

Appendix

A Proof of Lemma 2

Assume that the samples of D_i datasets are x_1^i, \dots, x_m^i . Without loss of generality, we assume that $x_i^0 = x_i^1$ for $1 \leq i \leq m-1$. Then we have

$$\begin{aligned} d_{\mathcal{F}}(\hat{\mu}_m^0, \hat{\mu}_m^1) &= \sup_{f \in \mathcal{F}} \{ \mathbb{E}_{x \sim \hat{\mu}_m^0} [f(x)] - \mathbb{E}_{x \sim \hat{\mu}_m^1} [f(x)] \} \\ &= \sup_{f \in \mathcal{F}} \left\{ \frac{1}{m} \sum_{i=1}^m f(x_i^0) - \frac{1}{m} \sum_{i=1}^m f(x_i^1) \right\} \\ &= \frac{1}{m} \sup_{f \in \mathcal{F}} \{ f(x_m^0) - f(x_m^1) \} \\ &\leq \frac{2\Delta}{m} \end{aligned}$$

B Proof of Lemma 3

From Lemma 1, we know that

$$\begin{aligned} \mathbb{P} \left[d_{\mathcal{F}}(\hat{\mu}_m^0, g_0) > \frac{1}{2} \tau_{k,\xi} \right] &\leq \xi \\ \mathbb{P} \left[d_{\mathcal{F}}(\hat{\mu}_m^1, g_1) > \frac{1}{2} \tau_{k,\xi} \right] &\leq \xi \end{aligned}$$

Therefore,

$$\mathbb{P} \left[d_{\mathcal{F}}(\hat{\mu}_m^0, g_0) \leq \frac{1}{2} \tau_{k,\xi} \wedge d_{\mathcal{F}}(\hat{\mu}_m^1, g_1) \leq \frac{1}{2} \tau_{k,\xi} \right] \geq 1 - 2\xi.$$

With probability at least $1 - 2\xi$, we have

$$\begin{aligned} d_{\mathcal{F}}(g_0, g_1) &= \sup_{f \in \mathcal{F}} \{ \mathbb{E}_{x \sim g_0} [f(x)] - \mathbb{E}_{x \sim g_1} [f(x)] \} \\ &= \sup_{f \in \mathcal{F}} \{ \mathbb{E}_{x \sim g_0} [f(x)] - \mathbb{E}_{x \sim \hat{\mu}_m^0} [f(x)] + \mathbb{E}_{x \sim \hat{\mu}_m^0} [f(x)] - \mathbb{E}_{x \sim \hat{\mu}_m^1} [f(x)] + \mathbb{E}_{x \sim \hat{\mu}_m^1} [f(x)] - \mathbb{E}_{x \sim g_1} [f(x)] \} \\ &\leq \sup_{f \in \mathcal{F}} \{ \mathbb{E}_{x \sim g_0} [f(x)] - \mathbb{E}_{x \sim \hat{\mu}_m^0} [f(x)] \} + \sup_{f \in \mathcal{F}} \{ \mathbb{E}_{x \sim \hat{\mu}_m^0} [f(x)] - \mathbb{E}_{x \sim \hat{\mu}_m^1} [f(x)] \} \\ &\quad + \sup_{f \in \mathcal{F}} \{ \mathbb{E}_{x \sim \hat{\mu}_m^1} [f(x)] - \mathbb{E}_{x \sim g_1} [f(x)] \} \\ &= \sup_{f \in \mathcal{F}} \{ \mathbb{E}_{x \sim \hat{\mu}_m^0} [f(x)] - \mathbb{E}_{x \sim g_0} [f(x)] \} + \sup_{f \in \mathcal{F}} \{ \mathbb{E}_{x \sim \hat{\mu}_m^0} [f(x)] - \mathbb{E}_{x \sim \hat{\mu}_m^1} [f(x)] \} \\ &\quad + \sup_{f \in \mathcal{F}} \{ \mathbb{E}_{x \sim \hat{\mu}_m^1} [f(x)] - \mathbb{E}_{x \sim g_1} [f(x)] \} \\ &\quad (\mathcal{F} \text{ is even}) \\ &= d_{\mathcal{F}}(\hat{\mu}_m^0, g_0) + d_{\mathcal{F}}(\hat{\mu}_m^0, \hat{\mu}_m^1) + d_{\mathcal{F}}(\hat{\mu}_m^1, g_1) \\ &\leq \tau_{k,\xi} + \frac{2\Delta}{m} \end{aligned}$$

