Heart Disease Prediction

Milestone: Model Exploration & Model Selection

Group 3

Mugdha Sanjay Parbat - 002142372

Pranav Chandrakant Pulkundwar - 002121679

Telephone

+1 (617) 901-8417

+1 (617) 901-8418

Email ID

parbat.m@northeastern.edu

pulkundwar.p@northeastern.edu

Percentage of contribution by Student 1: 50%

Percentage of contribution by Student 2: 50%

Submission Date: 4th April 2022

By Grpup - 3
Pranav Pulkundwar
Mugdha Parbat

1. Introduction

Data Set Problems

This dataset contains information about diagnosis of heart disease patients. We first perform the data exploration to understand the data dependancies. After that we use Machine learning models in order **to determine whether a person has heart disease or not.**

Notebook Contains

- Data exploration using libraries.(Section - 4)
- Building ML models that can predict whether patients has heart disease or not. (Section - 5, 6)

The machine learning models used in this project are:

1. K-Nearest Neighbour (KNN)
2. Support Vector Machine (SVM)
3. Naive Bayes
4. Decision Tree
5. Random Forest

2. Importing Libraries

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
import os
```

3. Importing Data Set

In [2]:
```
df = pd.read_csv("heart.csv")
df.head()
```

Out[2]:

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	target
0	63	1	3	145	233	1	0	150	0	2.3	0	0	1	1
1	37	1	2	130	250	0	1	187	0	3.5	0	0	2	1
2	41	0	1	130	204	0	0	172	0	1.4	2	0	2	1
3	56	1	1	120	236	0	1	178	0	0.8	2	0	2	1
4	57	0	0	120	354	0	1	163	1	0.6	2	0	2	1

4. Dataset Exploration

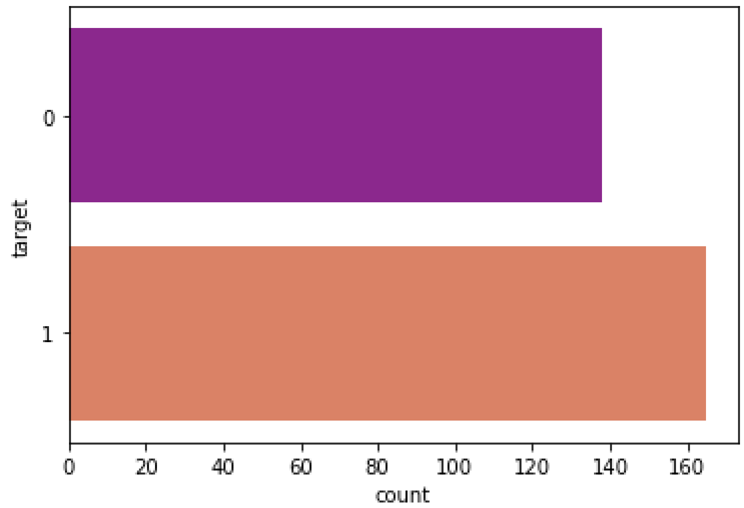
Exploring the dataset that has been imorted.

4.1 Target Distribution

In [3]:
```
df.target.value_counts()
```

Out[3]:
```
1    165
0    138
Name: target, dtype: int64
```

In [4]:
```
sns.countplot(y = "target", data = df, palette = 'plasma')
plt.show()
```



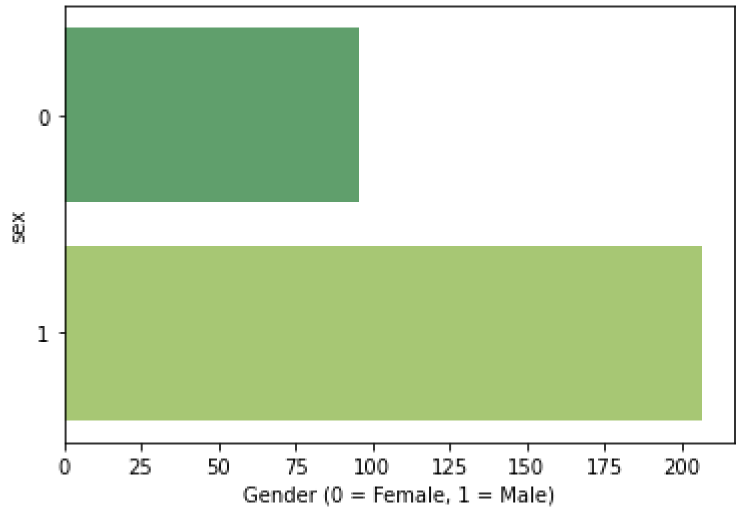
In [5]:
```
count_no_sick = len(df[df.target == 0])

count_sick = len(df[df.target == 1])

print("Percentage of patients without Heart disease: {}%".format((count_no_sick / (len(df.target))*100)))

print("Percentage of patients with Heart disease: {}%".format((count_sick / (len(df.target))*100)))
```

