Scikit-learn_Template

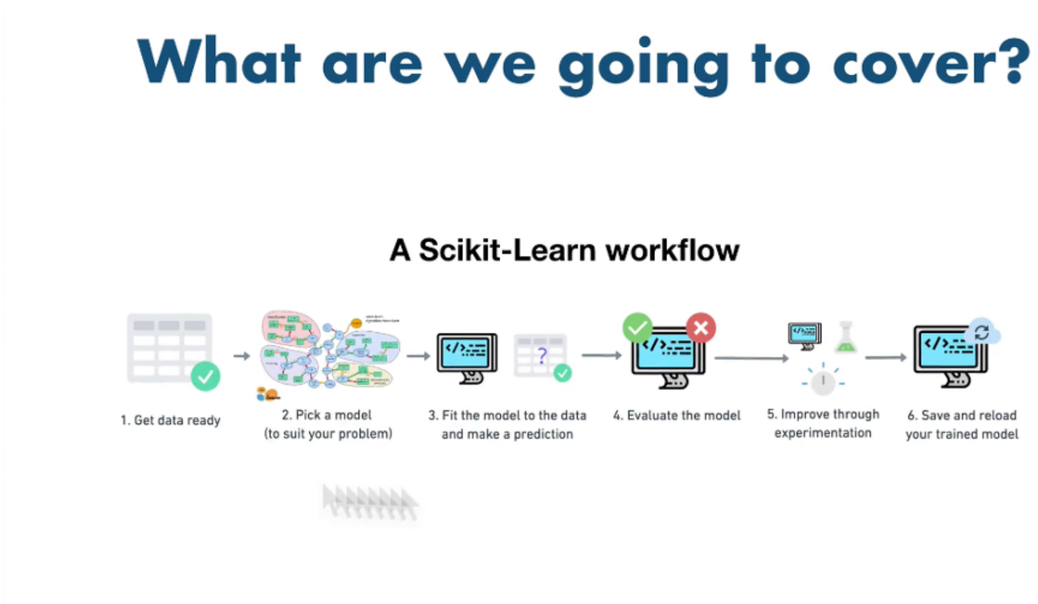
September 19, 2020

1 Scikit-learn_Template

2 Step 0: Standard Library Import

[1]:
```
from IPython.display import Image
Image(filename="SKlearning.png")
```

[1]:



[2]:
```
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
%matplotlib inline
```

3 Step 1: Get the Data Ready

``More data doesn't mean it's good. We only want useful data.'' Clean -> Transform ->Reduce

Three things to do:

(1) Split the data into feature and labels (usually `X' and `Y'), train and test sets;

(2) Filling (also called imputing) or disregarding missing value

(3) Converting non-numerial values to numerical values, aka feature coding

[3]:
```python
# Classification data
heart_disease = pd.read_csv("../skl/heart-disease.csv")
heart_disease.head()
```

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

   ca  thal  target
0   0     1       1
1   0     2       1
2   0     2       1
3   0     2       1
4   0     2       1
```

[4]:
```python
## Create X (features matrix) and Y the labels
x =heart_disease.drop("target", axis=1) #remove the target column, axis=1 means␣
↪column axis, not row axis=0
y =heart_disease["target"]
y.head()
```

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

[5]:
```python
## IMPORTANT: Split the data x into random training data and test data, split␣
↪the data y into training data and test data;
#80% use for training, 20% for testing; don't use all data for training
from sklearn.model_selection import train_test_split

#return 4 different values
x_train,x_test, y_train, y_test = train_test_split(x,y,test_size=0.2) #20% data␣
↪used for testing
```

```
x_train
```

[5]:

```
     age  sex  cp  trestbps  chol  fbs  restecg  thalach  exang  oldpeak  \
141   43    1   0       115   303    0        1      181      0      1.2
100   42    1   3       148   244    0        0      178      0      0.8
138   57    1   0       110   201    0        1      126      1      1.5
76    51    1   2       125   245    1        0      166      0      2.4
272   67    1   0       120   237    0        1       71      0      1.0
..   …  …  ..      …   …  …      …      …    …      …
296   63    0   0       124   197    0        1      136      1      0.0
95    53    1   0       142   226    0        0      111      1      0.0
237   60    1   0       140   293    0        0      170      0      1.2
242   64    1   0       145   212    0        0      132      0      2.0
21    44    1   2       130   233    0        1      179      1      0.4

     slope  ca  thal
141      1   0     2
100      2   2     2
138      1   0     1
76       1   0     2
272      1   0     2
..     …  ..   …
296      1   0     2
95       2   0     3
237      1   2     3
242      1   2     1
21       2   0     2

[242 rows x 13 columns]
```

[6]:

```
# can verify the 80% and 20% with below
heart_disease.shape,x_train.shape,x_test.shape,y_train.shape,y_test.shape
```

[6]: ((303, 14), (242, 13), (61, 13), (242,), (61,))

4 1.1 Make sure it's all numerical - encoder string features to vectors

[7]:

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

[7]:

	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
```

[8]:
```
len(car_sales)
```

[8]:
```
1000
```

[9]:
```
car_sales.dtypes
```

[9]:
```
Make              object
Colour            object
Odometer (KM)      int64
Doors              int64
Price              int64
dtype: object
```

4.0.1 Sk learn cannot deal with strings!!!

[9]:
```
#Only give the make, color, Odometer, doors, can the model predict the price of␣
↪$XXX?
##Step 1: Split X Y into 80% 20%
x =car_sales.drop("Price",axis=1)
y= car_sales["Price"]
x_train, x_test, y_train, y_test = train_test_split(x,y,test_size=0.2)

# step2:Choose the right model and hyperparameters
from sklearn.ensemble import RandomForestRegressor  # Classification ML model␣
↪is RandomForestClassifier
model=RandomForestRegressor() #n-estimator

# Step 3: Find the patterns in the traning data
model.fit(x_train,y_train)
model.score(x_test,y_test)
## sk learn cannot deal with strings!!!
```

```
      ␣
↪---------------------------------------------------------------------------

       ValueError                                Traceback (most recent call␣
↪last)

       <ipython-input-9-01282806cb62> in <module>
        10
        11 # Step 3: Find the patterns in the traning data
   ---> 12 model.fit(x_train,y_train)
        13 model.score(x_test,y_test)
        14 ## sk learn cannot deal with strings!!!
```

```
~/Desktop/sample_project/skl/lib/python3.8/site-packages/sklearn/
↪ensemble/_forest.py in fit(self, X, y, sample_weight)
    301                 "sparse multilabel-indicator for y is not supported."
    302             )
--> 303         X, y = self._validate_data(X, y, multi_output=True,
    304                                    accept_sparse="csc", dtype=DTYPE)
    305         if sample_weight is not None:


~/Desktop/sample_project/skl/lib/python3.8/site-packages/sklearn/base.py␣
↪in _validate_data(self, X, y, reset, validate_separately, **check_params)
    430                 y = check_array(y, **check_y_params)
    431             else:
--> 432                 X, y = check_X_y(X, y, **check_params)
    433             out = X, y
    434 


~/Desktop/sample_project/skl/lib/python3.8/site-packages/sklearn/utils/
↪validation.py in inner_f(*args, **kwargs)
     71                           FutureWarning)
     72         kwargs.update({k: arg for k, arg in zip(sig.parameters,␣
↪args)})
---> 73         return f(**kwargs)
     74     return inner_f
     75 


~/Desktop/sample_project/skl/lib/python3.8/site-packages/sklearn/utils/
↪validation.py in check_X_y(X, y, accept_sparse, accept_large_sparse, dtype,␣
↪order, copy, force_all_finite, ensure_2d, allow_nd, multi_output,␣
↪ensure_min_samples, ensure_min_features, y_numeric, estimator)
    794         raise ValueError("y cannot be None")
    795 
--> 796     X = check_array(X, accept_sparse=accept_sparse,
    797                     accept_large_sparse=accept_large_sparse,
    798                     dtype=dtype, order=order, copy=copy,


~/Desktop/sample_project/skl/lib/python3.8/site-packages/sklearn/utils/
↪validation.py in inner_f(*args, **kwargs)
     71                           FutureWarning)
     72         kwargs.update({k: arg for k, arg in zip(sig.parameters,␣
↪args)})
---> 73         return f(**kwargs)
```

```
         74     return inner_f
         75


        ~/Desktop/sample_project/skl/lib/python3.8/site-packages/sklearn/utils/
↪validation.py in check_array(array, accept_sparse, accept_large_sparse, dtype,␣
↪order, copy, force_all_finite, ensure_2d, allow_nd, ensure_min_samples,␣
↪ensure_min_features, estimator)
        597                     array = array.astype(dtype, casting="unsafe",␣
↪copy=False)
        598                 else:
    --> 599                     array = np.asarray(array, order=order,␣
↪dtype=dtype)
        600             except ComplexWarning:
        601                 raise ValueError("Complex data not supported\n"


        ~/Desktop/sample_project/skl/lib/python3.8/site-packages/numpy/core/
↪_asarray.py in asarray(a, dtype, order)
         83
         84     """
    ---> 85     return array(a, dtype, copy=False, order=order)
         86
         87


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

[10]:

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

# Create three categorical groups
categories_features = ["Make","Colour","Doors"]

one_hot=OneHotEncoder() # this is an encoder -- change strings combination into␣
↪array code
#tranform the categories_features columns into the encoders, then for the␣
↪columns not in the categories_features,
# leave it the same -- called "passthrough"
transformer=ColumnTransformer([("one_hot",one_hot,categories_features)],remainder="passthrough

transformed_x=transformer.fit_transform(x)
pd.DataFrame(transformed_x) # what is this? because we told SKL to make color␣
↪and door as categories
```

