삼성전자 AI 전문가 과정 - Case Study

GAN Lab: Understanding Complex Deep Generative Models using Interactive Visual Experimentation

hci lab
HUMAN × COMPUTER INTERACTION

Authors

- Minsuk Kahng, Nikhil Thorat, Polo Chau, Fernanda Viégas, and Martin Wattenberg
- VAST 2018
- Collaboration between Georgia Tech and Google Brain/PAIR

hci lab
HUMAN × COMPUTER INTERACTION

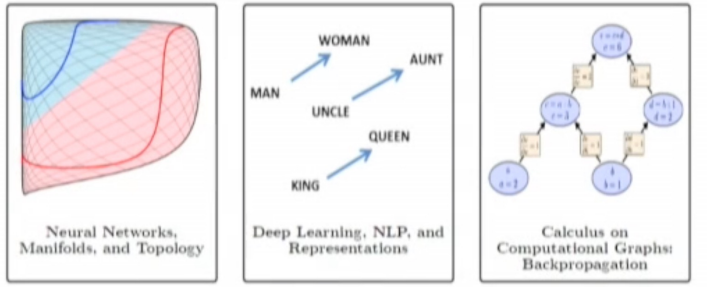
Deep Learning Visualization Tools

- Deep learning visualization tools presented at VIS

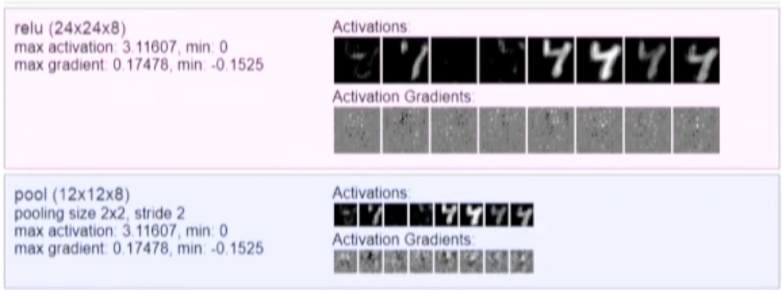
- Most tools are designed for experts

Introduction

- Many non-experts want to learn ML



Chrios Olah's blog

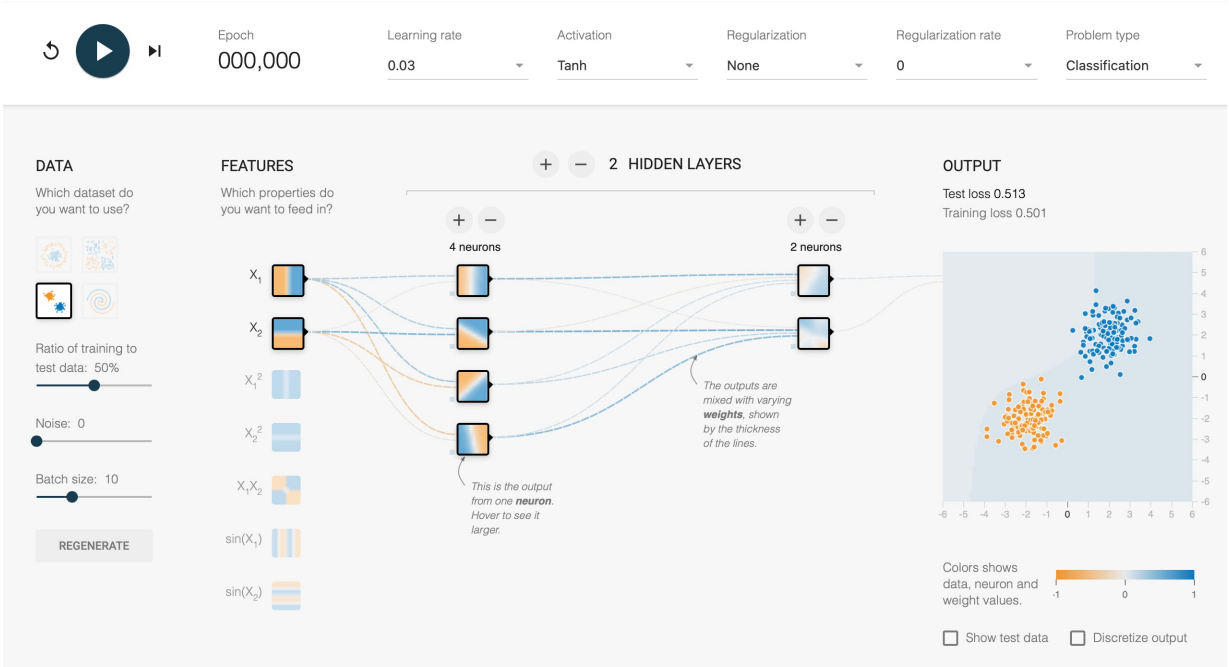


Andrej Karpathy's demo

- Can **VIS community** help this population?

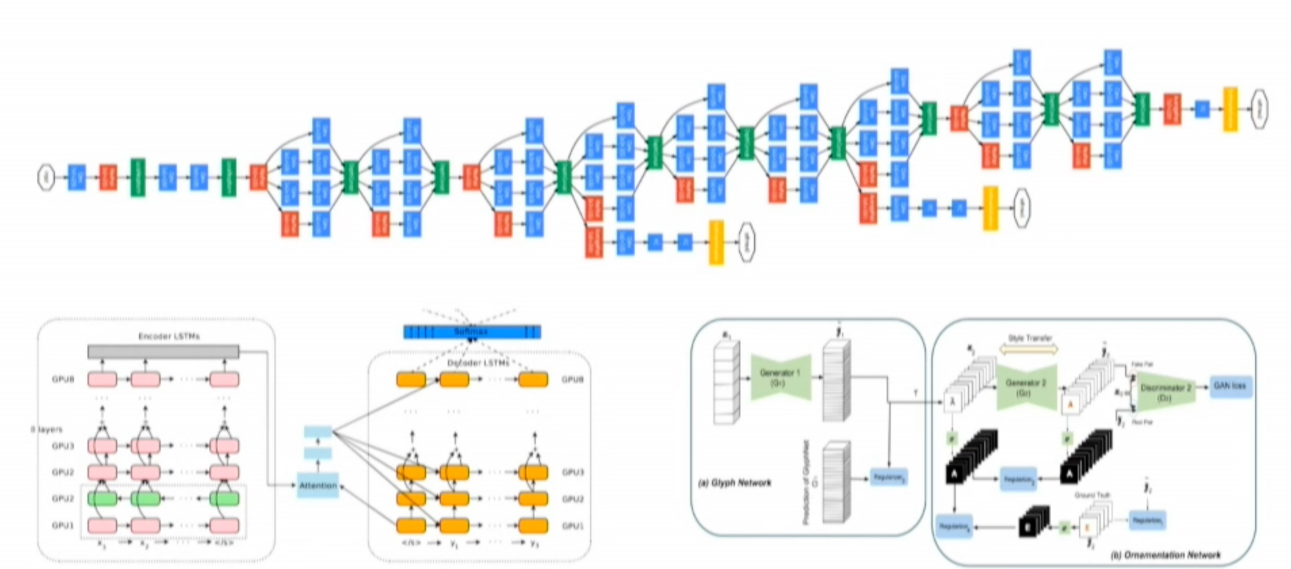
TensorFlow Playground

- http://playground.tensorflow.org/



Introduction

- Modern deep models are very complex



Generative Adversarial Networks (GANs)

- "the most interesting idea in the last 10 years in ML" – Yann LeCun
- Face images generated by BEGAN [Berthelot et al., 2017]

- Hard to understand and train even for experts

hci lab
HUMAN × COMPUTER INTERACTION

Why are GANs hard to understand?

- Because a GAN uses two *competing* neural networks

Generator
synthesizes outputs

Counterfeiter
makes fake bills

Discriminator
spots fake

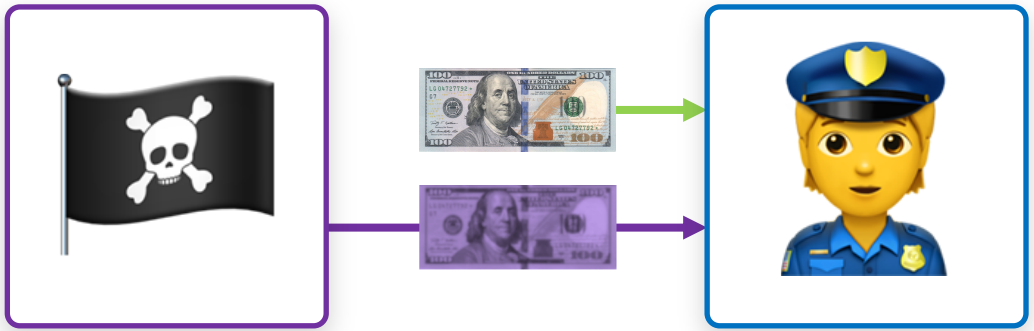
Police
spots fake bills

Why are GANs hard to understand?

