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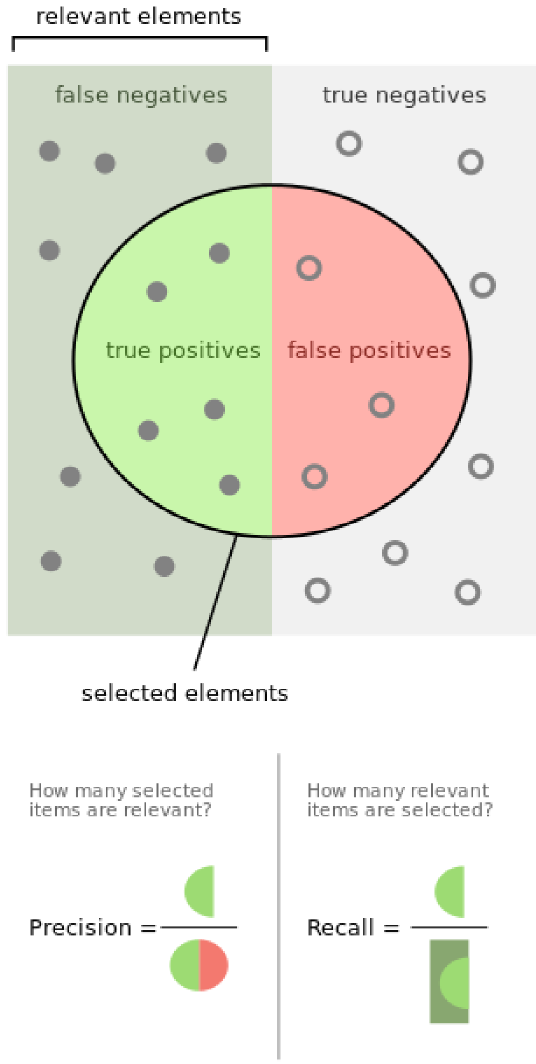
# F1 score

In statistical analysis of binary classification, the $F_1$ **score** (also **F-score** or **F-measure**) is a measure of a test's accuracy. It considers both the precision $p$ and the recall $r$ of the test to compute the score: $p$ is the number of correct positive results divided by the number of all positive results returned by the classifier, and $r$ is the number of correct positive results divided by the number of all relevant samples (all samples that should have been identified as positive). The $F_1$ score is the harmonic average of the precision and recall, where an $F_1$ score reaches its best value at 1 (perfect precision and recall) and worst at 0.




Precision and recall

## Contents



## Formulation

The traditional F-measure or balanced F-score (**$F_1$ score**) is the harmonic mean of precision and recall:

$$F_1 = \frac{2}{\frac{1}{\mathrm{recall}} + \frac{1}{\mathrm{precision}}} = 2 \cdot \frac{\mathrm{precision} \cdot \mathrm{recall}}{\mathrm{precision} + \mathrm{recall}}.$$

The general formula for positive real β is:

$$F_\beta = (1 + \beta^2) \cdot \frac{\mathrm{precision} \cdot \mathrm{recall}}{(\beta^2 \cdot \mathrm{precision}) + \mathrm{recall}}.$$

The formula in terms of Type I and type II errors

$$F_\beta = \frac{(1 + \beta^2) \cdot \mathrm{true\ positive}}{(1 + \beta^2) \cdot \mathrm{true\ positive} + \beta^2 \cdot \mathrm{false\ negative} + \mathrm{false\ positive}}.$$

Two other commonly used F measures are the $F_2$ measure, which weighs recall higher than precision (by placing more emphasis on false negatives), and the $F_{0.5}$ measure, which weighs recall lower than precision (by attenuating the influence of false negatives).

The F-measure was derived so that $F_\beta$ "measures the effectiveness of retrieval with respect to a user who attaches β times as much importance to recall as precision".[1] It is based on Van Rijsbergen's effectiveness measure

$$E = 1 - \left(\frac{\alpha}{p} + \frac{1 - \alpha}{r}\right)^{-1}.$$

Their relationship is $F_\beta = 1 - E$ where $\alpha = \frac{1}{1 + \beta^2}$.

The $F_1$ score is also known as the Sørensen–Dice coefficient or Dice similarity coefficient (DSC).

