Machines in a classroom: Towards human-like active learning

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Abstract. Machines usually employ a guess-and-check strategy to analyze data: they take the data, make a guess, check the answer, adjust it with regard to the correct one if necessary, and, in the end, they try again on a new data set. This "passive" learning technique normally requires an enormous amount of labeled data that has to provide the correct answers. An active learning environment guarantees better performance while training on less, but carefully chosen, data which reduces the costs of both annotating and analyzing large data sets. The core difference between an active and a passive learning procedure is that a machine while learning in an active learning environment requests instances based upon past queries and their responses. This leads to the optimal leveraging of both new and existing data.

The process of querying the information imitates a classroom instructional method that actively engages learners in the learning process. They replace or adapt their knowledge and understanding based on prior knowledge in response to learning opportunities provided by a teacher. This contrasts with a model of instruction whereby knowledge is transmitted from the teacher to learners, which typically presents passive learning. While human-like active learning integrates a variety of strategies and instructional models chosen by a teacher to contribute to learners' knowledge, machine active learning strategies are expected to be more versatile and self-sustaining. In particular, the best-known active learning strategies still need more adaptivity and learner-centricity that would allow them to work on most scenarios and datasets.

We fill this gap by mimicking human-like active learning or, to be exact, considering an active learning environment in an educational setting where multiple-choice testing is used as an in-class instrument to enrich learners' comprehension. Designing a pool of sensible incorrect items (or distractors) in multiple-choice tests eliminates pure guessing in the responses and, by that, increases the amount of information an item provides for adopting an active learning strategy. Besides, depending on their level of ability, learners may develop a rational strategy of ruling out the most unlikely responses, and then choosing at random among the remaining ones. The rate of success then also depends on the relationship between the item's parameters and learners' working knowledge. Finally, under no penalty or a low penalty for incorrect responses, learners are an incentive to guess, increasing measurement error. On the other hand, a high penalty does not discourage guessing: learners with high-risk aversion are more easily discouraged, so penalties introduce a bias in favor of risk-takers.

We propose a new strategy for pool-based sampling the correct answer and distractors to improve the information retrieval for the item's parameters such as guessing, forgetting, discrimination, and difficulty with regard to the four-parameter logistic item response theory (4PL IRT) model. In addition, we impose a penalty for incorrect responses to simulate more realistic learners' behavior in a classroom. The strategy allows for a new informativeness measure for unlabelled instances based on the definition of the IRT' item capacity that involves computing gradients. This means that the strategy based on the measure may be directly embedded in gradient-based learning models at a training step, thereby bringing the flexibility to an active learning framework. The capacity also assesses the amount of information for estimating learners' parameters based solely on the item parameter estimates. This knowledge of how a pool of items behaves in estimating learners' parameters permits the design of a sampling procedure with specific properties. As a result, the proposed approach to teaching a machine suggests a more adaptive and learner-centered method for stimulating active learning as well as adopting strategies that are successfully used in human learning.

Keywords: Active learning · Multiple-choice testing · Item response theory · Guessing strategy · Query strategy.