13 LBC | Machines in a classroom: Towards human-like active learning

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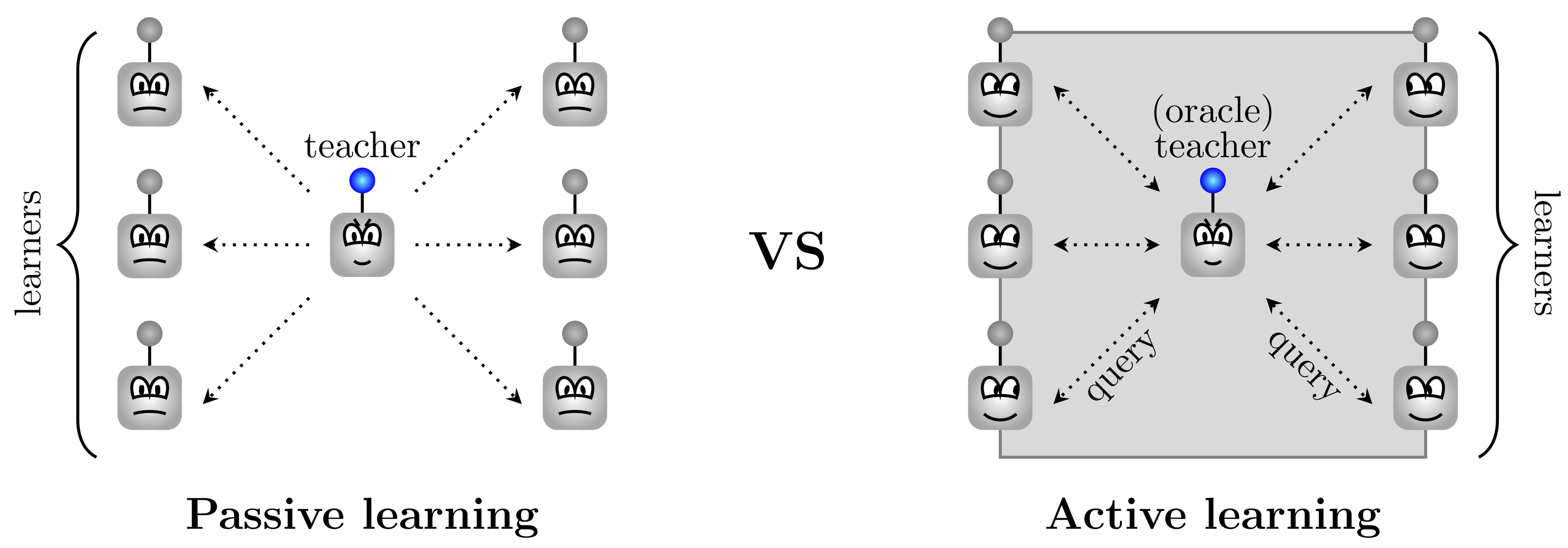
Introduction

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. Learning in an active learning environment, a machine requests instances based upon past queries and their responses. This leads to the optimal leveraging of both new and existing data.



