

Hierarchical Temporal Memory

Biological And Machine Intelligence

Felix Karg

August 31, 2019

LessWrong Community Weekend 2019

Content

What is Intelligence?

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Overview

Core Concepts

Hierarchy

Regions

Sparse Distributed

Representation

Learning

Overview

Spatial Pooler

Temporal Pooler

HTM Recap

Implications

Sources

Disclaimer:

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

Epistemic status

Epistemic status

- Evolving theories

Epistemic status

- Evolving theories
- Hypotheses partially verified

Epistemic status

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- Hypotheses partially verified
- Theories are constantly being updated

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

Tests for Intelligence

- Turing test

Tests for Intelligence

- Turing test
- 'IQ' tests

Tests for Intelligence

- Turing test
- 'IQ' tests
- Problem solving tests

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- Car driving skills

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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.

→ General solution.

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The Human Brain in Numbers

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Neurons in brain (total) 86 billion (100%)

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Neurons in brain (total)	86 billion (100%)
Neurons in cerebellum	69 billion (80%)

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Neurons in brain (total)	86 billion (100%)
Neurons in cerebellum	69 billion (80%)
Rel. size of cerebellum	10% of brain
Neurons in cerebral 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

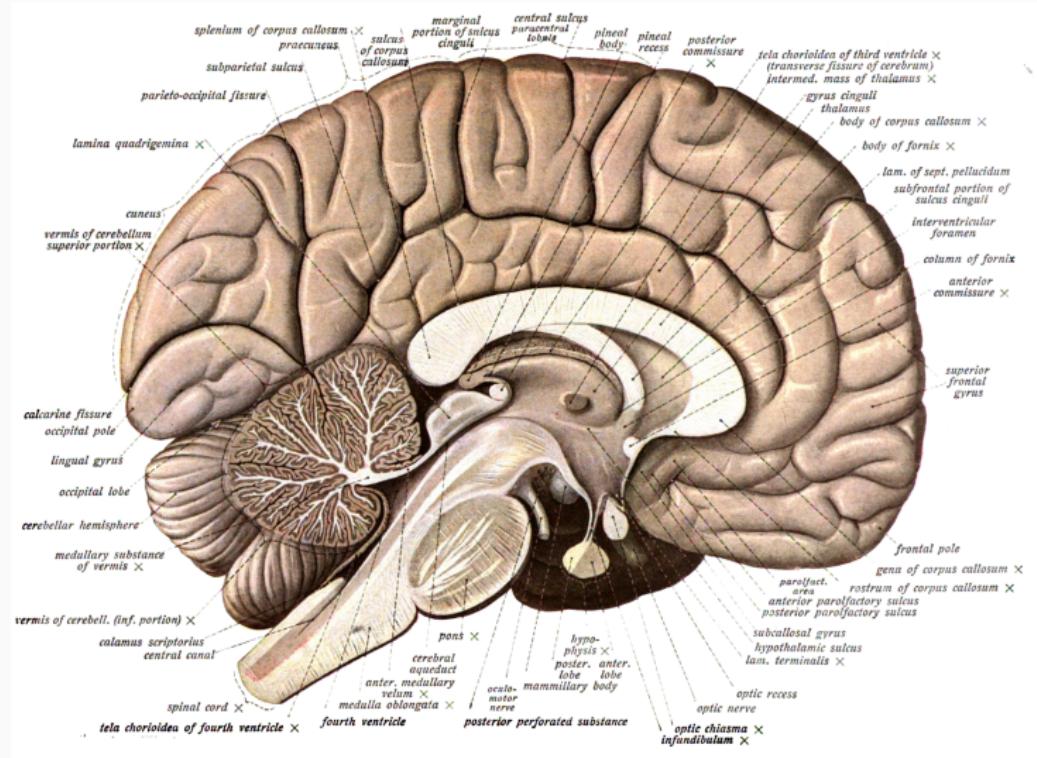
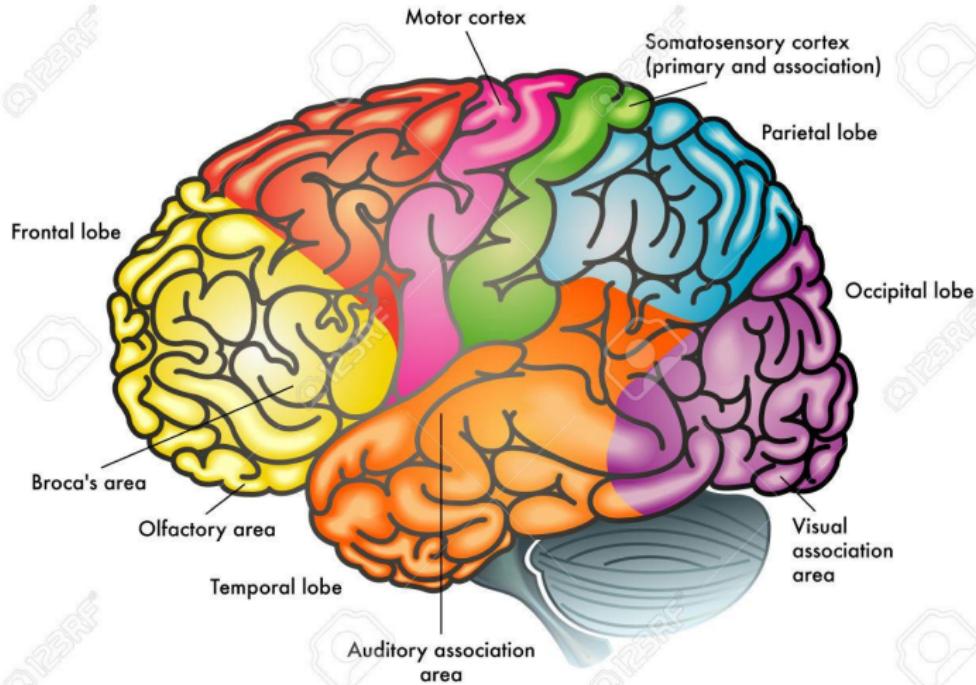


Image from [3].

The Human Brain - Different Areas



Cortical Column

“There is nothing visual about the visual cortex, and nothing auditory about the auditory cortex”

- Vernon Mountcastle

Cortical Column

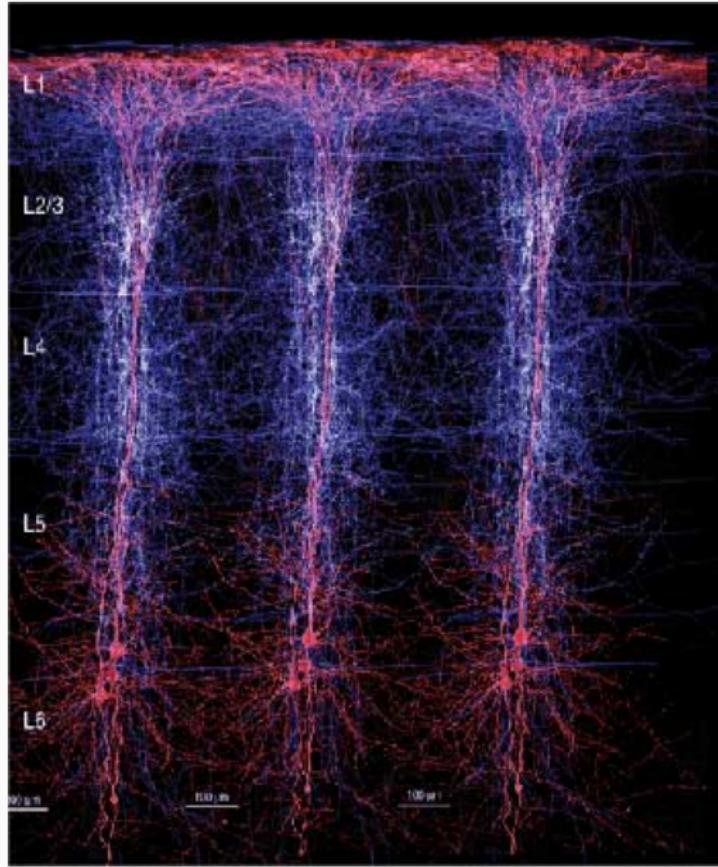


Image from [4].

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
- 80-120 up to 200-400 Neurons
- 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

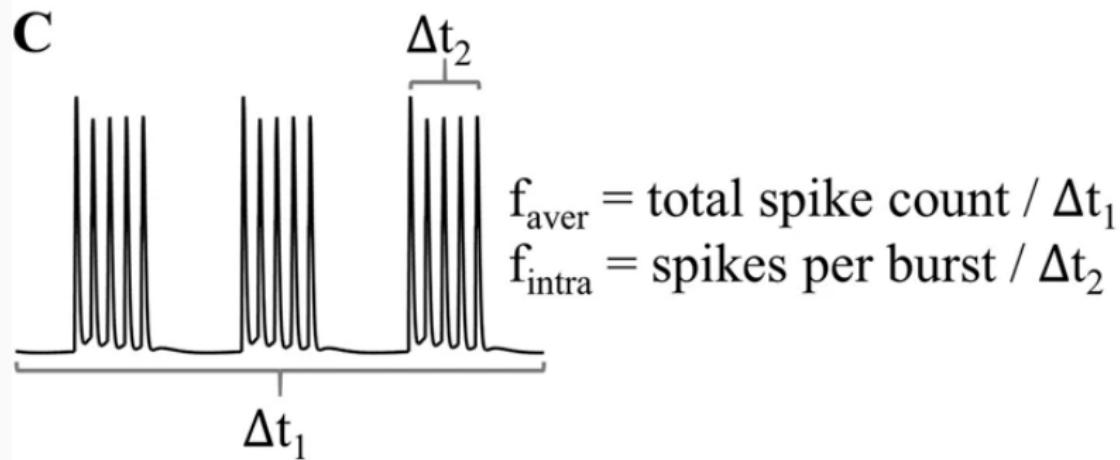


Image adapted from [7].

Neuron - Overview

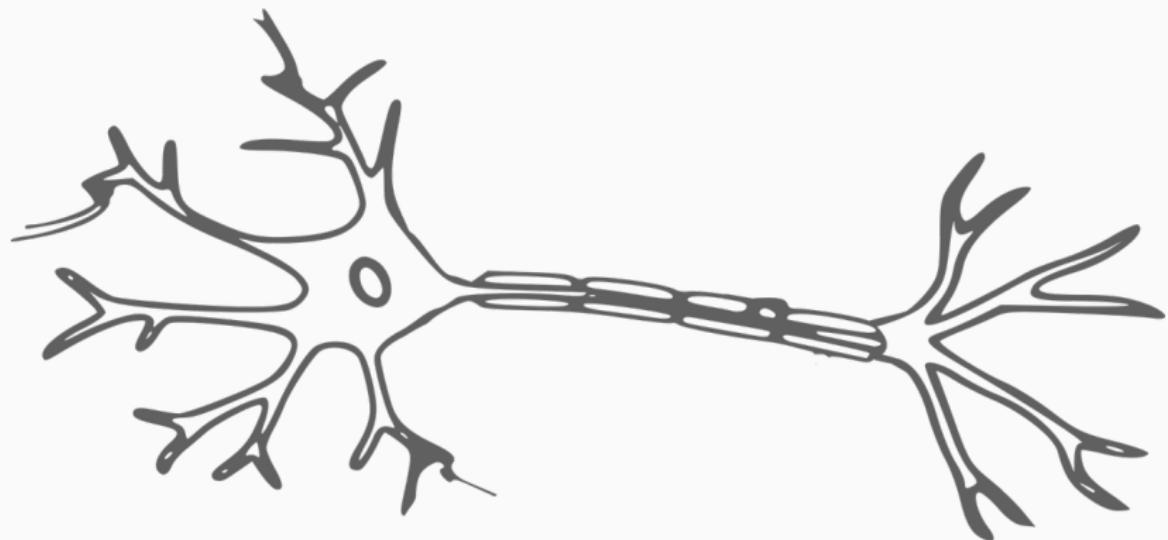


Image from [8].

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- Biologically constrained **Theory of Intelligence**

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- Biologically constrained **Theory of Intelligence**
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- Learning Algorithms

What is HTM?

- Biologically constrained **Theory of Intelligence**
 - First described in "On Intelligence"
 - **Based on Neuroscience** of the brain
- Learning Algorithms (of the brain)

Not Included in HTM

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- Firing rhythms

Not Included in HTM

- 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
- 'Anticipating' events
- 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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Attributes of HTM Algorithms

- can store, learn, infer and recall higher-order sequences
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- tested and implemented in software

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- 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.

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- Predictions are somewhat inherently time-based

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?

Why Hierarchy?

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

Why Hierarchy?

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

Especially when tasks change regularly.

Why Hierarchy? II

Why Hierarchy? II

- Reduced Training Time

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- Reduced Training Time
- Reduced Memory Usage

Why Hierarchy? II

- Reduced Training Time
- Reduced Memory Usage
- Introduce Generalizations

Why Hierarchy? II

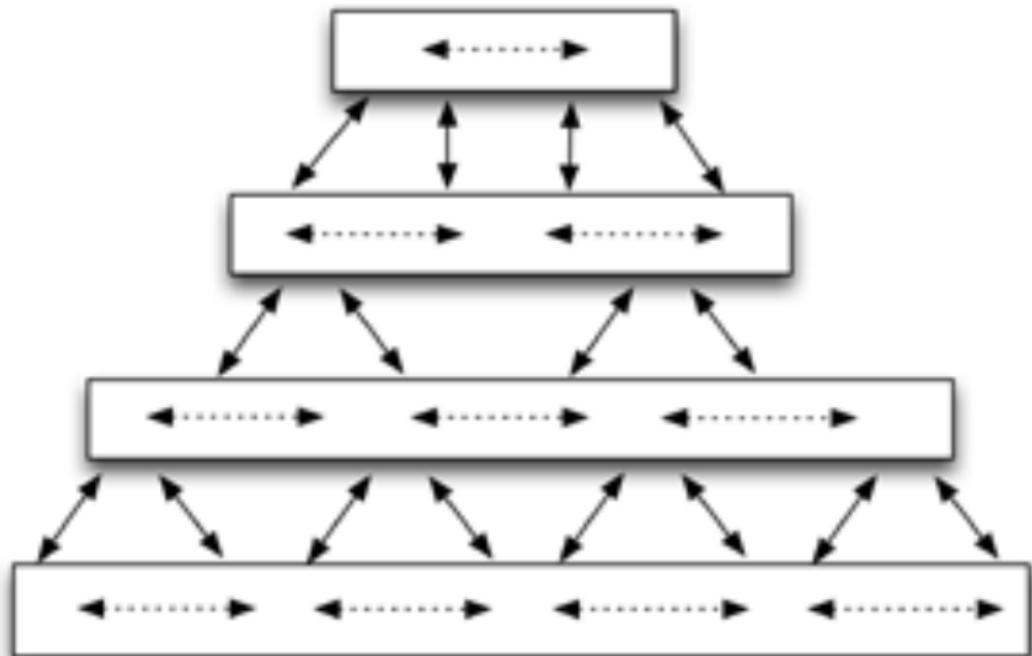
- Reduced Training Time
- Reduced Memory Usage
- Introduce Generalizations
- Learned patterns are recombined at higher levels

