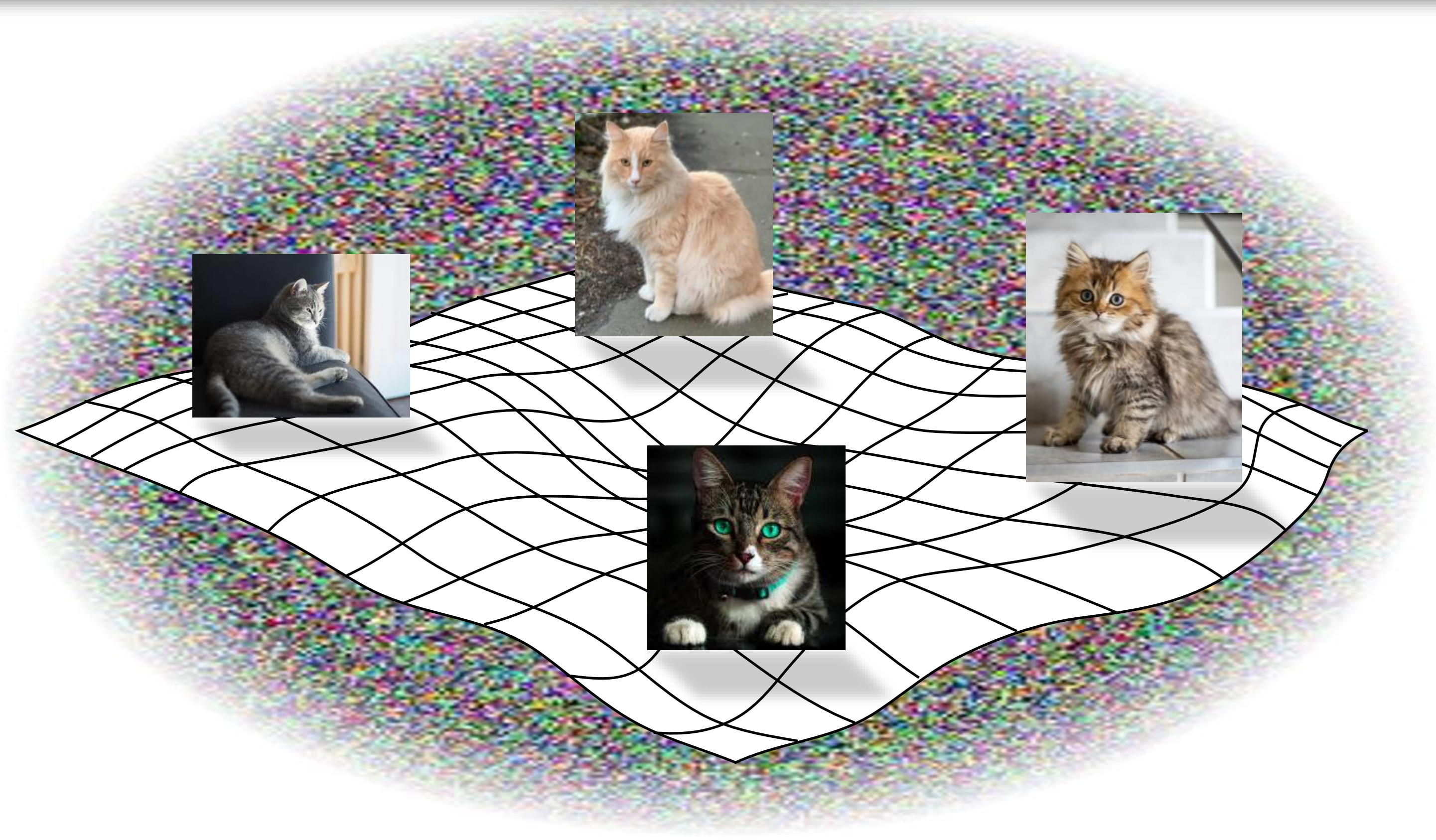
CS5670: Computer Vision

Image Manifolds & Image Synthesis (including GANS)



Most content from Abe Davis, with additional credit to Jin Sun and Phillip Isola

Announcements

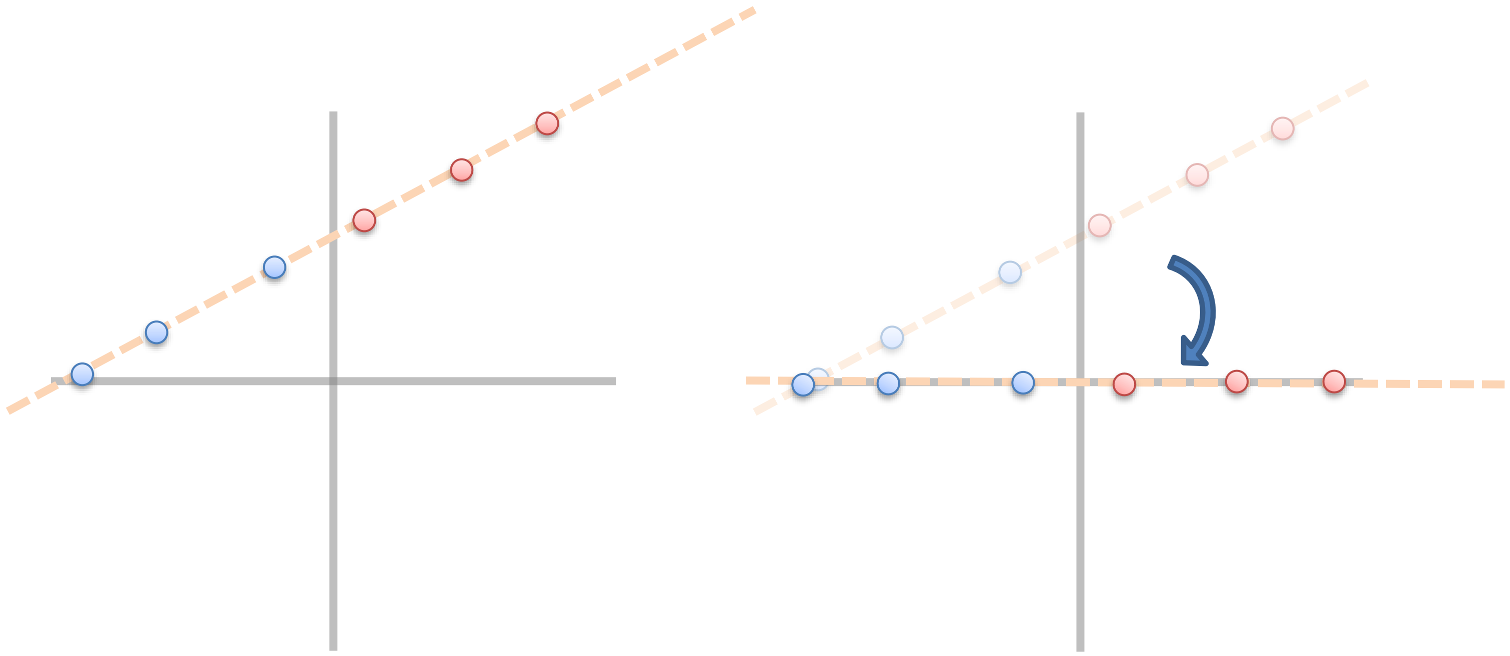
- In class final on May 10
  - Open book, open note (your own notes – please do not print out whole slide decks)
- Project 5 (Neural Radiance Fields) due tomorrow by 8:00 pm
- Course evaluations are open starting today (May 3)
  - We would love your feedback!
  - Small amount of extra credit for filling out
    - What you write is still anonymous, instructors only see whether students filled it out
  - https://apps.engineering.cornell.edu/CourseEval/

By Abe Davis

DIMENSIONALITY REDUCTION

Linear Dimensionality Reduction: 2D->1D

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

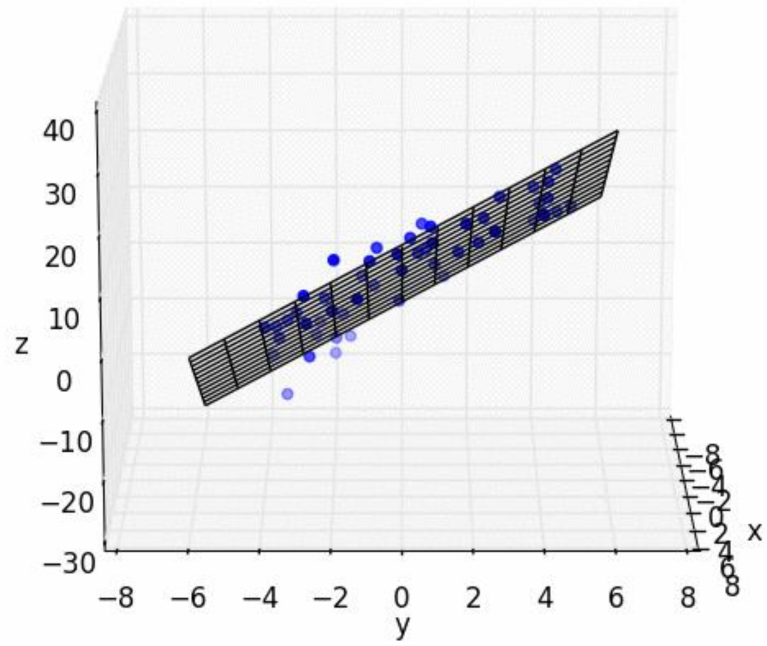


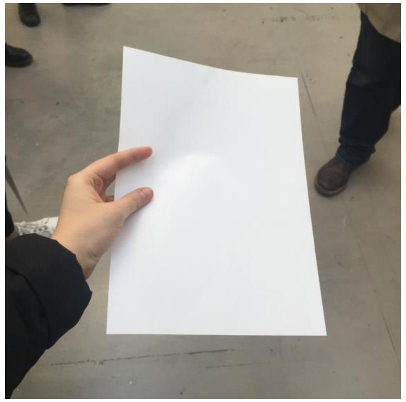
Linear Dimensionality Reduction: 3D->2D

- 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”

- More generally: look for the 2D subspace that best fits the data, and ignore the remaining dimensions





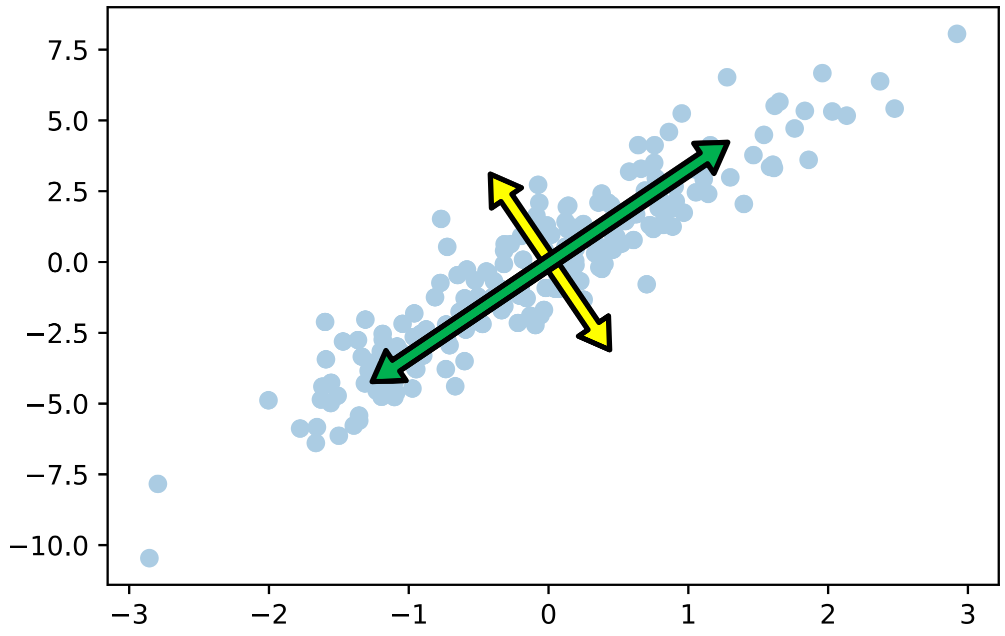
Think of this as data that sits on a flat sheet of paper, suspended in 3D space. We will come back to this analogy in a couple slides…

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***.

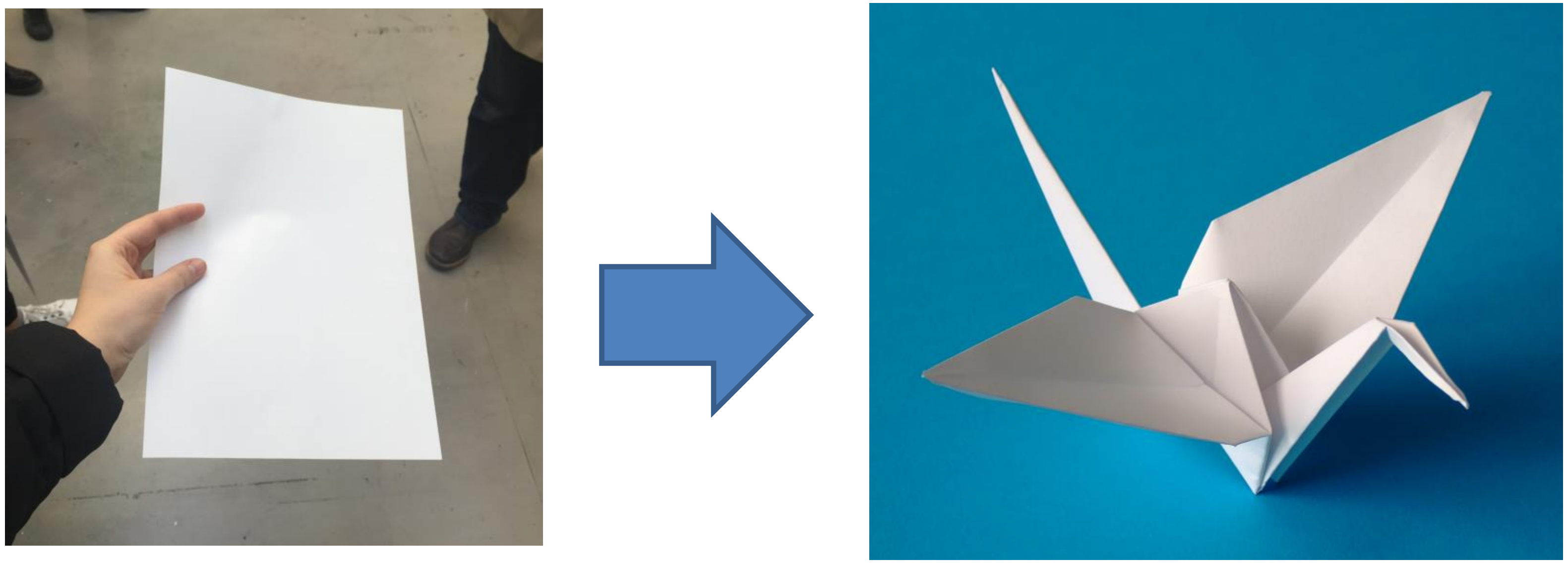
- Dimensionality reduction can be done by using only the first *k* principal components



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

Manifolds

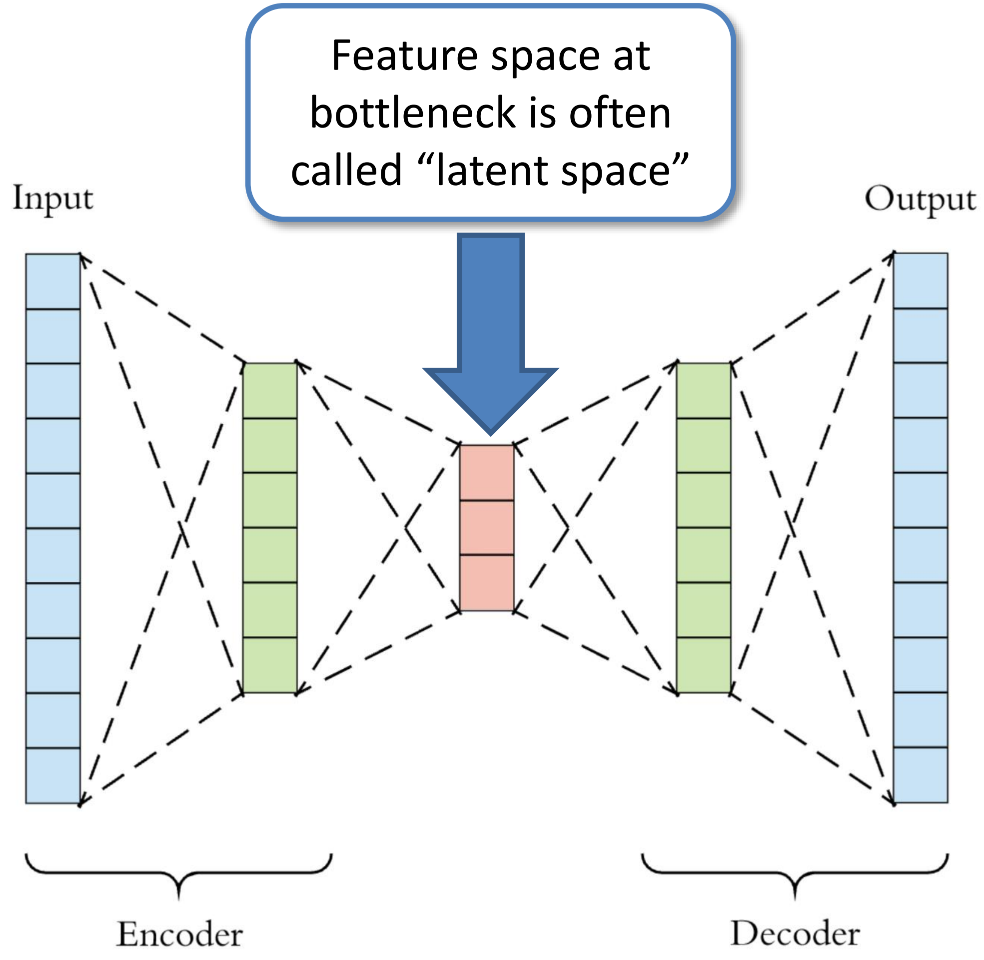
- Think of a piece of paper as a 2D subspace
- If we bend & fold it, it’s still locally a 2D subspace…
- A “manifold” is the generalization of this concept to higher dimensions…



Autoencoders: Dimensionality Reduction for Manifolds

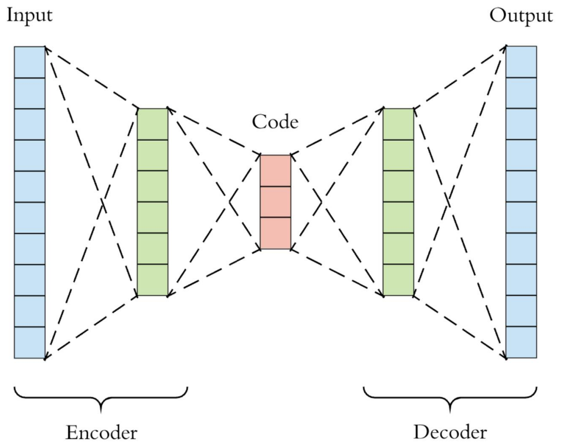
- Learn a non-linear transformation into some lower-dimensional space (encoder)
- Learn a transformation from lower-dimensional space back to original content (decoder)
- Loss function measures difference between input & output

- **Unsupervised**
  - No labels required!

