GETTING STARTED

8 Metrics to Measure Classification Performance

...explained in plain English

Rebecca Vickery · Follow

Published in Towards Data Science · 7 min read · Dec 7, 2021

Photo by Mauro Gigli on Unsplash

Classification is a type of supervised machine learning problem where the goal is to predict, for one or more observations, the category or class they belong to.

An important element of any machine learning workflow is the evaluation of the performance of the model. This is the process where we use the trained model to make predictions on previously unseen, labelled data. In the case of classification, we then evaluate how many of these predictions the model got right.

In real-world classification problems, it is usually impossible for a model to be 100% correct. When evaluating a model it is, therefore, useful to know, not only how wrong the model was, but in which way the model was wrong.

> "All models are wrong, but some are useful", George Box

For example, if we are trying to predict if a tumour is benign or cancerous, we might be happier to trade off the model incorrectly predicting that a tumour is cancerous in a small number of cases. Rather than have the serious consequences of missing a cancer diagnosis.

On the flip side if we were a retailer deciding which transactions were fraudulent we might be happier for a small number of fraudulent transactions to be missed. Rather than risk turning away good customers.

In both of these cases, we would optimise a model to perform better for certain outcomes and therefore we may use different metrics to select the final model to use. As a consequence of these trade-offs when selecting a classifier there are a variety of metrics you should use to optimise a model for your specific use case.

In the following article, I am going to give a simple description of eight different performance metrics and techniques you can use to evaluate a classifier.

1. Accuracy

The overall **accuracy** of a model is simply the number of correct predictions divided by the total number of predictions. An accuracy score will give a value between 0 and 1, a value of 1 would indicate a perfect model.

$$accuracy = CorrectPredictions/TotalPredictions$$

Accuracy. Image by Author

This metric should rarely be used in isolation, as on imbalanced data, where one class is much larger than another, the accuracy can be highly misleading.

If we go back to the cancer example. Imagine we have a dataset where only 1% of the samples are cancerous. A classifier that simply predicts all outcomes as benign would achieve an accuracy score of 99%. However, this model would, in fact, be useless and dangerous as it would never detect a cancerous observation.

2. Confusion Matrix

A **confusion matrix** is an extremely useful tool to observe in which way the model is wrong (or right!). It is a matrix that compares the number of predictions for each class that are correct and those that are incorrect.

In a confusion matrix, there are 4 numbers to pay attention to.

True positives: The number of positive observations the model correctly predicted as positive.

