# Hierarchical Temporal Memory

Biological And Machine Intelligence

Felix Karg

September 2, 2019

LessWrong Community Weekend 2019

## Content

**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

- Evolving theories
- Hypotheses partially verified
- Theories are constantly being updated

## Epistemic status

- Evolving theories
- Hypotheses partially verified
- Theories are constantly being updated
- This is not the newest information regarding this theory

# Content

# Tests for Intelligence

# Tests for Intelligence

- Turing test

# Tests for Intelligence

- Turing test
- 'IQ' tests

## Tests for Intelligence

- Turing test
- 'IQ' tests
- Problme solving tests

# Tests for Intelligence

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

## Tests for Intelligence

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

# Tests for Intelligence

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

But dogs, monkeys and dolphins fail them.

## 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 - Definition

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

# Intelligence - Overview

# Intelligence - Overview

Might not be best at specific task.

# Intelligence - Overview

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

# The Human Brain in Numbers

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

# The Human Brain in Numbers

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

# 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 |

# 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%) |

# 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 |

# 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

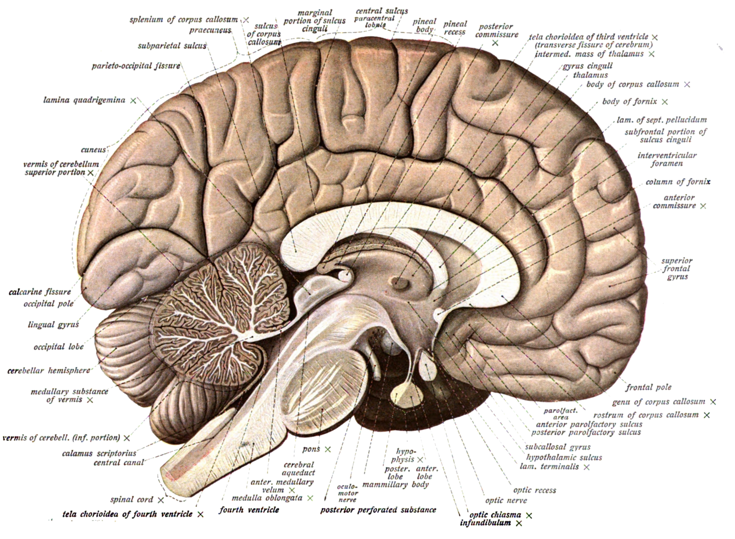
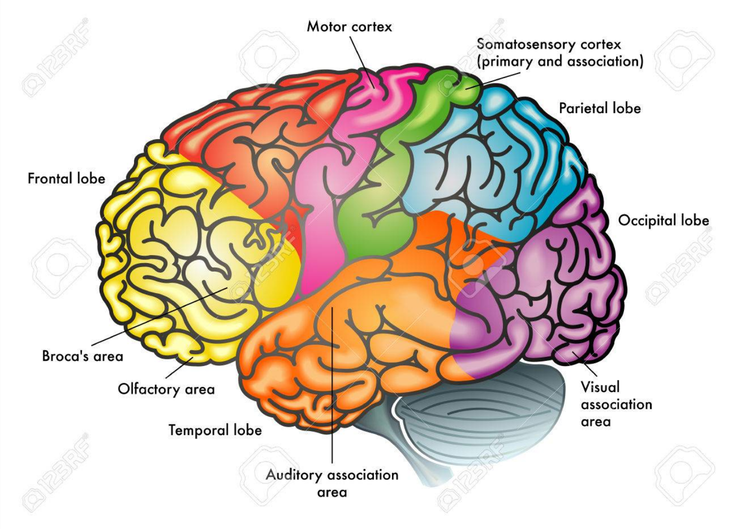



Image from [3].

# 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

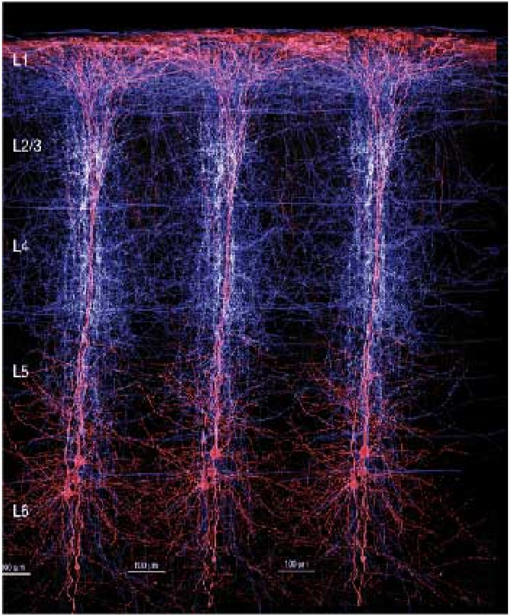



Image from [4].

# Cortical Column

- Everywhere in the Brain

# 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

# Neuron - Number of Connections

| | |
|---|---|
| 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

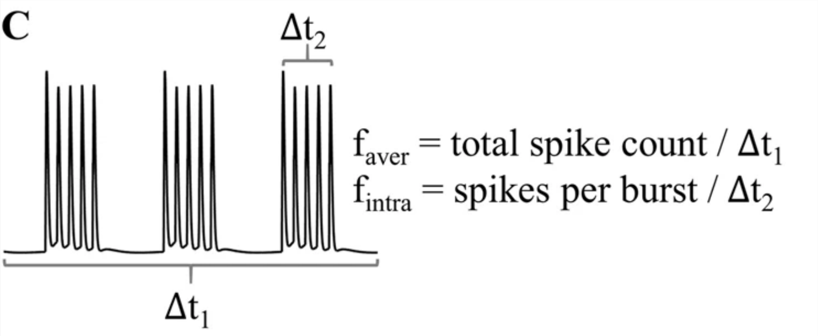



Image adapted from [7].

# Neuron - Overview

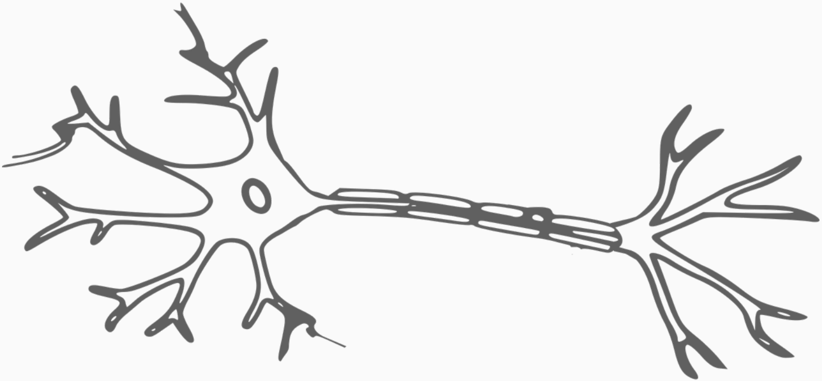


Image from [8].

