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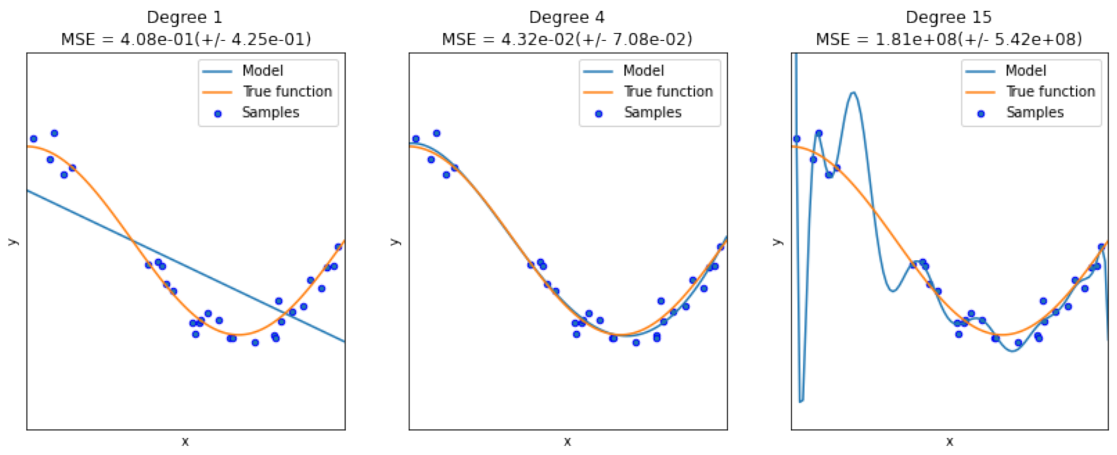
Overfitting and Underfitting

https://scikit-learn.org/stable/auto_examples/model_selection/plot_underfitting_overfitting.html

Program for understanding Overfitting and Underfitting

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import PolynomialFeatures
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import cross_val_score

def true_fun(X):
    return np.cos(1.5 * np.pi * X)

np.random.seed(0)

n_samples = 30
degrees = [1, 4, 15]

X = np.sort(np.random.rand(n_samples))
y = true_fun(X) + np.random.randn(n_samples) * 0.1

plt.figure(figsize=(14, 5))
for i in range(len(degrees)):
    ax = plt.subplot(1, len(degrees), i + 1)
    plt.setp(ax, xticks=(), yticks=())

    polynomial_features = PolynomialFeatures(degree=degrees[i],
include_bias=False)
    linear_regression = LinearRegression()
    pipeline = Pipeline(
        [
            ("polynomial_features", polynomial_features),
            ("linear_regression", linear_regression),
        ]
    )
    pipeline.fit(X[:, np.newaxis], y)

    # Evaluate the models using crossvalidation
    scores = cross_val_score(
        pipeline, X[:, np.newaxis], y,
scoring="neg_mean_squared_error", cv=10
    )
    X_test = np.linspace(0, 1, 100)
    plt.plot(X_test, pipeline.predict(X_test[:, np.newaxis]),
label="Model")
    plt.plot(X_test, true_fun(X_test), label="True function")
    plt.scatter(X, y, edgecolor="b", s=20, label="Samples")
    plt.xlabel("x")
    plt.ylabel("y")
    plt.xlim((0, 1))
    plt.ylim((-2, 2))
    plt.legend(loc="best")
    plt.title(
        "Degree {}\nMSE = {:.2e}(+/- {:.2e})".format(
            degrees[i], -scores.mean(), scores.std()
        )
    )
plt.show()
```



Overfitting (Printing accuracy at different steps)

https://machinelearningmastery.com/overfitting-machine-learning-models/

```
# evaluate decision tree performance on train and test sets with
different tree depths
from sklearn.datasets import make_classification
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from sklearn.tree import DecisionTreeClassifier
from matplotlib import pyplot

# define dataset
X, y = make_classification(n_samples=10000, n_features=20,
n_informative=5, n_redundant=15, random_state=1)
# summarize the dataset
print(X.shape, y.shape)
```

```
(10000, 20) (10000,)
```

```
# split into train test sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.3)
# summarize the shape of the train and test sets
print(X_train.shape, X_test.shape, y_train.shape, y_test.shape)
```

```
(7000, 20) (3000, 20) (7000,) (3000,)
```

```
train_scores, test_scores = list(), list()

