



CSE 435 Pattern Recognition

ROC curves

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A large crowd of people is gathered at a night concert. The stage is illuminated with bright blue and white lights, and a large amount of white confetti is being thrown into the air, creating a dense cloud of particles. The crowd is seen from behind, looking towards the stage. The image is framed by a white circular border.

No, it is not “Rock’n’Roll!”

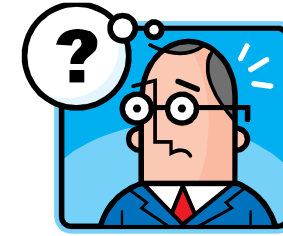
ROC curves



(Receiver Operating Characteristics)

- Positive and negative classes. Type I and Type II errors
- Sensitivity, Specificity, Recall, Precision
- Why is accuracy not sufficient? F1 measure
- Face detection example
- ROC curves

Recall: Confusion matrix



Guessed labels (assigned by D)

True labels

	ω_1		ω_j		ω_c
ω_1	a_{11}				
ω_i		...	a_{ij}		
ω_c					

The number of elements of the testing set whose true label is ω_i and D has assigned them to ω_j

Positives and negatives for a binary TEST

True	Assigned	
	Guilty (+)	Innocent (-)
	Guilty (+)	Innocent (-)
	TP Convict the guilty	FN Free the guilty
	FP Convict the innocent	TN Free the innocent

Positives and negatives for a binary TEST

True	Assigned	
	Disease (positive)	Healthy (negative)
	Disease (positive)	Healthy (negative)
	TP (true positives)	FN (false negatives)
	FP (false positives)	TN (true negative)

Positives and negatives for a binary TEST

True	Assigned	
	Disease (positive)	Healthy (negative)
	Disease (positive)	Healthy (negative)
	TP (true positives)	TYPE I ERROR
	TYPE II ERROR	TN (true negative)

Positives and negatives for a binary TEST

True	Assigned	
	Disease (positive)	Healthy (negative)
	Disease (positive)	Healthy (negative)
	TP (true positives)	FN (false negatives)
	FP (false positives)	TN (true negative)

Sensitivity of the test = $TP / (TP + FN)$

Specificity of the test = $TN / (TN + FP)$

Recall = Sensitivity of the test = $TP / (TP + FN)$

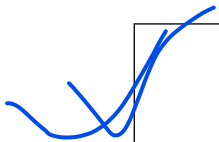
Precision = $TP / (TP + FP)$

Accuracy of the test = $(TP + TN) / (TP + TN + FP + FN)$

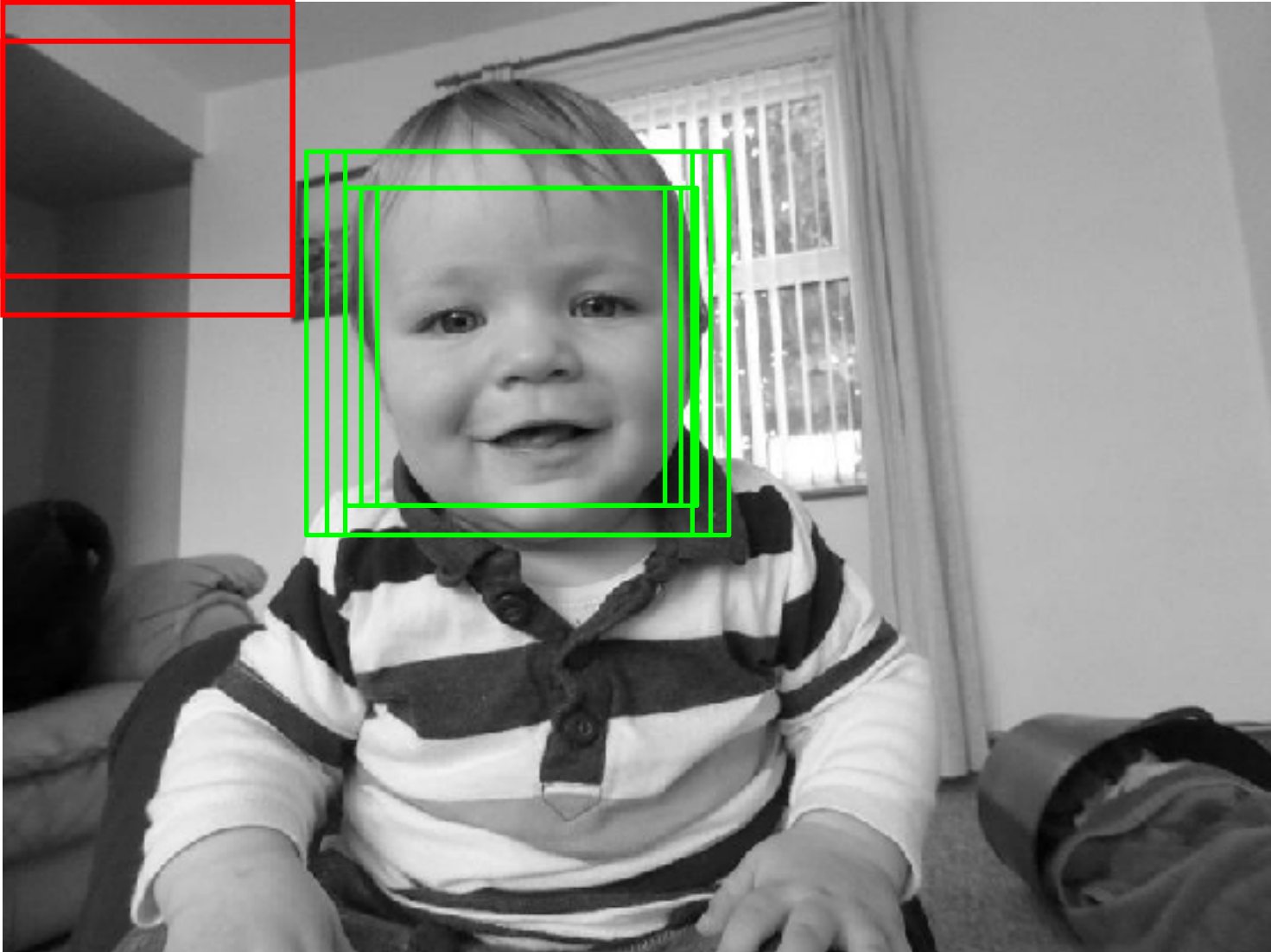
Why is ACCURACY not sufficient?

