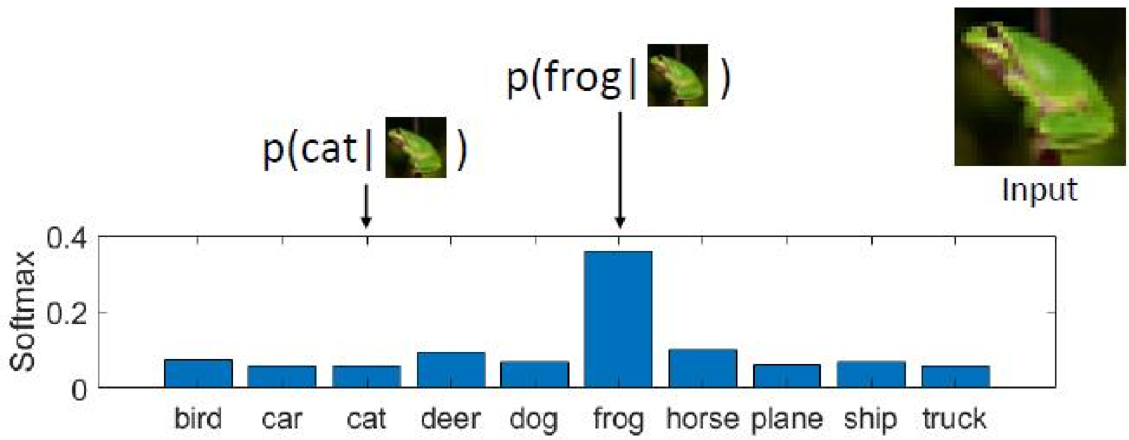
9 - Image generation

Generative vs. discriminative models

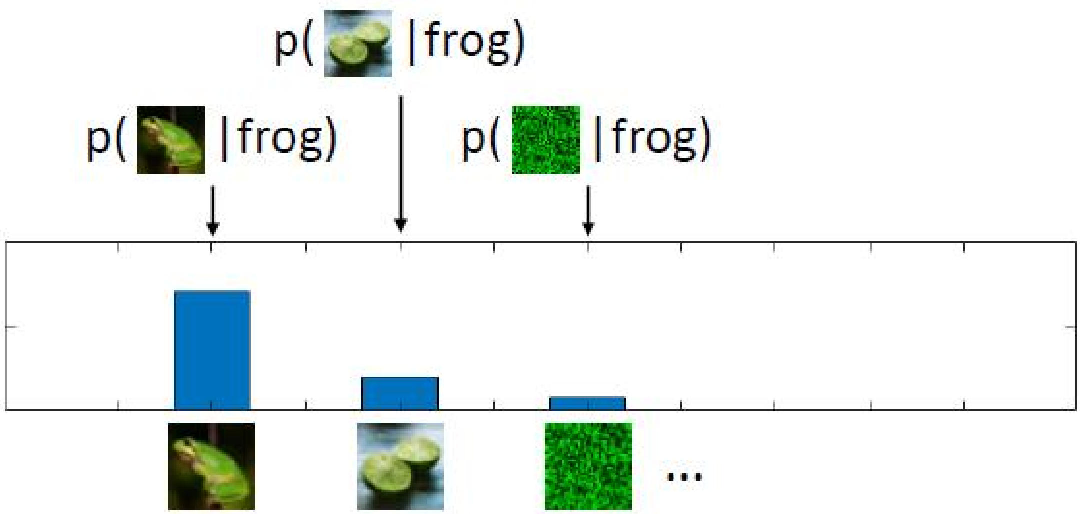
Discriminative models

- Learn conditional probability of class Y given attributes X: p(y|x)
- Input is an image
- Output is a probability density function over labels p(y|x)



