```
In [1]:
         import numpy as np
         import pandas as pd
         import matplotlib.pyplot as plt
         from sklearn.preprocessing import StandardScaler
         from sklearn.preprocessing import MinMaxScaler
         from sklearn.datasets import load iris
         from sklearn.linear model import LogisticRegression
         from sklearn.metrics import confusion matrix
         from sklearn import metrics
         import seaborn as sns
         import warnings
         from matplotlib.colors import ListedColormap
         from sklearn.naive bayes import GaussianNB
         from sklearn.metrics import confusion_matrix,accuracy_score
         from sklearn.model_selection import KFold
         from sklearn.model_selection import cross_val_score
In [2]:
         Diabetus = pd.read csv('C:/Users/andre/Desktop/ECGR HW/ECGR 4105/Diabetus.csv')
         Diabetus.head()
```

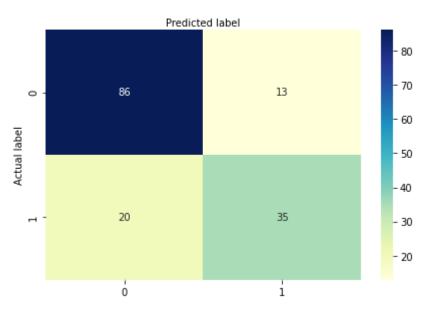
Out[2]:		Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	ВМІ	DiabetesPedigreeFunction	Age	0
	0	6	148	72	35	0	33.6	0.627	50	
	1	1	85	66	29	0	26.6	0.351	31	
	2	8	183	64	0	0	23.3	0.672	32	
	3	1	89	66	23	94	28.1	0.167	21	
	4	0	137	40	35	168	43.1	2.288	33	

In [3]: Diabetus.head(20)

Out[3]:		Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	вмі	DiabetesPedigreeFunction	Age
	0	6	148	72	35	0	33.6	0.627	50
	1	1	85	66	29	0	26.6	0.351	31
	2	8	183	64	0	0	23.3	0.672	32
	3	1	89	66	23	94	28.1	0.167	21
	4	0	137	40	35	168	43.1	2.288	33
	5	5	116	74	0	0	25.6	0.201	30
	6	3	78	50	32	88	31.0	0.248	26
	7	10	115	0	0	0	35.3	0.134	29
	8	2	197	70	45	543	30.5	0.158	53
	9	8	125	96	0	0	0.0	0.232	54
	10	4	110	92	0	0	37.6	0.191	30

```
Pregnancies Glucose BloodPressure SkinThickness Insulin BMI DiabetesPedigreeFunction Age
                                                         0
         11
                     10
                            168
                                           74
                                                                   38.0
                                                                                          0.537
                                                                                                  34
         12
                     10
                            139
                                           80
                                                         0
                                                                   27.1
                                                                                          1.441
                                                                                                  57
         13
                      1
                            189
                                           60
                                                        23
                                                               846
                                                                   30.1
                                                                                          0.398
                                                                                                  59
         14
                      5
                            166
                                           72
                                                        19
                                                               175
                                                                  25.8
                                                                                          0.587
                                                                                                  51
         15
                      7
                            100
                                            0
                                                         0
                                                                   30.0
                                                                                          0.484
                                                                                                  32
         16
                      0
                            118
                                           84
                                                        47
                                                               230 45.8
                                                                                          0.551
                                                                                                  31
         17
                      7
                            107
                                           74
                                                         0
                                                                   29.6
                                                                                          0.254
                                                                                                  31
         18
                      1
                            103
                                           30
                                                        38
                                                               83
                                                                   43.3
                                                                                          0.183
                                                                                                  33
         19
                      1
                            115
                                           70
                                                        30
                                                               96 34.6
                                                                                          0.529
                                                                                                 32
In [4]:
         X = Diabetus.iloc[:, [0,1,2,3,4,5,6,7]].values
         Y = Diabetus.iloc[:, 8].values
In [5]:
         X[0:10]
Out[5]: array([[6.000e+00, 1.480e+02, 7.200e+01, 3.500e+01, 0.000e+00, 3.360e+01,
                 6.270e-01, 5.000e+01],
                [1.000e+00, 8.500e+01, 6.600e+01, 2.900e+01, 0.000e+00, 2.660e+01,
                 3.510e-01, 3.100e+01],
                [8.000e+00, 1.830e+02, 6.400e+01, 0.000e+00, 0.000e+00, 2.330e+01,
                 6.720e-01, 3.200e+01],
                [1.000e+00, 8.900e+01, 6.600e+01, 2.300e+01, 9.400e+01, 2.810e+01,
                 1.670e-01, 2.100e+01],
                [0.000e+00, 1.370e+02, 4.000e+01, 3.500e+01, 1.680e+02, 4.310e+01,
                 2.288e+00, 3.300e+01],
                [5.000e+00, 1.160e+02, 7.400e+01, 0.000e+00, 0.000e+00, 2.560e+01,
                 2.010e-01, 3.000e+01],
                [3.000e+00, 7.800e+01, 5.000e+01, 3.200e+01, 8.800e+01, 3.100e+01,
                 2.480e-01, 2.600e+01],
                [1.000e+01, 1.150e+02, 0.000e+00, 0.000e+00, 0.000e+00, 3.530e+01,
                 1.340e-01, 2.900e+01],
                [2.000e+00, 1.970e+02, 7.000e+01, 4.500e+01, 5.430e+02, 3.050e+01,
                 1.580e-01, 5.300e+01],
                [8.000e+00, 1.250e+02, 9.600e+01, 0.000e+00, 0.000e+00, 0.000e+00,
                 2.320e-01, 5.400e+01]])
In [6]:
         from sklearn.model selection import train test split
         X train, X test, Y train, Y test = train test split(X, Y, train size=0.8, test size = 0
In [7]:
         SS X = StandardScaler()
         X train = SS X.fit transform(X train)
         X test = SS X.fit transform(X test)
In [8]:
          Logistic Class = LogisticRegression(random state=0)
          Logistic_Class.fit(X_train, Y_train)
```

