Implicit competitive regularization

Implicit competitive regularization in GANs

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What is the solution of a GAN

- Given a loss function L, the GAN objective is written as

$$\min_{\mathcal{G}} \max_{\mathcal{D}} L(\mathcal{G}, \mathcal{D})$$

- But what does this actually mean?
- Three main interpretations in the literature

What is the solution of a GAN

- **Viewpoint 1:** *GANs are defined by both players performing Gradient descent on their respective objective.*
- Problem: Simultaneous/alternating gradient descent has poor convergence properties
- Interpretation gives little guidance as to how to improve

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What is the solution of a GAN

- **Viewpoint 2:** *GANs are defined as minimizing (over $\mathcal{G}$) a function defined as maximum over $\mathcal{D}$*
- Problem: The resulting divergence (of the original GAN) is maximal almost everywhere for finite data distributions
- Mitigated by gradient penalties (WGAN etc.), but those require explicit choice of distance measure between samples

What is the solution of a GAN

- **Viewpoint 3:** *GANs are defined as trying to find a local Nash equilibrium of the minimax game*
- Problem: Alternating gradient descent often finds points that are *not* locally minimax
- These points can be good generative models
- Both algorithms guaranteed to converge to local Nash, and alternative notions of local equilibrium have been proposed

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Modeling algorithms as competing agents

- **Our point of view:** *GANs are modeled as agents competing in an iterative game.*
- Rather than devising new loss functions or local equilibrium concepts, embrace the modeling of agent behavior
- *"The goal is to capture the other player's king"* is not enough to model the *dynamics* of chess.

Modeling algorithms as competing agents

- Similarly, a loss function and a local solution concept are not enough to model GANs.
- Need to model:
  - What information do the players have access to?
  - Which *moves* are allowed?
  - What are the player's goals?
  - How do they account for each other's actions?

Modeling algorithms as competing agents

- We give an example where modeling of agent behavior stabilizes an otherwise unstable loss
- We provide empirical evidence that similar mechanisms are present in GAN training
- We provide a framework for modeling agent behavior based on their *beliefs*, *uncertainty*, and *anticipation* each other’s actions

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Implicit competitive regularization

- We show that CGD fits into this framework, and induces *implicit competitive regularization* (ICR)
- Extensive experiments on CIFAR10 show that CGD significantly improves robustness and performance
- Best results are obtained by CGD and WGAN loss (no gradient penalty). This can be seen as an integral probability metric associated to ICR.

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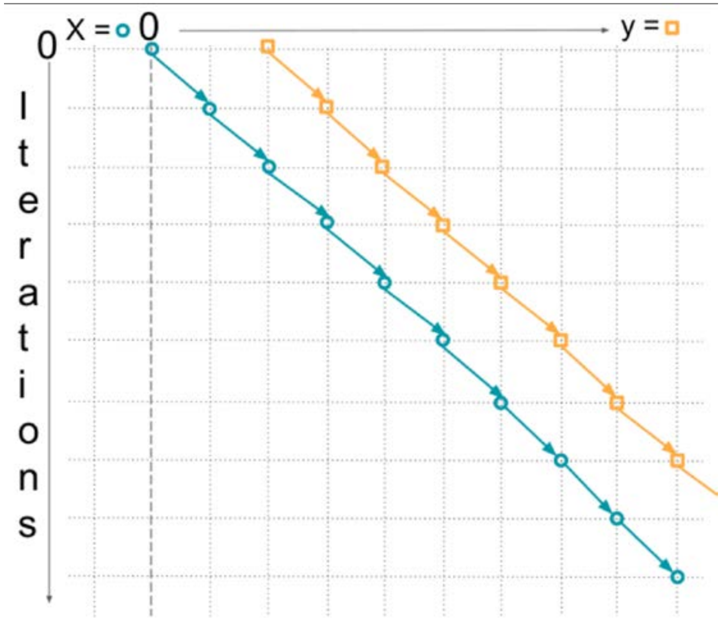
An illustrative example

- Consider the game
$$\min_x \max_y \; -\exp(x^2) - \alpha xy + \exp(y^2), \alpha \gg 1$$
- This game is meaningless when cast as minimization (over x) of a maximum over y
- It also does not have (local) Nash or Stackelberg equililbria. Does it have a meaningful solution?
- Consider three possible iterative games:

The global game

$$\min_x \max_y \; -\exp(x^2) - \alpha x y + \exp(y^2)$$

- Assume both players know the entire loss function
- They can move by a distance of at most 1.
- They aim to minimize their average loss in the limit of large numbers of iterations



