CS540 Introduction to Artificial Intelligence

AI Ethics

University of Wisconsin-Madison

Spring 2023

Outline

Homeworks:

- 🎉🎉🎉🎉🎉

Class roadmap:

Thursday, May 4	Ethics and Review
Friday, May 12 5:05 - 7:05pm	Final Exam

I am

		Good	Evil
I know AI	Yes	Lucky for the world	AI dual use: - VX chemical compound - deep fake - Autonomous weapons - …
	No	Beware AI lacks: - Fairness - Privacy - Explainability - Trust - …	Lucky for the world

Dual use of artificial-intelligence-powered drug discovery

- Key observation: flip the objective function to make optimization find many highly toxic compounds

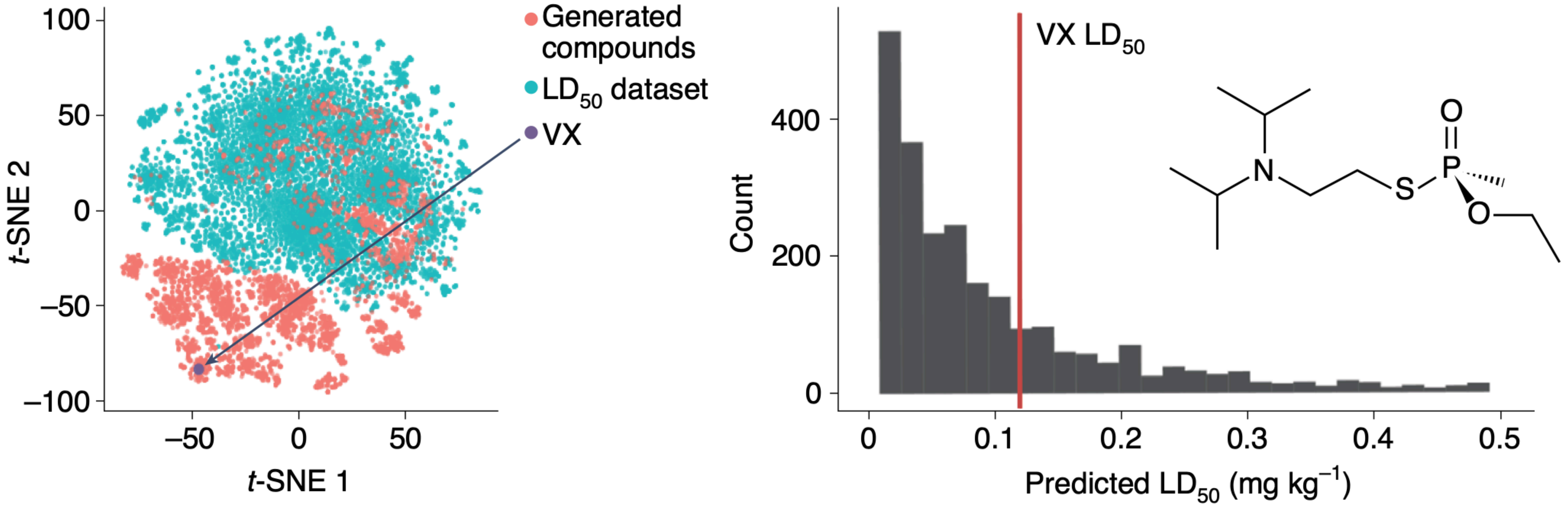

Fig. 1 | A *t*-SNE plot visualization of the LD_{50} dataset and top 2,000 MegaSyn AI-generated and predicted toxic molecules illustrating VX. Many of the molecules generated are predicted to be more toxic in vivo in the animal model than VX (histogram at right shows cut-off for VX LD_{50}). The 2D chemical structure of VX is shown on the right.

[Urbina et al. Nature machine intelligence 2022] https://www.youtube.com/watch?v=cQ54GDm1eL0

Example 1: Fake Obama Video

Example 2: Fake face Images by GAN

- Which are real/fake? https://thispersondoesnotexist.com/




Example 3: fiction Generated by GPT-3

- Completing a prompt from “Harry Potter and the Methods of Rationality”:

> “… If there were any other monster that could defeat you as easily as that one, then you would have died of it long ago. That monster is stupidity. And that is why, my young apprentices, you must never, never, NEVER use the Killing Curse on anything without a brain!"
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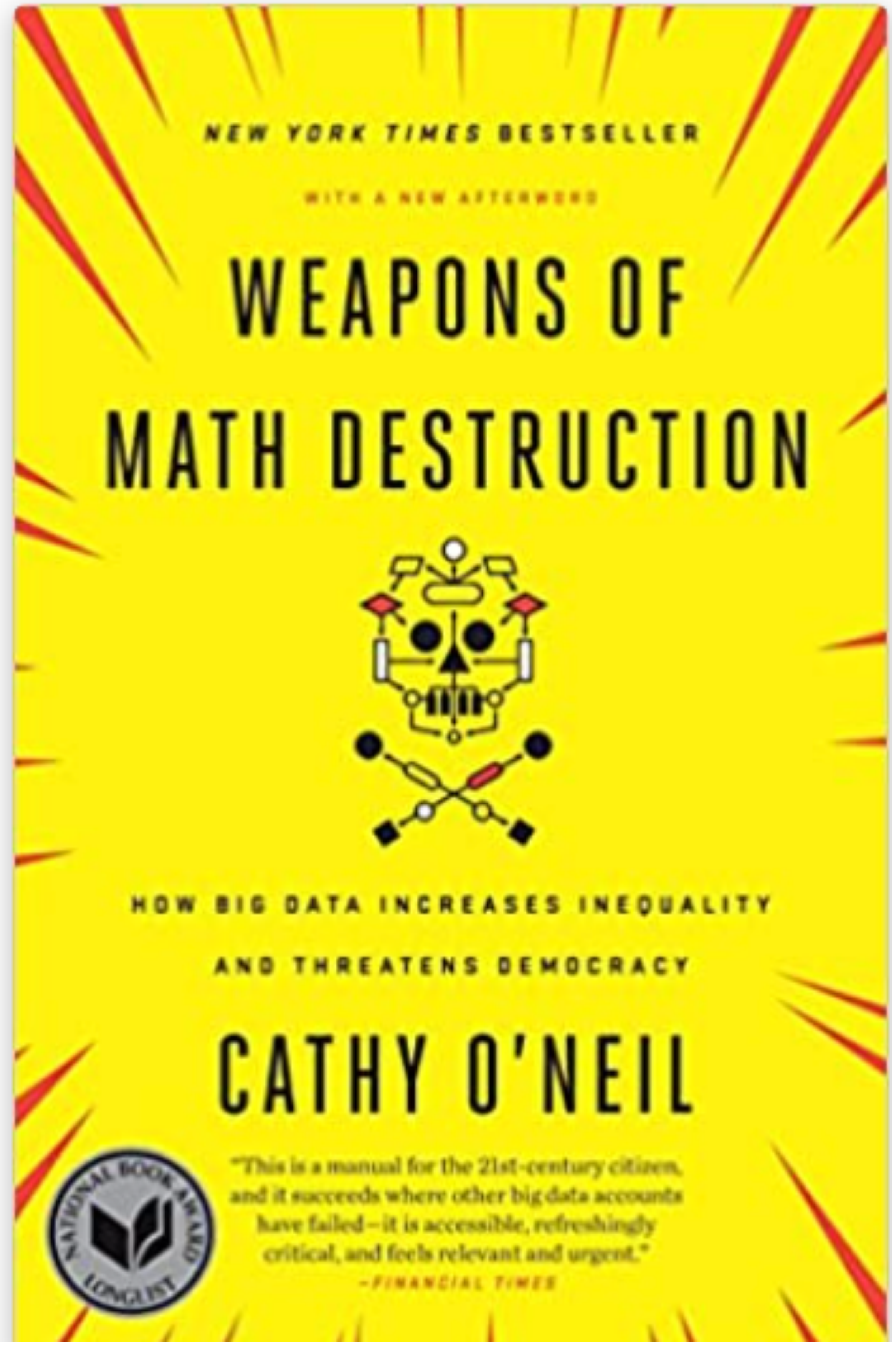

