BSCS 2019 - Neural Computation

VII - Topics from the intersection of AI and neuroscience

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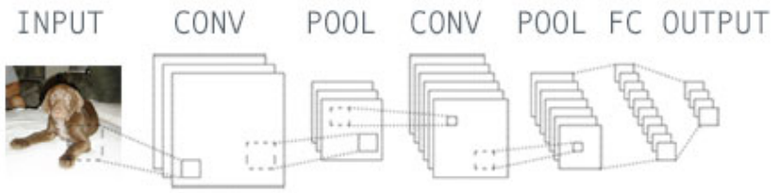
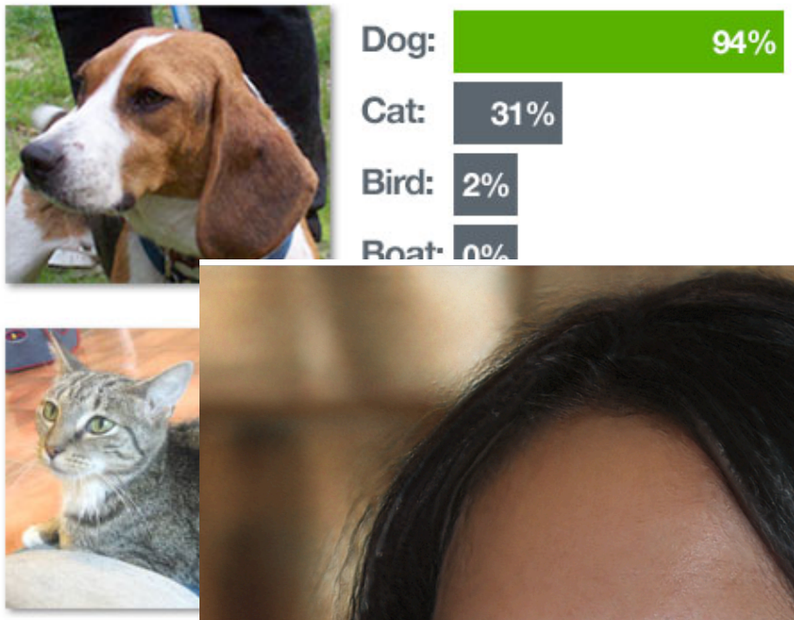
AI today


INPUT
CONV
POOL
CONV
POOL
FC
OUTPUT


Dog: 94%
Cat: 31%
Bird: 2%
Boat: 0%


thispersondoesnotexist.com


ALPHAGO
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LEE SEDOL
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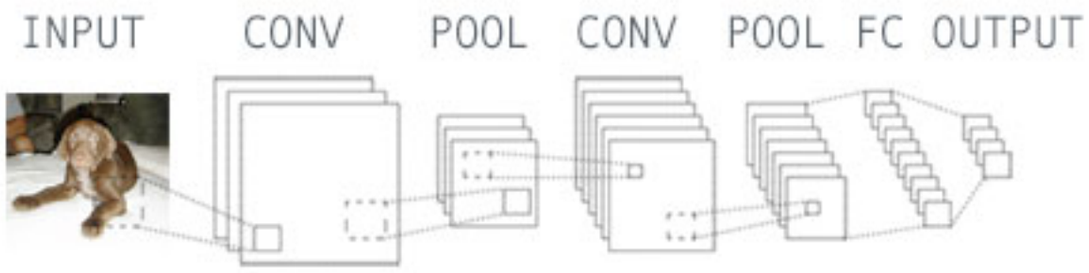
AlphaGo
Lee Sedol


Viper

AI today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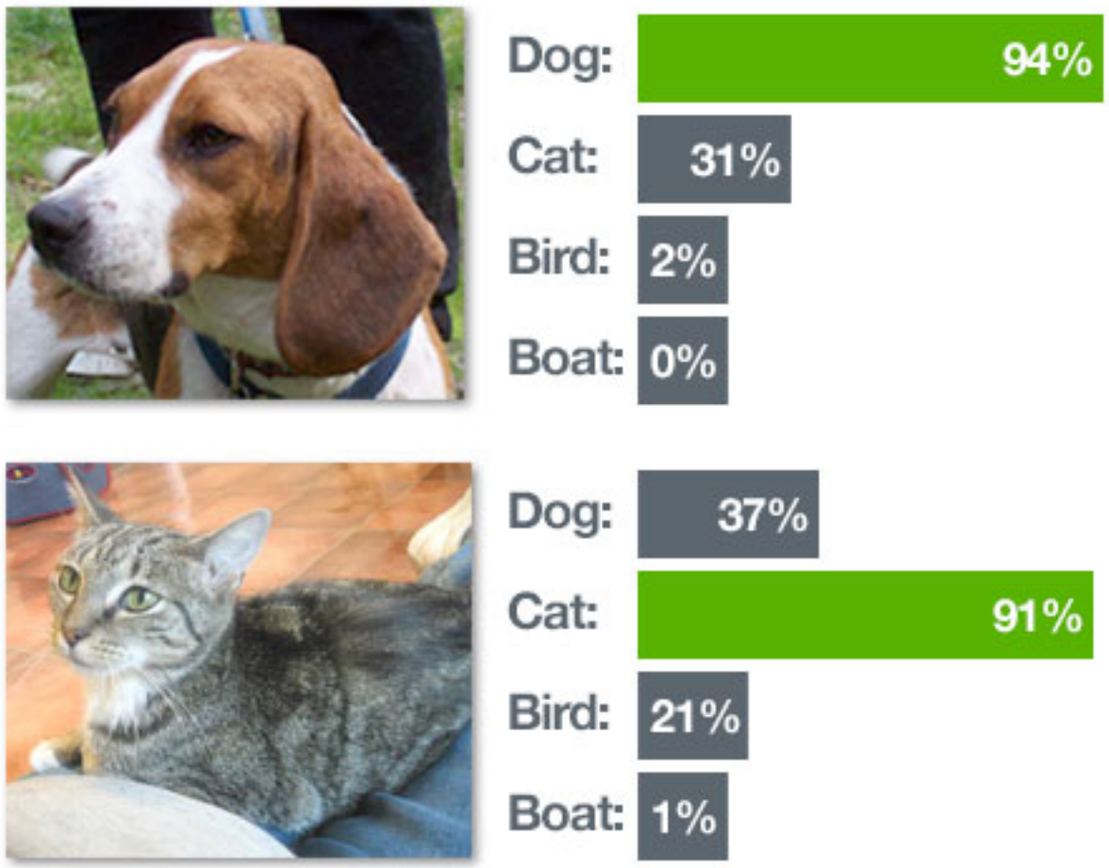
Dog: 94%
Cat: 31%
Bird: 2%
Boat: 0%
Dog: 37%
Cat: 91%
Bird: 21%
Boat: 1%


ALPHAGO
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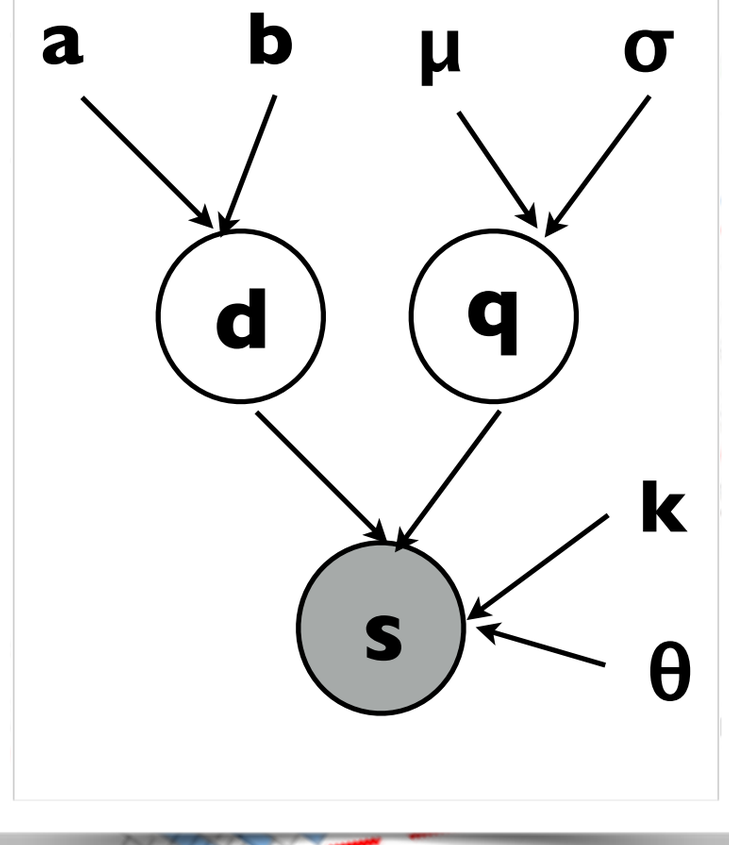
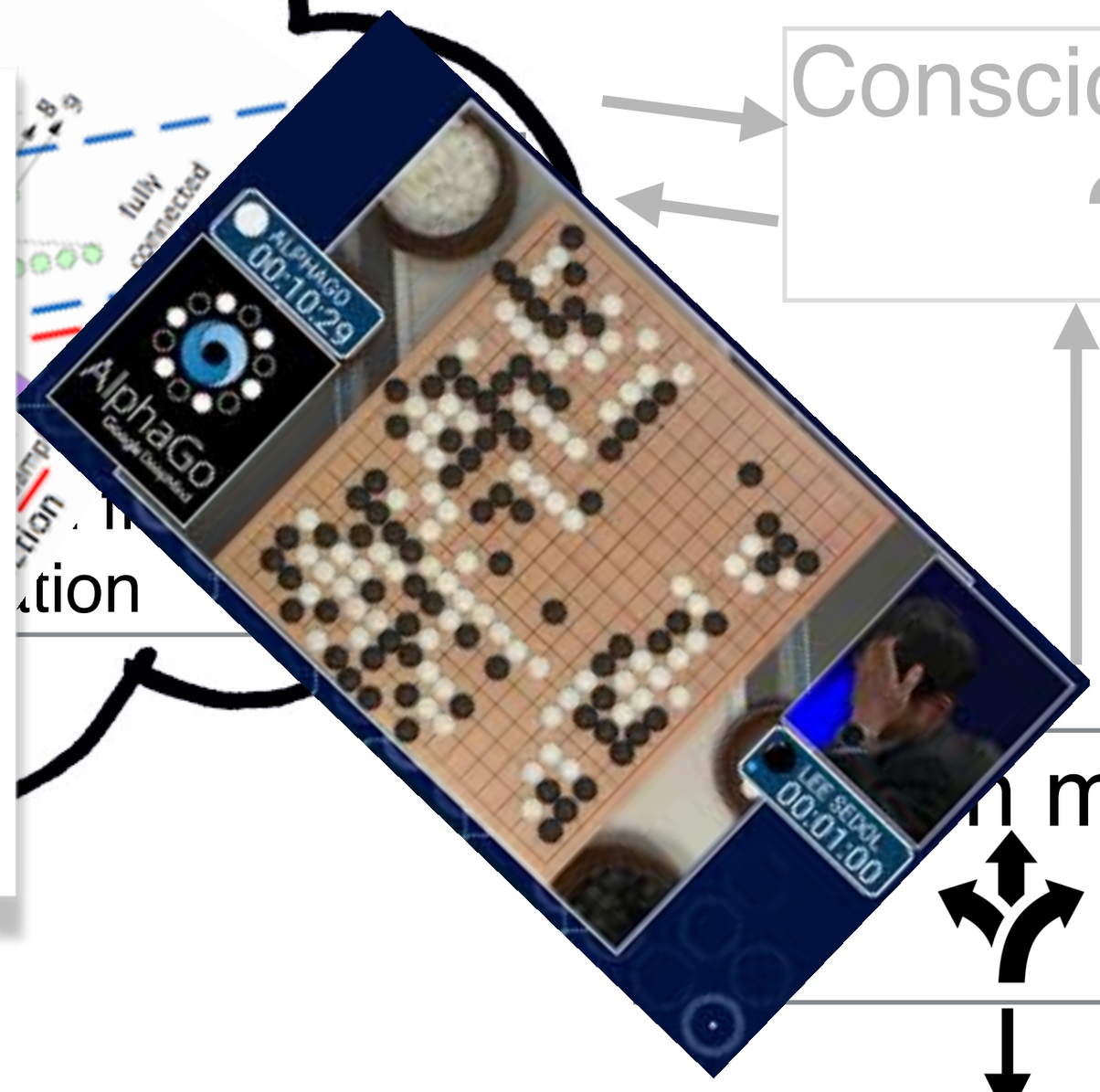
AlphaGo
Lee Sedol

Know





Consciousness

?

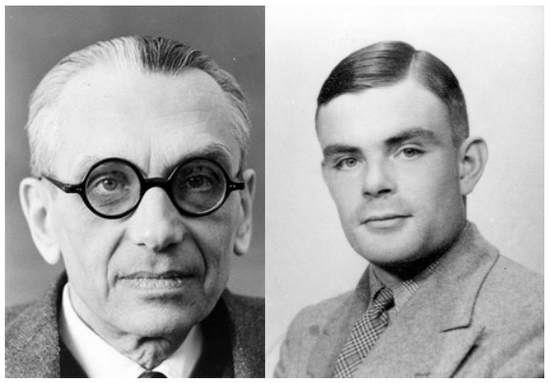
n making

Motor control

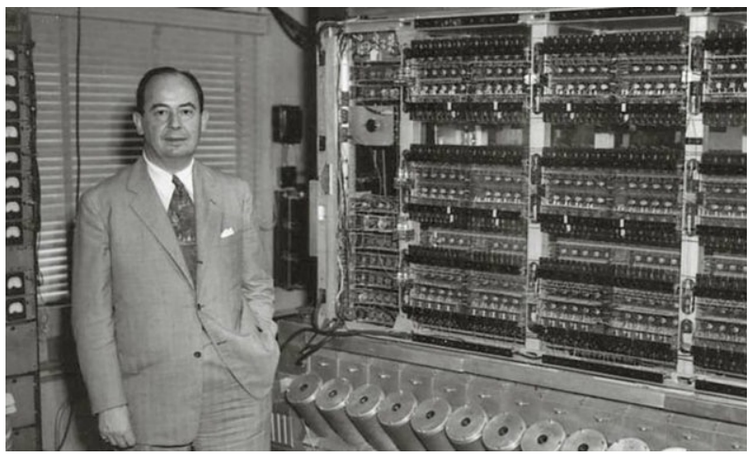
ption

The beginning of AI

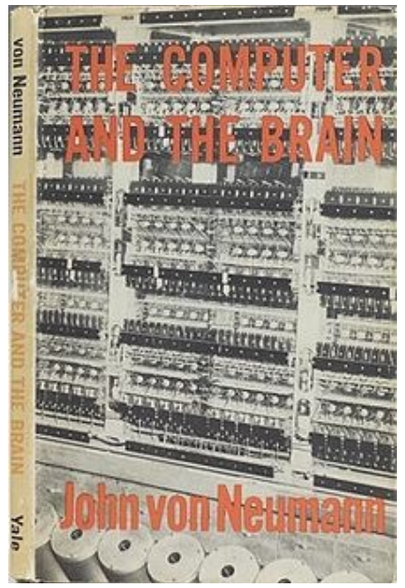
results in logic

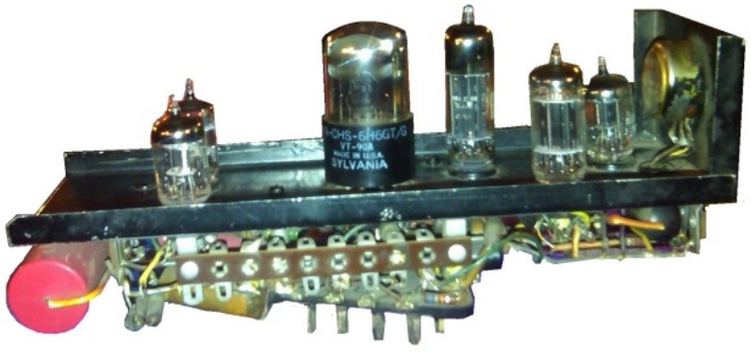


digital computer



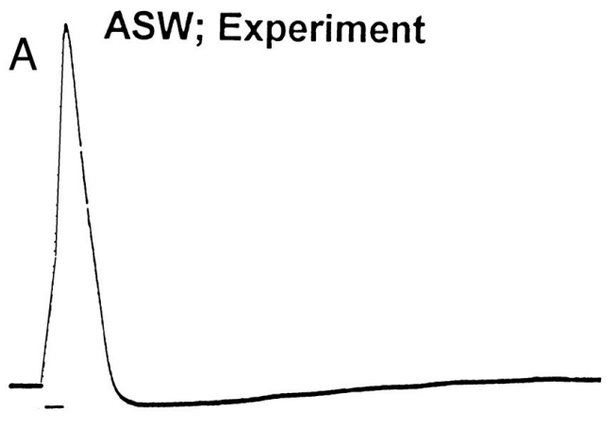
cybernetics



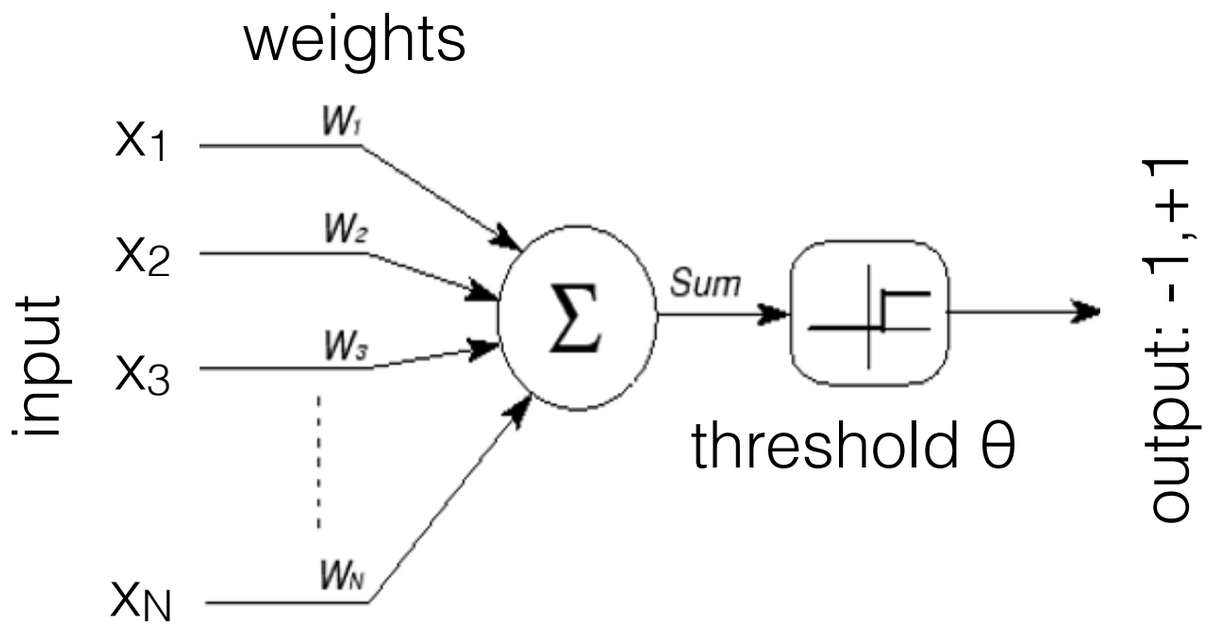


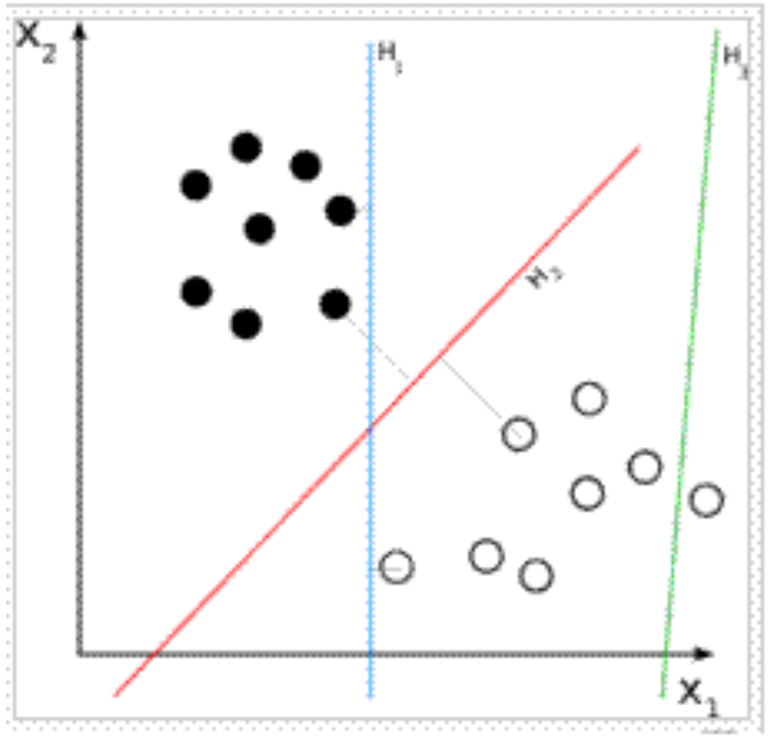
artificial neuron

neural recordings



Artificial neuron

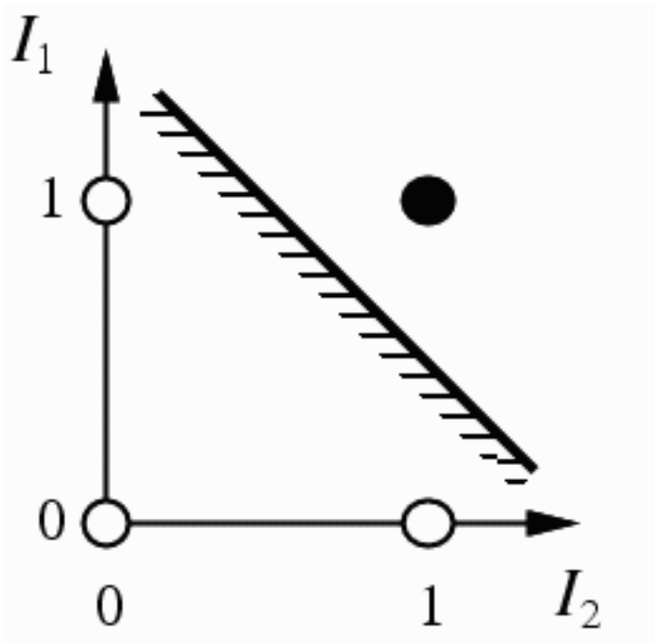




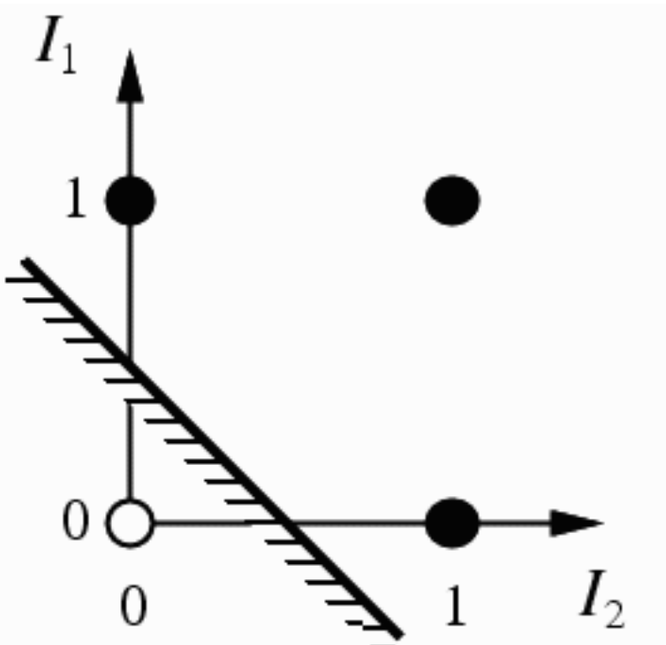
- we compare the weighted sum of inputs to a threshold
- two possible output values - a binary classification of input combinations
- linear separation

$$\theta = x_1 w_1 + x_2 w_2 \longrightarrow x_2 = \frac{-w_1}{w_2} x_1 + \frac{\theta}{w_2}$$

