Predicting heart disease using machine learning

This notebook looks into using various Python-based machine learning and data science libraries in an attempt to build a machine learning model capable of predicting whether or not someone has heart disease based on their medical attributes.

We're going to take the following approach:

1. Problem definition
2. Data
3. Evaluation
4. Features
5. Modelling
6. Experimentation

1. Problem Definition

In a statement,

> Given clinical parameters about a patient, can we predict whether or not they have heart disease?

2. Data

The original data came from the Cleavland data from the UCI Machine Learning Repository.
https://archive.ics.uci.edu/ml/datasets/heart+Disease

There is also a version of it available on Kaggle.
https://www.kaggle.com/datasets/sumaiyatasmeem/heart-disease-classification-dataset

3. Evaluation

> If we can reach 95% accuracy at predicting whether or not a patient has heart disease during the proof of concept, we'll pursue the project.

4. Features

This is where you'll get different information about each of the features in your data. You can do this via doing your own research (such as looking at the links above) or by talking to a subject matter expert (someone who knows about the dataset).

Create data dictionary

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)

Preparing the tools

We're going to use pandas, Matplotlib and NumPy for data analysis and manipulation.

In [32]:
```
# Import all the tools we need

# Regular EDA (exploratory data analysis) and plotting libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# we want our plots to appear inside the notebook
%matplotlib inline

# Models from Scikit-Learn
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier

# Model Evaluations
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.model_selection import RandomizedSearchCV, GridSearchCV
from sklearn.metrics import confusion_matrix, classification_report
from sklearn.metrics import precision_score, recall_score, f1_score
from sklearn.metrics import plot_roc_curve
```

Load data

In [4]:
```
df = pd.read_csv("heart-disease.csv")
df.shape # (rows, columns)
```

Out[4]:
```
(303, 14)
```

Data Exploration (exploratory data analysis or EDA)

The goal here is to find out more about the data and become a subject matter export on the dataset you're working with.

1. What question(s) are you trying to solve?
2. What kind of data do we have and how do we treat different types?
3. What's missing from the data and how do you deal with it?
4. Where are the outliers and why should you care about them?
5. How can you add, change or remove features to get more out of your data?

In [5]:
```
df.head()
```

Out[5]:

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	tar
0	63	1	3	145	233	1	0	150	0	2.3	0	0	1	
1	37	1	2	130	250	0	1	187	0	3.5	0	0	2	
2	41	0	1	130	204	0	0	172	0	1.4	2	0	2	

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	tar
3	56	1	1	120	236	0	1	178	0	0.8	2	0	2	
4	57	0	0	120	354	0	1	163	1	0.6	2	0	2	

In [6]:
```
df.tail()
```

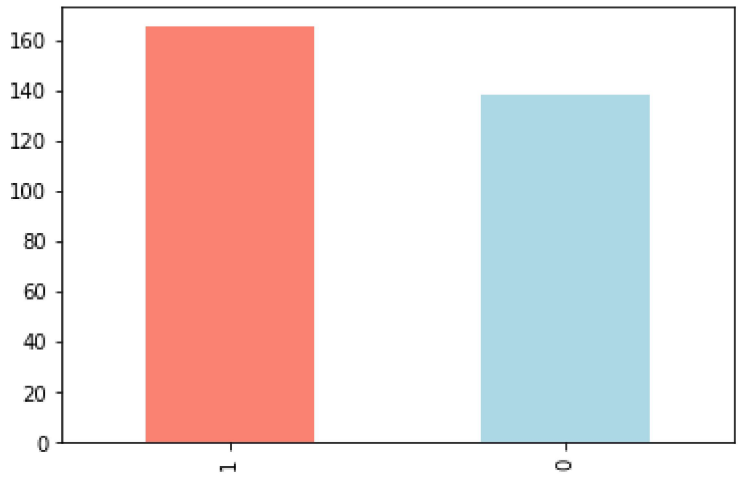
Out[6]:

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	t
298	57	0	0	140	241	0	1	123	1	0.2	1	0	3	
299	45	1	3	110	264	0	1	132	0	1.2	1	0	3	
300	68	1	0	144	193	1	1	141	0	3.4	1	2	3	
301	57	1	0	130	131	0	1	115	1	1.2	1	1	3	
302	57	0	1	130	236	0	0	174	0	0.0	1	1	2	

In [7]:
```
# Let's find out how many of each class there
df["target"].value_counts()
```

Out[7]:
```
1    165
0    138
Name: target, dtype: int64
```

In [9]:
```
df["target"].value_counts().plot(kind="bar", color=["salmon", "lightblue"]);
```



In [10]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 303 entries, 0 to 302
Data columns (total 14 columns):
age         303 non-null int64
sex         303 non-null int64
```

