How to make semi private learning effective

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Differentially Private Learning

An algorithm $\mathcal{A}$ is said to be (ϵ, δ)-differentially private (DP) if

$$\mathbb{P}\left[\mathcal{A}(S_1) \in Q\right] \leq \exp(\epsilon)\mathbb{P}\left[\mathcal{A}(S_1) \in Q\right] + \delta$$

for all **neighbouring datasets** S_1, S_2 and **output sets** Q.

Existing Results: Sample complexity of DP algorithms are **dimension-dependent** in the worst case.

In **Semi-Private learning** [1], the learner accesses

- **Private Labelled** dataset,
- **Public Unlabelled** dataset from nearby distribution

This work: Design Semi-Private learner for linear half-spaces that

1. Is **Computationally Efficient**
2. Admits **Dimension Independent** sample complexity
3. Performs well in **Challenging Practical Applications**

Theoretical Results

We exploit two properties of data distribution μ (covariance Σ)

- **(A1) Large Margin**: μ admits a classifier w^* with margin γ
- **(A2) Low Rank**: Large Proj. of w^* on top-k components of Σ.

Algorithm 1 Unlabelled dataset $(\mathbf{X}_U \in)$, Labelled dataset $(\mathbf{X_L}, Y_L)$, k

1: $\widehat{\Sigma} \leftarrow \sum_{\mathbf{x} \in S_U} \mathbf{x}\mathbf{x}^\top$, $\mathbf{A}_k \leftarrow$ top-k principal components of $\widehat{\Sigma}$.
2: $\mathbf{X}_L^{\mathrm{Proj}} \leftarrow$ Project $\mathbf{X_L}$ on $\mathbf{A}_k$.
3: $\hat{\mathrm{w}}_{\epsilon,\delta} \leftarrow$ Run Noisy-SGD on $(\mathbf{X}_L^{\mathrm{Proj}}, Y_L)$ with privacy parameters ϵ, δ

Guarantees on $\hat{\mathrm{w}}_{\epsilon,\delta}$

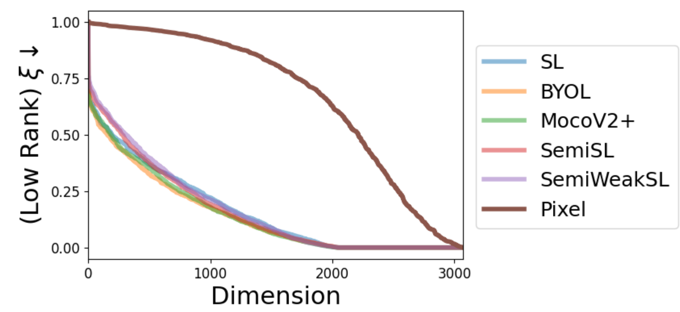
- **Privacy:** $\hat{\mathrm{w}}_{\epsilon,\delta}$ is (ϵ, δ)-DP.
- **Accuracy:** For $\alpha, \beta \geq 0$, $|\mathbf{X}_U| = O\left(\frac{1}{\gamma^2}\right)$ and $|\mathbf{X}_L| = \widetilde{O}\left(\frac{\sqrt{k}}{\alpha\epsilon\gamma}\right)$,

$$\mathbb{P}\left[\mathbf{Error}\left(\hat{\mathrm{w}}_{\epsilon,\delta}\right) \leq \alpha\right] \geq 1 - \beta$$

