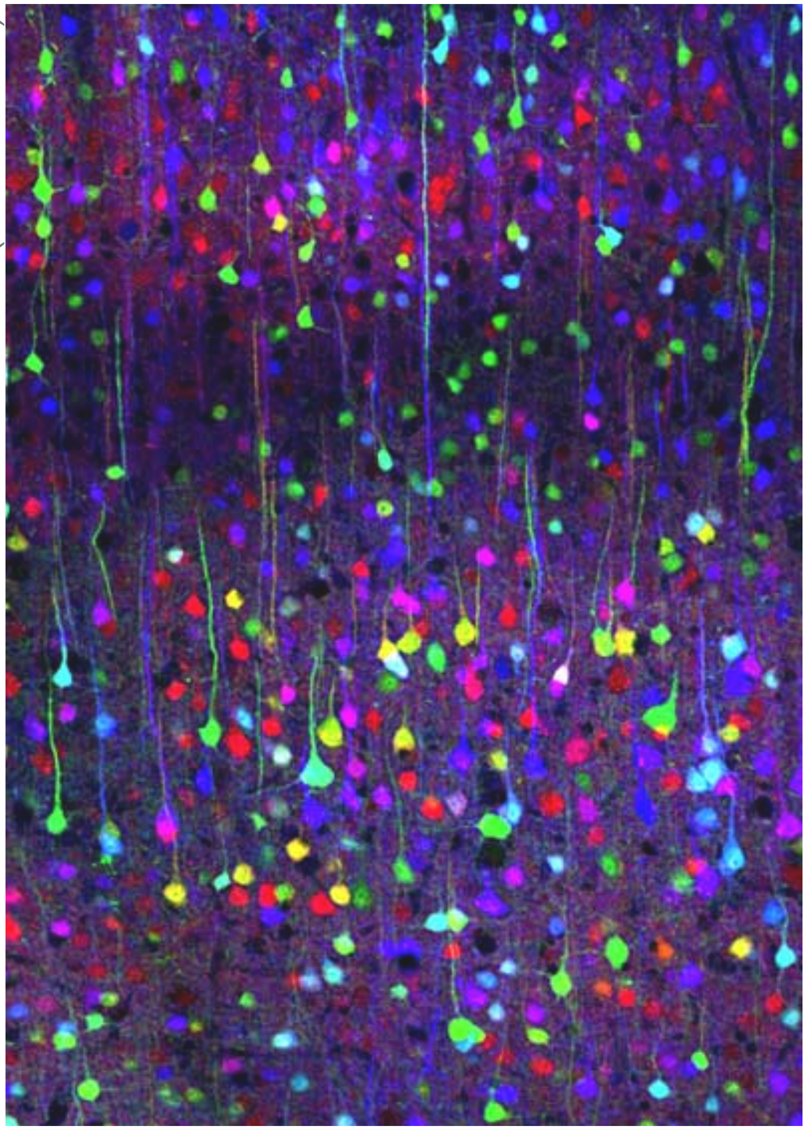
Information Processing & the Brain 2020/2021

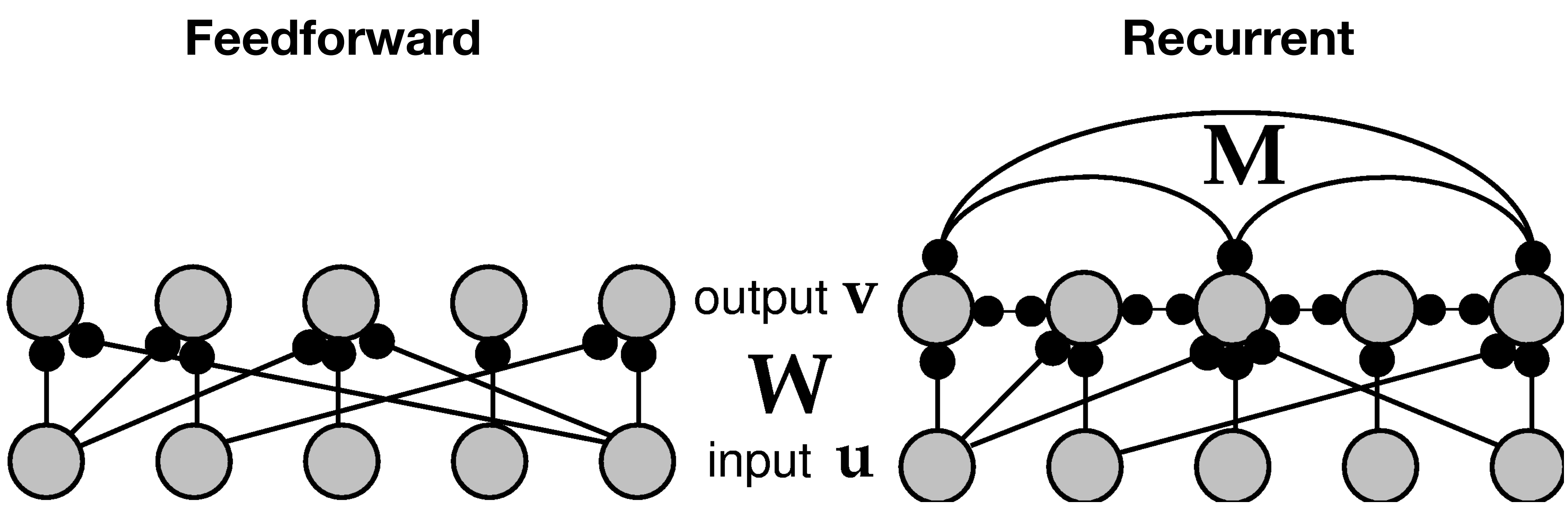
University of BRISTOL

Brainbow (Litchman Lab)



Lecture 7
Neural circuits and learning:
Microcircuits and RNNs
Brain vs Machine

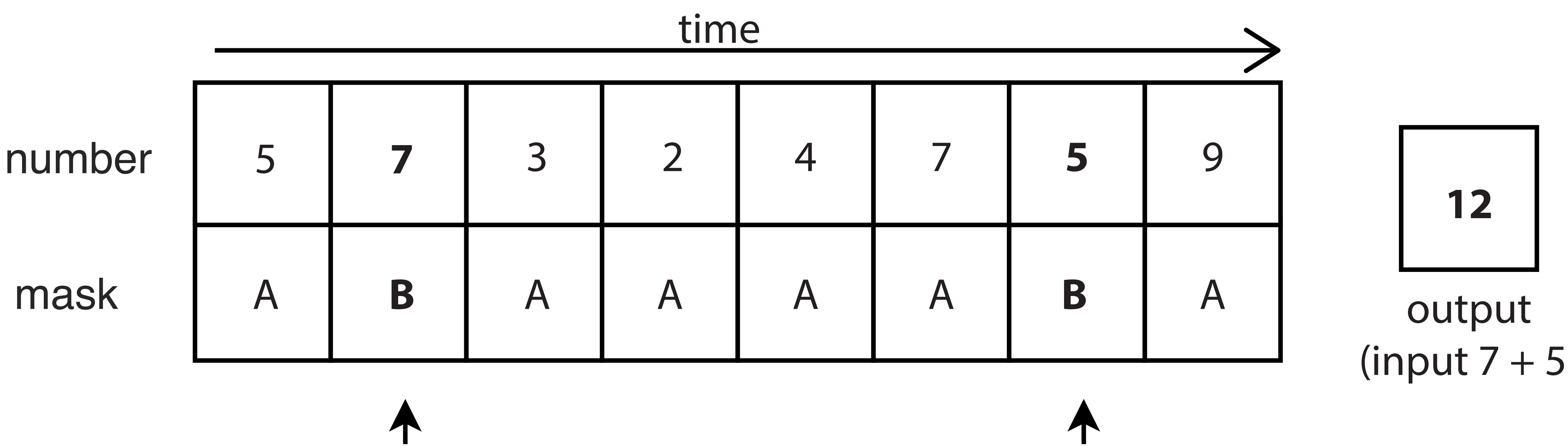
Previously on *IPB*…



Dayan and Abbott book (2001)

But, recurrent neural networks may benefit from additional structure…

How can you solve the delayed addition task with a RNN?



But, recurrent neural networks may benefit from additional structure…

Delayed addition task:

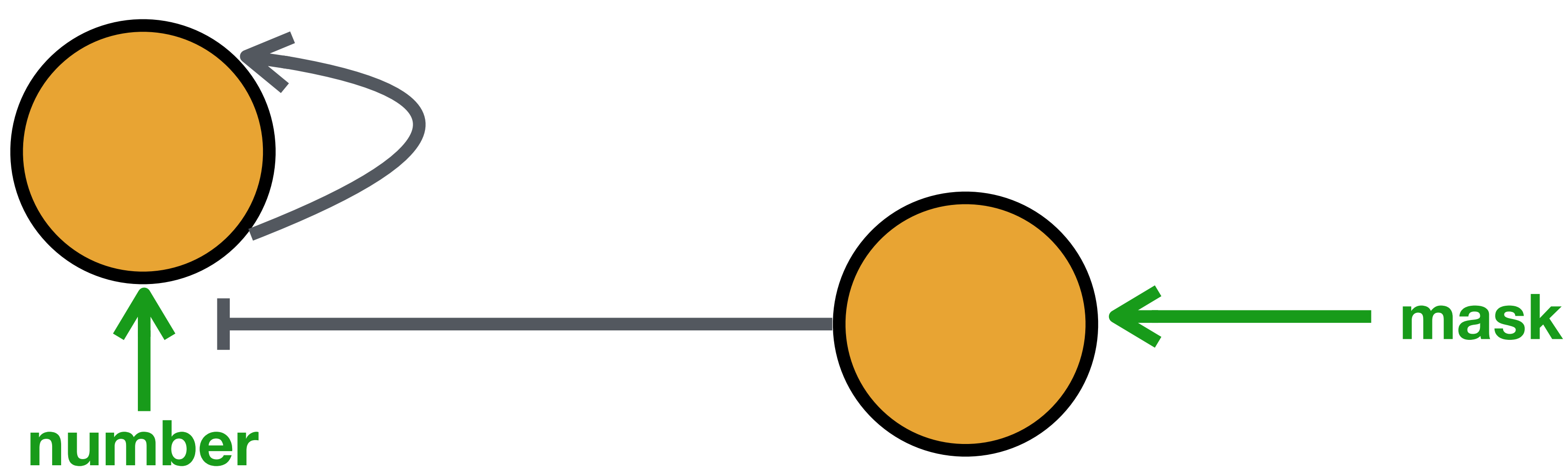
time →

number	5	**7**	3	2	4	7	**5**	9
mask	A	**B**	A	A	A	A	**B**	A

12

output
(input 7 + 5)

You would need an **integrator**: and **mask/gating** neuron:

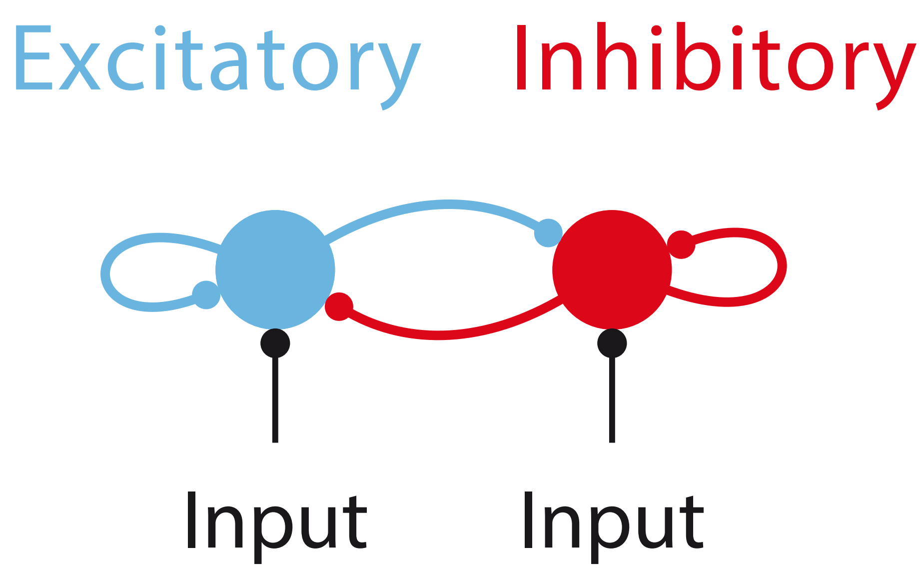


Outline

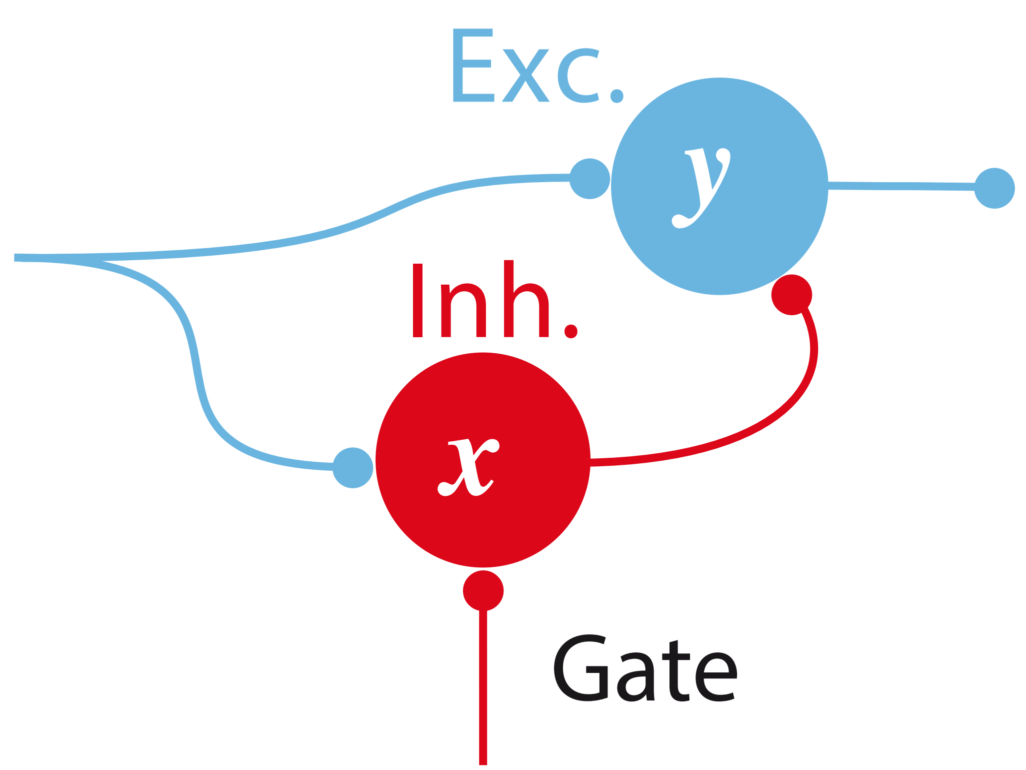
1. **Excitatory and inhibitory cell types, and their dynamics**
2. **Cortical excitatory and inhibitory microcircuits**
3. **Gated RNNs:** long short-term memory networks
4. **A biological plausible version:** Subtractive gated-RNNs
5. Brain vs machine

The excitatory and inhibitory dance

The brain contains two main types of neurons: **excitatory** (i.e. make synapses onto other neurons with positive synaptic weights) and **inhibitory** (i.e. make synapses onto other neurons with negative weights).

