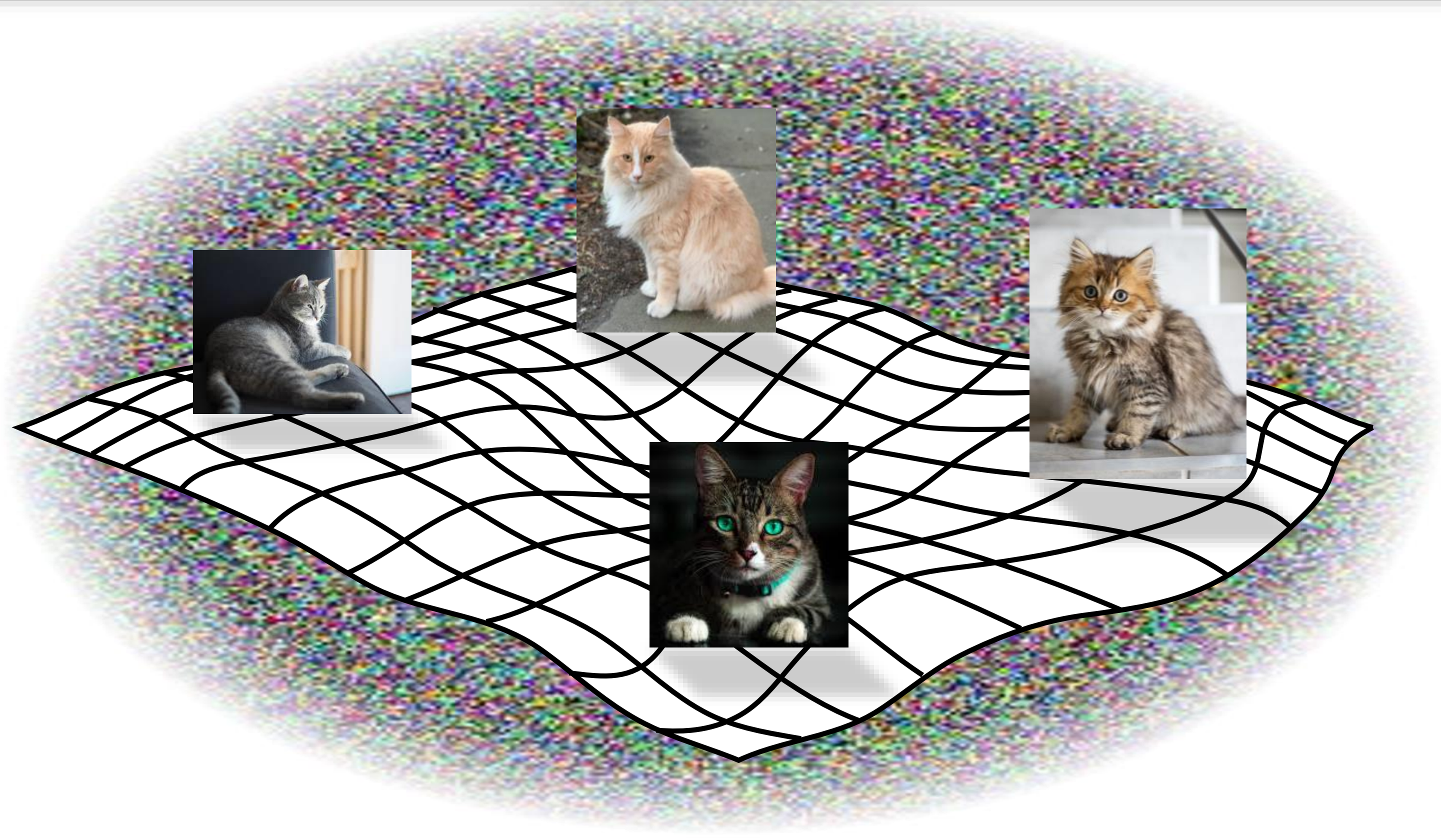
CS5670: Computer Vision

Image Manifolds & Image Synthesis (including GANS)



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

Announcements

- Take-home final May 12-17
- Project 5 (Convolutional Neural Networks) due Tuesday, May 11, 2021 (7:00 pm)

- Course evaluations are open this Friday, May 7 to May 17
  - 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
  - Link coming soon

Agenda

- Last time:
  - How to train convolutional neural networks (CNNs)

- This time:
  - One more note on training CNNs for new tasks
  - Dimensionality reduction
  - Neural networks that produce images
  - Generative Adversarial Networks (GANs)

Transfer Learning

“You need a lot of a data if you want to train/use CNNs”

Transfer Learning

"You need a lot of a data if you want to train/use CNNs"

BUSTED

Transfer Learning with CNNs

Donahue et al, "DeCAF: A Deep Convolutional Activation Feature for Generic Visual Recognition", ICML 2014
Razavian et al, "CNN Features Off-the-Shelf: An Astounding Baseline for Recognition", CVPR Workshops 2014

1. Train on Imagenet

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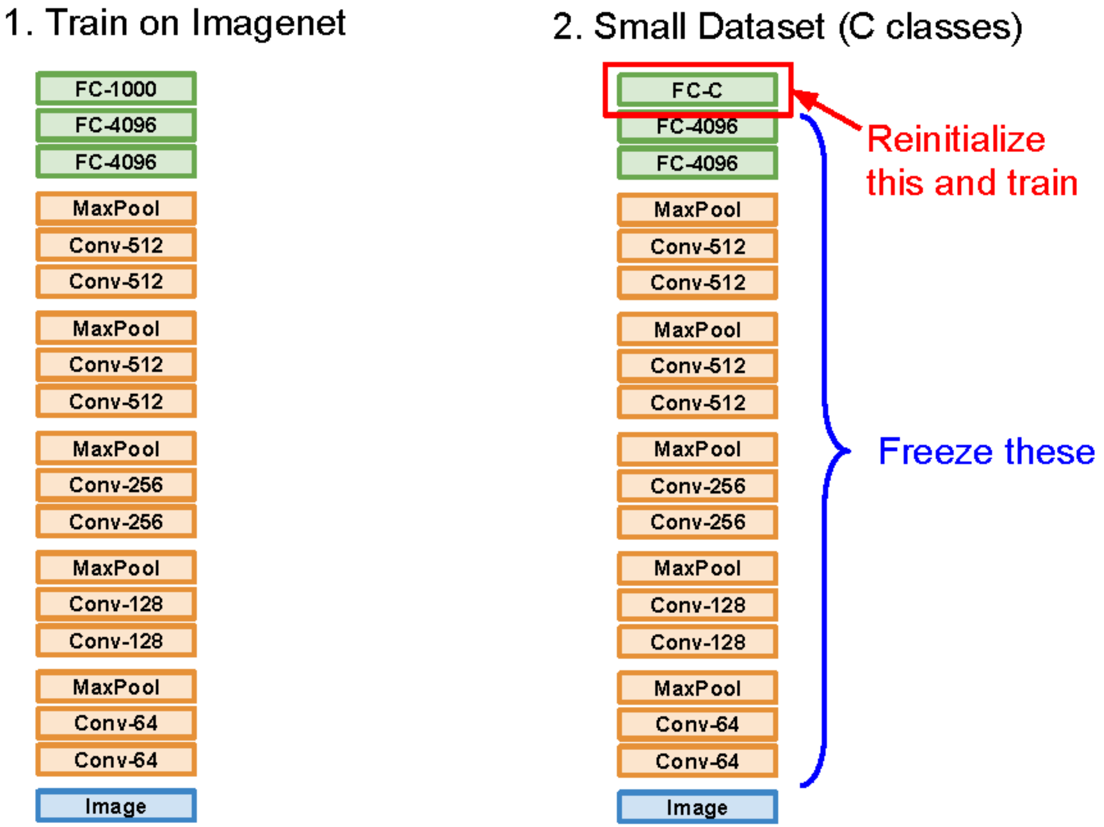

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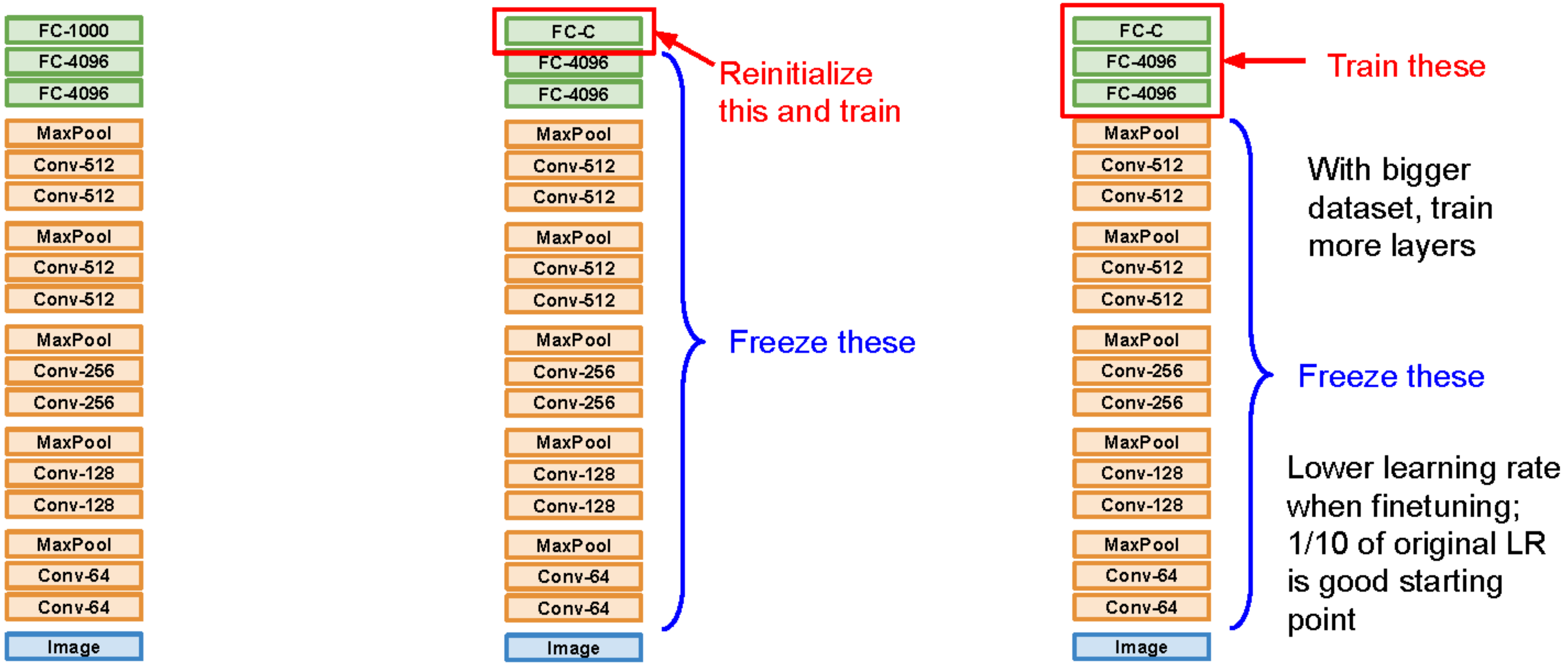
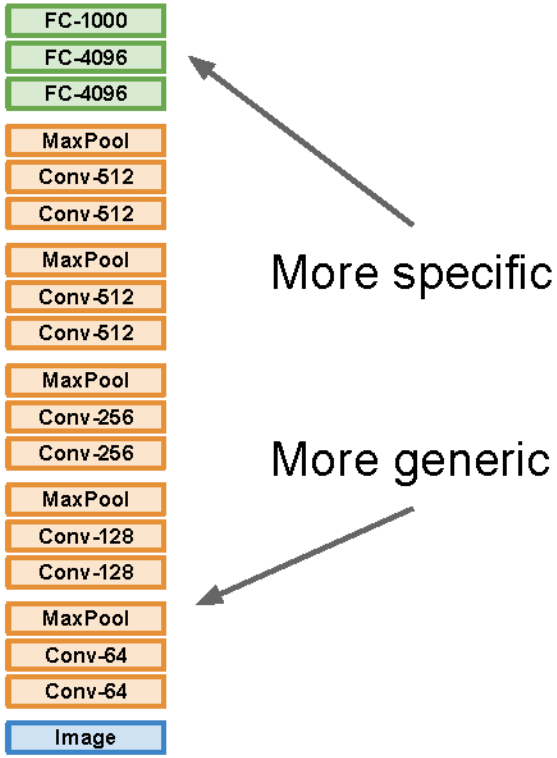
Transfer Learning with CNNs

1. Train on Imagenet

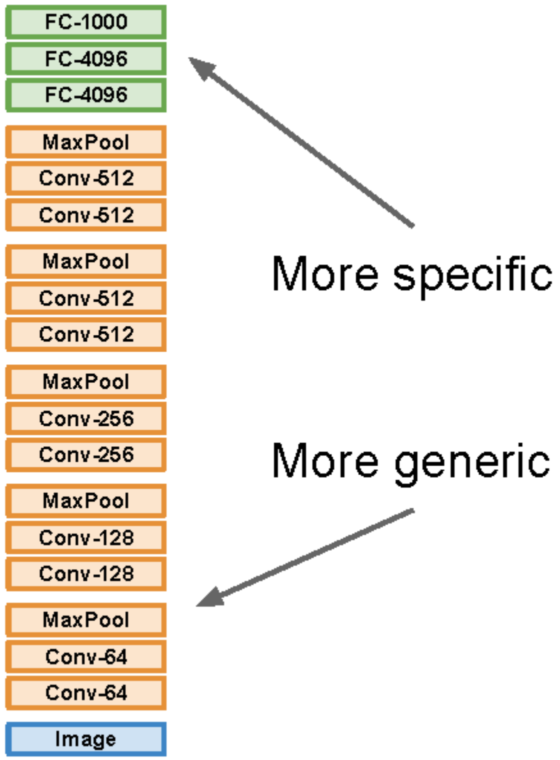
2. Small Dataset (C classes)

3. Bigger dataset

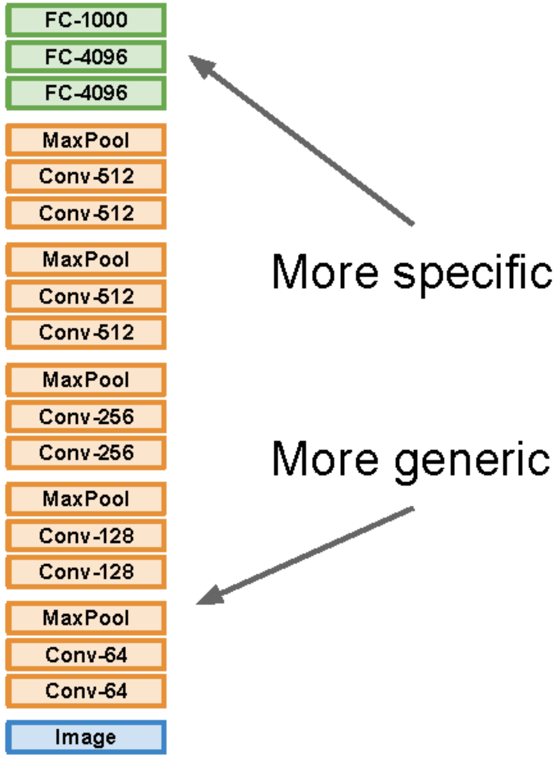




	very similar dataset	very different dataset
very little data	?	?
quite a lot of data	?	?



	very similar dataset	**very different dataset**
very little data	Use Linear Classifier on top layer	?
quite a lot of data	Finetune a few layers	?



	very similar dataset	very different dataset
very little data	Use Linear Classifier on top layer	You're in trouble… Try linear classifier from different stages
quite a lot of data	Finetune a few layers	Finetune a larger number of layers

Transfer learning with CNNs is pervasive…
(it's the norm, not an exception)

Object Detection
(Fast R-CNN)

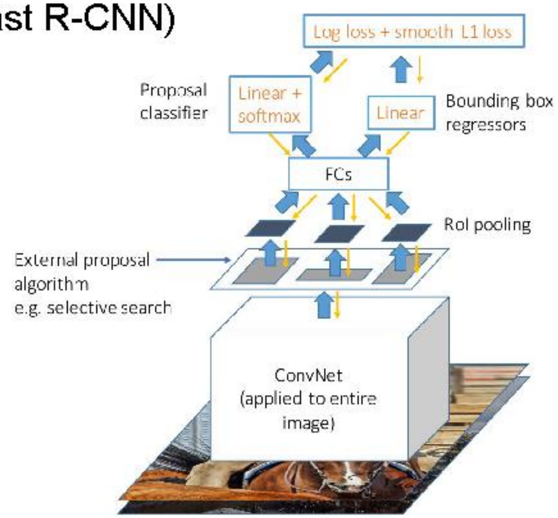
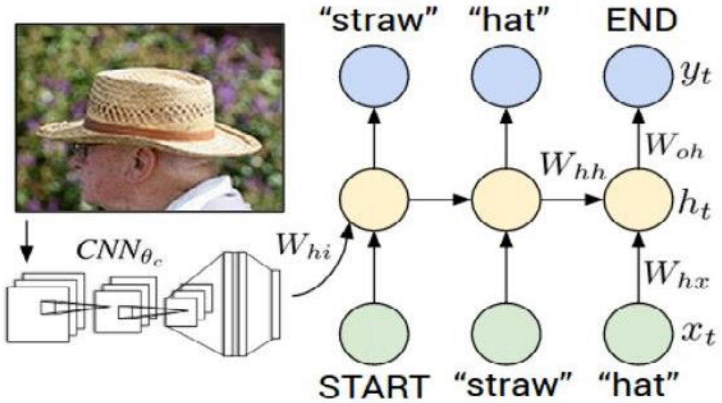


Image Captioning: CNN + RNN



Girshick, "Fast R-CNN", ICCV 2015

Karpathy and Fei-Fei, "Deep Visual-Semantic Alignments for Generating Image Descriptions", CVPR 2015

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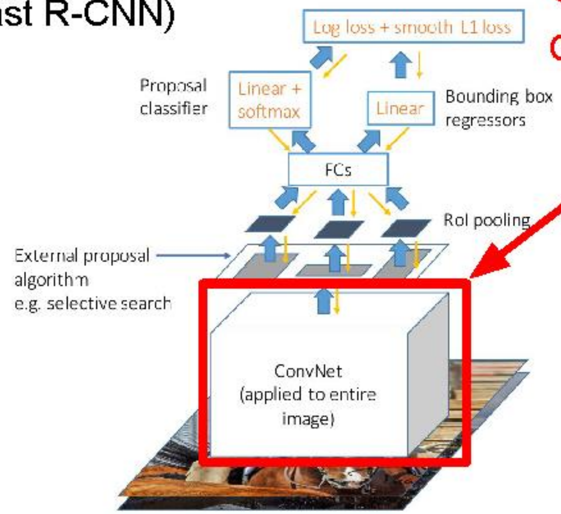

CNN pretrained on ImageNet

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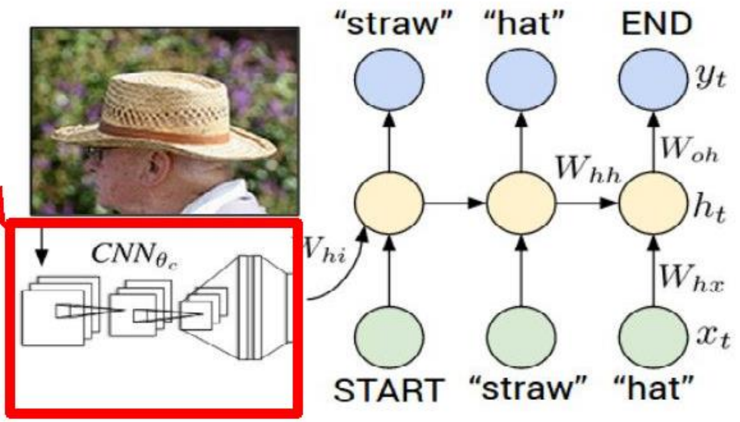

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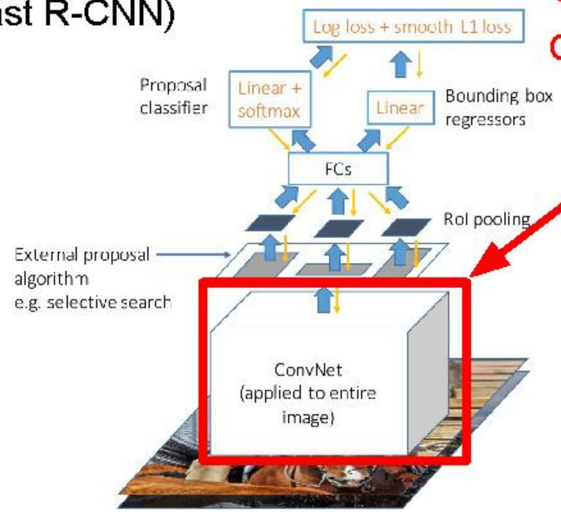

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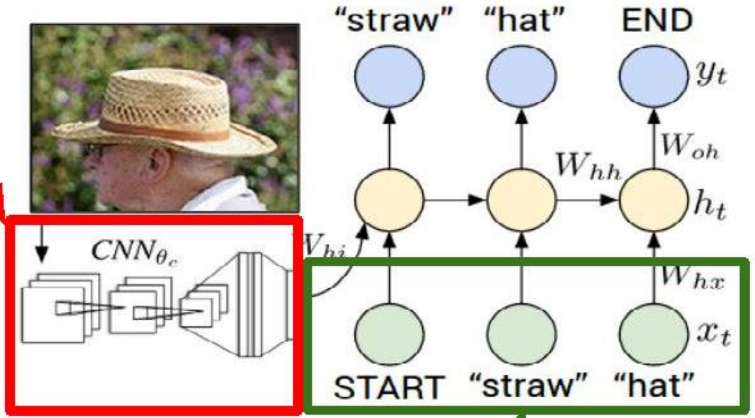


Word vectors pretrained with word2vec

Girshick, "Fast R-CNN", ICCV 2015

Karpathy and Fei-Fei, "Deep Visual-Semantic Alignments for Generating Image Descriptions", CVPR 2015

Takeaway for your projects and beyond:

Have some dataset of interest but it has < ~1M images?

