

CS5670: Computer Vision

Noah Snaveley

Synthesizing images with generative adversarial networks (GANs)



Automatically generated celebrities via GANs

Readings

- NIPS 2016 Tutorial on GANs
 - <https://arxiv.org/abs/1701.00160>

Announcements

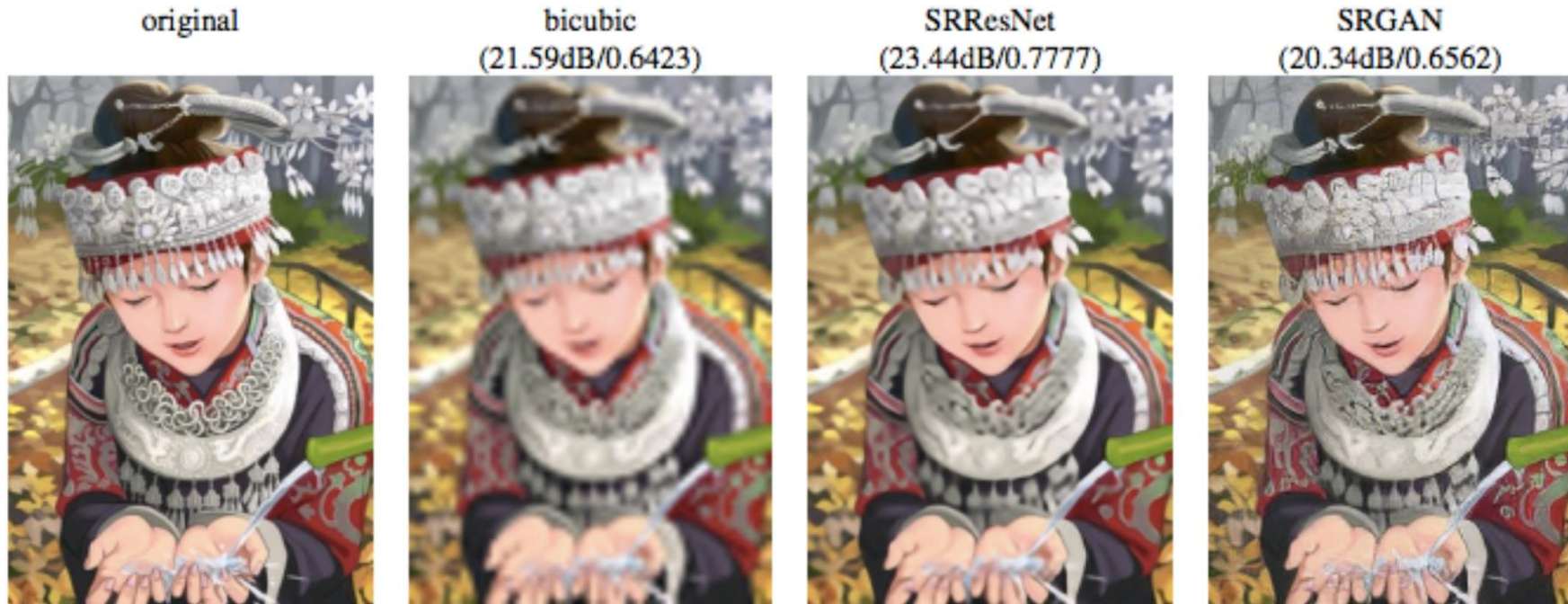
- Project 5 due Monday, 5/14 at 11:59pm
- Reminder: Course evals (5 bonus points)
 - <https://apps.engineering.cornell.edu/CourseEval>
- Final exam in class on Wednesday
 - Please arrange yourselves with at least one space between you and the closest person in the same row when you arrive

Today

- Generative adversarial networks
- Course review

Motivation: Synthesizing images

Single Image Super-Resolution



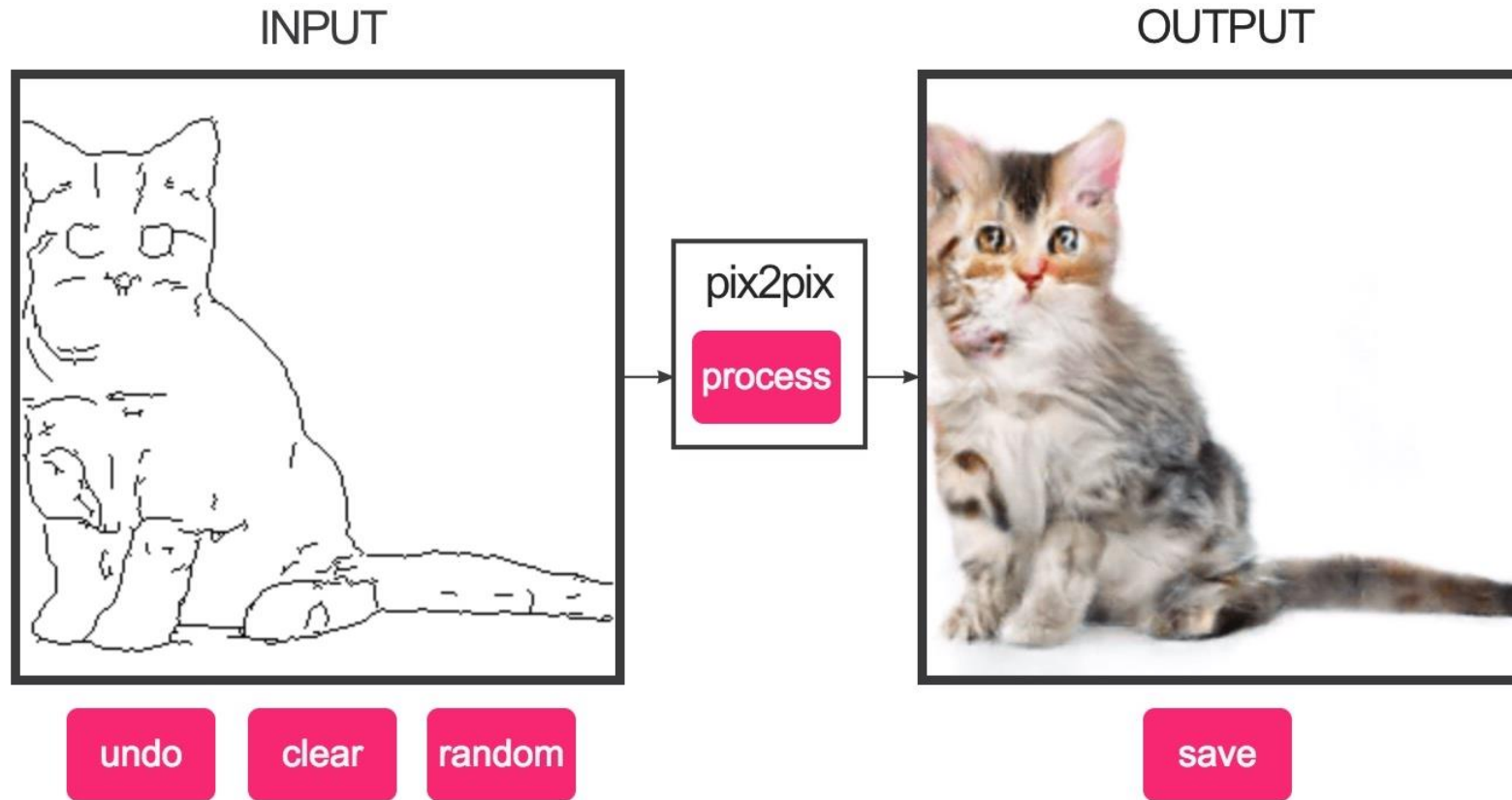
(Ledig et al 2016)

Motivation: Synthesizing images

Image to Image Translation



Demo

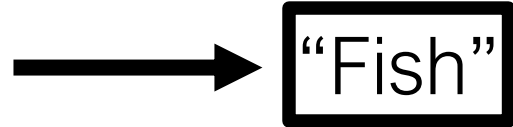


<https://affinelayer.com/pixsrv/>

Image classification



image X



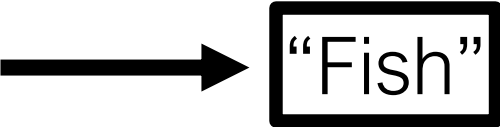
“Fish”

label Y

Image classification



image X



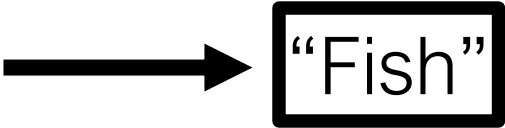
"Fish"

label Y

Image classification



image X



label Y

Image classification



⋮

image X

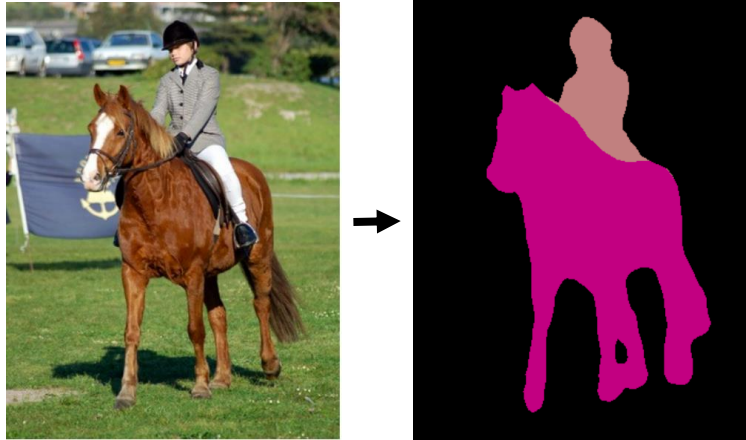


“Fish”

label Y

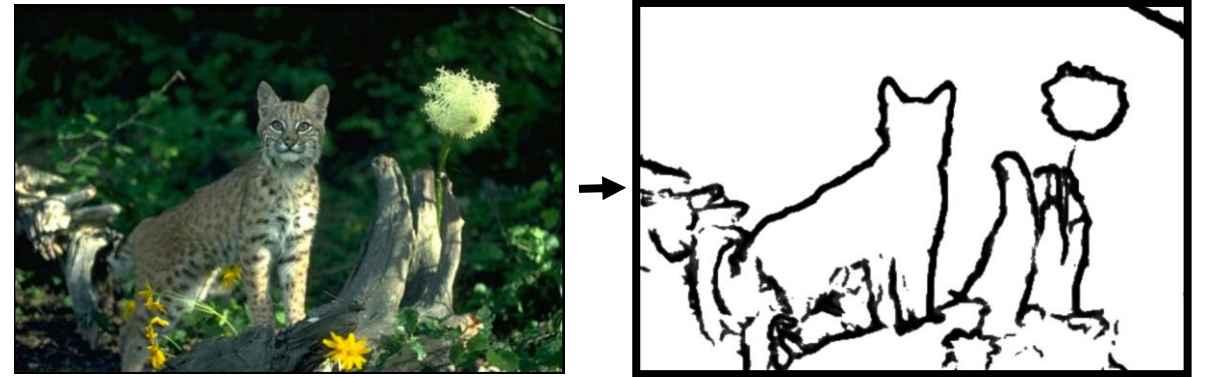
Image prediction (“structured prediction”)

Object labeling



[Long et al. 2015, ...]

Edge Detection



[Xie et al. 2015, ...]

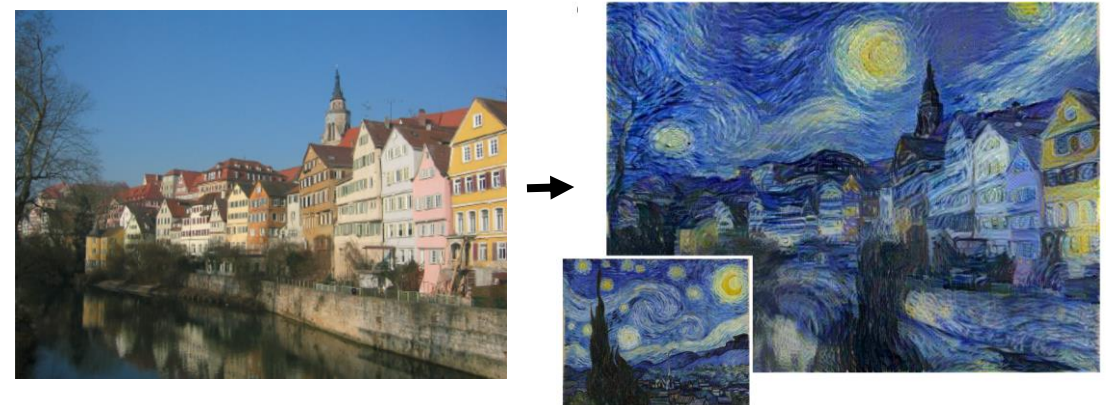
Text-to-photo

“this small bird has a pink breast and crown...”



[Reed et al. 2014, ...]

