UNIVERSITY OF CAMBRIDGE

Generative Adversarial Networks

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Introduction

- In this talk, I will guide you through a high level overview of **Generative Adversarial Networks** (GANs)—*one of the most popular ideas to hit deep learning in the past decade*.
- This will involve a journey through the essentials of how neural networks normally work. . .
- . . . followed by a dive into *turning horses into zebras*, *generating fake celebrities*, and anecdotes about how **pints can lead to wonderful science**.

Motivation: notMNIST

- Which characters do you see? (*How* did you conclude this?)

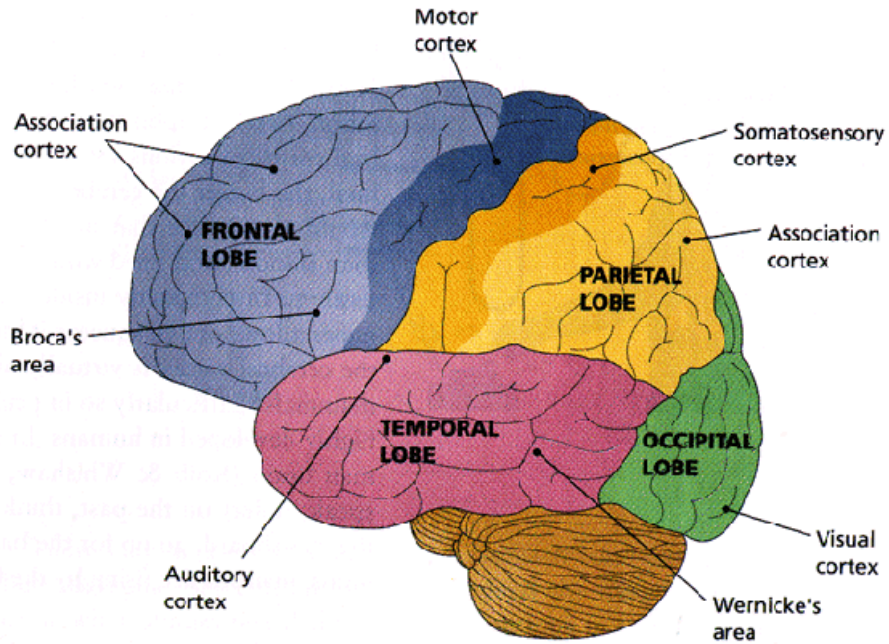
- Imagine someone asked you to write a program that recognises characters from arbitrary glyphs. . .

Intelligent systems

- Although the previous task was likely *simple* to you, you (probably) couldn't turn your thought process into a concise sequence of instructions for a program!
- Unlike a *"dumb"* program (that just blindly executes preprogrammed instructions), you've been exposed to a lot of `A` characters during your lifetimes, and eventually *"learnt"* the complex features making something an `A`!
- Desire to design such systems (capable of *generalising* from past experiences) is the essence of *machine learning*!
  - How many such systems do we know from nature?

Specialisation in the brain

- We know that *different parts* of the brain perform *different tasks*:

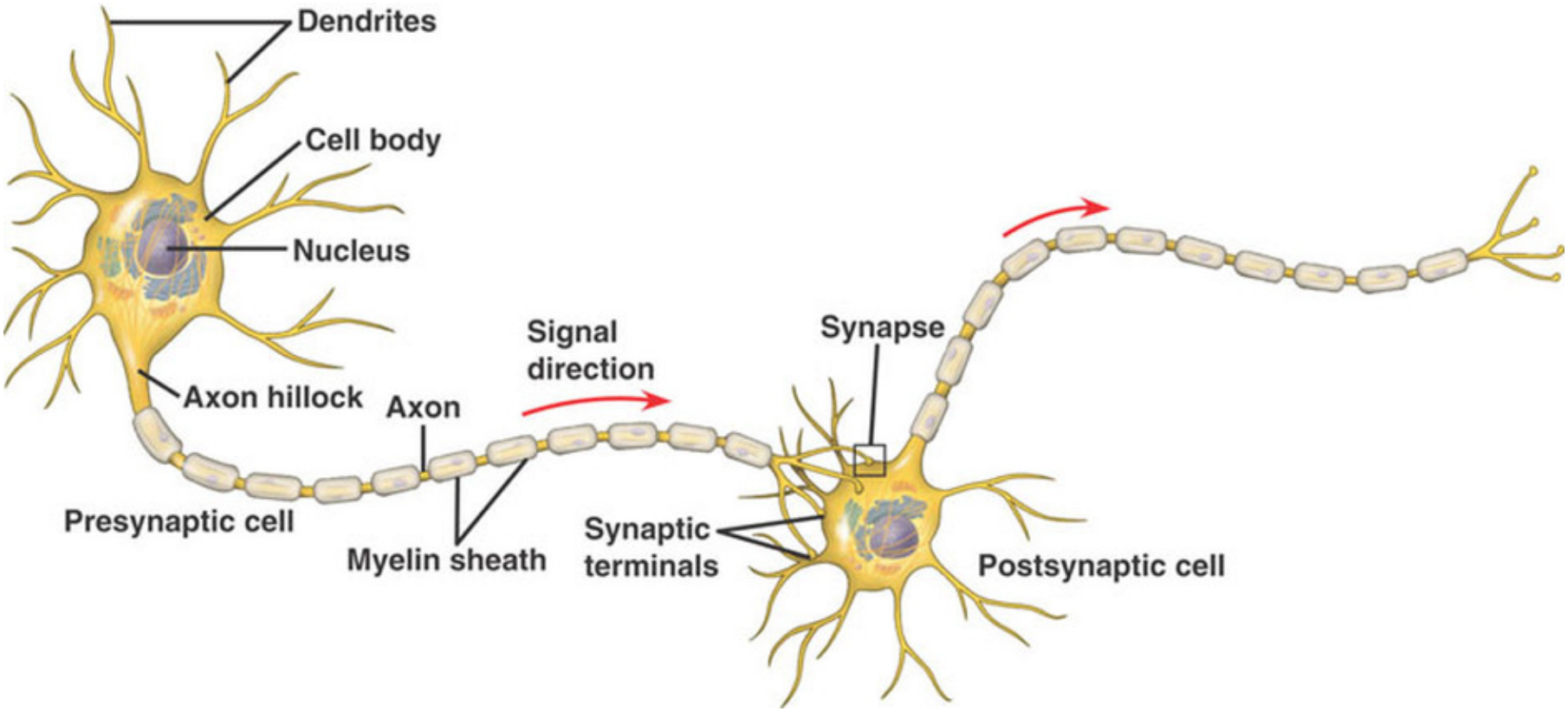


- There is increasing evidence that the brain:
  - Learns from *exposure to data*;
  - Is *not* preprogrammed!

Brain & data

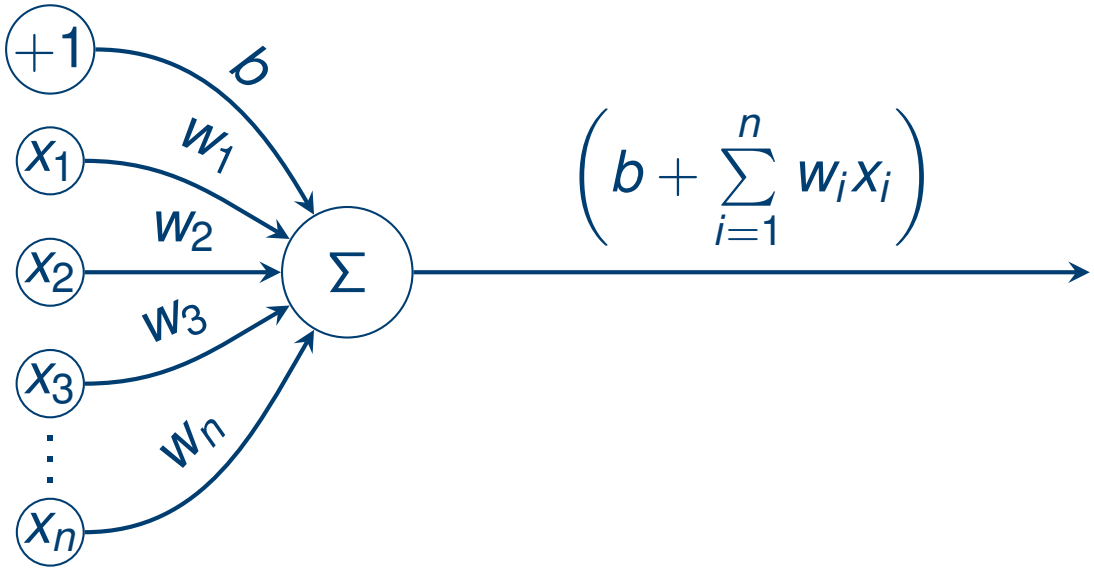
- The majority of what we know about the brain comes from studying *brain damage*:
  - Rerouting visual inputs into the auditory region of baby ferrets makes this region capable of dealing with visual input!
  - As far as we know (for now), the modified region works equally good as the visual cortex of healthy ferrets!
- If there are no major biological differences in learning to process different kinds of input. . .
- $\implies$ the brain likely uses a *general learning algorithm*, capable of adapting to a wide spectrum of inputs.
- We'd very much like to capture this algorithm!

