Hierarchical Temporal Memory

Biological And Machine Intelligence

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LessWrong Community Weekend 2019

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

Epistemic status

- Evolving theories
- Hypotheses partially verified
- Theories are constantly being updated
- This is the newest information regarding this theory

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Tests for Intelligence

- Turing test
- 'IQ' tests
- Problme solving tests
- Car driving skills
- ...

But dogs, monkeys and dolphins fail them.

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

Intelligence - Definition

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

Intelligence - Overview

Might not be best at specific task.

But can do a lot of different tasks quite well.

$\rightarrow$ General solution.

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The Human Brain in Numbers

Neurons in brain (total)	86 billion (100%)
Neurons in cerebellum	69 billion (80%)
Rel. size of cerebellum	10% of brain
Neurons in celebral cortex	16 billion (19%)
Rel. size of cerebral cortex	82% of brain
Neurons in brain stem	1 billion (1%)

Data from [2].

The Human Brain

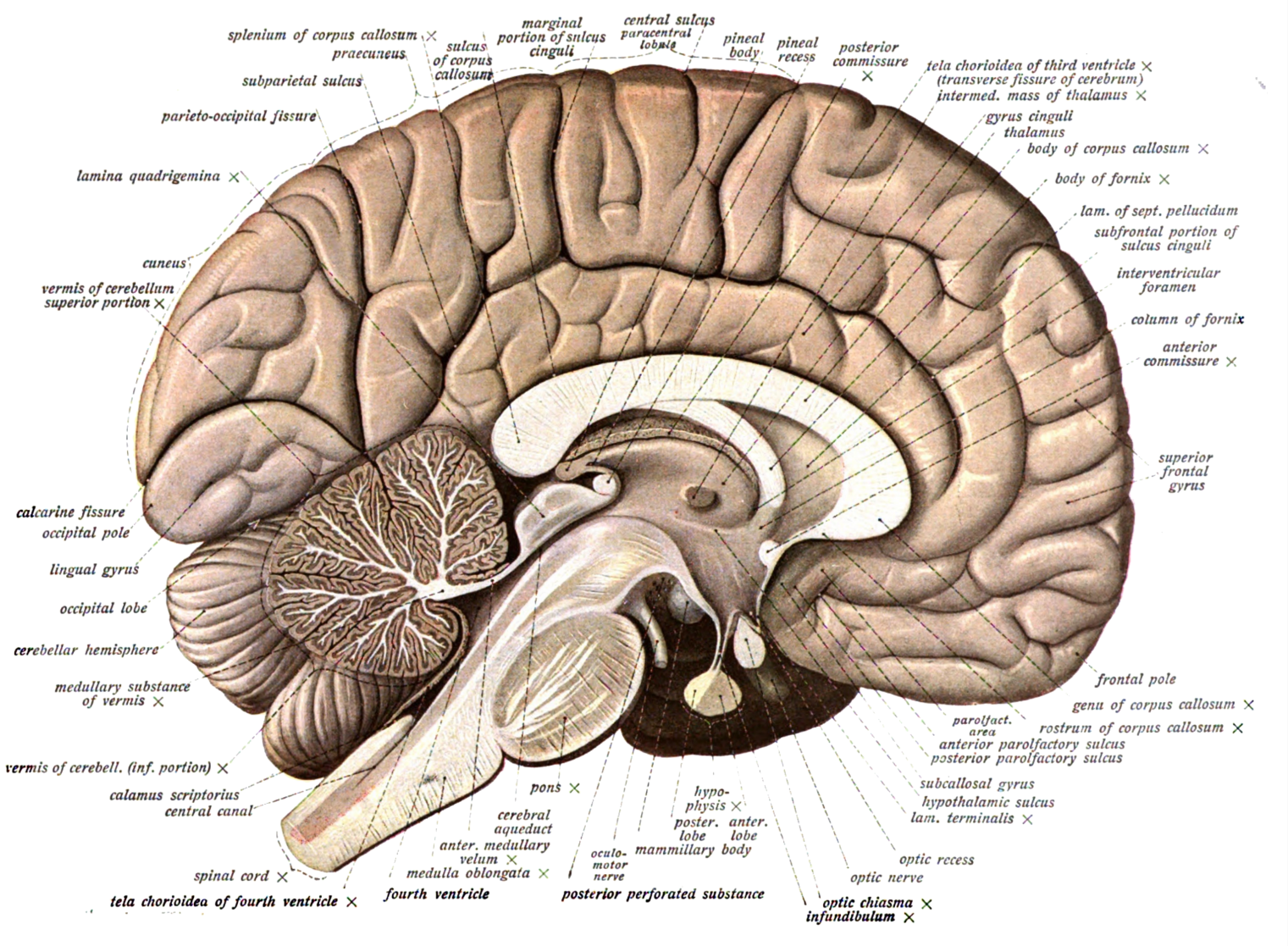
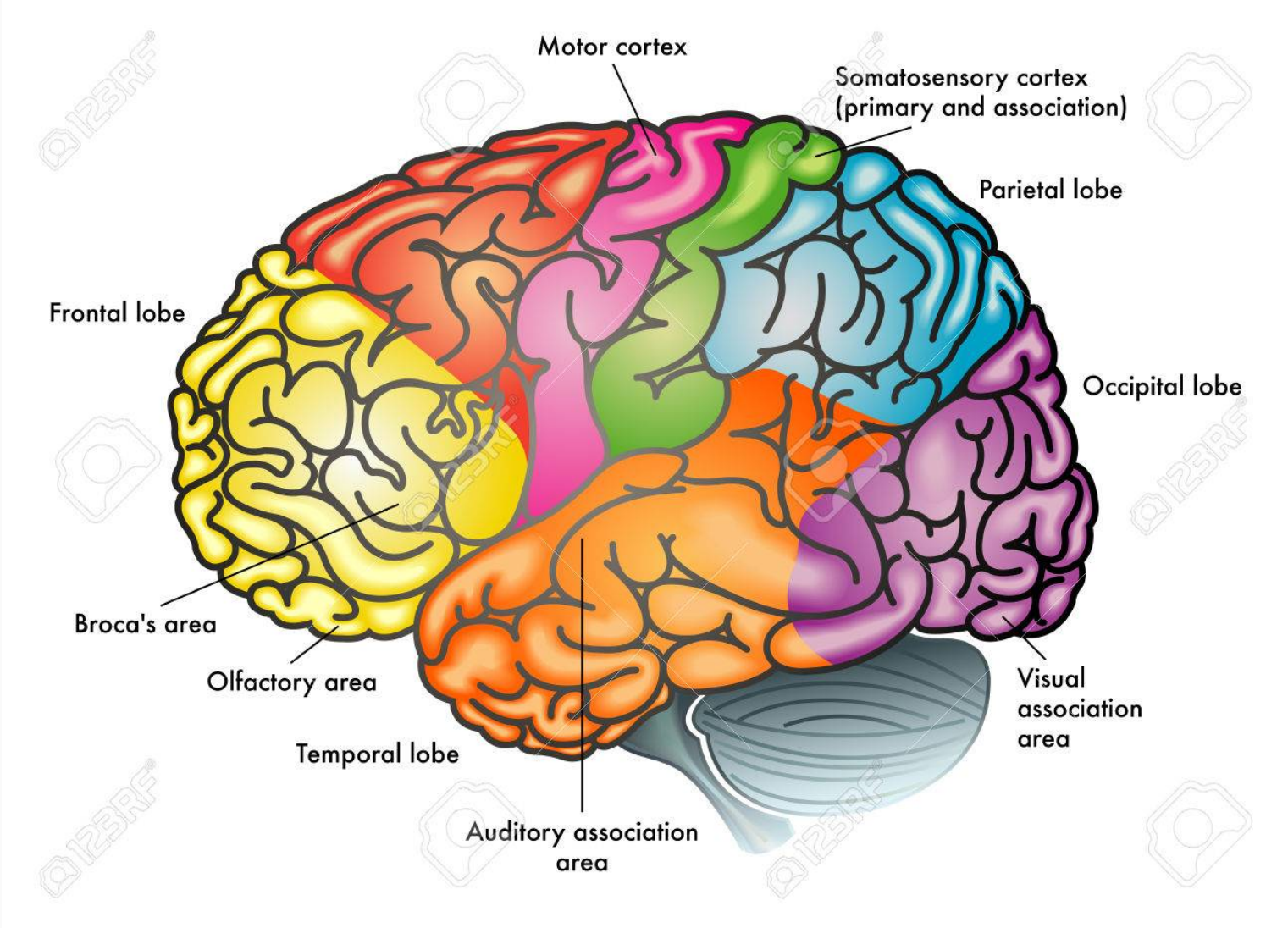