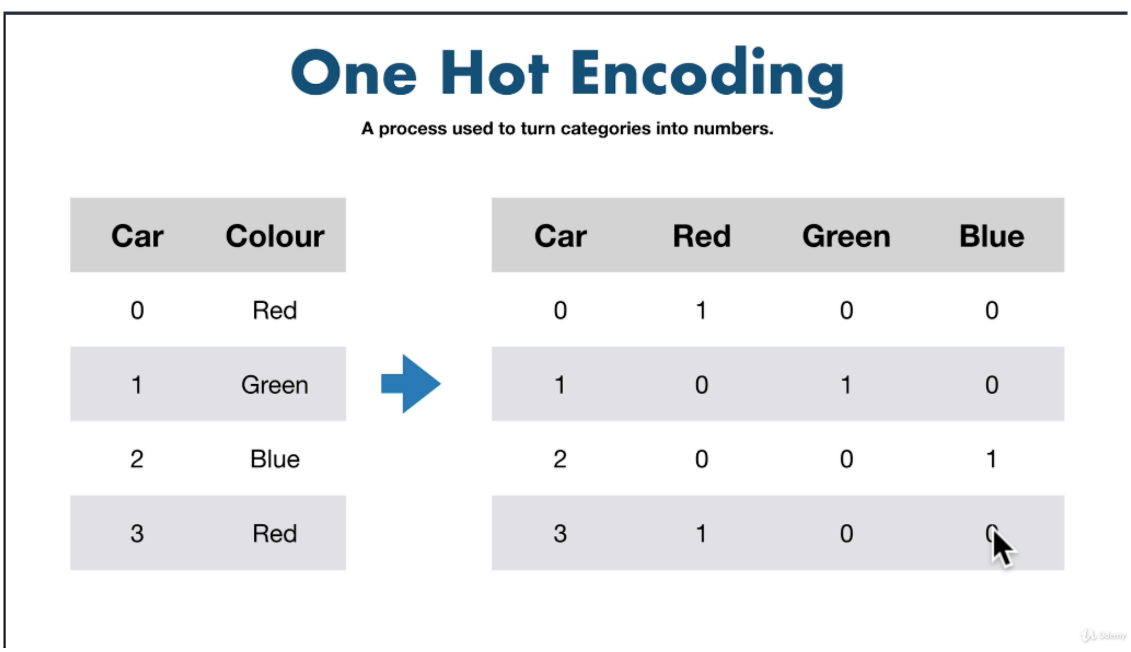
```
␣
↪---------------------------------------------------------------------------

    KeyError                                  Traceback (most recent call␣
↪last)

    ~/opt/miniconda3/lib/python3.7/site-packages/pandas/core/indexes/base.py␣
↪in get_loc(self, key, method, tolerance)
   2645             try:
-> 2646                 return self._engine.get_loc(key)
   2647             except KeyError:


    pandas/_libs/index.pyx in pandas._libs.index.IndexEngine.get_loc()


    pandas/_libs/index.pyx in pandas._libs.index.IndexEngine.get_loc()


    pandas/_libs/hashtable_class_helper.pxi in pandas._libs.hashtable.
↪PyObjectHashTable.get_item()


    pandas/_libs/hashtable_class_helper.pxi in pandas._libs.hashtable.
↪PyObjectHashTable.get_item()


    KeyError: 'Make'


During handling of the above exception, another exception occurred:


    KeyError                                  Traceback (most recent call␣
↪last)

    ~/opt/miniconda3/lib/python3.7/site-packages/sklearn/utils/__init__.py␣
↪in _get_column_indices(X, key)
    446             for col in columns:
--> 447                 col_idx = all_columns.get_loc(col)
    448                 if not isinstance(col_idx, numbers.Integral):


    ~/opt/miniconda3/lib/python3.7/site-packages/pandas/core/indexes/base.py␣
↪in get_loc(self, key, method, tolerance)
   2647             except KeyError:
```

```
-> 2648                 return self._engine.get_loc(self.
↪_maybe_cast_indexer(key))
   2649         indexer = self.get_indexer([key], method=method,␣
↪tolerance=tolerance)


    pandas/_libs/index.pyx in pandas._libs.index.IndexEngine.get_loc()


    pandas/_libs/index.pyx in pandas._libs.index.IndexEngine.get_loc()


    pandas/_libs/hashtable_class_helper.pxi in pandas._libs.hashtable.
↪PyObjectHashTable.get_item()


    pandas/_libs/hashtable_class_helper.pxi in pandas._libs.hashtable.
↪PyObjectHashTable.get_item()


    KeyError: 'Make'


The above exception was the direct cause of the following exception:


    ValueError                                Traceback (most recent call␣
↪last)

    <ipython-input-10-3ee3729266f7> in <module>
     11␣
↪transformer=ColumnTransformer([("one_hot",one_hot,categories_features)],remainder="passthrou
     12
---> 13 transformed_x=transformer.fit_transform(x)
     14 pd.DataFrame(transformed_x) # what is this? because we told SKL to␣
↪make color and door as categories


    ~/opt/miniconda3/lib/python3.7/site-packages/sklearn/compose/
↪_column_transformer.py in fit_transform(self, X, y)
    527         self._validate_transformers()
    528         self._validate_column_callables(X)
--> 529         self._validate_remainder(X)
    530
    531         result = self._fit_transform(X, y, _fit_transform_one)
```

```
    ~/opt/miniconda3/lib/python3.7/site-packages/sklearn/compose/
↪_column_transformer.py in _validate_remainder(self, X)
    325         cols = []
    326         for columns in self._columns:
--> 327             cols.extend(_get_column_indices(X, columns))
    328
    329         remaining_idx = sorted(set(range(self._n_features)) -␣
↪set(cols))


    ~/opt/miniconda3/lib/python3.7/site-packages/sklearn/utils/__init__.py␣
↪in _get_column_indices(X, key)
    454             raise ValueError(
    455                 "A given column is not a column of the dataframe"
--> 456             ) from e
    457
    458         return column_indices


    ValueError: A given column is not a column of the dataframe
```

[11]:
```
#What does the encoder do?
Image(filename="onehot.png")
```

[11]:



[12]:
```python
# similar function in pandas called dummies
dummies=pd.get_dummies(car_sales[["Make","Colour","Doors"]])
dummies
```

[12]:
```
     Doors  Make_BMW  Make_Honda  Make_Nissan  Make_Toyota  Colour_Black  \
0        4         0           1            0            0             0
1        5         1           0            0            0             0
2        4         0           1            0            0             0
3        4         0           0            0            1             0
4        3         0           0            1            0             0
..     …         …           …            …            …             …
995      4         0           0            0            1             1
996      3         0           0            1            0             0
997      4         0           0            1            0             0
998      4         0           1            0            0             0
999      4         0           0            0            1             0

     Colour_Blue  Colour_Green  Colour_Red  Colour_White
0              0             0           0             1
1              1             0           0             0
2              0             0           0             1
3              0             0           0             1
4              1             0           0             0
..           …             …           …             …
995            0             0           0             0
996            0             0           0             1
997            1             0           0             0
998            0             0           0             1
999            1             0           0             0

[1000 rows x 10 columns]
```

[13]:
```python
#Continue split data
x_train, x_test, y_train, y_test = train_test_split(transformed_x,y,test_size=0.
 ↪2)

# step2:Choose the right model and hyperparameters
from sklearn.ensemble import RandomForestRegressor  # Classification ML model␣
 ↪is RandomForestClassifier
model=RandomForestRegressor() #n-estimator

# Step 3: Find the patterns in the traning data
model.fit(x_train,y_train)

# metric, low fitting
model.score(x_test,y_test)
```

[13]: 0.2485327872550891

5 1.2 What if data has missing values? Method 1: Pandas

[13]:
```
#Import Car sales missing data
car_sales_missing=pd.read_csv("car-sales-extended-missing-data.csv")
car_sales_missing.head()
```

[13]:
```
     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
```

[14]:
```
car_sales_missing.isna().sum() #showing how many missing values
```

[14]:
```
Make             49
Colour           50
Odometer (KM)    50
Doors            50
Price            50
dtype: int64
```

5.0.1 SKL cannot work with data containing NaN !!!

[16]:
```
#Convert String with Encoder (Same as above)
from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import ColumnTransformer

x =car_sales_missing.drop("Price",axis=1)
y= car_sales_missing["Price"]

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

# Create three categorical groups
categories_features = ["Make","Colour","Doors"]

one_hot=OneHotEncoder() # this is an encoder -- change strings combination into␣
↪array code
#tranform the categories_features columns into the encoders, then for the␣
↪columns not in the categories_features,
# leave it the same -- called "passthrough"
transformer=ColumnTransformer([("one_hot",one_hot,categories_features)],remainder="passthrough
transformed_x=transformer.fit_transform(x)
```