```
cp          303 non-null int64
trestbps    303 non-null int64
chol        303 non-null int64
fbs         303 non-null int64
restecg     303 non-null int64
thalach     303 non-null int64
exang       303 non-null int64
oldpeak     303 non-null float64
slope       303 non-null int64
ca          303 non-null int64
thal        303 non-null int64
target      303 non-null int64
dtypes: float64(1), int64(13)
memory usage: 33.3 KB
```

In [11]:
```
# Are there any missing values?
df.isna().sum()
```

Out[11]:
```
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
```

In [12]:
```
df.describe()
```

Out[12]:

	age	sex	cp	trestbps	chol	fbs	restecg	
count	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	3
mean	54.366337	0.683168	0.966997	131.623762	246.264026	0.148515	0.528053	1
std	9.082101	0.466011	1.032052	17.538143	51.830751	0.356198	0.525860	
min	29.000000	0.000000	0.000000	94.000000	126.000000	0.000000	0.000000	
25%	47.500000	0.000000	0.000000	120.000000	211.000000	0.000000	0.000000	1
50%	55.000000	1.000000	1.000000	130.000000	240.000000	0.000000	1.000000	1
75%	61.000000	1.000000	2.000000	140.000000	274.500000	0.000000	1.000000	1
max	77.000000	1.000000	3.000000	200.000000	564.000000	1.000000	2.000000	2

Heart Disease Frequency according to Sex

In [14]:
```
df.sex.value_counts()
```

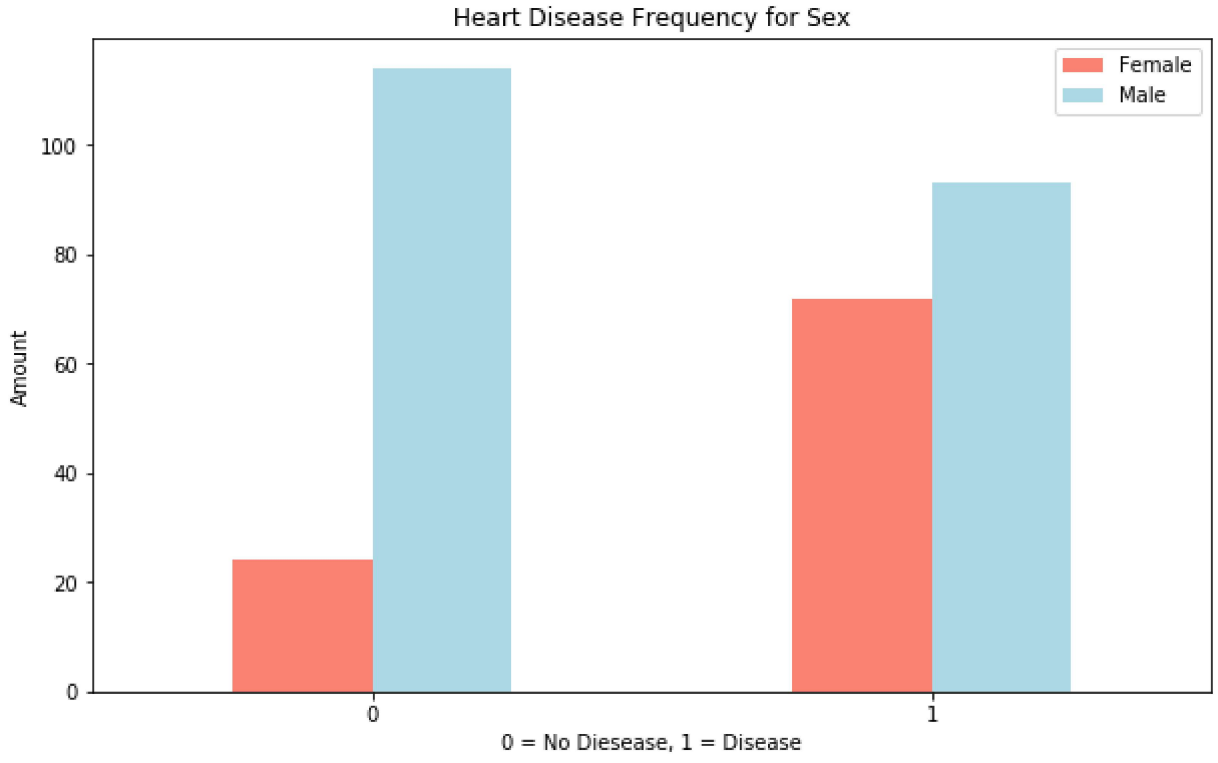
Out[14]:
```
1    207
0     96
Name: sex, dtype: int64
```

In [15]:
```
# Compare target column with sex column
pd.crosstab(df.target, df.sex)
```

Out[15]:

target	sex 0	1
0	24	114
1	72	93

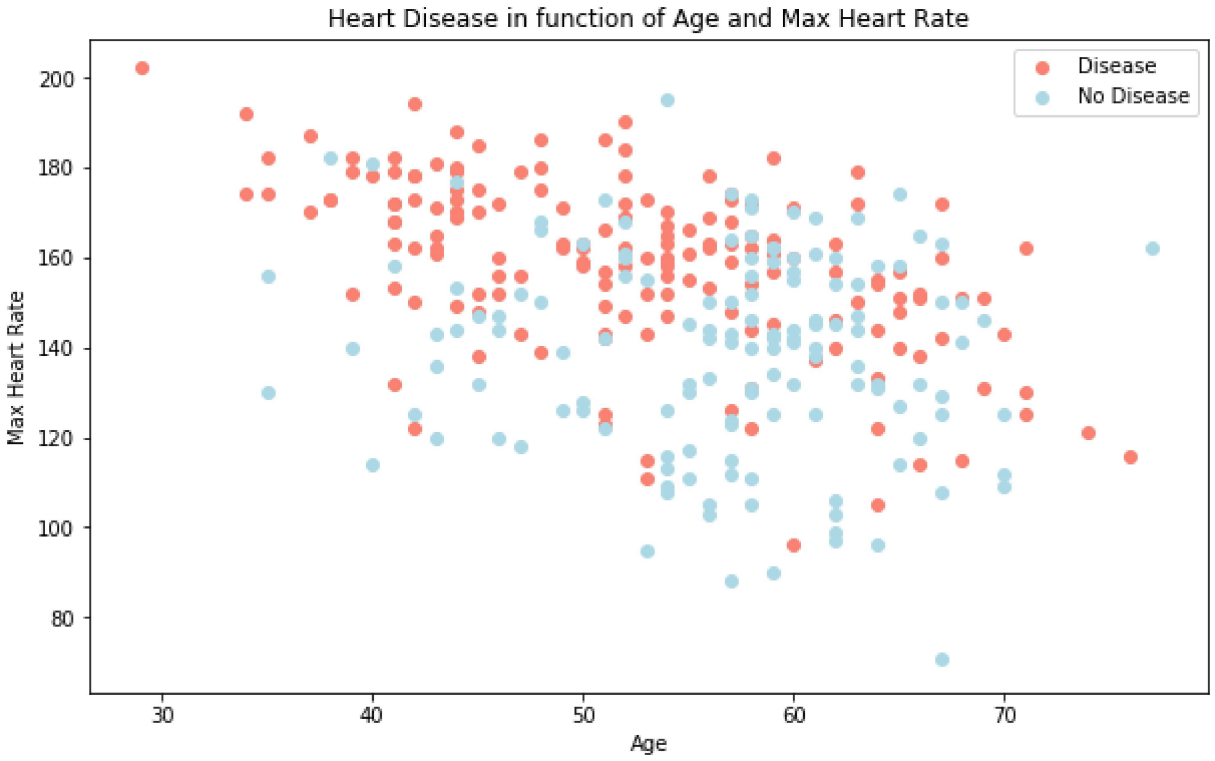
In [19]:
```
# Create a plot of crosstab
pd.crosstab(df.target, df.sex).plot(kind="bar",
                                    figsize=(10, 6),
                                    color=["salmon", "lightblue"])

plt.title("Heart Disease Frequency for Sex")
plt.xlabel("0 = No Diesease, 1 = Disease")
plt.ylabel("Amount")
plt.legend(["Female", "Male"]);
plt.xticks(rotation=0);
```



Age vs. Max Heart Rate for Heart Disease

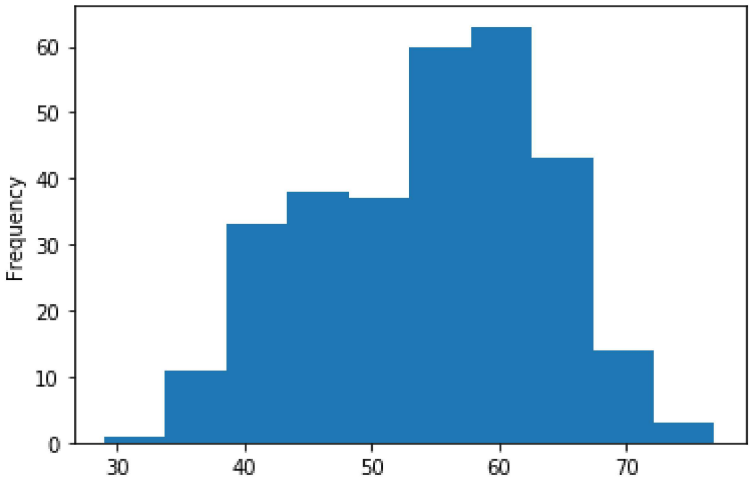
In [26]:

