Heart Disease Model Notebook

Will show the process of the heart disease prediction model was crafted.

- [pandas (https://pandas.pydata.org/)](https://pandas.pydata.org/) for data analysis.
- [NumPy (https://numpy.org/)](https://numpy.org/) for numerical operations.
- [Matplotlib (https://matplotlib.org/)](https://matplotlib.org/)/[seaborn (https://seaborn.pydata.org/)](https://seaborn.pydata.org/) for plotting or data visualization.
- [Scikit-Learn (https://scikit-learn.org/stable/)](https://scikit-learn.org/stable/) for machine learning modelling and evaluation.

In [1]:
```
# Process of importing useful libraries.
import pandas as pd
import numpy as np
import sklearn as sk
import matplotlib.pyplot as plot
import seaborn as sns
```

Heart Disease Data Dictionary

Describes the data being worked with.

The following are the features/independent variables that will be used to predict the target variable (heart disease or no heart disease).

1. age - age in years
2. sex - (1 = male; 0 = female)
3. cp - chest pain type
    - 0: Typical angina: chest pain related decrease blood supply to the heart
    - 1: Atypical angina: chest pain not related to heart
    - 2: Non-anginal pain: typically esophageal spasms (non heart related)
    - 3: Asymptomatic: chest pain not showing signs of disease
4. trestbps - resting blood pressure (in mm Hg on admission to the hospital)
    - anything above 130-140 is typically cause for concern
5. chol - serum cholestoral in mg/dl
    - serum = LDL + HDL + .2 * triglycerides
    - above 200 is cause for concern
6. fbs - (fasting blood sugar > 120 mg/dl) (1 = true; 0 = false)
    - '>126' mg/dL signals diabetes
7. restecg - resting electrocardiographic results
    - 0: Nothing to note
    - 1: ST-T Wave abnormality
        - can range from mild symptoms to severe problems
        - signals non-normal heart beat
    - 2: Possible or definite left ventricular hypertrophy
        - Enlarged heart's main pumping chamber
8. thalach - maximum heart rate achieved
9. exang - exercise induced angina (1 = yes; 0 = no)
10. oldpeak - ST depression induced by exercise relative to rest
    - looks at stress of heart during excercise
    - unhealthy heart will stress more
11. slope - the slope of the peak exercise ST segment

    - 0: Upsloping: better heart rate with excercise (uncommon)
    - 1: Flatsloping: minimal change (typical healthy heart)
    - 2: Downslopins: signs of unhealthy heart
12. ca - number of major vessels (0-3) colored by flourosopy
    - colored vessel means the doctor can see the blood passing through
    - the more blood movement the better (no clots)
13. thal - thalium stress result
    - 1,3: normal
    - 6: fixed defect: used to be defect but ok now
    - 7: reversable defect: no proper blood movement when excercising
14. target - have disease or not (1=yes, 0=no) (= the predicted attribute)

Note: No personal identifiable information (PPI) can be found in the dataset.

Data labels shorthand form to full form.

1. age age in years
2. sex (1 = male; 0 = female)
3. cp chest pain type
4. trestbps resting blood pressure (in mm Hg on admission to the hospital)
5. chol serum cholestoral in mg/dl
6. fbs (fasting blood sugar > 120 mg/dl) (1 = true; 0 = false)
7. restecg resting electrocardiographic results
8. thalach maximum heart rate achieved
9. exang exercise induced angina (1 = yes; 0 = no)
10. oldpeak ST depression induced by exercise relative to rest
11. slope the slope of the peak exercise ST segment
12. ca number of major vessels (0-3) colored by flourosopy
13. thal 3 = normal; 6 = fixed defect; 7 = reversable defect
14. target 1 or 0(1 = Heart Disease there, 0 = No Heart Disease)

In [2]:
```python
# Data being prepared.
# Data found at this link: https://www.kaggle.com/ronitf/heart-disease-uci

heart_dataset = pd.read_csv("heart-disease.csv")
heart_dataset
```

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
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
298	57	0	0	140	241	0	1	123	1	0.2	1	0	3	0
299	45	1	3	110	264	0	1	132	0	1.2	1	0	3	0
300	68	1	0	144	193	1	1	141	0	3.4	1	2	3	0
301	57	1	0	130	131	0	1	115	1	1.2	1	1	3	0
302	57	0	1	130	236	0	0	174	0	0.0	1	1	2	0

303 rows × 14 columns

In [3]:
```python
# Create X (independent variables matrix): this matrix holds the columns that contain indep
# the presence of heart disease.
X = heart_dataset.drop("target", axis=1)

# Create y (dependent variable): The variable to be predictd, the presence of heart disease
y = heart_dataset["target"]
```

Confirming that there are no missing values in the data set.

