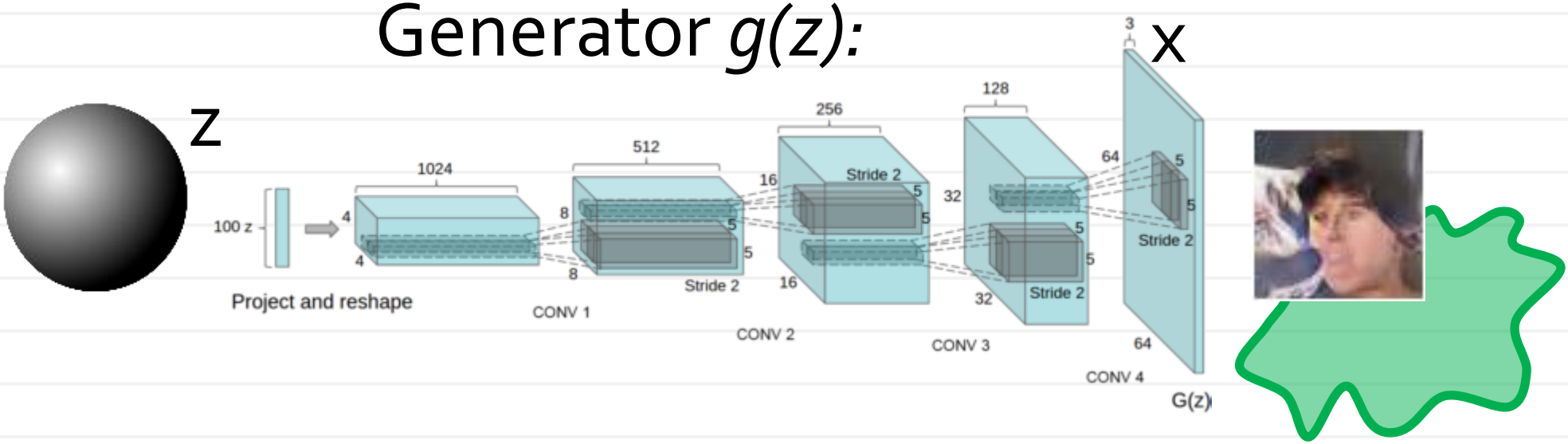
Lecture 8: Adversarial learning

Recap on Generative networks

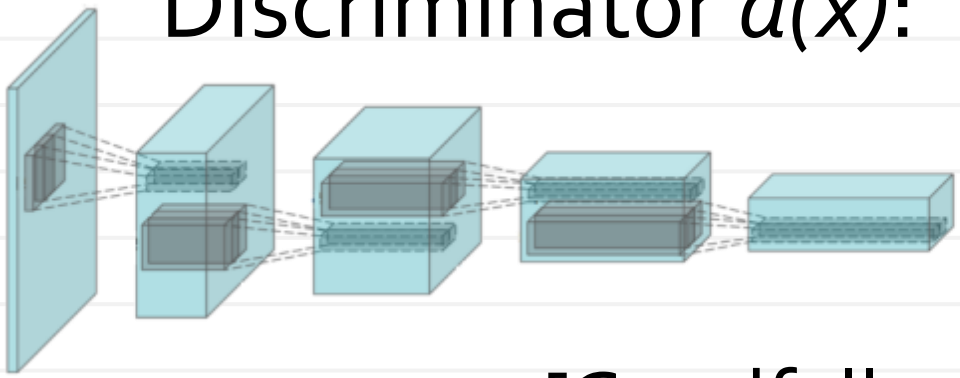
- ConvNets are natural tools for image synthesis
- Both conditional synthesis (e.g. superresolution) and unconditional sampling (latent models) is possible
- Training loss matters, pixelwise loss often leads to blurry results
- Pretrained ConvNets can be used to extract good statistics/loss-functions
- Can we get even better statistics/losses?

Generative Adversarial Networks

Generator *g(z)*:



Discriminator *d(x)*:



y [0;1]

x

[Goodfellow et al. 14]

GAN game: zero-sum variant

$$d: \mathcal{X} \to [0;1] \qquad g: \mathcal{Z} \to \mathcal{X}$$

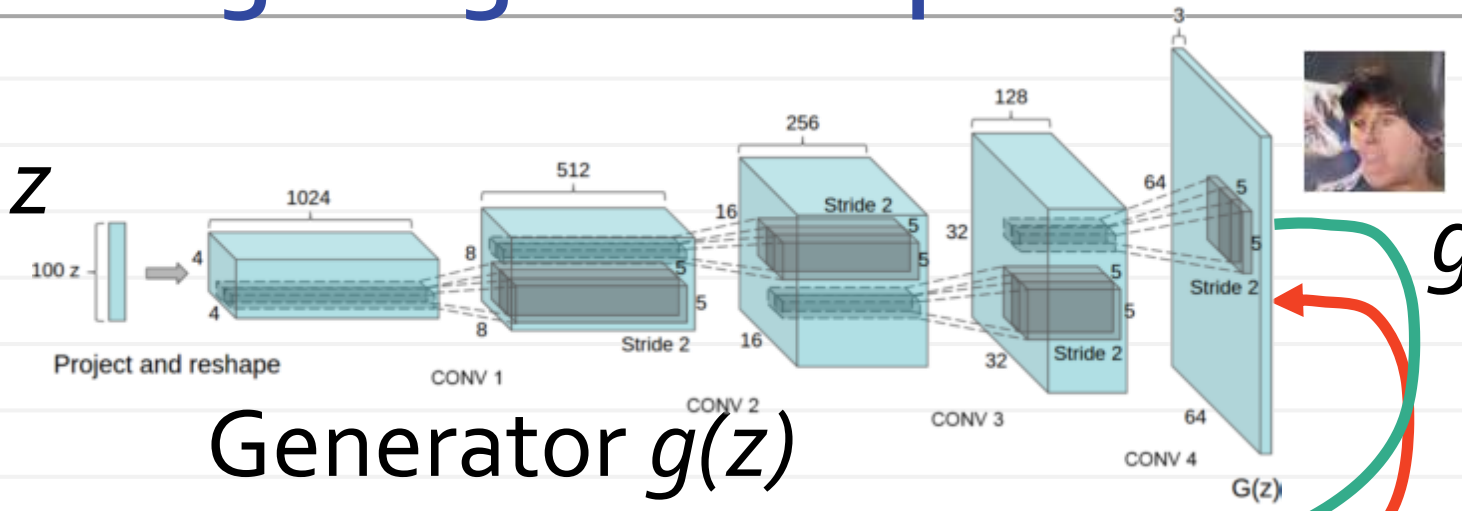
$$\min_g \max_d V(d,g) =$$

$$\mathbb{E}_{x \sim X}[\log d(x)] + \mathbb{E}_{z \sim Z}[\log(1 - d(g(z)))]$$

- Discriminator tries to increase the value of *V(d,g) (learns to tell p_{data} from p(g(z)))*
- Generator tries to decrease the value of *V(d,g) (fool the discriminator)*

[Goodfellow et al. 14]

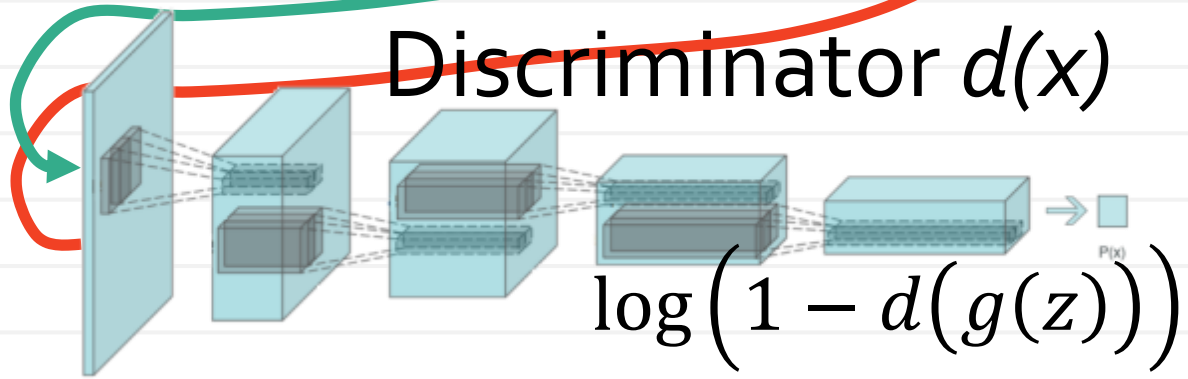
Updating the generator parameters



Generator $g(z)$

$g(z)$

Discriminator $d(x)$



$$\log\left(1 - d\left(g(z)\right)\right)$$

$$\min_g \max_d V(d,g) =$$

$$\mathbb{E}_{x\sim X}[\log d(x)] + \mathbb{E}_{z\sim Z}[\log(1 - d(g(z)))]$$

Optimal discriminator

Let us derive optimal *d(x)* given $p_{\text{data}}(x),\ p_{\text{gen}}(x)$

$$\min_g \max_d V(d,g) =$$

$$\mathbb{E}_{x\sim X}[\log d(x)] + \mathbb{E}_{z\sim Z}[\log(1-d(g(z)))]$$

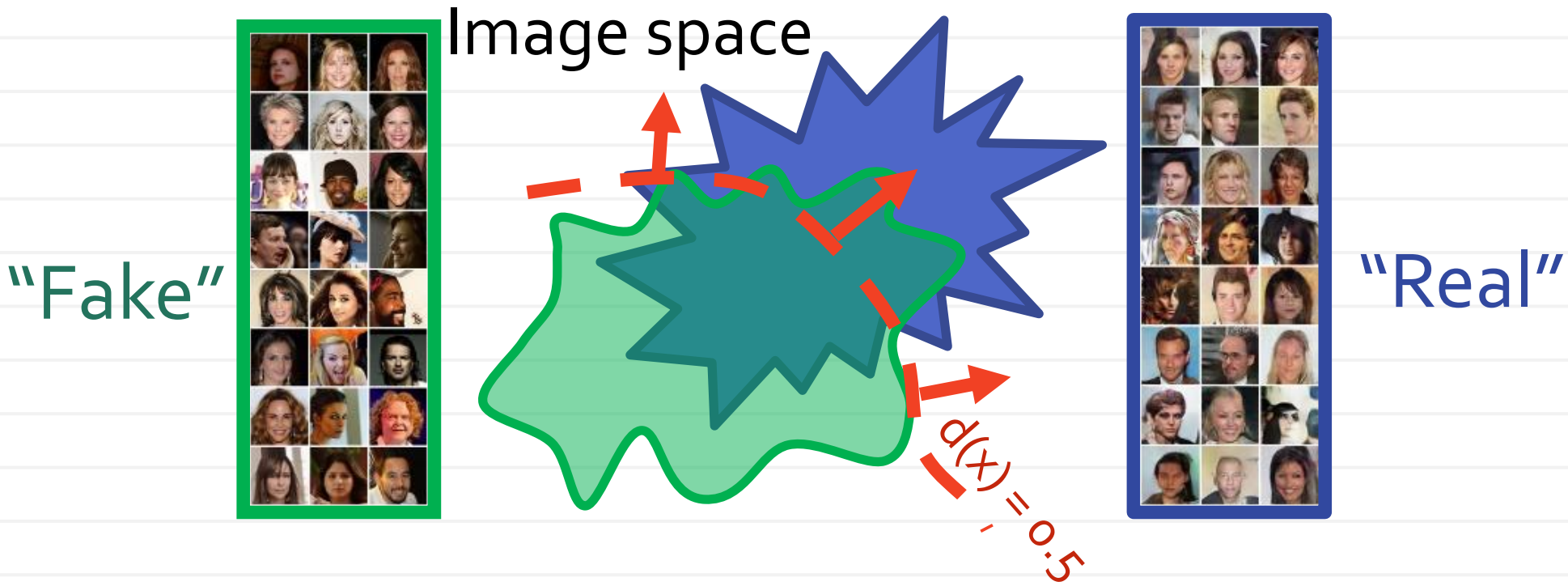
$$\frac{\delta V(d,g)}{\delta d(x)} = \frac{\delta[p_{\text{data}}(x)\log d(x) + p_{\text{gen}}(x)\log(1-d(x))]}{\delta d(x)}$$

$$= \frac{p_{\text{data}}(x)}{d(x)} - \frac{p_{\text{gen}}(x)}{1-d(x)} = 0$$

$$(1-d(x))p_{\text{data}}(x) - d(x)p_{\text{gen}}(x) = 0$$

$$d(x) = \frac{p_{\text{data}}(x)}{p_{\text{data}}(x) + p_{\text{gen}}(x)}$$

Updating the discriminator parameters



$$d(x) = \frac{p_{\text{data}}(x)}{p_{\text{data}}(x) + p_{\text{gen}}(x)}$$

Optimal discriminator works as *ratio estimator*

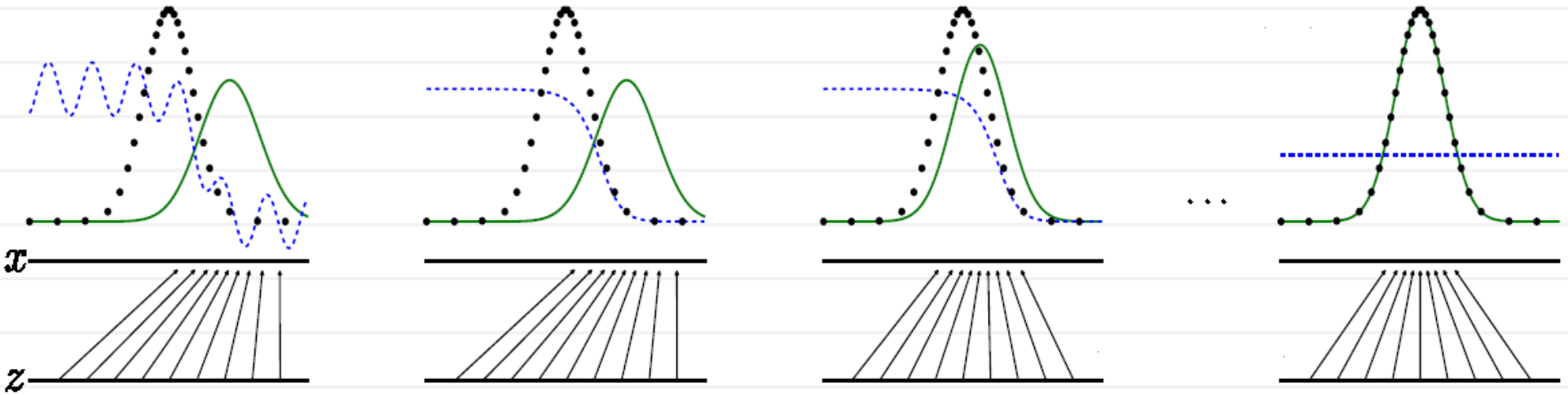
Adversarial learning turns high-D distribution alignment into classification

Adversarial learning

Looking for a *saddle point*:

$$\min_g \max_d V(d,g) =$$

$$\mathbb{E}_{x\sim X}[\log d(x)] + \mathbb{E}_{z\sim Z}[\log(1 - d(g(z)))]$$



[Goodfellow et al. 2014]

GAN game: practical variant

$$\min_g \max_d V(d,g) =$$

$$\mathbb{E}_{x\sim X}[\log d(x)] + \mathbb{E}_{z\sim Z}[\log(1-d(g(z)))]$$

Problem: generator gets *vanishing gradient* when the discriminator is much smarter.
Therefore, non-zero sum formulation is popular:

$$\max_d \mathbb{E}_{x\sim X}[\log d(x)] + \mathbb{E}_{z\sim Z}[\log(1-d(g(z)))]$$

$$\max_g \mathbb{E}_{z\sim Z}[\log d(g(z))]$$

[Goodfellow et al. 14]