- Because a GAN uses two *competing* neural networks

Generator
synthesizes outputs

Discriminator
spots fake

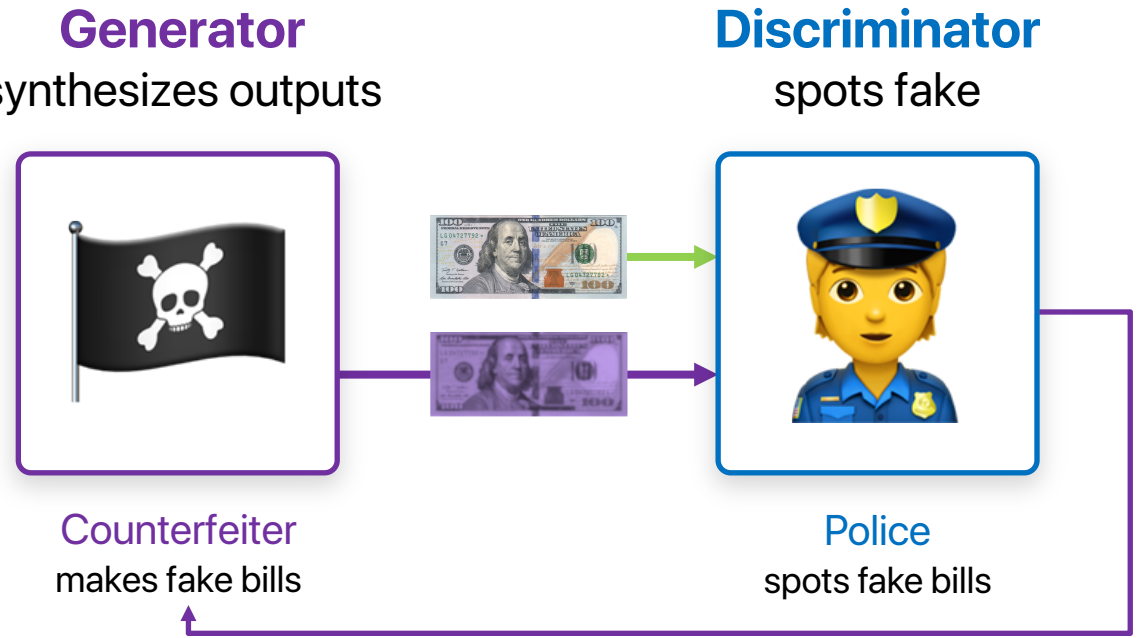


Counterfeiter
makes fake bills

Police
spots fake bills

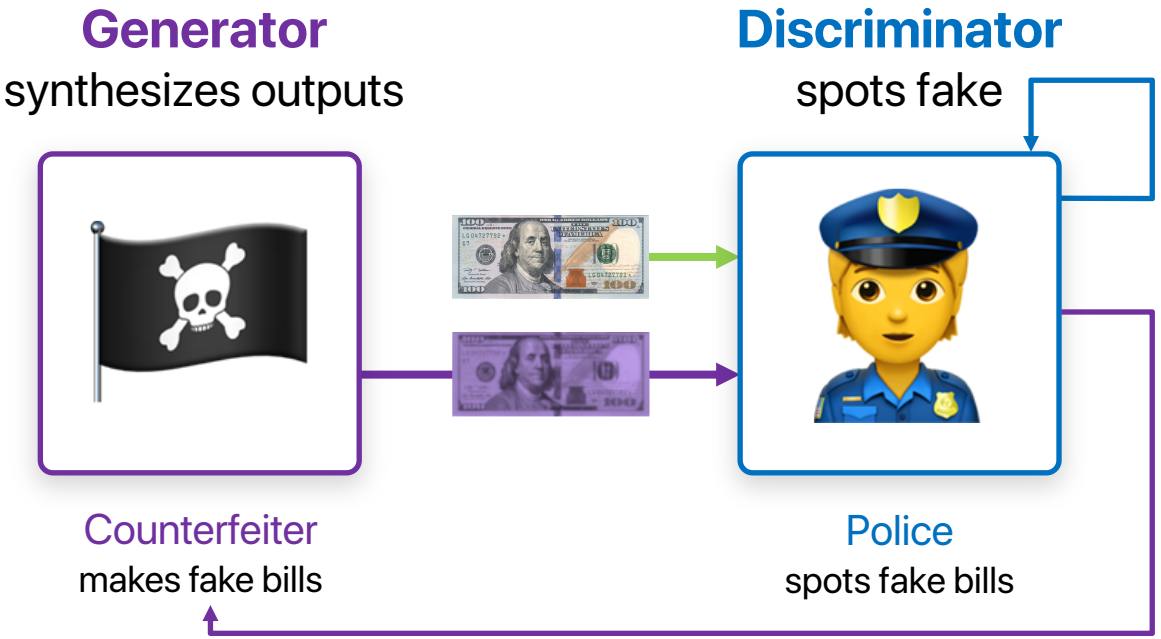
Why are GANs hard to understand?

- Because a GAN uses two *competing* neural networks



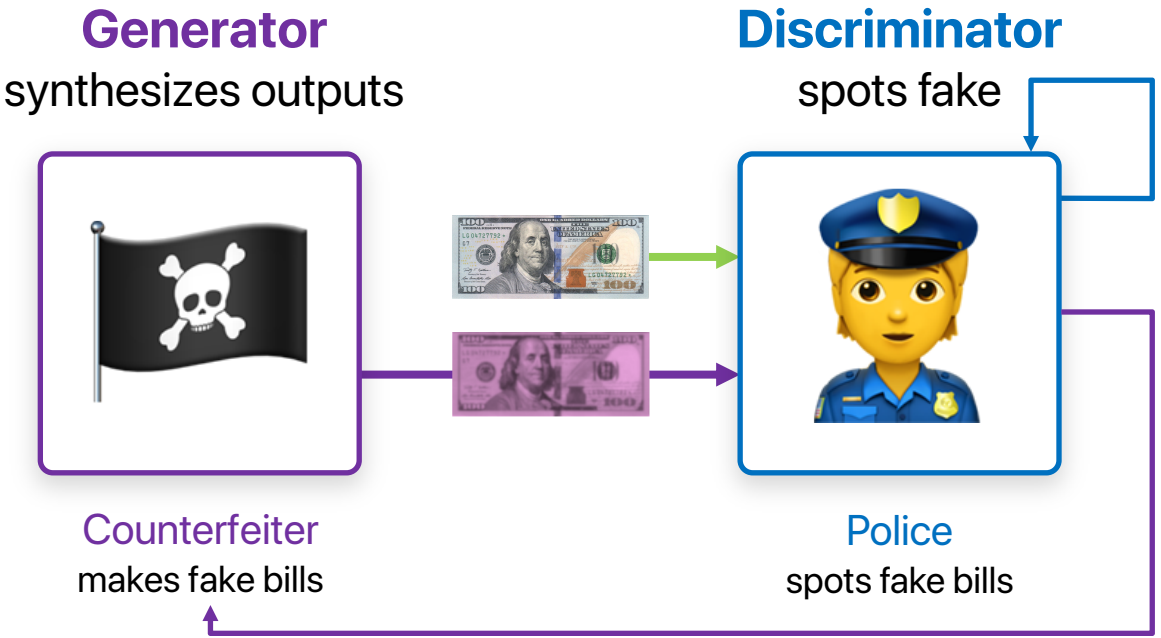
Why are GANs hard to understand?

- Because a GAN uses two *competing* neural networks



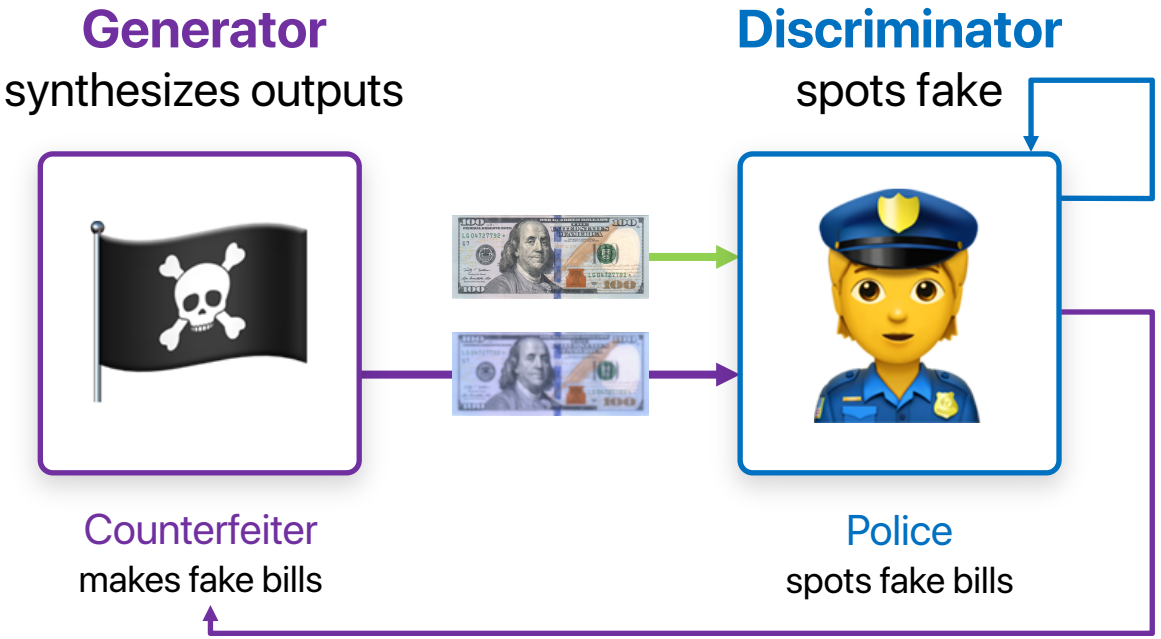
Why are GANs hard to understand?