Image from [3].

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

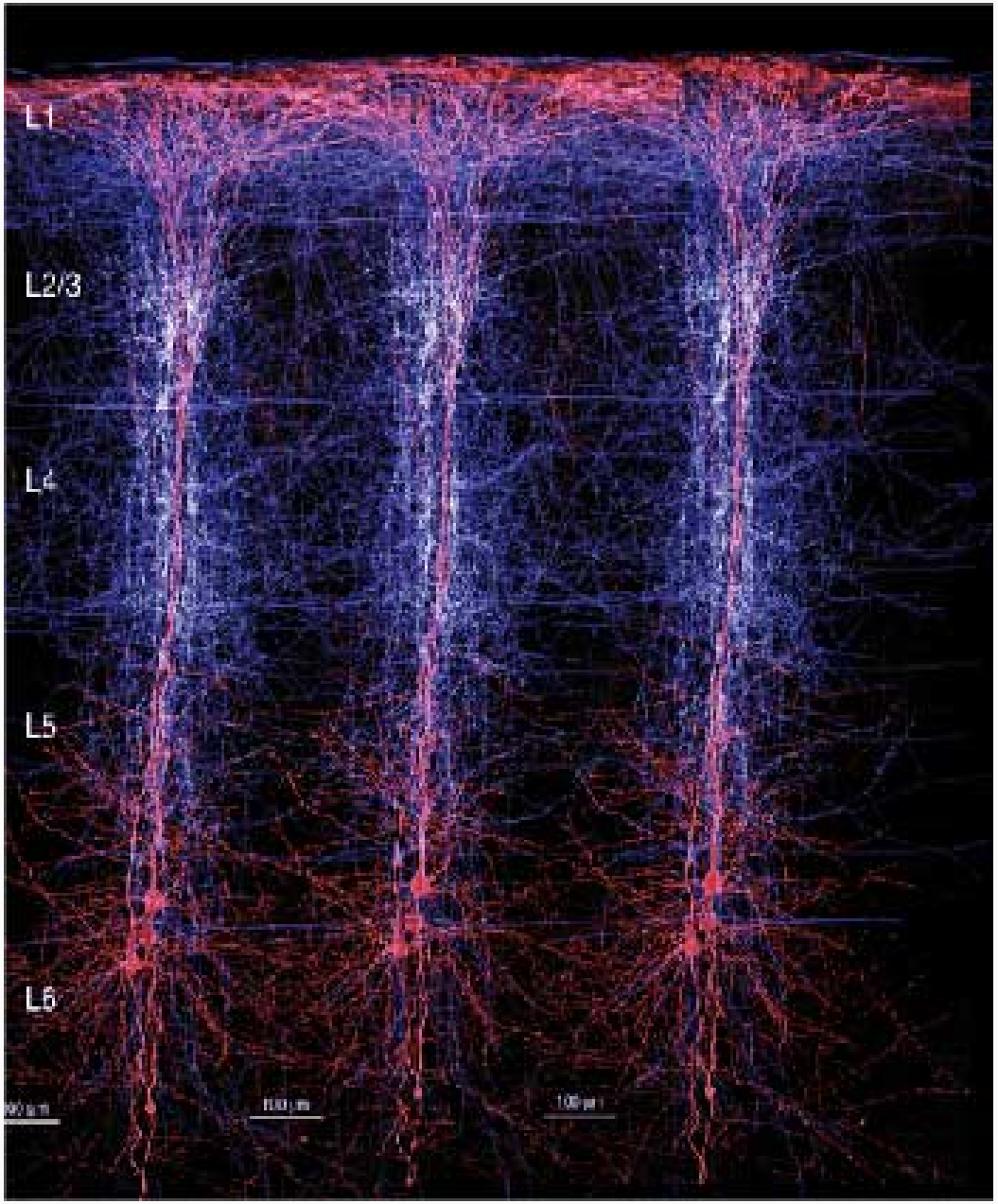


Image from [4].

Cortical Column

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

Neuron - Number of Connections

Min. n. of connections	1'000
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

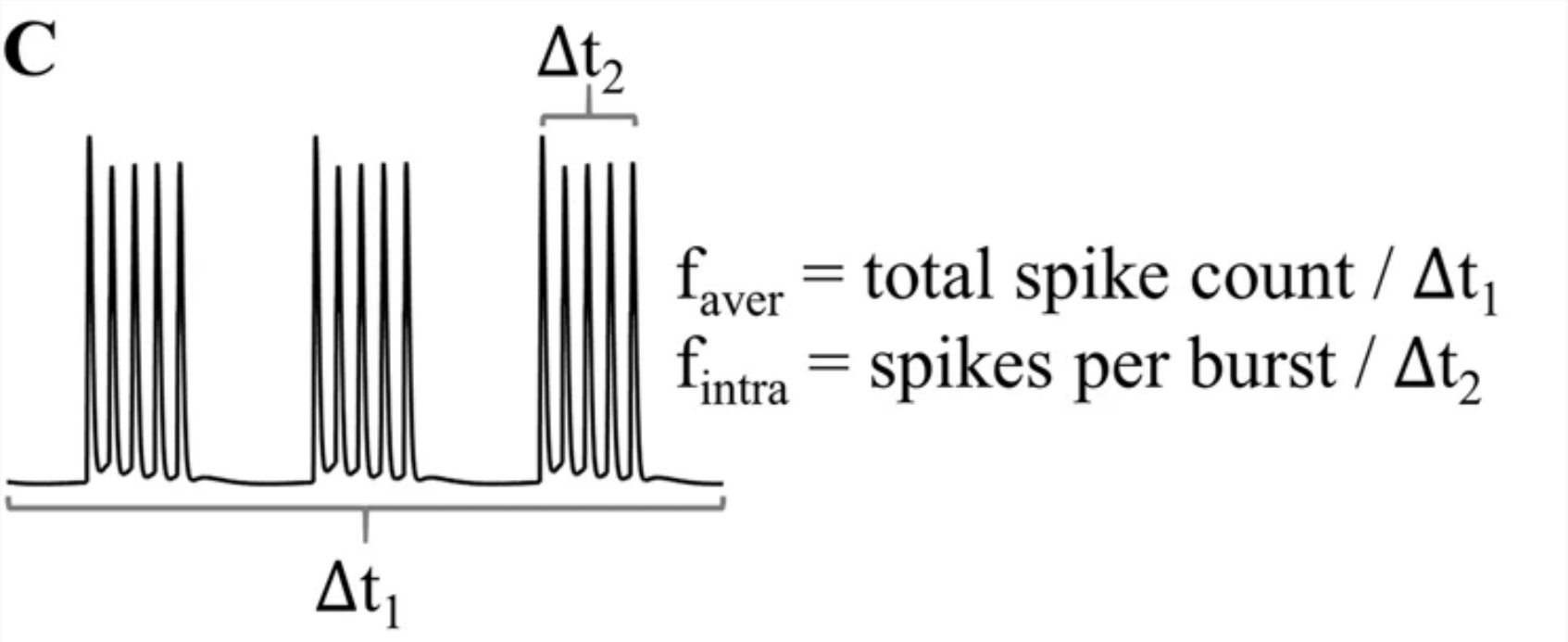


Image adapted from [7].

Neuron - Overview

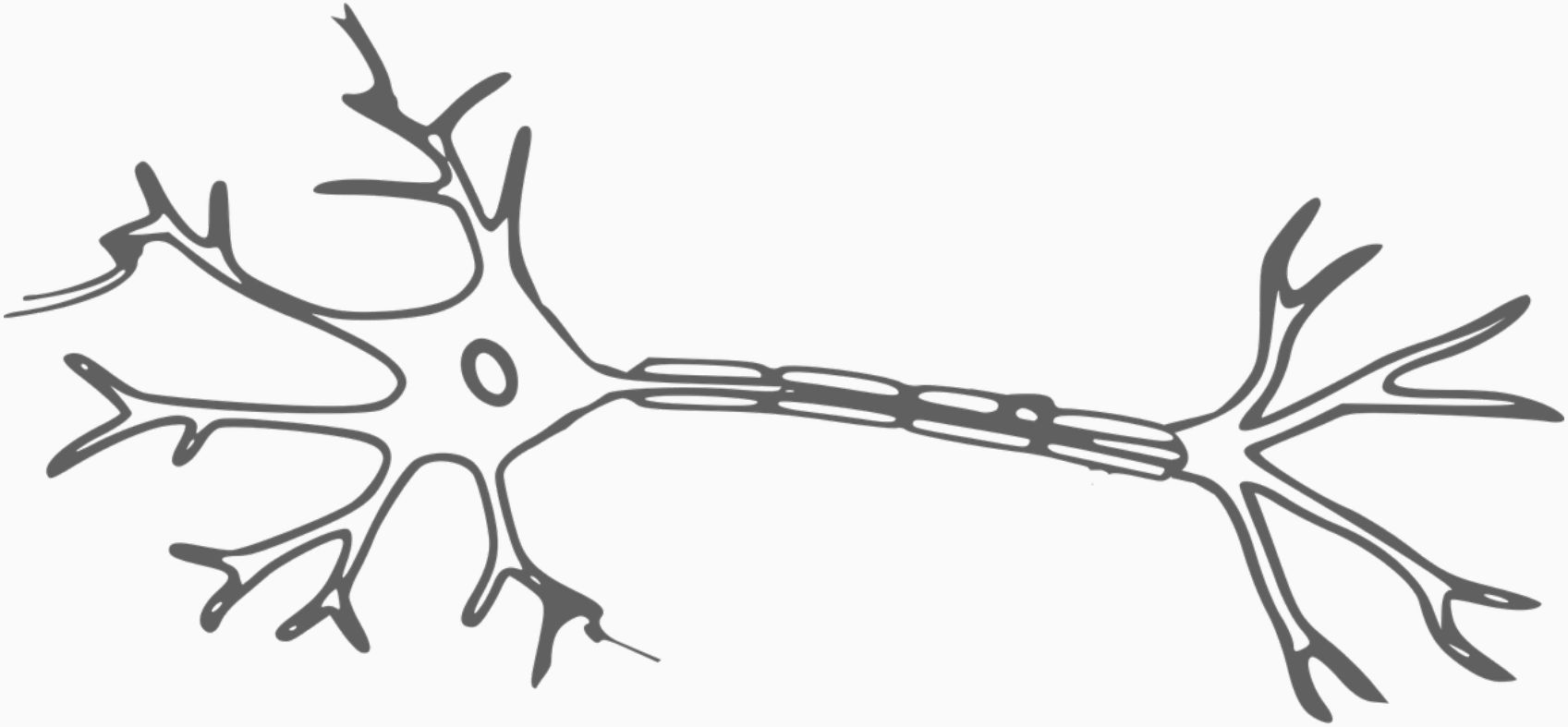


Image from [8].

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What is HTM?

- biologically constrained **theory of intelligence**
- originally described in "On Intelligence"
- **based on neuroscience** of the brain

$\rightarrow$ Learning Algorithms (of the brain)

Not Included in HTM

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

The brain as Prediction Machine

- Prediction of future sensory input
- 'Anticipating' events
- multiple connected regions
- Invariant representations
- Hierarchies of Concepts
- A sense of location

Attributes of HTM Algorithms

- can store, learn, infer and recall higher-order sequences
- learns unsupervised time-based patterns in unlabeled data on continuous streams
- 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)

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

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Why Hierarchy?

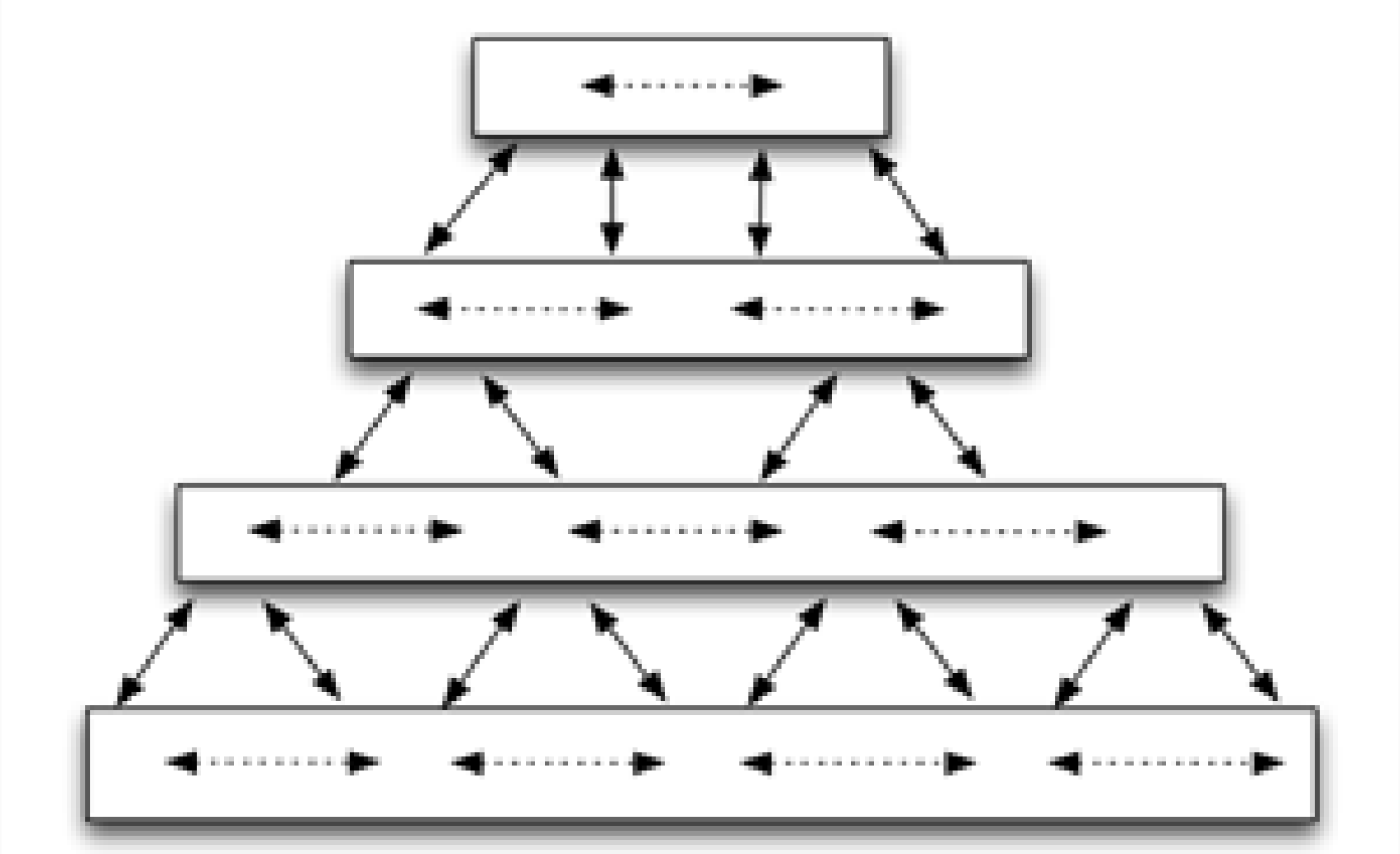
If there is a connection cost, hierarchies are more efficient [9].

Especially when tasks change regularly.