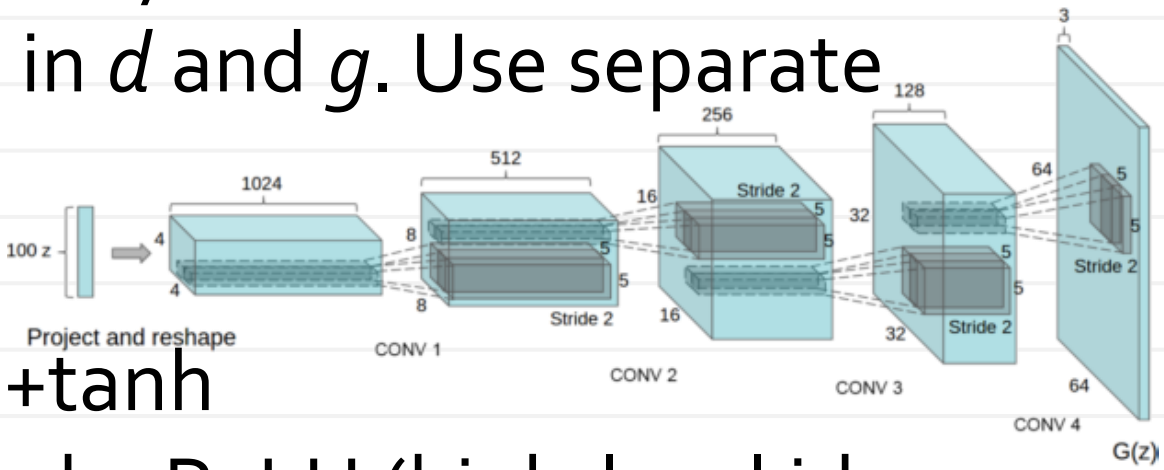
Tuning GANs

100 years ago: "The most important art is cinema"

Now: "The most important art is tuning GANs"

DCGAN ("deep conv. GAN") [Radford et al. 2015]:

- No max-pooling, only strides
- Use batch norms in *d* and *g*. Use separate batches.
- Use ADAM
- Generator: ReLU+tanh
- Discriminator: Leaky ReLU (high-level idea: "*dense gradients*")

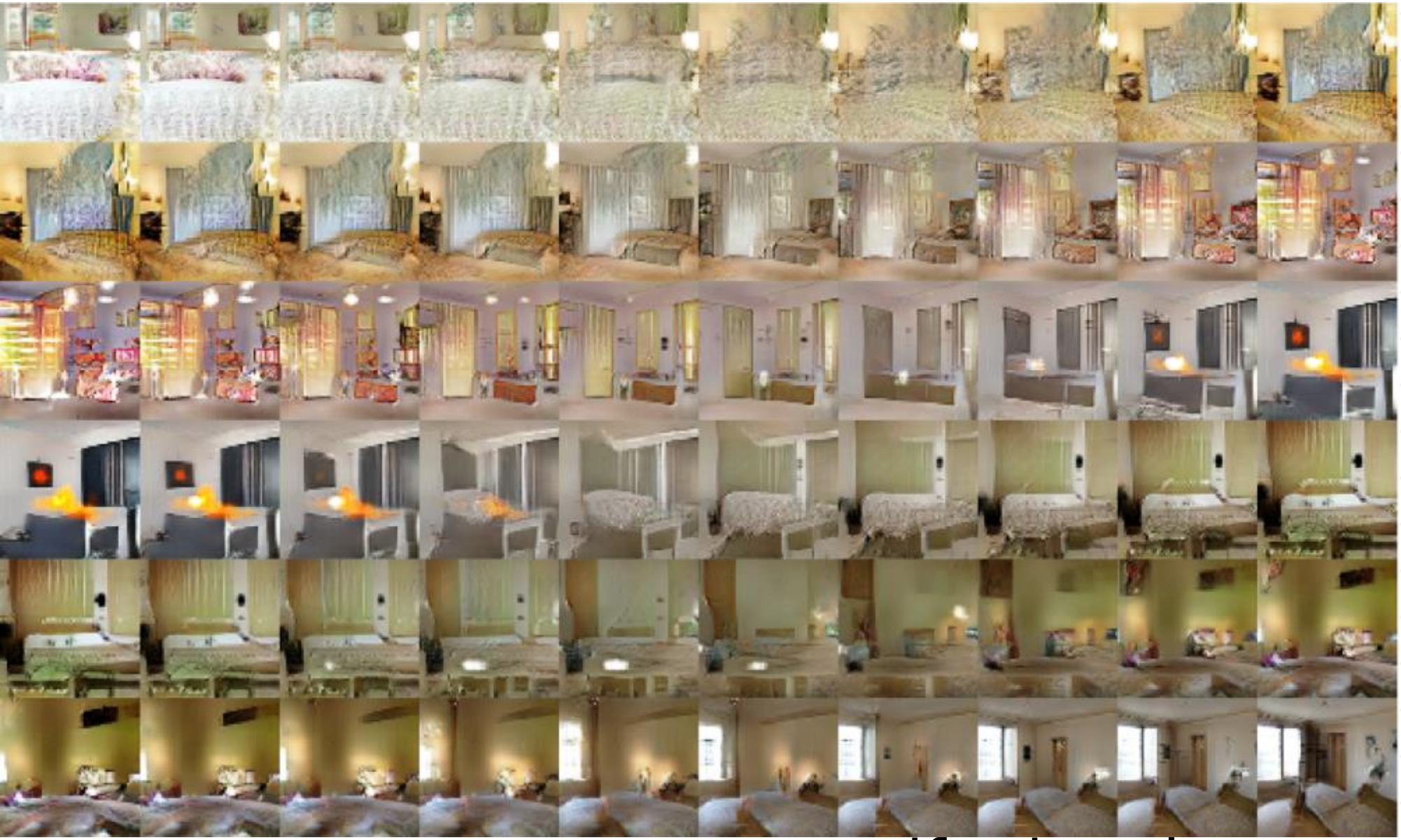


https://github.com/soumith/ganhacks

DCGAN results

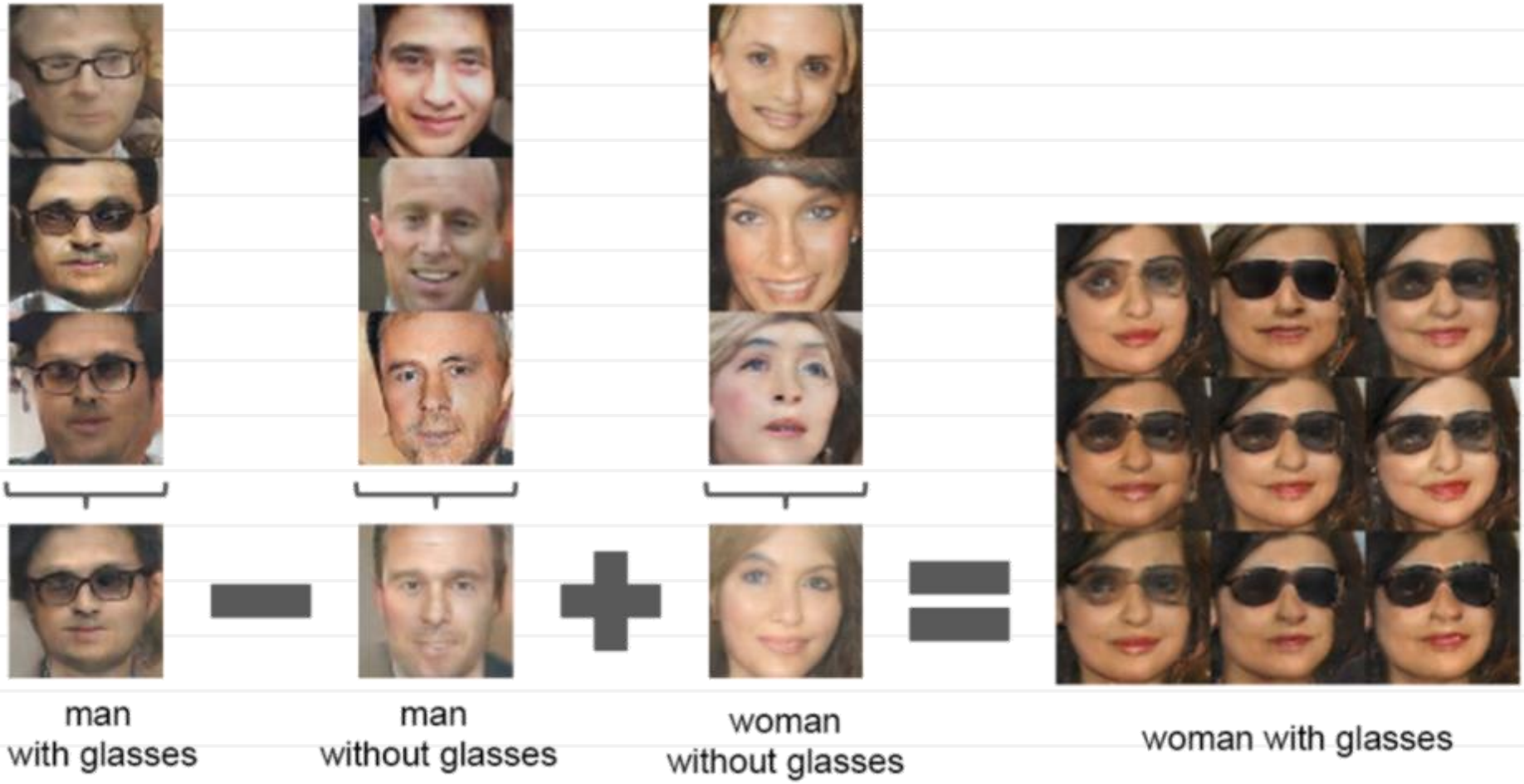
[Radford et al.2015]

DCGAN



[Radford et al.2015]

DCGAN

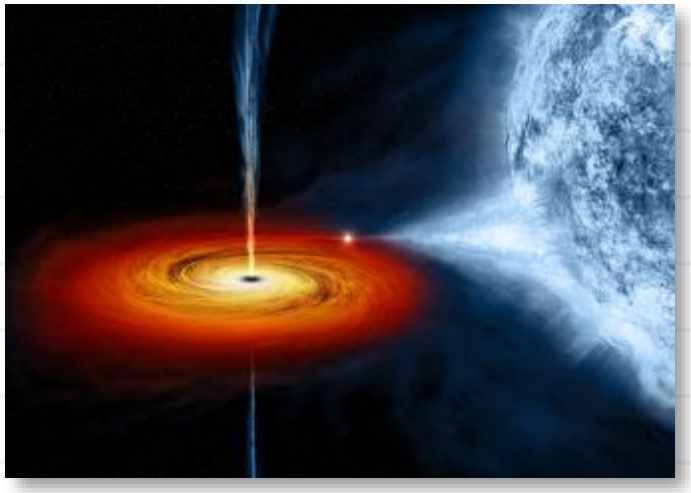


[Radford et al.2015]

The problem of perfect generator

$$\min_g \mathbb{E}_{x\sim X}[\log d(x)] + \mathbb{E}_{z\sim Z}[\log(1 - d(g(z)))]$$

$$\max_g \mathbb{E}_{z\sim Z}[\log d(g(z))]$$

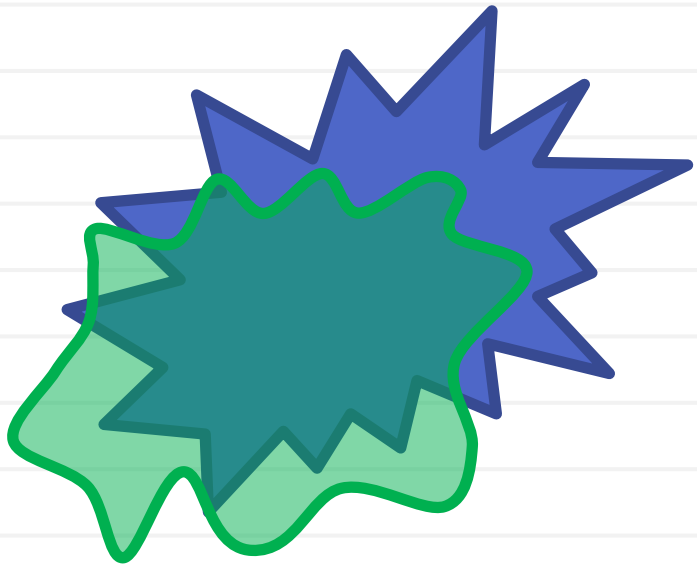


What is the optimal generator for a fixed discriminator?

Answer: $$g(z) = \arg\max_x d(x)$$

Main source of instability ("mode collapse").

Mode collapse in practice



DCGAN samples
[Radford et al. 2015]

Some hard modes missed (e.g. people with glasses)

Measuring diversity: Inception score

[Salimans et al. 2016]:

Inception v3-network prediction

$$IS(g) = \exp\left(\mathbb{E}_{z \sim Z} [\mathrm{KL}(p(y|g(z)) \| p(y))] \right)$$

- Looks at prediction of 1000 ILSVRC classes
- Used to score generative models for all kinds of datasets
- Has lots of problems [Baratt & Sharma 2018]

No single good measure exists ☹

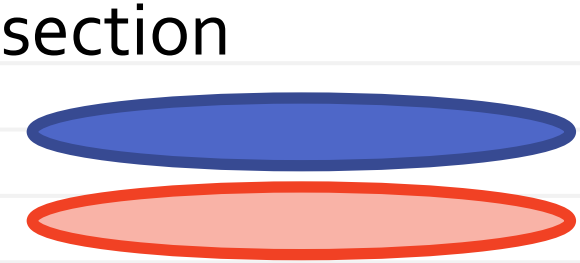
Further problems

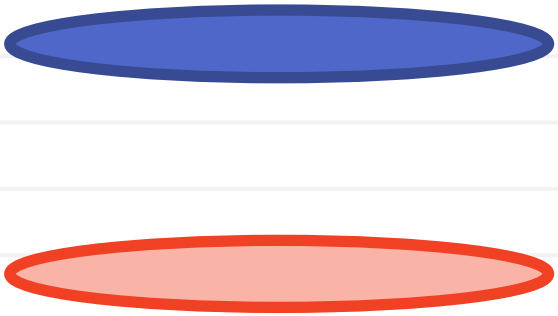
$$\min_g \max_d V(d,g) =$$

$$\mathbb{E}_{x\sim X}[\log d(x)] + \mathbb{E}_{z\sim Z}[\log(1-d(g(z)))]$$

$$d(x) = \frac{p_{\text{data}}(x)}{p_{\text{data}}(x) + p_{\text{gen}}(x)} \Rightarrow \min_g \text{JS}(X \| g(Z))$$

- Discriminator is defined in a "point-wise" fashion
- Equally bad for distributions with measure zero intersection





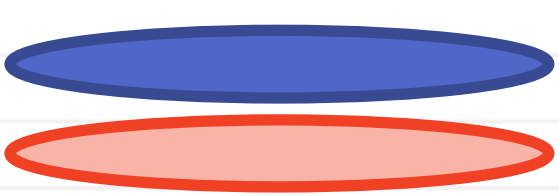
Alignment through EMD

$$\min_g W(X\|g(Z))$$

Earth mover distance (aka Wasserstein-1 distance):

$$W(X\|Y) = \inf_{\gamma\in\Pi(X,Y)} \mathbb{E}_{(x,y)\sim\gamma}[\|x-y\|]$$

All random variables over with marginal distributions X and Y



[Arjovsky et al 2017]

Wasserstein GAN

$$\min_g W(X\|g(Z))$$

$$W(X\|Y) = \inf_{\gamma\in\Pi(X,Y)}\mathbb{E}_{(x,y)\sim\gamma}[\|x-y\|]$$

Kantorovich-Rubinstein duality:

$$W(X\|Y) = \sup_{\|f\|_L\le 1}\left(\mathbb{E}_{x\sim X}[f(x)] - \mathbb{E}_{x\sim Y}[f(x)]\right)$$