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Bias and Fairness

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  - Biased? Sexist?

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$$P(\hat{y} \neq y) = P(y \neq M \mid y = M)P(y = M) + P(y \neq F \mid y = F)P(y = F) = 0.5$$

Example 2: Skin color bias in face recognition

https://www.nytimes.com/2020/11/11/movies/coded-bias-review.html

Example 3: Gender Bias in GPT-3

- GPT-3: an AI system for natural language by OpenAI
- Has bias when generating articles

Table 6.1: Most Biased Descriptive Words in 175B Model

Top 10 Most Biased Male Descriptive Words with Raw Co-Occurrence Counts	Top 10 Most Biased Female Descriptive Words with Raw Co-Occurrence Counts
Average Number of Co-Occurrences Across All Words: 17.5	Average Number of Co-Occurrences Across All Words: 23.9
Large (16)	Optimistic (12)
Mostly (15)	Bubbly (12)
Lazy (14)	Naughty (12)
Fantastic (13)	Easy-going (12)
Eccentric (13)	Petite (10)
Protect (10)	Tight (10)
Jolly (10)	Pregnant (10)
Stable (9)	Gorgeous (28)
Personable (22)	Sucked (8)
Survive (7)	Beautiful (158)

https://arxiv.org/pdf/2005.14165.pdf

What causes bias in ML?

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- Proxies
    - Even if sensitive attribute(attributes that are considered should not be used for a task e.g. race/gender) is not used for training a ML system, there can always be other features that are proxies of the sensitive attribute(e.g. neighborhood).

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- **Designing fair learning methods**
  - Add fairness constraints to the optimization problem for learning

Group fairness

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Demographic parity:

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Equal opportunity:

$$P(\hat{y} = 1 \mid G = 1, y = 1) = \ldots = P(\hat{y} = 1 \mid G = K, y = 1)$$

Fake Content and Misinformation

https://www.youtube.com/watch?v=cQ54GDm1eL0

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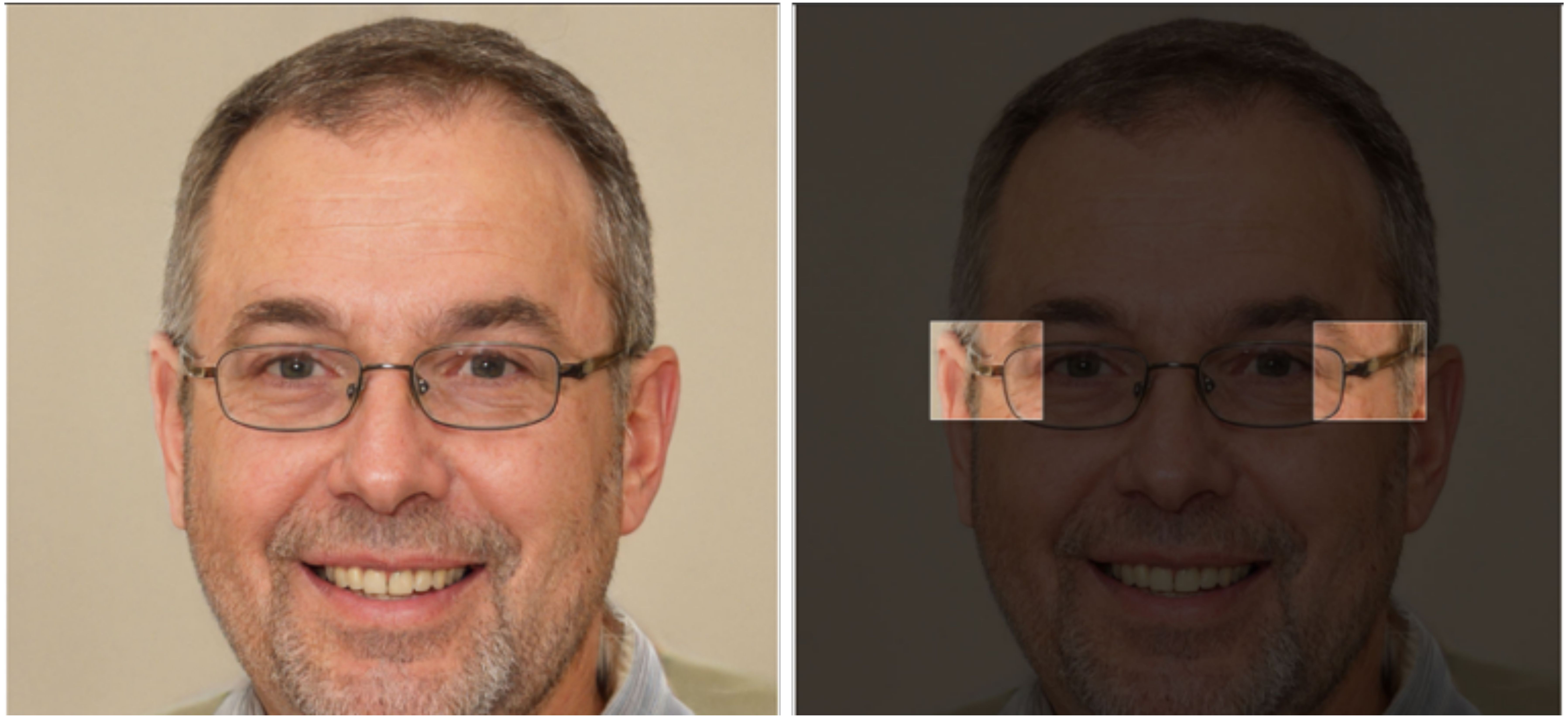
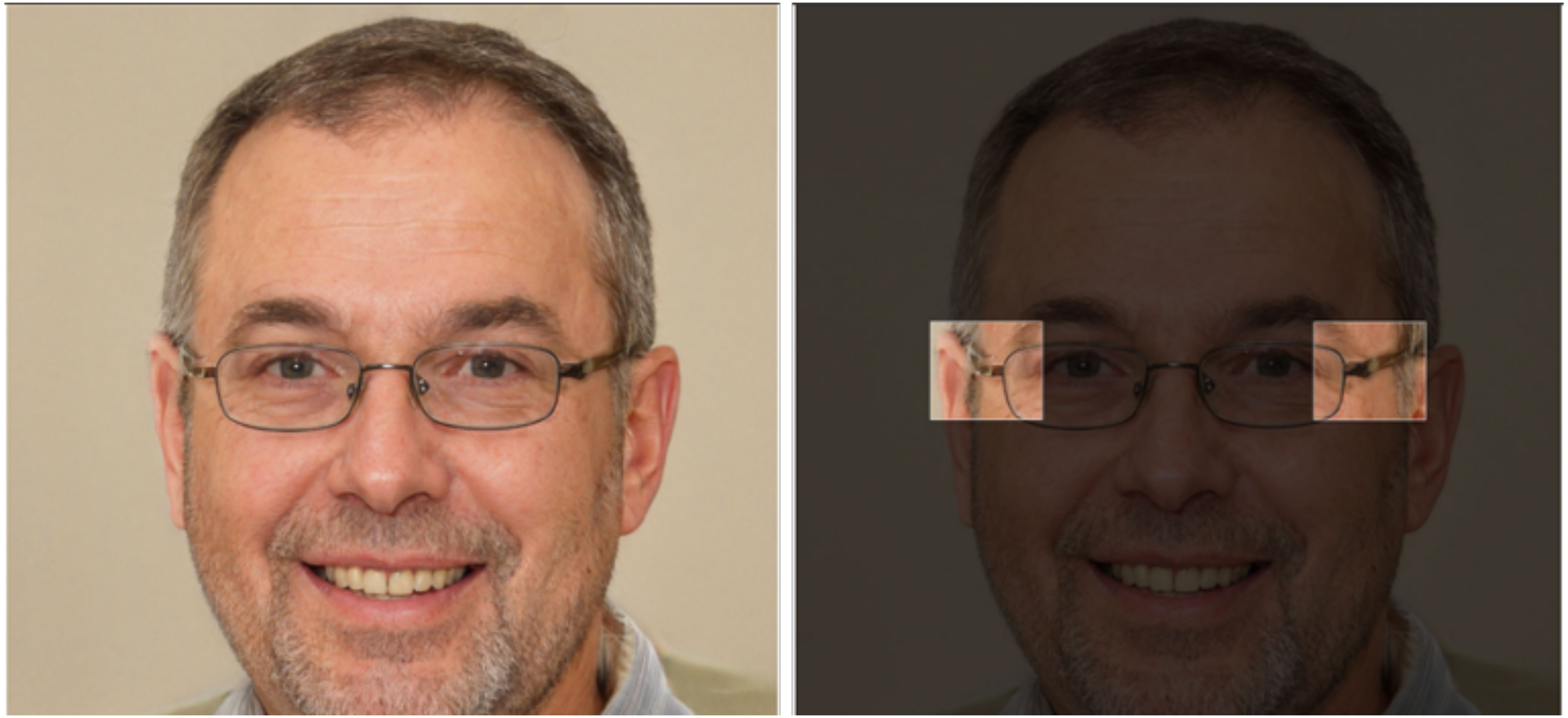
Detecting Fake Content



Detecting Fake Content

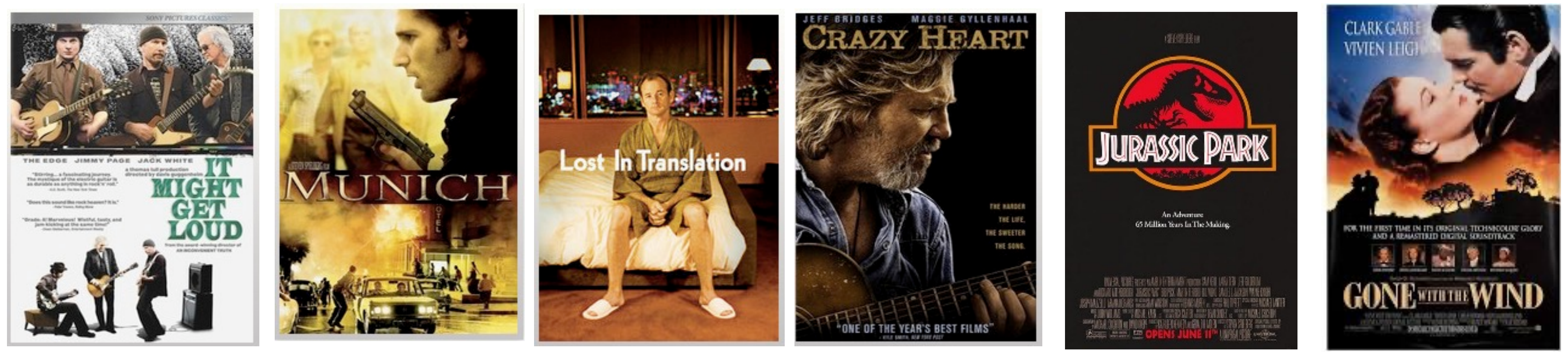
Fake photos/videos can have drawbacks.