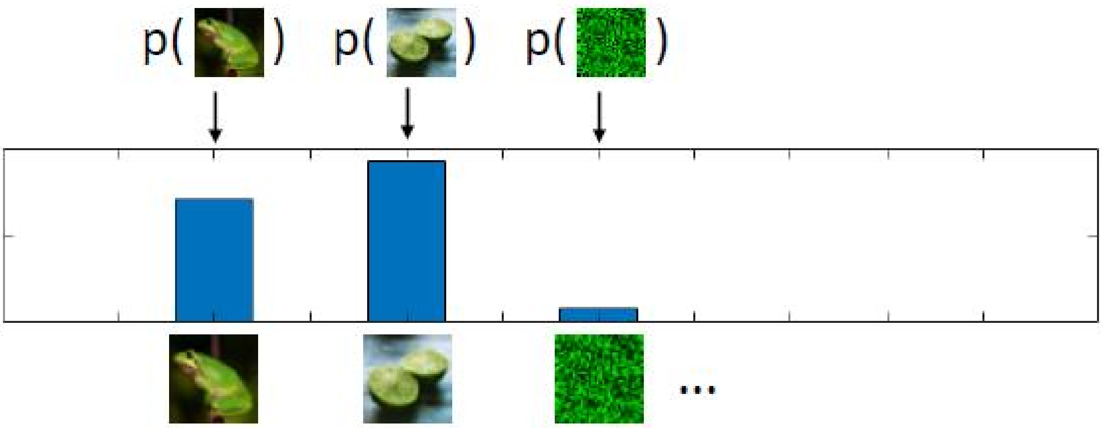
Generative models

- Generative models can generate new samples from the learned distribution
- Learn joint probability of attributes X and class Y: p(x,y)
- Generative model contains discriminative model: you can use the joint probability to get p(y|x)
- AND generative can do the reverse: p(x|y)
- Conditional generative model
  - Input is a label
  - Output is a probability density function over images p(x|y)



- Unconditional generative model

- Output is a probability distribution p(x)
- What is the probability that this is an image?



Bayes' rule

- Relationships between these models:

Conditional generative model

$$p(y|x) = \frac{p(x|y)p(y)}{p(x)}$$

Prior over labels

Discriminative model

Unconditional generative model

Discriminative model

$$p(x|y) = \frac{p(y|x)p(x)}{p(y)}$$

Unconditional generative model

Conditional generative model

Prior over labels

Summary - Generative vs. discriminative models

- Discriminative models produce a probability distribution over labels, given an image
- Generative models produce a probability distribution over images, given a label (conditional) or in general (unconditional)
- Difficult problem – what makes one set of pixels more probable than another?

Autoencoders

Unsupervised learning

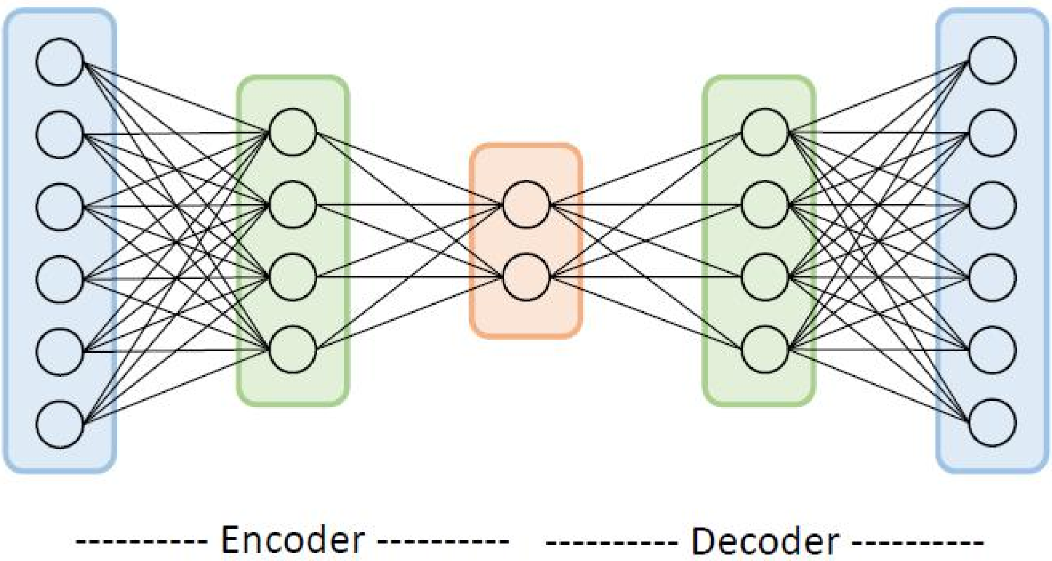
- Learn a model for unlabeled data
- Goal is to find a model that represents the data as well as possible, usually with fewer parameters
- Uses:
  - Simpler model for another ML system