# define the tree depths to evaluate
values = [i for i in range(1, 31)]

# evaluate a decision tree for each depth
for i in values:
    # configure the model
    model = DecisionTreeClassifier(max_depth=i)
    # fit model on the training dataset
    model.fit(X_train, y_train)
    # evaluate on the train dataset
    train_yhat = model.predict(X_train)
    train_acc = accuracy_score(y_train, train_yhat)
    train_scores.append(train_acc)
    # evaluate on the test dataset
    test_yhat = model.predict(X_test)
    test_acc = accuracy_score(y_test, test_yhat)
    test_scores.append(test_acc)
    # summarize progress
    print('>%d, train: %.3f, test: %.3f' % (i, train_acc, test_acc))
```

```
>1, train: 0.763, test: 0.767
>2, train: 0.804, test: 0.805
>3, train: 0.871, test: 0.868
>4, train: 0.906, test: 0.890
>5, train: 0.924, test: 0.901
>6, train: 0.937, test: 0.912
>7, train: 0.947, test: 0.917
>8, train: 0.956, test: 0.914
>9, train: 0.966, test: 0.917
>10, train: 0.975, test: 0.911
>11, train: 0.981, test: 0.913
>12, train: 0.985, test: 0.909
>13, train: 0.990, test: 0.909
>14, train: 0.993, test: 0.907
>15, train: 0.995, test: 0.905
>16, train: 0.996, test: 0.910
>17, train: 0.997, test: 0.908
>18, train: 0.998, test: 0.904
>19, train: 0.999, test: 0.905
>20, train: 0.999, test: 0.903
>21, train: 1.000, test: 0.902
```

```
>22, train: 1.000, test: 0.905
>23, train: 1.000, test: 0.903
>24, train: 1.000, test: 0.901
>25, train: 1.000, test: 0.901
>26, train: 1.000, test: 0.906
>27, train: 1.000, test: 0.905
>28, train: 1.000, test: 0.900
>29, train: 1.000, test: 0.900
>30, train: 1.000, test: 0.908
```

Cross-validation

https://scikit-learn.org/stable/modules/cross_validation.html

```
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn import datasets
from sklearn import svm

X, y = datasets.load_iris(return_X_y=True)
X.shape, y.shape
```

```
((150, 4), (150,))
```

Basic method to compute score

```
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.4, random_state=0)

X_train.shape, y_train.shape

X_test.shape, y_test.shape


clf = svm.SVC(kernel='linear', C=1).fit(X_train, y_train)
clf.score(X_test, y_test)
```

```
0.9666666666666667
```

Estimate the accuracy by splitting the data, computing the score 5 consecutive times (with different splits each time)

```
from sklearn.model_selection import cross_val_score
clf = svm.SVC(kernel='linear', C=1, random_state=42)
scores = cross_val_score(clf, X, y, cv=5)
scores
```

```
array([0.96666667, 1.        , 0.96666667, 0.96666667, 1.        ])
```

```
print("%0.2f accuracy with a standard deviation of %0.2f" %
(scores.mean(), scores.std()))
```

```
0.98 accuracy with a standard deviation of 0.02
```

Using the different scoring parameter

```
from sklearn import metrics

scores = cross_val_score(
    clf, X, y, cv=5, scoring='f1_macro')
scores
```

```
array([0.96658312, 1.        , 0.96658312, 0.96658312, 1.        ])
```

Specified multiple metrics of predefined scorer names

```
from sklearn.model_selection import cross_validate
from sklearn.metrics import recall_score

scoring = ['precision_macro', 'recall_macro']
clf = svm.SVC(kernel='linear', C=1, random_state=0)
scores = cross_validate(clf, X, y, scoring=scoring)
sorted(scores.keys())

scores['test_recall_macro']
```

```
array([0.96666667, 1.        , 0.96666667, 0.96666667, 1.        ])
```

Calculate cross validation score by passing a cross validation iterator

```
from sklearn.model_selection import ShuffleSplit
n_samples = X.shape[0]
cv = ShuffleSplit(n_splits=5, test_size=0.3, random_state=0)
cross_val_score(clf, X, y, cv=cv)
```

```
array([0.97777778, 0.97777778, 1.        , 0.95555556, 1.        ])
```

Use an iterable yielding (train, test) splits as arrays of indices

```
def custom_cv_2folds(X):
    n = X.shape[0]
    i = 1
    while i <= 2:
        idx = np.arange(n * (i - 1) / 2, n * i / 2, dtype=int)
        yield idx, idx
        i += 1

custom_cv = custom_cv_2folds(X)
cross_val_score(clf, X, y, cv=custom_cv)
```

```
array([1.        , 0.97333333])
```

Different type of Cross validation iterators

K-fold

```
import numpy as np
from sklearn.model_selection import KFold

X = ["a", "b", "c", "d"]
kf = KFold(n_splits=2)
for train, test in kf.split(X):
    print("%s %s" % (train, test))
```