1. Find a very large dataset that has similar data, train a big ConvNet there
2. Transfer learn to your dataset

Deep learning frameworks provide a "Model Zoo" of pretrained models so you don't need to train your own

TensorFlow: https://github.com/tensorflow/models
PyTorch: https://github.com/pytorch/vision

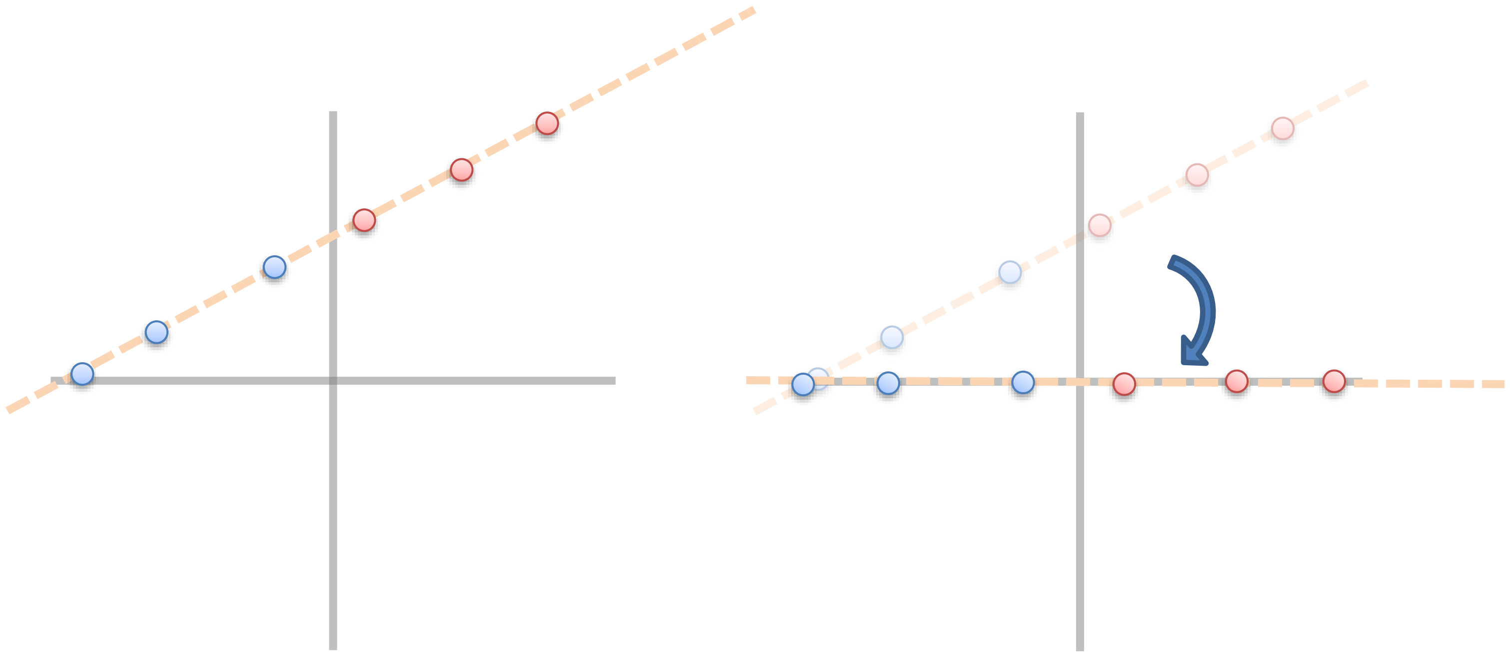
Common modern approach: start with a ResNet architecture pre-trained on ImageNet, and fine-tune on your (smaller) dataset

By Abe Davis

DIMENSIONALITY REDUCTION

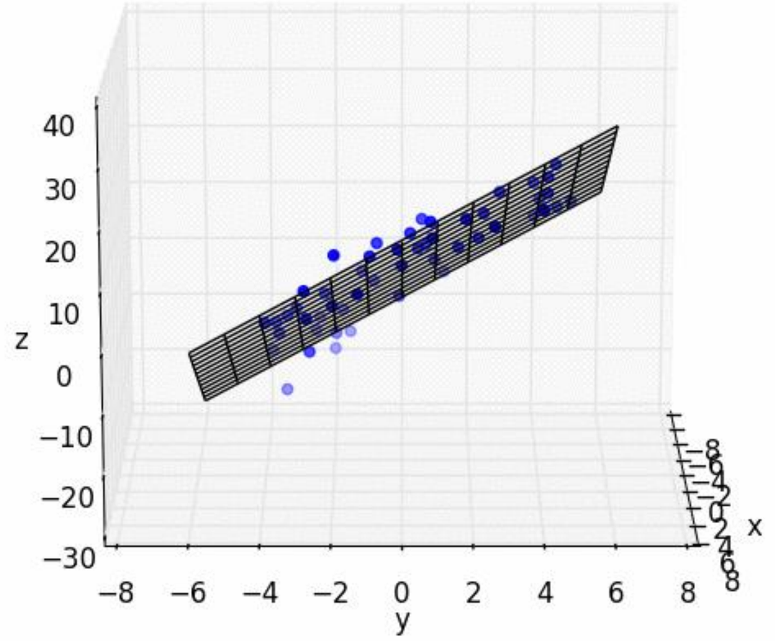
Linear Dimensionality Reduction: 2D->1D

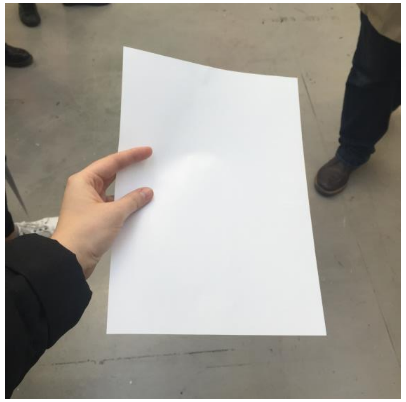
- Consider a bunch of data points in 2D
- Let’s say these points only differ along one line
- If so, we can translate and rotate our data so that it is 1D



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

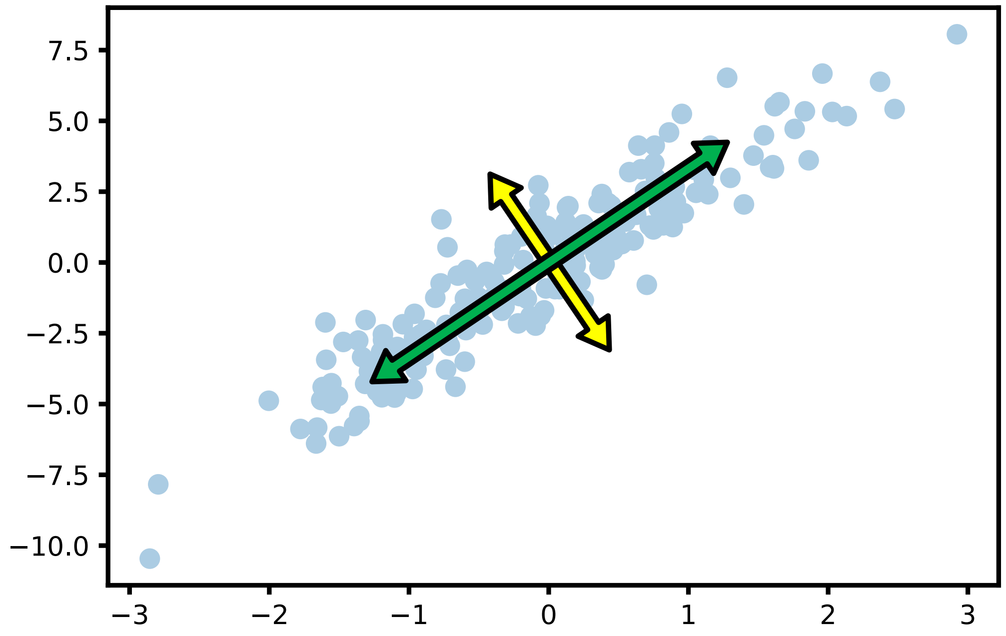




Think of this as data that sits on a flat sheet of paper, suspended in 3D space. We will come back to this analogy in a couple slides...

Generalizing Linear Dimensionality Reduction

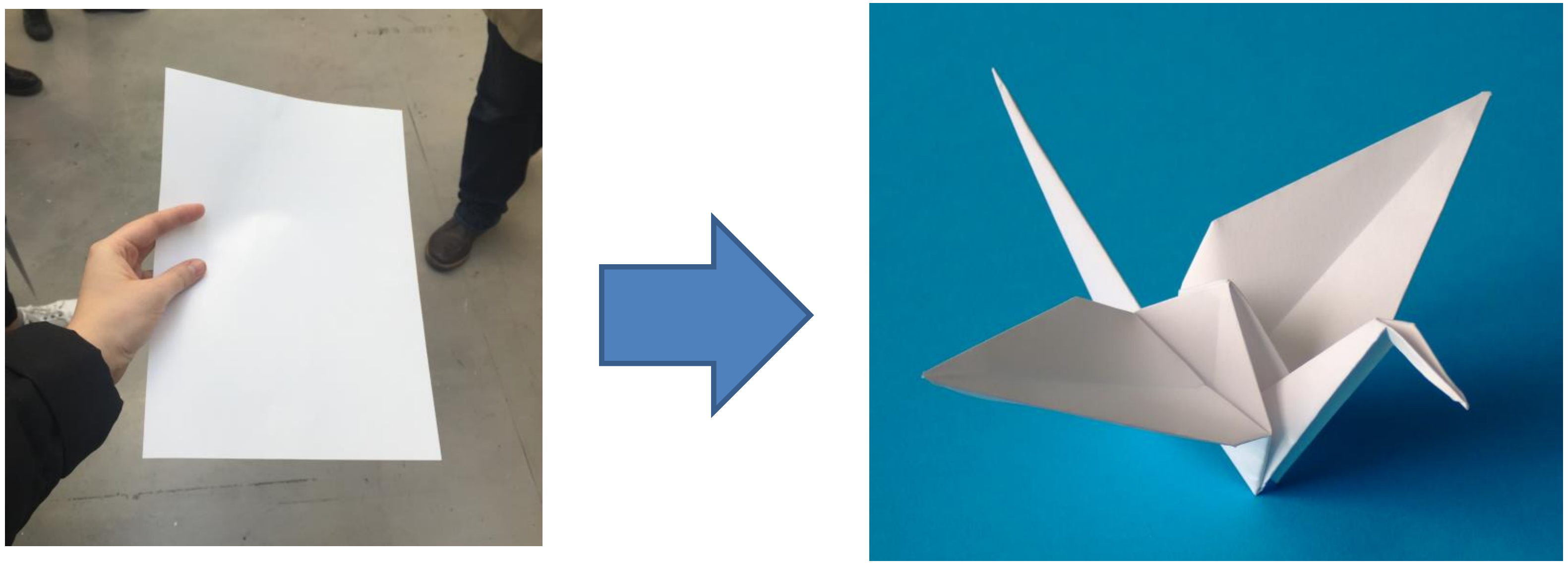
- ***Principal Components Analysis (PCA)***: find and order orthogonal axes by how much the data varies along each axis.
- The axes we find (ordered by variance of our data) are called ***principal components***.
- Dimensionality reduction can be done by using only the first *k* principal components



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

Manifolds

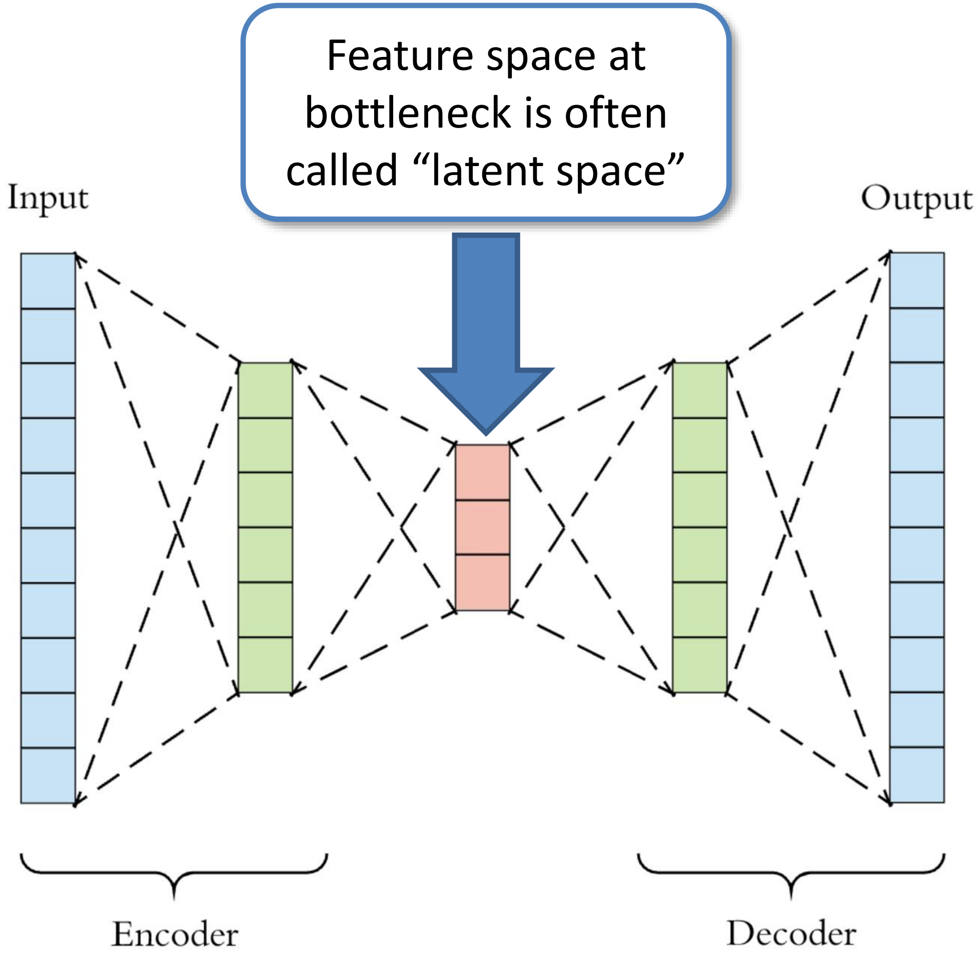
- Think of a piece of paper as a 2D subspace
- If we bend & fold it, it’s still locally a 2D subspace…
- A “manifold” is the generalization of this concept to higher dimensions…



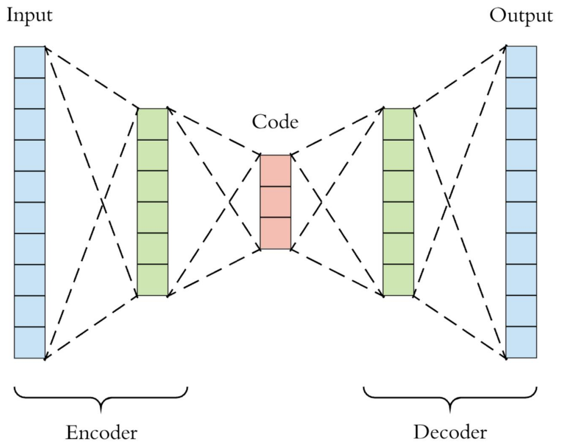
Autoencoders: Dimensionality Reduction for Manifolds

- 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

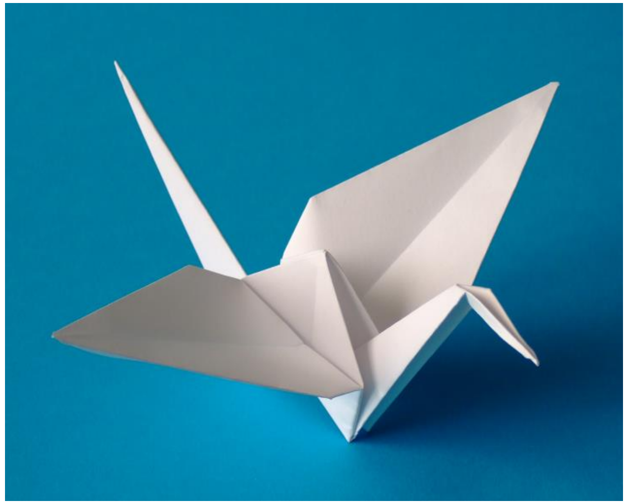
- **Unsupervised**
  - No labels required!



