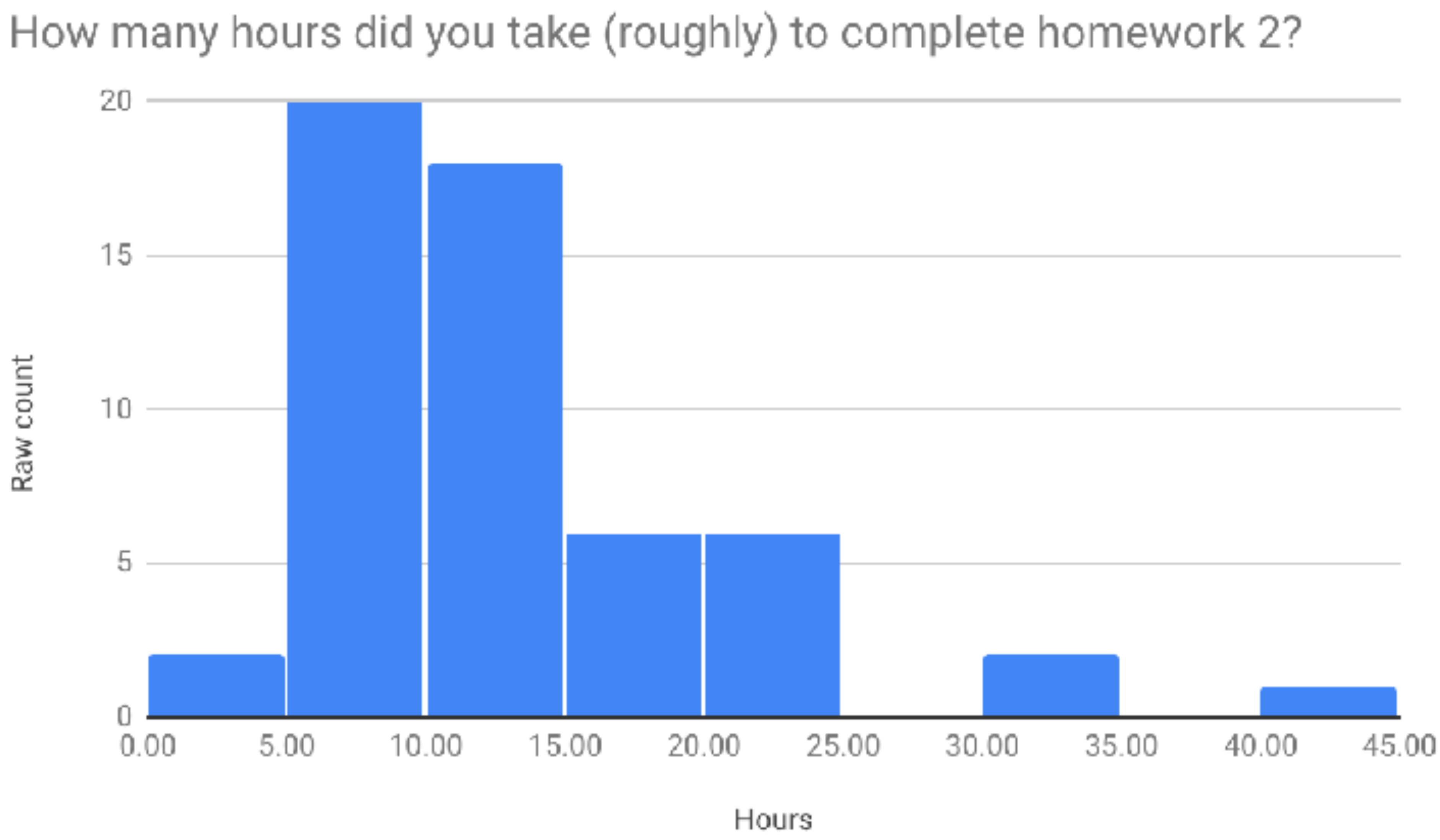
Carnegie Mellon University
Heinz College

95-865 Pittsburgh Lecture 12: Interpreting What Deep Nets are Learning, Other Deep Learning Topics, Wrap-up

