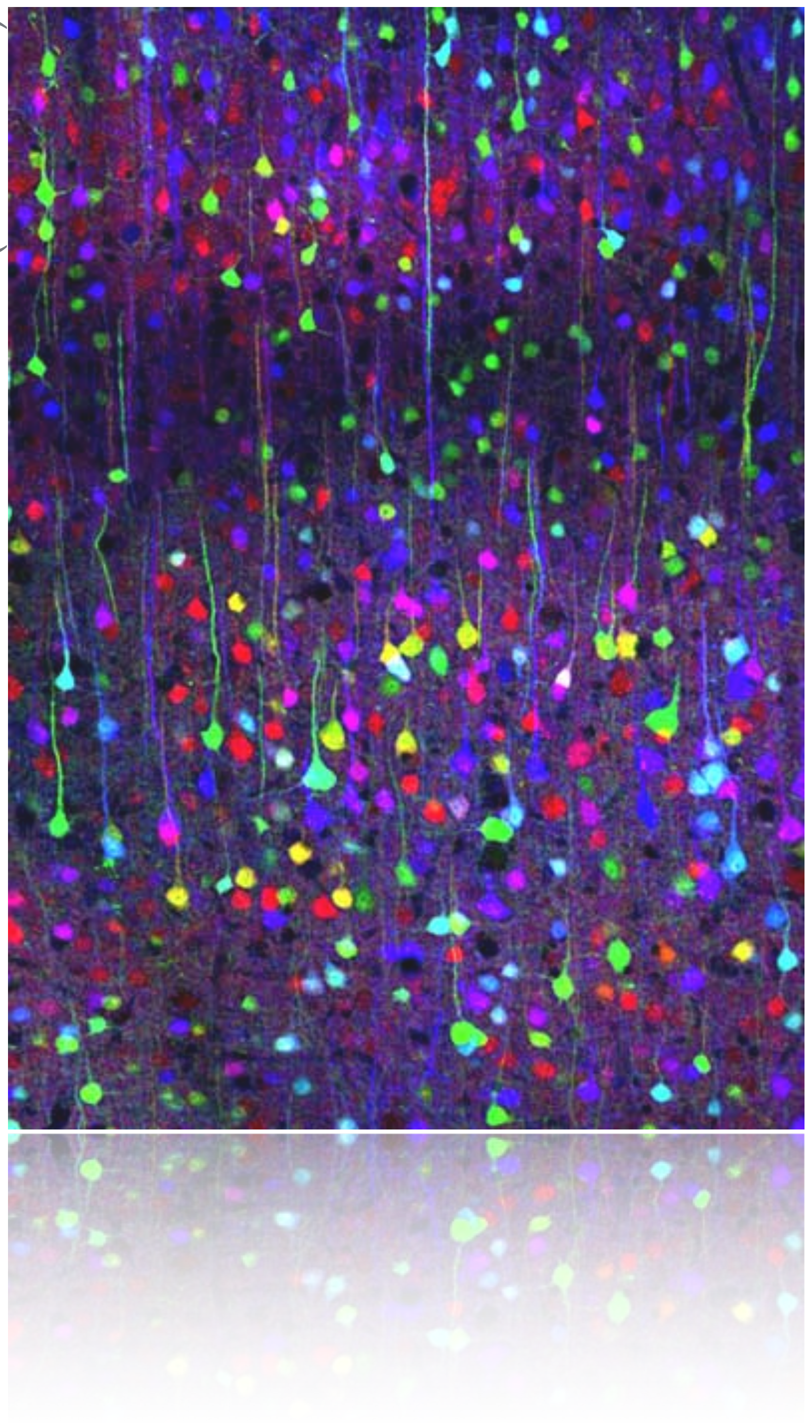
Information Processing & the Brain 21/22

University of BRISTOL



Brainbow (Litchman Lab)

IPB: Part 2

Lecture 1:
Neural circuits and learning

Rui Ponte Costa

What's going to happen?

- **Expectations**
  - Interactive lectures (BB quizzes, videos, simulations)
  - Research oriented (papers)
  - Neuroscience: a few theories, but mostly open
  - Lecturer and TA support on Teams/in person

What’s going to happen?

- **Labs** [formative]
  - *Implement* and *discuss* neural learning algorithms
  - Lab 1 [w5,7]: on supervised learning
  - Lab 2 [w7,8]: on reinforcement learning

- **TAs:**
  - Joe Pemberton
  - Dabal Pedamonti
  - Kevin Nejad

IPB: part 2
Neural circuits and learning

Temporal difference

Supervised learning

Balance

Pyramidal cells

Unsupervised learning

Synaptic plasticity

Backprop

Deep learning

Neural networks

Brain areas

Learning rules

Autoencoders

Reinforcement learning

States

LSTMs

Actions

Credit assignment

Neural circuits

Interneurons

RNNs

Optimization

Q-learning

Deep RL

Neuroscience

IPB: part 2
Neural circuits and learning

- **L1[4]: Neural circuits and learning: introduction**
- L2[4]: Supervised learning & backprop
- L3[5]: Visual system: deep learning?
- L4[5]: Reinforcement learning
- L5[6]: Unsupervised learning
- L6[6]: Temporal processing
- L7[7]: Recurrent neural networks
- L8[7]: Guest lecture

This lecture

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

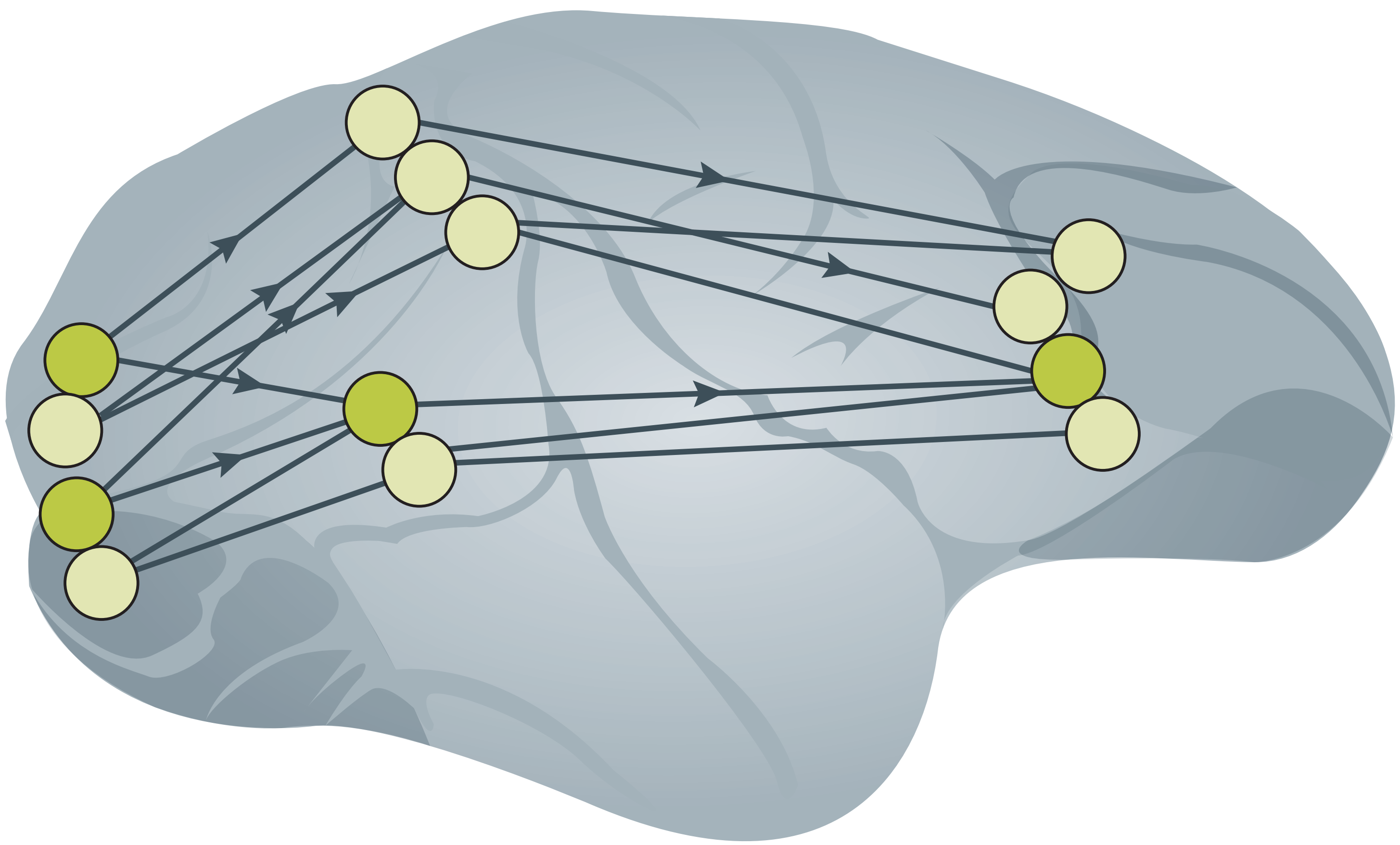
Given visual input how should you move?

