VAEs and GANs

Mihaela Rosca
@elaClaudia

Thanks to Shakir Mohamed, Balaji Lakshminarayanan
What are the biggest problems with training GANs?
Maximum likelihood

Find the model which gives highest likelihood to the data.

\[
\text{argmax}_\theta \mathbb{E}_{x \sim p^*} \log p_\theta(x)
\]
Maximum likelihood

Find the model which gives highest likelihood to the data.

\[ \arg\max_{\theta} \mathbb{E}_{x \sim p^*} \log p_{\theta}(x) \]
Maximum likelihood with latent variables

Leverage underlying data structure in generative process.

\[ p_\theta(x) = \int p_\theta(x|z)p(z)dz \]

\( z = \) latents
\( x = \) observed
Maximum likelihood with latent variables
Maximum likelihood with latent variables

$q(z|x)$
Maximum likelihood with latent variables

- explain $x$
- stay close to $p(z)$

$q(z|x)$
Variational autoencoders

\[ q(z|x) \]  
Encoder

\[ p(x|z) \]  
Generator

\[ \hat{z} \]  
\[ z \]  

\[ \text{explain } x \]  
\[ x_{\text{real}} \]  
\[ x_{\text{rec}} \]  

\[ KL \]

stay close to \( p(z) \)
Variational autoencoders

\[ KL[q_\eta(z|x) || p(z)] \]

\[ q(z|x) \Rightarrow \text{Encoder} \]

\[ x_{\text{real}} \]

\[ p(x|z) \Rightarrow \text{Generator} \]

\[ x_{\text{rec}} \]

\[ L \]

\[ \mathbb{E}_{q_\eta(z|x)} \left[ \log p_\theta(x|z) \right] \]
Variational autoencoders

- Encoder
  - $x_{real}$
  - $\hat{z}$

- Generator
  - $x_{rec}$

- KL divergence
  - $KL(\hat{z}, z)$

- Loss function
  - $L$

The variational autoencoder learns how to reconstruct by bringing samples close to reconstructions.
Inference

Learning distributions over representations.

Why:
- quantifying uncertainty
- imposing prior structure over learned representations
Imposing prior structure over representations

Higgins et al., beta-VAE: Learning Basic Visual Concepts with a Constrained Variational Framework

Mihaela Rosca 2018
VAE distribution matching in visible space
VAE distribution matching in latent space

Data

Low posterior VAE samples

Rosca, Lakshminarayanan, Mohamed: Distribution matching in variational inference
VAEs match **marginal** distributions by matching **conditional** distributions.

\[
q(z|x) \quad \text{Encoder} \quad p(x|z) \\
\hat{z} \quad KL \\
x_{\text{real}} \quad x_{\text{rec}} \\
L \quad z
\]
VAEs match **marginal** distributions by using **explicit** distributions.
GANs

- Marginal distribution matching
- Implicit distributions
Combining GANs and VAEs

VAEs

Hybrids

GANs
The promise of VAE-GAN hybrids

- Improve sample quality
- Improve representation learning
The promise of VAE-GAN hybrids

- Improve sample quality
- Improve representation learning
- Improve stability
- Improve diversity
VAE-GAN hybrids

- Adversarial Autoencoder
- Adversarial Variational Bayes
- VEEGAN
- ALI/BiGAN
- AlphaGAN
- ...

DeepMind
VAE-GAN hybrids via density ratios

Estimate the ratio of two distributions only from samples, by building a binary classifier to distinguish between them.

\[
\frac{p(x)}{p_\theta(x)} = \frac{\mathcal{D}(x)}{1 - \mathcal{D}(x)}
\]
Do VAE-GAN hybrids improve inference?
Adversarial autoencoders

Marginal distribution matching in latent space. Implicit encoder distribution.

Replace KL with a discriminator matching marginal distributions.
The effect of adversarial training on bounds

![Graph showing the effect of adversarial training on bounds for VAE and AAE.](image)
Classifier probabilities can be used for learning, but not for estimation.
The effect of adversarial training on representations

Learned VAE representations are sparse.

Learned AAE representations are not sparse.
Large latent sizes

VAE

AAE
Do VAE-GAN hybrids improve generation?
Marginal matching and implicit distributions using GANs both in latent and visible space.

VAE - GAN Hybrid (VGH)
Joint space hybrids - VEEGAN

Directly match in joint space.

Srivastava et al: VEEGAN: Reducing Mode Collapse in GANs using Implicit Variational Learning
Improving GAN stability

Inception score

<table>
<thead>
<tr>
<th>Method</th>
<th>VAE</th>
<th>DC-GAN</th>
<th>WGAN-GP</th>
<th>VEEGAN</th>
<th>AAE</th>
<th>VGH</th>
<th>VGH++</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inception score</td>
<td>2.0</td>
<td>3.5</td>
<td>4.5</td>
<td>5.5</td>
<td>6.0</td>
<td>7.5</td>
<td>8.0</td>
</tr>
</tbody>
</table>
Improving GAN stability

- Wasserstein distance

VAE  DC-GAN  WGAN-GP  VEEGAN  AAE  VGH  VGH++
Improving GAN diversity

- noised test set diversity
- test set diversity

Sample diversity

- VAE
- DC-GAN
- WGAN-GP
- VEEGAN
- AAE
- VGH
- VGH++
Improving VAE sample quality

VAE

VEEGAN

DeepMind

Mihaela Rosca 2018
Improving GAN sample quality

DCGAN

VEEGAN
At present, VAE-GAN hybrids do not improve distribution matching in latent and visible space.
Wait - how about CycleGAN?
Monet ↔ Photos
Monet → photo
photo → Monet
Zebras ↔ Horses
zebra → horse
horse → zebra
Summer ↔ Winter
summer → winter
winter → summer
Zhu, Park, Isola, Efros: Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks
But...

- Image to image translation versus image generation
  - No latent variables
  - More constrained
  - Easier to do architecture search
Currently, VAE-GANs do not deliver on their promise to stabilize GAN training or improve VAEs.
Currently, VAE-GANs do not deliver on their promise to stabilize GAN training or improve VAEs.

If you want good samples, use GANs.
If you care about representation learning, use VAEs.
THANK YOU

Credits
Shakir Mohamed, Balaji Lakshminarayanan

Additional Credits