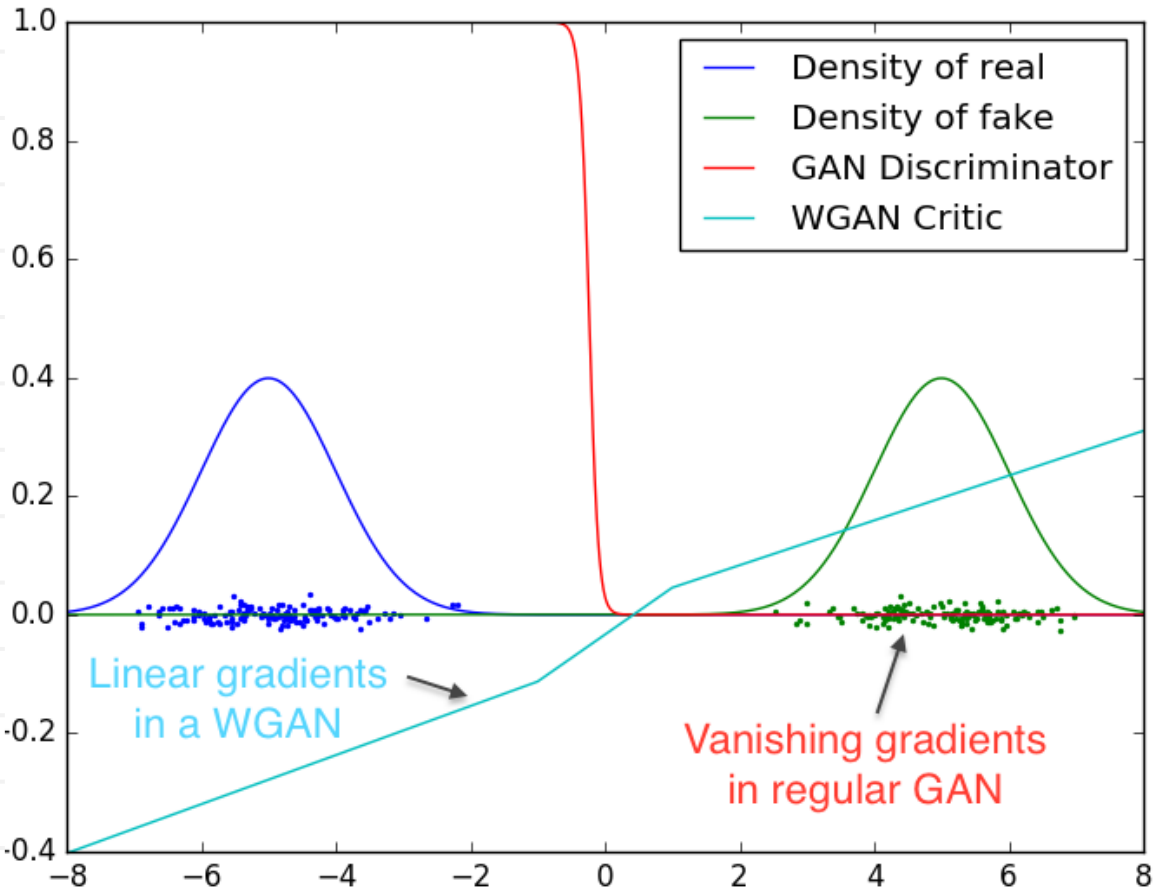
Wasserstein GAN [Arjovsky et al 2017]:

$$\min_g \max_{\|f\|_L\le 1}\left(\mathbb{E}_{x\sim X}[f(x)] - \mathbb{E}_{z\sim Z}[f(g(z))]\right)$$

(compare with the original GAN):

$$\min_g \max_d \mathbb{E}_{x\sim X}[\log d(x)] + \mathbb{E}_{z\sim Z}[\log(1-d(g(z)))]$$

WGAN vs GAN



$$\max_{\|f\|_L \leq 1} \left(\mathbb{E}_{x \sim X}[f(x)] - \mathbb{E}_{z \sim Z}[f(g(z))] \right)$$

$$\max_{d} \mathbb{E}_{x \sim X}[\log d(x)] + \mathbb{E}_{z \sim Z}[\log(1 - d(g(z)))]$$

Enforcing Lipshitz constant

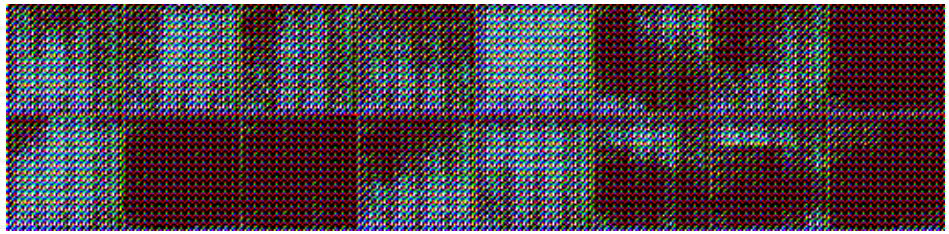
$$\min_{g} \max_{\|f\|_L \leq 1} \left(\mathbb{E}_{x \sim X}[f(x)] - \mathbb{E}_{z \sim Z}[f(g(z))] \right)$$

[Arjovsky et al. 2017]: implements *f(x)* as a deep network with the weights bounded to *[-0.01; 0.01]*

WGAN vs GAN

DCGAN generator:

"Bad" generator (no batchnorms, not enough filters):



[Arjovsky et al. 2017]

Enforcing Lipshitz constant: WGAN-GP

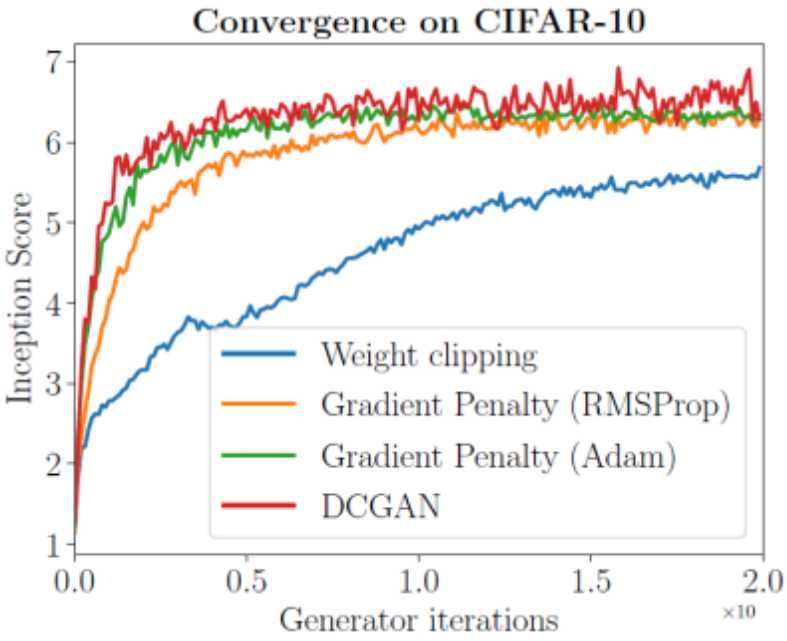
$$\min_{g} \max_{\|f\|_L \leq 1} \left(\mathbb{E}_{x \sim X}[f(x)] - \mathbb{E}_{z \sim Z}[f(g(z))] \right)$$

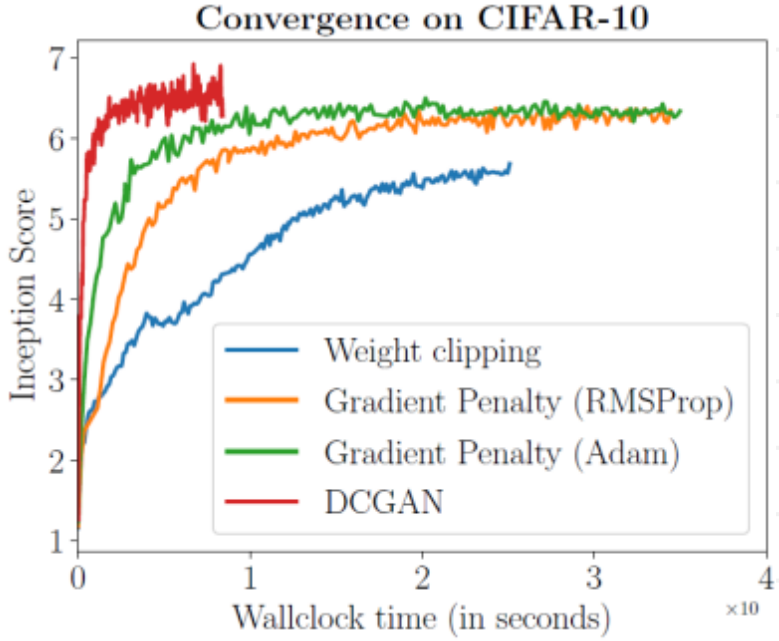
[Gulrajani et al. 2017]: do not clip weights, instead add the term to the objective:

$$+\lambda \mathbb{E}_{x \sim X^*}[(\|\nabla_x f(x)\|_2 - 1)^2]$$

- X* is an interpolation between X and g(Z).
- Need functionality that implements gradient computation as a feedforward network (PyTorch has it)

WGAN-GP


Convergence on CIFAR-10
Inception Score
Generator iterations
×10
Weight clipping
Gradient Penalty (RMSProp)
Gradient Penalty (Adam)
DCGAN


Convergence on CIFAR-10
Inception Score
Wallclock time (in seconds)
×10
Weight clipping
Gradient Penalty (RMSProp)
Gradient Penalty (Adam)
DCGAN

Spectral normalized GAN

Since $\|g_1 \circ g_2\|_{\text{Lip}} \leq \|g_1\|_{\text{Lip}} \cdot \|g_2\|_{\text{Lip}}$
let us bound Lipschitz constant for each layer

Lipschitz constant of matrix multiplication is the spectral radius. Let us enforce it to be 1:

$$\bar{W}_{\text{SN}}(W) := W/\sigma(W)$$

Fast computation via power iteration method:

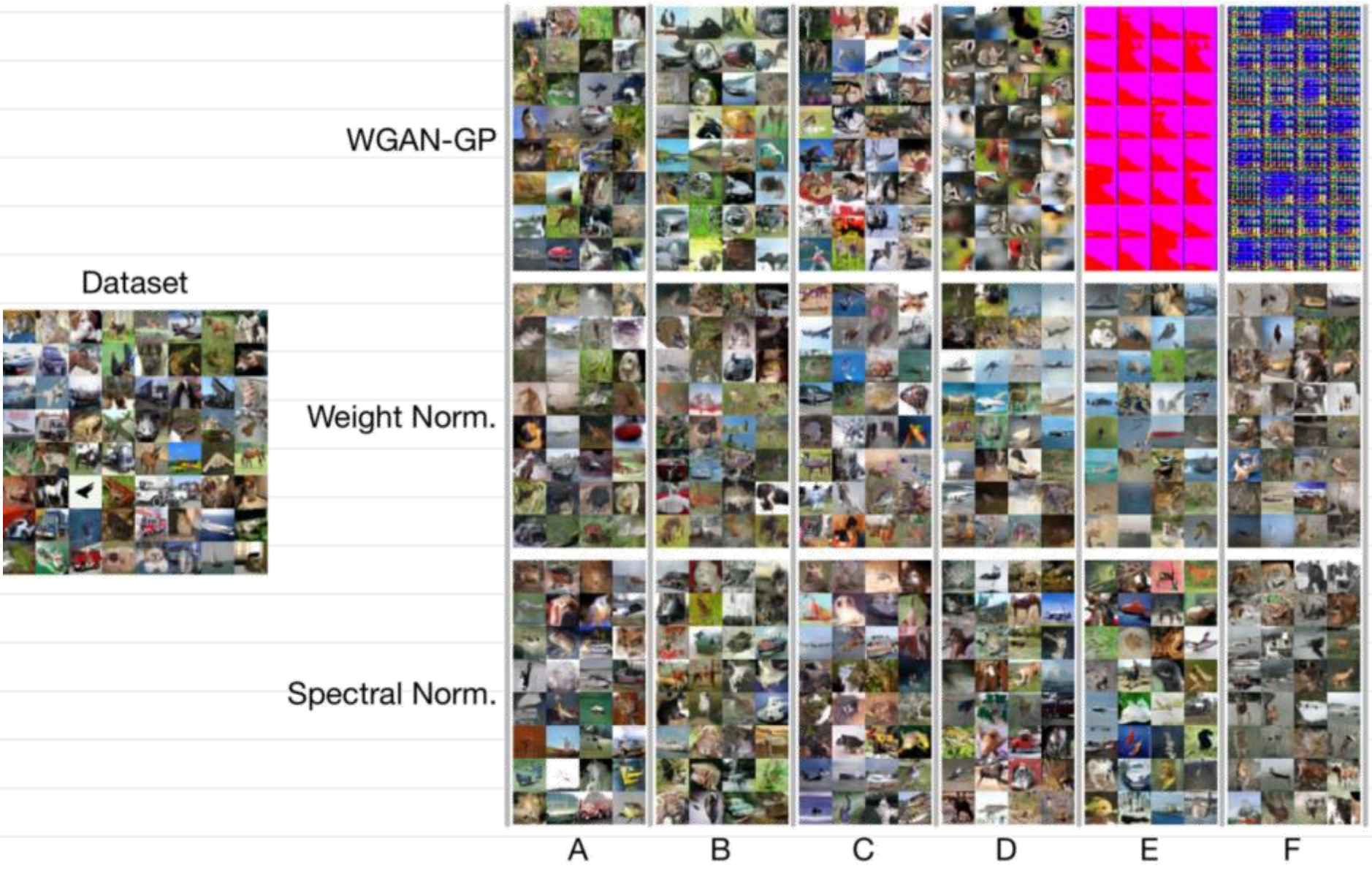
$$\tilde{\boldsymbol{v}} \leftarrow W^{\text{T}}\tilde{\boldsymbol{u}}/\|W^{\text{T}}\tilde{\boldsymbol{u}}\|_2,\ \tilde{\boldsymbol{u}} \leftarrow W\tilde{\boldsymbol{v}}/\|W\tilde{\boldsymbol{v}}\|_2 \qquad \sigma(W) \approx \tilde{\boldsymbol{u}}^{\text{T}} W \tilde{\boldsymbol{v}}$$

Backprop equations are also based on singular vectors.

For convolutional layers, spectral normalization is applied to the kernel reshaped as a Tx [S (2 δ +1)(2δ+1)] matrix.

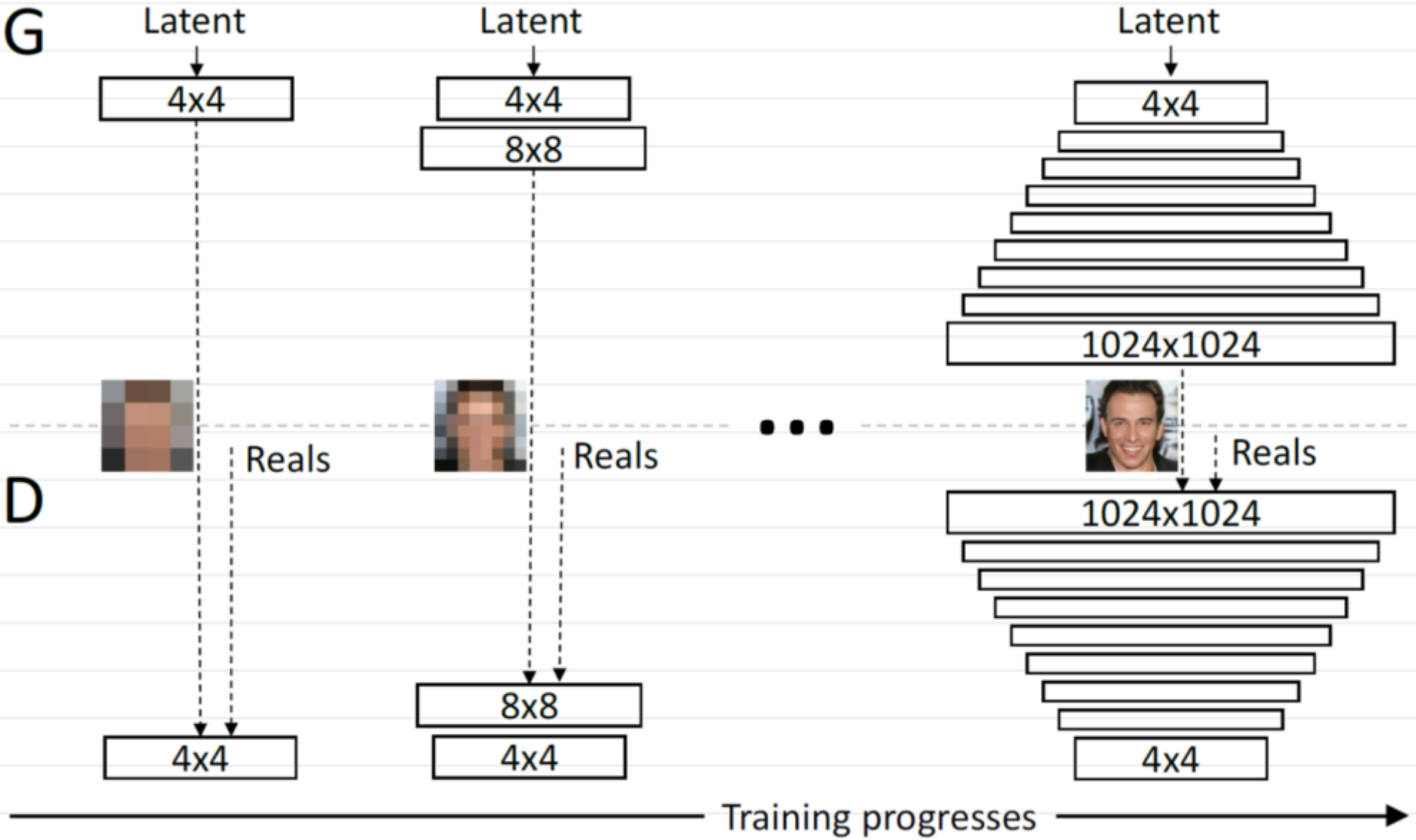
[Miyato et al. ICLR18]