# Diagnostic testing

This is related to the field of binary classification where recall is often termed as Sensitivity. There are several reasons that the $F_1$ score can be criticized in particular circumstances.[2]

| | | True condition | | | | |
|---|---|---|---|---|---|---|
| | Total population | Condition positive | Condition negative | Prevalence $= \frac{\Sigma \text{ Condition positive}}{\Sigma \text{ Total population}}$ | Accuracy (ACC) = $\frac{\Sigma \text{ True positive} + \Sigma \text{ True negative}}{\Sigma \text{ Total population}}$ | |
| **Predicted condition** | Predicted condition positive | **True positive**, Power | **False positive**, Type I error | Positive predictive value (PPV), Precision = $\frac{\Sigma \text{ True positive}}{\Sigma \text{ Predicted condition positive}}$ | False discovery rate (FDR) = $\frac{\Sigma \text{ False positive}}{\Sigma \text{ Predicted condition positive}}$ | |
| | Predicted condition negative | **False negative**, Type II error | **True negative** | False omission rate (FOR) = $\frac{\Sigma \text{ False negative}}{\Sigma \text{ Predicted condition negative}}$ | Negative predictive value (NPV) $= \frac{\Sigma \text{ True negative}}{\Sigma \text{ Predicted condition negative}}$ | |
| | | True positive rate (TPR), Recall, Sensitivity, probability of detection $= \frac{\Sigma \text{ True positive}}{\Sigma \text{ Condition positive}}$ | False positive rate (FPR), Fall-out, probability of false alarm $= \frac{\Sigma \text{ False positive}}{\Sigma \text{ Condition negative}}$ | Positive likelihood ratio (LR+) $= \frac{\text{TPR}}{\text{FPR}}$ | Diagnostic odds ratio (DOR) $= \frac{\text{LR+}}{\text{LR−}}$ | $F_1$ score = $\frac{2}{\frac{1}{\text{Recall}} + \frac{1}{\text{Precision}}}$ |
| | | False negative rate (FNR), Miss rate $= \frac{\Sigma \text{ False negative}}{\Sigma \text{ Condition positive}}$ | True negative rate (TNR), Specificity (SPC) $= \frac{\Sigma \text{ True negative}}{\Sigma \text{ Condition negative}}$ | Negative likelihood ratio (LR−) $= \frac{\text{FNR}}{\text{TNR}}$ | | |

# Applications

The F-score is often used in the field of information retrieval for measuring search, document classification, and query classification performance.[3] Earlier works focused primarily on the $F_1$ score, but with the proliferation of large scale search engines, performance goals changed to place more emphasis on either precision or recall[4] and so $F_\beta$ is seen in wide application.

The F-score is also used in machine learning.[5] Note, however, that the F-measures do not take the true negatives into account, and that measures such as the Matthews correlation coefficient, Informedness or Cohen's kappa may be preferable to assess the performance of a binary classifier.[2]

The F-score has been widely used in the natural language processing literature, such as the evaluation of named entity recognition and word segmentation.

# Difference from G-measure

While the F-measure is the harmonic mean of Recall and Precision, the G-measure is the geometric mean.[2]

# See also

- BLEU
- Matthews correlation coefficient
- METEOR
- NIST (metric)
- Precision and recall
- Receiver operating characteristic
- ROUGE (metric)
- Sørensen–Dice coefficient
- Uncertainty coefficient, aka Proficiency
- Word error rate (WER)

# References


1. Van Rijsbergen, C. J. (1979). *Information Retrieval* (http://www.dcs.gla.ac.uk/Keith/Preface.html) (2nd ed.). Butterworth.
2. Powers, David M W (2011). "Evaluation: From Precision, Recall and F-Measure to ROC, Informedness, Markedness & Correlation" (http://www.bioinfopublication.org/files/articles/2_1_1_JMLT.pdf) (PDF). *Journal of Machine Learning Technologies*. **2** (1): 37–63.

3. Beitzel., Steven M. (2006). *On Understanding and Classifying Web Queries* (Ph.D. thesis). IIT. CiteSeerX 10.1.1.127.634 (https://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.127.634).
4. X. Li; Y.-Y. Wang; A. Acero (July 2008). *Learning query intent from regularized click graphs* (https://pdfs.semanticscholar.org/6718/f8e95461456023196fe6409073151ab0513d.pdf) (PDF). *Proceedings of the 31st SIGIR Conference*
5. See, e.g., the evaluation of the [1] (https://dl.acm.org/citation.cfm?id=1119195)