Overview

- Assessing Classification Models
- Assessing Regression Models

Assessing Classification Models

Classifier

- Input: input pattern or feature vector $(x_1, x_2, ..., x_n)$
- Assign an input to one of possible classes $(W_1, W_2, ..., W_R)$
- Output: class $r \in \{1, \dots, R\}$
- For example, predict if a person is a donor (r=1) or not (r=0)

Example: Cat-finder!

Is there a (house) cat in the image?

Correct Answer (Ground Truth):	Yes	Yes	No	No
Algorithm's output:	Yes	No	Yes	No
	TP	FN	FP	TN

Metrics for recognition/ classification

- TP (true positives):
  - Number of samples identified correctly as belonging to a class/ category
- FP (false positive): (false alarms!)
  - Number of samples identified incorrectly as belonging to a class / category
- TN (true negative):
  - Number of samples identified correctly as NOT belonging to a class/ category
- FN (false negatives):
  - Number of samples identified incorrectly as NOT belonging to a class/ category
- Total number of samples = TP + FP + TN + FN

Computing Quadrants of a Confusion Matrix

Actual Target Value	Probability Target = 1	Predicted Target Value	Confusion Matrix Quadrant
0	0.641	1	false alarm
1	0.601	1	true positive
0	0.587	1	false alarm
1	0.585	1	true positive
1	0.575	1	true positive
0	0.562	1	false alarm
0	0.531	1	false alarm
1	0.504	1	true positive
0	0.489	0	true negative
1	0.488	0	false dismissal
0	0.483	0	true negative
0	0.471	0	true negative
0	0.457	0	true negative
1	0.418	0	false dismissal
0	0.394	0	true negative
0	0.384	0	true negative
0	0.372	0	true negative
0	0.371	0	true negative
0	0.341	0	true negative
1	0.317	0	false dismissal

We first must populate all four quadrants of the confusion matrix.

AT left, the probability threshold is 0.5

Percent Correct Classification (PCC)

$$PCC = (t\_n + t\_p)/(t\_p + t\_n + f\_p + f\_n)$$

Confusion Matrix		Predicted Class		
		0 (predicted value is negative)	**1** (predicted value is positive)	Total Actual (down)
Actual Class	**0** (actual value is negative)	t_n (true negative)	f_p (false positive, false alarm)	Total actual negatives tn + fp
	1 (actual value is positive)	f_n (false negative, false dismissal)	t_p (true positive)	Total actual positives tp + fn
	Total Predicted (across)	Total negative predictions tn + fn	Total positive predictions tp + fp	Total Examples tp + tn + fp + fn

For a highly- performing model, which cells should contain larger values?

Precision / Recall

- Recall: Percentage of objects successfully identified

$$Recall = \frac{TP}{TP + FN}$$

- Precision: Percentage of identified objects which are actually correct (not false alarms)

$$Precision = \frac{TP}{TP + FP}$$

- F- measure:

$$F_\beta = (1 + \beta^2) \cdot \frac{Precision \cdot Recall}{(\beta^2 \cdot Precision) + Recall}$$

