Heart Disease Prediction

Context

The database contains 76 attributes, but all published experiments refer to using a subset of 14 of them. In particular, the Cleveland database is the only one that has been used by ML researchers to this date.

Content

Attribute Information:

1. **age**
2. **sex**
3. **chest pain type (4 values)**
4. **resting blood pressure**
5. **serum cholestoral in mg/dl**
6. **fasting blood sugar > 120 mg/dl**
7. **resting electrocardiographic results (values 0,1,2)**
8. **maximum heart rate achieved**
9. **exercise induced angina**
10. **oldpeak = ST depression induced by exercise relative to rest**
11. **the slope of the peak exercise ST segment**
12. **number of major vessels (0-3) colored by flourosopy**
13. **thal: 3 = normal; 6 = fixed defect; 7 = reversable defect**
14. **The names and social security numbers of the patients were recently removed from the database, replaced with dummy values. One file has been "processed", that one containing the Cleveland database. All four unprocessed files also exist in this directory.**

Acknowledgements

Creators:

Hungarian Institute of Cardiology. Budapest: Andras Janosi, M.D. University Hospital, Zurich, Switzerland: William Steinbrunn, M.D. University Hospital, Basel, Switzerland: Matthias Pfisterer, M.D. V.A. Medical Center, Long Beach and Cleveland Clinic Foundation: Robert Detrano, M.D., Ph.D.

Import libraries

Let's first import all the necessary libraries. I'll use `numpy` and `pandas` to start with. For visualization, I will use `pyplot` subpackage of `matplotlib`, use `rcParams` to add styling to the plots and `rainbow` for colors. For implementing Machine Learning models and processing of data, I will use the `sklearn` library.

In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from matplotlib import rcParams
from matplotlib.cm import rainbow
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')
```

For processing the data, I'll import a few libraries. To split the available dataset for testing and training, I'll use the `train_test_split` method. To scale the features, I am using `StandardScaler`.

In [2]:

```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
```

Next, I'll import all the Machine Learning algorithms I will be using.

1. **K Neighbors Classifier**
2. **Support Vector Classifier**
3. **Decision Tree Classifier**
4. **Random Forest Classifier**

In [3]:

```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
```

Import dataset

Now that we have all the libraries we will need, I can import the dataset and take a look at it. The dataset is stored in the file `dataset.csv`. I'll use the pandas `read_csv` method to read the dataset.

In [4]:

```
dataset = pd.read_csv('dataset.csv')
```

The dataset is now loaded into the variable `dataset`. I'll just take a glimpse of the data using the `desribe()` and `info()` methods before I actually start processing and visualizing it.

In [5]:

```
dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 303 entries, 0 to 302
Data columns (total 14 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   age       303 non-null    int64
 1   sex       303 non-null    int64
 2   cp        303 non-null    int64
 3   trestbps  303 non-null    int64
 4   chol      303 non-null    int64
 5   fbs       303 non-null    int64
 6   restecg   303 non-null    int64
 7   thalach   303 non-null    int64
 8   exang     303 non-null    int64
 9   oldpeak   303 non-null    float64
 10  slope     303 non-null    int64
 11  ca        303 non-null    int64
 12  thal      303 non-null    int64
 13  target    303 non-null    int64
dtypes: float64(1), int64(13)
memory usage: 33.3 KB
```

Looks like the dataset has a total of 303 rows and there are no missing values. There are a total of `13 features` along with one target value which we wish to find.

In [6]:

```
dataset.describe()
```

Out[6]:

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpe

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpe
count	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000
mean	54.366337	0.683168	0.966997	131.623762	246.264026	0.148515	0.528053	149.646865	0.326733	1.0396
std	9.082101	0.466011	1.032052	17.538143	51.830751	0.356198	0.525860	22.905161	0.469794	1.1610
min	29.000000	0.000000	0.000000	94.000000	126.000000	0.000000	0.000000	71.000000	0.000000	0.0000
25%	47.500000	0.000000	0.000000	120.000000	211.000000	0.000000	0.000000	133.500000	0.000000	0.0000
50%	55.000000	1.000000	1.000000	130.000000	240.000000	0.000000	1.000000	153.000000	0.000000	0.8000
75%	61.000000	1.000000	2.000000	140.000000	274.500000	0.000000	1.000000	166.000000	1.000000	1.6000
max	77.000000	1.000000	3.000000	200.000000	564.000000	1.000000	2.000000	202.000000	1.000000	6.2000

The scale of each feature column is different and quite varied as well. While the maximum for `age` reaches 77, the maximum of `chol` (serum cholestoral) is 564.

Data Processing

After exploring the dataset, I observed that I need to convert some categorical variables into dummy variables and scale all the values before training the Machine Learning models. First, I'll use the `get_dummies` method to create dummy columns for categorical variables.

In [10]:

```
dataset = pd.get_dummies(dataset, columns = ['sex', 'cp', 'fbs', 'restecg', 'exang', 'slope', 'ca', 'thal'])
```

Now, I will use the `StandardScaler` from `sklearn` to scale my dataset.

In [29]:

```
standardScaler = StandardScaler()
columns_to_scale = ['age', 'trestbps', 'chol', 'thalach', 'oldpeak']
dataset[columns_to_scale] = standardScaler.fit_transform(dataset[columns_to_scale])
```

The data is not ready for our Machine Learning application.

Machine Learning

I'll now import `train_test_split` to split our dataset into training and testing datasets. Then, I'll import all Machine Learning models I'll be using to train and test the data.

In [12]:

```
y = dataset['target']
X = dataset.drop(['target'], axis = 1)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.33, random_state = 0)
```

K Neighbors Classifier

The classification score varies based on different values of neighbors that we choose. Thus, I'll plot a score graph for different values of K (neighbors) and check when do I achieve the best score.

In [13]:

```
knn_scores = []
for k in range(1,21):
    knn_classifier = KNeighborsClassifier(n_neighbors = k)
    knn_classifier.fit(X_train, y_train)
    knn_scores.append(knn_classifier.score(X_test, y_test))
```

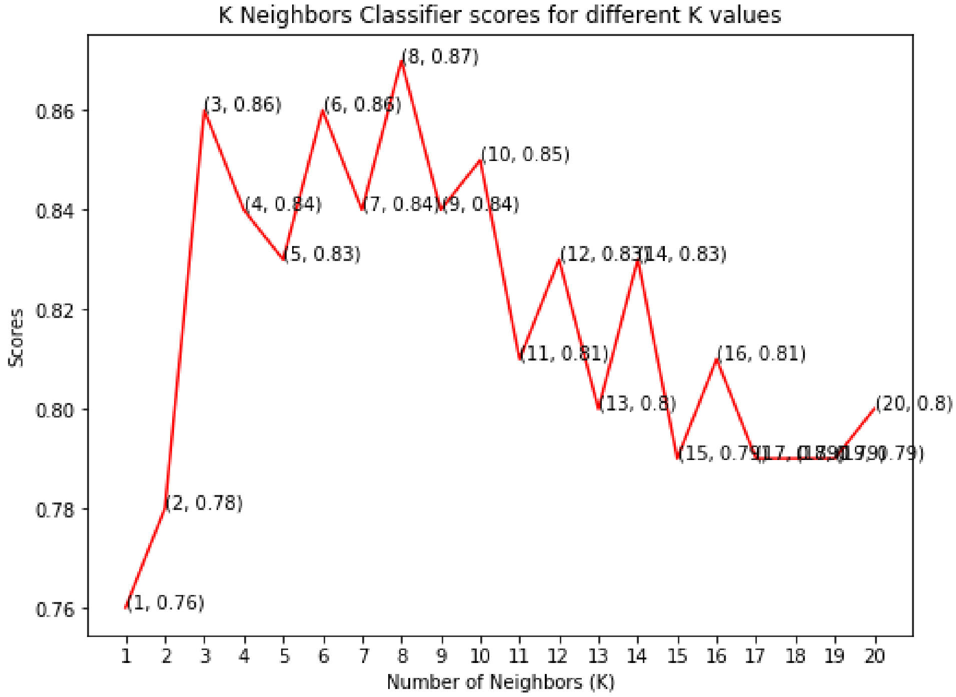
I have the scores for different neighbor values in the array `knn_scores`. I'll now plot it and see for which value of K did I get the best scores.

In [14]:

```
plt.plot([k for k in range(1, 21)], knn_scores, color = 'red')
for i in range(1,21):
    plt.text(i, knn_scores[i-1], (i, knn_scores[i-1]))
plt.xticks([i for i in range(1, 21)])
plt.xlabel('Number of Neighbors (K)')
plt.ylabel('Scores')
plt.title('K Neighbors Classifier scores for different K values')
```

Out[14]:

```
Text(0.5, 1.0, 'K Neighbors Classifier scores for different K values')
```



From the plot above, it is clear that the maximum score achieved was `0.87` for the 8 neighbors.

In [15]:

```
print("The score for K Neighbors Classifier is {}% with {} nieghbors.".format(knn_scores
[7]*100, 8))
```

```
The score for K Neighbors Classifier is 87.0% with 8 nieghbors.
```

Support Vector Classifier

There are several kernels for Support Vector Classifier. I'll test some of them and check which has the best score.

In [16]:

```
svc_scores = []
kernels = ['linear', 'poly', 'rbf', 'sigmoid']
for i in range(len(kernels)):
    svc_classifier = SVC(kernel = kernels[i])
    svc_classifier.fit(X_train, y_train)
    svc_scores.append(svc_classifier.score(X_test, y_test))
```

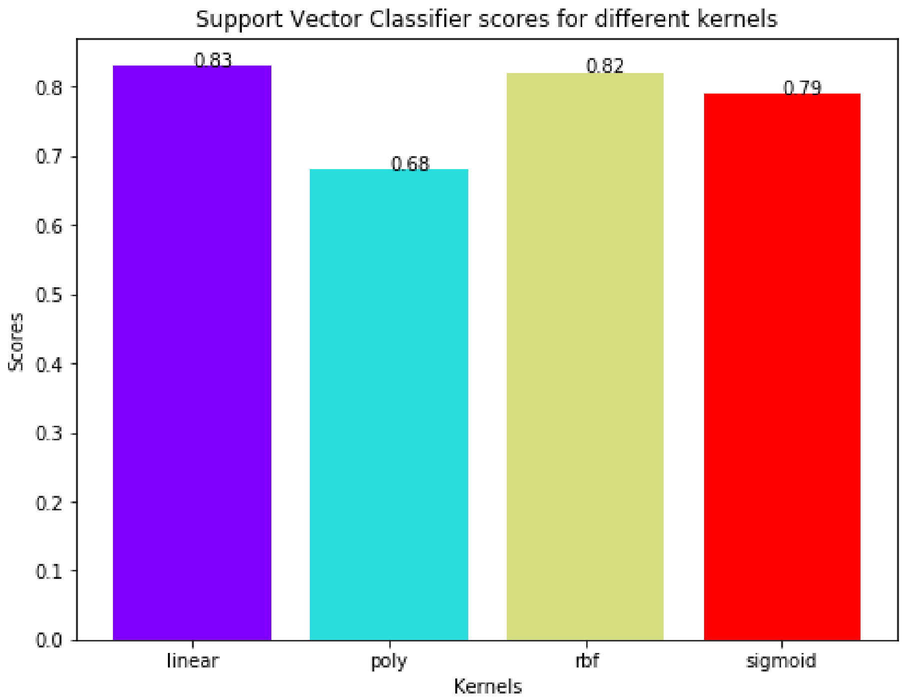
I'll now plot a bar plot of scores for each kernel and see which performed the best.

In [17]:

```
colors = rainbow(np.linspace(0, 1, len(kernels)))
plt.bar(kernels, svc_scores, color = colors)
for i in range(len(kernels)):
    plt.text(i, svc_scores[i], svc_scores[i])
plt.xlabel('Kernels')
plt.ylabel('Scores')
plt.title('Support Vector Classifier scores for different kernels')
```

Out[17]:

```
Text(0.5, 1.0, 'Support Vector Classifier scores for different kernels')
```



The `linear` kernel performed the best, being slightly better than `rbf` kernel.

In [18]:

```
print("The score for Support Vector Classifier is {}% with {} kernel.".format(svc_scores[
0]*100, 'linear'))
```

```
The score for Support Vector Classifier is 83.0% with linear kernel.
```

Decision Tree Classifier

Here, I'll use the Decision Tree Classifier to model the problem at hand. I'll vary between a set of `max_features` and see which returns the best accuracy.

In [19]:

```
dt_scores = []
for i in range(1, len(X.columns) + 1):
    dt_classifier = DecisionTreeClassifier(max_features = i, random_state = 0)
    dt_classifier.fit(X_train, y_train)
    dt_scores.append(dt_classifier.score(X_test, y_test))
```

I selected the maximum number of features from 1 to 30 for split. Now, let's see the scores for each of those cases.

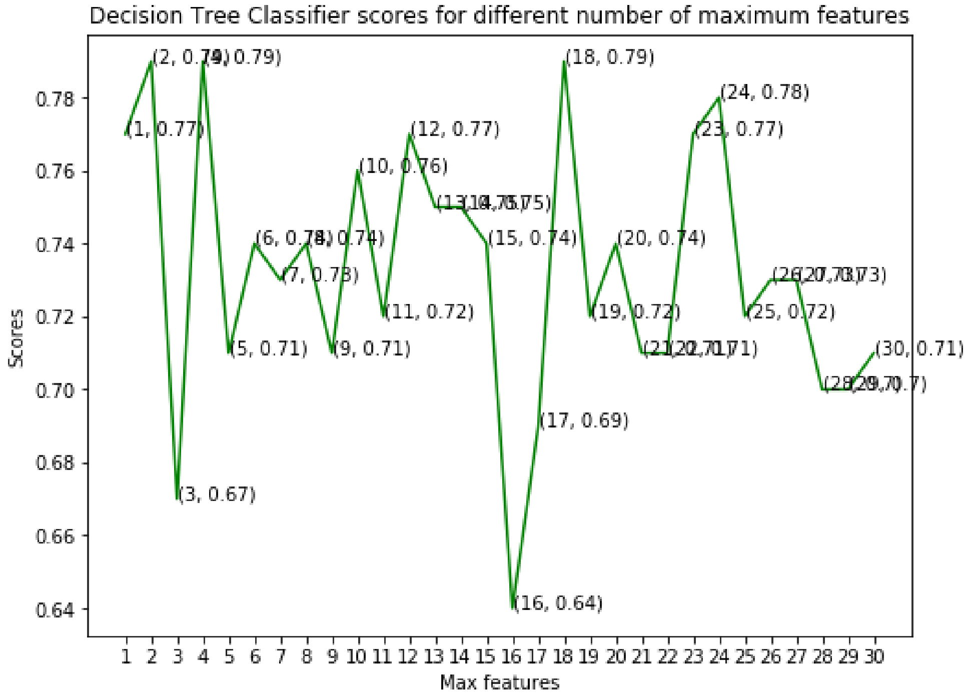
In [20]:

```
plt.plot([i for i in range(1, len(X.columns) + 1)], dt_scores, color = 'green')
for i in range(1, len(X.columns) + 1):
    plt.text(i, dt_scores[i-1], (i, dt_scores[i-1]))
plt.xticks([i for i in range(1, len(X.columns) + 1)])
plt.xlabel('Max features')
plt.ylabel('Scores')
```

```
plt.title('Decision Tree Classifier scores for different number of maximum features')
```

Out[20]:

```
Text(0.5, 1.0, 'Decision Tree Classifier scores for different number of maximum features'
)
```



The model achieved the best accuracy at three values of maximum features, `2`, `4` and `18`.

In [21]:

```
print("The score for Decision Tree Classifier is {}% with {} maximum features.".format(dt
_scores[17]*100, [2,4,18]))
```