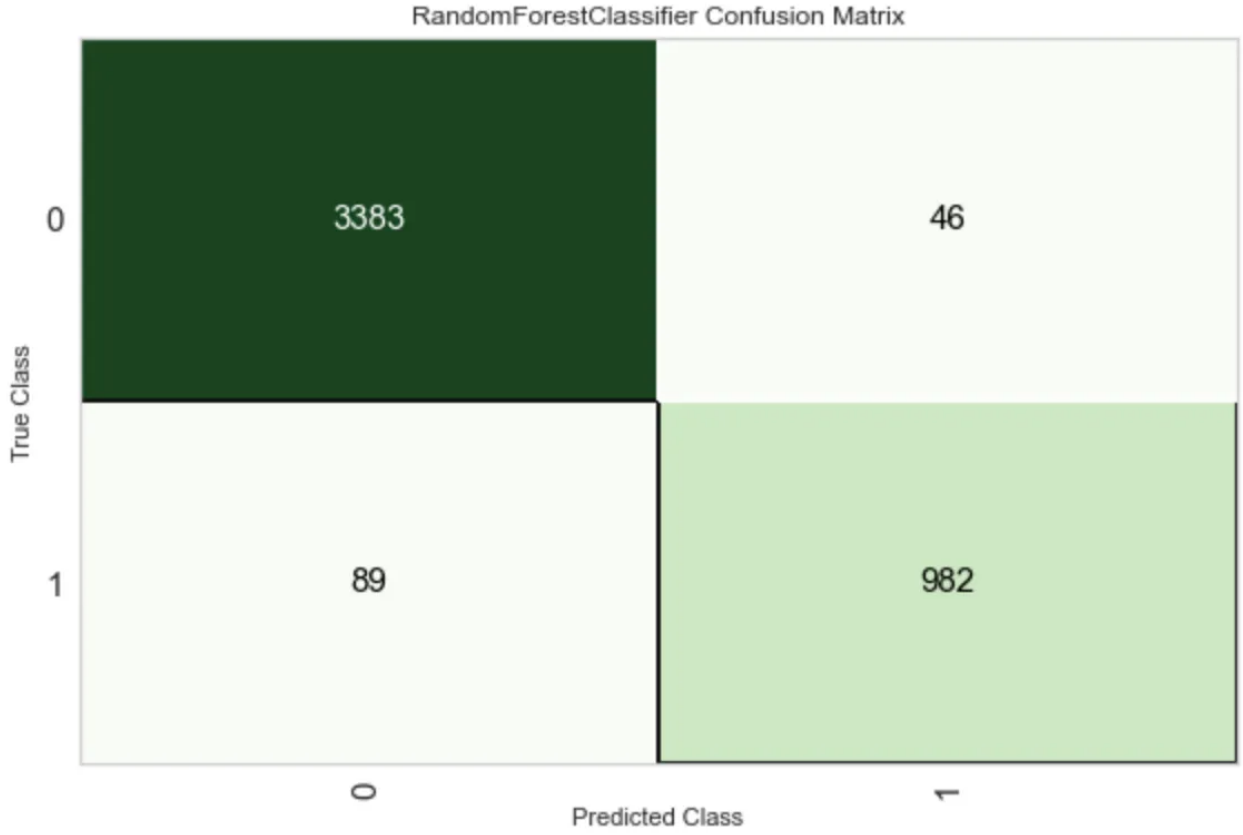
False-positive: The number of negative observations the model incorrectly predicted as positive.

True negative: The number of negative observations the model correctly predicted as negative.

False-negative: The number of positive observations the model incorrectly predicted as negative.

The image below shows a confusion matrix for a classifier. Using this we can understand the following:

- The model correctly predicted 3,383 negative samples but incorrectly predicted 46 as positive.
- The model correctly predicted 962 positive observations but incorrectly predicted 89 as negative.
- We can see from this confusion matrix that the data sample is imbalanced, with the negative class having a higher volume of observations.