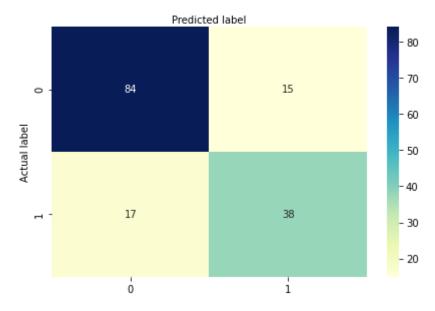
```
Out[8]: LogisticRegression(random_state=0)
In [9]:
          Y pred = Logistic Class.predict(X test)
In [10]:
          Y pred[0:9]
Out[10]: array([0, 0, 0, 0, 0, 0, 1, 0], dtype=int64)
In [11]:
          cnf_matrix = confusion_matrix(Y_test, Y_pred)
          cnf_matrix
Out[11]: array([[86, 13],
                [20, 35]], dtype=int64)
In [12]:
          print("Accuracy:",metrics.accuracy_score(Y_test, Y_pred))
          print("Precision:",metrics.precision_score(Y_test, Y_pred))
          print("Recall:", metrics.recall_score(Y_test, Y_pred))
         Accuracy: 0.7857142857142857
         Precision: 0.729166666666666
         Recall: 0.6363636363636364
In [13]:
          class names=[0,1] # name of classes
          fig, ax = plt.subplots()
          tick marks = np.arange(len(class names))
          plt.xticks(tick_marks, class_names)
          plt.yticks(tick_marks, class_names)
          # create heatmap
          sns.heatmap(pd.DataFrame(cnf matrix), annot=True, cmap="YlGnBu" ,fmt='g')
          ax.xaxis.set label position("top")
          plt.tight layout()
          plt.title('Confusion matrix', y=1.1)
          plt.ylabel('Actual label')
          plt.xlabel('Predicted label')
Out[13]: Text(0.5, 257.44, 'Predicted label')
```



```
In [14]:
          #2-Color Plot (Not Working)
          #warnings.filterwarnings('ignore')
          #X_set, Y_set= X_test, Y_test
          #X1,X2 = np.meshgrid(np.arange(start = X_set[:, 0].min() -1, stop= X_set[:, 0].max()+1,
                               np.arange(start = X_set[:, 1].min() -1, stop= X_set[:, 1].max()+1,
          #plt.contourf(X1,X2, Logistic_Class.predict(np.array([X1.ravel(), X2.ravel()]).T).resha
                        cmap = ListedColormap(('red', 'blue')))
                   plt.xlim((X1.min(),X1.max()))
                   plt.ylim((X2.min(), X2.max()))
          #for i,j in enumerate(np.unique(y_set)):
          #plt.scatter(X_set[y_set==j,0], X_set[y_set==j,1], c= ListedColormap(('red','blue'))(i)
          #plt.title('Logistic Regression(Test Set)')
          #plt.xlabel('Age')
          #plt.ylabel('Estimated Salary')
          #plt.legend()
          #plt.show()
 In [ ]:
In [15]:
          #Part 2: Gausian Bayes Thm
In [16]:
          classifier = GaussianNB()
          classifier.fit(X_train, Y_train)
Out[16]: GaussianNB()
In [17]:
          Y2 pred = classifier.predict(X test)
In [18]:
          cm = confusion_matrix(Y_test, Y2_pred)
          ac = accuracy_score(Y_test, Y2_pred)
```