```
# Create another figure
plt.figure(figsize=(10, 6))

# Scatter with postivie examples
plt.scatter(df.age[df.target==1],
            df.thalach[df.target==1],
            c="salmon")

# Scatter with negative examples
plt.scatter(df.age[df.target==0],
            df.thalach[df.target==0],
            c="lightblue")

# Add some helpful info
plt.title("Heart Disease in function of Age and Max Heart Rate")
plt.xlabel("Age")
plt.ylabel("Max Heart Rate")
plt.legend(["Disease", "No Disease"]);
```



In [27]:

```
# Check the distribution of the age column with a histogram
df.age.plot.hist();
```



Heart Disease Frequency per Chest Pain Type

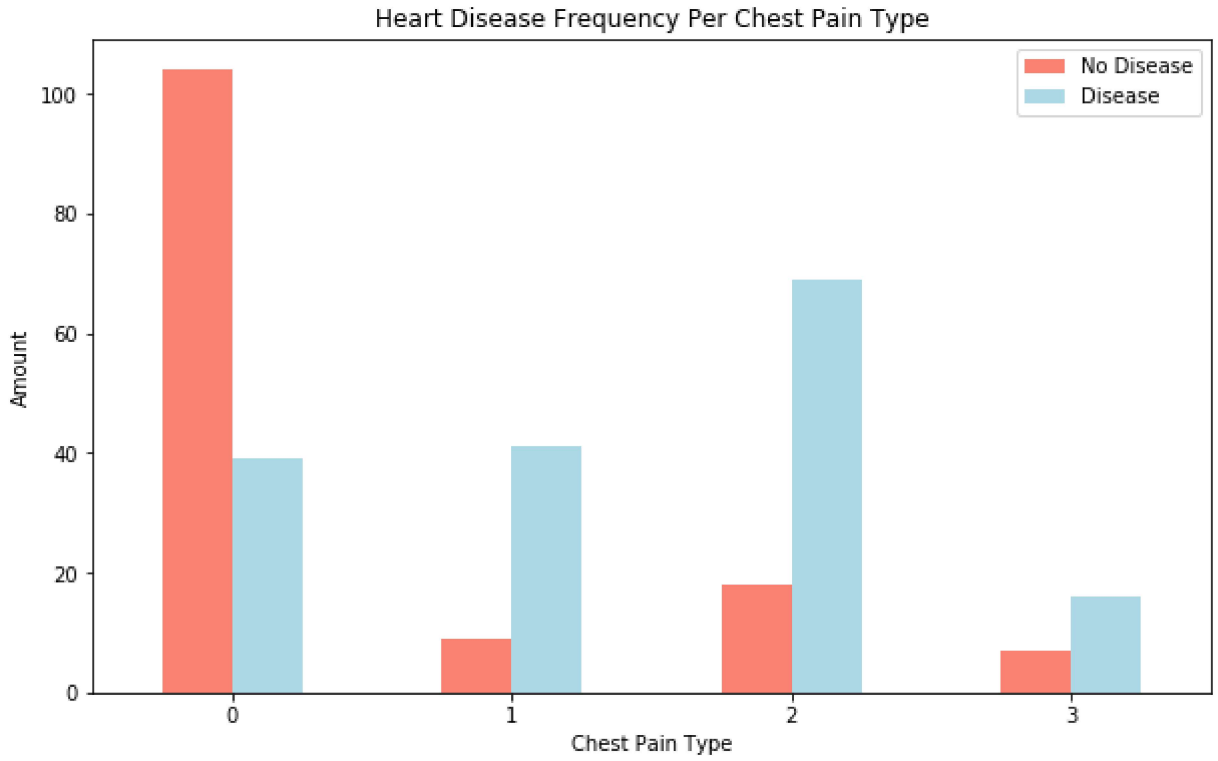
3. cp - chest pain type
    - 0: Typical angina: chest pain related decrease blood supply to the heart
    - 1: Atypical angina: chest pain not related to heart
    - 2: Non-anginal pain: typically esophageal spasms (non heart related)
    - 3: Asymptomatic: chest pain not showing signs of disease

In [28]:
```
pd.crosstab(df.cp, df.target)
```

Out[28]:

target	0	1
cp		
0	104	39
1	9	41
2	18	69
3	7	16

In [30]:
```
# Make the crosstab more visual
pd.crosstab(df.cp, df.target).plot(kind="bar",
                                   figsize=(10, 6),
                                   color=["salmon", "lightblue"])

