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PROJET

Objectifs :

Dans ce tutoriel, nous développons et évaluons un modèle de prédiction capable de prédire
l'insuffisance cardiaque d'un patient. Cette base contient 918 patients annotés par 12
caractéristiques.

-Importation les librairies:

```
In [1]: # Importing the libraries
        import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
```

-Importation des datasets:

```
In [2]: # Importing the dataset
        data_heart = pd.read_csv('heart.csv')
```

-Afficher et interpréter les données de la base Heart:

```
In [3]: #afficher la description de la base heart
        data_heart.describe()
```

Out[3]:

	Age	RestingBP	Cholesterol	FastingBS	MaxHR	Oldpeak	HeartDisease
count	918.000000	918.000000	918.000000	918.000000	918.000000	918.000000	918.000000
mean	53.510893	132.396514	198.799564	0.233115	136.809368	0.887364	0.553377
std	9.432617	18.514154	109.384145	0.423046	25.460334	1.066570	0.497414
min	28.000000	0.000000	0.000000	0.000000	60.000000	-2.600000	0.000000
25%	47.000000	120.000000	173.250000	0.000000	120.000000	0.000000	0.000000
50%	54.000000	130.000000	223.000000	0.000000	138.000000	0.600000	1.000000
75%	60.000000	140.000000	267.000000	0.000000	156.000000	1.500000	1.000000
max	77.000000	200.000000	603.000000	1.000000	202.000000	6.200000	1.000000

-afficher le contenu de matrice data heart de la base heart:

In [4]:
```
data_heart.head()
```

Out[4]:

	Age	Sex	ChestPainType	RestingBP	Cholesterol	FastingBS	RestingECG	MaxHR	ExerciseAngina	Oldpeak	ST_Slope	HeartDisease
0	40	M	ATA	140	289	0	Normal	172	N	0.0	Up	0
1	49	F	NAP	160	180	0	Normal	156	N	1.0	Flat	1
2	37	M	ATA	130	283	0	ST	98	N	0.0	Up	0
3	48	F	ASY	138	214	0	Normal	108	Y	1.5	Flat	1
4	54	M	NAP	150	195	0	Normal	122	N	0.0	Up	0

-afficher le contenu de vecteur target:

In [5]:
```
data_heart.HeartDisease
```

Out[5]:
```
0      0
1      1
2      0
3      1
4      0
      ..
913    1
914    1
915    1
916    1
917    0
Name: HeartDisease, Length: 918, dtype: int64
```

-afficher la dimension de matrice data_heart de la base heart:

In [6]:
```
data_heart.shape
```

Out[6]: (918, 12)

-afficher la dimension du vecteur target de la base heart:

In [7]:
```
data_heart.HeartDisease.shape
```

Out[7]: (918,)

-description de chaque variable:

In [8]:
```
data_heart.describe()
```

Out[8]:

	Age	RestingBP	Cholesterol	FastingBS	MaxHR	Oldpeak	HeartDisease
count	918.000000	918.000000	918.000000	918.000000	918.000000	918.000000	918.000000
mean	53.510893	132.396514	198.799564	0.233115	136.809368	0.887364	0.553377
std	9.432617	18.514154	109.384145	0.423046	25.460334	1.066570	0.497414
min	28.000000	0.000000	0.000000	0.000000	60.000000	-2.600000	0.000000
25%	47.000000	120.000000	173.250000	0.000000	120.000000	0.000000	0.000000
50%	54.000000	130.000000	223.000000	0.000000	138.000000	0.600000	1.000000
75%	60.000000	140.000000	267.000000	0.000000	156.000000	1.500000	1.000000
max	77.000000	200.000000	603.000000	1.000000	202.000000	6.200000	1.000000

-interprétation de vecteur HearDisease(target):

```
In [9]: data_heart.HeartDisease.value_counts()

Out[9]: 1    508
        0    410
        Name: HeartDisease, dtype: int64
```

