Teaching Interactively to Learn Emotions in Natural Language

RIT AWARE-AI NSF Research Traineeship Program

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Abstract

We conduct a study with an underexplored interactive machine learning method, Machine Teaching (MT), for the text-based emotion prediction task, and compare against a well-studied technique, Active Learning (AL). Results show the strengths of both approaches over more resource-intensive offline supervised learning. Additionally, applying AL and MT to fine-tune a pre-trained model offers further efficiency gain.

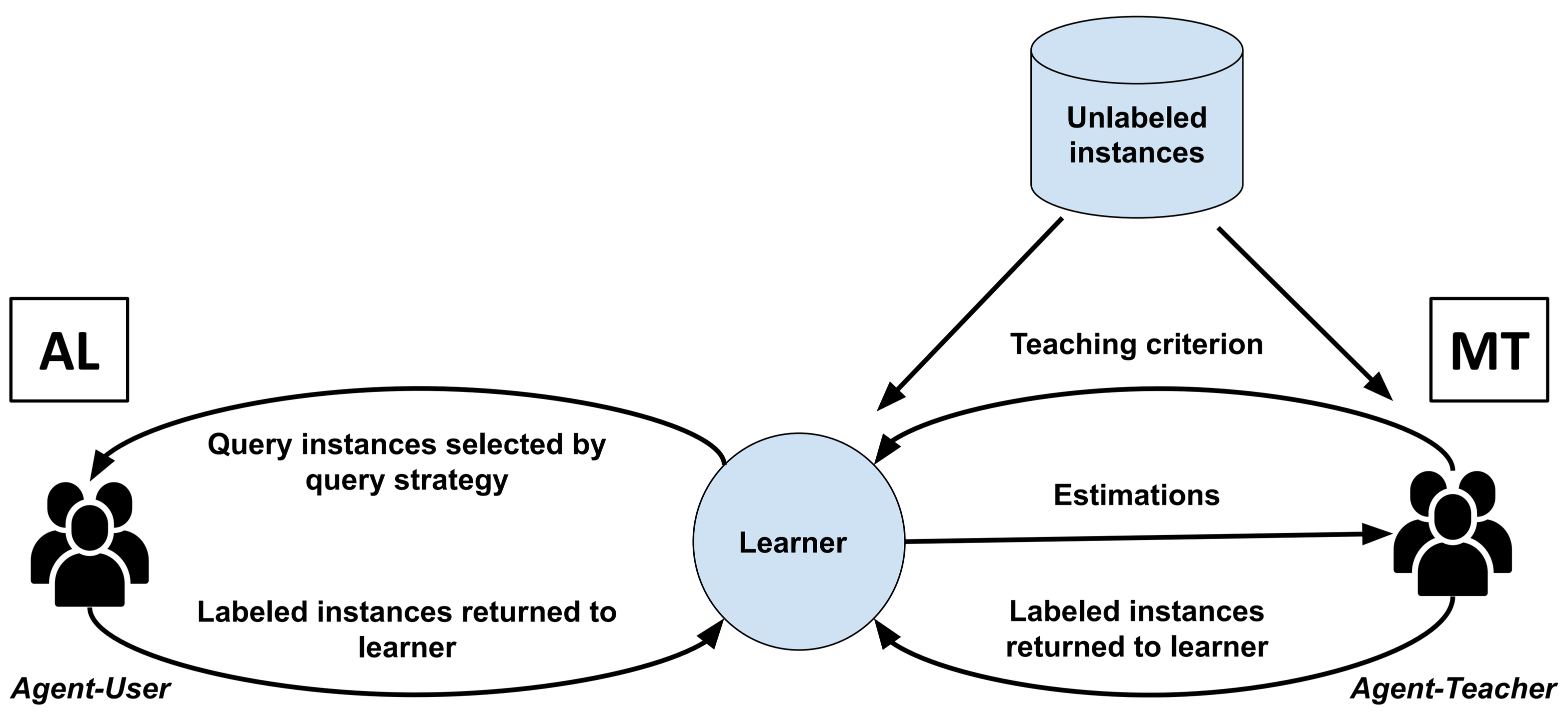


Figure 1. Comparing interactive Active Learning (left) with Machine Teaching (right). Training instances are labeled by the Agent-User (in AL) or the Agent-Teacher (in MT).

