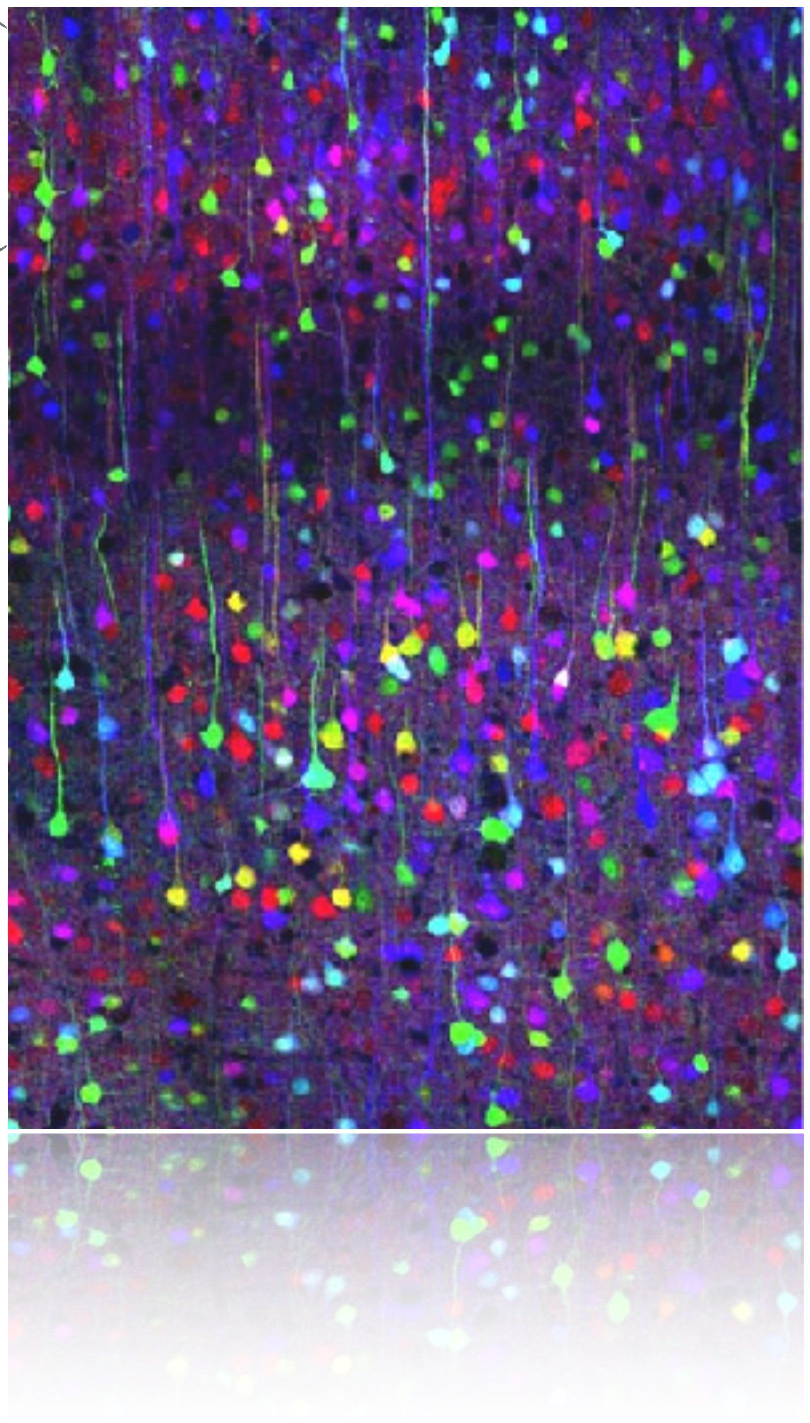
Neural Information Processing 2018/2019

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?

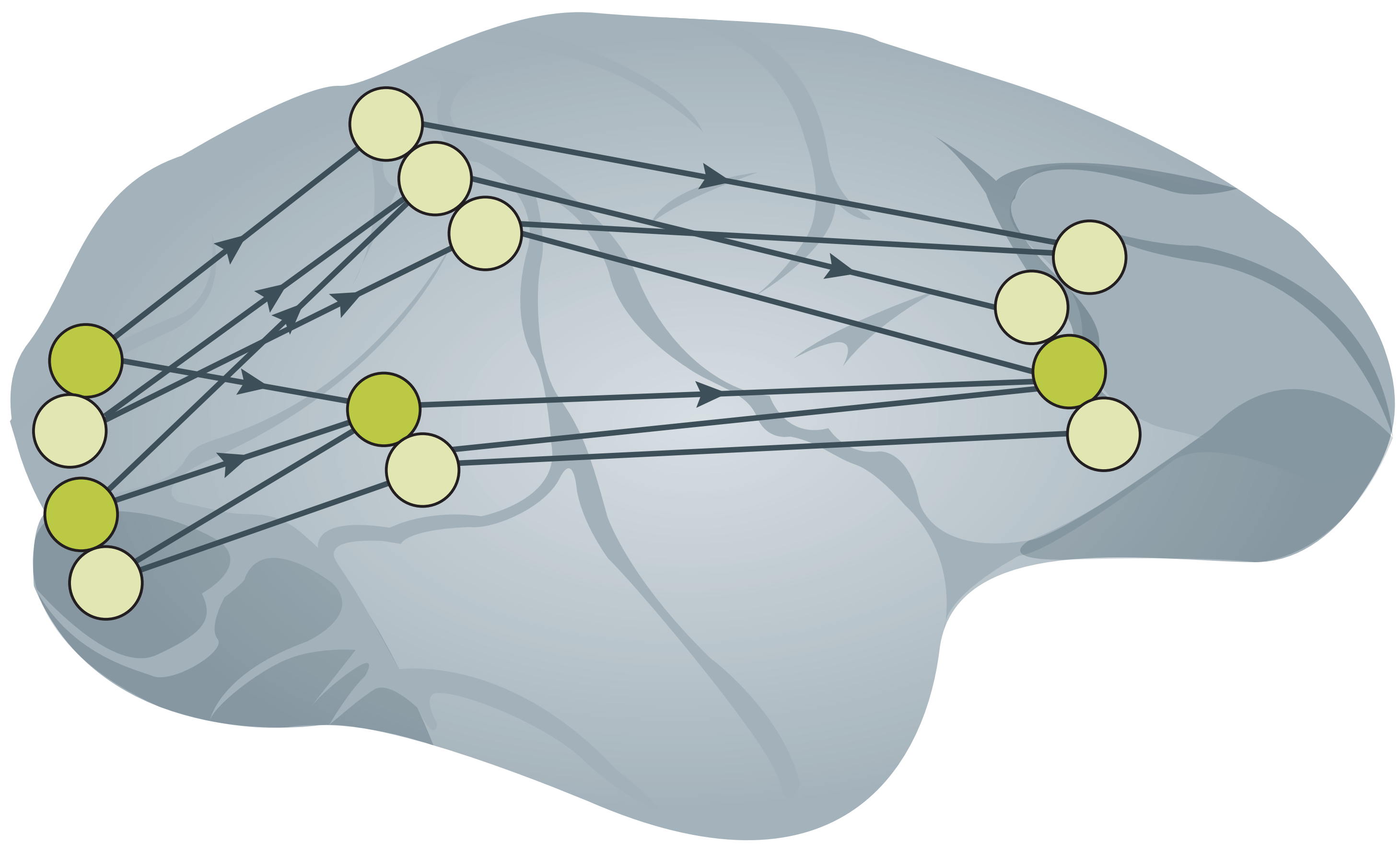
Visual input → Prepare movement → Hit (or not) the ball

How does the brain learn?

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

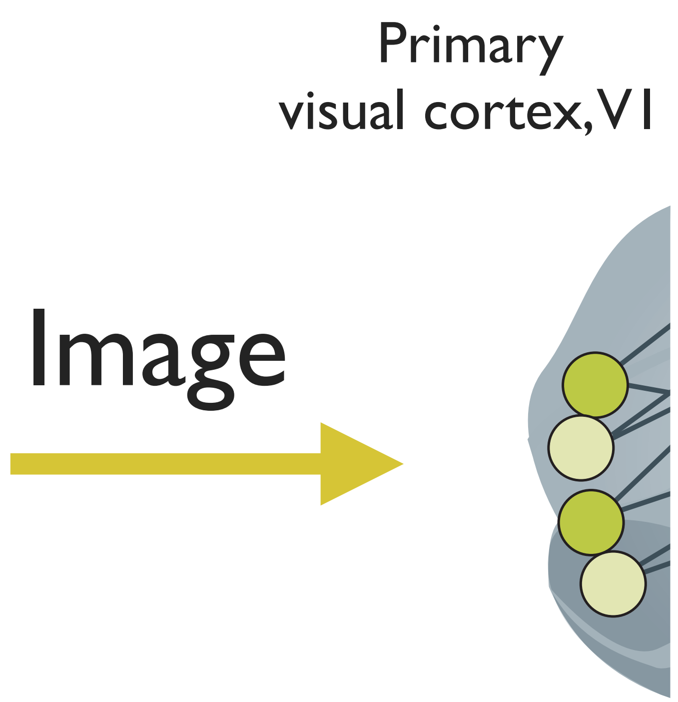
How to assign credit to ‘parameters’ in the brain?