A *real* neuron!



An *artificial* neuron!

Within this context sometimes also called a *perceptron* (. . .)



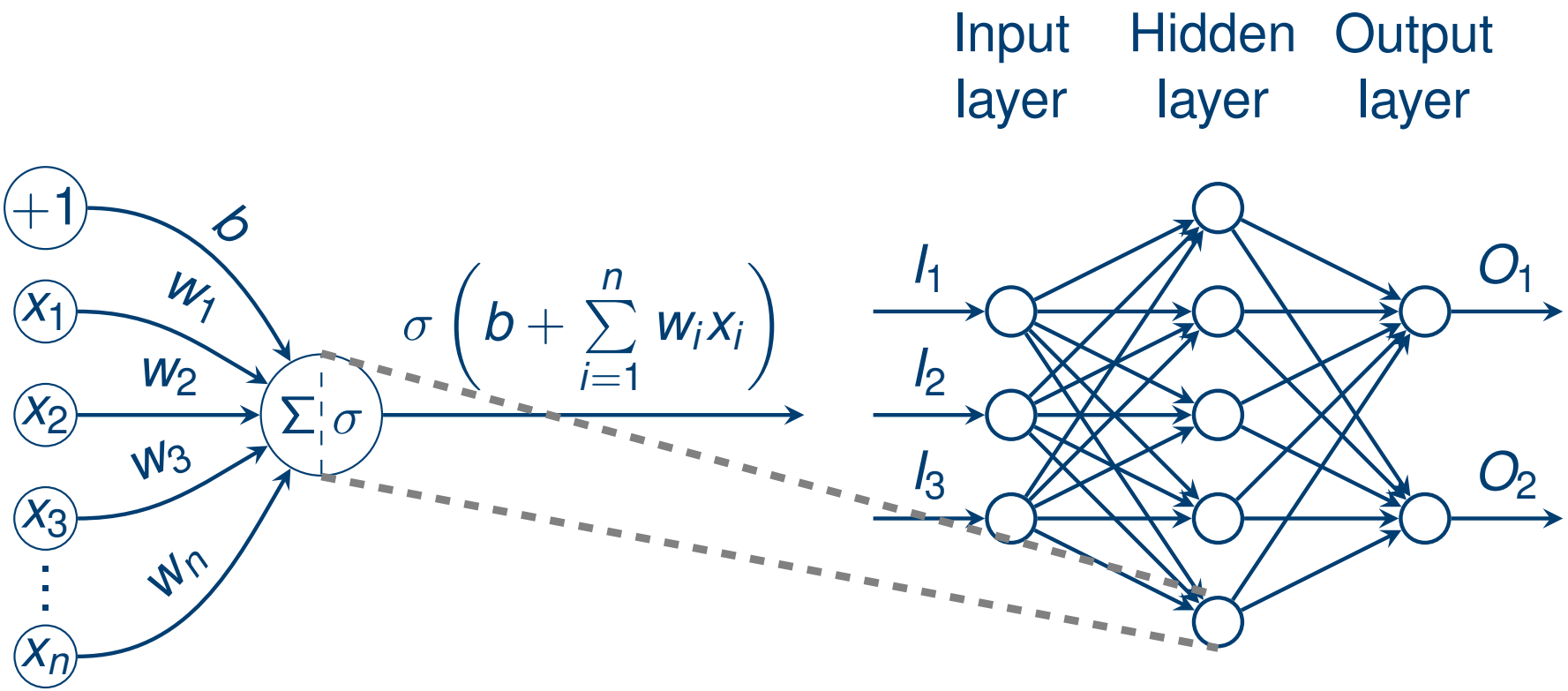
We *train* the neuron by exposing it to many $(\vec{x}, y)$ examples, and then adjusting $\vec{w}$ and b to make its output close to y when given $\vec{x}$ as input.

Neural networks and deep learning

- It is easy to extend a single neuron to a *neural network*—simply connect outputs of neurons to inputs of other neurons.
- Typically we organise neural networks in a sequence of *layers*, such that a single layer only processes output from the previous layer.
- By extension from a single neuron, we train the neural network by exposing it to many input-output pairs, and appropriately adjusting the parameters of all the neurons.

Multilayer perceptrons

The most potent feedforward architecture allows for full connectivity between layers—sometimes also called a *multilayer perceptron*.



Neural network depth

- I'd like to highlight a specific parameter: *the number of hidden layers*, i.e. *the network's depth*.
- What do you think, how many hidden layers are *sufficient* to learn any "useful" function?

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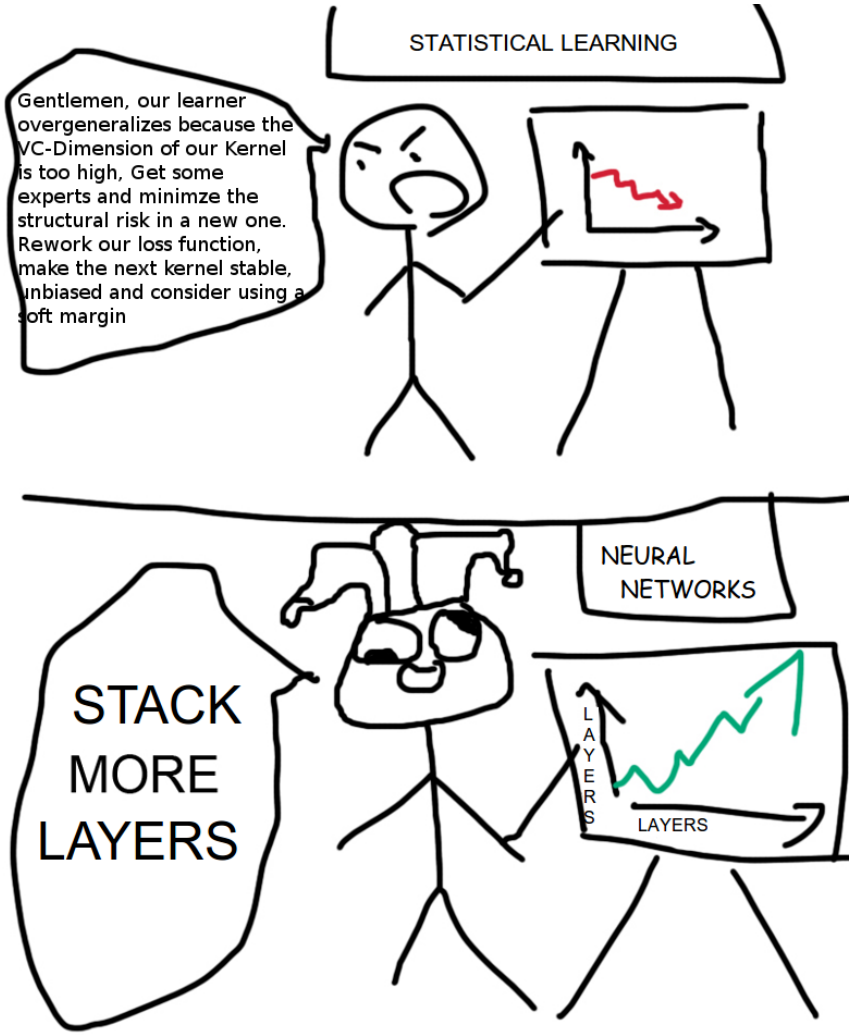
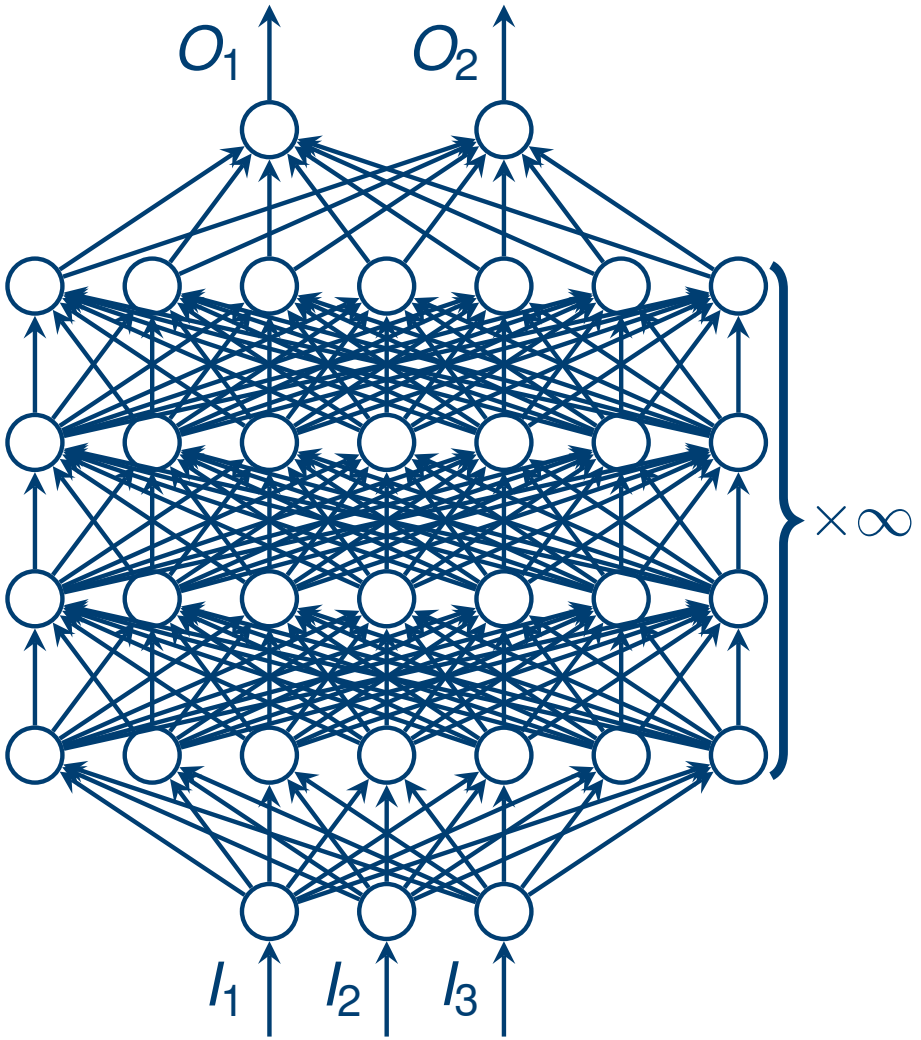
- What do you think, how many hidden layers are *sufficient* to learn any "useful" function?
- One! (*Cybenko's theorem*, 1989.)
- However, the number of neurons in this layer would need to be **astronomical** for almost all problems we care about.
- *We must go deeper. . .*
  - Every network with $>$ 1 hidden layer is considered *deep*!
  - Today's *state-of-the-art* networks often have over 150 layers.