Sometimes the number of negative cases is much greater than the number of positive cases. This is the usual case in medical screening for a rare disease. **UNBALANCED CLASS PROBLEM**

Suppose there are 1000 cases, 995 of which are negative cases and 5 of which are positive cases. If the system classifies them all as negative, the accuracy would be 99.5%, even though the classifier missed all positive cases. An alternative performance measure that accounts for this is based on the harmonic mean of precision and recall


$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Example of unbalanced classes: face detection



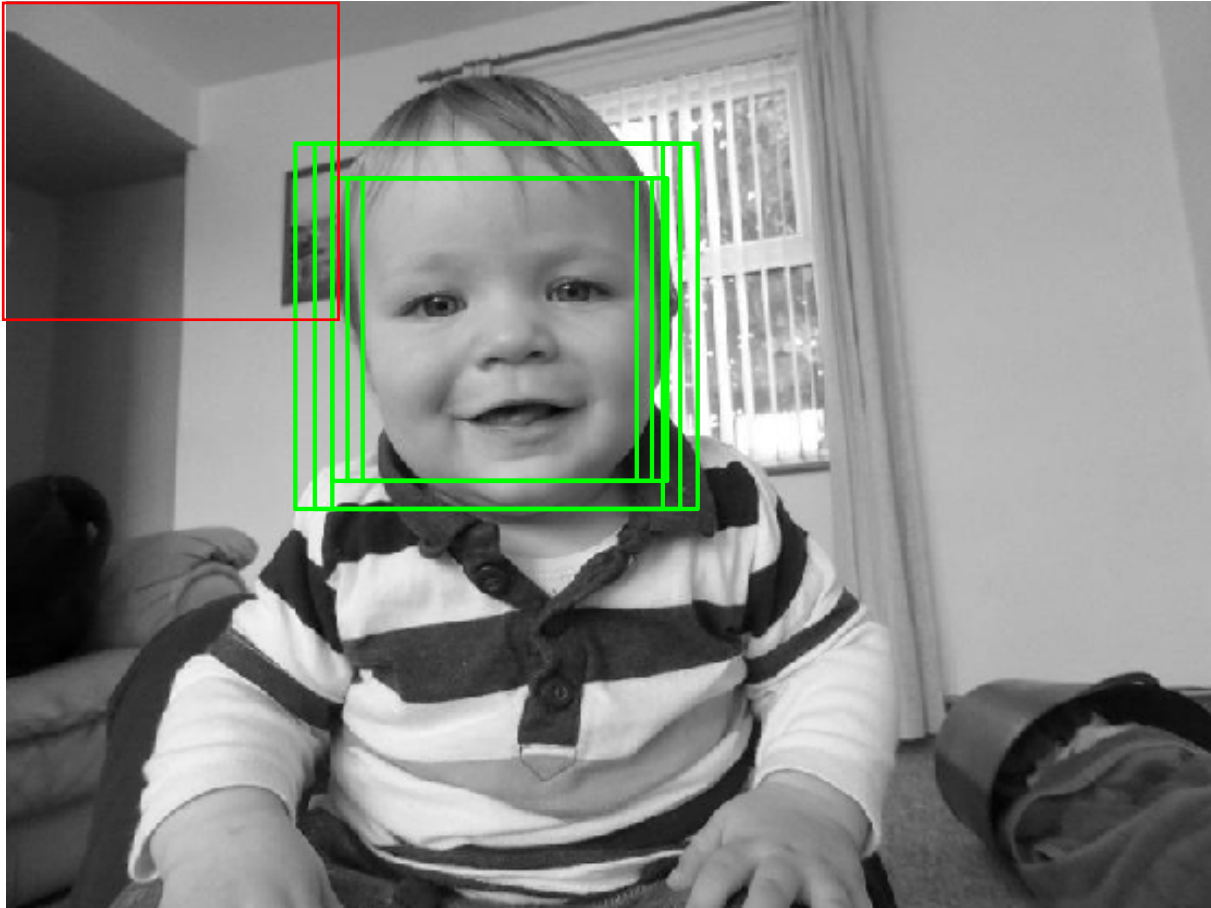
Prepare a data set
from this image

$c = 2$ classes:
"face" and "no face"

objects = squares of
a fixed size cropped
from the image

features = any set of
features extracted
from the square

Example of unbalanced classes: face detection



Square 25x25

Image size:
79x118

Positives: 6

Q1.
How many negatives are
there?

Suppose that we have a data set (obtained from images with faces) and a classifier D_{proper} .

		Assigned	
		Face (positive)	No face (negative)
True	Face (positive)	96	9
	No face (negative)	3,505	99,790

Total number of objects, $N = 96 + 9 + 3,505 + 99,790 = 103,400$

Sensitivity, $Sens = \frac{96}{105} = 0.9143$

Specificity, $Spec = \frac{99,790}{103,295} = 0.9659$

Accuracy

$$Acc = \frac{96 + 99,790}{103,400} = \mathbf{0.9660}$$

Suppose that we have a data set (obtained from images with faces) and a classifier D_{proper} .

True	Assigned	
	Face (positive)	No face (negative)
	Face (positive)	No face (negative)
Face (positive)	96	9
No face (negative)	3,505	99,790

Total number of objects, $N = 96 + 9 + 3,505 + 99,790 = 103,400$

$$\text{Recall} = \frac{96}{105} = 0.9143$$

$$\text{Precision} = \frac{96}{3,601} = 0.0267$$

F1 measure

$$F_1 = 2 \times \frac{0.9143 \times 0.0267}{0.9143 + 0.0267} = \mathbf{0.0519}$$

Now suppose that we have a classifier $D_{Negative}$ which **always** predicts “no face”

		Assigned	
		Face (positive)	No face (negative)
True	Face (positive)	0	105
	No face (negative)	0	103,295

Total number of objects, $N = 96 + 9 + 3,505 + 99,790 = 103,400$

Sensitivity, $Sens = \frac{0}{105} = 0$

Specificity, $Spec = \frac{103,295}{103,295} = 1$

Accuracy

$$Acc = \frac{103,295}{103,400} = \mathbf{0.9990}$$

Now suppose that we have a classifier $D_{Negative}$ which **always** predicts “no face”

		Assigned	
		Face	No face
True	Face (positive)	Is this a better classifier then?	
	No face (negative)	0	103,295

Total number of objects, $N = 96 + 9 + 3,505 + 99,790 = 103,400$

$$\text{Sensitivity, } Sens = \frac{0}{105} = 0$$

$$\text{Specificity, } Spec = \frac{103,295}{103,295} = 1$$

Accuracy

$$Acc = \frac{103,295}{103,400} = \mathbf{0.9990}$$

Now suppose that we have a classifier $D_{Negative}$ which **always** predicts “no face”

		Assigned	
		Face (positive)	No face (negative)
True	Face (positive)	0	105
	No face (negative)	0	103,295

Total number of objects, $N = 96 + 9 + 3,505 + 99,790 = 103,400$

$$\text{Recall} = \frac{0}{105} = 0$$

Precision = does not exist because there are no positive labels. But even if there were, and even if precision was equal to 1, $F_1 = 2 \times \frac{0 \times 1}{0 + 1} = 0$.