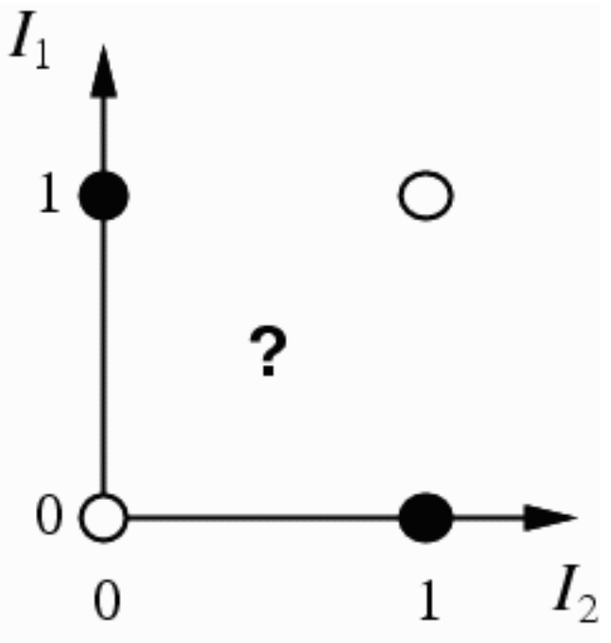
Logical operations by artificial neurons



(a) I_1 **and** I_2

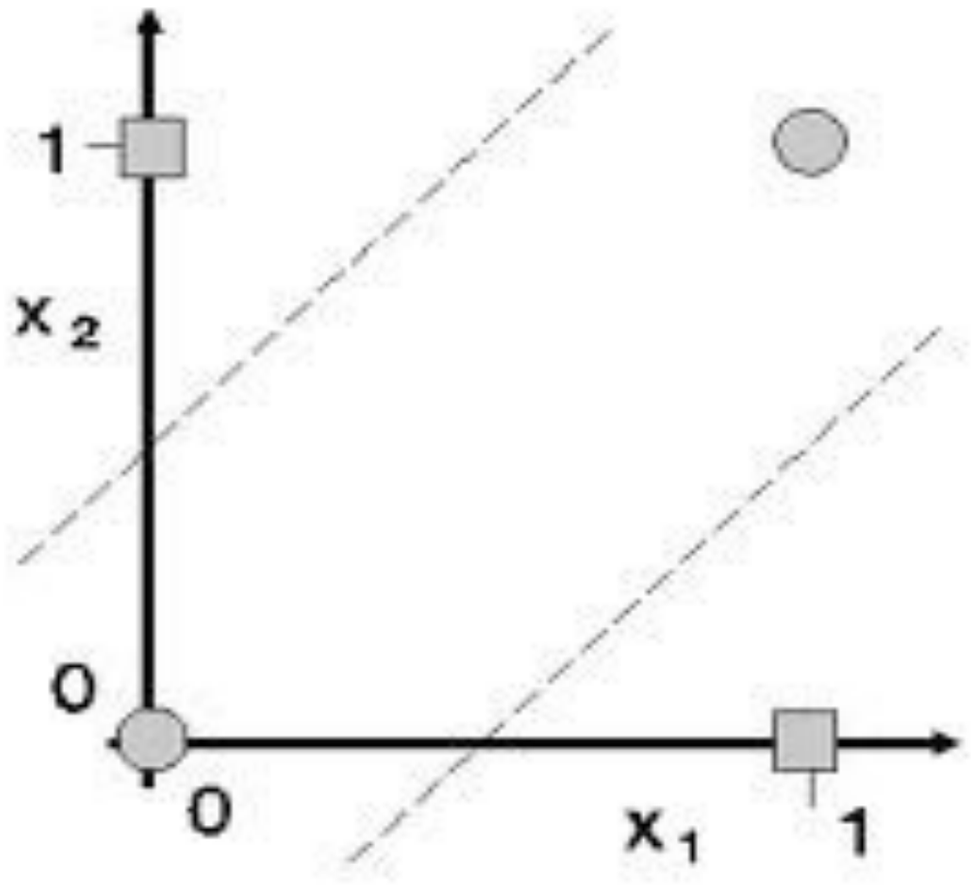


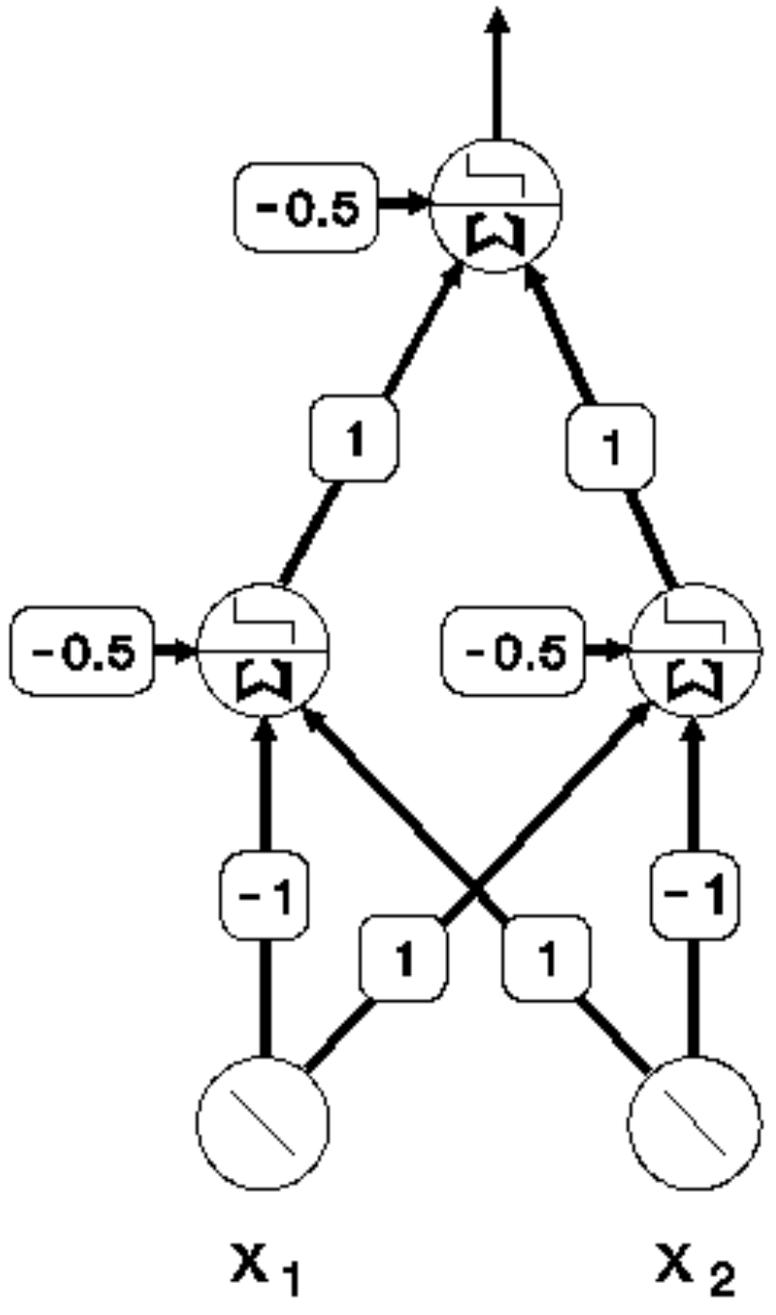
(b) I_1 **or** I_2



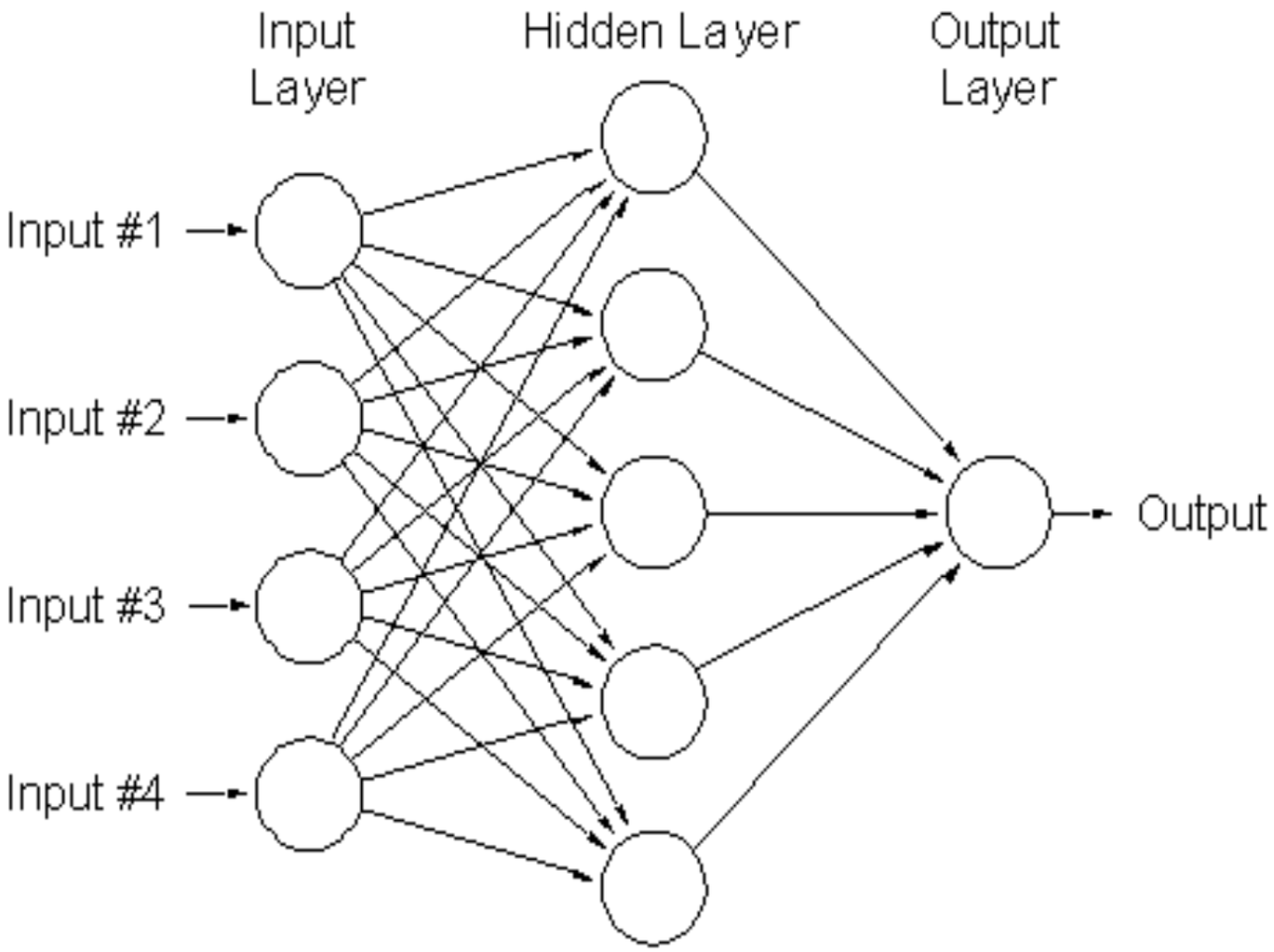
(c) I_1 **xor** I_2

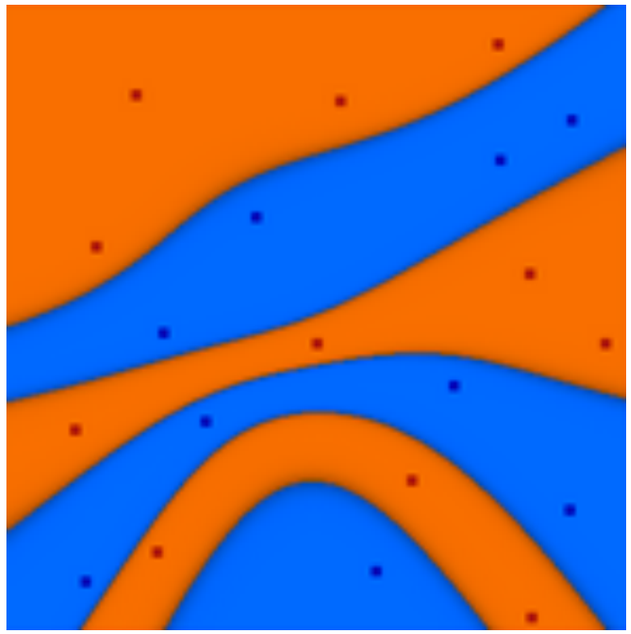
Solution of the XOR problem



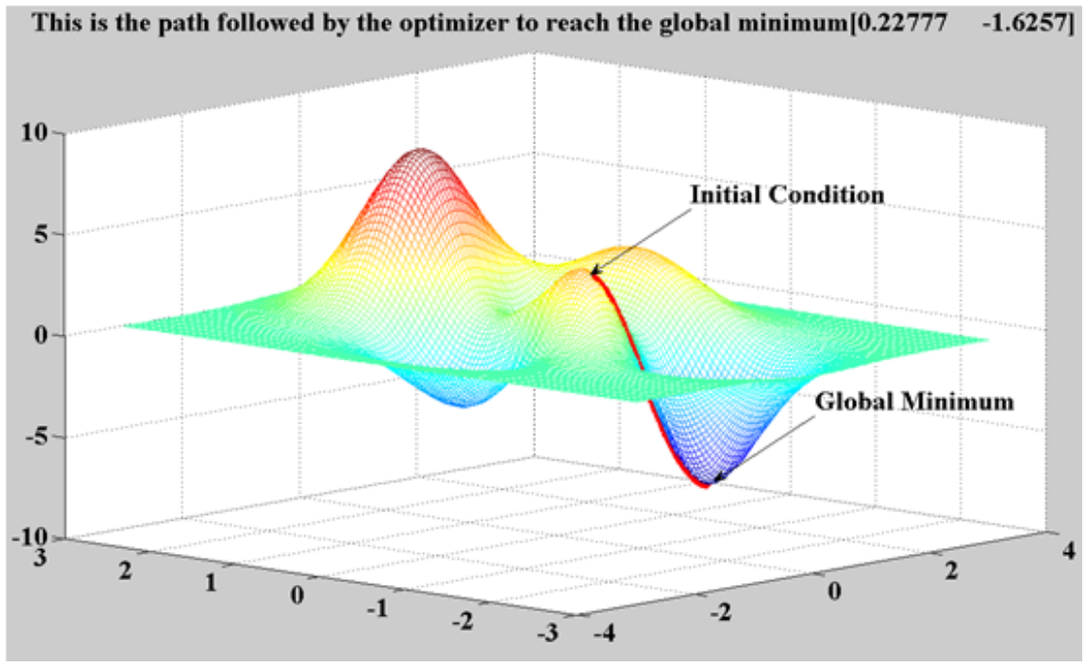


Multi-layer neural network





Gradient descent



- General scheme for parameter optimization
- At each point, we calculate the derivative of the error function with respect to the weights
- We move the weights towards the negative of the gradient
- Finds a local minimum

$$w_b = w_b - \epsilon \frac{\partial E}{\partial w_b}$$

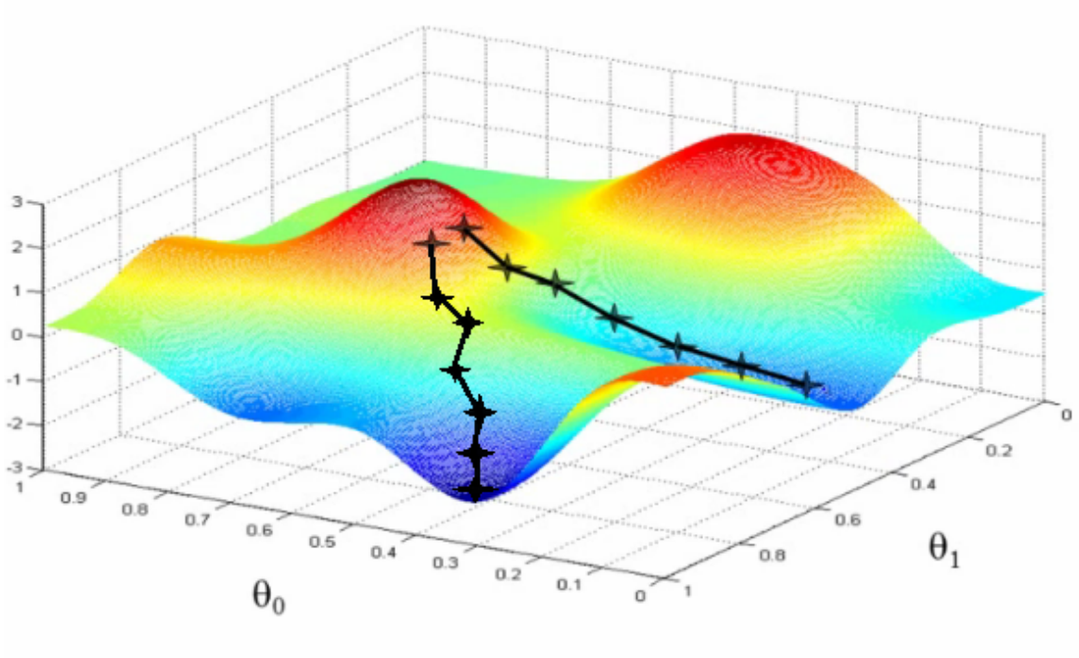
Looking for the best weight values

- given a specific dataset and a set of values for the synaptic weights, the network will misclassify a number of data samples

- we are looking for the weight values that minimize this error

- setting the many weights parallelly is a hard optimization problem

- the back propagation algorithm is a gradient search that finds an approximate optimum



Deep networks

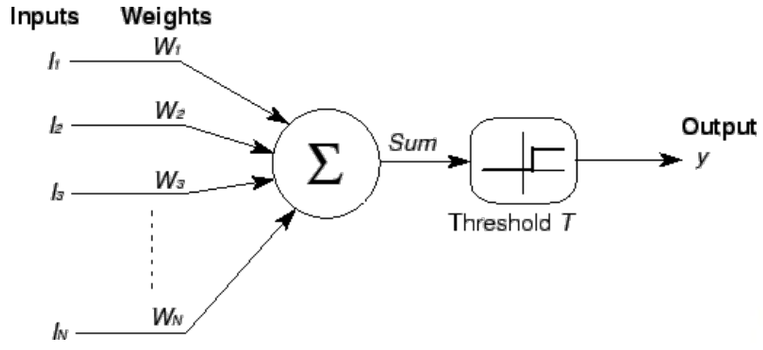
- Deep learning is a highly successful machine learning framework which is employed in a variety of computer tasks, including object recognition

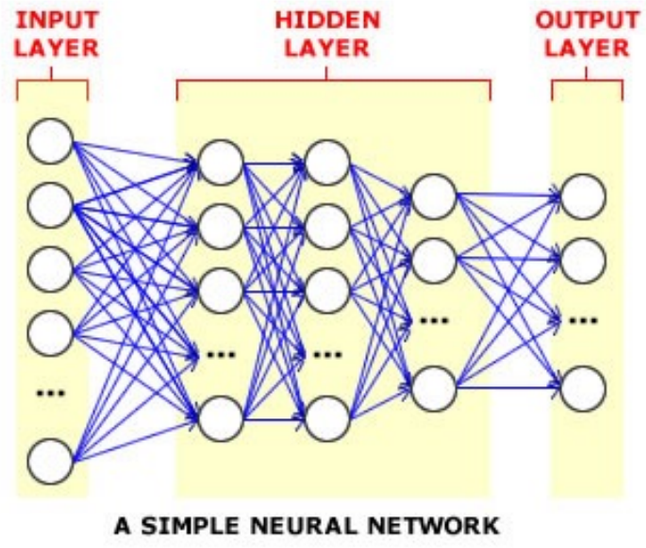
- It employs a computational architecture in which the basic element is a simplified model neuron