Deep neural networks





Quiz: What do we have here?

DeepBlue vs. AlphaGo

- Main idea (roughly) the same: *assume that a grandmaster is only capable of thinking k steps ahead*—then generate a (near-)optimal move when considering $k' > k$ steps ahead.
  - DeepBlue does this exhaustively, AlphaGo sparsely (discarding many "highly unlikely" moves).
- One of the key issues: when *stopping exploration*, how do we determine the *advantage* that player 1 has?

DeepBlue: Gather a team of *chess experts*, and define a function $f : \mathit{Board} \to \mathbb{R}$, to define this advantage.

AlphaGo: Feed the raw state of the board to a deep neural network, and have it *learn* the advantage function *by itself*.

- This highlights an important *paradigm shift* brought about by deep learning...

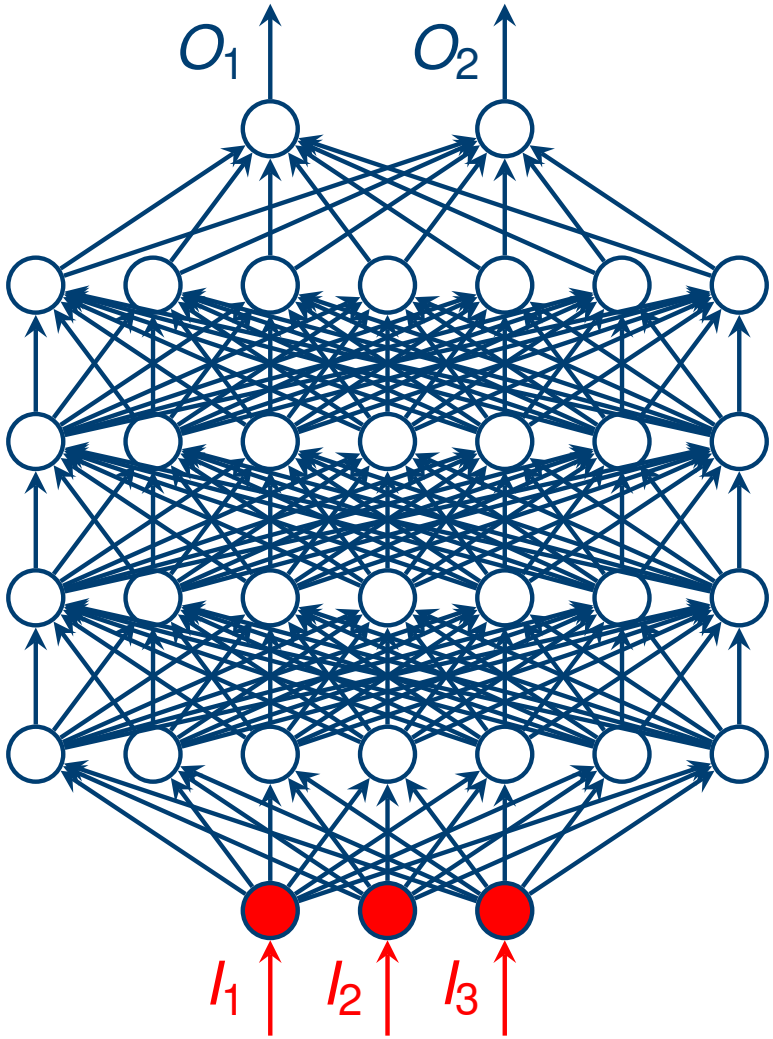
Feature engineering

- Historically, machine learning problems were tackled by defining a set of *features* to be manually extracted from raw data, and given as inputs for *"shallow"* models.
  - Many scientists built *entire PhDs* focusing on features of interest for just one such problem!
  - Generalisability: very small (often zero)!
- With deep learning, the network *learns the best features by itself*, directly from *raw data*!
  - For the first time connected researchers from fully distinct areas, e.g. *natural language processing* and *computer vision*.
  - $\Longrightarrow$ a person capable of working with deep neural networks may readily apply their knowledge to create state-of-the-art models in virtually any domain (assuming a large dataset)!

