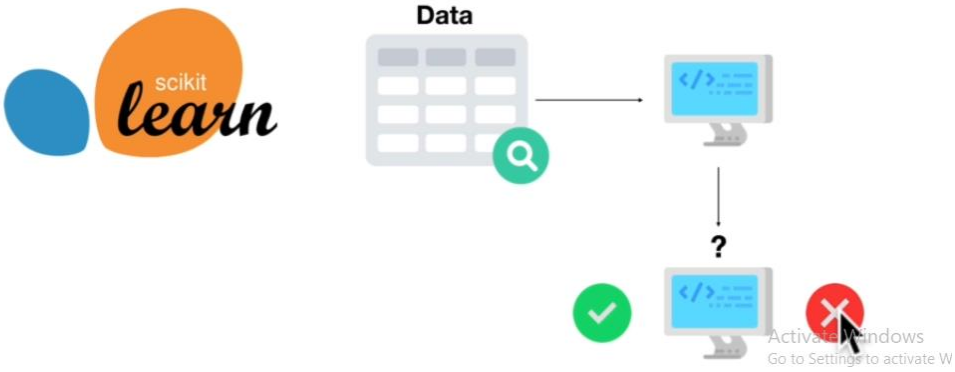
ML-6 cheat sheet remaining

SCIKIT-LEARN

Naqeeb410

Muhammad Naqeeb | Machine Learning / Scikit-Learn | August 11, 2021

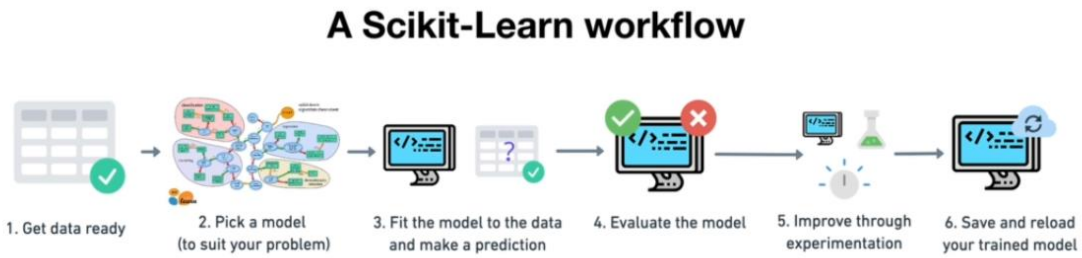
What is Scikit-Learn (sklearn)?

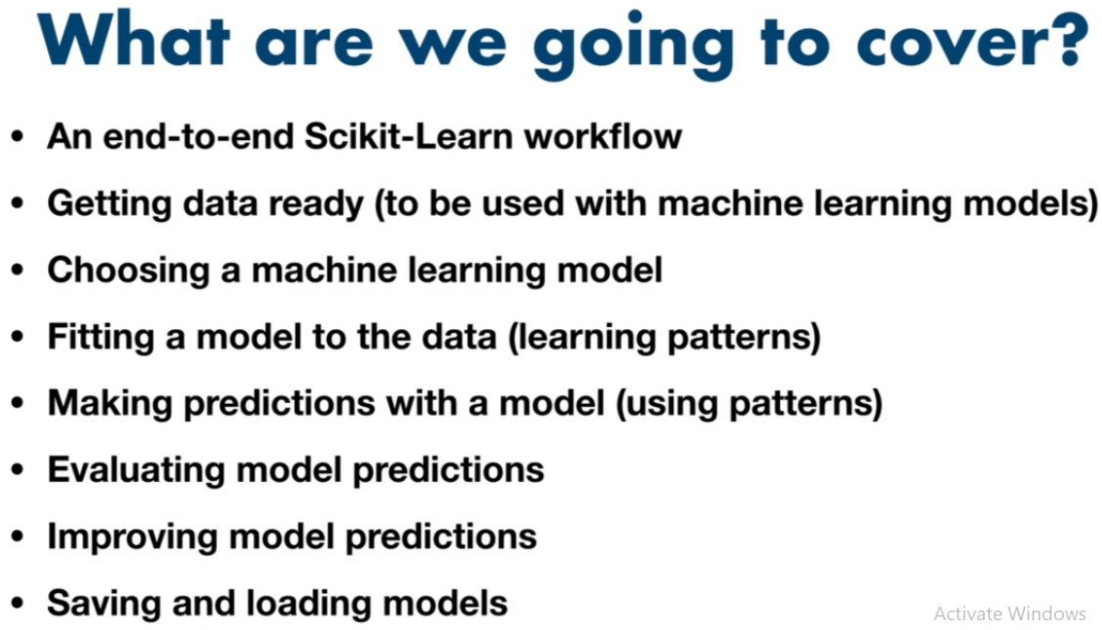


Scikit-Learn is a python machine learning library which means if we have data so, Scikit-Learn helps us build machine learning models, to make predictions or learn patterns within that data and then make predictions.

Why Scikit-Learn?

- Built on NumPy and Matplotlib (and Python)
- Has many in-built machine learning models
- Methods to evaluate your machine learning models
- Very well-designed API





We have to give it lots and lots of data and then we want to test to make sure that this data that we give in gives us the correct output. So, at the end of the day machine learning is simply a computer writing its own function based on the inputs and outputs.

Complete Workflow of Scikit-Learn

What we're going to cover.

0) An end to end. Scikit learn workflow.
1) getting the data ready
2) choose the right estimator / algorithm for our problems
3) fit the model / algorithm and use it to make predictions on our data.
4) evaluating a model
5) improve a model

6) save and load a trained model
7) putting it all together.

1. getting the data ready

```
# 1. getting the data ready
import pandas as pd
heart_disease = pd.read_csv("11.2 heart-disease.csv")
heart_disease
```

In [3]:
```
# 1. getting the data ready
import pandas as pd
heart_disease = pd.read_csv("11.2 heart-disease.csv")
heart_disease
```

Out[3]:

	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

```
# Create X (features matrix)
x = heart_disease.drop("target",axis=1)

# Create y (labels)
y = heart_disease["target"]
```

2. choose the right estimator / algorithm for our problems & hyperparameters

```
# 2. Choose the right model and hyperparameters
from sklearn.ensemble import RandomForestClassifier
clf = RandomForestClassifier(n_estimators= 100)

# We'll keep the default hyperparameters
```

```
clf.get_params()
```

In [5]:
```
# 2. Choose the right model and hyperparameters
from sklearn.ensemble import RandomForestClassifier
clf = RandomForestClassifier(n_estimators= 100)

# We'll keep the default hyperparameters
clf.get_params()
```

Out[5]:
```
{'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': None,
 'oob_score': False,
 'random_state': None,
 'verbose': 0,
 'warm_start': False}
```

3. fit the model to the data to train data

```
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)
```

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

```
x_train
```

In [8]:
```
x_train
```

Out[8]:

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal
256	58	1	0	128	259	0	0	130	1	3.0	1	2	3
149	42	1	2	130	180	0	1	150	0	0.0	2	0	2
96	62	0	0	140	394	0	0	157	0	1.2	1	0	2
20	59	1	0	135	234	0	1	161	0	0.5	1	0	3
260	66	0	0	178	228	1	1	165	1	1.0	1	2	3
...	...	...	...	...	...	...	...	...	...	...	...	...	...
251	43	1	0	132	247	1	0	143	1	0.1	1	4	3
87	46	1	1	101	197	1	1	156	0	0.0	2	0	3
270	46	1	0	120	249	0	0	144	0	0.8	2	0	3
278	58	0	1	136	319	1	0	152	0	0.0	2	2	2
153	66	0	2	146	278	0	0	152	0	0.0	1	1	2

242 rows × 13 columns

```
# make a predictions
# our model can't make pridiction on data which are not of same shape
y_label = clf.predict(np.array([0,2,3,4]))
# so it throw error
```

ValueError: Expected 2D array, got 1D array instead:
array=[0. 2. 3. 4.].

```
y_preds = clf.predict(x_test)
y_preds
```

In [11]:
```
y_preds = clf.predict(x_test)
y_preds
```

Out[11]:
```
array([1, 1, 0, 1, 0, 1, 0, 1, 1, 1, 0, 0, 0, 1, 0, 0, 0, 0,
1, 1, 1, 1,
       1, 1, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 1, 1, 1, 0, 1, 1,
0, 1, 1, 1,
       1, 1, 1, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 1, 1, 1], dt
ype=int64)
```

```
y_test
```

```
In [12]: y_test

Out[12]: 131    1
         2      1
         23     1
         71     1
         101    1
                ..
         74     1
         266    0
         93     1
         80     1
         67     1
         Name: target, Length: 61, dtype: int64
```

4. Evaluate the model on the training data and test data

```
#4. Evaluate the model on the training data and test data
clf.score(x_train, y_train)
```

```
In [13]: #4. Evaluate the model on the training data and test data
         clf.score(x_train, y_train)

Out[13]: 1.0
```

```
clf.score(x_test, y_test)
```

```
In [15]: clf.score(x_test, y_test)

Out[15]: 0.8360655737704918
```

```
from sklearn.metrics import classification_report, confusion_matrix,
accuracy_score

print(classification_report(y_test, y_preds))
```

```
In [17]: from sklearn.metrics import classification_report, confusion_matrix, accuracy_score

         print(classification_report(y_test, y_preds))
```

```
              precision    recall  f1-score   support

           0       0.77      0.83      0.80        24
           1       0.89      0.84      0.86        37

    accuracy                           0.84        61
   macro avg       0.83      0.84      0.83        61
weighted avg       0.84      0.84      0.84        61
```

```
confusion_matrix(y_test, y_preds )
```

```
In [18]: confusion_matrix(y_test, y_preds )

Out[18]: array([[20,  4],
                [ 6, 31]], dtype=int64)
```

```
accuracy_score(y_test, y_preds)
```

```
In [19]: accuracy_score(y_test, y_preds)

Out[19]: 0.8360655737704918
```

5. Improve a model

```
# 5. Improve a model
# Try different amount of n_estimators
np.random.seed(42)
for i in range(10, 100, 10):
    print(f"Trying model with {i} estimators...")
    clf = RandomForestClassifier(n_estimators = i).fit(x_train,
y_train)

    print(f"Model accuracy on test set:{clf.score(x_test, y_test) *
100:2f}%")
    print("")
```

```
Trying model with 10 estimators...
Model accuracy on test set:78.688525%

Trying model with 20 estimators...
Model accuracy on test set:81.967213%

Trying model with 30 estimators...
Model accuracy on test set:83.606557%

Trying model with 40 estimators...
Model accuracy on test set:80.327869%

Trying model with 50 estimators...
Model accuracy on test set:81.967213%

Trying model with 60 estimators...
Model accuracy on test set:83.606557%

Trying model with 70 estimators...
Model accuracy on test set:81.967213%

Trying model with 80 estimators...
Model accuracy on test set:80.327869%

Trying model with 90 estimators...
Model accuracy on test set:83.606557%
```

6. save a model and load it

```
# 6. save a model and load it
import pickle

pickle.dump(clf, open("Random_forst_model_1.pkl","wb"))
```

```
loaded_model = pickle.load(open("Random_forst_model_1.pkl","rb"))
loaded_model.score(x_test, y_test)
```

```
In [24]: loaded_model = pickle.load(open("Random_forst_model_1.pkl","rb"))
         loaded_model.score(x_test, y_test)

Out[24]: 0.8360655737704918
```

Now we breakdown each component and learn them one by one

1. Getting the data ready to be used with machine learning

now the reason we have to do so is because most the time data doesn't come ready to be used with a Scikit learn machine learning model.

Three main things we have to do:

1. Split the data into features and labels (usually `x` & `y`)
2. Filling (also called imputing) or disregarding missing values
3. Converting non-numerical values to numerical values (also called feature encoding)

Well we need a data set to begin with first and we our using heart disease data set.

So in this case we want to use the feature columns to predict Y.

X = **feature** = all the columns like (age, sex, cp, fbs, thal etc), which is use to predict **Y.**

Y = **labels** = which is going to be are **target** columns.

```
# importting data
heart_disease = pd.read_csv("11.2 heart-disease.csv")
```

```
# All the columns expect the 'target'
x = heart_disease.drop("target", axis = 1)
x.head()
```

In [42]:
```
# All the columns expect the 'target'
x = heart_disease.drop("target", axis = 1)
x.head()
```

Out[42]:

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

```
y = heart_disease["target"]
y.head(5)
```

In [45]:
```
y = heart_disease["target"]
y.head(5)
```

Out[45]:
```
0    1
1    1
2    1
3    1
4    1
Name: target, dtype: int64
```

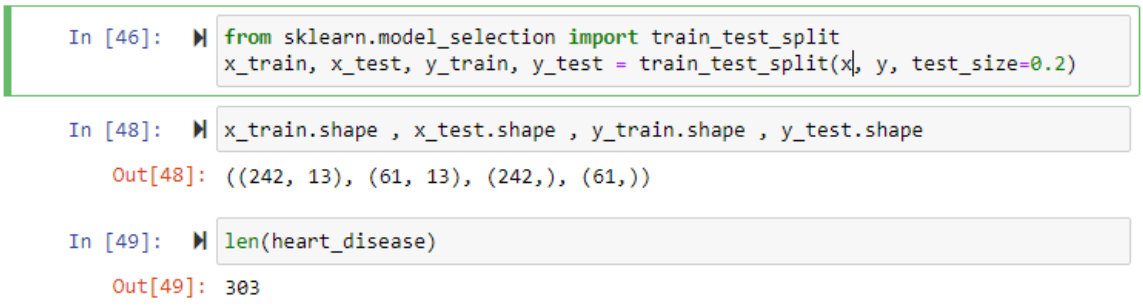
- Split data into training and testing data sets
- In machine learning one of the most fundamental principles is never evaluate or test your models on data that it is learned from.
- Scikit Learn has a convenient function which allowing us to do that.

Split data into training and testing data sets

```
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)
```

```
x_train.shape , x_test.shape , y_train.shape , y_test.shape
```

```
len(heart_disease)
```



Converting non-numerical values to numerical values

Make sure all the data is numerical.

