Universität Augsburg
Fakultät für Angewandte Informatik

Tutorial 10: Generative Adversarial Networks

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Generative Adversarial Networks

GANs

- Neural Networks that learn to mimic any distribution of data
  - Can be used to generate images, speech, music etc.
- Comprised of two nets, pitting one against the other (thus the “adversarial”)

Source: Zenva, youtube.com

Generative Adversarial Networks

GANs

- Two Adversarial Networks
  - **Discriminator**
    - Similar to networks you trained before
    - Maps features to labels
    - Learns the boundary between classes
  - **Generator**
    - Can be seen as the opposite to discriminative algorithms
    - Maps noise vectors to features
    - Models the distribution of individual classes

Generative Adversarial Networks

GANs

- Two-player minimax game

$$\min_G \max_D V(D,G) = \mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}(\boldsymbol{x})}[\log D(\boldsymbol{x})] + \mathbb{E}_{\boldsymbol{z}\sim p_{\boldsymbol{z}}(\boldsymbol{z})}[\log(1 - D(G(\boldsymbol{z})))].$$

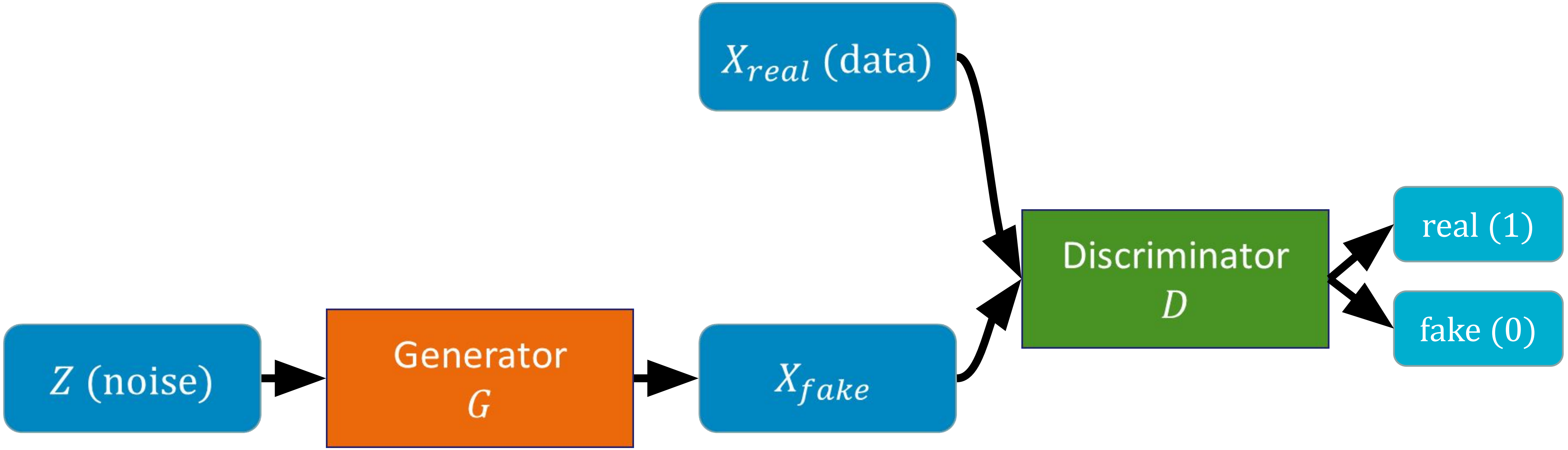
Discriminator output for real samples

Discriminator output for fake samples

- Train D to maximize the probability of assigning the correct label
- Train G to minimize log(1 - D(G(z)))