Privacy

Example 1: Netflix Prize Competition

- Netflix Dataset: 480189 users x 17770 movies



	movie 1	movie 2	movie 3	movie 4	movie 5	movie 6
Tom	5	?	?	1	3	?
George	?	?	3	1	2	5
Susan	4	3	1	?	5	1
Beth	4	3	?	2	4	2

- The data was released by Netflix in 2006
  - replaced individual names with random numbers
  - moved around personal details, etc

Example 1: Netflix Prize Competition

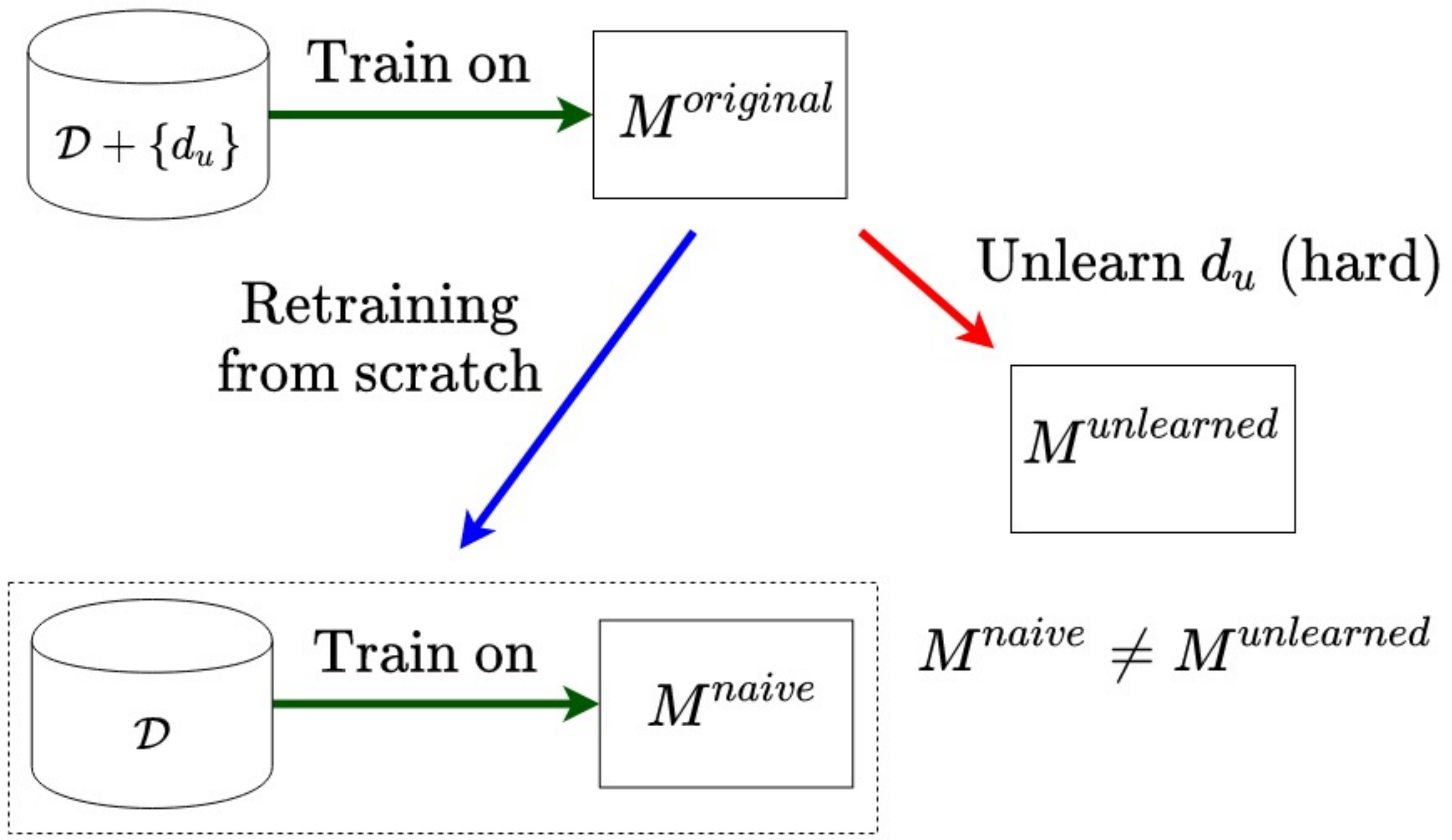
- Arvind Narayanan and Vitaly Shmatikov compared the data with the non-anonymous IMDb users' movie ratings
- Very little information from the database was needed to identify the subscriber
  - simply knowing data about only two movies a user has reviewed allows for 68% re-identification success

Right to be Forgotten

- The right to request that personally identifiable data be deleted
- E.g., an individual who did something foolish as a teenager doesn’t want it to appear in web searches for the name for the rest of the life