Confusion matrix example (plotted using Pycaret). Image by Author

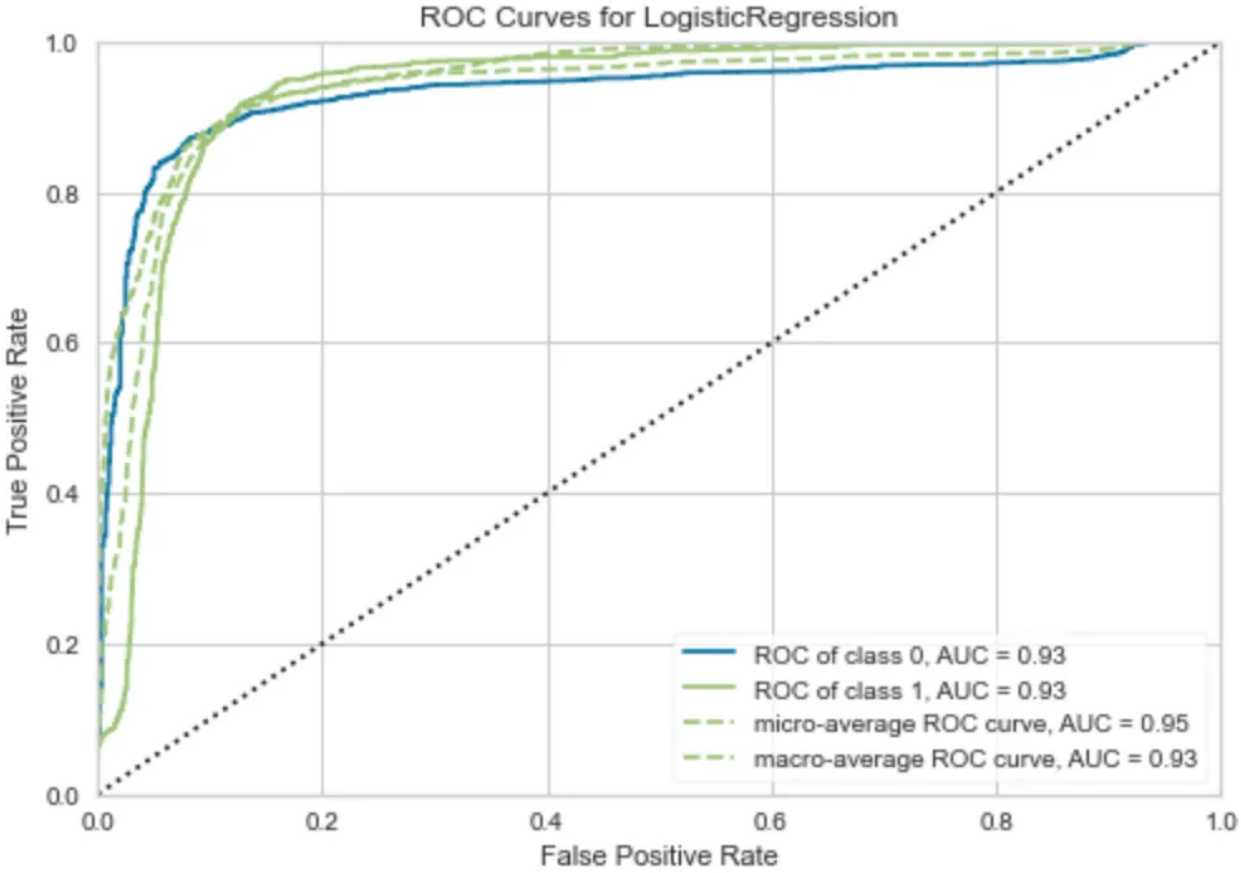
3. AUC/ROC

A classifier such as logistic regression will return the probability of an observation belonging to a particular class as the prediction output. For the model to be useful this is usually converted to a binary value e.g. either the

sample belongs to the class or it doesn't. To do this a classification threshold is used, for example, we might say that if the probability is above 0.5 then the sample belongs to class 1.

The **ROC** (Receiver Operating Characteristics) curve is a plot of the performance of the model (a plot of the true positive rate and the false positive rate) at all classification thresholds. The **AUC** is the measurement of the entire two-dimensional area under the curve and as such is a measure of the performance of the model at all possible classification thresholds.

ROC curves plot the accuracy of the model and therefore are best suited to diagnose the performance of models where the data is not imbalanced.



ROC curve example (plotted using Pycaret). Image by Author

4. Precision

Precision measures how good the model is at correctly identifying the positive class. In other words out of all predictions for the positive class how

many were actually correct? Using alone this metric for optimising a model we would be minimising the false positives. This might be desirable for our fraud detection example, but would be less useful for diagnosing cancer as we would have little understanding of positive observations that are missed.

$$precision = TP/TP + FP$$

Precision. Image by author

5. Recall

Recall tell us how good the model is at correctly predicting **all** the positive observations in the dataset. However, it does not include information about the false positives so would be more useful in the cancer example.

$$recall = TP/TP + FN$$

Usually, precision and recall are observed together by constructing a precision-recall curve. This can help to visualise the trade-offs between the two metrics at different thresholds.

6. F1 score

The **F1 score** is the harmonic mean of precision and recall. The F1 score will give a number between 0 and 1. If the F1 score is 1.0 this indicates perfect precision and recall. If the F1 score is 0 this means that either the precision or the recall is 0.

$$F1 = 2 \times precision \times recall / precision + recall$$

F1 score. Image by Author

7. Kappa

The **kappa** statistic compares the observed accuracy to an expected accuracy or the accuracy expected from random chance. One of the flaws of pure accuracy is that if a class is imbalanced then making predictions at random could give a high accuracy score. Kappa accounts for this by comparing the model accuracy to the expected accuracy based on the number of instances in each class.

