

Machine Learning

Dr Changjiang He, Dr Kuo-Ming Chao
Computer Science | School of Art
University of Roehampton

Lesson 4.2

Evaluation of Classification

Evaluation of Classification: Confusion Matrix

Confusion Matrix

A confusion matrix shows the number of correct and incorrect predictions made by the classification model compared to the actual outcomes (target value) in the data. The matrix is $N \times N$, where N is the number of target values (classes).

Performance of such models is commonly evaluated using the data in the matrix. The following table displays a 2×2 confusion matrix for two classes (Positive and Negative).

Confusion Matrix		Target			
		Positive	Negative		
Model	Positive	a	b	<i>Positive Predictive Value</i>	$a/(a+b)$
	Negative	c	d	<i>Negative Predictive Value</i>	$d/(c+d)$
		<i>Sensitivity</i>	<i>Specificity</i>	Accuracy = $(a+d)/(a+b+c+d)$	
		$a/(a+c)$	$d/(b+d)$		

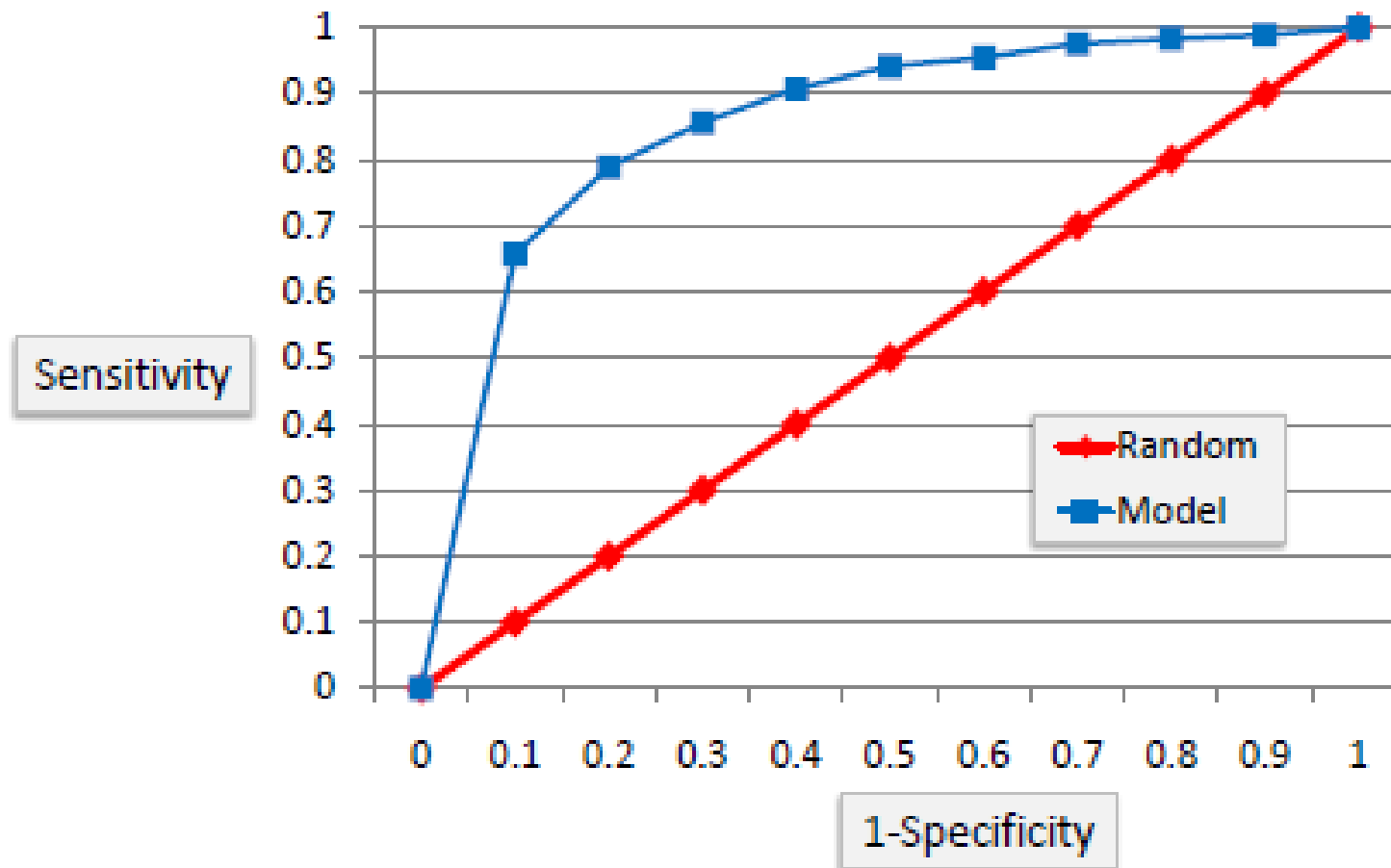
- **Accuracy:** the proportion of the total number of predictions that were correct.
- **Positive Predictive Value or Precision:** the proportion of positive cases that were correctly identified.
- **Negative Predictive Value:** the proportion of negative cases that were correctly identified.
- **Sensitivity or Recall:** the proportion of actual positive cases which are correctly identified.
- **Specificity:** the proportion of actual negative cases which are correctly identified.

