APS360 Artificial Intelligence Fundamentals

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Lecture 13; July 8, 2019

Agenda

Last class:

- Generative RNN
  - Training using teacher-forcing
  - Generating new sequences (temperature setting)

Today:

- Mid-Course Survey
- Progress Meeting
- Generative Adversarial Networks
- Adversarial Examples

Mid-Course Survey

https://forms.gle/WpcG8nirrNw9inXx9

- The survey is compeletely anonymous
- Only 5 questions – your response can be as short or as long as you want
- Help me improve your APS360 learning experience
- Use the survey to tell me anything you want

Project Progress Meeting

Why?

- So you have some one-on-one time with a ML researcher
- So that you're on the right track
- So that everyone on your team is contributing

Scheduling

- Email your TA with several times that you are available
- If you really can't find a time before July 15, please email me
- Send your TA your project proposal

Before the meeting...

- You should have all your data collected and cleaned
- You should be able to show your data to your TA, to give them some intuition about your problem
- There should be some code that the TA can look at

In the past, teams that have at least a baseline model implemented benefited most from the progress meeting.

Generative Models

Supervised vs Unsupervised Learning

From week 1:

- **Supervised Learning**: learning a function that maps an input to an output based on example input-output pairs
- **Unsupervised Learning**: learning the structure of some (unlabelled) data

Learning to generate new data is an **unsupervised learning** task

- Yes, there is a loss function
- There is an auxiliary task that we know the answer to
- But there is no "label" or "ground truth" with respect to the **actual task** that we want to accomplish.

Example

Q: Are these supervised or unsupervised learning task?

- Task 1: Predict the next character given all the previous characters in a "Trump tweet"
- Task 2: Generate a new "Trump tweet"

Example

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- Task 1: Predict the next character given all the previous characters in a “Trump tweet”
- Task 2: Generate a new “Trump tweet”

Task 1 is supervised, and is an example of a **discriminative model**

Task 2 is unsupervised, and is an example of a **generative model**.

Generative Models

- A **generative model** learns the *structure* of a set of input data, and can be used to **generate** new data
- Examples:
  - Autoencoders
  - RNN for text generation

Review Autoencoders - Code!

Autoencoder outputs are Blurry

These faces are generated using a variant of autoencoders

Autoencoders uses MSELoss

- Blurry images, blurry backgrounds
- Why? Because the loss function used to train an autoencoder is the **mean square error loss** (MSELoss)
- To minimize the MSE loss, autoencoders predict the "average" pixel – e.g. average the background

Can we use a better loss function?

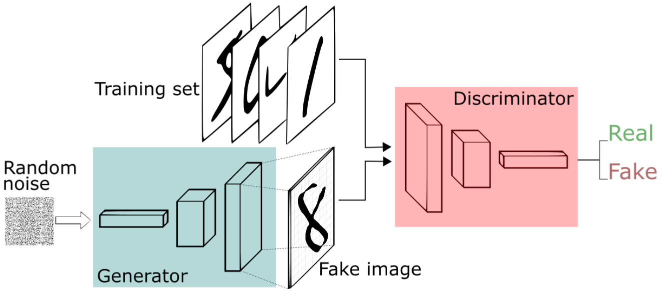
Generative Adversarial Network

Generative Adversarial Network

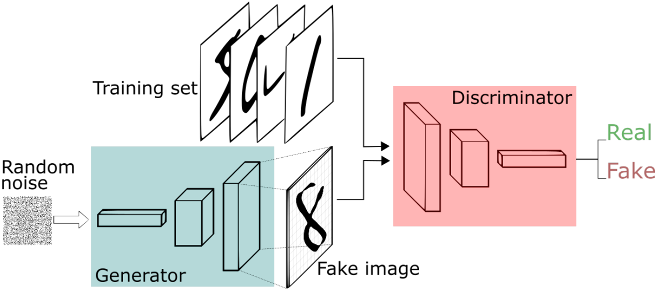
Idea: train two networks

- **Generator network**: try to fool the discriminator by generating real-looking images
- **Discriminator network**: try to distinguish between real and fake images

The loss function of the generator (the model we care about) is defined by the discriminator!