Essentially it tells us how the model is performing compared to a model that classifies observations at random according to the frequency of each class.

$$kappa = (ObservedAccuracy - ExpectedAccuracy)/(1 - ExpectedAccuracy)$$

Kappa statistic. Image by Author

Kappa returns a value at or below 1, negative values are possible. One drawback of this statistic is that there is no agreed standard to interpret its values. Although, a general interpretation of the metric was given by Landis and Koch in 1977.

K	Interpretation
<0	Poor agreement
0.0-0.20	Slight agreement
0.21-0.40	Fair agreement
0.41-0.60	Moderate agreement
0.61-0.80	Substantial agreement
0.81-1.0	Almost perfect agreement

Kappa interpretation (Landis and Koch 19771). Image by Author

8. MCC

MCC (Matthews Correlation Coefficient) is generally considered one of the best measurements of performance for a classification model. This is largely because, unlike any of the previously mentioned metrics, it takes all possible prediction outcomes into account. If there are imbalances in the classes this will therefore be accounted for.

The MCC is essentially a correlation coefficient between the observed and predicted classifications. As with any correlation coefficient, its value will lie

between -1.0 and +1.0. A value of +1 would indicate a perfect model.

$$\mathrm{MCC} = \frac{\mathrm{TP} \times \mathrm{TN} - \mathrm{FP} \times \mathrm{FN}}{\sqrt{(\mathrm{TP}+\mathrm{FP})(\mathrm{TP}+\mathrm{FN})(\mathrm{TN}+\mathrm{FP})(\mathrm{TN}+\mathrm{FN})}}$$

Matthews Correlation Coefficient. Image by Author

In this article, we have covered simple explanations for eight metrics for measuring the performance of classification models. In practice, rarely should any of these metrics be used alone. More commonly a data scientist would assess a number of these scores and weigh up the trade-offs that they reveal when optimising a model.

Assessing the performance of a classifier is generally not straightforward and highly dependant on the use case and available dataset. It is particularly important to understand the risk of being wrong in a particular direction so that you can produce a truly useful model.

Thanks for reading!

Data Science Machine Learning Artificial Intelligence Editors Pick

Getting Started

Written by Rebecca Vickery

Follow

21K Followers · Writer for Towards Data Science

Data Scientist | Writer | Speaker

More from Rebecca Vickery and Towards Data Science

Rebecca Vickery in Towards Data Science

6 Ways to Build Best Practices for Data Science Teams

Setting standards for high-performing data science teams

✨ · 7 min read · Mar 20

290 5

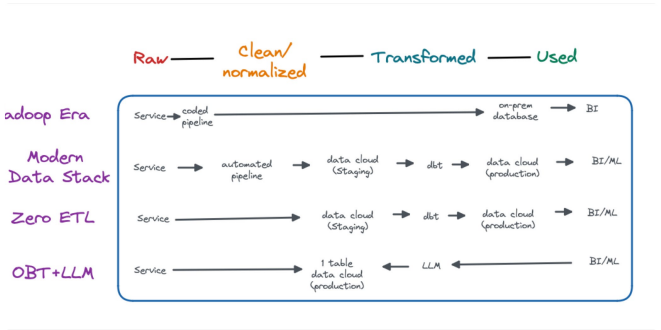
Jacob Marks, Ph.D. in Towards Data Science

How I Turned My Company's Docs into a Searchable Database with...

And how you can do the same with your docs

15 min read · Apr 25

1.6K 22



Barr Moses in Towards Data Science

Rebecca Vickery in Towards Data Science

Zero-ETL, ChatGPT, And The Future of Data Engineering

The post-modern data stack is coming. Are we ready?

