Challenges in GANs

Pavlos Protopapas

Game Theory

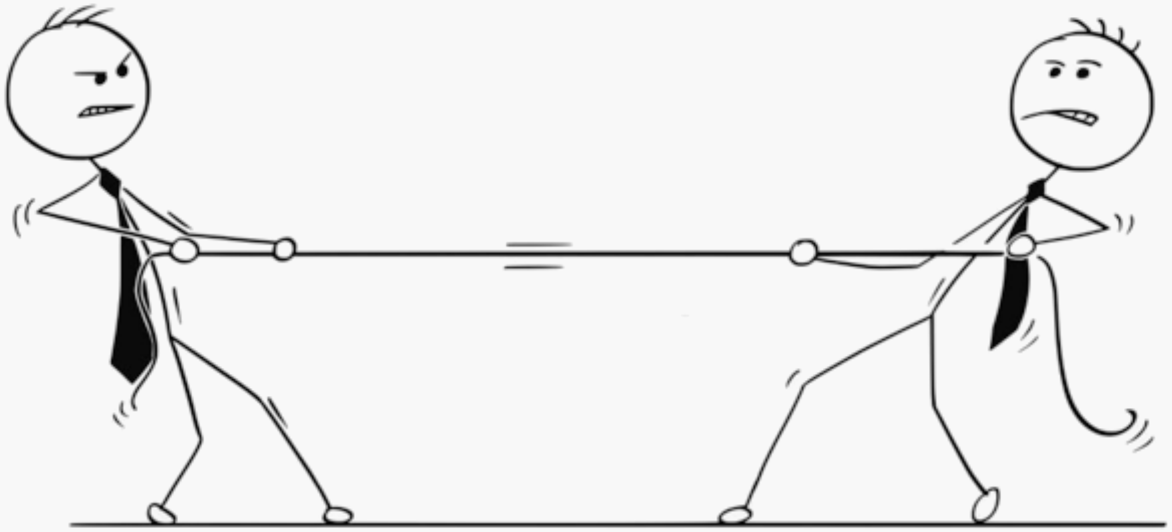
Positive-Sum Game: In some games there are unbounded resources. For example, in a game of poker, the pot can theoretically get larger and larger without limit.

Zero-Sum Game: Players compete for a fixed and limited
number of resources can change, the total number of resources remain constant.

Game Theory

In zero-sum games each player can try to set things up so that the other

minimax, or **minmax**, technique.



Winner Loser

Game Theory

Our goal in training the GAN is to produce two networks that are each as good

Instead, both networks have reached their peak ability given the other

Game theorists call this state a **Nash equilibrium**, where each network is at its best configuration with respect to the other.

Challenges: Convergence

Biggest challenge to using GANs in practice is their sensitivity to both structure and parameters.

If either the discriminator or generator gets better than the other too quickly, the other will never be able to catch up.

Also, there is no proof that they will **converge**.

GANs do seem to perform very well most of the time when we find the right parameters, but there's no guarar

Challenges: High Resolution Images

- easy for the discriminator to tell the generated fakes from the real images.

- Many pixels can lead to error gradients almost random directions, rather than getting closer to matching the inputs.

- Compute power, memory, and time to process large numbers of these big samples are also issues.

Challenges: High Resolution Images

Solution:

- Start by resizing the images: 512x512, 128x128, 64x64, ,4x4.
- Then build a small generator and discriminator, each with just a few layers of convolution.
- Train with the 4 by 4 images until it does well.
- Add a few more convolution layers to the end network, and now train them with 8 by 8 images.
- Again, when the results are good, add some more convolution layers to the end of each network and train them on 16 by 16 images.

More on this in the upcoming lectures!

Challenges: Mode collapse

We would like to use GAN to produce faces like the ones below from NVIDIA.

But the generator somehow finds one image that fools the discriminator.

Challenges: Mode collapse

A generator could then just produce that image every time independently of the input noise.

The discriminator will always say it is real, so the generator has accomplished its goal and stops learning.