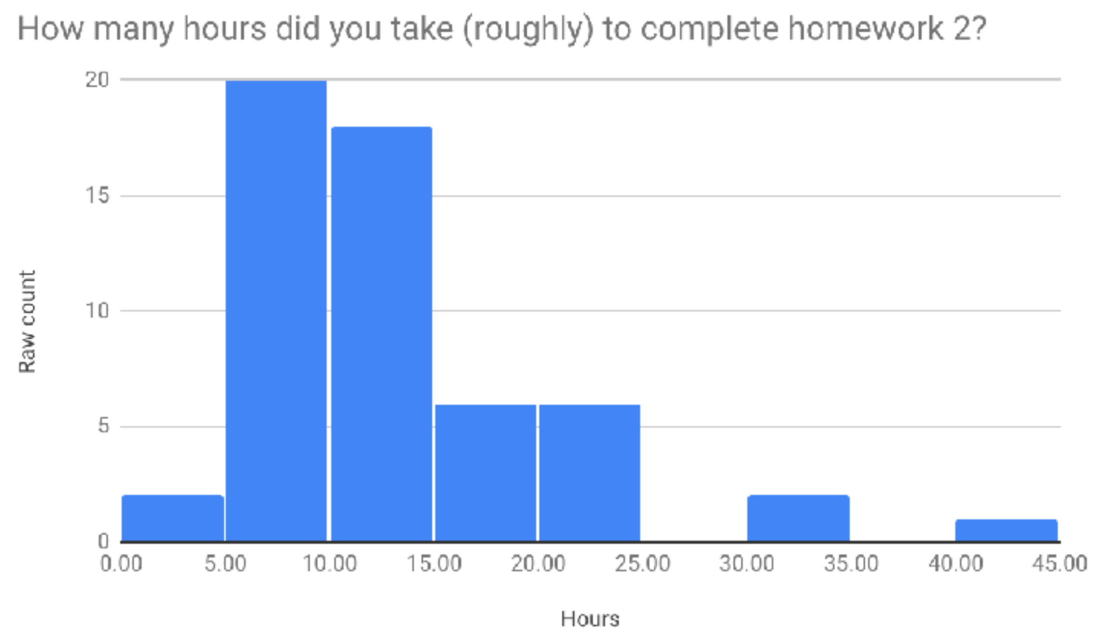
George Chen

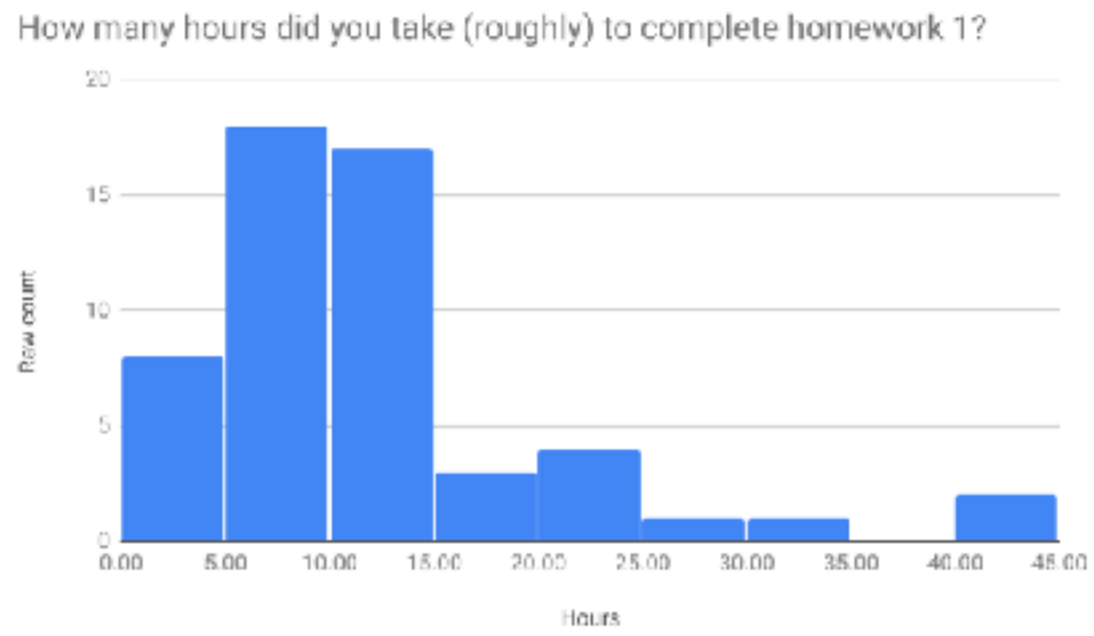
HW2 Questionnaire



This distribution is almost the same as for HW1

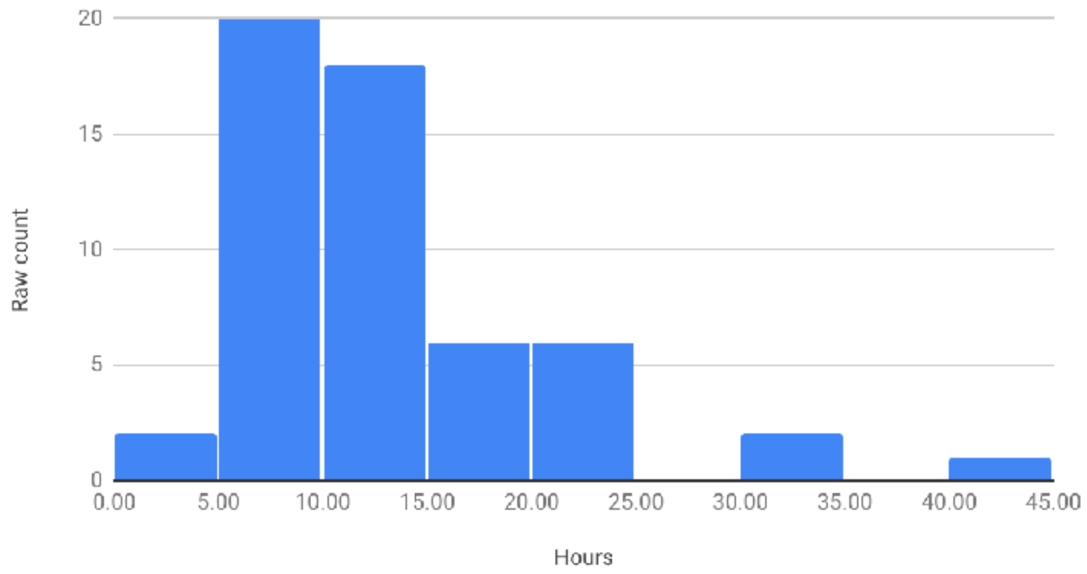
HW2 Questionnaire


How many hours did you take (roughly) to complete homework 2?


How many hours did you take (roughly) to complete homework 1?

This distribution is almost the same as for HW1

HW2 Questionnaire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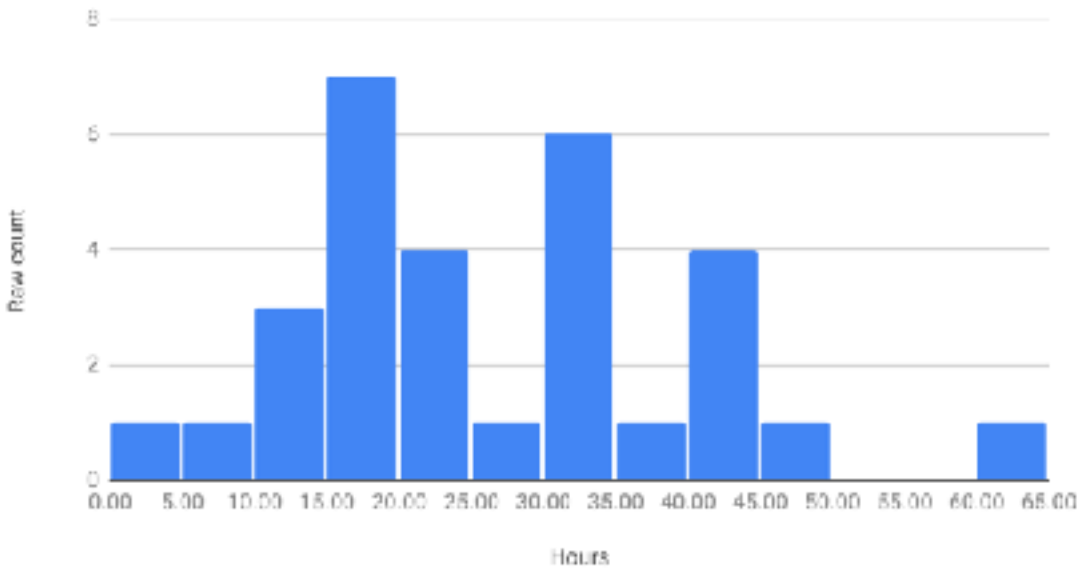
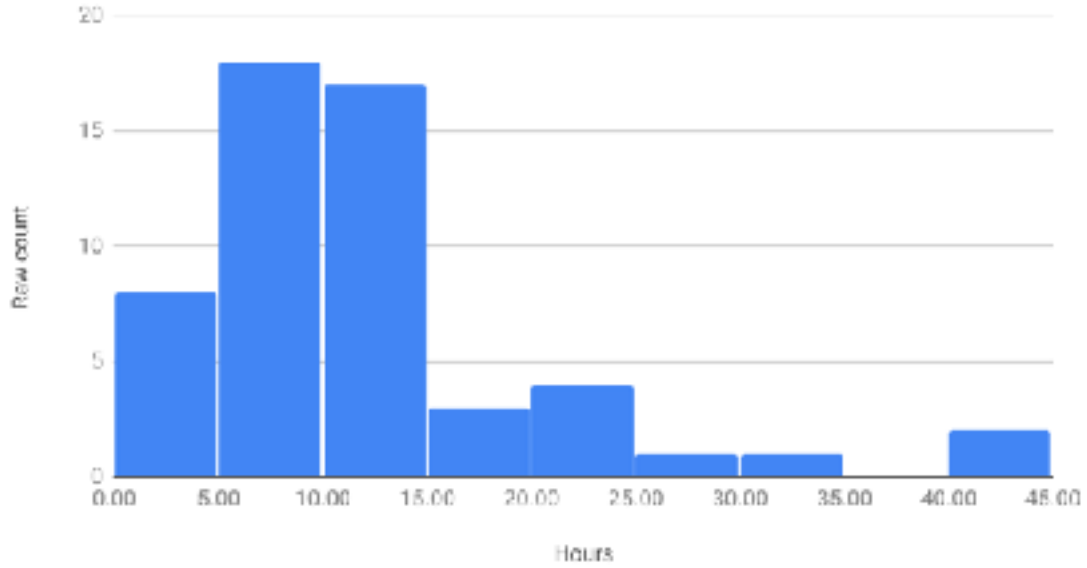

How many hours did you take (roughly) to complete homework 3?

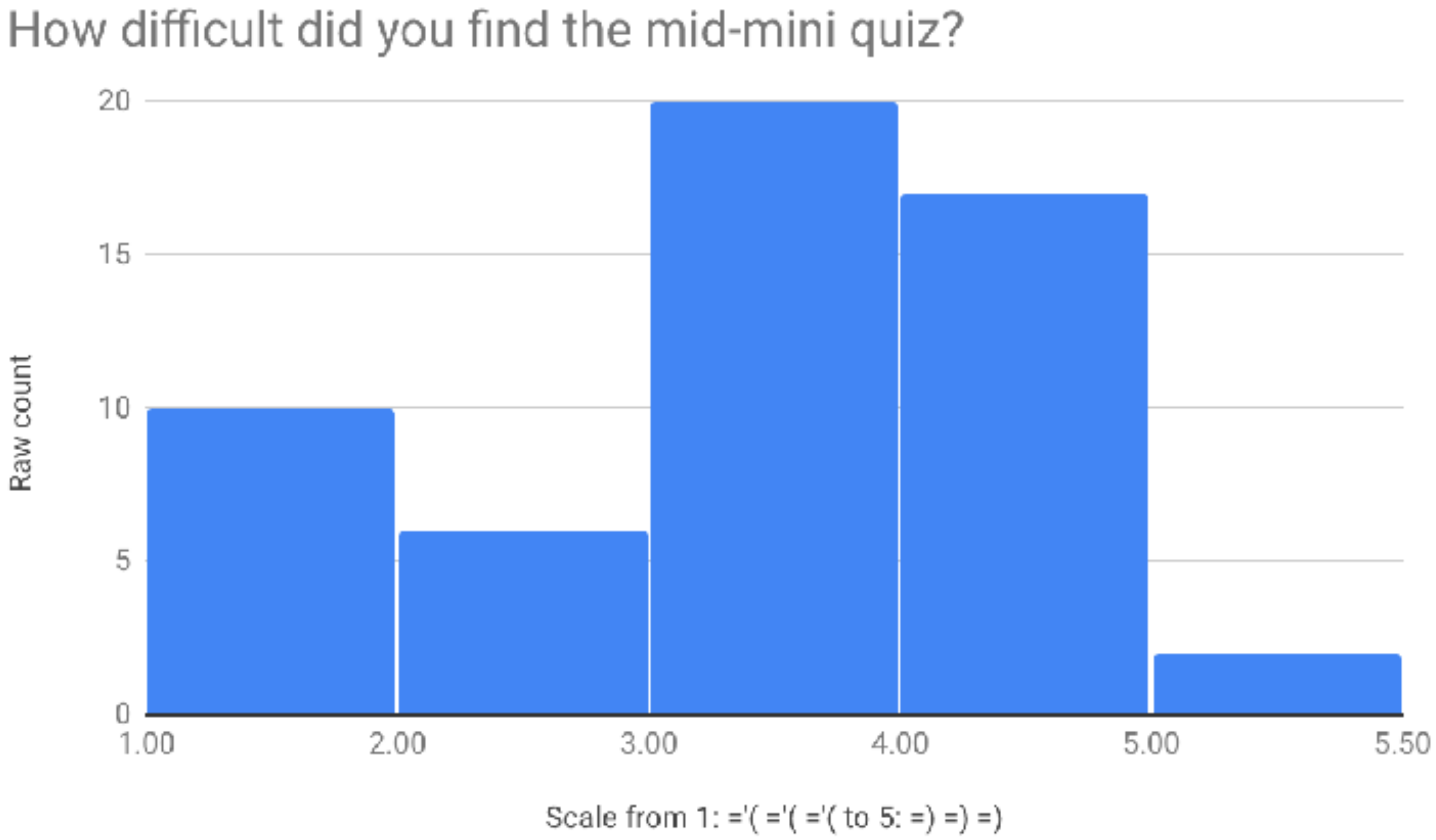

How many hours did you take (roughly) to complete homework 1?

