Open Questions about Generative Adversarial Networks

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Questions

1. What are the trade-offs between GANs and other generative models?
2. What sorts of distributions can GANs model?
3. How can we Scale GANs beyond image synthesis?
4. What can we say about the global convergence of the training dynamics?
5. How should we evaluate GANs and when should we use them?
6. How does GAN training scale with batch size?
7. What is the Relationship Between GANs and Adversarial Examples?
GANs Progress

Odena et al., 2016 [1]

Miyato et al., 2017 [3]

Zhang et al., 2018 [2]

Brock et al., 2018 [4]
Problem 1

What are the Trade-Offs Between GANs and other Generative Models?
Types of generative models

- Flow models
- Autoregressive models
- GANs

A.Odena: I’ve also left out VAEs entirely; they’re arguably no longer considered state-of-the-art at any tasks of record.
Types of generative models

**GAN:** minimax the classification error loss.

**VAE:** maximize ELBO.

**Flow-based generative models:** minimize the negative log-likelihood
Autoregressive generative models

- Autoregressive generative models are well known for sequence data (language modeling, time series, etc.)
- Less obviously applicable to arbitrary (non-sequential) observations

\[
p(x) = \prod_{k=1}^{D} p(x_k | x_{<k})
\]
Flow model example: Glow
Glow: interpolation in latent space
Glow: Manipulation of face attributes

(a) Smiling
(b) Pale Skin
(c) Blond Hair
(d) Narrow Eyes
(e) Young
(f) Male
Glow: Sampling temperature
Autoregressive example: PixelCNN
PixelCNN: generated from high-level latent representation
PixelCNN: Linear interpolation
Gan example: StyleGAN

(a) Traditional

(b) Style-based generator
StyleGAN: combining latent
### CAP theorem?

<table>
<thead>
<tr>
<th></th>
<th>Parallel</th>
<th>Efficient</th>
<th>Reversible</th>
</tr>
</thead>
<tbody>
<tr>
<td>GANs</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>Flow Models</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Autoregressive Models</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
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Problem 2

Given a distribution, what can we say about how hard it will be for a GAN to model that distribution?
Easiest dataset?

- MNIST
- CelebA
- CIFAR-10
- STL-10
- Imagenet
Strategies

● Synthetic Datasets
  ○ Study synthetic datasets to probe what traits affect learnability

● Modify Existing Theoretical Results
  ○ Take existing results and try to modify different properties of the dataset
Are GANs Created Equal?

<table>
<thead>
<tr>
<th>Data Set</th>
<th>Avg. FID</th>
</tr>
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<tbody>
<tr>
<td>CELEBA</td>
<td>2.27</td>
</tr>
<tr>
<td>CIFAR10</td>
<td>5.19</td>
</tr>
<tr>
<td>FASHION-MNIST</td>
<td>2.60</td>
</tr>
<tr>
<td>MNIST</td>
<td>1.25</td>
</tr>
</tbody>
</table>

(a) Bias and variance  
(b) Mode dropping  
(c) VGG vs Inception
Are GANs Created Equal?

(a) High precision, high recall
(b) High precision, low recall
(c) Low precision, high recall
(d) Low precision, low recall
Problem 3

- How can GANs be made to perform well on non-image data?

- Does scaling GANs to other domains require new training techniques, or does it simply require better implicit priors for each domain?
Promising domains

- **Text**
  - Discrete
  - Can't compete with LM

- **Structured Data**
  - One attempt on graphs

- **Audio**
  - Unsupervised audio synthesis
  - Outperform autoregressive models?
WGANG-GP character-level language model

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Geometric CNN

Diffusion distance
Anisotropic heat kernel
Geodesic polar coordinates
Problem 4

- When can we prove that GANs are globally convergent?
- Which neural network convergence results can be applied to GANs?
Techniques

● Simplifying Assumptions
  ○ Linear generator, gaussian data, and quadratic discriminator
  ○ Unimodal distributions

● Use Techniques from Normal Neural Networks
  ○ It’s argued that the non-convexity of deep neural networks isn’t a problem

● Game Theory
  ○ Some kind of approximate nash equilibrium
Problem 5

When should we use GANs instead of other generative models?

How should we evaluate performance in those contexts?
Proposed metrics

- Inception Score and FID
- MS-SSIM
  - Separately evaluate diversity
- AIS
  - Annealed importance sampling
- Geometry Score
- Precision and Recall
- Skill Rating
  - GAN discriminators can contain useful information
What should we use GANs for?

- Are not helpful for actual density model
- Focus GAN research on tasks where this is fine or even helpful

How evaluate?

- Humans
- Classifier two-sample test (C2STs)
Problem 6

- How does GAN training scale with batch size?
- How big a role does gradient noise play in GAN training?
- Can GAN training be modified so that it scales better with batch size?
Techniques

● Just do it
  ○ Some evidence improves quantitative results and reduces training time

● Optimal Transport GAN
  ○ Needs large batch

● Asynchronous SGD
  ○ Making use of new hardware
Problem 7

How does the adversarial robustness of the discriminator affect GAN training?
Is this concern realistic?

- Worry about accidental attacks
- Even accidental are less likely
  - Generator is only allowed to make one gradient update before the discriminator
  - Adversarial attacks are typically run for tens of iterations
  - Generator input is different every step
  - Optimization takes place in the space of parameters of the generator rather than in pixel space
References

- [https://distill.pub/2019/gan-open-problems/](https://distill.pub/2019/gan-open-problems/)
- CIFAR-CRM Deep Learning Summer School Université de Montréal, June 29th, 2017
- And 88 papers ...