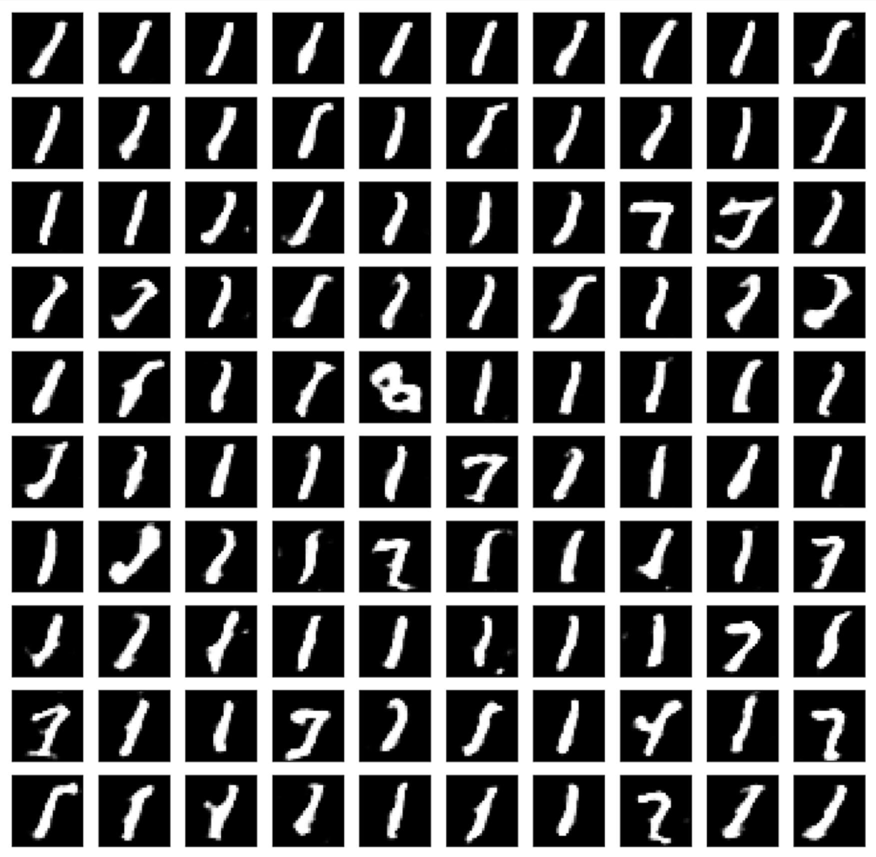
However, the problem is that every sample made by the generator is identical.

This problem of producing just one successful output over and over is called **mode collapse**.

Challenges: Mode collapse

Much more common is when the system produces the same few outputs, or minor variations of them.

This is called partial mode collapse.



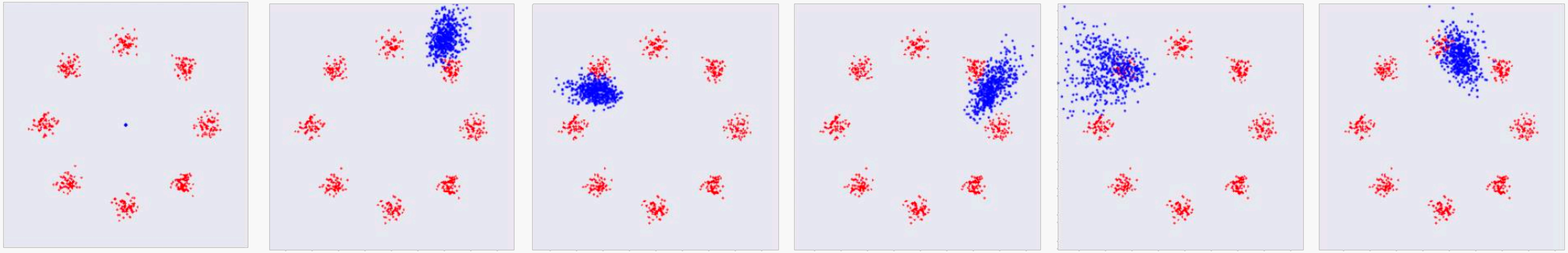
Challenges: Mode collapse

How do we deal with mode collapse?

- Extend the loss function with an additional term to measure the diversity of the outputs produced. If the outputs are all the same, or nearly the same, the discriminator can assign a larger error to the result.

- Use Wasserstein GAN   Covered in the next!