F_1 (β=1) is the most commonly used

Accuracy Metrics Computed from Confusion Matrices

$$PCC = \frac{t_p + t_n}{t_p + t_n + f_p + f_n}$$

$$Precision = \frac{t_p}{t_p + f_p}$$

$$Recall = \frac{t_p}{t_p + f_n}$$

$$False\ Alarm\ Rate\ (FA) = \frac{f_p}{t_n + f_p}$$

$$False\ Dismissal\ Rate\ (FD) = 1 - Recall = \frac{f_n}{t_p + f_n}$$

List of Formula

$$Sensitivity = Recall = \frac{t_p}{t_p + f_n}$$

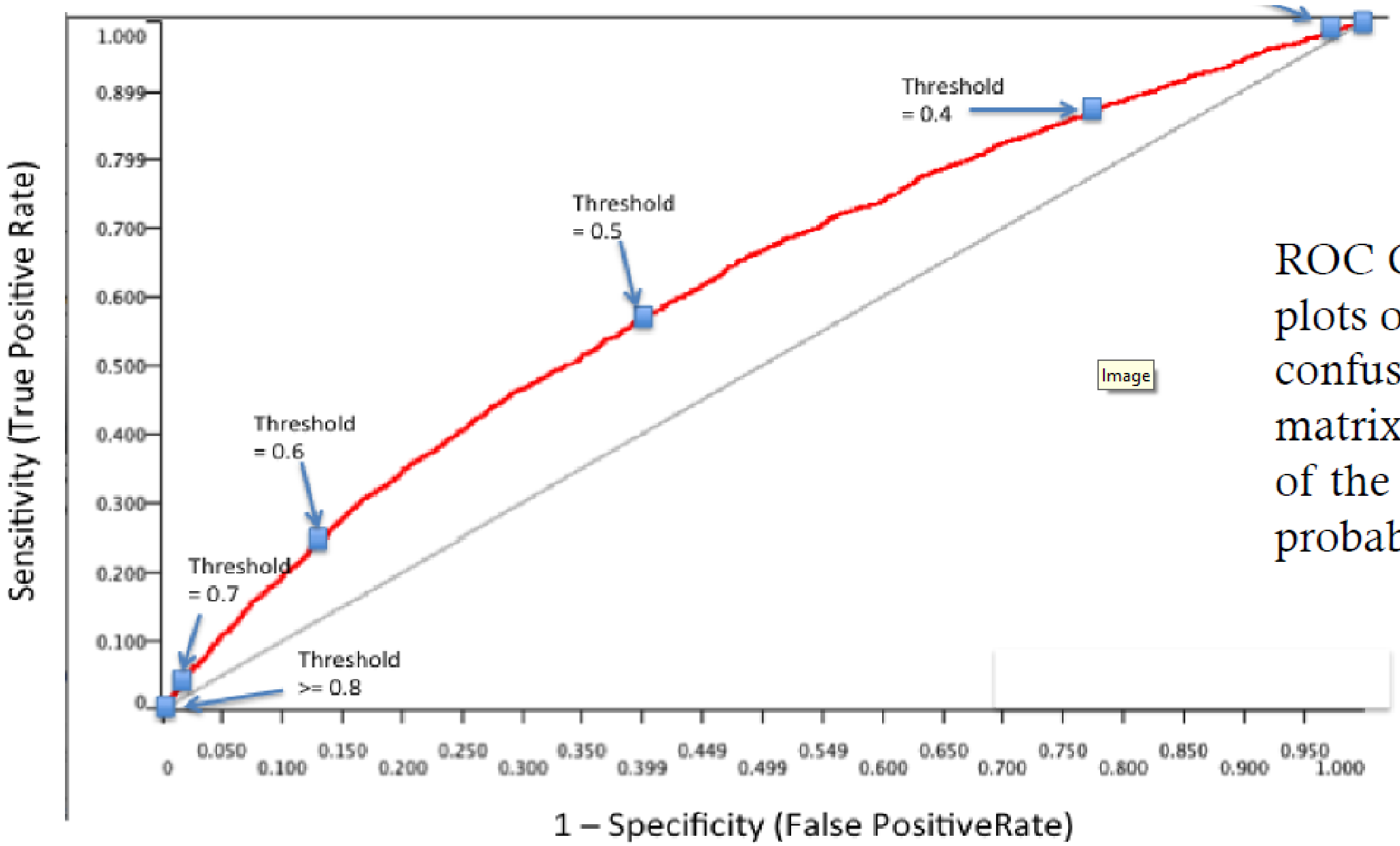
$$Specificity = True\ Negative\ Rate = \frac{t_n}{t_n + f_p}$$

