

Why is optimizing G in a situation where D is optimized the same as minimizing Jensen-Shannon Divergence?

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$$\begin{aligned}
 V(G, D) &= E_{x \sim p_{data}(x)}[\log(D(x))] + E_{z \sim p_z(z)}[\log(1 - D(G(z)))] \\
 E_{z \sim p_z(z)}[\log(1 - D(G(z)))] &= E_{y \sim p_g(y)}[\log(1 - D(y))] \\
 V(G, D) &= E_{x \sim p_{data}(x)}[\log(D(x))] + E_{y \sim p_g(y)}[\log(1 - D(y))] \\
 &= \int_x P_{data}(x) \log D(x) dx + \int_x P_g(x) \log(1 - D(x)) dx \\
 &= \int_x [P_{data}(x) \log D(x) + P_g(x) \log(1 - D(x))] dx
 \end{aligned}$$

Let, $a = P_{data}(x)$ and $b = P_g(x)$

$$f(x) = a \log(x) + b \log(1 - x)$$

$f(x)$ is a upper convex function so differentiate $f(x)$ to find optimal D

$$\frac{f(x)}{dx} = \frac{a}{x} - \frac{b}{1-x} = 0$$

$$a(x - 1) + bx = 0$$

$$(b + a)x - a = 0$$

$$x = \frac{a}{a+b}$$

$$\text{optimal } D^* = \frac{P_{data}(x)}{P_{data}(x) + P_g(x)}$$

Let's optimize G when D is optimization

$$\begin{aligned}
 \max_D V(G, D) &= V(G, D^*) \\
 &= \int_x [P_{data}(x) \log D^*(x) + P_g(x) \log(1 - D^*(x))] dx \\
 &= E_{x \sim p_{data}(x)}[\log(D^*(x))] + E_{x \sim p_g(x)}[\log(1 - D^*(x))] \\
 &= E_{x \sim p_{data}(x)}[\log \frac{p_{data}(x)}{p_{data}(x) + p_g(x)}] + E_{x \sim p_g(x)}[\log \frac{p_g(x)}{p_{data}(x) + p_g(x)}] \\
 &= E_{x \sim p_{data}(x)}[\log(p_{data}(x)) - \log(\frac{p_{data}(x) + p_g(x)}{2})] + E_{x \sim p_g(x)}[\log(p_g(x)) - \log(\frac{p_{data}(x) + p_g(x)}{2})] \\
 &\quad - \log(4) \\
 &= KL(p_{data} || \frac{p_{data} + p_g}{2}) + KL(p_g || \frac{p_{data} + p_g}{2}) - \log(4) \\
 &= 2 \times JSD(p_{data} || p_g) - \log(4)
 \end{aligned}$$

$$KL(P \parallel Q) = \sum_x P(x) \log \frac{P(x)}{Q(x)}$$

$$JSD(P \parallel Q) = \frac{1}{2} KL(P \parallel M) + \frac{1}{2} KL(Q \parallel M)$$

$$M = \frac{1}{2}(P + Q)$$

So, Optimization G is equal with minimizing Jensen–Shannon Divergence.