```
[2 3] [0 1]
[0 1] [2 3]
```

Repeated K-Fold

```
import numpy as np
from sklearn.model_selection import RepeatedKFold
X = np.array([[1, 2], [3, 4], [1, 2], [3, 4]])
random_state = 12883823
rkf = RepeatedKFold(n_splits=2, n_repeats=2,
random_state=random_state)
for train, test in rkf.split(X):
    print("%s %s" % (train, test))
```

```
[2 3] [0 1]
[0 1] [2 3]
[0 2] [1 3]
[1 3] [0 2]
```

Leave One Out (LOO)

```
from sklearn.model_selection import LeaveOneOut

X = [1, 2, 3, 4]
loo = LeaveOneOut()
for train, test in loo.split(X):
    print("%s %s" % (train, test))
```

```
[1 2 3] [0]
[0 2 3] [1]
[0 1 3] [2]
[0 1 2] [3]
```

Leave P Out (LPO)

```
from sklearn.model_selection import LeavePOut

X = np.ones(4)
lpo = LeavePOut(p=2)
for train, test in lpo.split(X):
     print("%s %s" % (train, test))
```

```
[2 3] [0 1]
[1 3] [0 2]
[1 2] [0 3]
[0 3] [1 2]
[0 2] [1 3]
[0 1] [2 3]
```

Stratified k-fold

```
from sklearn.model_selection import StratifiedKFold, KFold
import numpy as np
X, y = np.ones((50, 1)), np.hstack(([0] * 45, [1] * 5))
skf = StratifiedKFold(n_splits=3)
for train, test in skf.split(X, y):
    print('train -  {}   |   test -  {}'.format(
         np.bincount(y[train]), np.bincount(y[test])))
```

```
train -  [30  3]   |   test -  [15  2]
train -  [30  3]   |   test -  [15  2]
train -  [30  4]   |   test -  [15  1]
```

```
kf = KFold(n_splits=3)
for train, test in kf.split(X, y):
     print('train -  {}   |   test -  {}'.format(
                  np.bincount(y[train]), np.bincount(y[test])))
```

```
train -  [28  5]   |   test -  [17]
train -  [28  5]   |   test -  [17]
train -  [34]   |   test -  [11  5]
```

GroupShuffleSplit

```
from sklearn.model_selection import GroupShuffleSplit

X = [0.1, 0.2, 2.2, 2.4, 2.3, 4.55, 5.8, 0.001]
y = ["a", "b", "b", "b", "c", "c", "c", "a"]
groups = [1, 1, 2, 2, 3, 3, 4, 4]
gss = GroupShuffleSplit(n_splits=4, test_size=0.5, random_state=0)
for train, test in gss.split(X, y, groups=groups):
    print("%s %s" % (train, test))
```

```
[0 1 2 3] [4 5 6 7]
[2 3 6 7] [0 1 4 5]
[2 3 4 5] [0 1 6 7]
[4 5 6 7] [0 1 2 3]
```

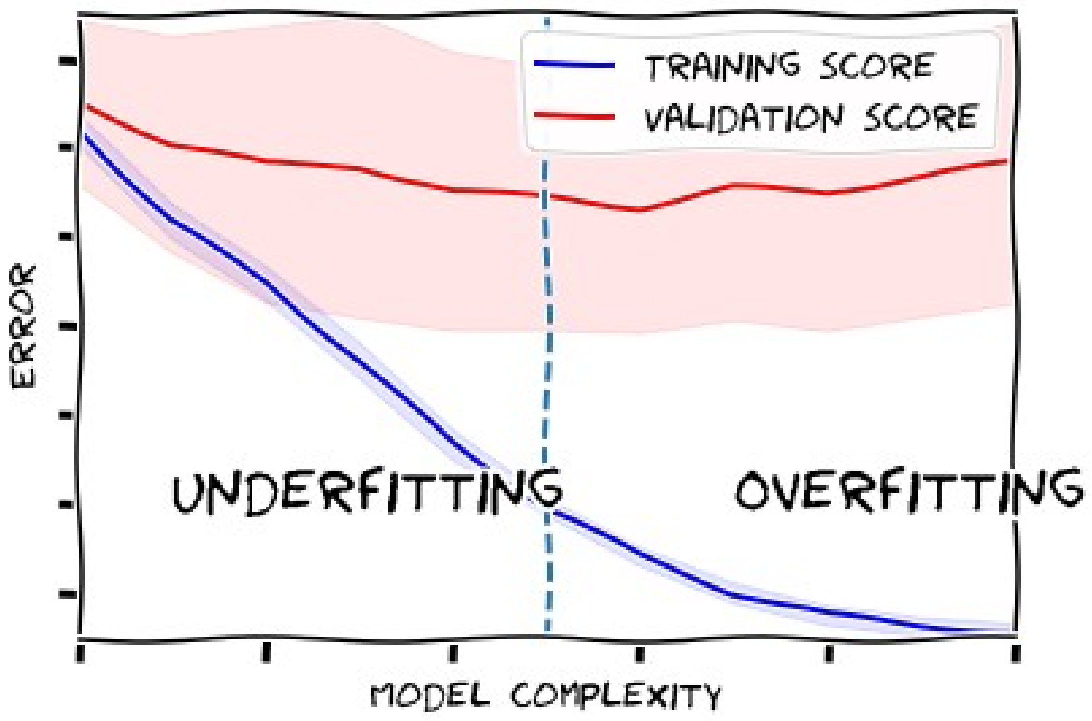
Validation curve

https://keeeto.github.io/blog/bias_variance/

https://scikit-learn.org/stable/modules/learning_curve.html