Spectral normalized GAN



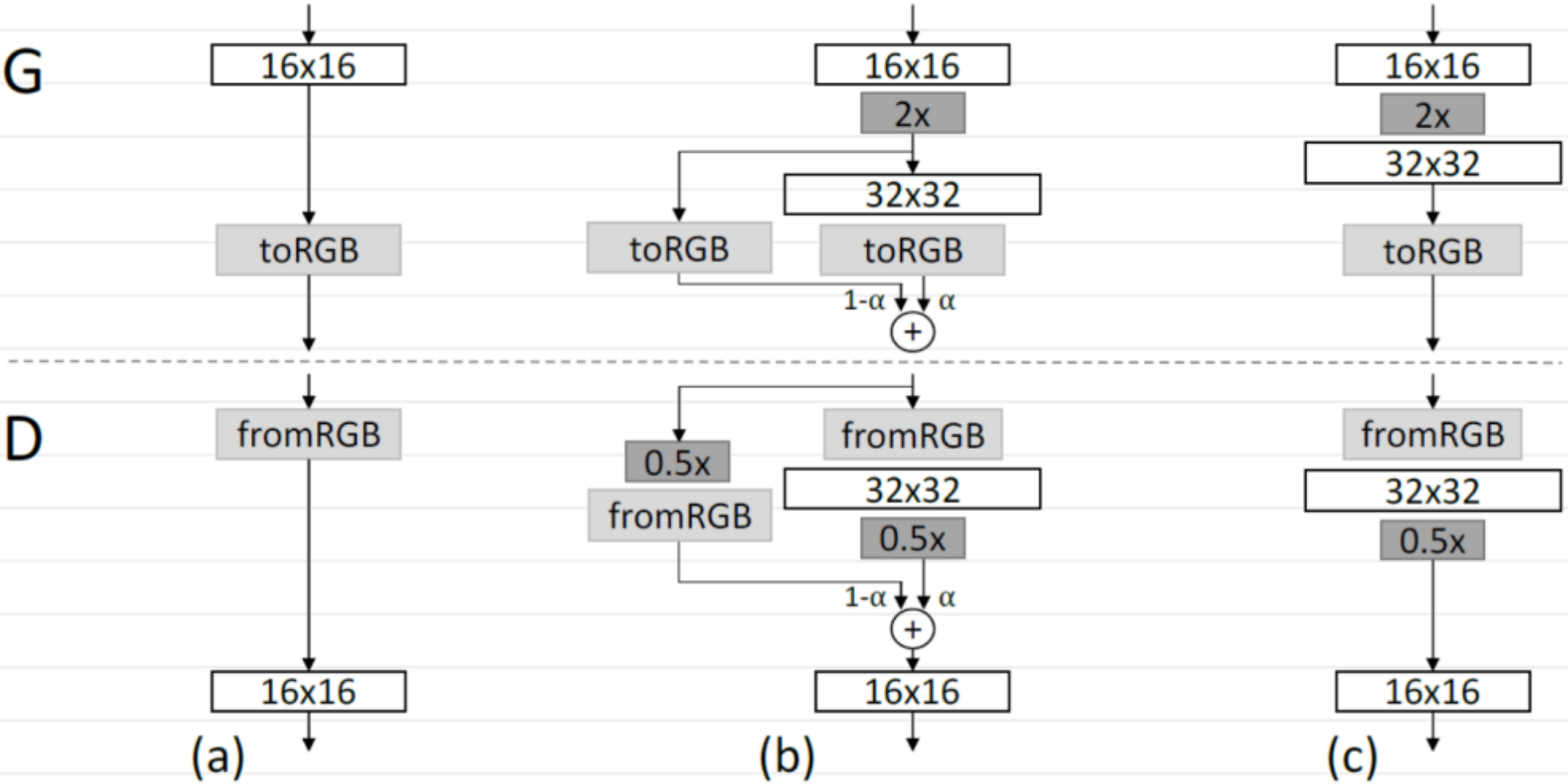
[Miyato et al. ICLR18]

Progressive growing of GANs



[Karras et al. 2017]

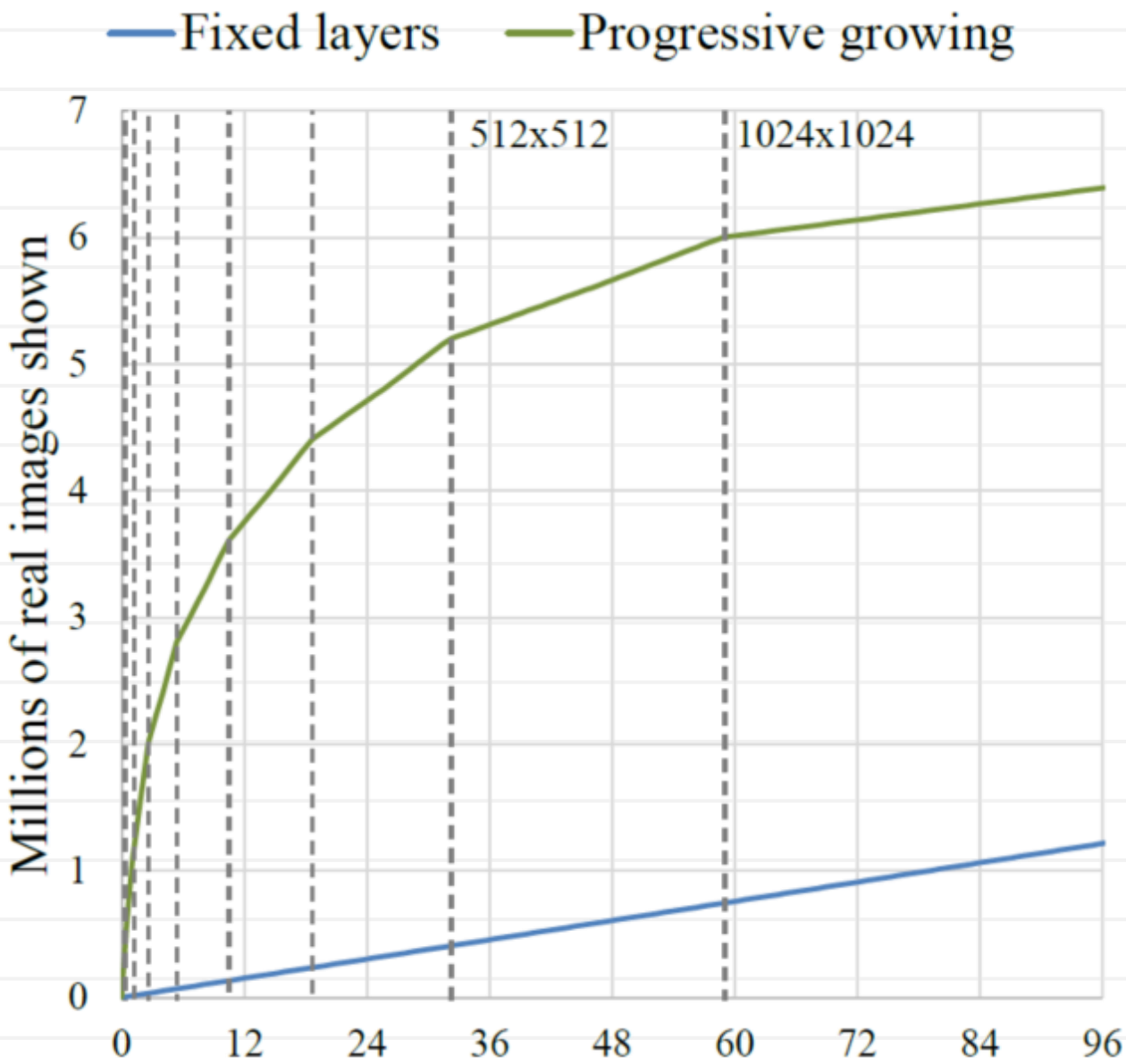
Progressive growing of GANs



- Uses WGAN-GP variant

[Karras et al. 2017]

Progressive growing of GANs



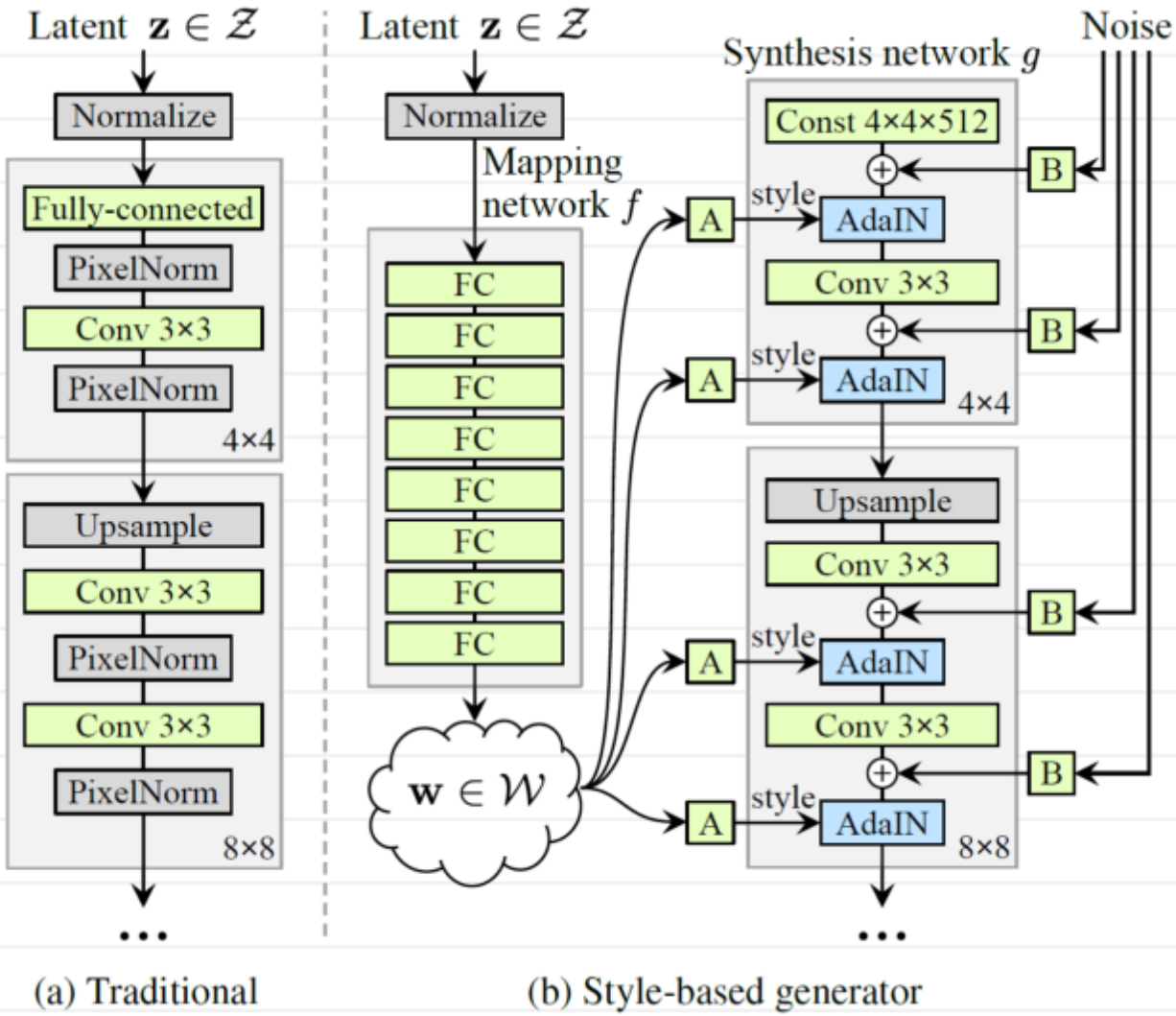
[Karras et al. 2017]

Progressive growing of GANs

Amazing samples at 1024 x 1024:

[Karras et al. 2017]

StyleGAN: architecture



(a) Traditional (b) Style-based generator

$$\mathrm{AdaIN}(\mathbf{x}_i, \mathbf{y}) = \mathbf{y}_{s,i} \frac{\mathbf{x}_i - \mu(\mathbf{x}_i)}{\sigma(\mathbf{x}_i)} + \mathbf{y}_{b,i}$$

[Karras et al. CVPR19]

StyleGAN: results

[Karras et al. CVPR19]

Are GANs good latent models?

Real

Sample

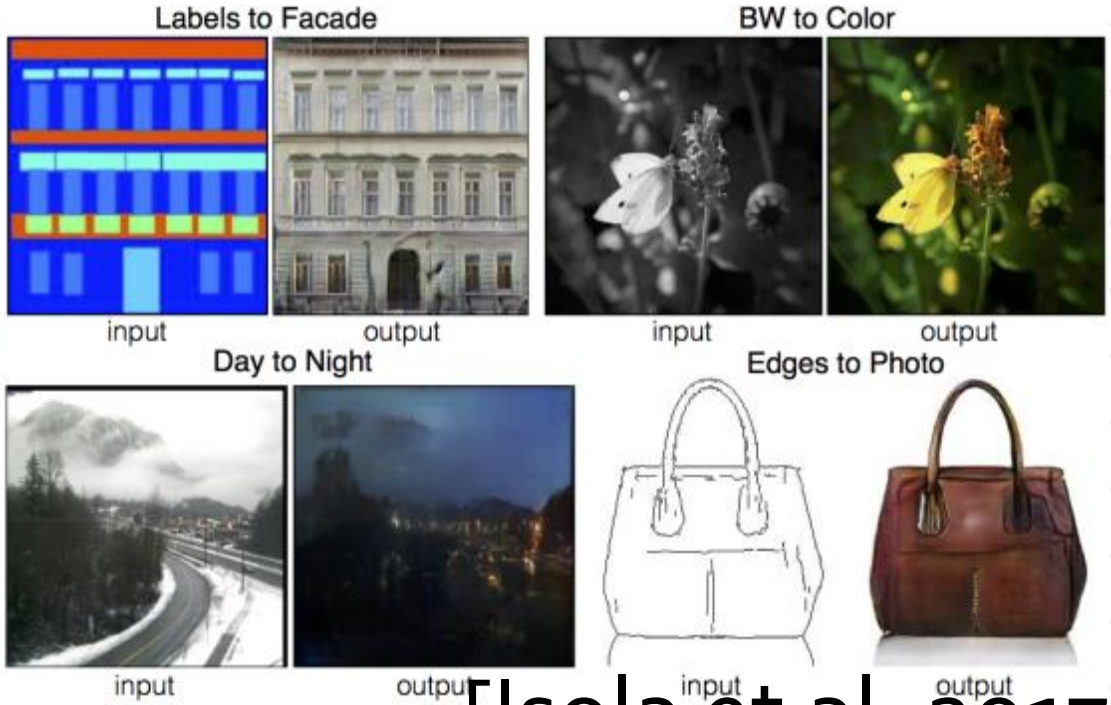
$$g(\arg\min_z \|g(z) - x\|^2)$$

[thanks to ShahRukh Athar]

Are GANs good latent models?