- Because a GAN uses two *competing* neural networks



Why are GANs hard to understand?

- Because a GAN uses two *competing* neural networks



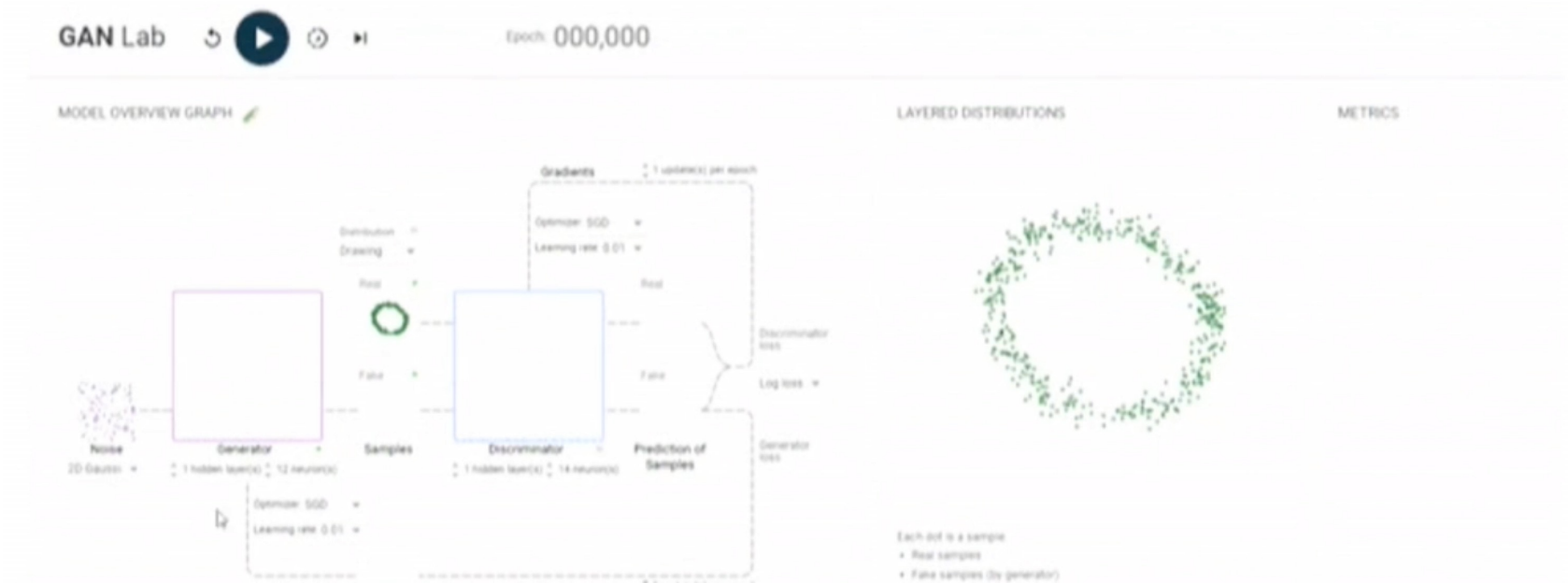
Why are GANs hard to understand?

- Because a GAN uses two *competing* neural networks

- How to explain this concept using visualization?

GAN Lab

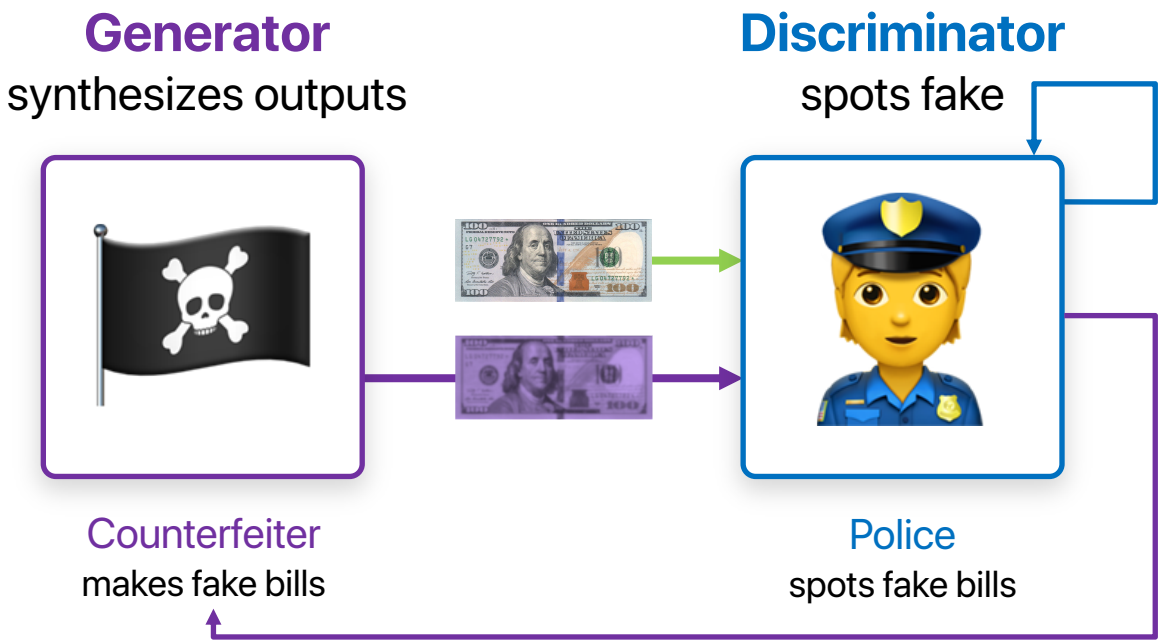
- First interactive tool for learning GANs in browser



Key contributions

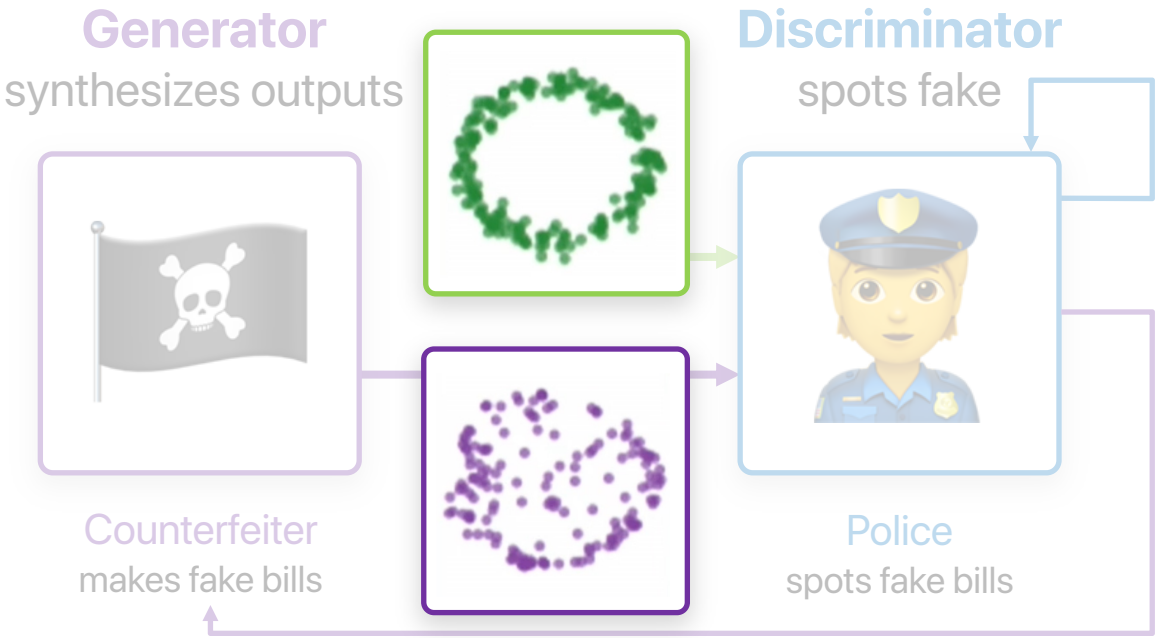
- Visualization of GAN's training process
- Interactive model training
- Browser-based implementation

How visualize?