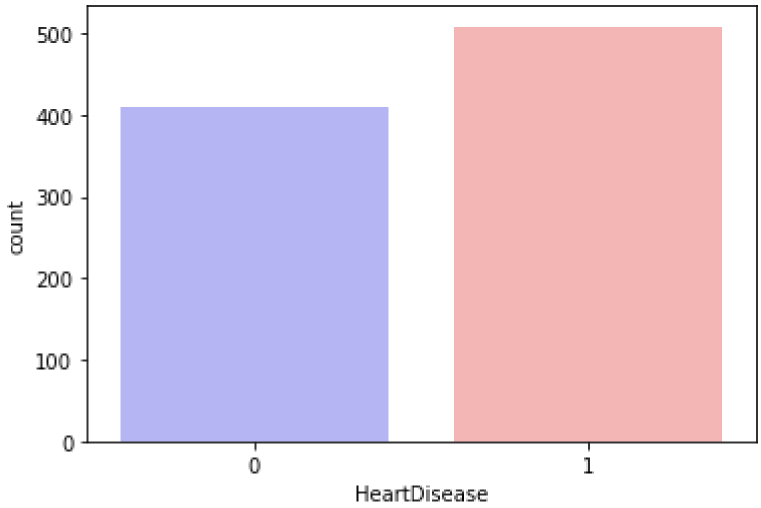
-Vérifier s'il y a des valeurs aberrantes dans la base:

```
In [10]: print(data_heart.isnull().sum())

         Age               0
         Sex               0
         ChestPainType     0
         RestingBP         0
         Cholesterol       0
         FastingBS         0
         RestingECG        0
         MaxHR             0
         ExerciseAngina    0
         Oldpeak           0
         ST_Slope          0
         HeartDisease      0
         dtype: int64
```

-Interprétation graphiquement de vecteur HearDisease(target):

```
In [11]: import seaborn as sns
         sns.countplot(x="HeartDisease", data=data_heart, palette="bwr")
         plt.show()
```



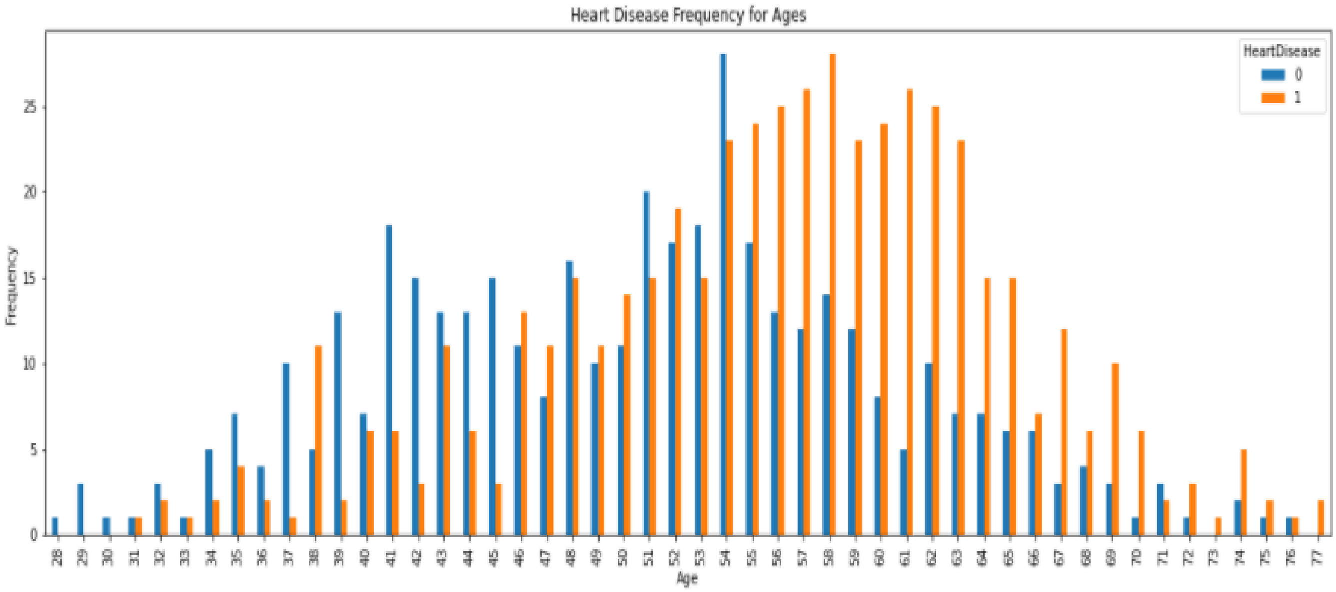
-Pourcentage de l'insuffisance cardiaque d'un patient:

In [12]:
```
countNoDisease = len(data_heart[data_heart.HeartDisease == 0])
countHaveDisease = len(data_heart[data_heart.HeartDisease == 1])
print("Percentage of Patients Haven't Heart Disease: {:.2f}%".format((countNoDisease / (len(data_heart.HeartDisease))*100)))
print("Percentage of Patients Have Heart Disease: {:.2f}%".format((countHaveDisease / (len(data_heart.HeartDisease))*100)))
```

```
Percentage of Patients Haven't Heart Disease: 44.66%
Percentage of Patients Have Heart Disease: 55.34%
```

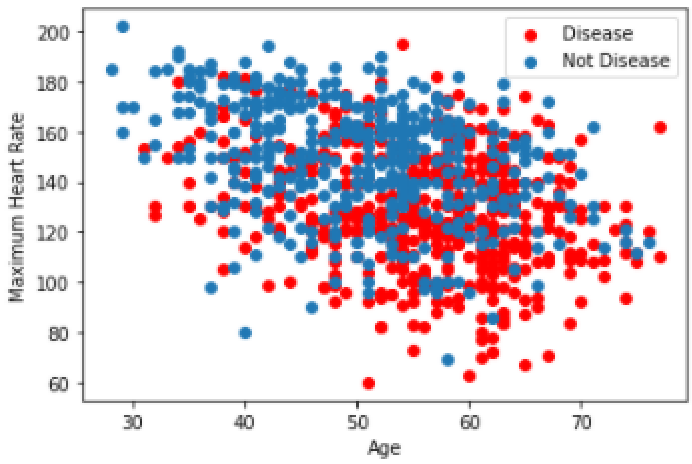
-l'insuffisance cardiaque d'un patient par rapport a son age :

```
pd.crosstab(data_heart.Age,data_heart.HeartDisease).plot(kind="bar",figsize=(20,6))
plt.title('Heart Disease Frequency for Ages')
plt.xlabel('Age')
plt.ylabel('Frequency')
plt.savefig('heartDiseaseAndAges.png')
plt.show()
```



-Maximun de l'insuffisance cardiaque d'un patient par rapport a son age:

```
plt.scatter(x=data_heart.Age[data_heart.HeartDisease==1], y=data_heart.MaxHR[(data_heart.HeartDisease==1)], c="red")
plt.scatter(x=data_heart.Age[data_heart.HeartDisease==0], y=data_heart.MaxHR[(data_heart.HeartDisease==0)])
plt.legend(["Disease", "Not Disease"])
plt.xlabel("Age")
plt.ylabel("Maximum Heart Rate")
plt.show()
```



-Normalisation de la base :

In [15]:
```python
from sklearn import preprocessing
label_encoder=preprocessing.LabelEncoder()
data_heart['Sex']=label_encoder.fit_transform(data_heart['Sex'])
data_heart['ChestPainType']=label_encoder.fit_transform(data_heart['ChestPainType'])
data_heart['RestingECG']=label_encoder.fit_transform(data_heart['RestingECG'])
data_heart['ExerciseAngina']=label_encoder.fit_transform(data_heart['ExerciseAngina'])
data_heart['ST_Slope']=label_encoder.fit_transform(data_heart['ST_Slope'])
data_heart
```

Out[15]:

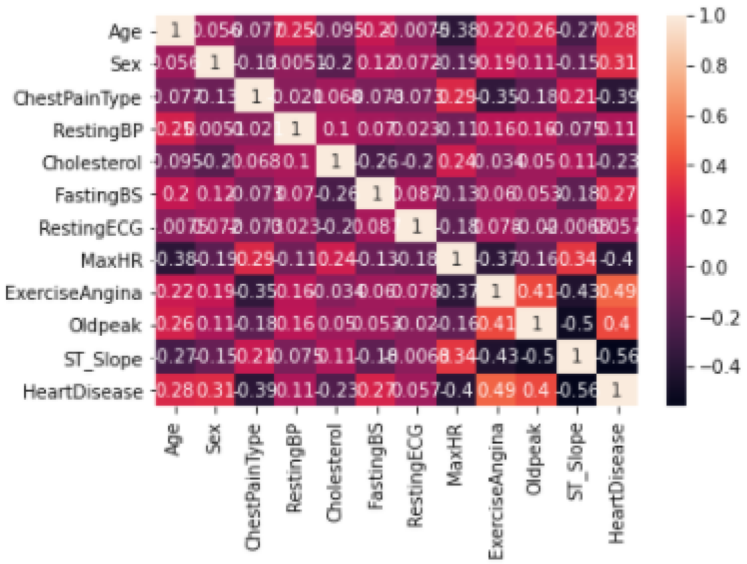
	Age	Sex	ChestPainType	RestingBP	Cholesterol	FastingBS	RestingECG	MaxHR	ExerciseAngina	Oldpeak	ST_Slope	HeartDisease
0	40	1	1	140	289	0	1	172	0	0.0	2	0
1	49	0	2	160	180	0	1	156	0	1.0	1	1
2	37	1	1	130	283	0	2	98	0	0.0	2	0
3	48	0	0	138	214	0	1	108	1	1.5	1	1
4	54	1	2	150	195	0	1	122	0	0.0	2	0
...	...	...	...	...	...	...	...	...	...	...	...	...
913	45	1	3	110	264	0	1	132	0	1.2	1	1
914	68	1	0	144	193	1	1	141	0	3.4	1	1
915	57	1	0	130	131	0	1	115	1	1.2	1	1
916	57	0	1	130	236	0	0	174	0	0.0	1	1
917	38	1	2	138	175	0	1	173	0	0.0	2	0

918 rows × 12 columns

-afficher la matrice de corrélation:

In [16]:
```python
sns.heatmap(data_heart.corr(),annot=True)
```

Out[16]: <AxesSubplot:>



```
In [17]: data_heart["ChestPainType"].value_counts()
```

```
Out[17]: 0    496
         2    203
         1    173
         3     46
         Name: ChestPainType, dtype: int64
```

```
In [18]: data_heart["ST_Slope"].value_counts()
```

```
Out[18]: 1    460
         2    395
         0     63
         Name: ST_Slope, dtype: int64
```

```
In [19]: data_heart.drop(data_heart[data_heart.ST_Slope==0].index,inplace=True)
         data_heart["ST_Slope"].value_counts()
```

```
Out[19]: 1    460
         2    395
         Name: ST_Slope, dtype: int64
```

-Initialisation des attributs:

```
In [20]: x = data_heart.drop('HeartDisease',axis=1).values
         y = data_heart['HeartDisease'].values
```

- Splitting the dataset into the Training set and Test set

```
In [21]: from sklearn.model_selection import train_test_split
         x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.25, random_state = 0)
```

-Feature Scaling

```
In [22]: from sklearn.preprocessing import StandardScaler
         sc = StandardScaler()
         x_train = sc.fit_transform(x_train)
         x_test = sc.transform(x_test)
```

Définition de svm:

Les SVM appartiennent à une famille d'algorithmes qui font appel à l'apprentissage dit supervisé,
et qui sont spécialisées dans la résolution de problèmes de discrimination et de régression mathématiques.

Définition de KNN:

La méthode des K plus proches voisins (KNN) a pour but de classifier des points cibles (classe méconnue) en fonction de leurs distances par rapport à des points constituant un échantillon d'apprentissage (c'est-à-dire dont la classe est connue a priori).

KNN est une approche de classification supervisée intuitive. Il s'agit d'une généralisation de la méthode du voisin le plus proche (NN). NN est un cas particulier de KNN, où k = 1.