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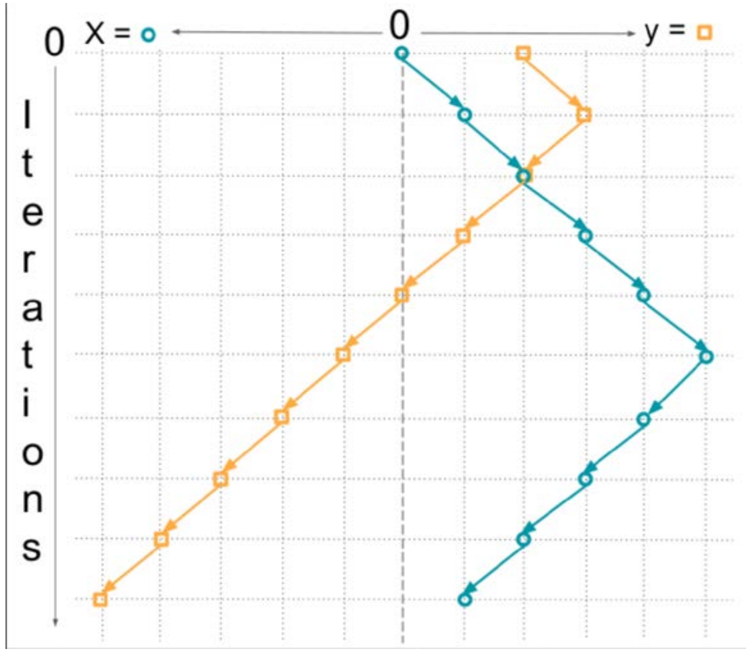
The myopic game

$$\min_x \max_y \; -\exp(x^2) - \alpha xy + \exp(y^2)$$

- Players only know their loss within distance 1
- They can move by a distance of at most 1.
- They aim to minimize their loss at the next iteration, assuming the other player to stay still



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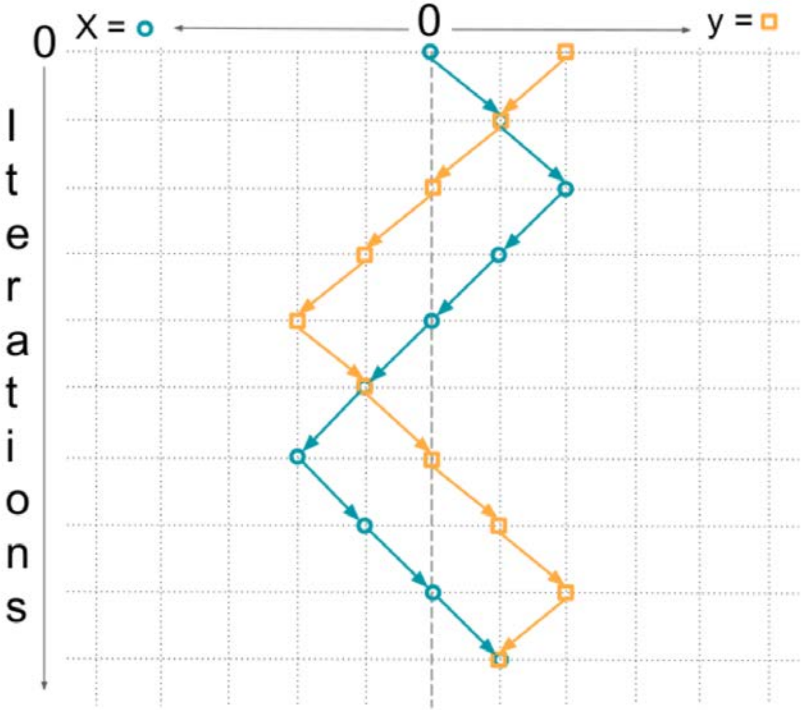
The predictive game

$$\min_x \max_y \; -\exp\left(x^2\right) - \alpha x y + \exp\left(y^2\right)$$

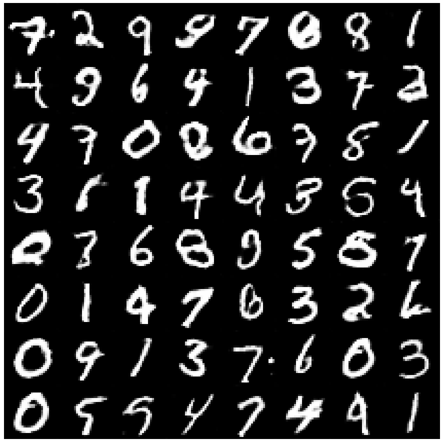
- Both players know both players’ loss in distance 1
- They can move by a distance of at most 1.
- They aim to minimize their loss at the next iteration, aware of the goals of the other player



