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Foreword

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This document was prepared by Joint Technical Committee ISO/IEC JTC 1, *Information technology*, Subcommittee SC 42, *Artificial intelligence*.

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Introduction

As academic, commercial and governmental researchers continue to improve machine learning models, consistent approaches and methods should be applied to machine learning classification performance assessment.

Advances in machine learning are often reported in terms of improved performance relative to the state of the art or a reasonable baseline. The choice of an appropriate metric to assess machine learning model classification performance depends on the use case and domain constraints. Further, the chosen metric can differ from the metric used during training. Machine learning model classification performance can be represented through the following examples:

— A new model achieves 97,8 % classification accuracy on a dataset where the state-of-the-art model achieves just 96,2 % accuracy.

— A new model achieves classification accuracy equivalent to the state of the art but requires much less training data than state-of-the-art approaches.

— A new model generates inferences 100x faster than state-of-the-art models while maintaining equivalent accuracy.

To determine whether these assertions are meaningful, aspects of machine learning classification performance assessment including model implementation, dataset composition and results calculation are taken into consideration. This document describes approaches and methods to ensure the relevance, legitimacy and extensibility of machine learning classification performance assertions.

Various AI stakeholder roles as defined in ISO/IEC 22989:2022, 5.17 can take advantage of the approaches and methods described in this document. For example, AI developers can use the approaches and methods when evaluating ML models.

Methodological controls are put in place when assessing machine learning performance to ensure that results are fair and representative. Examples of these controls include establishing computational environments, selecting and preparing datasets, and limiting leakage that potentially leads to misleading classification results. Clause 5 addresses this topic.

Merely reporting performance in terms of accuracy can be inappropriate depending on the characteristics of training data and input data. If a classifier is susceptible to majority class classification, grossly unbalanced training data can overstate accuracy by representing the prior probabilities of the majority class. Additional measurements that reflect more subtle aspects of machine learning classification performance, such as macro-averaged metrics, are at times more appropriate. Further, different types of machine learning classification, such as binary, multi-class and multi-label, are associated with specific performance metrics. In addition to these metrics, aspects of classification performance such as computational complexity, latency, throughput and efficiency can be relevant. Clause 6 addresses these topics.

Complications can arise as a result of the distribution of training data. Statistical tests of significance are undertaken to establish the conditions under which machine learning classification performance differs meaningfully. Specific training, validation and test methodologies are used in machine learning model development to address the range of potential scenarios. Clause 7 addresses these topics.

Annex A illustrates calculation of multi-class classification performance, using examples of positive and negative classifications. Annex B illustrates a receiver operating characteristic (ROC) curve derived from example data in Annex A.

Annex C summarizes results from machine learning classification benchmark tests.

Annex D discusses a chance-corrected cause-specific mortality fraction, a machine learning classification use case. Apart from these, this document does not address any issues related to benchmarking, applications or use cases.

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Information technology — Artificial intelligence — Assessment of machine learning classification performance

1 Scope

This document specifies methodologies for measuring classification performance of machine learning models, systems and algorithms.

2 Normative references

The following documents are referred to in the text in such a way that some or all of their content constitutes requirements of this document. For dated references, only the edition cited applies. For undated references, the latest edition of the referenced document (including any amendments) applies.

ISO/IEC 22989:2022, *Information technology — Artificial intelligence — Artificial intelligence concepts and terminology*

ISO/IEC 23053:2022, *Framework for Artificial Intelligence (AI) Systems Using Machine Learning (ML)*

3 Terms and definitions

For the purposes of this document, the terms and definitions in ISO/IEC 22989:2022, ISO/IEC 23053:2022, and the following apply.

ISO and IEC maintain terminology databases for use in standardization at the following addresses:

— ISO Online browsing platform: available at https://www.iso.org/obp

— IEC Electropedia: available at https://www.electropedia.org/

3.1 Classification and related terms

3.1.1
classification
method of structuring a defined type of item (objects or documents) into classes and subclasses in accordance with their characteristics

[SOURCE: ISO 7200:2004, 3.1]

3.1.2
classifier
trained model and its associated mechanism used to perform *classification* (3.1.1)

3.2 Metrics and related terms

3.2.1
evaluation
process of comparing the *classification* (3.1.1) predictions made by the model on data to the actual labels in the data

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3.2.2
false negative
miss
type II error
F_N
sample wrongly classified as negative

3.2.3
false positive
false alarm
type I error
F_P
sample wrongly classified as positive

3.2.4
true positive
T_P
sample correctly classified as positive

3.2.5
true negative
T_N
sample correctly classified as negative

3.2.6
accuracy
number of correctly classified samples divided by all classified samples

Note 1 to entry: It is calculated as $a = (T_P + T_N) / (T_P + F_P + T_N + F_N)$.

3.2.7
confusion matrix
matrix used to record the number of correct and incorrect *classifications* (3.1.1) of samples

3.2.8
F_1 **score**
F-score
F-measure
F_1-measure
harmonic mean of *precision* (3.2.9) and *recall* (3.2.10)

Note 1 to entry: It is calculated as $F_1 = 2T_P / (2T_P + F_P + F_N)$.

3.2.9
precision
positive predictive value
number of samples correctly classified as positive divided by all samples classified as positive

Note 1 to entry: It is calculated as $p = T_P / (T_P + F_P)$.

3.2.10
recall
true positive rate
sensitivity
hit rate
number of samples correctly classified as positive divided by all positive samples

Note 1 to entry: It is calculated as $r = T_P / (T_P + F_N)$.

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3.2.11
specificity
selectivity
true negative rate
number of samples correctly classified as negative divided by all negative samples

Note 1 to entry: It is calculated as $s = T_N / (T_N + F_P)$.

3.2.12
false positive rate
fall-out
number of samples incorrectly classified as positive divided by all negative samples

Note 1 to entry: It is calculated as $F_{P,R} = F_P / (F_P + T_N)$.

3.2.13
cumulative response curve
gain chart
graphical method of displaying *true positive rates* (3.2.10) and percentage of positive prediction in the total data across multiple thresholds

3.2.14
lift curve
graphical method of displaying on the y-axis the ratio of *true positive rate* (3.2.10) between the model and a random classifier, and on the x-axis the percentage of positive predictions in the total data across multiple thresholds

3.2.15
precision recall curve
PRC
graphical method for displaying *recall* (3.2.10) and *precision* (3.2.9) across multiple thresholds

Note 1 to entry: A PRC is more suitable than a ROC (receiver operating characteristic) curve for showing performance with imbalanced data.

3.2.16
receiver operating characteristic curve
ROC curve
graphical method for displaying *true positive rate* (3.2.10) and *false positive rate* (3.2.12) across multiple thresholds

3.2.17
cross-validation
method to estimate the performance of a machine learning method using a single dataset

Note 1 to entry: Cross-validation is typically used for validating design choices before training the final model.

3.2.18
majority class
class with the most samples in a dataset

4 Abbreviated terms

AI	artificial intelligence
ANOVA	analysis of variance
AUPRC	area under the precision recall curve

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