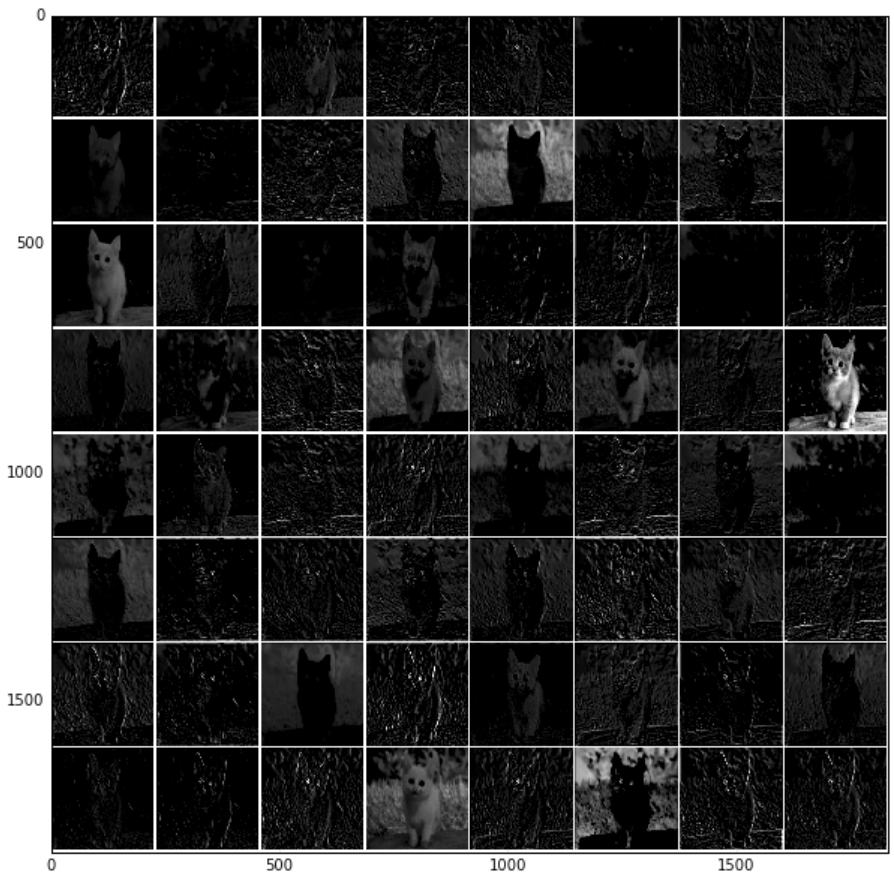
Representation learning

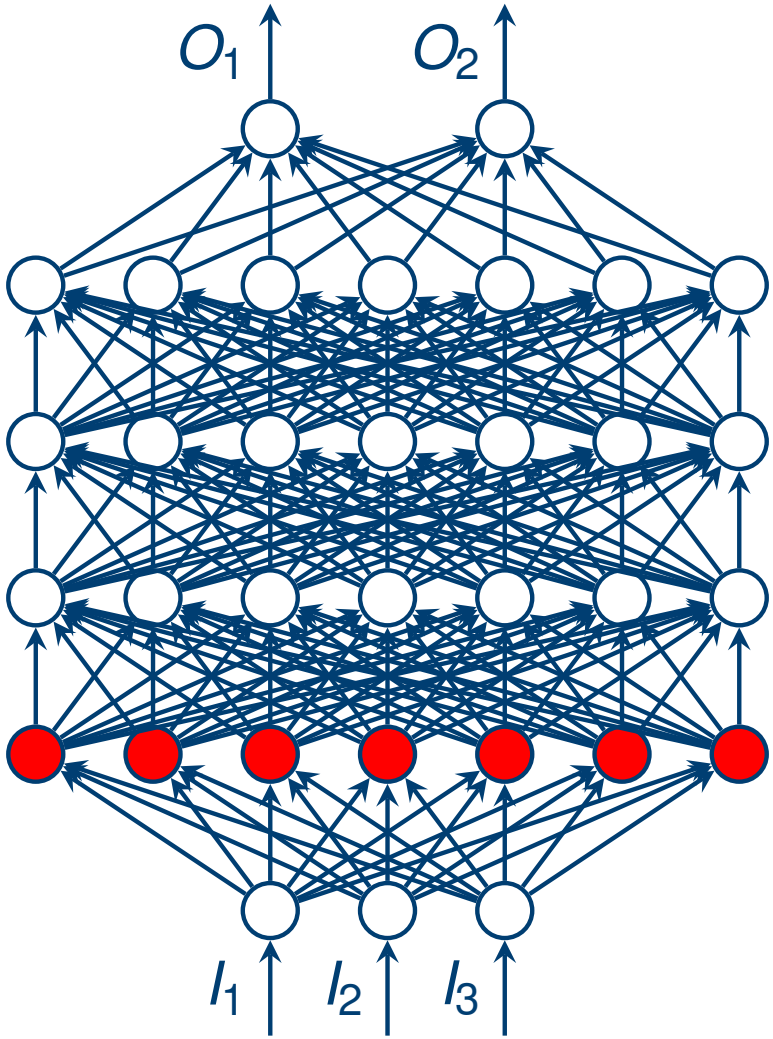
- As inputs propagate through the layers, the network captures more complex *representations* of them.
- It will be extremely valuable for us to be able to reason about these representations!
- Typically, models that deal with *images* will tend to have the best visualisations.

Passing data through the network: *Input*

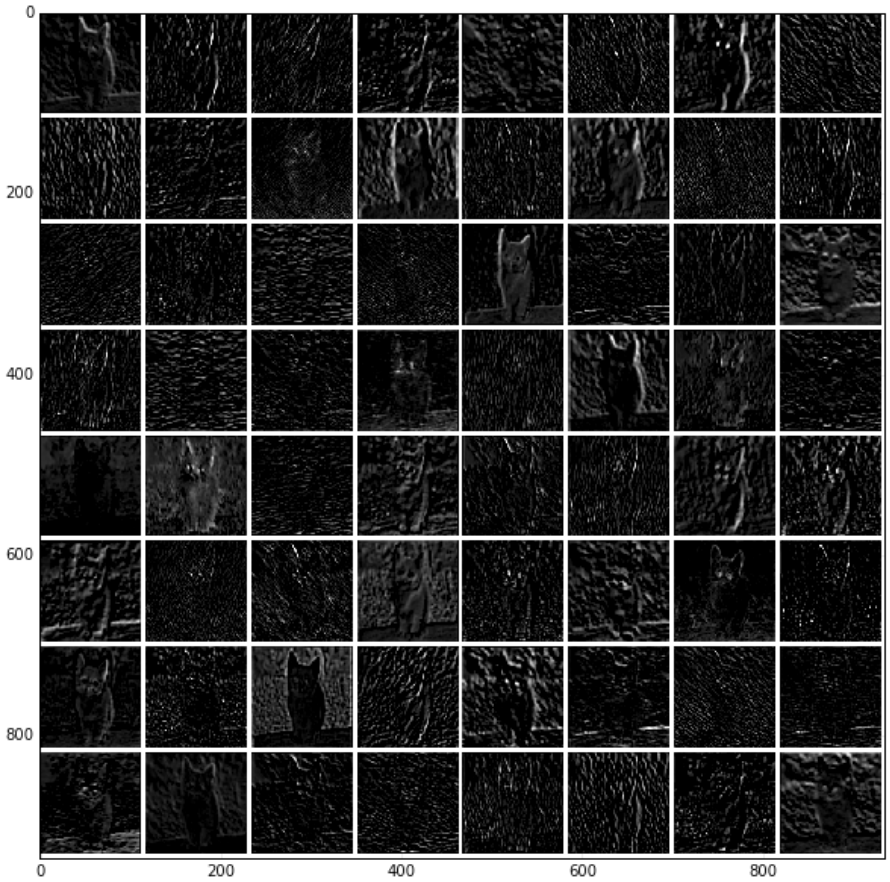


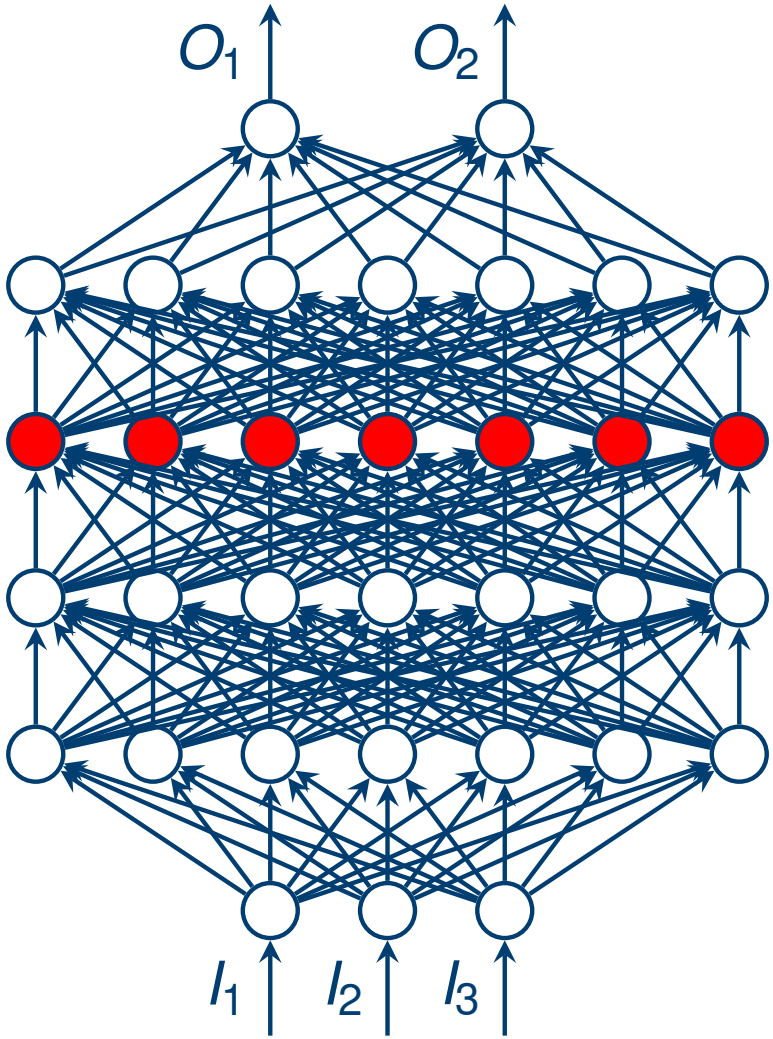
Passing data through the network: *Shallow layer*