# Add some communication
plt.title("Heart Disease Frequency Per Chest Pain Type")
plt.xlabel("Chest Pain Type")
plt.ylabel("Amount")
plt.legend(["No Disease", "Disease"])
plt.xticks(rotation=0);
```



In [33]:
```
df.head()
```

Out[33]:

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

In [46]:
```
# Make a correlation matrix
df.corr()
```

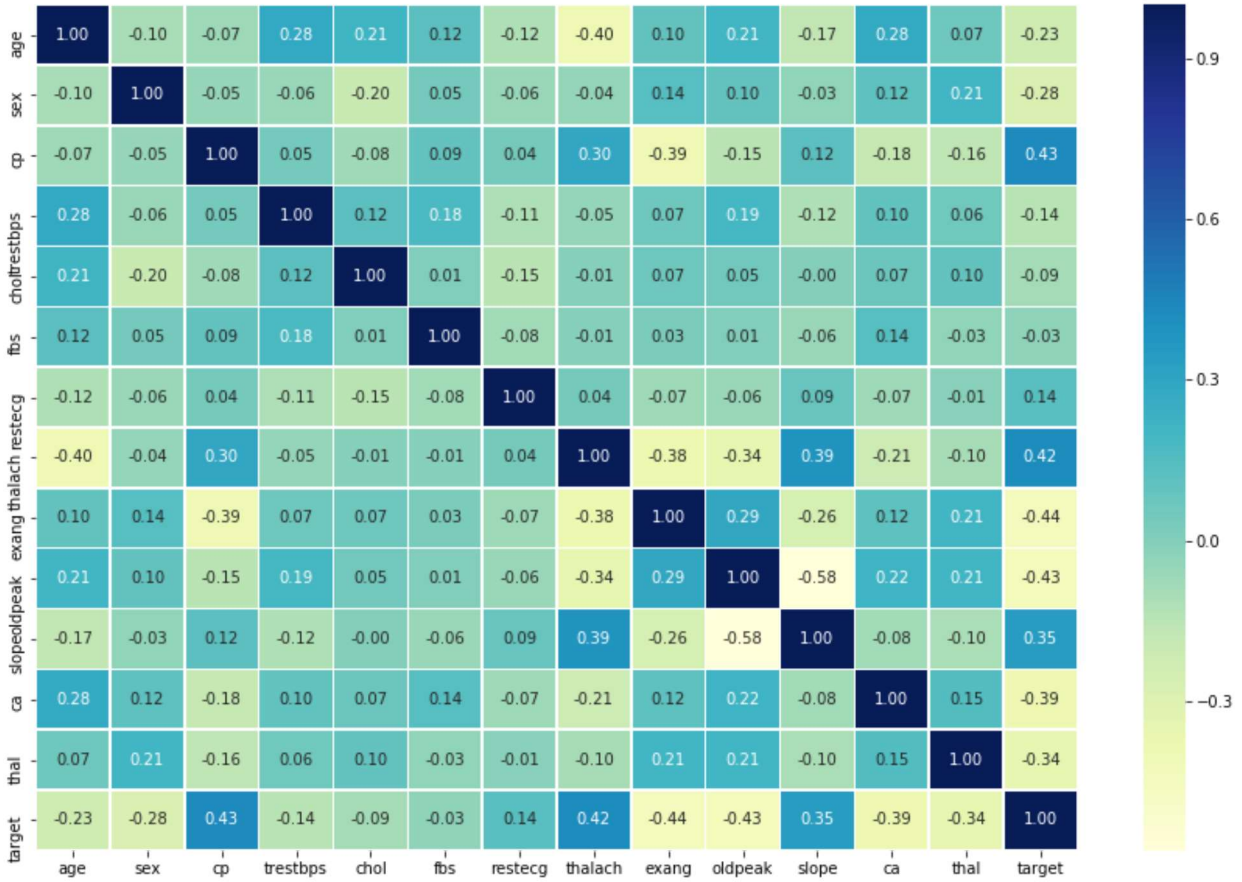
Out[46]:

	age	sex	cp	trestbps	chol	fbs	restecg	thalac
age	1.000000	-0.098447	-0.068653	0.279351	0.213678	0.121308	-0.116211	-0.39852
sex	-0.098447	1.000000	-0.049353	-0.056769	-0.197912	0.045032	-0.058196	-0.04402
cp	-0.068653	-0.049353	1.000000	0.047608	-0.076904	0.094444	0.044421	0.29576
trestbps	0.279351	-0.056769	0.047608	1.000000	0.123174	0.177531	-0.114103	-0.04669
chol	0.213678	-0.197912	-0.076904	0.123174	1.000000	0.013294	-0.151040	-0.00994
fbs	0.121308	0.045032	0.094444	0.177531	0.013294	1.000000	-0.084189	-0.00856
restecg	-0.116211	-0.058196	0.044421	-0.114103	-0.151040	-0.084189	1.000000	0.04412

	age	sex	cp	trestbps	chol	fbs	restecg	thalac
thalach	-0.398522	-0.044020	0.295762	-0.046698	-0.009940	-0.008567	0.044123	1.00000
exang	0.096801	0.141664	-0.394280	0.067616	0.067023	0.025665	-0.070733	-0.37881
oldpeak	0.210013	0.096093	-0.149230	0.193216	0.053952	0.005747	-0.058770	-0.34418
slope	-0.168814	-0.030711	0.119717	-0.121475	-0.004038	-0.059894	0.093045	0.38678
ca	0.276326	0.118261	-0.181053	0.101389	0.070511	0.137979	-0.072042	-0.21317
thal	0.068001	0.210041	-0.161736	0.062210	0.098803	-0.032019	-0.011981	-0.09643
target	-0.225439	-0.280937	0.433798	-0.144931	-0.085239	-0.028046	0.137230	0.42174

In [49]:
```
# Let's make our correlation matrix a little prettier
corr_matrix = df.corr()
fig, ax = plt.subplots(figsize=(15, 10))
ax = sns.heatmap(corr_matrix,
                 annot=True,
                 linewidths=0.5,
                 fmt=".2f",
                 cmap="YlGnBu");
bottom, top = ax.get_ylim()
ax.set_ylim(bottom + 0.5, top - 0.5)
```

Out[49]: (14.0, 0.0)



5. Modelling

In [50]:
```
df.head()
```

Out[50]:

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

In [51]:
```
# Split data into X and y
X = df.drop("target", axis=1)

y = df["target"]
```

In [52]:
```
X
```

Out[52]:

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal
0	63	1	3	145	233	1	0	150	0	2.3	0	0	1
1	37	1	2	130	250	0	1	187	0	3.5	0	0	2
2	41	0	1	130	204	0	0	172	0	1.4	2	0	2
3	56	1	1	120	236	0	1	178	0	0.8	2	0	2
4	57	0	0	120	354	0	1	163	1	0.6	2	0	2
...	...	...	...	...	...	...	...	...	...	...	...	...	...
298	57	0	0	140	241	0	1	123	1	0.2	1	0	3
299	45	1	3	110	264	0	1	132	0	1.2	1	0	3
300	68	1	0	144	193	1	1	141	0	3.4	1	2	3
301	57	1	0	130	131	0	1	115	1	1.2	1	1	3
302	57	0	1	130	236	0	0	174	0	0.0	1	1	2

303 rows × 13 columns

In [53]:
```
y
```

Out[53]:
```
0      1
1      1
2      1
3      1
4      1
      ..
298    0
299    0
300    0
301    0
302    0
Name: target, Length: 303, dtype: int64
```

In [54]:
```
# Split data into train and test sets
np.random.seed(42)