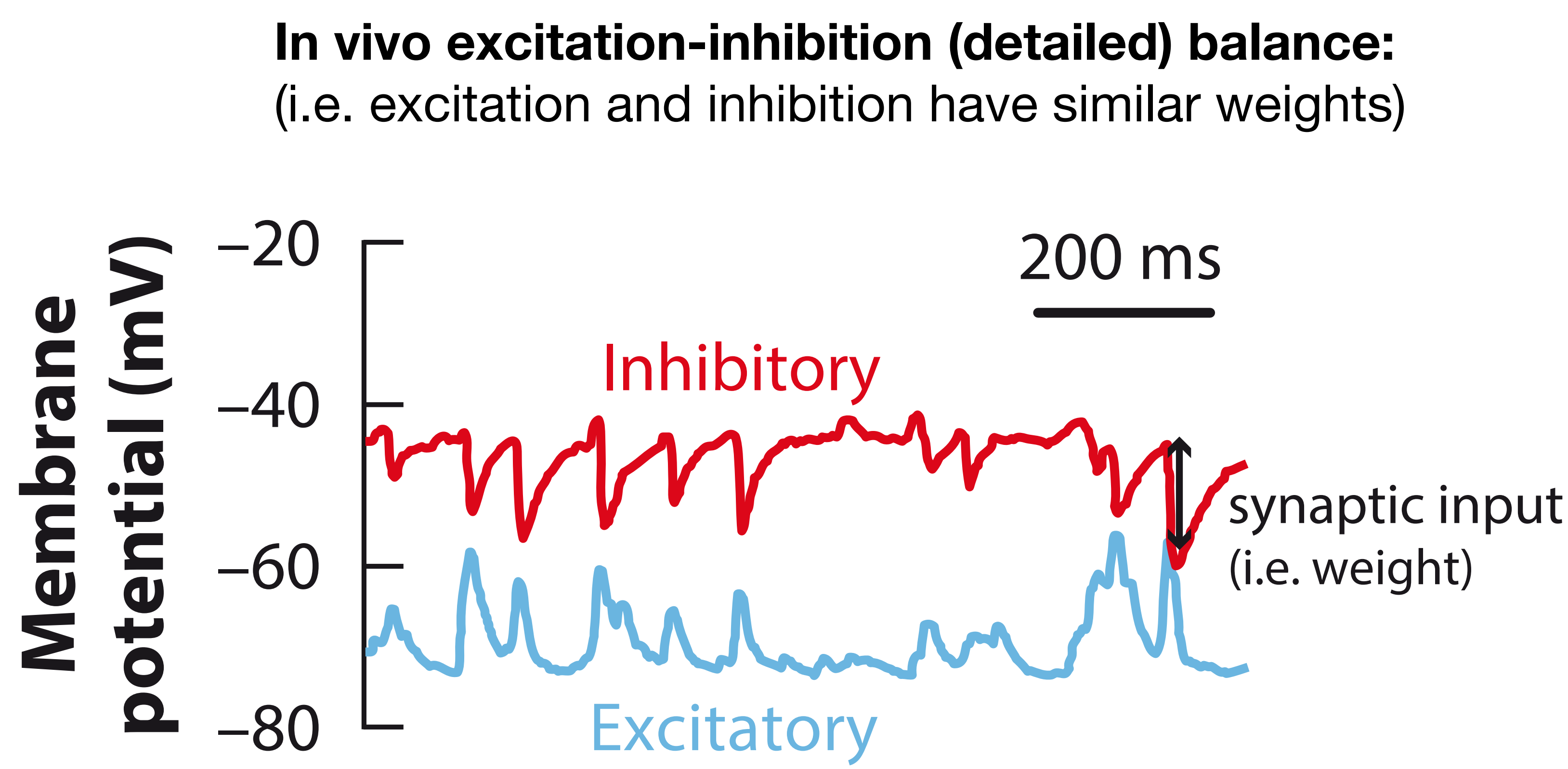


Inhibitory neurons act as gates:



Hennequin et al. review (2017)

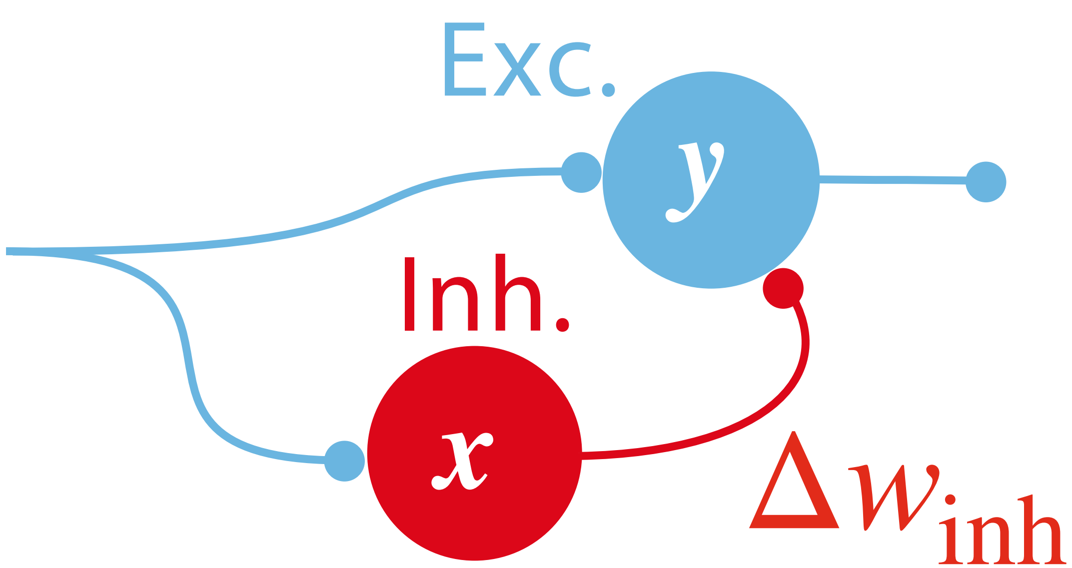
The excitatory and inhibitory dance



Okun and Lampl Nat. Neurosci. (2008)

Hennequin et al. review (2017)

Learning to balance excitation and inhibition



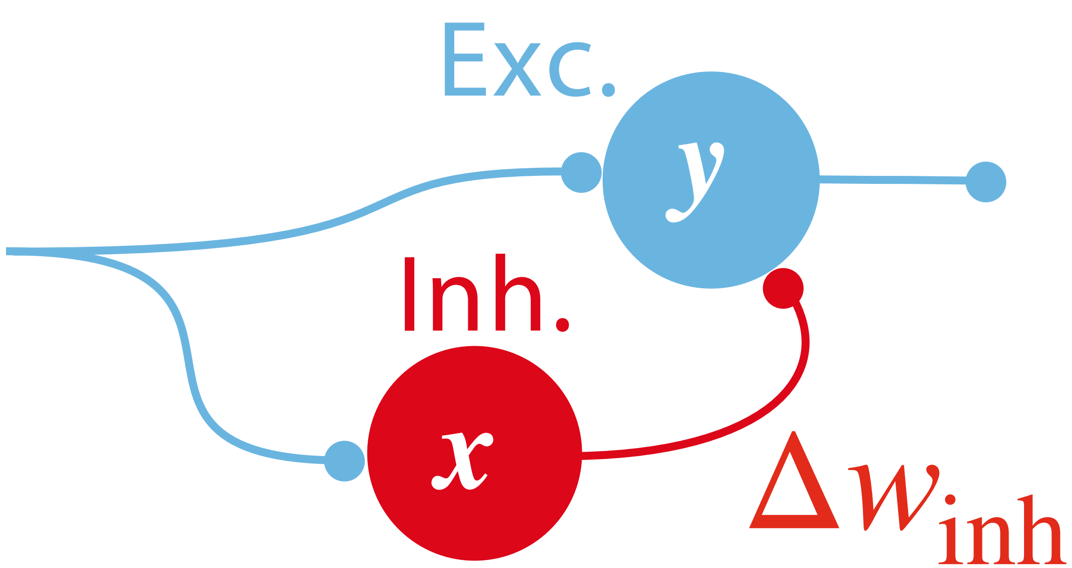
Inhibitory learning rule:

$$\Delta w_{\mathrm{inh}} = \eta x (y - r_0)$$

target rate

Vogels et al. Science (2011)

Learning to balance excitation and inhibition



Inhibitory learning rule:

$$\Delta w_{\text{inh}} = \eta x(y - r_0)$$

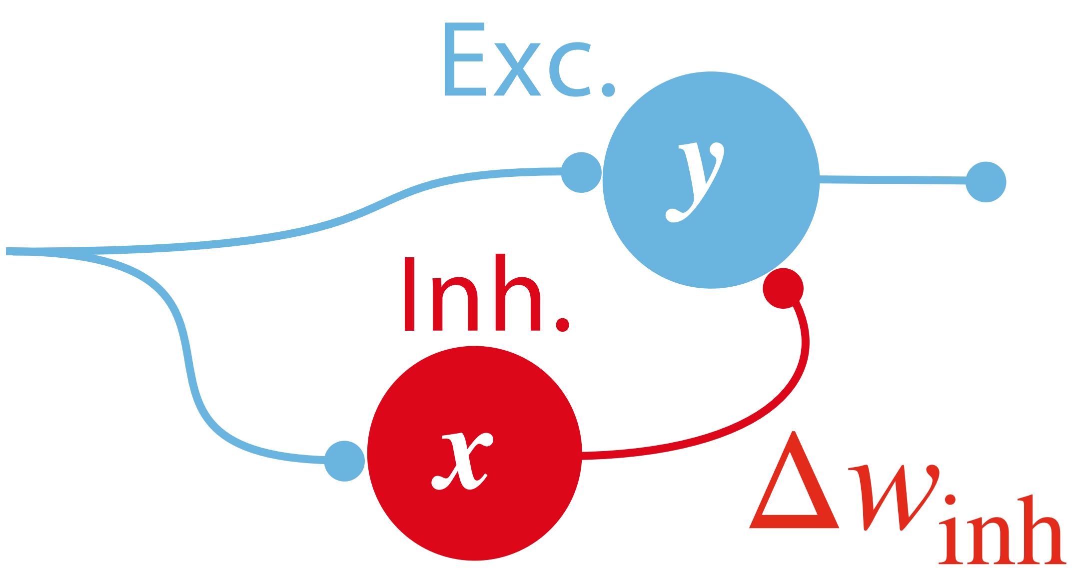
$$0 = \eta x(y - r_0)$$

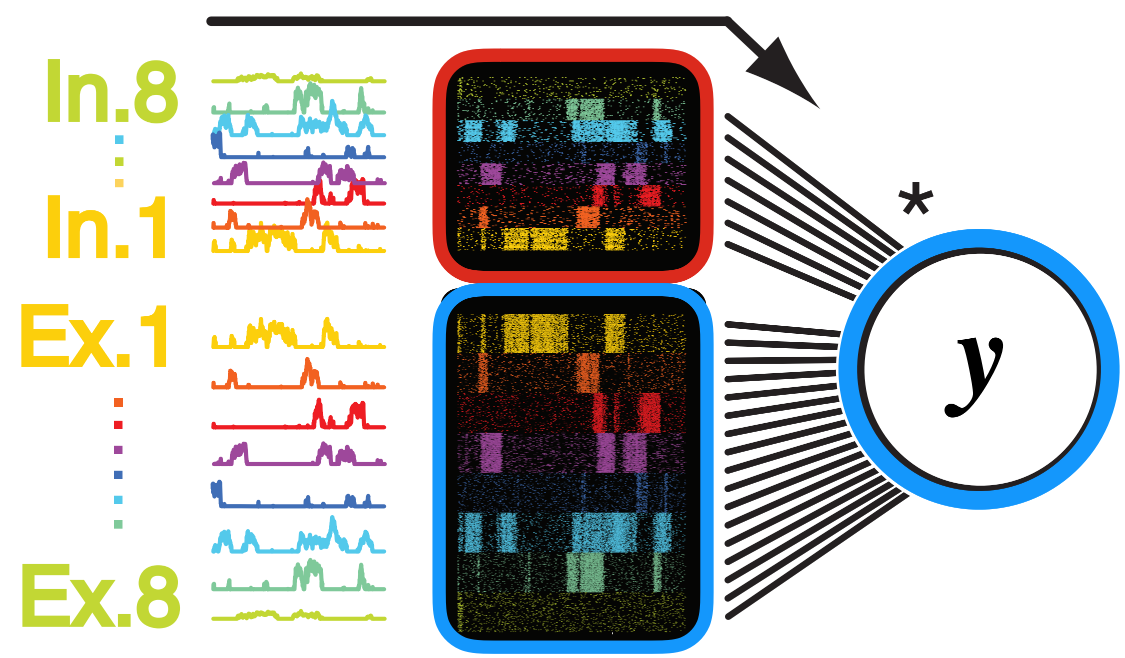
$$y = r_0$$

postsynaptic neuron, *y* = target rate (*r_0*)

Vogels et al. Science (2011)

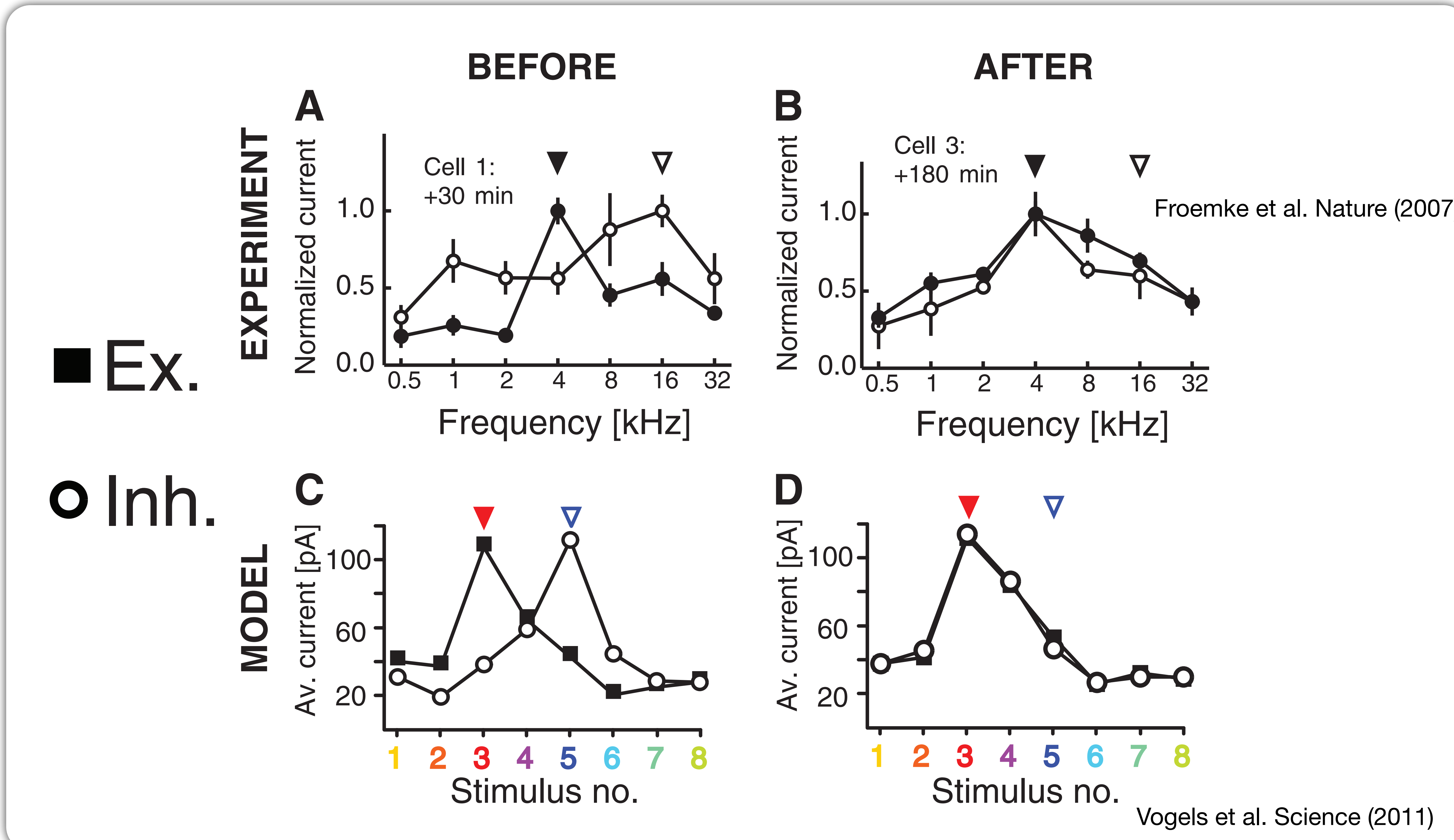
Learning to balance excitation and inhibition



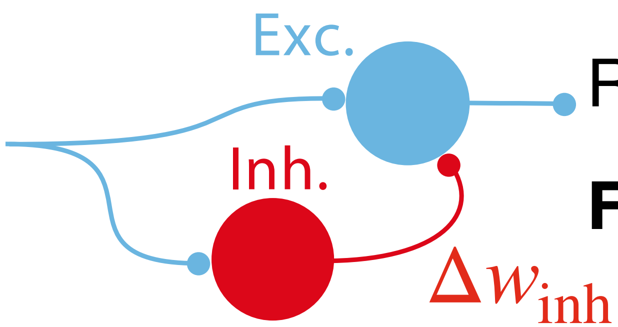


Vogels et al. Science (2011)

Inhibitory plasticity balances receptive fields



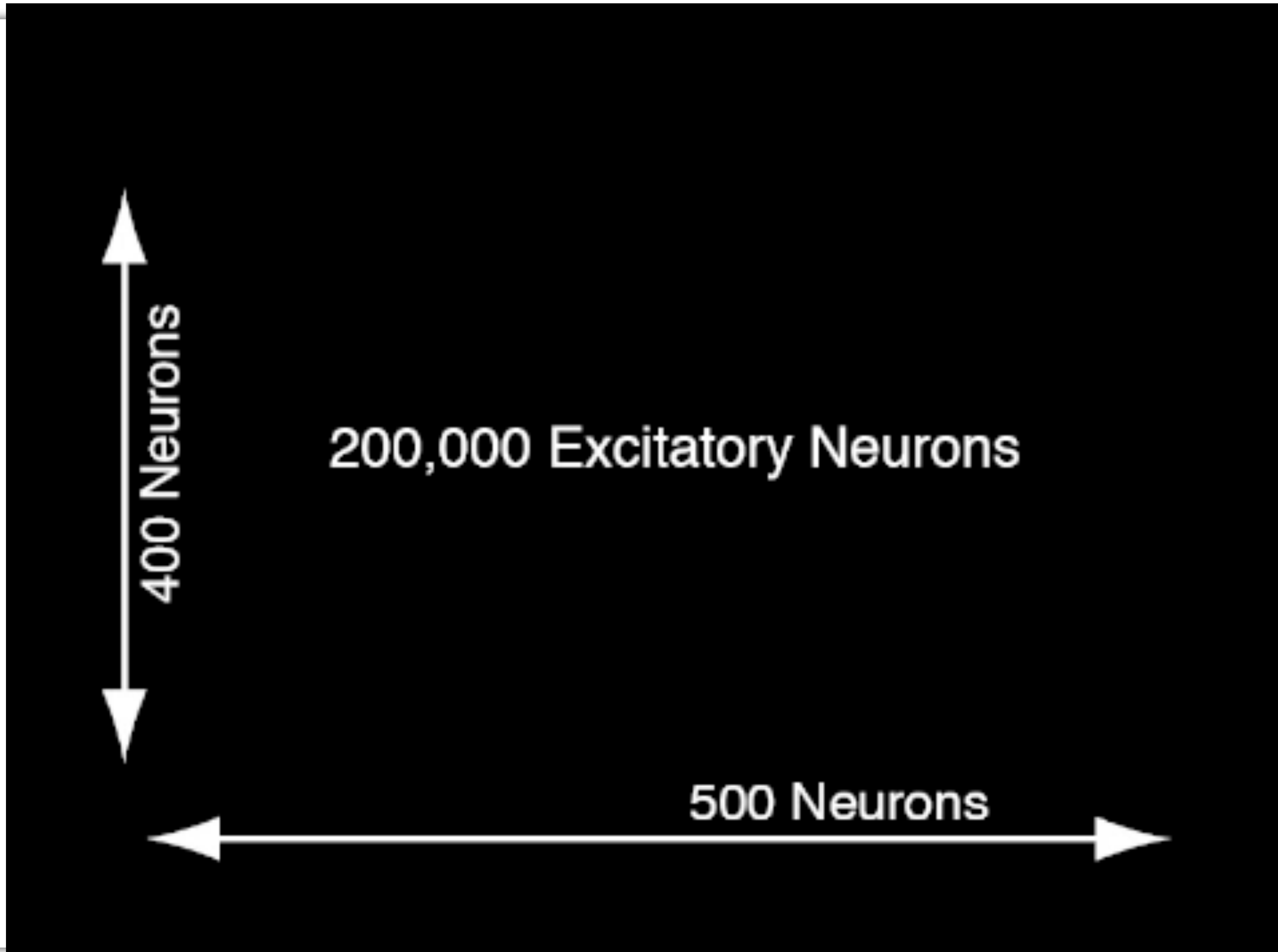
Inhibitory balance in a recurrent neural network



Recurrent network: 200 000 exc. neurons + ~40 000 inh. neurons

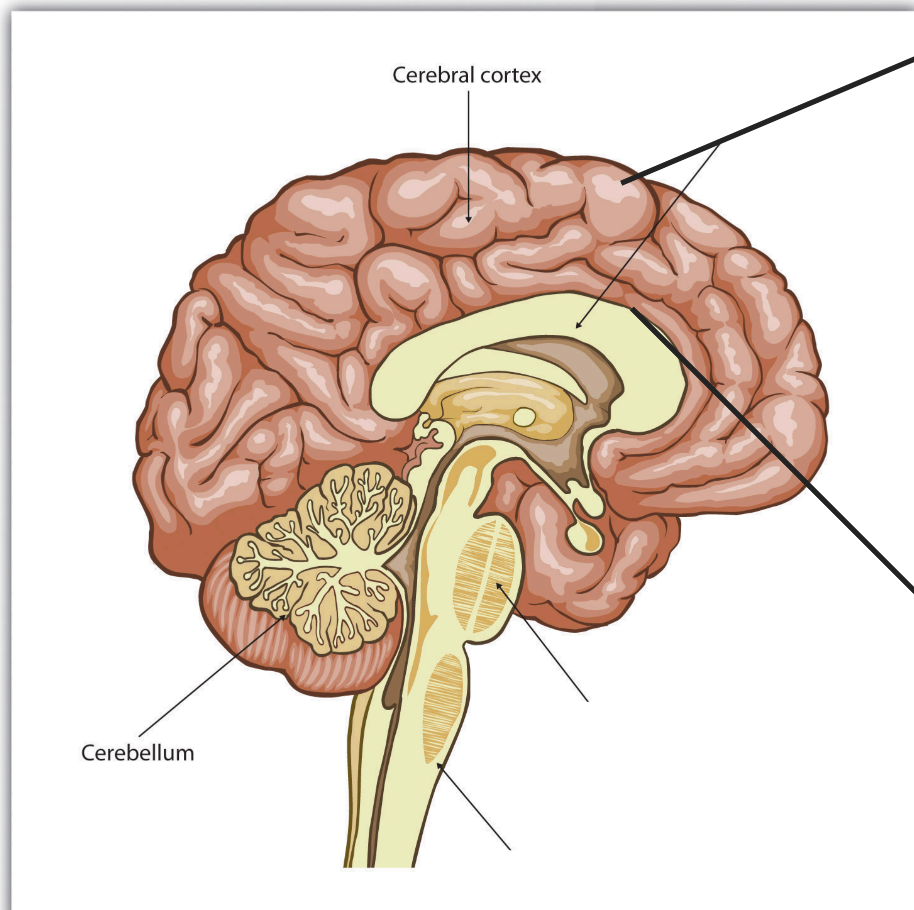
Features: keeps activity under control (homeostasis) and memories hidden

Vogels et al. Science (2011)



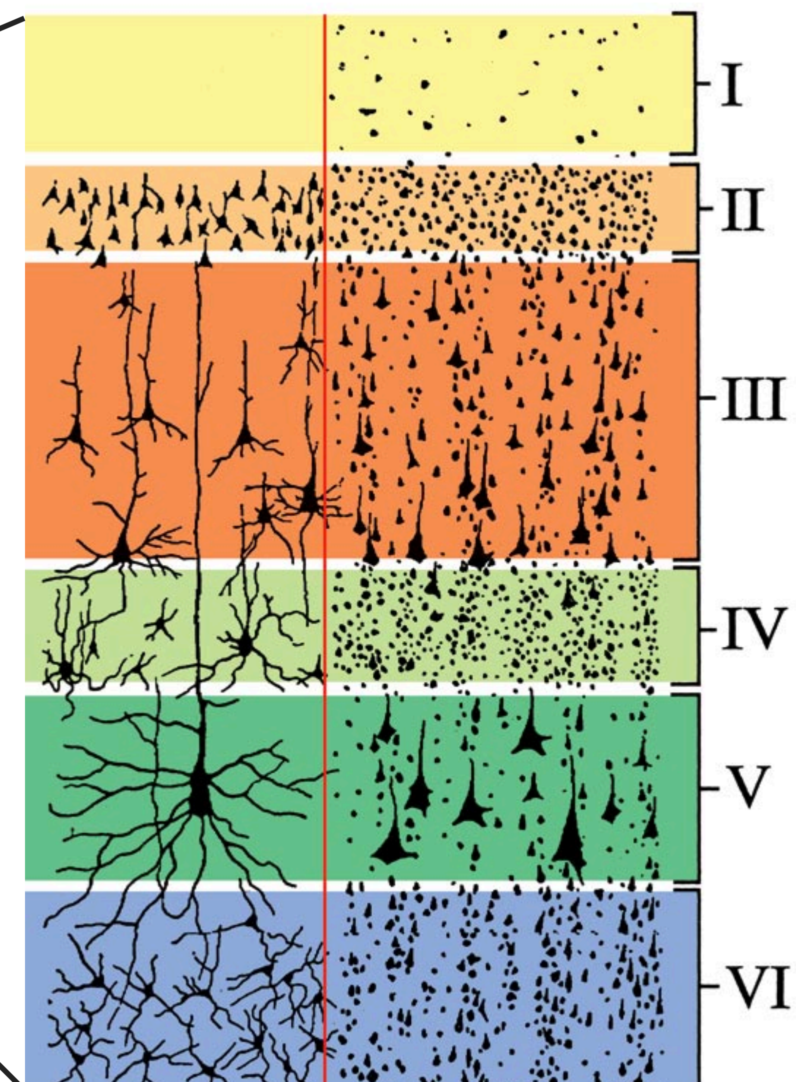
But cortical circuits are way more complicated..

The six neocortical layers



Introduction to Psychology 2015; lib.umn.edu

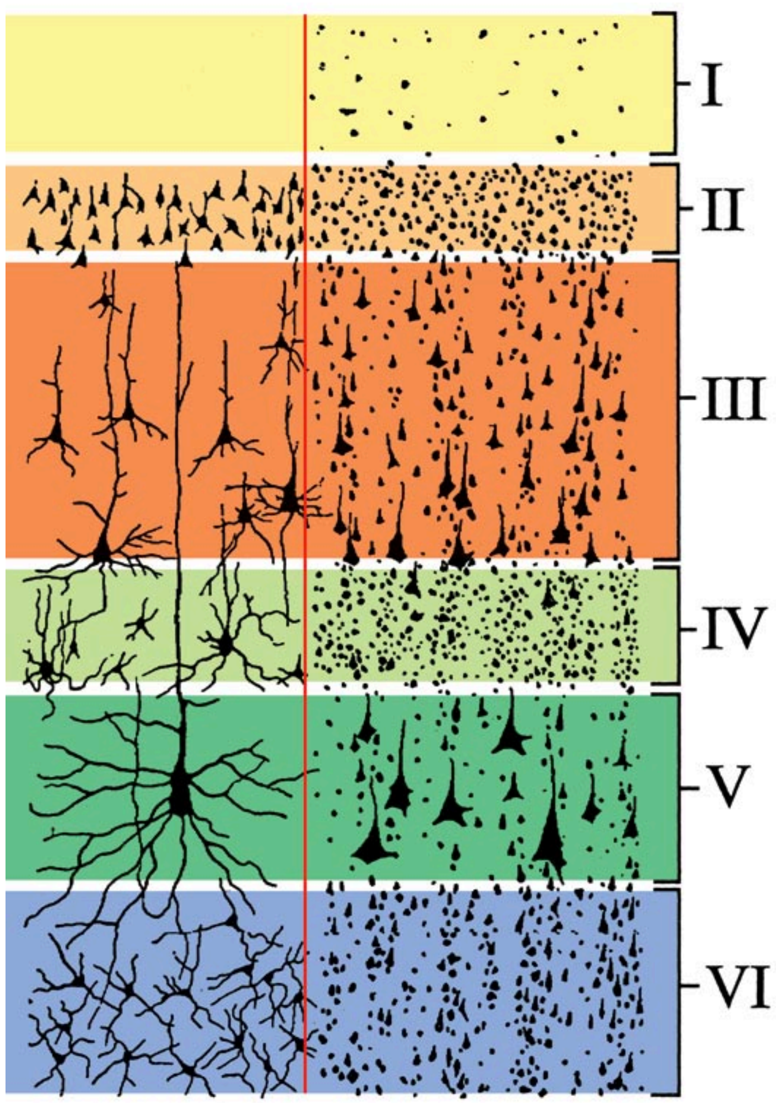
Neocortical layers



vanat.cvm.umn.edu/brain18

Why so much (apparent) complexity?

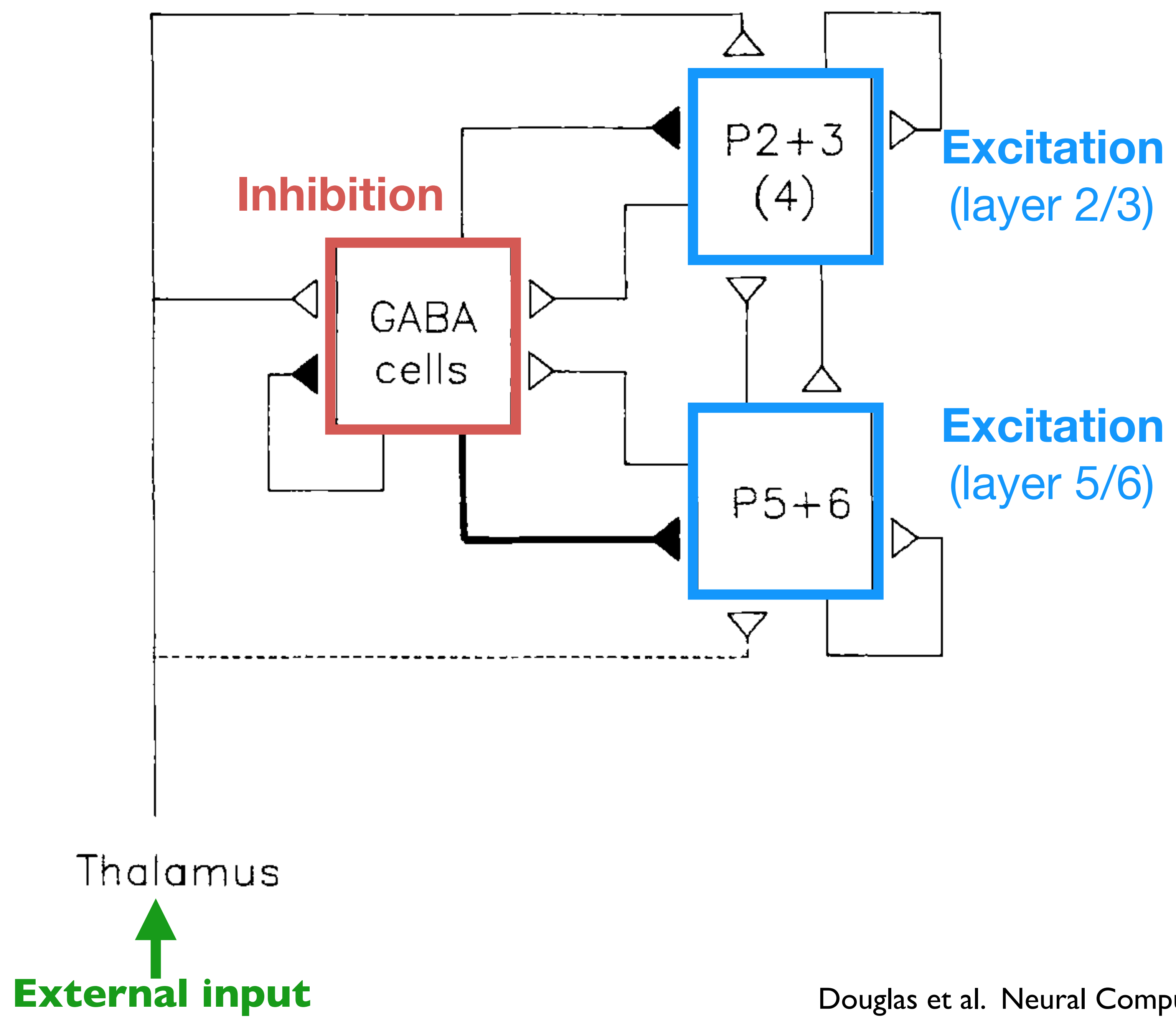
Layers



Hmm.. what's the neural basis of intelligence?

