Recent Progress in Generative Modeling

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Goal of OpenAI

- Make sure that AI is actually good for humanity
Goal of OpenAI

• Prevent concentration of AI power
• Build AI to benefit as many people as possible
• Build AI that will do what we want it to do
ML: what works?

- Deep supervised learning
  - Vision, speech, translation, language, ads, robotics
ML: what works?

- Deep supervised learning:
  - Get lots of input-output examples
  - Train a very large deep neural network
  - Convolutional or seq2seq with attention
  - Great results are likely
What’s next?

• Agents that achieve goals

• Systems that build a holistic understanding of the world

• Creative problem solving

• etc
Generative models

- Critical for many of the upcoming problems
What is a generative model?

• Learn your data distribution
  • Assign high probability to it
  • Learn to generate plausible structure
• Discover the “true” structure of the data
Generative models

• What are they good for?
• What can we do with them?
Conventional applications

• Good generative models will definitely enable the following:
  
  • Structured prediction (e.g., output text)
  
  • Much more robust prediction
  
  • Anomaly detection
  
  • Model-based RL
Speculative applications

- Really good feature learning
- Exploration in RL
- Inverse RL
- Good dialog that actually works
- “Understanding the world”
- Transfer learning
Generative models

- Three broad categories of generative models:
  - Variational Autoencoders
  - Generative adversarial networks
  - Autoregressive models
Improved techniques for training GANs

- Tim Salimans, Ian Goodfellow, Wojciech Zaremba, Vicki Cheung, Alec Radford, Xi Chen
Generative adversarial networks

- A generator $G(z)$ and a discriminator $D(x)$
- Discriminator aims to separate real data from generator samples
- Generator tries to fool the discriminator
- GANs often produce best samples so far
Generative adversarial networks

- Yann LeCun: *The most important [recent development], in my opinion, is adversarial training (also called GAN for Generative Adversarial Networks)*

  — from Quora Q&A session
Promising early results

• Best high-resolution image samples of any model so far:

  • Deep generative image models using a Laplacian pyramid of adversarial networks.
    — Denton et al.

  • DCGAN
    — Radford et al.
Hard to train

- The model is defined in terms of a minimax problem
- No cost function
- Hard to tell if progress is being made
Simple ideas for improving GAN training

- GANs fail to learn due to the collapse problem:
  - The generator becomes degenerate and the learning gets stuck
- Solution: the discriminator should see the entire mini batch
  - If all the cases are identical, it will be easier to discern
Results
Semi supervised learning with GANs

- Semi supervised learning is the problem of getting better classification using unlabelled data.
- A good generic semi supervised learning algorithm will improve all ML applications.
Semi supervised learning with GANs

• Discriminator should both tell the class of the training samples, and tell real samples from fake samples apart

• The specific way in which it is done is important, but it is technical, and I will not explain it

• The GAN training algorithm is also different here. Details are available offline.
Results

• MNIST: 50 supervised training cases + ensemble of 10 models = 1.4% test error

• CIFAR 10: 4000 supervised training cases = 18.5% test error

• Both results are new state of the art
Conclusions

• We have better methods for training GANs

• New simple way of using GANs to improve discriminative models

• New level of sample quality and semi-supervised learning accuracy
InfoGAN

• Xi Chen, Rein Houthooft, John Schulman, Ilya Sutskever, Pieter Abbeel
Disentangled representations

• Holy grail of representation learning
InfoGAN

- Train a GAN
- such that: a small subset of its variables is accurately predictable from the generated sample
- Straightforward to add this constraint
Actually works!
Exploration with generative models

• Rein Houthooft, Xi Chen, John Schulman, Filip De Turck, Pieter Abbeel
The problem

• In reinforcement learning, we take random actions
• Sometimes the actions do us good
• Then we do more of these actions in the future
Exploration

• Are random actions the best we can do?

• Surely not
Curiosity

- Key idea: take actions to maximize “information gain”
Formally

- Learn a Bayesian generative model of the environment
- For the action taken, calculate the amount of information gained about the environment by the generative model
- Add the amount of information to the reward
Actually works

- Extremely well on low-D environments
- Many unsolvable problems become solvable
- Current work: scaling up to high-D environments
Improving Variational Autoencoders with Inverse Autoregressive Flow

• Durk Kingma, Tim Salimans, Max Welling
The Helmholtz Machine

- Latent variable model
- Use an approximate posterior
- Maximize a lower bound to the likelihood
- Has been impossible to train
Reparameterization Trick

- The Helmholtz machine has been forever impossible to train

- The reparameterization trick of Kingma and Welling fixes this problem, whenever the latent variables are continuous
High-quality posterior

- Approximate posteriors matter
- Typical approximate posteriors are very simple
- Normal way of doing powerful posteriors is very expensive
- IAF = a new cheap way of getting extremely powerful posteriors
Results

• Best non-pixel-CNN log probabilities on CIFAR-10
• Excellent samples
• Currently training huge ImageNet models
Questions?