```
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt

from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import cross_val_score, learning_curve,
validation_curve



df_train = pd.read_csv('train.csv')
df_test = pd.read_csv('test.csv')
df_comb = df_train.append(df_test)

X = pd.DataFrame()

def encode_sex(x):
    return 1 if x == 'female' else 0

def family_size(x):
    size = x.SibSp + x.Parch
    return 4 if size > 3 else size

X['Sex'] = df_comb.Sex.map(encode_sex)
X['Pclass'] = df_comb.Pclass
X['FamilySize'] = df_comb.apply(family_size, axis=1)

fare_median = df_train.groupby(['Sex', 'Pclass']).Fare.median()
fare_median.name = 'FareMedian'

age_mean = df_train.groupby(['Sex', 'Pclass']).Age.mean()
age_mean.name = 'AgeMean'

def join(df, stat):
    return pd.merge(df, stat.to_frame(), left_on=['Sex', 'Pclass'],
right_index=True, how='left')
```

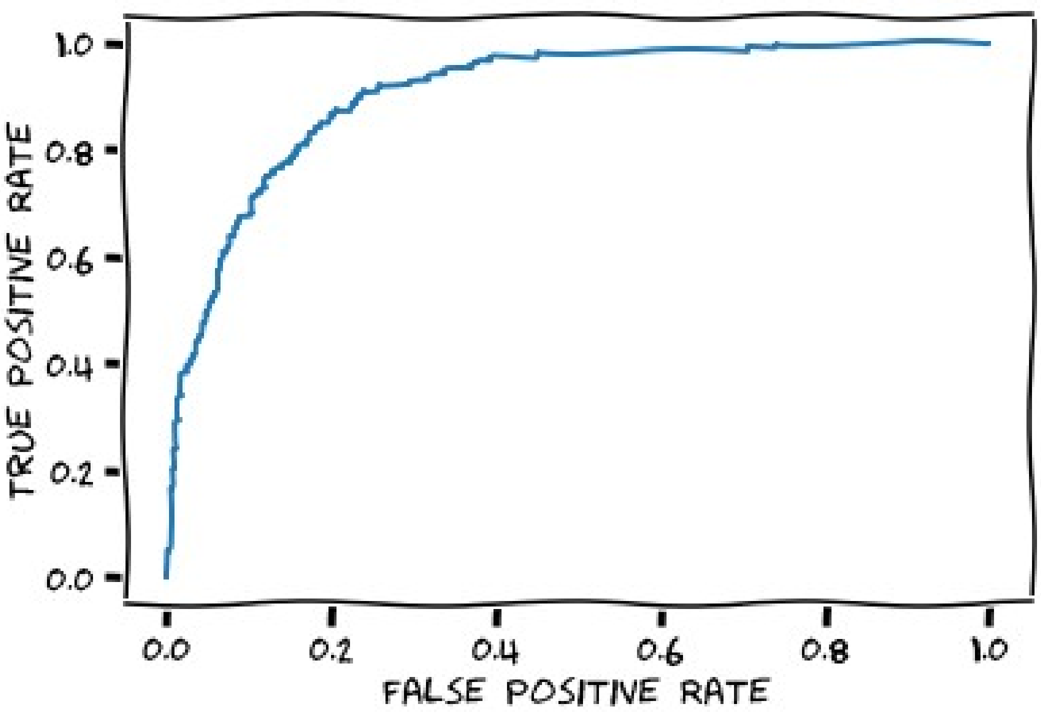
```
X['Fare'] = df_comb.Fare.fillna(join(df_comb, fare_median).FareMedian)
X['Age'] = df_comb.Age.fillna(join(df_comb, age_mean).AgeMean)

def quantiles(series, num):
    return pd.qcut(series, num, retbins=True)[1]

def discretize(series, bins):
    return pd.cut(series, bins, labels=range(len(bins)-1),
include_lowest=True)