Generative Adversarial Networks

GANs



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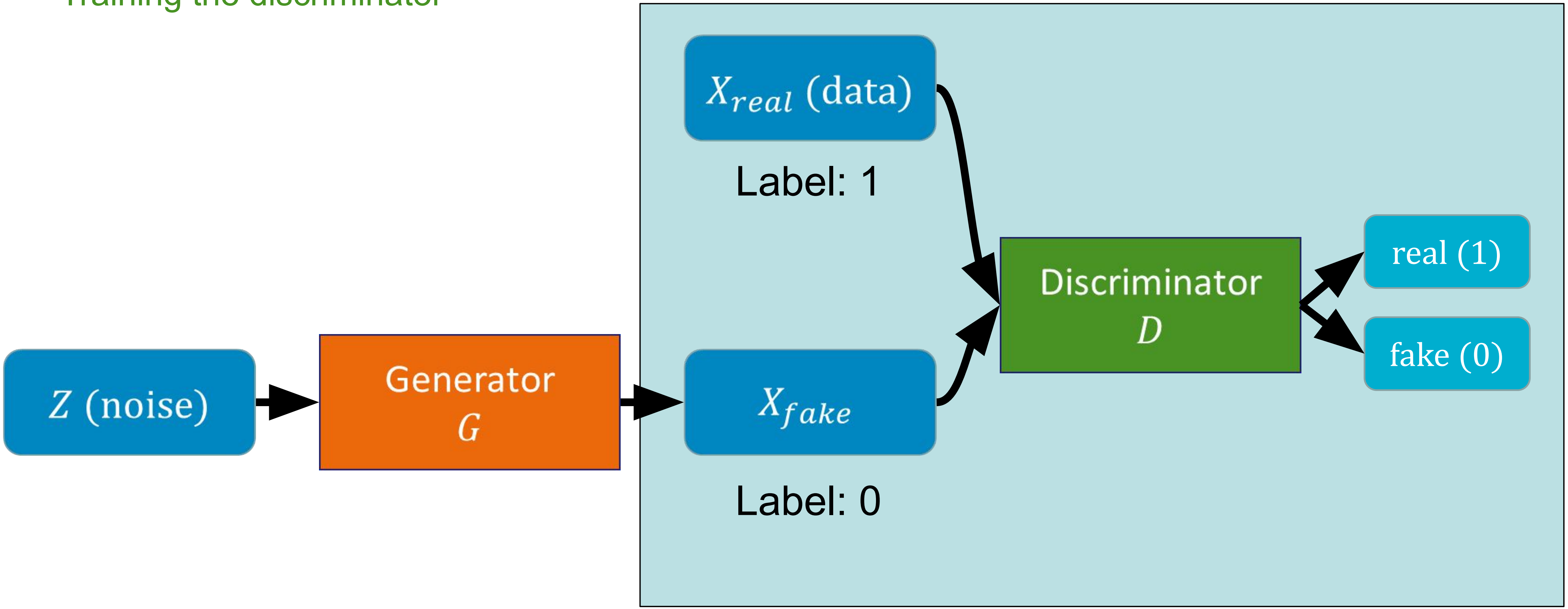
Training the discriminator



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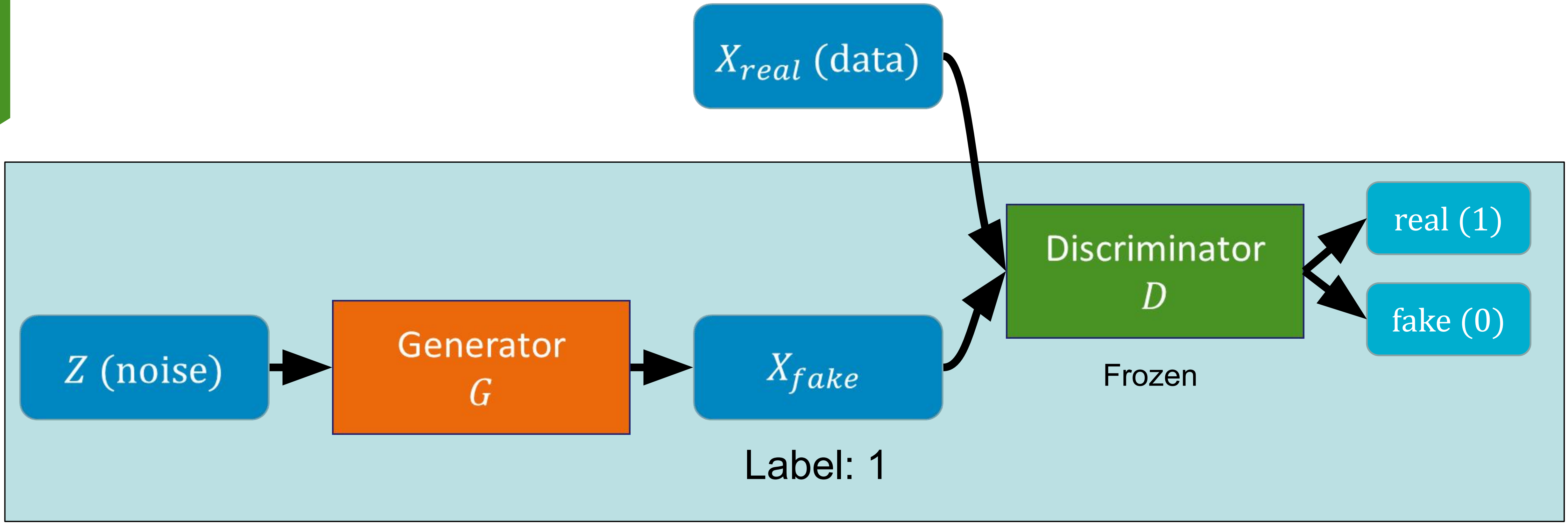
Training the generator



