Sever: A Robust Meta-Algorithm for Stochastic Optimization

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DEFENDING AGAINST DATA POISONING

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Given a labeled training set, where an (unknown) ε-fraction of them are adversarially corrupted, can we learn a model which **achieves good accuracy on a clean test set?**

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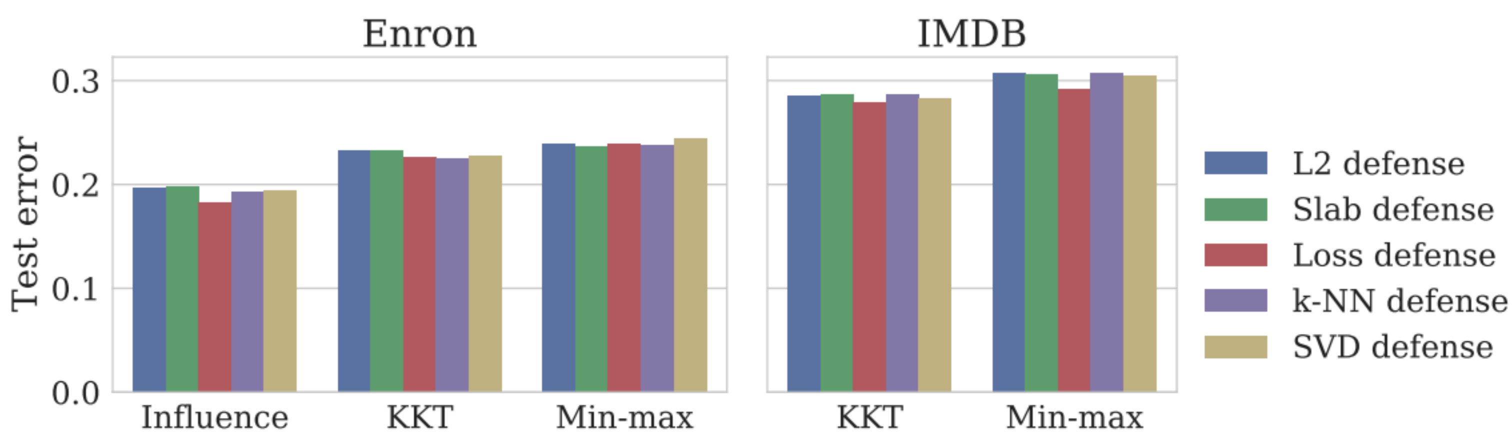

[Koh-Steinhardt-Liang '18]

Against known defenses, the test error can go up to 30%!

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Lots of work on related problems:

[Barreno-Nelson-Joseph-Tygar’10, Nasrabadi-Tran-Nguyen’11, Biggio-Nelson-Laskov’12, Nguyen-Tran’13, Newell-Potharaju-Xiang-Nita-Rotaru’14, Bhatia-Jain-Kar’15, Diakonikolas-Kamath-Kane-L-Moitra-Stewart’16, Bhatia-Jain-Kamalaruban-Kar’17, Balakrishnan-Du-L-Singh’17, Charikar-Steinhardt-Valiant’17, Steinhardt-Koh-Liang’17, Koh-Liang’17, Prasad-Suggala-Balakrishnan-Ravikumar’18, Diakonikolas-Kong-Stewart’18, Klivans-Kothari-Meka’18, Koh-Steinhardt-Liang’18…]

t-Liang ’18]

Agai … 0%!

OUR RESULTS

We present a framework for robust stochastic optimization

- **Strong theoretical guarantees** against strong adversarial models
- **Outperforms benchmark defenses** on state-of-the-art data poisoning attacks
- Works well in **high dimensions**
- Works with **black-box access** to any learner for any stochastic optimization task

SEVER

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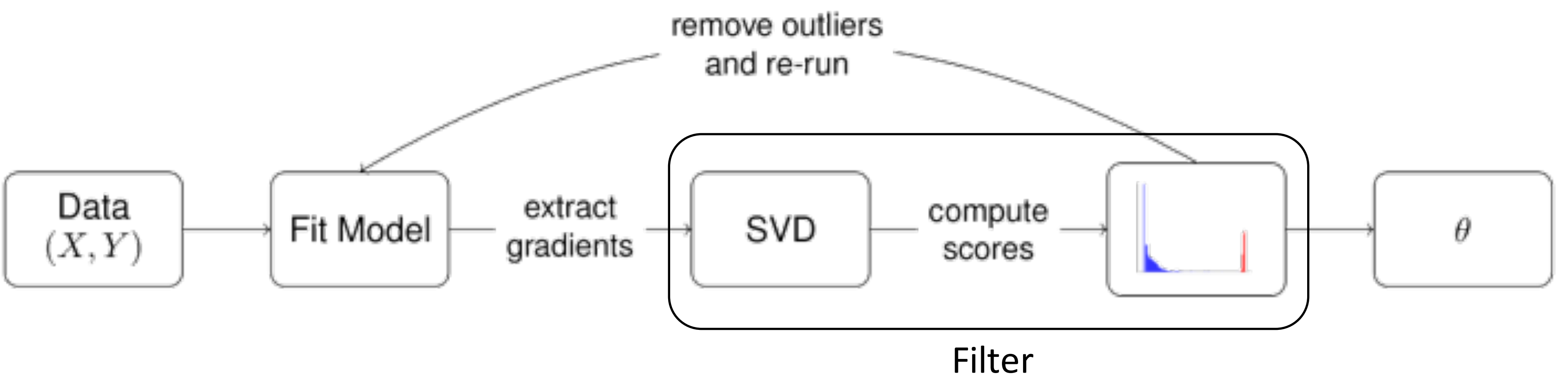