Evaluation of Classification: Confusion Matrix

Confusion Matrix		Target			
		Positive	Negative		
Model	Positive	70	20	<i>Positive Predictive Value</i>	0.78
	Negative	30	80	<i>Negative Predictive Value</i>	0.73
		<i>Sensitivity</i>	<i>Specificity</i>	Accuracy = 0.75	
		0.70	0.80		

Confusion Matrix		Target			
		Positive	Negative		
Model	Positive	a	b	<i>Positive Predictive Value</i>	$a/(a+b)$
	Negative	c	d	<i>Negative Predictive Value</i>	$d/(c+d)$
		<i>Sensitivity</i>	<i>Specificity</i>	Accuracy = $(a+d)/(a+b+c+d)$	
		$a/(a+c)$	$d/(b+d)$		

Evaluation of Classification: ROC



The ROC chart provides a means of comparison between classification models.

The ROC chart shows false positive rate on X-axis, the probability of target=1 when its true value is 0, against true positive rate on Y-axis, the probability of target=1 when its true value is 1.

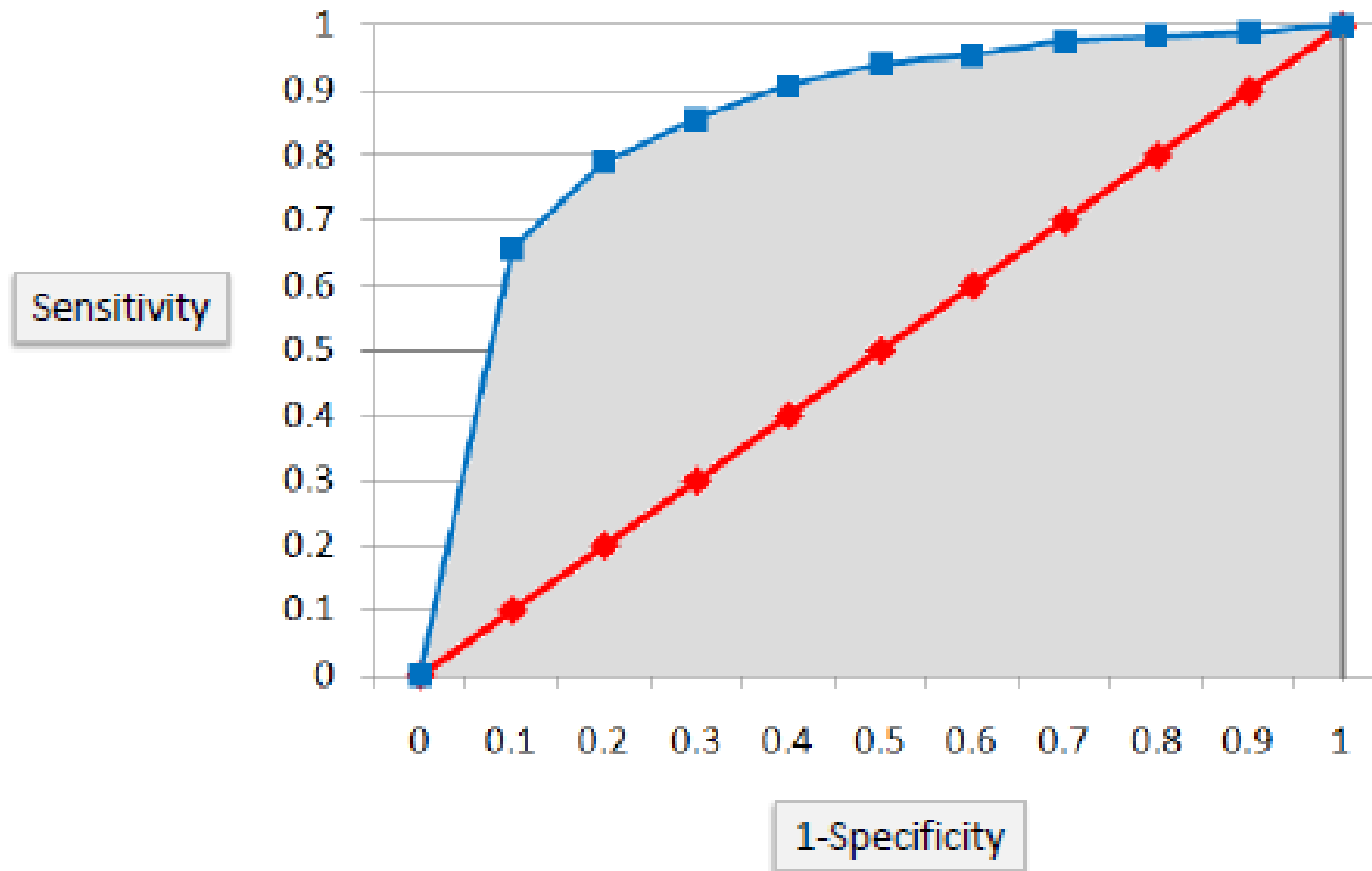
Ideally, the curve will climb quickly toward the top-left meaning the model has correct predictions.

Furthermore, the diagonal red line is for a random model.

Area Under the Curve (AUC)

The area under the ROC curve is often a measure of the quality of the classification models. A random classifier has an area under the curve of 0.5, while AUC for a perfect classifier is equal to 1. In practice, most of the classification models have an AUC between 0.5 and 1.

Evaluation of Classification: AUC



An area under the ROC curve of 0.8, for example, means that a randomly selected case from the group with the target equals 1 has a score larger than that for a randomly chosen case from the group with the target equals 0 in 80% of the time. Furthermore, when a classifier cannot distinguish between the two groups, the area will be equal to 0.5 (will coincide with the diagonal). Also, when there is a perfect separation of the two groups, i.e., no overlapping of the distributions, the area under the ROC curve reaches to 1 (the ROC curve will reach the upper left corner of the plot).