- Form of dimensionality reduction
- Potentially better generalization

- Like supervised machine learning algorithms, unsupervised algorithms may not work well in “raw” input spaces (text, images)
  - e.g. May not fit well. Distance(frog1, frog2) may be near to Distance(frog1, cat).
  - Because of light, pose, angle...
- Solution: Embeddings (e.g., from neural networks) might work better
  - But we have no labels to learn the embeddings for our task
  - Embeddings learned for a different task may not give a complete representation of the data

Autoencoders

- Essentially, neural networks for unsupervised learning (no labels)
- Sometimes called “self-supervised” learning
- Output of the network is whatever was passed to the network (e.g., an image)
- Hidden layer learns a lower-dimensional representation of the input: lower-dimensional set of features that explains the data
  - “Bottleneck” layer – smaller than the input
  - Represents the input in terms of latent variables
  - In the simplest case (one hidden layer with linear activation functions), this layer learns PCA
  - Need to be smaller than the input to form a good representation. If it has the same size as the input, it is just a copy.
  - Latent representation: Simplified representation of the input
  - Can be used as a feature embedding for other tasks
- Encoder/decoder architecture
  - Encode in a hidden layer
  - Hidden layer is smaller than the input (fewer neurons)
  - Decode to an output layer
  - Often the encoding and decoding weights are forced to be the same
- Goal: output the input



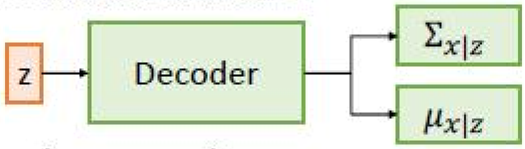
- Output and loss

- Unlike a standard NN, the output is not a class or regression value – it's the same type as the input (e.g., an image)
  - Activation function is chosen appropriately:
    - For a binary image, tanh or sigmoid
    - For a regular image, linear activation
  - Loss function = difference between input and output (e.g., MSE)
- Not a true generative model – no way to sample new data
  - You could "sample" by giving random latent variable values to the decoder, but no guarantee that these will produce real images

Variational autoencoder (VAE)

- Probabilistic version of an autoencoder: learn latent representation and sample from the model to generate new images
- Assume images are generated from some distribution over latent variables z
- Assume a simple prior p(z), e.g., uniform or Gaussian distribution
- Probabilistic decoder learns p(x|z)

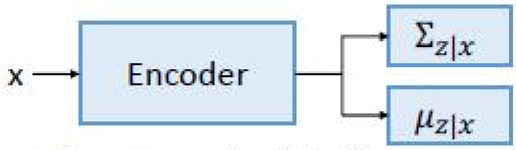
  - Input: latent variables z
  - Output: mean $\mu_{x|z}$ and diagonal covariance $\Sigma_{x|z}$, parameters of a Gaussian distribution that generates x conditional on z



  - $p(x|z) = \mathrm{N}(\mu_{x|z}, \Sigma_{x|z})$
  - Goal: maximize $p(x) = \frac{p(x|z)p(z)}{p(z|x)}$

