Classifier evaluation with imbalanced datasets

Knowledge base of performance evaluation measures for binary classification models

Basic evaluation measures from the confusion matrix

We introduce basic performance measures derived from the confusion matrix through this page. The confusion matrix is a two by two table that contains four outcomes produced by a binary classifier. Various measures, such as error-rate, accuracy, specificity, sensitivity, and precision, are derived from the confusion matrix. Moreover, several advanced measures, such as ROC and precision-recall, are based on them.

After studying the basic performance measures, don't forget to read our introduction to precision-recall plots (link) and the section on tools (link). Also take note of the issues with ROC curves and why in such cases precision-recall plots are a better choice (link).

Test datasets for binary classifier

A binary classifier produces output with two class values or labels, such as Yes/No and 1/0, for given input data. The class of interest is usually denoted as "positive" and the other as "negative".

A binary classifier produces output with two classes for given input data.

Test dataset for evaluation

A dataset used for performance evaluation is called a test dataset. It should contain the correct labels (observed labels) for all data instances. These observed labels are used to compare with the predicted labels for performance evaluation after classification.

> In binary classification, a test dataset has two labels; positive and negative.

Predictions on test datasets

The predicted labels will be exactly the same if the performance of a binary classifier is perfect, but it is uncommon to be able to develop a perfect binary classifier that is practical for various conditions.

> The performance of a binary classifier is perfect when it can predict the exactly same labels in a test dataset.

Hence, the predicted labels usually match with part of the observed labels.

> The predicted labels of a classifier match with part of the observed labels.

Confusion matrix from the four outcomes

A confusion matrix is formed from the four outcomes produced as a result of binary classification.

Four outcomes of classification

A binary classifier predicts all data instances of a test dataset as either positive or negative. This classification (or prediction) produces four outcomes – true positive, true negative, false positive and false negative.

- True positive (TP): correct positive prediction
- False positive (FP): incorrect positive prediction
- True negative (TN): correct negative prediction
- False negative (FN): incorrect negative prediction

Classification of a test dataset produces four outcomes – true positive, false positive, true negative, and false negative.

Confusion matrix

A confusion matrix of binary classification is a two by two table formed by counting of the number of the four outcomes of a binary classifier. We usually denote them as TP, FP, TN, and FN instead of “the number of true positives”, and so on.

		Predicted	
		Positive	**Negative**
Observed	**Positive**	TP (# of TPs)	FN (# of FNs)
	Negative	FP (# of FPs)	TN (# of TNs)

Basic measures derived from the confusion matrix

Various measures can be derived from a confusion matrix.

First two basic measures from the confusion matrix

Error rate (ERR) and accuracy (ACC) are the most common and intuitive measures derived from the confusion matrix.

Error rate

Error rate (ERR) is calculated as the number of all incorrect predictions divided by the total number of the dataset. The best error rate is 0.0, whereas the worst is 1.0.

Error rate is calculated as the total number of two incorrect predictions (FN + FP) divided by the total number of a dataset (P + N).

- $\mathrm{ERR} = \dfrac{\mathrm{FP} + \mathrm{FN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FN} + \mathrm{FP}} = \dfrac{\mathrm{FP} + \mathrm{FN}}{\mathrm{P} + \mathrm{N}}$

Accuracy

Accuracy (ACC) is calculated as the number of all correct predictions divided by the total number of the dataset. The best accuracy is 1.0, whereas the worst is 0.0. It can also be calculated by 1 – ERR.

Accuracy is calculated as the total number of two correct predictions (TP + TN) divided by the total number of a dataset (P + N).

- $\mathrm{ACC} = \dfrac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FN} + \mathrm{FP}} = \dfrac{\mathrm{TP} + \mathrm{TN}}{\mathrm{P} + \mathrm{N}}$

Other basic measures from the confusion matrix

Error costs of positives and negatives are usually different. For instance, one wants to avoid false negatives more than false positives or vice versa. Other basic measures, such as sensitivity and specificity, are more informative than accuracy and error rate in such cases.

Sensitivity (Recall or True positive rate)

Sensitivity (SN) is calculated as the number of correct positive predictions divided by the total number of positives. It is also called recall (REC) or true positive rate (TPR). The best sensitivity is 1.0, whereas the worst is 0.0.