Considering the data which have some objects

```
car_sales = pd.read_csv("car-sales-extended.csv")
car_sales.head()
```

```
In [4]: car_sales = pd.read_csv("car-sales-extended.csv")
        car_sales.head()
```

Out[4]:

	Make	Colour	Odometer (KM)	Doors	Price
0	Honda	White	35431	4	15323
1	BMW	Blue	192714	5	19943
2	Honda	White	84714	4	28343
3	Toyota	White	154365	4	13434
4	Nissan	Blue	181577	3	14043

```
In [5]: len(car_sales)
```

```
Out[5]: 1000
```

```
In [6]: car_sales.dtypes
```

```
Out[6]: Make             object
        Colour           object
        Odometer (KM)     int64
        Doors             int64
        Price             int64
        dtype: object
```

So first of all what we're going to do, is split the data into x and y so we'll use these four columns make, color, odometer, doors. By using these four we try and predict the price of a car.

```
# Split into x & y
x = car_sales.drop('Price',axis = 1)
y = car_sales["Price"]
```

```
# split into training and 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)
```

This following cell code give us error because two of are columns data is object and machine learning models work on numeric data,

So we have to convert are data to numeric values

```
# build a machine learning model
from sklearn.ensemble import RandomForestRegressor

# model / clf
model = RandomForestRegressor()
model.fit(x_train, y_train)
model.score( x_test, y_test)

# this will give us error because two of are columns data is object and
machine learning models work on numeric data,
# So we have to convert are data to numeric values
```

ValueError: could not convert string to float: 'Honda'

So, turning are data to numarical

```
# Turn the categories into numbers
from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import ColumnTransformer

categorical_features = ["Make","Colour", "Doors"]
one_hot = OneHotEncoder()
transformer = ColumnTransformer([("one_hot",
                                  one_hot,
                                  categorical_features)],
                                  remainder = "passthrough")

transformed_x = transformer.fit_transform(x)
transformed_x
```

In [10]:

```
# Turn the categories into numbers
from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import ColumnTransformer

categorical_features = ["Make","Colour", "Doors"]
one_hot = OneHotEncoder()
transformer = ColumnTransformer([("one_hot",
                                  one_hot,
                                  categorical_features)],
                                  remainder = "passthrough")

transformed_x = transformer.fit_transform(x)
transformed_x
```

Out[10]:

```
array([[0.00000e+00, 1.00000e+00, 0.00000e+00, ..., 1.00000e
+00,
        0.00000e+00, 3.54310e+04],
       [1.00000e+00, 0.00000e+00, 0.00000e+00, ..., 0.00000e
+00,
        1.00000e+00, 1.92714e+05],
       [0.00000e+00, 1.00000e+00, 0.00000e+00, ..., 1.00000e
+00,
        0.00000e+00, 8.47140e+04],
       ...,
       [0.00000e+00, 0.00000e+00, 1.00000e+00, ..., 1.00000e
+00,
        0.00000e+00, 6.66040e+04],
       [0.00000e+00, 1.00000e+00, 0.00000e+00, ..., 1.00000e
```

One Hot Encoding

A process used to turn categories into numbers.

Car	Colour
0	Red
1	Green
2	Blue
3	Red

Car	Red	Green	Blue
0	1	0	0
1	0	1	0
2	0	0	1
3	1	0	0

```
pd.DataFrame(transformed_x)
```

In [11]:
```
pd.DataFrame(transformed_x)
```

Out[11]:

	0	1	2	3	4	5	6	7	8	9	10	11	12
0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	1.0	0.0	35431.0
1	1.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	1.0	192714.0
2	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	1.0	0.0	84714.0
3	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	1.0	0.0	1.0	0.0	154365.0
4	0.0	0.0	1.0	0.0	0.0	1.0	0.0	0.0	0.0	1.0	0.0	0.0	181577.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...
995	0.0	0.0	0.0	1.0	1.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	35820.0
996	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	1.0	1.0	0.0	0.0	155144.0
997	0.0	0.0	1.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	1.0	0.0	66604.0
998	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	1.0	0.0	215883.0
999	0.0	0.0	0.0	1.0	0.0	1.0	0.0	0.0	0.0	0.0	1.0	0.0	248360.0

1000 rows × 13 columns

```
dummies = pd.get_dummies(car_sales[["Make","Colour","Doors"]])
dummies
```

In [12]:
```
dummies = pd.get_dummies(car_sales[["Make","Colour","Doors"]])
dummies
```

Out[12]:

	Doors	Make_BMW	Make_Honda	Make_Nissan	Make_Toyota	Colour_Black	Colour_Blue	Colour_Green	Colour_Red	Colour_White
0	4	0	1	0	0	0	0	0	0	1
1	5	1	0	0	0	0	1	0	0	0
2	4	0	1	0	0	0	0	0	0	1
3	4	0	0	0	1	0	0	0	0	1
4	3	0	0	1	0	0	1	0	0	0
...	...	...	...	...	...	...	...	...	...	...
995	4	0	0	0	1	1	0	0	0	0
996	3	0	0	1	0	0	0	0	0	1
997	4	0	0	1	0	0	1	0	0	0
998	4	0	1	0	0	0	0	0	0	1
999	4	0	0	0	1	0	1	0	0	0

1000 rows × 10 columns


```
# lets refit the model
np.random.seed(42)
x_train,x_test, y_train, y_test = train_test_split(transformed_x, y,
test_size=0.2)

model.fit(x_train, y_train)
```

```
model.score(x_test, y_test)
```

```
In [13]:
# lets refit the model
np.random.seed(42)
x_train,x_test, y_train, y_test = train_test_split(transformed_

model.fit(x_train, y_train)
```

```
Out[13]: RandomForestRegressor()
```

```
In [14]:
model.score(x_test, y_test)
```

```
Out[14]: 0.3235867221569877
```

what if there were missing values??

There's two main ways to deal with missing data.

- **(Option 1):** fill them with some value (Also known as imputation.)
- **(Option 2):** remove the samples with missing data altogether.

```
car_sales_missing = pd.read_csv("car-sales-extended-missing-data.csv")
car_sales_missing
```

In [56]:
```
car_sales_missing = pd.read_csv("car-sales-extended-missing-data.csv")
car_sales_missing
```

Out[56]:

	Make	Colour	Odometer (KM)	Doors	Price
0	Honda	White	35431.0	4.0	15323.0
1	BMW	Blue	192714.0	5.0	19943.0
2	Honda	White	84714.0	4.0	28343.0
3	Toyota	White	154365.0	4.0	13434.0
4	Nissan	Blue	181577.0	3.0	14043.0
...	...	...	...	...	...
995	Toyota	Black	35820.0	4.0	32042.0
996	NaN	White	155144.0	3.0	5716.0
997	Nissan	Blue	66604.0	4.0	31570.0
998	Honda	White	215883.0	4.0	4001.0
999	Toyota	Blue	248360.0	4.0	12732.0

1000 rows × 5 columns

```
# For counting missing values
car_sales_missing.isna().sum()
```

In [57]:
```
# For counting missing values
car_sales_missing.isna().sum()
```

Out[57]:
```
Make             49
Colour           50
Odometer (KM)    50
Doors            50
Price            50
dtype: int64
```

Option 1: Fill missing data with pandas

```
# Fill the "Make" column
car_sales_missing["Make"].fillna("missing", inplace = True)

# Fill the "Colour" column
car_sales_missing["Colour"].fillna("missing", inplace = True)
```

```
# Fill the "Odometer (KM)" column
car_sales_missing["Odometer (KM)"].fillna(car_sales_missing["Odometer
(KM)"].mean(), inplace = True)

# Fill the "Odometer (KM)" column
car_sales_missing["Doors"].fillna(4, inplace = True)
```

Option 1: Fill missing data with pandas

In [63]:
```
# Fill the "Make" column
car_sales_missing["Make"].fillna("missing", inplace = True)

# Fill the "Colour" column
car_sales_missing["Colour"].fillna("missing", inplace = True)

# Fill the "Odometer (KM)" column
car_sales_missing["Odometer (KM)"].fillna(car_sales_missing["Odometer (KM)"].mean(), inplace = True

# Fill the "Odometer (KM)" column
car_sales_missing["Doors"].fillna(4, inplace = True)
```

In [64]:
```
# check out  dataframe again
car_sales_missing.isna().sum()
```

Out[64]:
```
Make             0
Colour           0
Odometer (KM)    0
Doors            0
Price           50
dtype: int64
```

```
# Remove rows with missing price value
car_sales_missing.dropna(inplace=True)
```

In [65]:
```
# Remove rows with missing price value
car_sales_missing.dropna(inplace=True)
```

In [66]:
```
car_sales_missing.isna().sum()
```

Out[66]:
```
Make             0
Colour           0
Odometer (KM)    0
Doors            0
Price            0
dtype: int64
```

Option 2: Fill missing values with Scikit-Learn

```
car_sales_missing = pd.read_csv("car-sales-extended-missing-data.csv")
car_sales_missing
```

In [87]:
```
car_sales_missing = pd.read_csv("car-sales-extended-missing-data
car_sales_missing
```

Out[87]:

	Make	Colour	Odometer (KM)	Doors	Price
0	Honda	White	35431.0	4.0	15323.0
1	BMW	Blue	192714.0	5.0	19943.0
2	Honda	White	84714.0	4.0	28343.0
3	Toyota	White	154365.0	4.0	13434.0
4	Nissan	Blue	181577.0	3.0	14043.0
...	...	...	...	...	...
995	Toyota	Black	35820.0	4.0	32042.0
996	NaN	White	155144.0	3.0	5716.0
997	Nissan	Blue	66604.0	4.0	31570.0
998	Honda	White	215883.0	4.0	4001.0
999	Toyota	Blue	248360.0	4.0	12732.0

1000 rows × 5 columns

```
# drop the rows with no labels
car_sales_missing.dropna(subset=["Price"], inplace = True)
car_sales_missing.isna().sum()
```

In [74]:
```
# drop the rows with no labels
car_sales_missing.dropna(subset=["Price"], inplace = True)
car_sales_missing.isna().sum()
```

Out[74]:
```
Make            47
Colour          46
Odometer (KM)   48
Doors           47
Price            0
dtype: int64
```

```
# Split / creating into x & y
x = car_sales_missing.drop('Price',axis = 1)
y = car_sales_missing["Price"]
```

```
# fill missing values with Scikit-Learn
from sklearn.impute import SimpleImputer
from sklearn.compose import ColumnTransformer

# Fill categorical values with 'missing' & numerical with mean
# hear we are just defining imputer, imputer is just filling missing
data
cat_imputer = SimpleImputer(strategy = "constant",
fill_value="missing")
door_imputer = SimpleImputer(strategy = "constant", fill_value=4)
num_imputer = SimpleImputer(strategy = "mean")

# Define columns
cat_features = ["Make","Colour"]
door_features = ["Doors"]
num_features = ["Odometer (KM)"]

# Create an imputer (something that fills missing data)
imputer = ColumnTransformer([
    ("cat_imputer", cat_imputer, cat_features),
    ("door_imputer", door_imputer, door_features),
    ("num_imputer", num_imputer, num_features)
])


# Transform the data
filled_x = imputer.fit_transform(x)
filled_x
```

```
Out[88]: array([['Honda', 'White', 4.0, 35431.0],
                ['BMW', 'Blue', 5.0, 192714.0],
                ['Honda', 'White', 4.0, 84714.0],
                ...,
                ['Nissan', 'Blue', 4.0, 66604.0],
                ['Honda', 'White', 4.0, 215883.0],
                ['Toyota', 'Blue', 4.0, 248360.0]], dtype=object)
```

```
car_sales_filled = pd.DataFrame(filled_x, columns = ["Make",
"Colour","Doors", "Odometer (KM)" ])

car_sales_filled
```

In [89]:
```
car_sales_filled = pd.DataFrame(filled_x, columns = ["Make", "Colour","Doors", "Odometer (KM)" ])

car_sales_filled
```

Out[89]:

	Make	Colour	Doors	Odometer (KM)
0	Honda	White	4.0	35431.0
1	BMW	Blue	5.0	192714.0
2	Honda	White	4.0	84714.0
3	Toyota	White	4.0	154365.0
4	Nissan	Blue	3.0	181577.0
...	...	...	...	...
945	Toyota	Black	4.0	35820.0
946	missing	White	3.0	155144.0
947	Nissan	Blue	4.0	66604.0
948	Honda	White	4.0	215883.0
949	Toyota	Blue	4.0	248360.0

950 rows × 4 columns

In [90]:
```
car_sales_filled.isna().sum()
```

Out[90]:
```
Make            0
Colour          0
Doors           0
Odometer (KM)   0
dtype: int64
```

```
# lets try and convert our data to numbers
# Turn the categories into numbers
from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import ColumnTransformer

categorical_features = ["Make","Colour", "Doors"]
one_hot = OneHotEncoder()
transformer = ColumnTransformer([("one_hot",
                                  one_hot,
                                  categorical_features)],
                                  remainder = "passthrough")

transformed_x = transformer.fit_transform(car_sales_filled)
transformed_x
```

```
# Now we've got our data as numbers and filled (no missing values)
# letsfit a model

np.random.seed(42)
```

```
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import train_test_split

x_train, x_test, y_train, y_test = train_test_split(transformed_x, y,
test_size=0.2)


model = RandomForestRegressor()
model.fit(x_train, y_train)
model.score(x_test, y_test)
```

So, the process of filling missing values is called **imputation** and the process of turning your non numerical values into numerical values is referred to as **feature engineering** or **feature encoding**.

