UNT
UNIVERSITY OF NORTH TEXAS

CSCE 5218 & 4930
Deep Learning

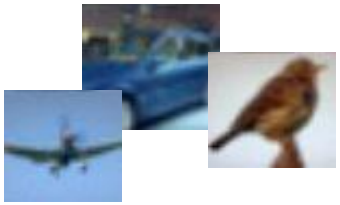
Advanced Topics

Slides adapted from Adriana Kovashka

Plan for this lecture

- Alternative representations
  - I. Graph networks
- Alternative learning mechanisms
  - II. Self supervision
  - III. Reinforcement learning
- Alternative tasks
  - IV. Generation
- V. Bias and ethics (optional)

Generative Models



Training data ~ $p_{data}(x)$

Generated samples ~ $p_{model}(x)$

Want to learn $p_{model}(x)$ similar to $p_{data}(x)$

Addresses density estimation, a core problem in unsupervised learning

Several flavors:

- Explicit density estimation: explicitly define and solve for $p_{model}(x)$
- Implicit density estimation: learn model that can sample from $p_{model}(x)$ w/o explicitly defining it

Why Generative Models?

- Realistic samples for artwork, super-resolution, colorization, etc.

- Generative models can be used to enhance training datasets with diverse synthetic data
- Generative models of time-series data can be used for simulation

Adapted from Serena Young

Taxonomy of Generative Models

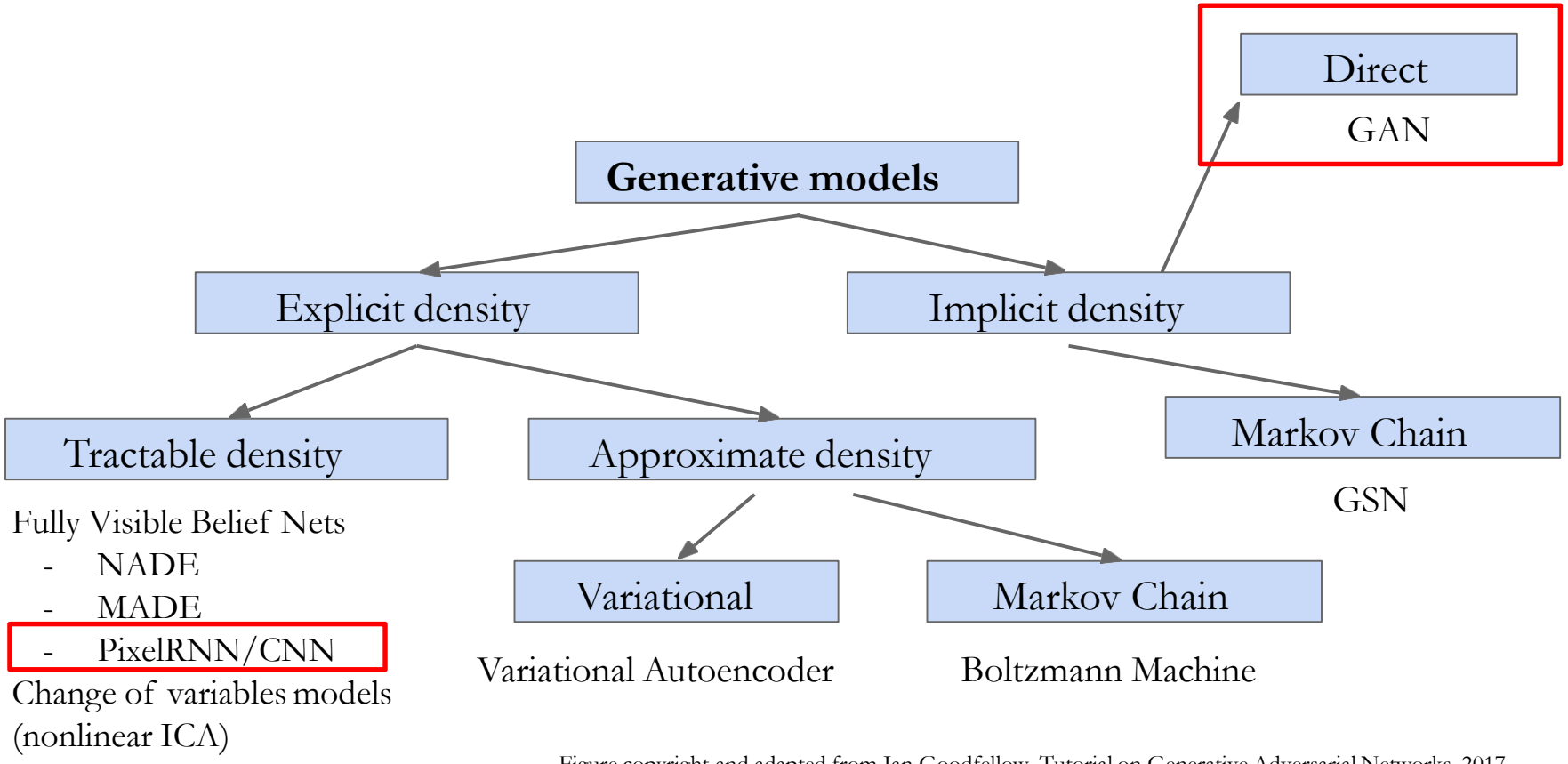


Figure copyright and adapted from Ian Goodfellow, Tutorial on Generative Adversarial Networks, 2017.

PixelRNN and PixelCNN

Fully visible belief network

Explicit density model

Use chain rule to decompose likelihood of an image x into product of 1-d distributions:

$$p(x) = \prod_{i=1}^{n} p(x_i | x_1, \ldots, x_{i-1})$$

Likelihood of image x

Probability of i'th pixel value given all previous pixels

Will need to define ordering of "previous pixels"

Then maximize likelihood of training data

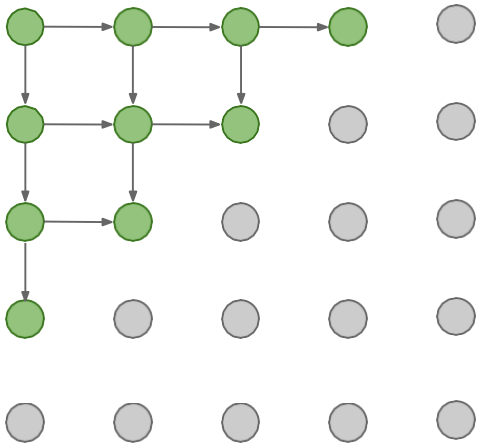
Complex distribution over pixel values => Express using a neural network!

PixelRNN

[van der Oord et al. 2016]

Generate image pixels starting from corner

Dependency on previous pixels modeled using an RNN (LSTM)



Drawback: sequential generation is slow!

PixelCNN

[van der Oord et al. 2016]

Still generate image pixels starting from corner

Dependency on previous pixels now modeled using a CNN over context region

Training: maximize likelihood of training images

$$p(x) = \prod_{i=1}^{n} p(x_i | x_1, ..., x_{i-1})$$

Softmax loss at each pixel

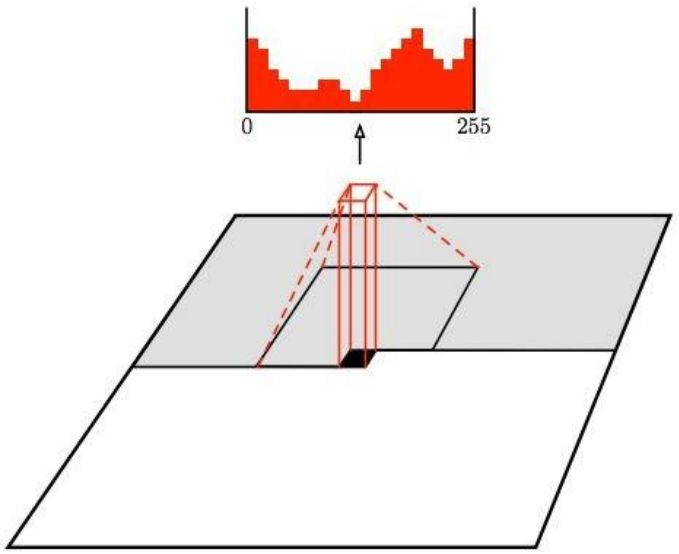


Figure copyright van der Oord et al., 2016.

Training is faster than PixelRNN (can parallelize convolutions since context region values known from training images)

Generation must still proceed sequentially => still slow

Generative Adversarial Networks

Ian Goodfellow et al., "Generative Adversarial Nets", NIPS 2014

Problem: Want to sample from complex, high-dimensional training distribution. No direct way to do this!

Solution: Sample from a simple distribution, e.g. random noise. Learn transformation to training distribution.

Q: What can we use to represent this complex transformation?

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Q: What can we use to represent this complex transformation?

A: A neural network!

Output: Sample from training distribution

Generator Network

Input: Random noise

z

Training GANs: Two-player game

Ian Goodfellow et al., "Generative Adversarial Nets", NIPS 2014

Generator network: try to fool the discriminator by generating real-looking images
Discriminator network: try to distinguish between real and fake images

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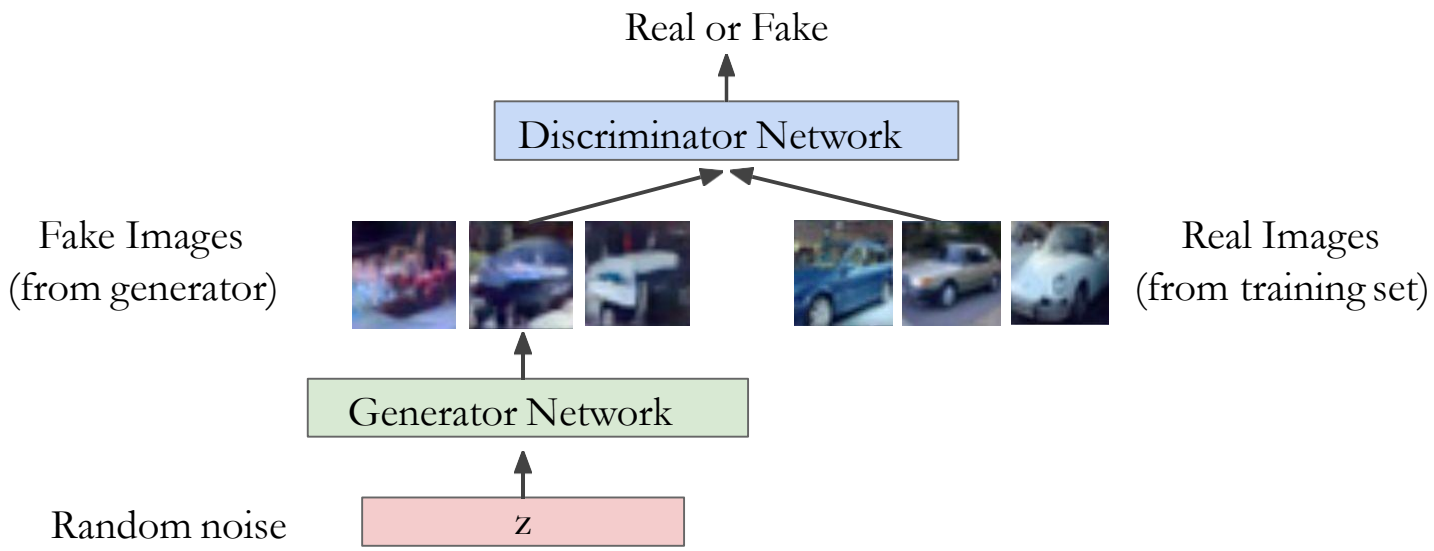

Adversarial Networks Framework

D tries to output 1

Differentiable function D

x sampled from data

D tries to output 0

Differentiable function D

x sampled from model

Differentiable function G

Input noise Z

Discriminator
Real vs. Fake

Generator
$x \sim G(z)$

Ian Goodfellow

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Generator network: try to fool the discriminator by generating real-looking images
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Train jointly in **minimax game**

Minimax objective function:

$$\min_{\theta_g} \max_{\theta_d} \left[\mathbb{E}_{x \sim p_{data}} \log D_{\theta_d}(x) + \mathbb{E}_{z \sim p(z)} \log(1 - D_{\theta_d}(G_{\theta_g}(z))) \right]$$

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Generator network: try to fool the discriminator by generating real-looking images
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Train jointly in **minimax game**

Discriminator outputs likelihood in (0,1) of real image

Minimax objective function:

$$\min_{\theta_g} \max_{\theta_d} \left[\mathbb{E}_{x \sim p_{data}} \log D_{\theta_d}(x) + \mathbb{E}_{z \sim p(z)} \log(1 - D_{\theta_d}(G_{\theta_g}(z))) \right]$$

Discriminator output for real data x

Discriminator output for generated fake data G(z)

- Discriminator (θ_d) wants to **maximize objective** such that D(x) is close to 1 (real) and D(G(z)) is close to 0 (fake)
- Generator (θ_g) wants to **minimize objective** such that D(G(z)) is close to 1 (discriminator is fooled into thinking generated G(z) is real)

Training GANs: Two-player game

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$$\min_{\theta_g} \max_{\theta_d} \left[\mathbb{E}_{x \sim p_{data}} \log D_{\theta_d}(x) + \mathbb{E}_{z \sim p(z)} \log(1 - D_{\theta_d}(G_{\theta_g}(z))) \right]$$

Alternate between:

1. **Gradient ascent** on discriminator

$$\max_{\theta_d} \left[\mathbb{E}_{x \sim p_{data}} \log D_{\theta_d}(x) + \mathbb{E}_{z \sim p(z)} \log(1 - D_{\theta_d}(G_{\theta_g}(z))) \right]$$

2. **Gradient descent** on generator

$$\min_{\theta_g} \mathbb{E}_{z \sim p(z)} \log(1 - D_{\theta_d}(G_{\theta_g}(z)))$$

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Alternate between:

1. **Gradient ascent** on discriminator

$$\max_{\theta_d} \left[\mathbb{E}_{x \sim p_{data}} \log D_{\theta_d}(x) + \mathbb{E}_{z \sim p(z)} \log(1 - D_{\theta_d}(G_{\theta_g}(z))) \right]$$

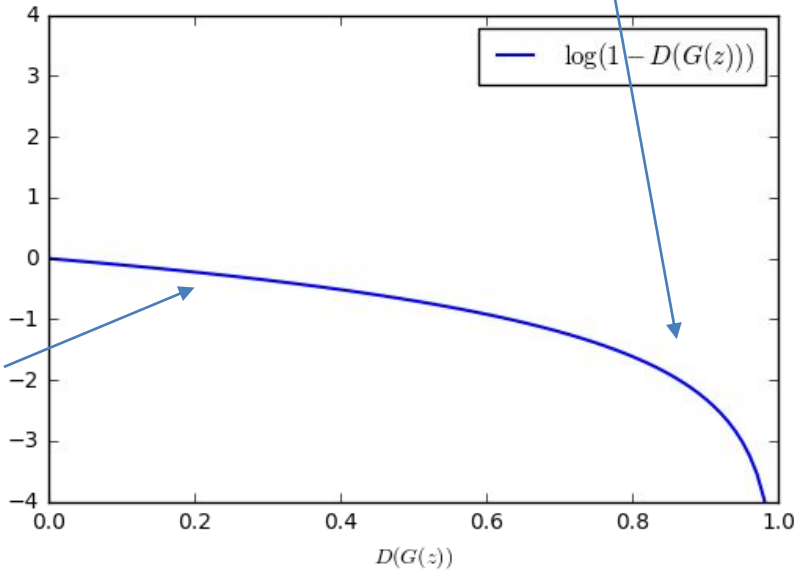
2. **Gradient descent** on generator

$$\min_{\theta_g} \mathbb{E}_{z \sim p(z)} \log(1 - D_{\theta_d}(G_{\theta_g}(z)))$$

In practice, optimizing this generator objective does not work well!

Gradient signal dominated by region where sample is already good

When sample is likely fake, want to learn from it to improve generator. But gradient in this region is relatively flat!



Adapted from Serena Young

Training GANs: Two-player game

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Minimax objective function:

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Alternate between:

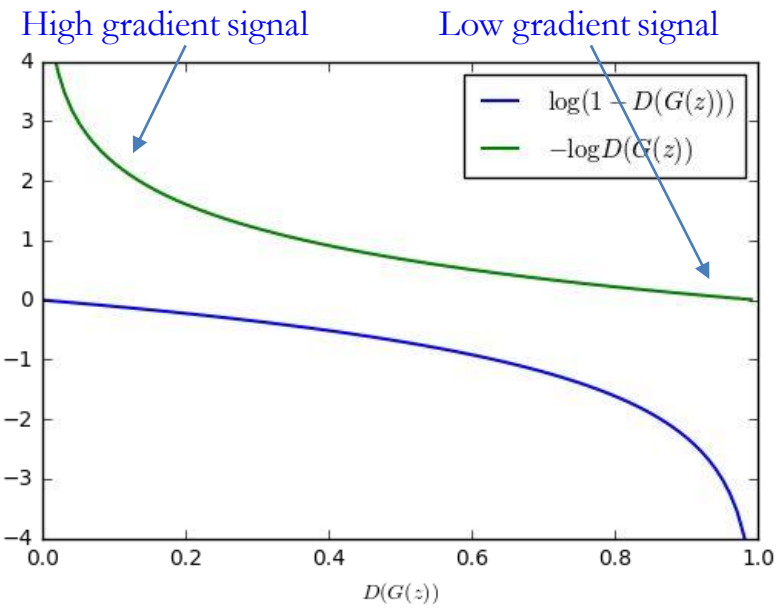
1. **Gradient ascent** on discriminator

$$\max_{\theta_d} \left[\mathbb{E}_{x \sim p_{data}} \log D_{\theta_d}(x) + \mathbb{E}_{z \sim p(z)} \log(1 - D_{\theta_d}(G_{\theta_g}(z))) \right]$$

2. **Instead: Gradient ascent** on generator, different objective

$$\max_{\theta_g} \mathbb{E}_{z \sim p(z)} \log(D_{\theta_d}(G_{\theta_g}(z)))$$

Instead of minimizing likelihood of discriminator being correct, now maximize likelihood of discriminator being wrong.
Same objective of fooling discriminator, but now higher gradient signal for bad samples => works much better!
Standard in practice.



