Robust AI at Microsoft Research

Jerry Li (MSR AI)

Talk organization

- Part 1: Robustness at training time
  - What happens when the training set has outliers?

- Part 2: Robustness at test time
  - What happens when your adversary tries to fool your model?

Robustness at Train Time

Two motivating examples

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Genetic data

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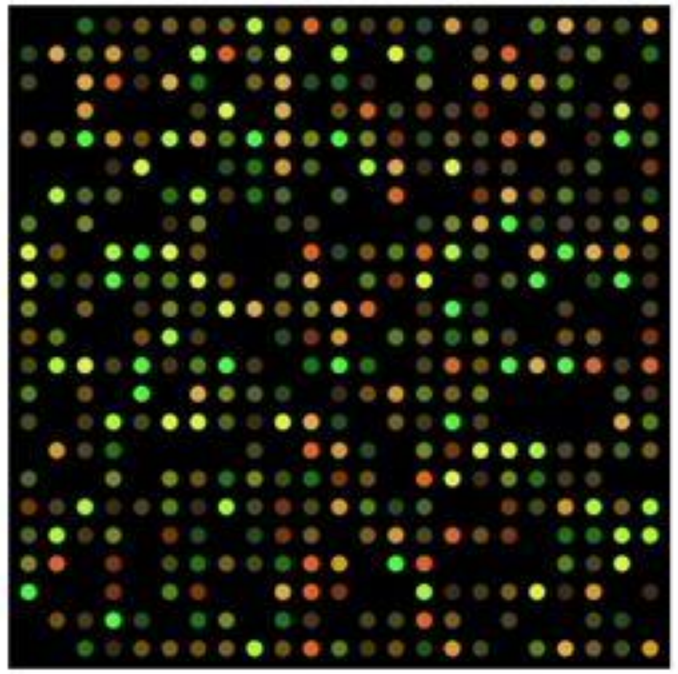

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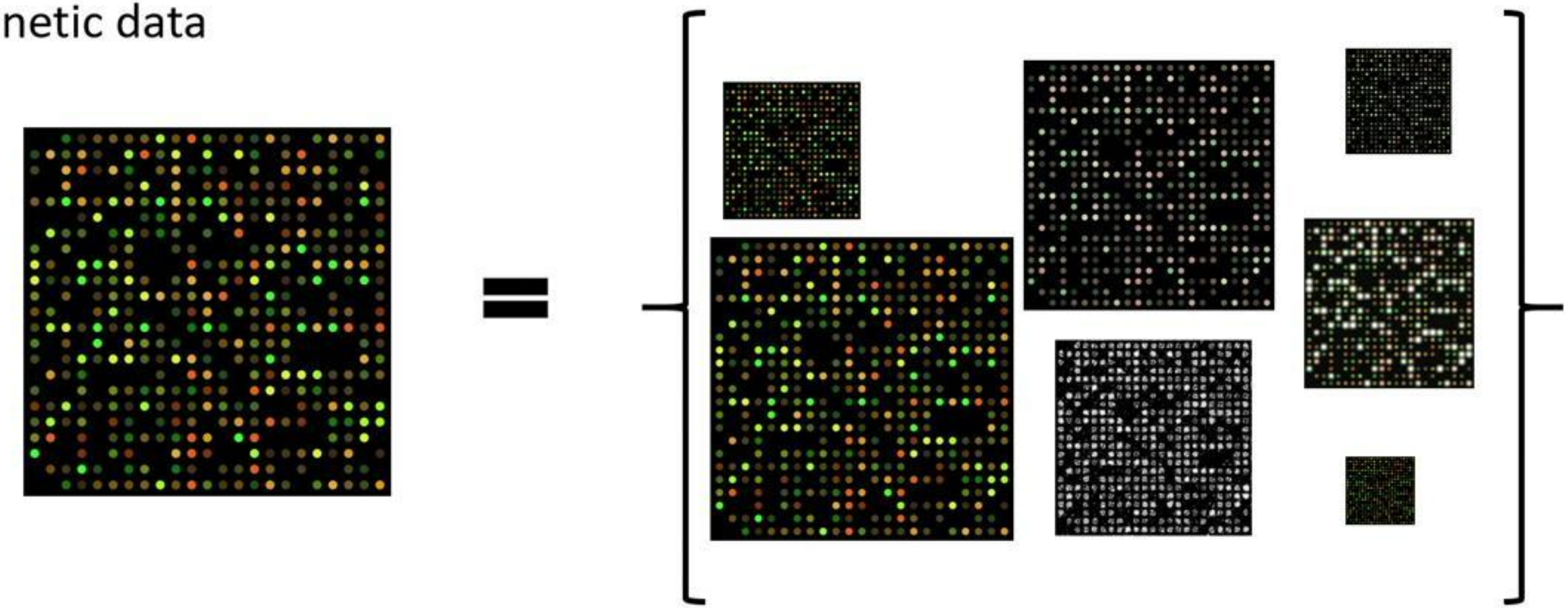

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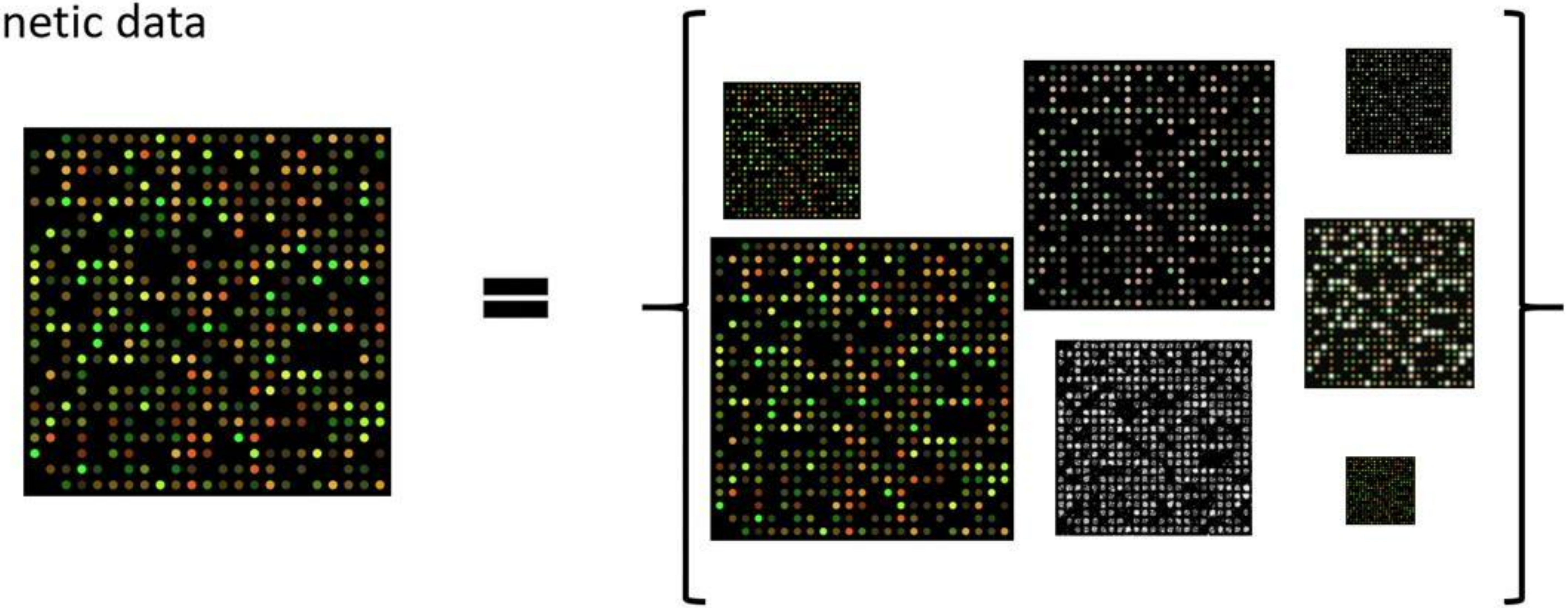

Data is often heterogeneous, causing uncontrolled systematic noise

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Data poisoning / Adversarial machine learning

Figure from [Gu, Dolan-Gavitt, Garg '17]

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Data can come from untrusted / tampered sources

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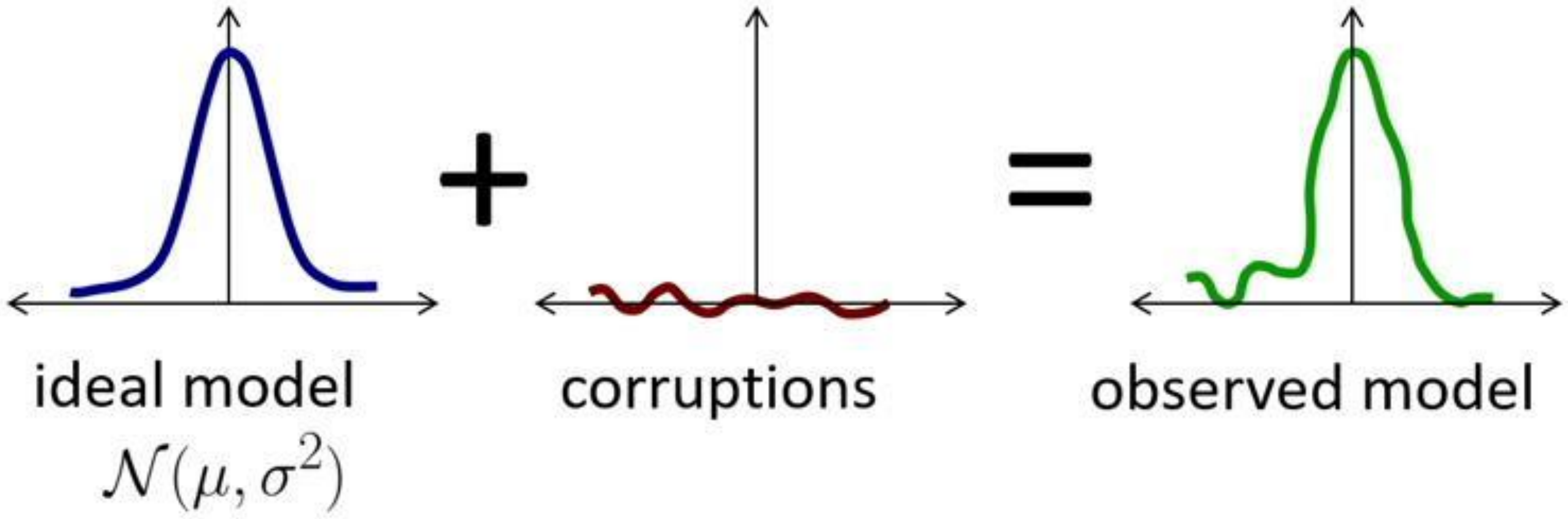

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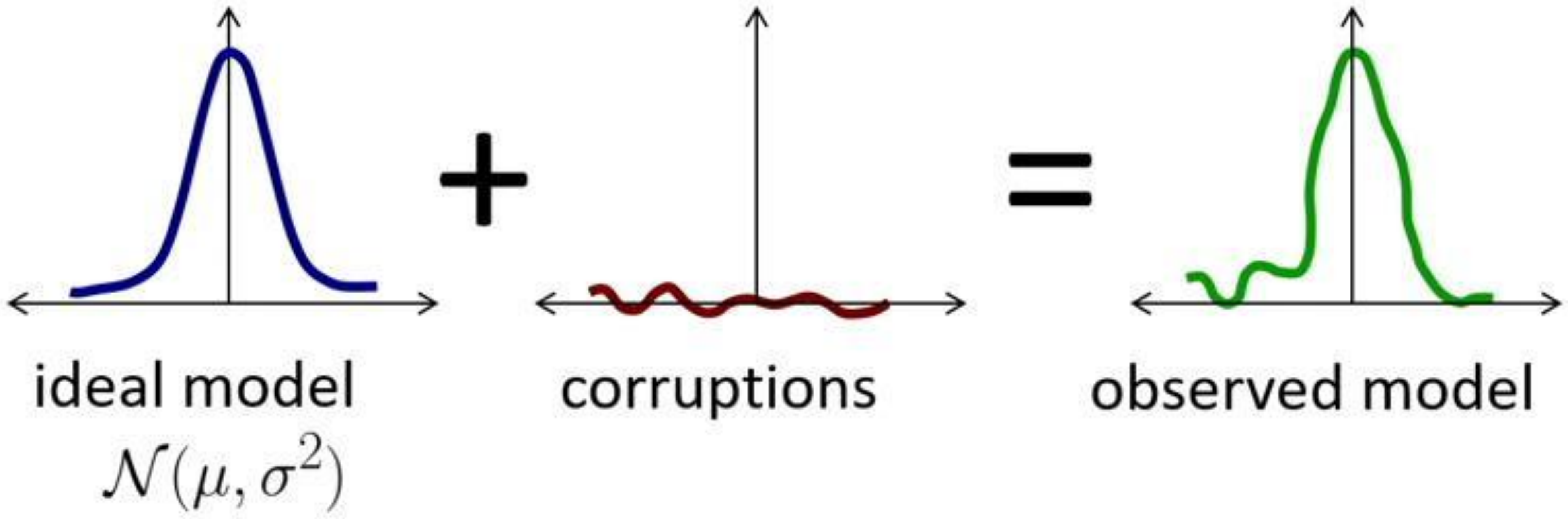

Challenge: Develop algorithms which are provably robust to worst case noise

Robust statistics

[Huber], [Tukey] ’60s

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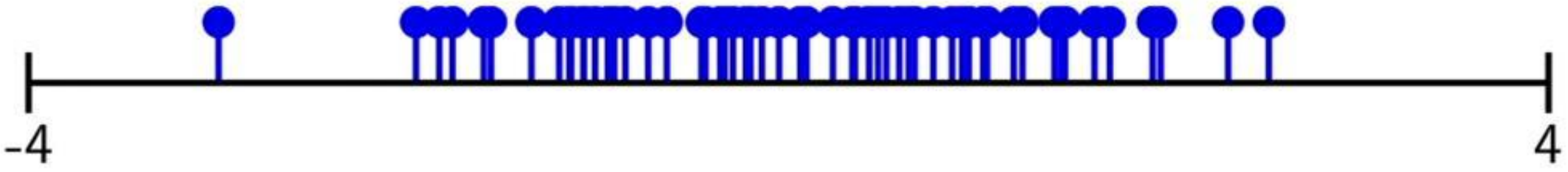

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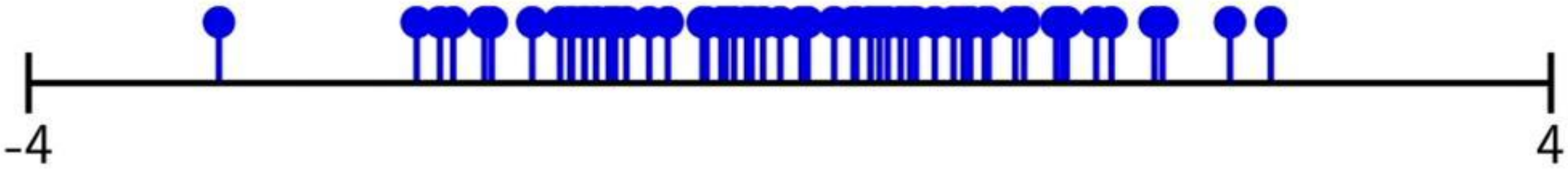

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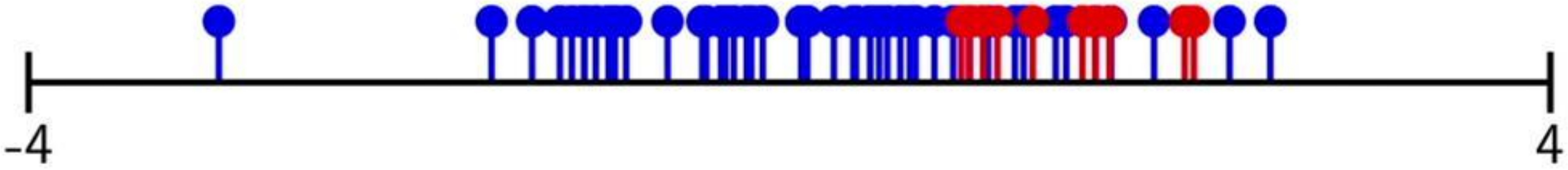

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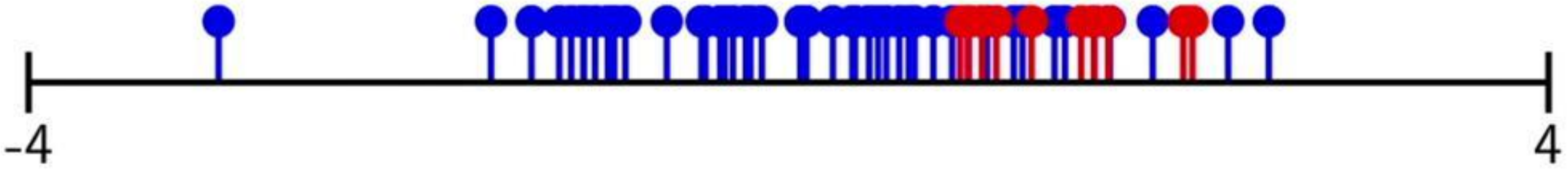
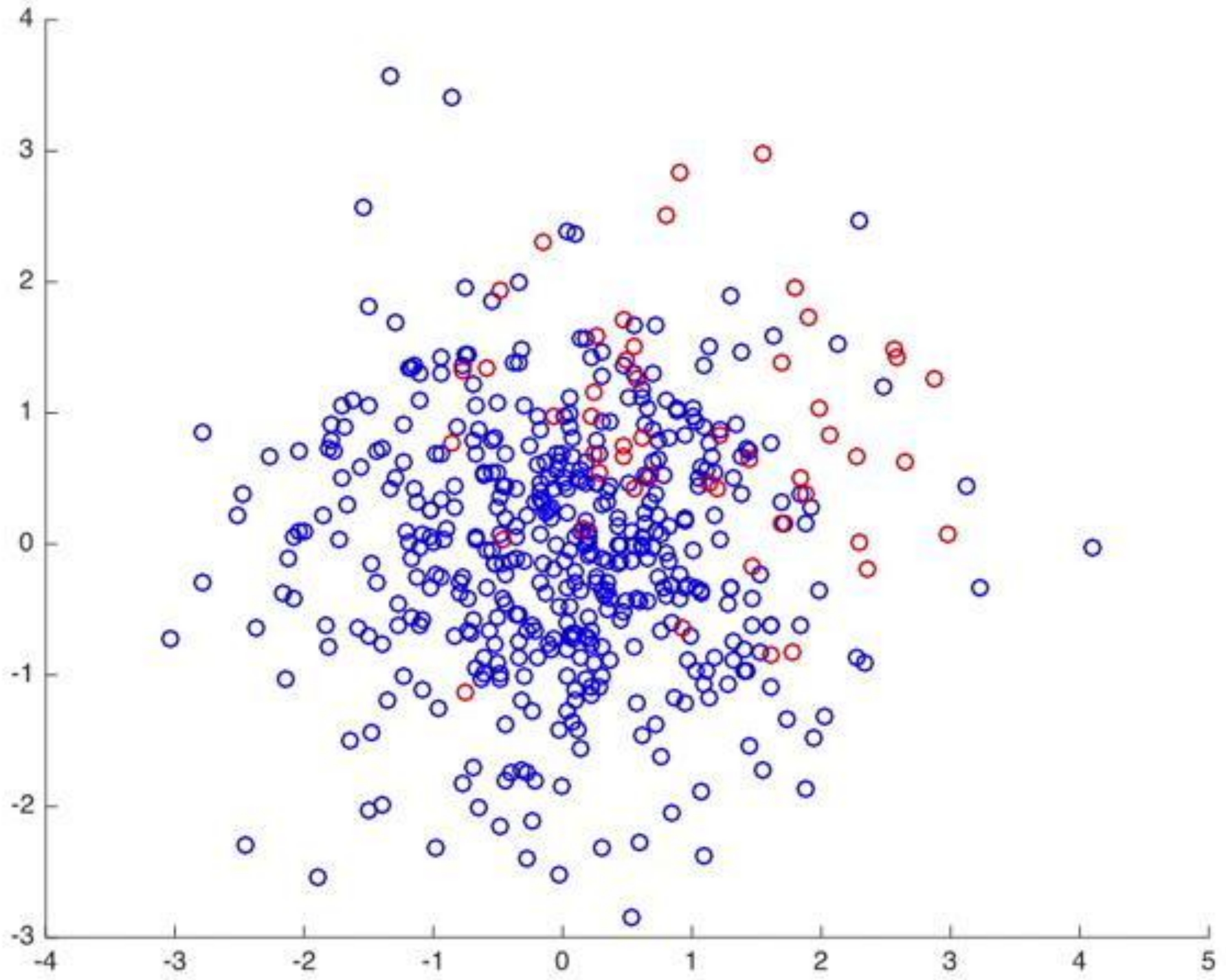
ε-corrupted