Compare:

D_{Proper}

Accuracy

$Acc = 0.9660$

$F_1 = 0.0519$

D_{Negative}

Accuracy

$Acc = 0.9990$

$F_1 = 0.0000$

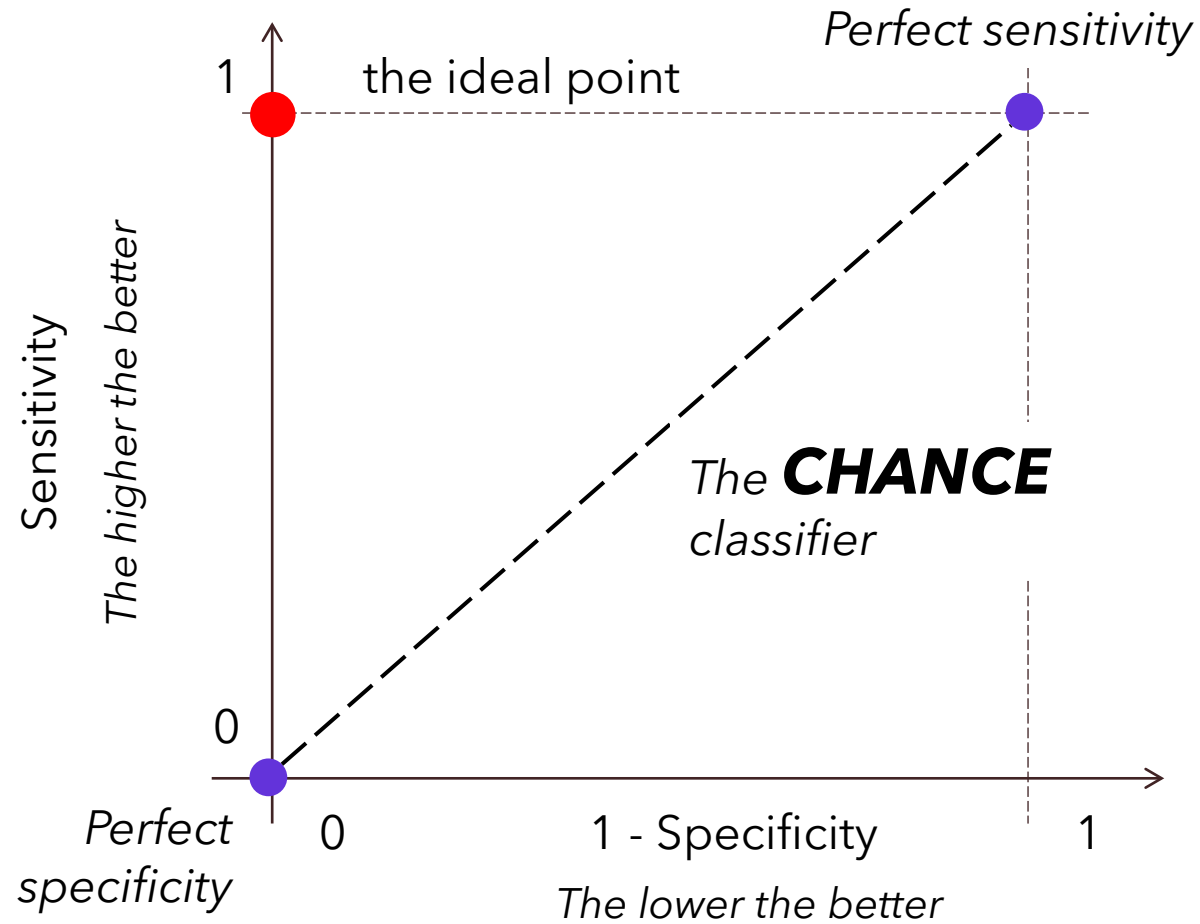
ROC curves

(**R**eciever **O**perating **C**haracteristic)