Challenges: Modal collapse

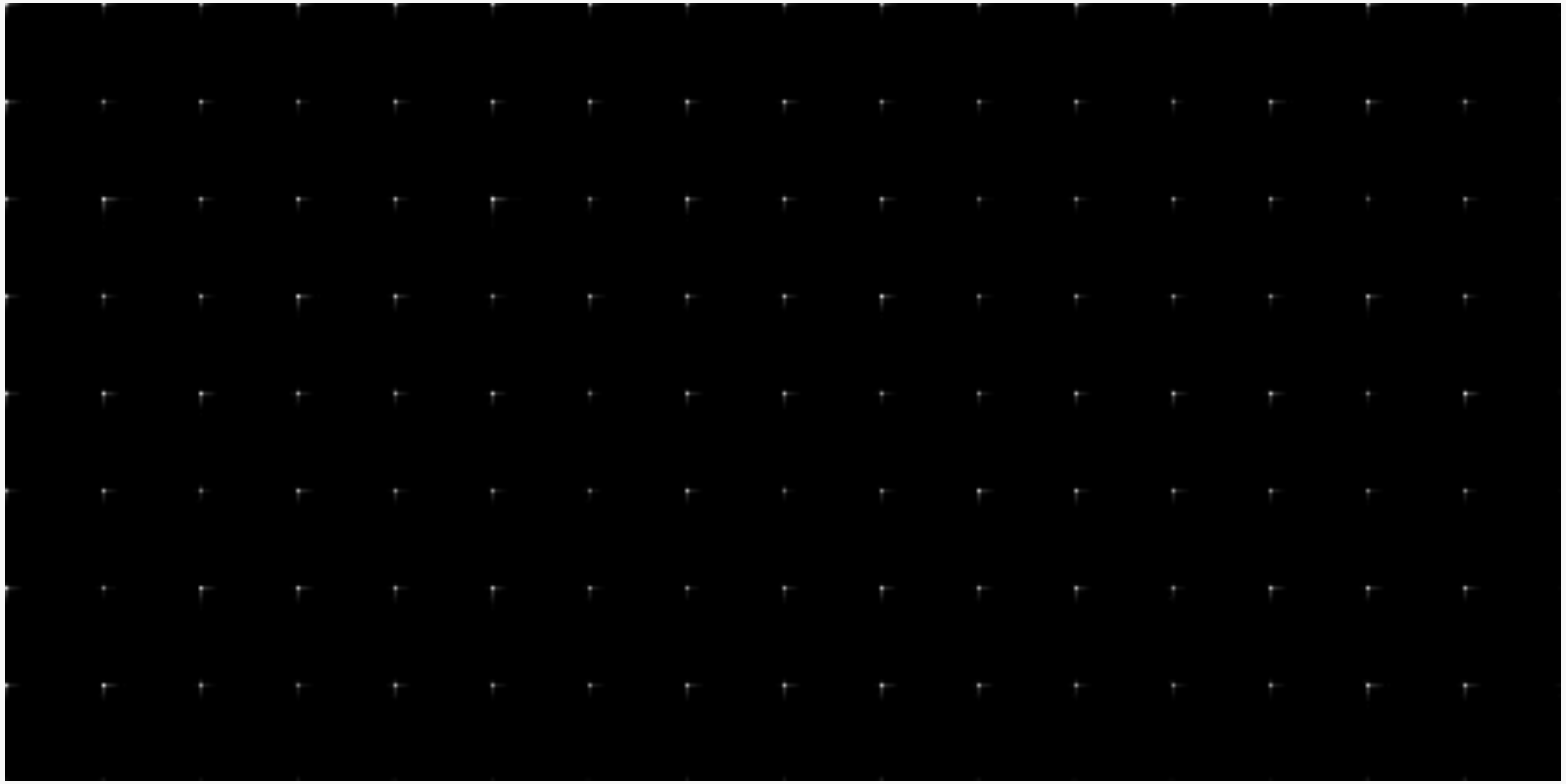


Step 0 | Step 5k | Step 10k | Step 15k | Step 20k | Step 25k

Mode Collapse seen for generated data (blue) compared to real data (red).

[Source]

Challenges: Modal collapse



Credit: German Garcia Jara