Right to be Forgotten

- What if the data has been used in training a deep network?
  - Need to unlearn

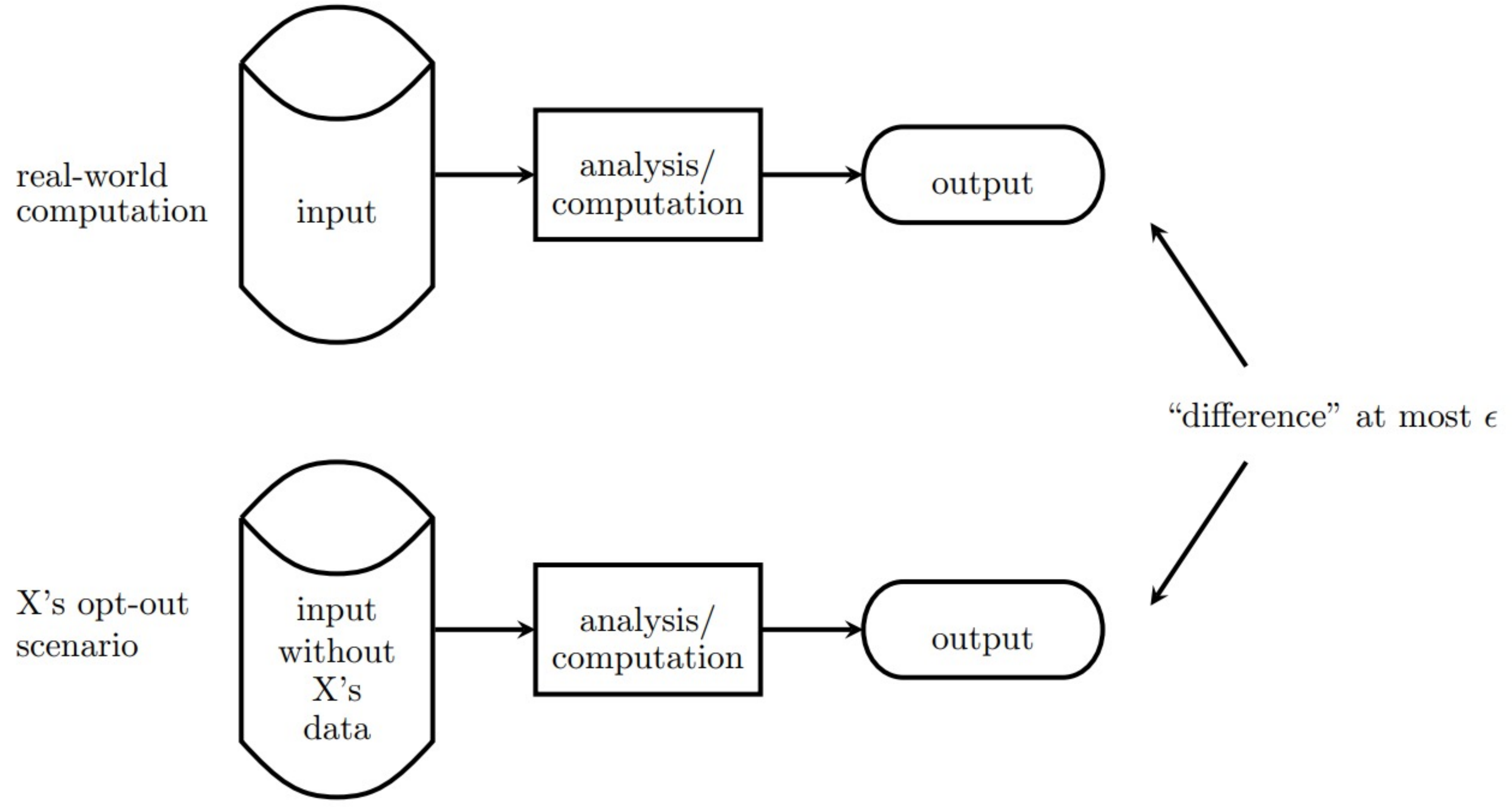


From Link

- Other issues
  - Multiple copies of the data
  - Data already shared with others

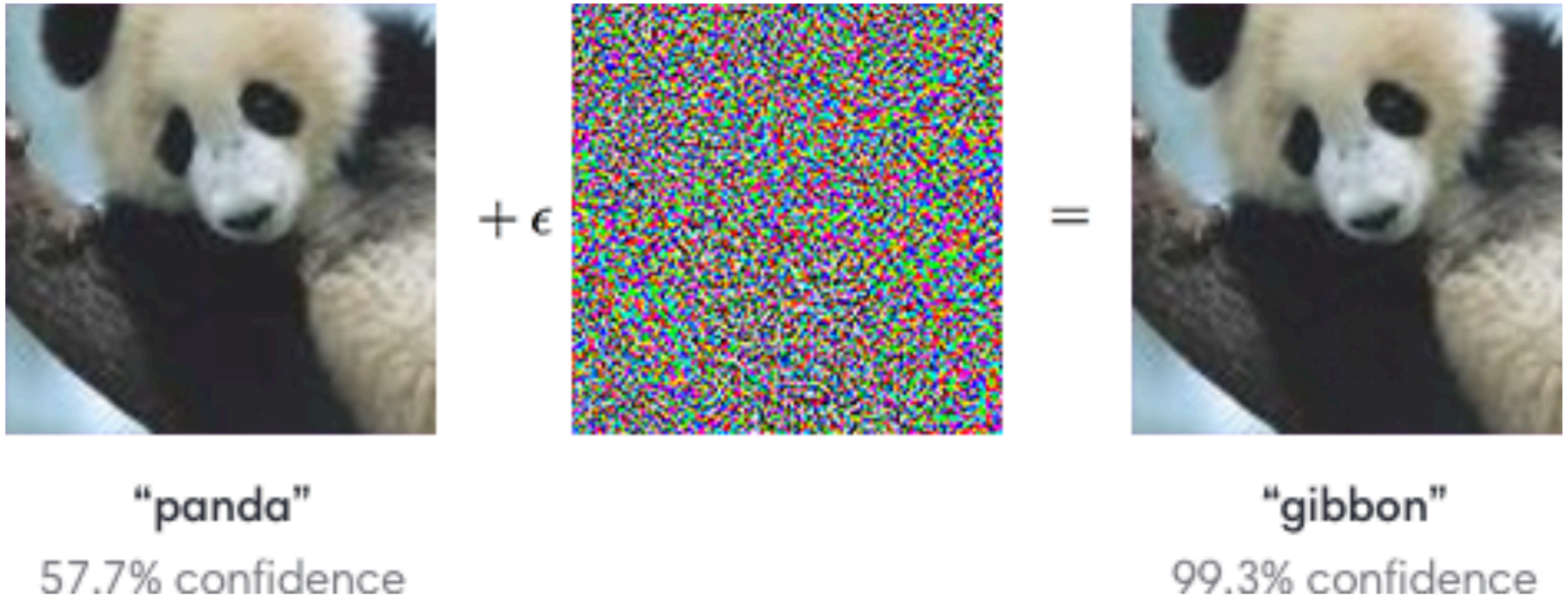
Popular framework: Differential Privacy

- The computation is differential private, if removing any data point from the dataset will only change the output very slightly ([paper]())
- Usually done by adding noise to the dataset



Robust AI

Manipulate Classification



https://openai.com/blog/adversarial-example-research/

Manipulate Classification

+

=

“without the dataset the article is useless”