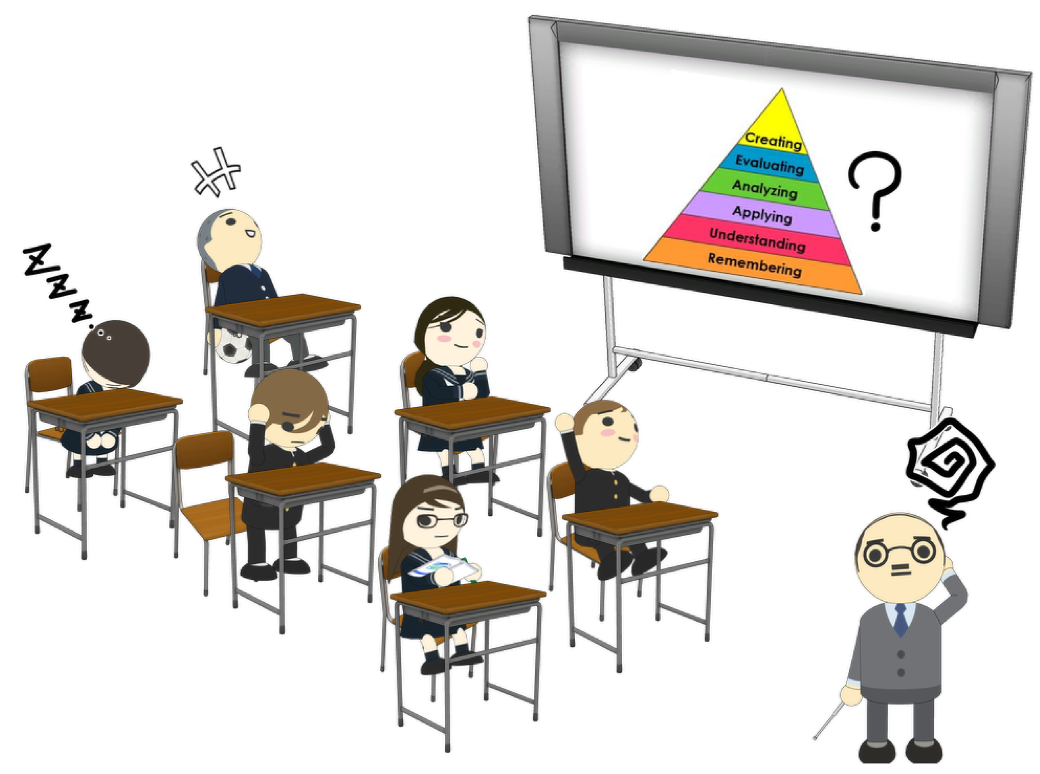
Problem statement

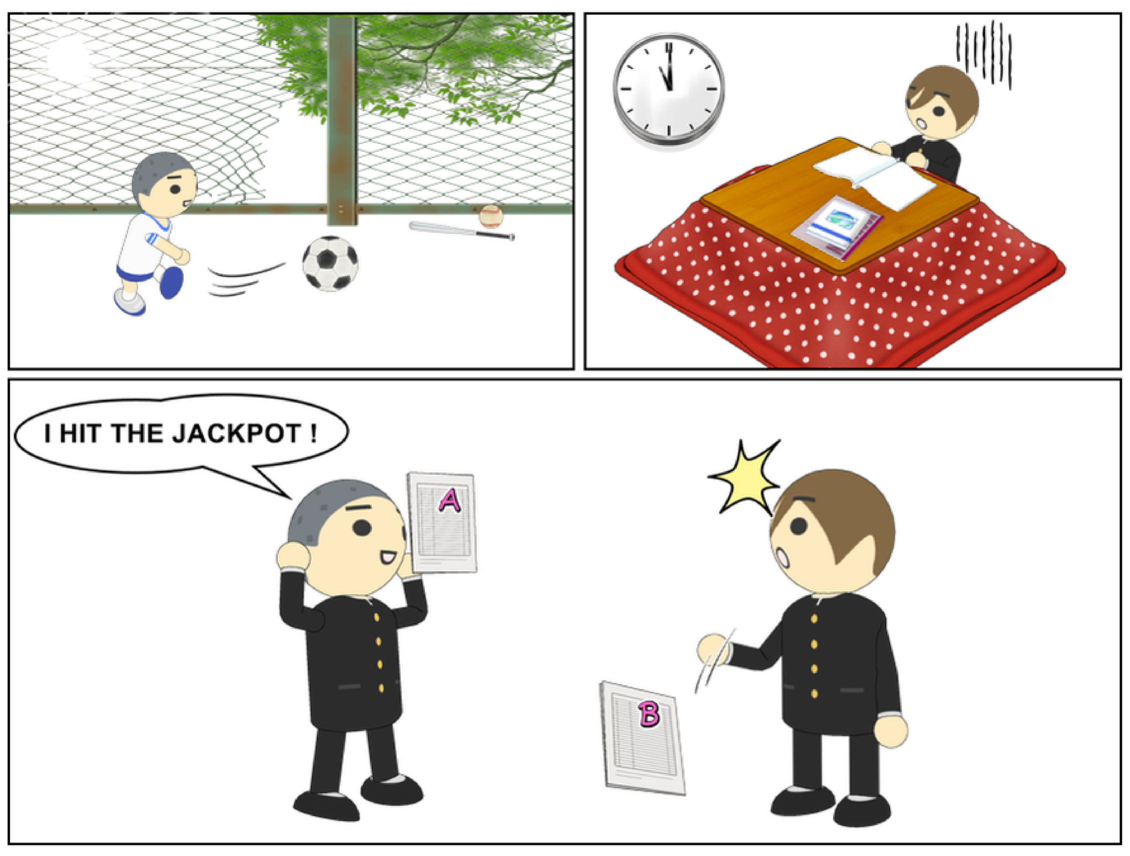
The best-known machine **active learning strategies** still need more adaptivity and learner-centricity that would allow them to **work on most scenarios and datasets**.