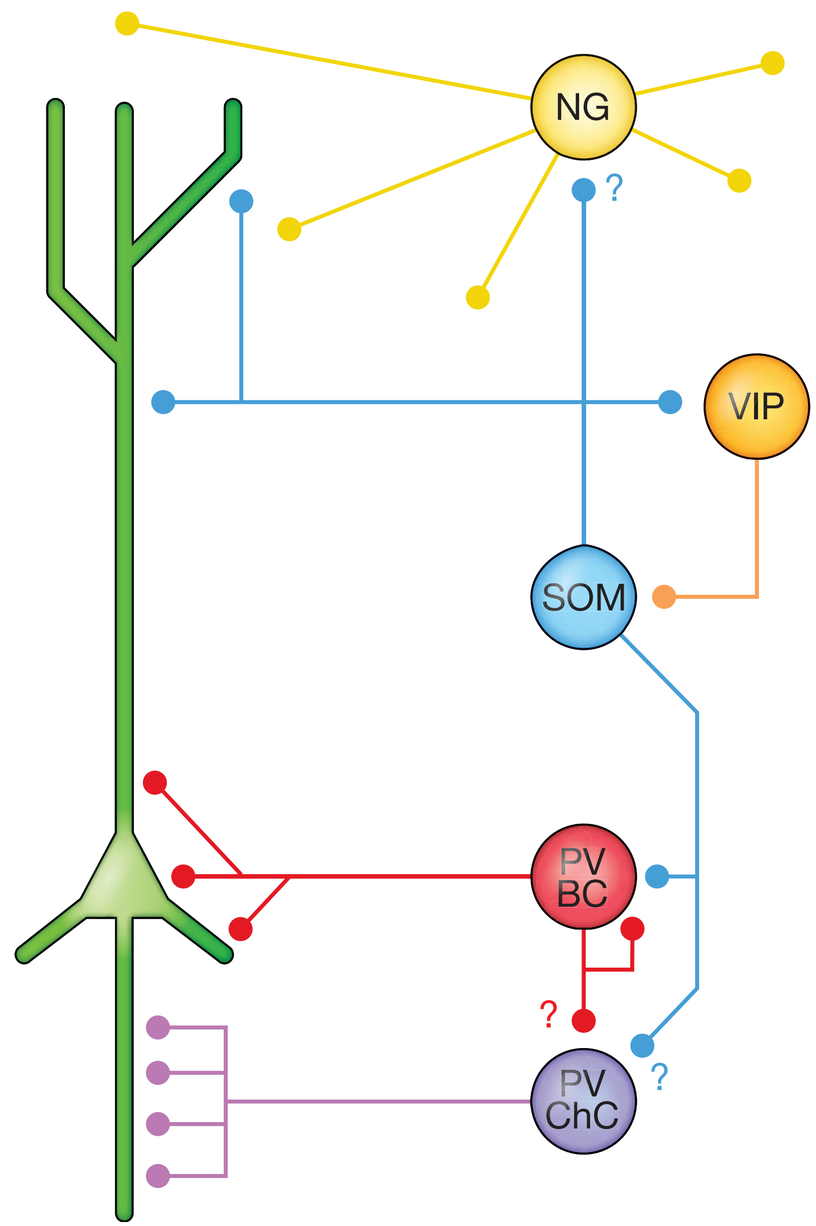
Ramon y Cajal

Structure of cortical microcircuits: canonical view



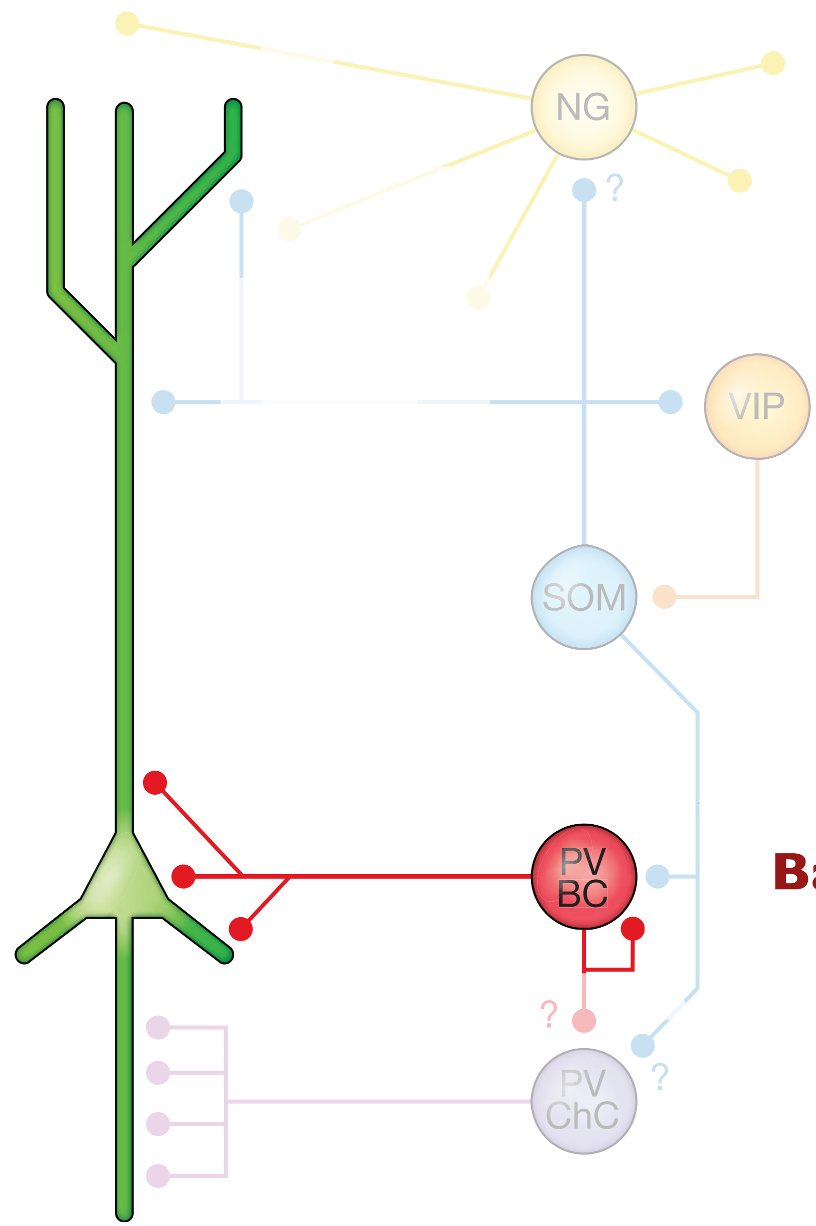
Douglas et al. Neural Computation 1989

Structure of cortical microcircuits:
inhibitory cells (gates)



Harris and Mrsic-Flogel. Nature Review 2013

Structure of cortical microcircuits:
inhibitory cells (gates)



Basket cells (~50% of INs)

Harris and Mrsic-Flogel. Nature Review 2013

Vogels and Abbott NatNeurosci. 2009

Machine learning recurrent neural networks: long short-term memory (LSTM)

- **LSTMs are state-of-the-art** (or close to) **in:**
  - Language modelling (Melis et al. 2017)
  - Caption generation (Lu et al. 2016)
  - Speech recognition (Chan et al. 2016)
  - Machine Translation (Luong et al,. 2015)
  - With new impressive applications every week

Hochreiter and Schmidhuber,
Neural Computation,(1997)

Machine learning recurrent neural networks: long short-term memory (LSTM)

- **LSTMs are state-of-the-art** (or close to) **in:**
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  - Speech recognition (Chan et al. 2016)
  - Machine Translation (Luong et al,. 2015)
  - With new impressive applications every week

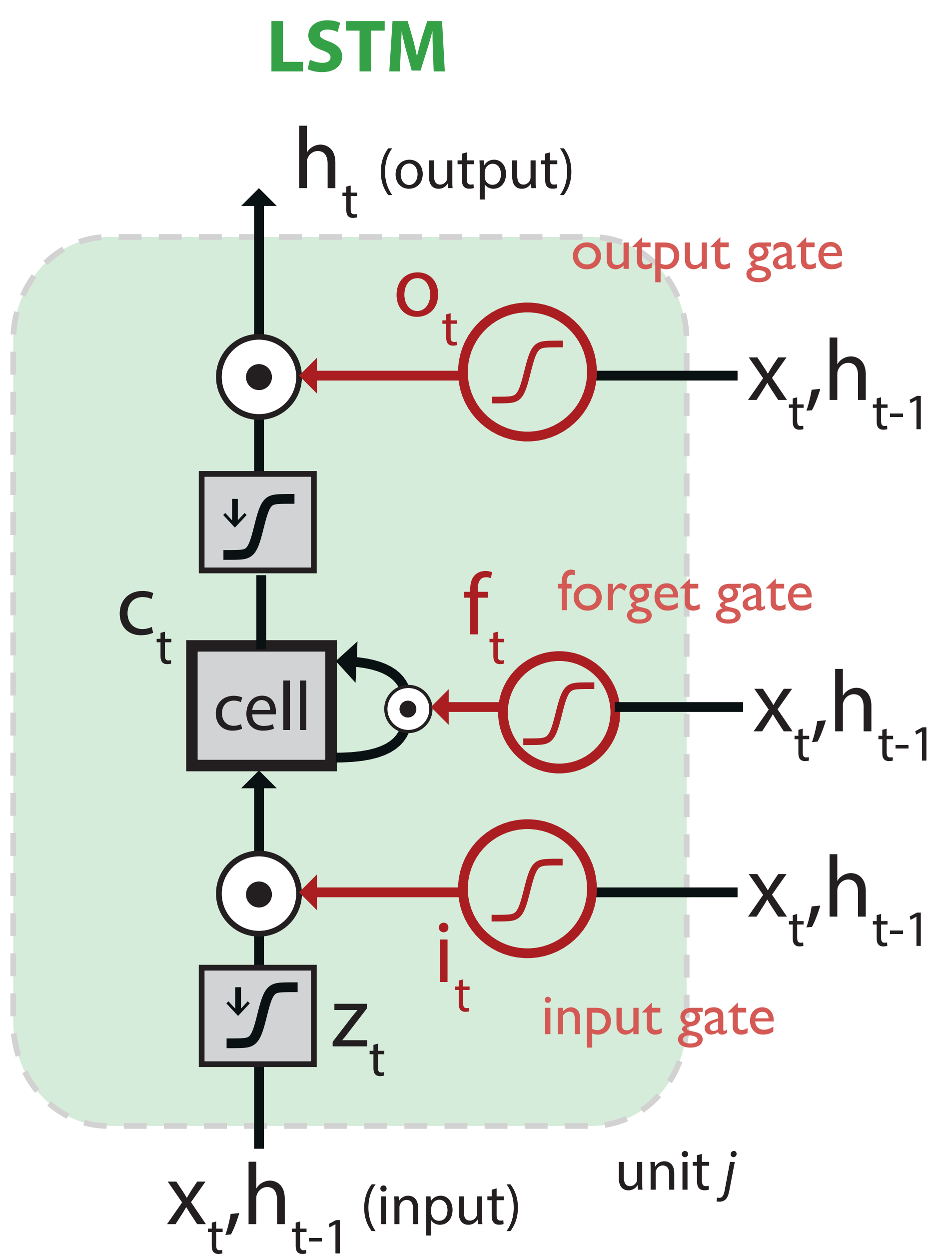
- **At the core of industry applications:**
  - Siri (Apple)
  - Translate (Google)
  - Alexa (Amazon)

Hochreiter and Schmidhuber,
Neural Computation,(1997)

Long short-term memory (LSTM)

Captures long and short-term dependencies!

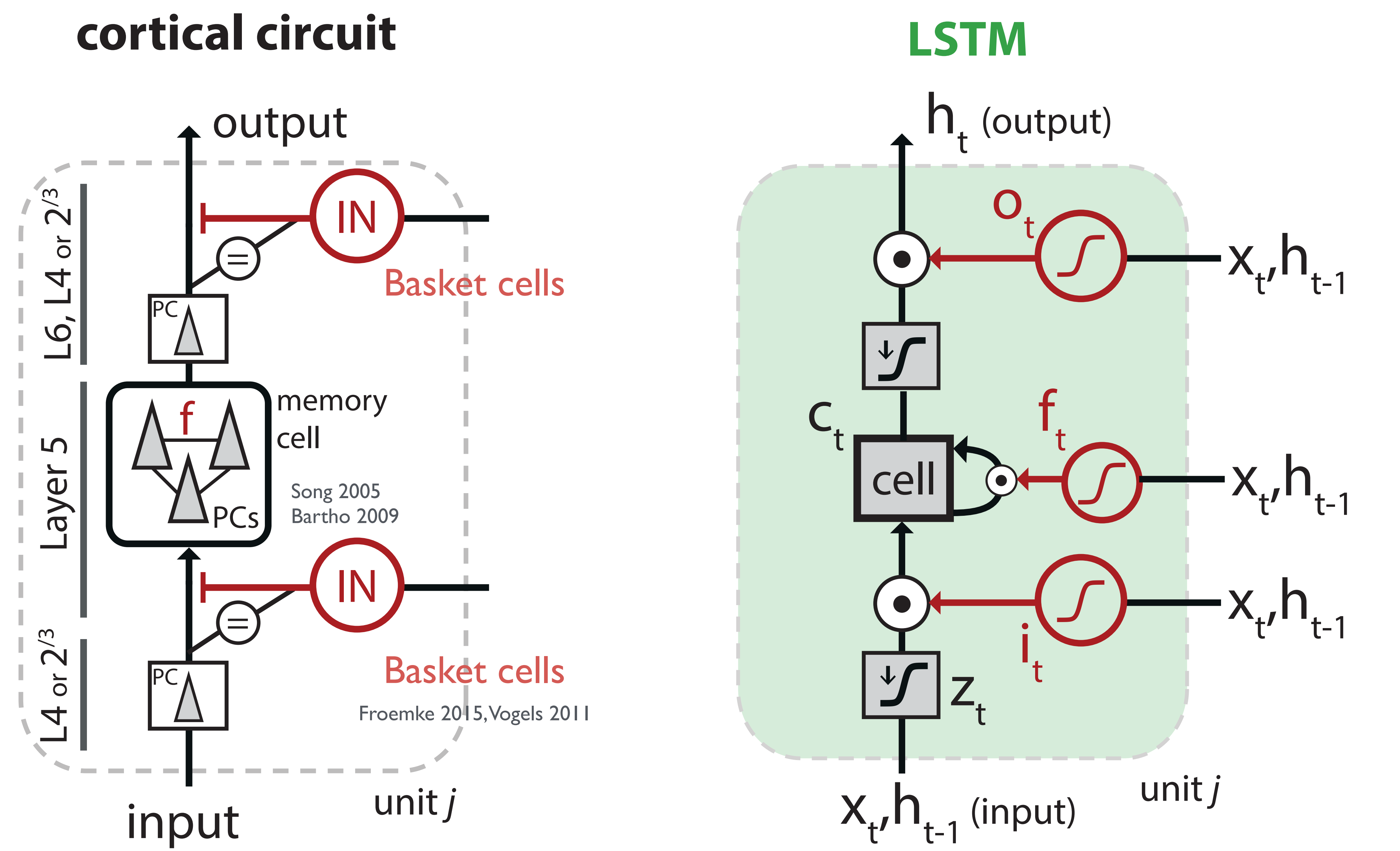
memory cell, c_t



⊙ denotes element-wise multiplication

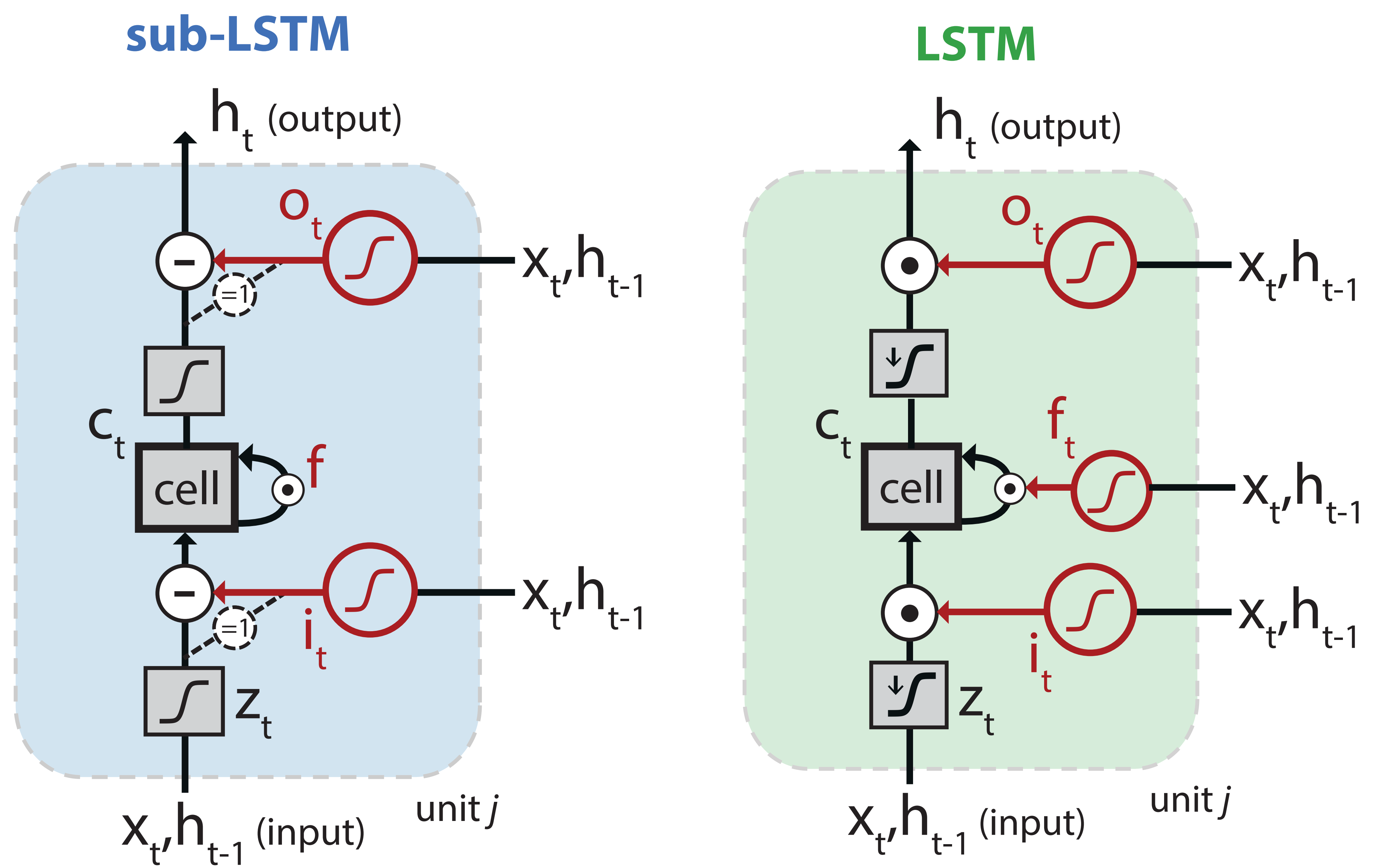
Hochreiter and Schmidhuber, Neural Computation,(1997)

Cortical circuits vs LSTMs



Costa et al. NIPS 2017

Cortical circuits vs LSTMs



Note: blue now represents subtractive gating

Costa et al. NIPS 2017

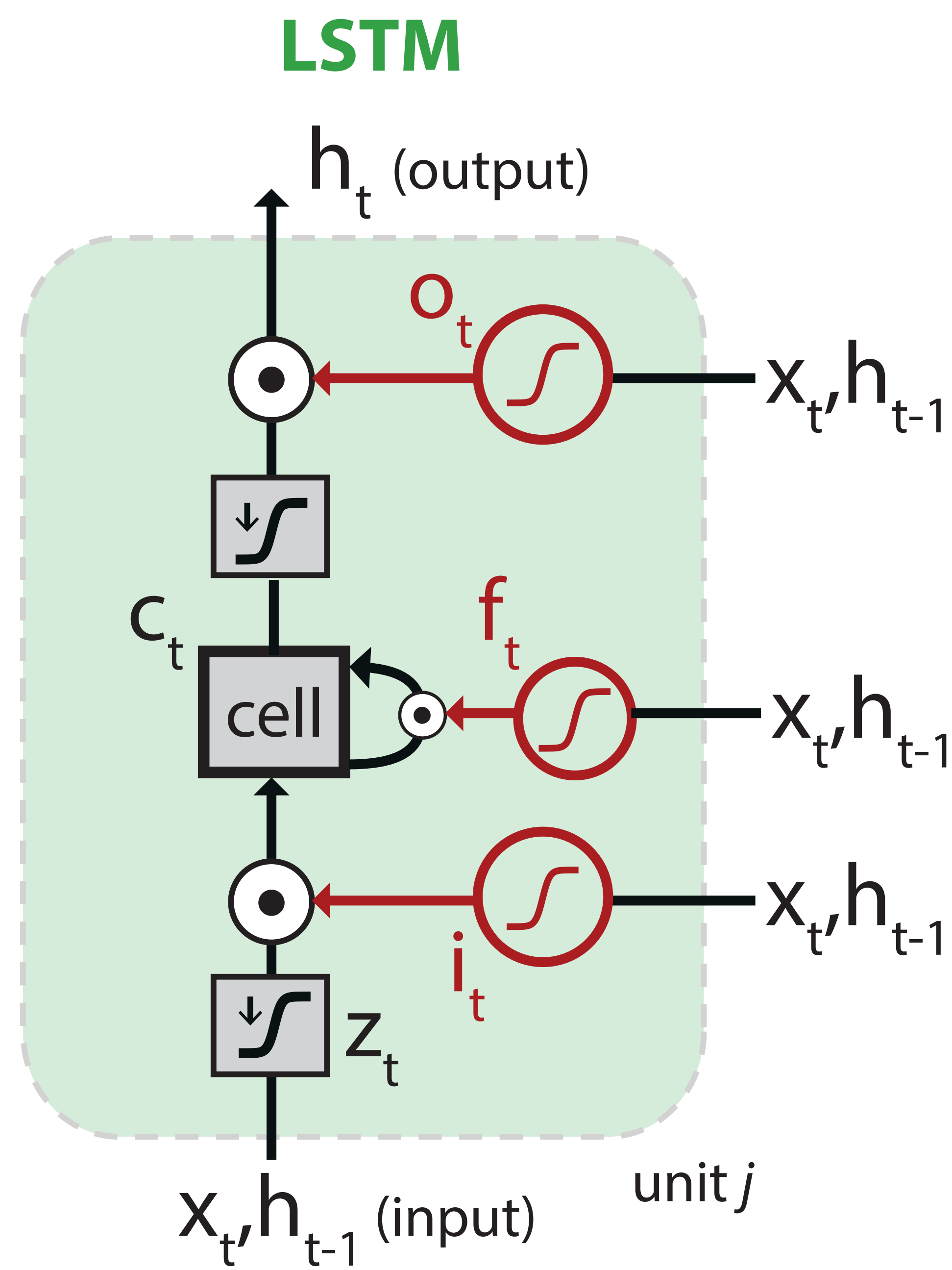
Quiz time!

Please go to BB
and solve quiz 7.

It should take you just a couple of minutes.

subtractive LSTMs

$$[\mathbf{f}_t, \mathbf{o}_t, \mathbf{i}_t]^T = \quad \boxed{\textbf{LSTM}} \quad \sigma(W\mathbf{x}_t + R\mathbf{h}_{t-1} + \mathbf{b}),$$



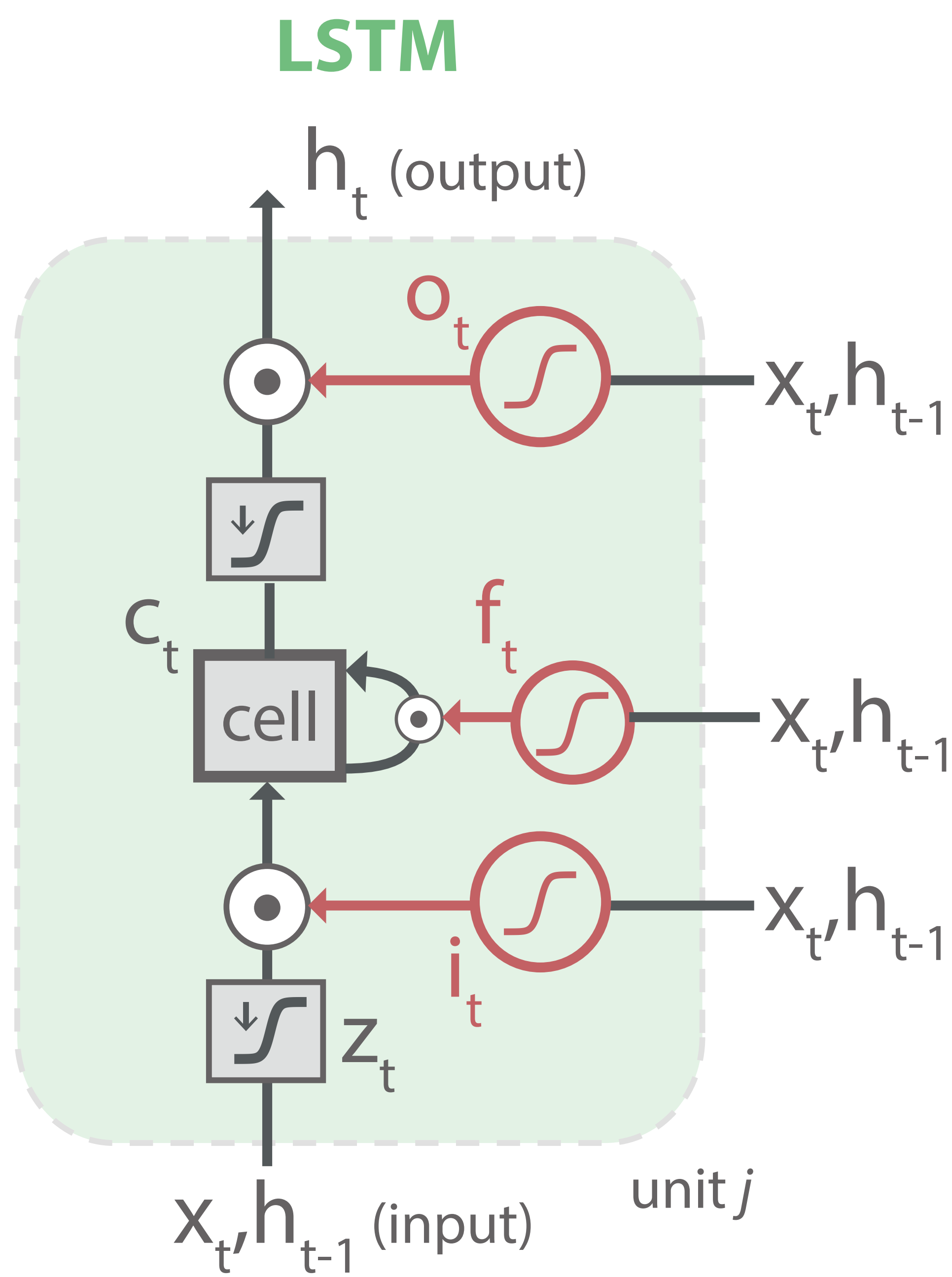
Costa et al. NIPS 2017

subtractive LSTMs

LSTM

$$[\mathbf{f}_t, \mathbf{o}_t, \mathbf{i}_t]^T = \sigma(W\mathbf{x}_t + R\mathbf{h}_{t-1} + \mathbf{b}),$$

$$\mathbf{z}_t = \tanh(W\mathbf{x}_t + R\mathbf{h}_{t-1} + \mathbf{b}),$$

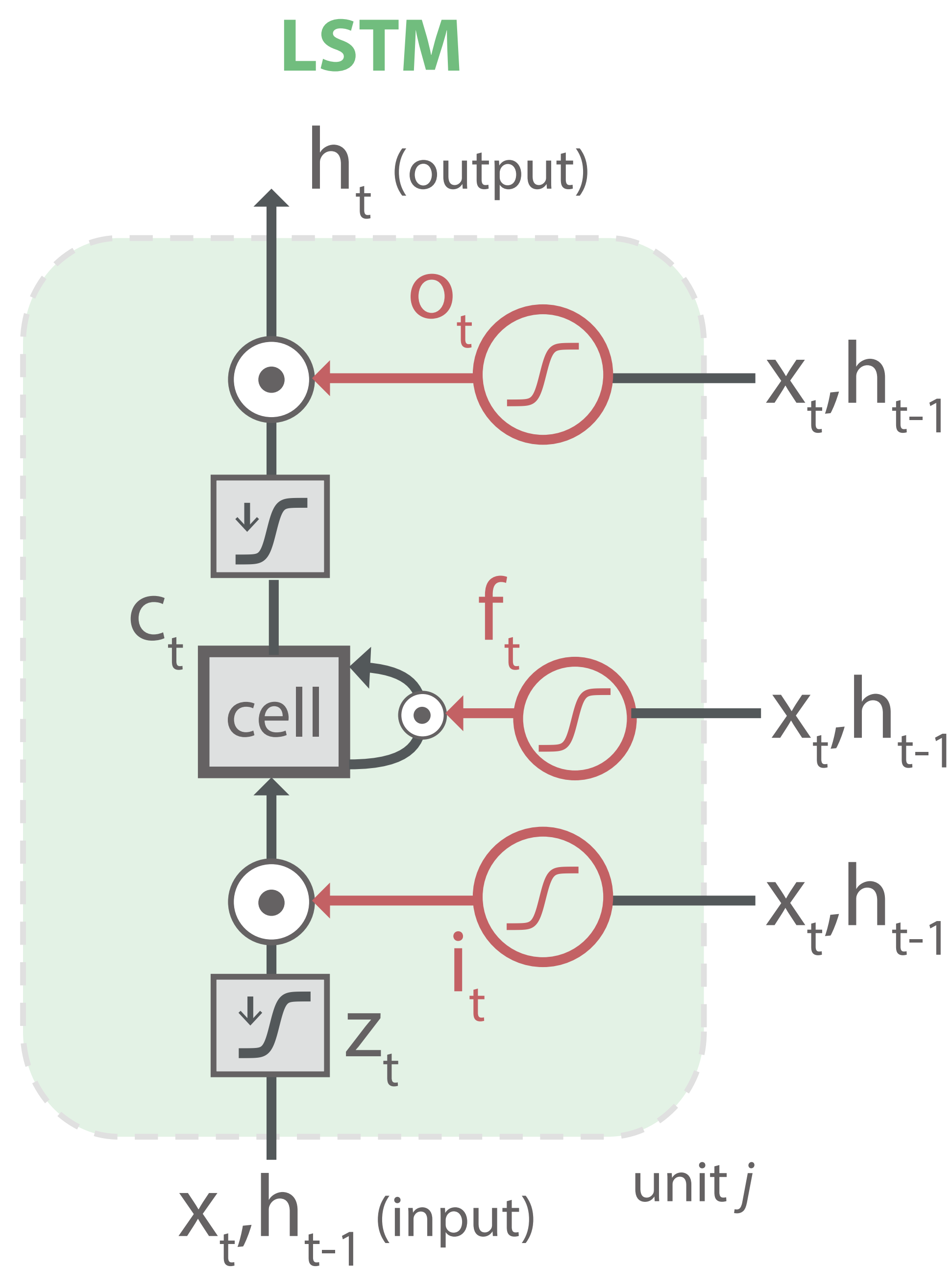


Costa et al. NIPS 2017

subtractive LSTMs

$\boxed{\textbf{LSTM}}$

$$
\begin{aligned}
[\mathbf{f}_t, \mathbf{o}_t, \mathbf{i}_t]^T &= \sigma(W\mathbf{x}_t + R\mathbf{h}_{t-1} + \mathbf{b}), \\
\mathbf{z}_t &= \tanh(W\mathbf{x}_t + R\mathbf{h}_{t-1} + \mathbf{b}), \\
\mathbf{c}_t &= \mathbf{c}_{t-1} \odot \mathbf{f}_t + \mathbf{z}_t \odot \mathbf{i}_t,
\end{aligned}
$$

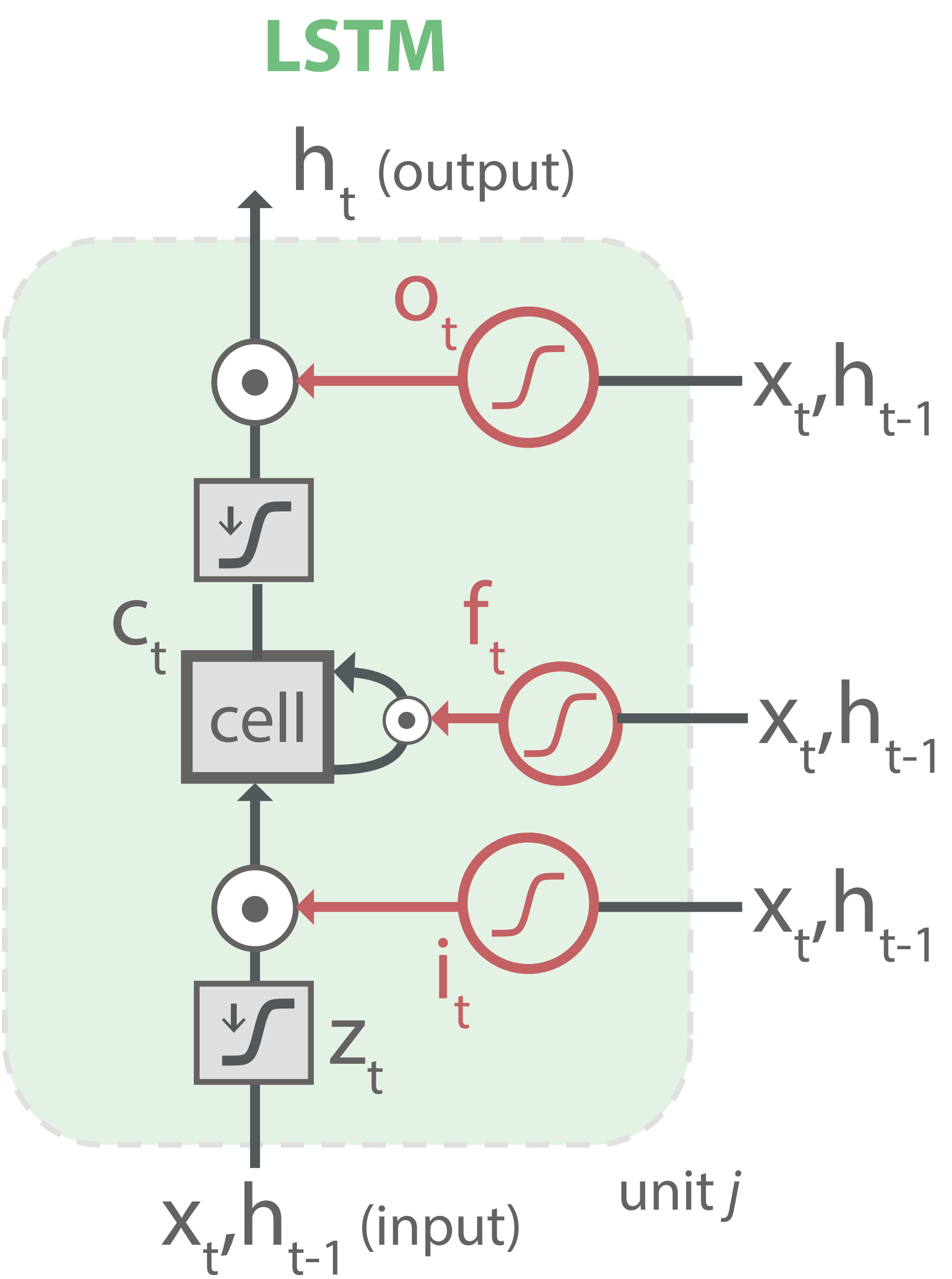


Costa et al. NIPS 2017

subtractive LSTMs

$$\boxed{\textbf{LSTM}}$$

$$
\begin{aligned}
[\mathbf{f}_t, \mathbf{o}_t, \mathbf{i}_t]^T &= \sigma(W\mathbf{x}_t + R\mathbf{h}_{t-1} + \mathbf{b}), \\
\mathbf{z}_t &= \tanh(W\mathbf{x}_t + R\mathbf{h}_{t-1} + \mathbf{b}), \\
\mathbf{c}_t &= \mathbf{c}_{t-1} \odot \mathbf{f}_t + \mathbf{z}_t \odot \mathbf{i}_t, \\
\mathbf{h}_t &= \tanh(\mathbf{c}_t) \odot \mathbf{o}_t.
\end{aligned}
$$

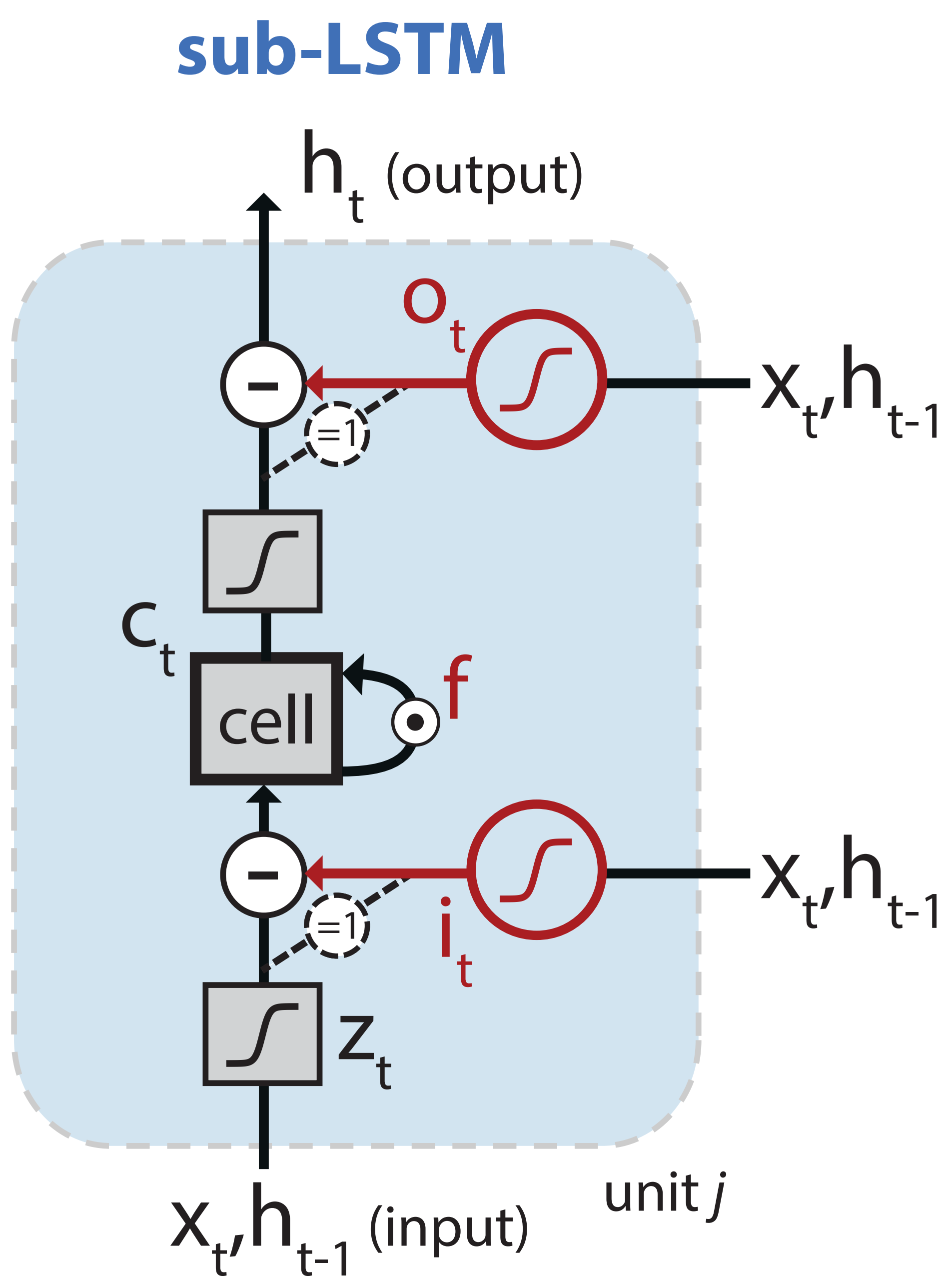


Costa et al. NIPS 2017

subtractive LSTMs

$\boxed{\textbf{subLSTM}}$

$$
\begin{aligned}
[\mathbf{f}_t, \mathbf{o}_t, \mathbf{i}_t]^T &= \sigma(W\mathbf{x}_t + R\mathbf{h}_{t-1} + \mathbf{b}), \\
\mathbf{z}_t &= \sigma(W\mathbf{x}_t + R\mathbf{h}_{t-1} + \mathbf{b}), \\
\mathbf{c}_t &= \mathbf{c}_{t-1} \odot \mathbf{f}_t + \mathbf{z}_t - \mathbf{i}_t, \\
\mathbf{h}_t &= \sigma(\mathbf{c}_t) - \mathbf{o}_t.
\end{aligned}
$$



Costa et al. NIPS 2017

subtractive LSTMs vs LSTMs

	subLSTM	LSTM
$[\mathbf{f}_t, \mathbf{o}_t, \mathbf{i}_t]^T =$	$\sigma(W\mathbf{x}_t + R\mathbf{h}_{t-1} + \mathbf{b}),$	$\sigma(W\mathbf{x}_t + R\mathbf{h}_{t-1} + \mathbf{b}),$
$\mathbf{z}_t =$	$\sigma(W\mathbf{x}_t + R\mathbf{h}_{t-1} + \mathbf{b}),$	$\tanh(W\mathbf{x}_t + R\mathbf{h}_{t-1} + \mathbf{b}),$
$\mathbf{c}_t =$	$\mathbf{c}_{t-1} \odot \mathbf{f}_t + \mathbf{z}_t - \mathbf{i}_t,$	$\mathbf{c}_{t-1} \odot \mathbf{f}_t + \mathbf{z}_t \odot \mathbf{i}_t,$
$\mathbf{h}_t =$	$\sigma(\mathbf{c}_t) - \mathbf{o}_t.$	$\tanh(\mathbf{c}_t) \odot \mathbf{o}_t.$

Costa et al. NIPS 2017

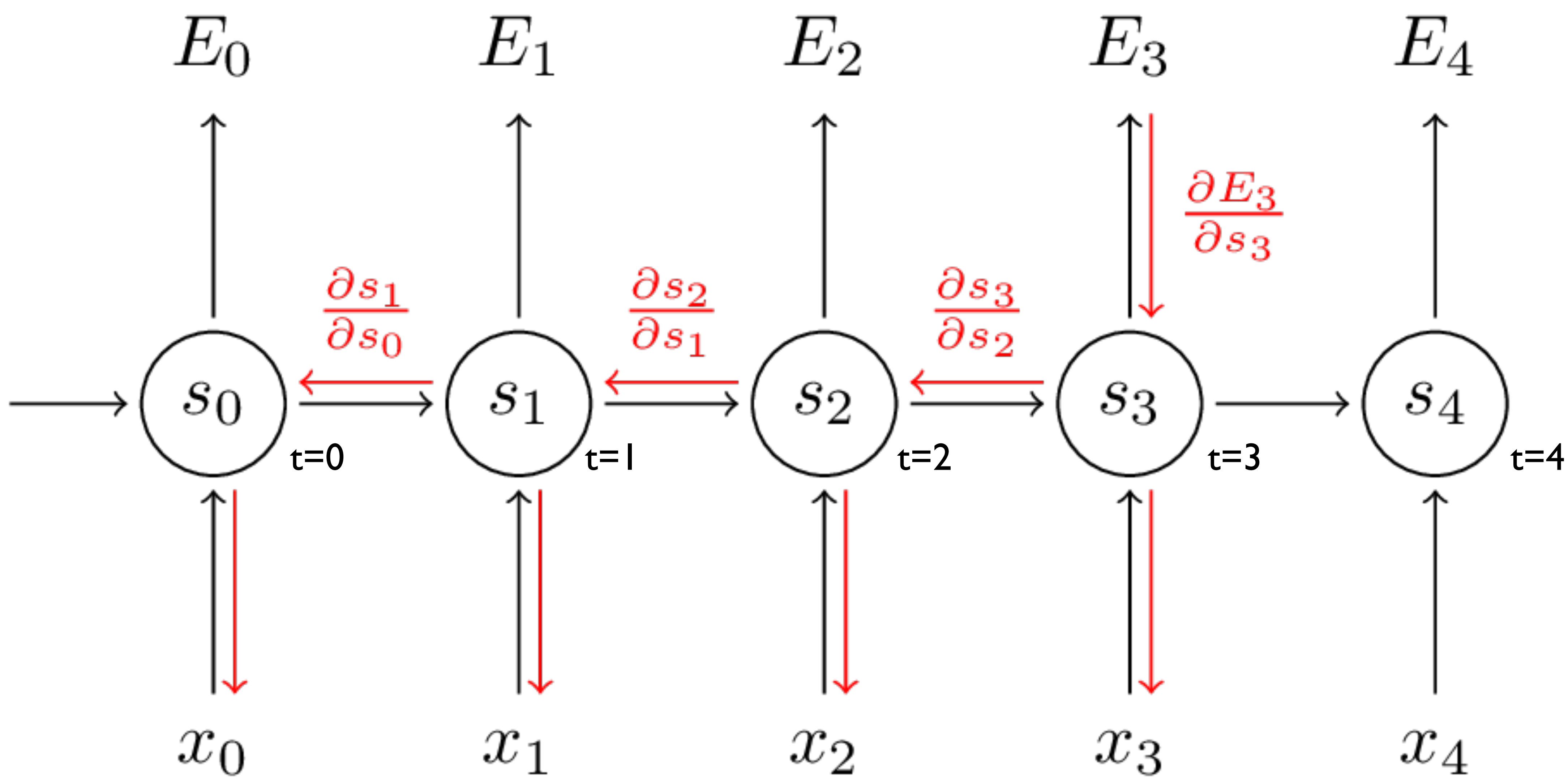
subtractive LSTMs vs LSTMs

	subLSTM	LSTM
$[\mathbf{f}_t, \mathbf{o}_t, \mathbf{i}_t]^T =$	$\sigma(W\mathbf{x}_t + R\mathbf{h}_{t-1} + \mathbf{b}),$	$\sigma(W\mathbf{x}_t + R\mathbf{h}_{t-1} + \mathbf{b}),$
$\mathbf{z}_t =$	$\sigma(W\mathbf{x}_t + R\mathbf{h}_{t-1} + \mathbf{b}),$	$\tanh(W\mathbf{x}_t + R\mathbf{h}_{t-1} + \mathbf{b}),$
$\mathbf{c}_t =$	$\mathbf{c}_{t-1} \odot \mathbf{f}_t + \boxed{\mathbf{z}_t - \mathbf{i}_t,}$	$\mathbf{c}_{t-1} \odot \mathbf{f}_t + \boxed{\mathbf{z}_t \odot \mathbf{i}_t,}$
$\mathbf{h}_t =$	$\boxed{\sigma(\mathbf{c}_t) - \mathbf{o}_t.}$	$\boxed{\tanh(\mathbf{c}_t) \odot \mathbf{o}_t.}$

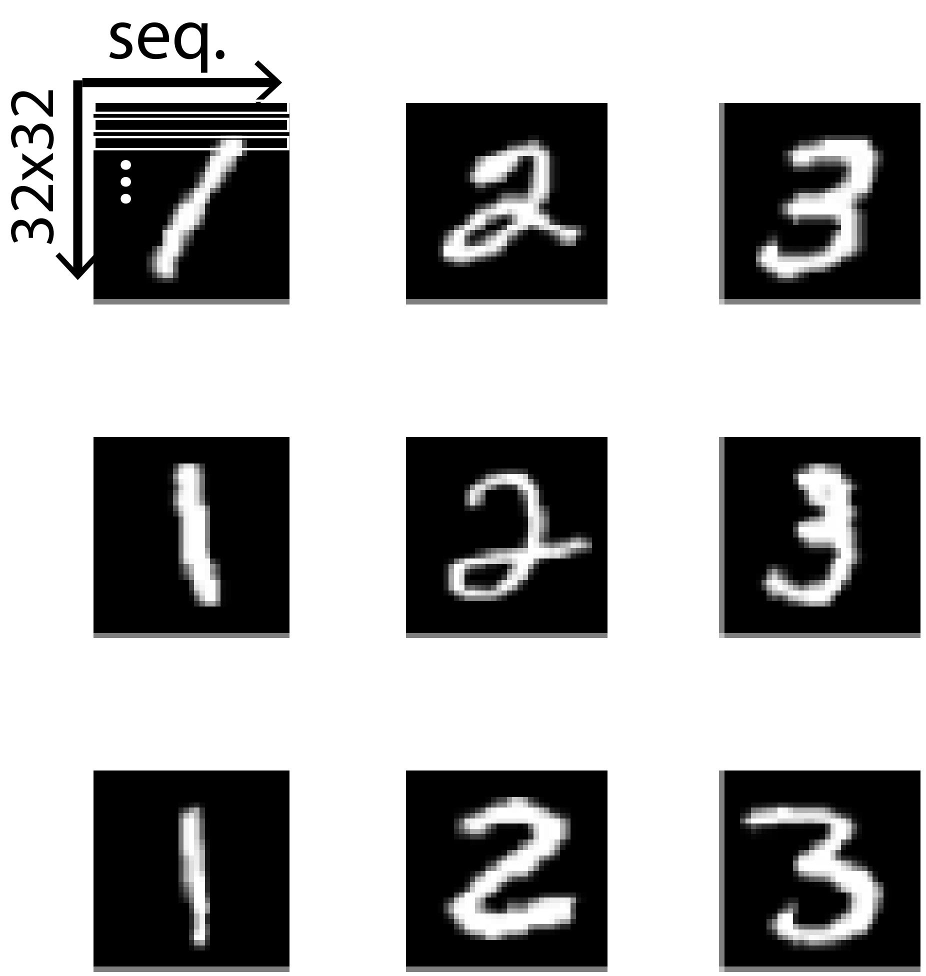
Costa et al. NIPS 2017

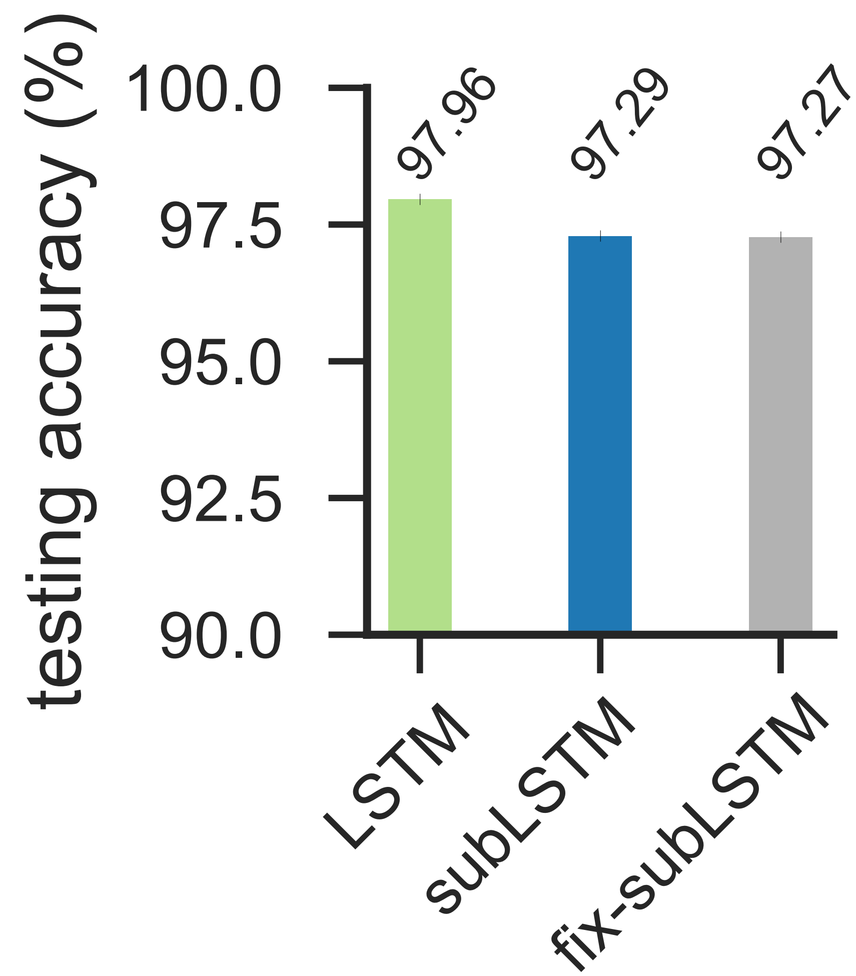
Gated RNNs are usually trained using BackPropagation Through Time (BPTT)

Similar to backprop, but now we unfold the network across time and backprop the gradients 'back in time' (each timestep is a layer).