Adapted from Serena Young

Training GANs: Two-player game

Ian Goodfellow et al., "Generative Adversarial Nets", NIPS 2014

Putting it together: GAN training algorithm

for number of training iterations **do**

  for k steps **do**

  - Sample minibatch of m noise samples $\{\boldsymbol{z}^{(1)}, \ldots, \boldsymbol{z}^{(m)}\}$ from noise prior $p_g(\boldsymbol{z})$.
  - Sample minibatch of m examples $\{\boldsymbol{x}^{(1)}, \ldots, \boldsymbol{x}^{(m)}\}$ from data generating distribution $p_{\text{data}}(\boldsymbol{x})$.
  - Update the discriminator by ascending its stochastic gradient:

$$\nabla_{\theta_d} \frac{1}{m} \sum_{i=1}^{m} \left[\log D_{\theta_d}(x^{(i)}) + \log(1 - D_{\theta_d}(G_{\theta_g}(z^{(i)}))) \right]$$

  end for

  - Sample minibatch of m noise samples $\{\boldsymbol{z}^{(1)}, \ldots, \boldsymbol{z}^{(m)}\}$ from noise prior $p_g(\boldsymbol{z})$.
  - Update the generator by ascending its stochastic gradient (improved objective):

$$\nabla_{\theta_g} \frac{1}{m} \sum_{i=1}^{m} \log(D_{\theta_d}(G_{\theta_g}(z^{(i)})))$$

end for

Training GANs: Two-player game

Ian Goodfellow et al., "Generative Adversarial Nets", NIPS 2014

Generator network: try to fool the discriminator by generating real-looking images
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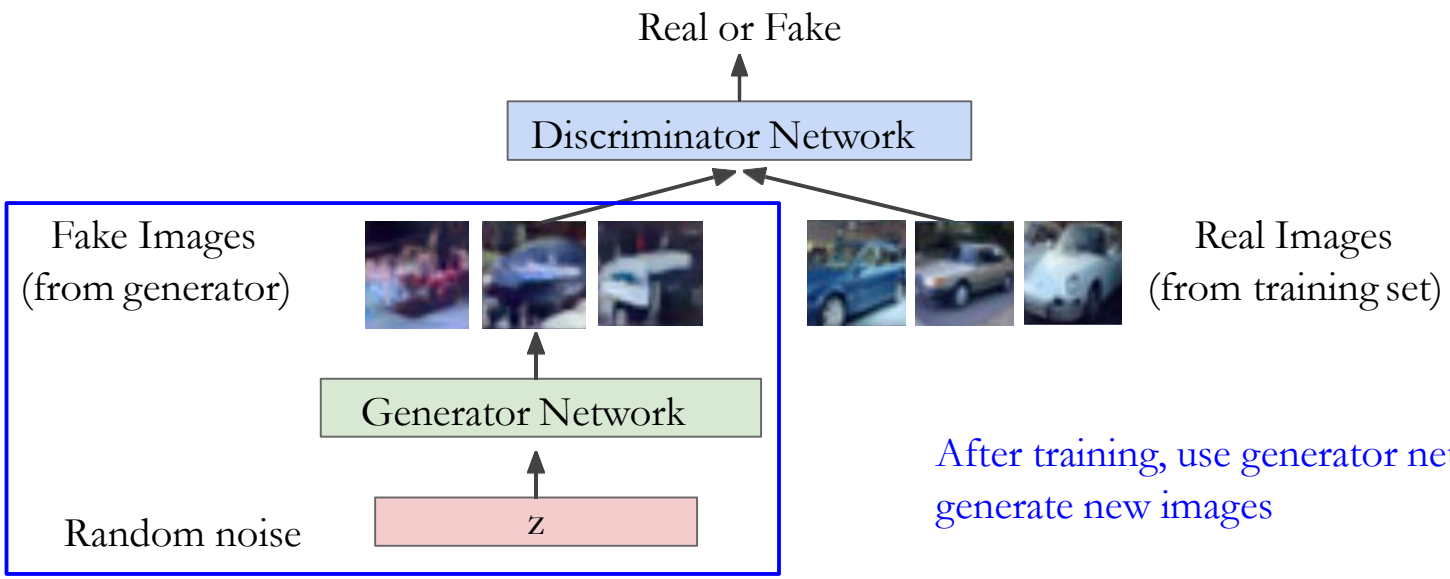


After training, use generator network to generate new images

Alternative loss functions

Name	Paper Link	Value Function
GAN	Arxiv	$L_D^{GAN} = E[\log(D(x))] + E[\log(1 - D(G(z)))]$ $L_G^{GAN} = E[\log(D(G(z)))]$
LSGAN	Arxiv	$L_D^{LSGAN} = E[(D(x) - 1)^2] + E[D(G(z))^2]$ $L_G^{LSGAN} = E[(D(G(z)) - 1)^2]$
WGAN	Arxiv	$L_D^{WGAN} = E[D(x)] - E[D(G(z))]$ $L_G^{WGAN} = E[D(G(z))]$ $W_D \leftarrow clip\_by\_value(W_D, -0.01, 0.01)$
WGAN_GP	Arxiv	$L_D^{WGAN\_GP} = L_D^{WGAN} + \lambda E[(\lvert\nabla D(\alpha x - (1 - \alpha G(z)))\rvert - 1)^2]$ $L_G^{WGAN\_GP} = L_G^{WGAN}$
DRAGAN	Arxiv	$L_D^{DRAGAN} = L_D^{GAN} + \lambda E[(\lvert\nabla D(\alpha x - (1 - \alpha x_p))\rvert - 1)^2]$ $L_G^{DRAGAN} = L_G^{GAN}$
CGAN	Arxiv	$L_D^{CGAN} = E[\log(D(x, c))] + E[\log(1 - D(G(z), c))]$ $L_G^{CGAN} = E[\log(D(G(z), c))]$
infoGAN	Arxiv	$L_{D,Q}^{infoGAN} = L_D^{GAN} - \lambda L_I(c, c')$ $L_G^{infoGAN} = L_G^{GAN} - \lambda L_I(c, c')$
ACGAN	Arxiv	$L_{D,Q}^{ACGAN} = L_D^{GAN} + E[P(class = c\|x)] + E[P(class = c\|G(z))]$ $L_G^{ACGAN} = L_G^{GAN} + E[P(class = c\|G(z))]$
EBGAN	Arxiv	$L_D^{EBGAN} = D_{AE}(x) + \max(0, m - D_{AE}(G(z)))$ $L_G^{EBGAN} = D_{AE}(G(z)) + \lambda \cdot PT$
BEGAN	Arxiv	$L_D^{BEGAN} = D_{AE}(x) - k_t D_{AE}(G(z))$ $L_G^{BEGAN} = D_{AE}(G(z))$ $k_{t+1} = k_t + \lambda(\gamma D_{AE}(x) - D_{AE}(G(z)))$

https://github.com/hwalsuklee/tensorflow-generative-model-collections
https://medium.com/@jonathan_hui/gan-wasserstein-gan-wgan-gp-6a1a2aa1b490

GAN training is challenging

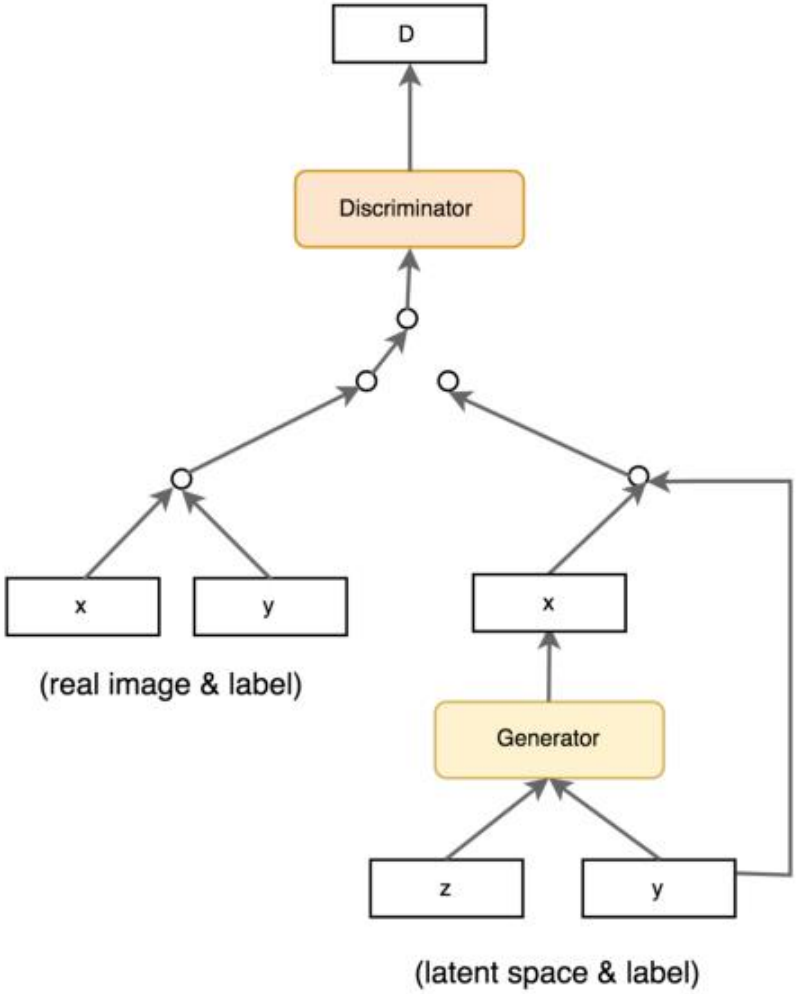
- Vanishing gradient – when discriminator is very good
- Mode collapse – too little diversity in the samples generated
- Lack of convergence because hard to reach Nash equilibrium
- Loss metric doesn't always correspond to image quality; Frechet Inception Distance (FID) is a decent choice

Tips and tricks

- Use batchnorm, ReLU
- Regularize norm of gradients
- Use one of the new loss functions
- Add noise to inputs or labels
- Append image similarity to avoid mode collapse
- Use labels, extra info when available (CGAN)
- …

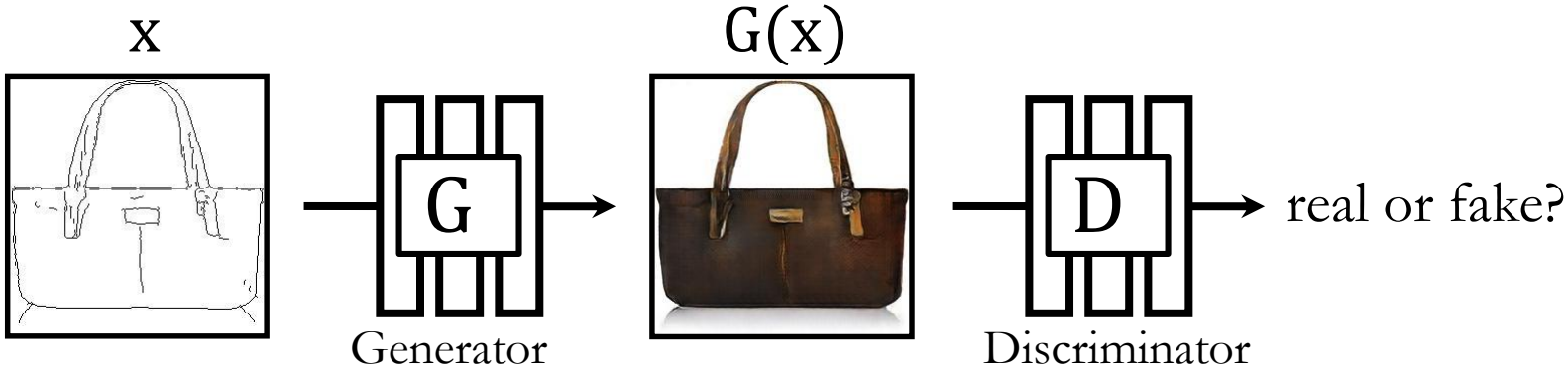
https://github.com/soumith/talks/blob/master/2017-ICCV_Venice/How_To_Train_a_GAN.pdf
https://towardsdatascience.com/gan-ways-to-improve-gan-performance-acf37f9f59b

Conditional GANs



https://medium.com/@jonathan_hui/gan-cgan-infogan-using-labels-to-improve-gan-8ba4de5f9c3d

GANs

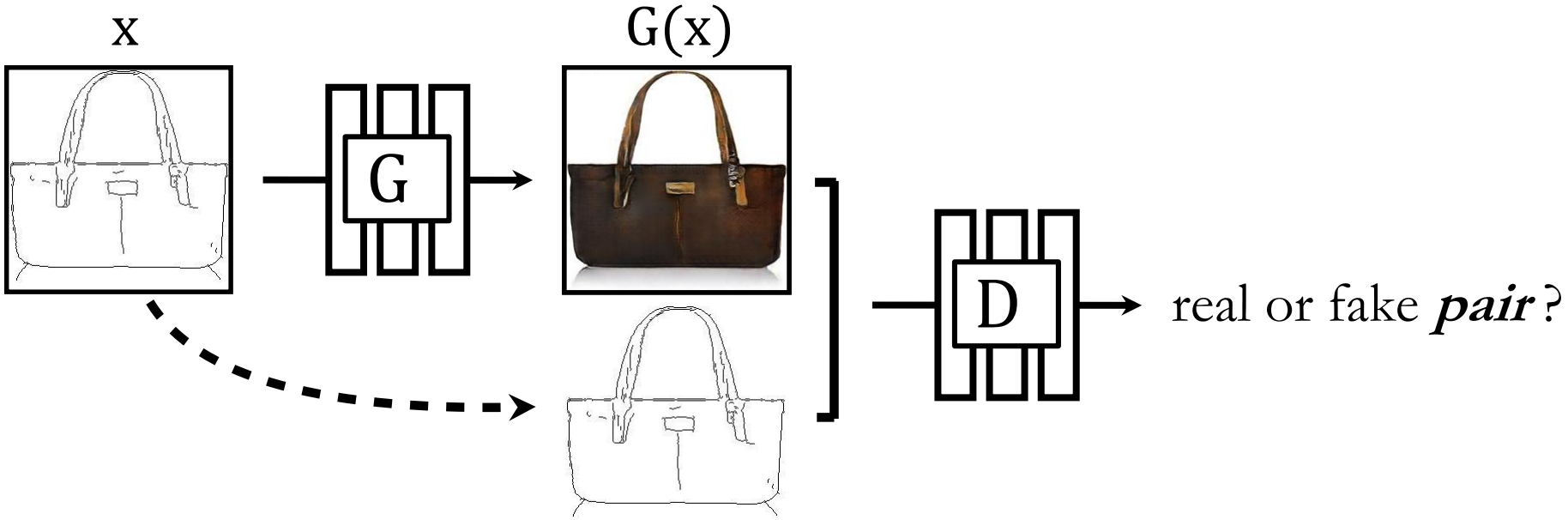


G: generate fake samples that can fool D

D: classify fake samples vs. real images

[Goodfellow et al. 2014]

Conditional GANs



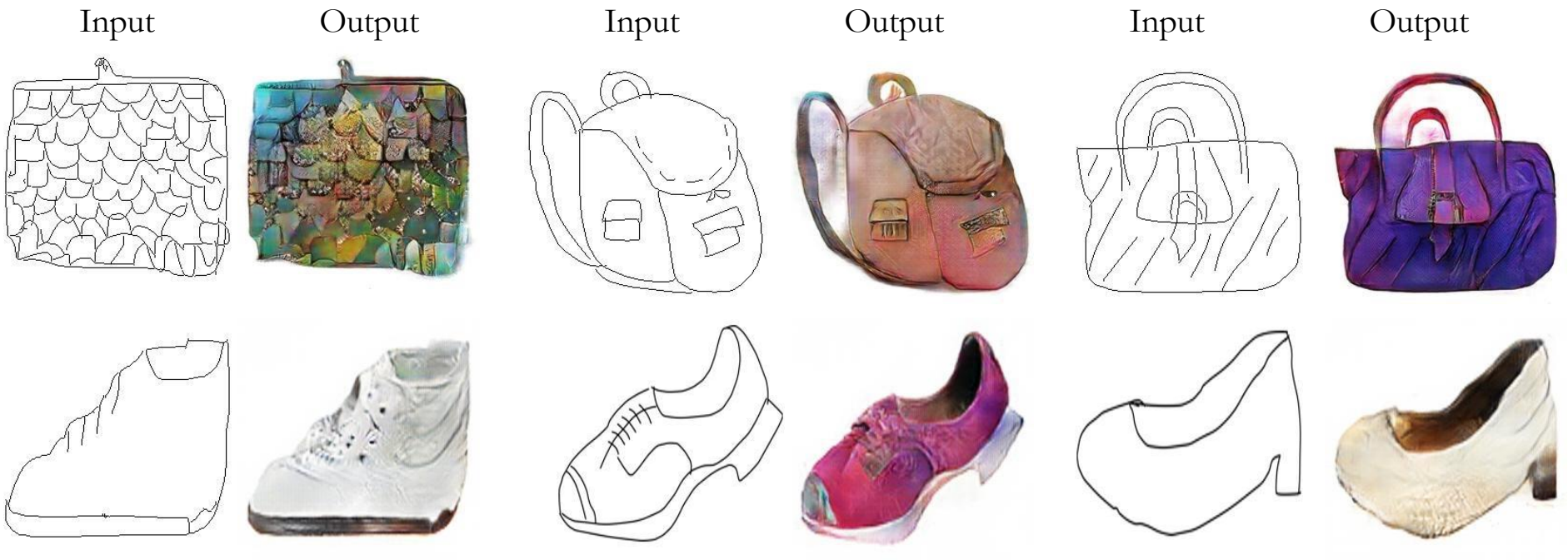
Adapted from Jun-Yan Zhu

Edges → Images

Edges from [Xie & Tu, 2015]

Pix2pix / CycleGAN

Sketches → Images

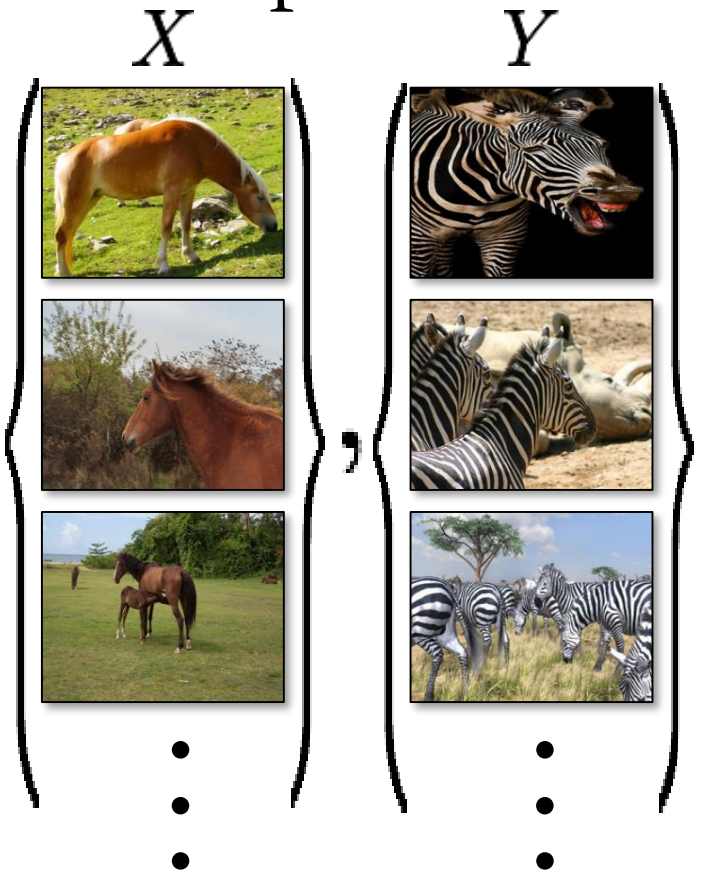


Trained on Edges → Images

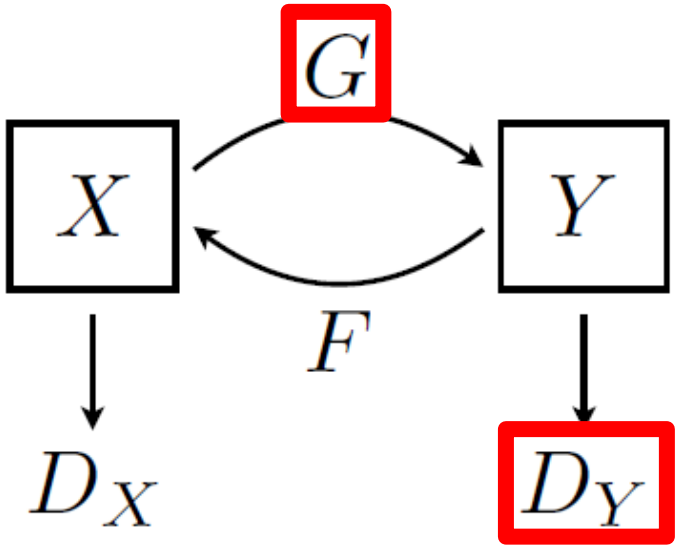
Data from [Eitz, Hays, Alexa, 2012]

Paired

Unpaired



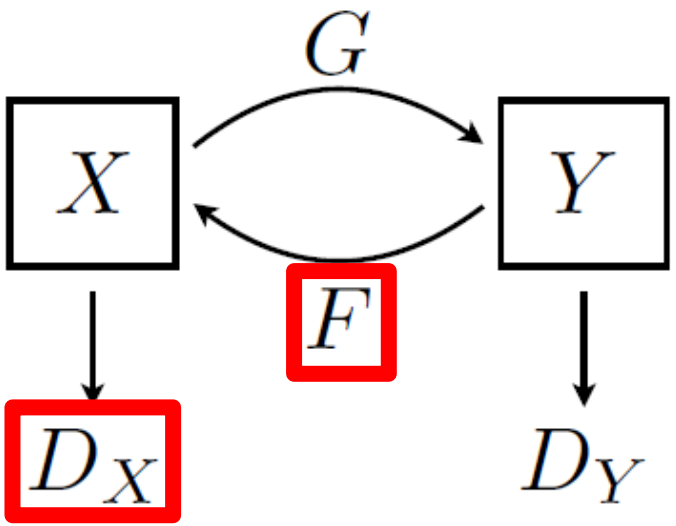
Cycle Consistency



Discriminator D_Y: $L_{GAN}(G(x), y)$
Real zebras vs. generated zebras

Zhu et al., "Unpaired Image-To-Image Translation Using Cycle-Consistent Adversarial Networks", ICCV 2017