Why Hierarchy? II

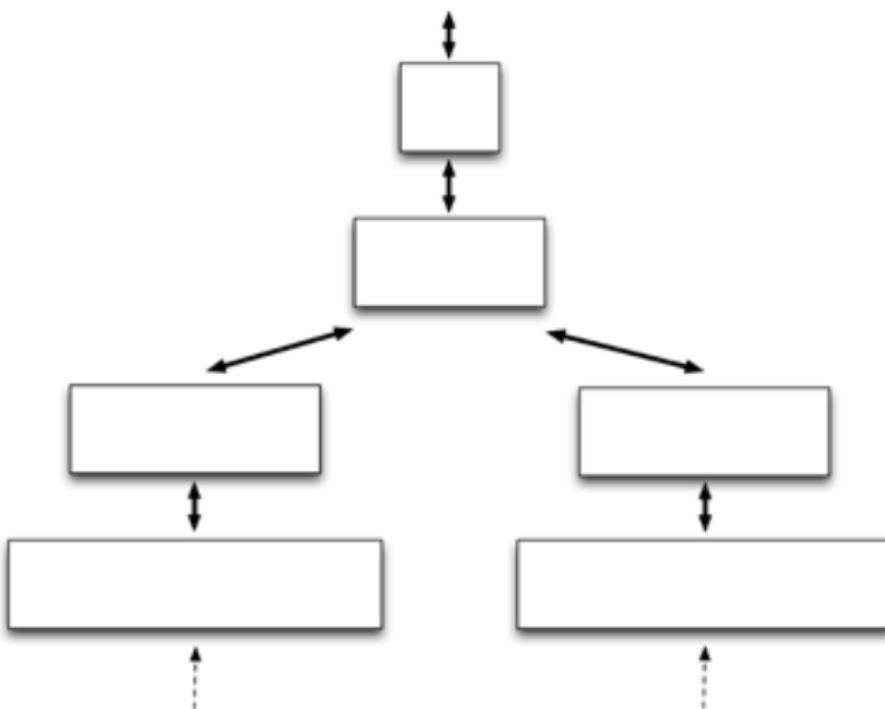
- Reduced Training Time
- Reduced Memory Usage
- Introduce Generalizations
- Learned patterns are recombined at higher levels
- Transfer Learning

What Hierarchy

What Hierarchy



Example Application



Audio

Video

How Many Levels?

How Many Levels?

- They always learn the best representation

How Many Levels?

- They always learn the best representation
- 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

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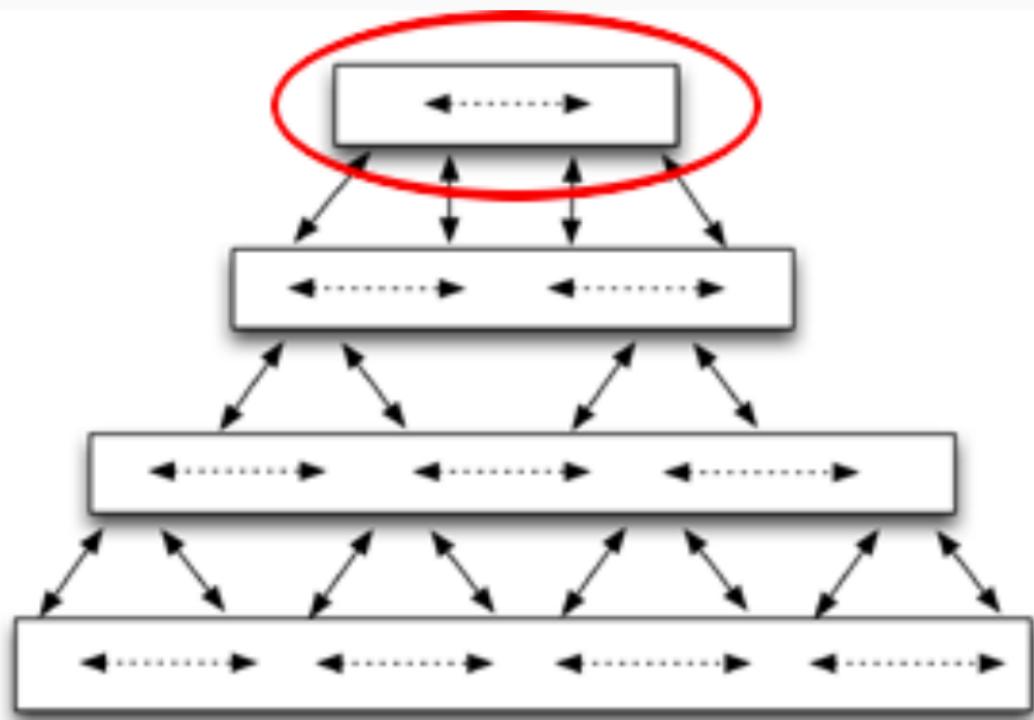
HTM Recap

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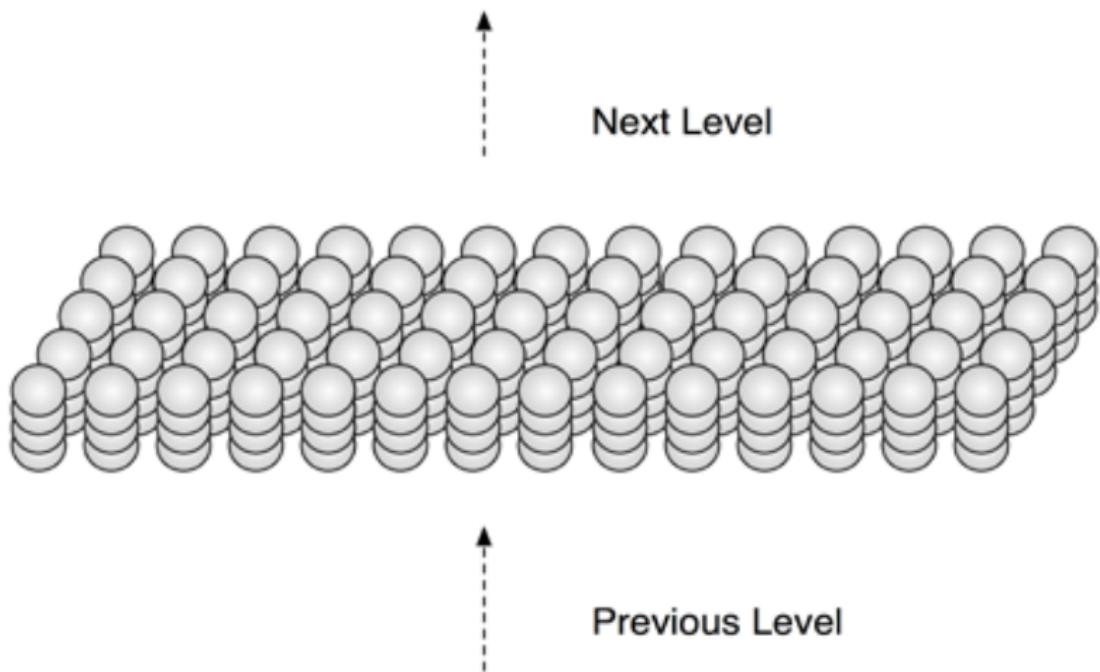
Sources

Region - Introduction

Region - Introduction



Region - Details



Region - Attributes

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- All Regions do basically the same

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- Based on Biological Regions in the Brain

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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

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Data Saving - Computer Science Solution

What is 01100101?

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, ...)

What is 01100101? Could be either one of:

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- Integer (101)

What is 01100101? Could be either one of:

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- Float (3328.0)

What is 01100101? Could be either one of:

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- (Byte-) String ('e')

What is 01100101? Could be either one of:

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(False, True, True, False,...)
- Integer (101)
- Float (3328.0)
- (Byte-) String ('e')
- Pointer to something else

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

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- Datastructure of the brain

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- Datastructure of the brain
- Sparse (around 2% are active)

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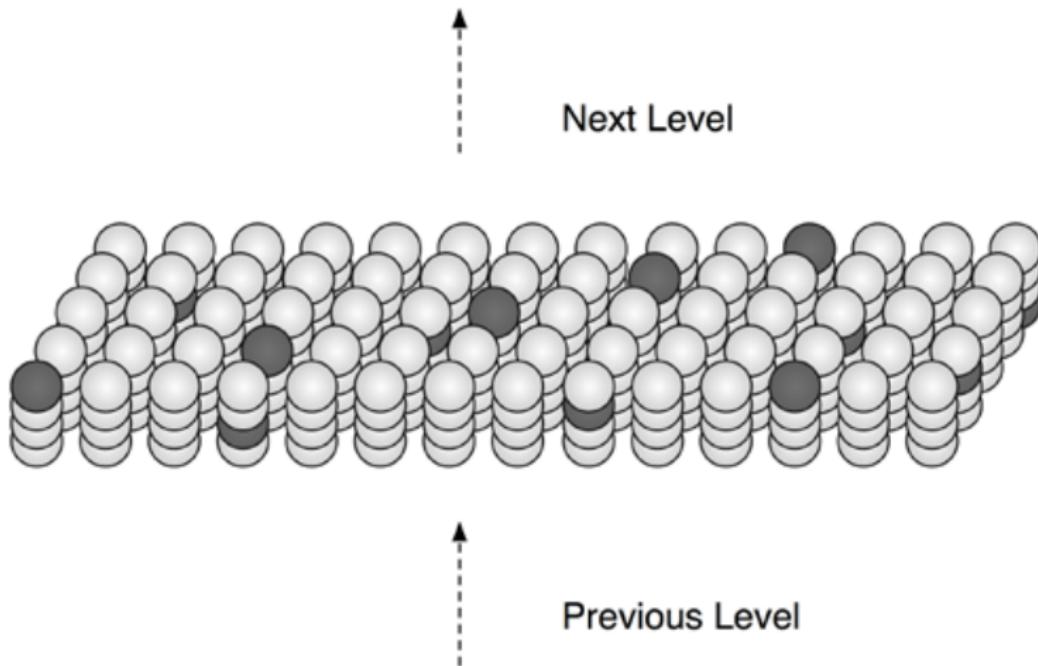
Sparse Distributed Representation - Introduction

- Datastructure of the brain
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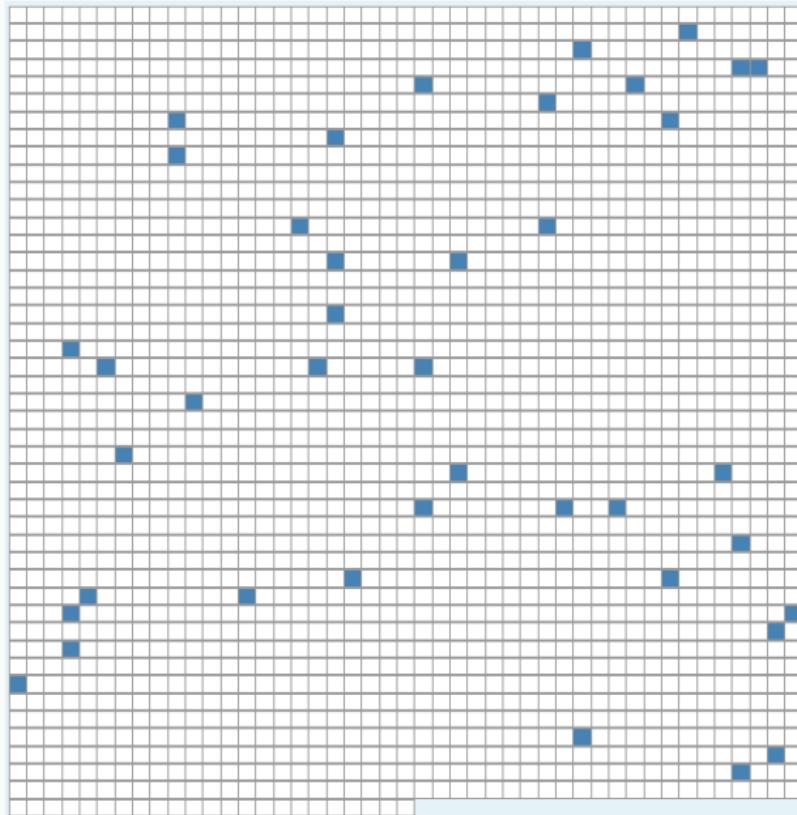
Sparse Distributed Representation - Introduction

- 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

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

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- Ep4/Classification

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Sparse Distributed Representation - Live Demos

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- Ep4/Classification
- Ep4/Union
- Ep5/Scalar Encoding

Sparse Distributed Representation - Live Demos

- Ep2/Capacity
- Ep2/Matching (Noise resistency)
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- 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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- The output should have similar sparsity for all inputs and have enough one-bits to handle noise and subsampling.

Encoders - Conclusion

- Semantically similar data should result in SDRs with overlapping active bits.
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Cited from [1].

HTM - Pipeline

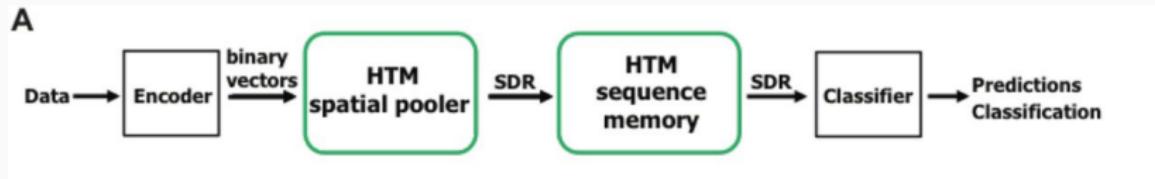


Image adapted from [10].

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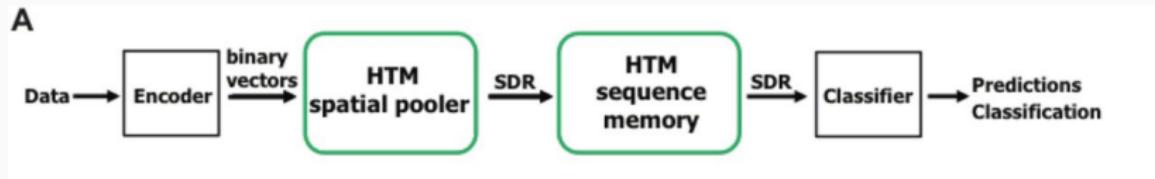


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- Data

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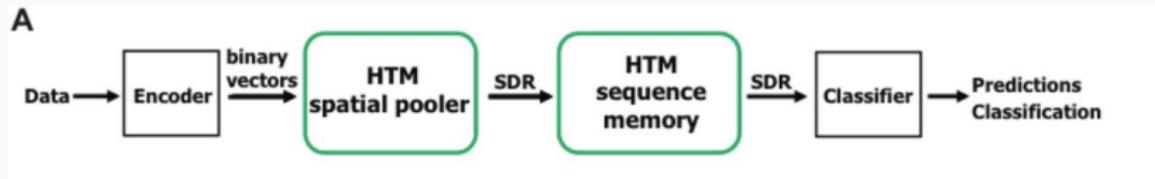


Image adapted from [10].