Définition de DecisionTreeClassifier:

sklearn.tree.DecisionTreeClassifier permet de réaliser une classification multi-classe à l'aide d'un arbre de décision.

-Training the SVM model on the Training set:

```
In [23]: from sklearn.svm import SVC
         classifier = SVC(kernel = 'linear', random_state = 0)
         classifier.fit(x_train, y_train)

Out[23]: SVC(kernel='linear', random_state=0)
```

-Predicting the Test set results:

```
In [24]: Y_pred = classifier.predict(x_test)
```

```
In [25]: print('Train Score',classifier.score(x_train,y_train))
         print('Test Score', classifier.score(x_test,y_test))

         Train Score 0.8533541341653667
         Test Score 0.8925233644859814
```

-import KNeighborsClassifier

In [53]:
```
from sklearn.neighbors import KNeighborsClassifier
#Setup a knn classifier with k neighbors
knn = KNeighborsClassifier(n_neighbors=5)
```

-Fit the model

In [54]:
```
knn.fit(x_train,y_train)
```

Out[54]: KNeighborsClassifier()

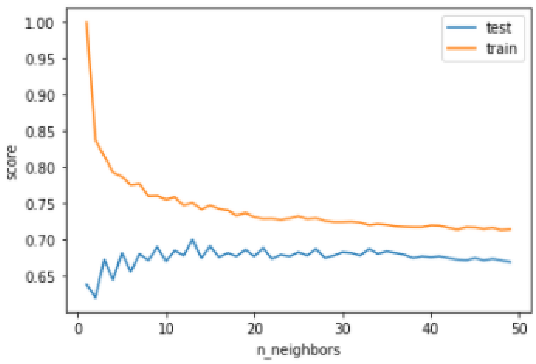
-Résultat:

In [55]:
```
y_pred_knn=knn.predict(x_test)
print('Train Score',knn.score(x_train,y_train))
print('Test Score', knn.score(x_test,y_test))
```

```
Train Score 0.8970358814352574
Test Score 0.8925233644859814
```

In [30]:
```
from sklearn.model_selection import validation_curve
k=np.arange(1,50)
train_score,test_score=validation_curve(knn,x,y,param_name='n_neighbors',param_range=k,cv=4)
plt.plot(k,test_score.mean(axis=1),label='test')
plt.plot(k,train_score.mean(axis=1),label='train')
plt.ylabel('score')
plt.xlabel('n_neighbors')
plt.legend()
```

Out[30]: <matplotlib.legend.Legend at 0xd1907c0>



-DecisionTreeClassifier Importation et résultat:

```
In [47]: col_names=list(data_heart.columns)
         predictors=col_names[0:9]
         target=col_names[11]
         from sklearn.model_selection import train_test_split
         train,test=train_test_split(data_heart,test_size=0.3,random_state=0)
         from sklearn.tree import DecisionTreeClassifier as DS
         model=DS(criterion='gini')
         #model=DS(criterion='entropy')
         model.fit(train[predictors],train[target])
         train_pred=model.predict(train[predictors])
         test_pred=model.predict(test[predictors])
         train_acc=np.mean(train_pred==train[target])
         test_acc=np.mean(test_pred==test[target])
         print(train_acc)
         print(test_acc)

         1.0
         0.8015564202334631
```

-Evaluation du SVM avec plusieurs combinaisons possibles d'hyper paramètres (CV=4)

```
In [44]: from sklearn.model_selection import validation_curve

         from sklearn import svm

         modelSVM=svm.SVC()

         train_scoreSVM,test_scoreSVM=validation_curve(modelSVM,x,y,param_name='kernel',param_range=['linear','poly','rbf'],cv=4)

         test_scoreSVM.mean(axis=1)

Out[44]: array([0.8244647 , 0.69815388, 0.6876234 ])
```

classifieurs	***Train Score***	***Test Score***
SVC	**0.8533541341653667**	**0.8925233644859814**
KNeighborsClassifier	**0.8970358814352574**	**0.8925233644859814**
DecisionTreeClassifier	**1.0**	**0.801556420233463**