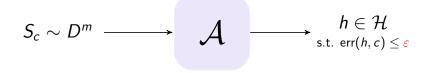
When are Local Queries Useful for Robust Learning?

P. Gourdeau, V. Kanade, M. Kwiatkowska and J. Worrell



University of Oxford

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Exact-in-the-ball: hypothesis = target in perturbation region ightarrow
ho = adversary's budget at test time

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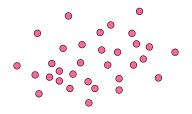
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What happens when we give more power to the learner?

Local Queries

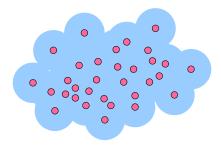
General idea:

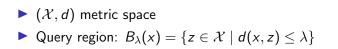


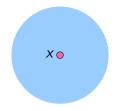
$$\blacktriangleright$$
 (\mathcal{X} , d) metric space

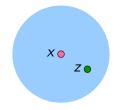
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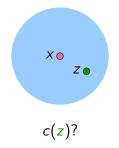
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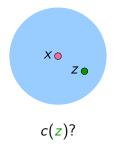






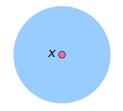


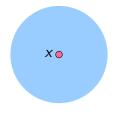




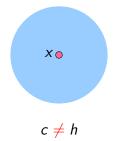
Theorem

Even when adding LMQs, robustly learning conjunctions still needs $\Omega(2^{\rho})$ joint sample and LMQ complexity under the uniform distribution

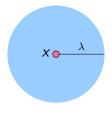




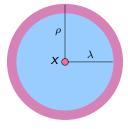
c = h?



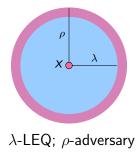




 λ -LEQ;



 λ -LEQ; ρ -adversary



Theorem

 $\lambda < \rho \implies$ robust learning is impossible for stable functions, including monotone conjunctions

$$X \circ \frac{\lambda = \rho}{\rho}$$

 λ -LEQ; ρ -adversary

Theorem

 $\lambda = \rho \implies$ robust learning is possible with a number of random examples m linear in the robust VC dimension (RVC) and a number of LEQ $r = m \cdot M$, where M is a mistake bound in the online model

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- LMQs don't help robust learning with conjunctions and superclasses
- ▶ LEQs enable robust learning iff $\lambda \ge \rho$ for many classes of functions
- We get (improved) bounds for specific classes:
 - conjunctions, linear classifiers
- Full picture isn't clear yet: many open problems!

Thank you!



Paper (arxiv version)