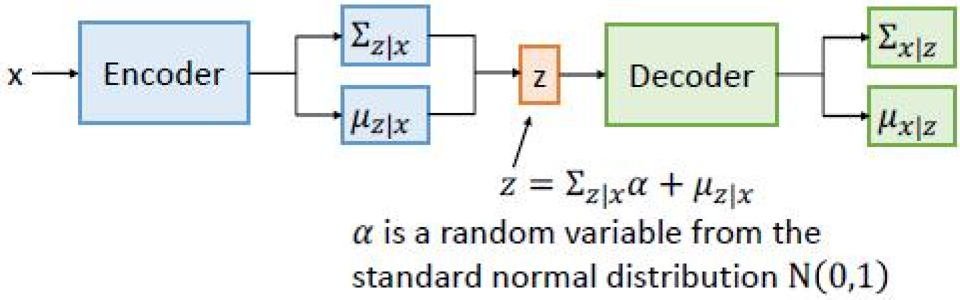
- Probabilistic encoder learns p(z|x)

  - Input: image x
  - Output: mean $\mu_{z|x}$ and diagonal covariance $\Sigma_{z|x}$, a Gaussian distribution over latent variables conditional on x



  - Learns approximation of $p(z|x)$: $q(z|x) = \mathrm{N}(\mu_{z|x}, \Sigma_{z|x})$

- Encoder and decoder are concatenated and trained jointly



- Goal: maximize the likelihood p(x)
- Loss is based on variational lower bound on p(x):

$$\log(p(x)) \geq E_{z \sim q(z|x)}[\log(p(x|z))] - D_{KL}(q(z|x), p(z))$$

Log likelihood of image x

Reconstruction quality: expected log likelihood of Decoder's reconstruction, with respect to Encoder's distribution over inputs

Kullback-Leibler divergence between the Encoder's estimate of p(z|x) and our prior p(z)=standard normal distribution

- Loss consists of two terms: reconstruction loss and regularisation loss
  - Reconstruction loss: encourages network to create output images as similar as possible to input images
  - Regularisation loss: encourages network to learn a latent representation z that is similar to the prior (standard normal distribution)
- Properties of the latent space
  - To be useful for generation, the latent space should be:
    - Continuous: nearby points in the latent space correspond to similar images
    - Complete: every point in the latent space corresponds to a valid image
  - Standard normal distribution satisfies both of these requirements
  - Use of diagonal covariance matrices ensures latent variables are independent
  - Latent space visualisation L9.1 P43
- Applications
  - Sampling new images L9.1 P41-42
  - Image manipulation L9.1 P44-46
    - Given the latent-variable representation z of image x, can change values of z to create variations on x
    - Nearby points in latent space correspond to similar images (continuity requirement) and axes are independent
    - But directions in latent space may not correspond to recognizable image properties (without additional constraints)
- Advantages
  - Learn approximations of p(z|x) and p(x|z), where z is a latent variable representation of the input x
  - Can be used to generate new instances of x
- Disadvantage: Outputs often blurry
  - Because of compression
  - More recent VAEs use better image representations to reduce blur

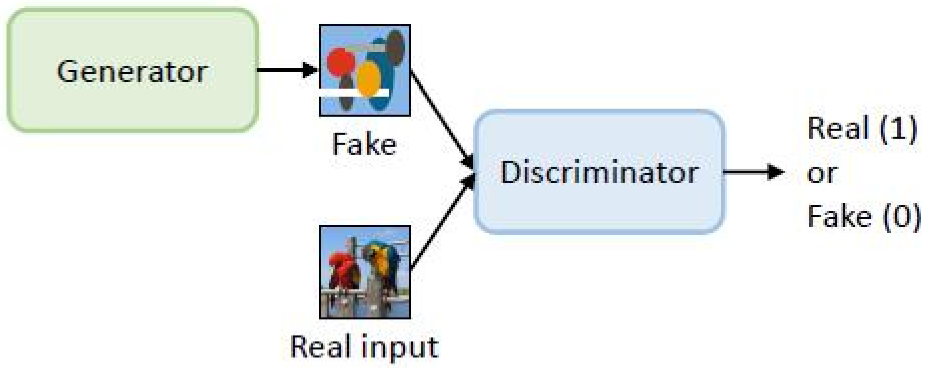
Summary - Autoencoder

- Autoencoders assume images can be generated from a low-dimensional space of latent variables
- Regular autoencoder – learns latent representation to reconstruct images
- Variational autoencoder – probabilistic version of autoencoder, can sample from the latent space