```
The score for Decision Tree Classifier is 79.0% with [2, 4, 18] maximum features.
```

Random Forest Classifier

Now, I'll use the ensemble method, Random Forest Classifier, to create the model and vary the number of estimators to see their effect.

In [22]:

```
rf_scores = []
estimators = [10, 100, 200, 500, 1000]
for i in estimators:
    rf_classifier = RandomForestClassifier(n_estimators = i, random_state = 0)
    rf_classifier.fit(X_train, y_train)
    rf_scores.append(rf_classifier.score(X_test, y_test))
```

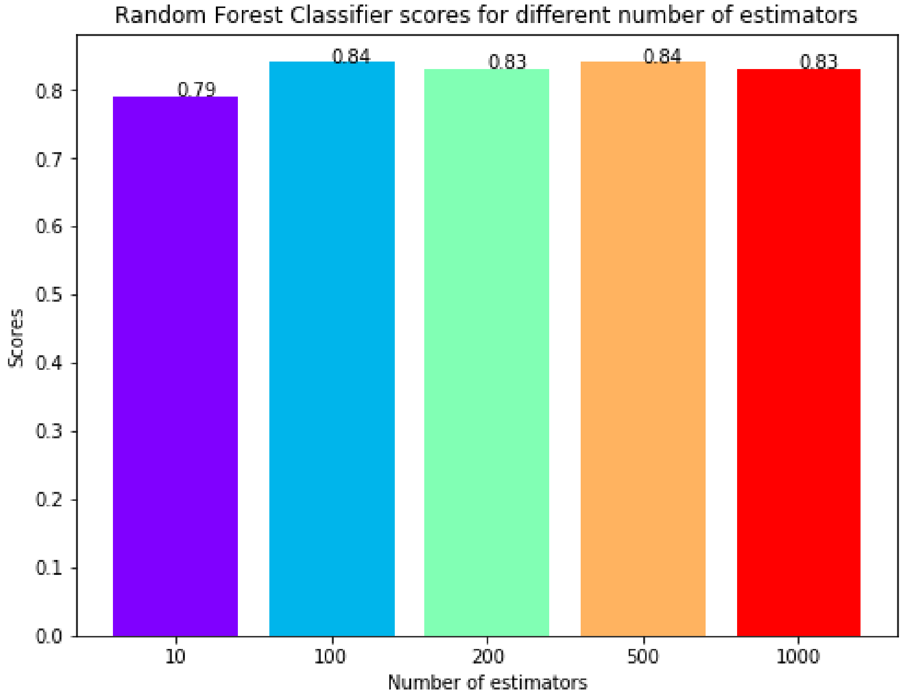
The model is trained and the scores are recorded. Let's plot a bar plot to compare the scores.

In [23]:

```
colors = rainbow(np.linspace(0, 1, len(estimators)))
plt.bar([i for i in range(len(estimators))], rf_scores, color = colors, width = 0.8)
for i in range(len(estimators)):
    plt.text(i, rf_scores[i], rf_scores[i])
plt.xticks(ticks = [i for i in range(len(estimators))], labels = [str(estimator) for est
imator in estimators])
plt.xlabel('Number of estimators')
plt.ylabel('Scores')
plt.title('Random Forest Classifier scores for different number of estimators')
```

Out[23]:

```
Text(0.5, 1.0, 'Random Forest Classifier scores for different number of estimators')
```



The maximum score is achieved when the total estimators are 100 or 500.

In [24]:

```
print("The score for Random Forest Classifier is {}% with {} estimators.".format(rf_score
s[1]*100, [100, 500]))
```

```
The score for Random Forest Classifier is 84.0% with [100, 500] estimators.
```

Conclusion

In this project, I used Machine Learning to predict whether a person is suffering from a heart disease. After importing the data, I analysed it using plots. Then, I did generated dummy variables for categorical features and scaled other features. I then applied four Machine Learning algorithms, `K Neighbors Classifier`, `Support Vector Classifier`, `Decision Tree Classifier` and `Random Forest Classifier`. I varied parameters across each model to improve their scores. In the end, `K Neighbors Classifier` achieved the highest score of `87%` with `8 nearest neighbors`.