Preview
(survey still in progress!)

HW3 appears to
take more time!

How hard will the final exam be?

How Students Felt About the Quiz



My guess: the final exam will be similarly difficult

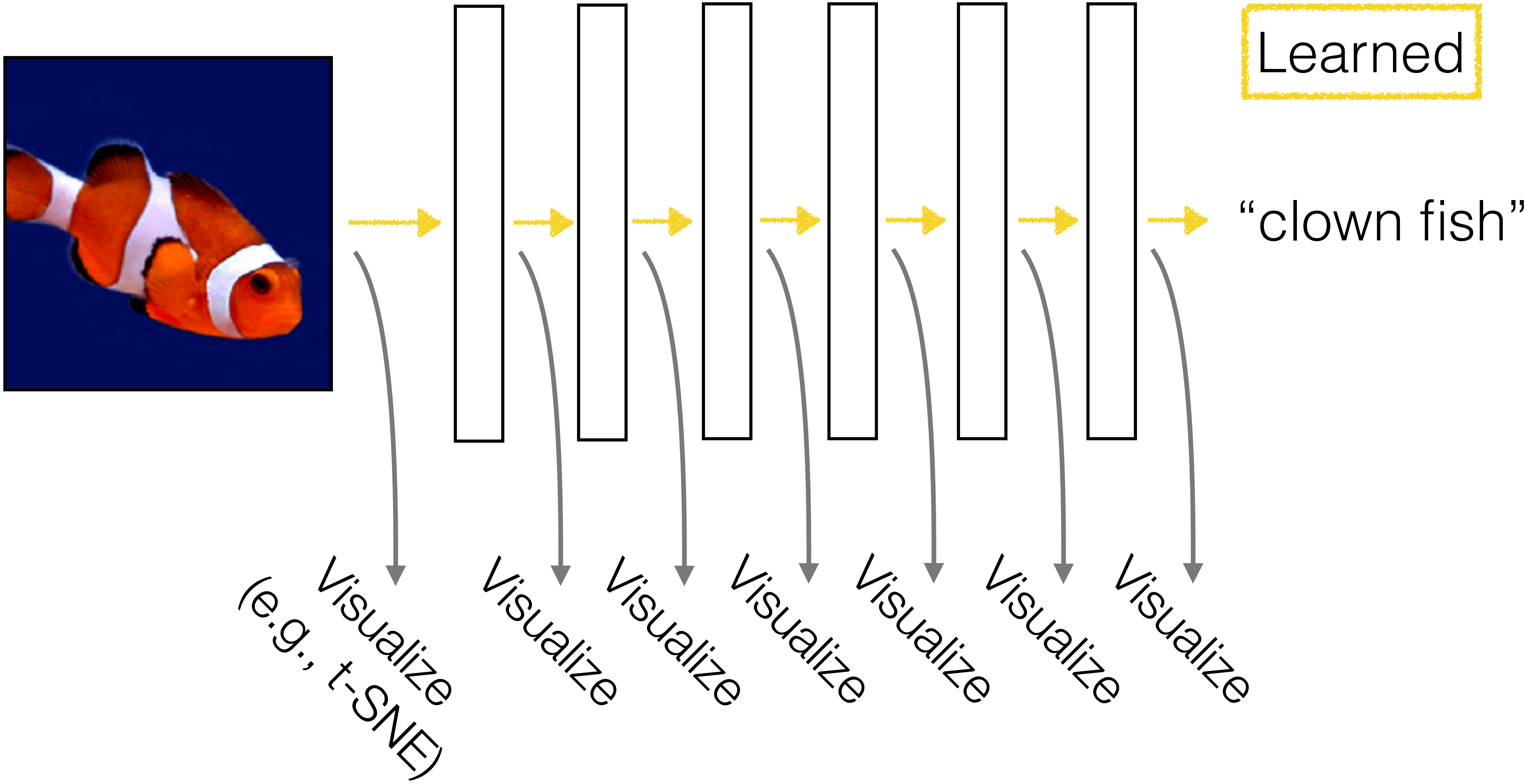
Today

- Interpreting what a deep net is learning

- High-level overview of a bunch of deep learning topics we didn’t get to

- Course wrap-up

What is a Deep Net Learning?



Learned

“clown fish”

Visualize (e.g., t-SNE)

Visualize

Visualize

Visualize

Visualize

Visualize

Visualize

1 strategy: just put in test images and visualize intermediate outputs

Another Strategy

How much does an output neuron depend on a specific input?

$$f(x, y) = x^2 + xy$$

$$\frac{\partial f(x, y)}{\partial x} = 2x + y$$

$$\frac{\partial f(x, y)}{\partial y} = x$$

For specific inputs *x* and *y:* look at how large these derivatives are!

Another Strategy

How much does an output neuron depend on a specific input?

$$f(x, y) = x^2 + xy$$

$$\frac{\partial f(x, y)}{\partial x} = 2x + y \quad = 2\ (0) + 0.5 = 0.5$$

e.g., *x* = 0, *y* = 0.5

$$\frac{\partial f(x, y)}{\partial y} = x \quad = 0$$

Conclude: in this case, *x* has larger effect on output than *y*

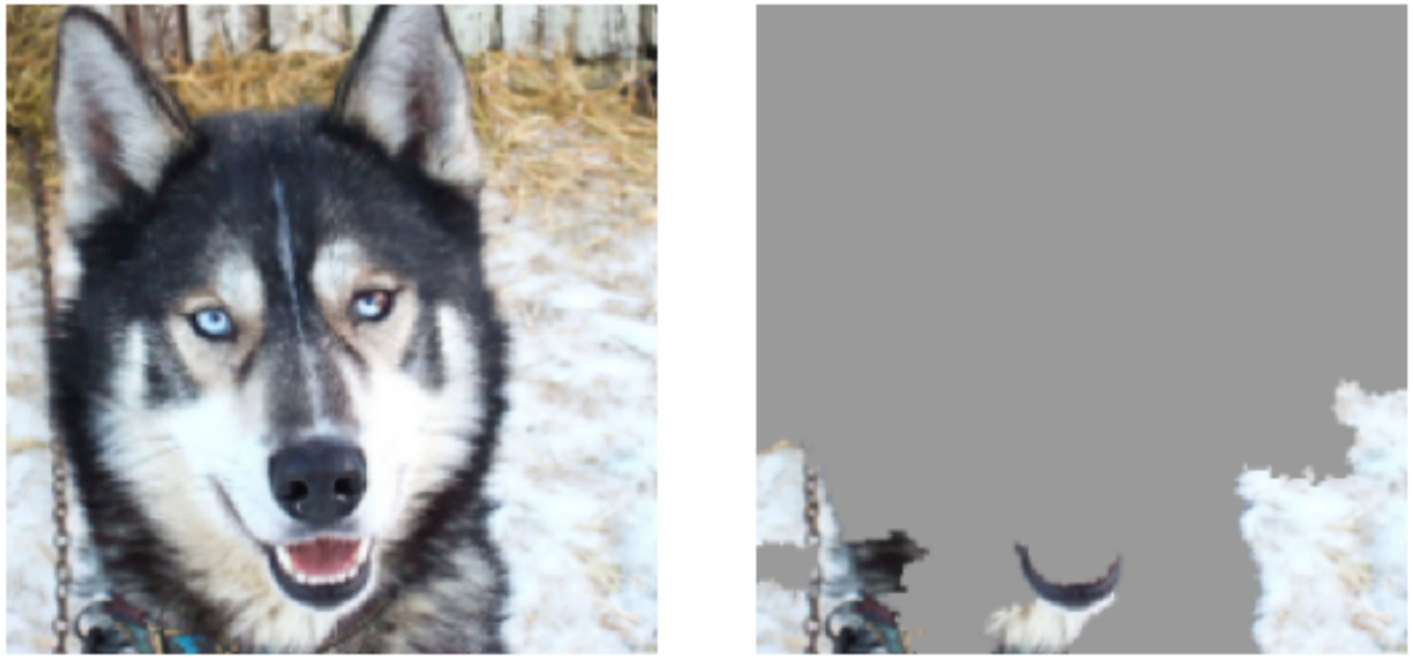
For specific inputs *x* and *y:* look at how large these derivatives are!

