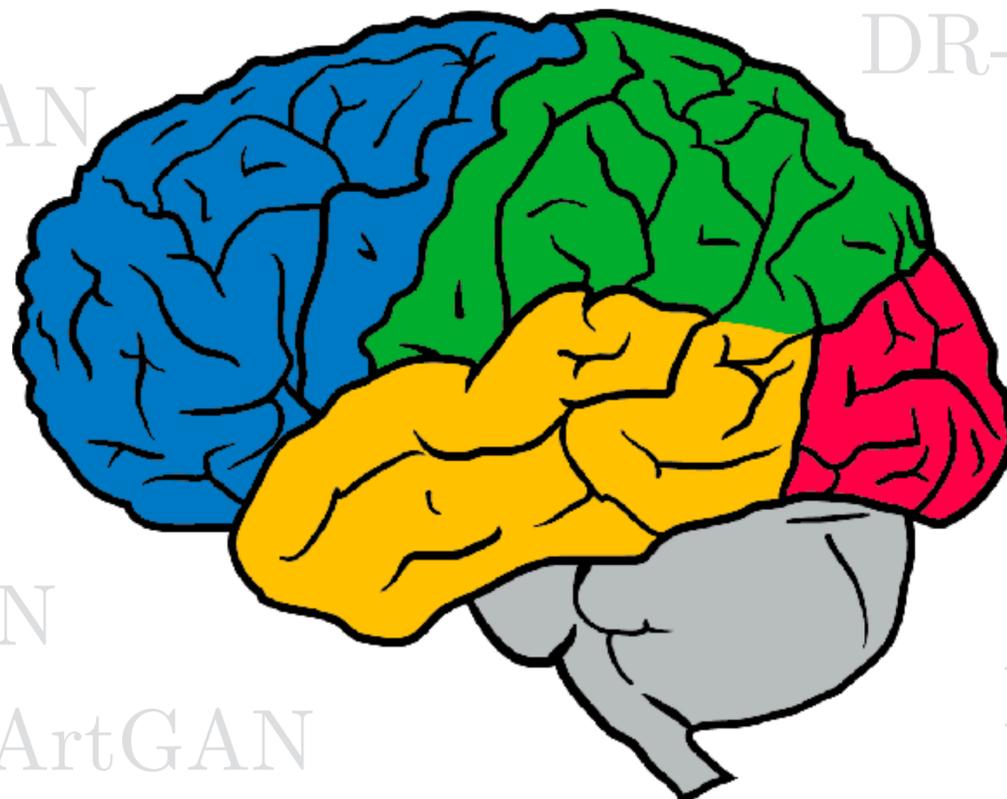


Introduction to GANs

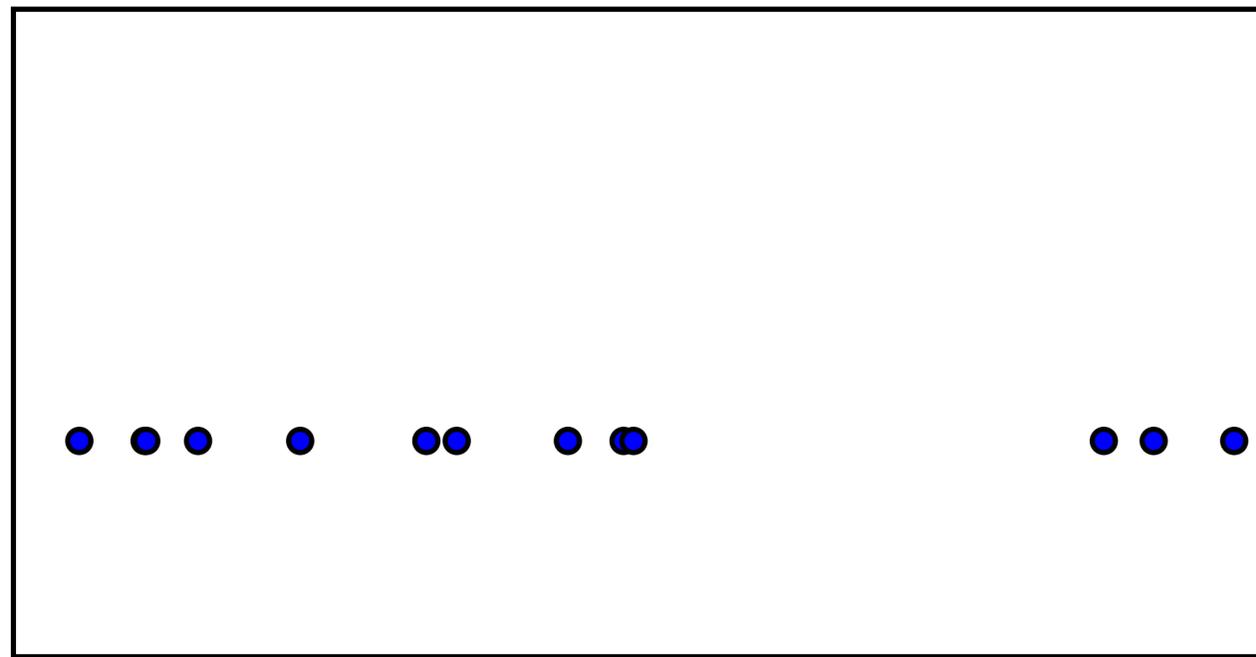
Ian Goodfellow, Staff Research Scientist, Google Brain