Generative Adversarial Networks

Examples

- MNIST

Generative Adversarial Networks

Examples

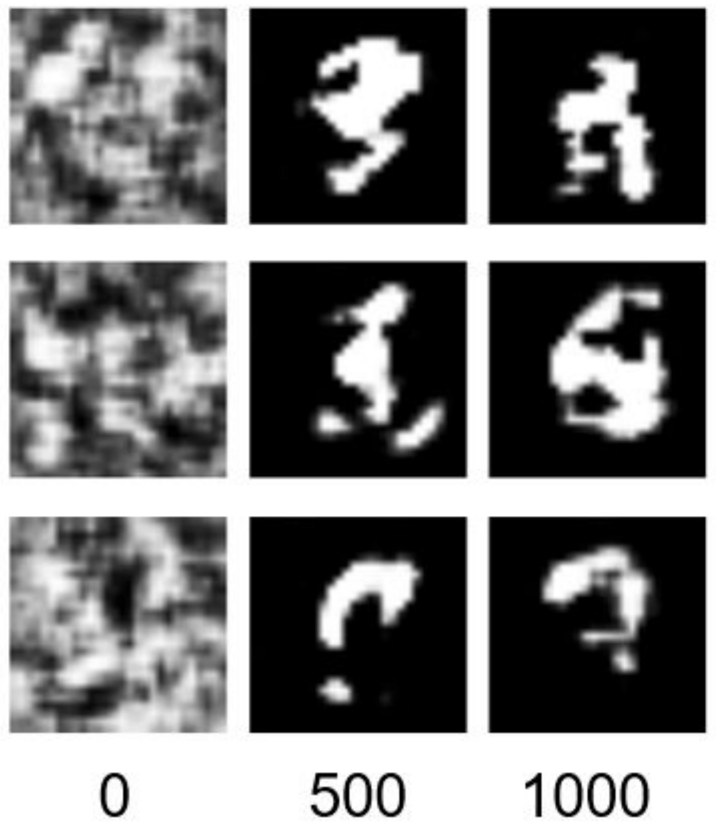
0

Iterations*

* might vary greatly

Generative Adversarial Networks

Examples



Iterations*

* might vary greatly

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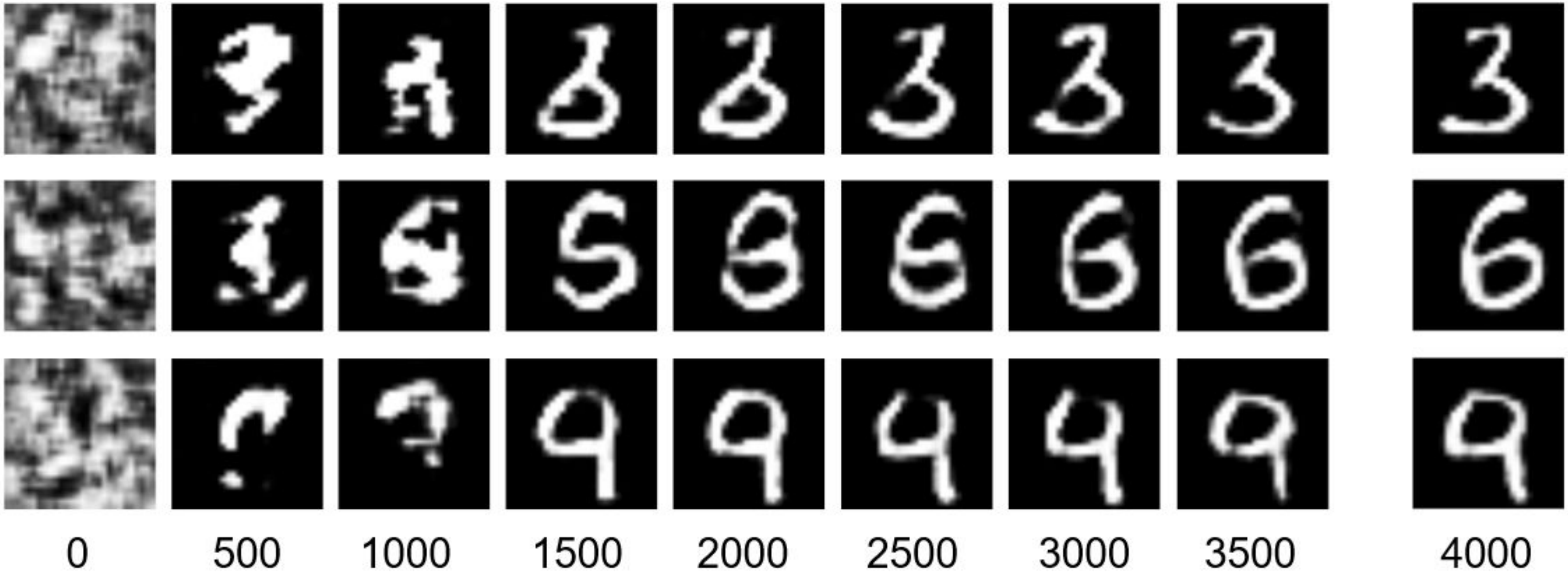
Examples