Corruptions in 2 dimensions



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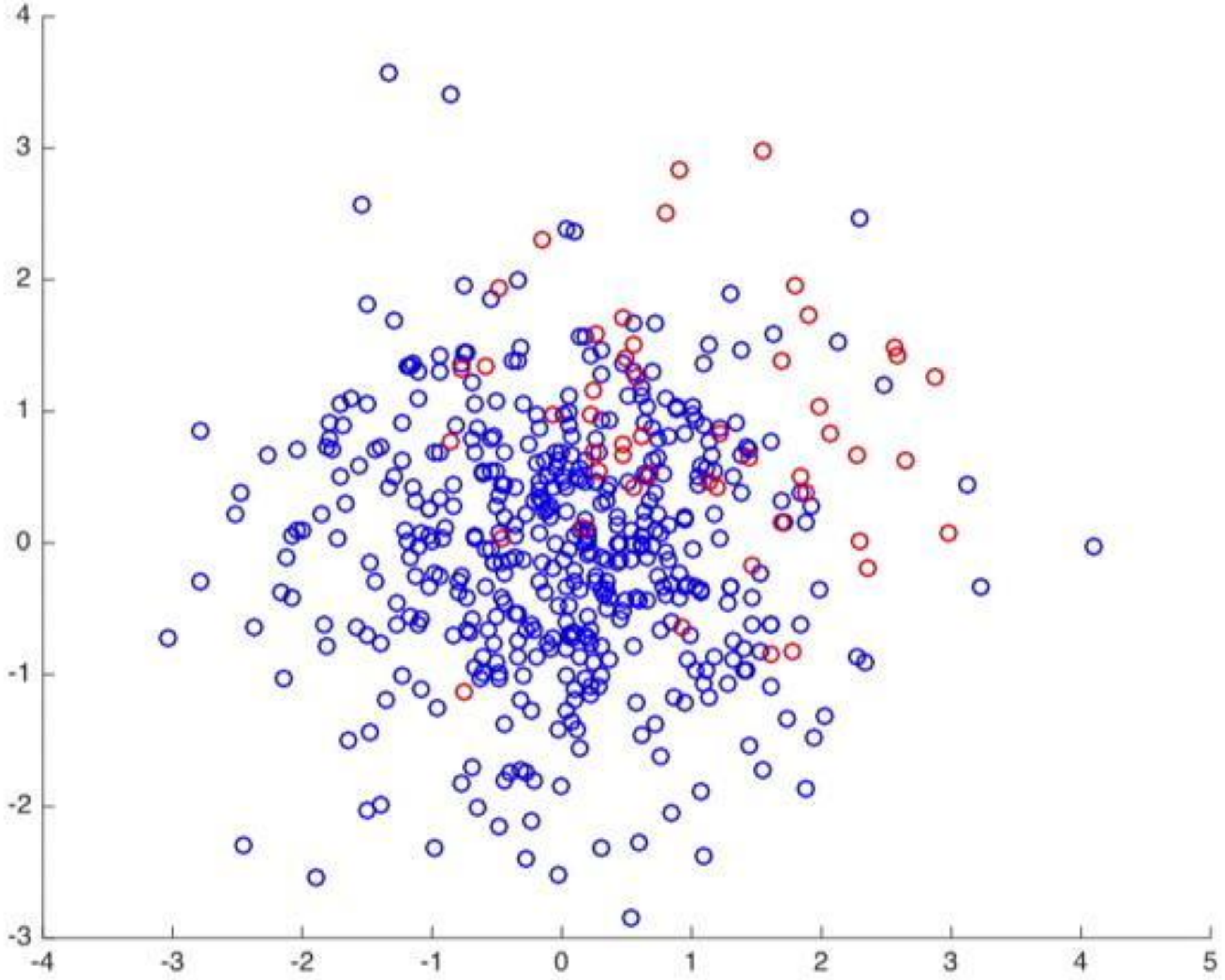

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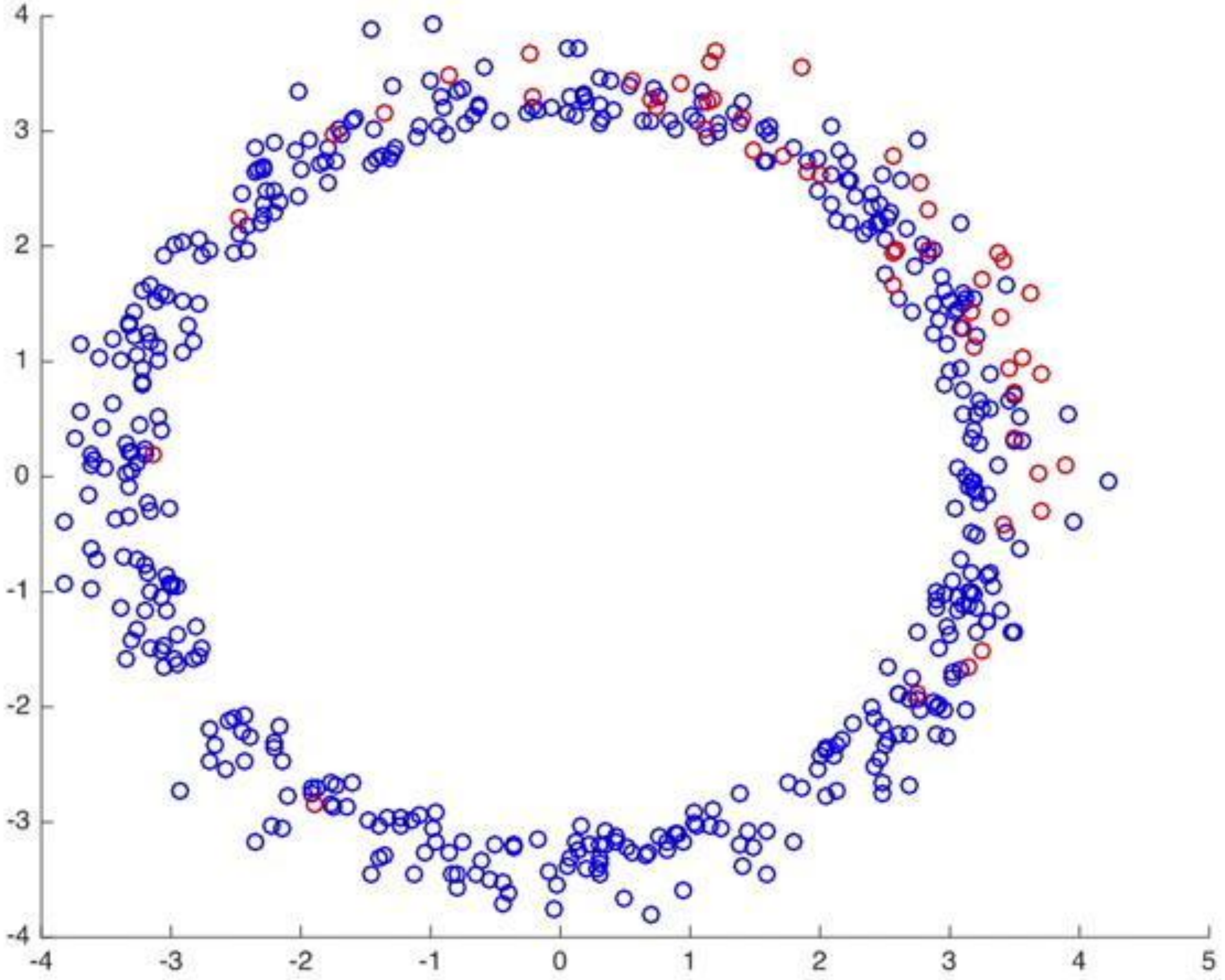

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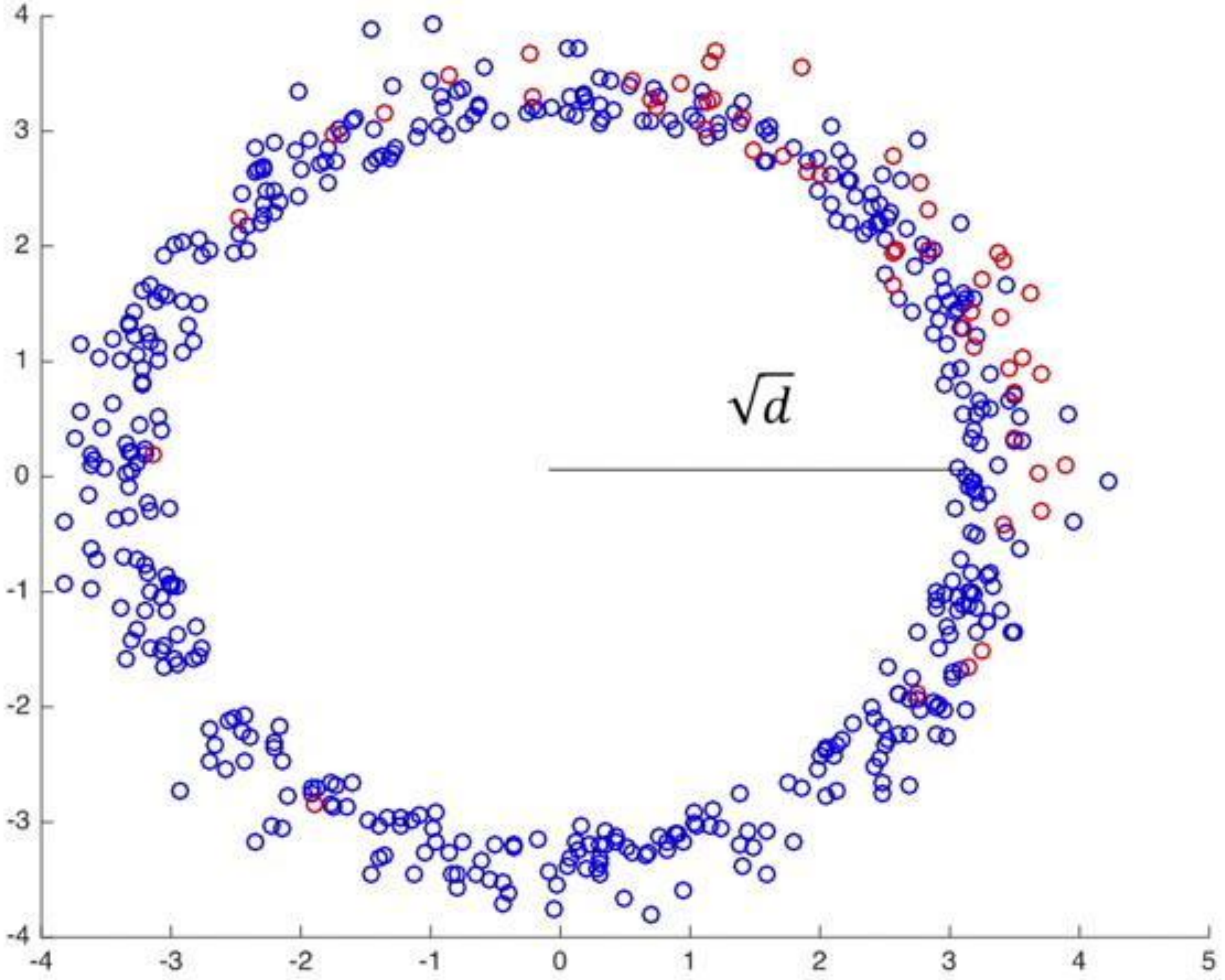

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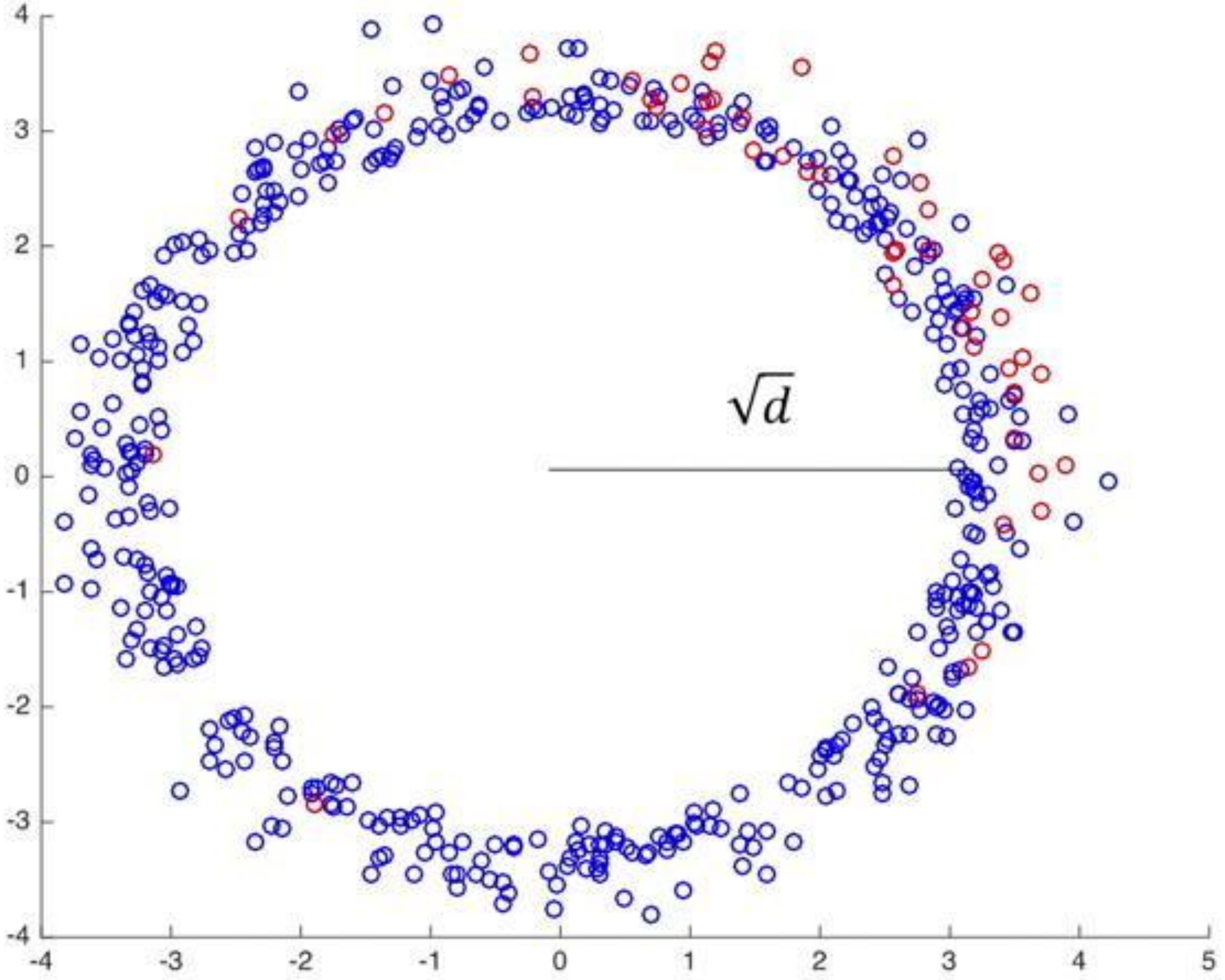

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Must look for corruptions globally

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Is efficient robust estimation possible in high dimensions? **Yes!**

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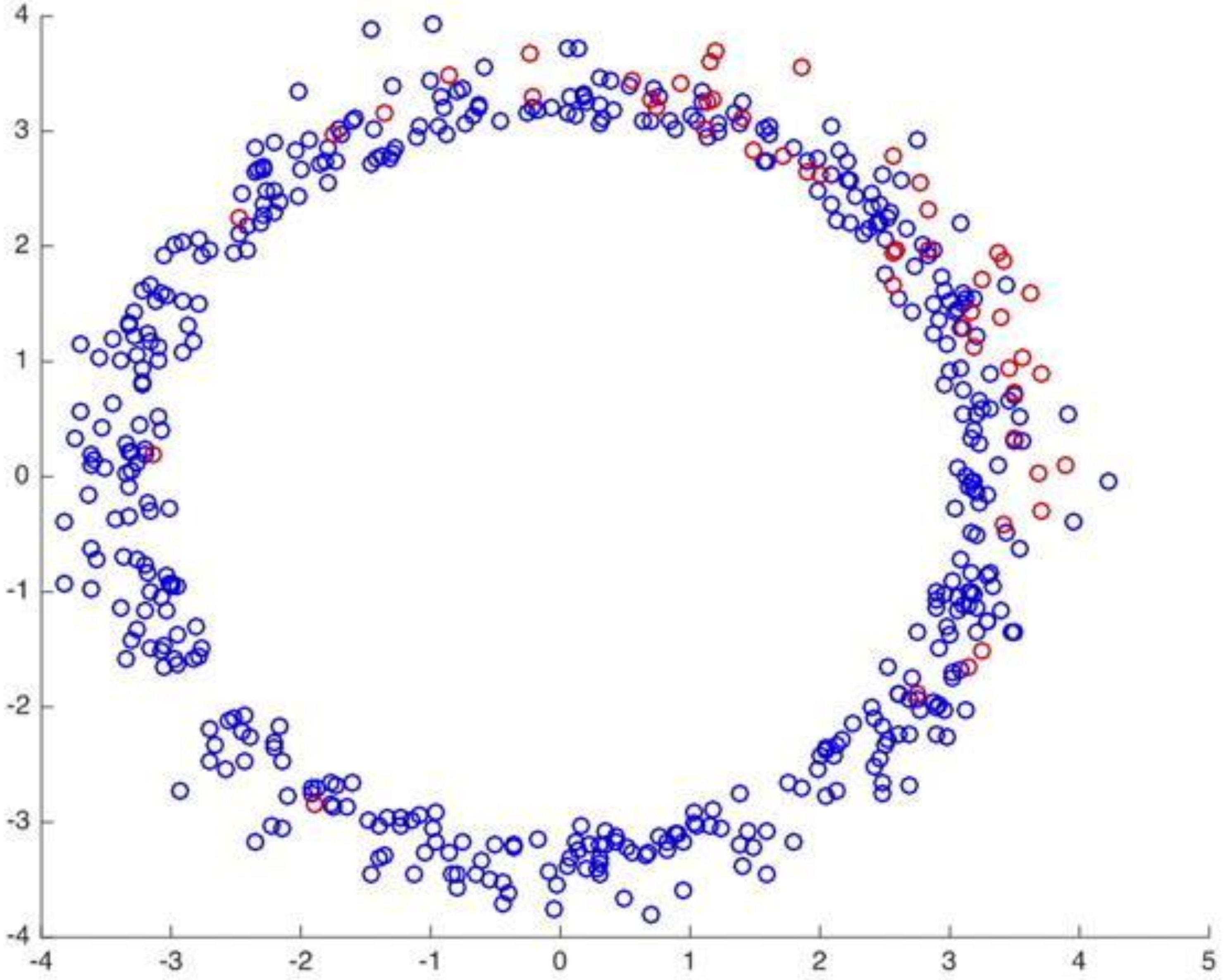