```
Percentage of patients without Heart disease: 45.54455445544555%
Percentage of patients with Heart disease: 54.45544554455446%
```

The above results tell us number of patients that have heart disease are higher than healthy patients.

4.2 Gender Distribution

In [6]:
```
sns.countplot(y = 'sex', data = df, palette = 'summer')
plt.xlabel("Gender (0 = Female, 1 = Male)")
plt.show()
```



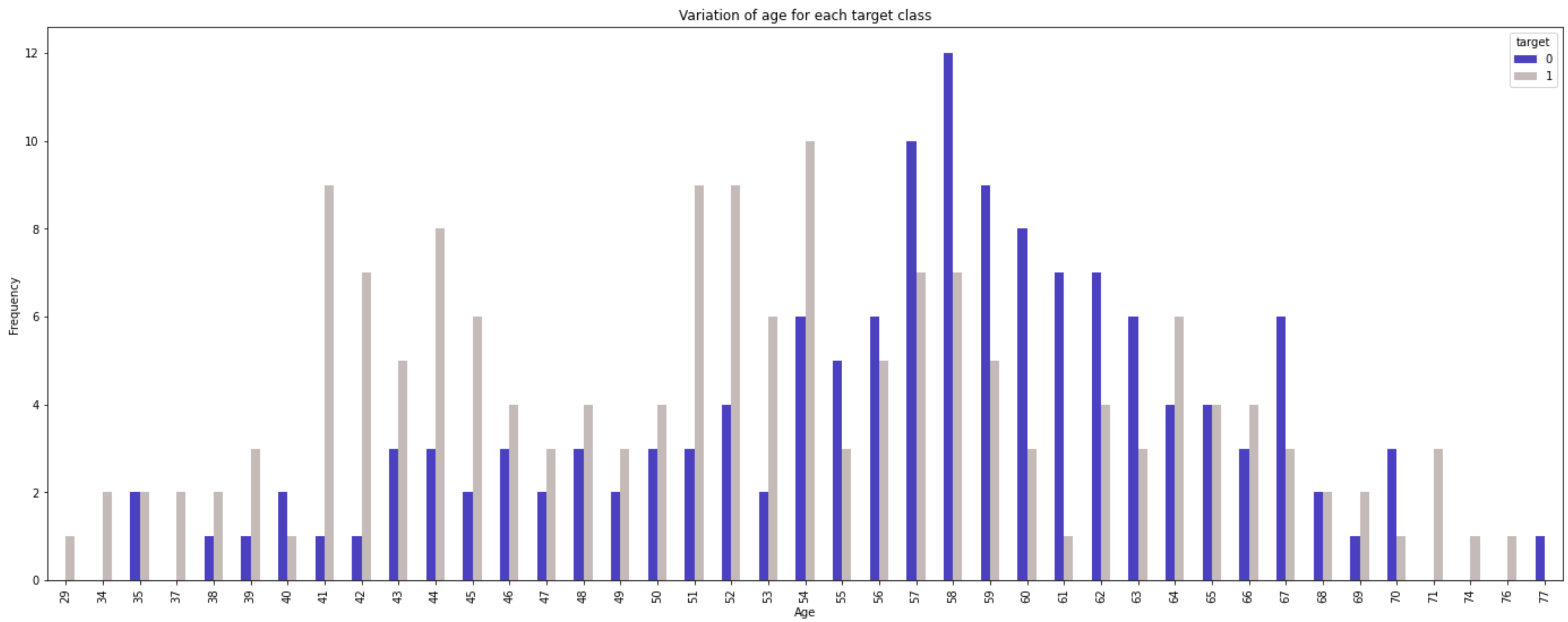
In [7]:
```
count_female = len(df[df.sex == 0])

count_male = len(df[df.sex == 1])

print("Percentage of Female: {}%".format((count_female / (len(df.sex))*100)))