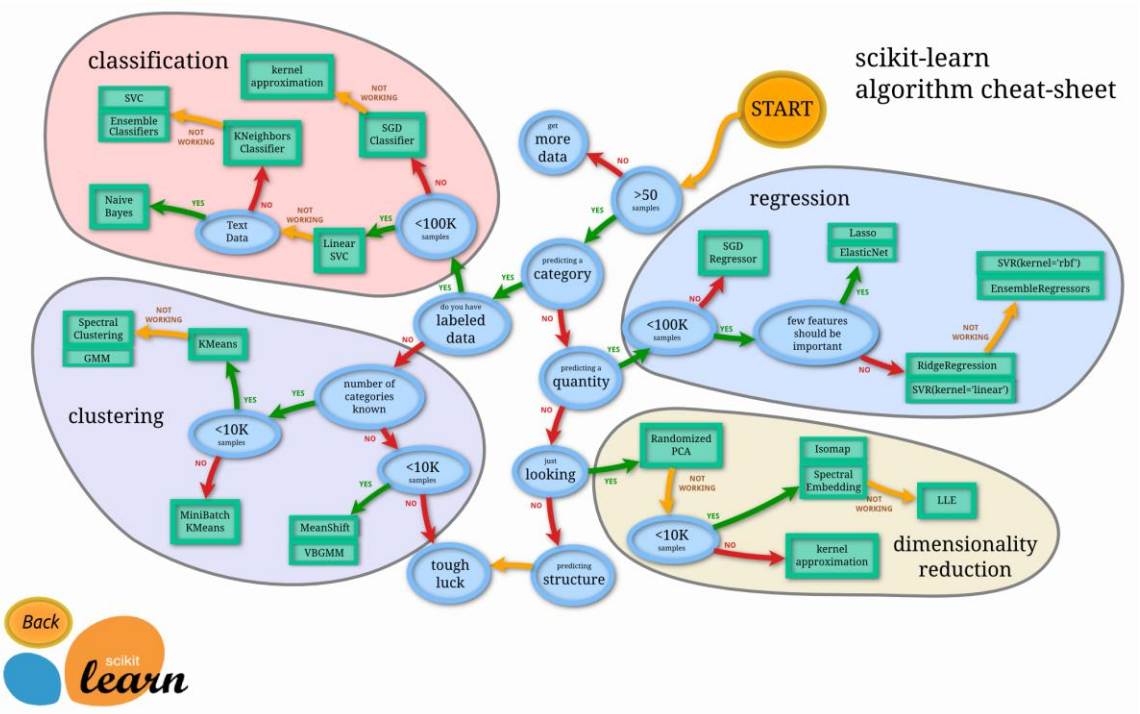
2. Choose the right estimator / algorithm for our problems

Scikit-learn users estimator as another term for machine learning model or algorithm.

Well some other things to note is that first of all before you choose an estimator / algorithm for your problem is you have to figure out what kind of problem are you working with:

- **`classification`** predicting whether a sample is one thing or another. so classification is like our heart disease problem. We're trying to predict whether someone has heart disease or not.
- And **`regression`** predicting a number like with the Boston Housing dataset or with our car sales data set. We're trying to predict a house price or a car price

Step 1. Check the socket line machine learning map.



[Choosing the right estimator — scikit-learn 0.24.2 documentation]

Picking a machine learning model for our regression problem

so what we're going to do is we're going to use one of scikit learn built in datasets and that's the Boston Housing data set. The **Boston Housing Dataset.** A Dataset derived from information collected by the U.S. Census Service concerning housing in the area of Boston Mass.

```
# import Boston housing dataset
from sklearn.datasets import load_boston
boston = load_boston()
boston
```

So it imports as a dictionary we've got **data** as one of the keys. **Target** is one of the keys. And then we have a **feature names.**

Turn it into a panda's data frame so that we can see it a little bit better than being a dictionary.

```
boston_df = pd.DataFrame(boston["data"], columns
=boston["feature_names"])
boston_df["target"] = pd.Series(boston["target"])
boston_df
```

In [95]:
```
boston_df = pd.DataFrame(boston["data"], columns =boston["feature_names"])
boston_df["target"] = pd.Series(boston["target"])
boston_df
```

Out[95]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT	target
0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1.0	296.0	15.3	396.90	4.98	24.0
1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	2.0	242.0	17.8	396.90	9.14	21.6
2	0.02729	0.0	7.07	0.0	0.469	7.185	61.1	4.9671	2.0	242.0	17.8	392.83	4.03	34.7
3	0.03237	0.0	2.18	0.0	0.458	6.998	45.8	6.0622	3.0	222.0	18.7	394.63	2.94	33.4
4	0.06905	0.0	2.18	0.0	0.458	7.147	54.2	6.0622	3.0	222.0	18.7	396.90	5.33	36.2
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
501	0.06263	0.0	11.93	0.0	0.573	6.593	69.1	2.4786	1.0	273.0	21.0	391.99	9.67	22.4
502	0.04527	0.0	11.93	0.0	0.573	6.120	76.7	2.2875	1.0	273.0	21.0	396.90	9.08	20.6
503	0.06076	0.0	11.93	0.0	0.573	6.976	91.0	2.1675	1.0	273.0	21.0	396.90	5.64	23.9
504	0.10959	0.0	11.93	0.0	0.573	6.794	89.3	2.3889	1.0	273.0	21.0	393.45	6.48	22.0
505	0.04741	0.0	11.93	0.0	0.573	6.030	80.8	2.5050	1.0	273.0	21.0	396.90	7.88	11.9

506 rows × 14 columns

```
# lets try the Ridge Regression model
from sklearn. linear_model import Ridge
```

```
#Setup random seed
np.random.seed(42)

# create the data
x = boston_df.drop("target", axis=1)
y = boston_df["target"]

# # split into train and test sets
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)

# Instantite Ridge model
model = Ridge()
model.fit(x_train,y_train)

# Check the score of the Ridge model on test data
model.score(x_test, y_test)
```

In [98]:
```
# Lets try the Ridge Regression model
from sklearn. linear_model import Ridge

#Setup random seed
np.random.seed(42)

# create the data
x = boston_df.drop("target", axis=1)
y = boston_df["target"]

# # split into train and test sets
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)

# Instantite Ridge model
model = Ridge()
model.fit(x_train,y_train)

# Check the score of the Ridge model on test data
model.score(x_test, y_test)
```

Out[98]: 0.6662221670168522

How do we improve this score / what if Rigde wasn't working...

In that case we refer back to the map ... we will try another model / estimator / algorithms

```
# Let's  try the Random Forest Regressor
from sklearn.ensemble import RandomForestRegressor

#Setup random seed
np.random.seed(42)

# create the data
x = boston_df.drop("target", axis=1)
y = boston_df["target"]

# # split into train and test sets
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)

# Instantite Random Forest Regressor
model = RandomForestRegressor()
model.fit(x_train,y_train)

# Check the score of the Random Forest Regressor model on test data
# Evaluate the Random Forest Regressor
model.score(x_test, y_test)
```

In [12]:
```
# Let's  try the Random Forest Regressor
from sklearn.ensemble import RandomForestRegressor

#Setup random seed
np.random.seed(42)

# create the data
x = boston_df.drop("target", axis=1)
y = boston_df["target"]

# # split into train and test sets
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)

# Instantite Random Forest Regressor
model = RandomForestRegressor()
model.fit(x_train,y_train)

# Check the score of the Random Forest Regressor model on test data
# Evaluate the Random Forest Regressor
model.score(x_test, y_test)
```

Out[12]:
```
0.8654448653350507
```

Just by changing the model or trying another model we improve are score from **0.6662221670168522** (Ridge model) to **0.8654448653350507** (Random Forest Regressor)

Choosing and estimator for a classification problem

First of all visit map

```
# importing data
heart_disease = pd.read_csv("11.2 heart-disease.csv")
heart_disease.head()
```

Consulting the map and it says to try LinearSVC

```
# Import the LinearSVC estimator class
from sklearn.svm import LinearSVC

#Setup random seed
np.random.seed(42)

# create the data
x = heart_disease.drop("target", axis=1)
y = heart_disease["target"]

# # split into train and test sets
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)

# Instantite LinearSVC
clf = LinearSVC()
clf.fit(x_train,y_train)

# Check the score of the LinearSVC model on test data
# Evaluate the LinearSVC
clf.score(x_test, y_test)
```

```
In [16]:
# Import the LinearSVC estimator class
from sklearn.svm import LinearSVC

#Setup random seed
np.random.seed(42)

# create the data
x = heart_disease.drop("target", axis=1)
y = heart_disease["target"]

# # split into train and test sets
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)

# Instantite LinearSVC
clf = LinearSVC()
clf.fit(x_train,y_train)

# Check the score of the LinearSVC model on test data
# Evaluate the LinearSVC
clf.score(x_test, y_test)

C:\Users\toshiba c55t-a\desktop\sample_project\env\lib\site-packages\sklearn\svm\_base.py:985: ConvergenceWarning: Liblinear
failed to converge, increase the number of iterations.
  warnings.warn("Liblinear failed to converge, increase "

Out[16]: 0.8688524590163934
```


Now comparing LinearSVC with Random Forest Regressor

```
# Let's  try the Random Forest Regressor for comparision with LinearSVC
from sklearn.ensemble import RandomForestRegressor

#Setup random seed
np.random.seed(42)

# create the data
x = heart_disease.drop("target", axis=1)
y = heart_disease["target"]

# # split into train and test sets
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)

# Instantite Random Forest Regressor
model = RandomForestRegressor()
model.fit(x_train,y_train)

# Check the score of the Random Forest Regressor model on test data
# Evaluate the Random Forest Regressor
model.score(x_test, y_test)
```

Tidbit:

- If you have structured data use ensemble method
- If you have unstructured data, use deep learning or transfer learning.

3. Fit the model / algorithm and use it to make predictions on our data.

3.1. Fitting the model to the data

Different name for:

- X = features, features variables, data
- y = labels, targets, target variables

```
# Import the RandomForestRegressor estimator class
from sklearn.ensemble import RandomForestRegressor

#Setup random seed
np.random.seed(42)

# create the data
x = heart_disease.drop("target", axis=1)
y = heart_disease["target"]

# # split into train and test sets
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)

# Instantite Random Forest Regressor
model = RandomForestRegressor()

### Fit the model to the data (trainind the machine learning model)
model.fit(x_train,y_train)


# Evaluate the Random Forest Regressor (Ue=se the patterns the model
has learned)
model.score(x_test, y_test)
```

3.2. Making predictions using a machine learning model

Two ways to make predictions

- predict()
- predict_proba()

making prediction using predict()

```
# Using upper LinearSVC estimator class model
# Use a trained model to make predictions

clf.predict(np.array([1,7,8,3,4])) # this doesn't work....
```

ValueError: Expected 2D array, got 1D array instead:
array=[1 7 8 3 4].

```
# Using upper LinearSVC estimator class model
clf.predict(x_test)
```

```
In [30]: # Using upper LinearSVC estimator class model
         clf.predict(x_test)

Out[30]: 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, 1, 0, 0, 1, 0, 0, 0], d
         type=int64)
```

```
np.array(y_test)
```

```
In [32]: np.array(y_test)

Out[32]: array([0, 0, 1, 0, 1, 1, 1, 0, 0, 1, 1, 1, 1, 0, 1, 1, 1, 0,
                0, 0, 1, 0,
                       0, 1, 1, 0, 0, 1, 0, 1, 1, 0, 0, 1, 1, 0, 1, 1, 1, 1,
                1, 1, 1, 1,
                       1, 0, 0, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0], d
                type=int64)
```

```
# compare predictions to truth labels to evaluate the mpdel
y_preds = clf.predict(x_test)
np.mean(y_preds == y_test)
```

```
In [33]: # compare predictions to truth labels to evaluate the mpdel
         y_preds = clf.predict(x_test)
         np.mean(y_preds == y_test)

Out[33]: 0.8688524590163934
```

```
clf.score(x_test,y_test)
```

```
from sklearn.metrics import accuracy_score
accuracy_score(y_test, y_preds)
```

```
In [34]: clf.score(x_test,y_test)

Out[34]: 0.8688524590163934
```

```
In [35]: from sklearn.metrics import accuracy_score
         accuracy_score(y_test, y_preds)

Out[35]: 0.8688524590163934
```

Make predictions with predict_proba()

`predict()` can also be used for regression models

```
from sklearn.ensemble import RandomForestRegressor

#Setup random seed
np.random.seed(42)

# create the data
x = boston_df.drop("target", axis=1)
y = boston_df["target"]

# split into train and test sets
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)

# Instantite Random Forest Regressor and fit model
model = RandomForestRegressor()
model.fit(x_train,y_train)

#Make predictions
y_preds = model.predict(x_test)
```

```
y_preds[:10]
```

```
np.array(y_test[:10])
```

```
# Compare the predictions to the truth
from sklearn.metrics import mean_absolute_error
mean_absolute_error(y_test, y_preds)
```

```
In [62]: y_preds[:10]

Out[62]: array([23.081, 30.574, 16.759, 23.46 , 16.893, 21.644, 19.11
         3, 15.334,
                21.14 , 20.639])

In [63]: np.array(y_test[:10])

Out[63]: array([23.6, 32.4, 13.6, 22.8, 16.1, 20. , 17.8, 14. , 19.6,
         16.8])

In [64]: # Compare the predictions to the truth
         from sklearn.metrics import mean_absolute_error
         mean_absolute_error(y_test, y_preds)

Out[64]: 2.136382352941176
```

This mean on average, for every single prediction 2.136382352941176 away for the target

4. Evaluating a model

There are 3 different APIs for evaluating the quality of a model's predictions:

1. Estimator `score` method
2. `Scoring` parameter
3. Metric functions / Problem-specific metric functions

4.1. Evaluating a model with the score method

Now we've already seen this one because this is basically the default. It's a way to get a quick sniff, a quick understanding of how our is doing.

```
from sklearn.ensemble import RandomForestClassifier

#Setup random seed
np.random.seed(42)
```

```
# create the data
x = heart_disease.drop("target", axis=1)
y = heart_disease["target"]

# split into train and test sets
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)

# Instantite Random Forest Regressor and fit model
clf = RandomForestClassifier()
clf.fit(x_train,y_train)
```

```
# Evaluating
clf.score(x_train, y_train)
```

```
clf.score(x_test, y_test)
```

```
In [13]: # Evaluating
         clf.score(x_train, y_train)

Out[13]: 1.0

In [14]: clf.score(x_test, y_test)

Out[14]: 0.8524590163934426
```