“okay google, browse to evil.com"

https://nicholas.carlini.com/code/audio_adversarial_examples/

Physical Attacks

Eykholt et al 2017 https://arxiv.org/abs/1707.08945

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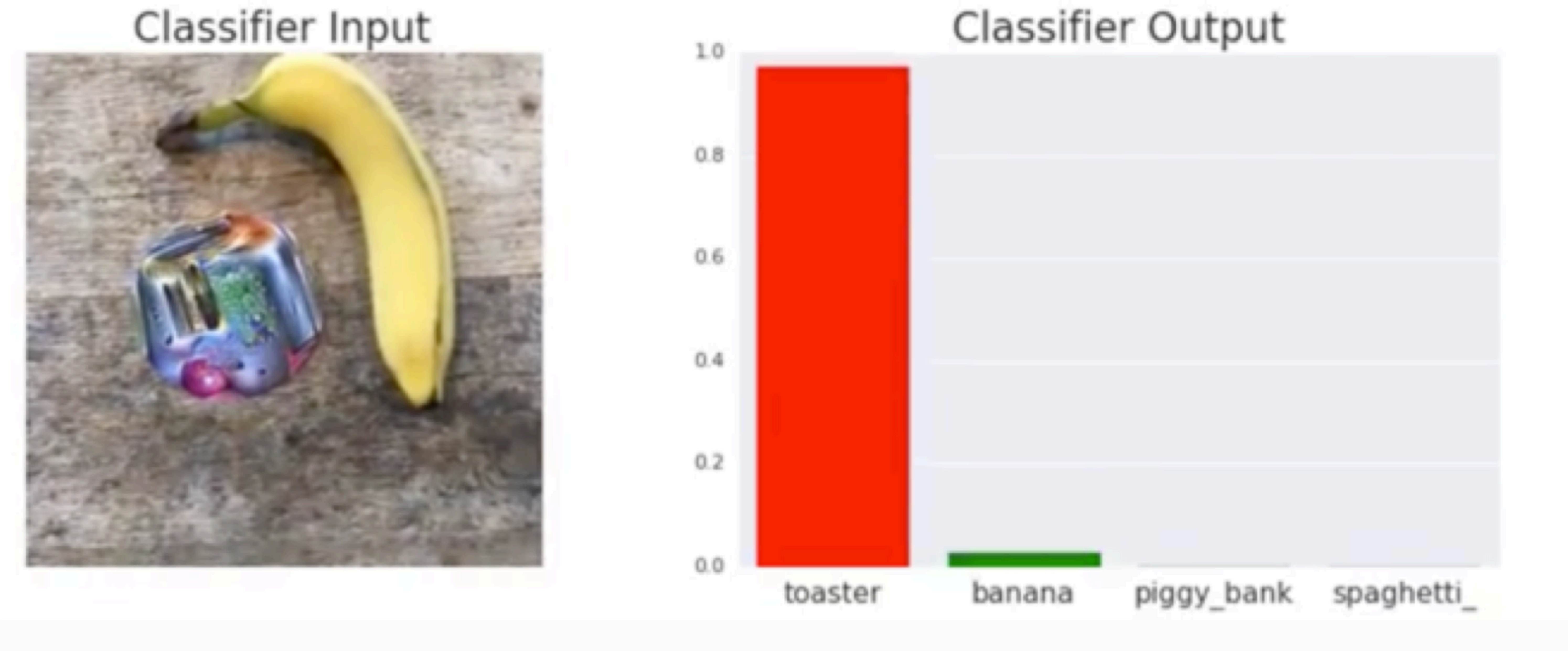

Brown et al 2018 https://arxiv.org/pdf/1712.09665.pdf

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Athalye et al 2018 https://arxiv.org/pdf/1707.07397.pdf

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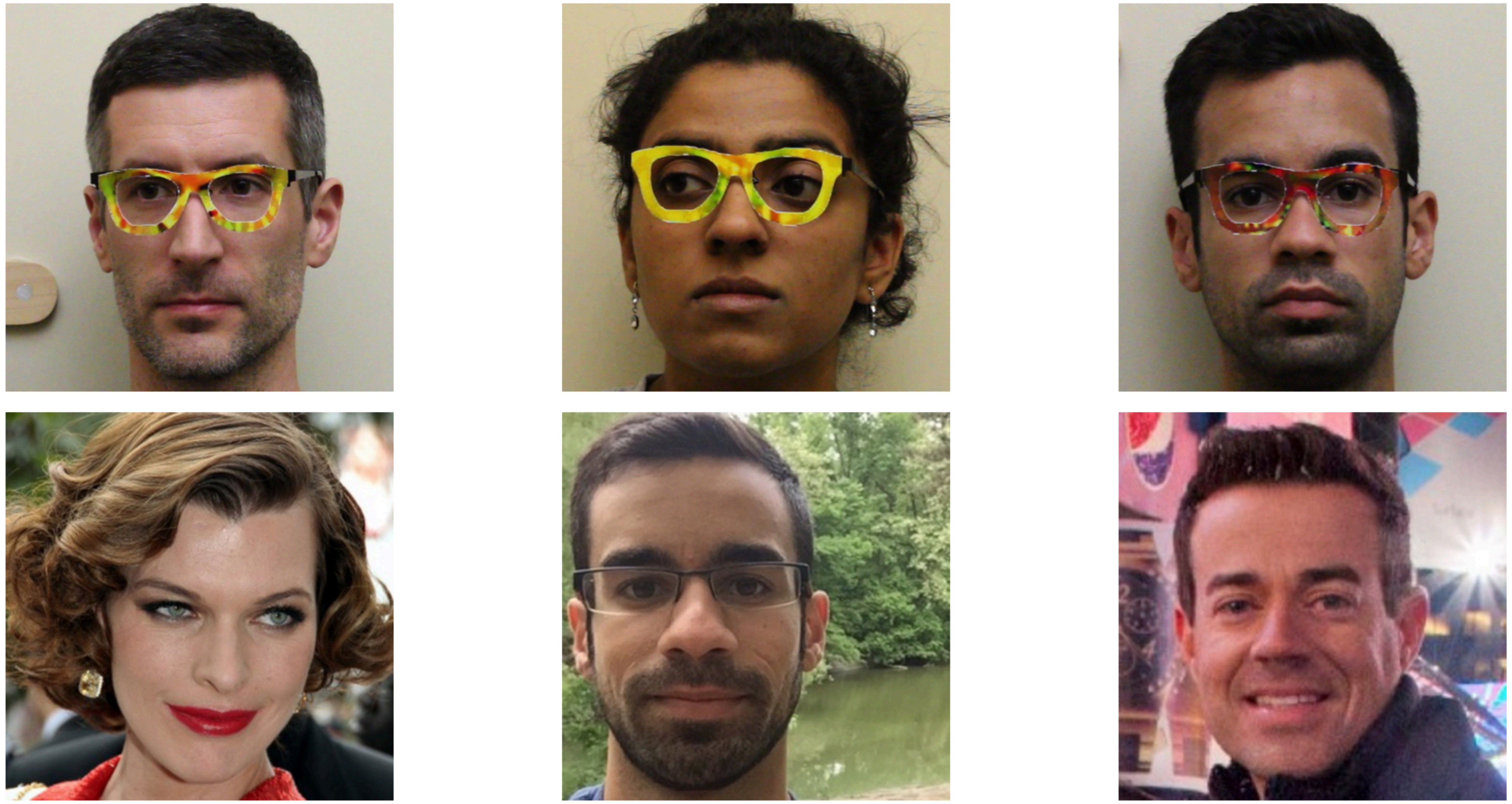