print("Percentage of Male: {}%".format((count_male / (len(df.sex))*100)))
```

```
Percentage of Female: 31.683168316831683%
Percentage of Male: 68.31683168316832%
```

Male patients are more prone to heart disease than female patients.

4.3 Variation of age for each target class

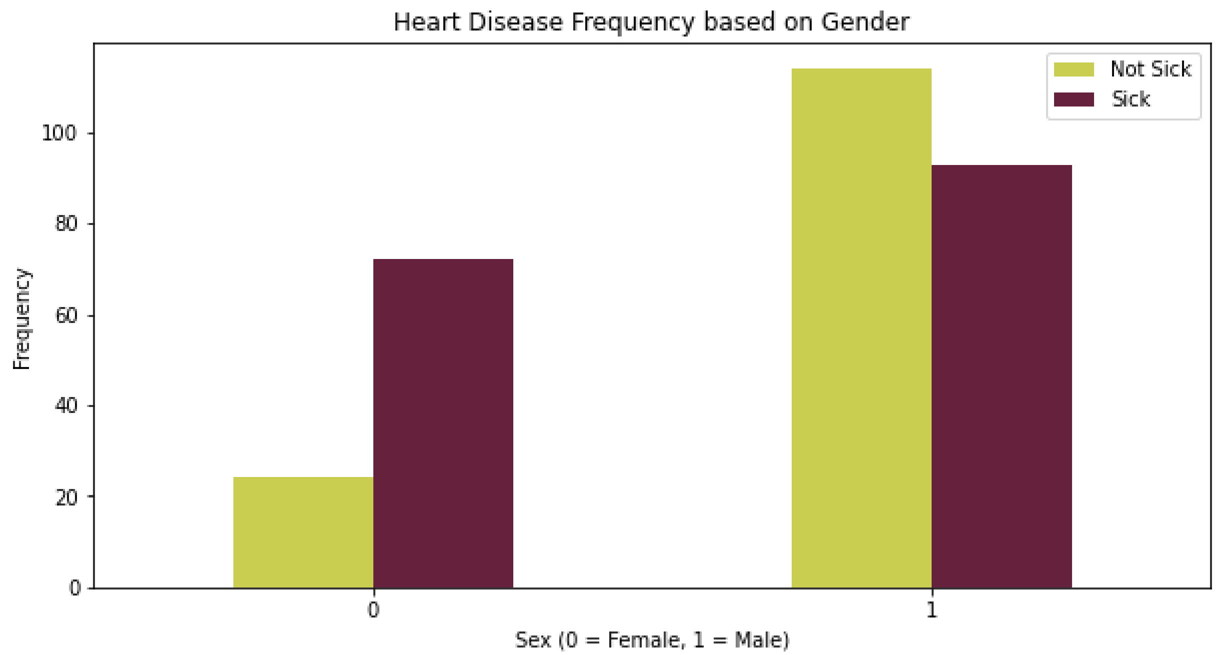
In [8]:
```
pd.crosstab(df.age,df.target).plot(kind = "bar", figsize = (24,9), color = ['#4B40C0','#C4BBB8' ])

plt.title('Variation of age for each target class')
plt.xlabel('Age')
plt.ylabel('Frequency')

plt.show()
```



Patients who have the most heart disease are in the age range of 41 to 54 years.
While patients who do not have heart disease are mostly in the age range of 54 to 64 years.

4.4 Heart Disease Frequency based on Gender

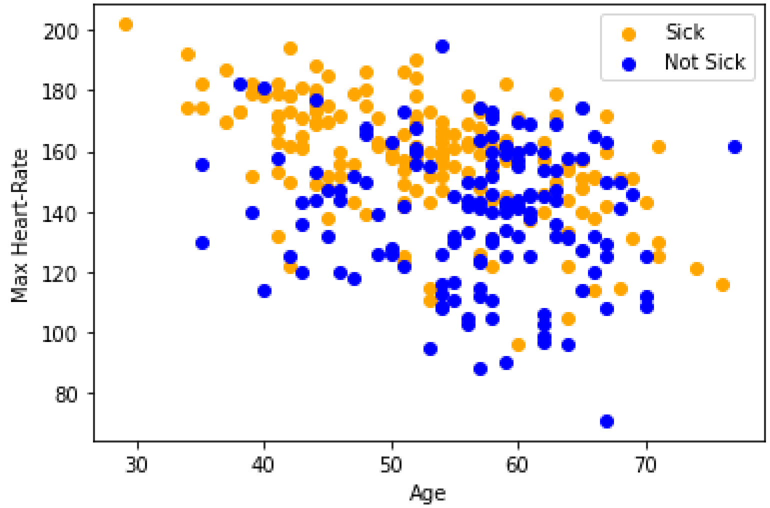
In [9]:
```
pd.crosstab(df.sex,df.target).plot(kind = "bar", figsize = (10,5), color = ['#C9CE50', '#66213D'])