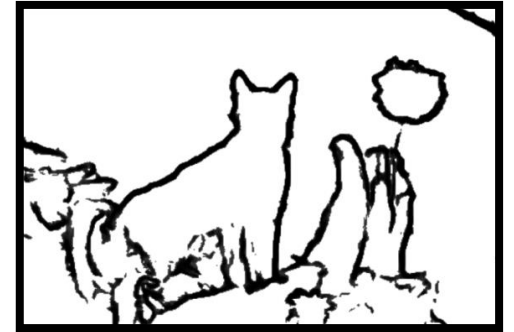
Style transfer



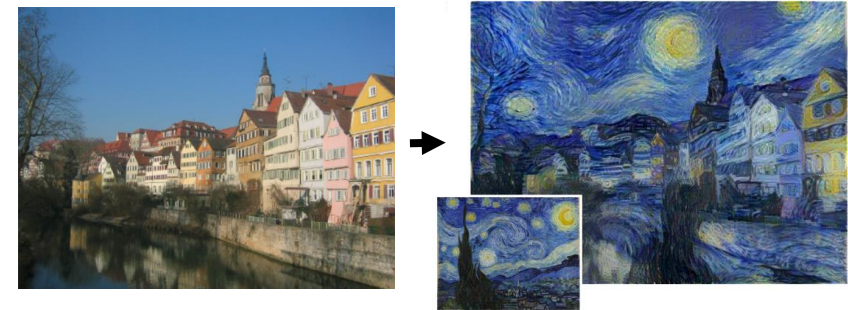
[Gatys et al. 2016, ...]

Challenges

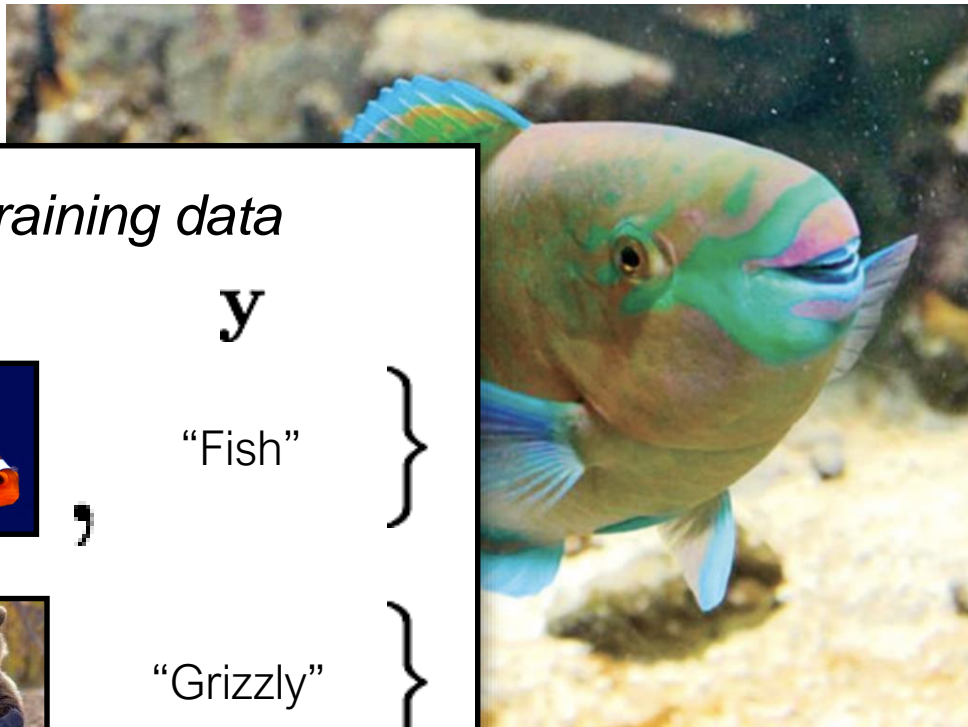
1. Output is high-dimensional, structured object
2. Uncertainty in mapping; many plausible outputs
3. Lack of supervised training data



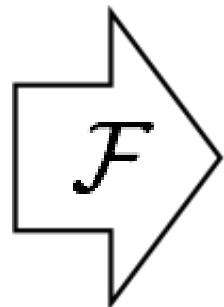
“this small bird has a pink breast and crown...”



\mathbf{x}






\mathbf{y}



“Fish”

Training data

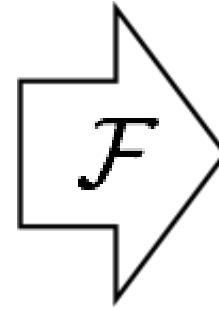
\mathbf{x}	\mathbf{y}
	“Fish”
	“Grizzly”
	“Chameleon”
\vdots	

$$\arg \min_{\mathcal{F}} \mathbb{E}_{\mathbf{x}, \mathbf{y}} [L(\mathcal{F}(\mathbf{x}), \mathbf{y})]$$

Objective function
(loss)

Convolutional Neural Network

\mathbf{x}



\mathbf{y}

“Fish”

$$\arg \min_{\mathcal{F}} \mathbb{E}_{\mathbf{x}, \mathbf{y}} [L(\mathcal{F}(\mathbf{x}), \mathbf{y})]$$

“**What** should I do”

“**How** should I do it?”

Basic loss functions

Prediction: $\hat{\mathbf{y}} = \mathcal{F}(\mathbf{x})$

Truth: \mathbf{y}

Classification (cross-entropy):

$$L(\hat{\mathbf{y}}, \mathbf{y}) = - \sum_i \hat{\mathbf{y}}_i \log \mathbf{y}_i \quad \longleftarrow$$

How many extra bits it takes to correct the predictions

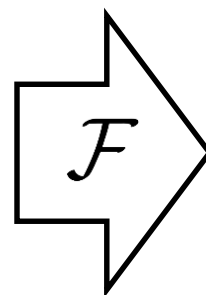
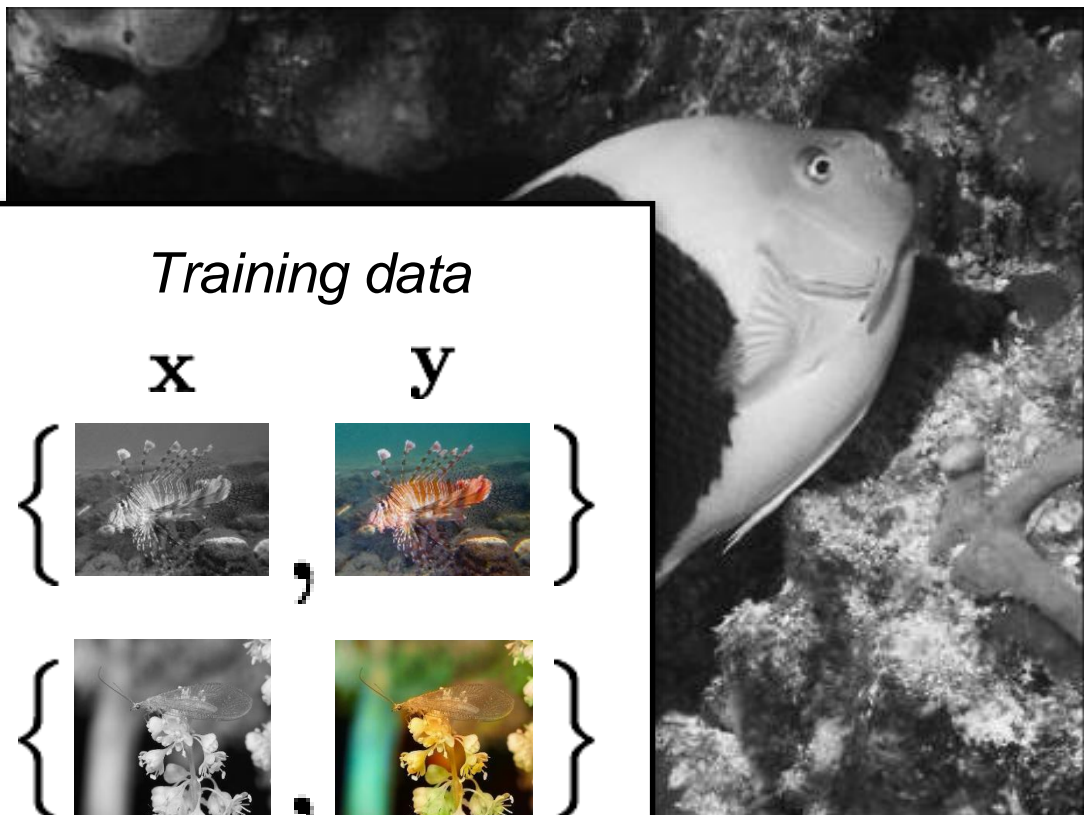
Least-squares regression:

$$L(\hat{\mathbf{y}}, \mathbf{y}) = \|\hat{\mathbf{y}} - \mathbf{y}\|_2 \quad \longleftarrow$$

How far off we are in Euclidean distance

x

y



Training data

x

y



⋮

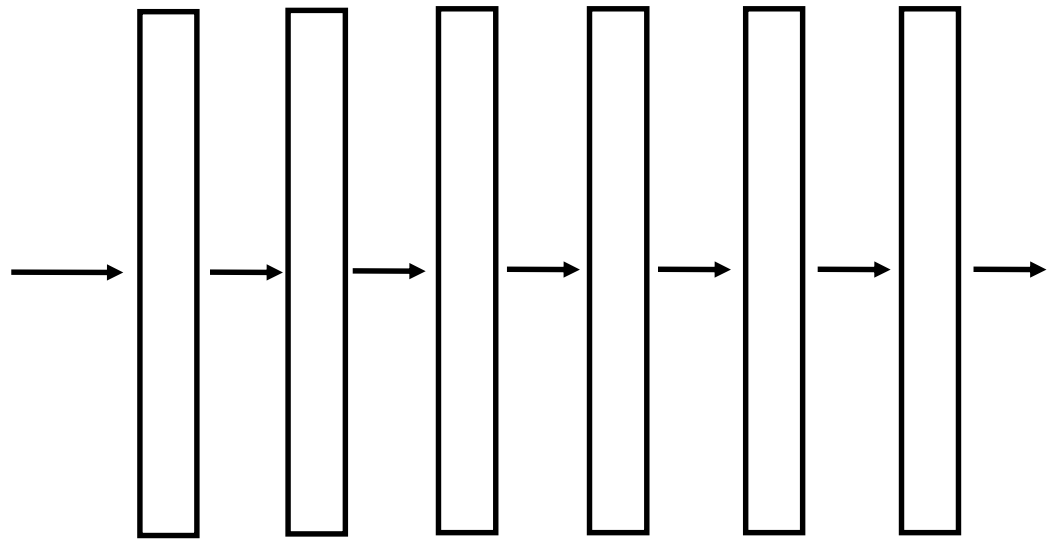
channel

Color information: ab channels

$$\arg \min_{\mathcal{F}} \mathbb{E}_{\mathbf{x}, \mathbf{y}} [L(\mathcal{F}(\mathbf{x}), \mathbf{y})]$$

Objective function
(loss)

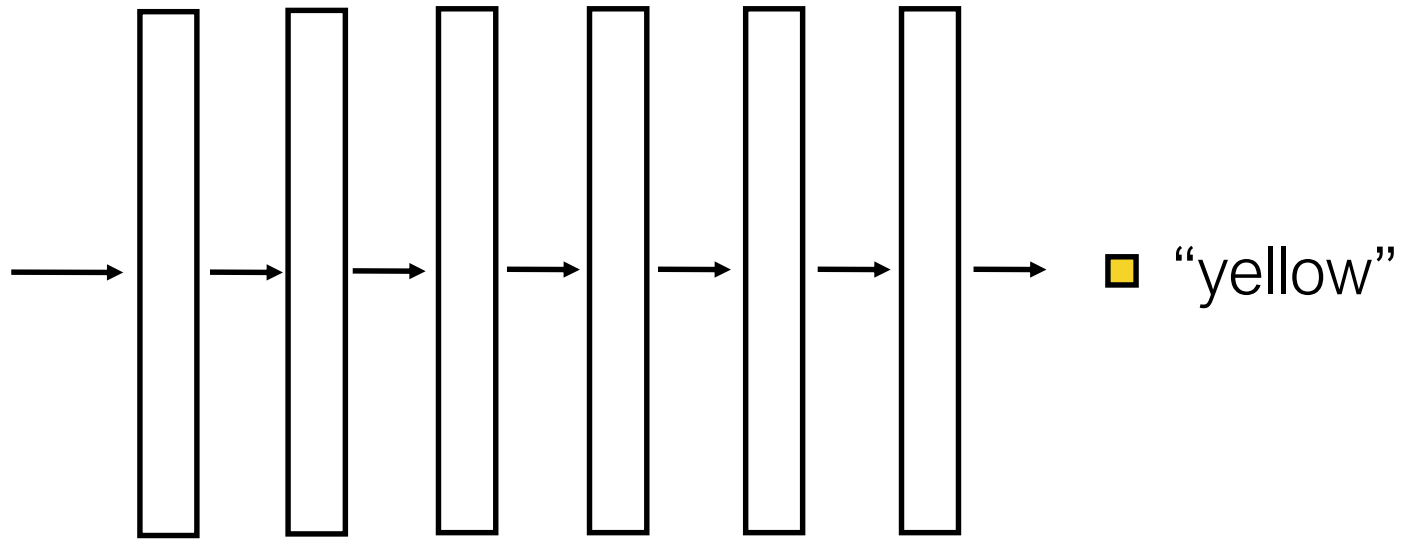
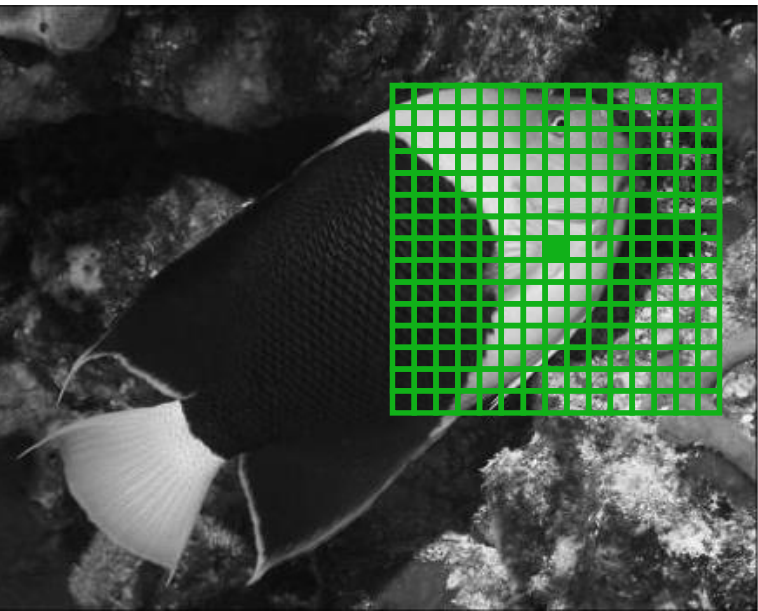
Neural Network