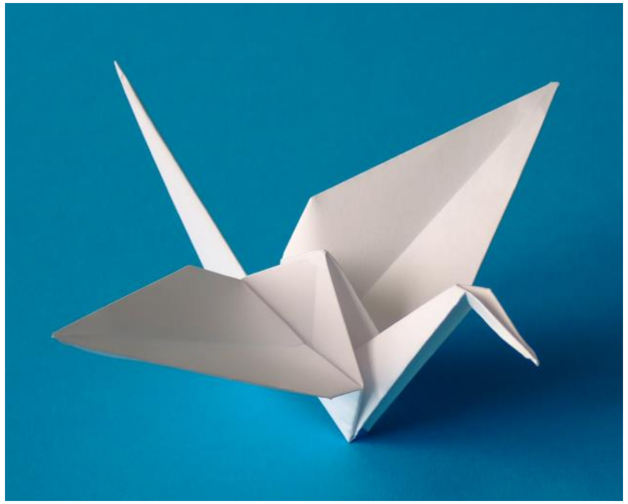


Autoencoders: Dimensionality Reduction for Manifolds

- 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

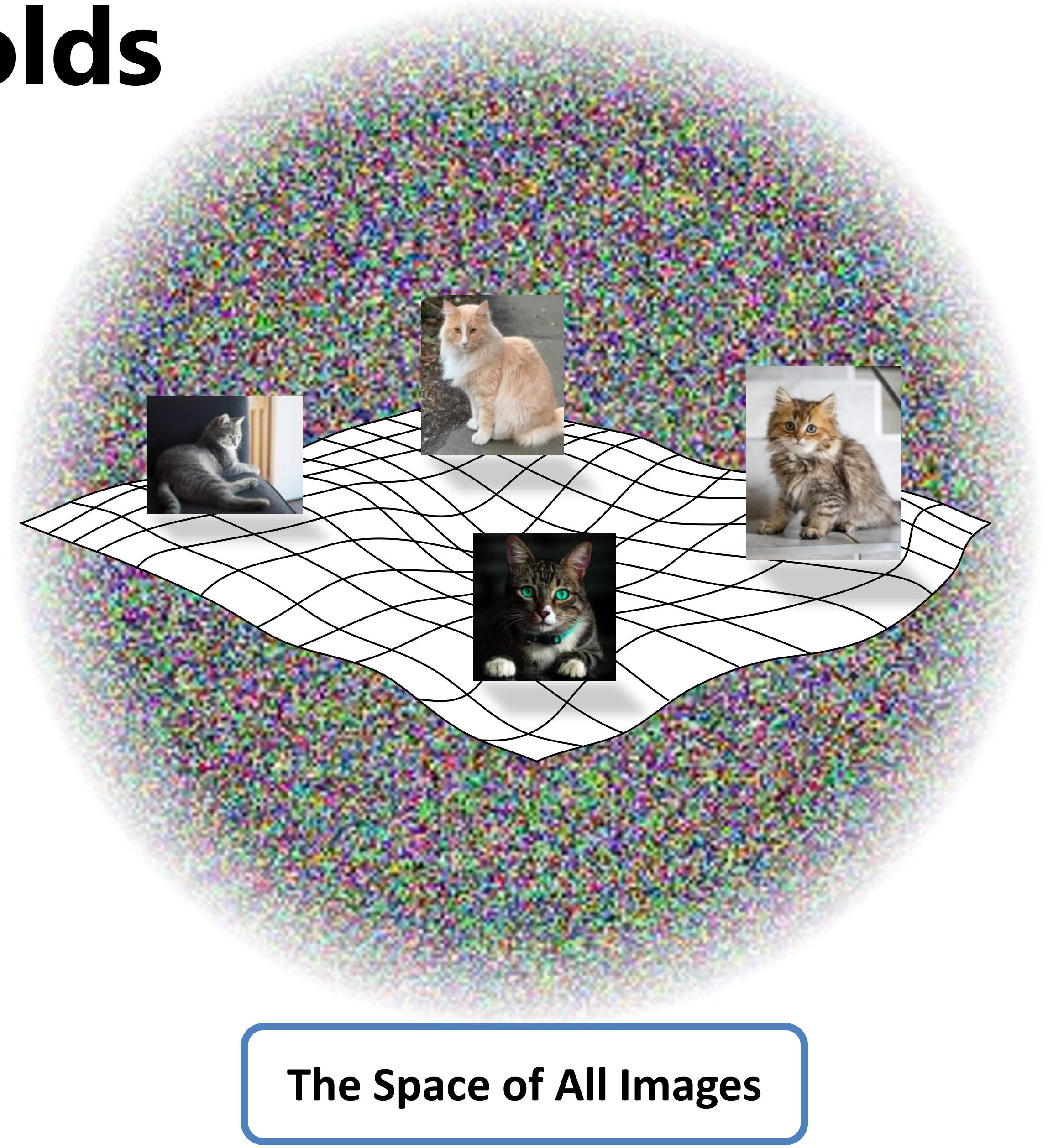
- Lets consider the space of all 100x100 images
- Now lets randomly sample that space…
- Conclusion: Most images are noise

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

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

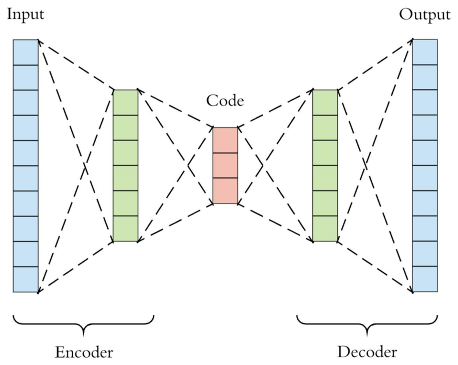
Natural Image Manifolds

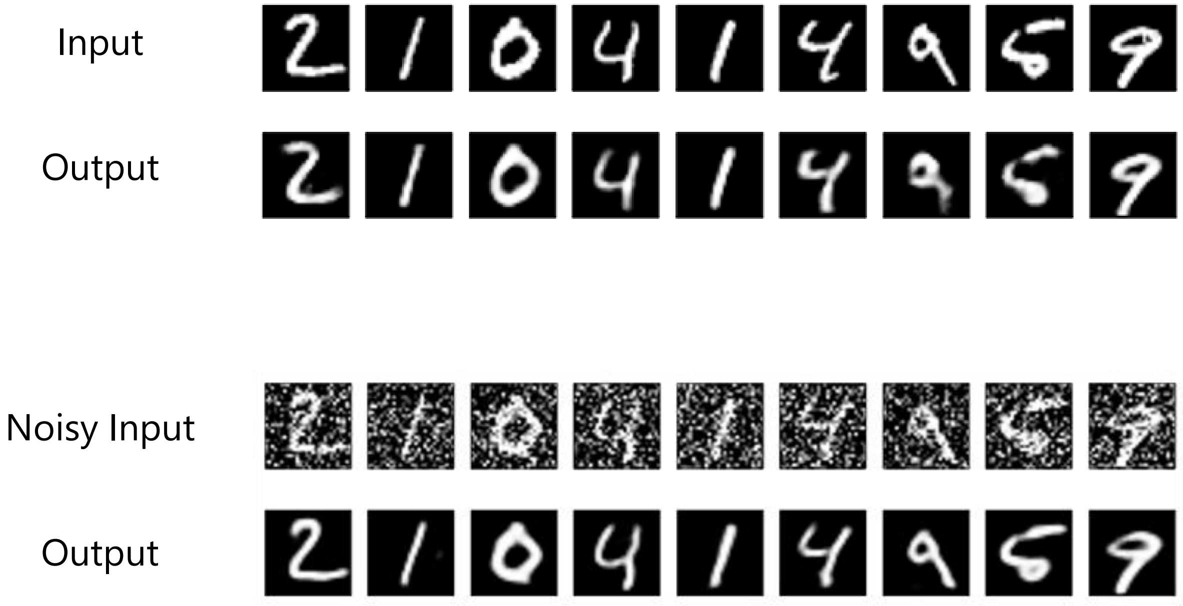
- Most images are "noise"
- "Meaningful" images tend to form some manifold within the space of all images
- Images of a particular class fall on manifolds within that manifold…



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

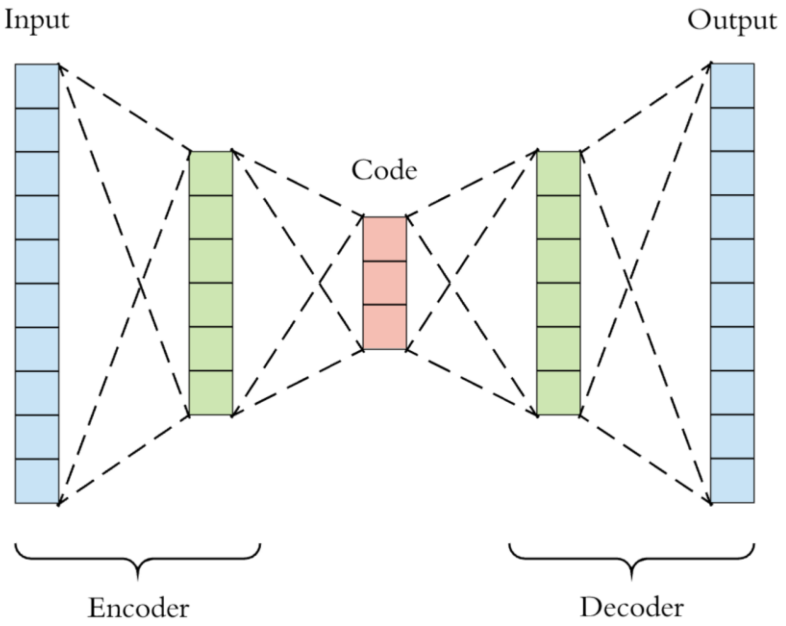


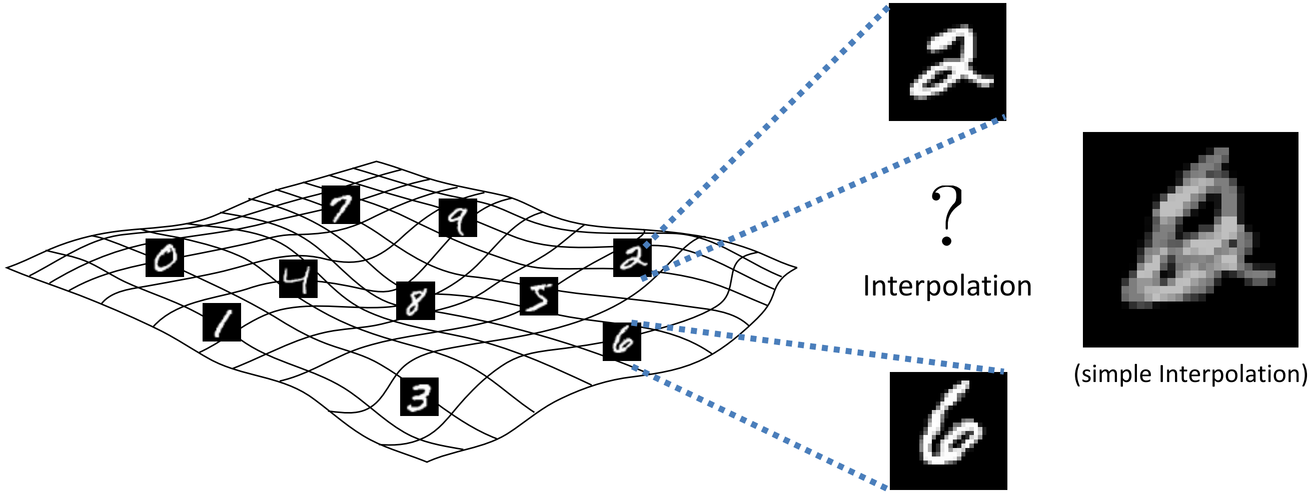


Examples from: https://blog.keras.io/building-autoencoders-in-keras.html

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



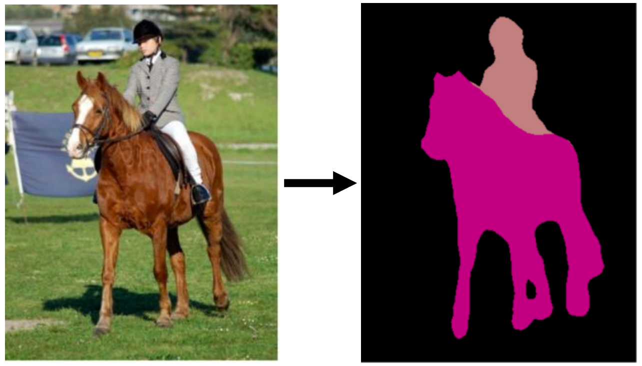


Abe Davis, with slides from Jin Sun, Phillip Isola, and Richard Zhang

IMAGE-TO-IMAGE APPLICATIONS

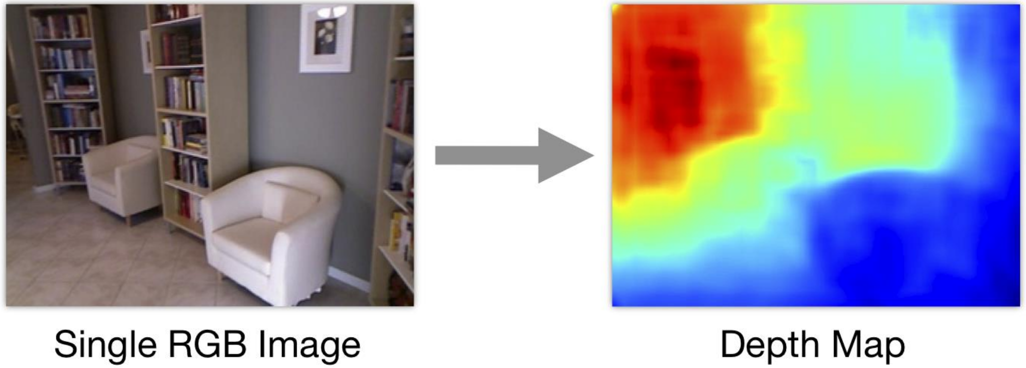
Image prediction ("structured prediction")

Object labeling



[Long et al. 2015, …]

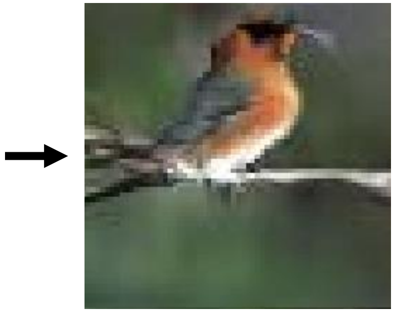
Depth prediction



[Eigen et al. 2014, …]

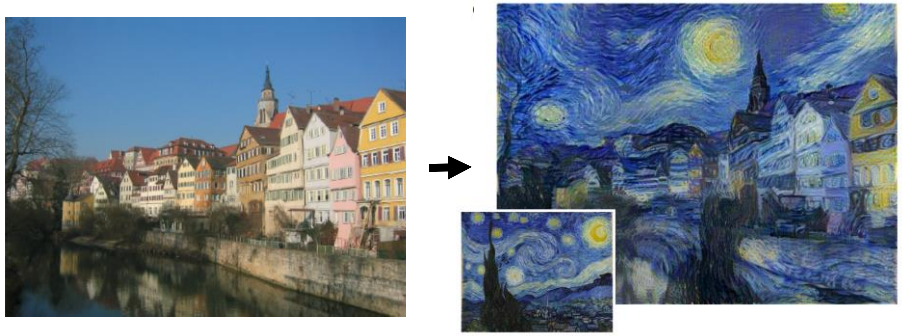
Text-to-photo

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



[Reed et al. 2016, …]

Style transfer



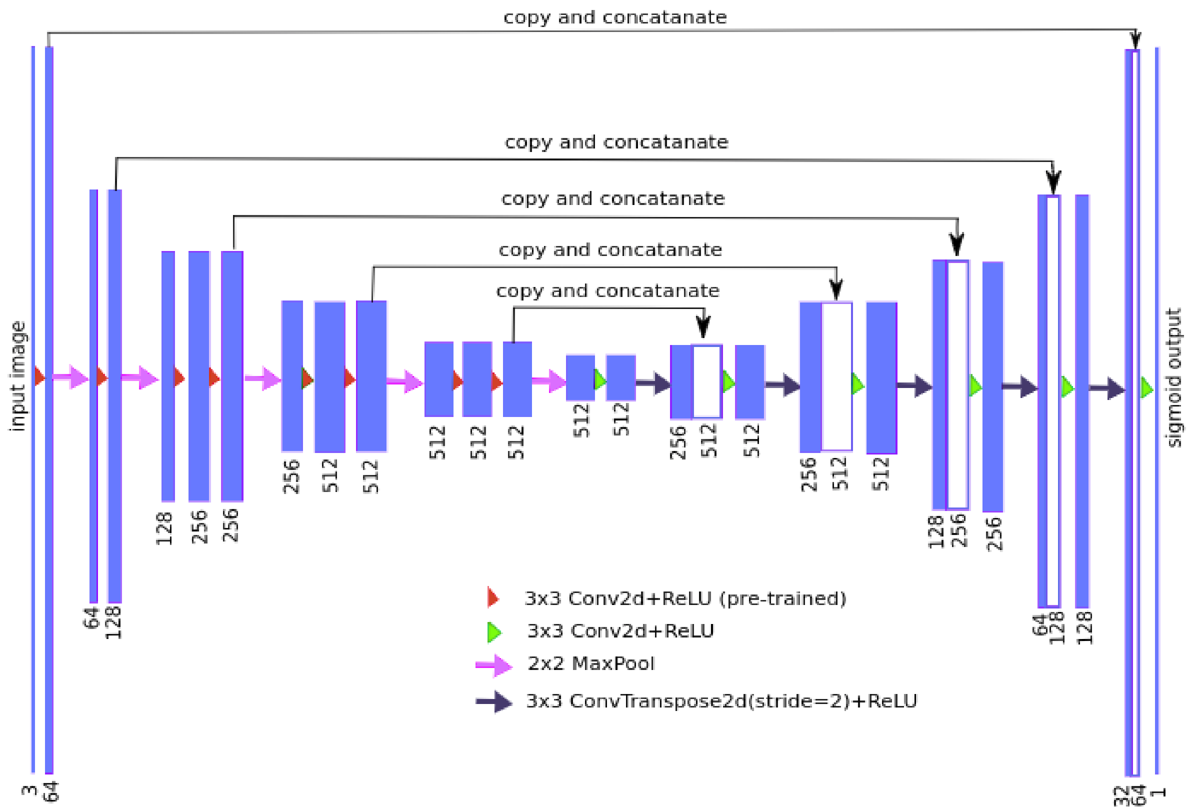
[Gatys et al. 2016, …]

Image classification vs. image translation

- For image classification, we map an image to a label (e.g., "cat")
- For image prediction/translation tasks, we map an image to another image-shaped thing (e.g., a depth map)
- What kind of convolutional neural network architecture can do this?