$$Type\ I\ Error = \frac{f_p}{t_p + t_n + f_p + f_n}$$

$$Type\ II\ Error = \frac{f_n}{t_p + t_n + f_p + f_n}$$

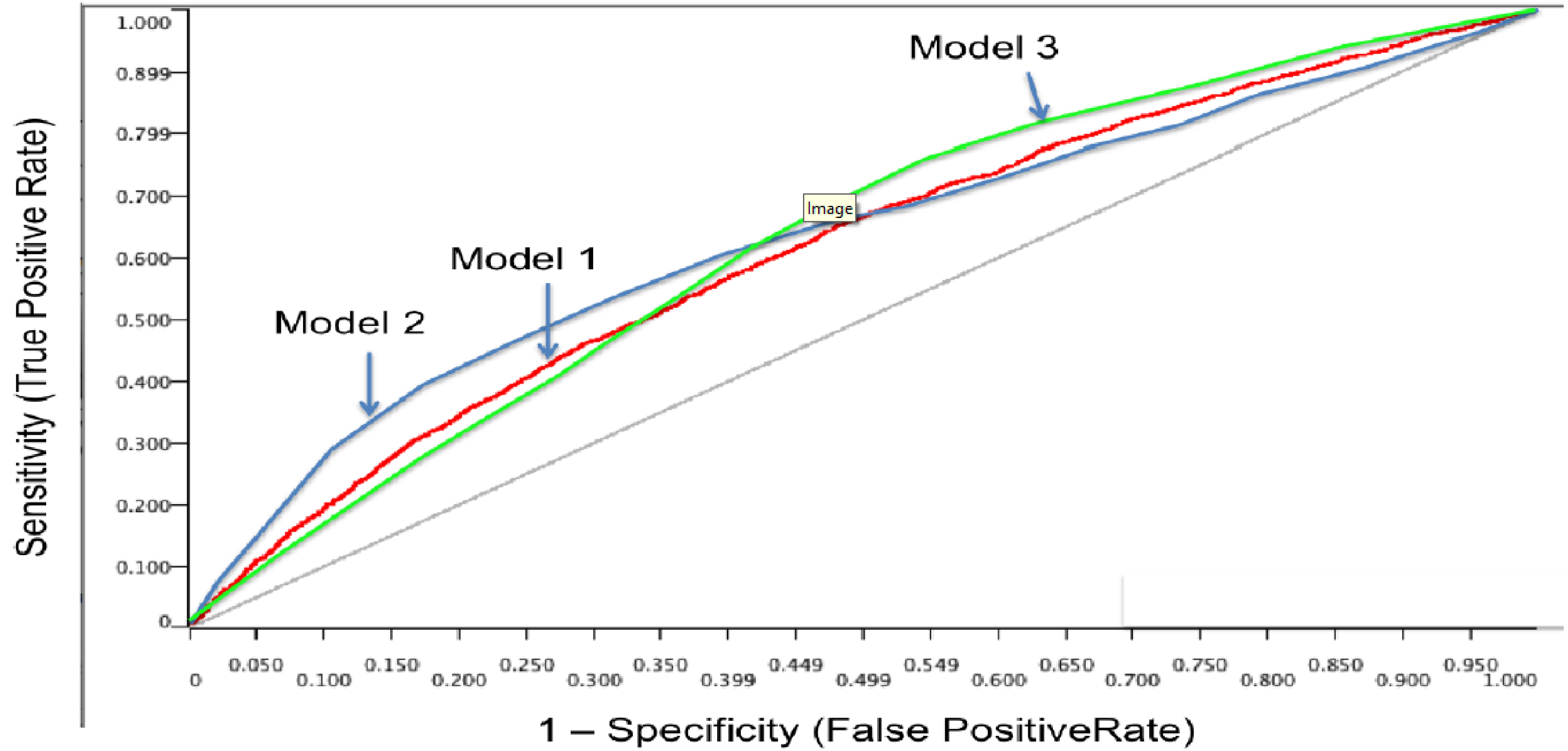
ROC Curves

Receiver Operating Characteristic (ignore this name!)



ROC Curves are plots of every confusion matrix threshold of the posterior probability

Comparison of Three Models using ROC Curves



PR Curves