Generative Adversarial Networks (GANs)

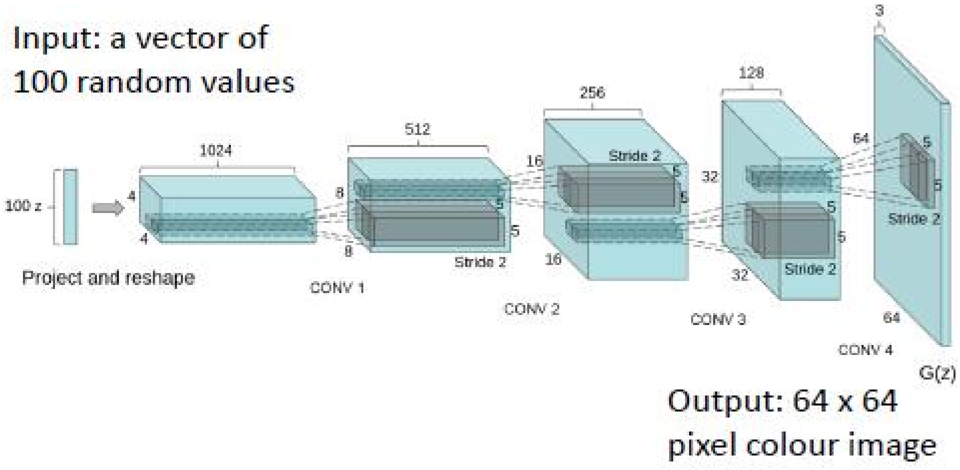
GAN architecture

- Generative Adversarial Networks (GANs) are neural networks that learn to generate instances from a particular distribution (e.g., images of faces)
- Actually consist of two neural networks: a generator and a discriminator
- Training involves a sort of competition between the two networks
- GAN is a pair of networks trained together: generator creates images based on latent input z, discriminator judges whether images are real vs. fake



Generator

- GAN Generator doesn't actually learn the probability distribution p(x), but learns to sample from it
- Generator input is a latent variable z with a simple prior (e.g., uniform random or standard normal)
- Generator output is an image
- Generator network learns a function to map p(z) to a distribution that approximates p(x)



Discriminator

- Discriminator learns to identify real inputs vs. fake inputs created by generator
- Neural network classifier with two output classes (real, fake)
- Architecture depends on task: e.g., for images the discriminator might be a CNN with several convolutional layers, followed by softmax

Training

- The networks are trained together on a combination of real data $\mathbf{x}$ and generator input $\mathbf{z}$
- Given a generator G and discriminator D:
  - Discriminator's goal is to correctly classify real vs. fake
  - Discriminator wants to maximize $D(\mathbf{x})$ and minimize $D(G(\mathbf{z}))$
  - Generator's goal is to fool the Discriminator
  - Generator wants to maximize $D(G(\mathbf{z}))$
- Can treat this as a zero-sum game with the goal of finding equilibrium between G and D
- GAN training objective is a minimax game:

$$\underbrace{\min_G \underbrace{\max_D \Big(\underbrace{E_{x\sim p_{data}}[\log(D(x))]}_{\substack{\text{Discriminator's} \\ \text{response to real} \\ \text{images}}} + \underbrace{E_{z\sim p(z)}[\log(1-D(G(z)))]}_{\substack{\text{1 - Discriminator's} \\ \text{response to fake images} \\ \text{produced by Generator}}} \Big)}_{\substack{\text{The Discriminator tries to maximize this by} \\ \text{learning weights for D that will give D(x)=1 for} \\ \text{real images and D(G(z))=0 for fake images}}}}_{\substack{\text{The Generator tries to minimize this by learning} \\ \text{weights that will give D(G(z)) = 1}}}$$