9 min read · Apr 3

1K 21

Why You Shouldn't Take a Data Science Masters Degree

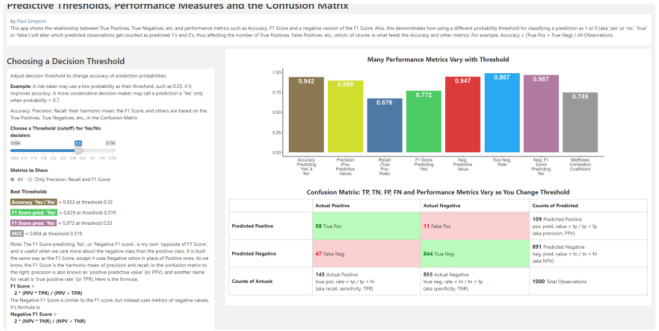
✦ · 5 min read · Jun 4, 2021

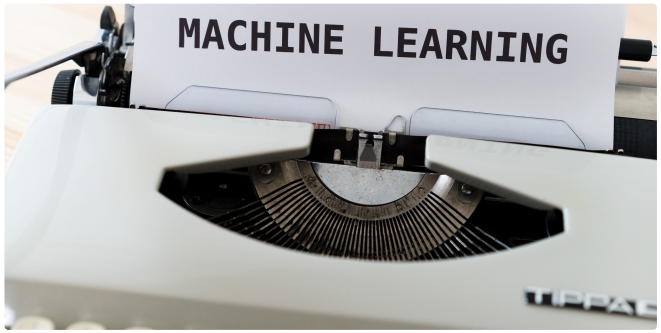
939 15

See all from Rebecca Vickery

See all from Towards Data Science

Recommended from Medium





Paul Simpson

Classification Model Accuracy Metrics, Confusion Matrix—and...

How do you compare several predictive binary classification models that you have...

✨ · 6 min read · Nov 2, 2022

7 1

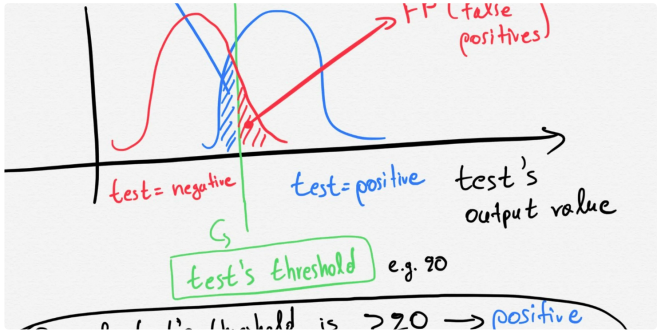
Aaron Zhu in Towards Data Science

Essential Evaluation Metrics for Classification Problems in Machin...

A Comprehensive Guide to Understanding and Evaluating the Performance of...

✨ · 10 min read · Mar 10

19



Anmol Tomar in Towards Data Science

Serafeim Loukas, PhD in Towards AI

Stop Using Elbow Method in K-means Clustering, Instead, Use...

Learn how to find the number of clusters in K-means clustering

✦ · 6 min read · Nov 17, 2022

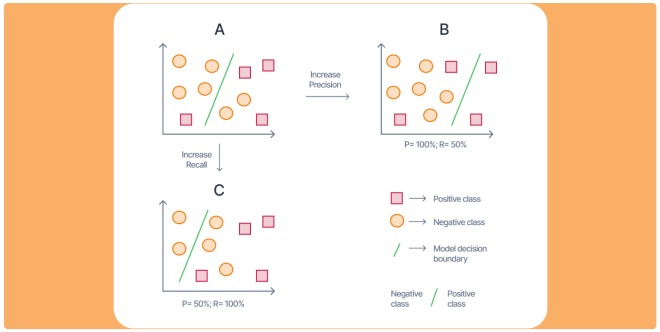
368 4

How To Estimate FP, FN, TP, TN, TPR, TNR, FPR, FNR & Accuracy f...

In this post, I explain how someone can read a confusion matrix and how to extract several...

✦ · 6 min read · Feb 5

64



vinay

What are Precision and Recall terminologies?

Precision and recall are two important concepts in the field of machine learning.

✦ · 2 min read · Dec 5, 2022

5

Samuel Flender in Towards Data Science

Class Imbalance in Machine Learning Problems: A Practical...

Five lessons from the trenches of applied data science

✦ · 8 min read · Oct 3, 2022

285 2

See more recommendations