

MedGAN Progressive GAN CoGAN LR-GAN CGAN IcGAN
b-GAN LS-GAN AffGAN LAPGAN DiscoGAN MPM-GAN AdaGAN
LSGAN InfoGAN CatGAN AMGAN iGAN IAN

GANs for Limited Labeled Data

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

NIPS 2017 Workshop on Limited Labeled Data: Weak Supervision and Beyond

MGAN

FF-GAN

Long Beach, 2017-12-09

GoGAN BS-GAN

C-VAE-GAN C-RNN-GAN

DR-GAN

DCGAN

MAGAN 3D-GAN

CCGAN

AC-GAN

GAWWN

DualGAN

BiGAN

Bayesian GAN

CycleGAN

GP-GAN

EBGAN

SN-GAN

AnoGAN

DTN

Context-RNN-GAN

MAD-GAN

ALI

f-GAN

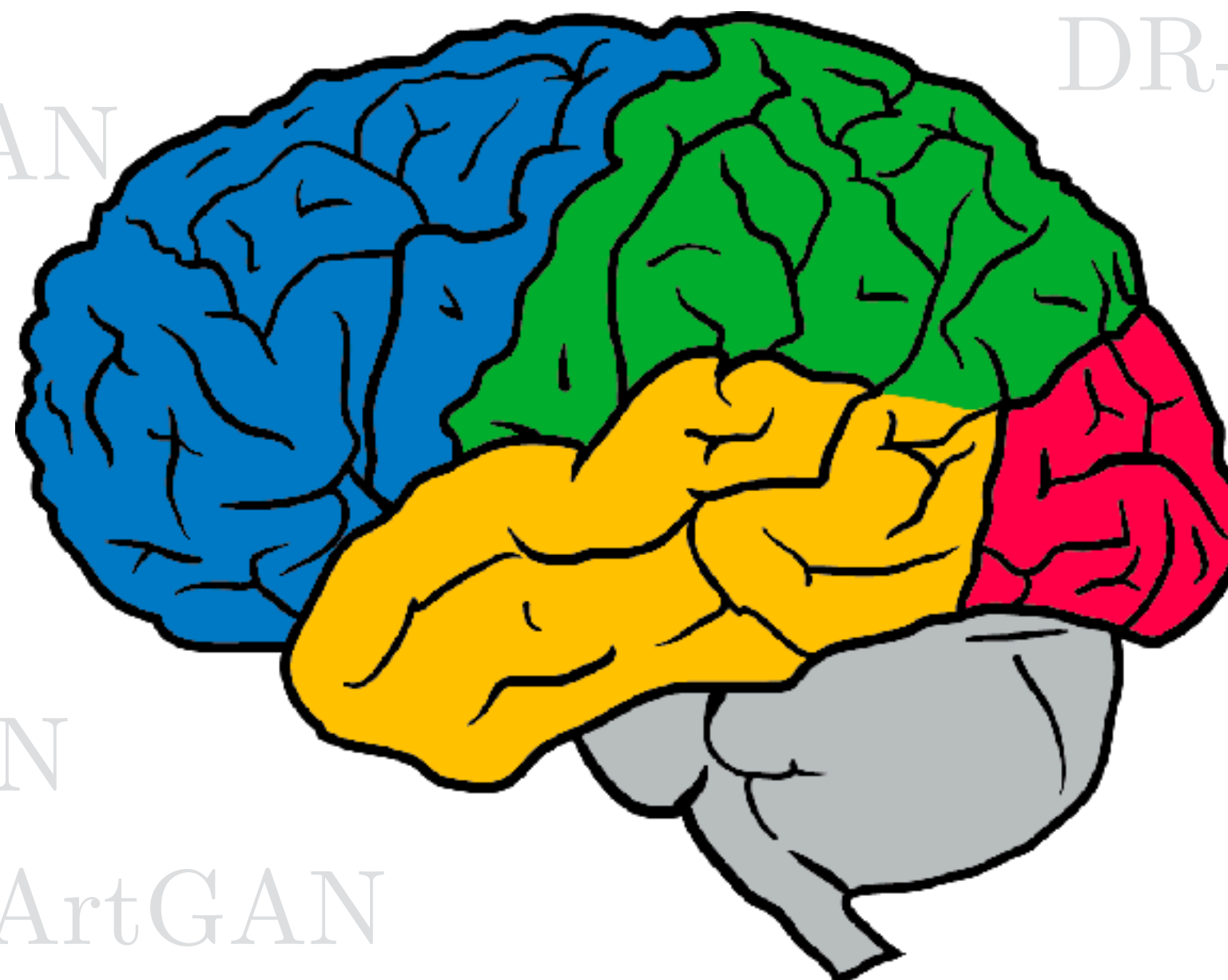
BEGAN

AL-CGAN

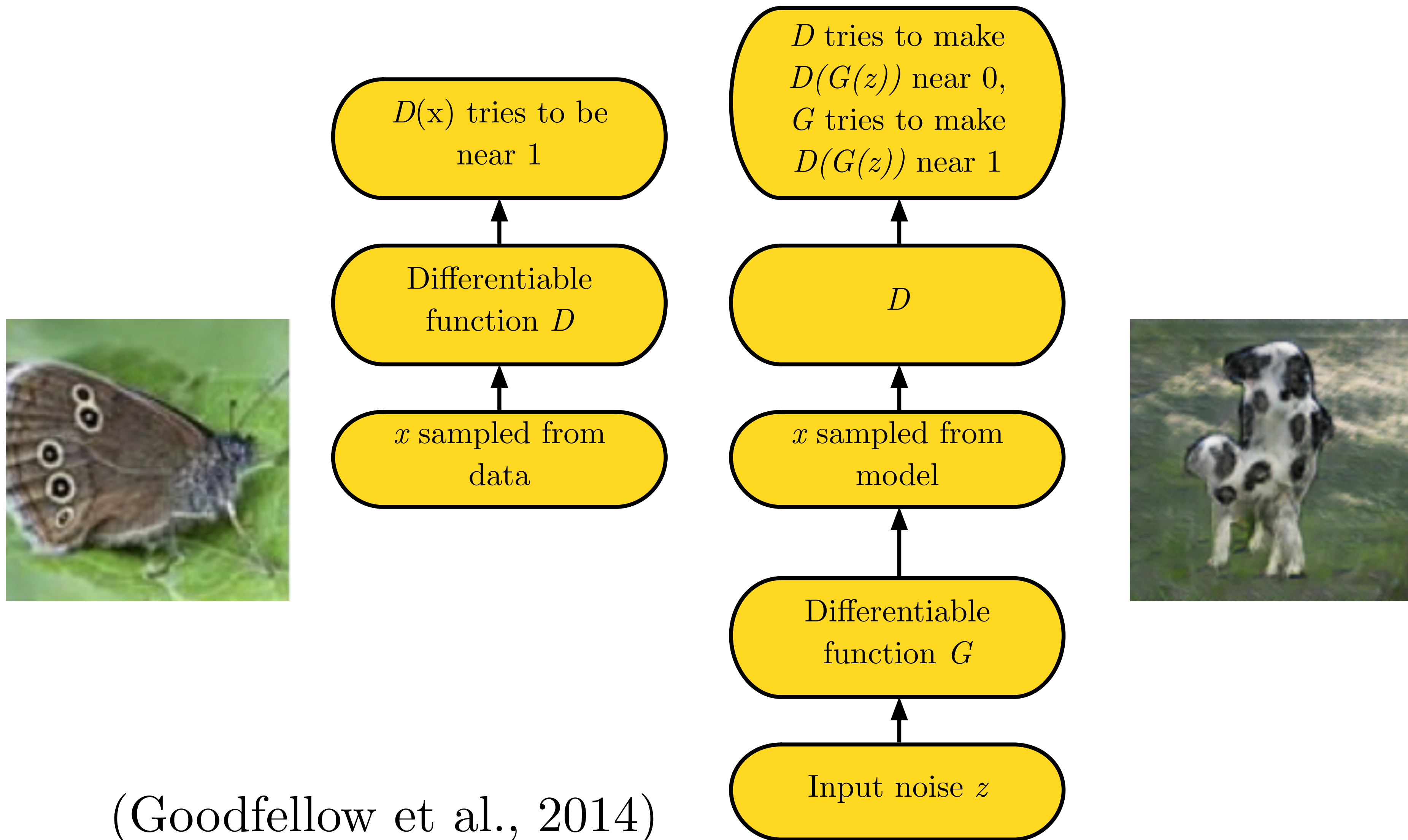
MARTA-GAN

ArtGAN

MalGAN



Adversarial Nets Framework



Overcoming limited data with GANs

- Missing data
 - Semi-supervised learning
- Set-member supervision
- Unsupervised correspondence learning
- Replace data collection with simulation
- Simulated environments and training data
- Domain adaptation

What is in this image?



(Yeh et al., 2016)

Generative modeling reveals a face

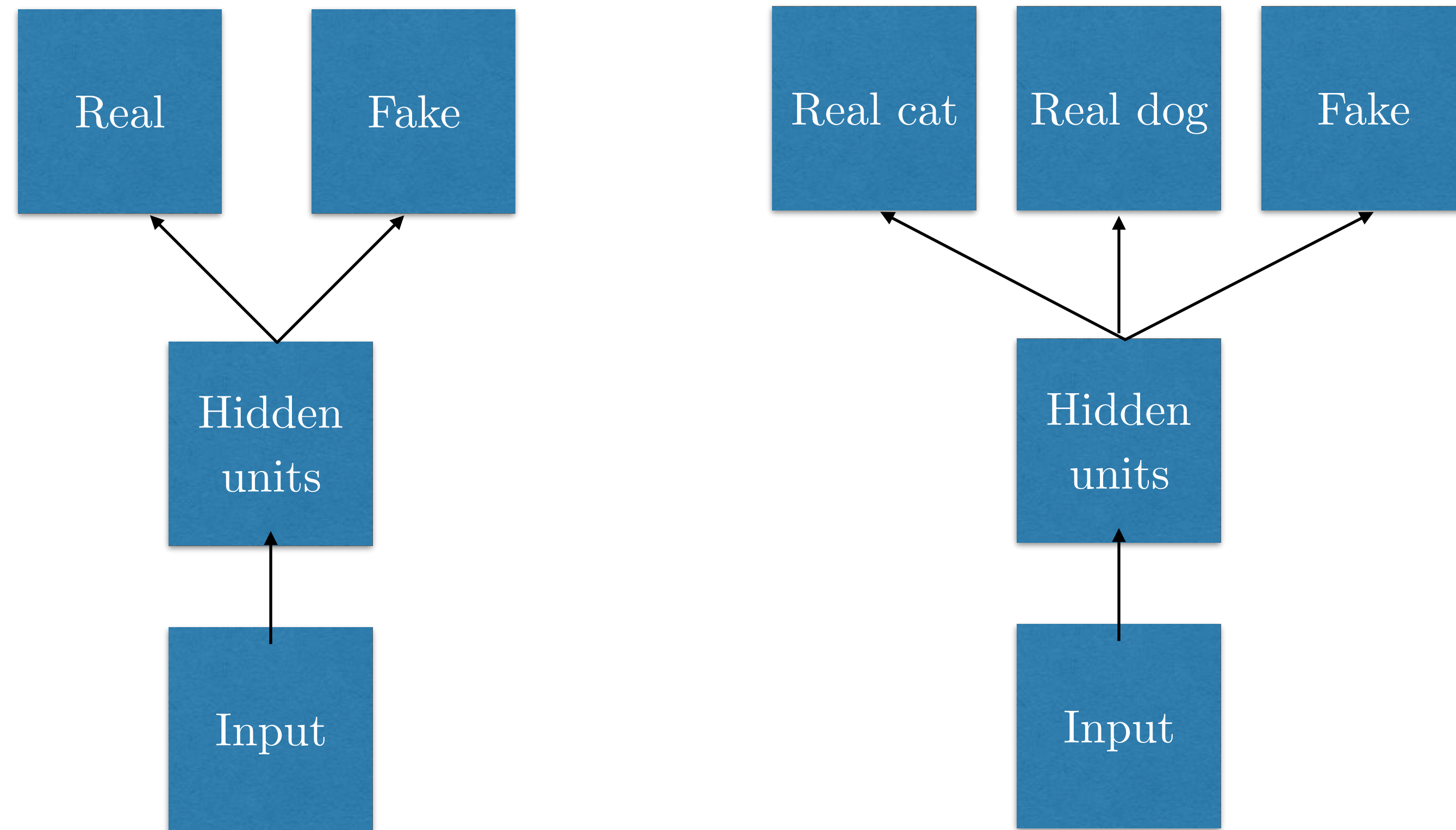


(Yeh et al., 2016)

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Supervised Discriminator



(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)

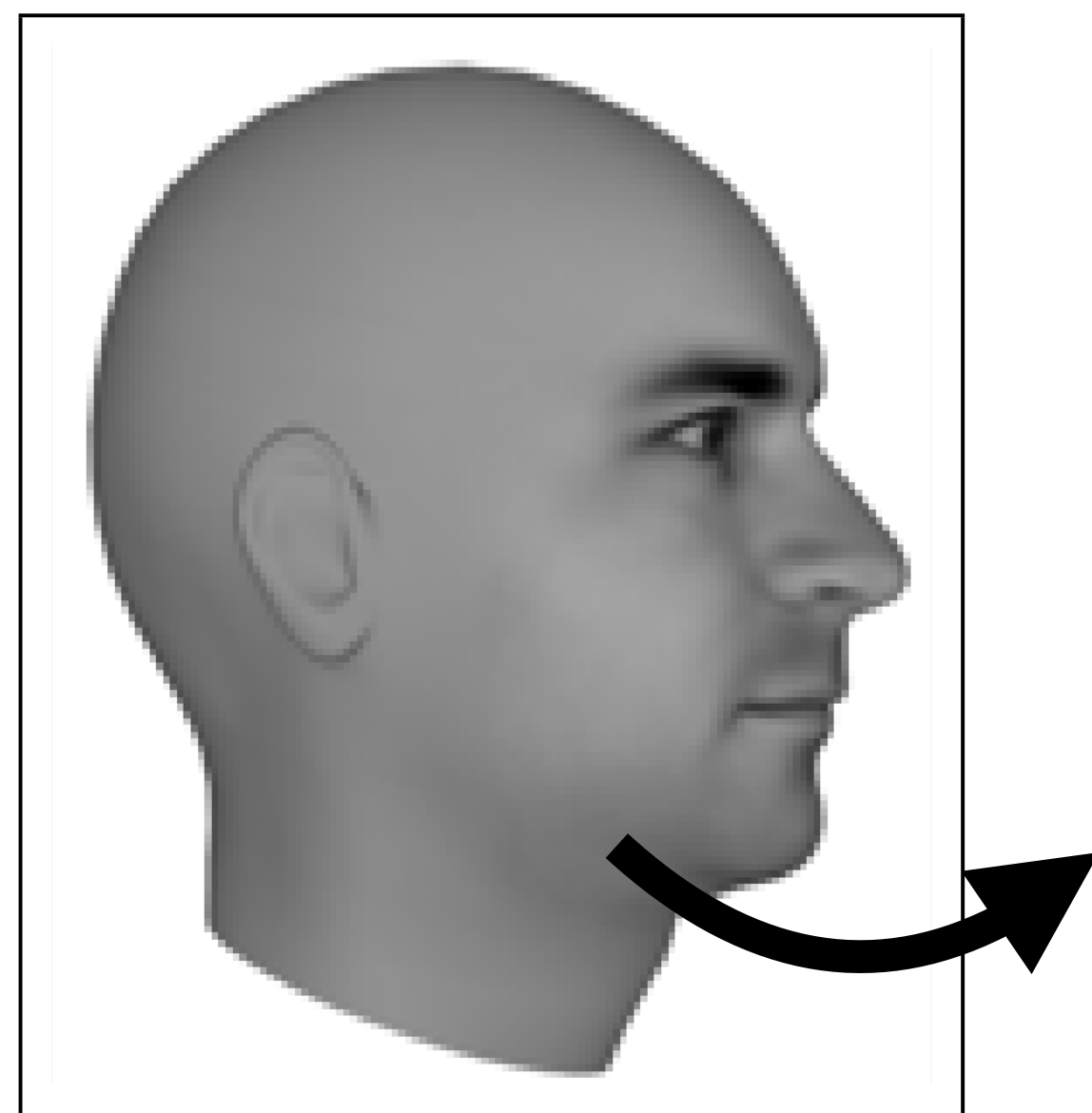
Useful for differential privacy: Papernot et al, 2016

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Next Video Frame Prediction

Ground Truth

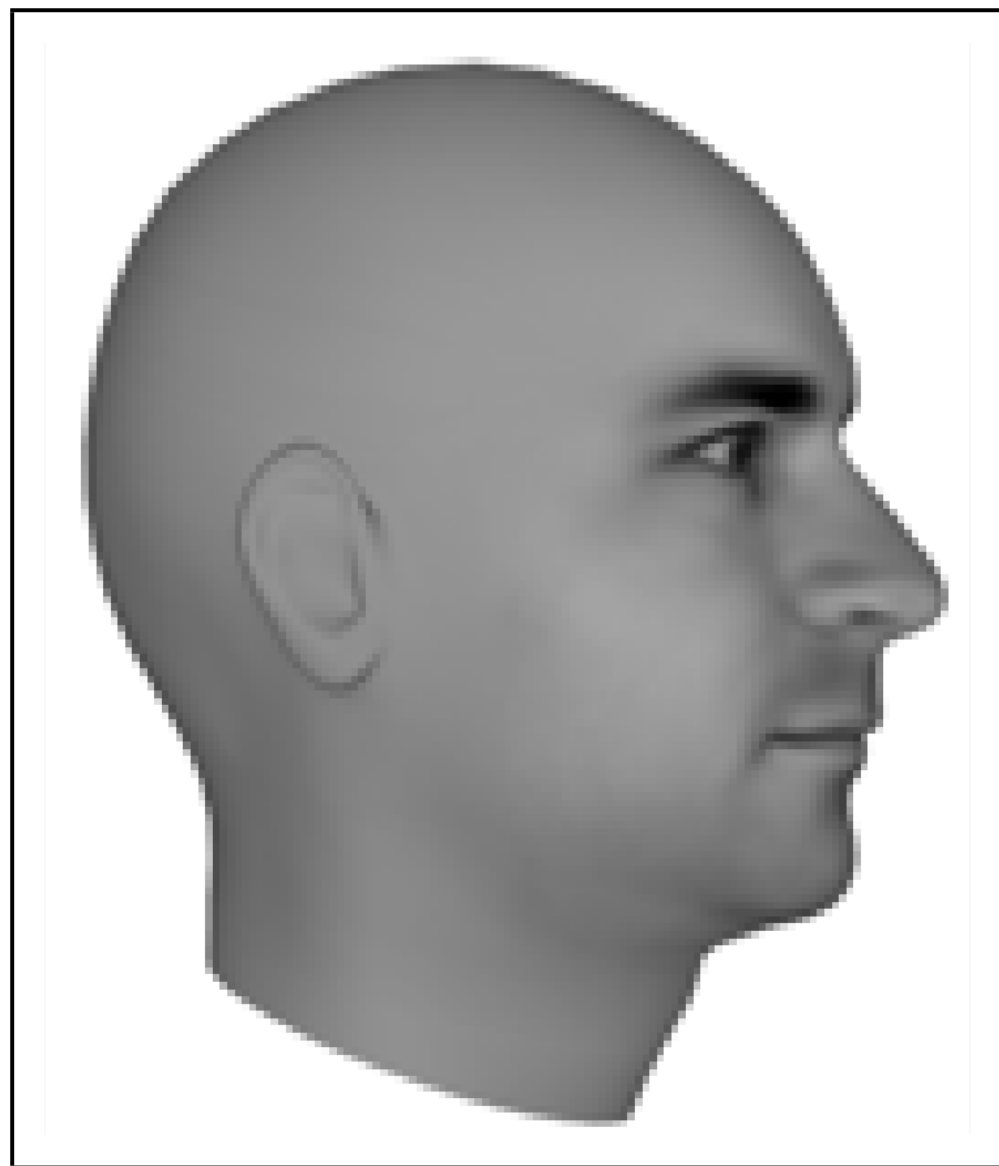


What happens next?

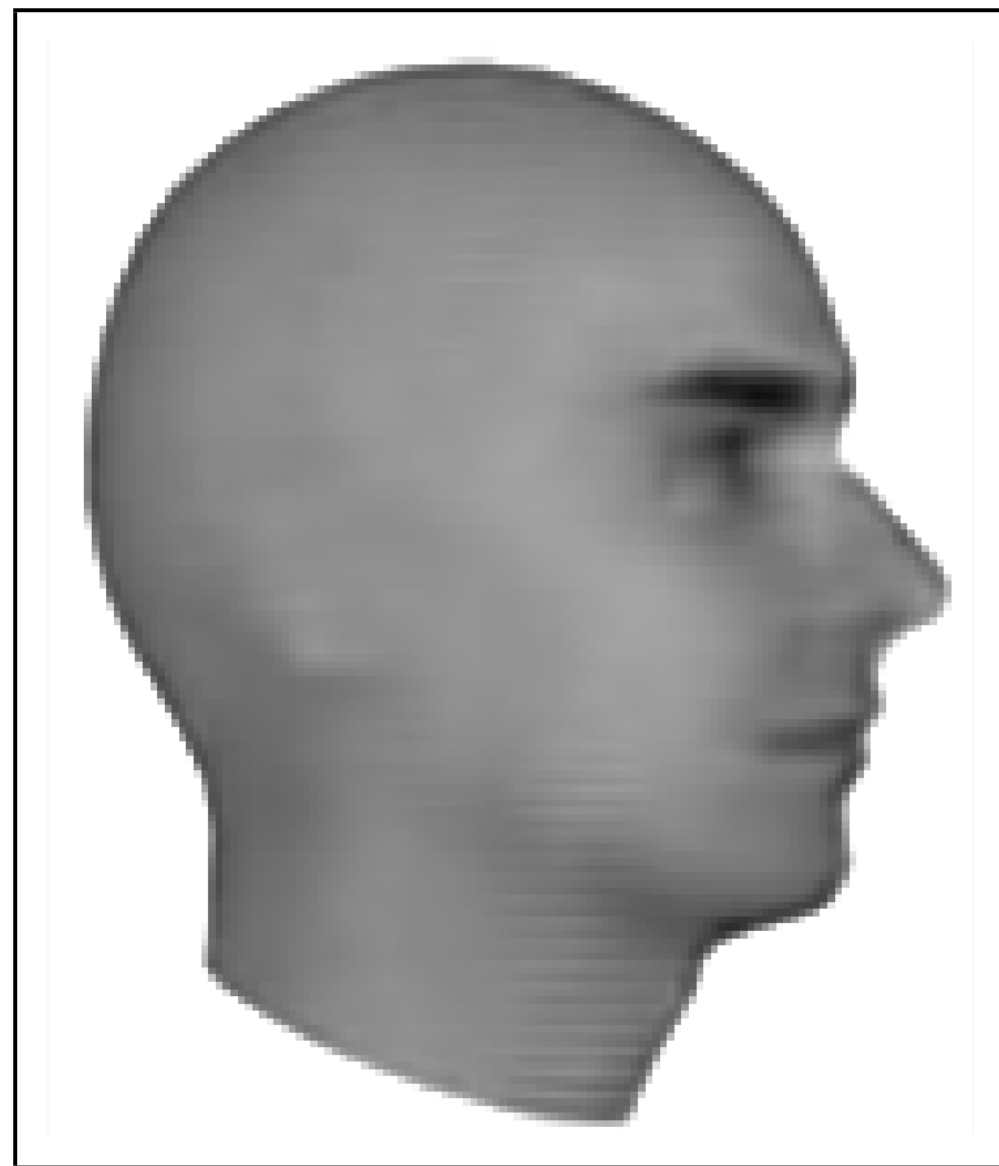
(Lotter et al 2016)

Next Video Frame Prediction

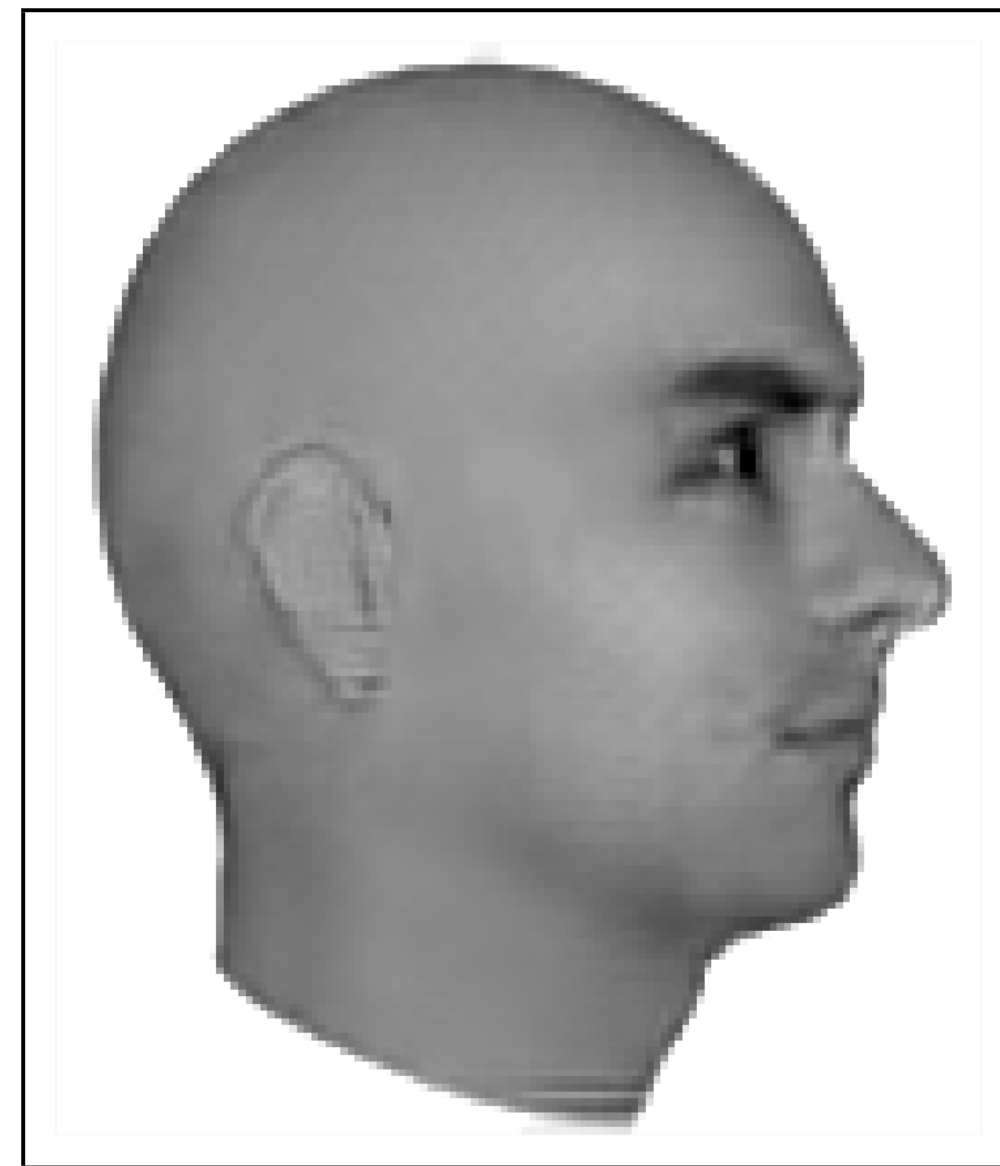
Ground Truth



MSE



Adversarial



(Lotter et al 2016)

Next Video Frame(s) Prediction

Mean Squared Error

Mean Absolute Error

Adversarial



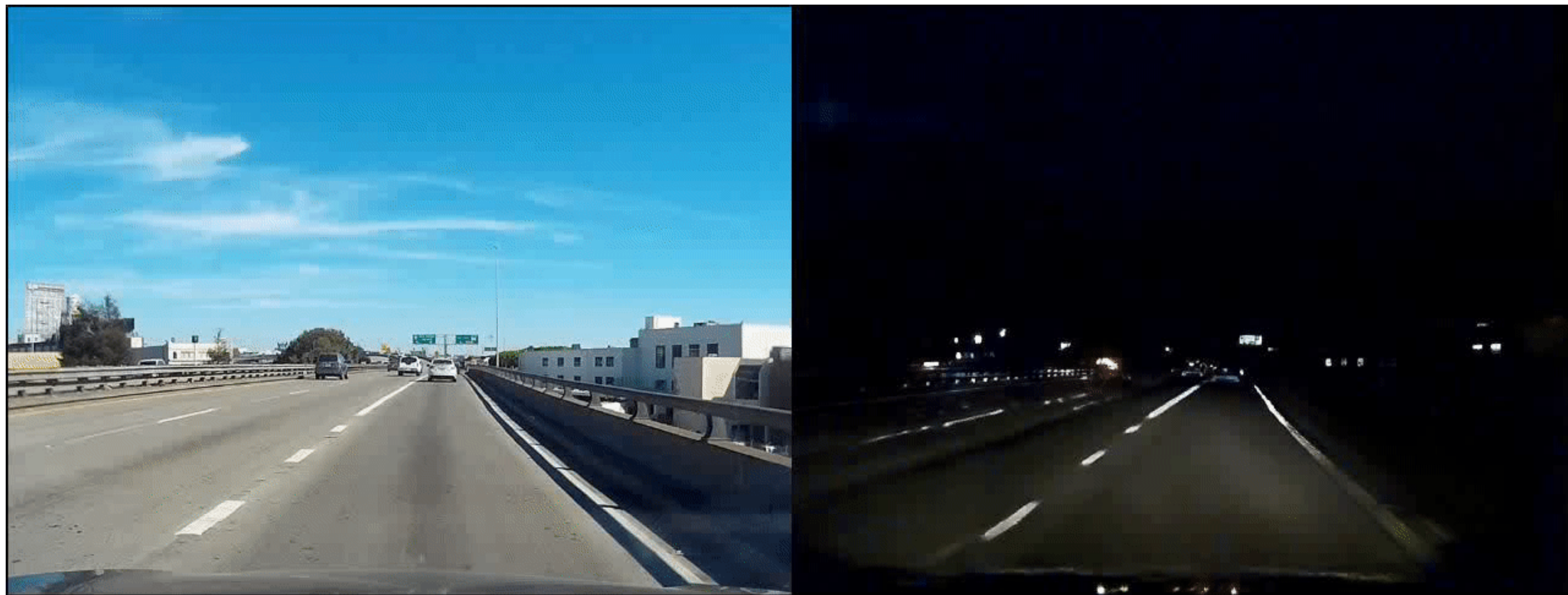
(Mathieu et al. 2015)

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Unsupervised Image-to-Image Translation

Day to night



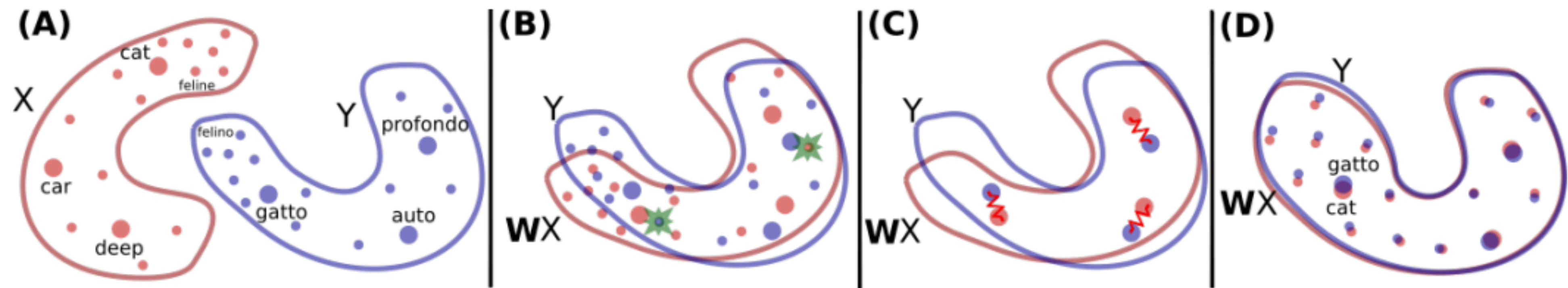
(Liu et al., 2017)

CycleGAN



(Zhu et al., 2017)

Translation without parallel corpora



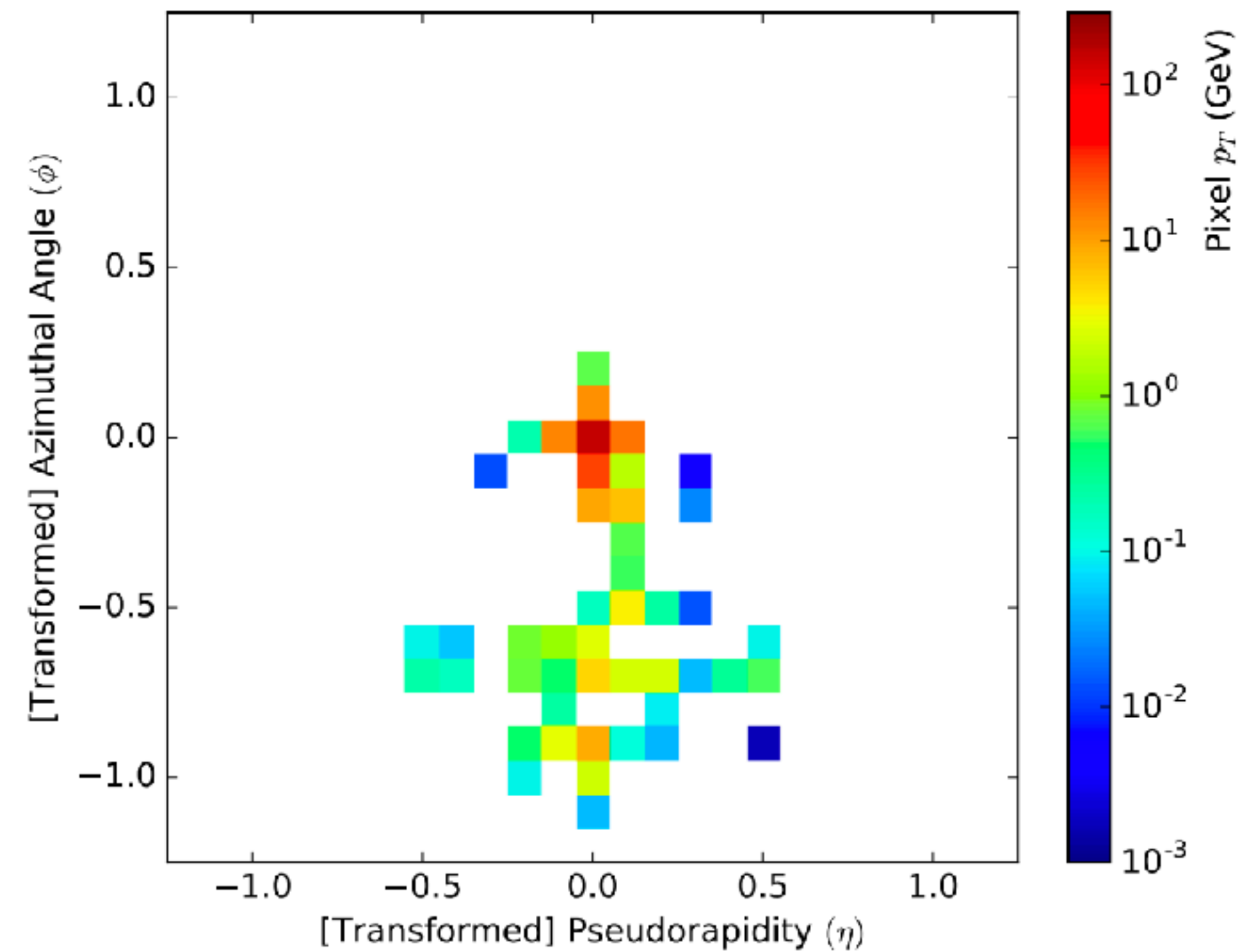
(Conneau et al., 2017)

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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)

Overcoming limited data with GANs

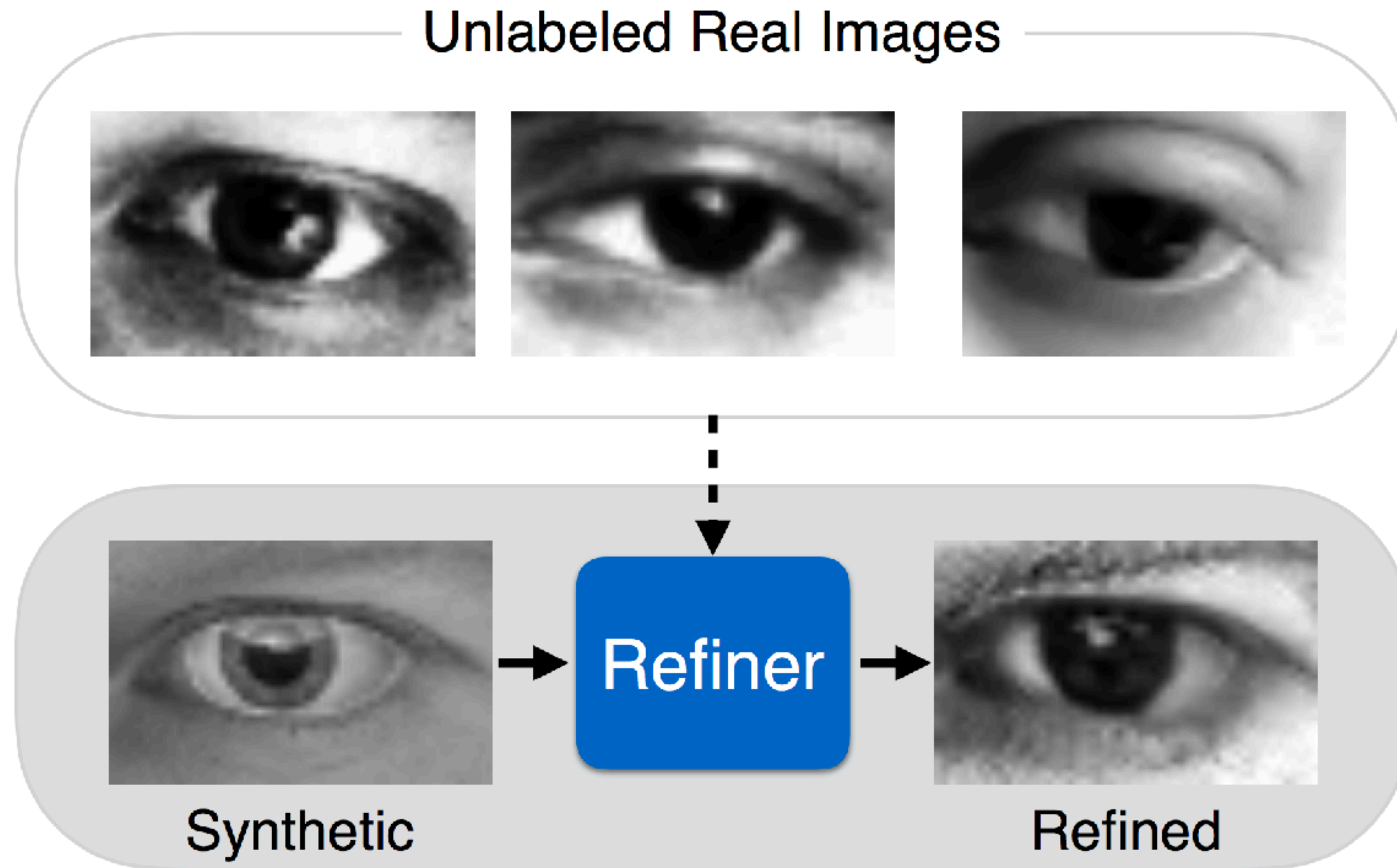
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TEACHING AID

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



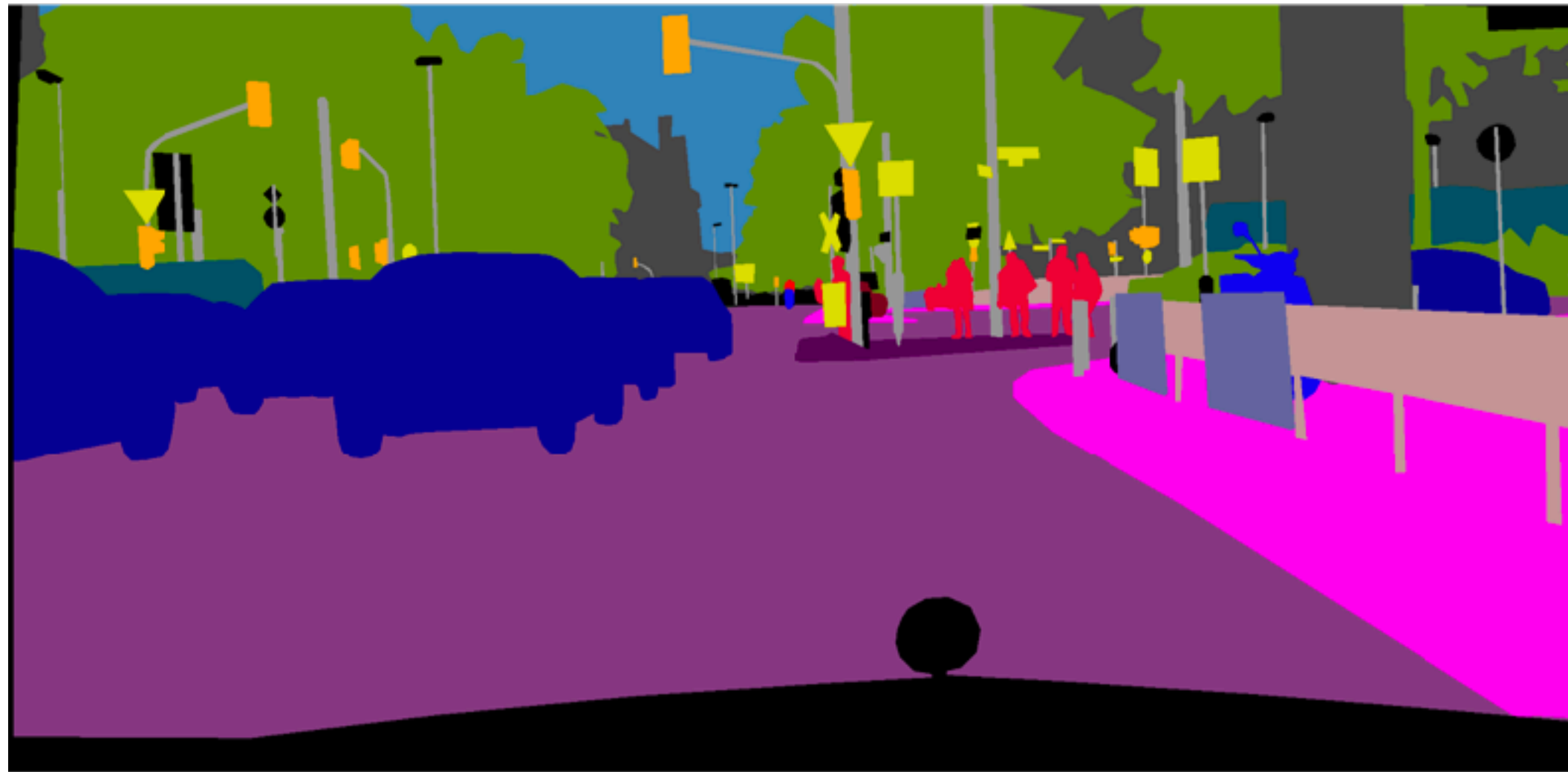
GANs for simulated training data



(Shrivastava et al., 2016)

Autonomous Driving Data

Input labels



Synthesized image



(Wang et al., 2017)

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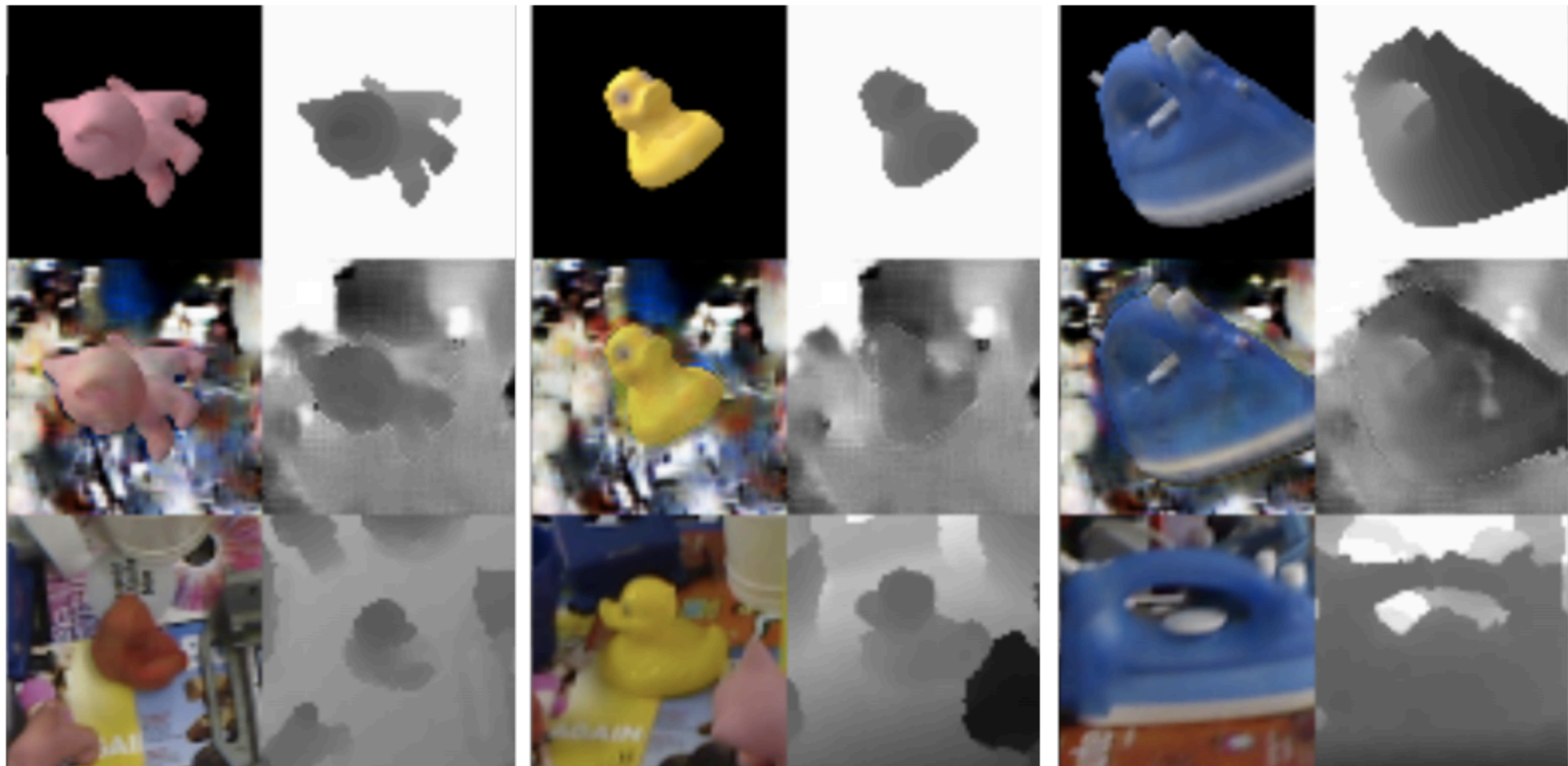
Domain Adaptation

- 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)

Questions