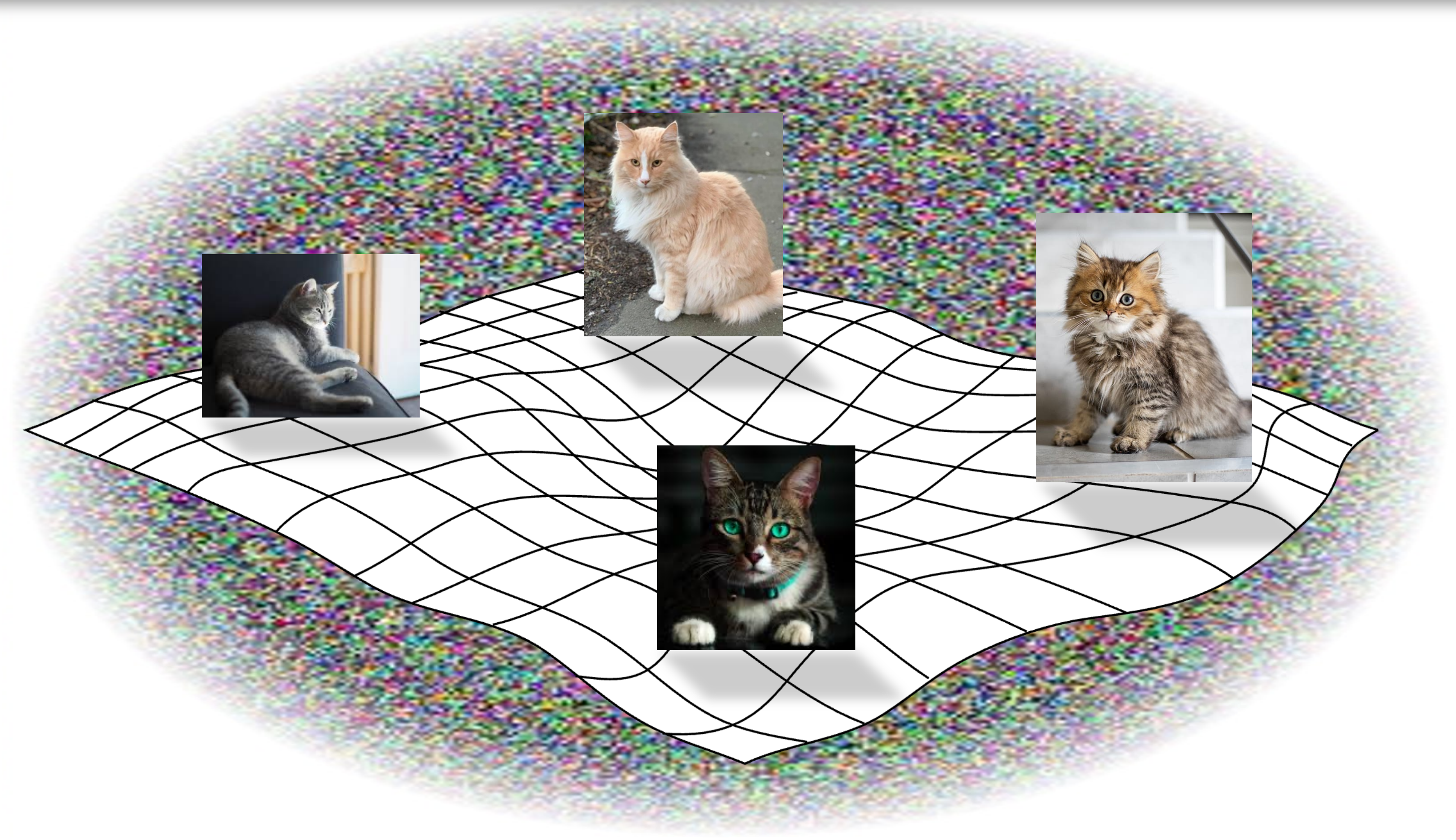
CS5670: Computer Vision

Image Manifolds & Image Generation



Some slides adapted from content by Abe Davis, Jin Sun, and Phillip Isola

Announcements

- Project 5 (Neural Radiance Fields) due tomorrow by 8:00 pm
- In class final next Tuesday, May 9
  - Open book, open note
  - “Notes” are meant to be notes you write up yourself – they will be limited to 15 pages front and back (although you likely won’t need anywhere near that many pages)
- Course evaluations are open
  - We would love your feedback!
  - Small amount of extra credit for filling out
    - What you write is still anonymous; instructors only see if students filled it out
  - https://apps.engineering.cornell.edu/CourseEval/

Readings

- Szeliski 2nd Edition Chapter 5.5.4
- 5-Minute Graphics from Steve Seitz:
  - Large Language Models from scratch
  - Large Language Models: Part 2
  - Text to Image in 5 minutes: Parti, Dall-E 2, Imagen
  - Text to Image: Part 2 -- how image diffusion works in 5 minutes

Agenda

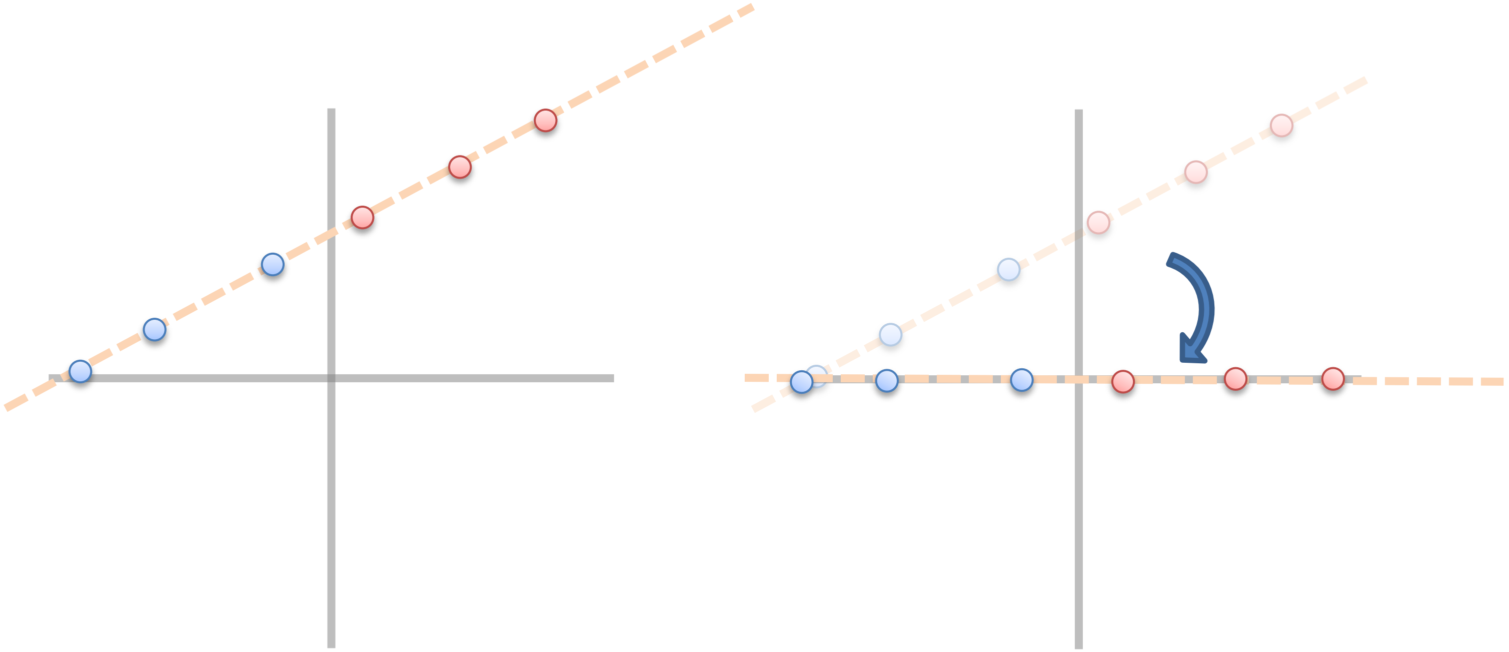
- The manifold of natural images
- Image-to-image methods and GANs
- Image synthesis methods
- Next time: diffusion models

By Abe Davis

DIMENSIONALITY REDUCTION

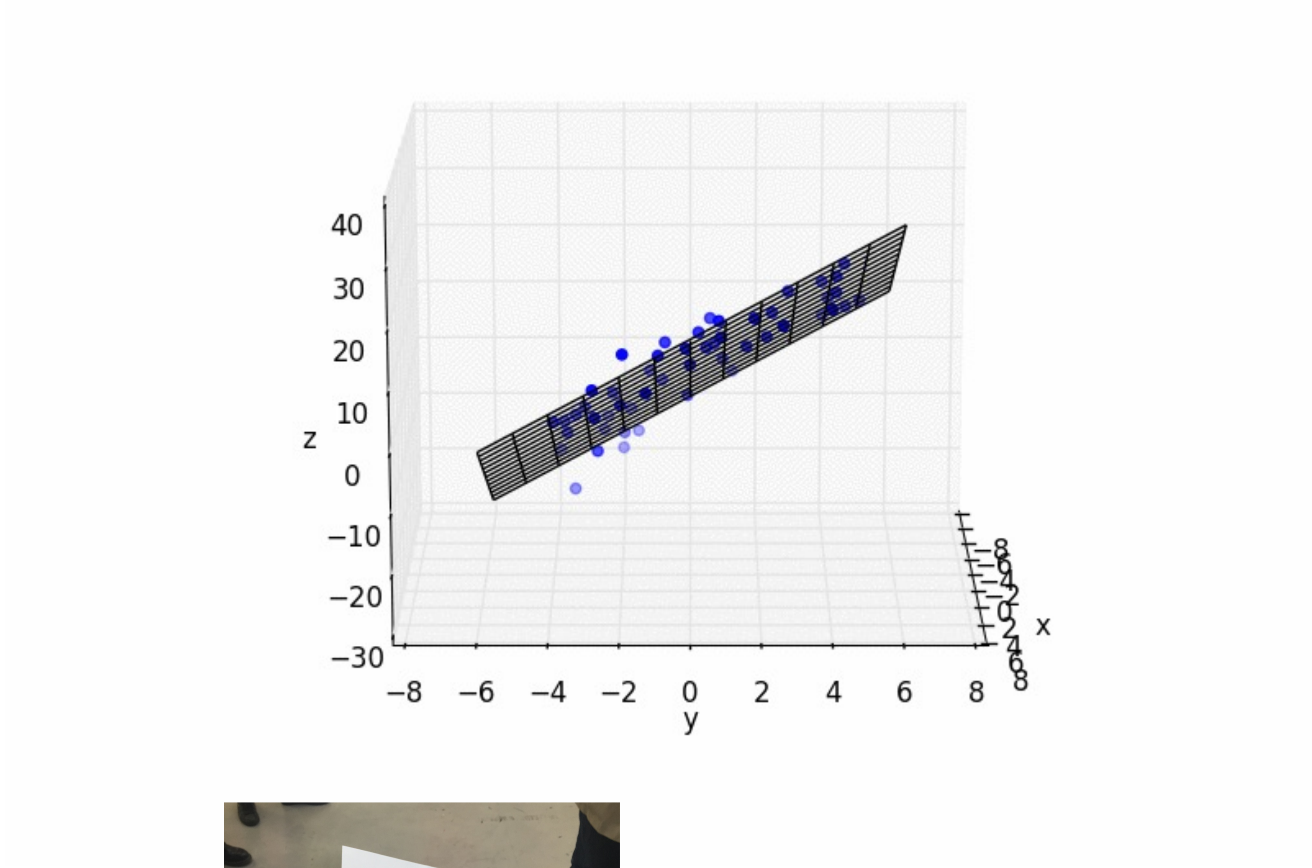
Linear Dimensionality Reduction: 2D->1D

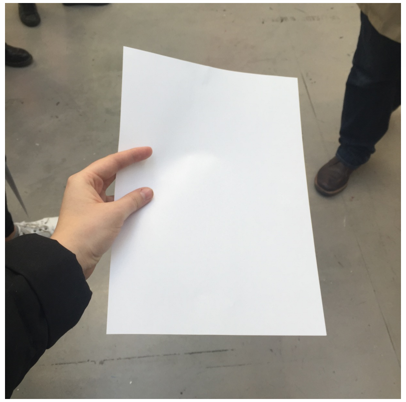
- Consider a bunch of data points in 2D
- Let’s say these points lie along a line
- If so, we can translate and rotate our data so that it is 1D



Linear Dimensionality Reduction: 3D->2D

- Similar to 1D case, we can fit a plane to the data, and transform our coordinate system so that plane becomes the x-y plane
- “Plane fitting”
- Now we only need to store two numbers for each point (and the plane parameters)
- More generally: look for the 2D subspace that best fits the data, and ignore the remaining dimensions





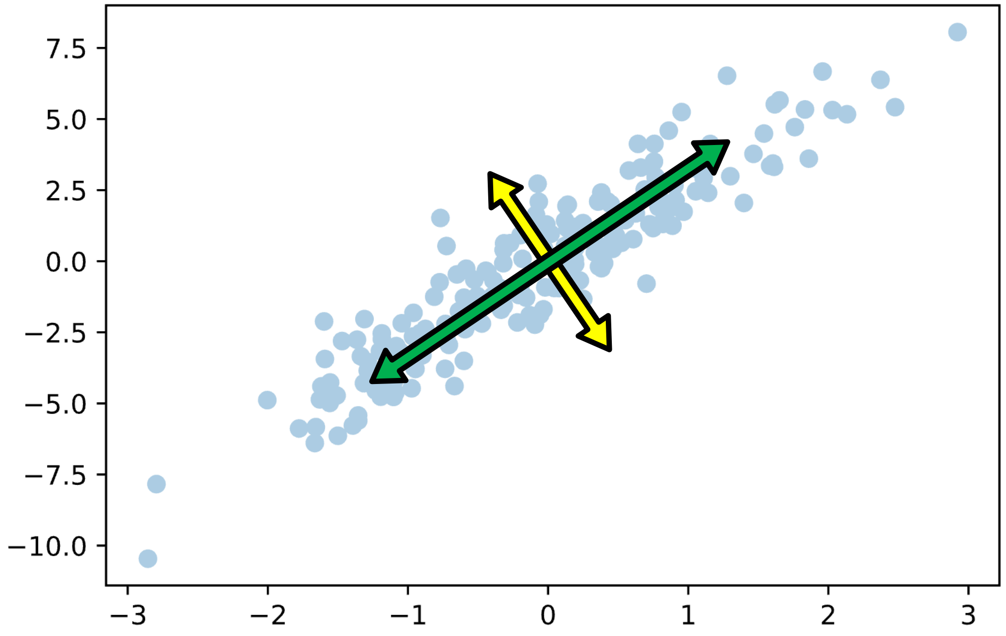
Think of this as data that sits on a flat sheet of paper, suspended in 3D space. We will come back to this analogy in a couple slides…

Generalizing Linear Dimensionality Reduction

- ***Principal Components Analysis (PCA)***: find and order orthogonal axes by how much the data varies along each axis.

- The axes we find (ordered by variance of our data) are called ***principal components***.

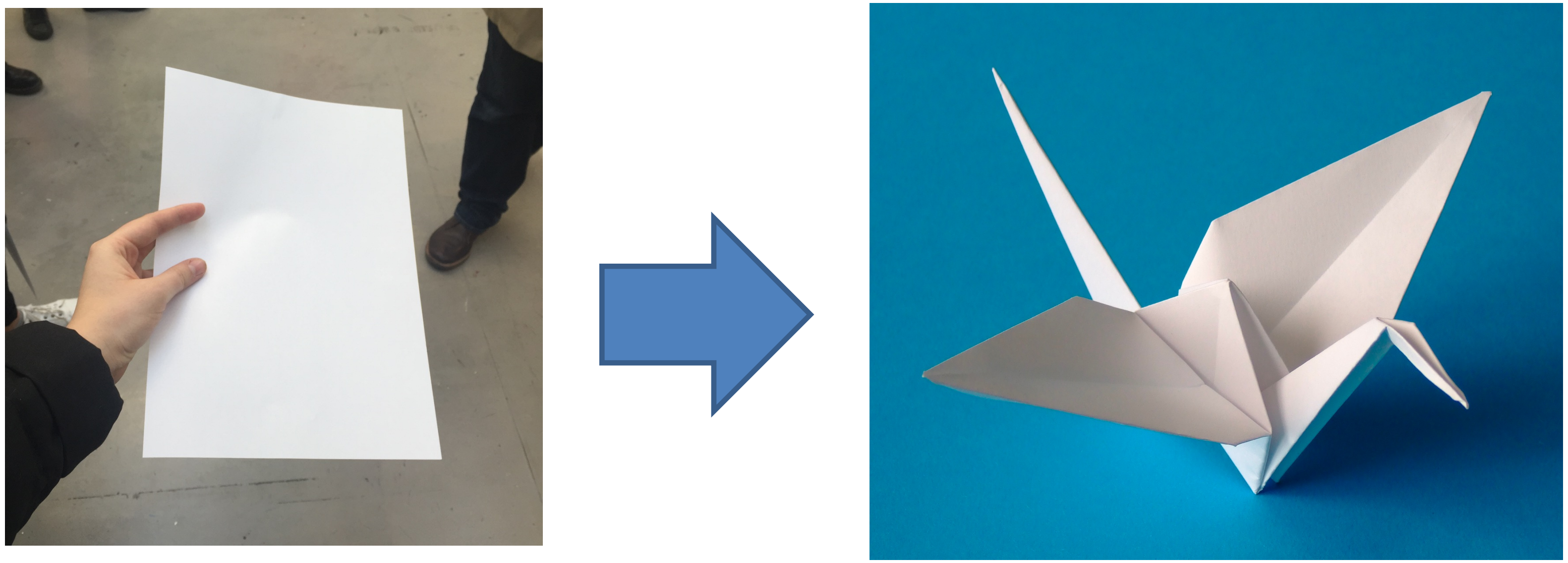
- Dimensionality reduction can be done by using only the first *k* principal components



Side Note: principal components are closely related to the eigenvectors of the covariance matrix for our data

Manifolds

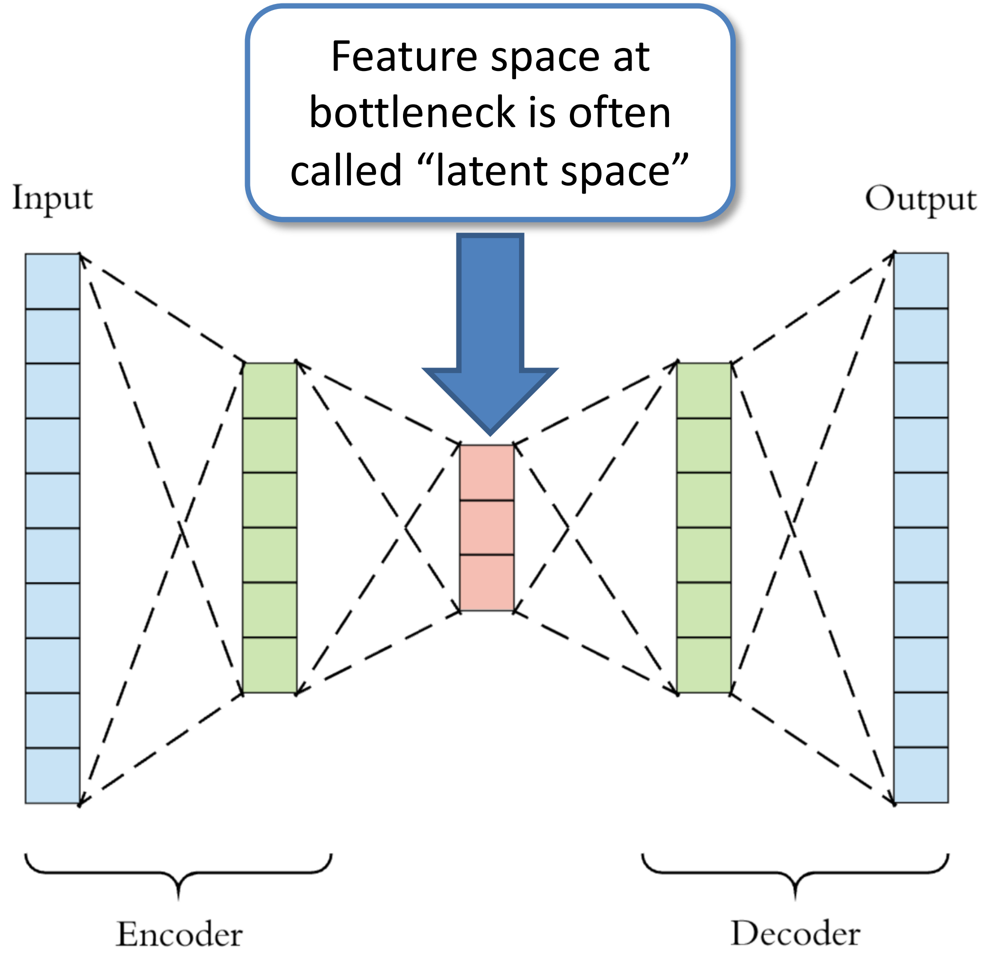
- Think of a piece of paper as a 2D subspace
- If we bend & fold it, it's still locally a 2D subspace…
- A "manifold" is the generalization of this concept to higher dimensions…



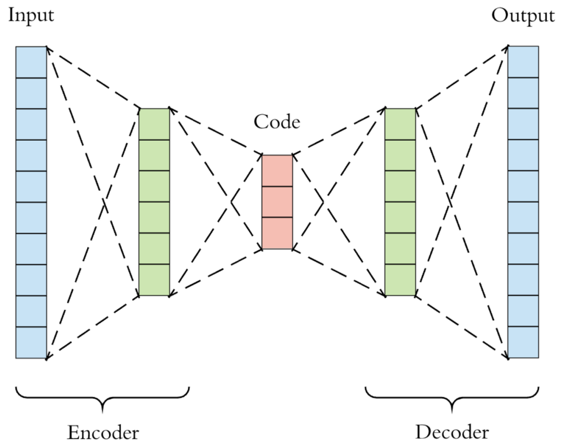
Autoencoders: Dimensionality Reduction for Manifolds

- Learn a non-linear (deep network) transformation into some lower-dimensional space (encoder)
- Learn a transformation from lower-dimensional space back to original content (decoder)
- Loss function measures difference between input & output

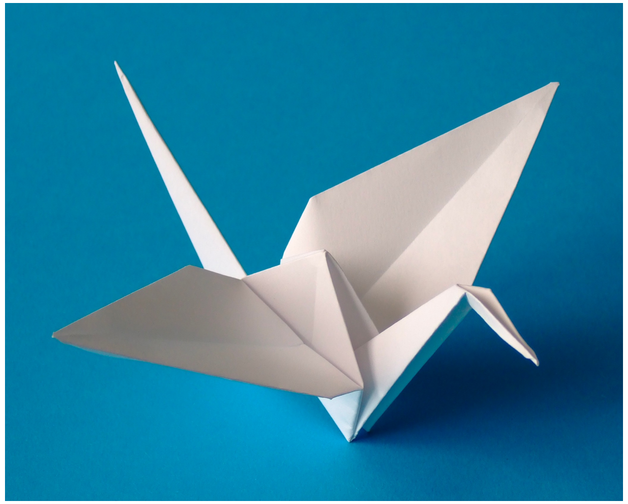
- **Unsupervised**
  - No labels required!



