ROC Analysis Assignment

Bianca Caissotti di Chiusano

In [46]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split
from numpy import trapz
from sklearn.neighbors import KNeighborsClassifier
from sklearn import metrics
```

In [24]:
```python
# Probabilistic classifier h has been first trained on some labeled training data and tested on test instances
# For each test instance x, classifier h outputs posterior probability of positive and negative class
```

In the ROC class there is the function compute_ROC_coordinates

This method first sorts the probabilities of predicting "tested_positive" for each test instance x in descending order.

With a for loop it is continuously updating a threshold t (like in the example in the slides), which starts from the greatest probability in the sorted probs until the lowest. For every threshold t, test instance with a probability above t we say should actually be tested_positive and everything below should be tested_negative. This is done in the code through the use of a variable called "truth". Once the threshold is set, we use another for loop to reiterate among all the test instances from the beginning.

We check the trueClass to the the actual output if it is tested_positive or tested_negative. For a test instance, if trueClass says tested_positive and the predicted probability in probs for that test instance is above the threshold t, then truth is also tested_positive and we add 1 to the True Positive (tp) counter. Same reasoning but with trueClass saying tested_negative, then we add 1 to the False Positive (fp) counter. We calculate the rates by dividing TP/P and FP/N and add to the coordinates.

In [52]:
```python
class ROC():
    # parametric constructor accepts Probs(estimated probs of the test instance for pos) and  TrueClass (true c
    def __init__(self, probs, trueClass):
        self.probs = probs
        self.trueClass = trueClass

    def compute_ROC_coordinates(self, probs, trueClass):
        # get pos class probs and true class
        # compute TPr and FPr coordinates

        # Sort the test instances into decreasing order of the probibility
        probs = probs.sort_values(ascending = False)
        trueClass = trueClass.reindex(probs.index)

        FPr = []
        TPr = []

        truth = False
        count= trueClass.value_counts()

        # In the beginning everything is either Fnegative or Tnegative
        coordinates.append([0, 0])

        # For each consecutive instance x in probs
        # Set the threshold value t equal to the probability Ppos of x and compute TPr and FPr of the discrete
        for i in range(len(probs)):
            tp = 0
            fp = 0
            t = probs.iloc[i]
            # under t its negative, above t is positive
            for j in range(len(probs)):
                if(probs.iloc[j] < t):
                    truth = "tested_negative"
                else:
                    truth = "tested_positive"
                if(trueClass.iloc[j]['class'] == "tested_positive" and truth == "tested_positive"):
                    tp = tp + 1
                else:
                    if(trueClass.iloc[j]['class'] == "tested_negative" and truth == "tested_positive"):
                        fp = fp + 1
            FPr.append(fp/count["tested_negative"])
            TPr.append(tp/count["tested_positive"])

        return TPr, FPr

    def plot_ROC(self, TPr, FPr):
        plt.plot(FPr,TPr)
        plt.xlabel('fpr')
        plt.ylabel('tpr')

    def compute_AUCROC(self, TPr, FPr):
        area = metrics.auc(FPr, TPr)
        return area
```

In [30]:
```python
# Probabilistic classifier KNN with the diabetes dataset
data = pd.read_csv("diabetes.csv")
data.head()
Y = data['class']
X = data.drop(['class'],axis=1)
data
```

Out[30]:

	preg	plas	pres	skin	insu	mass	pedi	age	class
0	6	148	72	35	0	33.6	0.627	50	tested_positive
1	1	85	66	29	0	26.6	0.351	31	tested_negative
2	8	183	64	0	0	23.3	0.672	32	tested_positive
3	1	89	66	23	94	28.1	0.167	21	tested_negative
4	0	137	40	35	168	43.1	2.288	33	tested_positive
...	...	...	...	...	...	...	...	...	...
763	10	101	76	48	180	32.9	0.171	63	tested_negative
764	2	122	70	27	0	36.8	0.340	27	tested_negative
765	5	121	72	23	112	26.2	0.245	30	tested_negative
766	1	126	60	0	0	30.1	0.349	47	tested_positive
767	1	93	70	31	0	30.4	0.315	23	tested_negative

768 rows × 9 columns

Splitting the diabetes data set into training and testing data. Using the KNN classifiers with 3-nearest neighbors

We define the true class to be the actual output that we know is correct from the data set.

In [31]:
```python
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.34, random_state=10)
classify = KNeighborsClassifier(n_neighbors=3)
classify.fit(X_train, Y_train)

trueClass = pd.DataFrame(Y_test).reset_index(drop=True)
trueClass
```

Out[31]:

	class
0	tested_negative
1	tested_negative
2	tested_negative
3	tested_positive
4	tested_negative
...	...
257	tested_negative
258	tested_positive
259	tested_positive
260	tested_negative
261	tested_negative

262 rows × 1 columns

Instead, probs is the prediction probabilities of input test data using the classifier

In [32]:
```python
probs = pd.DataFrame(classify.predict_proba(X_test))
probs
```

Out[32]:

	0	1
0	0.000000	1.000000
1	0.666667	0.333333
2	0.333333	0.666667
3	1.000000	0.000000
4	0.333333	0.666667
...	...	...
257	1.000000	0.000000
258	0.000000	1.000000
259	0.000000	1.000000
260	1.000000	0.000000
261	1.000000	0.000000

262 rows × 2 columns

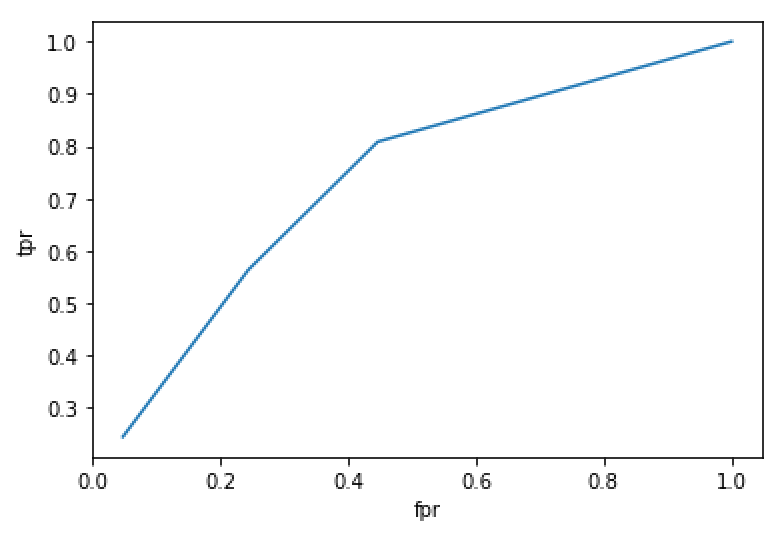
We can have a look at these probabilities

In [33]:
```python
probs = probs.iloc[:,1] # predicted probabilities of tested positive
probs
```

Out[33]:
```
0      1.000000
1      0.333333
2      0.666667
3      0.000000
4      0.666667
         ...
257    0.000000
258    1.000000
259    1.000000
260    0.000000
261    0.000000
Name: 1, Length: 262, dtype: float64
```

Calling the ROC class and passing as parameters probs and trueClass We then call the method to compute the coordinate that is going to return an X (FPr) and Y(TPr) to plot the ROC curve

In [53]:
```python
roc = ROC(probs, trueClass)
TPr, FPr = roc.compute_ROC_coordinates(probs, trueClass)
roc.plot_ROC(TPr, FPr)
```



In [54]:
```python
roc.compute_AUCROC(TPr, FPr)
```

Out[54]:
```
0.7188449848024316
```

Overall ROC is used to understand and analyse the performance of the classifier (in this case the KNN classifier). The area under the curve (AUC) indicates the separation of the classes. According to the readings "no realistic classifier should have an AUC less then 0.5". Already from our result we can see that the KNN classifier performed well. A high area means that there is good separation of the classes, thus better performance. From our area result, we have a pretty good separation of classes with our classifier.