

#### TEAM:

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# **ASSIGNMENT 2**

#### **Problem Statement:**

Using a dataset write a code that generates principal component analysis (PCA) and singular value decomposition (SVD).

Dataset: IRIS dataset

## 1)PCA

```
In [1]: from sklearn import datasets
from sklearn.decomposition import PCA

# import some data to play with
iris = datasets.load_iris()

data=iris['data']
c = PCA(n_components=2).fit_transform(data)
print(c)
```

```
[[-2.68412563  0.31939725]
[-2.71414169  -0.17700123]
[-2.88899057  -0.14494943]
[-2.74534286  -0.31829898]
[-2.72871654  0.32675451]
[-2.28085963  0.74133045]
[-2.82053775  -0.08946138]
[-2.62614497  0.16338496]
[-2.88638273  -0.57831175]
[-2.6727558  -0.11377425]
[-2.50694709  0.6450689 ]
[-2.50694709  0.6450689 ]
[-2.78610927  -0.235112 ]
[-3.22380374  -0.51139459]
[-2.64475039  1.17876464]
[-2.38603903  1.33806233]
[-2.62352788  0.81067951]
[-2.64829671  0.31184914]
[-2.19982032  0.87283904]
```



### 2)SVD

```
In [16]: from sklearn import datasets
        import seaborn as sns
        from scipy.linalg import svd
        import pandas as pd
        from sklearn.preprocessing import StandardScaler
        from sklearn.decomposition import TruncatedSVD
        df=pd.read csv('IRIS.csv')
        iris = datasets.load_iris()
        data=iris['data']
        u,sigma,Vt=svd(data)
        #print("U",u)
        #print("sigma\n",sigma)
        #print("Vt\n",Vt)
        X = df.iloc[:,0:4].values
        y = df.iloc[:,4].values
        X_scaled = StandardScaler().fit_transform(X)
        svd = TruncatedSVD(n_components=2)
        Y_fitted = svd.fit_transform(X_scaled)
        print(Y_fitted)
          [[-2.26454173e+00 5.05703903e-01]
           [-2.08642550e+00 -6.55404729e-01]
           [-2.36795045e+00 -3.18477311e-01]
           [-2.30419716e+00 -5.75367713e-01]
           [-2.38877749e+00 6.74767397e-01]
           [-2.07053681e+00 1.51854856e+00]
           [-2.44571134e+00 7.45626750e-02]
           [-2.23384186e+00 2.47613932e-01]
           [-2.34195768e+00 -1.09514636e+00]
           [-2.18867576e+00 -4.48629048e-01]
           [-2.16348656e+00 1.07059558e+00]
           [-2.32737775e+00 1.58587455e-01]
           [-2.22408272e+00 -7.09118158e-01]
           [-2.63971626e+00 -9.38281982e-01]
           [-2.19229151e+00 1.88997851e+00]
           [-2.25146521e+00 2.72237108e+00]
           [-2.20275048e+00 1.51375028e+00]
           [-2.19017916e+00 5.14304308e-01]
           [-1.89407429e+00 1.43111071e+00]
```