U-Net

- A popular network structure to generate same-sized output
- Similar to a convolutional autoencoder, but with “skip connections” that concatenate the output of earlier layers onto later layers
- Great for learning transformations from one image to another



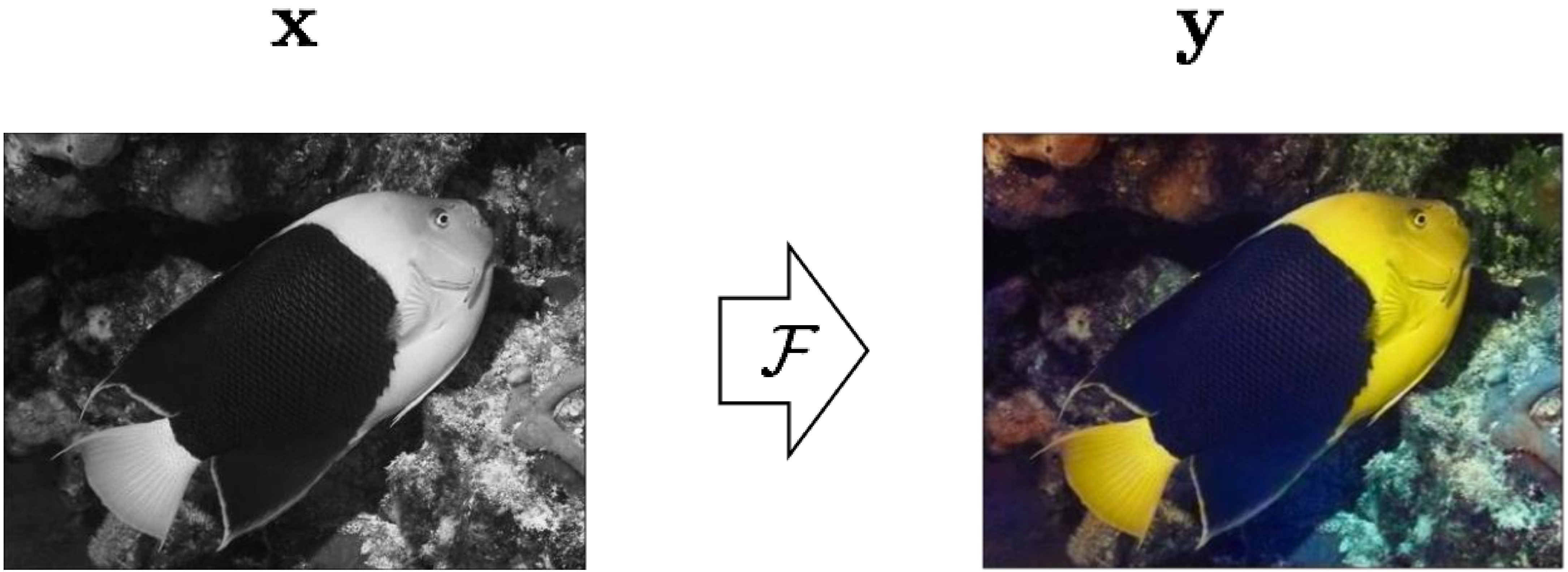


Image Colorization

from Jin Sun, Richard Zhang, Phillip Isola

$\mathbf{x}$

$$\xrightarrow{\mathcal{F}}$$

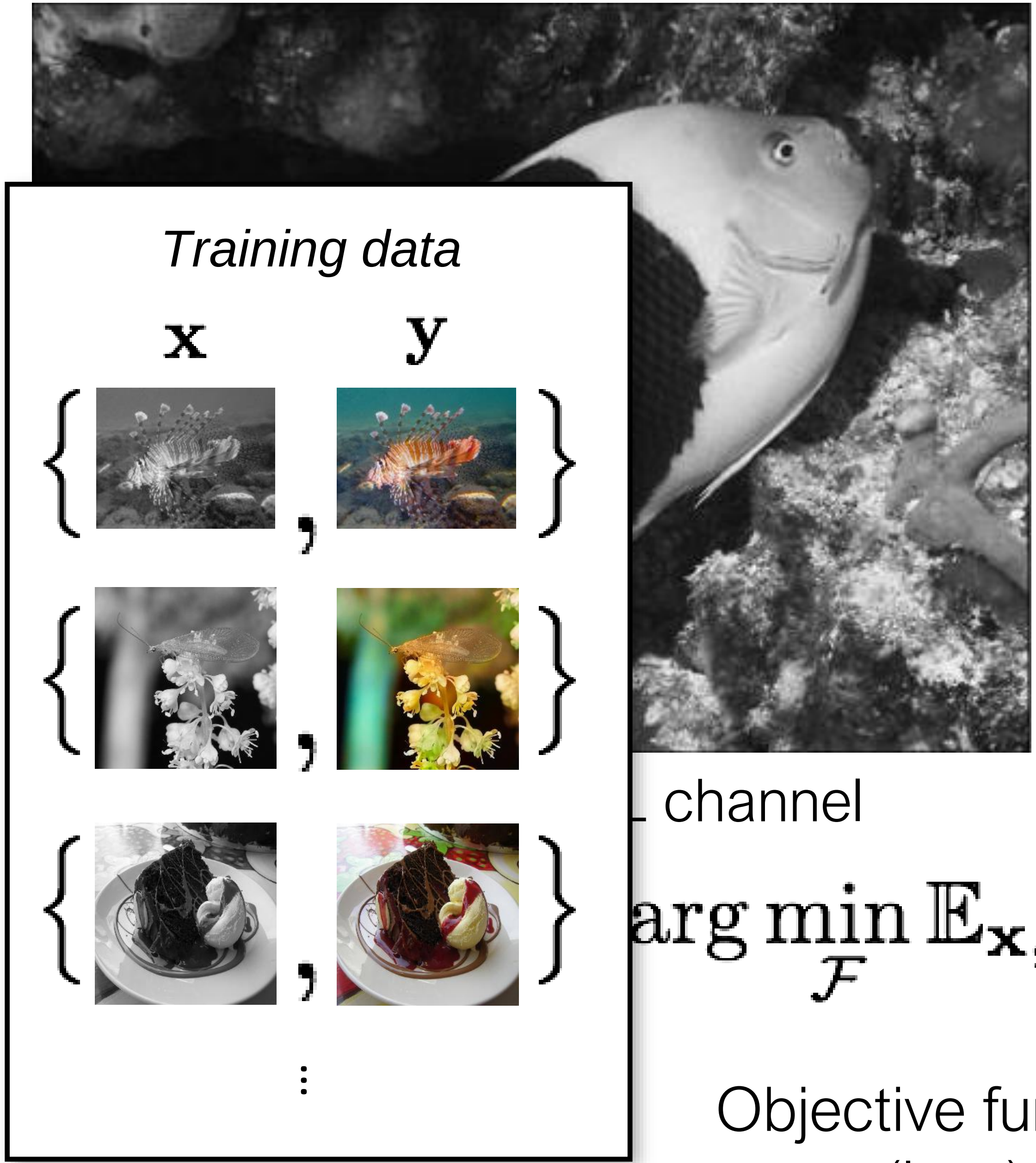
$\mathbf{y}$

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

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

from Jin Sun, Richard Zhang, Phillip Isola

$\mathbf{x}$ $\quad$ $\mathbf{y}$



$\mathcal{F}$

channel

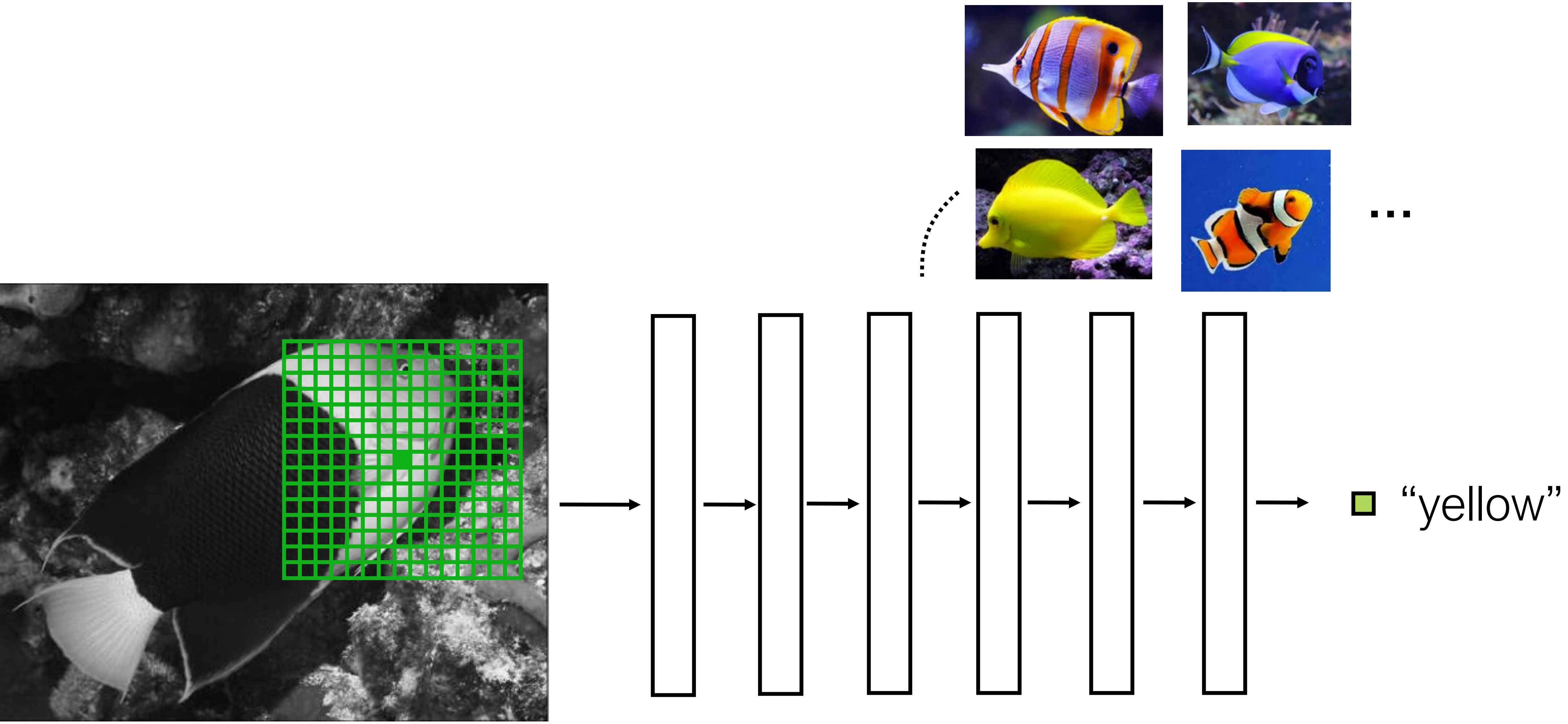
Color information: ab channels

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

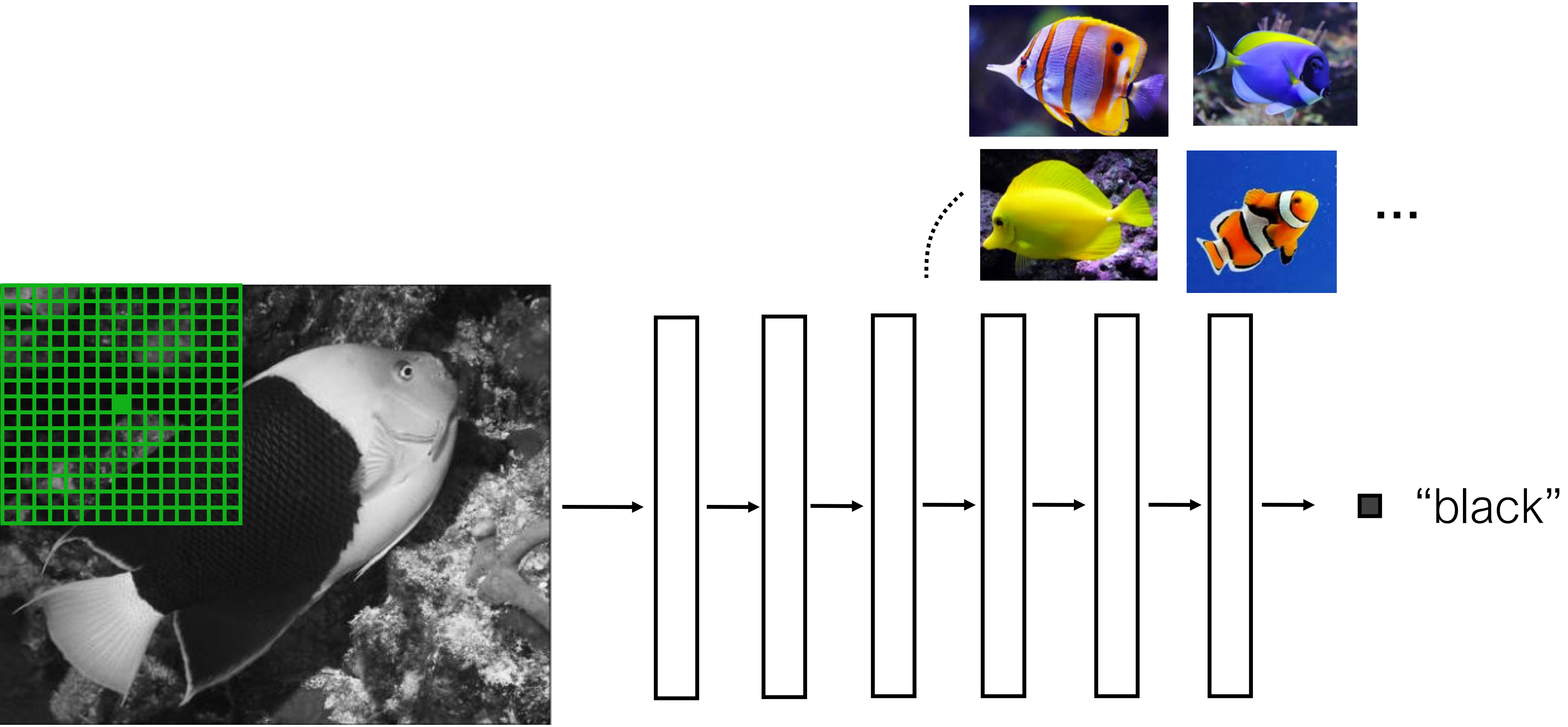
Objective function (loss)

