Recent Progress in Generative Modeling

Ilya Sutskever

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.

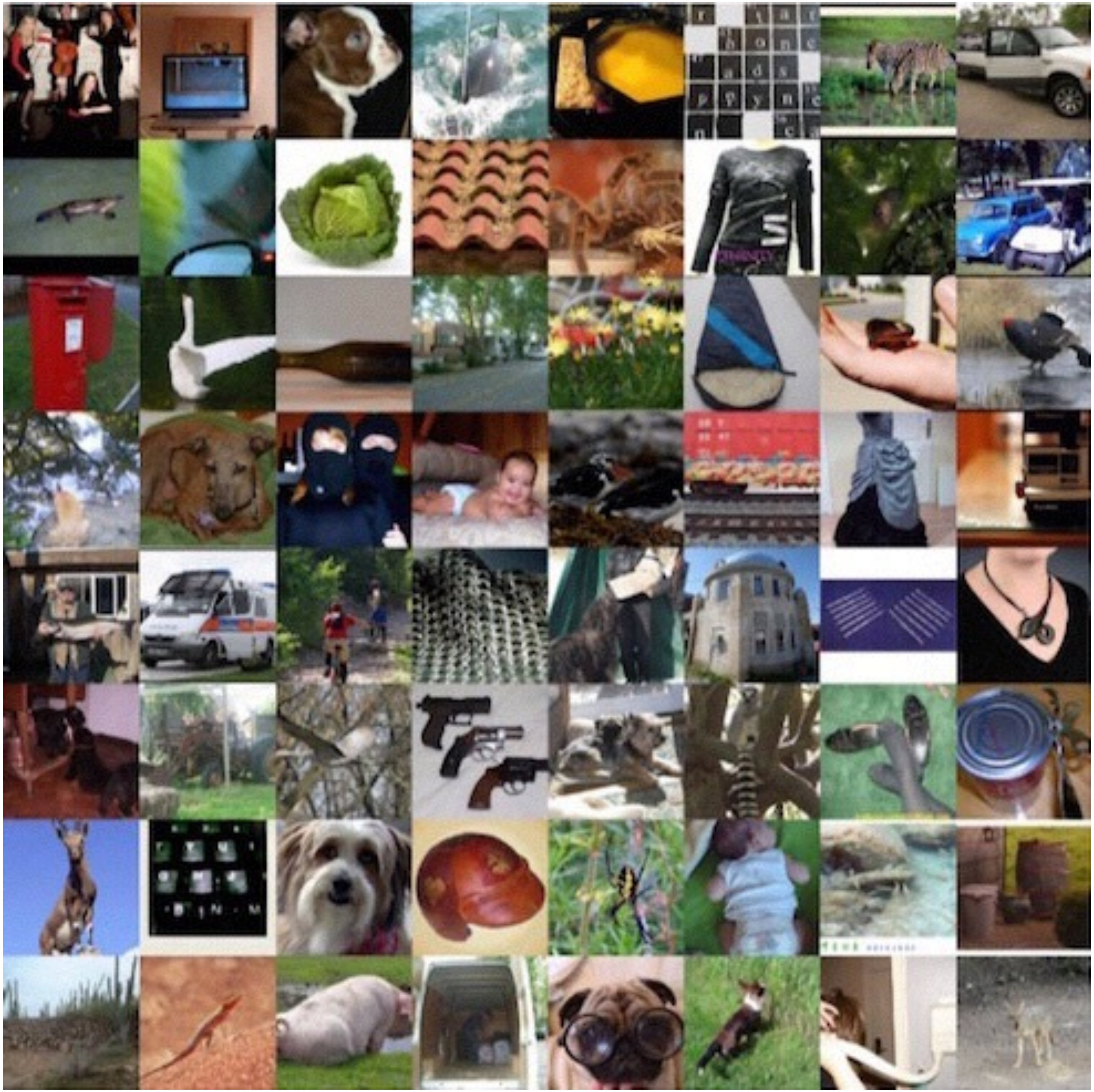
Hard to train

