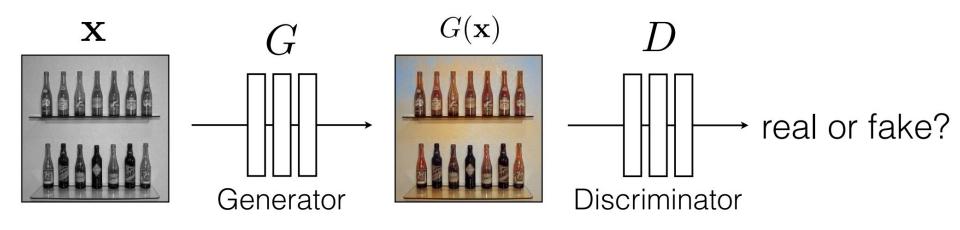
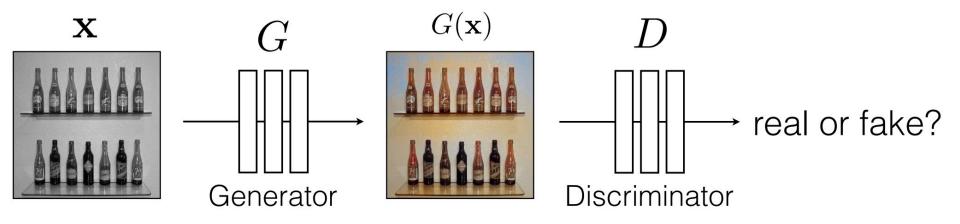


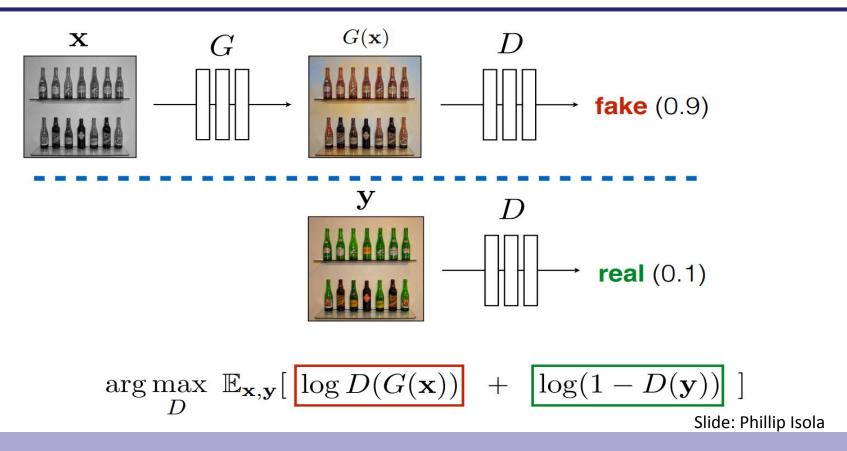
One-to-One Correspondence in the Domain is required: Colorization single transposed in the Domain is required in the Domain is r

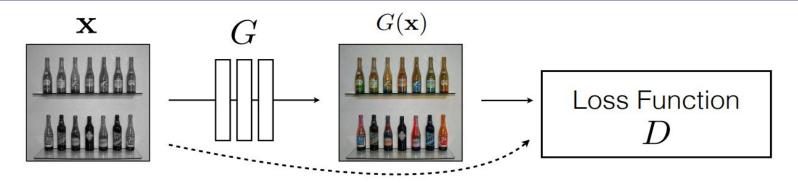




G tries to synthesize fake images that fool D

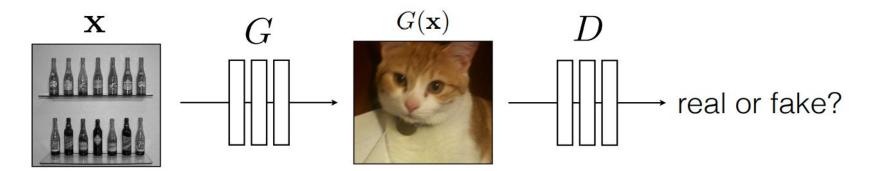
D tries to identify the fakes



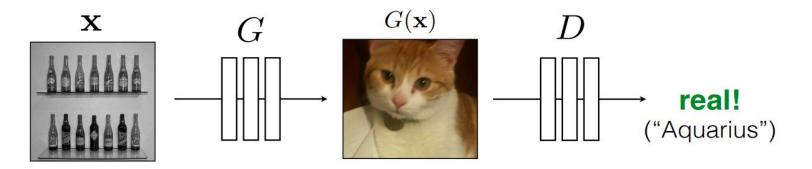


G's perspective: **D** is a loss function.