Autoencoders: Dimensionality Reduction for Manifolds



- Transformations that reduce dimensionality **cannot be invertible** in general



- An autoencoder tries to learn a transformation that is **invertible for points on some manifold**

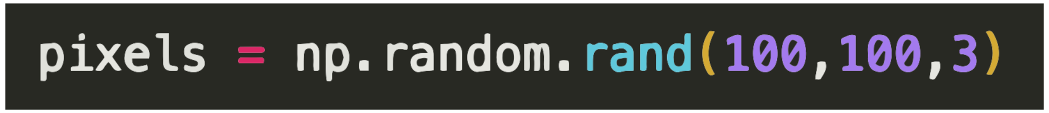
By Abe Davis

IMAGE MANIFOLDS

The Space of All Images

- Lets consider the space of all 100x100 images
- Now lets randomly sample that space…
- Conclusion: Most images are noise

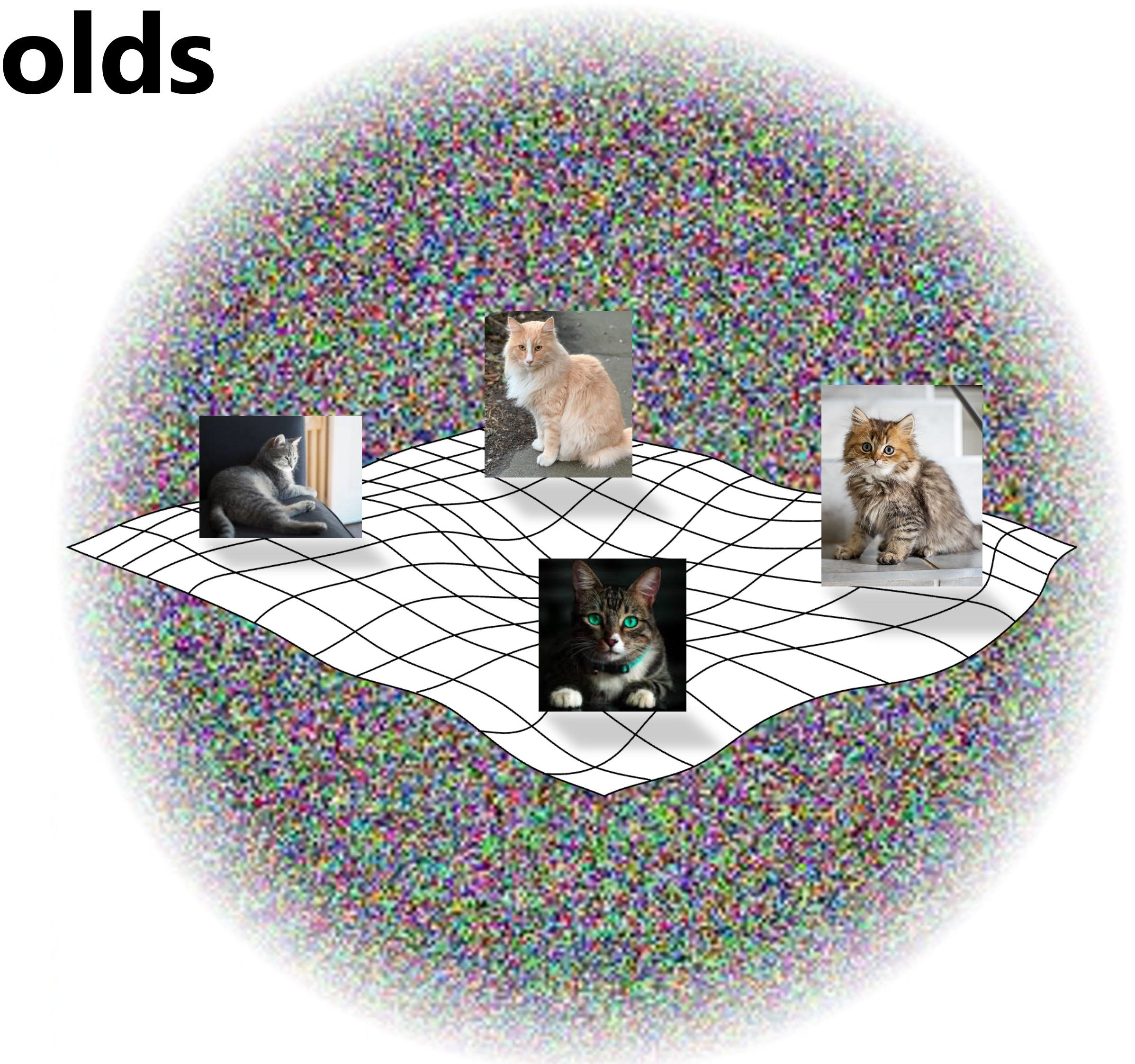
Question:
What do we expect a random uniform sample of all images to look like?



```
pixels = np.random.rand(100,100,3)
```

Natural Image Manifolds

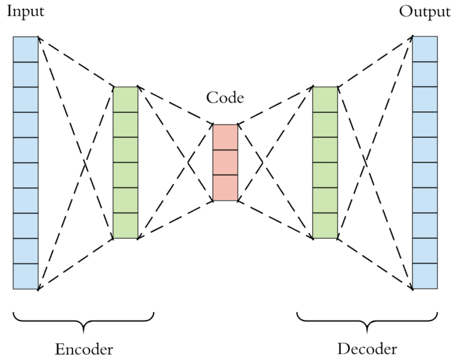
- Most images are “noise”
- “Meaningful” images tend to form some manifold within the space of all images
- Images of a particular class fall on manifolds within that manifold…

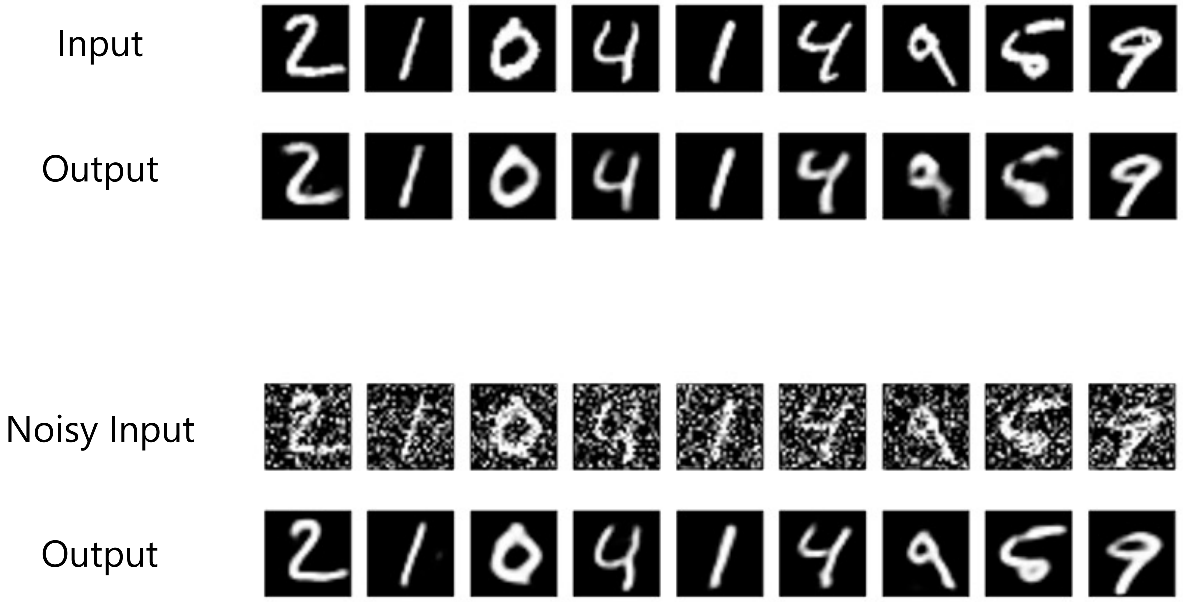


The Space of All Images

Denoising & the “Nullspace” of Autoencoders

- The autoencoder tries to learn a dimensionality reduction that is invertible for our data (data on some manifold)
- Most noise will be in the non-invertible part of image space (off the manifold)
- If we feed noisy data in, we will often get denoised data

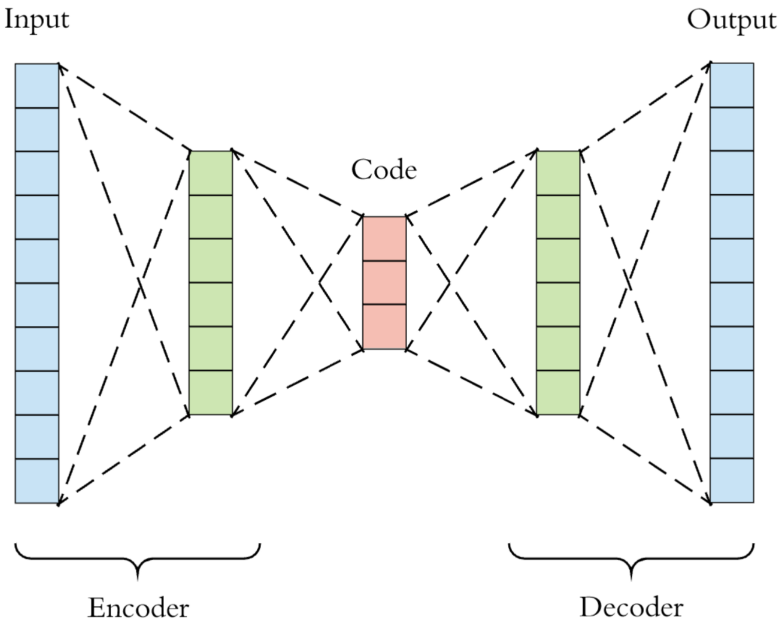


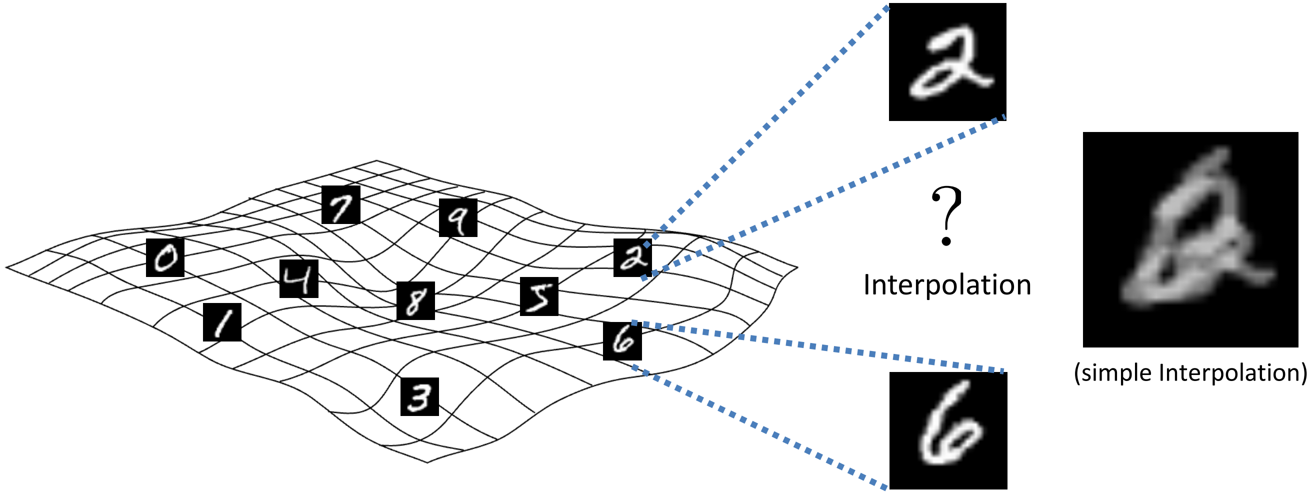


Examples from: https://blog.keras.io/building-autoencoders-in-keras.html

Problem

- Autoencoders can compress because data sits on a manifold
- This doesn't mean that every point in the latent space will be on the manifold…
- GANs (later this lecture) will learn a loss function that helps with this





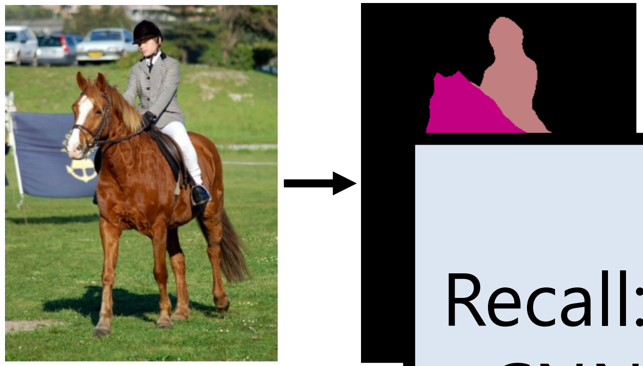
(simple Interpolation)

Abe Davis, with slides from Jin Sun, Phillip Isola, and Richard Zhang

IMAGE-TO-IMAGE APPLICATIONS

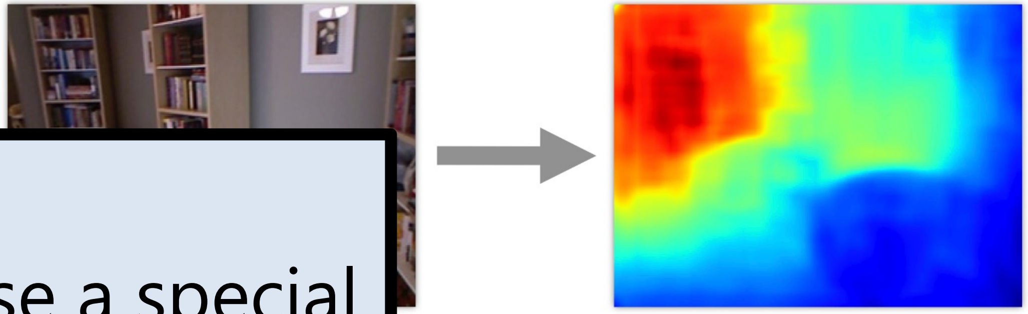
Image prediction ("structured prediction")

Object labeling



[Long et al. 201

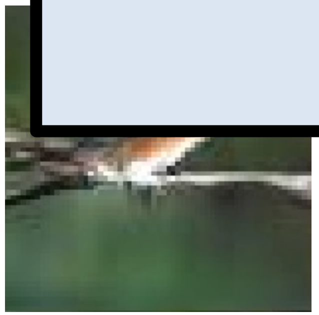
Depth prediction



Eigen et al. 2014, …]

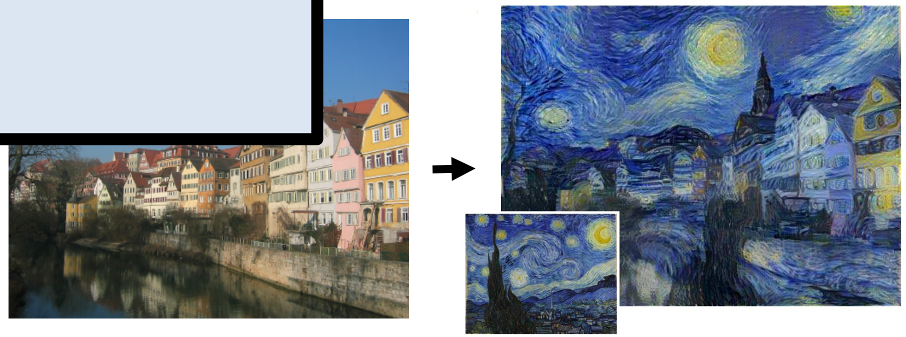
Text-to-ph

"this small bird has a pink breast and crown…" →



[Reed et al. 2016, …]

yle transfer



[Gatys et al. 2016, …]

Recall: we often use a special CNN architecture like a U-Net for such image-to-image mappings

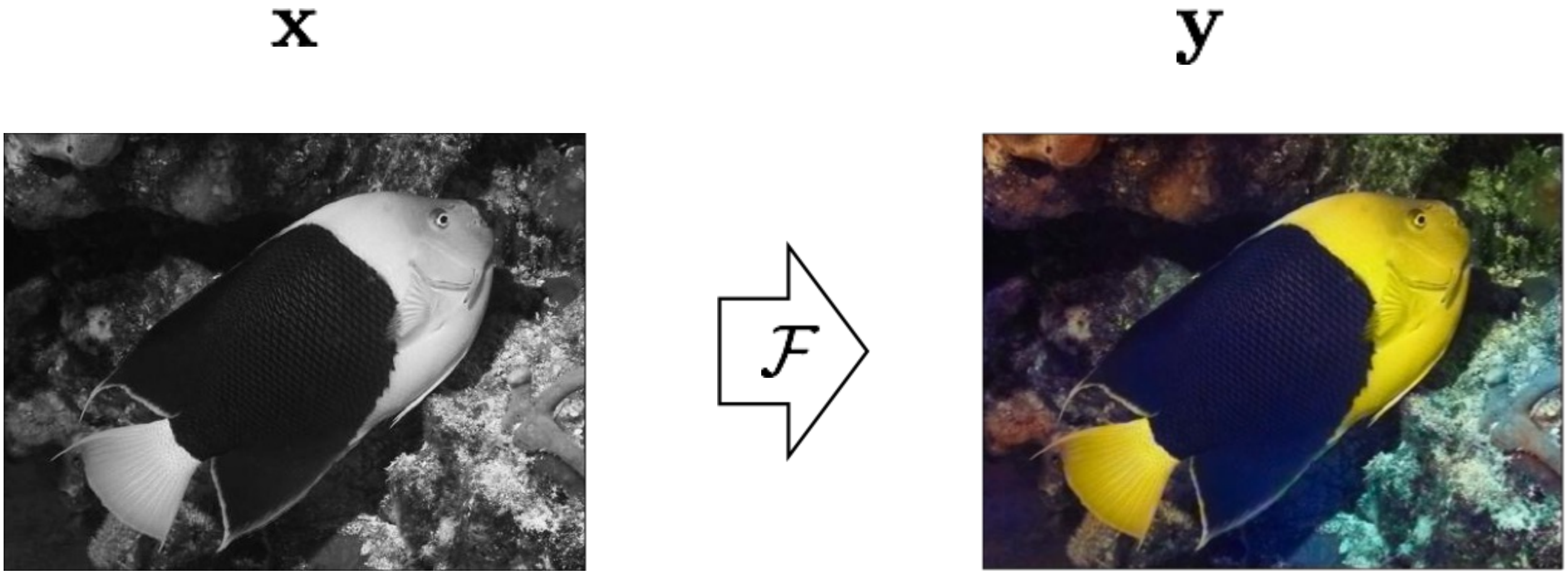
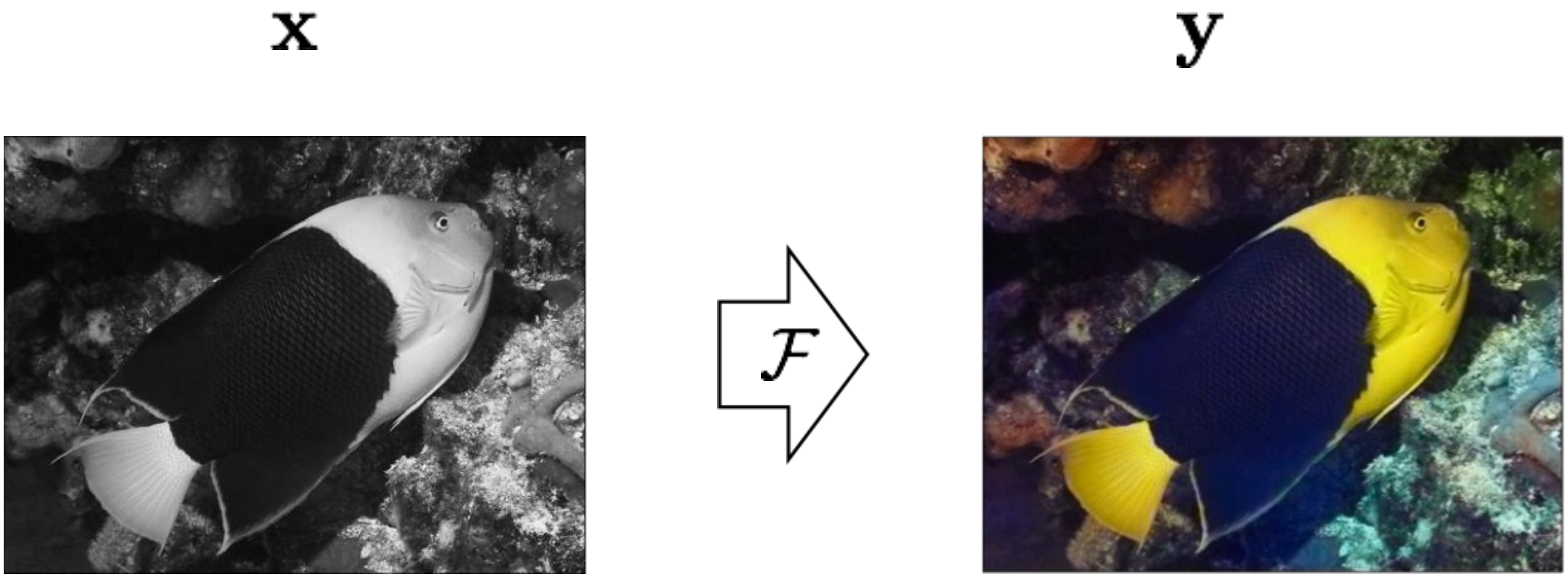


Image Colorization

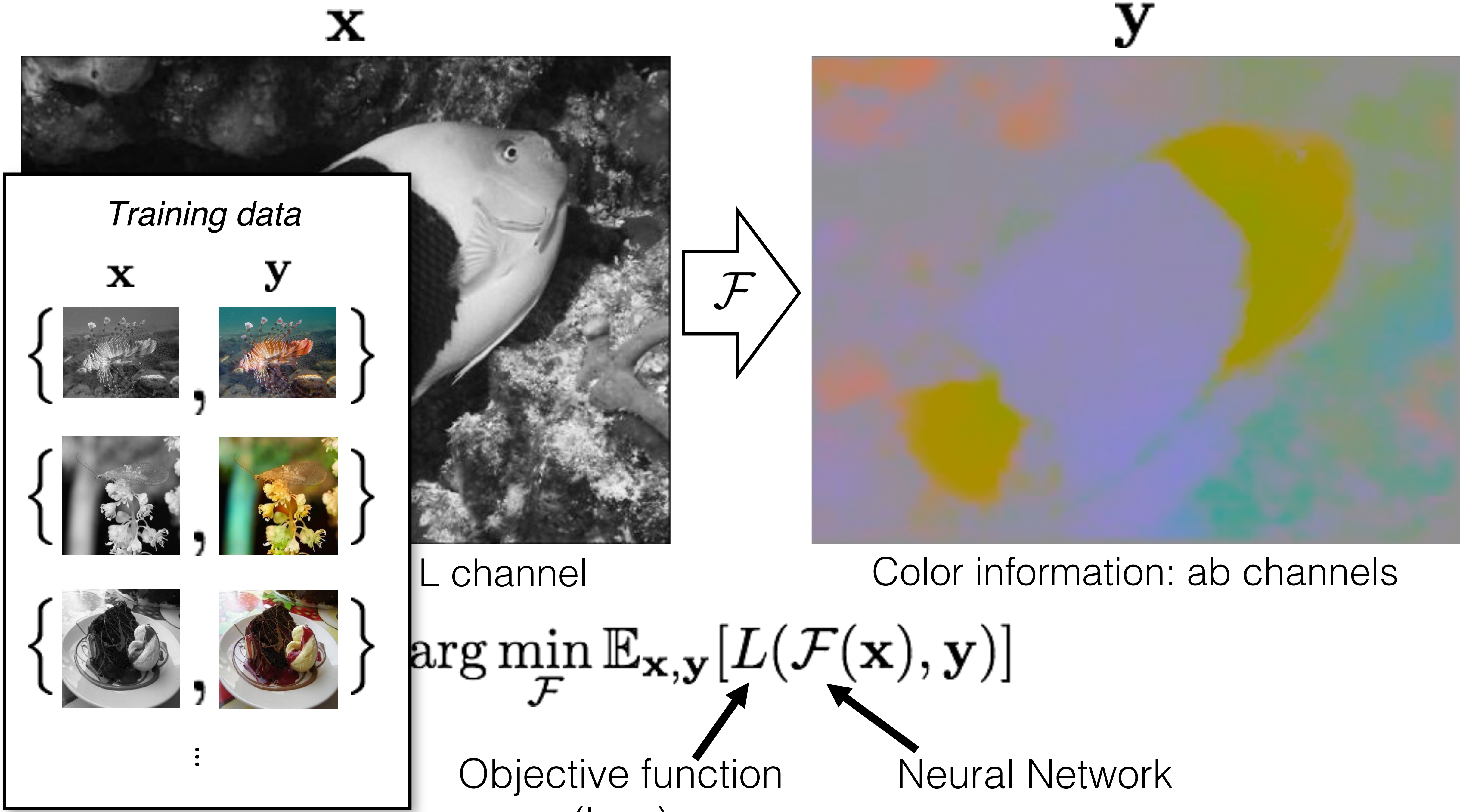
from Jin Sun, Richard Zhang, Phillip Isola