For any two neurons, we can look at how much one affects another

Interpreting Deep Nets

Demo

Example: Wolves vs Huskies



(a) Husky classified as wolf

(b) Explanation

Turns out the deep net learned that wolves are wolves because of snow…

➔ visualization is crucial!

Source: Ribeiro et al. “Why should I trust you? Explaining the predictions of any classifier.” KDD 2016.

There’s a lot more to deep learning that we didn’t cover

Keep in mind: we only covered the super basics!

Deep learning has lots of fads!

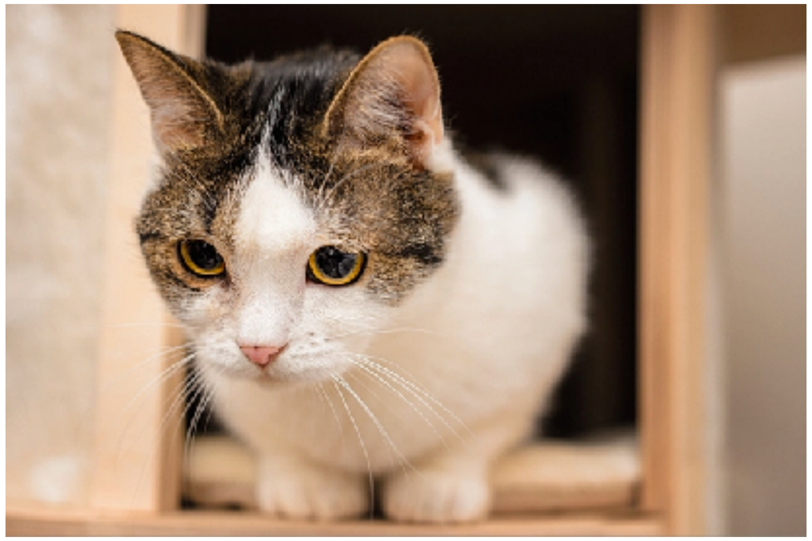
For example: pooling is on the way out, ResNets are all the rage

Dealing with Small Datasets

Data augmentation: generate perturbed versions of your training data to get larger training dataset

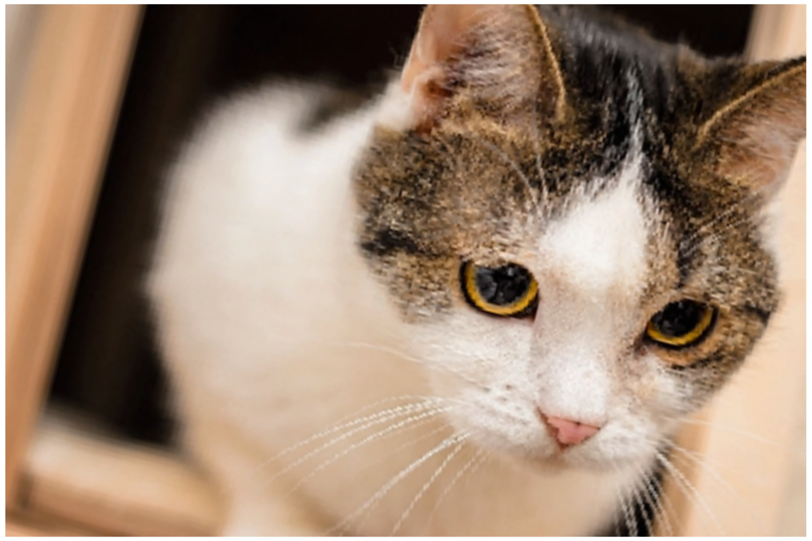
Training image

Training label: cat



Mirrored

Still a cat!



Rotated & translated

Still a cat!

We just turned 1 training example in 3 training examples

Allowable perturbations depend on data (e.g., for handwritten digits, rotating by 180 degrees would be bad: confuse 6’s and 9’s)

Dealing with Small Datasets

Fine tuning: if there's an existing pre-trained neural net, you could modify it for your problem that has a small dataset

Example: classify between Tesla's and Toyota's

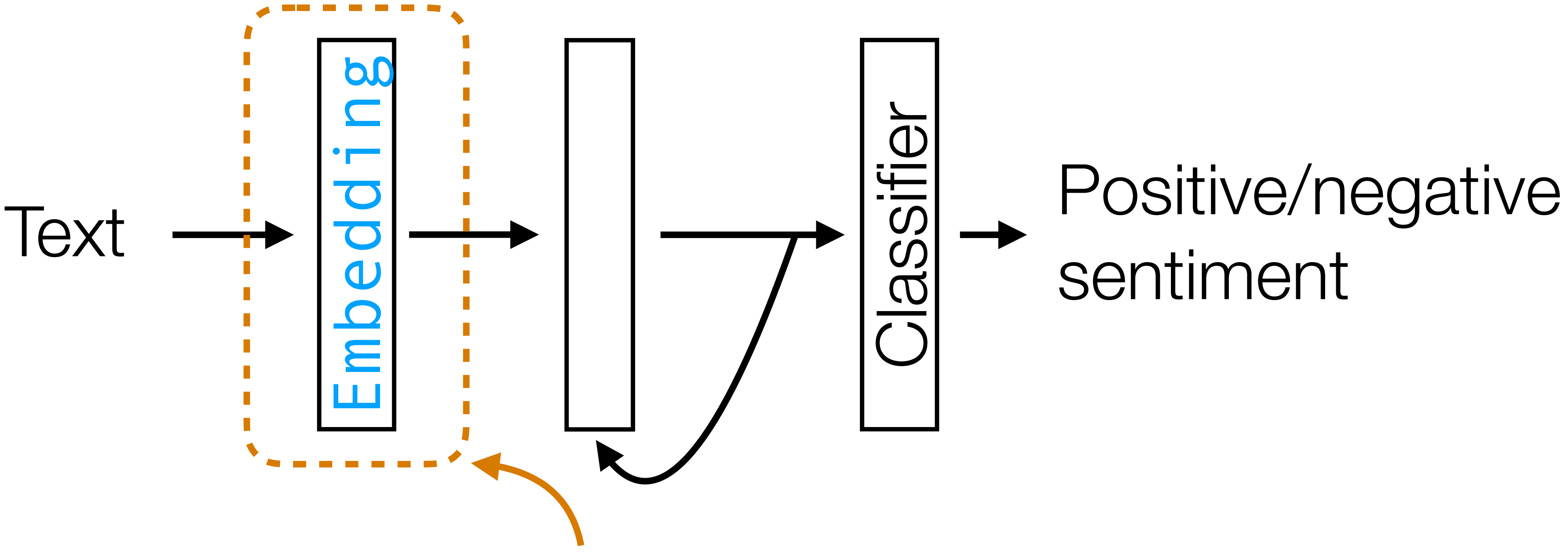
You collect photos from the internet of both, but your dataset size is small, on the order of 1000 images

Strategy: take existing pre-trained CNN for ImageNet classification and change final layer to do classification between Tesla's and Toyota's rather than classifying into 1000 objects

Dealing with Small Datasets

Fine tuning: if there's an existing pre-trained neural net, you could modify it for your problem that has a small dataset