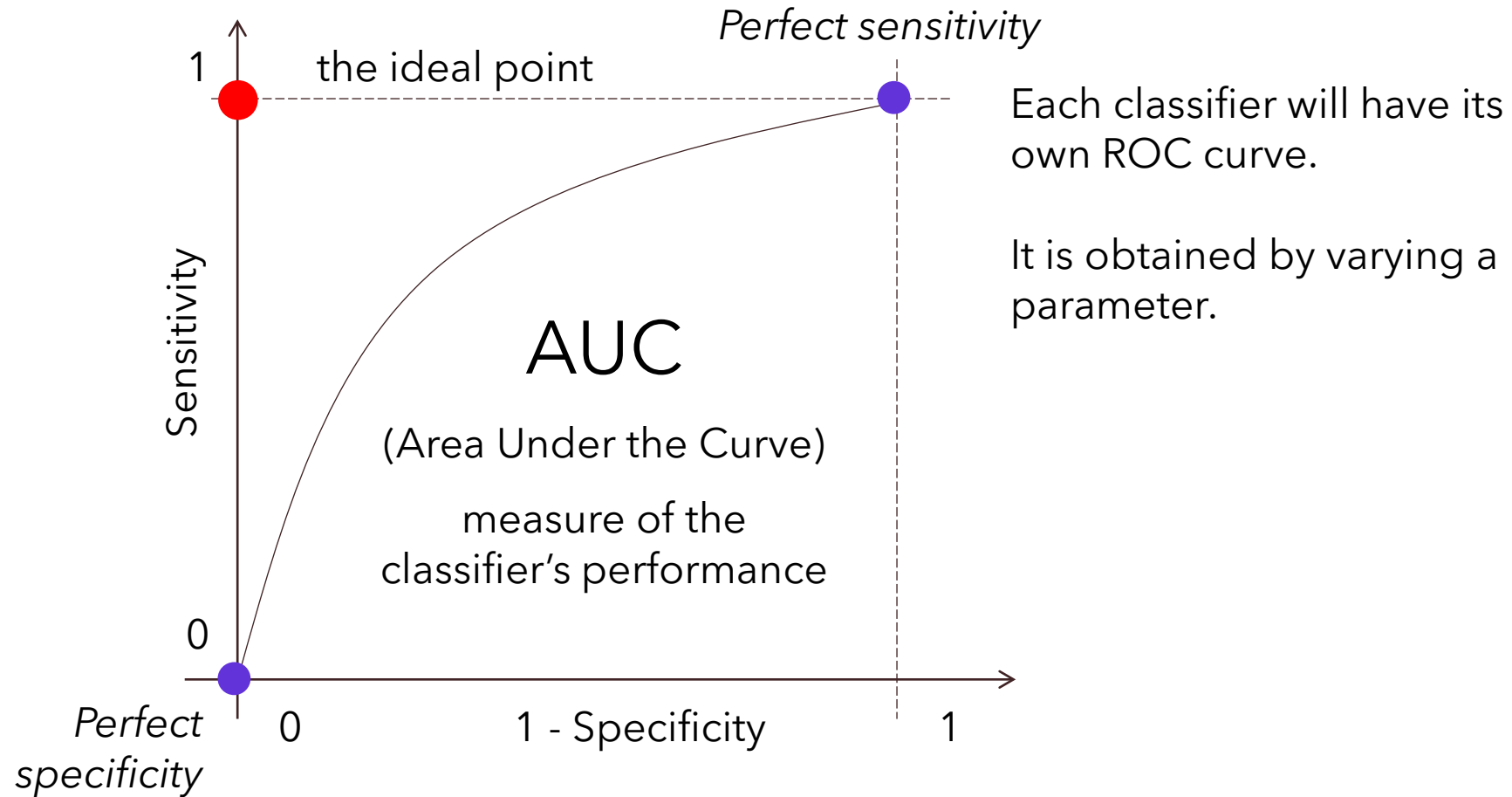
ROC curve is a graphical plot that illustrates the performance of a binary classifier (two classes).



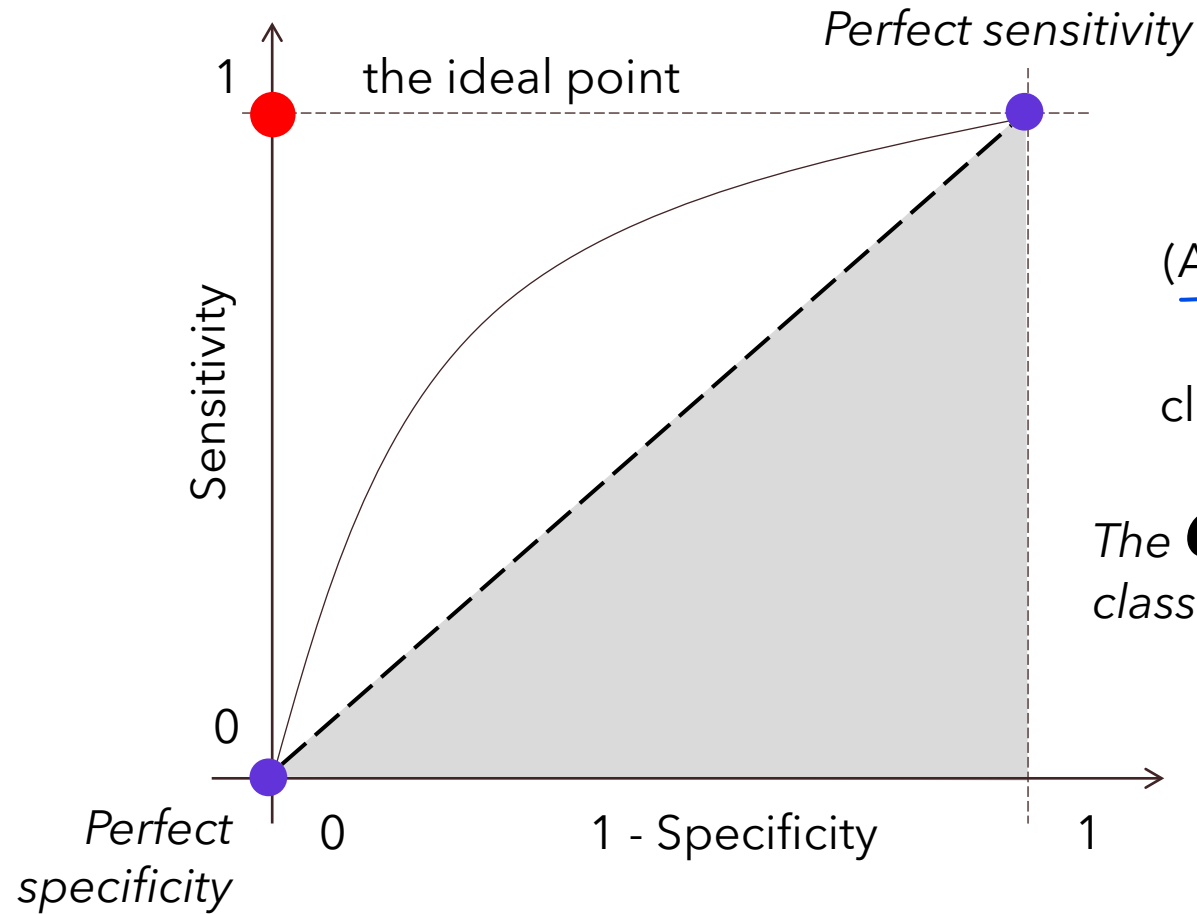
ROC curves (**R**eceiver **O**perating **C**haracteristic)