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

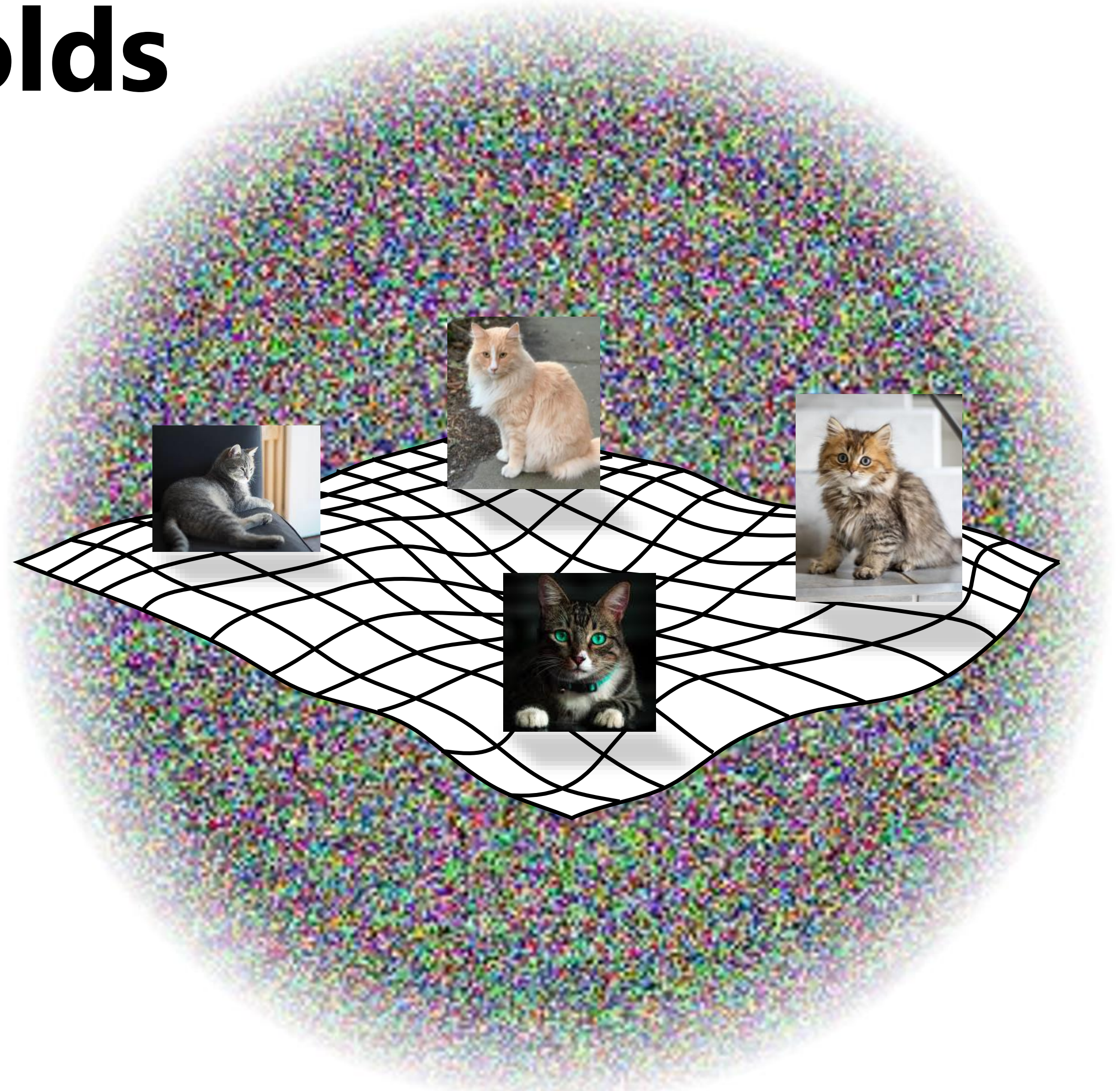
- Lets consider the space of all 100x100 images
- Now lets randomly sample that space…
- Conclusion: Most images are noise

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

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

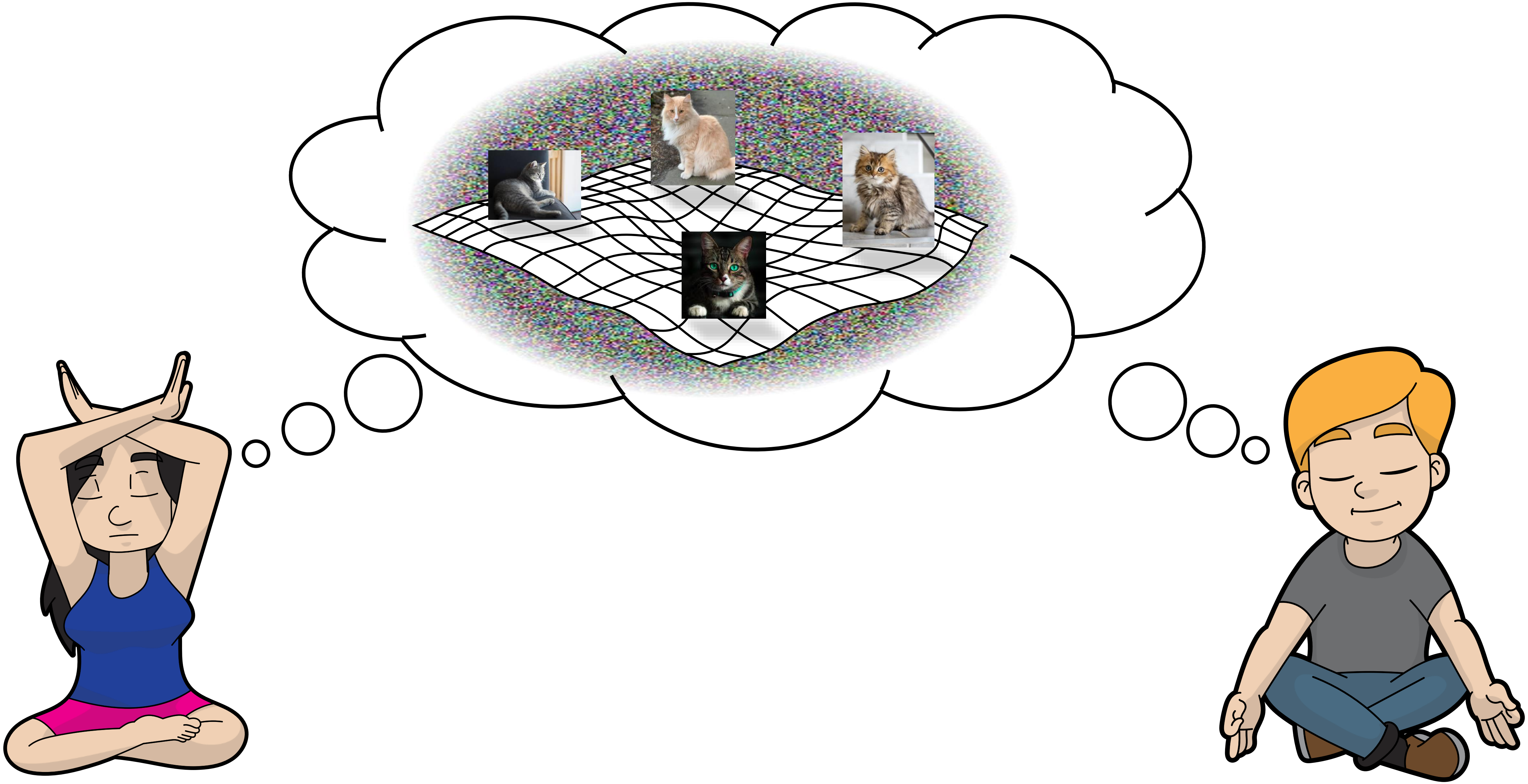
Natural Image Manifolds

- 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…



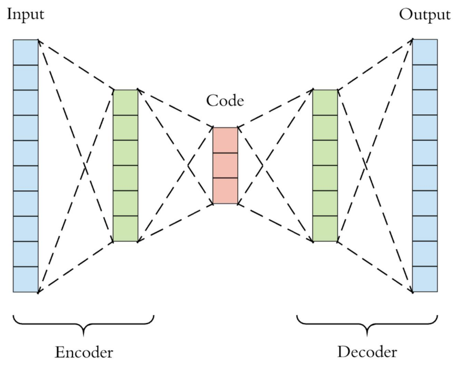
The Space of All Images

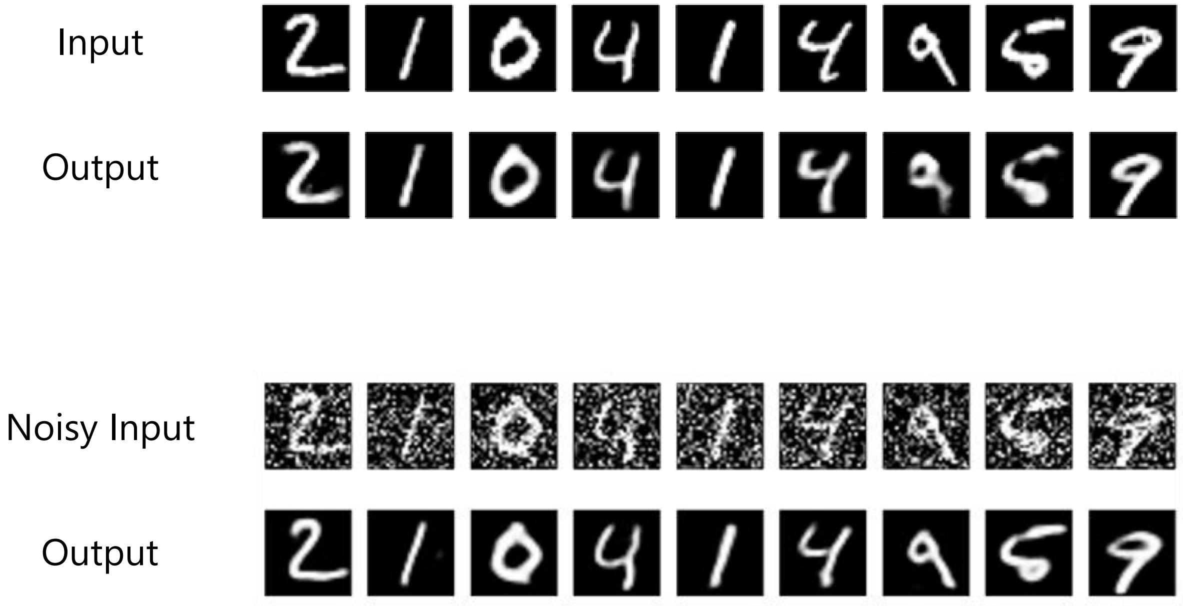
Natural Image Manifolds



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 out

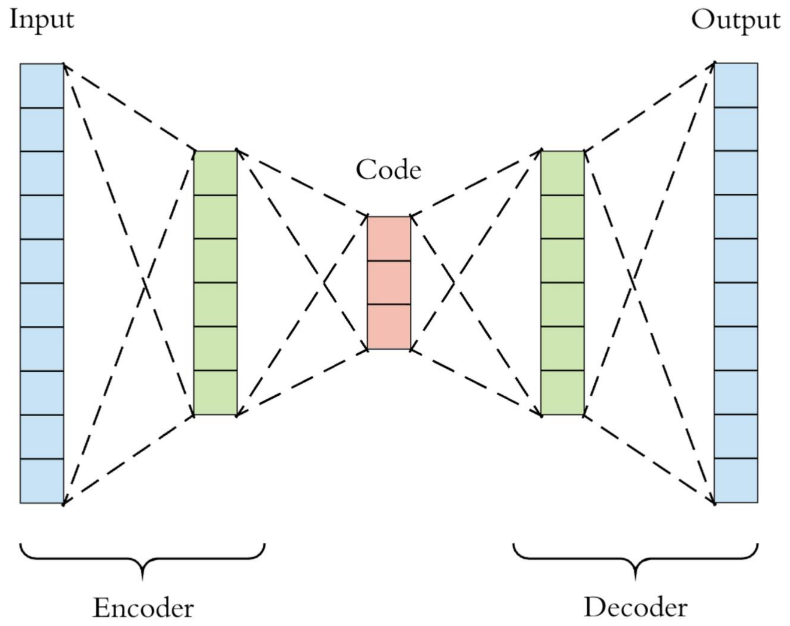


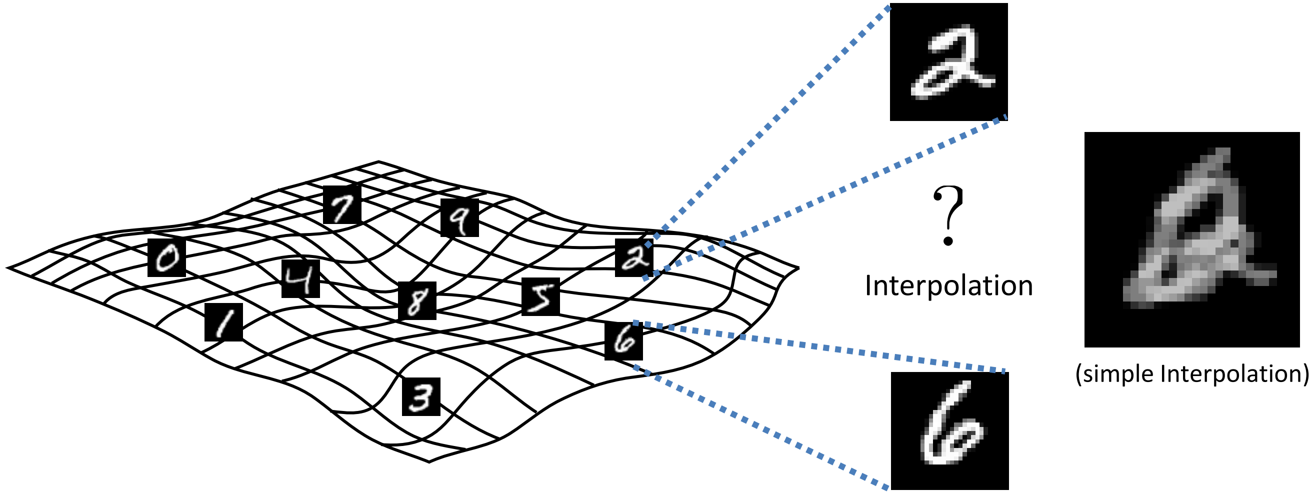


Examples from: https://blog.keras.io/building-autoencoders-in-keras.html

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…



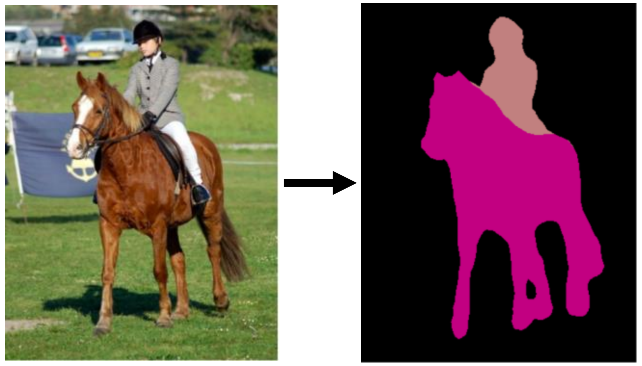


Abe Davis, with slides from Jin Sun, Phillip Isola, and Richard Zhang

IMAGE-TO-IMAGE APPLICATIONS

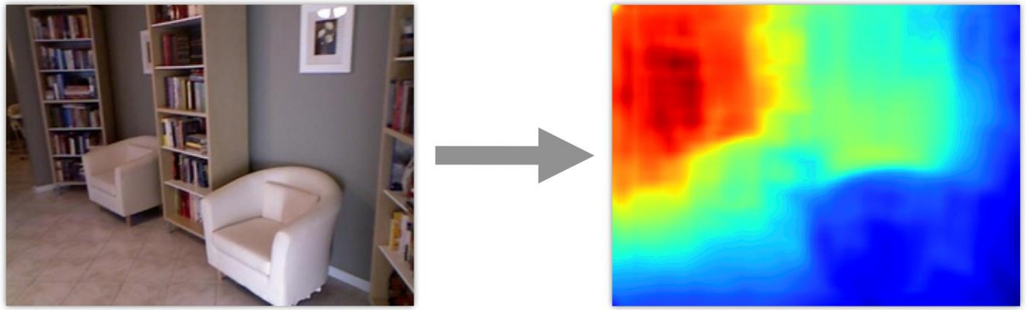
Image prediction (“structured prediction”)

Object labeling



[Long et al. 2015, …]

Depth prediction



Single RGB Image   Depth Map

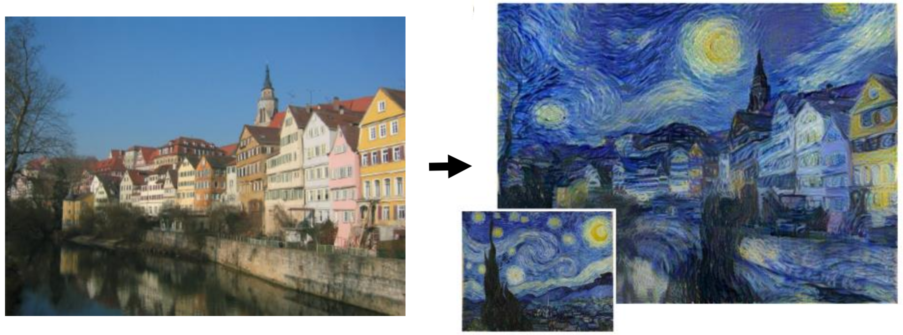
[Eigen et al. 2014, …]

Text-to-photo

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

[Reed et al. 2016, …]

Style transfer



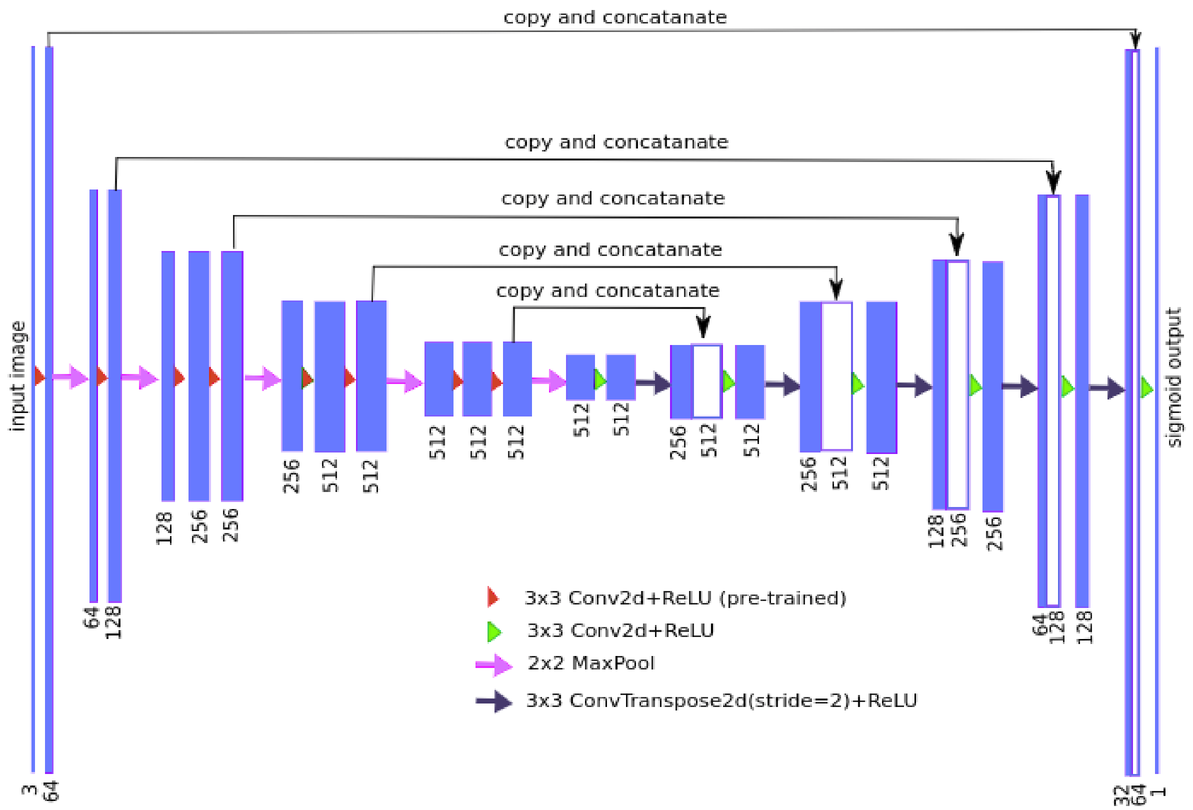
[Gatys et al. 2016, …]

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



$\mathbf{x}$ $\xrightarrow{\mathcal{F}}$ $\mathbf{y}$

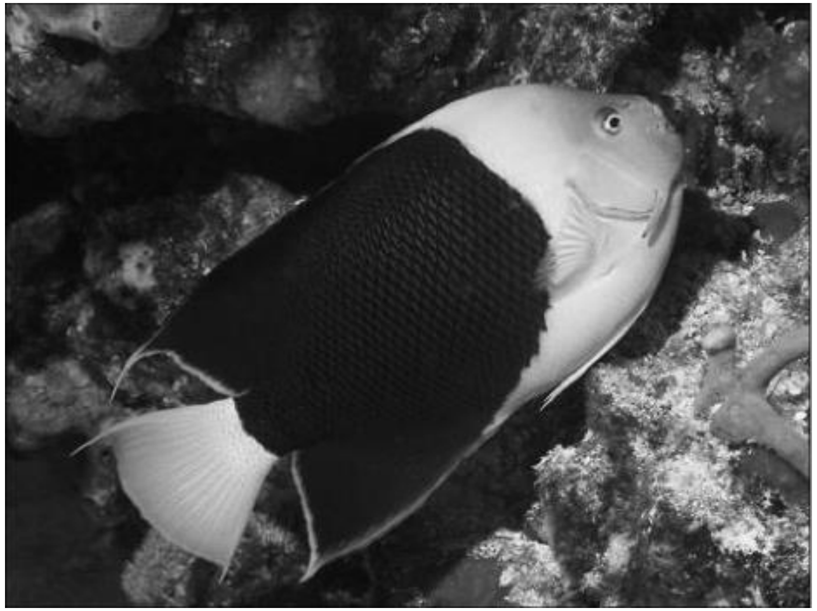
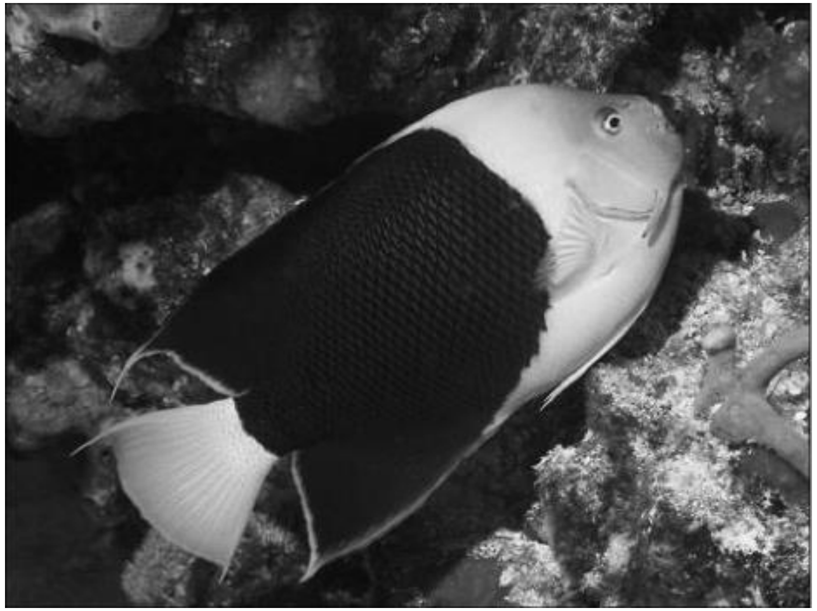