X['Fare'] = discretize(X.Fare, quantiles(df_comb.Fare, 10))
X['Age'] = discretize(X.Age, quantiles(df_comb.Age, 10))

X_train = X.iloc[:df_train.shape[0]]
X_test = X.iloc[df_train.shape[0]:]

y_train = df_train.Survived

clf_1 = RandomForestClassifier(n_estimators=100, bootstrap=True,
random_state=0)
clf_1.fit(X_train, y_train)
# Number of folds for cross validation
num_folds = 7

def plot_curve(ticks, train_scores, test_scores):
    train_scores_mean = -1 * np.mean(train_scores, axis=1)
    train_scores_std = -1 * np.std(train_scores, axis=1)
    test_scores_mean = -1 * np.mean(test_scores, axis=1)
    test_scores_std = -1 * np.std(test_scores, axis=1)

    plt.figure()
    plt.fill_between(ticks,
                     train_scores_mean - train_scores_std,
                     train_scores_mean + train_scores_std, alpha=0.1,
color="b")
    plt.fill_between(ticks,
                     test_scores_mean - test_scores_std,
                     test_scores_mean + test_scores_std, alpha=0.1,
color="r")
    plt.plot(ticks, train_scores_mean, 'b-', label='Training score')
    plt.plot(ticks, test_scores_mean, 'r-', label='Validation score')
    plt.legend(fancybox=True, facecolor='w')

    return plt.gca()

def plot_validation_curve(clf, X, y, param_name, param_range,
scoring='roc_auc'):
    plt.xkcd()
    ax = plot_curve(param_range, *validation_curve(clf, X, y,
cv=num_folds,
                                                   scoring=scoring,
param_name=param_name,

param_range=param_range, n_jobs=-1))
    ax.set_title('')
    ax.set_xticklabels([])
    ax.set_yticklabels([])
    ax.set_xlim(2,12)
    ax.set_ylim(-0.97, -0.83)
    ax.set_ylabel('Error')
    ax.set_xlabel('Model complexity')
    ax.text(9, -0.94, 'Overfitting', fontsize=22)
    ax.text(3, -0.94, 'Underfitting', fontsize=22)
    ax.axvline(7, ls='--')
    plt.tight_layout()


plot_validation_curve(clf_1, X_train, y_train, param_name='max_depth',
param_range=range(2,13))
```



ROC

https://www.statology.org/plot-roc-curve-python/

```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn import metrics
import matplotlib.pyplot as plt

#import dataset from CSV file on Github
url =
"https://raw.githubusercontent.com/Statology/Python-Guides/main/defaul
t.csv"
data = pd.read_csv(url)

#define the predictor variables and the response variable
X = data[['student', 'balance', 'income']]
y = data['default']

#split the dataset into training (70%) and testing (30%) sets
X_train,X_test,y_train,y_test =
train_test_split(X,y,test_size=0.3,random_state=0)

#instantiate the model
log_regression = LogisticRegression()

#fit the model using the training data
log_regression.fit(X_train,y_train)

LogisticRegression()

#define metrics
y_pred_proba = log_regression.predict_proba(X_test)[::,1]
fpr, tpr, _ = metrics.roc_curve(y_test,  y_pred_proba)

#create ROC curve
plt.plot(fpr,tpr)
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```


TRUE POSITIVE RATE
FALSE POSITIVE RATE
0.0
0.2
0.4
0.6
0.8
1.0
0.0
0.2
0.4
0.6
0.8
1.0

Task 1: Perform all of the above codes of Overfitting, Cross Validation, etc. with the help of the given reference link.

Task 2: Explain your analysis of the code. Make a detailed analysis that can also cover the following questions: (Submit the PDF of Report)

1) According to you, why do overfitting and underfitting occur, and how resolve them? What is the difference between them?

2) What kind of pattern did you analyze in the Train and Test score while running the code of overfitting?

3) What is cross-validation, and what did you analyze in a different type of validation that you performed?

4) Explain the analysis from generated ROC and validation curve and what they represent?

Task 3: Using the given Cross Validation iterators perform all types of Cross Validations we did in the task :

1) K-fold

2) Repeated K-Fold

3) Leave One Out (LOO)

Apart from this three, try to perform validation using three new iterators.

Task 4: With the help of the given code and references complete all of the following step:

1) Choose one new dataset. Train a overfitted model with the help of any machine learning technique, such as KNN, classification, regression.

2) Try to resolve the overfitting.

3) Calculate the Validation score by any two or three given techniques and Validation iterators.

4) Generate the validation curve

5) Predict the output of testing data.

6) Generate the ROC curve using the predicted data and actual data.