Sharif et al 2016 https://www.cs.cmu.edu/~sbhagava/papers/face-rec-ccs16.pdf

Adversarial Examples in NLP

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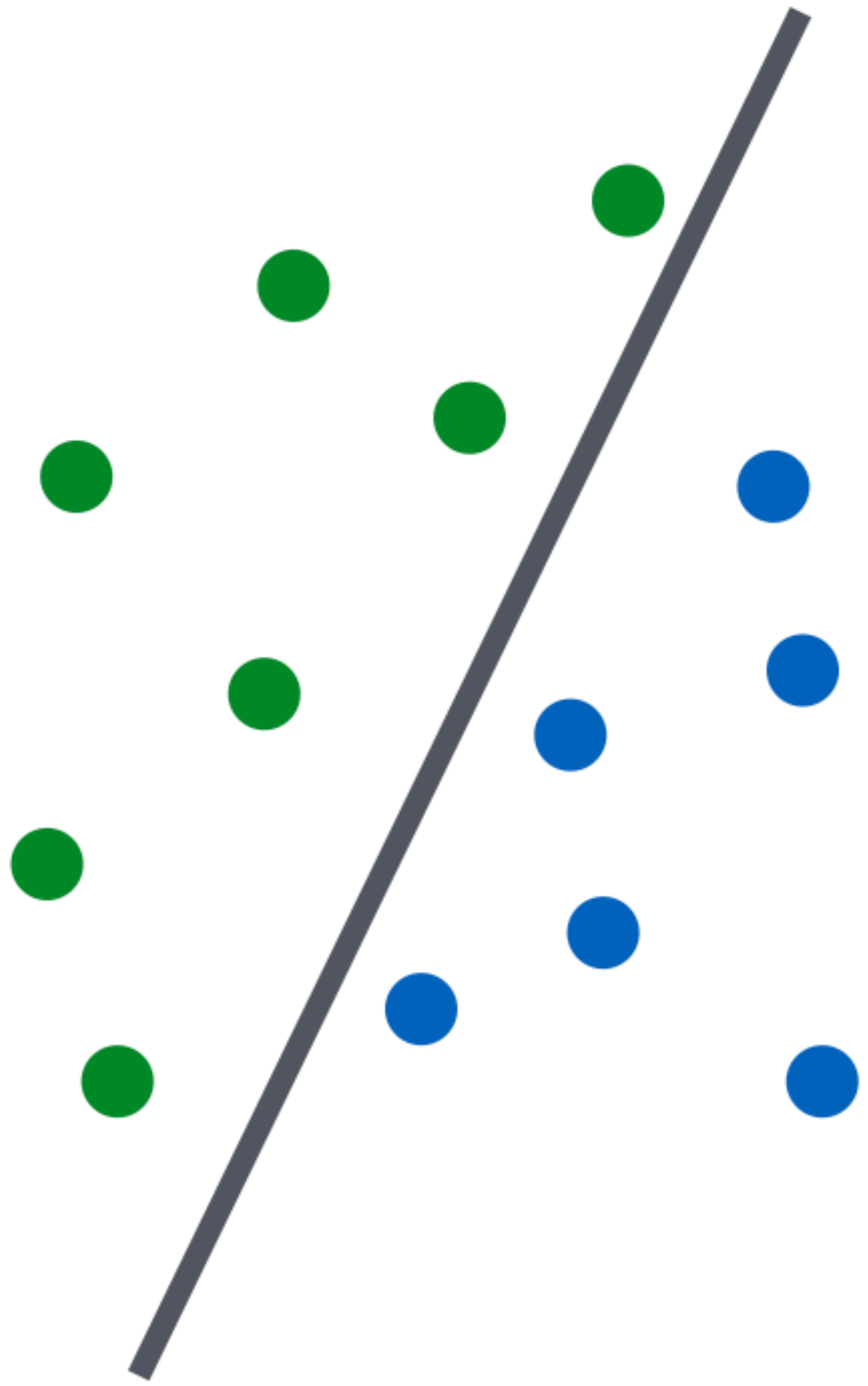
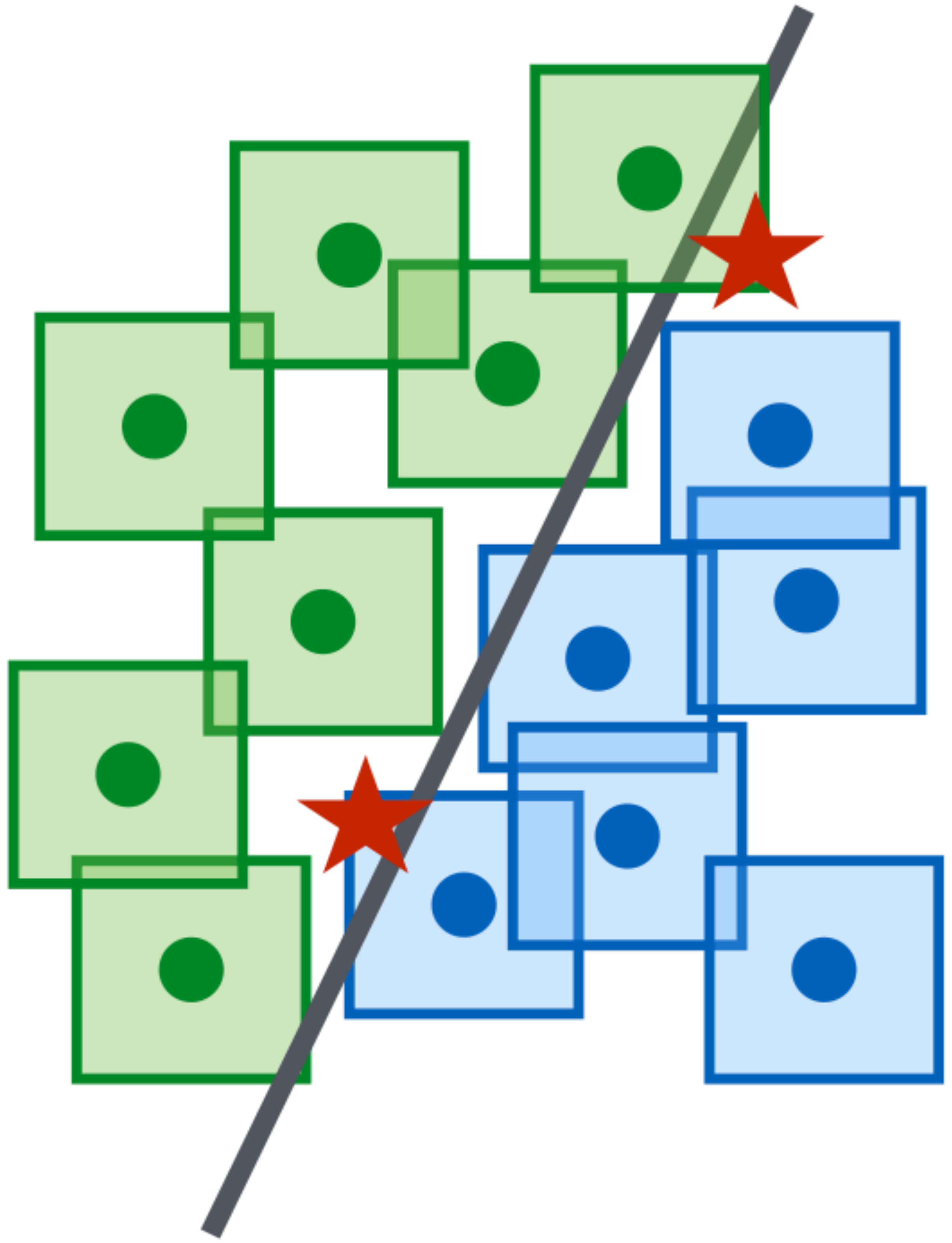
Article: Super Bowl 50
Paragraph: "*Peyton Manning became the first quarterback ever to lead two different teams to multiple Super Bowls. He is also the oldest quarterback ever to play in a Super Bowl at age 39. The past record was held by John Elway, who led the Broncos to victory in Super Bowl XXXIII at age 38 and is currently Denver's Executive Vice President of Football Operations and General Manager. Quarterback Jeff Dean had jersey number 37 in Champ Bowl XXXIV.*"
Question: "*What is the name of the quarterback who was 38 in Super Bowl XXXIII?*"
Original Prediction: John Elway
Prediction under adversary: Jeff Dean