# Content

# What is HTM?

# What is HTM?

- Biologically constrained **Theory of Intelligence**

# What is HTM?

- Biologically constrained **Theory of Intelligence**
- First described in "On Intelligence"

## What is HTM?

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

# What is HTM?

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

$\rightarrow$ Learning Algorithms

## What is HTM?

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

$\rightarrow$ Learning Algorithms (of the brain)

# Not Included in HTM

# Not Included in HTM

- Firing rythms

## 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

# The brain as Prediction Machine

- Prediction of future sensory input

# The brain as Prediction Machine

- Prediction of future sensory input
- 'Anticipating' events

# The brain as Prediction Machine

- Prediction of future sensory input
- 'Anticipating' events
- multiple connected regions

## The brain as Prediction Machine

- Prediction of future sensory input
- 'Anticipating' events
- multiple connected regions
- Invariant representations

## The brain as Prediction Machine

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

# 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

# Attributes of HTM Algorithms

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

# Attributes of HTM Algorithms

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

# 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

# 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

## 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

# 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

# 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.

# The role of Time

Crucial for learning, inference and prediction.

- Inference is hard on static information

## The role of Time

Crucial for learning, inference and prediction.

- Inference is hard on static information
- 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

# Content

# Content

# 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

# Why Hierarchy? II

- Reduced Training Time
- Reduced Memory Usage

# Why Hierarchy? II

- Reduced Training Time
- Reduced Memory Usage
- Introduce Generalizations

## Why Hierarchy? II

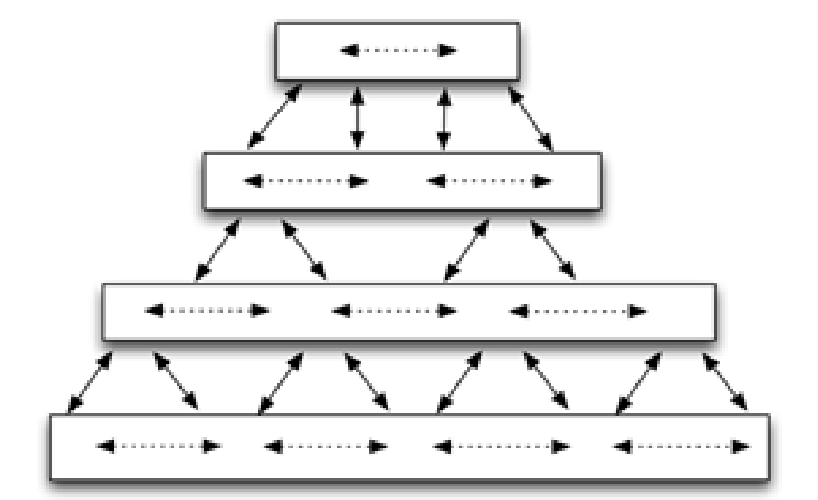
- Reduced Training Time
- Reduced Memory Usage
- Introduce Generalizations
- Learned patterns are recombined at higher levels

## Why Hierarchy? II

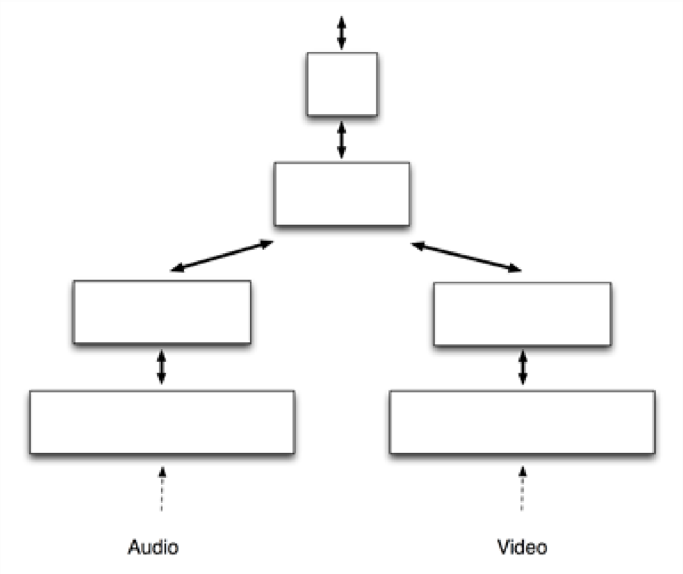
- Reduced Training Time
- Reduced Memory Usage
- Introduce Generalizations
- Learned patterns are recombined at higher levels
- Transfer Learning

# What Hierarchy

# What Hierarchy



# Example Application



# 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

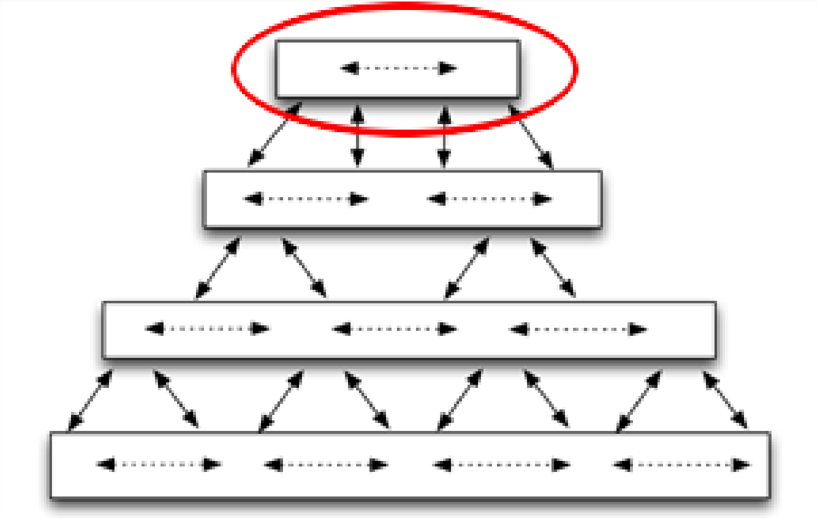
# How Many Levels?

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

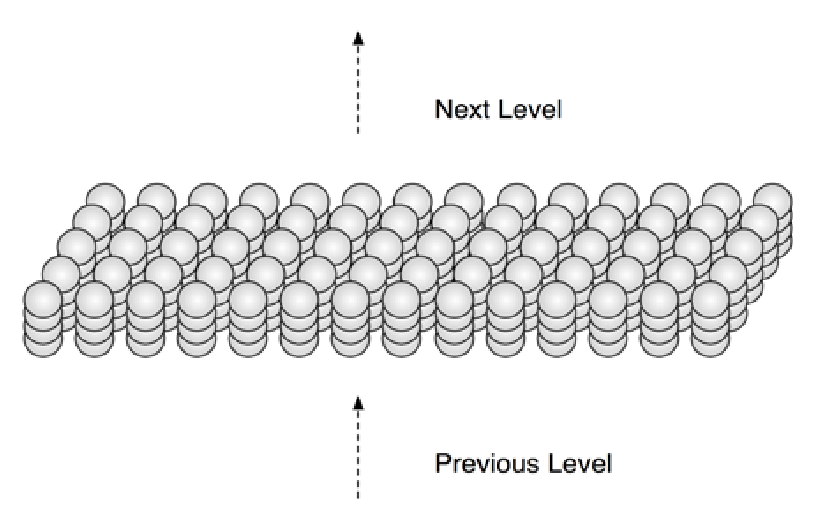
# Content

# Region - Introduction

# Region - Introduction



# Region - Details



# Region - Attributes

## Region - Attributes

- All Regions do basically the same

## Region - Attributes

- All Regions do basically the same
- Based on Biological Regions in the Brain

# 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

## 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

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

- Booleans
  (`False, True, True, False,...`)
- Integer (`101`)