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

How does the brain learn
to associate visual input with motor output?

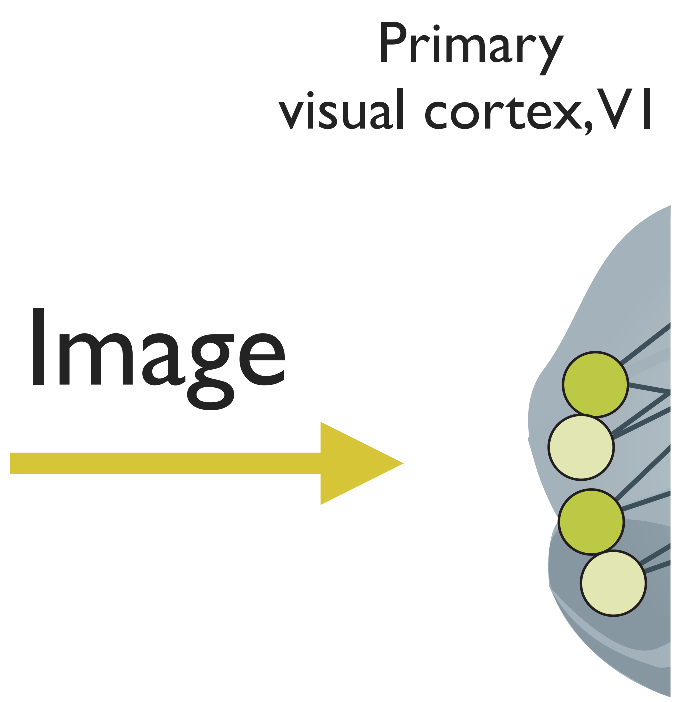
Visual input → Prepare movement → Hit (or not) the ball

(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?



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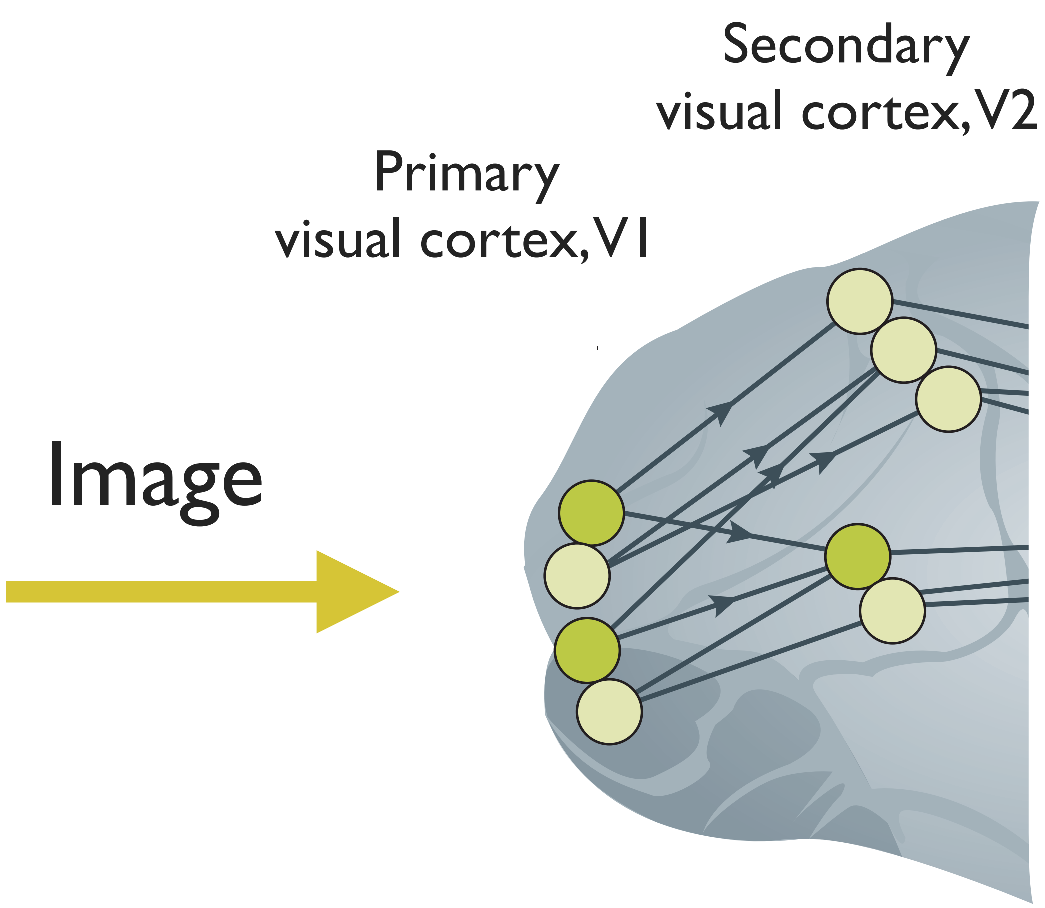

Roelfsema et al. Nature Neuroscience Rev 2018

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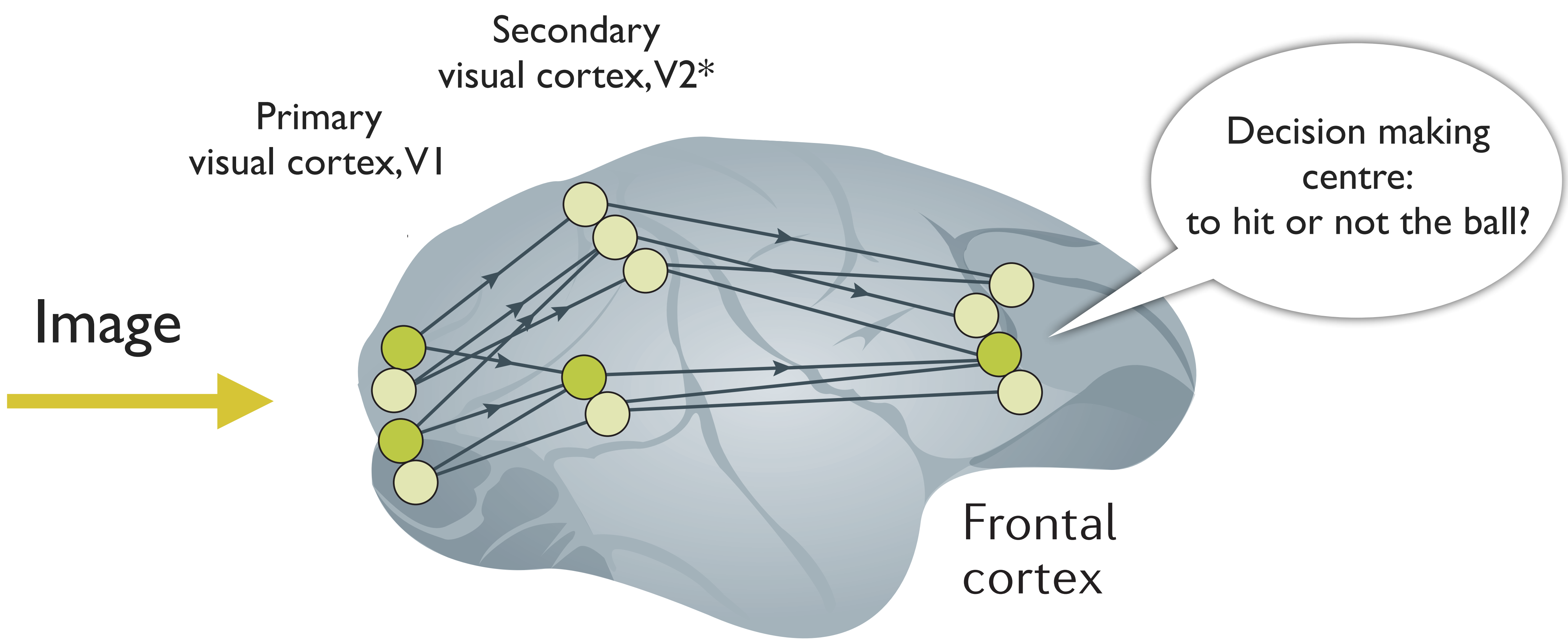
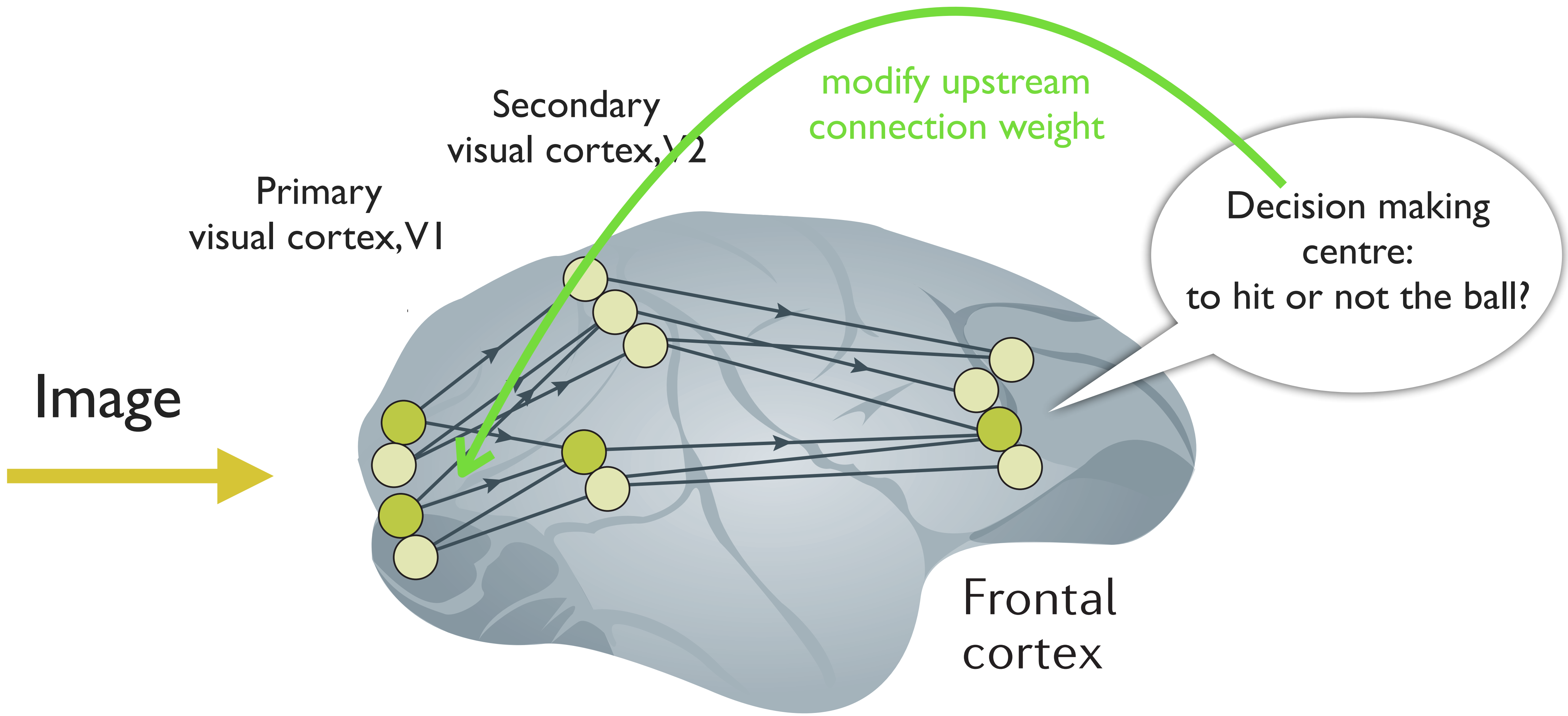


*: or associative cortices

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 *credit assignment*

Supervised Learning

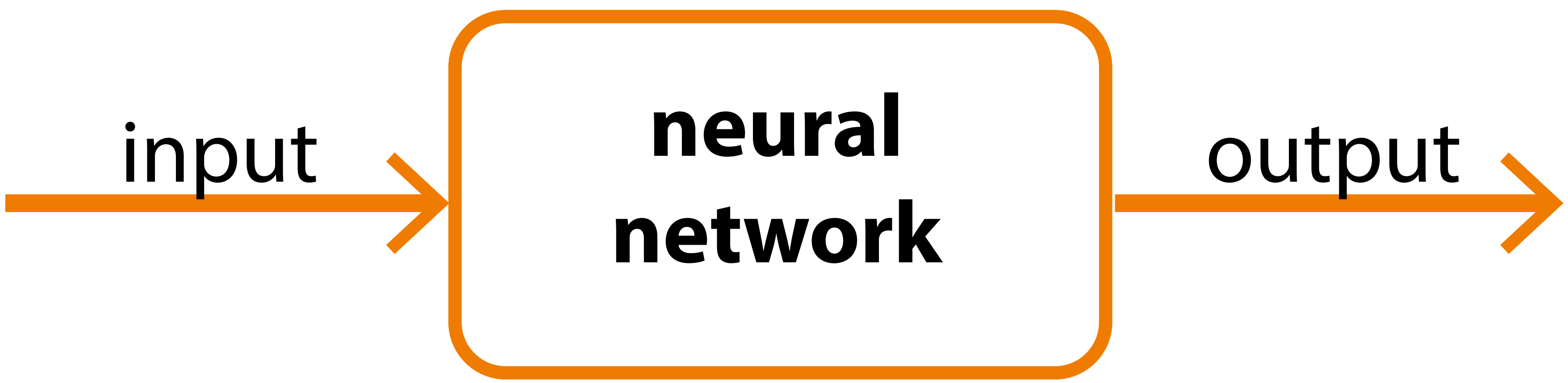
Unsupervised Learning

Reinforcement Learning

Three forms of *credit assignment*

Unsupervised Learning:

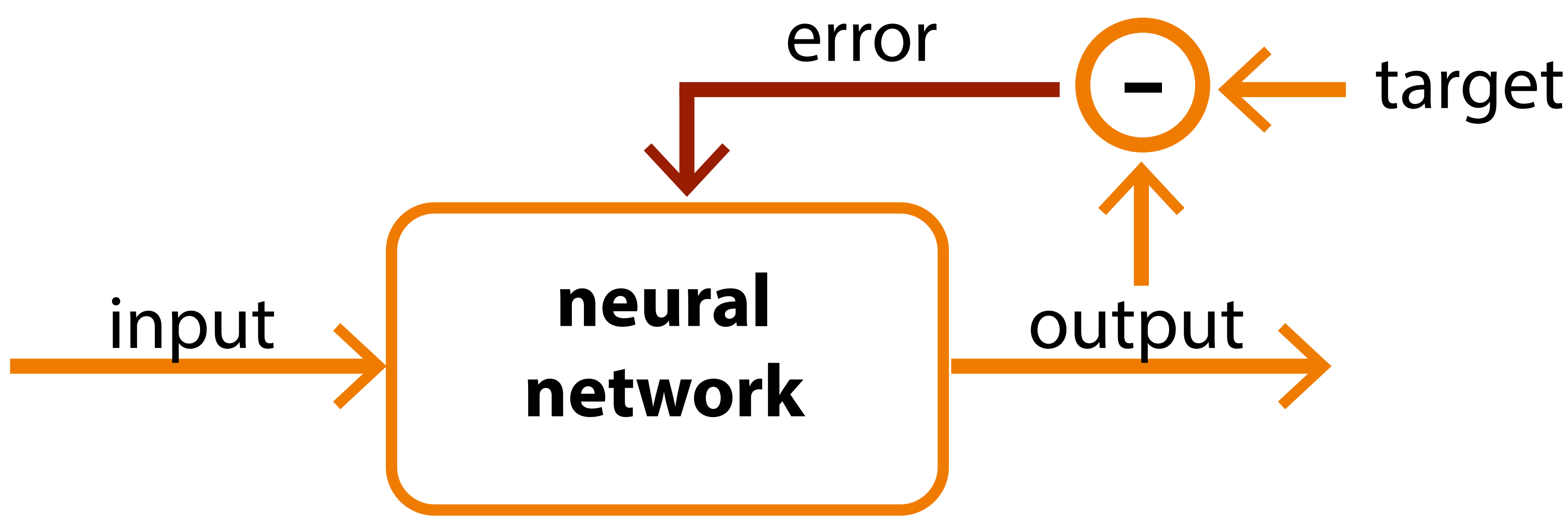
Extracts useful representations of input