(typically **synapses**)



Roelfsema et al. Nature Neuroscience Rev 2018

How to assign credit in the brain?



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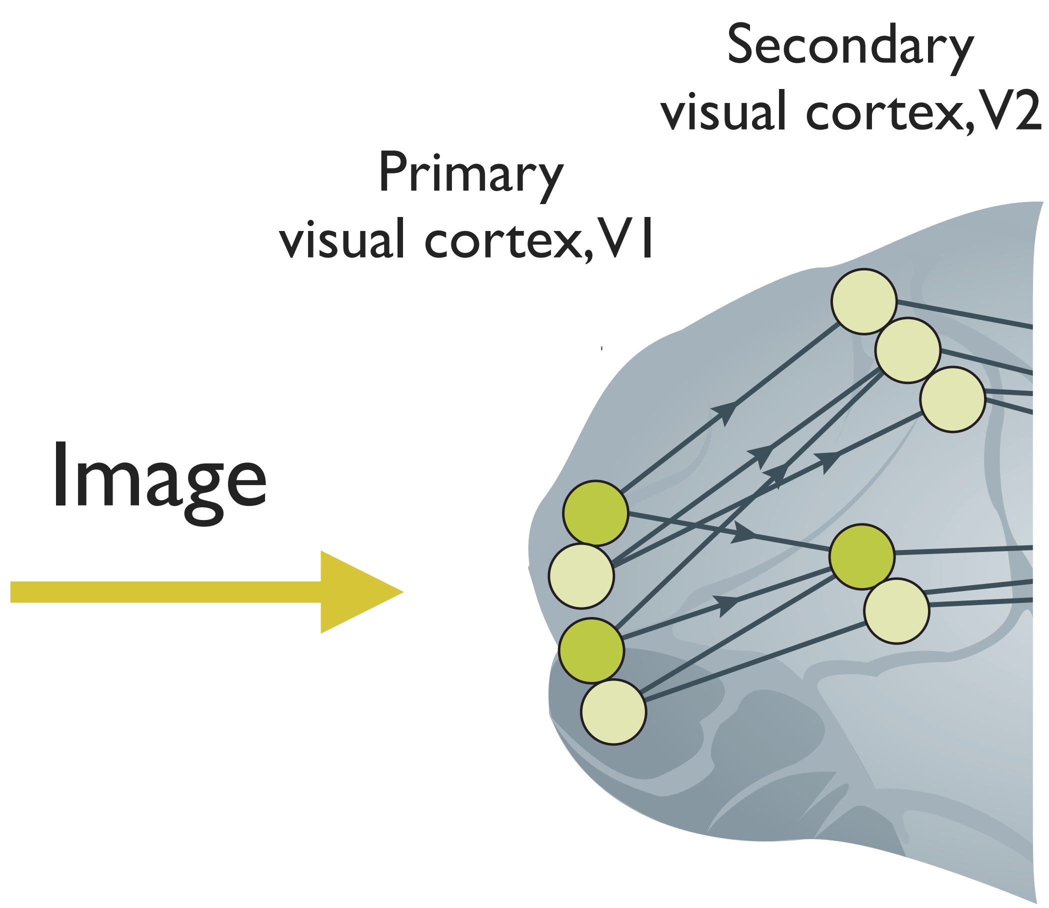

Roelfsema et al. Nature Neuroscience Rev 2018

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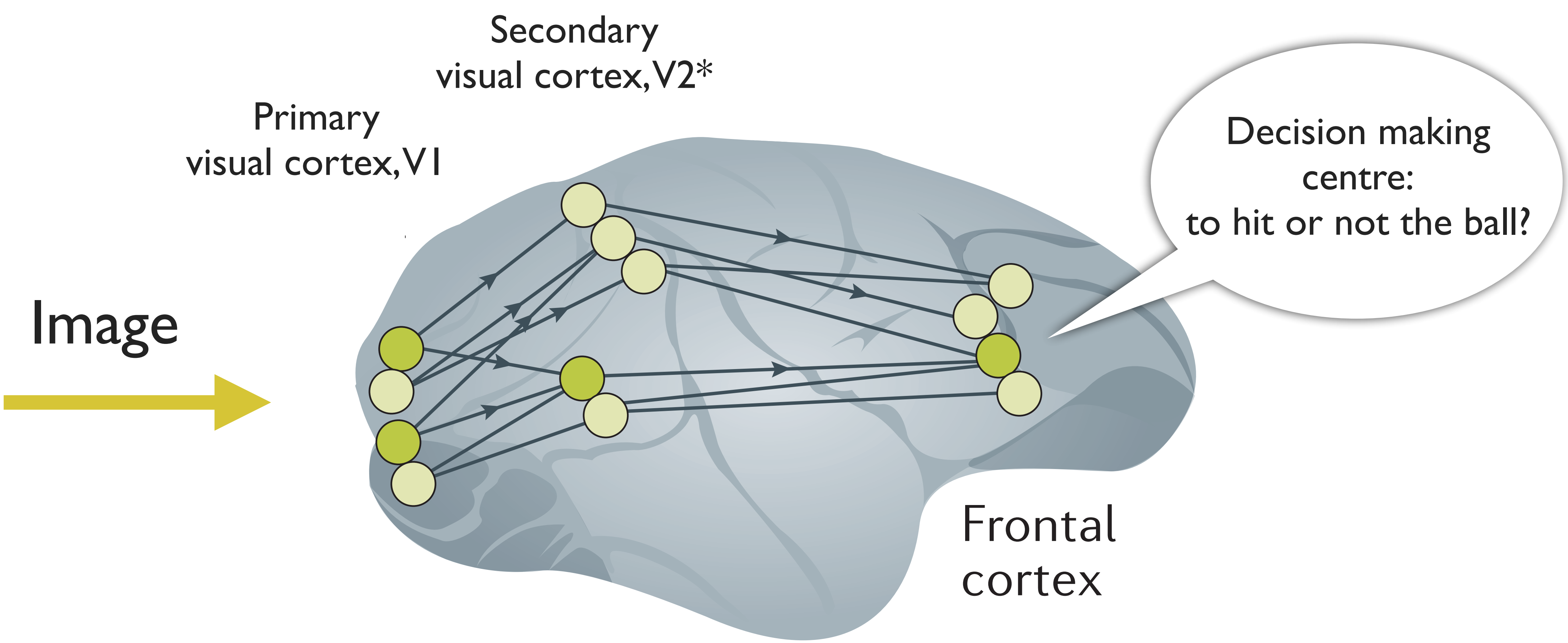
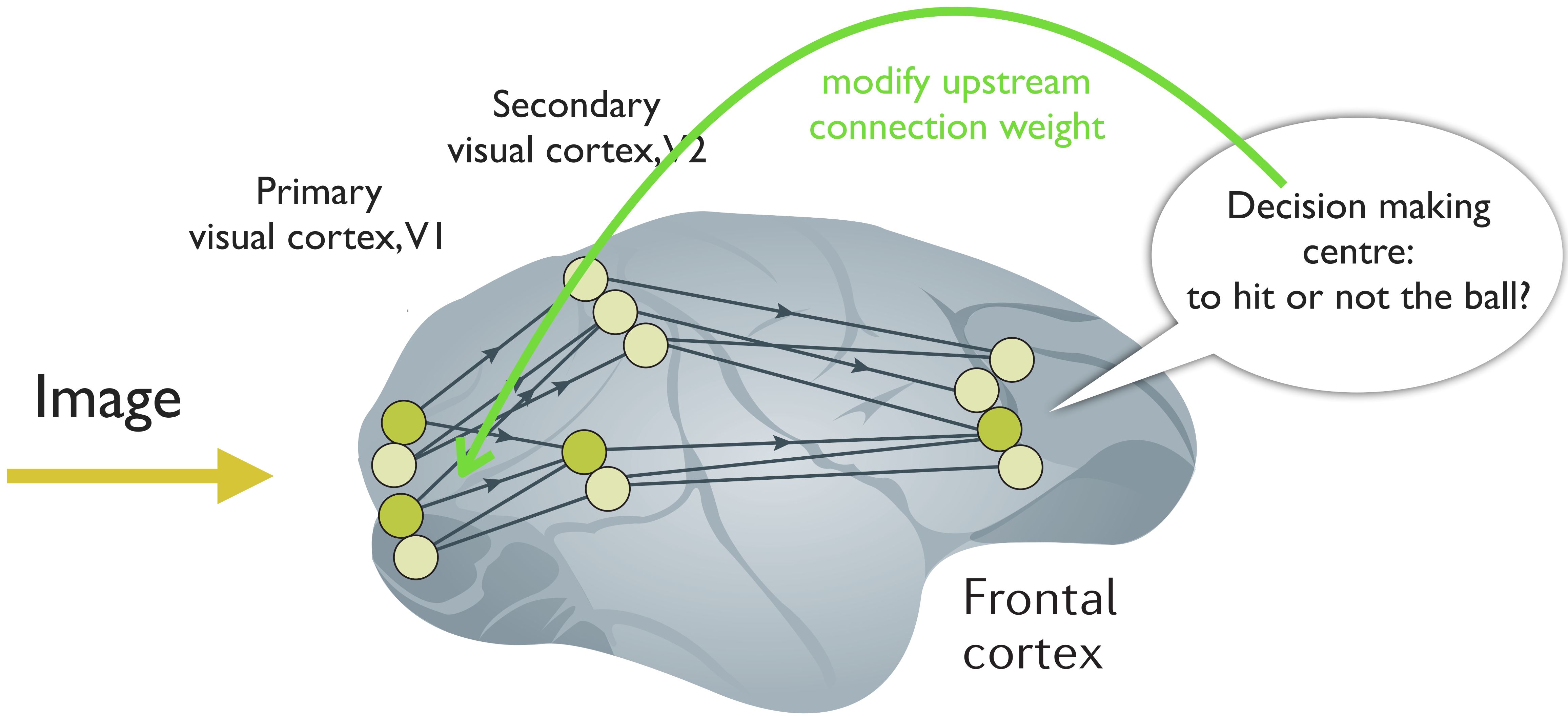