Image Colorization

from Jin Sun, Richard Zhang, Phillip Isola

$\mathbf{x}$ $\qquad\qquad$ $\mathbf{y}$

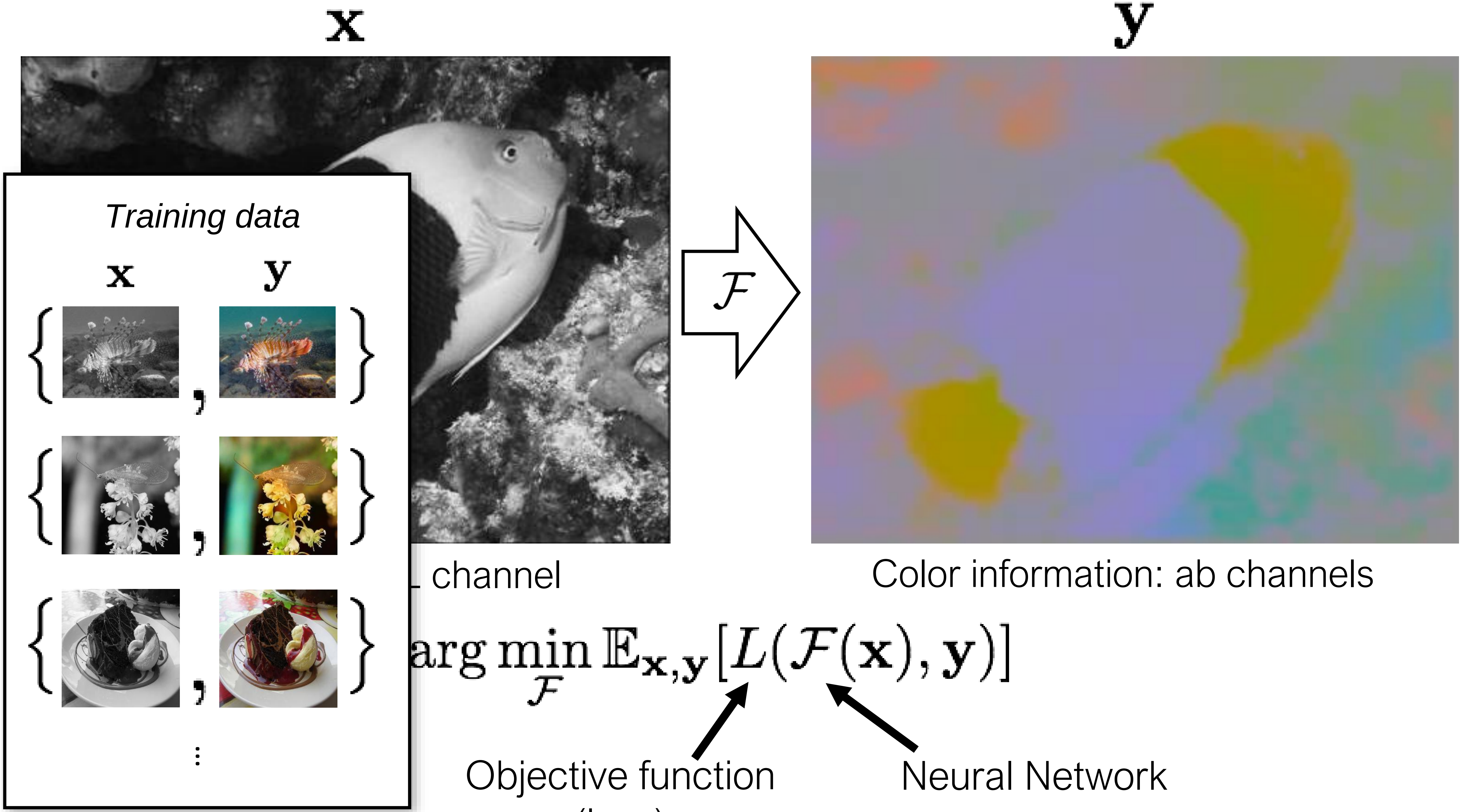


$\xrightarrow{\mathcal{F}}$

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

"**What** should I do" $\qquad$ "**How** should I do it?"

from Jin Sun, Richard Zhang, Phillip Isola



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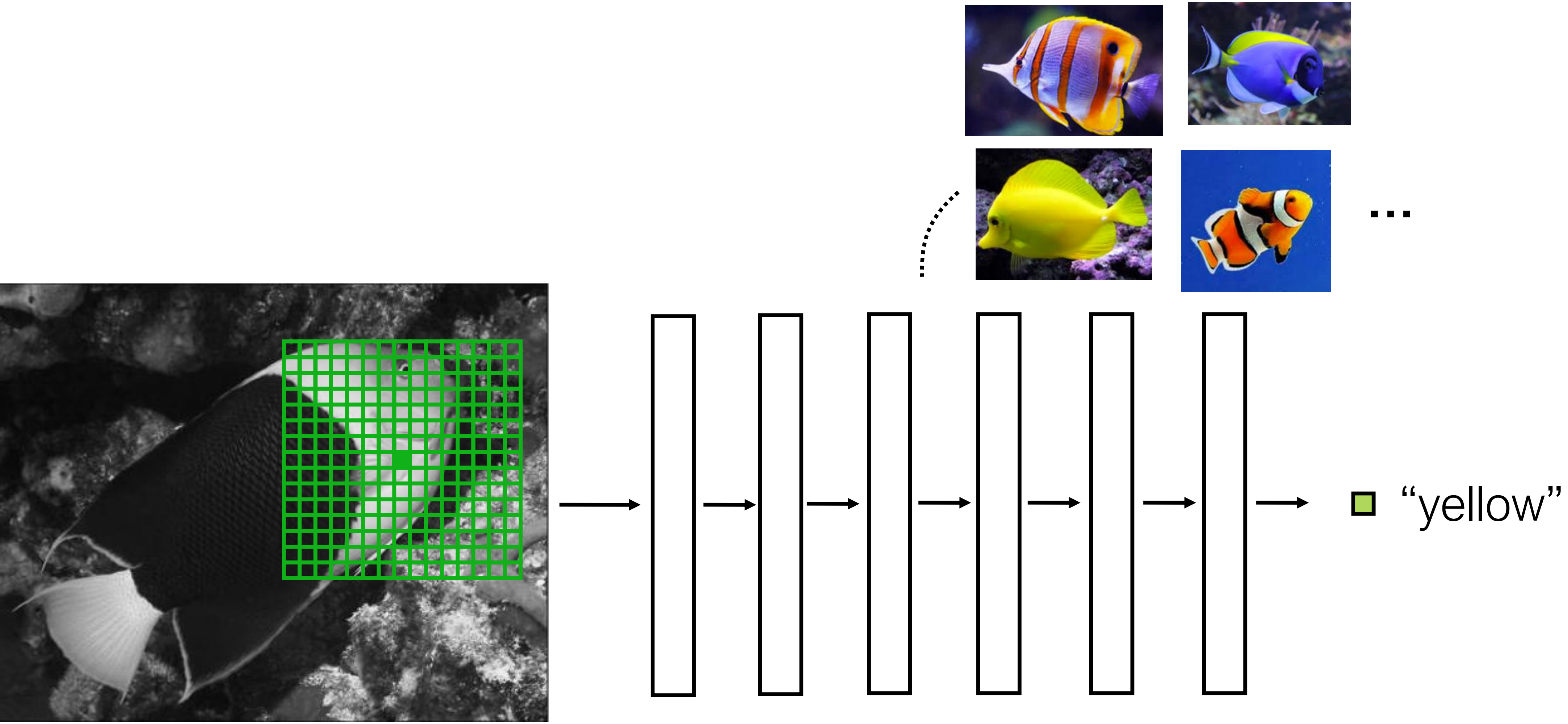

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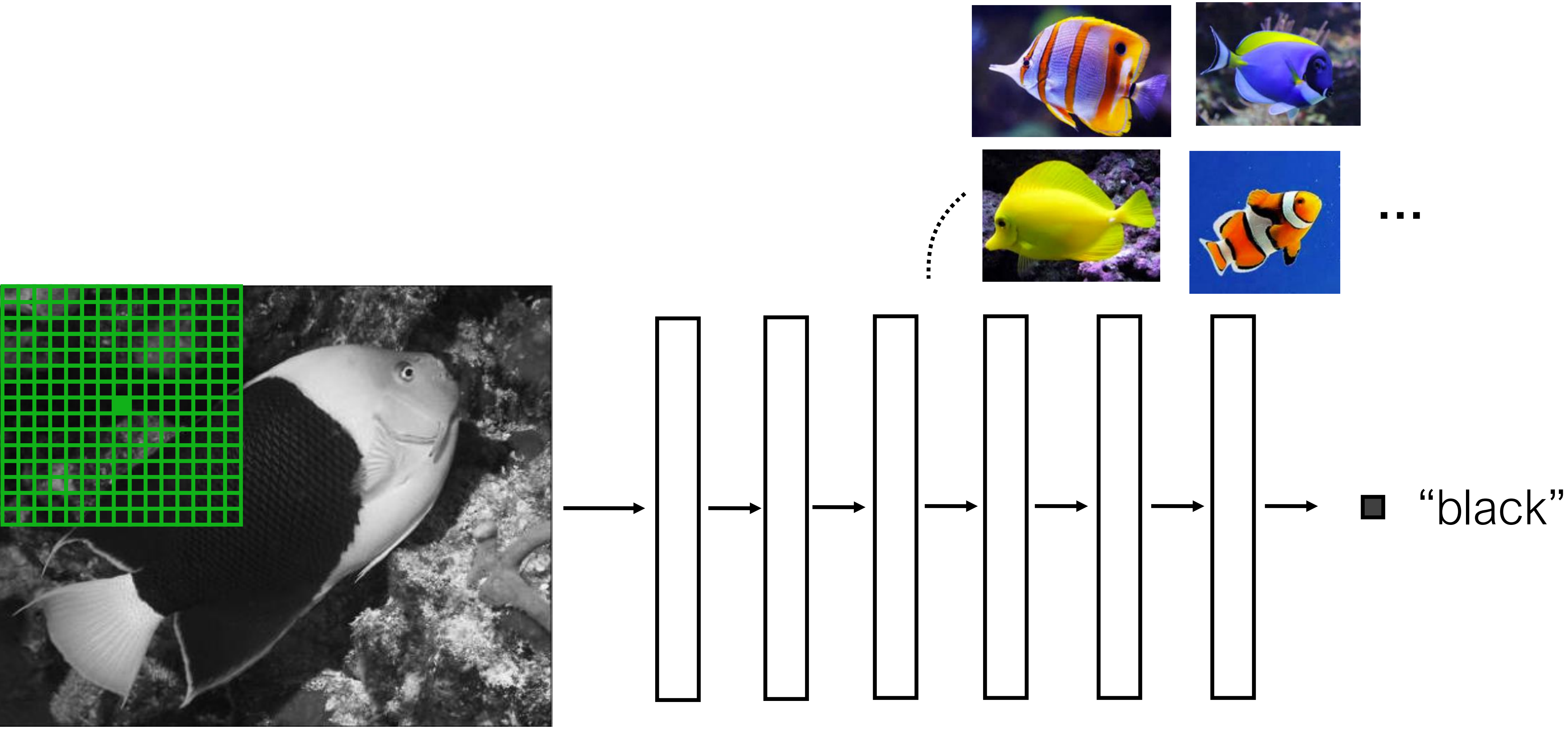

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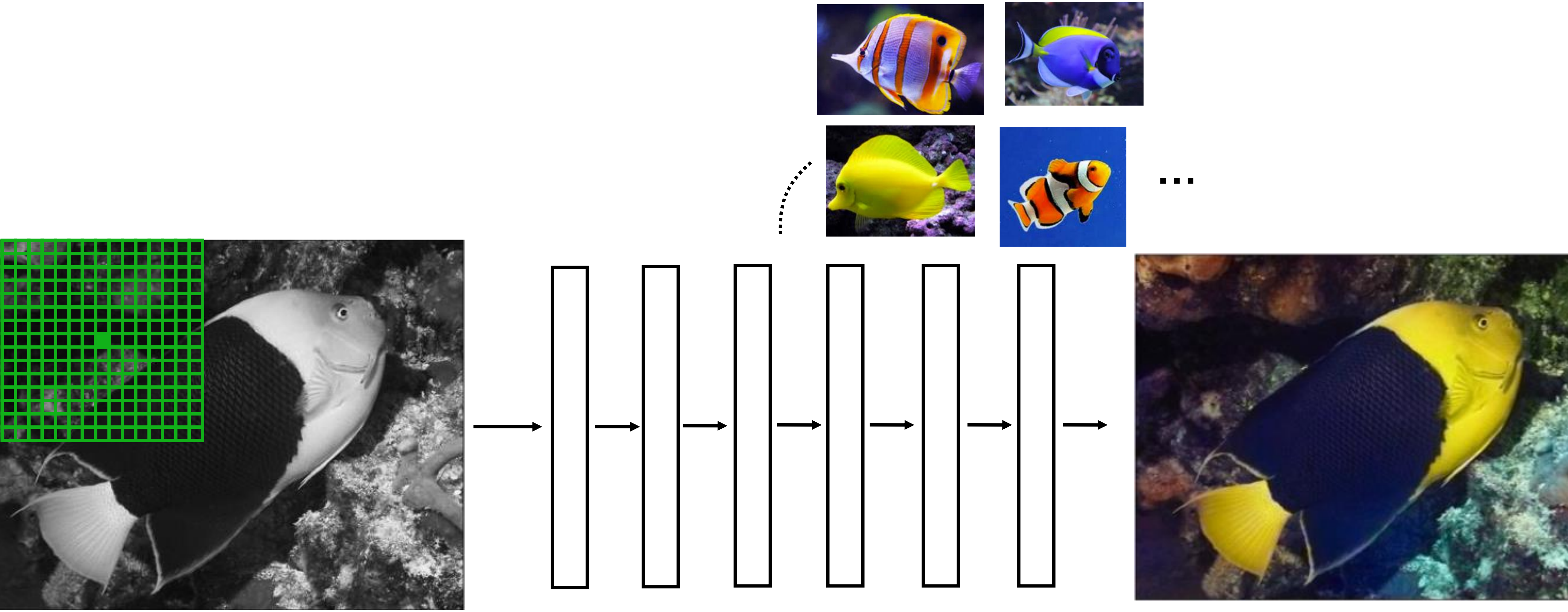


