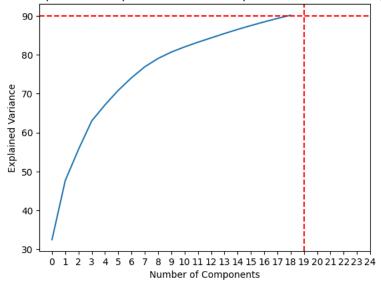
```
# Packages
import csv
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.cluster import KMeans
import warnings
warnings.filterwarnings('ignore')
#Load dataset
from google.colab import drive
drive.mount('/content/drive')
train_data = pd.read_csv("/content/drive/MyDrive/Post Undergrad/CS 5262: Machine Learning/train_data.csv")
df = pd.DataFrame(train_data)
test_data = pd.read_csv("/content/drive/MyDrive/Post Undergrad/CS 5262: Machine Learning/test_data.csv")
     Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
# Edit Data file train
dfx = df.copy()
X = dfx.drop("disease_status",axis=1)
X = X.drop("File_ID",axis=1)
X = X.drop("tSNE_1",axis=1)
X = X.drop("tSNE_2",axis=1)
y = df.iloc[:,44:]
X = pd.DataFrame(X)
y = pd.DataFrame(y)
# Edit Data file test
test_datax = test_data.copy()
Xtest = dfx.drop("disease_status",axis=1)
Xtest = Xtest.drop("File_ID",axis=1)
Xtest = Xtest.drop("tSNE_1",axis=1)
Xtest = Xtest.drop("tSNE_2",axis=1)
ytest = test_data.iloc[:,44:]
print(ytest)
            File_ID disease_status
     0
                 31
                 31
                                  0
     1
                                  a
     2
                 31
     3
                 31
                                  0
     4
                 31
     46723
                 27
                                  1
     46724
                                  1
                 27
     46725
                 26
                                  1
     46726
                 16
                                  1
     46727
                 17
     [46728 rows x 2 columns]
# Complete PCA
from sklearn.decomposition import PCA
pca = PCA(n_{components} = .90)
X_train_pca = pca.fit_transform(X)
X_test_pca = pca.transform(test_data.iloc[:,:42])
X_train_pca = pd.DataFrame(X_train_pca)
X_test_pca = pd.DataFrame(X_test_pca)
X_train_pca.columns = ["PC1","PC2","PCA3","PCA4","PCA5","PCA6","PCA7","PCA8","PCA9","PCA10","PCA11","PCA12","PCA13","PCA14","PCA15","PCA16",
test = X_test_pca.join(test_data.iloc[:,44:])
# Display how we chose number of PC
explained_variance = pca.explained_variance_ratio_
explained_variance = pca.explained_variance_ratio_
plt.plot(np.cumsum(explained_variance)*100)
plt.axhline(y = 90, color = 'r', linestyle = '--')
plt.axvline(x = 19, color = 'r', linestyle = '--')
plt.xticks(range(0,25))
plt.xlabel('Number of Components')
plt.ylabel("Explained Variance")
plt.title("Relationship Between Explained Variance Compared to Number of Components")
```

 ${\sf Text}({\tt 0.5,\ 1.0,\ 'Relationship\ Between\ Explained\ Variance\ Compared\ to\ Number\ of\ Components')}$ 

## Relationship Between Explained Variance Compared to Number of Components



print(X test pca)

```
2
0
      2.065260 2.837408 -3.046193 -1.421741 0.189240 -1.898389 1.847129
     -3.300881 1.209013 0.190181 0.706488 0.766812 1.604509 -0.497695
2
     -5.592737 -1.456376
                       2.469224 -1.712299 0.604456 -1.147351 1.143878
     -2.795340 -1.756877 -2.538769 1.319350 1.557766 3.924942 -3.256800
     -4.501865 -4.112488 1.097678 1.273828 -1.522866 2.227537 1.320202
46723 -3.923201 -4.490558
                       2.107046 0.361813 -2.443016
                                                 4.145321
46724 6.504190 -1.620971
                       0.425800 -1.590910 0.029881 1.404748 0.304200
46725 1.731255 4.385363 1.066837 -2.250015 -2.062843 1.233641 -0.861078
46726 6.104070 -2.361998 1.100090 -0.555060 1.238457 1.332134 0.398946
46727 -2.323189 -2.764531 -2.336211 1.213100 -2.914122 -0.012792 1.446788
                             9
                                      10
                                               11
                                                                13 \
0
      1.507118 -2.436506  0.623992 -0.112060  0.303669 -0.180848  0.142228
     -0.027334 -1.560305 1.682948 1.635736 -1.979390 -0.676116 2.053563
1
2
      0.037277 \ -1.718266 \quad 0.839413 \quad 0.050322 \ -1.092558 \quad 0.505751 \ -0.245638
46723 5.723486 2.721470 2.075391 0.674281 0.453538 0.656315 -1.373106
                       46724 -2.456482 -0.341142
46725 5.163595 0.869351 2.376043 2.943963 -2.474540 -0.648952 0.368044
46726 -2.280628 -1.053748 -0.893973 -0.755296  0.542654 -0.527036  0.013577
46727 -2.354774 0.046579 -0.484763 0.128513 0.263087 0.804200 -0.166092
           14
                    15
                             16
                                      17
                                               18
0
      0.911206 -0.052895 -0.465407 -0.401209 0.873088
      0.623632 2.049746 -2.081984 1.560676 1.172755
1
2
     -0.052396   0.107912   -0.013970   -0.180314   -0.273145
      2.102752 0.375789 0.893243 0.399323 -0.699122
3
     -0.946035
              0.067604
                       0.109420 0.110448 0.180827
46723 0.405445 0.131920 -0.965557 0.143121 0.146782
46724 -0.902980 -0.507832 -1.495366 0.617554 -0.246559
46725 0.833838 0.632201 0.700542 -0.460588 -1.100424
46726 -0.443016 -1.019344 -1.301008 0.541734 -0.666112
46727 -0.459190 -0.035664 0.615323 0.330930 -1.076969
```

[46728 rows x 19 columns]

```
for i, marker in enumerate(train_data.columns):
    fig, ax = plt.subplots()
    plt.scatter(X_train_pca.PC1, X_train_pca.PC2, c=train_data.iloc[:,i], s=5)
    plt.xlabel('PC 1')
    plt.ylabel('PC 2')
    plt.title("T cells")
    ax.set_aspect('equal')
    cbar = plt.colorbar()
    cbar.ax.set_ylabel(marker, rotation=270,labelpad=15)

plt.show()
```