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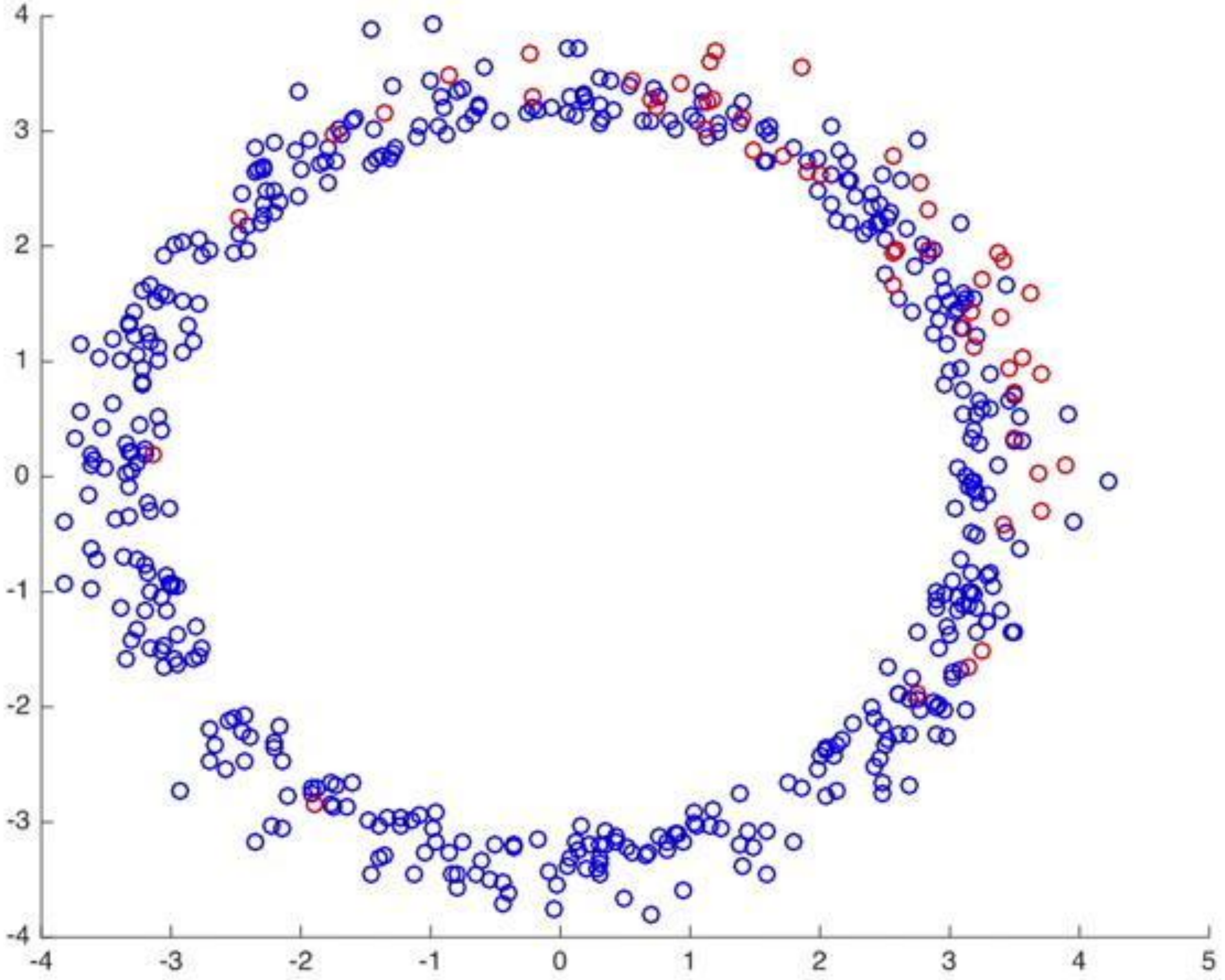

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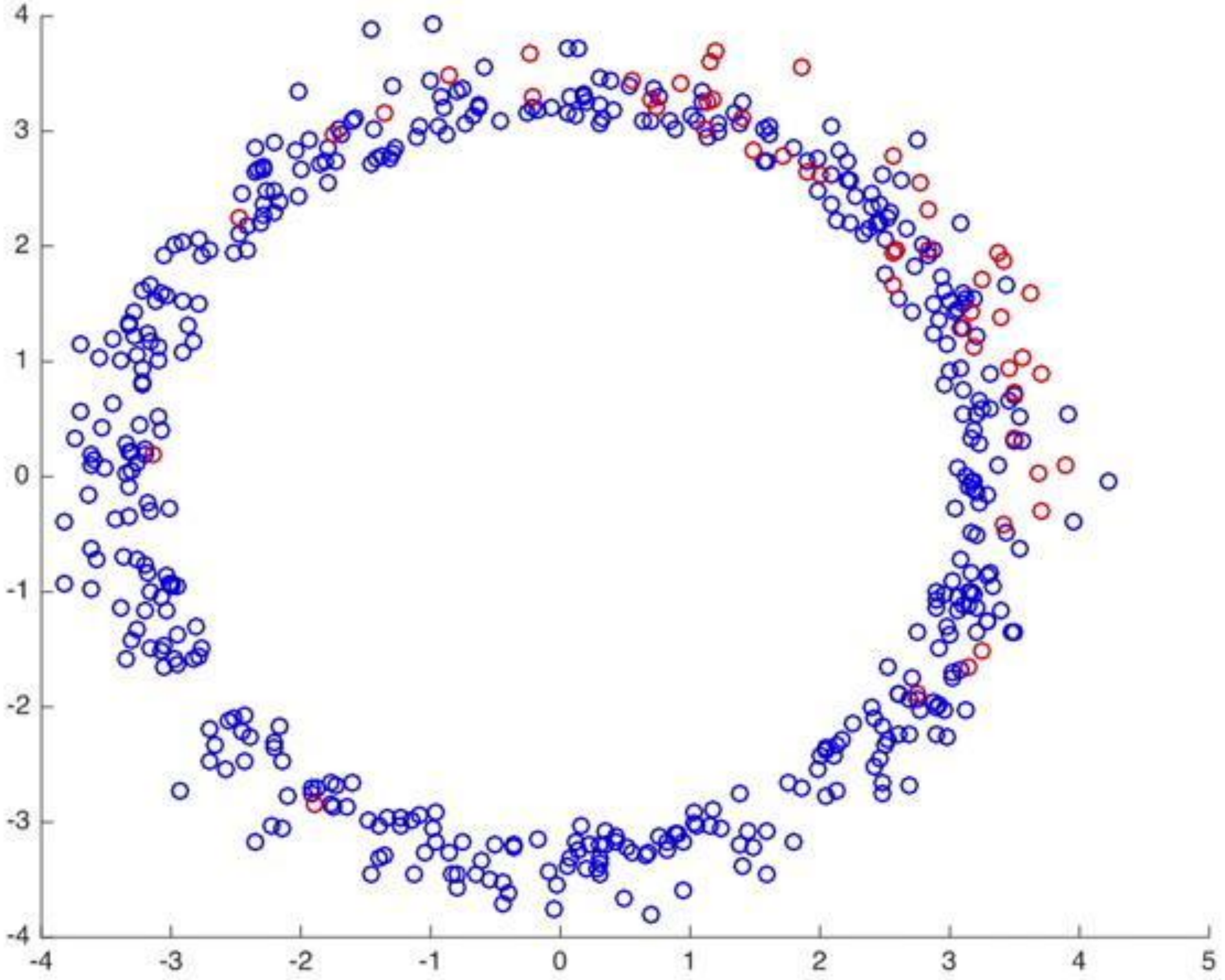

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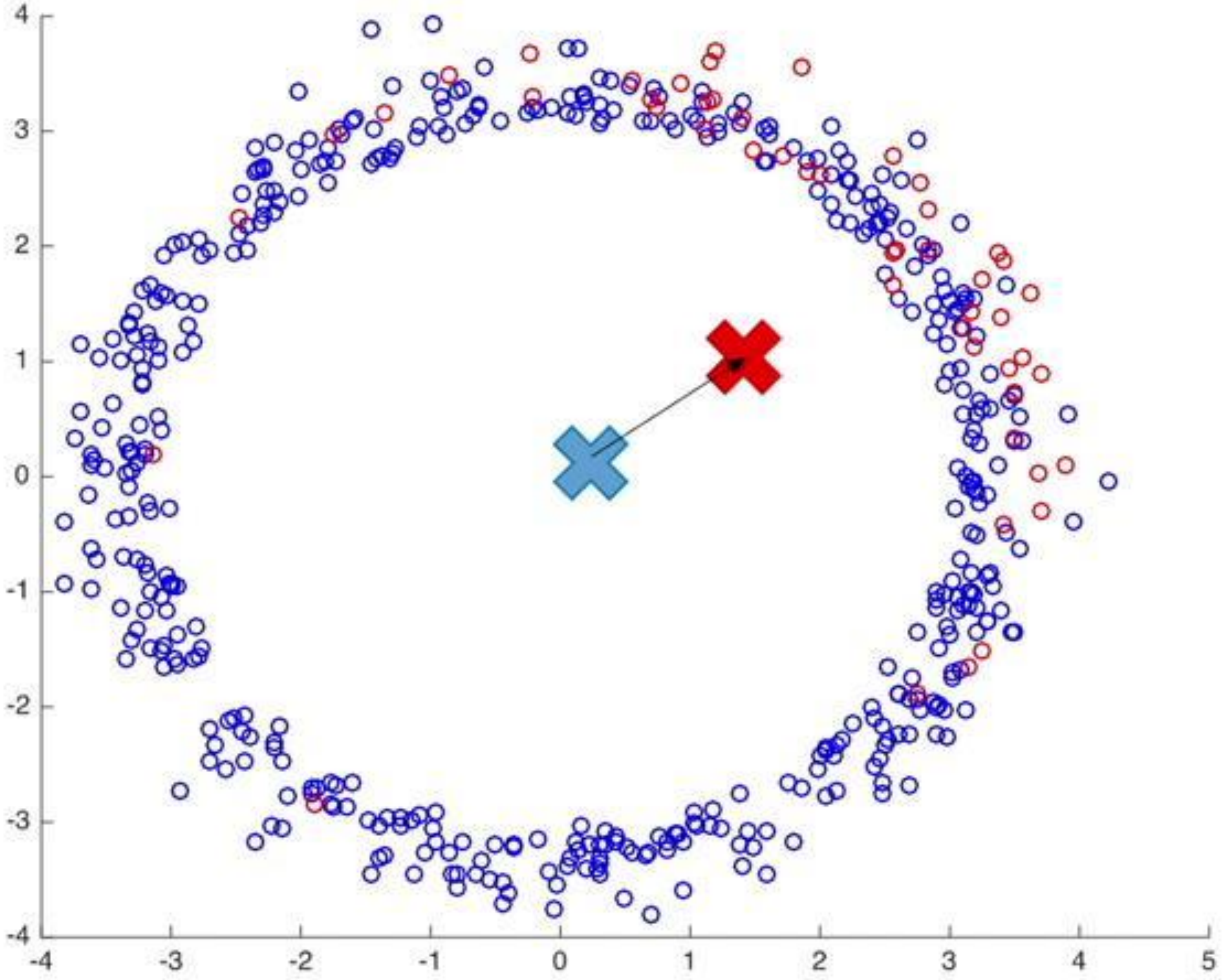

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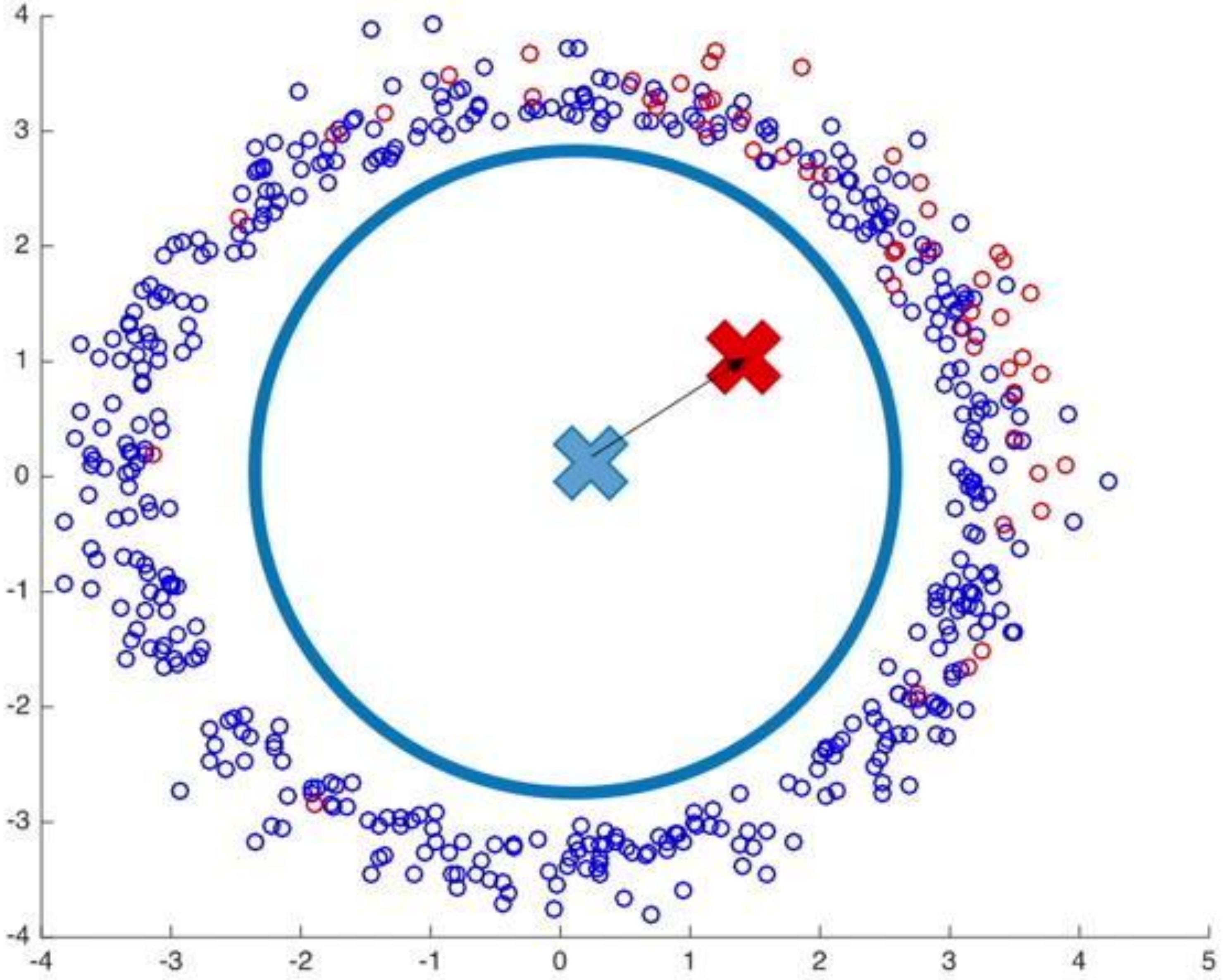

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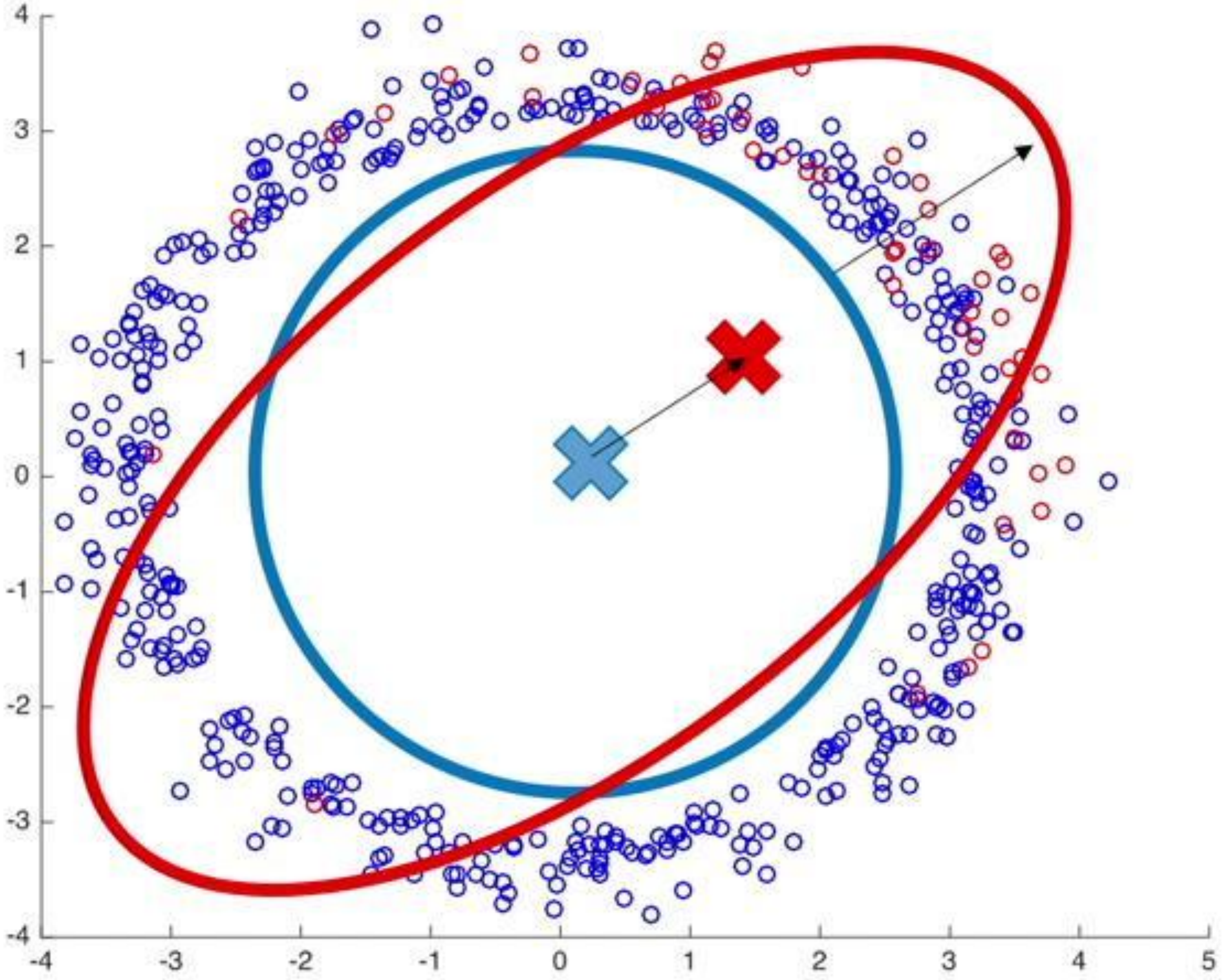

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   - The top eigenvector gives a direction where the bad points are prominent!