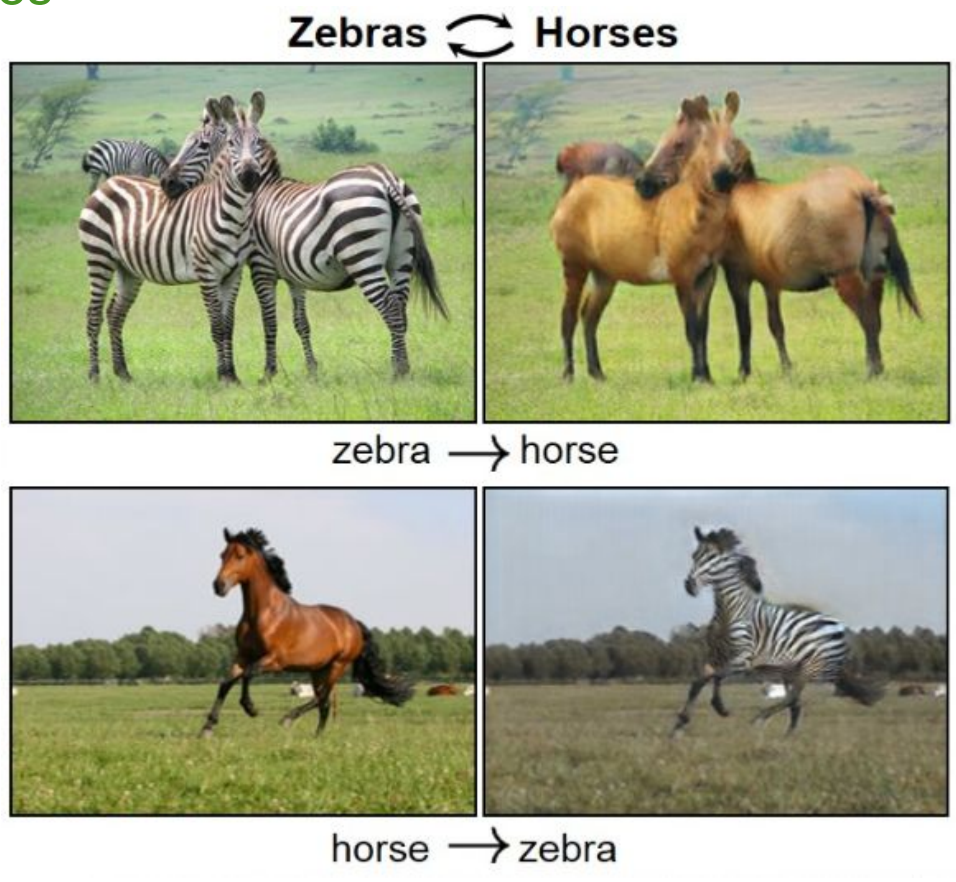


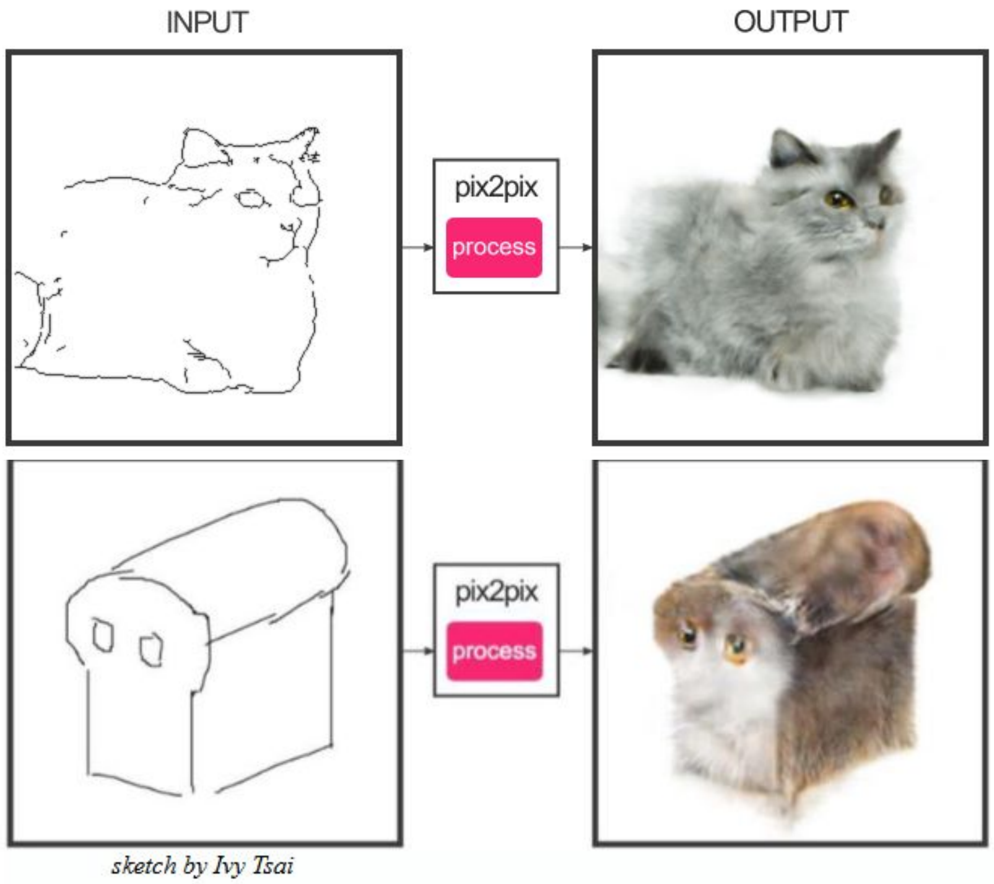
Iterations*

* might vary greatly

Generative Adversarial Networks

Examples



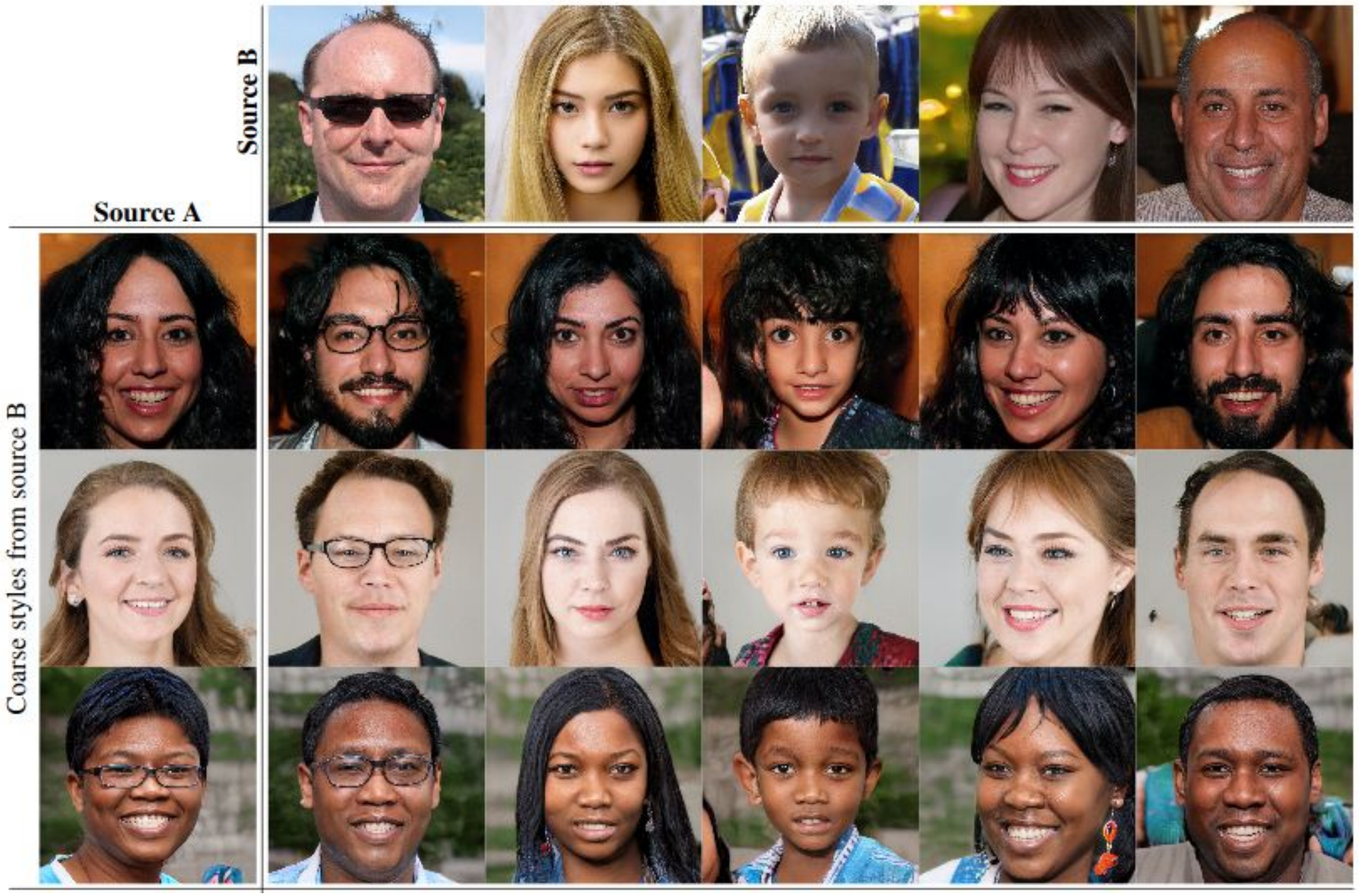


https://arxiv.org/abs/1703.10593
Jun-Yan Zhu, Taesung Park,
Phillip Isola, Alexei A. Efros

https://affinelayer.com/pixsrv/
By Christopher Hesse

Generative Adversarial Networks

Examples



https://arxiv.org/pdf/1812.04948.pdf
By T. Karas et al.