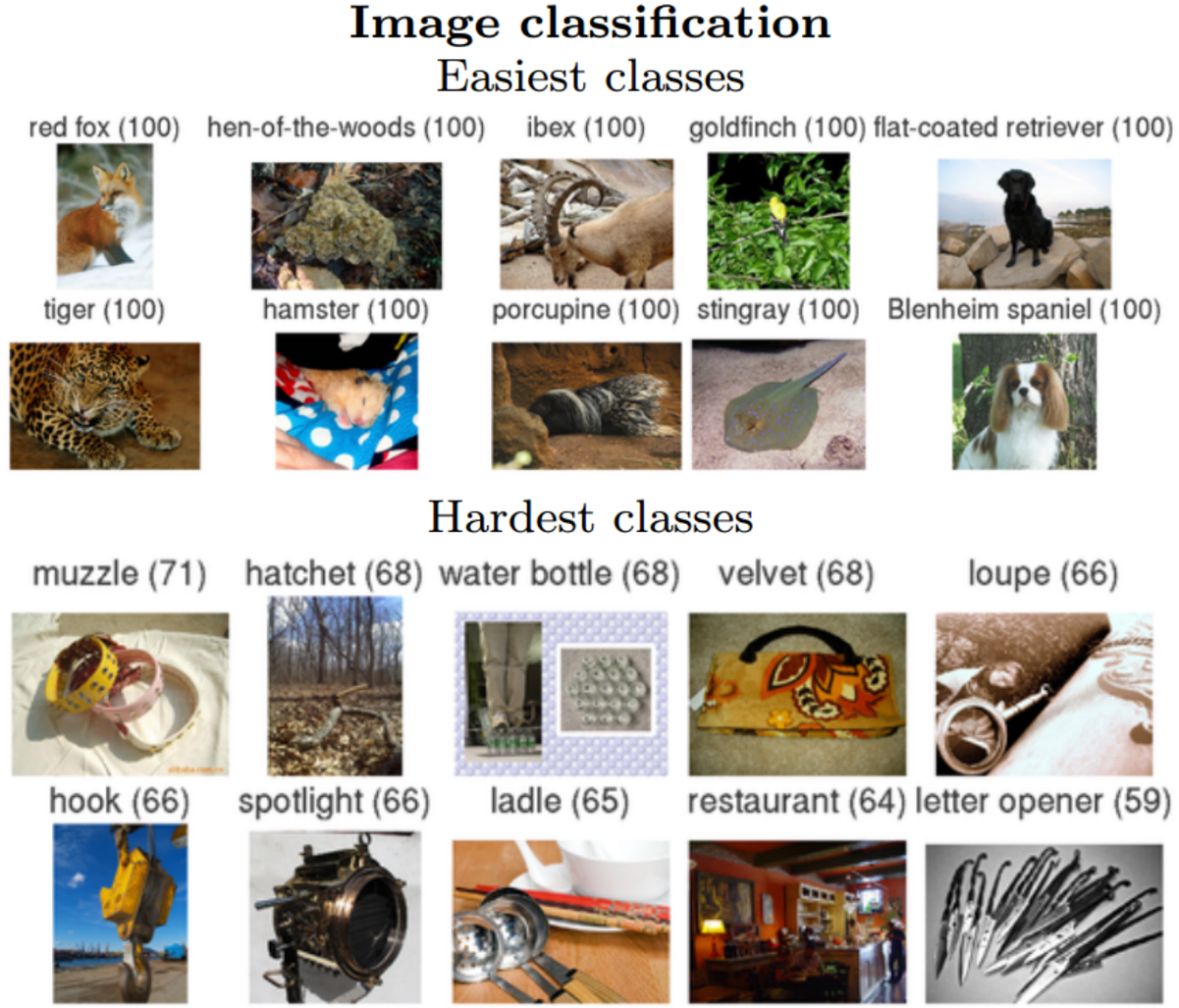
- the basic elements are organised into layers, connected by weights

- each layer performs a transformation of an input image

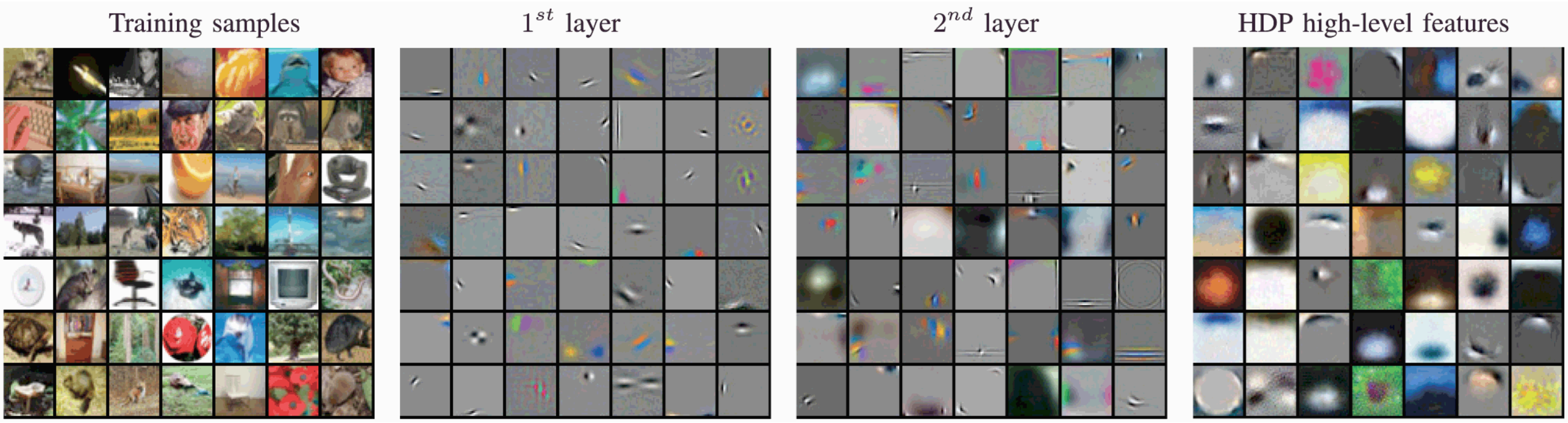
- network weights are tuned to perform classification of the inputs into categories - each category is an object

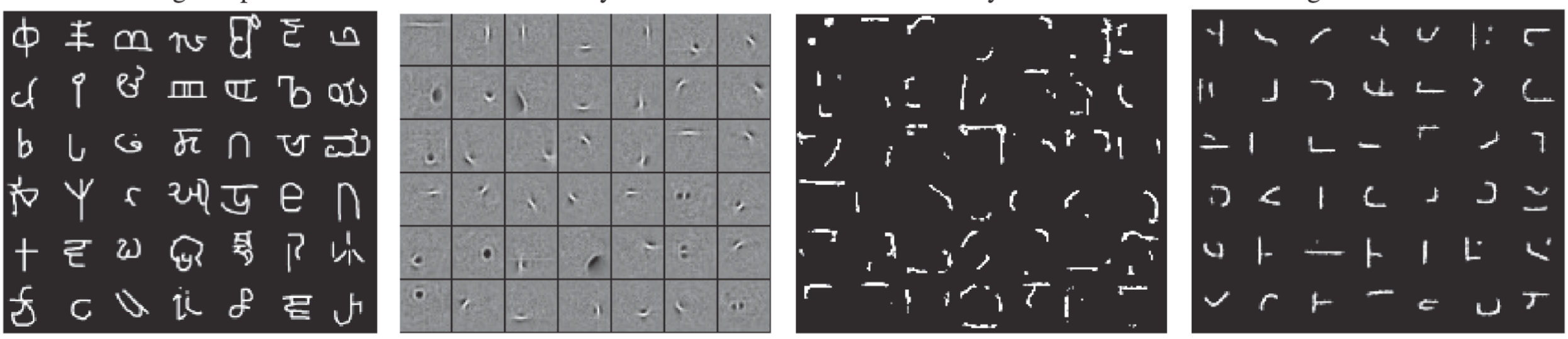




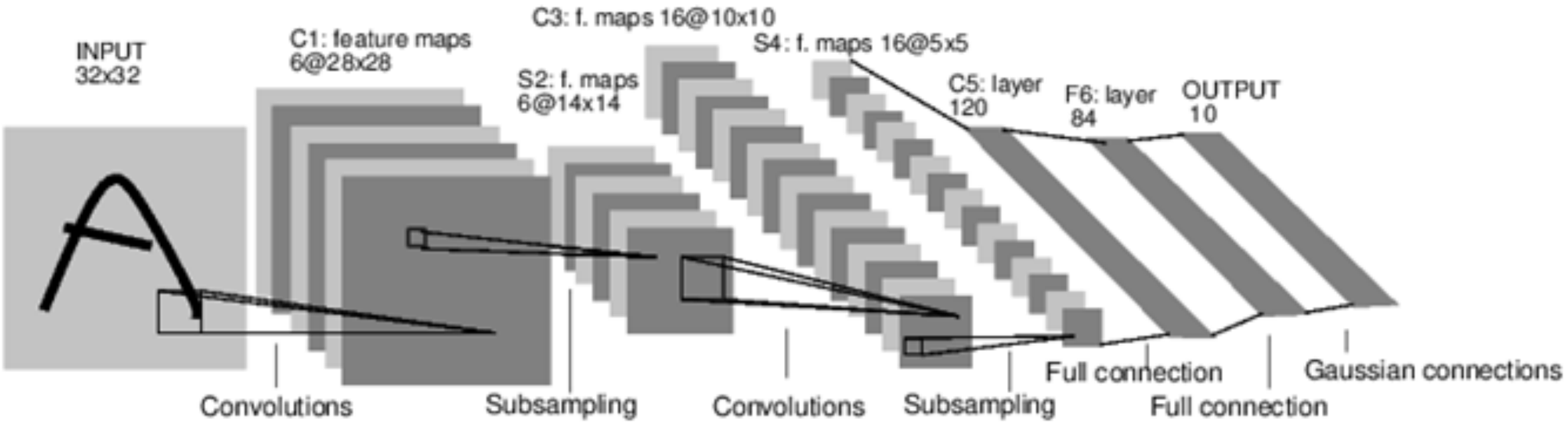


Visual features acquired by deep learning





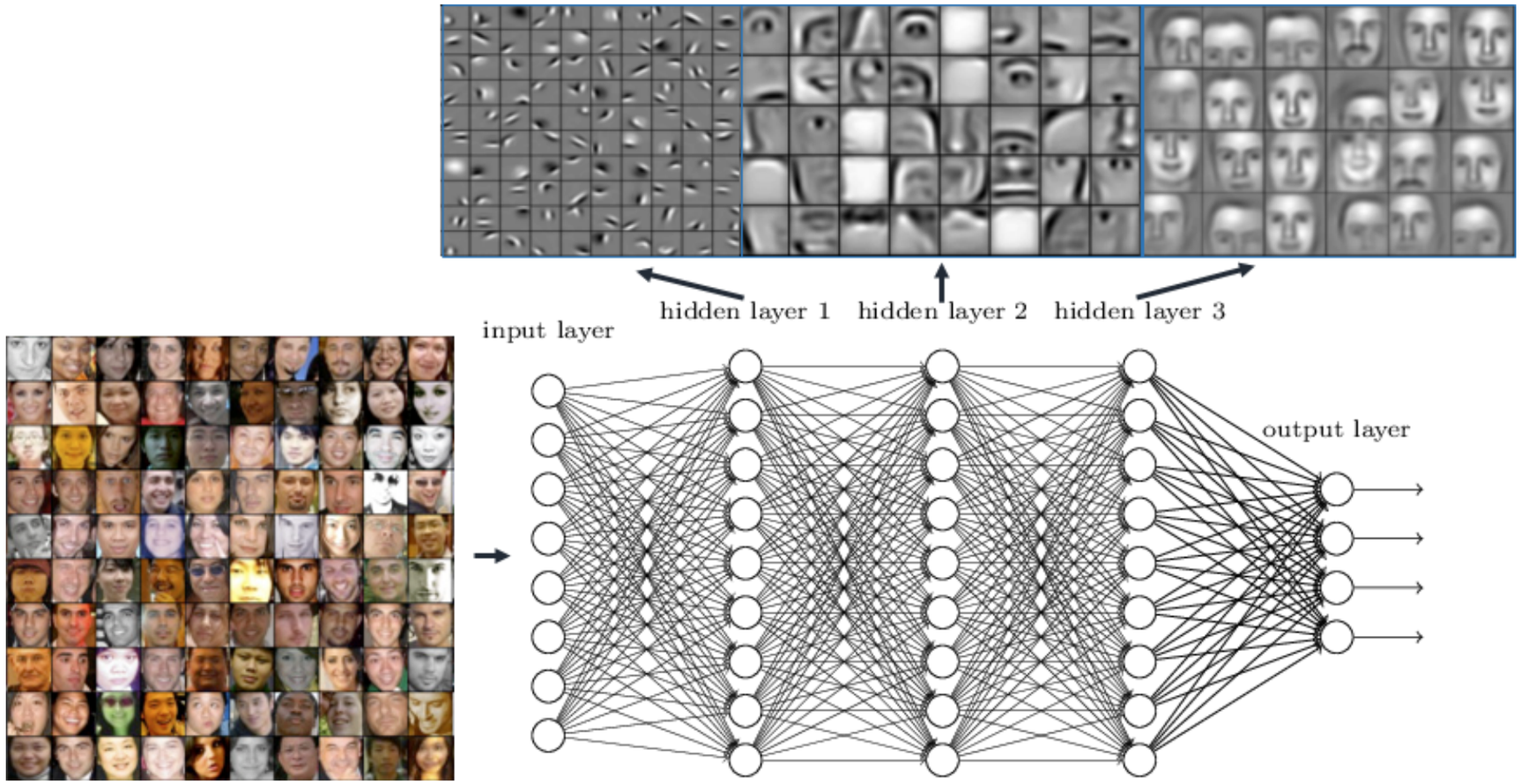
Convolutional networks

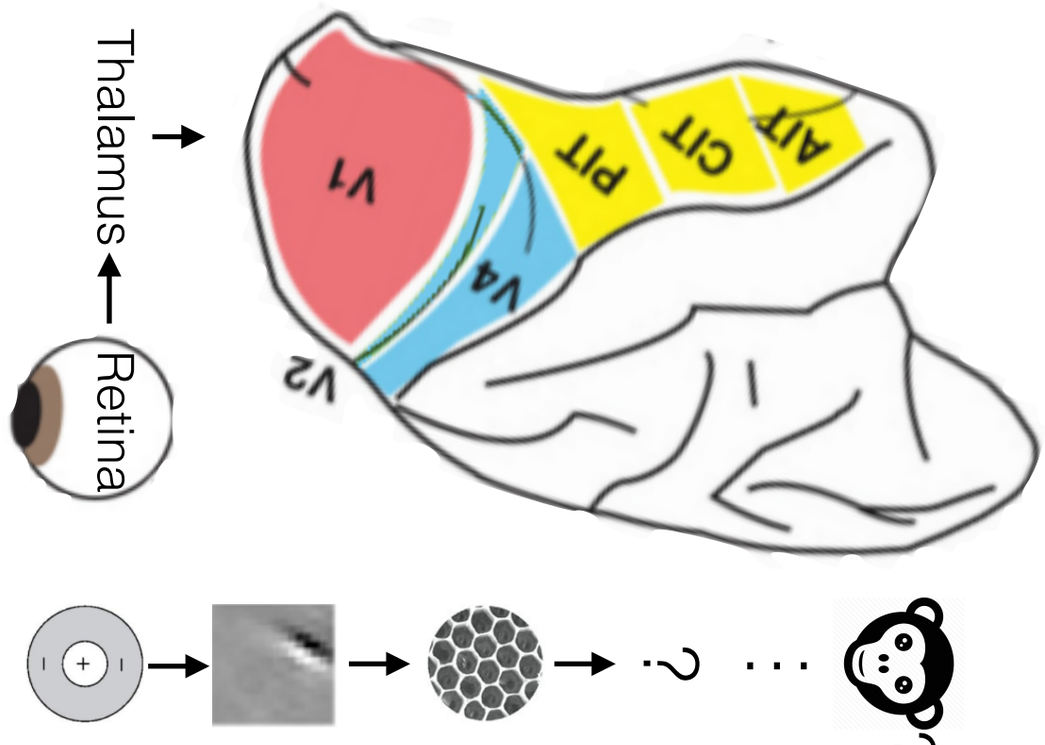


A Full Convolutional Neural Network (LeNet)

- Step1: a set of translation-invariant feature extractions
- Step 2: Subsampling the result to a lower-dimensional space
- repeat

Similarities to the visual cortex





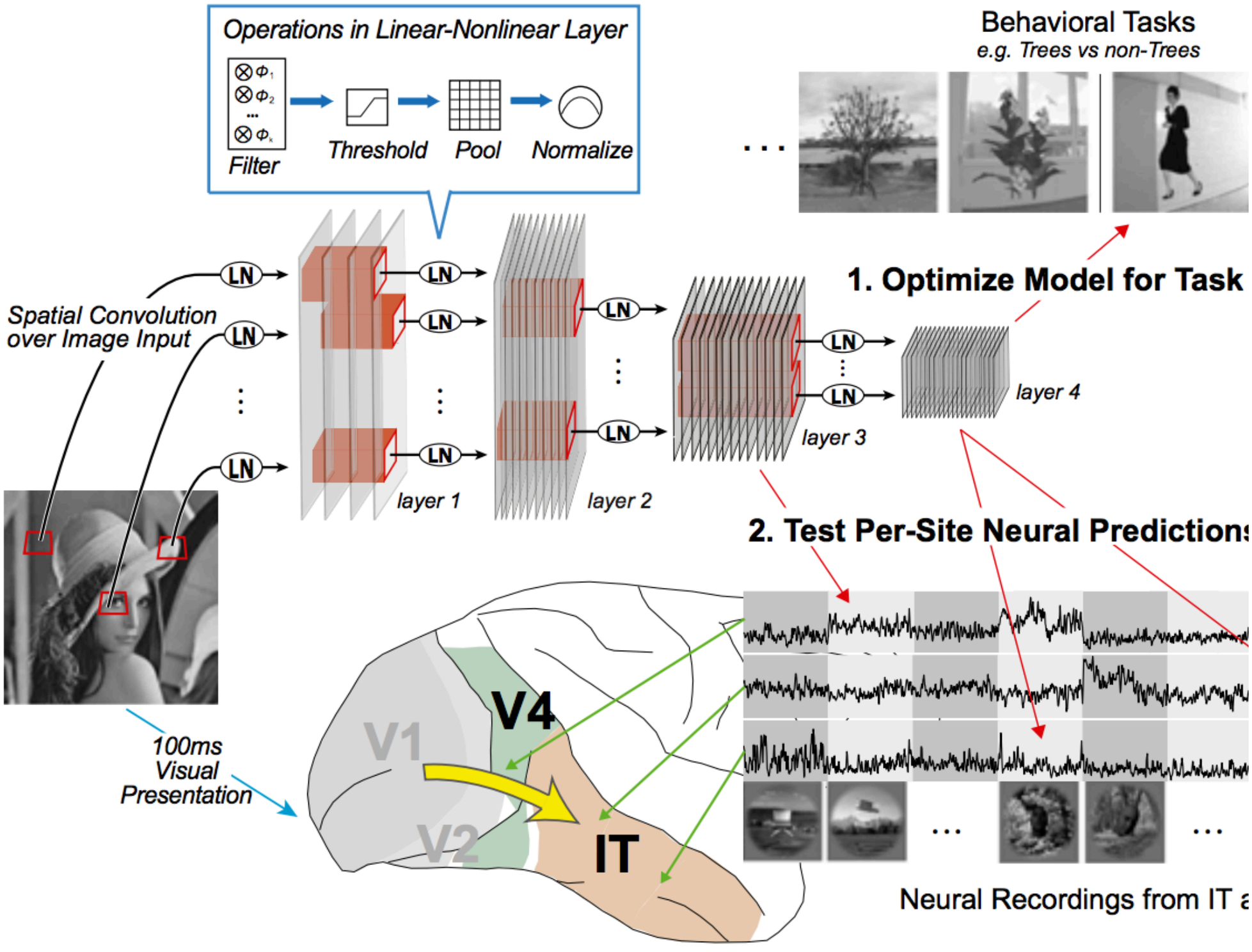
Human against machine

method	top-1 err.	top-5 err.
VGG [40] (ILSVRC'14)	-	8.43†
GoogLeNet [43] (ILSVRC'14)	-	7.89
VGG [40] (v5)	24.4	7.1
PReLU-net [12]	21.59	5.71
BN-inception [16]	21.99	5.81
ResNet-34 B	21.84	5.71
ResNet-34 C	21.53	5.60
ResNet-50	20.74	5.25
ResNet-101	19.87	4.60
ResNet-152	**19.38**	**4.49**

5.1

Andrej "the human benchmark" Karpathy

Prediction of neural activity with deep networks



Yamins et al 2014 **for V1: Cadena et al 2019**

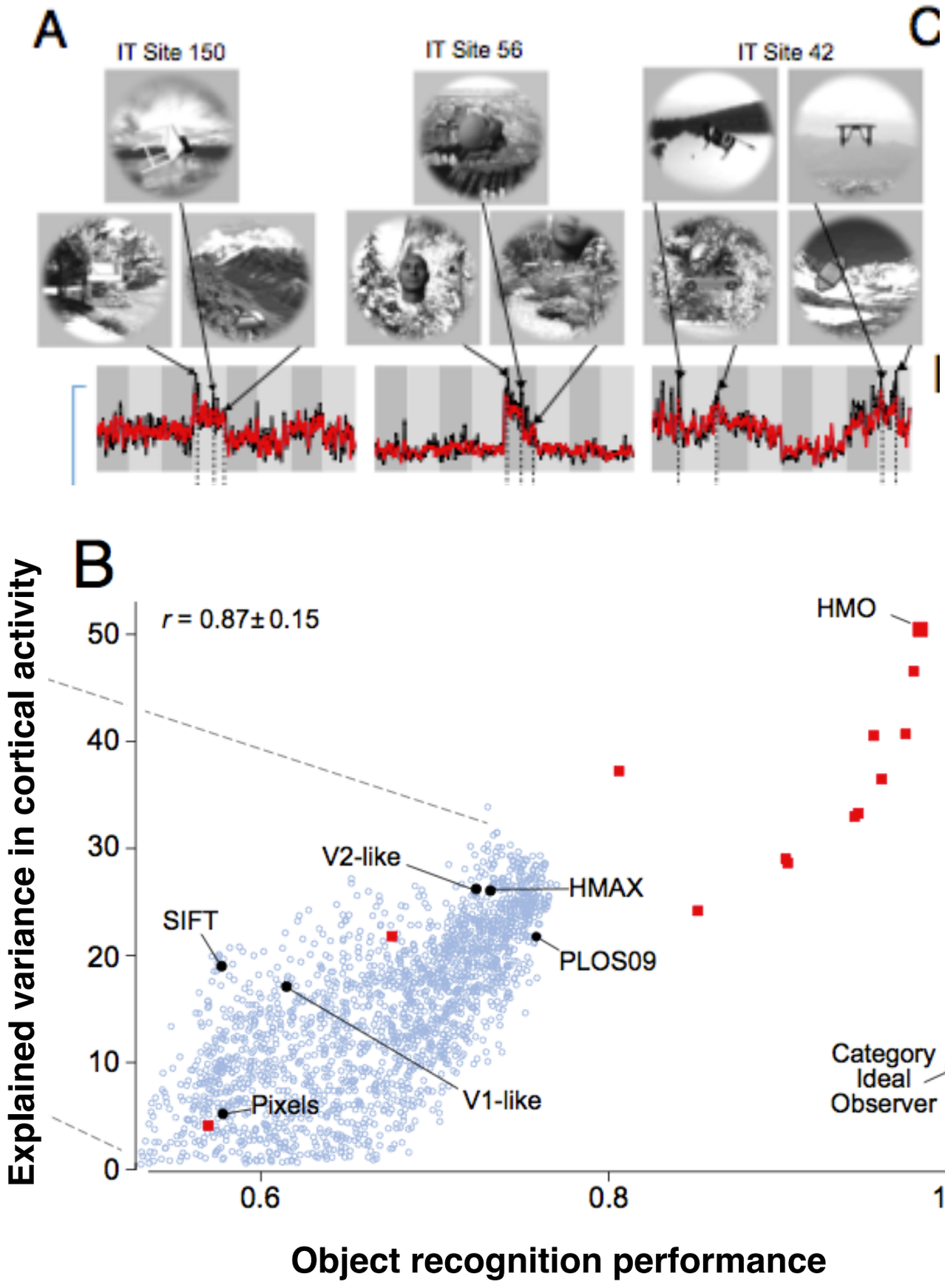
Deep convolutional networks' predictions of neural activity

