Overfitting and Underfitting

[https://scikit-learn.org/stable/auto_examples/model_selection/plot_underfitting_overfitting.html (https://scikit-learn.org/stable/auto_examples/model_selection/plot_underfitting_overfitting.html)](https://scikit-learn.org/stable/auto_examples/model_selection/plot_underfitting_overfitting.html)

Program for understanding Overfitting and Underfitting

In [4]:

```
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
```

In [5]:

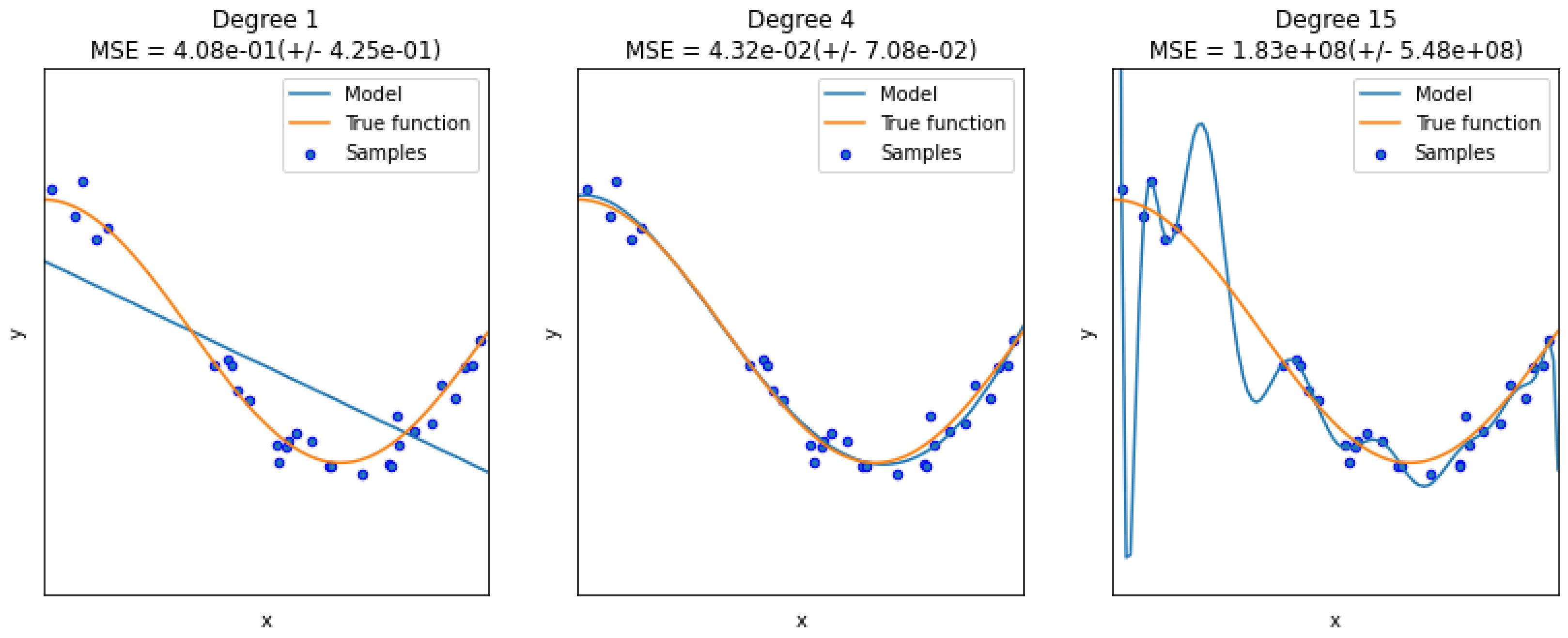
```
def true_fun(X):
    return np.cos(1.5 * np.pi * X)
```

In [6]:

```
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
```

In [7]:

```python
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/ (https://machinelearningmastery.com/overfitting-machine-learning-models/)](https://machinelearningmastery.com/overfitting-machine-learning-models/)

In [8]:

```
# 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
```

In [9]:
```
# 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,)
```

In [10]:
```
# 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,)
```

In [11]:
```
train_scores, test_scores = list(), list()

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

In [12]:

```python
# 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 (https://scikit-learn.org/stable/modules/cross_validation.html)](https://scikit-learn.org/stable/modules/cross_validation.html)

In [10]:

```
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
```

Out[10]:

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

In [22]:
```python
#TASK 4

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

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

Out[22]:
```
((178, 13), (178,))
```

Basic method to compute score

In [11]:
```python
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)
```

Out[11]:
```
0.9666666666666667
```

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

In [12]:
```
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
```

Out[12]:
```
array([0.96666667, 1.        , 0.96666667, 0.96666667, 1.        ])
```

In [13]:
```
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

In [14]:
```
from sklearn import metrics

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

Out[14]:
```
array([0.96658312, 1.        , 0.96658312, 0.96658312, 1.        ])
```

