MACHINE TEACHING OF ACTIVE SEQUENTIAL LEARNERS

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TL;DR:
- **HOW TO STEER AN ACTIVE MACHINE LEARNER THAT QUERIES LABELS SEQUENTIALLY?**
- **WE FORMULATE THE TEACHING PROBLEM AS A MARKOV DECISION PROCESS, WITH LABEL CHOICE AS ACTION.**
- **A TEACHER TEACHING WITH INCONSISTENT LABELS CAN BEAT CONSISTENT LABELS.**
- **WE FURTHER ENDOW THE LEARNER WITH A MODEL OF THE TEACHER.**
- **APPLIED TOWARDS MODELLING STRATEGIC USER BEHAVIOUR IN INTERACTIVE INTELLIGENT SYSTEMS.**
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INTRODUCTION

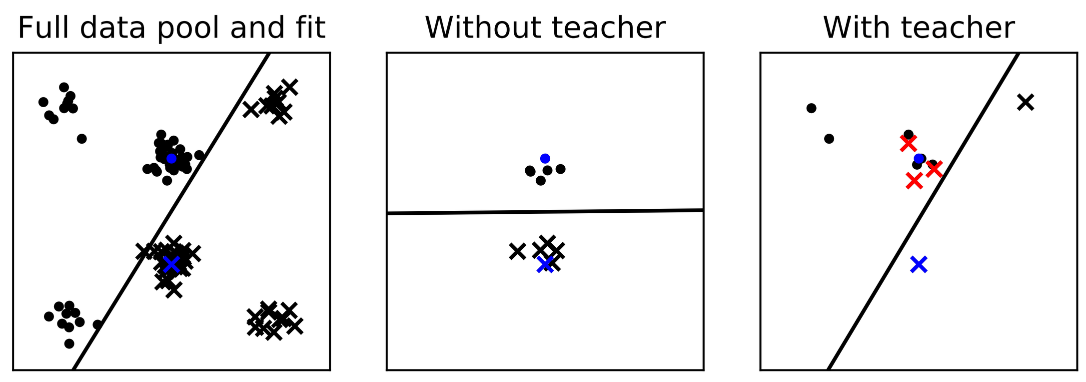
Machine teaching addresses the problem of finding the best training data that can guide a learning algorithm to a target model with minimal effort.

- Traditionally, the teacher provides data by sampling labels from the true data distribution (consistent teacher).
- Providing true labels can be sub-optimal in finite–horizon tasks for sequential learners that actively choose their queries (see right "Without teacher" panel).

Contributions

- We formulate this sequential teaching problem, as a Markov decision process, and allow the teacher to provide data inconsistent with the true distribution (see right "With teacher" panel).
- We address the complementary problem of the teaching-aware learner by endowing the learner with a model of the teacher. The final inference problem reduces to inverse reinforcement learning.
- We evaluate the formulation with multi-armed bandit learners in simulated experiments and a user study.

The approach gives tools to taking into account strategic (planning) behaviour of the users in interactive intelligent systems, such as recommendation engines.



Example of teaching effect on pool-based logistic regression active learner. Starting from blue data,

- the learner without teacher, fails to sample useful points from the pool to learn a good decision boundary.
- a planning teacher can help the learner by switching some labels (red points).

MODELLING

Task: Goal of the learner and the teacher is to learn and teach the best possible model of the true data distribution respectively. We consider Bayesian Bernoulli Bandits as a specific case of this task.
Interaction: At each iteration t, the bandit learner queries an arm i_t and the teacher provides a stochastic reward y_t.
Learner model:

- Logistic regression based contextual multi-armed bandit with Thompson sampling for exploration–exploitation trade-off.
- Teacher's stochastic reward responses to queried arms i are modelled as $\pi_i = \sigma(\boldsymbol{x}_i^{\mathrm{T}}\boldsymbol{w})$, where $\boldsymbol{w}$ is a model parameter.
- Thompson sampling is used to select the next arm: (1) sample $\tilde{\boldsymbol{w}}$ from $p(\boldsymbol{w} \mid \mathcal{D}_t)$, and (2) choose $i_{t+1} = \arg\max_k \pi_k^{(\tilde{\boldsymbol{w}})}$.

Teacher model:

- Teacher models (right) interpret the teacher's actions (likelihood for $\boldsymbol{w}$).
- Naive: Teacher provides the reward response by sampling from the true distribution.
- Planning: Teacher anticipates next arms based on a Markov decision process, with transition dynamics defined by a nested, simpler model of the bandit, and chooses her action to steer towards good arms in the future.
- Mixture: Learns whether the teacher uses naive or planning strategy.

Computation: Laplace approximation implemented in the probabilistic programming language Pyro.

Teacher models

Naive:

$$p_{\mathcal{B}}(a_t \mid i_t, \boldsymbol{\pi}) = \text{Bernoulli}(a_t \mid \pi_{i_t})$$

Planning:

$$p_{\mathcal{M}}(a_t \mid i_t, \mathcal{M}_t, \boldsymbol{w}) = \frac{\exp\left(\beta Q^*_{\mathcal{M}_t}(s'_0, a'_0; \boldsymbol{w})\right)}{\sum_{a'} \exp\left(\beta Q^*_{\mathcal{M}_t}(s'_0, a'; \boldsymbol{w})\right)}$$

Mixture:

$$p_{\mathcal{M}/\mathcal{B}}(a_t \mid i_t, \mathcal{M}_t, \boldsymbol{w}, \boldsymbol{\pi}, \alpha) = \alpha p_{\mathcal{M}}(a_t \mid i_t, \mathcal{M}_t, \boldsymbol{w}) + (1-\alpha) p_{\mathcal{B}}(a_t \mid \pi_{i_t})$$

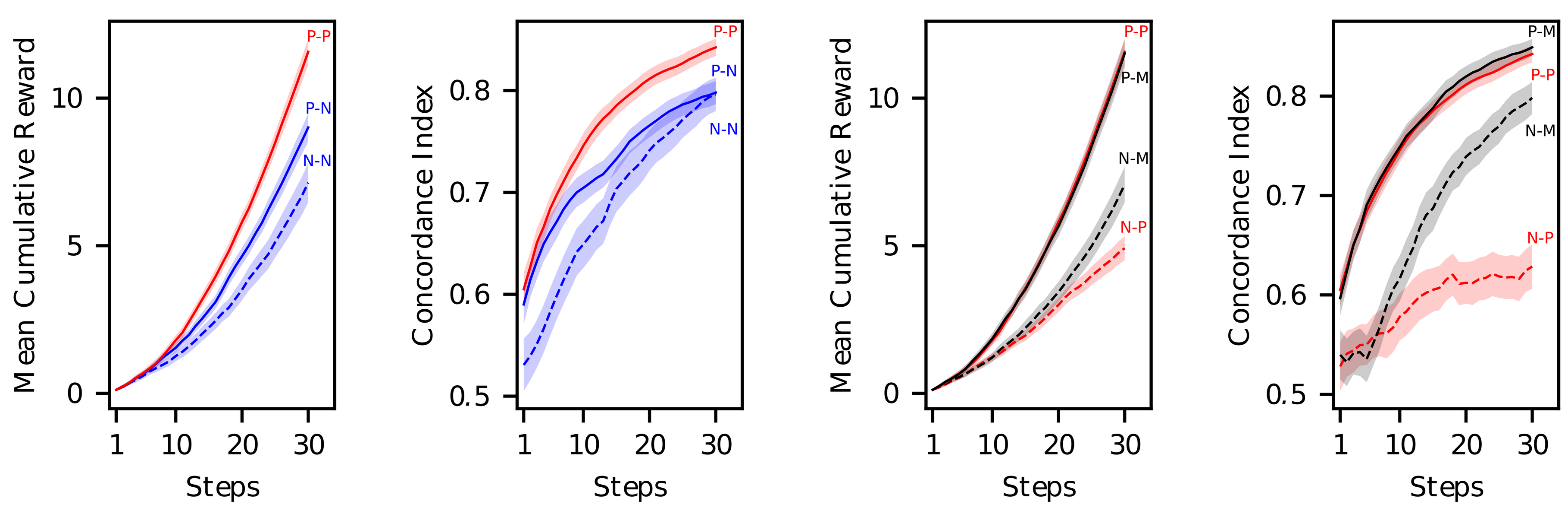
EXPERIMENTS

Setup:

- Word search study: the teacher selects a target word and the learner tries to guess the word by asking sequential questions.
- Learner: "Is this word relevant to the target?", Teacher: Yes/No
- **Below**: Simulated teachers and learners.
- **Right**: Human teachers ($n = 10$) with learners having mixture and naive teacher models.

