Neurons in 'active learning' learn less than they think

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Problem statement

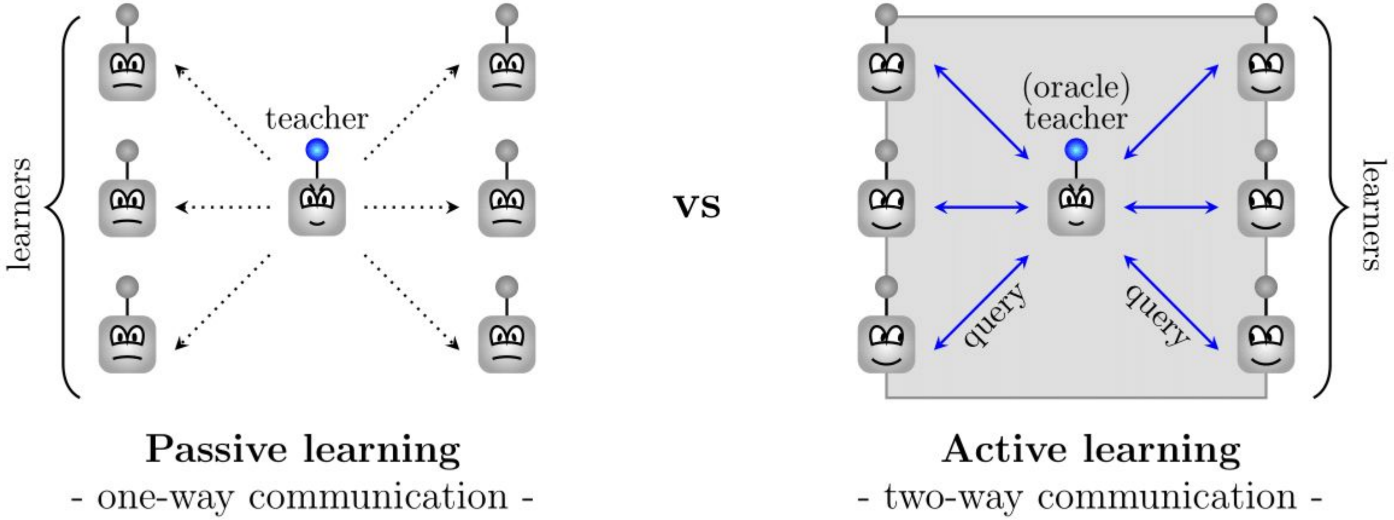


Figure 1. The concepts of learning environments: Passive vs. Active

Deep neural networks are not good at telling when they are not sure while working in an active learning environment.