Task 1: Pixel-by-pixel sequential MNIST (dataset of handwritten digits)





Costa et al. NIPS 2017

Task 2: Language modelling (word-based) Penn Treebank dataset

Penn Treebank dataset:
Training: 929k;   Validation: 73k;   Test: 82k;   Vocabulary: 10k

"…since then life has changed a lot for X"

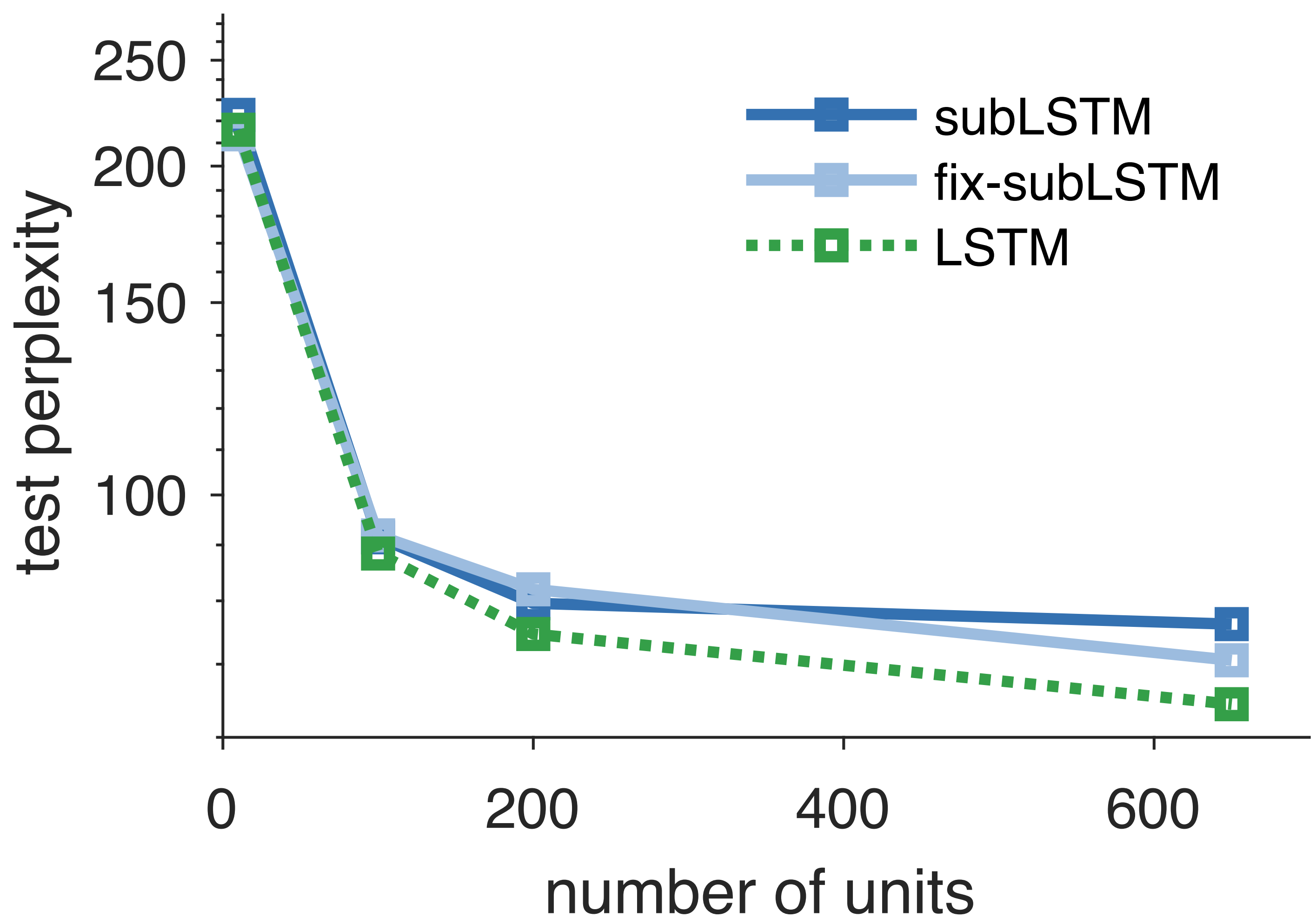
Costa et al. NIPS 2017

Task 2: Language modelling (word-based)
Penn Treebank dataset

Penn Treebank dataset:

Training: 929k; Validation: 73k; Test: 82k; Vocabulary: 10k

"...since then life has changed a lot for X"

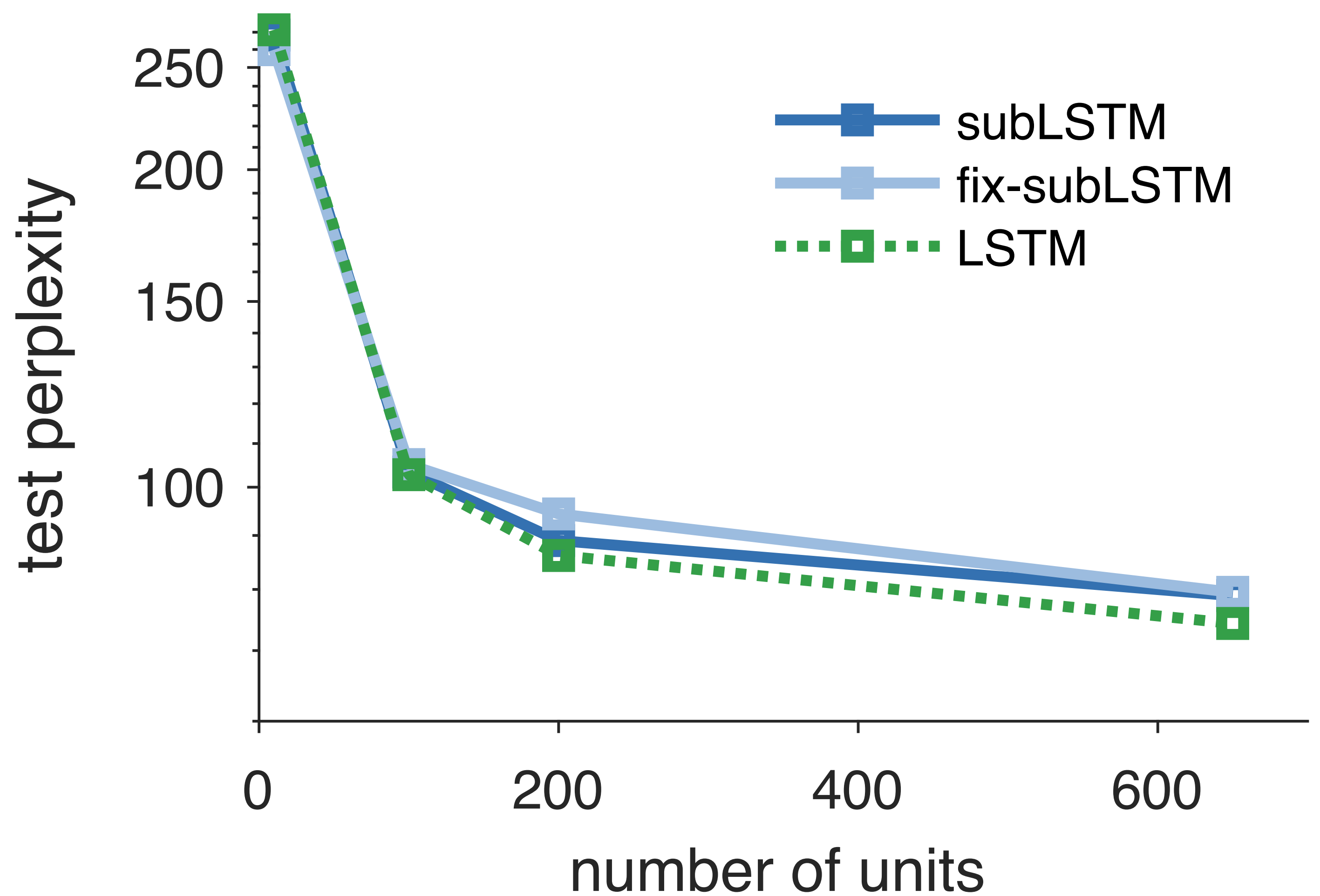


Costa et al. NIPS 2017

Task 3: Language modelling (word-based) Wikitext-2

Wikitext-2 dataset:

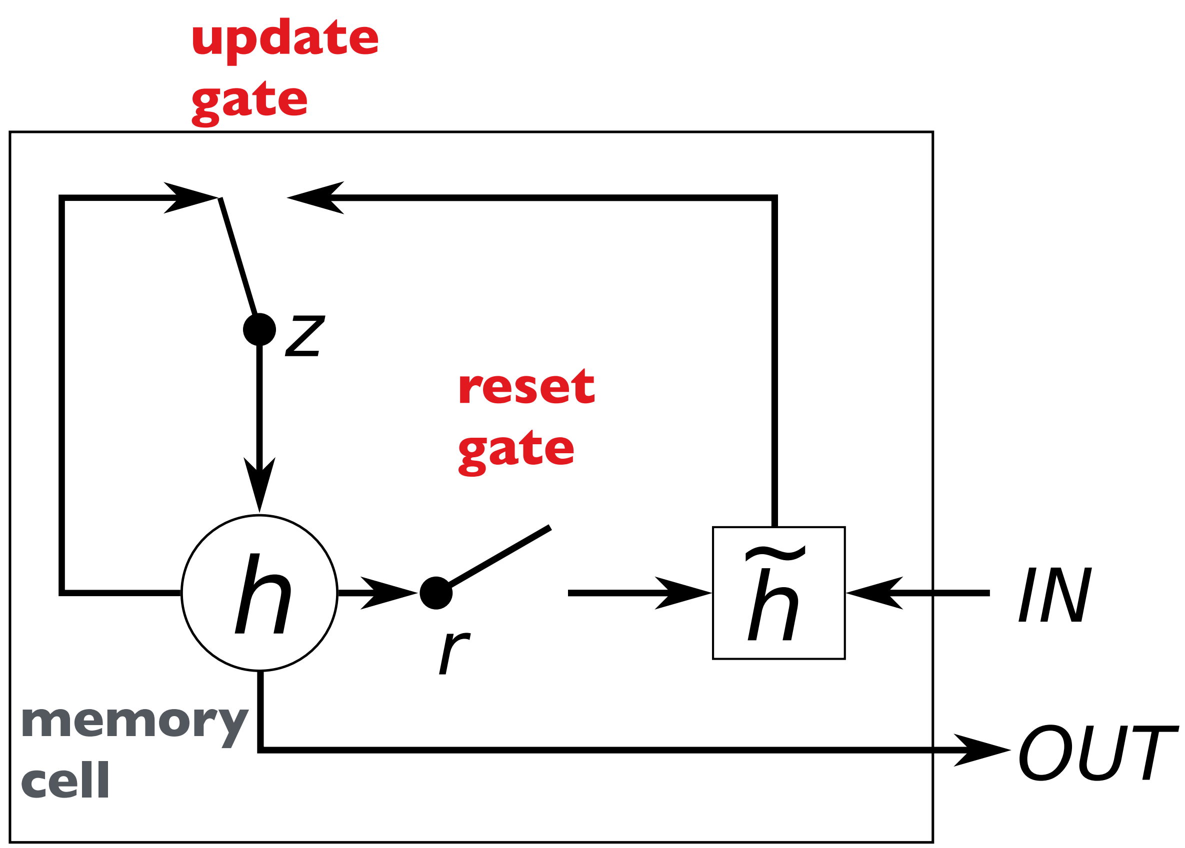
Training: 2000k; Validation: 217k; Test: 245k; Vocabulary: 33k



Costa et al. NIPS 2017

Gated recurrent units

There are other popular recurrent neural networks, such as the **gated recurrent units** (GRUs):



GRUs are simpler (less parameters) than LSTMs, and obtain competitive results in some tasks.

Chung et al. arXiv 2014

Summary

1. **Multiple excitatory and inhibitory cell types in the brain**

2. **Intricate microcircuits across multiple layers**

3. **Machine learning LSTMs are a form of gated-RNN good for capturing long-term dependencies** (e.g. language modelling)

4. **Cortical microcircuits have similar features to gated-RNNs but** (may) **operate with subtractive gating (subLSTMs)**

References

Text books:

Neuronal Dynamics: Gerstner et al. (2014)

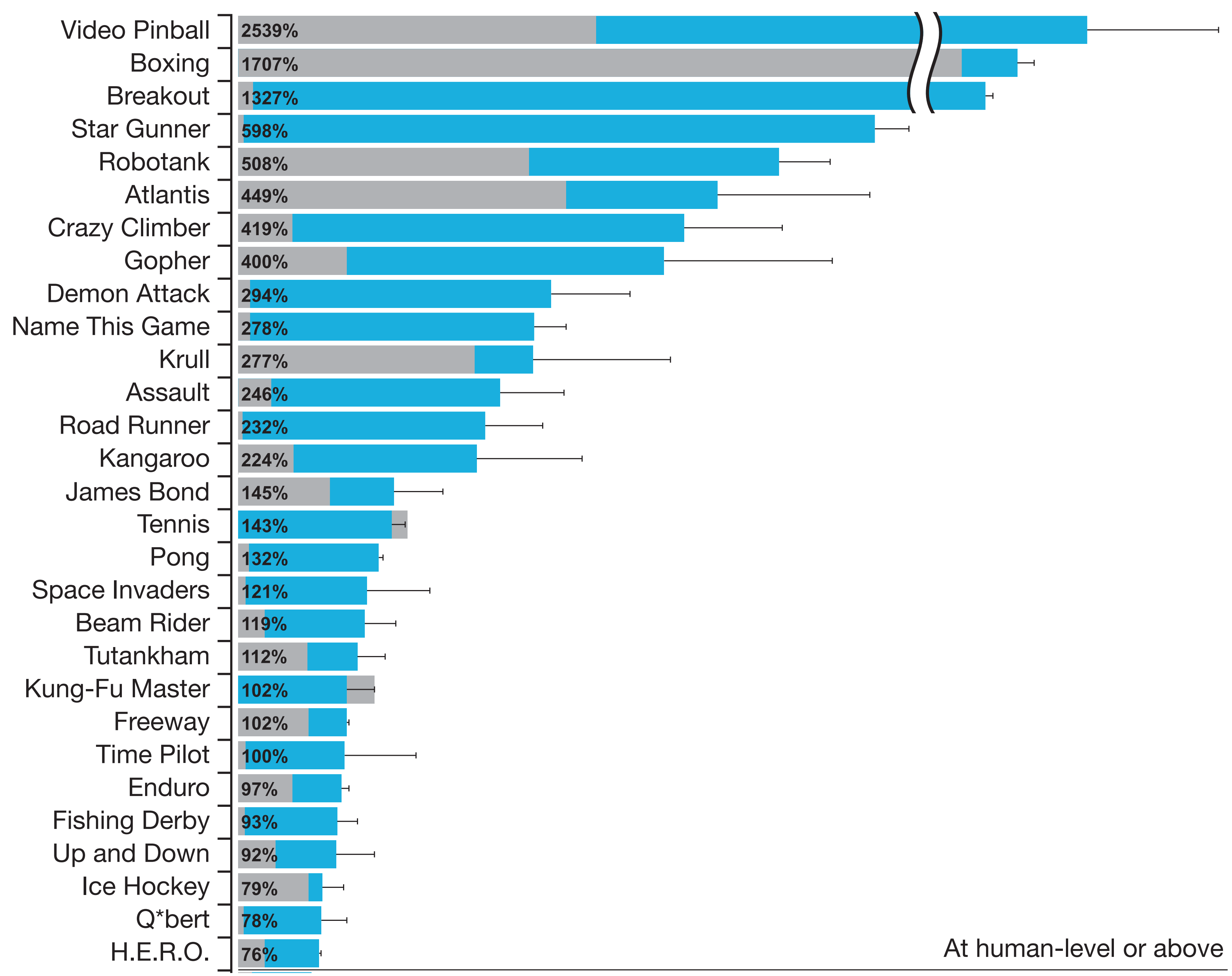
Deep Learning by Courville, Goodfellow and Bengio (2015)