Sensitivity is calculated as the number of correct positive predictions (TP) divided by the total number of positives (P).

- $\mathrm{SN} = \dfrac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} = \dfrac{\mathrm{TP}}{\mathrm{P}}$

Specificity (True negative rate)

Specificity (SP) is calculated as the number of correct negative predictions divided by the total number of negatives. It is also called true negative rate (TNR). The best specificity is 1.0, whereas the worst is 0.0.

Specificity is calculated as the number of correct negative predictions (TN) divided by the total number of negatives (N).

- $\mathrm{SP} = \dfrac{\mathrm{TN}}{\mathrm{TN} + \mathrm{FP}} = \dfrac{\mathrm{TN}}{\mathrm{N}}$

Precision (Positive predictive value)

Precision (PREC) is calculated as the number of correct positive predictions divided by the total number of positive predictions. It is also called positive predictive value (PPV). The best precision is 1.0, whereas the worst is 0.0.

Precision is calculated as the number of correct positive predictions (TP) divided by the total number of positive predictions (TP + FP).

- $\mathrm{PREC} = \dfrac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}}$

False positive rate

False positive rate (FPR) is calculated as the number of incorrect positive predictions divided by the total number of negatives. The best false positive rate is 0.0 whereas the worst is 1.0. It can also be calculated as 1 – specificity.

False positive rate is calculated as the number of incorrect positive predictions (FP) divided by the total number of negatives (N).

- $\mathrm{FPR} = \dfrac{\mathrm{FP}}{\mathrm{TN} + \mathrm{FP}} = 1 - \mathrm{SP}$

Correlation coefficient and F-score

Mathews correlation coefficient and F-score can be useful, but they are less frequently used than the other basic measures.

Matthews correlation coefficient

Matthews correlation coefficient (MCC) is a correlation coefficient calculated using all four values in the confusion matrix.

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

F-score

F-score is a harmonic mean of precision and recall.

- $\mathrm{F}_\beta = \dfrac{(1 + \beta^2)(\mathrm{PREC} \cdot \mathrm{REC})}{(\beta^2 \cdot \mathrm{PREC} + \mathrm{REC})}$

β is commonly 0.5, 1, or 2.

- $\mathrm{F}_{0.5} = \dfrac{1.25 \cdot \mathrm{PREC} \cdot \mathrm{REC}}{0.25 \cdot \mathrm{PREC} + \mathrm{REC}}$
- $\mathrm{F}_1 = \dfrac{2 \cdot \mathrm{PREC} \cdot \mathrm{REC}}{\mathrm{PREC} + \mathrm{REC}}$
- $\mathrm{F}_2 = \dfrac{5 \cdot \mathrm{PREC} \cdot \mathrm{REC}}{4 \cdot \mathrm{PREC} + \mathrm{REC}}$

An example of evaluation measure calculations

Let us assume that the outcome of some classification results in 6 TPs, 4 FNs, 8 TNs, and 2 FPs.

This example shows that a binary classifier has produced 6 TPs, 4 FNs, 2 FPs, and 8 TNs.

First, a confusion matrix is formed from the outcomes.

		Predicted	

		Positive	Negative
Observed	**Positive**	6	4
	Negative	2	8

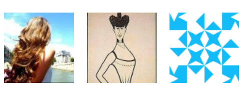
Then, the calculations of basic measures are straightforward once the confusion matrix is created.

measure		calculated value
Error rate	ERR	6 / 20 = 0.3
Accuracy	ACC	14 / 20 = 0.7
Sensitivity True positive rate Recall	SN TPR REC	6 / 10 = 0.6
Specificity True negative rate	SP TNR	8 / 10 = 0.8
Precision Positive predictive value	PREC PPV	6 / 8 =0.75
False positive rate	FPR	2 / 10 = 0.2

Other evaluation measures

Please see the following pages for more advanced evaluation measures.

- Basic concept of model-wide evaluation
- Introduction to the ROC (Receiver Operating Characteristics) plot
- Introduction to the precision-recall plot



3 bloggers like this.