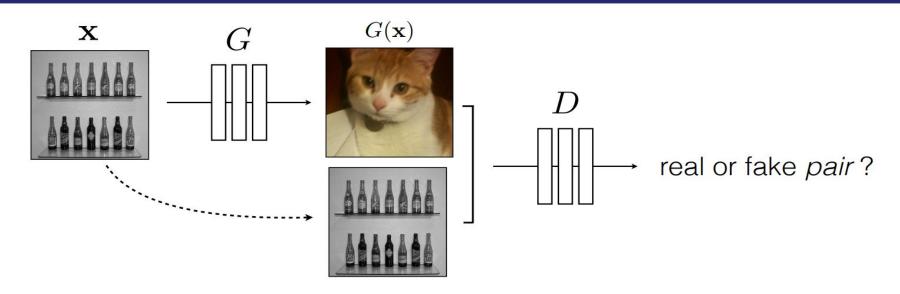
Rather than being hand-designed, it is *learned*.



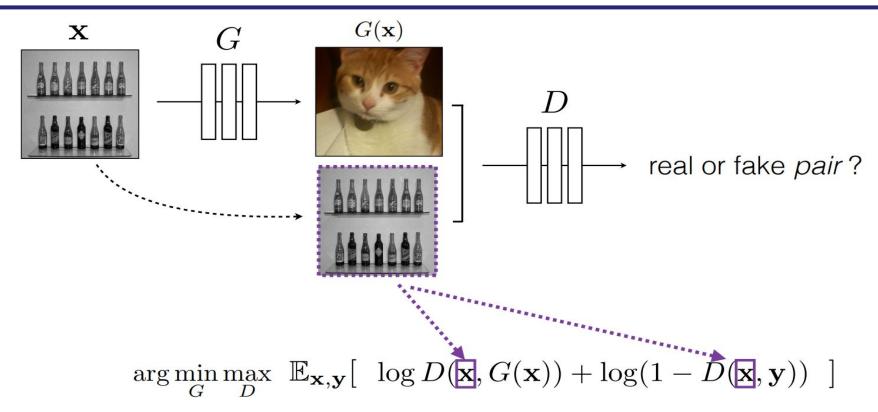
$$\underset{G}{\operatorname{arg\,min\,max}} \; \mathbb{E}_{\mathbf{x},\mathbf{y}}[\; \log D(G(\mathbf{x})) \; + \; \log(1-D(\mathbf{y})) \;]$$