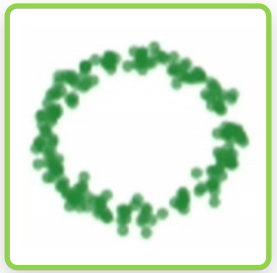
What data?

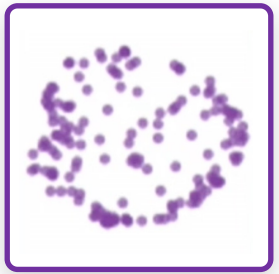
- 2D data distribution, instead of high-dimensional images



What data?

- 2D data distribution, instead of high-dimensional images
- Why 2D data points?
  - Easier to visualize data distribution
  - Easier for learners to track dynamics



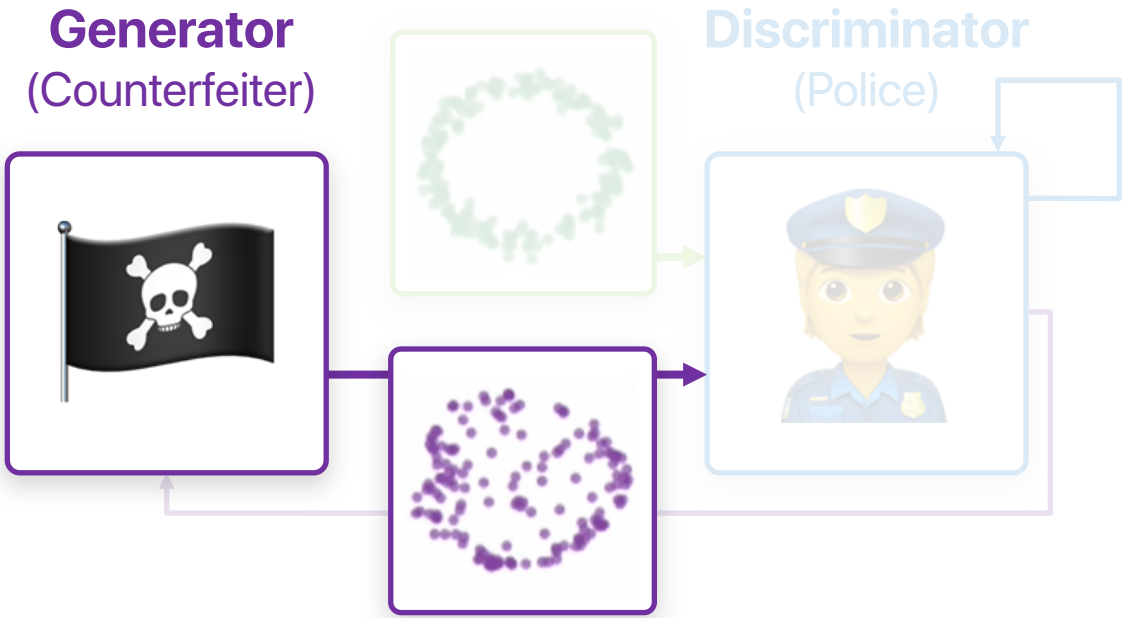


VER. 0.1

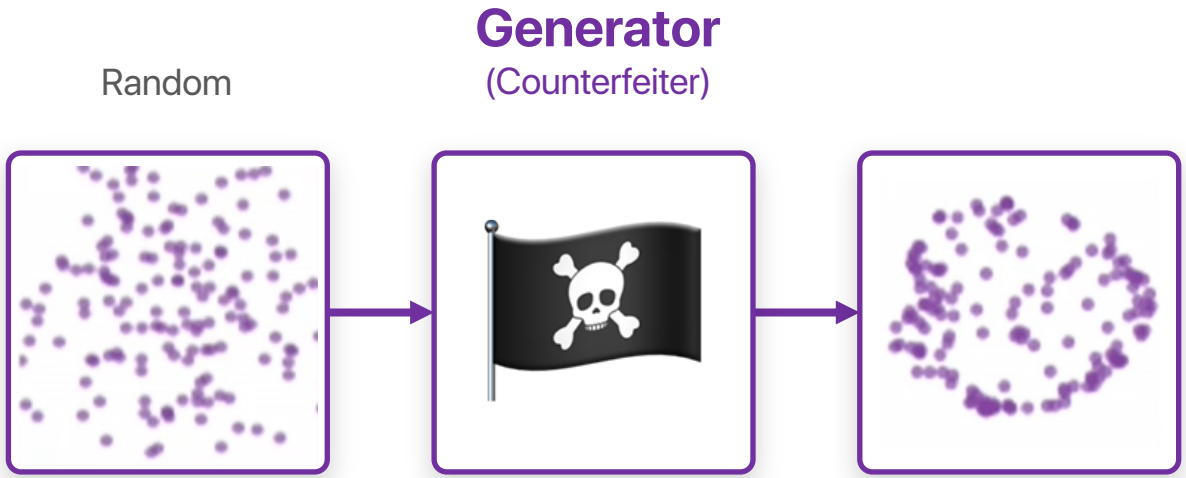
Real
(green)

Generated
(purple)

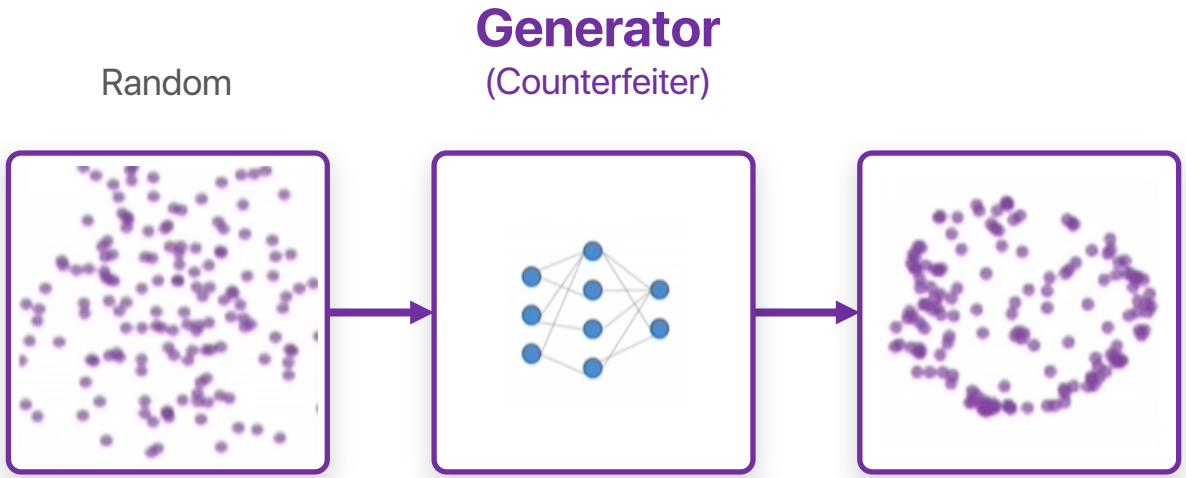
How to visually explain the generator?



How to visually explain the generator?



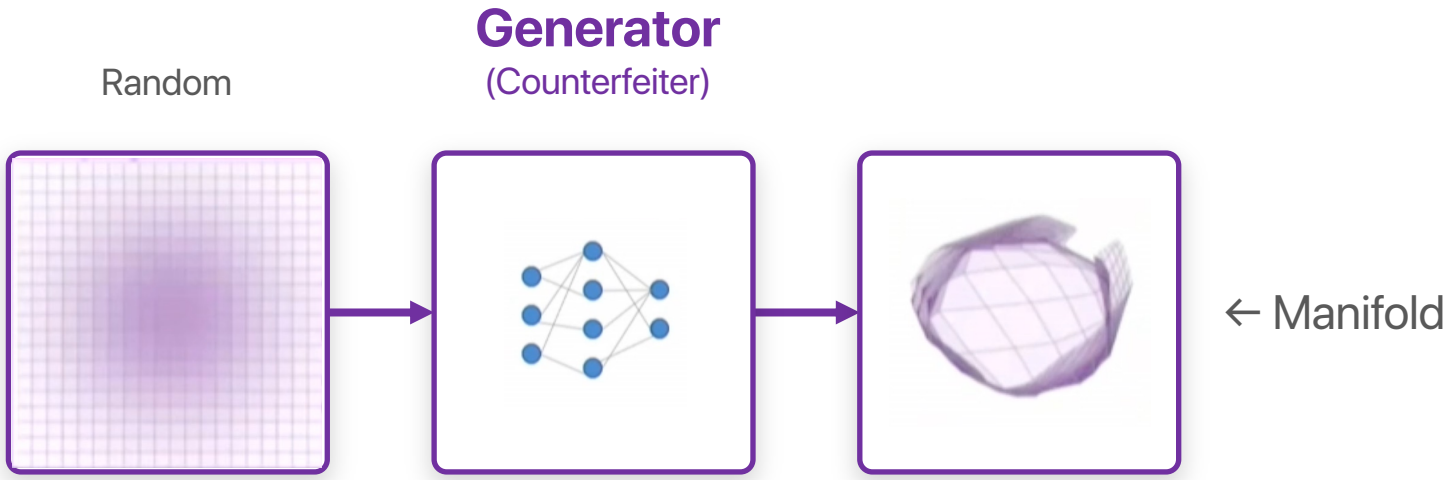
How to visually explain the generator?