from Jin Sun, Richard Zhang, Phillip Isola

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

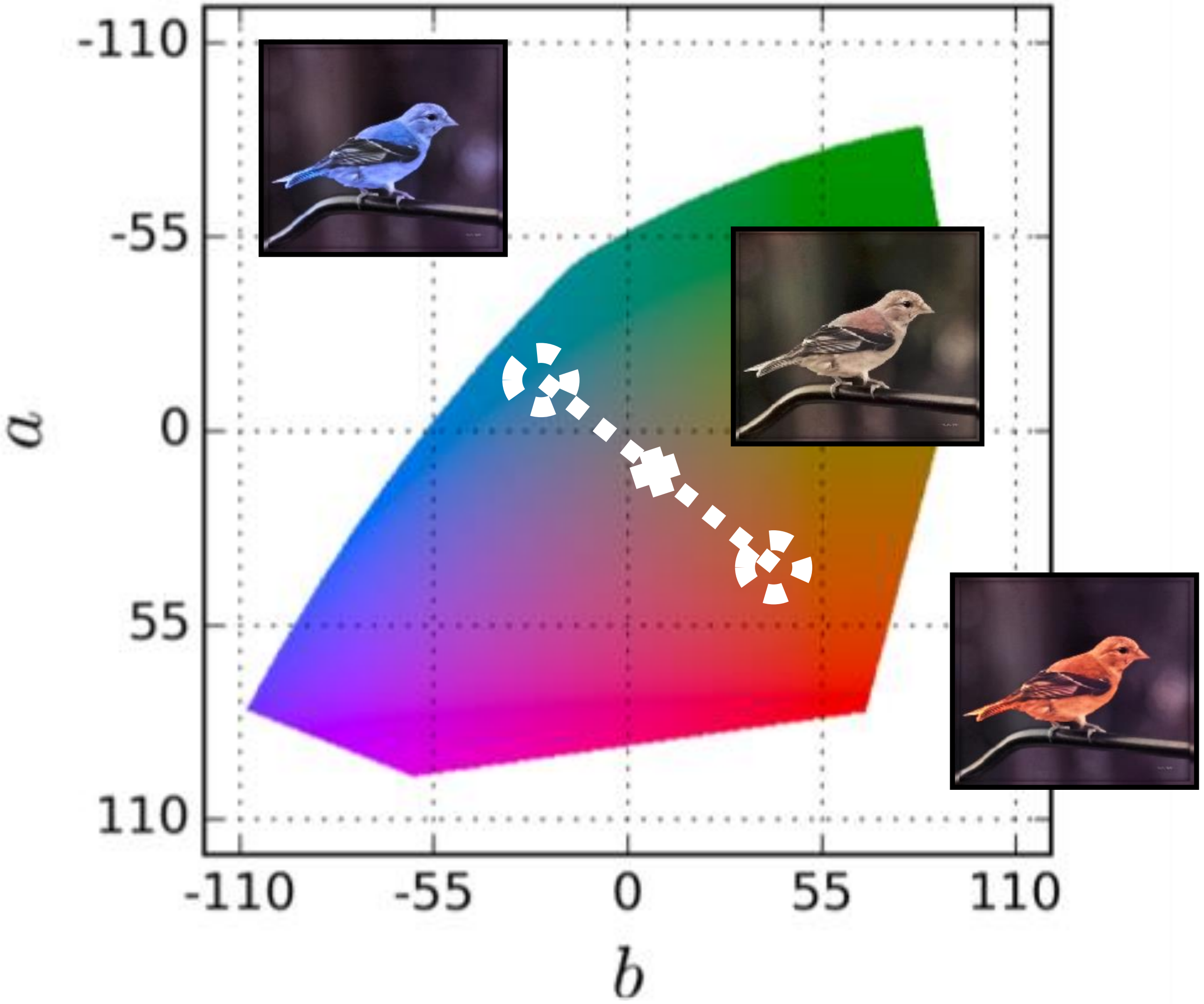
Designing loss functions

Input

Output

Ground truth

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



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

Designing loss functions

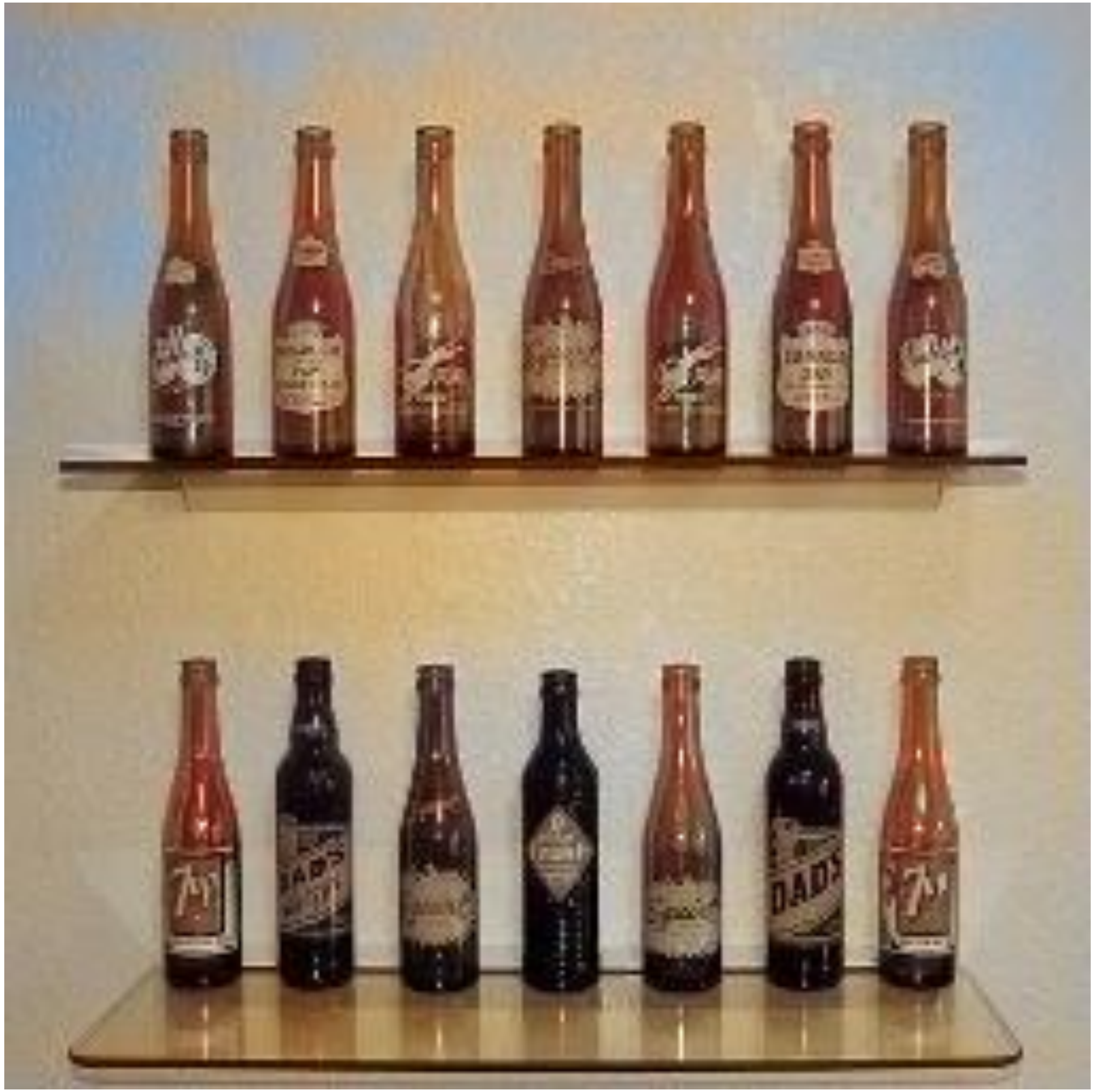
Input

Zhang et al. 2016

Ground truth

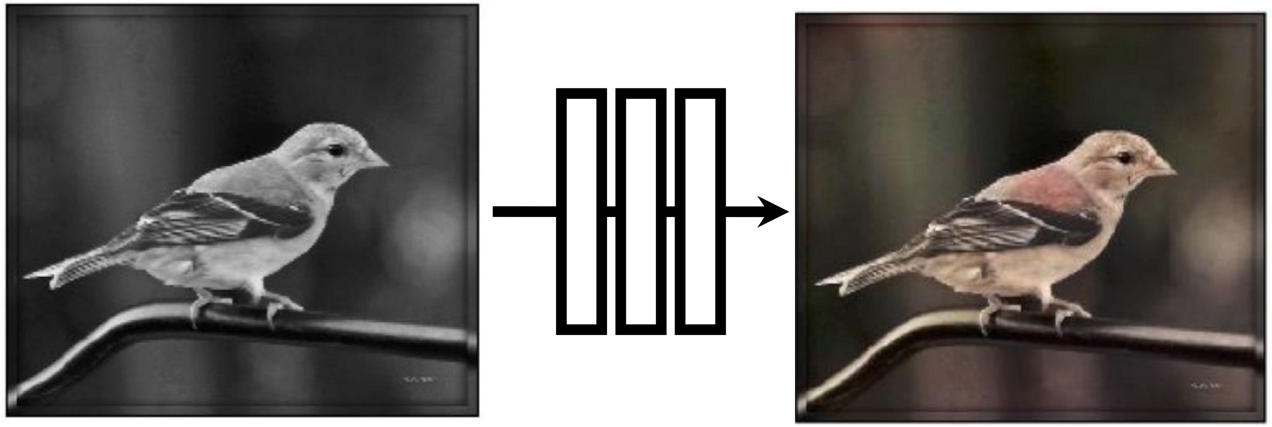
Color distribution cross-entropy loss with colorfulness enhancing term.

[Zhang, Isola, Efros, ECCV 2016]


DADS

Designing loss functions

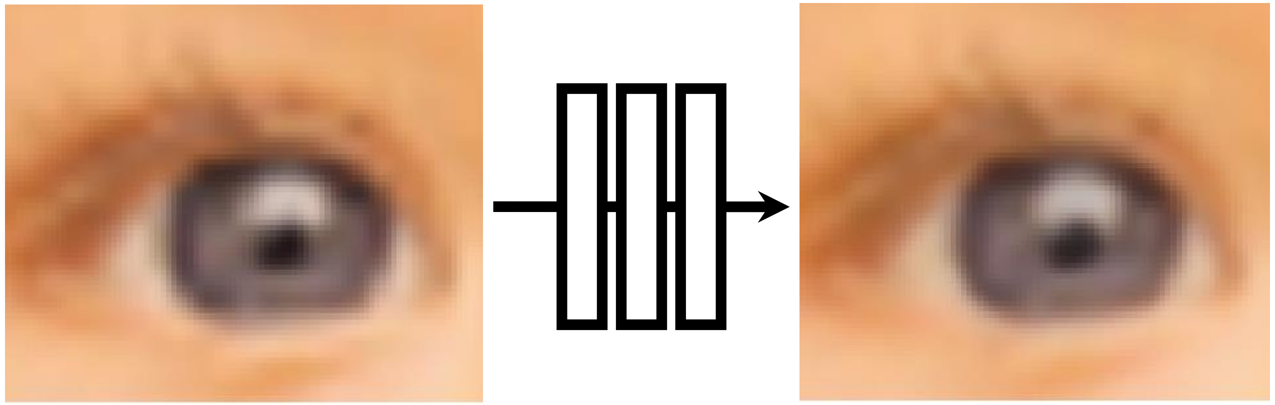
Image colorization



L2 regression

[Zhang, Isola, Efros, ECCV 2016]

Super-resolution

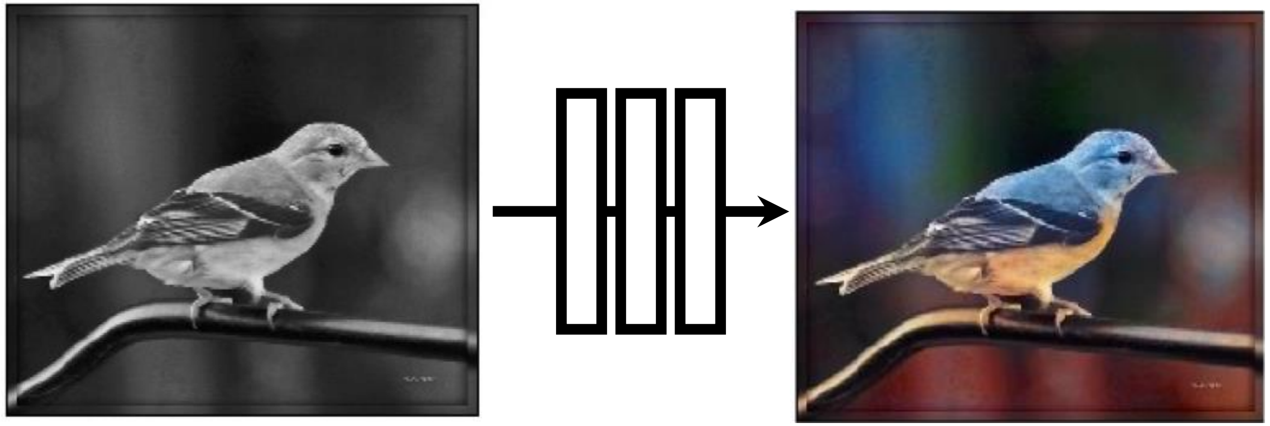


L2 regression

[Johnson, Alahi, Li, ECCV 2016]

Designing loss functions

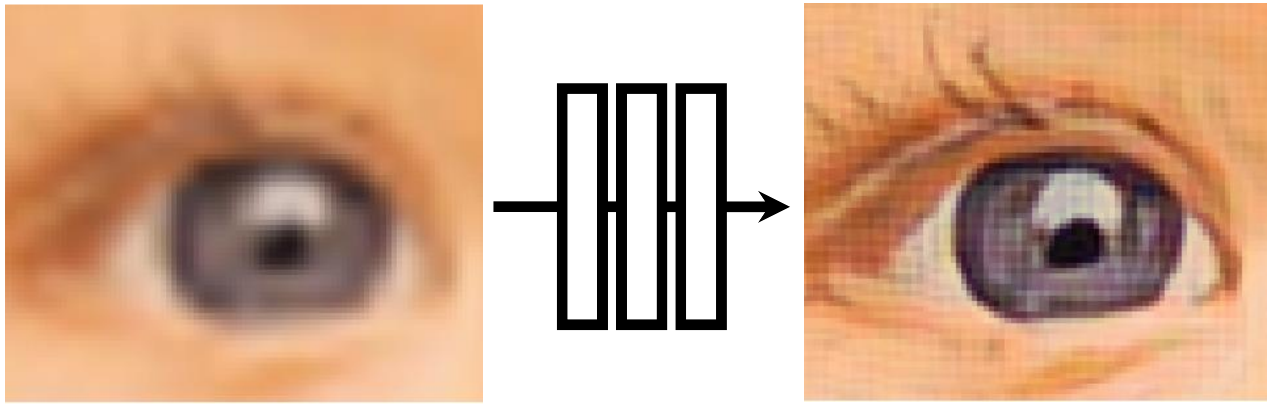
Image colorization



[Zhang, Isola, Efros, ECCV 2016]

Cross entropy objective,
with colorfulness term

Super-resolution

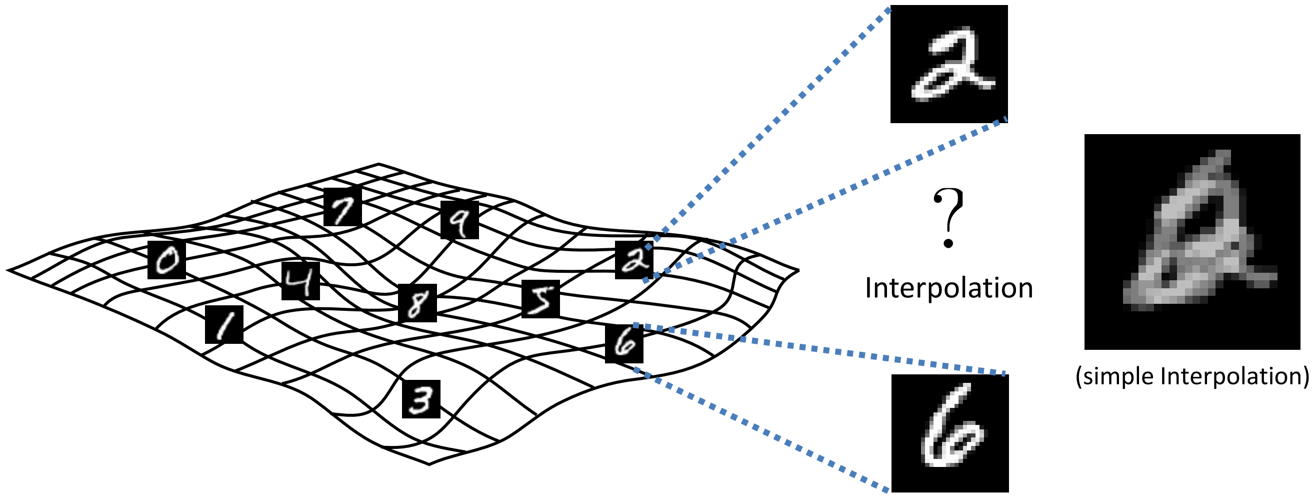


[Johnson, Alahi, Li, ECCV 2016]

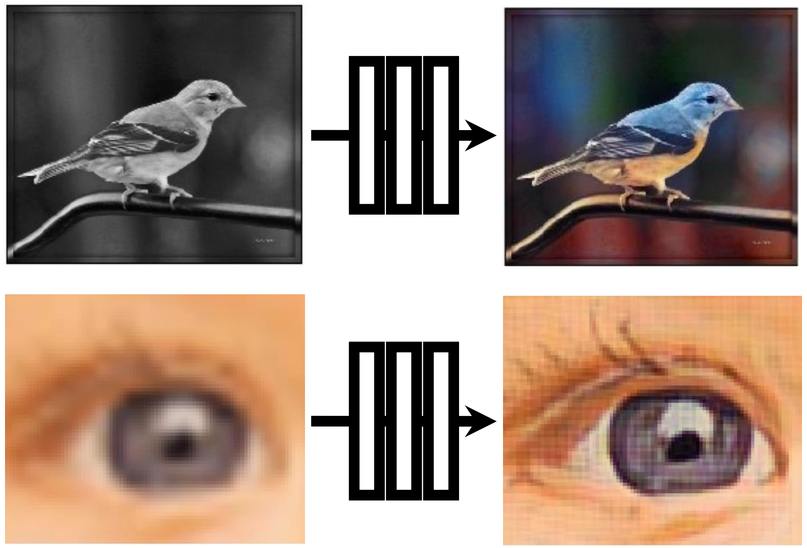
Deep feature covariance
matching objective

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

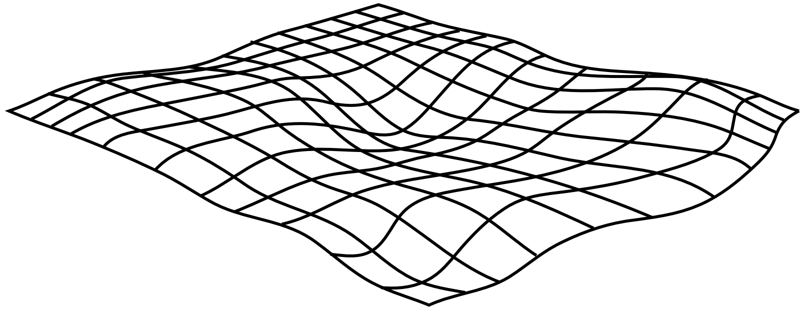


Abe Davis, with slides from Jin Sun and Phillip Isola

PART 3: GENERATIVE ADVERSARIAL NETWORKS (GANS)

Generative Adversarial Networks (GANs)

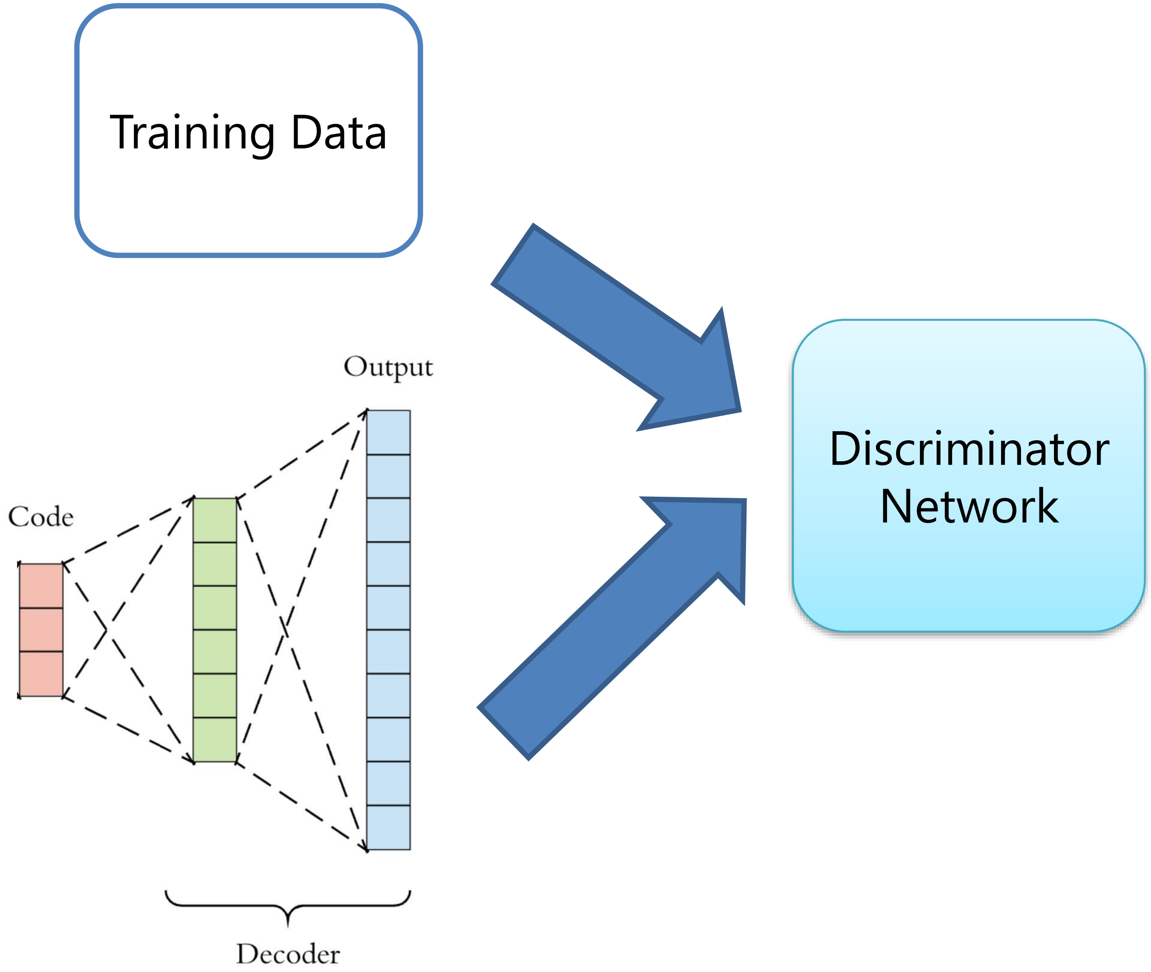
- Basic idea: Learn a mapping from some latent space to images on a particular manifold



- 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)

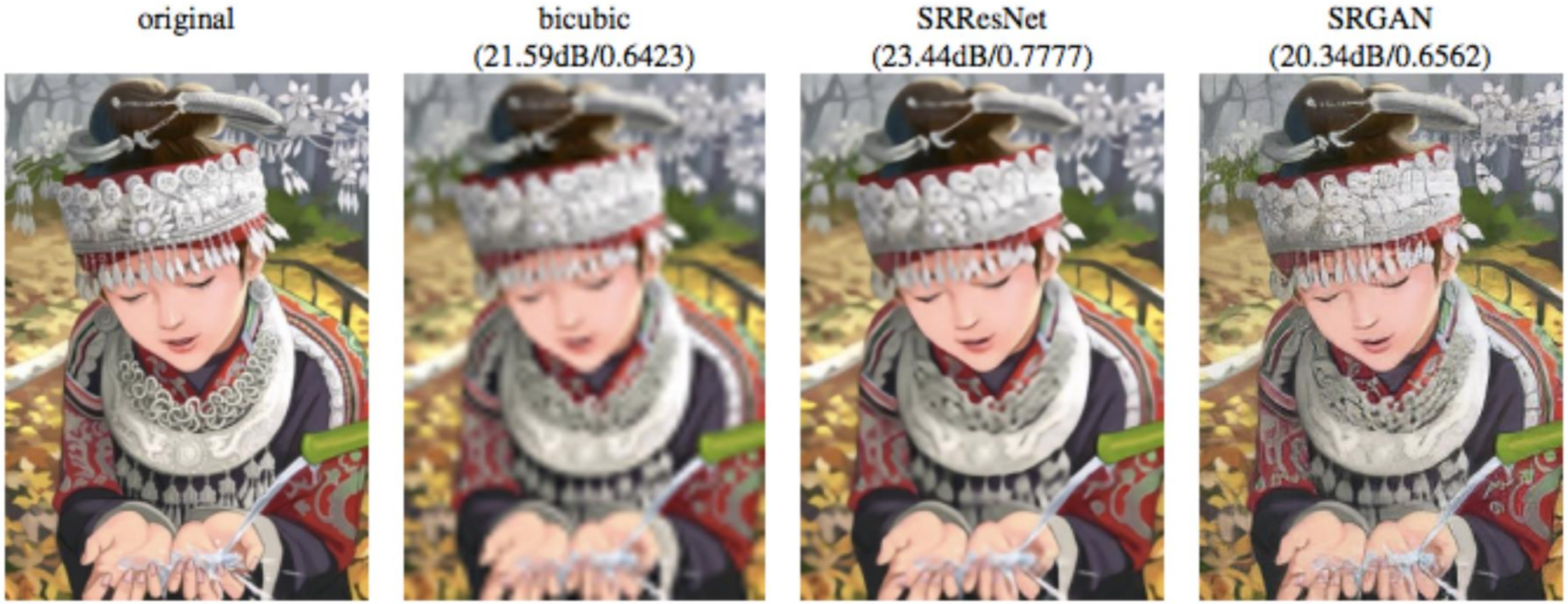
A

B

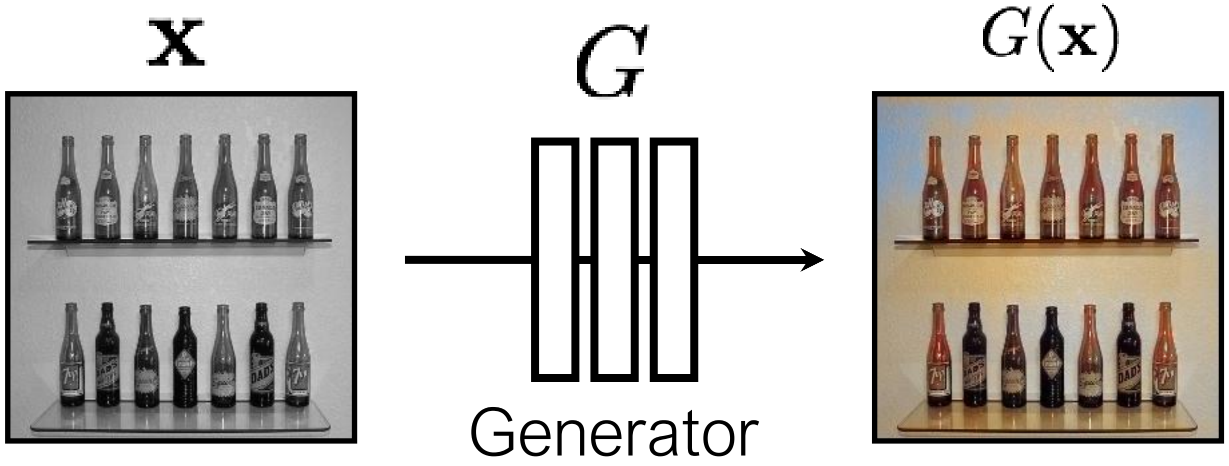
[Which face is real]?