Example: sentiment analysis RNN demo



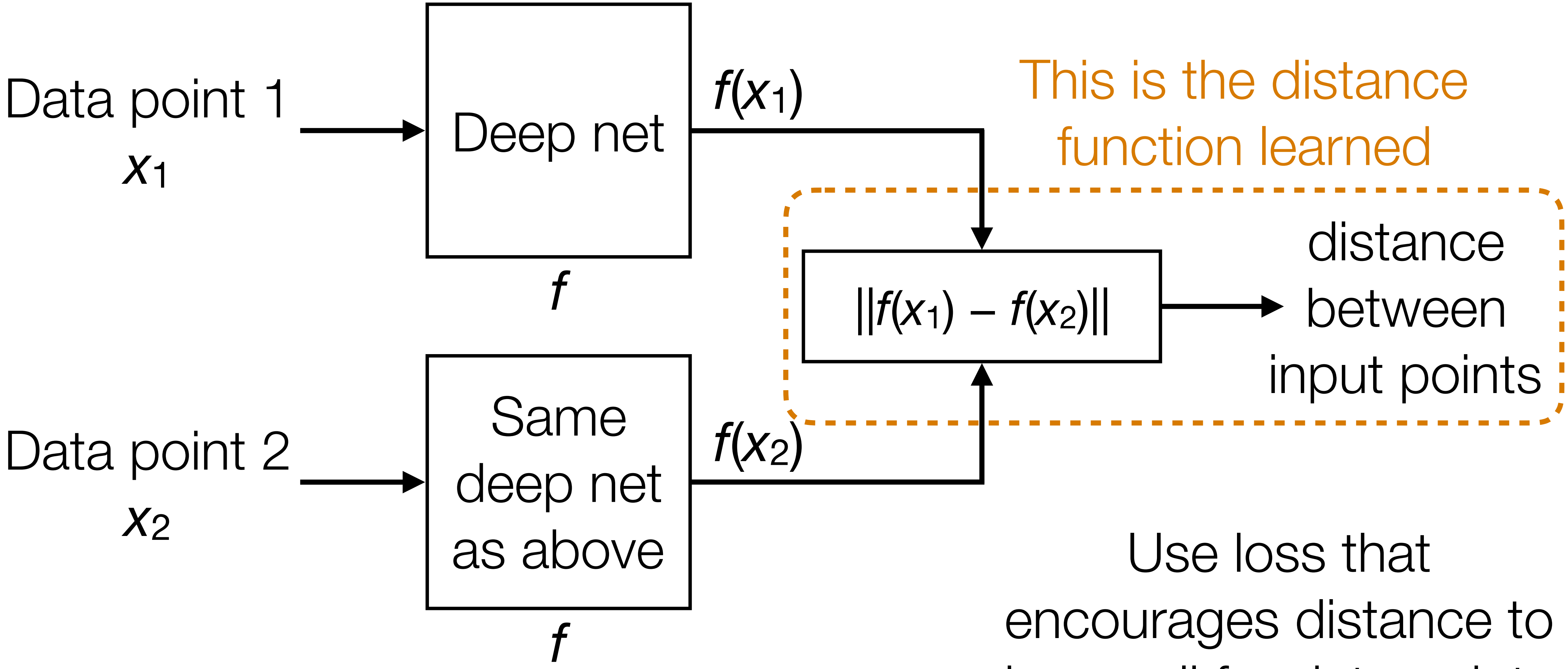
We fixed the weights here to come from GloVe and disabled training for this layer!

GloVe vectors pre-trained on massive dataset (Wikipedia + Gigaword)

IMDb review dataset is small in comparison

Learning Distances with Siamese Nets

Using labeled data, we can learn a distance function



Data point 1 x_1

Deep net

f

$f(x_1)$

Data point 2 x_2

Same deep net as above

f

$f(x_2)$

$\|f(x_1) - f(x_2)\|$

distance between input points

This is the distance function learned

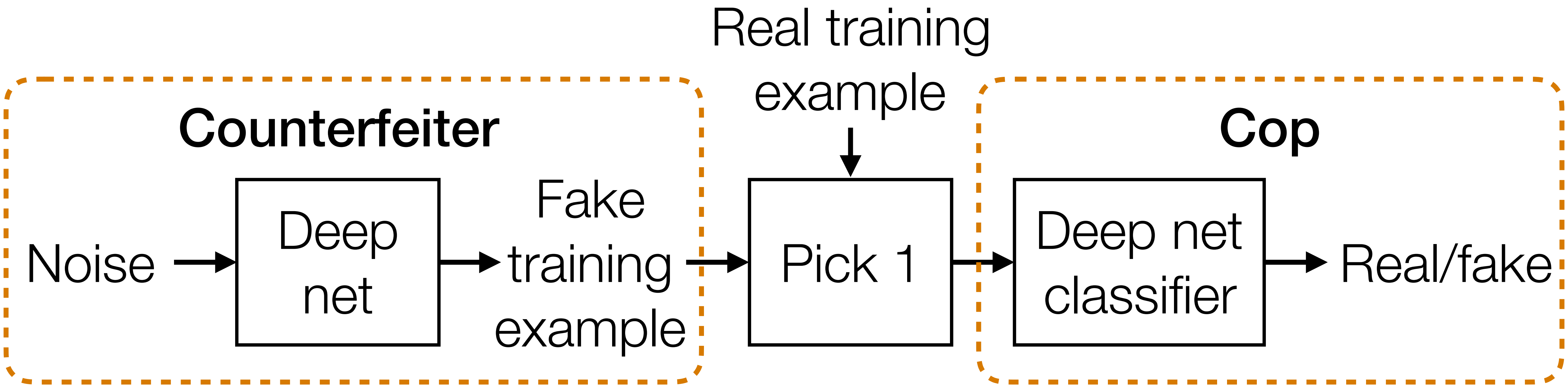
Use loss that encourages distance to be small for data points with same label and large otherwise

Note: we are learning the function *f*

Generate Fake Data that Look Real

Unsupervised approach: generate data that look like training data

Example: Generative Adversarial Network (GAN)



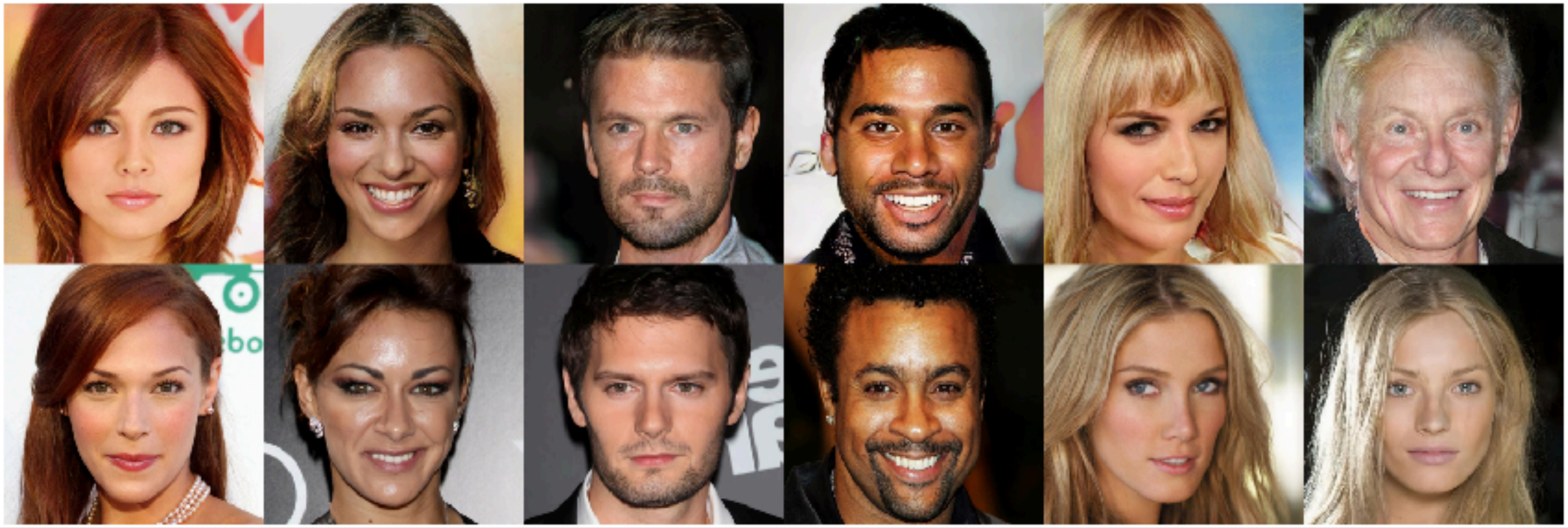
Counterfeiter tries to get better at tricking the cop

Cop tries to get better at telling which examples are real vs fake

Terminology: counterfeiter is the **generator**, cop is the **discriminator**

Other approaches: variational autoencoders, pixelRNNs/pixelCNNs

Generate Fake Data that Look Real



Fake celebrities generated by NVIDIA using GANs
(Karras et al Oct 27, 2017)

Google DeepMind's WaveNet makes fake audio that sounds like whoever you want using pixelRNNs (Oord et al 2016)