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

```
     ␣
↪---------------------------------------------------------------------------

      ValueError                                Traceback (most recent call␣
↪last)

      <ipython-input-16-c644d6445e95> in <module>
       16␣
↪transformer=ColumnTransformer([("one_hot",one_hot,categories_features)],remainder="passthrou
       17
   ---> 18 transformed_x=transformer.fit_transform(x)
       19 pd.DataFrame(transformed_x)
       20


      ~/Desktop/sample_project/skl/lib/python3.8/site-packages/sklearn/compose/
↪_column_transformer.py in fit_transform(self, X, y)
      529         self._validate_remainder(X)
      530
  --> 531         result = self._fit_transform(X, y, _fit_transform_one)
      532
      533         if not result:


      ~/Desktop/sample_project/skl/lib/python3.8/site-packages/sklearn/compose/
↪_column_transformer.py in _fit_transform(self, X, y, func, fitted)
      456             self._iter(fitted=fitted, replace_strings=True))
      457         try:
  --> 458             return Parallel(n_jobs=self.n_jobs)(
      459                 delayed(func)(
      460                     transformer=clone(trans) if not fitted else␣
↪trans,


      ~/Desktop/sample_project/skl/lib/python3.8/site-packages/joblib/parallel.
↪py in __call__(self, iterable)
     1027             # remaining jobs.
     1028             self._iterating = False
  -> 1029             if self.dispatch_one_batch(iterator):
     1030                 self._iterating = self._original_iterator is not None
     1031
```

```
    ~/Desktop/sample_project/skl/lib/python3.8/site-packages/joblib/parallel.
↪py in dispatch_one_batch(self, iterator)
    845                 return False
    846             else:
--> 847                 self._dispatch(tasks)
    848                 return True
    849


    ~/Desktop/sample_project/skl/lib/python3.8/site-packages/joblib/parallel.
↪py in _dispatch(self, batch)
    763         with self._lock:
    764             job_idx = len(self._jobs)
--> 765             job = self._backend.apply_async(batch, callback=cb)
    766             # A job can complete so quickly than its callback is
    767             # called before we get here, causing self._jobs to


    ~/Desktop/sample_project/skl/lib/python3.8/site-packages/joblib/
↪_parallel_backends.py in apply_async(self, func, callback)
    204     def apply_async(self, func, callback=None):
    205         """Schedule a func to be run"""
--> 206         result = ImmediateResult(func)
    207         if callback:
    208             callback(result)


    ~/Desktop/sample_project/skl/lib/python3.8/site-packages/joblib/
↪_parallel_backends.py in __init__(self, batch)
    568         # Don't delay the application, to avoid keeping the input
    569         # arguments in memory
--> 570         self.results = batch()
    571
    572     def get(self):


    ~/Desktop/sample_project/skl/lib/python3.8/site-packages/joblib/parallel.
↪py in __call__(self)
    250         # change the default number of processes to -1
    251         with parallel_backend(self._backend, n_jobs=self._n_jobs):
--> 252             return [func(*args, **kwargs)
    253                     for func, args, kwargs in self.items]
    254


    ~/Desktop/sample_project/skl/lib/python3.8/site-packages/joblib/parallel.
↪py in <listcomp>(.0)
```

```
    250         # change the default number of processes to -1
    251         with parallel_backend(self._backend, n_jobs=self._n_jobs):
--> 252             return [func(*args, **kwargs)
    253                     for func, args, kwargs in self.items]
    254 

~/Desktop/sample_project/skl/lib/python3.8/site-packages/sklearn/pipeline.py in _fit_transform_one(transformer, X, y, weight, message_clsname, message, **fit_params)
    738     with _print_elapsed_time(message_clsname, message):
    739         if hasattr(transformer, 'fit_transform'):
--> 740             res = transformer.fit_transform(X, y, **fit_params)
    741         else:
    742             res = transformer.fit(X, y, **fit_params).transform(X)

~/Desktop/sample_project/skl/lib/python3.8/site-packages/sklearn/preprocessing/_encoders.py in fit_transform(self, X, y)
    408         """
    409         self._validate_keywords()
--> 410         return super().fit_transform(X, y)
    411 
    412     def transform(self, X):

~/Desktop/sample_project/skl/lib/python3.8/site-packages/sklearn/base.py in fit_transform(self, X, y, **fit_params)
    688         if y is None:
    689             # fit method of arity 1 (unsupervised transformation)
--> 690             return self.fit(X, **fit_params).transform(X)
    691         else:
    692             # fit method of arity 2 (supervised transformation)

~/Desktop/sample_project/skl/lib/python3.8/site-packages/sklearn/preprocessing/_encoders.py in fit(self, X, y)
    383         """
    384         self._validate_keywords()
--> 385         self._fit(X, handle_unknown=self.handle_unknown)
    386         self.drop_idx_ = self._compute_drop_idx()
    387         return self

~/Desktop/sample_project/skl/lib/python3.8/site-packages/sklearn/preprocessing/_encoders.py in _fit(self, X, handle_unknown)
     72 
```

```
     73     def _fit(self, X, handle_unknown='error'):
---> 74         X_list, n_samples, n_features = self._check_X(X)
     75 
     76         if self.categories != 'auto':


    ~/Desktop/sample_project/skl/lib/python3.8/site-packages/sklearn/
↪preprocessing/_encoders.py in _check_X(self, X)
     58         for i in range(n_features):
     59             Xi = self._get_feature(X, feature_idx=i)
---> 60             Xi = check_array(Xi, ensure_2d=False, dtype=None,
     61                              force_all_finite=needs_validation)
     62             X_columns.append(Xi)


    ~/Desktop/sample_project/skl/lib/python3.8/site-packages/sklearn/utils/
↪validation.py in inner_f(*args, **kwargs)
     71                           FutureWarning)
     72         kwargs.update({k: arg for k, arg in zip(sig.parameters,␣
↪args)})
---> 73         return f(**kwargs)
     74     return inner_f
     75 


    ~/Desktop/sample_project/skl/lib/python3.8/site-packages/sklearn/utils/
↪validation.py in check_array(array, accept_sparse, accept_large_sparse, dtype,␣
↪order, copy, force_all_finite, ensure_2d, allow_nd, ensure_min_samples,␣
↪ensure_min_features, estimator)
    643 
    644         if force_all_finite:
--> 645             _assert_all_finite(array,
    646                                allow_nan=force_all_finite ==␣
↪'allow-nan')
    647 


    ~/Desktop/sample_project/skl/lib/python3.8/site-packages/sklearn/utils/
↪validation.py in _assert_all_finite(X, allow_nan, msg_dtype)
    103     elif X.dtype == np.dtype('object') and not allow_nan:
    104         if _object_dtype_isnan(X).any():
--> 105             raise ValueError("Input contains NaN")
    106 
    107 


    ValueError: Input contains NaN
```

[15]:
```
##### This order is differnt below. If using scikit, should split the train and␣
↪test first, then deal
# with N/A and encoder seperately, see 1.3
#1. Handle Missing Value: How to handle missing values?

# Option 1: fill missing data with Pandas
car_sales_missing["Make"].fillna("missing",inplace=True)
car_sales_missing["Colour"].fillna("missing",inplace=True)
car_sales_missing["Doors"].fillna(4,inplace=True)
car_sales_missing["Odometer (KM)"].fillna(car_sales_missing["Odometer (KM)"].
↪mean(),inplace=True)
# Check the missing value again
car_sales_missing.isna().sum()

#Option 2: Remove rows with missing price value
car_sales_missing =car_sales_missing.dropna()

# Check the missing value again, now all columns should have zero
car_sales_missing.isna().sum()

from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import ColumnTransformer

#####
#2. seperate into two groups, cuz after the encoder, the column names will be␣
↪1,2,3...
x =car_sales_missing.drop("Price",axis=1)
y =car_sales_missing["Price"]


#####
#3. encoder to handle strings: note - only encoder and transform x, cuz y is␣
↪doesn't have string groups.
# This has no impact on the data, only change the strings into matrix stype, no␣
↪impact on length
# Create three categorical groups
categories_features = ["Make","Colour","Doors"]

one_hot=OneHotEncoder() # this is an encoder -- change strings combination into␣
↪array code
#tranform the categories_features columns into the encoders, then for the␣
↪columns not in the categories_features,
# leave it the same -- called "passthrough"
transformer=ColumnTransformer([("one_hot",one_hot,categories_features)],remainder="passthrough
```

```
transformed_x =transformer.fit_transform(x) # when I use x, cannot populate the␣
↪right result
#pd.DataFrame(transformed_x) # what is this? because we told SKL to make color␣
↪and door as categories
pd.DataFrame(transformed_x)

#####
#4. Split the data
## Deal with missing data first, then splipt
x_train, x_test, y_train, y_test = train_test_split(transformed_x,y,test_size=0.
↪2)

# step2:Choose the right model and hyperparameters
from sklearn.ensemble import RandomForestRegressor  # Classification ML model␣
↪is RandomForestClassifier
model=RandomForestRegressor() #n-estimator

# Step 3: Find the patterns in the traning data
model.fit(x_train,y_train)

# metric, low fitting
model.score(x_test,y_test)
```

[15]: 0.13164603892474935

6 1.3 What if data has missing values? Method 2: Scikit-learn

Split your data first (into train/test), always keep your training & test data separate

Fill/transform the training set and test sets separately (this goes for filling data with pandas as well)

Don't use data from the future (test set) to fill data from the past (training set)

[16]:
```
car_missing_data = pd.read_csv("car-sales-extended-missing-data.csv")
car_missing_data.head()
```

[16]:

	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

[17]:
```
car_missing_data.isna().sum()
```

[17]:
```
Make             49
Colour           50
Odometer (KM)    50
Doors            50
Price            50
dtype: int64
```

[18]:
```
###1. Drop the missing y values using pandas, you can do fills with SKL below
car_missing_data.dropna(subset=["Price"],inplace=True) #dropthe nan in price␣
↪columns
car_missing_data.isna().sum()
```

[18]:
```
Make             47
Colour           46
Odometer (KM)    48
Doors            47
Price             0
dtype: int64
```

[19]:
```
#####2. Split into x and y
from sklearn.model_selection import train_test_split
x = car_missing_data.drop("Price", axis=1)
y = car_missing_data["Price"]

#####3. Split data into train and test 0.2
np.random.seed(42) #?
x_train, x_test, y_train, y_test = train_test_split(x,
                                                    y,
                                                    test_size=0.2)
x.isna().sum()
```

[19]:
```
Make             47
Colour           46
Odometer (KM)    48
Doors            47
dtype: int64
```

[20]:
```
##### 4.Fill missing values with Scikit-Learn
from sklearn.impute import SimpleImputer
from sklearn.compose import ColumnTransformer

# Define the filling methods - Fill categorical values with 'missing' &␣
↪numerical values with mean
cat_imputer = SimpleImputer(strategy="constant", fill_value="missing")
door_imputer = SimpleImputer(strategy="constant", fill_value=4)
num_imputer = SimpleImputer(strategy="mean")
```

```
# Define columns as features
cat_features = ["Make", "Colour"]
door_feature = ["Doors"]
num_features = ["Odometer (KM)"]

# Map: create an imputer (something that fills missing data) -- map the filling␣
↪methods to the features
imputer = ColumnTransformer([
    ("cat_imputer", cat_imputer, cat_features),
    ("door_imputer", door_imputer, door_feature),
    ("num_imputer", num_imputer, num_features)
])

# Fill train and test values separately
filled_x_train = imputer.fit_transform(x_train) # fit_transform imputes the␣
↪missing values from the training set and fills them simultaneously
filled_x_test = imputer.transform(x_test) # tranform takes the imputing missing␣
↪values from the training set and fills the test set with them

# Check filled X_train
filled_x_train

# Get our transformed data array's back into DataFrame's
car_sales_filled_train = pd.DataFrame(filled_x_train,
                                      columns=["Make", "Colour", "Doors",␣
↪"Odometer (KM)"])

car_sales_filled_test = pd.DataFrame(filled_x_test,
                                     columns=["Make", "Colour", "Doors",␣
↪"Odometer (KM)"])

# Check missing data in training set
car_sales_filled_train.isna().sum()

# Check missing data in test set
car_sales_filled_test.isna().sum()
```

[20]:
```
Make             0
Colour           0
Doors            0
Odometer (KM)    0
dtype: int64
```

[21]:
```
# Check to see the original... still missing values
car_missing_data.isna().sum()
```

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

[22]:
```python
#### 5. encoder strings - Again, keeping our training and test data separate.
# Import OneHotEncoder class from sklearn
from sklearn.preprocessing import OneHotEncoder

# Now let's one hot encode the features with the same code as before (Same as␣
↪above)
categorical_features = ["Make", "Colour", "Doors"]
one_hot = OneHotEncoder()
transformer = ColumnTransformer([("one_hot",
                                  one_hot,
                                  categorical_features)],
                                  remainder="passthrough")

# Fill train and test values separately
transformed_x_train = transformer.fit_transform(car_sales_filled_train) # fit␣
↪and transform the training data
transformed_x_test = transformer.transform(car_sales_filled_test) # transform␣
↪the test data

# Check transformed and filled X_train
transformed_x_train.toarray()

# step2: Choose the right model and hyperparameters
from sklearn.ensemble import RandomForestRegressor  # Classification ML model␣
↪is RandomForestClassifier
model=RandomForestRegressor() #n-estimator

# Step 3: Find the patterns in the traning data
model.fit(transformed_x_train,y_train)

# metric, low fitting
model.score(transformed_x_test,y_test)
```

[22]: 0.21735623151692096

[23]:
```python
len(car_sales_filled_train), len(car_sales_filled_test)
```

[23]: (760, 190)

Extension: Feature Scaling Once your data is all in numerical format, there's one more transformation you'll probably want to do to it. It's called Feature Scaling. In other words, making sure all of your numerical data is on the same scale.