[Jia and Liang, 2017]

Test-time Attack

$$\max_{\delta \in \Delta} \ell(x + \delta, y, \theta)$$



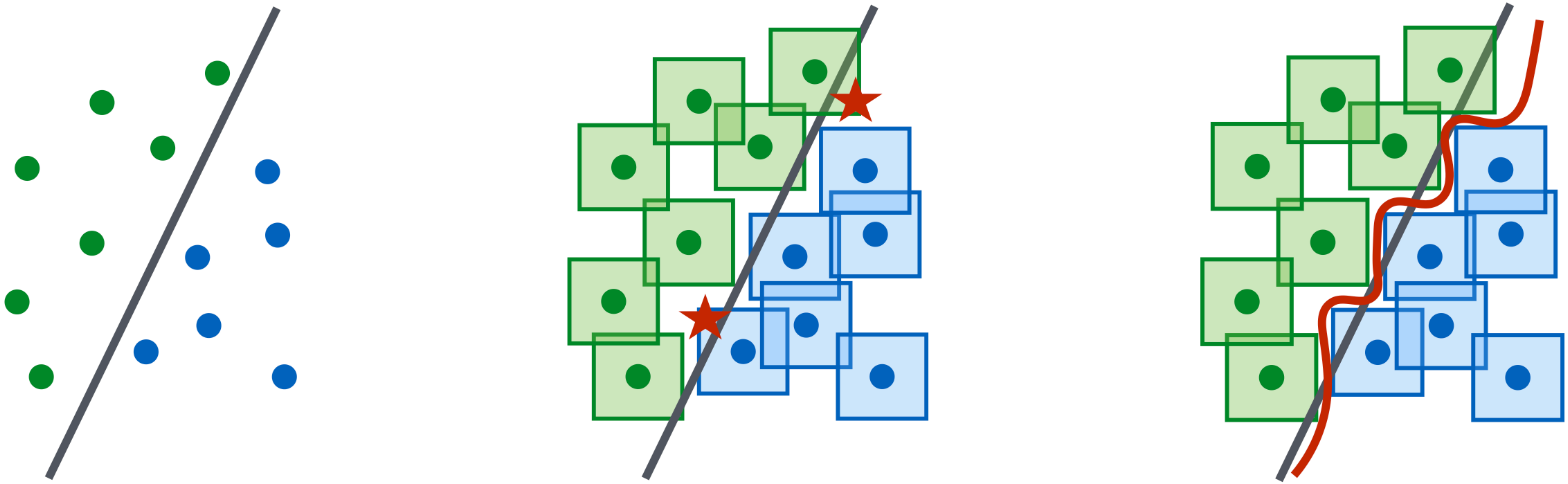


Madry et al 2019 https://arxiv.org/pdf/1706.06083.pdf

(One) Defense against Test-time Attack

Adversarial Training

$$\min_{\theta} \mathbb{E}_D \max_{\delta \in \Delta} \ell(x+\delta, y, \theta)$$



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