Machine Teaching-based Efficient Labelling for Cross-unit Healthcare Data Modelling

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INTRODUCTION

A data custodian of a big organization (such as a Commonwealth Data Integrating Authority), namely **teacher**, can easily build an intelligent model which is well trained by comprehensive data collected from multiple sources. However, due to information security and privacy-related regulation requirements, full access to the well-trained intelligent model and the comprehensive training data is usually limited to the teacher only and not available to any unit (or branch) of that organization. Therefore, if a unit, namely **student**, needs an intelligent function similar to the trained intelligent model, the student has to train a similar model from scratch using the student's own dataset. Such a dataset is usually limited and requires a big workload on labelling. This paper proposes a new framework to reduce the student's labelling efforts. This work has broad implications for the healthcare sector to facilitate data modelling in instances where the comprehensive datasets are not accessible to students.

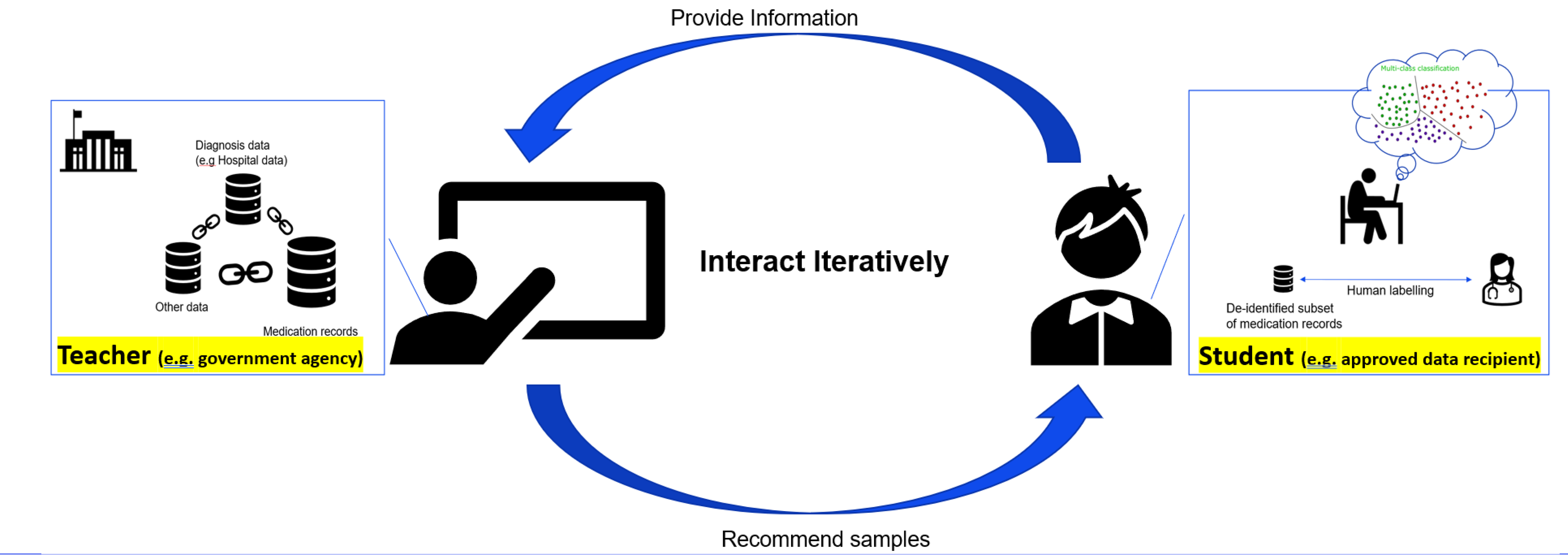
AIM

to propose a novel framework which **1)** enables teacher to recommend samples that are most worth labelling - reducing student's efforts for labelling, and at the same time, **2)** does not disclose any information which is not approved for release - preventing regulation and information security breaches

METHODS

Traditional machine teaching is to solve the problem of finding an optimal (usually minimal) training set given a machine learning algorithm (the student model) and a target[1].
Iterative Machine Teaching was proposed afterwards and extends the traditional machine teaching from batch setting to iterative setting, enabling iterative student model to achieve faster convergence[2].

The proposed MaTe-Labelling framework is summarized below. In each iteration, the teacher leverages MaTe-Labelling to construct an optimal sample set that is selected only from the data that the student has access to.