IEEE Workshop on Perception Beyond the Visible Spectrum

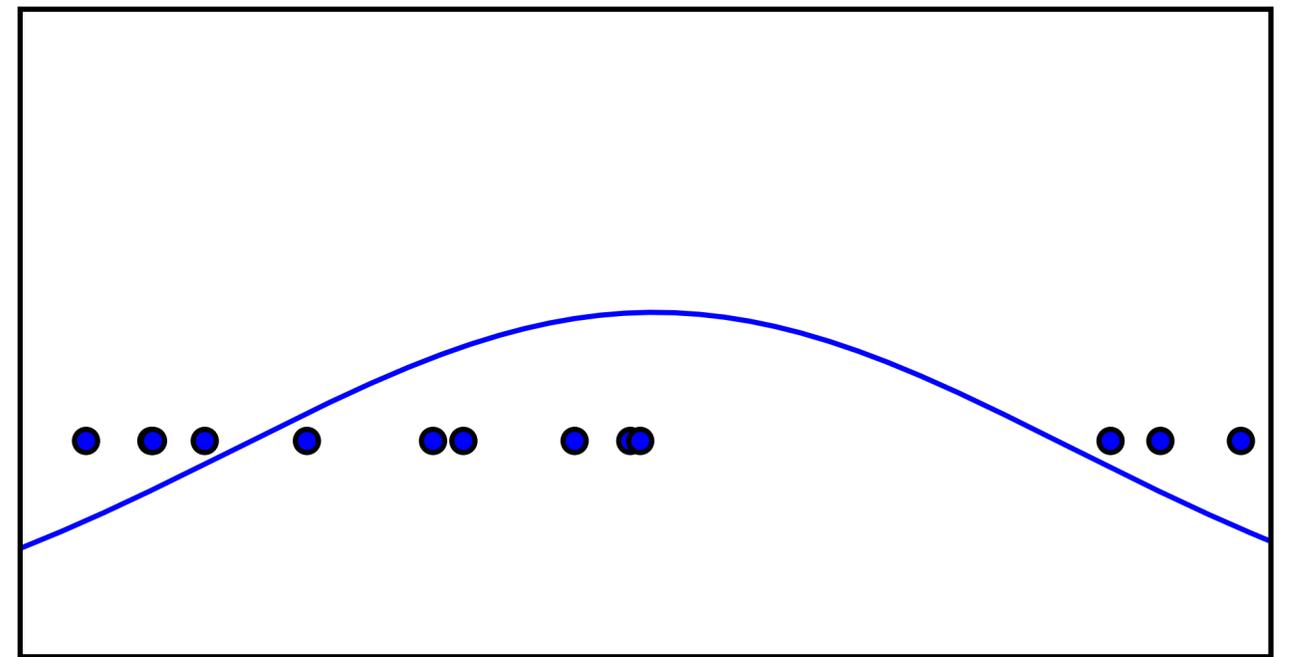
Salt Lake City, 2018-06-18



Generative Modeling: Density Estimation



Training Data



Density Function

Generative Modeling: Sample Generation

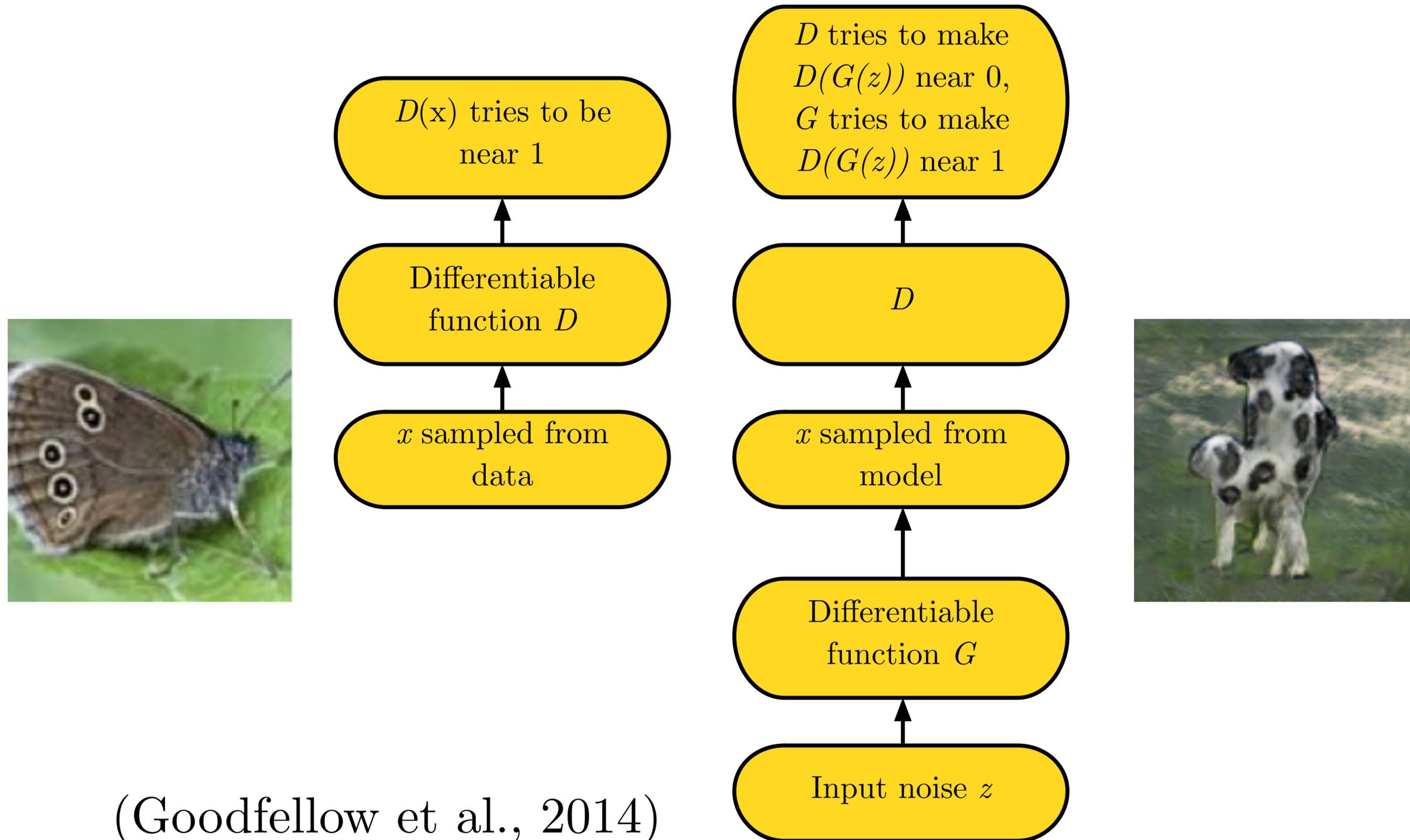


Training Data
(CelebA)



Sample Generator
(Karras et al, 2017)

Adversarial Nets Framework



Self-Attention GAN

State of the art FID on ImageNet: 1000 categories, 128x128 pixels



Goldfish



Redshank



Broccoli



Tiger Cat



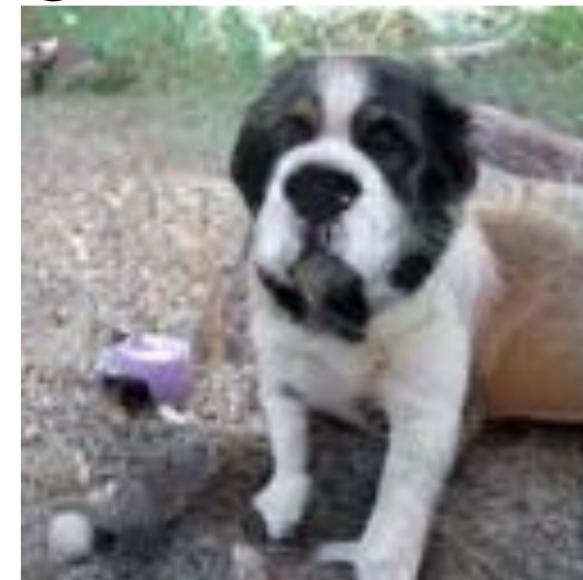
Geyser



Indigo Bunting



Stone Wall



Saint Bernard

(Zhang et al., 2018)

Self-Play

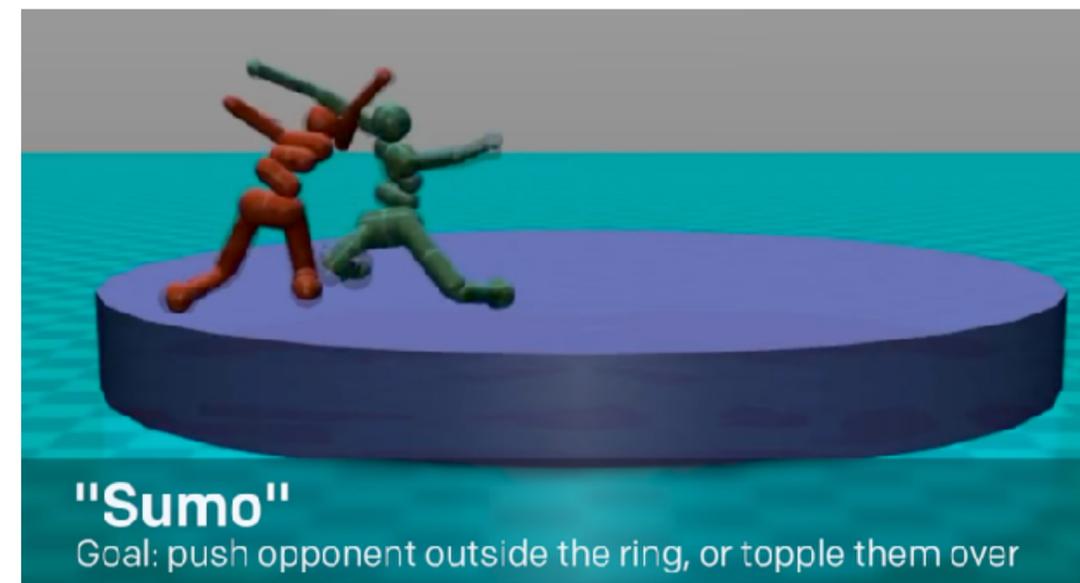
1959: Arthur Samuel's checkers agent



(Silver et al, 2017)



(OpenAI, 2017)



(Bansal et al, 2017)

What can you do with GANs?