- The inferotemporal cortex (IT) is thought to be involved in object recognition

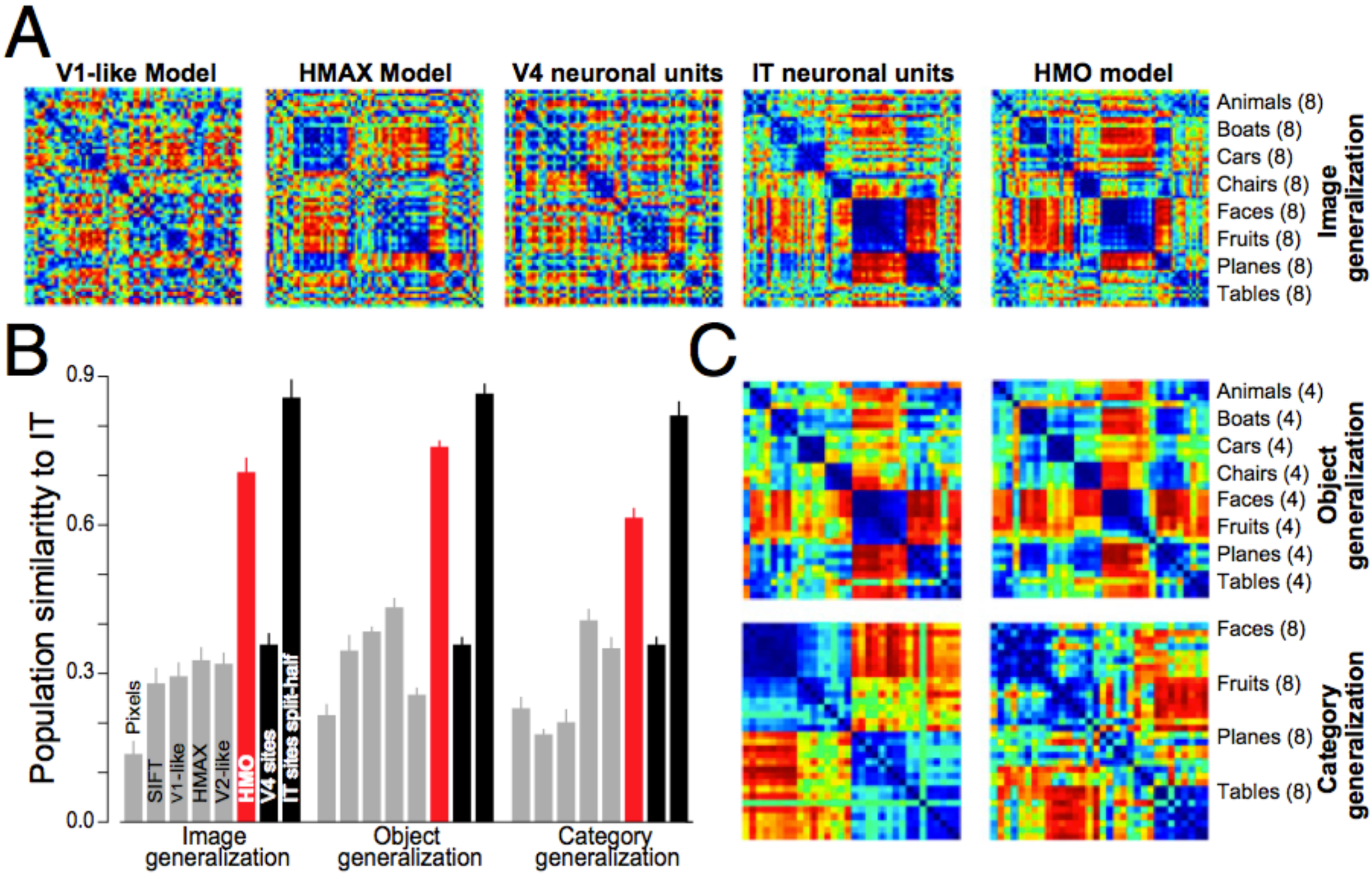
- A deep network is trained to recognise objects from images

- The top layer of the network is compared to measured activity in IT

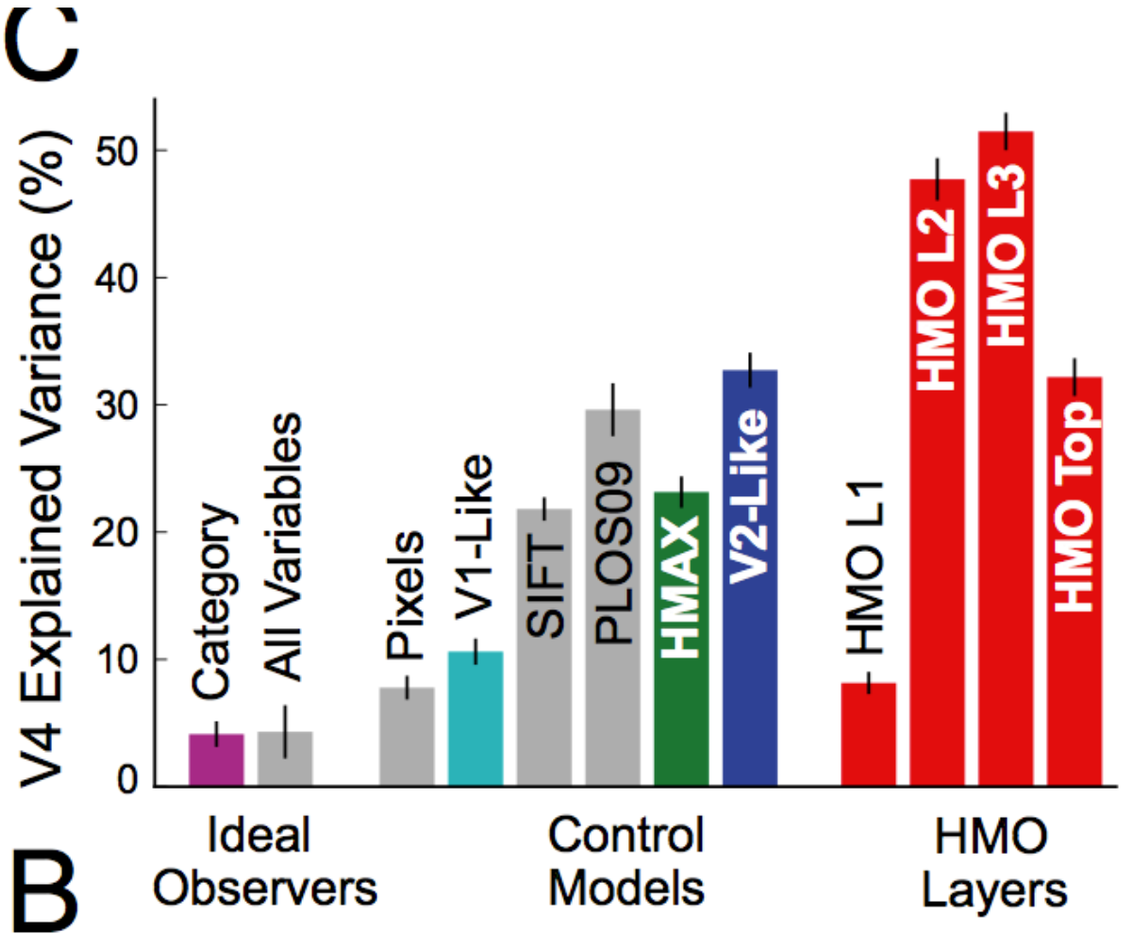
Yamins et al, 2014

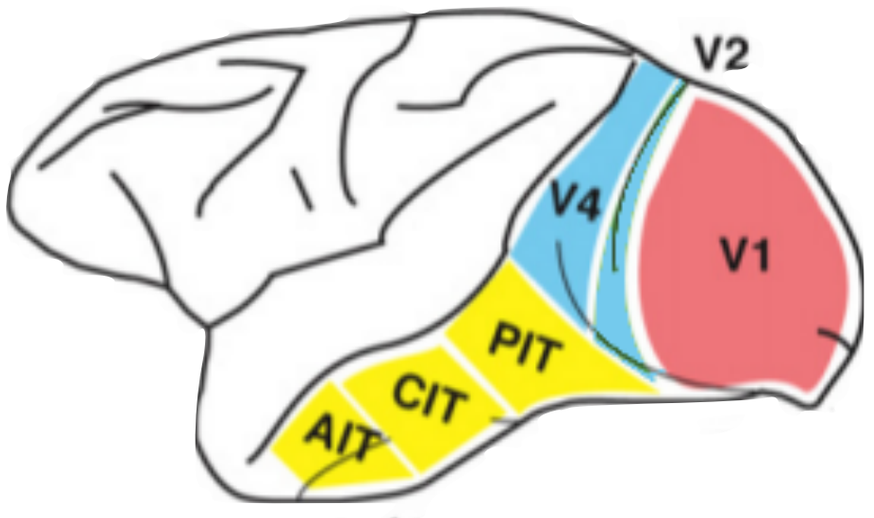


Population-level representational similarity



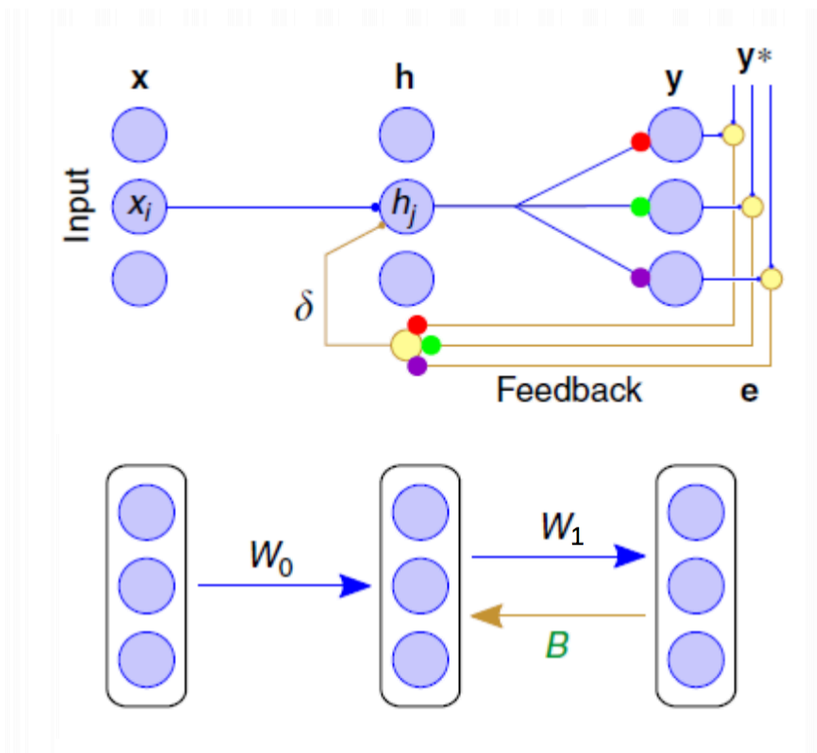
Predicting V4 activity

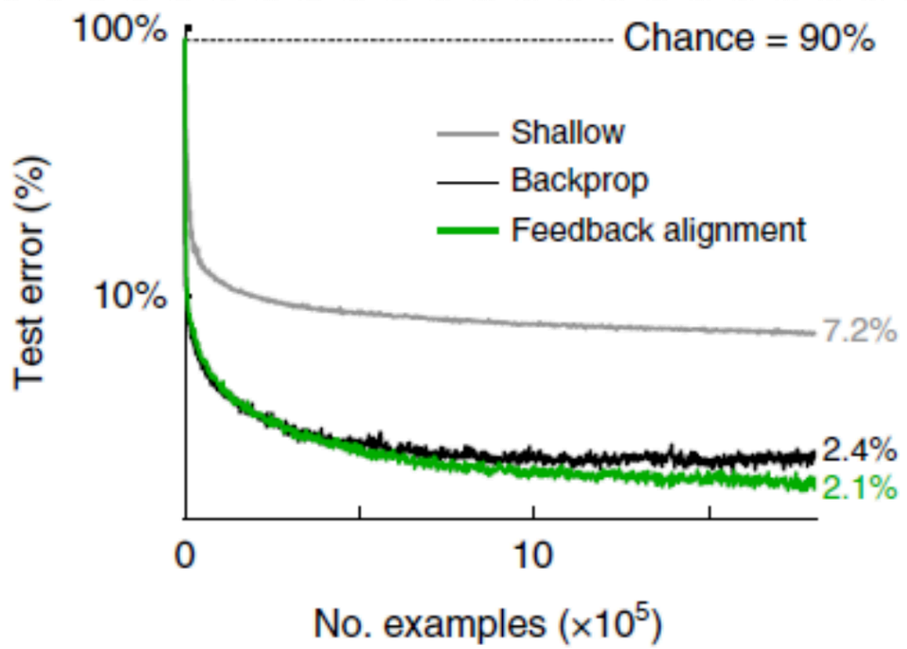




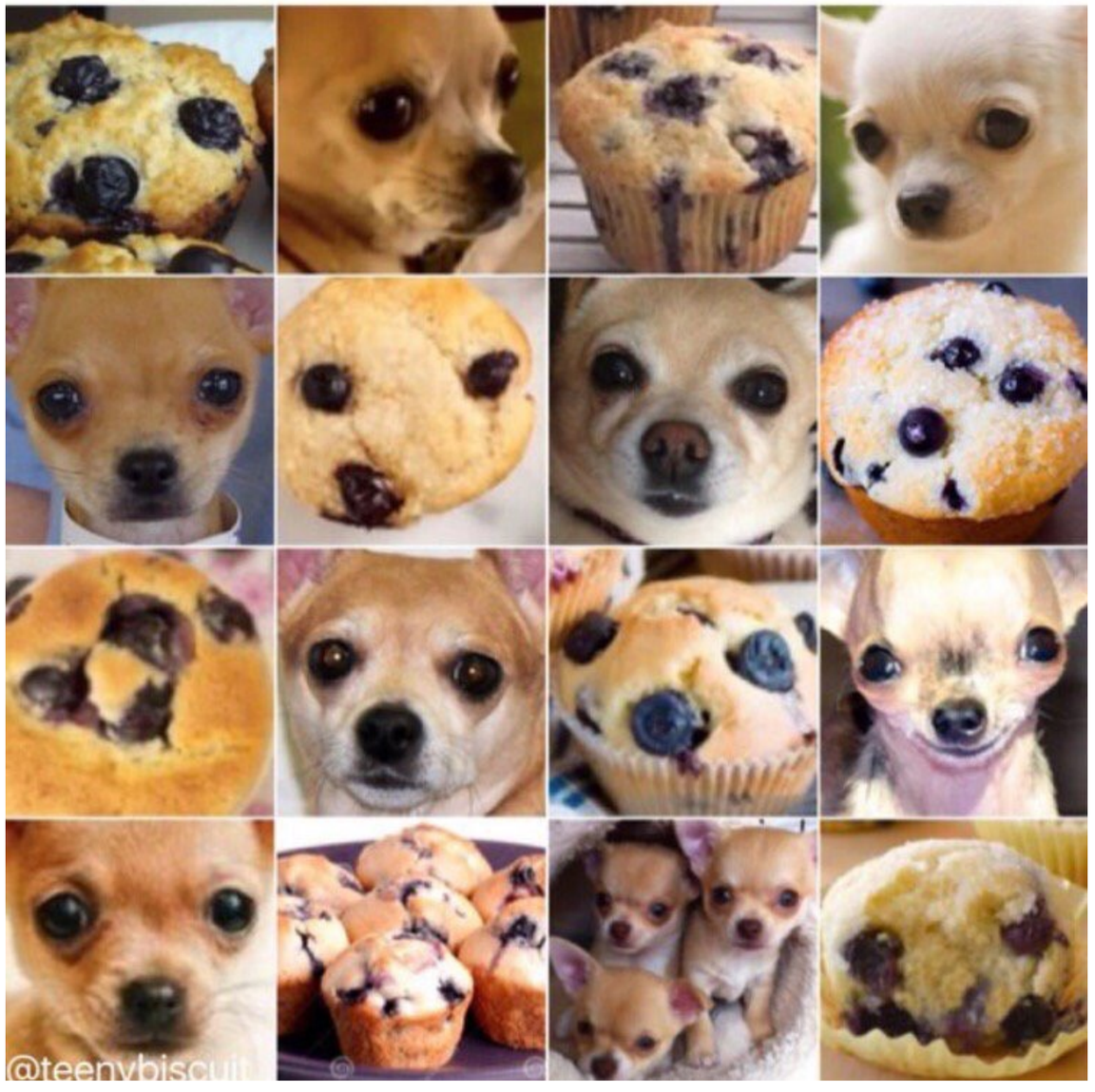
Biologically realistic error backpropagation?

- BP has multiple elements that are questionable from a biological point of view
  - explicit computation of the error term
  - feed-forward and feed-back weights are tied together
  - derivative of the activation function
  - …
- All major issues have solution by now

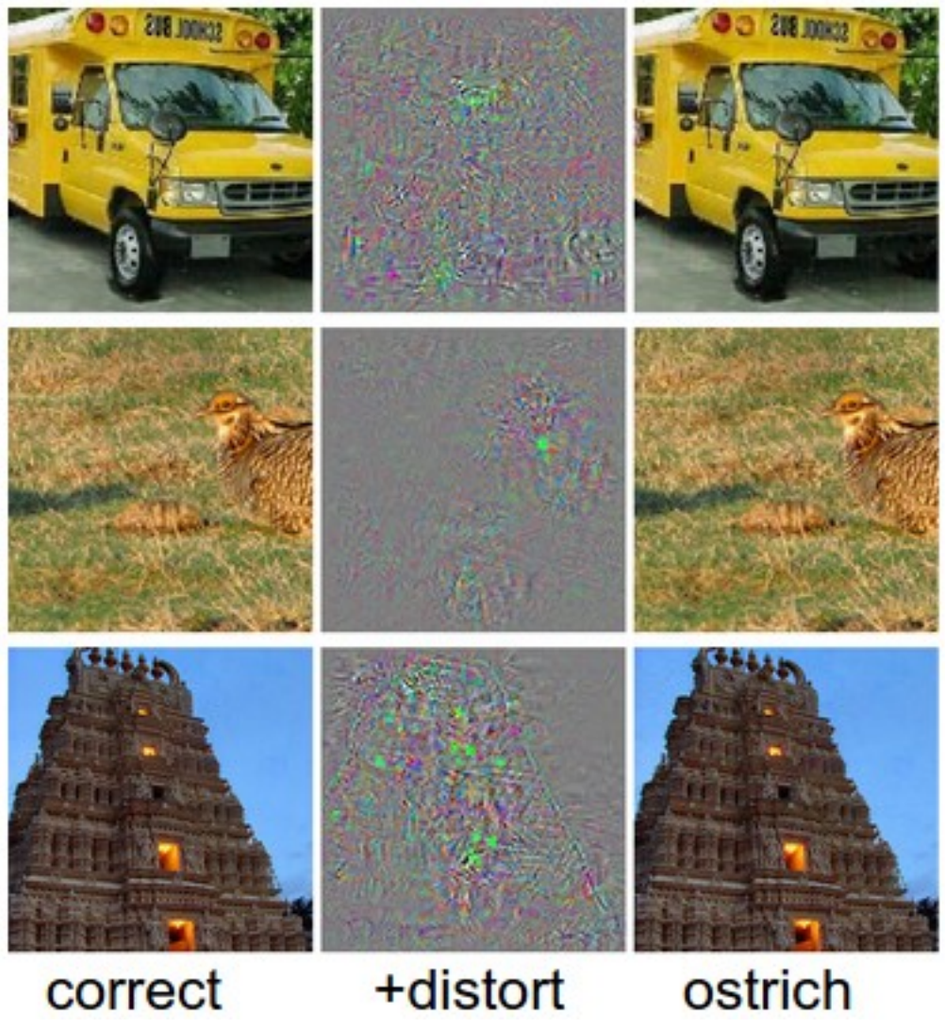




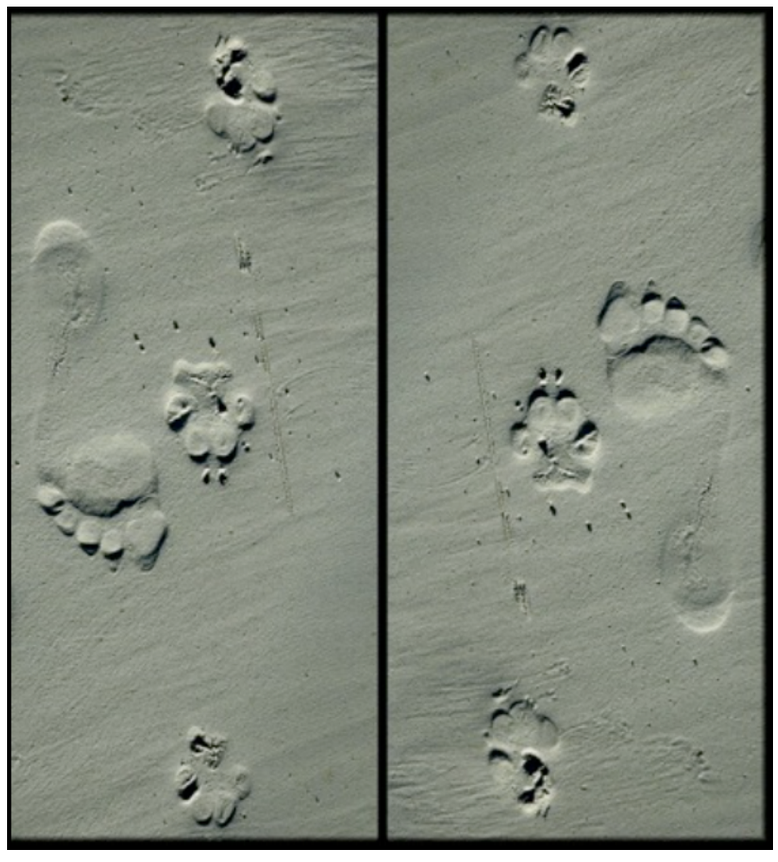
Problems with deep network models



Problems with deep network models



vs.