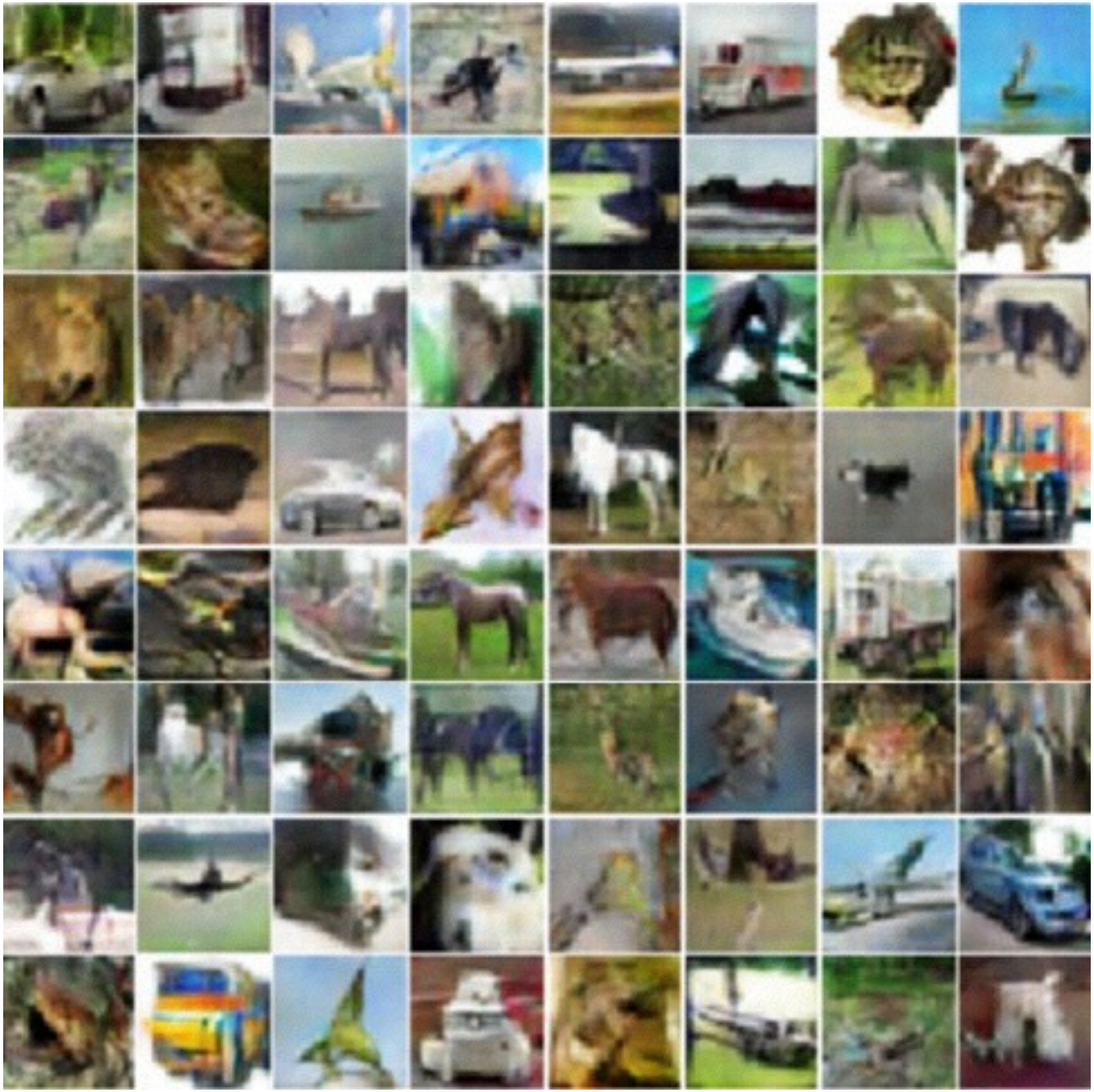
- The model is defined in terms of a minimax problem
- No cost function
- Hard to tell if progress is being made

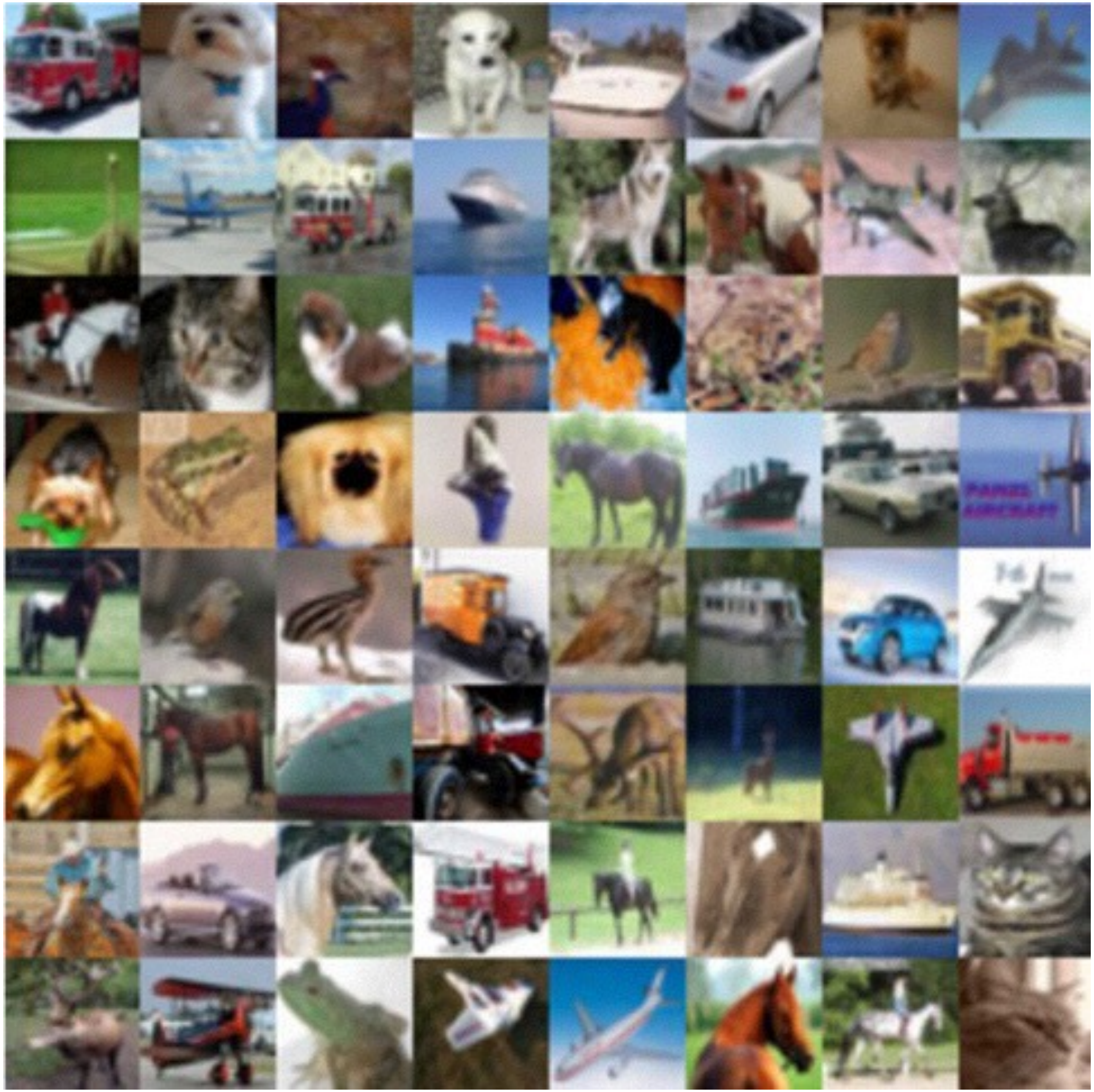