plt.title('Heart Disease Frequency based on Gender')

plt.xlabel('Sex (0 = Female, 1 = Male)')
plt.xticks(rotation = 0)

plt.legend(["Not Sick", "Sick"])
plt.ylabel('Frequency')

plt.show()
```



We observe that heart disease is dominant in women.
Meanwhile, lower number of men have heart disease.

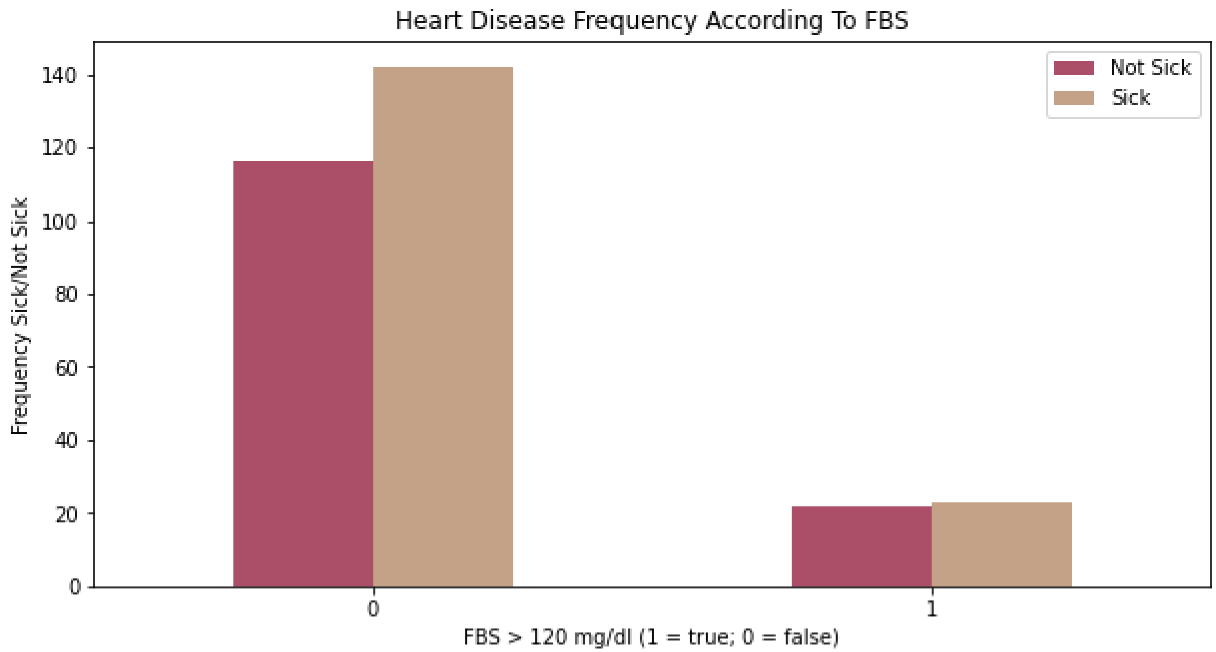
4.5 Scatter Plot based on Age

In [10]:
```
plt.scatter(x = df.age[df.target == 1], y = df.thalach[(df.target == 1)], c = "Orange")
plt.scatter(x = df.age[df.target == 0], y = df.thalach[(df.target == 0)], c = "blue")

plt.legend(["Sick", "Not Sick"])
plt.xlabel("Age")
plt.ylabel("Max Heart-Rate")