Let's do the same but for regression...

```
from sklearn.ensemble import RandomForestRegressor

#Setup random seed
np.random.seed(42)

# create the data
x = boston_df.drop("target", axis=1)
y = boston_df["target"]

# split into train and test sets
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)

# Instantite Random Forest Regressor and fit model
model = RandomForestRegressor()
model.fit(x_train,y_train)
```

```
model.score(x_test, y_test)
```

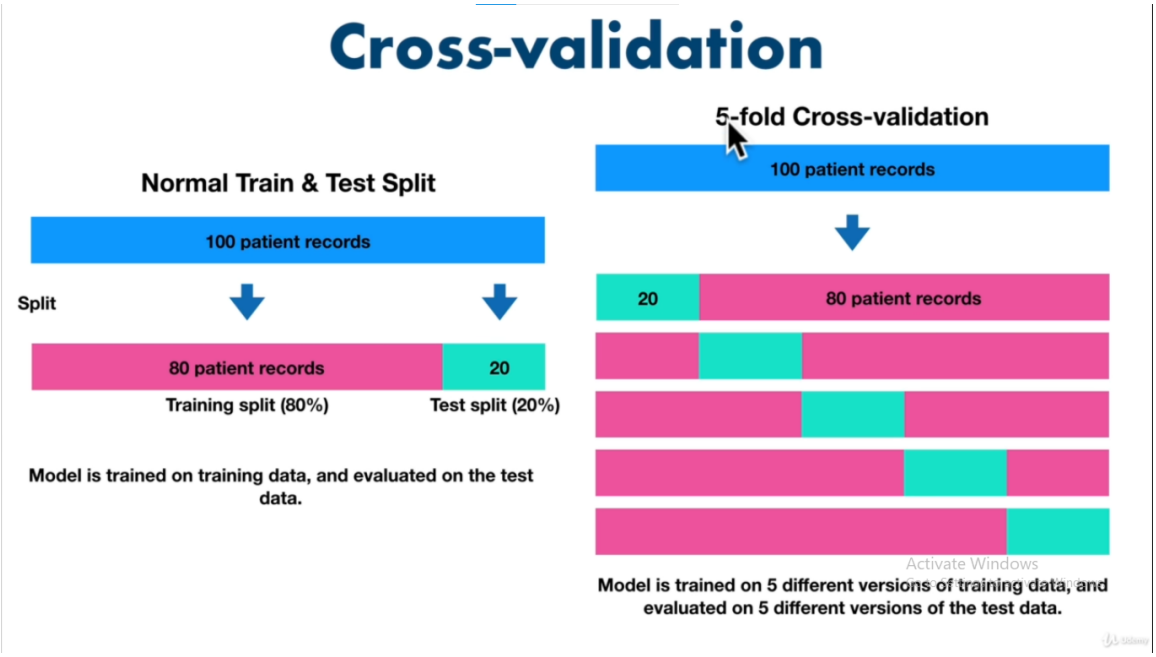
```
In [20]: model.score(x_test, y_test)
Out[20]: 0.8654448653350507
```

4.2. Evaluating a model using the `Scoring` parameter

```
from sklearn.model_selection import cross_val_score ##

from sklearn.ensemble import RandomForestClassifier

#Setup random seed
np.random.seed(42)

# create the data
x = heart_disease.drop("target", axis=1)
y = heart_disease["target"]

# split into train and test sets
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)

# Instantite Random Forest Regressor and fit model
clf = RandomForestClassifier()
clf.fit(x_train,y_train)
```

```
cross_val_score(clf, x, y, cv=5)
```

```
In [26]: cross_val_score(clf, x, y, cv=5)

Out[26]: array([0.78688525, 0.90163934, 0.78688525, 0.81666667, 0.8
         ])
```



In cross validation, it test on whole dataset, in our case (cv=5), In first it make first 20% as test split, then it move forward to the end. So testing is been done on all dataset. This will give us the array of scores.

- It avoid getting lucky scores.
- We end up having a model trained on all of the data

Now taking average of these five scores [cv = 5 (It can be any number)]

```
np.random.seed(42)

# Single training and test split score
clf_single_score = clf.score(x_test,y_test)

# take mean of 5-fold cross validation score
clf_cross_val_score = np.mean(cross_val_score(clf, x, y, cv=5))

# compare the two
```

```
clf_single_score, clf_cross_val_score
```

```
In [27]: np.random.seed(42)

         # Single training and test split score
         clf_single_score = clf.score(x_test,y_test)

         # take mean of 5-fold cross validation score
         clf_cross_val_score = np.mean(cross_val_score(clf, x, y, cv=5))

         # compare the two
         clf_single_score, clf_cross_val_score

Out[27]: (0.8524590163934426, 0.8248087431693989)
```

4.2.1 Classification model evaluation metrics

1. Accuracy
2. Area under ROC curve
3. Confusion matrix
4. Classification report

1. Accuracy

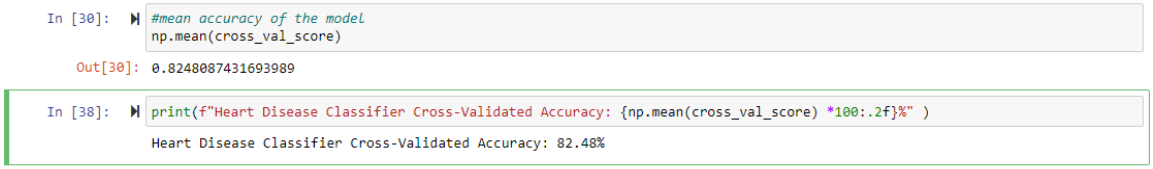
```
from sklearn.model_selection import cross_val_score
from sklearn.ensemble import RandomForestClassifier

#Setup random seed
np.random.seed(42)

# create the data
x = heart_disease.drop("target", axis=1)
y = heart_disease["target"]


# Instantite Random Forest Regressor
clf = RandomForestClassifier()
cross_val_score = cross_val_score(clf, x, y)
```

```
#mean accuracy of the model
```

```
np.mean(cross_val_score)
```

```
print(f"Heart Disease Classifier Cross-Validated Accuracy:
{np.mean(cross_val_score) *100:.2f}%" )
```

That mean 82.48%, are model will predict the right label so that of how you would present your models accuracy in print out.



that maean 82.48%, are model will pridict the right label so that of how you would present your models accuracy in print out

2. *Area under ROC curve*

Area under the receiver operating characteristic curve **(AUC/ROC)**.

- Area under curve (AUC)
- ROC curve

ROC curves are a comparison of a model's true positive rate (tpr) versus a model false positive rate (fpr).

- True positive = model predicts 1 when truth is 1
- False positive = model predicts 1 when truth is 0
- True negative = model predicts 0 when truth is 0
- False negative = model predicts 0 when truth is 1

```
from sklearn.metrics import roc_curve

# Make predictions with probabilities
y_probs = clf.predict_proba(x_test)

y_probs[:10]
```

```
In [44]: from sklearn.metrics import roc_curve

         # Make predictions with probabilities
         y_probs = clf.predict_proba(x_test)

         y_probs[:10]
```

```
Out[44]: array([[0.89, 0.11],
                [0.49, 0.51],
                [0.43, 0.57],
                [0.84, 0.16],
                [0.18, 0.82],
                [0.14, 0.86],
                [0.36, 0.64],
                [0.95, 0.05],
                [0.99, 0.01],
                [0.47, 0.53]])
```

ROC curves are a comparison of a model's **true positive rate (tpr)** versus a model **false positive rate (fpr)** So, we only want probabilities that the model has predicted for the positive class. And we wants Right values (index 1), so we use slicing

```
y_probs_positive = y_probs[:, 1]
y_probs_positive[:10]
```

```
# Calculating fpr, tpr and thresholds
fpr, tpr, thresholds = roc_curve(y_test,y_probs_positive)

# Check the false positive rate
fpr
```

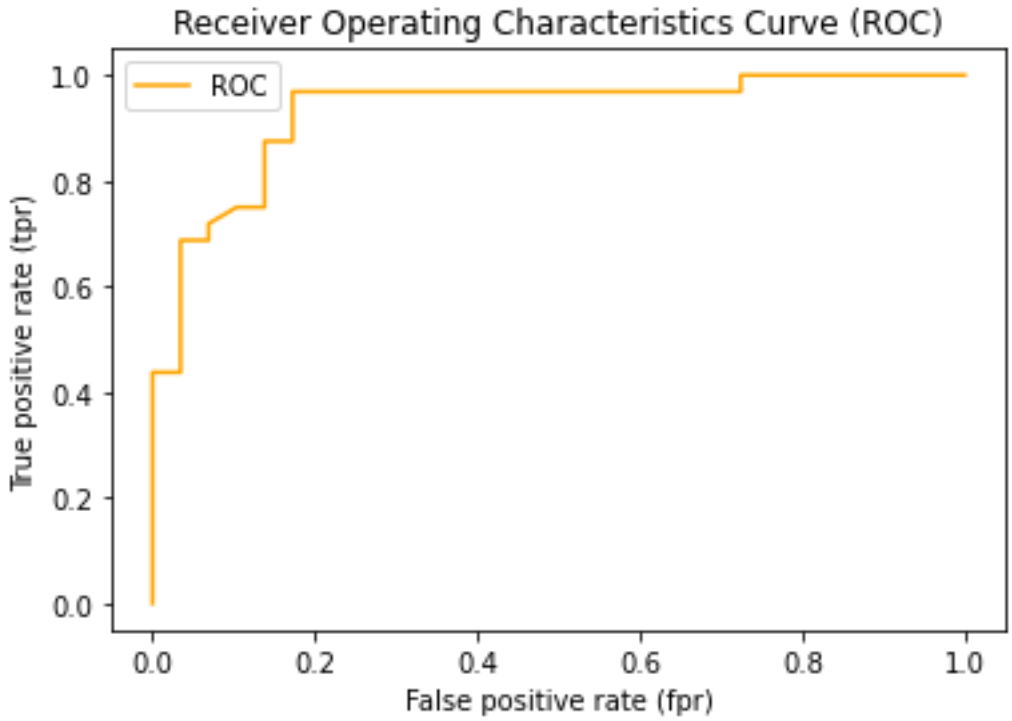
```
In [46]: y_probs_positive = y_probs[:, 1]
         y_probs_positive[:10]

Out[46]: array([0.11, 0.51, 0.57, 0.16, 0.82, 0.86, 0.64, 0.05, 0.01,
         0.53])
```

```
In [48]: # Calculating fpr, tpr and thresholds
         fpr, tpr, thresholds = roc_curve(y_test,y_probs_positive)

         # Check the false positive rate
         fpr

Out[48]: array([0.        , 0.        , 0.        , 0.        , 0.
         ,
                0.03448276, 0.03448276, 0.03448276, 0.03448276, 0.068
         96552,
                0.06896552, 0.10344828, 0.13793103, 0.13793103, 0.172
         41379,
                0.17241379, 0.27586207, 0.4137931 , 0.48275862, 0.551
         72414,
                0.65517241, 0.72413793, 0.72413793, 0.82758621, 1.
         ])
```

Looking at these on its own doesn't really make much sense, it's much easier to see it visually. Here the **ROC curve** comes into play.

```
# Create a function for plotting ROC curves
import matplotlib.pyplot as plt

def plot_roc_curve(fpr, tpr):
    """
    Plots a ROC curve givrn the false positive rate (fpr)
    and true positive rate (tpr) of a model
    """

    # Plot roc curve
    plt.plot(fpr, tpr, color = "orange", label="ROC")
    # Plot line with no predictive power (baseline)
    #plt.plot([0,1],[0,1], color='darkblue', linestyle="--
",label="Guessing")

    # customize the plot
    plt.xlabel("False positive rate (fpr)")
    plt.ylabel("True positive rate (tpr)")
    plt.title("Receiver Operating Characteristics Curve (ROC)")
    plt.legend()
    plt.show
```

```
plot_roc_curve(fpr, tpr)
```



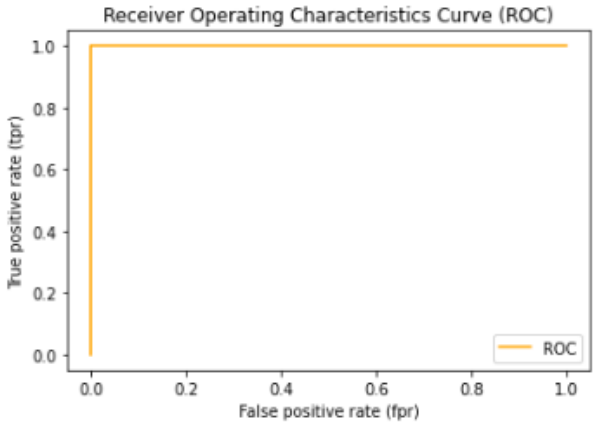

```
# auc = area under curve
from sklearn.metrics import roc_auc_score

roc_auc_score(y_test, y_probs_positive)
```

```
# Plot perface ROC curve and AUC score
fpr, tpr, thresholds = roc_curve(y_test,y_test)
# manually build
plot_roc_curve(fpr, tpr)
```

```
# perfect auc score
roc_auc_score(y_test, y_test)
```

```
In [17]:
# auc = area under curve
from sklearn.metrics import roc_auc_score

roc_auc_score(y_test, y_probs_positive)

Out[17]: 0.9304956896551724
```

```
In [19]:
# Plot perface ROC curve and AUC score
fpr, tpr, thresholds = roc_curve(y_test,y_test)
# manually build
plot_roc_curve(fpr, tpr)
```




```
In [20]:
# perfect auc score
roc_auc_score(y_test, y_test)

Out[20]: 1.0
```

3. *Confusion Matrix*

A `confusion` matrix is a quick way to compare the labels a model predicts and the actual labels it was supposed to predict.