Generate Fake Data that Look Real

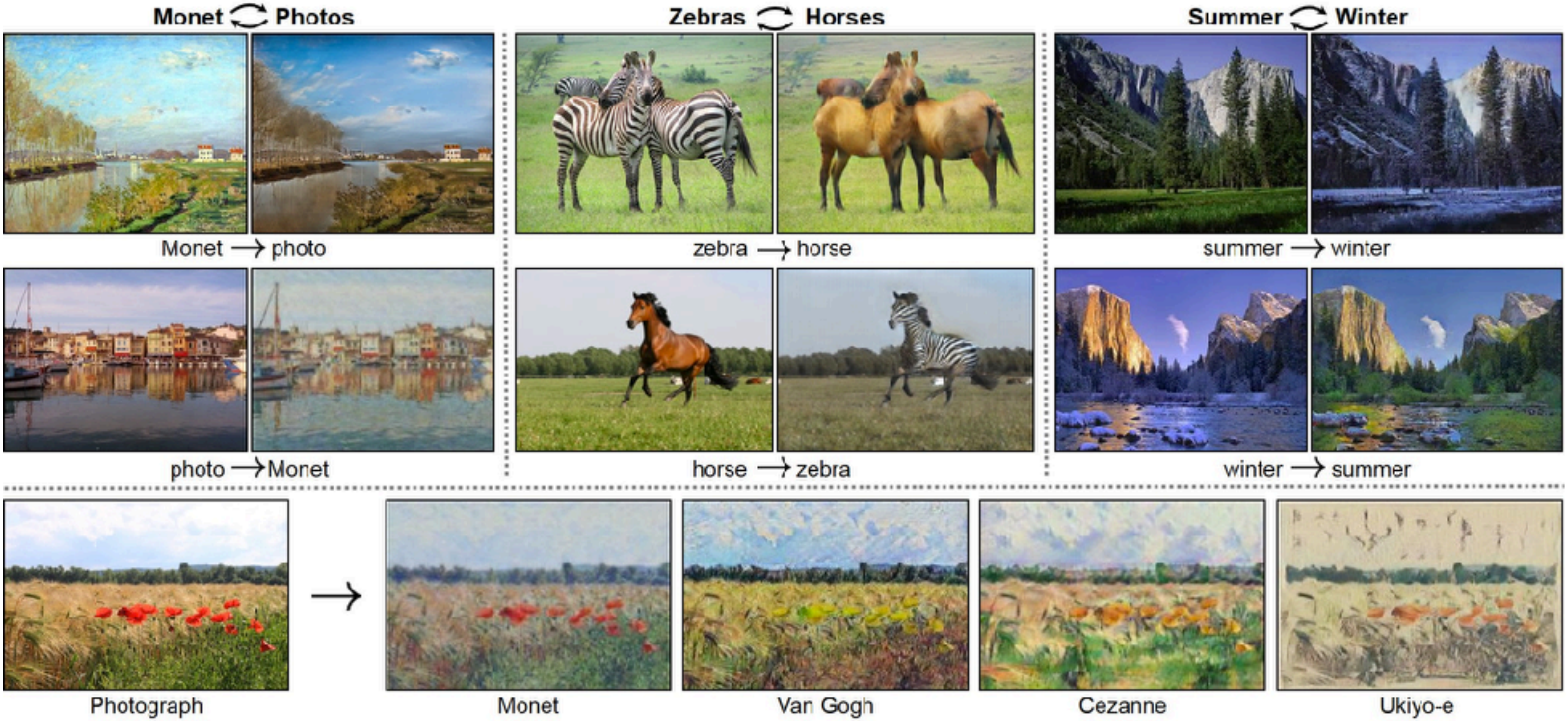
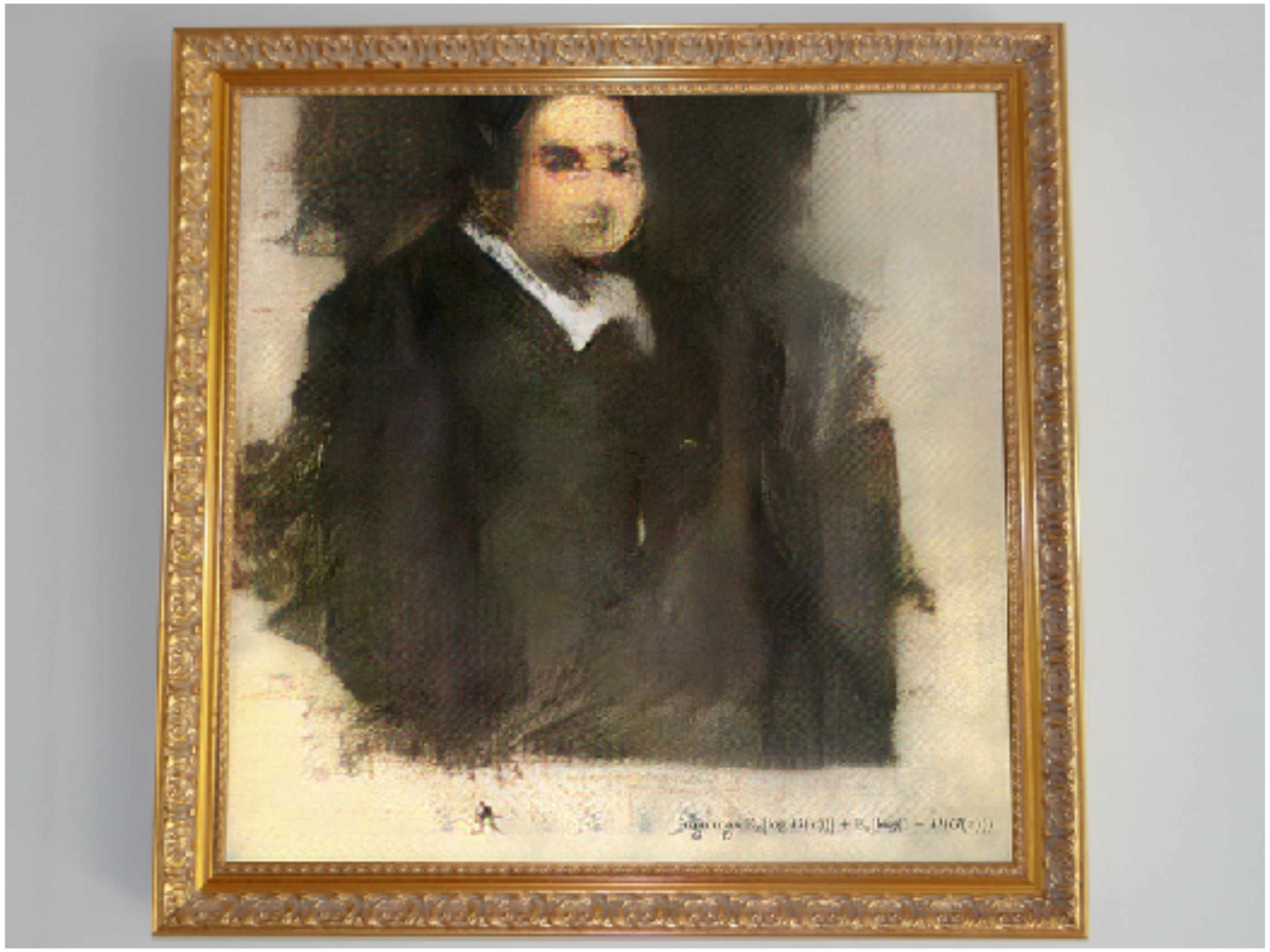


Image-to-image translation results from UC Berkeley using GANs (Isola et al 2017, Zhu et al 2017)