C Proof of Lemma 5

Define ρ_p, ρ_q as the probability (density) functions of p and q respectively. Assume set $S_0 = \{x : \log \rho_p(x) - \log \rho_q(x) \geq \epsilon\}$, then $\forall x \in S_0$, we have $\rho_p(x) \geq \rho_q(x)e^\epsilon$, and

$$\begin{aligned} s &\geq d_{\text{KL}}(p, q) + d_{\text{KL}}(q, p) \\ &= \int_x (\rho_p(x) - \rho_q(x)) (\log \rho_p(x) - \log \rho_q(x)) \\ &\geq \int_S (\rho_p(x) - \rho_q(x)) (\log \rho_p(x) - \log \rho_q(x)) \\ &\quad (\text{because } (\rho_p(x) - \rho_q(x)) (\log \rho_p(x) - \log \rho_q(x)) \geq 0 \quad \forall x) \\ &\geq \int_S \rho_p(x) (1 - e^{-\epsilon}) \epsilon \end{aligned}$$

i.e. $\mathbb{P}[M(D_0) \in S_0] \leq \frac{s}{\epsilon(1-e^{-\epsilon})}$. For any set S , we have

$$\begin{aligned} \mathbb{P}[M(D_0) \in S \setminus S_0] &= \int_{S \setminus S_0} \rho_p(x) dx \\ &\leq \int_{S \setminus S_0} \rho_q(x) e^\epsilon dx \\ &= e^\epsilon \mathbb{P}[M(D_1) \in S \setminus S_0] \end{aligned}$$

D Proof of Lemma 6

Recall that in Appendix D we get

$$\mathbb{P}\left[d_{\mathcal{F}}(\hat{\mu}_m^0, g_0) \leq \frac{1}{2}\tau_{k,\xi} \wedge d_{\mathcal{F}}(\hat{\mu}_m^1, g_1) \leq \frac{1}{2}\tau_{k,\xi}\right] \geq 1 - 2\xi.$$

With probability at least $1 - 2\xi$, we have

$$\begin{aligned} d_{\mathcal{F}}(g_0, g_1) &= \sup_{f \in \mathcal{F}} \{\mathbb{E}_{x \sim g_0} [f(x)] - \mathbb{E}_{x \sim g_1} [f(x)]\} \\ &= \sup_{f \in \mathcal{F}} \{\mathbb{E}_{x \sim g_0} [f(x)] - \mathbb{E}_{x \sim \hat{\mu}_m^0} [f(x)] + \mathbb{E}_{x \sim \hat{\mu}_m^0} [f(x)] - \mathbb{E}_{x \sim \hat{\mu}_m^1} [f(x)] + \mathbb{E}_{x \sim \hat{\mu}_m^1} [f(x)] - \mathbb{E}_{x \sim g_1} [f(x)]\} \\ &\geq - \sup_{f \in \mathcal{F}} \{\mathbb{E}_{x \sim g_0} [f(x)] - \mathbb{E}_{x \sim \hat{\mu}_m^0} [f(x)]\} + \sup_{f \in \mathcal{F}} \{\mathbb{E}_{x \sim \hat{\mu}_m^0} [f(x)] - \mathbb{E}_{x \sim \hat{\mu}_m^1} [f(x)]\} \\ &\quad - \sup_{f \in \mathcal{F}} \{\mathbb{E}_{x \sim \hat{\mu}_m^1} [f(x)] - \mathbb{E}_{x \sim g_1} [f(x)]\} \\ &= -d_{\mathcal{F}}(\hat{\mu}_m^0, g_0) + d_{\mathcal{F}}(\hat{\mu}_m^0, \hat{\mu}_m^1) - d_{\mathcal{F}}(\hat{\mu}_m^1, g_1) \\ &\geq \frac{\Delta'}{2m} - \tau_{k,\xi} \end{aligned}$$

E Proof of Lemma 7

Assume that $S = \{x \in X | p(x) > q(x)\}$ and $T = X \setminus S = \{x \in X | p(x) \leq q(x)\}$. Let $a_1 = \int_{x \in S} p(x) dx$, $b_1 = \int_{x \in S} q(x) dx$, $a_2 = \int_{x \in T} p(x) dx$, and $b_2 = \int_{x \in T} q(x) dx$. Because of the the differential privacy guarantee, we have

$$\begin{aligned} a_1 - \delta &\leq e^\epsilon b_1 \\ b_2 - \delta &\leq e^\epsilon a_2 \end{aligned}$$

Note that $a_1 + a_2 = 1$, $b_1 + b_2 = 1$. Therefore, we have

$$b_1 + a_2 \geq \frac{2 - 2\delta}{1 + e^\epsilon}$$

and

$$d_{\text{TV}}(p, q) = \frac{a_1 + b_2 - b_1 - a_2}{2} \leq \frac{e^\epsilon + 2\delta - 1}{e^\epsilon + 1}.$$