In essence, giving you an idea of where the model is getting confused.

```
from sklearn.metrics import confusion_matrix

y_preds = clf.predict(x_test)

confusion_matrix(y_test, y_preds)
```

```
In [22]: from sklearn.metrics import confusion_matrix

         y_preds = clf.predict(x_test)

         confusion_matrix(y_test, y_preds)

Out[22]: array([[24,  5],
                [ 4, 28]], dtype=int64)
```

```
# Visualize confusion matrix with pd.crosstab()
pd.crosstab(y_test,
            y_preds,
            rownames=["Actual Labels"],
            colnames=["Predicted Labels"] )
```

```
In [23]: # Visualize confusion matrix with pd.crosstab()
         pd.crosstab(y_test,
                     y_preds,
                     rownames=["Actual Labels"],
                     colnames=["Predicted Labels"] )
```

Out[23]:

Predicted Labels	0	1
Actual Labels		
0	24	5
1	4	28

So in our case where the actual label is 0 and the predicted label is 0 we have 22 examples and then where the predicted label is 1 and the actual label is 1 we have 24 examples

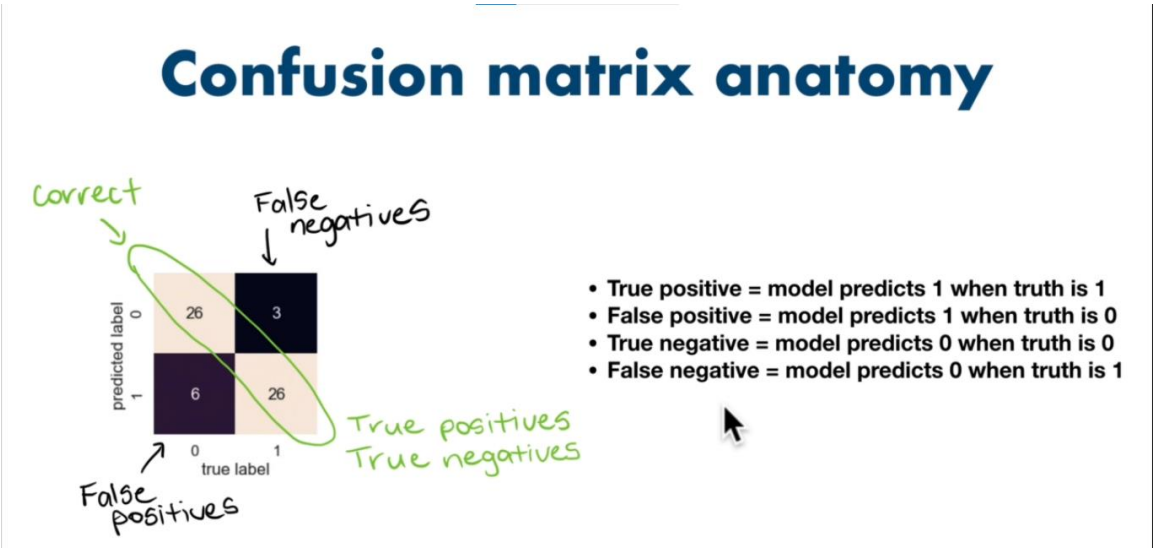
And now if we total all of these up **24 + 5 + 4 + 28 = 61** and our x_test / and their prediction is also **61**

In this case we have

- 4 False negative
- 5 False positive
- 24 True negative
- 28 true positive

```
In [28]: 24 + 5 + 4 + 28
Out[28]: 61
```

```
In [29]: len(y_preds) , len(x_test)
Out[29]: (61, 61)
```

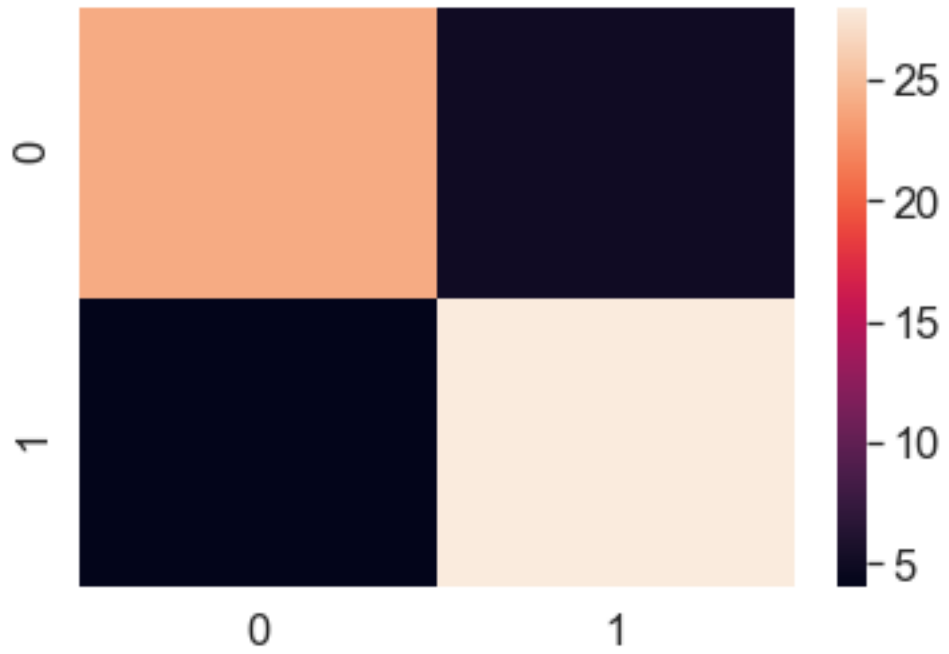


Make our confusion matrix more visual with Seaborn's heatmap() Seaborn heatmap plot rectangular data as a color-encoded matrix. Seabourn is a visualization library that is built on top of matplotlib and it's pretty relatively easy to use but we're going to mostly just take care of the heatmap function.

```
# installing libary/ package within jupyter notebook
# import sys
# !conda install --yes --prefix {sys.prefix} seaborn
```

```
# install seaborn module using anaconda command
# Make our confusion matrix more visual with Seaborn's heatmap()

import seaborn as sns

# Set the font scale
sns.set(font_scale = 1.5)

# Creat a confusion matrix
conf_mat = confusion_matrix(y_test, y_preds)
```

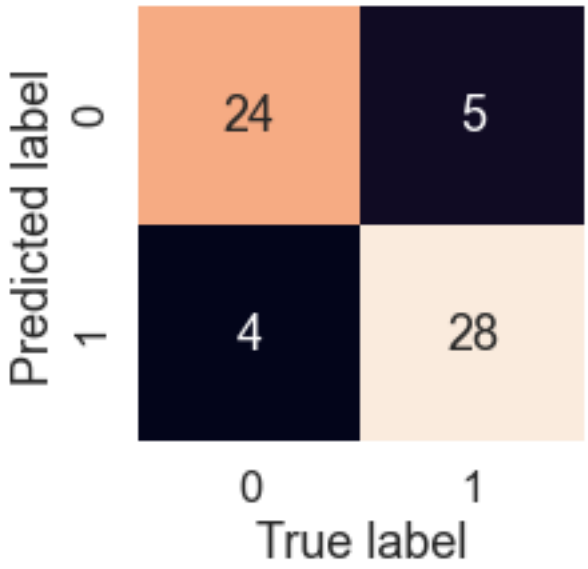
```
# plot it using seaborn
sns.heatmap(conf_mat)
```



Now fixing confusion matrix

Adding information to confusion mtrix

```
def plot_conf_mat(conf_mat):
    """
    Plot a confusion matrix using Seaborn's heatmap()
    """

    fig, ax = plt.subplots(figsize=(3,3))
    ax = sns.heatmap(conf_mat,
                     annot = True, #Annotate the boxes with conf_map info
                     cbar = False)

    plt.xlabel("True label")
    plt.ylabel("Predicted label")



plot_conf_mat(conf_mat)
```



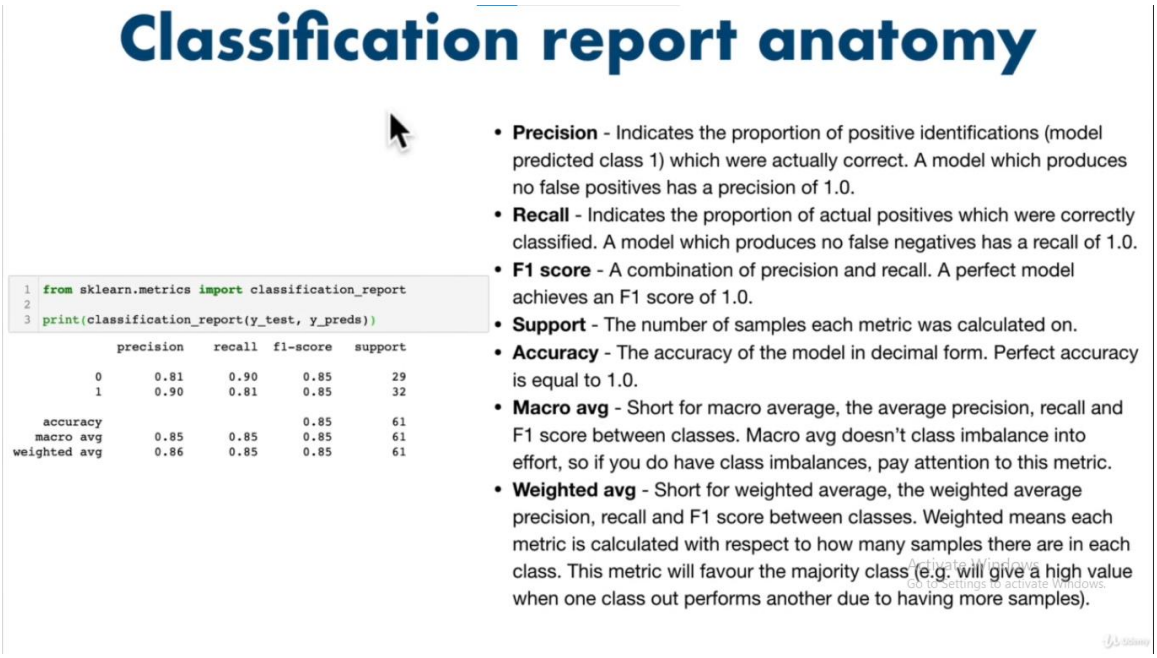
4. *Classification Report*

Classification report is also a collection of different evaluation metrics rather than a single one.

```
from sklearn.metrics import classification_report

print(classification_report(y_test, y_preds))
```

```
In [42]: from sklearn.metrics import classification_report

         print(classification_report(y_test, y_preds))
```

	precision	recall	f1-score	support
0	0.86	0.83	0.84	29
1	0.85	0.88	0.86	32
accuracy			0.85	61
macro avg	0.85	0.85	0.85	61
weighted avg	0.85	0.85	0.85	61



Lets see a scenario of **Classification Report**. So, for example, let's say there were 10000 people and one of them had a disease and you're asked to build a model to predict who has it.

So this is where precision and recall become valuable and in fact all the metrics in our classification report become valuable.

```
# where precision and recall become valuable
disease_true = np.zeros(10000)
disease_true[0] = 1 # only one positive value

disease_preds = np.zeros(10000) # model pridicts every case as 0

pd.DataFrame(classification_report(disease_true,
                                   disease_preds,
                                   output_dict=True))
```

Out[43]:

	0.0	1.0	accuracy	macro avg	weighted avg
precision	0.99990	0.0	0.9999	0.499950	0.99980
recall	1.00000	0.0	0.9999	0.500000	0.99990
f1-score	0.99995	0.0	0.9999	0.499975	0.99985
support	9999.00000	1.0	0.9999	10000.000000	10000.00000

To summarize classification metrics

- **Accuracy** is a good measure to start with if all classes are balanced (e.g. same amount of samples which are labelled with 0 or 1).
- **Precision** and **recall** become more important when classes are imbalanced
- If false positive predictions are worse then false negatives, aim for higher precision.
- If false negative predictions are worse then false positives, aim for higher recall
- **F1-score** is a combination of precision and recall

4.2.2. Regression model evaluation metrics

RandomForestRegressor

1. R^2 (pronounced r-squared) or coefficient of determination
2. Mean absolute error (MAE)
3. Mean Squared error (MSE)

Using boston dataset

```
# import Boston housing dataset
from sklearn.datasets import load_boston
boston = load_boston()
# So it imports as a dictionary we've got data as one of the keys.
Target is one of the keys. And then we have a feature names.
```

```
boston_df = pd.DataFrame(boston["data"], columns
=boston["feature_names"])
boston_df["target"] = pd.Series(boston["target"])
boston_df
```

```
from sklearn.ensemble import RandomForestRegressor

#Setup random seed
np.random.seed(42)

# create the data
x = boston_df.drop("target", axis=1)
y = boston_df["target"]

# split into train and test sets
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)

# Instantite Random Forest Regressor and fit model
model = RandomForestRegressor()
model.fit(x_train,y_train)
```

```
model.score(x_test, y_test)
```

1. *R^2 (pronounced r-squared) or coefficient of determination*

What R-squared does: Compares your model's predictions to the mean of the target. Values of R^2 can range from negative infinity(a very poor model) to 1 For example, if all your model does is predict the mean of the targets, it's a R^2 value would be 0. And if your model perfectly predicts a range of numbers it's R^2 value would be 1.

```
from sklearn.metrics import r2_score

# Fill an array with y_test mean
y_test_mean = np.full(len(y_test), y_test.mean())
```

```
r2_score(y_test, y_test_mean)
```

```
r2_score(y_test, y_test)
```

2. *. Mean absolute error (MAE)*

Mean Absolute Error (MAE) is the average of the absolute differences between predictions and actual values. So, it gives you an idea of how wrong your model predictions are.

```
# Mean absolute error (MAE)
from sklearn.metrics import mean_absolute_error

y_preds = model.predict(x_test)
mea = mean_absolute_error(y_test ,y_preds)
mea
```

In [7]:
```
# Mean absolute error (MAE)
from sklearn.metrics import mean_absolute_error

y_preds = model.predict(x_test)
mea = mean_absolute_error(y_test ,y_preds)
mea
```

Out[7]: 2.136382352941176

```
df = pd.DataFrame(data = {"actual values": y_test,
                          "predicted values": y_preds
})
df
```

In [9]:
```
df = pd.DataFrame(data = {"actual values": y_test,
                          "predicted values": y_preds
})
df
```

Out[9]:

	actual values	predicted values
173	23.6	23.081
274	32.4	30.574
491	13.6	16.759
72	22.8	23.460
452	16.1	16.893
...	...	...
412	17.9	13.159
436	9.6	12.476
411	17.2	13.612
86	22.5	20.205
75	21.4	23.832

102 rows × 2 columns

```
df["differences"] = df["predicted values"] - df["actual values"]
df
```

In [11]:
```
df["differences"] = df["predicted values"] - df["actual values"]
df
```

Out[11]:

	actual values	predicted values	differences
173	23.6	23.081	-0.519
274	32.4	30.574	-1.826
491	13.6	16.759	3.159
72	22.8	23.460	0.660
452	16.1	16.893	0.793
...	...	...	...
412	17.9	13.159	-4.741
436	9.6	12.476	2.876
411	17.2	13.612	-3.588
86	22.5	20.205	-2.295
75	21.4	23.832	2.432

102 rows × 3 columns

3. *Mean squared error*

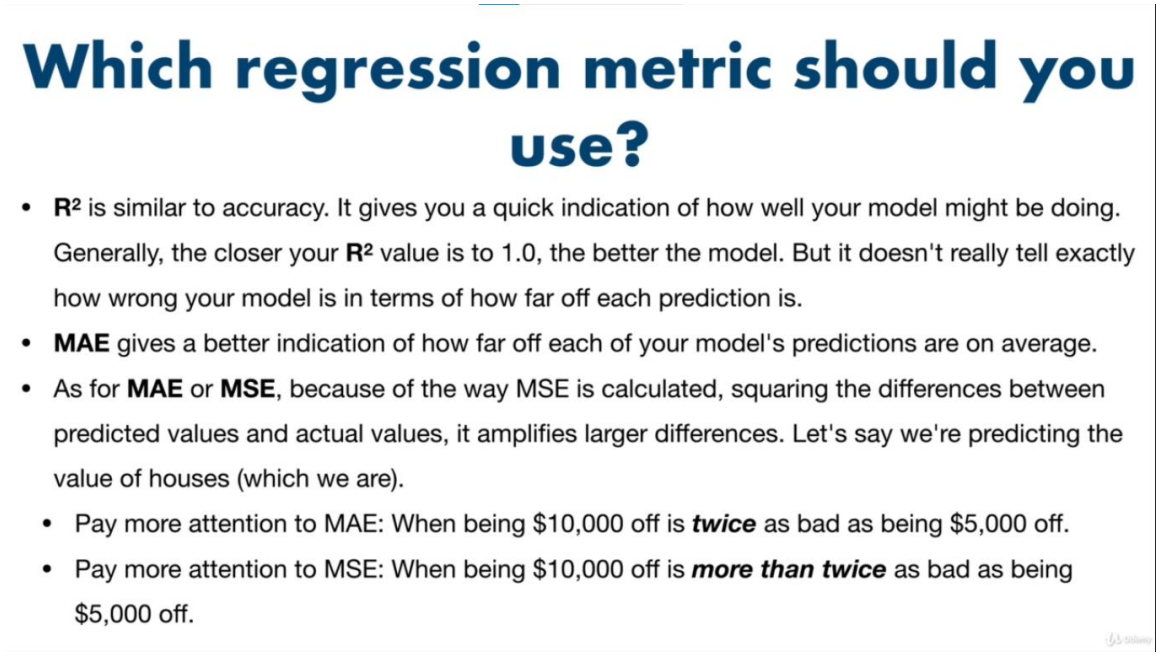
MSE will always be higher than mean absolute error because it squares the errors rather than only taking the absolute difference

```
# Mean squared error
from sklearn.metrics import mean_squared_error

y_preds = model.predict(x_test)
mse = mean_squared_error(y_test, y_preds)
mse
```

```
# Calculate MSE by hand (manually)
squared = np.square(df["differences"])
squared.mean()
```

```
In [12]:  # Mean squared error
          from sklearn.metrics import mean_squared_error

          y_preds = model.predict(x_test)
          mse = mean_squared_error(y_test, y_preds)
          mse

Out[12]:  9.867437068627442
```

```
In [15]:  # Calculate MSE by hand (manually)
          squared = np.square(df["differences"])
          squared.mean()

Out[15]:  9.867437068627439
```



Tidbit:

For regression models you want to **minimize mean**

squared error and **minimize mean absolute error** while **maximizing r squared** .

So does that make sense.

Minimize mean absolute error, minimize means squared error while maximizing R squared.

4.2.3 Finally using the scoring parameter

Classifier model

```
from sklearn.model_selection import cross_val_score
from sklearn.ensemble import RandomForestClassifier

#Setup random seed
np.random.seed(42)

# create the data
x = heart_disease.drop("target", axis=1)
y = heart_disease["target"]

# split into train and test sets
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)

# Instantite Random Forest Regressor and fit model
clf = RandomForestClassifier()
```

```
np.random.seed(42)
cv_acc = cross_val_score(clf, x, y, cv=5 )
cv_acc
```

```
In [20]: np.random.seed(42)
         cv_acc = cross_val_score(clf, x, y, cv=5 )
         cv_acc

Out[20]: array([0.81967213, 0.90163934, 0.83606557, 0.78333333, 0.78333
         333])
```

```
# Cross-validated accuracy
print(f'The cross-validated accuracy is: {np.mean(cv_acc)*100:.2f}%')
```

```
In [21]: # Cross-validated accuracy
         print(f'The cross-validated accuracy is: {np.mean(cv_acc)*100:.2f}%')

         The cross-validated accuracy is: 82.48%
```

```
np.random.seed(42)
cv_acc = cross_val_score(clf, x, y, cv=5, scoring="accuracy" )
print(f'The cross-validated accuracy is: {np.mean(cv_acc)*100:.2f}%')
```

```
In [22]: np.random.seed(42)
         cv_acc = cross_val_score(clf, x, y, cv=5, scoring="accuracy" )
         print(f'The cross-validated accuracy is: {np.mean(cv_acc)*100:.2f}%')

         The cross-validated accuracy is: 82.48%
```

```
# precision
cv_precision = cross_val_score(clf, x, y, cv=5, scoring="precision" )
cv_precision.mean()
```

```
In [26]: # precision
         cv_precision = cross_val_score(clf, x, y, cv=5, scoring="precision" )
         cv_precision.mean()

Out[26]: 0.8222673160173161
```

```
# recall
cv_recall = cross_val_score(clf, x, y, cv=5, scoring="recall" )
np.mean(cv_recall)
```

```
In [29]: # recall
         cv_recall = cross_val_score(clf, x, y, cv=5, scoring="recall" )
         np.mean(cv_recall)

Out[29]: 0.8606060606060606
```

```
cv_f1 = cross_val_score(clf, x, y, cv=5, scoring="f1" )
np.mean(cv_f1)
```

```
In [31]: cv_f1 = cross_val_score(clf, x, y, cv=5, scoring="f1" )
         np.mean(cv_f1)

Out[31]: 0.8252798417167047
```

How about regression model?

```
from sklearn.model_selection import cross_val_score
from sklearn.ensemble import RandomForestRegressor

#Setup random seed
np.random.seed(42)

# create the data
x = boston_df.drop("target", axis=1)
y = boston_df["target"]
```

```
model = RandomForestRegressor()
```

```
np.random.seed(42)
cv_r2 = cross_val_score(model, x, y, cv=5, scoring="r2")
np.mean(cv_r2)
```

```
# Mean absolute error
cv_mae = cross_val_score(model, x, y, cv=5,
scoring="neg_mean_absolute_error")
cv_mae
```

```
# Mean squared error
cv_mse = cross_val_score(model, x, y, cv=5,
scoring="neg_mean_squared_error")
cv_mse.mean()
```

```
In [40]: np.random.seed(42)
         cv_r2 = cross_val_score(model, x, y, cv=5, scoring="r2")
         np.mean(cv_r2)
Out[40]: 0.6243870737930857

In [43]: # Mean absolute error
         cv_mae = cross_val_score(model, x, y, cv=5, scoring="neg_mean_absolute_error")
         cv_mae
Out[43]: array([-2.13045098, -2.49771287, -3.45471287, -3.81509901, -3.11813861])

In [46]: # Mean squared error
         cv_mse = cross_val_score(model, x, y, cv=5, scoring="neg_mean_squared_error")
         cv_mse.mean()
Out[46]: -21.729149843894373
```

4.3. Using different evaluation matrics as Scikit-Learn functions

Classification evaluation functions

```
from sklearn.metrics import accuracy_score, precision_score,
recall_score, f1_score
from sklearn.ensemble import RandomForestClassifier
```

```
#Setup random seed
np.random.seed(42)

# create the data
x = heart_disease.drop("target", axis=1)
y = heart_disease["target"]

# # split into train and test sets
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)

# Instantite
clf = RandomForestClassifier()
clf.fit(x_train,y_train)

# Make some predictions
y_preds = clf.predict(x_test)

# Evaluate the classifier
print("Clssifier metrics on the test set")
print(f"Accuracy: {accuracy_score(y_test, y_preds)}")
print(f"Presision: {precision_score(y_test, y_preds)}")
print(f"Recall: {recall_score(y_test, y_preds)}")
print(f"F1: {f1_score(y_test, y_preds)}")
```

```
Clssifier metrics on the test set
Accuracy: 0.8524590163934426
Presision: 0.8484848484848485
Recall: 0.875
F1: 0.8615384615384615
```

Regression Evaluation Function

```
from sklearn.metrics import r2_score, mean_absolute_error,
mean_squared_error
from sklearn.ensemble import RandomForestRegressor

#Setup random seed
np.random.seed(42)

# create the data
x = boston_df.drop("target", axis=1)
y = boston_df["target"]

# split into train and test sets
```

```
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)

# Instantite Random Forest Regressor and fit model
model = RandomForestRegressor()
model.fit(x_train,y_train)

# Make predictions using our regression model
y_preds = model.predict(x_test)

# Evaluating the regression model
print("Regression model metrics on the test set")
print(f"R^2: {r2_score(y_test, y_preds)}")
print(f"MAE: {mean_absolute_error(y_test, y_preds)}")
print(f"MSE: {mean_squared_error(y_test, y_preds)}")
```

```
Regression model metrics on the test set
R^2: 0.8654448653350507
MAE: 2.136382352941176
MSE: 9.867437068627442
```

5. Improving a model

- First predictions = baseline predictions
- First model = baseline model

There's two main ways to improve the model

1. From a data perspective.

- **Could we collect more data? (generally the more data, the better)**

If there's 10000 examples rather than 1000 example of something chances are if there's patterns in that data the machine learning model will pick them up.

- **Improve our data**

For example, an hour car sales problem where we're using the make the color the odometer and the number of doors to try and predict the sale price of a car. So, what you would search for here is maybe more features about each car so you would have more information about each sample.

2. From a model perspective

- Is there a better model we could use?
- Could we improve the current model?

Parameters vs. Hyperparameters

Parameters = model finds these patterns in data

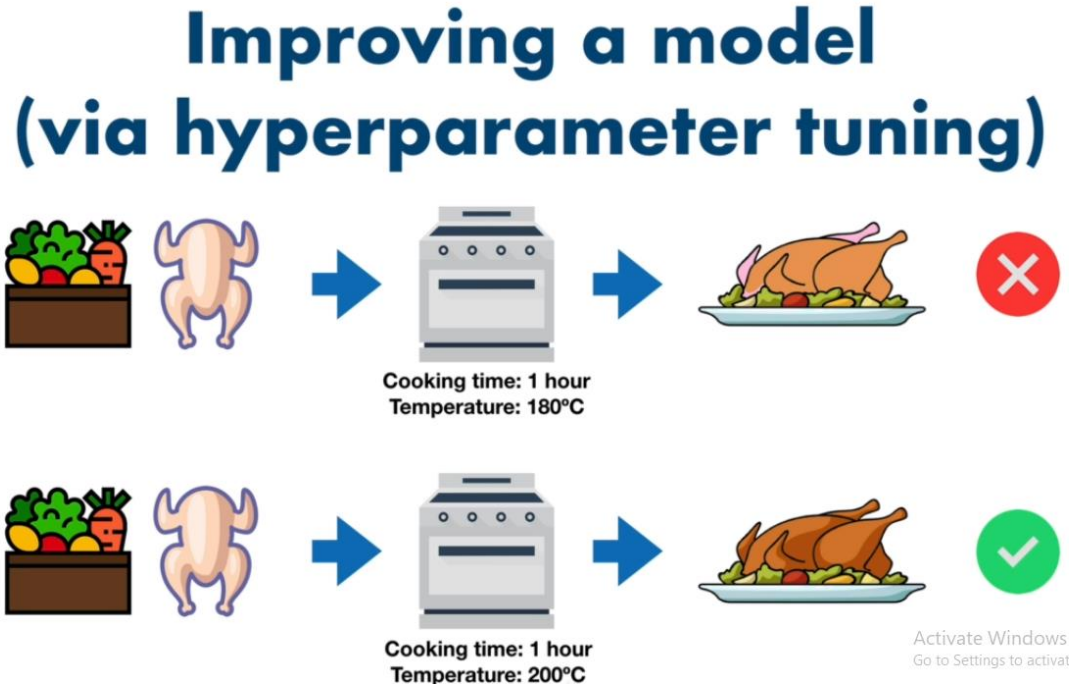
Hyperparameters = settings on a model you can adjust to (potentially) improve its ability to find patterns.