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

“**What** should I do” “**How** should I do it?”

from Jin Sun, Richard Zhang, Phillip Isola



L channel

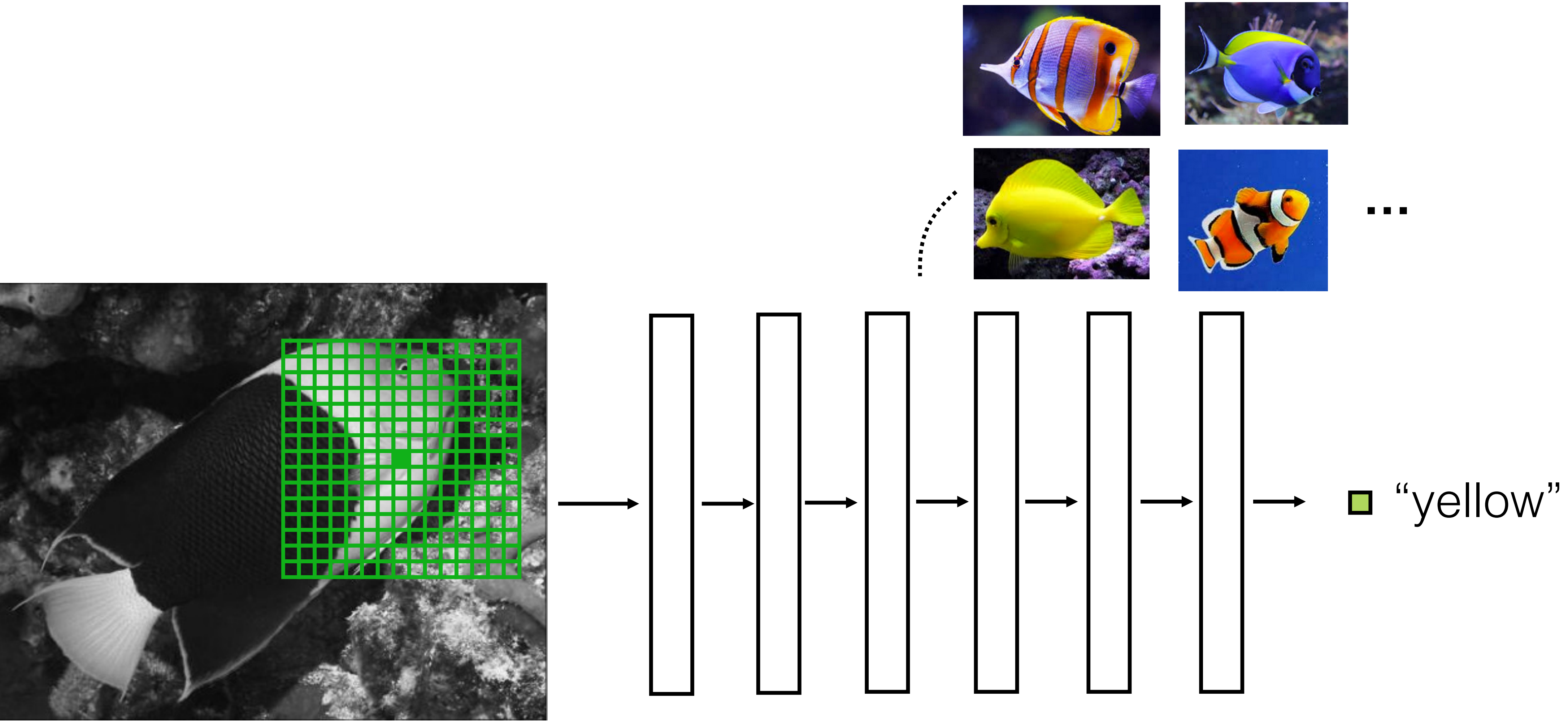
Color information: ab channels

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

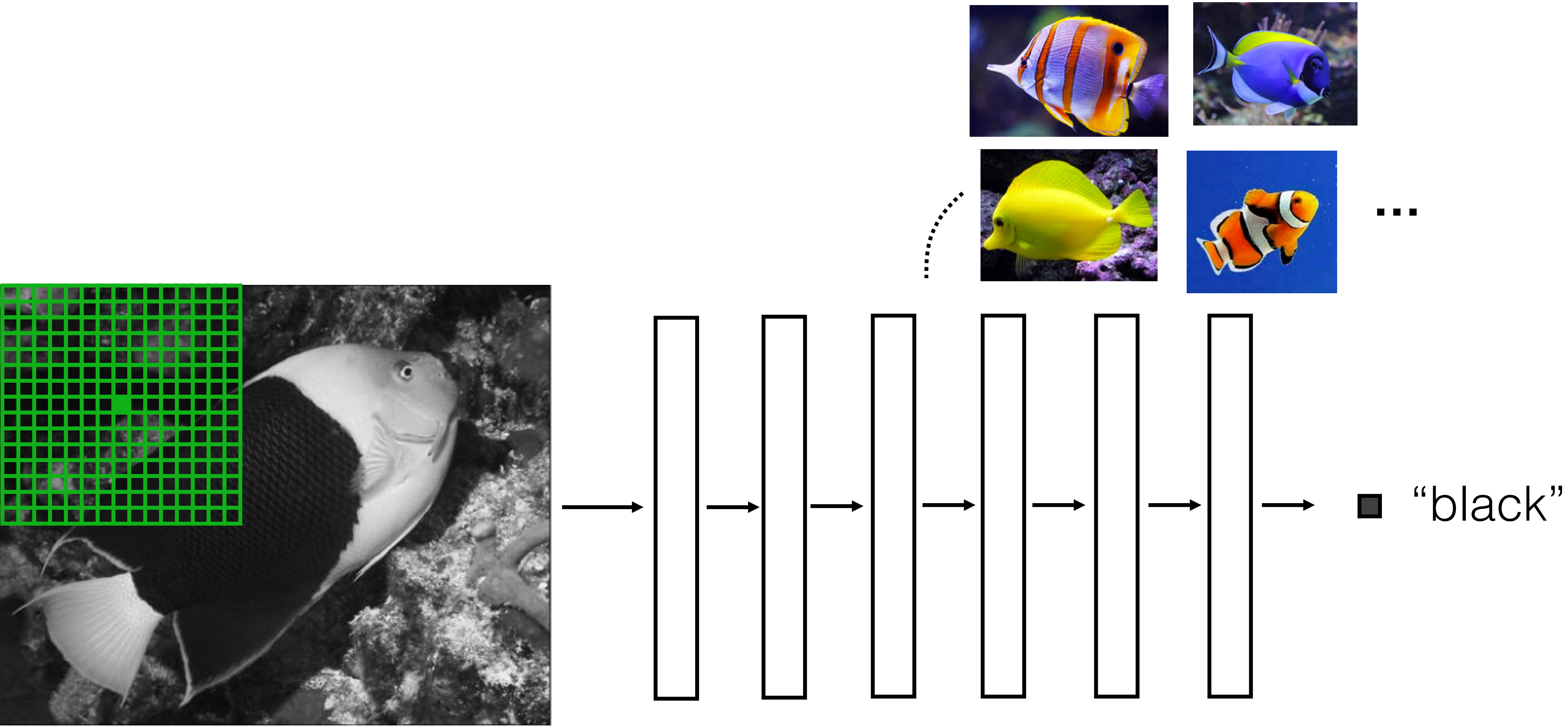
Objective function (loss)

Neural Network

from Jin Sun, Richard Zhang, Phillip Isola

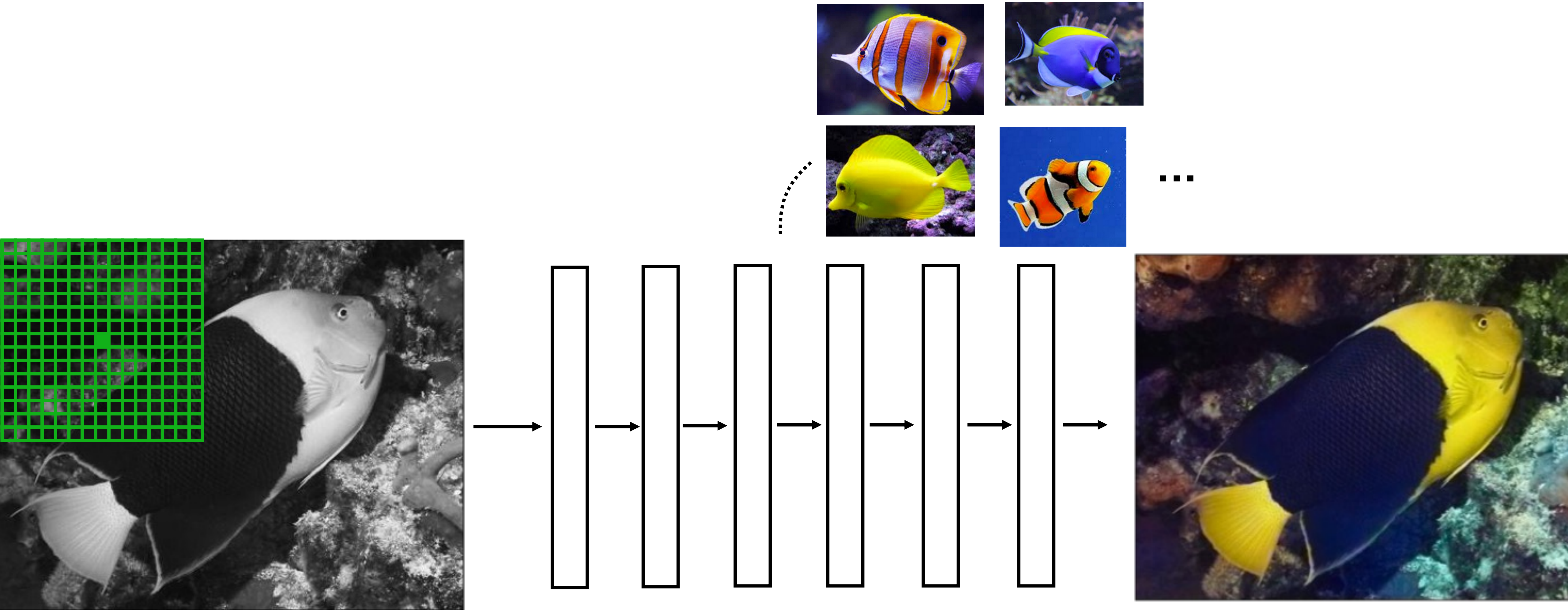


from Jin Sun, Richard Zhang, Phillip Isola



■ “black”

from Jin Sun, Richard Zhang, Phillip Isola



from Jin Sun, Richard Zhang, Phillip Isola

Recap: basic loss functions

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

Truth: $\mathbf{y}$

Classification (cross-entropy):

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

← How many extra bits it takes to correct the predictions

Least-squares regression:

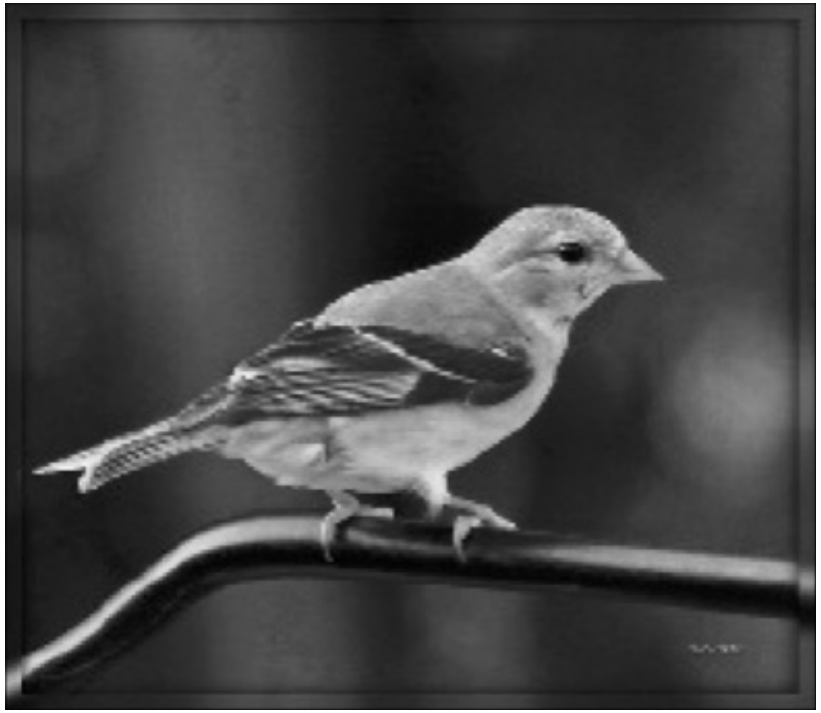
$$L(\hat{\mathbf{y}}, \mathbf{y}) = \|\hat{\mathbf{y}} - \mathbf{y}\|_2$$

← How far off we are in Euclidean distance

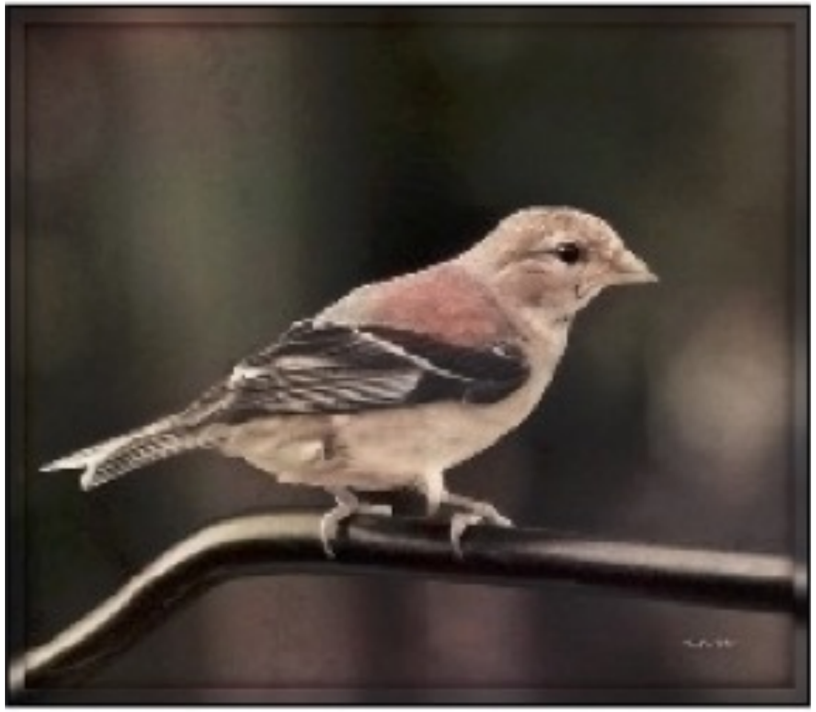
from Jin Sun, Richard Zhang, Phillip Isola

Designing loss functions

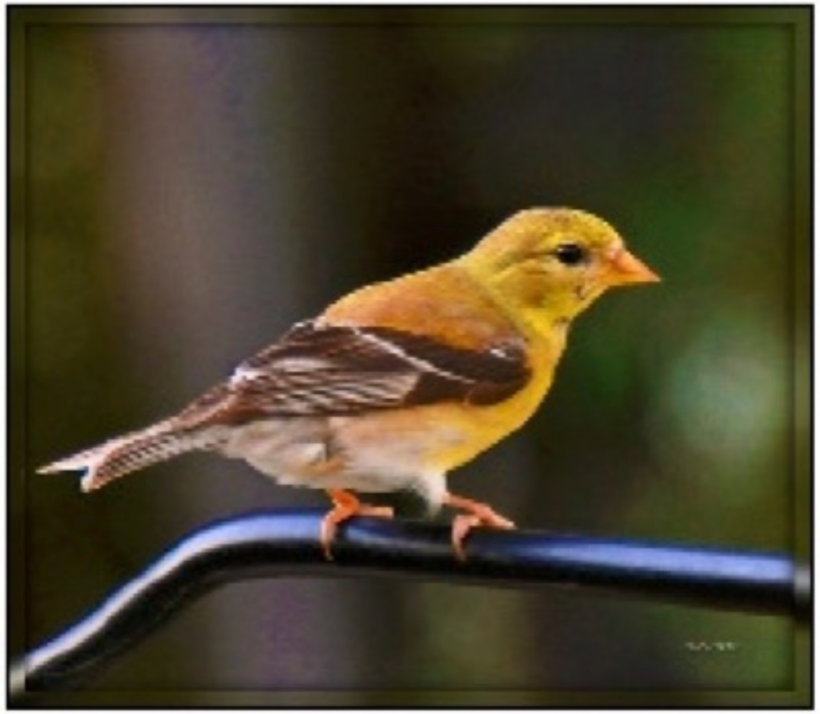
Input



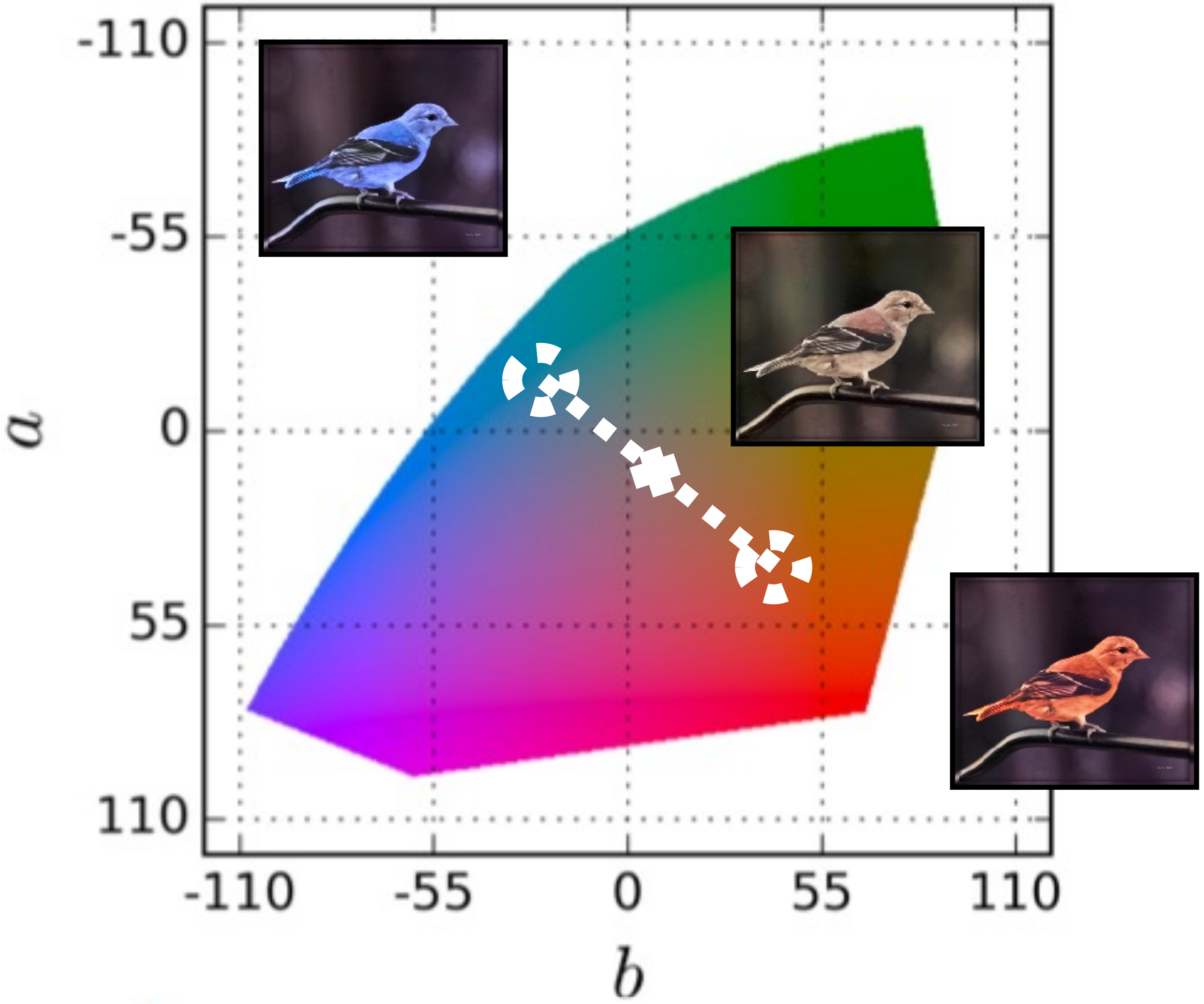
Output



Ground truth

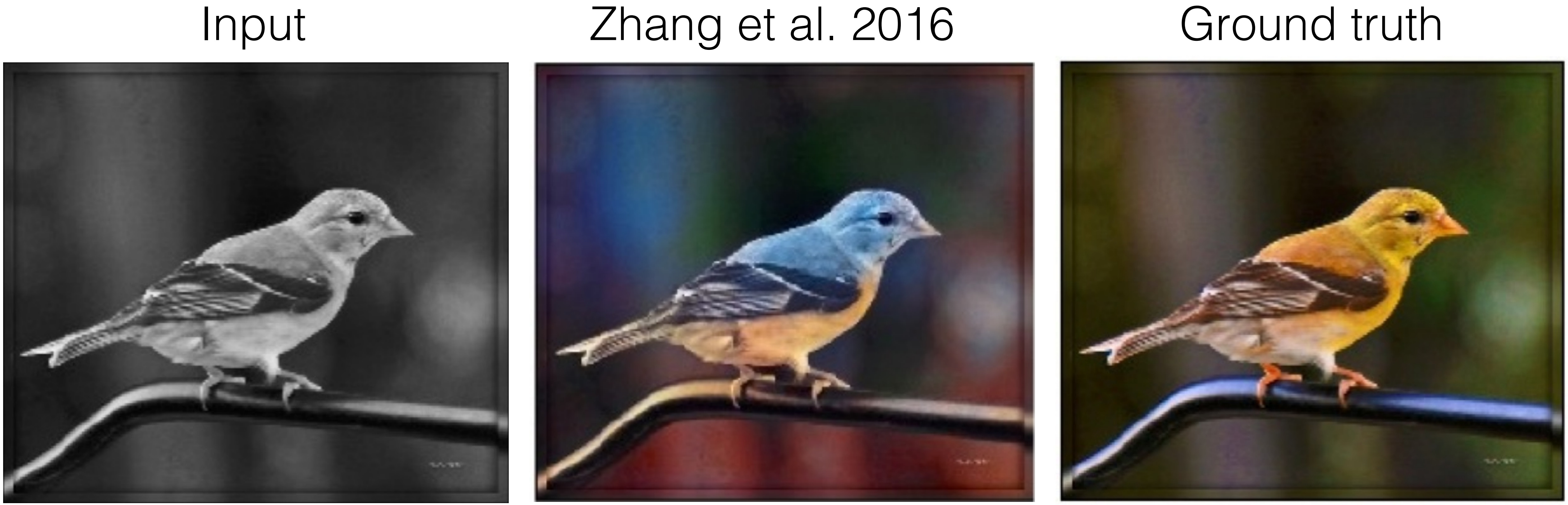


$$\mathrm{L}_2(\widehat{\mathbf{Y}}, \mathbf{Y}) = \frac{1}{2}\sum_{h,w}\|\mathbf{Y}_{h,w} - \widehat{\mathbf{Y}}_{h,w}\|_2^2$$



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

Designing loss functions



Input

Zhang et al. 2016

Ground truth

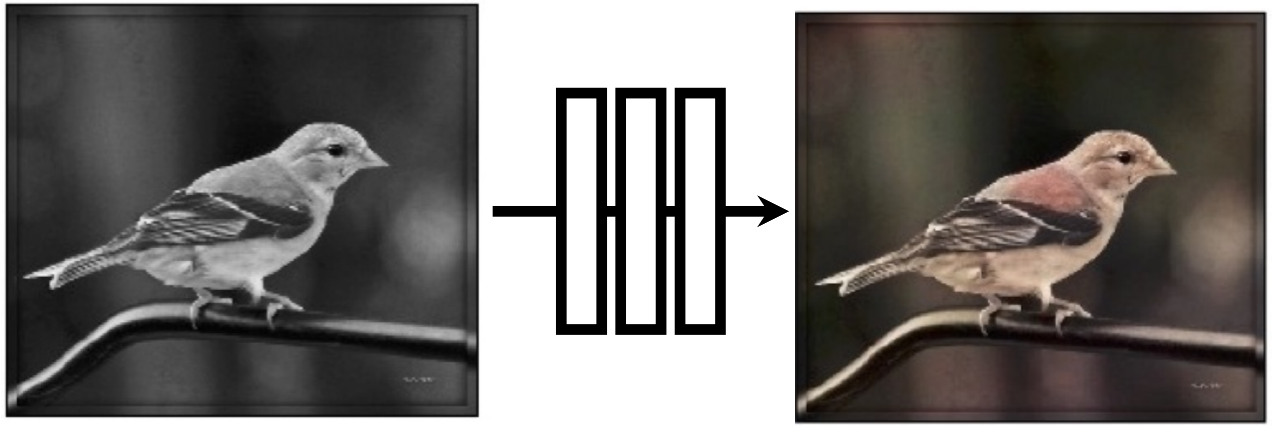
Color distribution cross-entropy loss with colorfulness enhancing term.