For example, say you were trying to predict the sale price of cars and the number of kilometres on their odometers varies from 6,000 to 345,000 but the median previous repair cost varies from 100 to 1,700. A machine learning algorithm may have trouble finding patterns in these wide-ranging variables.

To fix this, there are two main types of feature scaling.

Normalization (also called min-max scaling) - This rescales all the numerical values to between 0 and 1, with the lowest value being close to 0 and the highest previous value being close to 1. Scikit-Learn provides functionality for this in the MinMaxScalar class.

Standardization - This subtracts the mean value from all of the features (so the resulting features have 0 mean). It then scales the features to unit variance (by dividing the feature by the standard deviation). Scikit-Learn provides functionality for this in the StandardScalar class.

A couple of things to note.

Feature scaling usually isn't required for your target variable. Feature scaling is usually not required with tree-based models (e.g. Random Forest) since they can handle varying features.

7 Step 2: Choose the Right Estimator (Algorithm Model)

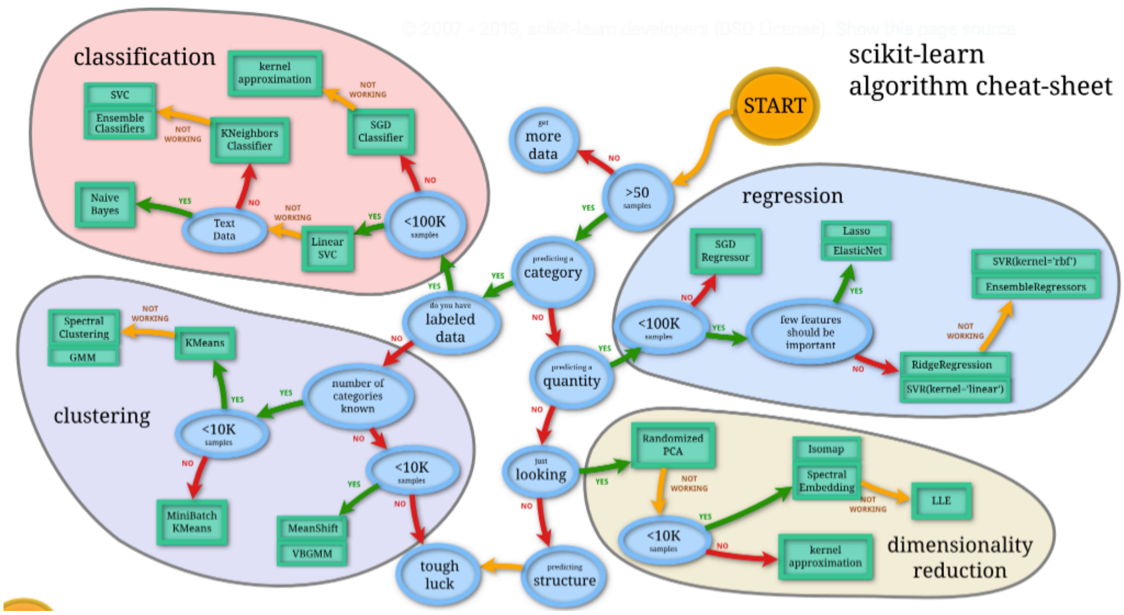
To pick a model we use the Scikit-Learn machine learning map.

Note: Scikit-Learn refers to machine learning models and algorithms as estimators.

Classification - predicting whether a sample is one thing or another Regression - predicting a number

[24]:
```
#https://scikit-learn.org/stable/tutorial/machine_learning_map/index.html
Image(filename="Pick_model.png")
```

[24]:



7.1 2.1 Picking a machine learning model for a regression problem¶

[27]:
```python
# Import Boston housing dataset for practice
from sklearn.datasets import load_boston
boston = load_boston()
boston_df = pd.DataFrame(boston["data"], columns=boston["feature_names"])
boston_df["target"] = pd.Series(boston["target"])
boston_df.head()
```

[27]:
```
      CRIM    ZN  INDUS  CHAS    NOX     RM   AGE     DIS  RAD    TAX  \
0  0.00632  18.0   2.31   0.0  0.538  6.575  65.2  4.0900  1.0  296.0
1  0.02731   0.0   7.07   0.0  0.469  6.421  78.9  4.9671  2.0  242.0
2  0.02729   0.0   7.07   0.0  0.469  7.185  61.1  4.9671  2.0  242.0
3  0.03237   0.0   2.18   0.0  0.458  6.998  45.8  6.0622  3.0  222.0
4  0.06905   0.0   2.18   0.0  0.458  7.147  54.2  6.0622  3.0  222.0

   PTRATIO       B  LSTAT  target
0     15.3  396.90   4.98    24.0
1     17.8  396.90   9.14    21.6
2     17.8  392.83   4.03    34.7
3     18.7  394.63   2.94    33.4
4     18.7  396.90   5.33    36.2
```

7.1.1 Ridge Regression Model

https://scikit-learn.org/stable/modules/linear_model.html#ridge-regression

[28]:
```python
# Let's 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
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)

# Instantiate 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)
```

[28]: 0.6662221670168522

How do we improve this score?

What if Ridge wasn't working? Use the enssamble method (the RandomForestRegressor)

Let's refer back to the map… https://scikit-learn.org/stable/tutorial/machine_learning_map/inde

7.1.2 RandomForestRegressor

https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.RandomForestRegressor.html#s

[29]:
```python
# Let's try the Random Forst 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 the data
#X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)

# Instatiate Random Forest Regressor
rf = RandomForestRegressor(n_estimators=100)
rf.fit(X_train, y_train)
```

```python
# Evaluate the Random Forest Regressor
rf.score(X_test, y_test)
```

[29]: 0.8922527442109116

7.2 2.2 Choosing an estimator for a classification problem

heart disease or no heart disease? Result is True or False

Let's go to the map… https://scikit-learn.org/stable/tutorial/machine_learning_map/index.html

Try LinearSVC first based on the map

[30]:
```python
heart_disease = pd.read_csv("heart-disease.csv")
heart_disease.head()
```

[30]:
```
   age  sex  cp  trestbps  chol  fbs  restecg  thalach  exang  oldpeak  slope  \
0   63    1   3       145   233    1        0      150      0      2.3      0
1   37    1   2       130   250    0        1      187      0      3.5      0
2   41    0   1       130   204    0        0      172      0      1.4      2
3   56    1   1       120   236    0        1      178      0      0.8      2
4   57    0   0       120   354    0        1      163      1      0.6      2

   ca  thal  target
0   0     1       1
1   0     2       1
2   0     2       1
3   0     2       1
4   0     2       1
```

[31]:
```python
# Do we have 50+, 100+ samples?
len(heart_disease)
```

[31]: 303

[32]:
```python
# Import the LinearSVC estimator class
from sklearn.svm import LinearSVC

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

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

# Split the data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
```

```python
# Instantiate LinearSVC
clf = LinearSVC(max_iter=20000) # there can be warnings if the max_iter is too␣
 ↪small,
                                # so cannot predict well
clf.fit(X_train, y_train)

# Evaluate the LinearSVC
clf.score(X_test, y_test)
```

```
/Users/yubeiliu/Desktop/sample_project/skl/lib/python3.8/site-
packages/sklearn/svm/_base.py:976: ConvergenceWarning: Liblinear failed to
converge, increase the number of iterations.
  warnings.warn("Liblinear failed to converge, increase "
```

[32]: 0.8688524590163934

[33]:
```python
heart_disease["target"].value_counts()
```

[33]:
```
1    165
0    138
Name: target, dtype: int64
```

Follow the map, see whether the RandomForestClassifier can perform better

[34]:
```python
# Import the RandomForestClassifier estimator class
from sklearn.ensemble import RandomForestClassifier

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

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

# Split the data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)

# Instantiate Random Forest Classifier
clf = RandomForestClassifier(n_estimators=100)
clf.fit(X_train, y_train)

# Evaluate the Random Forest Classifier
clf.score(X_test, y_test)
```

[34]: 0.8524590163934426

Tip:

1. If you have structured data, used ensemble methods
2. If you have unstructured data, use deep learning or transfer learning

Random Forest model deep dive These resources will help you understand what's happening inside the Random Forest models we've been using.

