

Lecture 23

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* Hamming Cost

Another interesting setting where a comprehensive solⁿ is available is the following:

$$\mathcal{X} = \mathcal{Y}, \quad c(x, y) = \mathbb{1}_{\{x \neq y\}} \quad \left. \vphantom{\mathcal{X} = \mathcal{Y}} \right\} P_2$$

Lemma (Maximal coupling) For $c(x, y) = \mathbb{1}_{\{x \neq y\}}$,

$$c(P, Q) = d_{TV}(P, Q)$$

$$\left(= \sup_{h: \mathcal{X} \rightarrow [-1, 1], \text{continuous}} \mathbb{E}_Q[h(X)] - \mathbb{E}_P[h(X)] \right)$$

Proof. We will only prove for discrete \mathcal{X} .

$$\begin{aligned} \mathbb{P}(X=Y) &= \sum_x \mathbb{P}(X=Y=x) \leq P(A^c) + Q(A) \quad \forall A \subseteq \mathcal{X} \\ &\leq 1 - d_{TV}(P, Q). \end{aligned}$$

$$\Rightarrow c(P, Q) \geq d_{TV}(P, Q).$$

For the other direction, let $A = \{x : P(x) \geq Q(x)\}$

$$\text{so that } d_{TV}(P, Q) = P(A) - Q(A).$$

$$\text{Let } \mathbb{P}_1(x, y) = \frac{\min\{P(x), Q(x)\} \mathbb{1}_{\{x=y\}}}{\sum_{x'} \min\{P(x'), Q(x')\}}$$

$$\text{and } \mathbb{P}_2(x, y) = \frac{(P(x) - Q(x))_+ (Q(y) - P(y))_+}{\sum_{x', y'} (P(x') - Q(x'))_+ (Q(y') - P(y'))_+}$$

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Note that

$$P_1(x, y) = \frac{\min\{P(x), Q(x)\} \mathbb{1}_{\{x=y\}}}{1 - d_{TV}(P, Q)}$$

$$P_2(x, y) = \frac{(P(x) - Q(x))(Q(y) - P(y)) \mathbb{1}_{\{x \in A, y \in A\}}}{d_{TV}^2(P, Q)}$$

$$\text{Let } P(x, y) = (1 - d_{TV}(P, Q)) P_1(x, y) + d_{TV}^2(P, Q) P_2(x, y).$$

$$\begin{aligned} \text{Thus, } P(X=Y) &= [1 - d_{TV}(P, Q)] P_1(X=Y) \\ &= 1 - d_{TV}(P, Q). \end{aligned}$$

(Note that this is not a deterministic coupling). \square

A transportation cost inequality is an upper bound for $C(P, Q)$.

For $c(x, y) = \mathbb{1}_{\{x \neq y\}}$, the so-called Pinsker's inequality showing $d_{TV}(P, Q) \leq \sqrt{2D(P||Q)}$ is an example.

[B] Link between transportation cost inequalities and measure concentration

Lemma (Transportation Lemma)

$$\Psi_{Z - \mathbb{E}Z}(\lambda) \leq \frac{\nu \lambda^2}{2} \quad \forall \lambda > 0$$

iff

$$\mathbb{E}_Q Z - \mathbb{E}_P Z \leq \sqrt{2\nu D(Q||P)} \text{ for all } Q \ll P.$$

Proof.

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Recall the Gibb's variational formula:

$$\log \mathbb{E}_P [e^{\lambda Z}] = \max_{Q \ll P} \lambda \mathbb{E}_Q [Z] - D(Q \| P),$$

$$\text{i.e., } \Psi_{Z - \mathbb{E}Z}(\lambda) = \max_{Q \ll P} \lambda (\mathbb{E}_Q Z - \mathbb{E}_P Z) - D(Q \| P).$$

Thus, if $\Psi_{Z - \mathbb{E}Z}(\lambda) \leq \frac{\nu \lambda^2}{2}$, $\forall Q \ll P$

$$D(Q \| P) \geq \lambda (\mathbb{E}_Q Z - \mathbb{E}_P Z) - \frac{\nu \lambda^2}{2}.$$

Maximizing the right-side over $\lambda \in \mathbb{R}$, we get

$$D(Q \| P) \geq \frac{(\mathbb{E}_Q Z - \mathbb{E}_P Z)^2}{2\nu}.$$

Conversely,

$$\mathbb{E}_Q Z - \mathbb{E}_P Z \leq \sqrt{2\nu D(Q \| P)}, \quad \forall Q \ll P,$$

implies that every $\lambda > 0$,

$$\begin{aligned} \Psi_{Z - \mathbb{E}Z}(\lambda) &\leq \sup_{Q \ll P} \lambda \sqrt{2\nu D(Q \| P)} - D(Q \| P) \\ &\leq \lambda^2 \sup_x \sqrt{2\nu x} - x^2 \\ &= \frac{\lambda^2 \nu}{2}. \quad \blacksquare \end{aligned}$$

The claim can be extended to any "nice" function g :

$$\Psi_{Z - \mathbb{E}Z}(\lambda) \leq g(\lambda) \Leftrightarrow \mathbb{E}_Q Z - \mathbb{E}_P Z \leq g^{-1}(D(Q \| P)).$$

McDiarmid Inequality via Transportation Lemma (4)