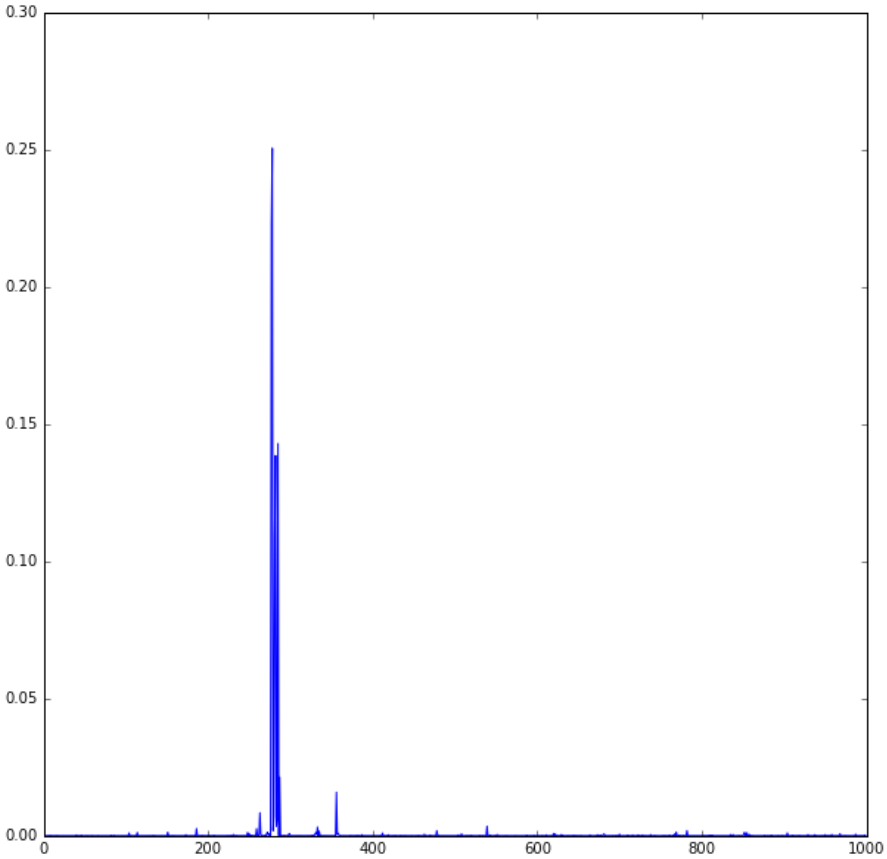


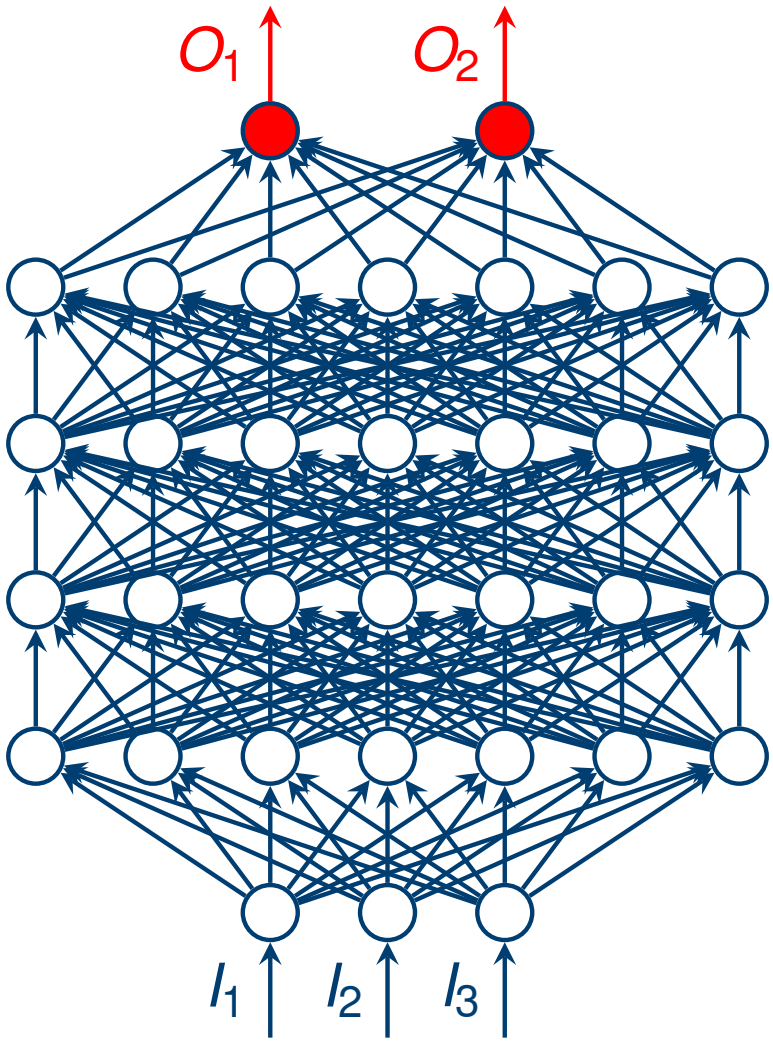
Passing data through the network: *Deep layer*



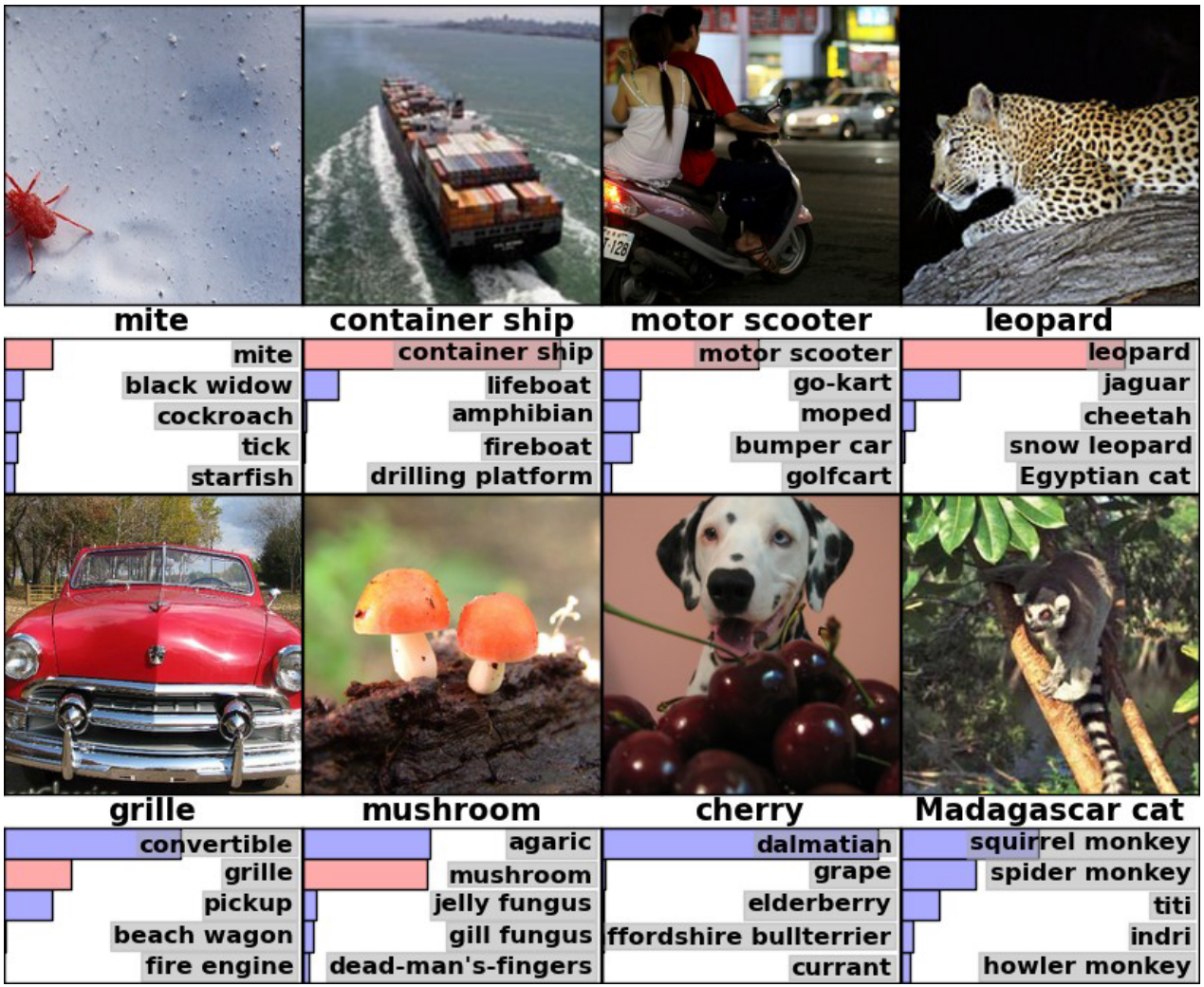


Passing data through the network: *Output*

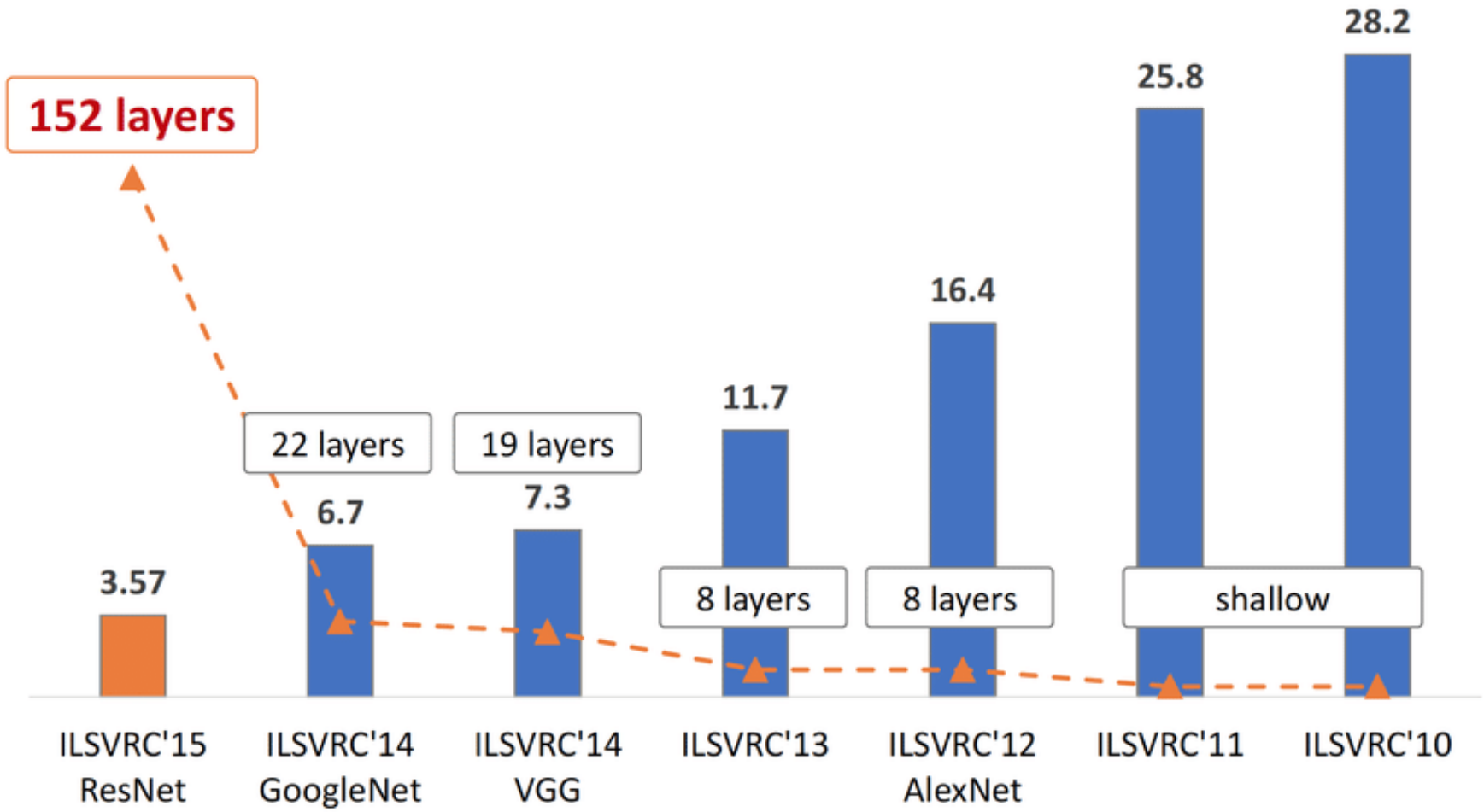




We're good at detecting what's in an image. . .