Conditional GANs

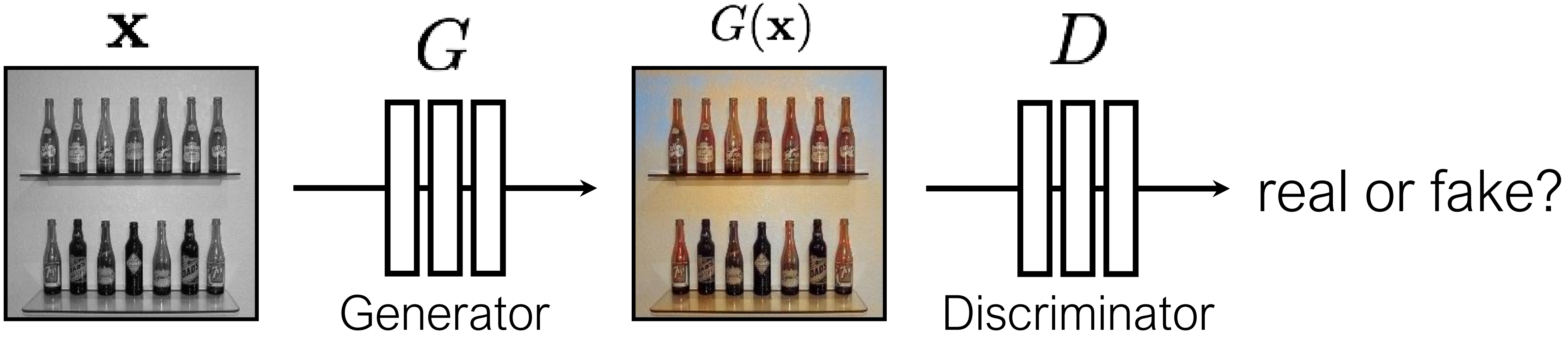
- Generate samples from a conditional distribution
- Example: generate high-resolution image conditioned on low resolution input



[Ledig et al 2016]



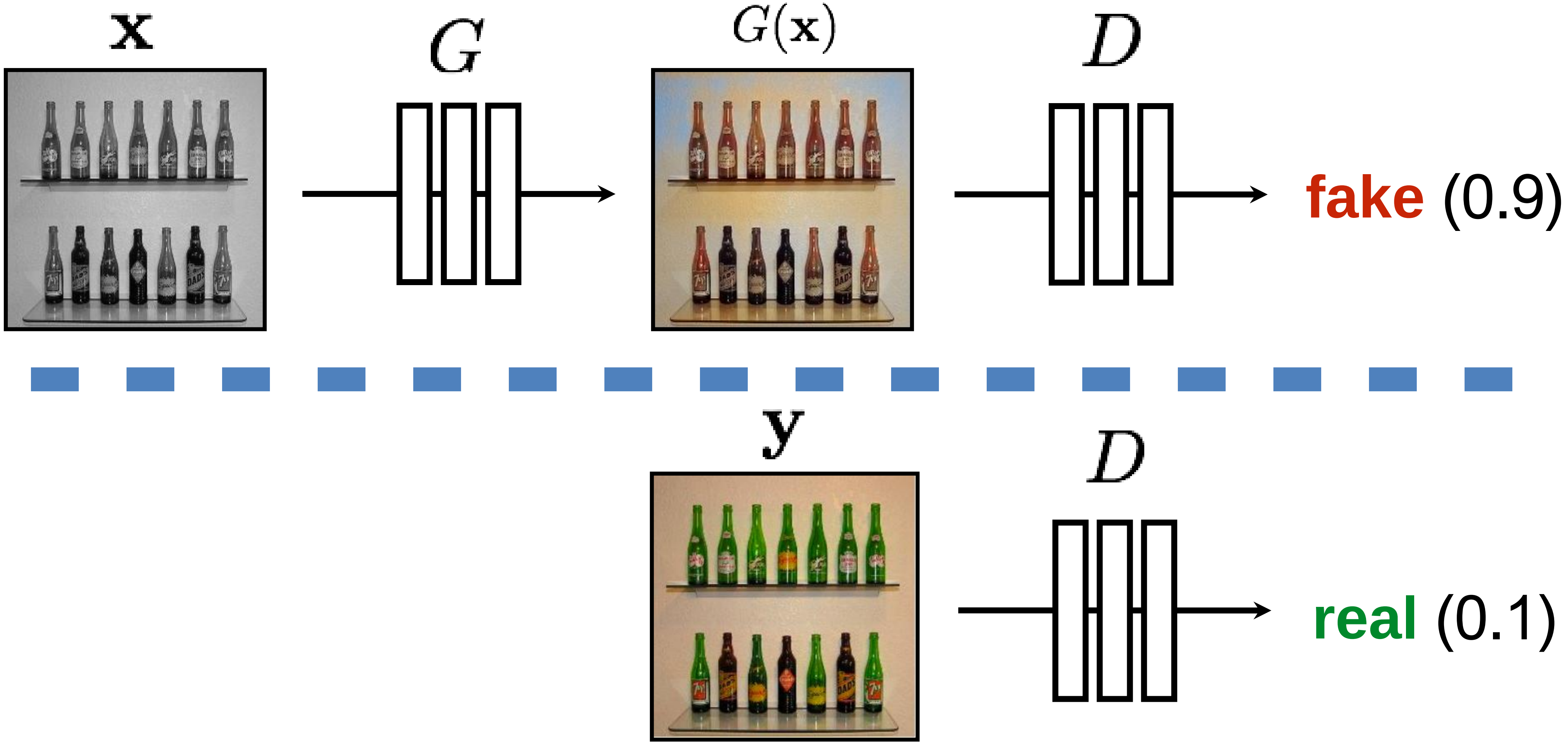
[Goodfellow et al., 2014]



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

D tries to identify the fakes

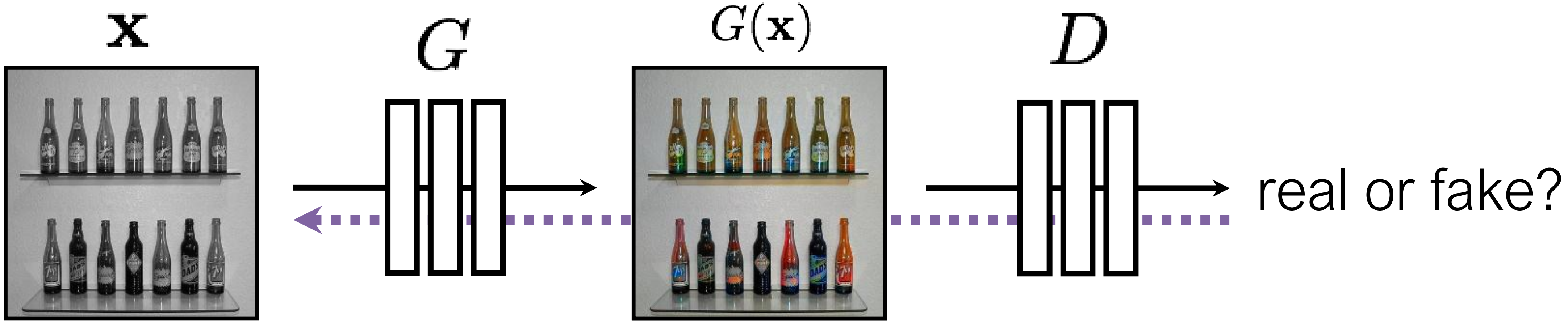
[Goodfellow et al., 2014]



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

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

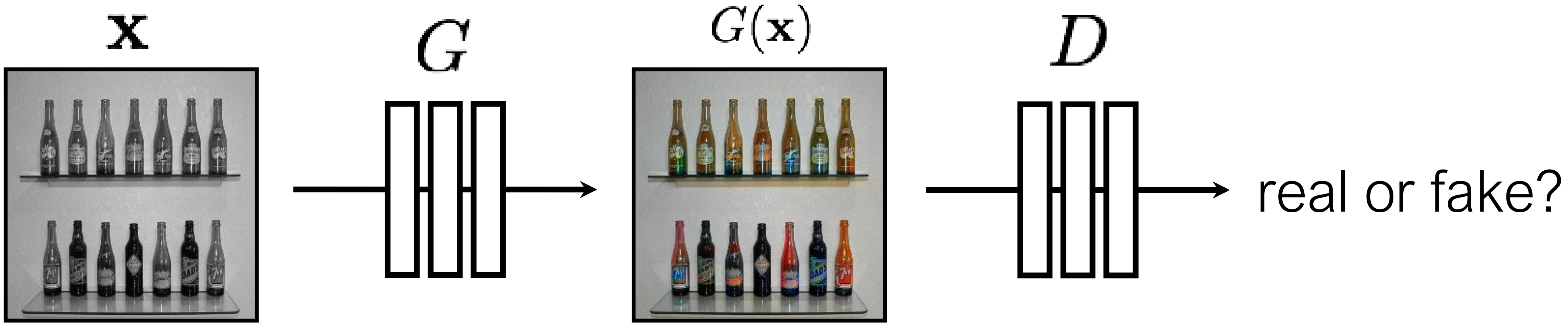
[Goodfellow et al., 2014]



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

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

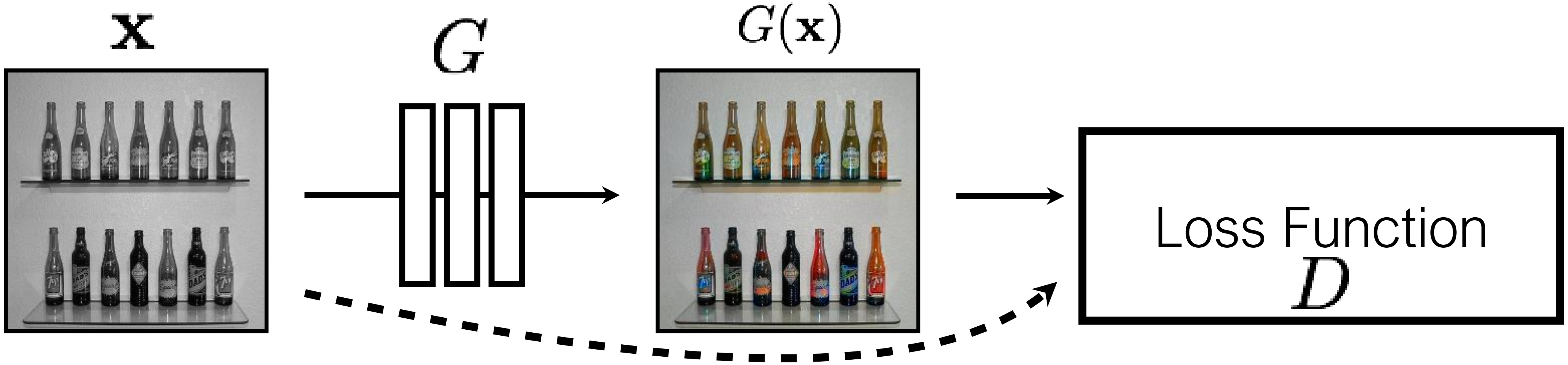
[Goodfellow et al., 2014]



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

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

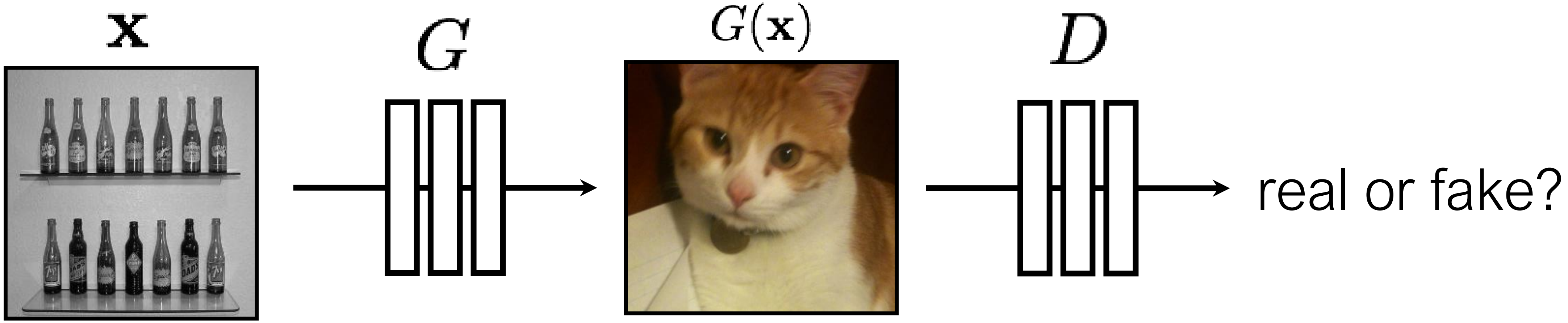
[Goodfellow et al., 2014]



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

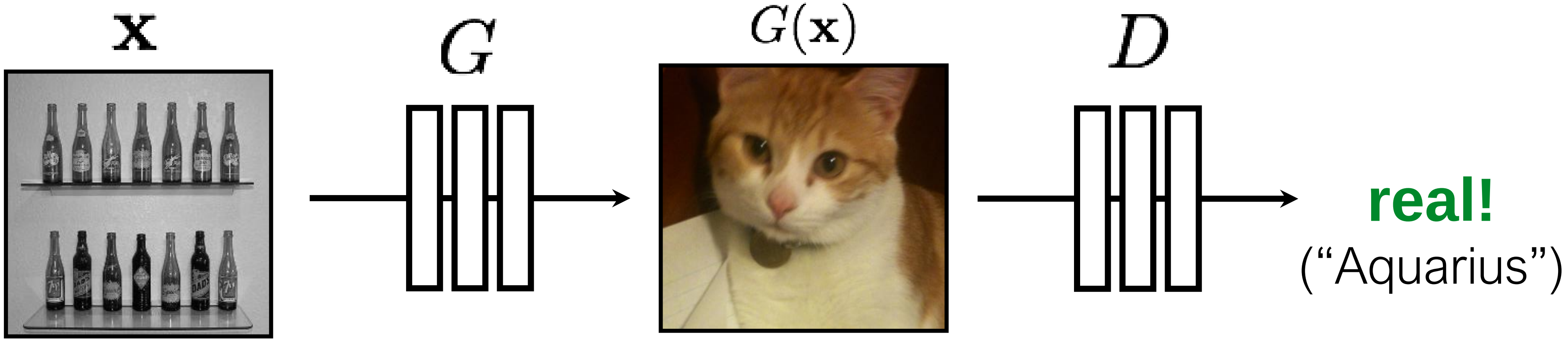
Rather than being hand-designed, it is *learned*.

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



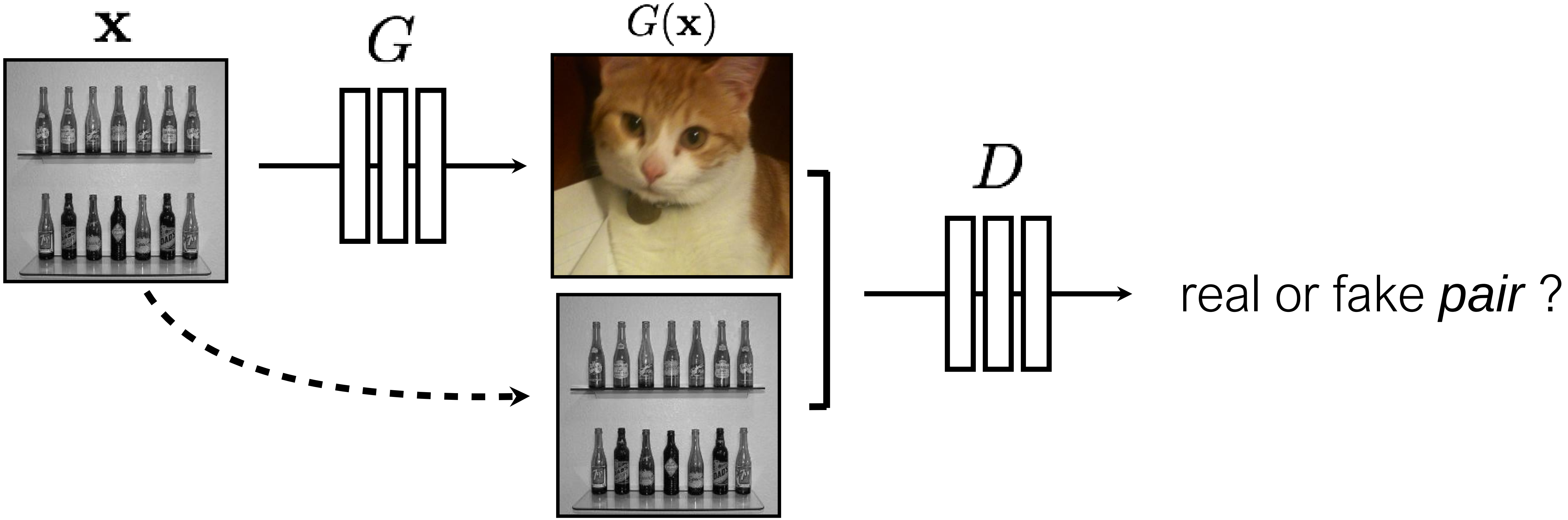
$$\arg\min_{G}\max_{D}\ \mathbb{E}_{\mathbf{x},\mathbf{y}}[\ \log D(G(\mathbf{x}))\ +\ \log(1-D(\mathbf{y}))\ ]$$

[Goodfellow et al., 2014]