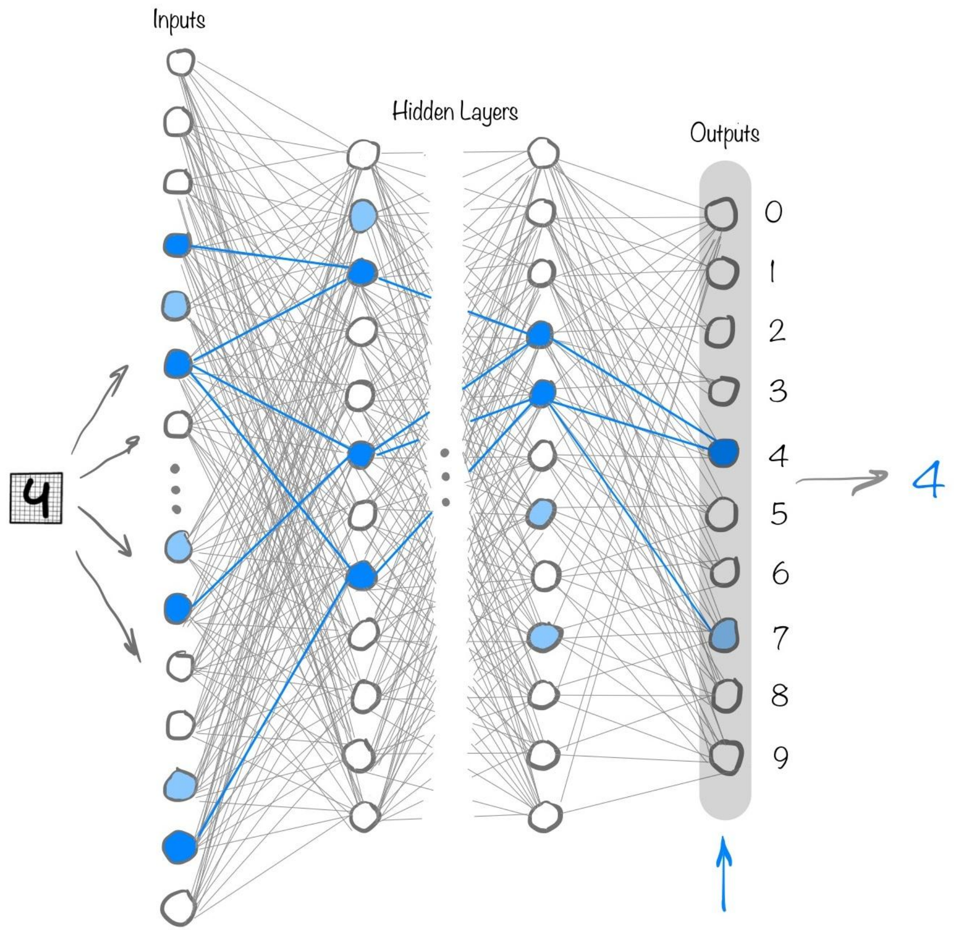
Problem statement

Deep neural networks

- have grown so complex that it seems impossible to follow their decision-making processes

We

- have little control over rebuilding it as it is not transparent to us

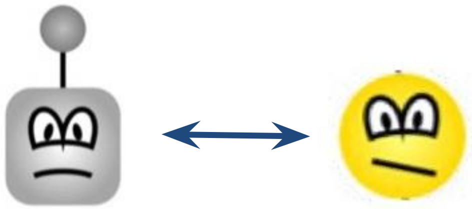


Research question:

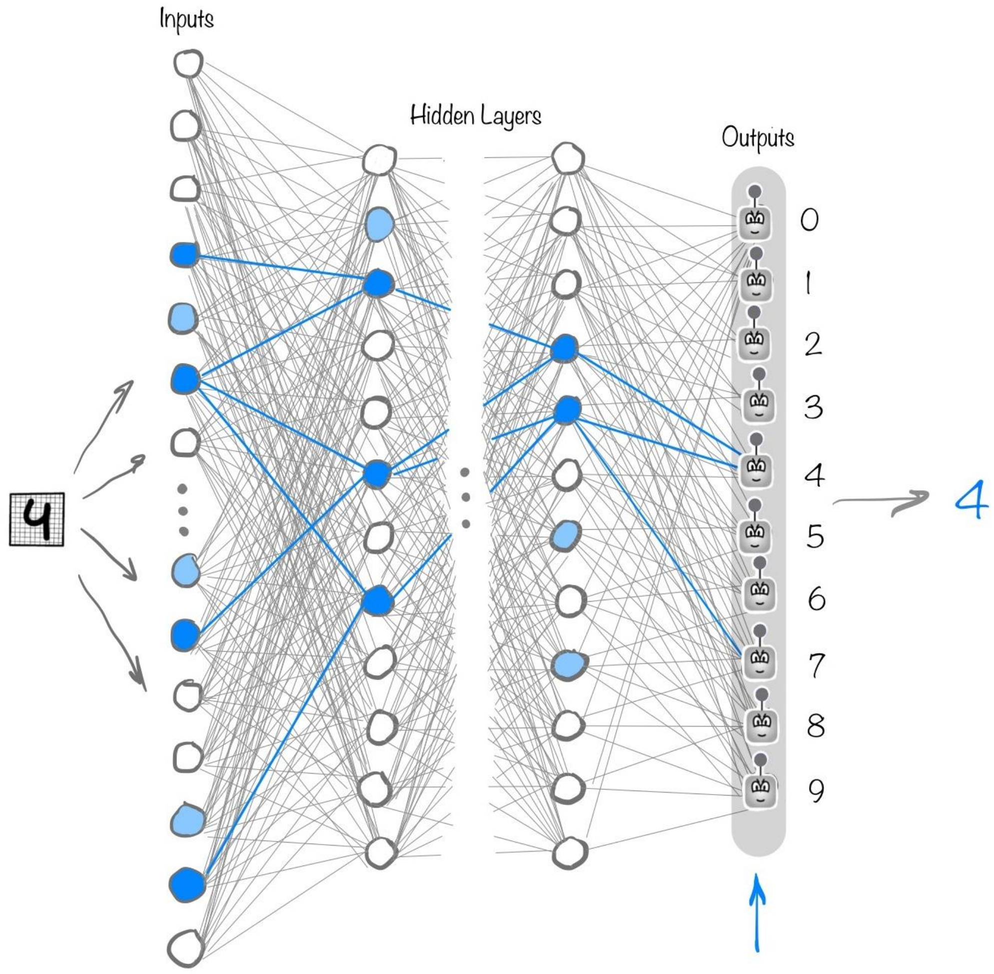
whether we can explain how networks come to decisions by imitating human-like reasoning in multiple-choice testing.

Testing framework

We measured classification proficiencies of a group of learners - neurons or network weights.



Learners in a testing framework: a neuron and a human



The learners are given multiple-choice tests to assess their level of proficiency - labelled examples.

The responses to the tests constitute behavioral observations.

Testing framework

We focused on the 4PL IRT model to assess the distance between a learner and an item as it defines the learner's clear response:

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

where $p(y_{ij} = 1|\theta_j, \alpha_i, \beta_i, a_i, b_i)$ is the probability of providing the correct answer $y_{ij} = 1$ to an item i by a learner j with the ability θ_j.

$\theta_j \geq \beta_i$

A strong learner

$\theta_j < \beta_i$

A weak learner

The parameters α_i, β_i, a_i, b_i introduce a set of learning behaviors: a discrimination factor, item difficulty, guessing and forgetting factors, respectively.

Information capacity

The information function measures the amount of information items provide:

$$S(\theta;\alpha_i,\beta_i,a_i,b_i)=\sum_{i=1}^{m}\frac{\alpha_i^2(p_i-a_i)^2\left((1-p_i)(b_i-a_i)-(p_i-a_i)(1-b_i)\right)^2}{p_i(1-p_i)(b_i-a_i)^2(1-a_i)^2}$$

where

$$p_i \equiv p(y_{ij}=1|\theta_j,\alpha_i,\beta_i,a_i,b_i).$$

The items' capacity is the maximum of the information function.

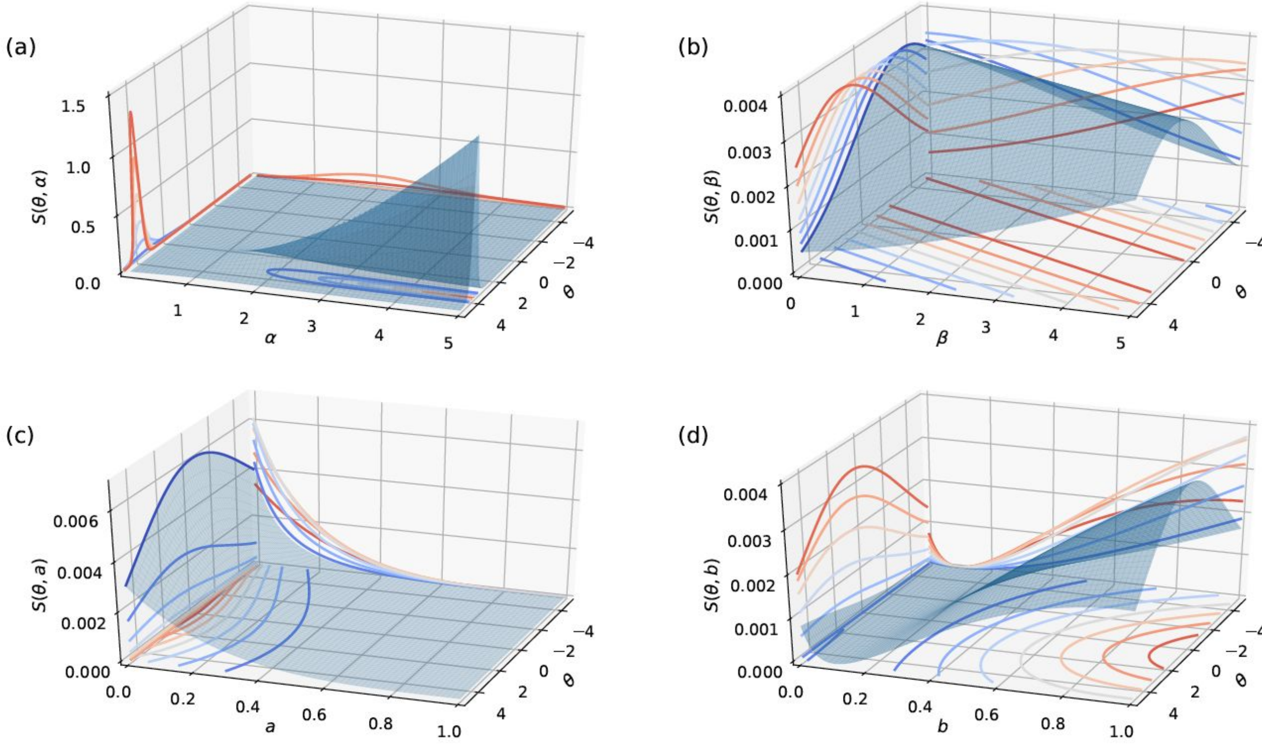


Figure 2. The projections of the information function on different planes: (a) α - plane; (b) β - plane; (c) a - plane; (d) b - plane