Three forms of *credit assignment*

Supervised Learning:

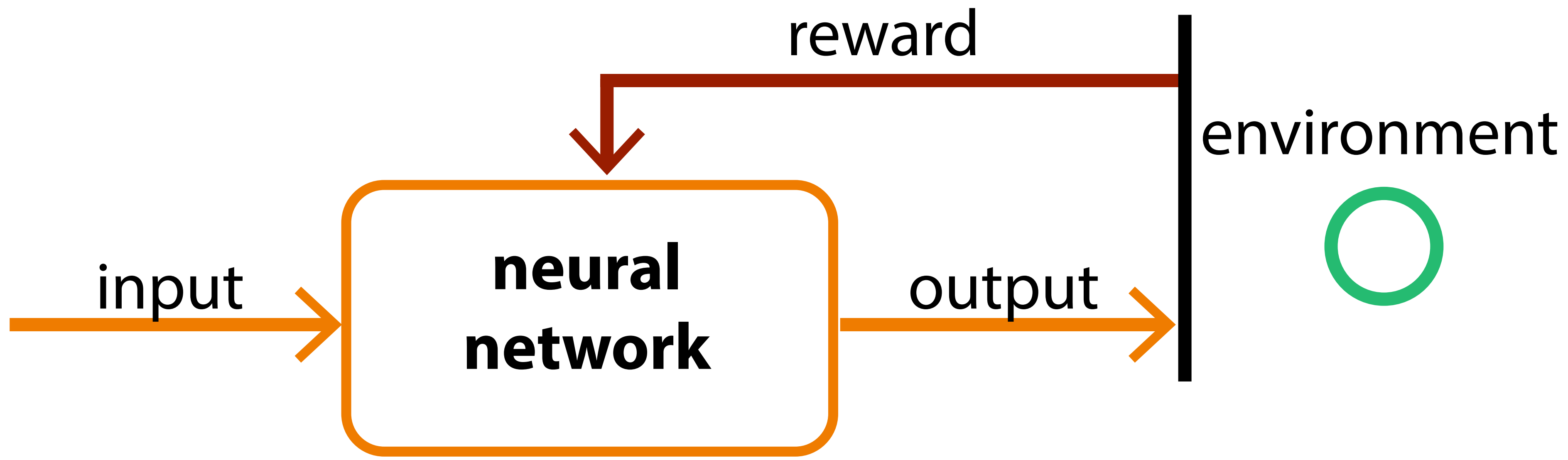
Relies on a teaching signal



Three forms of *credit assignment*

Reinforcement Learning:

Learn to navigate/survive an environment



Quiz time!

Please go to BB
and solve quiz 1.1.

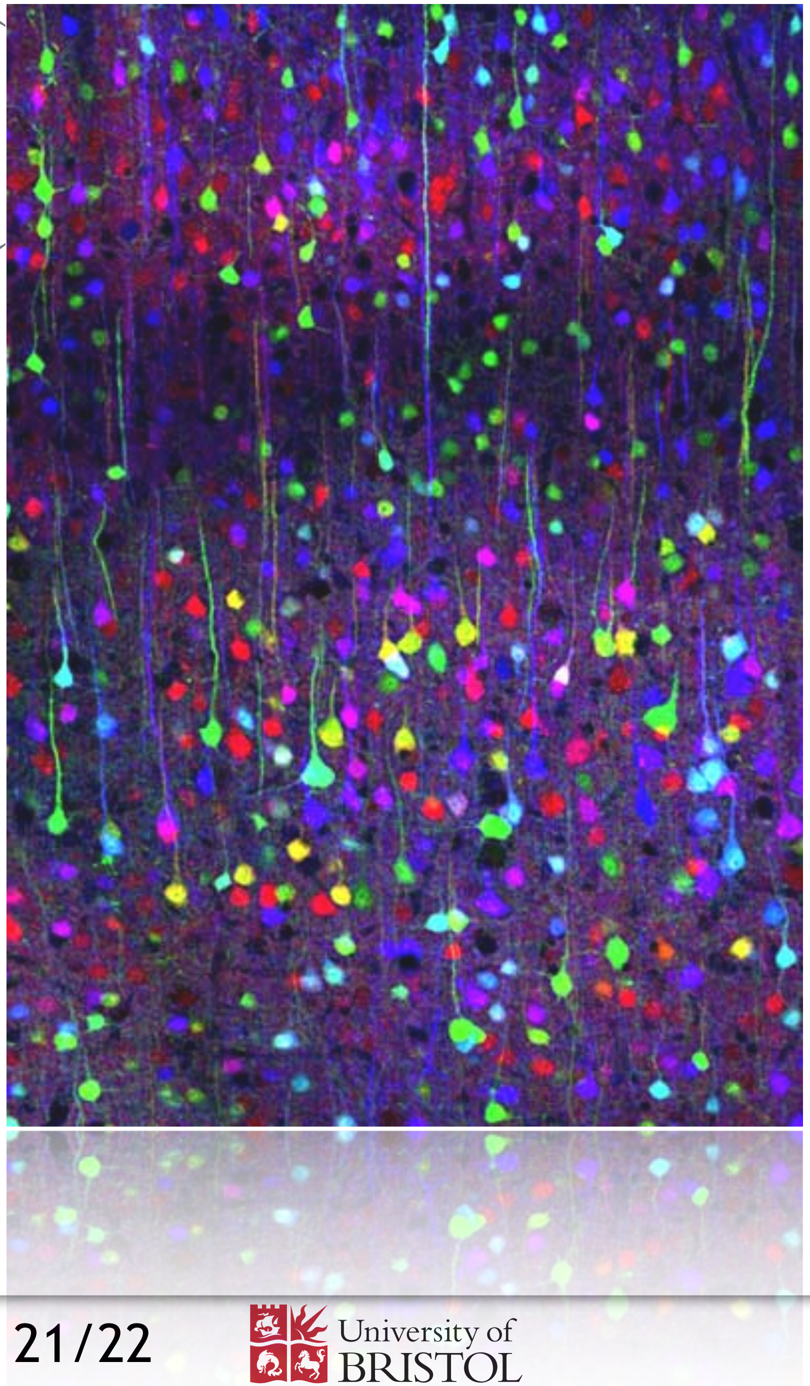
It should take you just a couple of minutes.

A feedforward neural network

The brain is like a tropical forest!

With many different neuron *types* and *architectures*..

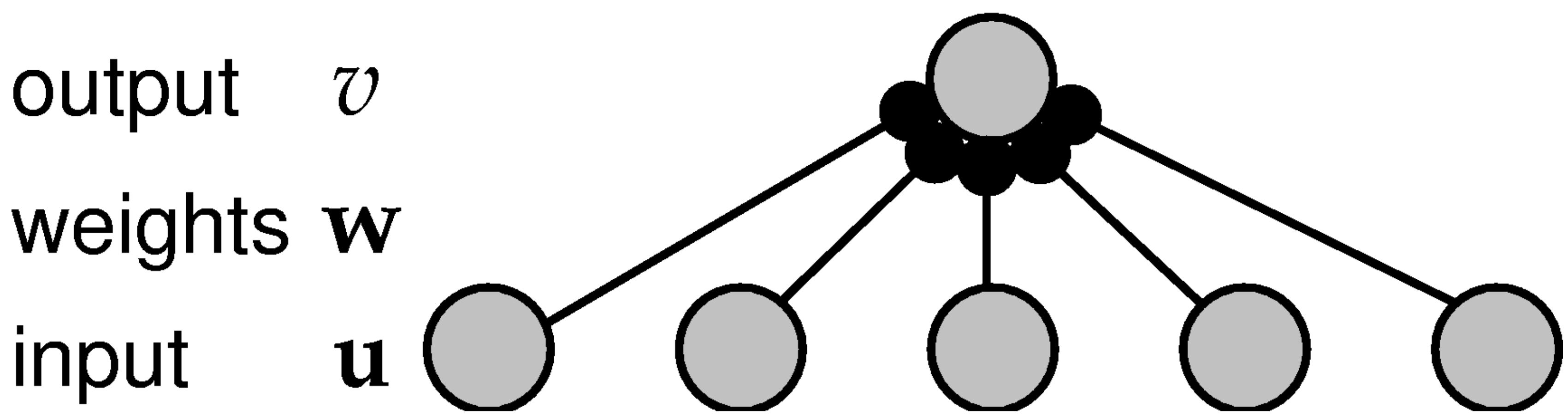
DeFelipe et al. Nat. Neurosci. Reviews 2013



Brainbow (Litchman Lab)

