

$$G: \mathcal{Z} \rightarrow \mathcal{X}$$

$$D: \mathcal{X} \rightarrow [0, 1]$$

$$L_D = \mathbb{E}_{\bar{x} \sim p_{data}} [\log D(\bar{x})] + \mathbb{E}_{\bar{x} \sim p_g} [\log (1 - D(\bar{x}))]$$

$$V(D, G) = \mathbb{E}_{\bar{x} \sim p_{data}} [\log D(\bar{x})] + \mathbb{E}_{\bar{z} \sim p_{\bar{z}}} [\log (1 - D(G(\bar{z})))]$$

max

$$L_G = \mathbb{E}_{\bar{x} \sim p_{\bar{x}}} [\log(1 - D(G(\bar{x})))] \rightarrow \min$$

$$\min_G \max_D V(D, G)$$

1) $G = \text{fix } D = ?$

$$L_D = \int \left(p_{\text{data}}(\bar{x}) \log D(\bar{x}) + p_g(\bar{x}) \log(1 - D(\bar{x})) \right) d\bar{x}$$

$$p_{\text{data}}(\bar{x}) \log a + p_g(\bar{x}) \log(1 - a) \xrightarrow{D(\bar{x})} \max$$

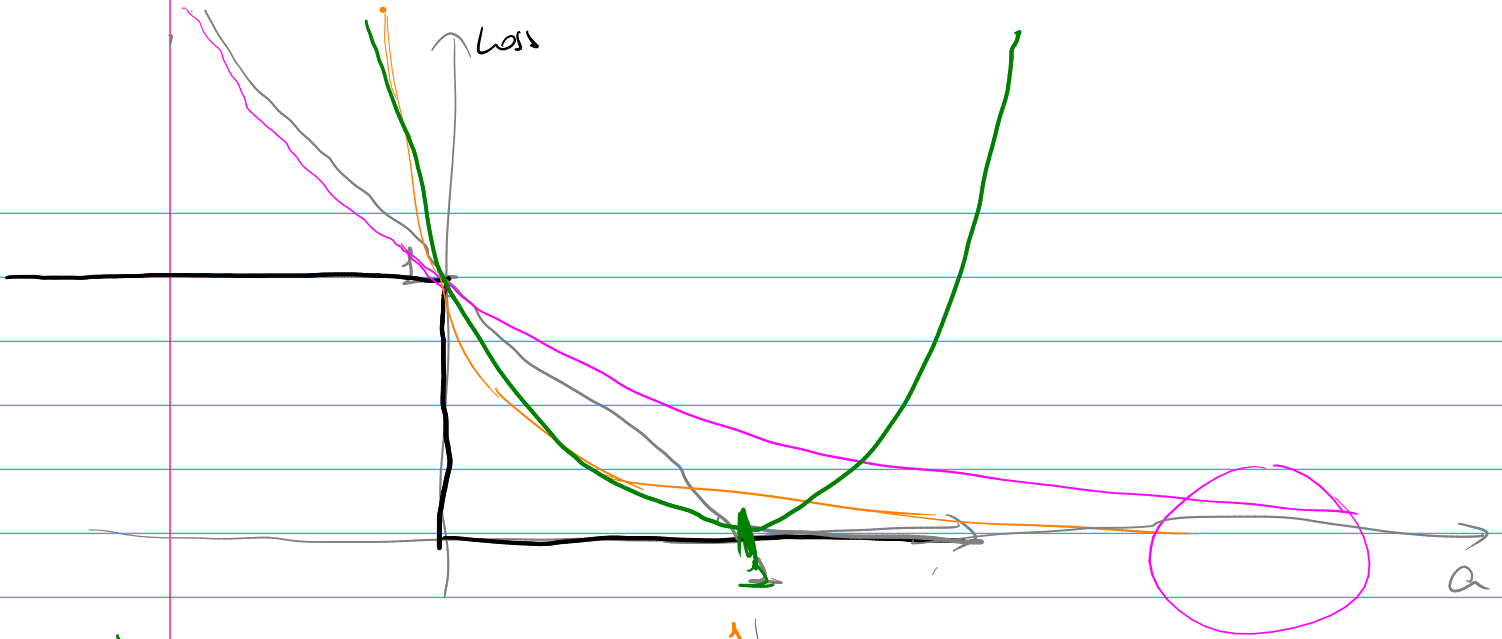
$$D^*(\bar{x}) = \frac{p_{\text{data}}(\bar{x})}{p_{\text{data}}(\bar{x}) + p_g(\bar{x})}$$

$$2) L_G = \int \left(p_d \log \frac{p_d}{\frac{p_d + p_g}{2}} + p_g \log \frac{p_g}{\frac{p_d + p_g}{2}} \right) d\bar{x} \xrightarrow{\text{min}} -2 \log 2$$

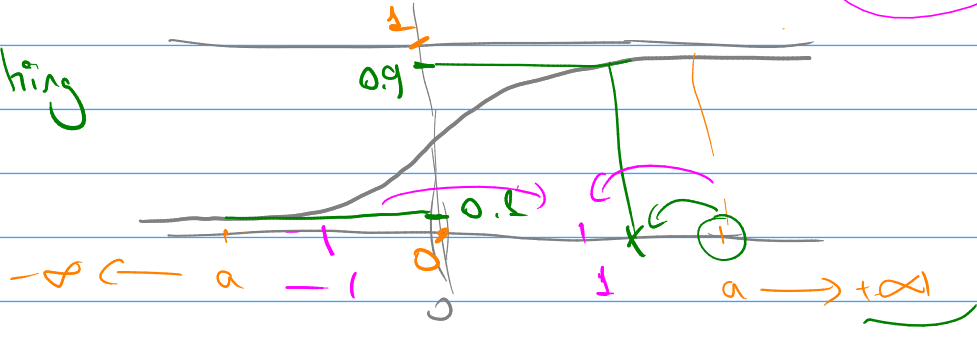
$$KL(p \parallel q) = \int p \log \frac{p}{q} d\bar{x}$$

