Implicit Performance Estimation for Score-Based Classifiers Using Cognitive Diagnosis

A Preprint

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Abstract

Score-based binary classifiers are widely used in machine learning. When it comes to their validation, well-known performance metrics, such as ROC-AUC, F1-score, and Accuracy, are most often used. However, all these metrics have their flaws and represent the performance of the classifier only from a certain angle. This work attempts to aggregate all traditional performance metrics using cognitive diagnosis models. Cognitive diagnosis models are widely researched in smart education and proved to be successful in estimating students' latent knowledge from their exercise solutions. In the context of binary classification, classifiers can be viewed as students and performance metrics as exercises. This reduction represents a novel approach to the validation of binary classifiers and produces latent knowledge attributes, which can be interpreted as new implicit performance attributes.

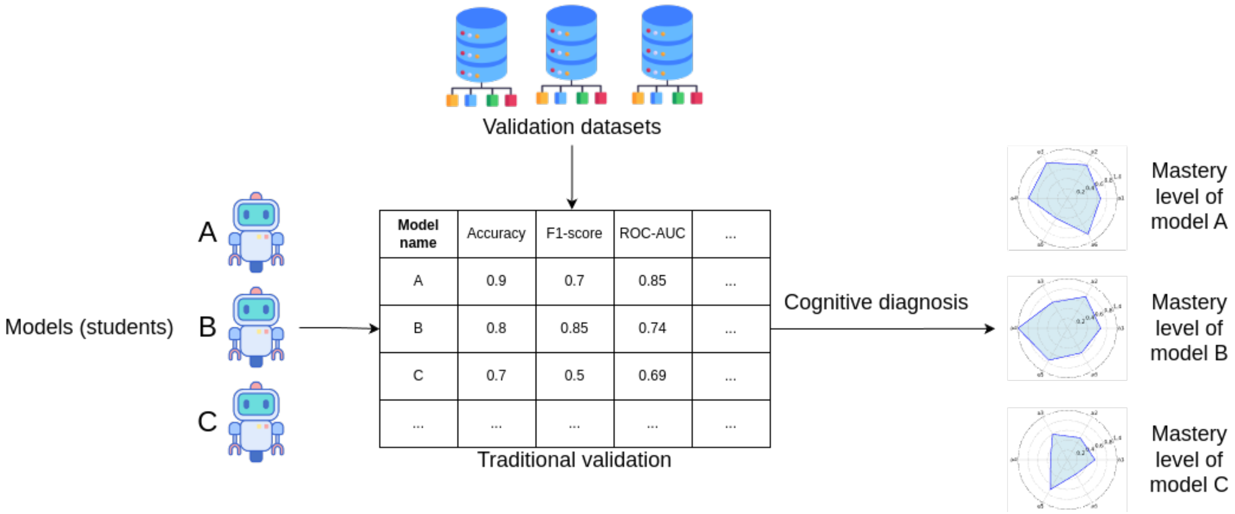
Keywords Validation · Binary classification · Cognitive diagnosis · Item Response Theory · Machine learning

1 Introduction

The validation is an important step in the machine learning models lifecycle. For this reason, many performance metrics (Accuracy, F1-score, ROC-AUC, etc.) have been developed. However, none of them can entirely characterize the model behavior [5, 4], and there is no clear agreement on which of them to use. It may be impossible to get the true attributes of the model by performing direct aggregation of the answers.

In psychometrics, it is believed that the desired attributes of the subject are only partially manifested in direct measurements. Applying this idea to ML validation, researchers actively try to create a better performance metric by using Item Response Theory (IRT) [16], a classical tool of the psychometrician [9, 11, 2]. However, IRT estimates only one latent attribute, which is not enough to completely describe the model, and the only non-one-dimensional approach approach only estimated the Recall equivalents in multi-class classification [7].

Validating models by their performance metrics can be reduced to the cognitive diagnosis task in smart education, where the goal is to estimate certain predefined attributes of the students by their exercise solutions. For the latter, a wide variety of models have been developed [8, 3, 15, 6]. This work is the first attempt to apply cognitive diagnosis models to create new, potentially better metrics from traditional ones.



Model name	Accuracy	F1-score	ROC-AUC	...
A	0.9	0.7	0.85	...
B	0.8	0.85	0.74	...
C	0.7	0.5	0.69	...
...	...	...	...	...

Figure 1: Validation using cognitive diagnosis framework

Our task is to create a framework that would allow estimating mastery of machine learning models for each predefined skill. For that problem, first traditional performance metrics from validation datasets are calculated, and then cognitive assessment is performed, which assigns mastery for each skill to every model. It's important to mention that this approach only works for a pool of models, not for a single one, due to the nature of cognitive diagnosis models.

We defined specific skills, and then performed experiments on score-based classifiers to obtain their cognitive mastery levels (1). The new metrics (mastery levels) turned out to be competitive with the traditional ones, describing the model from a slightly different angle and considering other models results, and, most importantly, allow using multiple validation datasets, thus capturing model behavior in different learning contexts.

The proposed validation framework can be used to perform validation and comparison of multiple binary classifiers. We also propose a method for adding newly created model to the pool of existing ones, and obtaining it's mastery levels. This might open the way to creating multi-skill ML model leaderbords, capturing multiple various datasets.

2 Related work

It is known that traditional performance metrics can't fully derscribe the model's performance, and each one of them has their flaws [4]. For example, in binary classification, Accuracy does not see the difference between errors in the positive and negative classes; Precision and Recall do not know the number of correctly identified negative classes (True Negative); ROC-AUC is sensitive to class imbalance [5].