In [4]:
```python
heart_dataset.isna().sum()
```

Out[4]:
```
age         0
sex         0
cp          0
trestbps    0
chol        0
fbs         0
restecg     0
thalach     0
exang       0
oldpeak     0
slope       0
ca          0
thal        0
target      0
dtype: int64
```

There are no missing values so no data filling is needed.

In [5]:
```
# Data balance checking. Confirming data set is balanced between positive and negative outc
heart_dataset.target.value_counts(normalize=True)
```

Out[5]:
```
1    0.544554
0    0.455446
Name: target, dtype: float64
```

Indeed the data set is almost balanced 50/50. So there is no need to rebalance the data.

Confirming now that all data is numerical and that no conversions will be needed.

In [6]:
```
heart_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
```

Random Forest Classifier Algorithm chosen.

It works well for both categorical and numerical data. Also avoids overfitting to training data, which improves accuracy.

In [7]:
```
from sklearn.ensemble import RandomForestClassifier
rfcModel = RandomForestClassifier(n_estimators=100)
```

In [8]:
```
# Fitting model to the training data. 80% training,20% testing
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
rfcModel.fit(X_train, y_train);
X_train
```

Out[8]:

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal
230	47	1	2	108	243	0	1	152	0	0.0	2	0	2
274	47	1	0	110	275	0	0	118	1	1.0	1	1	2
111	57	1	2	150	126	1	1	173	0	0.2	2	1	3
27	51	1	2	110	175	0	1	123	0	0.6	2	0	2
269	56	1	0	130	283	1	0	103	1	1.6	0	0	3
...	...	...	...	...	...	...	...	...	...	...	...	...	...
237	60	1	0	140	293	0	0	170	0	1.2	1	2	3
226	62	1	1	120	281	0	0	103	0	1.4	1	1	3
94	45	0	1	112	160	0	1	138	0	0.0	1	0	2
297	59	1	0	164	176	1	0	90	0	1.0	1	2	1
291	58	1	0	114	318	0	2	140	0	4.4	0	3	1

242 rows × 13 columns

In [9]:
```
# Evaluate the model on the training data and test data
rfcModel.score(X_train, y_train)
```

Out[9]:
```
1.0
```

In [10]:
```
# Model works perfectly on training data.
# Predictive method
# Now testing model on testing data.
rfcModel.score(X_test, y_test)
```

Out[10]:
```
0.8360655737704918
```

Model meets the requirement of being accurate more than 75% of the time which the company aimed for. So there is no need to improve the model.

In [11]:
```
# Returns probabilities of a classification label, this will be used
# later to return the probability of an estimate being correct.
rfcModel.predict_proba(X_test[:5])
# The first number is probability of 0 being the target value, the second number is probab
```

Out[11]:
```
array([[0.2 , 0.8 ],
       [0.03, 0.97],
       [0.68, 0.32],
       [0.97, 0.03],
       [0.99, 0.01]])
```

In [12]:
```
rfcModel.predict(X_test[:5])
# Confirms that prediction results match with aforemenetioned probabilities
```

Out[12]:
```
array([1, 1, 0, 0, 0], dtype=int64)
```

In [13]:
```
# Saving model and confirming it has been saved.
import pickle

pickle.dump(rfcModel, open("rfcHeartModel_v1.pkl", "wb"))
```

In [14]:
```
loaded_RFCmodel = pickle.load(open("rfcHeartModel_v1.pkl", "rb"))
loaded_RFCmodel.score(X_test, y_test)
```

