1 Learning sparse monomials with additive error

Problem 1.1. Given distribution $\mathcal{D}$ on R^p, learning a monomial $p(x) = c\sum_{k\in S} x_k^{\beta_k} + \eta$, where c is a normalized constant such that $\mathbb{E}_{x\sim\mathcal{D}}\left[c^2\sum_{k\in S} x_k^{2\beta_k}\right] = 1$, η is some noise, and $|S| = k$, with sampling complexity poly(k, p) and polynomial running time.

Thoughts 1.2. "Attribute-efficient learning of monomials over highly-correlated variables" is about the unnoised version.

2 Improving or giving lowerbounds of learning k-sparse, d-degree polynomials

Problem 2.1. As the title. Note that this k-sparse is based on the orthonormal basis in the given distribution.

Thoughts 2.2. "Learning Sparse Polynomial Functions" is about this topic. Can we improve the $\exp(d)$ factor or prove that it is actually essential?

What is the desired definition of SQ dimension? Is the one in "https://arxiv.org/pdf/1611.03473.pd useful?

First, read and try to understand "Gradient Descent for One-Hidden- Layer Neural Networks: Polynomial Convergence and SQ Lower Bounds". After that, hopefully I will get some intuition of contraints of query functions.

Can we reduce general queries to dot product queries if approximation permitted?

Can we follow the proof in "Weakly Learning DNF and Characterizing Statistical Query Learning Using Fourier Analysis" to some extent?