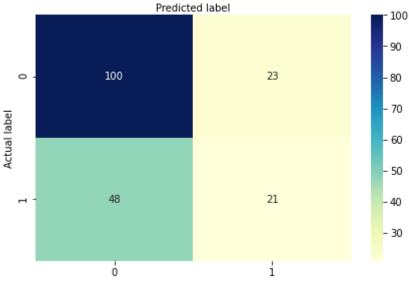
```
In [19]:
          print("Accuracy:",metrics.accuracy_score(Y_test, Y2_pred))
          print("Precision:",metrics.precision_score(Y_test, Y2_pred))
          print("Recall:", metrics.recall_score(Y_test, Y2_pred))
         Accuracy: 0.7922077922077922
         Precision: 0.7169811320754716
         Recall: 0.6909090909090909
In [20]:
          #Builds the matrix for problem 2
          cnf matrix = confusion matrix(Y test, Y2 pred)
          cnf matrix
Out[20]: array([[84, 15],
                 [17, 38]], dtype=int64)
In [21]:
          #Confusion Matrix problem 2
          class_names=[0,1] # name of classes
          fig, ax = plt.subplots()
          tick_marks = np.arange(len(class_names))
          plt.xticks(tick_marks, class_names)
          plt.yticks(tick marks, class names)
          # create heatmap
          sns.heatmap(pd.DataFrame(cnf matrix), annot=True, cmap="YlGnBu" ,fmt='g')
          ax.xaxis.set_label_position("top")
          plt.tight_layout()
          plt.title('Confusion matrix', y=1.1)
          plt.ylabel('Actual label')
          plt.xlabel('Predicted label')
```

# Out[21]: Text(0.5, 257.44, 'Predicted label')



```
In [22]:
In []:
```

```
In [ ]:
 In [ ]:
          #Part C: K-Fold of the Logistic Regression
In [23]:
          import numpy as np
          import pandas as pd
          from sklearn.model_selection import train_test_split
          from sklearn.neighbors import KNeighborsClassifier
          from sklearn import metrics
In [24]:
          \#Code\ for\ K = 10\ Folds
          dataset = pd.read_csv('C:/Users/andre/Desktop/ECGR HW/ECGR 4105/Diabetus.csv')
          X = dataset.iloc[:, [0, 7]]
          Y = dataset.iloc[:, 8]
          X train, X test, Y train, Y test = train test split(X,Y,random state =42)
          #the train test split function by default has a training (80%) and testing (20%) split
          knnclassifier = KNeighborsClassifier(n neighbos=10) #Number of folds
          knnclassifier.fit(X train,Y train)
          Y_pred = knnclassifier.predict(X_test)
          print("Accuracy:",metrics.accuracy_score(Y_test, Y_pred))
          print("Precision:", metrics.precision_score(Y_test, Y_pred))
          print("Recall:", metrics.recall score(Y test, Y pred))
         Accuracy: 0.6302083333333334
         Precision: 0.47727272727273
         Recall: 0.30434782608695654
In [25]:
          #Build the matrix for K = 10
          cnf matrix = confusion matrix(Y test, Y pred)
          cnf_matrix
Out[25]: array([[100, 23],
                 [ 48, 21]], dtype=int64)
In [26]:
          #Confusion Matrix for Problem 3 (K = 10)
          class_names=[0,1] # name of classes
          fig, ax = plt.subplots()
          tick marks = np.arange(len(class names))
          plt.xticks(tick_marks, class_names)
          plt.yticks(tick marks, class names)
          # create heatmap
          sns.heatmap(pd.DataFrame(cnf matrix), annot=True, cmap="YlGnBu" ,fmt='g')
          ax.xaxis.set label position("top")
          plt.tight layout()
          plt.title('Confusion matrix', y=1.1)
          plt.ylabel('Actual label')
          plt.xlabel('Predicted label')
Out[26]: Text(0.5, 257.44, 'Predicted label')
```