# Data Saving - Computer Science Solution

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

- Booleans (`False, True, True, False,...`)
- Integer (`101`)
- Float (`3328.0`)

# 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'`)

## 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

# 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

# Sparse Distributed Representation - Introduction

- Datastructure of the brain

# Sparse Distributed Representation - Introduction

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

## Sparse Distributed Representation - Introduction

- Datastructure of the brain
- Sparse (around 2% are active)
- Distributed (clusters are somewhat rare)

## Sparse Distributed Representation - Introduction

- Datastructure of the brain
- Sparse (around 2% are active)
- Distributed (clusters are somewhat rare)
- Inhibitory mechanisms

## 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'

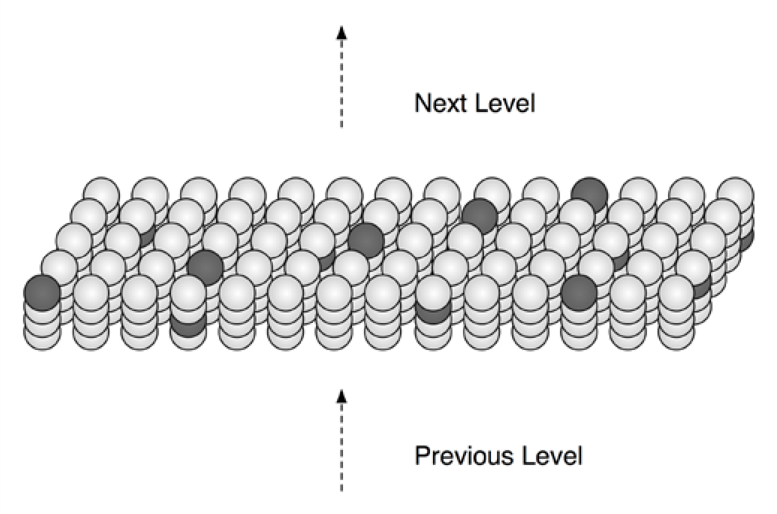
## Sparse Distributed Representation - Introduction

- 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

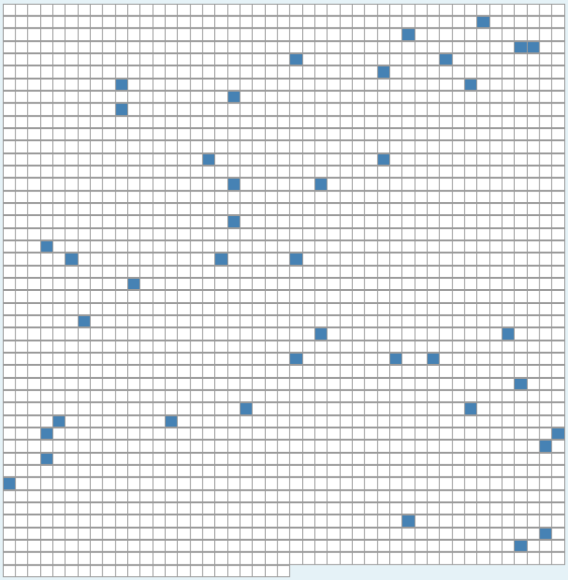
## Sparse Distributed Representation - Introduction

- 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

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

## Sparse Distributed Representation - Live Demos

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

# Sparse Distributed Representation - Live Demos

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

## Sparse Distributed Representation - Live Demos

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

# Encoders - Conclusion

- Semantically similar data should result in SDRs with overlapping active bits.

# Encoders - Conclusion

- Semantically similar data should result in SDRs with overlapping active bits.
- The same input should always produce the same SDR as output.

## 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.

## 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.

## 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].

# HTM - Pipeline


Image adapted from [10].

# HTM - Pipeline


Image adapted from [10].

- Data

# HTM - Pipeline


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


Image adapted from [10].

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

# Content

# Content

# Learning

# Learning

- Learning is purely statistical

# Learning

- Learning is purely statistical
- Looking for Spatial and Temporal Patterns

# Learning

- Learning is purely statistical
- Looking for Spatial and Temporal Patterns
- Regions themselves are limited

# Learning

- Learning is purely statistical
- Looking for Spatial and Temporal Patterns
- Regions themselves are limited
- Automatically adjusts to size of allocated Memory

# 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

# 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

# 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

# Inference

- Matching previously learned sequences

# Inference

- Matching previously learned sequences
- 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

# Prediction

- Matching stored sequences
- Can be thought of to be similar to a markov chain

# Prediction

- Matching stored sequences
- Can be thought of to be similar to a markov chain
- 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

## Prediction - Key Properties

- Continuity

# Prediction - Key Properties

- Continuity
- Occurs everywhere

## Prediction - Key Properties

- Continuity
- Occurs everywhere
- Context sensitivity

# Prediction - Key Properties

- Continuity
- Occurs everywhere
- Context sensitivity
- Stability

# Prediction - Key Properties

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

# Prediction - Key Properties

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

# Content

# Spatial Pooler - Introduction

# Spatial Pooler - Introduction

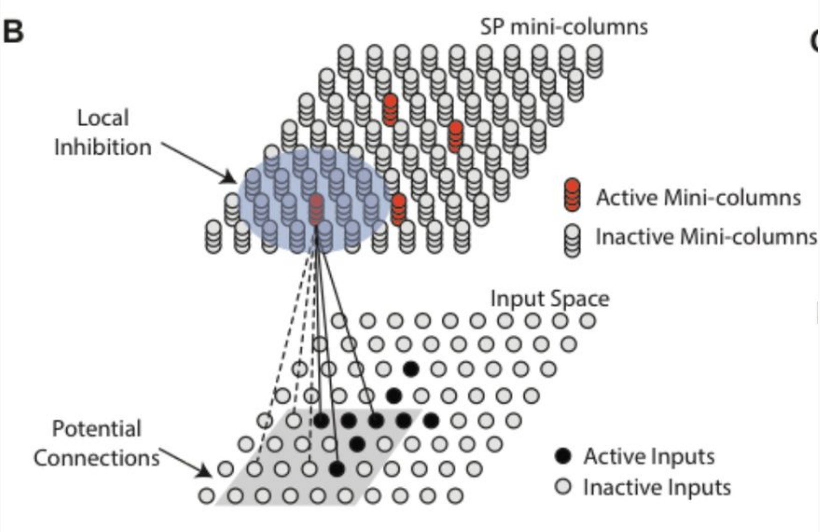



Image adapted from [10].

