

confusion matrix

terminology:-

IMAGE:-https://www.dataschool.io/content/images/2015/01/confusion_matrix_simple2.png

What can we learn from this matrix?

There are two possible predicted classes: "yes" and "no".

If we were predicting the presence of a disease, for example, "yes" would mean they have the disease, and "no" would mean they don't have the disease.

The classifier made a total of 165 predictions (e.g., 165 patients were being tested for the presence of that disease).

Out of those 165 cases, the classifier predicted "yes" 110 times, and "no" 55 times. In reality, 105 patients in the sample have the disease, and 60 patients do not.

Let's now define the most basic terms, which are whole numbers (not rates):

true positives (TP): These are cases in which we predicted yes (they have the disease), and they do have the disease.

true negatives (TN): We predicted no, and they don't have the disease.

false positives (FP): We predicted yes, but they don't actually have the disease. (Also known as a "Type I error.")

false negatives (FN): We predicted no, but they actually do have the disease. (Also known as a "Type II error.")

I've added these terms to the confusion matrix, and also added the row and column totals:

NEW IMAGE:-https://www.dataschool.io/content/images/2015/01/confusion_matrix2.png

This is a list of rates that are often computed from a confusion matrix for a binary classifier:

Accuracy: Overall, how often is the classifier correct?

$(TP+TN)/total = (100+50)/165 = 0.91$

Misclassification Rate: Overall, how often is it wrong?

$(FP+FN)/total = (10+5)/165 = 0.09$ equivalent to 1 minus Accuracy also known as "Error Rate"

True Positive Rate: When it's actually yes, how often does it predict yes?

$TP/actual\ yes = 100/105 = 0.95$

also known as "Sensitivity" or "Recall"

False Positive Rate: When it's actually no, how often does it predict yes?

$FP/actual\ no = 10/60 = 0.17$

True Negative Rate: When it's actually no, how often does it predict no?

$TN/actual\ no = 50/60 = 0.83$ equivalent to 1 minus False Positive Rate also known as "Specificity"

Precision: When it predicts yes, how often is it correct?

$TP / \text{predicted yes} = 100 / 110 = 0.91$

Prevalence: How often does the yes condition actually occur in our sample?

$\text{actual yes} / \text{total} = 105 / 165 = 0.64$

A couple other terms are also worth mentioning:

Null Error Rate: This is how often you would be wrong if you always predicted the majority class. (In our example, the null error rate would be $60 / 165 = 0.36$ because if you always predicted yes, you would only be wrong for the 60 "no" cases.) This can be a useful baseline metric to compare your classifier against. However, the best classifier for a particular application will sometimes have a higher error rate than the null error rate, as demonstrated by the Accuracy Paradox.

Cohen's Kappa: This is essentially a measure of how well the classifier performed as compared to how well it would have performed simply by chance. In other words, a model will have a high Kappa score if there is a big difference between the accuracy and the null error rate. (More details about Cohen's Kappa.)

F Score: This is a weighted average of the true positive rate (recall) and precision. (More details about the F Score.)

formula

image"<https://static.javatpoint.com/tutorial/machine-learning/images/confusion-matrix7.png>"

ROC Curve: This is a commonly used graph that summarizes the performance of a classifier over all possible thresholds. It is generated by plotting the True Positive Rate (y-axis) against the False Positive Rate (x-axis) as you vary the threshold for assigning observations to a given class. (More details about ROC Curves.)

And finally, for those of you from the world of Bayesian statistics, here's a quick summary of these terms from Applied Predictive Modeling:

In relation to Bayesian statistics, the sensitivity and specificity are the conditional probabilities, the prevalence is the prior, and the positive/negative predicted values are the posterior probabilities.

Want to learn more?

In my new 35-minute video, Making sense of the confusion matrix, I explain these concepts in more depth and cover more advanced topics:

How to calculate precision and recall for multi-class problems

How to analyze a 10-class confusion matrix

How to choose the right evaluation metric for your problem

Why accuracy is often a misleading metric