COMP47460

Big Ideas

Aonghus Lawlor
Derek Greene

School of Computer Science
Autumn 2018

What is machine learning?

“Machine learning is the science of getting computers to act without being explicitly programmed.“

- Andrew Ng

"The field of machine learning is concerned with the question of how to construct computer programs that automatically improve with experience."

- Tom Mitchell

Machine Learning

Machine Learning is the training of a model from data that generalises a decision against a performance measure.

Training a model suggests training examples.

A *model* suggests state acquired through experience.

Generalises a decision suggests the capability to make a decision based on inputs and anticipating unseen inputs in the future for which a decision will be required.

against a performance measure suggests a targeted need and directed quality to the model being prepared.

Types of Machine Learning

Machine Learning

Unsupervised Learning

- Clustering
- Dimensionality Reduction
  - PCA
  - SVD
  - k-Means

Supervised Learning

- Classification
  - kNN
  - Trees
  - Logistic Regression
  - Naive Bayes
- Regression

Types of Machine Learning

LEARNING

Representation: choosing the functions that can be learned, the set of hypotheses

one feature

$$h(X) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots$$

$$h_\beta(X) = \sum_j \beta_j x_j$$

assume x_0=1

many features

Evaluation: *loss function* for penalising errors:

$$J(\beta) = \sum_{i=1} \left(h_\beta(x_i) - y_i \right)^2$$

Optimisation:

$$\min_\beta J(\beta)$$

Types of Machine Learning

LEARNING

Representation: choosing the functions that can be learned, the set of hypotheses

one feature

$$h(X) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots$$

$$h_\beta(X) = \sum_j \beta_j x_j$$

assume x_0=1

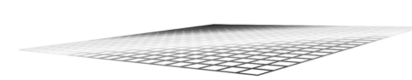
many features

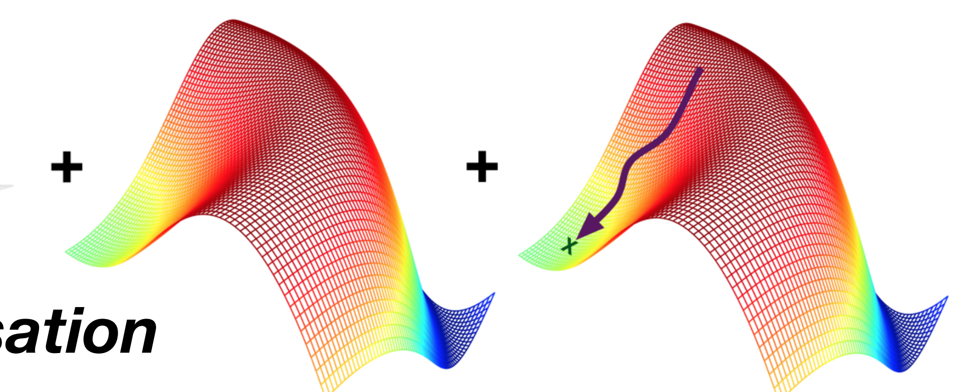
Evaluation: *loss function* for penalising errors:

$$J(\beta) = \sum_{i=1} \left(h_\beta(x_i) - y_i \right)^2$$

Optimisation:

$$\min_\beta J(\beta)$$





Learning = Representation + Evaluation + Optimisation

Generalisation

- Training Data
  - examples used to train the predictor
- Future Data
  - examples our predictor has not seen before

We want to do well on future data, not training data

Types of Machine Learning

Machine Learning

Unsupervised Learning

- Clustering
- Dimensionality Reduction
    - PCA
    - SVD
    - k-Means

Supervised Learning

- Classification
    - kNN
    - Trees
    - Logistic Regression
    - Naive Bayes
- Regression

Reinforcement Learning

we haven't mentioned RL in the module

Reinforcement Learning

Reinforcement Learning

Learning from interaction with an environment to achieve some long-term goal that is related to the state of the environment

The goal is defined by reward signal, which must be maximised

Agent must be able to partially/fully sense the environment state and take actions to influence the environment state

The state is typically described with a feature-vector

actions:

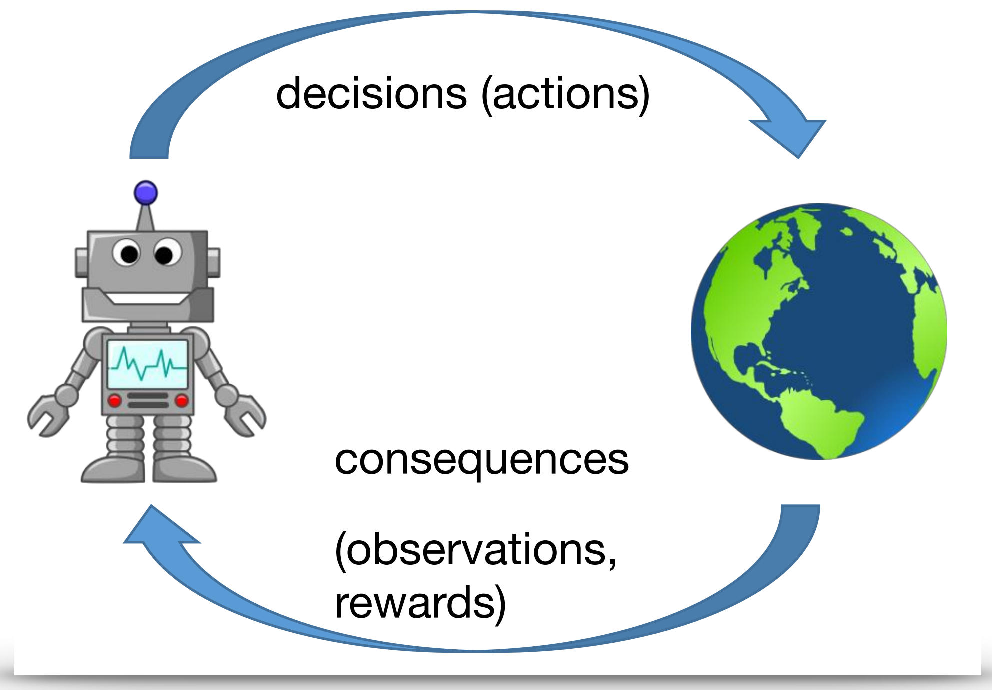
muscle contractions

observations:

sight, smell

reward:

food



Reinforcement Learning

We want to learn how to act to accomplish goals

Given an environment that contains rewards

We want to learn a policy for acting

Important differences from *classification*

- You don’t get examples of correct answers
- You have to try things in order to learn

Reinforcement Learning

- We want a reinforcement learning agent to earn lots of reward
- The agent must prefer past actions that have been found to be effective at producing reward
- The agent must exploit what it already knows to obtain reward
- The agent must select untested actions to discover reward-producing actions
- The agent must explore actions to make better action selections in the future
- Trade-off between exploration and exploitation

Reinforcement Learning

Reinforcement learning systems have 4 main elements:

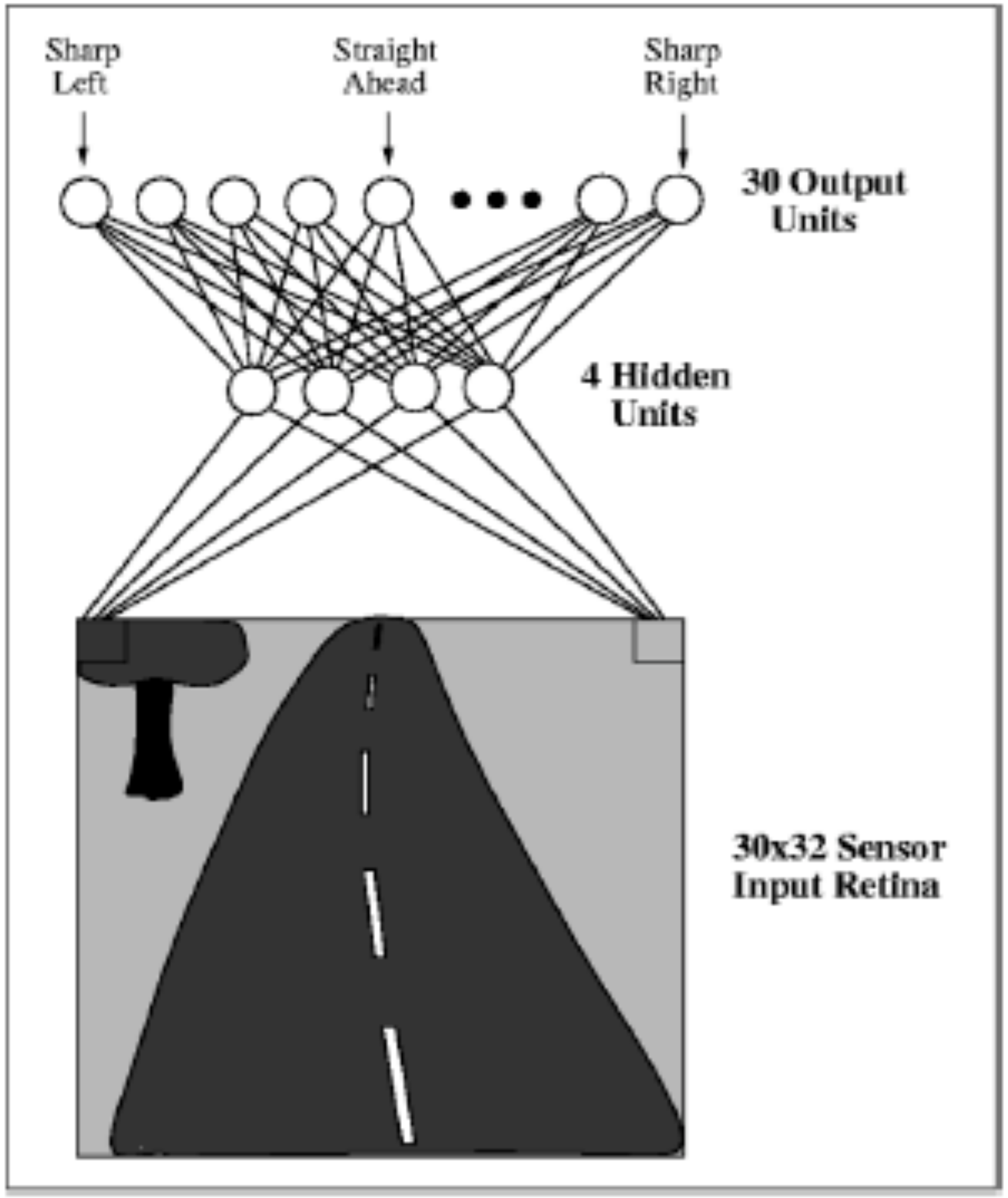
- –Policy
- –Reward signal
- –Value function
- –Optional model of the environment

Reinforcement Learning

Policy:

A policy is a mapping from the perceived states of the environment to actions to be taken when in those states

A reinforcement learning agent uses a policy to select actions given the current environment state



Reinforcement Learning

Reward:

The reward signal defines the goal

On each time step, the environment sends a single number called the reward to the reinforcement learning agent

The agent's objective is to maximise the total reward that it receives over the long run

The reward signal is used to alter the policy

»

scissors

Reward: jump as high as possible: It took years for athletes to find the right behaviour to achieve this

Demonstration: It was way easier for athletes to perfect the jump, once someone showed the right general trajectory

Fosbury flop

Reinforcement Learning

- The reward signal indicates what is good in the short run while the value function indicates what is good in the long run
- The value of a state is the total amount of reward an agent can expect to accumulate over the future, starting in that state
- Compute the value using the states that are likely to follow the current state and the rewards available in those states

Reinforcement Learning

- Use the values to make and evaluate decisions
- Action choices are made based on value judgements
- Prefer actions that bring about states of highest value instead of highest reward
- Rewards are given directly by the environment
- Values must continually be re-estimated from the sequence of observations that an agent makes over its lifetime

Reinforcement Learning

RL shapes behaviour using reinforcement

- *Agent* takes actions in an environment (in *episodes*)
- Those actions change the *state* and trigger rewards

Through experience, an agent learns a *policy* for acting

- Given a state, choose an action
- Maximise cumulative reward during an episode

Interesting things about this problem:

- Requires solving credit assignment
  - What action(s) are responsible for a reward?
- Requires both exploring and exploiting
  - Do what looks best, or see if something else is really best?

»

Reinforcement Learning

Useful with limited supervision: you know **what** you want, but not **how** to get it

Actions have consequences

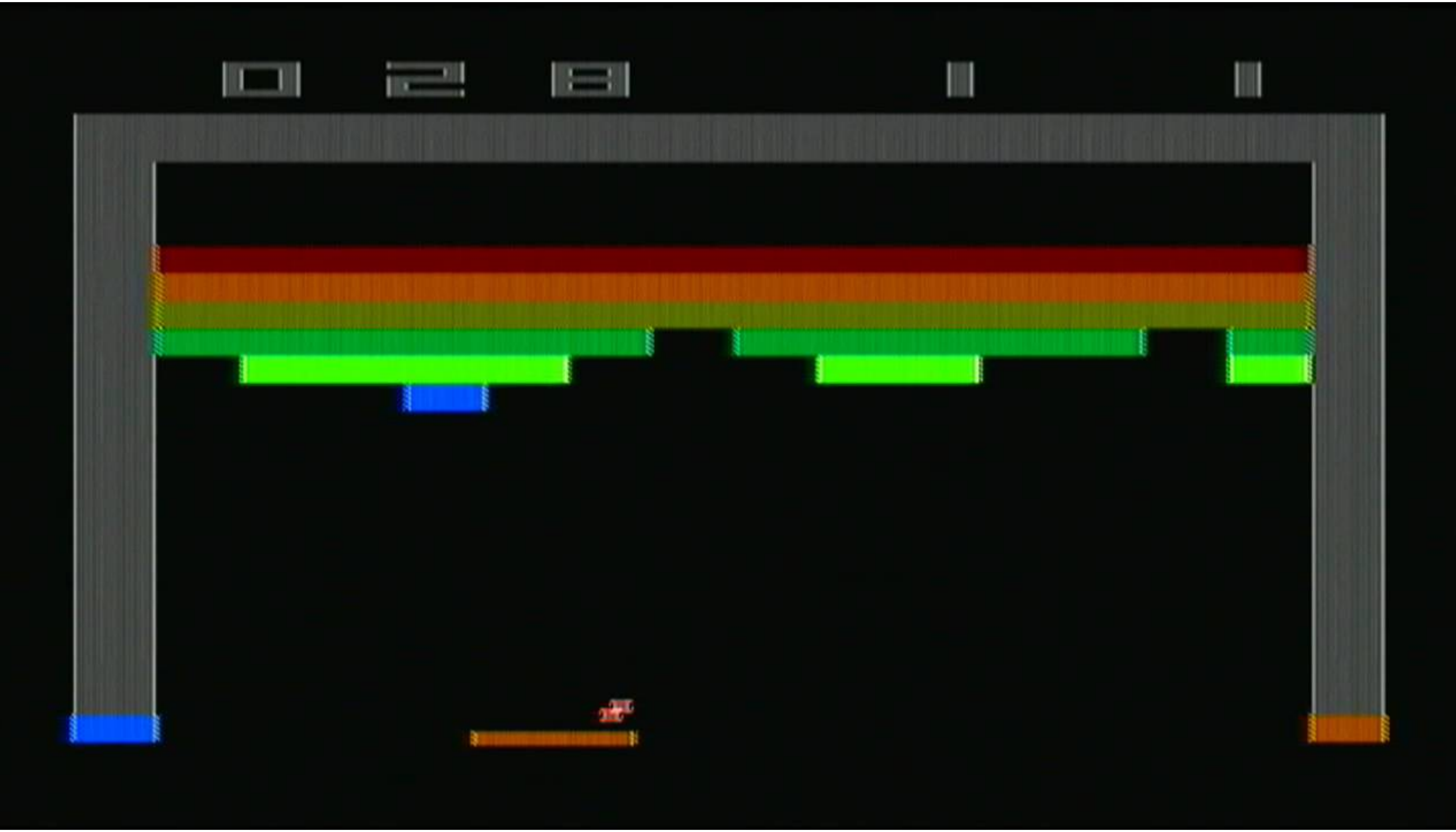
Not so useful when the system is making single isolated decisions e.g. classification, regression, or when that decision does not affect future decisions