# 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`!

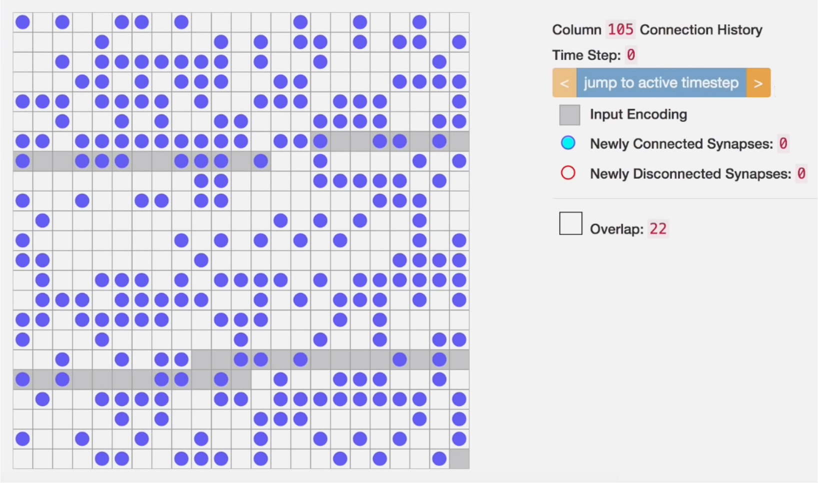
- Many Connections
- Only Columns with highest overlap scores continue
- Everyone else gets inhibited

# Spatial Pooler - Connection details

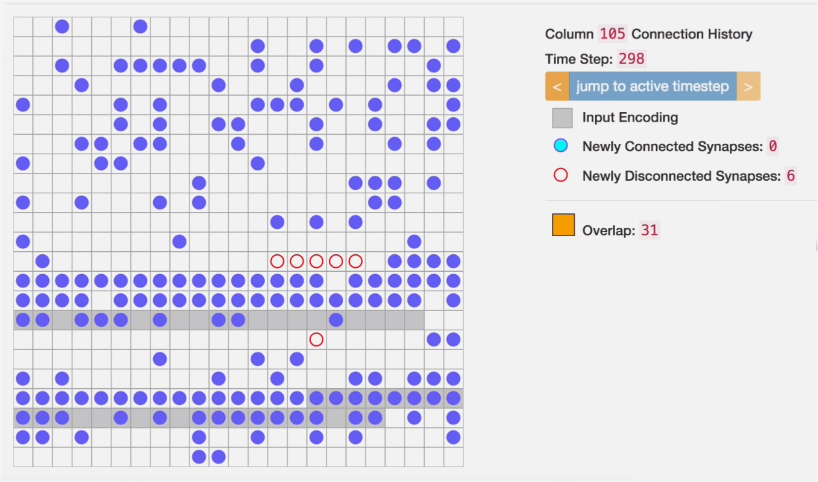
Show `Ep8/Learning Rules`!