- Simulated environments and training data
- Missing data
 - Semi-supervised learning
- Multiple correct answers
- Realistic generation tasks
- Model-based optimization
- Automated customization
- Domain adaptation

Autonomous Driving Data

Input labels

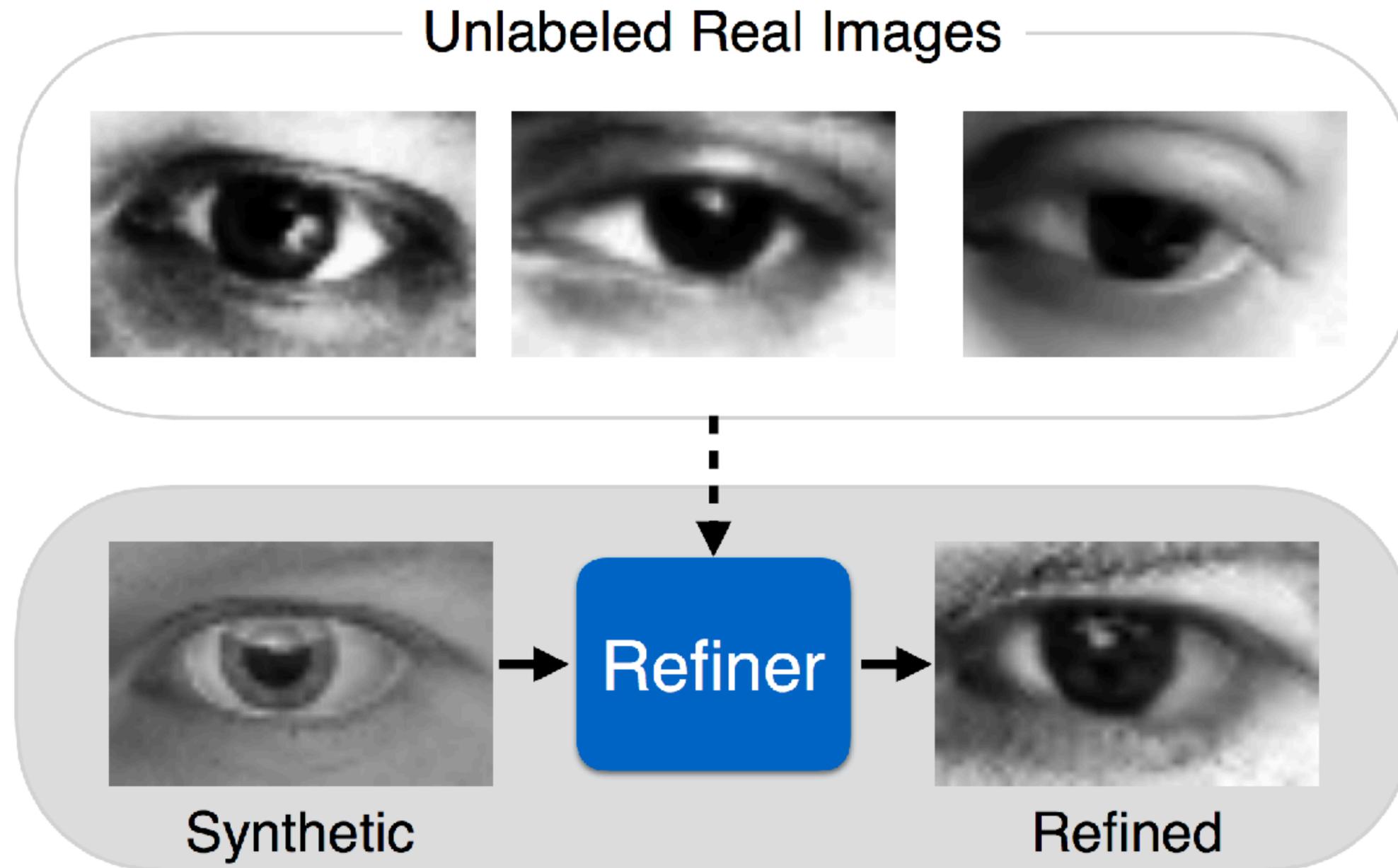


Synthesized image



(Wang et al., 2017)

GANs for simulated training data



(Shrivastava et al., 2016)

What can you do with GANs?

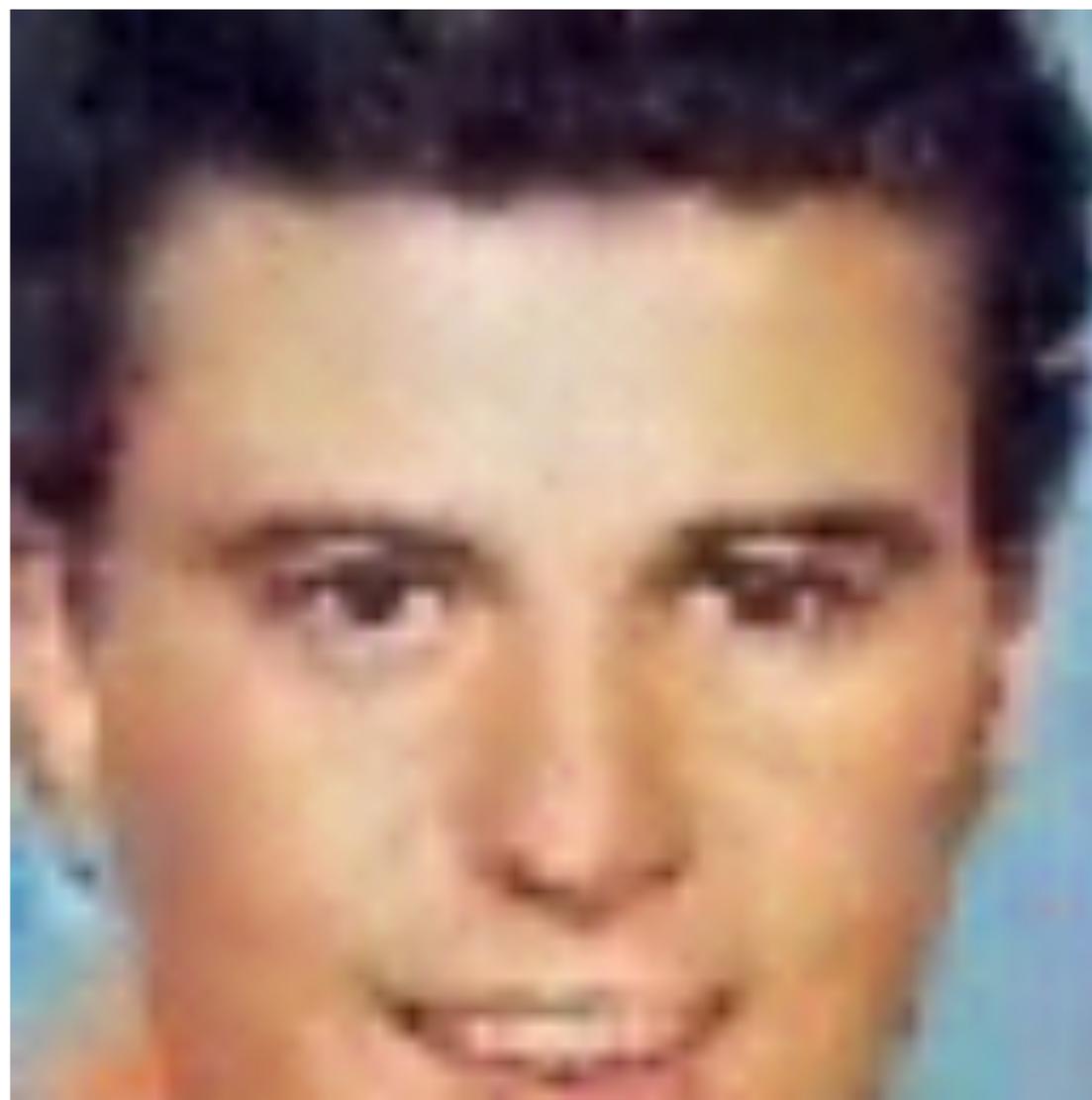
- Simulated environments and training data
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What is in this image?



