GANs

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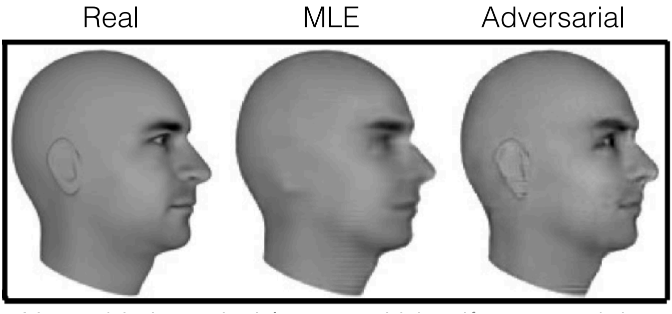
SLIDES ADAPTED FROM GRAHAM NEUBIG

Generative Models Ain't Perfect



(Lotter et al. 2015)

- Fitting conventional prob models focuses on common input
- Can be "fuzzy"
- Still better for smaller ammounts of data or if true objective is ML

Adversarial Training

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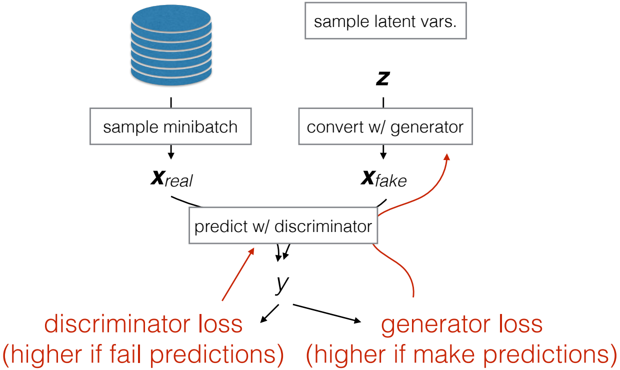
Training GAN



Training Equations

Discriminator

$$\ell_D(\theta_D, \theta_G) = -\mathbb{E}_{x \sim P_{\text{data}}}[\log D(x)] - \mathbb{E}_z[\log(1 - D(G(z)))]$$

- Real data should get high score
- Fake data should get low score

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Generator

$$\ell_G(\theta_D, \theta_G) = -\ell_D(\theta_D, \theta_G)$$

- If discriminator is very accurate, sometimes better to focus on non-saturating loss
- Focus on where you can confuse discriminator

$$\mathbb{E}_z[-\log D(G(z))] \tag{1}$$

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- Mode Collapse: generator maps all z to single x (other examples as side information)
- Over-confident discriminator (smoothing)

Problems with Discrete Data