

DSO530 Statistical Learning Methods

Lecture 4a: Classification IV

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Review question 1

Recall that a linear classifier means that its decision boundary is linear. Please show that logistic regression gives us linear classifiers. Concretely, show the classifier

$$1 \left(\frac{e^{3+9x_1+5x_2}}{1 + e^{3+9x_1+5x_2}} > 0.8 \right)$$

has a linear decision boundary.

Review question 2

What is the linear discriminant analysis model?

Review question 3

Is the following claim TRUE or FALSE: “As I collect more and more observations, I can usually achieve (close to) perfect classification.”

Review question 4

Is the following claim TRUE or FALSE: “For logistic regression, when I increase the decision threshold from 0.5 to 0.6, the type I error will increase as well”

K-nearest neighbors (KNN)

- 'KNN': to predict class label for an observation $X = x$, the K training observations that are closest to x are identified. Then x is assigned to the class to which the plurality of these observations belong
- Why did we say "plurality" instead of *majority*?
- Can predict the class label for any $x \in R^p$ (including the training observations) in this way
- Special cases: $K = 1$ and $K = n$
- KNN is a very different approach to classification. Can you name some differences from logistic regression and LDA?
- On training dataset, which choice of K gives the smallest error? Will you choose this K ?
- In general, as K increases, how will **training error** change? What about **test error**?
- Does KNN have linear decision boundaries?

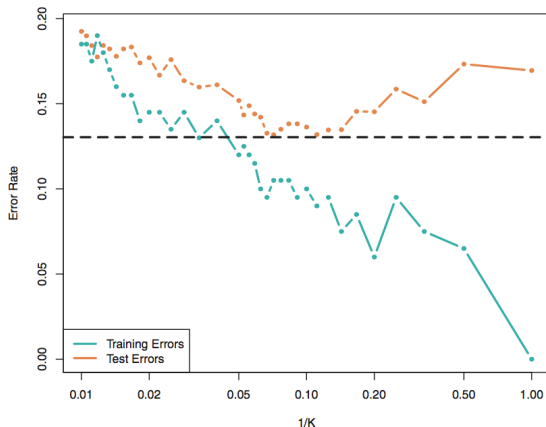


FIGURE 2.17. The KNN training error rate (blue, 200 observations) and test error rate (orange, 5,000 observations) on the data from Figure 2.13, as the level of flexibility (assessed using $1/K$) increases, or equivalently as the number of neighbors K decreases. The black dashed line indicates the Bayes error rate. The jumpiness of the curves is due to the small size of the training data set.

Figure 1: Training and test errors vs. $1/K$

```

import numpy as np
import pandas as pd
url="https://archive.ics.uci.edu/ml/machine-learning-databases/iris/iris.data"
# Assign colum names to the dataset
names = ['sepal-length', 'sepal-width', 'petal-length', 'petal-width', 'Class']
# Read dataset to pandas dataframe
dataset = pd.read_csv(url, names=names); dataset.head()

```

##	sepal-length	sepal-width	petal-length	petal-width	Class
## 0	5.1	3.5	1.4	0.2	Iris-setosa
## 1	4.9	3.0	1.4	0.2	Iris-setosa
## 2	4.7	3.2	1.3	0.2	Iris-setosa
## 3	4.6	3.1	1.5	0.2	Iris-setosa
## 4	5.0	3.6	1.4	0.2	Iris-setosa

- This is perhaps the best known database to be found in the pattern recognition literature. The data set contains 3 classes of 50 instances each, where each class refers to a type of iris plant. One class is linearly separable from the other 2; the latter are NOT linearly separable from each other.


```
np.unique(dataset["Class"])
```

```
## array(['Iris-setosa', 'Iris-versicolor', 'Iris-virginica'], dtype=object)
```

```
dataset.info()
```

```
## <class 'pandas.core.frame.DataFrame'>
## RangeIndex: 150 entries, 0 to 149
## Data columns (total 5 columns):
## sepal-length      150 non-null float64
## sepal-width       150 non-null float64
## petal-length      150 non-null float64
## petal-width       150 non-null float64
## Class             150 non-null object
## dtypes: float64(4), object(1)
## memory usage: 6.0+ KB
```

```
dataset.describe()
```

	sepal-length	sepal-width	petal-length	petal-width
## count	150.000000	150.000000	150.000000	150.000000
## mean	5.843333	3.054000	3.758667	1.198667
## std	0.828066	0.433594	1.764420	0.763161
## min	4.300000	2.000000	1.000000	0.100000
## 25%	5.100000	2.800000	1.600000	0.300000
## 50%	5.800000	3.000000	4.350000	1.300000
## 75%	6.400000	3.300000	5.100000	1.800000
## max	7.900000	4.400000	6.900000	2.500000