Problems with deep network models

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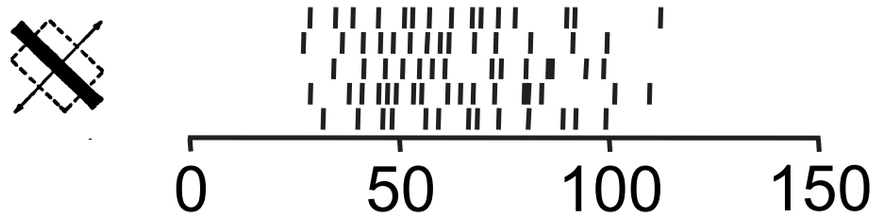
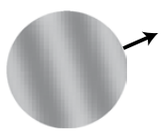
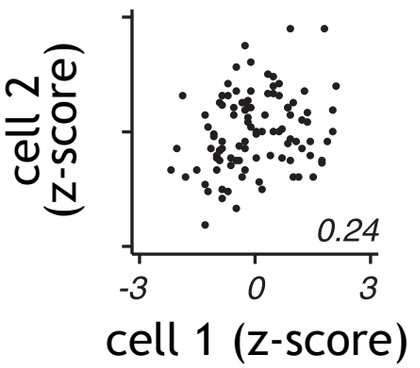


Gur & Snodderly, Cereb Cortex 2006





Kohn & Smith, J Neurosci 2005

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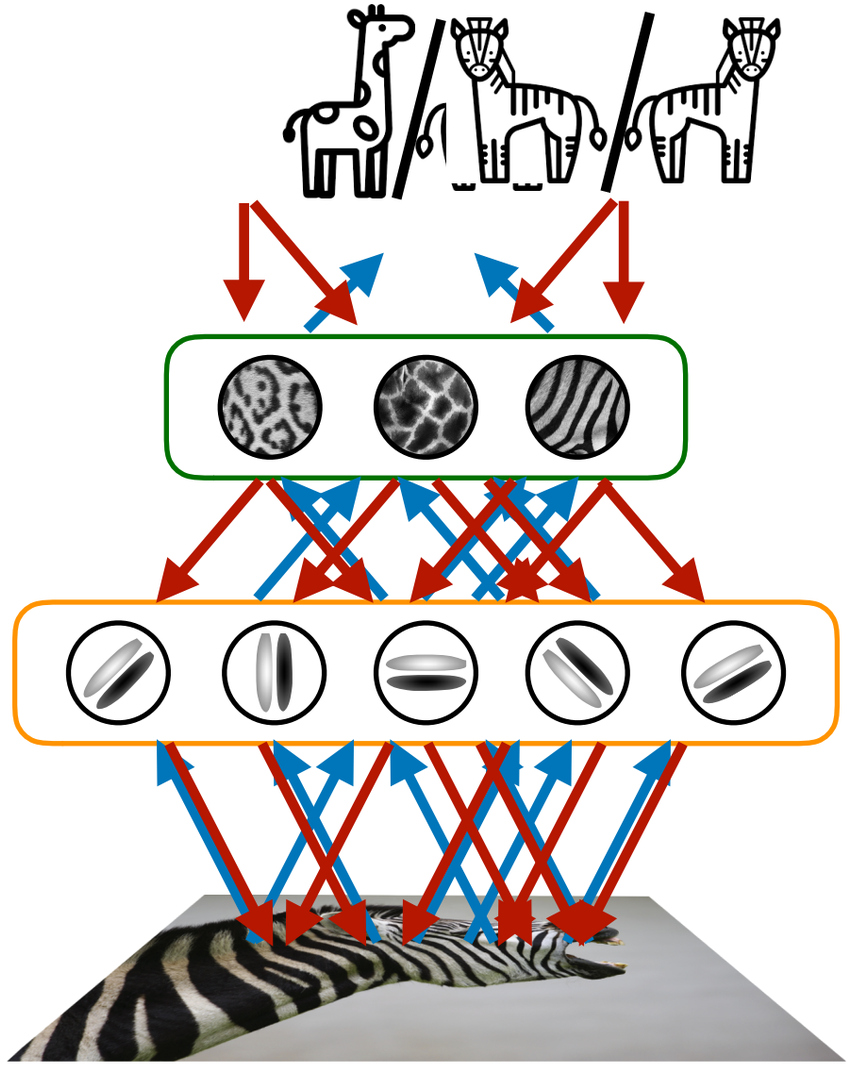
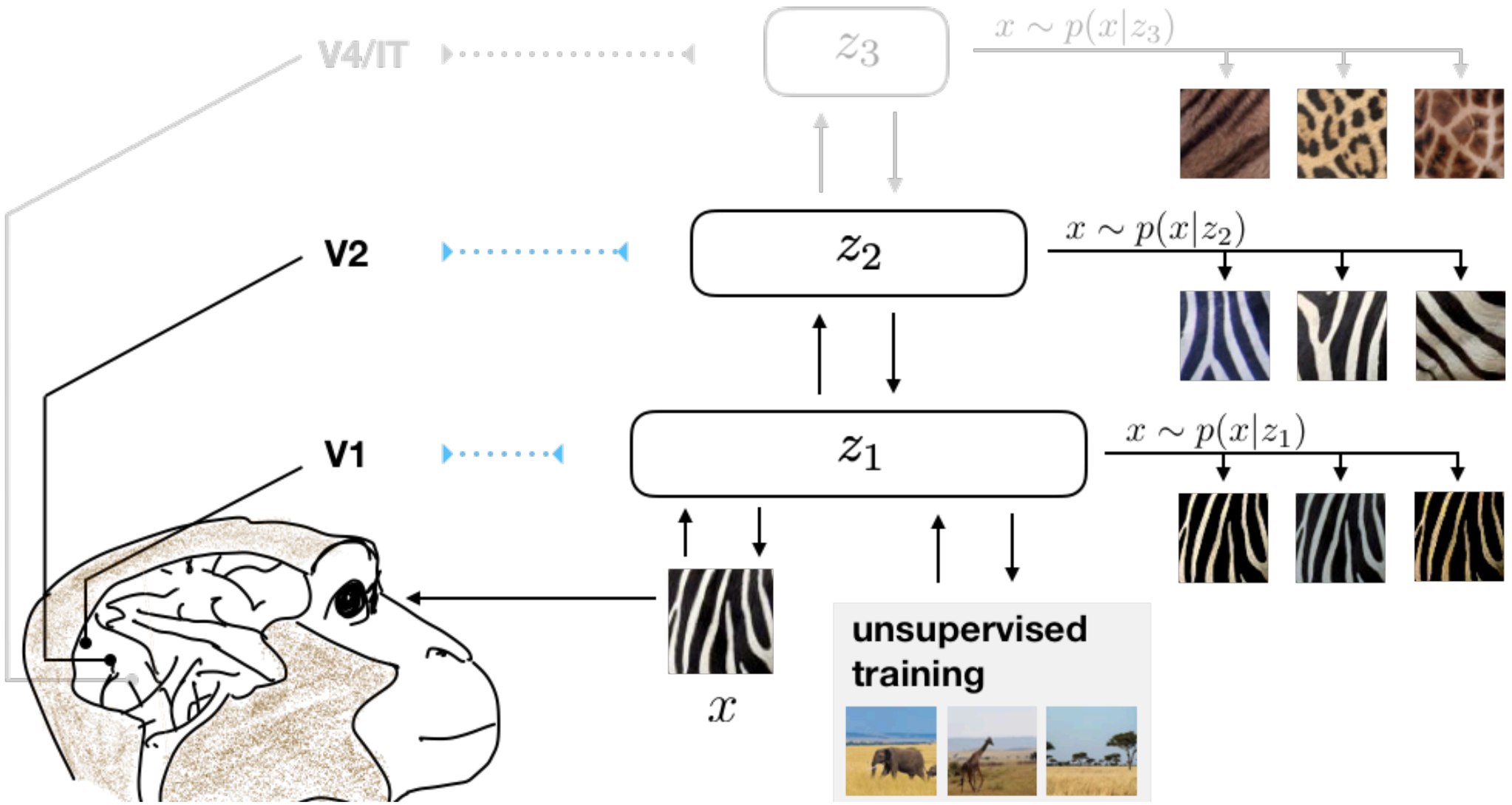
Probabilistic models vs. deep networks

- probabilistic models provide detailed predictions of stimulus statistics
    - most deep learning architectures don't explicitly account for variability
- probabilistic models are explicitly formalised hypotheses about neural computation
    - deep learning models are generic, very flexible computing architectures with no easy interpretation
- in probabilistic models it is often hard to implement inference, and each one is different
    - there are powerful existing methods to train deep learning models
- it is nontrivial to build a generative model if images that performs acceptably in an object recognition task
    - deep learning models do object recognition very well
- they can be combined to yield more powerful predictions

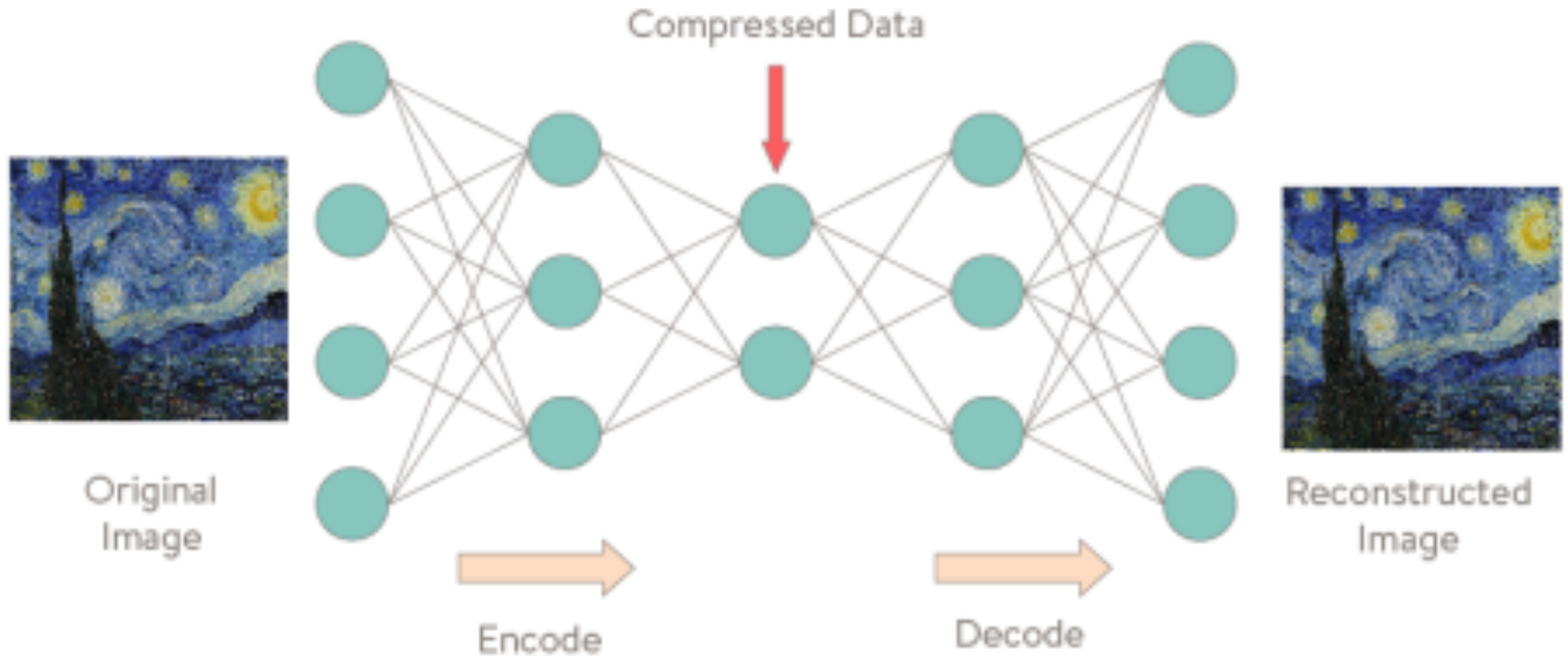


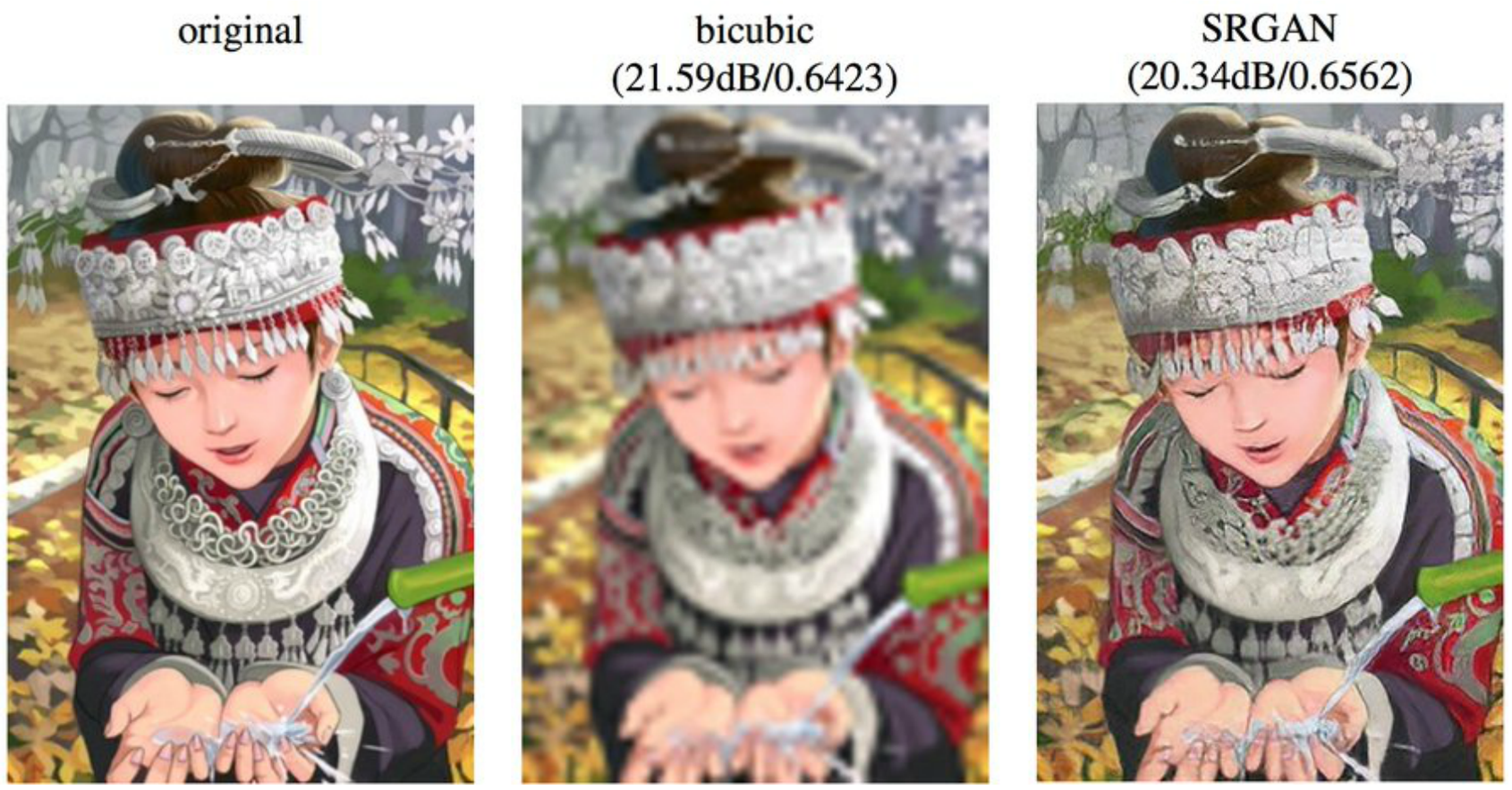
Bányai & Orbán, 2019, Curr Opin Neurobiol

Semantic compression of the visual input

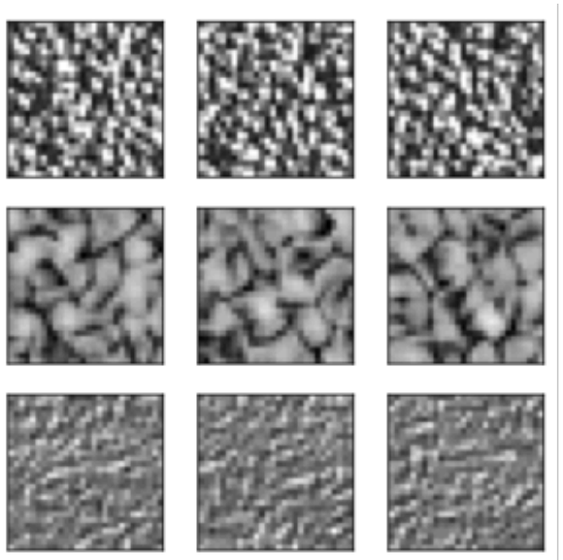


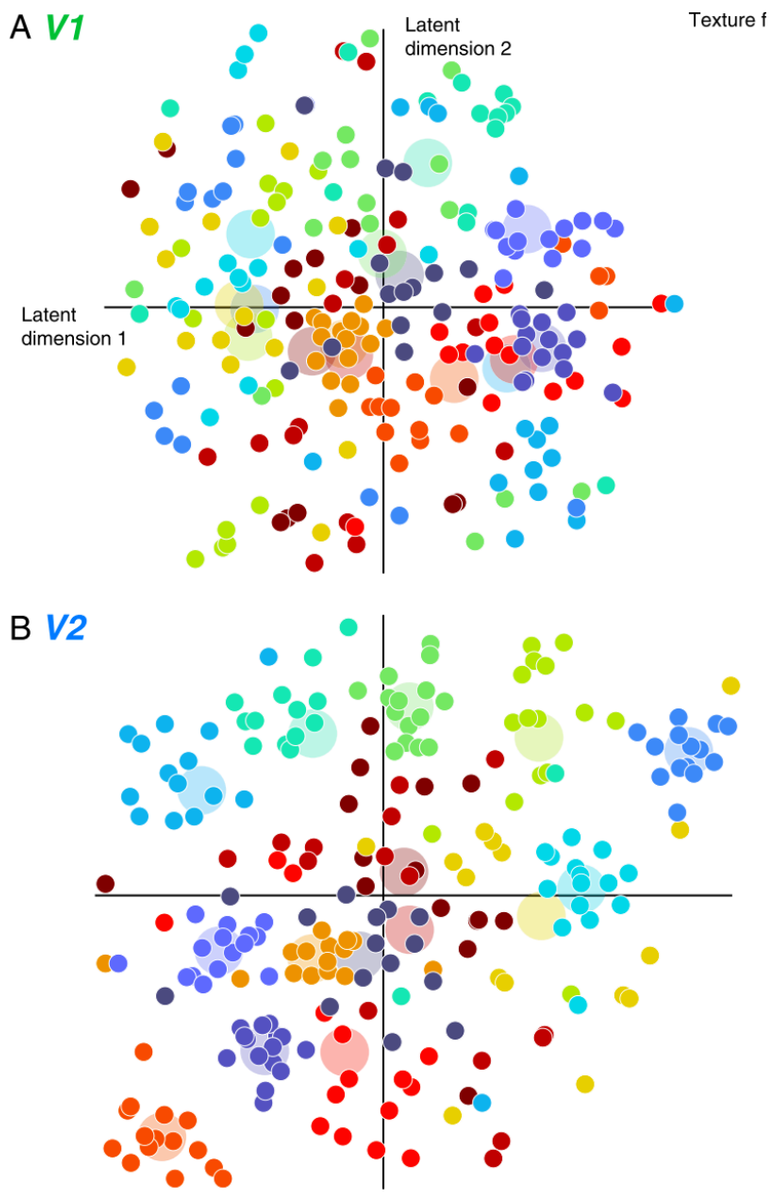
Variational autoencoders and compression