Relevant papers:

- Hennequin et al. Inhibitory Plasticity: Balance, Control, and Codependence. *Annual Review of Neuroscience*, (2017) [review on balanced neural networks]
- Greff et al. LSTM: A Search Space Odyssey, arXiv (2015)
- Costa et al. Cortical Microcircuits as Gated Recurrent Neural Networks. Neural Information Processing (2017) [paper that first introduced the mapping between gated-RNNs and cortical networks]
- Harris and Mrsic-Flogel. Nature Review (2013) [More general review on cortical microcircuits]

Brain vs **maquina**:

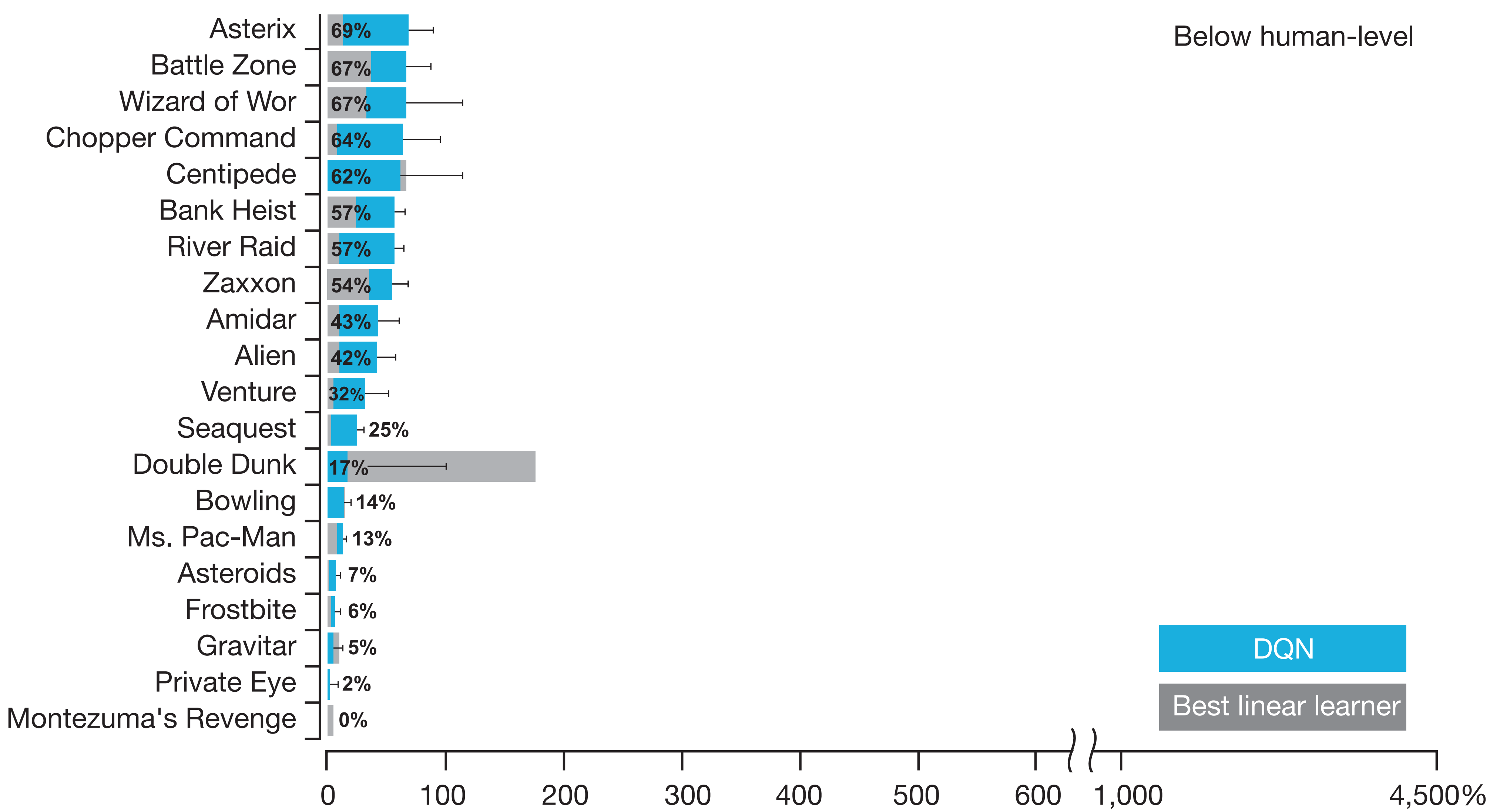
Super human performance in Atari games



Mnih et al. Nature 2015

Brain vs maquina:

Sub-human performance in Atari games



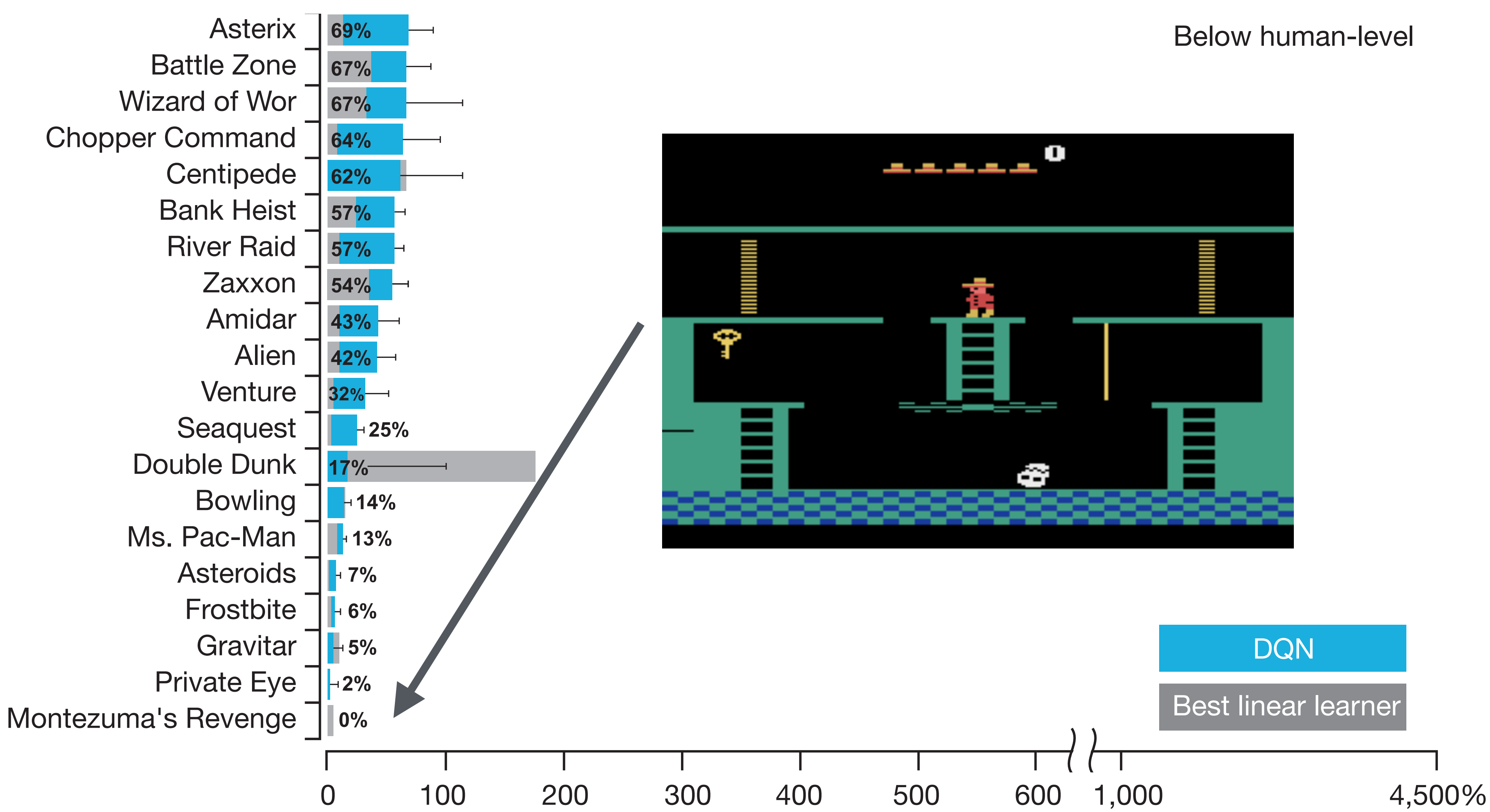
Mnih et al. Nature 2015

Thinking time..

Where do machines still fail fundamentally that we are very good at?

Brain vs maquina:

Machines fail to plan ahead



Mnih et al. Nature 2015

Brain vs maquina:

Learning to learn and think

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doi:10.1017/S0140525X16001837, e253

Building machines that learn and think like people

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Lake et al. BBS 2017

Lake et al. argue that:

Machines fail at building causal models of the world

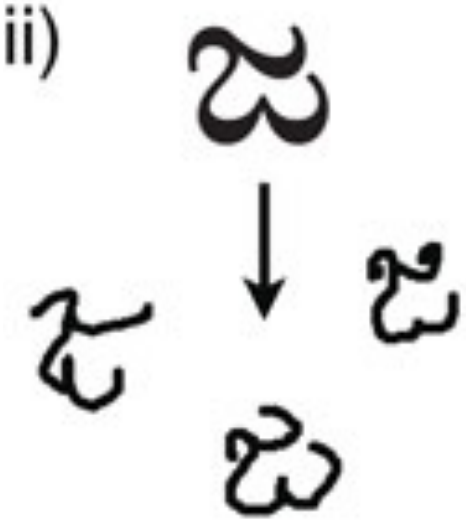
Machines fail: build causal models of the world that support explanation and understanding, rather than merely solving pattern recognition problems;

Given a single example of a alphabet:

i)

Humans quickly generate new examples:

ii)



Lake et al. BBS 2017

Lake et al. argue that:

Machines fail at compositionality

Identify the parts:

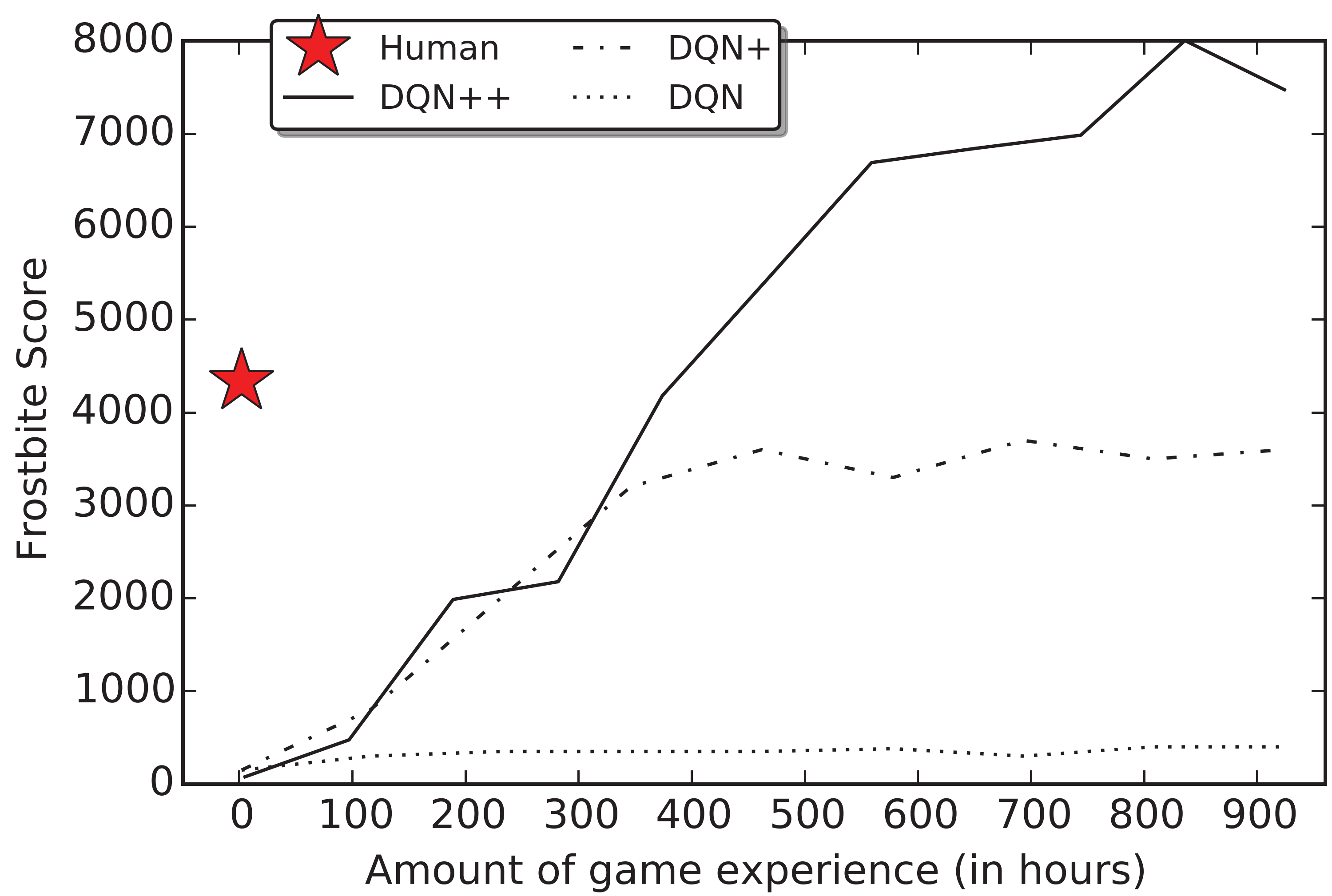
Map it to different objects to generate a new object:

Lake et al. BBS 2017

Lake et al. argue that:

Learning to learn/adapt rapidly

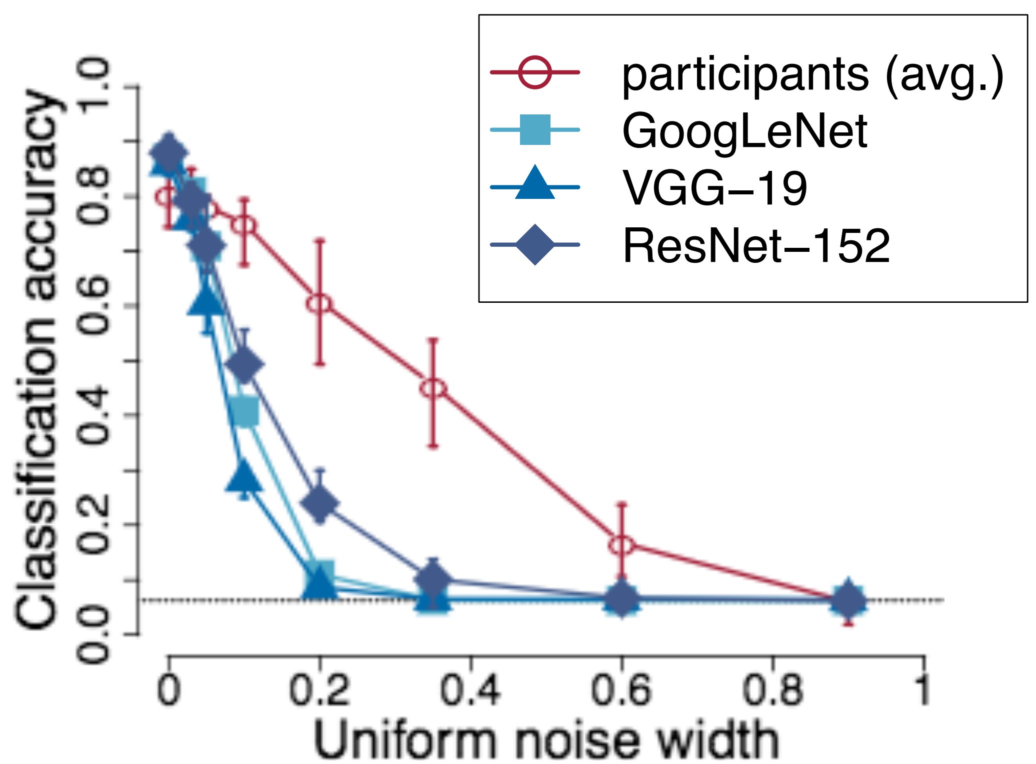
Machines fail in: learning-to-learn to rapidly acquire and generalize knowledge to new tasks and situations. And ground learning in intuitive theories of physics and psychology to support and enrich the knowledge that is learned



Also, current DQNs can only solve one task at a time (i.e. they fail in continual learning).

Brain vs maquina:
DNNs fail to generalize

Image classification



Geirhos et al. NeurIPS 2018

Brain vs maquina:

But, is this a fair comparison?

- **Humans have decades of experience** (with vast amounts of data)
- **Humans have built-in inductive biases** (e.g. built-in neural circuits)
- **Unlikely humans, ML methods are typically trained to solve one particular task**
- **The data+cost function+architecture is fundamental**