Three ways to adjust hyperparameters

1. By hand
2. Randomly with RandomSearchCV
3. Exhaustively with GridSearchCV

```
# How to find models hyperparameters
from sklearn.ensemble import RandomForestClassifier

clf = RandomForestClassifier()
#Once the model is Instantited, we can find hyperparameters by calling
a function

clf.get_params()

# sklearn calls hyperparameters as parameters
# Every models has it's own parameters / hyperparameters
```

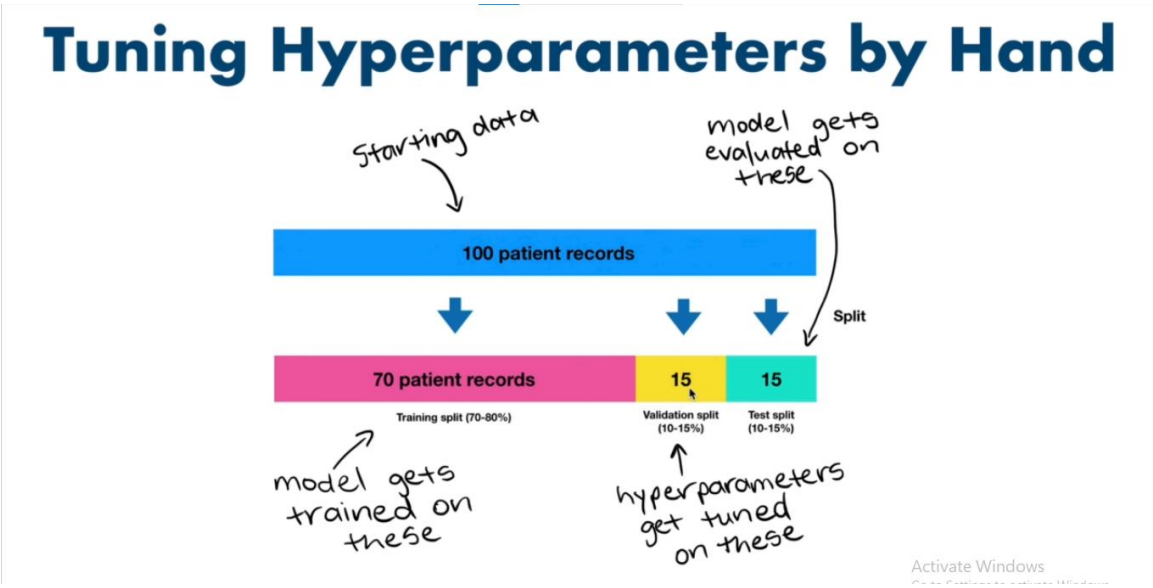
```
Out[53]: {'bootstrap': True,
          'ccp_alpha': 0.0,
          'class_weight': None,
          'criterion': 'gini',
          'max_depth': None,
          'max_features': 'auto',
          'max_leaf_nodes': None,
          'max_samples': None,
          'min_impurity_decrease': 0.0,
          'min_impurity_split': None,
          'min_samples_leaf': 1,
          'min_samples_split': 2,
          'min_weight_fraction_leaf': 0.0,
          'n_estimators': 100,
          'n_jobs': None,
          'oob_score': False,
          'random_state': None,
          'verbose': 0,
          'warm_start': False}
```

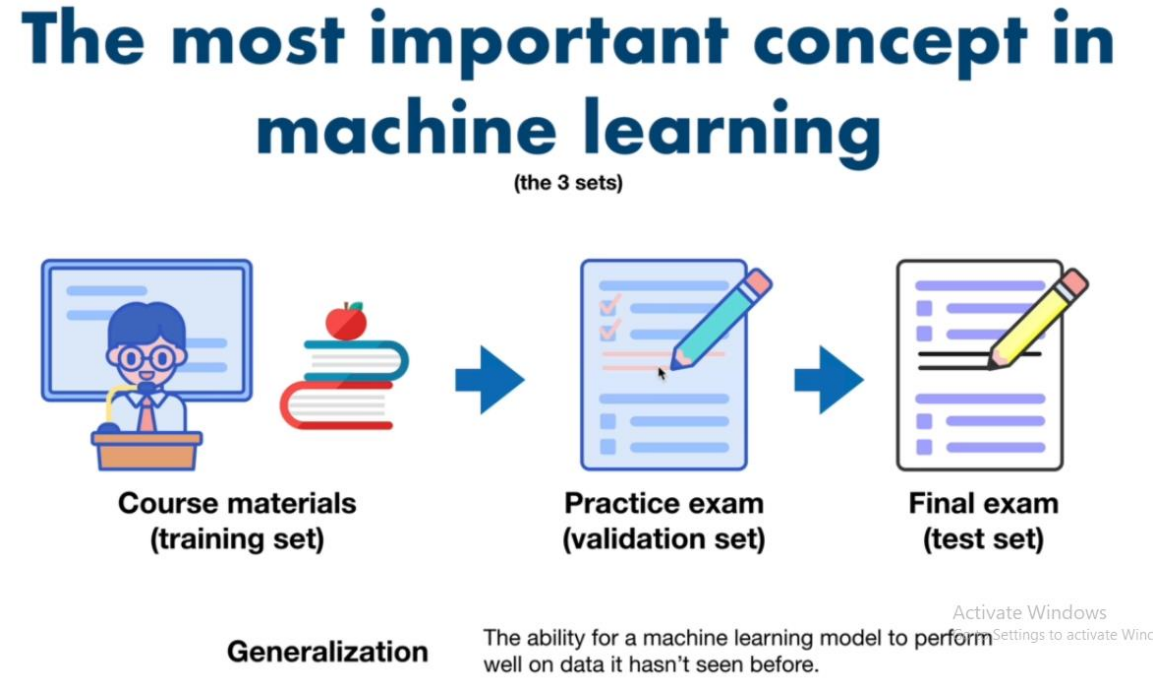


5.1 Tuning Hyperparameters by hand

So far we've talked about dealing with training and test data sets a model gets trained on the training set, it finds patterns and then it gets evaluated on the test set. So, it uses those patterns but hyper parameter tuning introduces a third set called as a **validation set.**

Let's make 3 sets training, validation and test





Parameters / hyperparameter which we can adjust

```
In [54]: clf.get_params()

Out[54]: {'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': None,
          'oob_score': False,
          'random_state': None,
          'verbose': 0,
          'warm_start': False}
```

We're going to try and adjust

- `max_depth`
- `max_features`
- `min_samples_leaf`
- `min_samples_split`
- `n_estimators`

Evaluation function for our classification problem

```
from sklearn.metrics import accuracy_score, precision_score,
recall_score, f1_score
```

```
def evaluate_preds(y_true, y_preds):
    """
    performs evaluation comparison on y_true labels vs. y_pred labels.
    on a classification models
    """

    accuracy = accuracy(y_true, y_preds)
```

```
    precision = precision_score(y_true, y_preds)
    recall = recall_score(y_true, y_preds)
    f1 = f1_score(y_true, y_preds)

    metric_dict = {
        "accuracy": round(accuracy,2),
        "precision": round(precision,2),
        "recall": round(recall,2),
        "f1": round(f1,2)
    }

    print(f"Acc:{accuracy * 100:.2f}%")
    print(f"precision:{precision * 100:.2f}")
    print(f"recall:{recall * 100:.2f}")
    print(f"f1:{f1 * 100:.2f}")

    return metric_dict
```

```
from sklearn.ensemble import RandomForestClassifier

#Setup random seed
np.random.seed(42)

#Shuffle the data
heart_disease_shuffled = heart_disease.sample(frac=1)


# create the data
x = heart_disease_shuffled.drop("target", axis=1)
y = heart_disease_shuffled["target"]

# split into train, validation and test sets
# We have to do it manually
train_split = round(0.7 * len(heart_disease_shuffled)) # 70% of data
valid_split = round(train_split + 0.15 * len(heart_disease_shuffled)) #
15% of data

X_train, y_train = x[:train_split], y[:train_split]

X_valid, y_valid = x[train_split:valid_split],
y[train_split:valid_split]

X_test, y_test = x[valid_split:], y[valid_split:]


# len(X_train), len(X_valid), len(X_test) # Checking

clf = RandomForestClassifier()
```

```
clf.fit(X_train, y_train)

# Make baseline predictions
y_preds = clf.predict(X_valid)
# We predict on the validation data because we want to tune our model
on the validation split.

# Evaluate the classifier on validation set
# evaluate_preds manually crated function
baseline_metrics = evaluate_preds(y_valid, y_preds)
baseline_metrics
```

```
Acc:82.22%
precision:0.81
recall:0.88
f1:0.85

Out[23]: {'accuracy': 0.82, 'precision': 0.81, 'recall': 0.88, 'f1': 0.85}
```

Adjusting hyperparameters by hand

```
np.random.seed(42)

# Create a second classifier with different hyperparameters
clf_2 = RandomForestClassifier(n_estimators=100)
clf_2.fit(X_train, y_train)
#diffrent model same data

# Make predictions with diffrent hyperparameters
y_preds_2 = clf_2.predict(X_valid)


# Evalute the 2nd classifier
clf_2_metrices = evaluate_preds(y_valid, y_preds_2)
```

In [28]:

```
np.random.seed(42)

# Create a second classifier with different hyperparameters
clf_2 = RandomForestClassifier(n_estimators=100)
clf_2.fit(X_train, y_train)
#diffrent model same data

# Make predictions with diffrent hyperparameters
y_preds_2 = clf_2.predict(X_valid)


# Evalute the 2nd classifier
clf_2_metrices = evaluate_preds(y_valid, y_preds_2)
```

```
Acc:82.22%
precision:0.81
recall:0.88
f1:0.85
```

```
clf_3 = RandomForestClassifier(n_estimators=100, max_depth=10)
clf_3.fit(X_train, y_train)
#diffrent model same data

# Make predictions with diffrent hyperparameters
y_preds_3 = clf_3.predict(X_valid)


# Evalute the 3nd classifier
clf_3_metrices = evaluate_preds(y_valid, y_preds_3)
```

In [30]:

```
clf_3 = RandomForestClassifier(n_estimators=100, max_depth=10)
clf_3.fit(X_train, y_train)
#diffrent model same data

# Make predictions with diffrent hyperparameters
y_preds_3 = clf_3.predict(X_valid)


# Evalute the 2nd classifier
clf_2_metrices = evaluate_preds(y_valid, y_preds_3)
```

```
Acc:80.00%
precision:0.81
recall:0.84
f1:0.82
```

5.2 Hyperparameter tuning with RandomSearchCV (RandomizedSearchCV)

```
from sklearn.model_selection import RandomizedSearchCV

grid = {
    "n_estimators":[10,100,200,1000,1200],
    "max_depth":[None,5, 10, 20, 30],
    "max_features":["auto","sqrt"],
    "min_samples_split":[2,4,6],
    "min_samples_leaf":[1, 2, 4]

}

np.random.seed(42)
x = heart_disease_shuffled.drop("target", axis=1)
y = heart_disease_shuffled["target"]

# split into train and test sets
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)

# Instantite Random Forest Classifier
clf = RandomForestClassifier(n_jobs = 1)


# Setup RandomSearchCV
rs_clf = RandomizedSearchCV(estimator = clf,
                        param_distributions = grid,
                        n_iter=10, # number of models to try
                        cv = 5,
                        verbose = 2)

# fit the RandomSearchCV version of clf

rs_clf.fit(x_train, y_train)
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits
[CV] END max_depth=None, max_features=sqrt, min_samples_leaf=4, min_s
amples_split=6, n_estimators=100; total time=   0.4s
[CV] END max_depth=None, max_features=sqrt, min_samples_leaf=4, min_s
amples_split=6, n_estimators=100; total time=   0.5s
[CV] END max_depth=None, max_features=sqrt, min_samples_leaf=4, min_s
amples_split=6, n_estimators=100; total time=   0.4s
[CV] END max_depth=None, max_features=sqrt, min_samples_leaf=4, min_s
amples_split=6, n_estimators=100; total time=   0.4s
[CV] END max_depth=None, max_features=sqrt, min_samples_leaf=4, min_s
amples_split=6, n_estimators=100; total time=   0.4s
[CV] END max_depth=30, max_features=sqrt, min_samples_leaf=2, min_sam
ples_split=6, n_estimators=200; total time=   0.9s
[CV] END max_depth=30, max_features=sqrt, min_samples_leaf=2, min_sam
ples_split=6, n_estimators=200; total time=   0.9s
[CV] END max_depth=30, max_features=sqrt, min_samples_leaf=2, min_sam
ples_split=6, n_estimators=200; total time=   1.0s
[CV] END max_depth=30, max_features=sqrt, min_samples_leaf=2, min_sam
ples_split=6, n_estimators=200; total time=   0.9s
[CV] END max_depth=30, max_features=sqrt, min_samples_leaf=2, min_sam
```

```
# Which combinations of these give the best result
rs_clf.best_params_
```

```
# Making predictions with the best hyperparameters
rs_y_preds = rs_clf.predict(x_test)

# Evaluate the predictions
rs_metrics = evaluate_preds(y_test, rs_y_preds)
```

In [41]:
```
# Which combinations of these give the best result
rs_clf.best_params_
```

Out[41]:
```
{'n_estimators': 200,
 'min_samples_split': 6,
 'min_samples_leaf': 1,
 'max_features': 'auto',
 'max_depth': 10}
```

In [44]:
```
# Making predictions with the best hyperparameters
rs_y_preds = rs_clf.predict(x_test)

# Evaluate the predictions
rs_metrics = evaluate_preds(y_test, rs_y_preds)
```

```
Acc:81.97%
precision:0.76
recall:0.89
f1:0.82
```

5.3 Hyperparameter tuning with GridSearchCV

Key difference here between randomize search and grid search CV is that randomize search CV has a parameter called n_iter.which we can set to limit the number of models to try. So, in our case we used 10. GridSearchCV will go through every single combination that is available here.