$$L_G = KL\left(p_{\text{data}} \parallel \frac{p_{\text{data}} + p_g}{2}\right) + KL\left(p_g \parallel \frac{p_{\text{data}} + p_g}{2}\right) =$$

$$= \text{JSD}(p_{\text{data}} \parallel p_g) \xrightarrow{G} \min$$



Label smoothing



Adversarial loss functions

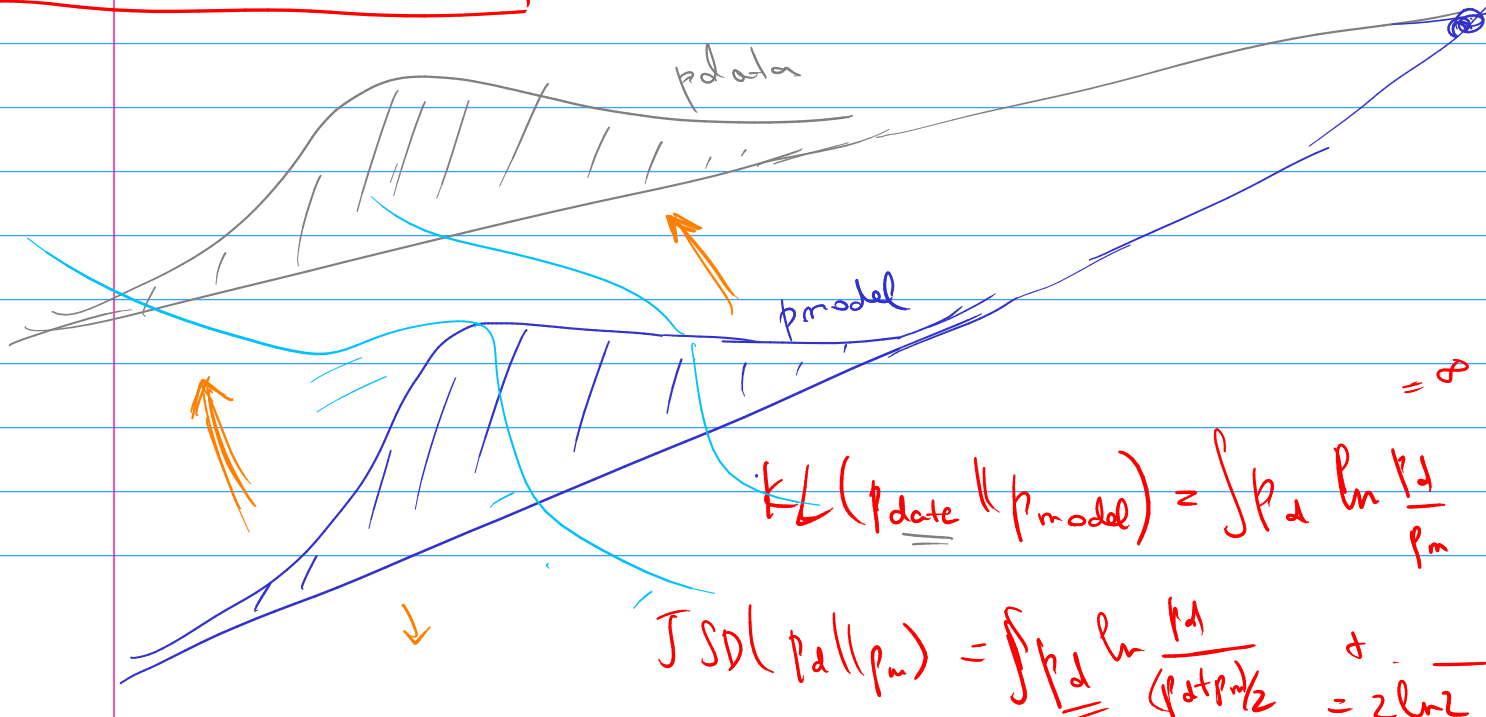
LSGAN

$$L_D = \mathbb{E}_{\bar{x} \sim p_{data}} [(D(\bar{x}) - b)^2] + \mathbb{E}_{\bar{x} \sim p_g} [(b(\bar{x}) - a)^2]$$

$$L_G = \mathbb{E}_{\bar{z} \sim p_z} [(D(G(\bar{z})) - c)^2]$$

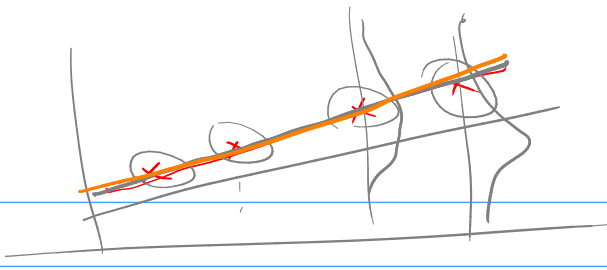
$a=0, -1$
 $b=c=1$

Wasserstein GANs



$$KL(p_{data} || p_{model}) = \int p_{data} \ln \frac{p_{data}}{p_{model}}$$

$$JSD(p_{data} || p_{model}) = \int p_{data} \ln \frac{p_{data}}{(p_{data} + p_{model})/2} + \dots = 2 \ln 2$$



$$p(y | \bar{w}, \bar{x}) = \mathcal{N}(y | \bar{w}^T \bar{x}, \sigma^2)$$

$$y(\bar{x}) = \bar{w}_*^T \bar{x} + \mathcal{N}(0, \sigma^2)$$

