

STAT 562 Lecture 6 Evaluating Classification Model

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Many classification models returns a probability. You can use the returned probability "as is" or convert the returned probability to a binary value.

- ▶ To map a logistic regression value to a binary category, you must define a classification threshold.
- ▶ Value above that threshold indicates positive class; a value below indicates negative class 0.
- ▶ Thresholds are problem-dependent, and are therefore values that you must tune.
- ▶ Choosing a threshold is assessing how much you'll suffer for making a mistake.

Accuracy is one metric for evaluating classification models. Informally, accuracy is the fraction of predictions our model got right.





$$Accuracy = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}}$$

In many cases, accuracy is a poor or misleading metric.

- ▶ Most often when different kinds of mistakes have different costs
- ▶ Class imbalance, when positives or negatives are extremely rare

True Positives and False Positives

For class-imbalanced problems, useful to separate out different kinds of errors using a 2×2 confusion matrix (error-matrix):

		PREDICTIVE VALUES	
		POSITIVE (CAT)	NEGATIVE (DOG)
ACTUAL VALUES	POSITIVE (CAT)	<p>TRUE POSITIVE</p>  <p>3</p>	<p>FALSE NEGATIVE</p>  <p>1</p> <p>TYPE II ERROR</p>
	NEGATIVE (DOG)	<p>FALSE POSITIVE</p>  <p>2</p> <p>TYPE I ERROR</p>	<p>TRUE NEGATIVE</p>  <p>4</p>

- ▶ A true positive (TP) is an outcome where the model correctly predicts the positive class.
- ▶ A true negative (TN) is an outcome where the model correctly predicts the negative class.
- ▶ A false positive (FP) is an outcome where the model incorrectly predicts the positive class.
- ▶ A false negative (FN) is an outcome where the model incorrectly predicts the negative class.

Using the terms of positives and negatives, we define the following metrics.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

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

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

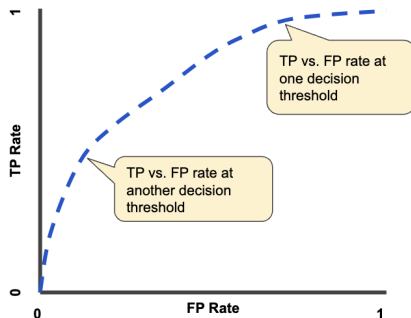
- ▶ Precision is the proportion of positive identifications was actually correct.
- ▶ Recall is the proportion of actual positives was identified correctly.

An ROC curve (receiver operating characteristic curve) is a graph showing the performance of a classification model at all classification thresholds.

This curve plots two parameters:

- ▶ True Positive Rate (TPR) = $TP/(TP+FN)$. This is the same as recall.
- ▶ False Positive Rate (FPR) = $FP/(FP+TN)$.

An ROC curve plots TPR vs. FPR at different classification thresholds.



Area under the ROC Curve (AUC) measures the entire two-dimensional area underneath the entire ROC curve (0,0) to (1,1).



AUC provides an aggregate measure of performance across all possible classification thresholds. It represents the probability that a random positive example has higher score (predicted probability to be positive) than a random negative example.