Specified multiple metrics of predefined scorer names

In [15]:
```
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']
```

Out[15]:
```
array([0.96666667, 1.        , 0.96666667, 0.96666667, 1.        ])
```

Calculate cross validation score by passing a cross validation iterator

In [16]:
```
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)
```

Out[16]:
```
array([0.97777778, 0.97777778, 1.        , 0.95555556, 1.        ])
```

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

In [17]:
```
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)
```

Out[17]:
```
array([1.        , 0.97333333])
```

Different type of Cross validation iterators

K-fold

In [18]:
```
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]
```

In [33]:
```
# TASK 4

import numpy as np
from sklearn.model_selection import KFold

X = ["a", "b", "c", "d"]
kf = KFold(n_splits=4)
for train, test in kf.split(X):
    print("%s %s" % (train, test))
```

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

Repeated K-Fold

In [19]:
```
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)

In [20]:
```
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]
```

Validation curve

[https://keeeto.github.io/blog/bias_variance/ (https://keeeto.github.io/blog/bias_variance/)](https://keeeto.github.io/blog/bias_variance/)

[https://scikit-learn.org/stable/modules/learning_curve.html (https://scikit-learn.org/stable/modules/learning_curve.html)](https://scikit-learn.org/stable/modules/learning_curve.html)

In [81]:

```
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
```

In [82]:

```
df_train = pd.read_csv('C:/Users/chepu/OneDrive/Documents/SUBJECTS/FALL 2022/SD for AI/ICE7/Data For Validation Curve
df_test = pd.read_csv('C:/Users/chepu/OneDrive/Documents/SUBJECTS/FALL 2022/SD for AI/ICE7/Data For Validation Curve/
df_comb = df_train.append(df_test)
#df_comb = df_train.concat(df_test)
X = pd.DataFrame()
```

```
C:\Users\chepu\AppData\Local\Temp\ipykernel_9372\1116284294.py:3: FutureWarning: The frame.append method is depreca
ted and will be removed from pandas in a future version. Use pandas.concat instead.
  df_comb = df_train.append(df_test)
```

In [83]:
```python
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)
```

In [84]:
```python
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)
```

In [85]:
```python
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))
```

In [86]:
```python
X_train = X.iloc[:df_train.shape[0]]
X_test = X.iloc[df_train.shape[0]:]

y_train = df_train.Survived
```

In [87]:
```python
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
```

In [88]:
```python
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()
```

In [94]:

```
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()
```

In [95]:

```python
import matplotlib.font_manager
plot_validation_curve(clf_1, X_train, y_train, param_name='max_depth', param_range=range(2,13))
```

```
findfont: Font family 'xkcd Script' not found.
findfont: Font family 'Humor Sans' not found.
findfont: Font family 'Comic Neue' not found.
findfont: Font family 'xkcd' not found.
findfont: Font family 'xkcd Script' not found.
findfont: Font family 'Humor Sans' not found.
findfont: Font family 'Comic Neue' not found.
findfont: Font family 'xkcd' not found.
findfont: Font family 'xkcd Script' not found.
findfont: Font family 'Humor Sans' not found.
findfont: Font family 'Comic Neue' not found.
findfont: Font family 'xkcd' not found.
findfont: Font family 'xkcd Script' not found.
findfont: Font family 'Humor Sans' not found.
findfont: Font family 'Comic Neue' not found.
findfont: Font family 'xkcd' not found.
findfont: Font family 'xkcd Script' not found.
findfont: Font family 'Humor Sans' not found.
findfont: Font family 'Comic Neue' not found.
findfont: Font family 'xkcd' not found.
```

ROC

[https://www.statology.org/plot-roc-curve-python/ (https://www.statology.org/plot-roc-curve-python/)](https://www.statology.org/plot-roc-curve-python/)

In [40]:

```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
```

In [47]:

```python
#import dataset from CSV file on Github
url = "https://raw.githubusercontent.com/Statology/Python-Guides/main/default.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)
```

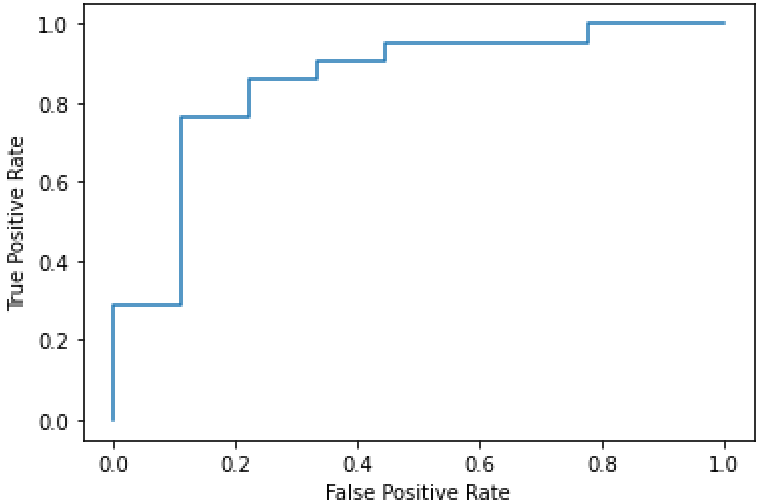
Out[47]:

```
LogisticRegression()
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [42]:

```python
#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)

#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()
```

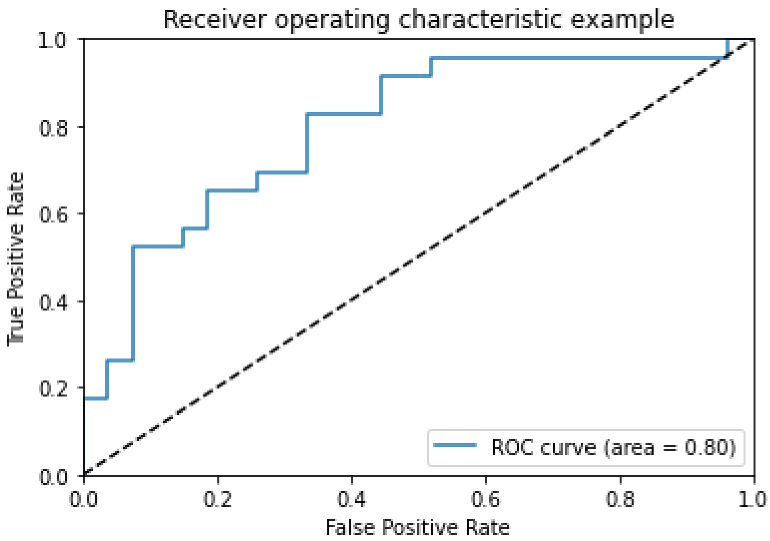


In [38]:

```python
import numpy as np
import pylab as pl
from sklearn import svm, datasets
from sklearn.utils import shuffle
from sklearn.metrics import roc_curve, auc

random_state = np.random.RandomState(0)

# Import some data to play with
iris = datasets.load_iris()
X = iris.data
y = iris.target

# Make it a binary classification problem by removing the third class
X, y = X[y != 2], y[y != 2]
n_samples, n_features = X.shape

# Add noisy features to make the problem harder
X = np.c_[X, random_state.randn(n_samples, 200 * n_features)]

# shuffle and split training and test sets
X, y = shuffle(X, y, random_state=random_state)
half = int(n_samples / 2)
X_train, X_test = X[:half], X[half:]
y_train, y_test = y[:half], y[half:]

# Run classifier
classifier = svm.SVC(kernel='linear', probability=True)
probas_ = classifier.fit(X_train, y_train).predict_proba(X_test)

# Compute ROC curve and area the curve
fpr, tpr, thresholds = roc_curve(y_test, probas_[:, 1])
roc_auc = auc(fpr, tpr)
print('Area under the ROC curve : %f" % roc_auc')

# Plot ROC curve
pl.clf()
pl.plot(fpr, tpr, label='ROC curve (area = %0.2f)' % roc_auc)
pl.plot([0, 1], [0, 1], 'k--')
pl.xlim([0.0, 1.0])
pl.ylim([0.0, 1.0])
```

```
pl.xlabel('False Positive Rate')
pl.ylabel('True Positive Rate')
pl.title('Receiver operating characteristic example')
pl.legend(loc="lower right")
pl.show()
```

```
Area under the ROC curve : %f" % roc_auc
```



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.

TASK 3

In [50]:

```
#Random permutations cross-validation a.k.a. Shuffle & Split
from sklearn.model_selection import ShuffleSplit
X = np.arange(10)
ss = ShuffleSplit(n_splits=5, test_size=0.25, random_state=0)
for train_index, test_index in ss.split(X):
    print("%s %s" % (train_index, test_index))
```

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

In [51]:

```
#Leave One Group Out
from sklearn.model_selection import LeaveOneGroupOut
X = [1, 5, 10, 50, 60, 70, 80]
y = [0, 1, 1, 2, 2, 2, 2]
groups = [1, 1, 2, 2, 3, 3, 3]
logo = LeaveOneGroupOut()
for train, test in logo.split(X, y, groups=groups):
    print("%s %s" % (train, test))
```

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

In [52]:

```
#Leave P Groups Out
from sklearn.model_selection import LeavePGroupsOut
X = np.arange(6)
y = [1, 1, 1, 2, 2, 2]
groups = [1, 1, 2, 2, 3, 3]
lpgo = LeavePGroupsOut(n_groups=2)
for train, test in lpgo.split(X, y, groups=groups):
    print("%s %s" % (train, test))
```

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

TASK 4 - Attached a separate file

In [ ]:

In [ ]: