Hierarchical Temporal Memory

Biological And Machine Intelligence

Felix Karg

August 28, 2019

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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- Problme solving tests

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But dogs, monkeys and dolphins fail them.

Tests for Intelligence

- Turing test
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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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Might not be best at specific task.

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 (total)	86 billion (100%)

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Rel. size of cerebral cortex	82% of brain
Neurons in brain stem	1 billion (1%)

Data from [2].

The Human Brain

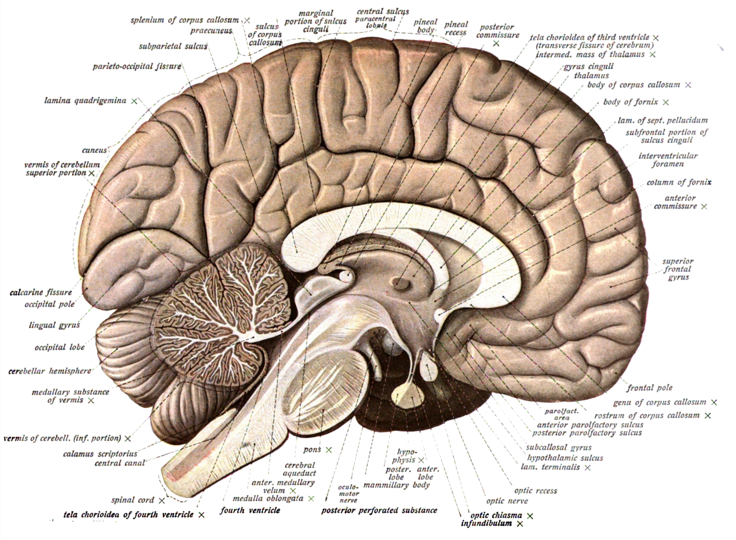
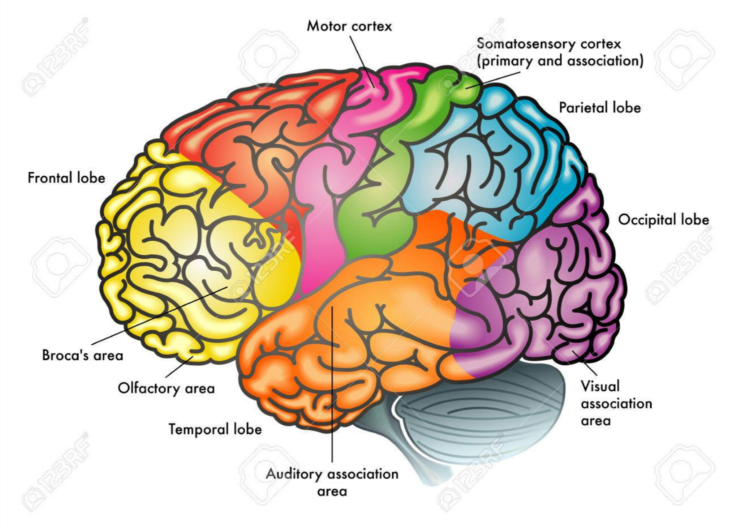


Image from [3].

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

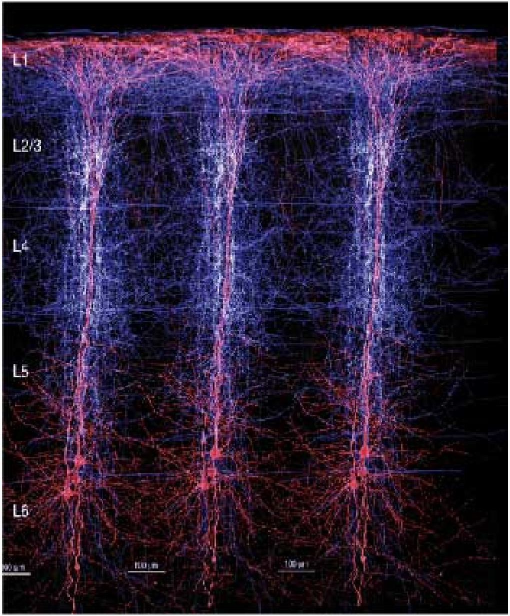


Image from [4].

Cortical Column

- Everywhere in the Brain

Cortical Column

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

Cortical Column

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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

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

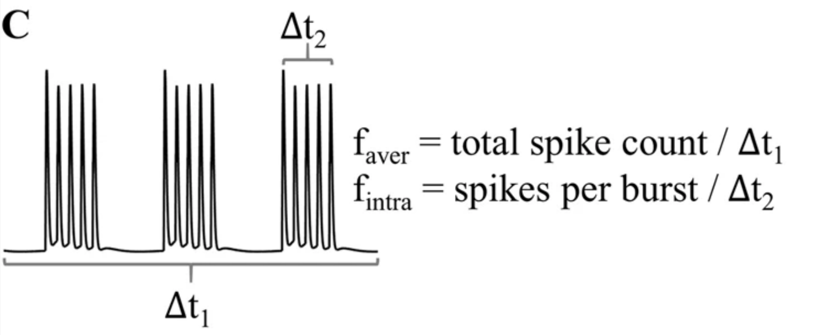

Image adapted from [7].

Neuron - Overview

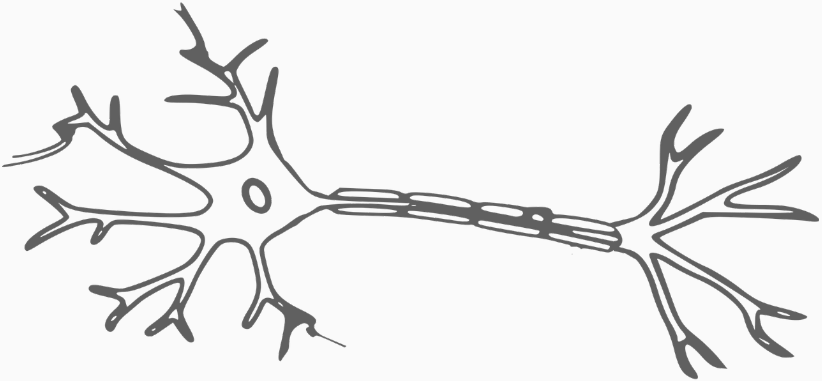

Image from [8].

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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- Firing rythms
- Emotions

Not Included in HTM

- Firing rythms
- 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

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

Attributes of HTM Algorithms

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- can store, learn, infer and recall higher-order sequences

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- 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.

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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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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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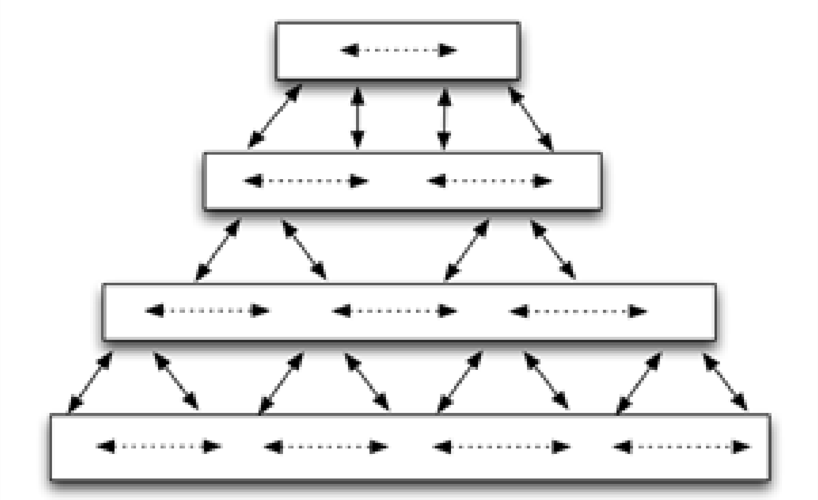
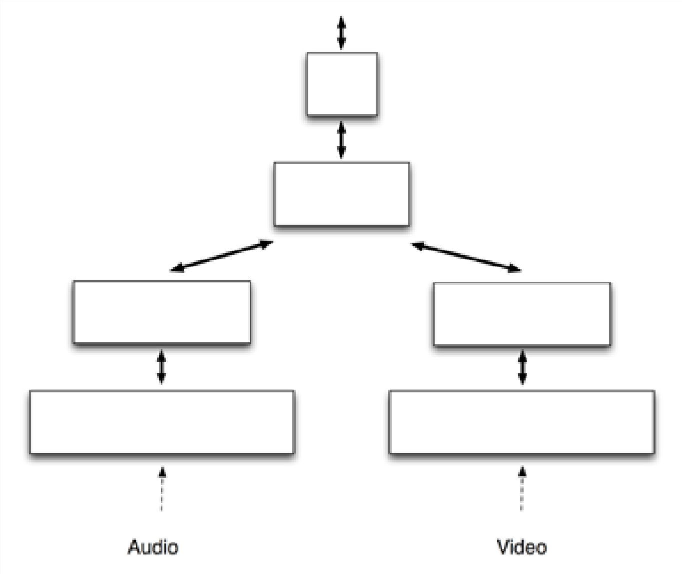
- Transfer Learning

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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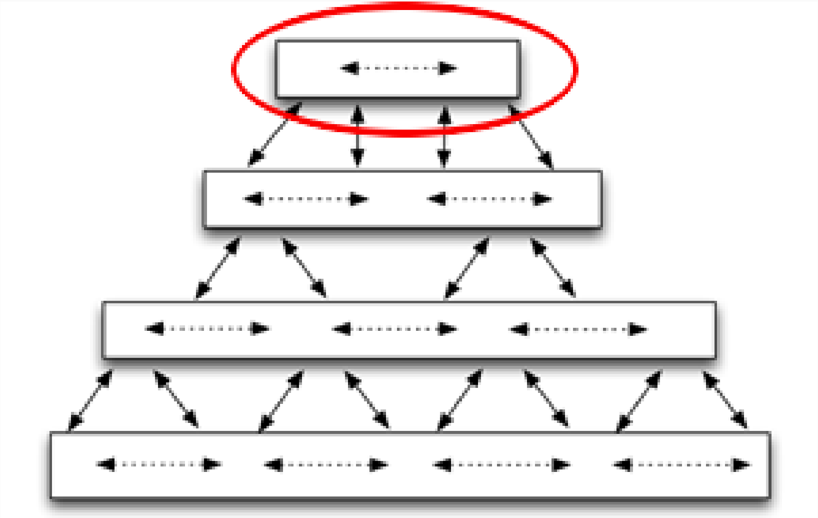
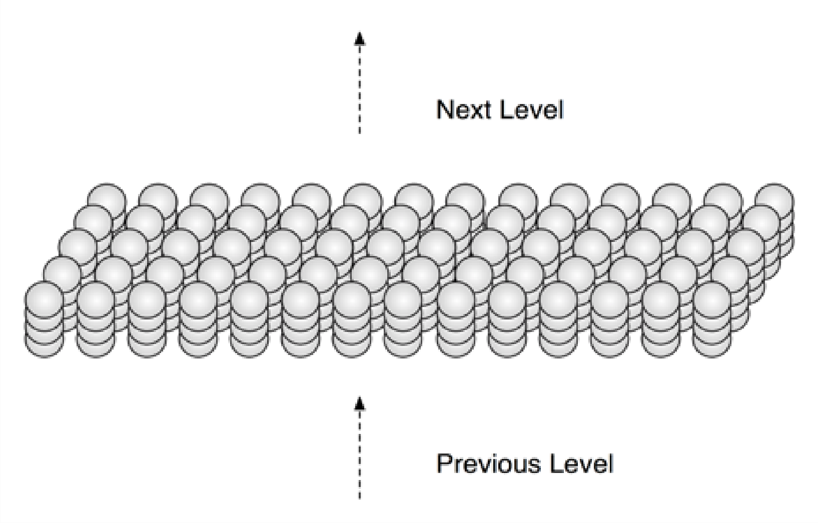


Region - Details



Region - Attributes

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- HTM Regions are similar to Layer 3 of the Neocortex

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

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,...`)

Data Saving - Computer Science Solution

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- Pointer to something else
- Part of some other Datastructure

Biological observation:
We use only part of our brain!

Sparse Distributed Representation - Introduction

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- Datastructure of the brain
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- Inhibitory mechanisms
- Neuron states actually have 'meaning'
- Combined, they give context as well
- Many mechanisms in the brain would not work otherwise

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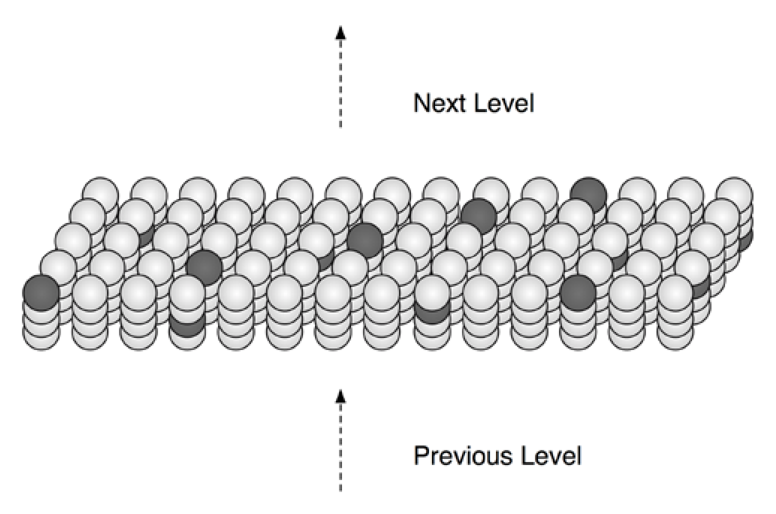

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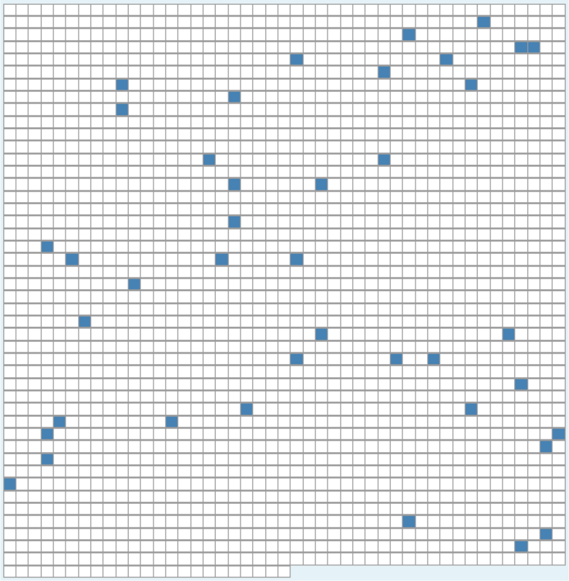

Live Demo!

Sparse Distributed Representation - Live Demos

Sparse Distributed Representation - Live Demos

- Ep2/Capacity

Sparse Distributed Representation - Live Demos

- Ep2/Capacity
- Ep2/Matching (Noise resistency)

Sparse Distributed Representation - Live Demos

- Ep2/Capacity
- Ep2/Matching (Noise resistency)
- Ep3/Subsampling

Sparse Distributed Representation - Live Demos

- Ep2/Capacity
- Ep2/Matching (Noise resistency)
- Ep3/Subsampling
- Ep4/Classification

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- Ep4/Union

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- Ep5/Scalar Encoding

Sparse Distributed Representation - Live Demos

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- Ep3/Subsampling
- Ep4/Classification
- Ep4/Union
- Ep5/Scalar Encoding
- Ep6/Date Encoding

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

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Cited from [1].

Content

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- takes longer to learn high-level concepts with lower levels missing

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 suffice

Prediction

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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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- Continuity
- Occurs everywhere

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- Context sensitivity

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- Anomaly Detection

Prediction - Key Properties

- Continuity
- Occurs everywhere
- Context sensitivity
- Stability
- 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

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End

Cortical Column

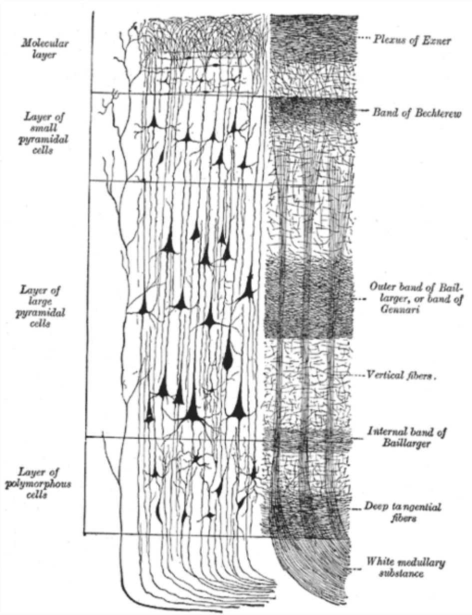

Image from [10]

Cortical Column II