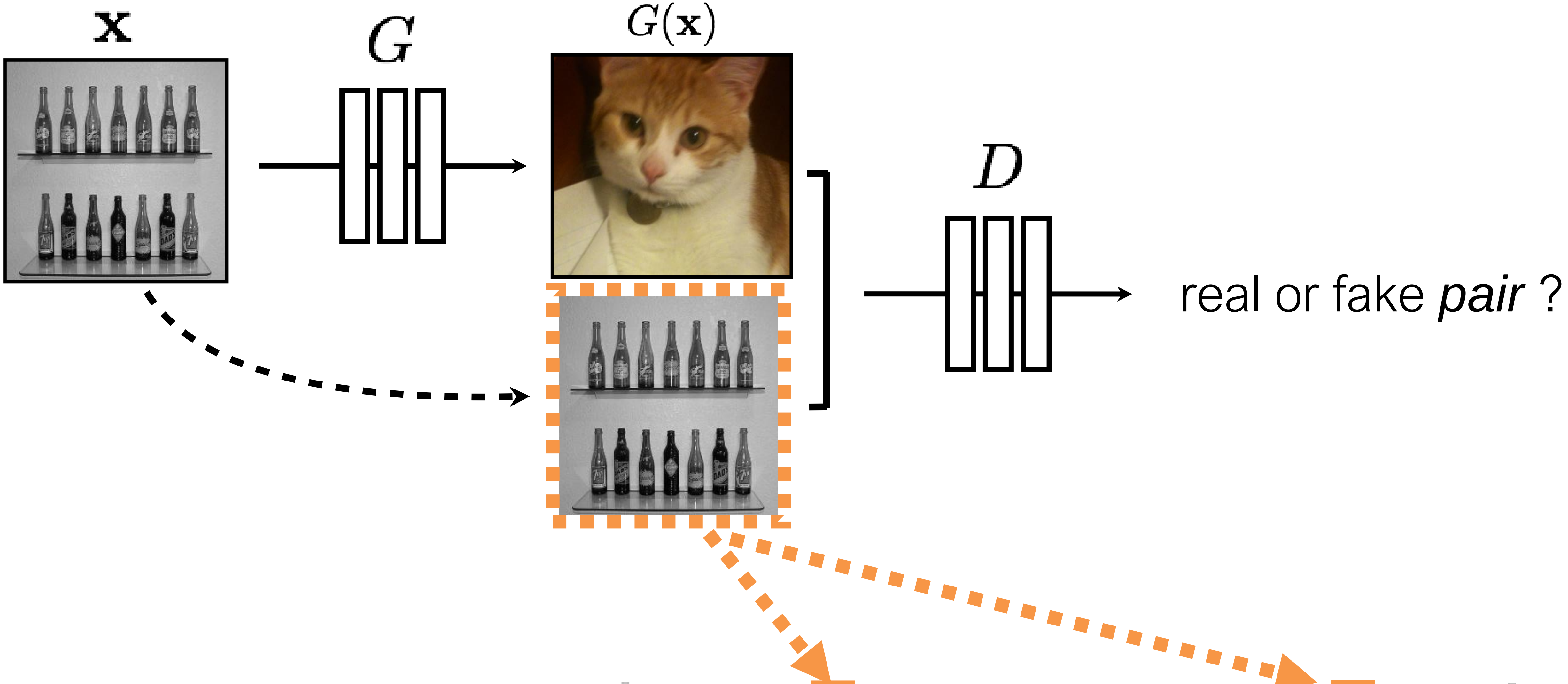
$$\arg\min_G \max_D \; \mathbb{E}_{\mathbf{x},\mathbf{y}}[\; \log D(G(\mathbf{x})) \; + \; \log(1 - D(\mathbf{y})) \;]$$

[Goodfellow et al., 2014]



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

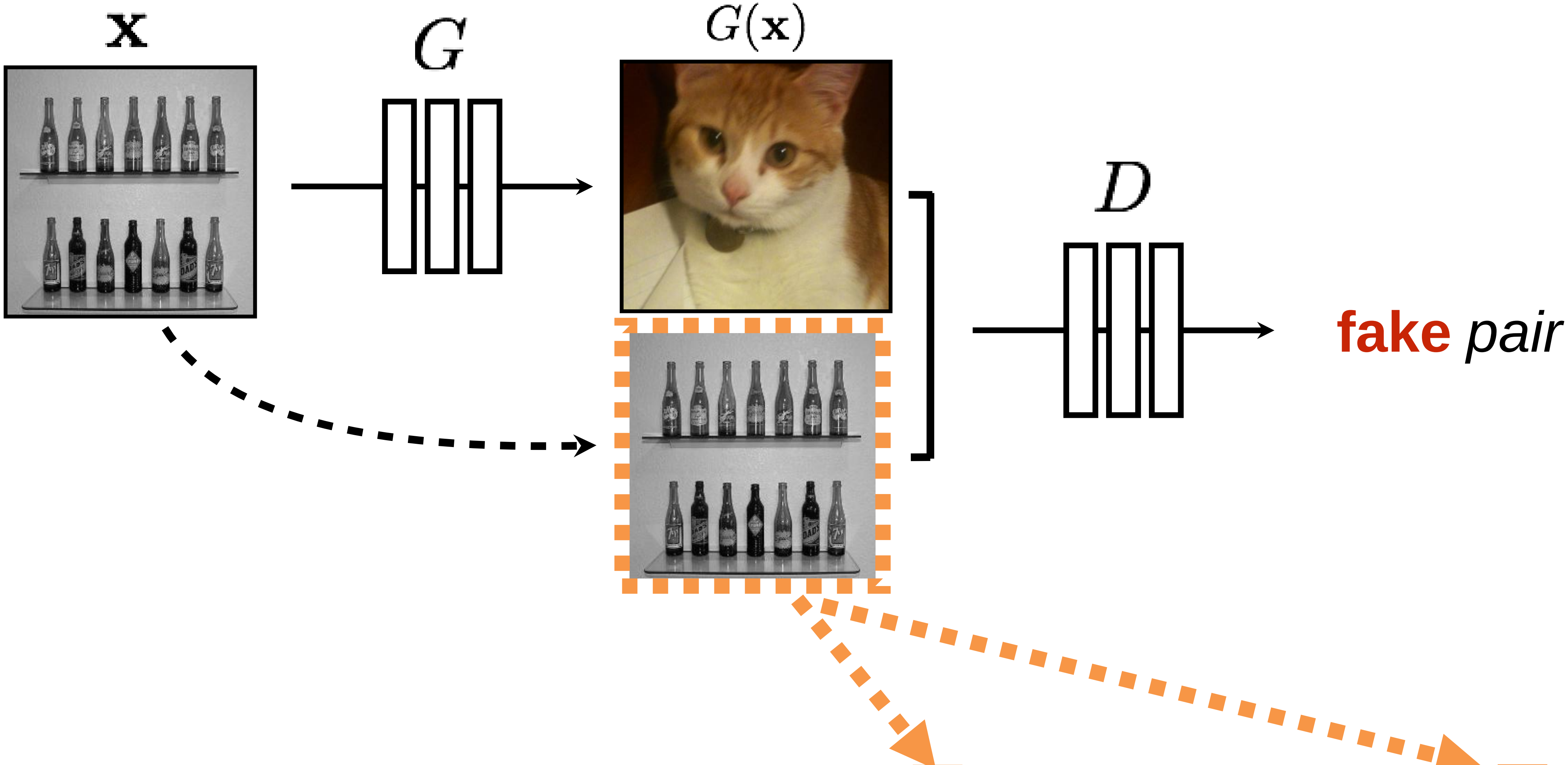
[Goodfellow et al., 2014]
[Isola et al., 2017]



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

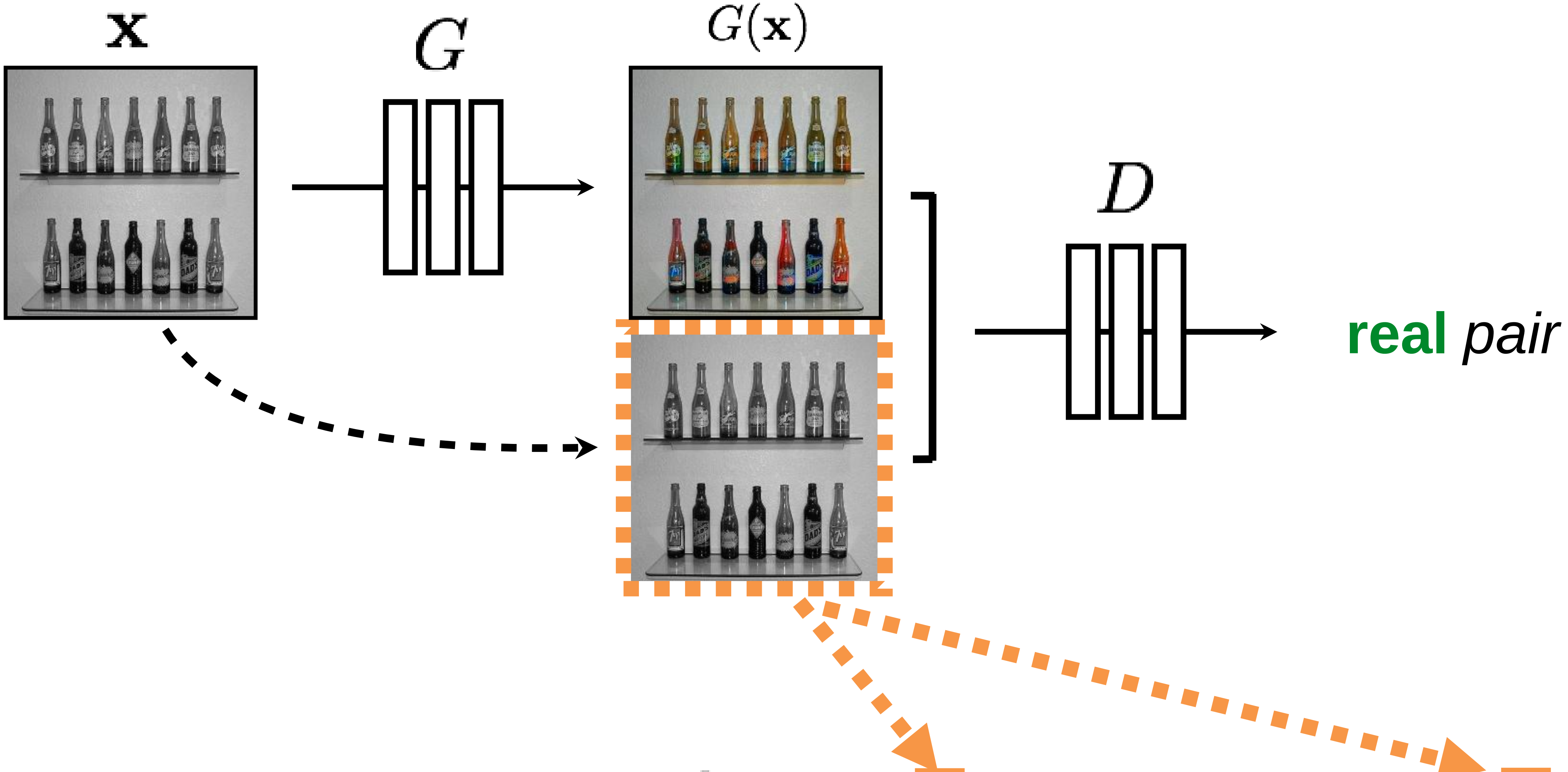
[Goodfellow et al., 2014]

[Isola et al., 2017]



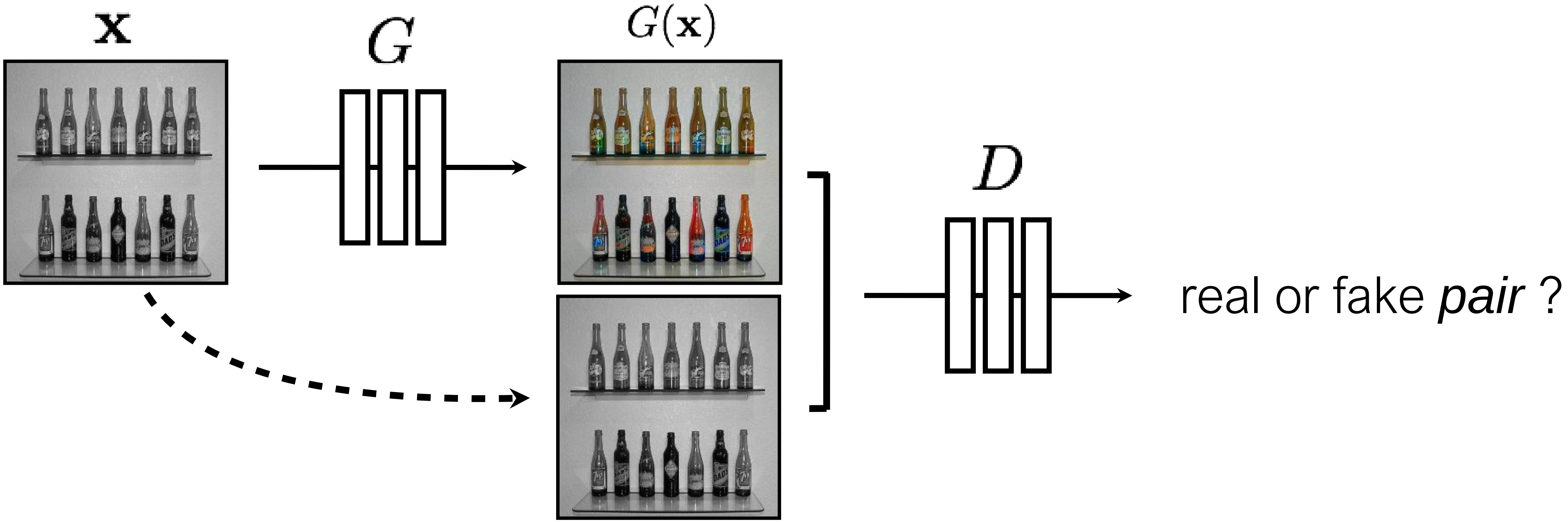
$$\arg\min_G \max_D \; \mathbb{E}_{\mathbf{x},\mathbf{y}}[\; \log D(\boxed{\mathbf{x}}, G(\mathbf{x})) + \log(1 - D(\boxed{\mathbf{x}}, \mathbf{y})) \;]$$

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



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

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



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

[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

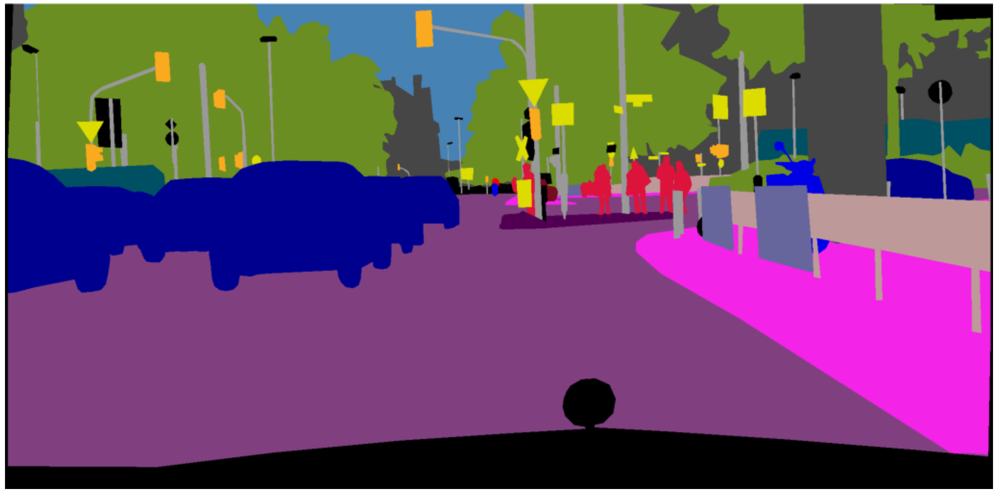
Output

Groundtruth

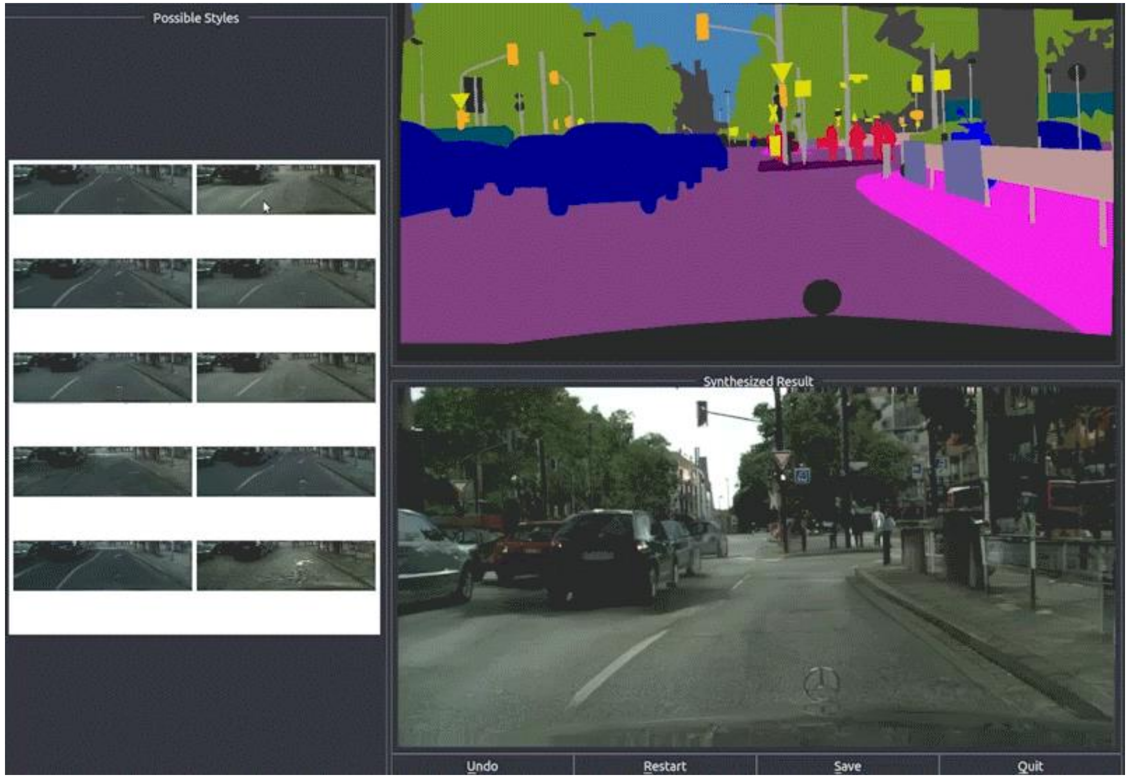
Data from
[maps.google.com]

Labels → Street Views

Input labels

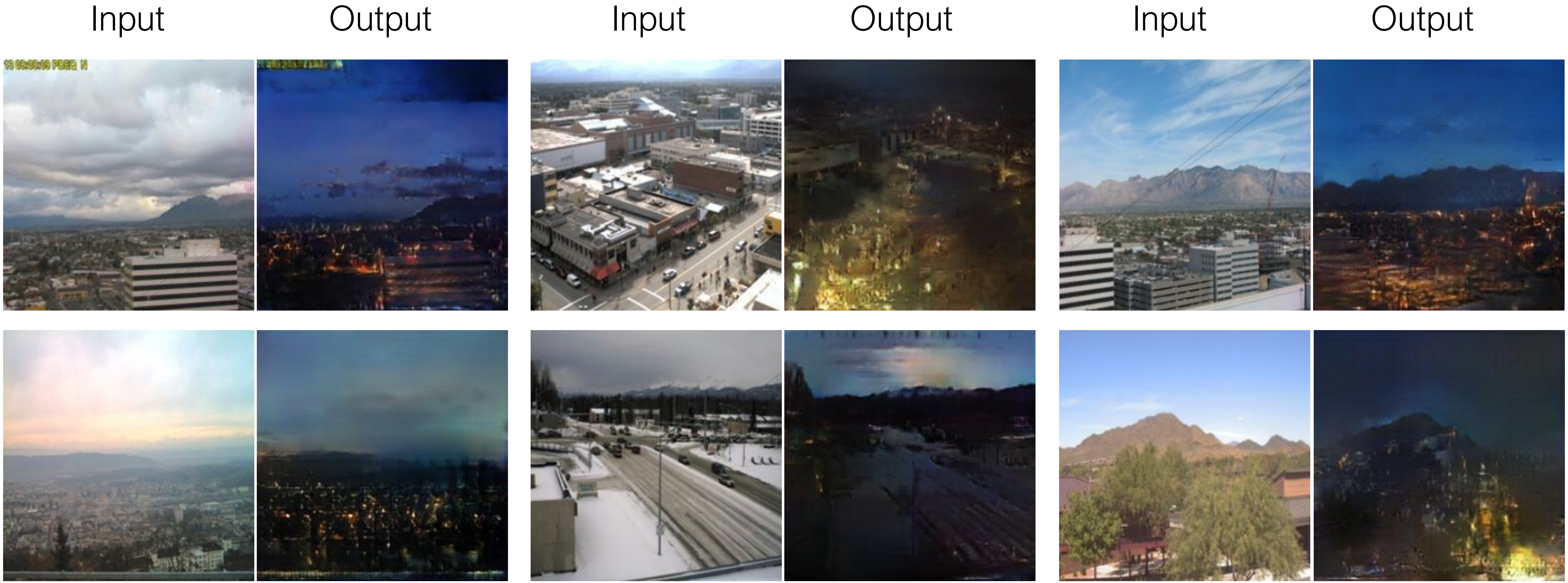


Synthesized image



Data from [Wang et al, 2018]