Cycle Consistency

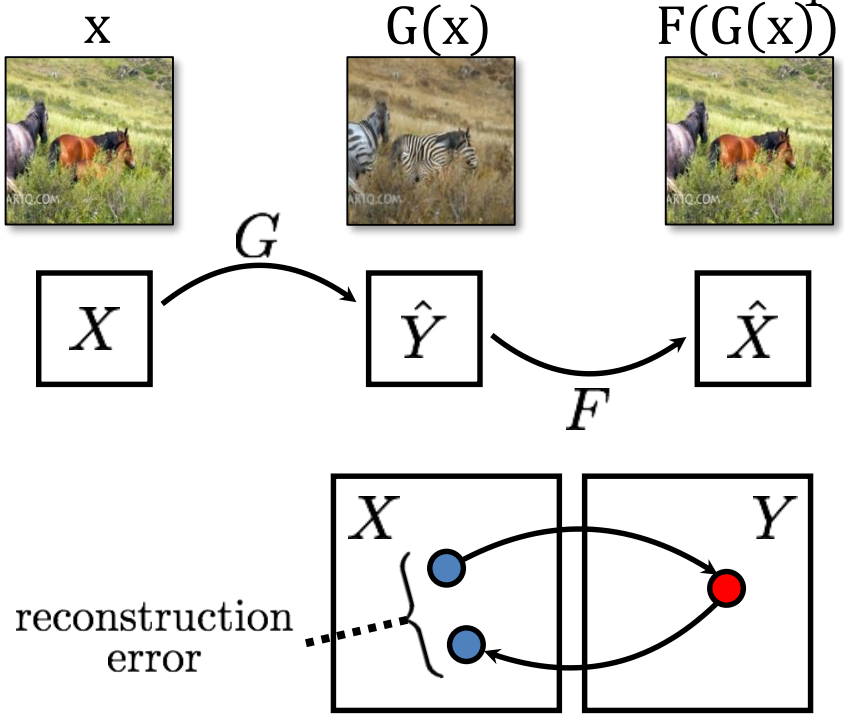


Discriminator D_Y: $L_{GAN}(G(x), y)$
Real zebras vs. generated zebras
Discriminator D_X: $L_{GAN}(F(y), x)$
Real horses vs. generated horses

Zhu et al., "Unpaired Image-To-Image Translation Using Cycle-Consistent Adversarial Networks", ICCV 2017

Cycle Consistency

Forward cycle loss: $\|F(G(x)) - x\|_1$



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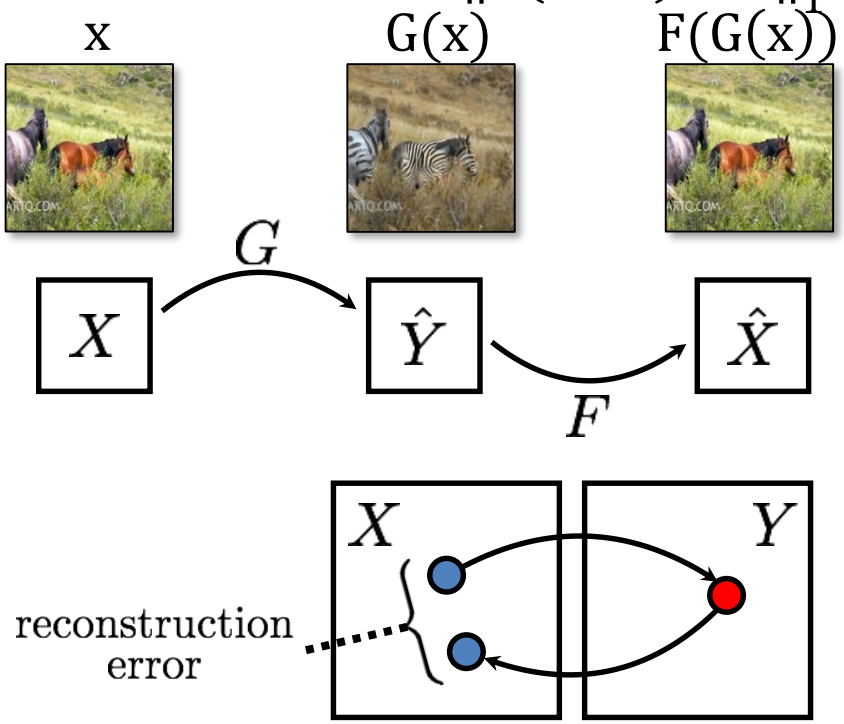
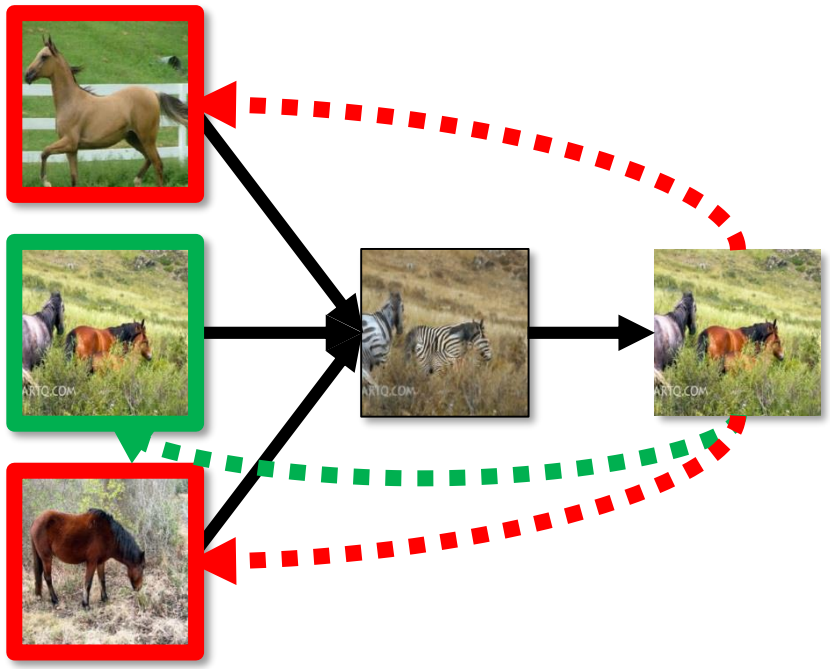


Small cycle loss



Helps cope with mode collapse

Zhu et al., "Unpaired Image-To-Image Translation Using Cycle-Consistent Adversarial Networks", ICCV 2017

Training Details: Objective

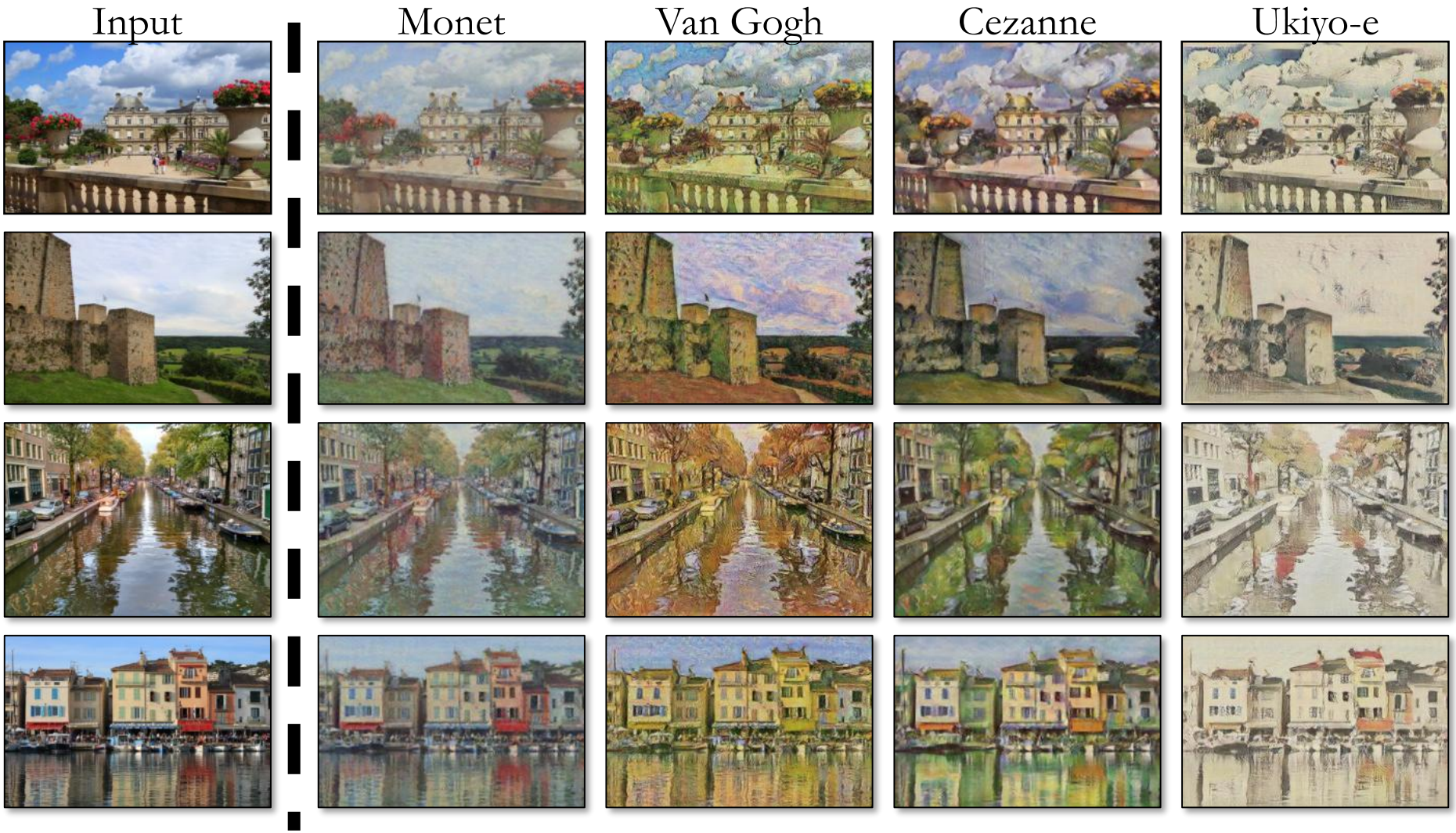
$$\mathcal{L}_{\text{GAN}}(G, D_Y, X, Y) = \mathbb{E}_{y \sim p_{\text{data}}(y)}[\log D_Y(y)] + \mathbb{E}_{x \sim p_{\text{data}}(x)}[\log(1 - D_Y(G(x))],$$

$$\mathcal{L}_{\text{cyc}}(G, F) = \mathbb{E}_{x \sim p_{\text{data}}(x)}[\|F(G(x)) - x\|_1] + \mathbb{E}_{y \sim p_{\text{data}}(y)}[\|G(F(y)) - y\|_1].$$

$$\mathcal{L}(G, F, D_X, D_Y) = \mathcal{L}_{\text{GAN}}(G, D_Y, X, Y) + \mathcal{L}_{\text{GAN}}(F, D_X, Y, X) + \lambda \mathcal{L}_{\text{cyc}}(G, F),$$

$$G^*, F^* = \arg \min_{G,F} \max_{D_x, D_Y} \mathcal{L}(G, F, D_X, D_Y).$$

Zhu et al., "Unpaired Image-To-Image Translation Using Cycle-Consistent Adversarial Networks", ICCV 2017



Pix2pix / CycleGAN

Pix2pix / CycleGAN

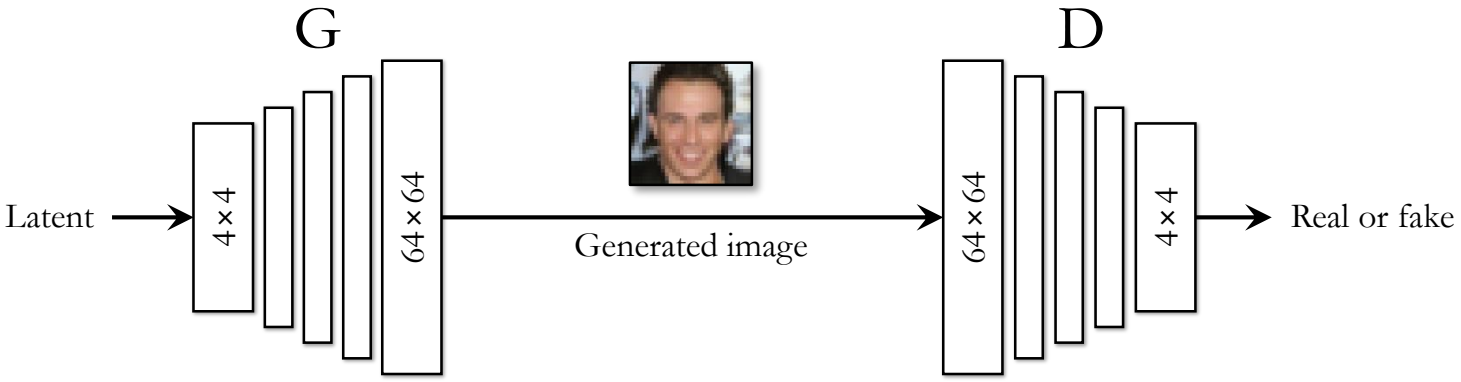
Pix2pix / CycleGAN

Pix2pix / CycleGAN

Celebrities Who Never Existed

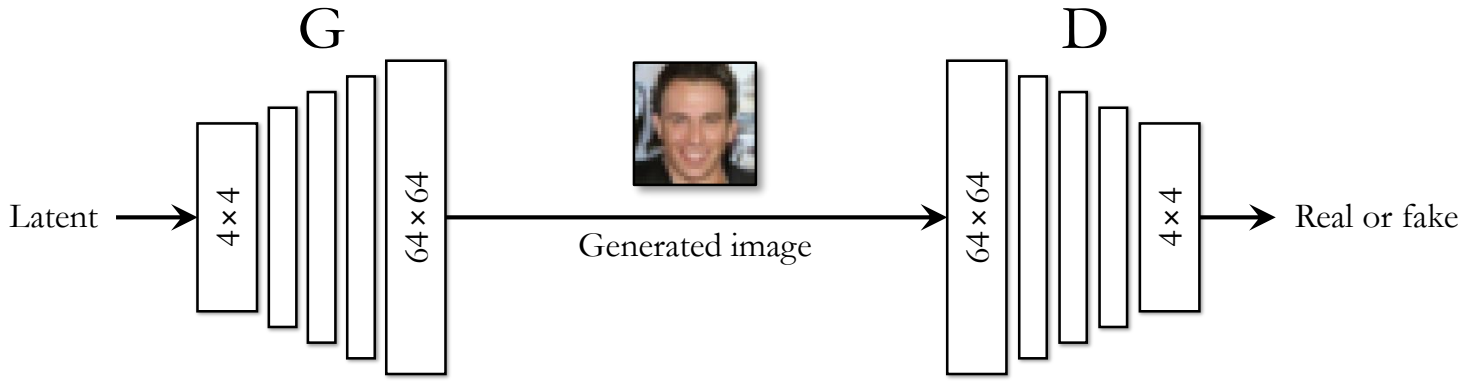
Karras et al., "Progressive Growing of GANs for Improved Quality, Stability, and Variation", ICLR 2018

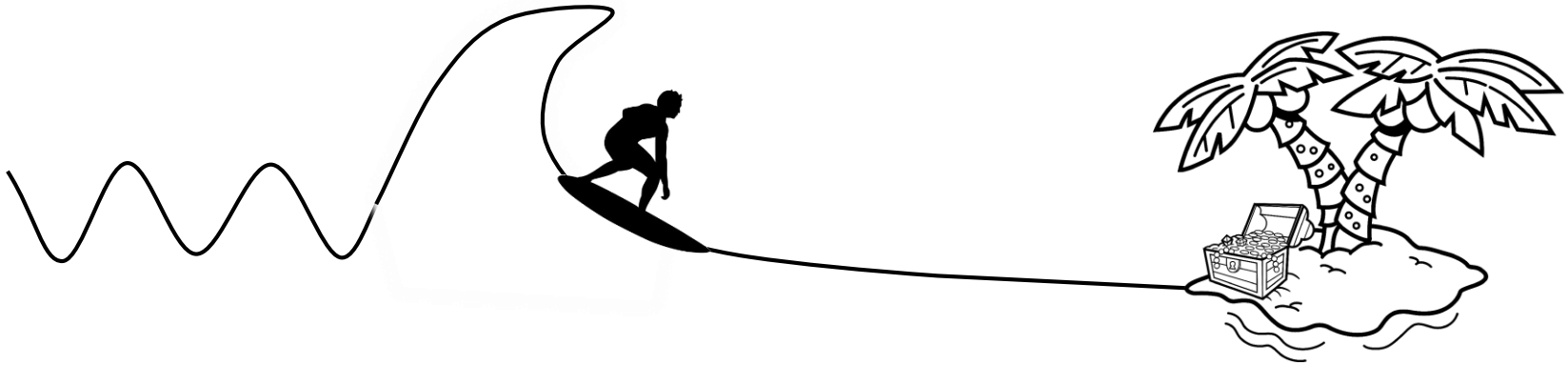
Progressive generation



Karras et al., "Progressive Growing of GANs for Improved Quality, Stability, and Variation", ICLR 2018

Progressive generation





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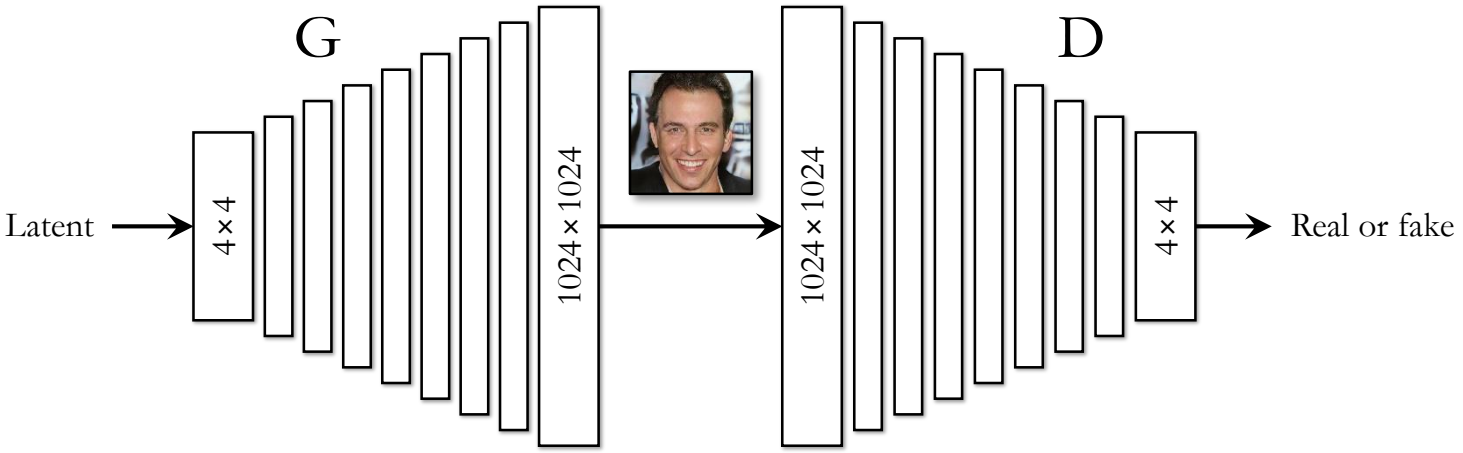
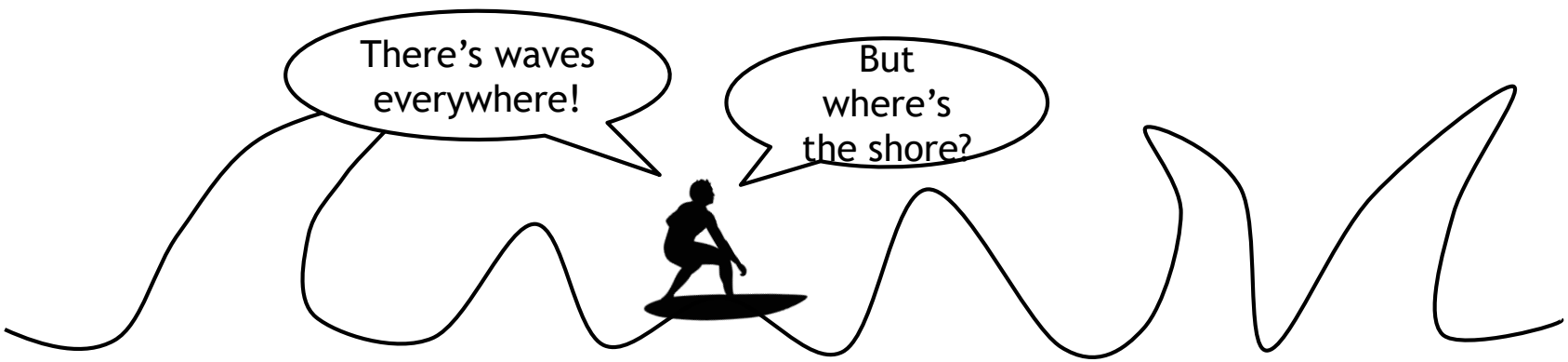
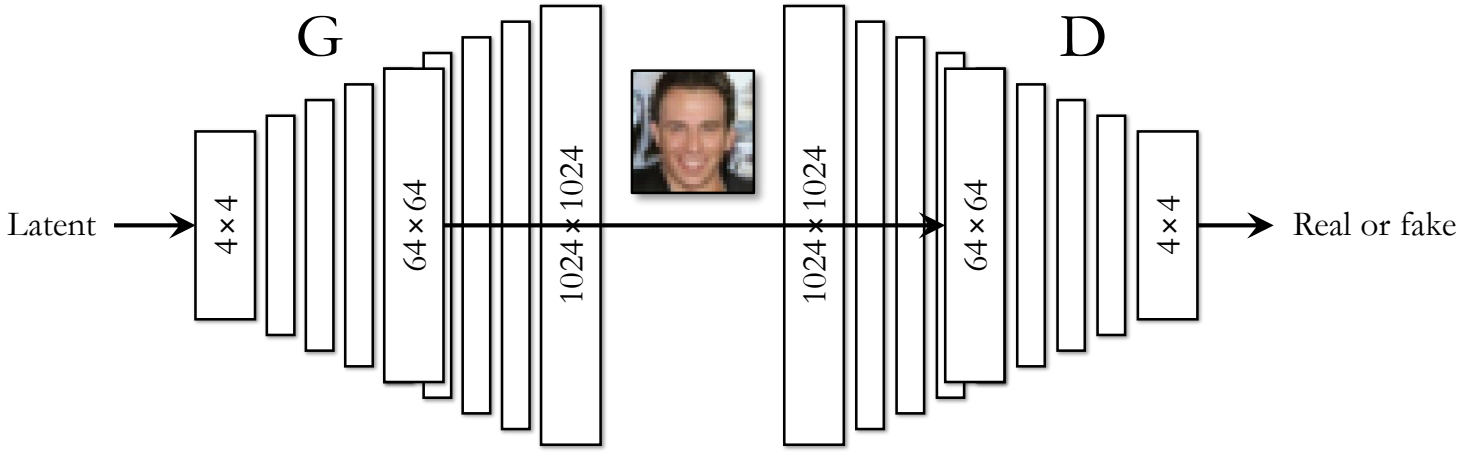
Progressive generation

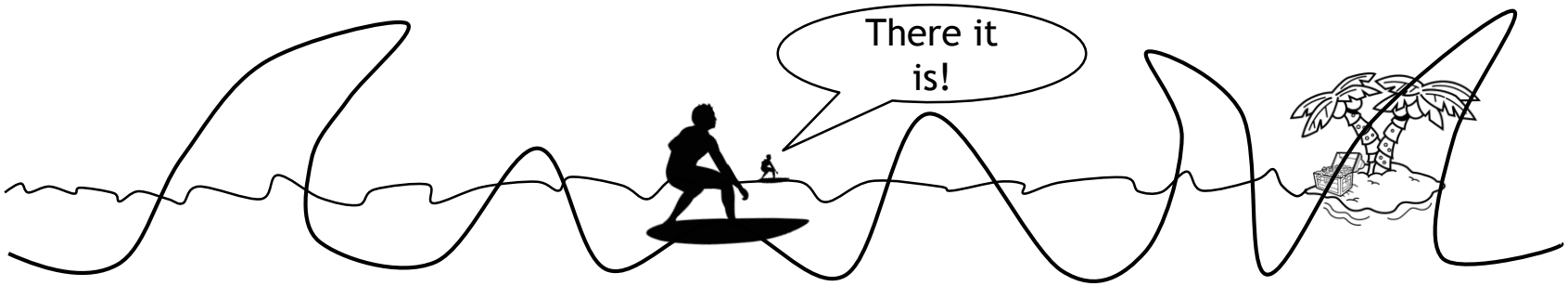




Karras et al., "Progressive Growing of GANs for Improved Quality, Stability, and Variation", ICLR 2018

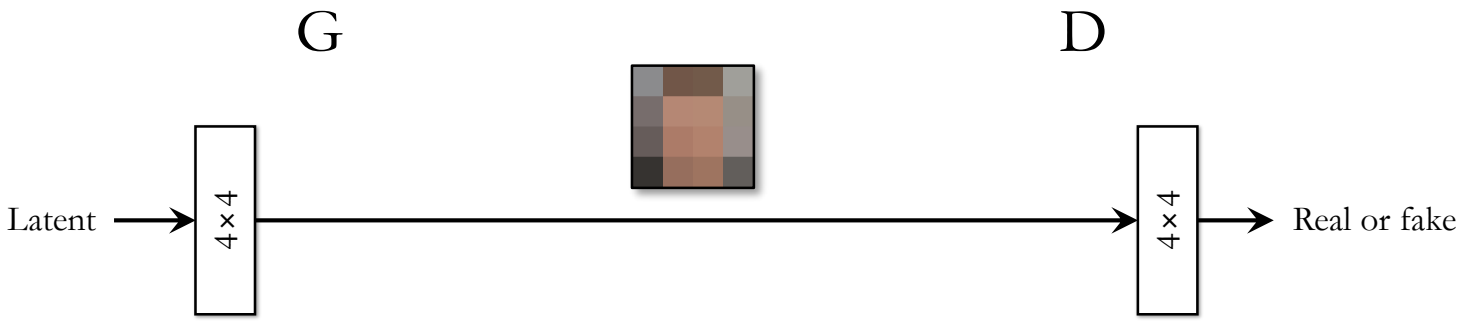
Progressive generation

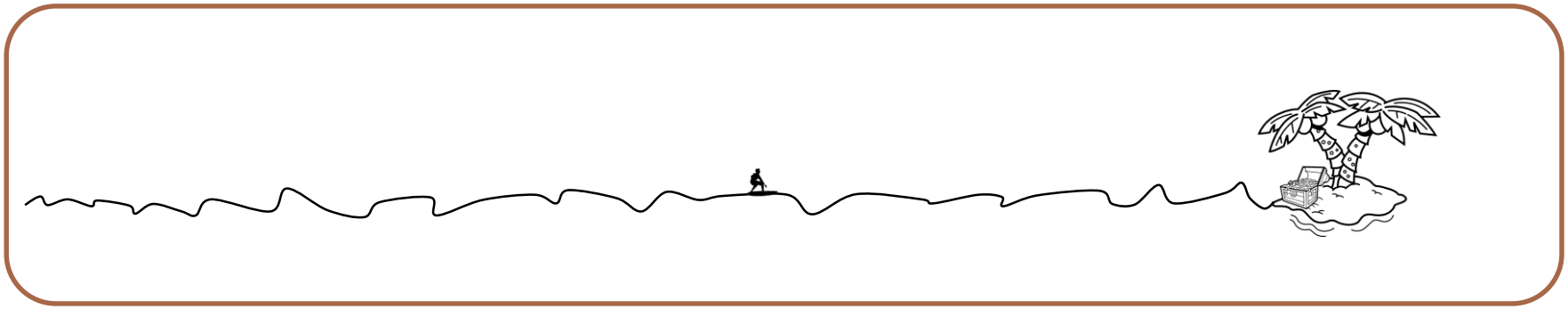




Karras et al., "Progressive Growing of GANs for Improved Quality, Stability, and Variation", ICLR 2018

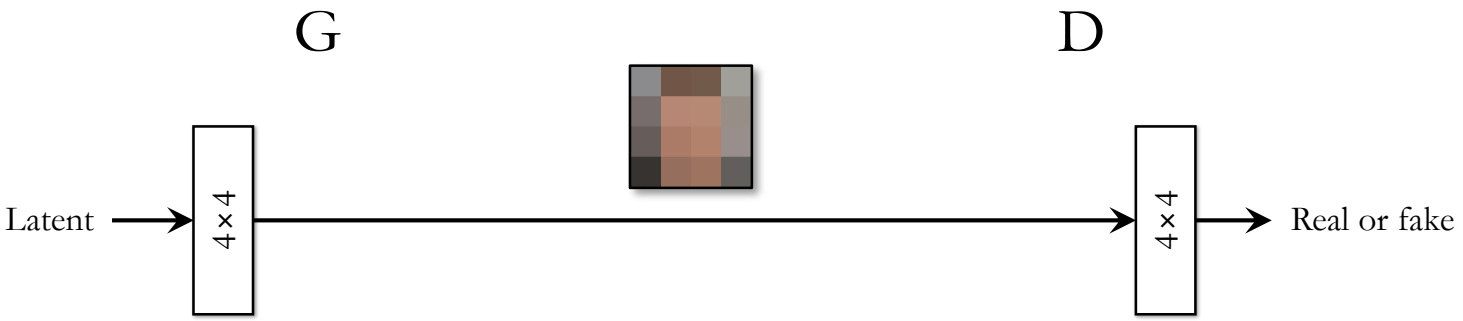
Progressive generation

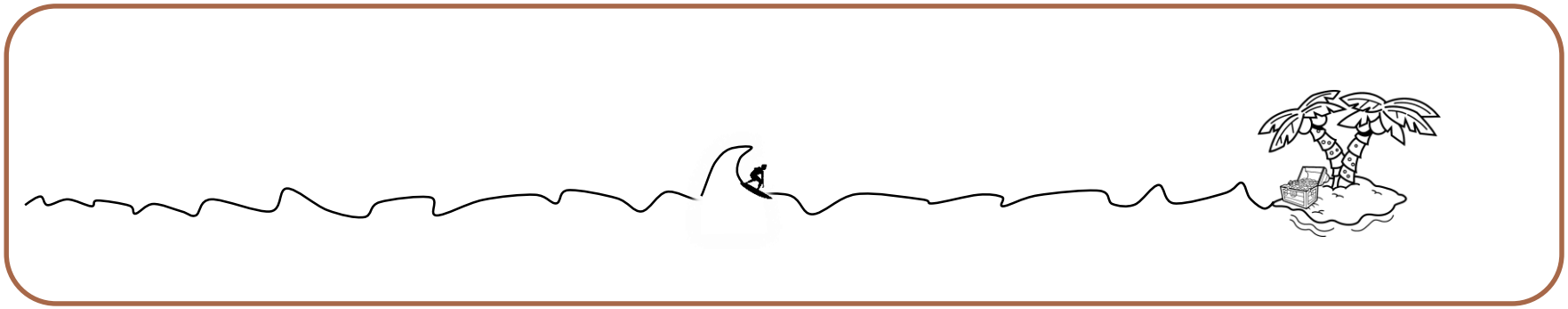




Karras et al., "Progressive Growing of GANs for Improved Quality, Stability, and Variation", ICLR 2018

Progressive generation





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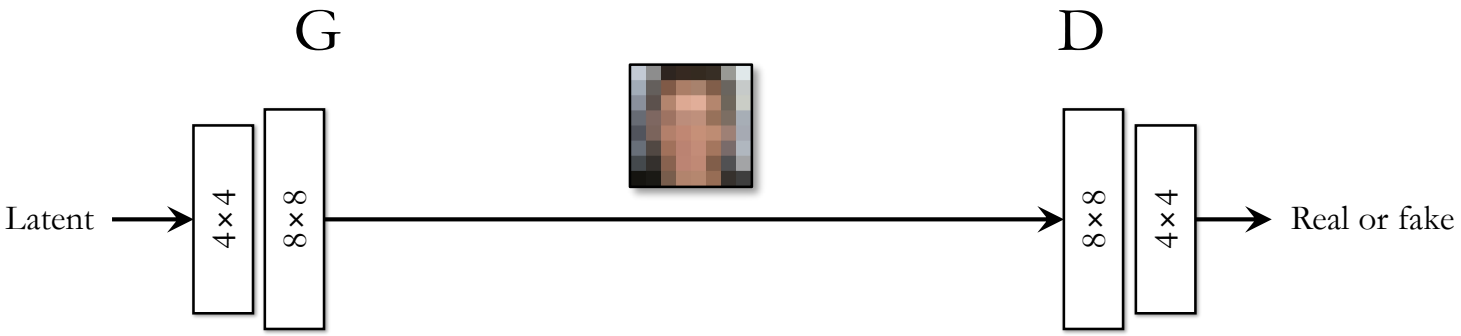
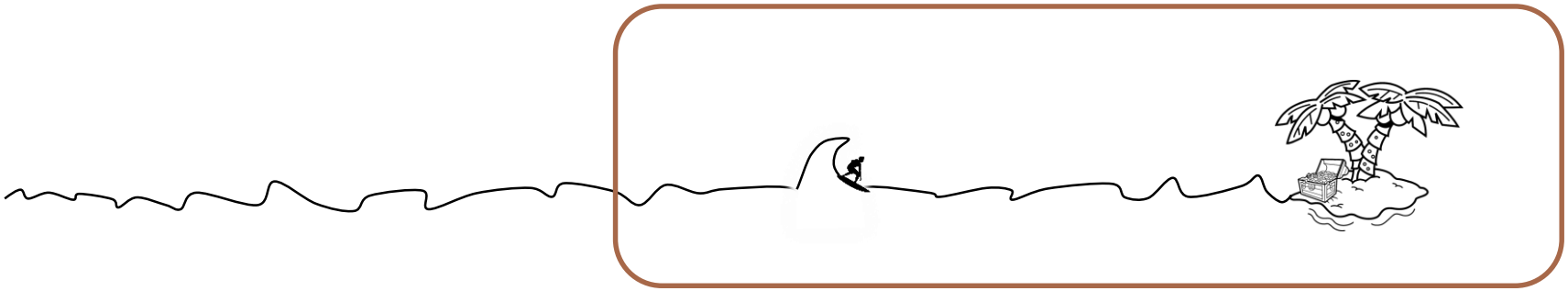
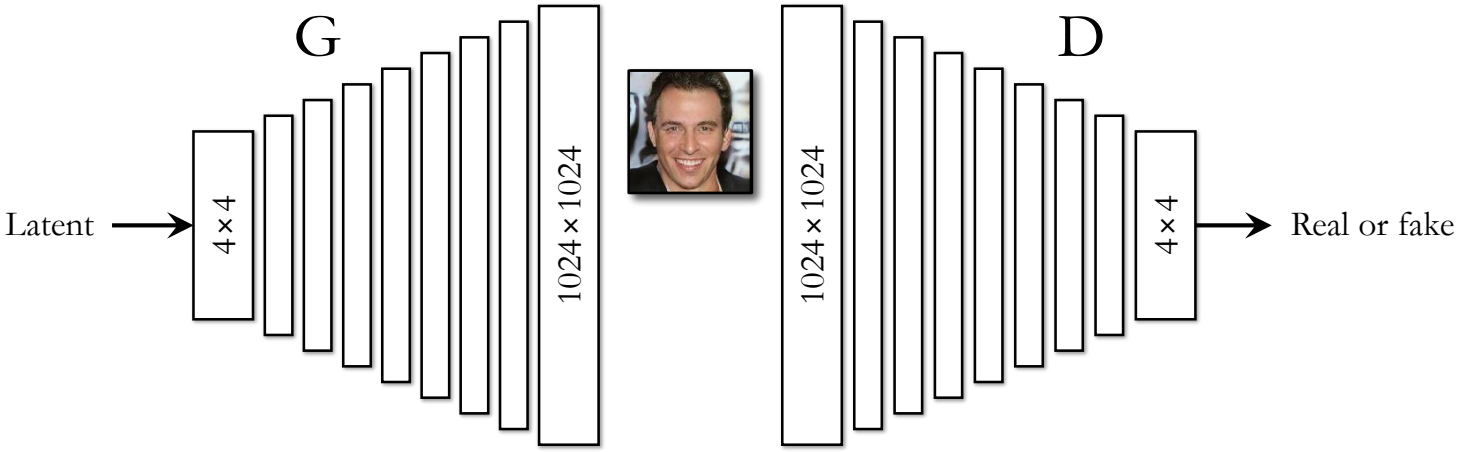
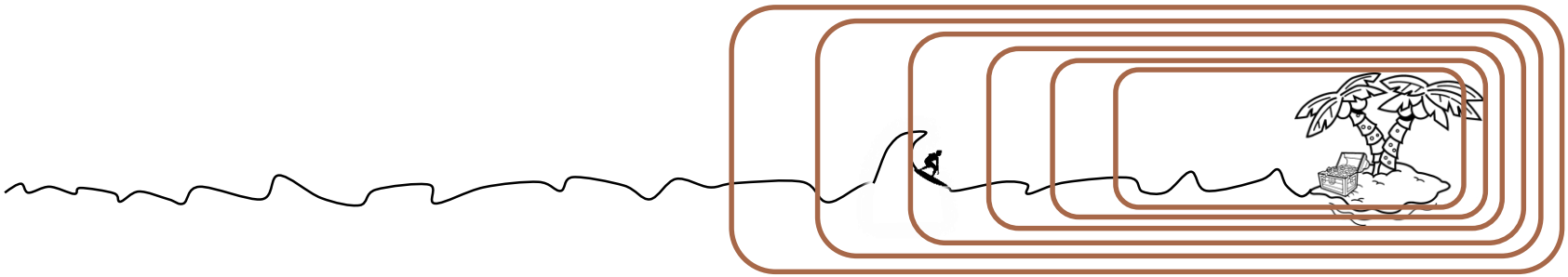




Karras et al., "Progressive Growing of GANs for Improved Quality, Stability, and Variation", ICLR 2018

Progressive generation





Karras et al., "Progressive Growing of GANs for Improved Quality, Stability, and Variation", ICLR 2018

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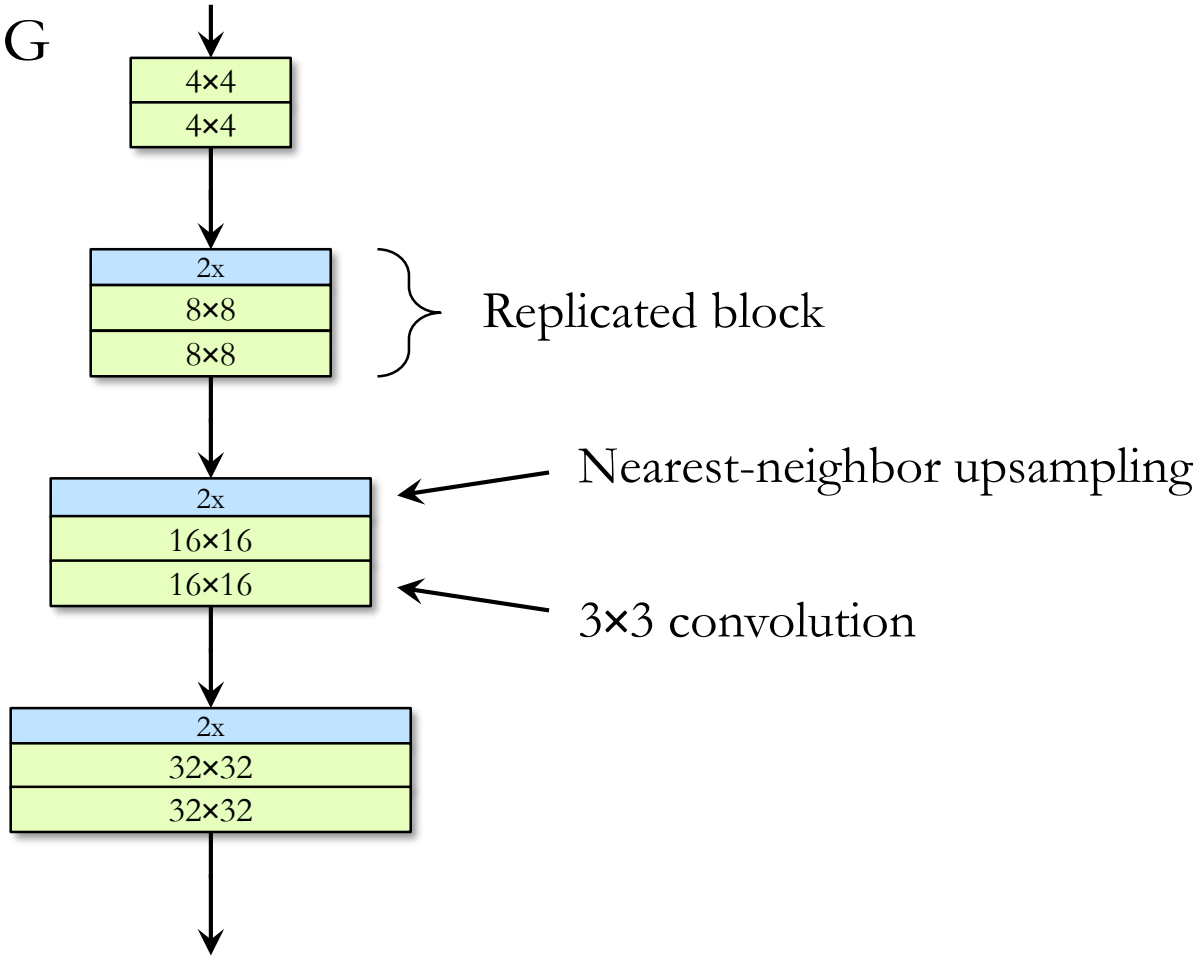

Karras et al., "Progressive Growing of GANs for Improved Quality, Stability, and Variation", ICLR 2018

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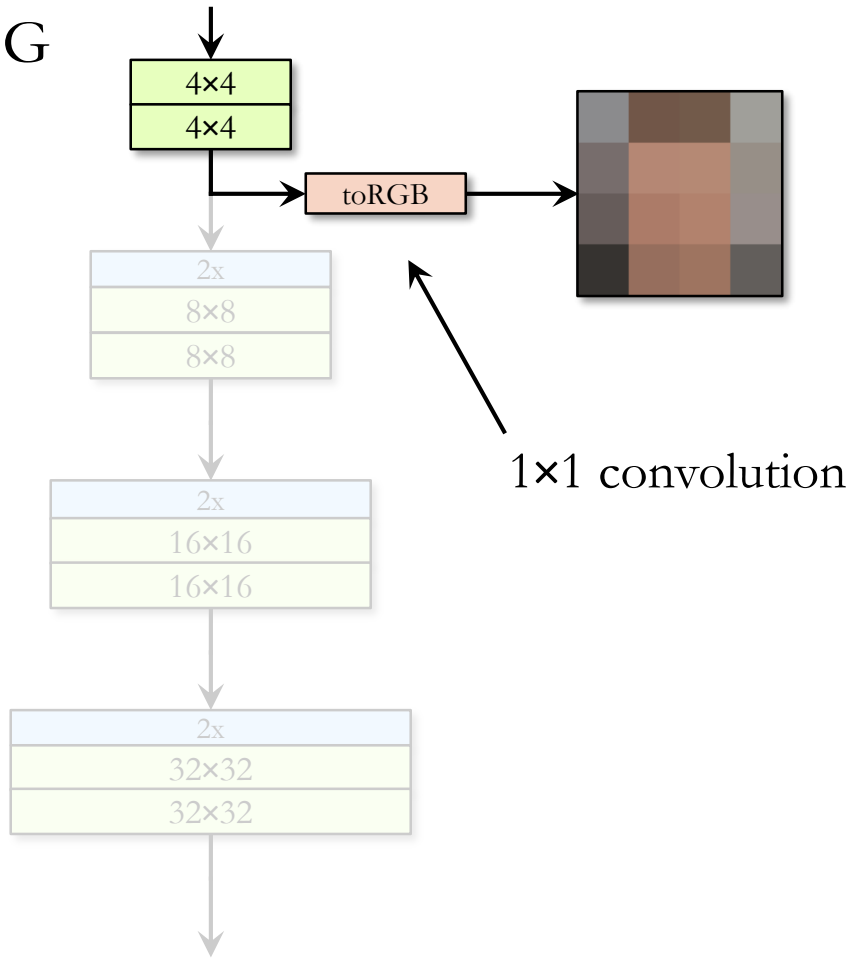
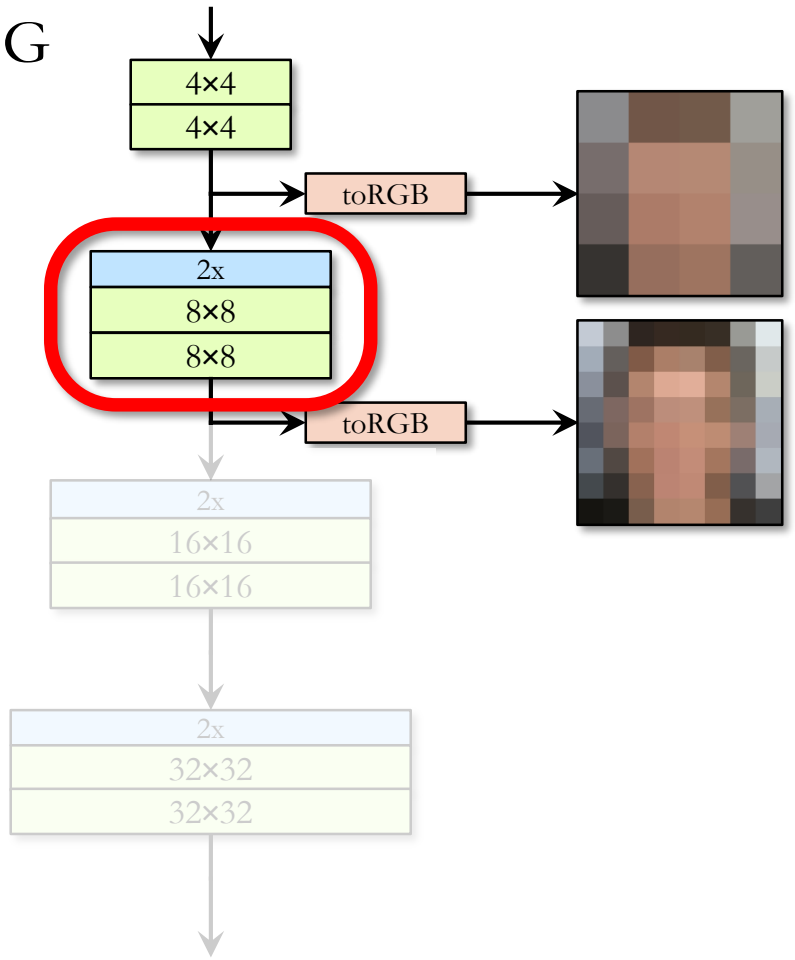


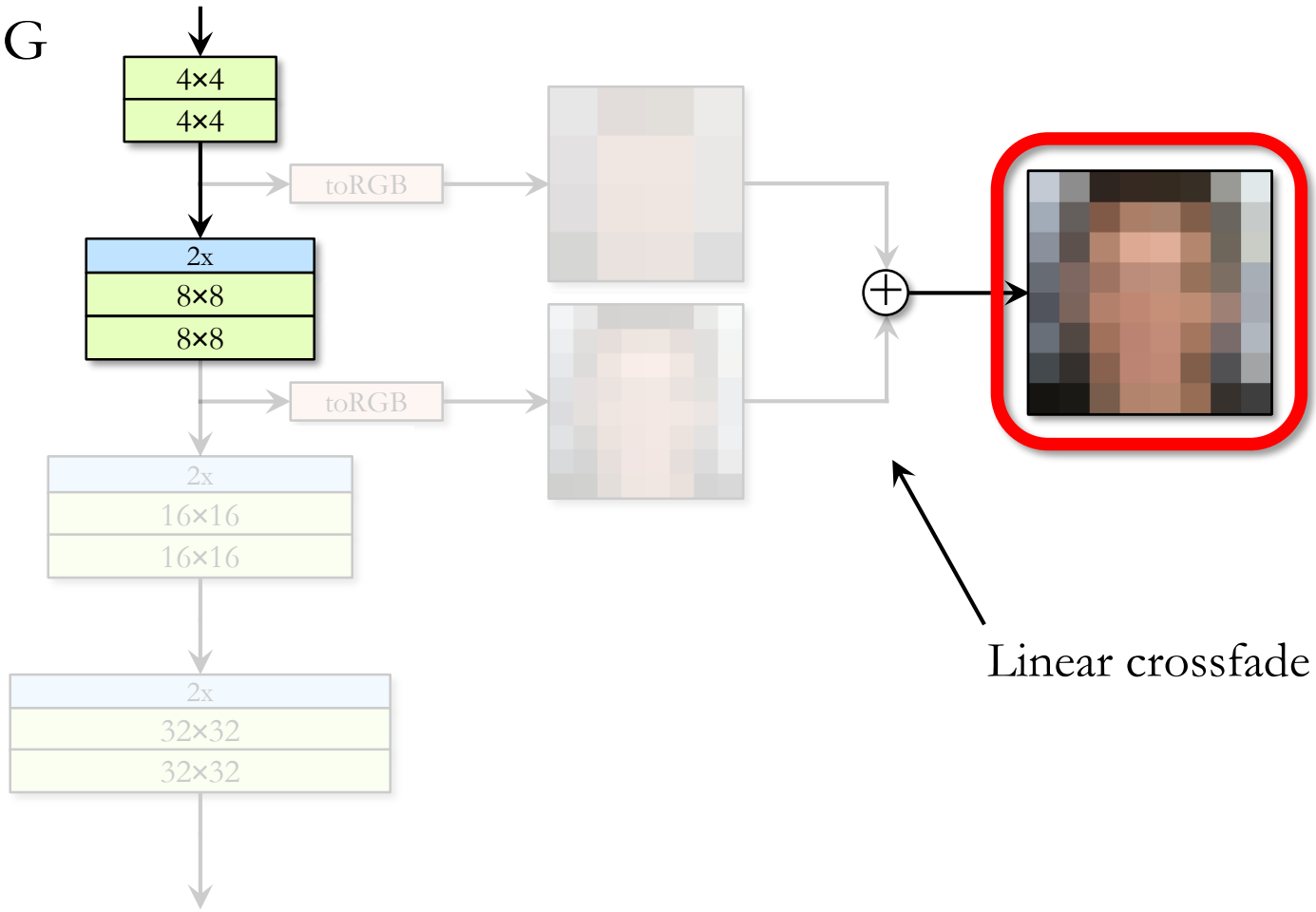
Karras et al., "Progressive Growing of GANs for Improved Quality, Stability, and Variation", ICLR 2018

Progressive generation



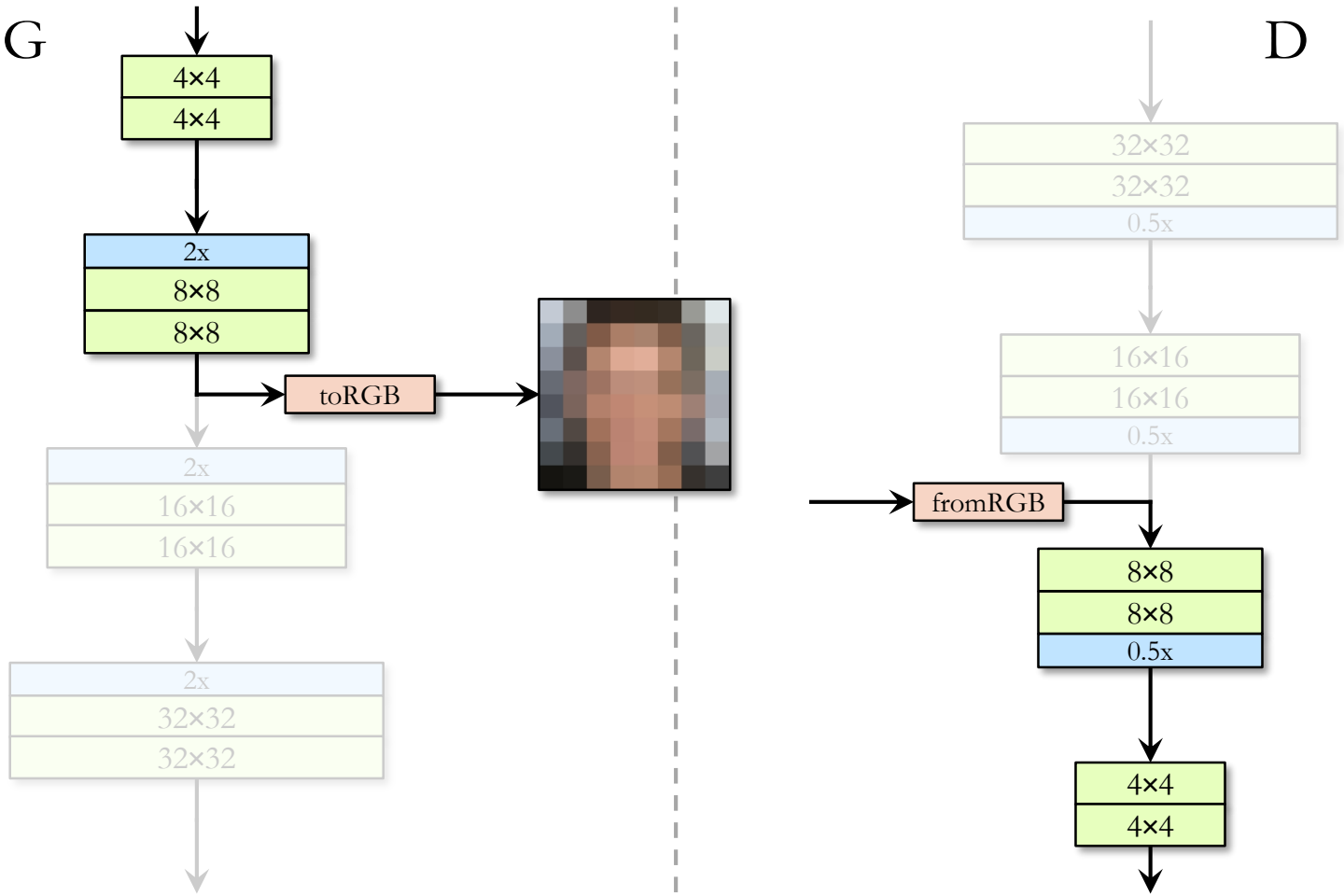
Karras et al., "Progressive Growing of GANs for Improved Quality, Stability, and Variation", ICLR 2018

Progressive generation



Karras et al., "Progressive Growing of GANs for Improved Quality, Stability, and Variation", ICLR 2018

Progressive generation

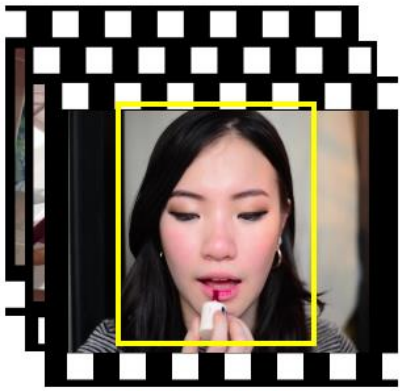


Karras et al., "Progressive Growing of GANs for Improved Quality, Stability, and Variation", ICLR 2018

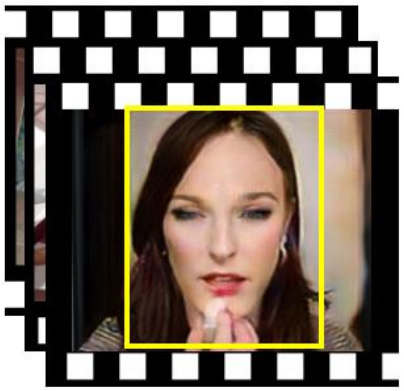
Part V: Ethics (Politics, Privacy, Bias)

- Privacy
- Security and adversarial perturbations
- Bias
- AI for the people

GANs for Privacy (Action Detection)



Identity: Jessica
Action: Applying Make-up on Lips



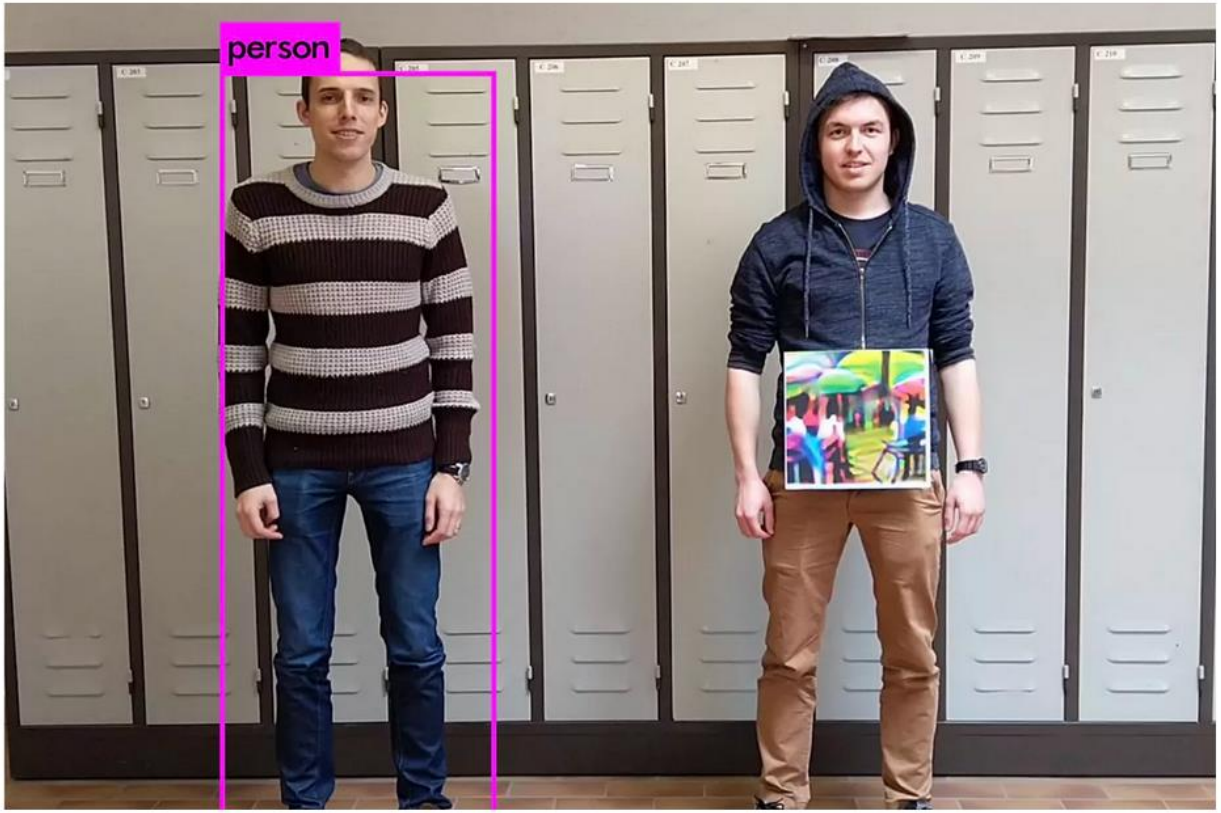
Identity: ???
Action: Applying Make-up on Lips

Ren et al., "Learning to Anonymize Faces for Privacy Preserving Action Detection", ECCV 2018

Adversarial Attacks

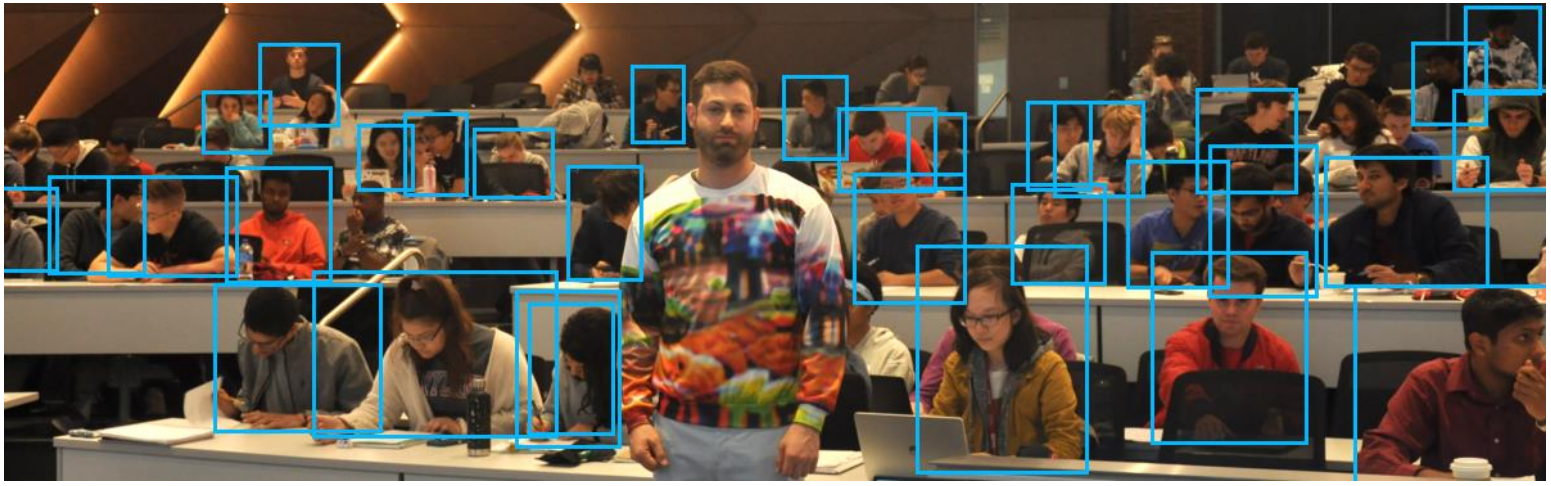
https://bair.berkeley.edu/blog/2017/12/30/yolo-attack/

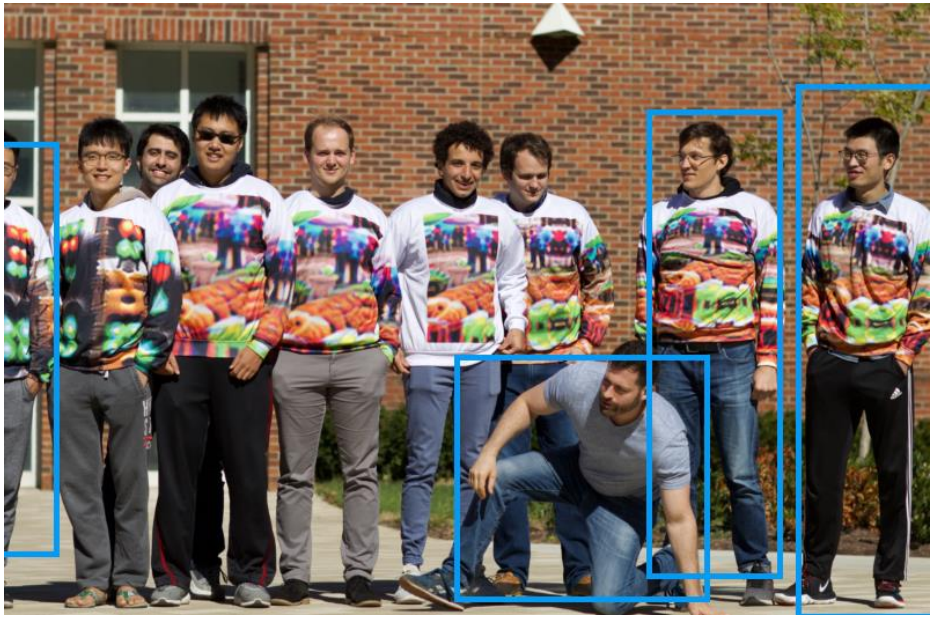
Adversarial Attacks



https://www.theverge.com/2019/4/23/18512472/fool-ai-surveillance-adversarial-example-yolov2-person-detection

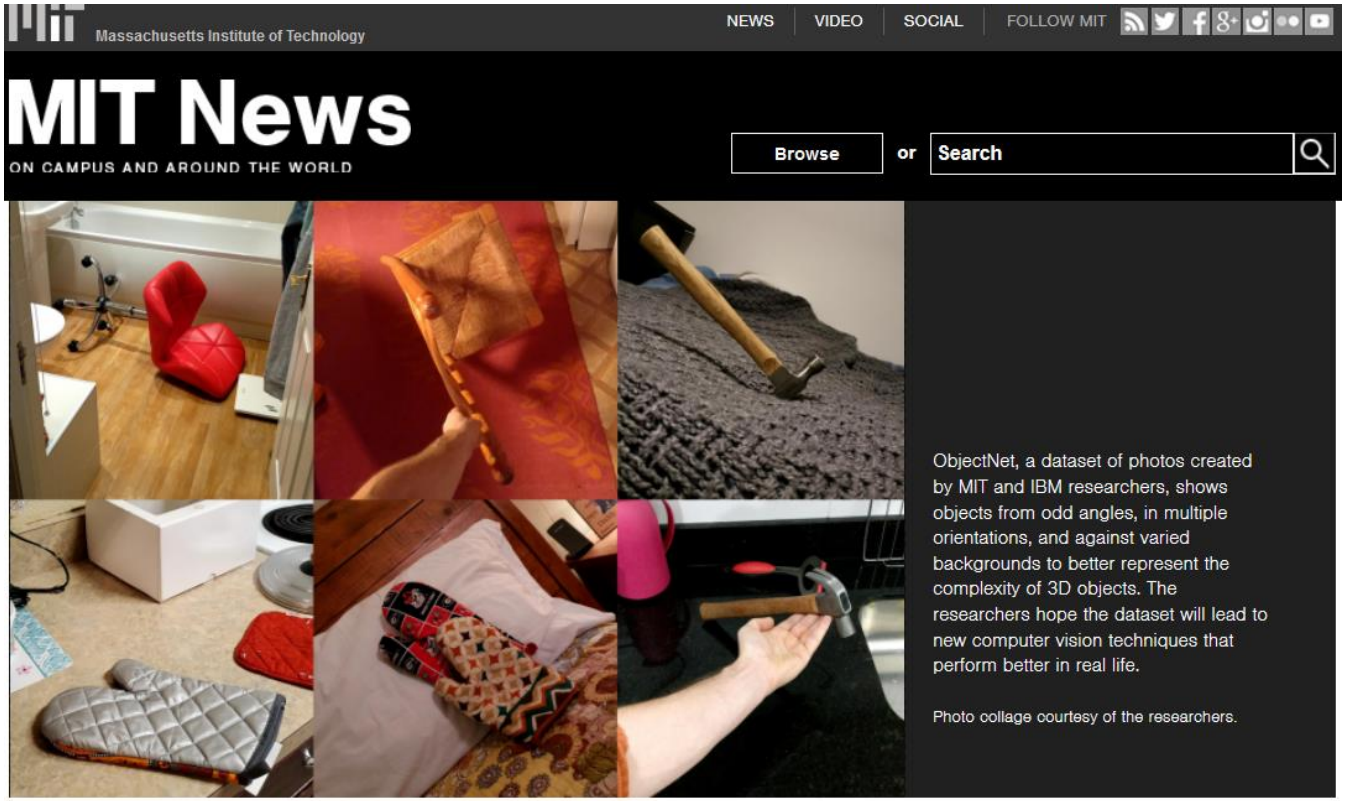
Adversarial Attacks





Tom Goldstein https://www.cs.umd.edu/~tomg/projects/invisible/

Adversarial Attacks



This object-recognition dataset stumped the world's best computer vision models

Objects are posed in varied positions and shot at odd angles to spur new AI techniques.

http://news.mit.edu/2019/object-recognition-dataset-stumped-worlds-best-computer-vision-models-1210

Bias in the Vision and Language of Artificial Intelligence

Margaret Mitchell
Senior Research Scientist
Google AI

Conversation AI


Andrew Zaldivar


Me


Simone Wu


Parker Barnes

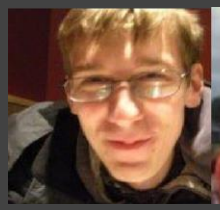

Lucy Vasserman


Ben Hutchinson


Elena Spitzer


Deb Raji

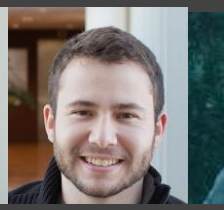

Timnit Gebru


Adrian Benton


Brian Zhang


Dirk Hovy


Josh Lovejoy


Alex Beutel


Blake Lemoine


Hee Jung Ryu


Hartwig Adam


Blaise Agüera y Arcas

What do you see?

- Bananas
- Stickers
- Dole Bananas
- Bananas at a store
- Bananas on shelves
- Bunches of bananas
- Bananas with stickers on them
- Bunches of bananas with stickers on them on shelves in a store

...We don't tend to say

Yellow Bananas

What do you see?

Green Bananas

Unripe Bananas

What do you see?

Ripe Bananas

Bananas with spots

Bananas good for banana bread

What do you see?

Yellow Bananas?

Yellow **is prototypical for bananas**

Prototype Theory

One purpose of categorization is to **reduce the infinite differences** among stimuli **to** behaviourally and **cognitively usable proportions**

There may be some central, prototypical notions of items that arise from stored typical properties for an object category (Rosch, 1975)

May also store exemplars (Wu & Barsalou, 2009)

Fruit

Bananas
"Basic Level"

Unripe Bananas,
Cavendish Bananas

A man and his son are in a terrible accident and are rushed to the hospital in critical care.

The doctor looks at the boy and exclaims "I can't operate on this boy, he's my son!"

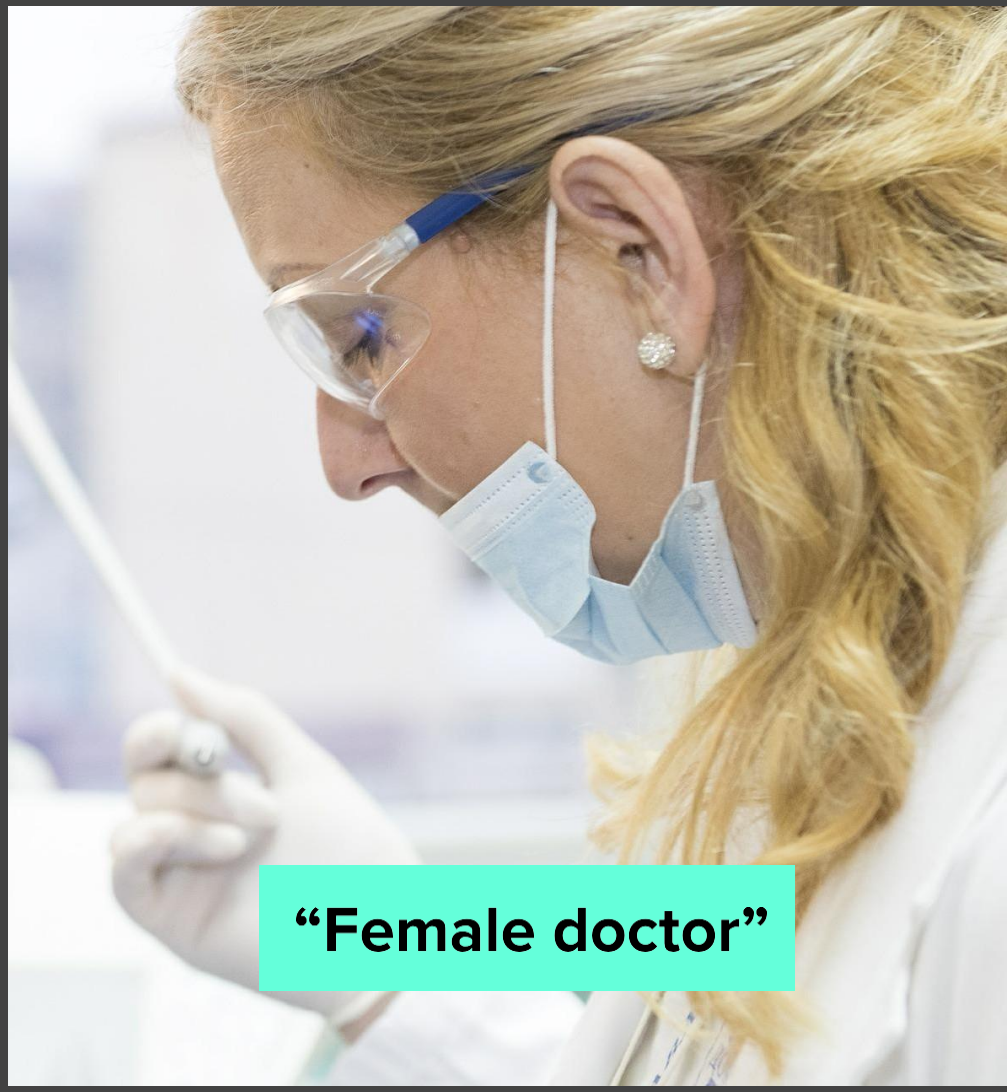
How could this be?

Margaret Mitchell

A man and his son are in a terrible accident and are rushed to the hospital in critical care.

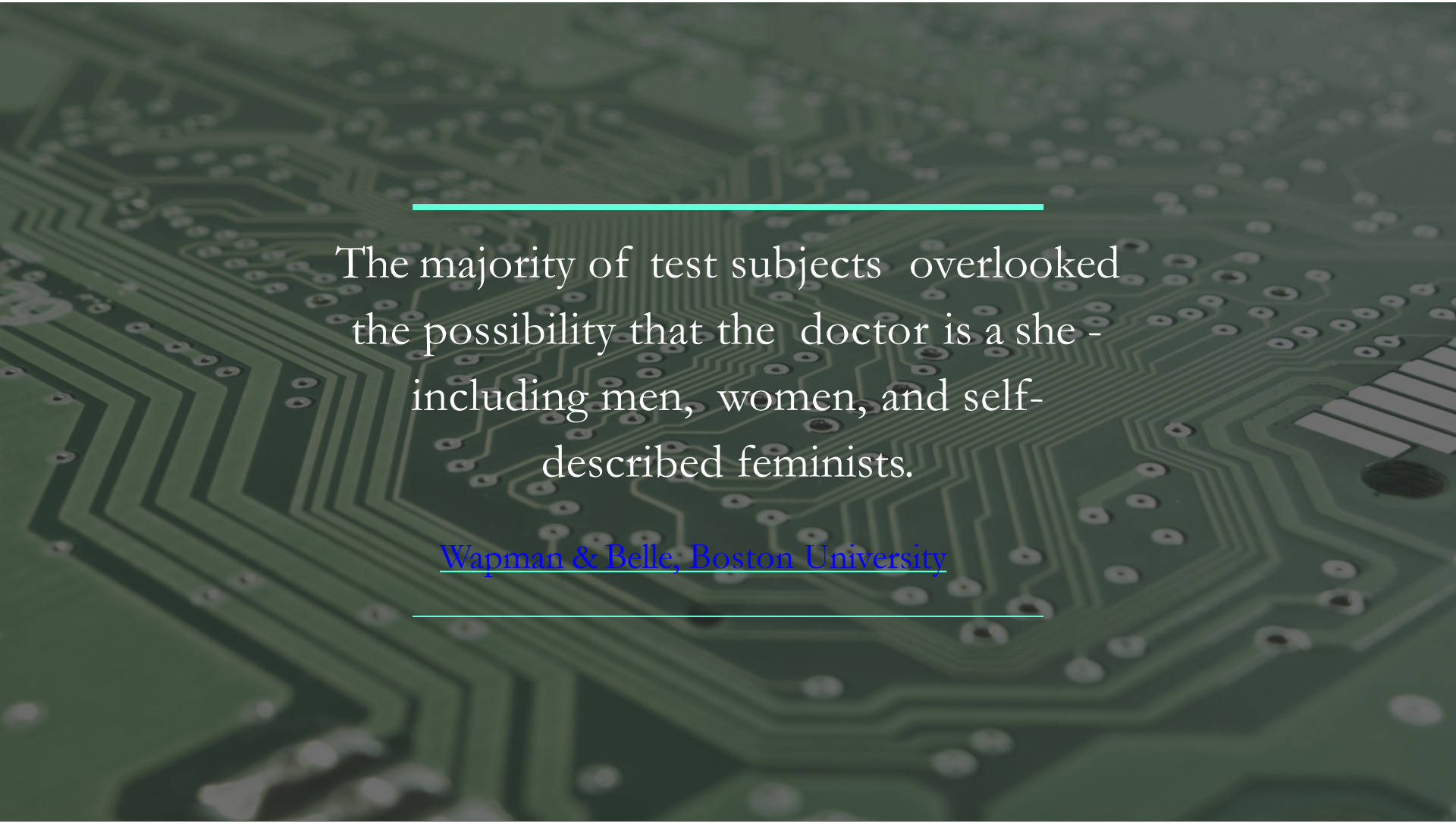
The doctor looks at the boy and exclaims "I can't operate on this boy, he's my son!"

How could this be?




“Doctor”


“Female doctor”


The majority of test subjects overlooked the possibility that the doctor is a she - including men, women, and self-described feminists.
Wapman & Belle, Boston University

Human Reporting Bias

The **frequency** with which **people write** about actions, outcomes, or properties is **not a reflection of real-world frequencies** or the degree to which a property is characteristic of a class of individuals

Bias in Language

Extreme *she* occupations

1. homemaker	2. nurse	3. receptionist
4. librarian	5. socialite	6. hairdresser
7. nanny	8. bookkeeper	9. stylist
10. housekeeper	11. interior designer	12. guidance counselor

Extreme *he* occupations

1. maestro	2. skipper	3. protege
4. philosopher	5. captain	6. architect
7. financier	8. warrior	9. broadcaster
10. magician	11. figher pilot	12. boss

Figure 1: The most extreme occupations as projected on to the *she*−*he* gender direction on g2vNEWS. Occupations such as *businesswoman*, where gender is suggested by the orthography, were excluded.

Gender stereotype *she-he* analogies.

sewing-carpentry	register-nurse-physician	housewife-shopkeeper
nurse-surgeon	interior designer-architect	softball-baseball
blond-burly	feminism-conservatism	cosmetics-pharmaceuticals
giggle-chuckle	vocalist-guitarist	petite-lanky
sassy-snappy	diva-superstar	charming-affable
volleyball-football	cupcakes-pizzas	hairdresser-barber

Gender appropriate *she-he* analogies.

queen-king	sister-brother	mother-father
waitress-waiter	ovarian cancer-prostate cancer	convent-monastery

Figure 2: **Analogy examples**. Examples of automatically generated analogies for the pair *she-he* using the procedure described in text. For example, the first analogy is interpreted as *she*:*sewing* :: *he*:*carpentry* in the original w2vNEWS embedding. Each automatically generated analogy is evaluated by 10 crowd-workers are to whether or not it reflects gender stereotype. Top: illustrative gender stereotypic analogies automatically generated from w2vNEWS, as rated by at least 5 of the 10 crowd-workers. Bottom: illustrative generated gender-appropriate analogies.

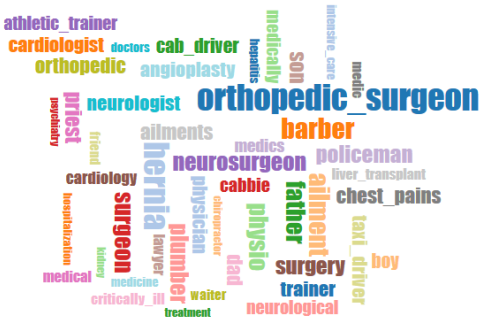
Bolukbasi et al., "Man is to Computer Programmer as Woman is to Homemaker? Debiasing Word Embeddings", NIPS 2016

Bias in Language

he (158)

she (42)

he (47)



she (153)

http://wordbias.umiacs.umd.edu/

Bias in Vision

Fig. 1: Examples where our proposed model (Equalizer) corrects bias in image captions. The overlaid heatmap indicates which image regions are most important for predicting the gender word. On the left, the baseline predicts gender incorrectly, presumably because it looks at the laptop (not the person). On the right, the baseline predicts the gender correctly but it does not look at the person when predicting gender and is thus not acceptable. In contrast, our model predicts the correct gender word and correctly considers the person when predicting gender.

Burns et al., "Women also Snowboard: Overcoming Bias in Captioning Models", ECCV 2018

Bias in Vision

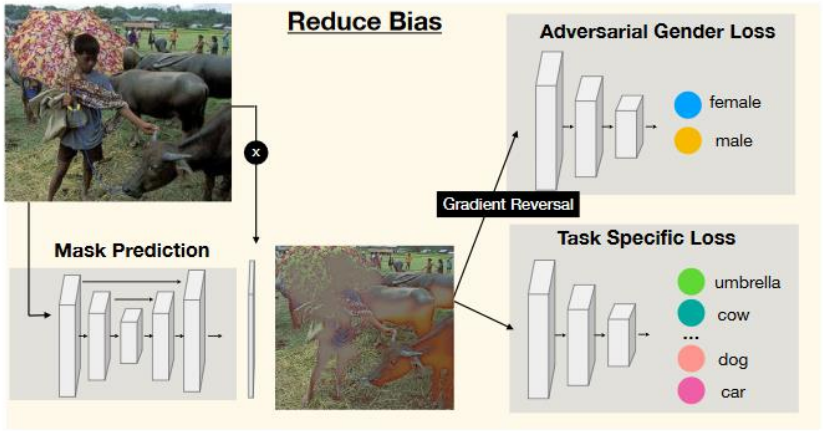


Figure 2. In our bias mitigation approach, we learn a task-specific model with an adversarial loss that removes features corresponding to a protected variable from an intermediate representation in the model – here we illustrate our pipeline to visualize the removal of features in image space through an auto-encoder network.

Figure 3. Images after adversarial removal of gender when applied to the image space. The objective was to preserve information about objects and verbs, e.g. scissors, banana (COCO) or vaulting, lifting (imSitu) while removing gender correlated features.

Wang et al., "Balanced Datasets Are Not Enough: Estimating and Mitigating Gender Bias in Deep Image Representations", ICCV 2019


Training data are collected and annotated
Model is trained
Media are filtered, ranked, aggregated, or generated
People see output


Biases in Data

Biases in Data

Selection Bias: Selection does not reflect a random sample

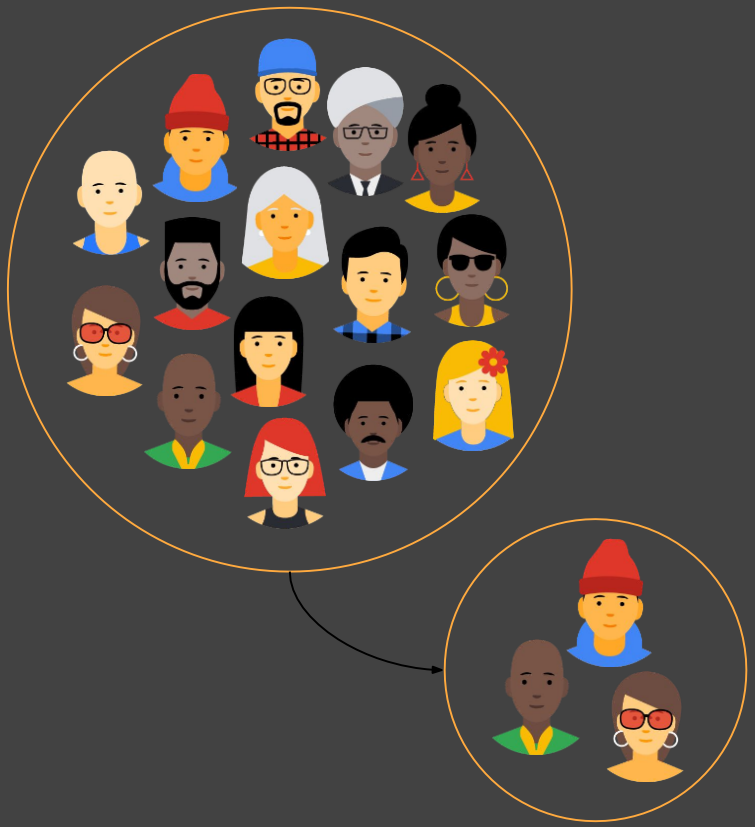
CREDIT

Biases in Data

Out-group homogeneity bias: Tendency to see outgroup members as more alike than ingroup members

Biases in Data →
Biased Data Representation

It's possible that you have an appropriate amount of data for every group you can think of but that some groups are represented less positively than others.



Biases in Data → Biased Labels

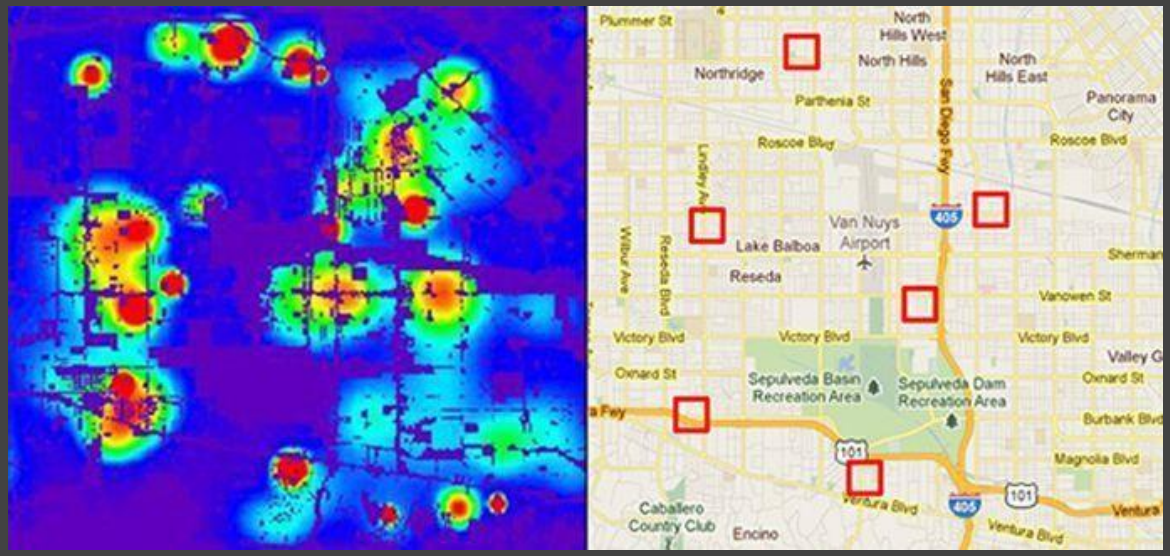
Annotations in your dataset will reflect the worldviews of your annotators.

https://ai.googleblog.com/2018/09/introducing-inclusive-images-competition.html

Margaret Mitchell

Predicting Policing

- Algorithms identify potential crime hot-spots
- Based on where crime is previously reported, not where it is known to have occurred
- Predicts future events from past



CREDIT

Smithsonian. *Artificial Intelligence Is Now Used to Predict Crime. But Is It Biased?* 2018

Predicting Sentencing

- Prater (who is white) rated **low risk** after shoplifting, despite two armed robberies; one attempted armed robbery.
- Borden (who is black) rated **high risk** after she and a friend took (but returned before police arrived) a bike and scooter sitting outside.
- Two years later, Borden has not been charged with any new crimes. Prater serving 8-year prison term for grand theft.

CREDIT

ProPublica. Northpointe: Risk in Criminal Sentencing. 2016.

Predicting Criminality

Israeli startup, Faception

> *"Faception is first-to-technology and first-to-market with proprietary computer vision and machine learning technology for profiling people and* ***revealing their personality based only on their facial image****."*

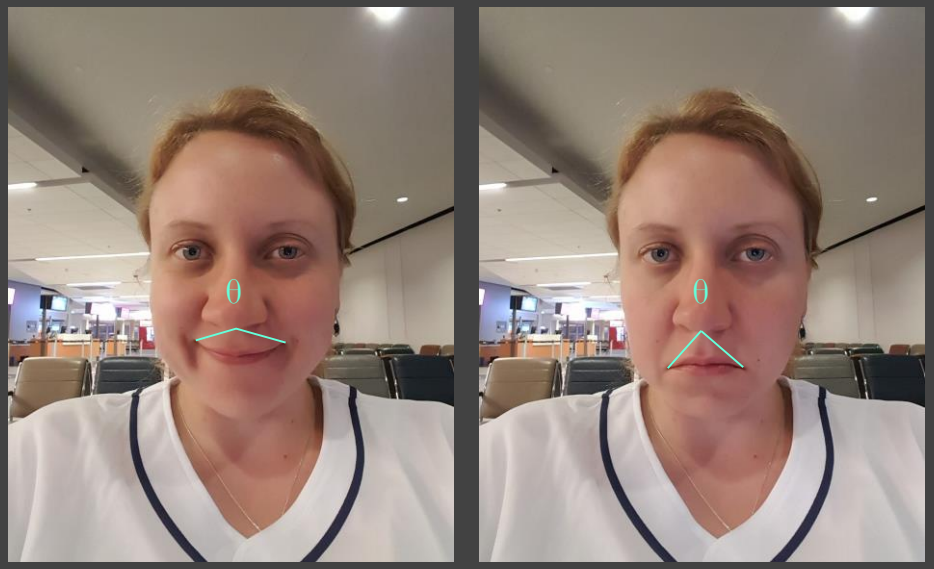
Offering specialized engines for recognizing "High IQ", "White-Collar Offender", "Pedophile", and "Terrorist" from a face image.

Main clients are in homeland security and public safety.

Predicting Criminality

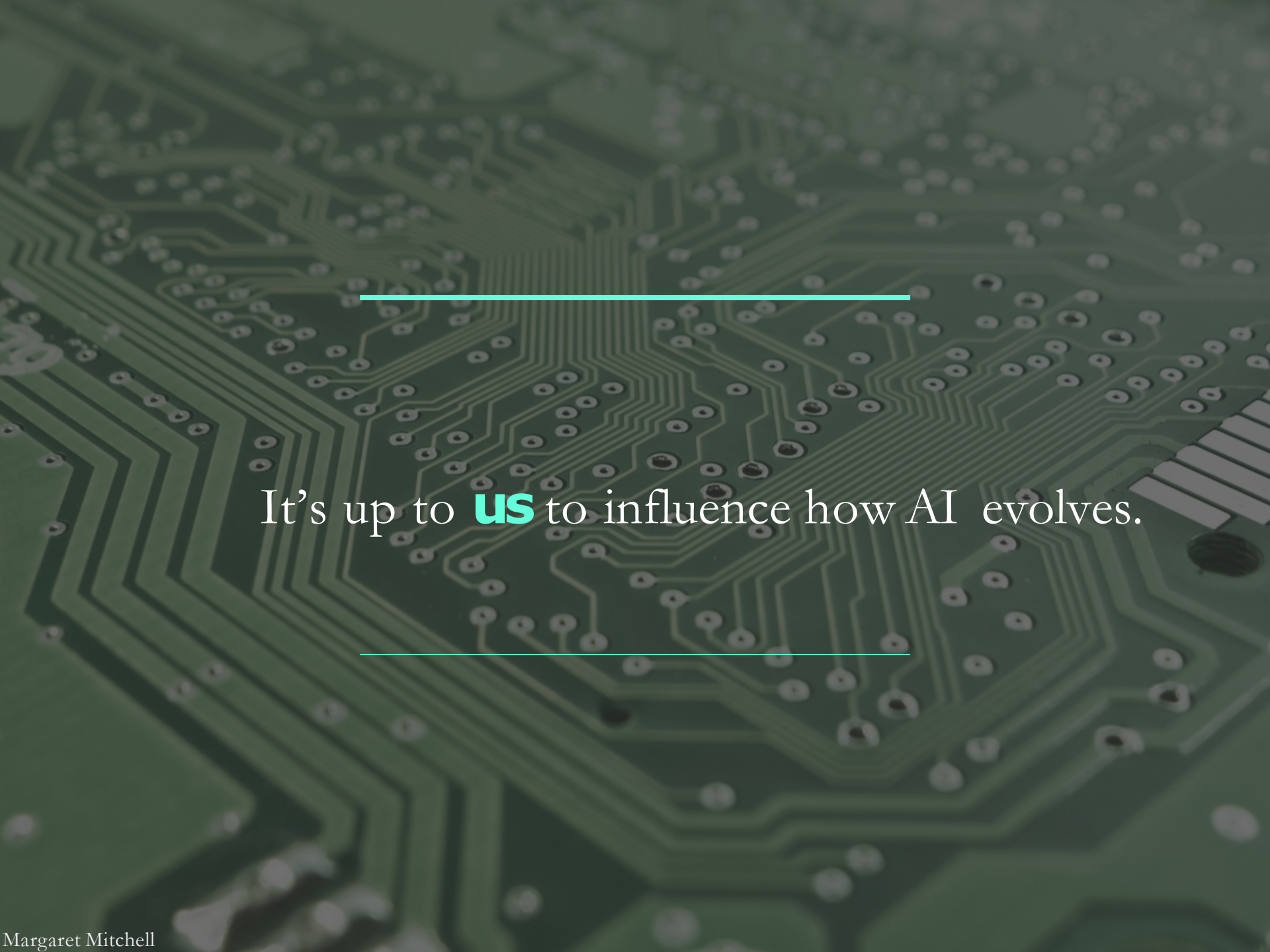
"Automated Inference on Criminality using Face Images" Wu and Zhang, 2016. arXiv

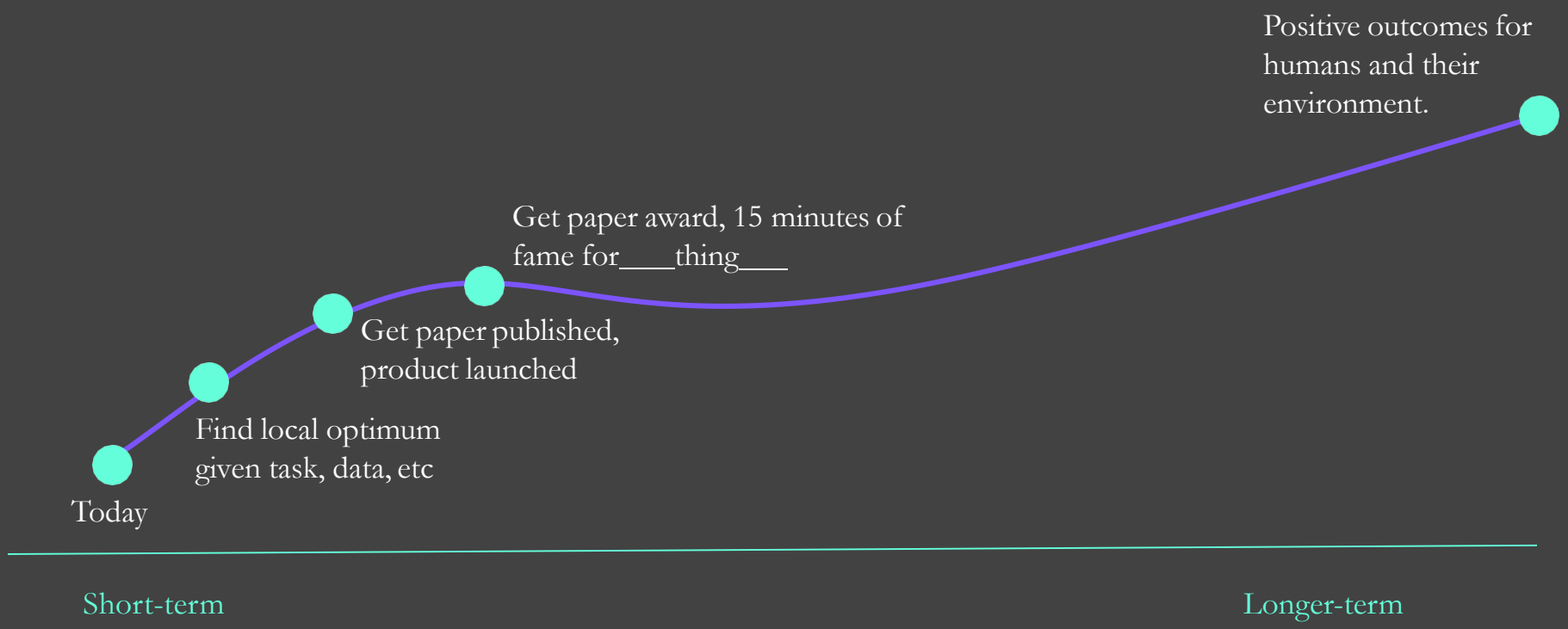
1,856 closely cropped images of faces;
Includes "wanted suspect" ID pictures
from specific regions.

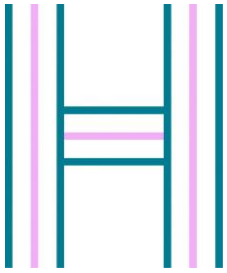


"[…] angle θ from nose tip to two mouth corners is on average 19.6% smaller for criminals than for non-criminals …"

See our longer piece on Medium, "Physiognomy's New Clothes"

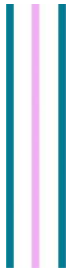

It's up to us to influence how AI evolves.
Margaret Mitchell


Positive outcomes for humans and their environment.
Get paper award, 15 minutes of fame for____thing____
Get paper published, product launched
Find local optimum given task, data, etc
Today
Short-term
Longer-term



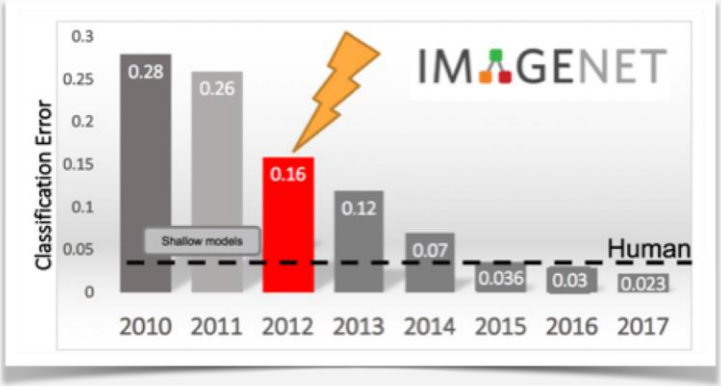
The development of AI should be guided by a concern for its impact on **human** society.

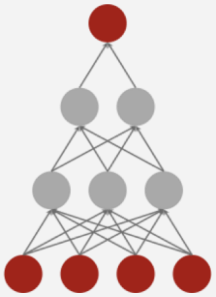
AI should **augment** human skills, not replace them.



AI must incorporate more of the versatility, nuance, and depth of the human **intellect**.

From academic backwater to center of attention in 5 years





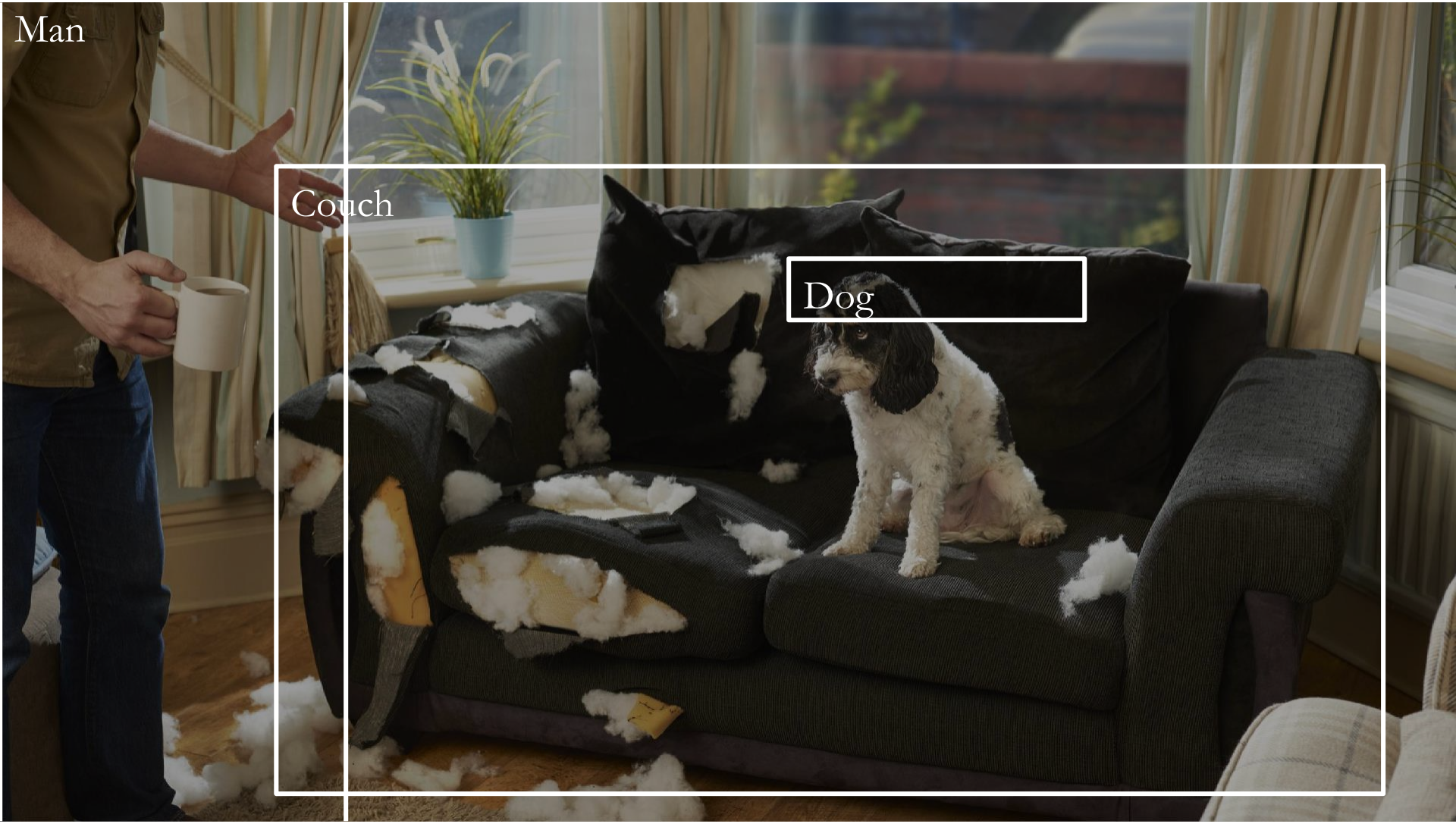
The Deep Learning Revolution

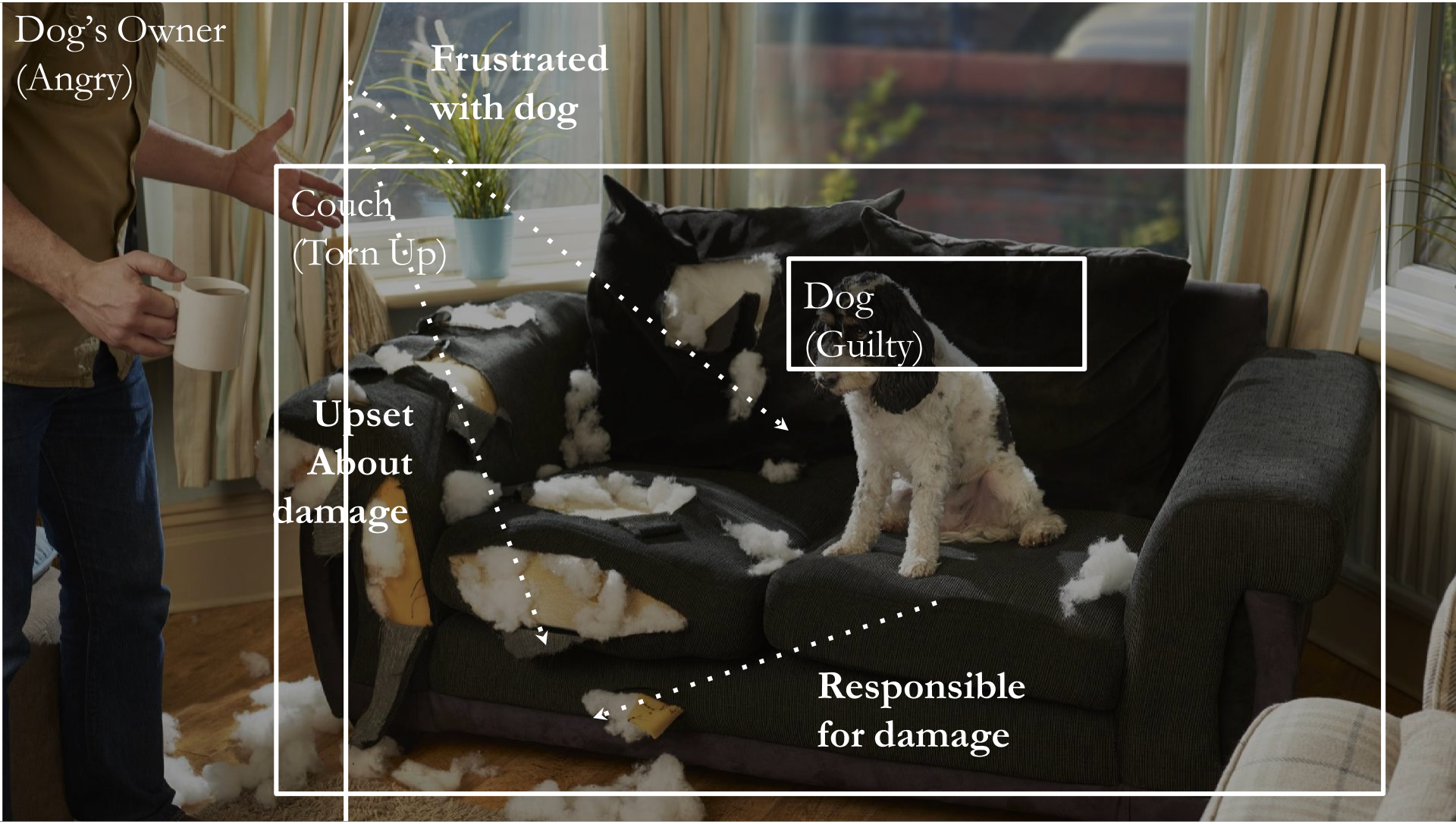
What happened?

I am hurt

Hello, hurt! ! 😊

The limits of chatbot conversation

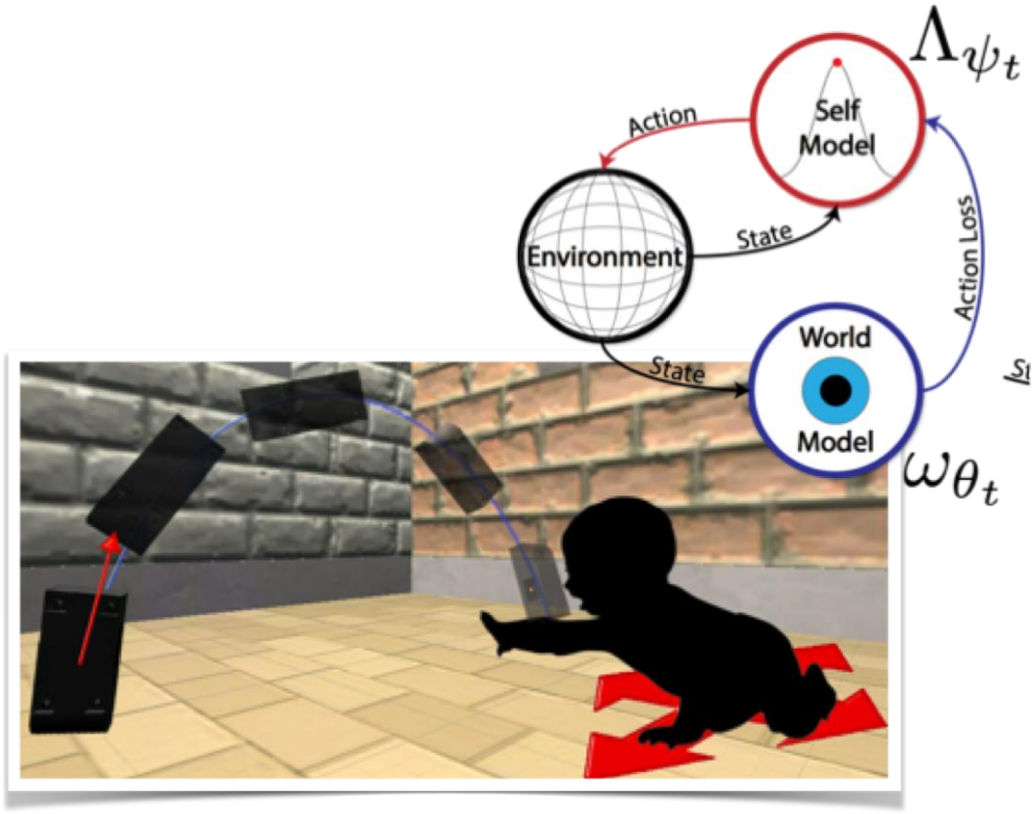

Man
Couch
Dog


Dog's Owner
(Angry)
Frustrated
with dog
Couch
(Torn Up)
Dog
(Guilty)
Upset
About
damage
Responsible
for damage

Context | Situational Awareness | Prior Knowledge

Curiosity-based Learning

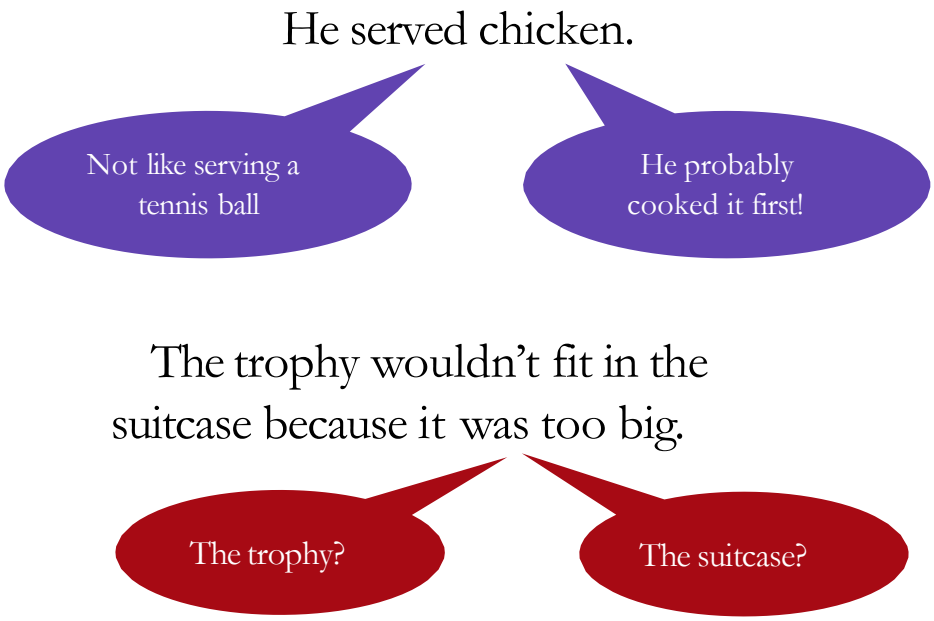
- A baby's learning is exploratory, curiosity-driven, multi-modal, active and social.
- Can we model this process and apply it in machines?



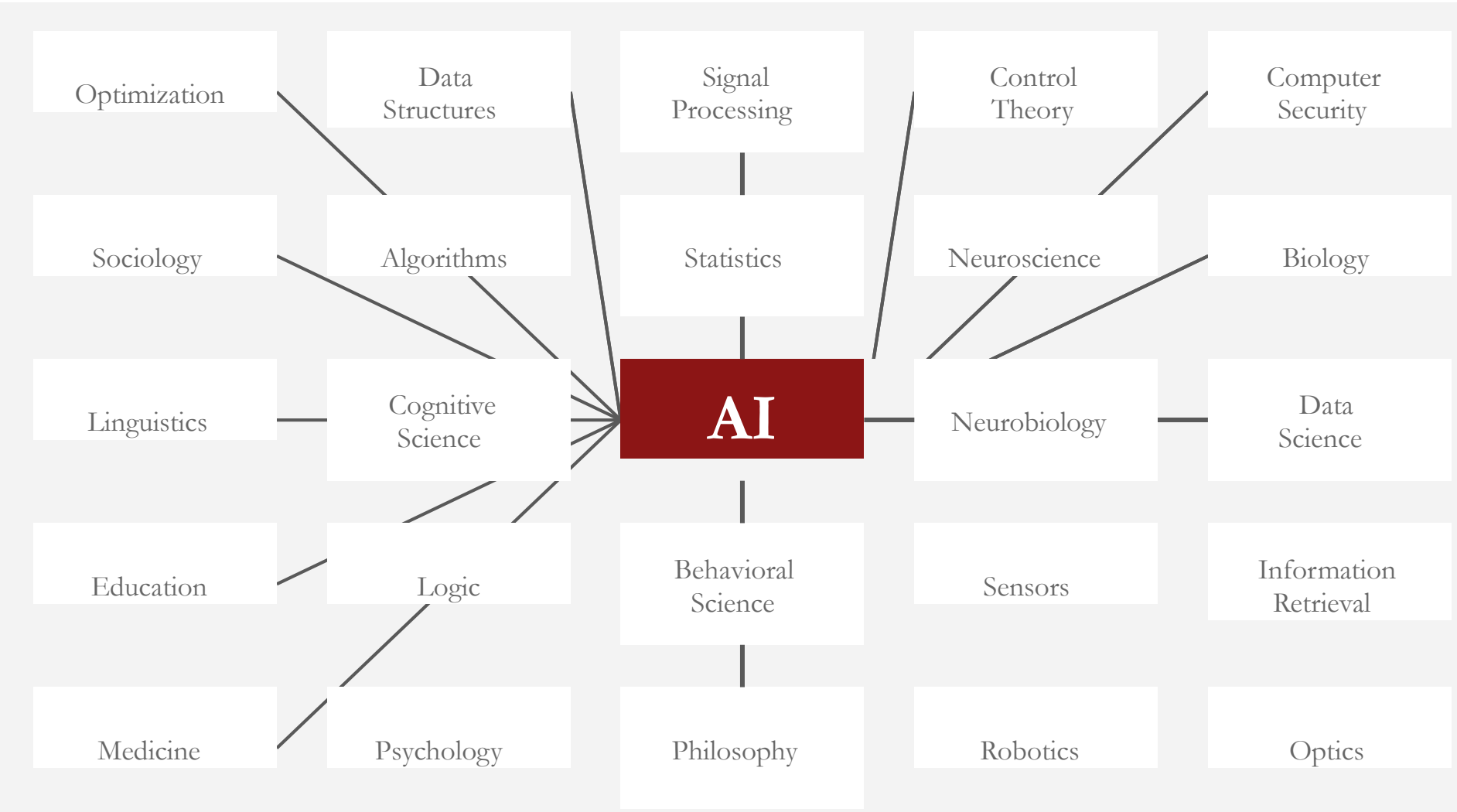
Mrowca, Haber, Fei-Fei & Yamins, *CogSci*, 2018

"Thinking slow" Commonsense knowledge and reasoning

- Reasoning requires combining previously acquired knowledge to address new tasks
- Can a neural network reason more like a human?



Hudson and Manning, 2018


Optimization
Data Structures
Signal Processing
Control Theory
Computer Security
Sociology
Algorithms
Statistics
Neuroscience
Biology
Linguistics
Cognitive Science
AI
Neurobiology
Data Science
Education
Logic
Behavioral Science
Sensors
Information Retrieval
Medicine
Psychology
Philosophy
Robotics
Optics

~50%

current work activities can be theoretically automated now

100%

current work activities can be potentially **enhanced** by intelligent technology

Enhancing human care with intelligent systems

Hospital-Acquired Infections

99,000 Deaths

Annually

Unmonitored Elderly Fall Injuries

$36.4 Billion

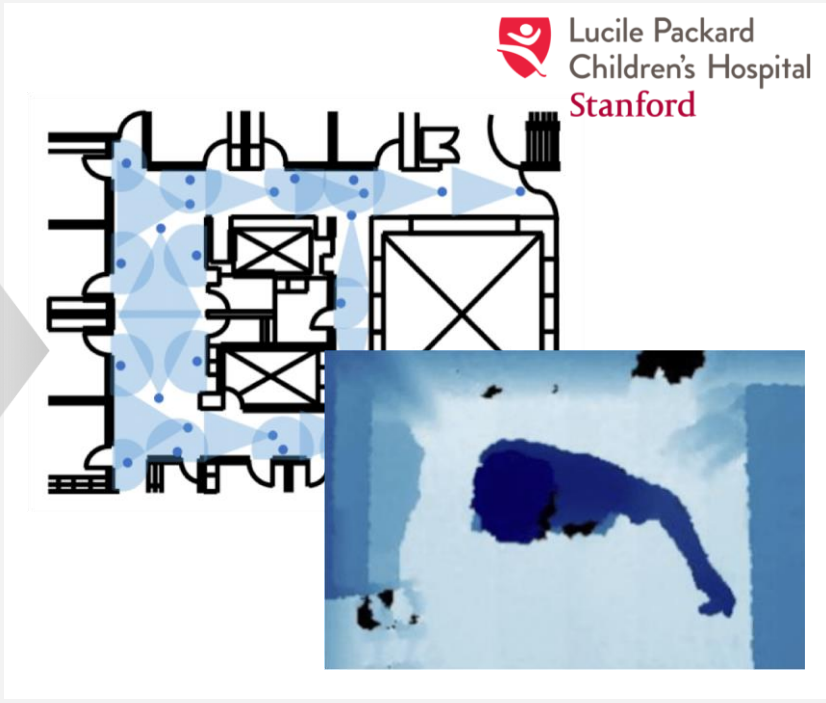
Annually

A. Houser, W. Fox-Grage & K. Ujvari, *AARP Public Policy Institute*, 2012)

Airtek Indoor Air Solutions. 2014. Calfee.

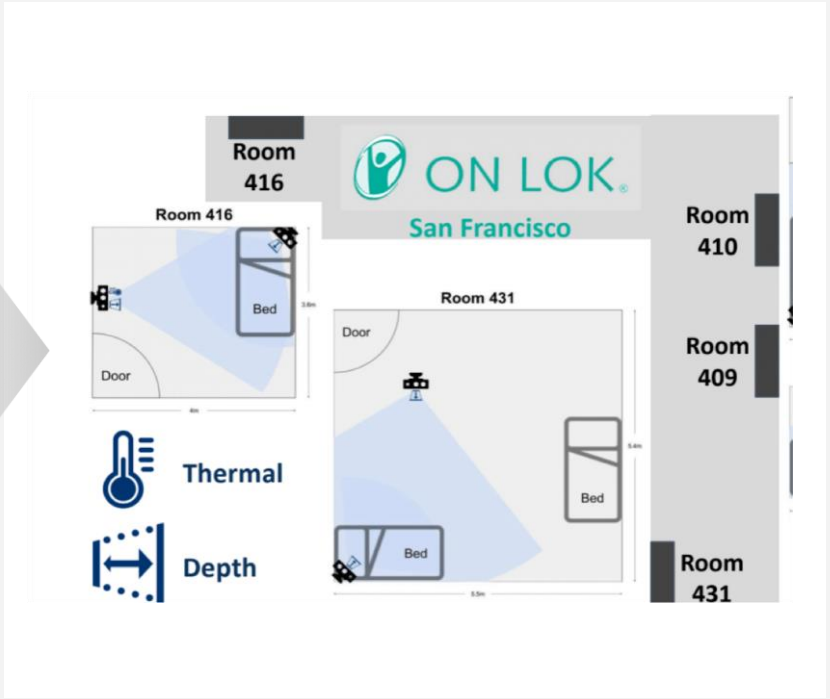
Annual Review of Medicine 2012

From: Inconsistent hand hygiene



To: Intelligent monitors placed throughout hospitals

A. Haque, A. Singh, A. Alahi, S. Yeung, M. Guo, A. Luo, J. Jopling, L. Downing, W. Beninati, T, Platchek, A. Milstein & L. Fei-Fei, *Under review*
A. Haque, E. Peng, A. Luo, A. Alahi,S. Yeung & L. Fei-Fei, *ECCV*, 2016



From: Ineffective wearables, lack of human caretakers

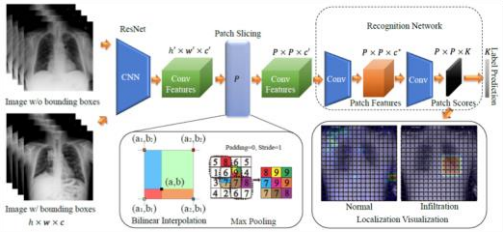
To: Intelligent monitors placed throughout senior living homes

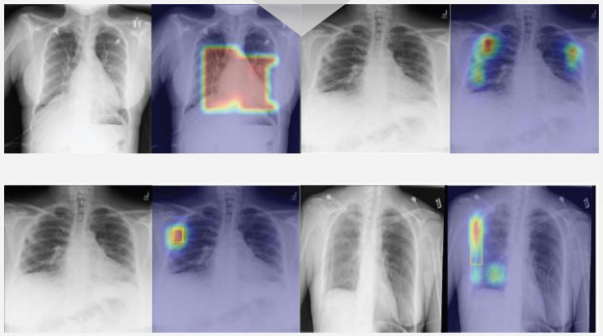
A. Luo, T. Hsieh, R. Rege, A. Mehra,G. Pusiol, L. Downing, A. Milstein & L. Fei-Fei. *In preparation.*

Giving human specialists more time


Lowers costs
Improves safety and outcomes
Reduces burden on human caregivers

An algorithm for automating simple radiology analysis





More time for human specialists to do what they do best

Z. Li, C. Wang, M. Han, Y. Xue, W. Wei, Li-J. Li, L. Fei-Fei, *CVPR, 2018*