A feedforward neural network

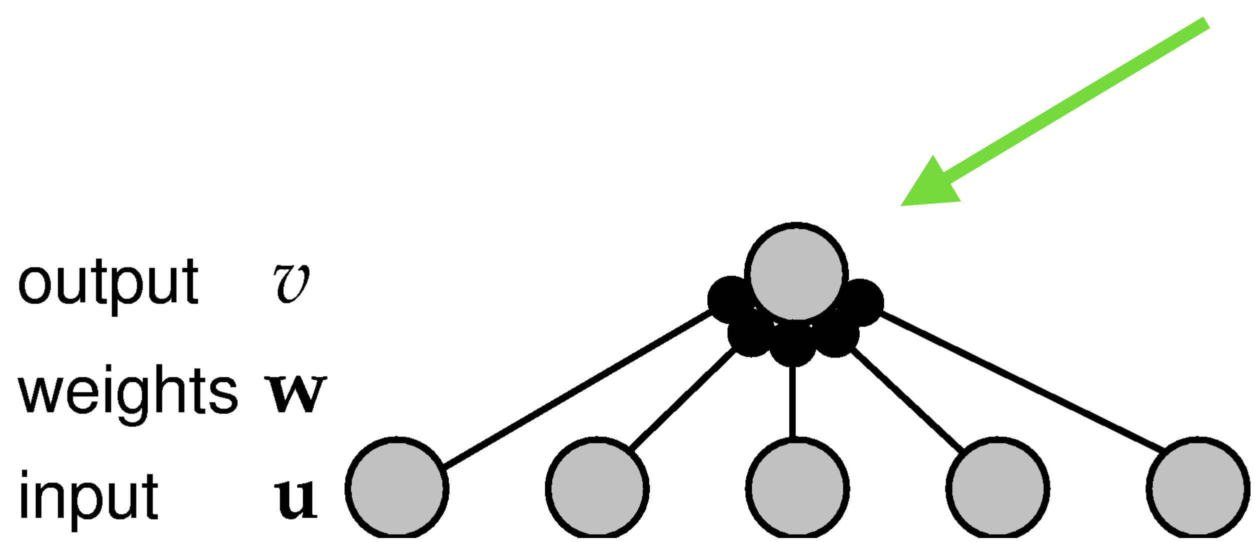
In theoretical neuroscience we need to abstract out some of this complexity to get at the principles of information processing in the brain!



Supervised learning

Goal: Classify input into different categories

Teaching signal, *y*



Supervised learning

output, $v = f(wu)$

where f is some (non)linear function

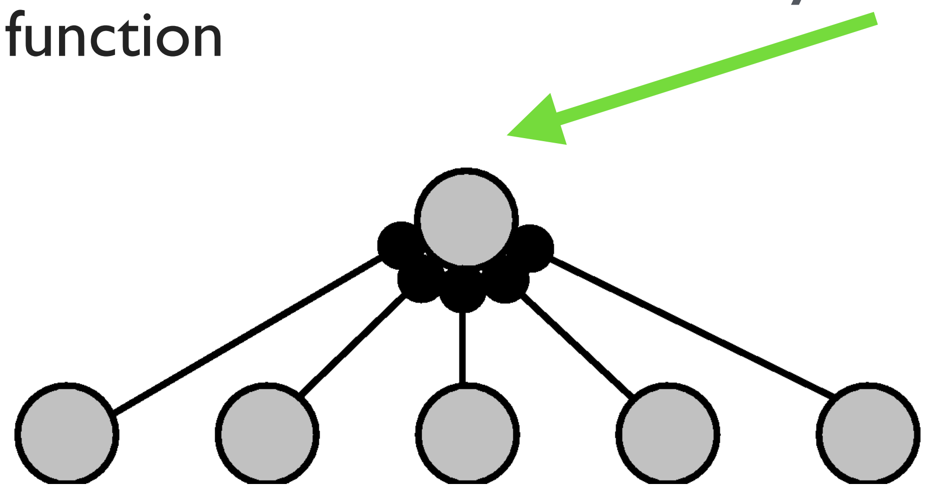
Predator, yes/no?