Simple ideas for improving GAN training

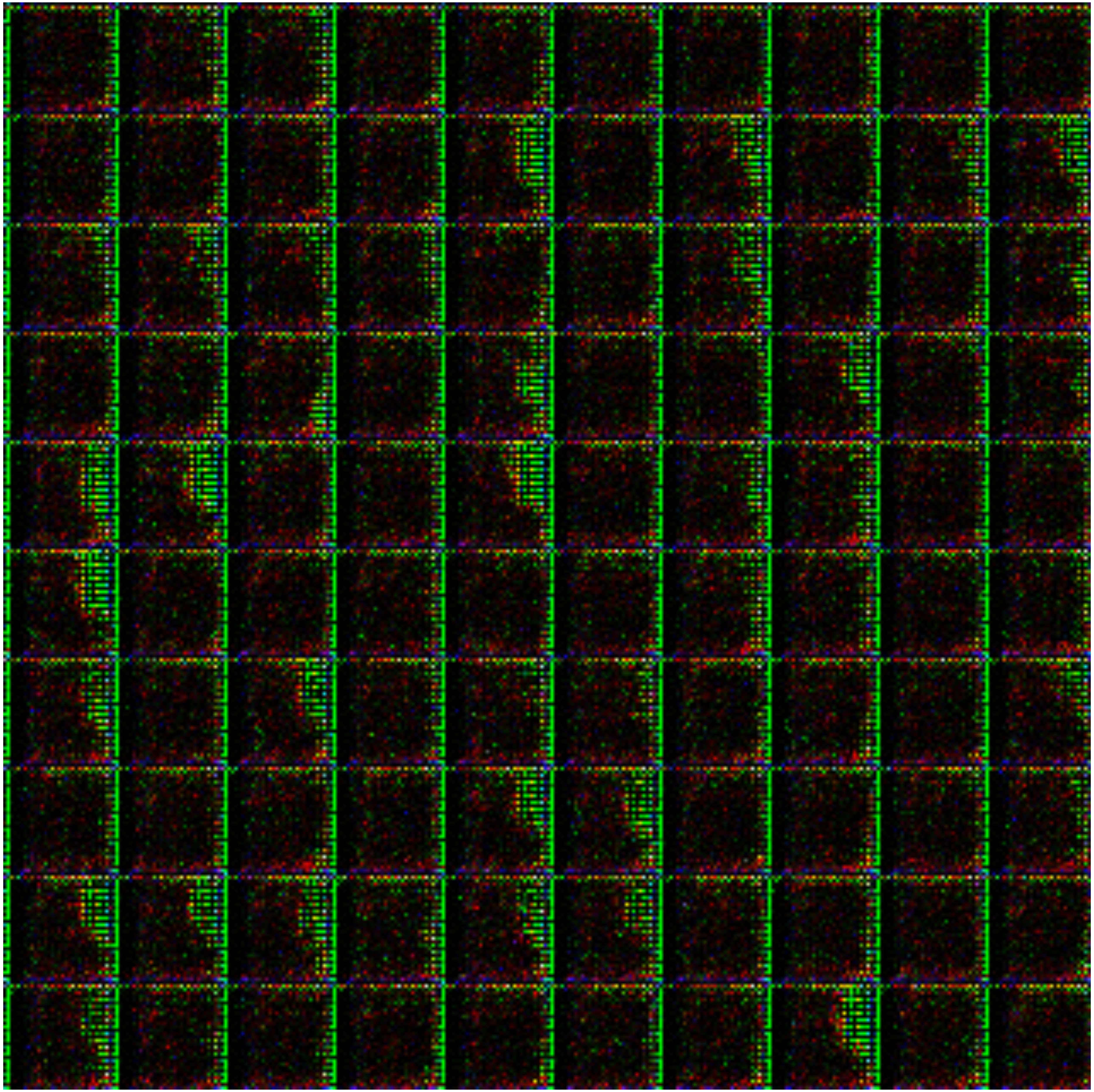
- GANs fail to learn due to the *collapse problem*:
  - The generator becomes