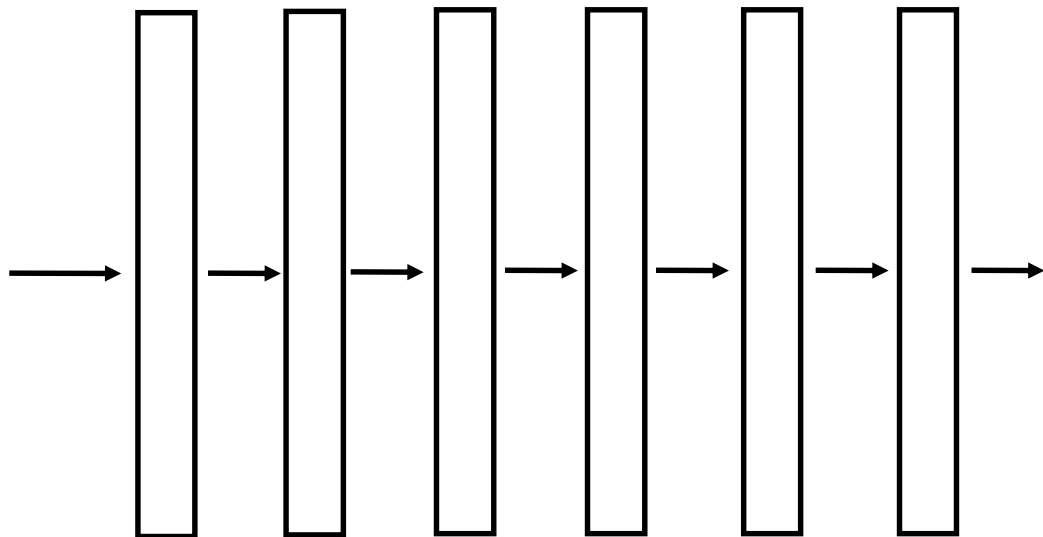
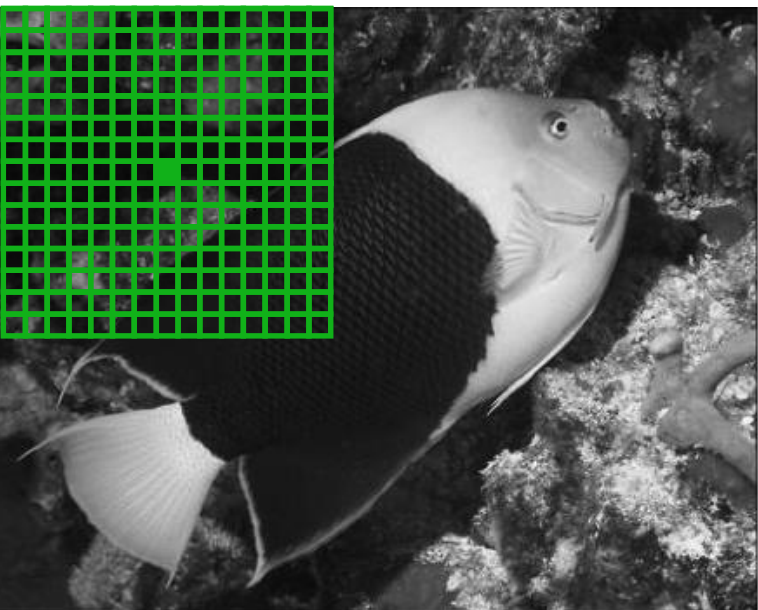
“rockfish”



...



...



Designing loss functions

Input



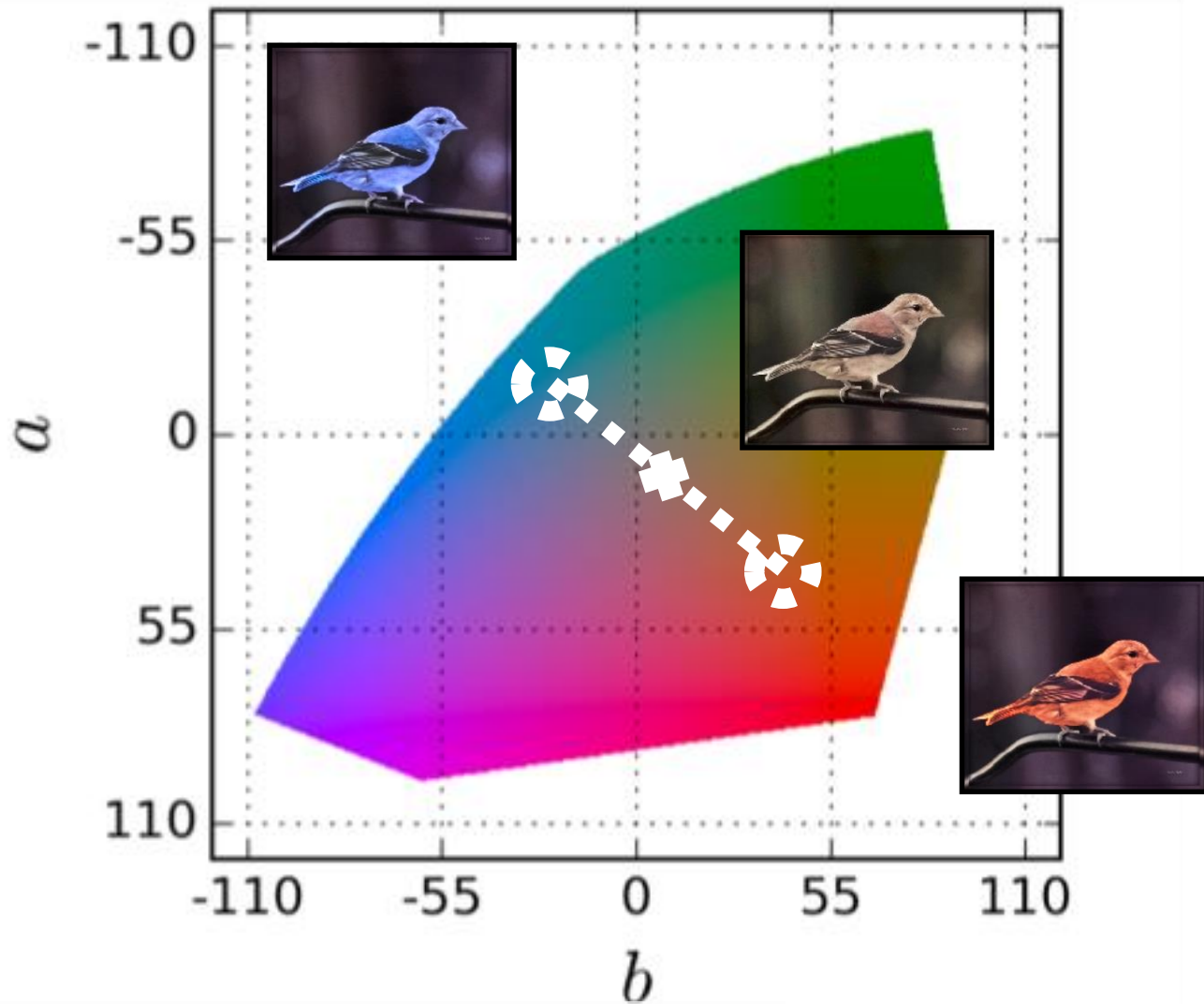
Output



Ground truth



$$L_2(\hat{\mathbf{Y}}, \mathbf{Y}) = \frac{1}{2} \sum_{h,w} \|\mathbf{Y}_{h,w} - \hat{\mathbf{Y}}_{h,w}\|_2^2$$



$$L_2(\hat{\mathbf{Y}}, \mathbf{Y}) = \frac{1}{2} \sum_{h,w} \|\mathbf{Y}_{h,w} - \hat{\mathbf{Y}}_{h,w}\|_2^2$$

Designing loss functions

Input



Zhang et al. 2016

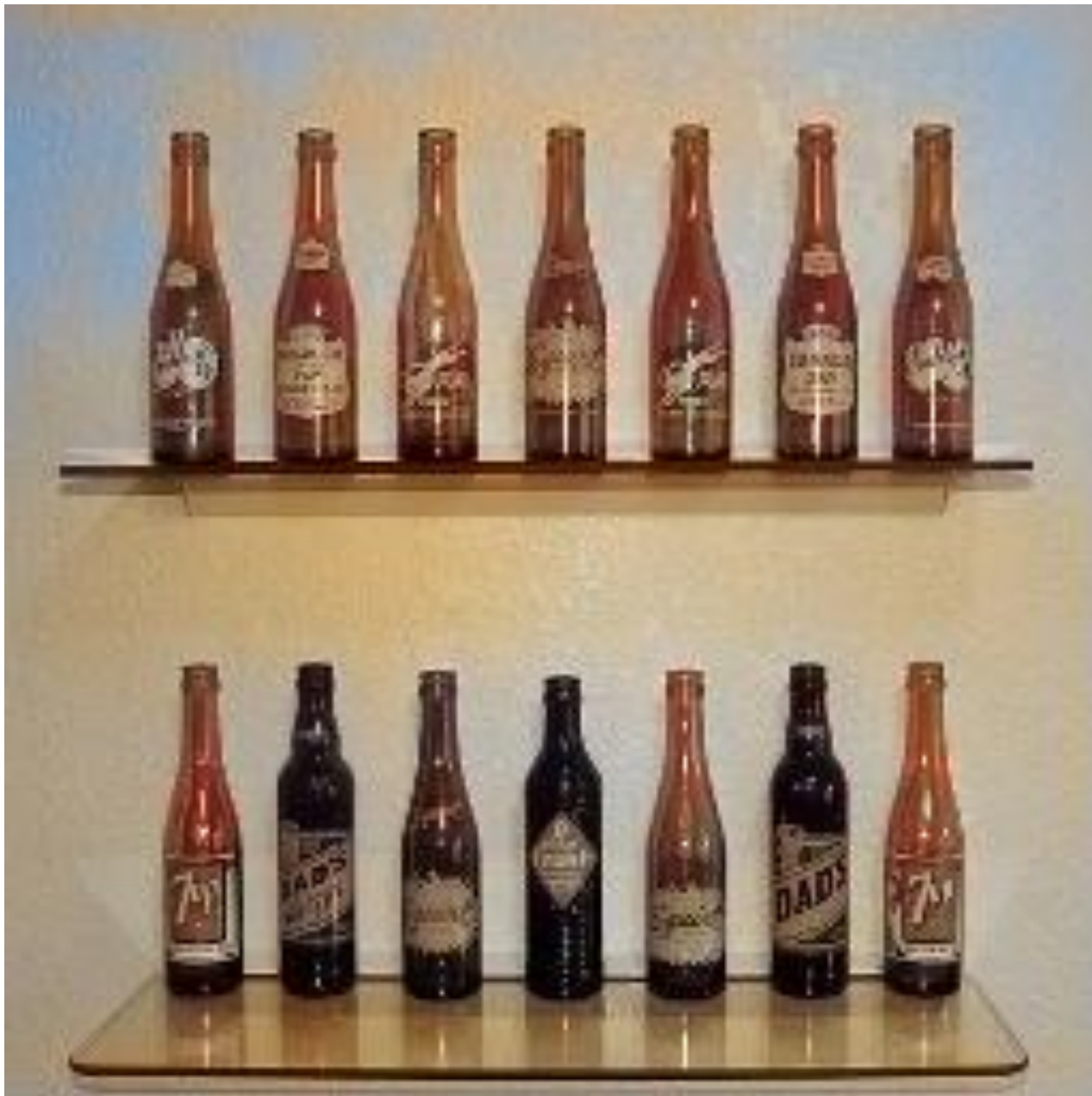


Ground truth



Color distribution cross-entropy loss with colorfulness enhancing term.