Random Forest Wikipedia

Random Forest Wikipedia (simple version)

Random Forests in Python by yhat

An Implementation and Explanation of the Random Forest in Python by Will Koehrsen

8 Step 3: Make a prediction

8.1 3.1 Fitting the model to the data

Different names for:

X = features, features variables, data

y = labels, targets, target variables

[35]:
```
# Import the RandomForestClassifier estimator class
from sklearn.ensemble import RandomForestClassifier

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

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

# Split the data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)

# Instantiate Random Forest Classifier
clf = RandomForestClassifier(n_estimators=100)

# Fit the model to the data (training the machine learning model)
clf.fit(X_train, y_train)  #fit function


# Evaluate the Random Forest Classifier (use the patterns the model has learned)
clf.score(X_test, y_test)
```

[35]: 0.8524590163934426

[36]:
```
# when passing all x_train, fit will find the pattern in y label
x.head()
```

[36]:
```
     Make Colour  Odometer (KM)  Doors
0   Honda  White        35431.0    4.0
1     BMW   Blue       192714.0    5.0
2   Honda  White        84714.0    4.0
3  Toyota  White       154365.0    4.0
4  Nissan   Blue       181577.0    3.0
```

[37]:
```
y.tail()
```

[37]:
```
298    0
299    0
300    0
301    0
302    0
Name: target, dtype: int64
```

[38]:
```
# Step 3: Find the patterns in the traning data
model.fit(x_train,y_train)

# metric, low fitting
model.score(x_test,y_test)
```

```
       ␣
↪---------------------------------------------------------------------------

       ValueError                                Traceback (most recent call␣
↪last)

       <ipython-input-38-42bd1a5353b1> in <module>
         1 # Step 3: Find the patterns in the traning data
   ----> 2 model.fit(x_train,y_train)
         3
         4 # metric, low fitting
         5 model.score(x_test,y_test)


       ~/Desktop/sample_project/skl/lib/python3.8/site-packages/sklearn/
↪linear_model/_ridge.py in fit(self, X, y, sample_weight)
       760         self : returns an instance of self.
       761         """
   --> 762         return super().fit(X, y, sample_weight=sample_weight)
       763
       764
```

```
    ~/Desktop/sample_project/skl/lib/python3.8/site-packages/sklearn/
↪linear_model/_ridge.py in fit(self, X, y, sample_weight)
    540         _accept_sparse = _get_valid_accept_sparse(sparse.issparse(X),
    541                                                   self.solver)
--> 542         X, y = self._validate_data(X, y,
    543                                    accept_sparse=_accept_sparse,
    544                                    dtype=_dtype,


    ~/Desktop/sample_project/skl/lib/python3.8/site-packages/sklearn/base.py␣
↪in _validate_data(self, X, y, reset, validate_separately, **check_params)
    430                 y = check_array(y, **check_y_params)
    431             else:
--> 432                 X, y = check_X_y(X, y, **check_params)
    433             out = X, y
    434


    ~/Desktop/sample_project/skl/lib/python3.8/site-packages/sklearn/utils/
↪validation.py in inner_f(*args, **kwargs)
     71                           FutureWarning)
     72         kwargs.update({k: arg for k, arg in zip(sig.parameters,␣
↪args)})
---> 73         return f(**kwargs)
     74     return inner_f
     75


    ~/Desktop/sample_project/skl/lib/python3.8/site-packages/sklearn/utils/
↪validation.py in check_X_y(X, y, accept_sparse, accept_large_sparse, dtype,␣
↪order, copy, force_all_finite, ensure_2d, allow_nd, multi_output,␣
↪ensure_min_samples, ensure_min_features, y_numeric, estimator)
    794         raise ValueError("y cannot be None")
    795
--> 796     X = check_array(X, accept_sparse=accept_sparse,
    797                     accept_large_sparse=accept_large_sparse,
    798                     dtype=dtype, order=order, copy=copy,


    ~/Desktop/sample_project/skl/lib/python3.8/site-packages/sklearn/utils/
↪validation.py in inner_f(*args, **kwargs)
     71                           FutureWarning)
     72         kwargs.update({k: arg for k, arg in zip(sig.parameters,␣
↪args)})
---> 73         return f(**kwargs)
     74     return inner_f
     75
```

```
    ~/Desktop/sample_project/skl/lib/python3.8/site-packages/sklearn/utils/
↪validation.py in check_array(array, accept_sparse, accept_large_sparse, dtype,␣
↪order, copy, force_all_finite, ensure_2d, allow_nd, ensure_min_samples,␣
↪ensure_min_features, estimator)
    597                     array = array.astype(dtype, casting="unsafe",␣
↪copy=False)
    598                 else:
--> 599                     array = np.asarray(array, order=order,␣
↪dtype=dtype)
    600             except ComplexWarning:
    601                 raise ValueError("Complex data not supported\n"


    ~/Desktop/sample_project/skl/lib/python3.8/site-packages/numpy/core/
↪_asarray.py in asarray(a, dtype, order)
     83
     84     """
---> 85     return array(a, dtype, copy=False, order=order)
     86
     87


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

8.2 3.2 Make predictions using a machine learning model - predict()

2 ways to make predictions:

1. predict()
2. predict_proba()

[39]:
```
# Step 3: Make a prediction, cannot use different size from the training
y_preds=clf.predict(np.array([0,1,2,3])) ## So this doesn't work
```

```
    ␣
↪---------------------------------------------------------------------------

    ValueError                                Traceback (most recent call␣
↪last)

    <ipython-input-39-e7497bd4c61c> in <module>
      1 # Step 3: Make a prediction, cannot use different size from the␣
↪training
----> 2 y_preds=clf.predict(np.array([0,1,2,3])) ## So this doesn't work
```

```
~/Desktop/sample_project/skl/lib/python3.8/site-packages/sklearn/
↪ensemble/_forest.py in predict(self, X)
    627                 The predicted classes.
    628             """
--> 629             proba = self.predict_proba(X)
    630 
    631             if self.n_outputs_ == 1:


~/Desktop/sample_project/skl/lib/python3.8/site-packages/sklearn/
↪ensemble/_forest.py in predict_proba(self, X)
    671             check_is_fitted(self)
    672             # Check data
--> 673             X = self._validate_X_predict(X)
    674 
    675             # Assign chunk of trees to jobs


~/Desktop/sample_project/skl/lib/python3.8/site-packages/sklearn/
↪ensemble/_forest.py in _validate_X_predict(self, X)
    419             check_is_fitted(self)
    420 
--> 421             return self.estimators_[0]._validate_X_predict(X,␣
↪check_input=True)
    422 
    423         @property


~/Desktop/sample_project/skl/lib/python3.8/site-packages/sklearn/tree/
↪_classes.py in _validate_X_predict(self, X, check_input)
    386             """Validate X whenever one tries to predict, apply,␣
↪predict_proba"""
    387             if check_input:
--> 388                 X = check_array(X, dtype=DTYPE, accept_sparse="csr")
    389                 if issparse(X) and (X.indices.dtype != np.intc or
    390                                     X.indptr.dtype != np.intc):


~/Desktop/sample_project/skl/lib/python3.8/site-packages/sklearn/utils/
↪validation.py in inner_f(*args, **kwargs)
     71                           FutureWarning)
     72             kwargs.update({k: arg for k, arg in zip(sig.parameters,␣
↪args)})
---> 73             return f(**kwargs)
     74         return inner_f
```

```
     75


     ~/Desktop/sample_project/skl/lib/python3.8/site-packages/sklearn/utils/
↪validation.py in check_array(array, accept_sparse, accept_large_sparse, dtype,␣
↪order, copy, force_all_finite, ensure_2d, allow_nd, ensure_min_samples,␣
↪ensure_min_features, estimator)
    618             # If input is 1D raise error
    619             if array.ndim == 1:
--> 620                 raise ValueError(
    621                     "Expected 2D array, got 1D array instead:
↪\narray={}.\n"
    622                     "Reshape your data either using array.
↪reshape(-1, 1) if "


    ValueError: Expected 2D array, got 1D array instead:
array=[0. 1. 2. 3.].
Reshape your data either using array.reshape(-1, 1) if your data has a␣
↪single feature or array.reshape(1, -1) if it contains a single sample.
```

[40]:
```
X_test.head()
```

[40]:
```
     age  sex  cp  trestbps  chol  fbs  restecg  thalach  exang  oldpeak  \
179   57    1   0       150   276    0        0      112      1      0.6
228   59    1   3       170   288    0        0      159      0      0.2
111   57    1   2       150   126    1        1      173      0      0.2
246   56    0   0       134   409    0        0      150      1      1.9
60    71    0   2       110   265    1        0      130      0      0.0

     slope  ca  thal
179      1   1     1
228      1   0     3
111      2   1     3
246      1   2     3
60       2   1     2
```

[41]:
```
y_preds=clf.predict(X_test)
y_preds
```

[41]:
```
array([0, 1, 1, 0, 1, 1, 1, 0, 0, 1, 1, 0, 1, 0, 1, 1, 1, 0, 0, 0, 0, 0,
       1, 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])
```

[42]:
```
np.array(y_test)
```

[42]: 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])

[43]:
```
# This is how the .score was calculated
#Compare prediction to truth labels to evaluate the model
y_preds=clf.predict(X_test)
np.mean(y_preds==y_test)
```

[43]: 0.8524590163934426

[44]:
```
clf.score(X_test,y_test)
```

[44]: 0.8524590163934426

Example - predict used on Regression type of model

[45]:
```
boston_df.head()
```

[45]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	\
0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1.0	296.0	
1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	2.0	242.0	
2	0.02729	0.0	7.07	0.0	0.469	7.185	61.1	4.9671	2.0	242.0	
3	0.03237	0.0	2.18	0.0	0.458	6.998	45.8	6.0622	3.0	222.0	
4	0.06905	0.0	2.18	0.0	0.458	7.147	54.2	6.0622	3.0	222.0	

	PTRATIO	B	LSTAT	target
0	15.3	396.90	4.98	24.0
1	17.8	396.90	9.14	21.6
2	17.8	392.83	4.03	34.7
3	18.7	394.63	2.94	33.4
4	18.7	396.90	5.33	36.2

[46]:
```
from sklearn.ensemble import RandomForestRegressor

np.random.seed(42)