# Split into train & test set
X_train, X_test, y_train, y_test = train_test_split(X,
                                                    y,
                                                    test_size=0.2)
```

In [55]:
```
X_train
```

Out[55]:

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal
132	42	1	1	120	295	0	1	162	0	0.0	2	0	2
202	58	1	0	150	270	0	0	111	1	0.8	2	0	3
196	46	1	2	150	231	0	1	147	0	3.6	1	0	2
75	55	0	1	135	250	0	0	161	0	1.4	1	0	2
176	60	1	0	117	230	1	1	160	1	1.4	2	2	3
...	...	...	...	...	...	...	...	...	...	...	...	...	...
188	50	1	2	140	233	0	1	163	0	0.6	1	1	3
71	51	1	2	94	227	0	1	154	1	0.0	2	1	3
106	69	1	3	160	234	1	0	131	0	0.1	1	1	2
270	46	1	0	120	249	0	0	144	0	0.8	2	0	3
102	63	0	1	140	195	0	1	179	0	0.0	2	2	2

242 rows × 13 columns

In [56]:
```
y_train, len(y_train)
```

Out[56]:
```
(132    1
 202    0
 196    0
 75     1
 176    0
```

```
      ..
188    0
71     1
106    1
270    0
102    1
Name: target, Length: 242, dtype: int64, 242)
```

Now we've got our data split into training and test sets, it's time to build a machine learning model.

We'll train it (find the patterns) on the training set.

And we'll test it (use the patterns) on the test set.

We're going to try 3 different machine learning models:

1. Logistic Regression
2. K-Nearest Neighbours Classifier
3. Random Forest Classifier

In [57]:

```
# Put models in a dictionary
models = {"Logistic Regression": LogisticRegression(),
          "KNN": KNeighborsClassifier(),
          "Random Forest": RandomForestClassifier()}

# Create a function to fit and score models
def fit_and_score(models, X_train, X_test, y_train, y_test):
    """
    Fits and evaluates given machine learning models.
    models : a dict of differetn Scikit-Learn machine learning models
    X_train : training data (no labels)
    X_test : testing data (no labels)
    y_train : training labels
    y_test : test labels
    """
    # Set random seed
    np.random.seed(42)
    # Make a dictionary to keep model scores
    model_scores = {}
    # Loop through models
    for name, model in models.items():
        # Fit the model to the data
        model.fit(X_train, y_train)
        # Evaluate the model and append its score to model_scores
        model_scores[name] = model.score(X_test, y_test)
    return model_scores
```

In [58]:

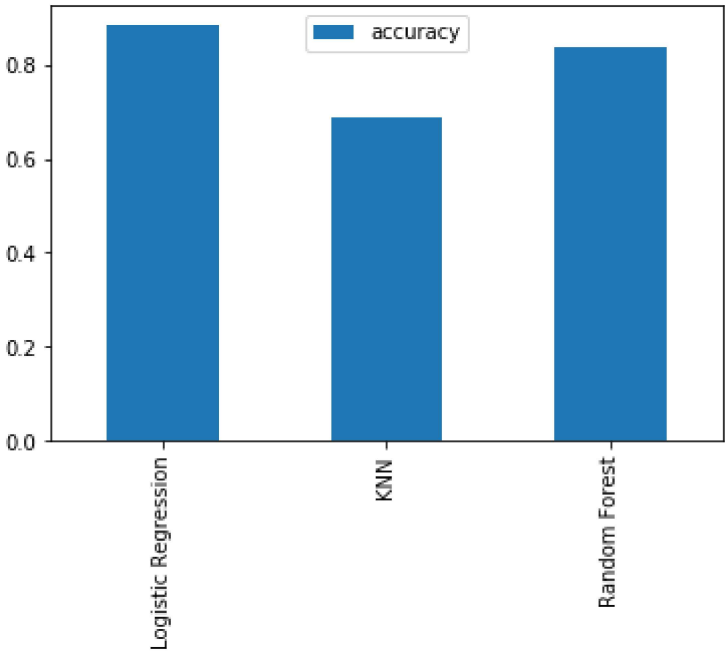
```
model_scores = fit_and_score(models=models,
                             X_train=X_train,
                             X_test=X_test,
                             y_train=y_train,
                             y_test=y_test)

model_scores
```

```
/Users/daniel/Desktop/ml-course/heart-disease-project/env/lib/python3.6/site-packages/
sklearn/linear_model/_logistic.py:939: ConvergenceWarning: lbfgs failed to converge (s
tatus=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html.
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
```

Out[58]:
```
{'Logistic Regression': 0.8852459016393442,
 'KNN': 0.6885245901639344,
 'Random Forest': 0.8360655737704918}
```

Model Comparison

In [61]:
```
model_compare = pd.DataFrame(model_scores, index=["accuracy"])
model_compare.T.plot.bar();
```



Now we've got a baseline model... and we know a model's first predictions aren't always what we should based our next steps off. What should we do?

Let's look at the following:

- Hypyterparameter tuning
- Feature importance
- Confusion matrix
- Cross-validation
- Precision
- Recall
- F1 score
- Classification report

- ROC curve
- Area under the curve (AUC)

Hyperparameter tuning (by hand)

In [63]:
```
# Let's tune KNN

train_scores = []
test_scores = []