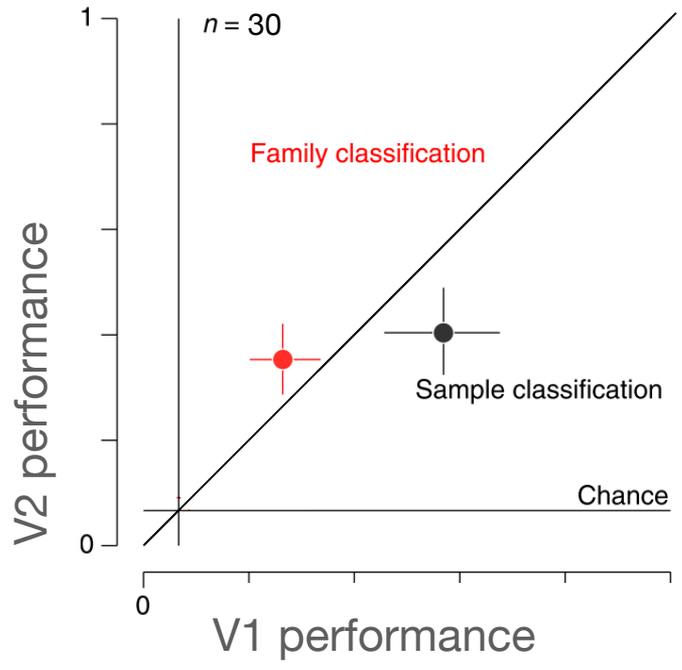




Neural representation of textures

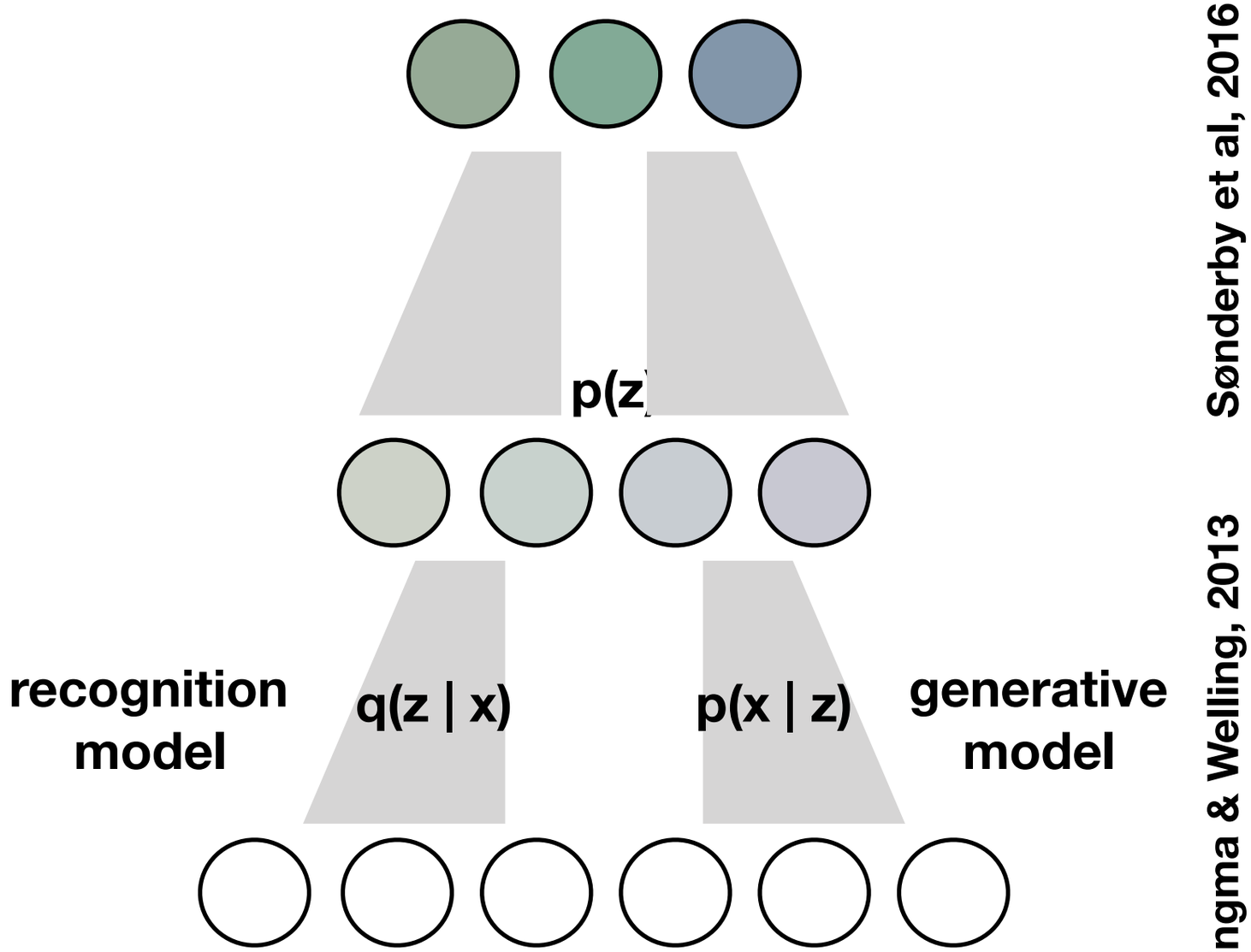




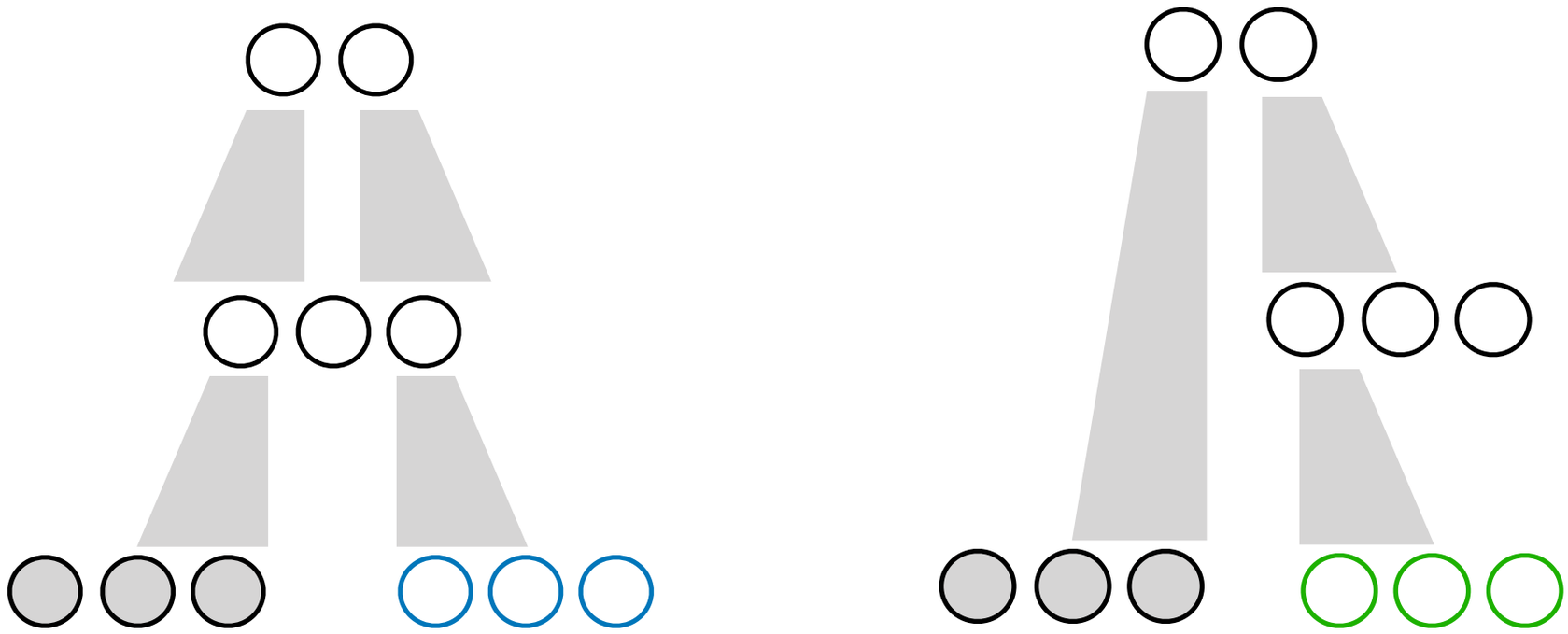


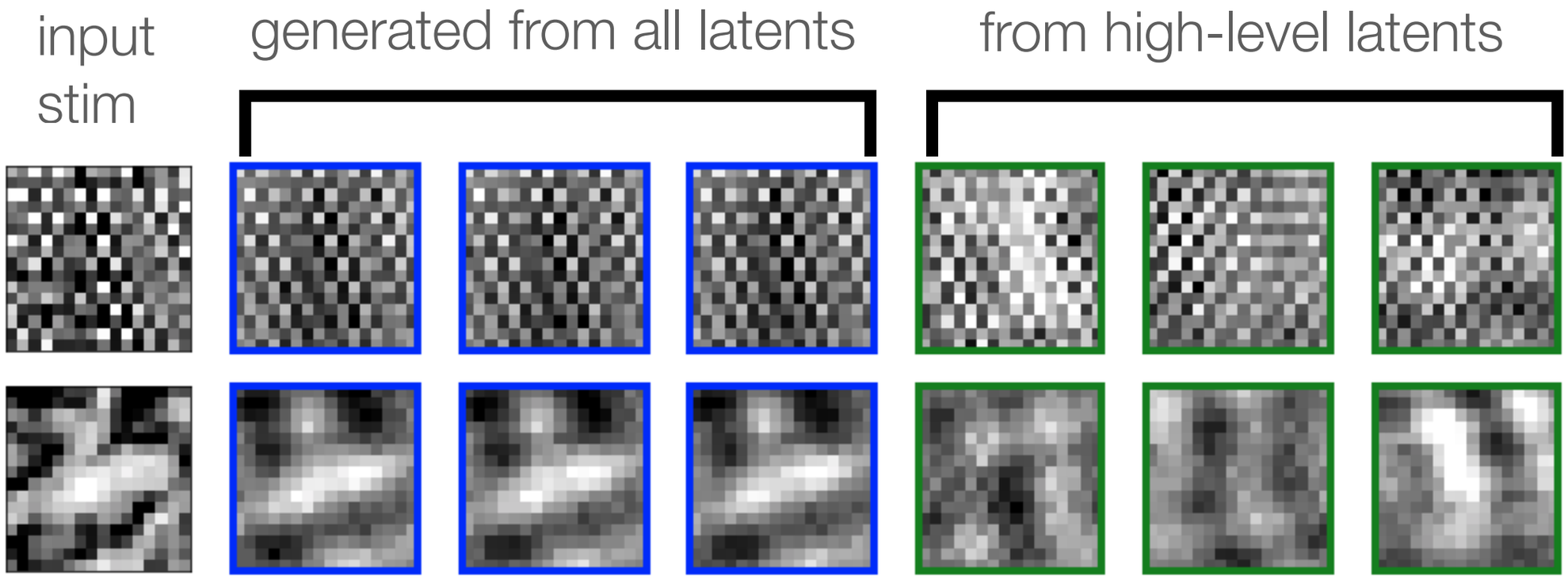
Ziemba et al, 2016, PNAS

High-dimensional hierarchical generative models

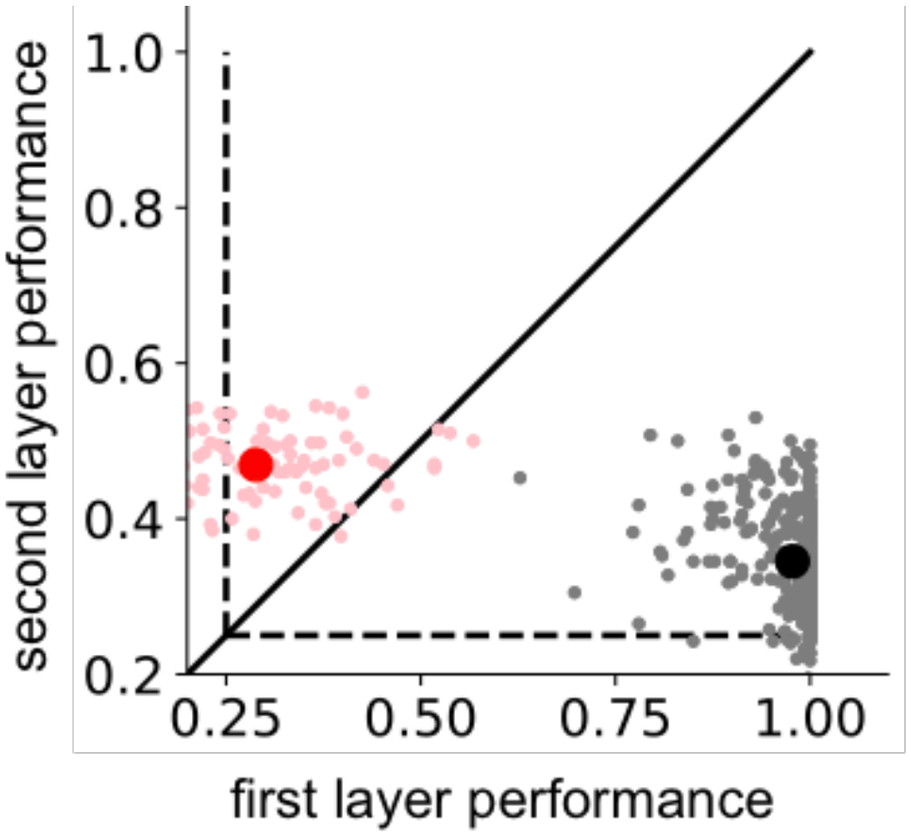


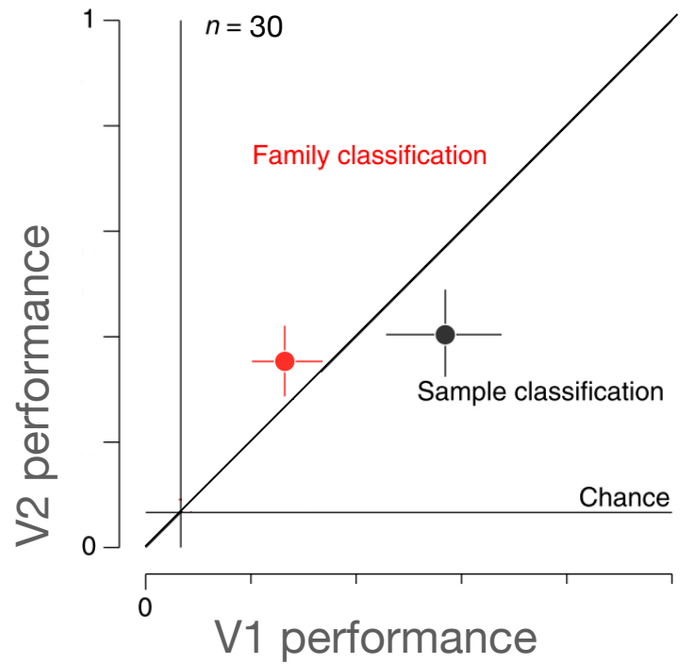
Semantic compression of textures





Representation of texture families in the model



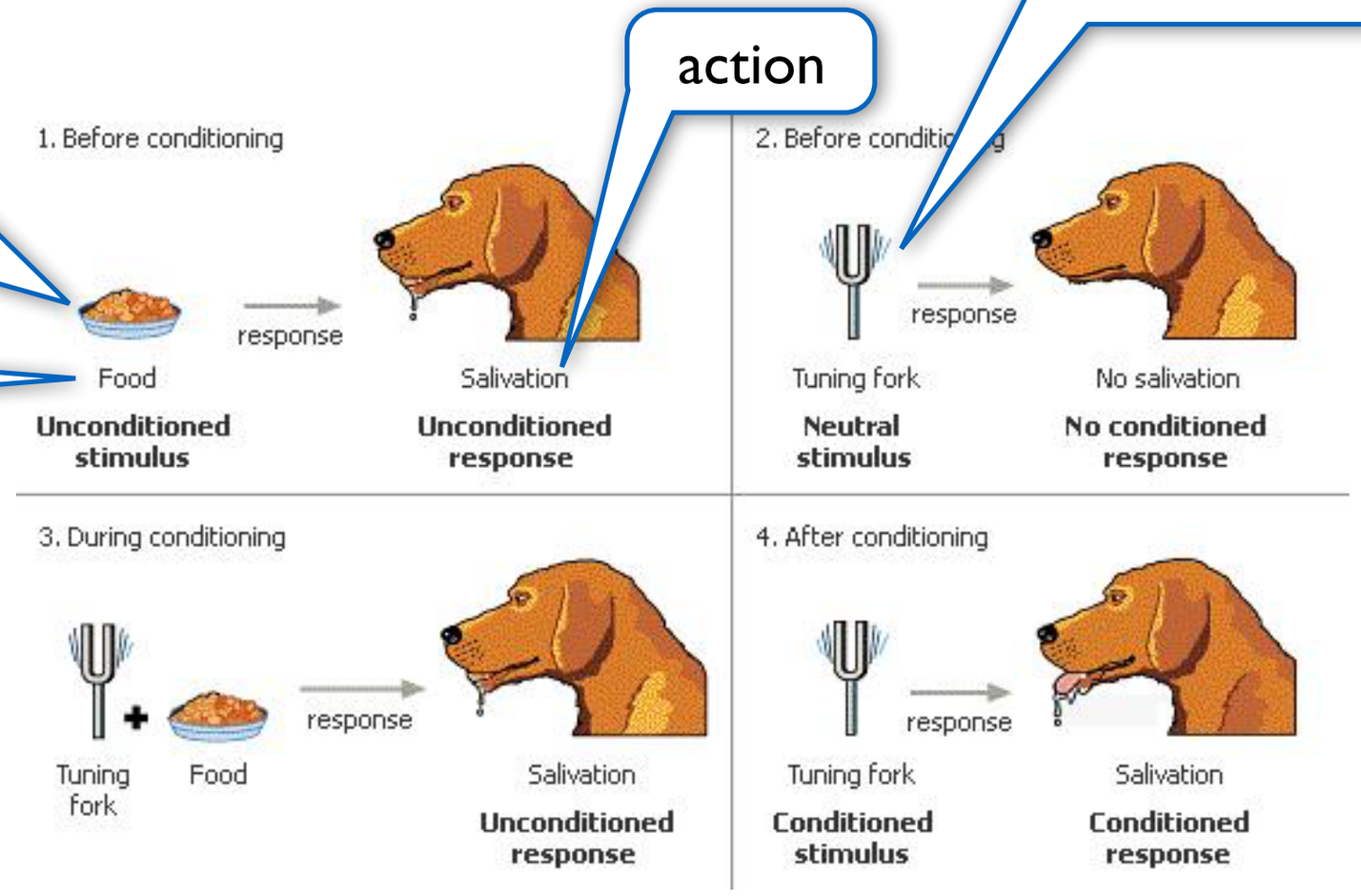


Bányai, Nagy & Orbán, 2019, CCN

Predicting reward

Pavlovian - classical conditioning

- unconditioned stimulus, conditioned stimulus



unconditioned stimulus: smell & view of food

reward

action

conditioned stimulus: sound of bell

instrumental - operant conditioning

- the actions of the animal determine the reward

Knowledge

Past events

Learned regularities of the world

Inferred information from actual observation

Consciousness

?

Decision making

Motor control

Perception

How to build a decision making model on top of the perceptual one?

- We need to choose a target variable from the model that we will try to optimise - this will be called the reward

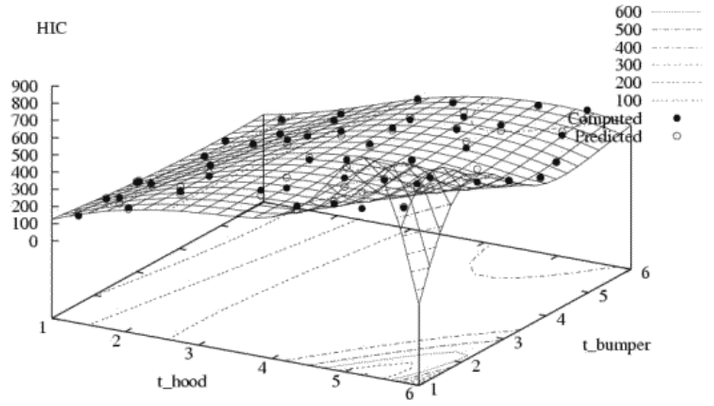
- Motor output will be modelled a fixed set of possible actions that make modifications in the environment

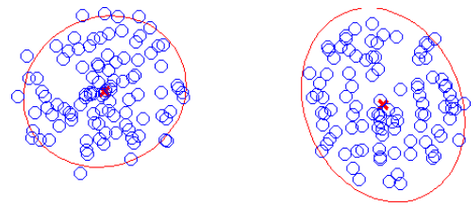
- A combination of inferred values for the latent variables is called a (perceived) state of the environment

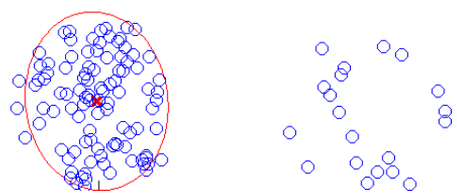
- We have to figure out which action to choose in every state

Basic types of learning problems

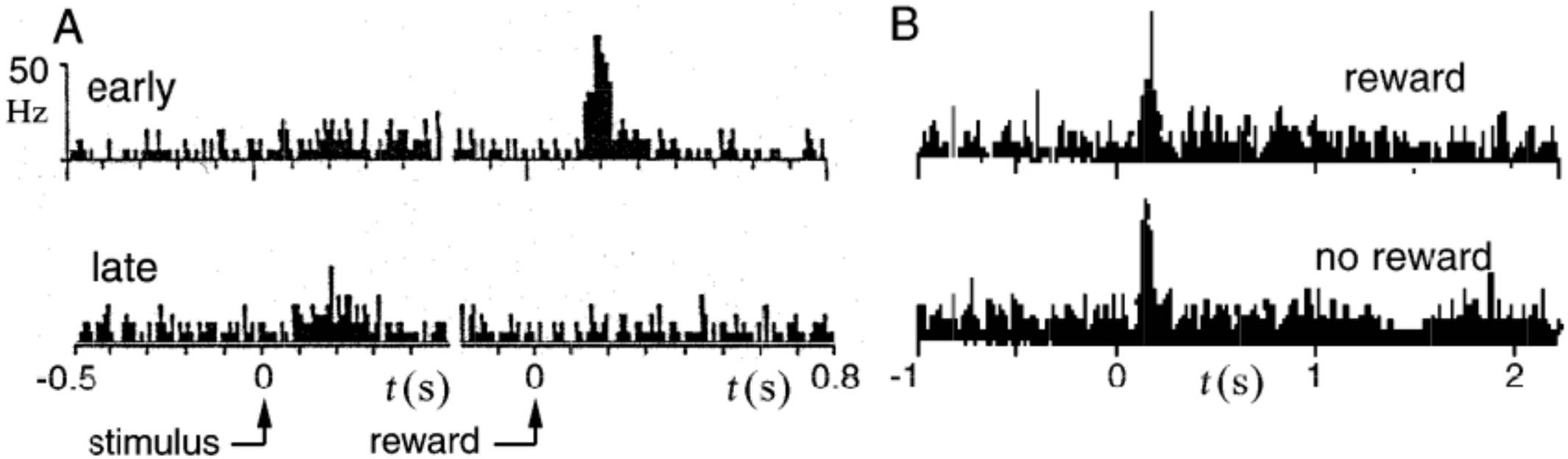
- Supervised
  - data: input-output pairs
  - approximate the mapping between them
  - discrete output: classification
  - continuous: regression
- Unsupervised
  - data: set of values
  - fit a predefined structure on it
  - find the optimal representation: clustering, filtering
- Reinforcement
  - data: state information and sparse reward
  - learn optimal strategies
  - active learning





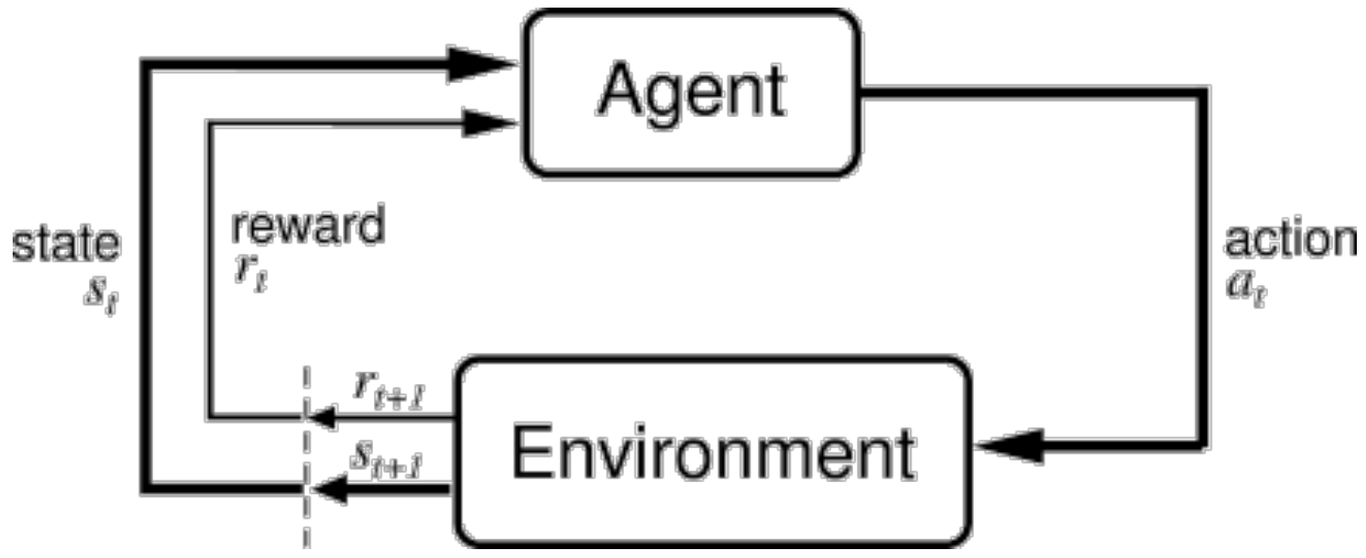


Reward encoding in the cortex



- Dopamin neurons in the monkey's cortex respond according to the learned association between indicator variables and reward
- Activity is proportional to surprise