Day → Night



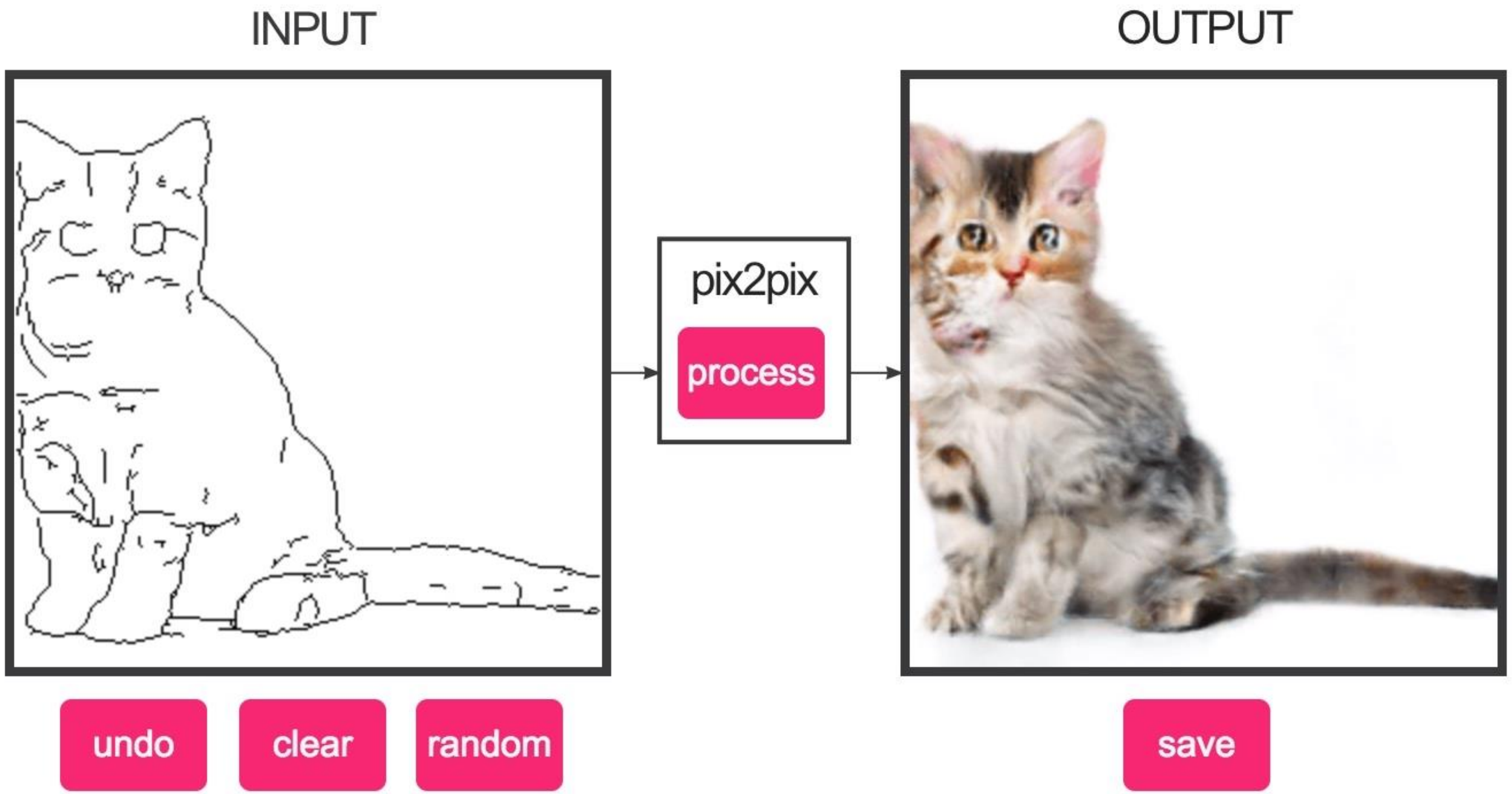
Data from [Laffont et al., 2014]

Edges → Images

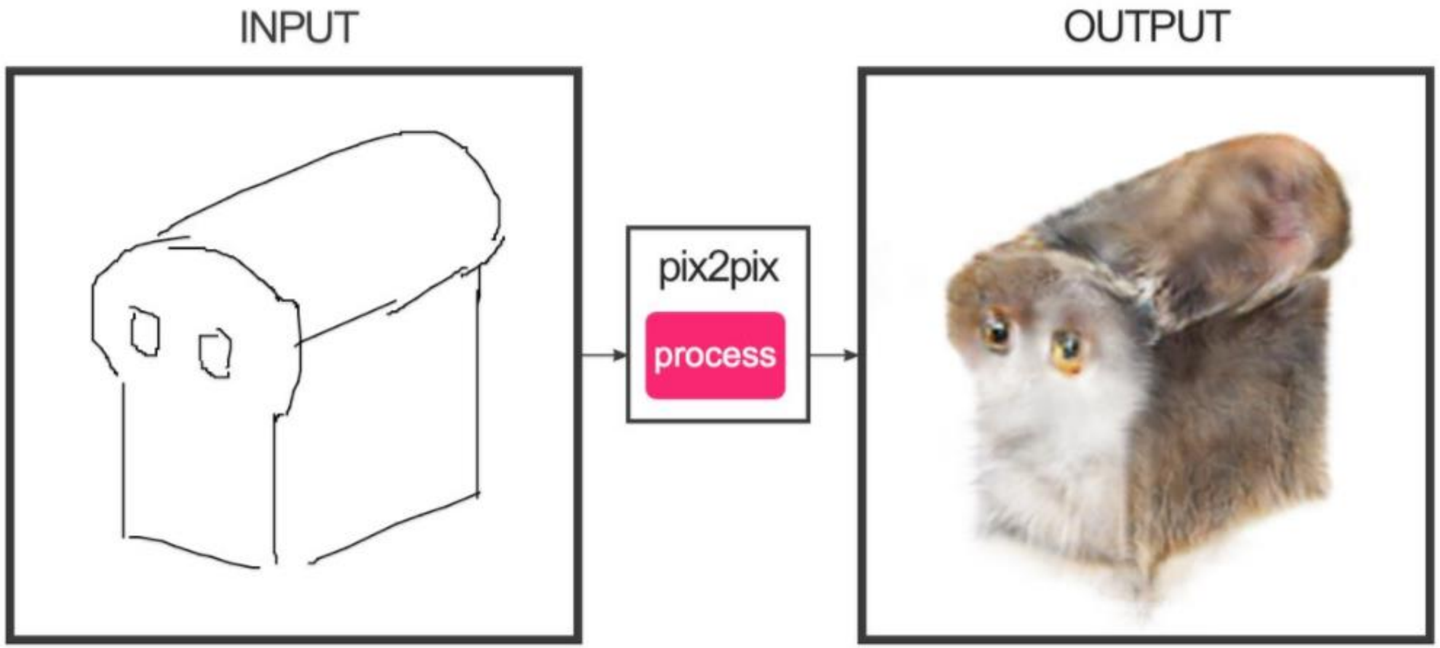
Input Output Input Output Input Output

Edges from [Xie & Tu, 2015]

Demo



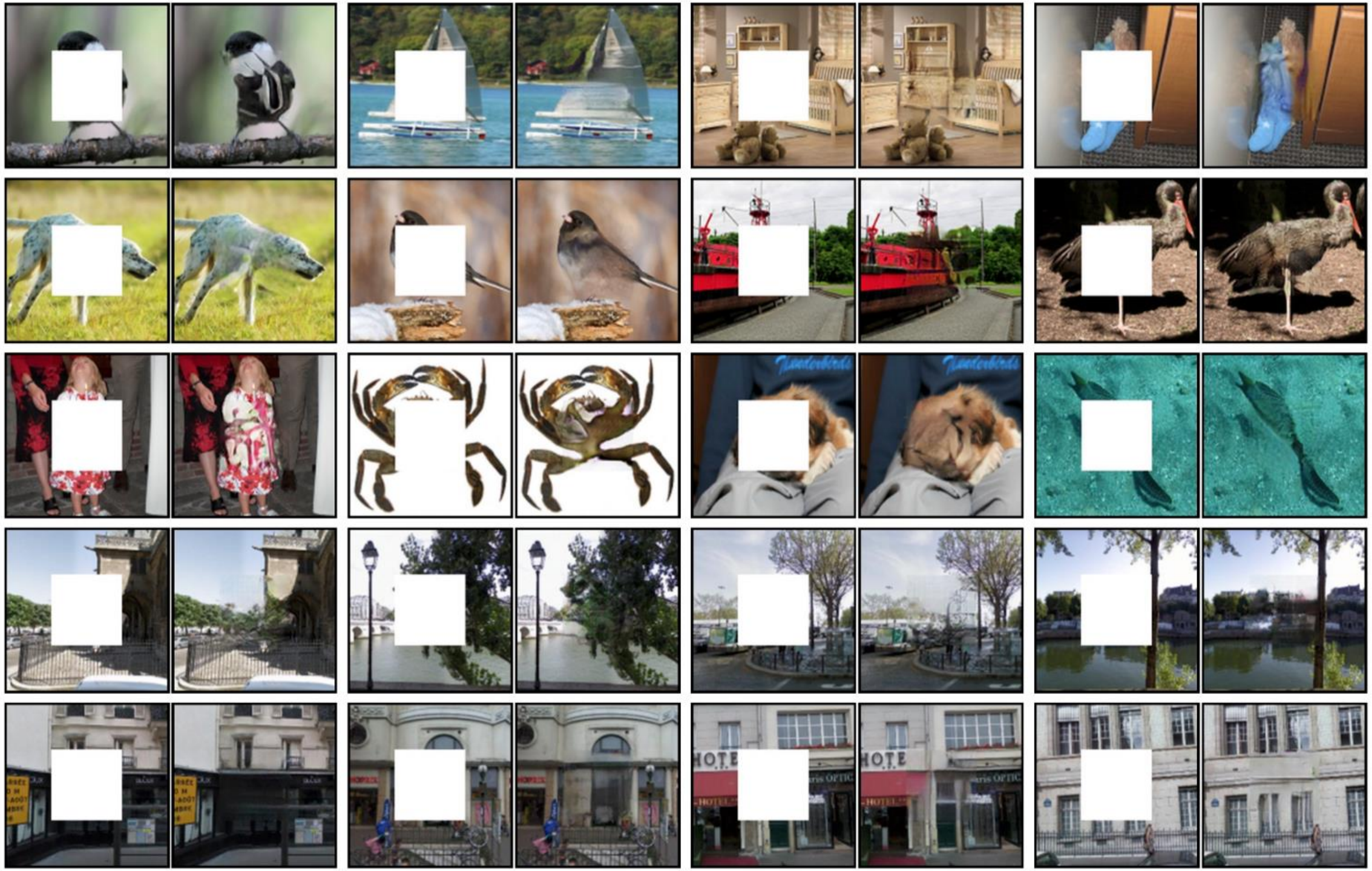
https://affinelayer.com/pixsrv/



Ivy Tasi @ivymyt

Vitaly Vidmirov @vvid

Image Inpainting



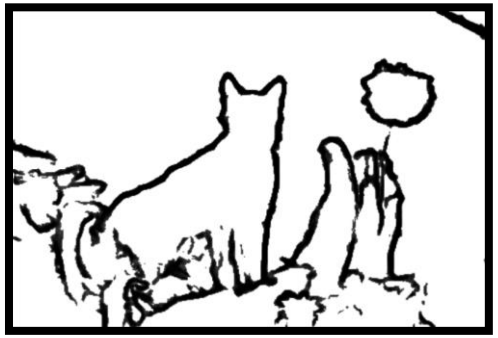
Data from [Pathak et al., 2016]

Pose-guided Generation

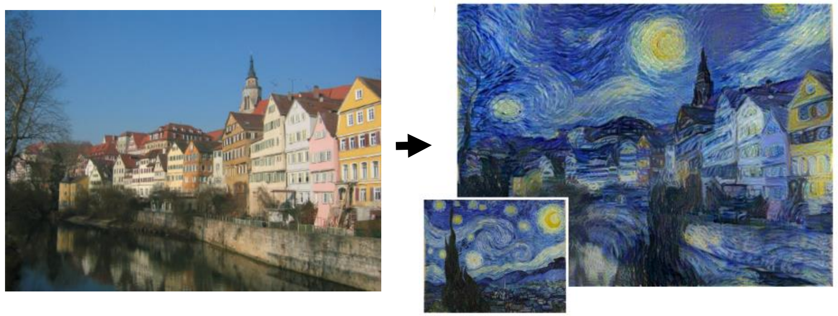
Data from [Ma et al., 2018]

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
- Lack of supervised training data
  - Approach: ?



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



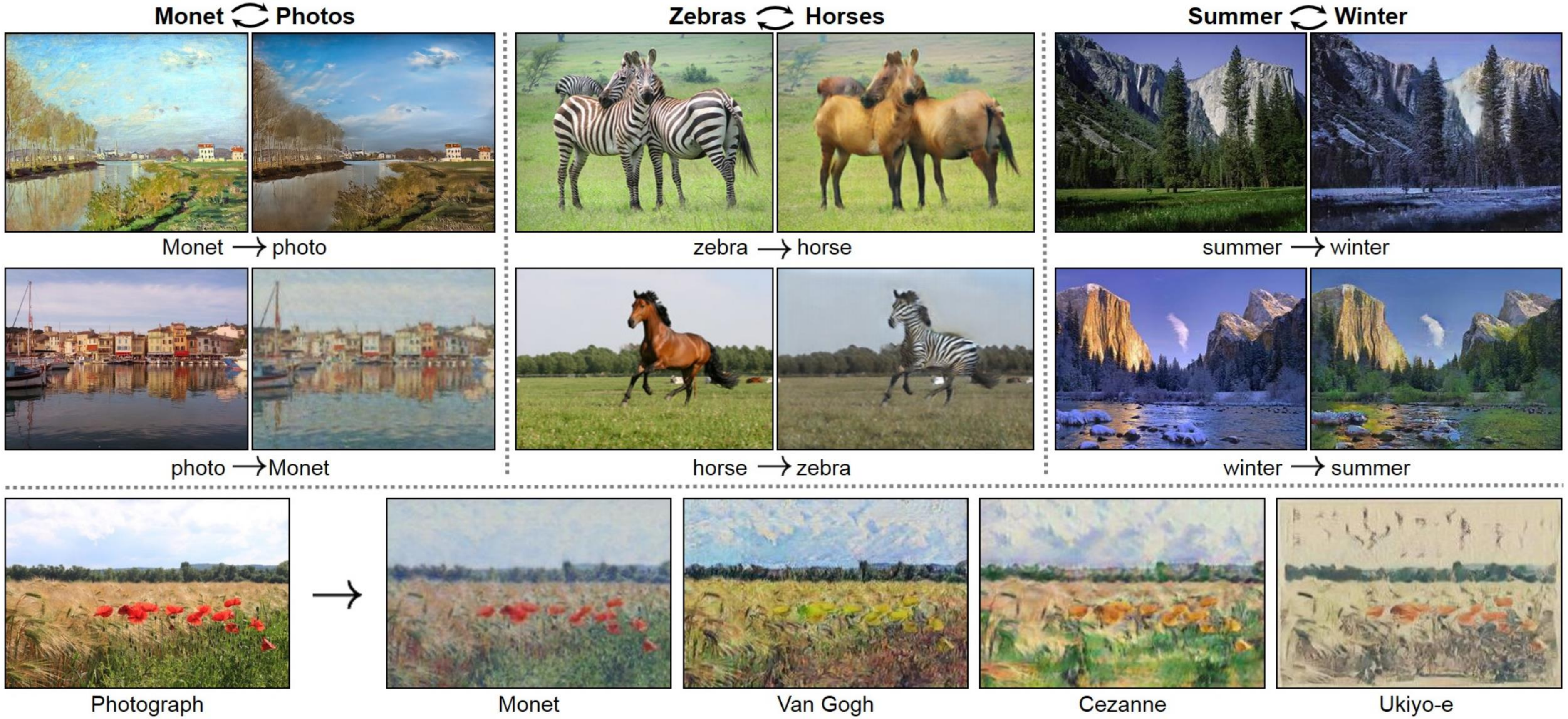
Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks

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

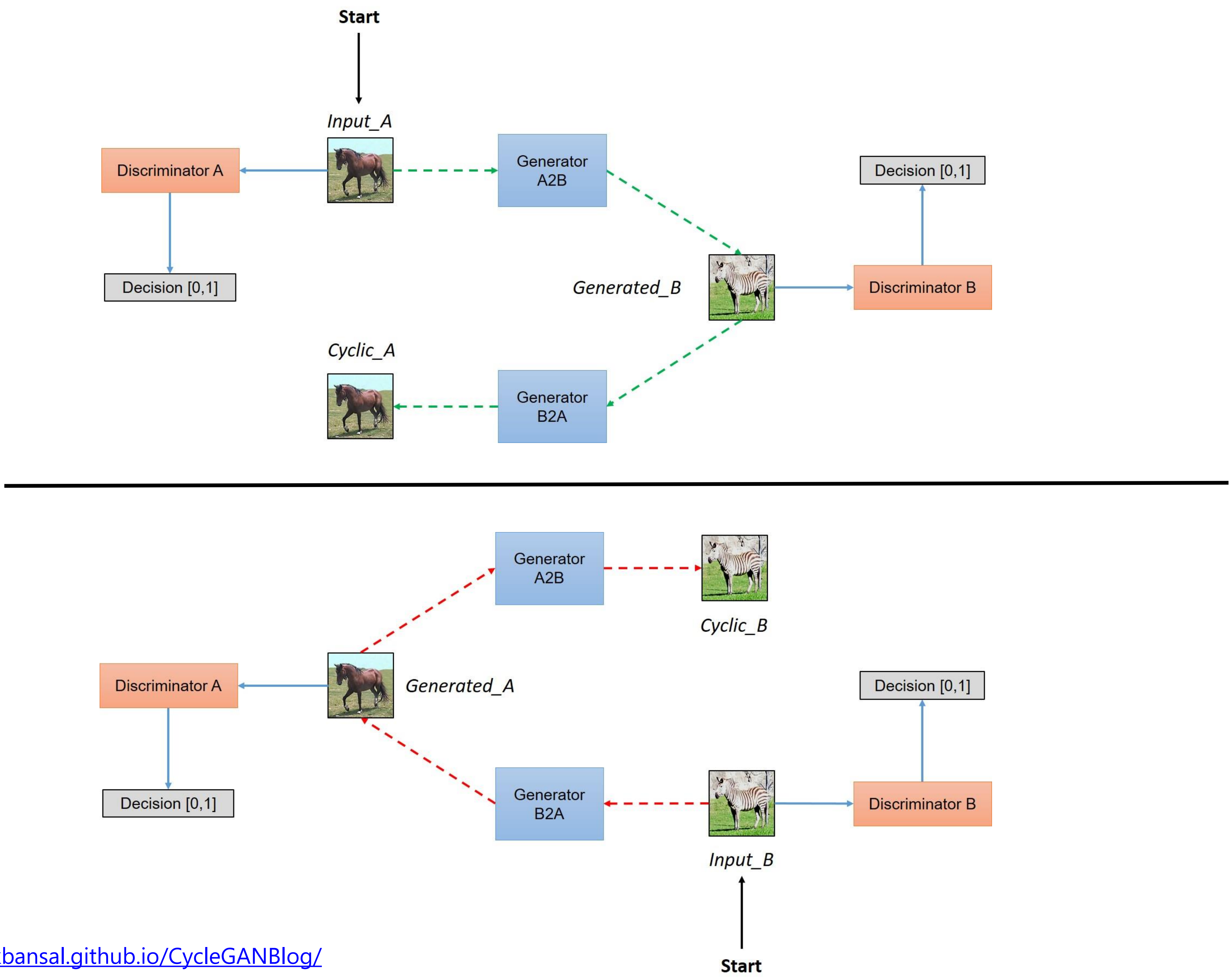
UC Berkeley

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

StyleGAN2

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

Questions?