[Zhang, Isola, Efros, ECCV 2016]



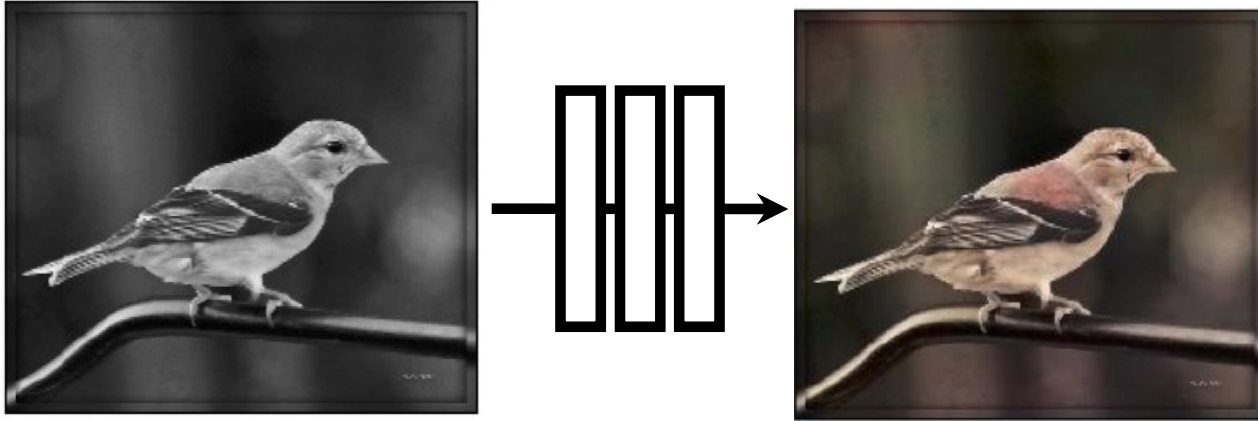
Designing loss functions



Be careful what you wish for!

Designing loss functions

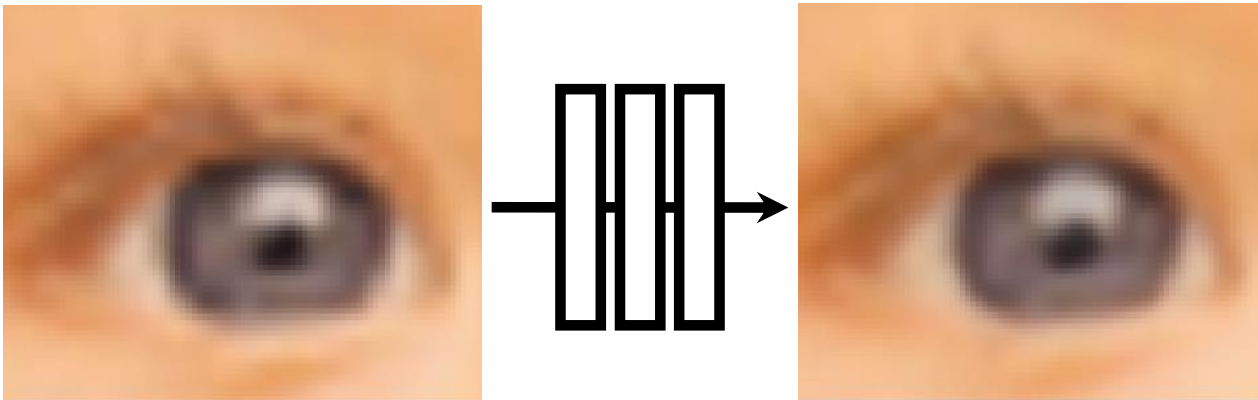
Image colorization



[Zhang, Isola, Efros, ECCV 2016]

L2 regression

Super-resolution

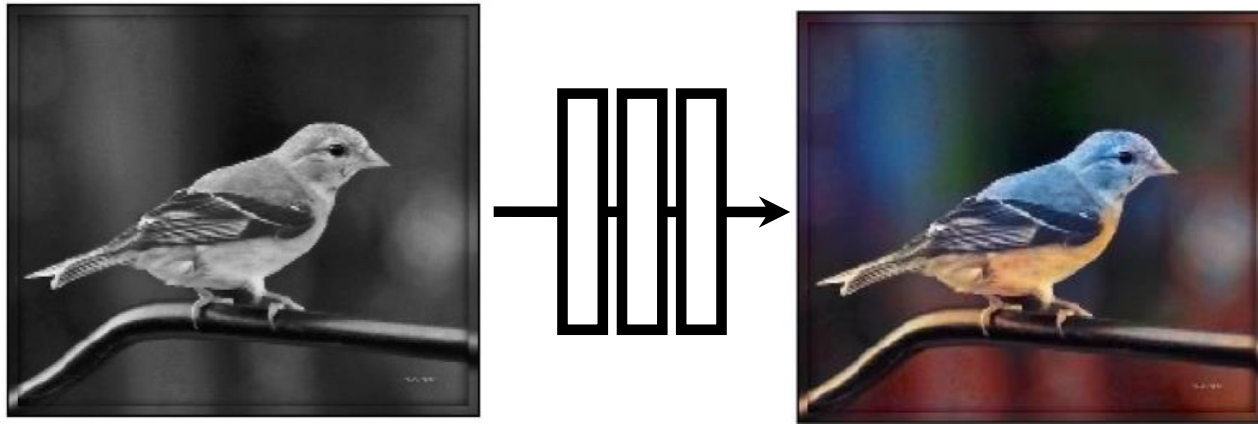


[Johnson, Alahi, Li, ECCV 2016]

L2 regression

Designing loss functions

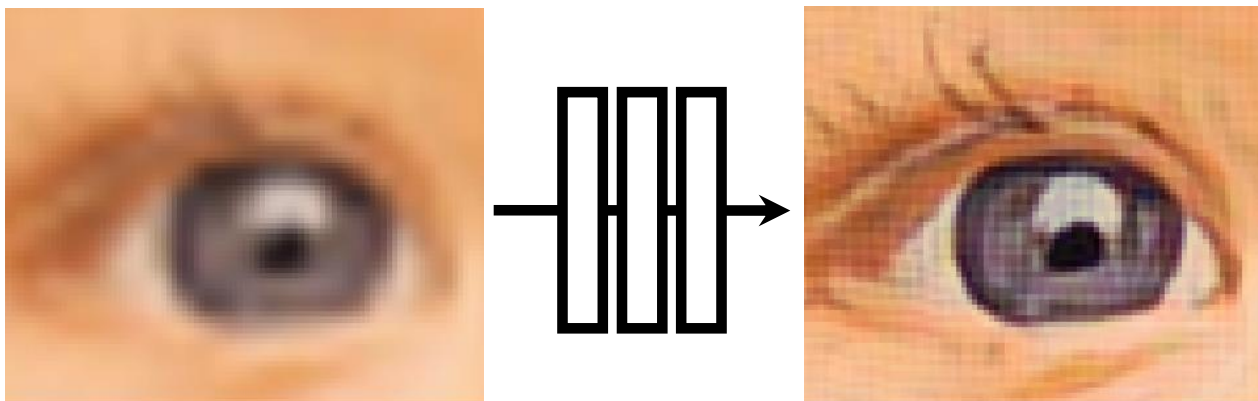
Image colorization



[Zhang, Isola, Efros, ECCV 2016]

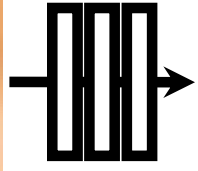
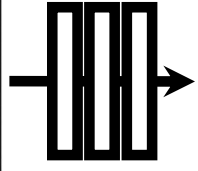
Cross entropy objective,
with colorfulness term

Super-resolution



[Johnson, Alahi, Li, ECCV 2016]

Deep feature covariance
matching objective



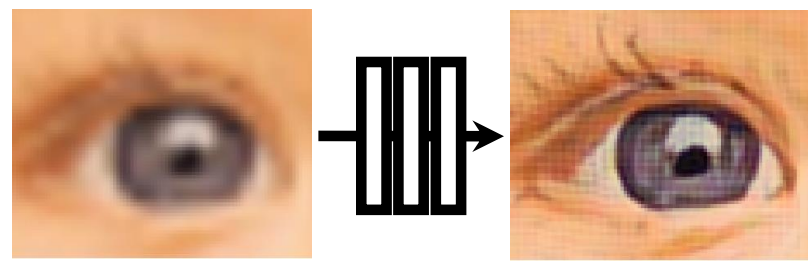
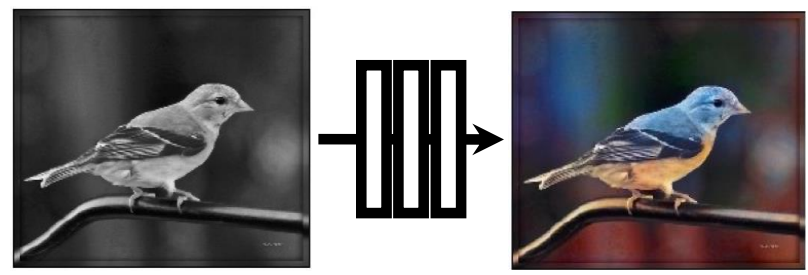
⋮

⋮



Universal loss?

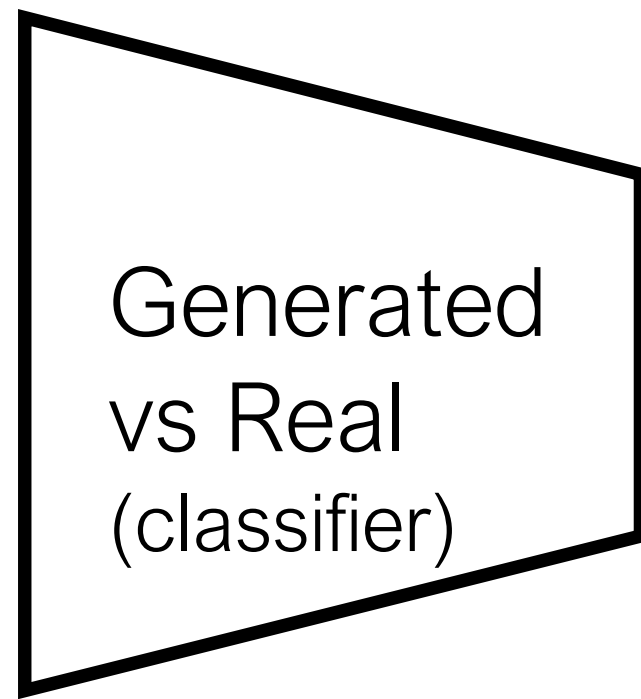
Generated images



⋮

⋮

“Generative Adversarial Network” (GANs)



Real photos



...



[Goodfellow, Pouget-Abadie, Mirza, Xu, Warde-Farley, Ozair, Courville, Bengio 2014]

Conditional GANs



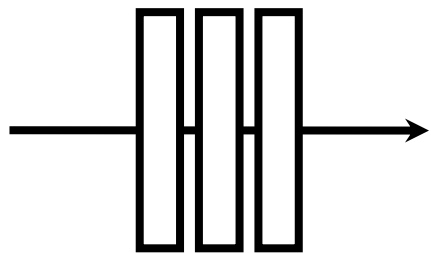
[Goodfellow et al., 2014]

[Isola et al., 2017]