- If the discriminator is too good:
  - Easily rejects all fake inputs
  - Not much information to train the generator
- If the discriminator is too bad:
  - Easily confused by fake inputs that don't look real
  - Generator will learn a poor solution
- Training can be difficult – hard to find a balance between discriminator and generator

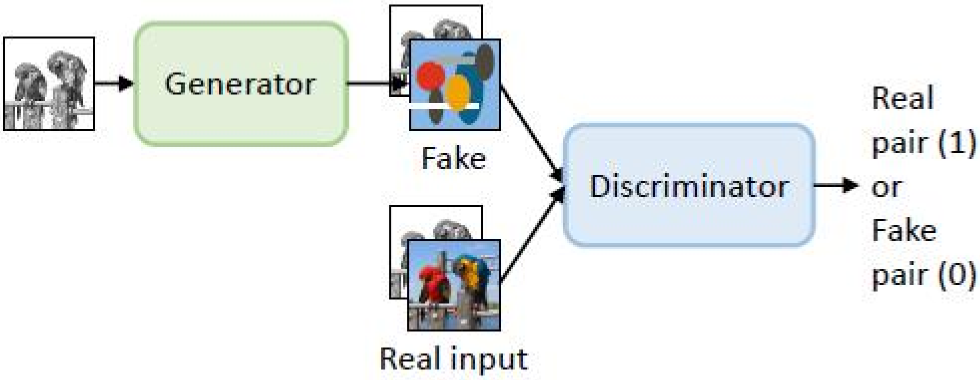
Evaluating GANs

- GAN equilibrium does not necessarily mean the GAN has found a good solution
- GAN evaluation is important, because successful training does not necessarily mean the generator's output is similar to p(x)
- Generally check for:
  - Memorisation
  - Realism
  - Diversity
- How to tell if a GAN has learned? Ideally:
  - Outputs should not be identical to inputs (memorised training data)

        - Visualise k nearest neighbours in training dataset L9.2 P22
    - Outputs should look like inputs (look “real” and not “fake”)
        - Evaluating realism L9.2 P24-26
            - Gold standard: human evaluation (but this is slow and expensive)
            - Automatic methods compare responses of an image classifier (e.g., a CNN trained on ImageNet) to real vs. GAN-generated images
        - Inception score
            - Within a class, all images should be confidently classified with the correct label
            - Across classes, the GAN should produce a wide variety of confidently-classified images
            - Advantages
                - Automatic, efficient
                - Neural network responses correlate with human judgements of image quality
            - Disadvantages
                - Doesn’t require high diversity within categories
                - Sensitive to noise, adversarial images
    - Outputs should be as diverse as real data (avoid mode collapse = the generator only creates one or a few outputs)
        - The GAN isn’t just memorizing training examples
        - But does it capture all of the diversity in the training set?
        - Birthday paradox L9.2 P31
            - Suppose a generator that can produce N discrete outputs, all equally likely
            - Experiment: take a small sample of s outputs and count duplicates
                - The odds of observing duplicates in a sample of size s can be used to compute N
                - A sample of about sqrt(N) outputs is likely to contain at least one pair of duplicates
        - Example duplicates L9.2 P33
        - Most GANs tested produced about the same diversity (number of different images) as was in their training set

Conditional GANs

- Conditional model: learn p(x|y) rather than p(x)
- Both Discriminator and Generator take y as additional input



- If x-y pairs are available, can use the standard GAN architecture with additional input y
- What if you don't have a dataset of real x-y pairs?
  - CycleGAN: train a pair of Generators to map x->y and y->x L9.2 P38-40

Summary - GANs

Advantages

- GANs can generate samples from complex probability distributions without actually representing the distribution

Disadvantages

- Can be unstable / hard to train
- Difficult to evaluate
- Even models that don't show complete mode collapse tend to have lower-than-desired diversity