[Zhang, Isola, Efros, ECCV 2016]

7up
DADS
DADS
7up

Designing loss functions

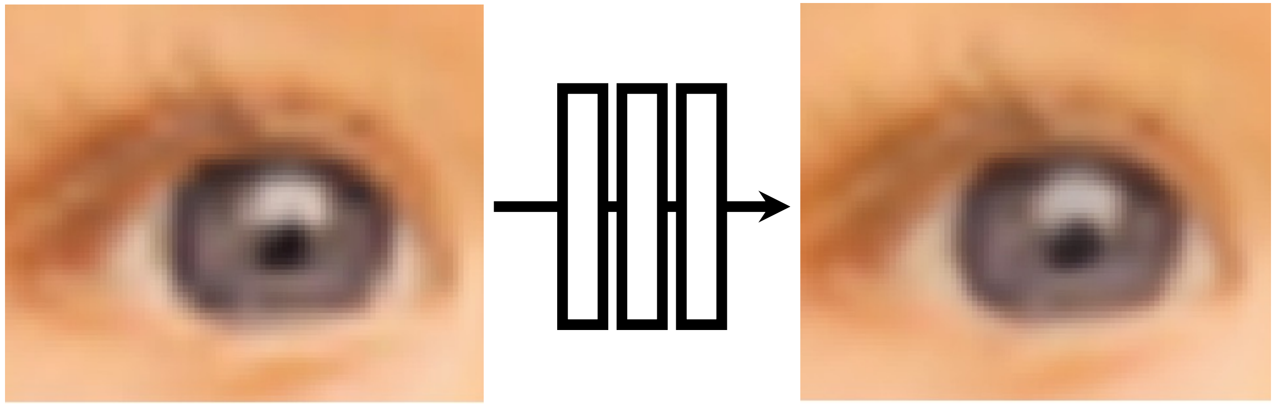
Image colorization



[Zhang, Isola, Efros, ECCV 2016]

L2 regression

Super-resolution

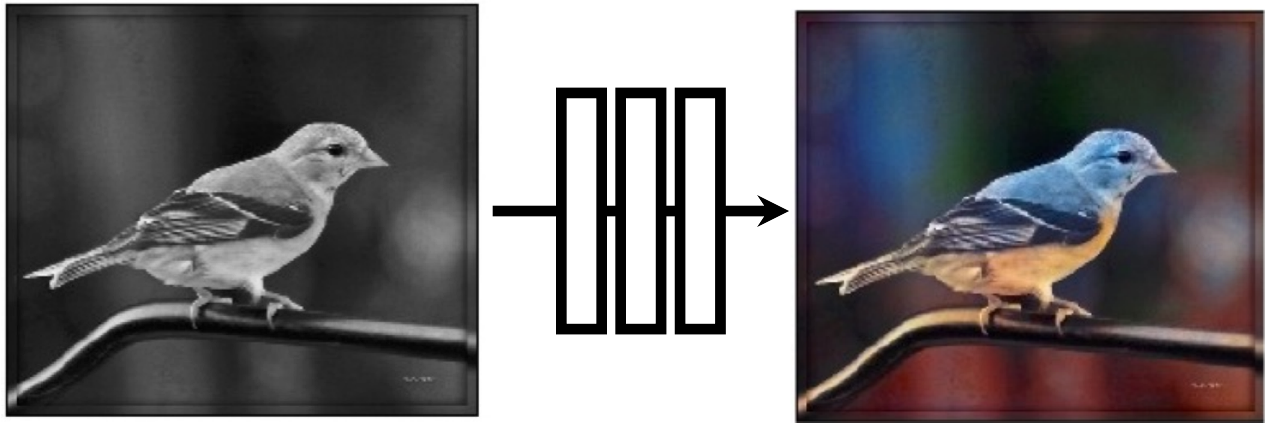


[Johnson, Alahi, Li, ECCV 2016]

L2 regression

Designing loss functions

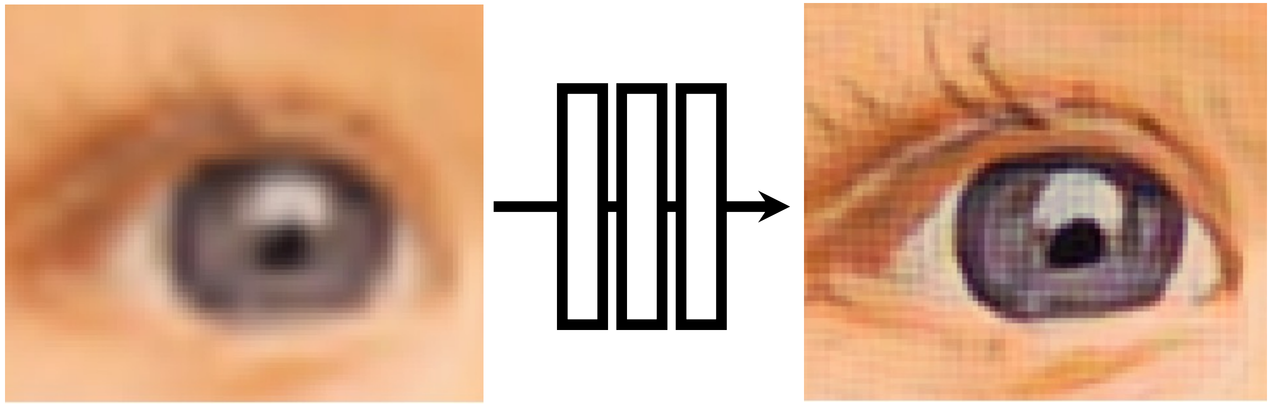
Image colorization



[Zhang, Isola, Efros, ECCV 2016]

Cross entropy objective, with colorfulness term

Super-resolution

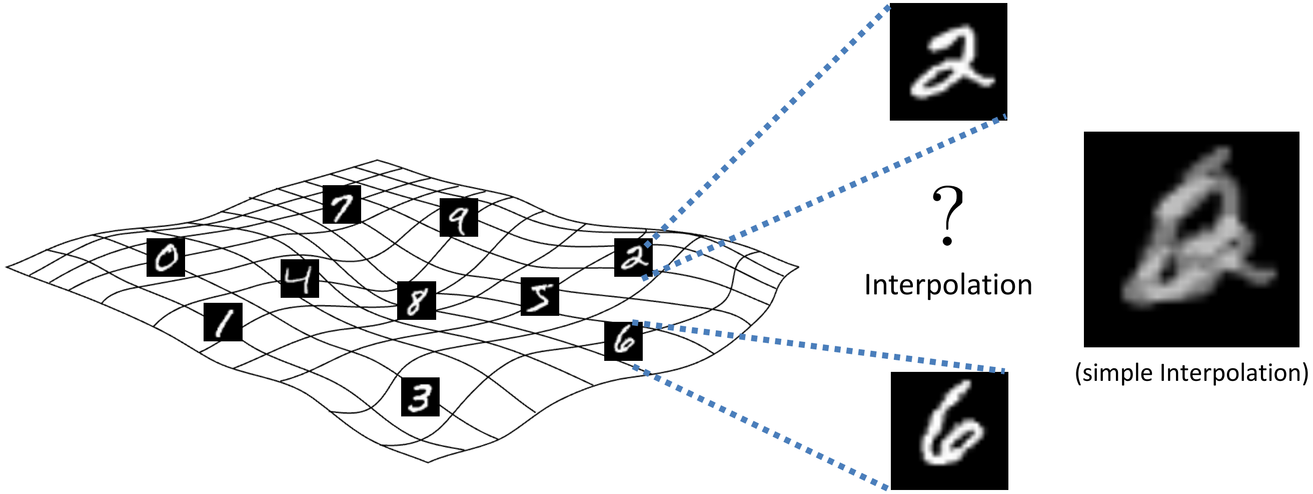


[Johnson, Alahi, Li, ECCV 2016]

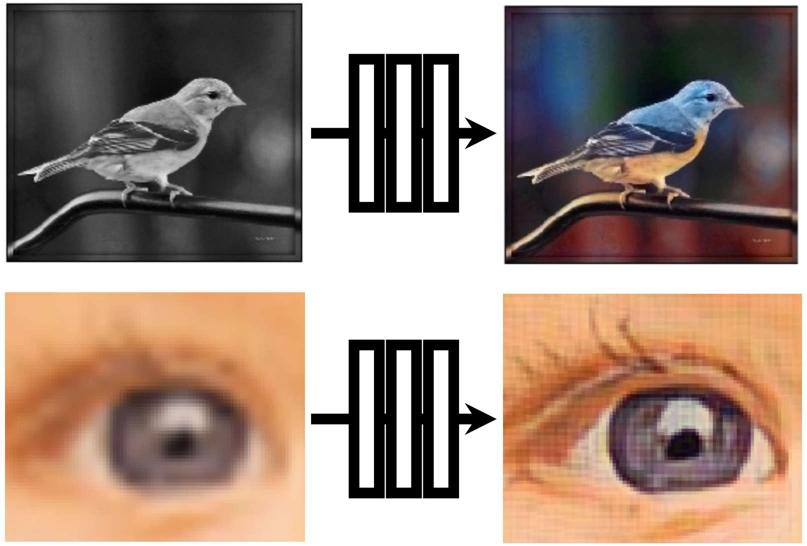
Deep feature covariance matching objective

Better Loss Function: Sticking to the Manifold

- How do we design a loss function that penalizes images that aren’t on the image manifold?



- Key insight: we will *learn* our loss function by training a network to discriminate between images that are on the manifold and images that aren’t

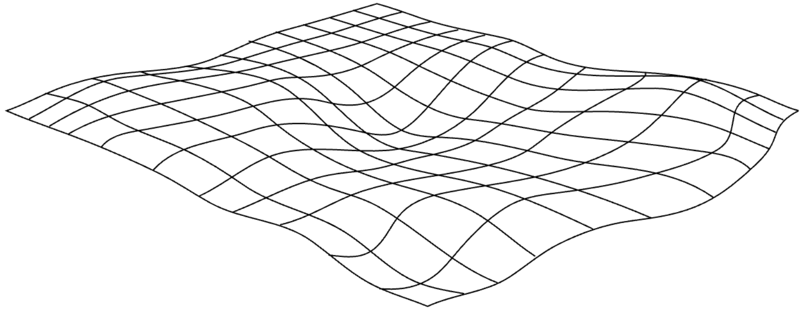


Abe Davis, with slides from Jin Sun and Phillip Isola

PART 3: GENERATIVE ADVERSARIAL NETWORKS (GANS)

Generative Adversarial Networks (GANs)

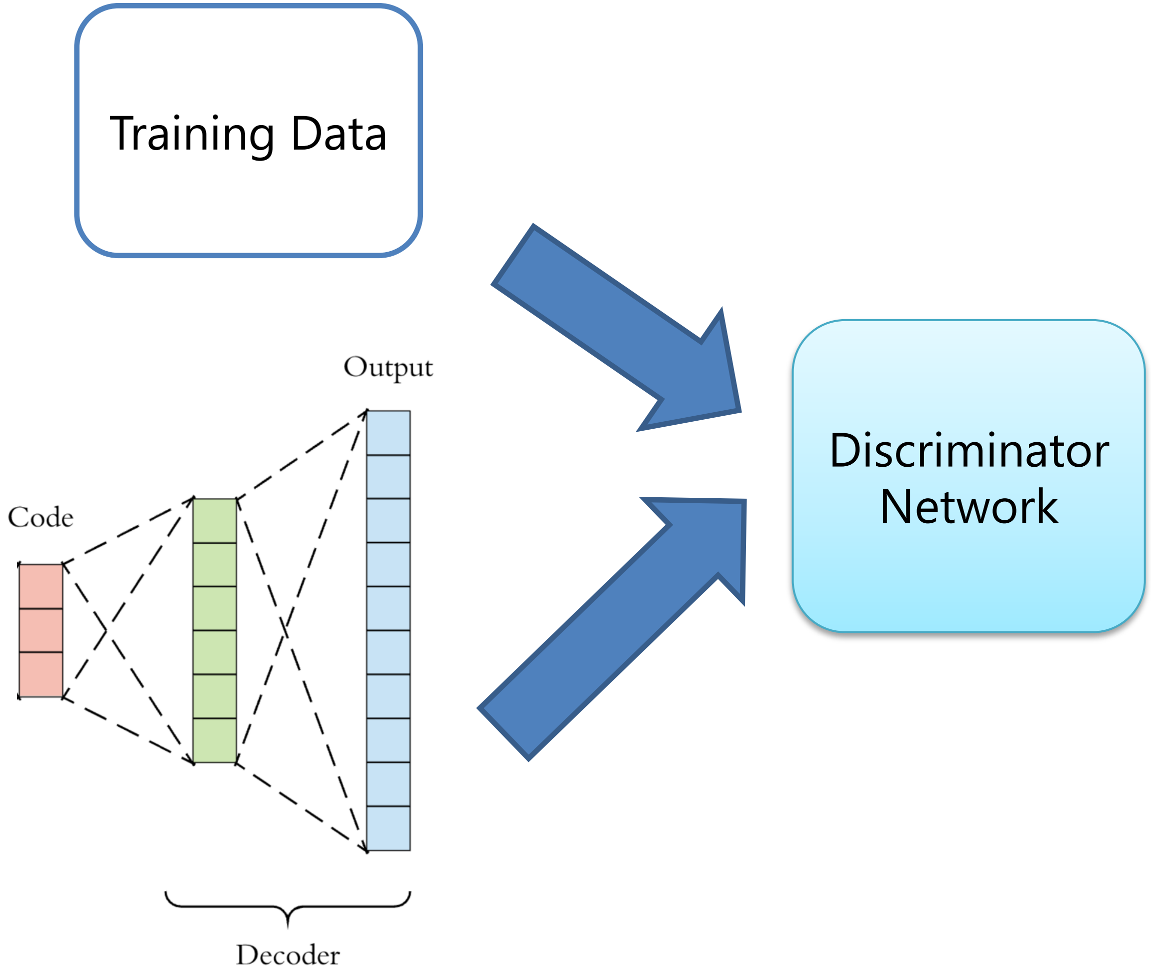
- Basic idea: Learn a mapping from some latent space to images on a particular manifold



- Example of a ***Generative Model:***
  - We can think of classification as a way to compute some P(x) that tells us the probability that image x is a member of a class.
  - Rather than simply evaluating this distribution, a generative model tries to learn a way to sample from it

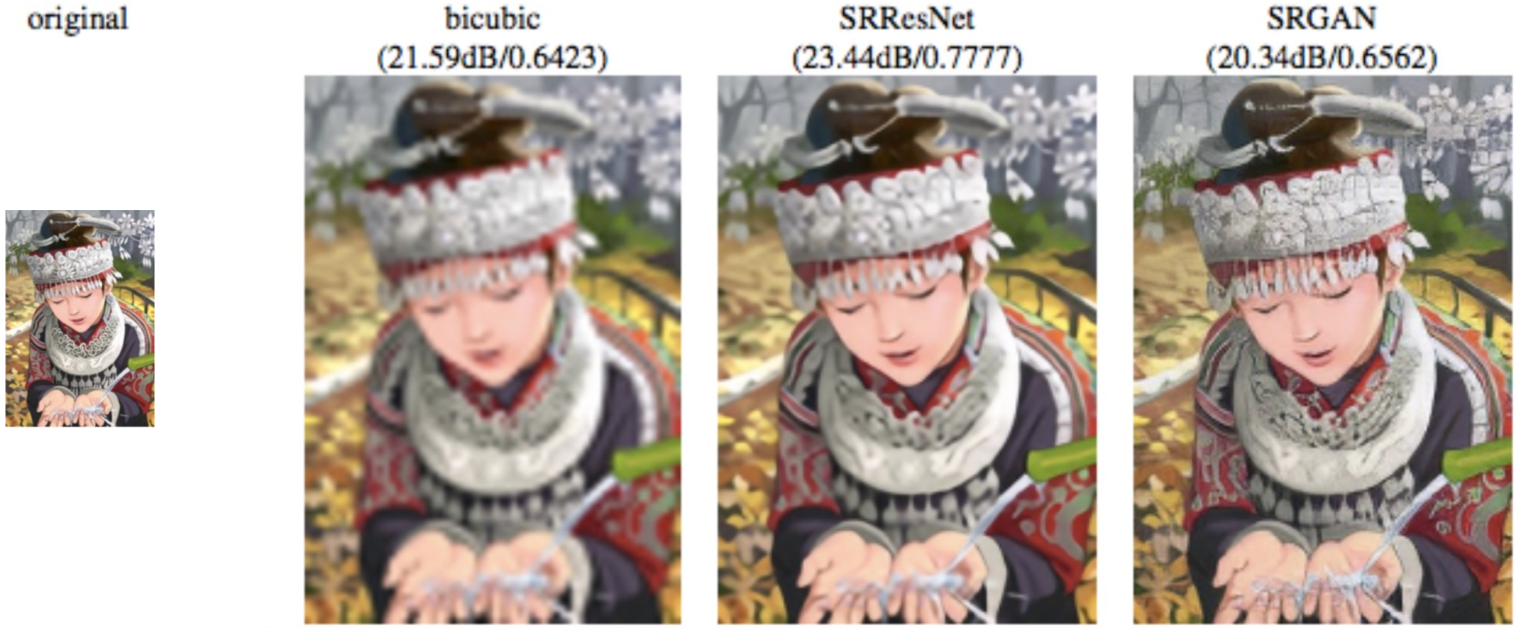
Generative Adversarial Networks (GANs)

- Generator network has similar structure to the decoder of our autoencoder
  - Maps from some latent space to images
- We train it in an adversarial manner against a discriminator network
  - Generator takes image noise, and tries to create output indistinguishable from training data
  - Discriminator tries to distinguish between generator output and

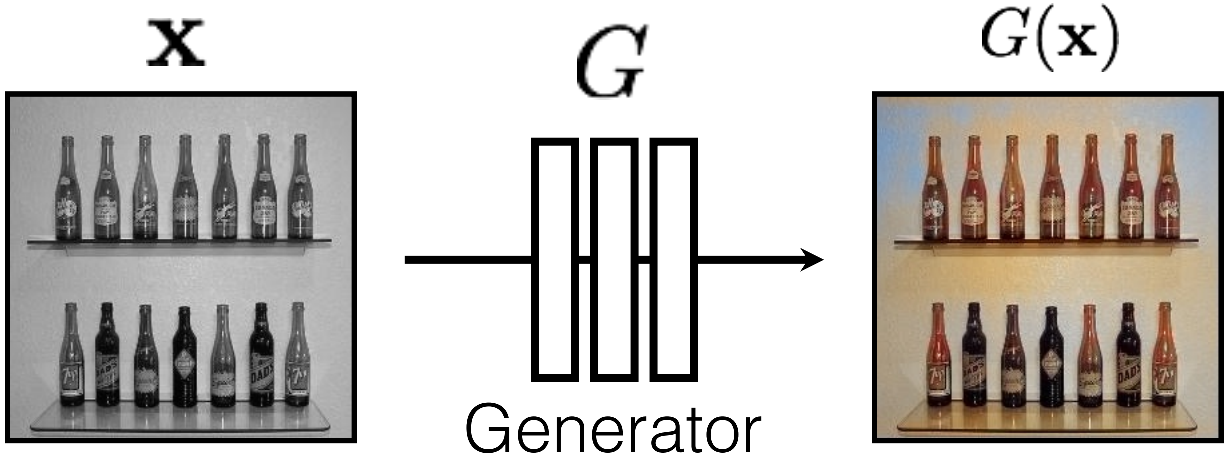


First: Conditional GANs

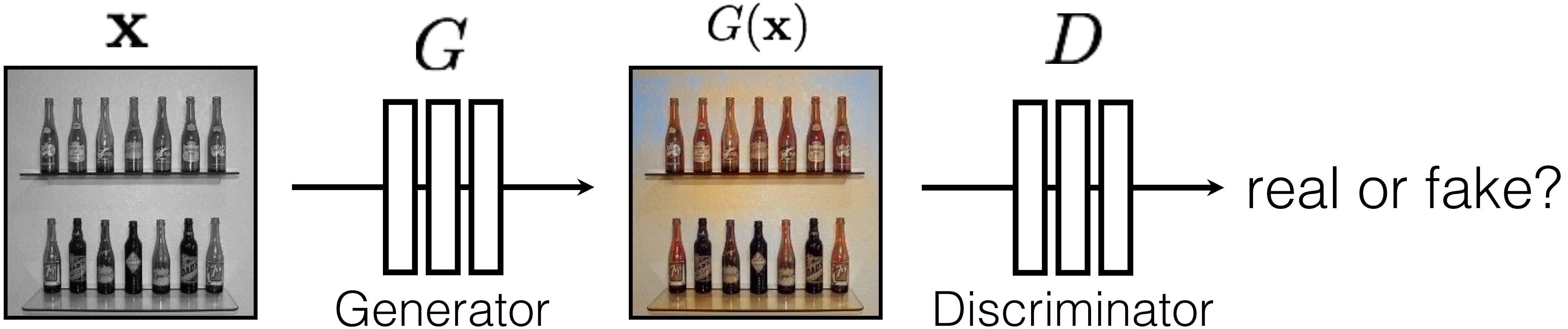
- Generate samples from a *conditional distribution* (conditioned on some other input)
- Example: generate high-resolution image conditioned on low resolution input