(Yeh et al., 2016)

Generative modeling reveals a face

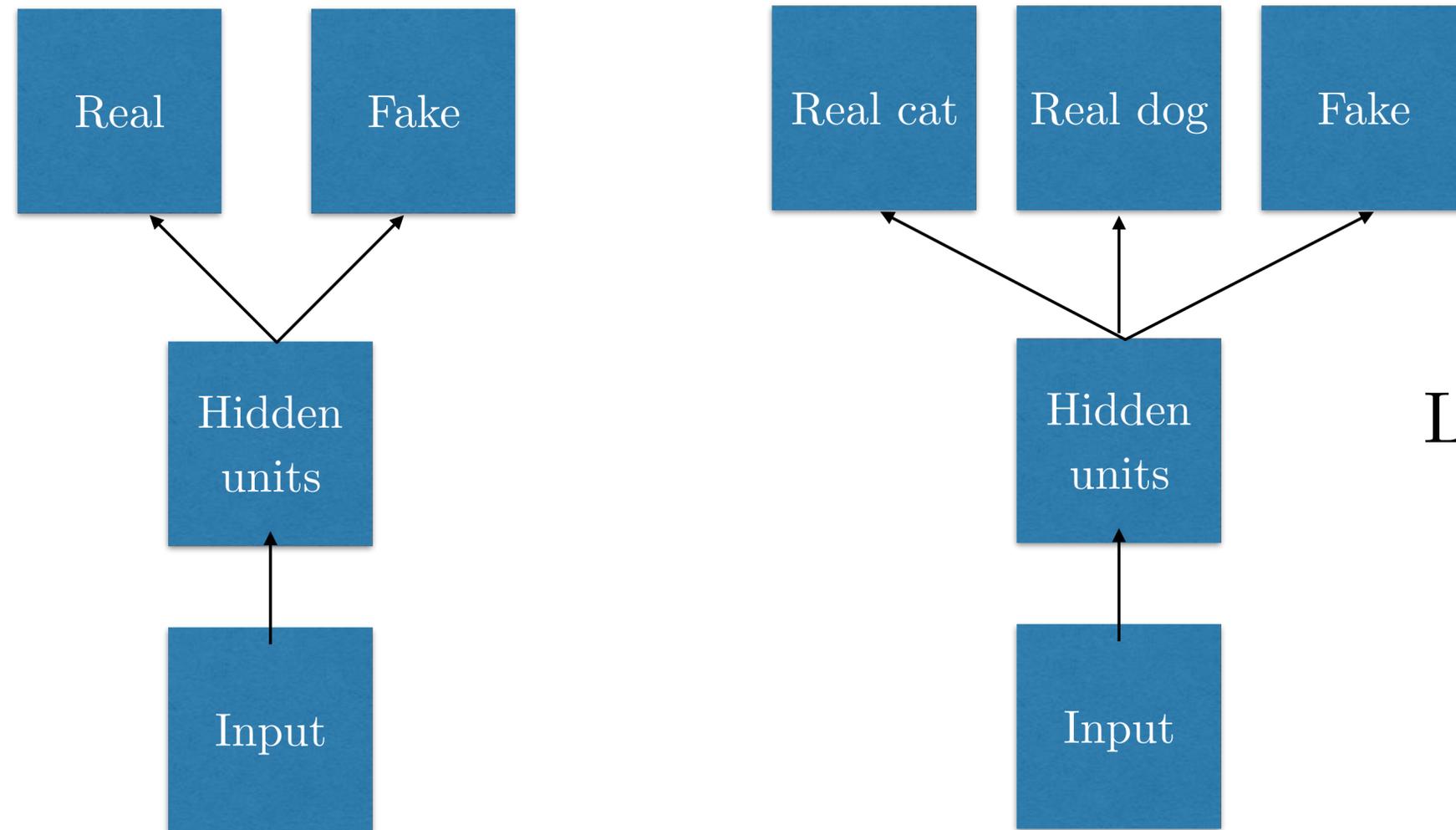


(Yeh et al., 2016)

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Supervised Discriminator for Semi-Supervised Learning



Learn to read with
100 labels rather
than 60,000

(Odena 2016, Salimans et al 2016)

Semi-Supervised Classification

MNIST: 100 training labels \rightarrow 80 test mistakes

SVHN: 1,000 training labels \rightarrow 4.3% test error

CIFAR-10: 4,000 labels \rightarrow 14.4% test error

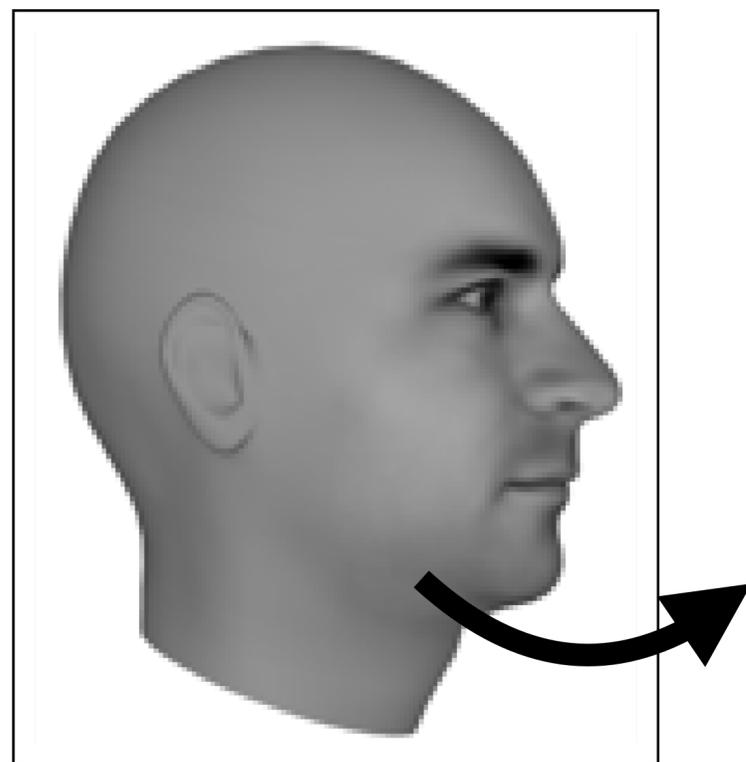
(Dai et al 2017)

