A simple polynomial-time approximation algorithm for the total variation distance between two product distributions

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Total variation (TV) distance

Data: two distributions *P* and *Q* over state space Ω

Question: how to measure the difference between *P* and *Q*



Total variation (TV) distance between P and Q over state space Ω

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

Total variation distance

Total variation (TV) distance between P and Q over state space Ω $d_{TV}(P,Q) = \frac{1}{2} \sum_{x \in \Omega} |P(x) - Q(x)| = \max_{S \subseteq \Omega} |P(S) - Q(S)|$ P

Properties of TV distance

- metric (triangle inequality)
- bounded
- data processing inequality
- various characterisations

Applications of TV distance

- property testing
- Markov chain mixing time
- approximate algorithms
- learning algorithms

Compute TV distance

[Bhattacharyya, Gayen, Meel, Myrisiotis, Pavan, Vinodchandran, 2022]

- **Input:** descriptions of two distributions P, Q over Ω
- **Output**: the total variation distance between *P* and *Q*

Trivial algorithm: enumerate all $x \in \Omega$ and $\operatorname{add} \frac{1}{2}|P(x) - Q(x)|$ together

Challenge:

- distributions P and Q have succinct descriptions
- $|\Omega|$ can be **exponentially large** w.r.t. the size of input

TV distance between two product distributions

 P_1, P_2, \dots, P_n and Q_1, Q_2, \dots, Q_n over finite domain $[s] = \{0, 1, \dots, s - 1\}$ P, Q two **product distributions** over **domain** $[s]^n$

$$P = P_1 \times P_2 \times \dots \times P_n \text{ and } Q = Q_1 \times Q_2 \times \dots \times Q_n$$

i.e. $\forall \sigma \in [s]^n, P(\sigma) = \prod_{i=1}^n P_i(\sigma_i) \text{ and } Q(\sigma) = \prod_{i=1}^n Q_i(\sigma_i)$

Compute TV distance between two product distributions [Bhattacharyya, Gayen, Meel, Myrisiotis, Pavan, Vinodchandran, 2022]

- Input: distributions $\{P_i, Q_i | 1 \le i \le n\}$ specifying P and Q
- **Output**: the total variation distance between *P* and *Q*

Input size: 2ns = O(n) numbers, each of poly(n) bits Sample space size of P, Q: s^n

Theorem [Bhattacharyya, Gayen, Meel, Myrisiotis, Pavan, Vinodchandran, 2022] Computing TV distance between two **Boolean** (s = 2) product distributions is **#P complete**.

Approximate TV distance between two product distributions

• Input: distributions $\{P_i, Q_i | 1 \le i \le n\}$ specifying P and Qan error bound $0 < \epsilon < 1$

• **Output:** a random number \hat{d} such that $\Pr[(1 - \epsilon)d_{TV}(P, Q) \le \hat{d} \le (1 + \epsilon)d_{TV}(P, Q)] \ge 2/3$

One challenge for approximation

 $d_{TV}(P,Q)$ can be exponentially small

V.S.



Theorem [Bhattacharyya, Gayen, Meel, Myrisiotis, Pavan, Vinodchandran, 2022]

There is an **FPRAS** for the TV distance between two **Boolean** product distributions if $\frac{1}{2} \le P_i(1) \le 1$ and $0 \le Q_i(1) \le P_i(1)$ for all $1 \le i \le n$ additional condition: a marginal lower bound

FPRAS (Full Poly-time Randomised Approximation Scheme)

An algorithm solves the approximation problem in time $poly(n, 1/\epsilon)$

Open Problem: FPRAS for **general** product distributions

Our results

Main Theorem [F, Guo, Jerrum, Wang, SOSA 2023]

There is an **FPRAS** for the TV distance between two product distributions

- running time $O(n^2/\epsilon^2)$
- work for *arbitrary finite* domain
- no extra condition on distributions

TV distance and coupling

- **Distributions:** P and Q over the domain Ω
- Coupling: a joint distribution $(X, Y) \in \Omega \times \Omega$ such that $X \sim P$ and $Y \sim Q$

Coupling Lemma (Coupling inequality)

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For any coupling (X, Y) of P and Q,
d_{TV}(P, Q) \leq \Pr[X \neq Y]
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There exists an **optimal coupling** of *P* and *Q* such that $d_{TV}(P,Q) = \Pr[X \neq Y]$

Greedy coupling between two product distributions

P, *Q* two product distributions over Boolean domain $\Omega = [s]^n$

 $P = P_1 \times P_2 \times \cdots \times P_n$ and $Q = Q_1 \times Q_2 \times \cdots \times Q_n$

- Greedy coupling $(X, Y) = ((X_1, X_2, ..., X_n), (Y_1, Y_2, ..., Y_n))$ of P and Q
- Couple each (X_i, Y_i) independently using the optimal coupling of P_i and Q_i

Non optimal: \exists product distributions, s.t. $\Pr_{\text{greedy}}[X \neq Y] > d_{TV}(P, Q)$

n-Approximation: \forall product distributions,

$$d_{TV}(P,Q) \leq \Pr_{\text{greedy}} [X \neq Y] \leq n \cdot d_{TV}(P,Q)$$

$$\uparrow$$
Coupling Lemma
$$Proved by a Union Bound$$

Property of greedy coupling: greedy coupling and TV distance

$$R = \frac{d_{TV}(P,Q)}{\Pr_{\text{greedy}}[X \neq Y]} \ge \frac{1}{n}$$

Proposition: In greedy coupling, the probability of $X \neq Y$ is easy to compute

$$\Pr_{\text{greedy}}[X \neq Y] = 1 - \Pr[X = Y] = 1 - \prod_{i=1}^{n} (1 - d_{TV}(P_i, Q_i))$$

Our idea: try to estimate the ratio

$$R = \frac{d_{TV}(P,Q)}{\Pr_{\text{greedy}}[X \neq Y]}$$

 $d_{TV}(P,Q)$ can be **exponentially small** but the ratio R is **lower bounded by** 1/n

Our Estimator [F., Guo, Jerrum, Wang, SOSA 2023]

• π : distribution over $[s]^n$ s.t.

 $\forall \sigma$

$$\in [s]^n$$
, $\pi(\sigma) = \Pr_{\text{greedy}}[X = \sigma \mid X \neq Y]$

distribution of X in the greedy coupling conditional on $X \neq Y$

• $f: a \text{ function } [s]^n \to \mathbb{R}_{>0} \text{ s.t.}$

$$\forall \sigma \in [s]^n, \qquad f(\sigma) = \frac{\Pr[X = \sigma \land X \neq Y]}{\Pr_{\text{greedy}}[X = \sigma \land X \neq Y]}$$

• **Estimator**: $f(\sigma)$ where $\sigma \sim \pi$

$$\mathbb{E}_{\sigma \sim \pi}[f(\sigma)] = \frac{d_{TV}(P,Q)}{\Pr_{\text{greedy}}[X \neq Y]} = R \ge \frac{1}{n}$$

Low variance

 $\operatorname{Var}_{\sigma \sim \pi}[f(\sigma)] \leq 1$

Efficient computation

Correct expectation

- a random sample of $\sigma \sim \pi$ can be generated in time O(n)
- given any $\sigma \in \{0,1\}^n$, $f(\sigma)$ can be computed in time O(n)

Summary and open problems

Summary: an FPRAS for the TV distance between two product distributions



Open problems:

- Deterministic approximate algorithm (FPTAS)?
- Beyond the product distributions?

Thanks Q&A