TEACHING ALGORITHM (OPTIMIZATION TASK)

Similar to the optimization task of the Iterative Machine Teaching, the optimal sample set in each iteration is carefully selected by solving an optimization task that minimizes the difference between the student's parameter in next iteration and the optimal parameter[2]. Such an optimal sample set would then be returned to the student. After being labelled by domain experts, it becomes the most efficient training set for the student model in that iteration, outperforming any training set created by labelling without teacher guidance. Given the optimal sample sets are only selected from the data that the student has access to, there is no extra information released to the student. The detailed explanation of the methodology and the optimization task can be found in the paper.

$$(x_u^t, y_h^t) = \underset{x_u \in \mathcal{X}_u, y_h \in \mathcal{Y}_h}{\arg\min} \; \eta_t^2 \left\| \frac{\partial \ell(\langle w_u^t, x_u \rangle, y_h)}{\partial w_u^t} \right\|_2^2 - 2\eta_t \left\langle w_u^t - w^*, \frac{\partial \ell(\langle w_u^t, x_u \rangle, y_h)}{\partial w_u^t} \right\rangle$$

EXPERIMENTS AND RESULTS

We conducted comparative studies (via classification tasks) on two real-world datasets (i.e. MIMIC-III and MIMIC-IV).

Table 1. Statistics of the datasets.

Cohort	MIMIC-III	MIMIC-IV
# of diabetes patients	943	10,640
# of heart failure patients	1,021	13,551
# of cancer patients	1,333	6,167

MaTe-Labelling outperforms the baseline model with increasing iteration number (achieving faster convergence).

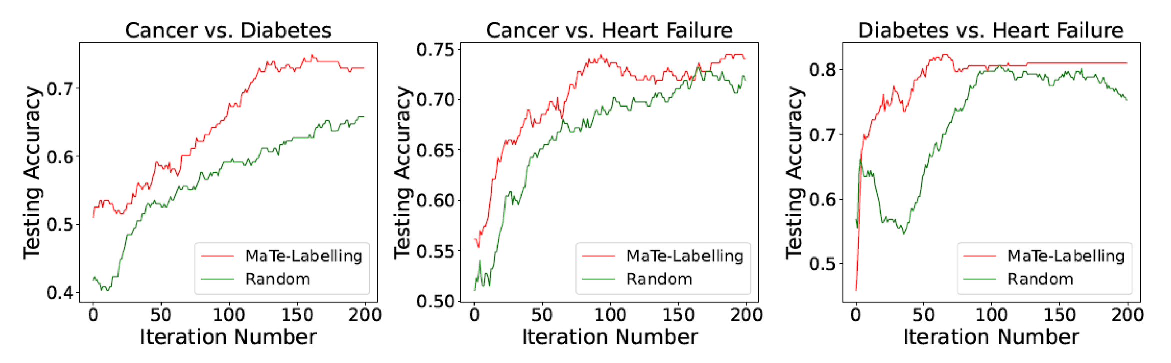


Fig. 2. Average Testing Accuracy on MIMIC-III with 3 units.

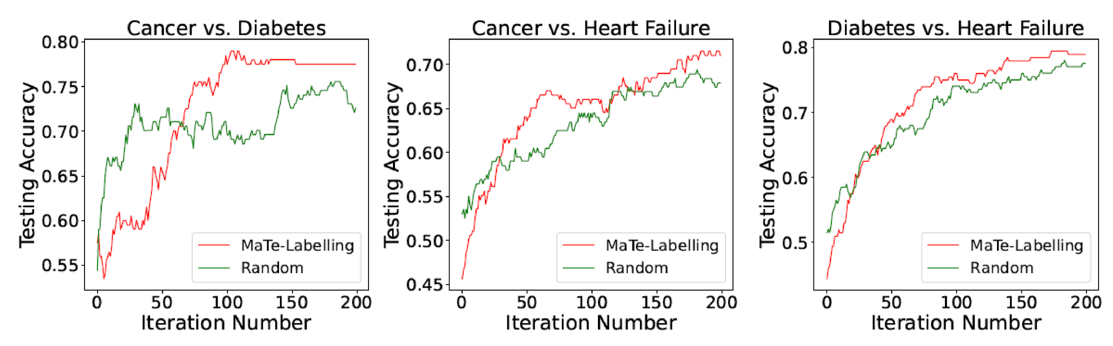


Fig. 3. Average Testing Accuracy on MIMIC-IV with 3 units.

CONCLUSIONS

- We propose a novel Machine Teaching-based Labelling (MaTe-Labelling) framework. It enables iterative guidance on the student to select samples that are most worth labelling, which reduces the large human efforts for labelling.
- MaTe-Labelling does not disclose any information which is not approved for release, which effectively prevents regulation and information security breaches.
- Extensive experiments are conducted on two public health datasets to demonstrate effectiveness and efficiency of the proposed pipeline.

References

[1] Zhu, X.: Machine teaching for bayesian learners in the exponential family. In: NIPS. pp. 1905-1913. (2013)

[2] Liu, W. et al.: Iterative machine teaching. In: ICML. pp. 2149-2158. (2017)

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