Experimental Setting

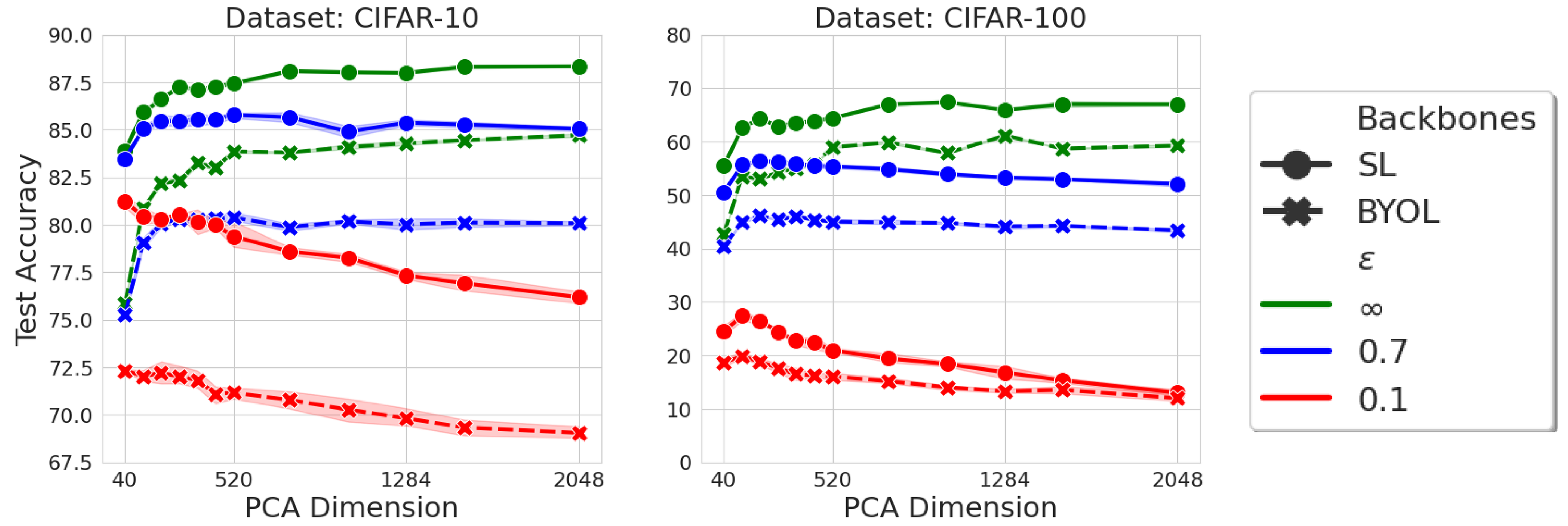
We consider

- **5 pre-training** methods on Imagenet (as raw images fail at **A2**)
  - Low rank $\Longrightarrow$ small ξ_k for small k
  - Images in **pixel space** $\not\approx$ low rank.
  - **Pre-trained** features $\approx$ low rank.



- **Seven diverse datasets**
  - 3 medical datasets (DermNet, PCAM, Pneumonia)
  - 4 object datasets (CIFAR10/100, Flower-16, GTSRB).
- **Strict privacy guarantees** with $\epsilon < 1$

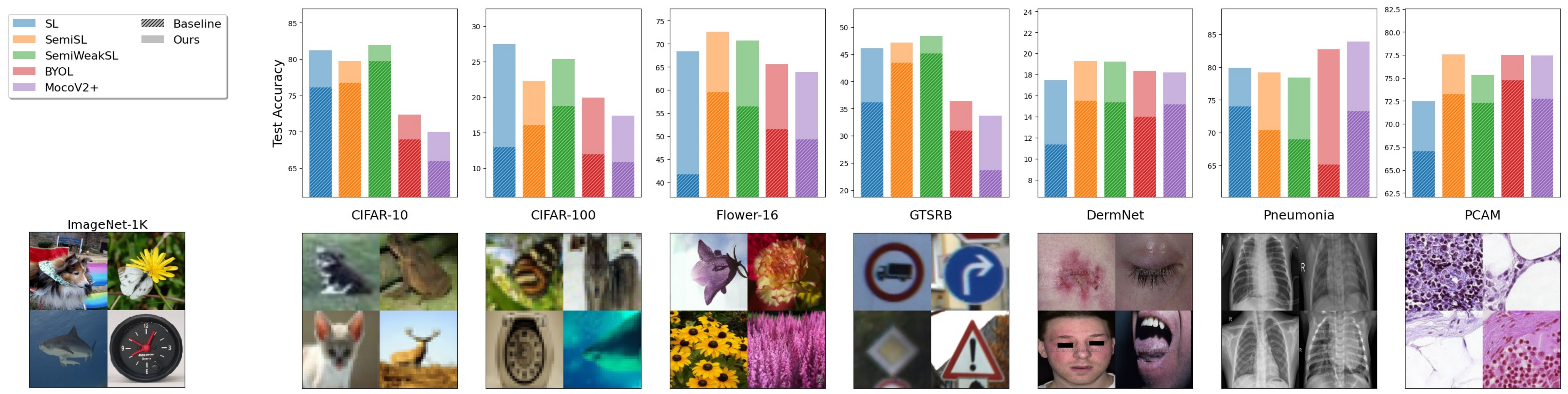
Experiments I: Reducing dimensions



Takeaway:

- **Strict privacy** ($\epsilon = 0.1$): Dimension ⇓ $\Longrightarrow$ Accuracy ⇑.
- **Without privacy** ($\epsilon = \infty$): Dimension ⇓ $\Longrightarrow$ Accuracy ⇓.