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

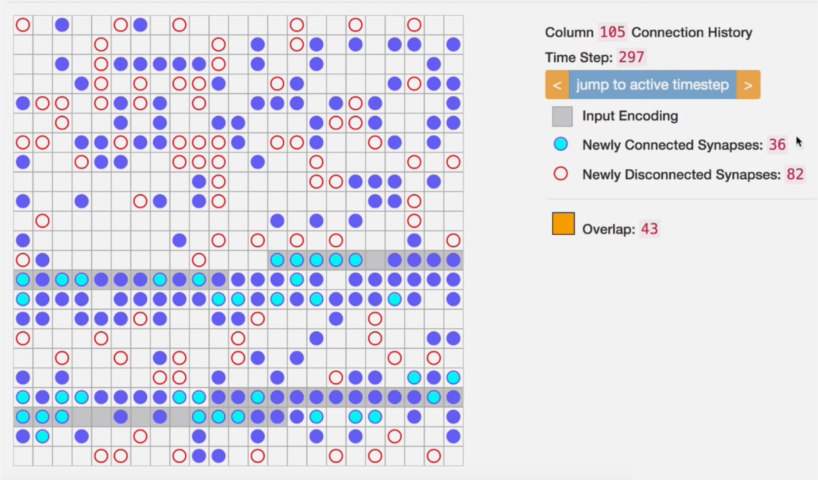
# Spatial Pooler - Learning Details i



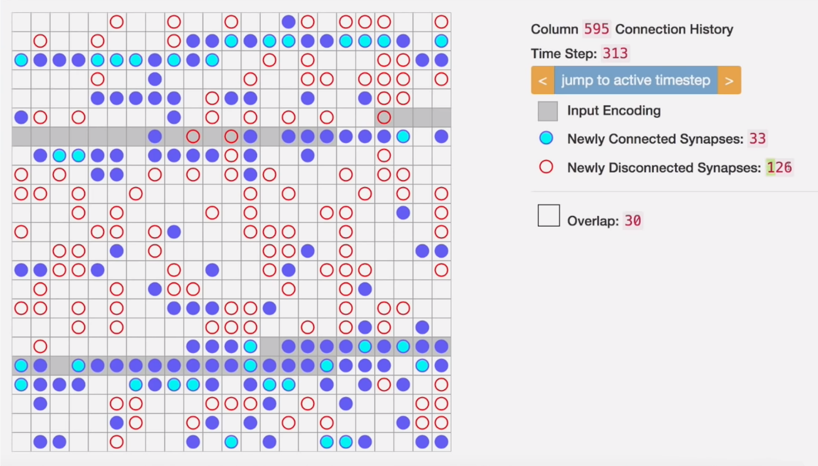
# Spatial Pooler - Learning Details ii



# Spatial Pooler - Learning Details iii

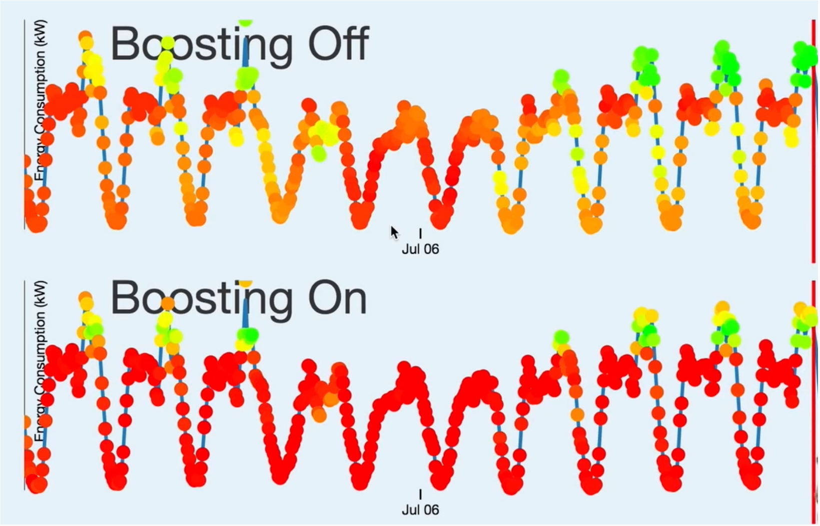


# Spatial Pooler - Learning Details iv

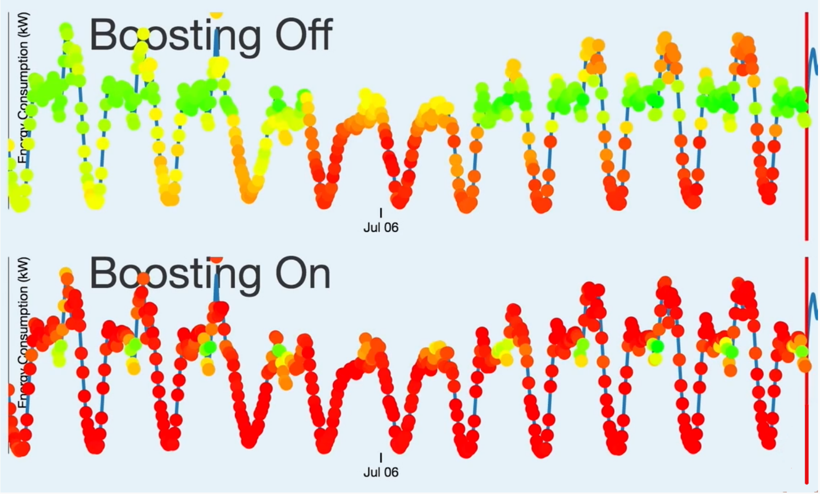


# Spatial Pooler - Boosting i

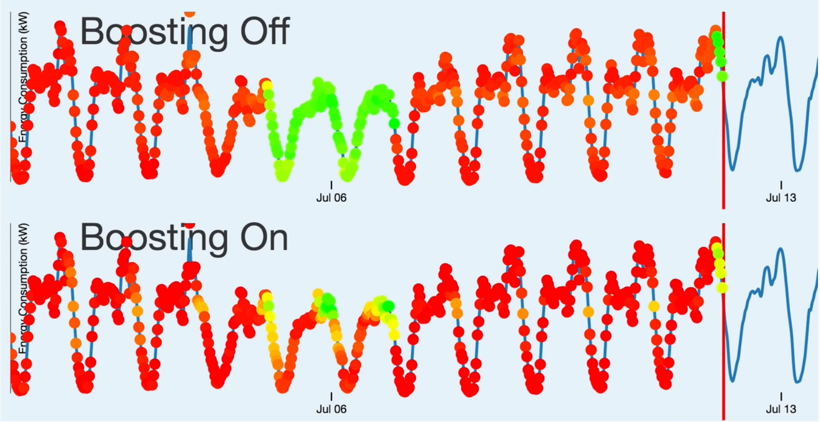
# Spatial Pooler - Boosting ii



# 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

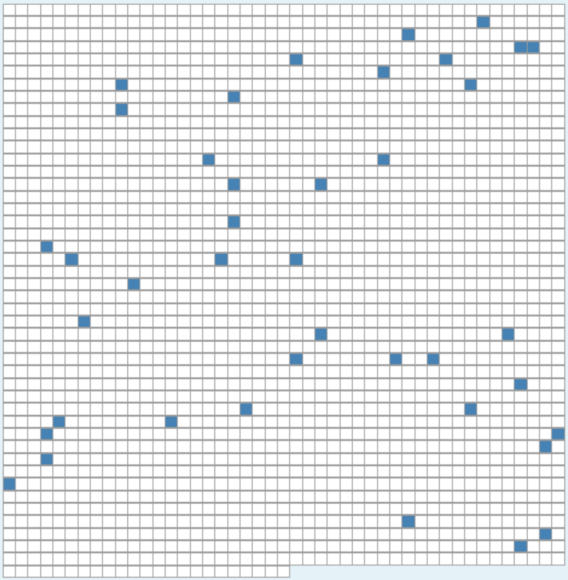
1. Initializing with random variables
2. Compute overlap scores (+Boost)
3. Inhibition
4. Updating Permanence values
5. Repeat from step 2 with new input

# Content

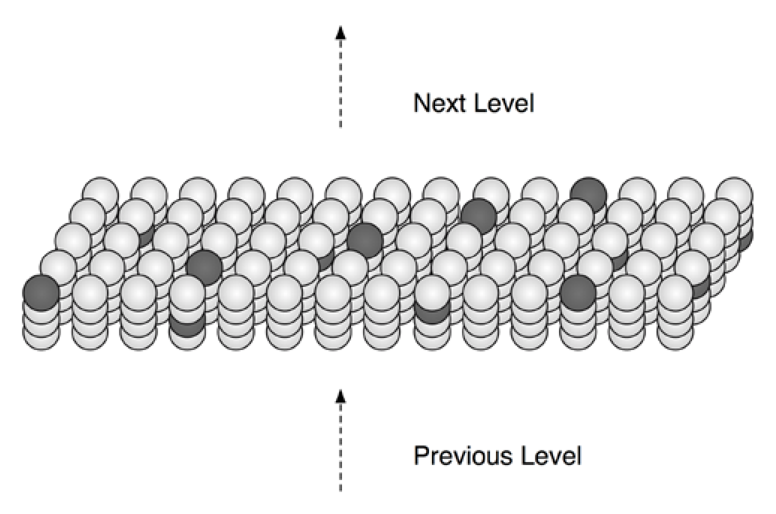
# Temporal Pooler - Pipeline


Image adapted from [10].

# Temporal Pooler - Introduction



# Temporal Pooler - Introduction



# Temporal Pooler - Steps

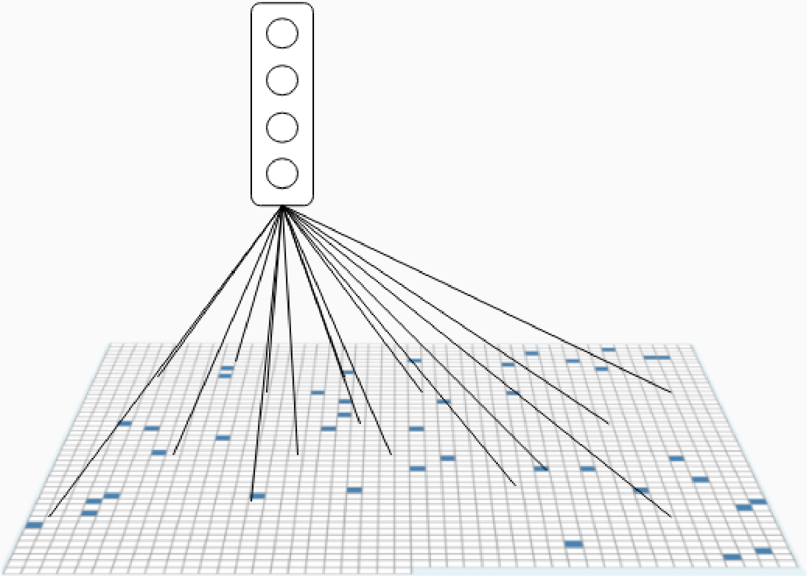
# Temporal Pooler - Steps

1. Form representation in context of previous states

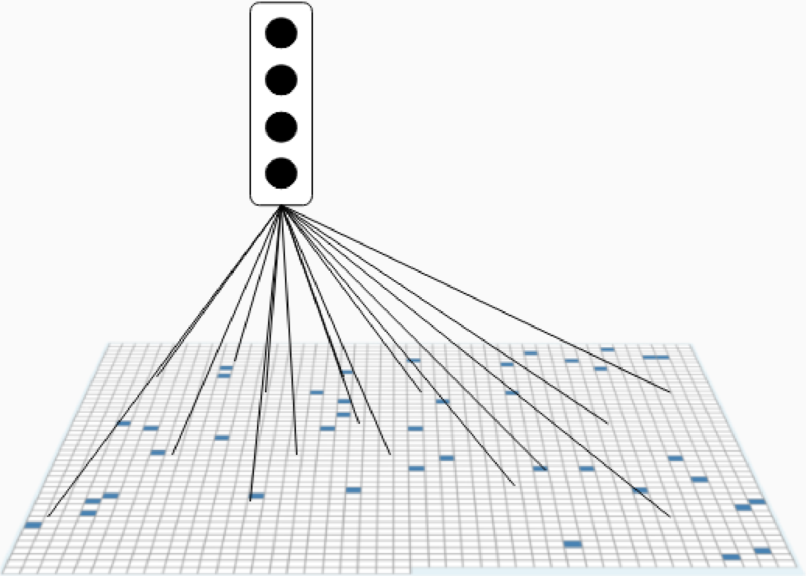
# Temporal Pooler - Steps

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

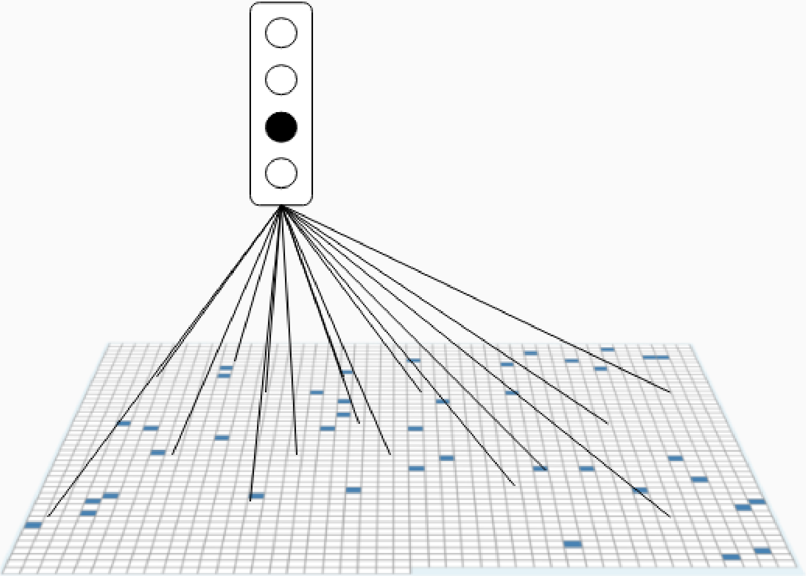
# Temporal Pooler - Selecting Winner Cells



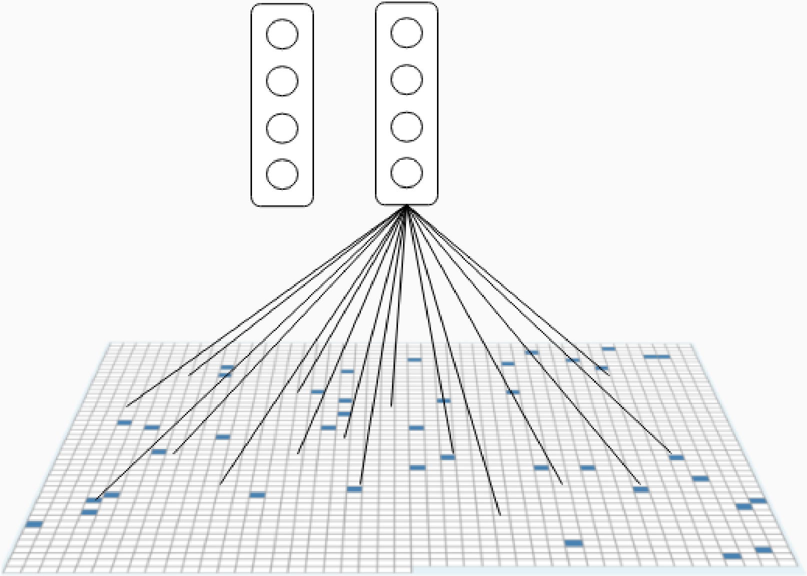
# Temporal Pooler - Selecting Winner Cells



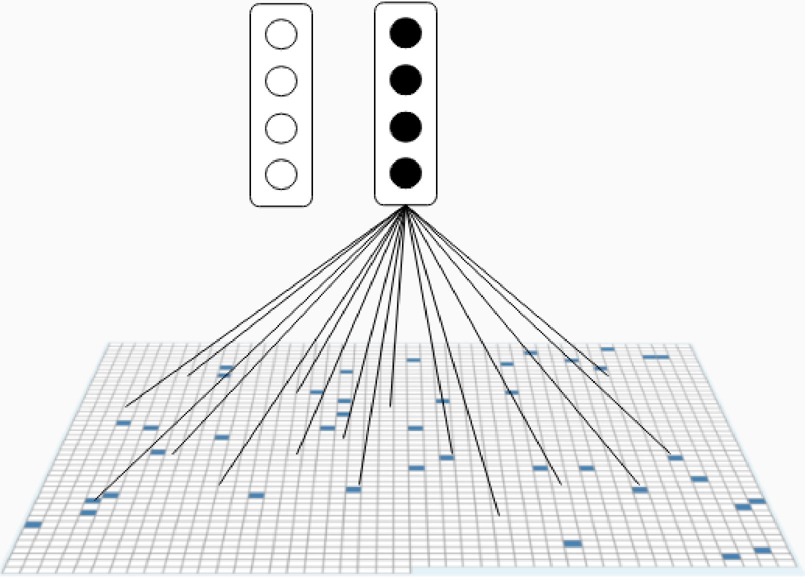
# Temporal Pooler - Selecting Winner Cells



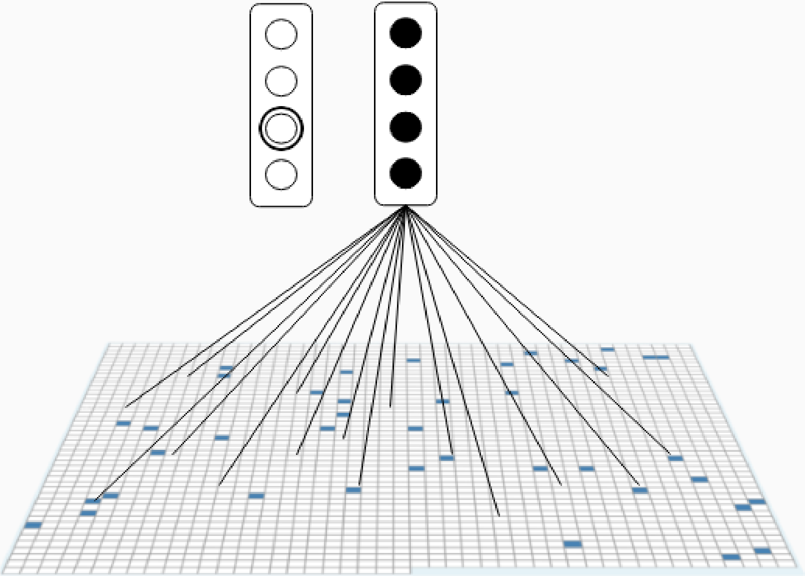
# Temporal Pooler - Selecting Winner Cells