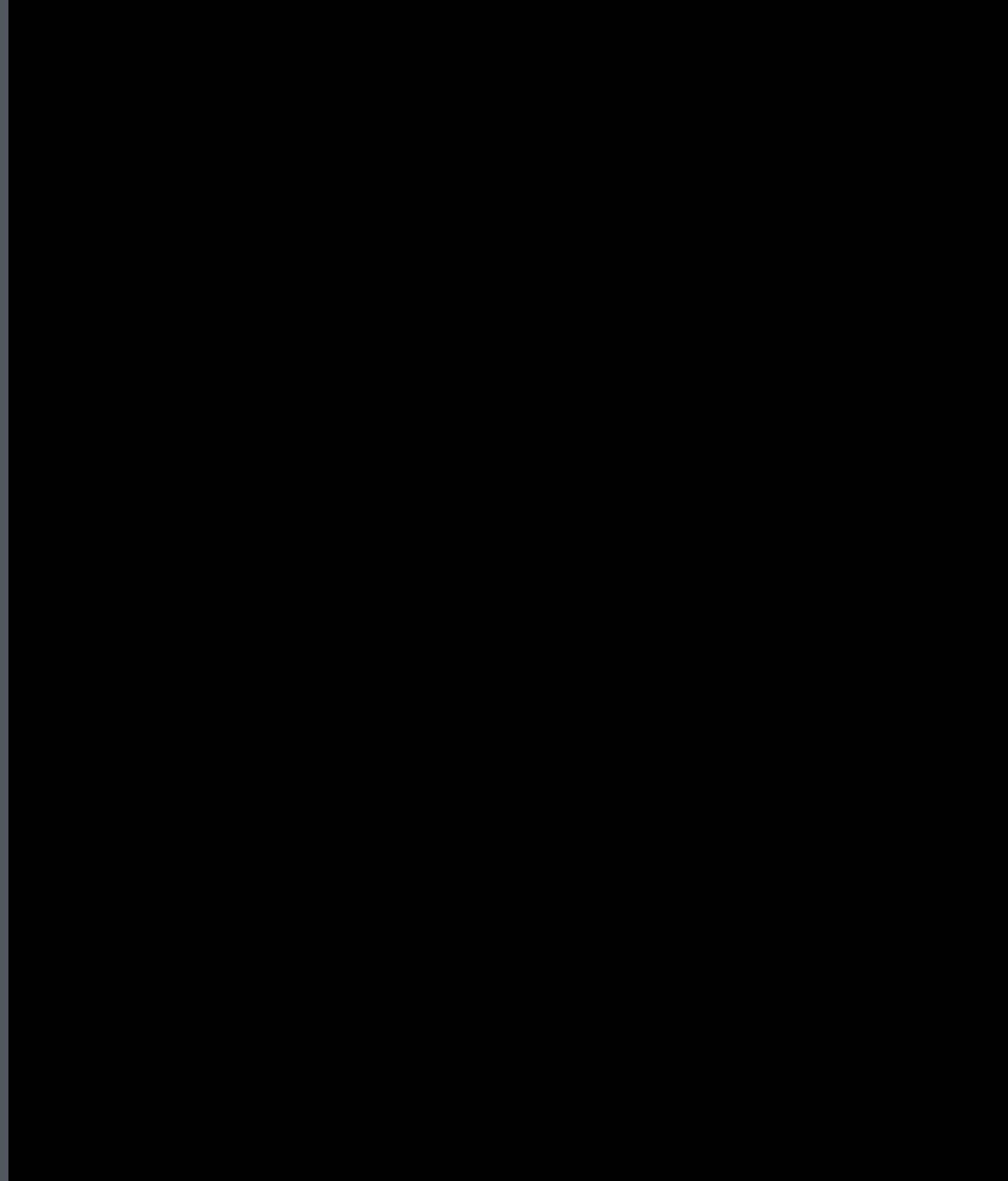
Autonomous Vehicles

Finance

Robotics

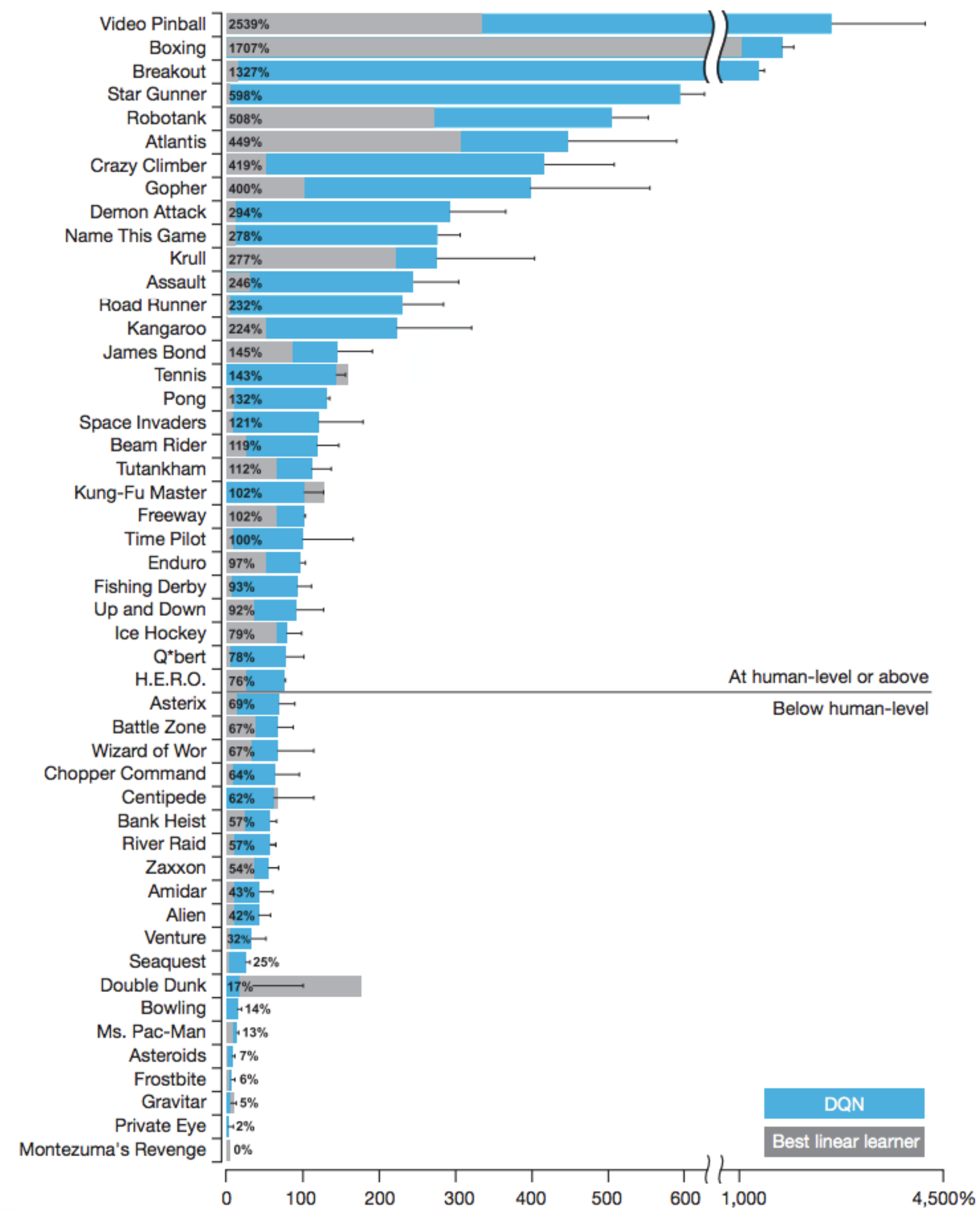
Atari Breakout





Playing Computer Games

- Deep Mind's deep Q-network agent trained only on the pixels of the video game and the game score as inputs
- able to surpass the performance of all previous algorithms and achieve a level comparable to that of a professional human games tester across a set of 49 games, using the same algorithm, network architecture and hyper parameters.
- first artificial agent that is capable of learning to excel at a diverse array of challenging tasks.



Mnih, Volodymyr, Koray Kavukcuoglu, David Silver, Andrei A. Rusu, Joel Veness, Marc G. Bellemare, Alex Graves et al. "Human-level control through deep reinforcement learning." *Nature* 518, no. 7540 (2015): 529-533.

Supervised vs Reinforcement Learning

- In supervised learning, there's an external "supervisor", which has knowledge of the environment and who shares it with the agent to complete the task.

- In some tasks there are so many combinations of subtasks that creating a "supervisor" is impractical (eg. in a chess game, there are tens of thousands of moves that can be played)

- It is more feasible to learn from one's own experiences and gain knowledge from them.

- In both supervised and reinforcement learning, there is a mapping between input and output, but in reinforcement learning, there is a reward function which acts as a feedback to the agent

Unsupervised vs Reinforcement Learning

- In unsupervised learning there is no direct mapping from input to output.

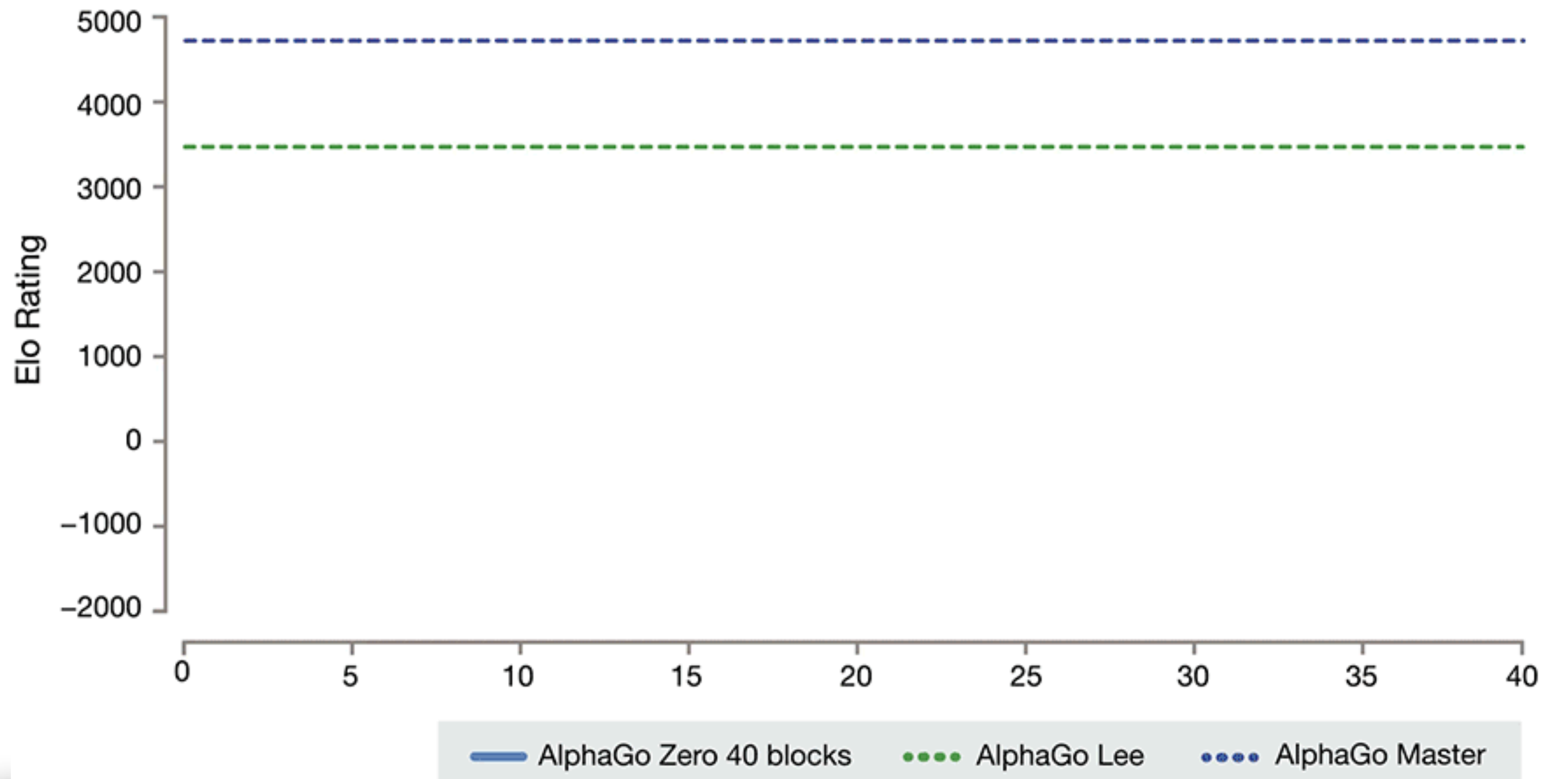
- In unsupervised learning, the main task is to find the underlying patterns rather than the mapping (eg. if the task is to suggest a movie to a user, an unsupervised learning algorithm will look at similar movies which the person has previously watched).

- A reinforcement learning algorithm will get constant feedback from the user by suggesting a few movies and then build a "knowledge graph" of which movies the person will like.

AlphaGo0

AlphaGo Zero becomes its own teacher.

The system starts off with a neural network that knows *nothing* about the game of Go.