Active learning in an educational setting integrates a variety of strategies and instructional models to contribute to learners’ knowledge. In particular, in multiple-choice testing:

1) depending on their level of ability, learners may develop a rational strategy of ruling out the most unlikely responses;

2) under no penalty or a low penalty for incorrect responses, learners have an incentive to guess, increasing measurement errors.





Designing a pool of sensible incorrect items (distractors) eliminates pure guessing in the responses. This **increases the amount of information** an item provides for adopting an active learning strategy.

Methodology

To address the posed problem, **we suggest**:

1) a new strategy for pool-based sampling correct answers and distractors with regard to 4PL IRT model;

2) a penalty for incorrect responses to simulate more realistic learners’ behavior in a classroom.

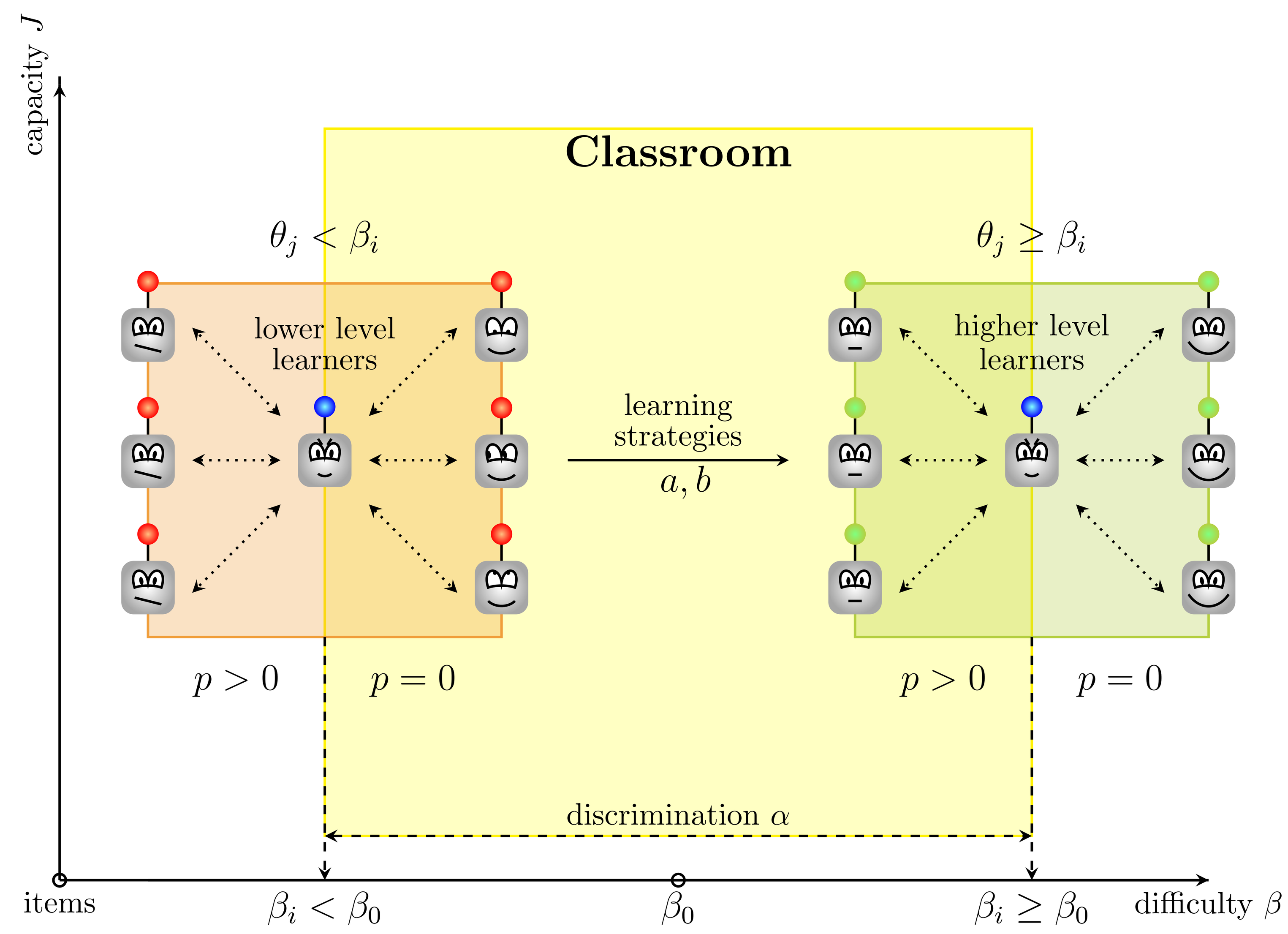
A new pool-based strategy

The strategy allows for more efficient information retrieval for the item’s parameters such as learning strategies for guessing a_i and forgetting b_i, a discrimination factor α_i that allows us to differentiate between learners with different levels of knowledge (locations) θ_j, and items difficulty β_i with regard to the four-parameter logistic item response theory (4PL IRT) model:

$$p(x_{ij}=1|\theta_j,\alpha_i,\beta_i,a_i,b_i) = a_i + \frac{b_i - a_i}{1+\exp(-\alpha_i(\theta_j-\beta_i))},$$