Generative Adversarial Networks

Difficulties

- Balancing discriminator and generator
- Small changes in hyperparameters may have a large impact on training
- Loss values are difficult to interpret / unintuitive
- Might never converge

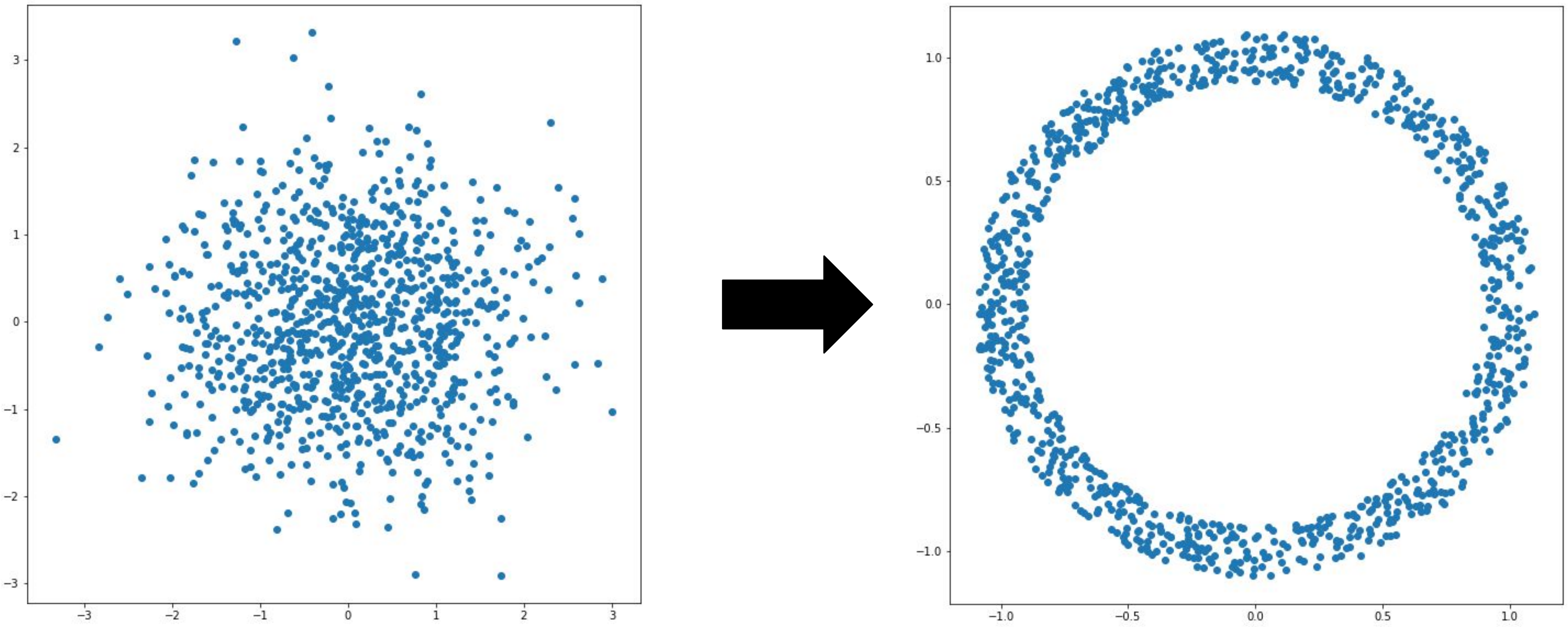
Generative Adversarial Networks

Tips for training

- Implement as a binary classification problem
- Train the discriminator before the generator
- Discriminator and generator should not differ too much in complexity
- If your solution for Exercise 2 does not converge after 20,000 iterations something may be wrong
- Best way to check if your setup works is to look at the generated examples