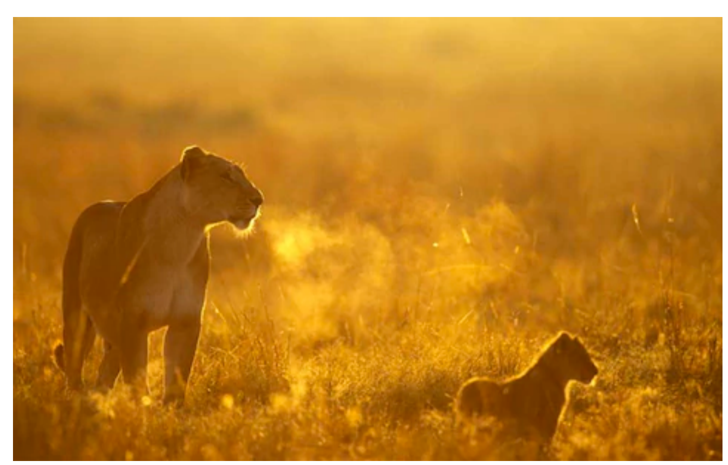
$y = \{1,0\}$

output v

weights $\mathbf{w}$

input $\mathbf{u}$





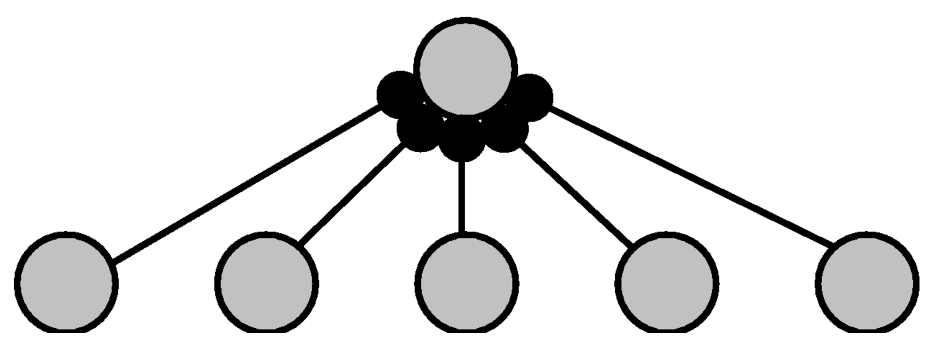
Supervised learning

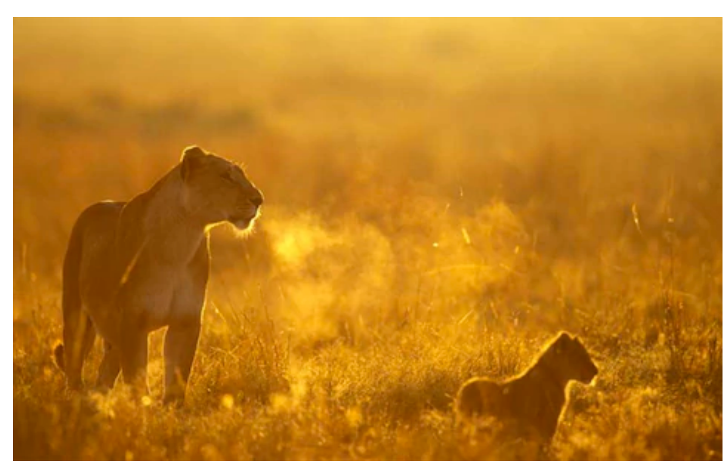
Minimise cost

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

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

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





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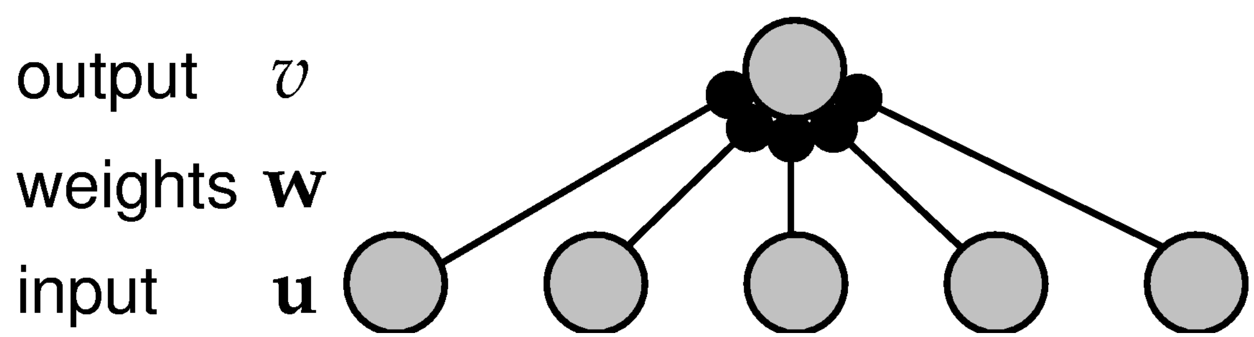
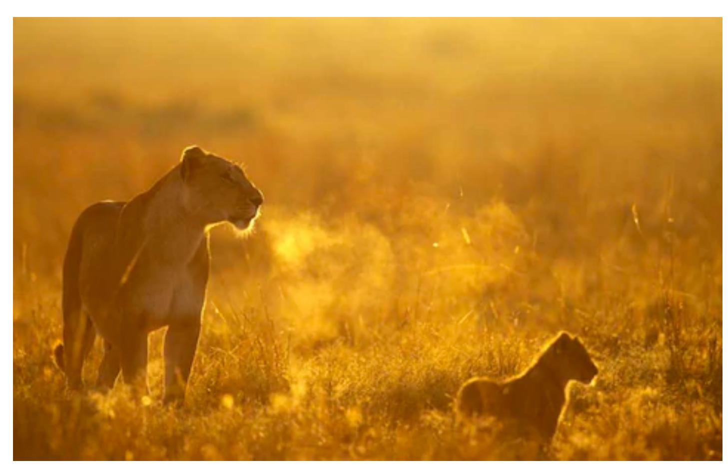
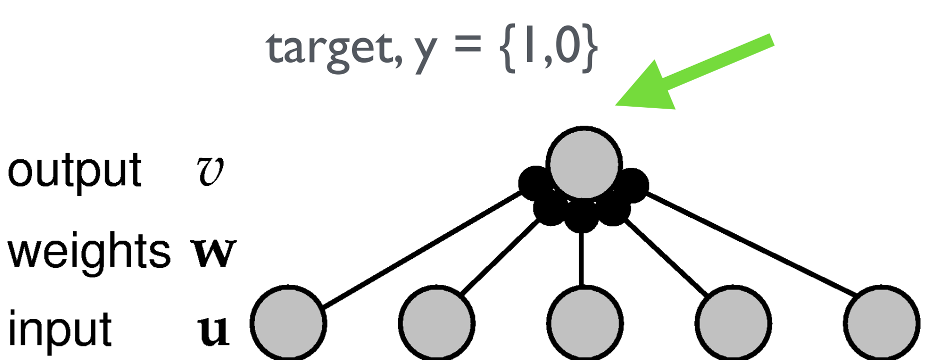
$y = \{1,0\}$





Supervised learning

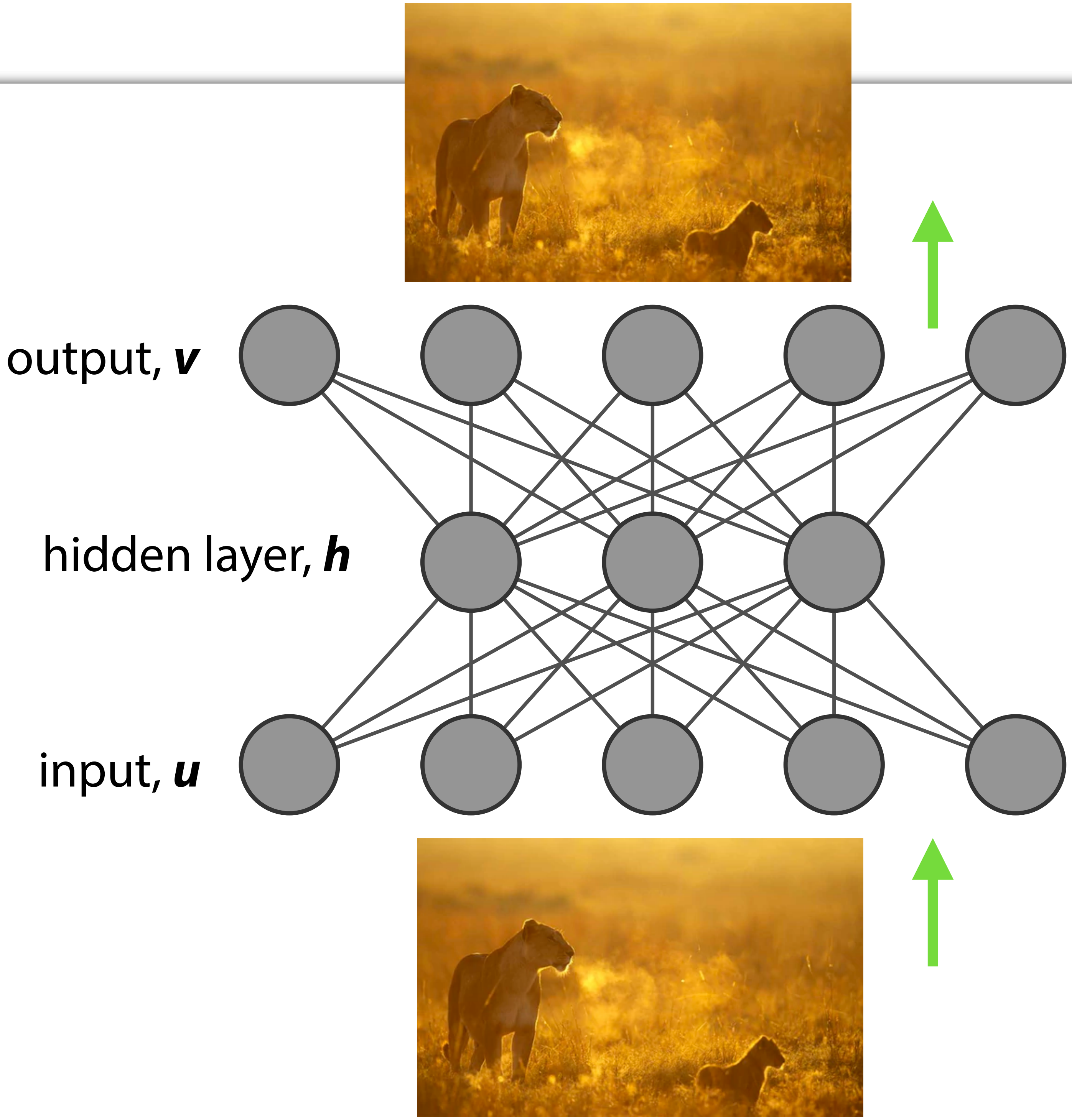


$$\text{cost} = (v - y)^2$$

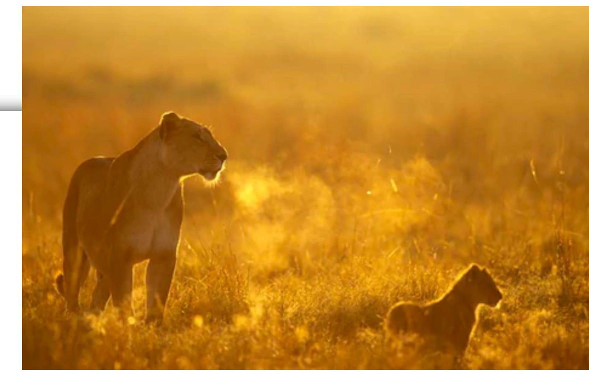
- The learning rules for **w** can be derived from the cost (or error) function for a particular network: e.g. using the popular backpropagation algorithm
- Examples of methods that use supervised learning:
  - Convolutional neural networks
  - Recurrent neural networks
  - Linear regression
- Animals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

