Generative Models
Generating Images

How to generate new data of certain types

- generate text that looks like our training data
- generate images that look like our training data

Models:

- Generative RNNs
- Autoencoder
- Variational Autoencoder (VAE)
- Generative Adversarial Networks

We’ll talk about autoencoders and VAEs today
Autoencoders

There are two ways of thinking of an image autoencoder:

- a model that will eventually help us generate new images
- a model that finds a low-dimensional representation of images

Both are considered unsupervised learning tasks, since no labels are involved.

However, we do have a dataset of unlabelled images.
Idea: In order to learn to generate images, we’ll learn to **reconstruct** images from a low-dimensional representation.

An image autoencoder has two components:
Idea: In order to learn to generate images, we’ll learn to reconstruct images from a low-dimensional representation.

An image autoencoder has two components:

1. An encoder neural network that takes the image as input, and produces a low-dimensional embedding.
Idea: In order to learn to generate images, we’ll learn to **reconstruct** images from a low-dimensional representation.

An image autoencoder has two components:

1. An **encoder** neural network that takes the image as input, and produces a low-dimensional embedding.

2. A **decoder** neural network that takes the low-dimensional embedding as input, and reconstructs the image.

A good, low-dimensional representation should allow us to reconstruct everything about the image.
The components of an autoencoder

**Encoder:**
- Input = image
- Output = low-dimensional embedding

**Decoder:**
- Input = low-dimensional embedding
- Output = image
Why autoencoders?

- **Dimension reduction:**
  - find a low dimensional representation of the image
- **Image Generation:**
  - generate new images not in the training set
  - (Any guesses on how we can do this?)
Image Encoder Architecture

What would the architecture of the encoder look like?

- We could use a MLP, but there are some issues (recall: what are these issues?)
- But we can also use a convolutional neural network!

We can use downsampling to reduce the dimensionality of the data
What would the architecture of the decoder look like?

We need to be able to **increase** the image resolution.

We haven’t learned how to do this yet!
Transpose Convolution
Transpose Convolution

Used to increase the resolution of a feature map.

This is useful for:

- image generation problems
- pixel-wise prediction problems
A prediction problem where we label the content of each pixel is known as a **pixel-wise prediction problem**

Figure 1: [http://deeplearning.net/tutorial/fcn_2D_segm.html](http://deeplearning.net/tutorial/fcn_2D_segm.html)

Q: How do we generate pixel-wise predictions?
What we need:

We need to be able to **up-sample** features, i.e. to obtain high-resolution features from low-resolution features

- Opposite of max-pooling OR
- Opposite of a strided convolution

We need an **inverse** convolution – a.k.a a **deconvolution** or **transpose convolution**.
Architectures with Transpose Convolution

More than one upsampling layer

**DeconvNet:**

VGG-16 (conv+Relu+MaxPool) + mirrored VGG (Unpooling+‘deconv’+Relu)

Architectures with Transpose Convolution 2
Inverse Convolution

```python
>>> x = torch.randn(2, 8, 64, 64)
>>> conv = nn.Conv2d(in_channels=8,
...                   out_channels=8,
...                   kernel_size=5)
>>> y = conv(x)
>>> y.shape
```

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should get the same shape back!
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>>> convt = nn.ConvTranspose2d(in_channels=8,
...                              out_channels=8,
...                              kernel_size=5)
>>> x = convt(y)
>>> x.shape
```

should get the same shape back!
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Inverse Convolution + Padding

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should get the same shape back!
```
Inverse Convolution + Stride

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...                   out_channels=8,
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...                   stride=2)

>>> y = conv(x)
```

```python
>>> y.shape
```

```
... almost the same shape ...
```
Inverse Convolution + Stride

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y = conv(x)

y.shape

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...                           out_channels=8,
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...                           stride=2)
>>> x = convt(y)
>>> x.shape

... almost the same shape ...
```
Transpose Convolution Layer

(a) Convolutional layer: the input size is $W_1 = H_1 = 5$; the receptive field $F = 3$; the convolution is performed with stride $S = 1$ and no padding ($P = 0$). The output Y is of size $W_2 = H_2 = 3$.

(b) Transposed convolutional layer: input size $W_1 = H_1 = 3$; transposed convolution with stride $S = 2$; padding with $P = 1$; and a receptive field of $F = 3$. The output Y is of size $W_2 = H_2 = 5$.

Figure 2: https://www.mdpi.com/2072-4292/9/6/522/htm

More at https://github.com/vdumoulin/conv_arithmetic
nn.ConvTranspose2d(in_channels=8,
    out_channels=8,
    kernel_size=5,
    stride=2,
    output_padding=1)  # +1 to output
    # width/height
Autoencoder
Let’s get back to the autoencoder

Recall that we want a model that **generates images** that looks like our training data.

Idea:

- In order to learn to generate images, we’ll learn to **reconstruct** images from a low-dimensional representation.
- A good, low-dimensional representation should allow us to reconstruct everything about the image.
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- Image Generation:
  - generate new images not in the training set

Autoencoders are not used for **supervised learning**. The task is *not* to predict something about the image!

Autoencoders are considered a **generative model**.
How to train autoencoders?

- **Loss function:**
  - How close were the reconstructed image from the original?
  - **Mean Square Error Loss:** look at the mean square error across all the pixels.

- **Optimizer:**
  - Just like before!
  - Commonly used for other network architectures too

- **Training loop:**
  - Just like before!
Let’s train an autoencoder for MNIST
Structure in the Embedding Space

The dimensionality reduction means that there will be structure in the embedding space.

If the dimensionality of the embedding space is not too large, similar images should map to similar locations.
Interpolating in the Embedding Space
Generating New Images

Q: Can we pick a random point in the embedding space, and decode it to get an image of a digit?

A: Unfortunately not necessarily. Can we figure out why not?
Autoencoder Overfitting

Overfitting can occur if the size of the embedding space is too large.

If the dimensionality of the embedding space is small, then the neural network needs to map similar images to similar locations.

If the dimensionality of the embedding space is too large, then the neural network can simply memorize the images!
Q: Why do autoencoders produce blurry images?

Hint: it has to do with the use of the MSE Loss.