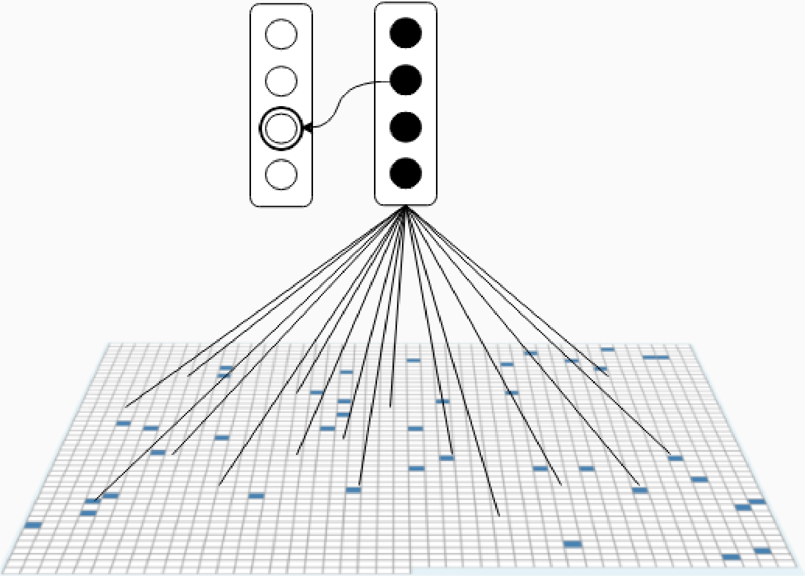
# Temporal Pooler - Selecting Winner Cells



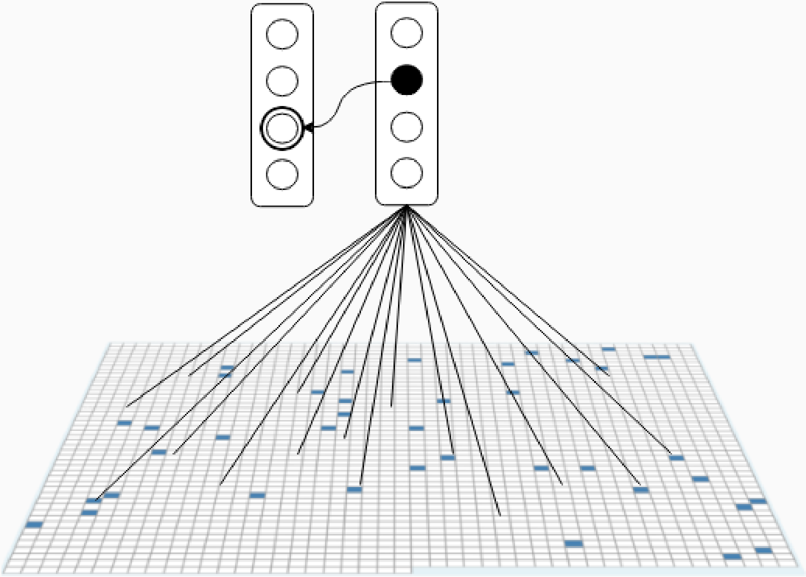
# Temporal Pooler - Selecting Winner Cells



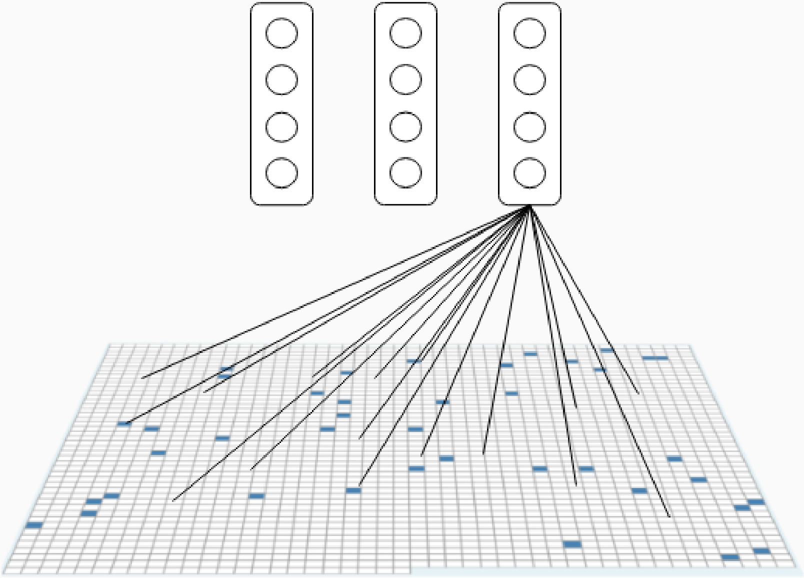
# Temporal Pooler - Selecting Winner Cells



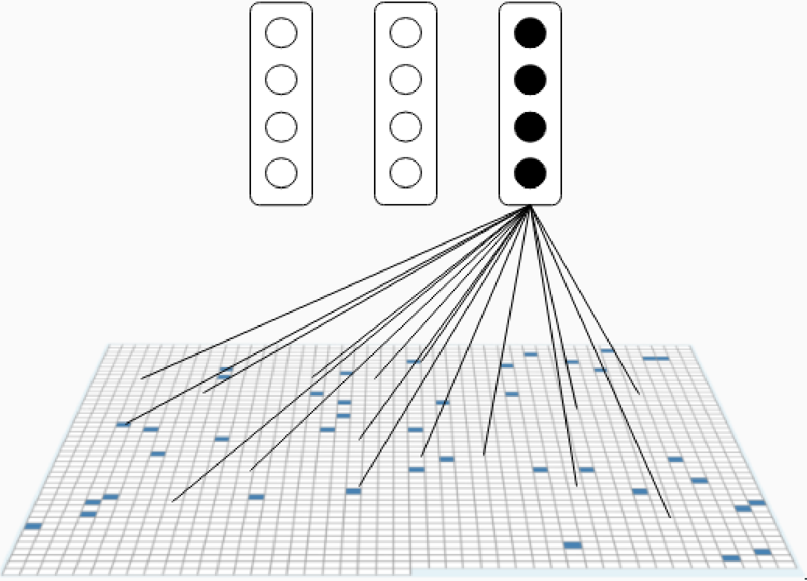
# Temporal Pooler - Selecting Winner Cells