- Data
- SDR Encoded Data

HTM - Pipeline

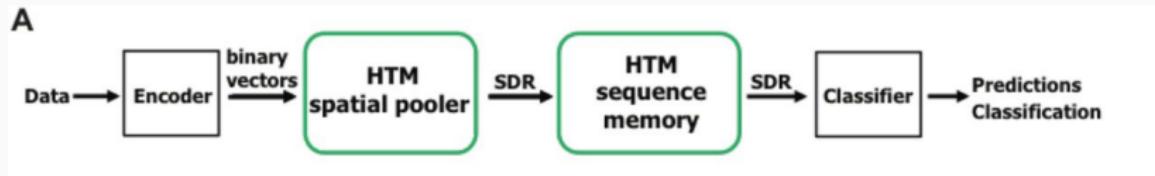


Image adapted from [10].

- Data
- SDR Encoded Data
- Spatial Pooler

HTM - Pipeline

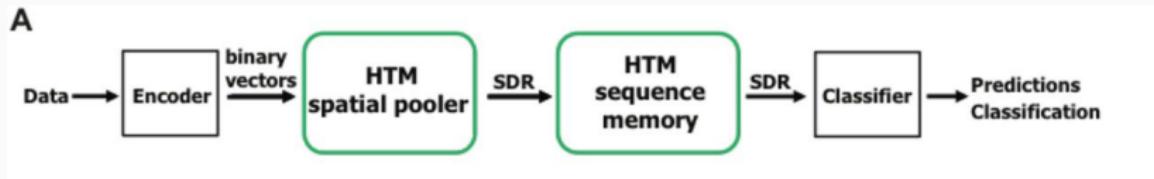


Image adapted from [10].

- Data
- SDR Encoded Data
- Spatial Pooler
- Temporal Pooler

HTM - Pipeline

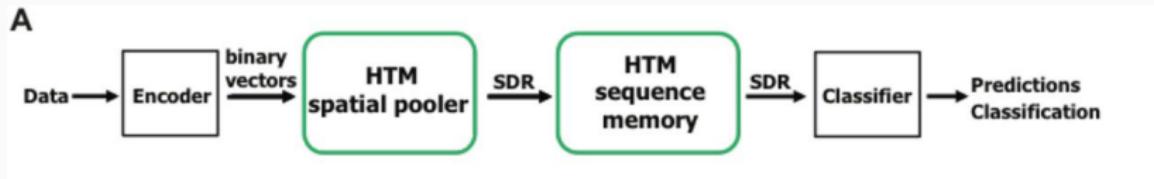


Image adapted from [10].

- Data
- SDR Encoded Data
- Spatial Pooler
- Temporal Pooler
- Classifier

HTM - Pipeline

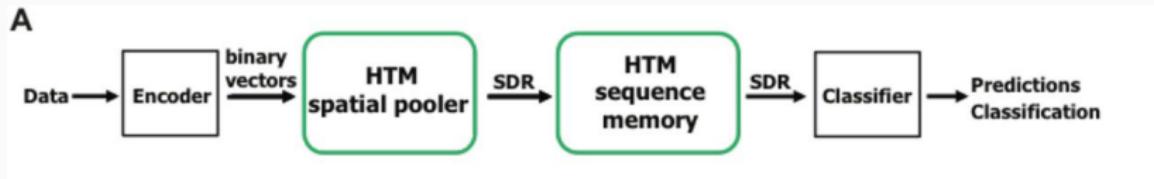


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- Data
- SDR Encoded Data
- Spatial Pooler
- Temporal Pooler
- Classifier
- Prediction/Classification

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Learning

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- Learning is purely statistical

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- Looking for Spatial and Temporal Patterns

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Learning

- Learning is purely statistical
- Looking 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

Inference

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- Example: recognizing a melody

Inference

- Matching previously learned sequences
- Example: recognizing a melody
- There are only novel experiences

Inference

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

Prediction

Prediction

- Matching stored sequences

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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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- Continuity
- Occurs everywhere

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- Occurs everywhere
- Context sensitivity

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Prediction - Key Properties

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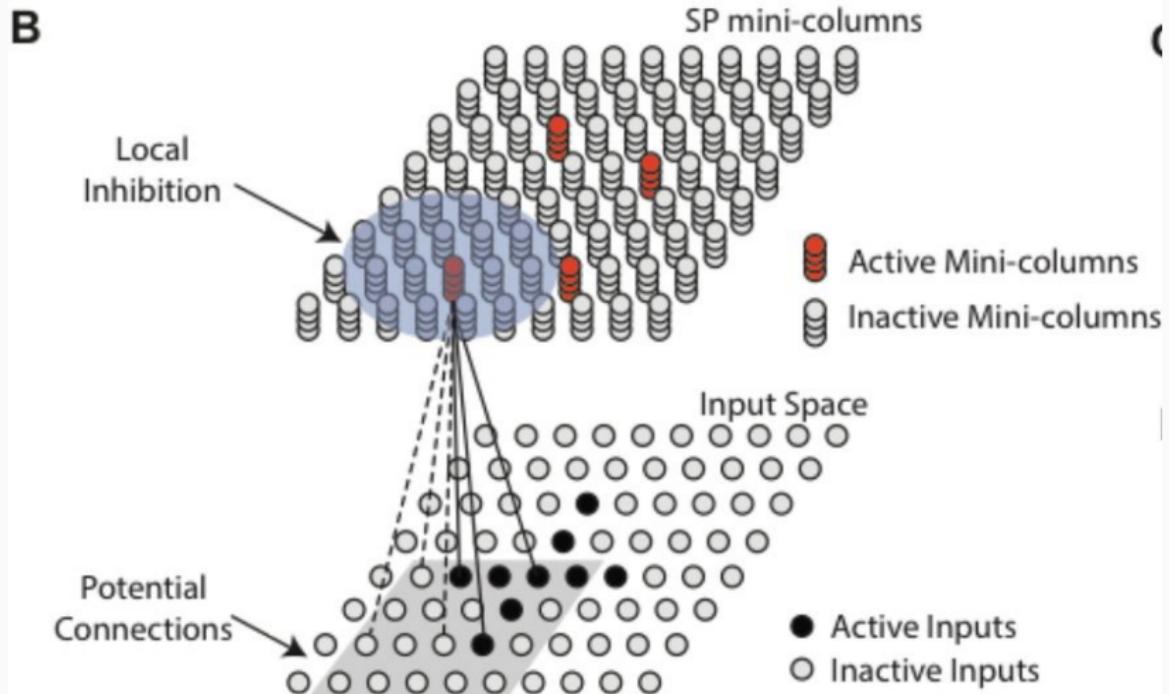


Image adapted from [10].

Spatial Pooler - Connection details

Show Ep8/Learning Rules!

Spatial Pooler - Connection details

Show Ep8/Learning Rules!

- Many Connections

Spatial Pooler - Connection details

Show Ep8/Learning Rules!

- Many Connections
- Only Columns with highest overlap scores continue

Spatial Pooler - Connection details

Show Ep8/Learning Rules!

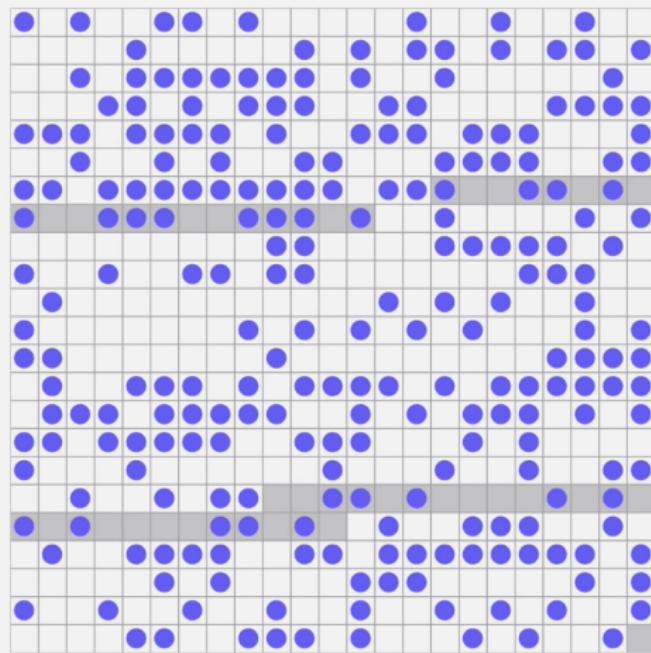
- Many Connections
- Only Columns with highest overlap scores continue
- Everyone else gets inhibited

Spatial Pooler - Connection details

Show Ep8/Learning Rules!

- Many Connections
- Only Columns with highest overlap scores continue
- Everyone else gets inhibited
- Next: Updating Permanence Values

Spatial Pooler - Learning Details i



Column 105 Connection History

Time Step: 0

< jump to active timestep >

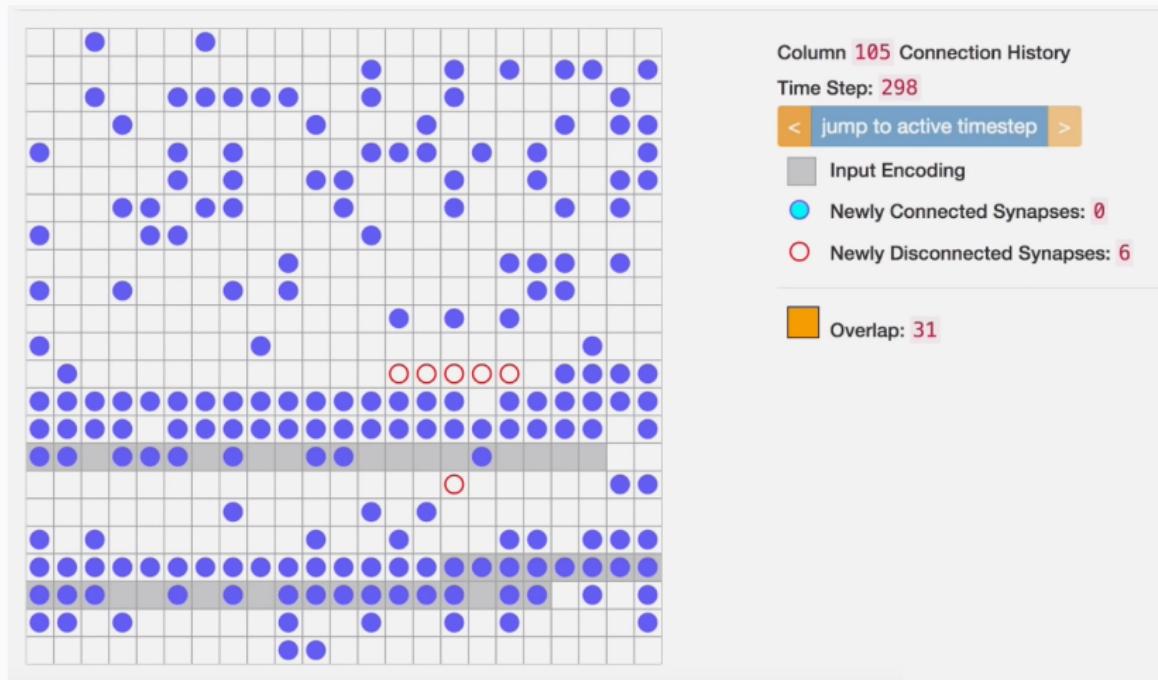
Input Encoding

Newly Connected Synapses: 0

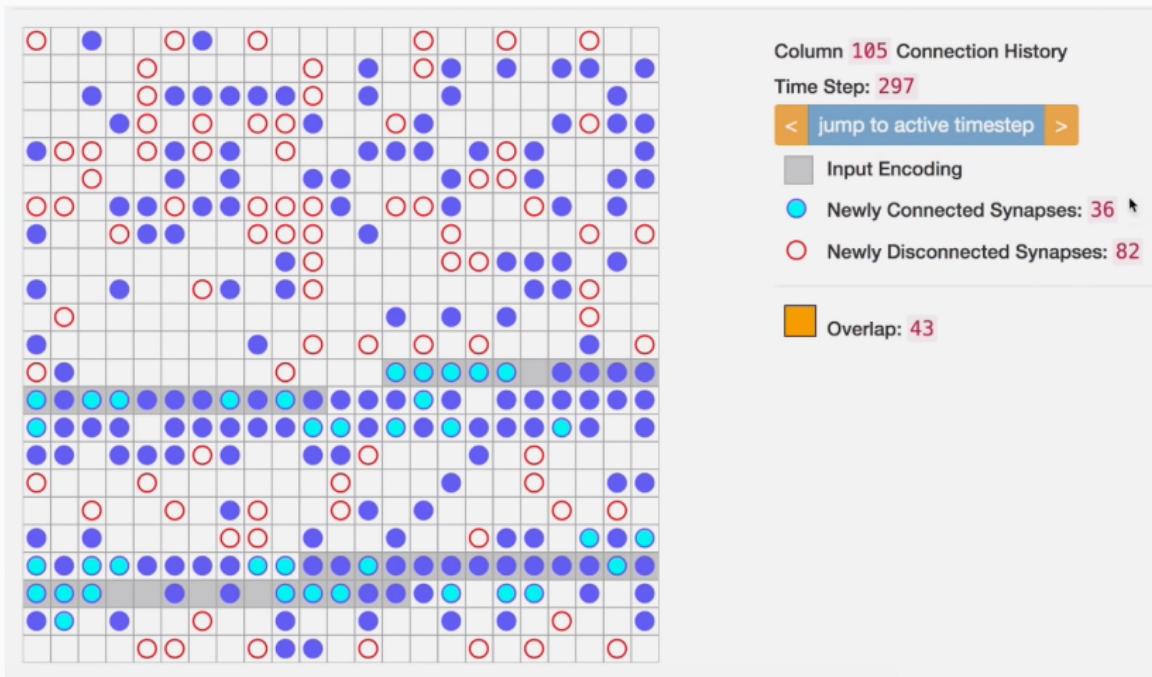
Newly Disconnected Synapses: 0

Overlap: 22

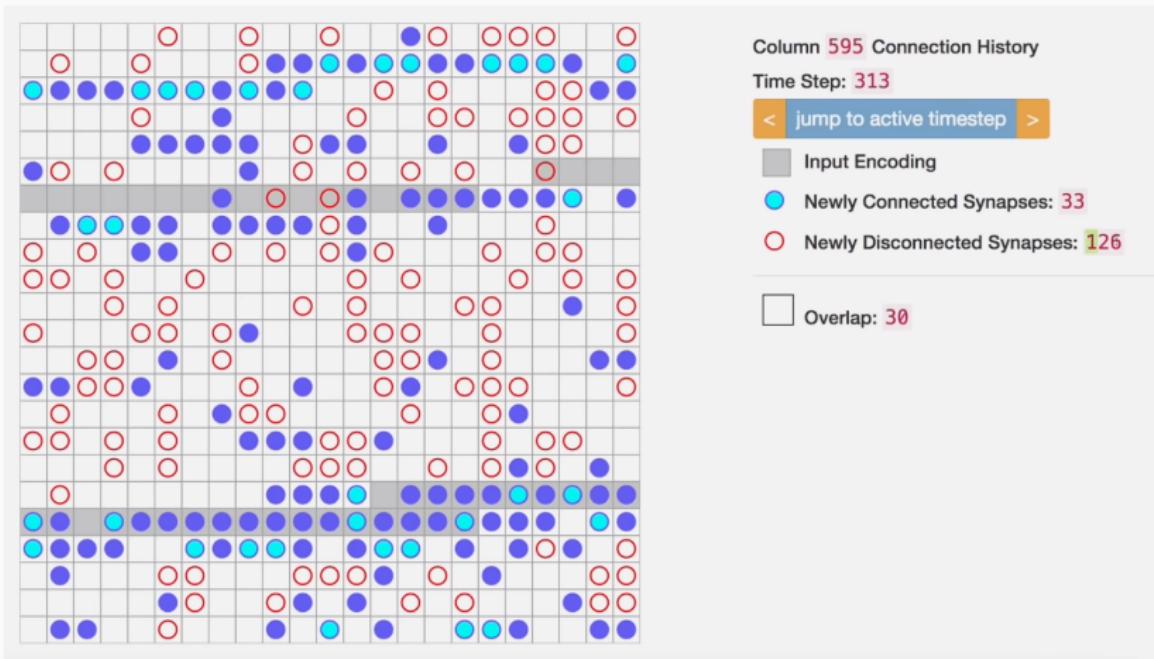
Spatial Pooler - Learning Details ii



Spatial Pooler - Learning Details iii

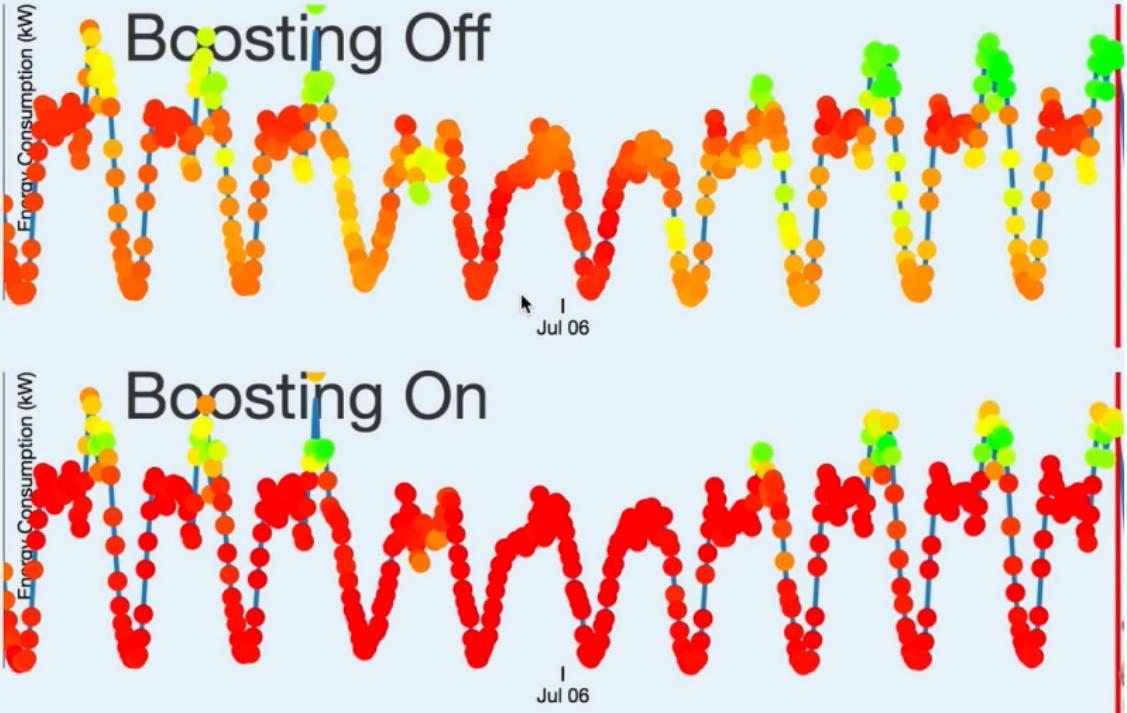


Spatial Pooler - Learning Details iv

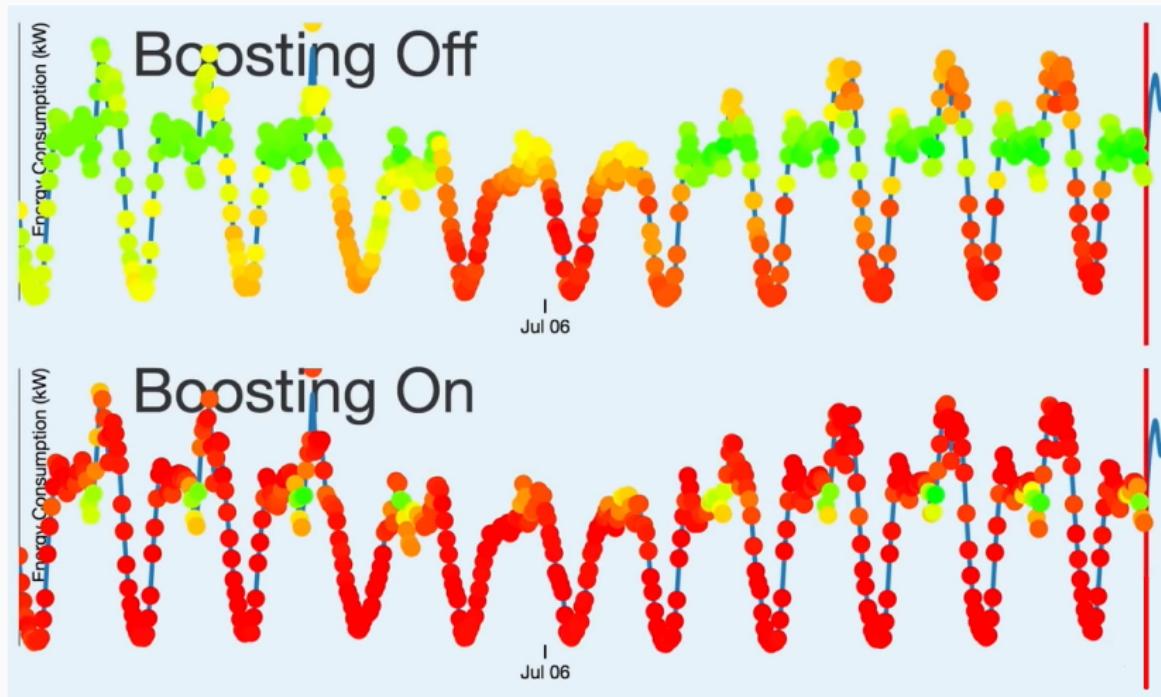


Spatial Pooler - Boosting i

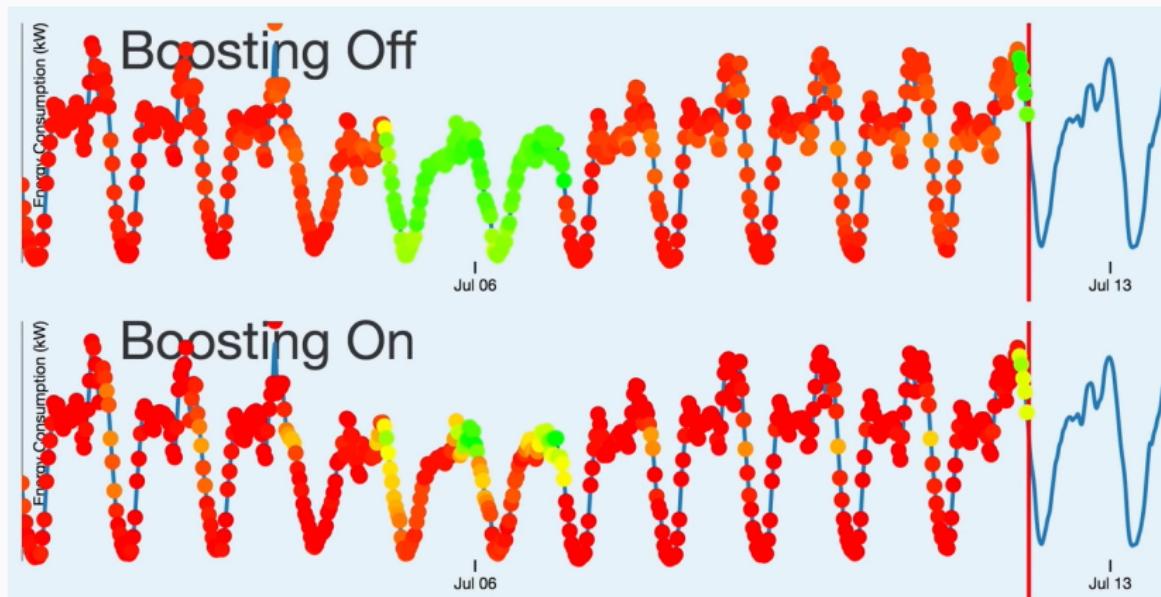
Spatial Pooler - Boosting ii



Spatial Pooler - Boosting iii



Spatial Pooler - Boosting iv



Spatial Pooler - Parameters

Spatial Pooler - Parameters

- Algorithm Structure (receptive field)

Spatial Pooler - Parameters

- Algorithm Structure (receptive field)
- Inhibition

Spatial Pooler - Parameters

- Algorithm Structure (receptive field)
- Inhibition
- Learning rates

Spatial Pooler - Parameters

- Algorithm Structure (receptive field)
- Inhibition
- Learning rates
- Column Activity

Spatial Pooler - Phases

Spatial Pooler - Phases

1. Initializing with random variables

Spatial Pooler - Phases

1. Initializing with random variables
2. Compute overlap scores (+Boost)

Spatial Pooler - Phases

1. Initializing with random variables
2. Compute overlap scores (+Boost)
3. Inhibition

Spatial Pooler - Phases

1. Initializing with random variables
2. Compute overlap scores (+Boost)
3. Inhibition
4. Updating Permanence values

Spatial Pooler - Phases

1. Initializing with random variables
2. Compute overlap scores (+Boost)
3. Inhibition
4. Updating Permanence values
5. Repeat from step 2 with new input

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Temporal Pooler - Pipeline

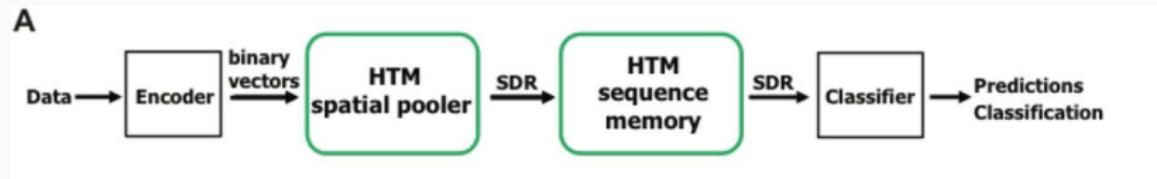
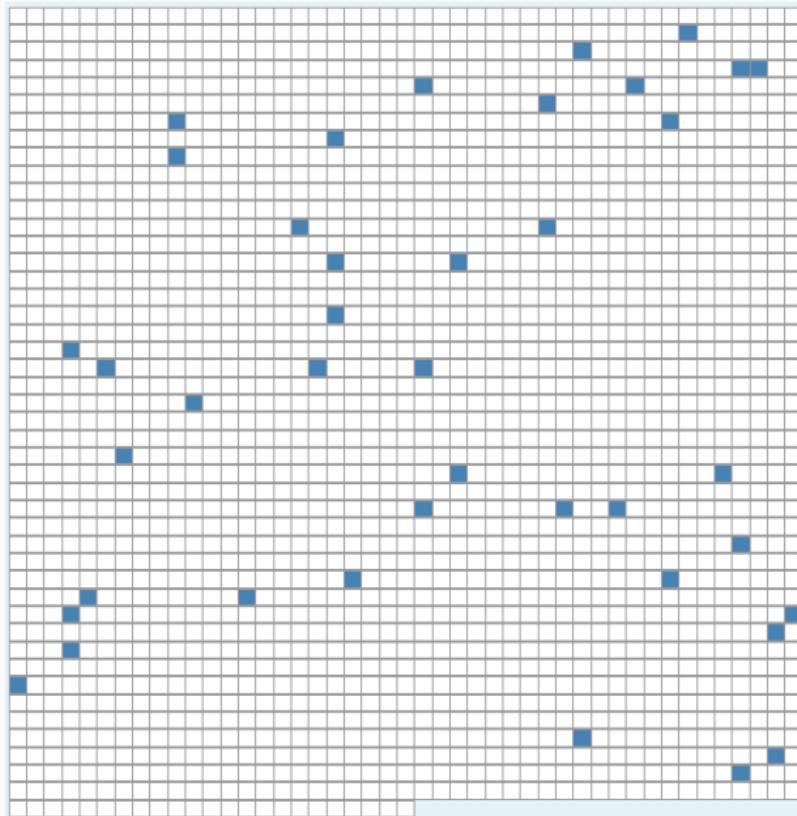
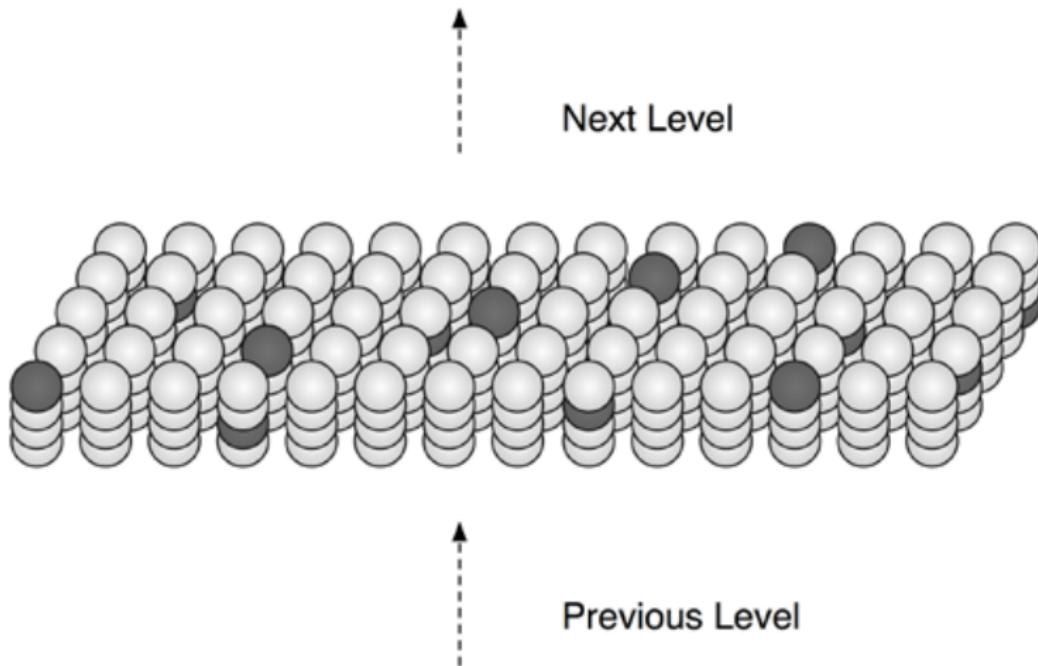


Image adapted from [10].

Temporal Pooler - Introduction



Temporal Pooler - Introduction



Temporal Pooler - Steps

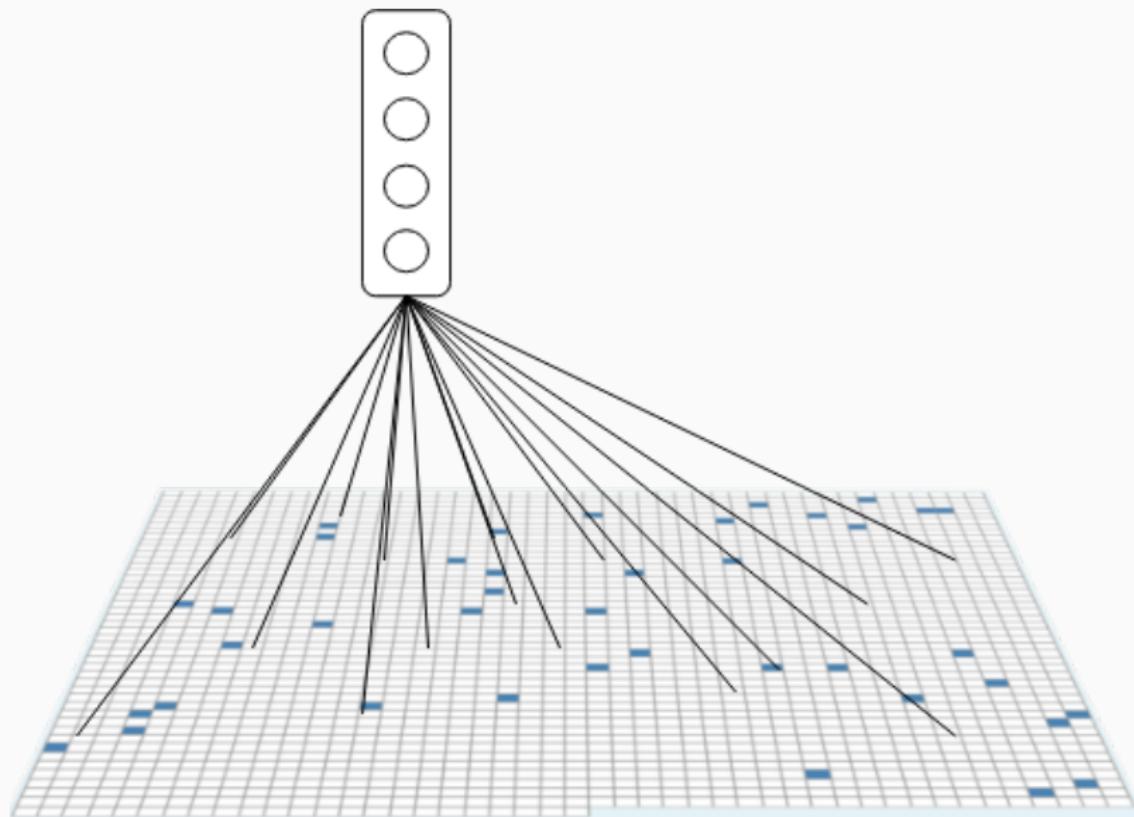
Temporal Pooler - Steps

1. Form representation in context of previous states

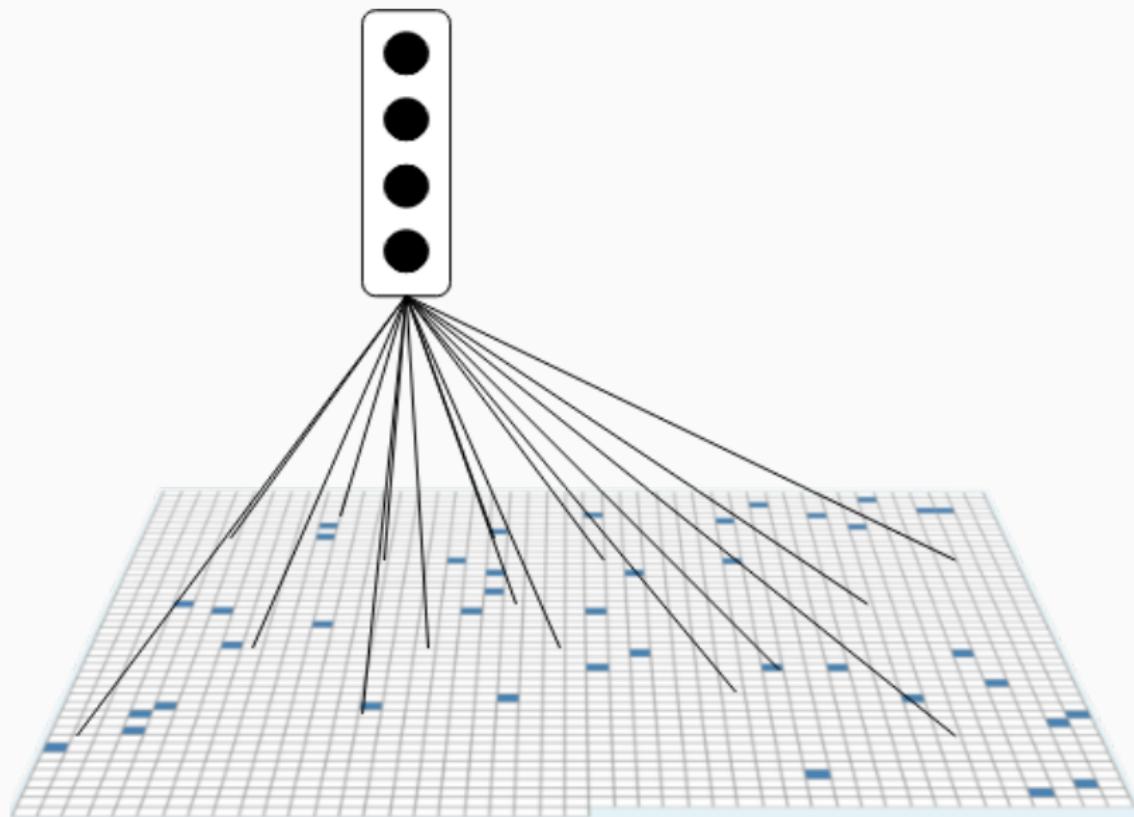
Temporal Pooler - Steps

1. Form representation in context of previous states
2. Form predictions based on previous inputs

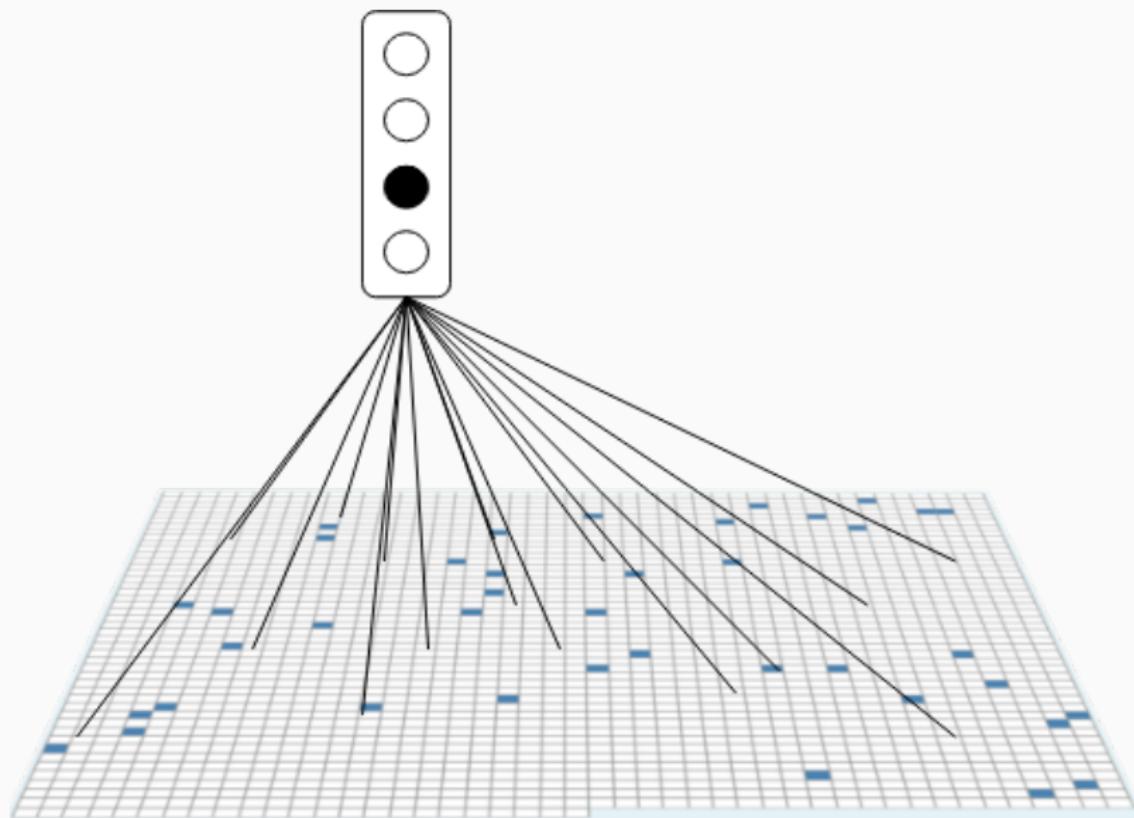
Temporal Pooler - Selecting Winner Cells



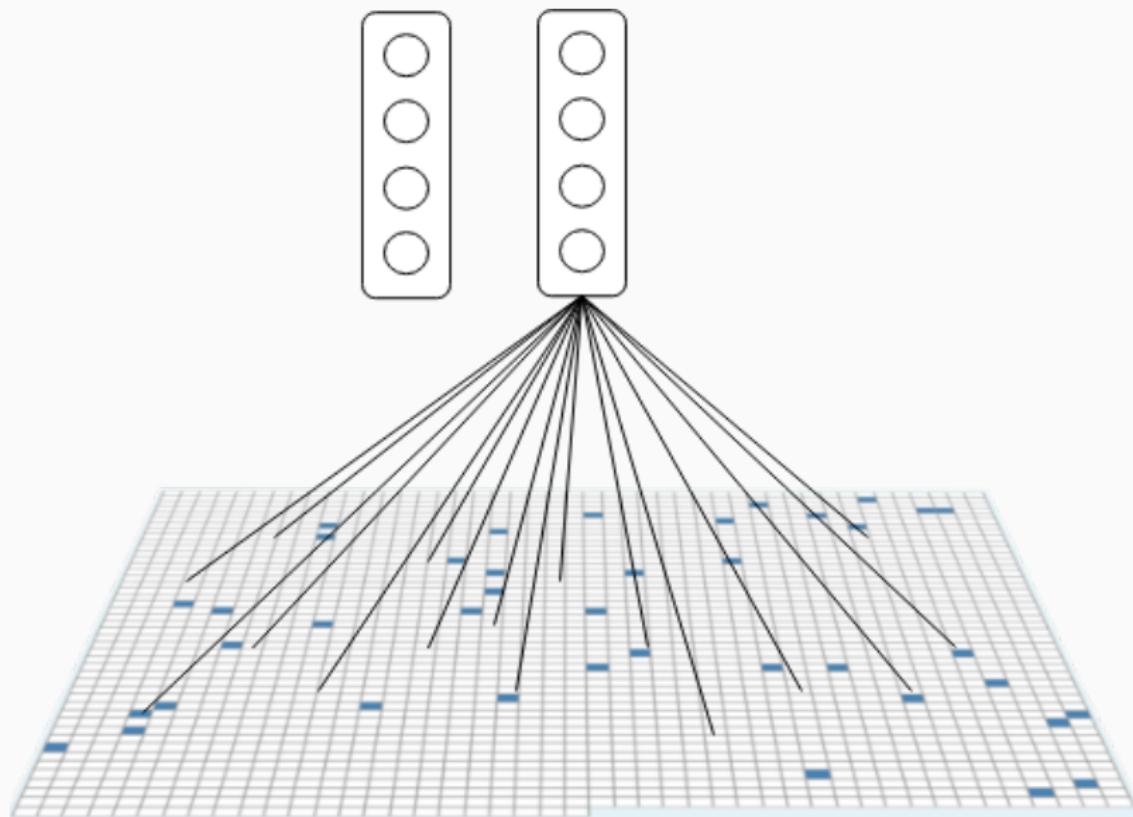
Temporal Pooler - Selecting Winner Cells



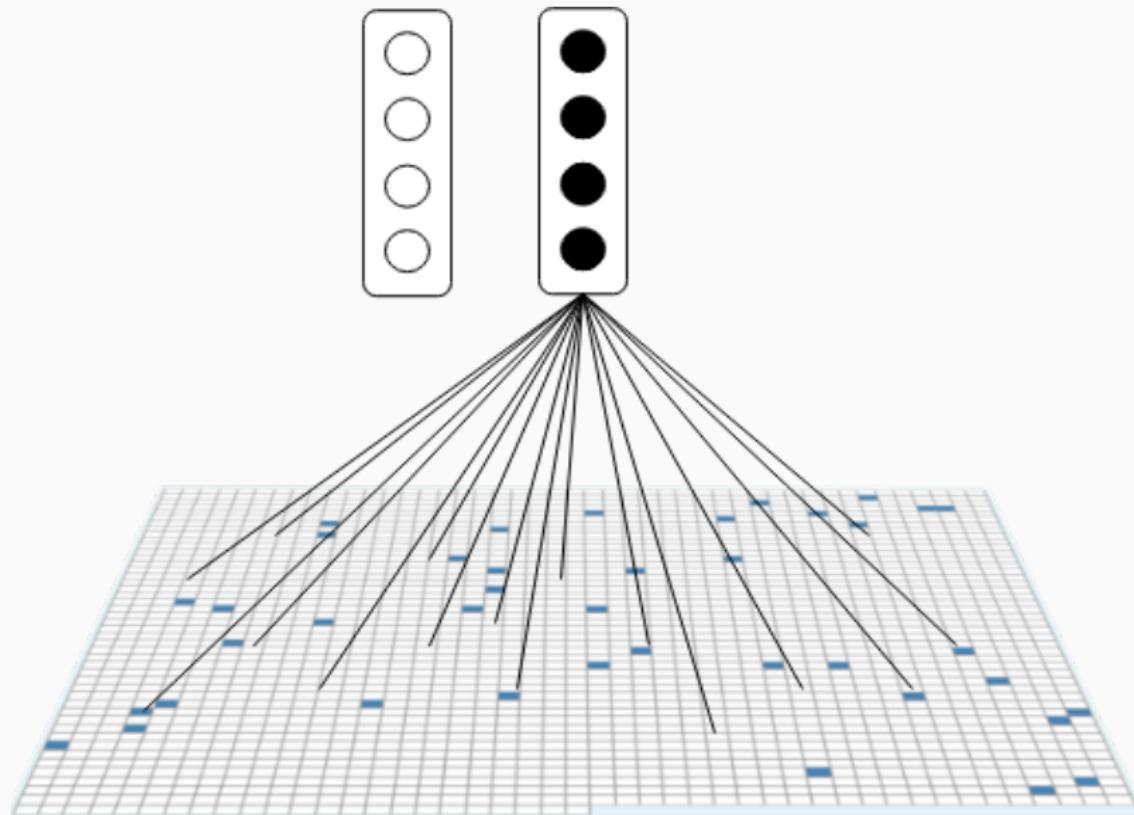
Temporal Pooler - Selecting Winner Cells



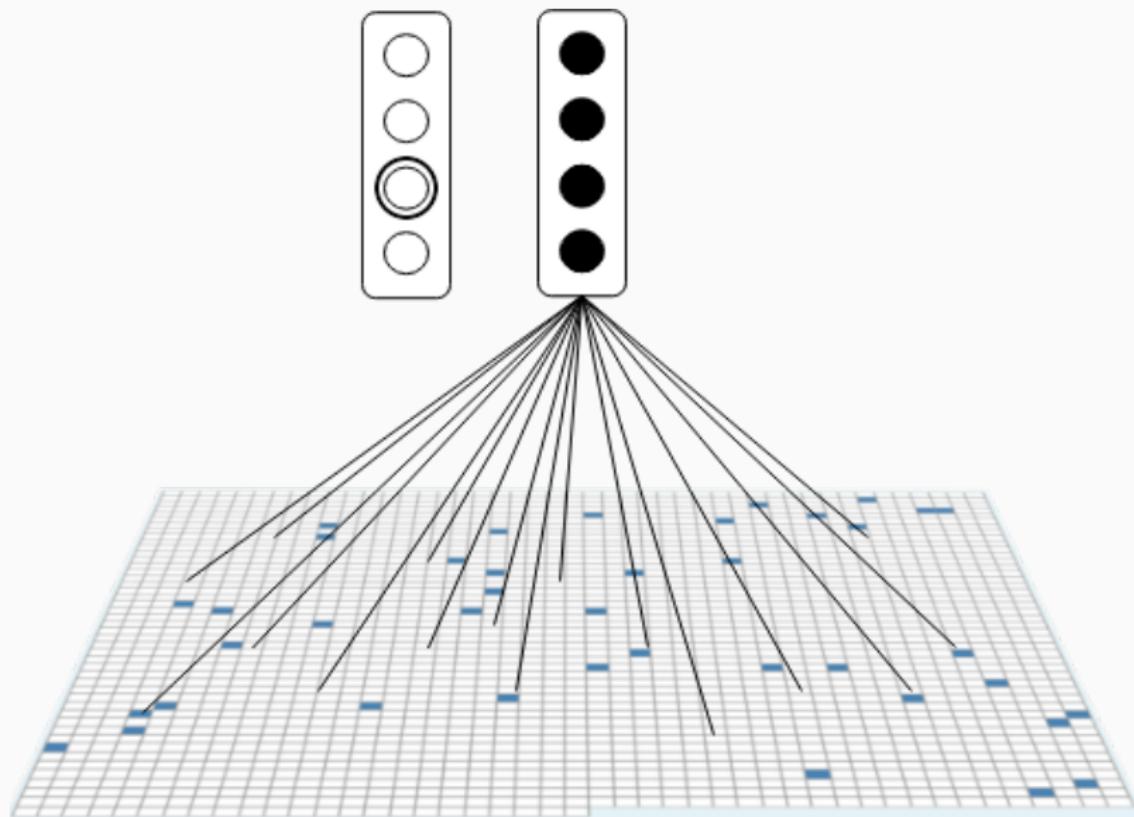
Temporal Pooler - Selecting Winner Cells



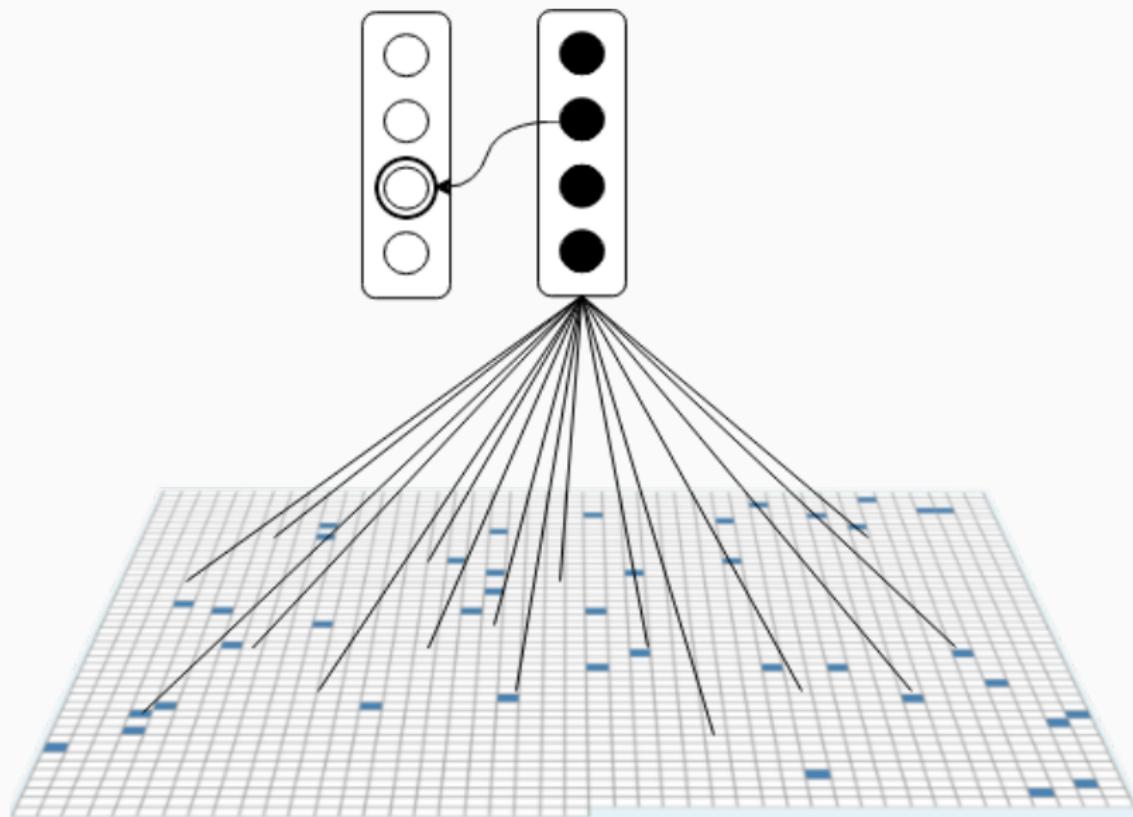
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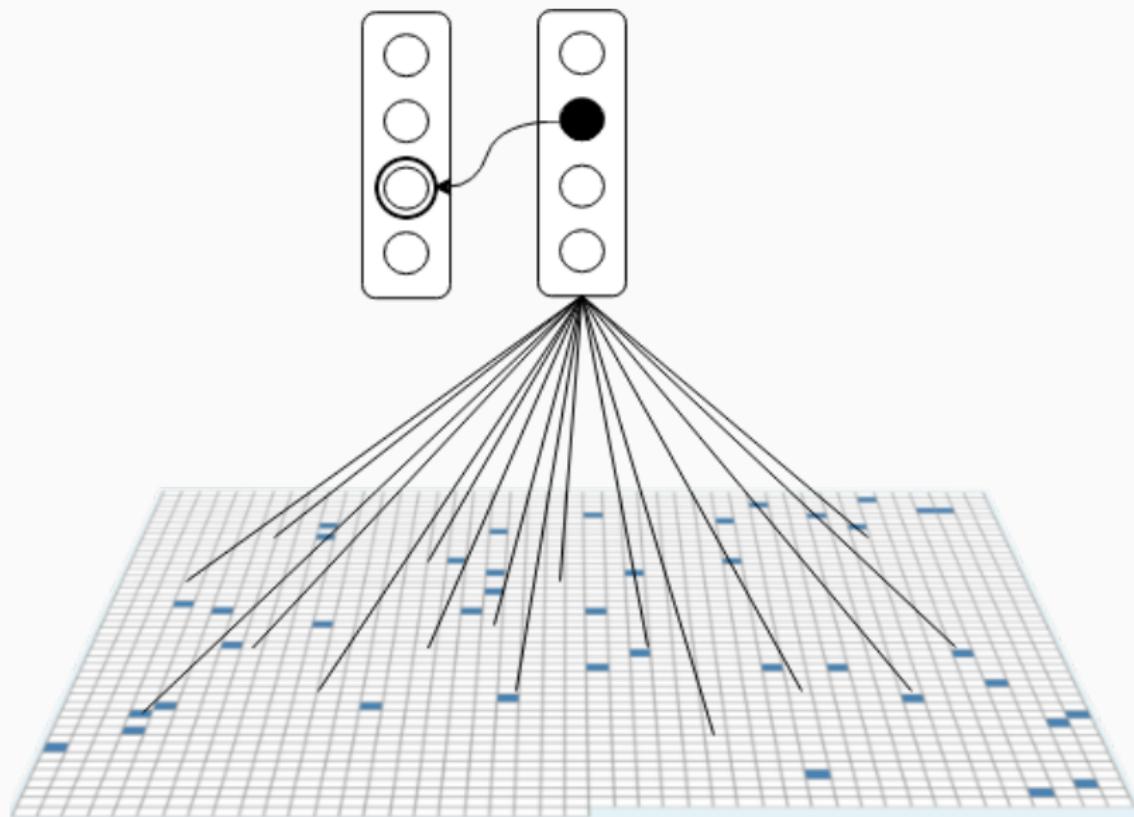
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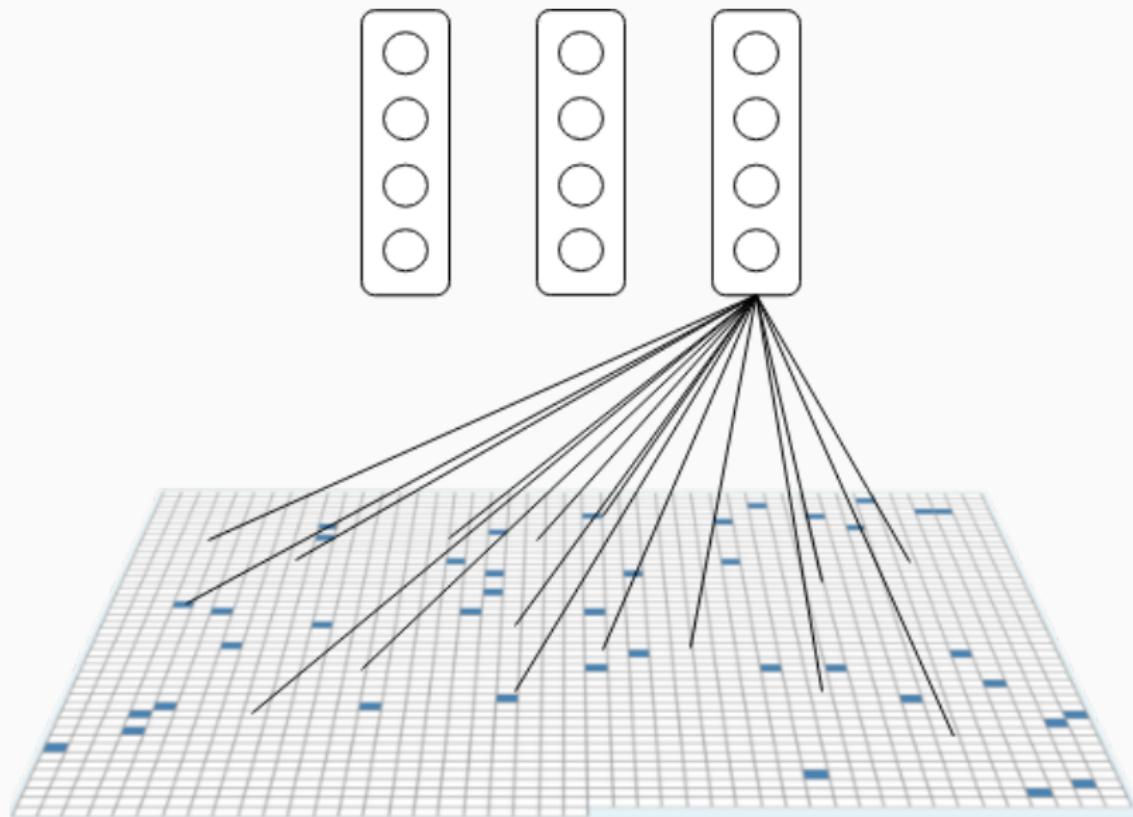
Temporal Pooler - Selecting Winner Cells



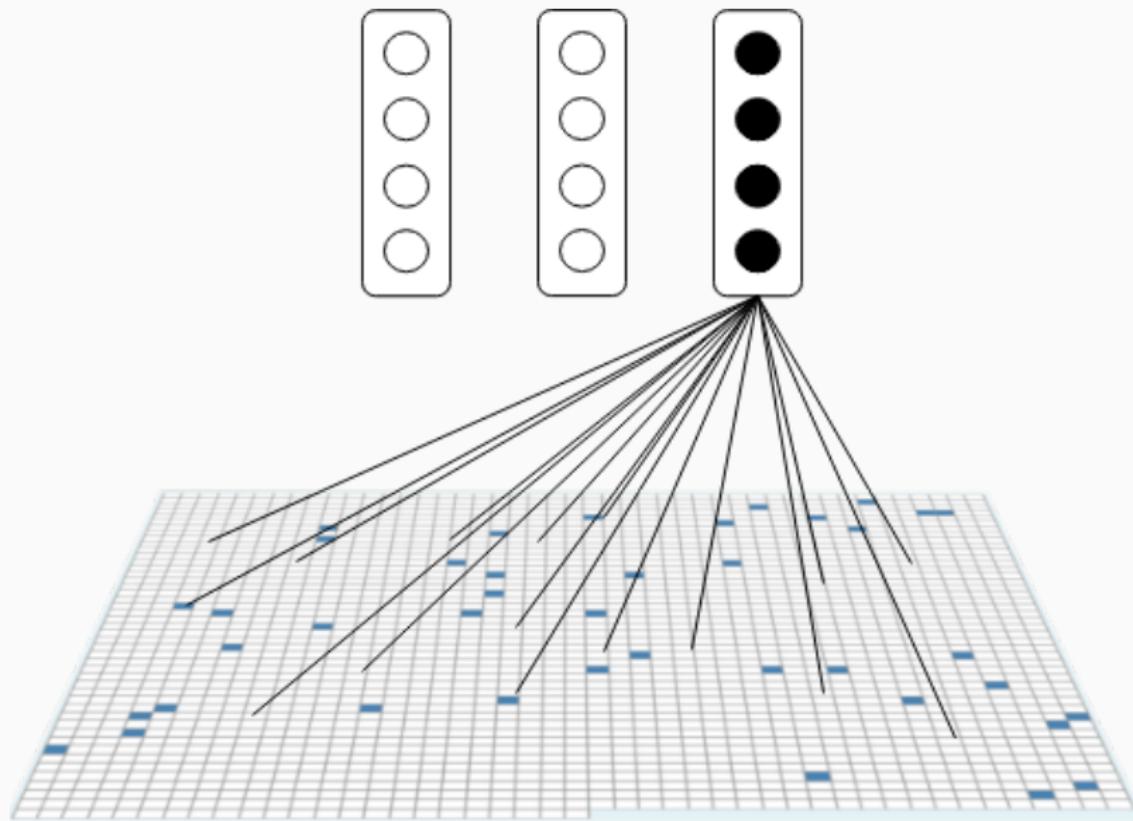
Temporal Pooler - Selecting Winner Cells



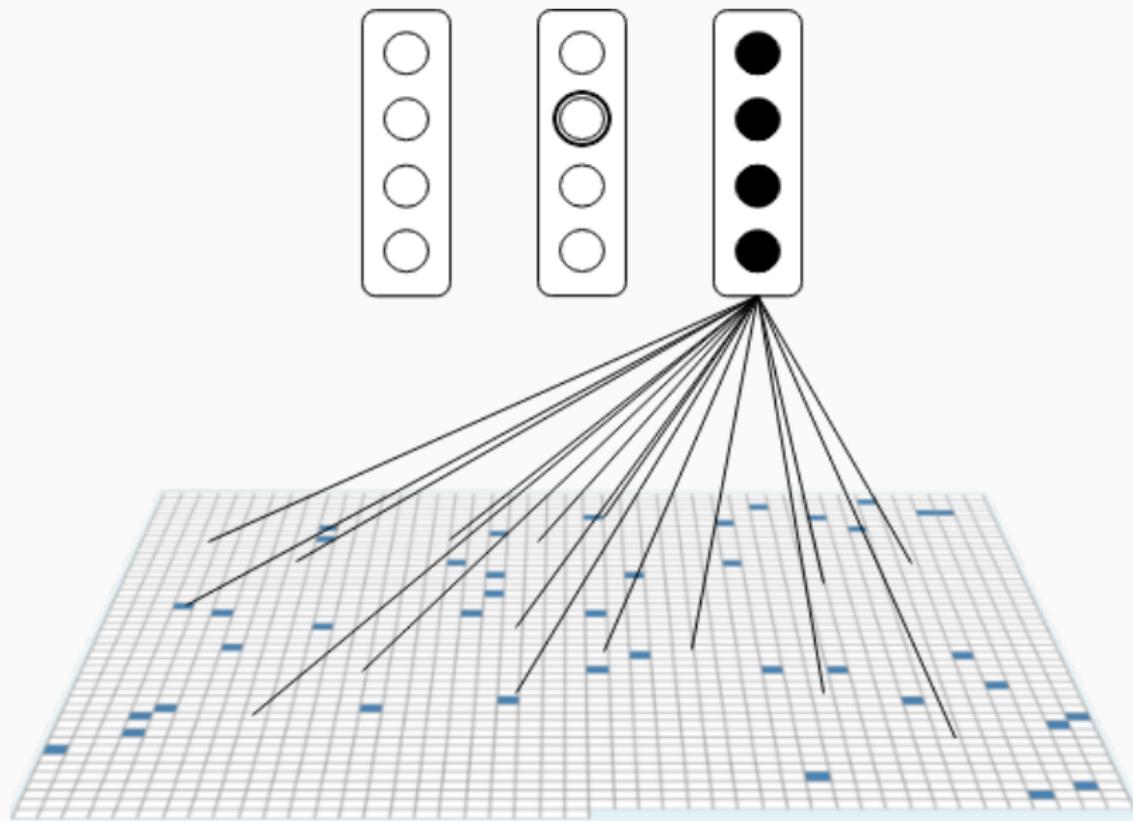
Temporal Pooler - Selecting Winner Cells



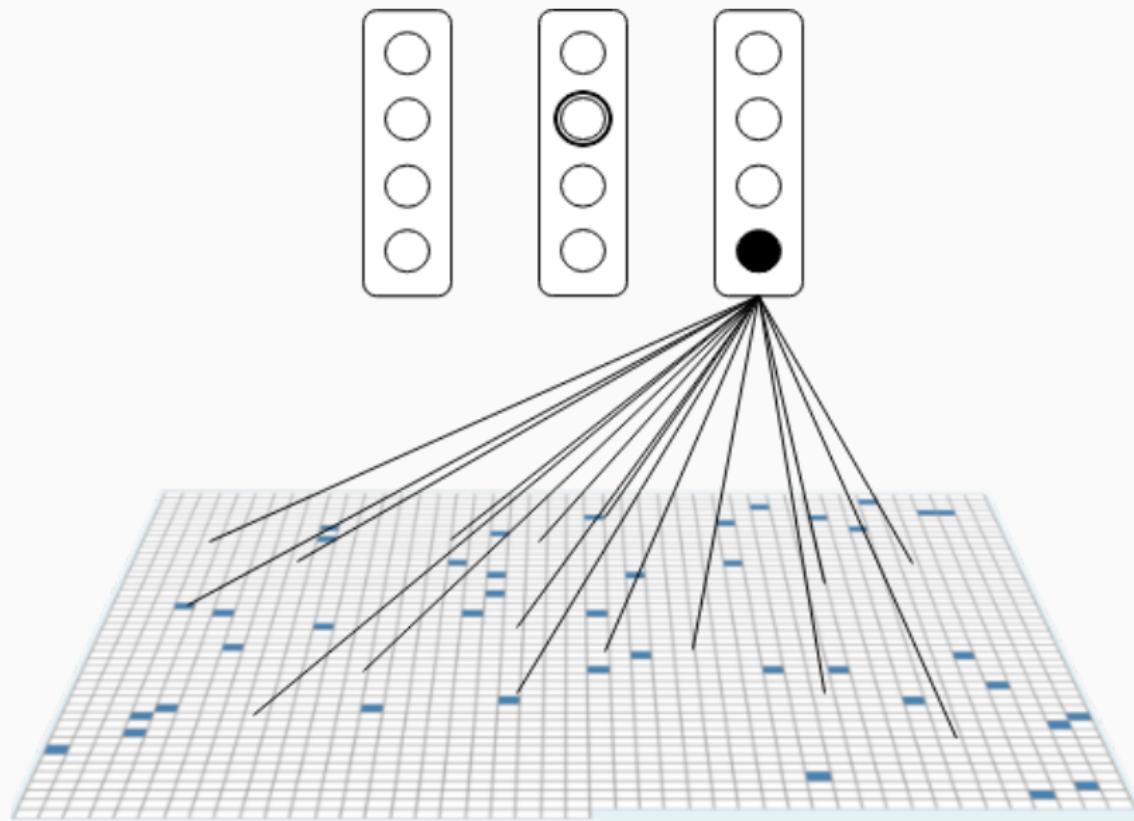
Temporal Pooler - Selecting Winner Cells



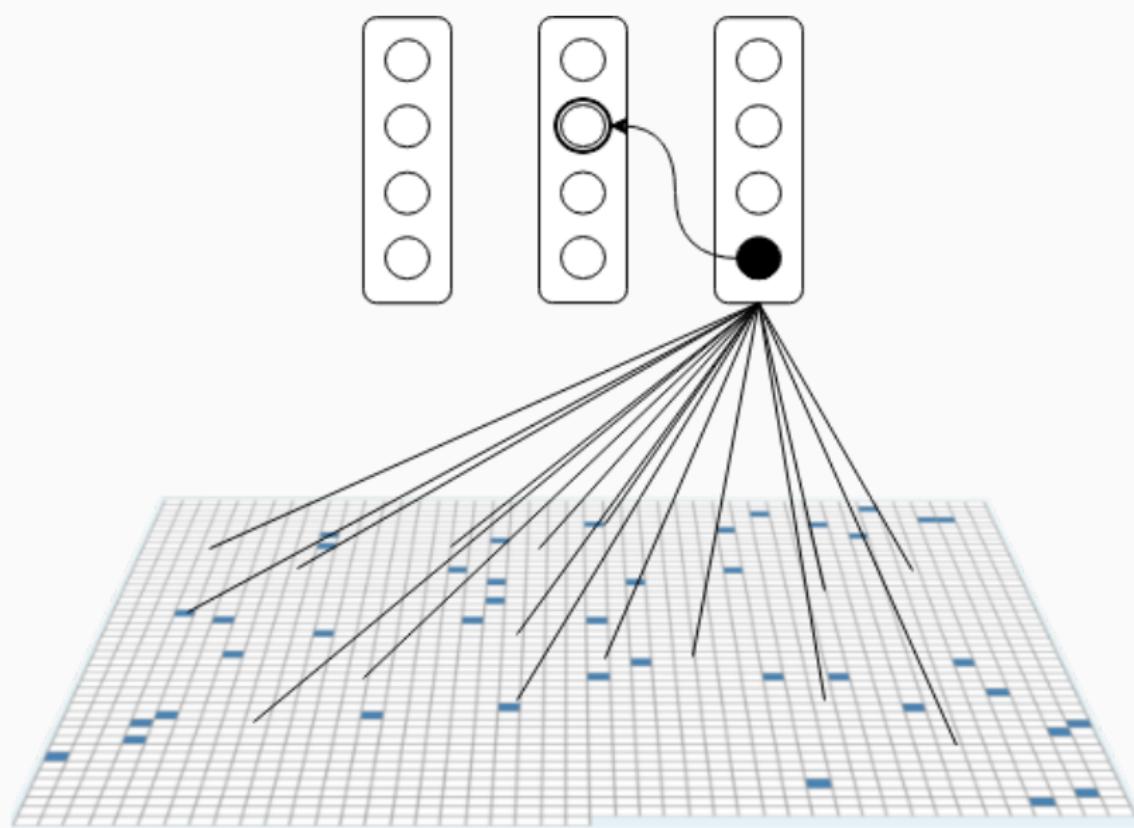
Temporal Pooler - Selecting Winner Cells



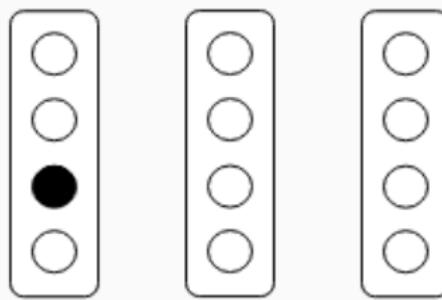
Temporal Pooler - Selecting Winner Cells



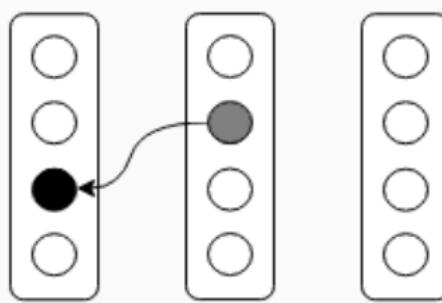
Temporal Pooler - Selecting Winner Cells



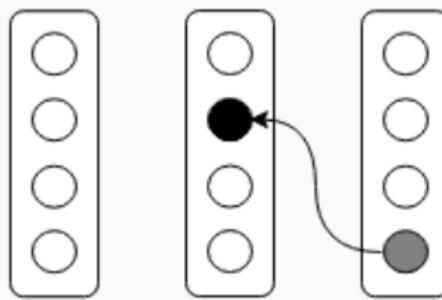
Temporal Pooler - Selecting Winner Cells



Temporal Pooler - Selecting Winner Cells



Temporal Pooler - Selecting Winner Cells



Temporal Memory - Example I



We are very busy

Temporal Memory - Example I



We

are

very

busy



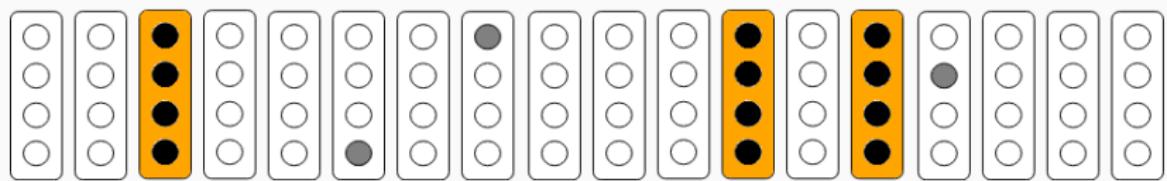
You

are

very

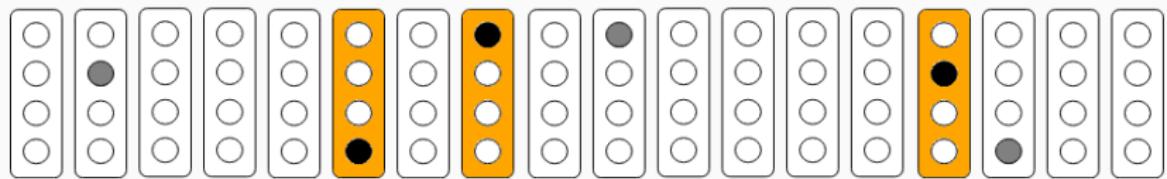
knowledgeable

Temporal Memory - Example I



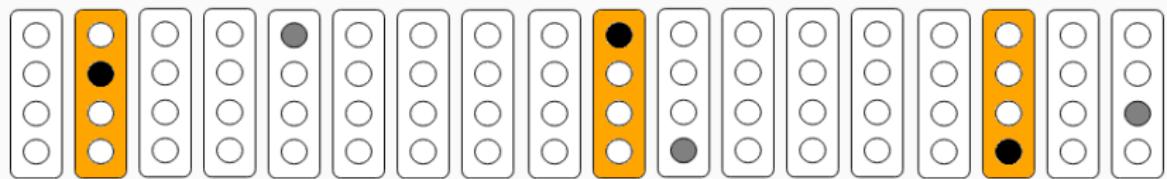
We

Temporal Memory - Example I



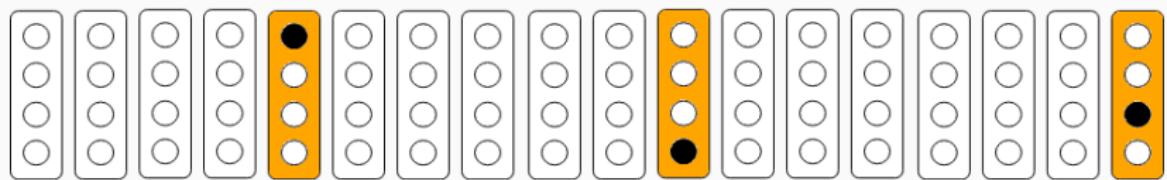
We are

Temporal Memory - Example I



We are very

Temporal Memory - Example I



We are very busy

Temporal Memory - Example I



We

are

very

busy



You

are

very

knowledgeable

Temporal Memory - Example I



We

are

very

busy

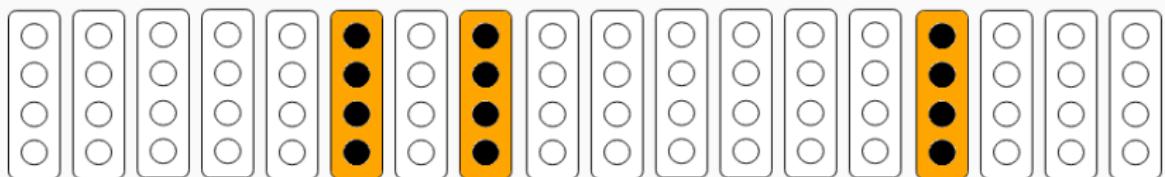


You

are

very

knowledgeable



are

Temporal Memory - Example I



We



are



very



busy

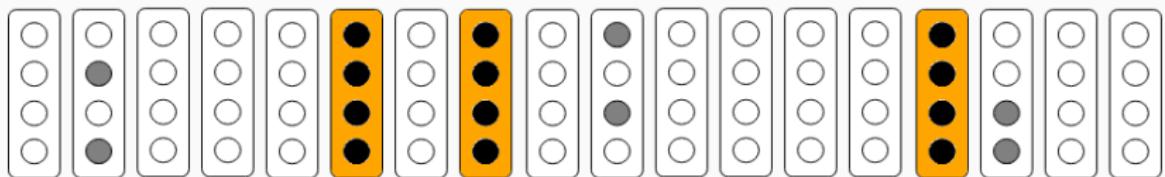


You

are

very

knowledgeable



are

Temporal Memory - Example I



We

are

very

busy

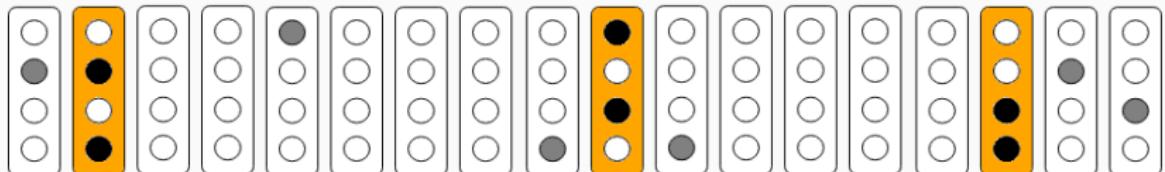


You

are

very

knowledgeable



very

Temporal Memory - Advanced

Temporal Memory - Advanced

- Within a region

Temporal Memory - Advanced

- Within a region
- But also across

Temporal Memory - Advanced

- Within a region
- But also across
- Up and Down

Temporal Memory - Advanced

- Within a region
- But also across
- Up and Down
- There are much more connections
DOWN than UP

Temporal Memory - Advanced

- Within a region
- But also across
- Up and Down
- There are much more connections
DOWN than UP
- In fact, about 90% go either sideways or
DOWN

Temporal Memory - Example II

Temporal Memory - Example II

- I ate a pear

Temporal Memory - Example II

- I **ate** a pear
- I have **eight** pears

Temporal Memory - Example II

- I **ate** a pear
- I have **eight** pears
- I ...

Temporal Memory - Example II

- I **ate** a pear
 - I have **eight** pears
-
- I ...
 - I have ...

Temporal Memory - Example II

- I **ate** a pear
 - I have **eight** pears
-
- I ...
 - I have ...

Temporal predictions add to the threshold for the spatial pooler!

Q: If you have an SDR with 10 000 Cells and 200 active, how much difference would saving only 20 of them make?

Q: If you have an SDR with 10 000 Cells and 200 active, how much difference would saving only 20 of them make?

A: Due to the property of SDRs, it is *very* unlikely that they activate in a totally unrelated pattern.

Temporal Pooler - Closing notes

Temporal Pooler - Closing notes

- Every Column will have a winner cell

Temporal Pooler - Closing notes

- Every Column will have a winner cell
- Bursting can happen on single columns as well

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Biology

- The Neocortex is only a part of the brain

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- The smallest computational units are called 'Cortical Columns'

- The Neocortex is only a part of the brain
- The smallest computational units are called 'Cortical Columns'
- Every Neuron has on average 7'000 Connections

HTM Theory

HTM Theory

- Biologically constrained, based on Neuroscience

HTM Theory

- Biologically constrained, based on Neuroscience
- Everything is predicting everything

HTM Theory

- Biologically constrained, based on Neuroscience
- Everything is predicting everything
- Closest to how the brain really works

HTM Theory

- Biologically constrained, based on Neuroscience
- Everything is predicting everything
- Closest to how the brain really works
- Time is important

Sparse Distributed Representation

Sparse Distributed Representation

- Data structure of the Brain

Sparse Distributed Representation

- Data structure of the Brain
- Sparse (very few ON-bits)

Sparse Distributed Representation

- Data structure of the Brain
- Sparse (very few ON-bits)
- Distributed

Sparse Distributed Representation

- Data structure of the Brain
- Sparse (very few ON-bits)
- Distributed
- Required for other mechanisms

Sparse Distributed Representation

- Data structure of the Brain
- Sparse (very few ON-bits)
- Distributed
- Required for other mechanisms
- Encoders are important!

Learning

- Only statistical

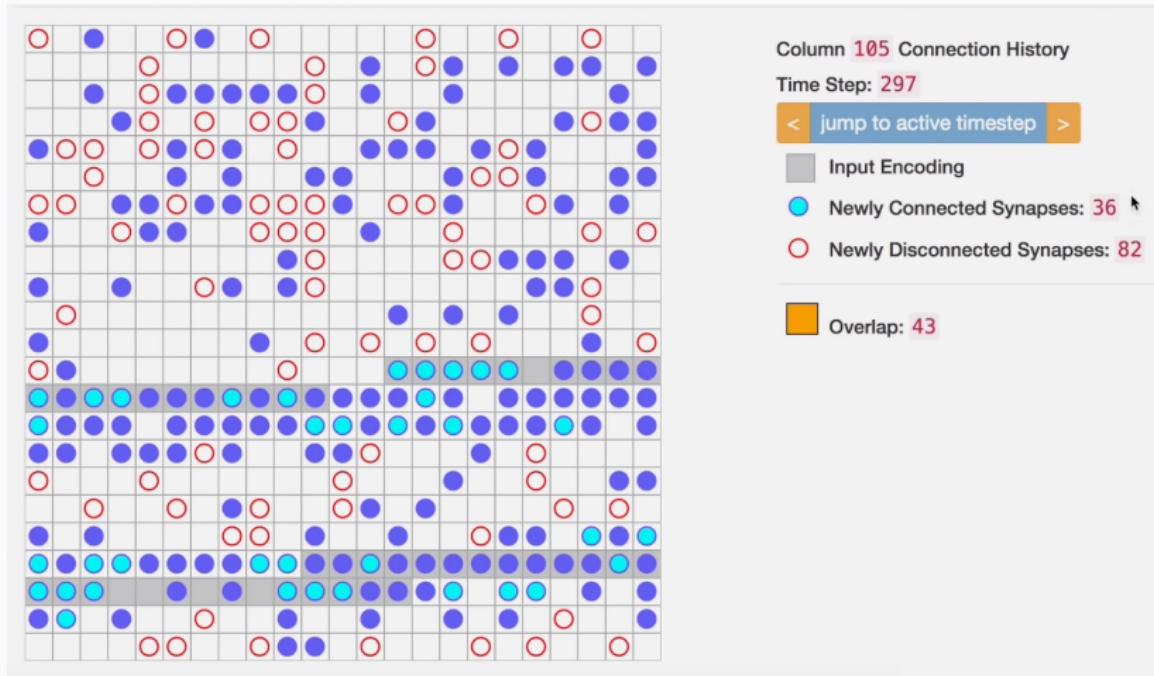
- Only statistical
- Based on Prediction and Inference

- Only statistical
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- Spatial and Temporal patterns

- Only statistical
- Based on Prediction and Inference
- Spatial and Temporal patterns
- Context sensitive

- Only statistical
- Based on Prediction and Inference
- Spatial and Temporal patterns
- Context sensitive
- Trying to minimize Errors (Bursting)

Spatial Pooler



Spatial Pooler

Spatial Pooler

- Calculate Overlap Scores (+Boosting)

Spatial Pooler

- Calculate Overlap Scores (+Boosting)
- Inhibit

Spatial Pooler

- Calculate Overlap Scores (+Boosting)
- Inhibit
- Update connection values

Temporal Pooler

Temporal Pooler

- Form representations in context of previous states

Temporal Pooler

- Form representations in context of previous states
- Form predictions based on previous inputs

Temporal Pooler

- Form representations in context of previous states
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- Context dependent

Temporal Pooler

- Form representations in context of previous states
- Form predictions based on previous inputs
- Context dependent
- Can modulate spatial pooler results

Temporal Pooler

- Form representations in context of previous states
- Form predictions based on previous inputs
- Context dependent
- Can modulate spatial pooler results
- One cell can represent many different concepts!

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Implications - Models

Your brain is creating predictive models for everything.

Implications - Models

Your brain is creating predictive models for everything.

You are only familiar with what you have already thought about.

Implications - Models

Your brain is creating predictive models for everything.

You are only familiar with what you have already thought about.

Learning is the active creation of new models (spatial and temporal patterns).

Implications - Learning

While Learning, you need about 90 percent more capacity than after having mastered something.

Implications - Learning

While Learning, you need about 90 percent more capacity than after having mastered something.

'AHA-Moment' is when models line up, and bursting ceases.

Implications - Learning

While Learning, you need about 90 percent more capacity than after having mastered something.

'AHA-Moment' is when models line up, and bursting ceases.

Smarter people have clearer models and have less overall brain activity (higher efficiency). ^{102/120}

Implications - Brain Parameters

There is also a varying threshold for the spatial pooler activations.

Implications - Brain Parameters

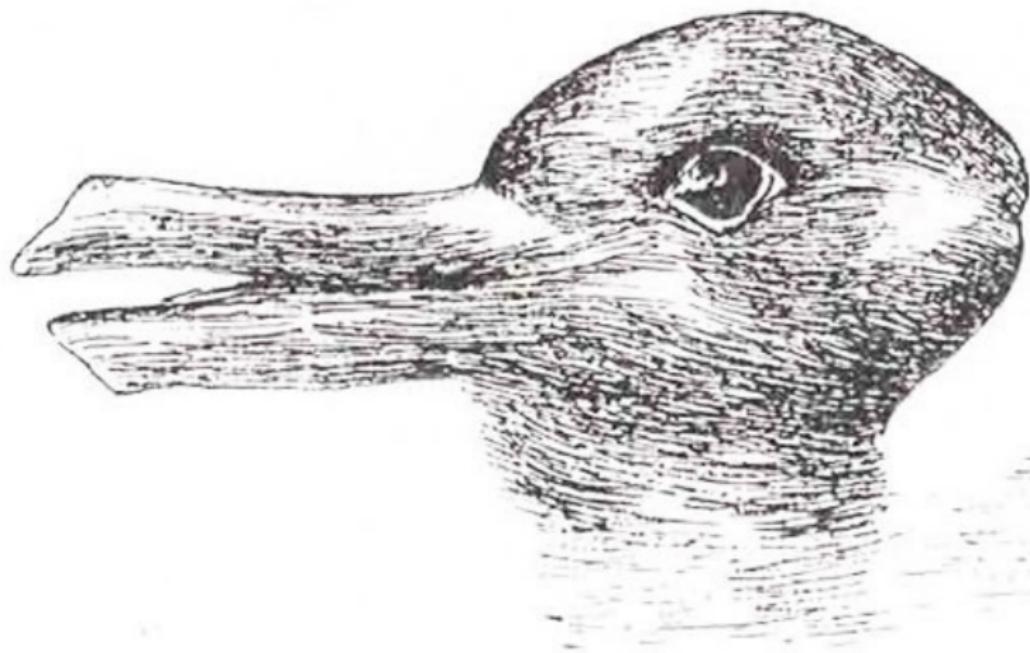
There is also a varying threshold for the spatial pooler activations.

This probably also changes during sleep.

Implications - Conformation Bias

Conformation Bias is a predictable result from the temporal pooler.

Implications - Inhibition in the Visual System



Implications - Top-Down Processing I

You can probably read this easily despite the misspellings.

Implications - Top-Down Processing I

Yuo cna porbalby raed tihs esaliy desptie teh
msispeillgns.

A vheclie epxledod at a plocie cehckipont
near the UN haduqertares in Bagahdd on
Mnoday kilinlg the bmober and an Irgai
polcie offceir

Implications - Top-Down Processing II

Aoccdrnig to a rscheearch at Cmabrigde Uinervtisy, it deosn't mttaer in waht oredr the ltteers in a wrod are, the olny iprmoetnt tihng is taht the frist and lsat ltteer be at the rghit pclae. The rset can be a toatl mses and you can sitll raed it wouthit porbelm. Tihs is bcuseae the huamn mnid deos not raed ervey lteter by istlef, but the wrod as a wlohe.

Implications - Bottom-Up-Gradient

There is a parameter for how much predictive states count for the spatial pooler.

Implications - Bottom-Up-Gradient

There is a parameter for how much predictive states count for the spatial pooler.

Which one would be better?

Implications - Bottom-Up-Gradient

There is a parameter for how much predictive states count for the spatial pooler.

Which one would be better?

Possibility: Predictive states count less for Autistic people.

Implications - Hallucinating

Hallucinating is just active boosting in the human brain.

Implications - Hallucinating

Hallucinating is just active boosting in the human brain.

Concentration going awry as well ...

Implications - Hallucinating

Hallucinating is just active boosting in the human brain.

Concentration going awry as well ...

Phantom limbs ...

Implications - Reticular Activating System

Ever noticed after buying something,
everyone has the same thing?

Implications - Priming Bias

Implications - Priming Bias

Priming really leaves some predictive states, even though it never gets high enough in the hierarchy to notice it consciously.

Implications - Bayesian Reasoning

The brain is constantly weighing alternatives and selecting the likeliest - as far as it is aware.

Implications - Meaning

Something has meaning if it is a well-connected concept.

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Sources

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

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- ❑ Y. Cui, S. Ahmad, and J. Hawkins, “The htm spatial pooler—a neocortical algorithm for online sparse distributed coding,” *Frontiers in computational neuroscience*, vol. 11, p. 111, 2017.

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End

Cortical Column

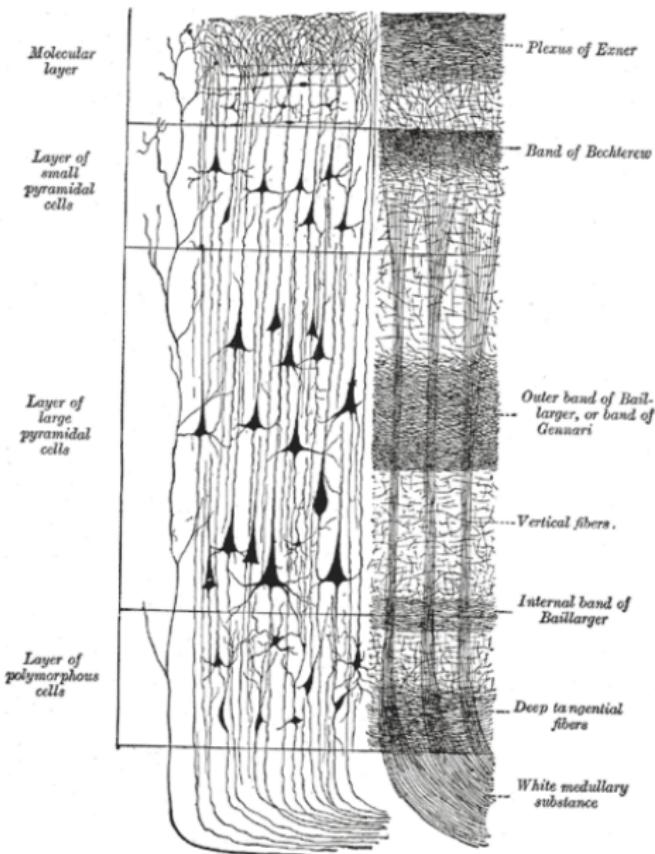


Image from [11]

Cortical Column II