Suppose $f: \mathcal{X}^n \rightarrow \mathbb{R}$ satisfies BDP with constants $c = (c_1, \dots, c_n)$.
Let P be a product distribution on \mathcal{X}^n and Q be any dist. on \mathcal{X}^n . Consider $P \in \mathcal{P}(P, Q)$. Then,

$$\begin{aligned} \mathbb{E}_Q[f(X)] - \mathbb{E}_P[f(X)] &= \mathbb{E}[f(X) - f(Y)] \\ &\leq \mathbb{E}\left[\sum_{i=1}^n c_i \mathbb{1}_{\{X_i \neq Y_i\}}\right] \\ &= \sum_{i=1}^n c_i P(X_i \neq Y_i) \end{aligned}$$

Thus,
$$\mathbb{E}_Q[f(X)] - \mathbb{E}_P[f(X)] \leq \sqrt{\sum_{i=1}^n c_i^2} \cdot \sqrt{\sum_{i=1}^n P(X_i \neq Y_i)^2}$$

Therefore, by Transportation Lemma, it suffices to show

$$\exists \text{ a coupling } P \in \mathcal{P}(P, Q) \text{ such that, } \quad (\#)$$
$$\sum_{i=1}^n P(X_i \neq Y_i)^2 \leq \frac{1}{2} \cdot D(Q \| P) \quad \forall Q \ll P$$

to get
$$\Psi_{2-\mathbb{E}^2}(\lambda) \leq \left(\sum_{i=1}^n c_i^2\right) \lambda^2 / 8 \quad \forall \lambda > 0,$$

which in turn leads to

$$P(f(X) > \mathbb{E}f(X) + t) \leq \exp(-2t^2 / \sum_{i=1}^n c_i^2).$$

Hence, Transportation Lemma allows us to reduce conc. bounds to Transportation Cost Inequality such as (#).

D Pinsker's inequality

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$$d_{TV}(P, Q) = \sup_A P(A) - Q(A)$$

Lemma (Pinsker's inequality)

For two distributions P and Q on \mathcal{X} s.t. $Q \ll P$. Then,

$$d_{TV}(P, Q)^2 \leq \frac{1}{2} D(Q \| P).$$

Proof. Note that for $A^* \stackrel{\text{def}}{=} \{ \frac{dQ}{dP} \geq 1 \}$,

$$d_{TV}(P, Q) = Q(A^*) - P(A^*) = \mathbb{E}_Q Z - \mathbb{E}_P Z$$

where $Z = \mathbb{1}_{A^*}$. Note that by Hoeffding's lemma,

$$\Psi_{Z - \mathbb{E}Z}(\lambda) \leq \frac{\lambda^2}{8}.$$

Thus, by Transportation Lemma,

$$\mathbb{E}_Q Z - \mathbb{E}_P Z \leq \sqrt{\frac{1}{2} D(Q \| P)}. \quad \square$$

E Marton's Transportation Cost Inequality

Theorem. For $X = (X_1, \dots, X_n) \sim P = P_1 \otimes \dots \otimes P_n$ and Q s.t.

$Q \ll P$, let $Y = (Y_1, \dots, Y_n) \sim Q$. Then, there exists a coupling

\mathbb{P} of P and Q s.t.

$$\sum_{i=1}^n \mathbb{P}(X_i \neq Y_i)^2 \leq \frac{1}{2} D(Q \| P).$$

Proof. For $n=1$, maximal coupling lemma gives

$$\mathbb{P}(X \neq Y)^2 = d^2(P, Q) \leq \frac{1}{2} D(Q \| P).$$

We can complete the proof by induction.

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Given $y^k = y^k$, consider the maximal coupling

$$P_{X_{k+1}, Y_{k+1} | X^k, Y^k} \in \mathcal{P}(P_{X_{k+1}}, Q_{Y_{k+1}} | Y^k = y^k).$$

$$\text{Then, } P(X_{k+1} \neq Y_{k+1} | X^k = x^k, Y^k = y^k)$$

$$= d_{TV}(P_{X_{k+1}}, Q_{Y_{k+1}} | Y^k = y^k)$$

$$\leq \sqrt{\frac{1}{2} D(Q_{Y_{k+1}} | Y^k = y^k \| P_k)}$$

$$\Rightarrow P(X_{k+1} \neq Y_{k+1}) \leq \mathbb{E}_{Q_{Y^k}} \left[\sqrt{\frac{1}{2} D(Q_{Y_{k+1}} | Y^k \| P_k)} \right]$$

$$\leq \sqrt{\frac{1}{2} \mathbb{E}_{Q_{Y^k}} [D(Q_{Y_{k+1}} | Y^k \| P_k)]}.$$

$$\text{Thus, } \sum_{i=1}^n P(X_i \neq Y_i)^2 \leq \frac{1}{2} \sum_{i=1}^n D(Q_{Y_i} \| P_i | Q_{Y^{i-1}})$$

$$= \frac{1}{2} D(Q_{Y^n} \| P).$$

Note that our constructed coupling P_{X^n, Y^n}

$$\text{satisfies } P_{X^k, Y^k} = P_{X^k} \cdot P_{Y^k | Y^{k-1}} \cdot P_{X^{k-1}, Y^{k-1}}.$$