Map an input point into a new position

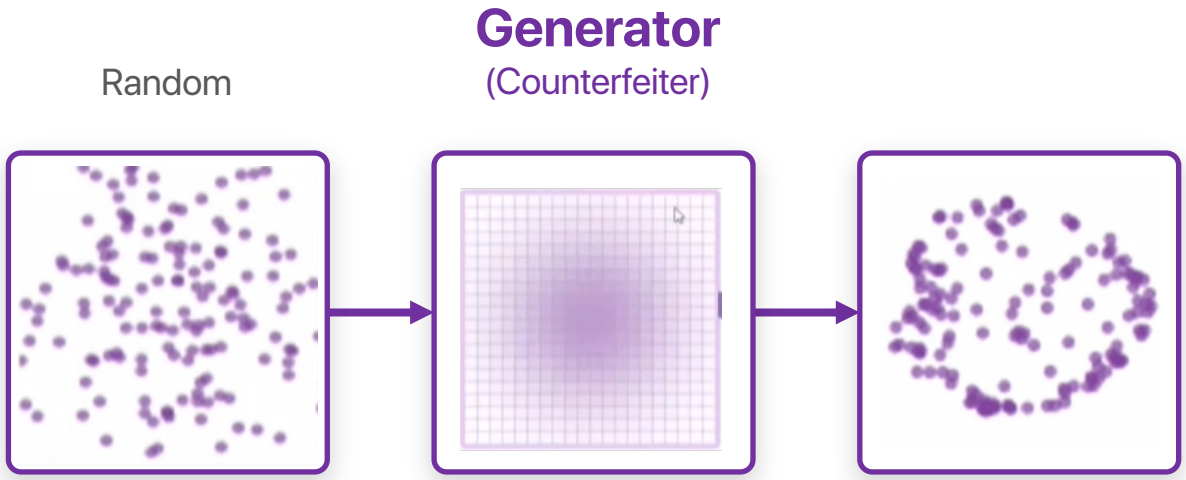
How to visually explain the generator?

- Grids, showing density



Map an input point into a new position

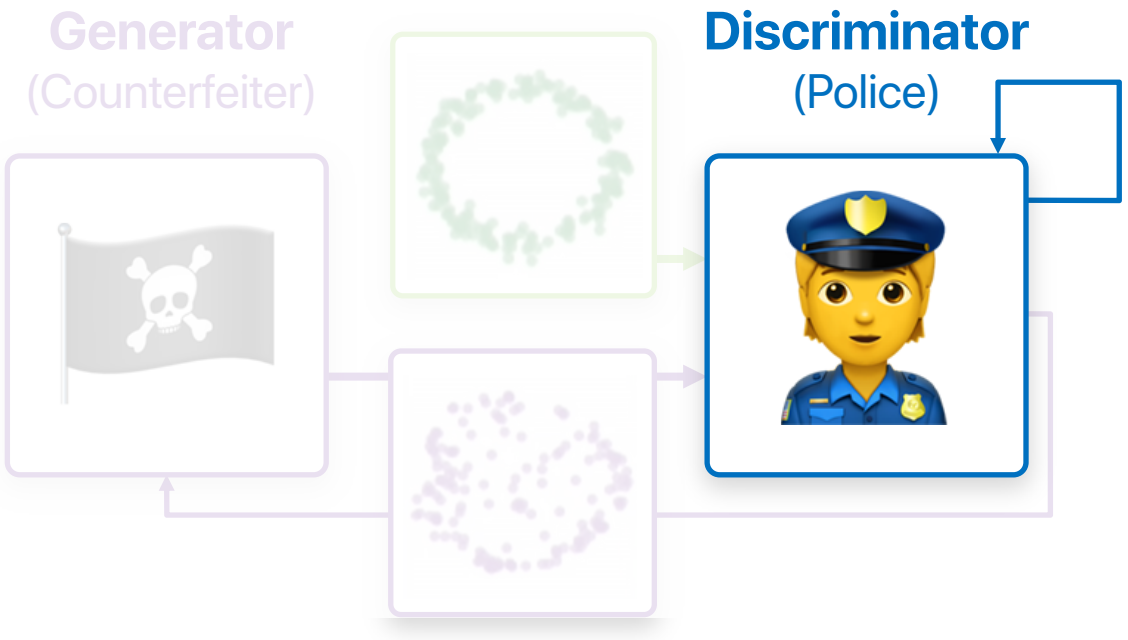
How to visually explain the generator?



Map an input point into a new position

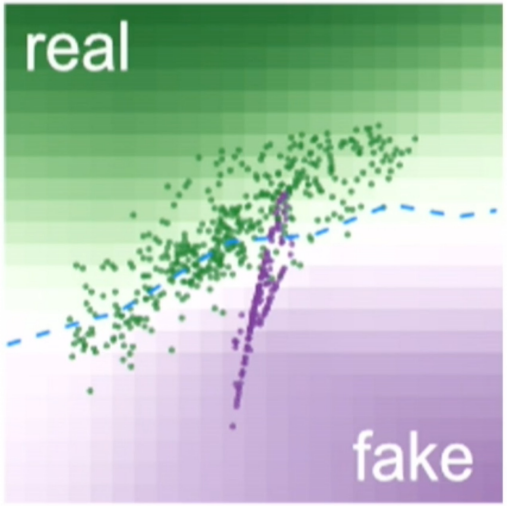
How to visually explain the generator?

How to visually explain the discriminator?



How to visually explain the discriminator?

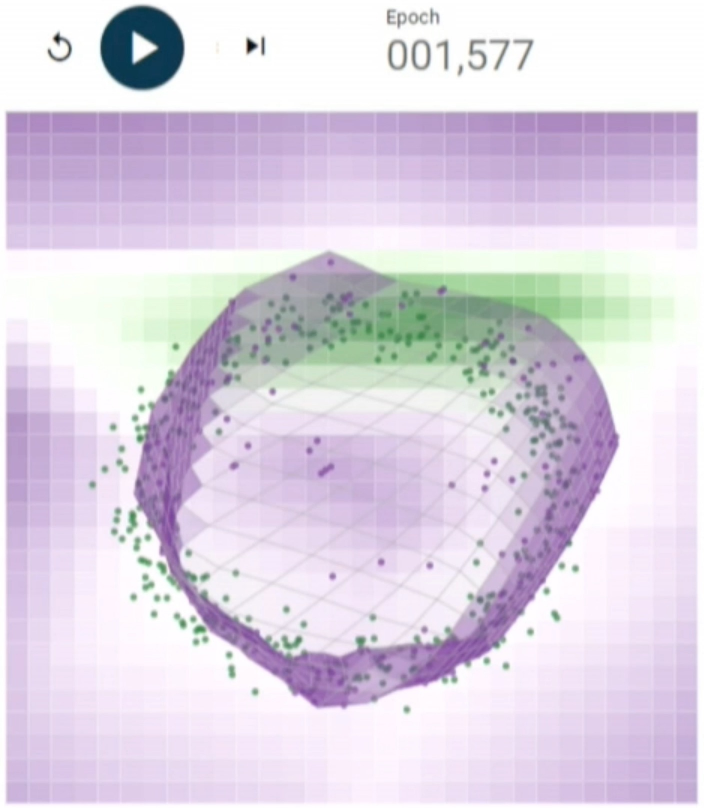
- 2D heatmap, to represent its binary classification