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import PolynomialFeatures
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import cross_val_score

from sklearn.datasets import load_wine
X, y = make_classification(n_samples=5000, n_features=20,
n_informative=15)

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, shuffle=True)

print(len(X),len(X_train),len(X_test))

5000 4000 1000

from sklearn.neighbors import KNeighborsClassifier
# Create KNN classifier
knn = KNeighborsClassifier(n_neighbors = 3)
# Fit the classifier to the data
knn.fit(X_train,y_train)

KNeighborsClassifier(n_neighbors=3)

#show first 5 model predictions on the test data
knn.predict(X_test)[0:5]

array([0, 1, 1, 1, 1])

knn.score(X_test, y_test)

0.934

from sklearn.model_selection import ShuffleSplit
n_samples = X.shape[0]
cv = ShuffleSplit(n_splits=5, test_size=0.3, random_state=0)
cross_val_score(clf, X, y, cv=cv)

array([0.74066667, 0.73266667, 0.726     , 0.74866667, 0.72      ])

def custom_cv_2folds(X):
    n = X.shape[0]
    i = 1
    while i <= 2:
        idx = np.arange(n * (i - 1) / 2, n * i / 2, dtype=int)
        yield idx, idx
        i += 1
```

```
custom_cv = custom_cv_2folds(X)
cross_val_score(clf, X, y, cv=custom_cv)
```

```
array([0.748 , 0.7364])
```

```
import numpy as np
from sklearn.model_selection import KFold

X = ["a", "b", "c", "d"]
kf = KFold(n_splits=2)
for train, test in kf.split(X):
     print("%s %s" % (train, test))
```

```
[2 3] [0 1]
[0 1] [2 3]
```

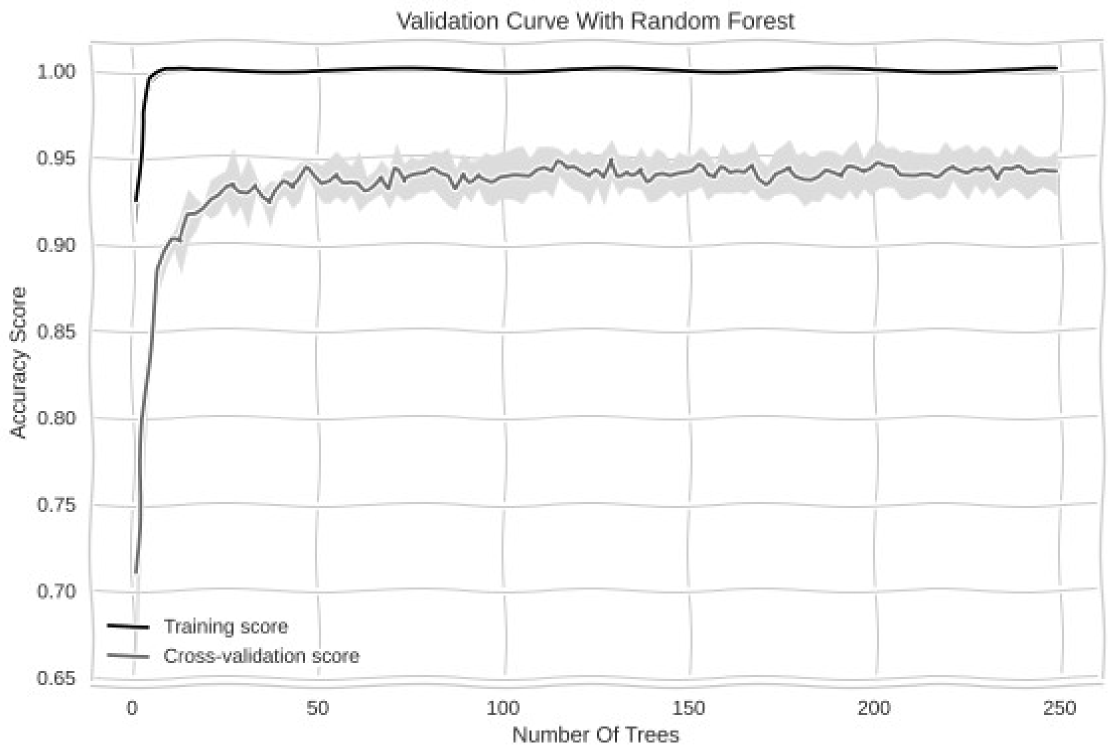
```
import numpy as np
from sklearn.model_selection import RepeatedKFold
X = np.array([[1, 2], [3, 4], [1, 2], [3, 4]])
random_state = 12883823
rkf = RepeatedKFold(n_splits=2, n_repeats=2,
random_state=random_state)
for train, test in rkf.split(X):
    print("%s %s" % (train, test))
```