Neural Network

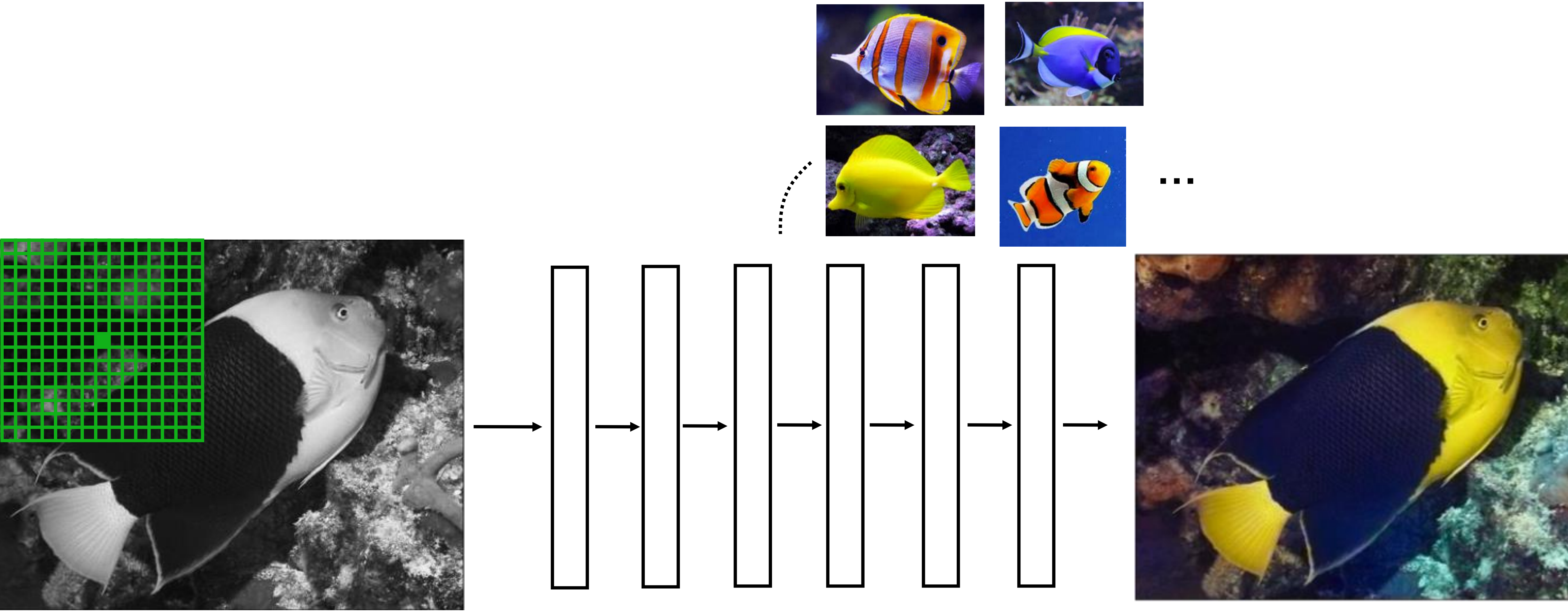
from Jin Sun, Richard Zhang, Phillip Isola



from Jin Sun, Richard Zhang, Phillip Isola



from Jin Sun, Richard Zhang, Phillip Isola



from Jin Sun, Richard Zhang, Phillip Isola

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

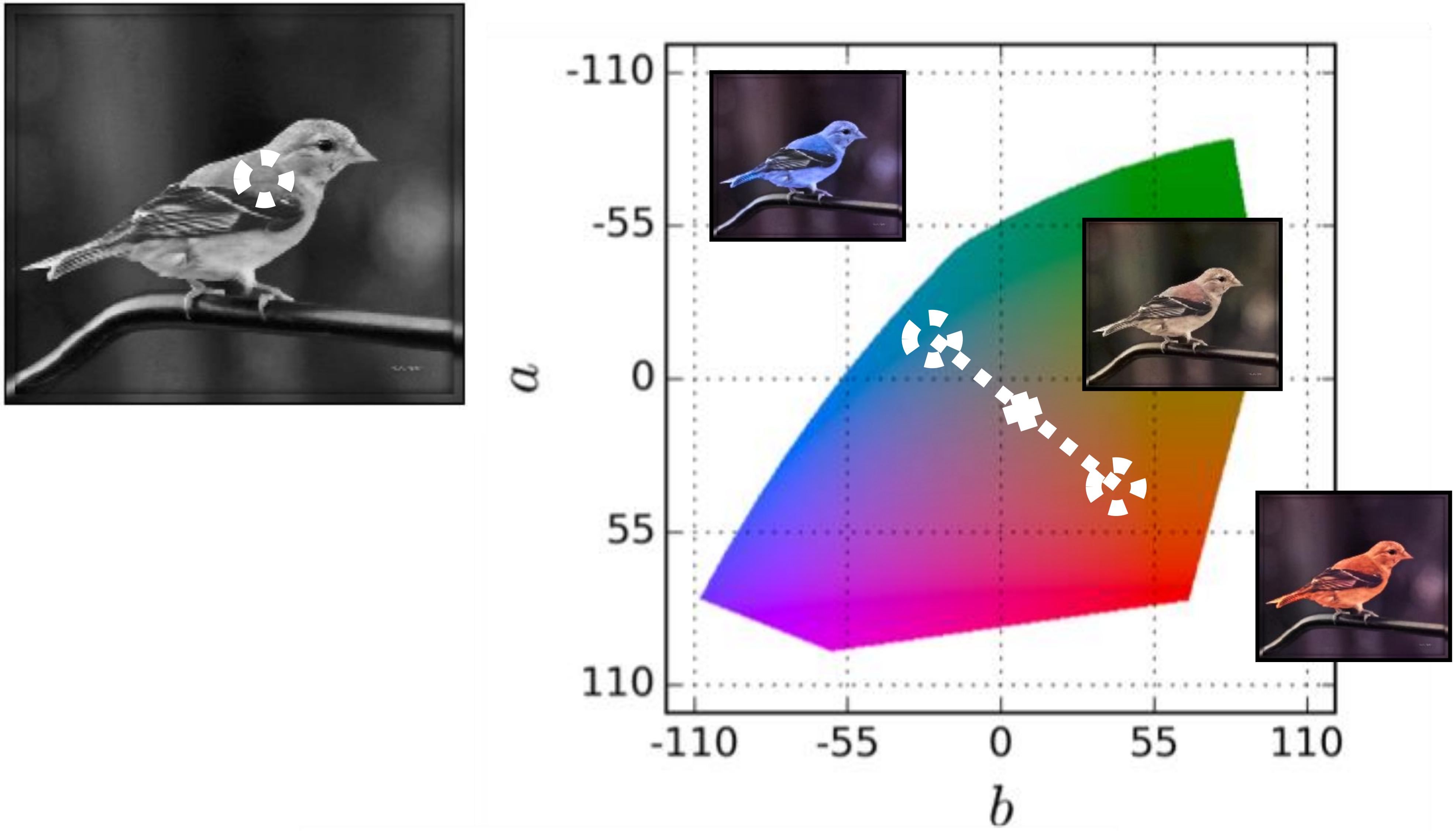
Designing loss functions

Input

Output

Ground truth

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



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

Designing loss functions

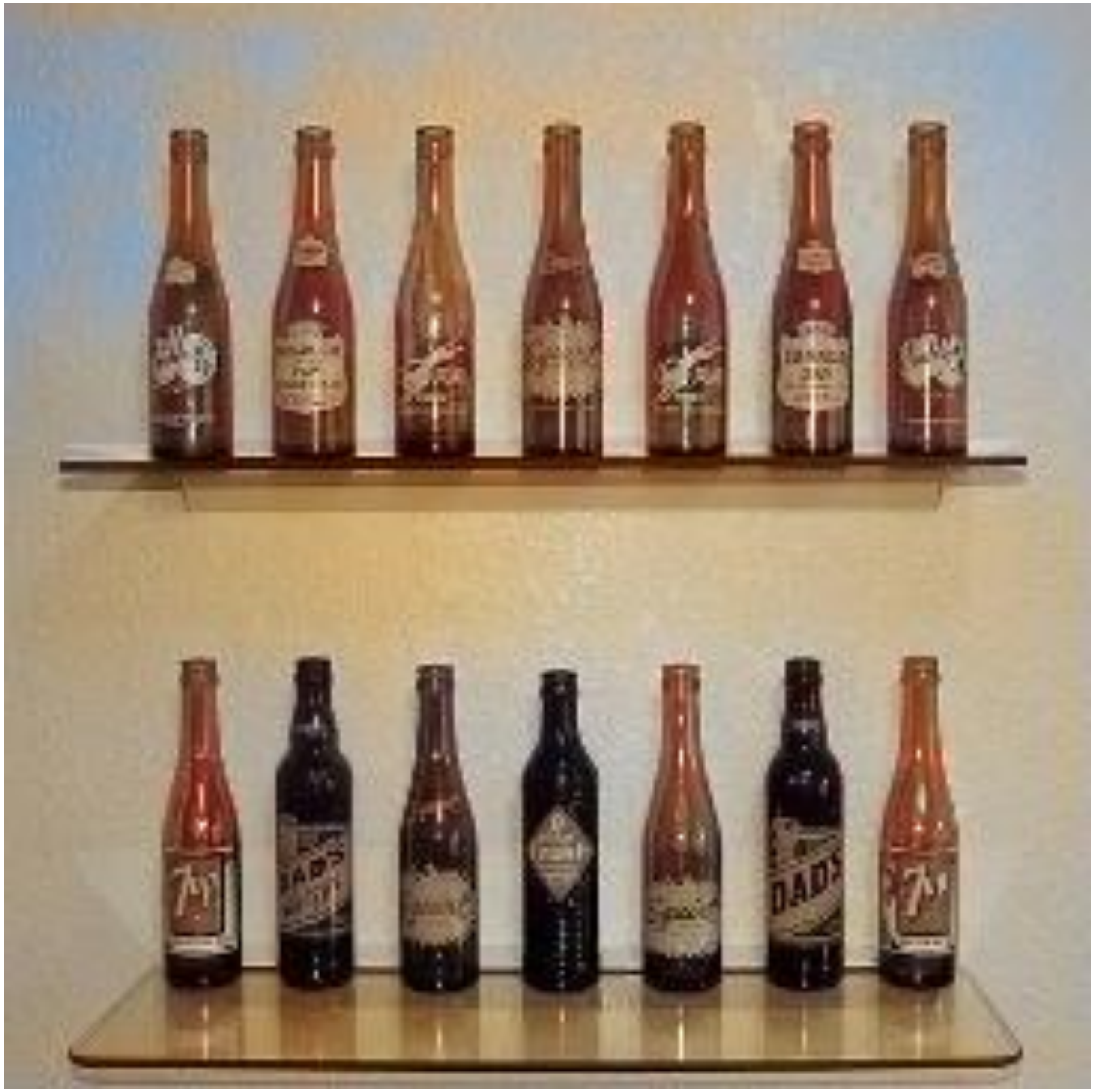
Input

Zhang et al. 2016

Ground truth

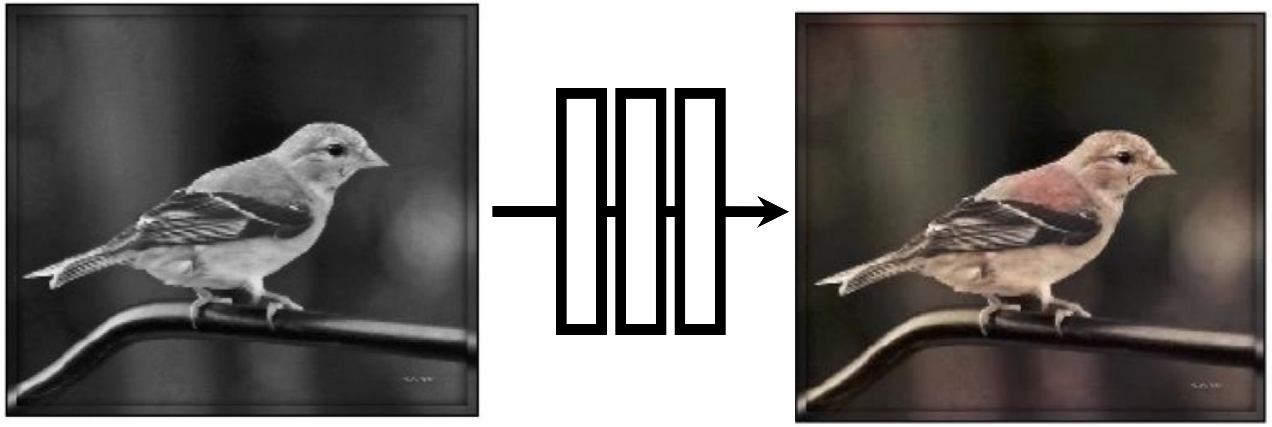
Color distribution cross-entropy loss with colorfulness enhancing term.

[Zhang, Isola, Efros, ECCV 2016]


DADS

Designing loss functions

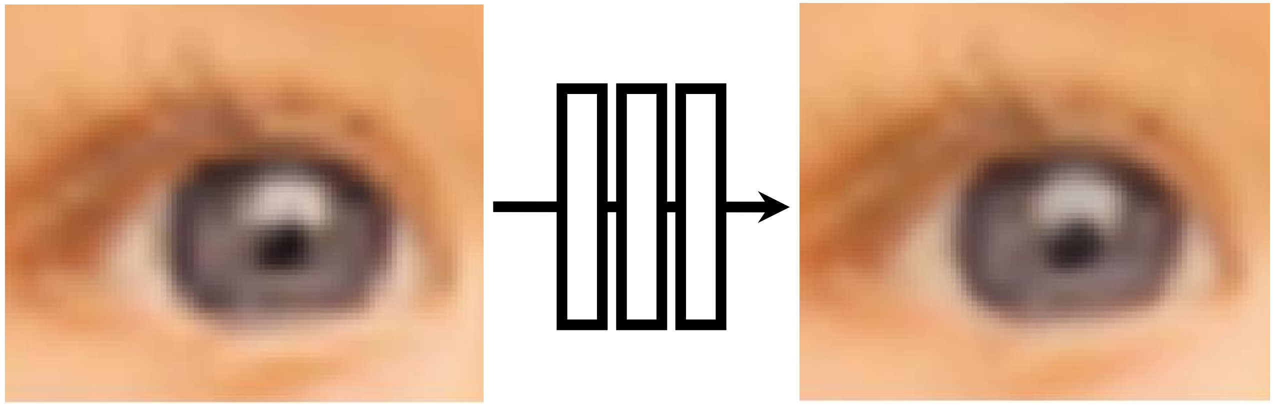
Image colorization



[Zhang, Isola, Efros, ECCV 2016]

L2 regression

Super-resolution

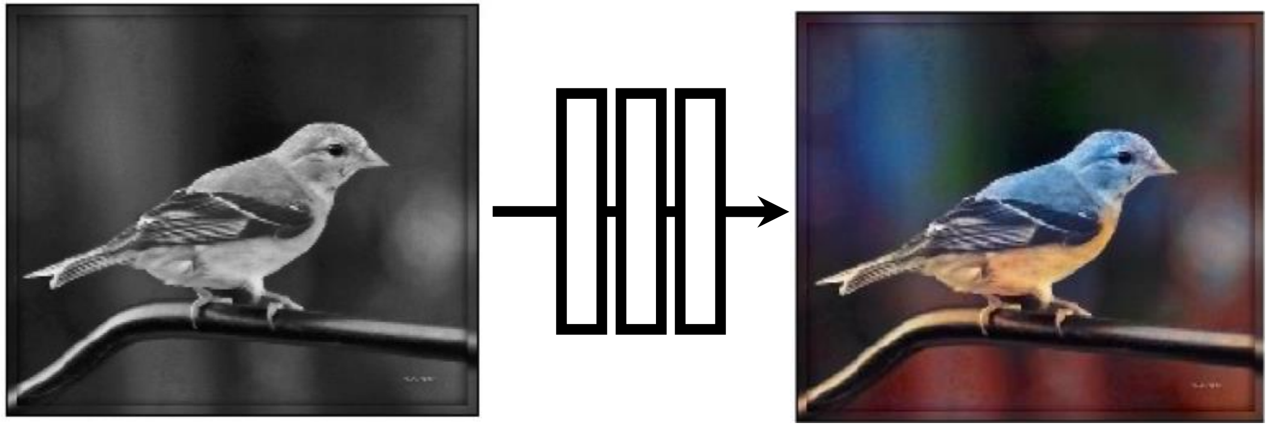


[Johnson, Alahi, Li, ECCV 2016]

L2 regression

Designing loss functions

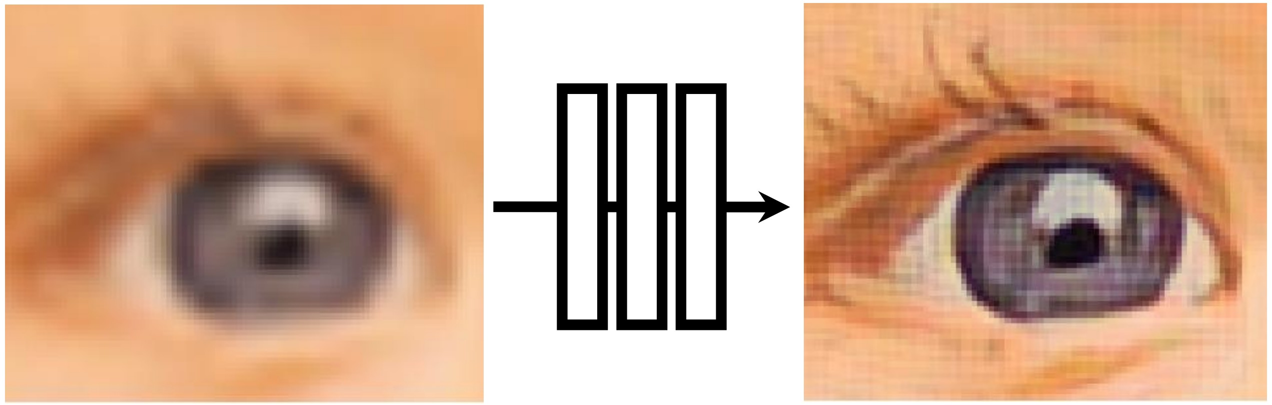
Image colorization



[Zhang, Isola, Efros, ECCV 2016]

Cross entropy objective, with colorfulness term

Super-resolution

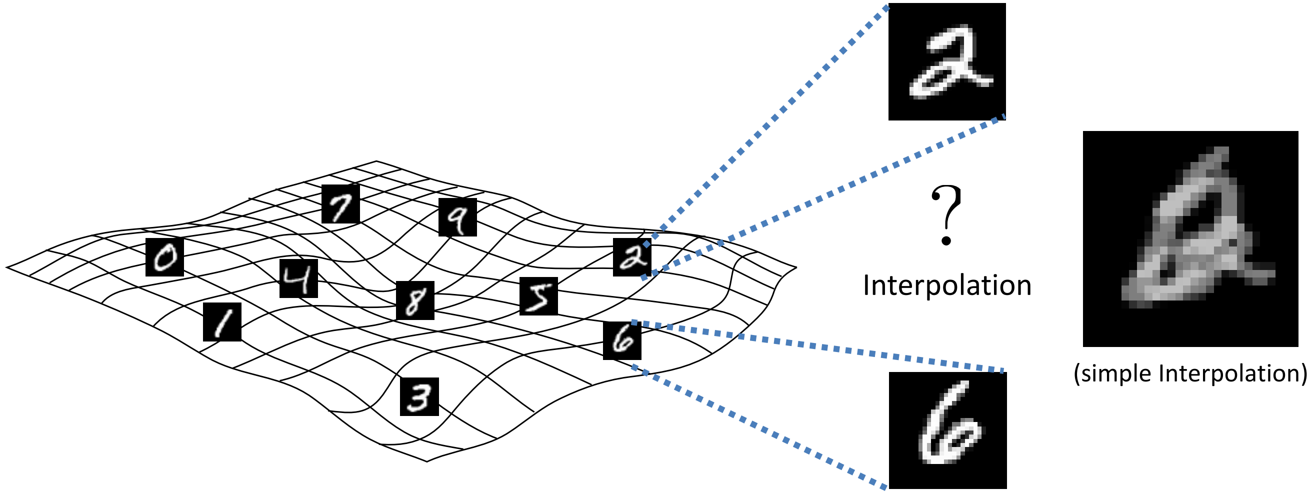


[Johnson, Alahi, Li, ECCV 2016]