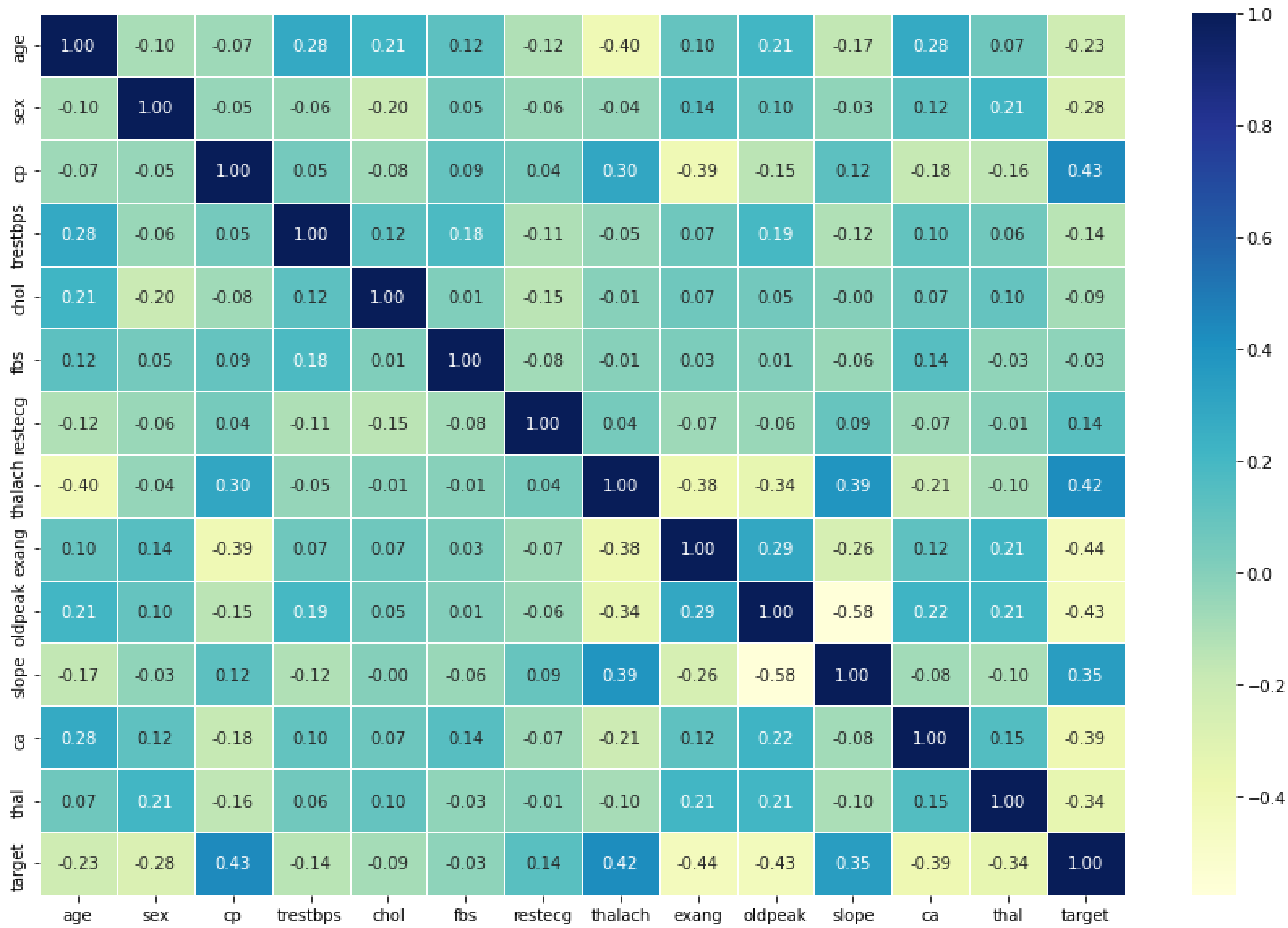
Out[14]:
```
0.8360655737704918
```

In [15]:
```
# Correlation matrix to describe the data, this is a descriptive method.
# Shows correlation betweeen various variables
# Find the correlation between our independent variables, this will appear on the website
corr_matrix = heart_dataset.corr()
corr_matrix
```