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1. Certifies that the true gradient of the loss function is close to 0
2. Removes more bad points than good points

GUARANTEES

Theorem (informal): Suppose we have a distribution $\mathcal{D}$ over convex functions f, and $\mathrm{Cov}\left[\nabla f(\theta)\right] \preccurlyeq \sigma^2 I$. Suppose we have $f_1(\theta), f_2(\theta), \ldots, f_n(\theta)$ drawn from $\mathcal{D}$, where ε-fraction of them are adversarial. Under mild assumptions on $\mathcal{D}$, then given enough samples, SEVER outputs a $\hat{\theta}$ so that w.h.p.

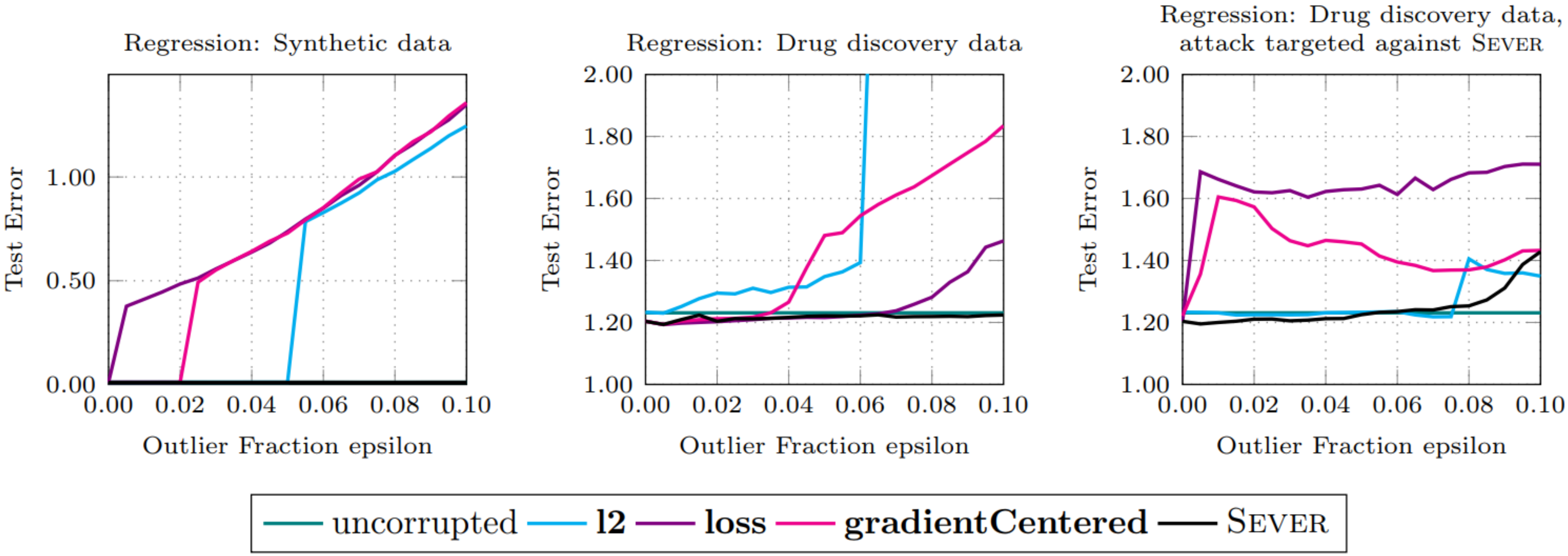
$$\bar{f}(\hat{\theta}) - \min_{\theta} f(\theta) < O\left(\sqrt{\sigma^2 \varepsilon}\right).$$