[Ledig et al 2016]



[Goodfellow et al., 2014]



$\mathbf{x}$

G

Generator

$G(\mathbf{x})$

D

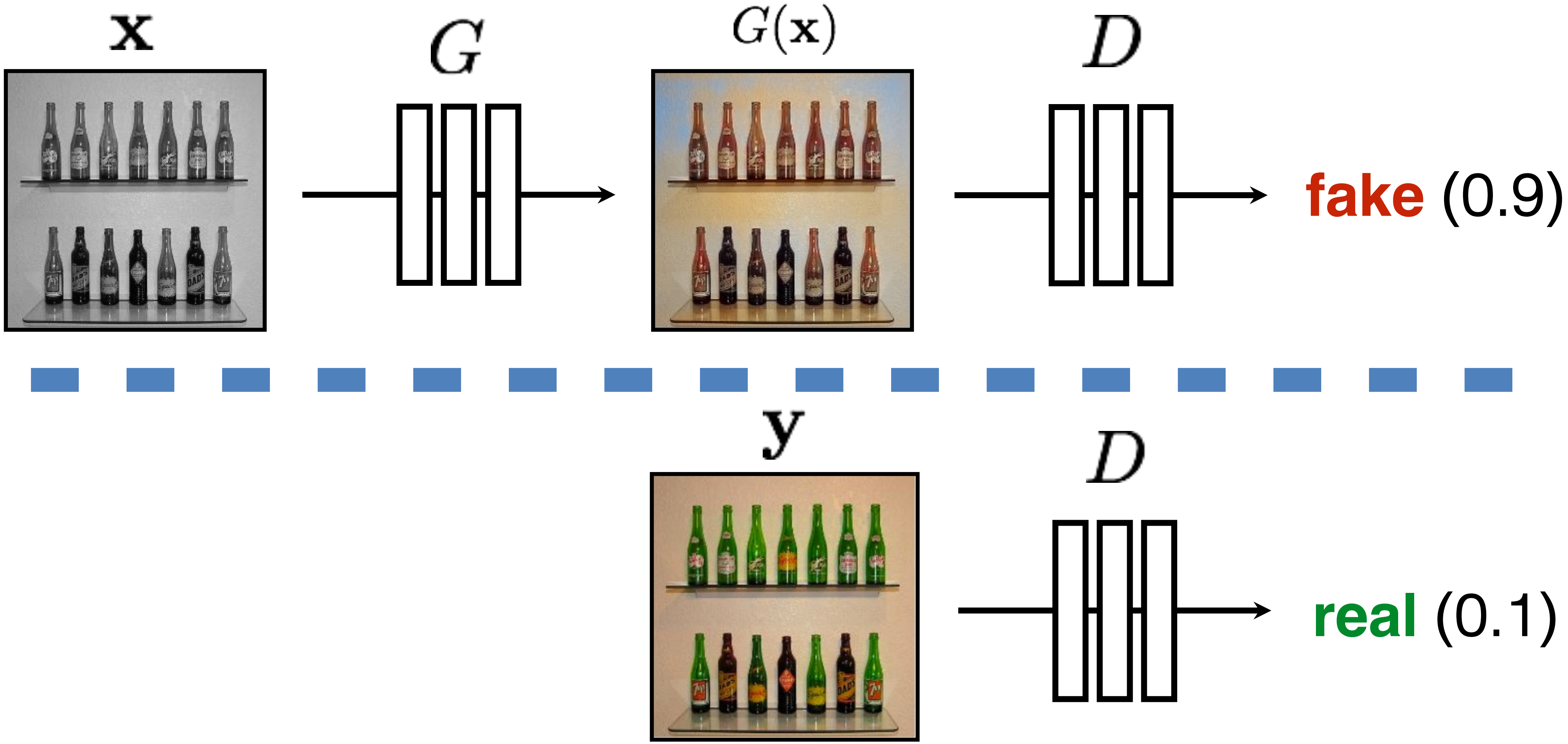
Discriminator

real or fake?

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

D tries to identify the fakes

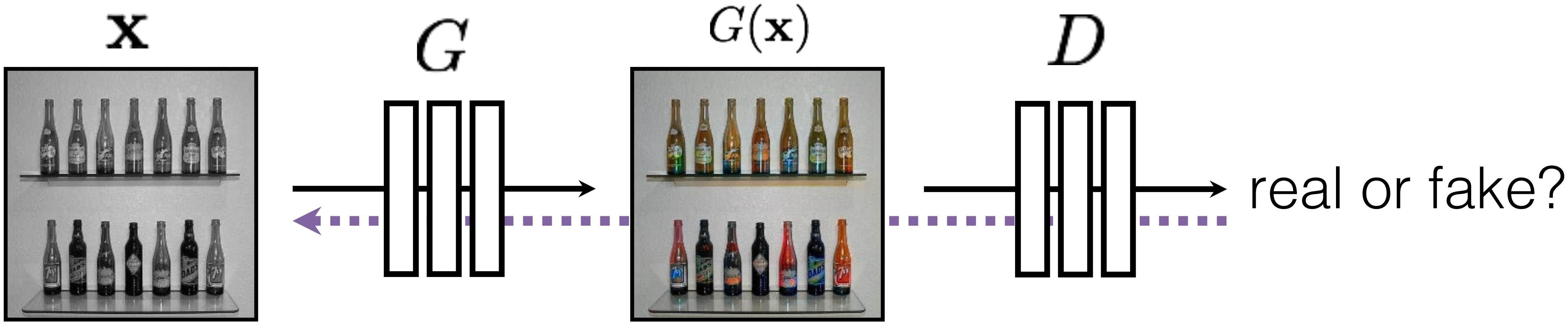
[Goodfellow et al., 2014]



(Identify generated images as fake) (Identify training images as real)

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

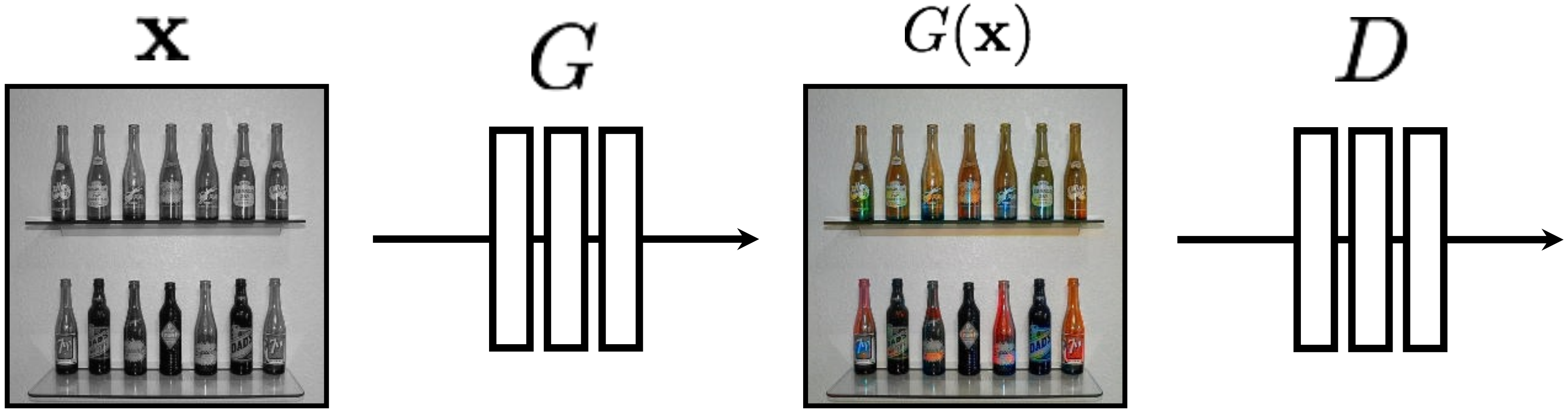
[Goodfellow et al., 2014]



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

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

[Goodfellow et al., 2014]

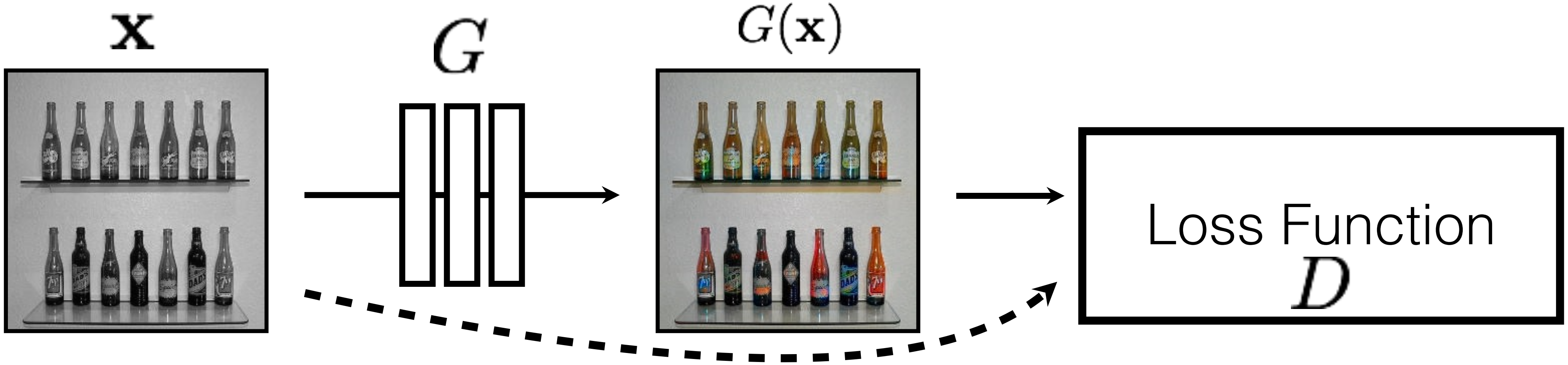


real or fake?

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

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

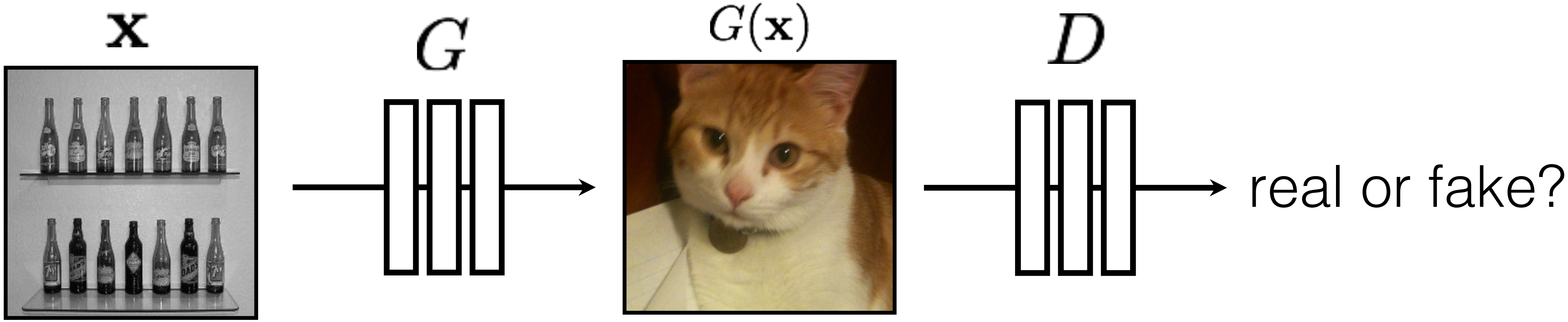
[Goodfellow et al., 2014]



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

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

[Goodfellow et al., 2014]
[Isola et al., 2017]



$\mathbf{x}$

G

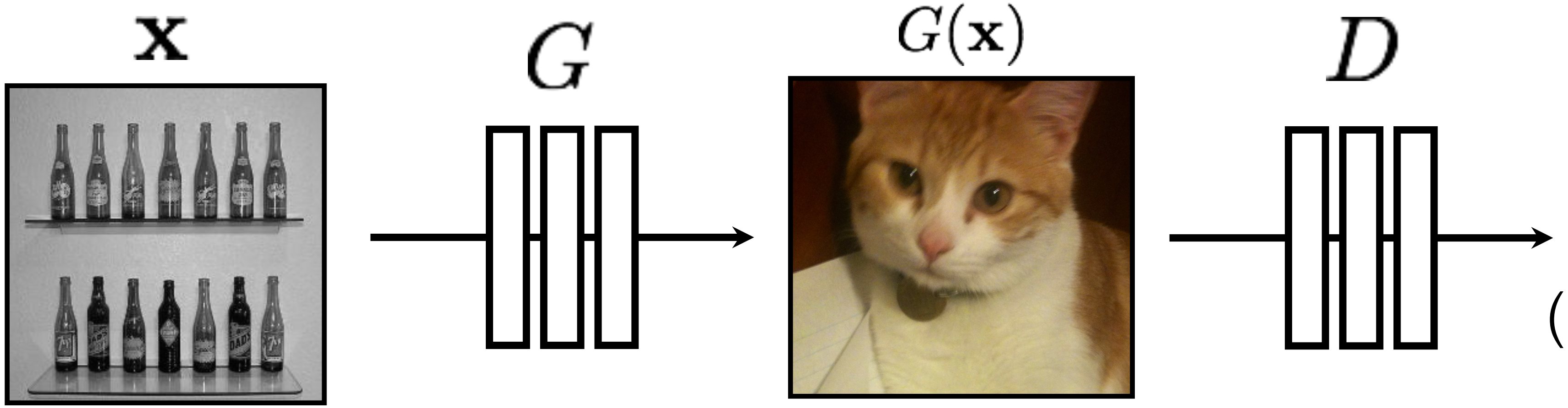
$G(\mathbf{x})$

D

real or fake?

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

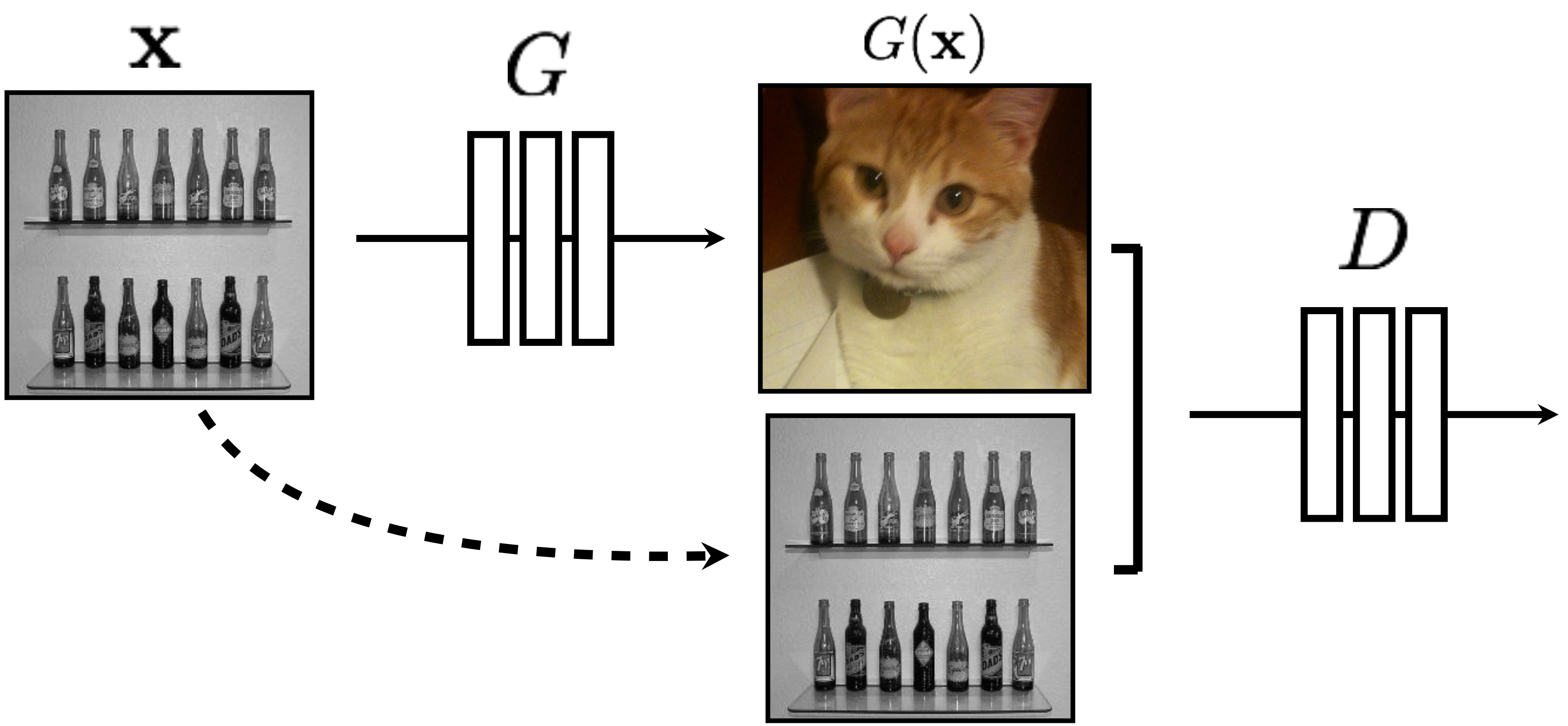
[Goodfellow et al., 2014]



real!
(“Aquarius”)

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

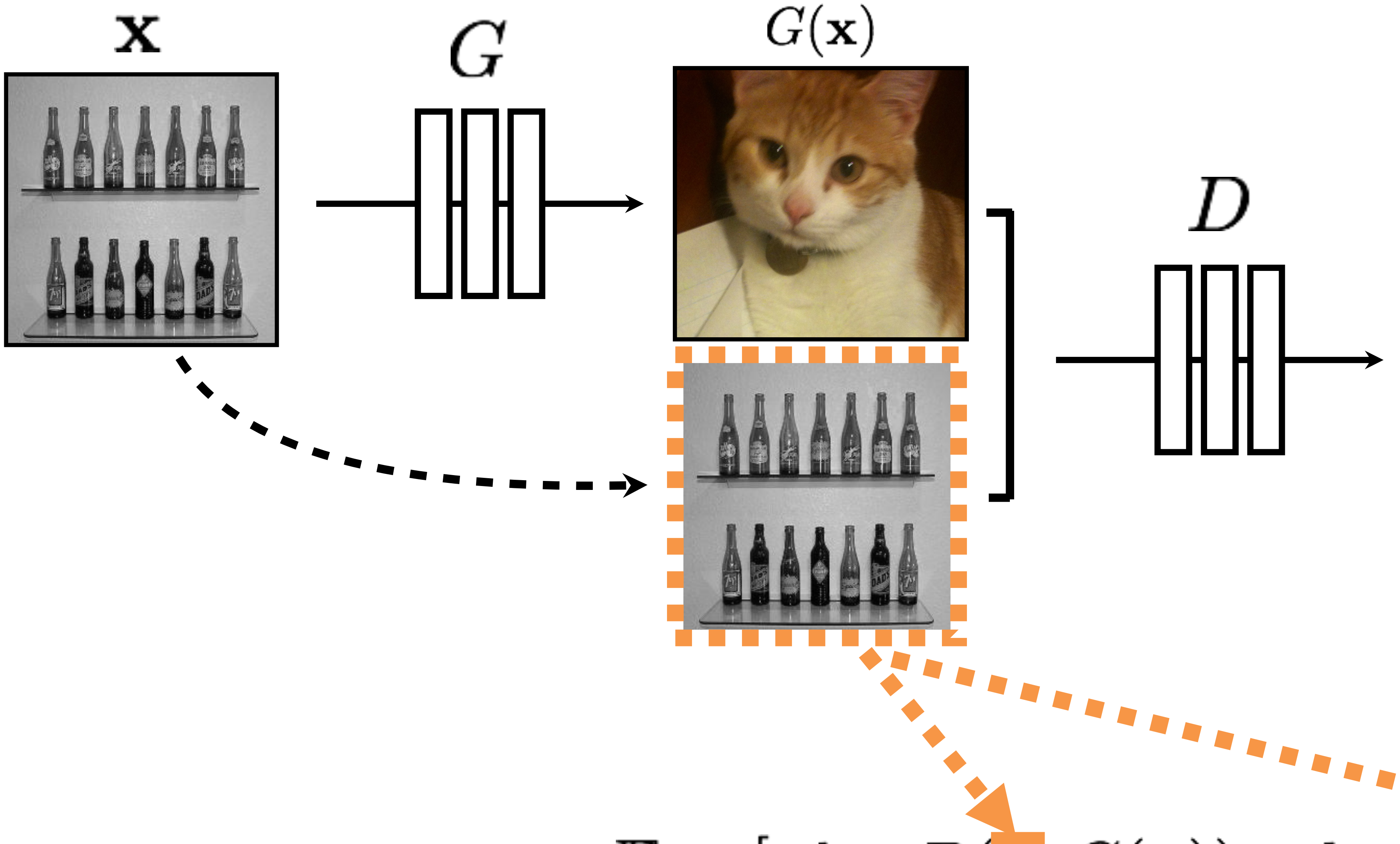
[Goodfellow et al., 2014]



real or fake *pair* ?

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

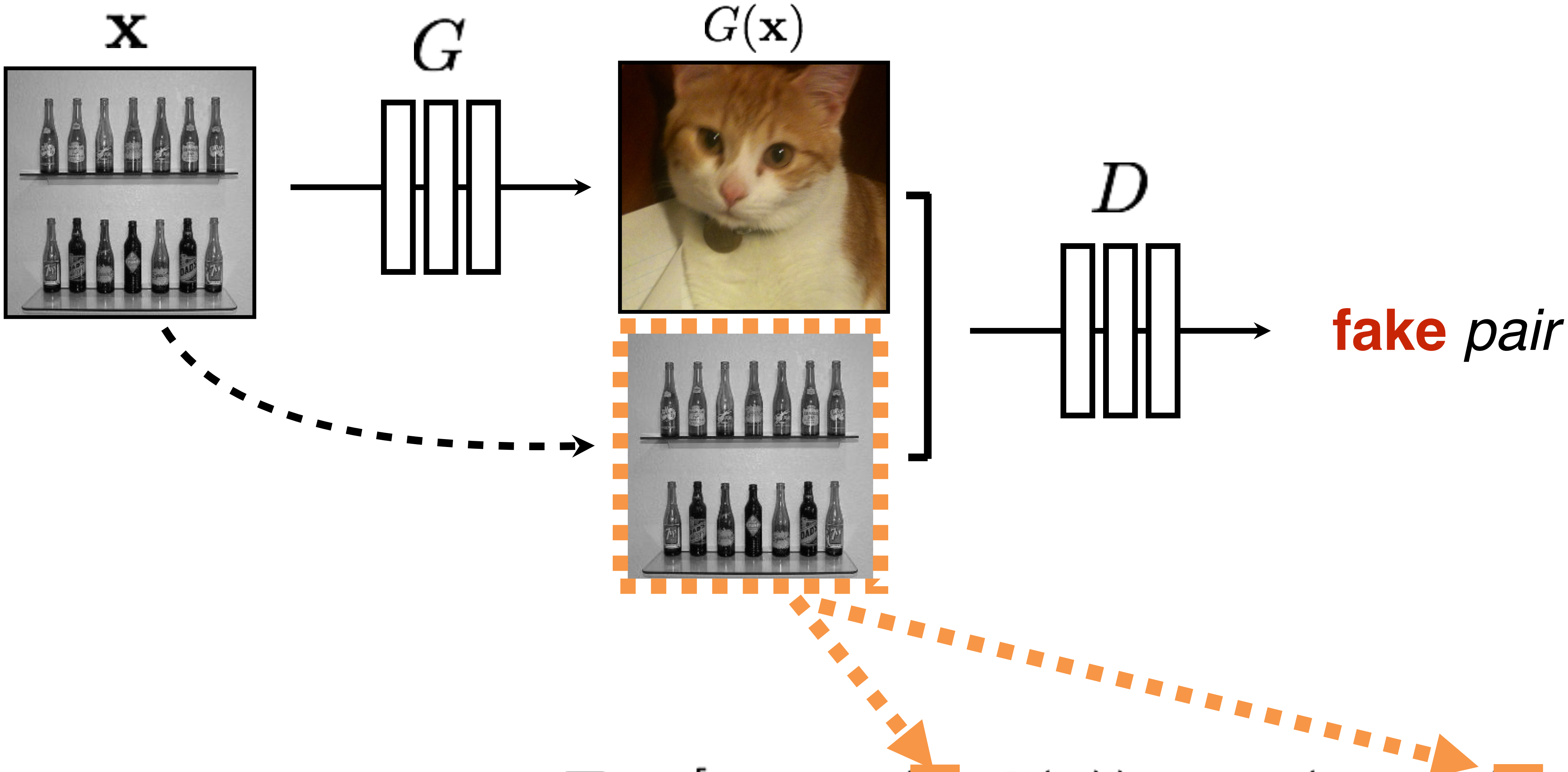
[Goodfellow et al., 2014]
[Isola et al., 2017]



real or fake *pair* ?