\mathbf{x}

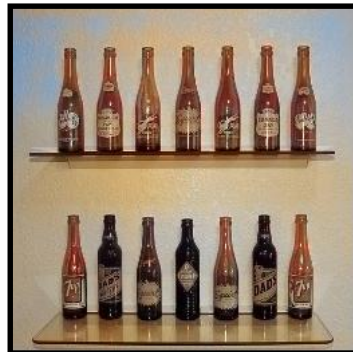


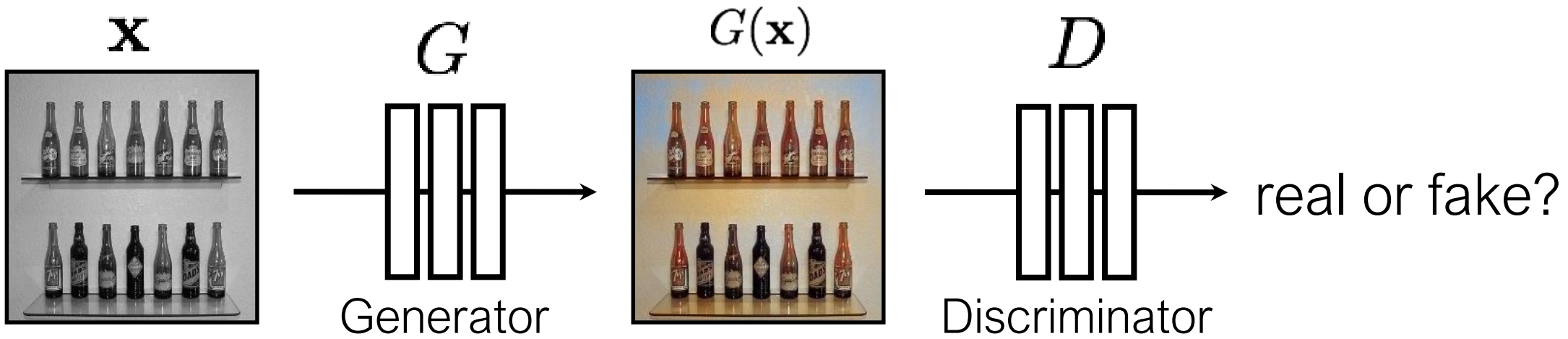
G



Generator

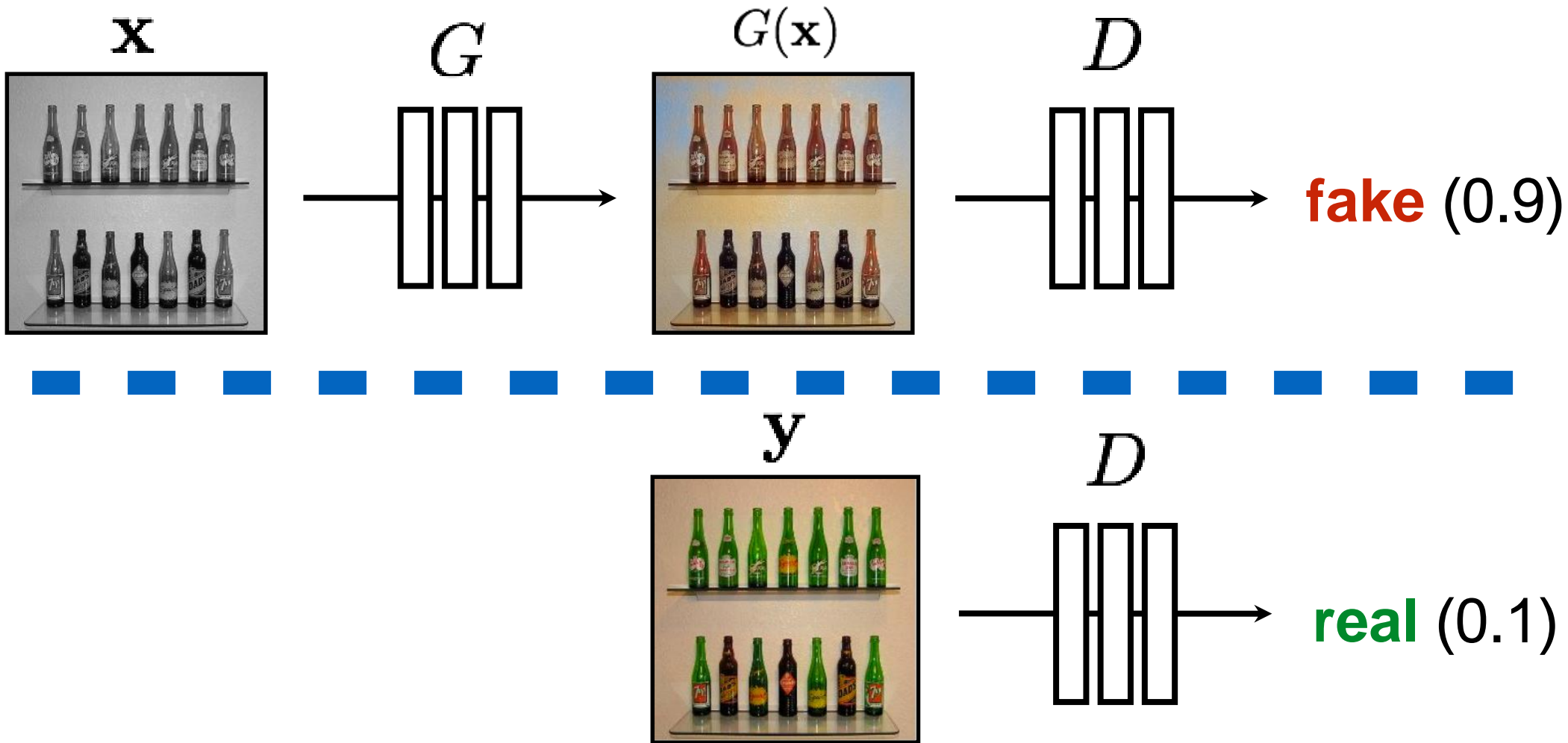
$G(\mathbf{x})$



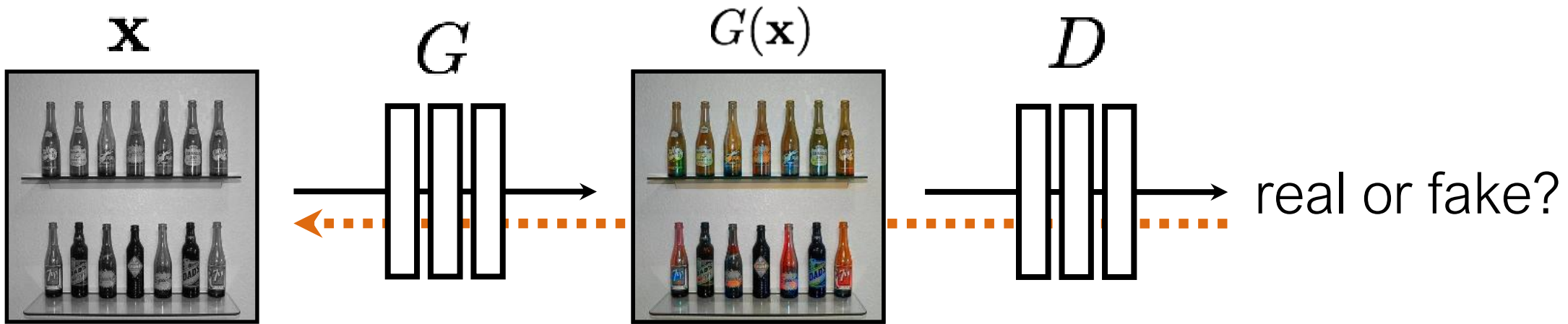


G tries to synthesize fake images that fool **D**

D tries to identify the fakes

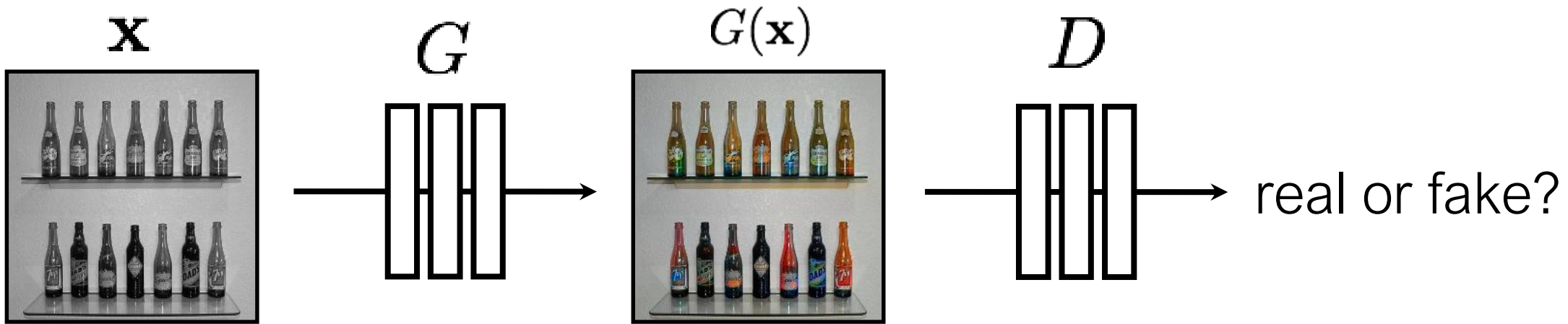


$$\arg \max_D \mathbb{E}_{\mathbf{x}, \mathbf{y}} [\log D(G(\mathbf{x})) + \log(1 - D(\mathbf{y}))]$$



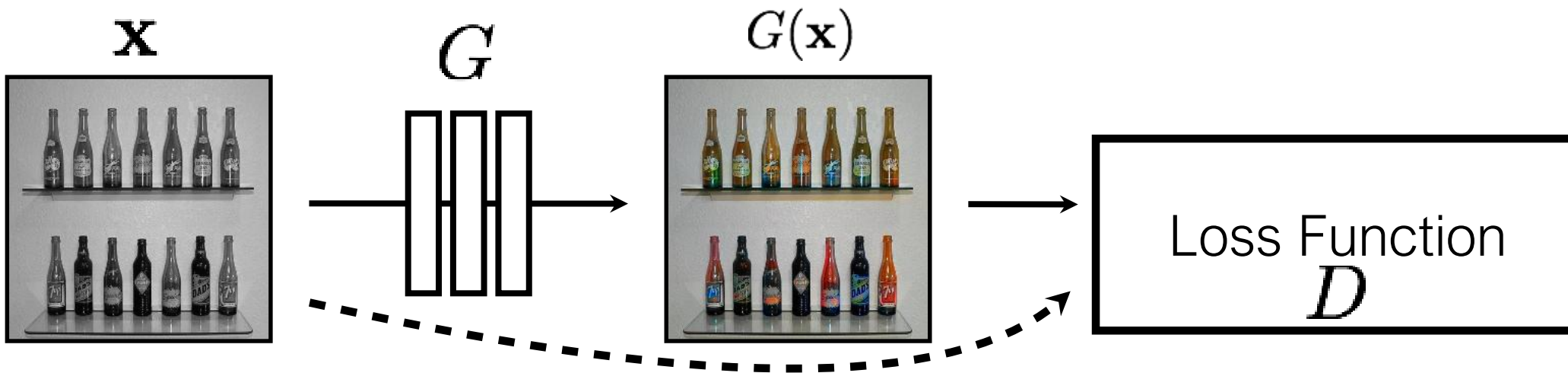
G tries to synthesize fake images that *fool* **D**:

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



G tries to synthesize fake images that *fool* the *best* **D**:

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

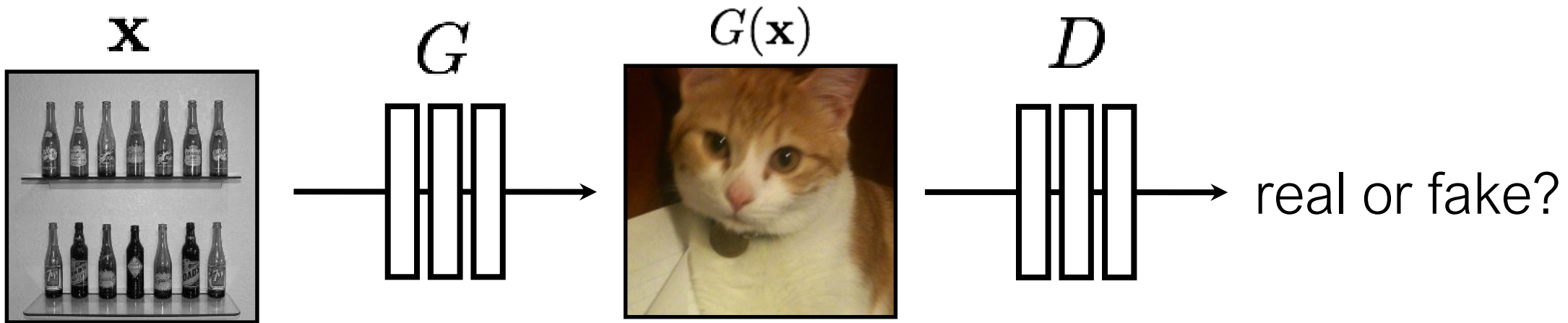


G's perspective: **D** is a loss function.

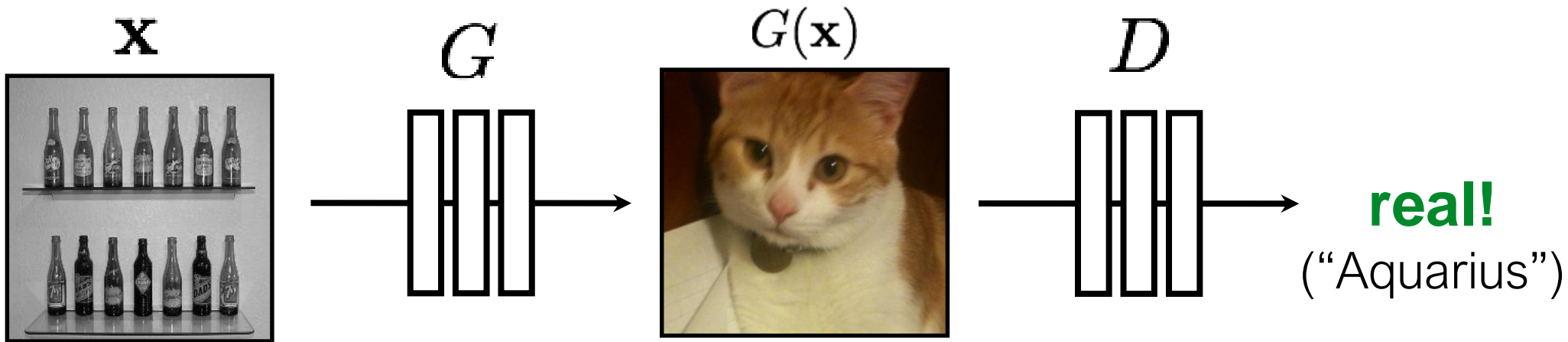
Rather than being hand-designed, it is *learned*.

