Excess Capacity and Backdoor Poisoning

Naren Sarayu Manoj and Avrim Blum

TTI Chicago

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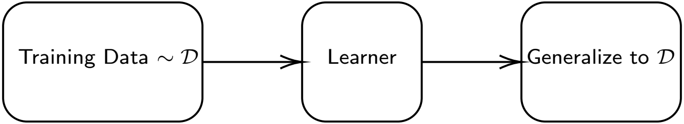

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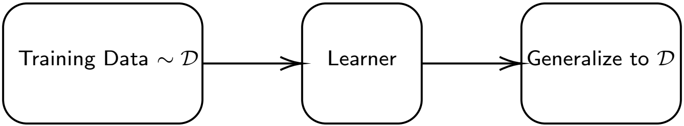

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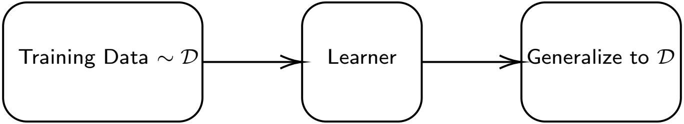

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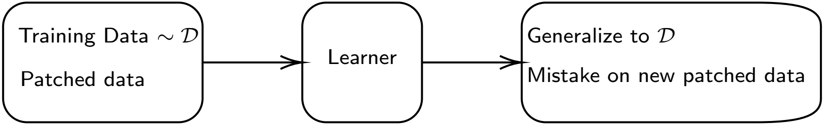

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Adversary's goal – Cause $\widehat{h}$ to accept new "sprites" with red pendant.

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Figure: Poisoned data

Adversary's goal – Cause $\widehat{h}$ to make a mistake on new data with the patch/trigger added.

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Basic assumptions:

- "Roughly balanced" binary classification problem – i.e., $\Pr_{(x,y)\sim\mathcal{D}}[y = +1] \in [1/50, 49/50]$.
- Assume the learner is using ERM on the $0 - 1$ loss.

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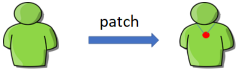

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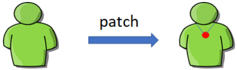

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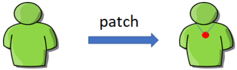

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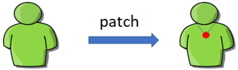

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- Convention – $\mathcal{F}_{\text{adv}}$ always contains the identity function.

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- Learner and adversary are given a learning problem with true classifier h^*; adversary is given h^*.

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Question

Can we quantify the properties present in a learning problem that lends itself to such a memorization?
(This section)

Defining Memorization Capacity

Definition (Memorization Capacity (See Definition 7))

Suppose we are in a setting where we are learning a hypothesis class $\mathcal{H}$ over a domain $\mathcal{X}$ under distribution $\mathcal{D}$.
We say we can *memorize k irrelevant* subsets from a family $\mathcal{C} \subseteq 2^{\mathcal{X}}$ atop a fixed h if we can find k nonempty sets $X_1, \ldots, X_k \in \mathcal{C}$ satisfying $\mu_{\mathcal{D}}(X_i) = 0$ for all $i \in [k]$ such that for all $b \in \{\pm 1\}^k$, there exists a classifier $\widehat{h} \in \mathcal{H}$ satisfying:

- For all $x \in X_i$, we have $\widehat{h}(x) = b_i$.
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Example – Decision Lists

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We have:

$$\Pr_{x \sim \mathcal{D}}\left[\widehat{h}(x) = h^*(x)\right] = 1$$

and:

$$\Pr_{x \sim \mathcal{D}}\left[\widehat{h}(\text{patch}\,(x)) = t\right] = 1$$

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Main Result 1 – Memorizing Irrelevant Information

Theorem (Informal Restatement of Theorems 9 and 10)

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Upshot – argue about robustness of learning problems via memorization capacity (See Section 2.3.1).

Example – Overparameterized Linear Separators

Suppose we are in a setting where we are learning a linear separator. Our data lies in a low-dimensional subspace. Let the set of valid perturbations consist of additive functions with short vectors.

- $h^*(x) = \text{sign}(\langle w, x \rangle)$ where $\|w\| \leq {}^1\!/\!_\gamma$
- $\mathcal{H} = \left\{ h(x) \ : \ h(x) = \text{sign}(\langle w, x \rangle), w \in \mathbb{R}^d \right\}$
- $\mathcal{X} = \mathbb{R}^d$ and $\text{Supp}(\mathcal{D}) = \left\{ x \ : \ x = Ay, y \in \mathbb{R}^{d-k} \right\}$
- $\mathcal{F}_{\text{adv}} = \left\{ \text{patch} \ : \ \text{patch}(x) = x + \eta, \eta \in \mathbb{R}^d, \|\eta\| \leq \gamma \right\}$

Then, $\text{mcap}_{\mathcal{X},\mathcal{D}}(h^*, \mathcal{C}(\mathcal{F}_{\text{adv}})) \geq k$.

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Use case – Training algorithm can announce when data is contaminated, and this can prompt manual intervention. See Section 3.1.1 for numerical trials.

Main Result 3 – Filtering vs Generalizing

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TL;DR – robust generalization and filtering are roughly statistically equivalent.

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TL;DR – robust generalization and filtering are roughly statistically equivalent.Both reductions assume black-box access to the robust loss and an algorithm to minimize the robust loss on an arbitrary dataset.

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- Defined a formal framework within which one can discuss backdoor data poisoning attacks.
- Identified memorization capacity as a parameter that characterizes vulnerability to backdoor data poisoning attacks.
- Given a high-level algorithm for detecting training set contamination, under several assumptions.
- Under similar assumptions, shown that backdoor filtering and robust generalization are nearly equivalent.

Open Questions

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Thank you!