. . . even exceeding human performance. . .

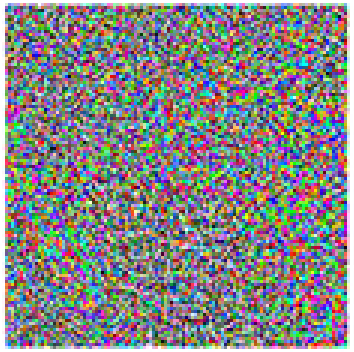


. . . or are we???

x

"panda"
57.7% confidence

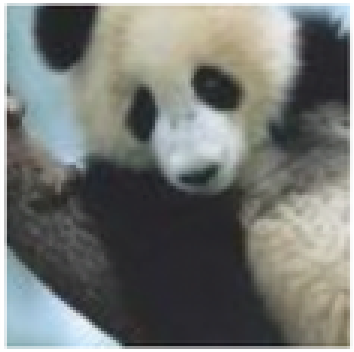
$+ .007 \times$



$\text{sign}(\nabla_{\boldsymbol{x}} J(\boldsymbol{\theta}, \boldsymbol{x}, y))$

"nematode"
8.2% confidence

$=$



$\boldsymbol{x} + \epsilon\text{sign}(\nabla_{\boldsymbol{x}} J(\boldsymbol{\theta}, \boldsymbol{x}, y))$

"gibbon"
99.3 % confidence

The importance of *understanding* data

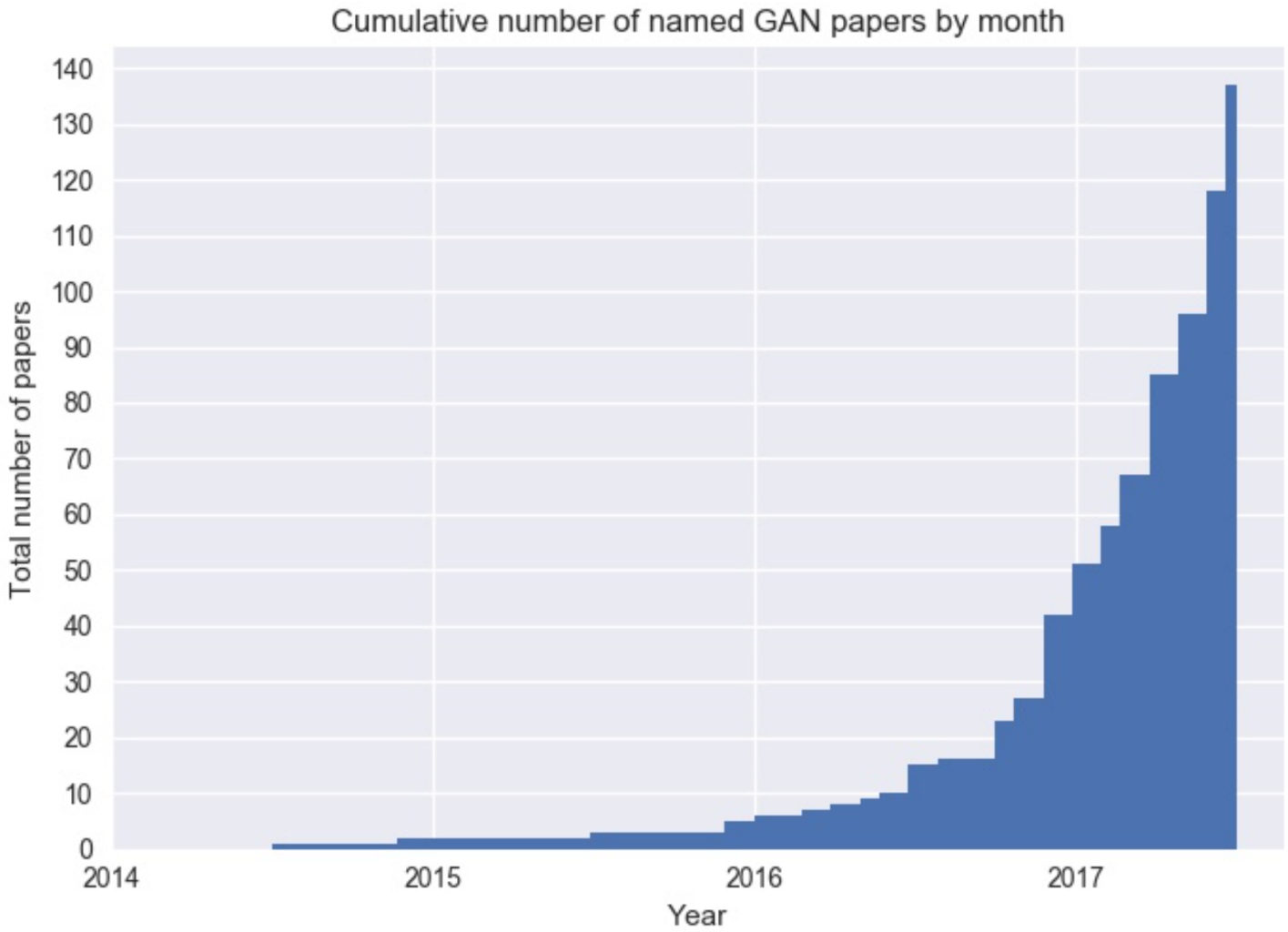
Generative modelling

“What I cannot create, I do not understand.” —Richard Feynman

Generative Adversarial Networks

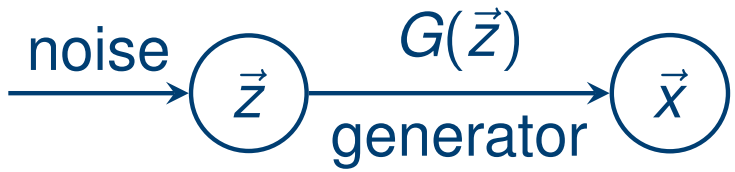
- *"The most important one, in my opinion, is adversarial training (also called GAN for **Generative Adversarial Networks**). This, and the variations that are now being proposed is the most interesting idea in the last 10 years in ML, in my opinion."*
  —Yann LeCun
  (Director of Research, *Facebook AI Research*)

GANs are **everywhere**



The **generator**

- Imagine that we had a neural network, G, capable of generating new data from random inputs $\vec{z}$...



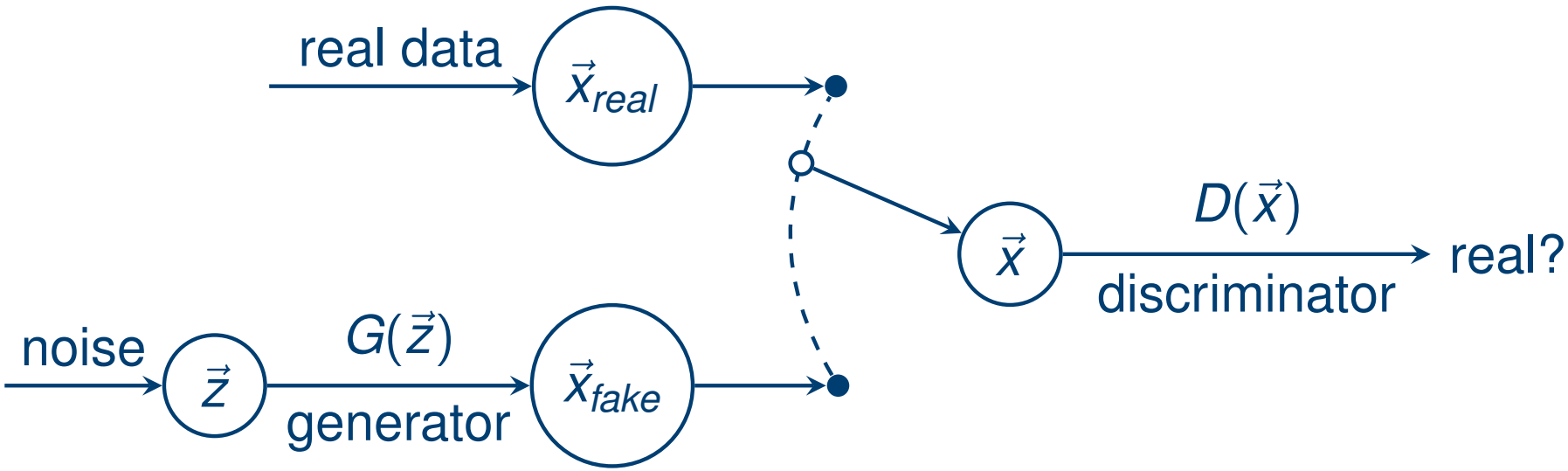
  We will call this neural network the **generator**.