[Goodfellow et al., 2014]

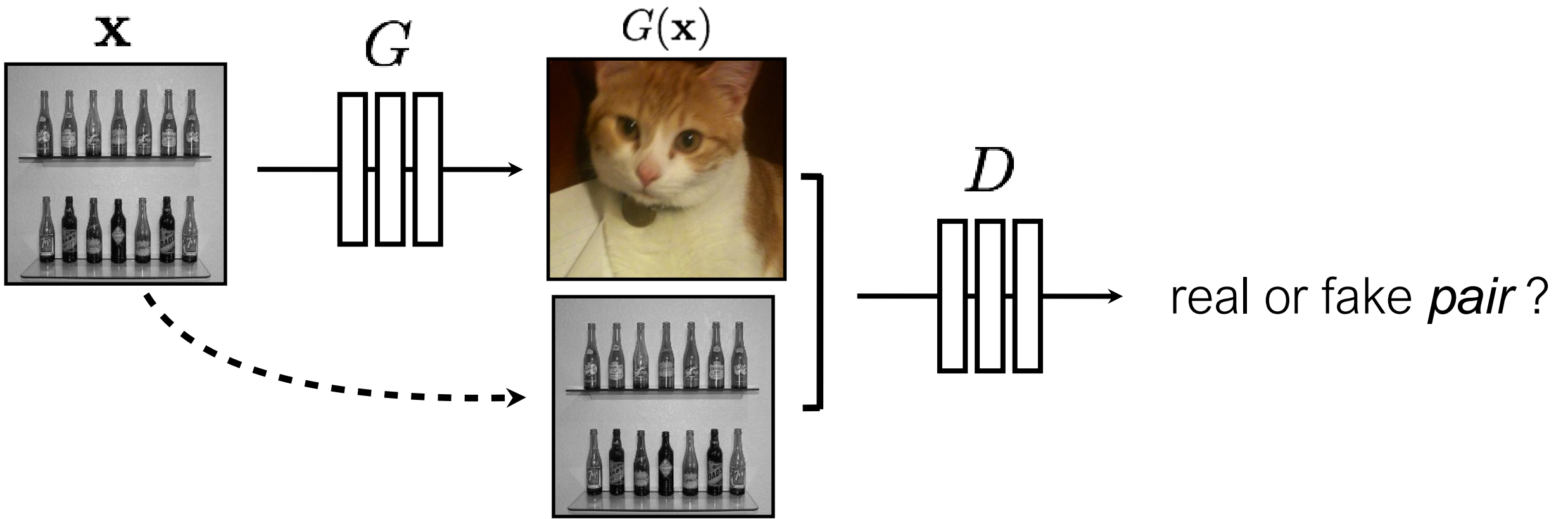
[Isola et al., 2017]



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



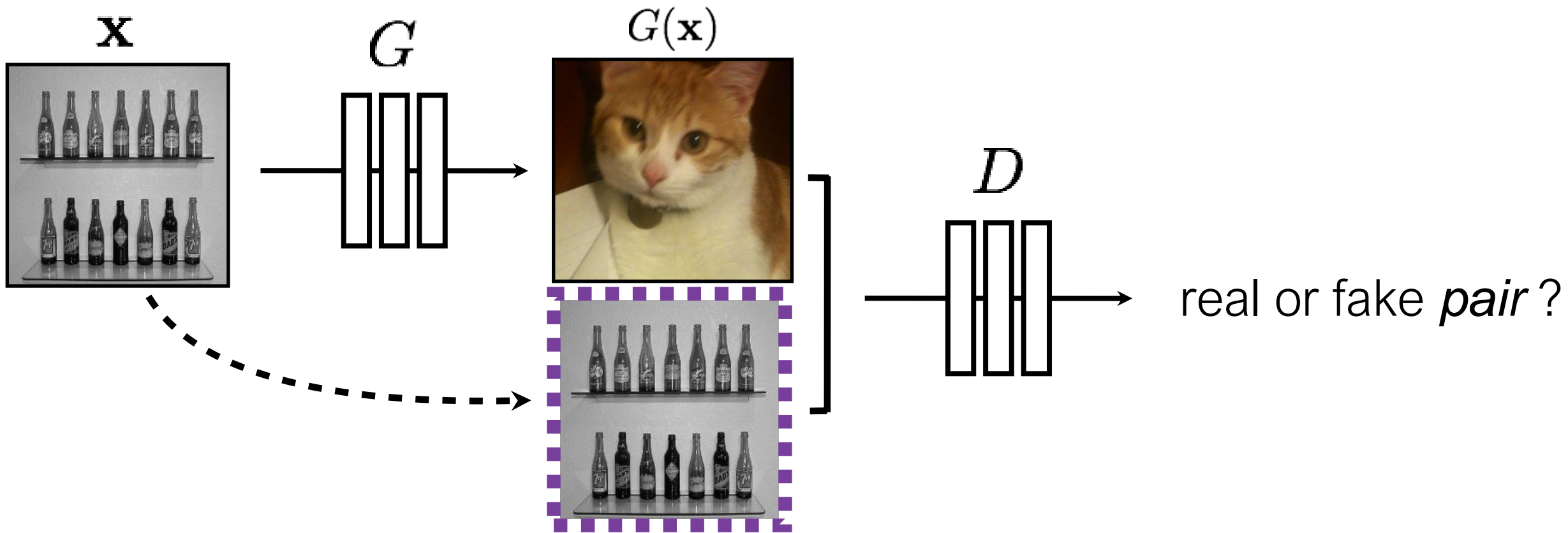
$$\arg \min_G \max_D \mathbb{E}_{\mathbf{x}, \mathbf{y}} [\log D(G(\mathbf{x})) + \log(1 - D(\mathbf{y}))]$$



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

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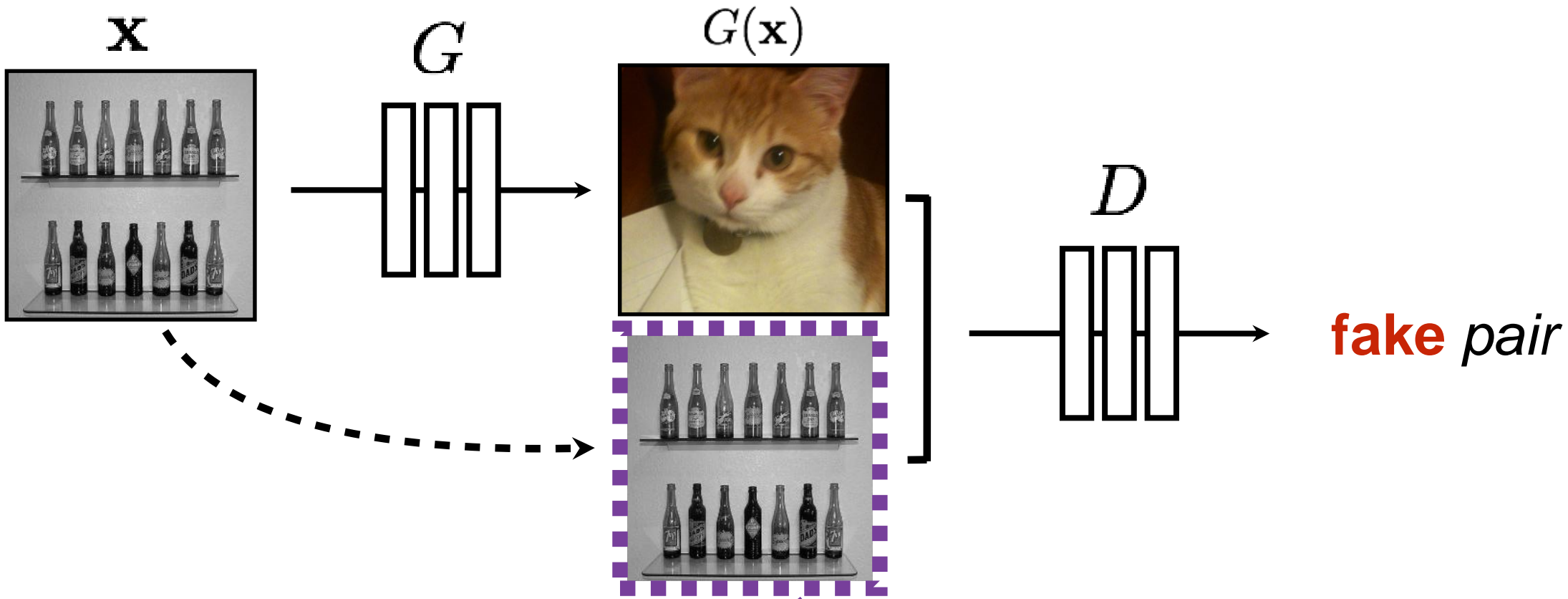
[Isola et al., 2017]



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

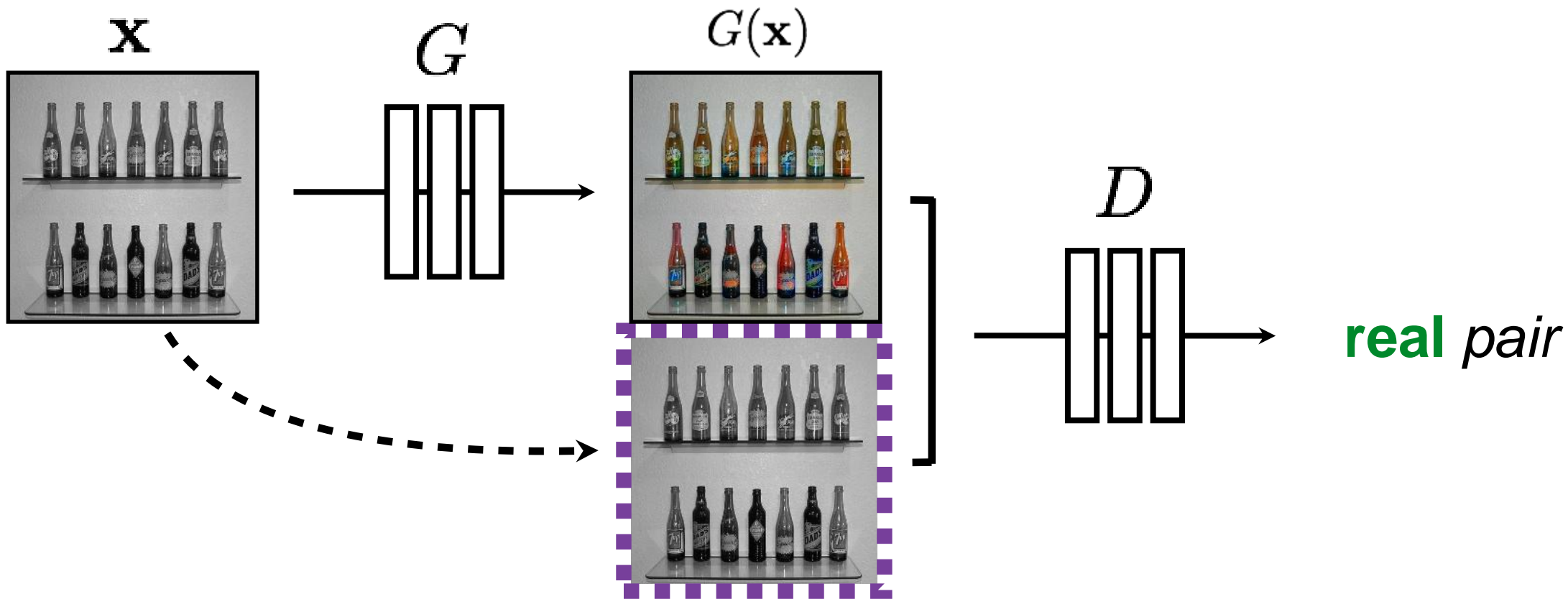
[Goodfellow et al., 2014]

[Isola et al., 2017]