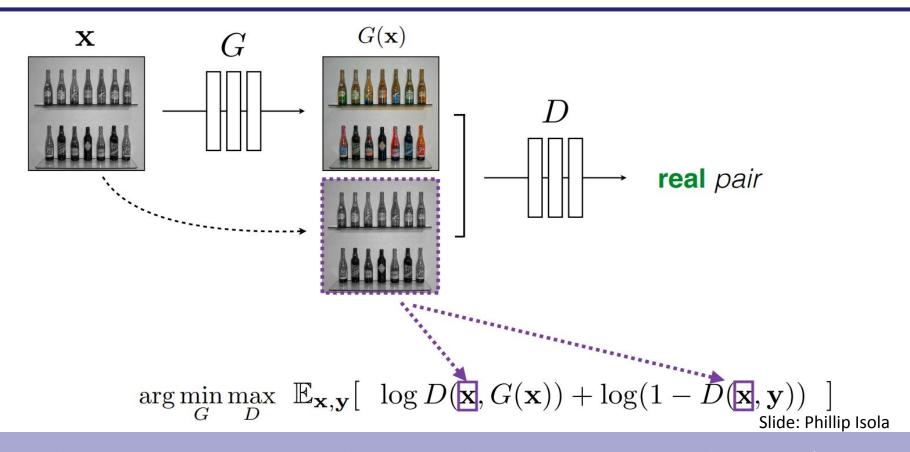


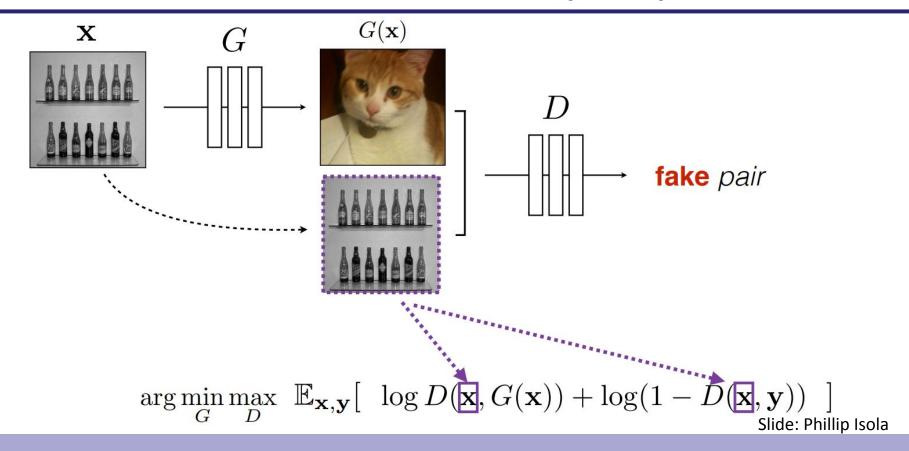
$$\arg\min_{G} \max_{D} \mathbb{E}_{\mathbf{x},\mathbf{y}} [\log D(G(\mathbf{x})) + \log(1 - D(\mathbf{y}))]$$

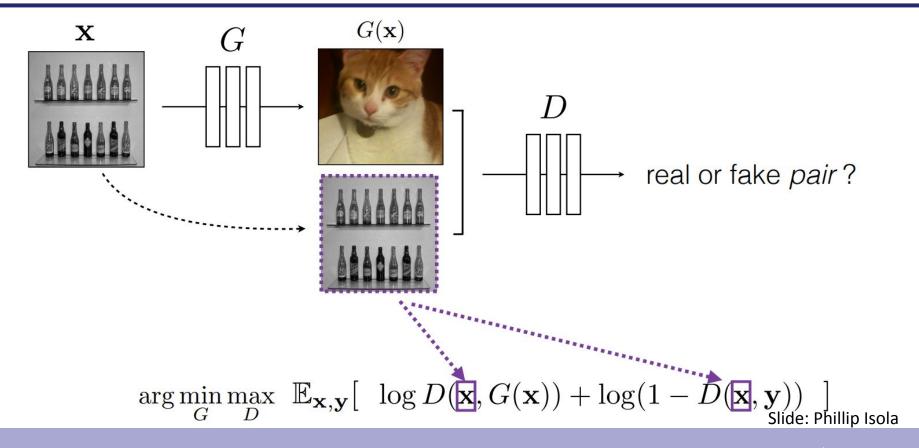


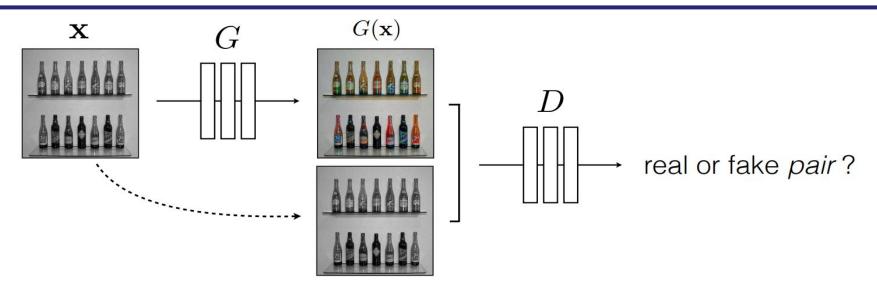
$$\arg\min_{G} \max_{D} \mathbb{E}_{\mathbf{x},\mathbf{y}} [\log D(G(\mathbf{x})) + \log(1 - D(\mathbf{y}))]$$











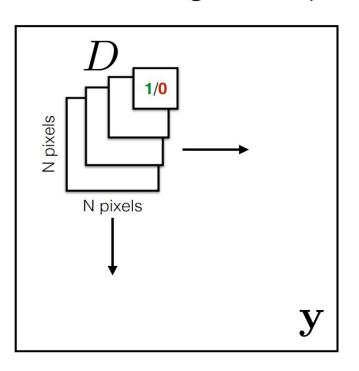
$$\arg\min_{G} \max_{D} \mathbb{E}_{\mathbf{x},\mathbf{y}} \left[\log D(\mathbf{x}, G(\mathbf{x})) + \log(1 - D(\mathbf{x}, \mathbf{y})) \right]$$

$$G^* = \arg\min_{G} \max_{D} \mathcal{L}_{cGAN}(G, D) + \lambda \mathcal{L}_{L1}(G)$$