# Create a list of differnt values for n_neighbors
neighbors = range(1, 21)

# Setup KNN instance
knn = KNeighborsClassifier()

# Loop through different n_neighbors
for i in neighbors:
    knn.set_params(n_neighbors=i)

    # Fit the algorithm
    knn.fit(X_train, y_train)

    # Update the training scores list
    train_scores.append(knn.score(X_train, y_train))

    # Update the test scores list
    test_scores.append(knn.score(X_test, y_test))
```

In [64]:
```
train_scores
```

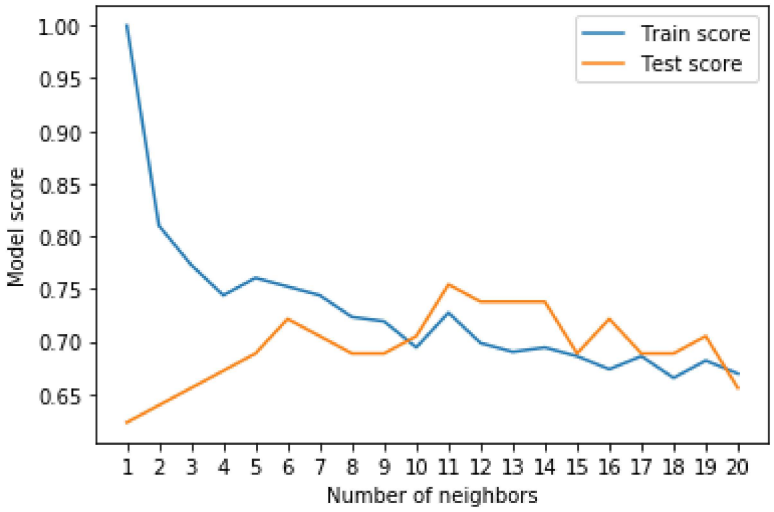
Out[64]:
```
[1.0,
 0.8099173553719008,
 0.7727272727272727,
 0.743801652892562,
 0.7603305785123967,
 0.7520661157024794,
 0.743801652892562,
 0.7231404958677686,
 0.71900826446281,
 0.6942148760330579,
 0.7272727272727273,
 0.6983471074380165,
 0.6900826446280992,
 0.6942148760330579,
 0.6859504132231405,
 0.6735537190082644,
 0.6859504132231405,
 0.6652892561983471,
 0.6818181818181818,
 0.6694214876033058]
```

In [66]:
```
test_scores
```

Out[66]:
```
[0.6229508196721312,
 0.639344262295082,
 0.6557377049180327,
 0.6721311475409836,
 0.6885245901639344,
 0.7213114754098361,
 0.7049180327868853,
 0.6885245901639344,
 0.6885245901639344,
 0.7049180327868853,
 0.7540983606557377,
 0.7377049180327869,
 0.7377049180327869,
 0.7377049180327869,
 0.6885245901639344,
 0.7213114754098361,
 0.6885245901639344,
 0.6885245901639344,
 0.7049180327868853,
 0.6557377049180327]
```

In [68]:
```
plt.plot(neighbors, train_scores, label="Train score")
plt.plot(neighbors, test_scores, label="Test score")
plt.xticks(np.arange(1, 21, 1))
plt.xlabel("Number of neighbors")
plt.ylabel("Model score")
plt.legend()

print(f"Maximum KNN score on the test data: {max(test_scores)*100:.2f}%")
```

```
Maximum KNN score on the test data: 75.41%
```



Hyperparameter tuning with RandomizedSearchCV

We're going to tune:

- LogisticRegression()
- RandomForestClassifier()

... using RandomizedSearchCV

In [78]:
```
# Create a hyperparameter grid for LogisticRegression
log_reg_grid = {"C": np.logspace(-4, 4, 20),
                "solver": ["liblinear"]}

# Create a hyperparameter grid for RandomForestClassifier
rf_grid = {"n_estimators": np.arange(10, 1000, 50),
           "max_depth": [None, 3, 5, 10],
           "min_samples_split": np.arange(2, 20, 2),
           "min_samples_leaf": np.arange(1, 20, 2)}
```

Now we've got hyperparameter grids setup for each of our models, let's tune them using RandomizedSearchCV...

In [74]:
```
# Tune LogisticRegression

np.random.seed(42)

# Setup random hyperparameter search for LogisticRegression
rs_log_reg = RandomizedSearchCV(LogisticRegression(),
                                param_distributions=log_reg_grid,
                                cv=5,
                                n_iter=20,
                                verbose=True)

# Fit random hyperparameter search model for LogisticRegression
rs_log_reg.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 20 candidates, totalling 100 fits
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done 100 out of 100 | elapsed:    0.6s finished
```

Out[74]:
```
RandomizedSearchCV(cv=5, error_score=nan,
                   estimator=LogisticRegression(C=1.0, class_weight=None,
                                                dual=False, fit_intercept=True,
                                                intercept_scaling=1,
                                                l1_ratio=None, max_iter=100,
                                                multi_class='auto', n_jobs=None,
                                                penalty='l2', random_state=None,
                                                solver='lbfgs', tol=0.0001,
                                                verbose=0, warm_start=False),
                   iid='deprecated', n_iter=20, n_jobs=None,
                   param_distributions={'C':...
       4.83293024e-03, 1.27427499e-02, 3.35981829e-02, 8.85866790e-02,
       2.33572147e-01, 6.15848211e-01, 1.62377674e+00, 4.28133240e+00,
       1.12883789e+01, 2.97635144e+01, 7.84759970e+01, 2.06913808e+02,
```

```
       5.45559478e+02, 1.43844989e+03, 3.79269019e+03, 1.00000000e+04]),
                                        'solver': ['liblinear']},
                   pre_dispatch='2*n_jobs', random_state=None, refit=True,
                   return_train_score=False, scoring=None, verbose=True)
```

In [75]:
```
rs_log_reg.best_params_
```

Out[75]:
```
{'solver': 'liblinear', 'C': 0.23357214690901212}
```

In [76]:
```
rs_log_reg.score(X_test, y_test)
```

Out[76]:
```
0.8852459016393442
```

Now we've tuned LogisticRegression(), let's do the same for RandomForestClassifier()...

In [79]:
```
# Setup random seed
np.random.seed(42)

# Setup random hyperparameter search for RandomForestClassifier
rs_rf = RandomizedSearchCV(RandomForestClassifier(),
                           param_distributions=rf_grid,
                           cv=5,
                           n_iter=20,
                           verbose=True)

# Fit random hyperparameter search model for RandomForestClassifier()
rs_rf.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 20 candidates, totalling 100 fits
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done 100 out of 100 | elapsed:  1.1min finished
```

Out[79]:
```
RandomizedSearchCV(cv=5, error_score=nan,
                   estimator=RandomForestClassifier(bootstrap=True,
                                                    ccp_alpha=0.0,
                                                    class_weight=None,
                                                    criterion='gini',
                                                    max_depth=None,
                                                    max_features='auto',
                                                    max_leaf_nodes=None,
                                                    max_samples=None,
                                                    min_impurity_decrease=0.0,
                                                    min_impurity_split=None,
                                                    min_samples_leaf=1,
                                                    min_samples_split=2,
                                                    min_weight_fraction_leaf=0.0,
                                                    n_estimators=100,
                                                    n_jobs...
                   param_distributions={'max_depth': [None, 3, 5, 10],
                                        'min_samples_leaf': array([ 1,  3,  5,  7,
9, 11, 13, 15, 17, 19]),
                                        'min_samples_split': array([ 2,  4,  6,  8,
10, 12, 14, 16, 18]),
                                        'n_estimators': array([ 10,  60, 110, 160, 2
10, 260, 310, 360, 410, 460, 510, 560, 610,
       660, 710, 760, 810, 860, 910, 960])},
```

