f_01
                              f_02
                                        f_03
                                                  f_04
                                                            f_05
                                                                     f_06 \
    0 -0.387661 -0.910925 0.646339 0.593247 -0.827513 0.742537
                                                                 2.259595
    1 - 0.687692 - 0.456304 \ 0.651517 \ 0.998566 - 1.646285 \ 0.872187 - 0.094171
    2 0.811646 0.315062 -1.157490 -0.617645 0.104846 0.792654 1.988812
    3 -0.499240 0.220421 0.264822 0.236501 0.413118 -1.204295 0.135775
    4 -0.669699 -1.036502 -0.264824 -1.820792 -0.289060 -1.833230 0.780070
           f_07
                     f_08
                              f_09
                                           f_19
                                                     f_20
                                                              f_21
                                                                        f_22 \
    0 -0.966957 1.495756 0.985589 ... -0.470556 -0.759687 -0.759855 -0.711374
    1 \ -0.966957 \ -0.899682 \ -0.370146 \ \dots \ -0.421218 \ -0.096589 \ -1.780561 \ -0.541965
    2 -0.152360 1.016668 -0.539613 ... -0.406047 -1.599997 1.195026 2.230884
    3 0.119173 -1.139226 0.816123 ... 0.620883 1.272866 0.536791 0.724818
    4 0.662238 0.058493 -0.539613 ... -1.614418 -0.439562 0.326431 0.216847
           f 23
                     f_24
                              f 25
                                        f_26
                                                  f 27
                                                           f 28
    0 0.900450 -0.684752 0.765463 0.956962 1.058161 0.682993
    1 0.444898 1.025522 -0.135542 -0.548094 0.366201 -1.584807
    2 0.079360 -1.515641 -0.581523 0.975549 -0.919385 -2.201516
    4 -1.488190 0.840835 -0.625954 1.161430 -0.377376 -1.134840
    [5 rows x 29 columns]
    K-means Clustering
[]: # Initialize the KMeans model with the desired number of clusters
    kmeans = KMeans(n_clusters=3)
    kmeans_cluster = kmeans.fit_predict(df_scaled)
    df_scaled['Cluster'] = kmeans_cluster
    df_scaled.head()
```

