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## Lab 9 - CCPS 844 Data Mining

## Salman AlMaskati

## Answer the following questions and submit a PDF file on the D2L.

Select a dataset of your choice.

Χ

- Find number of optimal features from your dataset using the Recursive feature elimination with cross-validation.
- Prepare a dataset with optimal features and call info and describe methods on it
- Apply PCA on the dataset (with optimal features) to get a dataset with reduced dimenion
- There should be a reason to pick n\_components to reduce the dimension of the dataset by using PCA
- What is the dimension of the dataset before and after applying PCA?

```
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.svm import SVC
from sklearn.model_selection import StratifiedKFold
from sklearn.feature_selection import RFECV
from sklearn.datasets import make_classification
%matplotlib inline

In []:

df= pd.read_csv("pima-indians-diabetes.csv",index_col=0)
df

features = ['pregnant','glucose','bp','skin','insulin','bmi','pedigree','age']
X=df[features]
y=df.label
```

```
Out[ ]:
               pregnant glucose bp skin insulin bmi pedigree age
            1
                      6
                                        35
                                                 0 33.6
                                                             0.627
                             148
                                 72
                                                                    50
            2
                      1
                                        29
                                                0 26.6
                                                             0.351
                              85
                                  66
                                                                    31
            3
                      8
                             183
                                  64
                                         0
                                                0 23.3
                                                             0.672
                                                                    32
                      1
                                  66
                                        23
                                                94 28.1
                                                             0.167
                                                                    21
                              89
            5
                             137
                                  40
                                        35
                                               168 43.1
                                                             2.288
                                                                    33
         764
                     10
                             101
                                  76
                                        48
                                               180 32.9
                                                             0.171
                                                                    63
         765
                             122 70
                                        27
                                                0 36.8
                                                             0.340
                                                                    27
         766
                      5
                             121 72
                                        23
                                               112 26.2
                                                             0.245
                                                                    30
```

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	pregnant	glucose	bp	skin	insulin	bmi	pedigree	age
767	1	126	60	0	0	30.1	0.349	47
768	1	93	70	31	0	30.4	0.315	23

768 rows × 8 columns

```
In [ ]:
          from sklearn.linear model import LogisticRegression
          logit=LogisticRegression(multi_class='ovr',solver='lbfgs',max_iter=1000)
In [ ]:
          rfecv = RFECV(estimator=logit, step=1, cv=StratifiedKFold(10), scoring='accuracy')
          rfecv.fit(X, y)
         RFECV(cv=StratifiedKFold(n_splits=10, random_state=None, shuffle=False),
Out[]:
               estimator=LogisticRegression(max_iter=1000, multi_class='ovr'),
               scoring='accuracy')
In [ ]:
          print(f"Optimal number of features : {rfecv.n features }")
         Optimal number of features : 8
In [ ]:
          plt.figure()
          plt.xlabel("Number of features selected")
          plt.ylabel("Cross validation score (nb of correct classifications)")
          plt.plot(range(1, len(rfecv.grid_scores_) + 1), rfecv.grid_scores_)
          plt.show()
         Cross validation score (nb of correct classifications)
           0.76
           0.74
           0.72
           0.70
           0.68
           0.66
                              Number of features selected
In [ ]:
          print(df.info())
          print(df.describe())
         <class 'pandas.core.frame.DataFrame'>
         Int64Index: 768 entries, 1 to 768
         Data columns (total 9 columns):
                         Non-Null Count Dtype
              Column
              pregnant 768 non-null
                                          int64
```

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```
glucose
                        768 non-null
          1
                                         int64
          2
                        768 non-null
             bp
                                         int64
          3
              skin
                        768 non-null
                                         int64
          4
              insulin
                        768 non-null
                                         int64
          5
              bmi
                        768 non-null
                                         float64
          6
              pedigree
                        768 non-null
                                         float64
          7
              age
                        768 non-null
                                         int64
          8
              label
                        768 non-null
                                         int64
        dtypes: float64(2), int64(7)
        memory usage: 60.0 KB
        None
                  pregnant
                                glucose
                                                 bp
                                                            skin
                                                                     insulin
                                                                                      bmi
               768.000000
                            768.000000
                                         768.000000
                                                                  768.000000
                                                     768.000000
                                                                               768.000000
        count
                                                                   79.799479
        mean
                  3.845052
                            120.894531
                                          69.105469
                                                       20.536458
                                                                                31.992578
        std
                  3.369578
                             31.972618
                                          19.355807
                                                       15.952218
                                                                  115.244002
                                                                                 7.884160
                  0.000000
                                                        0.000000
                                                                    0.000000
                                                                                 0.000000
        min
                              0.000000
                                           0.000000
        25%
                  1.000000
                             99.000000
                                          62.000000
                                                        0.000000
                                                                    0.000000
                                                                                27.300000
        50%
                  3.000000
                            117.000000
                                                       23.000000
                                                                   30.500000
                                                                                32.000000
                                          72.000000
        75%
                  6.000000
                            140.250000
                                          80.000000
                                                       32.000000
                                                                  127.250000
                                                                                36.600000
                 17.000000
                            199.000000
                                         122.000000
                                                       99.000000
                                                                  846.000000
                                                                                67.100000
        max
                  pedigree
                                              label
                                    age
        count
               768.000000
                            768.000000
                                         768.000000
                  0.471876
                             33.240885
                                           0.348958
        mean
        std
                  0.331329
                             11.760232
                                           0.476951
        min
                  0.078000
                             21.000000
                                           0.000000
        25%
                  0.243750
                              24.000000
                                           0.000000
        50%
                  0.372500
                              29.000000
                                           0.000000
        75%
                  0.626250
                              41.000000
                                           1.000000
        max
                  2.420000
                              81.000000
                                           1.000000
        PCA
In [ ]:
         from sklearn import decomposition
         pca X = X
         pca = decomposition.PCA(n components=2)
         pca.fit(pca X)
         pca_X = pca.transform(X)
         pca X.shape
         print(f"Dimenstions before PCA: {X.shape}\nDimenstions after PCA: {pca X.shape}")
        Dimenstions before PCA: (768, 8)
        Dimenstions after PCA: (768, 2)
In [ ]:
In [ ]:
```