Dimensionality Reduction

Principal Component Analysis

Out of the m independent variables, PCA selects $n < m$ new independent variables that explain the most variance **regardless of the dependent variable.** Since dependent variable is not considered, PCA is an unsupervised model.

Numerical --> continuous, discreate

Categorical --> nominal, ordinal

--> yes/no

--> 400, 200, 250, 150

In [1]:

```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
```

In [2]:

```
df = pd.read_csv('https://raw.githubusercontent.com/AP-State-Skill-Development-Corporation/

df.head()
```

Out[2]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunctio
0	6	148	72	35	0	33.6	0.62
1	1	85	66	29	0	26.6	0.35
2	8	183	64	0	0	23.3	0.67
3	1	89	66	23	94	28.1	0.16
4	0	137	40	35	168	43.1	2.28

In [3]:

```
df.shape
```

Out[3]:

```
(768, 9)
```

In [4]:

```
df.isnull().sum()
```

Out[4]:

```
Pregnancies                 0
Glucose                     0
BloodPressure               0
SkinThickness               0
Insulin                     0
BMI                         0
DiabetesPedigreeFunction    0
Age                         0
Outcome                     0
dtype: int64
```

In [5]:

```
df.duplicated().sum()
```

Out[5]:

```
0
```

In [6]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 768 entries, 0 to 767
Data columns (total 9 columns):
 #   Column                    Non-Null Count  Dtype  
---  ------                    --------------  -----  
 0   Pregnancies               768 non-null    int64  
 1   Glucose                   768 non-null    int64  
 2   BloodPressure             768 non-null    int64  
 3   SkinThickness             768 non-null    int64  
 4   Insulin                   768 non-null    int64  
 5   BMI                       768 non-null    float64
 6   DiabetesPedigreeFunction  768 non-null    float64
 7   Age                       768 non-null    int64  
 8   Outcome                   768 non-null    int64  
dtypes: float64(2), int64(7)
memory usage: 54.1 KB
```

In [7]:

```
df.describe()
```

Out[7]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	Diabet
count	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	
mean	3.845052	120.894531	69.105469	20.536458	79.799479	31.992578	
std	3.369578	31.972618	19.355807	15.952218	115.244002	7.884160	
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	1.000000	99.000000	62.000000	0.000000	0.000000	27.300000	
50%	3.000000	117.000000	72.000000	23.000000	30.500000	32.000000	
75%	6.000000	140.250000	80.000000	32.000000	127.250000	36.600000	
max	17.000000	199.000000	122.000000	99.000000	846.000000	67.100000	

single class-> 1/0

multi class - drug -> drugx,drugy,drugz

multi label class --> comedy, horror

1. KNN
2. Logistic
3. SVC
4. Decision
5. Random Forest

In [8]:

```
import seaborn as sns

sns.pairplot(df,hue = 'Outcome')
```

Out[8]:

<seaborn.axisgrid.PairGrid at 0x18b98b82970>

Logistic Regression ¶

In [9]:

```
X = df.drop('Outcome',axis = 1)
y = df['Outcome']
```

In [10]:

```
# Split in training and testing
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,random_state = 7)
```

In [11]:

```
from sklearn.linear_model import LogisticRegression
clf = LogisticRegression()
clf.fit(X_train, y_train)
```

```
C:\Users\Jesus\anaconda3\lib\site-packages\sklearn\linear_model\_logistic.p
y:762: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html (https://scik
it-learn.org/stable/modules/preprocessing.html)
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regre
ssion (https://scikit-learn.org/stable/modules/linear_model.html#logistic-re
gression)
  n_iter_i = _check_optimize_result(
```

Out[11]:

```
LogisticRegression()
```

In [12]:

```
y_pred = clf.predict(X_test)
```

In [13]:

```
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred)
cm
```

Out[13]:

```
array([[127,  20],
       [ 37,  47]], dtype=int64)
```

In [14]:

```
clf.score(X_test, y_test)
```

Out[14]:

```
0.7532467532467533
```

In [15]:

```
# Split in training and testing
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=3,random_state = 42)
```

In [16]:

```
X_train.head()
```

Out[16]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunct
690	8	107	80	0	0	24.6	0.
473	7	136	90	0	0	29.9	0.
204	6	103	72	32	190	37.7	0.
97	1	71	48	18	76	20.4	0.
336	0	117	0	0	0	33.8	0.

In [17]:

```
# Always scale data for good results on PCA
from sklearn.preprocessing import StandardScaler
X_sca = StandardScaler()
X_train = X_sca.fit_transform(X_train)
X_test = X_sca.transform(X_test)
```

In [18]:

```
X_train[0:5,:]
```

Out[18]:

```
array([[ 1.23168349, -0.43604825,  0.56160593, -1.28775566, -0.69294238,
        -0.93586599,  1.15656737,  0.06294811],
       [ 0.93510248,  0.47024091,  1.07773825, -1.28775566, -0.69294238,
        -0.26437369, -0.79299869,  1.4242287 ],
       [ 0.63852147, -0.56105365,  0.14870008,  0.71926405,  0.95559722,
         0.72386024, -0.44895762,  1.84962888],
       [-0.84438358, -1.56109686, -1.09001747, -0.15880707, -0.03352654,
        -1.46799195, -0.45197552, -0.95801234],
       [-1.14096459, -0.12353475, -3.56745259, -1.28775566, -0.69294238,
         0.22974327,  1.38592809,  0.91374848]])
```

In [19]:

```
from sklearn.decomposition import PCA
pca = PCA()
pca.fit_transform(X_train)
explained_variance_ratio = pca.explained_variance_ratio_
print(explained_variance_ratio)
```

```
[0.26171944 0.21677862 0.128557   0.10958539 0.09494264 0.08534802
 0.05253743 0.05053145]
```

In [20]:

```
# Extract top 2 principal components
pca = PCA(n_components=2)
X_train = pca.fit_transform(X_train)
X_test = pca.transform(X_test)
explained_variance = pca.explained_variance_ratio_
print(explained_variance)
```

```
[0.26171944 0.21677862]
```

In [21]:

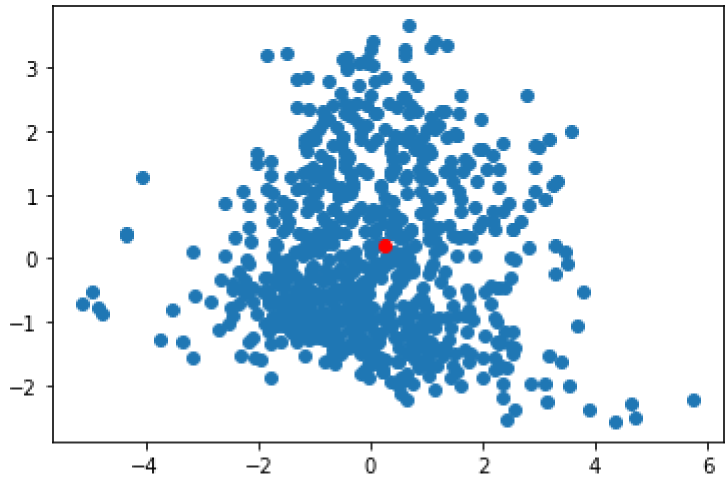
```
X_train
```

Out[21]:

```
array([[-0.78397591,  1.34563612],
       [-0.23714761,  2.44484824],
       [ 1.21249591,  0.96614483],
       ...,
       [ 1.85090101,  0.80663508],
       [-1.74219774, -0.89044531],
       [-1.38214951, -0.25137068]])
```

In [22]:

```
plt.scatter(X_train[:,0],X_train[:,1])
plt.scatter(explained_variance[0],explained_variance[1],c = 'r')
plt.show()
```



In [23]:

```
from sklearn.linear_model import LogisticRegression
clf = LogisticRegression()
clf.fit(X_train, y_train)
```

Out[23]:

```
LogisticRegression()
```

In [24]:

```
y_pred = clf.predict(X_test)
```

In [25]:

```
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred)
cm
```

Out[25]:

```
array([[3]], dtype=int64)
```

In [26]:

```
from sklearn.metrics import accuracy_score

accuracy_score(y_test, y_pred)
```

Out[26]:

```
1.0
```