ROC curves (**R**eciever **O**perating **C**haracteristic)



ROC curves (**R**eceiver **O**perating **C**haracteristic)



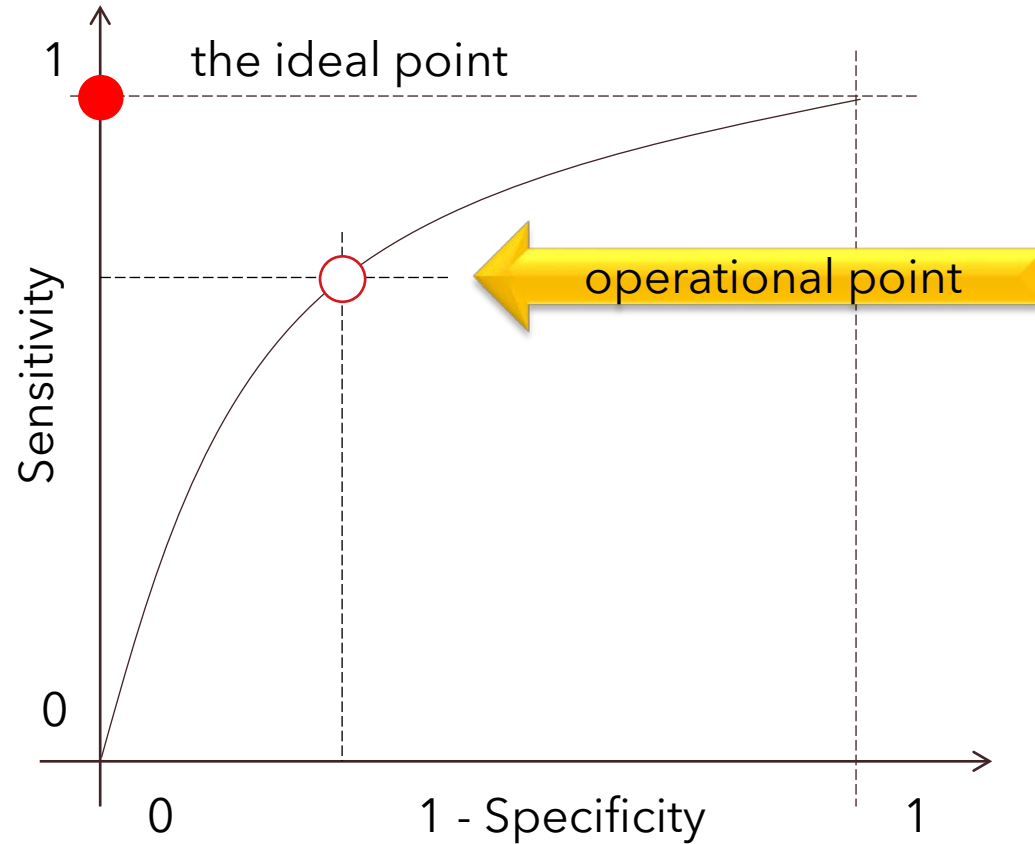
AUC

(Area Under the Curve)

measure of the
classifier's performance

The **CHANCE**
classifier has $AUC = 0.5$

ROC curves (Receiver Operating Characteristic)