Generate Fake Art

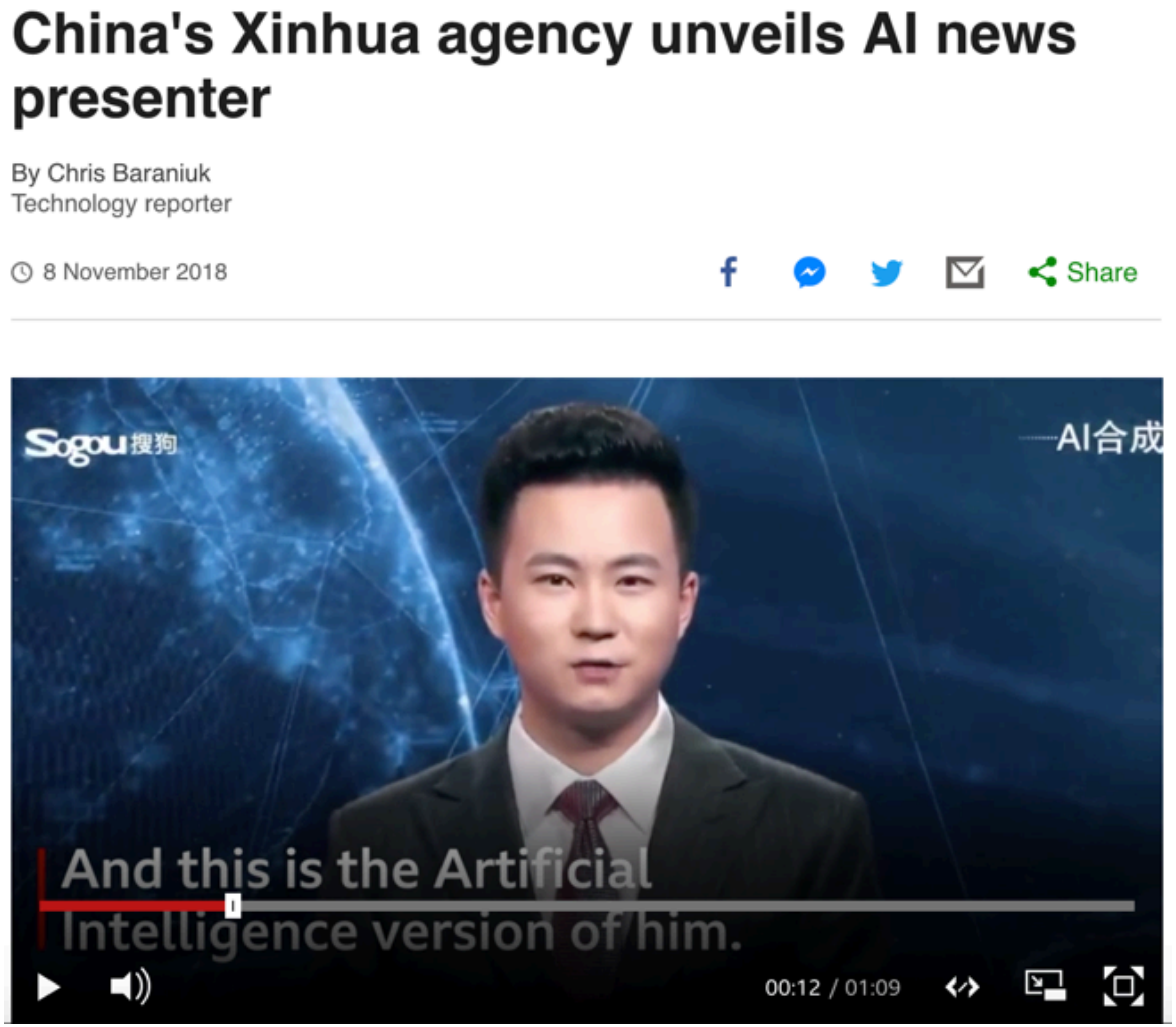


October 2018: estimated to go for $7,000-$10,000

10/25/2018: Sold for $432,500

Source: https://www.npr.org/2018/10/22/659680894/a-i-produced-portrait-will-go-up-for-auction-at-christie-s

AI News Anchor



China's Xinhua agency unveils AI news presenter

By Chris Baraniuk
Technology reporter

8 November 2018

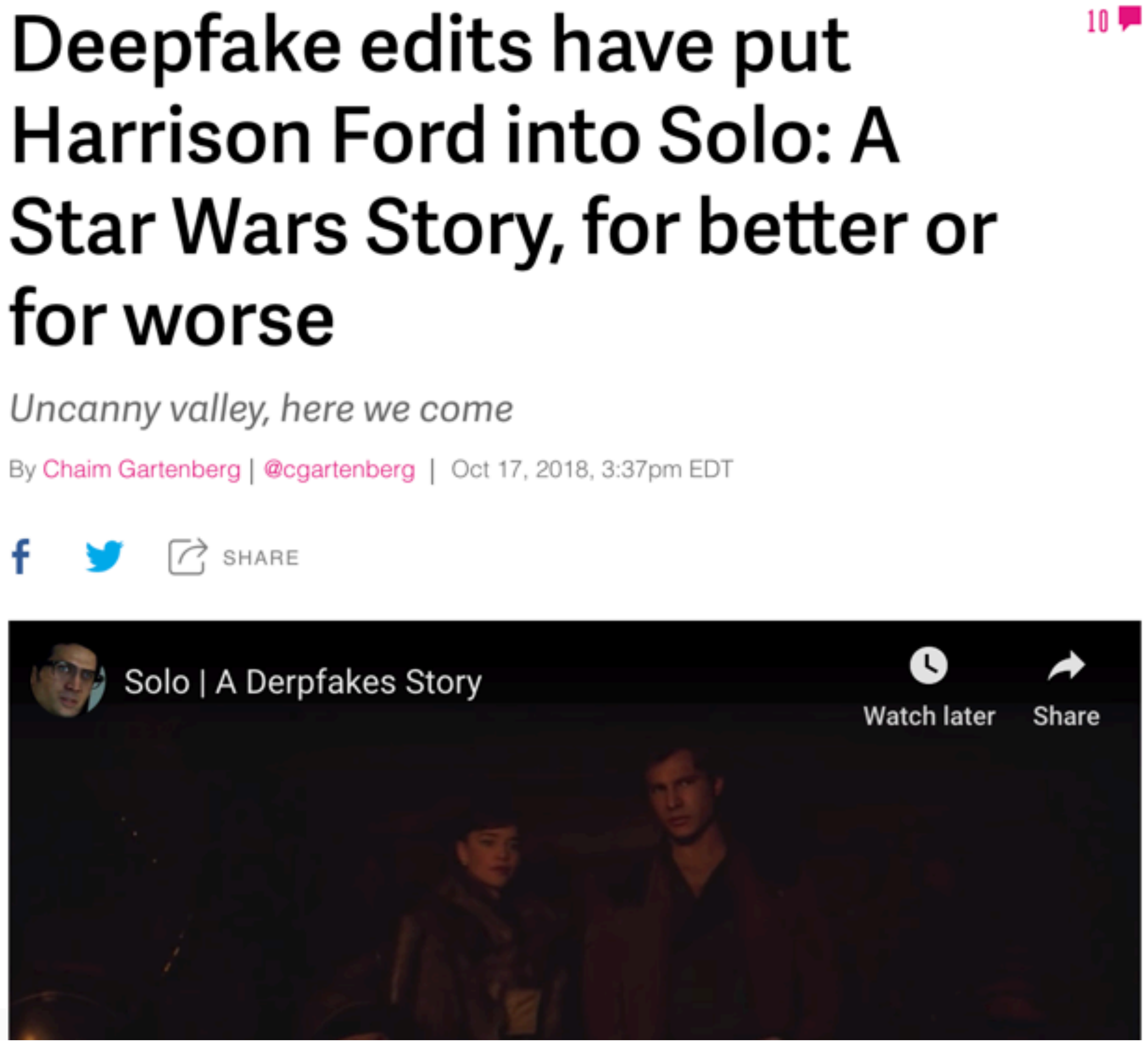
Share

And this is the Artificial Intelligence version of him.

00:12 / 01:09

Source: https://www.bbc.com/news/technology-46136504

Harrison Ford as Young Han Solo



Deepfake edits have put Harrison Ford into Solo: A Star Wars Story, for better or for worse

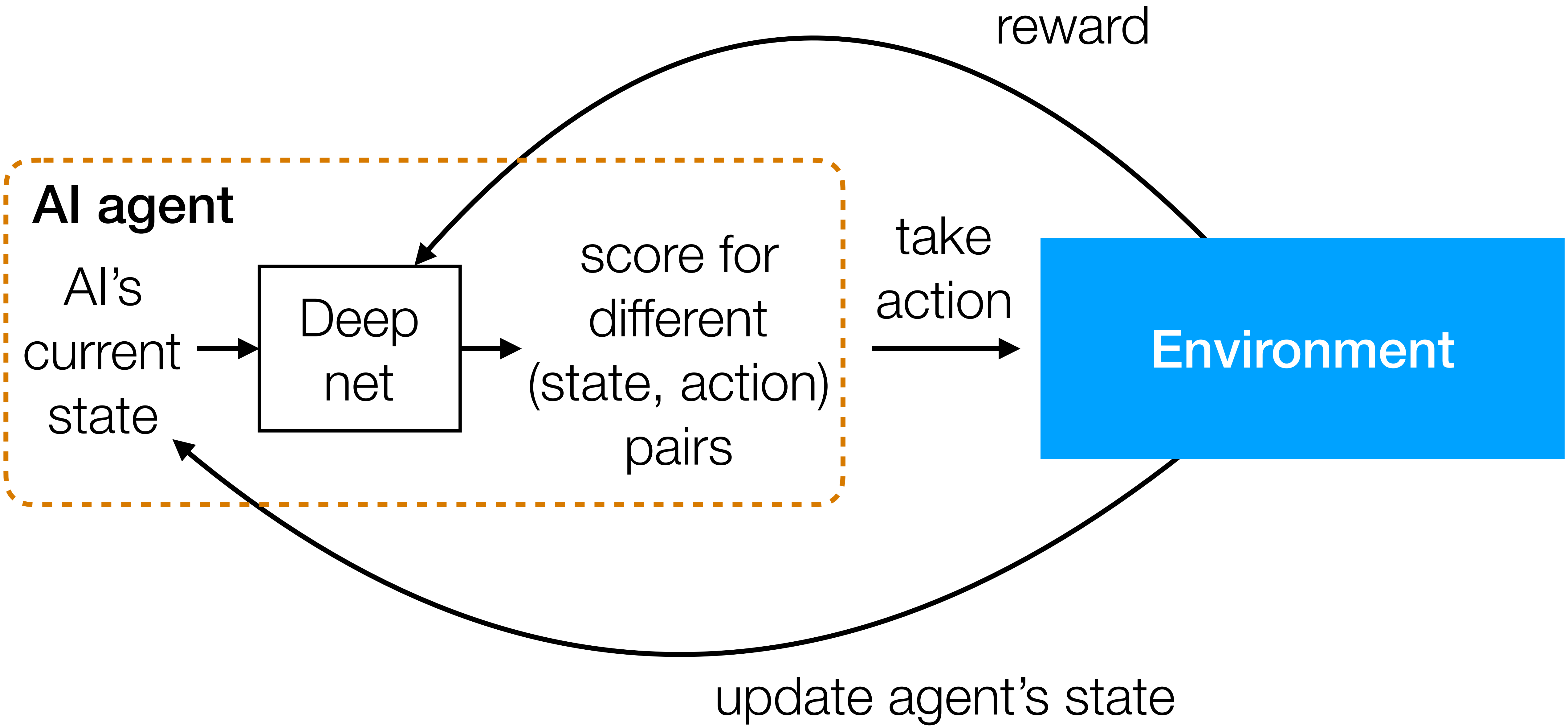
Uncanny valley, here we come

By Chaim Gartenberg | @cgartenberg | Oct 17, 2018, 3:37pm EDT

Source: https://www.theverge.com/2018/10/17/17990162/deepfake-edits-harrison-ford-han-solo-a-star-wars-story-alden-ehrenreich