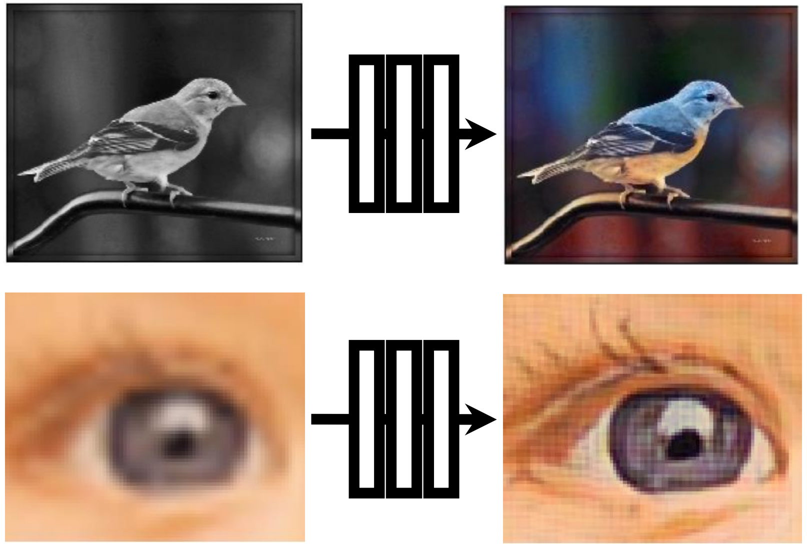
Deep feature covariance matching objective

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

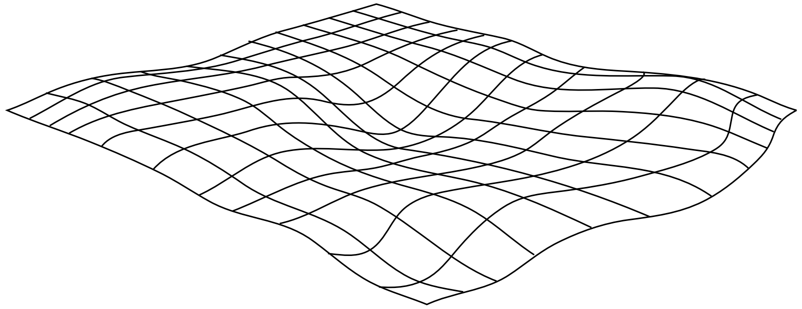


Abe Davis, with slides from Jin Sun and Phillip Isola

PART 3: GENERATIVE ADVERSARIAL NETWORKS (GANS)

Generative Adversarial Networks (GANs)

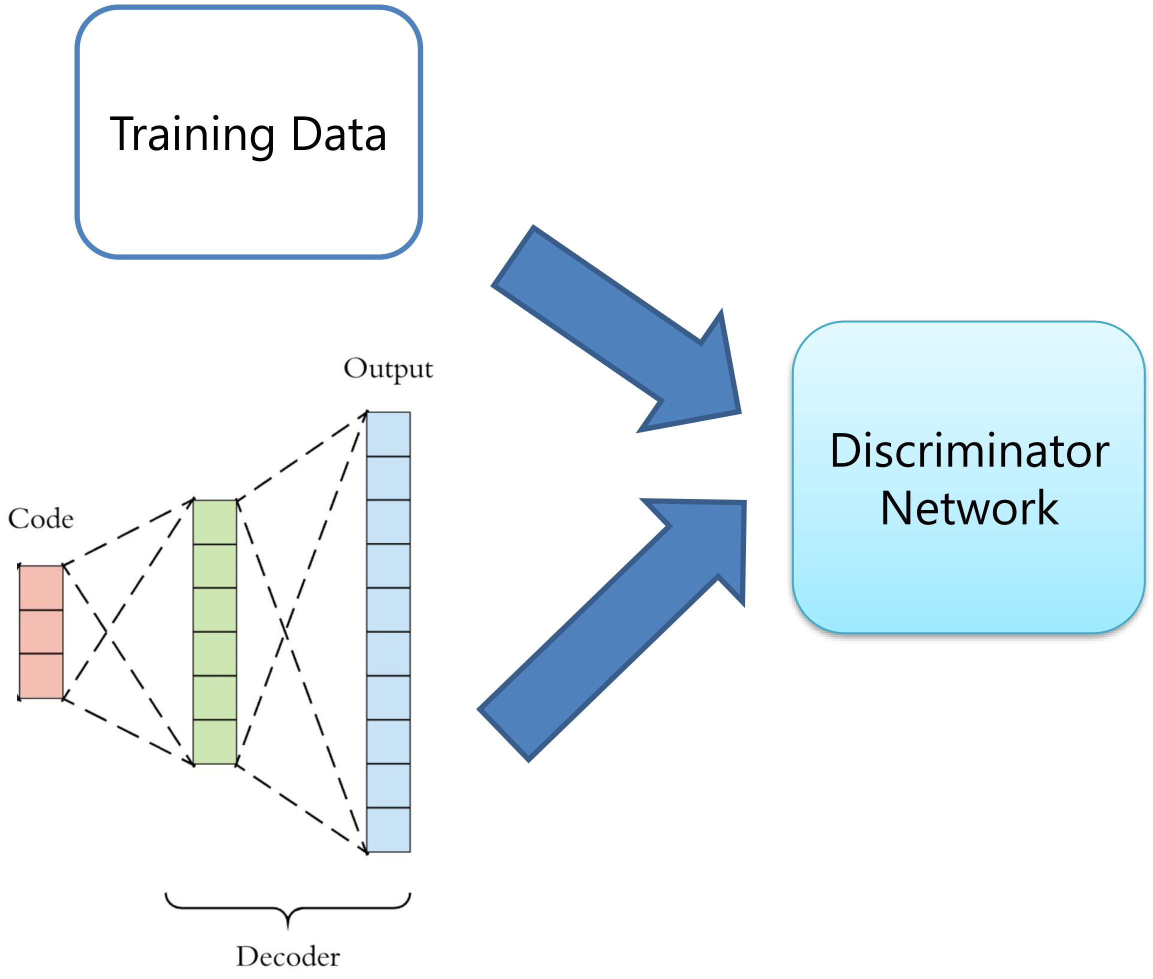
- Basic idea: Learn a mapping from some latent space to images on a particular manifold



- 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 tries to create output indistinguishable from training data
  - Discriminator tries to distinguish between generator output and training data



Example: Randomly Sampling the Space of Face Images

(Using Generative Adversarial Networks (GANs)

A

B

[Which face is real]?

Example: Randomly Sampling the Space of Face Images

(Using Generative Adversarial Networks (GANs)

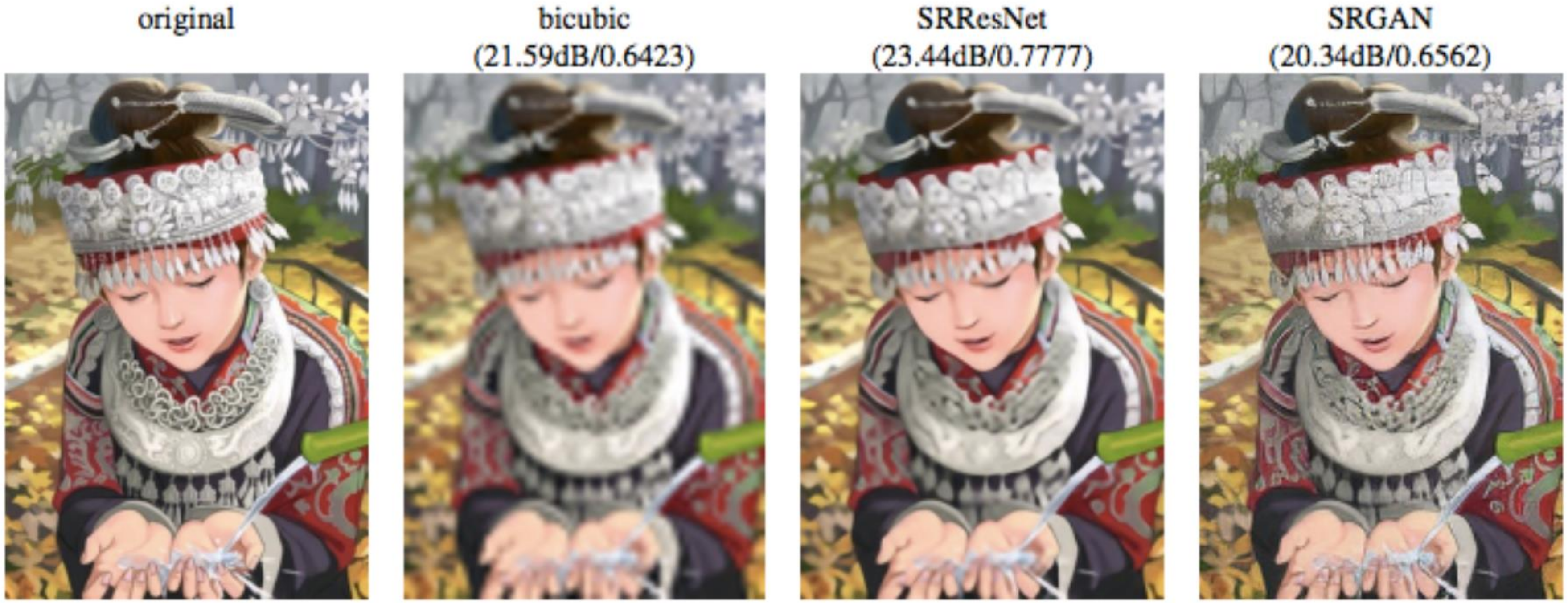
A

B

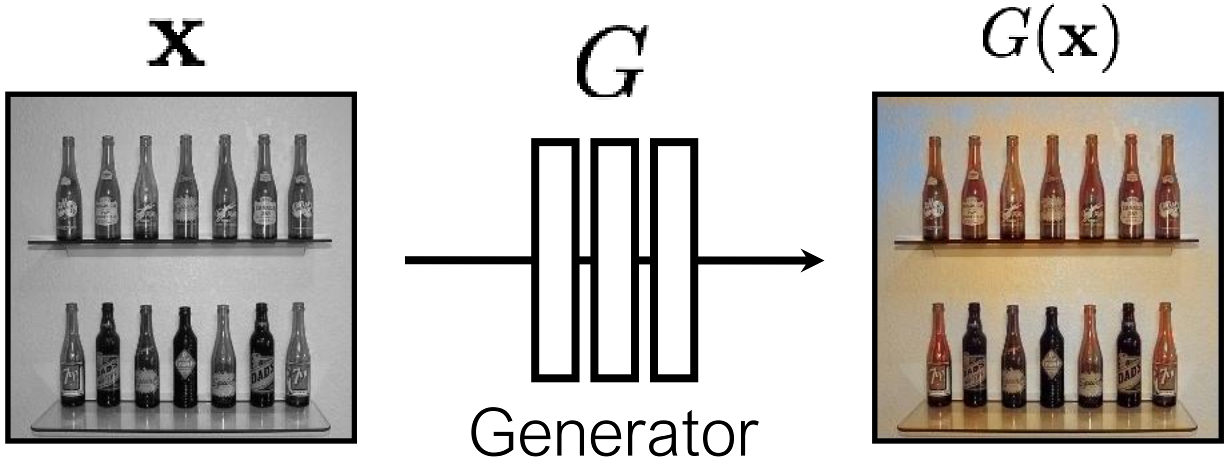
[Which face is real](#)?

Conditional GANs

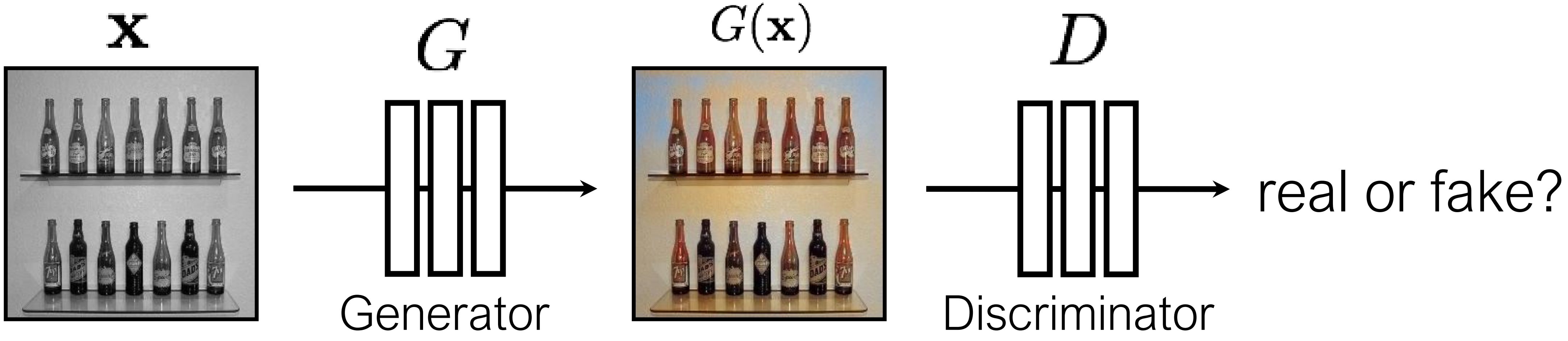
- Generate samples from a conditional distribution
- Example: generate high-resolution image conditioned on low resolution input



[Ledig et al 2016]



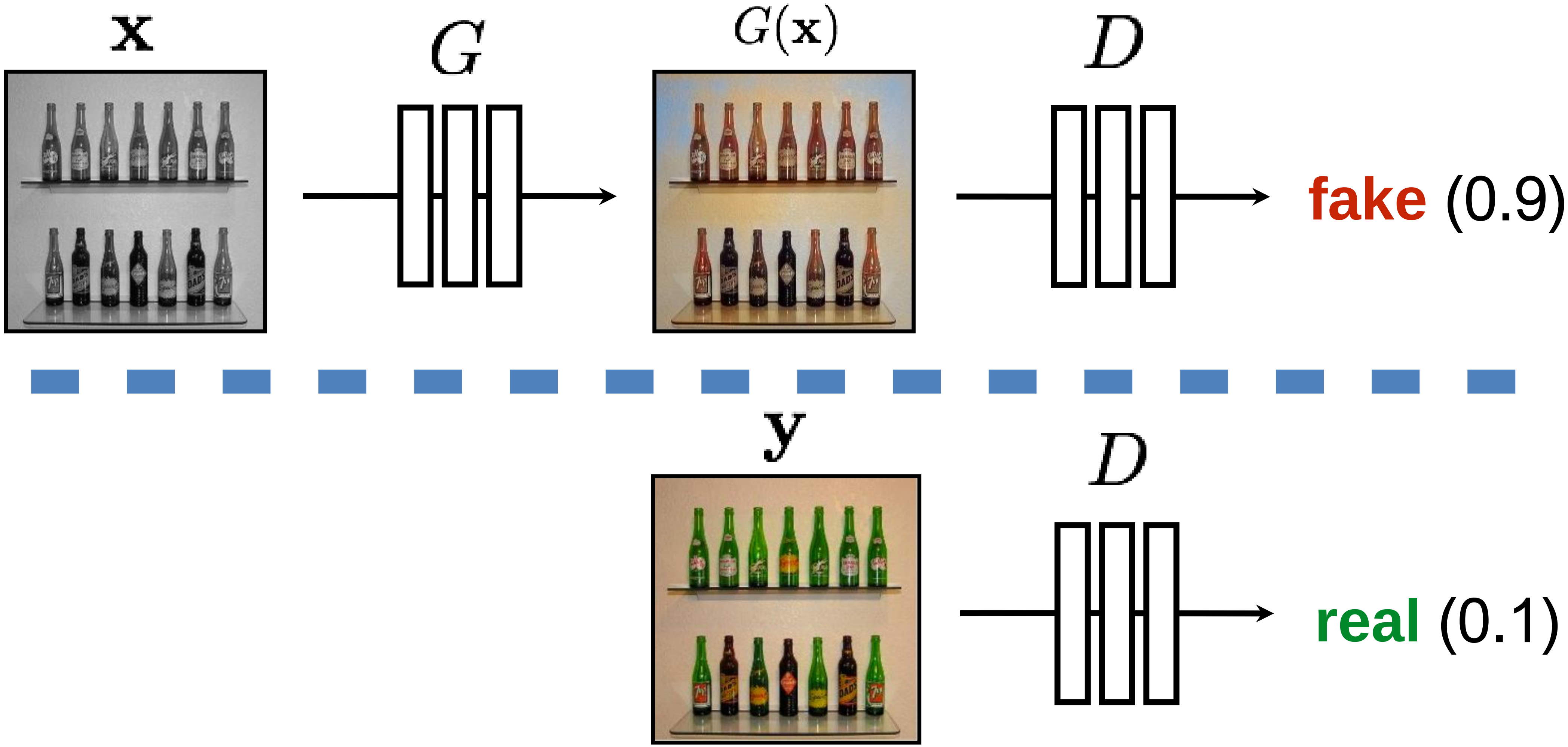
[Goodfellow et al., 2014]



