EE2211 Tutorial 10

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Q1

We have two classifiers showing the same accuracy with the same cross-validation. The more complex model (such as a 9th-order polynomial model) is preferred over the simpler one (such as a 2nd-order polynomial model).

a) True

b) False

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a) True

b) False

Q2

We have 3 parameter candidates for a classification model, and we would like to choose the optimal one for deployment. As such, we run 5-fold cross-validation.

Once we have completed the 5-fold cross-validation, in total, we have trained ________ classifiers. Note that, we treat models with different parameters as different classifiers.

A) 10

B) 20

C) 25

D) 15

Q2

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Once we have completed the 5-fold cross-validation, in total, we have trained ________ classifiers. Note that, we treat models with different parameters as different classifiers.

A) 10

B) 20

C) 25

D) 15

In each fold, we train 3 classifiers, so 5 folds give 15 classifiers.

Q3

Suppose the binary classification problem, which you are dealing with, has highly imbalanced classes. The majority class has 99 hundred samples and the minority class has 1 hundred samples. Which of the following metric(s) would you choose for assessing the classification performance?

a) Classification Accuracy
b) Cost sensitive accuracy
c) Precision and recall
d) None of these

Q3

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a) Classification Accuracy
b) Cost sensitive accuracy
c) Precision and recall
d) None of these

	$\hat{P}$ (predicted)	$\hat{N}$ (predicted)	
P (actual)	TP	FN	Recall TP/(TP+FN)
N (actual)	FP	TN	
	Precision TP/(TP+FP)		Accuracy (TP+TN)/(TP+TN+FP+FN)

Q4

Given below is a scenario for Training error rate Tr, and Validation error rate Va for a machine learning algorithm. You want to choose a hyperparameter (P) based on Tr and Va. Which value of P will you choose based on the above table?

a) 10
b) 9
c) 8
d) 7
e) 6

P	Tr	Va
10	0.10	0.25
9	0.30	0.35
8	0.22	0.15
7	0.15	0.25
6	0.18	0.15

Q4

Given below is a scenario for Training error rate Tr, and Validation error rate Va for a machine learning algorithm. You want to choose a hyperparameter (P) based on Tr and Va. Which value of P will you choose based on the above table?

a) 10
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P	Tr	Va
10	0.10	0.25
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8	0.22	0.15
7	0.15	0.25
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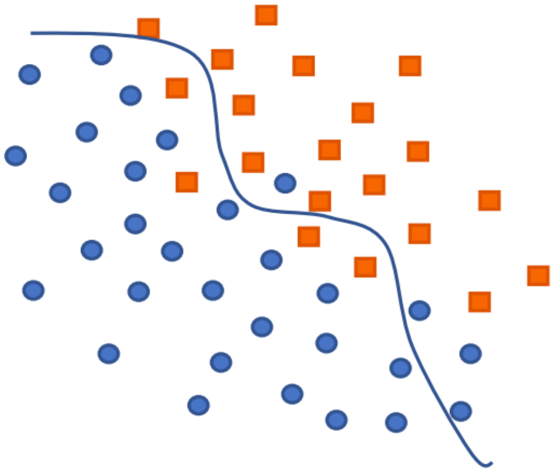
Q5

(Binary and Multicategory Confusion Matrices)

Tabulate the confusion matrices for the following classification problems.

a) Binary problem (the class-1 and class-2 data points are respectively indicated by squares and circles)



Q5

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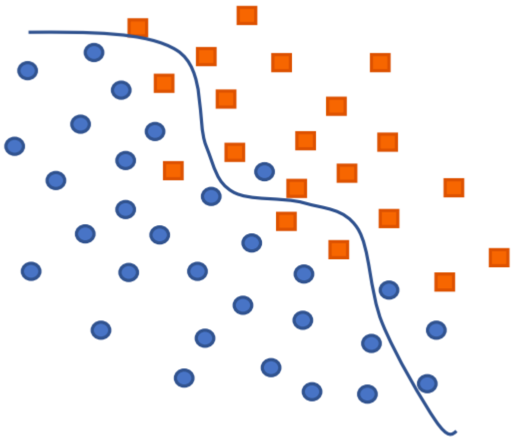
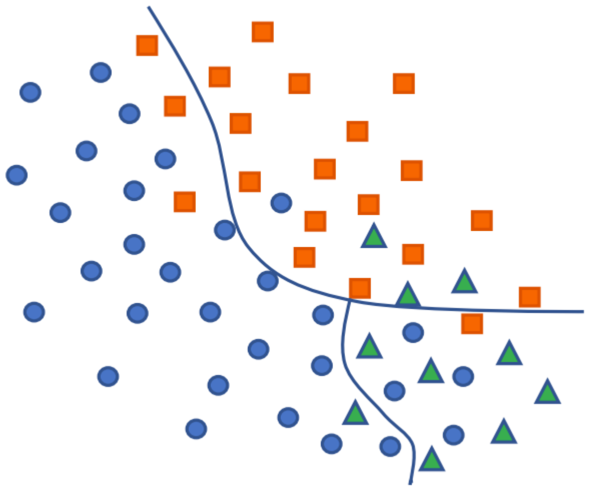