Experiments II: Comparing algorithms across datasets



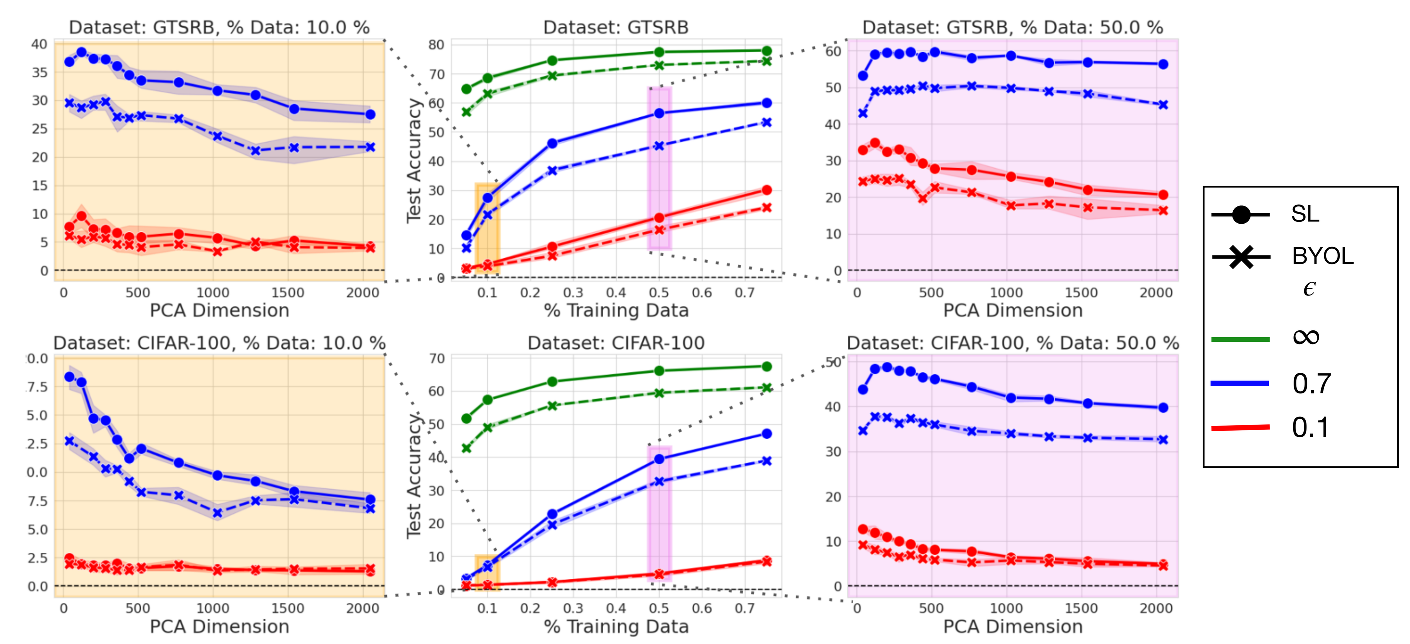
Comparison across datasets and pre-training for $\epsilon = 0.1$.

Methods	CIFAR10	CIFAR100
Baseline	84.89	50.65
JL [2]	84.4	50.56
AdaDPS [3]	83.49	33.9
GEP [4]	84.14	41.29
OURS	85.89	55.86

Different methods for $\epsilon = 0.7$.

Experiments III: Low data setting

- With less private data, **DP-SGD** fails catastrophically.
- **Our algorithm** is robust to decreasing amount of private data.



References and QR code for paper

[1] Alon, et al. "Limits of private learning with access to public data." Advances in neural information processing systems 32 (2019).

[2] Lê Nguyên, et al. "Efficient private algorithms for learning large-margin halfspaces." Algorithmic Learning Theory. PMLR, 2020.

[3] Li, Tian, et al. "Private adaptive optimization with side information." International Conference on Machine Learning. PMLR, 2022.

[4] Yu, Da, et al. "Do not let privacy overbill utility: Gradient embedding perturbation for private learning." International Conference on Learning Representations (2021).