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

D tries to identify the fakes

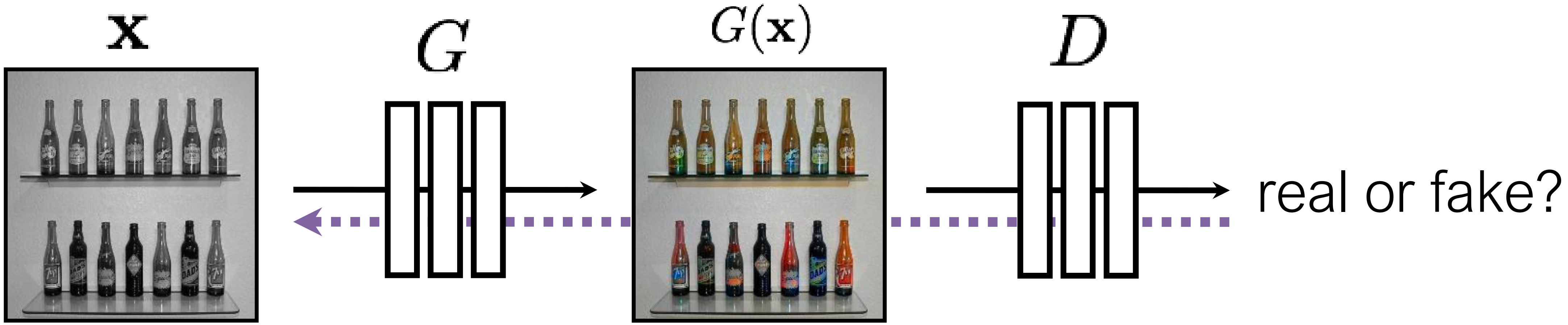
[Goodfellow et al., 2014]



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

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

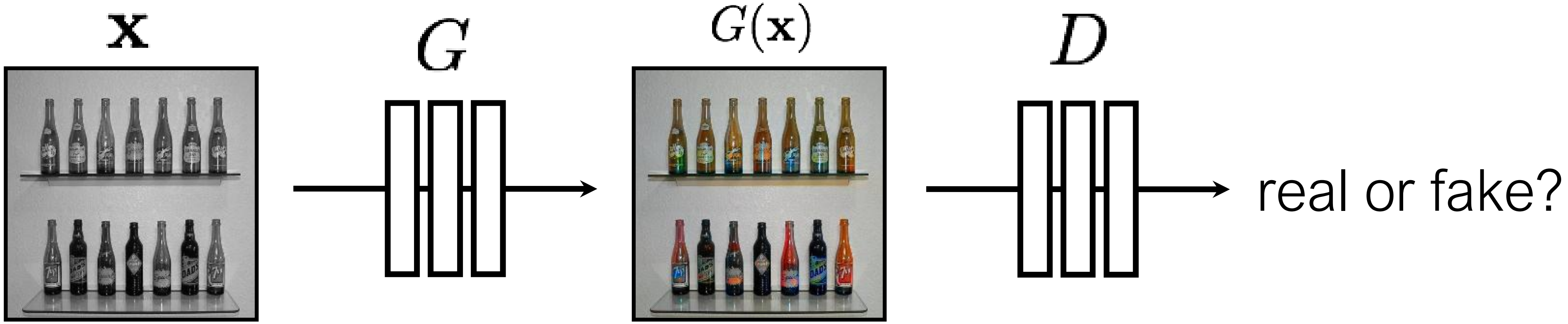
[Goodfellow et al., 2014]



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

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

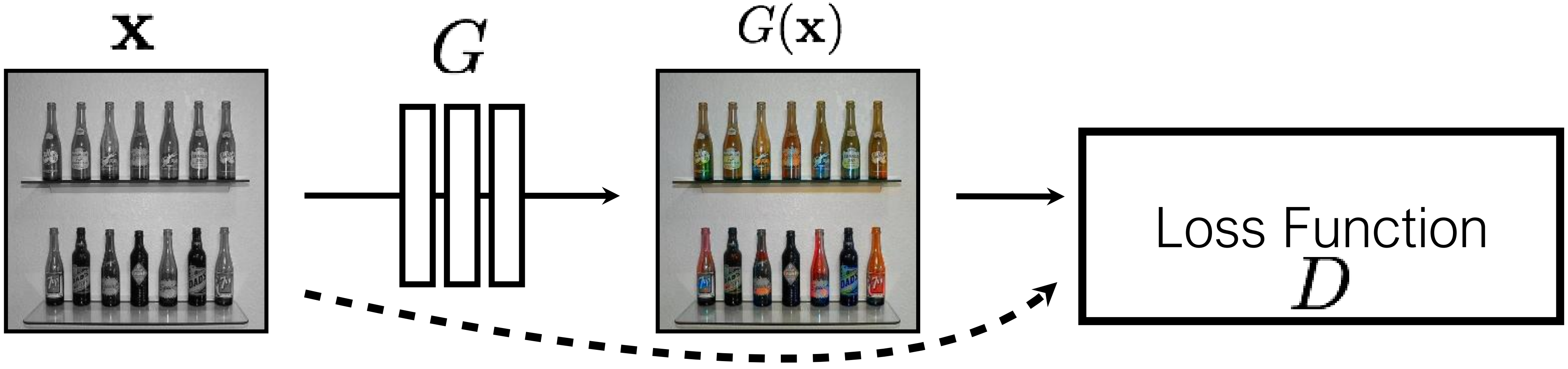
[Goodfellow et al., 2014]



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

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

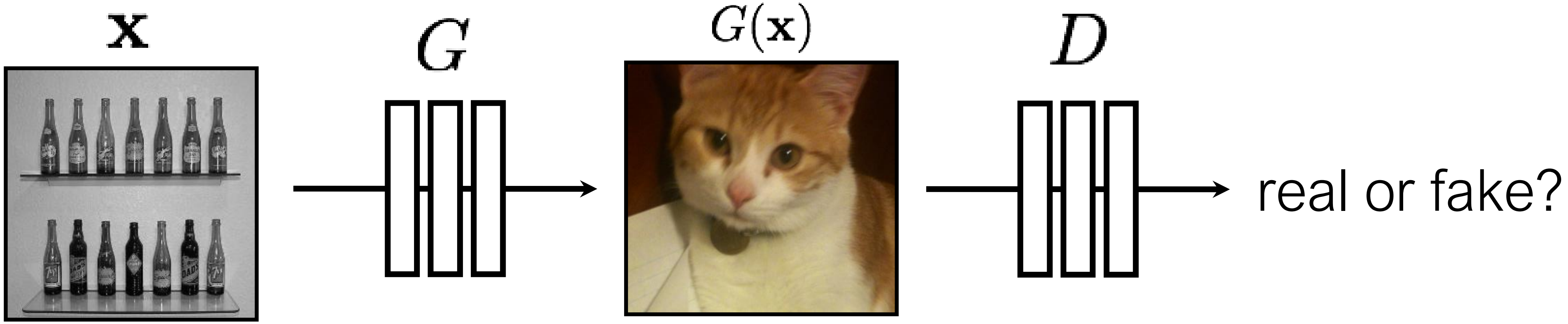
[Goodfellow et al., 2014]



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

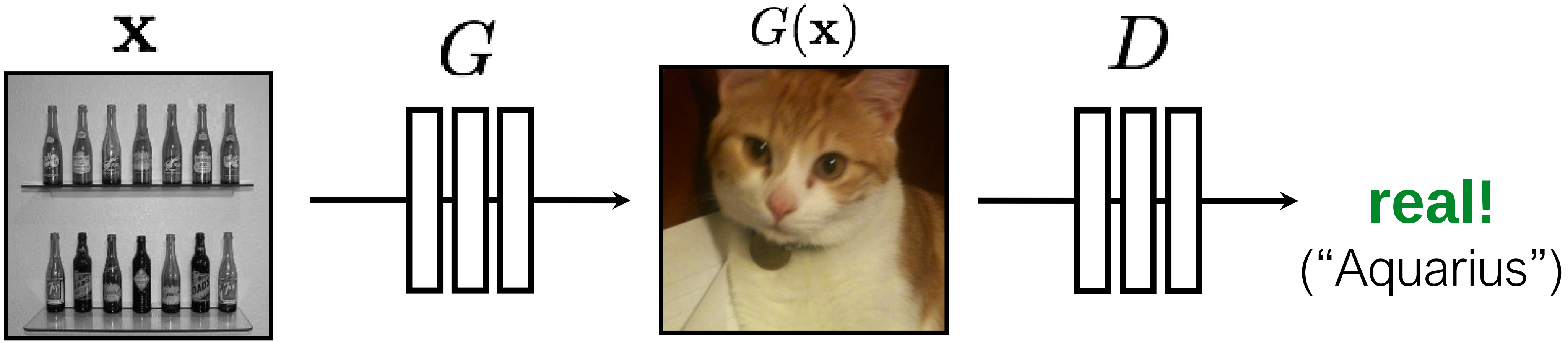
Rather than being hand-designed, it is *learned*.

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



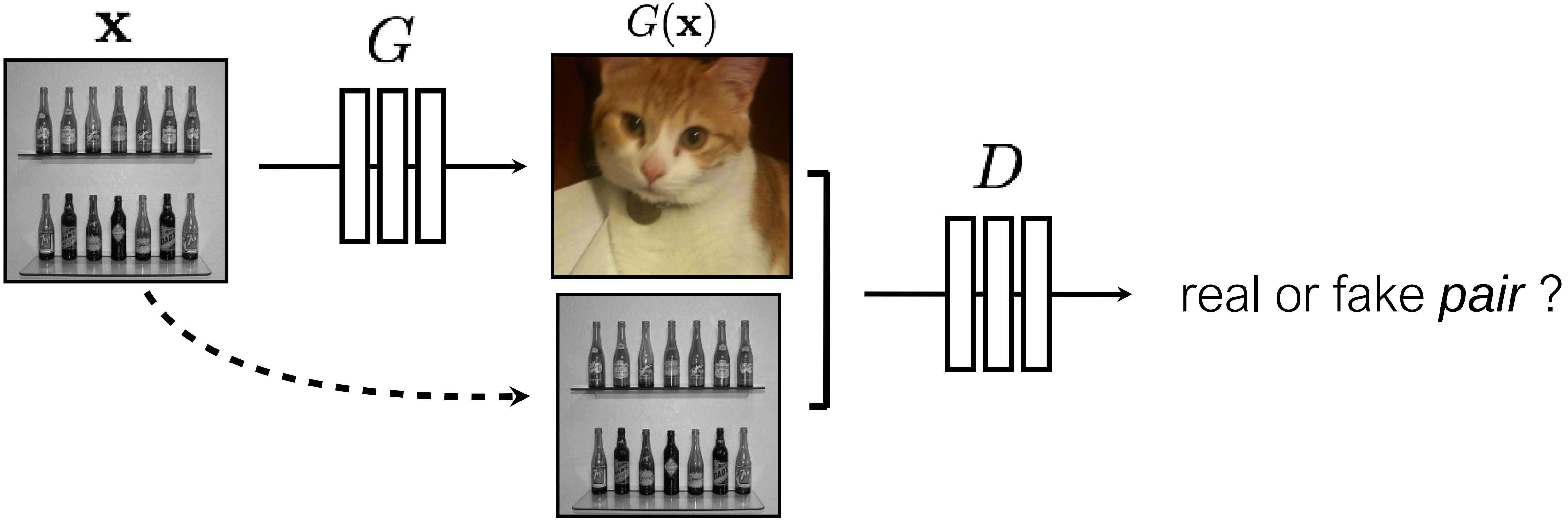
$$\arg\min_G \max_D \; \mathbb{E}_{\mathbf{x},\mathbf{y}}[\; \log D(G(\mathbf{x})) \quad + \quad \log(1 - D(\mathbf{y})) \;]$$

[Goodfellow et al., 2014]



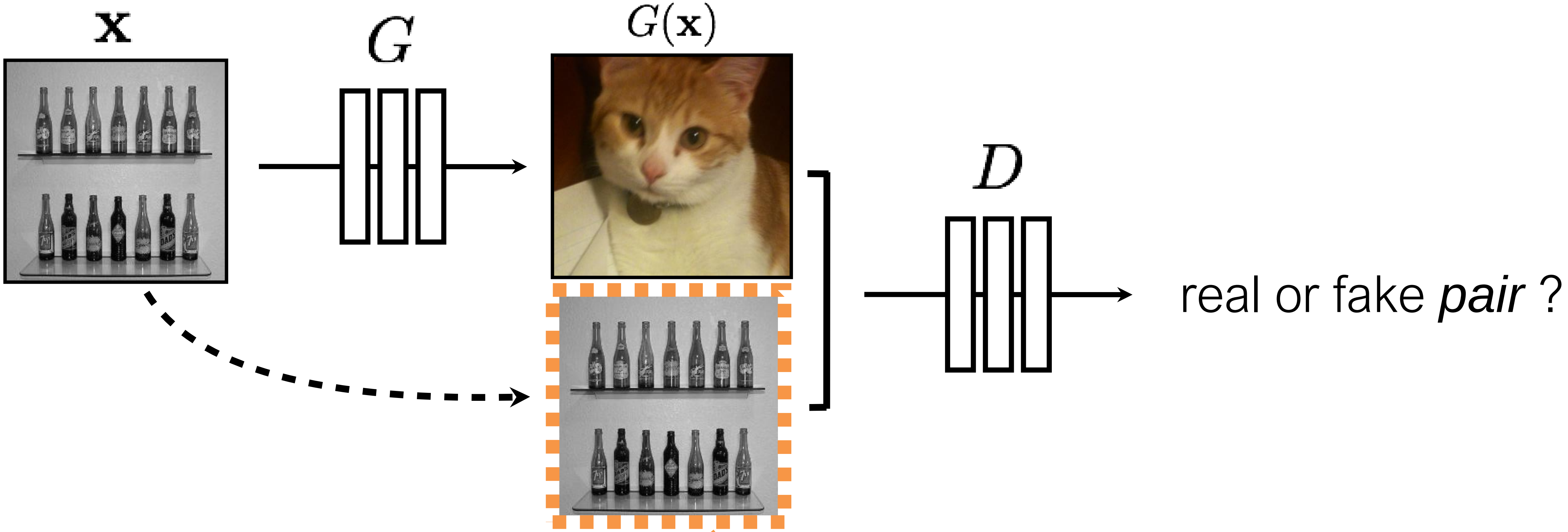
$$\arg\min_{G}\max_{D}\ \mathbb{E}_{\mathbf{x},\mathbf{y}}[\ \log D(G(\mathbf{x})) \quad + \quad \log(1 - D(\mathbf{y}))\ \ ]$$

[Goodfellow et al., 2014]



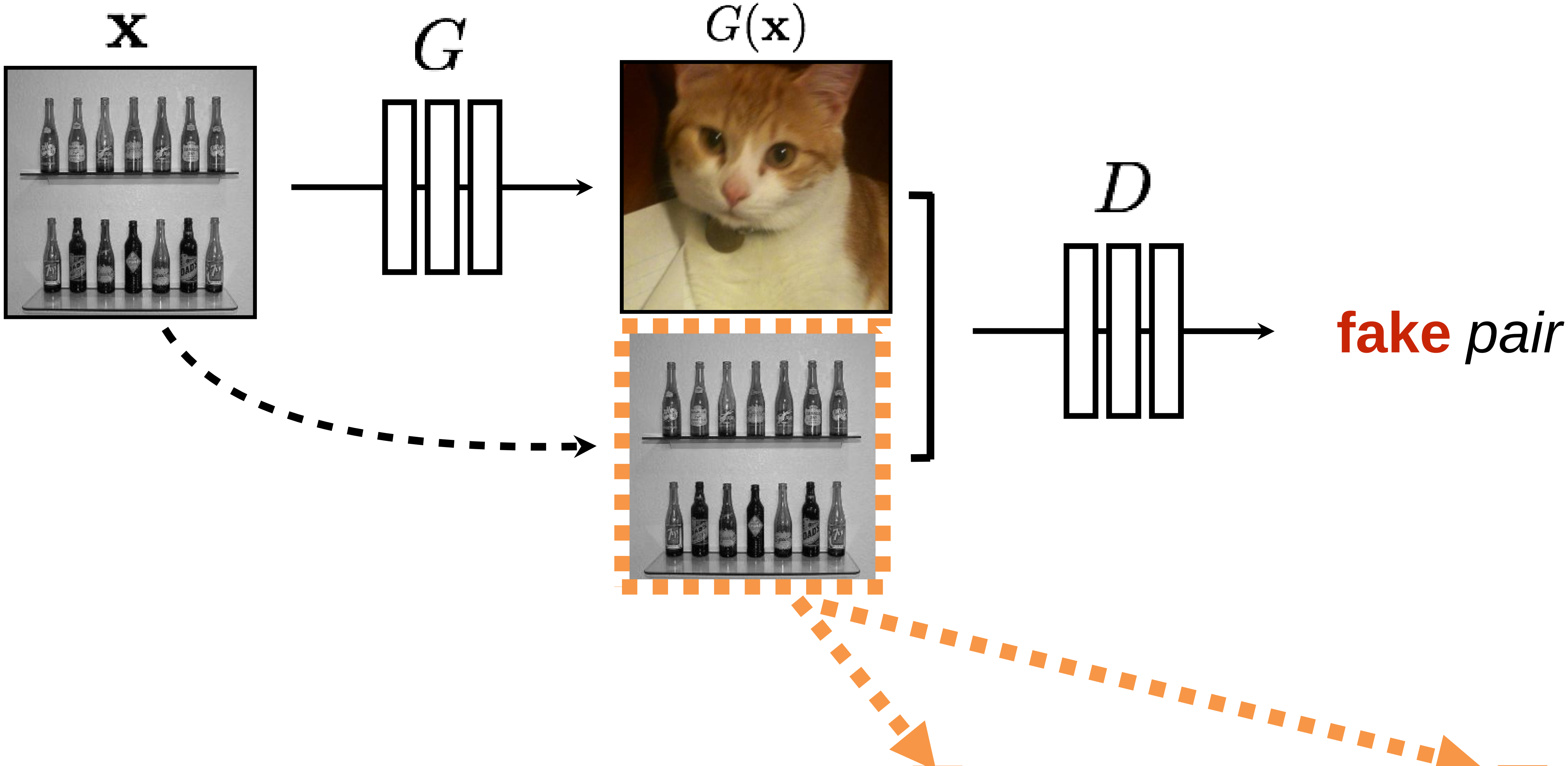
$$\arg\min_G \max_D \; \mathbb{E}_{\mathbf{x},\mathbf{y}}[\; \log D(G(\mathbf{x})) \quad + \quad \log(1 - D(\mathbf{y})) \;]$$