- What we want to do is make the output of this generator match the properties of **real data**.
- But how can we check if a synthetic input has properties similar to real data?

The **discriminator**

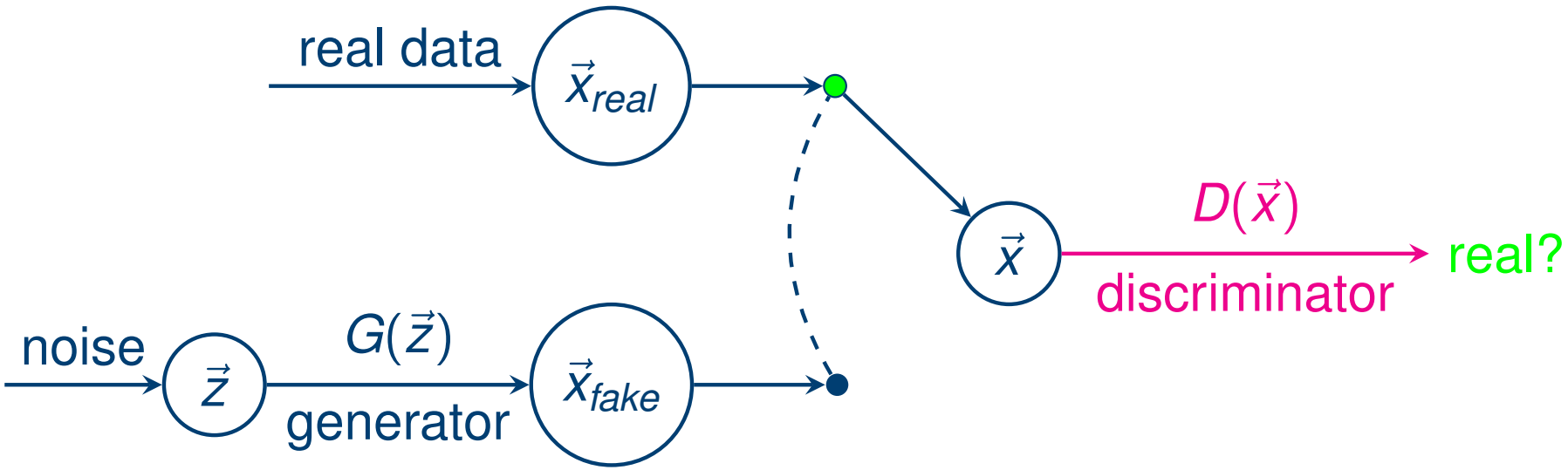
- Checking for properties by looking over full data (e.g. individual image pixels) is **hard**.
- We can utilise a *neural network* to extract underlying features from inputs, and examine those.
- If these features are “good enough”, the network should be capable of *telling real and synthetic inputs apart*!
- Call this network the **discriminator**, $D(\vec{x})$.
- Essentially, a *binary classifier*, telling whether $\vec{x}$ is real or synthetic. **N.B.** The discriminator effectively **specifies the *error*** that we want the generator to minimise!

The GAN framework (Goodfellow *et al.*, 2014)



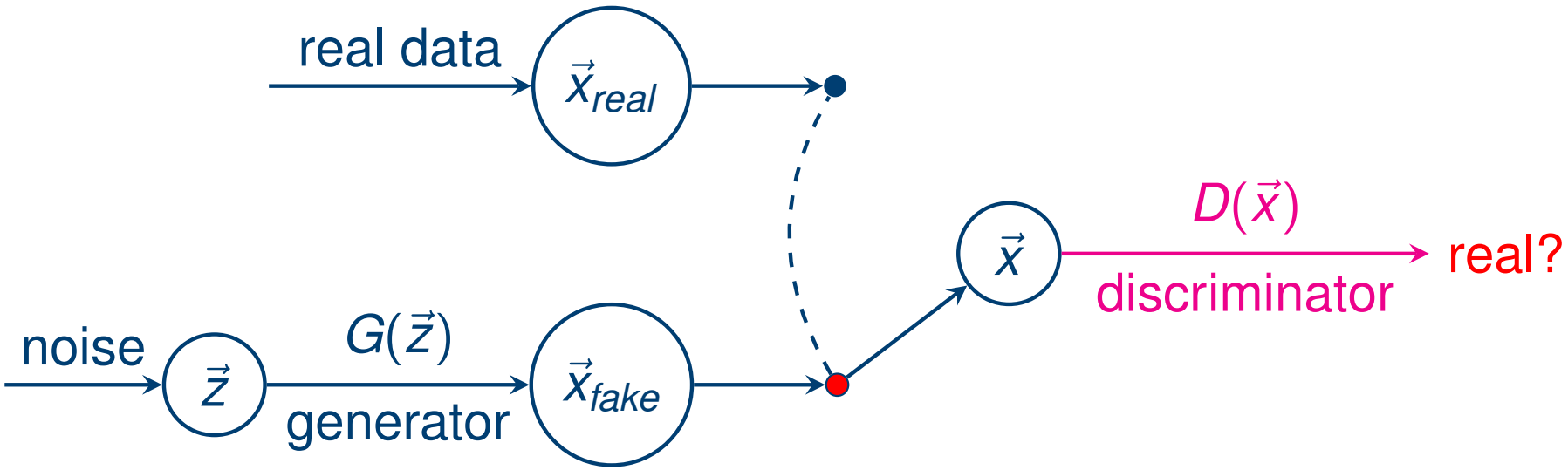
Two neural networks *playing a game*. . .
Alternate updating their weights; hopefully they *improve* together!

The GAN framework—update step 1



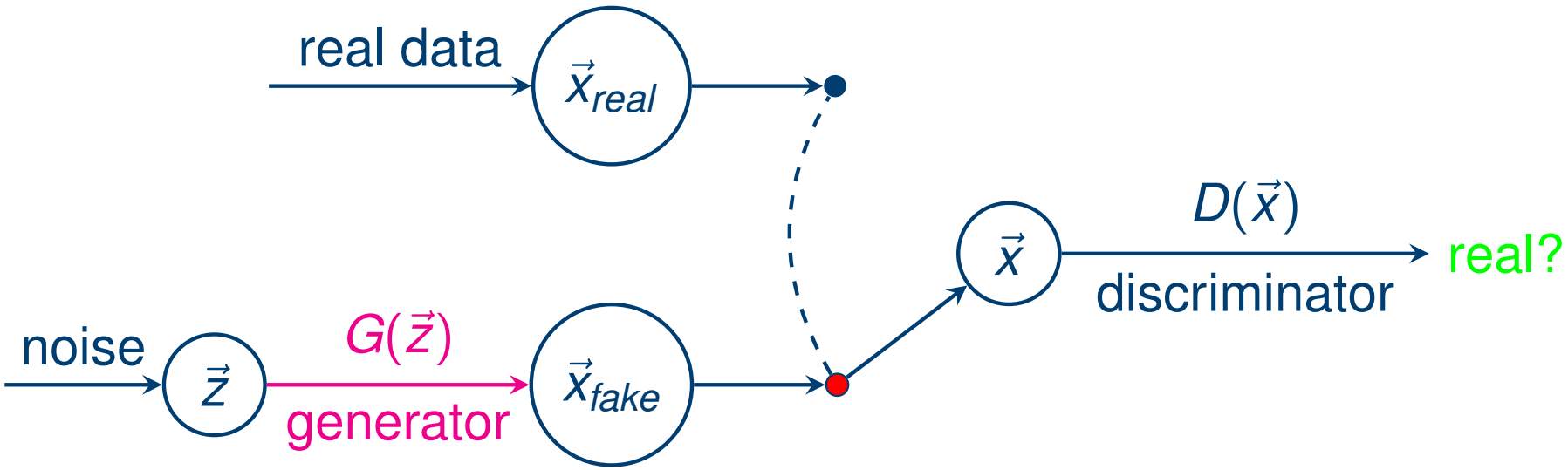
Train discriminator to say '**real**' on real data.

The GAN framework—update step 2



Train discriminator to say **'fake'** on fake data.

The GAN framework—update step 3



Train generator to make discriminator say **'real'** on fake data.

The desired final outcome

$$\min_G \max_D V(D,G) = \mathbb{E}_{\vec{x}\sim p_{data}(\vec{x})}[\log D(\vec{x})] + \mathbb{E}_{\vec{z}\sim p_\theta(\vec{z})}[\log(1 - D(G(\vec{z})))]$$

- Assuming everything goes well, concluding the training process we obtain **two** very useful networks!
  - The **generator**, $G(\vec{z})$, becomes capable of generating extremely useful synthetic examples.
  - The **discriminator**, $D(\vec{x})$, becomes a high-quality **feature extractor** from data.
- Let's see how good these synthetic examples from $G(\vec{z})$ actually get...

