(https://google.com/racialequity?authuser=0)

Classification: Thresholding

ated Time: 2 minutes

Logistic regression returns a probability. You can use the returned probability "as is" (for example, the probability that the user will click on this ad is 0.00023) or convert the returned probability to a binary value (for example, this email is spam).

A logistic regression model that returns 0.9995 for a particular email message is predicting that it is very likely to be spam. Conversely, another email message with a prediction score of 0.0003 on that same logistic regression model is very likely not spam. However, what about an email message with a prediction score of 0.6? In order to map a logistic regression value to a binary category, you must define a **classification threshold** (also called the **decision threshold**). A value above that threshold indicates "spam"; a value below indicates "not spam." It is tempting to assume that the classification threshold should always be 0.5, but thresholds are problem-dependent, and are therefore values that you must tune.

The following sections take a closer look at metrics you can use to evaluate a classification model's predictions, as well as the impact of changing the classification threshold on these predictions.

'Tuning" a threshold for logistic regression is different from tuning hyperparameters such as learning rate. osing a threshold is assessing how much you'll suffer for making a mistake. For example, mistakenly labe ›am message as spam is very bad. However, mistakenly labeling a spam message as non-spam is unplea rdly the end of your job.

:rms

- ıary classification ://developers.google.com/machine-ıg/glossary?authuser=0#binary_classification)
- classification model (https://developers.google.com/machine-learning/glossary?authuser=0#classification_model)