In 2016, the first attempt of applying psychometric tools for ML validation was made [9], where the author tried to apply IRT [16] for estimated a better version of Accuracy for multi-class classifiers. That study created a great interest for other researchers in applying IRT in machine learning. IRT-based ensembles were proposed [2], where the weights are the IRT scores. IRT-based leaderboard for NLP models validation [11]. Researchers also tried to use IRT to reduce the validation dataset [10], or to make manual validation more efficient [13]. An attempt was made to use IRT for clustering examples in multi-dataset NLP benchmarks [12].

One of the advantages of using IRT for evaluation is that it assigns parameters to every item (object in the dataset), which can later be used to enhance interpretation [11]. The framework for estimating this parameters for newly generated questions was proposed [1].

Another widely researched area is the cognitive diagnosis task, where it is required to estimate students' mastery levels on every predefined skill by looking at their exercise solutions, and exercise-skill correspondence matrix, which is also known as Q-matrix. Previously, only classical models like DINA [3] or multidimensional IRT (MIRT) [14] models were used. But in 2022, there was a first attempt of using deep cognitive diagnosis model with trainable interaction function, this deep model was called NeuralCD [15]. Later, a lot of extensions of NeuralCD appeared, which were designed to fix some of its flaws, most apparent of which is the lack of knowledge association [15, 6, 8].

To our knowledge, there has been only one attempt of using cognitive diagnosis models for machine learning models validation. In 2023, Camilla framework was proposed for validating deep computer vision multi-class classifiers [7]. The authors estimated the new equivalents of respective Recalls for each class and argued that they describe the performance better by taking into account difficult and easy samples. However, despite their success, we believe that for binary classifiers estimating 2 Recall equivalents is not enough for the full description of the model performance. Our approach is different from the described above in several ways:

- Binary classification task is considered instead of the multi-class.
- Performance metrics are used as exercises instead of the objects.
- Multiple validation datasets are used instead of one, with retraining classifiers for each dataset. This can potentially test the algorithm performance in different learning contexts.

3 Problem statement

Quantity	Description
$\mathcal{D} = \{\mathcal{D}_1, \dots, \mathcal{D}_L\}$	Set of datasets
$\mathcal{S} = \{s_1, \dots, s_N\}$	Set of models (students)
$\hat{\mathcal{E}} = \{\hat{e}_1, \dots, \hat{e}_{\hat{M}}\}$	Set of performance metrics (exercises)
$\mathcal{E} = \{e_1, \dots, e_M\}, M = \hat{M} \times D$	Set of performance metrics, taking datasets into account
$\mathcal{K} = \{\mathcal{K}_1, \dots, \mathcal{K}_K\}$	Set of concepts
L	Number of datasets
N	Number of models (students)
$\hat{M}$	Number of performance metrics (exercises)
K	Number of concepts
T	Number of response logs
$l \in \{1, \dots, L\}$	Index of the dataset
$i \in \{1, \dots, N\}$	Index of the student
$j \in \{1, \dots, M\}$	Index of the exercise
$k \in \{1, \dots, K\}$	Index of the concept
$t \in \{1, \dots, T\}$	Index of the response log
$x^s \in \{0, 1\}^N$	One-hot representation of the model (student)
$x^e \in \{0, 1\}^M$	One-hot representation of the performance metric (exercise)
$Q = \{Q_{jk}\}_{\hat{M} \times K} \in [0, 1]^{\hat{M} \times K}$	Q-matrix
$G \in \{0, 1\}^{K \times K}$	Directed Acyclic Graph (DAG) of concept dependency
$y \in [0, 1]$	Model output
$R = \{(x^s_t, x^e_t, r_t)\}_{t=1}^T$	Response logs
$r \in [0, 1]$	Result of solving the exercise (value of the performace metric)
$\mathcal{M} = \{m_{ik}\}_{N \times K} \in [0, 1]^{N \times K}$	Latent students' mastery levels
$\mathcal{L}$	Loss function

Table 1: Definitions

Task definition *Suppose there are L datasets $\mathcal{D} = \{\mathcal{D}_1, \dots, \mathcal{D}_L\}$, N machine learning models (algorithms) $\mathcal{S}\{s_1, \dots, s_N\}$, $\hat{M}$ traditional performance metrics $\hat{\mathcal{E}} = \{\hat{e}_1, \dots, \hat{e}_{\hat{M}}\}$, and K predefined skills (or concepts) $\mathcal{K} = \{\mathcal{K}_1, \dots, \mathcal{K}_K\}$. Q-matrix $Q \in \mathbb{R}^{\hat{M} \times K}$ is a binary matrix that represents correspondence between performance metrics and concepts: $Q_{jk} = 1 \iff$ knowledge of concept $\mathcal{K}_k$ is required for having a high value of $\hat{e}_j$. Computing performance metrics $\hat{\mathcal{E}}$ for each dataset forms a set of response logs $R = \{(x^s, x^e, r)\}_{t=1}^T$, where $T = N \times M$, $M = \hat{M} \times L$ — a triples consisting of one-hot representation of model (student), performance metric (exercise), taking the index of dataset in the account, and the metric $r \in [0, 1]$, normalized to [0, 1]. The desired models' mastery levels for all concepts can be represented as matrix $\mathcal{M} = \{m_{ik}\} \in [0, 1]^{N \times K}$, where m_{ik} is the mastery level of student s_i for the concept $\mathcal{K}_k$; $m_{ik} = 1$ represents total knowledge of the concept, and $m_{ik} = 0$ — total ignorance. The task is to infer the mastery matrix $\mathcal{M}$ using cognitive diagnosis model by predicting the responses r_t.*

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