*: or associative cortices

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

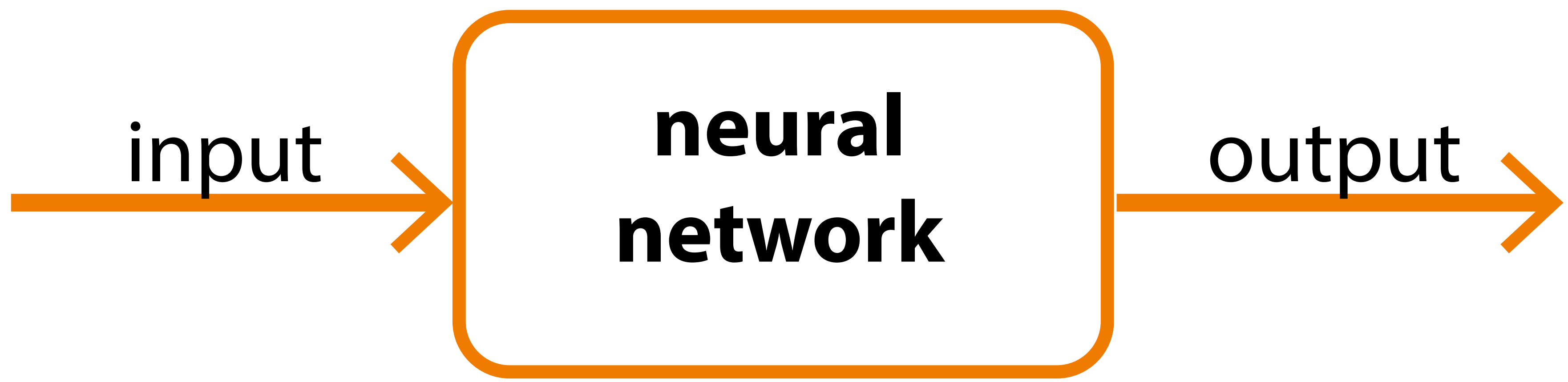
Unsupervised Learning

Reinforcement Learning

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

Unsupervised Learning:

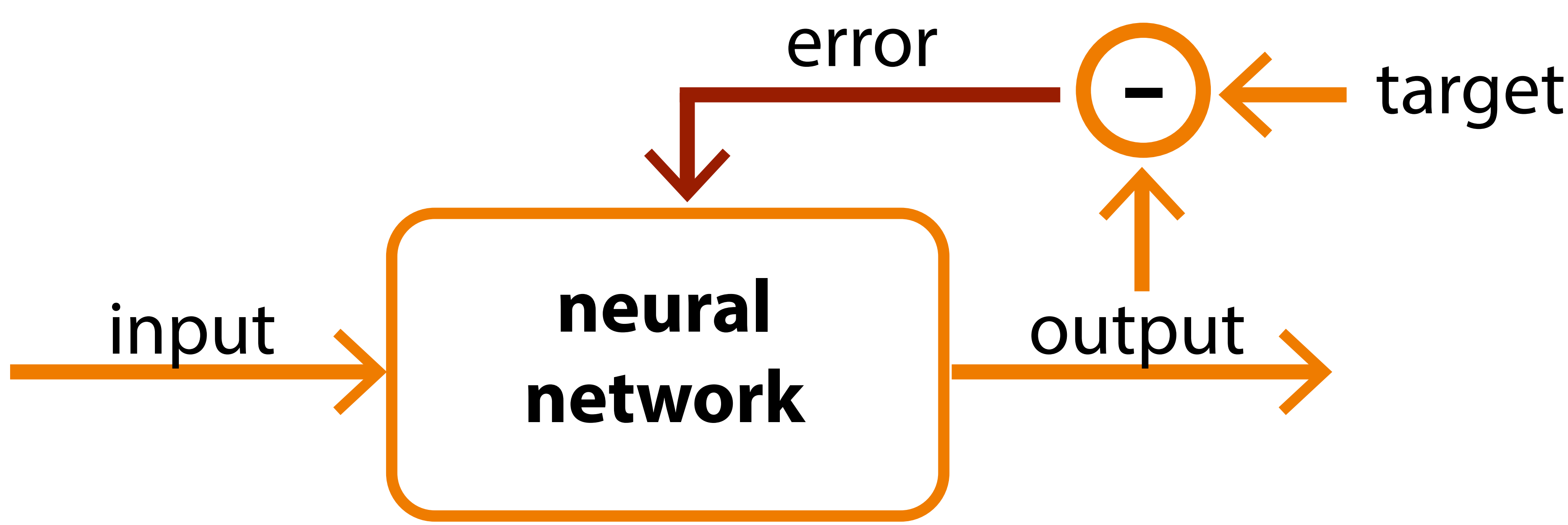
Extracts useful representations of input



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

Supervised Learning:

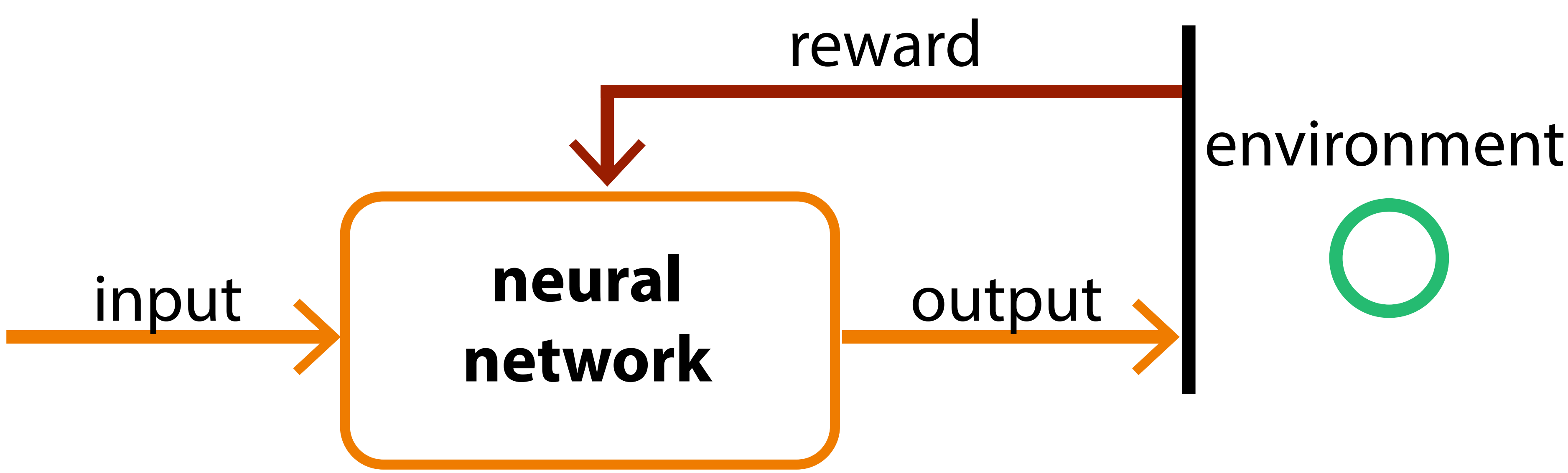
Relies on a teaching signal



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

Reinforcement Learning:

Learn to navigate/survive an environment

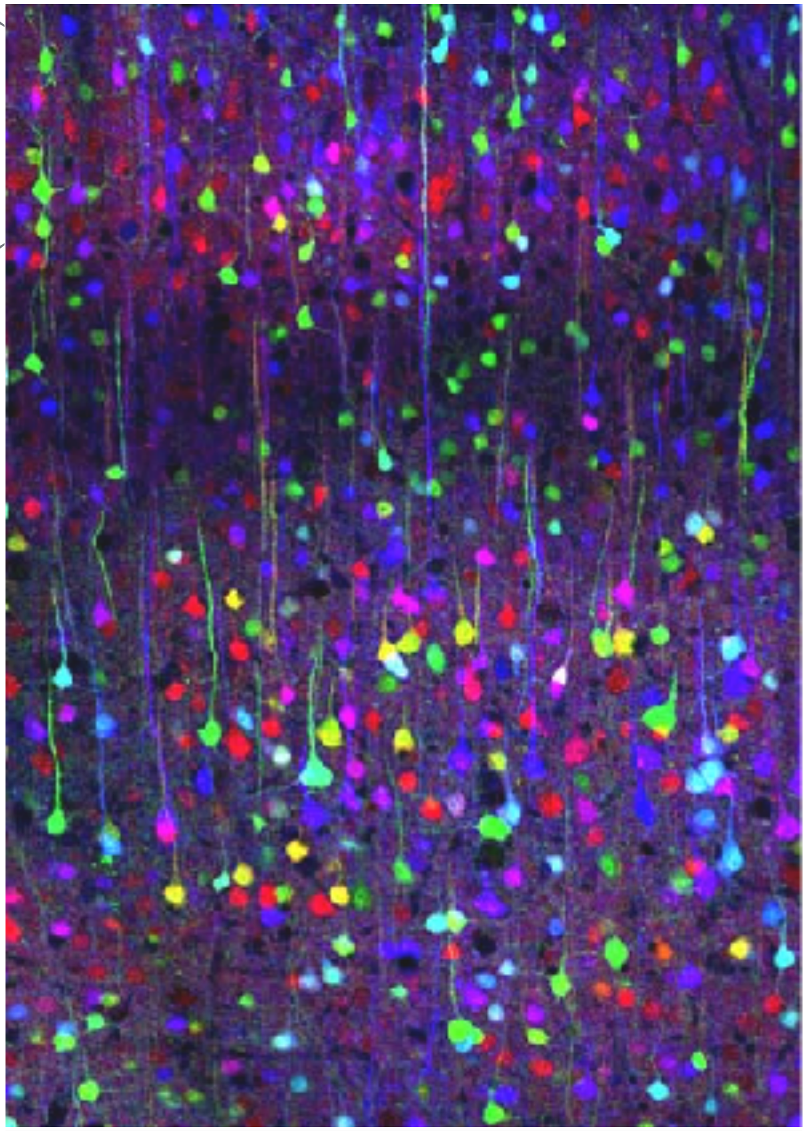


A feedforward neural network

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

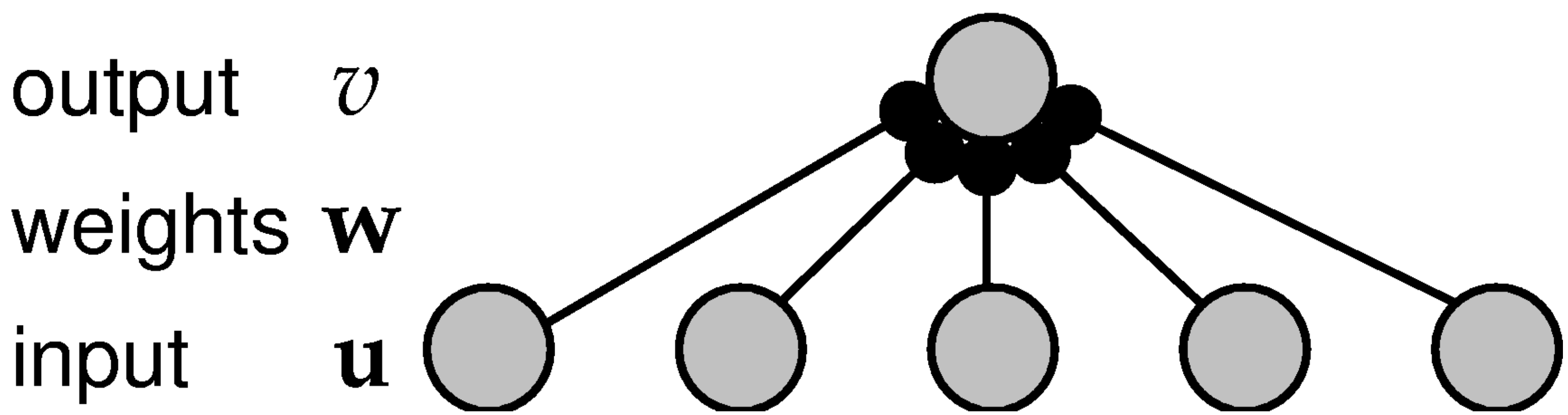
DeFelipe et al. Nat. Neurosci. Reviews 2013

Brainbow (Litchman Lab)