GAN Architecture

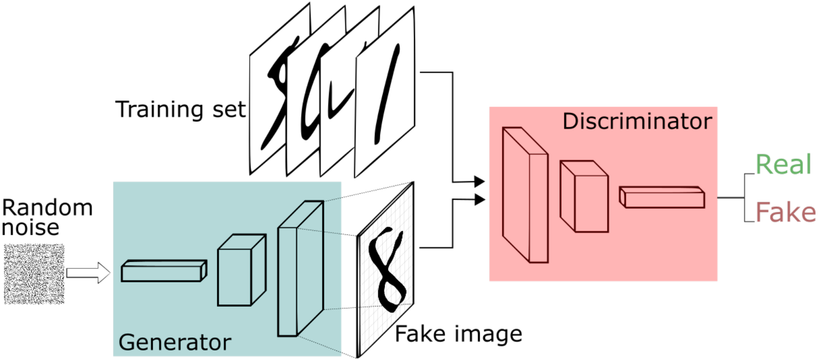


- **Generator network**:
  - Input: a random noise vector (Q: Why do we need to input noise?)
  - Output: a generated image
- **Discriminator network**: try to distinguish between real and fake images
  - Input: an image
  - Output: a binary label (real vs fake)

Training GANs: two-player (minmax) game

Play a minmax game:

- the discriminator will try to do the best job it can
- the generator is set to make the discriminator as wrong as possible



Loss function for min-max game

Tune **discriminator** weights to:

- **maximize** the probability that the
  - discriminator labels a real image as real
  - discriminator labels a generated image as fake
  - Q: What loss function should we use?

Loss function for min-max game

Tune **discriminator** weights to:

- **maximize** the probability that the
  - discriminator labels a real image as real
  - discriminator labels a generated image as fake
  - Q: What loss function should we use?

Tune **generator** weights to:

- **maximize** the probability that...
  - discriminator labels a generated image as real
  - Q: What loss function should we use?

Training

Alternate between:

- Training the discriminator
- Training the generator

Caveat before we look at code

- Can work very well, but very difficult to train!
- Difficult to numerically see whether there is progress
  - Plotting the "training curve" (discriminator/generator loss) doesn't help much
- Takes a long time to train (a long time before we see progress)
- To make the GAN train faster, we'll use:
  - LeakyReLU Activations instead of ReLU
  - Batch Normalization (later)

GAN: Discriminator

```python
class Discriminator(nn.Module):
  def __init__(self):
    super().__init__()
    self.model = nn.Sequential(
      nn.Linear(28*28, 300),
      nn.LeakyReLU(0.2, inplace=True),
      nn.Linear(300, 100),
      nn.LeakyReLU(0.2, inplace=True),
      nn.Linear(100, 1))
  def forward(self, x):
    x = x.view(x.size(0), -1)
    out = self.model(x)
    return out.view(x.size(0))
```

Leaky Relu activation

Like a relu, but "leaks" data:

- $f(x) = x$ if $x >= 0$
- $f(x) = \alpha x$ if $x < 0$

You've implemented this in assignment 1.

Reason:

- Always have some information pass through in the forwards pass
- Always have some information pass back in the backwards pass
- Better weight updates during the backwards pass

GAN: Generator

```python
class Generator(nn.Module):
  def __init__(self):
    super().__init__()
    self.model = nn.Sequential(
      nn.Linear(100, 300),
      nn.LeakyReLU(0.2, inplace=True),
      nn.Linear(300, 28*28),
      nn.Sigmoid())

  def forward(self, x):
    out = self.model(x).view(x.size(0), 1, 28, 28)
    return out
```

Training the Discriminator

```
#images = batch of images
#batch_size = images.size(0)
noise = torch.randn(batch_size, 100)
fake_images = generator(noise)
inputs = torch.cat([images, fake_images])
labels = torch.cat([torch.zeros(batch_size)), # real
                    torch.ones(batch_size)]) # fake
d_outputs = discriminator(inputs)
d_loss = criterion(d_outputs, labels)
```

(Labels: real=0, fake=1)

Training the Generator

```
noise = torch.randn(batch_size, 100)
fake_images = generator(noise)
outputs = discriminator(fake_images)
generator.zero_grad()
g_loss = criterion(outputs, torch.zeros(batch_size))
```

(Labels: real=0, fake=1)

Let's run the code!

Mode Collapse

- Mode = “average”
- GAN model learns to generate one type of input data (e.g. only digit 1)
- Generating anything else leads to detection by discriminator
- Generator gets stuck in that local optima

Batch Normalization

Normalization on input data helps training. But what about the hidden activations?

- **Training time**: normalize activations based on mini-batch statistics, and keep track of those statistics
- **Test time**: normalize activations based on saved statistics

Balance between Generator and Discriminator

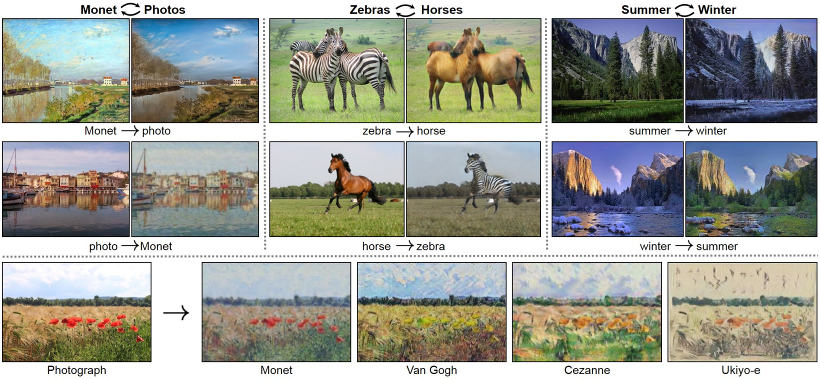
If the discriminator is too good, then the generator will not learn