	Disease +	Healthy -
Disease +	10	4
Healthy -	8	13

$$\text{Sensitivity} = 10/14 = \mathbf{71.4\%}$$

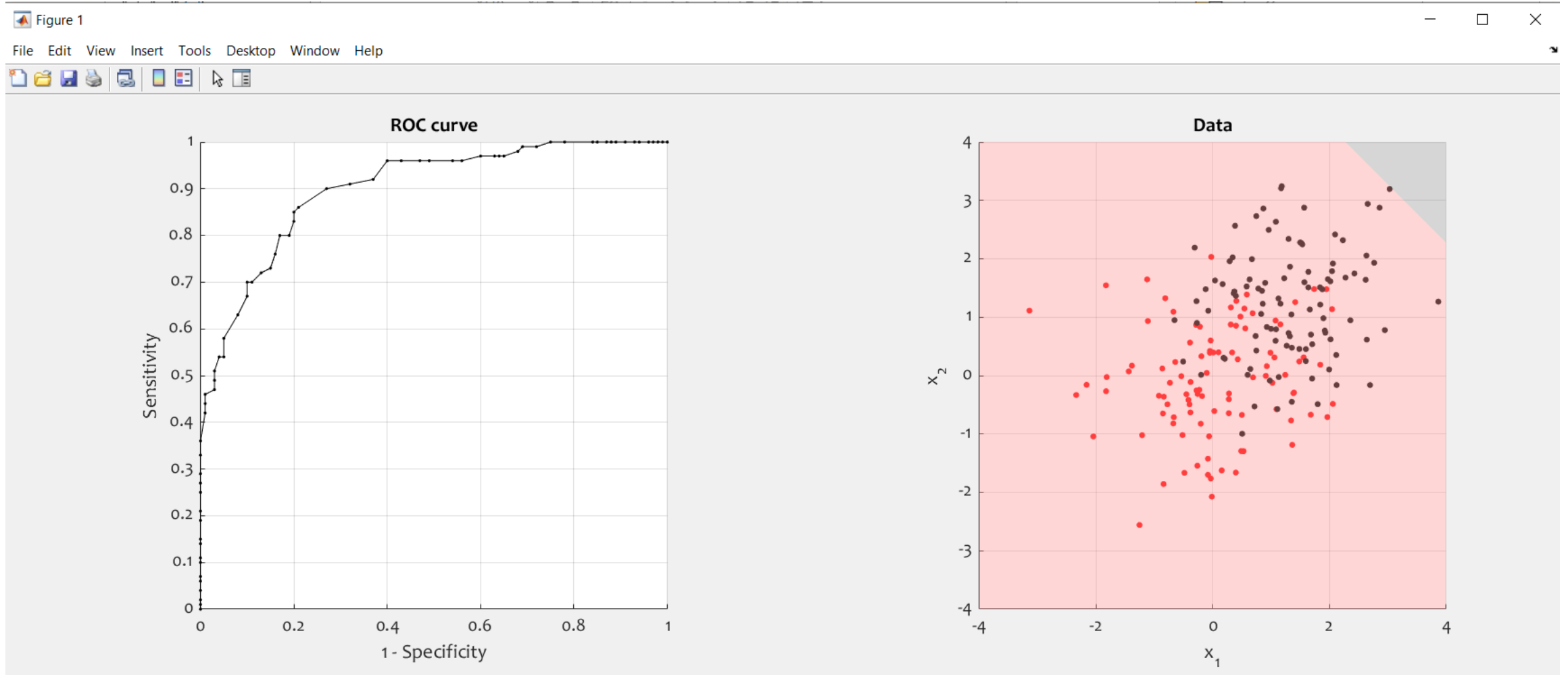
$$\text{Specificity} = 13/21 = 61.9\%$$

$$1\text{-Specificity} = \mathbf{38.1\%}$$

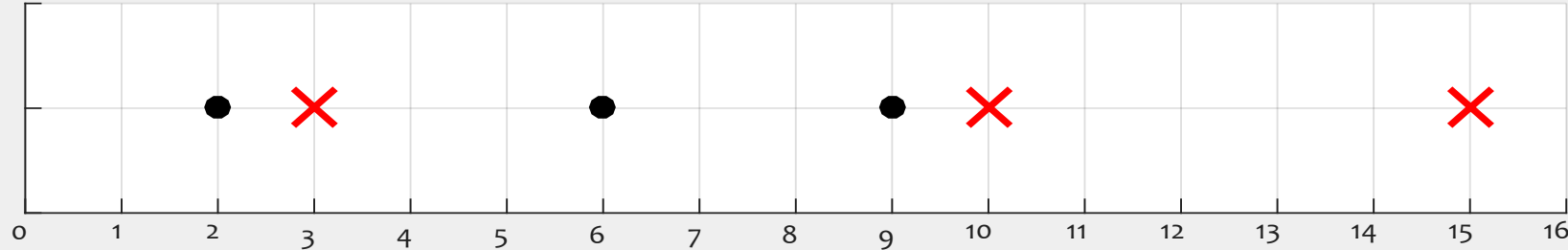
Q2. Plot the operational point for the classifier D, defined by the confusion matrix below