	$P_{\hat{1}}$	$P_{\hat{2}}$
P_1	16	4
P_2	4	26

Q5

Tabulate the confusion matrices for the following classification problems.

b) Three-category problem (the class-1, class-2 and class-3 data points are respectively indicated by squares, circles and triangles)



Q5

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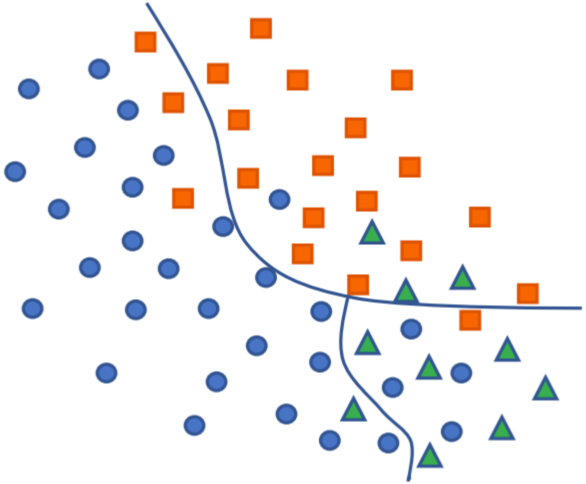


	$P_{\hat{1}}$	$P_{\hat{2}}$	$P_{\hat{3}}$
P_1	16	3	1
P_2	1	25	4
P_3	3	1	6

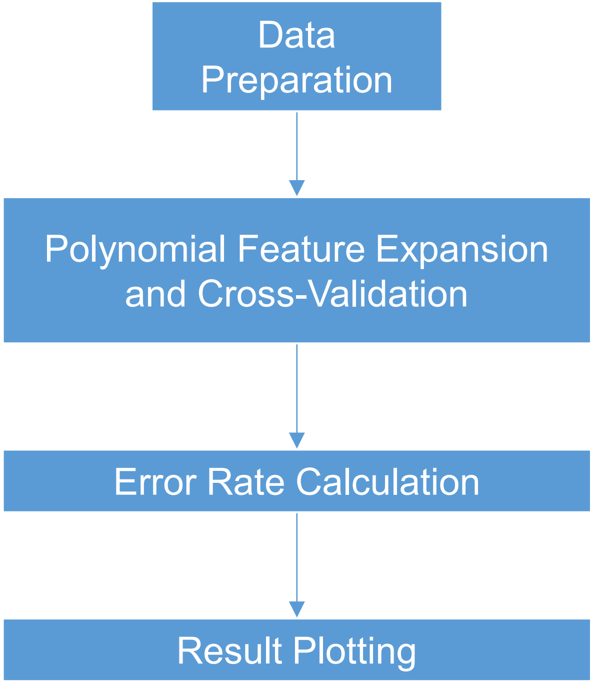
Q6 (python)

(5-fold Cross-Validation)

Get the data set “from sklearn.datasets import load_iris”. Perform a 5-fold Cross-validation to observe the best polynomial order (among orders 1 to 10 and without regularization) for validation prediction. Note that, you will have to partition the whole dataset for training/validation/test parts, where the size of validation set is the same as that of test. Provide a plot of the average 5-fold training and validation error rates over the polynomial orders. The randomly partitioned data sets of the 5-fold shall be maintained for reuse in evaluation of future algorithms

Q6

Block diagram



- One-Hot Encoding
- Data Splitting

- 5-Fold Splitting
- Feature Expansion
- Least-Squares Solution

Q6

```
##--- load data from scikit ---##
import numpy as np
import pandas as pd
print("pandas version: {}".format(pd.__version__))
import sklearn
print("scikit-learn version: {}".format(sklearn.__version__))
from sklearn.datasets import load_iris
iris_dataset = load_iris()
X = np.array(iris_dataset['data'])
y = np.array(iris_dataset['target'])
## one-hot encoding
Y = list()
for i in y:
    letter = [0, 0, 0]
    letter[i] = 1
    Y.append(letter)
Y = np.array(Y)
test_Idx = np.random.RandomState(seed=2).permutation(Y.shape[0])
X_test = X[test_Idx[:25]]
Y_test = Y[test_Idx[:25]]
X = X[test_Idx[25:]]
Y = Y[test_Idx[25:]]
```

- One-Hot Encoding: The target variable, y, is converted to a one-hot encoding format (Y) for each class (e.g., [1,0,0] for class 0, [0,1,0] for class 1, etc.).