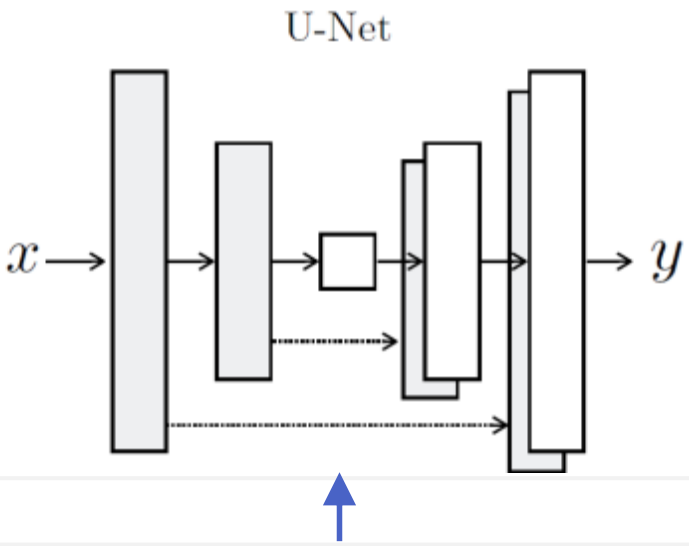
[Zhu et al. 2016]

Pix2pix: an image-conditional GAN

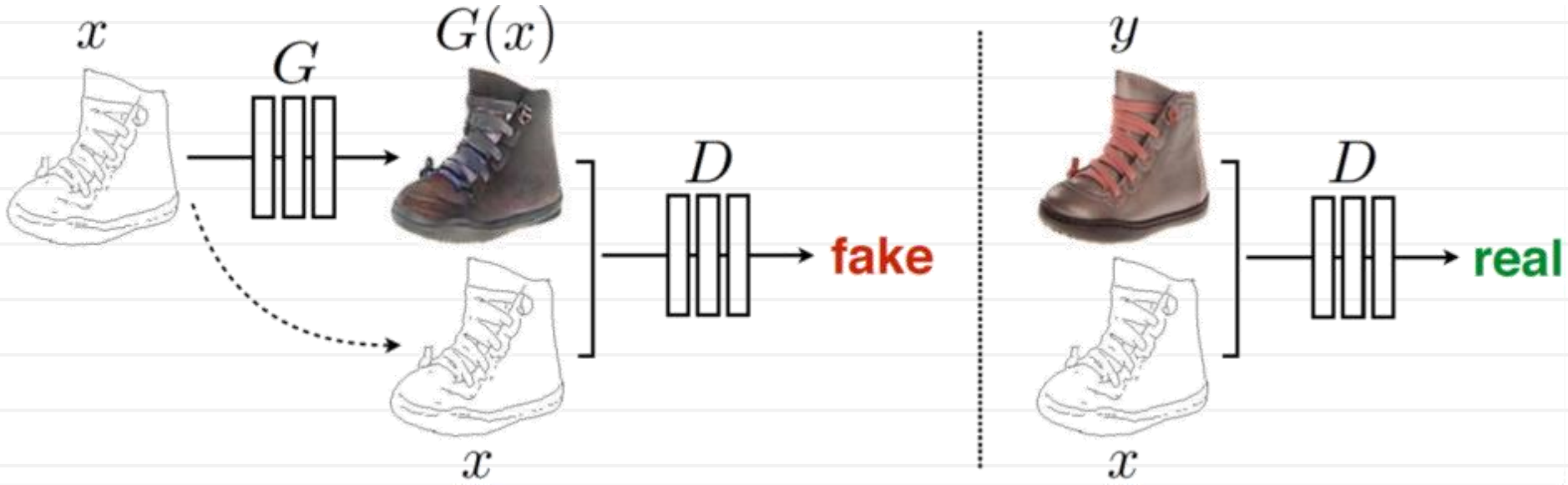


[Isola et al. 2017]

Pix2pix: a conditional GAN



- Use a combination of L1-loss and adversarial loss
- Adversarial loss is computed for patches ("PatchGAN")



[Isola et al. 2017]

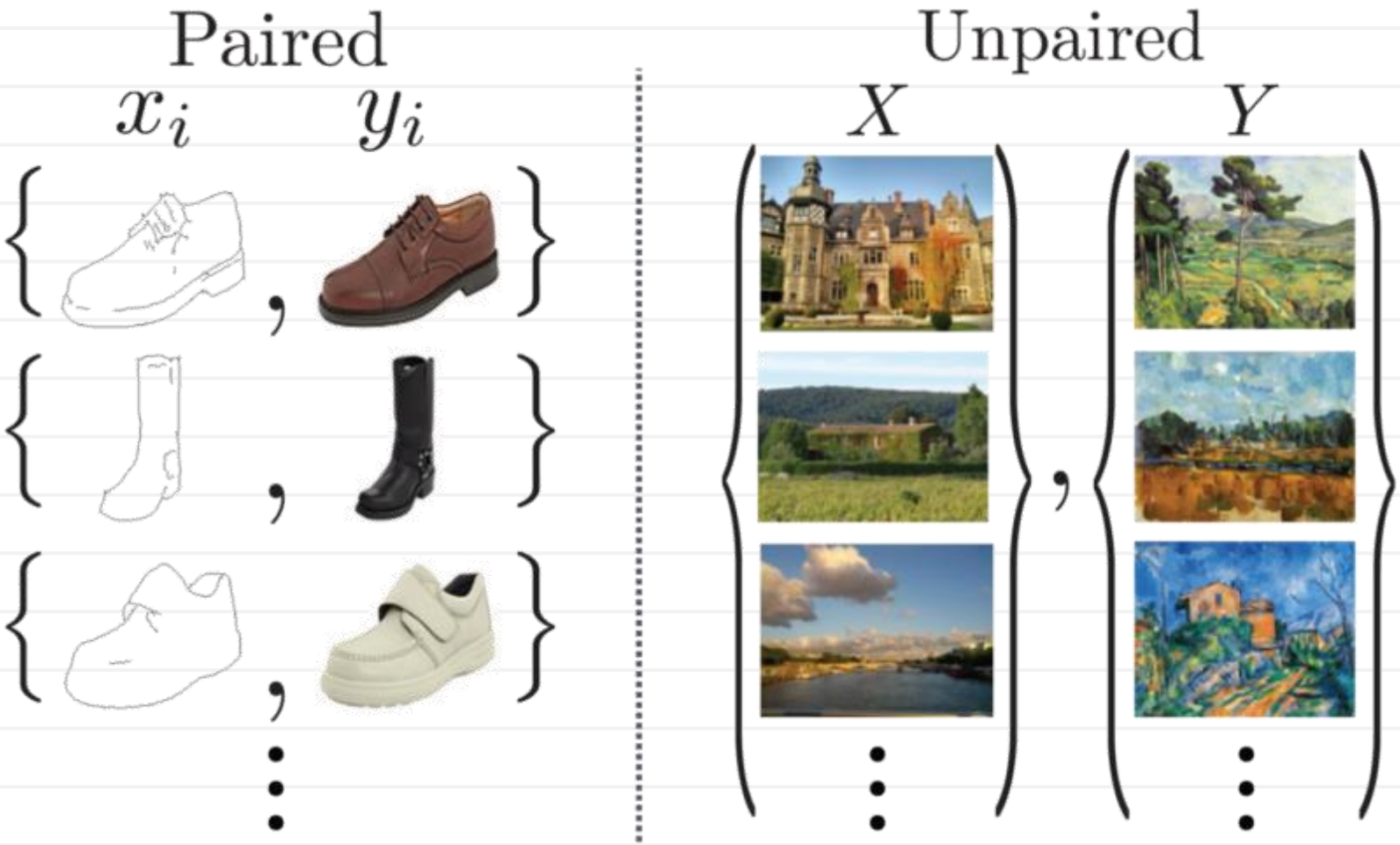
GAN still fails at multi-modal tasks

Impressive generalizations:

Colorization examples (still model collapse):

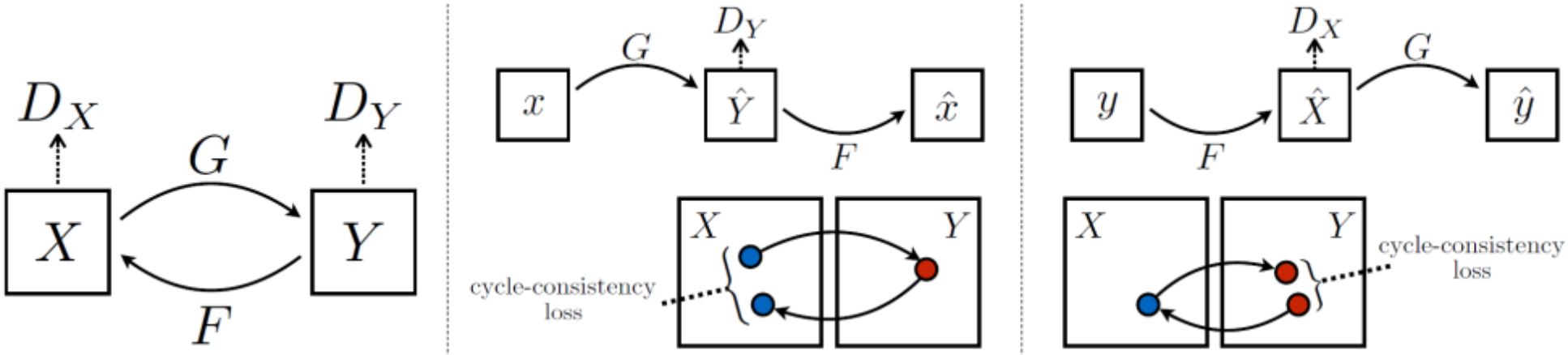
[Isola et al. 2017]

Unaligned image translation: CycleGAN



[Zhu et al. ICCV 2017]

Unaligned image translation: CycleGAN



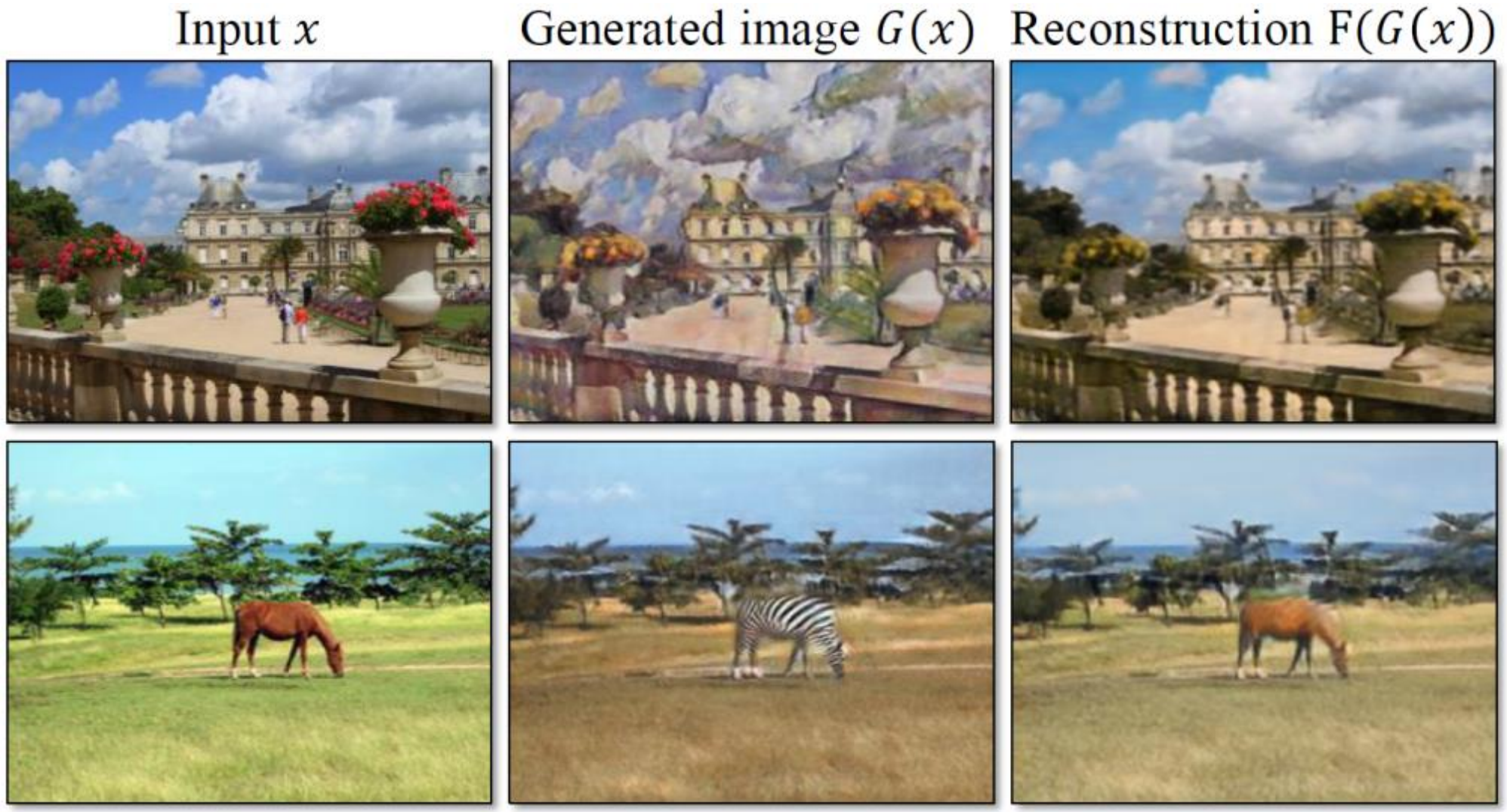
$$L_{\text{adv}} = \mathbb{E}_{x \sim X}\left[\sum_p -\log D_y(G(x)[p])\right]$$

$$L_{\text{cycle}} = \mathbb{E}_{x \sim X}\left[\|F(G(x)) - x\|_1\right]$$

$$L_{\text{identity}} = \mathbb{E}_{y \sim Y}\left[\|G(y) - y\|^2\right]$$

[Zhu et al. ICCV 2017]

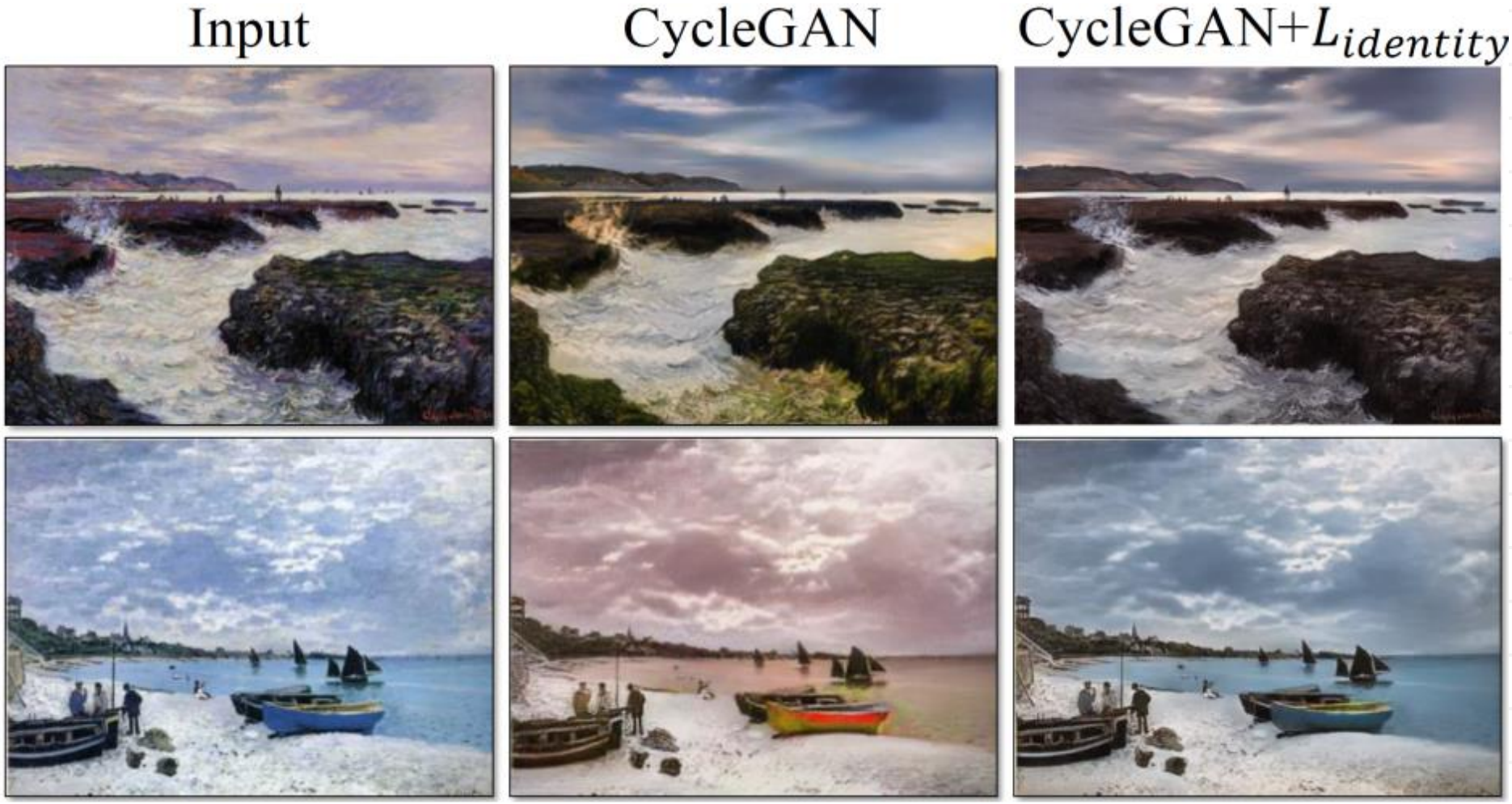
Unaligned image translation: CycleGAN



[Zhu et al. ICCV 2017]