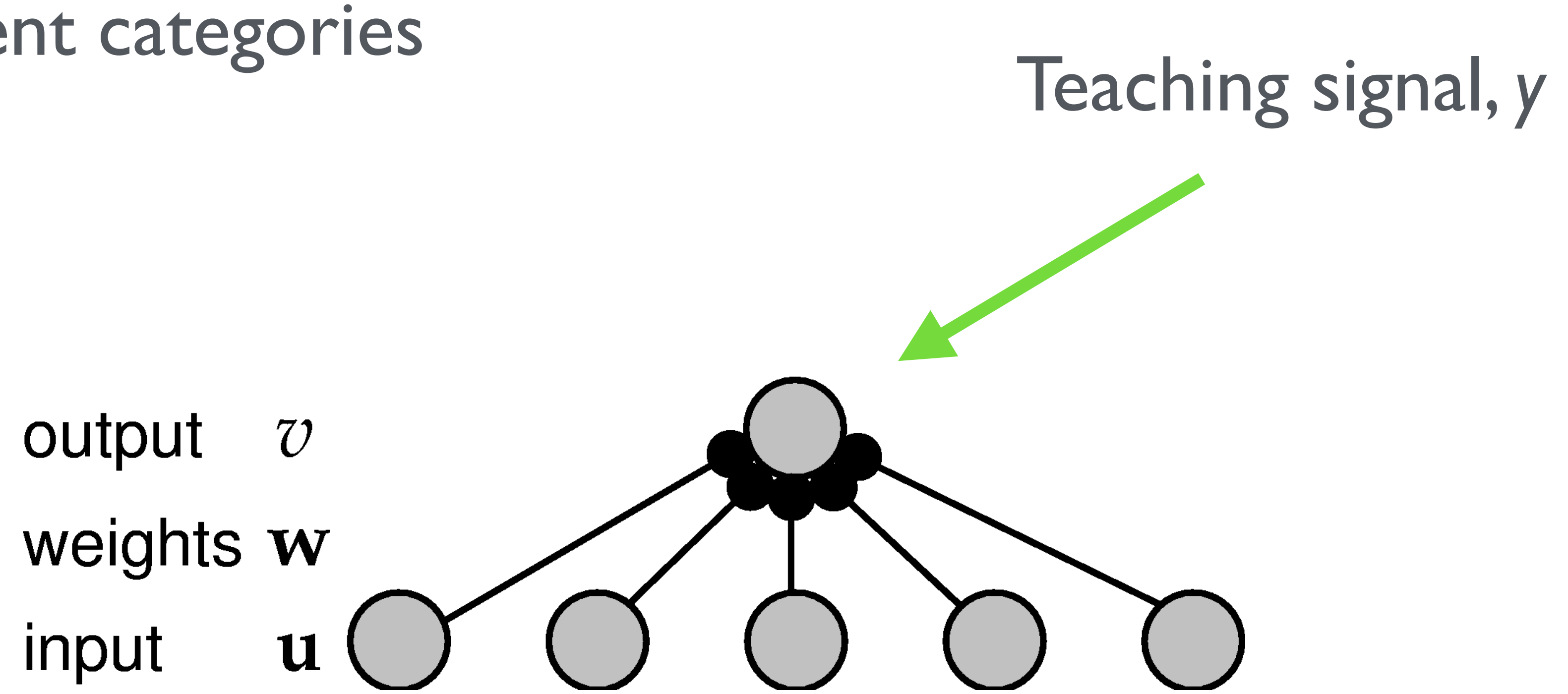
A feedforward neural network

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

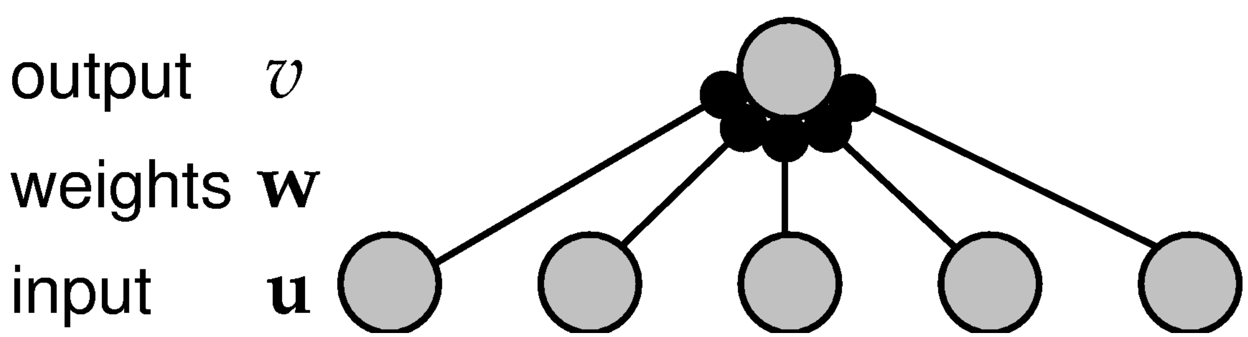


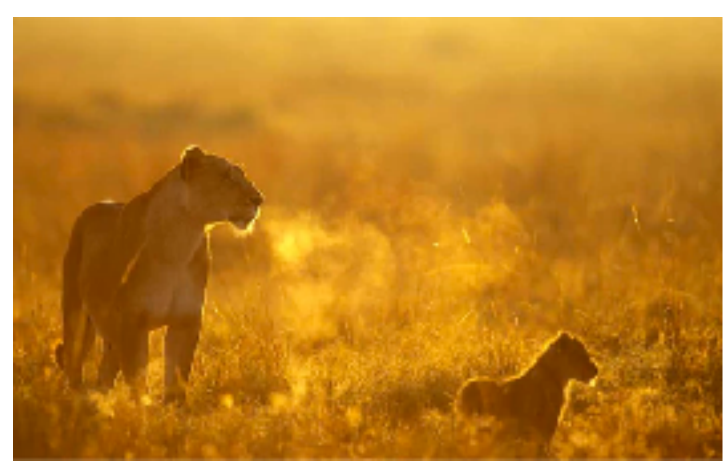
Supervised learning

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

where *f* is some (non)linear function

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





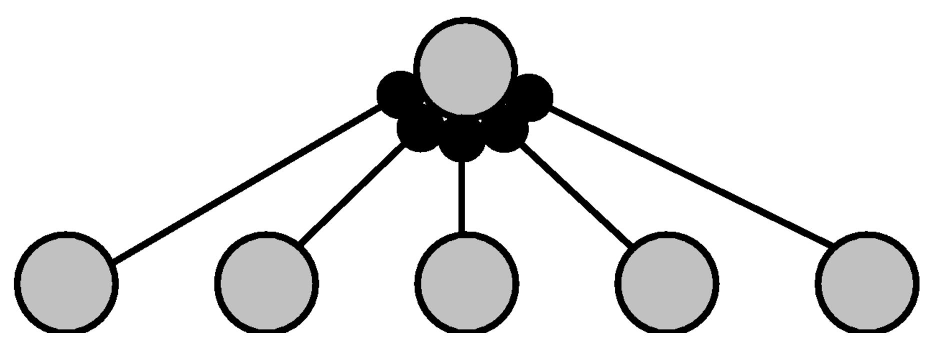
Supervised learning

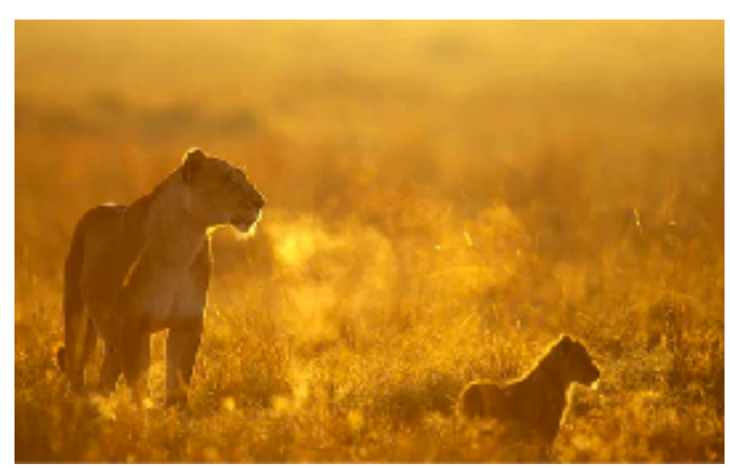
Minimise cost

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

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

output v
weights $\mathbf{w}$
input $\mathbf{u}$





Supervised learning

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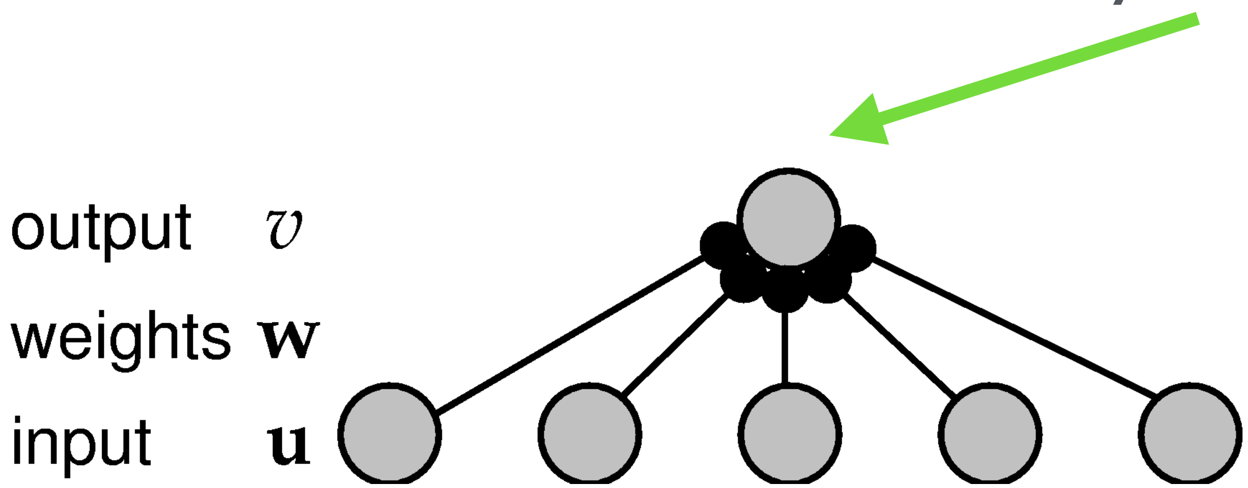
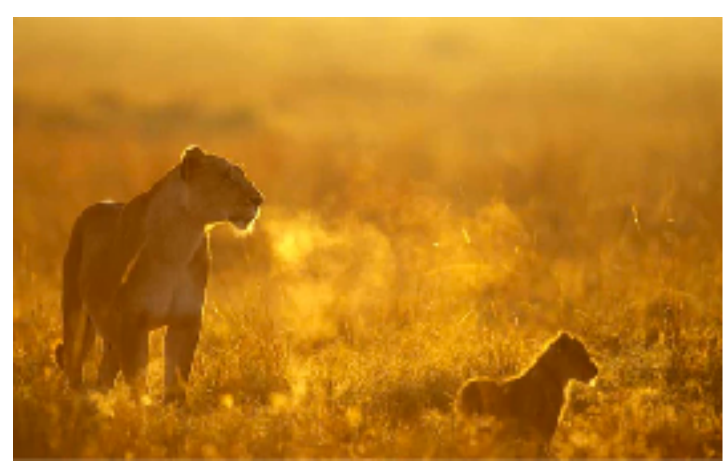
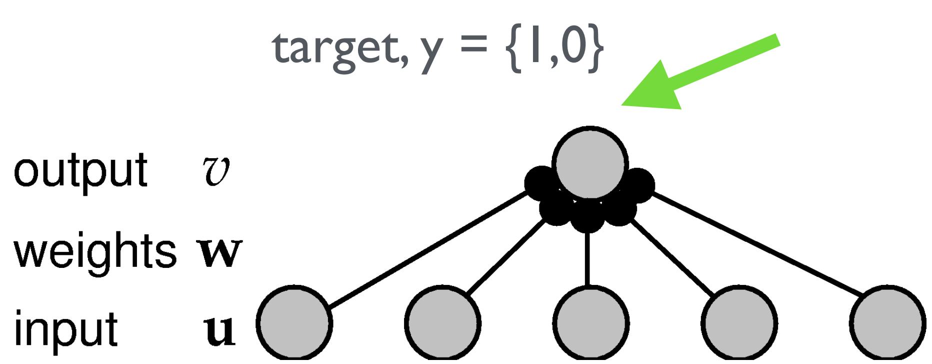