Information capacity

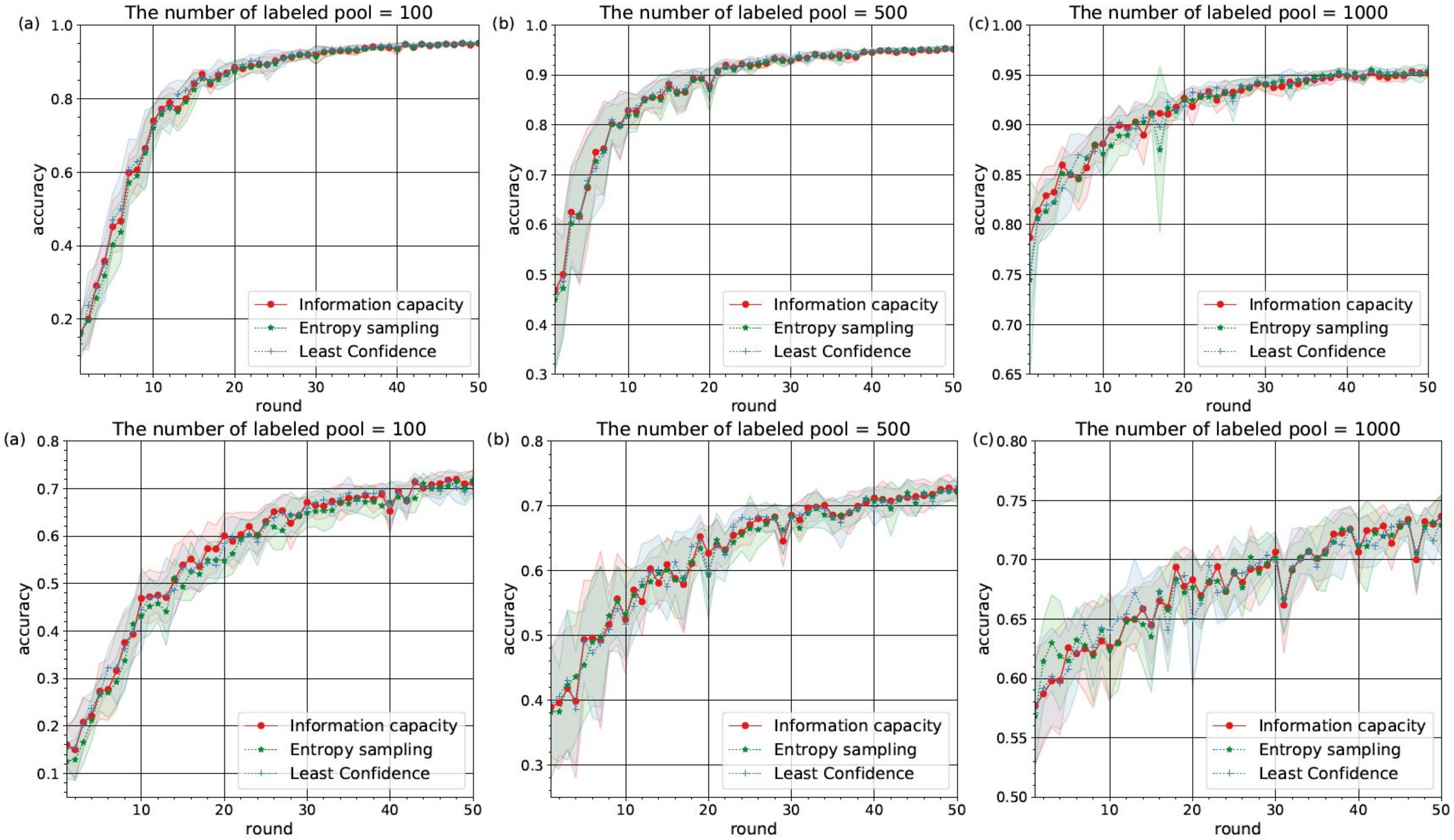
Algorithm 1 Pool-based active learning with Information Capacity strategy

1: **procedure** INFORMATIONCAPACITY($m_{\text{train}}, m_{\text{test}}$)
2: Initialize a labeled training set L;
3: Initialize an unlabeled training pool $U = m_{\text{train}} - L$;
4: Initialize a learning behavior of learners B with regard to a set of parameters α, β, a, b;
5: Train a group of learners on the labeled set L;
6: Measure performance of the group of learners on the test set m_{test};
7: Initialize several rounds n_{round} and several queried examples $|L_S|$;
8: **for** *round* $\in n_{\text{round}}$ **do**
9: Estimate the probabilities with regard to (1) based on the learning behavior B;
10: Sort the unlabeled items in U according to (4) based on the probabilities from the step 9;
11: Query the items L_S with the smallest of the maximum capacity S in a *round*;
12: $L \leftarrow L \cup L_S$;
13: $U \leftarrow U \setminus L_S$;
14: Retrain a group of learners on the labeled set L;
15: Measure performance of the group of learners on the test set m_{test};
16: **end for**
17: **return** The performance of the learners with the interpretation of their learning behavior.

Results

MNIST

Fashion MNIST



Information Capacity performs similarly to Least Confidence and Entropy Sampling but brings more transparency into a deep learning process.