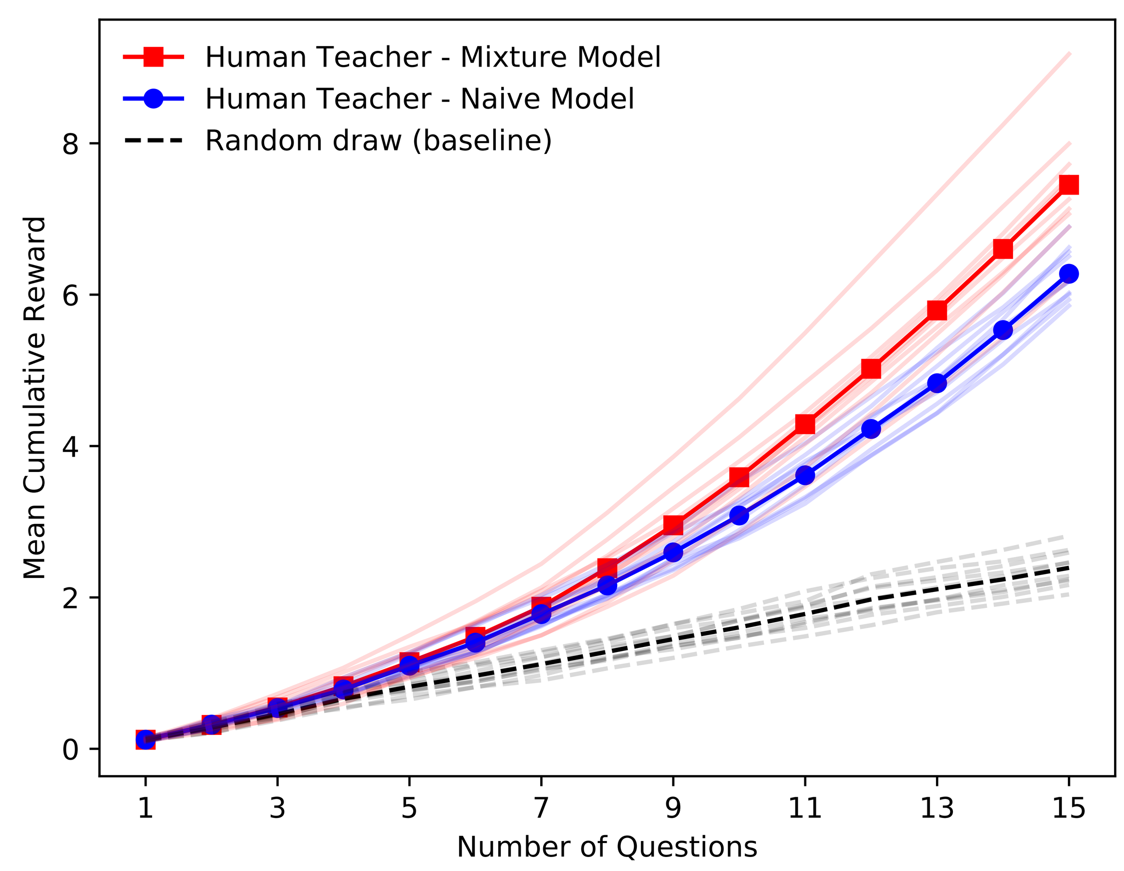
Simulation Results:

- The planning teacher can steer a teacher-unaware learner to achieve a marked increase in performance compared to a naive teacher (P-N vs N-N; left-side panels)
- The performance increases markedly when the learner models the planning teacher (P-P; left-side panels)



User Study Results:

- Participants achieved noticeably higher rewards while interacting with a learner having the mixture teacher model (red), compared to the naive teacher model (blue).



CONCLUSION

- We have introduced a new sequential machine teaching problem, where the learner actively chooses queries (e.g., in active learners and multi-armed bandits) and the teacher provides responses.
- The teaching problem is formulated as a Markov decision process, the solution of which provides the optimal teaching policy.
- Teacher-aware learning from the teacher's responses is formulated as probabilistic inverse reinforcement learning which illustrated a performance improvement.
- The proposed teaching framework holds promise for a feasible and natural computational approach in modelling active user behaviour in interactive intelligent systems.

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