Text Summary Report:

Abstract:

% We present two different approaches for parameter learning in several mixture models in one dimension. Our first approach uses complex-analytic methods and applies to Gaussian mixtures with shared variance, binomial mixtures with shared success probability, and Poisson mixtures, among others. An example result is that $\exp(O(N^{1/3}))$ samples suffice to exactly learn a mixture of $k<N$ Poisson distributions, each with integral rate parameters bounded by N. Our second approach uses algebraic and combinatorial tools and applies to binomial mixtures with shared trial parameter N anddiffering success parameters, as well as to mixtures of geometric distributions. Again, as an example, for binomial mixtures with k components and success parameters discretized to resolution ϵ, $O(k^2(\nicefrac{N}{\epsilon})^{\nicefrac{8}{\sqrt{\epsilon}}})$ samples suffice to exactly recover the parameters. For some of these distributions, our results represent the first guarantees for parameter estimation.

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Learning Mixtures via Characteristic Functions

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Omitted Proofs

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Extension to higher dimensions

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