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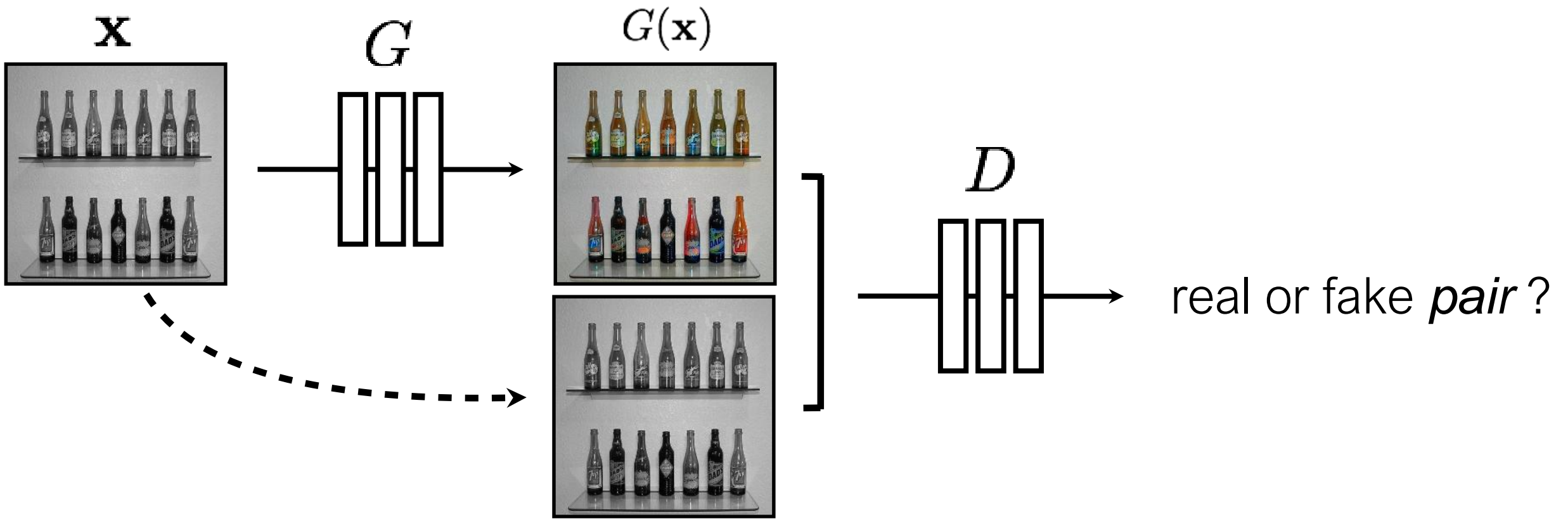
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$$\arg \min_G \max_D \mathbb{E}_{\mathbf{x}, \mathbf{y}} [\log D(\mathbf{x}, G(\mathbf{x})) + \log(1 - D(\mathbf{x}, \mathbf{y}))]$$

[Goodfellow et al., 2014]

[Isola et al., 2017]



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

[Goodfellow et al., 2014]

[Isola et al., 2017]

BW \rightarrow Color

Input

Output



Input

Output



Input

Output



Input



Output



Groundtruth



Data from
[maps.google.com]



Input

Output

Groundtruth

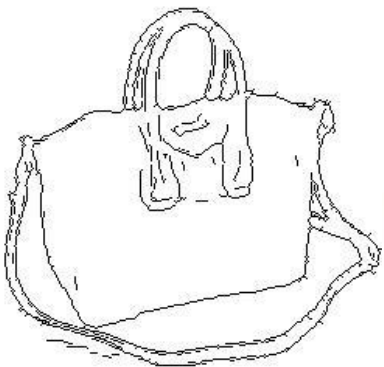


Data from [[maps.google.](https://maps.google.com)

Edges \rightarrow Images

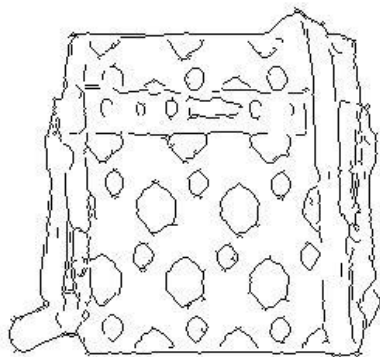
Input

Output



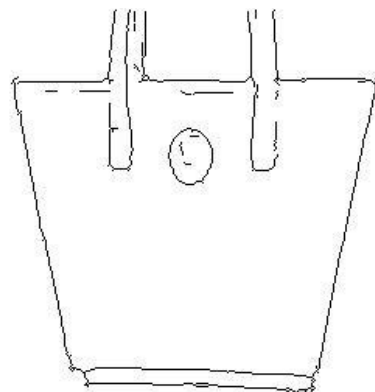
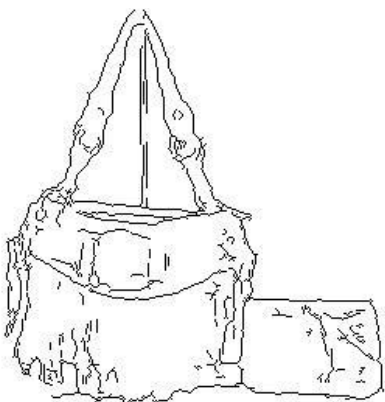
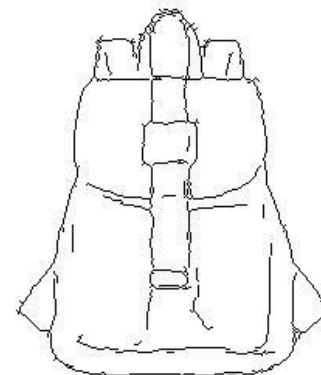
Input

Output



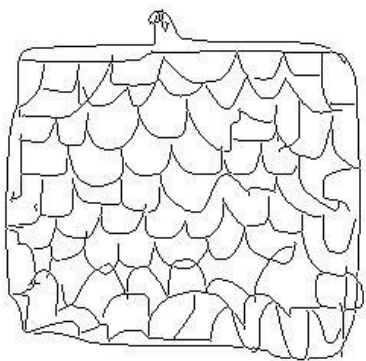
Input

Output



Sketches → Images

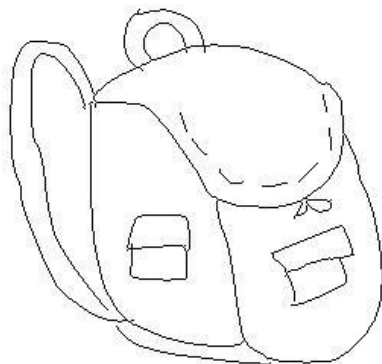
Input



Output



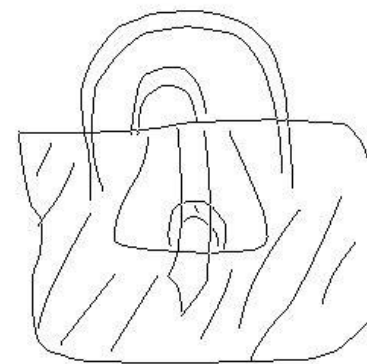
Input



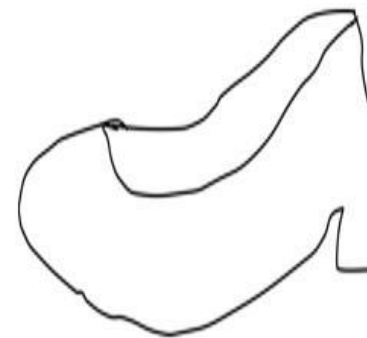
Output



Input

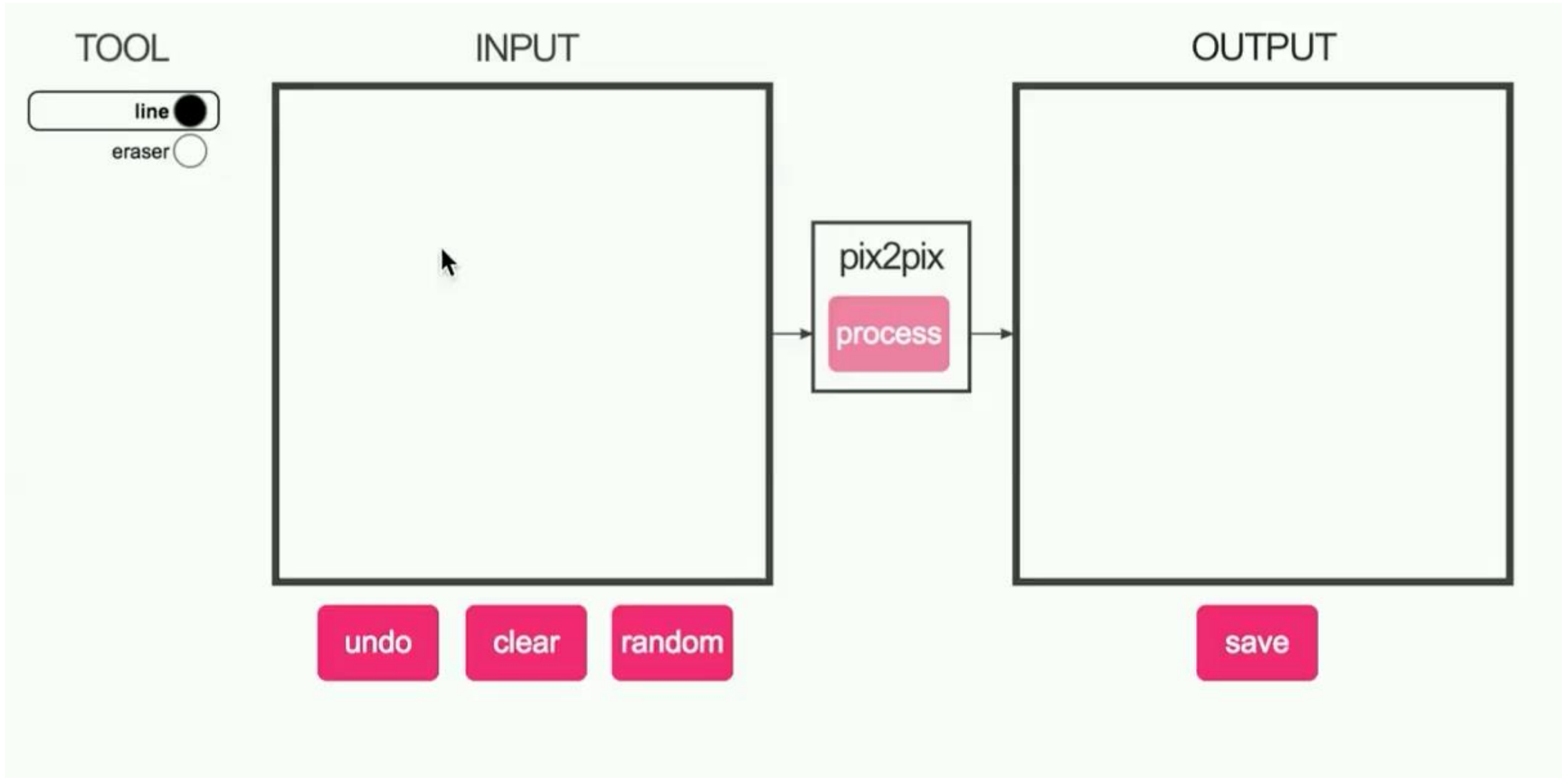


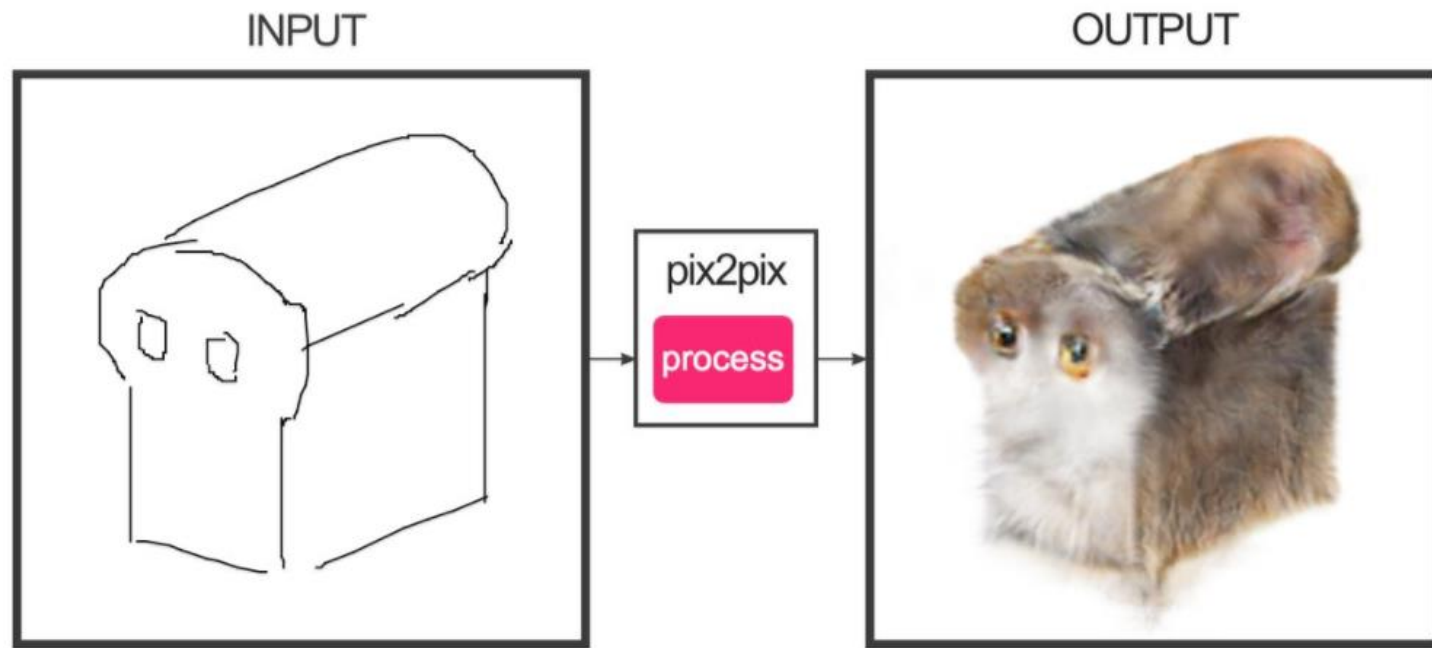
Output



Trained on Edges → Images

#edges2cats [Chris Hesse]