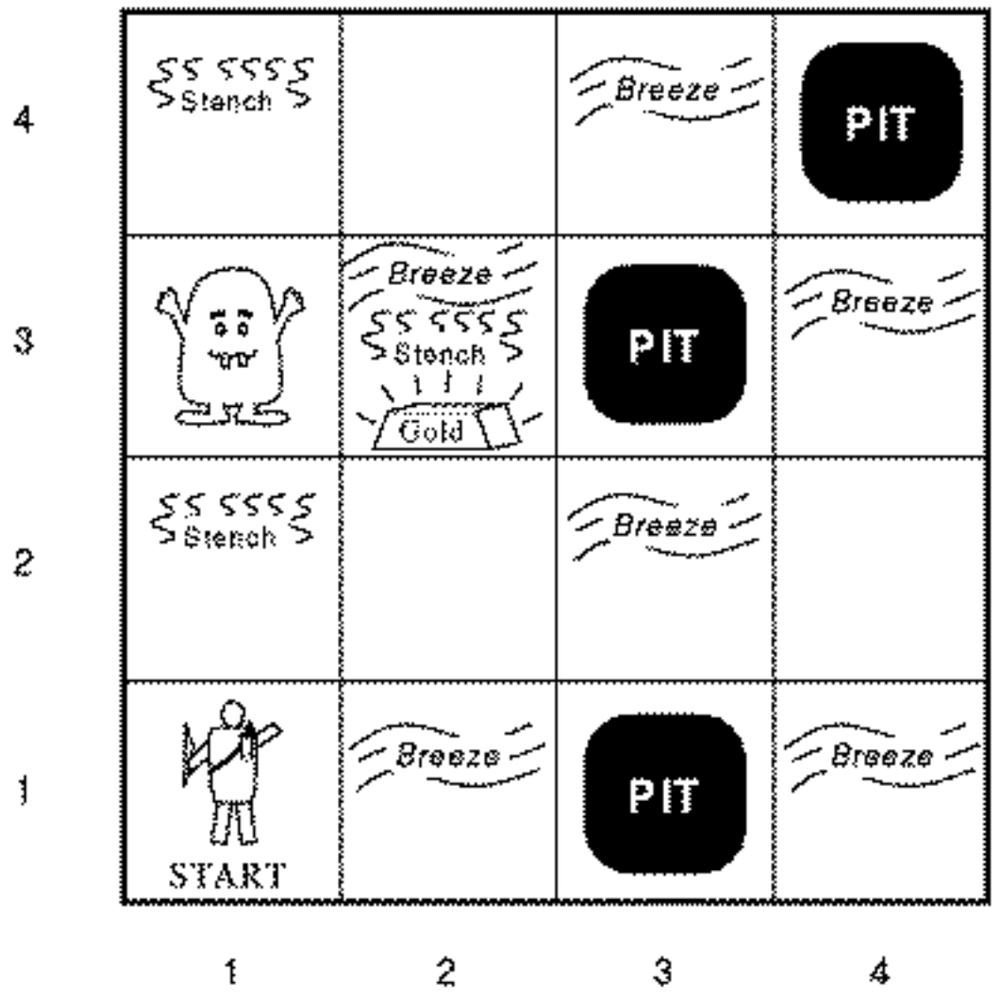
Agent-environment framework



- The environment communicates towards the agent which state it’s in
- Reward is given in some states to the agent
- The agent pushes the environment to new states by its actions

Learning the value of states

- Simplest case: there is a finite number of states of the environment
- each state *s* is a combination of inferred values for the latent variables of the mental model (e.g. we take the *a posteriori* most probable values)
- for each state we assign a value, *V(s)*, that encodes the desirability of that state
- after each decision, at time *t*, we update the estimation of state values using previous estimations and the reward
- intuition: a value of a state is determined by the reward, and the value of other states that are accessible from it through a few actions



Russell & Norvig, 1995

https://cs.stanford.edu/people/karpathy/reinforcejs/gridworld_td.html

Reinforcement learning

- The goal of RL is to maximize reward in the long run
- We have to learn how useful certain states and actions are to do that
- Trial and error
- Set values based on reward
- Propagate value to states without reward

Temporal Difference learning

- We learn from prediction error
- The value of the state we stepped on makes the previously visited state more similar to itself
- We can propagate to earlier states too

$$V(S_t) \leftarrow V(S_t) + \alpha[R_{t+1} + \gamma V(S_{t+1}) - V(S_t)]$$

Previous estimate

Reward t+1

Discounted value on the next step

TD Target

Action selection

- Now we have the state value function
  - V: s -> R
- In order to choose an action, we need to know that from the current state, which action leads to which other state
  - M: (s,a) -> s
  - or more generally, M: (s1,s2,a) -> P
  - this function, M, is called the **model** of the environment
- In each RL setting in which we learn a state-value function, we have to learn a model function as well
  - these are called **model-based** solutions

Model-free RL

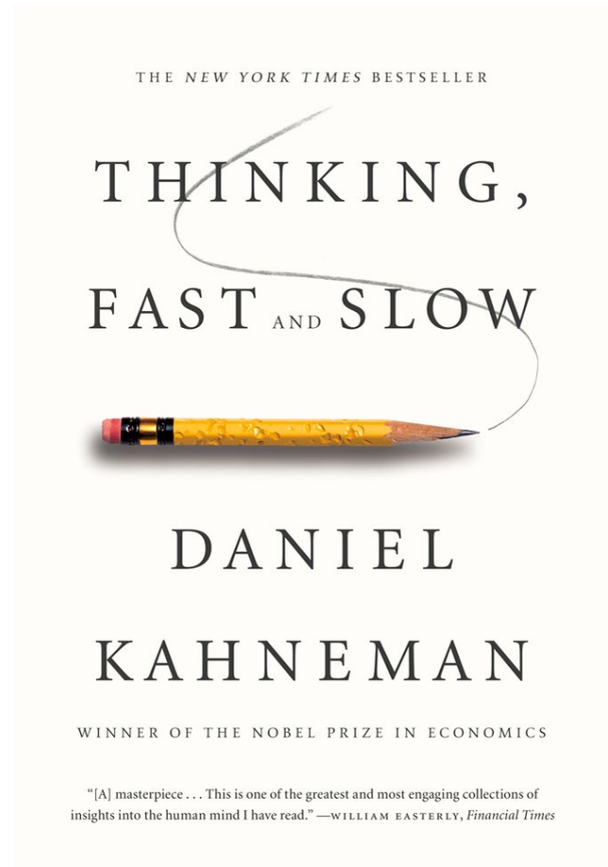
- Instead of learning the model of the environment, we can learn the value of state-action pairs directly
  - the function Q: (s,a) -> R
    - the TD rule applies nicely here as well
    - action selection only requires the Q function, not the model

$$Q_{t+1}(s_t, a_t) = Q_t(s_t, a_t) + \epsilon \left[r_{t+1} + \gamma \max_a Q_t(s_t + 1, a) - Q_t(s_t, a_t) \right]$$

Deliberative and reactive systems

- The Q function has (#states x #actions) parameters, while the V only has (#states)
  - it requires much more observations to estimate Q reliably than it does to estimate V
- The learned model can be reused in a different task, a model-free agent has to start from scratch

- In model-based solutions, action-selection takes a lot more computation
  - but you can make long-term plans using the model
  - model-free solutions can be regarded as a bunch reflexes
  - the two systems can complement each other at different stages of proficiency



Exploration vs. exploitation

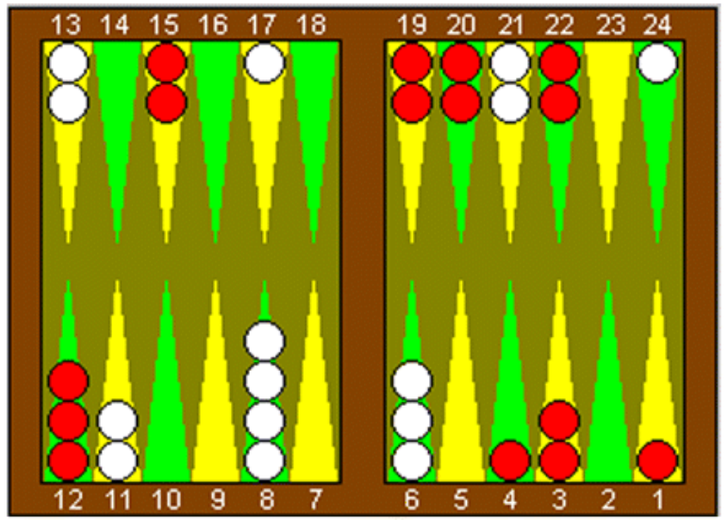
- When we don’t know anything about the environment yet, it doesn’t make sense to repeat the first series of actions that led to some reward
- When we know more, we can just use the best strategy we found
- Usual way: act randomly in the beginning, gradually increase of probability of choosing the action we think is best

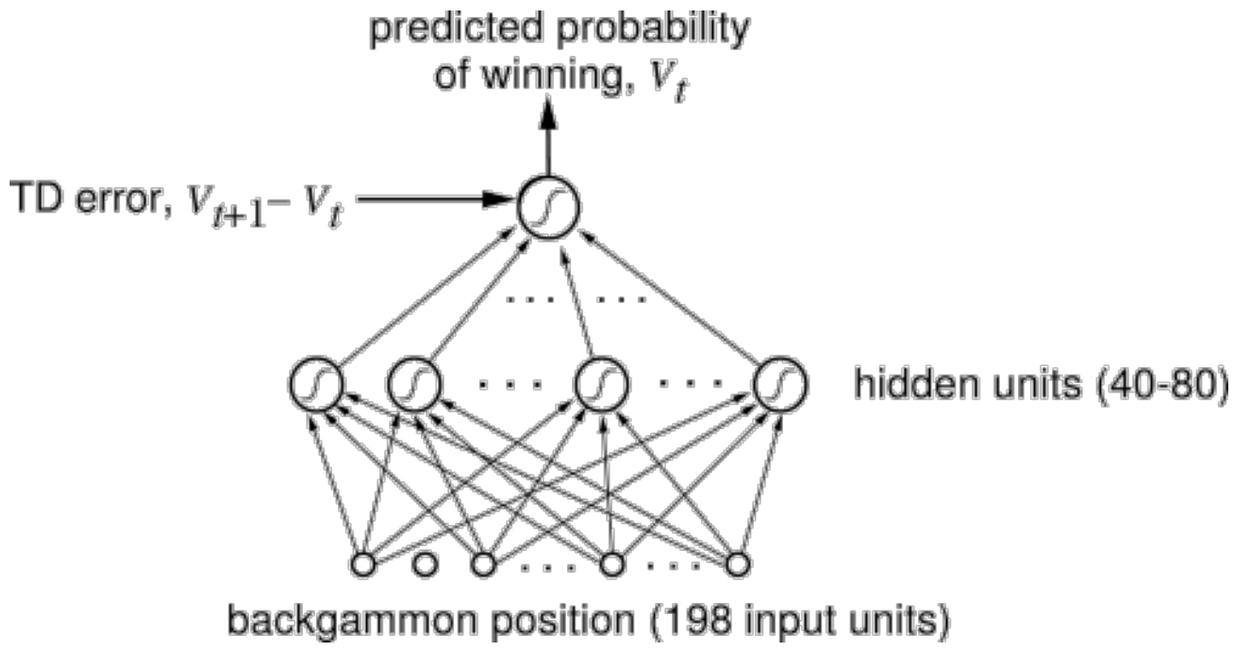
Representation of the value function

- If there are not so many, we can use a table
- With large and continuous spaces
  - we can only represent state variables
  - we need to generalise to states never visited
  - feedforward neural networks are a good choice
  - we have to construct a desired output for backpropagation at each step from the prediction error

TD learning with a neural network

- Gerald Tesauro: TD-Gammon
  - feed-forward neural network
  - Input: states attainable by possible actions
  - Output: state value (winning probability)
- At each step, we have to calculate an output error for the network
  - based on the reward signal
- Result: comparable to best human players
- Total training time today: 5s





TD using a neural representation

- Using the prediction error for learning
- Update of the state value in the neural representation:

$$w(\tau) \leftarrow w(\tau) + \varepsilon\delta(t)u(t-\tau) \qquad \delta(t) = \sum_t r(t+\tau) - v(t)$$

- Calculating the prediction error
  - Ideally we'd need the sum of future rewards
  - We use a single-step local approximation

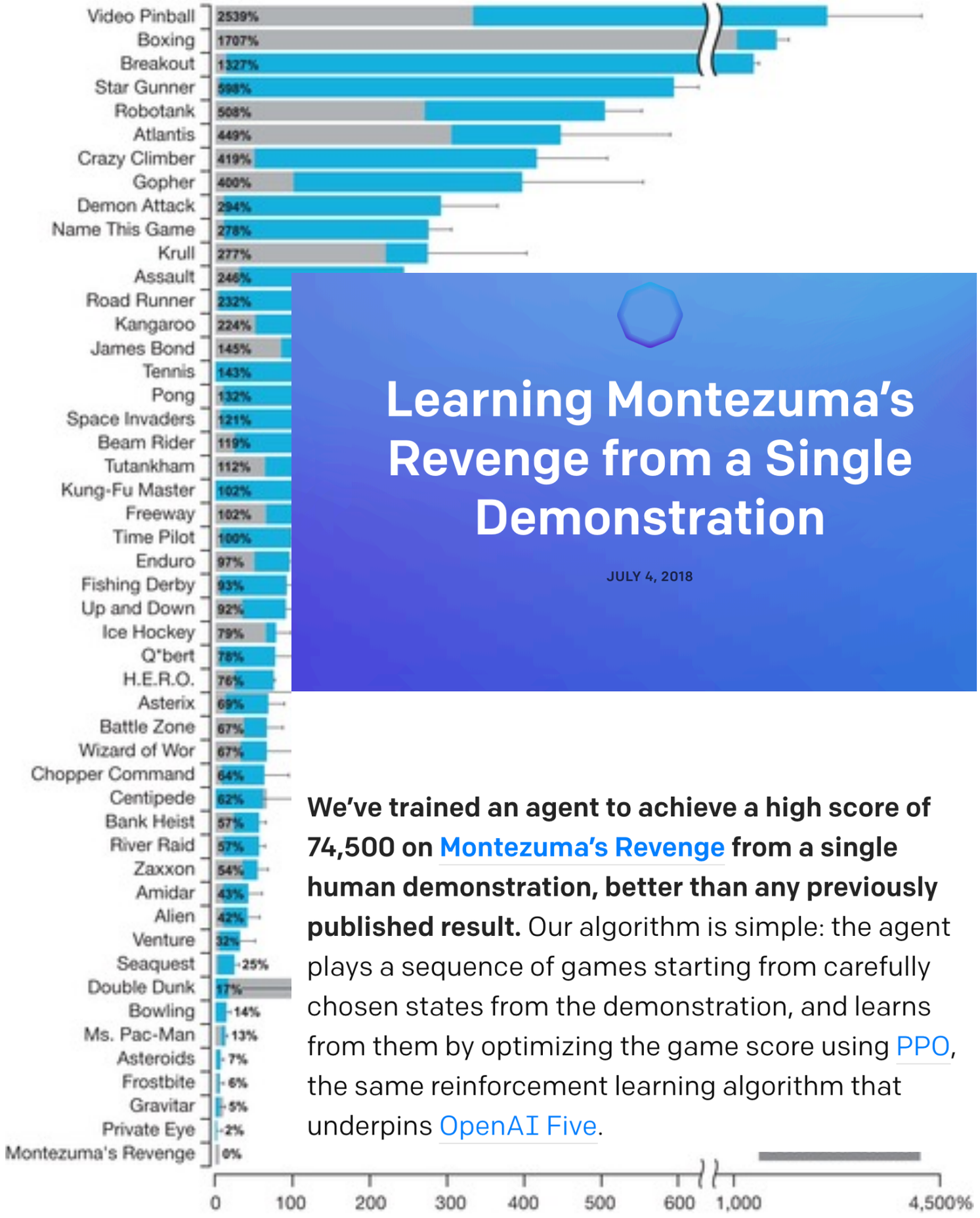
$$\sum_t r(t+\tau) - v(t) \approx r(t) + v(t+1)$$

  - If the environment is observable, this converges to an optimal strategy
- We can propagate the error back to previous states too

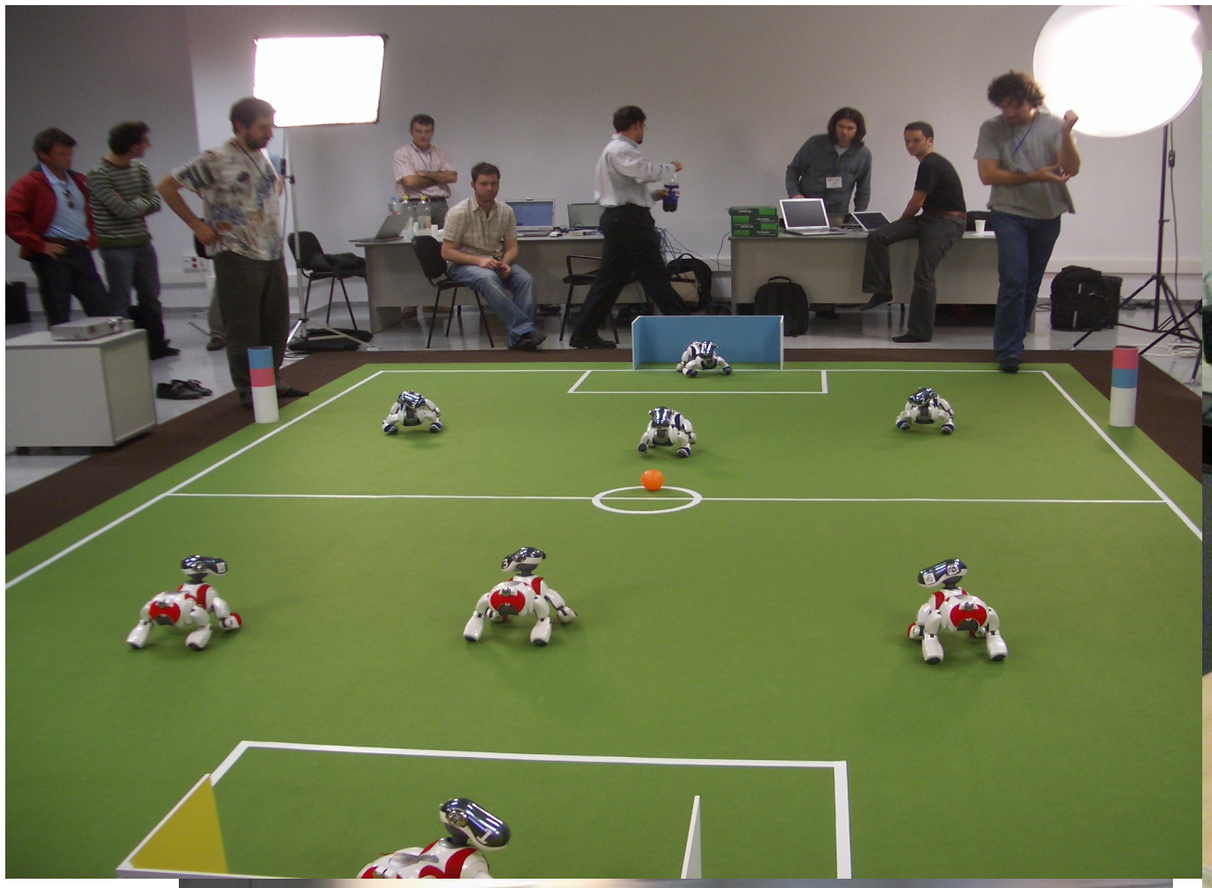
Learning to play computer games

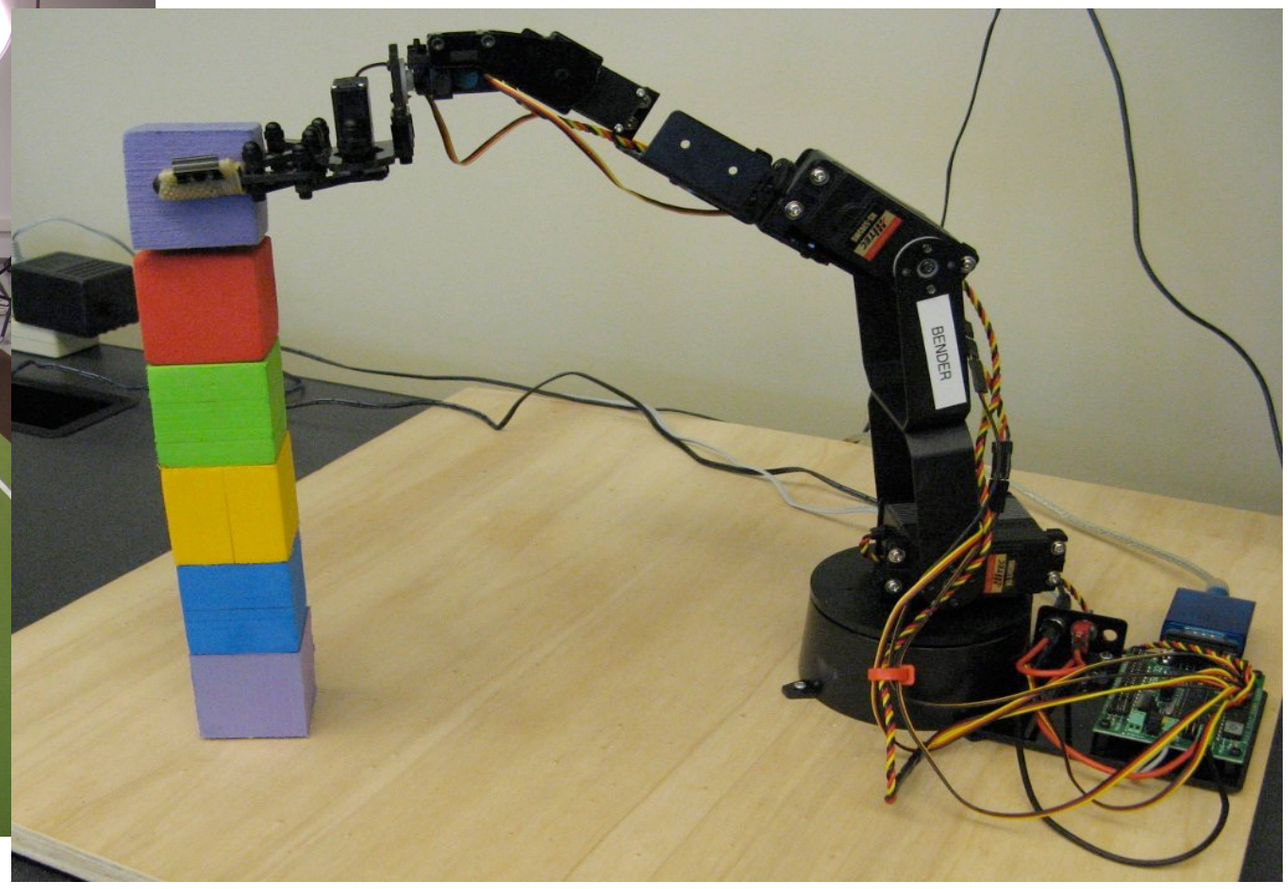
- reinforcement learning combined with deep networks
- observation: computer screen & score

