Invertible Normalizing Flows

ECE57000: Artificial Intelligence, Fall 2019
David I. Inouye
Announcements

- Quiz moved to Friday
  - Same content (i.e., up to DCGANs, not today)
GAN Limitation:
Cannot compute density values

- Evaluation of GANs is challenging
  - (Explicit density models could use test log likelihood)
  - “I think this looks better than that”

- Inception scores
  - Train separate image classifier
  - See if passing fakes to classifier produces a high confidence prediction

- Cannot use for classification or outlier detection
GAN Limitation: Challenging to train because of careful balance between discriminator and generator

1. Assumptions on possible $D$ and $G$
   1. Theory – All possible $D$ and $G$
   2. Reality – Only functions defined by a neural network

2. Assumptions on optimality
   1. Theory – Both optimizations are solved perfectly
   2. Reality – The inner maximization is only solved approximately, and this interacts with outer minimization

3. Assumption on expectations
   1. Theory – Expectations over true distribution
   2. Reality – Empirical expectations over finite sample; for images, much of the high-dimensional space does not have samples

- GANs can be very difficult/finicky to train
GAN Limitation: Cannot go from observed to latent space, i.e. $x \rightarrow z$ not possible/easy

- Cannot manipulate an observed image in latent space
  - Cannot do the following, $x \rightarrow z$, $z' = z + 3$, $z' \rightarrow x'$
  - Rather, must start from fake image based on random $z$

All fake images->
Normalizing flows use invertible deep models for the generator which allow more capabilities

- Transforming between observed/input and latent space is easy
  - \( x = G(z) \)
  - \( z = G^{-1}(x) \)

- Simple sampling like GANs
  - \( z \sim \text{SimpleDistribution} \)
  - \( x = G(z) \sim \hat{p}_g(x) \), which is estimated distribution

- **Exact density** is computable via change of variables
  - Standard maximum likelihood estimation can be used for training
Highly realistic random samples from powerful flow model (GLOW)

Figure 1: Synthetic celebrities sampled from our model; see Section 3 for architecture and method, and Section 5 for more results.
Interpolation between real images using GLOW

Figure 5: Linear interpolation in latent space between real images.

Transformations of real image along various features

Figure 6: Manipulation of attributes of a face. Each row is made by interpolating the latent code of an image along a vector corresponding to the attribute, with the middle image being the original image.
Back to maximum likelihood estimation (MLE): **How** can we compute the likelihood for normalizing flows?

- **Suppose**
  - \( z \sim \text{Uniform}([0,1]) \), i.e., \( p_z(z) = 1 \) (latent space is uniform)
  - \( G(z) = 2z \)
  - Thus, \( x = G(z) = 2z \).

- What is the density function of \( x \), what is \( p_x(x) \)?