- Remember that we are using the discriminator like a “loss function” for the generator
- If the discriminator is too good, small changes in the generator weights won’t change the discriminator output
- If small changes in generator weights make no difference, then we can’t incrementally improve the generator

GAN now

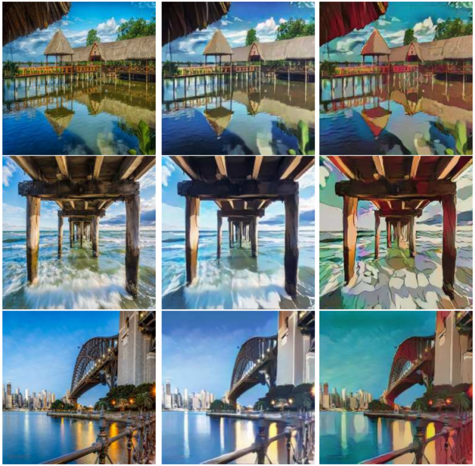
https://arxiv.org/pdf/1710.10196.pdf (2018)

CycleGAN



https://junyanz.github.io/CycleGAN/ (2017)

CartoonGAN



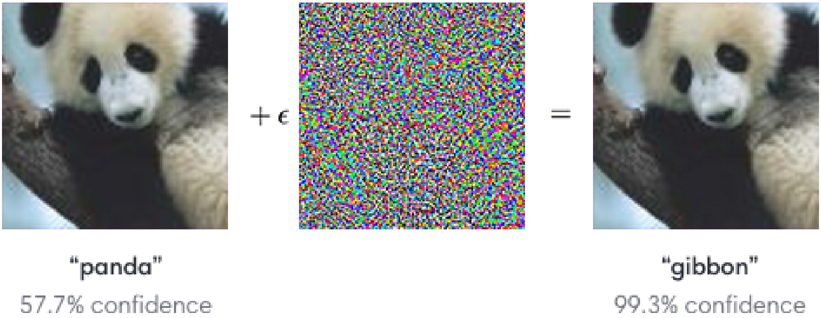
(a) input photo (b) Shinkai style (c) Hayao style

Figure 5. Some results of different artistic styles generated by CartoonGAN. (a) Input real-world photos. (b) Makoto Shinkai style. (c) Miyazaki Hayao style.

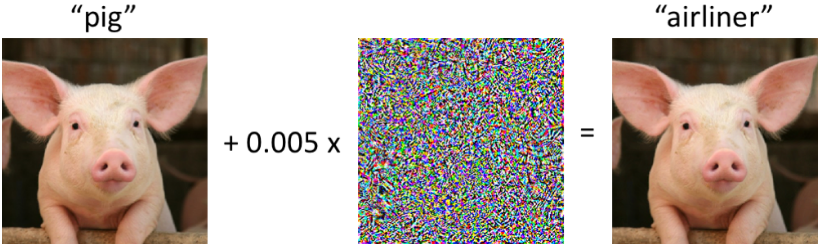
http://openaccess.thecvf.com/content_cvpr_2018/papers/Chen_Cartoon

Adversarial Examples

What is this a picture of?



What is this a picture of?



Adversarial attack

Goal: Choose a small perturbation ϵ on an image x so that a neural network f misclassifies $x + \epsilon$.

Approach:

Use the same optimization process to choose ϵ to minimize the probability that

$$f(x + \epsilon) = correctclass$$

We are treating ϵ as the **parameters**.

Targeted vs Non-Targeted Adversarial Attack

Non-targeted attack

Minimize the probability that $f(x + \epsilon) = correctclass$

Targeted attack

Maximize the probability that $f(x + \epsilon) = targetclass$

White-box Adversarial Attack

- Assumes that the model is known
- We need to know the architectures and weights of f to optimize ϵ

Black-box Adversarial Attack

- Don't know the architectures and weights of f to optimize ϵ
- Substitute model mimicking target model with known, differentiable function
  - adversarial attacks often transfer across models!

Printed Objects

https://openai-public.s3-us-west-2.amazonaws.com/blog/2017-07/robust-adversarial-examples/iphone.mp4

3D Objects

https://www.youtube.com/watch?v=piYnd_wYlT8

Printed Pictures

https://www.youtube.com/watch?v=MIbFvK2S9g8&feature=youtu.be

Defenses Against Adversarial Attack

- Active area of research

Failed Defenses

- Generative pre-training
- Adding noise at test time
- Averaging many models
- Weight decay
- Adding noise at training time
- Adding adversarial noise at training time
- Dropout