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

# Split into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)

# Instantiate and fit model
model = RandomForestRegressor(n_estimators=100).fit(X_train, y_train)
```

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

[47]:
```
y_preds[:10]
```

[47]:
```
array([23.081, 30.574, 16.759, 23.46 , 16.893, 21.644, 19.113, 15.334,
       21.14 , 20.639])
```

[48]:
```
np.array(y_test[:10])
```

[48]:
```
array([23.6, 32.4, 13.6, 22.8, 16.1, 20. , 17.8, 14. , 19.6, 16.8])
```

[49]:
```
# Compare the predictions to the truth
from sklearn.metrics import mean_absolute_error
mean_absolute_error(y_test, y_preds)
```

[49]:
```
2.136382352941176
```

8.3 3.3 Make predictions using a machine learning model-predict_proba()

use this if someone asks you ``what's the probability your model is assigning to each prediction?''

[50]:
```
# predict_proba() returns probabilities of a classification label
clf.predict_proba(X_test[:5])
# this means , "0" prob = 0.89, "1" prob = 0.11, so the first returned value in␣
↪next cell is 0.
```

[50]:
```
array([[0.47, 0.53],
       [0.52, 0.48],
       [0.47, 0.53],
       [0.47, 0.53],
       [0.47, 0.53]])
```

[51]:
```
# Let's predict() on the same data...
clf.predict(X_test[:5])
```

[51]:
```
array([1, 0, 1, 1, 1])
```

[52]:
```
X_test[:5]
```

[52]:
```
        CRIM    ZN  INDUS  CHAS    NOX     RM   AGE     DIS   RAD    TAX  \
173  0.09178   0.0   4.05   0.0  0.510  6.416  84.1  2.6463   5.0  296.0
274  0.05644  40.0   6.41   1.0  0.447  6.758  32.9  4.0776   4.0  254.0
491  0.10574   0.0  27.74   0.0  0.609  5.983  98.8  1.8681   4.0  711.0
72   0.09164   0.0  10.81   0.0  0.413  6.065   7.8  5.2873   4.0  305.0
452  5.09017   0.0  18.10   0.0  0.713  6.297  91.8  2.3682  24.0  666.0
```

```
     PTRATIO       B  LSTAT
173     16.6  395.50   9.04
274     17.6  396.90   3.53
491     20.1  390.11  18.07
72      19.2  390.91   5.52
452     20.2  385.09  17.27
```

[53]:
```
heart_disease["target"].value_counts()
```

[53]:
```
1    165
0    138
Name: target, dtype: int64
```

[54]:
```
boston_df.head()
```

[54]:
```
      CRIM    ZN  INDUS  CHAS    NOX     RM   AGE     DIS  RAD    TAX  \
0  0.00632  18.0   2.31   0.0  0.538  6.575  65.2  4.0900  1.0  296.0
1  0.02731   0.0   7.07   0.0  0.469  6.421  78.9  4.9671  2.0  242.0
2  0.02729   0.0   7.07   0.0  0.469  7.185  61.1  4.9671  2.0  242.0
3  0.03237   0.0   2.18   0.0  0.458  6.998  45.8  6.0622  3.0  222.0
4  0.06905   0.0   2.18   0.0  0.458  7.147  54.2  6.0622  3.0  222.0

   PTRATIO       B  LSTAT  target
0     15.3  396.90   4.98    24.0
1     17.8  396.90   9.14    21.6
2     17.8  392.83   4.03    34.7
3     18.7  394.63   2.94    33.4
4     18.7  396.90   5.33    36.2
```

[55]:
```
from sklearn.ensemble import RandomForestRegressor

np.random.seed(42)

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

# Split into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)

# Instantiate and fit model
model = RandomForestRegressor(n_estimators=100).fit(X_train, y_train)

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

[56]:
```
y_preds[:10]
```

[56]:
```
array([23.081, 30.574, 16.759, 23.46 , 16.893, 21.644, 19.113, 15.334,
       21.14 , 20.639])
```

[57]:
```
np.array(y_test[:10])
```

[57]:
```
array([23.6, 32.4, 13.6, 22.8, 16.1, 20. , 17.8, 14. , 19.6, 16.8])
```

[58]:
```
# Compare the predictions to the truth
from sklearn.metrics import mean_absolute_error
mean_absolute_error(y_test, y_preds)
```

[58]:
```
2.136382352941176
```

9 Step 4: Evaluate the Model

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

1. Estimator score method: Estimators have a score method providing a default evaluation criterion for the problem they are designed to solve. This is not discussed on this page, but in each estimator's documentation.
2. Scoring parameter: Model-evaluation tools using cross-validation (such as model_selection.cross_val_score and model_selection.GridSearchCV) rely on an internal scoring strategy. This is discussed in the section The scoring parameter: defining model evaluation rules.
3. Metric functions: The metrics module implements functions assessing prediction error for specific purposes. These metrics are detailed in sections on Classification metrics, Multilabel ranking metrics, Regression metrics and Clustering metrics.

Finally, Dummy estimators are useful to get a baseline value of those metrics for random predictions.

9.1 4.1 Evaluating a model with the score method

[65]:
```
# Step 4: evaluatate the model on the training data and test data
# mean accuracy on the given test data and labels
from sklearn.ensemble import RandomForestClassifier

np.random.seed(42)

X = heart_disease.drop("target", axis=1)
y = heart_disease["target"]

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
```

```
clf = RandomForestClassifier()

clf.fit(X_train, y_train)
```

[65]: RandomForestClassifier()

[66]:
```
clf.score(X_train, y_train)
```

[66]: 1.0

[67]:
```
#.score Return the mean accuracy on the given test data and labels.
clf.score(X_test, y_test)
```

[67]: 0.8524590163934426

Let's do the same but for regression…

[68]:
```
from sklearn.ensemble import RandomForestRegressor

np.random.seed(42)

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

# Split into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)

# Instantiate and fit model
model = RandomForestRegressor(n_estimators=100).fit(X_train, y_train)
```

[69]:
```
# .score() Return the coefficient of determination R^2 of the prediction.
model.score(X_test, y_test)
```

[69]: 0.8654448653350507

9.2 4.2 Evaluating a model using the scoring parameter

[70]:
```
from sklearn.model_selection import cross_val_score  ## imported cross_val_score

from sklearn.ensemble import RandomForestClassifier

np.random.seed(42)

X = heart_disease.drop("target", axis=1)
y = heart_disease["target"]
```

```python
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)

clf = RandomForestClassifier(n_estimators=100)

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

[71]:
```python
clf.score(X_test, y_test)
```

[71]: 0.8524590163934426

[72]:
```python
cross_val_score(clf, X, y, cv=5)
```

[72]:
```
array([0.81967213, 0.86885246, 0.81967213, 0.78333333, 0.76666667])
```

[73]:
```python
cross_val_score(clf, X, y, cv=10)
```

[73]:
```
array([0.90322581, 0.80645161, 0.87096774, 0.9       , 0.86666667,
       0.8       , 0.73333333, 0.86666667, 0.73333333, 0.8       ])
```

[74]:
```python
np.random.seed(42)

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

# Take the 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
```

[74]: (0.8524590163934426, 0.8248087431693989)

[82]:
```python
# Default scoring parameter of classifier = mean accuracy
clf.score()
```

[82]: 0.9702970297029703

[76]:
```python
# Scoring parameter set to None by default
#    X, y,    test train
# cv=5  an array of 5 difference scores,     data 5 test
# scoring none by default     score paremeter
cross_val_score(clf, X, y, cv=5, scoring=None)
```

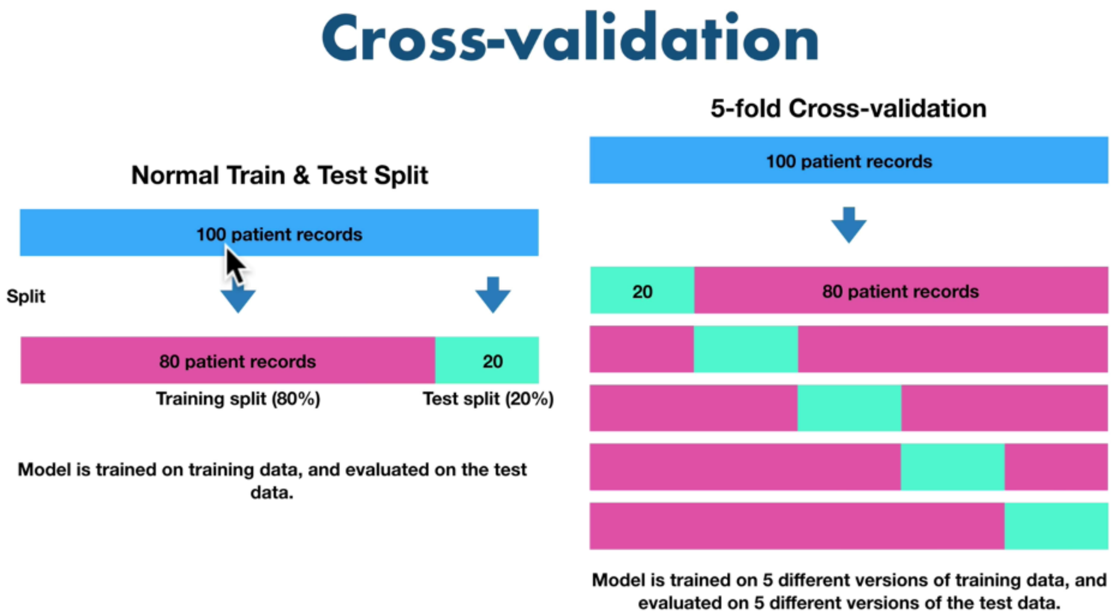
[76]:
```
array([0.78688525, 0.86885246, 0.80327869, 0.78333333, 0.76666667])
```

[81]:
```python
cross_val_score(clf, X, y, cv=10, scoring=None)
```

[81]: array([0.87096774, 0.80645161, 0.83870968, 0.9   , 0.9   ,
       0.8   , 0.76666667, 0.9   , 0.73333333, 0.76666667])

[80]:
```python
from IPython.display import Image
Image(filename="cross_vali.png")
```

[80]:



9.2.1 4.2.1 Classification model evaluation metrics

1.Accuracy

2.Area under ROC curve

3.Confusion matrix

4.Classification report

9.2.2 1.Accuracy - how likely can the model predict the right label?

[83]:
```python
heart_disease.head()
```

[83]:

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

   ca thal target

```
0   0     1       1
1   0     2       1
2   0     2       1
3   0     2       1
4   0     2       1
```

[87]:
```
from sklearn.model_selection import cross_val_score
from sklearn.ensemble import RandomForestClassifier

np.random.seed(42)

X = heart_disease.drop("target", axis=1)
y = heart_disease["target"]

clf = RandomForestClassifier(n_estimators=100)
cross_val_score = cross_val_score(clf, X, y, cv=5)
```

[85]:
```
np.mean(cross_val_score)
```

[85]:
```
0.8248087431693989
```

[86]:
```
print(f"Heart Disease Classifier Cross-Validated Accuracy: {np.
 ↪mean(cross_val_score) *100:.2f}%")
```