Identity loss: useful component

$$L_{\text{identity}} = \mathbb{E}_{y \sim Y}\left[\|G(y) - y\|^2\right]$$

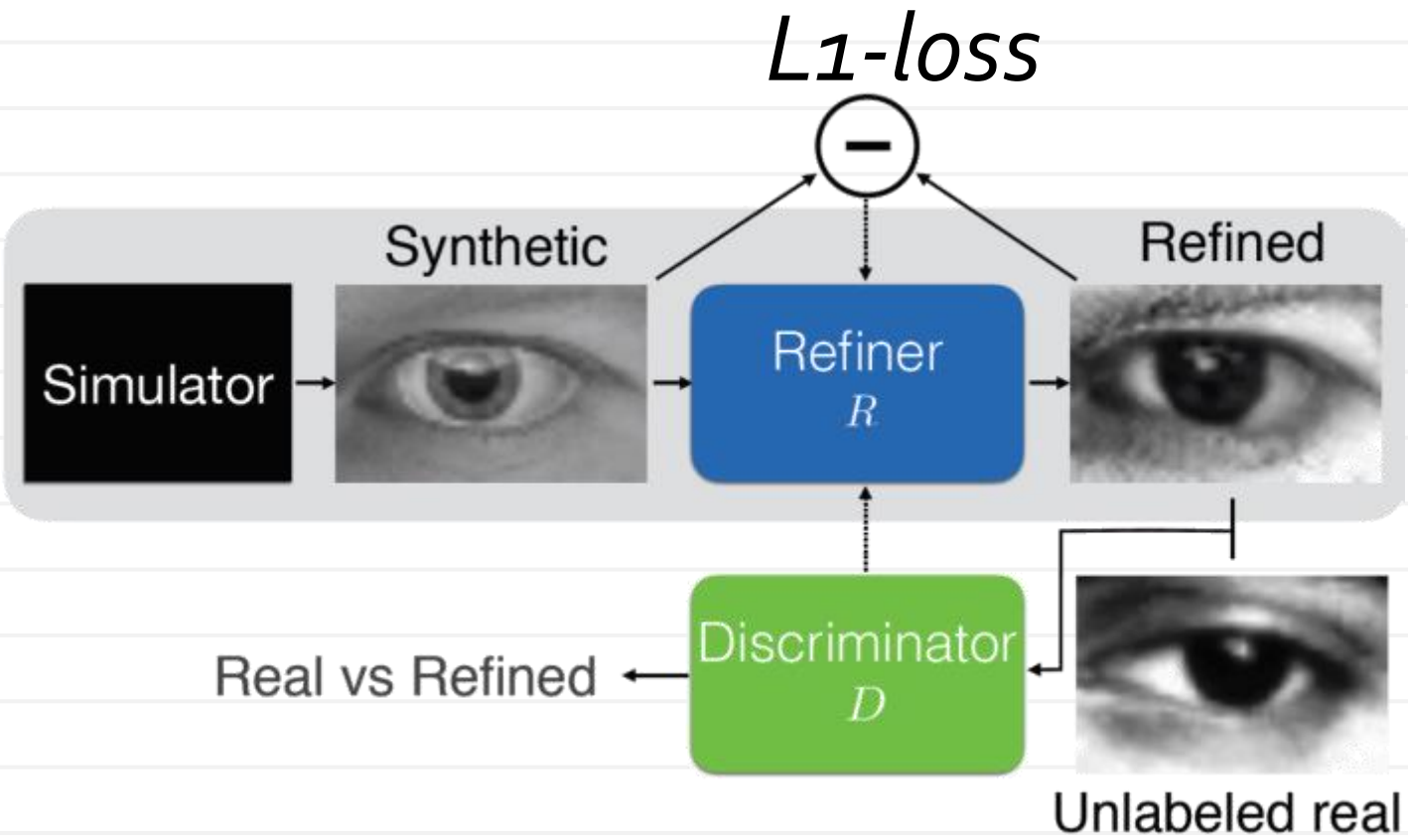


[Zhu et al. ICCV 2017]

Superresolution with GANs

[Ledig et al. 2017]

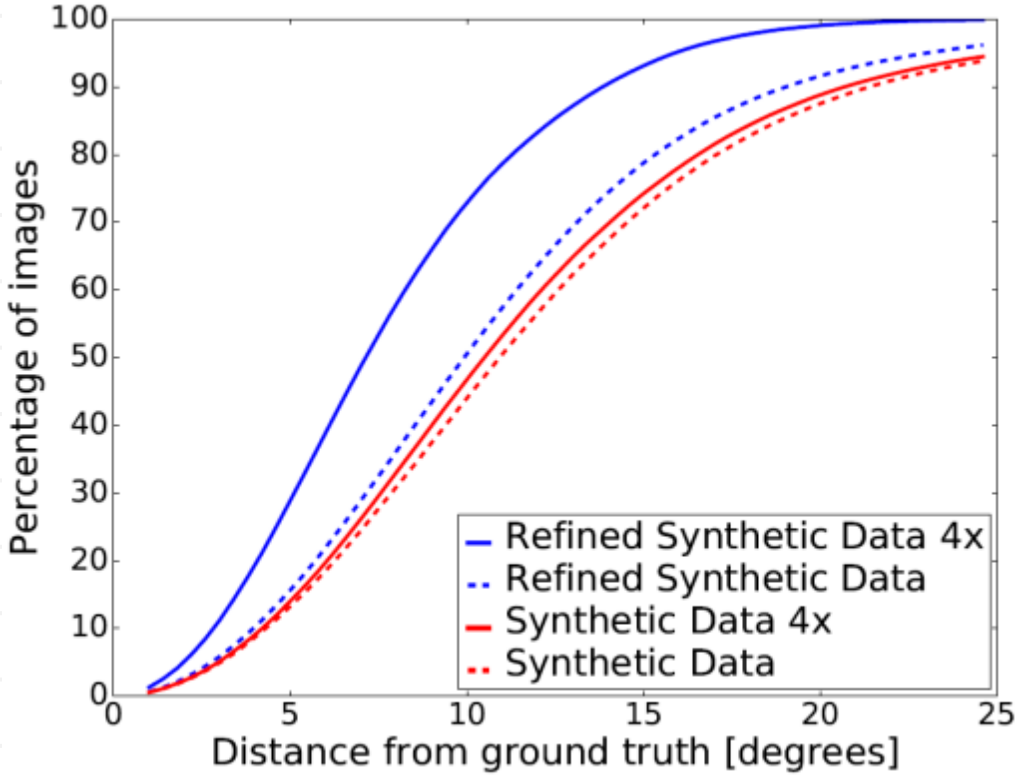
GAN for generating synthetic training data



- Using local (PatchGAN-type)discriminators
- Using history-based regularization of discriminators

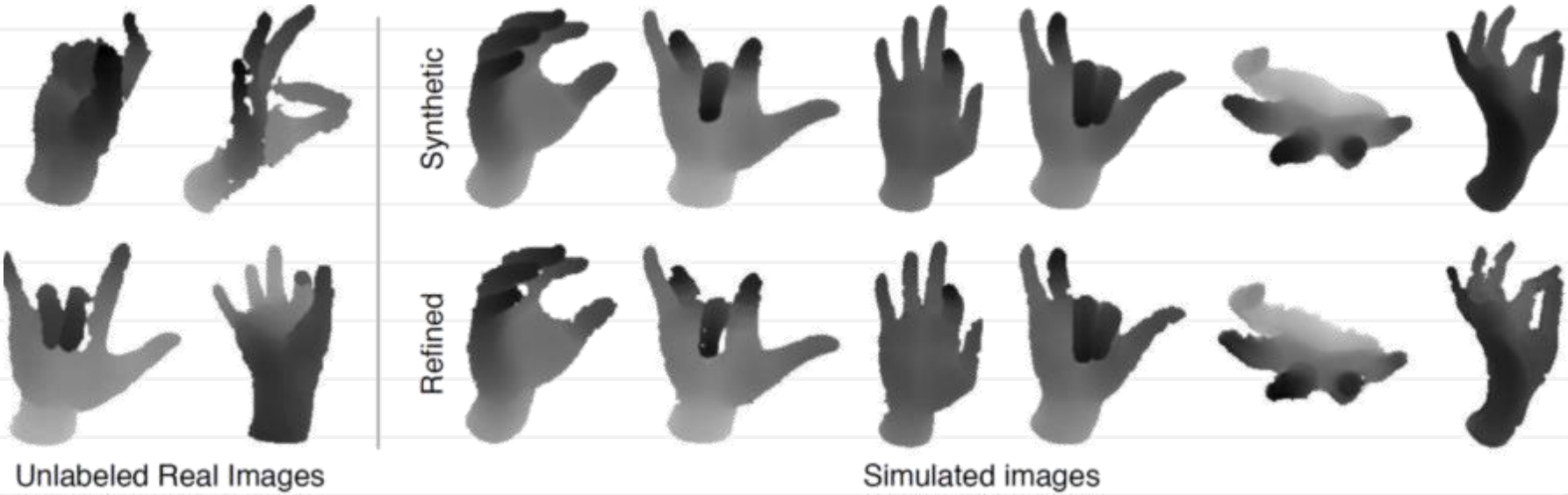
[Srivastava et al. CVPR17]

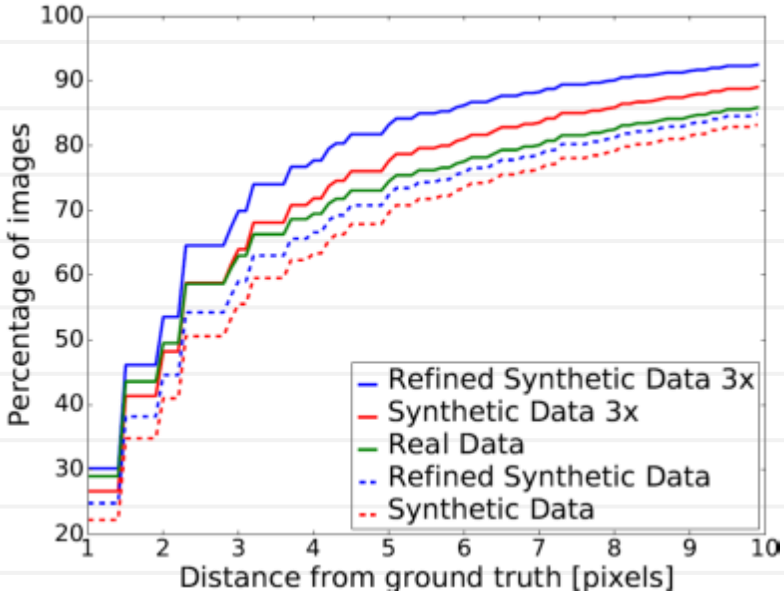
GAN for generating synthetic training data



[Srivastava et al. CVPR17]

GAN for generating synthetic training data





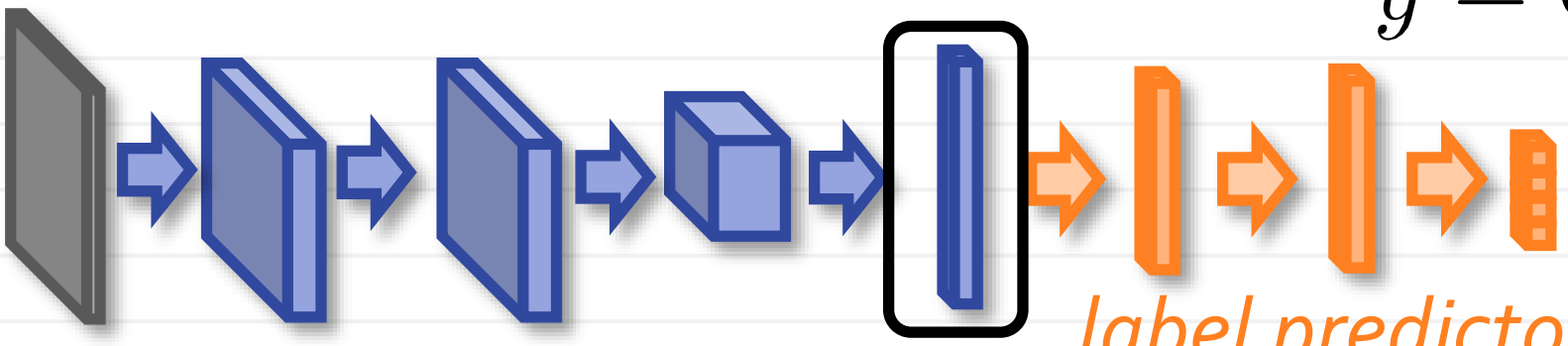
[Srivastava et al. CVPR17]

More examples: (semi-)synthetic to real

Domain shift inside a deep architecture

$$\mathbf{f} = G_f(\mathbf{x}; \theta_f)$$

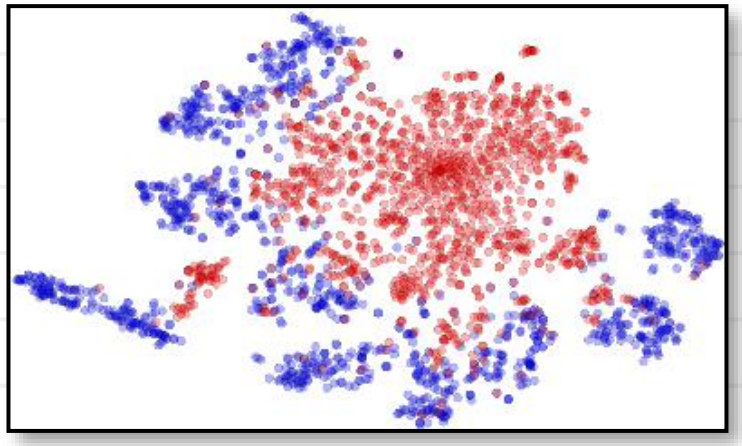
$$y = G_y(\mathbf{f}; \theta_y)$$



feature extractor

label predictor

When trained on source only, feature distributions do not match:



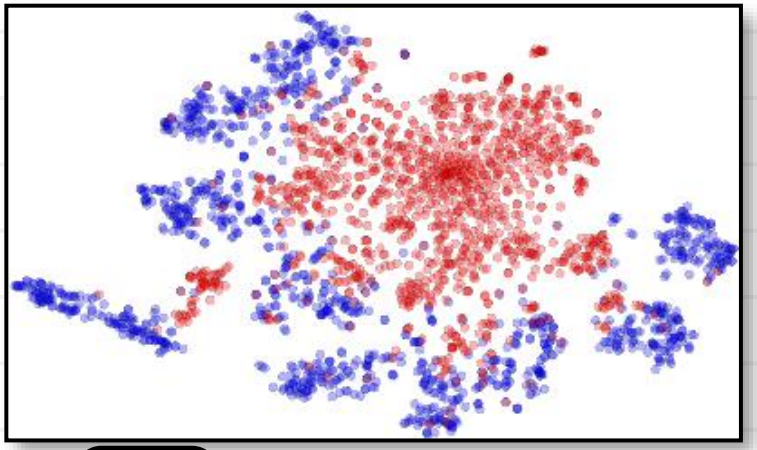
$$S(\mathbf{f}) = \{G_f(\mathbf{x}; \theta_f) \,|\, \mathbf{x} \sim S(\mathbf{x})\}$$

