MedGAN ID-CGAN CoGAN LR-GAN CGAN IcGAN

b-GAN LS-GAN AffGAN LAPGAN DiscoGAN MPM-GAN AdaGAN

LSGAN InfoGAN CatGAN AMGAN iGAN IAN

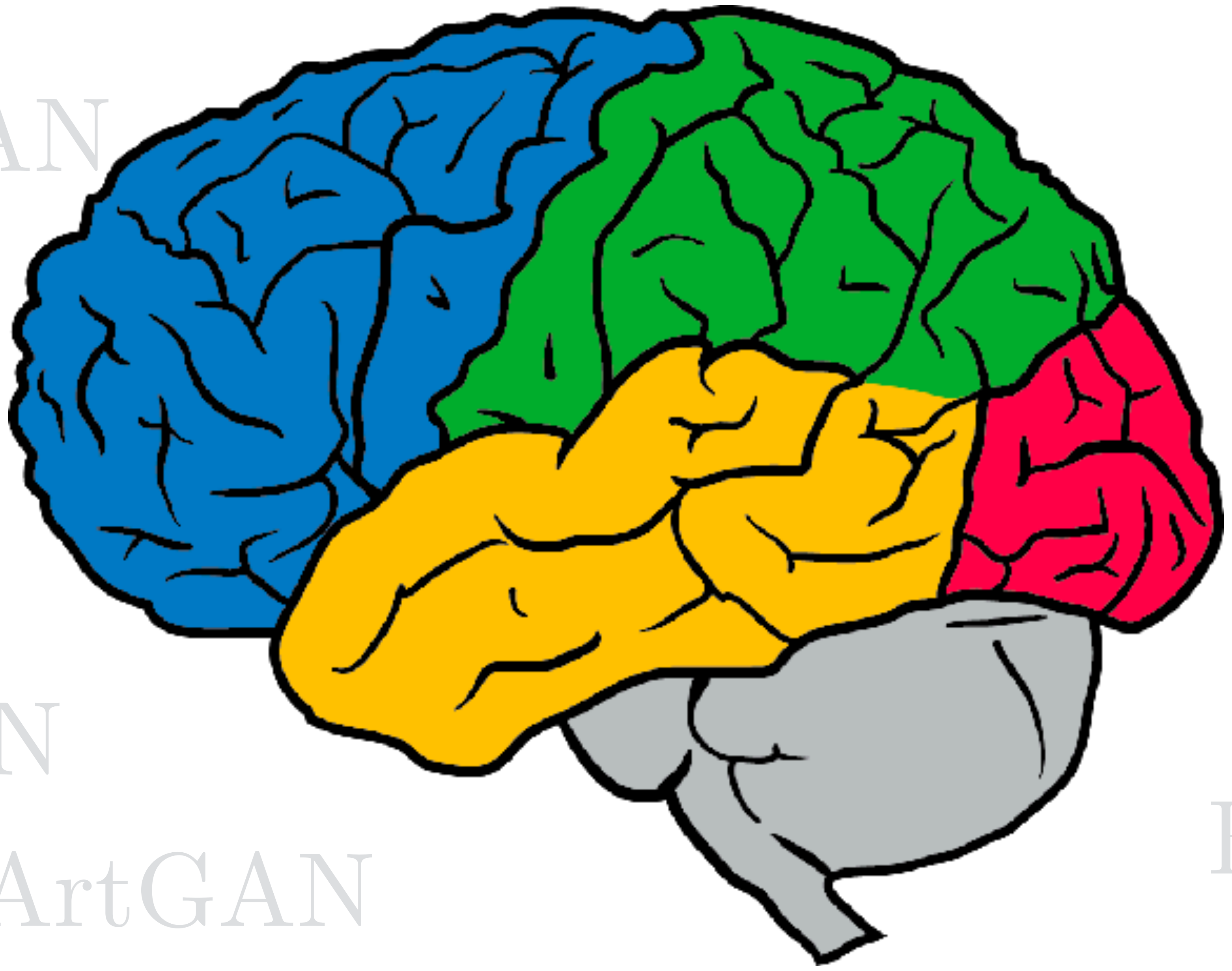
# Generative Adversarial Networks

McGAN Ian Goodfellow, Staff Research Scientist, Google Brain MIX+GAN

C-RNN-GAN Adobe Research Seminar DR-GAN

MGAN San Jose, California 2017-05-09 GoGAN BS-GAN

C-VAE-GAN FF-GAN



CCGAN DCGAN AC-GAN

MAGAN 3D-GAN

GAWWN DualGAN BiGAN CycleGAN

Bayesian GAN GP-GAN

AnoGAN

EBGAN DTN

Context-RNN-GAN MAD-GAN

ALI BEGAN AL-CGAN

MARTA-GAN f-GAN ArtGAN MalGAN

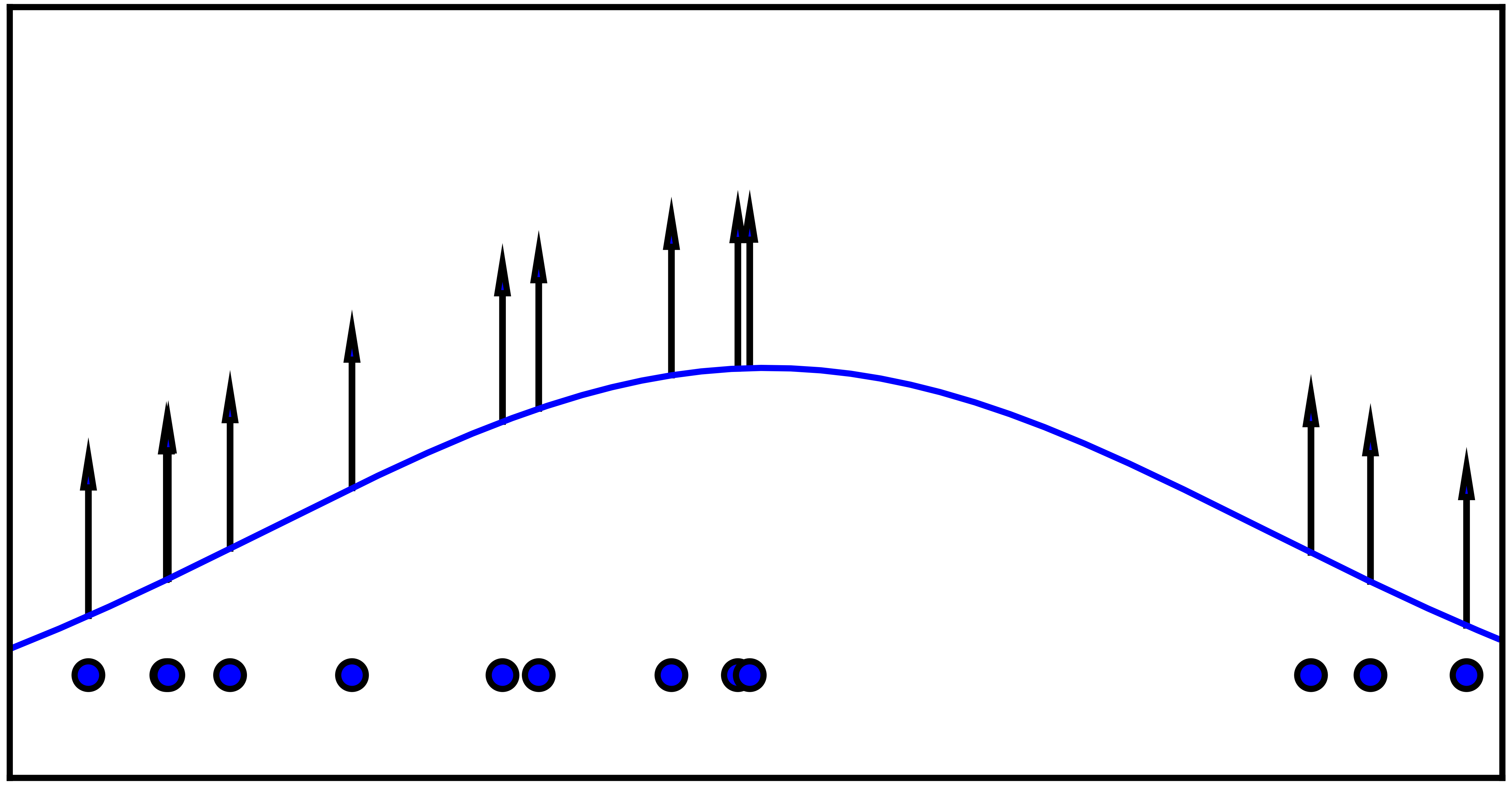
# Generative Modeling

- Density estimation

- Sample generation

Training examples Model samples

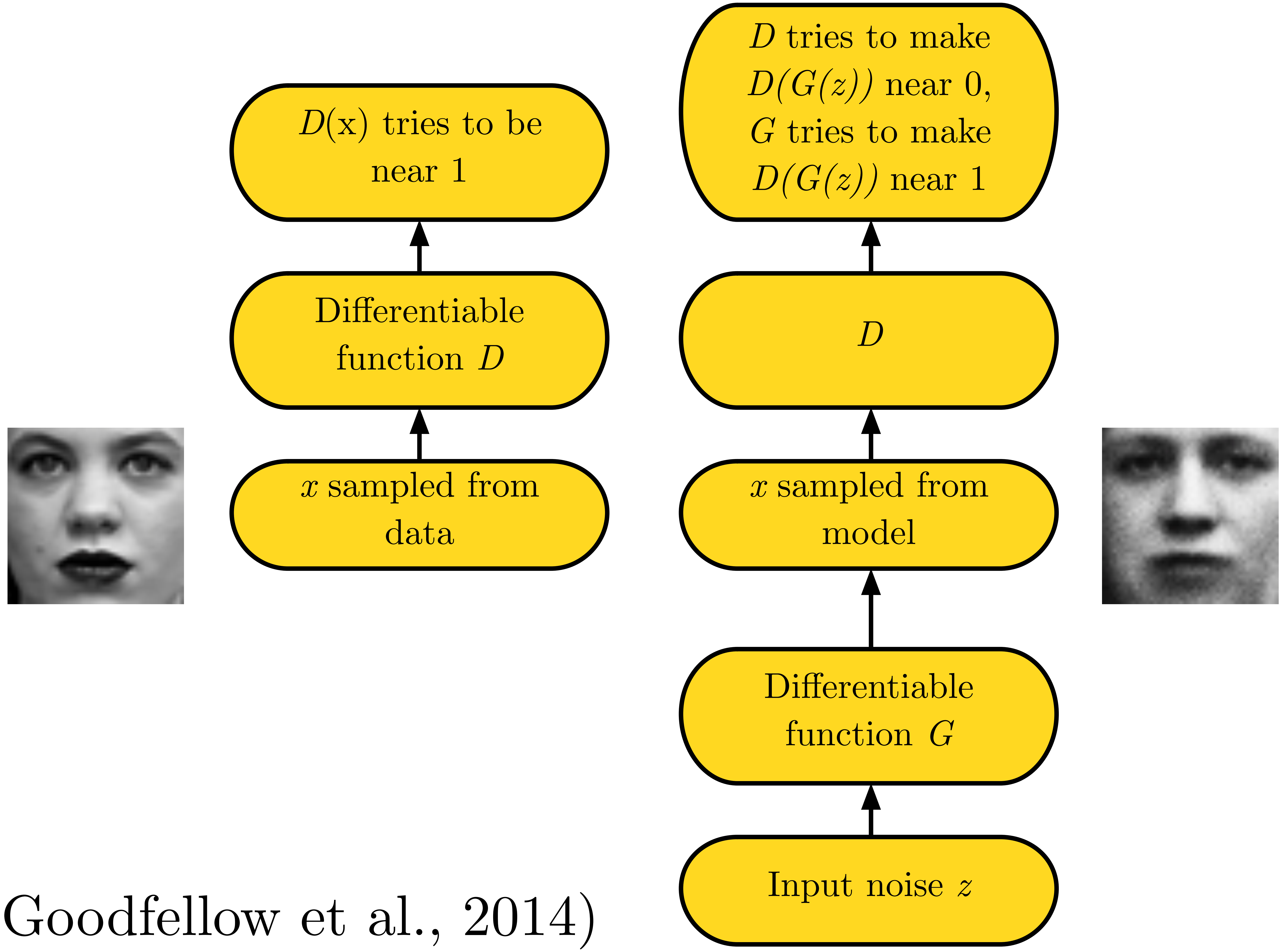
# Maximum Likelihood



$$\boldsymbol{\theta}^* = \arg\max_{\boldsymbol{\theta}} \mathbb{E}_{x \sim p_{\text{data}}} \log p_{\text{model}}(\boldsymbol{x} \mid \boldsymbol{\theta})$$

(Goodfellow 2017)

# Adversarial Nets Framework




(Goodfellow et al., 2014)

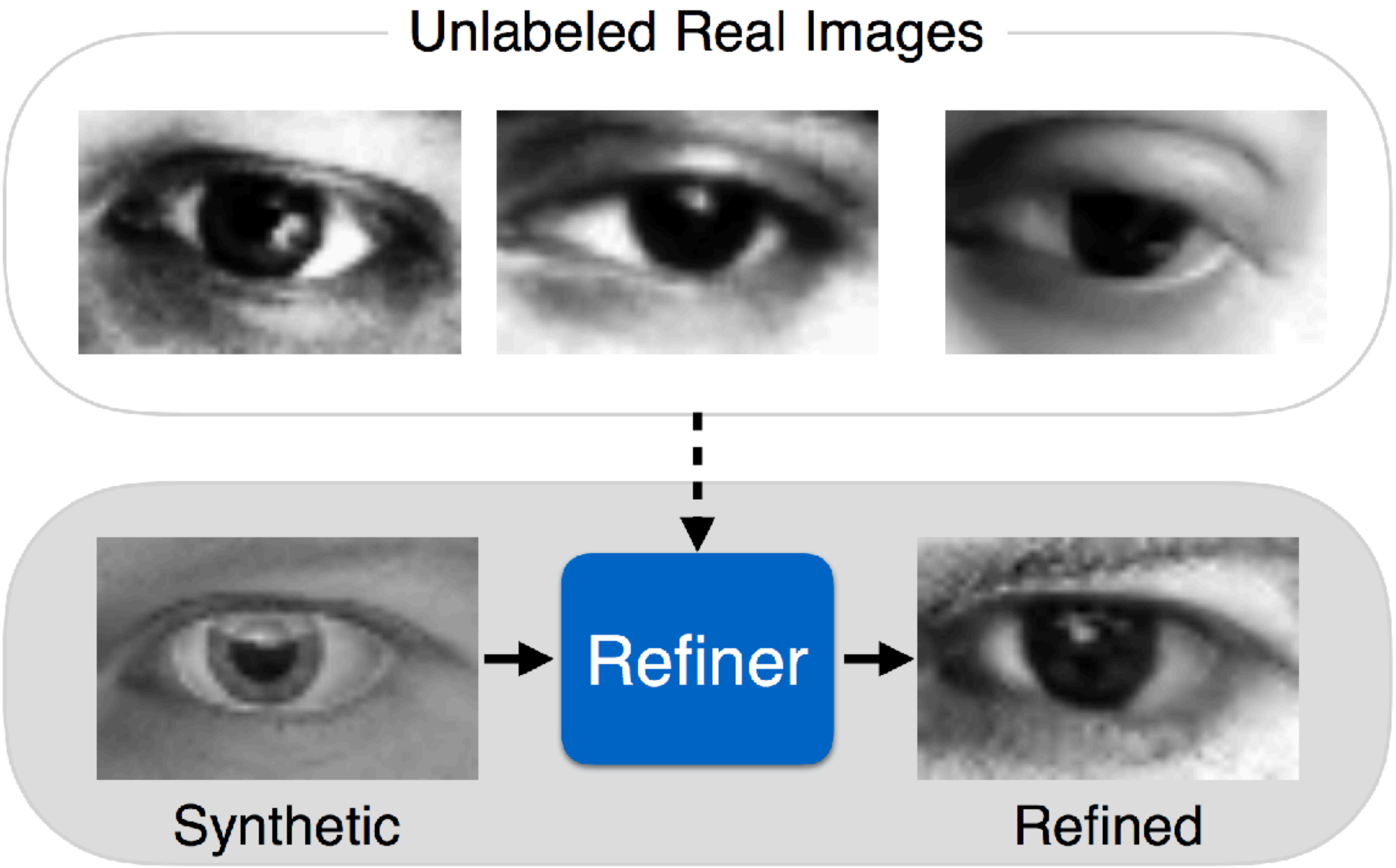
# What can you do with GANs?

- Simulated environments and training data
- Missing data
  - Semi-supervised learning
- Multiple correct answers
- Realistic generation tasks
- Simulation by prediction
- Solve inference problems
- Learn useful embeddings

TEACHING AID

# Apple's first research paper tries to solve a problem facing every company working on AI

# GANs for simulated training data




(Shrivastava et al., 2016)

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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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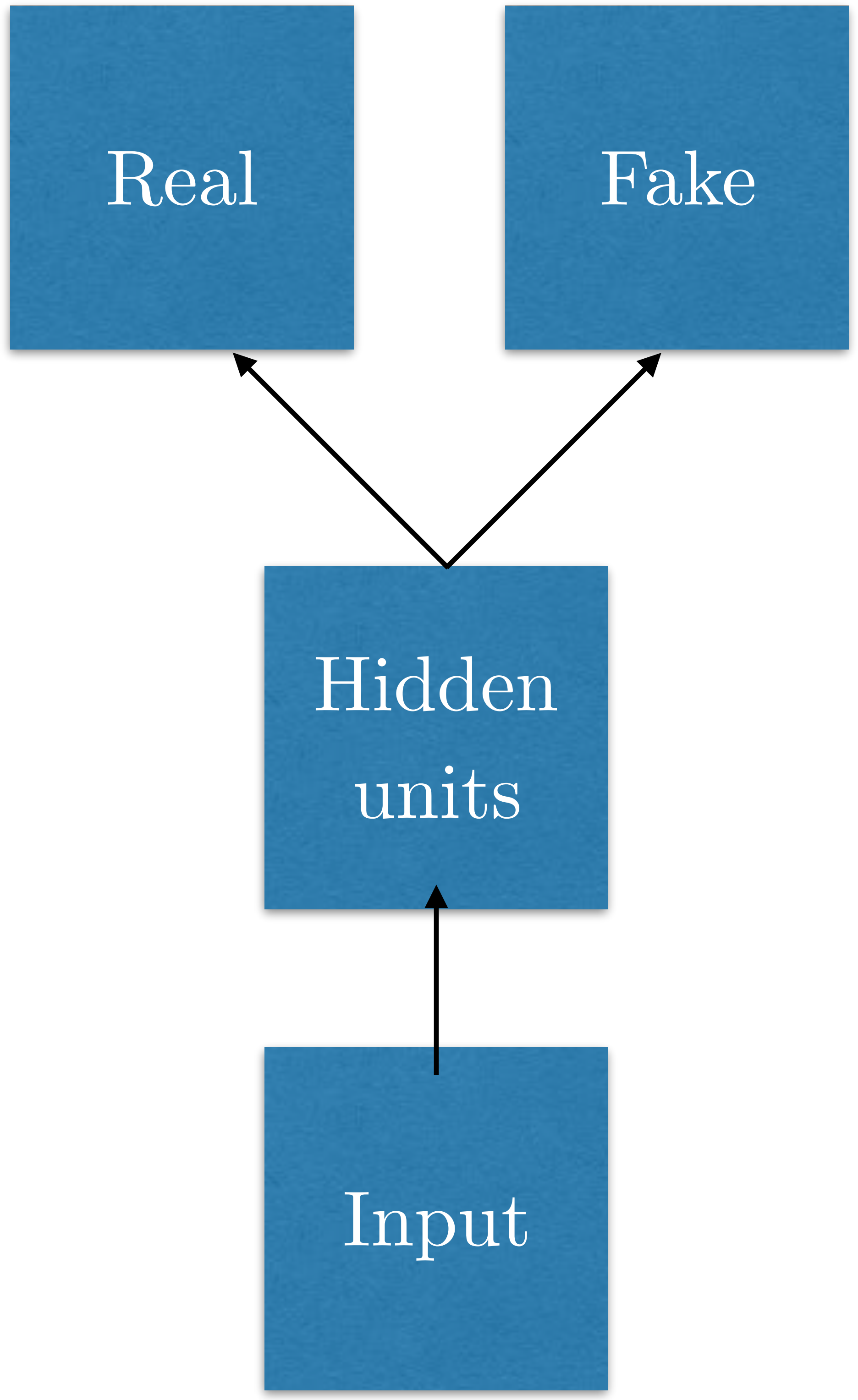
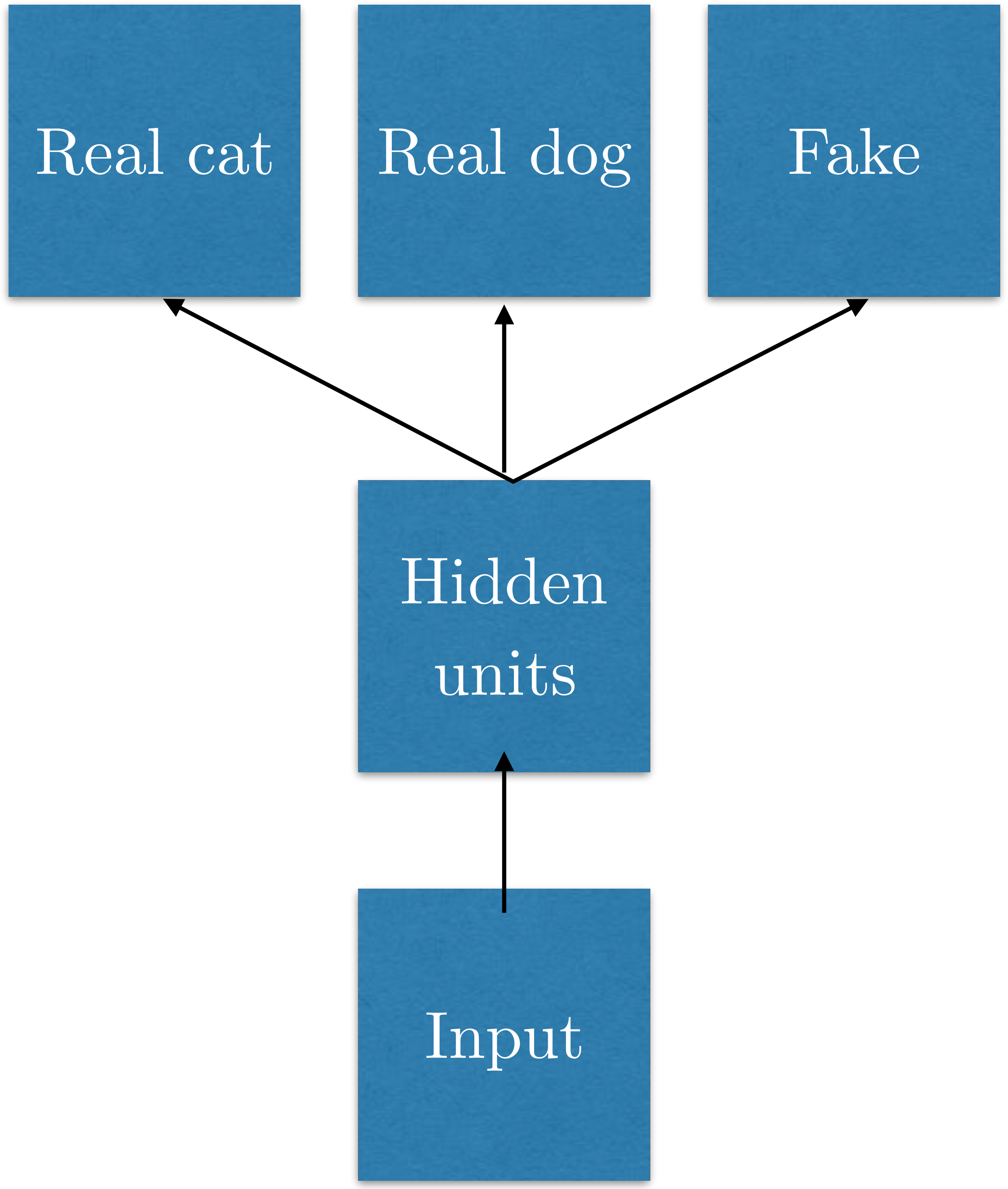
(Goodfellow 2017)

# Supervised Discriminator




(Odena 2016, Salimans et al 2016)

# Semi-Supervised Classification

## MNIST (Permutation Invariant)

| Model | Number of incorrectly predicted test examples for a given number of labeled samples | | | |
|---|---|---|---|---|
| | 20 | 50 | 100 | 200 |
| DGN [21] | | | $333 \pm 14$ | |
| Virtual Adversarial [22] | | | 212 | |
| CatGAN [14] | | | $191 \pm 10$ | |
| Skip Deep Generative Model [23] | | | $132 \pm 7$ | |
| Ladder network [24] | | | $106 \pm 37$ | |
| Auxiliary Deep Generative Model [23] | | | $96 \pm 2$ | |
| Our model | $1677 \pm 452$ | $221 \pm 136$ | $93 \pm 6.5$ | $90 \pm 4.2$ |
| Ensemble of 10 of our models | $1134 \pm 445$ | $142 \pm 96$ | $86 \pm 5.6$ | $81 \pm 4.3$ |

(Salimans et al 2016)

# Semi-Supervised Classification

## CIFAR-10

| Model | Test error rate for a given number of labeled samples | | | |
|---|---|---|---|---|
| | 1000 | 2000 | 4000 | 8000 |
| Ladder network [24] | | | $20.40 \pm 0.47$ | |
| CatGAN [14] | | | $19.58 \pm 0.46$ | |
| Our model | $21.83 \pm 2.01$ | $19.61 \pm 2.09$ | $18.63 \pm 2.32$ | $17.72 \pm 1.82$ |
| Ensemble of 10 of our models | $19.22 \pm 0.54$ | $17.25 \pm 0.66$ | $15.59 \pm 0.47$ | $14.87 \pm 0.89$ |

## SVHN

| Model | Percentage of incorrectly predicted test examples for a given number of labeled samples | | |
|---|---|---|---|
| | 500 | 1000 | 2000 |
| DGN [21] | | $36.02 \pm 0.10$ | |
| Virtual Adversarial [22] | | $24.63$ | |
| Auxiliary Deep Generative Model [23] | | $22.86$ | |
| Skip Deep Generative Model [23] | | $16.61 \pm 0.24$ | |
| Our model | $18.44 \pm 4.8$ | $8.11 \pm 1.3$ | $6.16 \pm 0.58$ |
| Ensemble of 10 of our models | | $5.88 \pm 1.0$ | |

(Salimans et al 2016)

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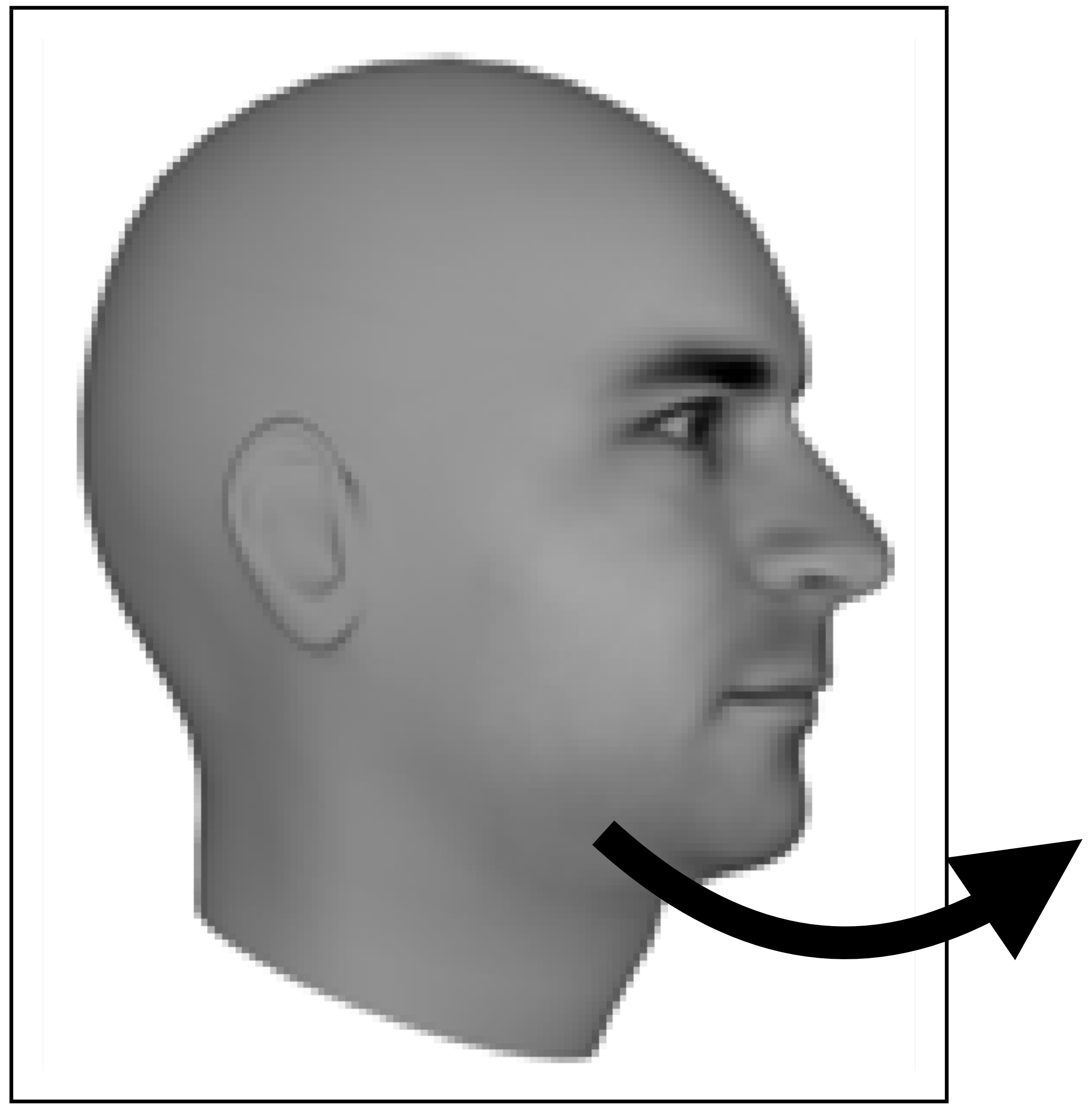
(Goodfellow 2017)

# Next Video Frame Prediction

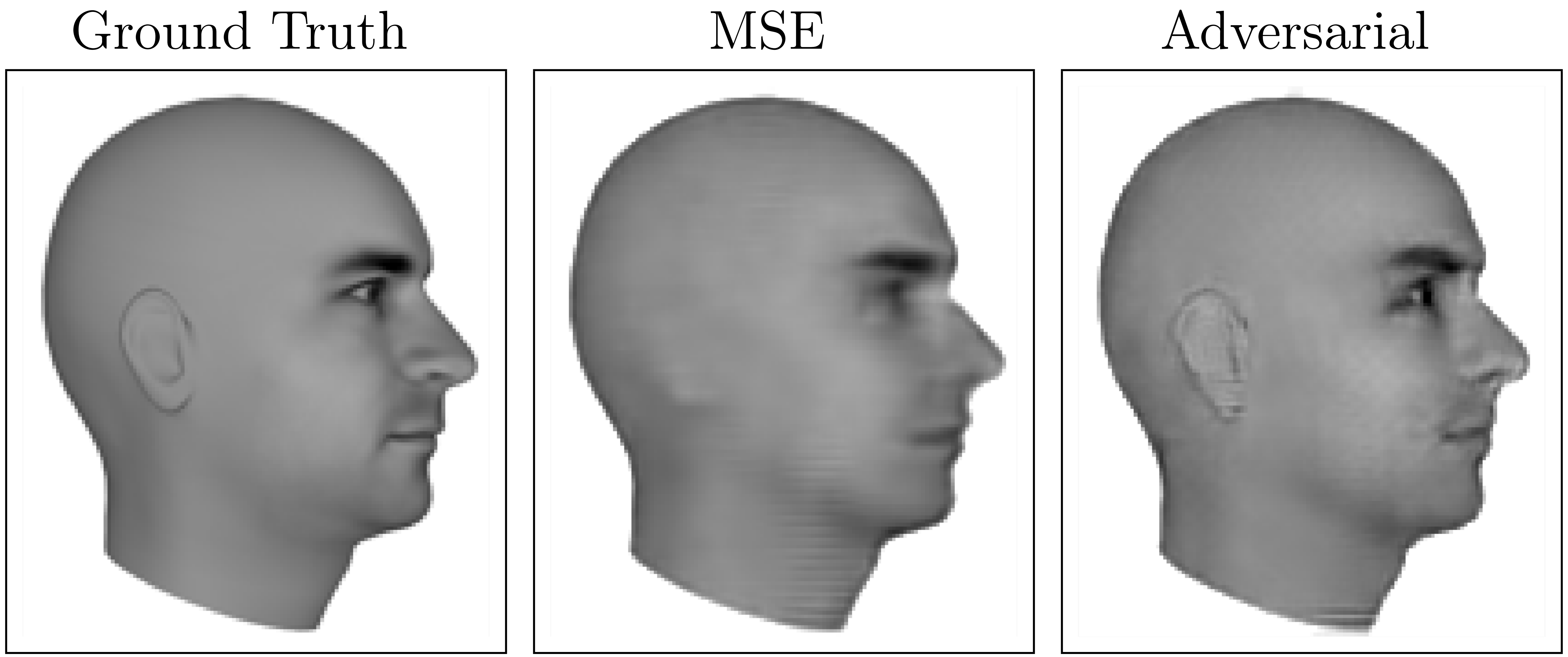
Ground Truth



What happens next?

(Lotter et al 2016)

# Next Video Frame Prediction




(Lotter et al 2016)

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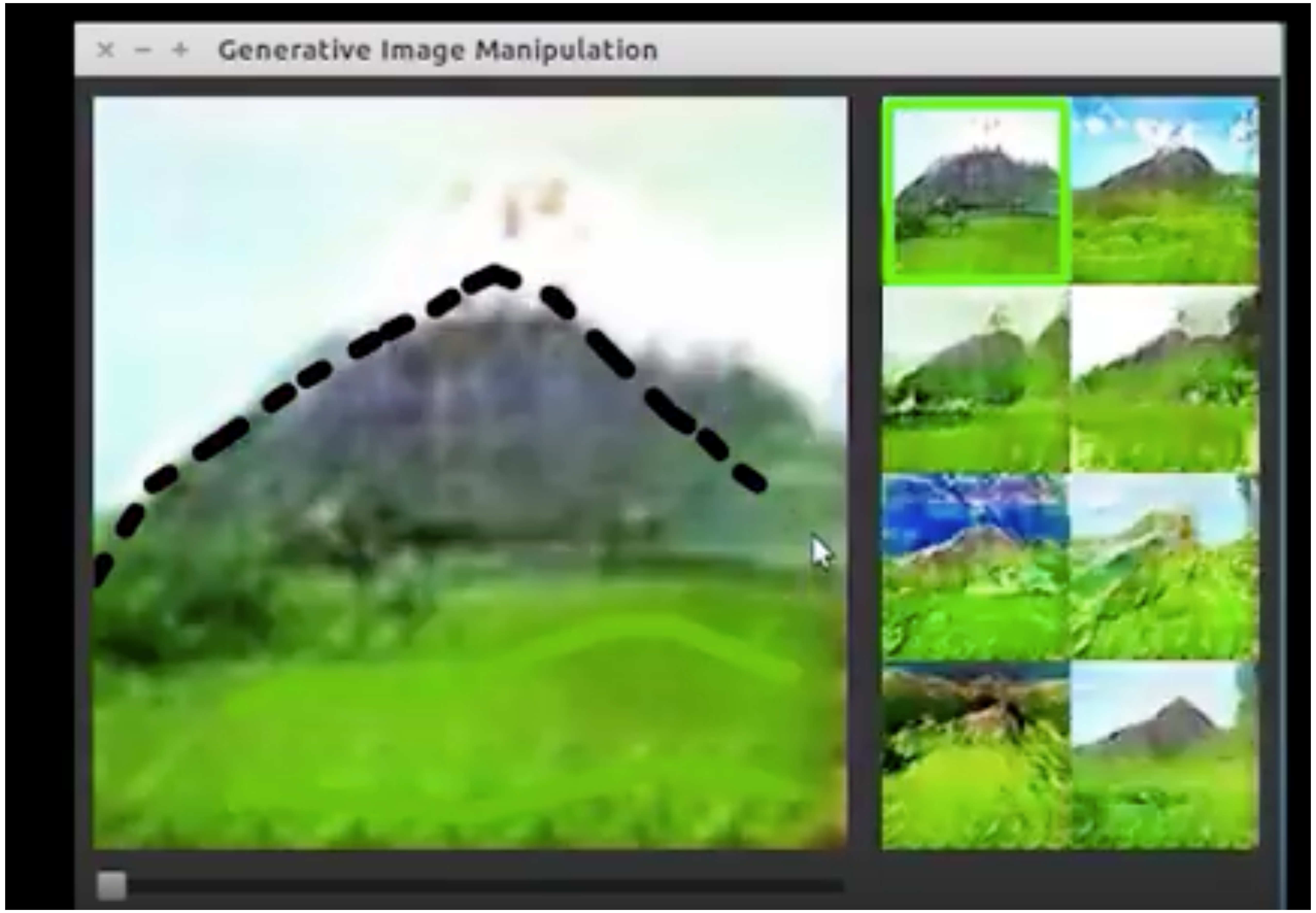
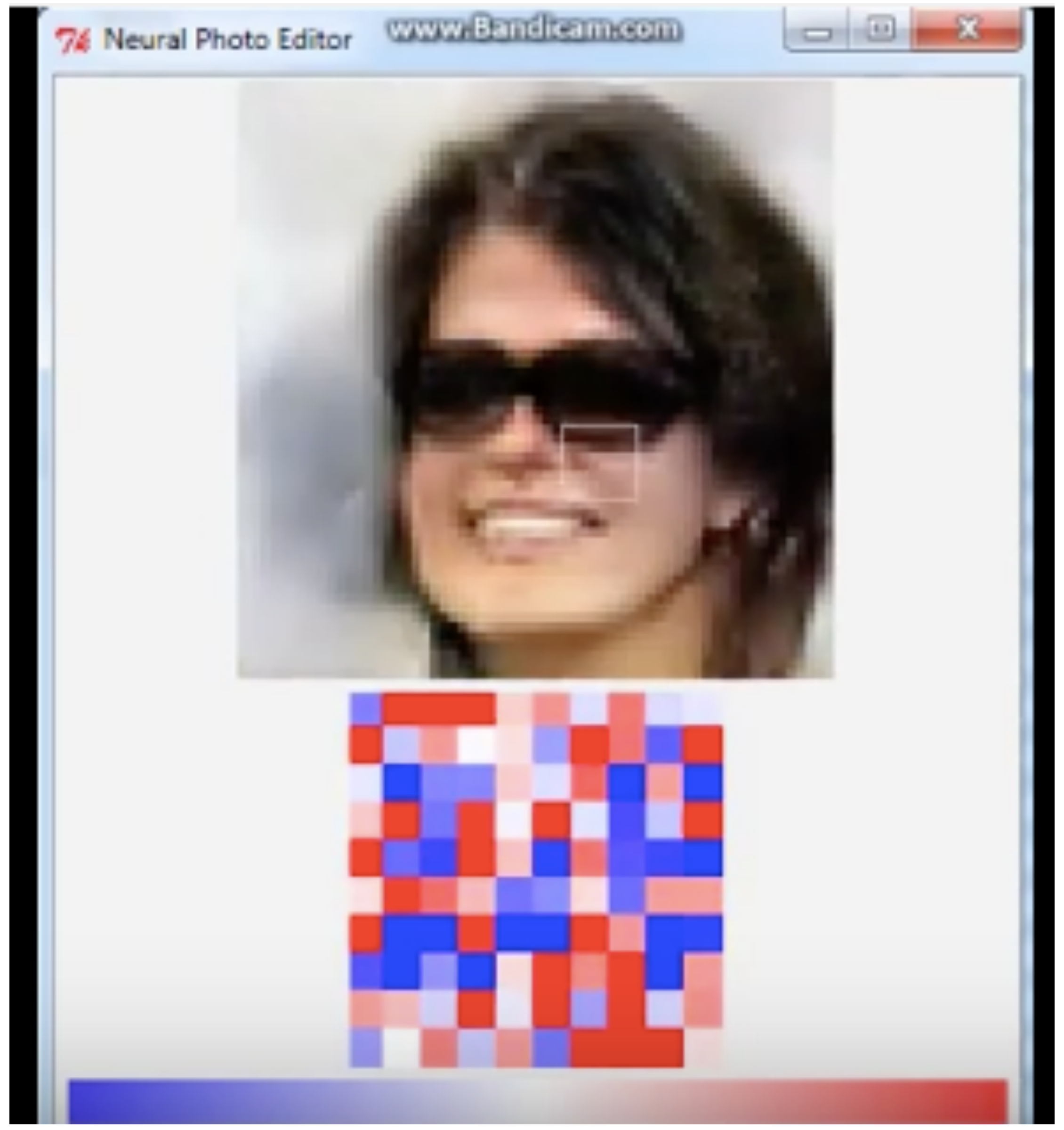
# iGAN




youtube

(Zhu et al., 2016)

# Introspective Adversarial Networks




youtube

(Brock et al., 2016)

# Image to Image Translation



(Isola et al., 2016)

# Unsupervised Image-to-Image Translation

Day to night

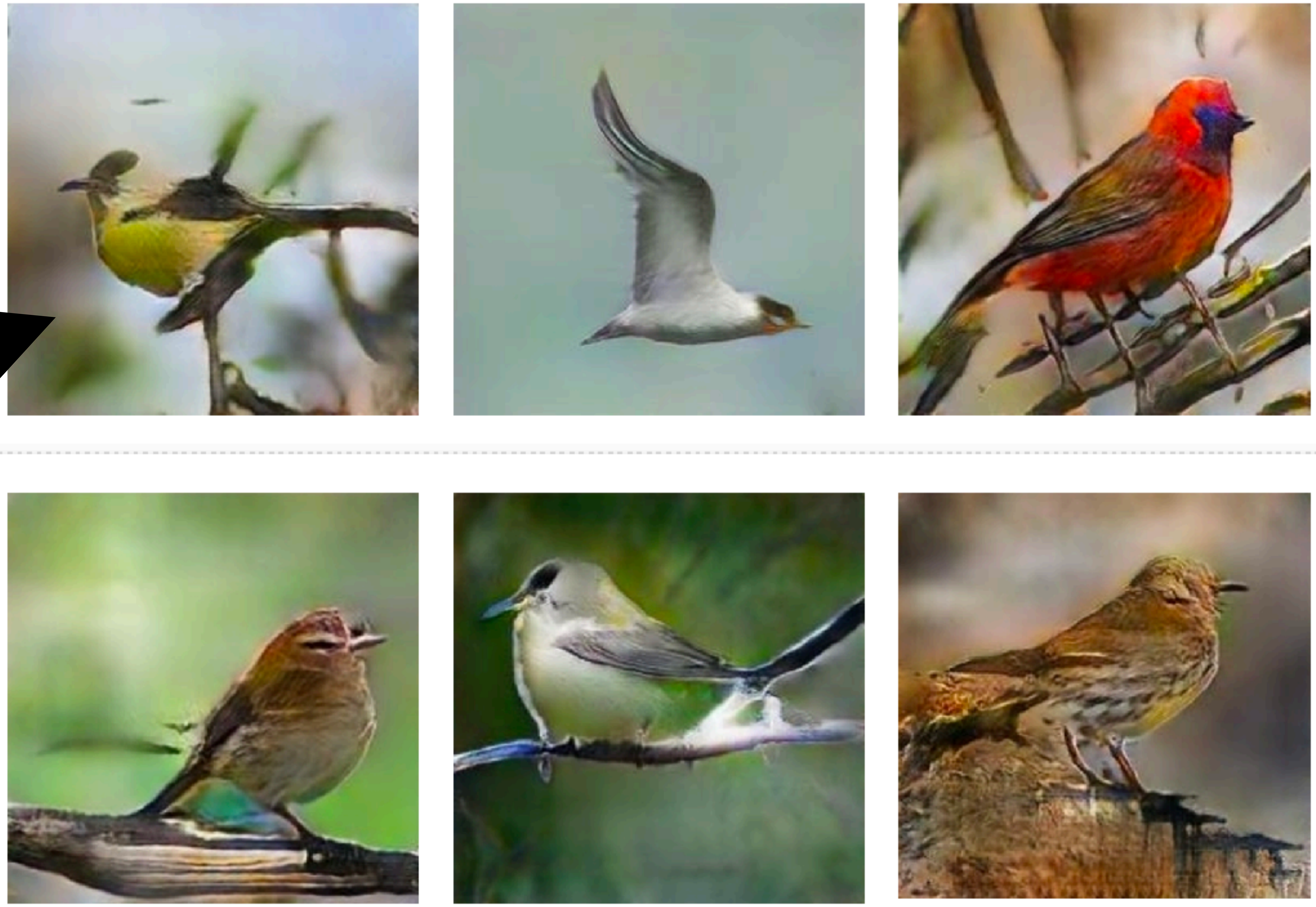
(Liu et al., 2017)

# 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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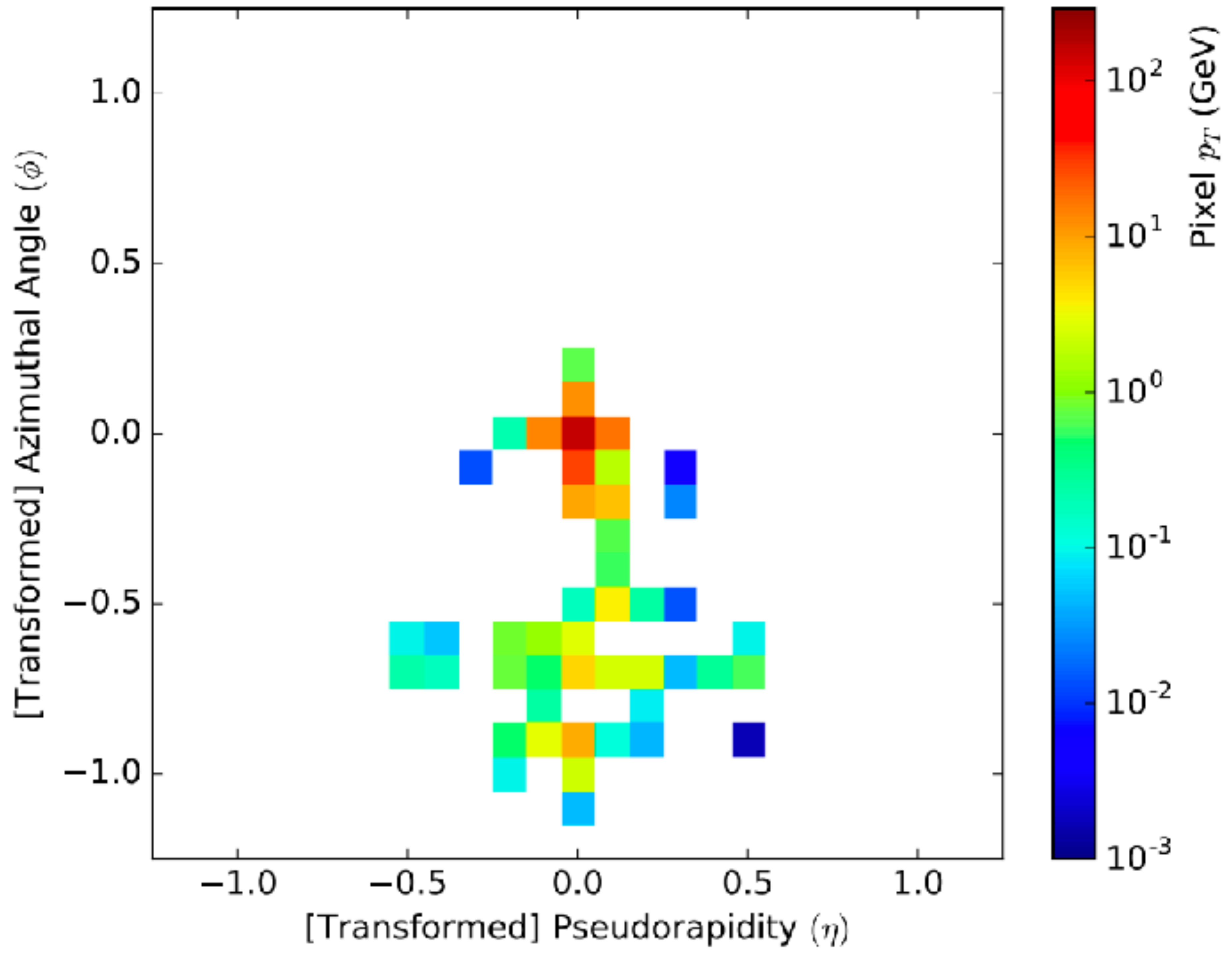
# Simulating particle physics

Save millions of dollars of CPU time by predicting outcomes of explicit simulations




(de Oliveira et al., 2017)

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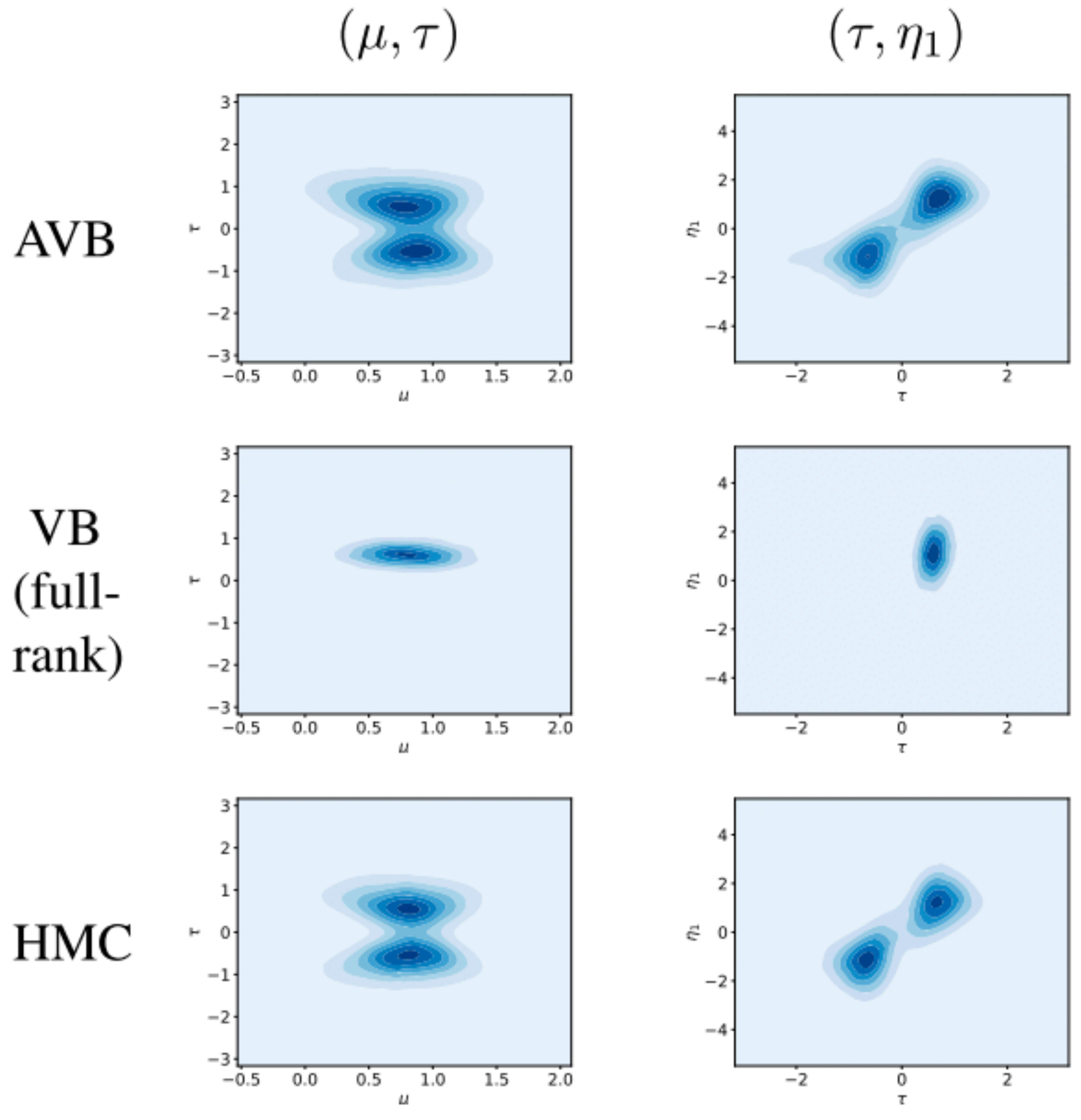
# Adversarial Variational Bayes




(Mescheder et al, 2017)

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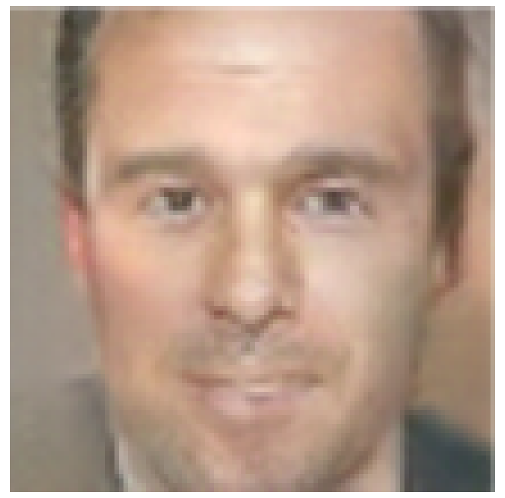
# Vector Space Arithmetic

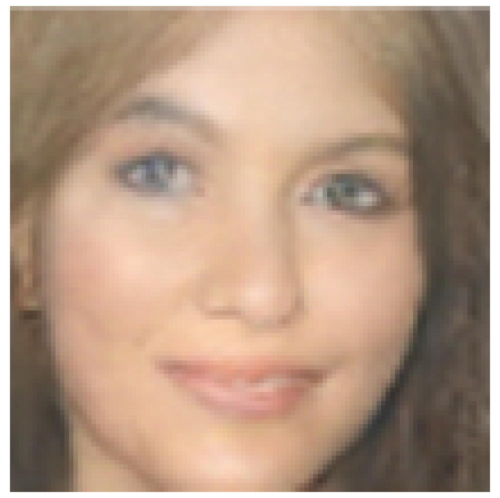
Man with glasses

-



Man

+



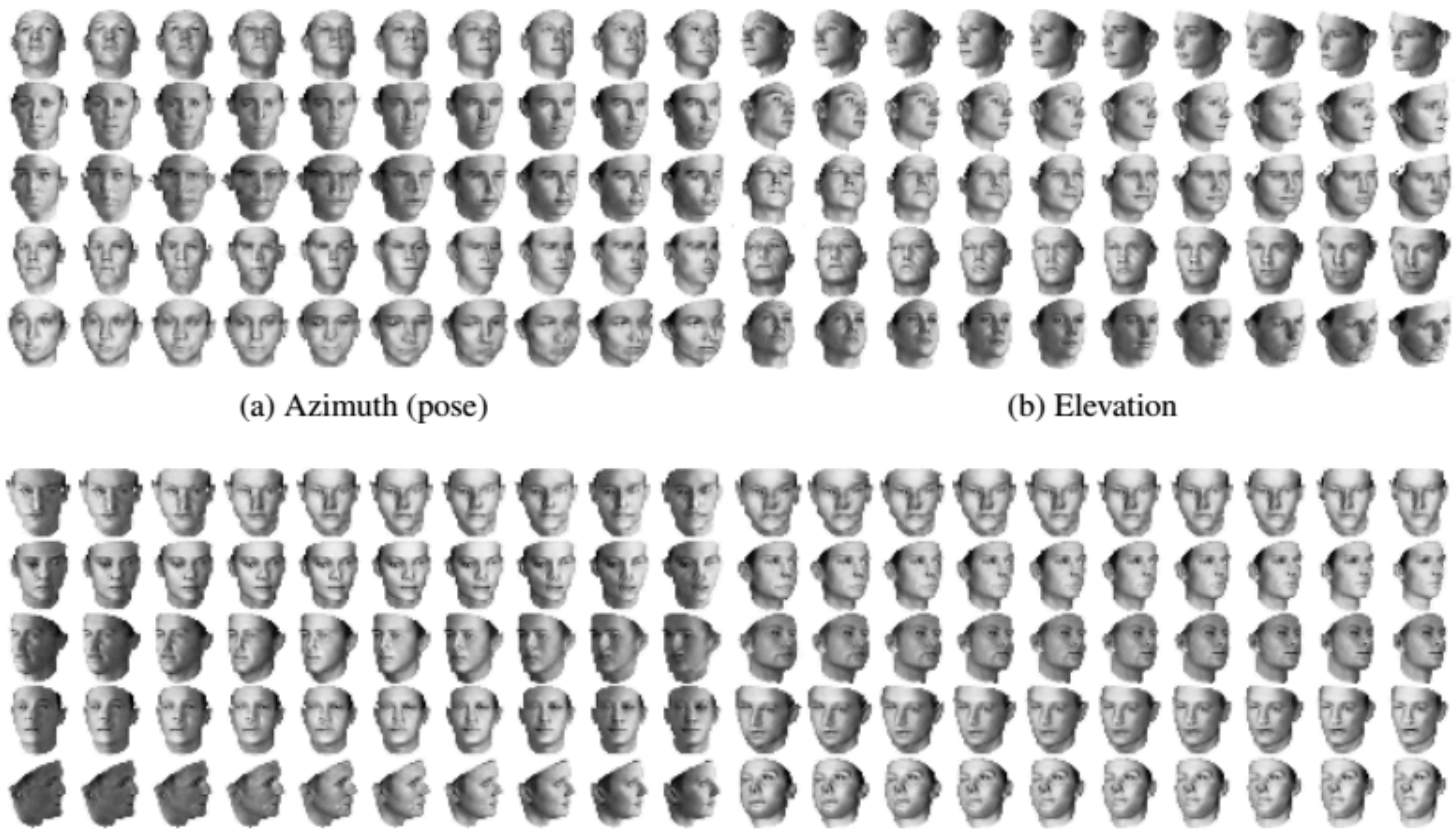
Woman

=

Woman with Glasses

(Radford et al, 2015)

# Learning interpretable latent codes / controlling the generation process

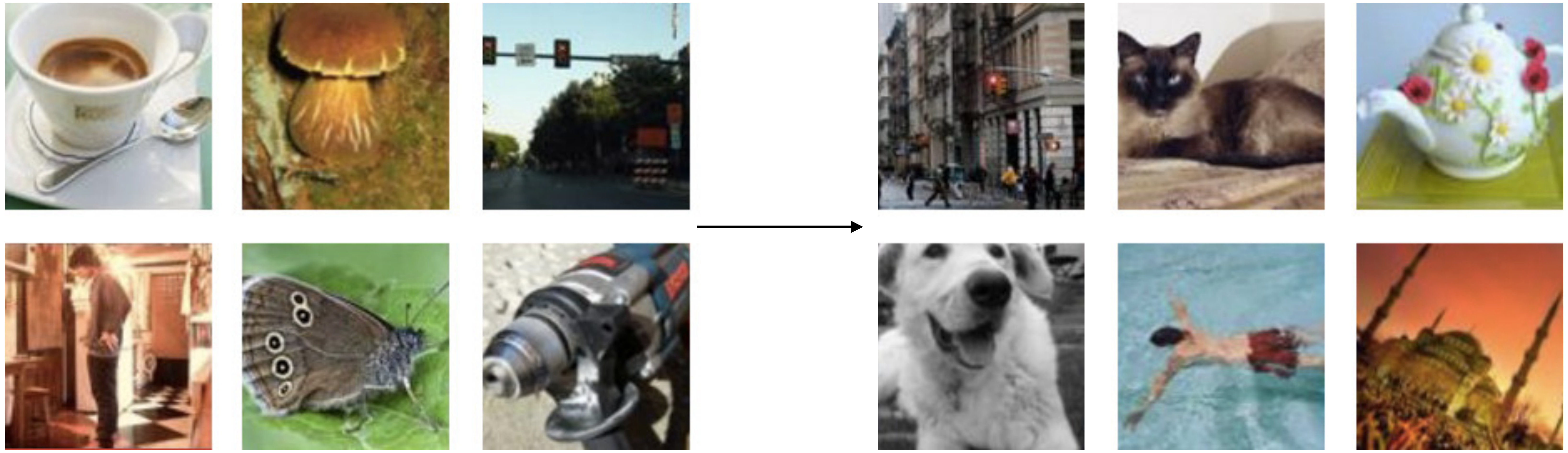


(a) Azimuth (pose) (b) Elevation

(c) Lighting (d) Wide or Narrow

InfoGAN (Chen et al 2016)

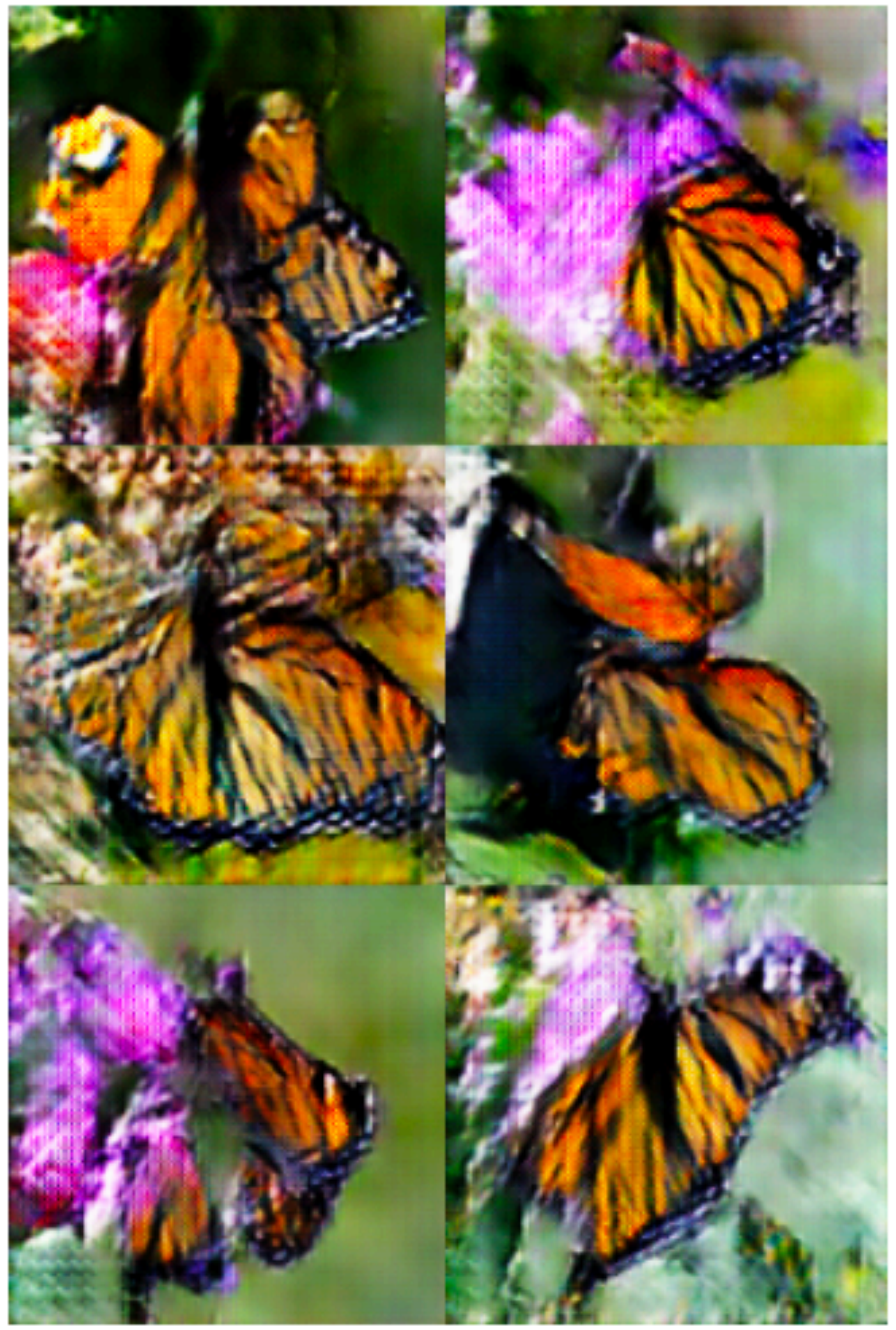
# How long until GANs can do this?



Training examples Model samples

(Goodfellow 2017)

# AC-GANs



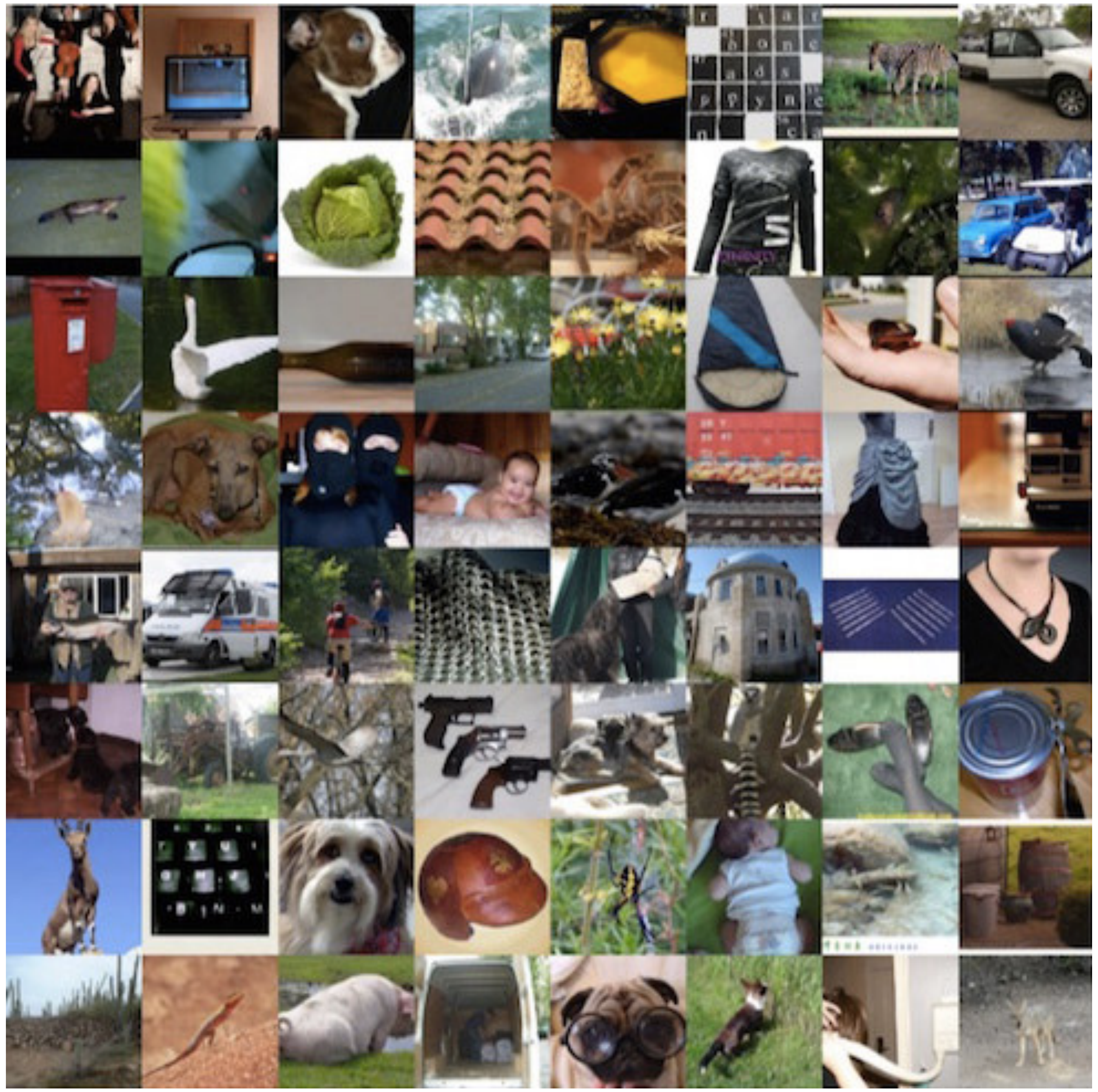
monarch butterfly

goldfinch

daisy

(Odena et al., 2016)

# Minibatch GAN on ImageNet

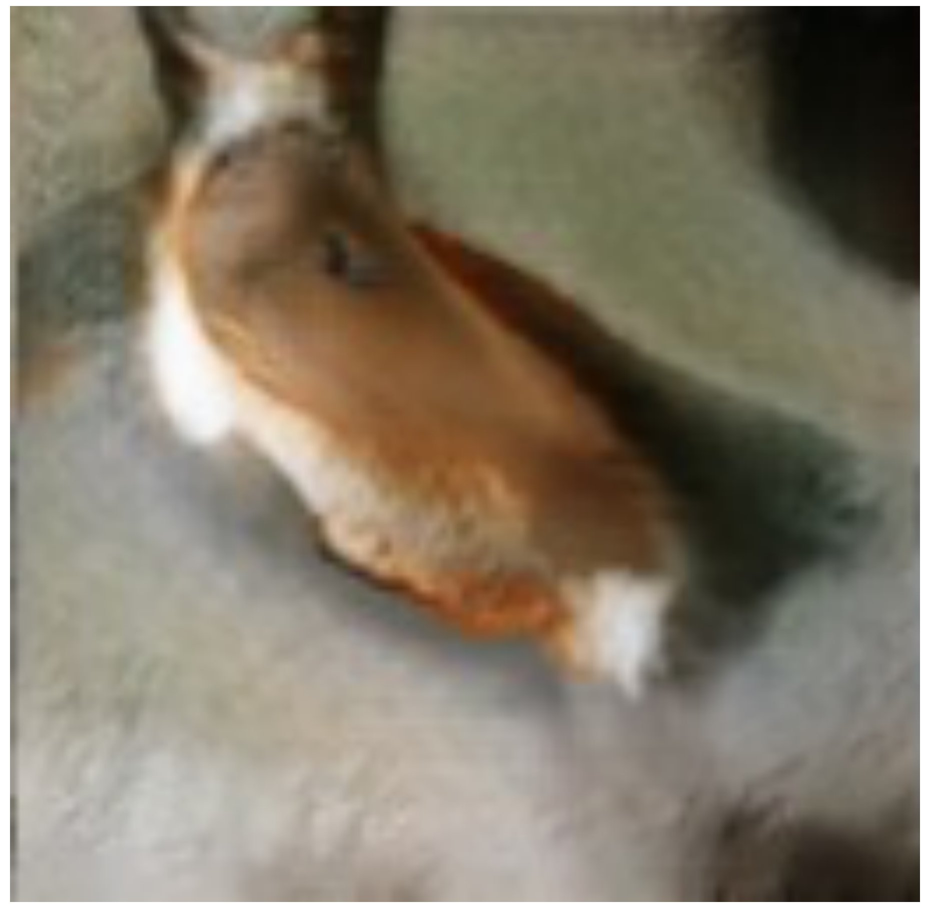


(Salimans et al., 2016)

# Cherry-Picked Results

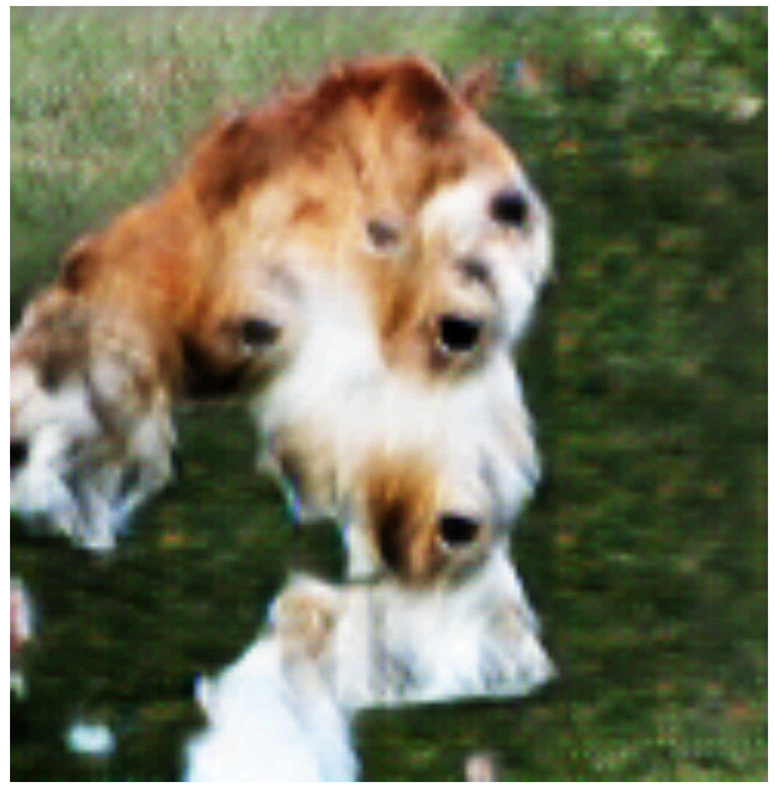






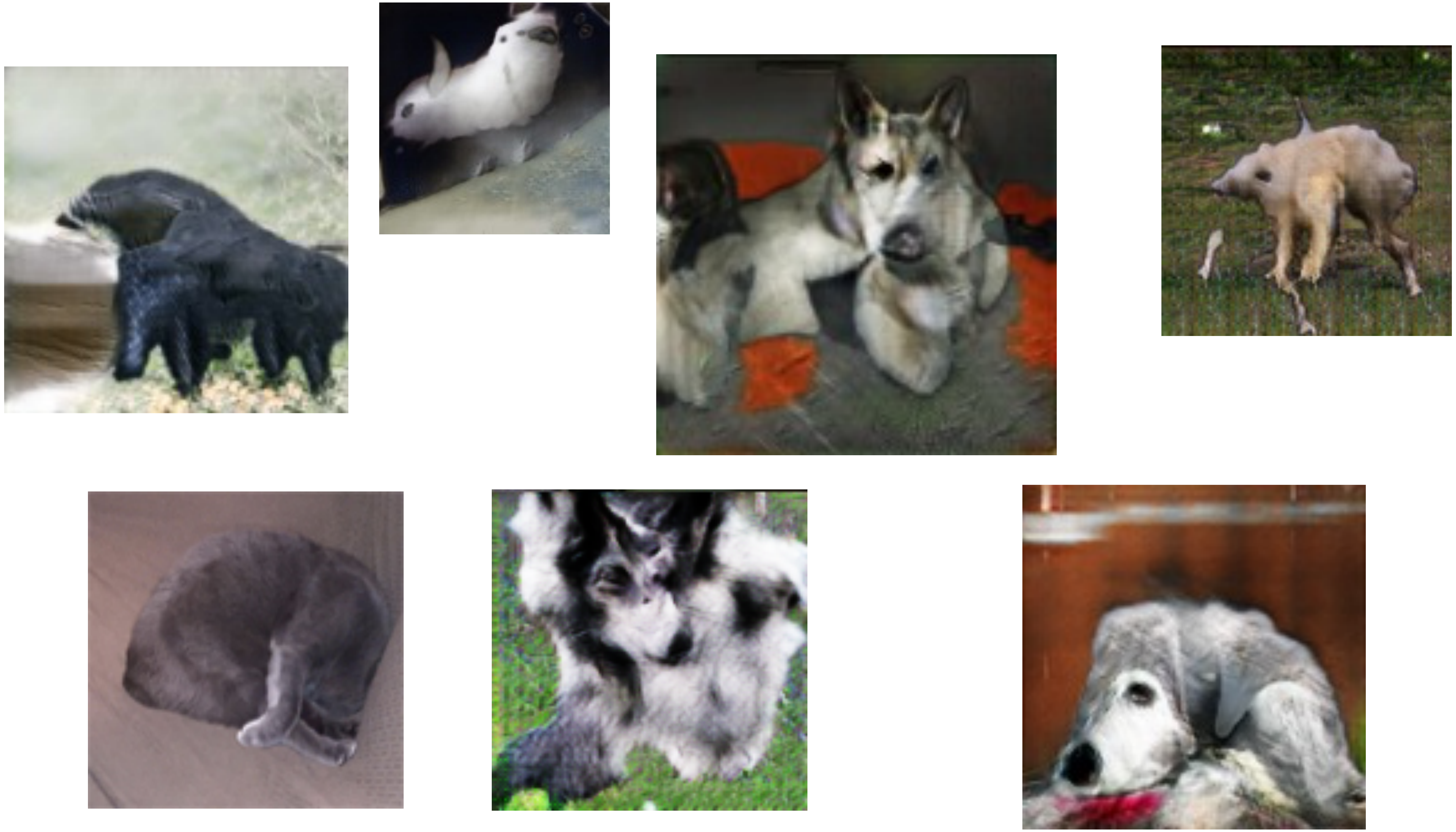
(Goodfellow 2017)

# Problems with Counting



(Goodfellow 2017)

# Problems with Perspective

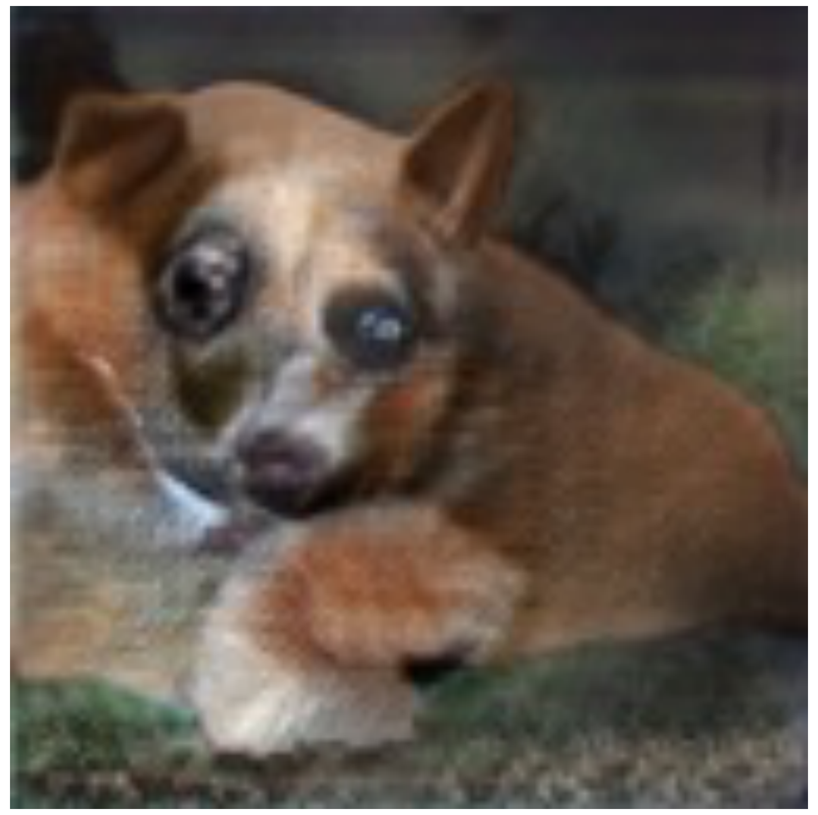
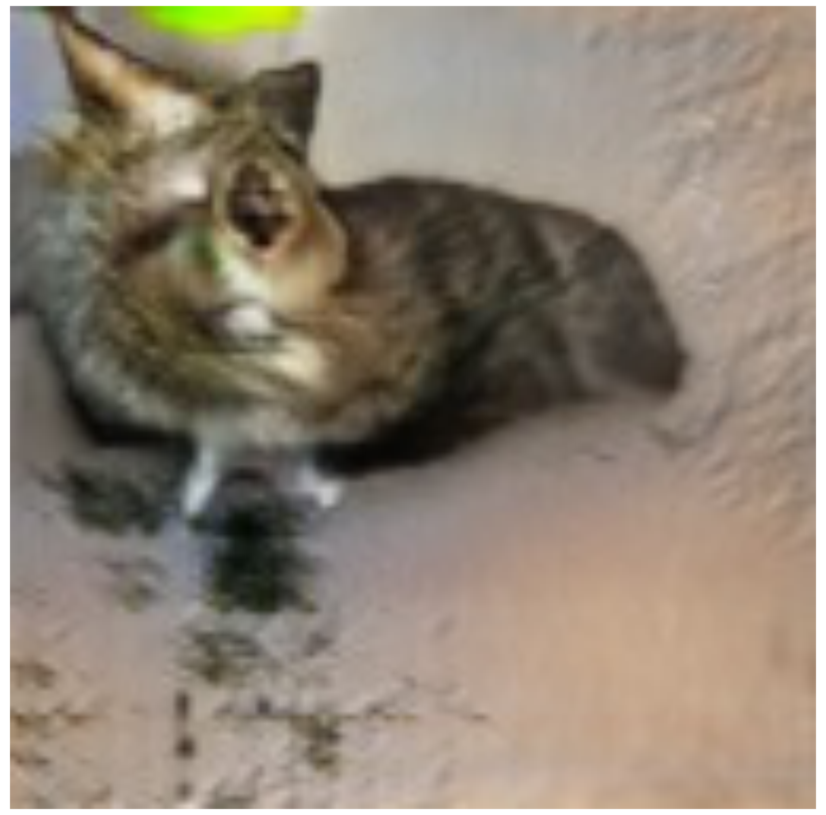


(Goodfellow 2017)

# Problems with Global Structure





(Goodfellow 2017)

# This one is real

(Goodfellow 2017)

# Conclusion

- GANs are generative models based on game theory
- GANs open the door to a wide range of engineering tasks
- There are still important research challenges to solve before GANs can generate arbitrary data

(Goodfellow 2017)