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Next Video Frame Prediction

Ground Truth

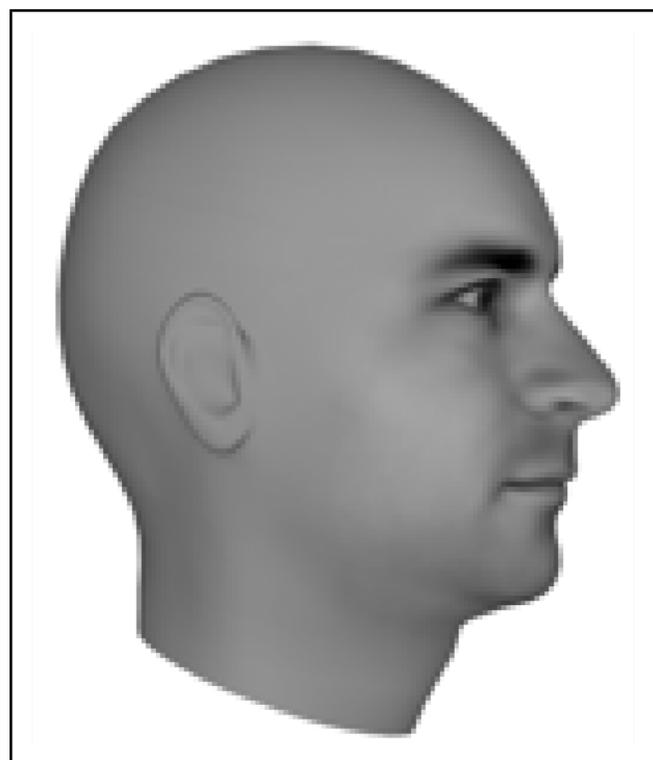


What happens next?

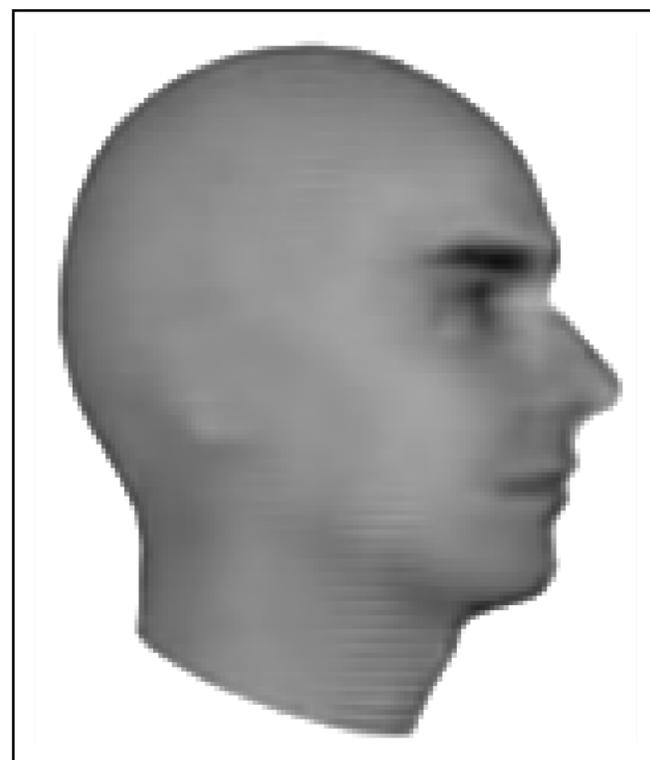
(Lotter et al 2016)

Next Video Frame Prediction

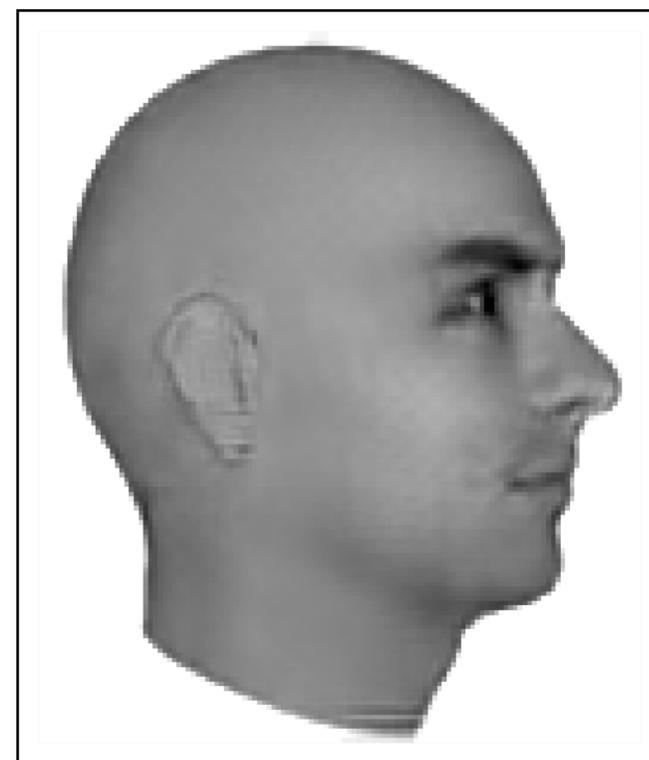
Ground Truth



MSE



Adversarial



(Lotter et al 2016)