Ivy Tasi @ivymyt



Vitaly Vidmirov @vvid

Hallucinations

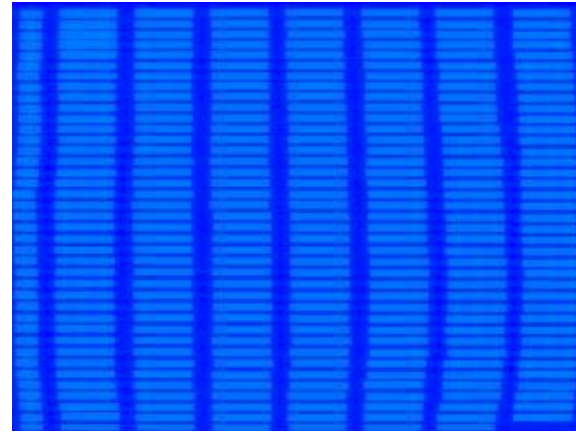
Input



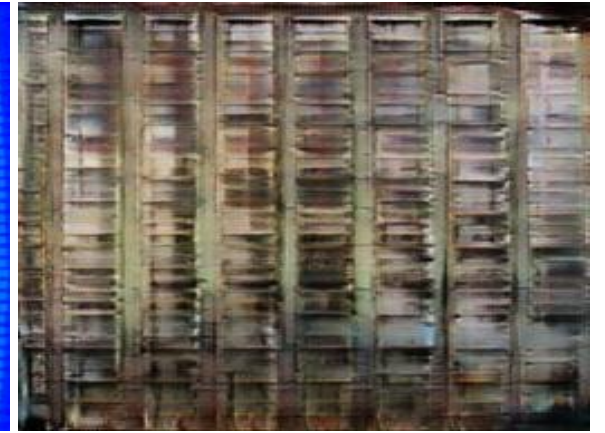
Output



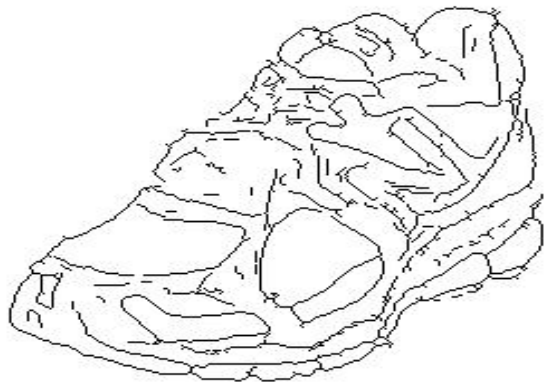
Input



Output



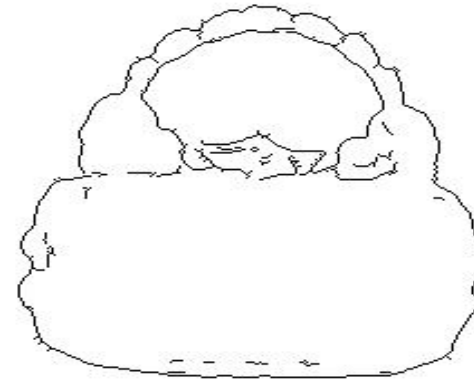
Input



Output



Input



Output



Challenges —> Solutions

1. Output is high-dimensional, structured object
—> **Use a deep net, D, to analyze output!**

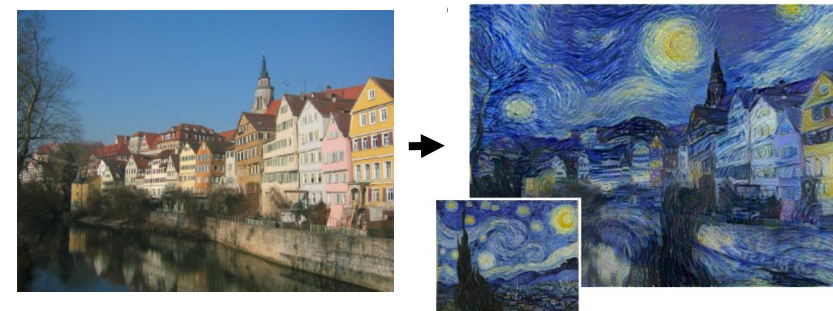


2. Uncertainty in mapping; many plausible outputs

“this small bird has a pink breast and crown...”

—> **D only cares about “plausibility”, doesn’t hedge**

3. Lack of supervised training data



Challenges —> Solutions

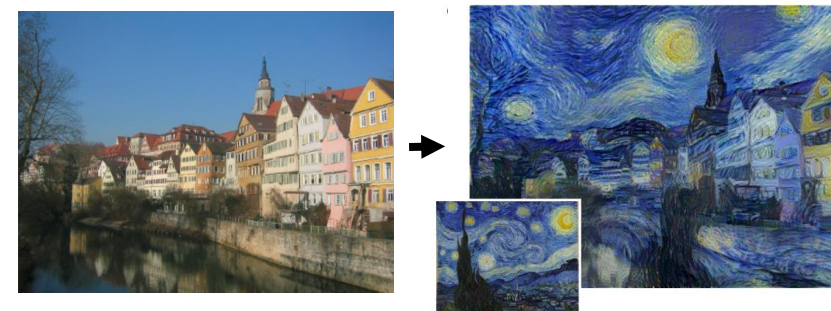
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2. Uncertainty in mapping; many plausible outputs
—> **D only cares about “plausibility”, doesn’t hedge**

“this small bird has a pink breast and crown...”

3. **Lack of supervised training data**



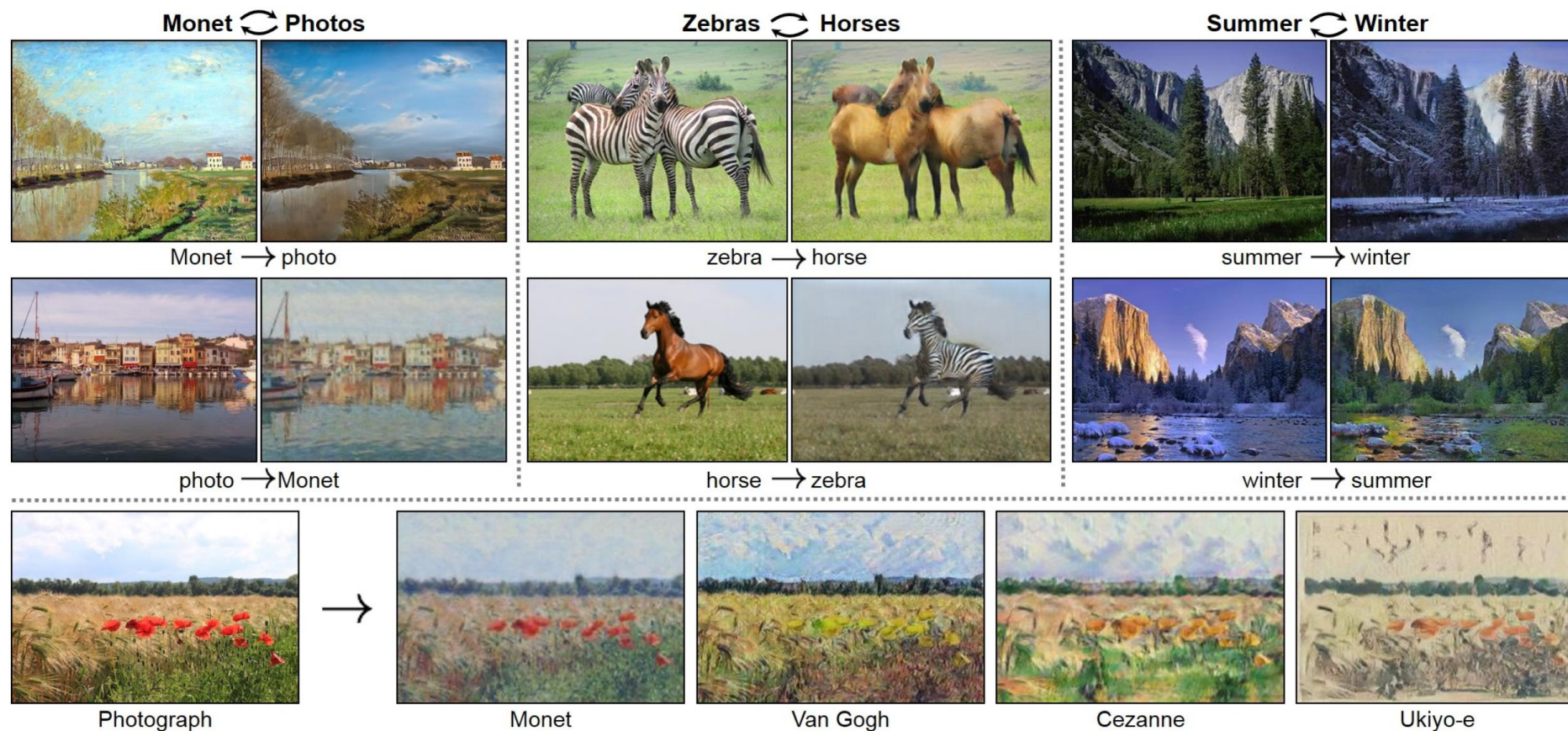
Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks

Jun-Yan Zhu* **Taesung Park*** **Phillip Isola** **Alexei A. Efros**

UC Berkeley

In ICCV 2017

[Paper] [Code (Torch)] [Code (PyTorch)]



<https://junyanz.github.io/CycleGAN/>

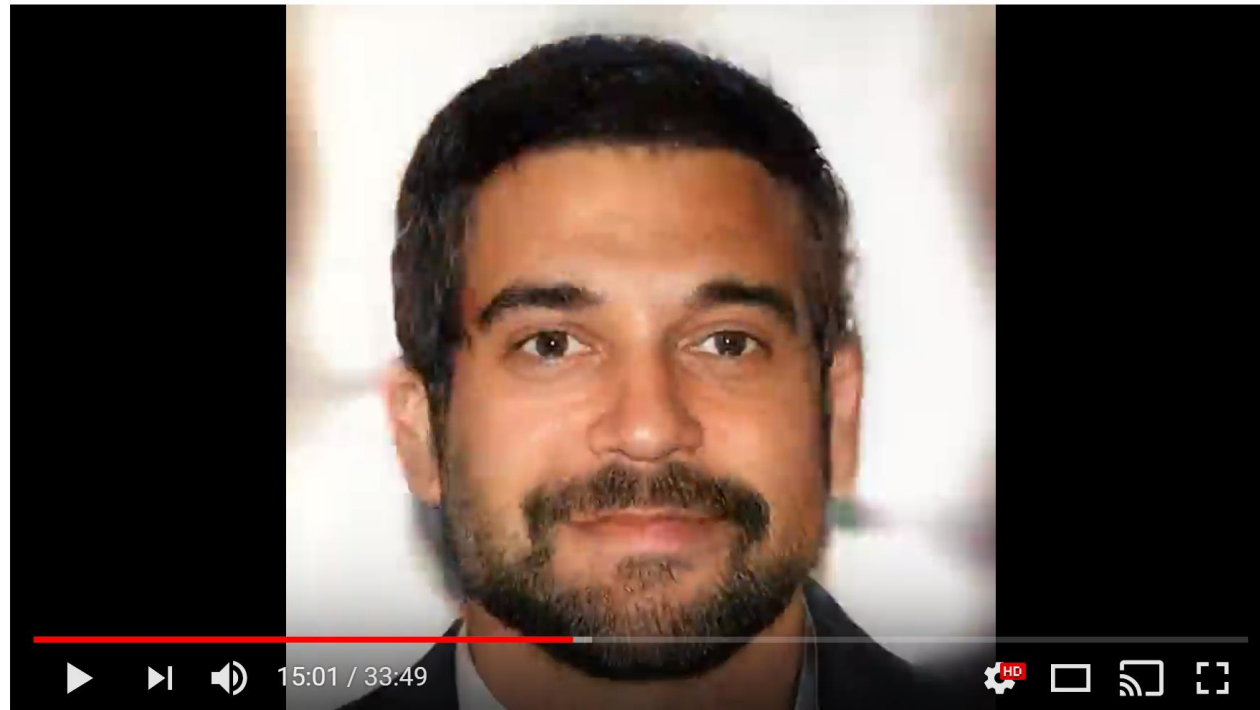


Progressive GANs



YouTube Red

Search



Fake Celebs with Progressive Growing of GANs

30 minutes of fake celebrities

https://www.youtube.com/watch?v=f8xSD4HO_8k

Questions?