where $p(x_{ij}=1|\theta_j,\alpha_i,\beta_i,a_i,b_i)$ is the probability of providing the correct response $x_{ij}=1$ by a learner with j to an item i. The rate of success mainly depends on the relationship between the item’s parameters and learners’ working knowledge.

The figure below depicts **the proposed pool-based strategy** to increase the items capacity J with regard to the items’ difficulty β_i, learners’ locations θ_j, strategies a_i and b_i, and penalty announcement p. **The strategy is aimed at “moving” learners along the difficulty axis while keeping high values for the capacity axis.**



A new informativeness measure

The strategy allows for a new informativeness measure for unlabelled instances based on the definition of m items’ information J:

$$J(\theta) = -\mathcal{E}\left[\frac{\partial^2}{\partial\theta^2}\ln L\right] = \sum_{i=1}^{m}\frac{p_i'^2}{p_i(1-p_i)} = \frac{1}{\sigma_e^2(\hat\theta|\theta)},$$

$$\ln L(x_{ij}|\theta_j,\alpha_i,\beta_i,a_i,b_i) = \sum_{i=1}^{m}(x_{ij}\ln(p_i)+(1-x_{ij})\ln(1-p_i)), \qquad p_i \equiv p(x_{ij}=1|\theta_j,\alpha_i,\beta_i,a_i,b_i),$$

where $\sigma_e^2(\hat\theta|\theta)$ is the asymptotic variance error of the estimate θ. The items’ capacity can be defined as the maximum of the information function $J(\theta)_{\max}$.

The gradient-based definition of the items’ capacity makes it possible **to employ the strategy** based on the new informativeness measure **at a training step**, thereby bringing **more flexibility and adaptivity** to an active learning framework.

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