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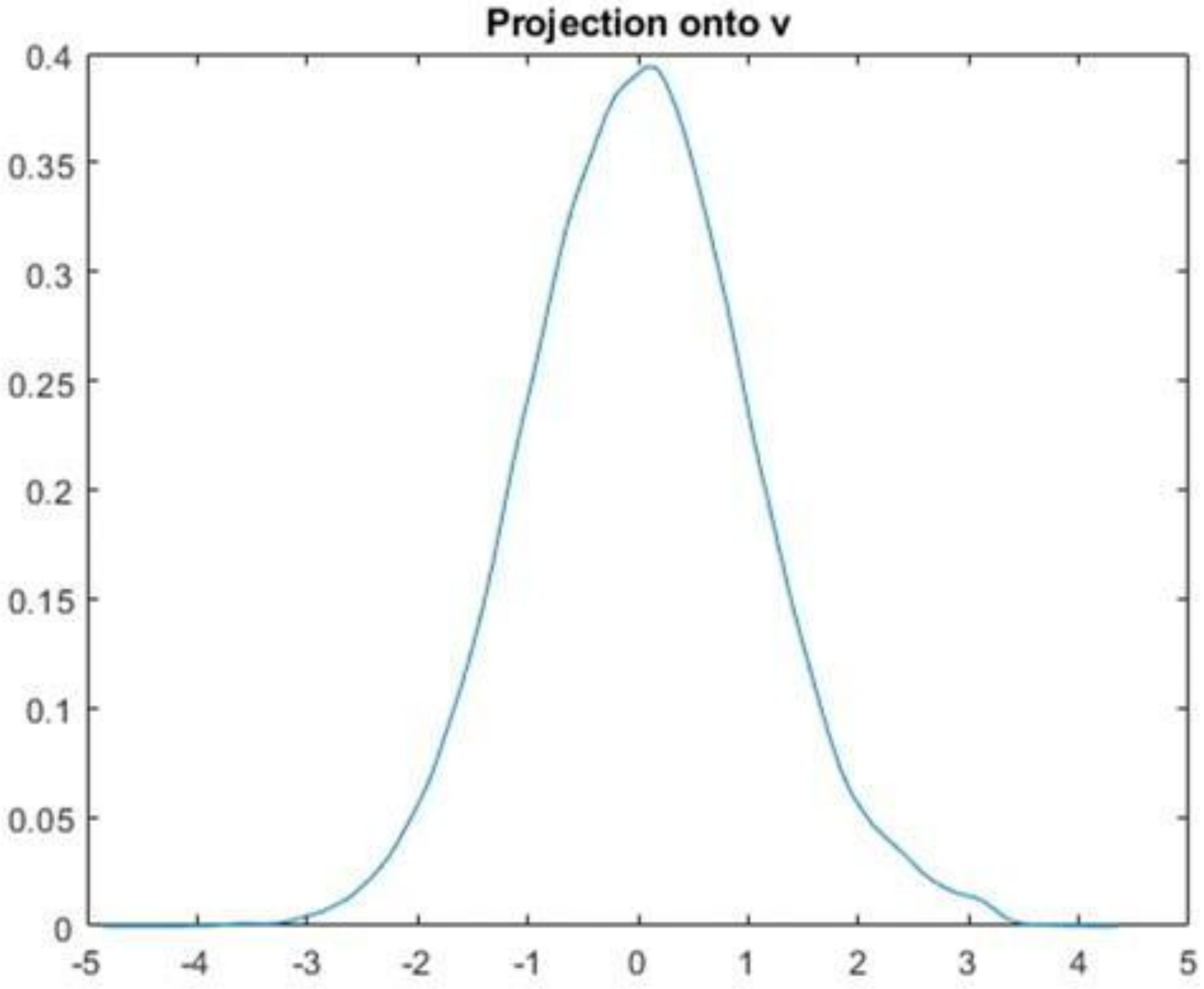

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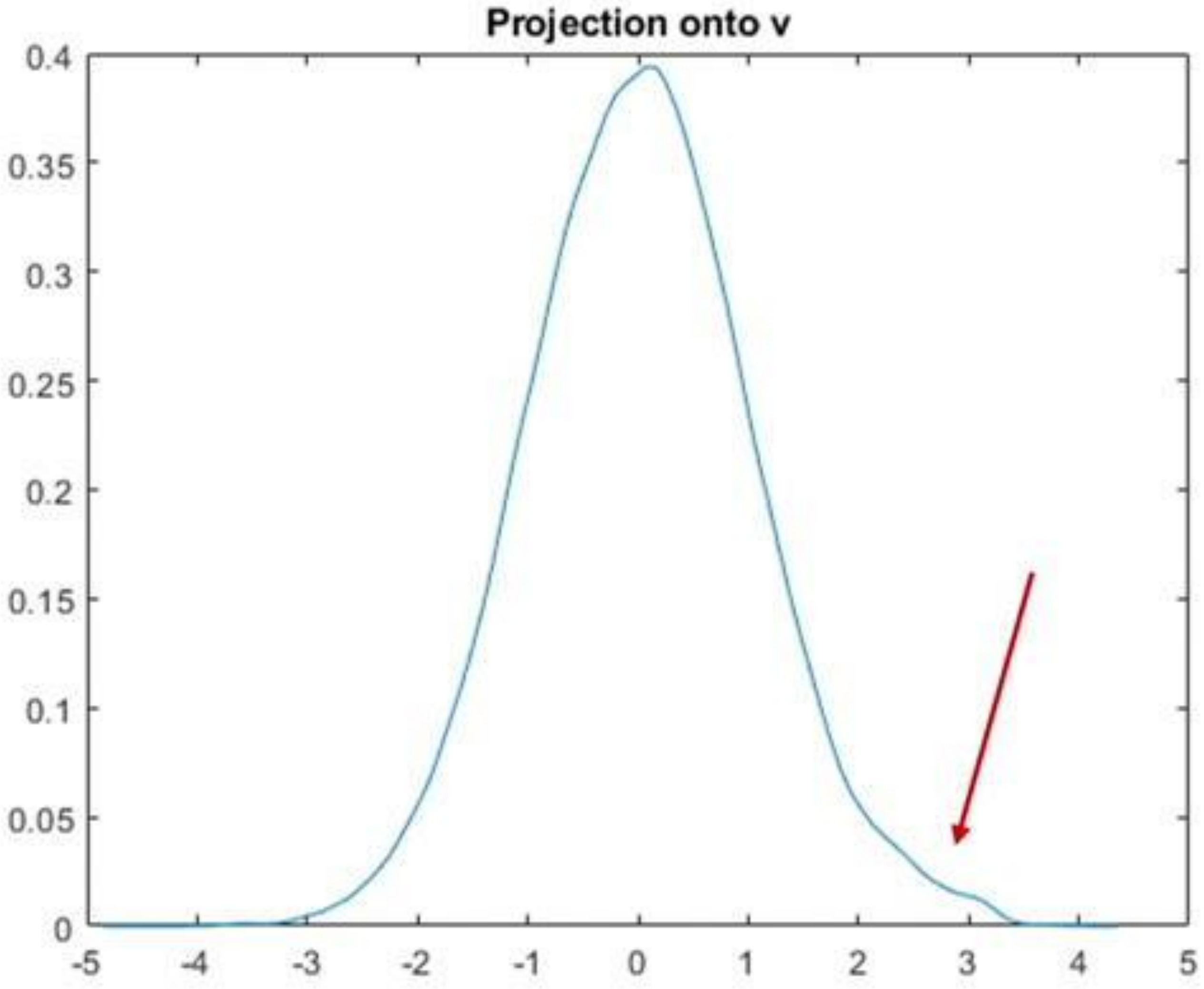

A single iteration runs in nearly linear time!

Our Results

Given an ε-corrupted set of samples that is sufficiently large from...	...we can efficiently get an estimate of the true mean to ℓ_2 error:
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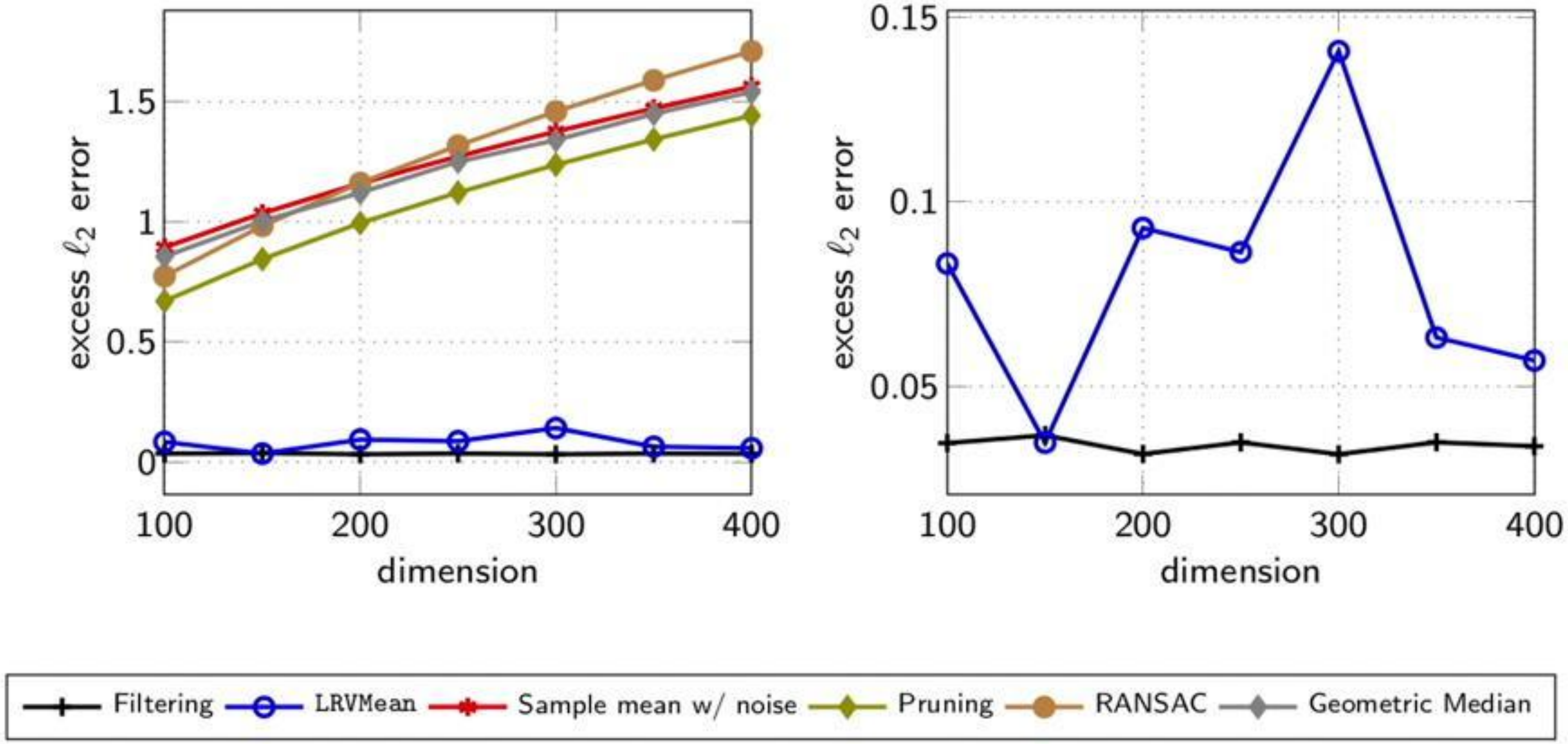
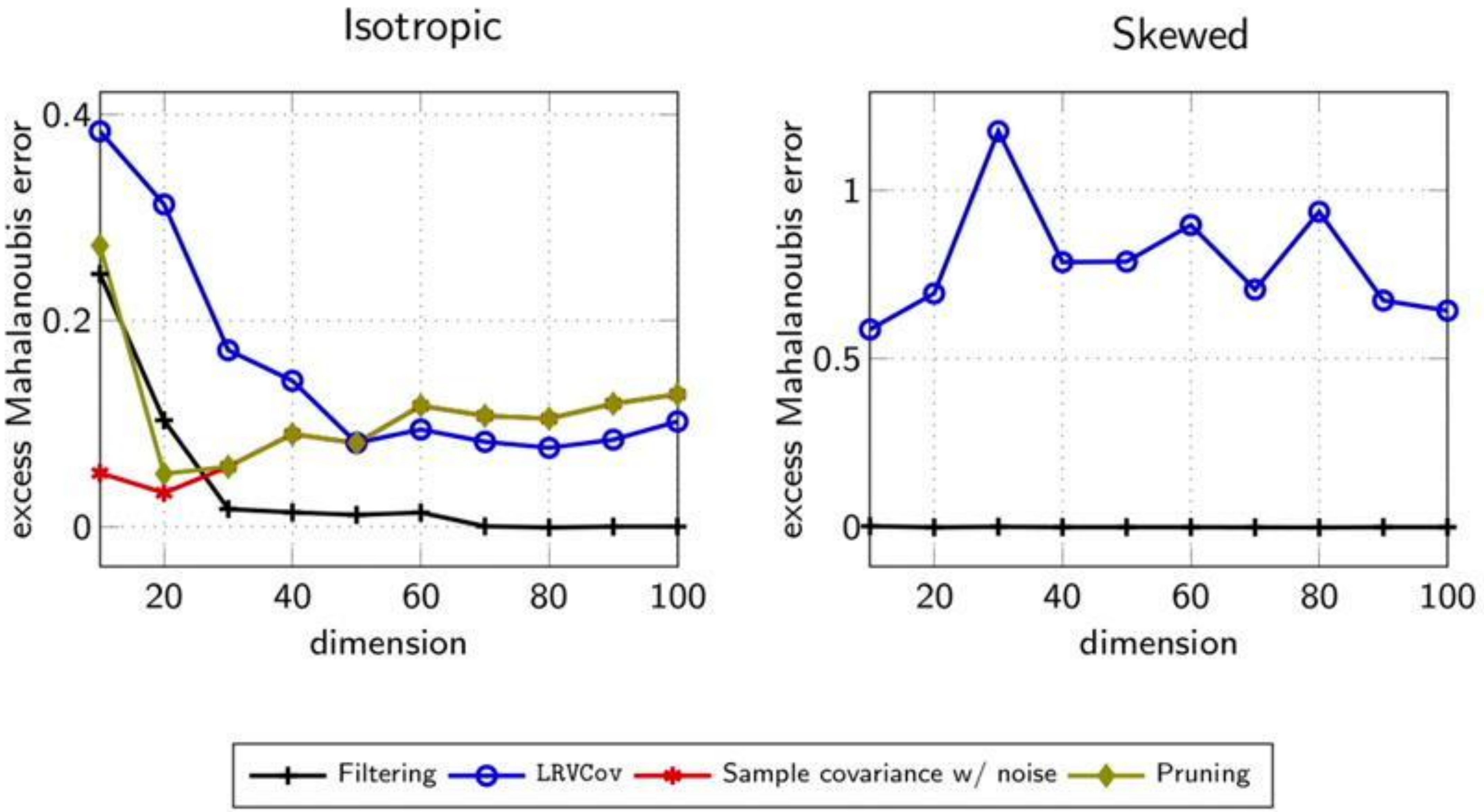
For all cases, these are the first efficient dimension-independent guarantees!

Also sparsity [L17, DBS17], list learning [CSV17, MV17], graphical models [DKS18], general norms [SCV17], federated learning [QV17], sparse regression [KKM18, CLL19] etc...

Synthetic Experiments, Unknown Mean

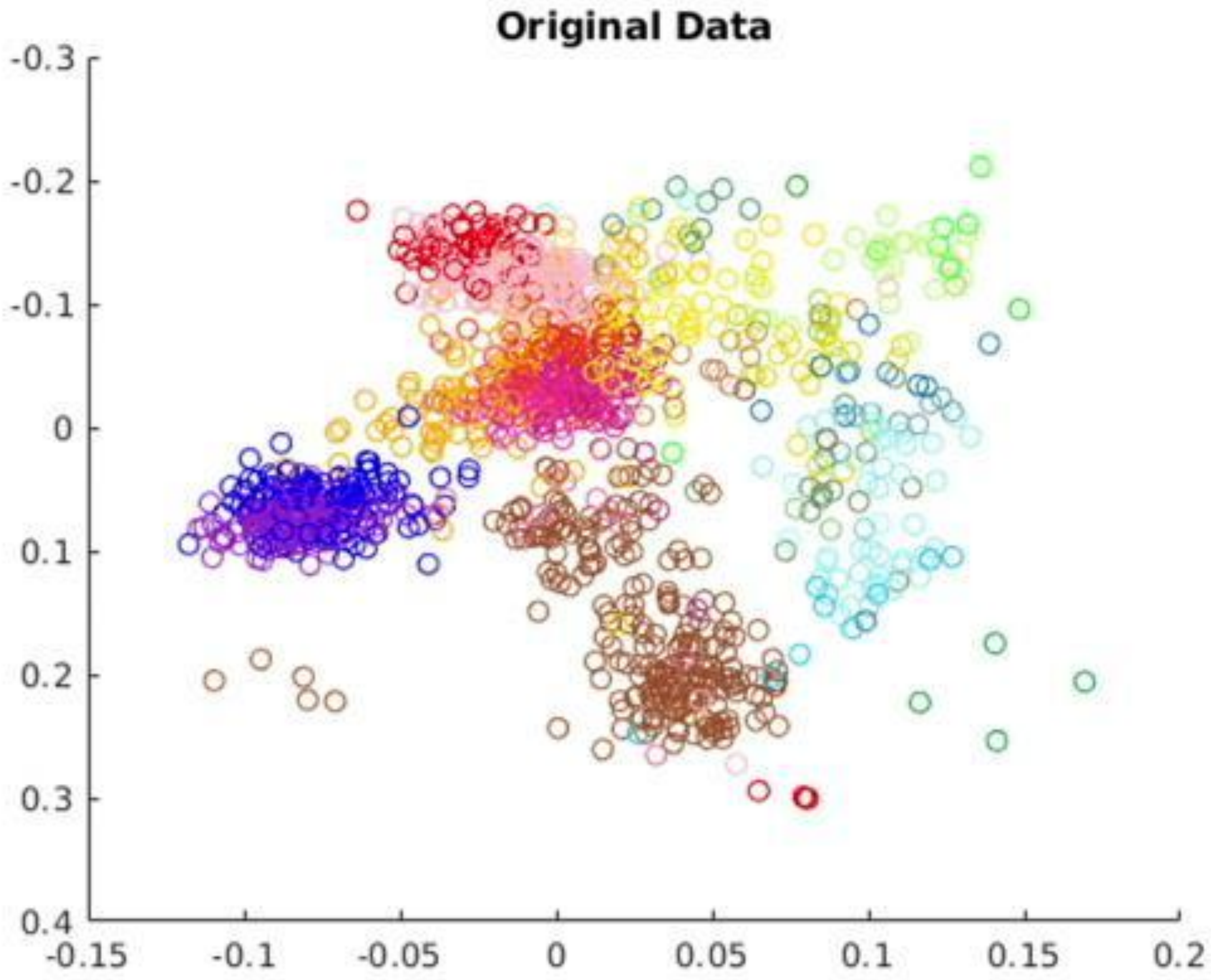


Synthetic Experiments, Unknown Covariance



Gene Expression PCA Contains Europe

- Genes Mirror Geography in Europe. [Novembre et al.], *Nature* ‘08



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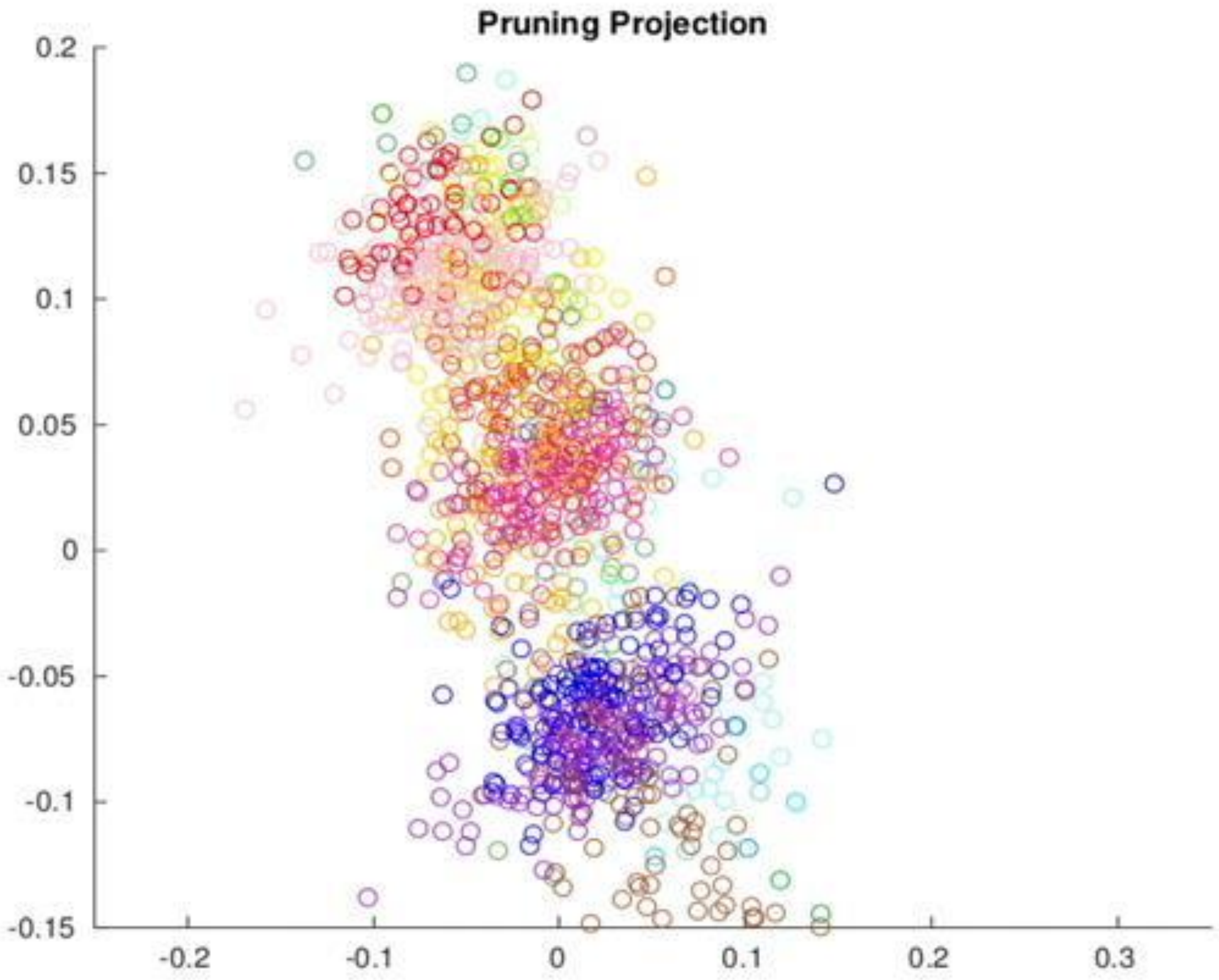