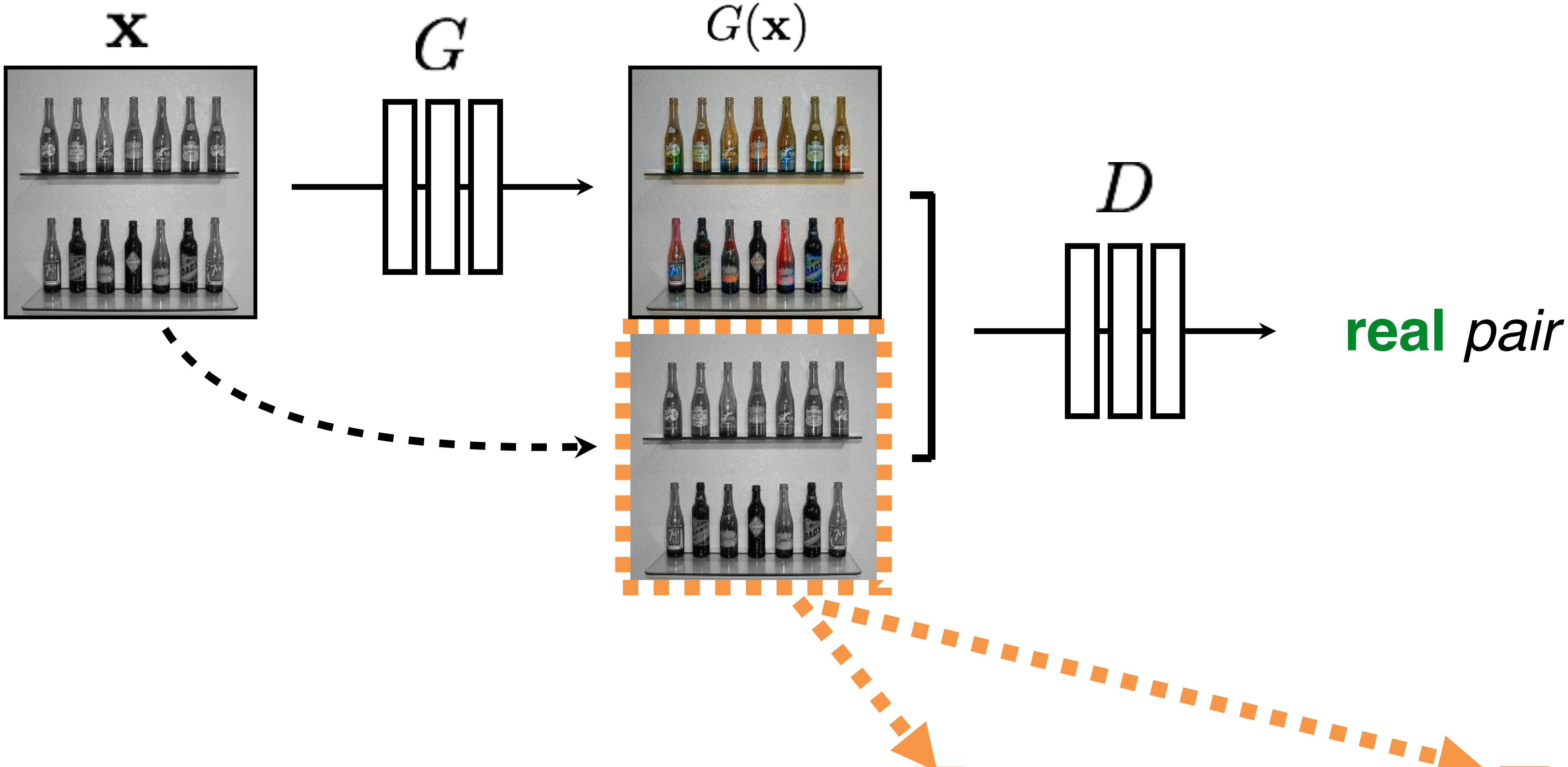
$$\arg\min_{G}\max_{D}\ \mathbb{E}_{\mathbf{x},\mathbf{y}}[\ \log D(\boxed{\mathbf{x}}, G(\mathbf{x})) + \log(1 - D(\boxed{\mathbf{x}}, \mathbf{y}))\ ]$$

[Goodfellow et al., 2014]
[Isola et al., 2017]



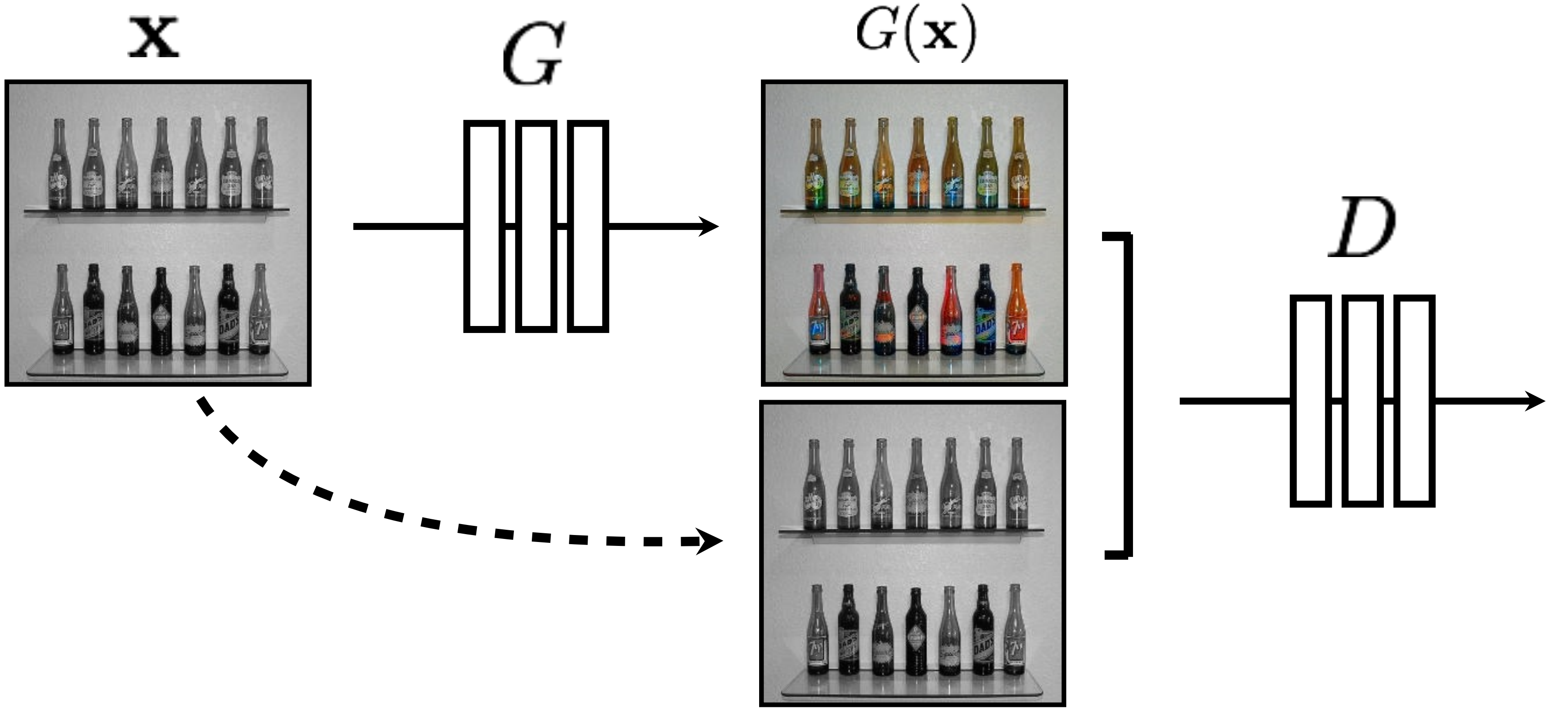
$$\arg\min_{G}\max_{D} \;\; \mathbb{E}_{\mathbf{x},\mathbf{y}}[\;\; \log D(\boxed{\mathbf{x}}, G(\mathbf{x})) + \log(1 - D(\boxed{\mathbf{x}}, \mathbf{y})) \;\;]$$

[Goodfellow et al., 2014]
[Isola et al., 2017]



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

[Goodfellow et al., 2014]
[Isola et al., 2017]



real or fake *pair* ?

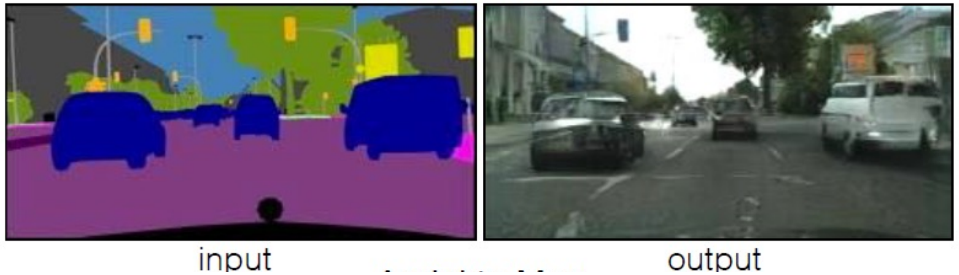
$$\arg\min_{G}\max_{D}\ \mathbb{E}_{\mathbf{x},\mathbf{y}}[\ \log D(\mathbf{x}, G(\mathbf{x})) + \log(1 - D(\mathbf{x},\mathbf{y}))\ \ ]$$

[Goodfellow et al., 2014]
[Isola et al., 2017]

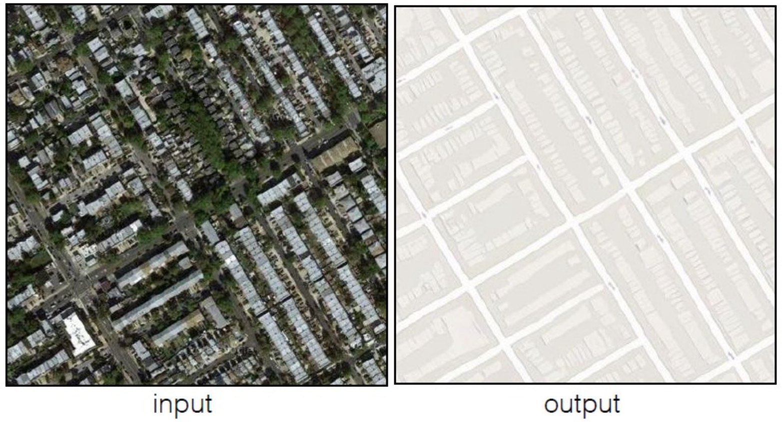
More Examples of Image-to-Image Translation with GANs

- We have pairs of corresponding training images
- Conditioned on one of the images, sample from the distribution of likely corresponding images

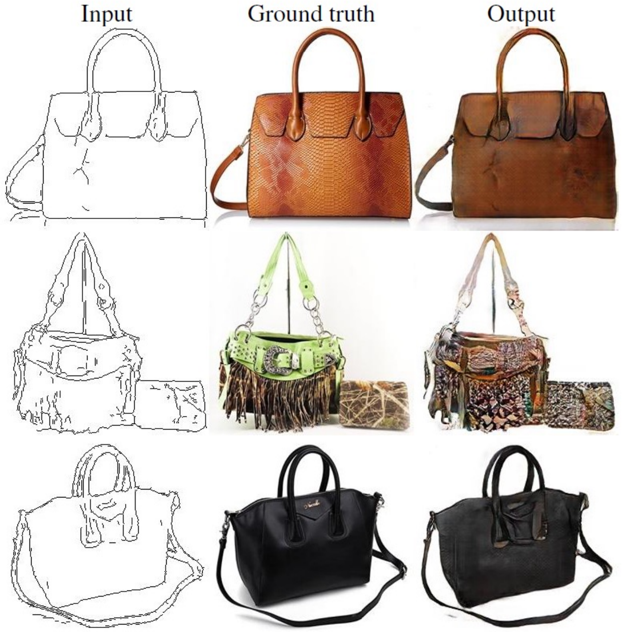
Segmentation to Street Image



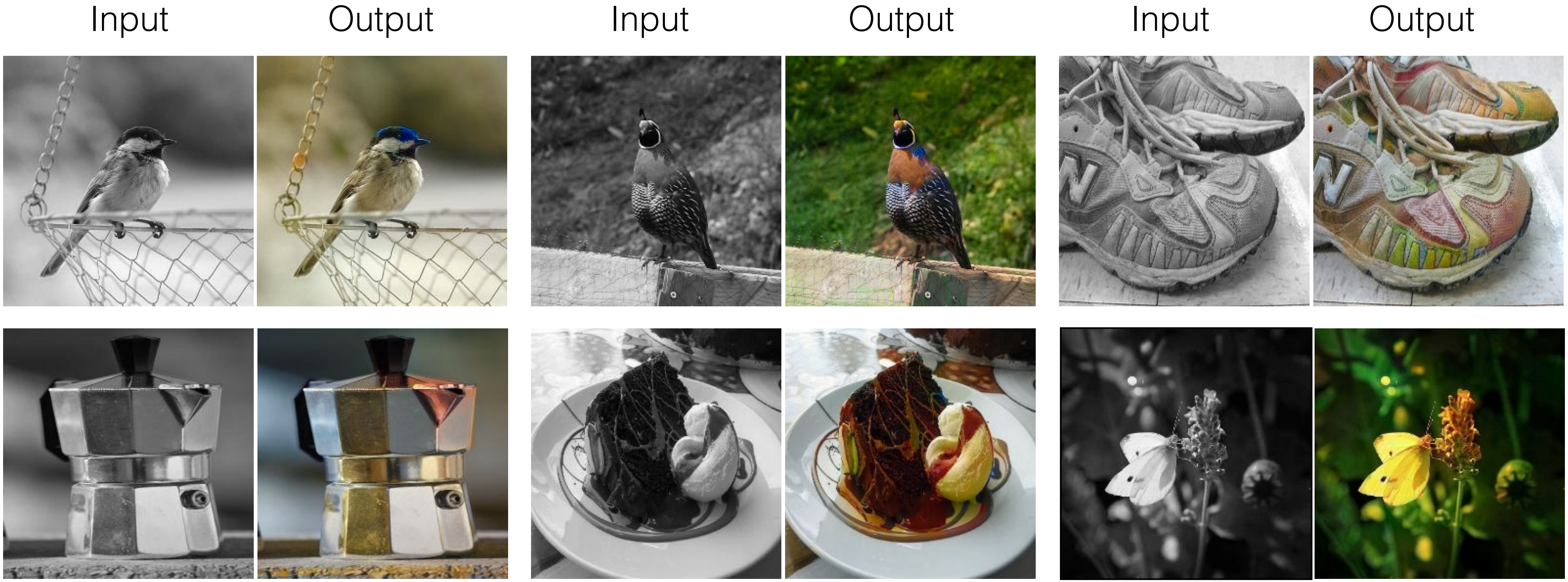
Aerial Photo To Map



Edges to Image

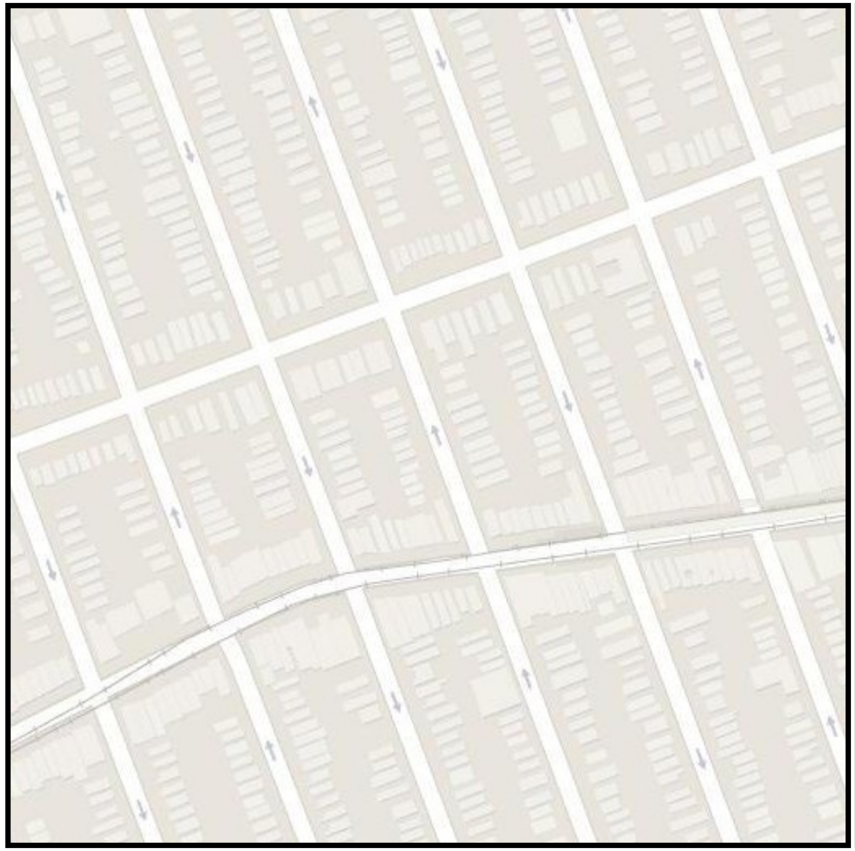


BW → Color

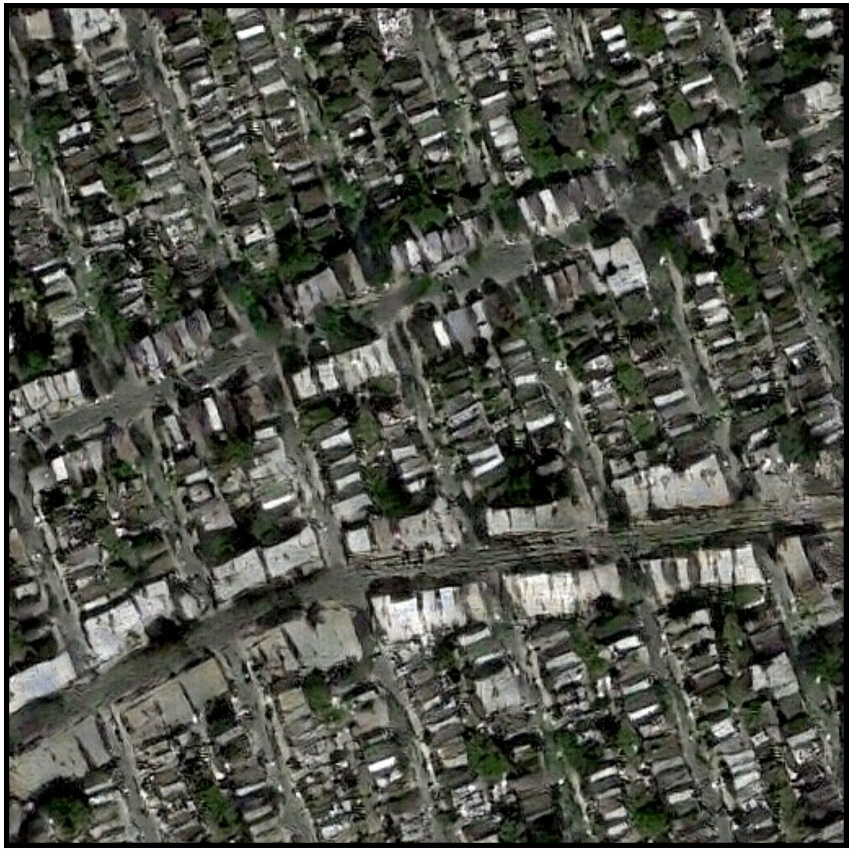


Data from [Russakovsky et al. 2015]

