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 data if you want to train/use CNNs”
Transfer Learning

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

1. Train on Imagenet

Razavian et al., "CNN Features Off-the-Shelf: An astounding Baseline for Recognition", CVPR Workshops 2014
Transfer Learning with CNNs

1. Train on Imagenet

   FC-1000
   FC-4096
   FC-4096
   MaxPool
   Conv-612
   Conv-612
   MaxPool
   Conv-612
   Conv-612
   MaxPool
   Conv-256
   Conv-256
   MaxPool
   Conv-128
   Conv-128
   MaxPool
   Conv-64
   Conv-64
   Image

2. Small Dataset (C classes)

   FC-C
   FC-4096
   FC-4096
   MaxPool
   Conv-612
   Conv-612
   MaxPool
   Conv-612
   Conv-612
   MaxPool
   Conv-256
   Conv-256
   MaxPool
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   Conv-64
   Image

Reinitialize this and train

Freeze these
Transfer Learning with CNNs

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   Conv-256
   MaxPool
   Conv-128
   Conv-128
   MaxPool
   Conv-64
   Conv-64
   Image

   Reinitialize this and train

   Freeze these

3. Bigger dataset

   FC-C
   FC-4096
   FC-4096
   MaxPool
   Conv-612
   Conv-612
   MaxPool
   Conv-612
   Conv-612
   MaxPool
   Conv-256
   Conv-256
   MaxPool
   Conv-128
   Conv-128
   MaxPool
   Conv-64
   Conv-64
   Image

   Train these

   With bigger dataset, train more layers

   Freeze these

   Lower learning rate when finetuning; 1/10 of original LR is good starting point
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<th>More generic</th>
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### More specific vs. More generic

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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
Figure copyright Ross Girshick, 2015. Reproduced with permission.

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Transfer learning with CNNs is pervasive…
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Object Detection (Fast R-CNN)

CNN pretrained on ImageNet

Image Captioning: CNN + RNN

Word vectors pretrained with word2vec

Girshick, "Fast R-CNN", ICCV 2015
Figure copyright Ross Girshick, 2015. Reproduced with permission.

Figure copyright IEEE, 2015. Reproduced for educational purposes.
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
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
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.
The Space of All Images

• Lets consider the space of all 100x100 images

• Now let's 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...
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**

[Style transfer] → [Starry Night]  
[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
arg min_{\mathcal{F}} \mathbb{E}_{x,y}[L(\mathcal{F}(x), y)]

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

from Jin Sun, Richard Zhang, Phillip Isola
Training data

\[
\mathbf{x}, \mathbf{y}
\]

\[
\{\{\text{image 1}, \text{image 2}\}, \{\text{image 3}, \text{image 4}\}, \ldots\}
\]

Objective function

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

Color information: \(ab\) channels

Neural Network

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

Truth: $y$

Classification (cross-entropy):

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

How many extra bits it takes to correct the predictions

Least-squares regression:

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

How far off we are in Euclidean distance

from Jin Sun, Richard Zhang, Phillip Isola
Designing loss functions

\[ L_2(\hat{Y}, Y) = \frac{1}{2} \sum_{h,w} \| Y_{h,w} - \hat{Y}_{h,w} \|_2^2 \]
\[ L_2(\hat{Y}, Y) = \frac{1}{2} \sum_{h,w} \| Y_{h,w} - \hat{Y}_{h,w} \|_2^2 \]
Designing loss functions

Color distribution cross-entropy loss with colorfulness enhancing term.

[Zhang, Isola, Efros, ECCV 2016]
Designing loss functions

Image colorization

Super-resolution

L2 regression

[Zhang, Isola, Efros, ECCV 2016]

[L2 regression

[Johnson, Alahi, Li, ECCV 2016]
Designing loss functions

Image colorization

Cross entropy objective, with colorfulness term

[Zhang, Isola, Efros, ECCV 2016]

Super-resolution

Deep feature covariance matching objective

[Johnson, Alahi, Li, ECCV 2016]
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
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))

Which face is real?
Example: Randomly Sampling the Space of Face Images
(Using Generative Adversarial Networks (GANs))

Which face is real?

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]
Generator $G$ tries to synthesize fake images that fool Discriminator $D$

$D$ tries to identify the fakes

[Goodfellow et al., 2014]
(Identify generated images as fake)  (Identify training images as real)

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

[Goodfellow et al., 2014]
G tries to synthesize fake images that fool D:

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

[Goodfellow et al., 2014]
G tries to synthesize fake images that fool the best D:

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

[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}_{x,y}[ \log D(G(x)) + \log(1 - D(y)) ]

[Goodfellow et al., 2014]
\[
\text{arg min}_G \max_D \mathbb{E}_{x,y} \left[ \log D(G(x)) + \log(1 - D(y)) \right]
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\arg\min_G \max_D \mathbb{E}_{x,y} \left[ \log D(x, G(x)) + \log(1 - D(x, y)) \right]
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[Goodfellow et al., 2014]  
[Isola et al., 2017]
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[Goodfellow et al., 2014]
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[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
BW → Color

Data from [Russakovsky et al. 2015]
Data from [maps.google.com]
Labels → Street Views

Data from [Wang et al, 2018]
Day → Night

Data from [Laffont et al., 2014]
Edges → Images

Edges from [Xie & Tu, 2015]
Demo

https://affinelayer.com/pixsrv/
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/
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?