Generative Adversarial Networks

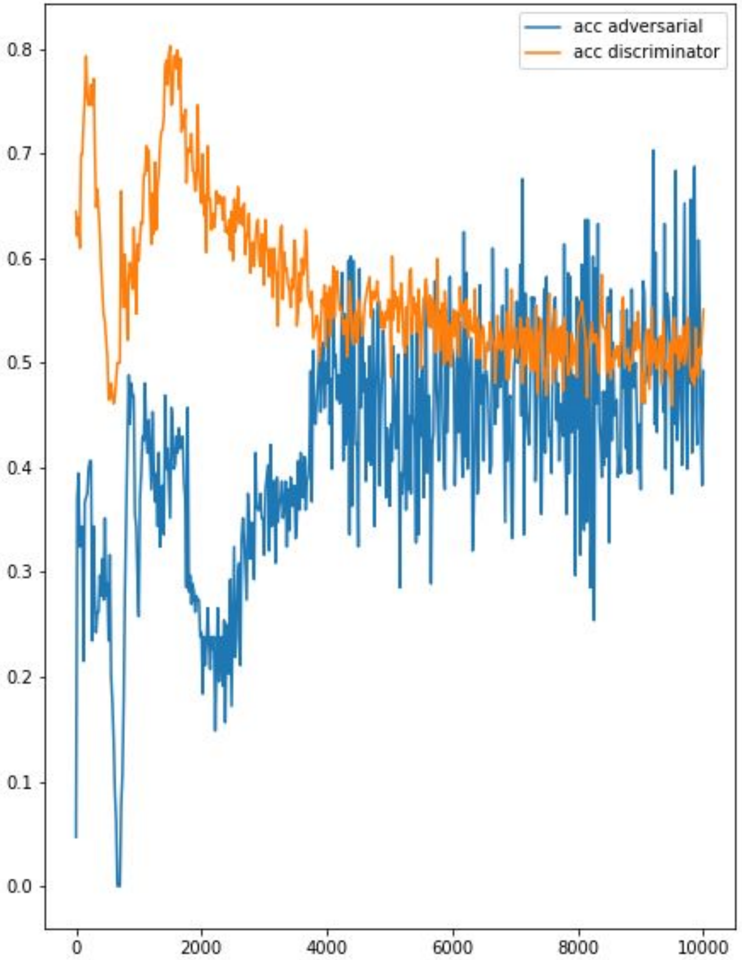
Exercise 2 - Task

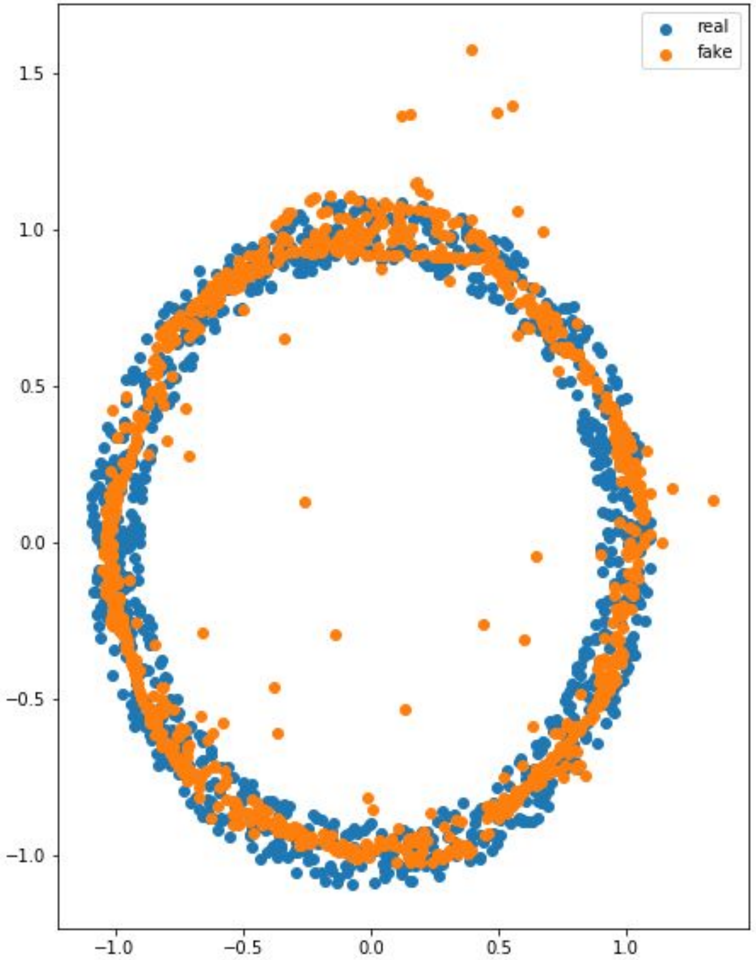


Generative Adversarial Networks

Exercise 2 - Possible Solution

* Plot might look completely different in your experiment





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