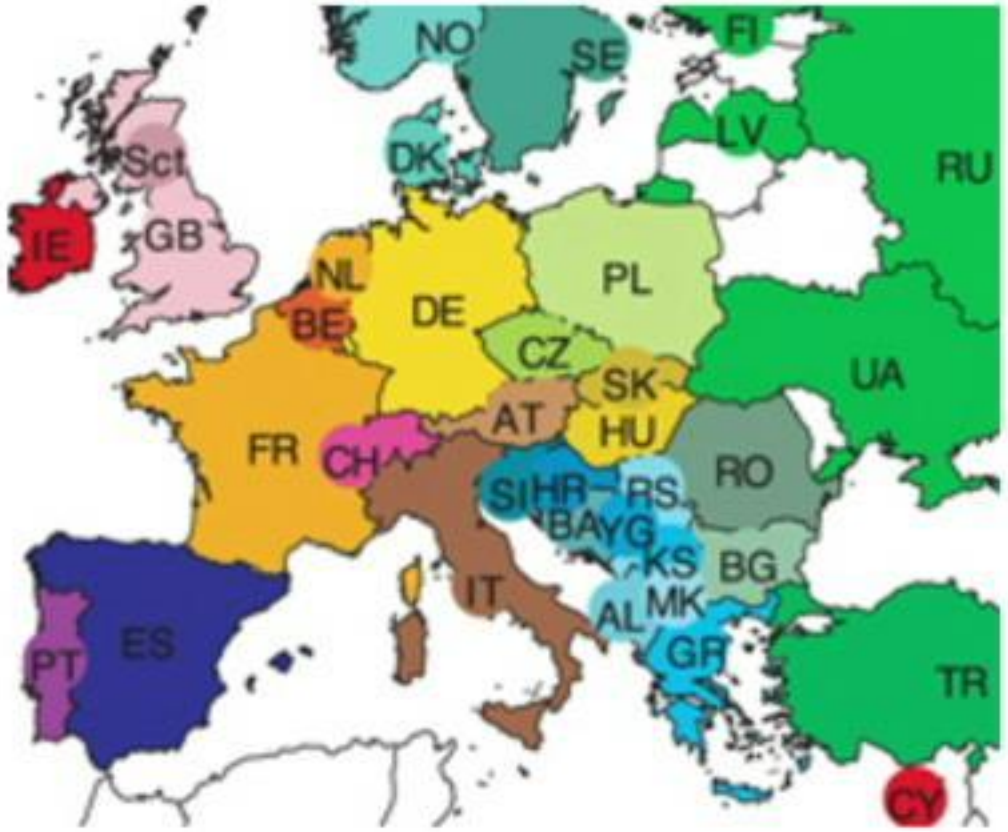

Our Algorithms Fix Europe!

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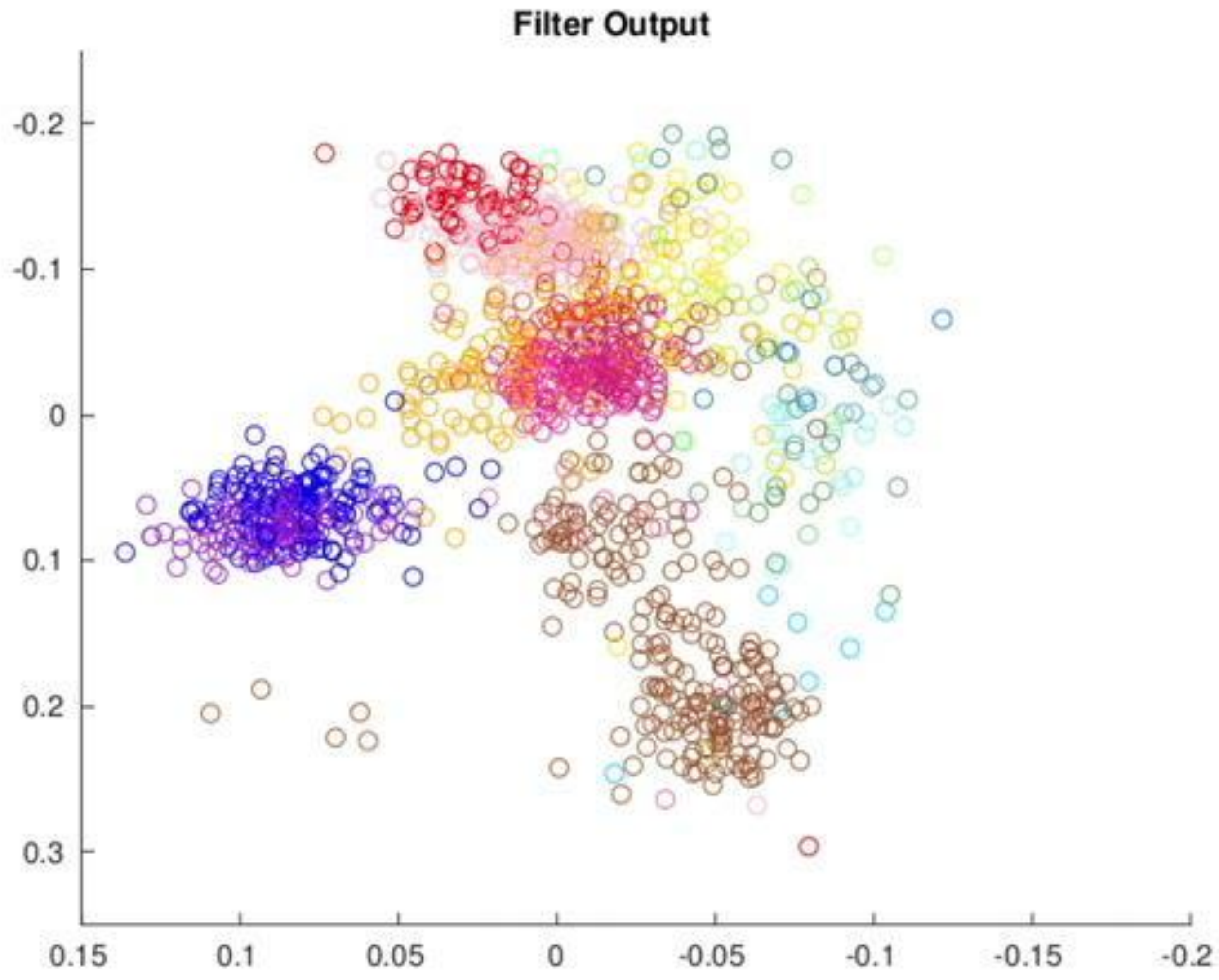

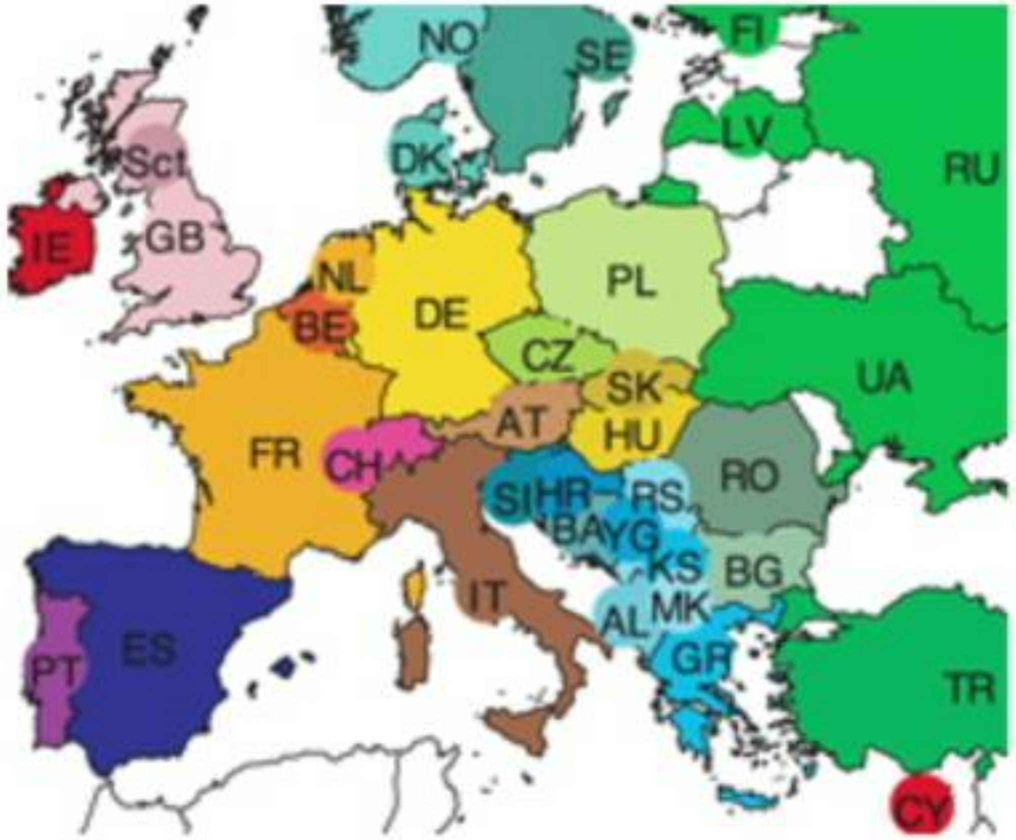

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Recent work of [Dong, Hopkins, L] give a more sophisticated score motivated by robust outlier detection called **quantum entropy (QUE) scoring**

QUE scores outperform previous SOTA on both synthetic and real world outlier detection tasks!

Experimental setup (synthetic)

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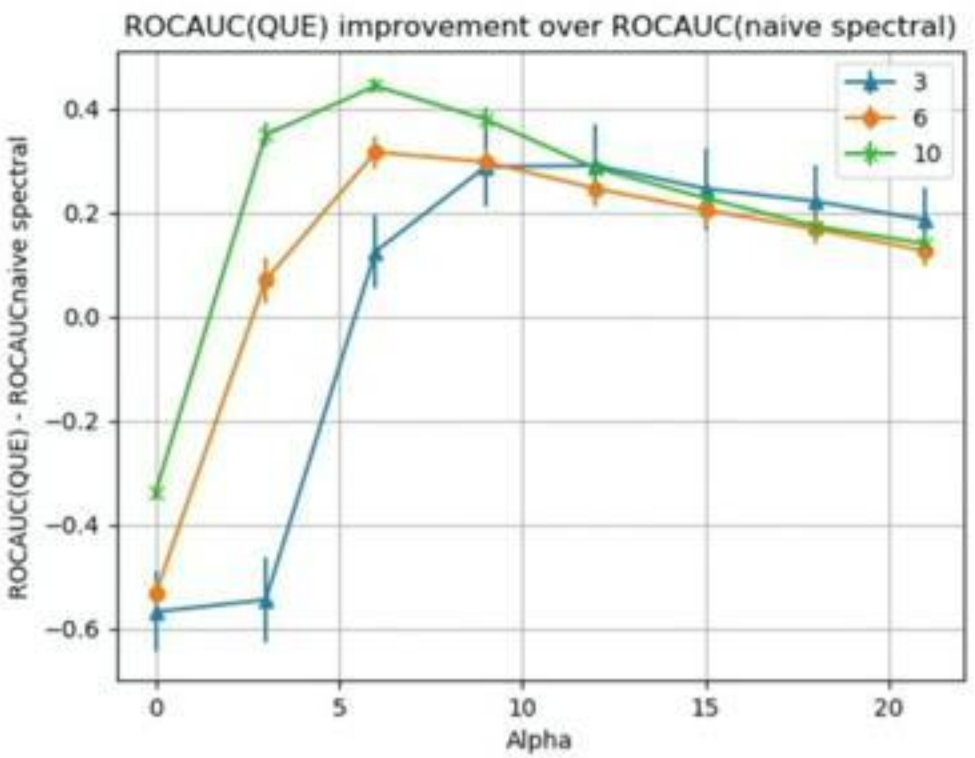

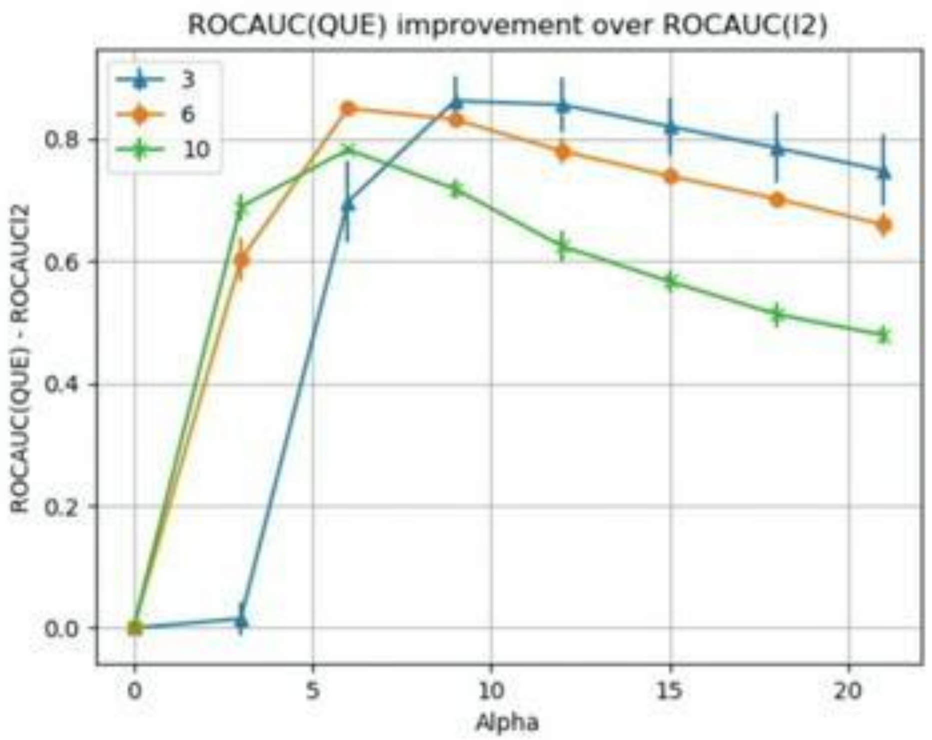

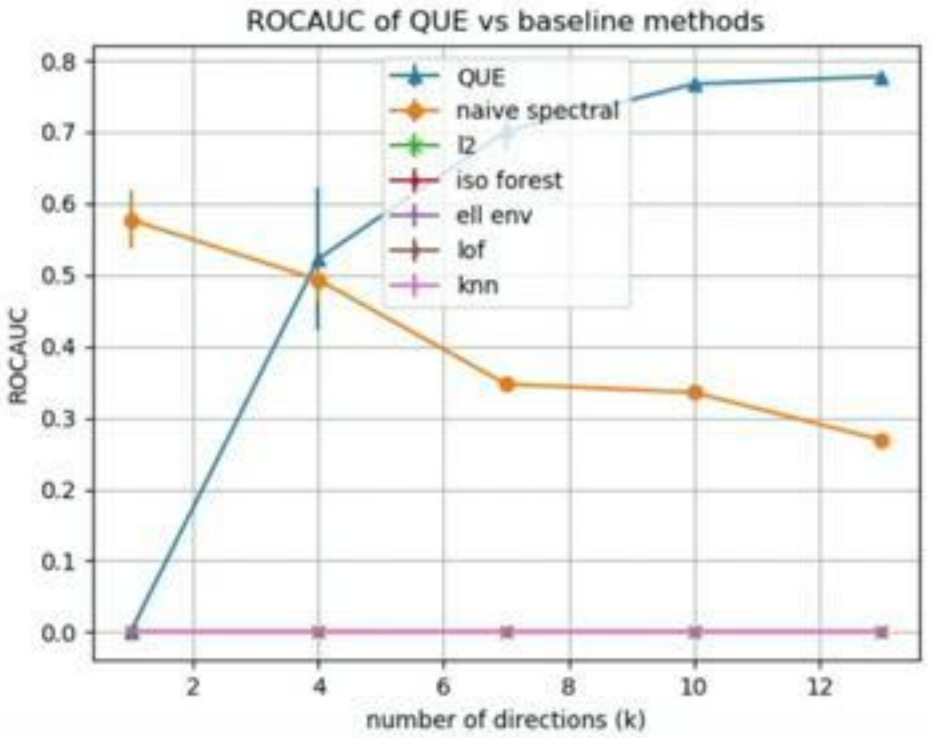

Experimental setup (CIFAR-10)

[Dong, Hopkins, L], to appear, NeurIPS 2020

- Inliers are images CIFAR-10, outliers are images from CIFAR-10 grouped into k groups, where each group has some set of "dead" pixels
- We whiten the data using another set of uncorrupted images from CIFAR-10.

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Challenge: Given ε-corrupted samples from $\mathcal{D}$, minimize f

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Better: only filter at minimizer of the empirical risk!