Reconstruction loss is added

$$\mathcal{L}_{L1}(G) = \mathbb{E}_{x,y,z}[\|y - G(x,z)\|_1]$$

Shrinking the capacity: Patch Discriminator

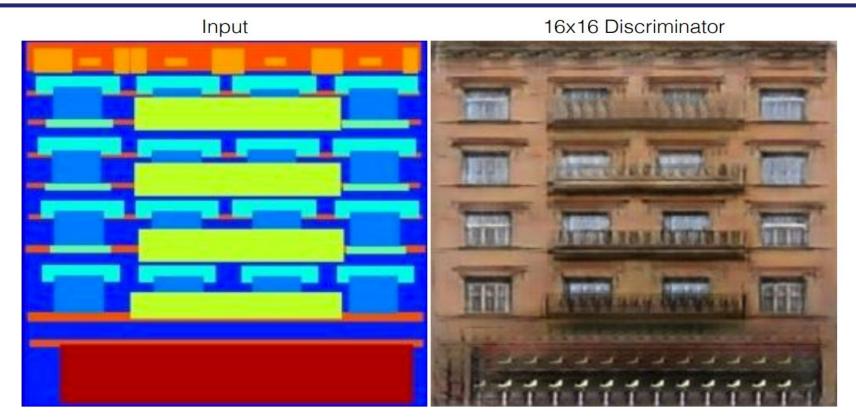


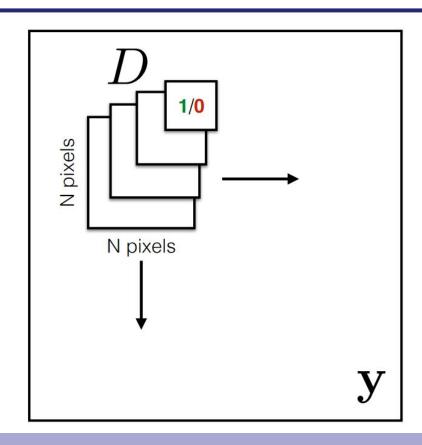
Rather than penalizing if output *image* looks fake, penalize if each overlapping *patch* in output looks fake

[Li & Wand 2016] [Shrivastava et al. 2017] [Isola et al. 2017]

[Isola et al. 2017] Slide: Phillip Isola

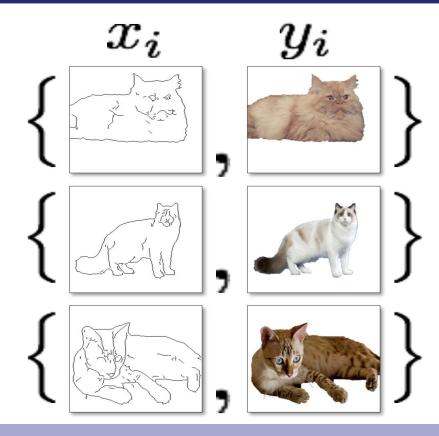




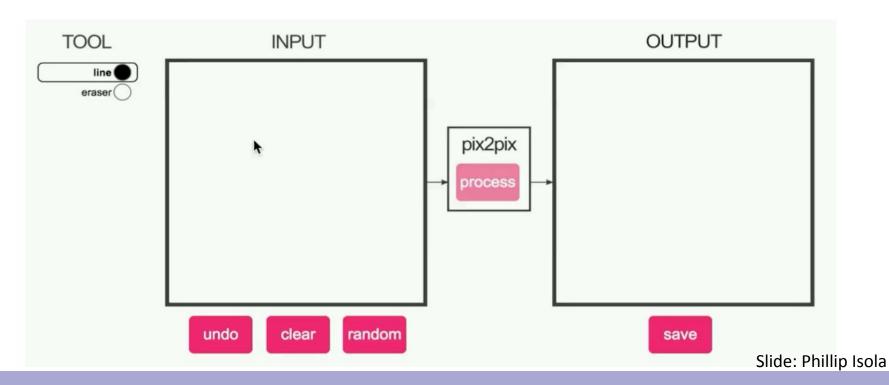


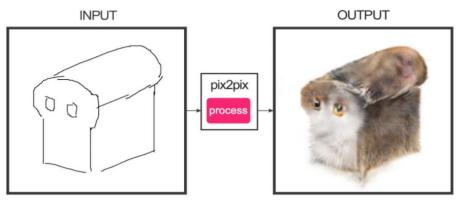
Rather than penalizing if output *image* looks fake, penalize if each overlapping *patch* in output looks fake

- Faster, fewer parameters
- More supervised observations
- Applies to arbitrarily large images



#edges2cats [Chris Hesse]





Ivy Tasi @ivymyt



Vitaly Vidmirov @vvid

BW → Color