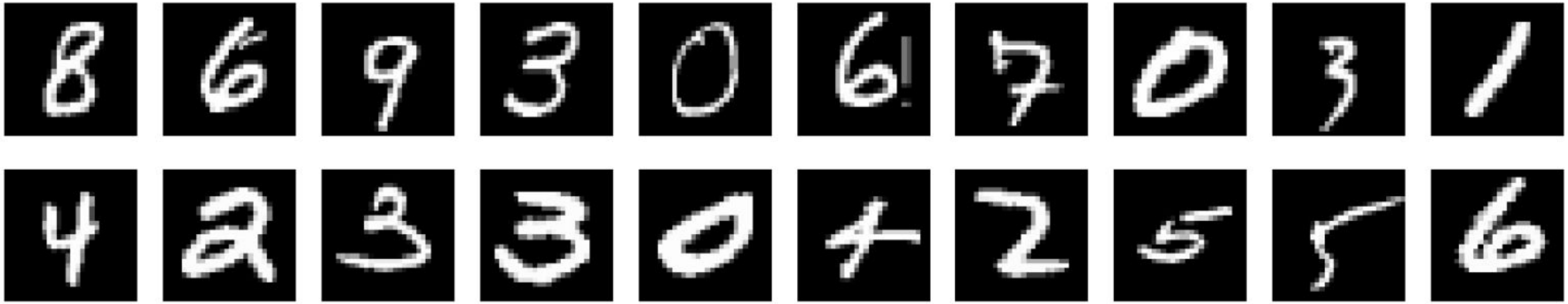
Exercise 3 - HIGHLY RECOMMENDED



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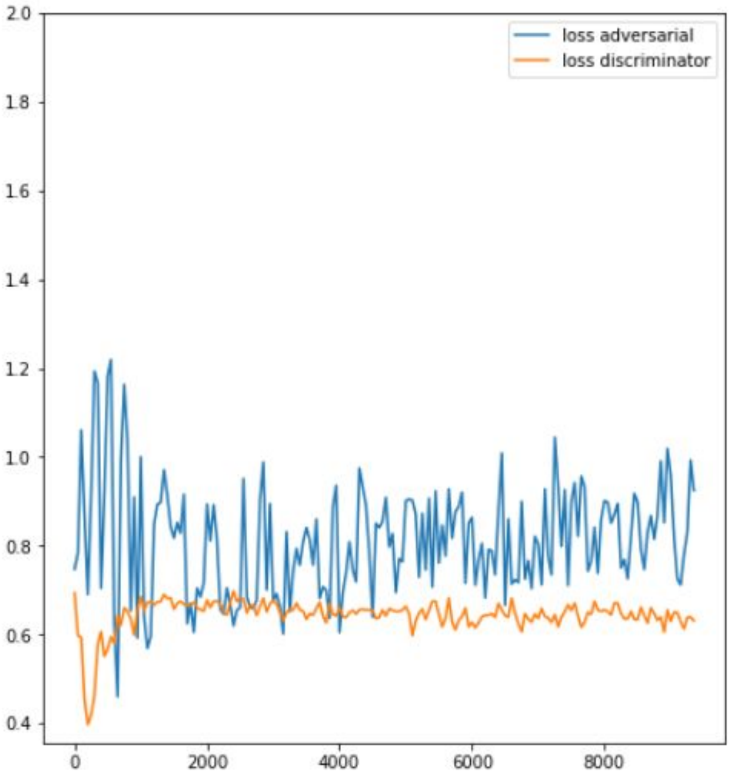
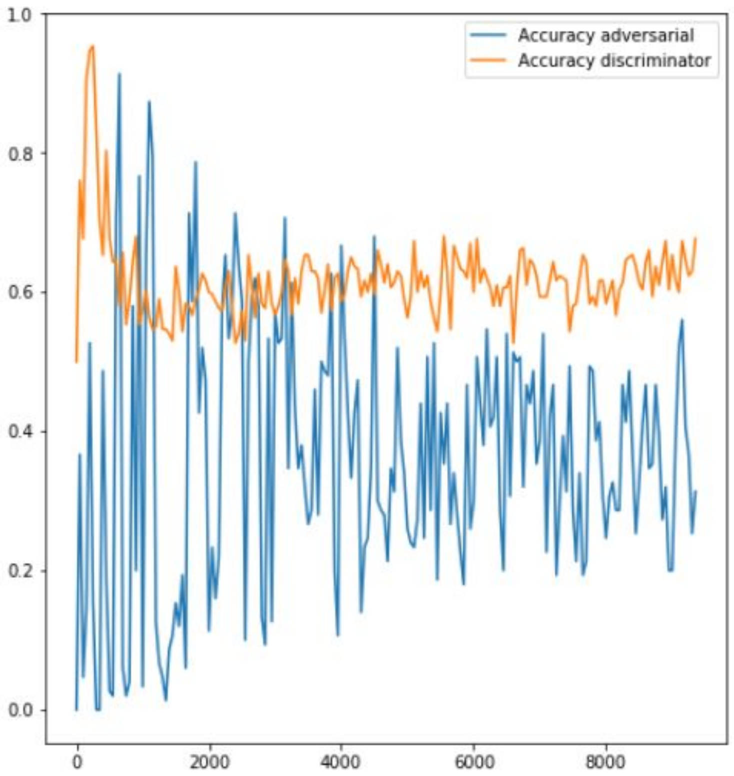
Exercise 3 - Possible Solution





* Plots might look completely different in your experiment