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Theorem: Suppose ℓ is convex, and Cov $[\nabla \ell(X, w)] \preccurlyeq \sigma^2 I$. Under mild assumptions on $\mathcal{D}$, then SEVER outputs a $\widehat{w}$ so that w.h.p.

$$f(\widehat{w}) - \min_w f(w) < O\left(\sqrt{\sigma^2 \varepsilon}\right).$$

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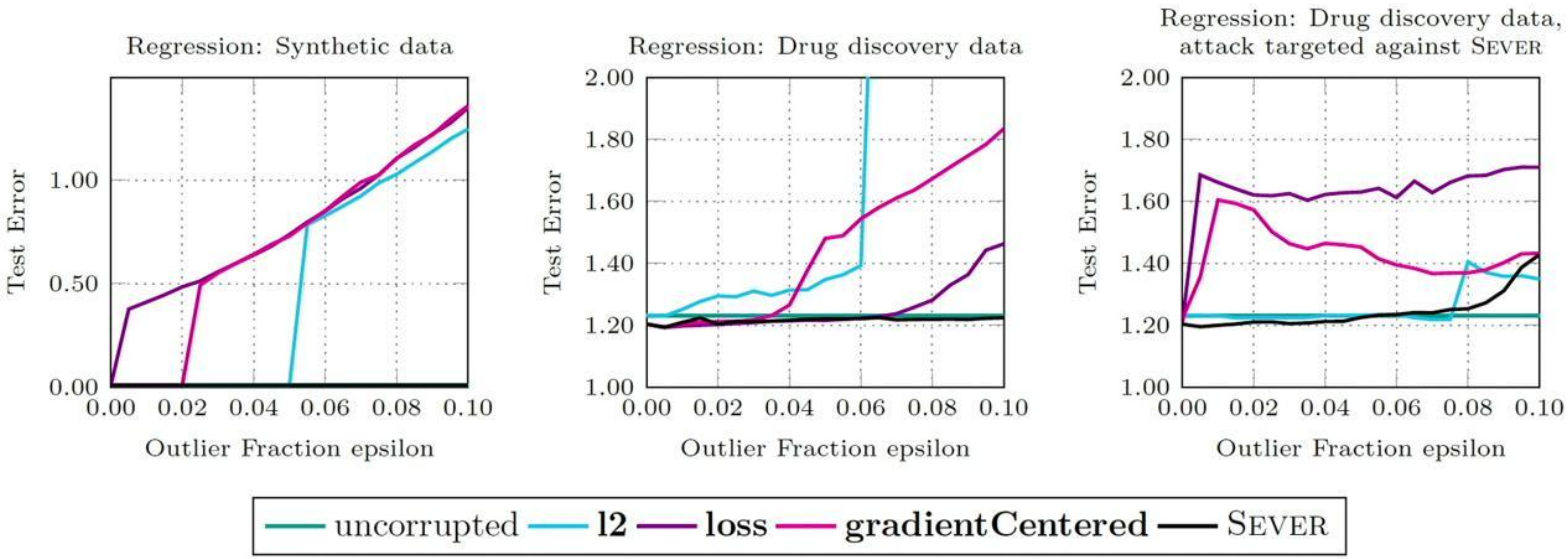
Sample complexity / runtime bounds are polynomial but not super tight

For specific instances (e.g. SVM, regression), we obtain tighter bounds

Performance for ridge regression



SEVER: Robust stochastic optimization

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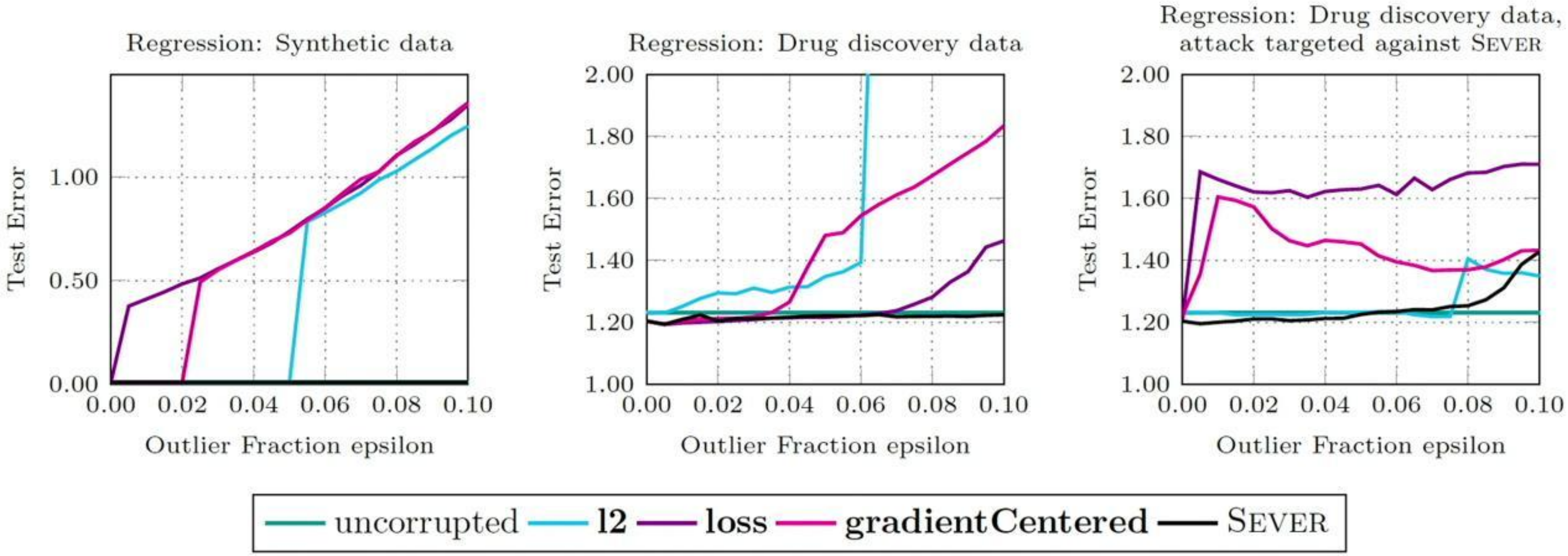

Beyond(er) robust statistics: backdoor attacks

[Tran, L, Madry], NeurIPS'18

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Attacks against ResNet on CIFAR10:

Natural Poisoned Natural Poisoned

"airplane" "bird" "automobile" "cat"

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Attacks against ResNet on CIFAR10:

These attacks convince the network that the implanted watermark is a strong signal for classification

As a result, the learned representation amplifies the signal of the watermark, creating a backdoor

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So what happens to the training set at the learned representation level?

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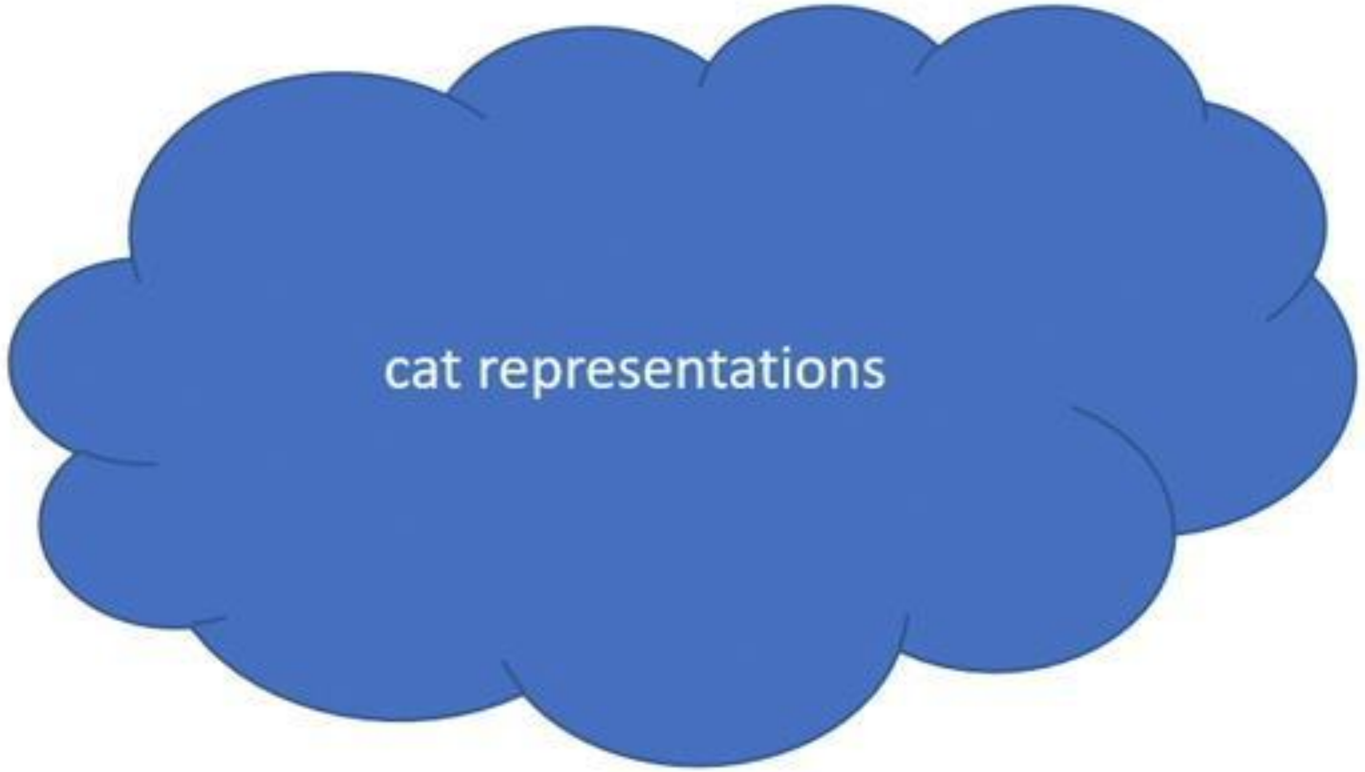

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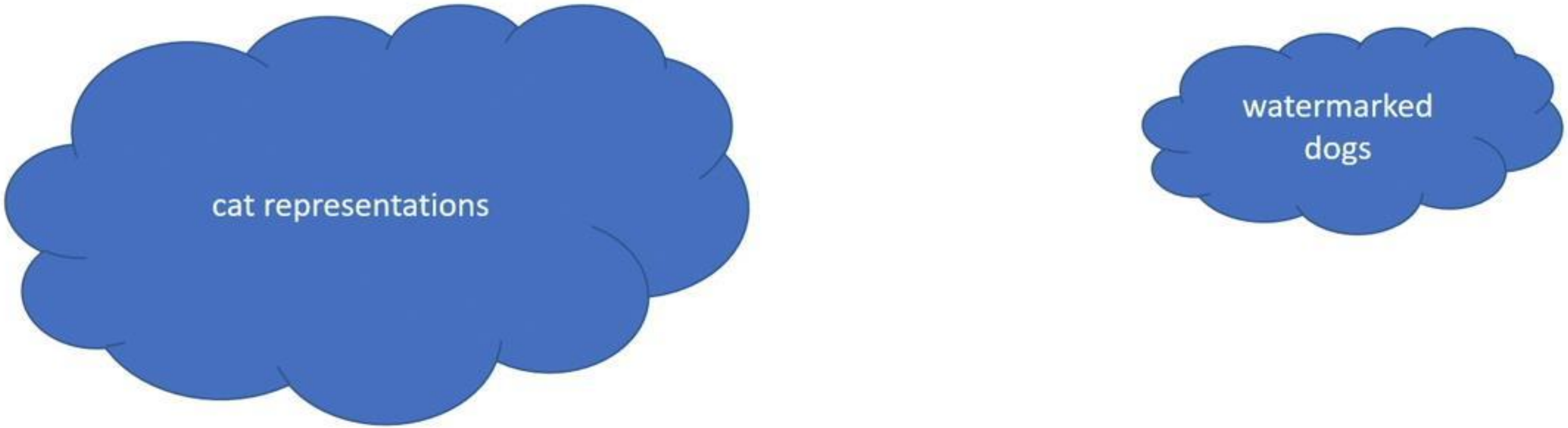

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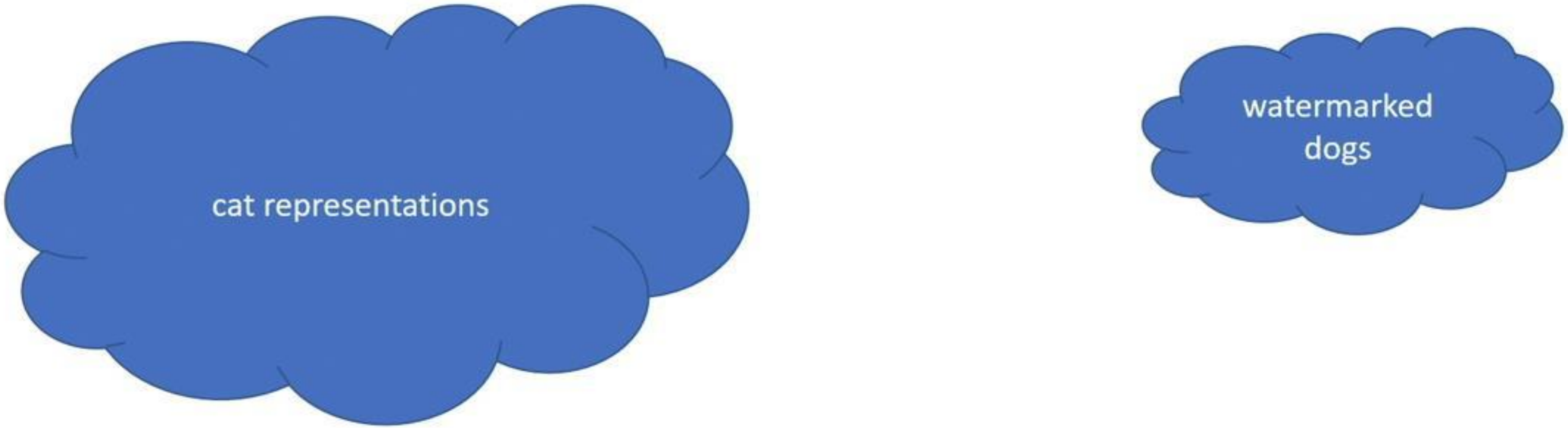

Empirically, results in a noticeable perturbation in the covariance ⇒ our algorithms can detect the corruptions!

Beyond(er) robust statistics: backdoor attacks

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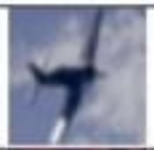
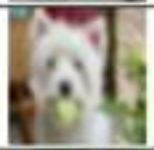
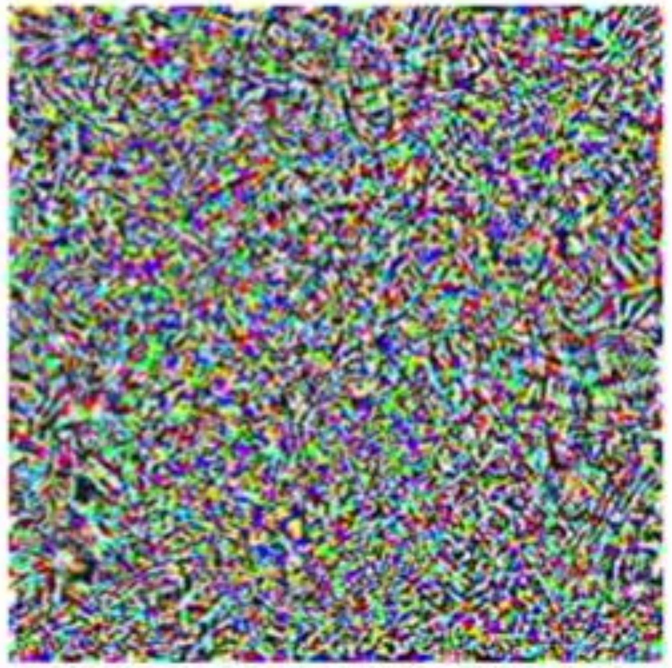
Sample	Target	Epsilon	Nat 1	Pois 1	# Pois Left	Nat 2	Pois 2	Std Pois
	bird	5%	92.27%	74.20%	57	92.64%	2.00%	1.20%
		10%	92.32%	89.80%	7	92.68%	1.50%	
	cat	5%	92.45%	83.30%	24	92.24%	0.20%	0.10%
		10%	92.39%	92.00%	0	92.44%	0.00%	
	dog	5%	92.17%	89.80%	7	93.01%	0.00%	0.00%
		10%	92.55%	94.30%	1	92.64%	0.00%	
	horse	5%	92.60%	99.80%	0	92.57%	1.00%	0.80%
		10%	92.26%	99.80%	0	92.63%	1.20%	
	cat	5%	92.86%	98.60%	0	92.79%	8.30%	8.00%
		10%	92.29%	99.10%	0	92.57%	8.20%	
	deer	5%	92.68%	99.30%	0	92.68%	1.10%	1.00%
		10%	92.68%	99.90%	0	92.74%	1.60%	
	frog	5%	92.87%	88.80%	10	92.61%	0.10%	0.30%
		10%	92.82%	93.70%	3	92.74%	0.10%	
	bird	5%	92.52%	97.90%	0	92.69%	0.00%	0.00%
		10%	92.68%	99.30%	0	92.45%	0.50%	

Robustness at Test Time

Adversarial examples for NNs

"pig"

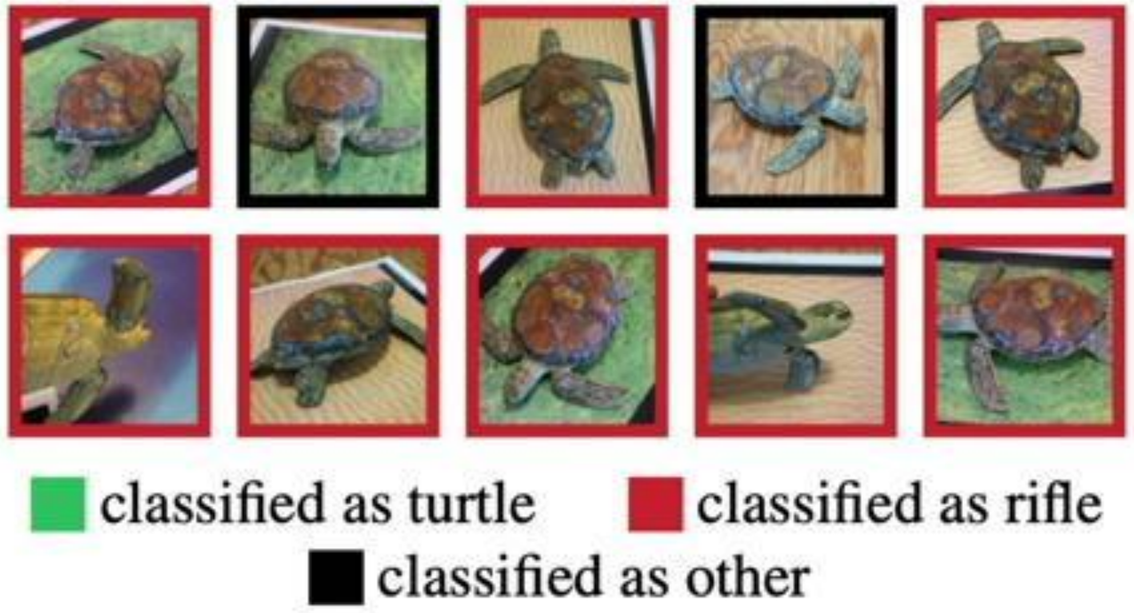
+ 0.005 x

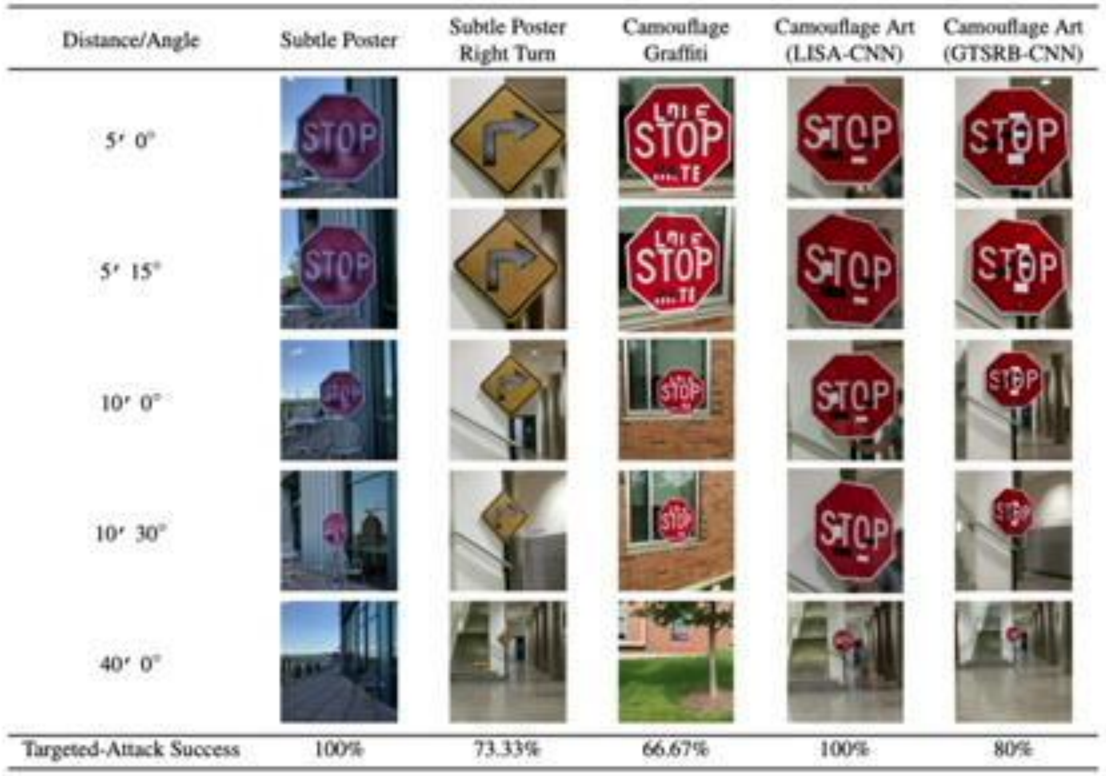


=

"airliner"

This is a real problem!