Mnih et al, 2015



Learning physical movement with RL

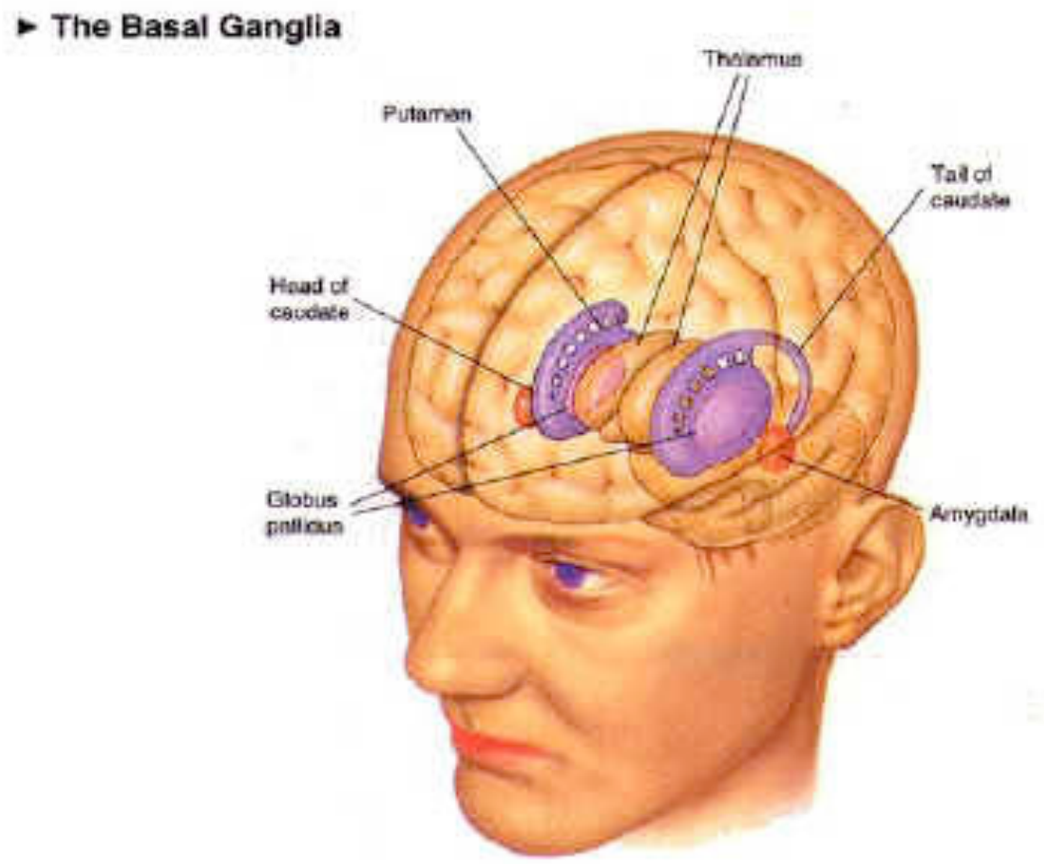


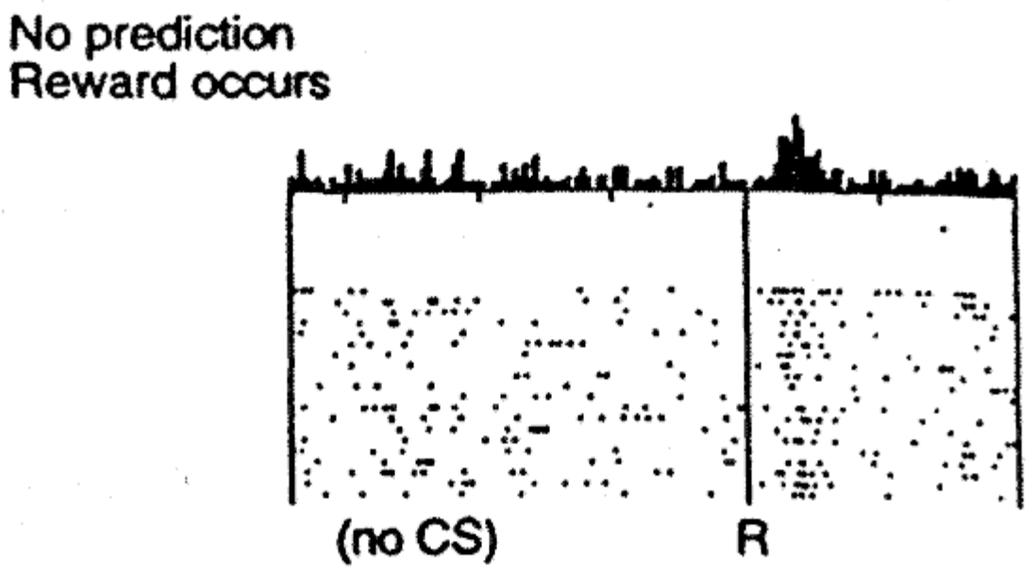


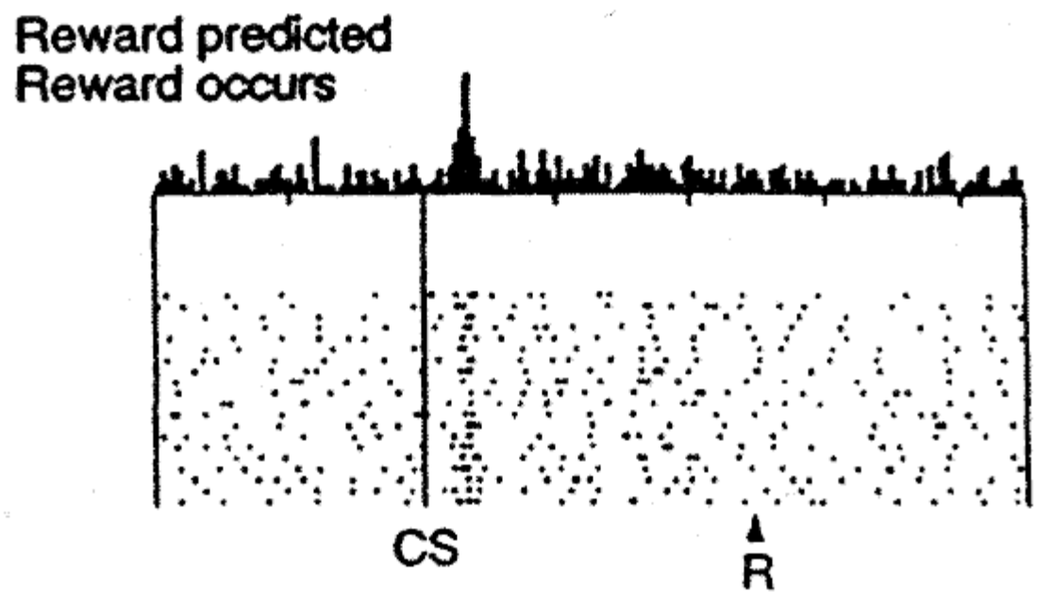
The effect of reward in dopaminerg cell of basal ganglia

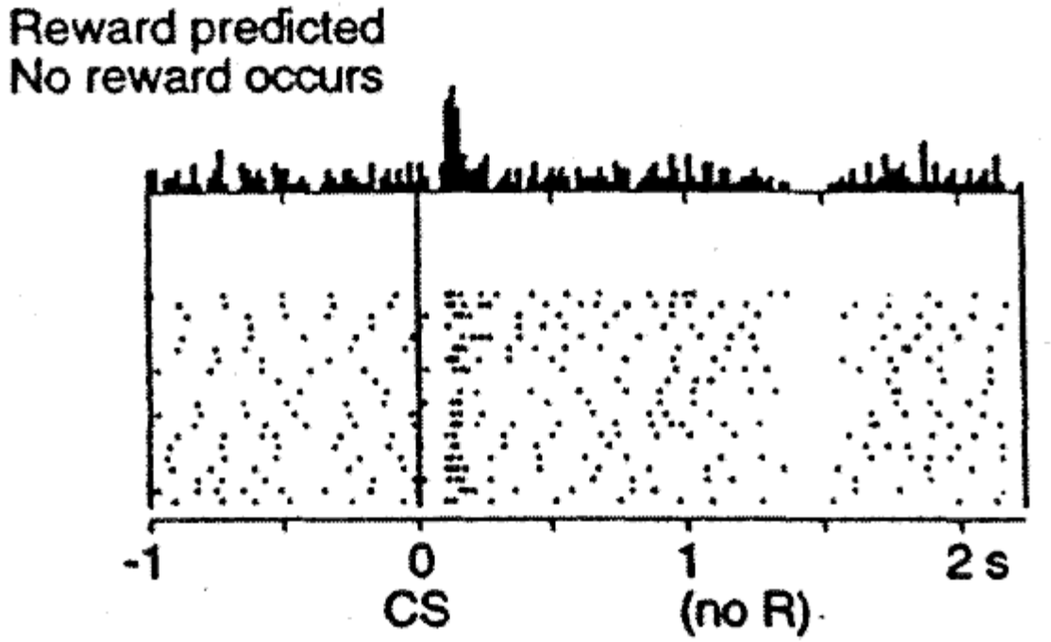
An interpretation:

Dopamine cells signals the difference between the expected and received reward.

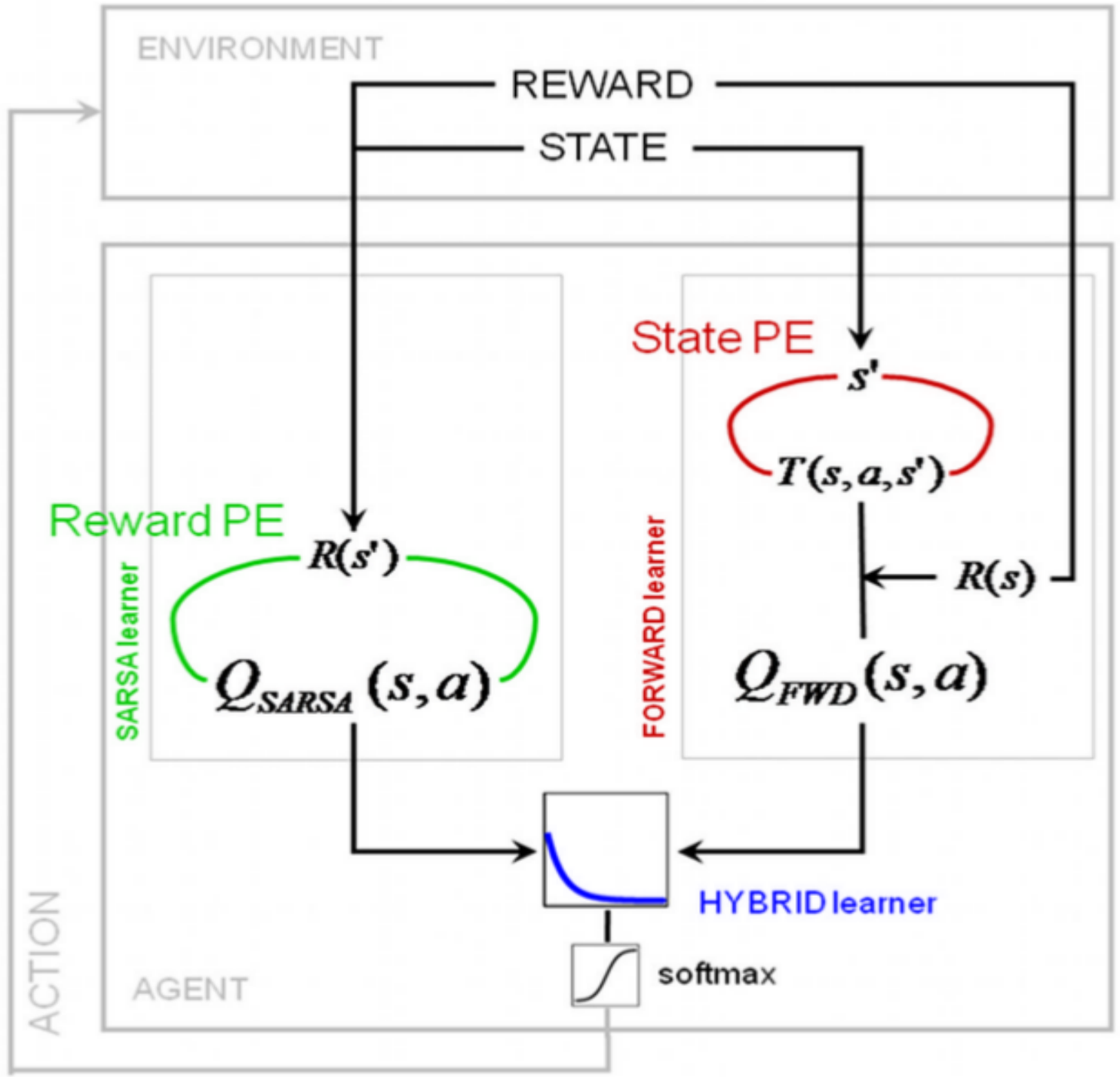






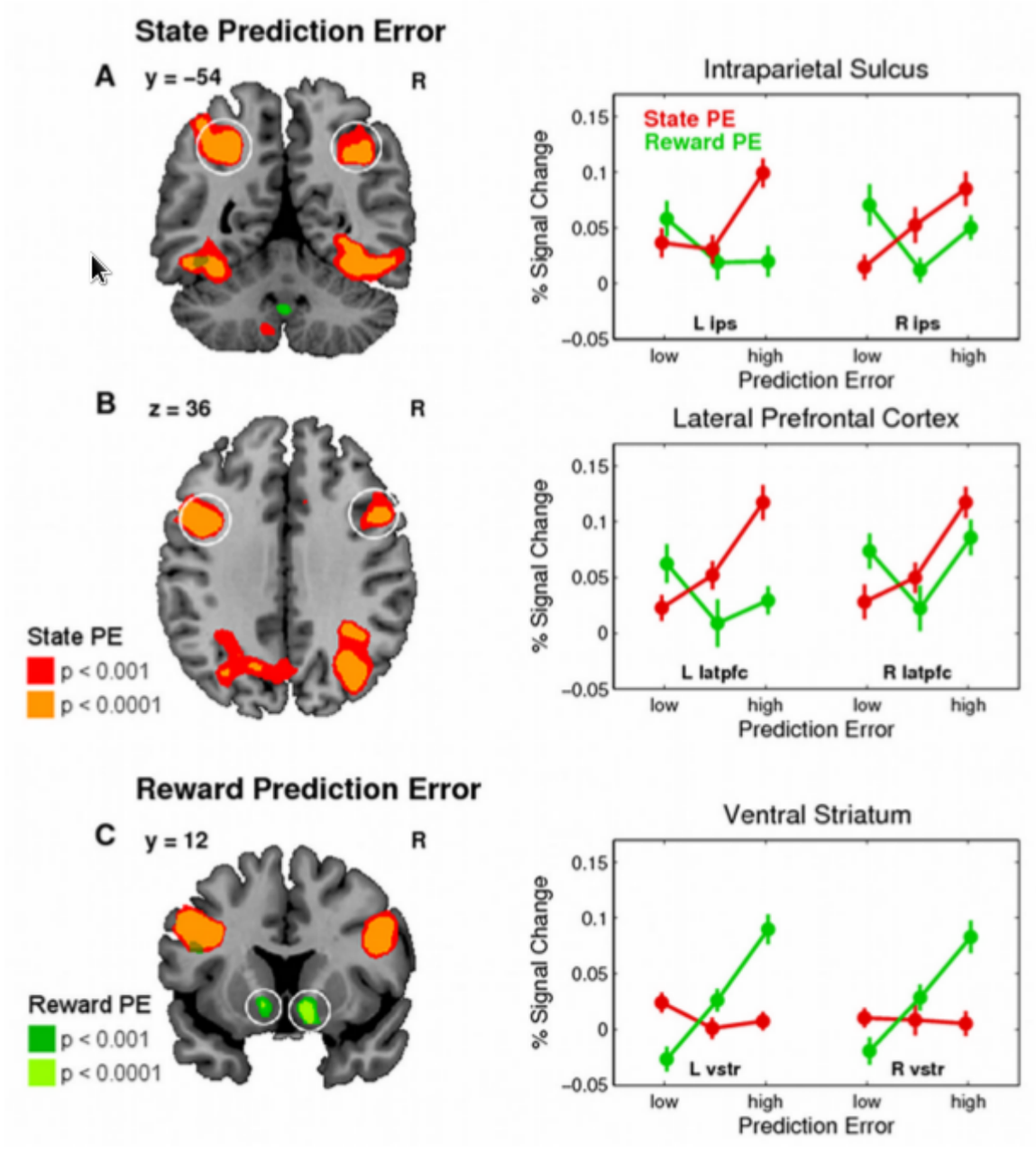


- Glascher, Daw Dayan, O'Doherty, *Neuron,* 2010.
- Correlation of brain activity with model-based and model-free reinforcement learning algorithms



Strategy learning in the cortex

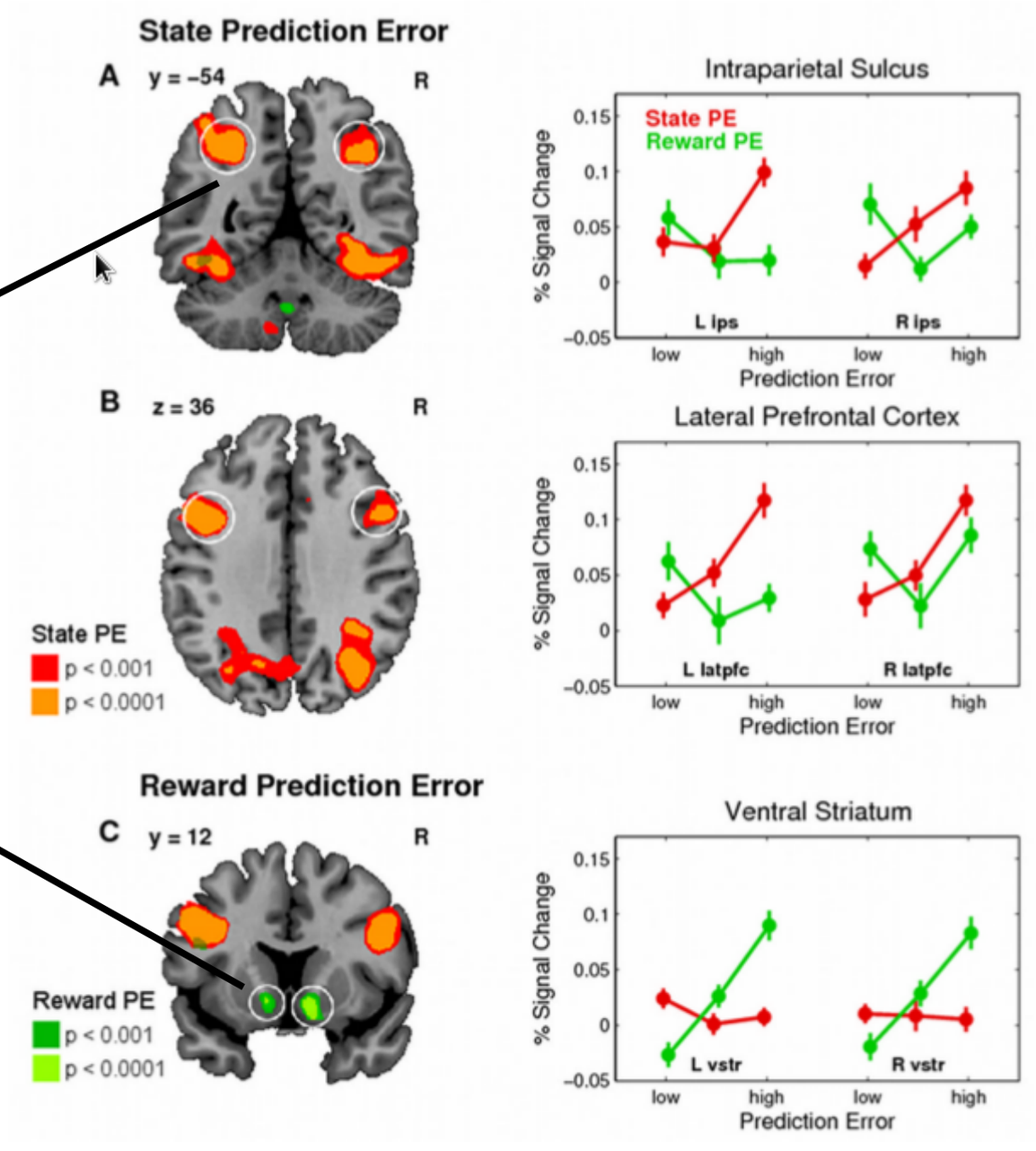
- Model-based and model-free RL
- correlates of quantities related to both can be found with fMRI



Neural correlates of RL solutions

Deliberative model-based RL
prefrontal and parietal cortex

Reactive model-free RL
subcortical structures



The Big Program of the Brain

```
function MotorOutput = Brain(SensoryInput)

 if (Dead ~= 1)
      for i = 1: NumSenses
           ExtractedFeatures(i) = ProcessSense(i, SensoryInput);
      end
      WorldModel = UpdateWorldModel(ExtractedFeatures,InternalState);
      MotorOutput = GenerateAction(WorldModel);
end
```