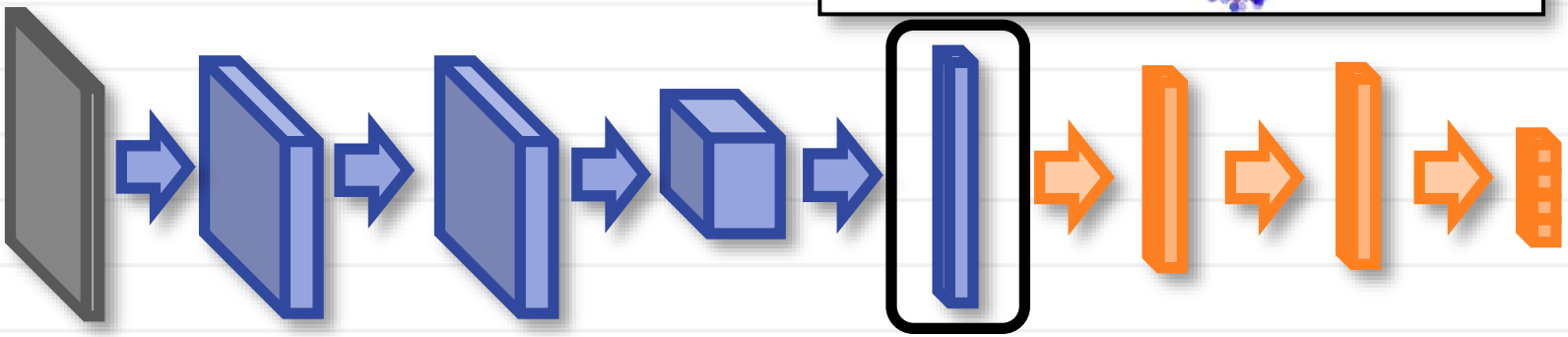
$$T(\mathbf{f}) = \{G_f(\mathbf{x}; \theta_f) \,|\, \mathbf{x} \sim T(\mathbf{x})\}$$

[Ganin et al. 2015]

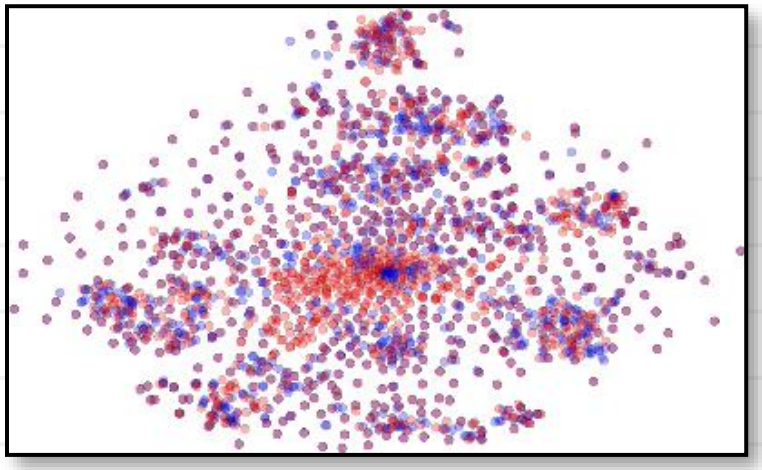
Idea 1: domain-invariant features wanted

Feature distribution without adaptation:



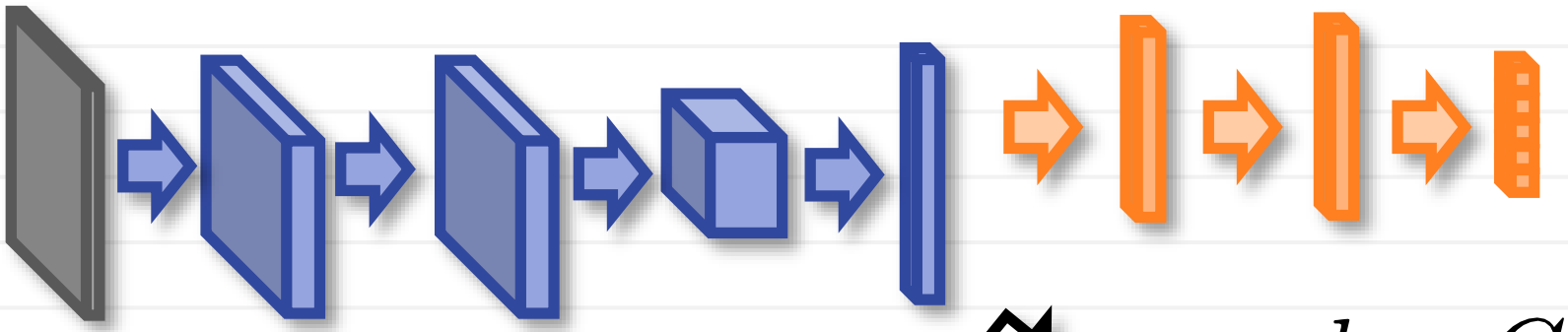


Our goal (after adaptation):



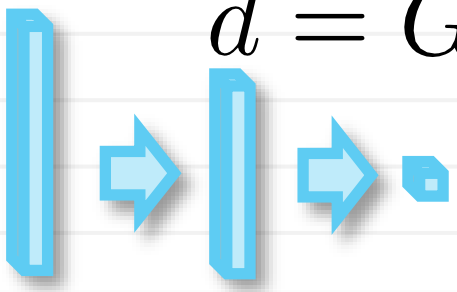
[Ganin et al. 2015]

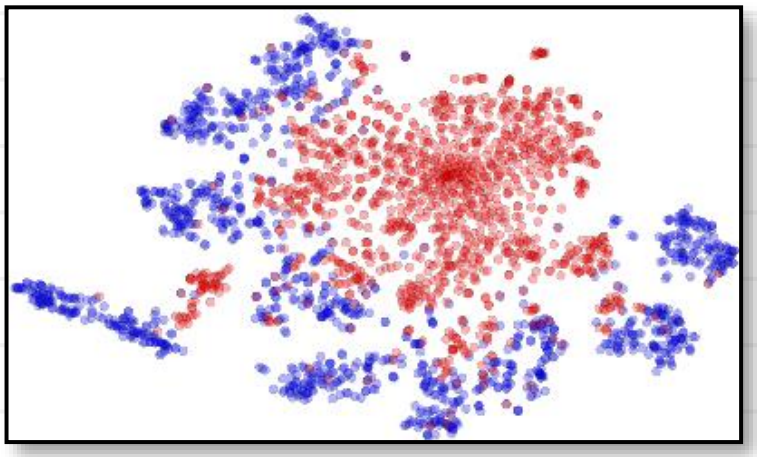
Idea 2: measuring domain shift



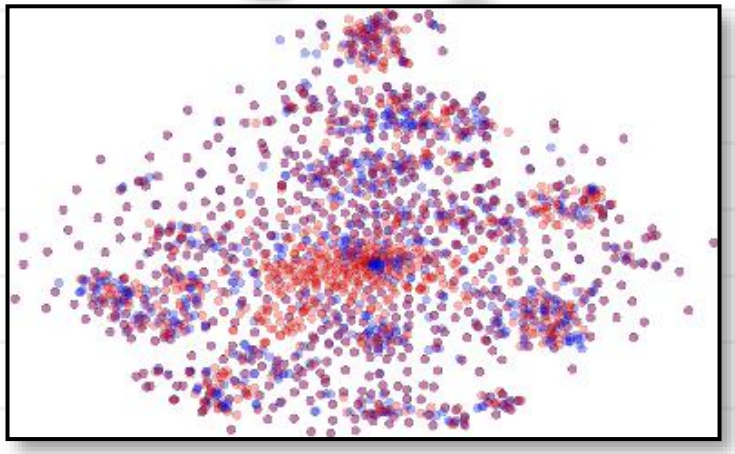
$$d = G_d(\mathbf{f}; \theta_d)$$

Domain classifier:





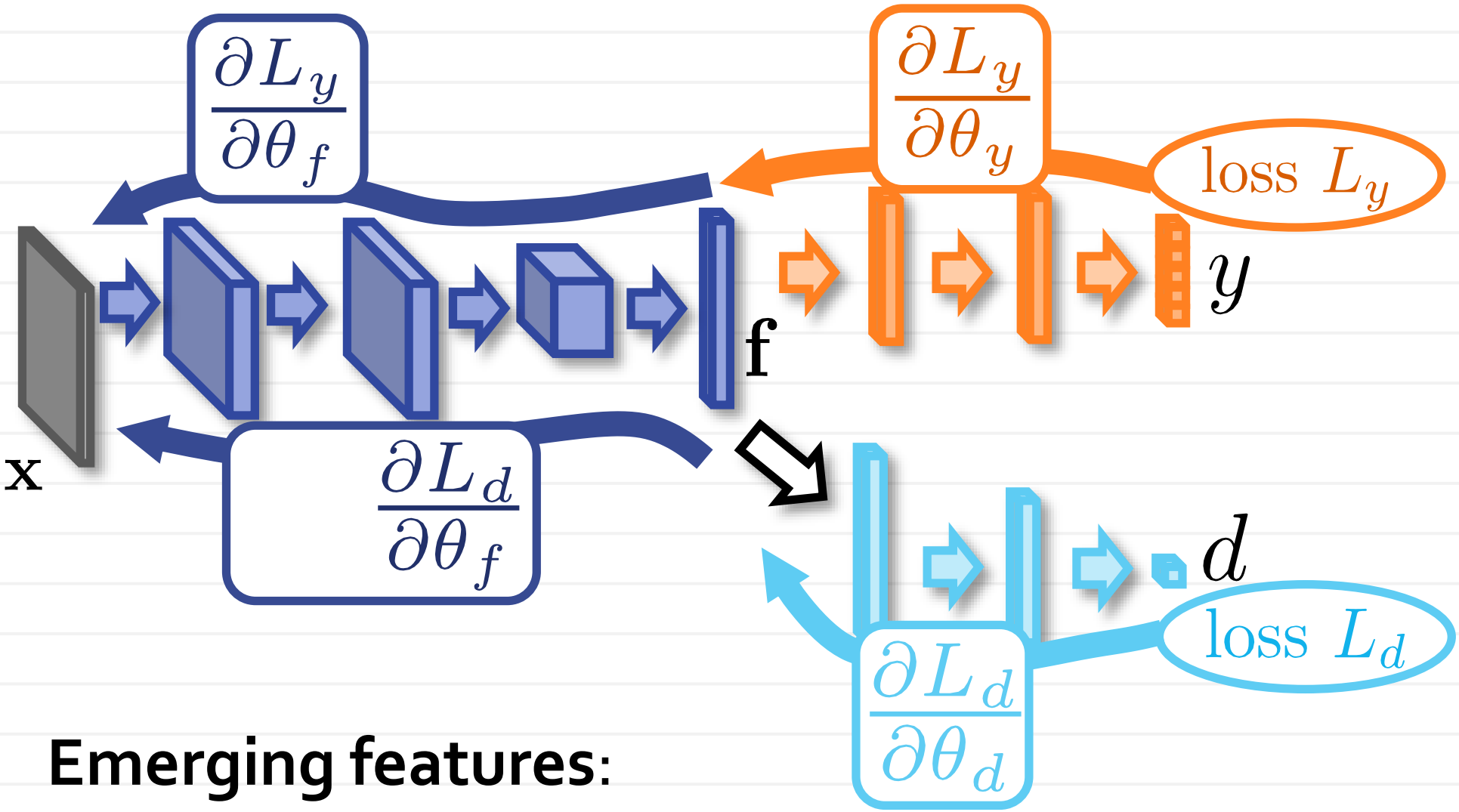
Domain loss low



Domain loss high

[Ganin et al. 2015]

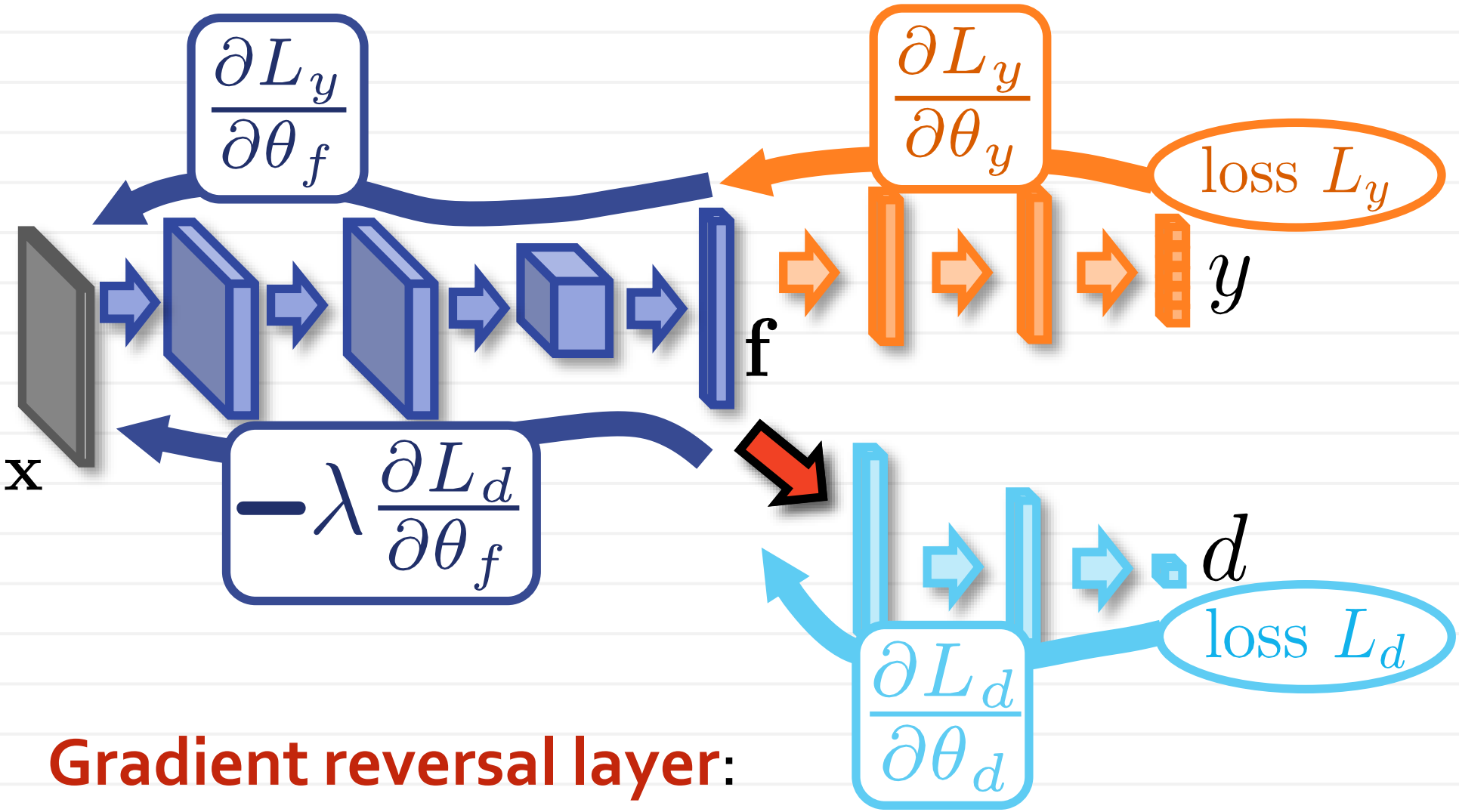
Idea 3: minimizing domain shift



Emerging features:

- Discriminative (good for predicting *y*)
- Domain-discriminative (good for predicting *d*)