24 thoughts on “Basic evaluation measures from the confusion matrix”

Sarah Ahmad

December 20, 2016 at 9:07 am

well explained.

Like

Voncile

April 24, 2017 at 4:56 am

It’s a relief to find soneome who can explain things so well

Like

Sujit

February 5, 2017 at 8:09 pm

Excellent explanation..great understanding…

Like

M. Edison

February 24, 2017 at 11:47 am

The explanation and the examples are very nice….

Like

Debasmita

April 26, 2017 at 1:59 pm

Very nice illustration and explanation.

Like

Bhagya Krishna

June 8, 2017 at 1:21 pm

Very precise, simple yet clear description and any one can easily understand and remember it. Thanks for the wonder full post.

Like

Olinca

August 10, 2017 at 4:52 pm

"False positive rate (FPR) is calculated as the number of incorrect negative predictions… " Should not be: incorrect positive predictions?

Like

> **takaya**
>
> August 10, 2017 at 11:02 pm
>
> Oops. I just corrected it. Thank you very much for your help!
>
> Like

Pingback: What is true positive and true negative – confusion matrix | Vikas D More

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shunnu

September 22, 2017 at 6:23 pm

very nice explanation.Thank u so much

★ Like

ZaCook

November 5, 2017 at 4:05 am

Great explanation, everything makes sense now!! Thank you!

★ Like

Ayse

January 15, 2018 at 1:03 pm

very smooth explanation. i have a small question. for multiple classes, how am i going to calculate the error rate. according to this, i calculate the class.error for each classes but the general "OOB estimate of error rate" is different from what the algorithm calculates. What could have been the thing I miss? Many thanks

★ Like

takaya

January 16, 2018 at 8:46 am

The calculation of the error rate is still the same even for multi-class classifications as: (# of misclassified instances) / (# of total instances). Some of machine learning methods that use bootstrap resampling require no validation datasets during training because they can use OOB instead. For instance, you can calculate an error rate for each subsample, and then you can aggregate all of them to calculate the mean error rate. You still need a test data set to evaluate your final model, though.

★ Like

Pearapon S.
March 24, 2018 at 6:34 am

Very Very good explanation. Thank you

Like

Kok Wei Khong
April 18, 2018 at 1:23 pm

When evaluating these values, are there acceptable values that we can say it's good/bad?

Like

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takaya
April 18, 2018 at 9:04 pm

No, not really. You need to consider other factors, such as your problem domain, test data sets and so on, to estimate whether the performance of your model is good or bad from these metrics. But, you can always use them for comparisons among multiple models and hypotheses.

Like

Chinnu
May 9, 2018 at 11:53 am

Good and Clear explanation.

Like

Ibrar hussain
July 18, 2018 at 9:10 am

A.A

Sir! i am using Weka tool and run DecisionTable classifier model and get confusion Matrix but i need to Label as a TP,TN,FP and FN

a b Class

2781 0 a = No

26 425 b = Yes

So, please help me sirr

Regards

★ Like

takaya

July 18, 2018 at 11:38 am

Assume that the labels Yes (b) and No (a) respectively represent positive and negative, and the matrix is as follows:

a . b . <– predicted/classified labels
2781 . 0 . (a = No in your test set)
26 . 425 . (b = Yes in your test set)

Then, TPs = 425, TNs = 2781, FPs = 0 and FNs = 26.

★ Like

Ibrar hussain

July 18, 2018 at 1:38 pm

A lot of thanks takaya.....

Regards
Ibrar

★ Like

Sreelatha
August 21, 2018 at 11:07 am

Excellent explanation and most of the research papers do not cover many of these parameters

★ Like

Pingback: python tensorflow 深度学习 自然语言处理 COMP4650 COMP6490 文本分析 – PowCoder

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Smule Singer
January 4, 2019 at 12:28 pm

Very nice explanation.
I have a question, Shouldn't Precision (Positive Predictive Value) be 60% i.e. 6(TP)/6(TP)+4(FP)=0.6.
Thanks in advance.

★ Like

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takaya
January 4, 2019 at 3:56 pm

The number of FPs is not 4 but 2 in the example above. So, precision is 0.75 as 6 / (6 + 2).

★ Liked by 2 people