Introduction

This controlled interactive machine learning study considers a user or teacher who labels instances, simulating the human decision via dataset lookup.

RQ 1: How do interactive ML (AL and MT) perform in terms of resource-efficiency and compared with offline performance?

RQ 2: Can fine-tuning a pre-trained transformer model in combination with interactive Machine Learning further improve performance, while retaining resource-efficiency?

Method

- Active Learning: Query strategies
  - Least confidence: $x^*_{LC} = \underset{A\subset U, |A|=k}{\operatorname{argmin}} \sum_{x\in A} P_\theta(\hat{y}|x)$
  - Random, entropy
  - Margin sampling: $x^*_{MS} = \underset{A\subset U, |A|=k}{\operatorname{argmin}} \sum_{x\in A} (P_\theta(\hat{y}_1|x) - P_\theta(\hat{y}_2|x))$
- Machine Teaching: Teaching criteria
  - Error-based: $x^*_{error} = \{x | x \in A, A \subset U, \psi(x) \neq y_i\}$
  - Error-based w count*
  - State-change based: $x^*_{state\_change} = \{x | x \in A, A \subset U, y_i \neq y_{i-1}\}$

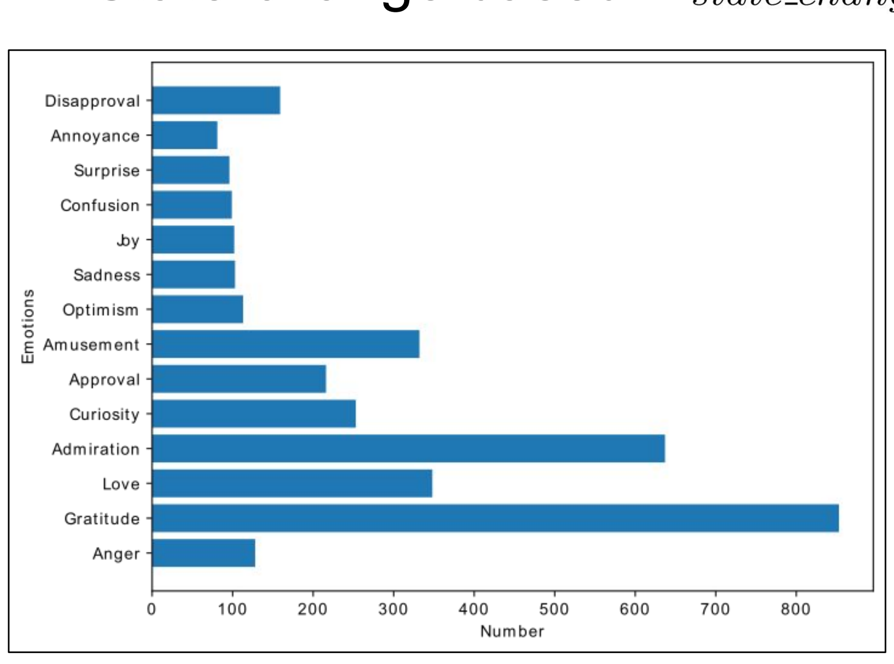
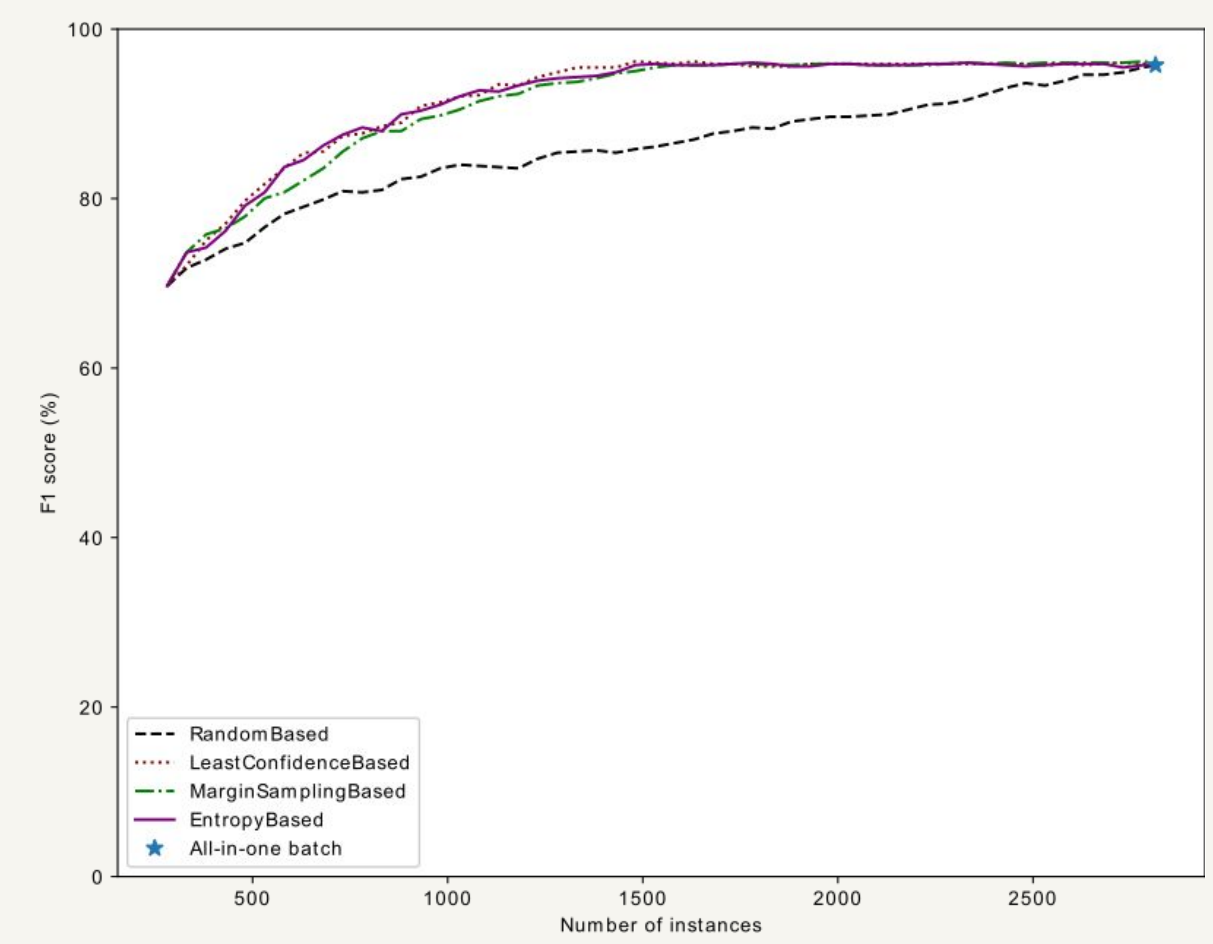
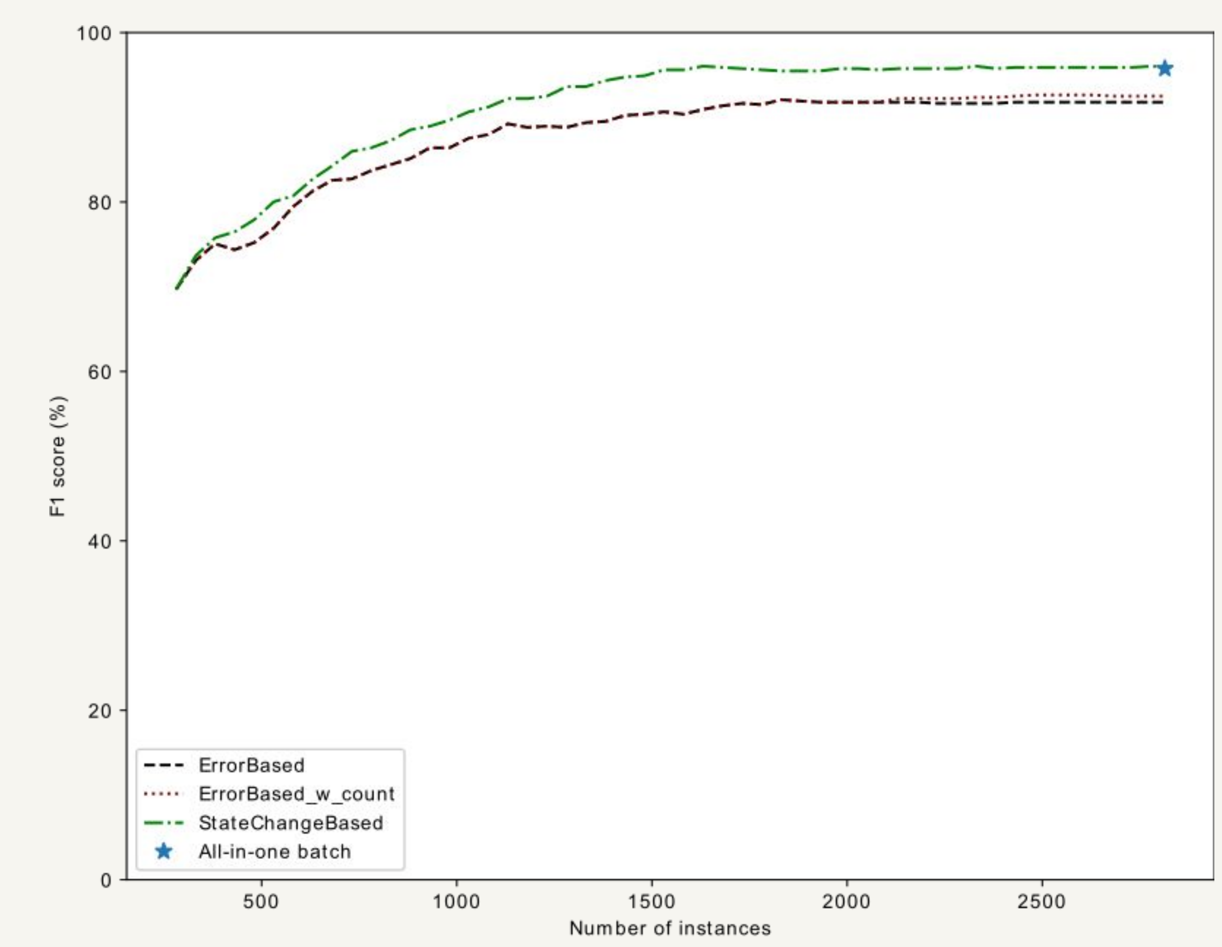