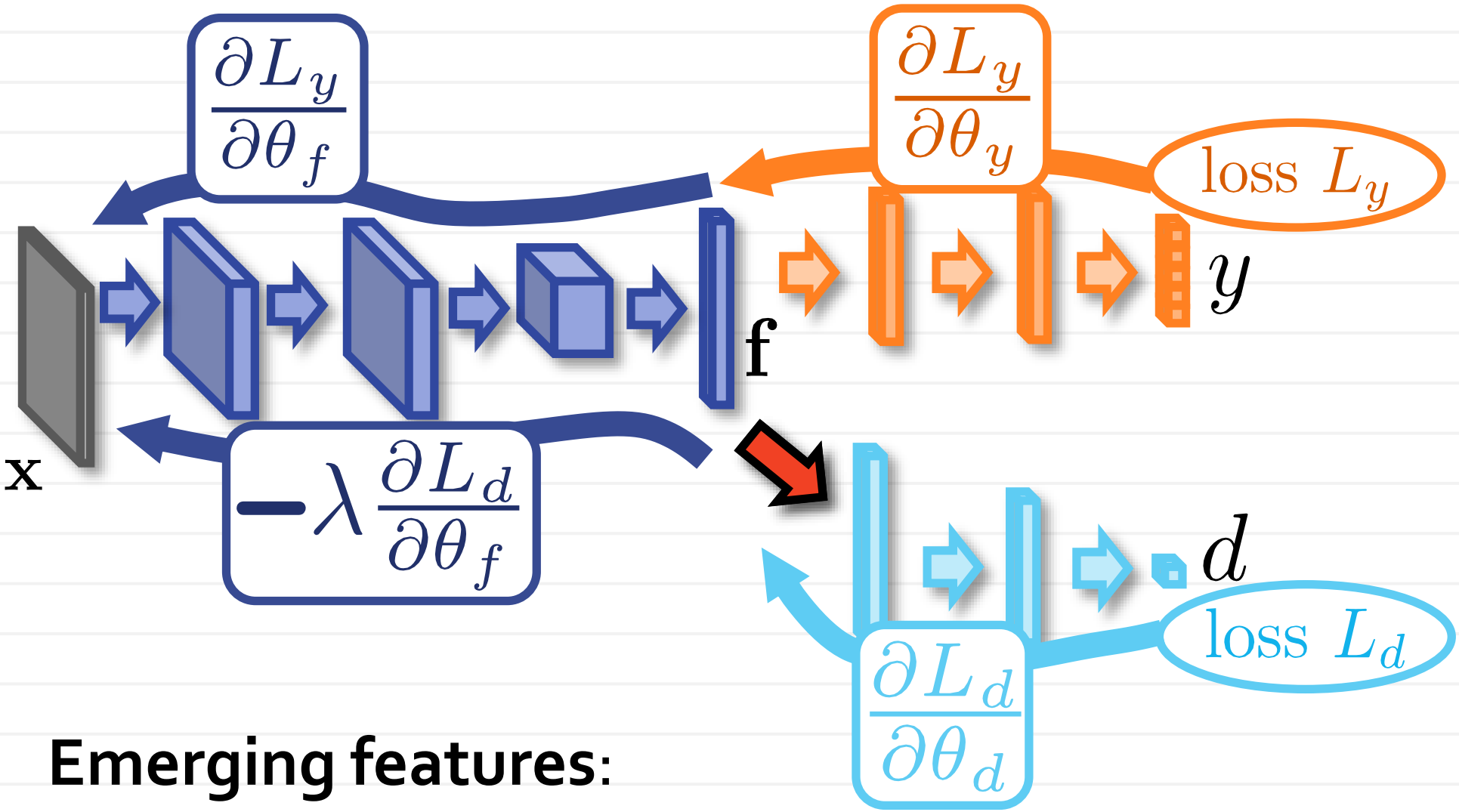
Idea 3: minimizing domain shift



Gradient reversal layer:

- Copies data without change at forwardprop
- Multiplies the gradient by -λ at backprop

Idea 3: minimizing domain shift



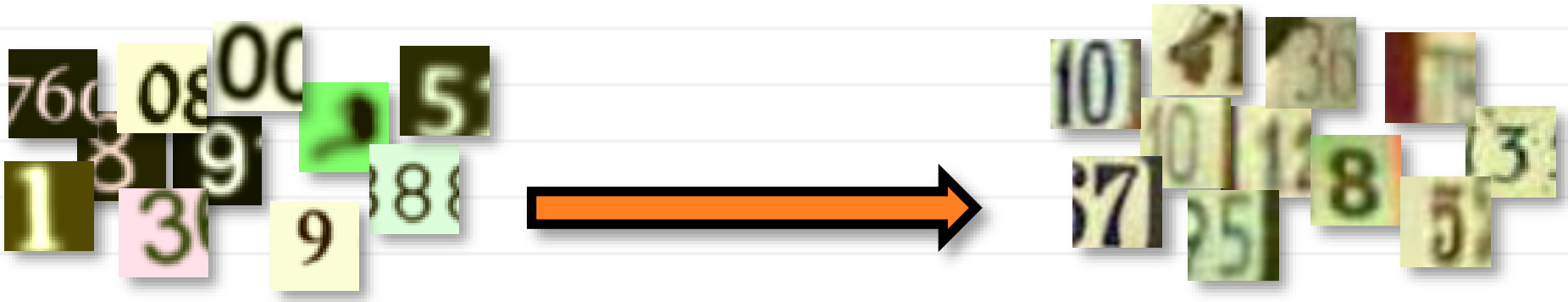
Emerging features:

- Discriminative (good for predicting *y*)
- Domain-invariant (not good for predicting *d*)

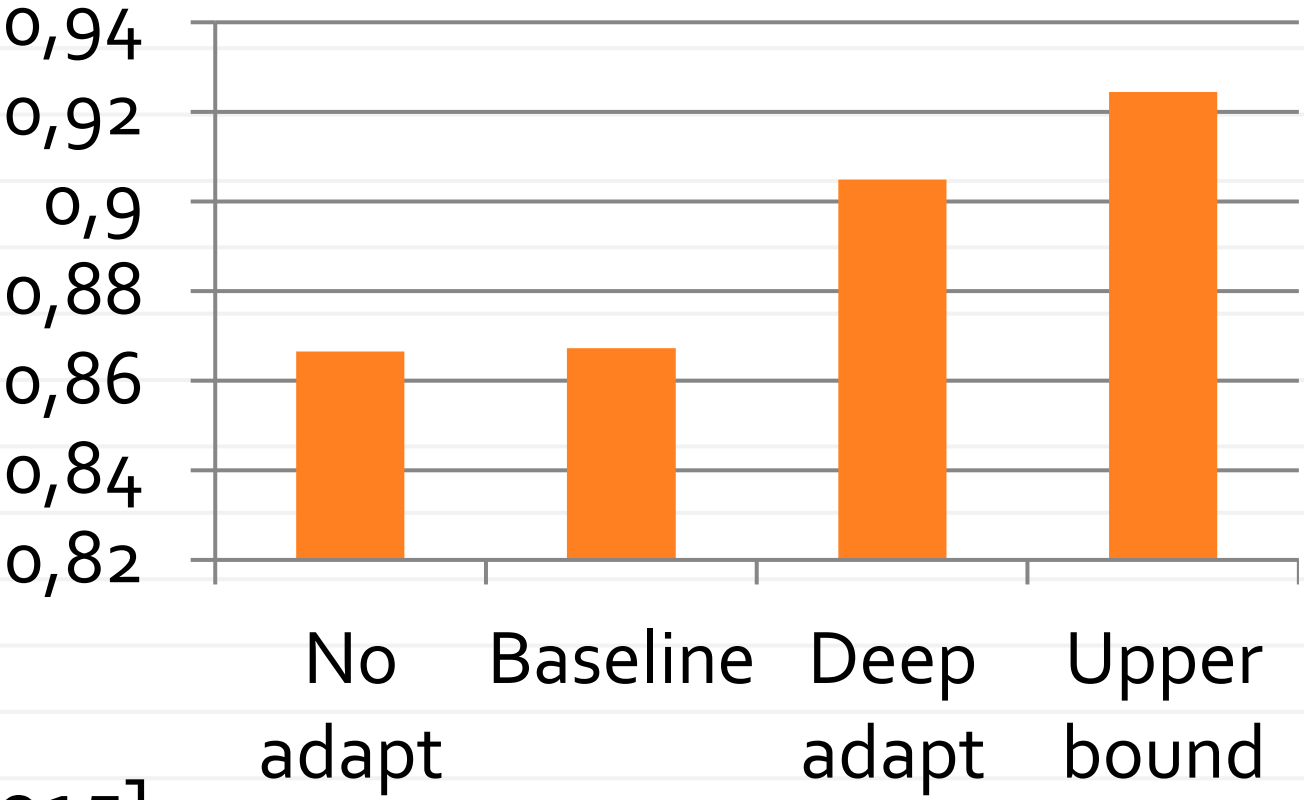
Gradient reversal layer

```
class GradReversalLayer : Layer {

        float lambda;

        blob forward (blob x)      {
                return x
        }

        blob backward(blob dzdy) {
                return multiply(dzdy, -lambda)
        }
}
```

Example: from synthetic to real

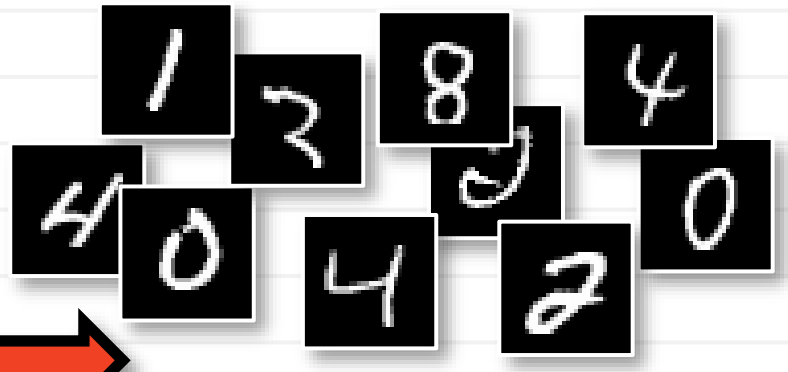


"Windows digits" "House numbers"



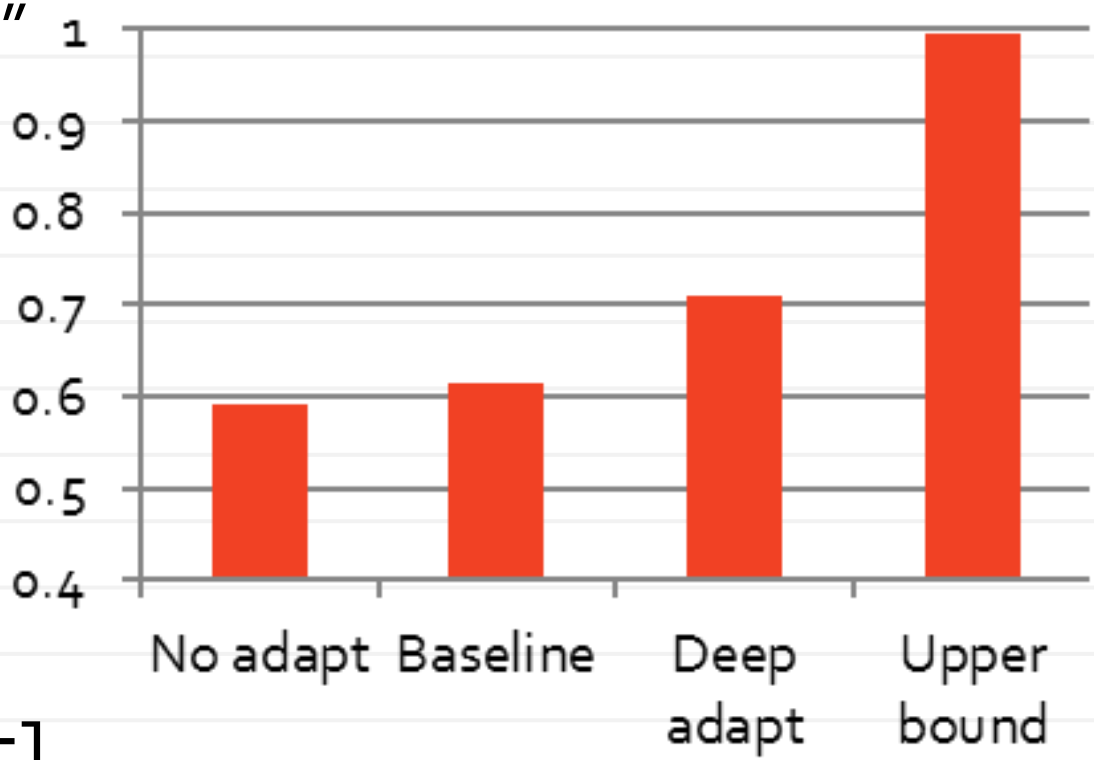
[Ganin et al. 2015]

Example: large gap



MNIST

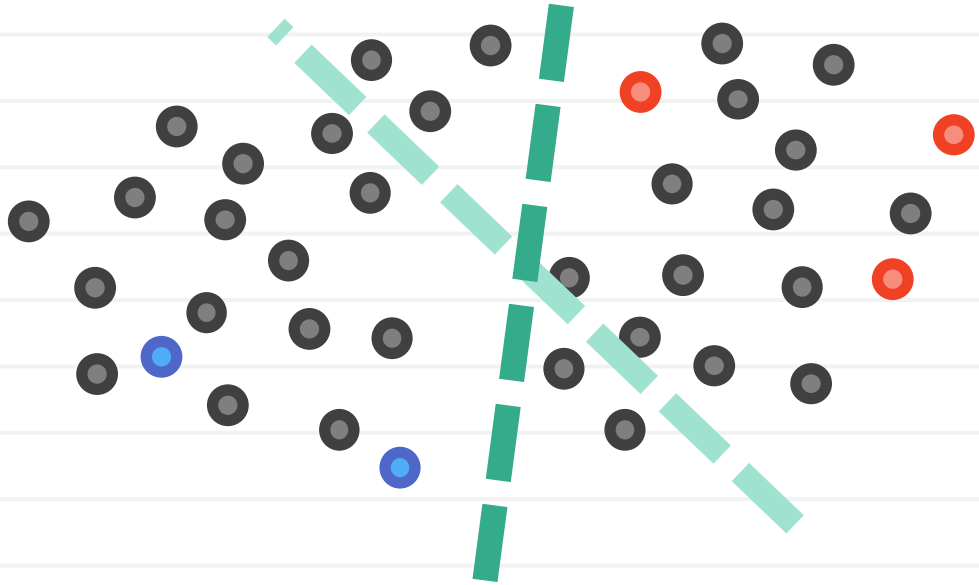
"House numbers"



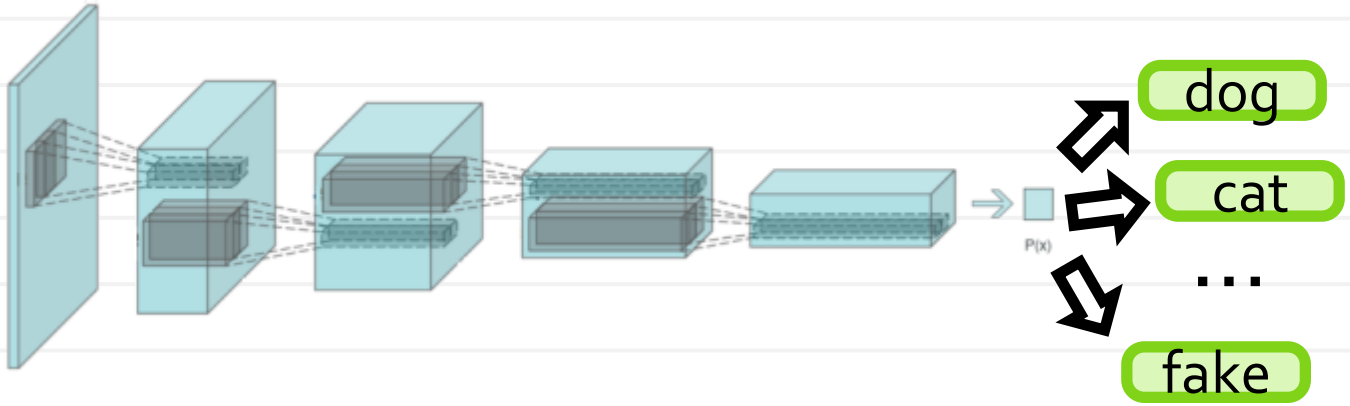
Reverse direction does not work ☹

[Ganin et al. 2015]

Semi-supervised learning



New discriminator/classifier:



[Salimans et al. 2016]

Semi-supervised learning

$$\max_f = \mathbb{E}_{x,y\sim(X,Y)} \log \frac{f(x)[y]}{1 - f(x)[K+1]}$$

Standard log-loss

$$+ \mathbb{E}_{x\sim X}\left[\log(1 - f(x)[K+1])\right]$$

$$+ \mathbb{E}_{z\sim Z}\left[\log f(g(z))[K+1]\right]$$

Unsupervised loss

Perturbed MNIST results:

Model	Number of incorrectly predicted test examples for a given number of labeled samples			
	20	50	100	200
DGN [21]			333 ± 14	
Virtual Adversarial [22]			212	
CatGAN [14]			191 ± 10	
Skip Deep Generative Model [23]			132 ± 7	
Ladder network [24]			106 ± 37	
Auxiliary Deep Generative Model [23]			96 ± 2	
Our model	1677 ± 452	221 ± 136	93 ± 6.5	90 ± 4.2
Ensemble of 10 of our models	1134 ± 445	142 ± 96	86 ± 5.6	81 ± 4.3

[Salimans et al. 2016]

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