```
                       pre_dispatch='2*n_jobs', random_state=None, refit=True,
                       return_train_score=False, scoring=None, verbose=True)
```

In [80]:
```
# Find the best hyperparameters
rs_rf.best_params_
```

Out[80]:
```
{'n_estimators': 210,
 'min_samples_split': 4,
 'min_samples_leaf': 19,
 'max_depth': 3}
```

In [81]:
```
# Evaluate the randomized search RandomForestClassifier model
rs_rf.score(X_test, y_test)
```

Out[81]:
```
0.8688524590163934
```

Hyperparamter Tuning with GridSearchCV

Since our LogisticRegression model provides the best scores so far, we'll try and improve them again using GridSearchCV...

In [83]:
```
# Different hyperparameters for our LogisticRegression model
log_reg_grid = {"C": np.logspace(-4, 4, 30),
                "solver": ["liblinear"]}

# Setup grid hyperparameter search for LogisticRegression
gs_log_reg = GridSearchCV(LogisticRegression(),
                          param_grid=log_reg_grid,
                          cv=5,
                          verbose=True)

# Fit grid hyperparameter search model
gs_log_reg.fit(X_train, y_train);
```

```
Fitting 5 folds for each of 30 candidates, totalling 150 fits
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done 150 out of 150 | elapsed:    1.1s finished
```

In [84]:
```
# Check the best hyperparmaters
gs_log_reg.best_params_
```

Out[84]:
```
{'C': 0.20433597178569418, 'solver': 'liblinear'}
```

In [85]:
```
# Evaluate the grid search LogisticRegression model
gs_log_reg.score(X_test, y_test)
```

Out[85]:
```
0.8852459016393442
```

Evaluting our tuned machine learning classifier, beyond accuracy

- ROC curve and AUC score
- Confusion matrix
- Classification report
- Precision
- Recall
- F1-score

... and it would be great if cross-validation was used where possible.

To make comparisons and evaluate our trained model, first we need to make predictions.

In [87]:
```
# Make predictions with tuned model
y_preds = gs_log_reg.predict(X_test)
```

In [88]:
```
y_preds
```

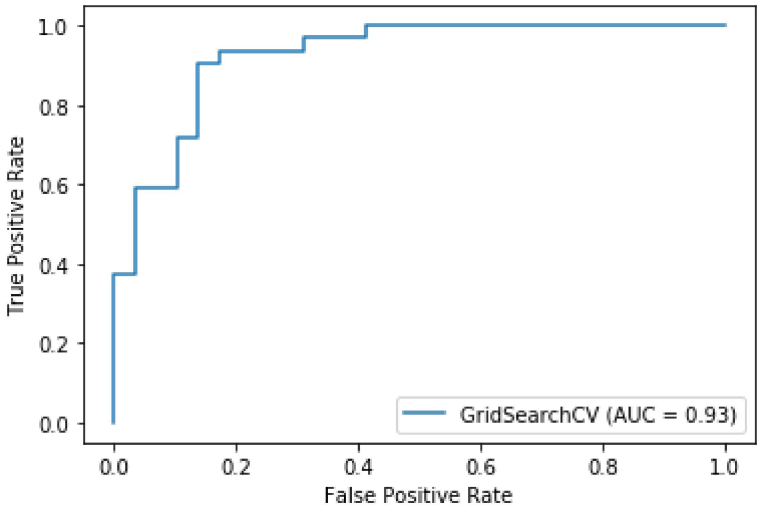
Out[88]:
```
array([0, 1, 1, 0, 1, 1, 1, 0, 0, 1, 1, 0, 1, 0, 1, 1, 1, 0, 0, 0, 1, 0,
       0, 1, 1, 1, 1, 1, 0, 1, 0, 0, 0, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 0, 1, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0])
```

In [89]:
```
y_test
```

Out[89]:
```
179    0
228    0
111    1
246    0
60     1
      ..
249    0
104    1
300    0
193    0
184    0
Name: target, Length: 61, dtype: int64
```

In [90]:
```
# Plot ROC curve and calculate and calculate AUC metric
plot_roc_curve(gs_log_reg, X_test, y_test)
```

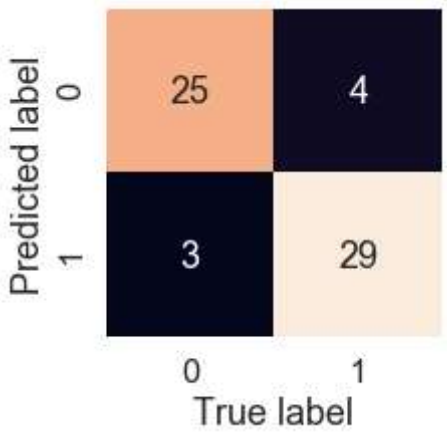
Out[90]:
```
<sklearn.metrics._plot.roc_curve.RocCurveDisplay at 0x1a1fab0748>
```



In [91]:
```
# Confusion matrix
print(confusion_matrix(y_test, y_preds))
```

```
[[25  4]
 [ 3 29]]
```

In [96]:
```
sns.set(font_scale=1.5)

def plot_conf_mat(y_test, y_preds):
    """
    Plots a nice looking confusion matrix using Seaborn's heatmap()
    """
    fig, ax = plt.subplots(figsize=(3, 3))
    ax = sns.heatmap(confusion_matrix(y_test, y_preds),
                     annot=True,
                     cbar=False)
    plt.xlabel("True label")
    plt.ylabel("Predicted label")

    bottom, top = ax.get_ylim()
    ax.set_ylim(bottom + 0.5, top - 0.5)

plot_conf_mat(y_test, y_preds)
```



Now we've got a ROC curve, an AUC metric and a confusion matrix, let's get a classification report as well as cross-validated precision, recall and f1-score.

In [97]:
```
print(classification_report(y_test, y_preds))
```

```
              precision    recall  f1-score   support

           0       0.89      0.86      0.88        29
           1       0.88      0.91      0.89        32