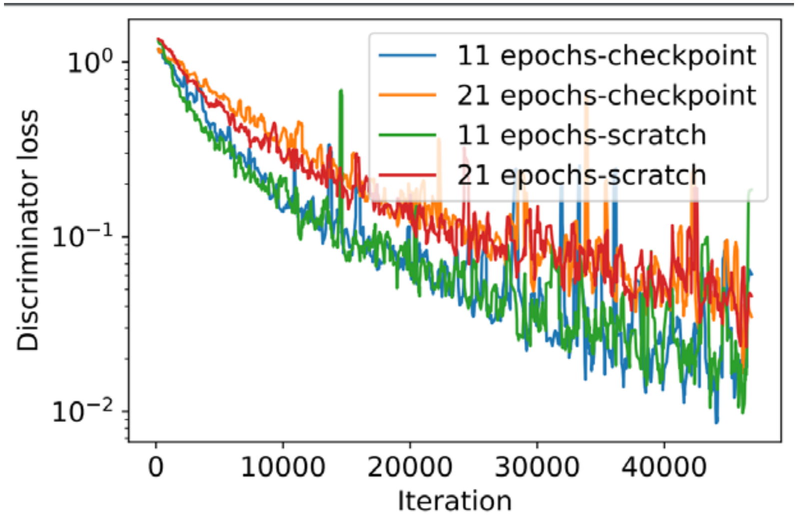
What about GANs?

- Limited information and awareness of their opponent could stabilize the example
- What does this have to do with GANs?

What about GANs?

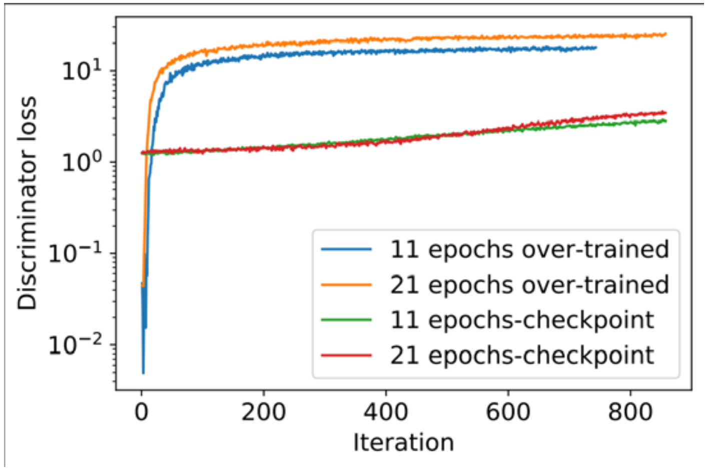


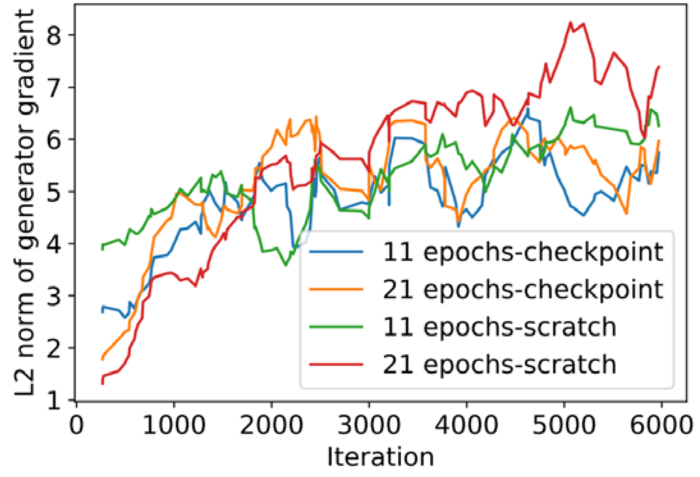
- Train a GAN on MNIST for 11 and 21 epochs
- Fix the generator and
  - Continue training the discriminator
  - Train the discriminator from scratch
- Discriminator loss drops!



What about GANs?

- Now, fix the "overtrained" discriminator and start training the generator
- Discriminator loss increases rapidly, beyond the original value!
- Indicated by increasing generator gradient





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Implicit competitive regularization

- A discriminator aware of its opponent would not overtrain, to avoid retaliation of the generator
- Thus, a suitable notion of rational behavior can regularize training even for loss functions that are meaningless as minimum of a maximum
- Claim: Competitive gradient descent uses this *implicit competitive regularization* to stabilize GAN training.