We less the parameter, to compute less, if we compute more parameters it uses more system resources

```
grid_2 = { 'n_estimators': [100, 200, 500],
           'max_depth': [None],
           'max_features': ['auto', 'sqrt'],
           'min_samples_split': [6],
           'min_samples_leaf': [1, 2]}
```

```
from sklearn.model_selection import GridSearchCV, train_test_split

np.random.seed(42)

x = heart_disease_shuffled.drop("target", axis=1)
y = heart_disease_shuffled["target"]

# split into train and test sets
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)

# Instantite Random Forest Classifier
clf = RandomForestClassifier(n_jobs = 1)

# Setup GridSearchCV
gs_clf = GridSearchCV(estimator = clf,
                      param_grid = grid_2,
                      cv = 5,
                      verbose = 2)

# fit the GridSearchCV version of clf

gs_clf.fit(x_train, y_train)
print("Run")
```

```
[CV] END max_depth=None, max_features=sqrt, min_samples_leaf=1, min_samp
les_split=6, n_estimators=500; total time=   2.1s
[CV] END max_depth=None, max_features=sqrt, min_samples_leaf=2, min_samp
les_split=6, n_estimators=200; total time=   0.8s
[CV] END max_depth=None, max_features=sqrt, min_samples_leaf=2, min_samp
les_split=6, n_estimators=200; total time=   0.8s
[CV] END max_depth=None, max_features=sqrt, min_samples_leaf=2, min_samp
les_split=6, n_estimators=200; total time=   0.8s
[CV] END max_depth=None, max_features=sqrt, min_samples_leaf=2, min_samp
les_split=6, n_estimators=200; total time=   0.8s
[CV] END max_depth=None, max_features=sqrt, min_samples_leaf=2, min_samp
les_split=6, n_estimators=200; total time=   0.9s
[CV] END max_depth=None, max_features=sqrt, min_samples_leaf=2, min_samp
les_split=6, n_estimators=500; total time=   2.3s
[CV] END max_depth=None, max_features=sqrt, min_samples_leaf=2, min_samp
les_split=6, n_estimators=500; total time=   2.1s
[CV] END max_depth=None, max_features=sqrt, min_samples_leaf=2, min_samp
les_split=6, n_estimators=500; total time=   2.1s
[CV] END max_depth=None, max_features=sqrt, min_samples_leaf=2, min_samp
les_split=6, n_estimators=500; total time=   2.1s
[CV] END max_depth=None, max_features=sqrt, min_samples_leaf=2, min_samp
les_split=6, n_estimators=500; total time=   2.1s
Run
```

```
gs_clf.best_params_
```

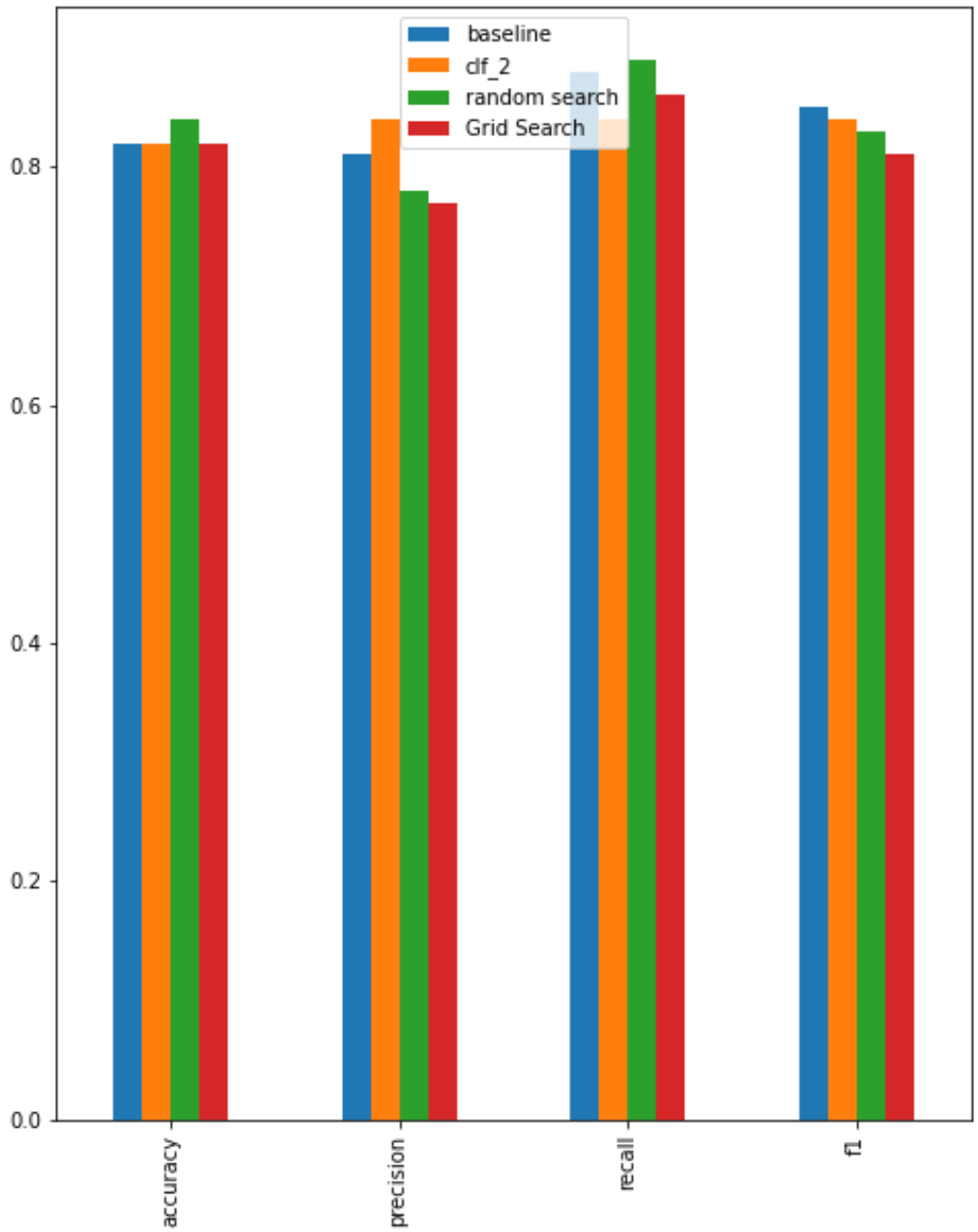
```
gs_y_preds = gs_clf.predict(x_test)

# evaluating the prsdictions
gs_metrics = evaluate_preds(y_test, gs_y_preds)
```

```
In [18]: gs_clf.best_params_

Out[18]: {'max_depth': None,
          'max_features': 'auto',
          'min_samples_leaf': 2,
          'min_samples_split': 6,
          'n_estimators': 200}
```

```
In [20]: gs_y_preds = gs_clf.predict(x_test)

         # evaluating the prsdictions
         gs_metrics = evaluate_preds(y_test, gs_y_preds)

         Acc:81.97%
         precision:0.77
         recall:0.86
         f1:0.81
```

Let's compare our different models metrics

```
compare_metrics = pd.DataFrame({
    "baseline": baseline_metrics,
    "clf_2":clf_2_metrices,
    "random search": rs_metrics,
    "Grid Search":gs_metrics
})

compare_metrics.plot.bar(figsize=(8,10))
```



Tip

Correlation analysis.

Well correlation analysis simply means which attributes have correlations.

So, let's say one column is correlated to another column.

Let's say we're trying to sell our home and there's two columns one column is the size of the land that the house is on and the other column is the size of the House and the floor space.

Now let's say that when we're analyzing our data we notice that pretty much all houses that have a large land size also have a large floor space size and they're just correlated the prices go up the same every time the land increases and every time the floor space increases in this case these attributes have high correlation with each other.

In this case we can actually remove this from our analysis or from building our model because it might not affect our model.

This gets to our next point or **forward/ backwards attribute selection.**

Well we can try training our model using different techniques.

Backward attributes selection essentially says train the model on all the attributes and then slowly to start taking away attributes or columns to train your model. It does that affect your model, does it improve the model

Forward attribute selection is the opposite. Start with just one column when you train the model and keep adding one attribute at a time until you get the accuracy to plateau. That is if you keep increasing columns and let's say after the fiftieth column all the other attributes say you added just don't improve the model. Well then maybe we might not need it.

This idea of correlation analysis. The forward /backward attribute selection are all ways for us to test our model reduce our data if we want to and play with our model instead of just assuming if we include everything, everything will make the model better. That's often not usually the case.

6. Saving and loading Trained machine learning models

Two ways to save and load machine learning models.

1. With Python's `pickle` module.
2. with the `joblib` module.

6.1 pickle module

```
import pickle

# Save an extisting model to file
pickle.dump(gs_clf, open("gs_random_forest_model_1.pk1","wb"))
```

```
# Load a saved model
loaded_pickle_model =
pickle.load(open("gs_random_forest_model_1.pk1","rb"))
```

```
# Make some predictions
pickle_y_Preds = loaded_pickle_model.predict(x_test)
evaluate_preds(y_test, pickle_y_Preds)
```

pickle module

```
In [42]: import pickle

         # Save an extisting model to file
         pickle.dump(gs_clf, open("gs_random_forest_model_1.pk1","wb"))
```

```
In [43]: # Load a saved model
         loaded_pickle_model = pickle.load(open("gs_random_forest_model_1.pk1","rb"))
```

```
In [44]: # Make some predictions
         pickle_y_Preds = loaded_pickle_model.predict(x_test)
         evaluate_preds(y_test, pickle_y_Preds)

         Acc:81.97%
         precision:0.77
         recall:0.86
         f1:0.81

Out[44]: {'accuracy': 0.82, 'precision': 0.77, 'recall': 0.86, 'f1': 0.81}
```

6.2 joblib module.

```
from joblib import dump, load

# Save model to file
dump(gs_clf, filename="gs_random_forest_model_2.joblib")
```

```
# Import a saved joblib model
loaded_joblib_model = load(filename="gs_random_forest_model_2.joblib")
```

```
# Make and evaluate joblib model
joblib_y_preds = loaded_joblib_model.predict(x_test)
evaluate_preds(y_test, joblib_y_preds)
```

joblib module.

```
In [45]: from joblib import dump, load

         # Save model to file
         dump(gs_clf, filename="gs_random_forest_model_2.joblib")

Out[45]: ['gs_random_forest_model_2.joblib']

In [46]: # Import a saved joblib model
         loaded_joblib_model = load(filename="gs_random_forest_model_2.joblib")

In [48]: # Make and evaluate joblib model
         joblib_y_preds = loaded_joblib_model.predict(x_test)
         evaluate_preds(y_test, joblib_y_preds)

         Acc:81.97%
         precision:0.77
         recall:0.86
         f1:0.81

Out[48]: {'accuracy': 0.82, 'precision': 0.77, 'recall': 0.86, 'f1': 0.81}
```

7. Putting it all together

Steps we want to do (all in one)

- Fill missing data
- Convert data to numbers
- Build a model on the data

```
# Getting data ready
import pandas as pd
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import OneHotEncoder

# Modelling
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import train_test_split, GridSearchCV

# Setup random seed
import numpy as np
np.random.seed(42)
```

```
# Import data and drop rows with missing labels
data = pd.read_csv("car-sales-extended-missing-data.csv")
data.dropna(subset = ["Price"], inplace = True)

# Define different features and transformer pipeline
categorical_features = ["Make", "Colour"]
categorical_transformer = Pipeline(steps=[
    ("imputer",SimpleImputer(strategy="constant",
fill_value="missing")),
    ("onehot", OneHotEncoder(handle_unknown="ignore"))
])


door_features = ["Doors"]
door_transformer = Pipeline(steps=[
    ("imputer",SimpleImputer(strategy="constant", fill_value=4))

])

numaric_feature = ["Odometer (KM)"]
numaric_transformer = Pipeline(steps=[
    ("imputer",SimpleImputer(strategy="mean"))
])


# Setup preprocessing steps fill missing values, then convert to
numbers
preprocessor = ColumnTransformer(
transformers=[
      ("cat",categorical_transformer, categorical_features),
      ("door",door_transformer, door_features ),
      ("num",numaric_transformer, numaric_feature)
])


# Creating a preprocessing and modelling pipeline
model = Pipeline(steps=[("preprocessor",preprocessor),
                        ("model",RandomForestRegressor())])

# Split data
X = data.drop("Price", axis=1)
y = data["Price"]

# split into train and test sets
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)

# Fit and score the model
```

```
model.fit(X_train, y_train)
model.score(X_test, y_test)
```

Output : 0.22188417408787875

It's also possible to use `GridSearchCV` or `RandomizedSearchCV` with our `Pipeline`

```
# Use GridSearchCV with our regression Pipeline
from sklearn.model_selection import GridSearchCV

pipe_grid = {
    "preprocessor__num__imputer__strategy": ["mean", "median"],
    "model__n_estimators": [100, 1000],
    "model__max_depth":[None, 5],
    "model__max_features":["auto"],
    "model__min_samples_split":[2, 4]

}

gs_model = GridSearchCV(model, pipe_grid, cv=5, verbose=2)
gs_model.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 16 candidates, totalling 80 fits
[CV] END model__max_depth=None, model__max_features=auto, model__min_
samples_split=2, model__n_estimators=100, preprocessor__num__imputer_
_strategy=mean; total time=   0.7s
[CV] END model__max_depth=None, model__max_features=auto, model__min_
samples_split=2, model__n_estimators=100, preprocessor__num__imputer_
_strategy=mean; total time=   0.7s
[CV] END model__max_depth=None, model__max_features=auto, model__min_
samples_split=2, model__n_estimators=100, preprocessor__num__imputer_
_strategy=mean; total time=   0.7s
[CV] END model__max_depth=None, model__max_features=auto, model__min_
samples_split=2, model__n_estimators=100, preprocessor__num__imputer_
_strategy=mean; total time=   0.7s
[CV] END model__max_depth=None, model__max_features=auto, model__min_
samples_split=2, model__n_estimators=100, preprocessor__num__imputer_
_strategy=mean; total time=   0.7s
[CV] END model__max_depth=None, model__max_features=auto, model__min_
samples_split=2, model__n_estimators=100, preprocessor__num__imputer_
_strategy=median; total time=   0.7s
[CV] END model__max_depth=None, model__max_features=auto, model__min_
```

```
gs_model.score(X_test, y_test)
```

Output : 0.3339554263158365