- The four predictors are on the same scale
- In the slides, we will not use feature rescaling. After you go home, please try the feature rescaling step and see if the result becomes better.

```
from sklearn.model_selection import train_test_split
X = dataset.iloc[:, :-1].values
y = dataset.iloc[:, 4].values
X_train, X_test, y_train, y_test=\
    train_test_split(X, y, test_size=0.20, random_state=5, stratify=y)

from sklearn.neighbors import KNeighborsClassifier
classifier = KNeighborsClassifier(n_neighbors=5)
classifier.fit(X_train, y_train)

## KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
##                      metric_params=None, n_jobs=None, n_neighbors=5, p=2,
##                      weights='uniform')
```

- There are many default parameters here. We just pay attention to weights.

```
y_pred = classifier.predict(X_test)
np.mean(y_pred != y_test)
```

```
## 0.03333333333333333
```

- After you go home, try practice different settings, such as `random_state=100`, `n_neighbors = 3`, `n_neighbors = 7`

Understanding different errors

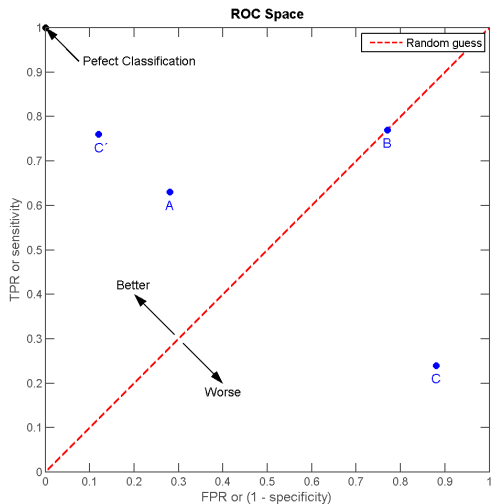
		<i>Predicted class</i>		
		– or Null	+ or Non-null	Total
<i>True class</i>	– or Null	True Neg. (TN)	False Pos. (FP)	N
	+ or Non-null	False Neg. (FN)	True Pos. (TP)	P
	Total	N*	P*	

Figure 2

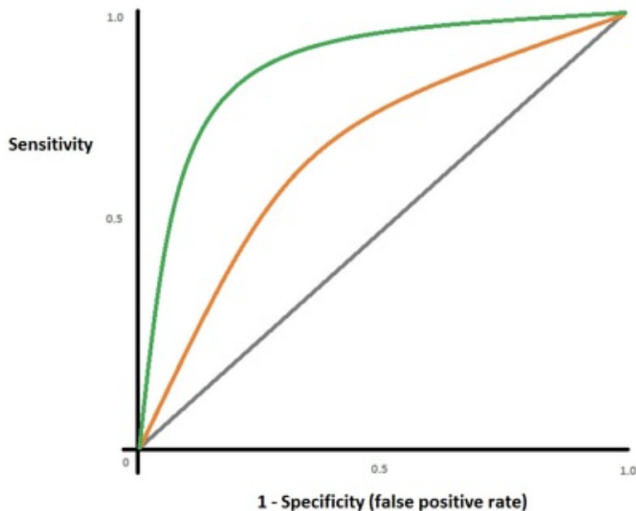
Name	Definition	Synonyms
False Pos. rate	FP/N	Type I error, 1–Specificity
True Pos. rate	TP/P	1–Type II error, power, sensitivity, recall
Pos. Pred. value	TP/P*	Precision, 1–false discovery proportion
Neg. Pred. value	TN/N*	

Figure 3

Receiver operating characteristic (ROC) space



Receiver operating characteristic (ROC) curves



- Which curve is better? One way to judge: area under the curve (AUC)

Data science vs. statistics

- Optional and for fun only
- https://www.youtube.com/watch?v=uHGICi9jOWY&feature=youtu.be&fbclid=IwAR1tTAIEhgUrHk815BIMj0PxC8XYRLz62pA_V6C__xSWXk3ZAF8uoj9l0JQ
- In some sense, the first half of DSO 530 is more of statistics, and the second half is more data science (machine learning)