    accuracy                           0.89        61
   macro avg       0.89      0.88      0.88        61
weighted avg       0.89      0.89      0.89        61
```

Calculate evaluation metrics using cross-validation

We're going to calculate accuracy, precision, recall and f1-score of our model using cross-validation and to do so we'll be using `cross_val_score()`.

In [98]:
```
# Check best hyperparameters
gs_log_reg.best_params_
```

Out[98]:
```
{'C': 0.20433597178569418, 'solver': 'liblinear'}
```

In [99]:
```
# Create a new classifier with best parameters
clf = LogisticRegression(C=0.20433597178569418,
                         solver="liblinear")
```

In [100…
```
# Cross-validated accuracy
cv_acc = cross_val_score(clf,
                         X,
                         y,
                         cv=5,
                         scoring="accuracy")
cv_acc
```

Out[100…
```
array([0.81967213, 0.90163934, 0.86885246, 0.88333333, 0.75      ])
```

In [102…
```
cv_acc = np.mean(cv_acc)
cv_acc
```

Out[102…
```
0.8446994535519124
```

In [103…
```
# Cross-validated precision
cv_precision = cross_val_score(clf,
                         X,
                         y,
                         cv=5,
                         scoring="precision")
cv_precision=np.mean(cv_precision)
cv_precision
```

Out[103… 0.8207936507936507

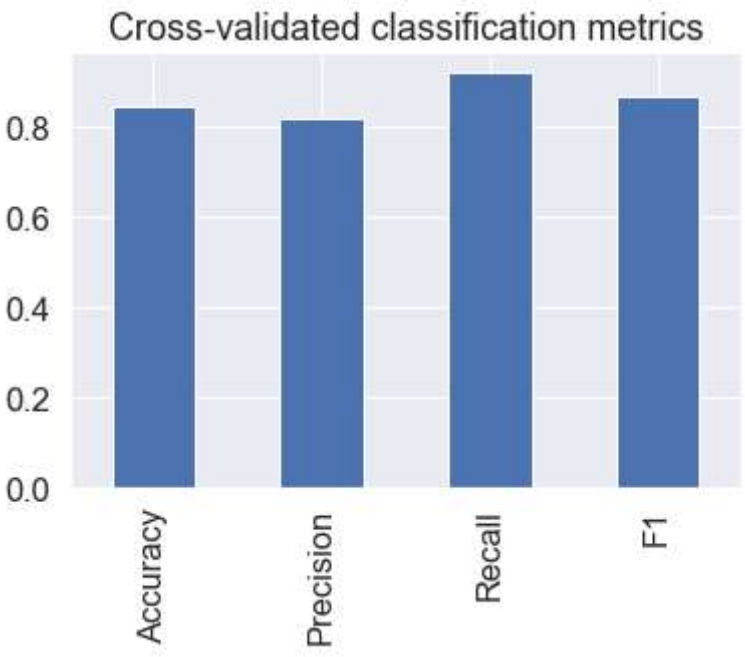
In [104…
```
# Cross-validated recall
cv_recall = cross_val_score(clf,
                            X,
                            y,
                            cv=5,
                            scoring="recall")
cv_recall = np.mean(cv_recall)
cv_recall
```

Out[104… 0.9212121212121213

In [105…
```
# Cross-validated f1-score
cv_f1 = cross_val_score(clf,
                            X,
                            y,
                            cv=5,
                            scoring="f1")
cv_f1 = np.mean(cv_f1)
cv_f1
```

Out[105… 0.8673007976269721

In [107…
```
# Visualize cross-validated metrics
cv_metrics = pd.DataFrame({"Accuracy": cv_acc,
                           "Precision": cv_precision,
                           "Recall": cv_recall,
                           "F1": cv_f1},
                          index=[0])

cv_metrics.T.plot.bar(title="Cross-validated classification metrics",
                      legend=False);
```



Feature Importance

Feature importance is another as asking, "which features contributed most to the outcomes of the model and how did they contribute?"

Finding feature importance is different for each machine learning model. One way to find feature importance is to search for "(MODEL NAME) feature importance".

Let's find the feature importance for our LogisticRegression model...

In [110…

```
# Fit an instance of LogisticRegression
clf = LogisticRegression(C=0.20433597178569418,
                         solver="liblinear")

clf.fit(X_train, y_train);
```

In [111…

```
# Check coef_
clf.coef_
```

Out[111…

```
array([[ 0.00316727, -0.86044582,  0.66067073, -0.01156993, -0.00166374,
         0.04386131,  0.31275787,  0.02459361, -0.60413038, -0.56862852,
         0.45051617, -0.63609863, -0.67663375]])
```

In [114…

```
df.head()
```

Out[114…

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

In [113…

```
# Match coef's of features to columns
feature_dict = dict(zip(df.columns, list(clf.coef_[0])))
feature_dict
```

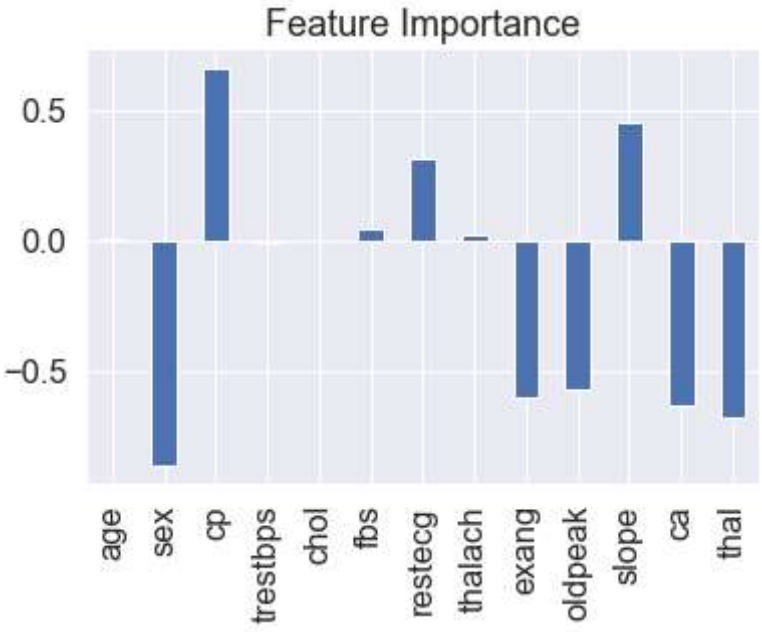
Out[113…

```
{'age': 0.0031672721856887734,
 'sex': -0.860445816920919,
 'cp': 0.6606707303492849,
 'trestbps': -0.011569930902919925,
 'chol': -0.001663741604035976,
 'fbs': 0.04386130751482091,
 'restecg': 0.3127578715206996,
 'thalach': 0.02459360818122666,
 'exang': -0.6041303799858143,
```

```
'oldpeak': -0.5686285194546157,
'slope': 0.4505161679452401,
'ca': -0.6360986316921434,
'thal': -0.6766337521354281}
```

In [115…

```
# Visualize feature importance
feature_df = pd.DataFrame(feature_dict, index=[0])
feature_df.T.plot.bar(title="Feature Importance", legend=False);
```



In [117…

```
pd.crosstab(df["sex"], df["target"])
```

Out[117…

target	0	1
sex		
0	24	72
1	114	93

In [119…

```
pd.crosstab(df["slope"], df["target"])
```

Out[119…

target	0	1
slope		
0	12	9
1	91	49
2	35	107

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

6. Experimentation

If you haven't hit your evaluation metric yet... ask yourself...

- Could you collect more data?
- Could you try a better model? Like CatBoost or XGBoost?
- Could you improve the current models? (beyond what we've done so far)
- If your model is good enough (you have hit your evaluation metric) how would you export it and share it with others?