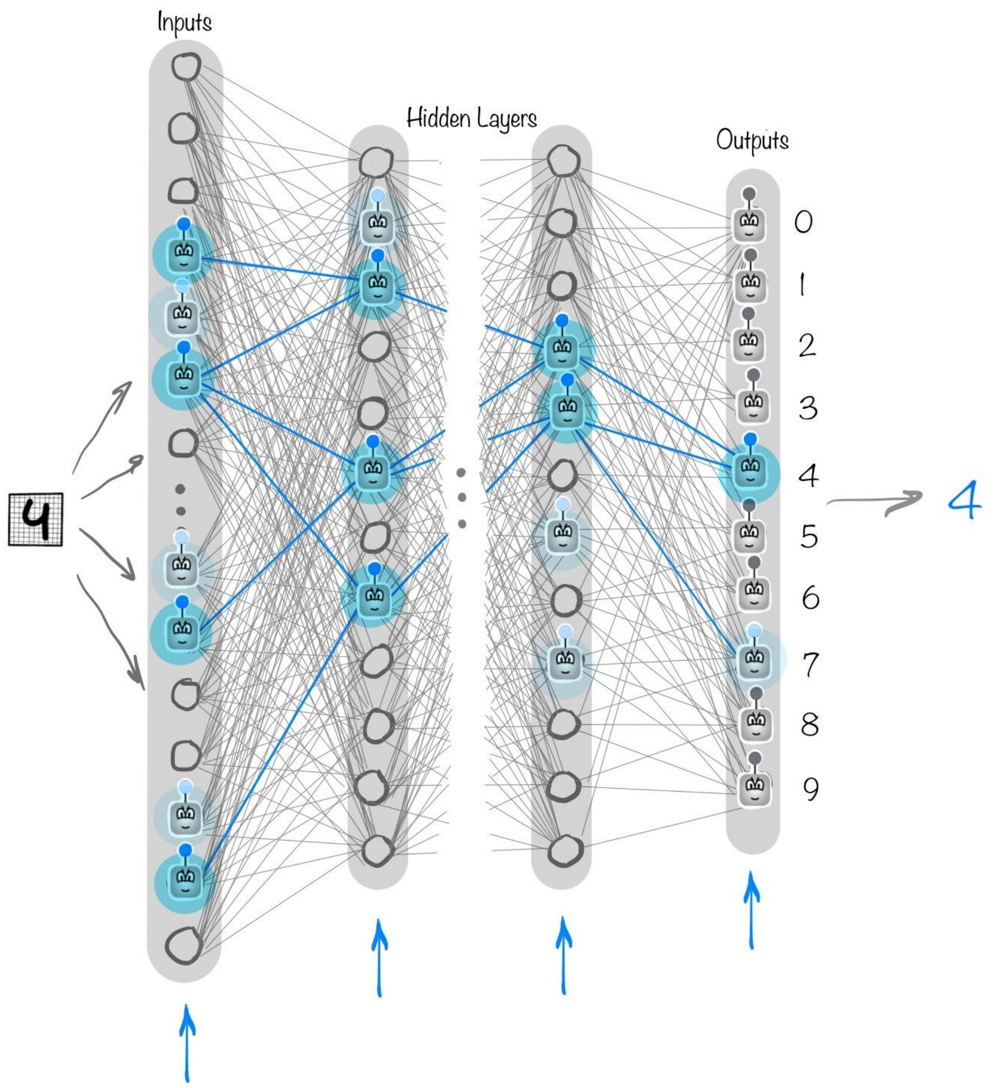
Results

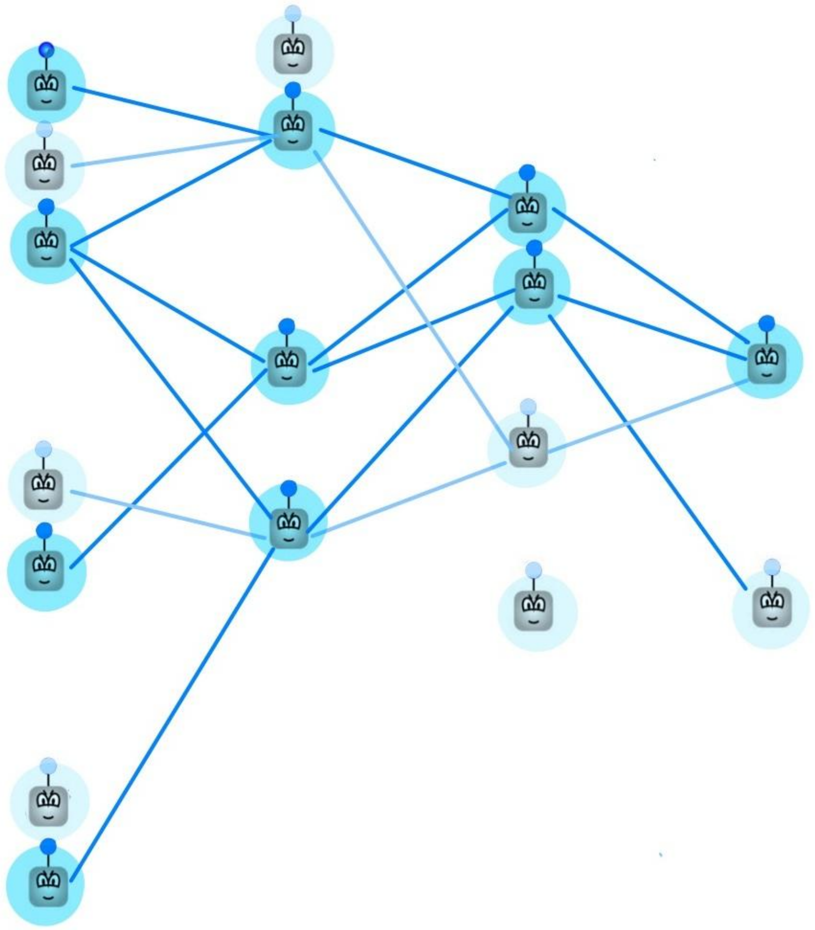
The pre-defined parameters for Information Capacity revealed the following learners' behavior:

The learners had a success probability $b_i = 0.9$ due to partial forgetting while they guessed correctly with the probability $a_i = 0.1$ on the item i of the difficulty $\beta_i = 4$, which discriminated the learners and items with $\alpha_i = 0.25$.

Least Confidence and Entropy Sampling can be interpreted by the scenario in which each learner (neuron) in a neural network shares the revealed behavior.

Considering the complexity of deep networks, these backbone strategies seem limited.





By modeling learning behaviors, Information Capacity allows exploring **novel neural networks**, **not limited to gradient-based methods** and **primitive connectionist models**.

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Article

From Knowledge Transmission to Knowledge Construction: A Step 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 try again on a new data set. 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. This issue becomes even more critical for deep learning applications. Human-like active learning integrates a variety of strategies and instructional models chosen by a teacher to contribute to learners' knowledge, while machine active learning strategies lack versatile tools for shifting the focus of instruction away from knowledge transmission to learners' knowledge construction. We approach this gap by considering an active learning environment in an educational setting. We propose a new strategy that measures the information capacity of data using the information function from the four-parameter logistic item response theory (4PL IRT). We compared the proposed strategy with the most common active learning strategies—Least Confidence and Entropy Sampling. The results of computational experiments showed that the Information Capacity strategy shares similar behavior but provides a more flexible framework for building transparent knowledge models in deep learning.

Keywords: item information; pool-based sampling; multiple-choice testing; item response theory; active learning; deep learning

1. Introduction

The passive learning technique normally requires an enormous amount of labeled data that has to provide the correct answers (see Figure 1). 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 [1–10]. In uncertainty sampling, which has been reported to be successful in numerous scenarios and settings [11,12], a machine requests instances which cause uncertainty. This leads to the optimal leveraging of both new and existing data [13].

The process of querying the information imitates a classroom instructional method that actively engages learners in the learning process [14–16]. 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. Active learning in an educational setting integrates a variety of strategies and instructional models chosen by a teacher to contribute to learners' knowledge [17].

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