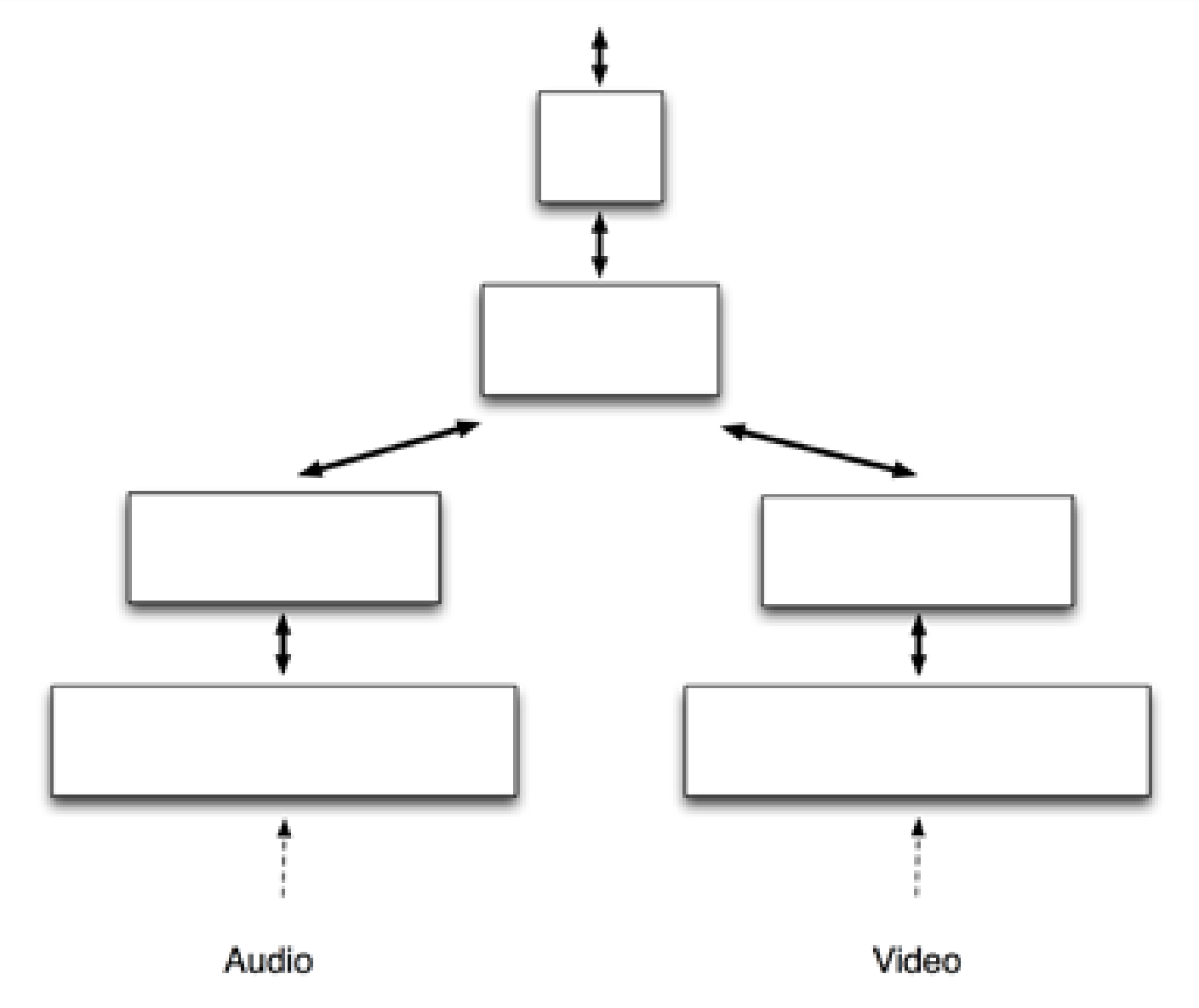
Why Hierarchy? II

- Reduced Training Time
- Reduced Memory Usage
- Introduce Generalizations
- Learned patterns are recombined at higher levels
- Transfer Learning

What Hierarchy



Example Application



How Many Levels?

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

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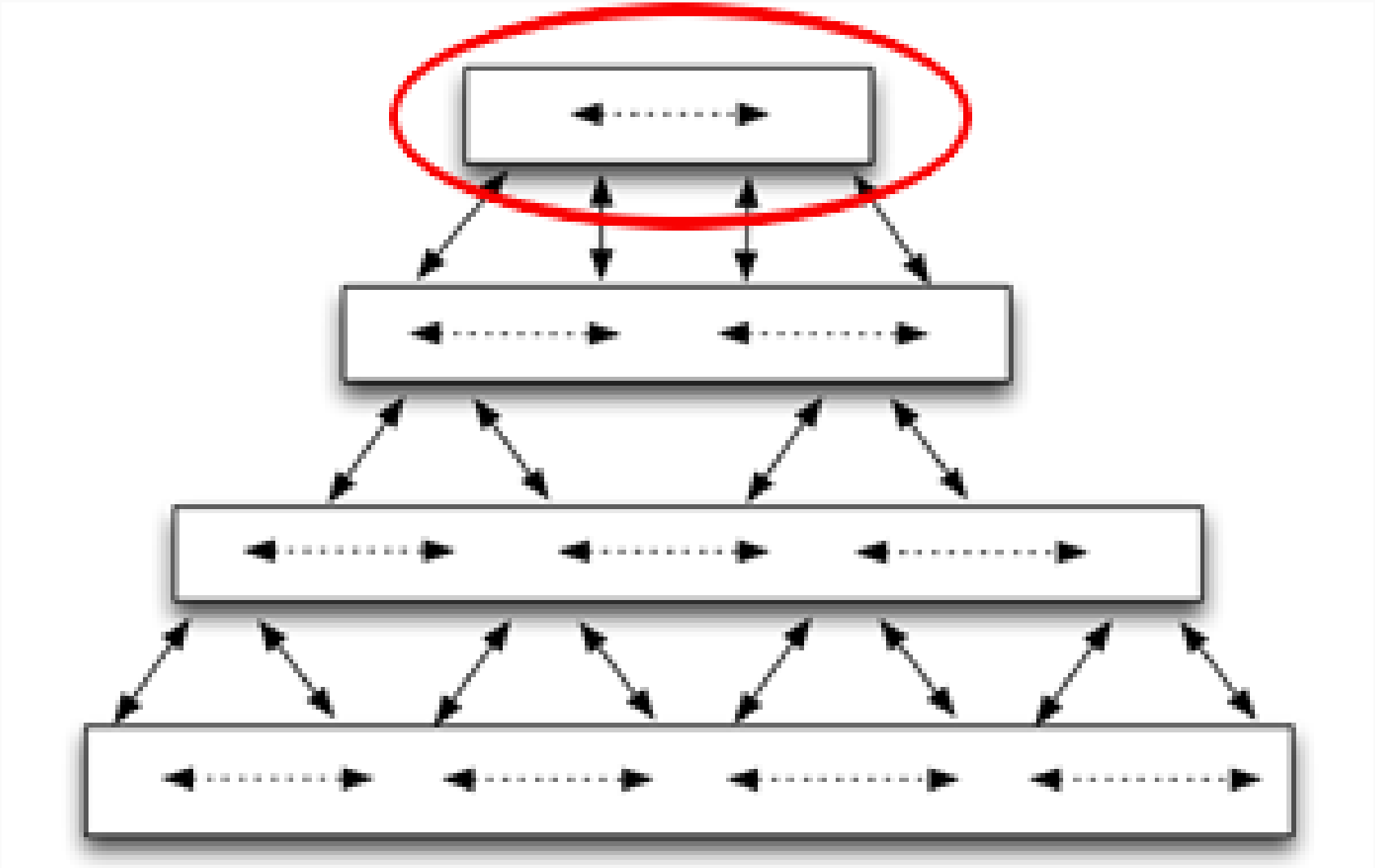
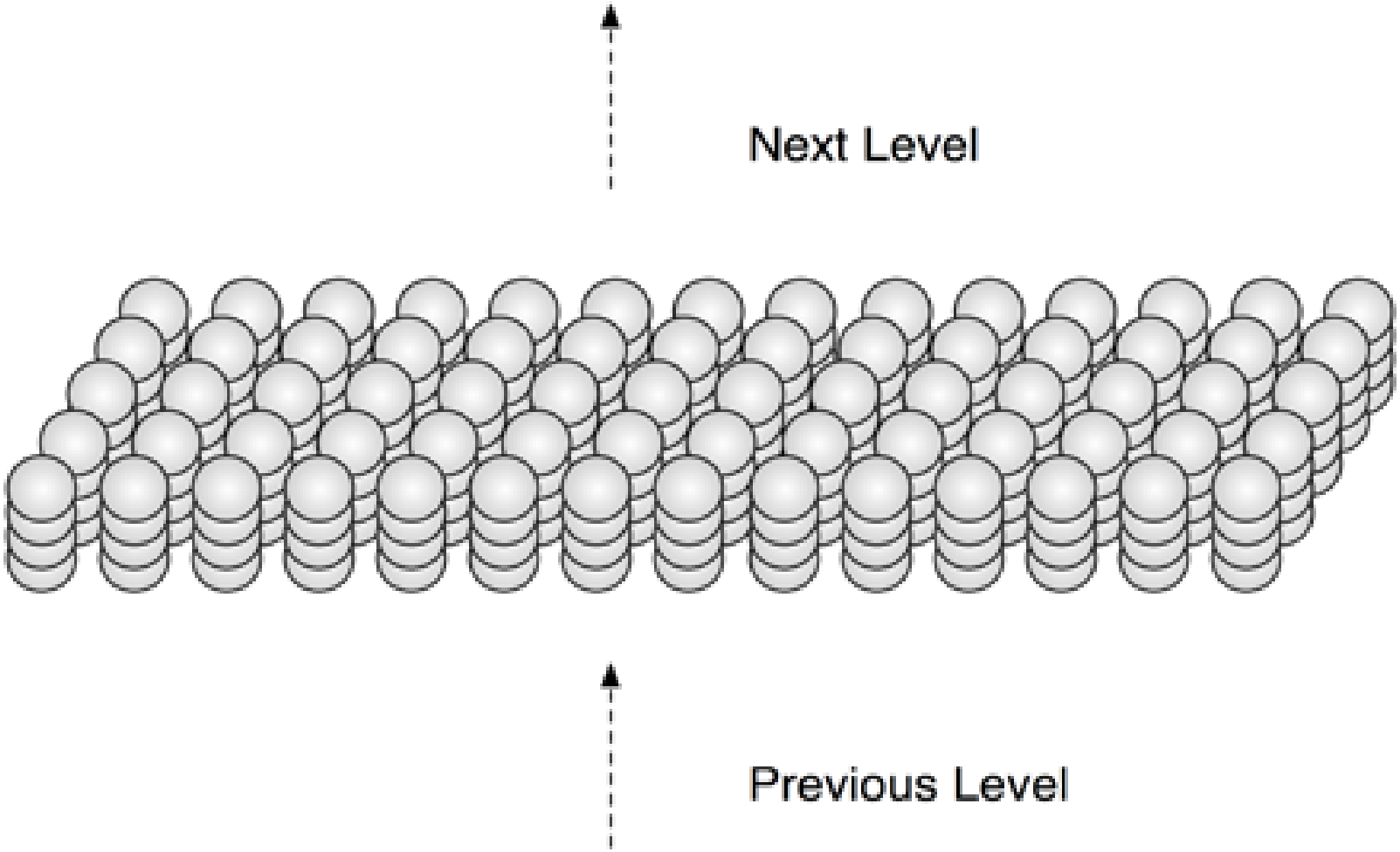
Region - Introduction



Region - Details



Region - Attributes

- 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

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Data Saving - Computer Science Solution

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

- Booleans

  (`False, True, True, False,...`)
- Integer (`101`)
- Float (`3328.0`)
- (Byte-) String (`'e'`)
- Pointer to something else
- Part of some other Datastructure

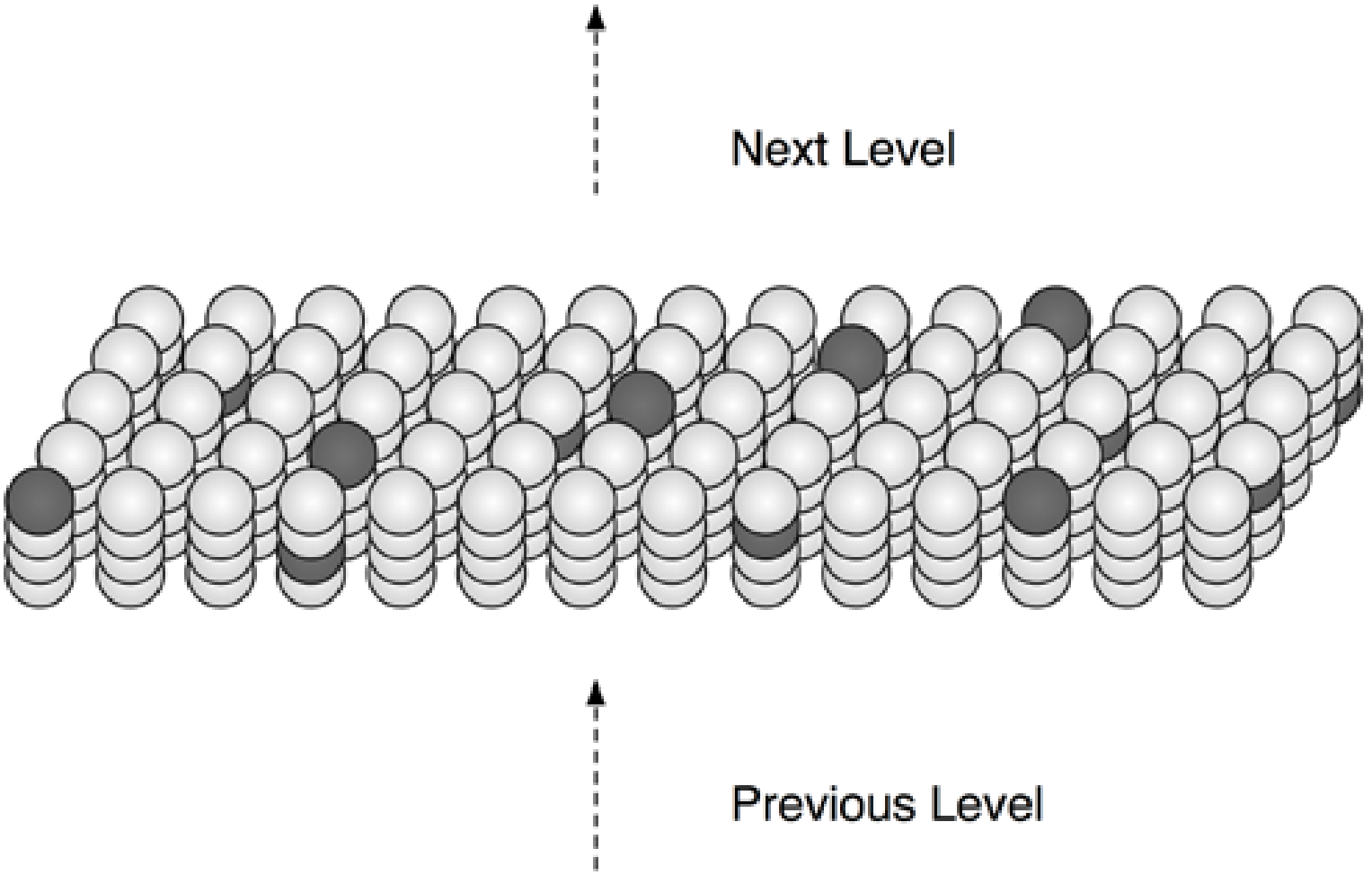
Biological observation:

We use only part of our brain!

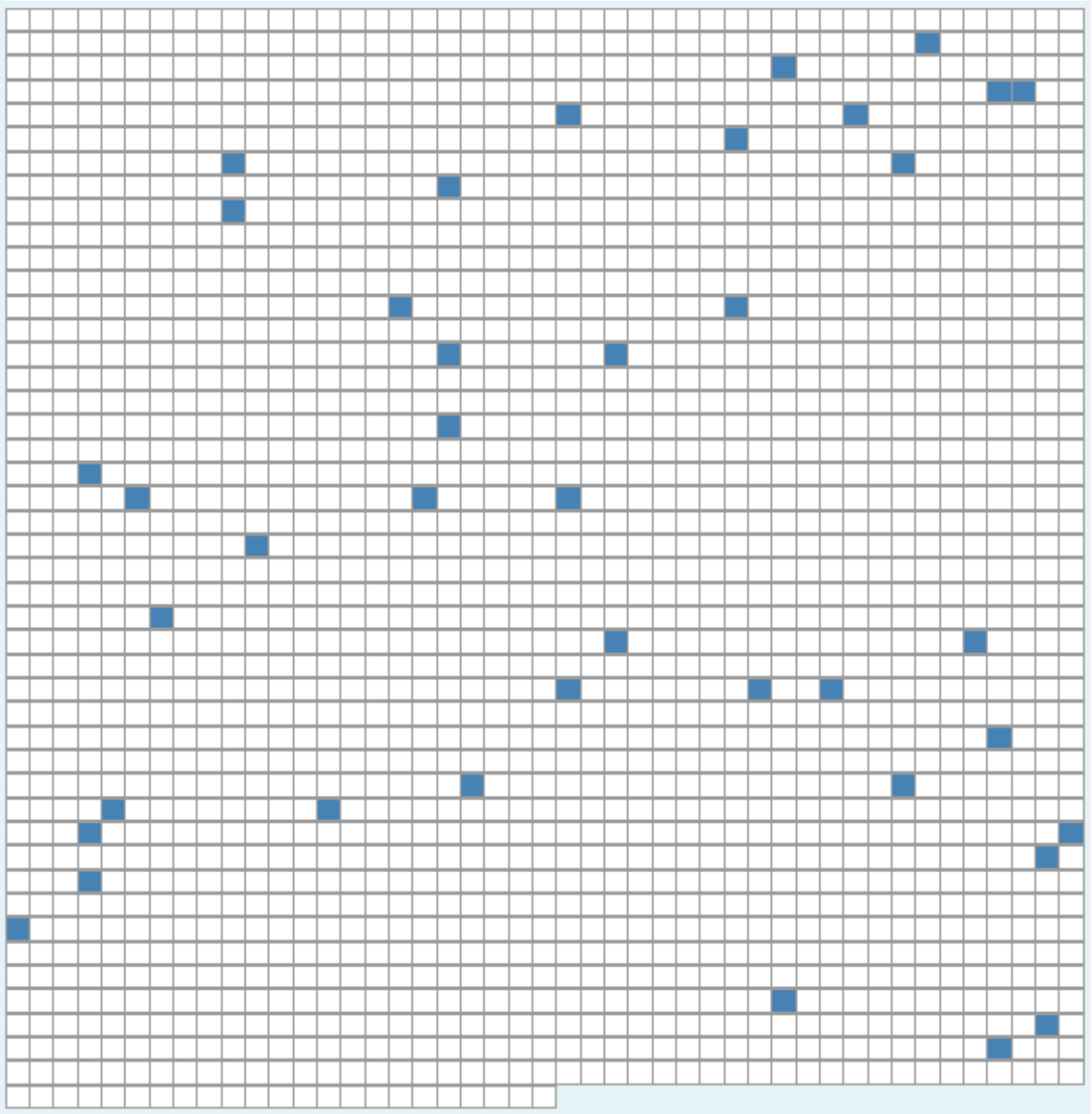
Sparse Distributed Representation - Introduction

- 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

Sparse Distributed Representation - Example



Sparse Distributed Representation - Example



Live Demo!

Sparse Distributed Representation - Live Demos

- Ep2/Capacity
- Ep2/Matching (Noise resistency)
- Ep3/Subsampling
- Ep4/Classification
- Ep4/Union
- Ep5/Scalar Encoding
- Ep6/Date Encoding
- Ep5/RDSE - Number Encoding

Encoders - Conclusion

- Semantically similar data should result in SDRs with overlapping active bits.
- The same input should always produce the same SDR as output.
- The output should have the same dimensionality (total number of bits) for all inputs.
- The output should have similar sparsity for all inputs and have enough one-bits to handle noise and subsampling.

Cited from [1].

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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

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

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

- Continuity
- Occurs everywhere
- Context sensitivity
- Stability
- Anomaly Detection
- Noise robustness

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Open Questions

- Neuron fire frequency

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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

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Cortical Column

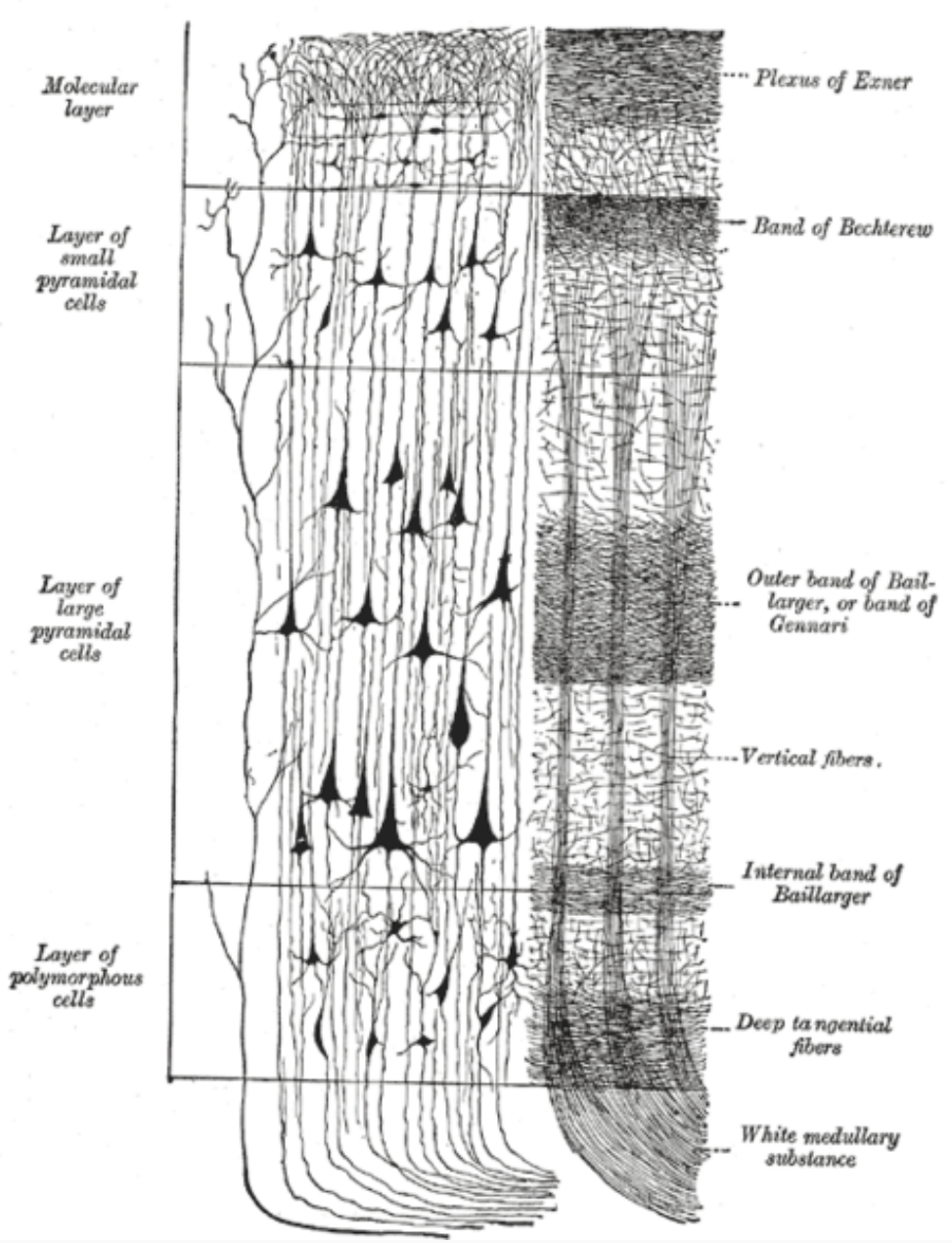

Image from [10]

Cortical Column II