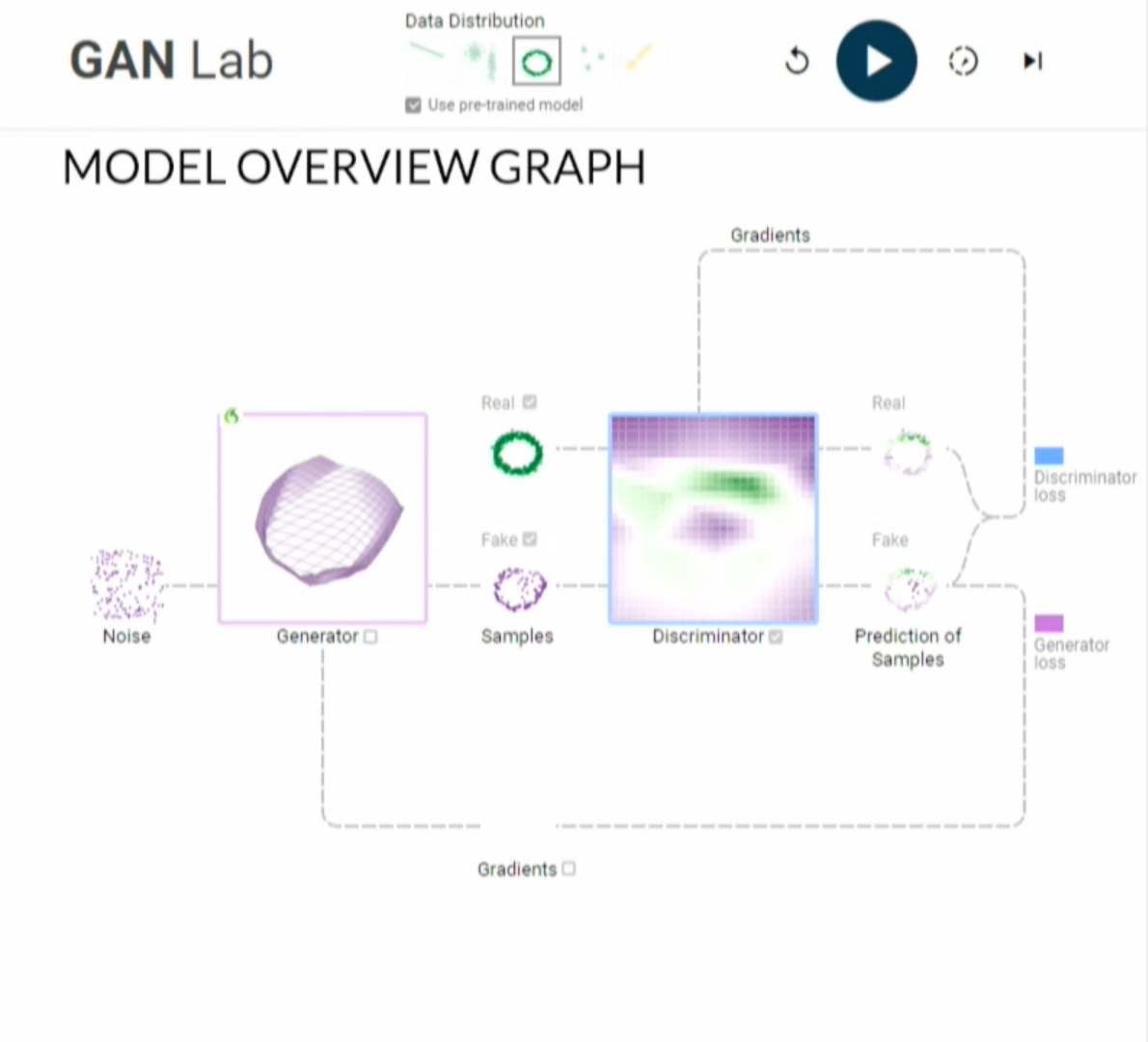


Samples in this region are likely real.

Samples are likely fake.

VER. 0.5


Epoch
001,577
Each dot is a 2D data sample: real samples, fake samples.
Background colors of grid cells represent discriminator's classifications.
Samples in green regions are likely to be real; those in purple regions likely fake.
Manifold represents generator's transformation results from noise space.
Opacity encodes density: darker purple means more samples in smaller area.

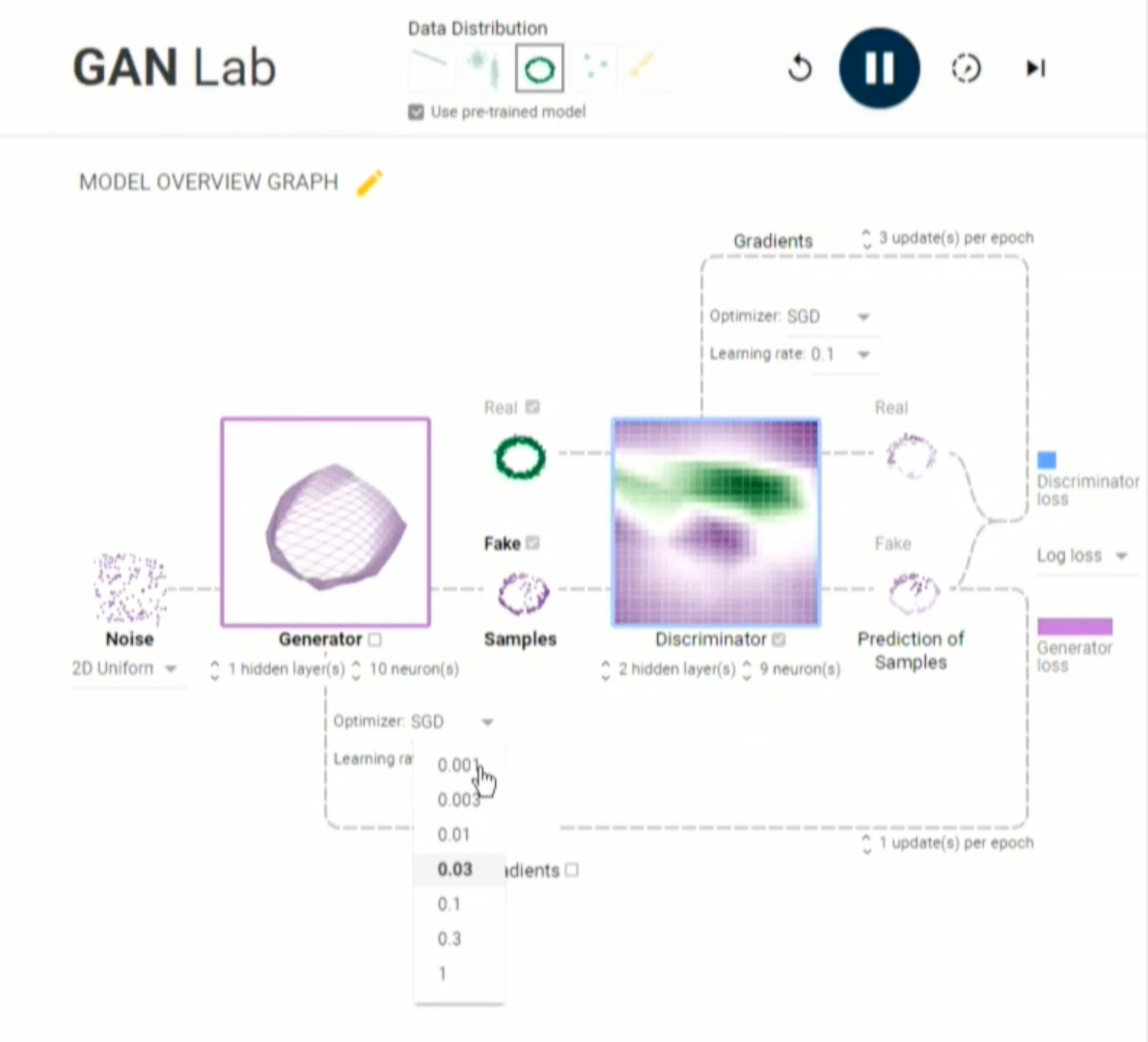


How does it help?

- Building mental models for GANs
- Tracking data flow
- Locating hyperparameters