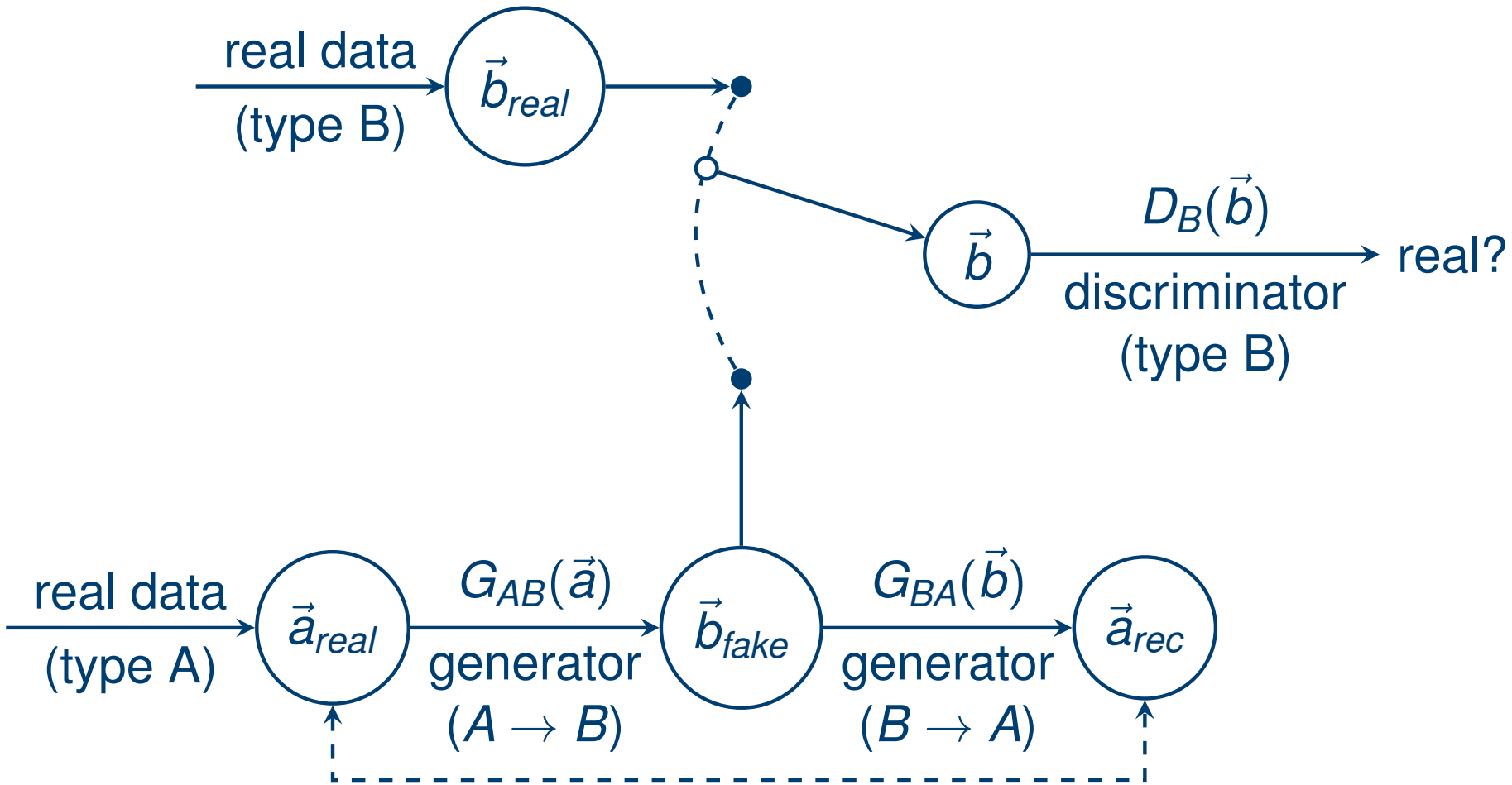
Generating fake celebrities (*Karras et al., 2018*)

A step further—domain transfer

- Similar ideas can be applied in order to *transform data from one type to another*...
- We learn **two generators**, G_{AB} and G_{BA}, to transfer inputs from type A to type B, and vice-versa.
- We also learn the **two discriminators**, D_A and D_B.
- Besides the usual GAN game, we also can enforce *cycle consistency*: $G_{BA}(G_{AB}(\vec{a})) \sim \vec{a}$.
  - This means that if we transform an input of type A to type B, then transform the result back into type A, we should be able to recover the original input.

We arrive at the remarkably powerful *CycleGAN* model...

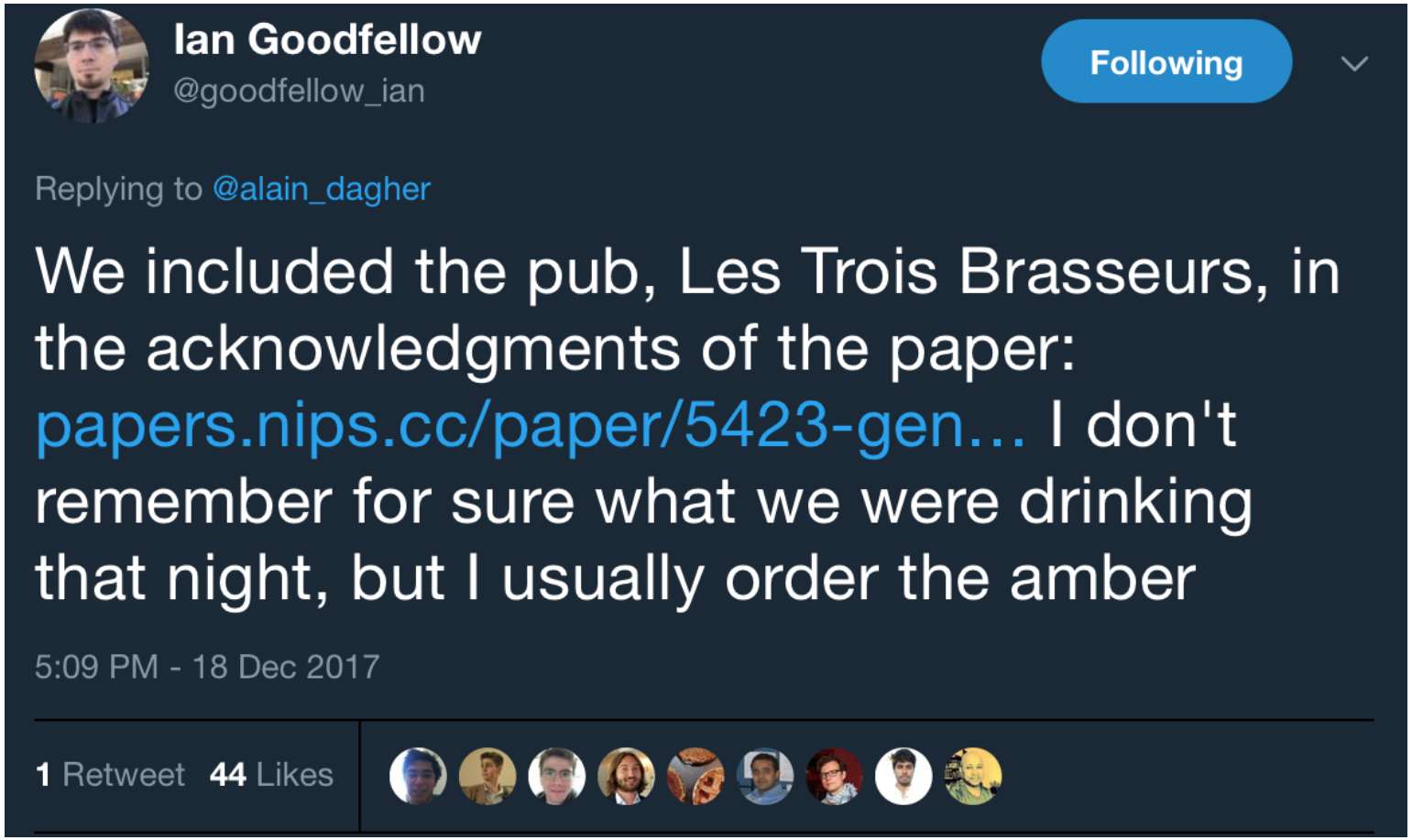
Domain transfer: *CycleGAN* (*Zhu et al., 2017*)



Domain transfer: *CycleGAN* (*Zhu et al., 2017*)

Where did this all begin?

A true *pint of science*. . .



. . . credited in the paper.

Acknowledgments

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An overview of historical deep learning ideas

- Initially, we needed to extract hand-crafted features before applying a machine learning model to them.
  - **Deep neural networks** can perform feature extraction by themselves.
- Then, we needed to decide on how to estimate the *error* of our network's prediction.
  - **GANs** use a neural network (the *discriminator*) to compute this!
- We need to figure out a correct way to reduce this error.
  - **Learn how to learn**?

Thank you!

Questions?

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