Supervised learning



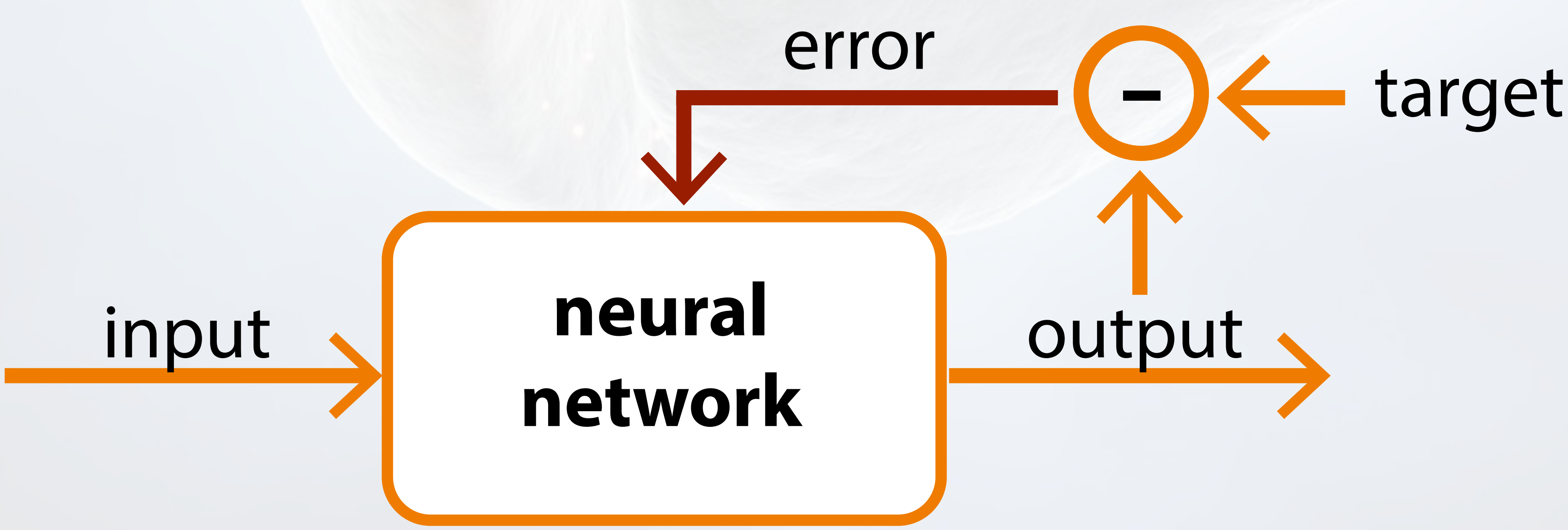
$$\text{cost} = (v - y)^2$$

- 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

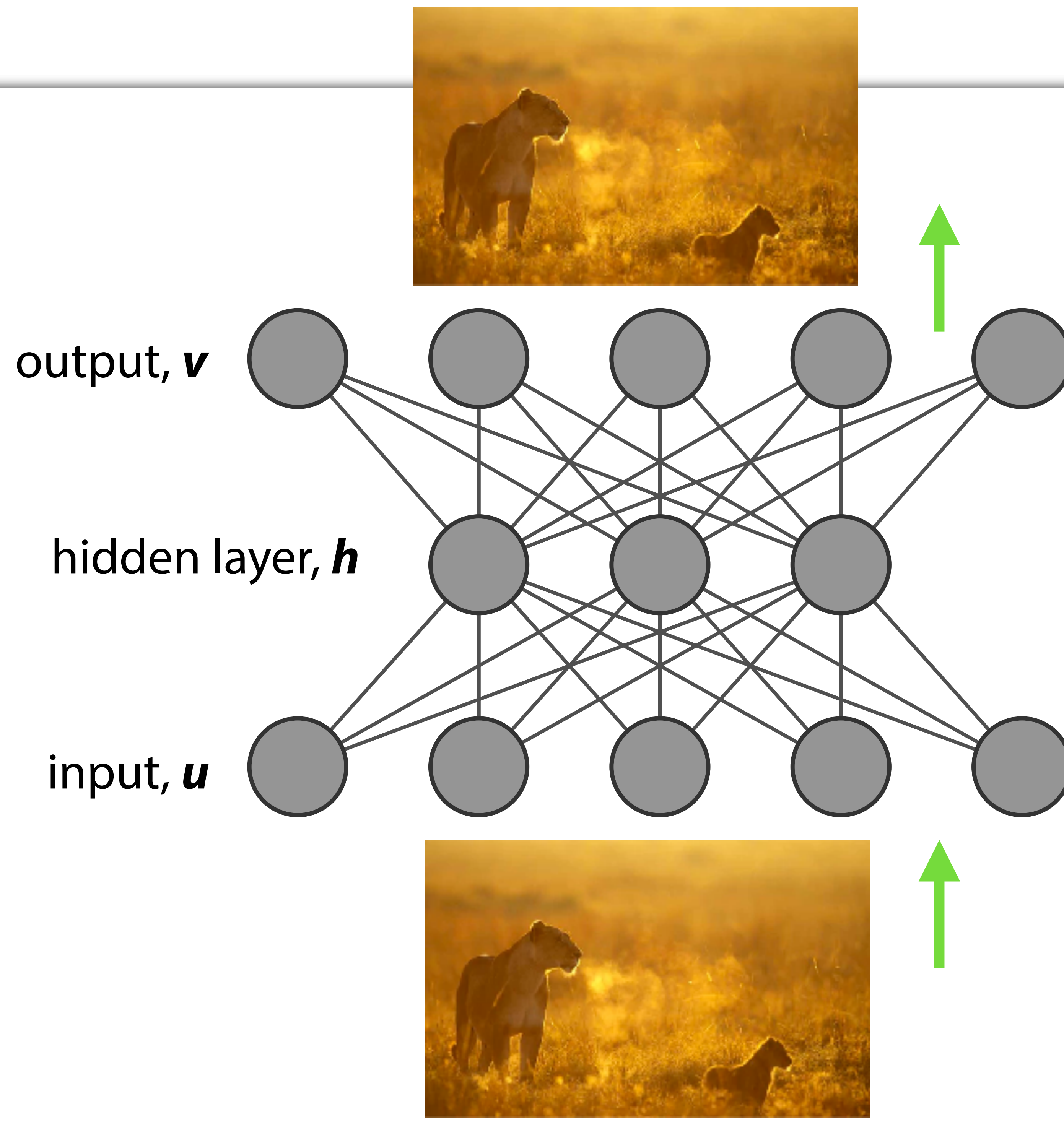
groups of 2-3 (5 min)