- Data Splitting: The dataset is split into training (X and Y) and test sets (X_test and Y_test). The test set contains 25 samples randomly selected, and the rest are used for training.

Q6

```
from sklearn.preprocessing import PolynomialFeatures
error_rate_train_array = []
error_rate_val_array = []
##--- Loop for Polynomial orders 1 to 10 ---##
for order in range(1,11):
    error_rate_train_array_fold = []
    error_rate_val_array_fold = []
    # Random permutation of data
    Idx = np.random.RandomState(seed=8).permutation(Y.shape[0])
    # Loop 5 times for 5-fold
    for k in range(0,5):
        ##--- Prepare training, validation, and test data for the 5-fold ---#
        # Prepare indexing for each fold
        X_val = X[Idx[k*25:(k+1)*25]]
        Y_val = Y[Idx[k*25:(k+1)*25]]
        Idxtrn = np.setdiff1d(Idx, Idx[k*25:(k+1)*25])
        X_train = X[Idxtrn]
        Y_train = Y[Idxtrn]
```

The code performs polynomial classification by expanding features to polynomial forms of varying degrees (1 to 10). For each polynomial order, it uses 5-fold cross-validation:

- 5-Fold Splitting: For each fold, the code separates 25 samples for validation and the remaining samples for training.

Q6

```python
##--- Polynomial Classification ---##
poly = PolynomialFeatures(order)
P = poly.fit_transform(X_train)
Pval = poly.fit_transform(X_val)
if P.shape[0] > P.shape[1]: # over-/under-determined cases
    reg_L = 0.00*np.identity(P.shape[1])
    inv_PTP = np.linalg.inv(P.transpose().dot(P)+reg_L)
    pinv_L = inv_PTP.dot(P.transpose())
    wp = pinv_L.dot(Y_train)
else:
    reg_R = 0.00*np.identity(P.shape[0])
    inv_PPT = np.linalg.inv(P.dot(P.transpose())+reg_R)
    pinv_R = P.transpose().dot(inv_PPT)
    wp = pinv_R.dot(Y_train)
```

- Feature Expansion: Using PolynomialFeatures, the input features are expanded to the specified polynomial order.
- Least-Squares Solution: It calculates weights wp to fit the model by solving a system of equations based on whether the system is overdetermined or underdetermined.

Q6

```python
    ##--- trained output ---##
    y_est_p = P.dot(wp);
    y_cls_p = [[1 if y == max(x) else 0 for y in x] for x in y_est_p ]
    m1tr = np.matrix(Y_train)
    m2tr = np.matrix(y_cls_p)
    # training classification error count and rate computation
    difference = np.abs(m1tr - m2tr)
    error_train = np.where(difference.any(axis=1))[0]
    error_rate_train = len(error_train)/len(difference)
    error_rate_train_array_fold += [error_rate_train]
    ##--- validation output ---##
    yval_est_p = Pval.dot(wp);
    yval_cls_p = [[1 if y == max(x) else 0 for y in x] for x in yval_est_p ]
    m1 = np.matrix(Y_val)
    m2 = np.matrix(yval_cls_p)
    # validation classification error count and rate computation
    difference = np.abs(m1 - m2)
    error_val = np.where(difference.any(axis=1))[0]
    error_rate_val = len(error_val)/len(difference)
    error_rate_val_array_fold += [error_rate_val]
# store results for each polynomial order
error_rate_train_array += [np.mean(error_rate_train_array_fold)]
error_rate_val_array += [np.mean(error_rate_val_array_fold)]
```

For each fold and polynomial order:

- The code evaluates predictions on both training and validation sets.
- For both sets, it computes the classification error rate as the proportion of incorrectly classified samples.

Q6


Training and Validation Error Rates
Training
Validation
0.0
0.1
0.2
0.3
0.4
0.5
0.6
Error Rates
2
4
6
8
10
Order

THANK YOU