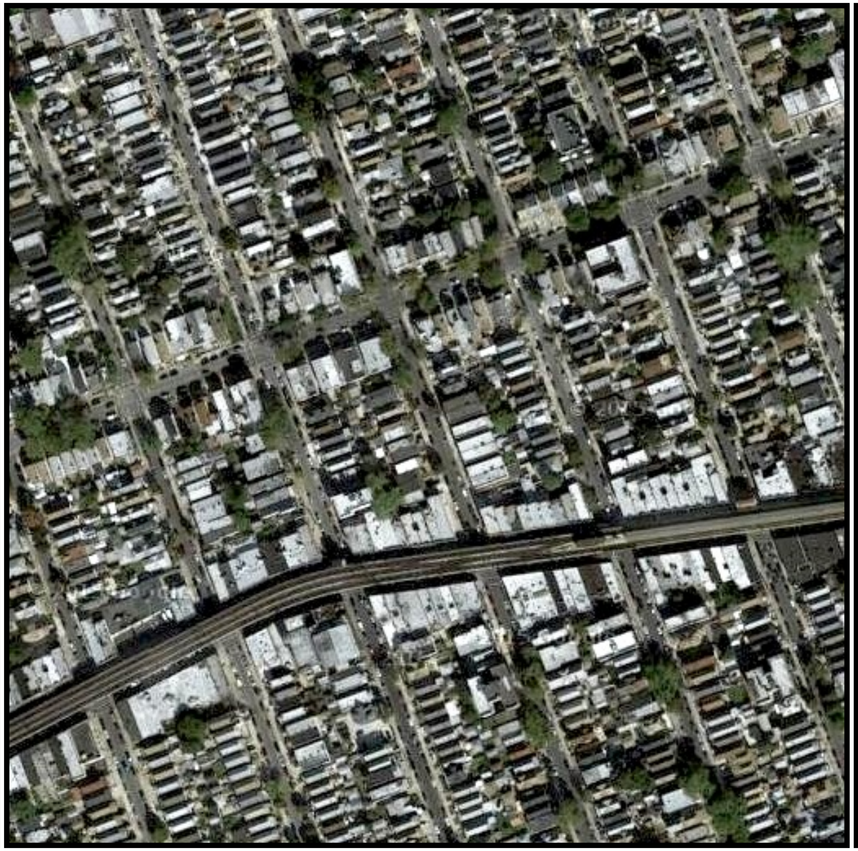
Input



Output



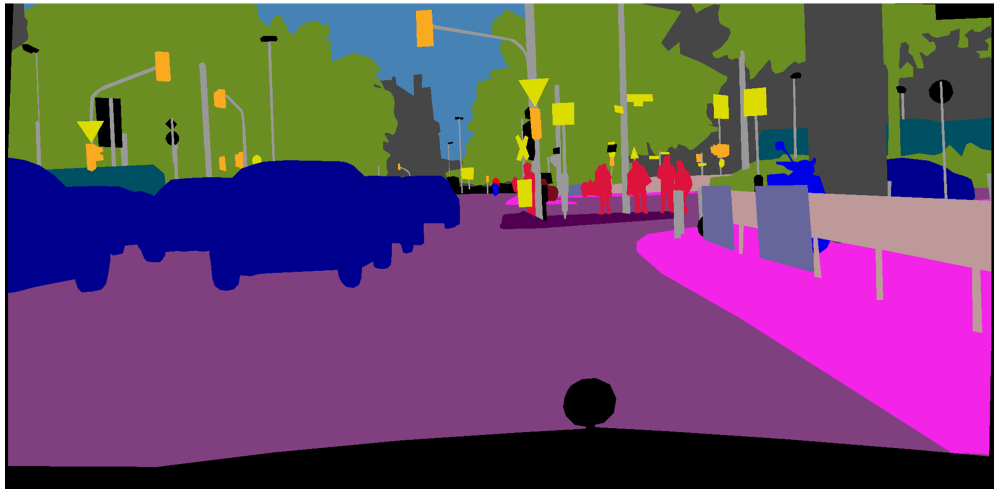
Groundtruth



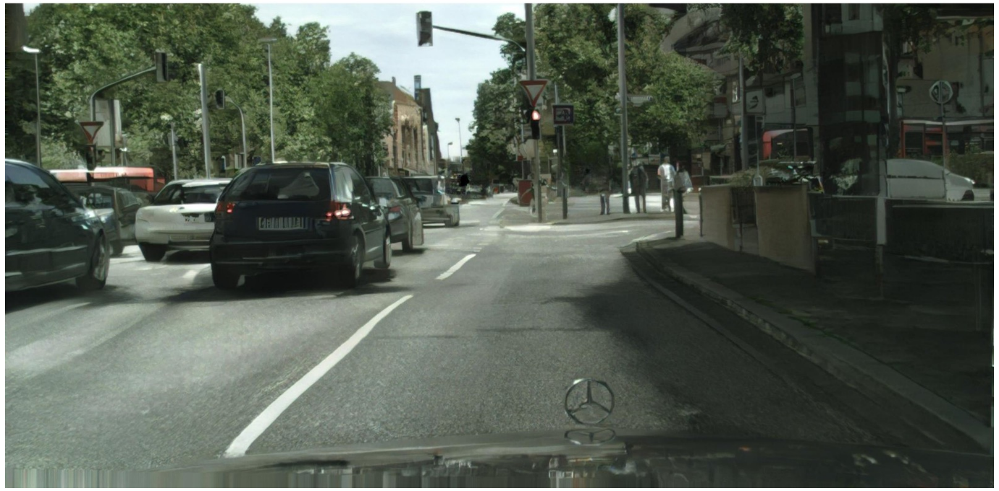
Data from
[maps.google.com]

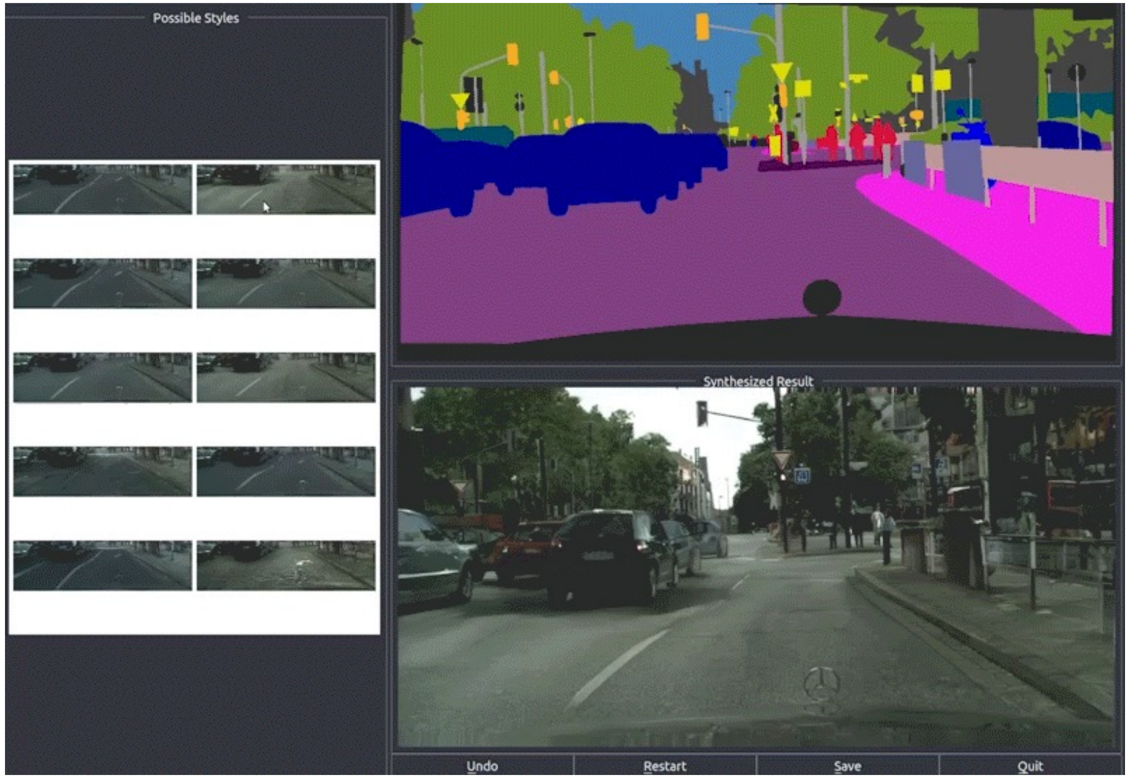
Labels → Street Views

Input labels



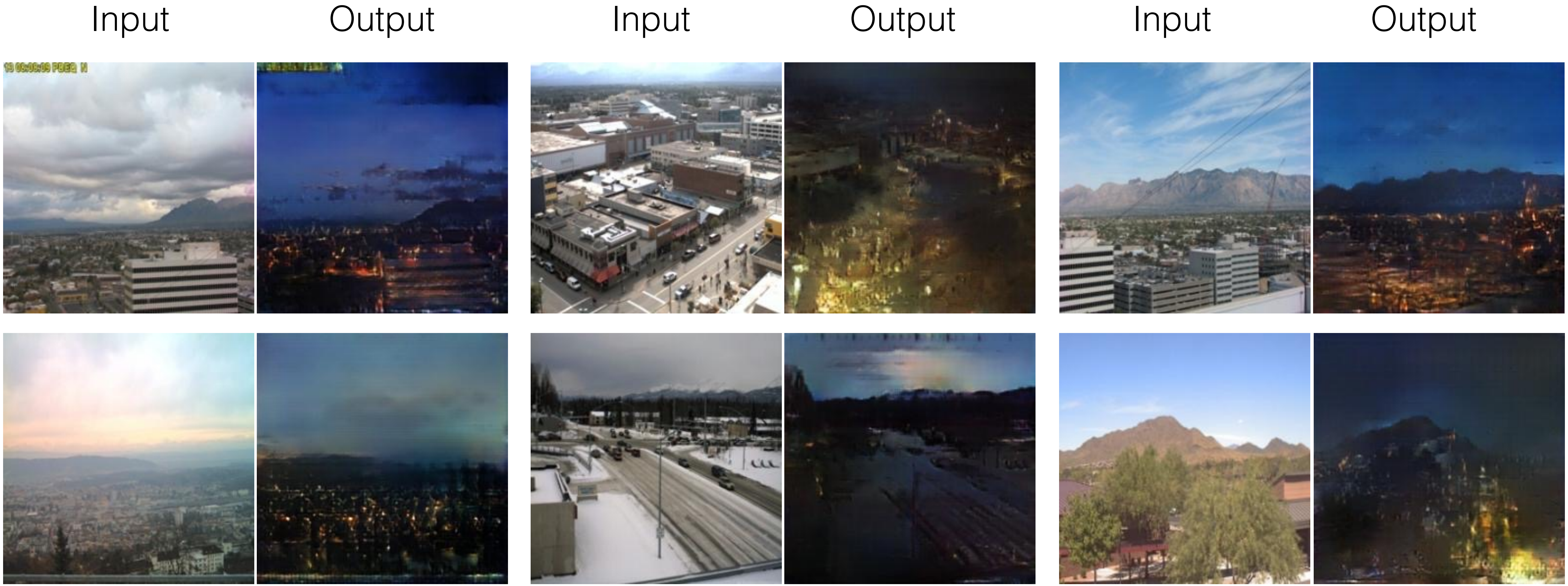
Synthesized image





Data from [Wang et al, 2018]

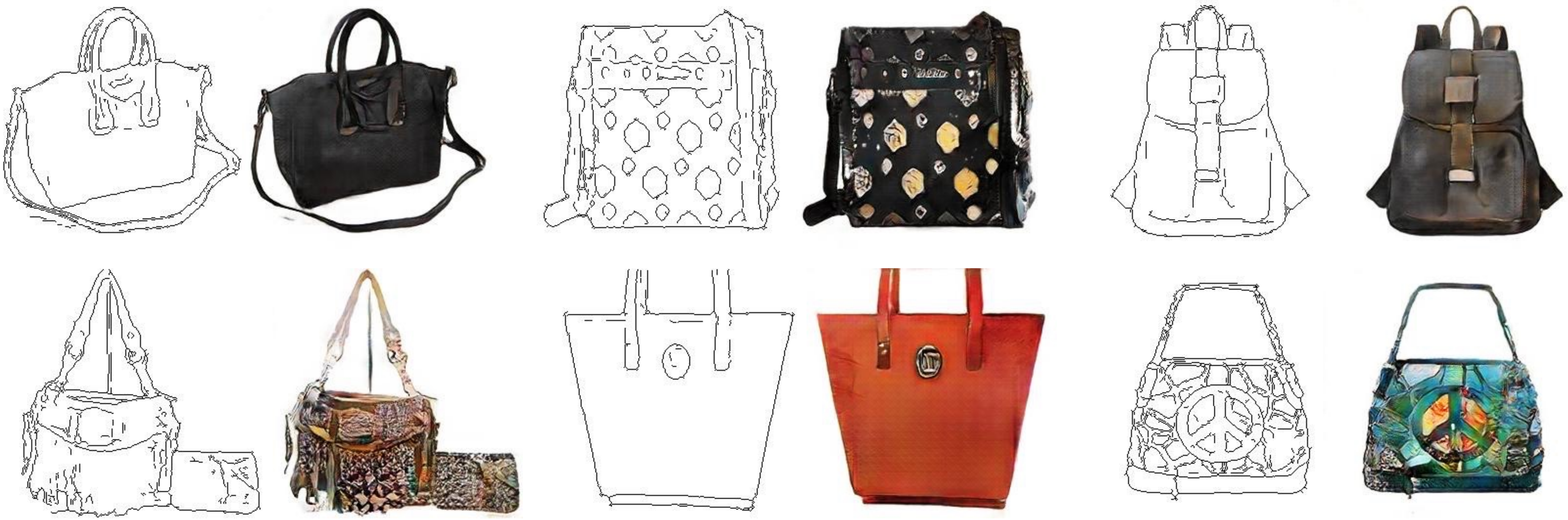
Day → Night



Data from [Laffont et al., 2014]

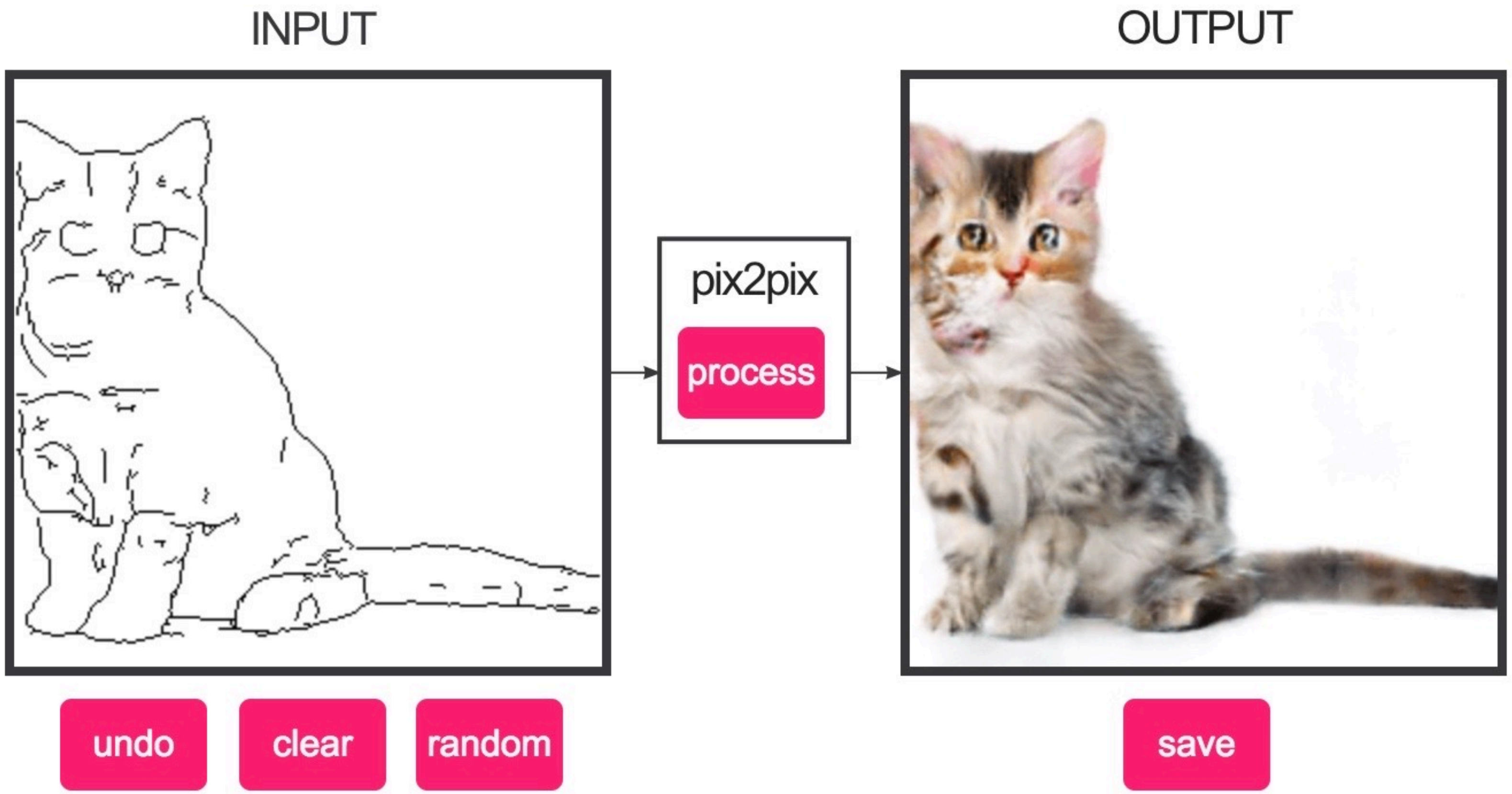
Edges → Images

Input Output Input Output Input Output

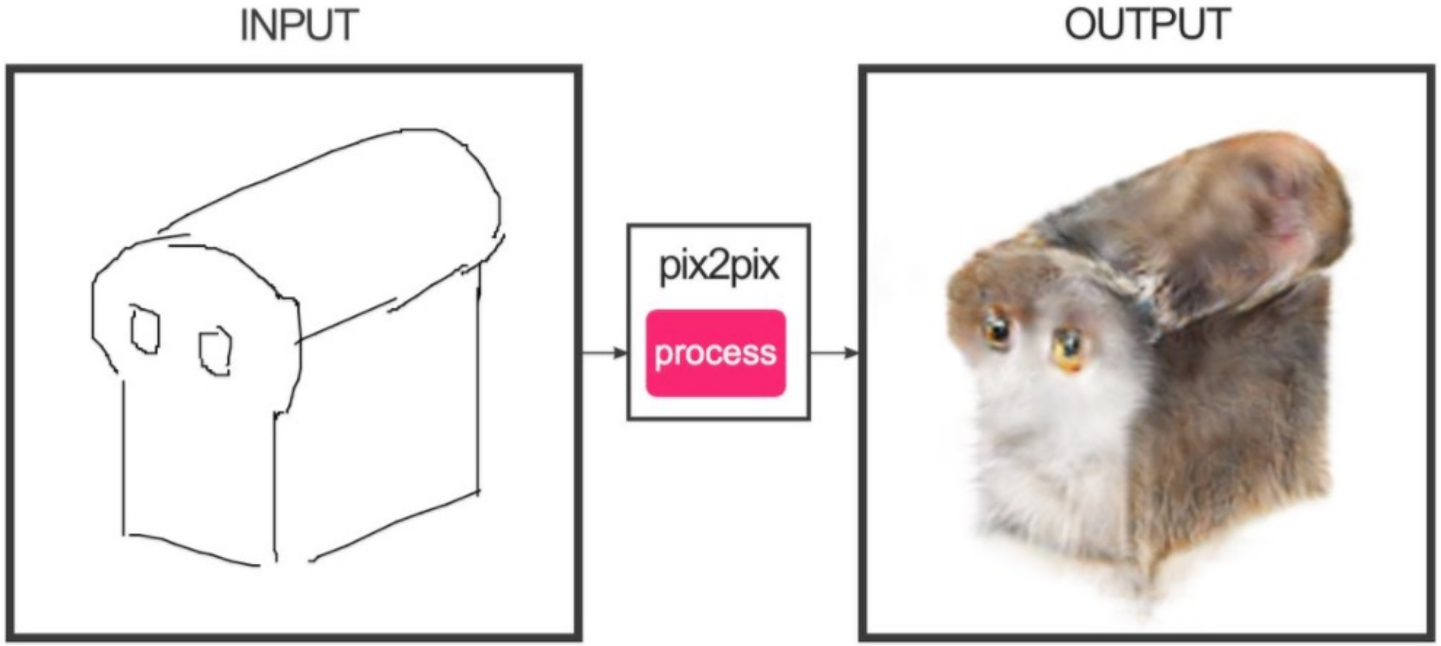


Edges from [Xie & Tu, 2015]

Demo



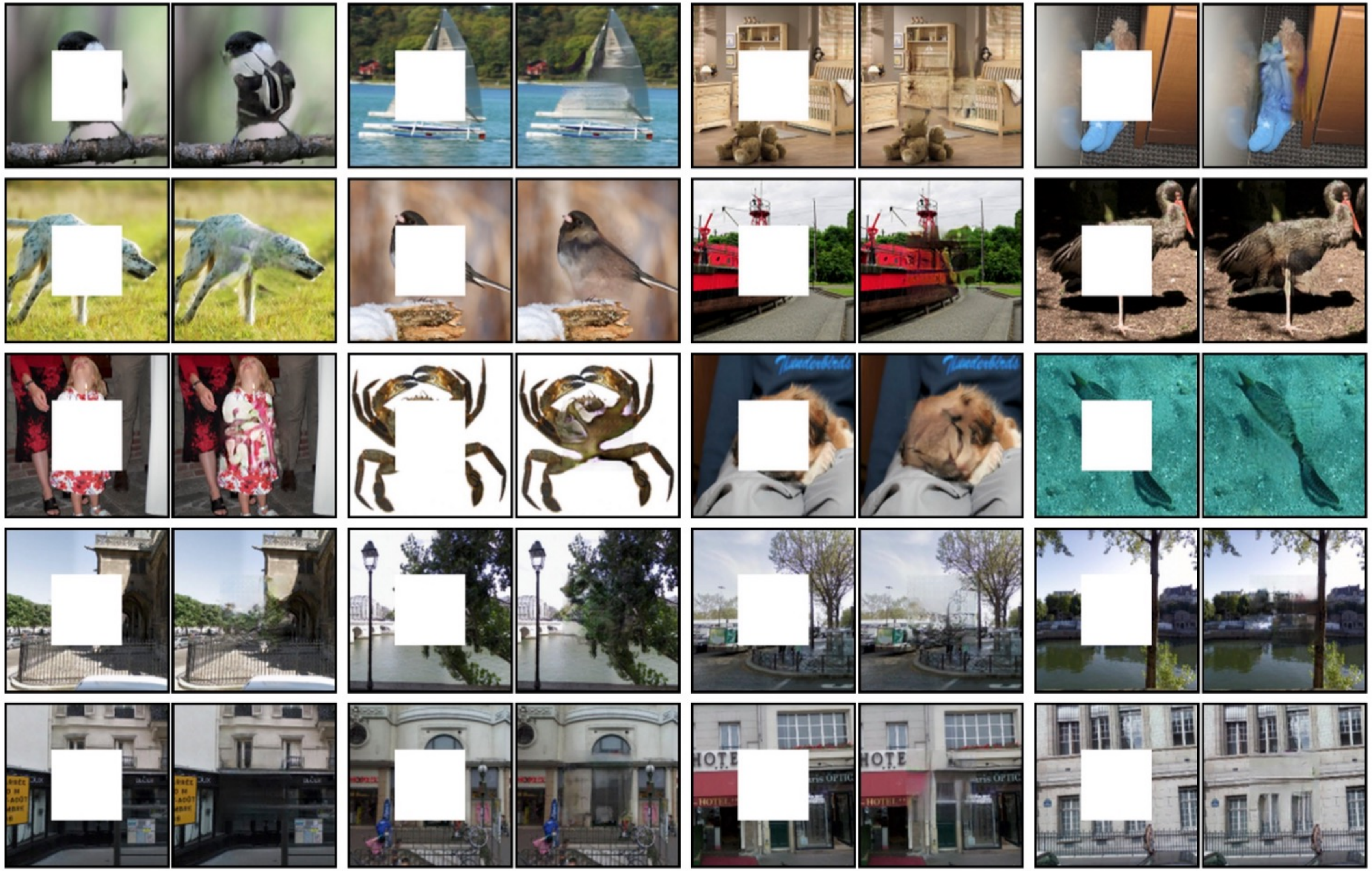
https://affinelayer.com/pixsrv/



Ivy Tasi @ivymyt

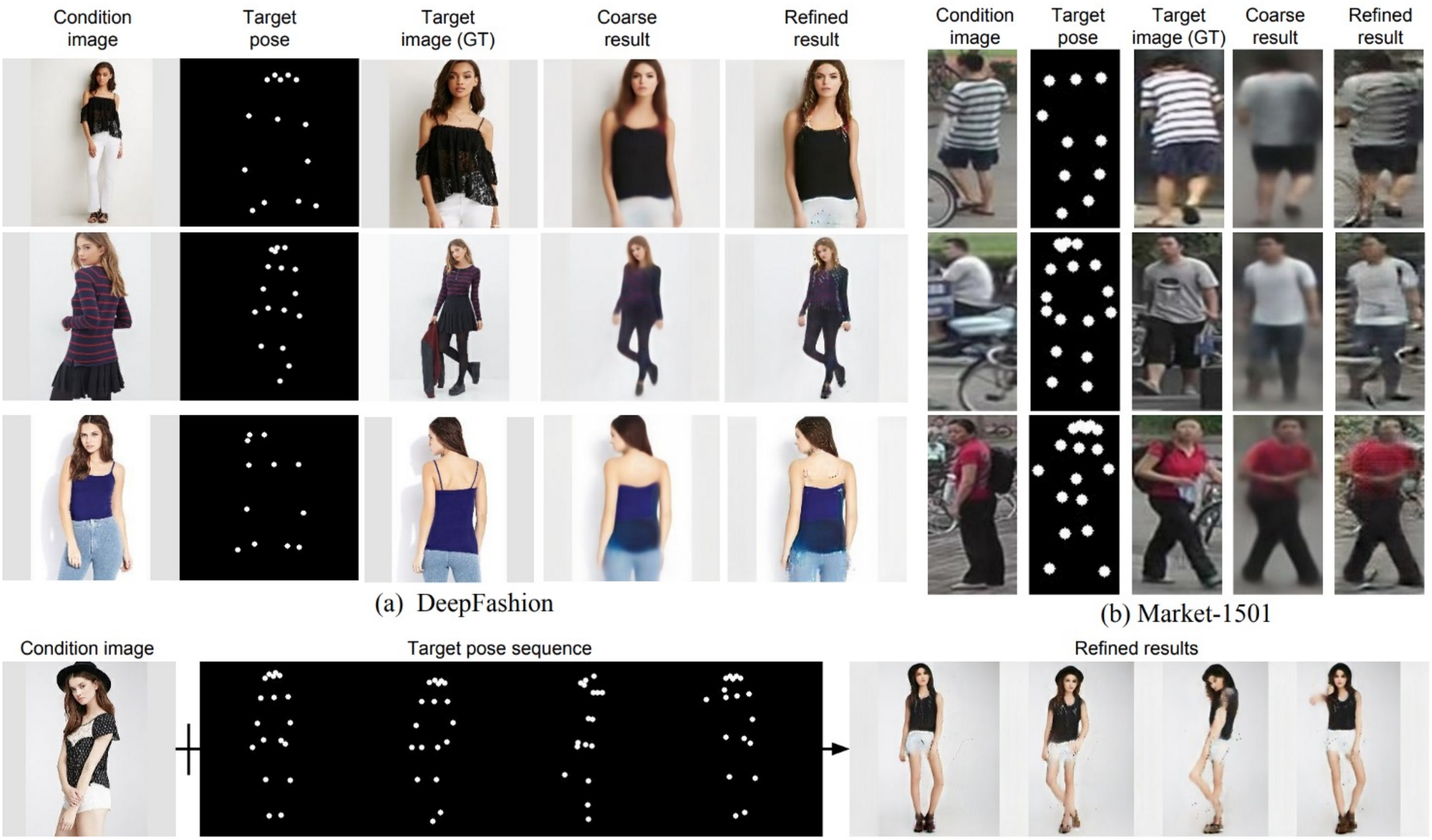
Vitaly Vidmirov @vvid

Image Inpainting



Data from [Pathak et al., 2016]