```
Heart Disease Classifier Cross-Validated Accuracy: 82.48%
```

9.2.3 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 postive rate (tpr) versus a models 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

ROC curves and AUC metrics are evaluation metrics for binary classification models (a model which predicts one thing or another, such as heart disease or not).

The ROC curve compares the true positive rate (tpr) versus the false positive rate (fpr) at different classification thresholds.

The AUC metric tells you how well your model is at choosing between classes (for example, how well it is at deciding whether someone has heart disease or not). A perfect model will get an AUC score of 1.

[88]:
```
# Create X_test... etc
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
```

[89]:
```
from sklearn.metrics import roc_curve  ## import roc_curve

# Fit the classifier
clf.fit(X_train, y_train)

# Make predictions with probabilities, probabilities of zero or one,
y_probs = clf.predict_proba(X_test)

y_probs[:10], len(y_probs)
```

[89]:
```
(array([[0.51, 0.49],
        [0.17, 0.83],
        [0.51, 0.49],
        [0.72, 0.28],
        [0.43, 0.57],
        [0.12, 0.88],
        [0.3 , 0.7 ],
        [0.97, 0.03],
        [0.15, 0.85],
        [0.4 , 0.6 ]]),
 61)
```

[90]:
```
# we only extract the probabiliries for positive result (y=1), in this case, we␣
↪want the column #1 result

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

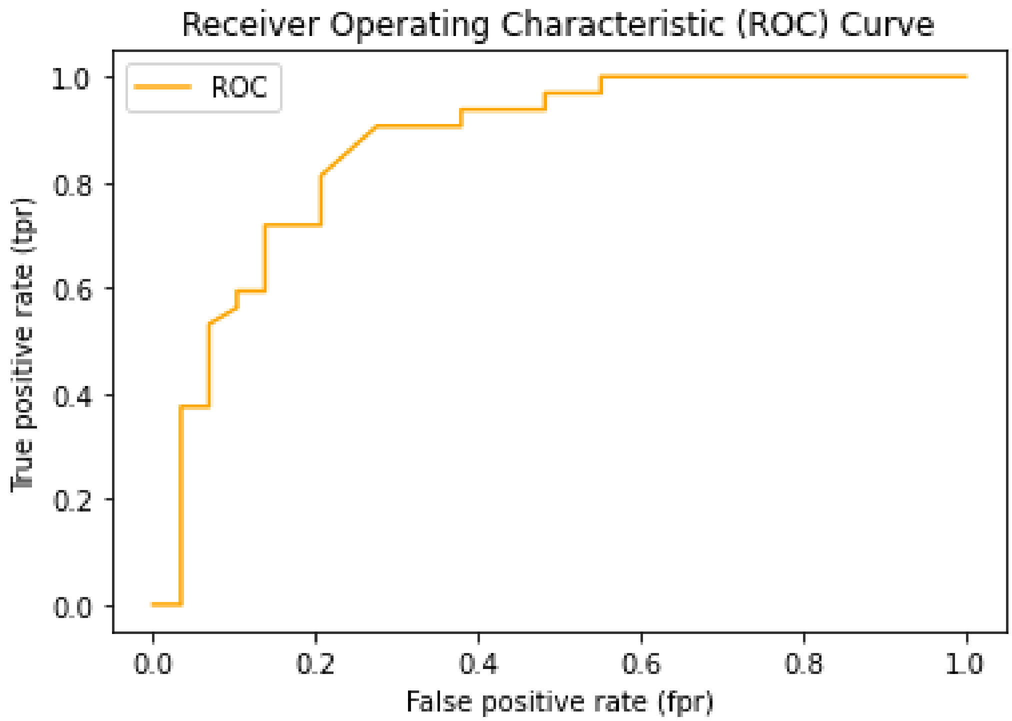
[90]:
```
array([0.49, 0.83, 0.49, 0.28, 0.57, 0.88, 0.7 , 0.03, 0.85, 0.6 ])
```

[92]:
```
# Caculate fpr, tpr and thresholds: roc_curve is restricted to the binary␣
↪classification task.
# fpr: array, shape = [>2]   Increasing false positive rates such that element␣
↪i is the false
# positive rate of predictions with score >= thresholds[i].
#
#tpr : array, shape = [>2] Increasing true positive rates such that element i␣
↪is the true positive
# rate of predictions with score >= thresholds[i].
#
#thresholds : array, shape = [n_thresholds] Decreasing thresholds on the␣
↪decision function used to compute
```

```
# fpr and tpr. `thresholds[0]` represents no instances being predicted
# and is arbitrarily set to `max(y_score) + 1`.

fpr, tpr, thresholds = roc_curve(y_test, y_probs_positive)

# Check the false positive rates
fpr
```

[92]:
```
array([0.        , 0.03448276, 0.03448276, 0.03448276, 0.03448276,
       0.03448276, 0.03448276, 0.06896552, 0.06896552, 0.06896552,
       0.10344828, 0.10344828, 0.13793103, 0.13793103, 0.13793103,
       0.20689655, 0.20689655, 0.20689655, 0.27586207, 0.37931034,
       0.37931034, 0.48275862, 0.48275862, 0.55172414, 0.55172414,
       1.        ])
```

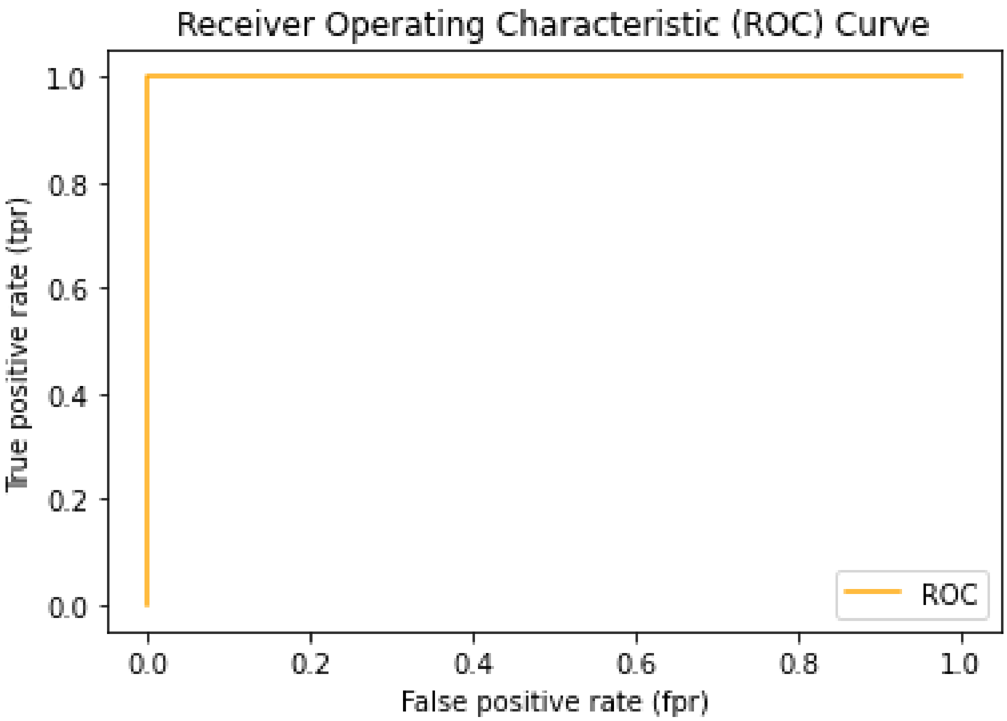
[93]:
```
# Create a function for plotting ROC curves
import matplotlib.pyplot as plt

def plot_roc_curve(fpr, tpr):
    """
    Plots a ROC curve given 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 Characteristic (ROC) Curve")
    plt.legend()
    plt.show()

plot_roc_curve(fpr, tpr) # compare the false positive to the true positive
```



[94]:
```
from sklearn.metrics import roc_auc_score ## what's this metric?
#
roc_auc_score(y_test, y_probs_positive)
```

[94]: 0.8669181034482759

[95]:
```
# Plot perfect ROC curve and AUC score
fpr, tpr, thresholds = roc_curve(y_test, y_test)
plot_roc_curve(fpr, tpr)
```



[96]:
```
# Perfect AUC score
roc_auc_score(y_test, y_test)
```

[96]: 1.0

9.2.4 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.

[97]:
```
from sklearn.metrics import confusion_matrix

y_preds = clf.predict(X_test)

confusion_matrix(y_test, y_preds)
```

[97]:
```
array([[23,  6],
       [ 6, 26]])
```

[99]:
```
#  predict actual label
# Visualize confusion matrix with pd.crosstab()
pd.crosstab(y_test,
```

```
             y_preds,
             rownames=["Actual Labels"],
             colnames=["Predicted Labels"])
```

[99]:
```
Predicted Labels   0   1
Actual Labels
0                 23   6
1                  6  26
```

[100]:
```
22 + 7 + 8 + 24
```

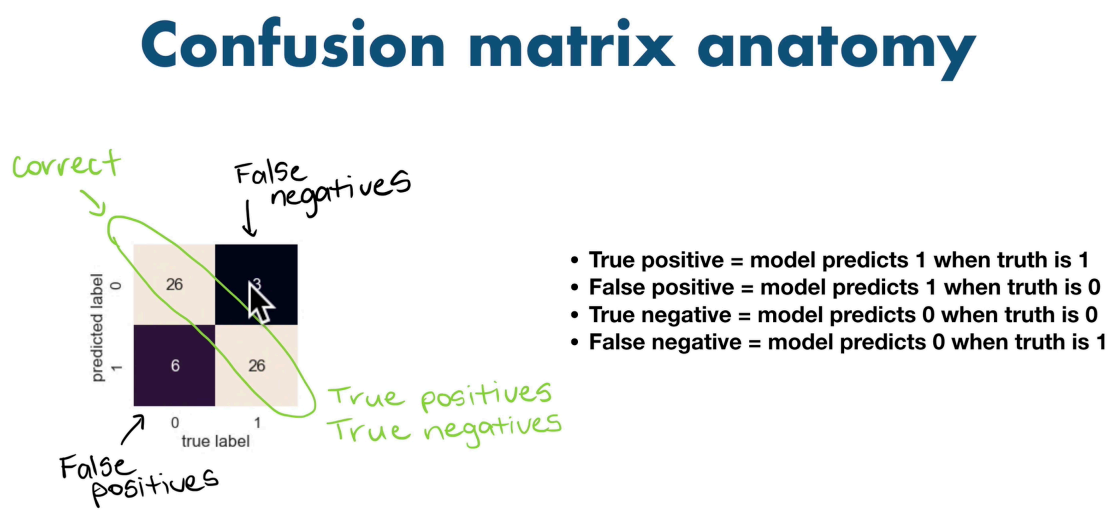
[100]: 61

[101]:
```
len(X_test)
```

[101]: 61

[102]:
```
from IPython.display import Image
Image(filename="confusion.png")
```

[102]:



[ ]:
```
# # How install a conda package into the current envrionment from a Jupyter␣
↪Notebook
# import sys
# !conda install --yes --prefix {sys.prefix} seaborn
```

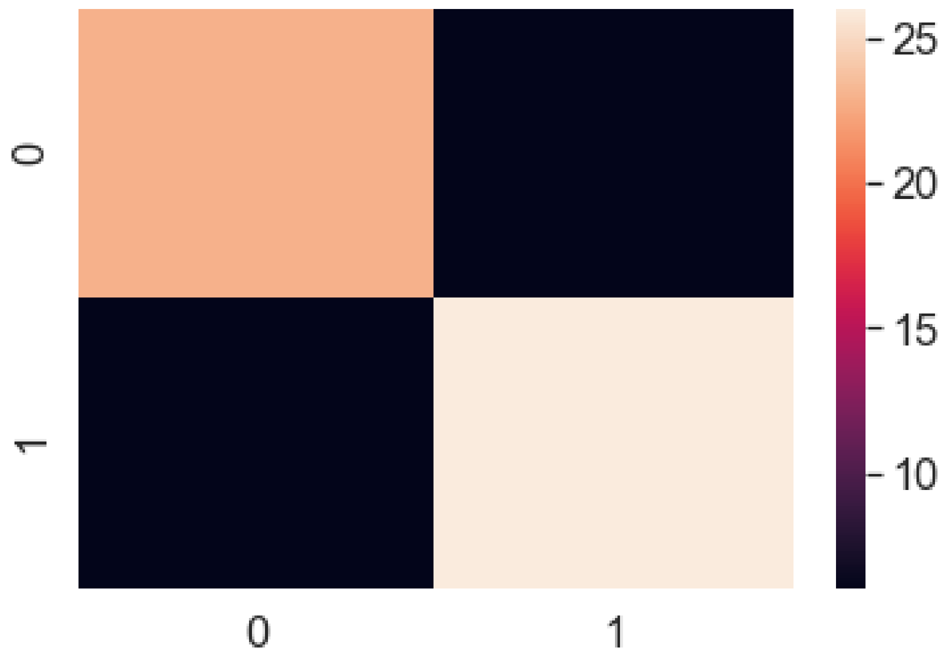
[107]:
```
import sys
!conda install --yes --prefix {sys.prefix} seaborn
```

```
Collecting package metadata (current_repodata.json): done
```

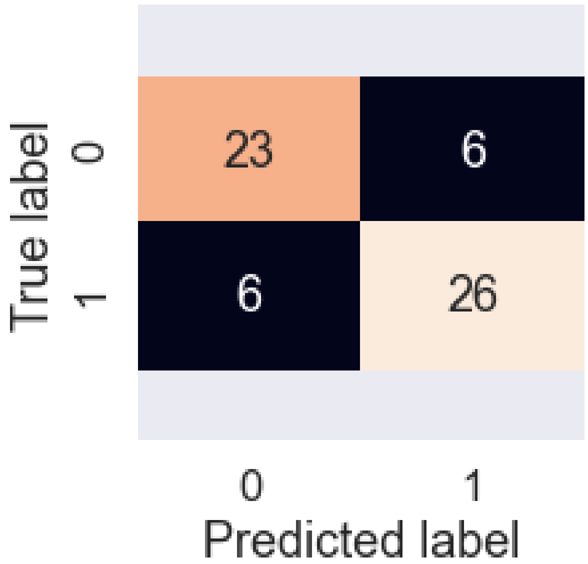
```
Solving environment: done

## Package Plan ##

  environment location: /Users/yubeiliu/Desktop/sample_project/skl

  added / updated specs:
    - seaborn


The following packages will be downloaded:

    package                    |            build
    ---------------------------|-----------------
    ca-certificates-2020.6.24  |                0         125 KB
    seaborn-0.10.1             |             py_0         163 KB
    ------------------------------------------------------------
                                           Total:         288 KB

The following NEW packages will be INSTALLED:

  seaborn            pkgs/main/noarch::seaborn-0.10.1-py_0

The following packages will be UPDATED:

  ca-certificates                                2020.1.1-0 --> 2020.6.24-0



Downloading and Extracting Packages
seaborn-0.10.1       | 163 KB    | ##################################### | 100%
ca-certificates-2020 | 125 KB    | ##################################### | 100%
Preparing transaction: done
Verifying transaction: done
Executing transaction: done
```

[108]:

```python
# Make our confusion matrix more visual with Seaborn's heatmap()
import seaborn as sns ## use seaborn-heatmap

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

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

# Plot it using Seaborn
sns.heatmap(conf_mat);
```

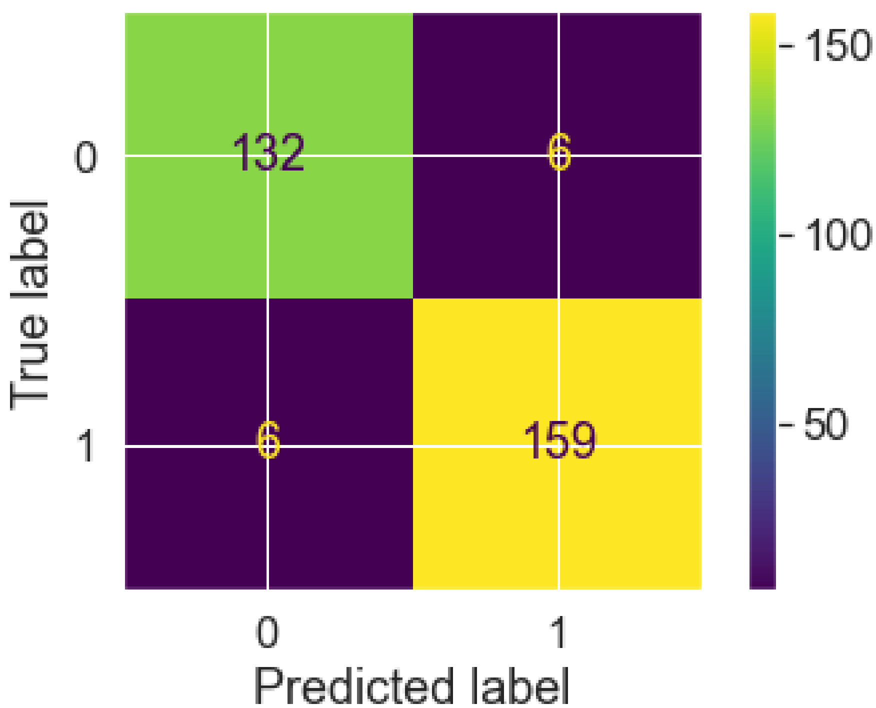


[109]:
```
def plot_conf_mat(conf_mat):
    """
    Plots a confusion matrix using Seaborn's heatmap().
    """
    fig, ax = plt.subplots(figsize=(3,3))
    ax = sns.heatmap(conf_mat,
                     annot=True, # Annotate the boxes with conf_mat info
                     cbar=False)
    plt.xlabel("Predicted label")
    plt.ylabel("True label")

    # Fix the broken annotations (this happened in Matplotlib 3.1.1)
    bottom, top = ax.get_ylim()
    ax.set_ylim(bottom + 0.5, top-0.5);

plot_conf_mat(conf_mat)
```




```
[110]: from sklearn.metrics import plot_confusion_matrix

plot_confusion_matrix(clf, X, y)
```

```
[110]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x11e98d340>
```



[111]:
```python
from sklearn.metrics import classification_report

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

```
              precision    recall  f1-score   support

           0       0.79      0.79      0.79        29
           1       0.81      0.81      0.81        32

    accuracy                           0.80        61
   macro avg       0.80      0.80      0.80        61
weighted avg       0.80      0.80      0.80        61
```

[ ]:
```python
# Where precision and recall become valuable
disease_true = np.zeros(10000)
disease_true[0] = 1 # only one positive case

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

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

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 than false negatives, aim for higher precision.

If false negative predictions are worse than false positives, aim for higher recall.

F1-score is a combination of precision and recall.

10 Step 5: Improve a Model

[ ]:
```python
# try different amount of n_estimateros to make the model more precise
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(" ")
```

```
#based on below, we can use 20 estimators
```

11 Step 6: Save a Model and Load It

[ ]:
```
# Save the model
import pickle

pickle.dump(clf,open("random_forst_model_1.pkl","wb")) #write binary
```

[ ]:
```
# Open the model
loaded_model = pickle.load(open("random_forst_model_1.pkl","rb")) #read binary
loaded_model.score(x_test,y_test)
```

12 Warnings and Errors

For example: if n_estimator is not specified, a default will be created

[ ]:
```
import warnings
# this can ignore all warnings -- but what if the warnings are important?
warnings.filterwarnings("ignore")
#reset to default, other warnings will come back
warnings.filterwarnings("default")
```

[ ]:
```
import sklearn
sklearn.show_versions()

# how to upgrade the package inside the environment?
# Terminal --> conda activate ///skl --> conda list: showing all the packages␣
↪we have
# --> conda update scikit-learn (or oether package name): this can only update␣
↪to the newest version competible with
# the current python version
# --> conda search scikit-learn --info (or other pacakge name): to see what␣
↪version is available and what dependencies
# the dependencies can be version of python, etc. If I uninstall all pythons␣
↪and make install all new versions required
# in the dependencies, then I can update the lib.
```

[1]:
```

```

```
    File "<ipython-input-1-fe3f7017c96b>", line 1
  git clone https://github.com/yubeiliu/
↪2020_MachineLearning_ScikitLearnTemplate.git
```

```
              ^
SyntaxError: invalid syntax
```

```
[ ]:
```