Next Video Frame(s) Prediction

Mean Squared Error

Mean Absolute Error

Adversarial

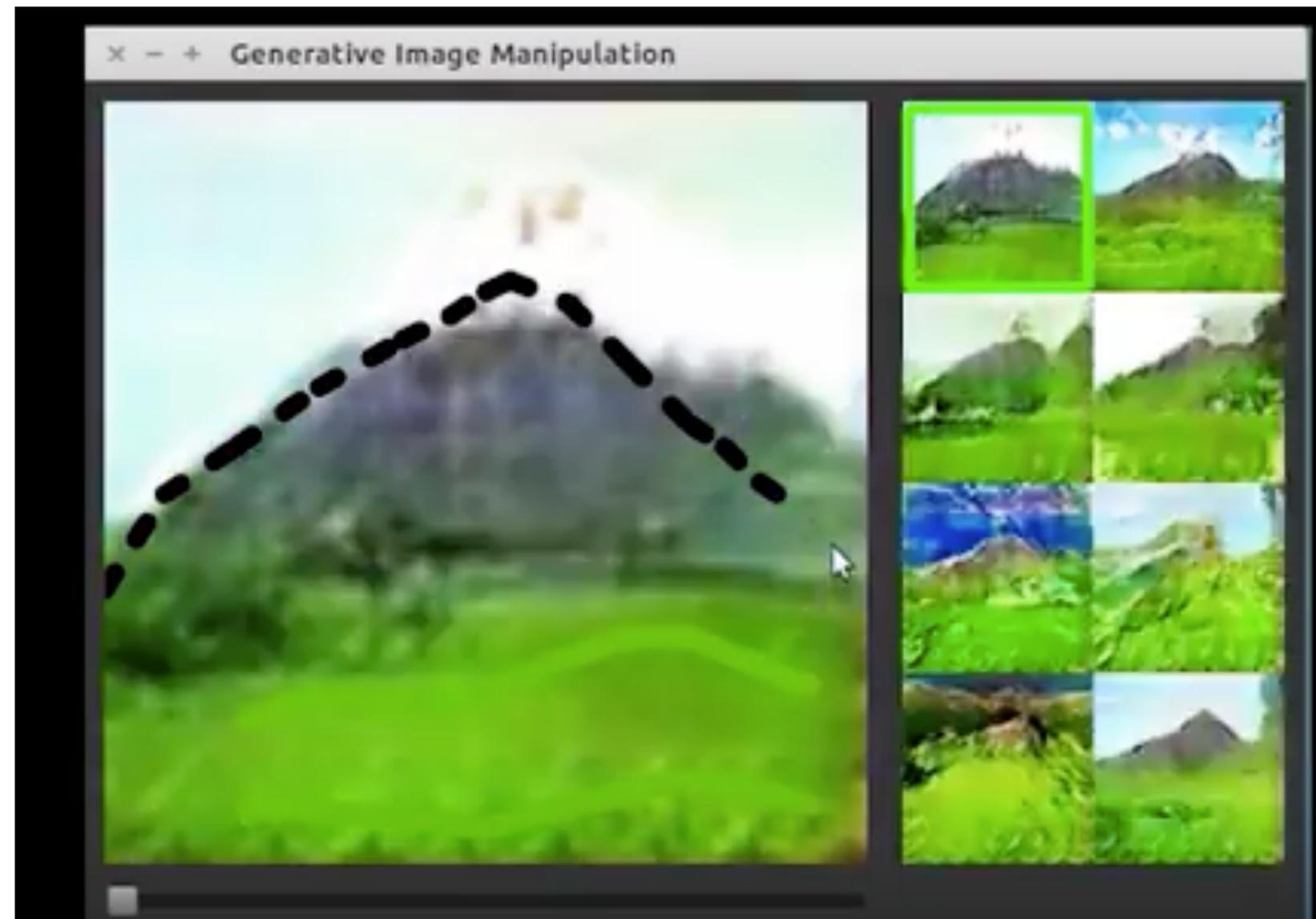


(Mathieu et al. 2015)

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iGAN



youtube

(Zhu et al., 2016)

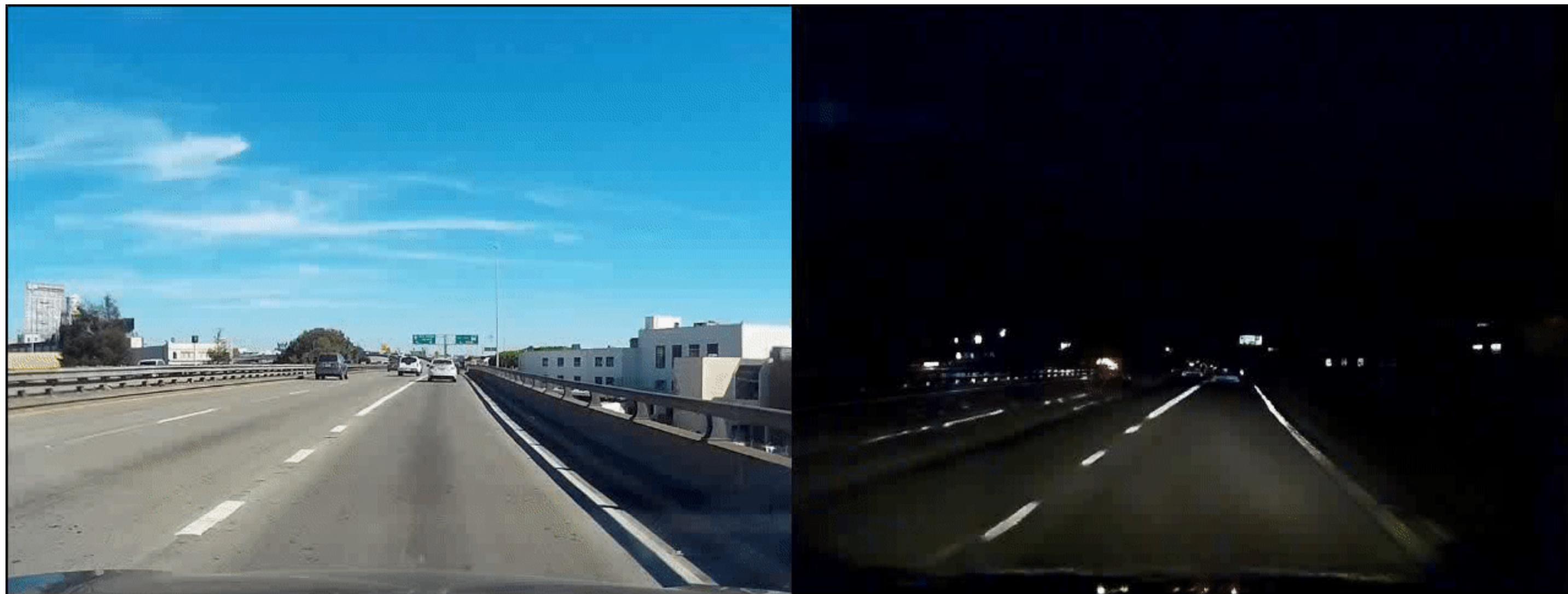
Image to Image Translation



(Isola et al., 2016)

Unsupervised Image-to-Image Translation

Day to night



(Liu et al., 2017)

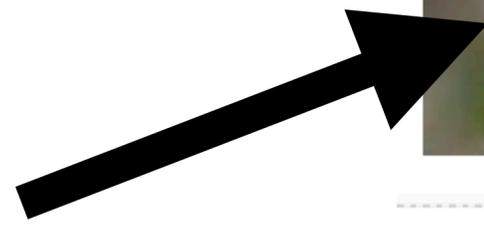
CycleGAN



(Zhu et al., 2017)

Text-to-Image Synthesis

This bird has a yellow belly and tarsus, grey back, wings, and brown throat, nape with a black face