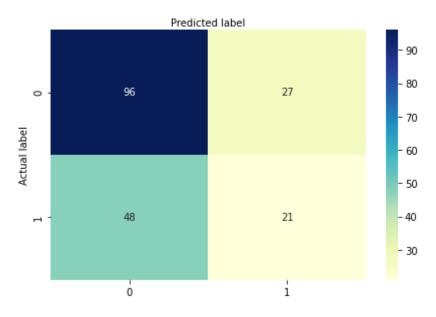


```
In [ ]:
 In [ ]:
 In [ ]:
In [27]:
          \#Code\ for\ K = 5\ folds
          dataset = pd.read csv('C:/Users/andre/Desktop/ECGR HW/ECGR 4105/Diabetus.csv')
          X = dataset.iloc[:, [0, 7]]
          Y = dataset.iloc[:, 8]
          X train, X test, Y train, Y test = train test split(X,Y,random state =42)
          knnclassifier = KNeighborsClassifier(n neighbors=5) #Number of folds
          knnclassifier.fit(X_train,Y_train)
          Y pred = knnclassifier.predict(X test)
          print("Accuracy:",metrics.accuracy_score(Y_test, Y_pred))
          print("Precision:",metrics.precision_score(Y_test, Y_pred))
          print("Recall:", metrics.recall score(Y test, Y pred))
         Accuracy: 0.609375
         Precision: 0.4375
         Recall: 0.30434782608695654
In [28]:
          #Build the Matrix for K = 5
          cnf matrix = confusion matrix(Y test, Y pred)
          cnf_matrix
Out[28]: array([[96, 27],
                [48, 21]], dtype=int64)
In [29]:
          #Confusion Matrix for K = 5
          class_names=[0,1] # name of classes
          fig, ax = plt.subplots()
          tick marks = np.arange(len(class names))
```

```
plt.xticks(tick_marks, class_names)
plt.yticks(tick_marks, class_names)
# create heatmap
sns.heatmap(pd.DataFrame(cnf_matrix), annot=True, cmap="YlGnBu" ,fmt='g')
ax.xaxis.set_label_position("top")
plt.tight_layout()
plt.title('Confusion matrix', y=1.1)
plt.ylabel('Actual label')
plt.xlabel('Predicted label')
```

## Out[29]: Text(0.5, 257.44, 'Predicted label')

### Confusion matrix



In [30]: #For K-Fold = 10
#When applying K-Fold Classification, the Accuracy increased by a moderate ammount
#as well as the precision model. The significant difference is that the recall score
#doubled

In [31]:
#For K-fold = 5
#With K = 5, as expected form the previos trial, the accuracy and precision
#increased marginally from the initioal condition with no folds
#although these scores arent as large as the K=10 trial.
#But with the Recall score, there is not a significant difference between the trial wit

In [ ]:

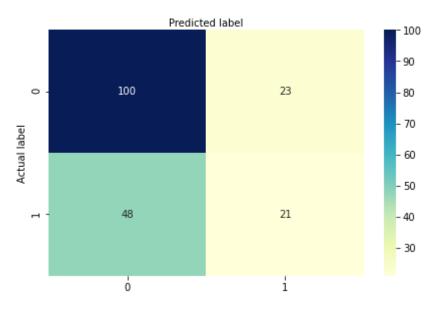
In [ ]:

In [ ]:

In [32]: #Part 4: K-Fold of the Nieve Bayes #This does not make sense as applying K-Fold #Nieve bayes is a clasifier for probablility

```
In [33]:
          dataset = pd.read csv('C:/Users/andre/Desktop/ECGR HW/ECGR 4105/Diabetus.csv')
          X = dataset.iloc[:, [0, 7]]
          Y = dataset.iloc[:, 8]
          X_train, X_test, Y_train, Y_test = train_test_split(X,Y,random_state =42)
          #the train_test split function by default has a training (80%) and testing (20%) split
          knnclassifier = KNeighborsClassifier(n neighbors=10) #Number of folds
          knnclassifier.fit(X train,Y train)
          Y pred2 = knnclassifier.predict(X test)
          print("Accuracy:",metrics.accuracy_score(Y_test, Y_pred2))
          print("Precision:", metrics.precision_score(Y_test, Y_pred2))
          print("Recall:", metrics.recall score(Y test, Y pred2))
         Accuracy: 0.6302083333333334
         Precision: 0.47727272727273
         Recall: 0.30434782608695654
In [34]:
          cnf matrix = confusion matrix(Y test, Y pred2)
          cnf matrix
Out[34]: array([[100,
                       23],
                [ 48, 21]], dtype=int64)
In [35]:
          class names=[0,1] # name of classes
          fig, ax = plt.subplots()
          tick marks = np.arange(len(class names))
          plt.xticks(tick_marks, class_names)
          plt.yticks(tick marks, class names)
          # create heatmap
          sns.heatmap(pd.DataFrame(cnf matrix), annot=True, cmap="YlGnBu",fmt='g')
          ax.xaxis.set label position("top")
          plt.tight layout()
          plt.title('Confusion matrix', y=1.1)
          plt.ylabel('Actual label')
          plt.xlabel('Predicted label')
```

# Out[35]: Text(0.5, 257.44, 'Predicted label')



In [ ]: