Visual Forensics and Societal Impacts

Jun-Yan Zhu

16-726 Learning-based Image Synthesis, Spring 2023

Many slides were adopted from Richard Zhang, Sheng-Yu Wang, Frédo Durand, Alyosha Efros, etc.

MGM Lion (https://www.snopes.com/fact-check/leo-the-lion-mgm-logo/)

Topics

- Fake Images and Forensics
- Copyrights/Law
- Biases
- …

Visual Forensics

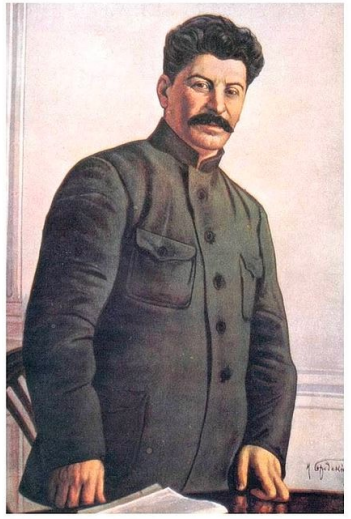
+ deep/shallow fake

+ misinformation

Photo manipulation old as photography

Joseph Stalin

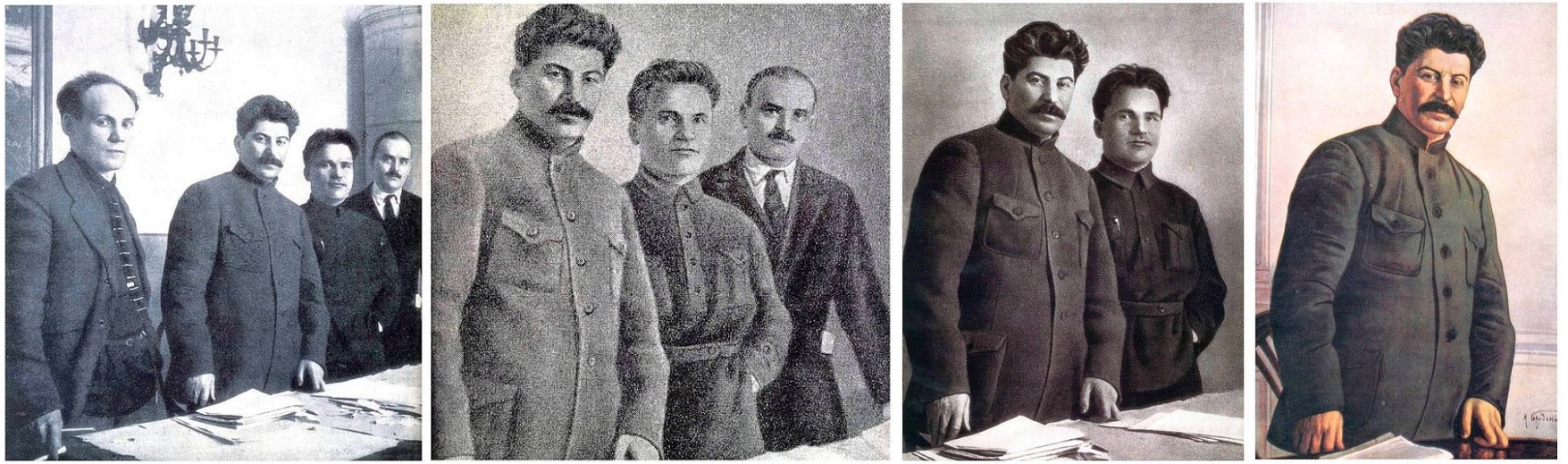


Slides credit: Richard Zhang

AI: democratizing image **editing**

Joseph Stalin



“DeepFakes”

Slides credit: Richard Zhang

More fake photos/videos

- https://www.quora.com/What-are-some-of-the-most-widely-circulated-fake-pictures

Slides credit: Frédo Durand

More fake photos/videos

- https://www.snopes.com/fact-check/category/photos/

Did Bruce Lee Play Ping-Pong with Nunchaku?

Written by: ***David Mikkelson***

Nov 27, 2012

Expertly playing ping-pong using nunchaku rather than a paddle is certainly an impressive feat, ...

Read More

Bruce Lee plays Ping Pong?

https://www.snopes.com/fact-check/bruce-lee-ping-pong/

Miscaptioned photos

https://www.snopes.com/fact-check/snow-walls/

Context matters

Slides credit: Frédo Durand

Context matters

Slides credit: Frédo Durand

Don’t hold up signs

Slides credit: Frédo Durand

News and Fake news

- Photo editing / deep fake
- Photo retouching
- Fake caption (time/place/people)
- Selective choice of photos to take, publish
- Choice of topics to cover and emphasize

- Why do lawyers/scholars fake less often?

Slides credit: Frédo Durand

Detect Shallow Fake

Early works in Visual Forensics

- Detect alterations
  - e.g., inconsistent lighting, inconsistent noise, cloning boundary, etc.
- Analyze patterns:
  - physical, geometric, optical, sensor, and image file properties

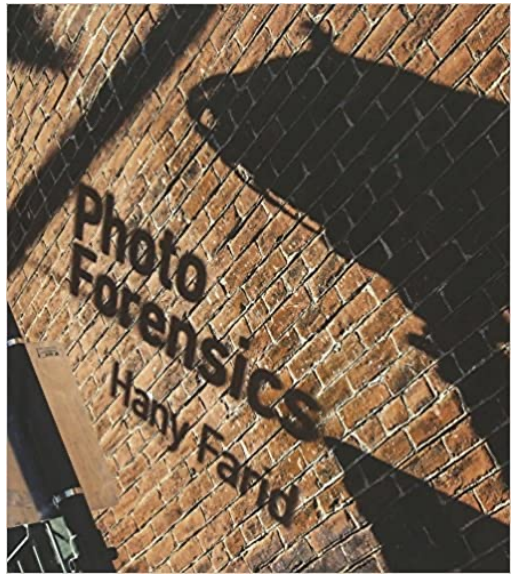
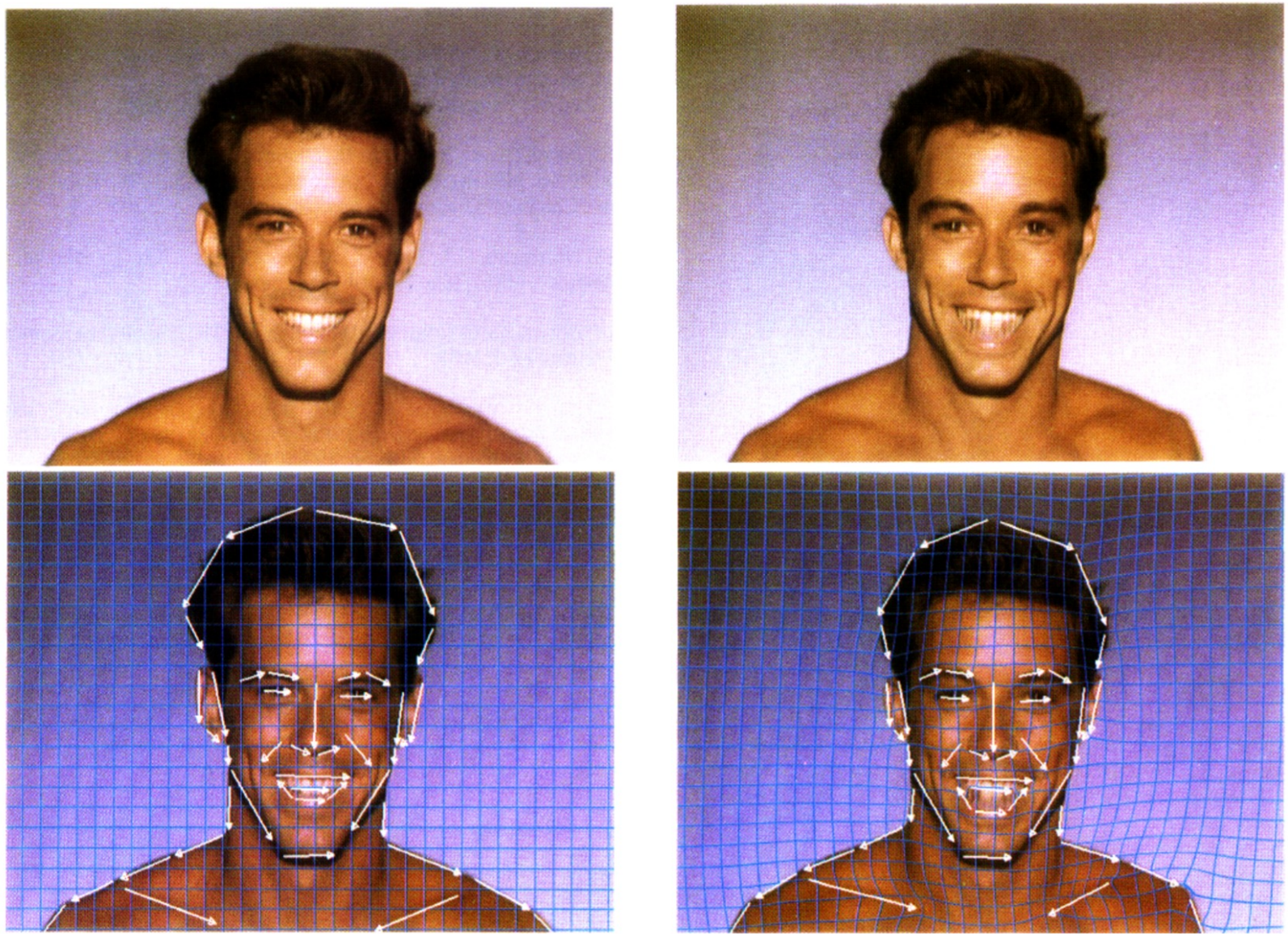


Photo Forensics (The MIT Press)
Hany Farid (https://farid.berkeley.edu/)

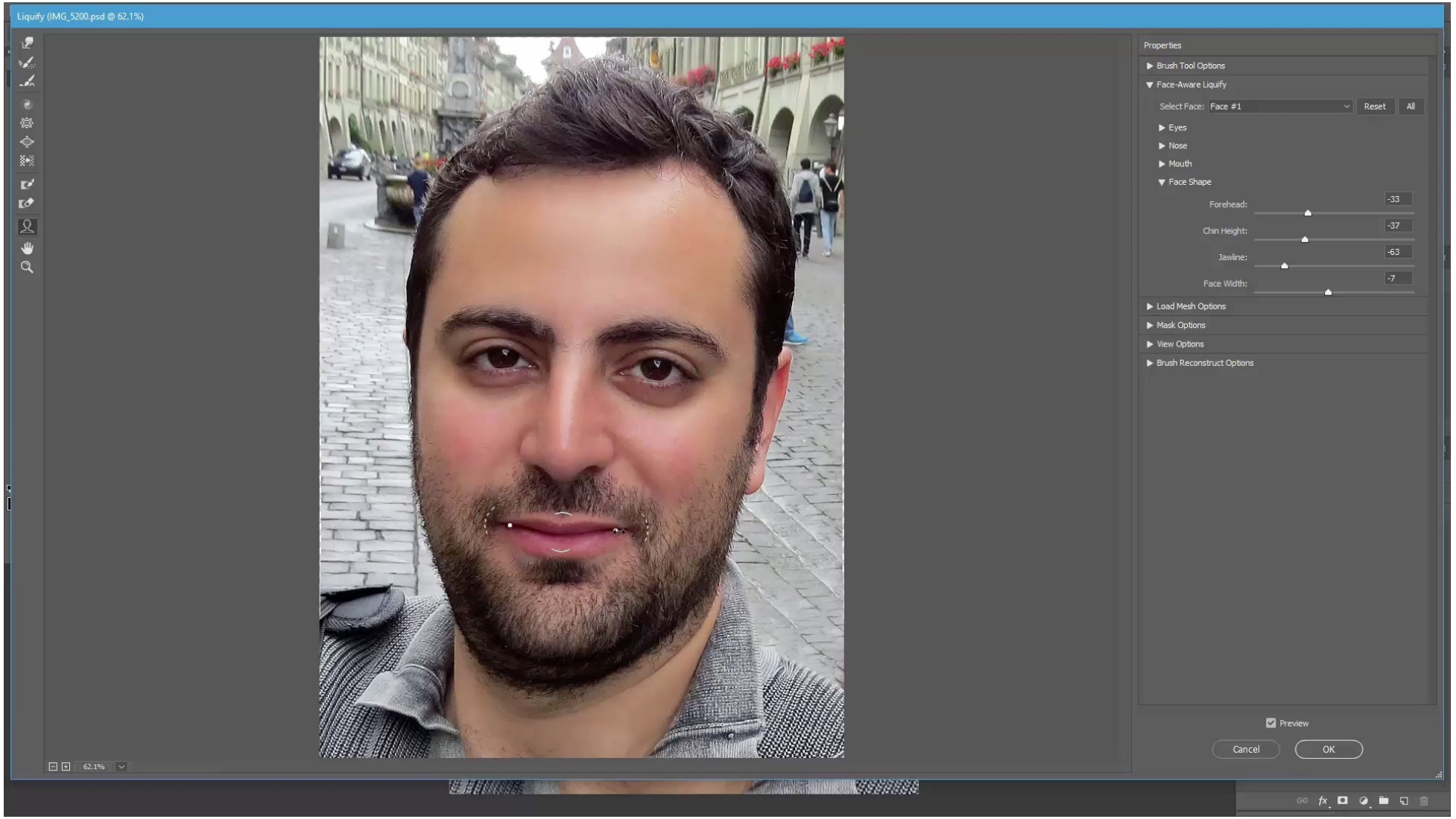
“Shallow” fakes



Feature-Based Image Metamorphosis (Beier et al. 1992)

Slides credit: Richard Zhang

Photoshop Face-Aware Liquify

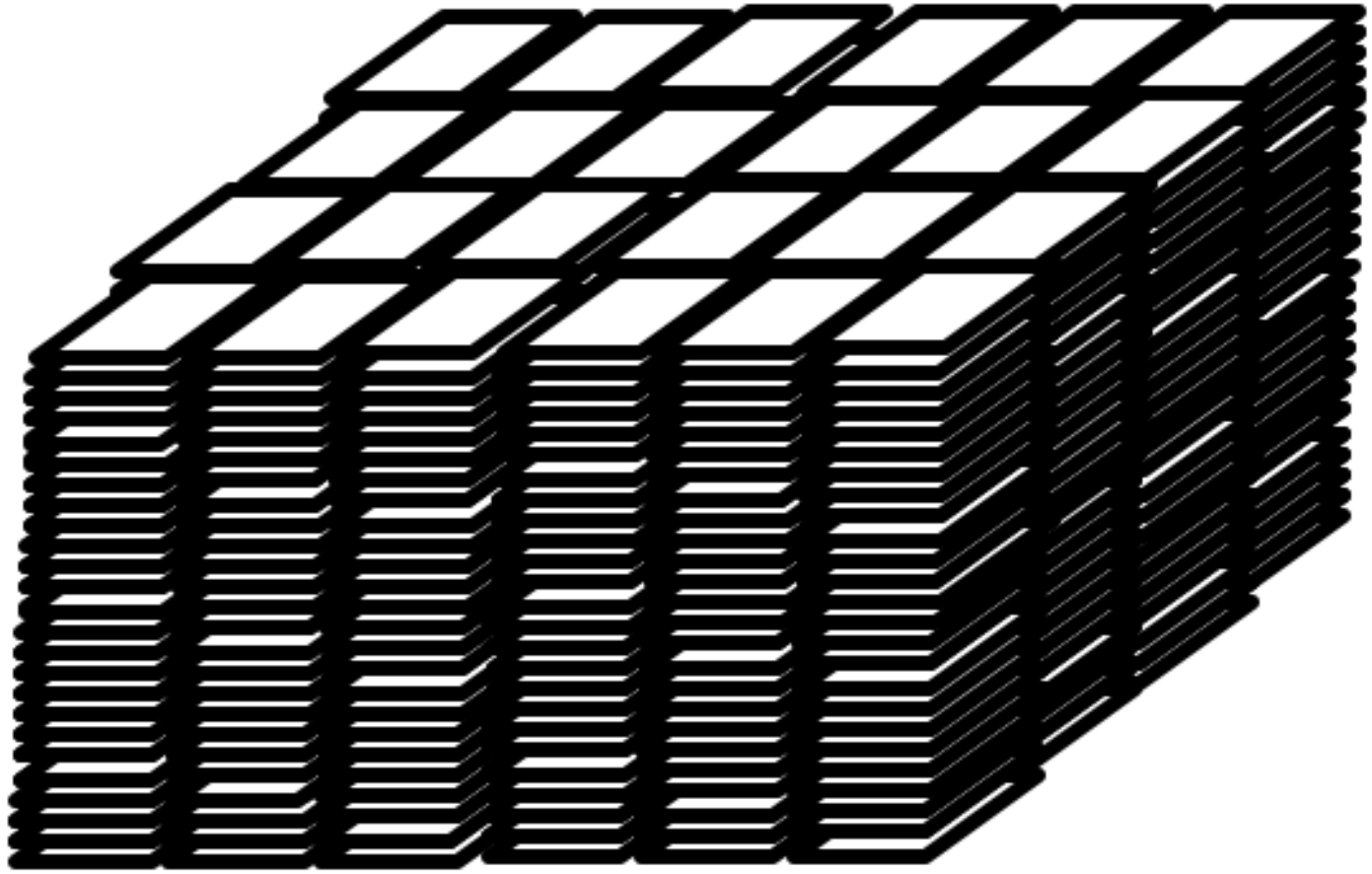


Slides credit: Richard Zhang

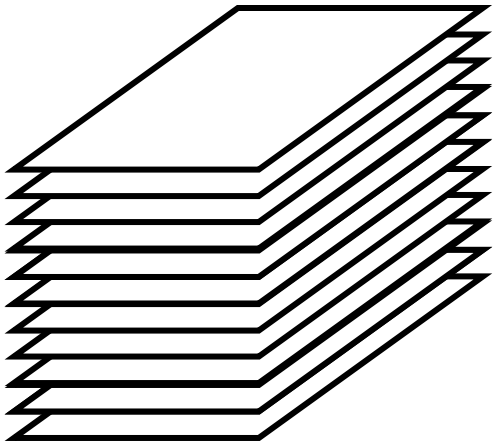
https://www.youtube.com/watch?v=5Qqv_C6iVvQ

Supervised Learning?

Billions!



<< Billions



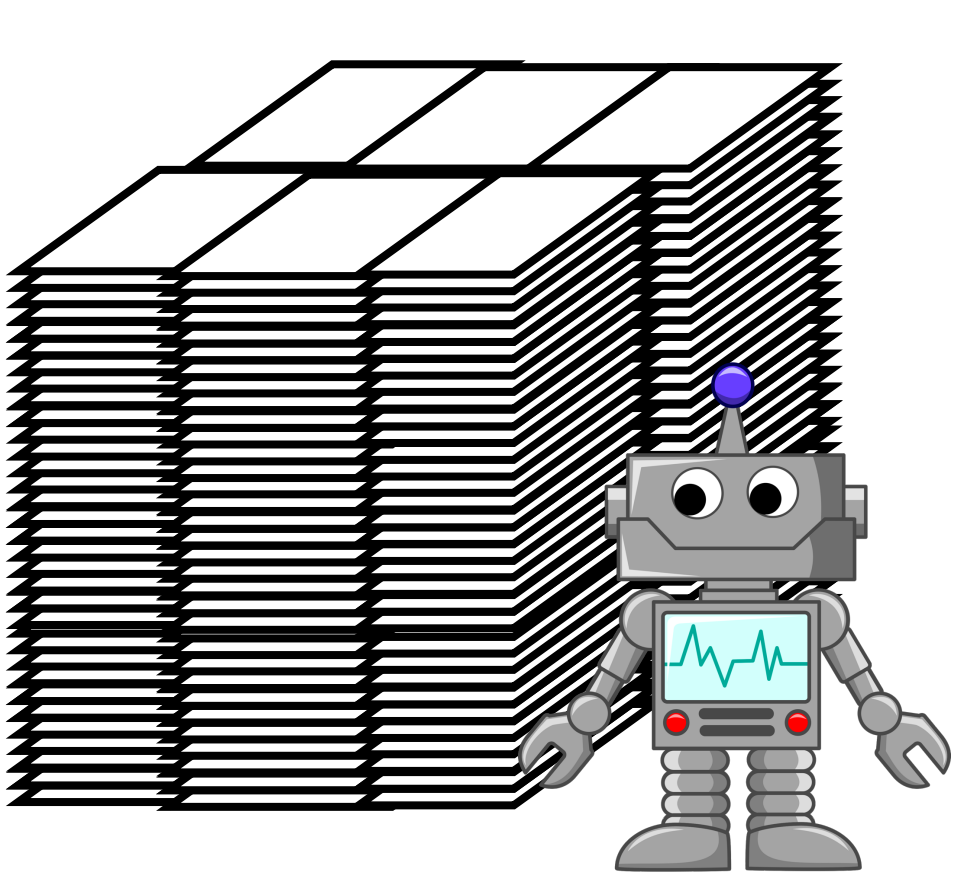
Labeled manipulated images

Natural Images

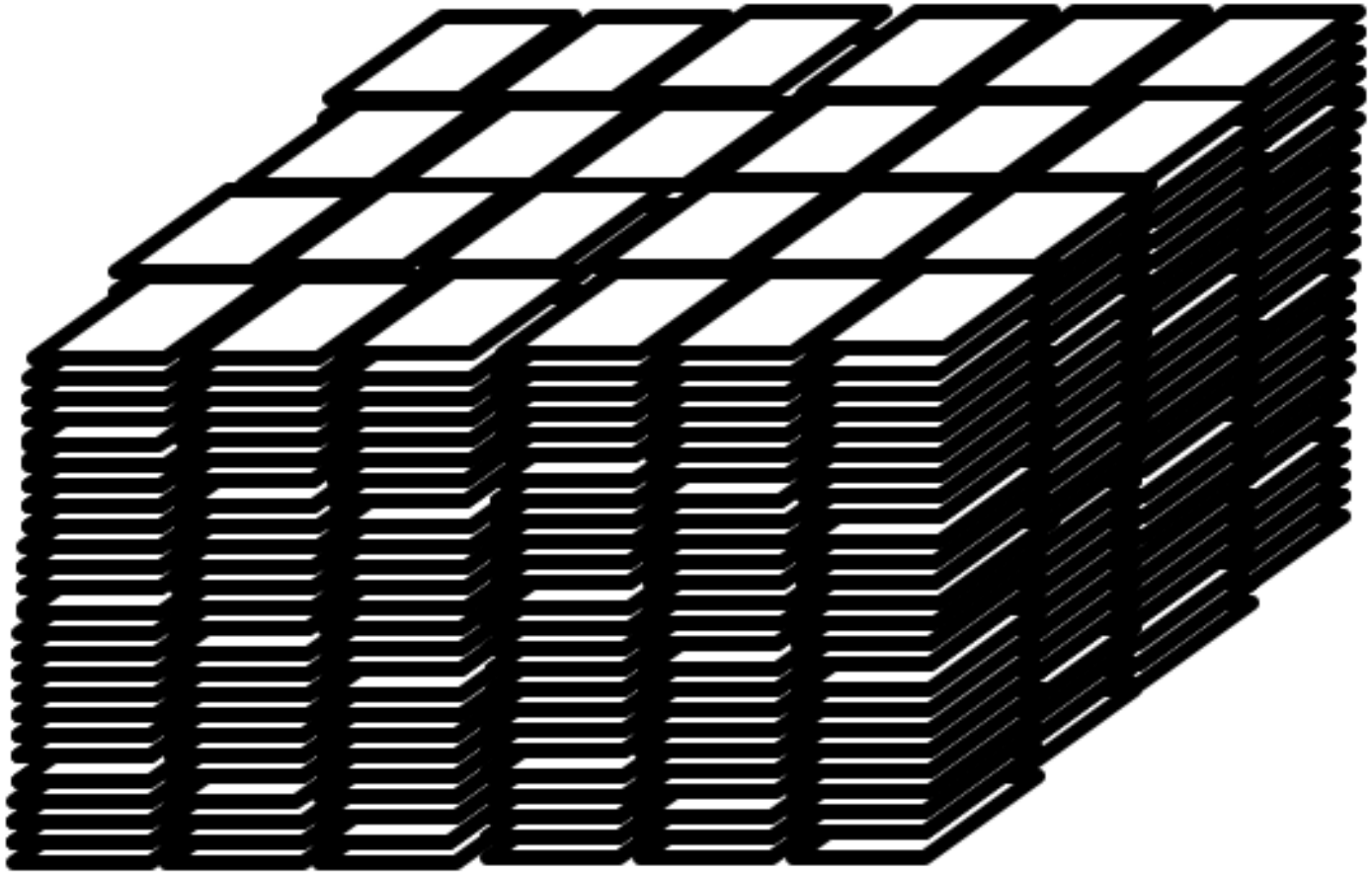
Slides credit: Richard Zhang

Supervised Learning with Self-Generated Data

Billions!



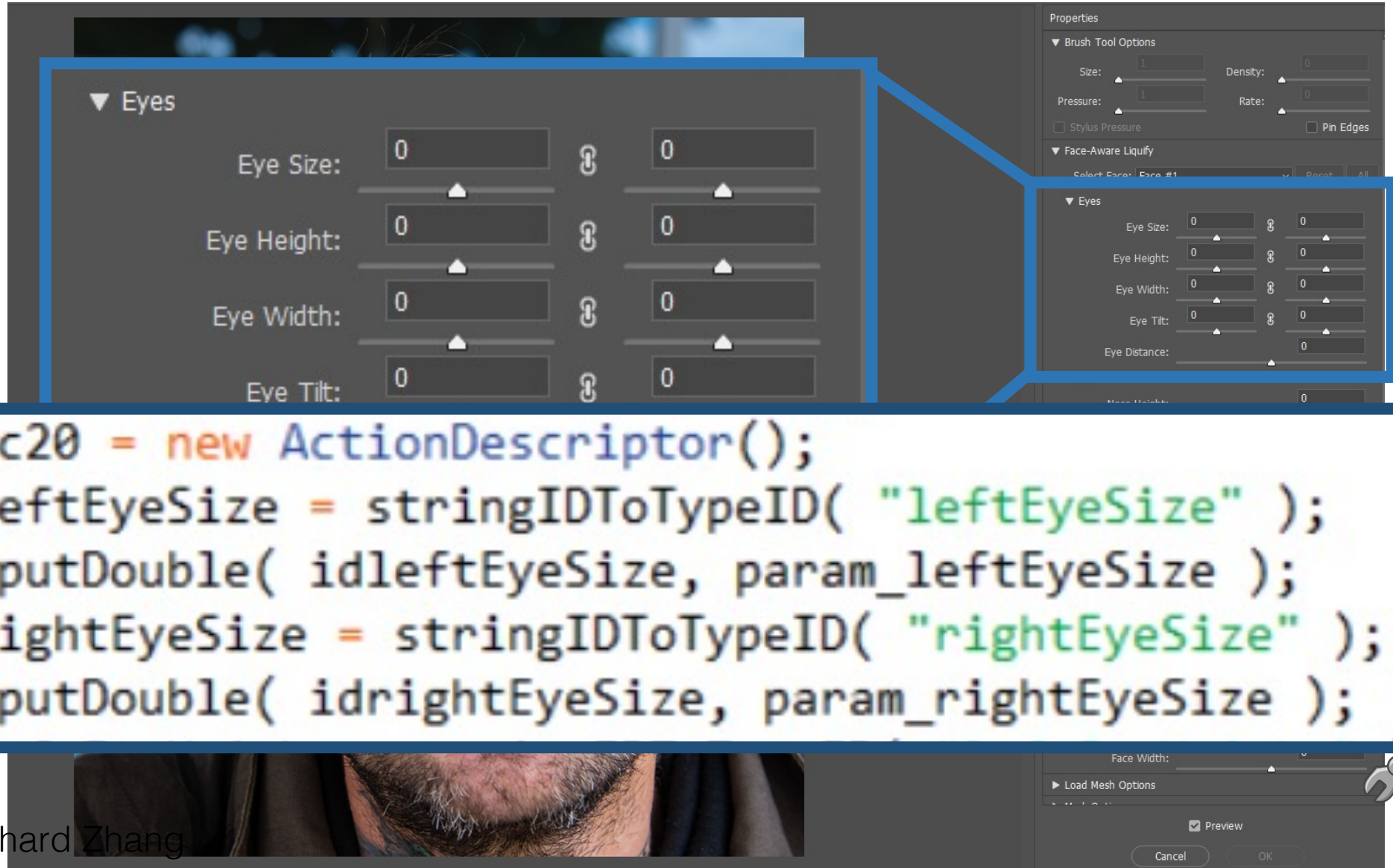
Self-generated data



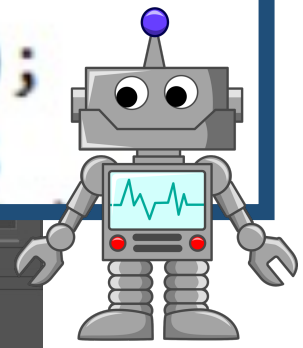
Natural Images

Slides credit: Richard Zhang

Scripting Photoshop




```
var desc20 = new ActionDescriptor();
var idleftEyeSize = stringIDToTypeID( "leftEyeSize" );
desc20.putDouble( idleftEyeSize, param_leftEyeSize );
var idrightEyeSize = stringIDToTypeID( "rightEyeSize" );
desc20.putDouble( idrightEyeSize, param_rightEyeSize );
```

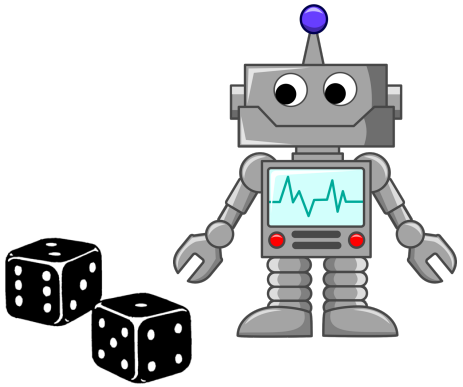


Slides credit: Richard Zhang

Original

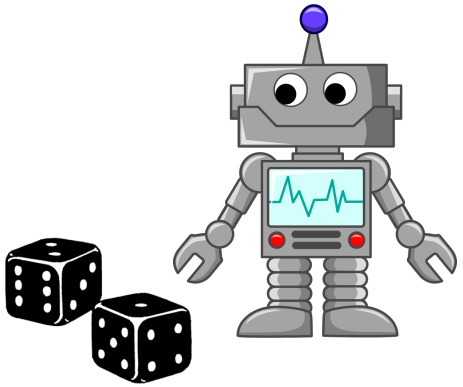
Slides credit: Richard Zhang

#1 modification



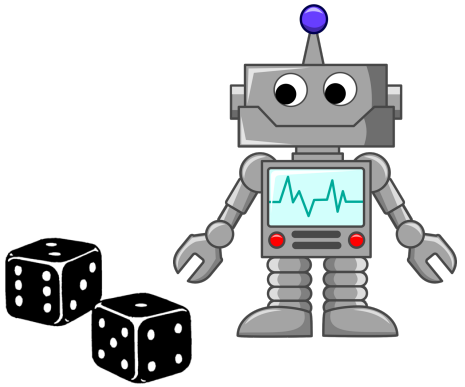
Slides credit: Richard Zhang

#2 modification



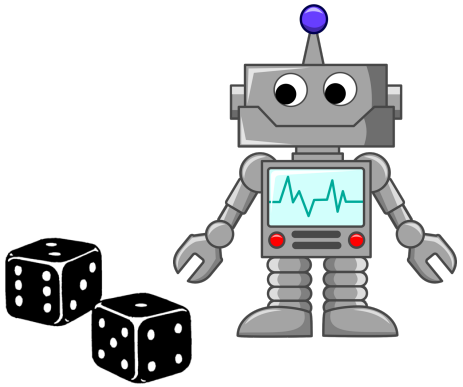
Slides credit: Richard Zhang

#3 modification



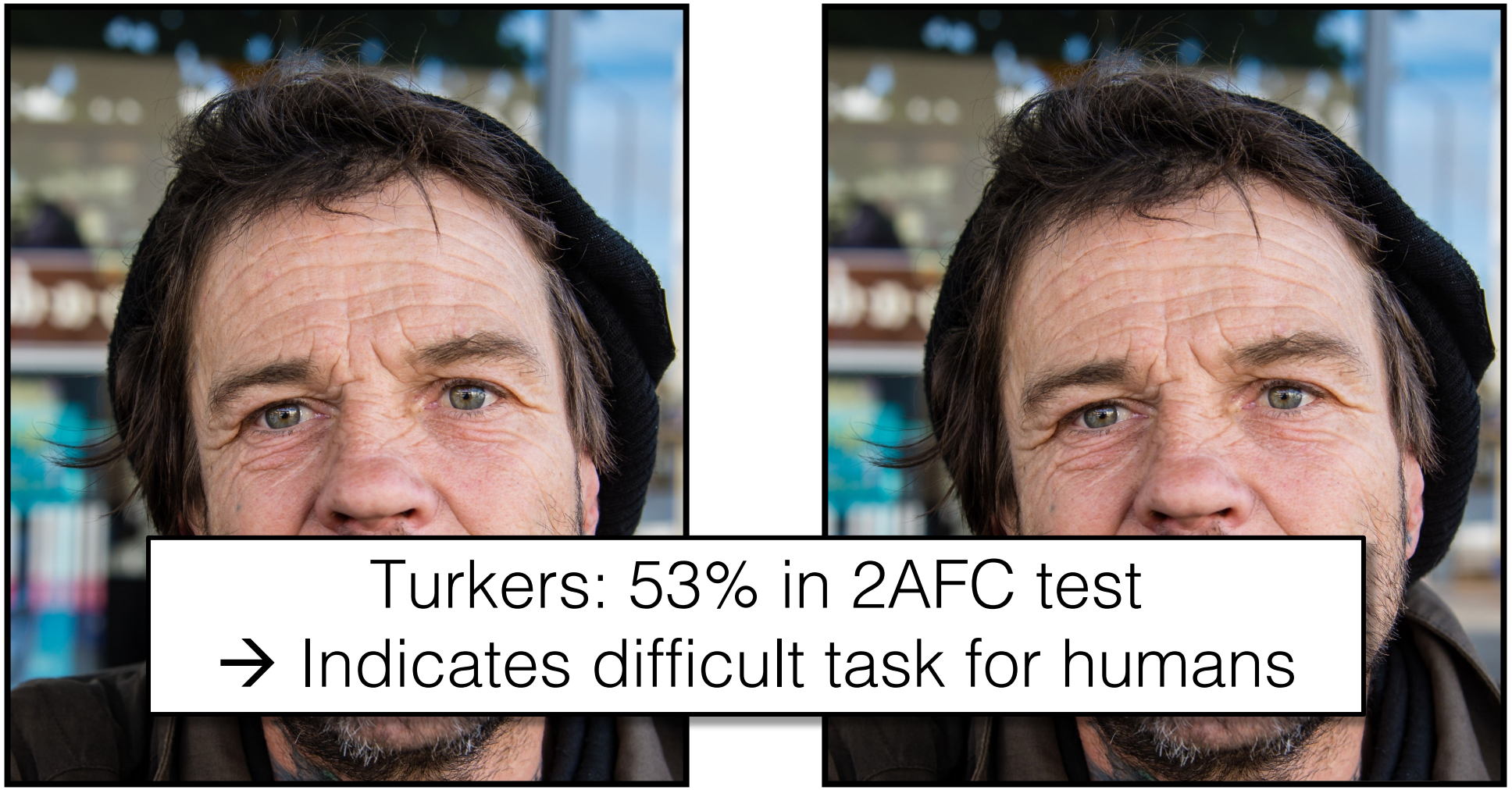
Slides credit: Richard Zhang

#4 modification



Slides credit: Richard Zhang

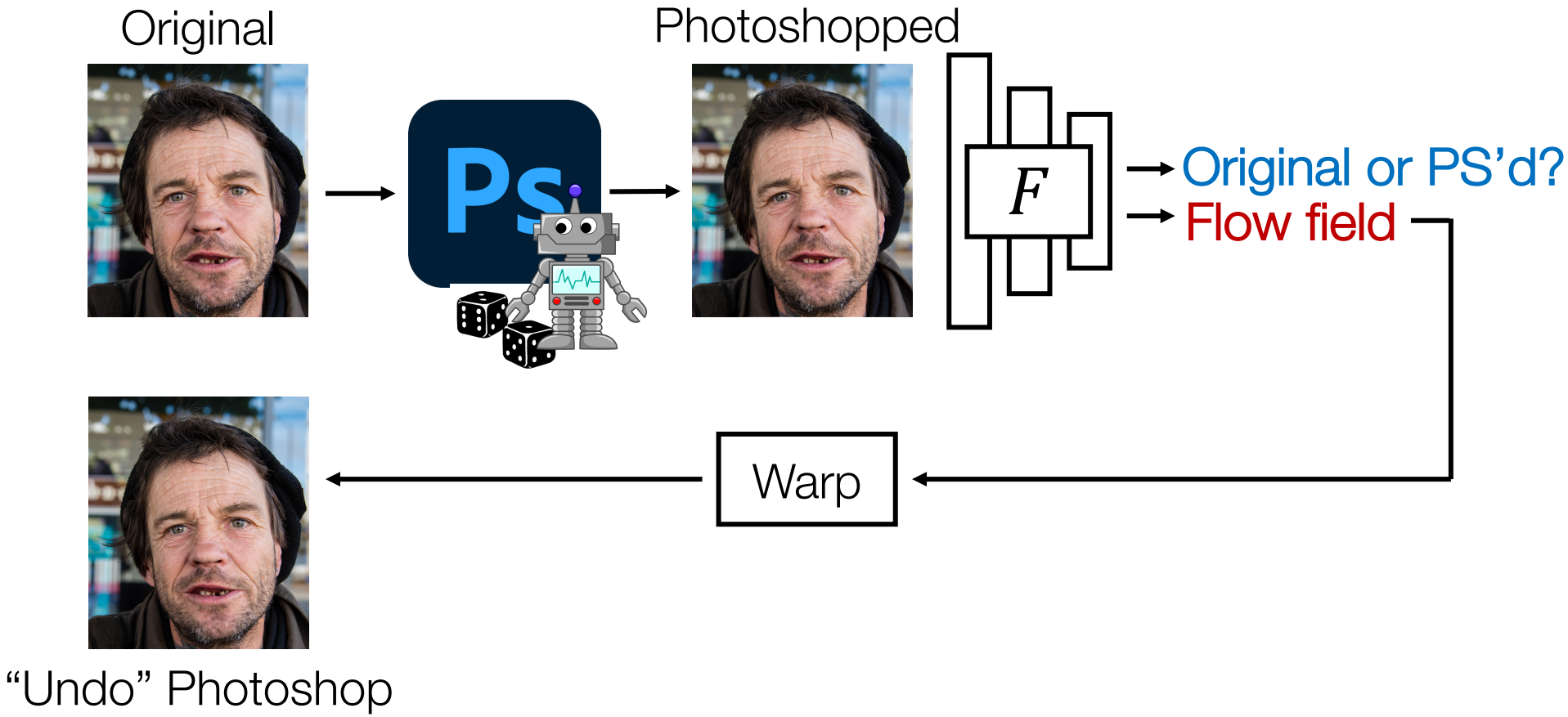
User study: Which image is modified?



Turkers: 53% in 2AFC test
→ Indicates difficult task for humans

Slides credit: Richard Zhang

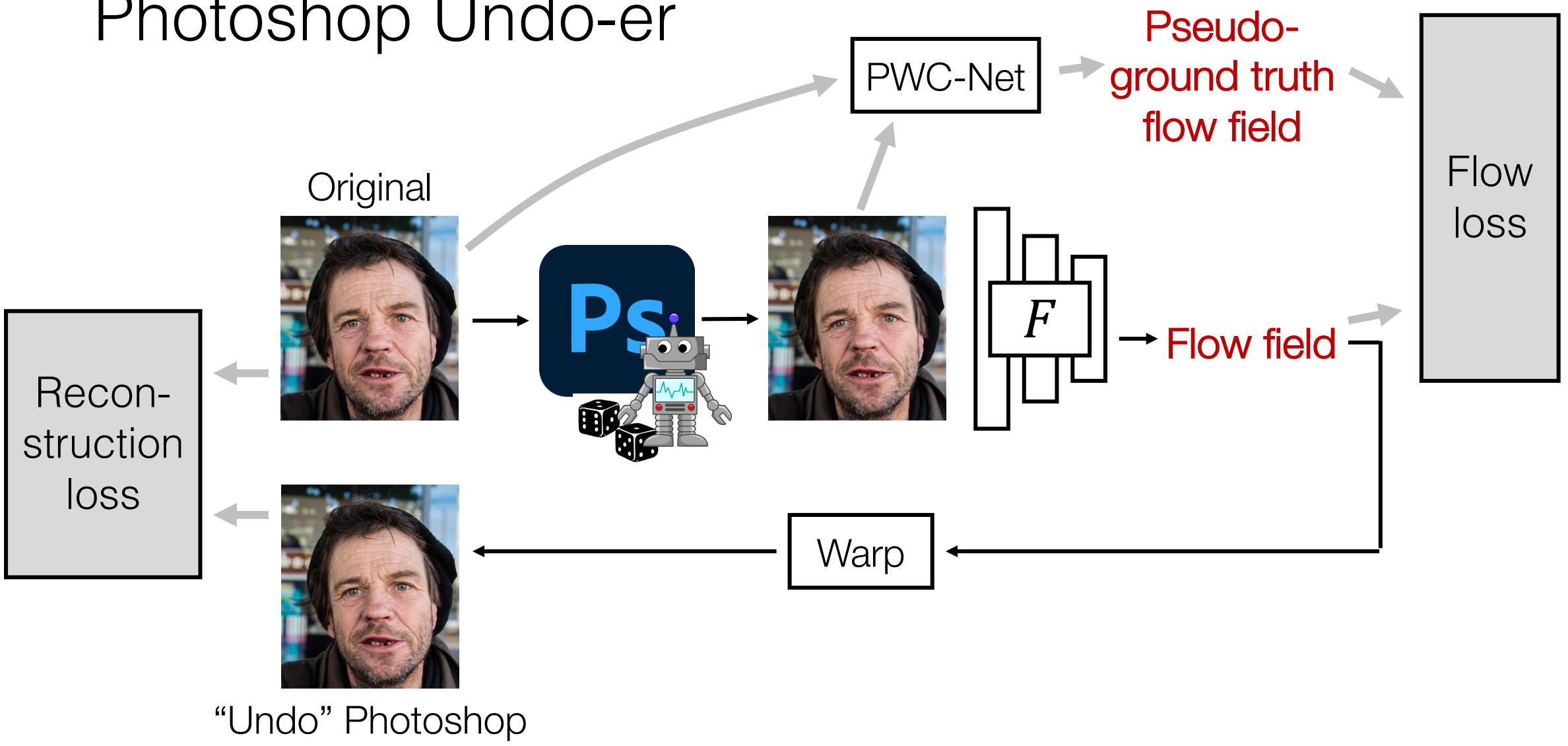
Photoshop Detector



Slides credit: Richard Zhang

Detecting Photoshopped Faces by Scripting Photoshop [Wang et al., ICCV 2019]

Photoshop Undo-er



Slides credit: Richard Zhang

Detecting Photoshopped Faces by Scripting Photoshop [Wang et al., ICCV 2019]

Manipulated?

Slides credit: Richard Zhang

Manipulated? **Yes**

Slides credit: Richard Zhang

Flow prediction

Slides credit: Richard Zhang

Suggested “undo”

Slides credit: Richard Zhang

Original

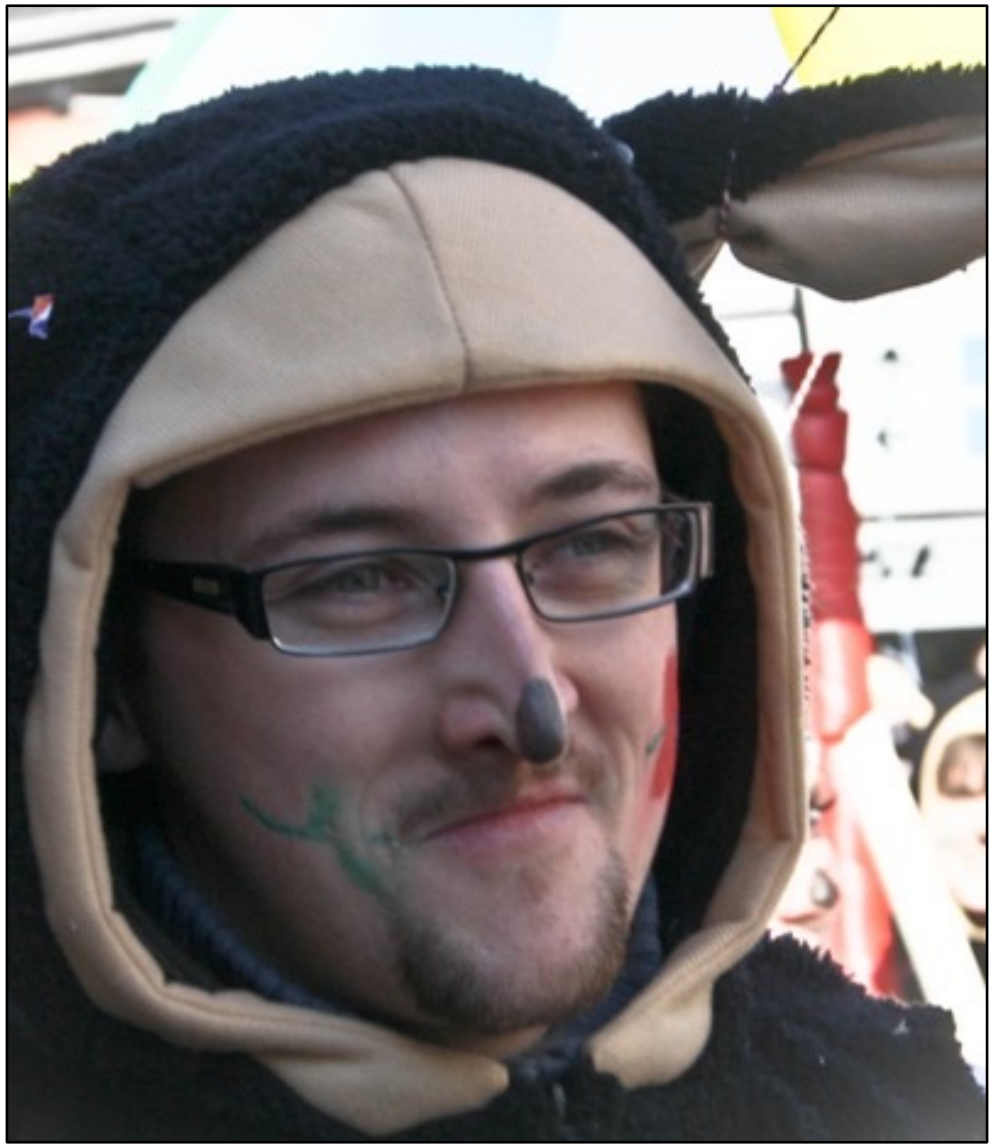
Slides credit: Richard Zhang

Manipulated vs. Original

Slides credit: Richard Zhang

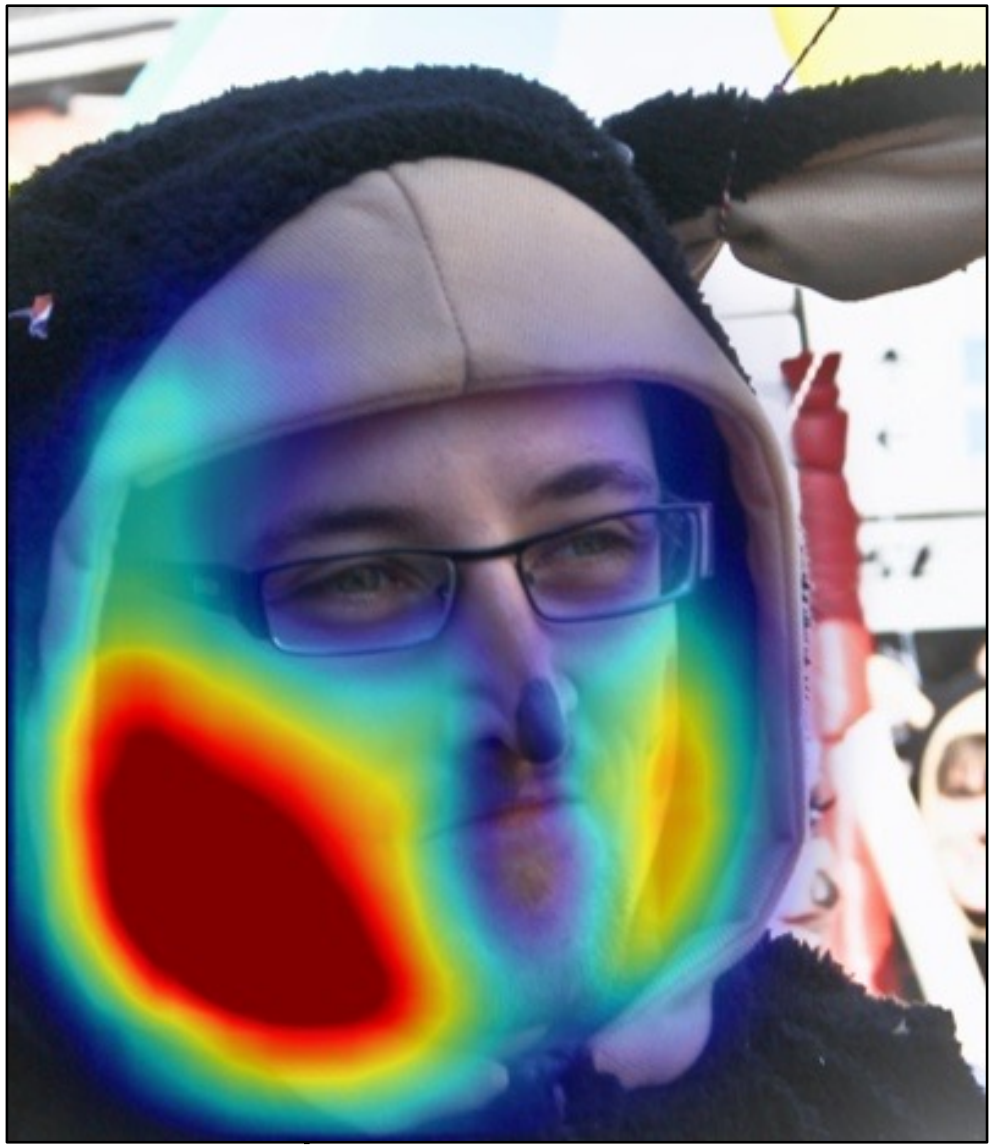
Undo vs. Original

Slides credit: Richard Zhang



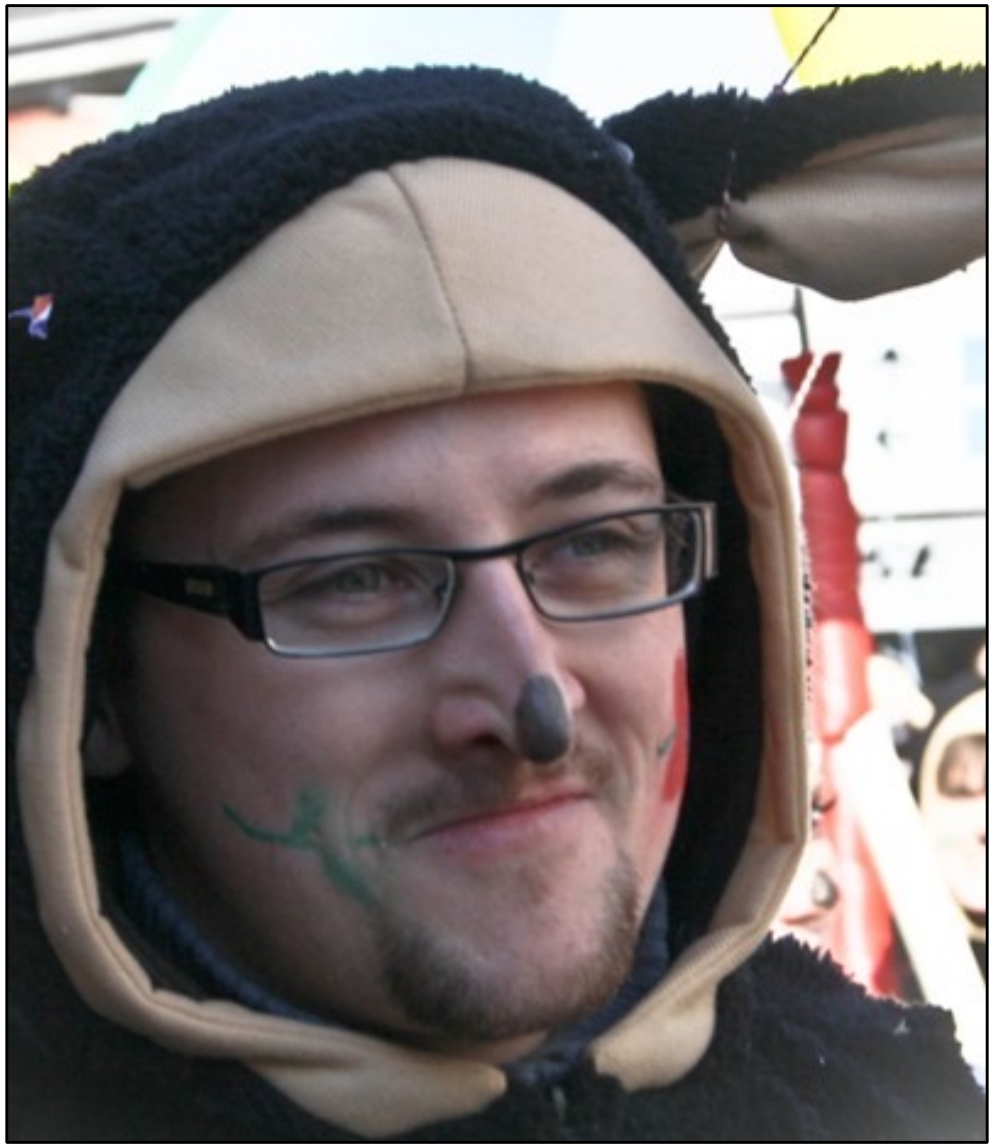
Manipulated

Slides credit: Richard Zhang



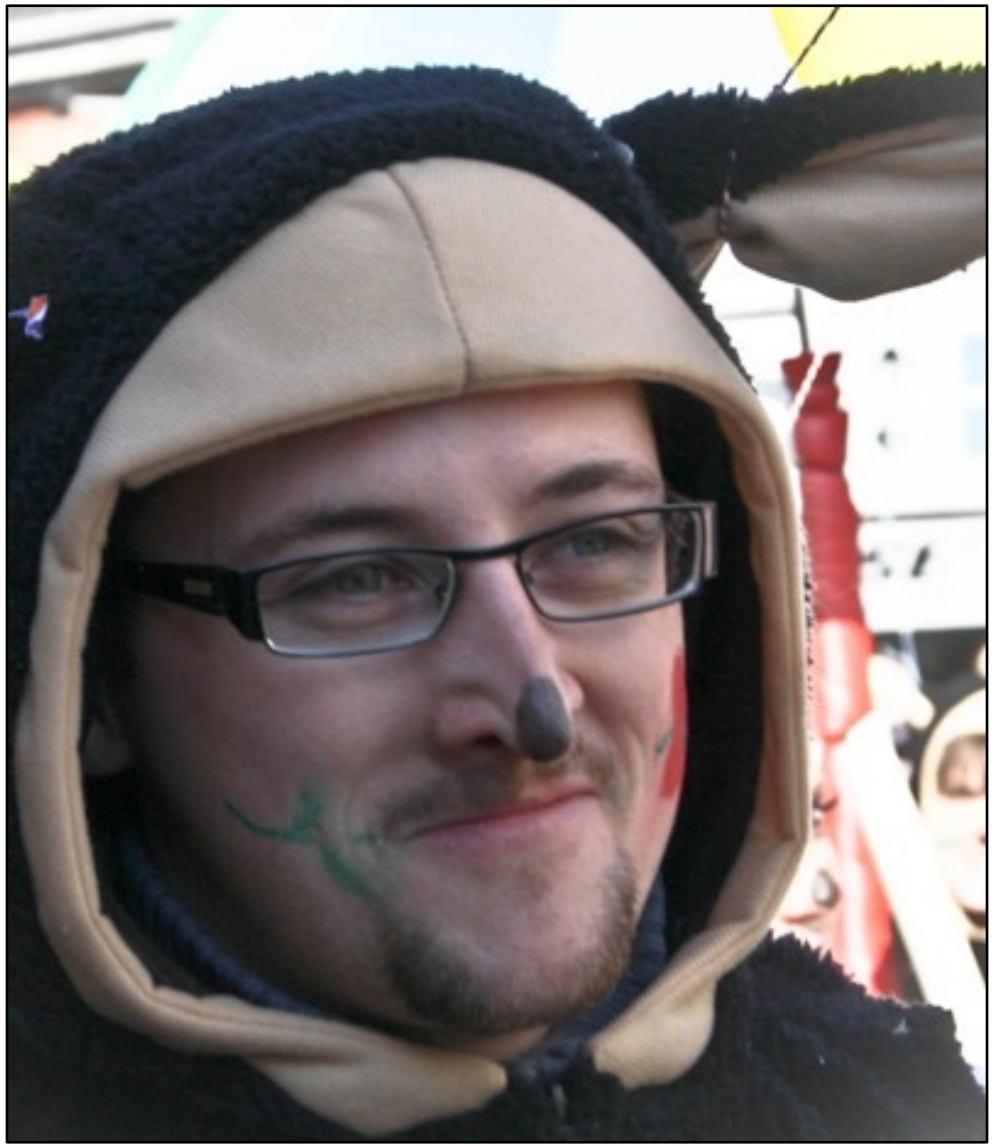
Flow prediction

Slides credit: Richard Zhang



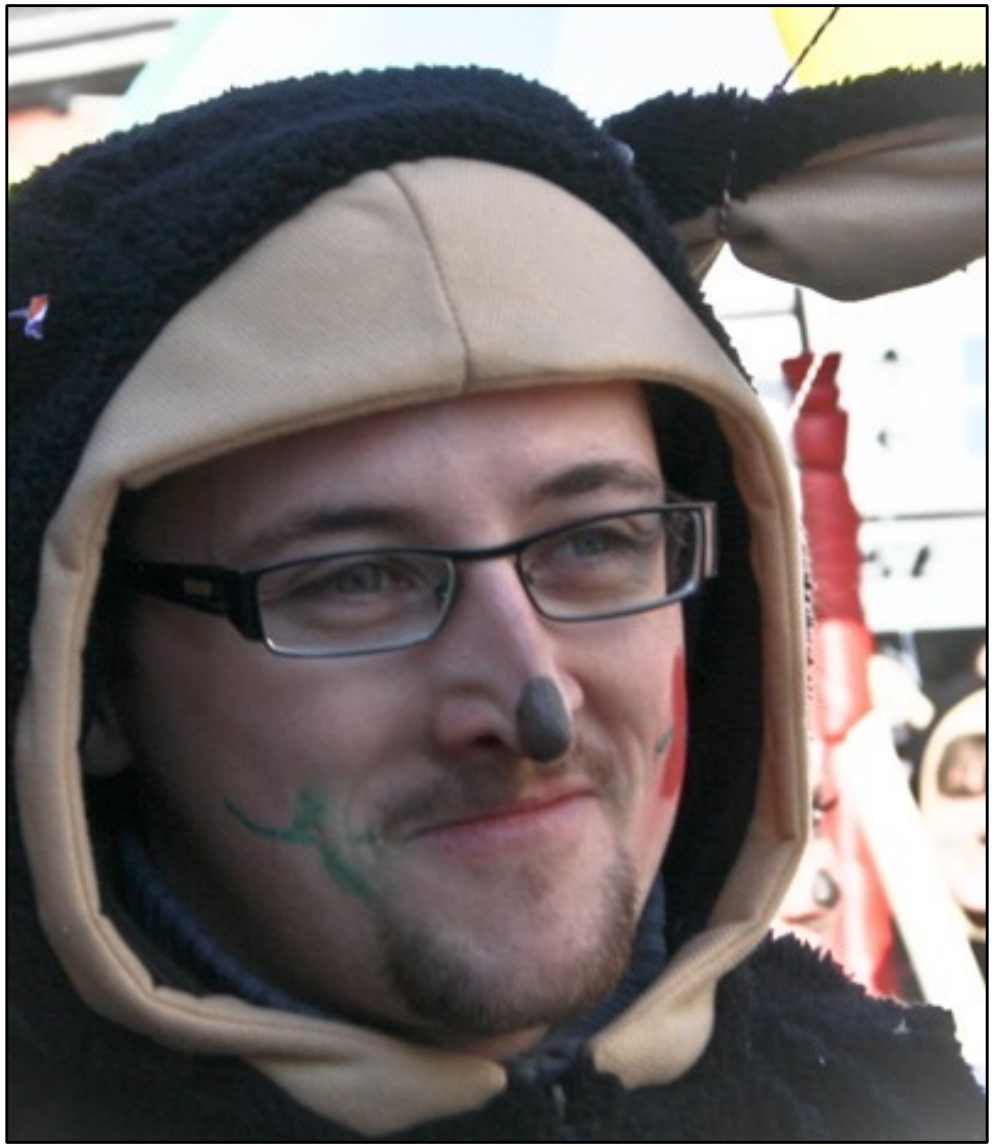
Suggested “undo”

Slides credit: Richard Zhang



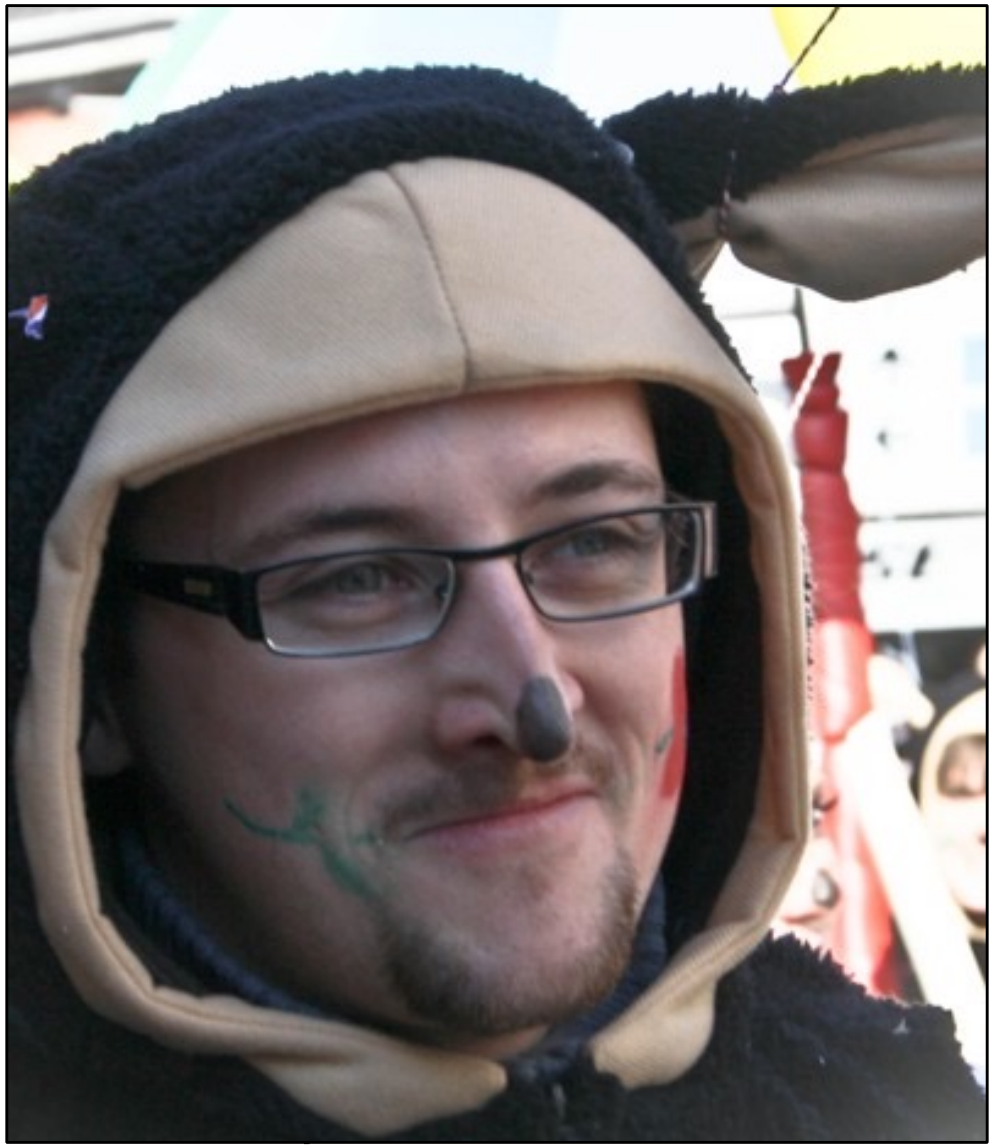
Original

Slides credit: Richard Zhang



Manipulated vs. Original

Slides credit: Richard Zhang



Undo vs. Original

Artist-generated example

Manipulated

Slides credit: Richard Zhang

Artist-generated example

Flow prediction

Slides credit: Richard Zhang

Artist-generated example

Suggested “undo”

Slides credit: Richard Zhang

Artist-generated example

Original photo

Slides credit: Richard Zhang

Artist-generated example

Manipulated vs. Original

Slides credit: Richard Zhang

Artist-generated example

Undo vs. Original

Slides credit: Richard Zhang

Senses of generalization

- Post-processing
- Heldout artist data
- Different warp domain
- Different image domains

Slides credit: Richard Zhang

Snapchat warps

Original Photo

Slides credit: Richard Zhang

Snapchat warps

Manipulated Photo

Slides credit: Richard Zhang

Snapchat warps

Flow Prediction

Slides credit: Richard Zhang

Snapchat warps

Suggested “Undo”

Slides credit: Richard Zhang

Snapchat warps

Some generalization across warp methods

Original Photo

Slides credit: Richard Zhang

Different image domain

Slides credit: Richard Zhang

Different image domain

Slides credit: Richard Zhang

Different image domain

Slides credit: Richard Zhang

Predicted warp (not successful)

Does not generalize well to arbitrary image;
Indicates some specialization to high-level features

Slides credit: Richard Zhang

Discussion

- Given a relatively static tool, directly specialize
- Representation learns a combination of low and high-level cues
- Data augmentation helps generalization

Slides credit: Richard Zhang

Detect Deep Fake

Making fake images is getting easier

“Deepfakes”

GANs

Can we create a “universal” detector?

Slides credit: Richard Zhang

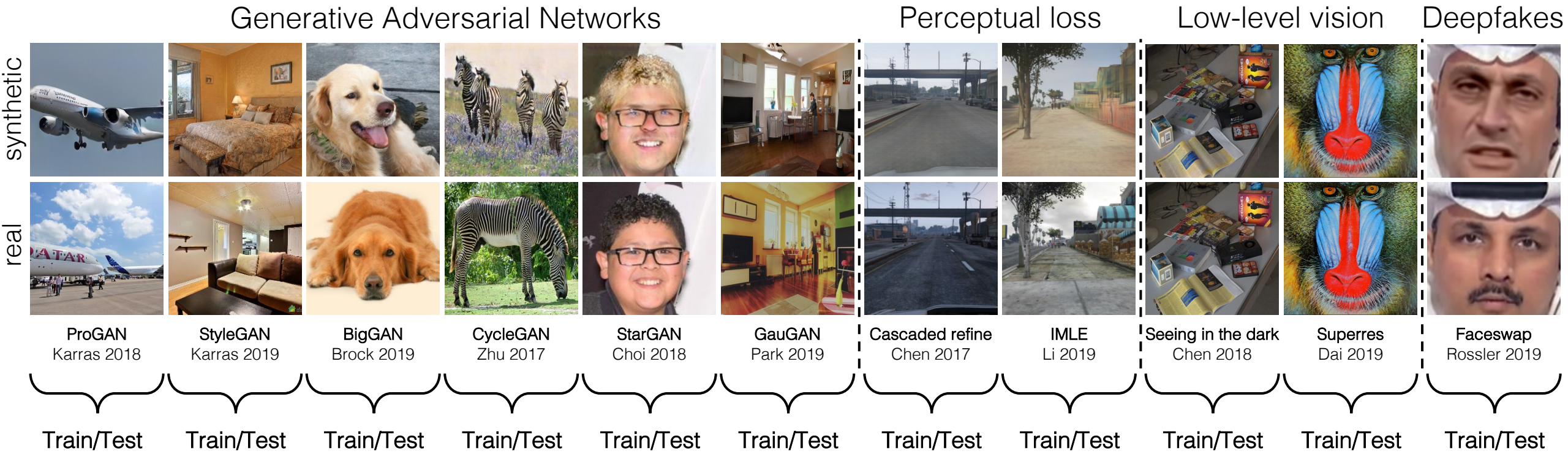
DeepFakes (https://github.com/deepfakes/faceswap)

Face2Face (Thies et al. 2016)

Slides credit: Richard Zhang

Lip-syncing Obama (Suwajanakorn et al. 2017)

Dataset of CNN-generated fakes

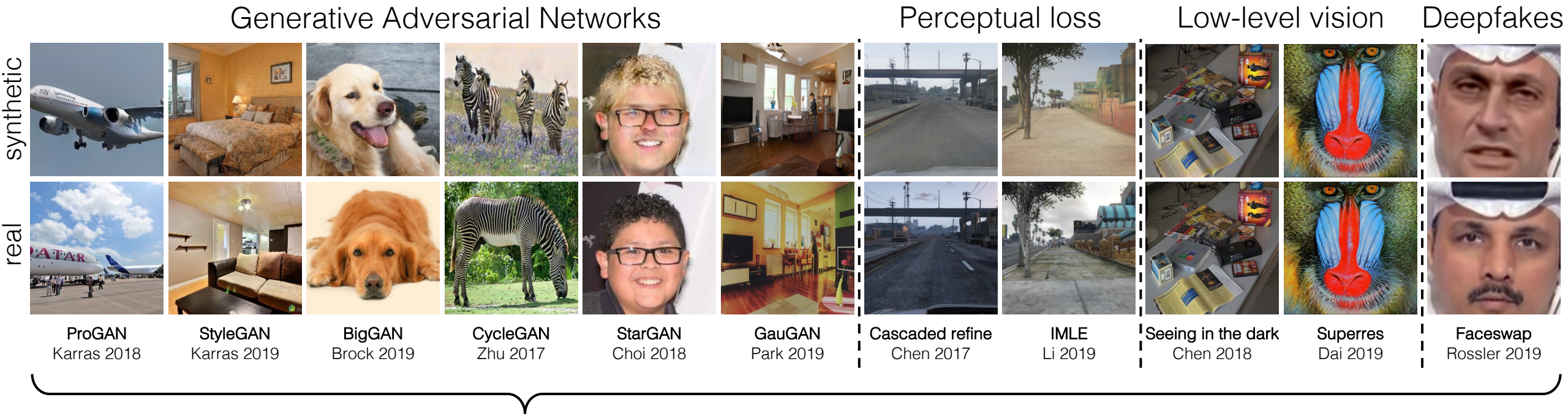


Test: ??? et al. 20XX

Can we create a “universal” detector?

Slides credit: Richard Zhang

Dataset of CNN-generated fakes

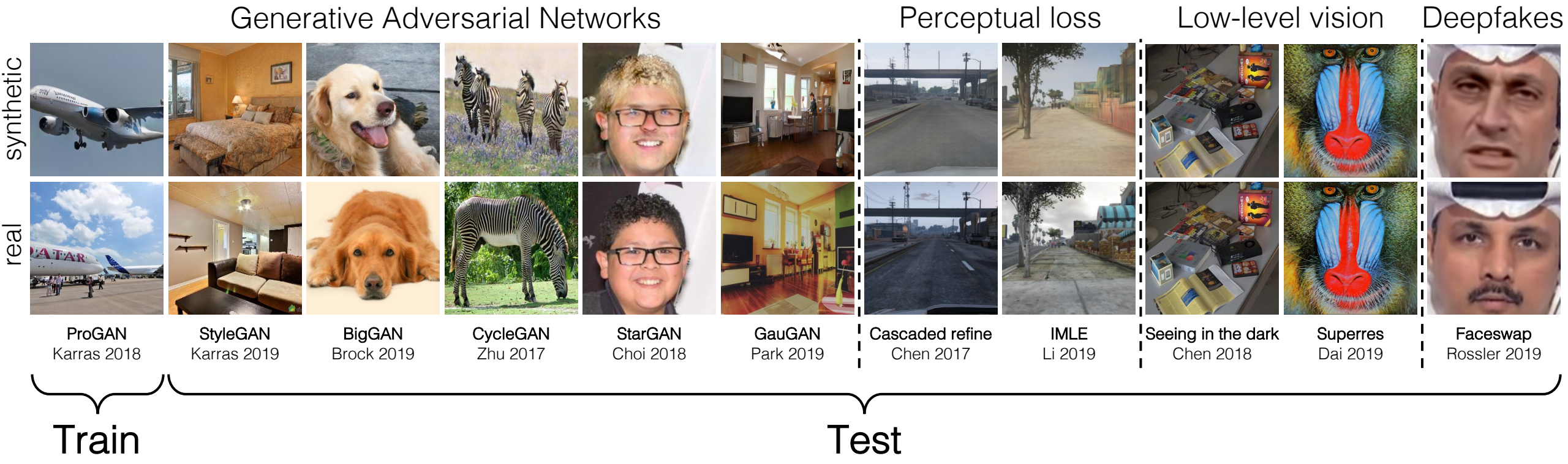


Train ⟶ **Test:** ??? et al. 20XX

Can we create a “universal” detector?

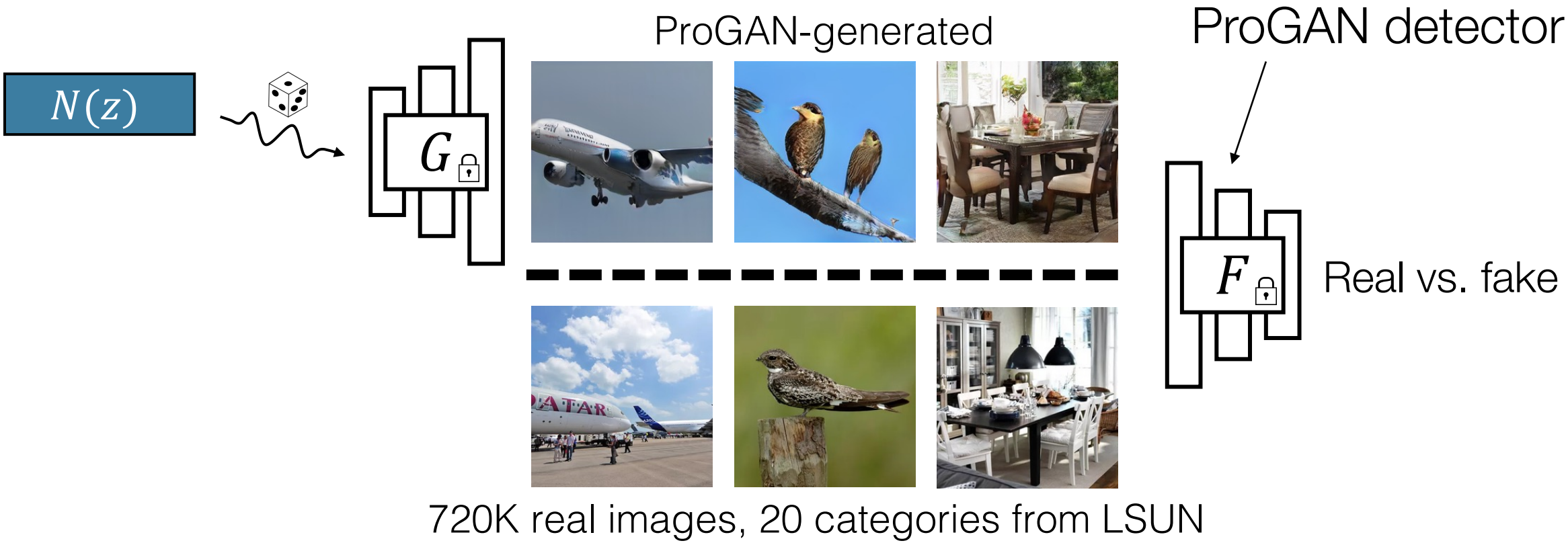
Slides credit: Richard Zhang

Dataset of CNN-generated fakes



Many **differences** (architecture, dataset, objective)

Training on ProGAN



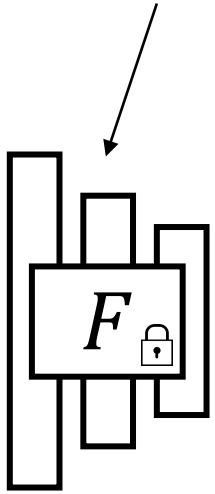
CNN-generated images are surprisingly easy to spot... for now [Wang et al., CVPR 2020]

Testing across architectures

Synthesized images from **other** CNNs

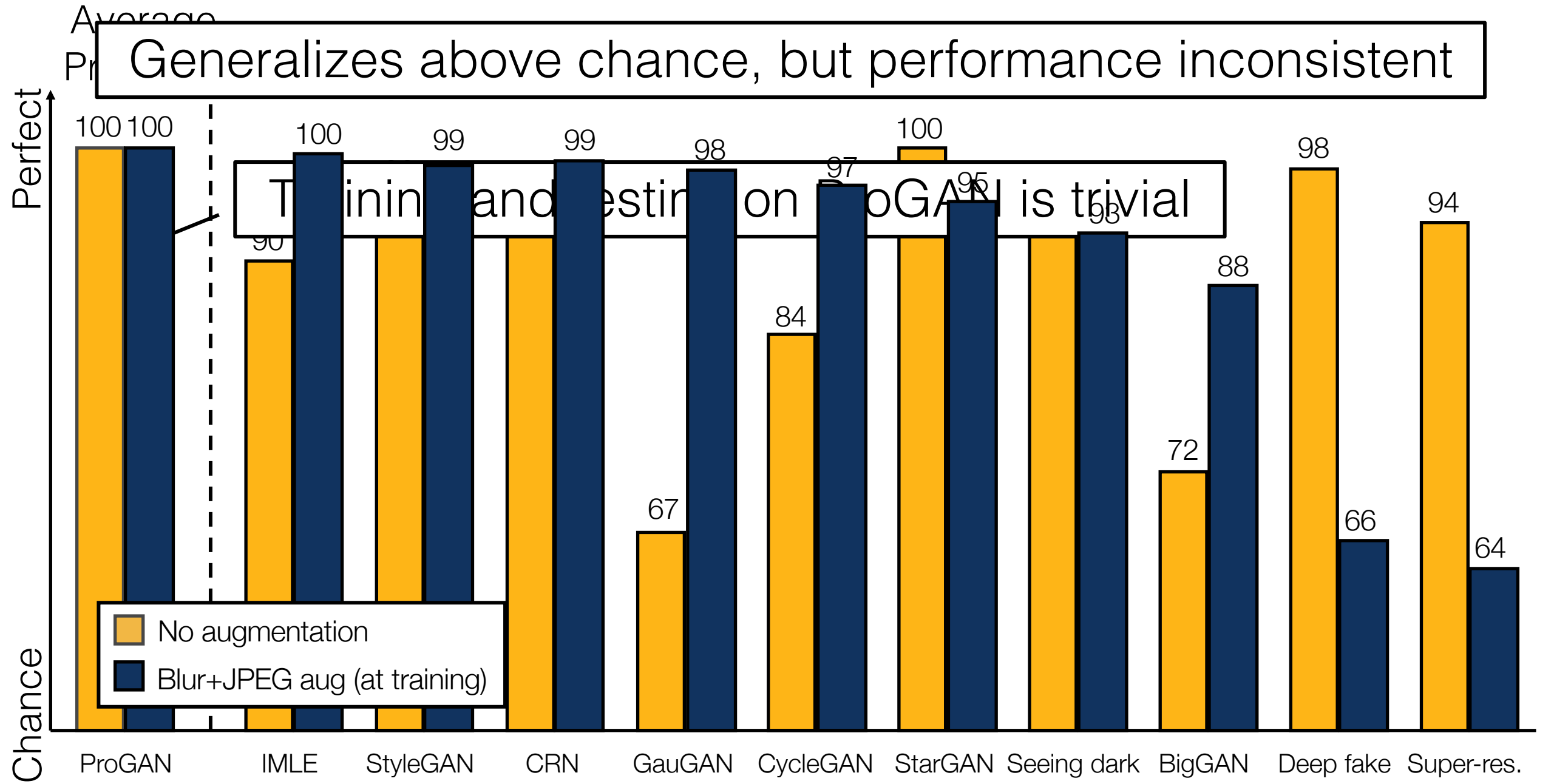
Real images

ProGAN detector



Real vs. fake

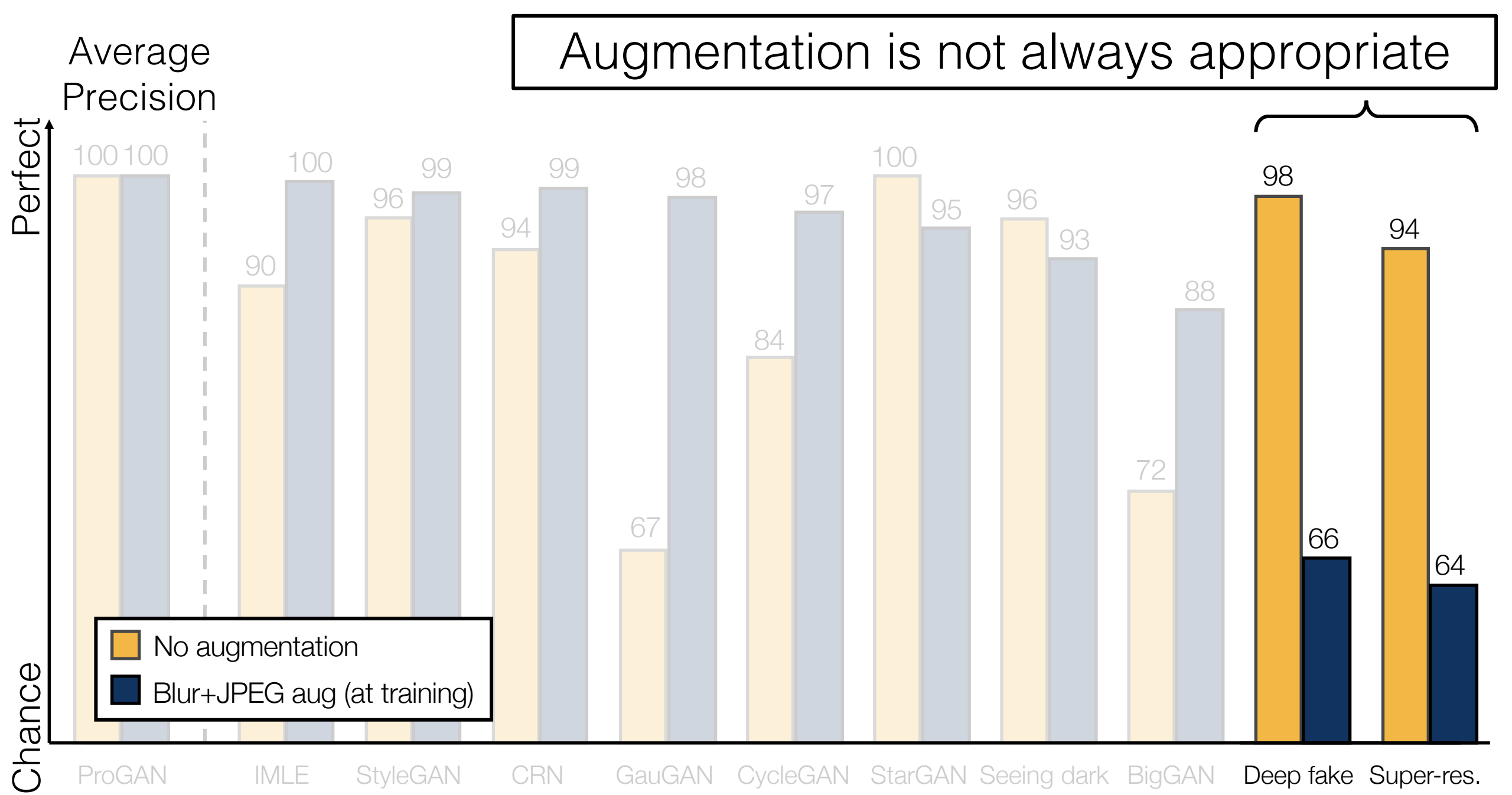
CNN-generated images are surprisingly easy to spot... for now [Wang et al., CVPR 2020]



Slides credit: Richard Zhang

[Wang et al., CVPR 2020]

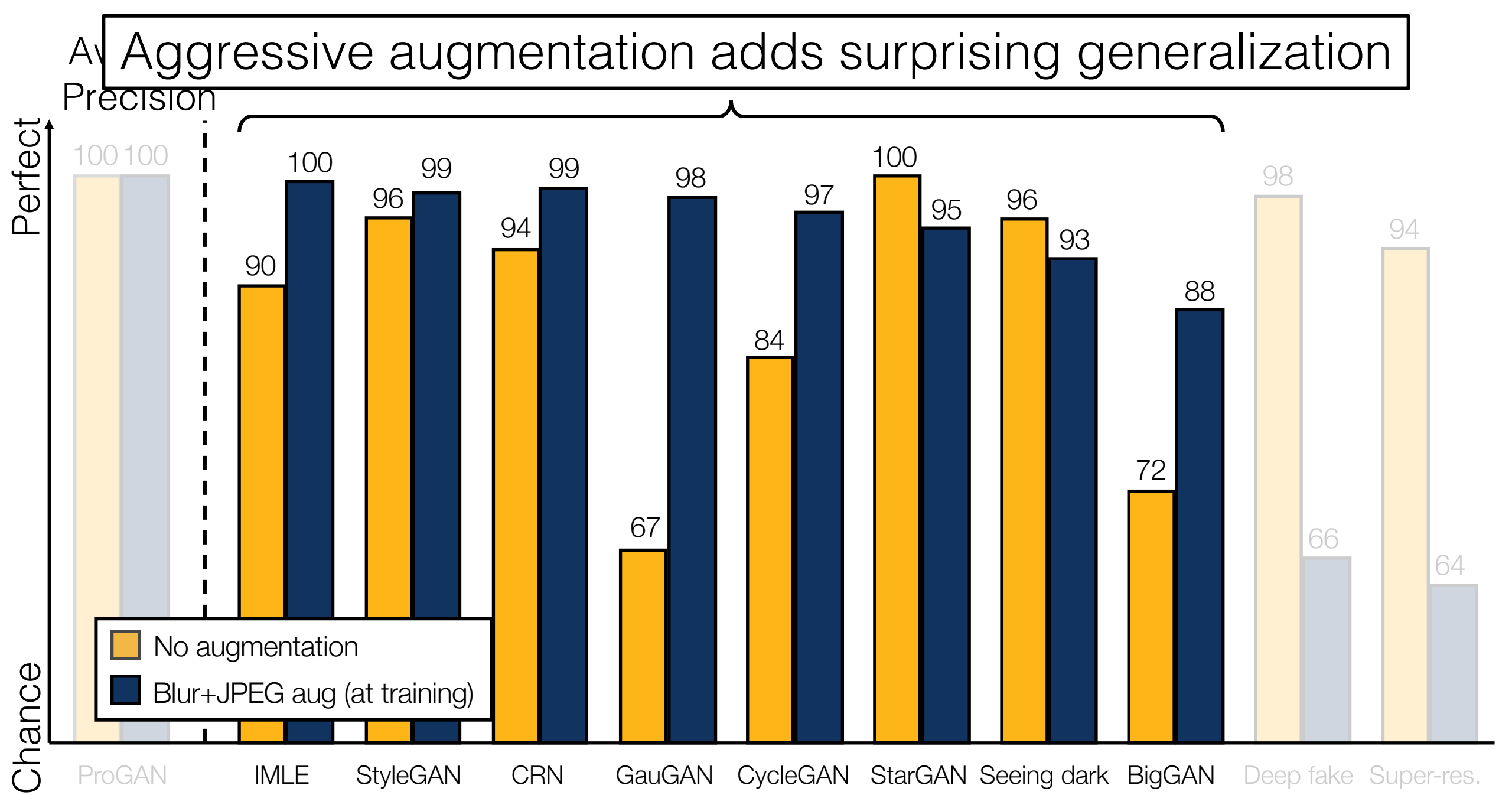
Augmentation is not always appropriate



Slides credit: Richard Zhang

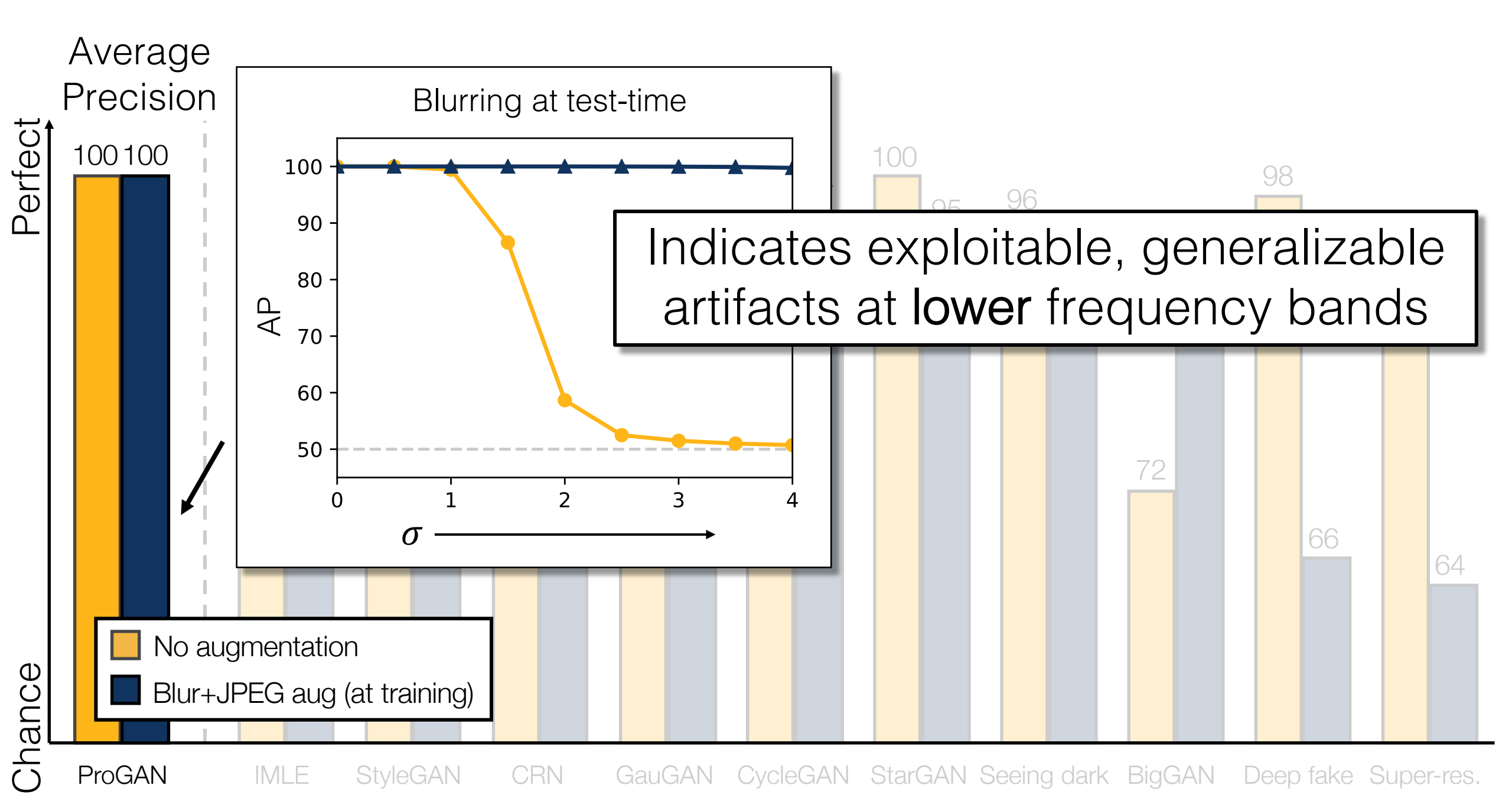
[Wang et al., CVPR 2020]

Aggressive augmentation adds surprising generalization



Slides credit: Richard Zhang

[Wang et al., CVPR 2020]



Slides credit: Richard Zhang

[Wang et al., CVPR 2020]

Discussion

- Suggests CNN-generated images have common artifacts

- Artifacts can be detected by a simple classifier!
  - StyleGAN2 (released **after** the paper): 100% AP on FFHQ
  - Maybe generalizes beyond CNNs [Chai et al. ECCV 2020]
  - **Note**: AP is computed on a collection of images;
    a real/fake decision on a per-image basis is more difficult

- Situation may not persist
  - GANs train with a discriminator
  - Future architecture changes (does not generalize well to Diffusion models)

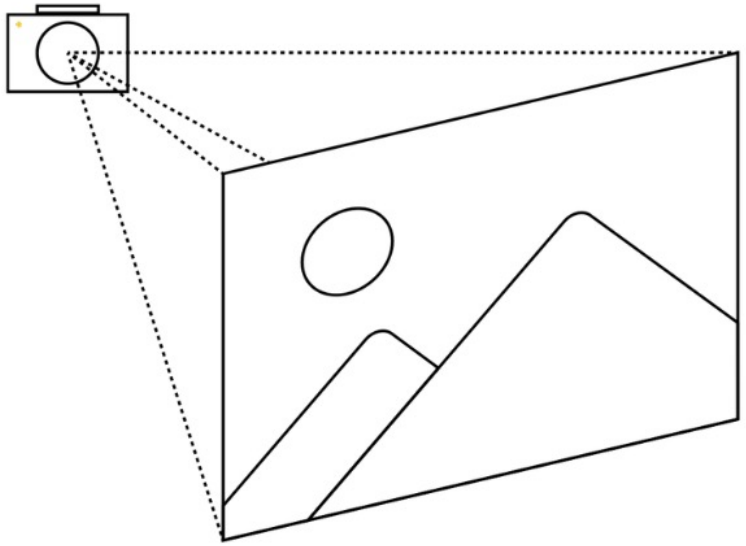
Slides credit: Richard Zhang

Discussion

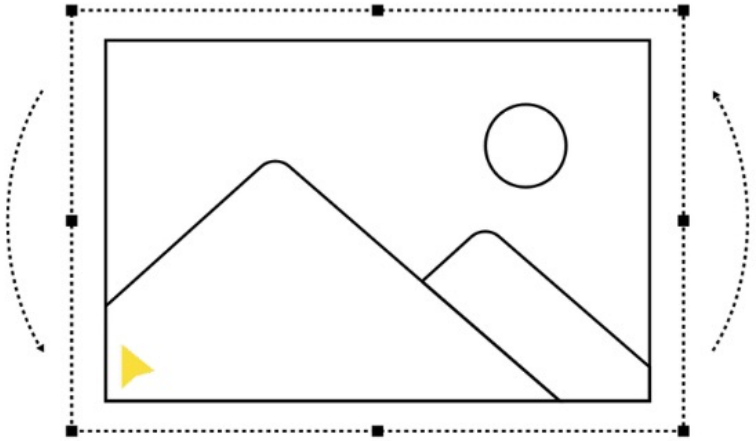
- Suggests a multi-prong approach
  - For rapidly evolving tools, continuously training and generalize
  - For relatively static tools, specialize
- Synthesis and manipulations for creative uses
- Detection is only a piece of the puzzle
  - e.g., Content Authenticity Initiative: https://contentauthenticity.org/, collaboration between Adobe, New York Times, and Twitter

Slides credit: Richard Zhang

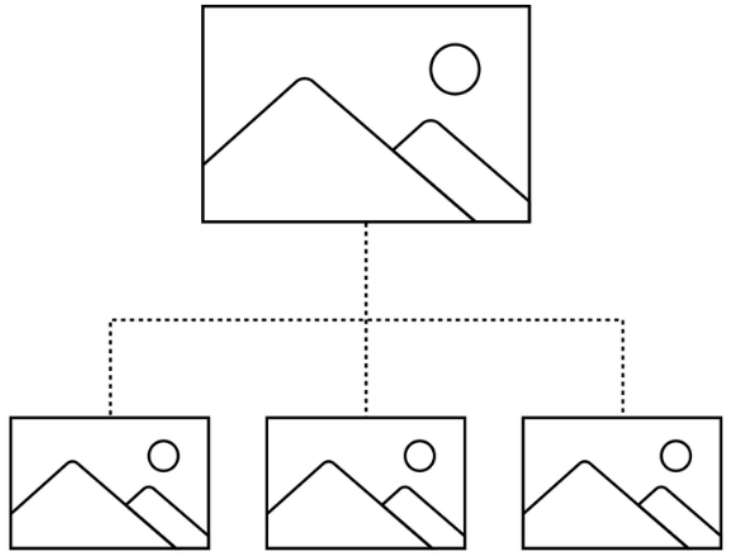
Content Authenticity (prove what is real)



Capture



Editing



Publishing and sharing

https://contentauthenticity.org/

Copyrights

+ Disclaimer: I am not a lawyer
+ Human creator’s rights
+ Diverse opinions
+ Evolving landscape

Copyrighted content?

- Copyrighted images
- Company IPs / logos
- Artist styles of living artists

Getty Images

Greg Rutkowski

Ongoing Legal Battles

ARTIFICIAL INTELLIGENCE / TECH / LAW

Getty Images sues AI art generator Stable Diffusion in the US for copyright infringement

/ Getty Images has filed a case against Stability AI, alleging that the company copied 12 million images to train its AI model 'without permission ... or compensation.'

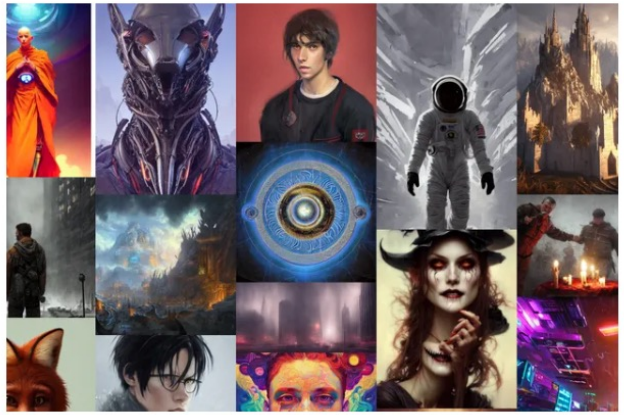
By JAMES VINCENT
Feb 6, 2023, 11:56 AM EST | 16 Comments / 16 New

An illustration from Getty Images' lawsuit, showing an original photograph and a similar image (complete with Getty Images watermark) generated by Stable Diffusion. Image: Getty Images

Getty Images has filed a lawsuit in the US against Stability AI, creators of open-source AI art generator Stable Diffusion, escalating its legal battle against the firm.

ARTIFICIAL INTELLIGENCE / TECH / CREATORS

AI art tools Stable Diffusion and Midjourney targeted with copyright lawsuit



/ The suit claims generative AI art tools violate copyright law by scraping artists' work from the web without their consent.

By JAMES VINCENT
Jan 16, 2023, 6:28 AM EST | 28 Comments / 28 New

A collage of AI-generated images created using Stable Diffusion. Image: *The Verge via Lexica*

A trio of artists have launched a lawsuit against Stability AI and Midjourney, creators of AI art generators Stable Diffusion and Midjourney, and artist portfolio platform DeviantArt, which recently created its own AI art generator, DreamUp.

Source: The Verge

Ongoing Legal Battles

REUTERS® World Business Markets Legal Breakingviews Technology Investigations Sports

Copyright | Technology | Intellectual Property | Litigation | Data Privacy

2 minute read · February 22, 2023 8:41 PM EST · Last Updated 2 months ago

AI-created images lose U.S. copyrights in test for new technology

By Blake Brittain

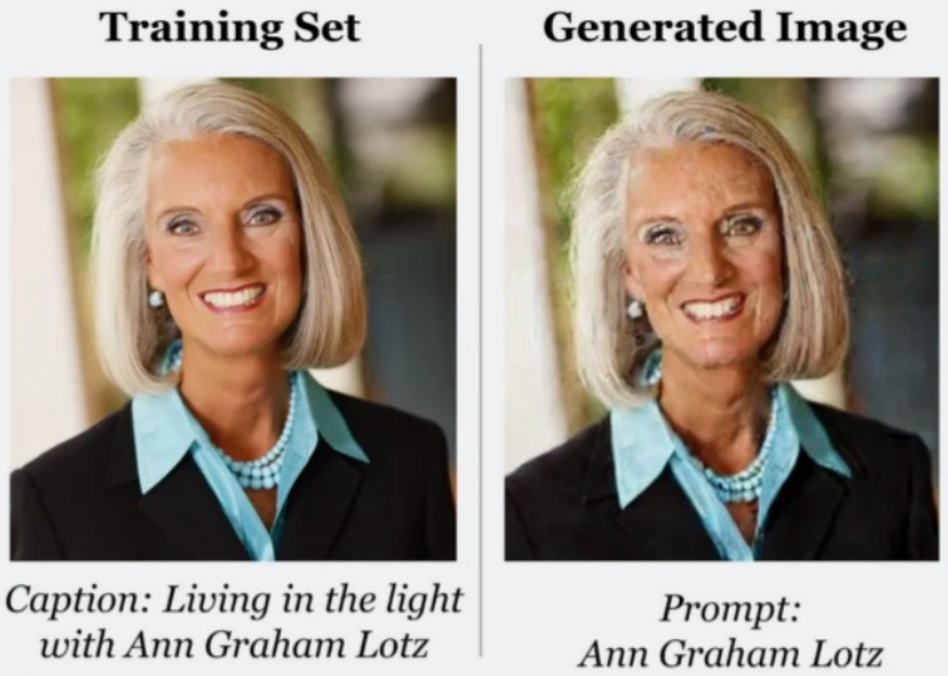
REUTERS/Andrew Kelly

Feb 22 (Reuters) - Images in a graphic novel that were created using the artificial-intelligence system Midjourney should not have been granted copyright protection, the U.S. Copyright Office said in a letter seen by Reuters.

I'm not so sure. As we've seen, a key assumption for a "non-expressive use" defense is that Stable Diffusion only learns uncopyrightable facts—not creative expression—from its training images. That's *mostly* true. But it's not entirely true. And the exceptions could greatly complicate Stability AI's legal defense.

Stable Diffusion's copying problem

Here's one of the most awkward examples for Stability AI:



Enlarge

https://arstechnica.com/

Memorized training images

Real Image

Stable Diffusion

`Ann Graham Lotz`

Extracting Training Data from Diffusion Models [Carlini et al., 2023]

Memorized training images

- Step 1: Identifying duplicates in the training data
- Step 2: Generating many images with the selected prompt
- Step 2: Image matching

Extracting Training Data from Diffusion Models [Carlini et al., 2023]

Memorized style

Greg Rutkowski

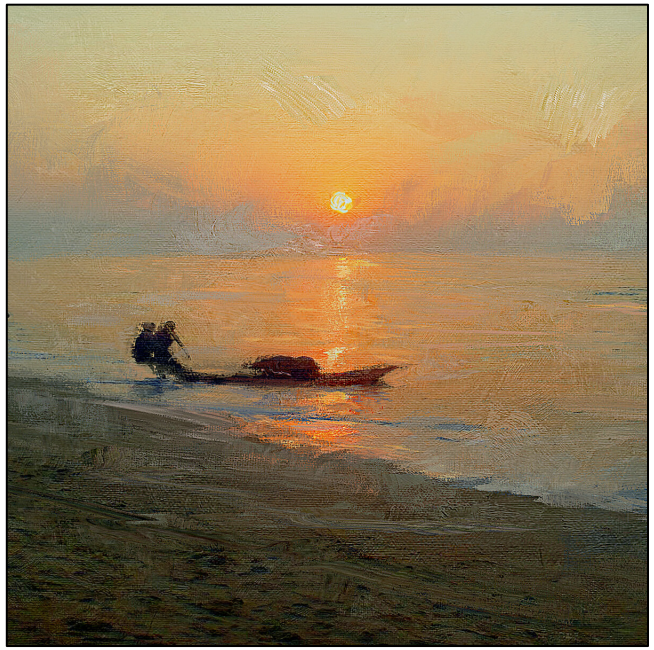


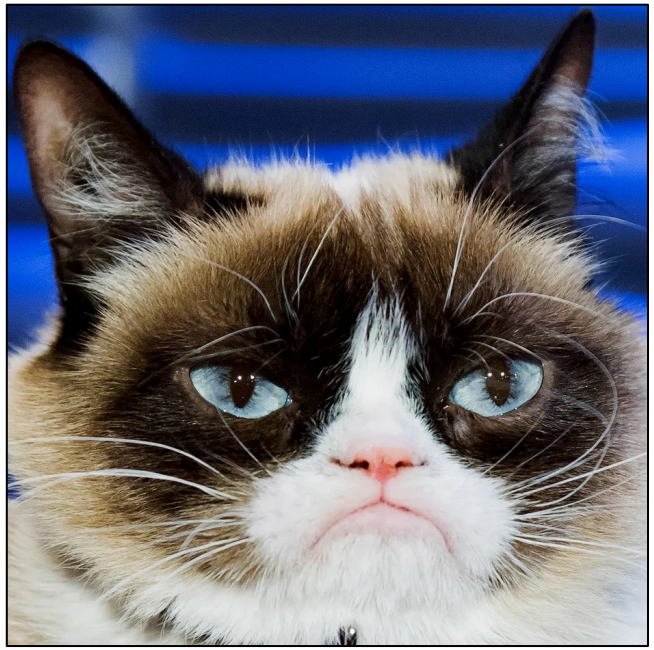
*image credit: https://rutkowski.artstation.com

Stable Diffusion

A painting of a boat on the water in the style of Greg Rutkowski

Memorized instances

Grumpy cat

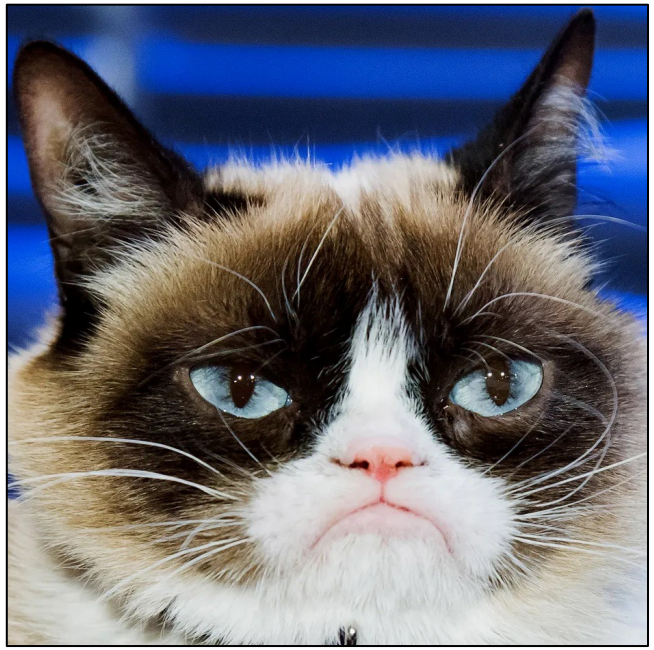


Stable Diffusion

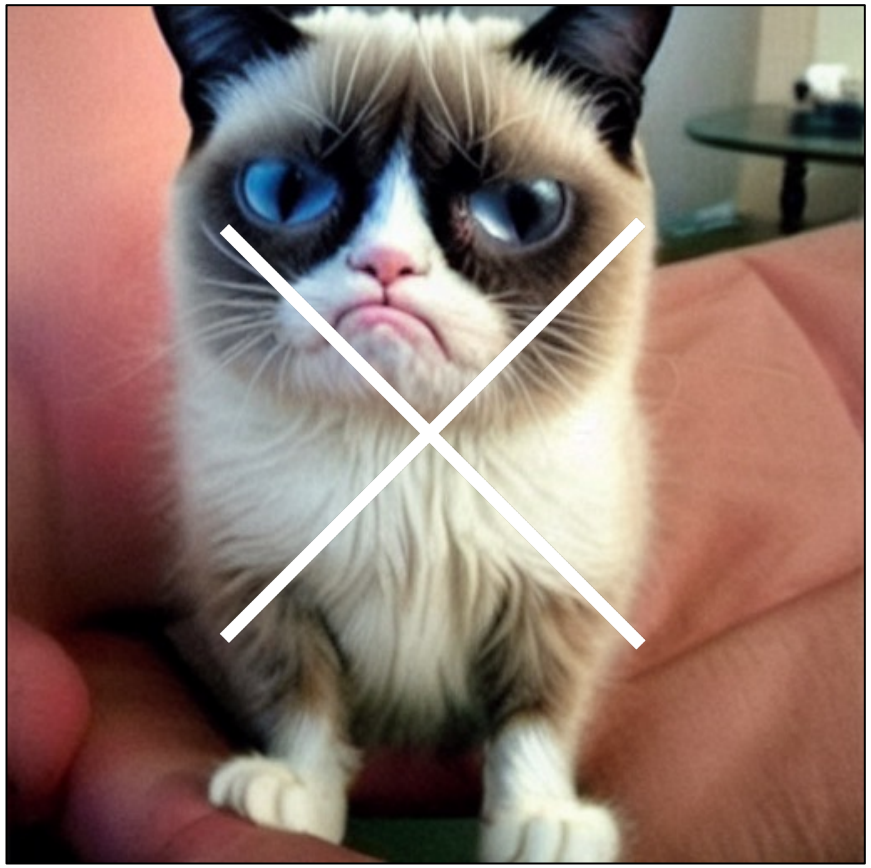
What a cute Grumpy cat

Concept ablation

Grumpy cat

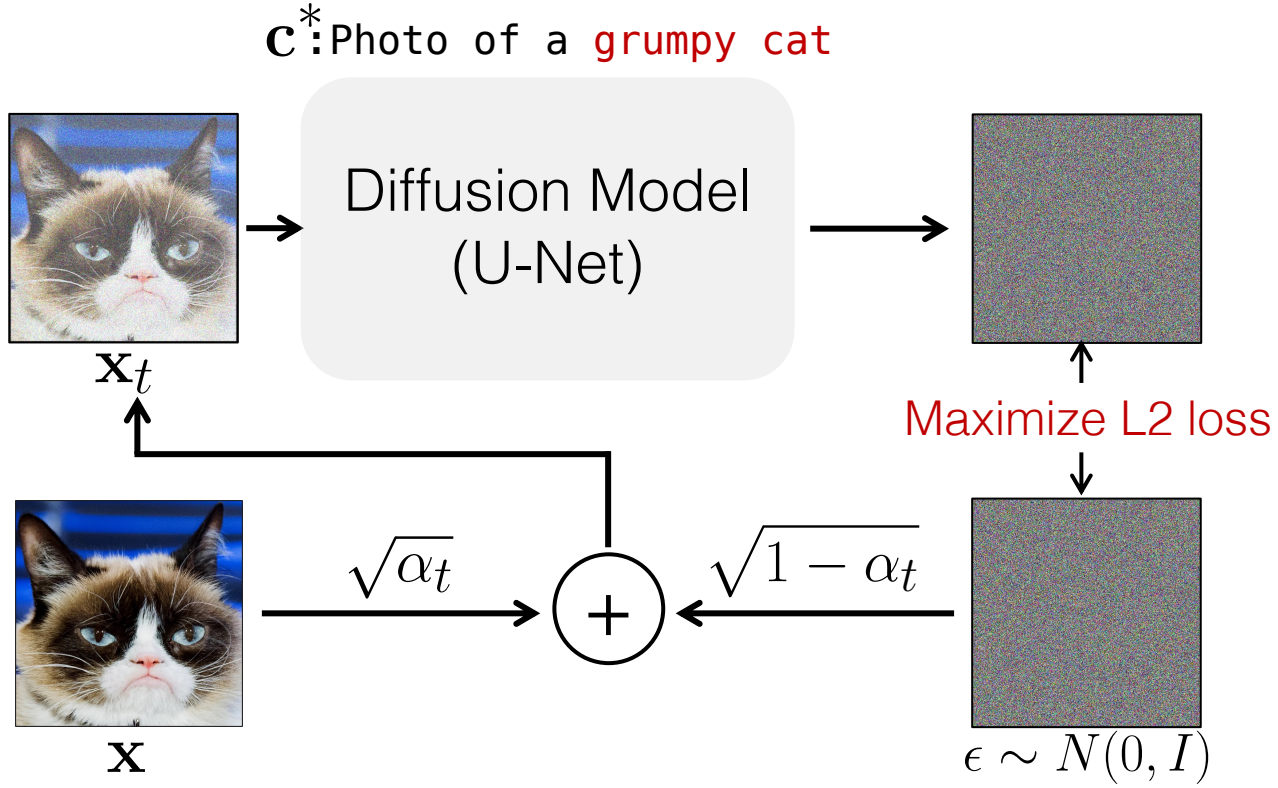


Ablated Stable Diffusion



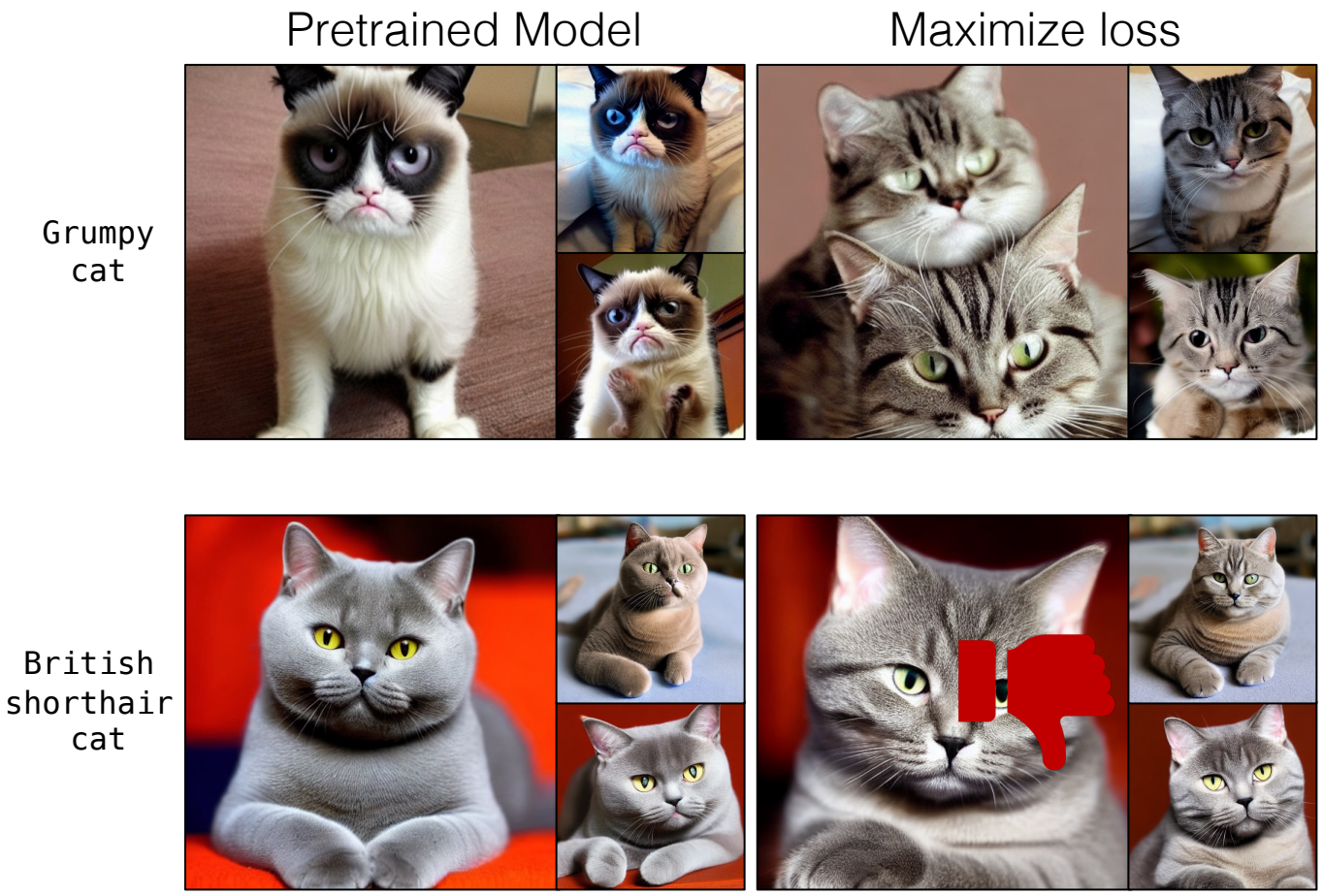
What a cute Grumpy cat

Baseline: maximize loss



[Kumari et al., arXiv 2023]

Baseline: maximize loss

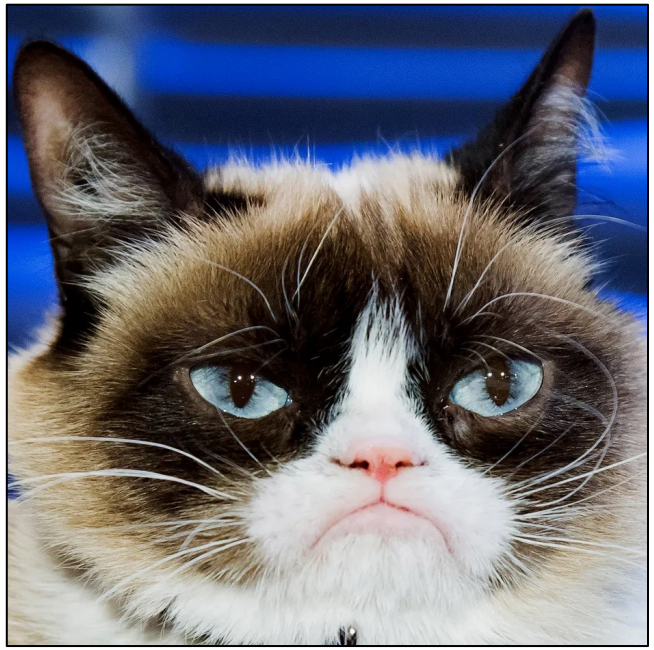


Changes the nearby concepts

[Kumari et al., arXiv 2023]

Concept ablation

Grumpy cat



Ablated Stable Diffusion

`What a cute Grumpy cat`

[Kumari et al., arXiv 2023]

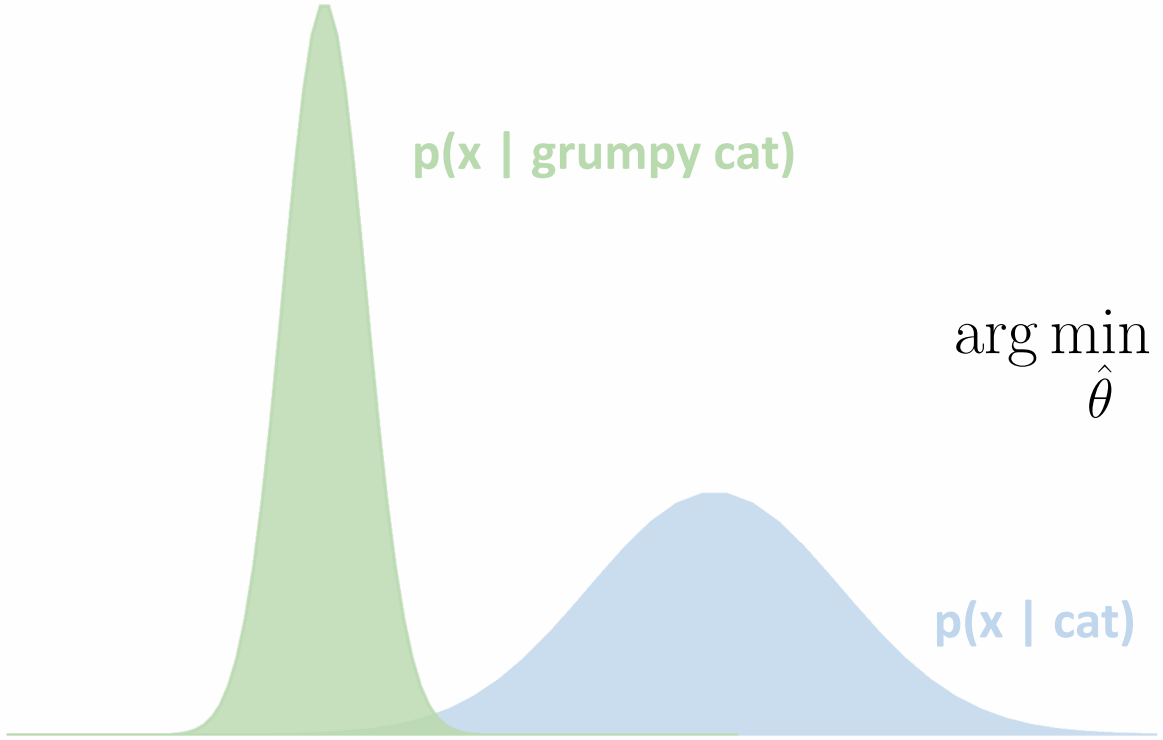
Concept ablation

[Kumari et al., arXiv 2023]

Concept ablation

[Kumari et al., arXiv 2023]

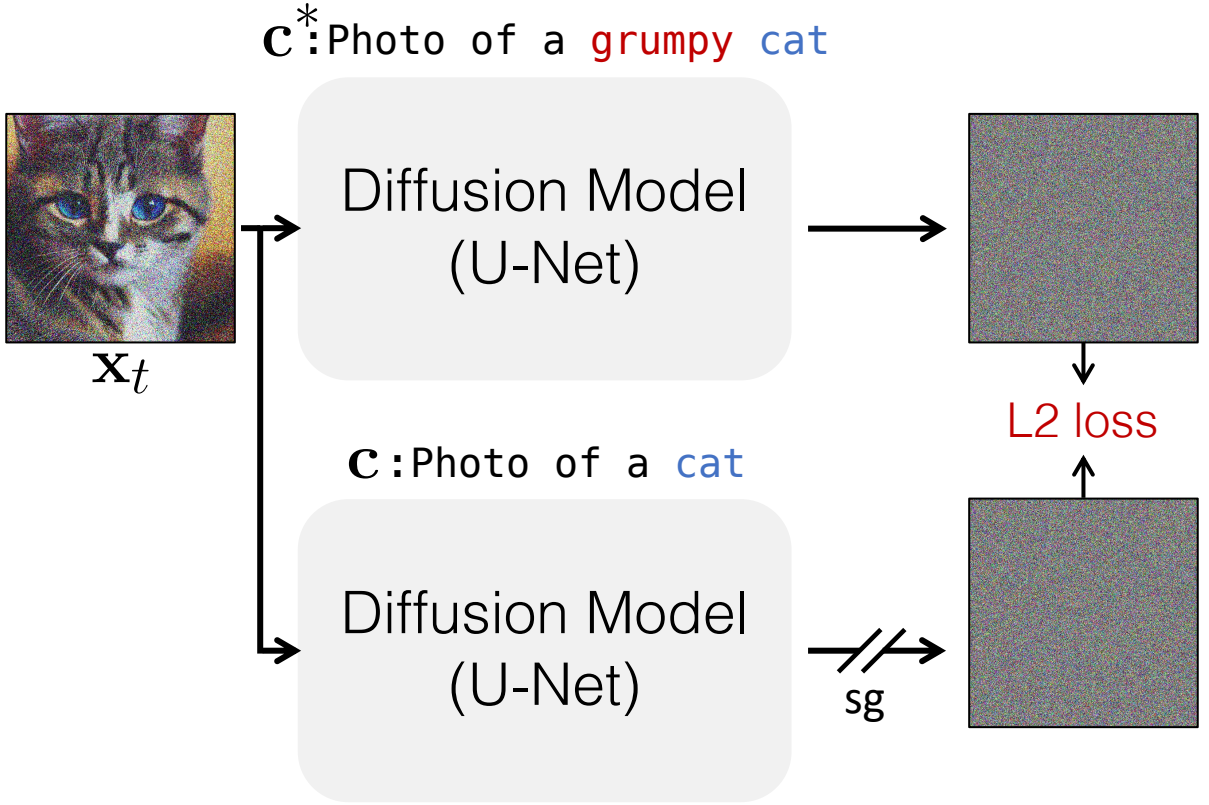
Model-based concept ablation



$$\arg\min_{\hat{\theta}} KL(p_{\hat{\theta}}(\mathbf{x}|\text{grumpy cat})||p_{\theta}(\mathbf{x}|\text{cat}))$$

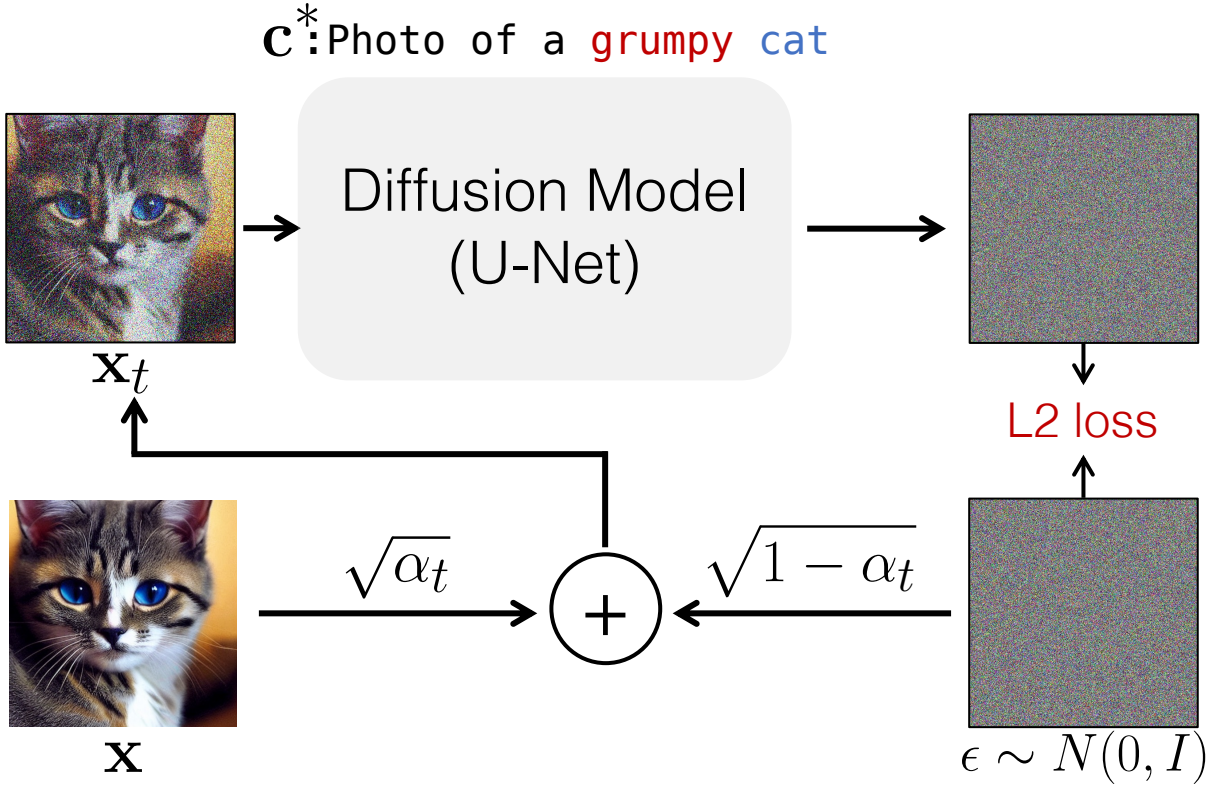
[Kumari et al., arXiv 2023]

Model-based concept ablation



[Kumari et al., arXiv 2023]

Noise-based concept ablation



[Kumari et al., arXiv 2023]

Qualitative comparison

[Kumari et al., arXiv 2023]

Ablating R2D2

Stable Diffusion

Ablated Stable Diffusion

`The future is now with this amazing home automation R2D2`

[Kumari et al., arXiv 2023]

Ablating R2D2

Stable Diffusion

Ablated Stable Diffusion

The possibilities are endless with this versatile R2D2

[Kumari et al., arXiv 2023]

Ablating Snoopy

Stable Diffusion

Ablated Stable Diffusion

`A devoted Snoopy accompanying its owner on a road trip`

[Kumari et al., arXiv 2023]

Ablating Snoopy

Stable Diffusion

Ablated Stable Diffusion

`A confident Snoopy standing tall and proud after a successful training session`

[Kumari et al., arXiv 2023]

Ablating Van Gogh

Stable Diffusion

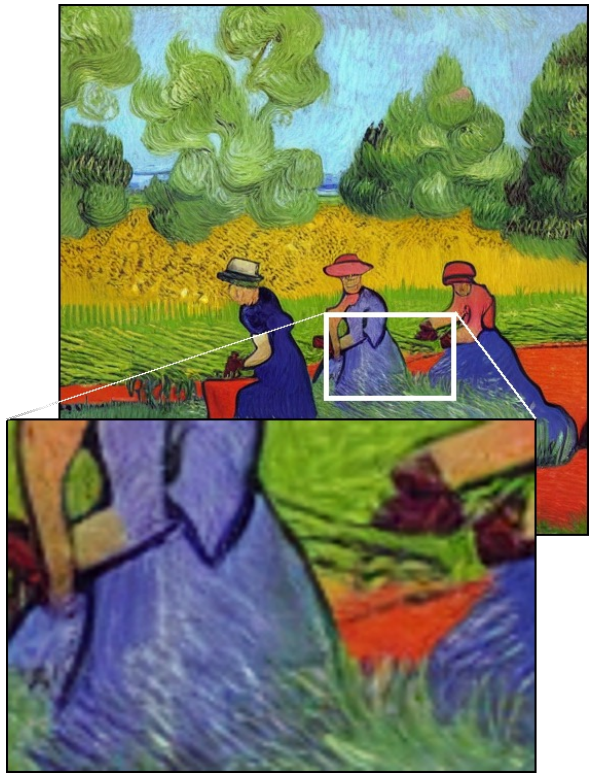
Ablated Stable Diffusion

`Painting of olive trees in the style of Van Gogh`

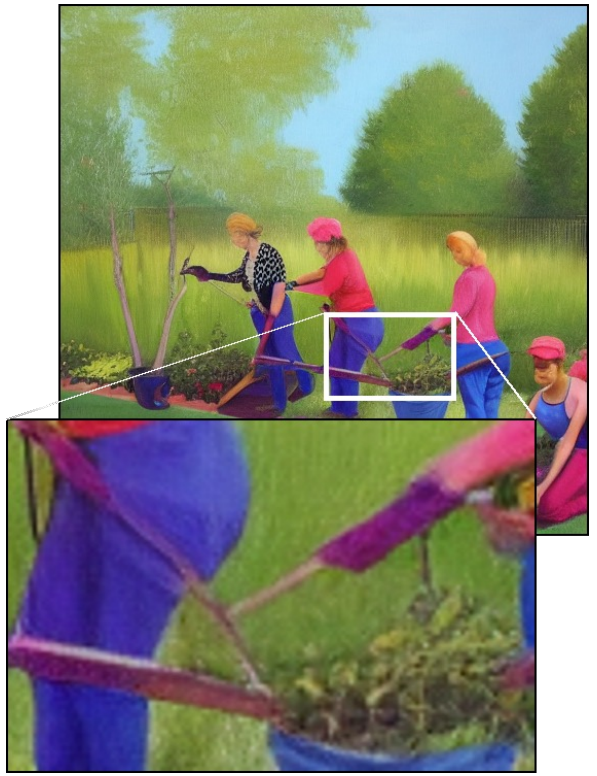
[Kumari et al., arXiv 2023]

Ablating Van Gogh

Stable Diffusion



Ablated Stable Diffusion



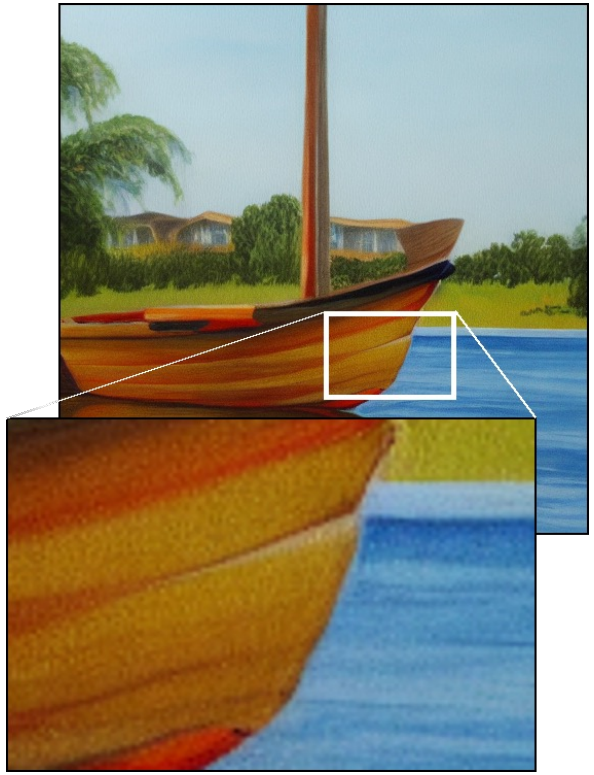
`Painting of women working in the garden, in the style of Van Gogh`

[Kumari et al., arXiv 2023]

Ablating Greg Rutkowski

Stable Diffusion

Ablated Stable Diffusion



A painting of a boat on the water in the style of Greg Rutkowski

[Kumari et al., arXiv 2023]

Ablating Greg Rutkowski

Stable Diffusion

Ablated Stable Diffusion

`Painting of a group of people on a dock by Greg Rutkowski`

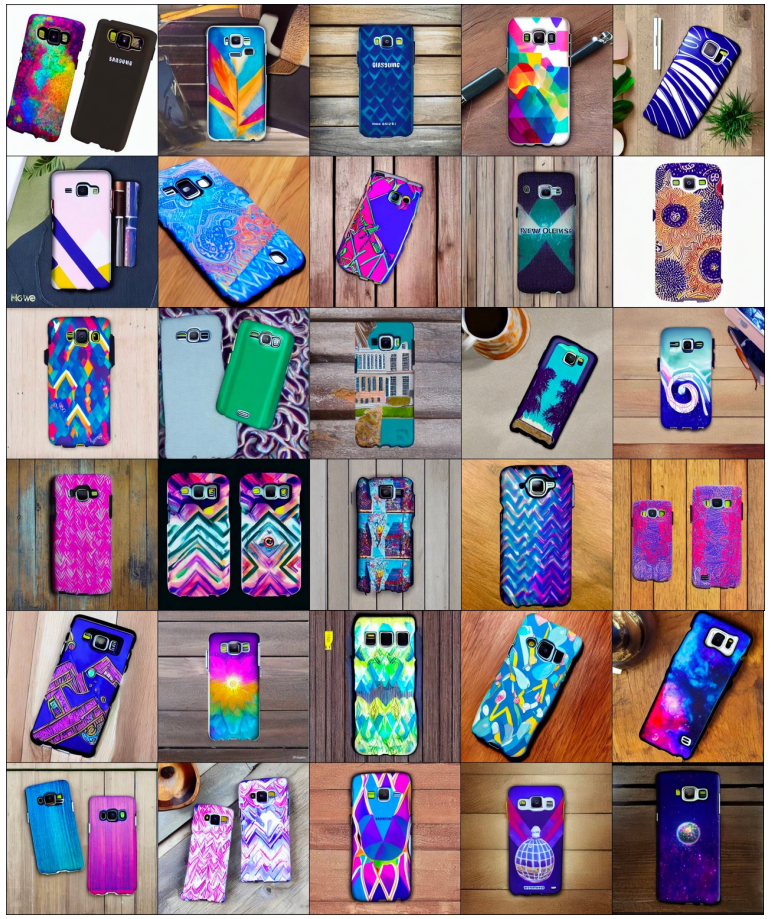
[Kumari et al., arXiv 2023]

Ablating memorized images

Real Image

Stable Diffusion

Ablated Stable Diffusion



New Orleans House Galaxy Case

[Kumari et al., arXiv 2023]

Ablating memorized images

Real Image

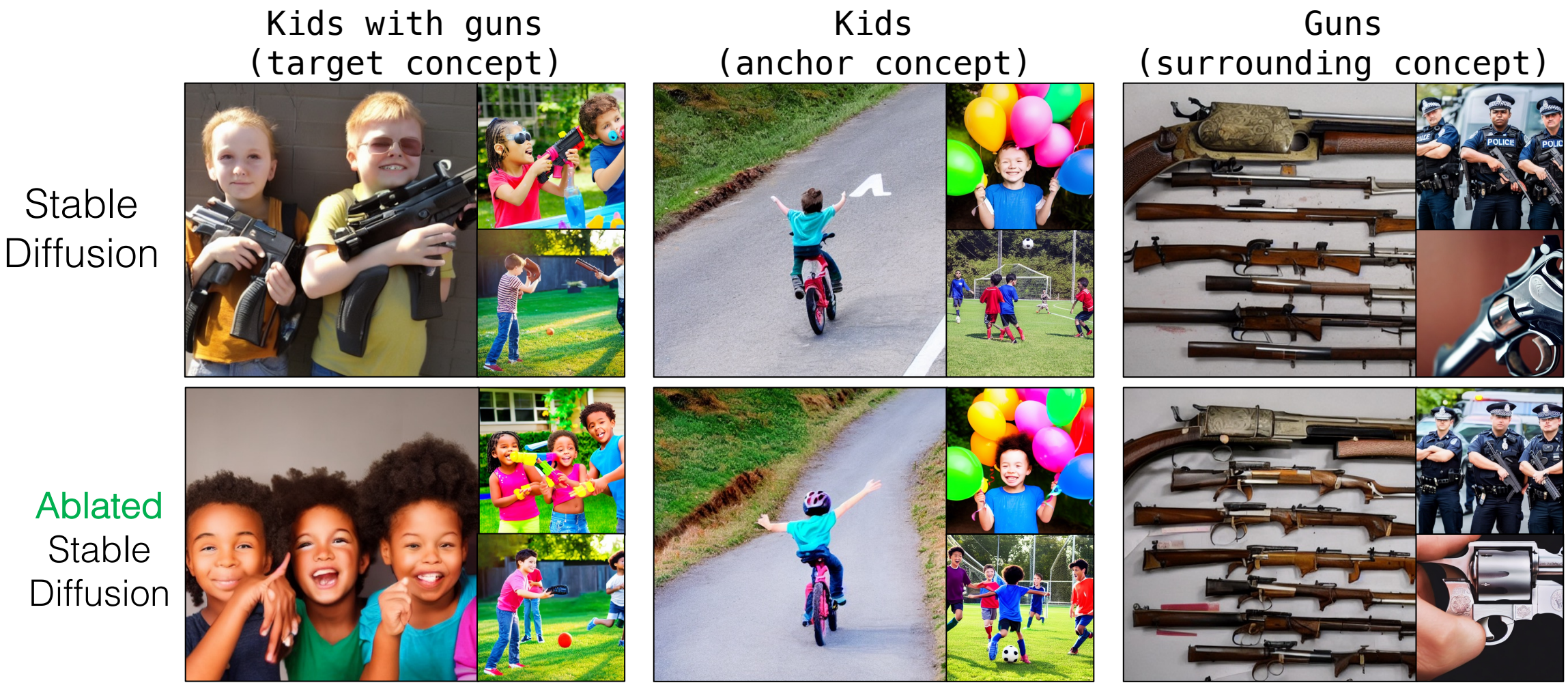
Stable Diffusion

Ablated Stable Diffusion

Ann Graham Lotz

[Kumari et al., arXiv 2023]

Ablating composition of concepts



[Kumari et al., arXiv 2023]

Other works

1. **Erasing Concepts from Diffusion Models.** Rohit Gandikota, Joanna Materzynska, Jaden Fiotto-Kaufman, and David Bau. arXiv preprint arXiv:2303.07345 (2023).

2. **Forget-Me-Not: Learning to Forget in Text-to-Image Diffusion** Models. Eric Zhang, Kai Wang1, Xingqian Xu, Zhangyang Wang, Humphrey Shi. arXiv preprint arXiv:2303.17591 (2023).

Biases

Danger and Ethical Concerns

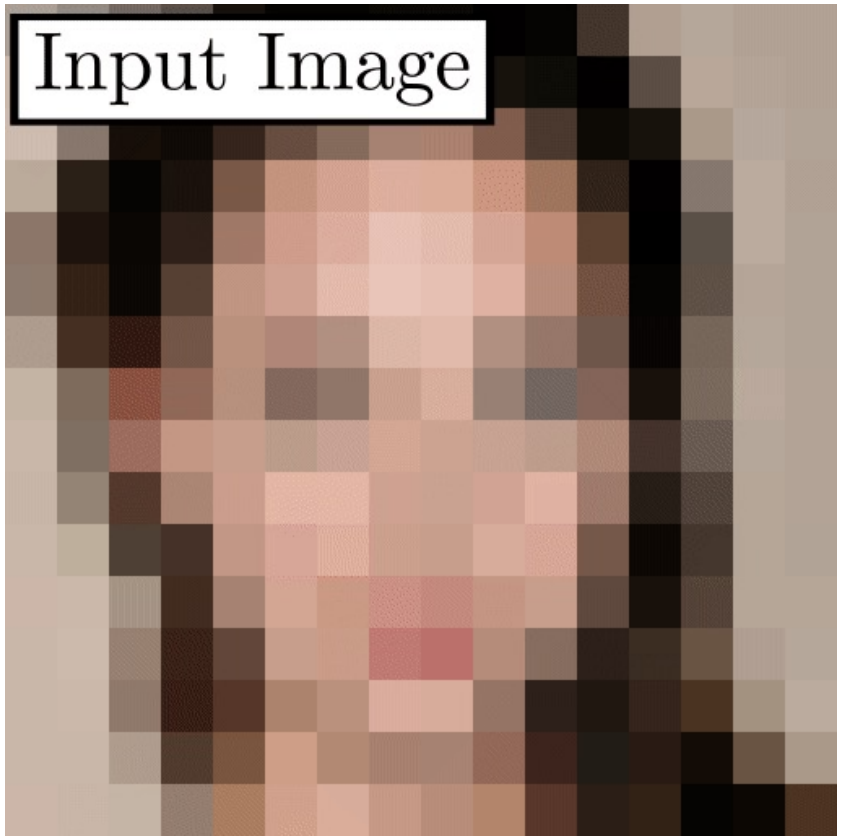


Image Super-resolution system PULSE [Menon et al., CVPR 2020]

Super-resolution with GANs Inversion and StyleGAN

Danger and Ethical Concerns

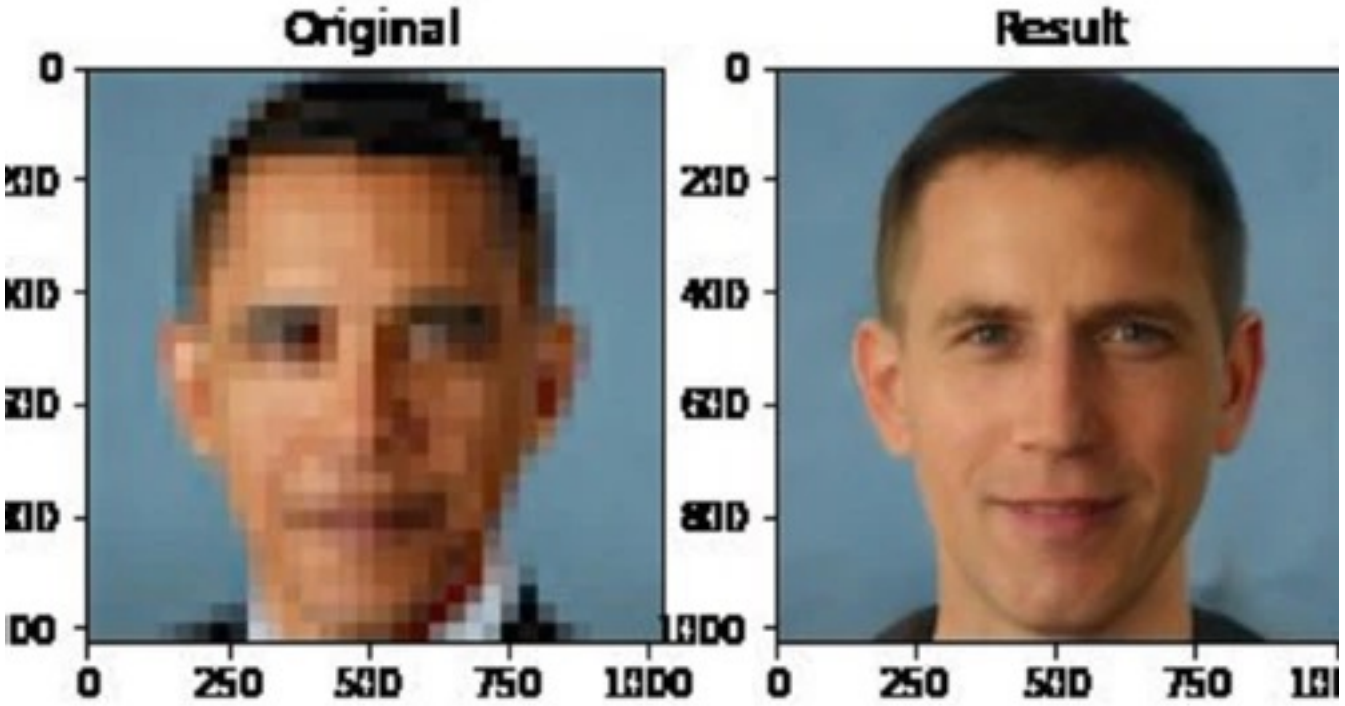
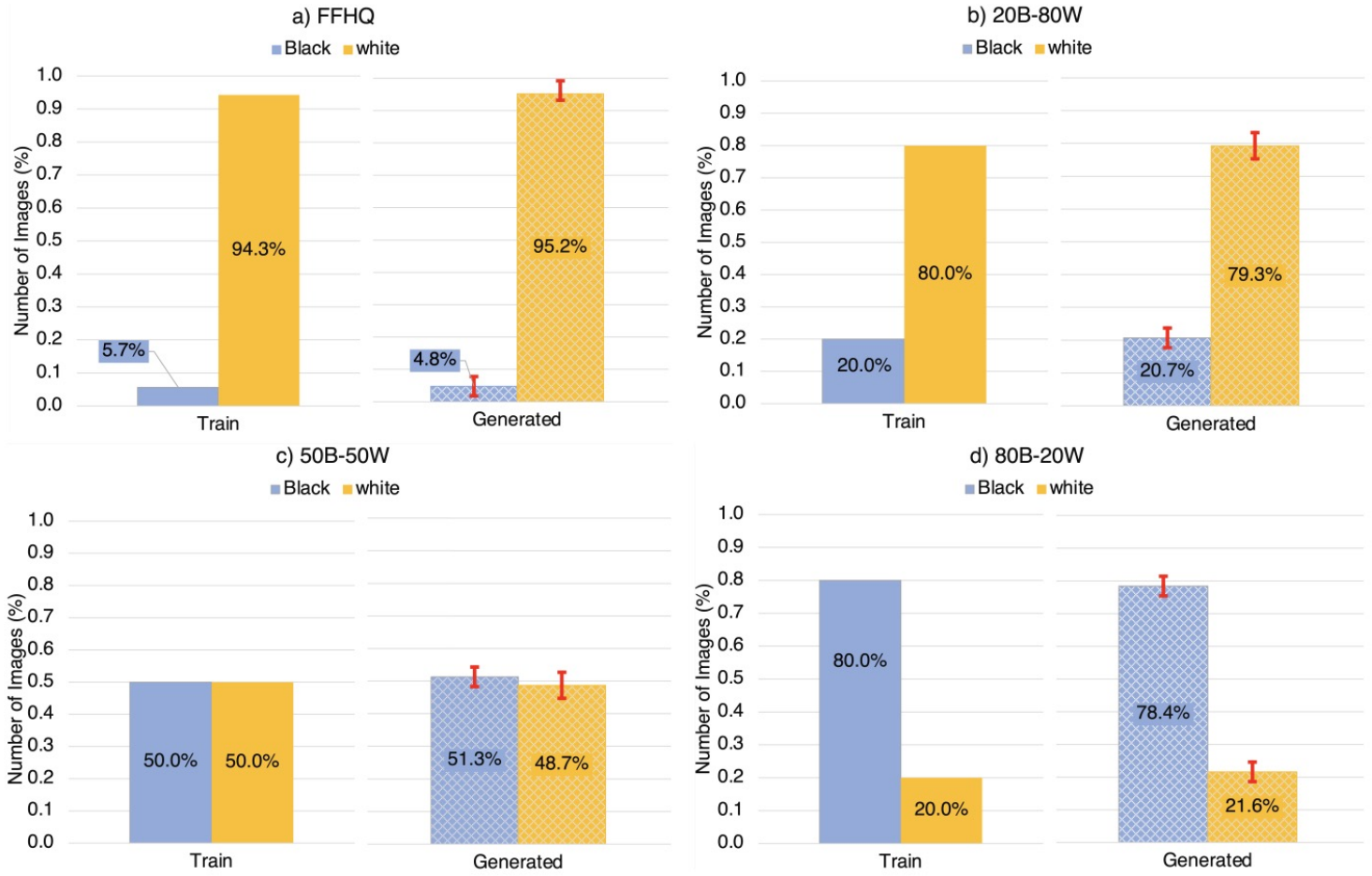


Image Super-resolution system PULSE [Menon et al., CVPR 2020]

GAN models



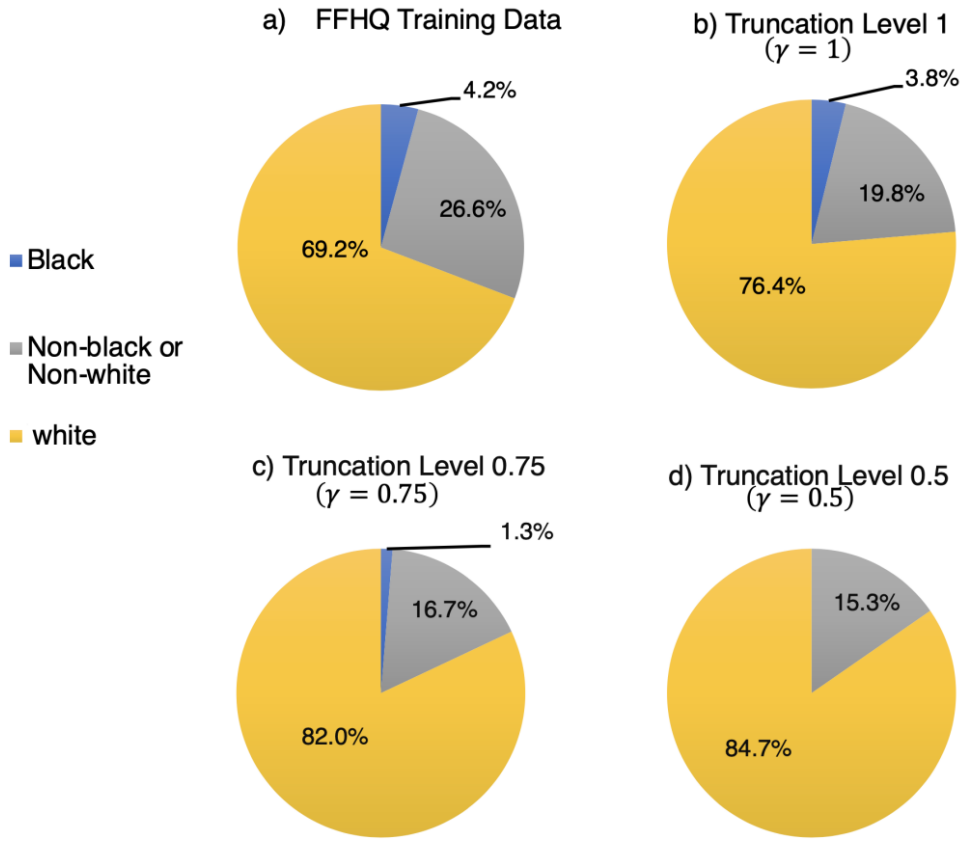
Studying Bias in GANs through the Lens of Race [Maluleke et al., 2022]

GAN models

Truncation Trick reduces diversity

$$w' = \gamma\, w + (1-\gamma)\, \bar{w}$$

Sampled code — Average code



Studying Bias in GANs through the Lens of Race [Maluleke et al., 2022]

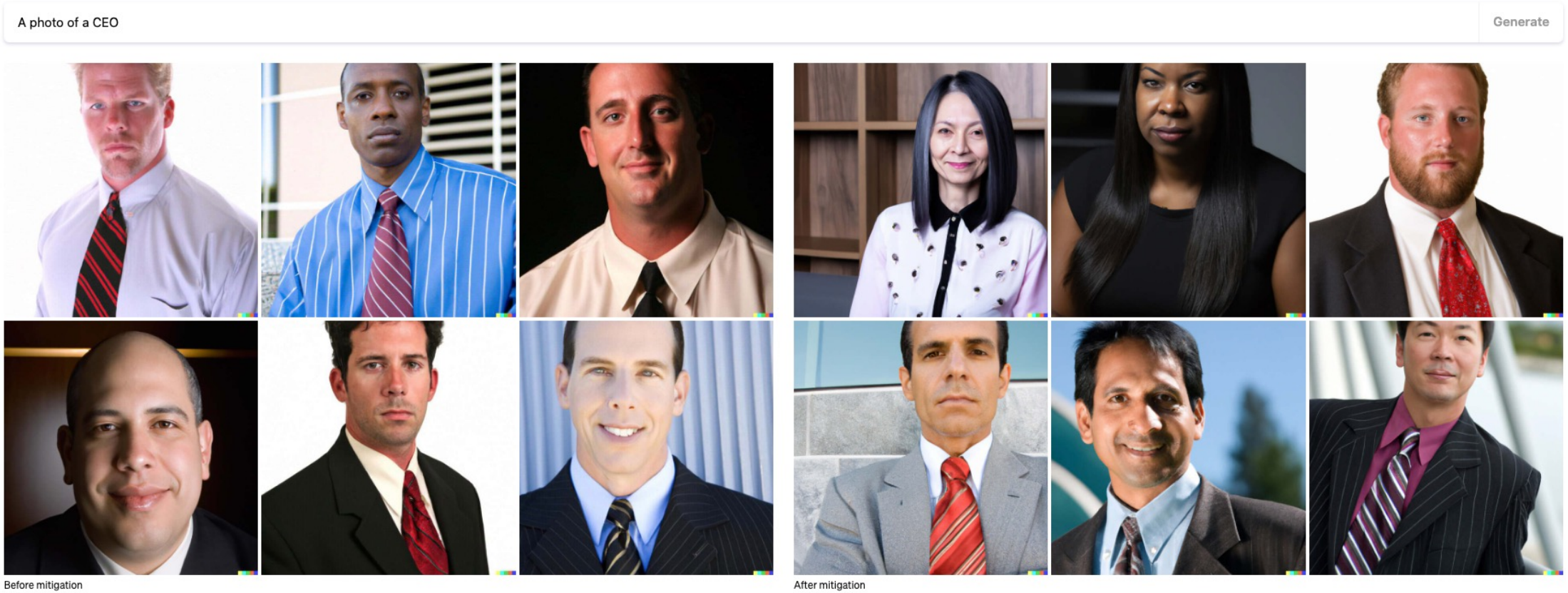
Text-to-Image Models

Managers

Native Americans

https://www.technologyreview.com/2023/03/22/1070167/these-news-tool-let-you-see-for-yourself-how-biased-ai-image-models-are/

Text-to-Image Models (quick fixes?)



https://openai.com/blog/reducing-bias-and-improving-safety-in-dall-e-2

Quick fixes or long-term solutions?