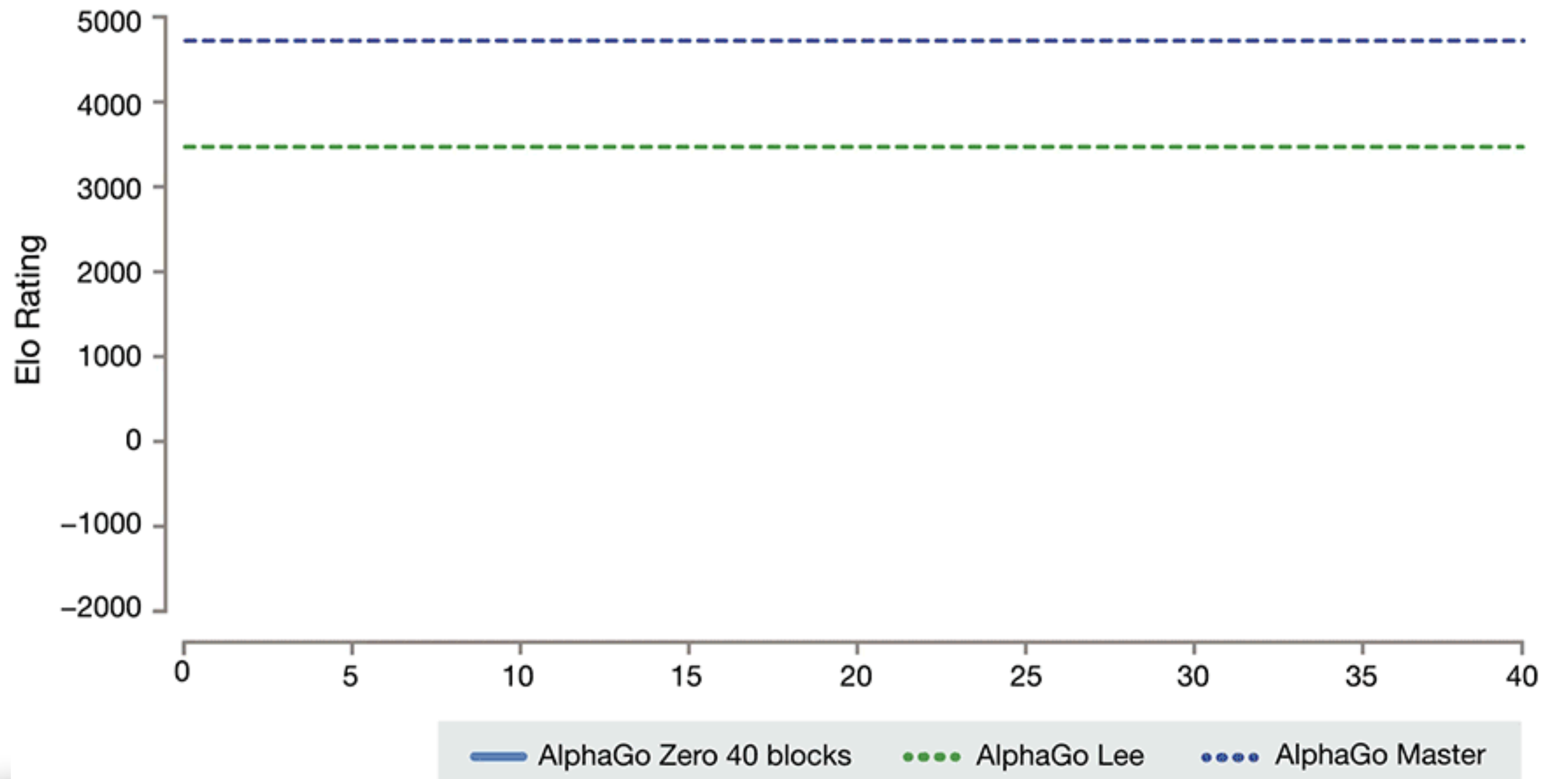


It then plays games against itself, by combining this neural network with a powerful search algorithm. As it plays, the neural network is tuned and updated to predict moves, as well as the eventual winner of the games.

AlphaGo0

AlphaGo Zero becomes its own teacher.

The system starts off with a neural network that knows *nothing* about the game of Go.

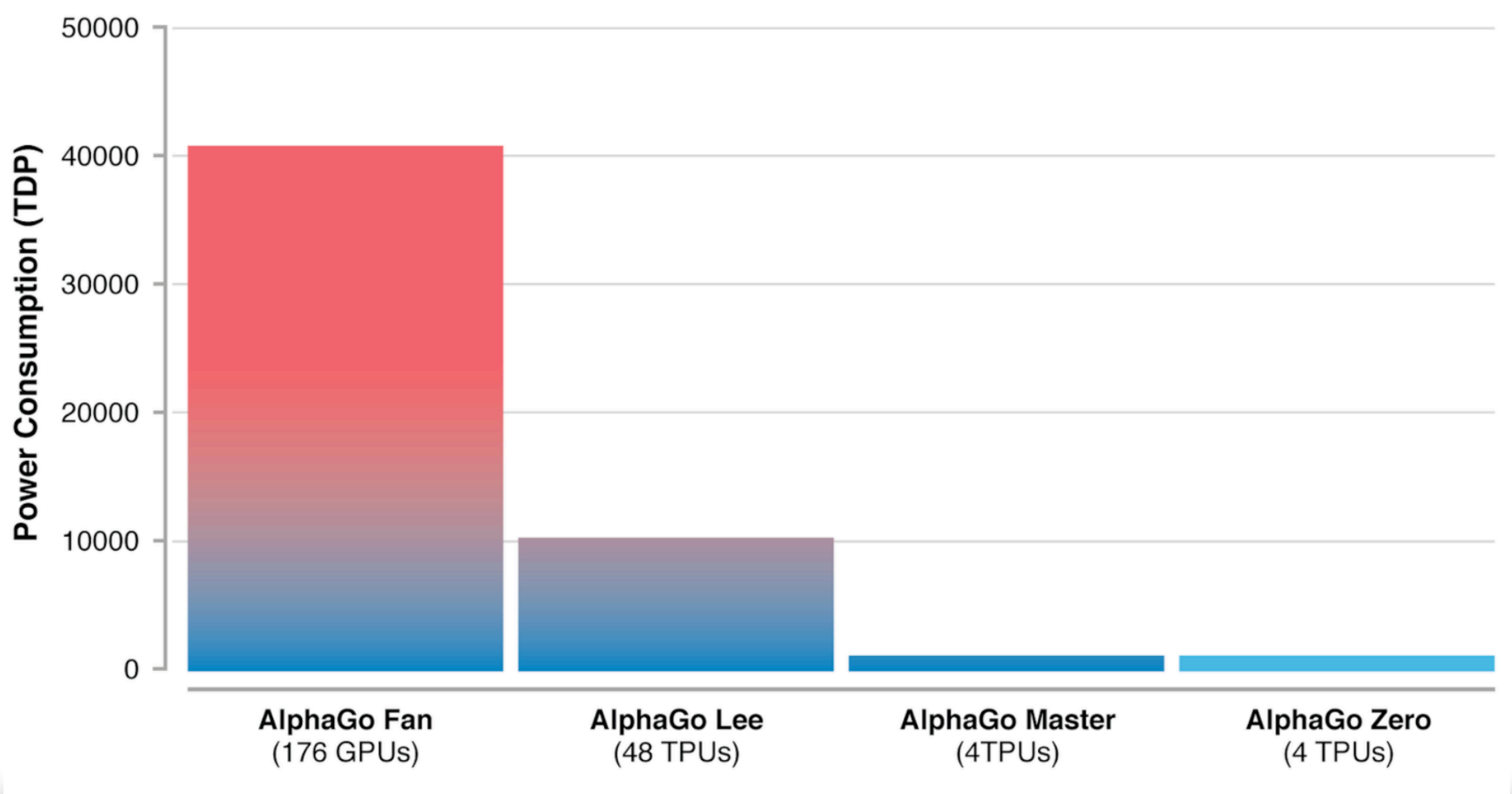


It then plays games against itself, by combining this neural network with a powerful search algorithm. As it plays, the neural network is tuned and updated to predict moves, as well as the eventual winner of the games.

AlphaGo0

Over the course of millions of AlphaGo vs AlphaGo games, the system progressively learned the game of Go from scratch, accumulating thousands of years of human knowledge during a period of just a few days.

AlphaGo Zero also discovered new knowledge, developing unconventional strategies and creative new moves that echoed and surpassed the novel techniques it played in the games against Lee Sedol and Ke Jie.



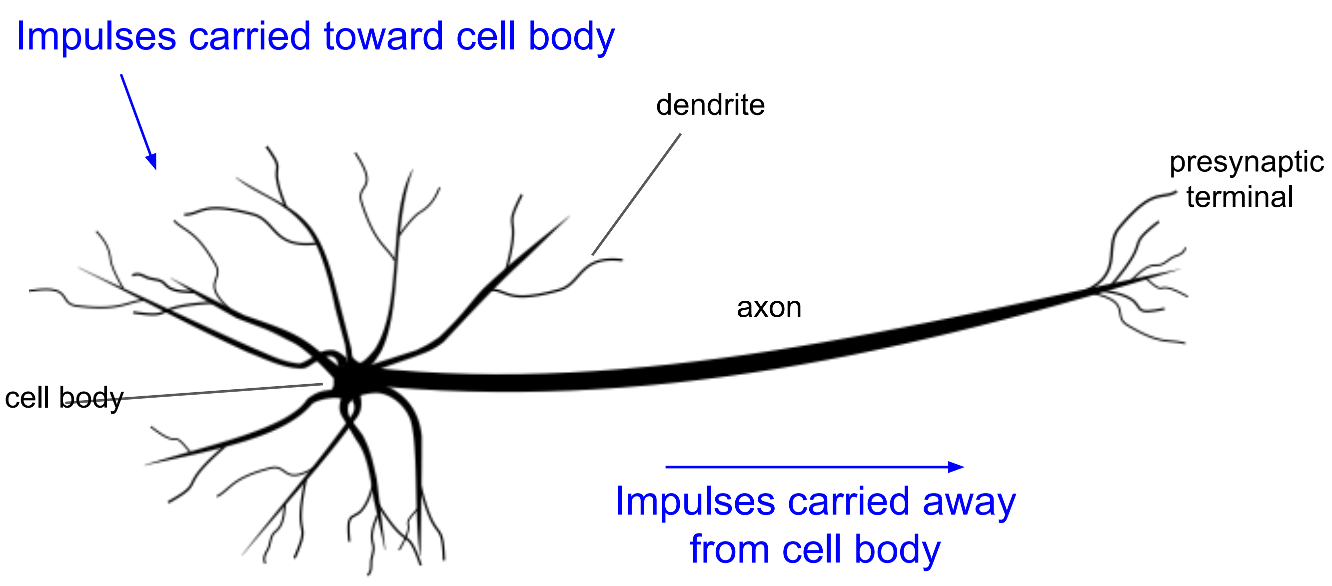
Neural Networks

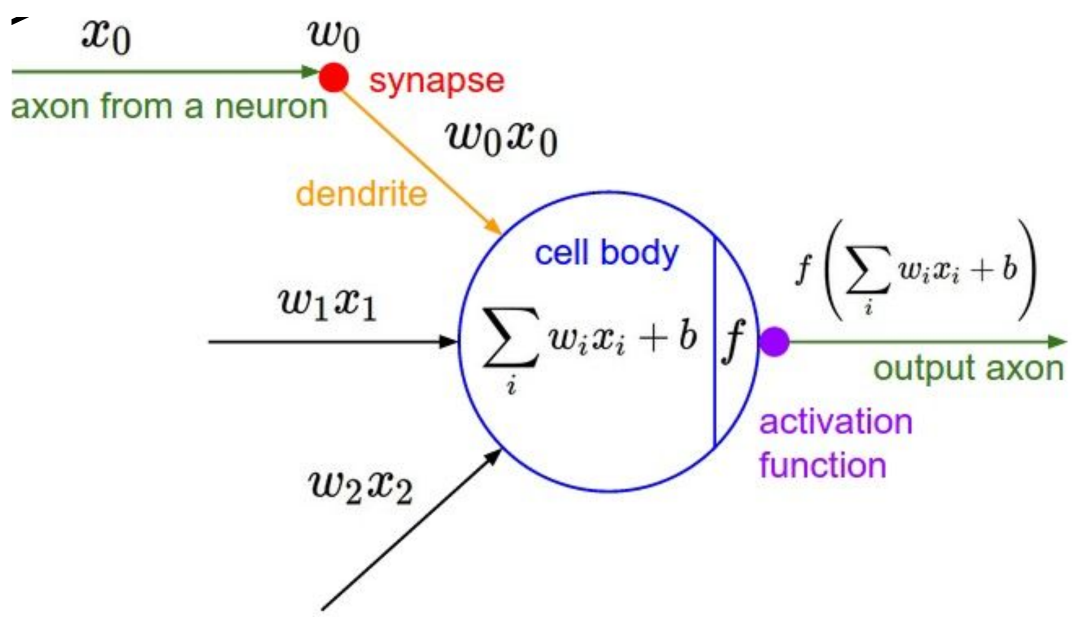
Neural Networks

Brains are made up of neurons which “fire” by emitting electrical signals to other neurons after being sufficiently “activated”.

Neurons are malleable in terms of how much a signal from other neurons will add to the activation level of the neuron

the weights of the connecting neurons are trained to make the neural connections more useful, just like the parameters in a linear regression can be trained to improve the mapping from input to output).





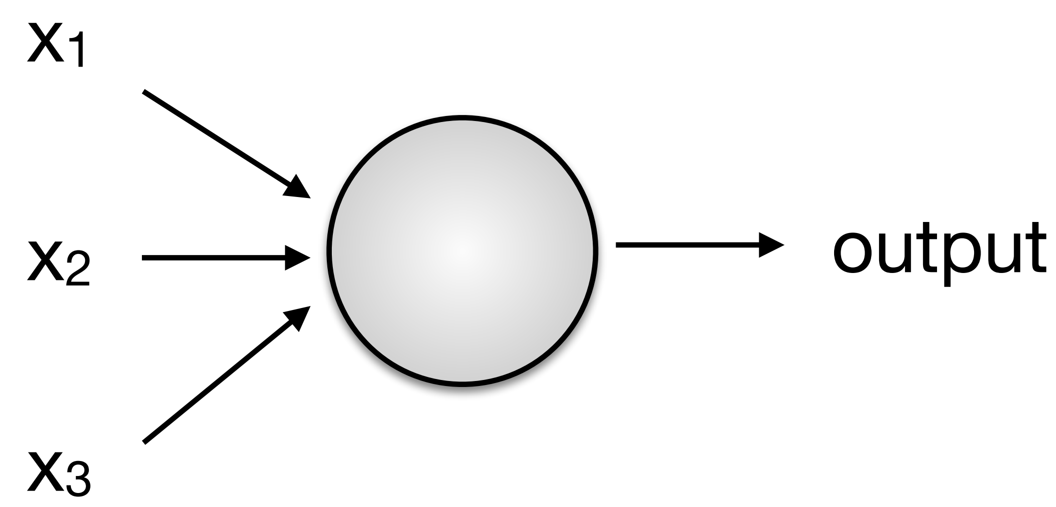
Neural Networks

- You recognise those digits very easily
- In each hemisphere of our brain, humans have a primary visual cortex, also known as V1, containing 140 million neurons, with tens of billions of connections between them.
- And yet human vision involves not just V1, but an entire series of visual cortices - V2, V3, V4, and V5 - doing progressively more complex image processing.
- We carry in our heads a supercomputer, tuned by evolution over hundreds of millions of years, and superbly adapted to understand the visual world.
- Humans are incredibly good at making sense of what our eyes show us.

Perceptron

A perceptron takes several binary inputs, and produces a single binary output

the perceptron is a device that makes decisions by weighing up evidence



$$\text{output} = \begin{cases} 0 & \text{if } \sum_j w_j x_j \leq \text{ threshold} \\ 1 & \text{if } \sum_j w_j x_j > \text{ threshold} \end{cases}$$

Neural Network

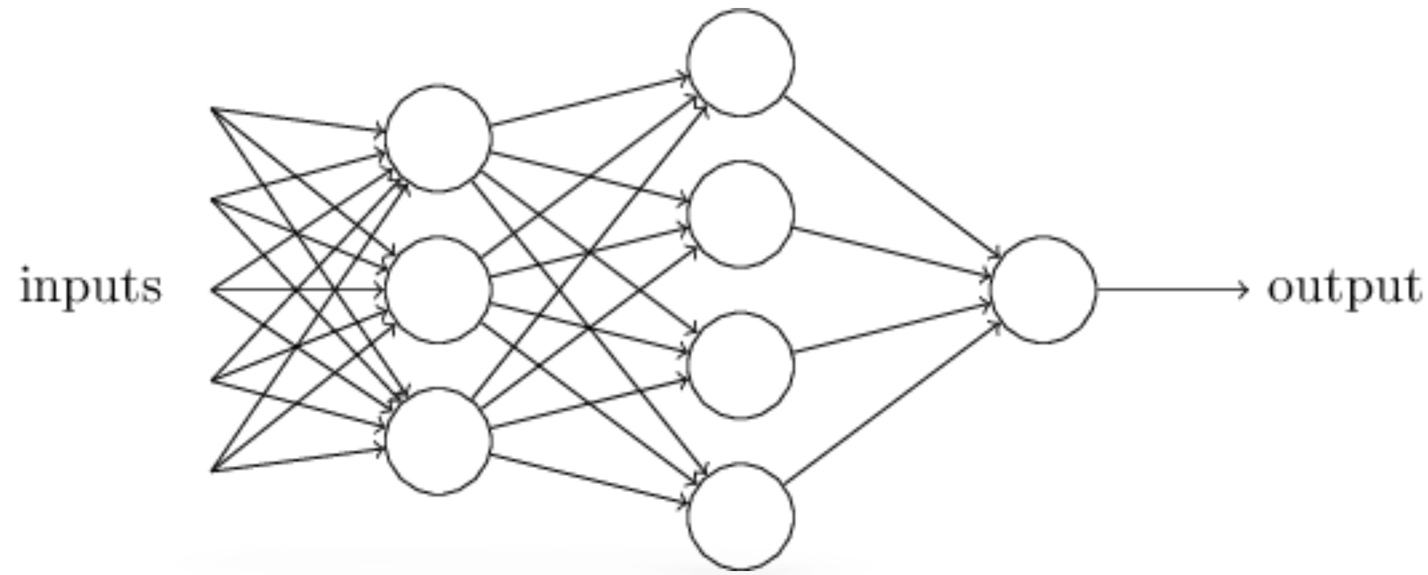
a complex network of perceptrons could make quite subtle decisions

The first column of perceptrons - what we'll call the first *layer* of perceptrons - is making three very simple decisions, by weighing the input evidence.

The perceptrons in the 2nd layer are making a decision by weighing up the results from the first layer of decision-making.

Even more complex decisions can be made by the perceptron in the third layer.

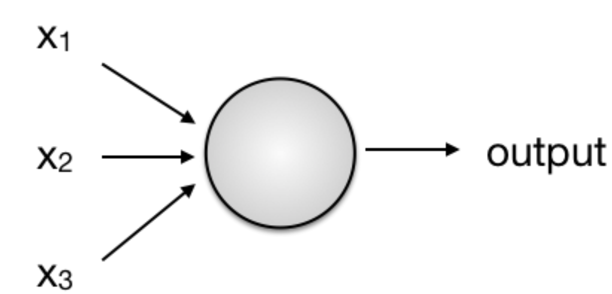
A many-layer network of perceptrons can engage in sophisticated decision making.



$$\text{output} = \begin{cases} 0 & \text{if } \sum_j w_j x_j \leq \text{ threshold} \\ 1 & \text{if } \sum_j w_j x_j > \text{ threshold} \end{cases}$$

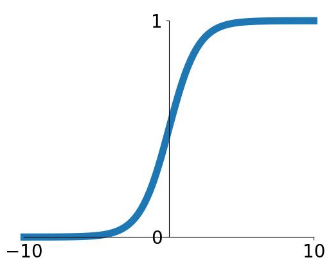
Activation Functions

- to enable the neurons to learn we have a choice of activation functions
- activation functions control the output response for a given change in the input



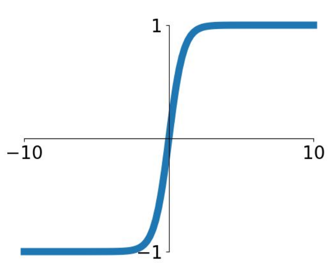
Sigmoid

$\sigma(x) = \frac{1}{1+e^{-x}}$



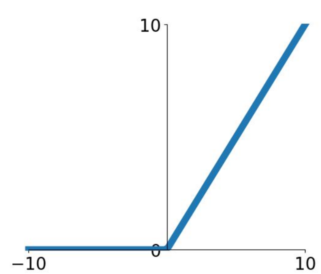
tanh

$\tanh(x)$



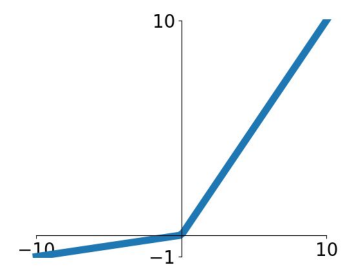
ReLU

$\max(0, x)$



Leaky ReLU

$\max(0.1x, x)$

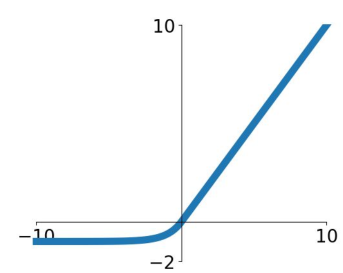


Maxout

$\max(w_1^T x + b_1, w_2^T x + b_2)$

ELU

$$\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$



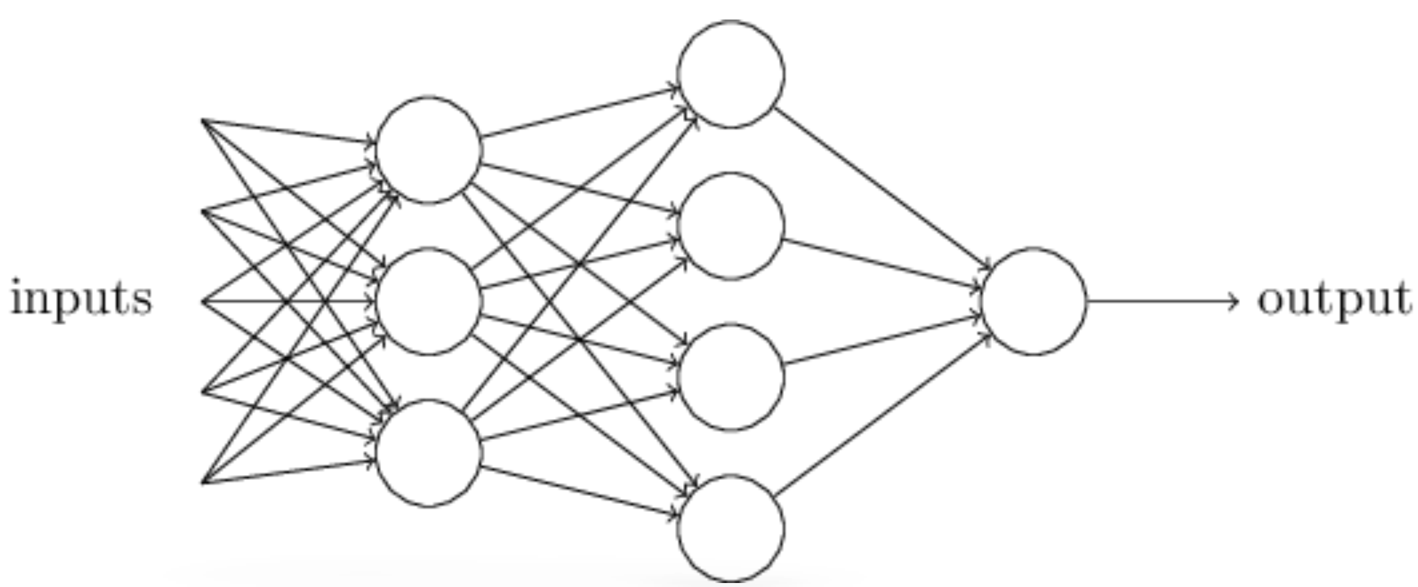
Neural Network

Each “edge” has an associated weight or parameter

Output is a weighted sum of the inputs

Goal: learn the weights that best predict the output

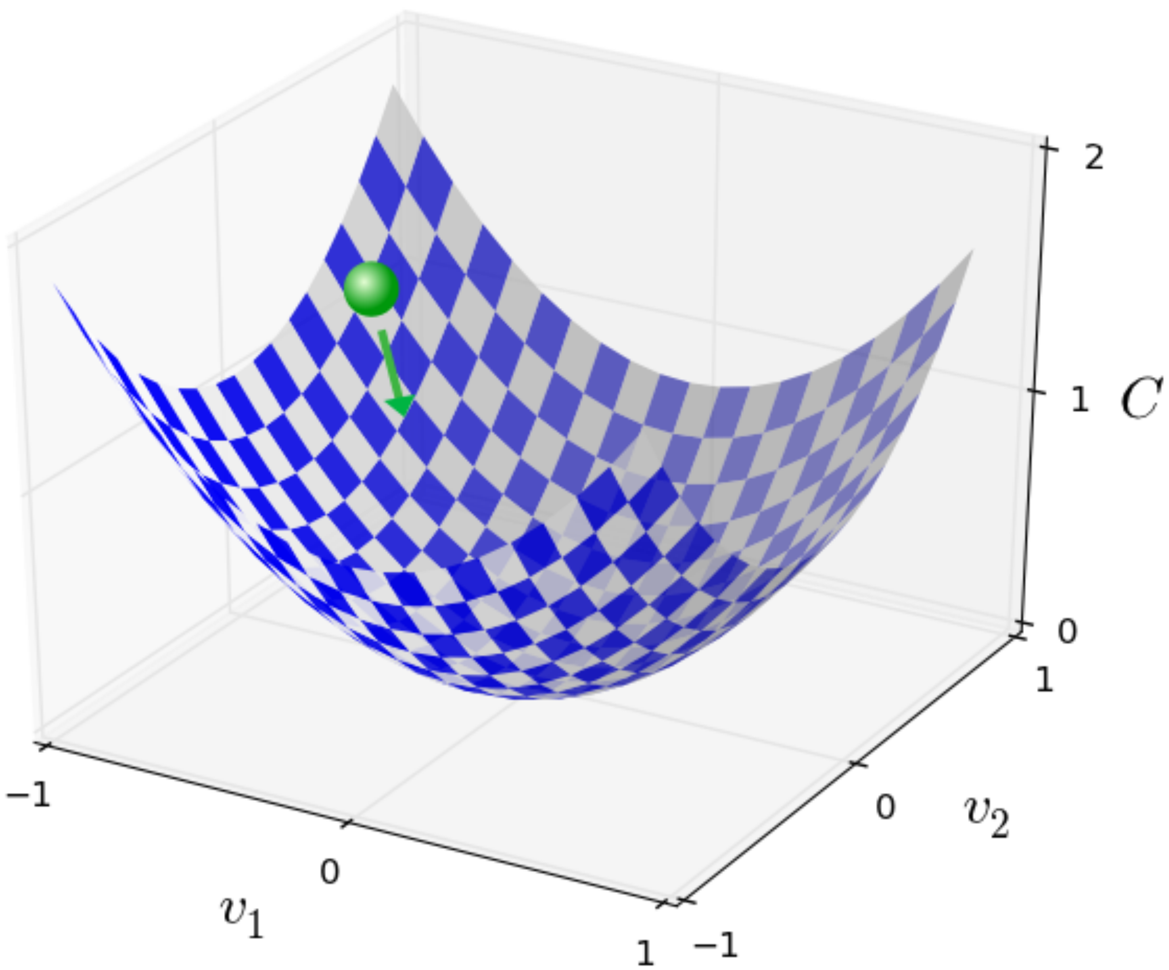
Adding more layers gives us a flexible non-linear function of the inputs



$$C(w, b) \equiv \frac{1}{2n} \sum_x \|y(x) - a\|^2$$

Neural Network

- use gradient descent to find the weights and biases which minimise the cost function



$$C(w,b) \equiv \frac{1}{2n} \sum_x \|y(x) - a\|^2$$

$$v \rightarrow v' = v - \eta \nabla C$$

Deep Neural Networks

Deep Neural Networks

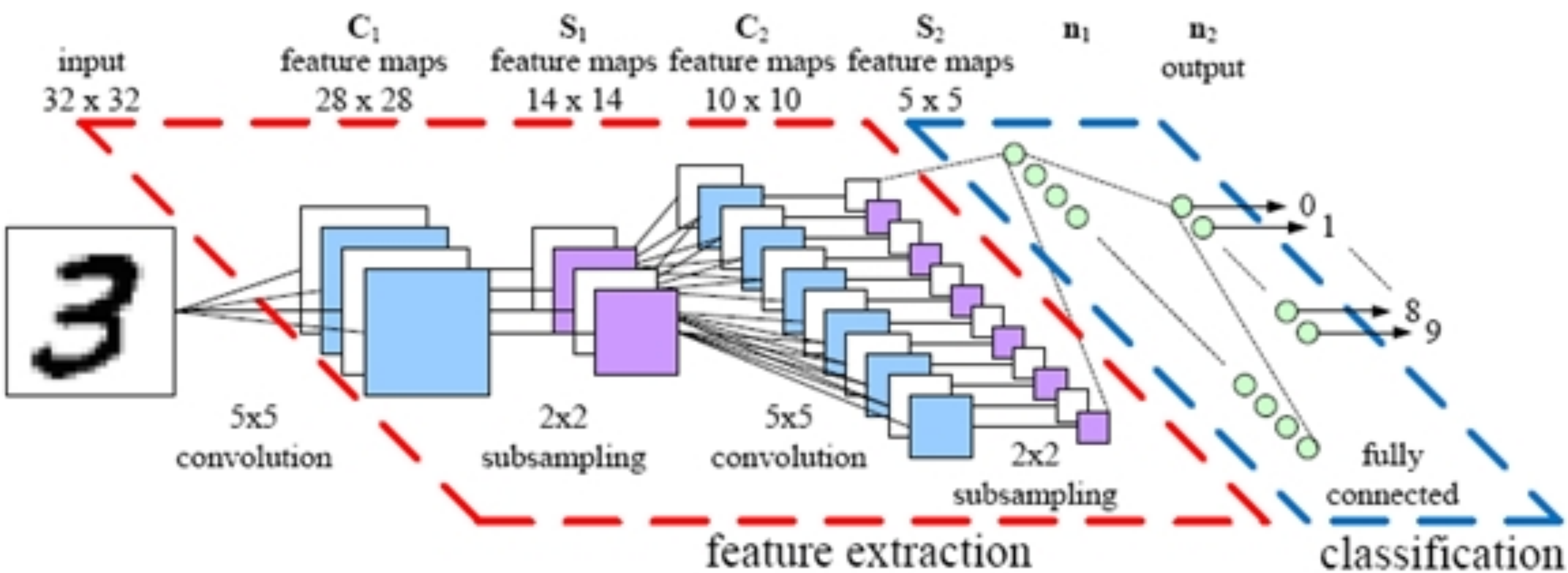
- create deep networks
- many hidden layers
- ability to learn a complex hierarchy of concepts
- more powerful than shallow neural networks
- more difficult to train and understand
- features are discovered from the data
- performance improves with more data

GoogleNet

27 layers

Deep Neural Networks

- Convolutional neural networks
- developed for image classification
- several layers which build a hierarchy of features
- the last layers do the classification

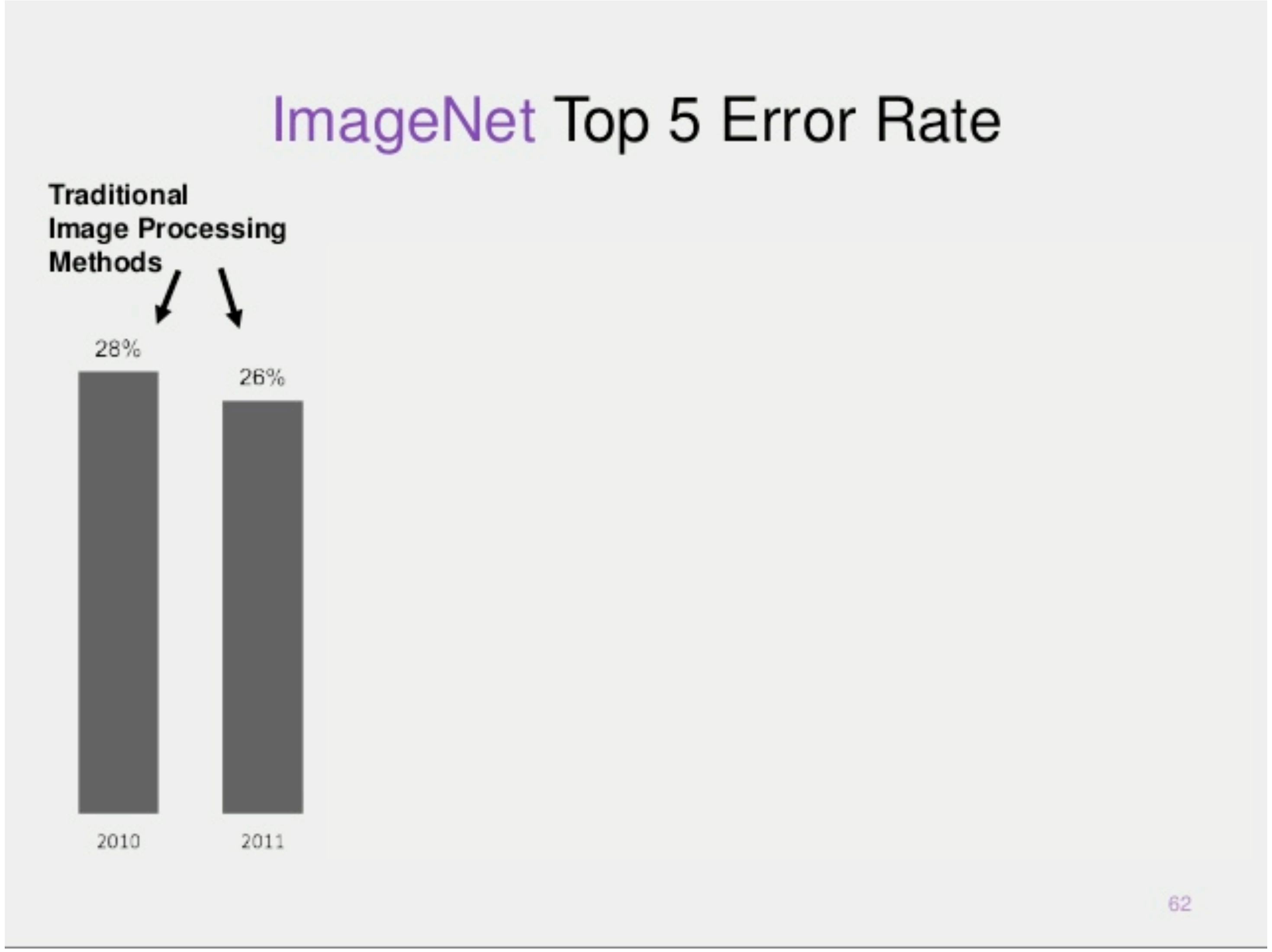


ImageNet

- **ImageNet** is a large visual database designed for use in visual object recognition software research.
- As of 2016, over ten million URLs of images have been hand-annotated by ImageNet to indicate what objects are pictured
- ImageNet Large Scale Visual Recognition Challenge (ILSVRC) is a competition where research teams evaluate their algorithms on the given data set, and compete to achieve higher accuracy on several visual recognition tasks.

ImageNet

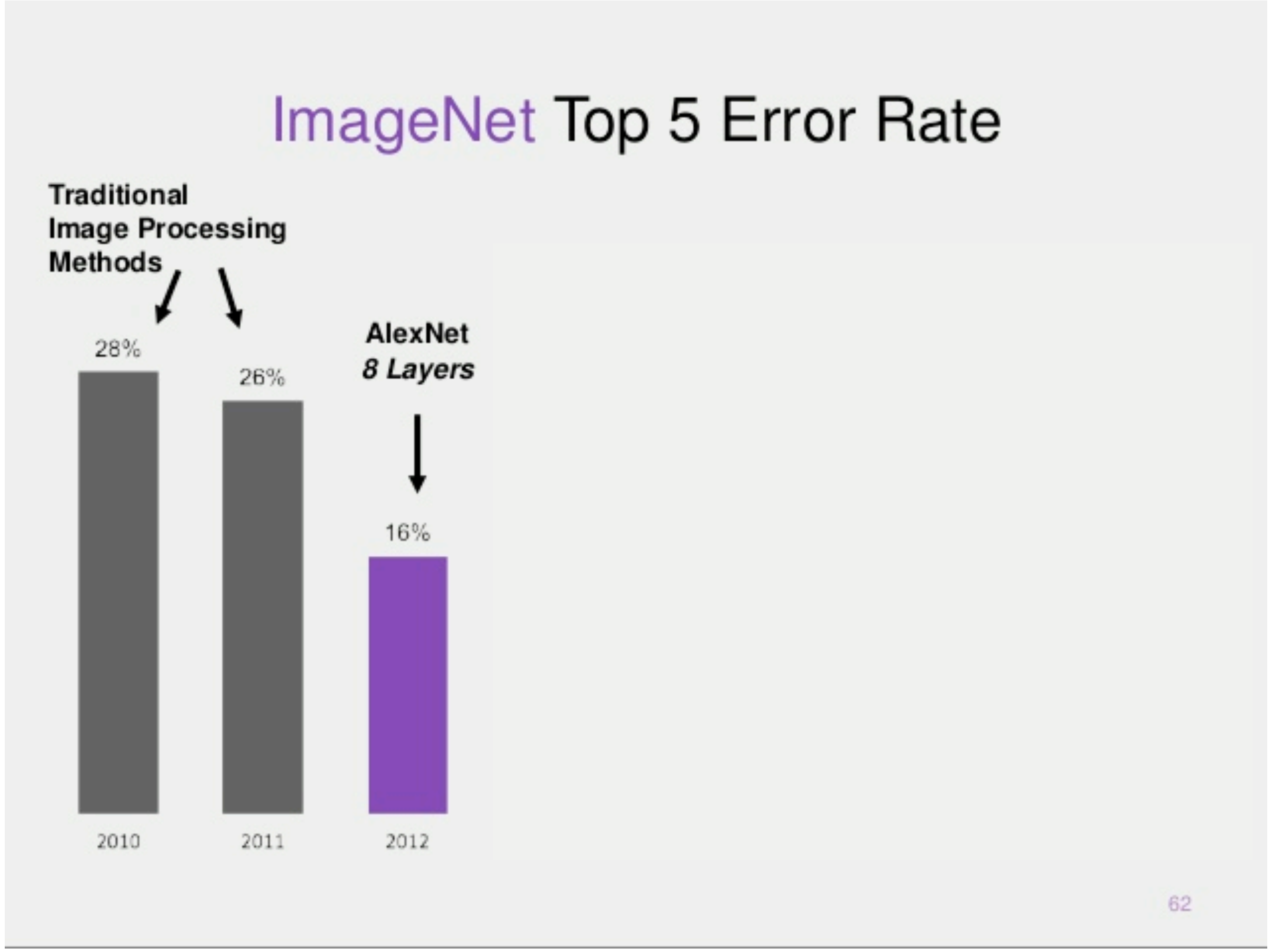
- **ImageNet** is a large visual database designed for use in visual object recognition software research.
- As of 2016, over ten million URLs of images have been hand-annotated by ImageNet to indicate what objects are pictured
- ImageNet Large Scale Visual Recognition Challenge (ILSVRC) is a competition where research teams evaluate their algorithms on the given data set, and compete to achieve higher accuracy on several visual recognition tasks.



Human performance ~5.1%

ImageNet

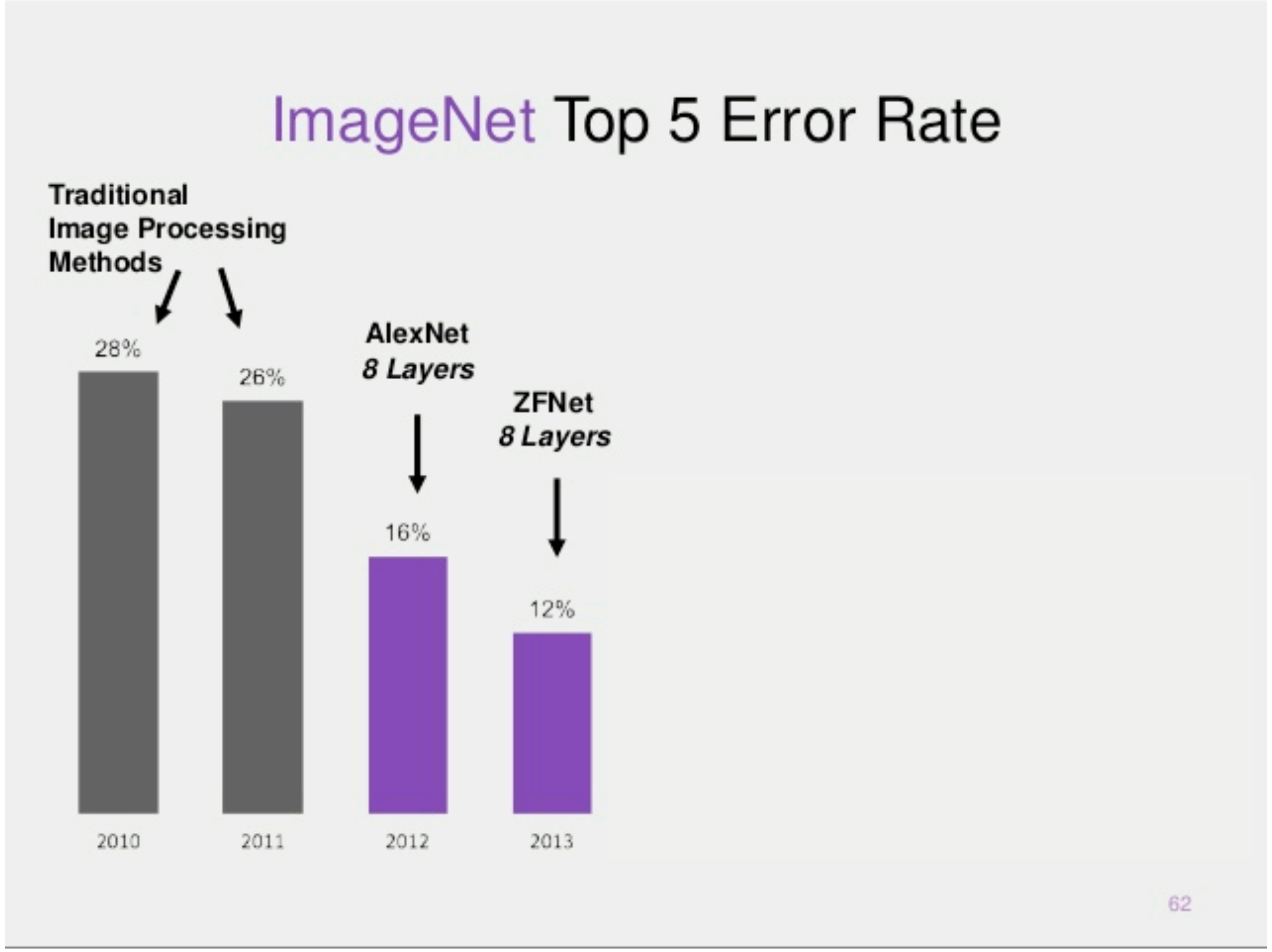
- **ImageNet** is a large visual database designed for use in visual object recognition software research.
- As of 2016, over ten million URLs of images have been hand-annotated by ImageNet to indicate what objects are pictured
- ImageNet Large Scale Visual Recognition Challenge (ILSVRC) is a competition where research teams evaluate their algorithms on the given data set, and compete to achieve higher accuracy on several visual recognition tasks.



Human performance ~5.1%

ImageNet

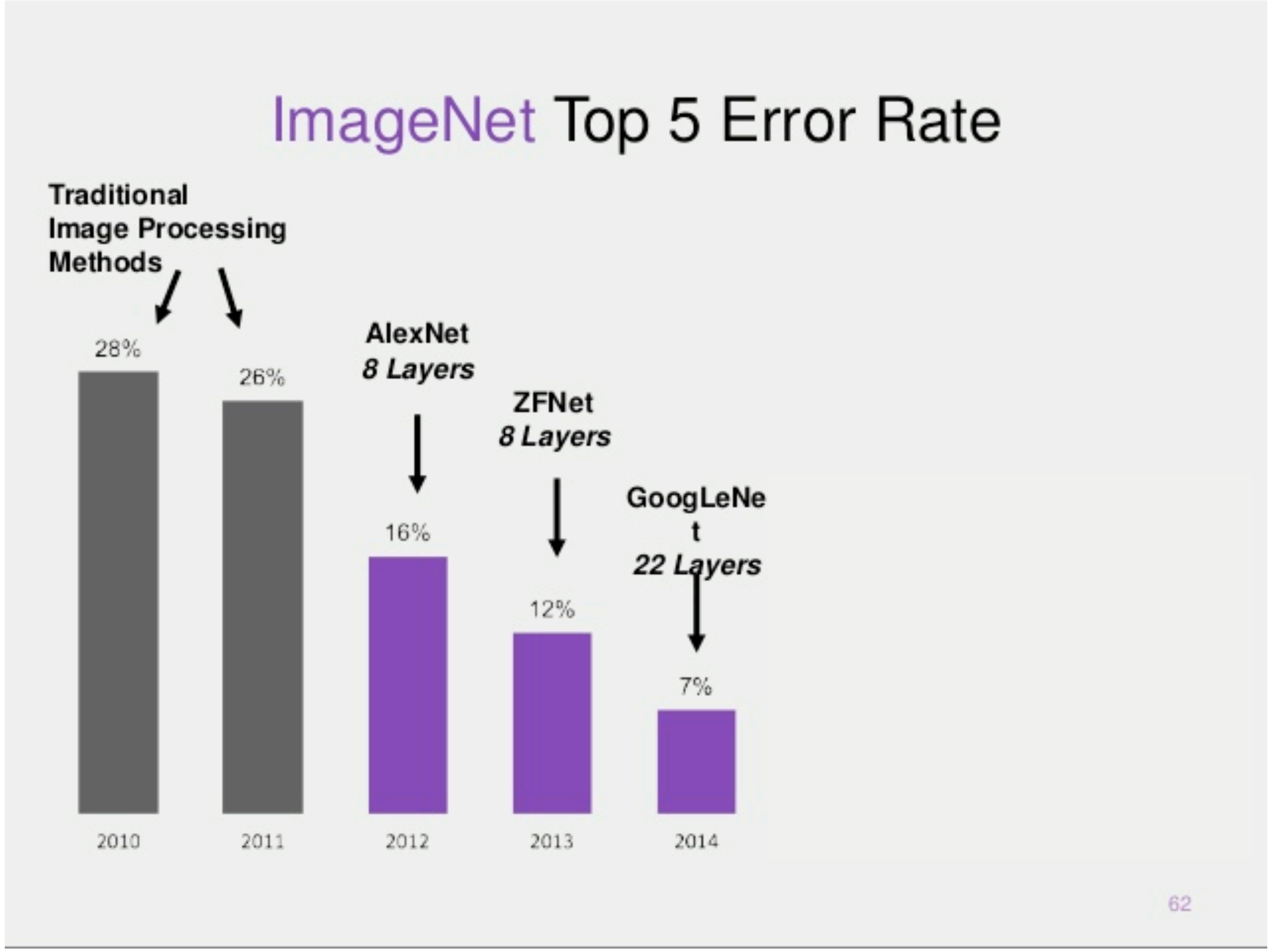
- **ImageNet** is a large visual database designed for use in visual object recognition software research.
- As of 2016, over ten million URLs of images have been hand-annotated by ImageNet to indicate what objects are pictured
- ImageNet Large Scale Visual Recognition Challenge (ILSVRC) is a competition where research teams evaluate their algorithms on the given data set, and compete to achieve higher accuracy on several visual recognition tasks.



Human performance ~5.1%

ImageNet

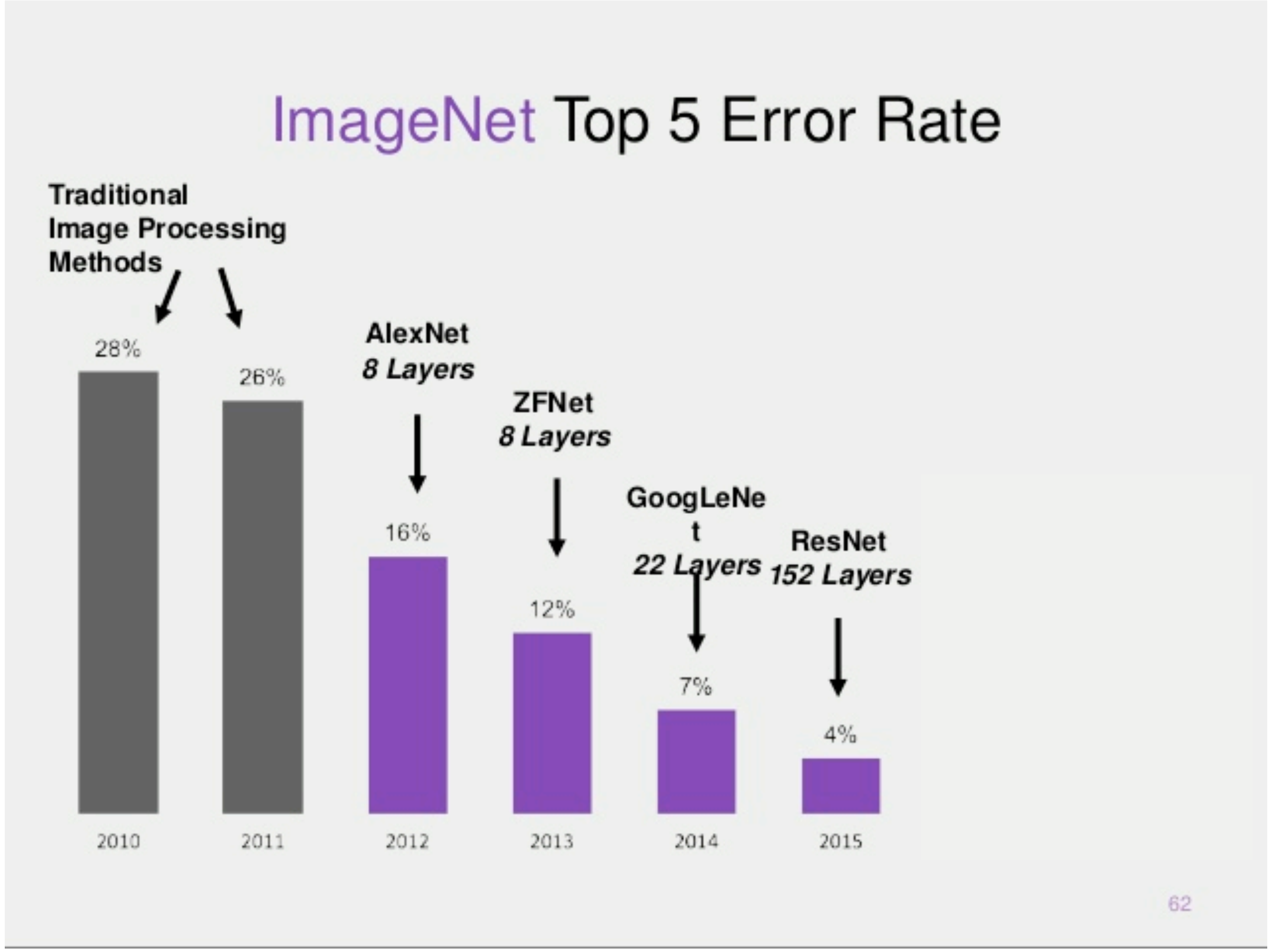
- **ImageNet** is a large visual database designed for use in visual object recognition software research.
- As of 2016, over ten million URLs of images have been hand-annotated by ImageNet to indicate what objects are pictured
- ImageNet Large Scale Visual Recognition Challenge (ILSVRC) is a competition where research teams evaluate their algorithms on the given data set, and compete to achieve higher accuracy on several visual recognition tasks.



Human performance ~5.1%

ImageNet

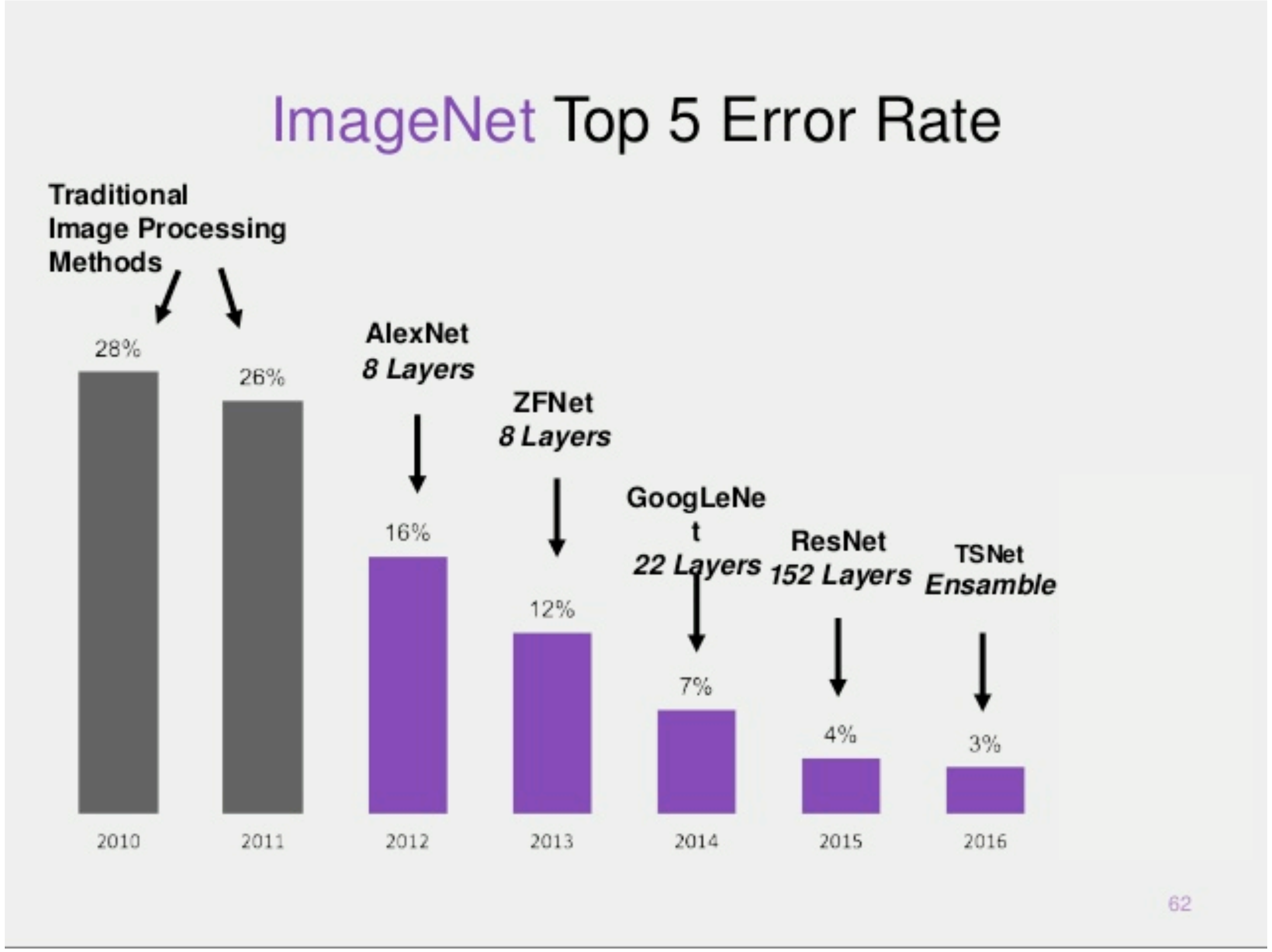
- **ImageNet** is a large visual database designed for use in visual object recognition software research.
- As of 2016, over ten million URLs of images have been hand-annotated by ImageNet to indicate what objects are pictured
- ImageNet Large Scale Visual Recognition Challenge (ILSVRC) is a competition where research teams evaluate their algorithms on the given data set, and compete to achieve higher accuracy on several visual recognition tasks.



Human performance ~5.1%

ImageNet

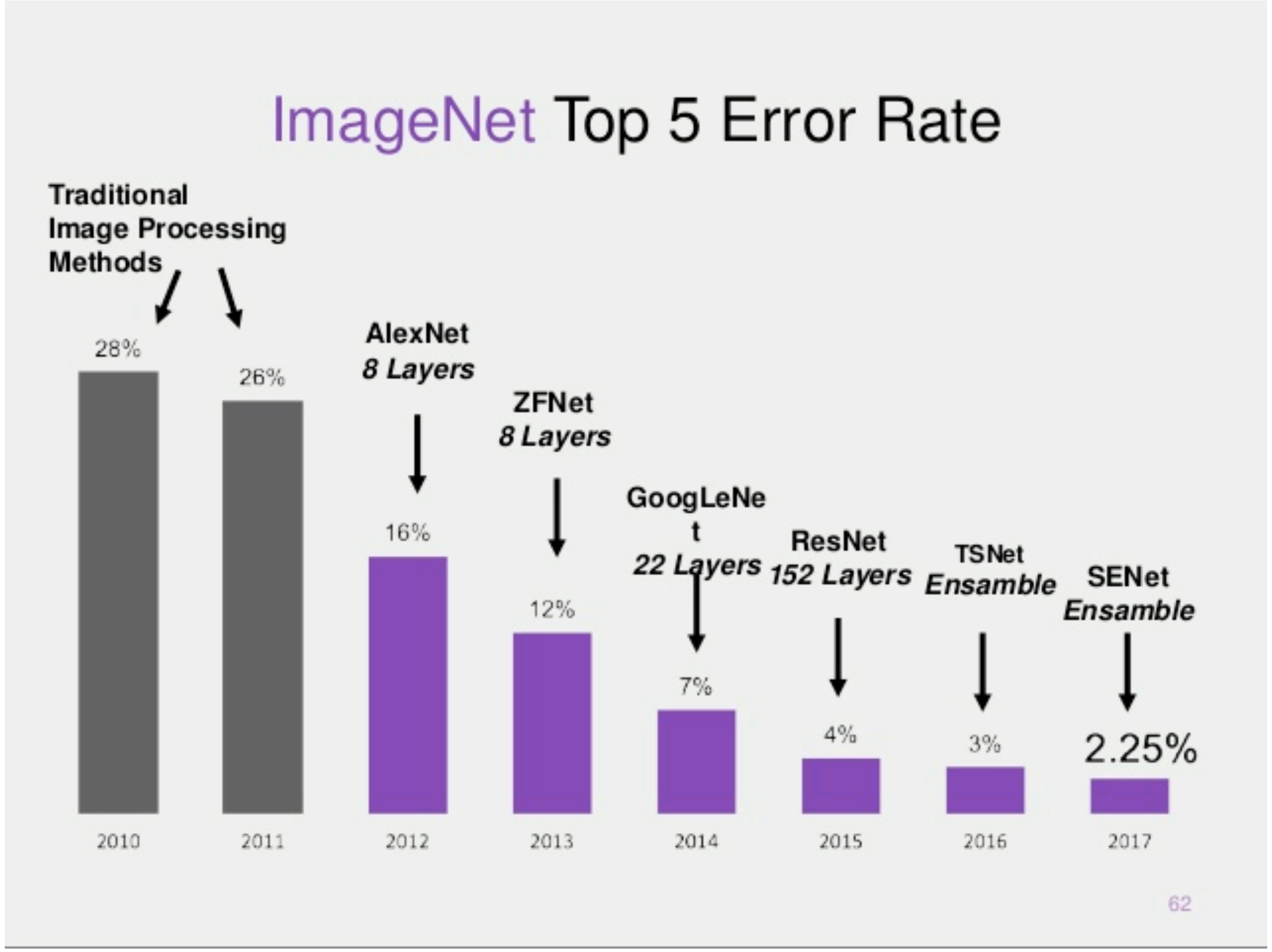
- **ImageNet** is a large visual database designed for use in visual object recognition software research.
- As of 2016, over ten million URLs of images have been hand-annotated by ImageNet to indicate what objects are pictured
- ImageNet Large Scale Visual Recognition Challenge (ILSVRC) is a competition where research teams evaluate their algorithms on the given data set, and compete to achieve higher accuracy on several visual recognition tasks.



Human performance ~5.1%

ImageNet

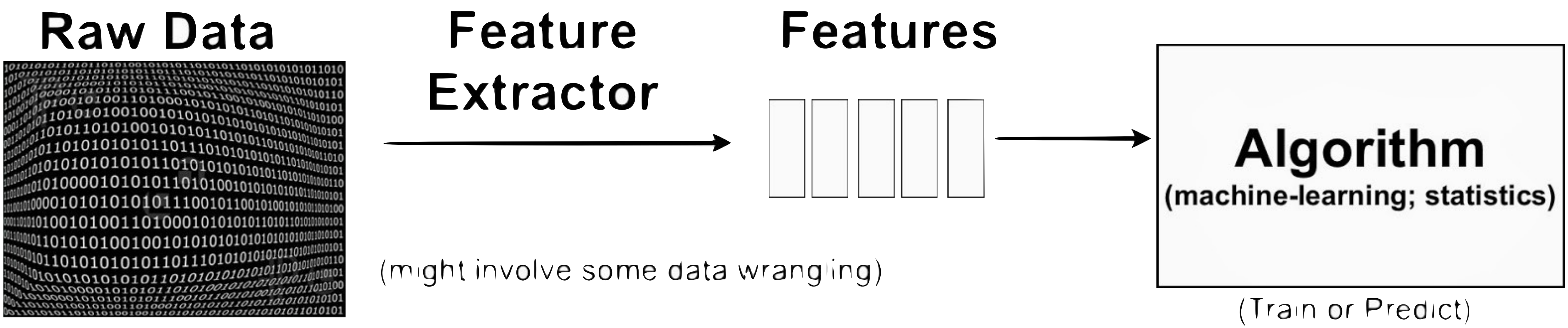
- **ImageNet** is a large visual database designed for use in visual object recognition software research.
- As of 2016, over ten million URLs of images have been hand-annotated by ImageNet to indicate what objects are pictured
- ImageNet Large Scale Visual Recognition Challenge (ILSVRC) is a competition where research teams evaluate their algorithms on the given data set, and compete to achieve higher accuracy on several visual recognition tasks.



Human performance ~5.1%

Learning Features

- Machine learning is *not* a one-shot process of building a dataset and running a learner
- More often an iterative process of running the learner, analysing the results, modifying the data and/or the learner, and repeating.



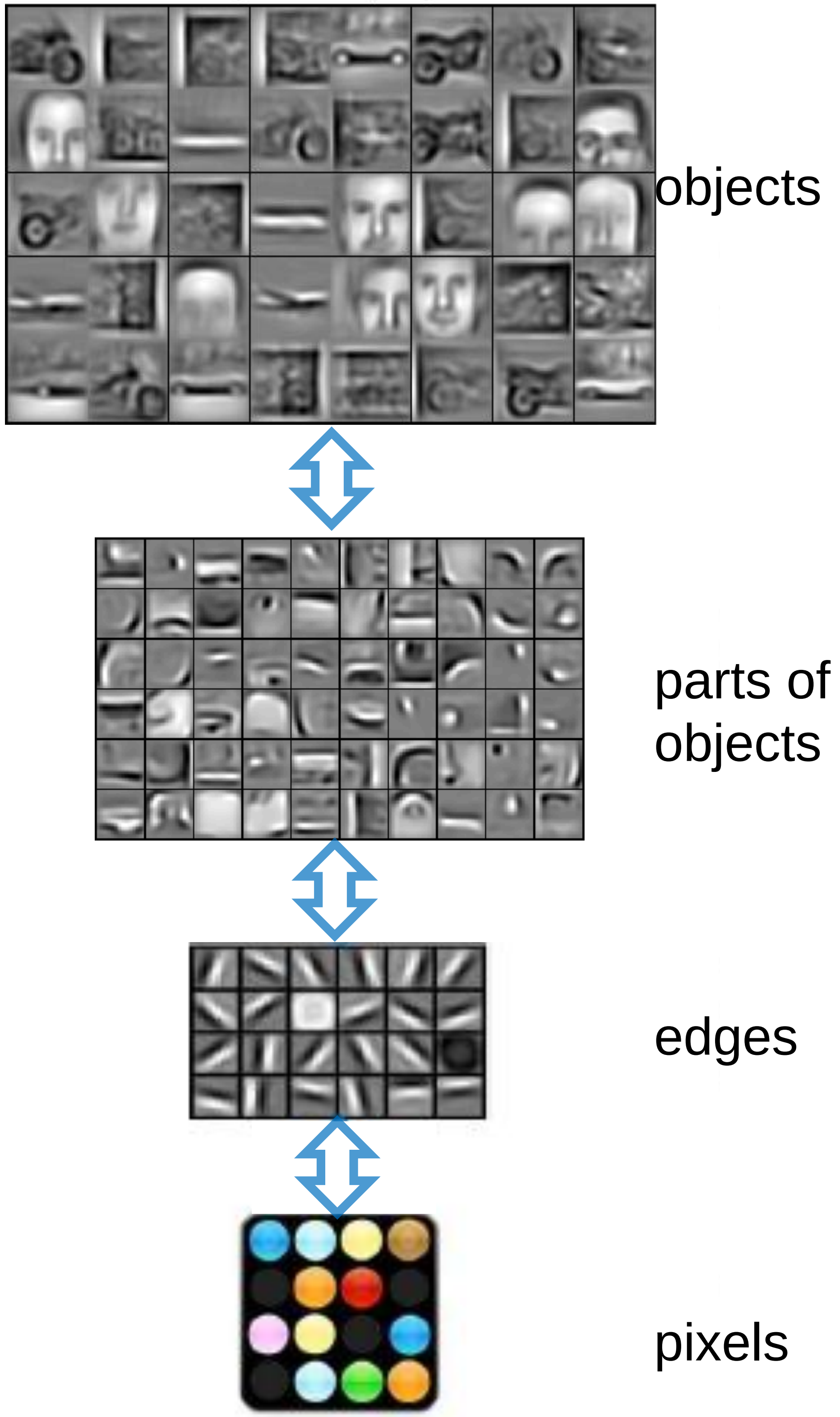
Learning Features

What are the hidden layers actually learning?

Deep architectures can be representationally efficient.

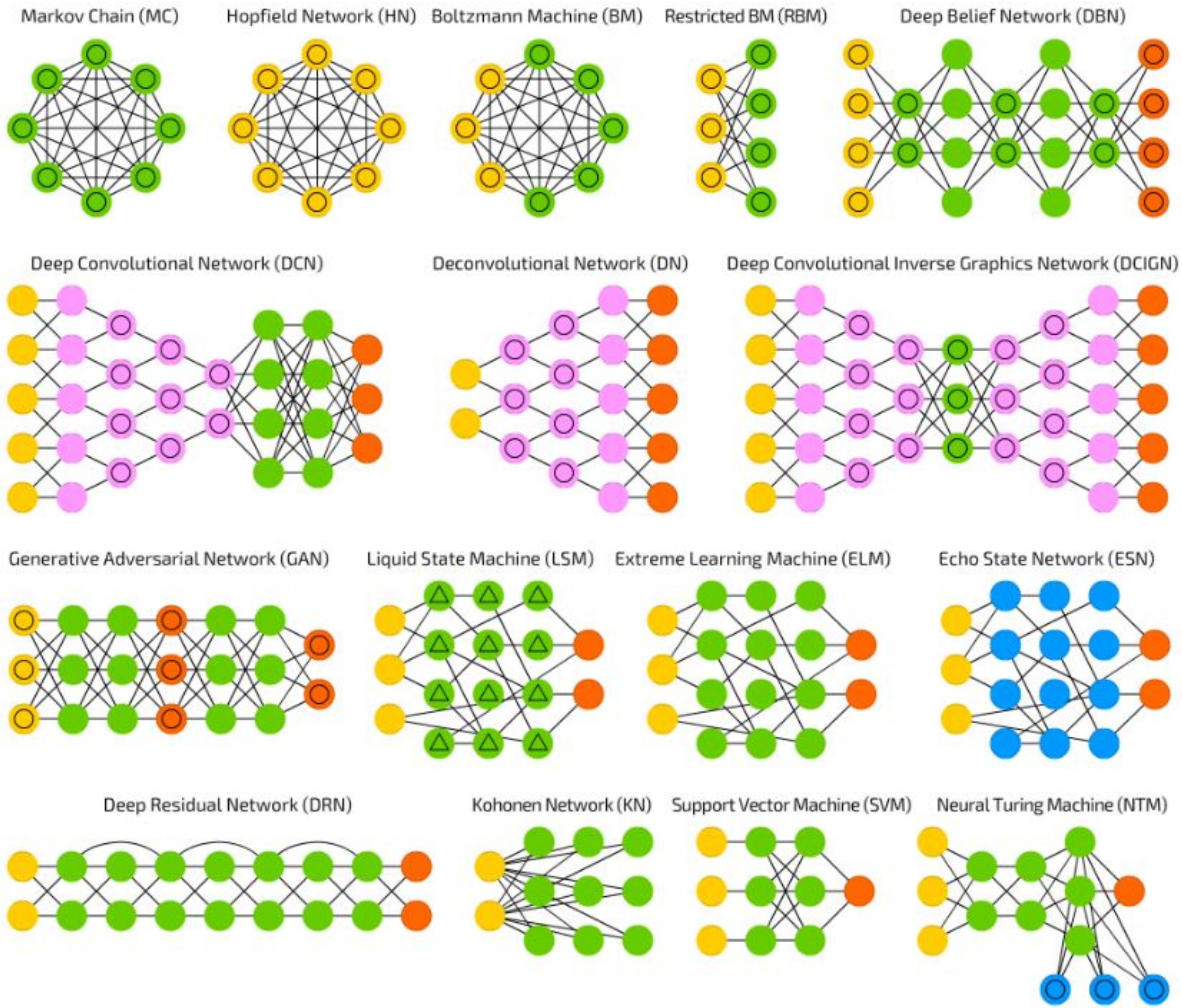
Natural progression from low level to high level structures.

Can share the lower-level representations for multiple tasks.




no more handcrafted features!

Other Architecture types



Deep Learning

Special architectures for different problem domains.

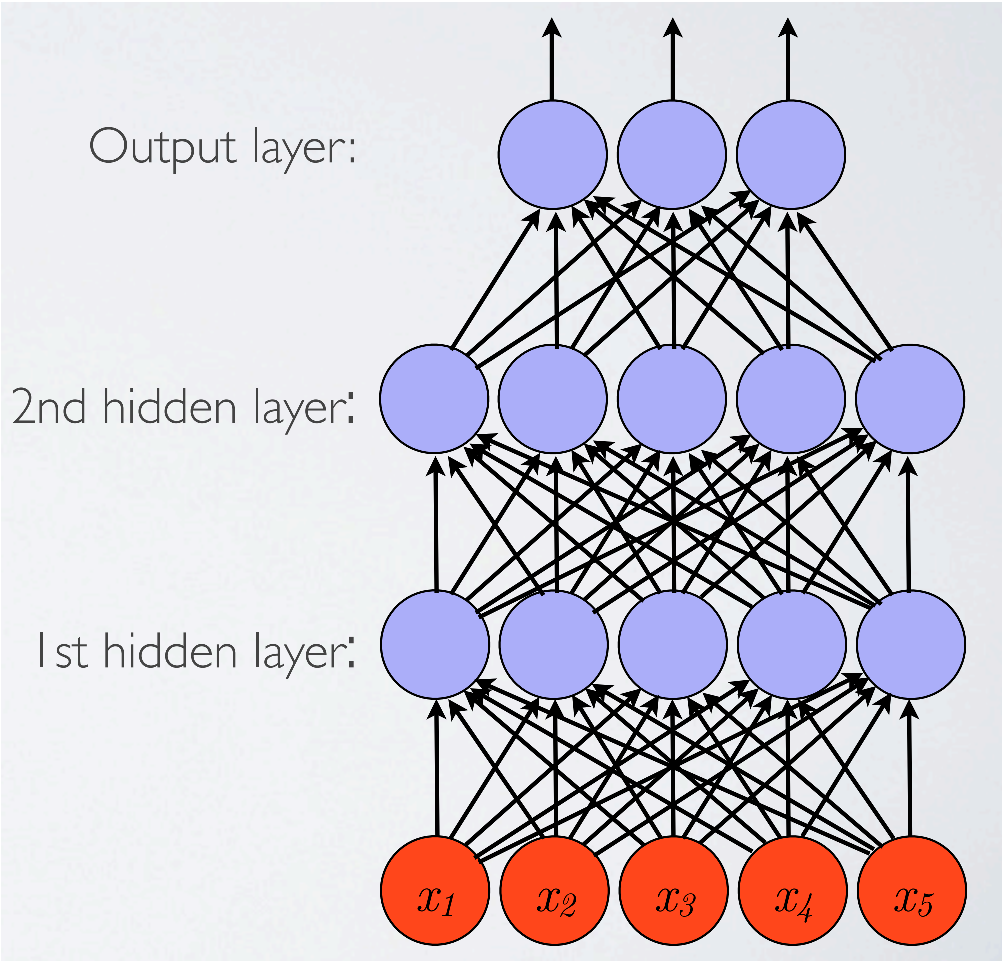
Computer vision => Convolutional neural nets.

Text and Speech => Recurrent neural nets.

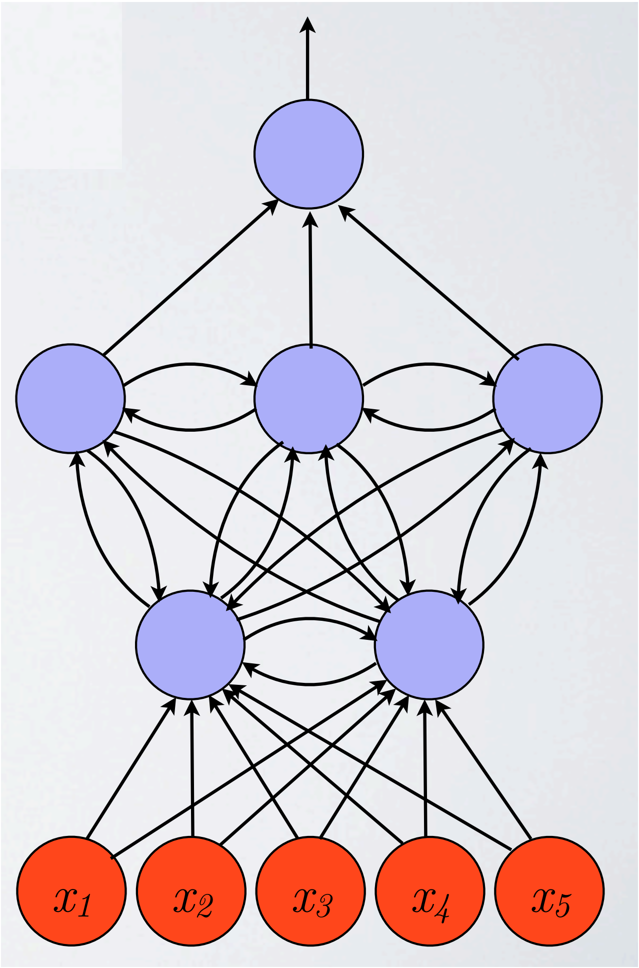
Recurrent Neural Networks

Recurrent Neural Network (RNN)

- RNN’s can have arbitrary topology
- no fixed direction for information flow
- delays associated with connections (every directed cycle contains a delay)



feed-forward



recurrent

RNN

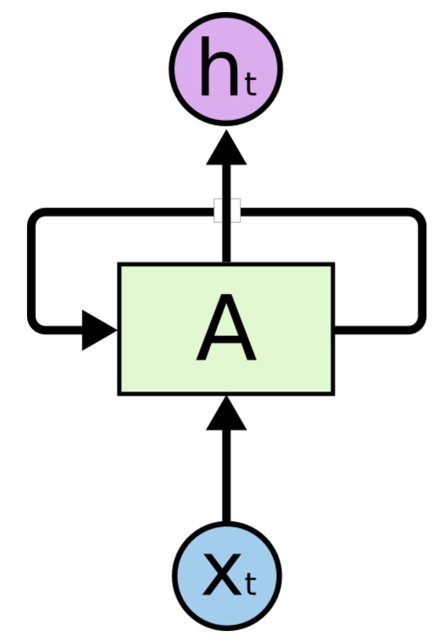
What can we represent with cycles?

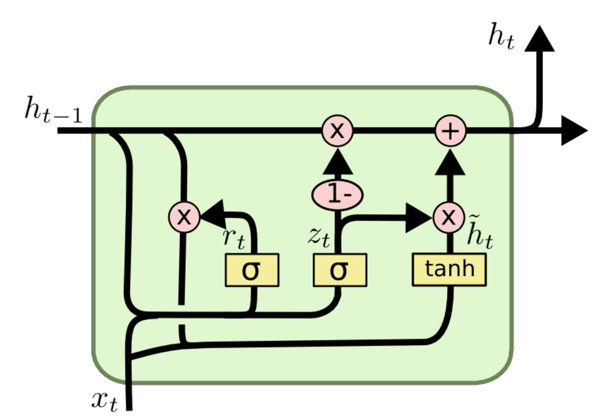
- Store an internal dynamic state.
- Summarise or encode sequences, time-series.
- Can capture oscillatory patterns.
- Can ignore some portion of a sequence.
- Hard: Sequences with long dependencies

.

RNN's

- RNN's are networks with loops in them, allowing information to persist
- RNN's struggle with long term dependencies
- Long Short Term Memory networks – usually just called "LSTMs" – are a special kind of RNN, capable of learning long-term dependencies.
- Their structure allows them to remember information for long periods of time





$$z_t = \sigma\left(W_z \cdot [h_{t-1}, x_t]\right)$$

$$r_t = \sigma\left(W_r \cdot [h_{t-1}, x_t]\right)$$

$$\tilde{h}_t = \tanh\left(W \cdot [r_t * h_{t-1}, x_t]\right)$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

LSTM

LSTM architecture has existed for many years (Hochreiter & Schmidhuber 1997).

Several state-of-the-art results:

- Cursive hand writing recognition (Graves & Schmidhuber, 2009)
- Speech recognition (Graves, Mohamed & Hinton, 2013)
- Machine translation (Sutskever, Vinyals & Le, 2014)
- Question-answer (Weston et al., 2015)
- Unstructured dialogue response generation (Serban et al., 2016)

Main model for language understanding & generation tasks.

Natural Language Processing

Natural Language Processing

mid-1970s: HMMs for speech recognition

⇒ probabilistic models

early 2000s: conditional random fields for part-of-speech tagging

⇒ structured prediction

early 2000s: Latent Dirichlet Allocation for modelling text documents

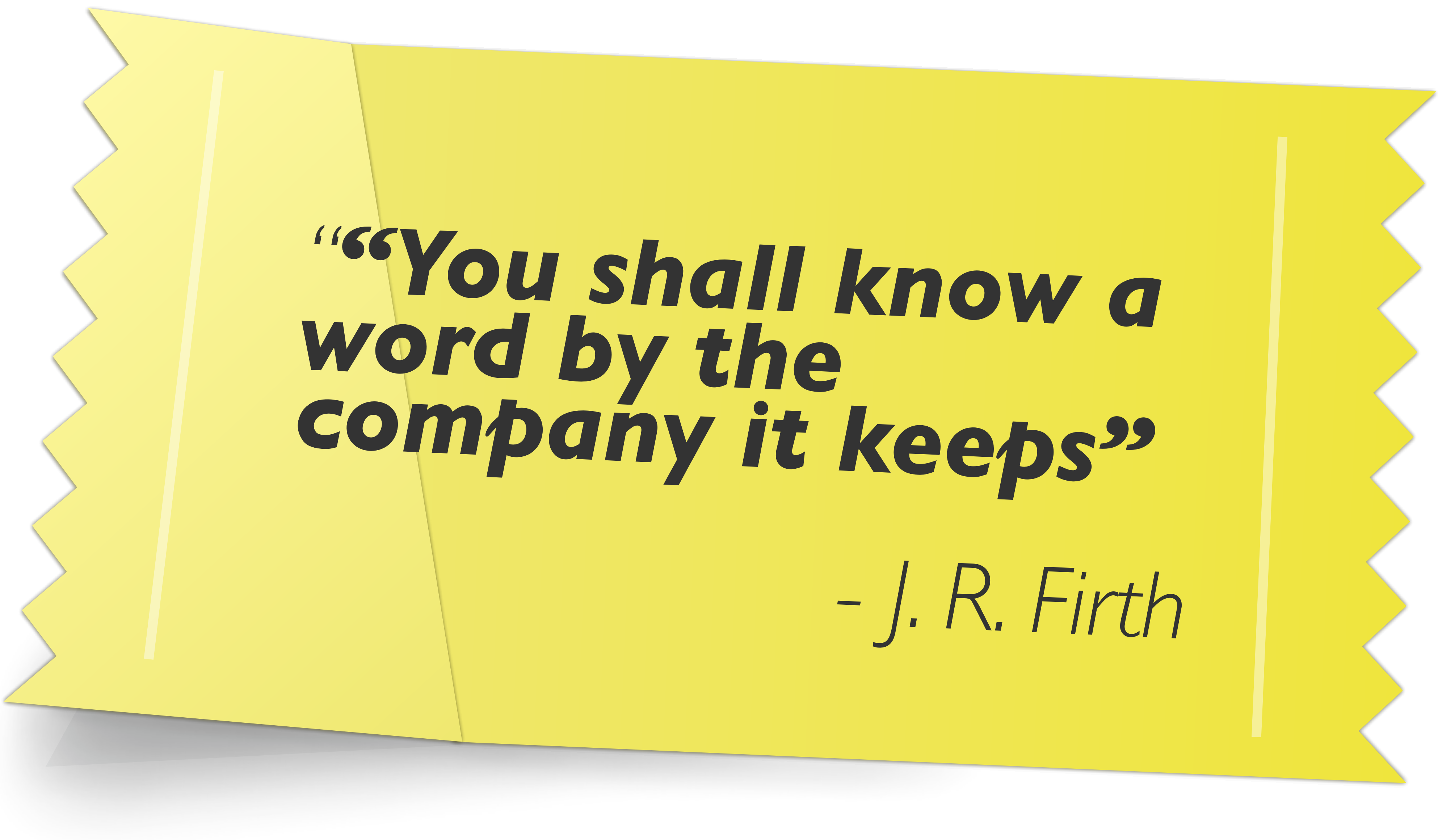
⇒ topic modelling

mid 2010s: sequence-to-sequence models for machine translation

⇒ neural networks with memory/state

Word Representations

represent a word in the context of its neighbours



Word Representations

Distributional Hypothesis:

- derived from semantic theory of language use
- words that are used and occur in the same context tend to have similar meanings

government debt problems turned into banking crises as has happened in...

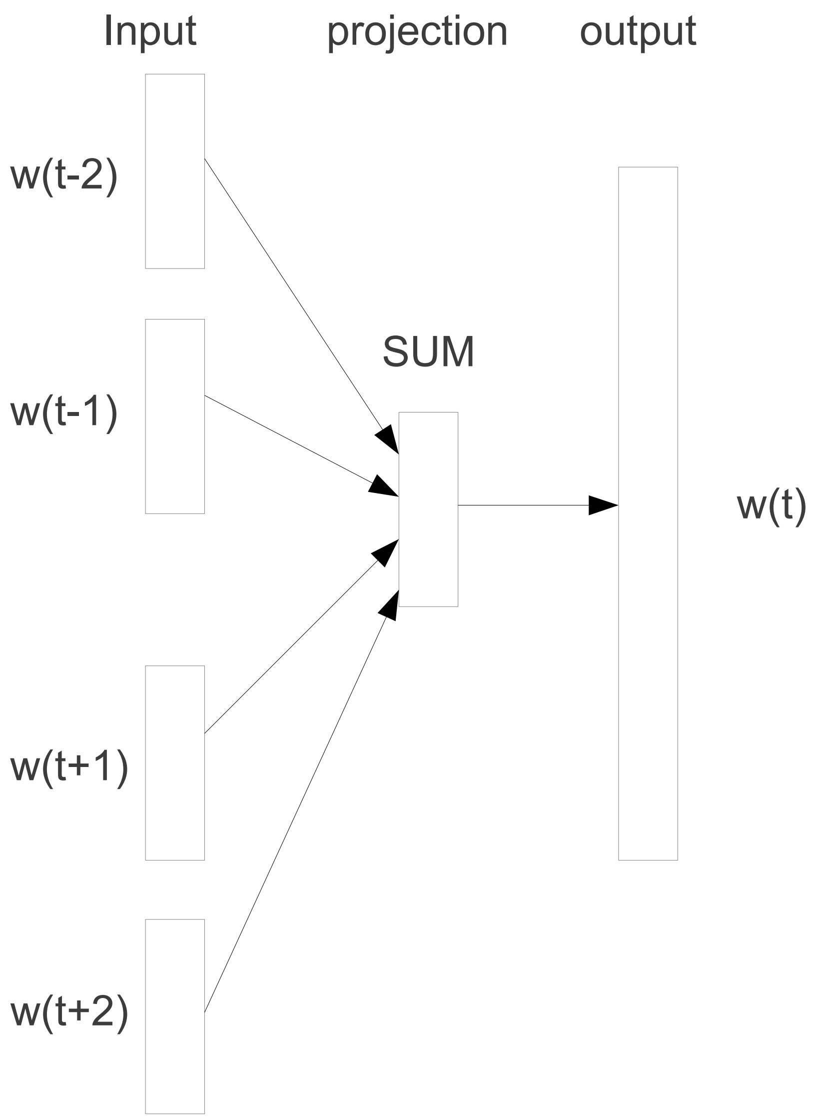
saying that Europe needs unified banking regulation to replace the hodgepodge...

syntactic

semantic

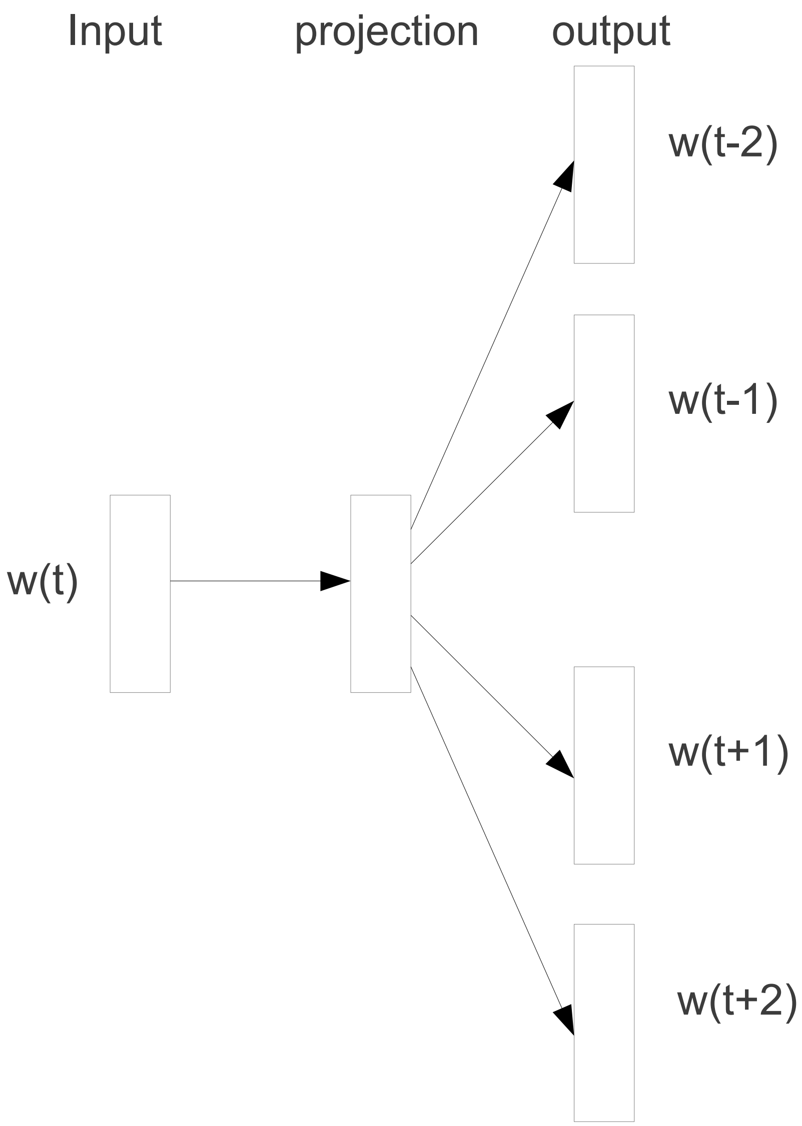
Word Vectors

Build a neural network which learns the word vectors from the context



continuous bag-of-words

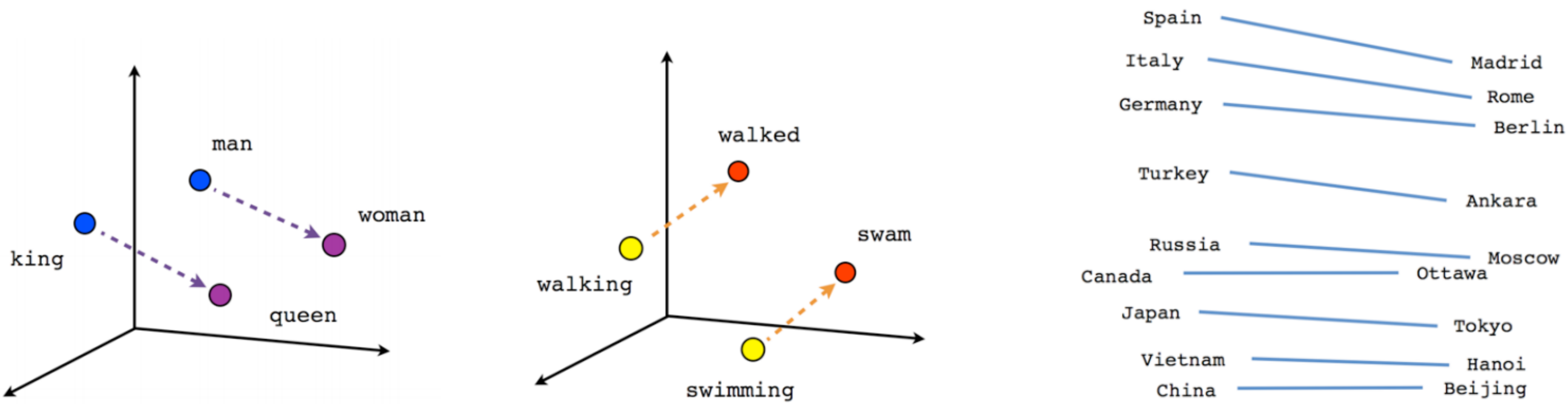
Predicts the current word given the context



skip-gram

Predicts the surrounding words given the current word

Neural Embeddings



Male-Female

Verb tense

Country-Capital

Neural embeddings have interesting geometries

These patterns capture “relational similarities”

Can be used to solve analogies:

a is to a^* as b is to b^*

Summary

- Looked at a few areas of Machine Learning which we didn't get to in the module
- Reinforcement learning is a different category to supervised/unsupervised learning
  - goal is to maximise a reward
  - want to learn how to act to maximise the reward
- Neural networks
  - deep learning
  - convolutional neural networks
- Natural Language Processing
  - word vectors

Summary

Machine Learning and Artificial Intelligence are making great strides in many areas

Still not clear which problems are the hard ones:

30 years ago it was a major challenge to beat a chess grandmaster- now a program on your MacBook Pro can easily do it.

What about other games, Go? poker? video games?

Need to be able to formulate the problem and the objectives clearly before we start to solve it

We also need to be able to explain and understand what we have learned

There is lots of work still to be done!

"the problem with that is you're building these narrowly defined systems that can do one thing and do it extremely well, or do a handful of things. And what we really want is a system that can do a hundred thousand things, and then when the hundred thousand-and-first thing comes along that it's never seen before, we want it to learn from its experience to be able to apply the experience it's gotten in solving the first hundred thousand things to be able to quickly learn how to do thing hundred thousand-and-one."

- Jeff Dean (Google)