	Positive +	Negative -
Positive +	8	2
Negative -	100	900

ROC curves - MATLAB illustration



Q3. Build a ROC curve for a threshold classifier for the following one-dimensional classification problem (red crosses are class 'positive'):



1. (If the points are given in random order, sort x and re-arrange the labels to match the sorted objects.)
2. Suppose that there is a threshold between every pair of consecutive objects. Starting with a threshold on the **left of the smallest x** , calculate the sensitivity and specificity assuming that all points above the threshold are labelled as class positive (This gives sensitivity 1 and specificity 0).
3. Repeat for all possible thresholds moving to the right, one object at a time. The obtained pairs (sens, spec) will define the points of the ROC curve.
4. Plot sensitivity (y-axis) versus 1-specificity (x-axis). Voila!

Answers to some questions:

Q1.

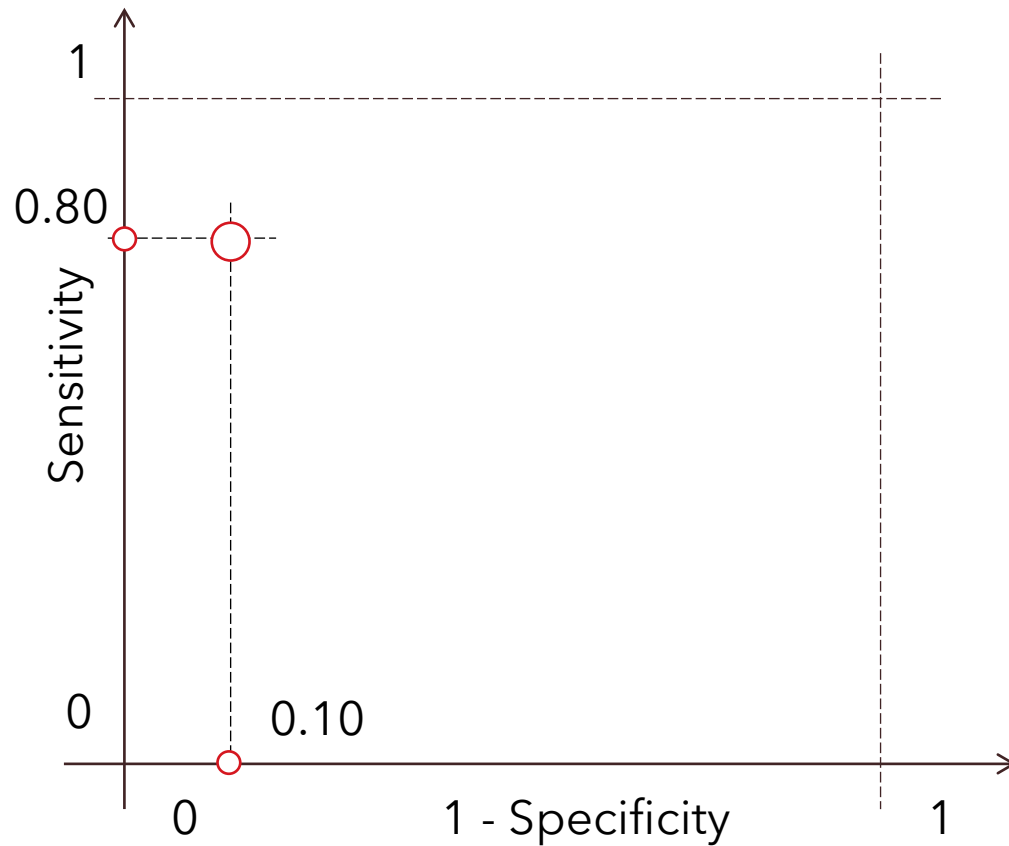
In each row, there are $118 - 25 + 1 = 94$ squares.

The number of rows with squares is $79 - 25 + 1 = 55$ squares.

The total number of squares is therefore $94 \times 55 = 5170$.

The number of negatives is $5170 - 6 = 5164$ squares.

Q2 Plot the operational point for the classifier D, defined by the confusion matrix below



	Positive +	Negative -
Positive +	8	2
Negative -	100	900

$$\text{Sens} = 8 / (8 + 2) = 0.8$$

$$\text{Spec} = 900 / (100 + 900) = 0.9$$

$$1 - \text{Spec} = 1 - 0.9 = 0.1$$

Q3.