- **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

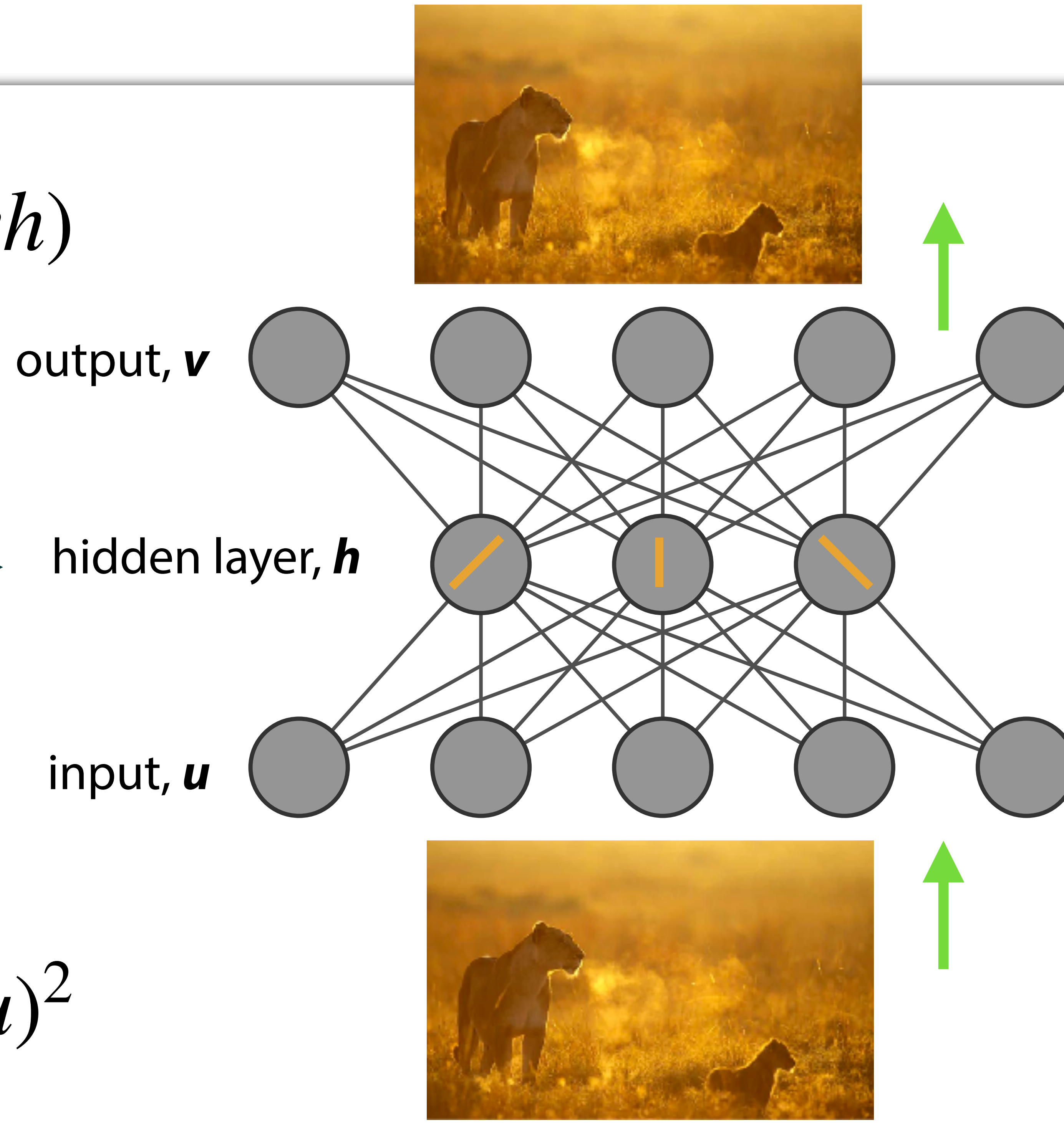
Goal: Extract a representation of the input
(dimensionality reduction)



Unsupervised learning

output, $v = f(wh)$

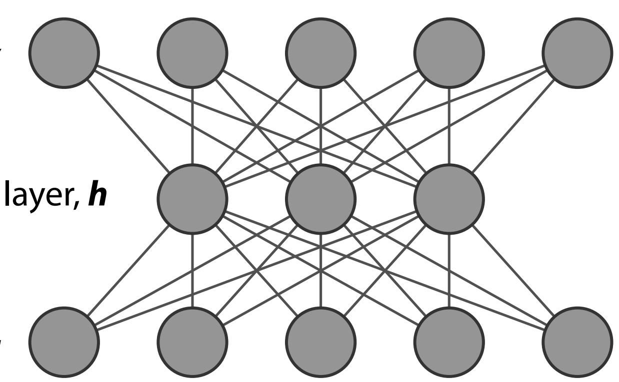
Learned representation
(e.g. edges)



Minimise cost

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

Unsupervised learning

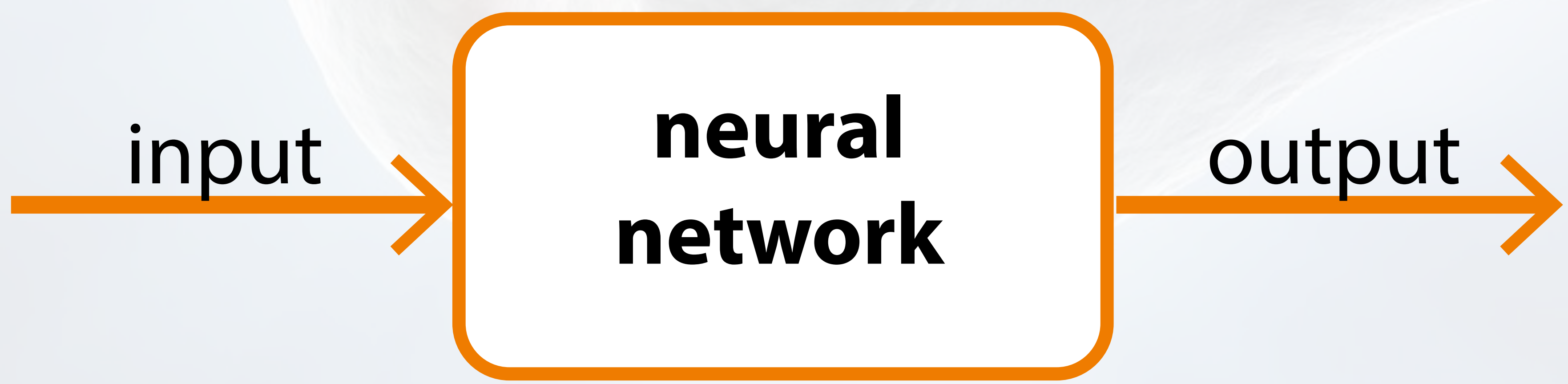


- The learning rules for **w** can be derived from the cost (or error) function for a particular network, e.g. sparse coding algorithm.
- Examples of unsupervised learning methods:
  - Sparse coding (akin to PCA)
  - Restricted Boltzmann Machines
  - Autoencoders
- Animals are bombarded with vast streams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

Group discussion

groups of 2-3 (5 min)

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



Group discussion

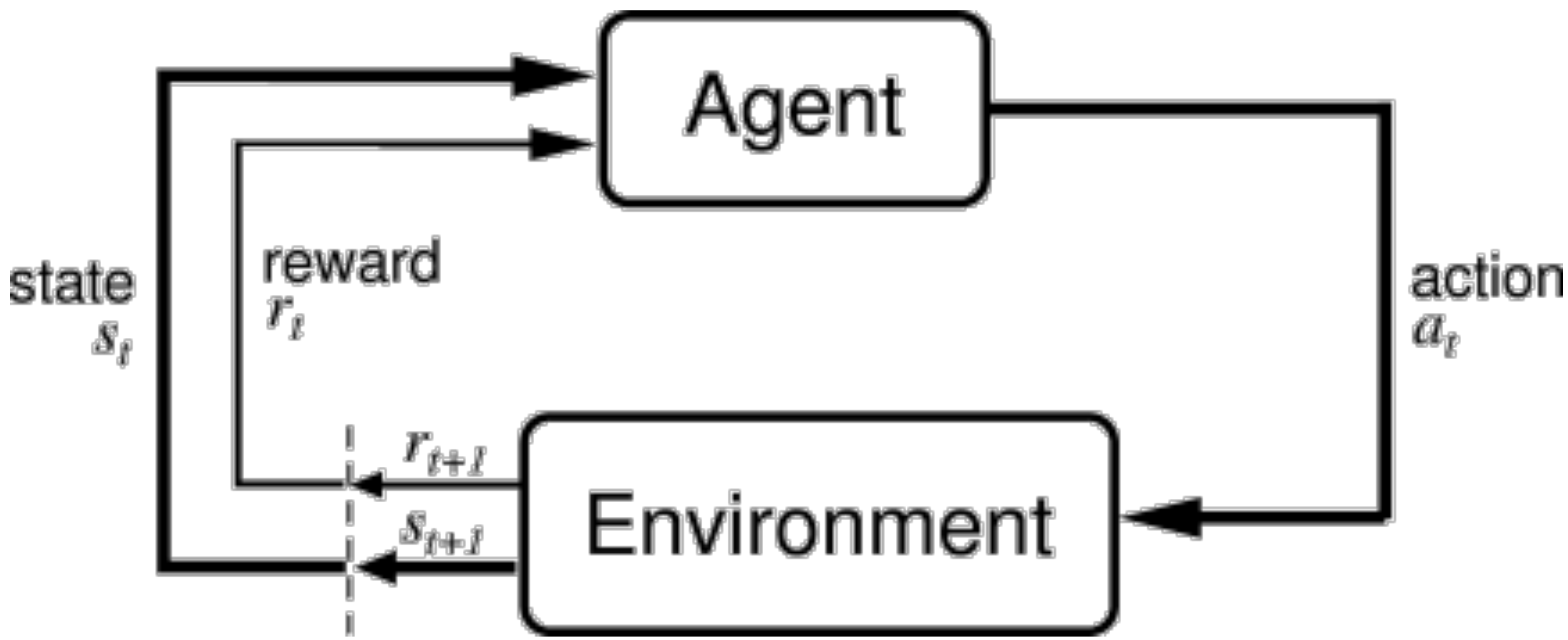
groups of 2-3 (5 min)