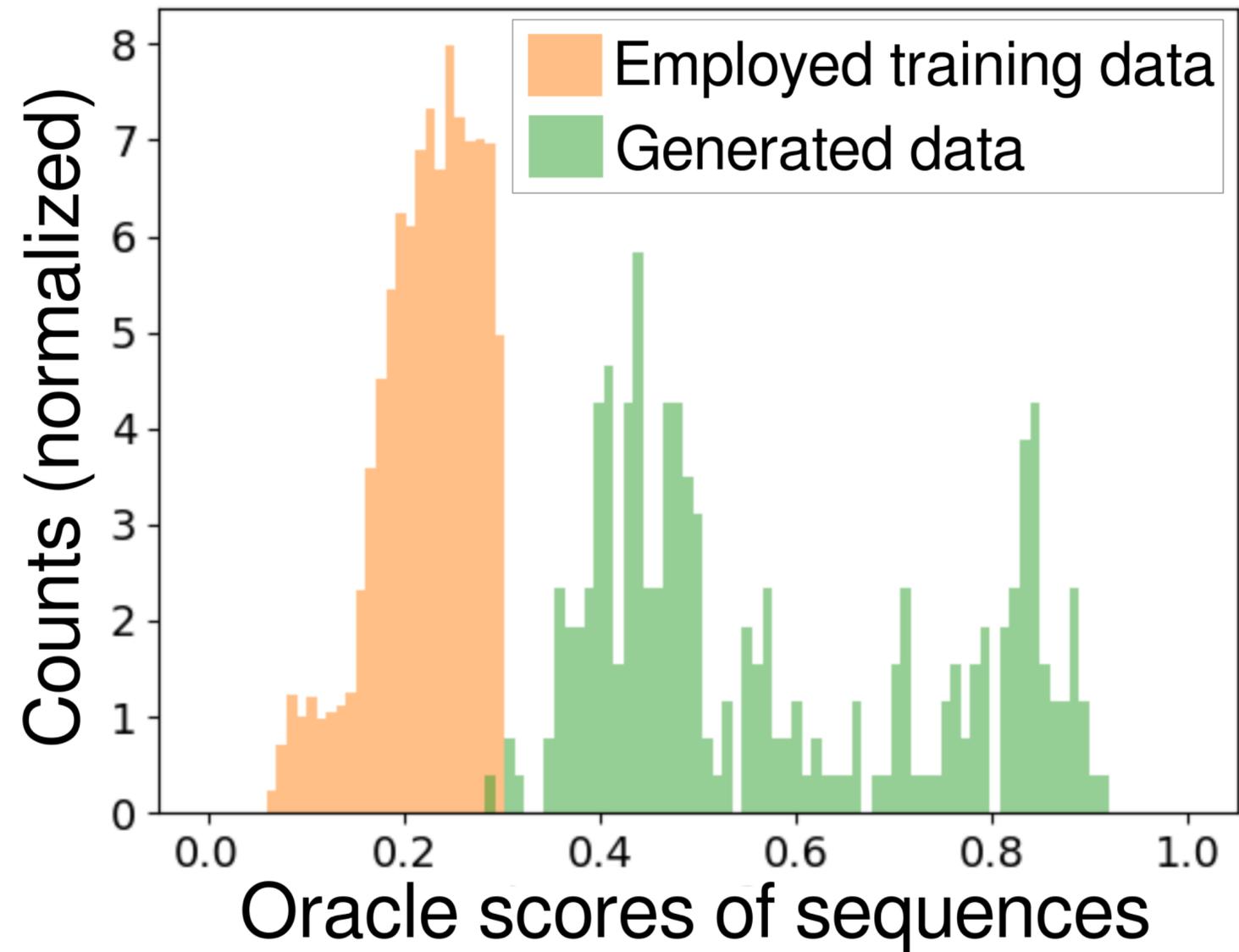


(Zhang et al., 2016)

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Designing DNA to optimize protein binding

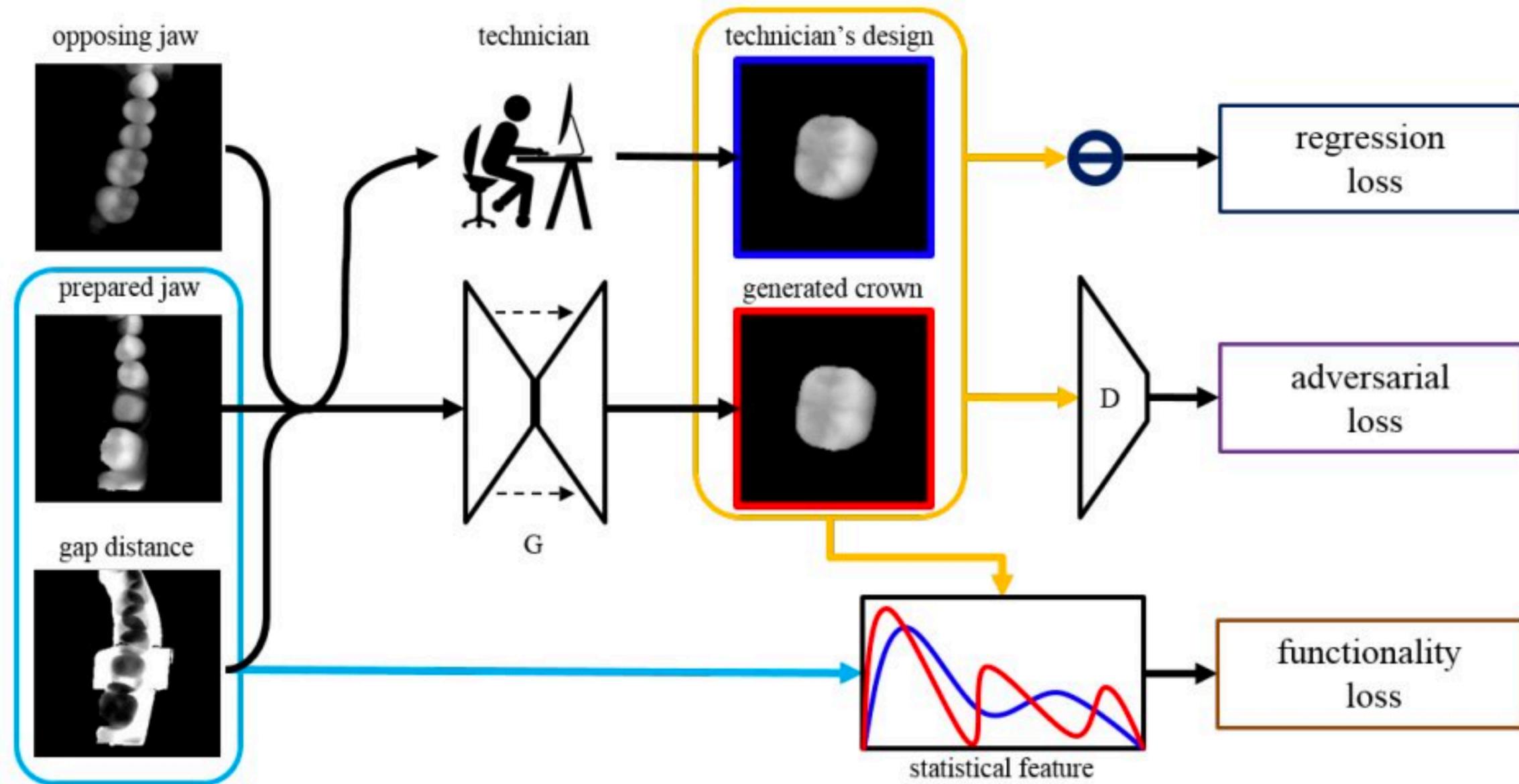


(Killoran et al, 2017)

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Personalized GANufacturing



(Hwang et al 2018)