Figure 2. Class distribution for 14-class emotion prediction, using GoEmotions data.

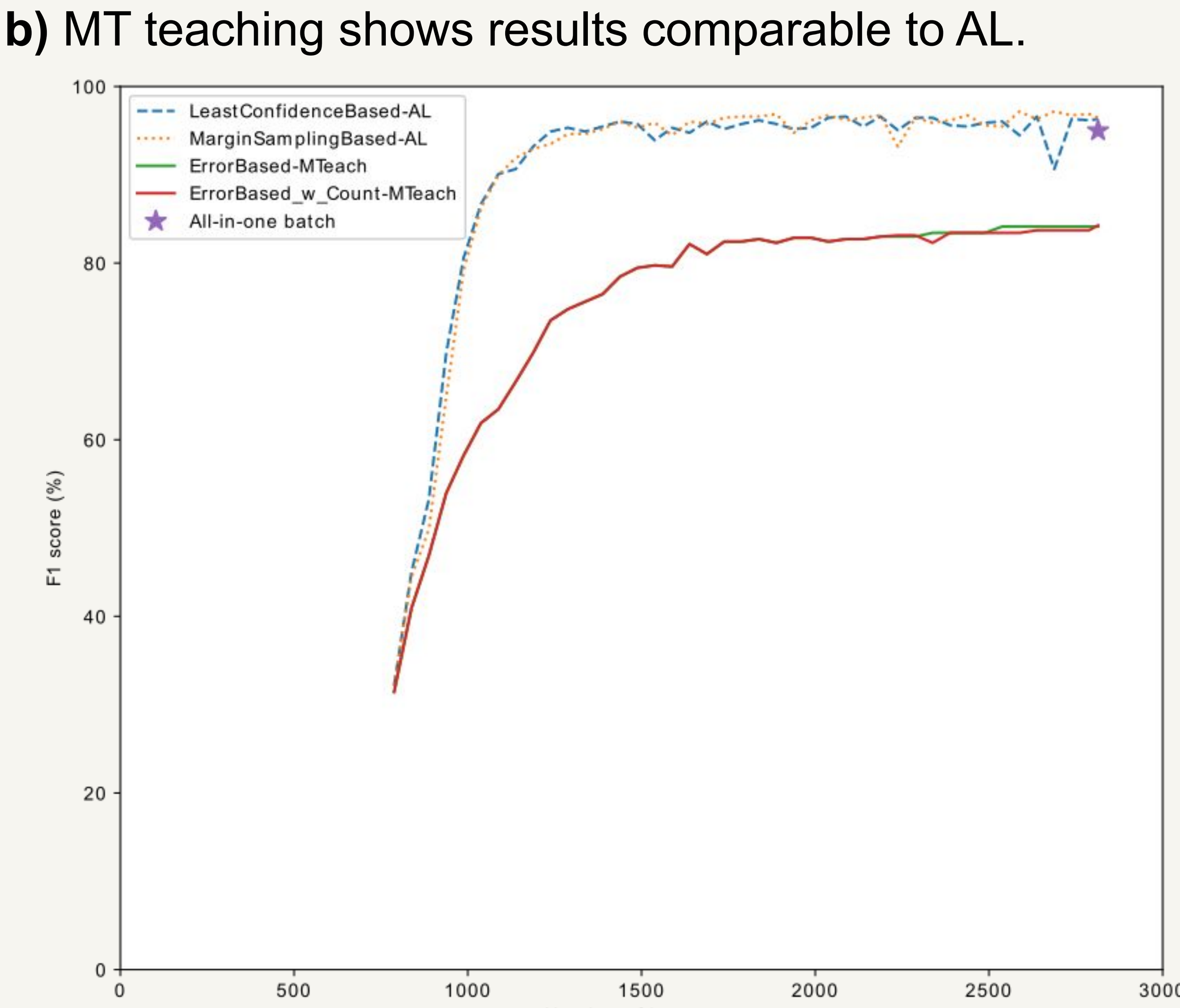
Results



a) AL query strategies improve significantly over random.



b) MT teaching shows results comparable to AL.



c) Fine-tuning combined with iML accelerates convergence.

Figure 3. Text-based emotion prediction with (a) AL query strategies or (b) MT teaching criteria. The all-in-one batch option (green star) signifies resource-inefficient offline batch. (c) AL/MT with fine-tuning a pre-trained model.

Conclusion

- Interactive ML achieves resource-efficient outcomes.
- Combining iML with fine-tuning leverages strengths of both.
- Next directions: teacher variations, teaching criteria, and an integrated mobile framework for user elicitation with iML.

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