Hierarchical Temporal Memory

Biological And Machine Intelligence

Felix Karg

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LessWrong Community Weekend 2019

Content

Disclaimer:

Disclaimer: I don't really know what I'm talking about.

Epistemic status

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- Evolving theories

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- Hypotheses partially verified

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- Theories are constantly being updated
- This is the newest information regarding this theory

Content

Tests for Intelligence

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- Turing test

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- 'IQ' tests

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- Problme solving tests

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But dogs, monkeys and dolphins fail them.

Tests for Intelligence

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- 'IQ' tests
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But dogs, monkeys and dolphins fail them.

Focusing on human-like performance is **limiting.**

Intelligence - Definition

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Intelligence: The degree of flexibility in both learning and behaviour [1].

Intelligence - Overview

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Might not be best at specific task.

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But can do a lot of different tasks quite well.

Intelligence - Overview

Might not be best at specific task.

But can do a lot of different tasks quite well.

$\rightarrow$ General solution.

Content

The Human Brain in Numbers

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Neurons in brain stem	1 billion (1%)

Data from [2].

The Human Brain

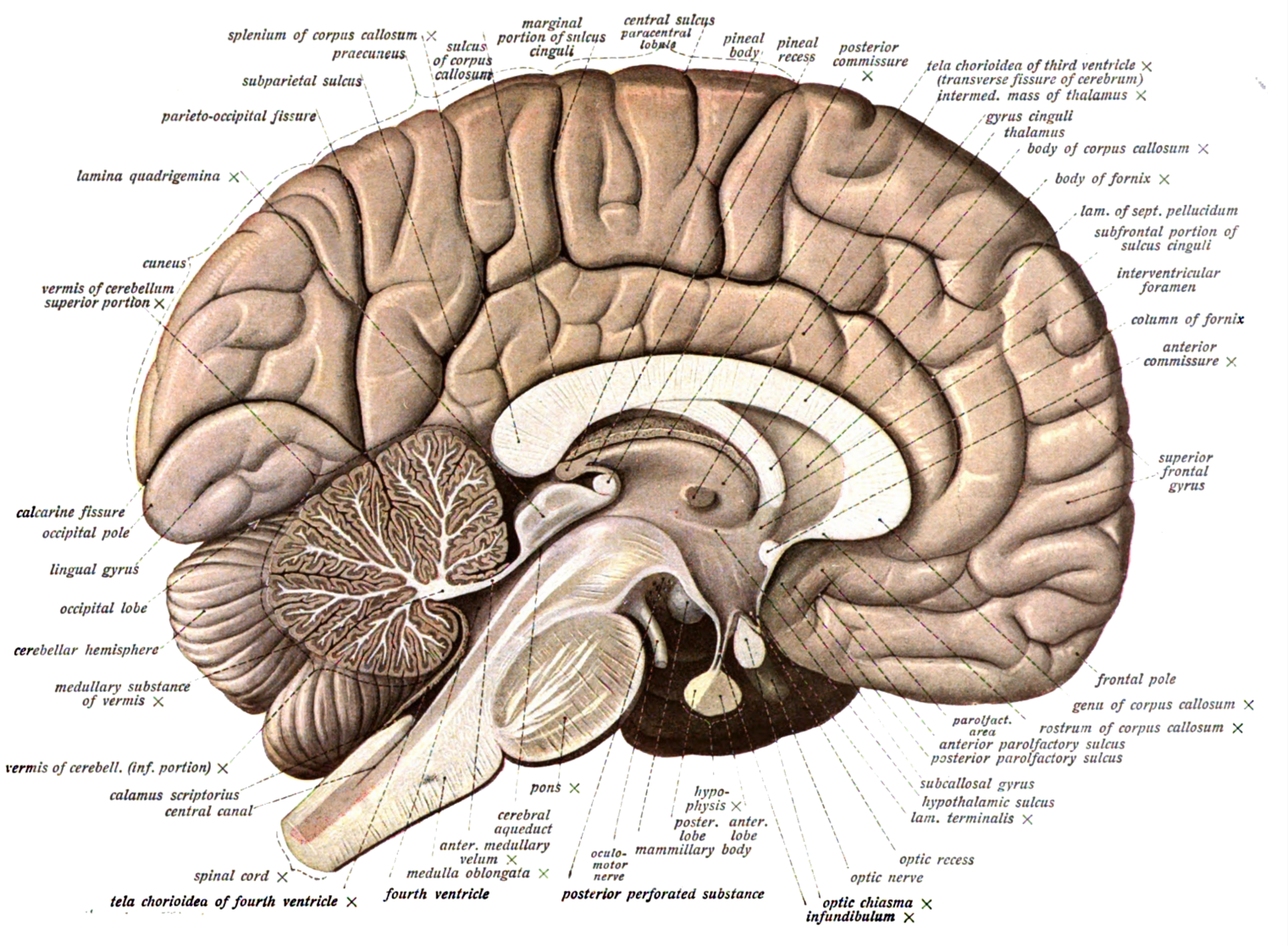
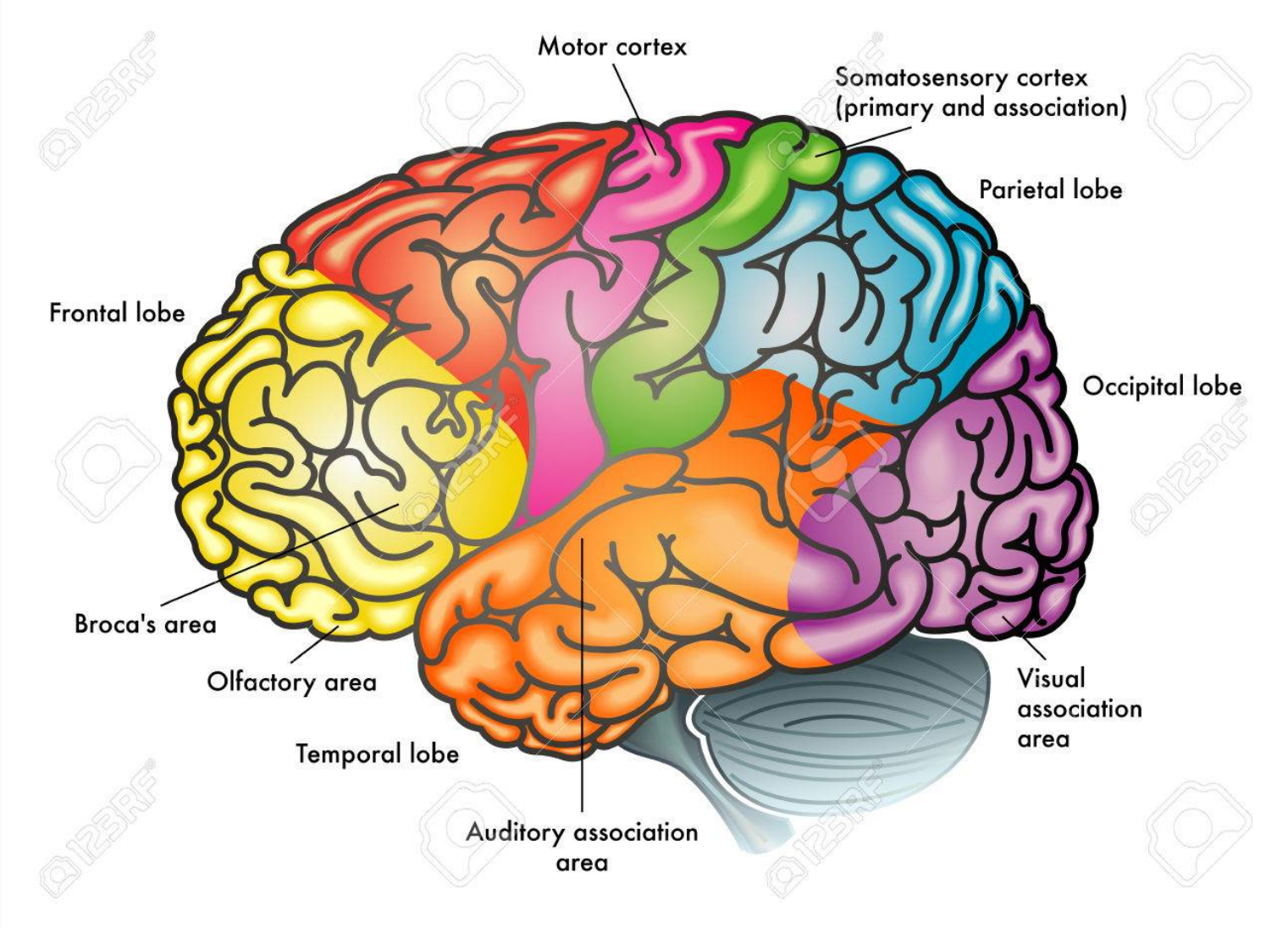


Image from [3].

The Human Brain - Different Areas



Roberto Biasini © 123RF.com

Cortical Column

"There is nothing visual about the visual cortex, and nothing auditory about the auditory cortex"

- Vernon Mountcastle

Cortical Column

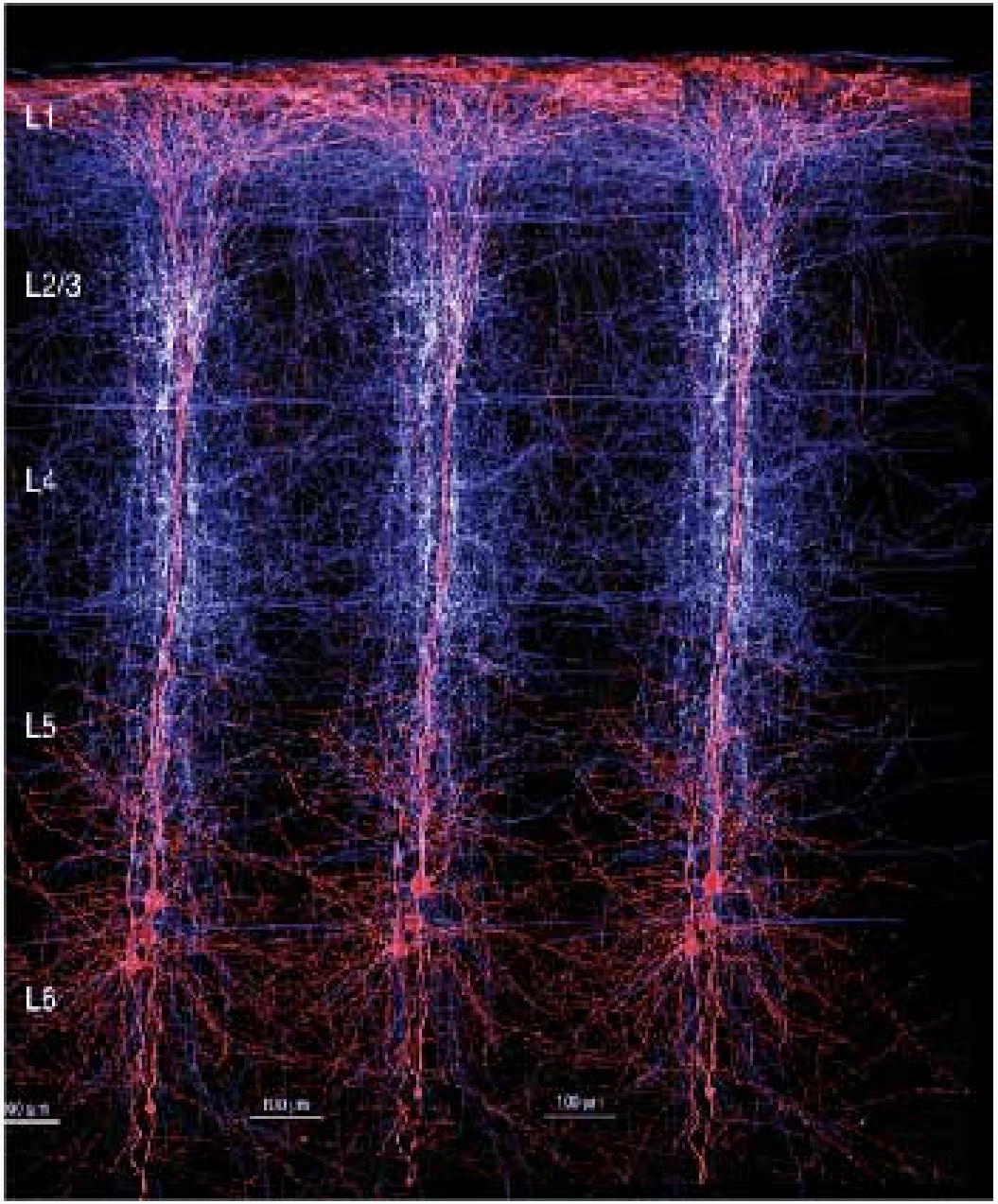


Image from [4].

Cortical Column

- Everywhere in the Brain

Cortical Column

- Everywhere in the Brain
- 80-120 up to 200-400 Neurons

Cortical Column

- Everywhere in the Brain
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- Smallest symbol unit

Cortical Column

- Everywhere in the Brain
- 80-120 up to 200-400 Neurons
- Smallest symbol unit
- Activity has meaning

Neuron - Number of Connections

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Min. n. of connections	1'000
Avg. n. of connections	7'000
Max. n. of connections	10'000

Neuron - Number of Connections

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Avg. n. of connections	7'000
Max. n. of connections	10'000
Firing Rate	20-250 Hz (453 Hz [5])

Connection data from [2] and firing rate from [6].

Neuron - Spike Frequencies

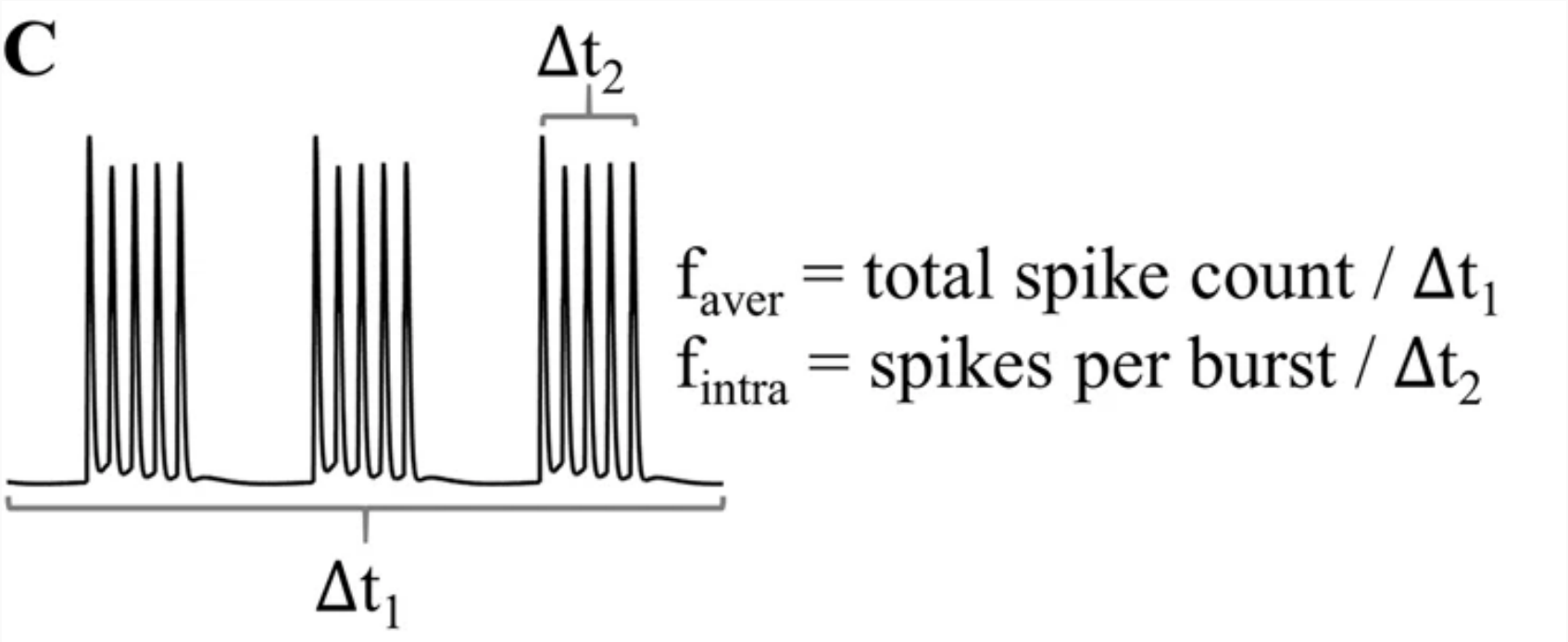

Image adapted from [7].

Neuron - Overview

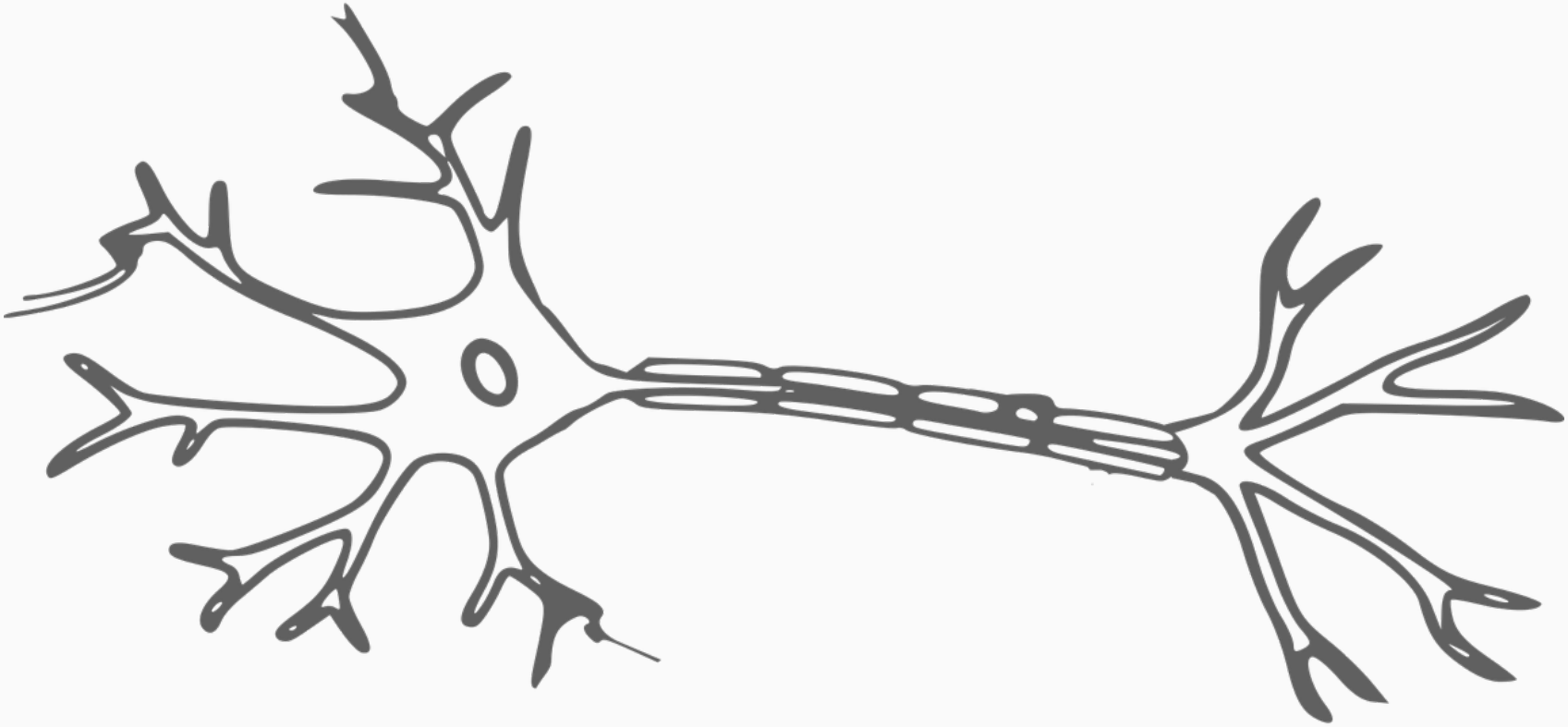

Image from [8].

Content

What is HTM?

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- biologically constrained **theory of intelligence**

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$\rightarrow$ Learning Algorithms

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$\rightarrow$ Learning Algorithms (of the brain)

Not Included in HTM

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- Firing rythms

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- Emotions

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- Emotions
- Basic Behaviours

Not Included in HTM

- Firing rythms
- Emotions
- Basic Behaviours
- Sleep (yet)

The brain as Prediction Machine

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- Prediction of future sensory input

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- 'Anticipating' events

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The brain as Prediction Machine

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- multiple connected regions
- Invariant representations
- Hierarchies of Concepts
- A sense of location

Attributes of HTM Algorithms

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- robust against noise
- can learn multiple patterns at once
- suited for prediction, anomaly detection, classification
- tested and implemented in software
- commercially used (anomaly detection, NLP)

Content

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Why Hierarchy?

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If there is a connection cost, hierarchies are more efficient [9].

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Especially when tasks change regularly.

Why Hierarchy? II

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- Reduced Training Time

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- Reduced Memory Usage

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Why Hierarchy? II

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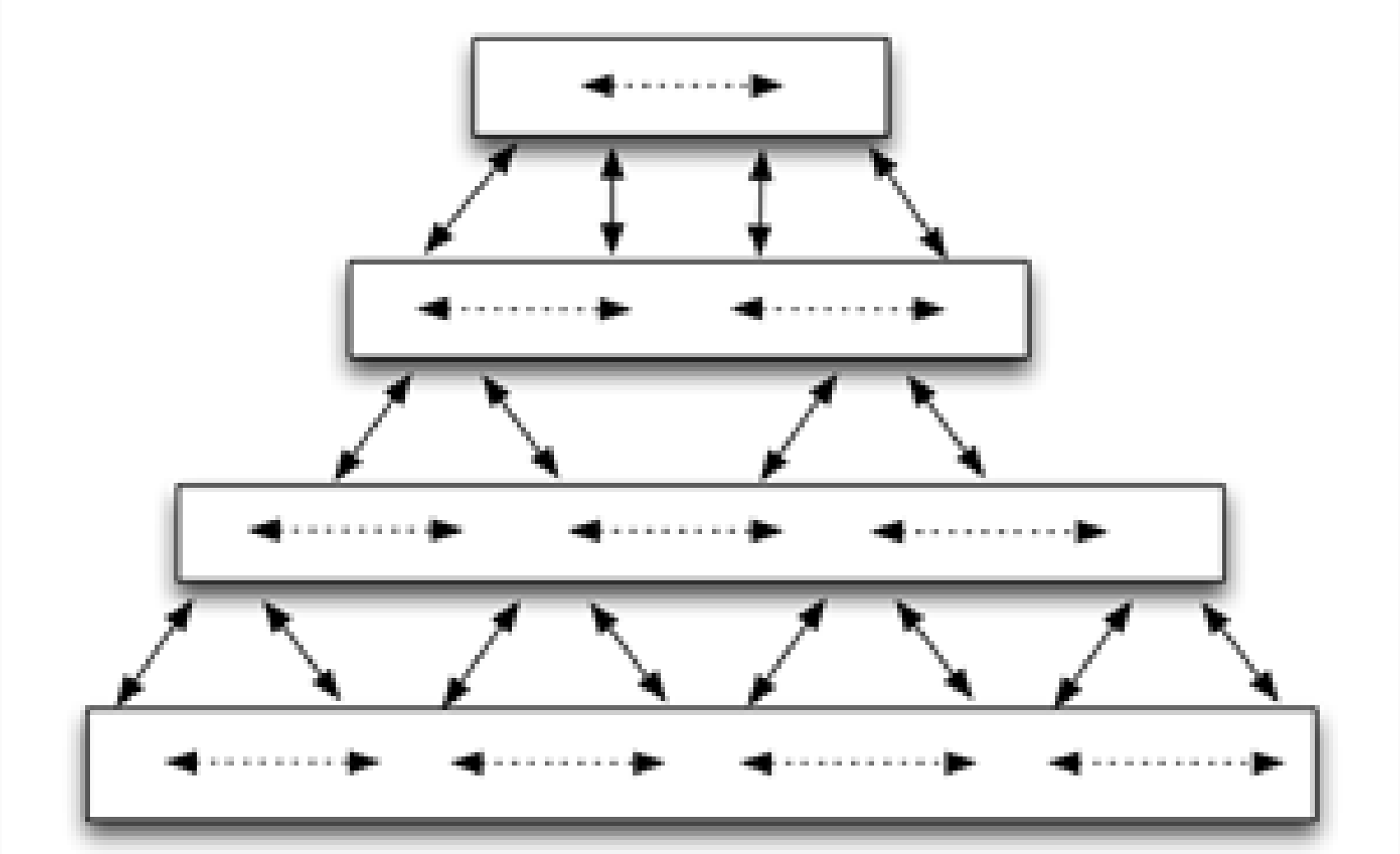
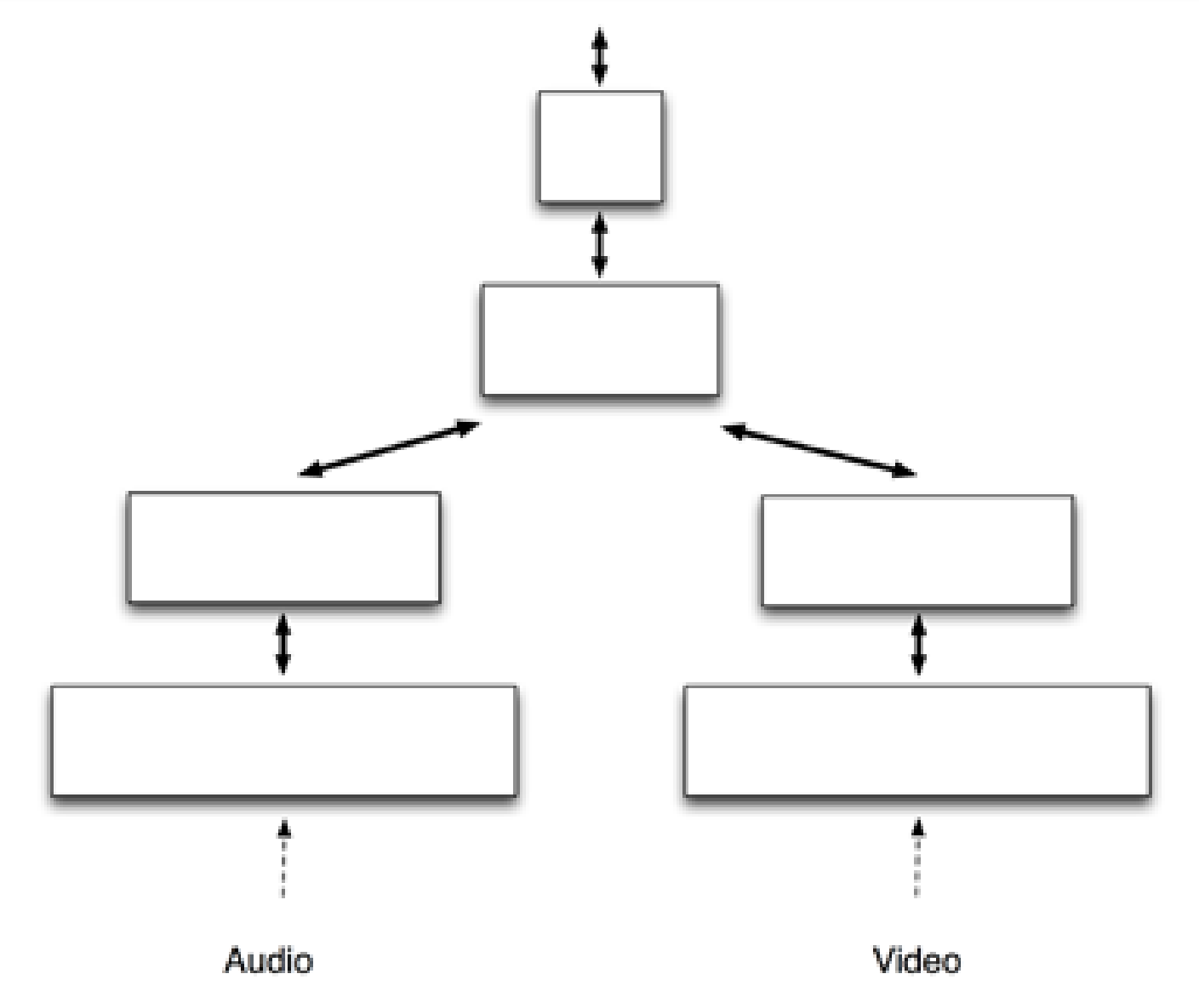
- Transfer Learning

What Hierarchy

What Hierarchy



Example Application



How Many Levels?

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- They always learn the best representation

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- Tradeoff between depth and layer size

How Many Levels?

- They always learn the best representation
- Tradeoff between depth and layer size
- Simple problems can be solved with one region

Content

Region - Introduction

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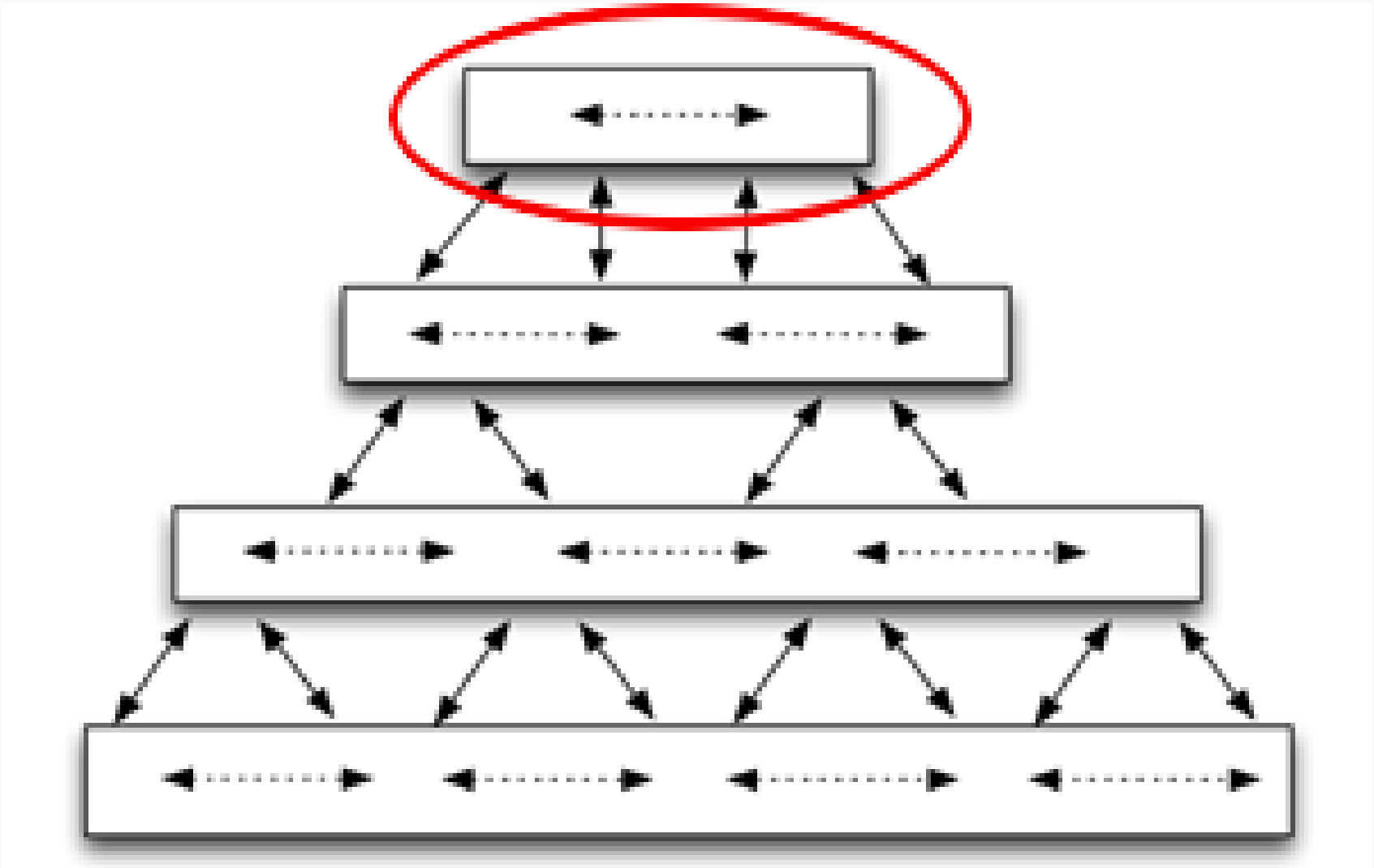
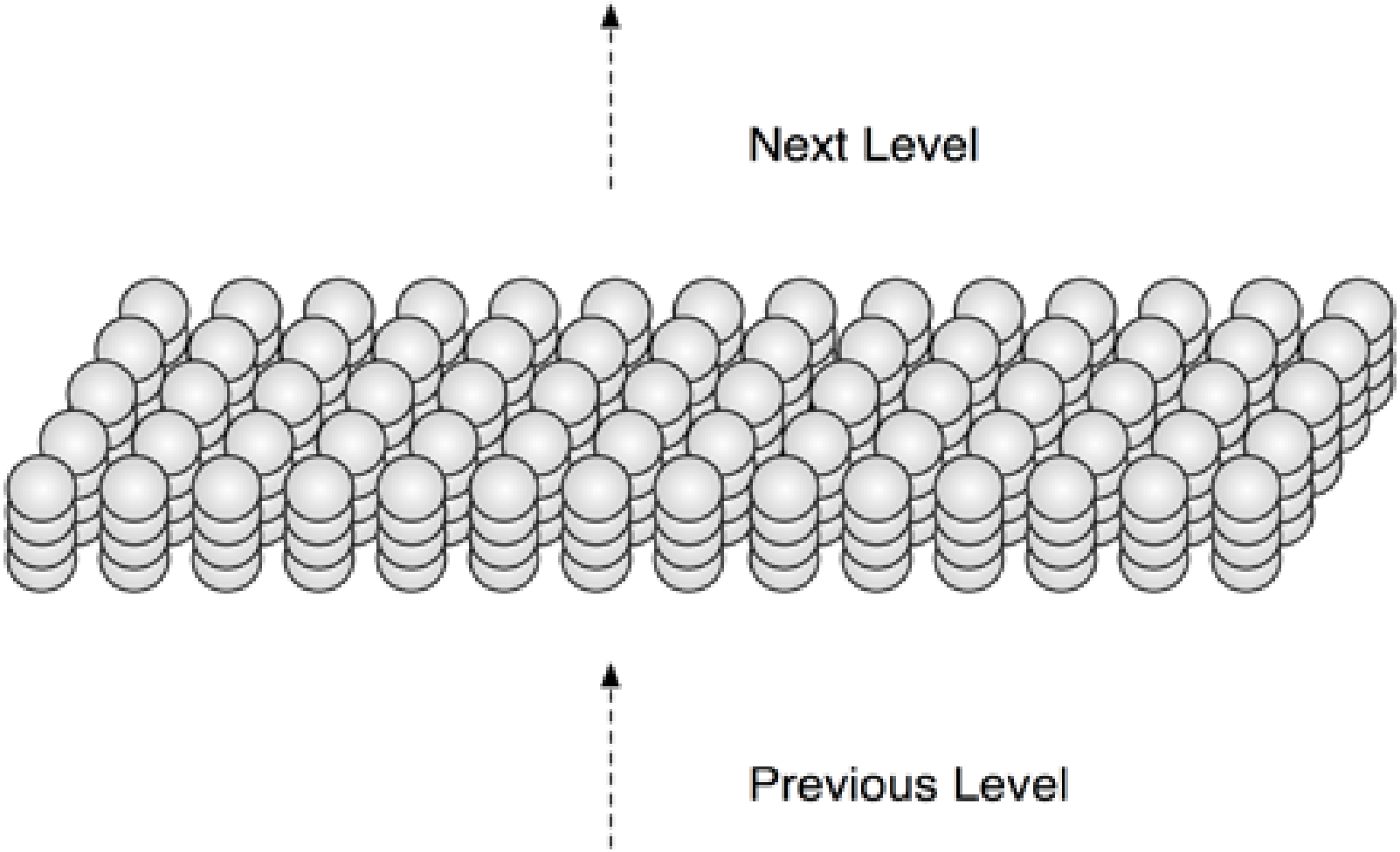


Region - Details



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- All Regions do basically the same
- Based on Biological Regions in the Brain
- HTM Regions are similar to Layer 3 of the Neocortex
- Can do Inference and Prediction even on complex data

Content

Data Saving - Computer Science Solution

What is 01100101?

Data Saving - Computer Science Solution

What is 01100101? Could be either one of:

Data Saving - Computer Science Solution

What is `01100101`? Could be either one of:

- Booleans

  (`False, True, True, False,...`)

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- Part of some other Datastructure

Biologically, this does not work out.

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We use only 10% of our Brain, right?

Sparse Distributed Representation - Example

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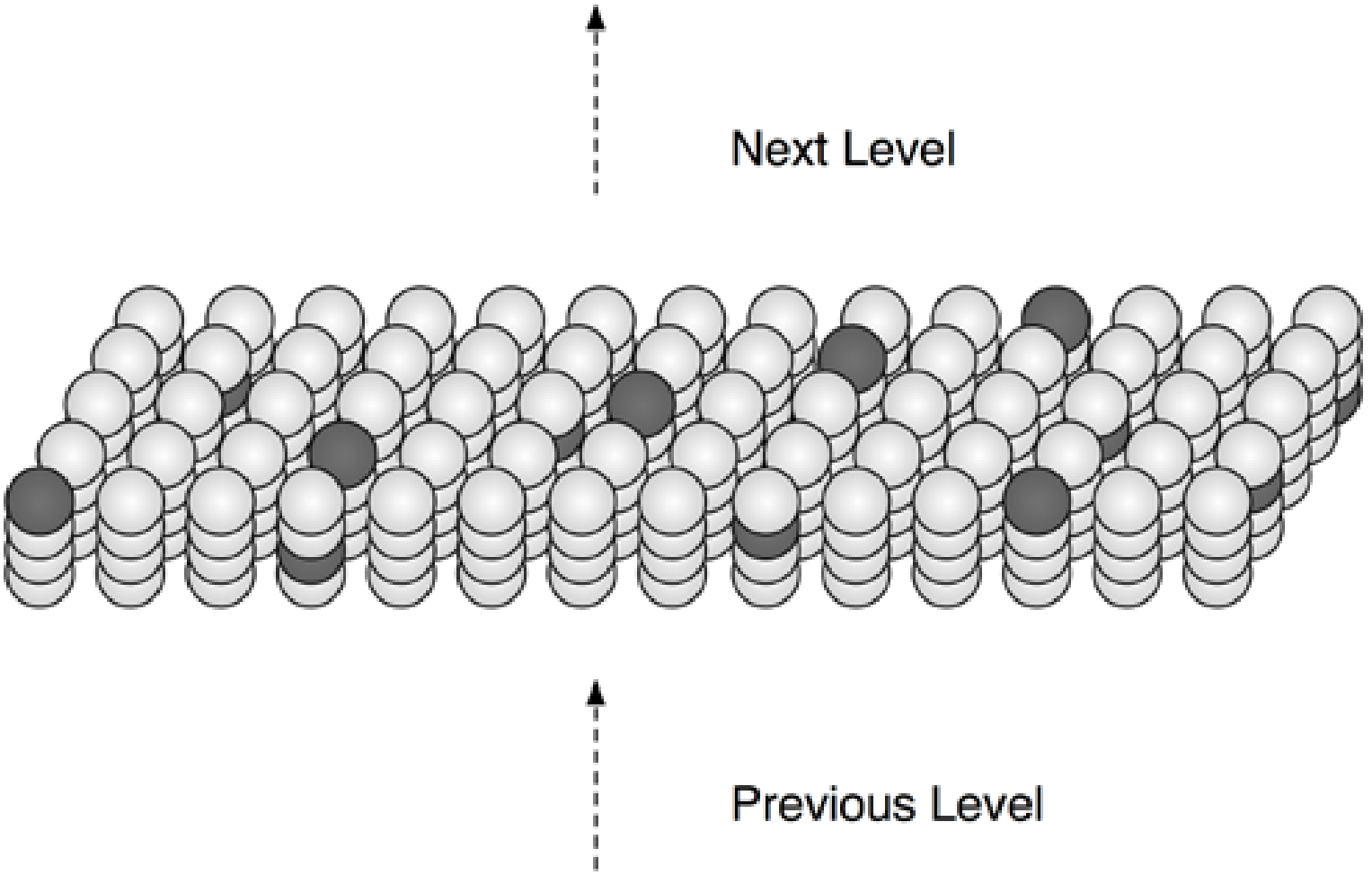
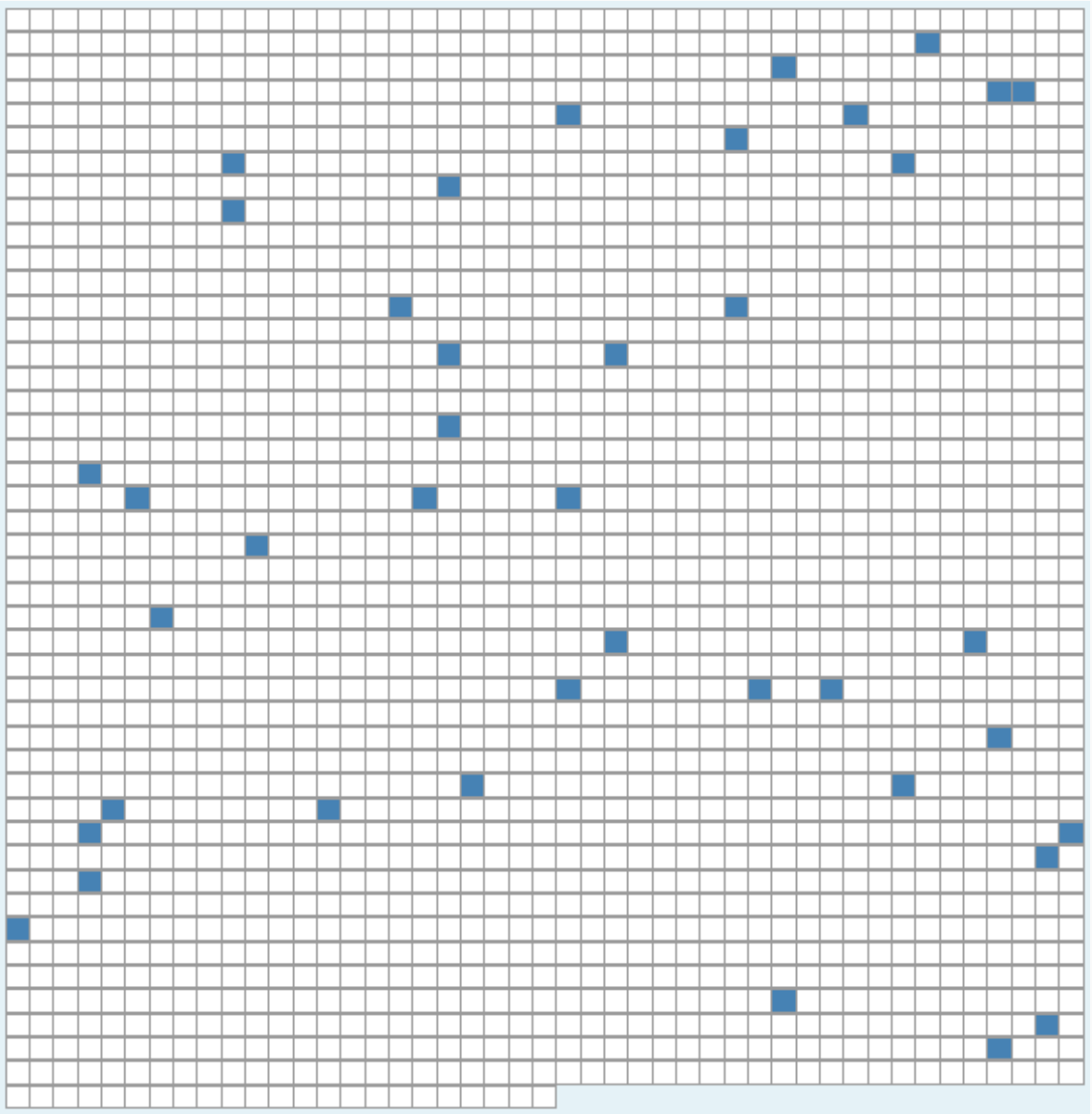


Sparse Distributed Representation - Example



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- Distributed (clusters are somewhat rare)

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- Combined, they give context as well

Sparse Distributed Representation - Introduction

- Datastructure of the brain
- Sparse (around 2% are active)
- Distributed (clusters are somewhat rare)
- Inhibitory Mechanisms
- Neuron states actually have 'meaning'
- Combined, they give context as well
- Many mechanisms in the brain would not work otherwise

The role of Time

Crucial for learning, inference and prediction.

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- Inference is hard on static information

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The role of Time

Crucial for learning, inference and prediction.

- Inference is hard on static information
- Predictions are somewhat inherently time-based
- Learning is hard without feedback

Content

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Learning

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Learning

- Learning is purely statistical
- Lookign for Spatial and Temporal Patterns
- Regions themselves are limited
- Automatically adjusts to size of allocated Memory
- Automatic On-Line learning
- takes longer to learn high-level concepts with lower levels missing
- only a precursor for inference and prediction

Inference

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- Matching previously learned sequences

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- Example: recognizing a Melody

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- There are only novel experiences

Inference

- Matching previously learned sequences
- Example: recognizing a Melody
- There are only novel experiences
- Partial SDR matches

Prediction

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- Takes up a considerable amount of memory

Prediction

- Matching stored sequences
- Can be thought of to be similar to a markov chain
- Takes up a considerable amount of memory
- Integral to how the brain works

Prediction - Key Properties

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- Continuity

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- Context sensitivity

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- Continuity
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- Context sensitivity
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- Anomaly Detection
- Noise robustness

Content

Content

Content

Content

Open Questions

- Neuron fire frequency

Content

Sources i

The slides are online: `https://github.com/fkarg/things-to-talk-about/blob/master/htm/main.pdf`

Drop me a mail: fkarg10@gmail.com

Sources ii

- J. Hawkins, S. Ahmad, S. Purdy, and A. Lavin, "Biological and machine intelligence (bami)." Initial online release 0.4, 2016.
- S. Herculano-Houzel, "The human brain in numbers: a linearly scaled-up primate brain," *Frontiers in human neuroscience*, vol. 3, p. 31, 2009.
- D. J. Sobotta, "An anatomical illustration from sobotta's human anatomy 1908." `https://upload.wikimedia.org/wikipedia/commons/e/ea/Sobo_1909_624.png`, 1908.

Sources iii

Licensed under CC BY-SA 3.0; Accessed 2019-08-17.


B. B. Project, "Cortical column." `https://www.mada.org.il/brain/tools-e.html`, 2012.
Accessed 2019-08-18.


B. Wang, W. Ke, J. Guang, G. Chen, L. Yin, S. Deng, Q. He, Y. Liu, T. He, R. Zheng, *et al.*, "Firing frequency maxima of fast-spiking neurons in human, monkey, and mouse neocortex," *Frontiers in cellular neuroscience*, vol. 10, p. 239, 2016.

Sources iv

- A. Impacts, "Neuron firing rates in humans." `https://aiimpacts.org/rate-of-neuron-firing/`, 2015.
  Accessed 2019-08-18.
- G. Yi and W. M. Grill, "Average firing rate rather than temporal pattern determines metabolic cost of activity in thalamocortical relay neurons," *Scientific reports*, vol. 9, no. 1, p. 6940, 2019.

Sources v

- Pixabay.com, "Brain neuron nerves." `pixabay.com`. **Pixabay License (free for commercial and noncommercial use, no attribution required), Accessed 2019-08-21.**
- H. Mengistu, J. Huizinga, J.-B. Mouret, and J. Clune, "The evolutionary origins of hierarchy," *PLoS computational biology*, vol. 12, no. 6, p. e1004829, 2016.