Pose-guided Generation



(a) DeepFashion

(b) Market-1501

(c) Generating from a sequence of poses

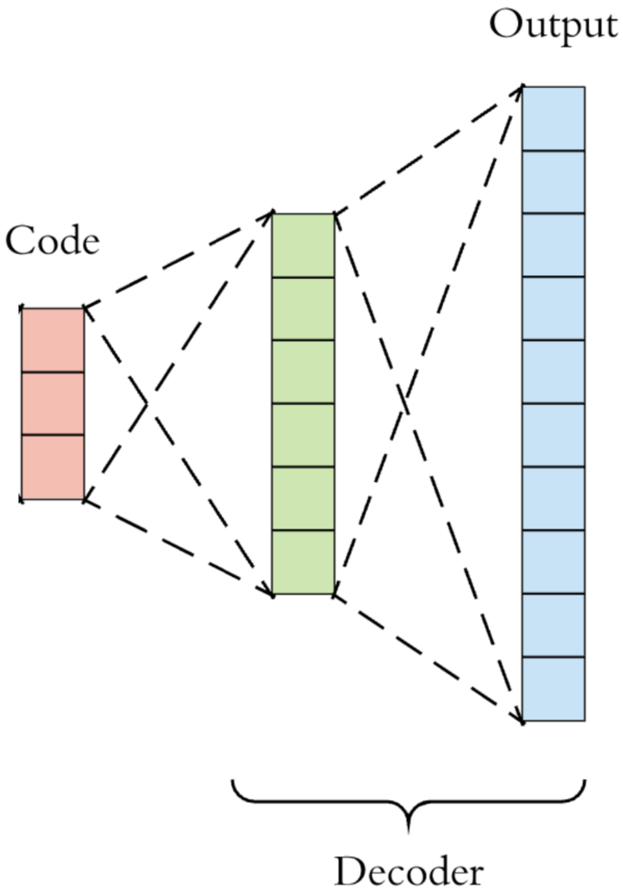
Data from [Ma et al., 2018]

Challenges —> Solutions

- Output is high-dimensional, structured object
  - Approach: Use a deep net, D, to analyze output!
- Uncertainty in mapping; many plausible outputs
  - Approach: D only cares about “plausibility”, doesn’t hedge

Unconditional GANs:
Learning an image manifold for a category

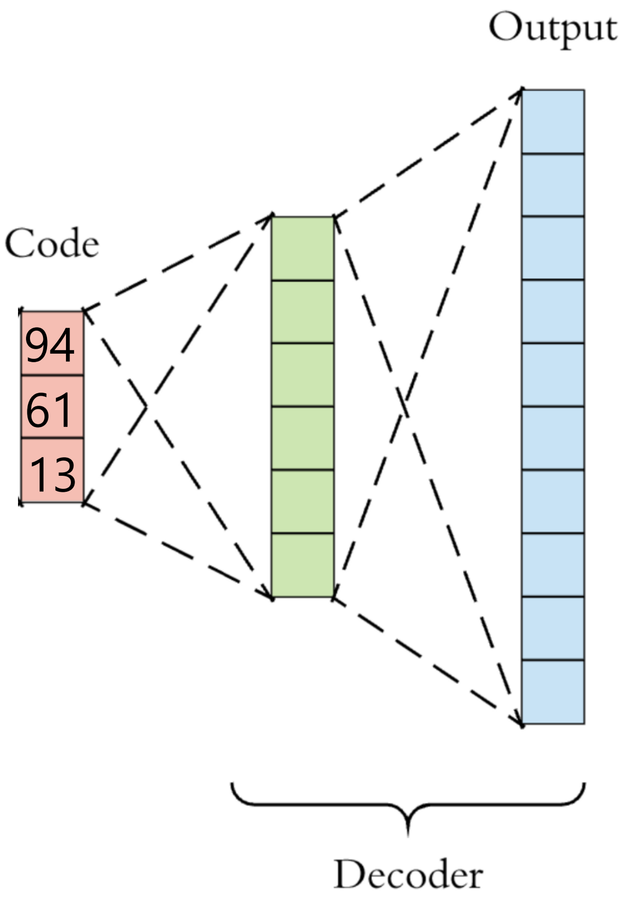
Category-specific
image dataset
(FFHQ)



Latent code (“noise”)-to-image decoder network

Unconditional GANs:
Learning an image manifold for a category

Category-specific image dataset (FFHQ)

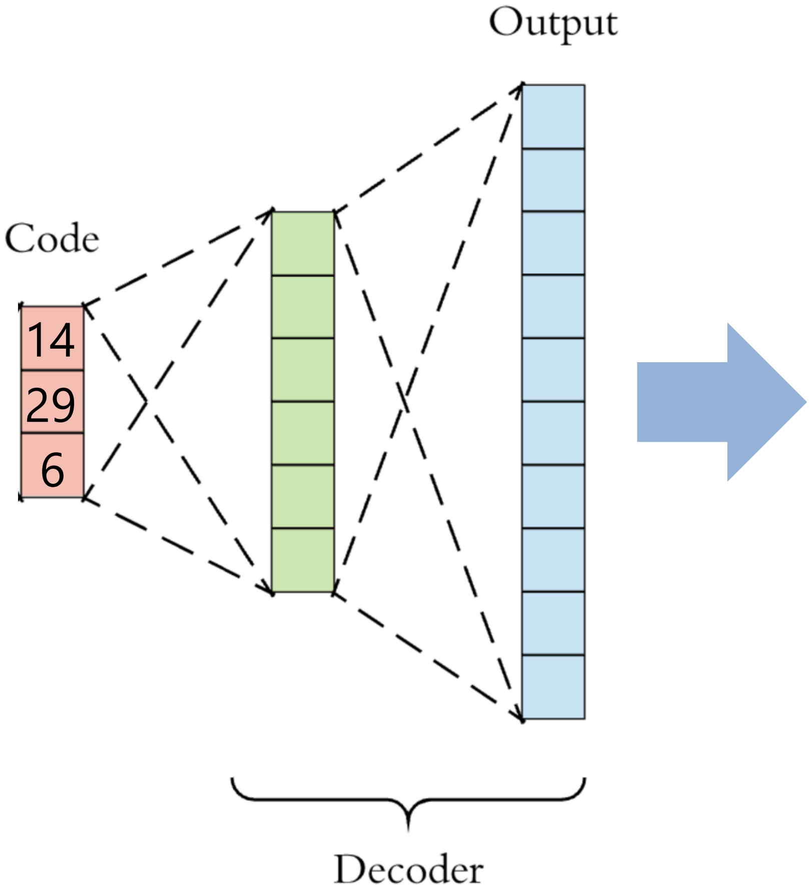


Output image

Latent code (“noise”)-to-image decoder network

Unconditional GANs:
Learning an image manifold for a category

Category-specific image dataset (FFHQ)

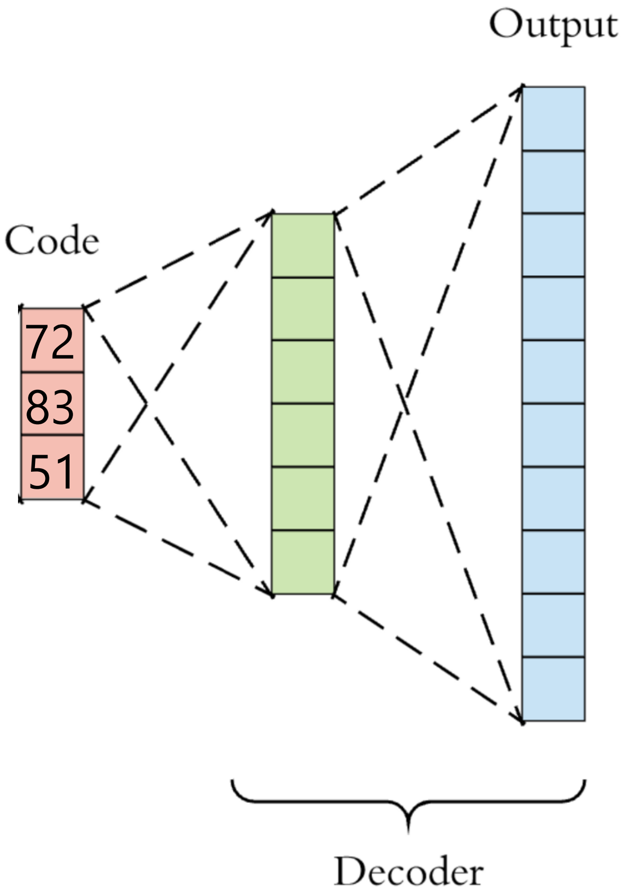


Output image

Latent code ("noise")-to-image decoder network

Unconditional GANs:
Learning an image manifold for a category

Category-specific
image dataset
(FFHQ)

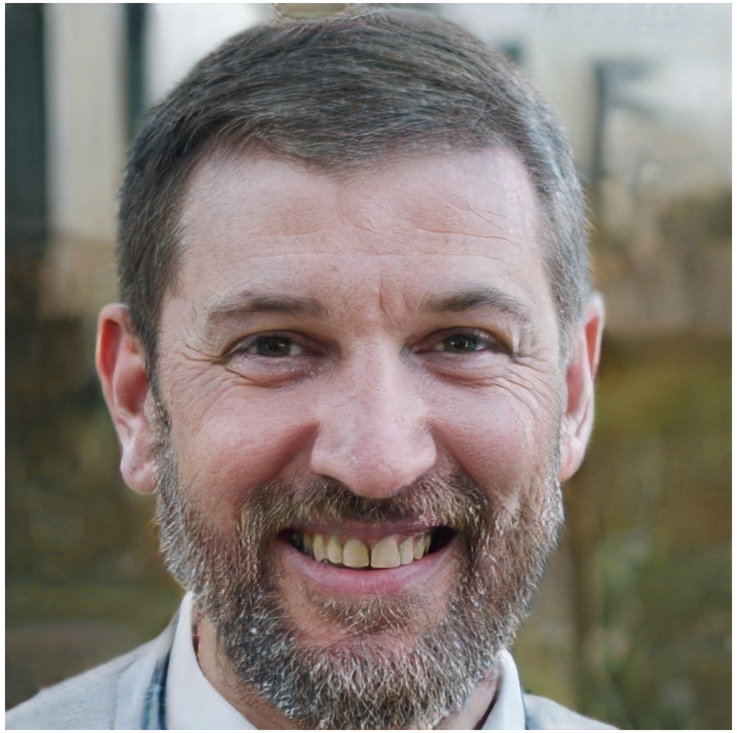


Output image

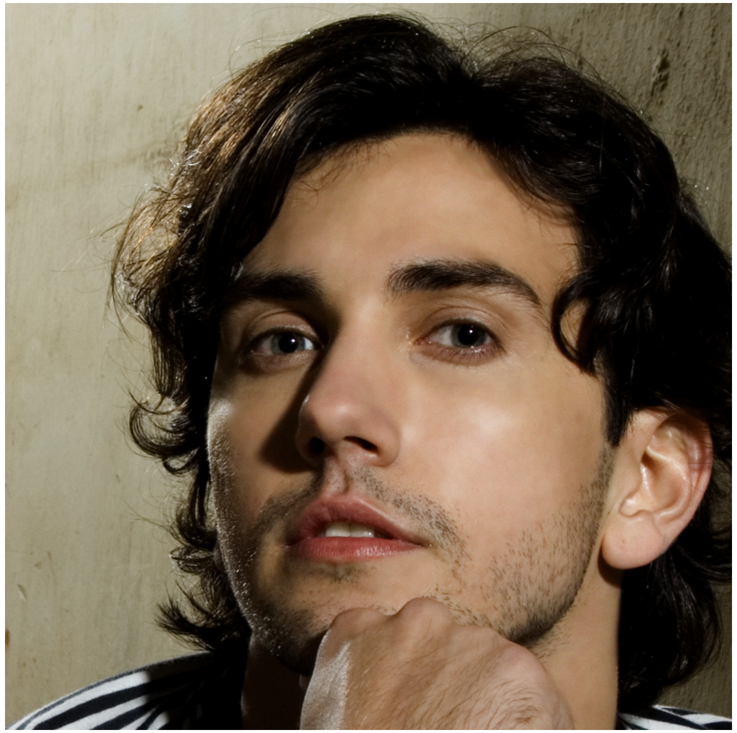
Latent code (“noise”)-to-image decoder network

Example: Randomly Sampling the Space of Face Images

(Using Generative Adversarial Networks (GANs)



A



B

Which face is real?

slido

Which face is real?

ⓘ Start presenting to display the poll results on this slide.

Example: Randomly Sampling the Space of Face Images

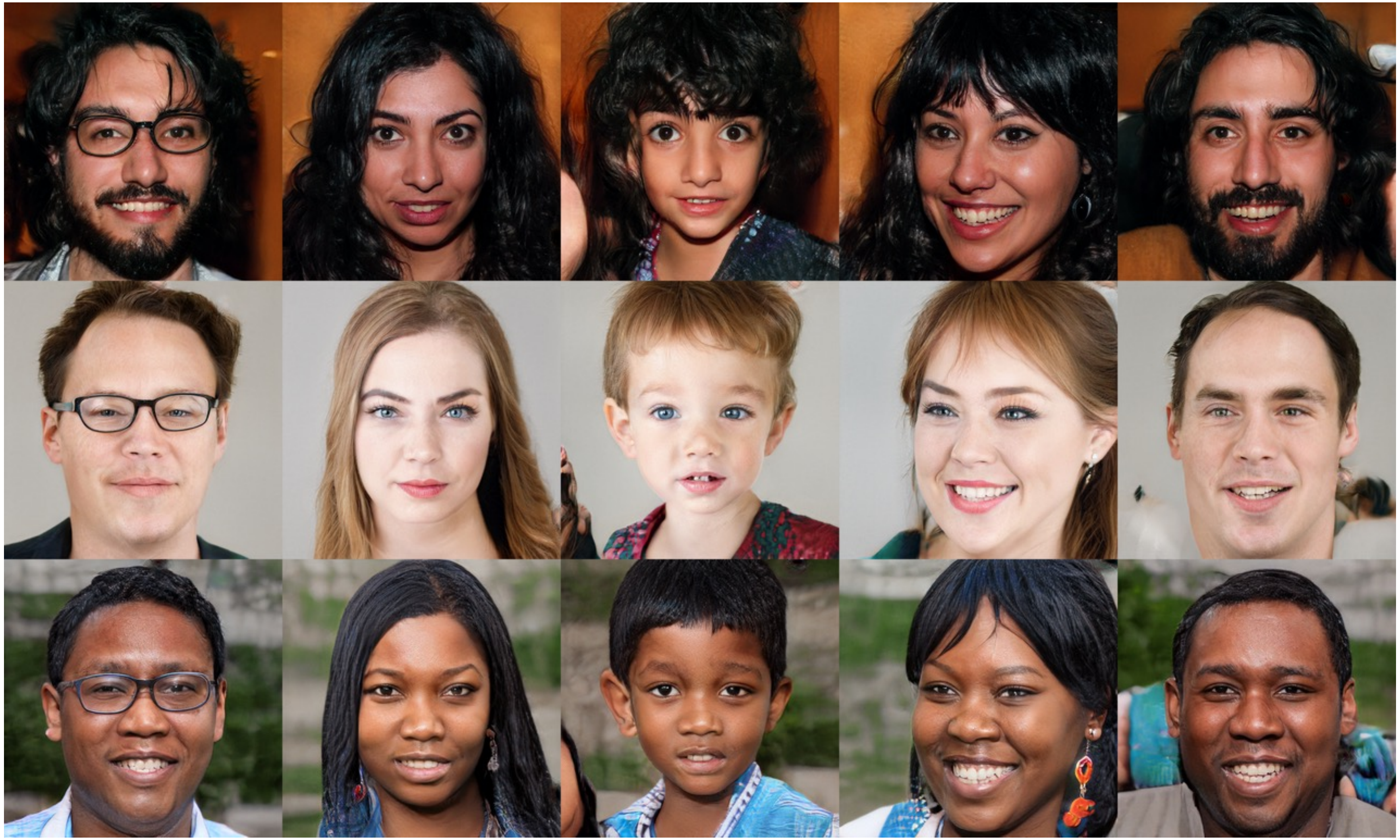
(Using Generative Adversarial Networks (GANs)

A

B

Which face is real?

StyleGAN



A Style-Based Generator Architecture for Generative Adversarial Networks

Tero Karras, Samuli Laine, Timo Aila

https://github.com/NVlabs/stylegan

StyleGAN2 [2020]

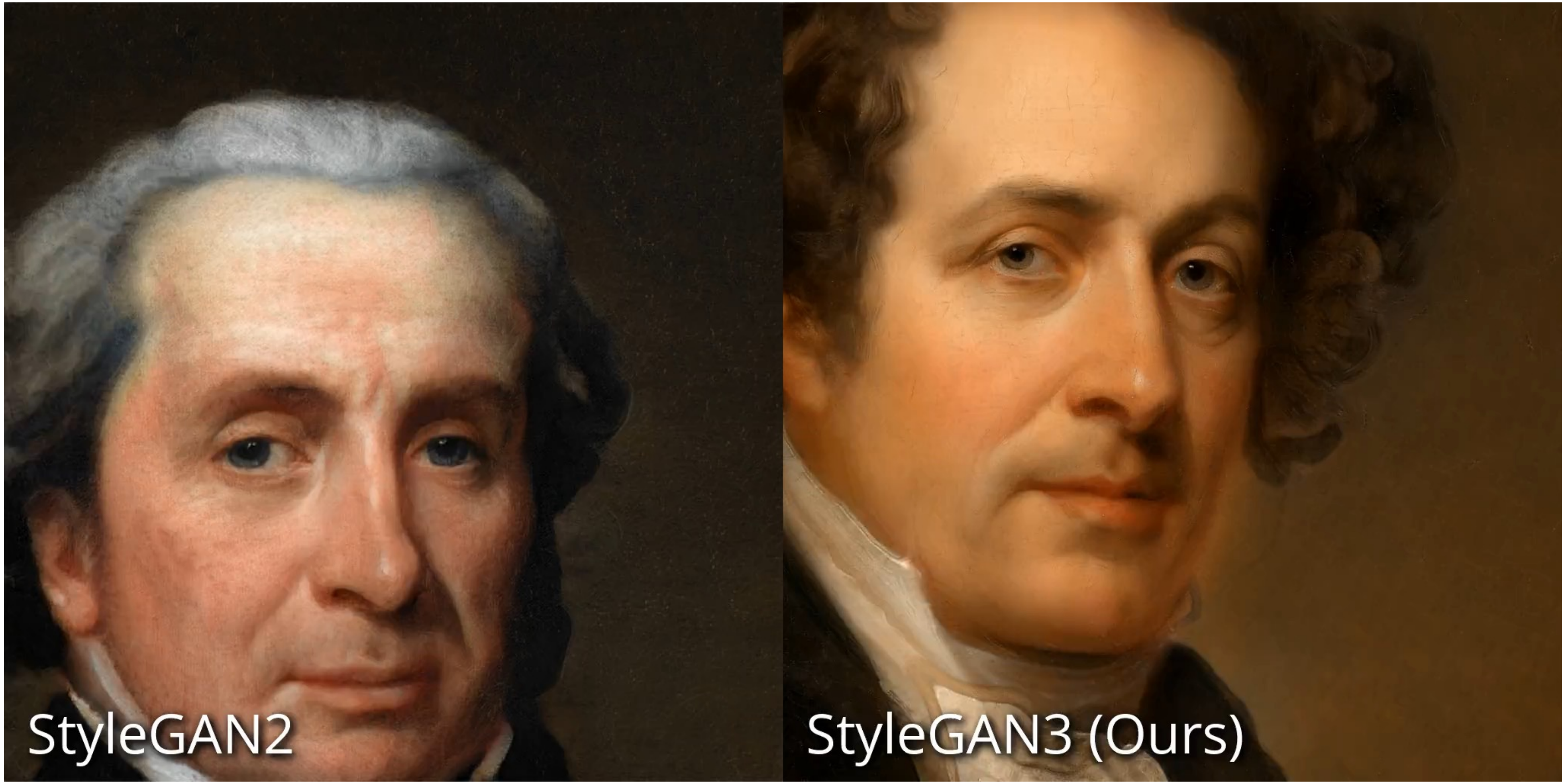
Analyzing and Improving the Image Quality of StyleGAN
Tero Karras, Samuli Laine, Miika Aittala, Janne Hellsten, Jaakko Lehtinen, Timo Aila

https://github.com/NVlabs/stylegan2

StyleGAN3 [2021]

Alias-Free Generative Adversarial Networks (StyleGAN3)
Tero Karras, Miika Aittala, Samuli Laine, Erik Härkönen, Janne Hellsten, Jaakko Lehtinen, Timo Aila

GAN models trained on animal faces: interpolating between latent codes



GAN models trained on MetFaces: interpolating between latent codes

Limitation

- The unconditional models above must be trained per-category:
  - We have a separate model for every category – an animal face model, broccoli model, horse model, etc…
- What if we want to generate an image from **any** description?
- Next time: diffusion and text-to-image models

Questions?