Unsupervised learning

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



Unsupervised learning

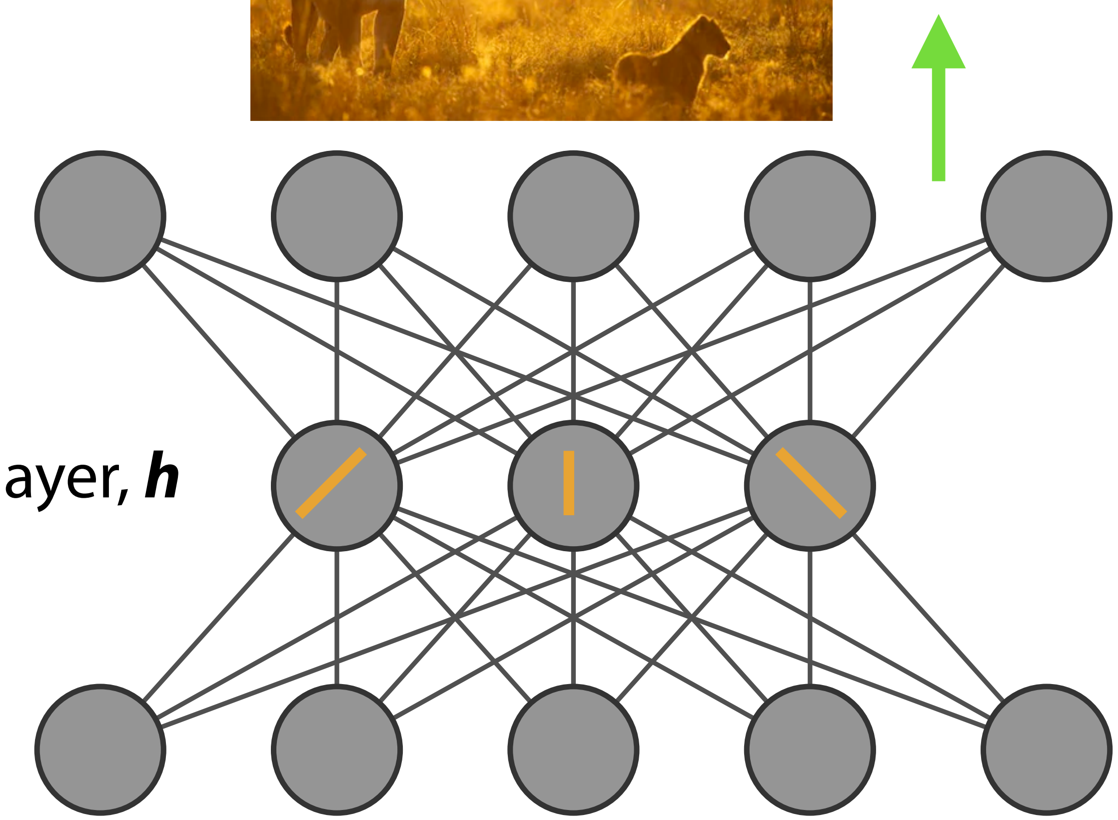


$$\text{output}, v = f(wh)$$

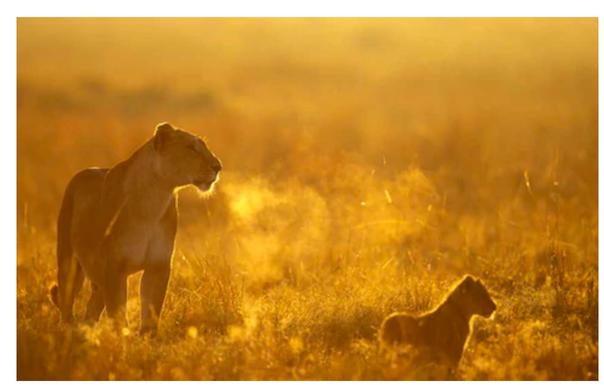
output, ***v***

Learned representation
(e.g. edges)

hidden layer, ***h***



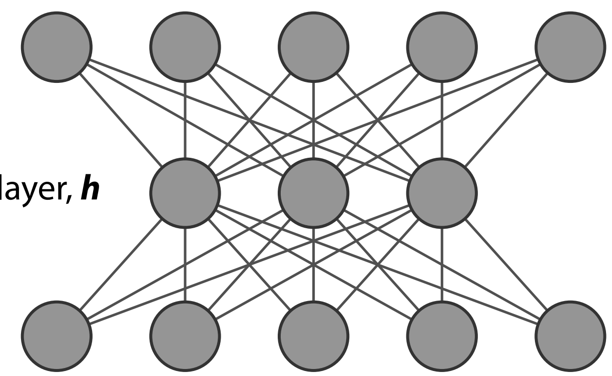
input, ***u***



Minimise cost

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

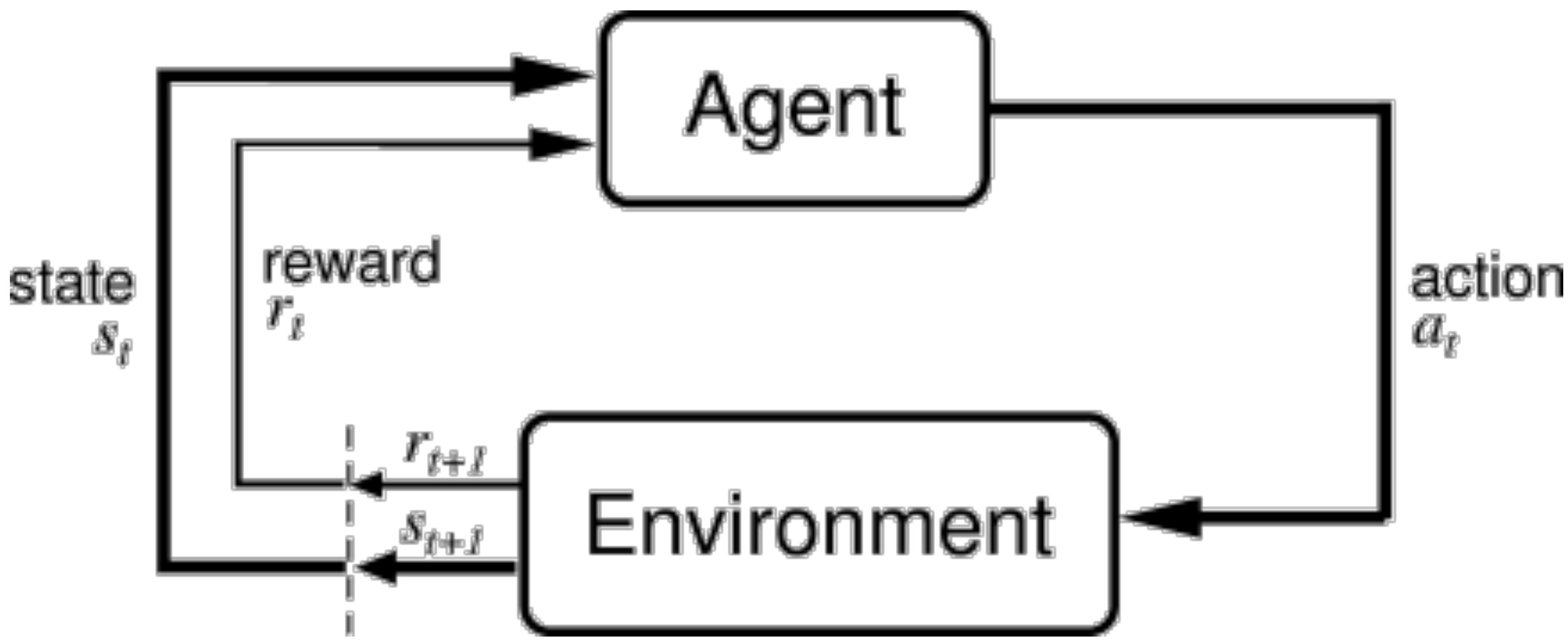
Unsupervised learning



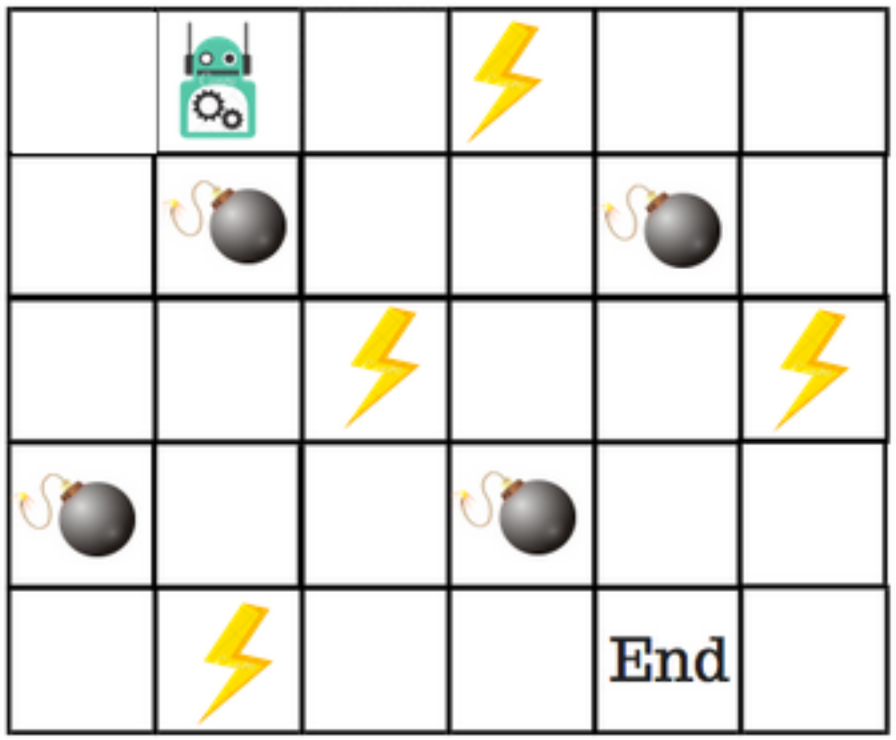
- The learning rules for **w** can be derived from the cost (or error) function for a particular network, e.g. sparse coding algorithm.
- Examples of unsupervised learning methods:
  - Sparse coding (akin to PCA)
  - Restricted Boltzmann Machines
  - Autoencoders
- Animals are bombarded with vast streams of sensory input with no supervisor