degenerate and the learning gets stuck
- Solution: the discriminator should see the entire mini batch
  - If all the cases are identical, it will be easier to discern

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

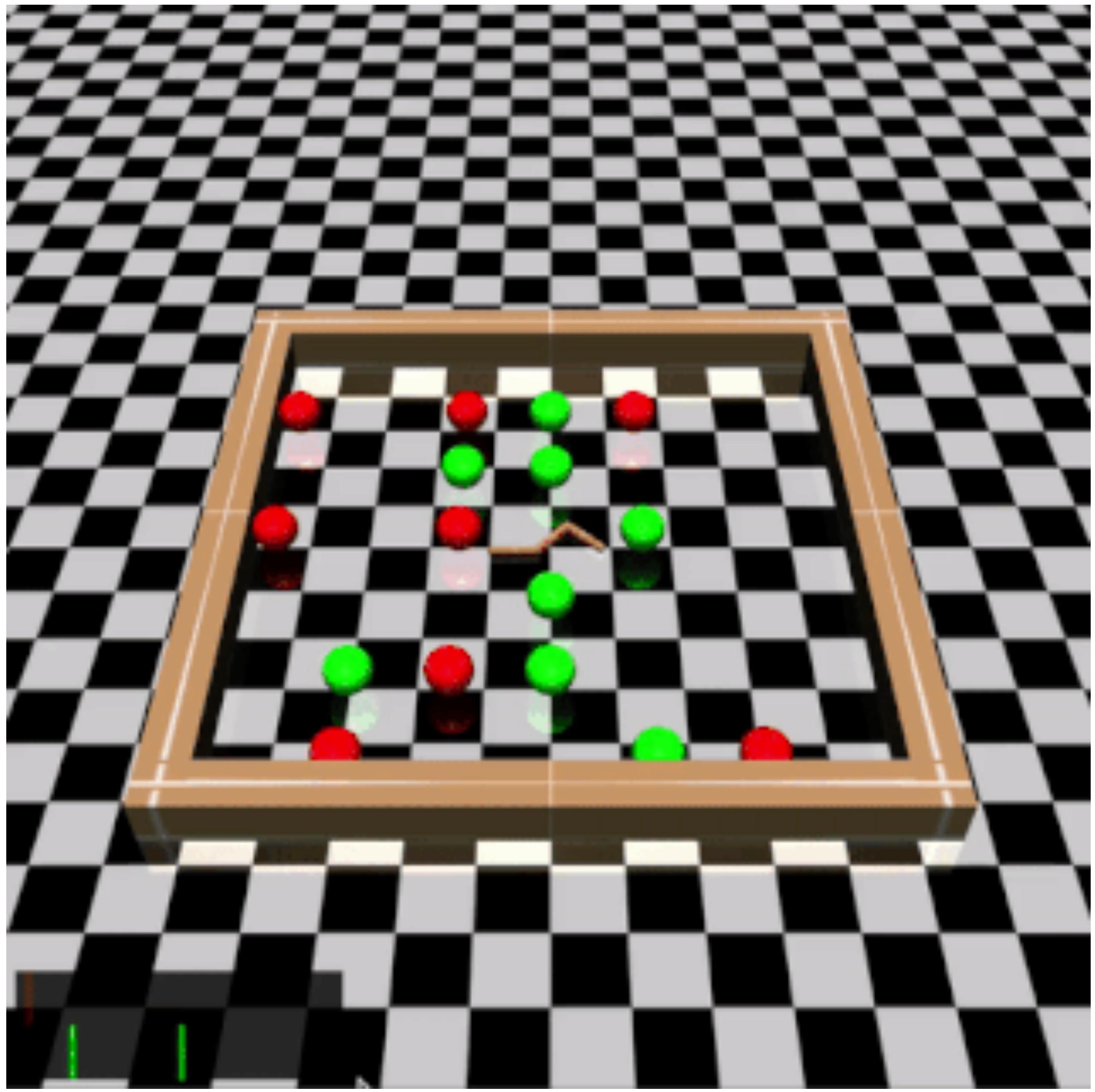
- Learn a Bayesian generative model of the environment

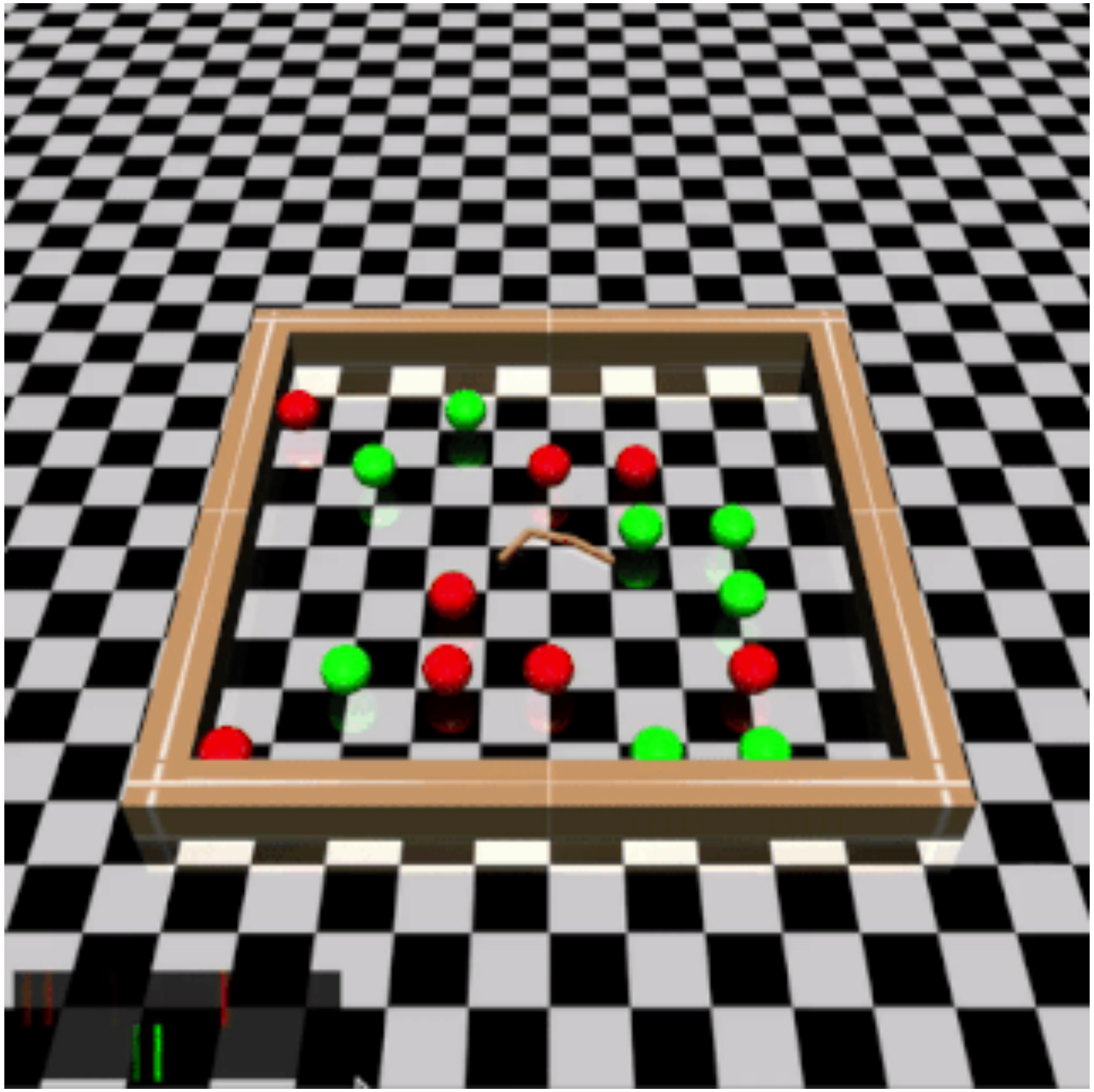
- For the action taken, calculate the amount of information gained about the environment by the generative model

- 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?