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

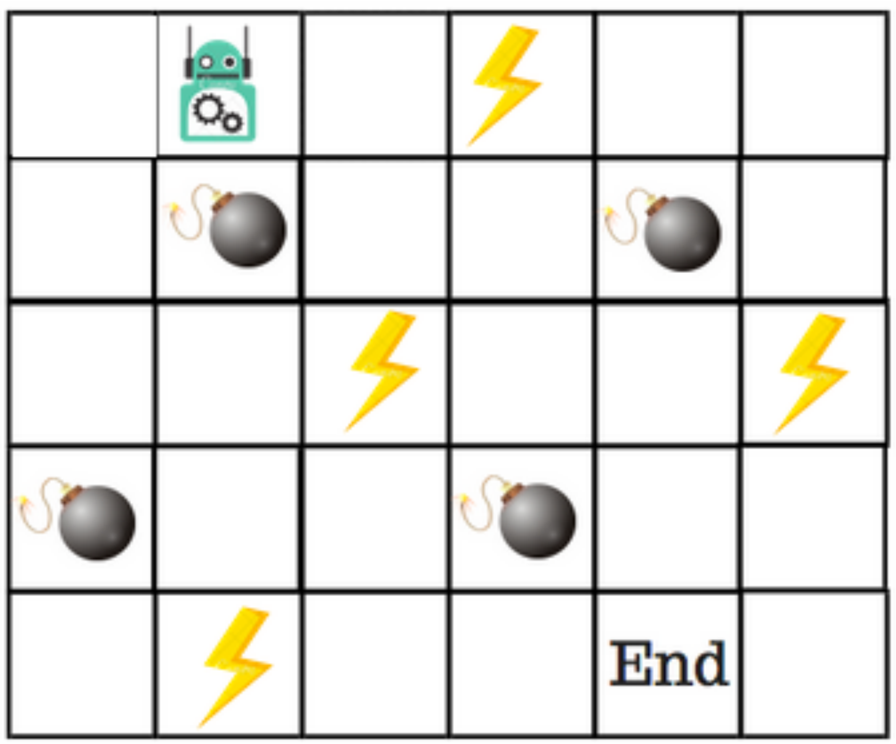
- **Hint: Learn important statistics of the environment**

Reinforcement learning

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



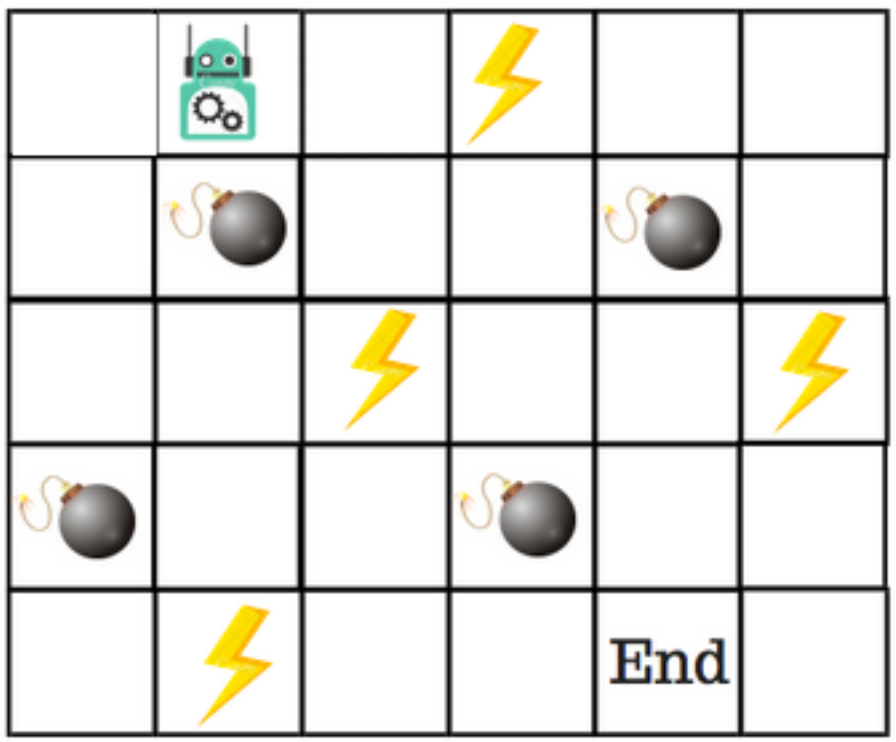
Reinforcement learning



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

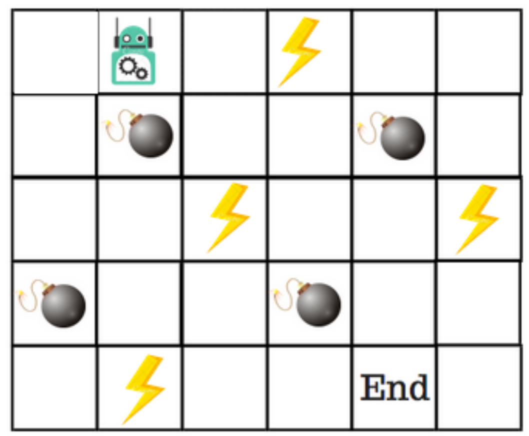
Actions :	↑	→	↓	←
Start	0	0	0	0
Nothing / Blank	0	0	0	0
Power	0	0	0	0
Mines	0	0	0	0
END	0	0	0	0

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

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

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

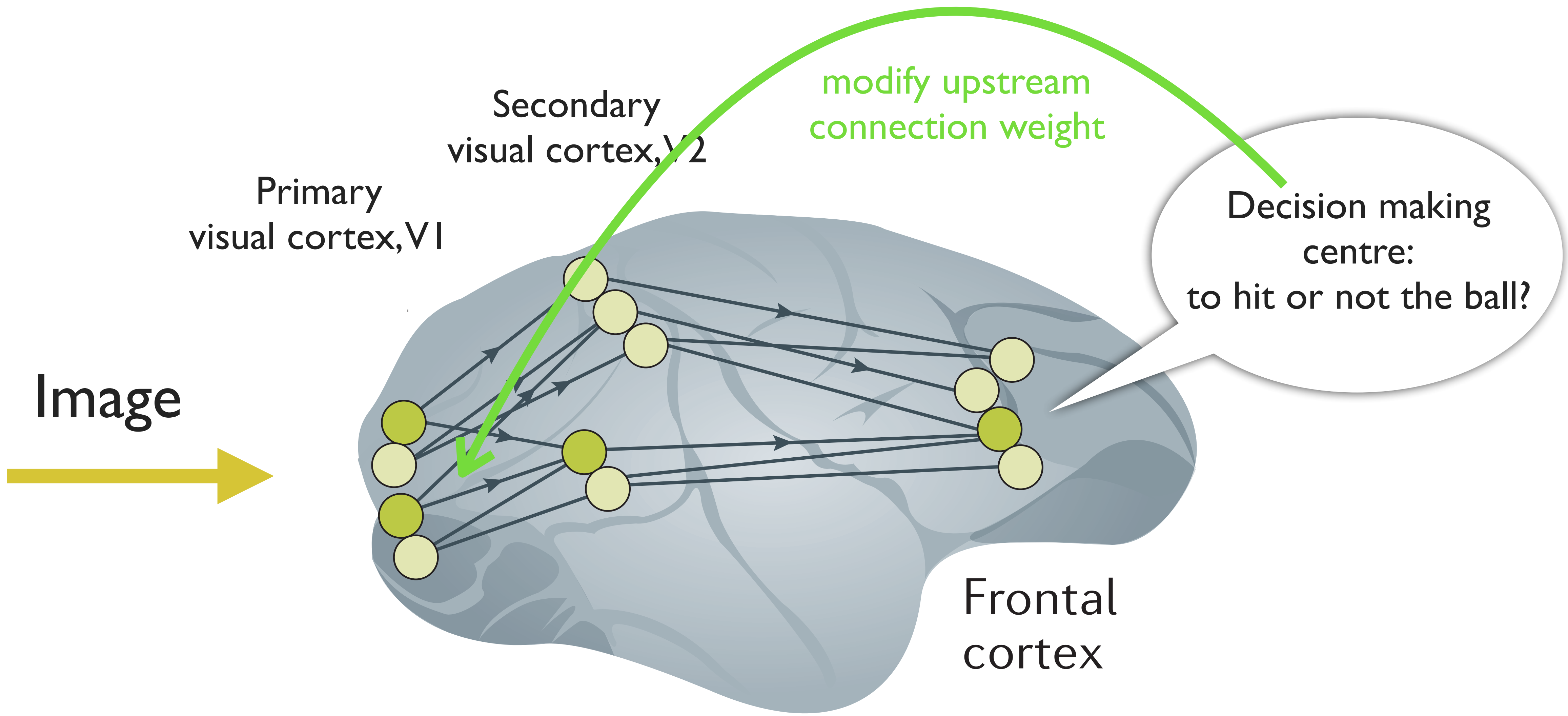
Questions?

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?



Unsupervised and reinforcement learning are the dominant views,
but recent research also suggest an important role for supervised 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)
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