Reinforcement learning

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



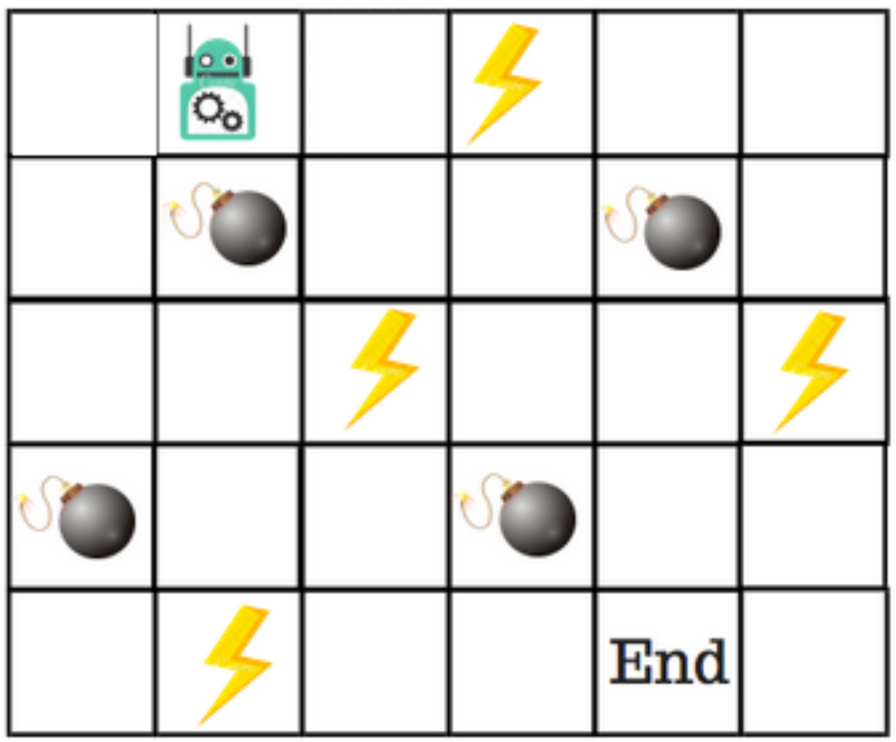
Reinforcement learning



Value table/policy

0.2	0.1	0.1	**0.9**	0.7	0.5
0.1	**0**	0.1	0.5	**0**	0.8
0.5	0.5	**1**	0.8	0.9	**1**
0	0.8	0.7	**0**	0.9	0.9
0.6	**1**	0.8	0.9	1	0.9

Reinforcement learning



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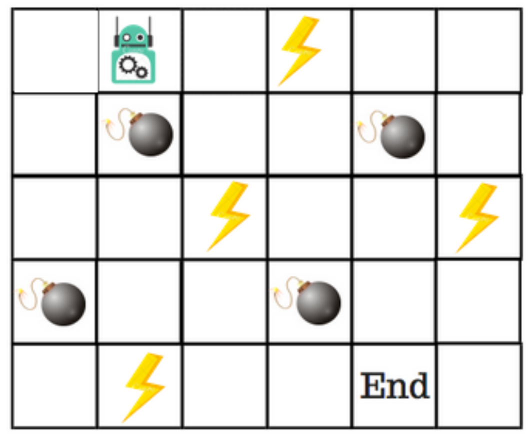
Update value table with temporal difference (TD) learning:

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

λ: discount factor

Reinforcement learning



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0	0.8	0.7	**0**	0.9	0.9
0.6	**1**	0.8	0.9	1	0.9

- 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

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

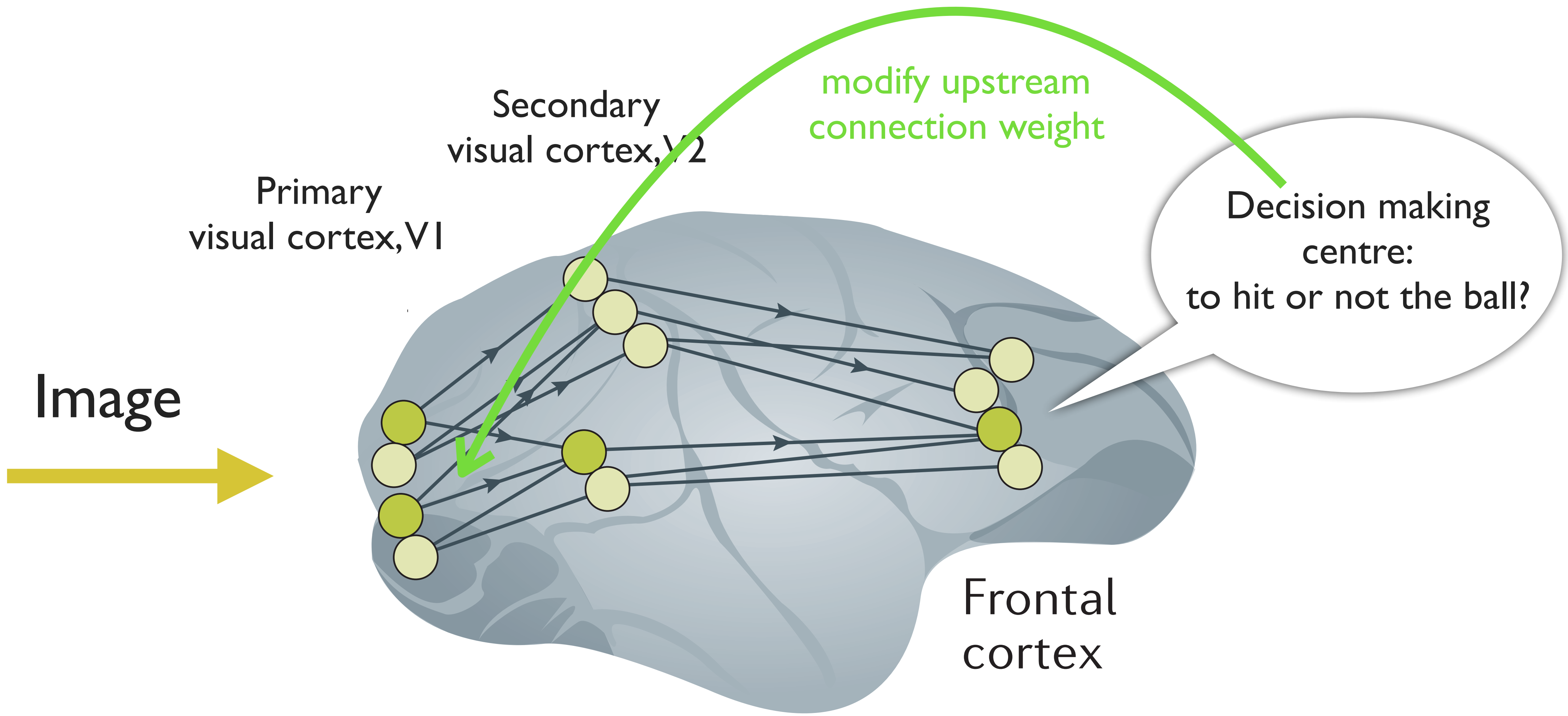
Reinforcement Learning

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

Summary

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

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!

Questions?

reddit.com/r/comsm0075/

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)

Next lecture..

- L1[4]: Neural circuits and learning: introduction
- **L2[4]: Supervised learning & backprop**
- L3[5]: Visual system: deep learning?
- L4[5]: Reinforcement learning
- L5[6]: Unsupervised learning
- L6[6]: Temporal processing
- L7[7]: Recurrent neural networks
- L8[7]: Guest lecture