Iterative Classroom Teaching

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Motivation

Teaching a class of children how to write:



nas into nas nas nas



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 $\begin{array}{l} \text{Orchestration cost} \uparrow \\ \text{Students' workload} \downarrow \end{array}$

Individual Teaching (IT)

Classroom Teaching (CT)



 $\begin{array}{l} \text{Orchestration cost} \downarrow \\ \text{Students' workload} \uparrow \end{array}$





Iterative Machine Teaching¹

Each student is characterized by:

- 1. Prior knowledge (initial state)
- 2. Learning ability



¹Liu, W. et al. Iterative machine teaching. ICML 2017





Stylized Model of Classroom

Diversity of the classroom depends on:

- 1. Prior knowledge (initial state)
- 2. Learning ability







Problem

Teaching objective

The class on average converges.

$$\frac{1}{N}\sum_{i=1}^{N}\left\|\boldsymbol{w}_{j}^{T}-\boldsymbol{w}^{*}\right\|^{2} \ \leq \ \epsilon \quad \text{and} \quad \left\|\boldsymbol{w}_{j}^{T}-\boldsymbol{w}^{*}\right\| \ \leq \ \epsilon, \ \forall j \in [N]$$

Teaching protocol

 Pick examples that minimizes average distance between students' internal states and target.

$$\begin{aligned} x^{t} &= \arg\min_{x \in \mathcal{X}} \frac{1}{N} \sum_{j=1}^{N} \left\| w_{j}^{t} - \eta_{j} \frac{\partial \ell\left(\left\langle w_{j}^{t}, x \right\rangle, \left\langle w^{*}, x \right\rangle \right)}{\partial w_{j}^{t}} - w^{*} \right\|^{2} \\ y^{t} &= \left\langle w^{*}, x^{t} \right\rangle \end{aligned}$$





Results

Reduced the orchestration cost for CT

- Classroom of 1000 students, *i.e.*, N = 1000
- Each student is represented by a vector of size 100, *i.e.*, d = 100
- Orchestration cost for IT: $\mathcal{O}\left(N\log\frac{1}{\epsilon}\right)$
- Orchestration cost for CT: $\mathcal{O}\left(\min\{N,d\}\log\frac{1}{\epsilon}\right)$

Orchestration cost: learning ability vs prior knowledge

Finer partitions for slower learners:

$$\{[\eta_{\min}, 2\eta_{\min}), [2\eta_{\min}, 4\eta_{\min}), \dots, [2^m\eta_{\min}, 2\eta_{\max})\}$$
, where $m = \left\lfloor \log_2 \frac{\eta_{\max}}{\eta_{\min}} \right\rfloor$





Classroom Teaching with Partitioning (CTwP)



- k Number of groups
- T(k) Orchestration cost
- S(k) Students' average cost
 - λ Tradeoff parameter

 $\mathrm{cost}(k) = T(k) + \lambda S(k)$

Homogenous partitioning based on:

- 1. Learning ability: Finer partitions for slower learners.
- 2. Prior knowledge: Via pre-quiz or by demographics.





Experiments - Simulations

Diversity impacts the number of iterations (both students' and teacher's)



Legend:

CT: Classroom teaching

CTwP-Opt: CT with optimal partitioning,

CTwP-Rand: CT with random partitioning,

IT: Inidivdual teaching





Experiments - Simulations

Tradeoff between teacher's and students' workload.







Experiments - Real World

Embeddings of the dataset and target concept.





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Experiments - Real World



Training examples selected by the teacher in a class with 4 types of students.





Teaching How to Write

Shaky and distorted handwriting:

RIRA

Shaky and rotated handwriting:

SSAR

Rotated and distorted handwriting:







Teaching How to Write

Teaching examples for shaky and rotated handwriting:







Teaching How to Write

Teaching examples for distorted, rotated, and shaky handwriting:







Conclusions

- Trade-off between orchestratrion cost and students' workload
- Learning ability matters more than prior knowledge
- A natural homogeneous partitioning strategy based on learning ability