plt.show()
```



4.6 Heart Disease Frequency According To FBS

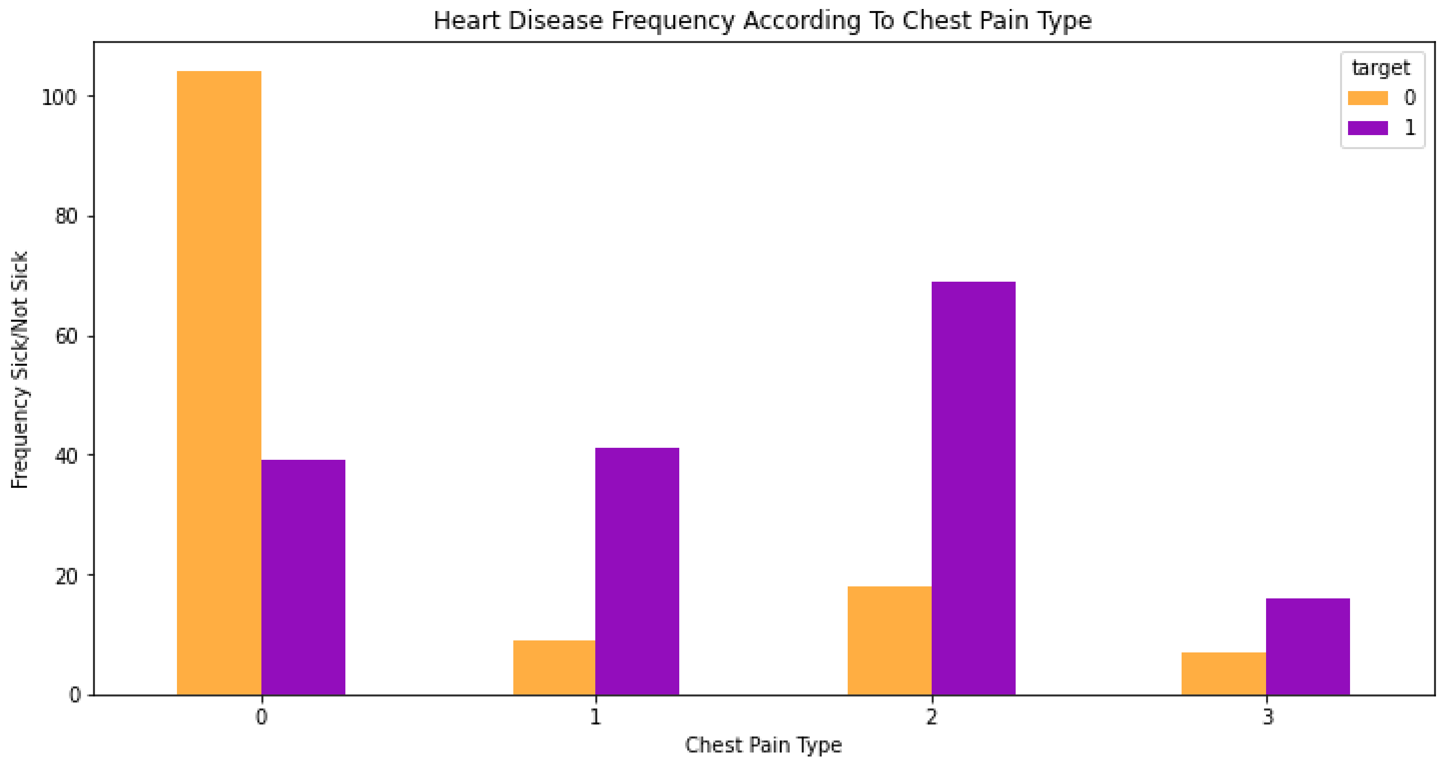
In [11]:
```
pd.crosstab(df.fbs,df.target).plot(kind = "bar", figsize = (10,5), color = ['#AB4E68','#C4A287' ])
plt.title('Heart Disease Frequency According To FBS')
plt.xlabel('FBS > 120 mg/dl (1 = true; 0 = false)')
plt.xticks(rotation = 0)
plt.legend(["Not Sick", "Sick"])
plt.ylabel('Frequency Sick/Not Sick')
plt.show()
```



The number of patients who have / do not have heart disease is higher in those who do not do fasting blood sugar.

4.7 Heart Disease Frequency According To Chest Pain Type

In [12]:
```
pd.crosstab(df.cp,df.target).plot(kind = "bar", figsize = (12,6), color = ['#FFAE42','#930DBC' ])
plt.title('Heart Disease Frequency According To Chest Pain Type')
plt.xlabel('Chest Pain Type')
plt.xticks(rotation = 0)
plt.ylabel('Frequency Sick/Not Sick')
plt.show()
```



Chest pain type level 0 has higher number of patients that don't have heart disease.
While chest pain type level 2 has higher number of patients that have heart disease.

5. Dataset Preparation

5.1 Creating Dummy Variables

Transforming categorical variables using one-hot encoding technique. One hot encoding makes our training data more useful and expressive, and it can be rescaled easily. This improves predictions and classification accuracy of our ML models.

In [13]:

```
cp = pd.get_dummies(df['cp'], prefix = "cp") #pd.get_dummies turns our data into binary vectors,
#sklearn also has classes which an carry out one hot encoding but pd.get_dummies keeps the code precise
thal = pd.get_dummies(df['thal'], prefix = "thal")
slope = pd.get_dummies(df['slope'], prefix = "slope")

frames = [df, cp, thal, slope]
df = pd.concat(frames, axis = 1)
df.head()
```

Out[13]:

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	...	cp_1	cp_2	cp_3	thal_0	thal_1	thal_2	thal_3	slope_0	slop
0	63	1	3	145	233	1	0	150	0	2.3	...	0	0	1	0	1	0	0	1	
1	37	1	2	130	250	0	1	187	0	3.5	...	0	1	0	0	0	1	0	1	
2	41	0	1	130	204	0	0	172	0	1.4	...	1	0	0	0	0	1	0	0	
3	56	1	1	120	236	0	1	178	0	0.8	...	1	0	0	0	0	1	0	0	
4	57	0	0	120	354	0	1	163	1	0.6	...	0	0	0	0	0	1	0	0	

5 rows × 25 columns

5.2 Dropping Unnecessary Variables

The variables that unnecessary will be deleted.

In [14]:
```
df = df.drop(columns = ['cp', 'thal', 'slope'])
df.head()
```

Out[14]:

	age	sex	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	ca	...	cp_1	cp_2	cp_3	thal_0	thal_1	thal_2	thal_3	slope_0	slop
0	63	1	145	233	1	0	150	0	2.3	0	...	0	0	1	0	1	0	0	1	
1	37	1	130	250	0	1	187	0	3.5	0	...	0	1	0	0	0	1	0	1	
2	41	0	130	204	0	0	172	0	1.4	0	...	1	0	0	0	0	1	0	0	
3	56	1	120	236	0	1	178	0	0.8	0	...	1	0	0	0	0	1	0	0	
4	57	0	120	354	0	1	163	1	0.6	0	...	0	0	0	0	0	1	0	0	

5 rows × 22 columns

6. Models

6.1 K-Nearest Neighbour (KNN)

In [15]:
```
y = df.target.values
x_data = df.drop(['target'], axis = 1)


x = (x_data - np.min(x_data)) / (np.max(x_data) - np.min(x_data)).values #normalising data
x_train, x_test, y_train, y_test = train_test_split(x,y,test_size = 0.2,random_state=0)

x_train = x_train.T
y_train = y_train.T
x_test = x_test.T
y_test = y_test.T
```

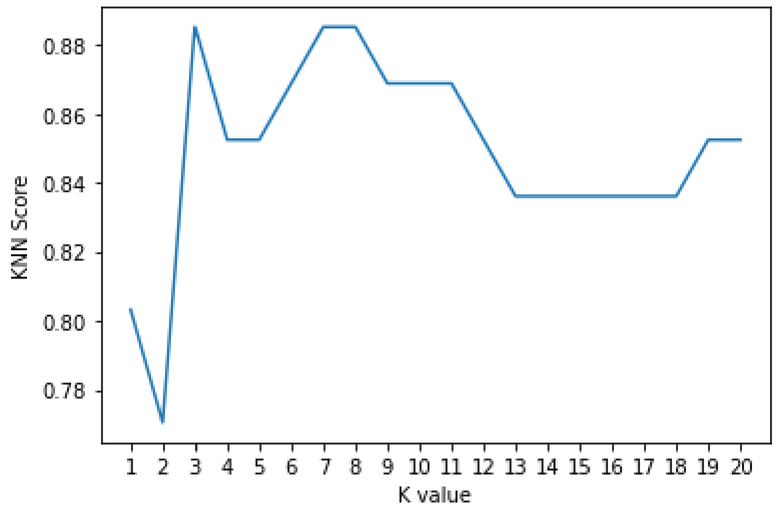
In [16]:

```
from sklearn.neighbors import KNeighborsClassifier

knn = KNeighborsClassifier(n_neighbors = 2)
knn.fit(x_train.T, y_train.T)

prediction = knn.predict(x_test.T)

print("{} NN Score: {}%".format(2, knn.score(x_test.T, y_test.T) * 100))
```

```
2 NN Score: 77.04918032786885%
```

This classifier looks for the classes of K nearest neighbours of the given data point and based on the majority of class, it assigns a class to this data point.The number of neighbours can be varied. In this project, we varied them from 1 to 20 neighbours, and found out which scored the most.

In [17]:
```
score_list = []
for i in range(1,21):
    knn2 = KNeighborsClassifier(n_neighbors = i)
    knn2.fit(x_train.T, y_train.T)
    score_list.append(knn2.score(x_test.T, y_test.T))

plt.plot(range(1,21), score_list)

plt.xticks(np.arange(1,21,1))

plt.xlabel("K value")
plt.ylabel("KNN Score")

plt.show()

print("KNN Score Max {}%".format((max(score_list)) * 100))
```




```
KNN Score Max 88.52459016393442%
```

Then, we plotted line graph of all the neighbours and the test score of each of the neighbours, to find which has the best maximum score.

6.2 SVM

In [18]:
```
from sklearn.svm import SVC

svm = SVC(random_state = 5)
svm.fit(x_train.T, y_train.T)
```

Out[18]:
```
SVC(random_state=5)
```

SVC forms hyperplanes/tubes which seperate classes as much as possible by adjusting the distance between the data points and the hyperplane. There are kernels which decide the hyperplane, in this project we tried the following:- linear, poly, rbf, sigmoid

In [19]:
```
svc_scores = []
kernels = ['linear', 'poly', 'rbf', 'sigmoid']
for i in range(len(kernels)):
    svc_classifier = SVC(kernel = kernels[i])
    svc_classifier.fit(x_train.T, y_train.T)
    svc_scores.append(svc_classifier.score(x_test.T,y_test.T))
```

In [20]:
```
svc_scores
```

Out[20]:
```
[0.8524590163934426, 0.819672131147541, 0.8852459016393442, 0.7868852459016393]
```

In [21]:
```
print("Test Accuracy of SVM: {}%".format(max(svc_scores)*100))
```

```
Test Accuracy of SVM: 88.52459016393442%
```

Clearly 'rbf' performed the best for this dataset by acheiving the highest score of ~88.52%

6.3 Gaussian Naive Bayes

Gausian Naive Bayes is used when the data is continuous and assumed to have gaussian distribution.

In [22]:
```
from sklearn.naive_bayes import GaussianNB
gnb = GaussianNB()
gnb.fit(x_train.T, y_train.T)
print("Test Accuracy of Gaussian Naive Bayes: {}%".format(gnb.score(x_test.T,y_test.T) * 100))
```

```
Test Accuracy of Gaussian Naive Bayes: 86.88524590163934%
```

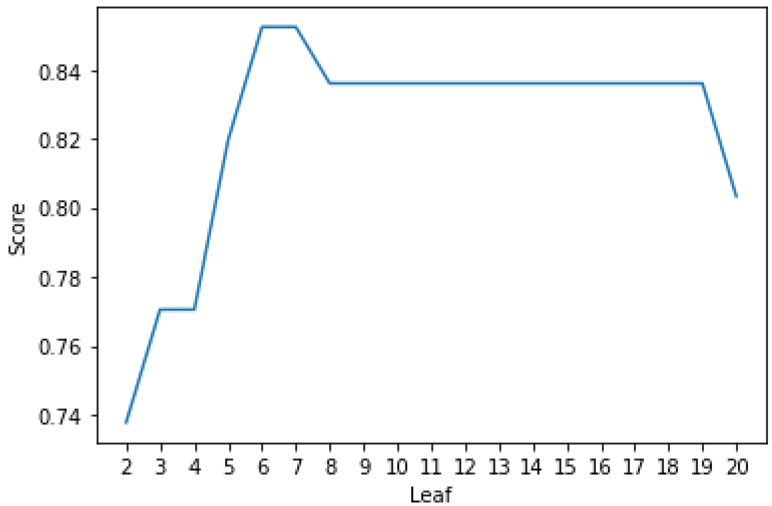
6.4 Decision Tree

Decision tree forms decision trees and it assigns the class values to each data point. We range the features from 1 to 30 (30 is the total number of features in the dataset after creating dummy variables). In this case, we can vary the maximum number of features to be considered while making the model.

In [23]:
```
from sklearn.tree import DecisionTreeClassifier

dt = DecisionTreeClassifier()
dt.fit(x_train.T, y_train.T)

print("Accuracy of Decision Tree: {}%".format(dt.score(x_test.T, y_test.T) * 100))
```