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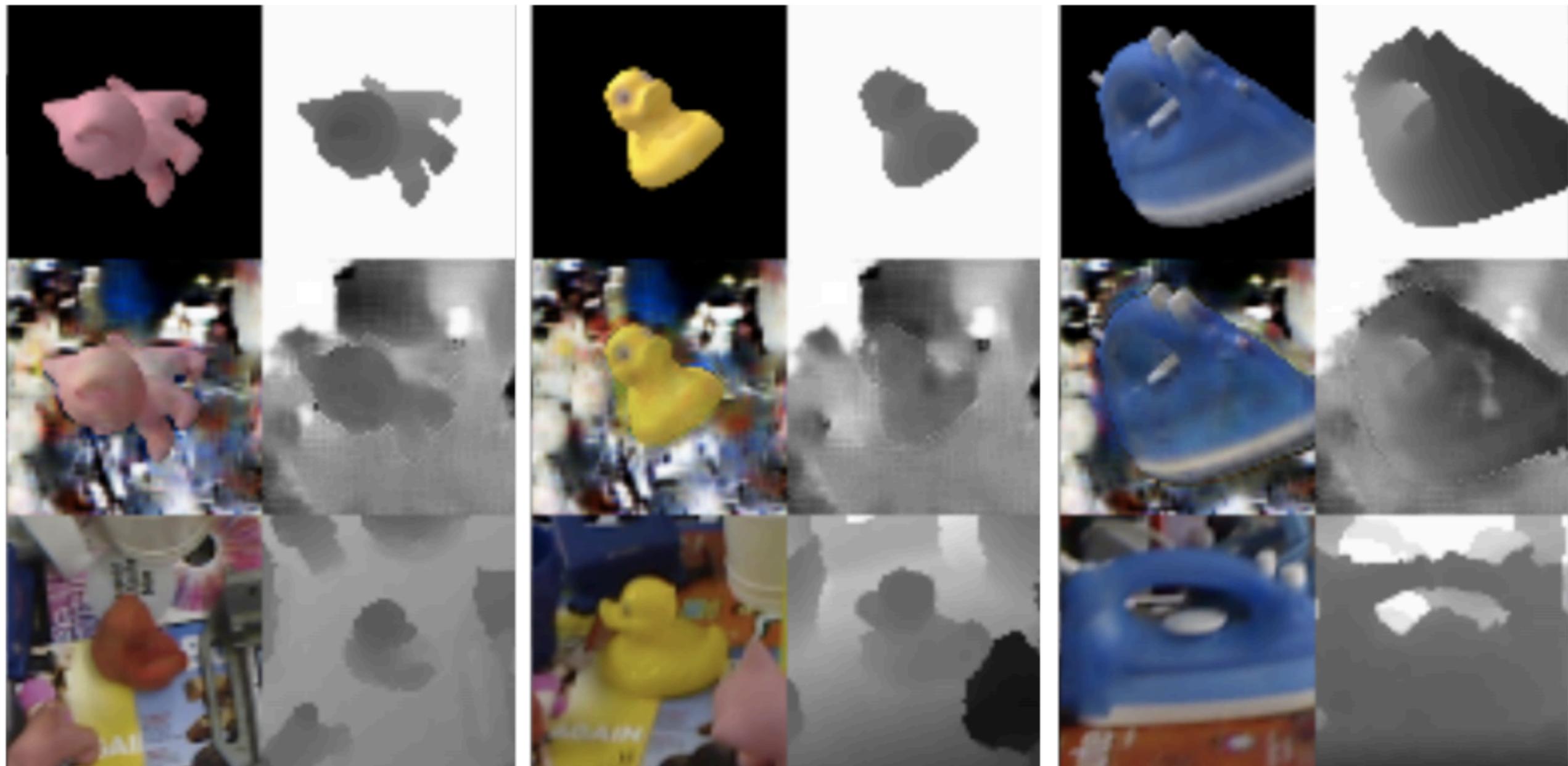
Domain Adaptation

- Domain Adversarial Networks (Ganin et al, 2015)



- Professor forcing (Lamb et al, 2016): Domain-Adversarial learning in RNN hidden state

GANs for domain adaptation

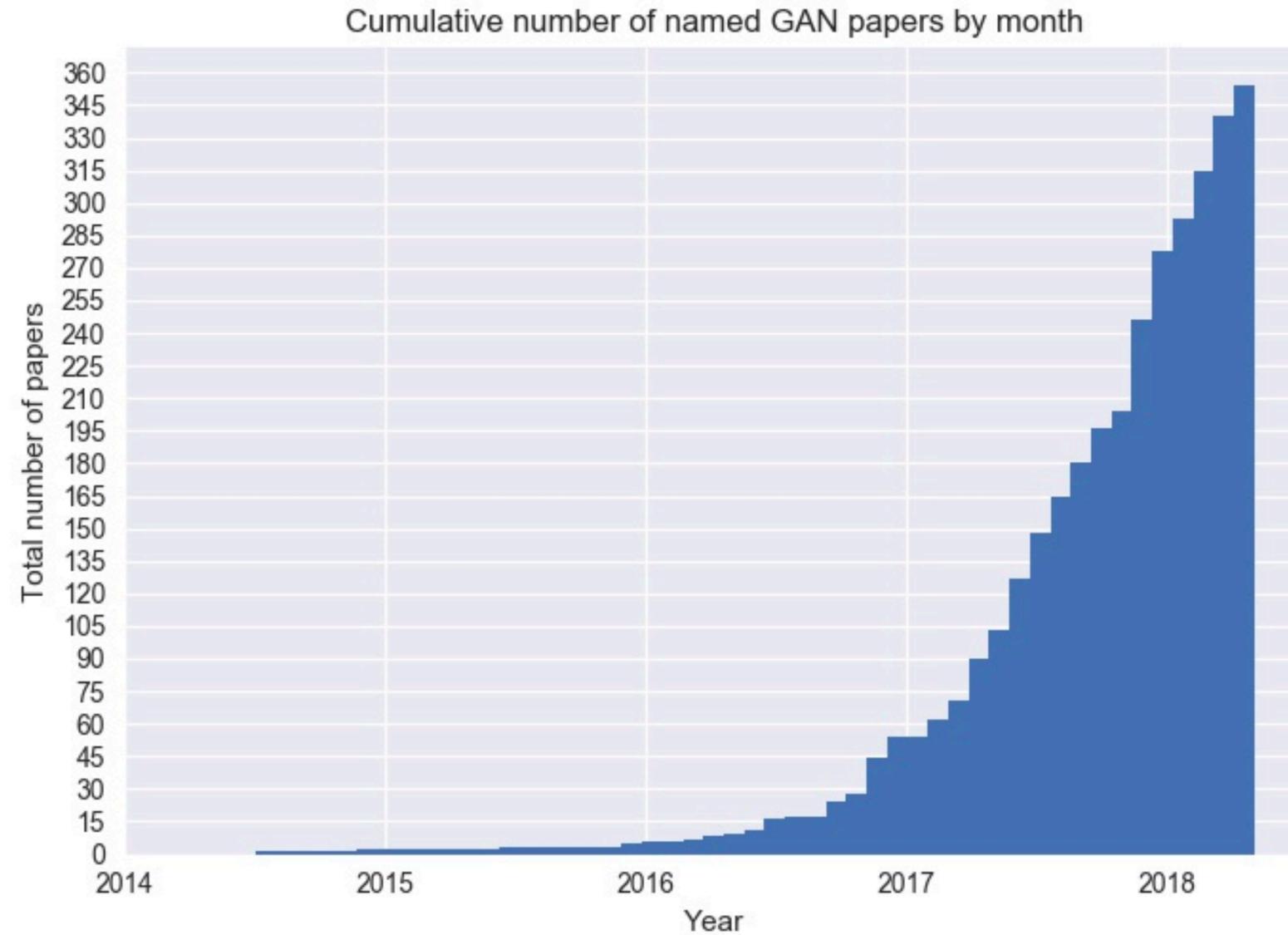


(Bousmalis et al., 2016)

Tips and Tricks

- Spectral normalization (Miyato et al 2017) in both discriminator and generator (Zhang et al 2018)
- Different learning rate for generator and discriminator (Heusel et al 2017)
- No need to run discriminator more often than generator (Zhang et al 2018)
- Many different loss functions all work well (Lucic et al 2017); spend more time tuning hyperparameters than trying different losses

Track updates at the GAN Zoo



<https://github.com/hindupuravinash/the-gan-zoo>

Questions