Computational Explorations of Total Variation Distance

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What Is All About

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Definition (Total variation distance)

For probability distributions P, Q over a common finite domain D, the total variation (TV) distance between P and Q is

$$d_{\text{TV}}(P, Q) := \frac{1}{2} \sum_{x \in D} |P(x) - Q(x)|.$$

What Is All About

TV distance is important, because it has many desirable properties: It is a metric, it is bounded in [0,1], and is invariant with respect to bijections.

▶ Bhattacharyya, Gayen, Meel, Myrisiotis, Pavan, and Vinodchandran [BGM⁺23] proved that exact computation of TV distance between products of Bernoulli distributions is #P-hard.

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- Sahai and Vadhan [SV03] showed that TV distance is SZK-hard to additively estimate for distributions samplable by Boolean circuits.

On an algorithmic note, Bhattacharyya, Gayen, Meel, and Vinodchandran [BGMV20] designed efficient algorithms to additively estimate the TV distance between distributions that are efficiently samplable and efficiently computable.

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- ► Later, Feng, Liu, and Liu [FLL24] gave an FPTAS for the same task.

Bhattacharyya, Gayen, Meel, Myrisiotis, Pavan, and Vinodchandran [BGM⁺24] gave a novel reduction from TV distance estimation to probabilistic inference.

This connection yields an FPRAS for estimating the TV distance between Bayes nets of small treewidth.

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- ▶ Bhattacharyya, Feng, Srivastava [BFS25] studied TV distance between Gaussians.

Our Results: Mixtures of Product Distributions

A *mixture of product distributions* is a probability distribution over products of Bernoulli distributions.

Theorem

There is an efficient deterministic algorithm such that, given two mixtures of product distributions P and Q, decides whether P=Q or not.

This result is proved using elementary linear algebra techniques.

The equality P = Q can be seen as a system of equations, that may be captured by a small basis of coefficient vectors.

To check these equations, one may only check it for the basis vectors!

This yields an efficient inductive algorithm to check equivalence.

Our Results: Ising Models

Ising models are probabilistic graphical models which are very popular in statistical physics.

Theorem

If NP $\not\subseteq$ RP, then there is no FPRAS that estimates the TV distance between Ising models.

This proof is based on the observation that

estimating the partition function of Ising models can be reduced to estimating TV distance between Ising models.

The result then follows from a result by Jerrum and Sinclair [JS93], where they show that

if NP $\not\subseteq$ RP, then there is no FPRAS that estimates the partition function of Ising models.

Open Problems

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Can our ideas be extended to checking equivalence between mixtures of some subclass of Bayes net distributions, such as Bayes net distributions whereby their underlying graph is a tree or has small treewidth?

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- Can our ideas be extended to checking equivalence between mixtures of some subclass of Bayes net distributions, such as Bayes net distributions whereby their underlying graph is a tree or has small treewidth?
- Can we extend this complexity-theoretic hardness of approximation result to other classes of probability distributions, such as factor graphs or general undirected probabilistic graphical models?

Our Work on arXiv

Our Work on arXiv



Thank You!

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