(a) (b) (c)

Formal definition

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- A classifier $f: \mathbb{R}^d \to \mathcal{Y}$

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An adversarial example for $x \in \mathbb{R}^d$ is a point $x + \delta$ for $\delta \in S$ s.t.

$$f(x) \neq f(x + \delta)$$

Empirical defenses

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- Many of these have been broken, often within weeks or months of publication
- One notable exception: adversarial training [Madry et al '18]

Adversarial training

Standard training:

Given current model θ_t, data point (X, y), and loss function L, we apply the first order update:

$$\theta_{t+1} \leftarrow \theta_t - \eta_t \cdot \nabla_\theta L(f_\theta(X), y)$$

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where X' is an adversarial perturbation to X for f_θ

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- However, these often don't scale, or get much worse numbers than empirical defenses.
- A recent approach that might bridge the gap: **randomized smoothing** [Lecuyer et al, Li et al, Cohen et al]

Randomized smoothing

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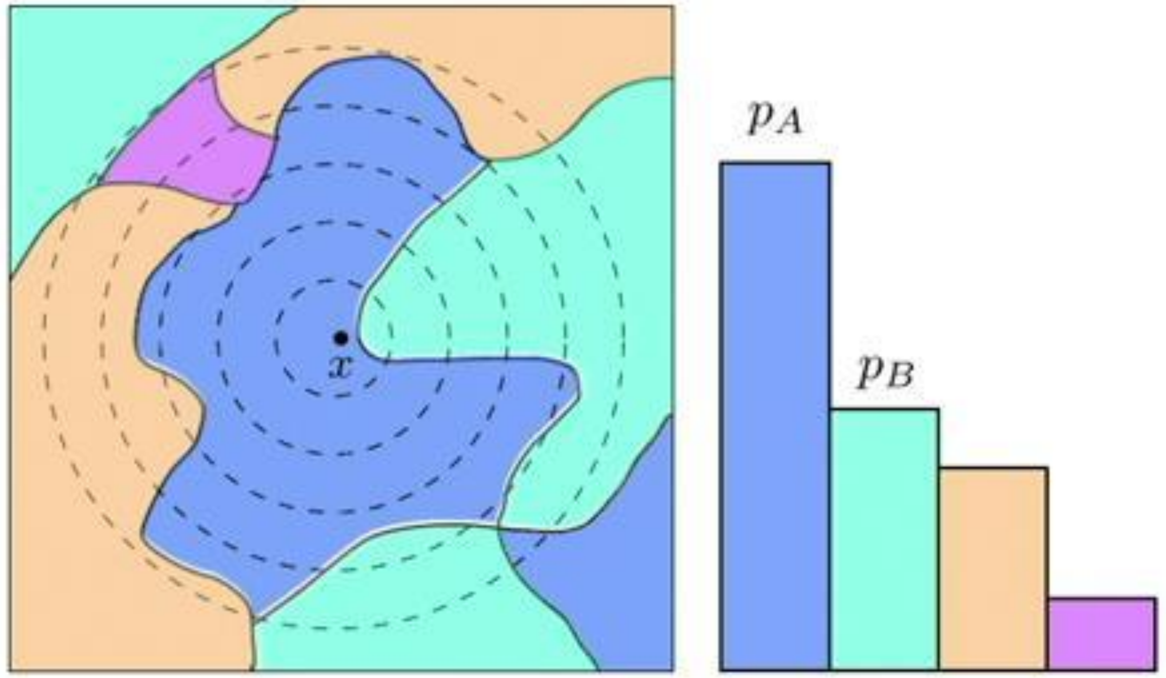

Image from: [Cohen et al'19]

Certifiable robustness of randomized smoothing

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Theorem [Cohen et al'19]: Let G be a soft classifier, and let $x \in \mathbb{R}^d$. Let $a, b \in \mathcal{Y}$ be the most likely and second most likely class for x under G, with probabilities p_a, p_b respectively. Then

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for all δ satisfying

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In practice: can simulate G, p_a, p_b via Monte-Carlo sampling.

Training smoothed networks

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Our idea: Directly robustify smoothed network via adversarial training on **smoothed loss**

SmoothAdv

[Salman, Yang, L, Zhang, Zhang, Razenshteyn, Bubeck], to appear, NeurIPS 2020

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Given data and label (x, y), want to find $\hat{x}$ that maximizes loss of G in an ℓ_2 ball around x wrt cross-entropy loss L_{CE}.

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We call this the **SmoothAdv** objective.

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We then do adversarial training with this objective.

SmoothAdv is not the Gaussian Augmentation Objective

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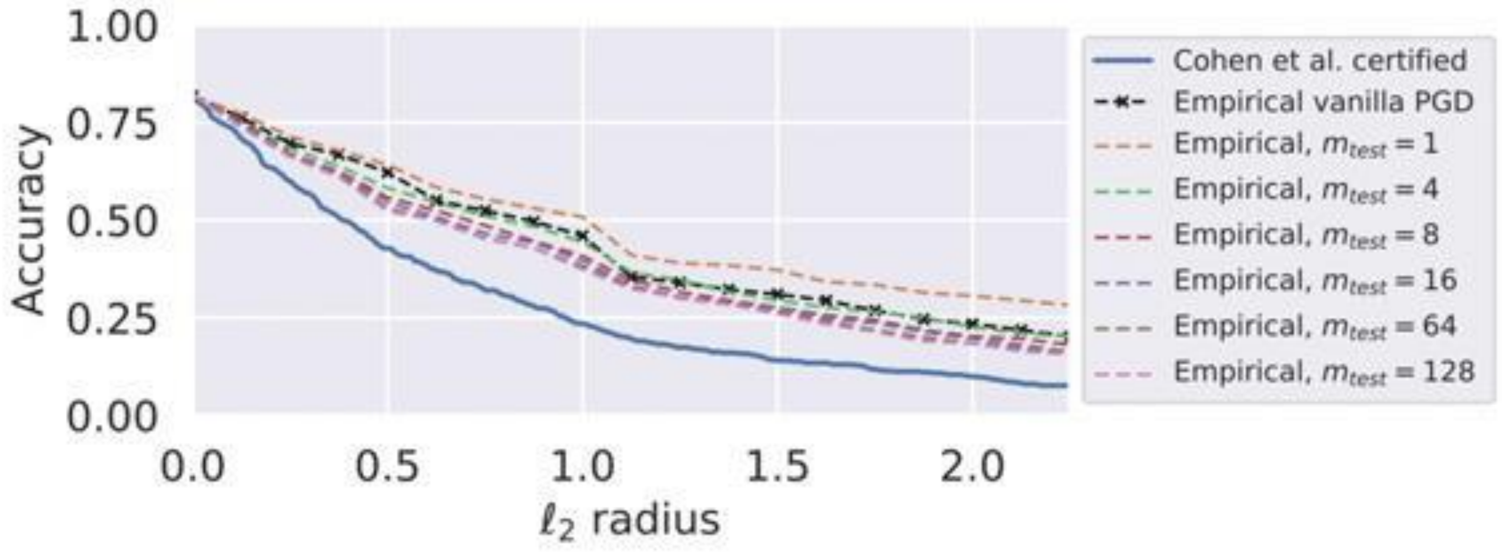
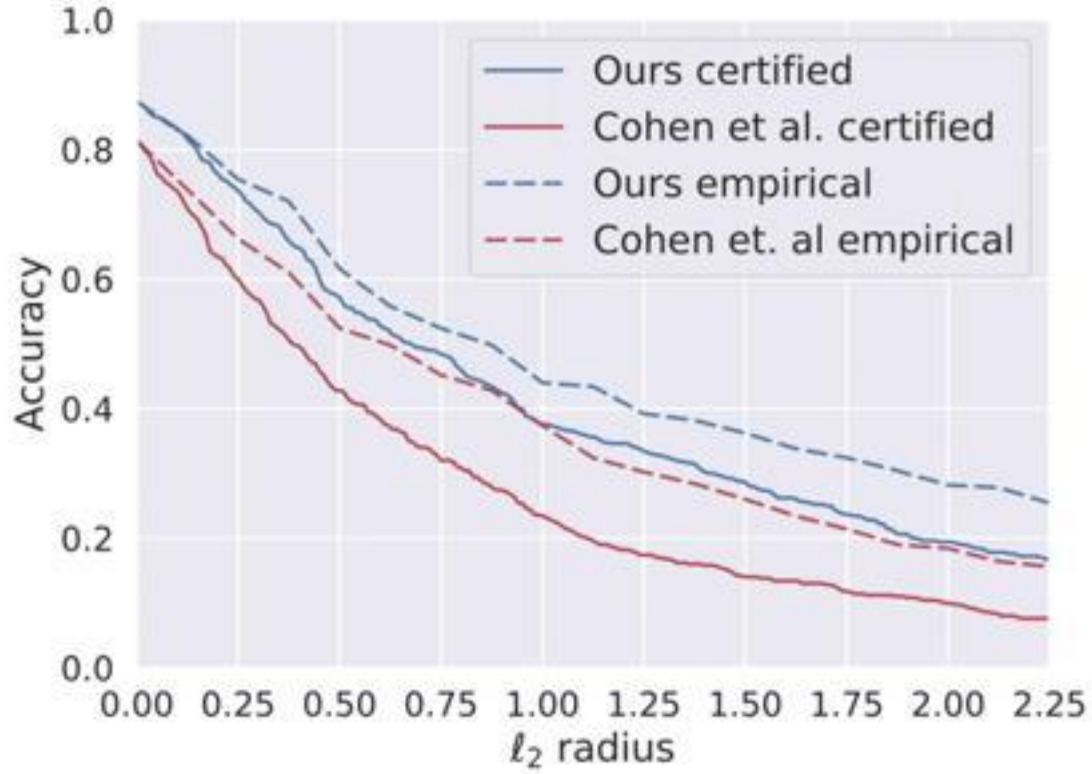
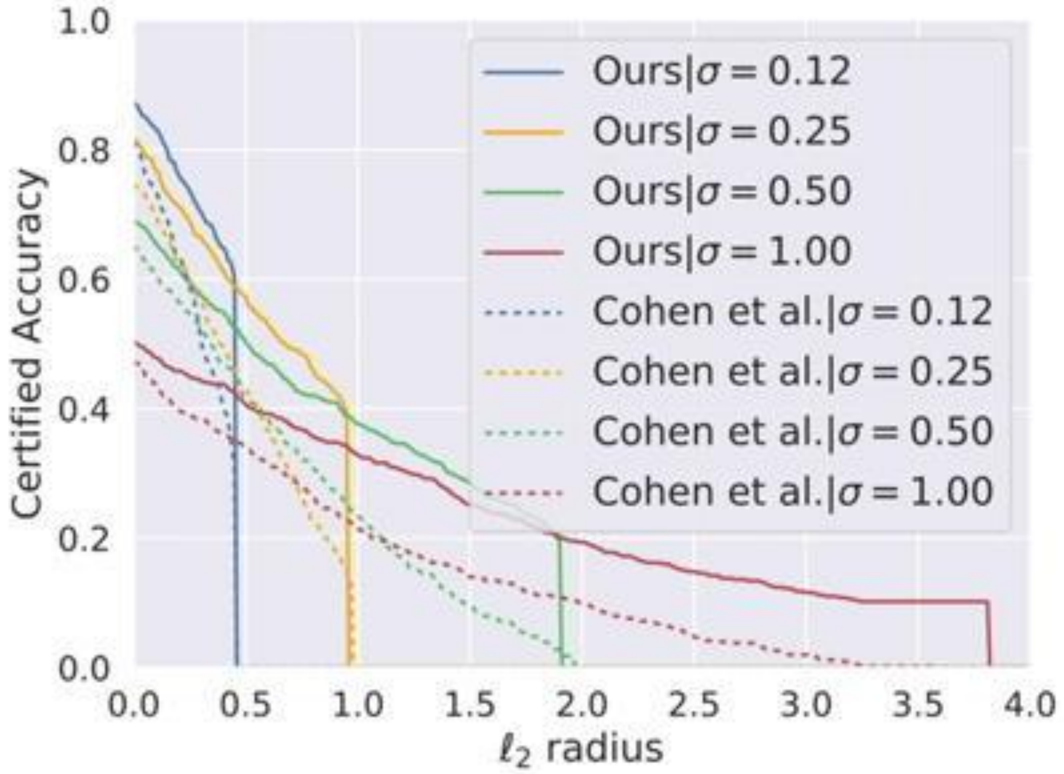


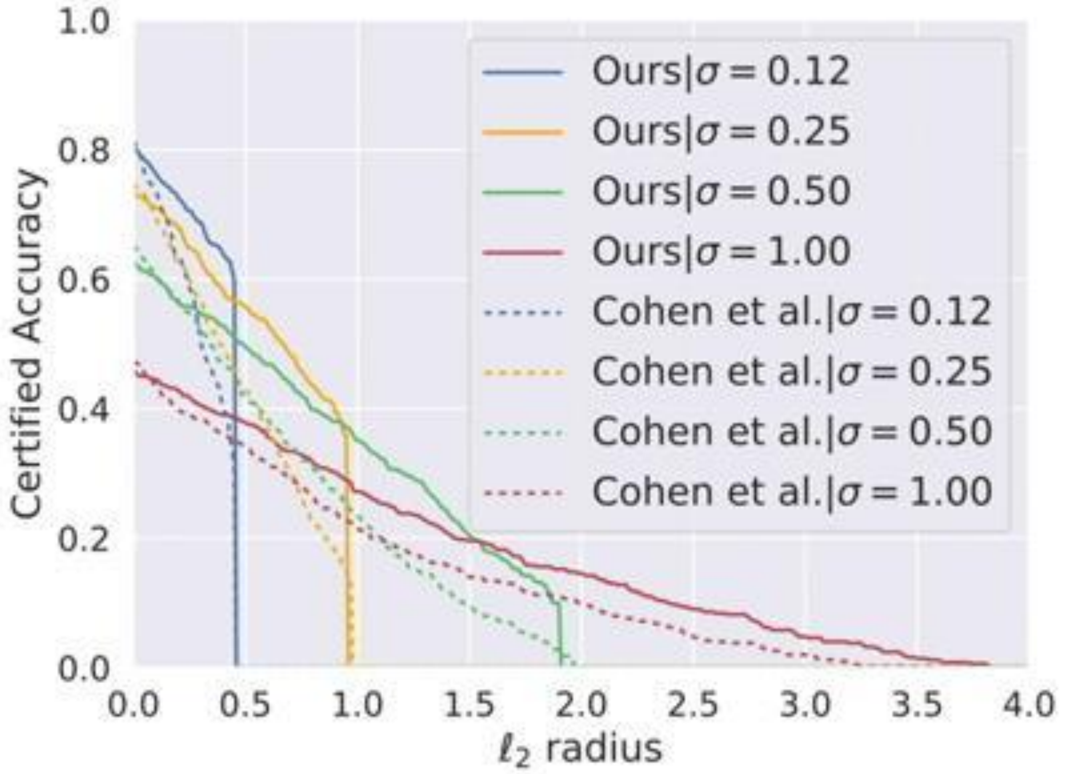
Results: CIFAR10



Upper envelope

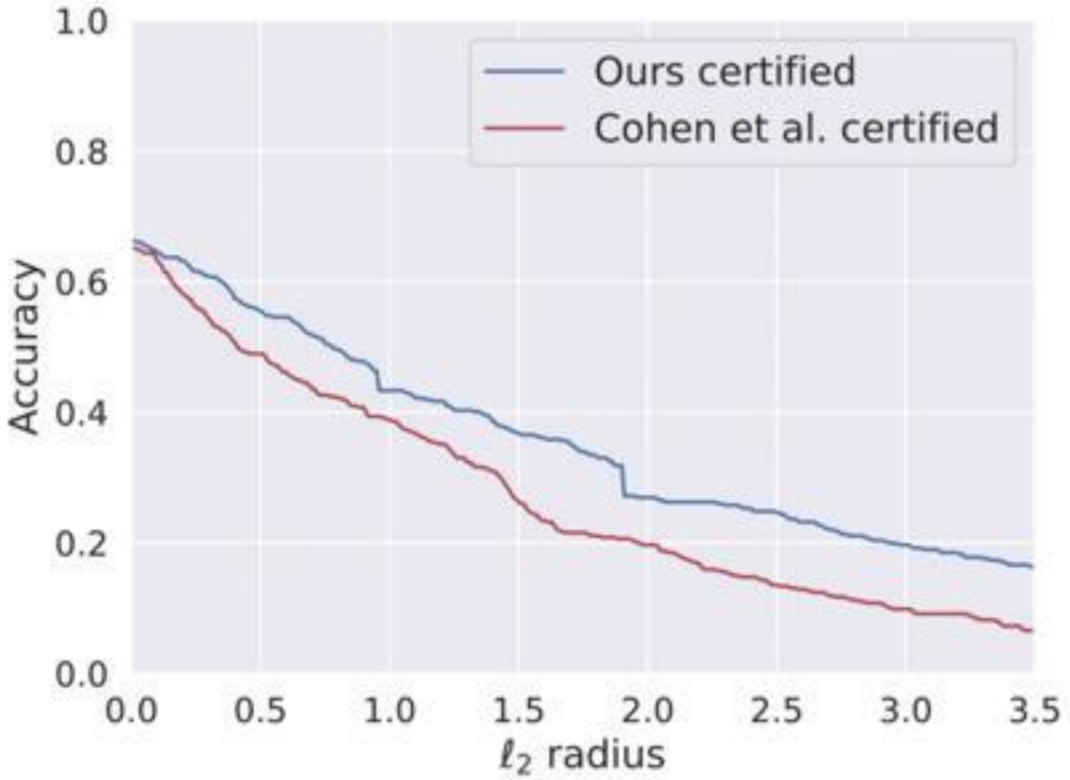


Upper envelope per σ



Representative models per σ

Results: Imagenet



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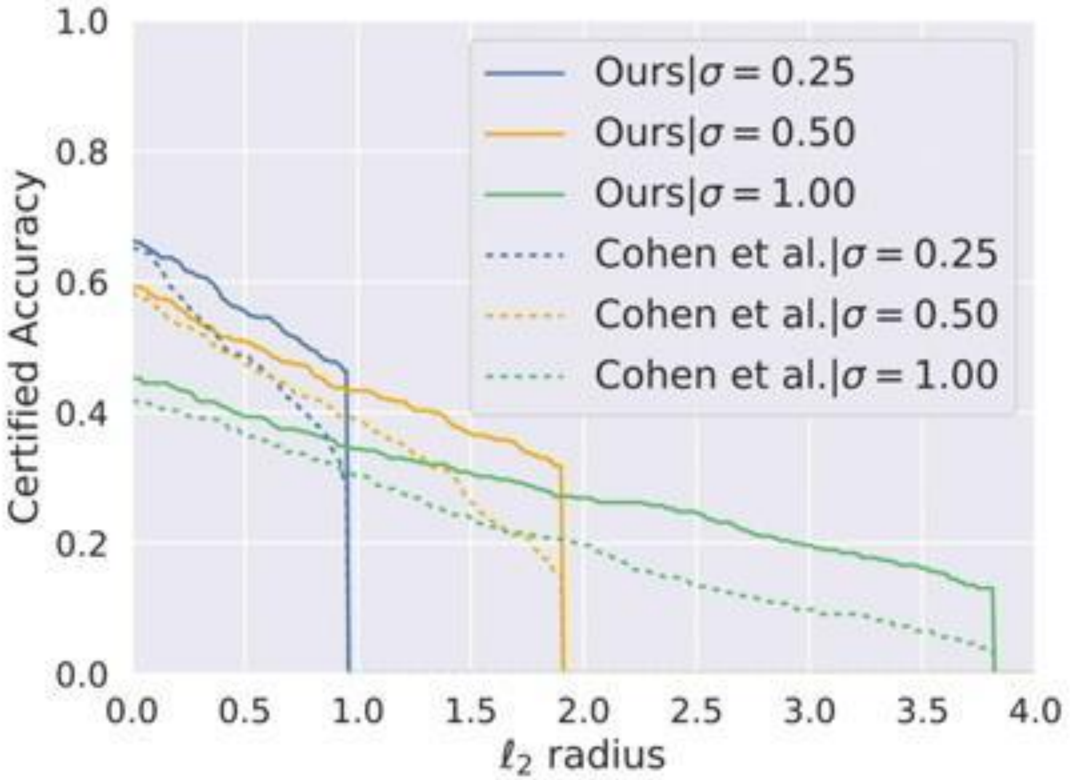

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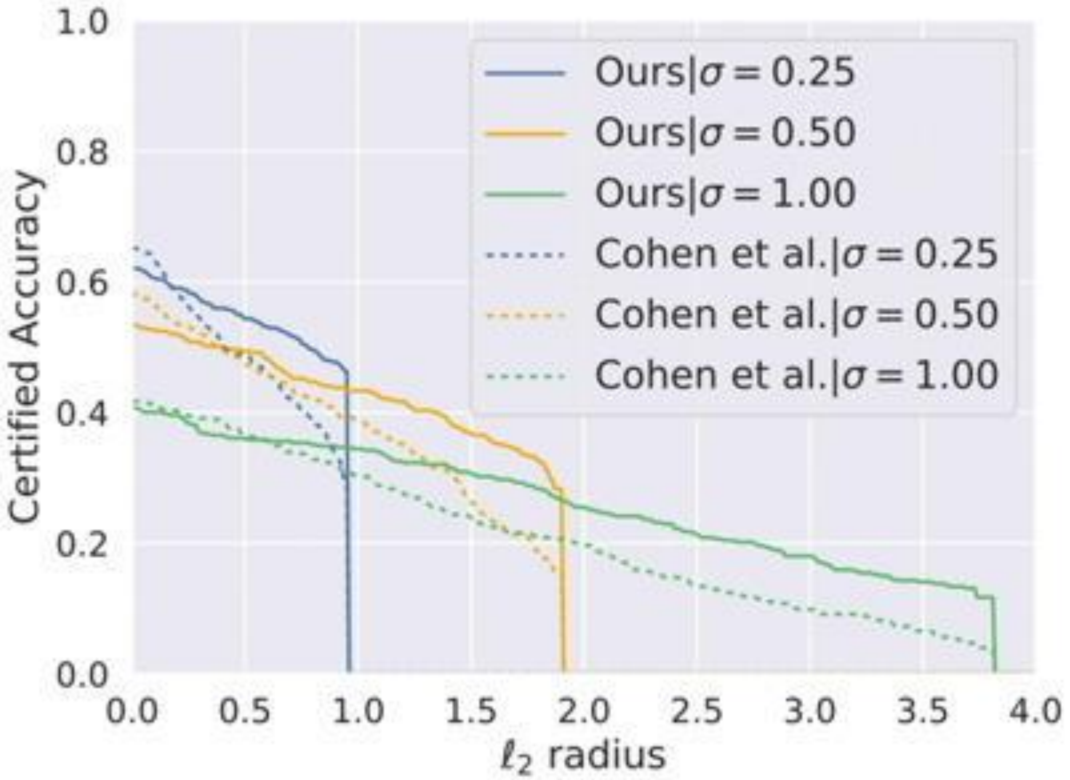
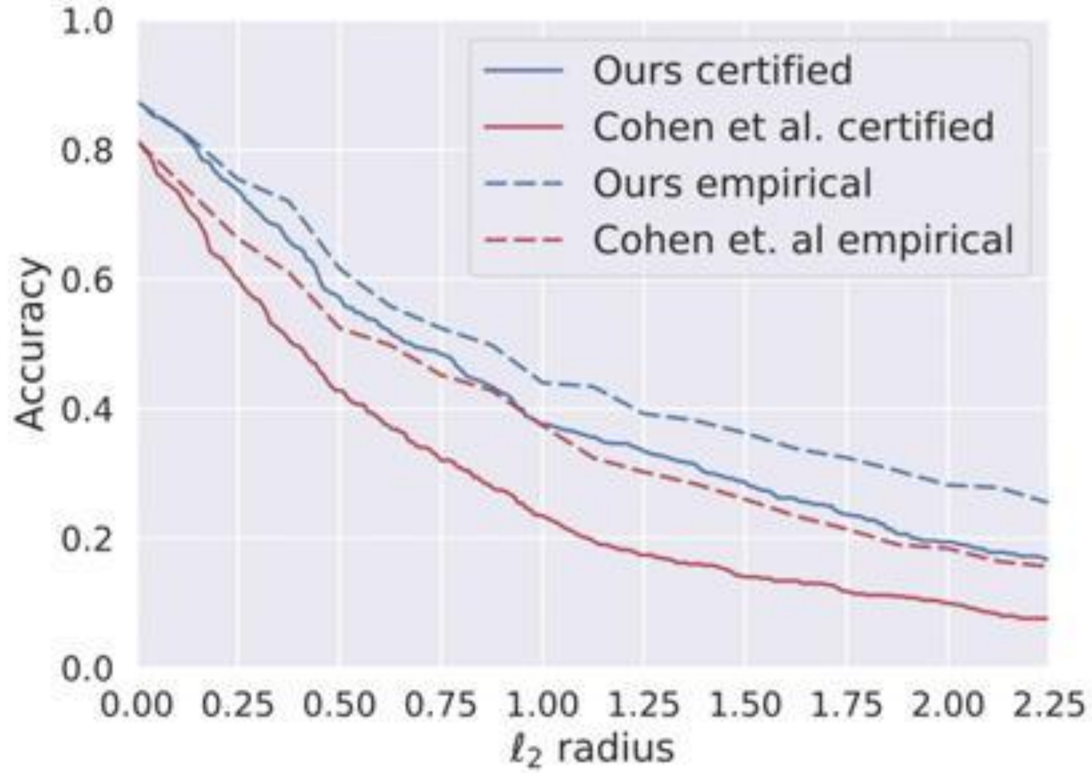
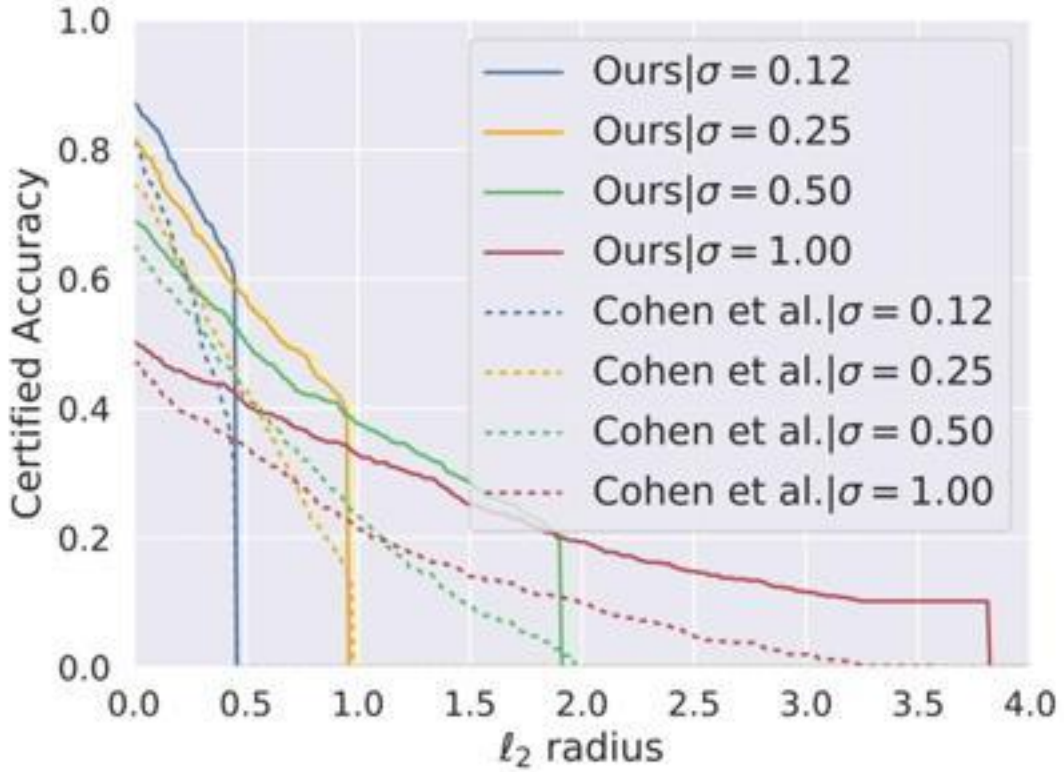


Representative models per σ

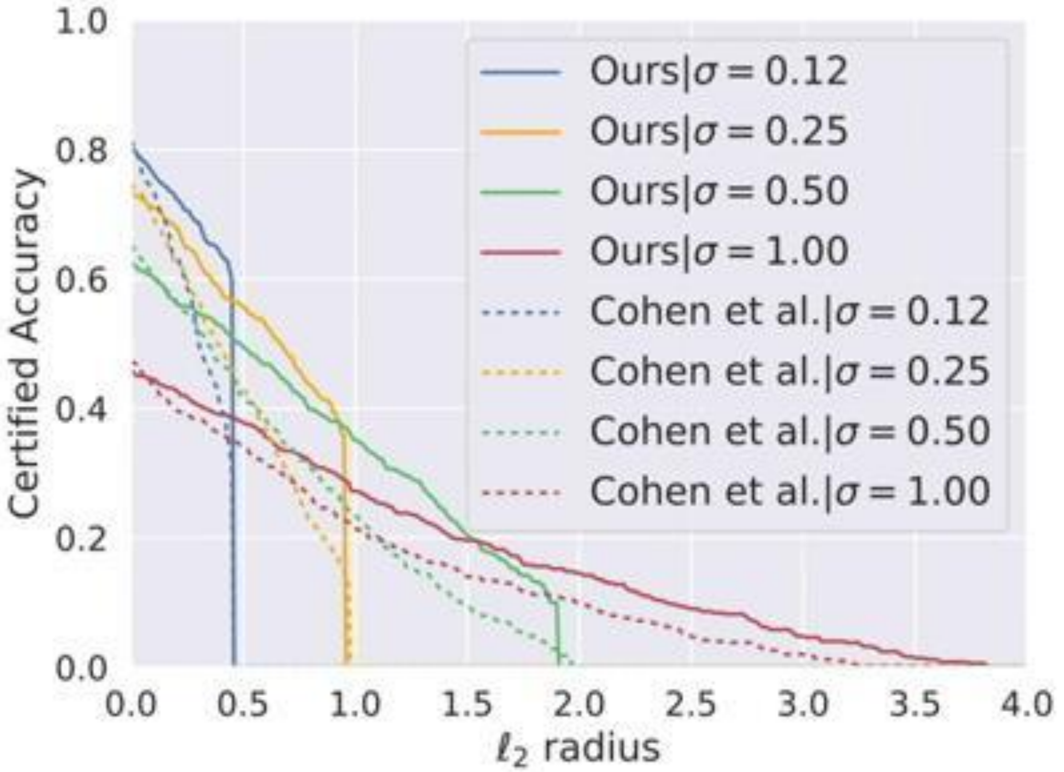
Results: CIFAR10



Upper envelope



Upper envelope per σ



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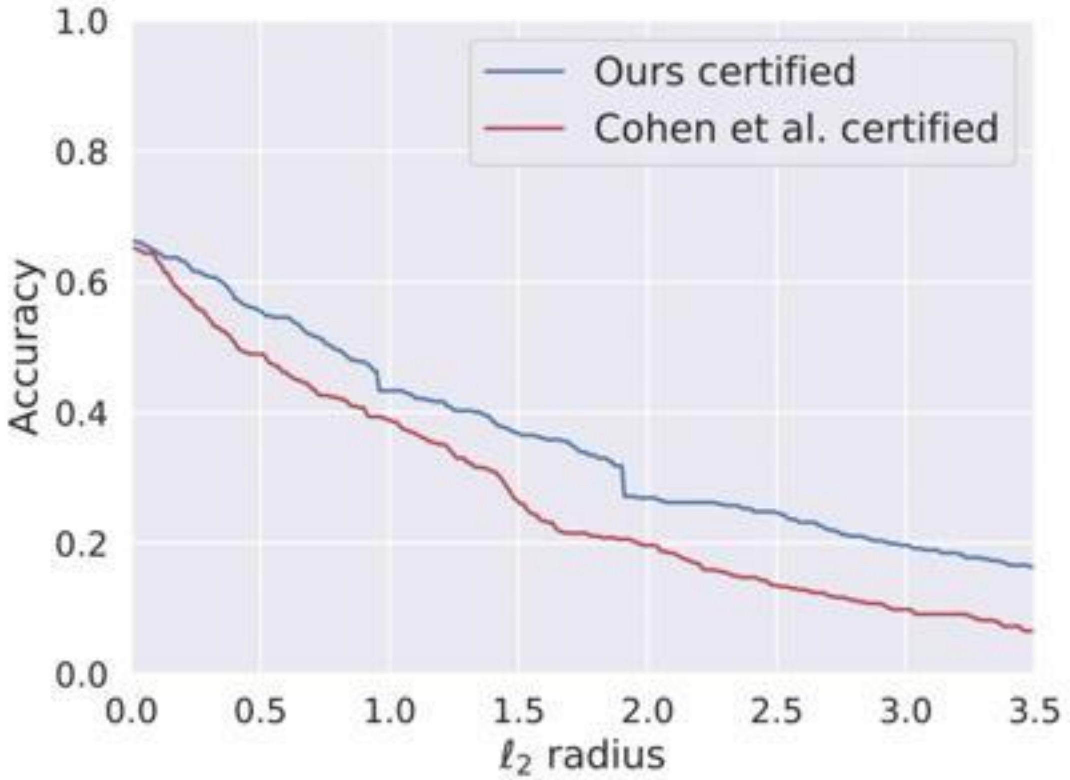

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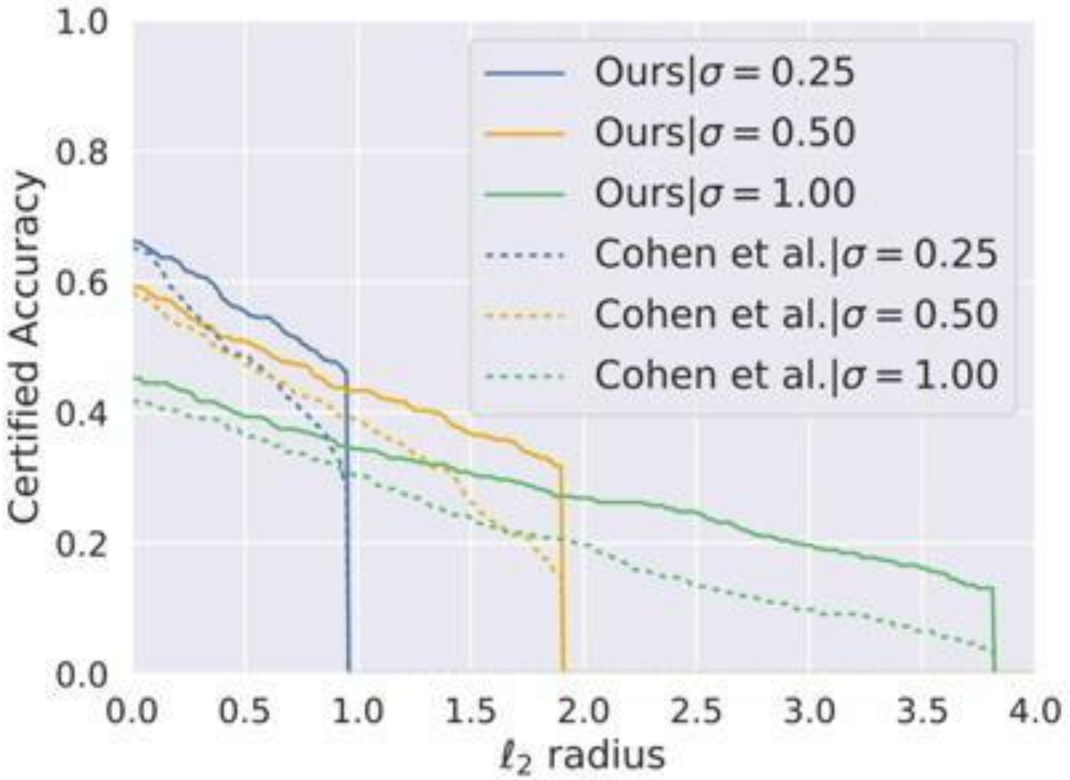

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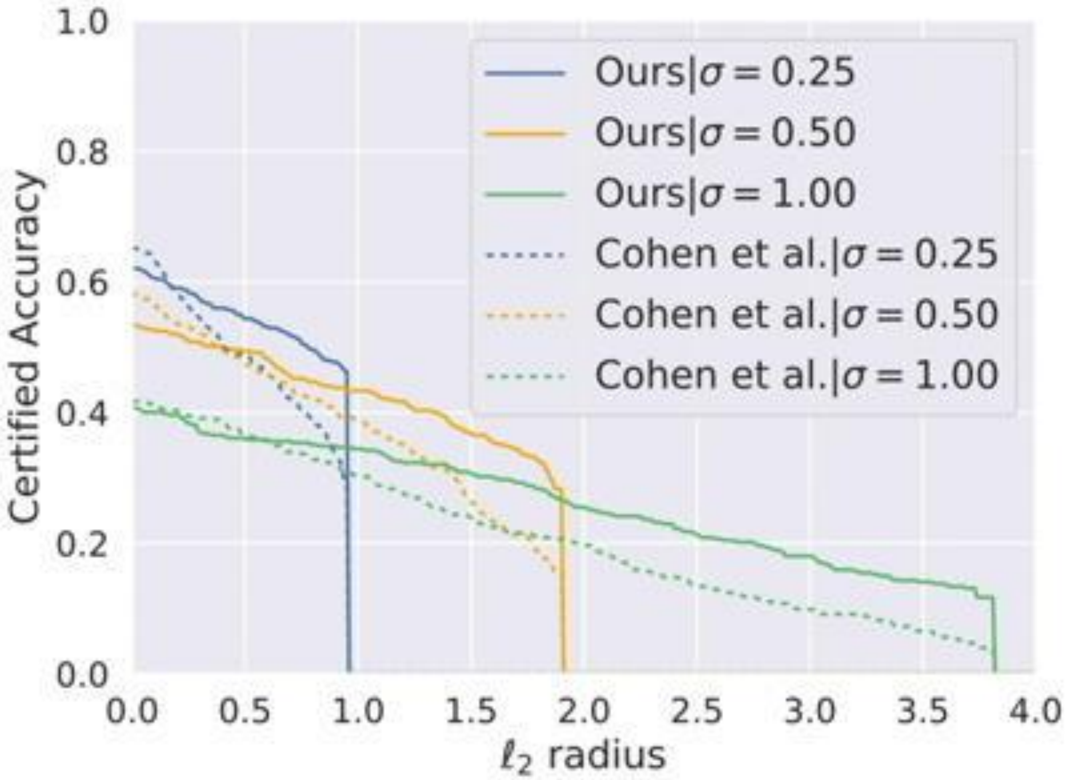

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- Hendrycks et al. 2019 showed that pretraining on downscaled Imagenet improves empirical robust accuracy on CIFAR10
  - In contrast to clean accuracy, which sees little difference
- We pretrained our own SmoothAdv model on downscale Imagenet then finetuned (i.e. training the last layer) on CIFAR10, again using SmoothAdv, obtaining a significant bump in provable robust accuracy for small radii

ℓ_2 radius (CIFAR10)	**0.25**	**0.5**	**0.75**	**1.0**	**1.25**	**1.5**	**1.75**	**2.0**	**2.25**
Cohen et al.	60	43	32	23	17	14	12	10	8
Ours	74	57	48	38	33	29	24	19	17
Ours + pretrain	80	63	51	37	34	30	25	20	17

Directions in Robust ML

- As ML and AI are used for increasingly sensitive tasks, it becomes incredibly important to understand their robustness properties.

- These theoretical insights often directly lead to better practical algorithms.

- Still many exciting theoretical and applied questions to consider!