```
Accuracy of Decision Tree: 78.68852459016394%
```

In [24]:
```
score_list_DT = []
for i in range(2,21):
    dt2 = DecisionTreeClassifier(max_leaf_nodes = i)
    dt2.fit(x_train.T, y_train.T)
    score_list_DT.append(dt2.score(x_test.T, y_test.T))

plt.plot(range(2,21), score_list_DT)

plt.xticks(np.arange(2,21,1))

plt.xlabel("Leaf")
plt.ylabel("Score")

plt.show()

print("Decision Tree Max Score: {}%".format((max(score_list_DT)) * 100))
```




```
Decision Tree Max Score: 85.24590163934425%
```

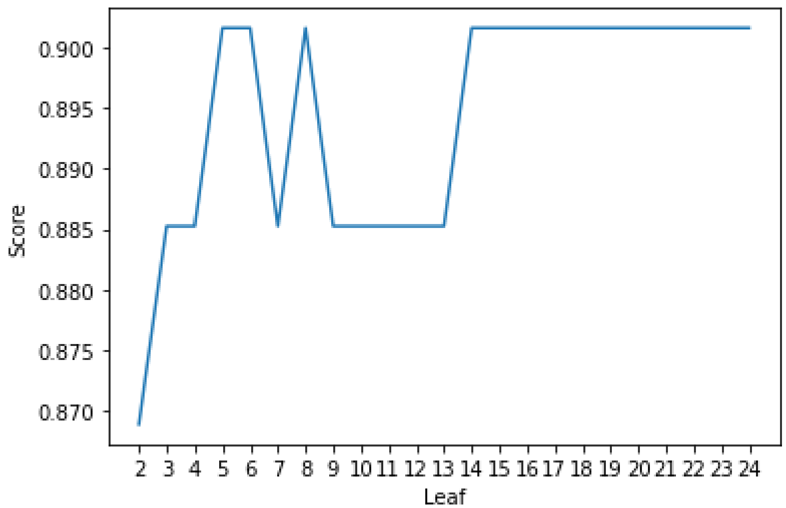
6.5 Random Forest

Random forest is the next level of decision trees. It makes forests of trees where each tree is formed by a random selection of features from all the features. We varied the number of trees from 2 to 25.

In [25]:
```
from sklearn.ensemble import RandomForestClassifier

rf = RandomForestClassifier(n_estimators = 1000, random_state = 2)
rf.fit(x_train.T, y_train.T)

print("Random Forest Accuracy Score : {}%".format(rf.score(x_test.T,y_test.T)*100))
```

```
Random Forest Accuracy Score : 88.52459016393442%
```

In [26]:
```
score_list_RF = []
for i in range(2,25):
    rf2 = RandomForestClassifier(n_estimators = 1000, random_state = 2, max_leaf_nodes = i)
    rf2.fit(x_train.T, y_train.T)
    score_list_RF.append(rf2.score(x_test.T, y_test.T))

plt.plot(range(2,25), score_list_RF)
plt.xticks(np.arange(2,25,1))
plt.xlabel("Leaf")
plt.ylabel("Score")
plt.show()
print("RF Score Max {}%".format((max(score_list_RF)) * 100))
```




```
RF Score Max 90.1639344262295%
```

7. Model Comparison

from the scores below, we can see that the random forest model worked the best with an accuracy of 90.16%.

In [27]:

```
compare_models = pd.DataFrame({'Model': ["KNN", "SVM", "Gaussian NB", "Decision Tree", "Random Forest"],
                               'Accuracy': [86.89, 88.52, 88.52, 86.89, 90.16]})
compare_models.sort_values(by='Accuracy', ascending=False)
```

Out[27]:

	Model	Accuracy
4	Random Forest	90.16
1	SVM	88.52
2	Gaussian NB	88.52
0	KNN	86.89
3	Decision Tree	86.89

In [28]:
```
models = ["Logistic Regression", "KNN", "SVM", "Naive Bayes", "Decision Tree", "Random Forest", "Gradien
accuracy = [86.89, 88.52, 88.52, 86.89, 85.25, 90.16, 85.25]
colors = ["#FFAE42", "#4B40C0", "#AB4E68", "#C4A287","#170F11","#C4BBB8", "#930DBC"]

sns.set_style("darkgrid")
plt.figure(figsize=(20,8))
plt.yticks(np.arange(0,100,10))
plt.ylabel("Accuracy %")
plt.xlabel("Algorithms")
sns.barplot(x = models, y = accuracy, palette = colors)
plt.show()
```