```
[2 3] [0 1]
[0 1] [2 3]
[0 2] [1 3]
[1 3] [0 2]
```

```
import matplotlib.pyplot as plt
import numpy as np
from sklearn.datasets import load_wine
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import validation_curve

wine = load_wine()

# Create feature matrix and target vector
X, y = wine.data, wine.target

train_scores, test_scores = list(), list()

# define the tree depths to evaluate
values = [i for i in range(1, 31)]

for i in values:
    # configure the model
    model = RandomForestClassifier(max_depth=i)
    # fit model on the training dataset
    model.fit(X_train, y_train)
    # evaluate on the train dataset
    train_yhat = model.predict(X_train)
    train_acc = accuracy_score(y_train, train_yhat)
    train_scores.append(train_acc)
    # evaluate on the test dataset
    test_yhat = model.predict(X_test)
    test_acc = accuracy_score(y_test, test_yhat)
    test_scores.append(test_acc)
    # summarize progress
    print('>%d, train: %.3f, test: %.3f' % (i, train_acc, test_acc))
    plt.show()
```

```
>1, train: 0.903, test: 0.893
>2, train: 0.922, test: 0.909
>3, train: 0.984, test: 0.960
>4, train: 0.996, test: 0.980
>5, train: 0.998, test: 0.987
>6, train: 0.999, test: 0.993
>7, train: 1.000, test: 0.993
>8, train: 1.000, test: 0.993
>9, train: 1.000, test: 0.996
>10, train: 1.000, test: 0.996
>11, train: 1.000, test: 0.993
>12, train: 1.000, test: 0.993
>13, train: 1.000, test: 0.996
>14, train: 1.000, test: 0.991
>15, train: 1.000, test: 0.991
>16, train: 1.000, test: 0.993
>17, train: 1.000, test: 0.991
>18, train: 1.000, test: 0.991
>19, train: 1.000, test: 0.993
>20, train: 1.000, test: 0.987
>21, train: 1.000, test: 0.993
>22, train: 1.000, test: 0.989
>23, train: 1.000, test: 0.996
>24, train: 1.000, test: 0.993
>25, train: 1.000, test: 0.996
>26, train: 1.000, test: 0.996
>27, train: 1.000, test: 0.993
>28, train: 1.000, test: 0.996
>29, train: 1.000, test: 0.993
>30, train: 1.000, test: 0.991
```

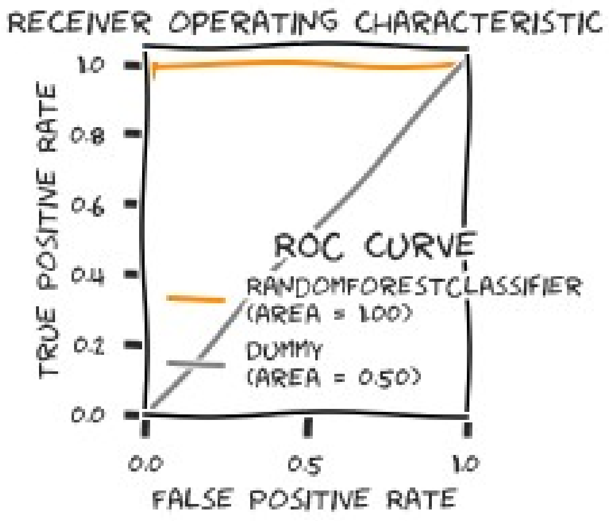
```
param_range = np.arange(1, 250, 2)

# Calculate accuracy on training and test set using range of parameter
values
train_scores, test_scores = validation_curve(RandomForestClassifier(),

                                             X,
                                                             y,

param_name="n_estimators",
                                                             param_range=param_range,
                                                             cv=3,
                                                             scoring="accuracy",
                                                             n_jobs=-1)
# Calculate mean and standard deviation for training set scores
train_mean = np.mean(train_scores, axis=1)
train_std = np.std(train_scores, axis=1)

# Calculate mean and standard deviation for test set scores
test_mean = np.mean(test_scores, axis=1)
test_std = np.std(test_scores, axis=1)

# Plot mean accuracy scores for training and test sets
plt.plot(param_range, train_mean, label="Training score",
color="black")
plt.plot(param_range, test_mean, label="Cross-validation score",
color="dimgrey")

# Plot accurancy bands for training and test sets
plt.fill_between(param_range, train_mean - train_std, train_mean +
train_std, color="gray")
plt.fill_between(param_range, test_mean - test_std, test_mean +
test_std, color="gainsboro")