Deep Reinforcement Learning

The machinery behind AlphaGo and similar systems

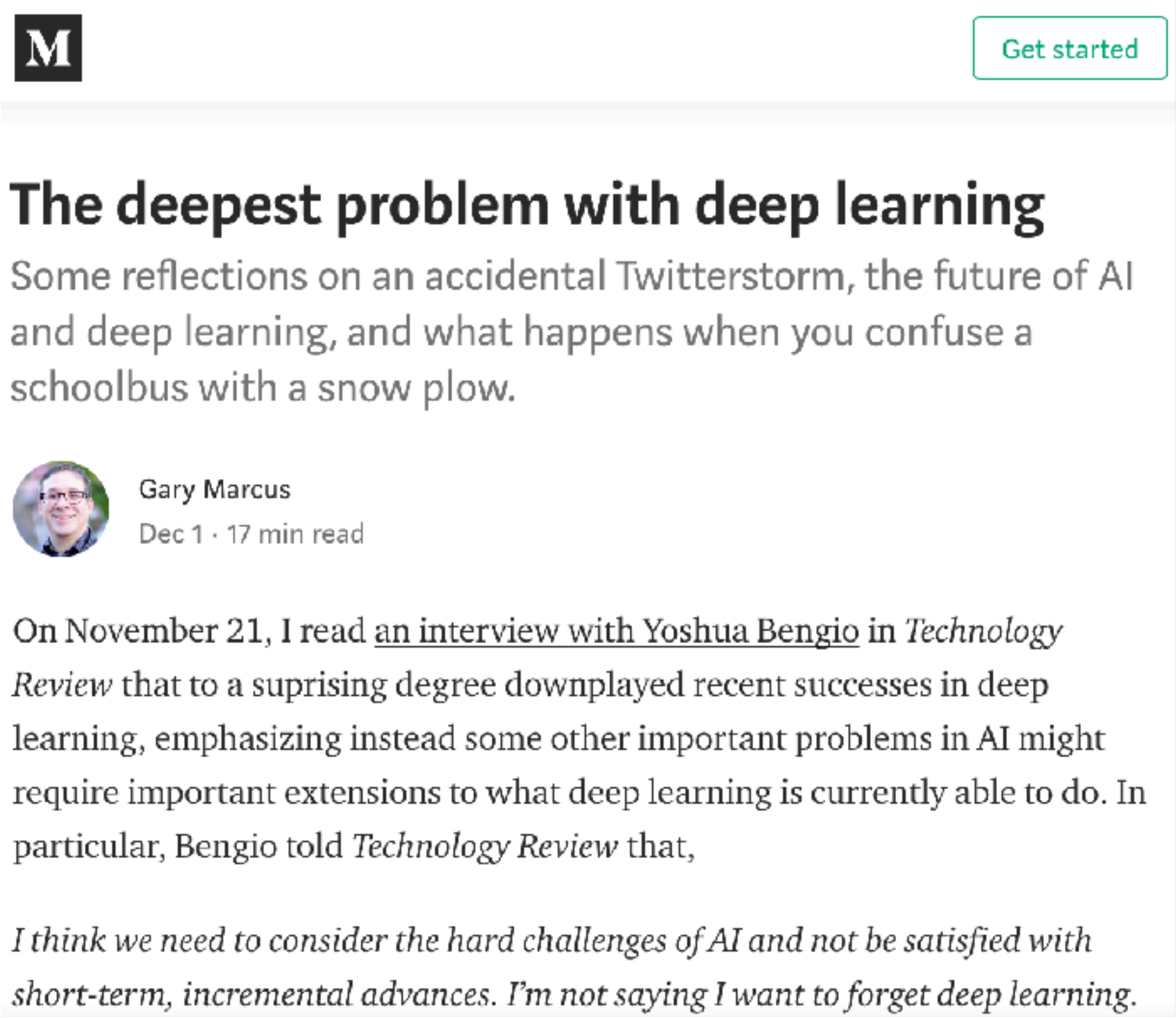


Overfitting is Not a Problem?

- In many real-life examples of very large deep nets (lots of parameters): *without regularization*, even when training error goes to 0, validation error keeps decreasing/does not significantly increase!
- Accepted wisdom currently: if you're using an "over-parametrized" deep net for classification, you want to overfit (and get 0 training error)!
  - "Understanding deep learning requires rethinking generalization" (Zhang et al ICLR 2017)
  - Mikhail Belkin at Ohio State University has a bunch of 2018 theory papers that analyze this behavior in which overfitting does not hurt you and instead has good prediction performance

The Future of Deep Learning

- Deep learning currently is still very limited in what it can do — the layers do simple operations and have to be differentiable
  - Adversarial examples at test time remain a problem
  - Doing an elaborate function approximation (curve fitting)
  - The resulting learned function (computer program) is comprised of a series of basic operations, possibly with a `for` loop (for RNN's)
- Still lots of engineering and expert knowledge used to design some of the best systems (e.g., AlphaGo)
  - How do we get away with using less expert knowledge?
- How do we do lifelong learning?



The deepest problem with deep learning

Some reflections on an accidental Twitterstorm, the future of AI and deep learning, and what happens when you confuse a schoolbus with a snow plow.

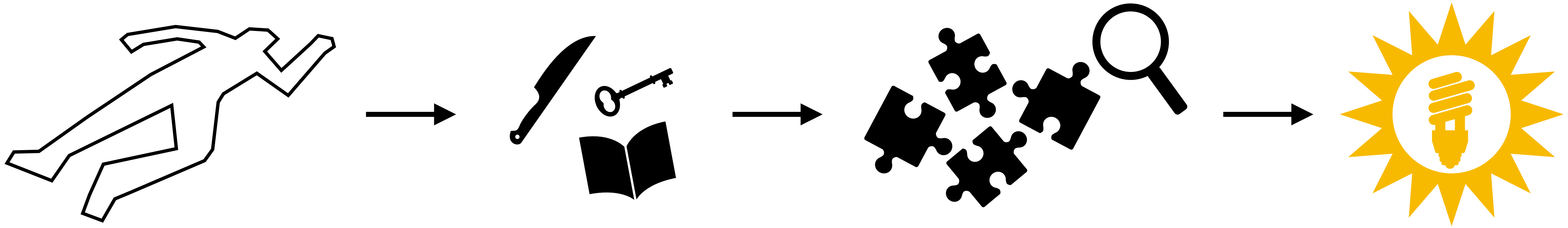
Gary Marcus
Dec 1 · 17 min read

On November 21, I read an interview with Yoshua Bengio in *Technology Review* that to a suprising degree downplayed recent successes in deep learning, emphasizing instead some other important problems in AI might require important extensions to what deep learning is currently able to do. In particular, Bengio told *Technology Review* that,

I think we need to consider the hard challenges of AI and not be satisfied with short-term, incremental advances. I'm not saying I want to forget deep learning.

Source: https://medium.com/@GaryMarcus/the-deepest-problem-with-deep-learning-91c5991f5695

Unstructured Data Analysis



Question

The dead body

This is provided by a practitioner

Data

The evidence

Some times you have to collect more evidence!

Finding Structure

Puzzle solving, careful analysis

Exploratory data analysis

Insights

When? Where? Why? How? Perpetrator catchable?

Answer original question

There isn't always a follow-up prediction problem to solve

95-865 Some Parting Thoughts

- Remember to **visualize steps of your data analysis pipeline**
  - Helpful in debugging & interpreting intermediate/final outputs
- Very often there are *tons* of models/design choices to try
  - Come up with **quantitative metrics** that make sense for your problem, and use these metrics to **evaluate models (think about how we chose hyperparameters!)**
  - But don't blindly rely on metrics without **interpreting results in the context of your original problem!**
- Often times you won't have labels! If you really want labels:
  - Manually obtain labels (either you do it or crowdsource)
  - Set up self-supervised learning task
- There is a *lot* we did not cover — **keep learning!**