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



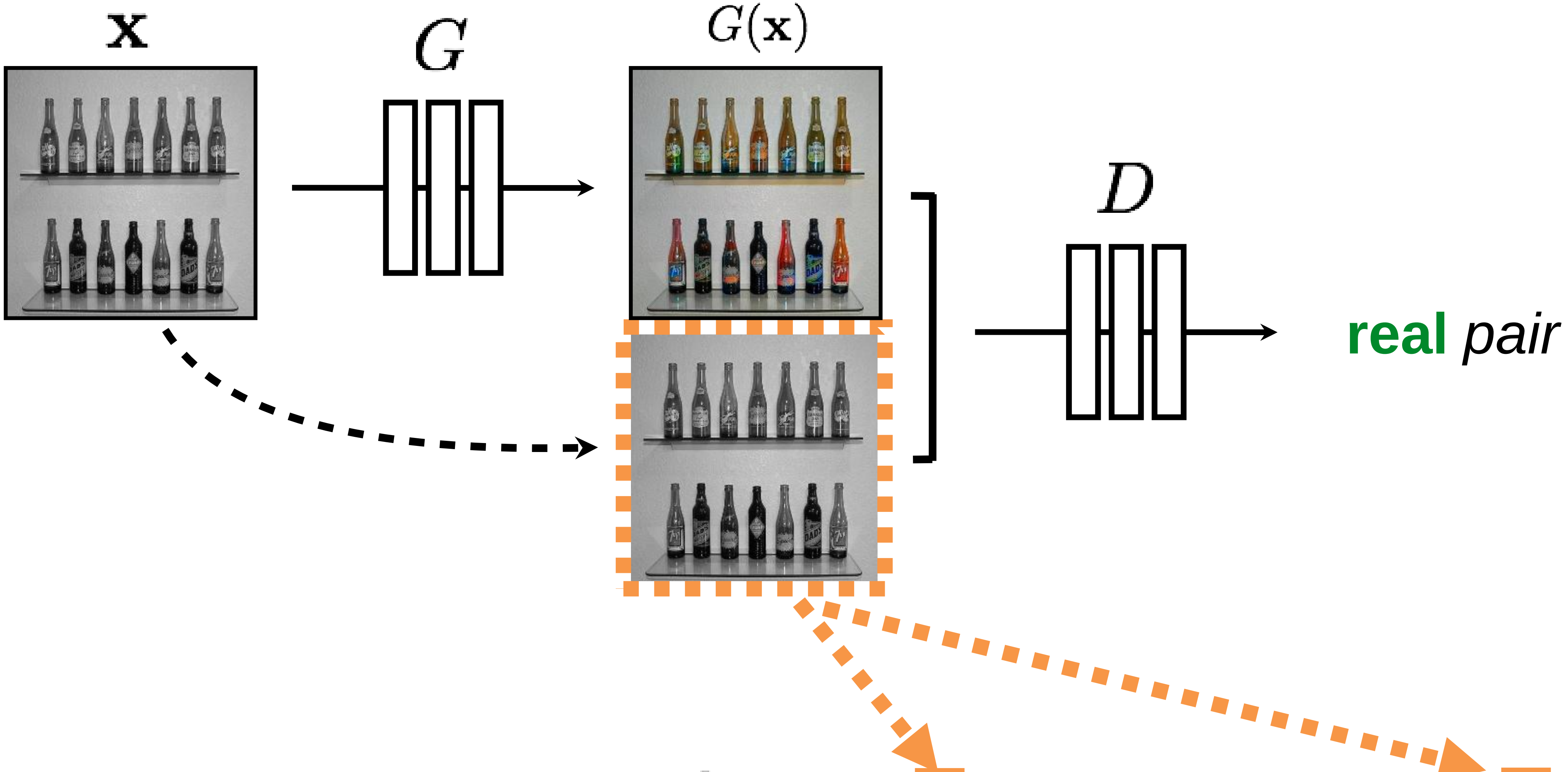
$$\arg\min_G \max_D \; \mathbb{E}_{\mathbf{x},\mathbf{y}}[\; \log D(\boxed{\mathbf{x}}, G(\mathbf{x})) + \log(1 - D(\boxed{\mathbf{x}}, \mathbf{y})) \;]$$

[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]



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

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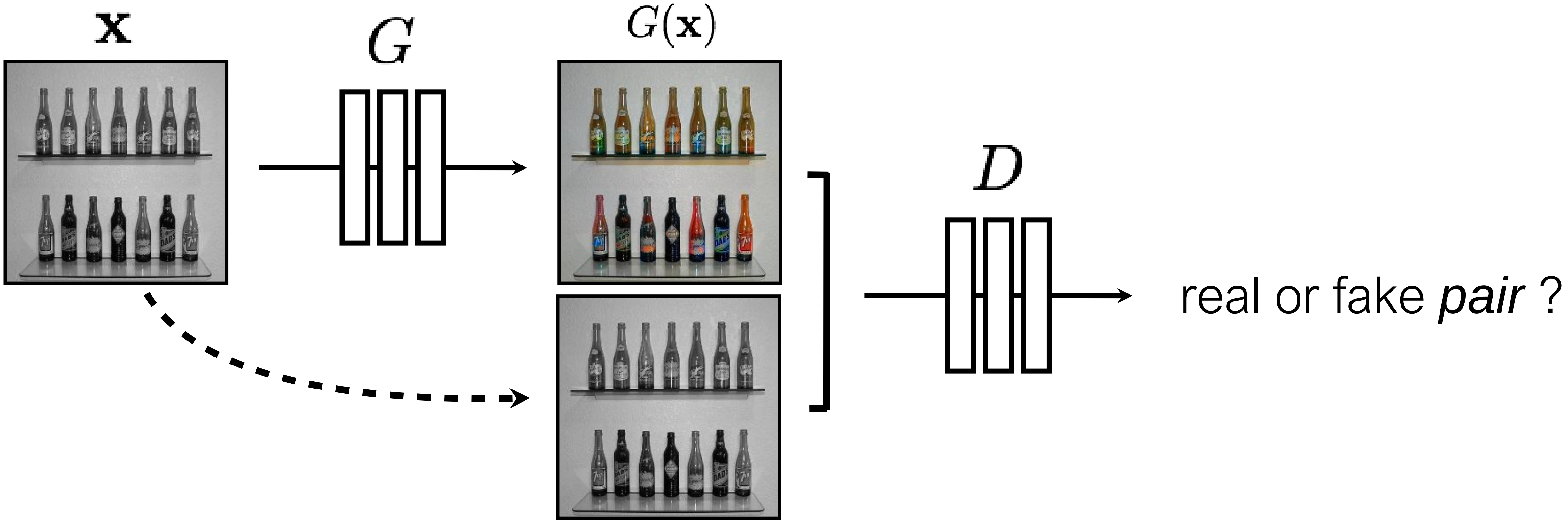
[Isola et al., 2017]



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

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

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

Input Output Input Output Input Output

Data from [Russakovsky et al. 2015]

Input

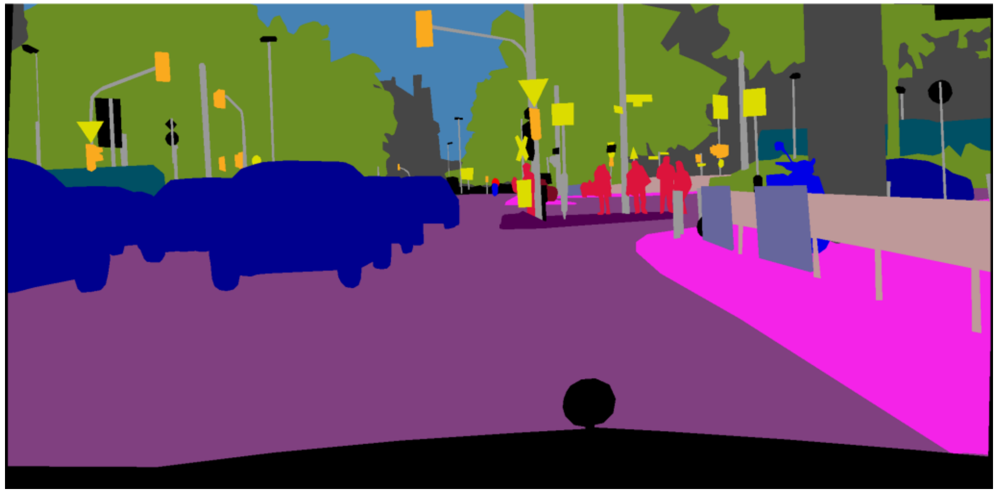
Output

Groundtruth

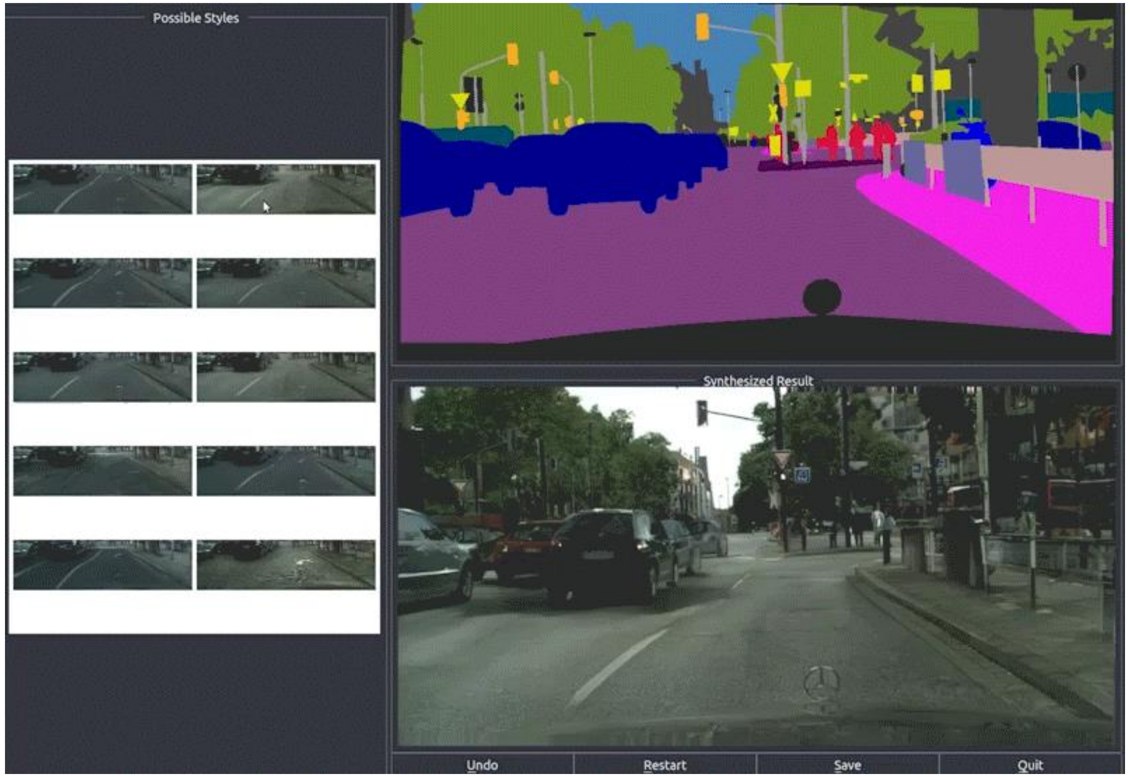
Data from
[maps.google.com]

Labels → Street Views

Input labels



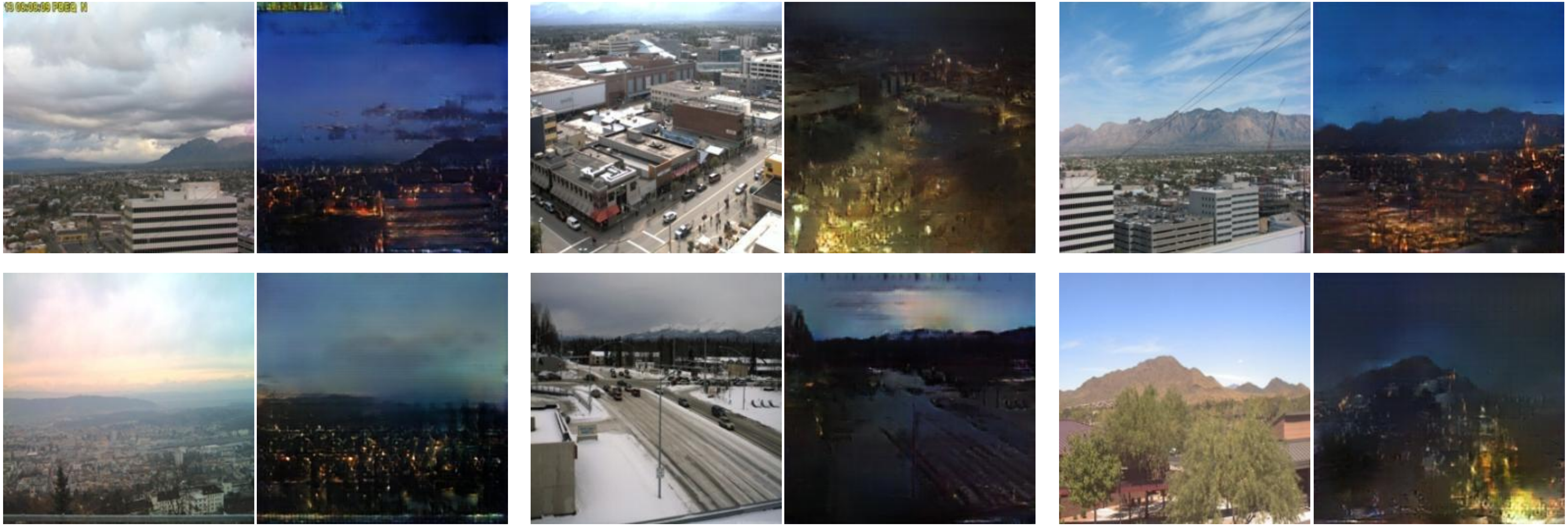
Synthesized image



Data from [Wang et al, 2018]

Day → Night

Input Output Input Output Input Output



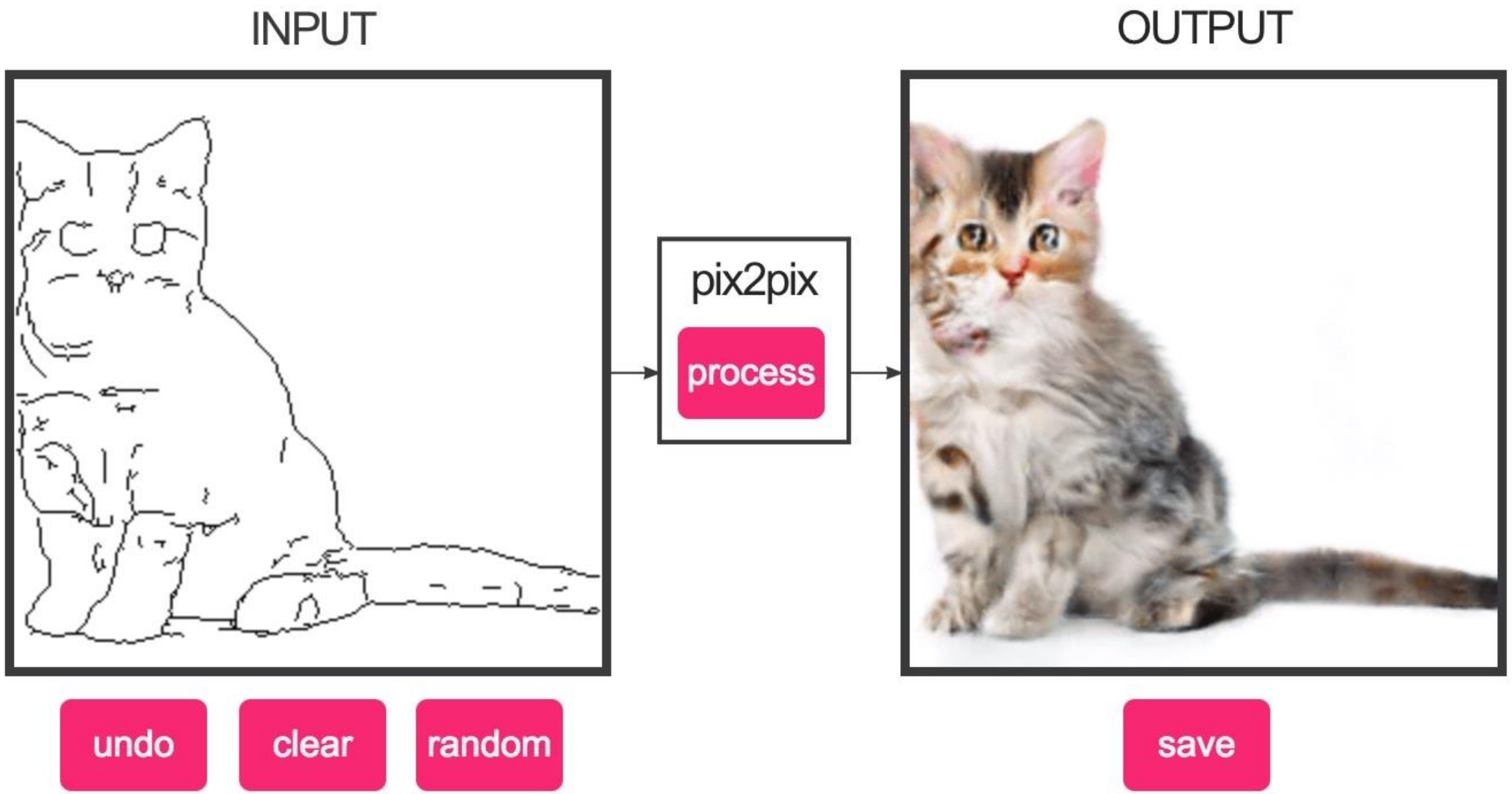
Data from [Laffont et al., 2014]

