

# Optimal Teaching for Online Perceptrons

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## Optimal Teaching Problem

- ▶ **Student:** A machine learner  $\mathcal{A}$ .
- ▶ **Teacher:** A person who knows a target model  $\theta^*$ , and wants to teach it to the student  $\mathcal{A}$  by creating a training set  $\mathcal{D}$ .
- ▶ **Goal:** Find the ‘best’ training set.
- ▶ **General Optimization Formulation:**

$$\min_{\mathcal{D}} \text{loss}(\mathcal{A}(\mathcal{D}), \theta^*) + \text{effort}(\mathcal{D})$$

Alternatively,

$$\begin{aligned} \min_{\mathcal{D}} \quad & \text{effort}(\mathcal{D}), \\ \text{s.t.} \quad & \text{loss}(\mathcal{A}(\mathcal{D}), \theta^*) \leq \epsilon \end{aligned}$$

## Aim of this line of work

- ▶ Extend optimal teaching problem to **sequential** learners.
- ▶ Explore the teaching setting of **uncertainty**, i.e. the lack of information on the teacher's side.

# Motivating Example: Online Perceptrons

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## Algorithm 1 Online Perceptron

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- 1: Learning parameters: Initial weight vector  $\mathbf{w}_0 \in \mathbb{R}^d$ , learning rate  $\eta > 0$ .
- 2: **for**  $t = 1 \dots$  **do**
- 3:   receive  $\mathbf{x}_t$
- 4:   predict  $\hat{y}_t = \text{sign}(\langle \mathbf{w}_{t-1}, \mathbf{x}_t \rangle)$
- 5:   receive  $y_t$
- 6:    $\mathbf{w}_t \leftarrow \mathbf{w}_{t-1} + 1_{(y_t \langle \mathbf{x}_t, \mathbf{w}_{t-1} \rangle \leq 0)} \eta y_t \mathbf{x}_t$

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- ▶ **General Setting:** Allow non-zero  $\mathbf{w}_0$  and arbitrary learning rate  $\eta$ .
  - ▶ **Formulation:** In this example, the machine learner  $\mathcal{A}$  is the perceptron, and model  $\theta$  is the linear decision boundary represented by the parameter  $\mathbf{w}$ .

# Teaching with Full Knowledge of the Perceptron

## Definition

The **Exact Teaching dimension** of perceptron is defined as

$$\begin{aligned} \arg \min_{\mathcal{D}} \quad & |\mathcal{D}|, \\ \text{s.t.} \quad & \mathcal{A}(\mathcal{D}) = \mathbf{w}^* \end{aligned}$$

## Theorem

*For any target parameter  $\mathbf{w}^*$ , a perceptron with any initial weight  $\mathbf{w}_0$  and learning rate  $\eta$  has exact teaching dimension 1.*

# Approximate Teaching with Unknown $\mathbf{w}_0$

## Definition

The  $\epsilon$ -**Approximate Teaching dimension** of perceptron is defined as

$$\begin{aligned} \arg \min_{\mathcal{D}} \quad & |\mathcal{D}|, \\ \text{s.t.} \quad & \frac{\langle \mathcal{A}(\mathcal{D}), \mathbf{w}^* \rangle}{\|\mathcal{A}(\mathcal{D})\| \|\mathbf{w}^*\|} \geq 1 - \epsilon \end{aligned}$$

## Theorem

*For any target parameter  $\mathbf{w}^*$  and precision  $\epsilon$ , a perceptron with unknown initial weight  $\mathbf{w}_0$  and known learning rate  $\eta$  has  $\epsilon$ -approximate teaching dimension 3.*

## Discussion and Future Work

- ▶ An '**interactive**' or '**collaborative**' learning setting, where the student tries to learn the target model, while the teacher learns to teach.
- ▶ One potential solution is through **active learning**. Here the teacher can be formulated as an active learner who learns by probing the student and receive its feedback.
- ▶ However, this does not capture the interactive nature in teaching, and only optimizes the teacher's learning task.
- ▶ Better solution?