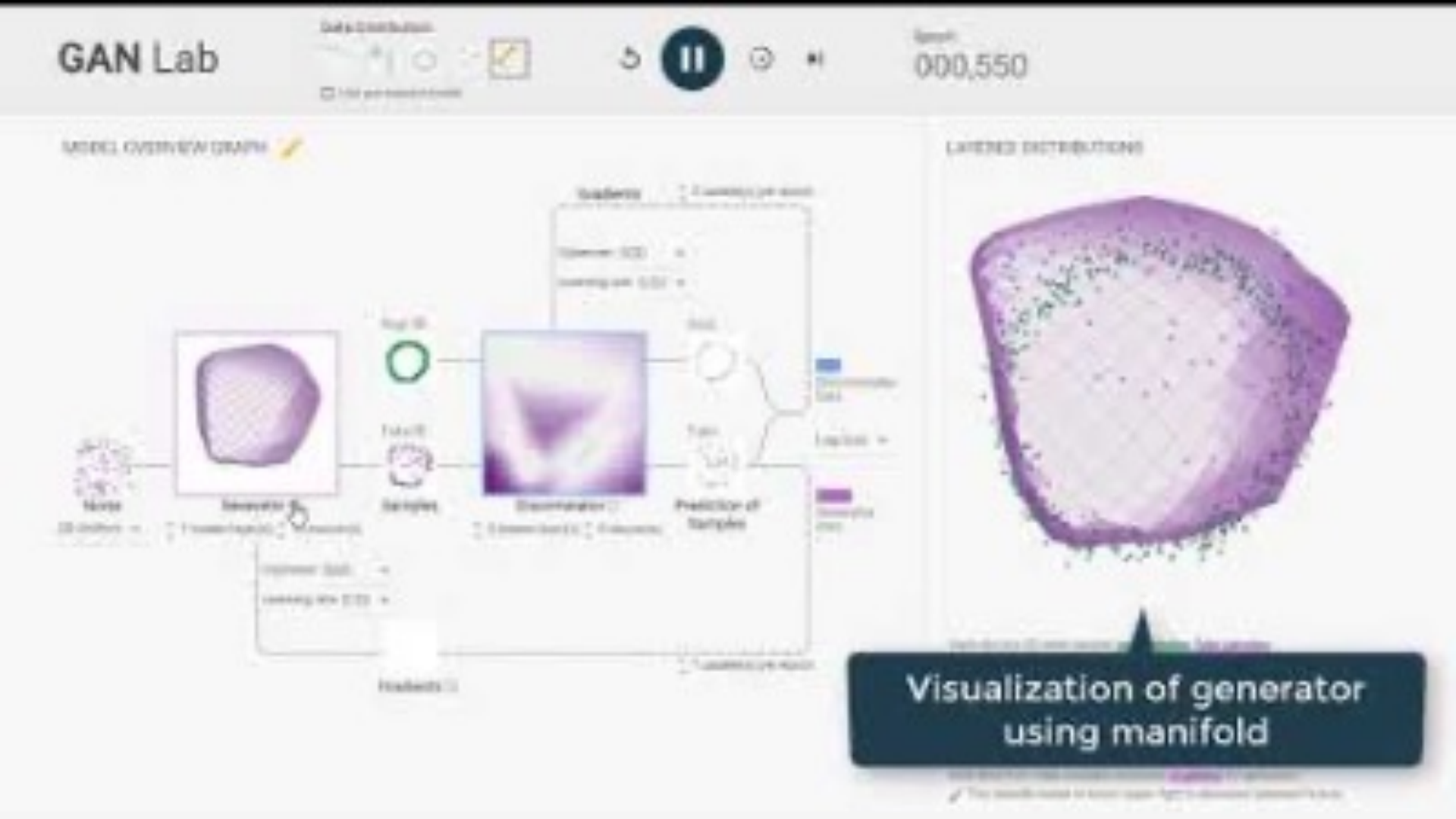
How does it help?

- Building mental models for GANs
- Tracking data flow
- Locating hyperparameters



How does it help?

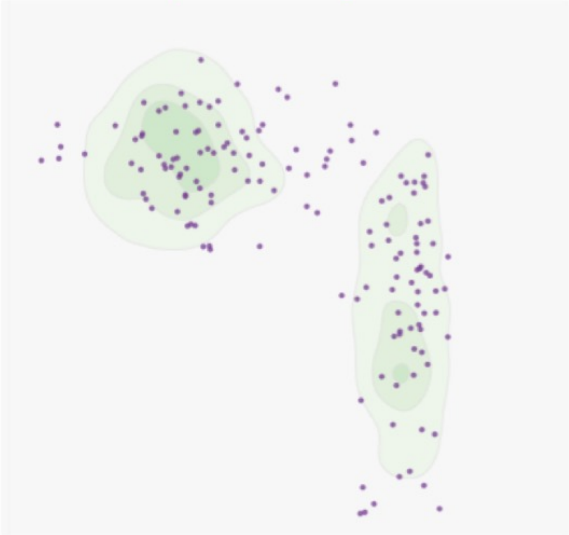
- Building mental models for GANs
- Tracking data flow
- Locating hyperparameters


GAN Lab
000,550
Visualization of generator using manifold

Evaluating how well the distribution of fake samples

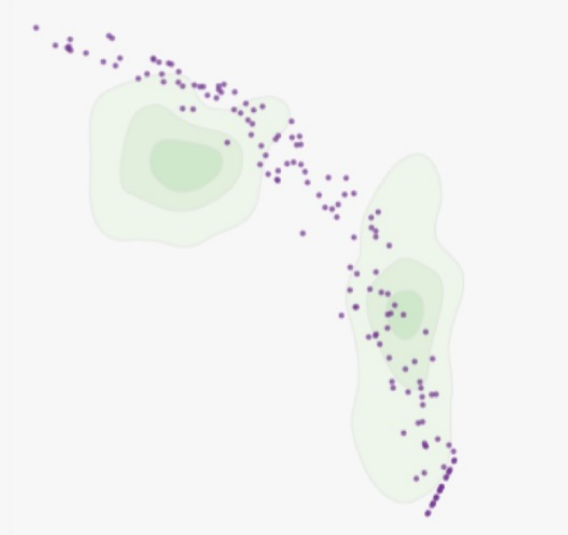
Good

Distribution of fake samples are similar to real samples' density contour

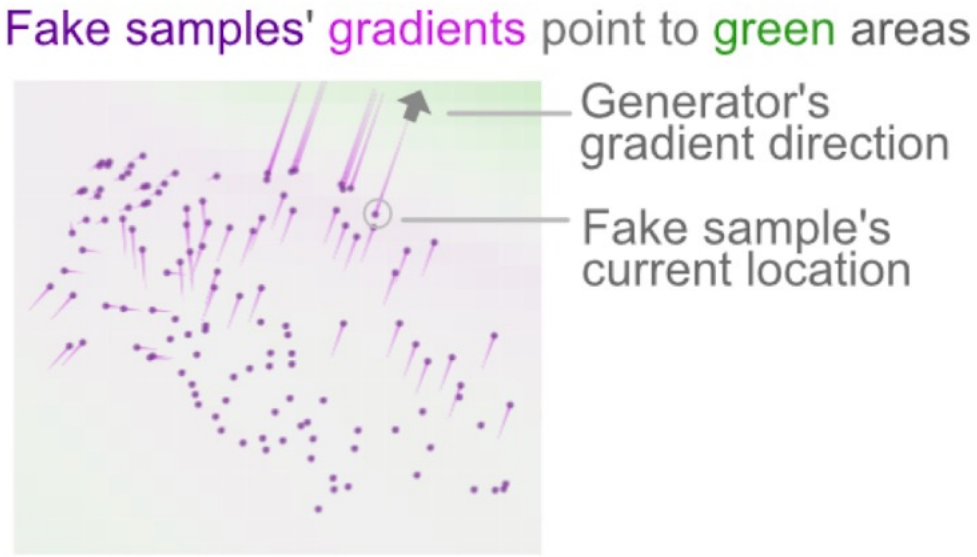


Bad

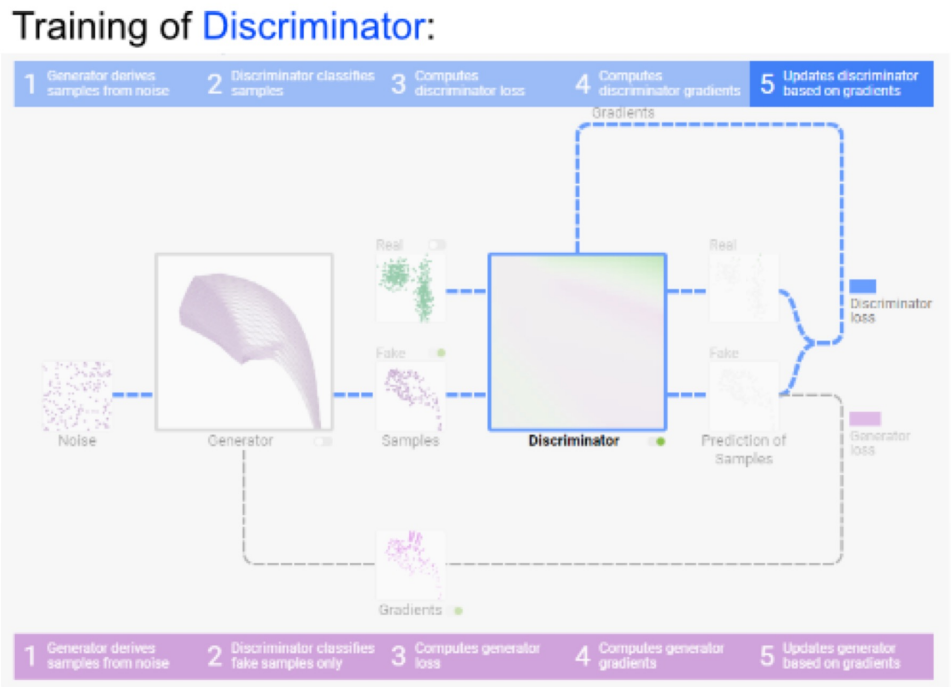
Distributions of fake and real samples do not match well



