Overfitting and Underfitting

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

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.

```
# evaluate knn performance on train and test sets with different numbers of neighbors
from sklearn.datasets import load_breast_cancer
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from matplotlib import pyplot
```

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

```
# create dataset
from sklearn.tree import DecisionTreeClassifier

from sklearn.ensemble import RandomForestClassifier
X, y = load_breast_cancer(return_X_y=True)
# split into train test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3)
# define lists to collect scores
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 = 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))
    # plot of train and test scores vs tree depth
    pyplot.plot(values, train_scores, '-o', label='Train')
    pyplot.plot(values, test_scores, '-o', label='Test')
    pyplot.legend()
    pyplot.show()
```

```
>1, train: 0.940, test: 0.901
>2, train: 0.965, test: 0.942
>3, train: 0.985, test: 0.959
>4, train: 0.985, test: 0.953
>5, train: 0.992, test: 0.953
>6, train: 0.997, test: 0.959
```

2) Try to resolve the overfitting.

The depth of the tree increases, performance on train and test will improve to a point, and as the tree gets too deep, it will begin to overfit the training dataset at the expense of worse performance on the test set.

We would choose a tree depth of 7 before the model begins to overfit the training dataset.

```
>20, train: 1.000, test: 0.959
```

```
values = [i for i in range(1,10)]
# 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: 0.935, test: 0.889
>2, train: 0.955, test: 0.912
>3, train: 0.982, test: 0.918
>4, train: 0.990, test: 0.936
>5, train: 0.997, test: 0.930
>6, train: 1.000, test: 0.924
>7, train: 1.000, test: 0.912
>8, train: 1.000, test: 0.924
>9, train: 1.000, test: 0.918
```

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

```
#basic method is calculate score
model.score(X_test, y_test)
```

```
0.9181286549707602
```

```
# Estimate the accuracy by splitting the data, computing the score 5 consecutive times (with
from sklearn.model_selection import cross_val_score
scores = cross_val_score(model, X, y, cv=5)
scores
```

```
array([0.9122807 , 0.9122807 , 0.92105263, 0.95614035, 0.89380531])
```

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

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

```
#  Using the different scoring parameter
from sklearn import metrics

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

```
array([0.89941445, 0.9066492 , 0.91474865, 0.94345238, 0.89000649])
```

```
#k fold vaidation iterator

import numpy as np
from sklearn.model_selection import KFold

kf = KFold(n_splits=5)
for train, test in kf.split(X):
    print("%s %s" % (train, test))
```

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```

```
#leaveoneout validation iterator
from sklearn.model_selection import LeaveOneOut

loo = LeaveOneOut()
for train, test in loo.split(X):
    print("%s %s" % (train, test))
```

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```

```
#repeated k fold
import numpy as np
from sklearn.model_selection import RepeatedKFold
random_state = 100000
rkf = RepeatedKFold(n_splits=2, n_repeats=2, random_state=random_state)
for train, test in rkf.split(X):
    print("%s %s" % (train, test))
```

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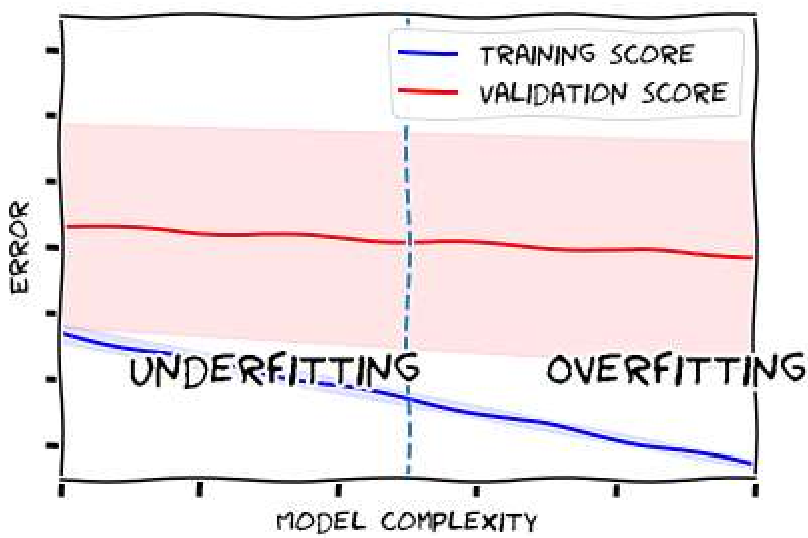
```

4) Generate the validation curve

```
# Number of folds for cross validation
from sklearn.model_selection import validation_curve
ticks = np.logspace(-1,21,20)
train_scores, test_scores = validation_curve(model, X, y, param_name="max_depth", param_range
plot_validation_curve(ticks, train_scores, test_scores)
```




```
def plot_validation_curve(ticks, train_scores, test_scores):
    plt.xkcd()
    ax = plot_curve(ticks, train_scores, test_scores)
    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()
```

```
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()
```

5) Predict the output of testing data.

```
predictions = model.predict(X_test)
correct_predictions = np.nonzero(predictions == y_test)[0]
incorrect_predictions = np.nonzero(predictions != y_test)[0]
print(len(correct_predictions)," classified correctly")
print(len(incorrect_predictions)," classified incorrectly")
```

```
157  classified correctly
14  classified incorrectly
```

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

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

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

```
[1. 0. 1. 0. 1. 1. 1. 0. 1. 1. 1. 0. 1. 0. 1. 1. 1. 1. 0. 1. 1. 1. 1. 1.
 1. 0. 1. 1. 1. 0. 1. 0. 1. 0. 0. 0. 1. 1. 0. 0. 1. 0. 0. 1. 0. 0. 0. 1.
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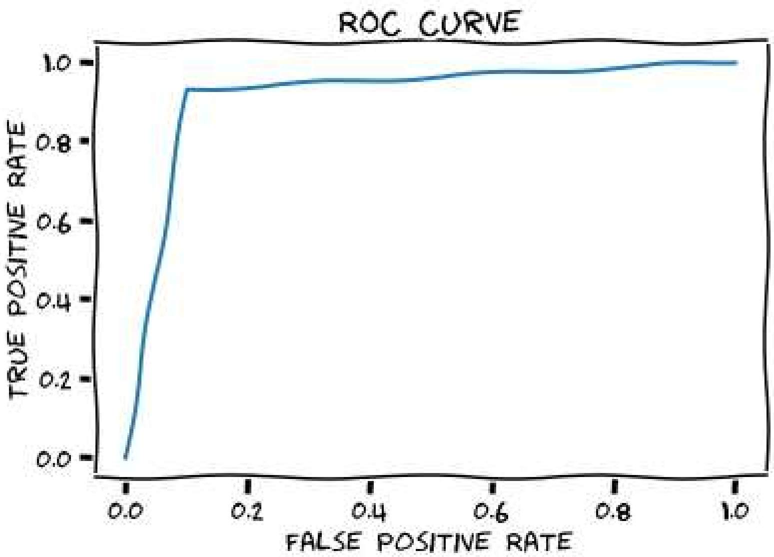

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