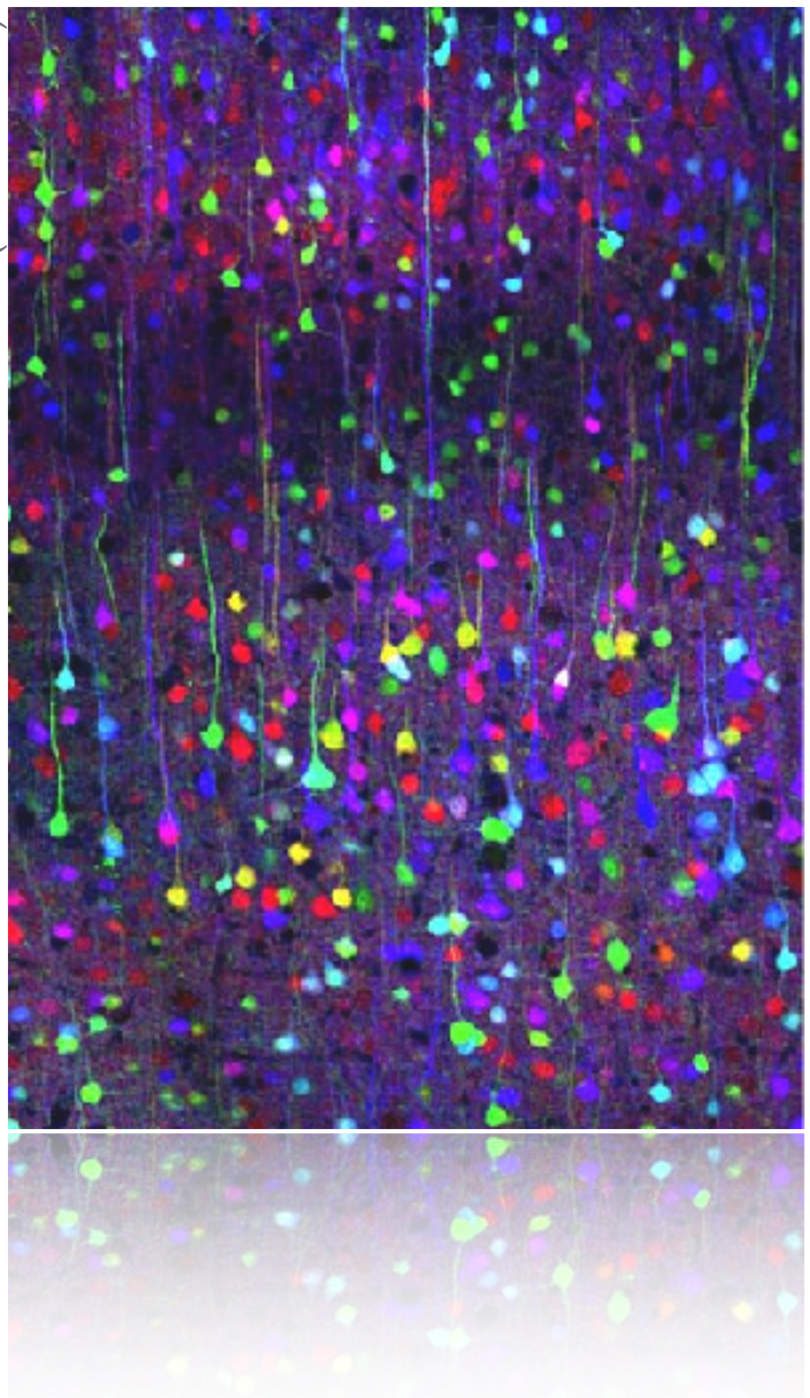
Neural Information Processing 2018/2019

University of BRISTOL

Brainbow (Litchman Lab)



Lecture 10: Neural circuits and learning

Rui Ponte Costa

Outline

A short overview on the credit assignment problem and the different forms of learning in the brain (and machine learning):

Supervised learning

Unsupervised learning

Reinforcement learning

Given visual input how should you move?

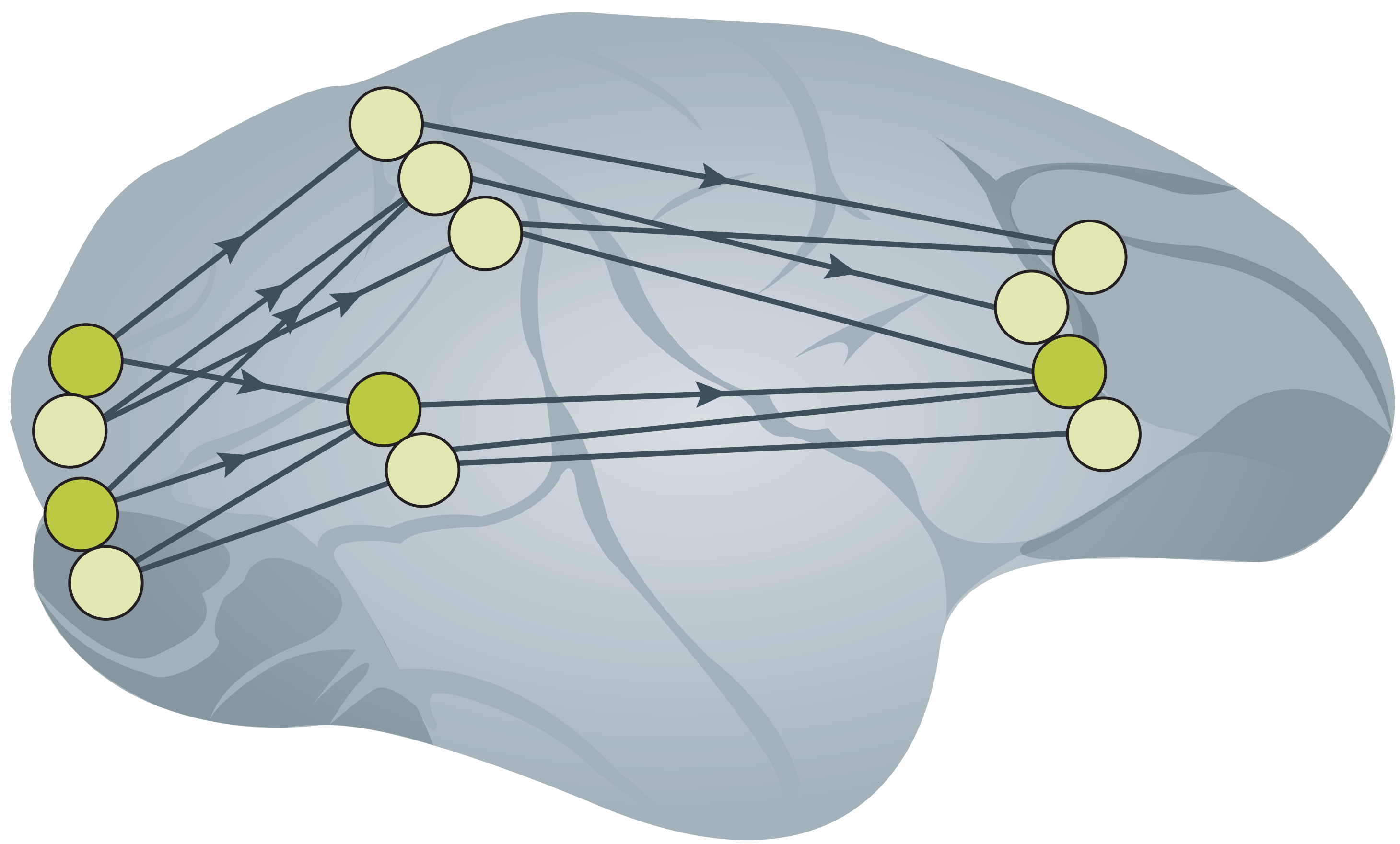
Visual input → Prepare movement → Hit (or not) the ball

How does the brain learn?

Visual input → Prepare movement → Hit (or not) the ball

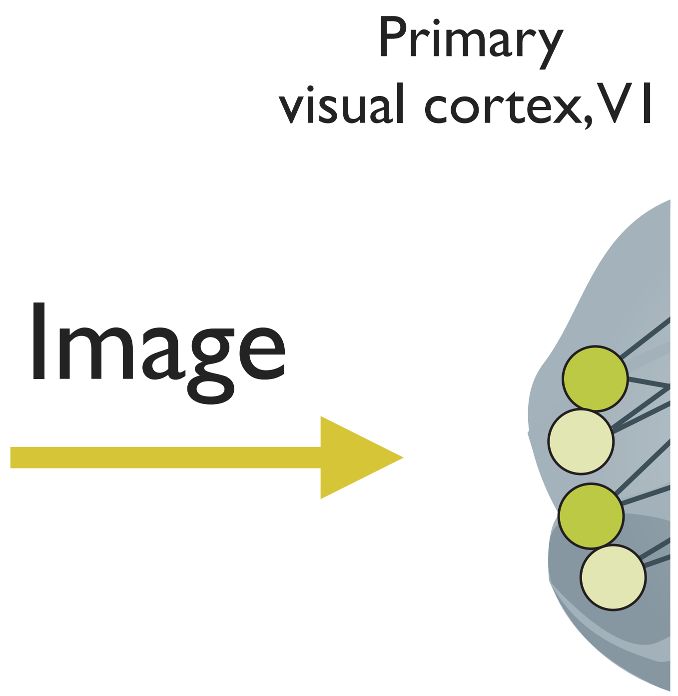
(typically **synapses**)

How to assign credit to ‘parameters’ in the brain?



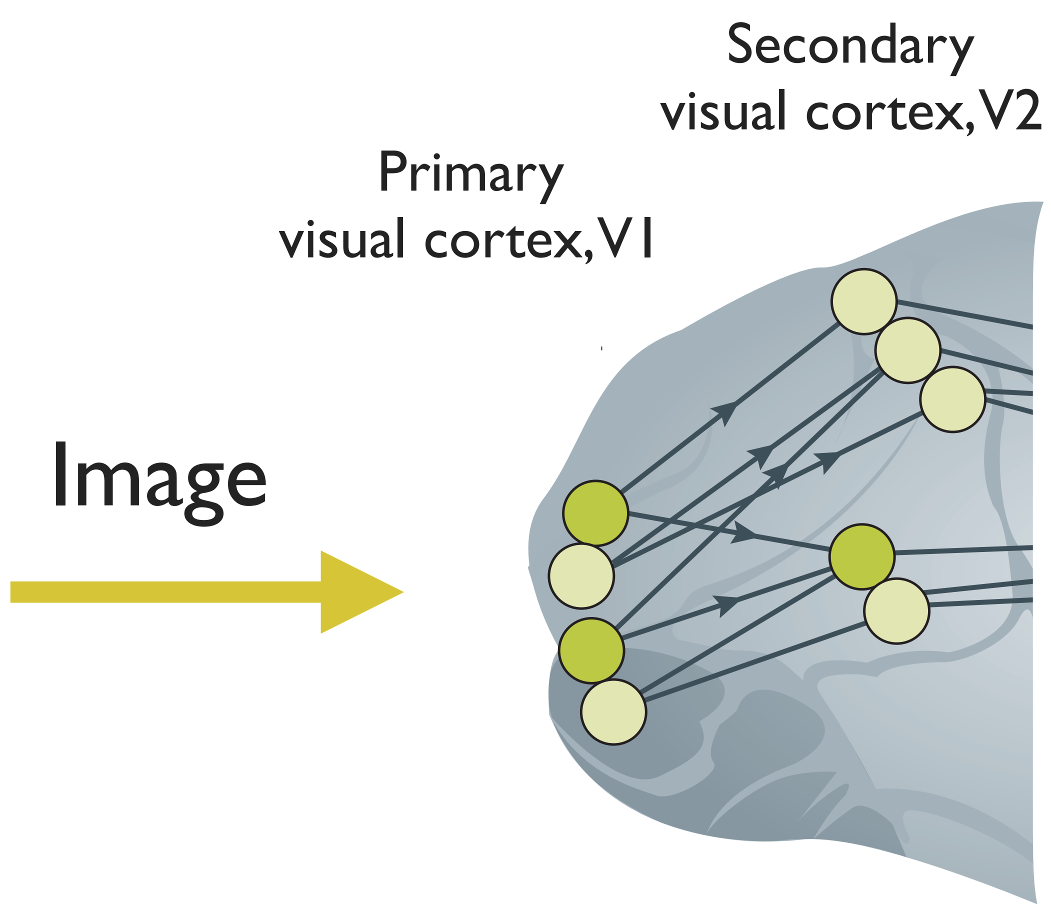
Roelfsema et al. Nature Neuroscience Rev 2018

How to assign credit in the brain?



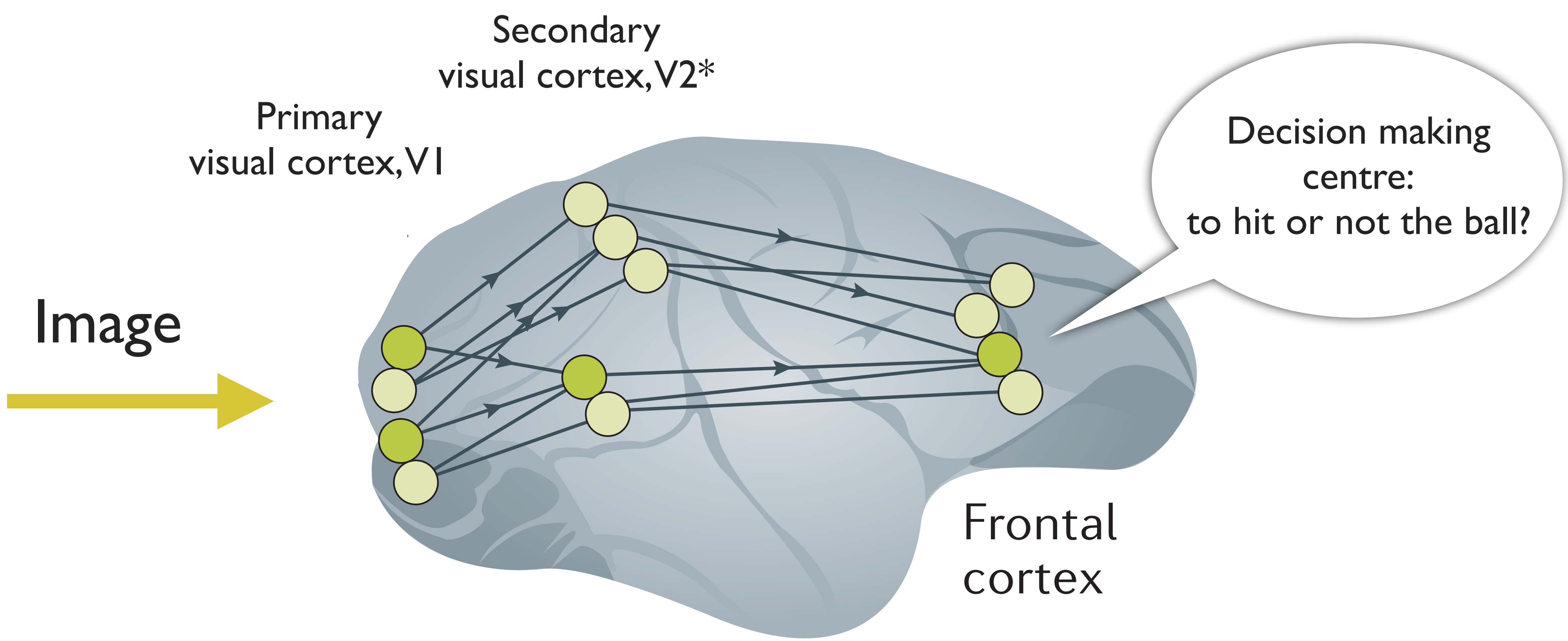
Roelfsema et al. Nature Neuroscience Rev 2018

How to assign credit in the brain?



Roelfsema et al. Nature Neuroscience Rev 2018

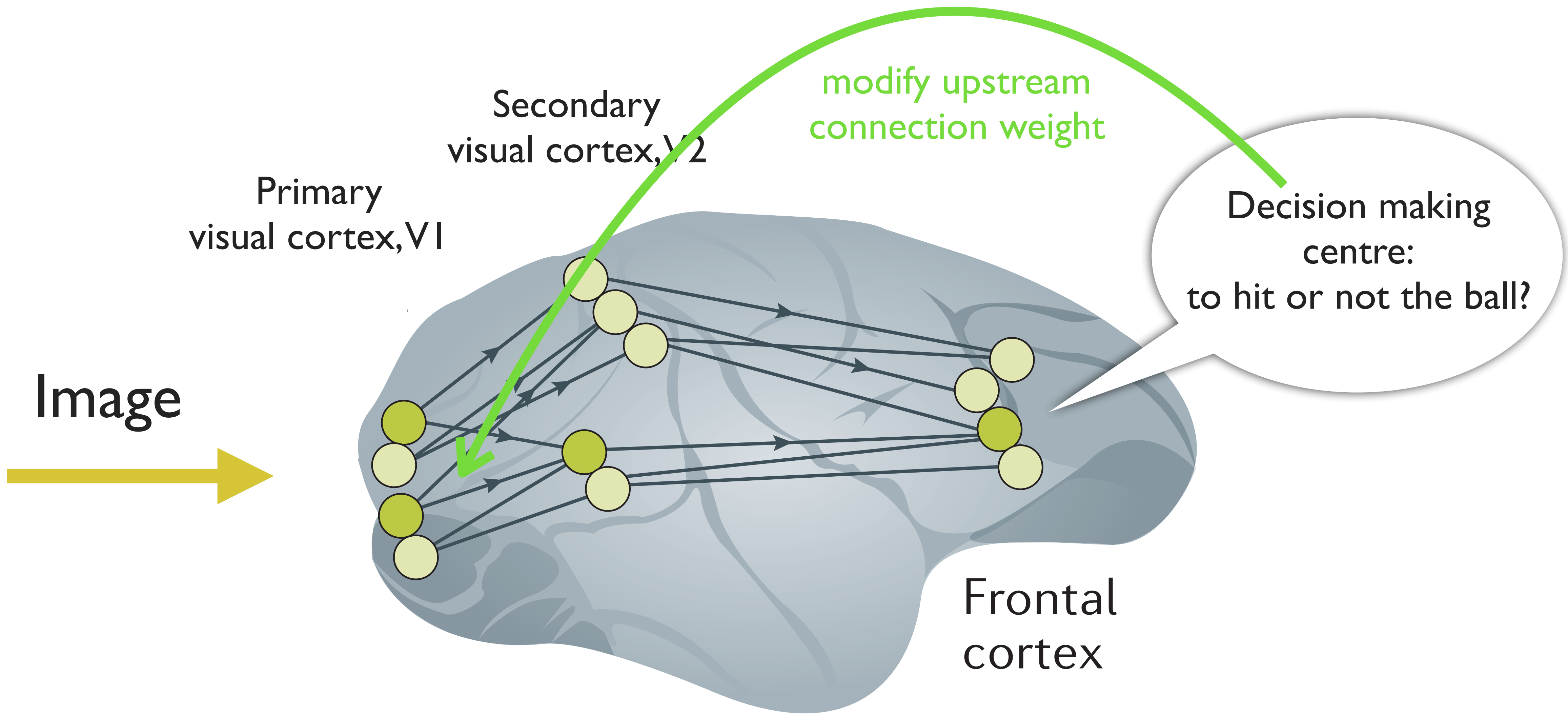
How to assign credit in the brain?



*: or associative cortices

Roelfsema et al. Nature Neuroscience Rev 2018

How to assign credit in the brain?



Credit assignment problem:
Which neural properties (e.g. connection weights) should be modified to improve a given behaviour?

Roelfsema et al. Nature Neuroscience Rev 2018

Three forms of (direct or indirect) *credit assignment*

Supervised Learning

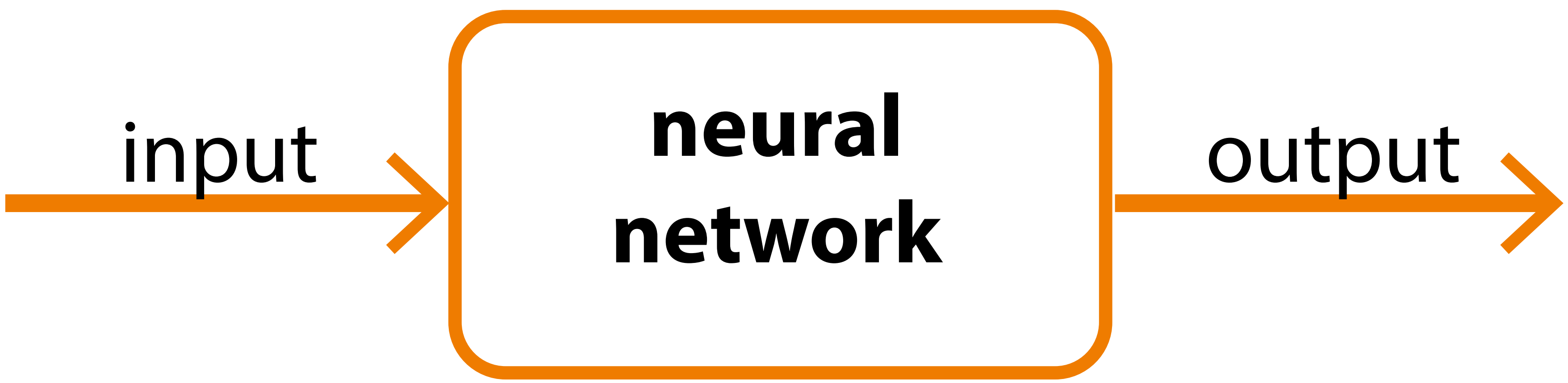
Unsupervised Learning

Reinforcement Learning

Three forms of (direct or indirect) *credit assignment*

Unsupervised Learning:

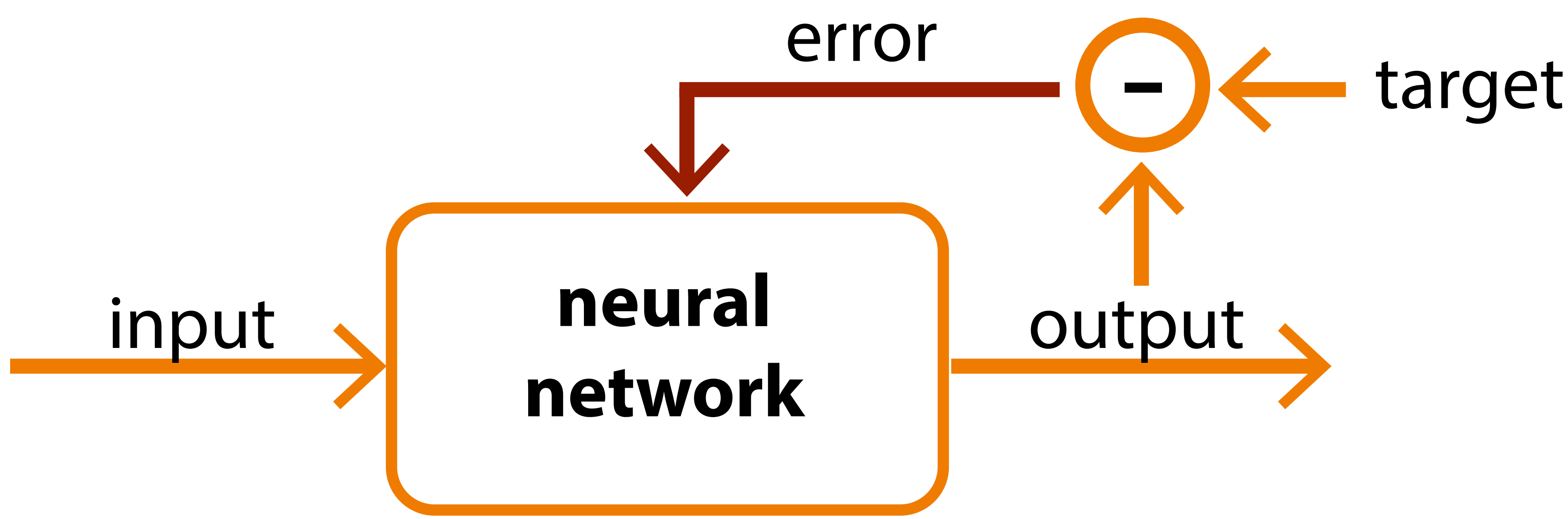
Extracts useful representations of input



Three forms of (direct or indirect) *credit assignment*

Supervised Learning:

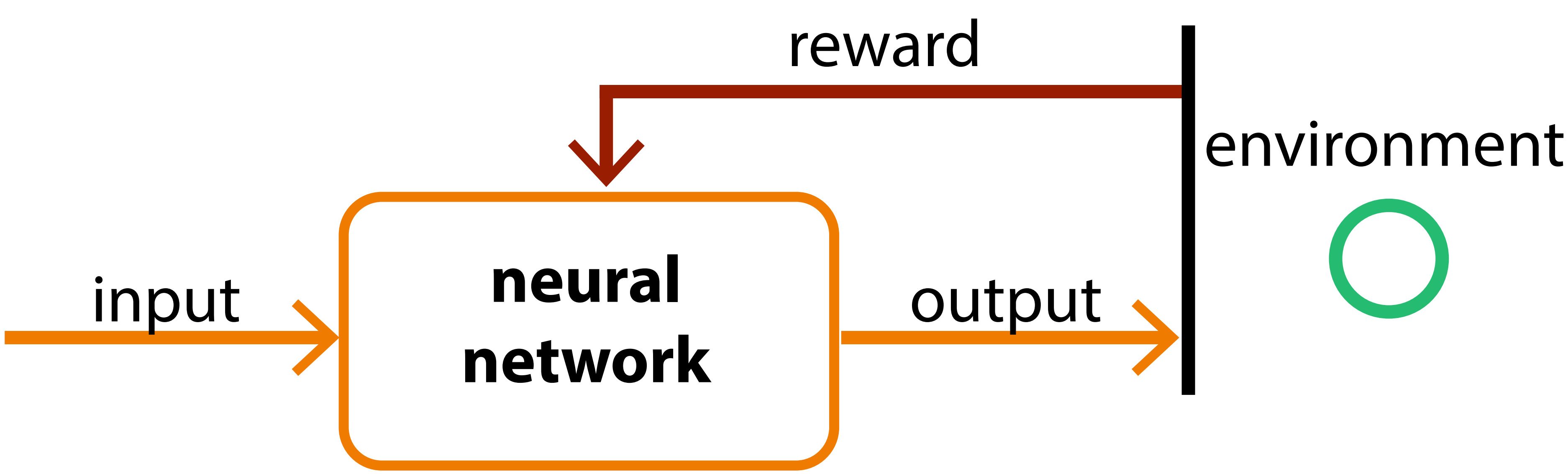
Relies on a teaching signal



Three forms of (direct or indirect) *credit assignment*

Reinforcement Learning:

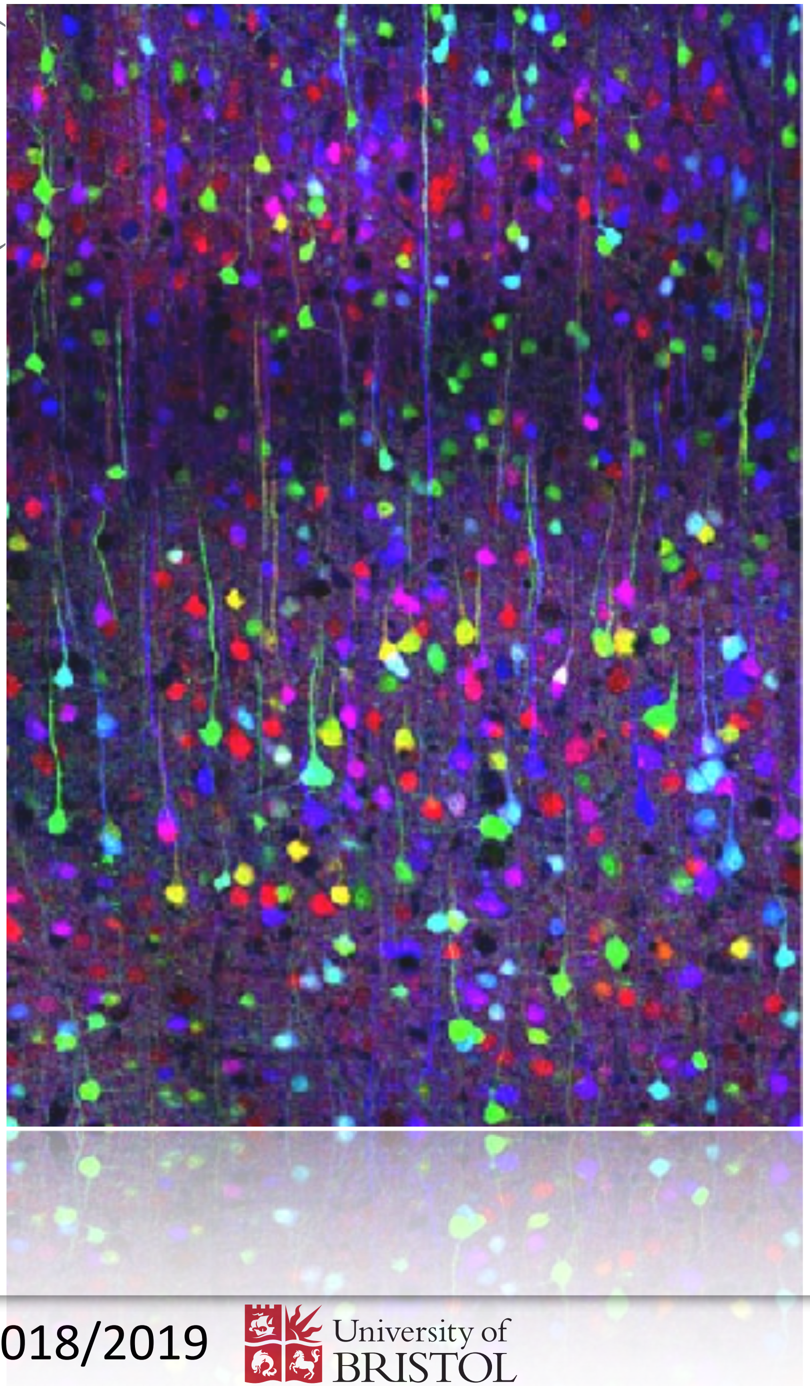
Learn to navigate/survive an environment



A feedforward neural network

The brain is like a tropical forest!
With many different neuron *types* and *architectures*..

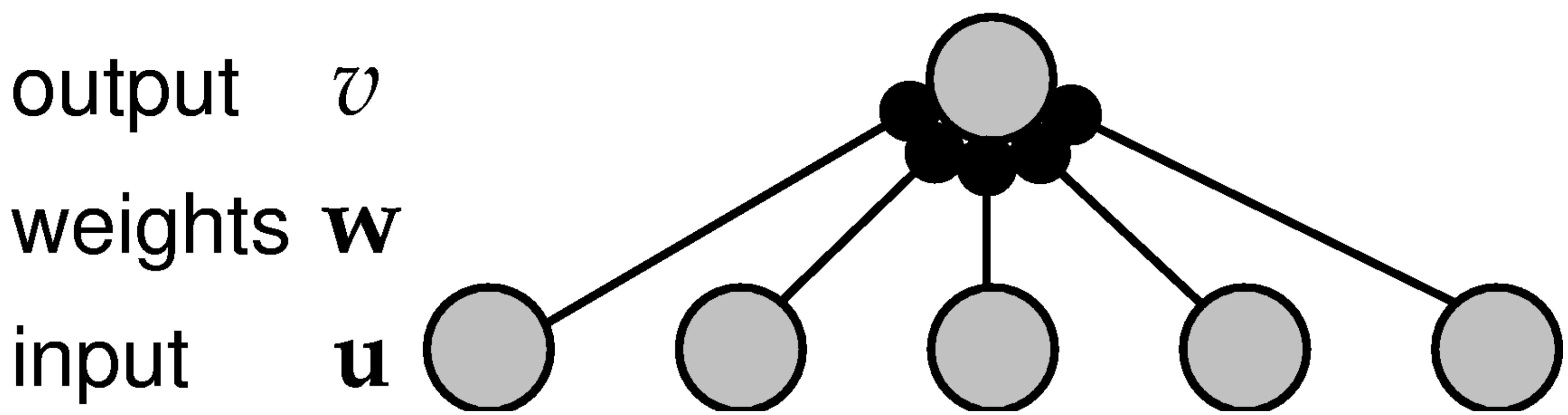
DeFelipe et al. Nat. Neurosci. Reviews 2013



Brainbow (Litchman Lab)

A feedforward neural network

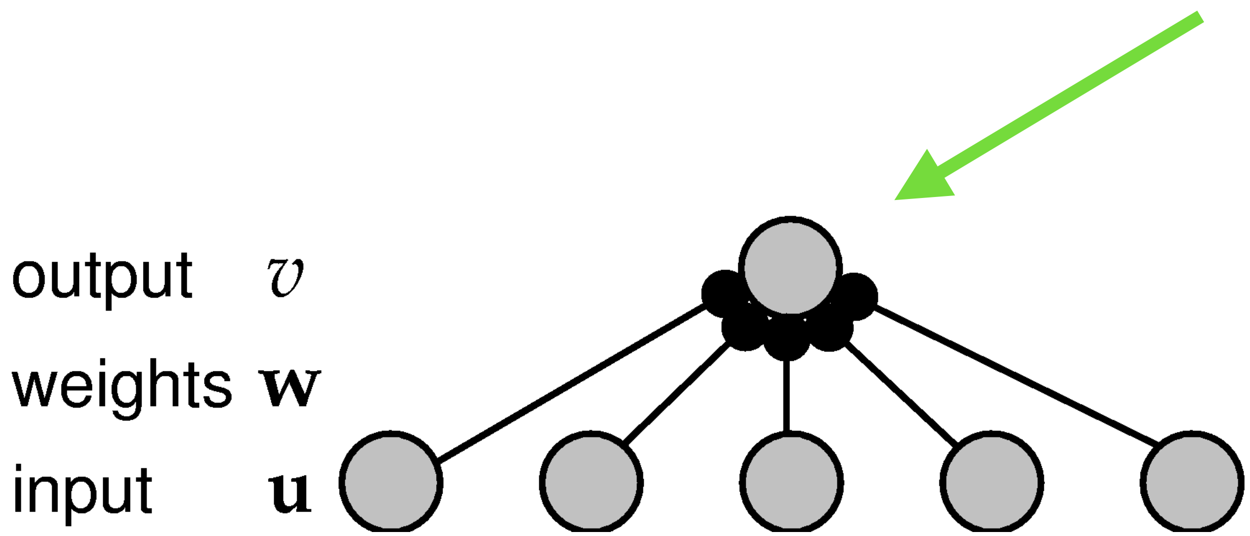
In theoretical neuroscience we need to abstract out some of this complexity to get at the principles of information processing in the brain!



Supervised learning

Goal: Classify input into different categories

Teaching signal, *y*

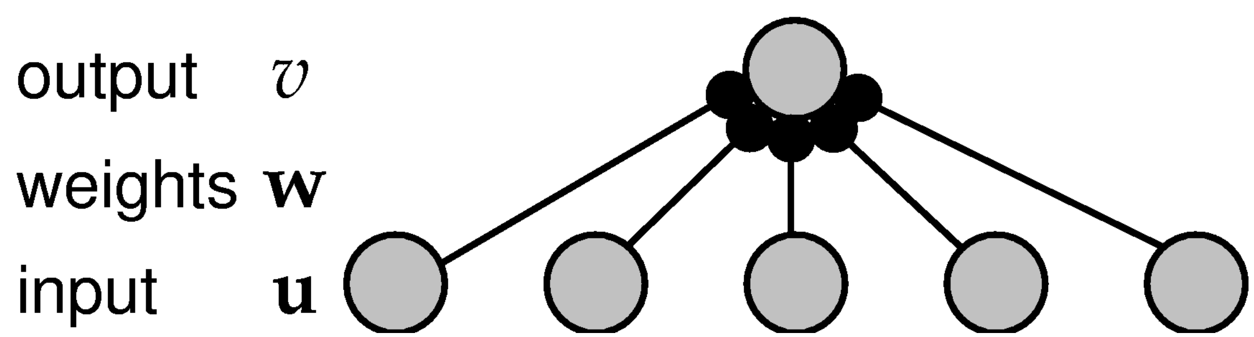


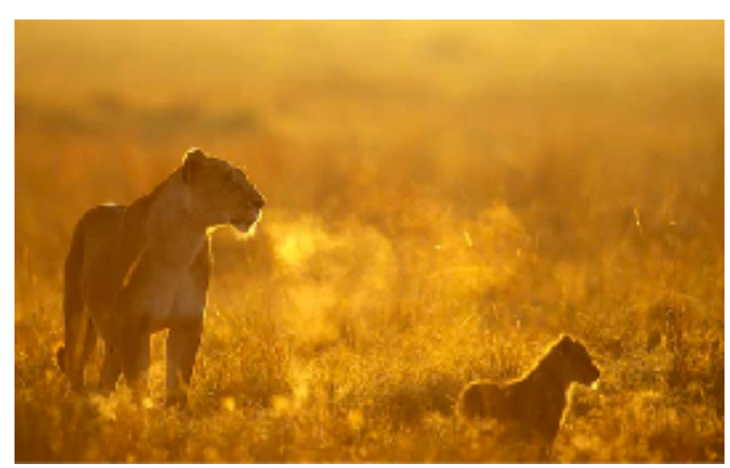
Supervised learning

$$\text{output}, v = f(wu)$$

where *f* is some (non)linear function

Predator, yes/no?
y = {1,0}



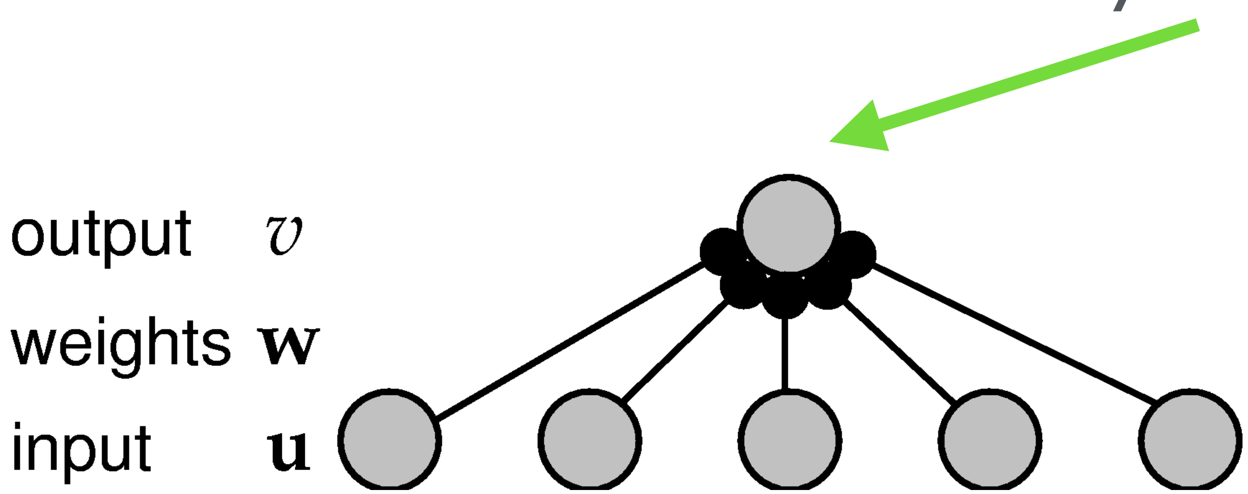


Supervised learning

Minimise cost

$$\text{cost} = (v - y)^2$$

Predator, yes/no?
$y = \{1,0\}$



Supervised learning

Minimise cost

$$\text{cost} = (v - y)^2$$

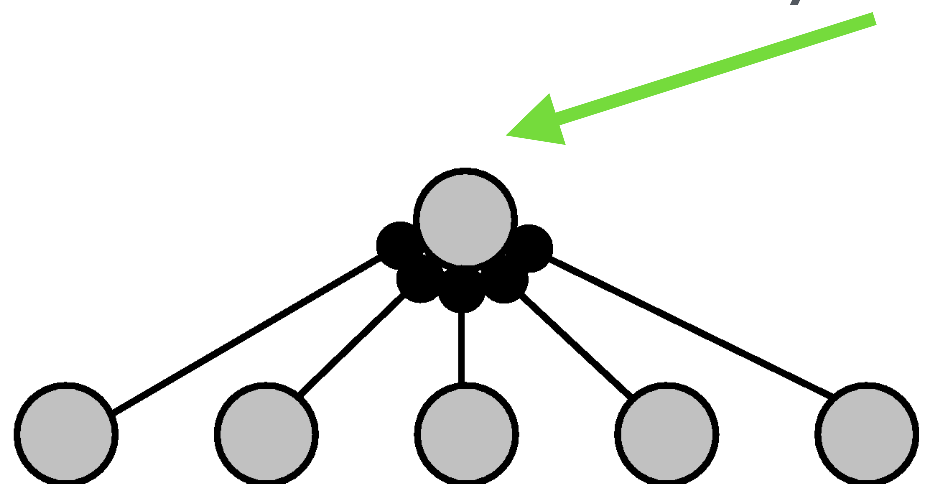
Predator, yes/no?

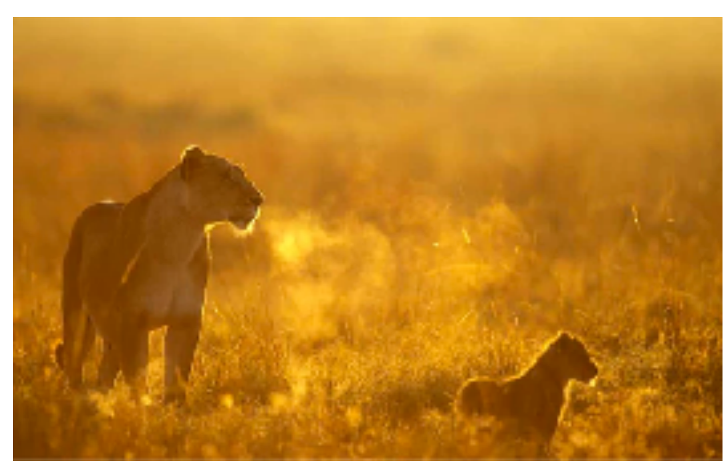
$y = \{1,0\}$

output v

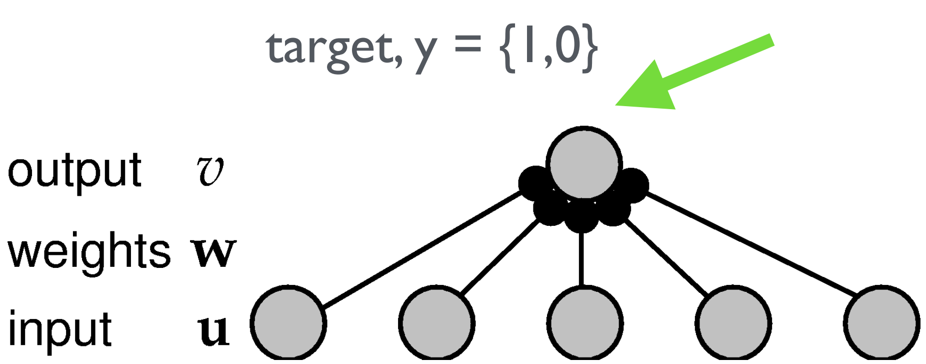
weights $\mathbf{w}$

input $\mathbf{u}$





Supervised learning



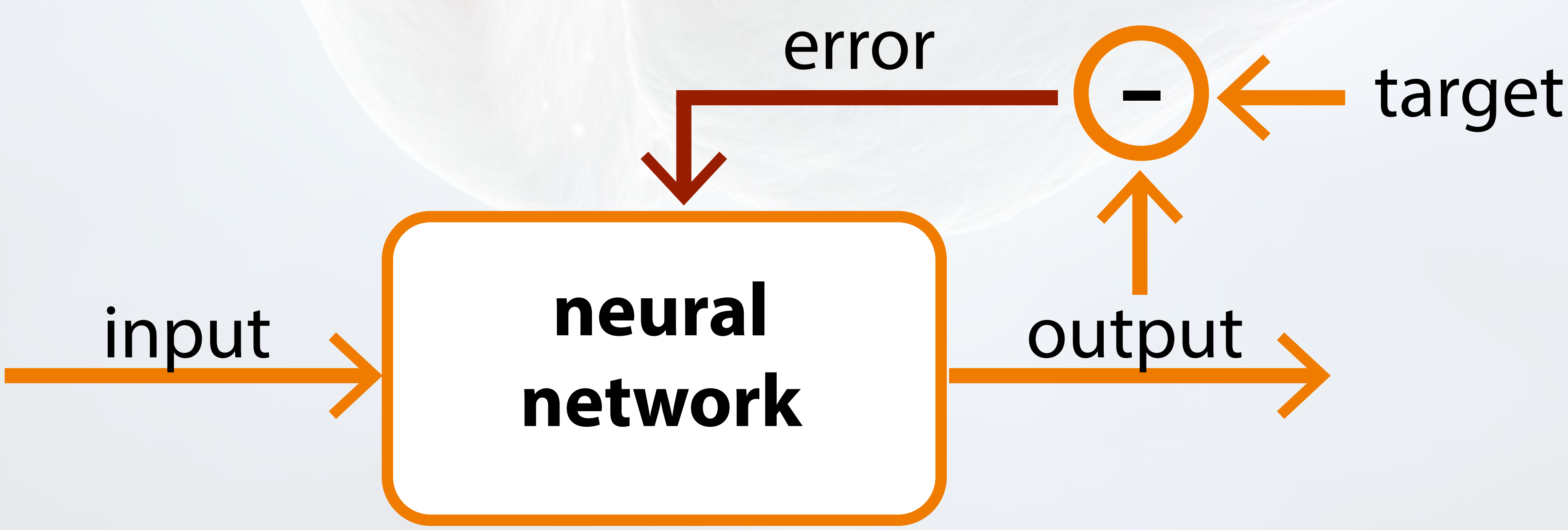
$$\text{cost} = (v - y)^2$$

- The learning rules for **w** can be derived from the cost (or error) function for a particular network: e.g. using the popular backpropagation algorithm
- Examples of methods that use supervised learning:
  - Convolutional neural networks
  - Recurrent neural networks
  - Deep learning methods in general
- Animals experience some degree of supervised learning (e.g. with external teacher)

Group discussion

groups of 2-3 (5 min)

- **Can you think of examples of teaching signals that may inform the brain during learning?**



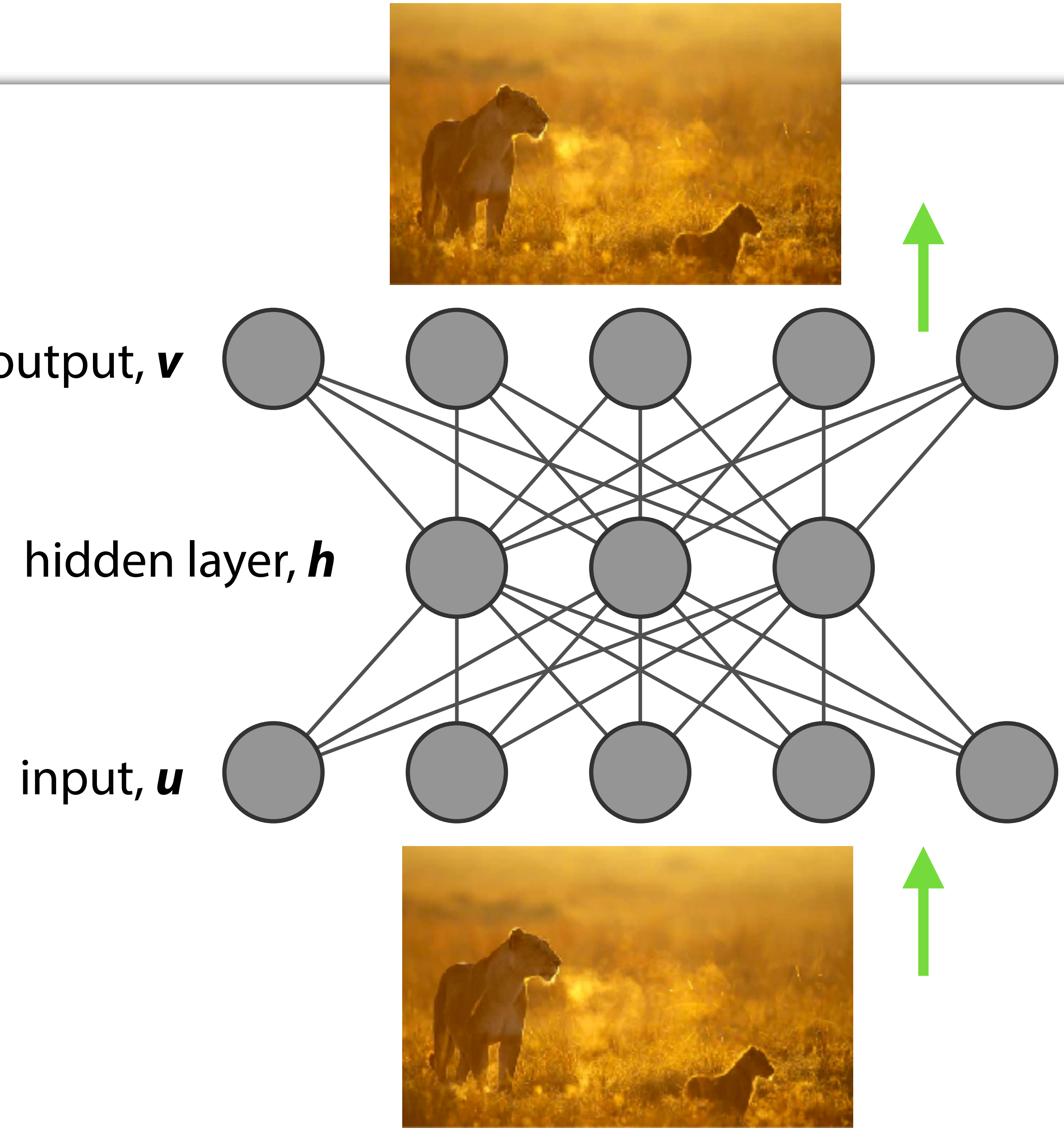
Group discussion
groups of 2-3 (5 min)

- **Can you think of examples of teaching signals that may inform the brain during learning?**

- **Hint: Think in the context of a classroom**

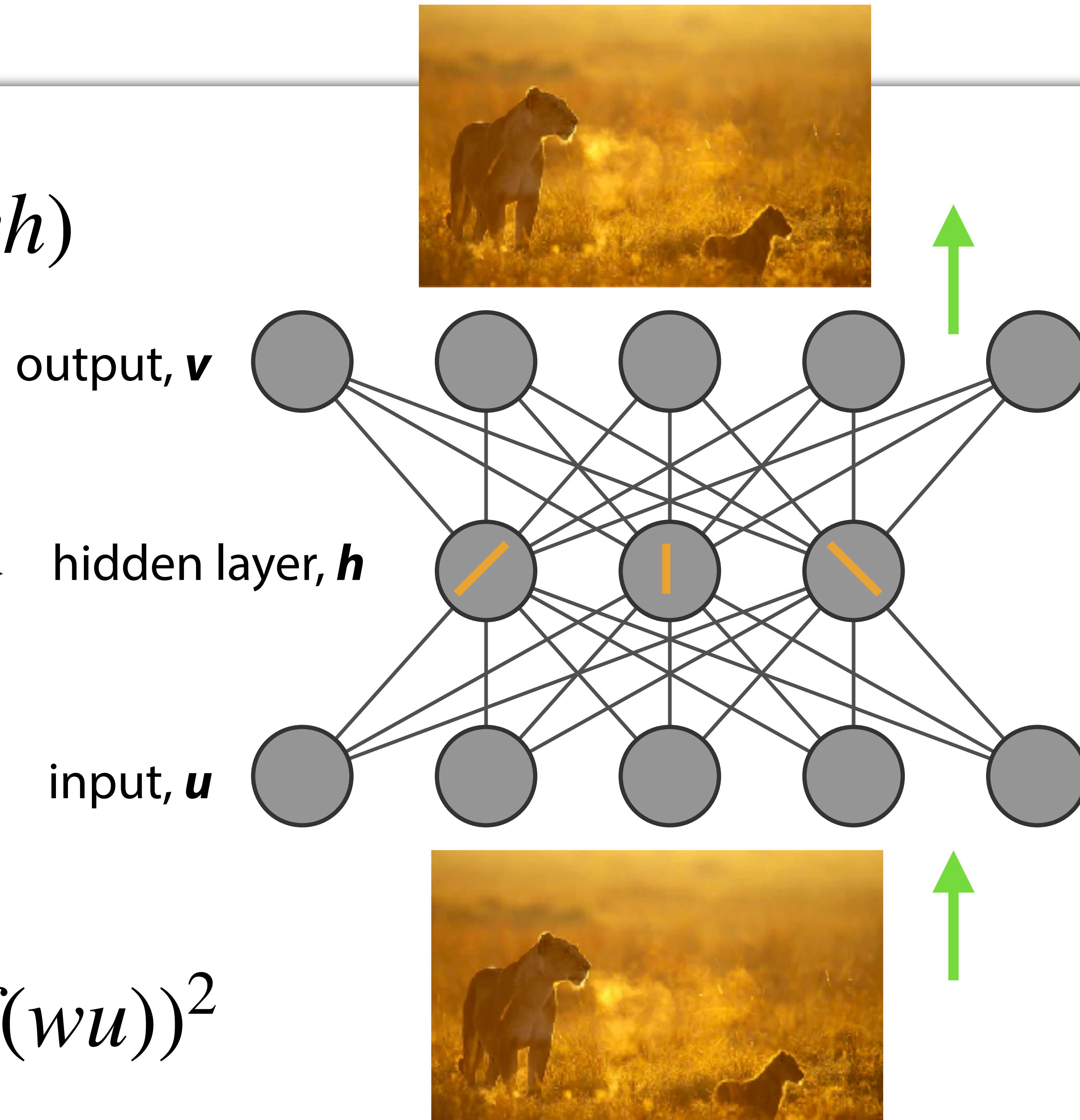
Unsupervised learning

Goal: Extract a representation of the input
(dimensionality reduction)



Unsupervised learning

output, $v = f(wh)$

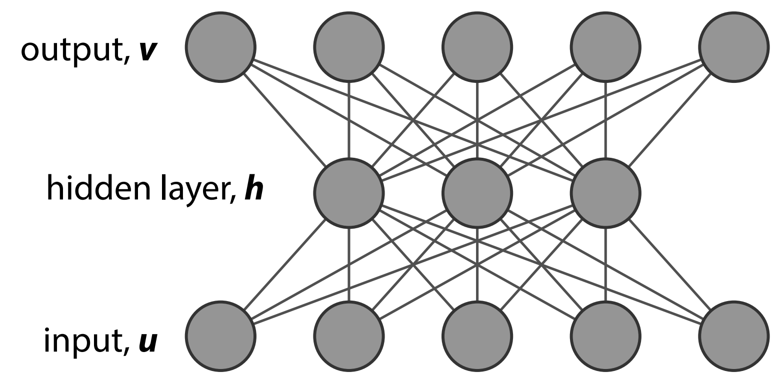


Learned representation
(e.g. edges)

Minimise cost

$$\text{cost} = (v - f(wu))^2$$

Unsupervised learning

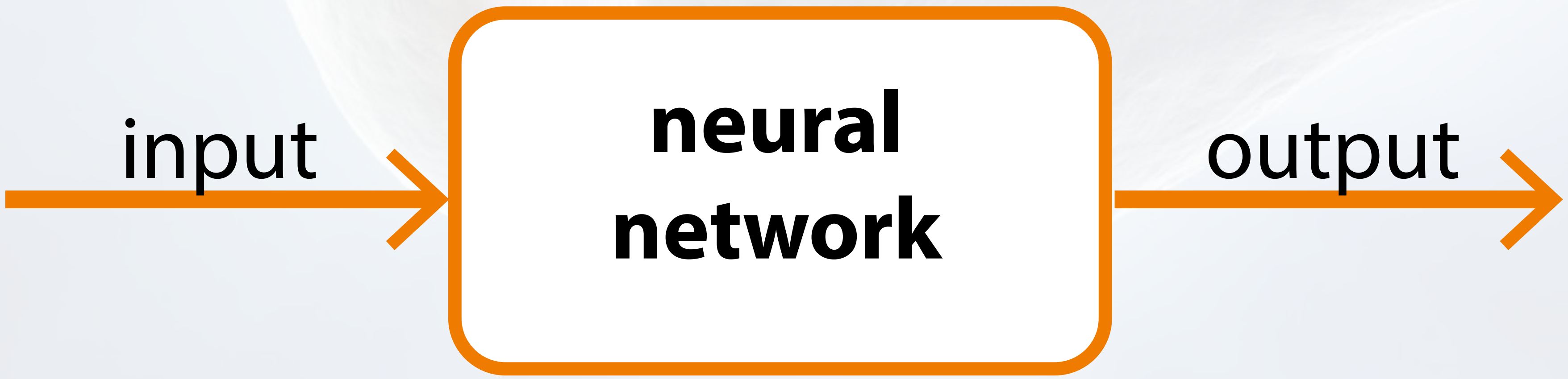


- The learning rules for **w** can be derived from the cost (or error) function for a particular network, e.g. sparse coding algorithm.
- Examples of unsupervised learning methods:
  - Sparse coding (akin to PCA)
  - Restricted Boltzmann Machines
  - Autoencoders
- Animals are bombarded with vast streams of sensory input

Group discussion

groups of 2-3 (5 min)

- **Why would it be useful for the brain to form representations?**



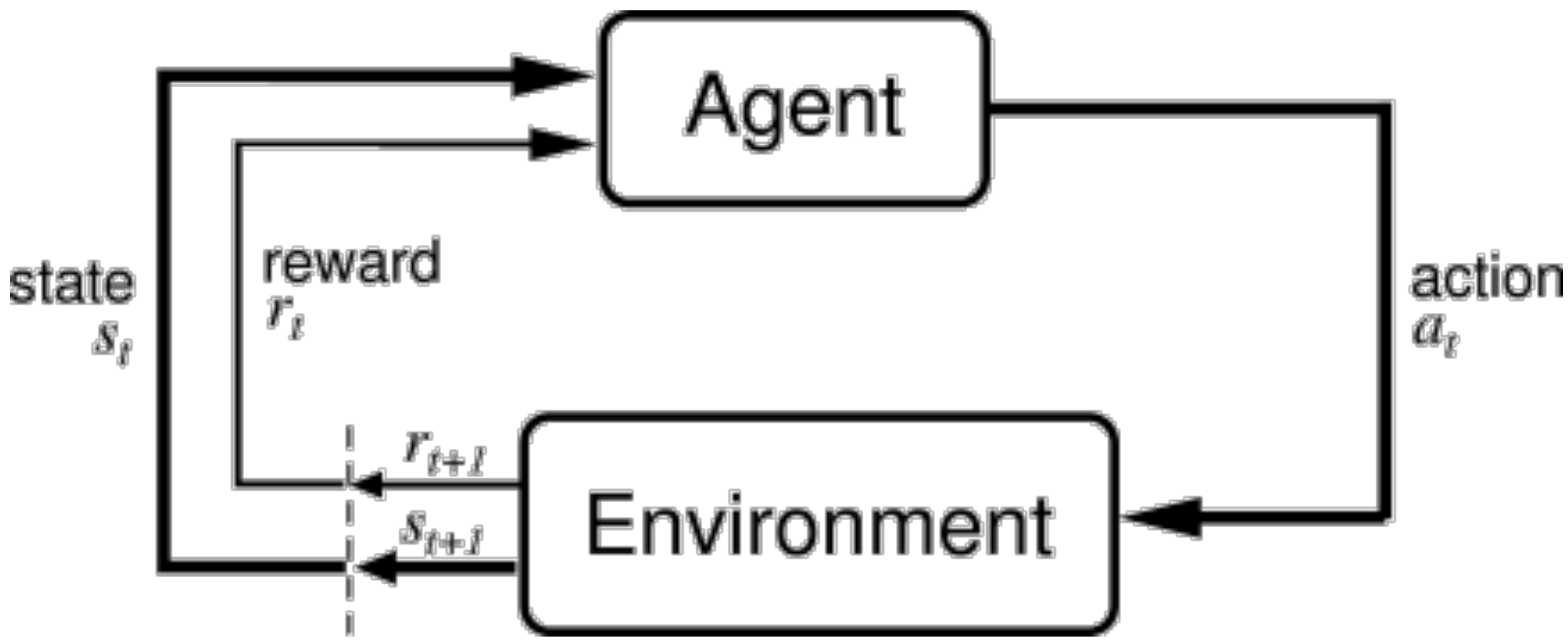
Group discussion
groups of 2-3 (5 min)

- **Why would it be useful for the brain to form representations?**

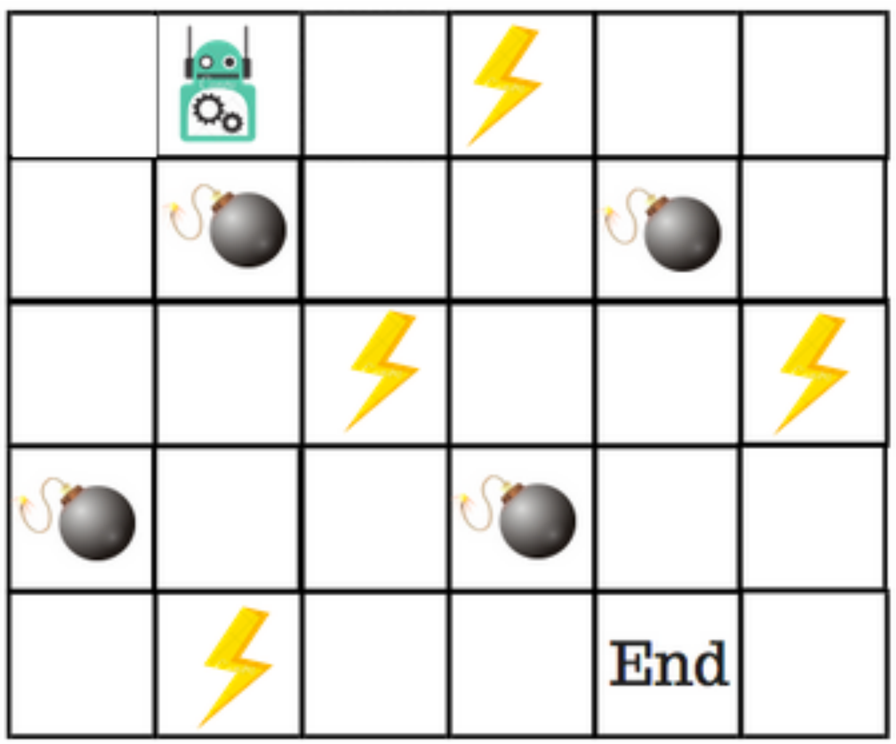
- **Hint: Learn important statistics of the environment**

Reinforcement learning

Goal: Find best policy (which actions to take) to maximise reward



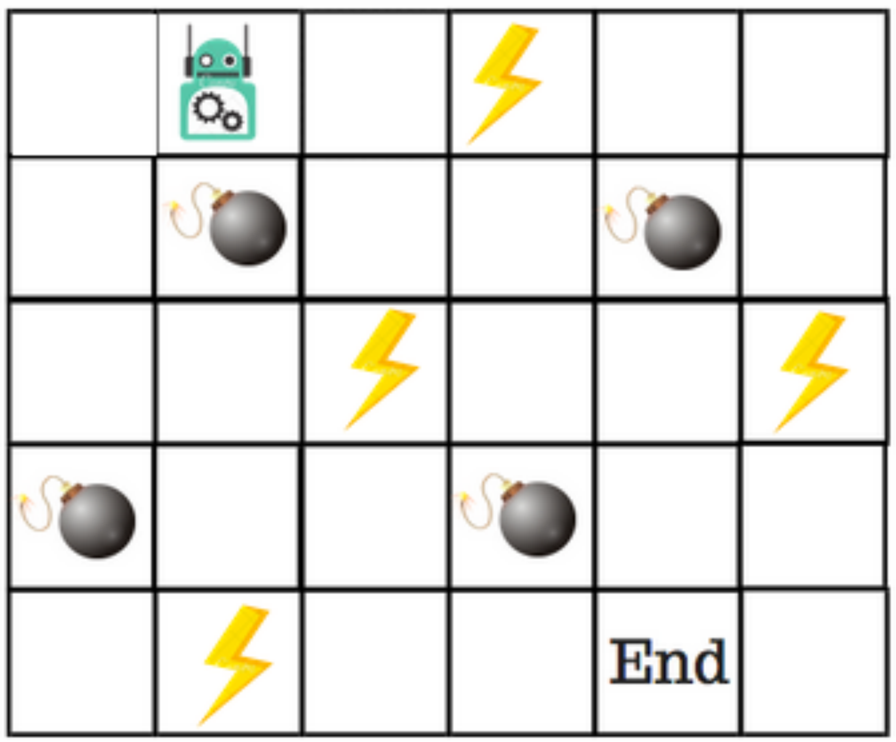
Reinforcement learning



Value table/policy

Actions :	↑	→	↓	←
Start	0	0	0	0
Nothing / Blank	0	0	0	0
Power	0	0	0	0
Mines	0	0	0	0
END	0	0	0	0

Reinforcement learning



Value table/policy

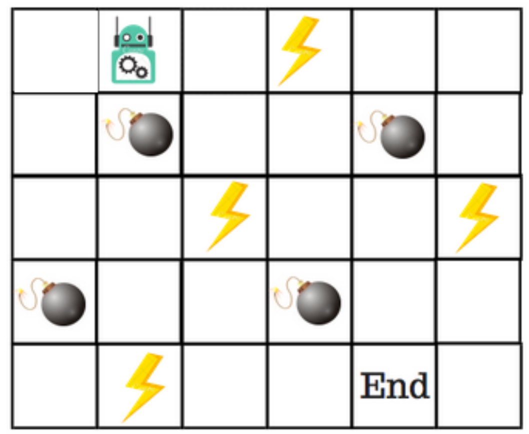
Actions :	↑	→	↓	←
Start	0	0	0	0
Nothing / Blank	0	0	0	0
Power	0	0	0	0
Mines	0	0	0	0
END	0	0	0	0

Update value table with temporal difference (TD) learning:

$$\underbrace{V(S_t)}_{\text{value}} = V(S_t) + (\overbrace{\underbrace{R_{t+1}}_{\text{reward}} + \lambda \underbrace{V(S_{t+1})}_{\text{future value}}}^{\text{learned value}} - V_t)$$

λ: discount factor

Reinforcement learning



Actions :	↑	→	↓	←
Start	0	0	0	0
Nothing / Blank	0	0	0	0
Power	0	0	0	0
Mines	0	0	0	0
END	0	0	0	0

- The *TD learning equation* enables the agent to gradually learn to predict *future reward* (R), based on *value estimates* (V_{t+1}).
- Examples of reinforcement learning methods:
  - Temporal difference (TD) learning
  - Q-learning
  - Deep Q-learning
- Because of the role of rewards RL is a common framework in neuroscience

Different objective/cost functions of learning

Supervised Learning

$$\text{cost} = (v - y)^2$$

Unsupervised Learning

$$\text{cost} = (v - f(wu))^2$$

Reinforcement Learning

$$\underbrace{V(S_t)}_{\text{value}} = V(S_t) + (\overbrace{\underbrace{R_{t+1}}_{\text{reward}} + \lambda \underbrace{V(S_{t+1})}_{\text{future value}}}^{\text{learned value}} - V_t)$$

Summary

- Different forms of learning (or credit assignment) in the brain
- Supervised, unsupervised and reinforcement learning

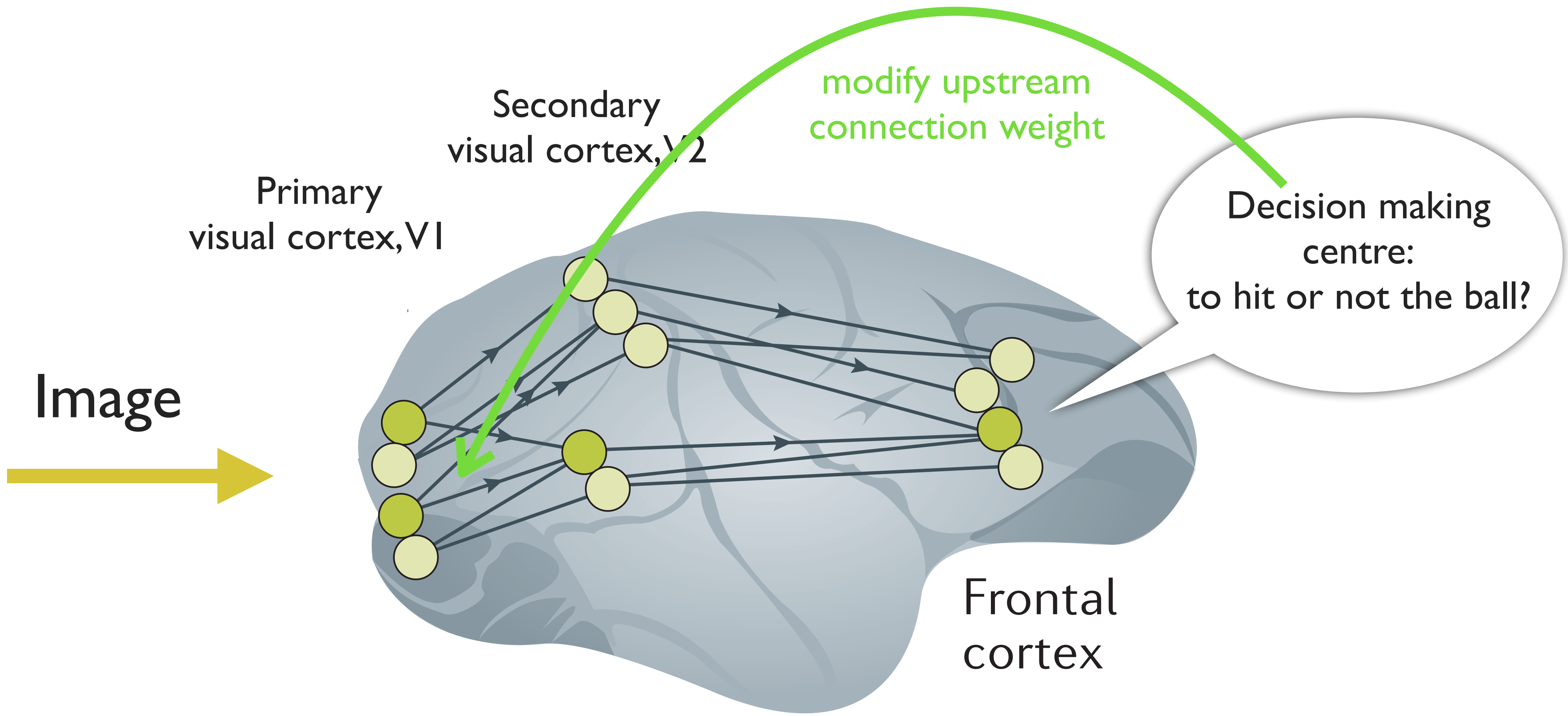
Questions?

Group discussion

groups of 2-3 (5 min)

- **Which form of learning is more biologically <u>plausible</u> and why?**

How to assign credit in the brain?



<u>Unsupervised</u> and <u>reinforcement</u> learning are the dominant views,
but recent research also suggest an important role for <u>supervised</u> learning!

Upcoming lectures

- L10: Neural circuits and learning: introduction
  - Visual processing
    - L11: Visual cortex
    - L11: Convolutional neural networks
  - Learning in the brain
    - L12: Supervised learning: The backpropagation algorithm/cerebellum
    - L13: Unsupervised learning: Sparse coding and Boltzmann Machines
    - L14: Reinforcement learning: TD learning, Q learning, deep RL and dopamine
  - Temporal processing in the brain
    - L14: Auditory cortex and recurrent neural networks
    - L15: Gated recurrent neural networks

References

Text books:

General theoretical neuroscience: Dayan and Abbott, Principles of Neuroscience (Chapter III)

Deep Learning by Courville, Goodfellow and Bengio

Reinforcement Learning: Sutton & Barto, Reinforcement Learning: An Introduction (see online the newer 2018 edition)

Others: Mackay book on Information Theory, Inference and Learning; Rumelhart and McClelland, Parallel Distributed Processing books

Relevant papers:

- Roelfsema and Holtmaat, Nature Neuroscience Reviews 2018 (recent review on the credit assignment problem)
- Olshausen and Field, Nature 1996 (seminal paper on sparse coding)
- Schultz et al. Science 1997 (seminal paper on neural substrates of reinforcement learning)

Course work

https://github.com/comsm0021/2018_19

- Implement a classical algorithm:
  - Backpropagation algorithm (supervised)
  - Sparse coding (unsupervised)
  - Temporal difference learning (reinforcement)

  - **Explain** the behaviour of the algorithm and **contrast** the algorithm you have chosen with the other two in terms of biological plausibility and performance. Note: Please support your statements with relevant citations.

  - Deadline: 7th of December 2018
  - Teaching assistants: Anne-Lene Sax (anne-lene.sax@bristol.ac.uk)
    Milton Llera Montero (m.lleramontero@bristol.ac.uk)