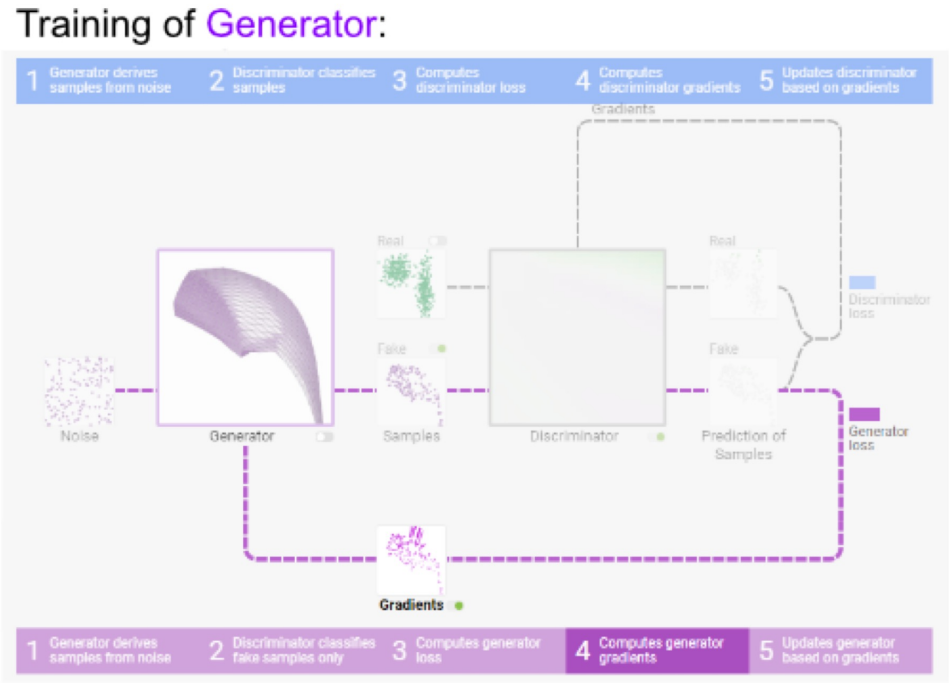
Understanding the interplay between discriminator and generator



Training of Discriminator

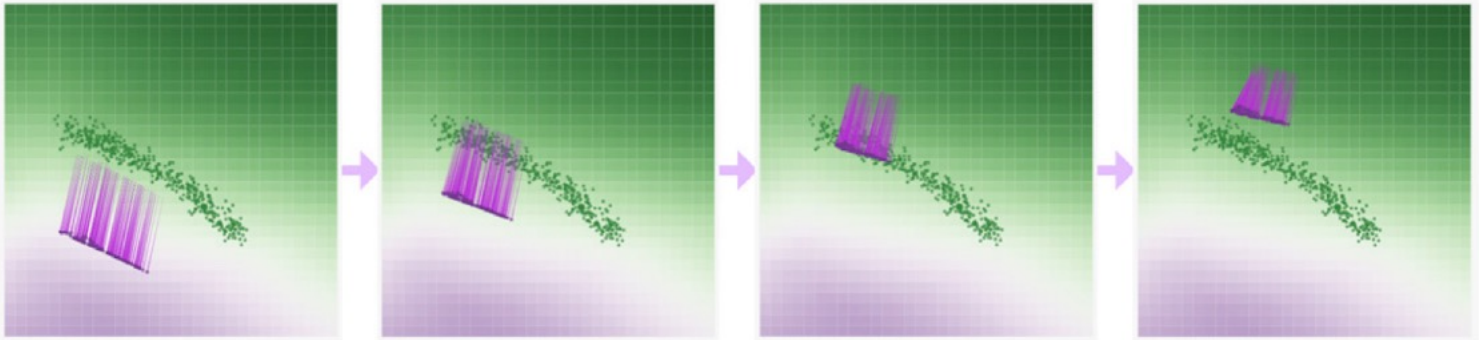


Training of Generator



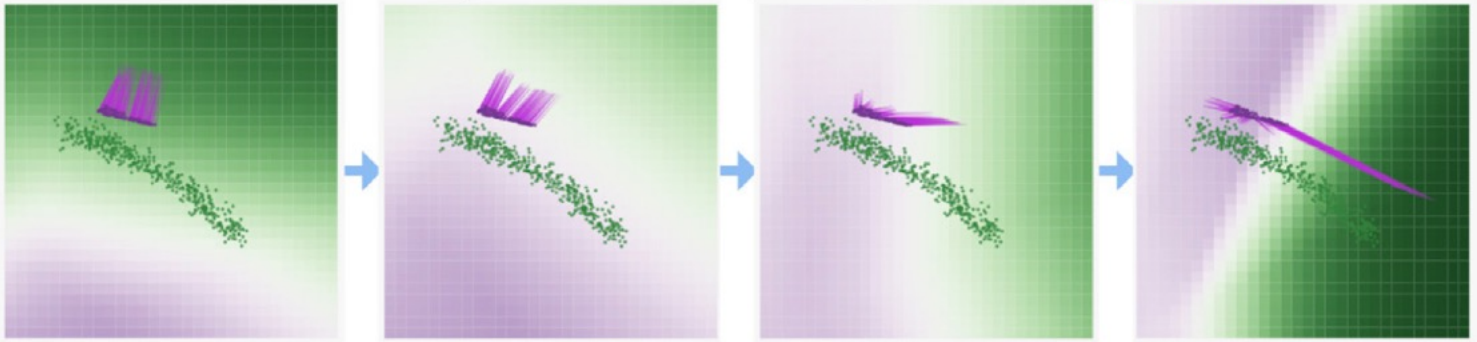
Training of Generator

Training **generator** moves fake samples towards real samples.
But without updating discriminator, they move to undesired positions



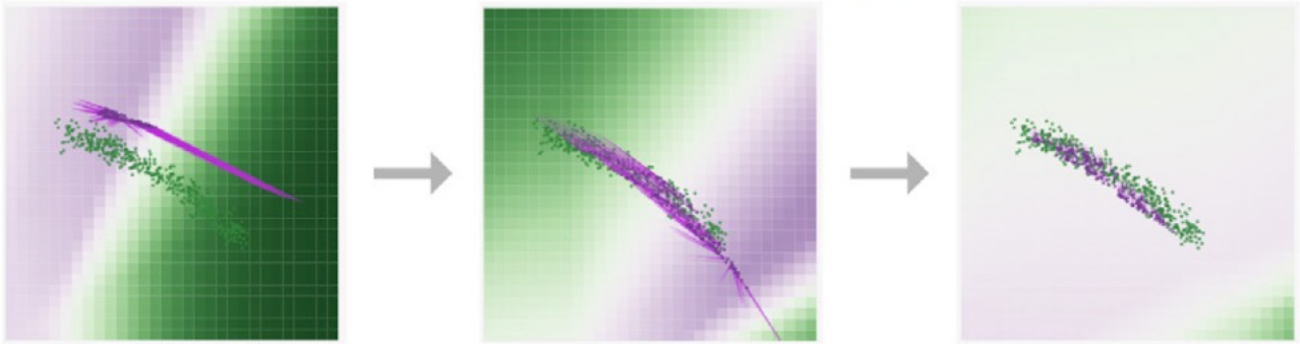
Training of discriminator

Training **discriminator** does not update fake samples, but updates classification boundary used to compute generator's gradients



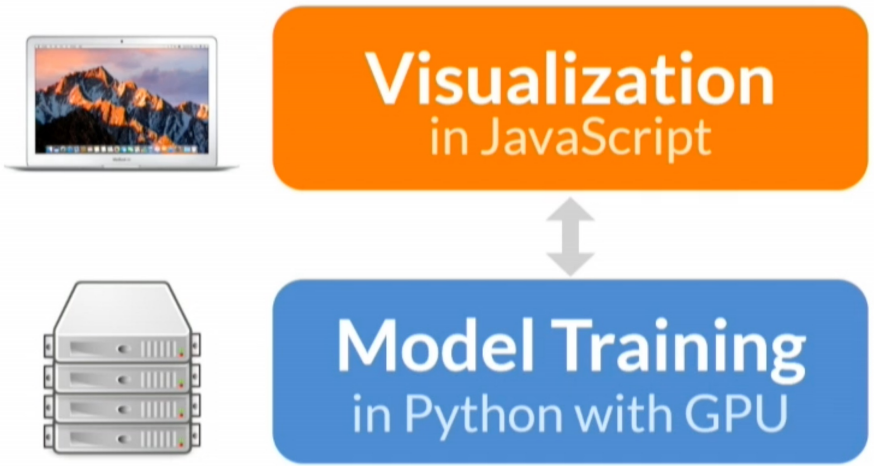
Training of discriminator

Updating both submodels leads to generating fake samples whose distribution match that of real samples



GAN Lab broadens education access

- Conventional Deep Learning Visualization



GAN Lab broadens education access

- Everything done in browser, using TensorFlow.js

Visualization
in JavaScript

Model Training
also in JavaScript

Accelerated by WebGL

hci lab
HUMAN × COMPUTER INTERACTION

Demo

- bit.ly/gan-lab