Can also give results for non-convex objectives

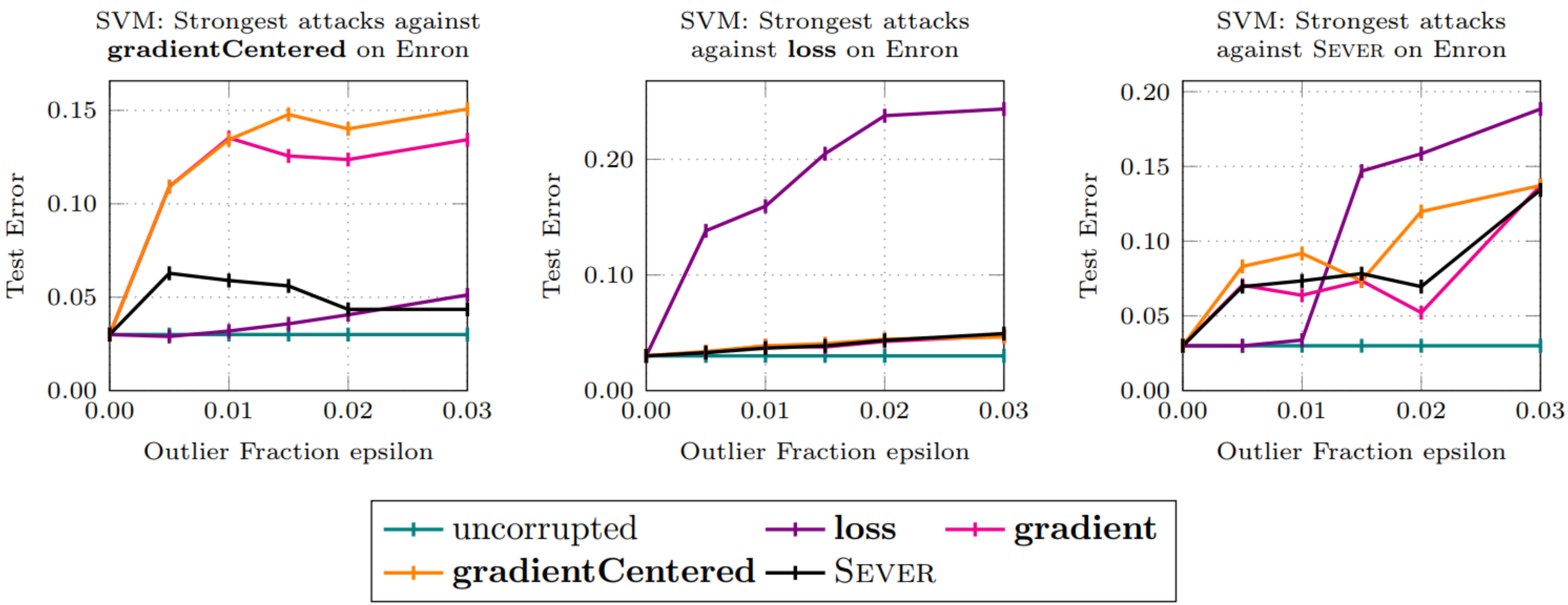
Sample complexity / runtime are polynomial but not super tight

For GLMs (e.g. SVM, regression), we obtain tight(er) bounds

EMPIRICAL EVALUATION: REGRESSION



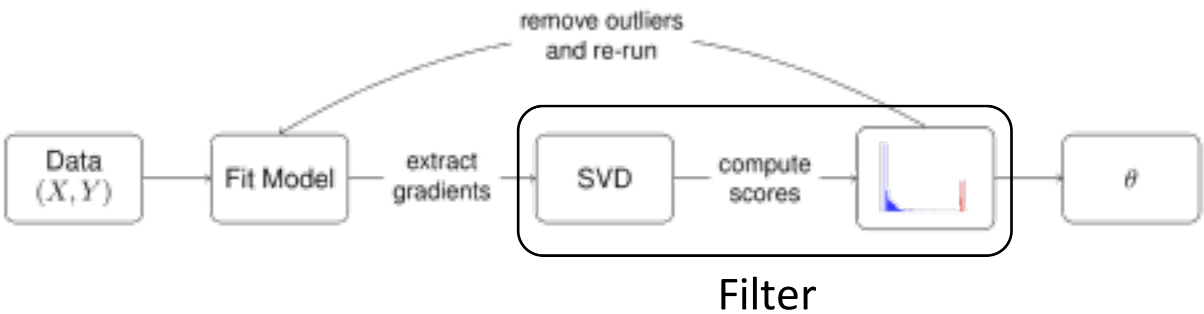
EMPIRICAL EVALUATION: SVM



CONCLUSIONS

Main question: can you learn a good classifier from poisoned data?

Sever is a meta-algorithm for robust stochastic optimization



Based on connections to robust mean estimation

Interested? See poster #143 this evening!