```
1.4. Set the value of `n_init` explicitly to suppress the warning
      warnings.warn(
[]:
            f_00
                                f_02
                                          f_03
                                                    f_04
                      f_01
                                                              f_05
                                                                        f_06 \
     0 -0.387661 -0.910925 0.646339 0.593247 -0.827513 0.742537
                                                                    2.259595
     1 \ -0.687692 \ -0.456304 \ \ 0.651517 \ \ 0.998566 \ -1.646285 \ \ 0.872187 \ -0.094171
     2 0.811646 0.315062 -1.157490 -0.617645 0.104846 0.792654
                                                                    1.988812
     3 -0.499240 0.220421 0.264822 0.236501 0.413118 -1.204295 0.135775
     4 -0.669699 -1.036502 -0.264824 -1.820792 -0.289060 -1.833230 0.780070
            f_07
                      f 08
                                f 09 ...
                                             f 20
                                                       f 21
                                                                 f 22
                                                                           f 23 \
     0 -0.966957 1.495756 0.985589 ... -0.759687 -0.759855 -0.711374 0.900450
     1 - 0.966957 - 0.899682 - 0.370146 ... - 0.096589 - 1.780561 - 0.541965 0.444898
     2 -0.152360 1.016668 -0.539613 ... -1.599997 1.195026 2.230884 0.079360
     3 0.119173 -1.139226 0.816123 ... 1.272866 0.536791 0.724818 -1.223687
     4 0.662238 0.058493 -0.539613 ... -0.439562 0.326431 0.216847 -1.488190
            f_24
                      f_25
                                f_26
                                          f_27
                                                    f_28 Cluster
     0 -0.684752 0.765463 0.956962 1.058161 0.682993
                                                                2
     1 1.025522 -0.135542 -0.548094 0.366201 -1.584807
                                                                0
     2 -1.515641 -0.581523 0.975549 -0.919385 -2.201516
                                                                2
     3 0.819203 -1.171348 -0.393916 -0.104892 0.309668
                                                                1
     4 0.840835 -0.625954 1.161430 -0.377376 -1.134840
     [5 rows x 30 columns]
[]: df_scaled['Cluster'].value_counts()
[]: Cluster
     2
          4863
     0
          4638
          2281
     Name: count, dtype: int64
[]: # Reduce the dimensionality of the data using PCA
     pca = PCA(n_components=2)
     df_pca = pca.fit_transform(df_scaled)
     # Plot the clusters
     plt.figure(figsize=(8, 6))
     plt.scatter(df_pca[:, 0], df_pca[:, 1], c=kmeans_cluster, cmap='viridis', s=20)
     plt.title('KMeans Clustering')
     plt.xlabel('Principal Component 1')
     plt.ylabel('Principal Component 2')
     plt.colorbar(label='Cluster')
```

/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870:

FutureWarning: The default value of `n_init` will change from 10 to 'auto' in

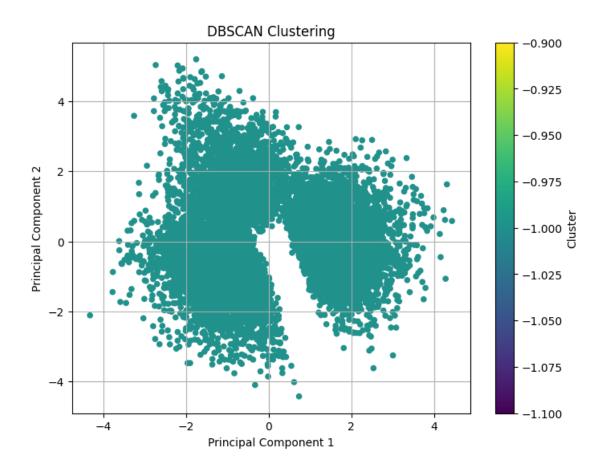
```
plt.grid(True)
plt.show()
```



DBSCAN Clustering

```
[]: dbscan = DBSCAN(eps=0.25, min_samples=5)
    dbscan_cluster = dbscan.fit_predict(df_scaled)

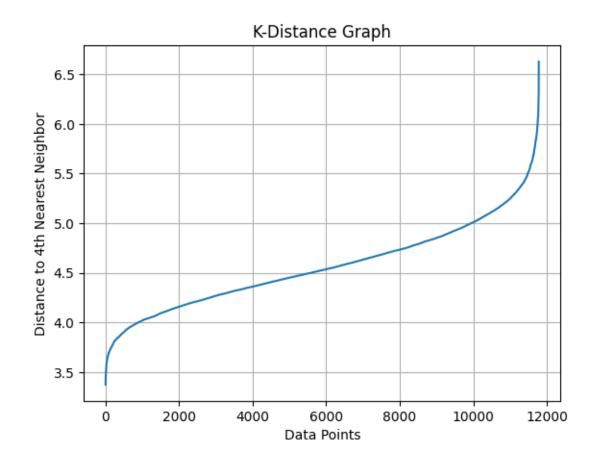
[]: plt.figure(figsize=(8, 6))
    plt.scatter(df_pca[:, 0], df_pca[:, 1], c=dbscan_cluster, cmap='viridis', s=20)
    plt.title('DBSCAN Clustering')
    plt.xlabel('Principal Component 1')
    plt.ylabel('Principal Component 2')
    plt.colorbar(label='Cluster')
    plt.grid(True)
    plt.show()
```



KNN Clustering

```
[]: # Compute the k-nearest neighbors of each data point
k = 4  # Choose an appropriate value of k
neigh = NearestNeighbors(n_neighbors=k)
neigh.fit(df_scaled)
distances, _ = neigh.kneighbors(df_scaled)

# Sort the distances and plot the k-distance graph
sorted_distances = np.sort(distances[:, -1])
plt.plot(np.arange(len(df_scaled)), sorted_distances)
plt.xlabel('Data Points')
plt.ylabel(f'Distance to {k}th Nearest Neighbor')
plt.title('K-Distance Graph')
plt.grid(True)
plt.show()
```



[]: