clustering-pca

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0.0.1 This assignment uses the sklearn.datasets.load_wine() datasets that has 13 dimentionality. I apply the built-in KMeans and then my own KMeans to perform the clustering. Then PCA is performed to reduce the dimensionality to 2 and 3. And then the clusters along with their centers are plotted in 2D and 3D.

0.0.2 WINE dataset Dimensionality = 13 and ideally Clusters = 3

[ ]:
```python
from sklearn.datasets import load_wine
from sklearn.cluster import KMeans
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler
import numpy as np
import matplotlib.pyplot as plt
from mpl_toolkits.mplot3d import Axes3D

wine = load_wine()
X = wine.data
Y = wine.target
print(X.shape)
print(wine.feature_names)
print(wine.target_names)
```

```
(178, 13)
['alcohol', 'malic_acid', 'ash', 'alcalinity_of_ash', 'magnesium',
'total_phenols', 'flavanoids', 'nonflavanoid_phenols', 'proanthocyanins',
'color_intensity', 'hue', 'od280/od315_of_diluted_wines', 'proline']
['class_0' 'class_1' 'class_2']
```

0.0.3 Target Array

[ ]:
```python
print("The Actual Labels of the Dataset:")
print(Y)
```

```
The Actual Labels of the Dataset:
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2]
```

0.1 KMeans Built-in and My Own

0.1.1 Built-in KMEANS

[ ]:
```
print("Time for built-in KMeans:")
%timeit kmeans = KMeans(n_clusters = 3, init = "random", n_init = "auto",␣
↪max_iter = 300, random_state = 42).fit(X)
km = KMeans(n_clusters = 3, init = "random", n_init = "auto", max_iter = 300)
kmeans = km.fit(X)
labelK = kmeans.labels_
```

```
Time for built-in KMeans:
10.6 ms ± 419 µs per loop (mean ± std. dev. of 7 runs, 100 loops each)
```

[ ]:
```
print(kmeans.cluster_centers_)
```

```
[[1.38044681e+01 1.88340426e+00 2.42617021e+00 1.70234043e+01
  1.05510638e+02 2.86723404e+00 3.01425532e+00 2.85319149e-01
  1.91042553e+00 5.70255319e+00 1.07829787e+00 3.11404255e+00
  1.19514894e+03]
 [1.25166667e+01 2.49420290e+00 2.28855072e+00 2.08231884e+01
  9.23478261e+01 2.07072464e+00 1.75840580e+00 3.90144928e-01
  1.45188406e+00 4.08695651e+00 9.41159420e-01 2.49072464e+00
  4.58231884e+02]
 [1.29298387e+01 2.50403226e+00 2.40806452e+00 1.98903226e+01
  1.03596774e+02 2.11112903e+00 1.58403226e+00 3.88387097e-01
  1.50338710e+00 5.65032258e+00 8.83967742e-01 2.36548387e+00
  7.28338710e+02]]
```

0.1.2 Accuracy of Built-in KMEANS

[ ]:
```
print("The labels as generated by built-in KMeans:")
print(labelK)
arr = labelK - Y
arr = arr[arr == 0]
print("\nThe Accuracy of the built-in KMeans:")
print(len(arr)/len(Y))
```

```
The labels as generated by built-in KMeans:
[0 0 0 0 2 0 0 0 0 0 0 0 0 0 0 0 0 0 0 2 2 2 0 0 2 2 0 0 2 0 0 0 0 0 0 2 2
 0 0 2 2 0 0 2 2 0 0 0 0 0 0 0 0 0 0 0 0 0 1 2 1 2 1 1 2 1 1 2 2 2 1 1 0
 2 1 1 1 2 1 1 2 2 1 1 1 1 1 2 2 1 1 1 1 1 2 2 1 2 1 2 1 1 1 2 1 1 1 1 2 1
 1 2 1 1 1 1 1 1 1 2 1 1 1 1 1 1 1 1 1 2 1 1 2 2 2 2 1 1 1 2 2 1 1 2 2 1 2
 2 1 1 1 1 2 2 2 1 2 2 2 1 2 1 2 2 1 2 2 2 2 1 1 2 2 2 2 2 1]

The Accuracy of the built-in KMeans:
0.702247191011236
```

0.1.3 My Own KMEANS

[ ]:
```
def kmeans(x, k, iter):
  n, d = x.shape
  centroids = x[np.random.choice(n, k, replace = False)]
  for i in range(iter):
    distances = np.linalg.norm(x[: ,np.newaxis, : ] - centroids, axis = -1)
    labels = np.argmin(distances, axis = 1)
    for j in range(k):
      centroids[j] = np.mean(x[labels == j], axis = 0)
  return centroids, labels
```

0.1.4 Accuracy of MY KMEANS

[ ]:
```
print("Time taken for my KMeans to run:")
%timeit centers, labels = kmeans(X, 3, 300)
centers, labels = kmeans(X, 3, 300)
print("\nThe Labels generated by my KMeans")
print(labels)
arr = labels - Y
arr = arr[arr == 0]
print("\nThe Accuracy of my KMeans:")
print(len(arr)/len(Y))
```

```
Time taken for my KMeans to run:
59.6 ms ± 11.8 ms per loop (mean ± std. dev. of 7 runs, 10 loops each)

The Labels generated by my KMeans
[0 0 0 0 2 0 0 0 0 0 0 0 0 0 0 0 0 0 0 2 2 2 0 0 2 2 0 0 2 0 0 0 0 0 0 2 2
 0 0 2 2 0 0 2 2 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 2 1 2 1 1 2 1 1 2 2 2 1 1 0
 2 1 1 1 2 1 1 2 2 1 1 1 1 1 2 2 1 1 1 1 1 2 2 1 2 1 2 1 1 1 2 1 1 1 1 2 1
 1 2 1 1 1 1 1 1 1 2 1 1 1 1 1 1 1 1 1 2 1 1 2 2 2 2 1 1 1 2 2 1 1 2 2 1 2
 2 1 1 1 1 2 2 2 1 2 2 2 1 2 1 2 2 1 2 2 2 2 1 1 2 2 2 2 2 1]

The Accuracy of my KMeans:
0.702247191011236
```

0.2 My Own PCA

0.2.1 The Code

[ ]:
```
def My_PCA(X, k):
  means = np.mean(X, axis = 0)
  stds = np.std(X, axis = 0)
  # Scaling the X: same as StandardScaler()
  My_X_scaled = (X - means)/stds
  # Computing the Covariance Matrix of Scaled X
  cov = np.cov(My_X_scaled.T)
```

```
    # Finding EigenValues and EigenVectors of Covariance Matrix
    values, vectors = np.linalg.eig(cov)
    #Adjusting the signs of the EigenVectors
    max_abs_idx = np.argmax(np.abs(vectors), axis=0)
    signs = np.sign(vectors[max_abs_idx, range(vectors.shape[0])])
    vectors = vectors*signs[np.newaxis,:]
    vectors = vectors.T
    # Finding the Indices of the largest EigenValues
    indices = np.argsort(values)[::-1]
    eig = vectors[indices]
    # Taking only the Top k EigenVectors
    W = eig[:k]
    # Finally projection of Original Scaled data using the Top k EigenVectors
    X_proj = My_X_scaled @ W.T
    return X_proj
```

0.2.2 My PCA with 2 dimensions

[ ]:
```
X_2D = My_PCA(X, 2)
X_2D[:,1] = -X_2D[:,1]
print(X_2D.shape)
print()
print("Time for built-in KMeans:")
%timeit kmeans = KMeans(n_clusters = 3, init = "k-means++", n_init = "auto",␣
↪max_iter = 300, random_state = 42).fit(X_2D)
km = KMeans(n_clusters = 3, init = "random", n_init = "auto", max_iter = 300)
kmeans = km.fit(X_2D)
labelK = kmeans.labels_
```

```
(178, 2)

Time for built-in KMeans:
2.19 ms ± 93.8 µs per loop (mean ± std. dev. of 7 runs, 100 loops each)
```

0.2.3 Accuracy of KMeans on PCA-2

[ ]:
```
print("The labels as generated by built-in KMeans:")
print(labelK)
arr = labelK - Y
arr = arr[arr == 0]
print("\nThe Accuracy of the built-in KMeans:")
print(len(arr)/len(Y))
```

```
The labels as generated by built-in KMeans:
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 0 1 0
 1 1 1 1 1 1 1 1 1 2 1 1 1 1 1 1 1 1 1 1 1 0 1 1 0 1 1 1 1 1 1 1 1 1 1 1 1
```

```
 1 1 1 1 1 1 1 1 1 1 0 1 1 1 1 1 1 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2]

The Accuracy of the built-in KMeans:
0.9662921348314607
```

0.2.4 The 3 centers in 2-Dimensions

[ ]:
```python
print("The 3 centers in 2-dimensional space are:")
center = kmeans.cluster_centers_
print(center)
```

```
The 3 centers in 2-dimensional space are:
[[ 2.26614991 -0.86559213]
 [-0.16278513  1.76758824]
 [-2.74392982 -1.2141906 ]]
```

[ ]:
```python
model = PCA(n_components = 2)
scal = StandardScaler()
X_new = scal.fit_transform(X)
model.fit(X_new)
their2D = model.transform(X_new)
print(their2D[:10])
print()
print(X_2D[:10])
```

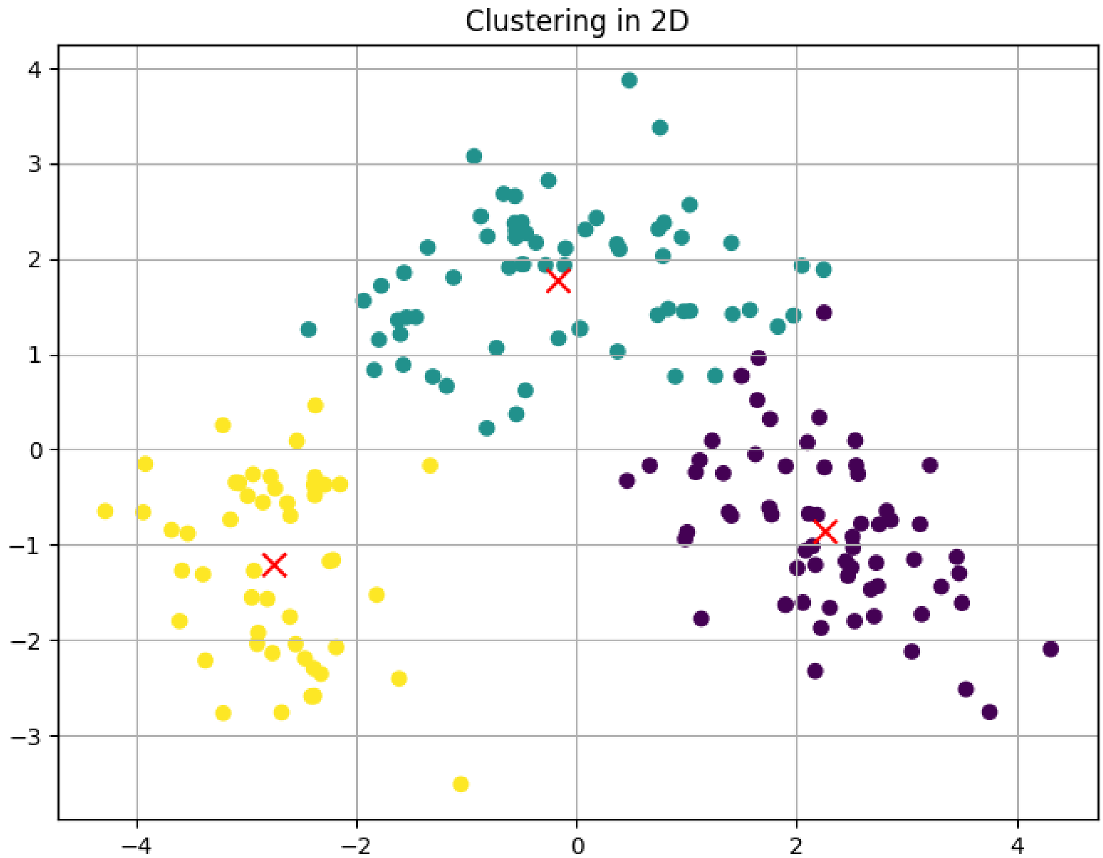
```
[[ 3.31675081 -1.44346263]
 [ 2.20946492  0.33339289]
 [ 2.51674015 -1.0311513 ]
 [ 3.75706561 -2.75637191]
 [ 1.00890849 -0.86983082]
 [ 3.05025392 -2.12240111]
 [ 2.44908967 -1.17485013]
 [ 2.05943687 -1.60896307]
 [ 2.5108743  -0.91807096]
 [ 2.75362819 -0.78943767]]

[[ 3.31675081 -1.44346263]
 [ 2.20946492  0.33339289]
 [ 2.51674015 -1.0311513 ]
 [ 3.75706561 -2.75637191]
 [ 1.00890849 -0.86983082]
 [ 3.05025392 -2.12240111]
 [ 2.44908967 -1.17485013]
 [ 2.05943687 -1.60896307]
 [ 2.5108743  -0.91807096]
 [ 2.75362819 -0.78943767]]
```

0.2.5 Comparison between Built-in and My PCA

[ ]:
```
plt.figure(figsize = (15, 6))
plt.subplot(1, 2, 1)
plt.scatter(X_2D[:, 0], X_2D[:, 1], c = Y)
plt.title("Projected Points in 2D using my PCA")
plt.grid()

plt.subplot(1, 2, 2)
plt.scatter(their2D[:, 0], their2D[:, 1], c = Y)
plt.title("Projected Points in 2D using built-in PCA")
plt.grid()
plt.show()
```

0.2.6 Visualizing Clustering in 2D

[ ]:
```
plt.figure(figsize = (8, 6))
plt.scatter(X_2D[:, 0], X_2D[:, 1], c = labelK)
plt.scatter(center[:, 0], center[:, 1], marker = "x", s = [100]*3, color =␣
↪"red")
plt.title("Clustering in 2D")
plt.grid()
plt.show()
```



0.2.7 My PCA with 3 dimensions

[ ]:
```
X_3D = My_PCA(X, 3)
X_3D[:,1] = -X_3D[:,1]
print(X_3D.shape)
print()
print("Time for built-in KMeans:")
%timeit kmeans = KMeans(n_clusters = 3, init = "k-means++", n_init = "auto",␣
 ↪max_iter = 300, random_state = 42).fit(X_3D)
km = KMeans(n_clusters = 3, init = "random", n_init = "auto", max_iter = 300)
kmeans = km.fit(X_3D)
labelK = kmeans.labels_
```

```
(178, 3)

Time for built-in KMeans:
2.25 ms ± 76.8 µs per loop (mean ± std. dev. of 7 runs, 100 loops each)
```

0.2.8 Accuracy of KMeans on PCA-3

[ ]:
```python
print("The labels as generated by built-in KMeans:")
print(labelK)
arr = labelK - Y
arr = arr[arr == 0]
print("\nThe Accuracy of the built-in KMeans:")
print(len(arr)/len(Y))
```

```
The labels as generated by built-in KMeans:
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 2 1 1 1 1 1 1 1 1 1 1 1 0
 1 1 1 1 1 1 1 1 1 2 1 1 1 1 1 1 1 1 1 1 1 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 2 1 1 0 1 1 1 1 1 1 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2]

The Accuracy of the built-in KMeans:
0.9662921348314607
```

0.2.9 The 3 centers in 3-Dimensions

[ ]:
```python
print("The 3 centers in 2-dimensional space are:")
center = kmeans.cluster_centers_
print(center)
```

```
The 3 centers in 2-dimensional space are:
[[ 2.27619360e+00 -9.32054027e-01  1.52803156e-03]
 [-3.69566084e-02  1.77223945e+00  1.86138728e-01]
 [-2.72003575e+00 -1.12565126e+00 -2.39093241e-01]]
```

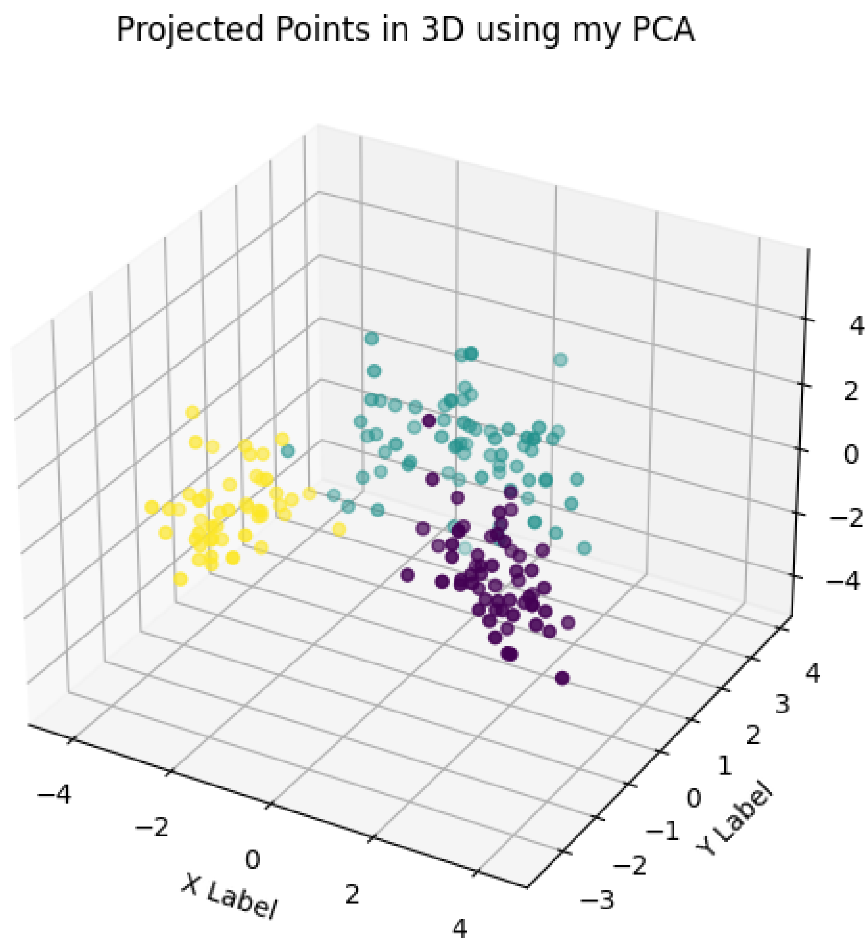
[ ]:
```python
model = PCA(n_components = 3)
scal = StandardScaler()
X_new = scal.fit_transform(X)
model.fit(X_new)
their3D = model.transform(X_new)
print(their3D[:10])
print()
print(X_3D[:10])
```

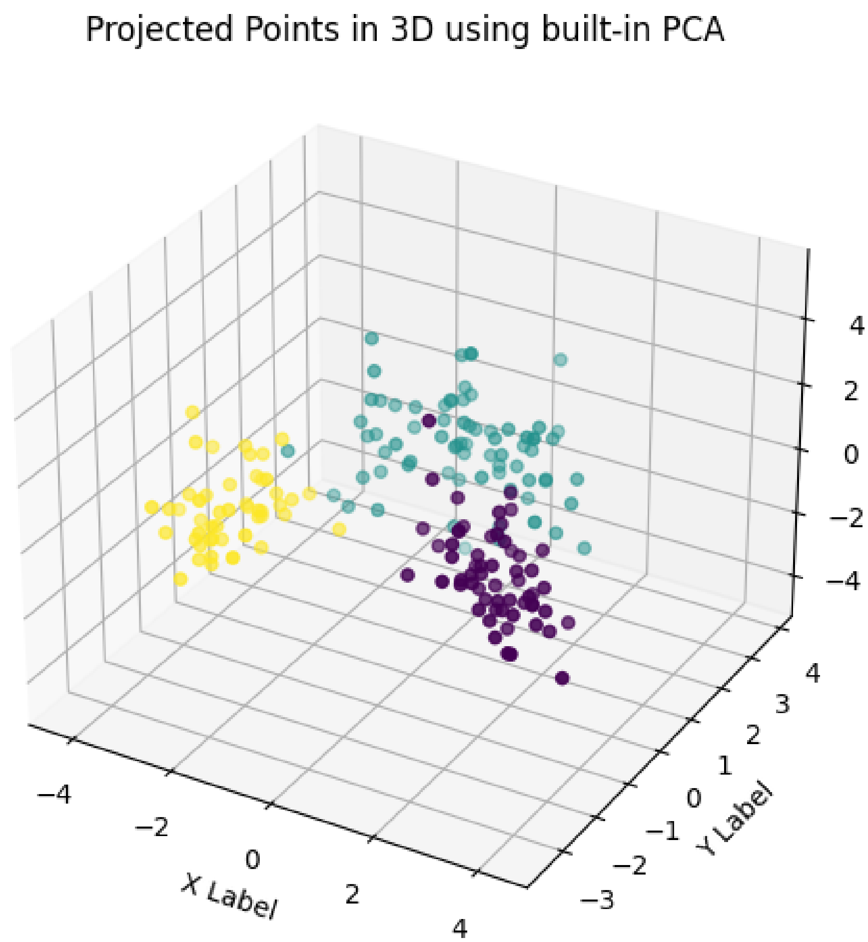
```
[[ 3.31675081 -1.44346263 -0.16573904]
 [ 2.20946492  0.33339289 -2.02645737]
 [ 2.51674015 -1.0311513   0.98281867]
 [ 3.75706561 -2.75637191 -0.17619184]
 [ 1.00890849 -0.86983082  2.02668822]
 [ 3.05025392 -2.12240111 -0.62939583]
 [ 2.44908967 -1.17485013 -0.97709489]
 [ 2.05943687 -1.60896307  0.14628188]
 [ 2.5108743  -0.91807096 -1.77096903]
```

```
 [ 2.75362819 -0.78943767 -0.98424749]]

[[ 3.31675081 -1.44346263 -0.16573904]
 [ 2.20946492  0.33339289 -2.02645737]
 [ 2.51674015 -1.0311513   0.98281867]
 [ 3.75706561 -2.75637191 -0.17619184]
 [ 1.00890849 -0.86983082  2.02668822]
 [ 3.05025392 -2.12240111 -0.62939583]
 [ 2.44908967 -1.17485013 -0.97709489]
 [ 2.05943687 -1.60896307  0.14628188]
 [ 2.5108743  -0.91807096 -1.77096903]
 [ 2.75362819 -0.78943767 -0.98424749]]
```

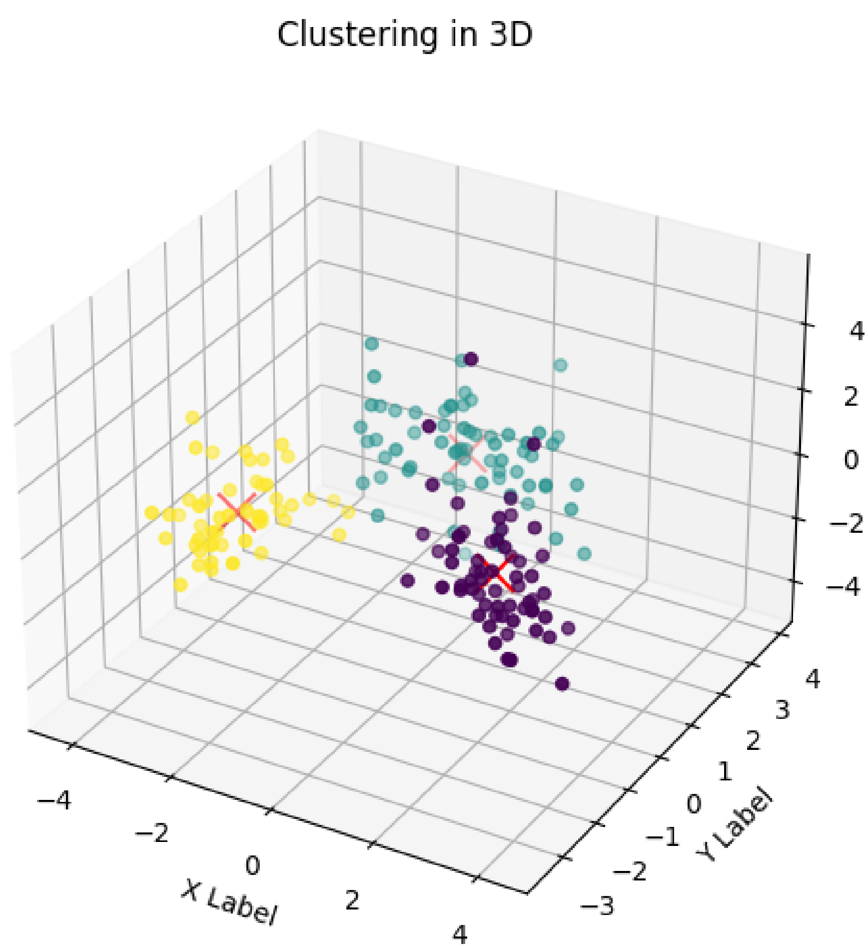
0.2.10 Comparison between Built-in and My PCA

[ ]:
```
fig = plt.figure(figsize = (10, 6))
ax = fig.add_subplot(111, projection='3d')
ax.scatter(X_3D[:, 0], X_3D[:, 1], X_3D[:, 2], c = Y)
ax.set_xlabel('X Label')
ax.set_ylabel('Y Label')
ax.set_zlabel('Z Label')
plt.title("Projected Points in 3D using my PCA")
plt.grid()
plt.show()

fig = plt.figure(figsize = (10, 6))
ax = fig.add_subplot(111, projection='3d')
ax.scatter(their3D[:, 0], their3D[:, 1], their3D[:, 2], c = Y)
ax.set_xlabel('X Label')
ax.set_ylabel('Y Label')
ax.set_zlabel('Z Label')
plt.title("Projected Points in 3D using built-in PCA")
plt.grid()
plt.show()
```


Projected Points in 3D using my PCA
X Label
Y Label
−4
−2
0
2
4
−3
−2
−1
0
1
2
3
4
4
2
0
−2
−4




```
[ ]: fig = plt.figure(figsize = (10, 6))
     ax = fig.add_subplot(111, projection='3d')
     ax.scatter(X_3D[:, 0], X_3D[:, 1], X_3D[:, 2], c = labelK)
     ax.scatter(center[:, 0], center[:, 1], center[:, 2], s = [200]*3, marker = "x",␣
      ↪color = "red")
     ax.set_xlabel('X Label')
     ax.set_ylabel('Y Label')
     ax.set_zlabel('Z Label')
     plt.title("Clustering in 3D")
     plt.grid()
     plt.show()
```


Clustering in 3D
X Label
Y Label
−4
−2
0
2
4
−3
−2
−1
0
1
2
3
4
−4
−2
0
2
4