Privately Learning Thresholds: Closing the Exponential Gap

Abstract:

We study the sample complexity of learning threshold functions under the constraint of differential privacy. Unlike the non-private case, where the sample complexity is independent of the domain size, it turns out that for private learning the sample complexity must depend on the domain size $|X|$. Our current understanding of this task places its sample complexity somewhere between $\log^* |X|$ and $2^{\log^* |X|}$, where at least three different algorithms are known with sample complexity exponential in $\log^* |X|$. In this work we reduce this gap significantly, and show that the sample complexity is at most polynomial in $\log^* |X|$.

Joint work with Haim Kaplan, Katrina Ligett, Yishay Mansour, and Moni Naor.