# Create plot
plt.title("Validation Curve With Random Forest")
plt.xlabel("Number Of Trees")
plt.ylabel("Accuracy Score")
plt.tight_layout()
plt.legend(loc="best")
plt.show()
```



```
from sklearn.datasets import load_wine
wine = load_wine()


from sklearn.naive_bayes import GaussianNB
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(wine.data,
wine.target)
clf = GaussianNB()
clf.fit(X_train, y_train)


GaussianNB()

predicted = clf.predict(X_test)
expected = y_test
print(predicted)

[5 7 1 5 7 7 7 4 7 4 2 0 7 2 7 0 4 3 5 7 7 7 9 9 3 3 3 5 8 5 4 0 5 7 5
9 0
 8 7 2 2 1 6 1 4 6 7 9 6 2 7 1 6 8 7 7 7 7 3 8 2 8 1 8 4 2 0 5 7 7 3 1
8 1
 7 2 7 2 8 7 7 7 4 6 0 5 8 9 8 7 6 0 6 0 1 9 7 4 1 2 0 7 5 6 1 8 8 7 0
8 6
 0 5 6 4 3 5 6 5 0 6 3 7 1 1 3 4 7 6 6 9 8 4 6 6 4 3 2 7 6 6 6 6 3 8 7
8 6
 7 4 2 2 1 6 8 1 8 7 5 3 8 2 8 8 4 2 1 2 7 8 0 6 9 9 8 0 5 0 1 3 7 6 7
5 5
```

```
 7 7 6 0 6 2 2 1 7 4 9 7 9 1 8 8 7 6 8 2 1 7 8 2 2 6 8 2 3 7 9 4 1 4 3
9 6
 8 8 9 0 6 5 9 9 6 6 7 5 6 5 2 8 7 8 7 8 3 7 5 7 8 0 9 4 1 0 3 6 6 0 2
7 4
 8 6 0 7 4 9 1 7 7 2 4 8 9 0 8 6 9 2 1 9 2 1 0 2 0 4 5 9 3 7 3 6 3 8 1
6 5
 1 0 2 8 5 4 6 6 2 1 9 6 1 4 8 3 9 4 5 5 2 4 7 3 3 6 1 2 9 0 9 5 5 0 1
1 6
 5 8 4 9 2 8 2 0 5 4 0 7 4 7 3 2 8 0 6 7 6 5 4 8 5 7 6 0 5 2 3 2 1 7 2
5 7
 1 7 6 4 4 7 0 1 0 1 8 6 5 5 5 5 2 6 7 6 3 2 7 7 3 9 5 4 1 6 8 3 2 2 0
7 2
 8 1 7 4 8 9 2 0 3 1 3 4 8 5 4 8 3 8 1 8 5 7 9 6 3 9 9 9 8 1 3 3 5 0 2
0 4
 4 0 8 7 1 3]
```

```
from sklearn import datasets

from sklearn.linear_model import LogisticRegression
from sklearn.metrics import roc_curve, roc_auc_score
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt

dataset = datasets.load_wine()
X = dataset.data
y = dataset.target

from sklearn import datasets, ensemble, metrics, model_selection,
dummy
import matplotlib.pyplot as plt

wine = datasets.load_wine()

# First we work only on sevens:
sevens = (wine.target == 7)

classifier = ensemble.RandomForestClassifier()
most_frequent = dummy.DummyClassifier(strategy='most_frequent')

X_train, X_test, y_train, y_test = model_selection.train_test_split(
    wine.data, sevens, random_state=0)

y_score = classifier.fit(X_train, y_train).predict_proba(X_test)
most_frequent_score = most_frequent.fit(X_train,
                                        y_train).predict_proba(X_test)

fpr, tpr, _ = metrics.roc_curve(y_test, y_score[:, 1])
roc_auc = metrics.auc(fpr, tpr)

fpr_dummy, tpr_dummy, _ = metrics.roc_curve(y_test,
                                                          most_frequent_score[:, 1])
roc_auc_dummy = metrics.auc(fpr_dummy, tpr_dummy)

plt.figure(figsize=(3, 3))
lw = 2
plt.plot(fpr, tpr, color='darkorange',
         lw=lw, label='RandomForestClassifier\n(area = %0.2f)' %
roc_auc)
plt.plot(fpr_dummy, tpr_dummy, color='.5',
         lw=lw, label='Dummy\n(area = %0.2f)' % roc_auc_dummy)
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic')
plt.legend(loc="lower left", title='ROC curve')
plt.tight_layout()
plt.show()
```


RECEIVER OPERATING CHARACTERISTIC
TRUE POSITIVE RATE
FALSE POSITIVE RATE
ROC CURVE
RANDOMFORESTCLASSIFIER
(AREA = 1.00)
DUMMY
(AREA = 0.50)