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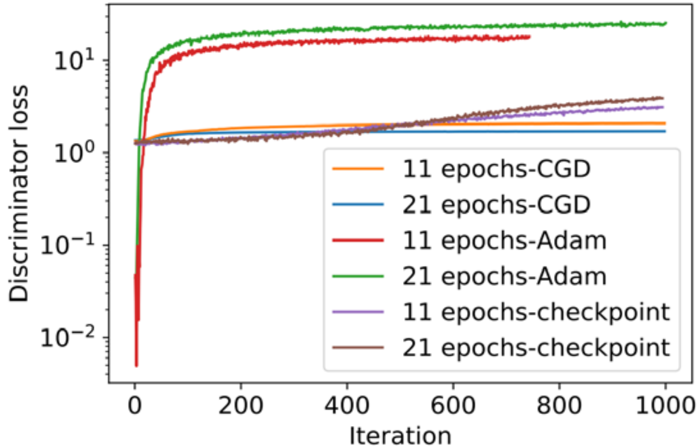
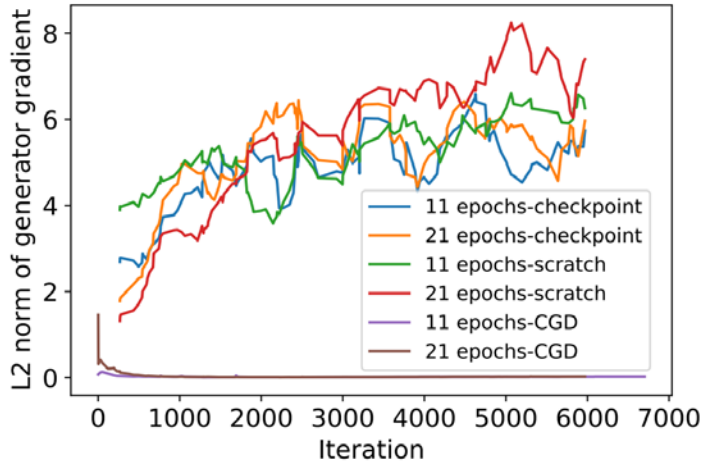
CGD uses ICR

- Proceed as before, but this time use CGD to overtrain the discriminator
- With CGD, the overtrained discriminator is *more* robust!





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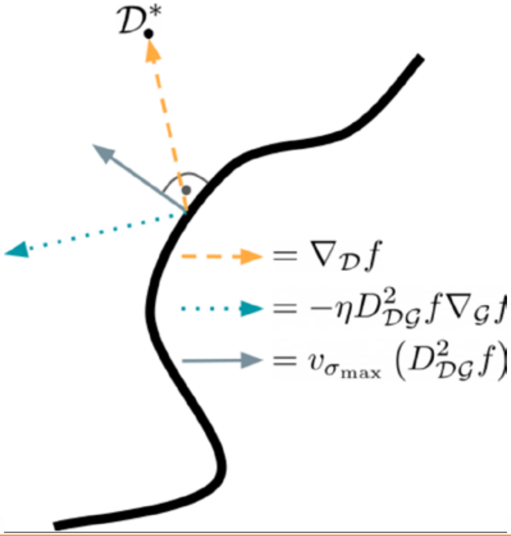
CGD uses ICR

- Consider again the CGD update

$$-\eta\left(\mathrm{Id} - \eta^2 D_{xy}^2 f\ D_{yx}^2 g\right)^{-1}\left(\nabla_x f - \eta D_{xy}^2 f\ \nabla_y g\right)$$

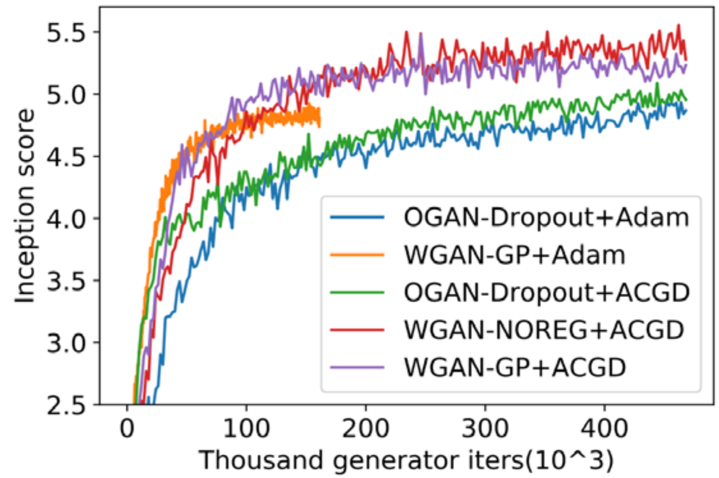
- The competitive term reduces the other player's gradient
- The equilibrium term favors updates close to a "robust manifold"

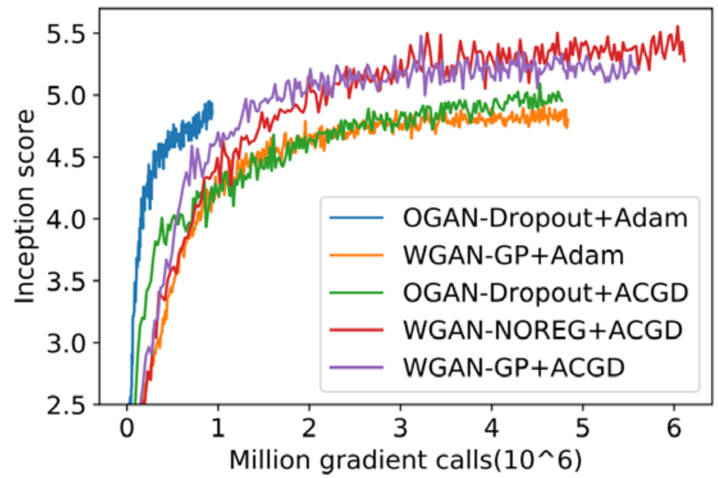


Numerical results

- We use architecture intended for WGAN-GP, no additional hyperparameter tuning
- Consider original and WGAN loss, regularized with gradient penalty, weight decay, or dropout
- Compare performance of Adam and ACGD (CGD with RMSProp)

Numerical results





- Best performance is achieved by WGAN loss with ACGD (and no regularization)
- Counting gradient calls, the original GAN with dropout achieves faster training

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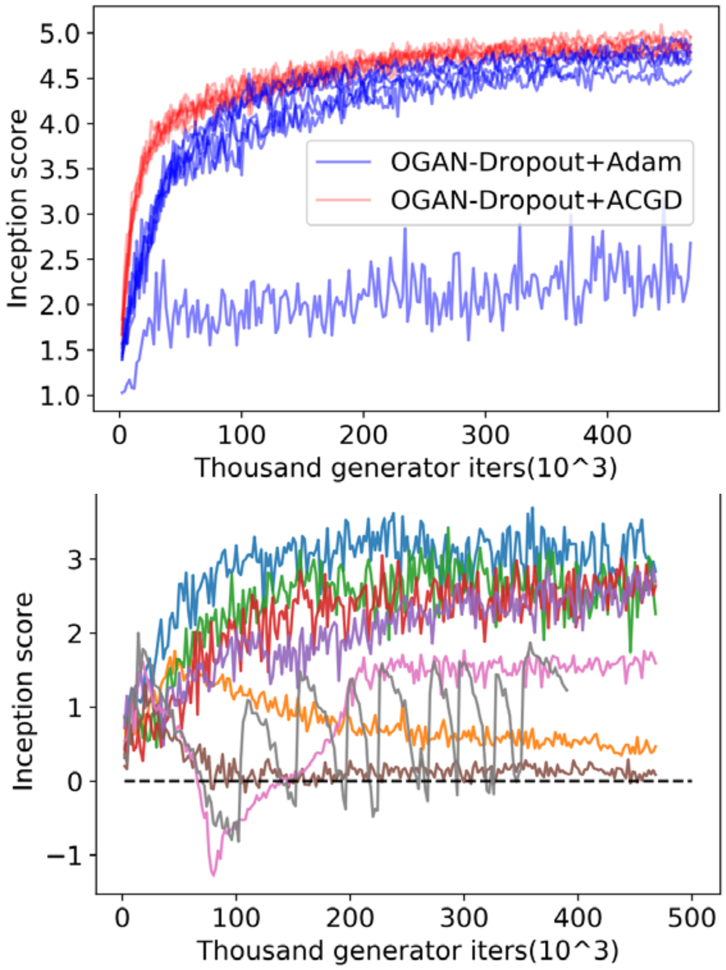
Numerical results

- We try different random seeds…
- …and models (plotting difference between inception scores)
- ACGD achieves significantly more consistent performance



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Conclusion

- We provide a mechanism, *implicit competitive regularization* (ICR), by which suitable notions of rational behavior can stabilize GAN training
- We show that CGD utilizes ICR to obtain stabilize GAN training, without any explicit regularization
- Outlook: Can we use more sophisticated modeling of agents to improve algorithms?

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