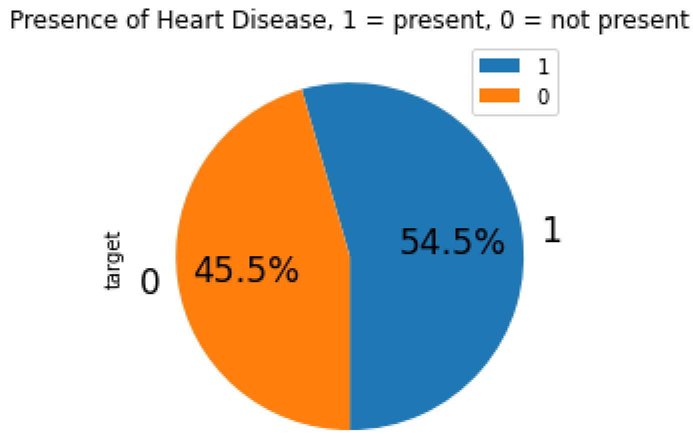
Out[15]:

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	old
age	1.000000	-0.098447	-0.068653	0.279351	0.213678	0.121308	-0.116211	-0.398522	0.096801	0.21
sex	-0.098447	1.000000	-0.049353	-0.056769	-0.197912	0.045032	-0.058196	-0.044020	0.141664	0.09
cp	-0.068653	-0.049353	1.000000	0.047608	-0.076904	0.094444	0.044421	0.295762	-0.394280	-0.14
trestbps	0.279351	-0.056769	0.047608	1.000000	0.123174	0.177531	-0.114103	-0.046698	0.067616	0.19
chol	0.213678	-0.197912	-0.076904	0.123174	1.000000	0.013294	-0.151040	-0.009940	0.067023	0.05
fbs	0.121308	0.045032	0.094444	0.177531	0.013294	1.000000	-0.084189	-0.008567	0.025665	0.00
restecg	-0.116211	-0.058196	0.044421	-0.114103	-0.151040	-0.084189	1.000000	0.044123	-0.070733	-0.05
thalach	-0.398522	-0.044020	0.295762	-0.046698	-0.009940	-0.008567	0.044123	1.000000	-0.378812	-0.34
exang	0.096801	0.141664	-0.394280	0.067616	0.067023	0.025665	-0.070733	-0.378812	1.000000	0.28
oldpeak	0.210013	0.096093	-0.149230	0.193216	0.053952	0.005747	-0.058770	-0.344187	0.288223	1.00
slope	-0.168814	-0.030711	0.119717	-0.121475	-0.004038	-0.059894	0.093045	0.386784	-0.257748	-0.57
ca	0.276326	0.118261	-0.181053	0.101389	0.070511	0.137979	-0.072042	-0.213177	0.115739	0.22
thal	0.068001	0.210041	-0.161736	0.062210	0.098803	-0.032019	-0.011981	-0.096439	0.206754	0.21
target	-0.225439	-0.280937	0.433798	-0.144931	-0.085239	-0.028046	0.137230	0.421741	-0.436757	-0.43

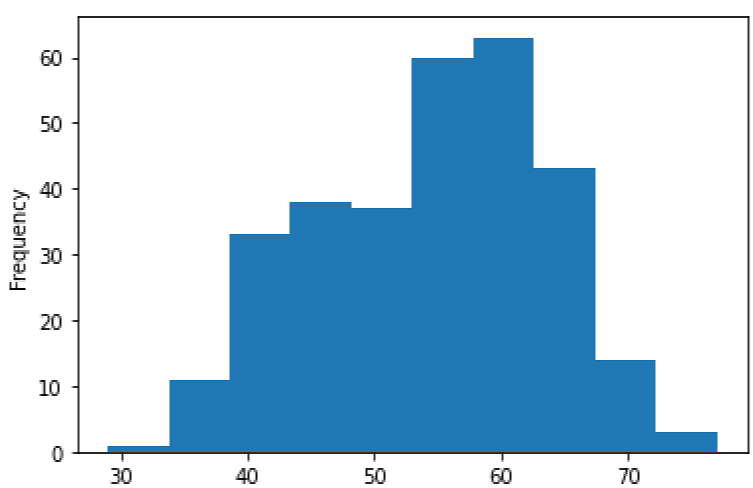
In [16]:
```python
# Seaborn correlation matrix heat map.
corr_matrix = heart_dataset.corr()
plot.figure(figsize=(15, 10))
sns.heatmap(corr_matrix,
            annot=True,
            linewidths=0.5,
            fmt= ".2f",
            cmap="YlGnBu");
```



```
In [17]: heart_dataset.target.value_counts().plot(kind="pie", autopct='%1.1f%%', startangle=270, for
         , title = 'Presence of Heart Disease, 1 = present, 0 = not present');
         # First Data visualization, shows piechart of how many patients have heart disease in the d
         # interactive version of this will be found on the website.
```

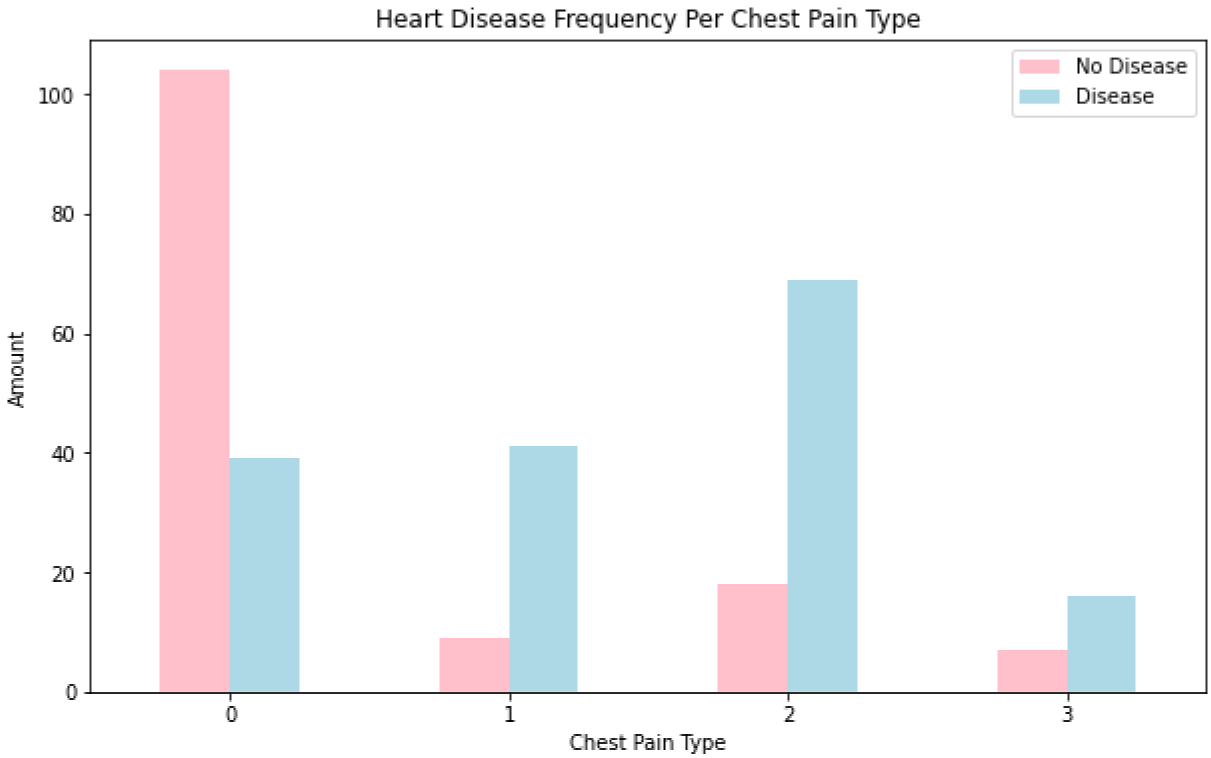



```
In [18]: # Distribution of the age column shown in a histogram
         # Second Data visualization, aninteractive version of this will be found on the website.
         heart_dataset.age.plot.hist();
```



In [19]:
```
# Plot that shows relationships between chest pain type and presence of heart disease.
# Third Data Visualization, will show up in an interactive format on the website.
pd.crosstab(heart_dataset.cp, heart_dataset.target)
pd.crosstab(heart_dataset.cp, heart_dataset.target).plot(kind="bar",
                                   figsize=(10, 6),
                                   color=["pink", "lightblue"])

# Plot labels
plot.title("Heart Disease Frequency Per Chest Pain Type")
plot.xlabel("Chest Pain Type")
plot.ylabel("Amount")
plot.legend(["No Disease", "Disease"])
plot.xticks(rotation=0);
```



That is all for this code.