Edges → Images

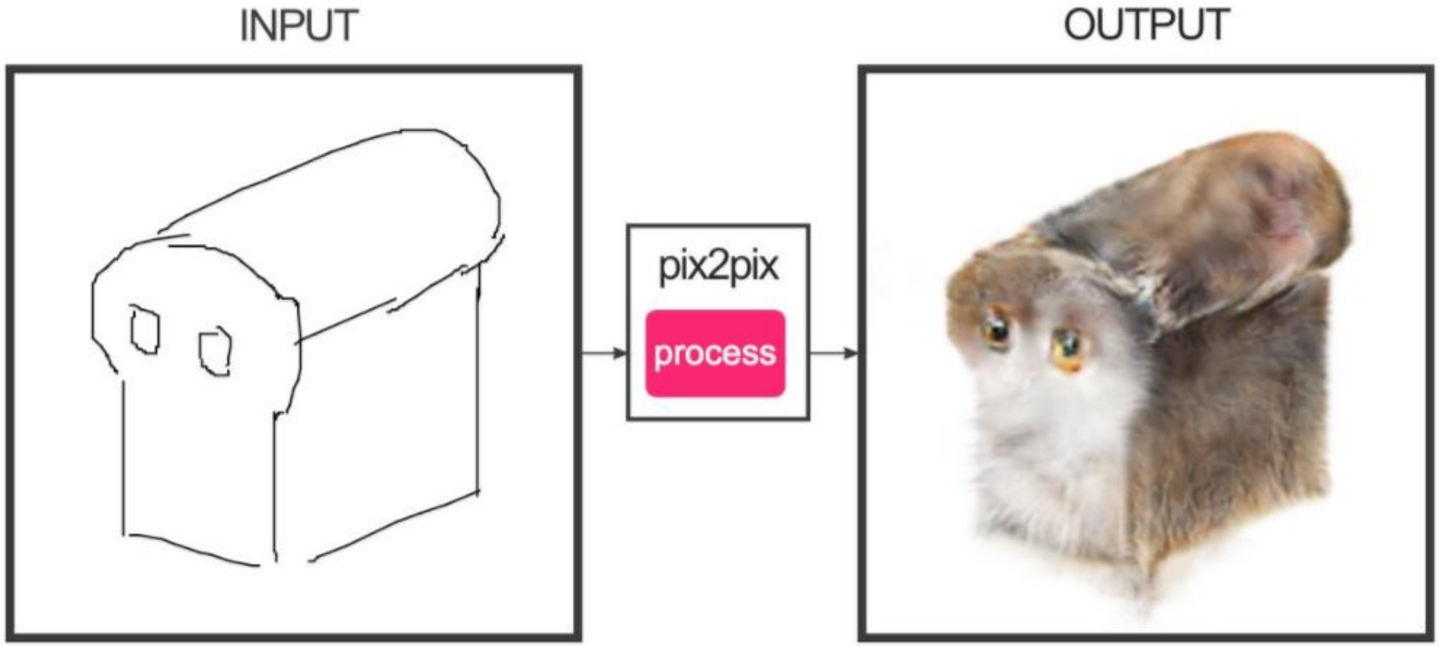
Input Output Input Output Input Output

Edges from [Xie & Tu, 2015]

Demo



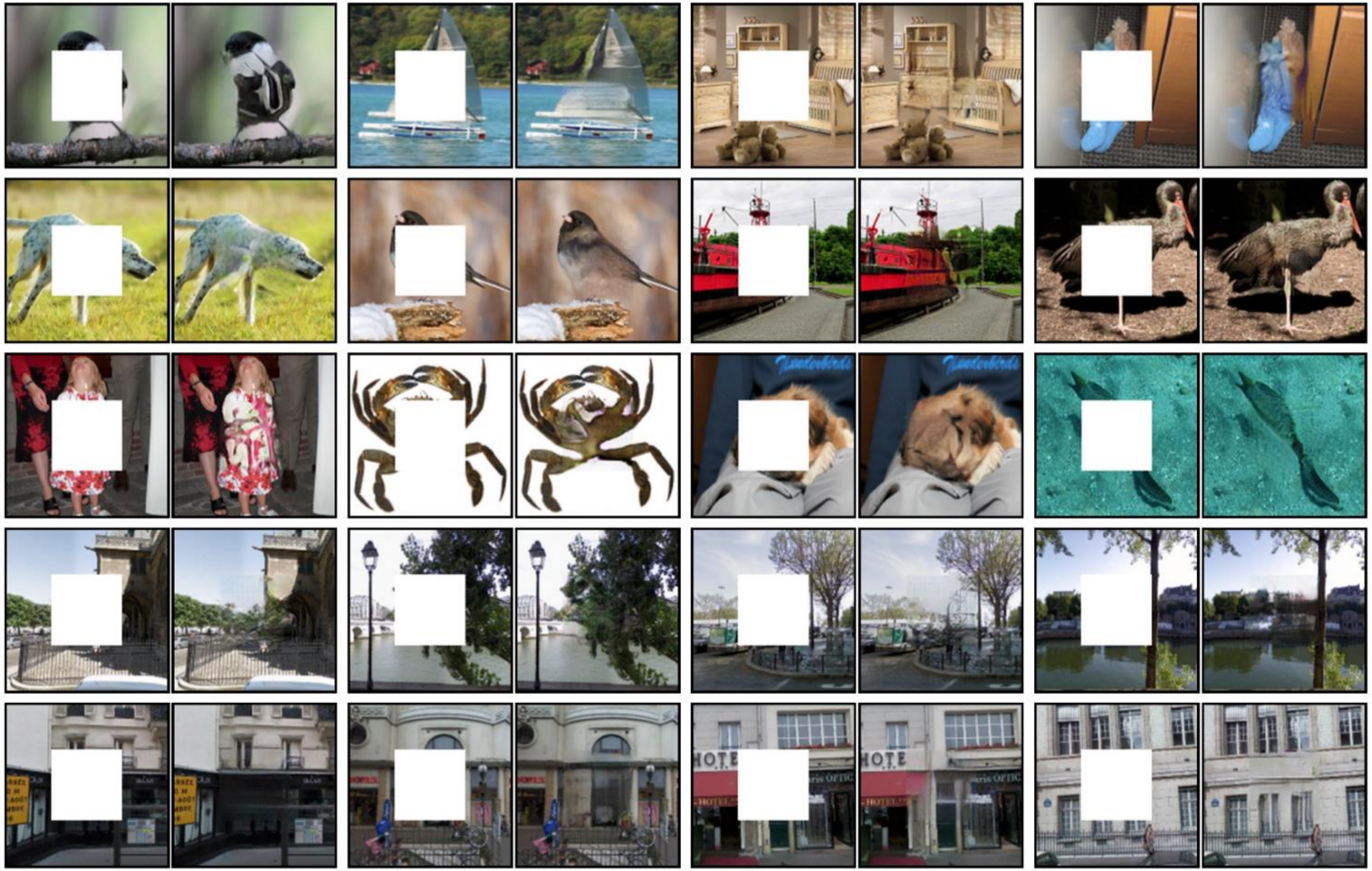
https://affinelayer.com/pixsrv/



Ivy Tasi @ivymyt

Vitaly Vidmirov @vvid

Image Inpainting



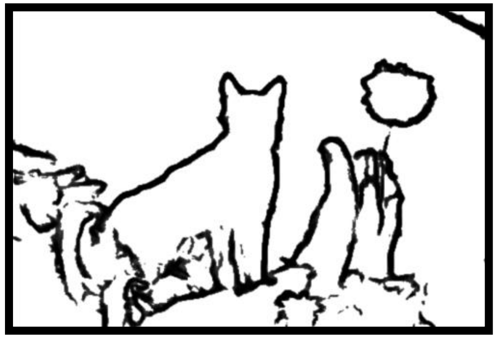
Data from [Pathak et al., 2016]

Pose-guided Generation

Data from [Ma et al., 2018]

Challenges —> Solutions

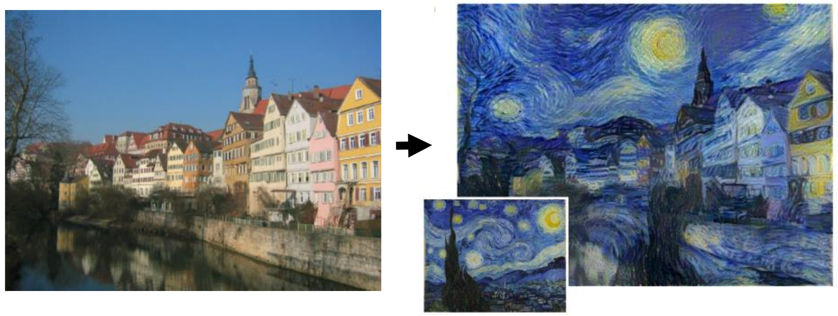
- Output is high-dimensional, structured object
  – Approach: Use a deep net, D, to analyze output!



- Uncertainty in mapping; many plausible outputs
  – Approach: D only cares about “plausibility”, doesn’t hedge

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

- Lack of supervised training data
  – Approach: ?



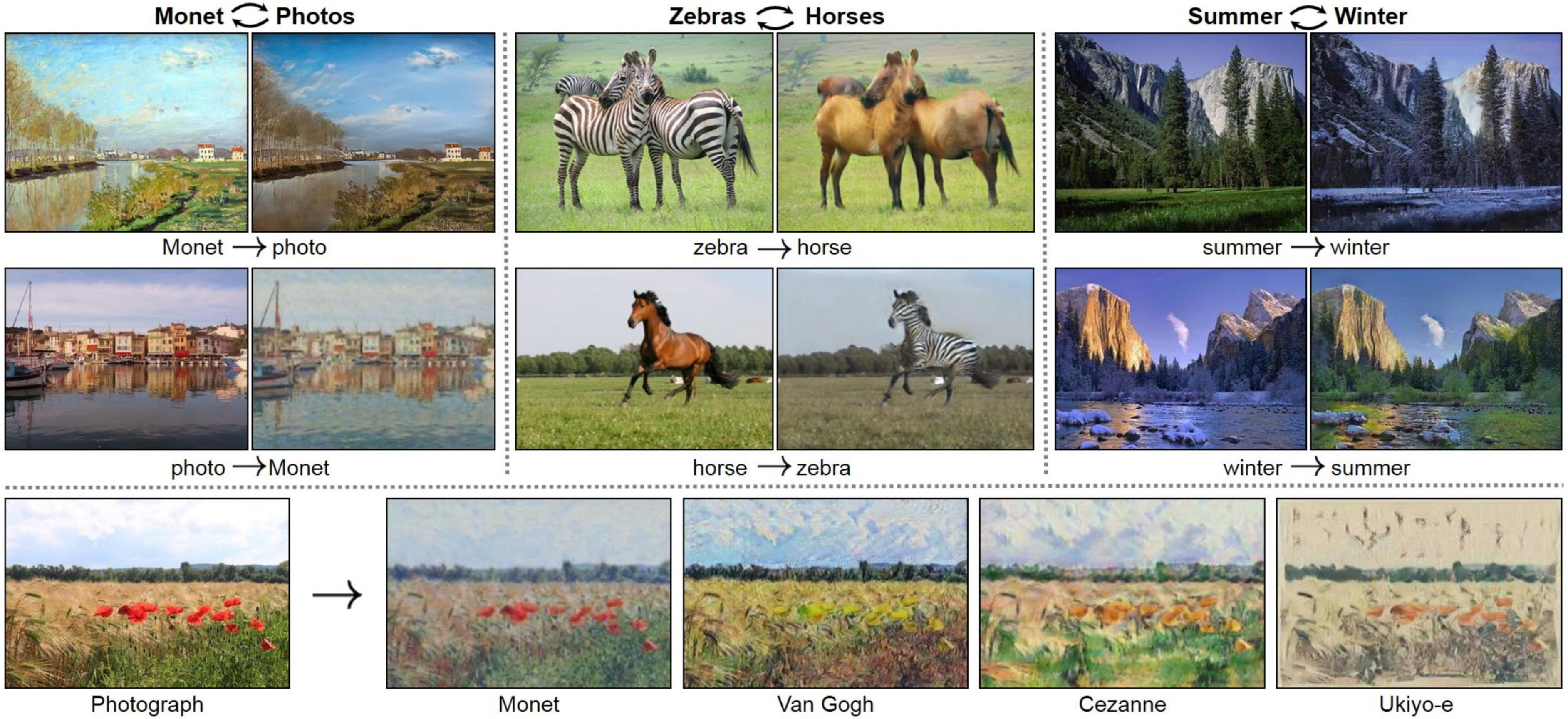
Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks

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

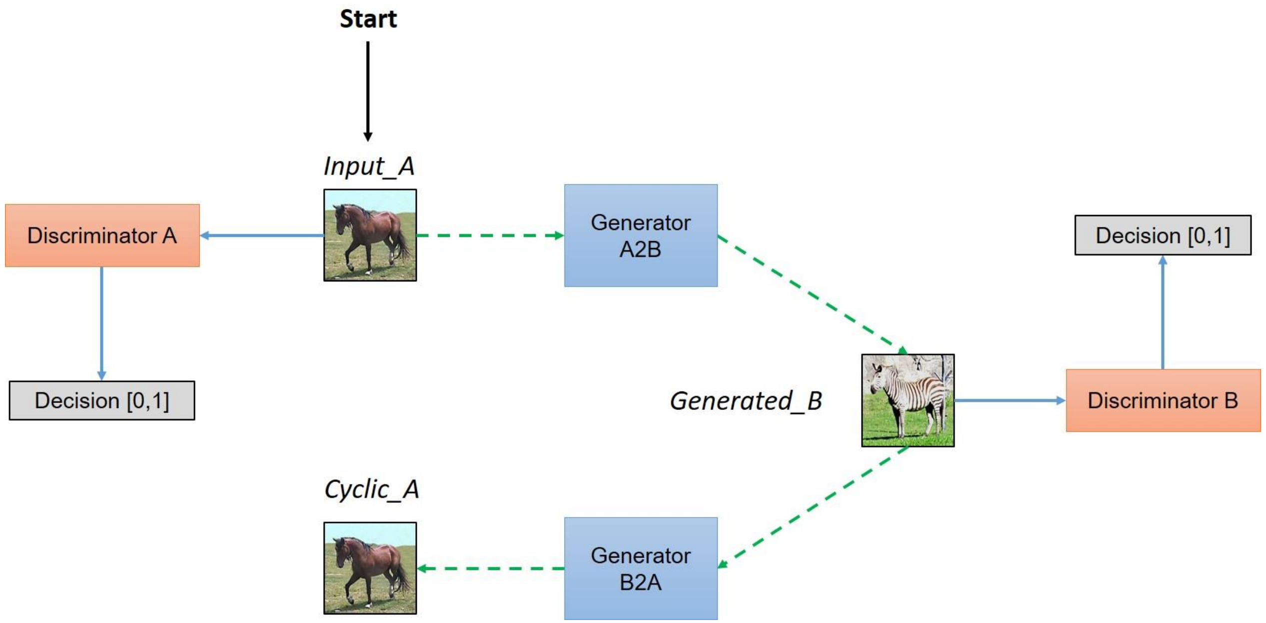
UC Berkeley

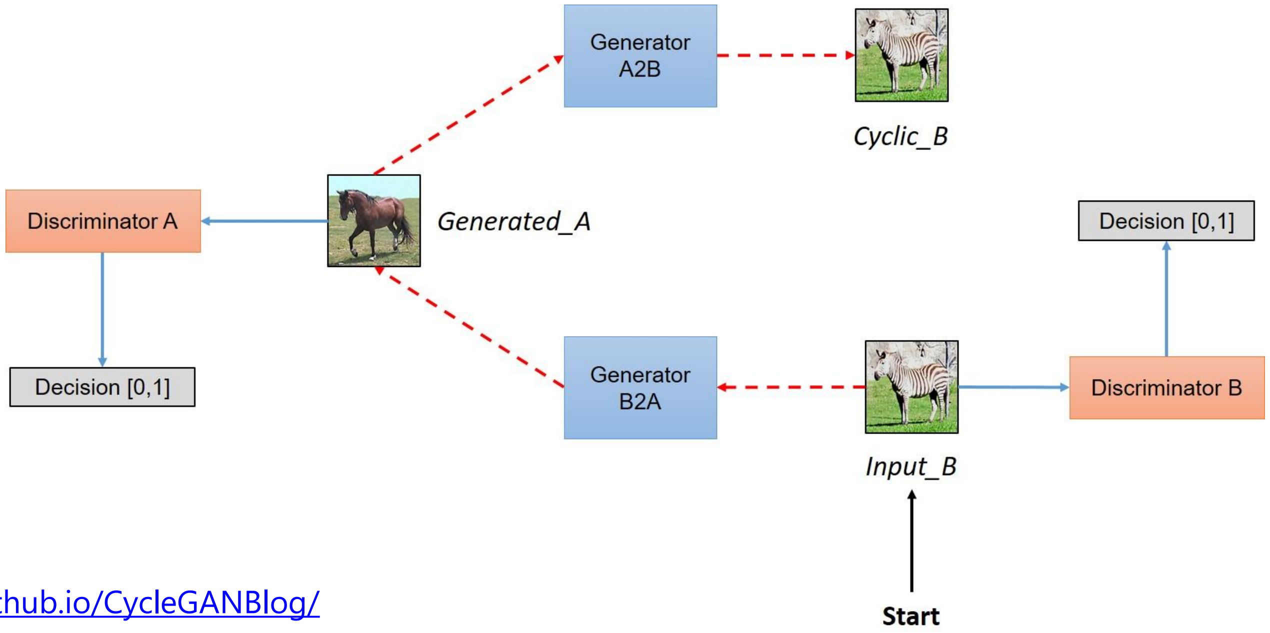
In ICCV 2017

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



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





https://hardikbansal.github.io/CycleGANBlog/

StyleGAN

A Style-Based Generator Architecture for Generative Adversarial Networks

Tero Karras, Samuli Laine, Timo Aila

https://github.com/NVlabs/stylegan

Real-time image stylization

https://stadia.dev/blog/behind-the-scenes-with-stadias-style-transfer-ml/

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

Questions?