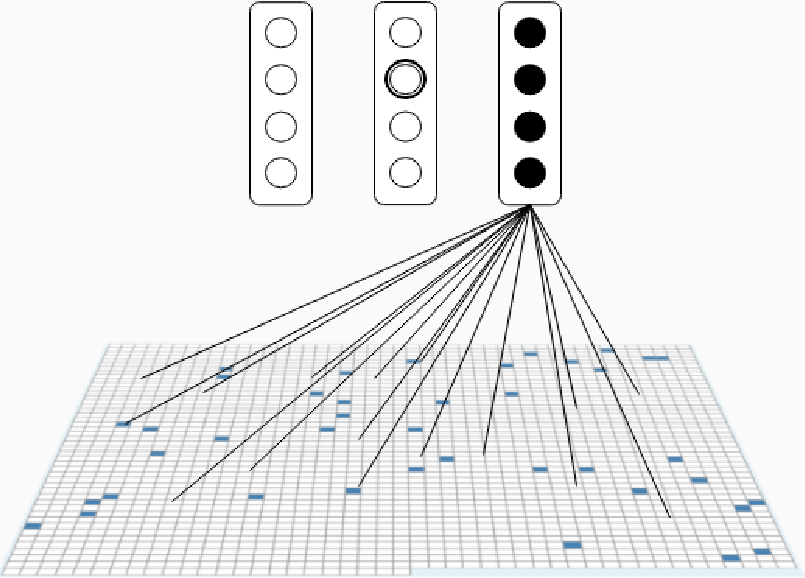
# Temporal Pooler - Selecting Winner Cells



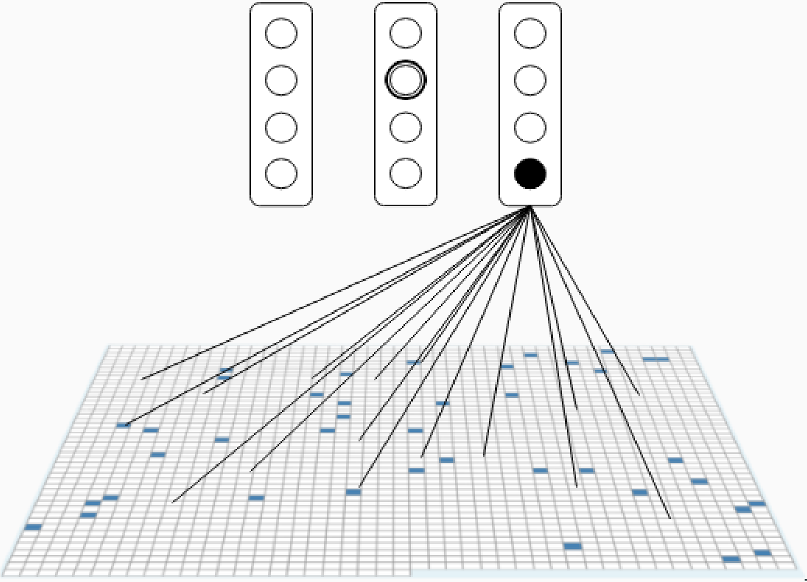
# Temporal Pooler - Selecting Winner Cells



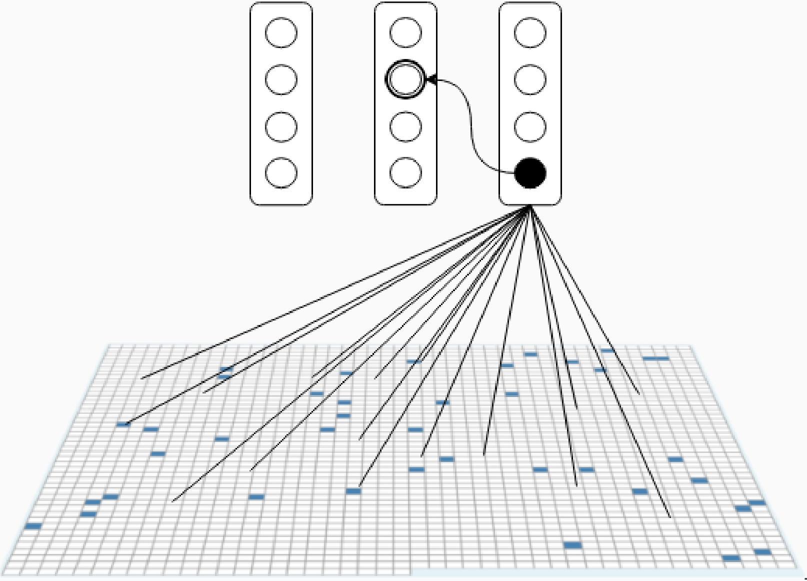
# Temporal Pooler - Selecting Winner Cells



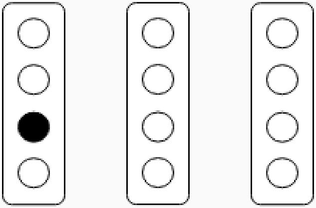
# Temporal Pooler - Selecting Winner Cells



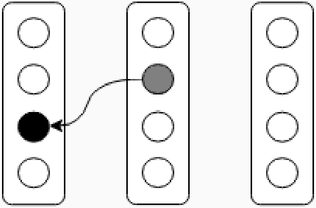
# Temporal Pooler - Selecting Winner Cells



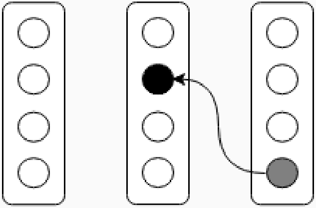
# Temporal Pooler - Selecting Winner Cells



# Temporal Pooler - Selecting Winner Cells



# Temporal Pooler - Selecting Winner Cells



# Temporal Memory - Example I

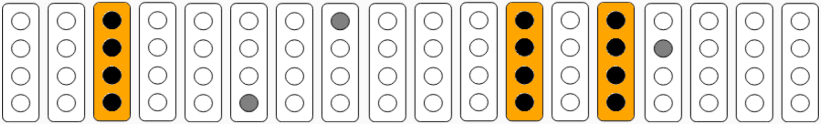
We are very busy

# Temporal Memory - Example I

We are very busy

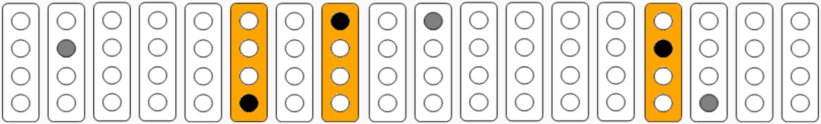
You are very knowledgeab

# Temporal Memory - Example I



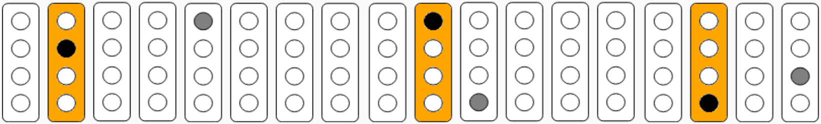
We

# Temporal Memory - Example I



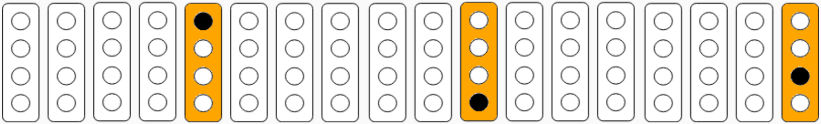
We are

# Temporal Memory - Example I



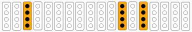
We are very

# Temporal Memory - Example I

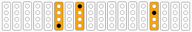


We are very busy

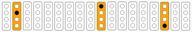
# Temporal Memory - Example I



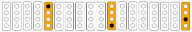
We



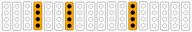
are



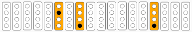
very



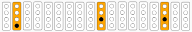
busy



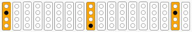
You



are

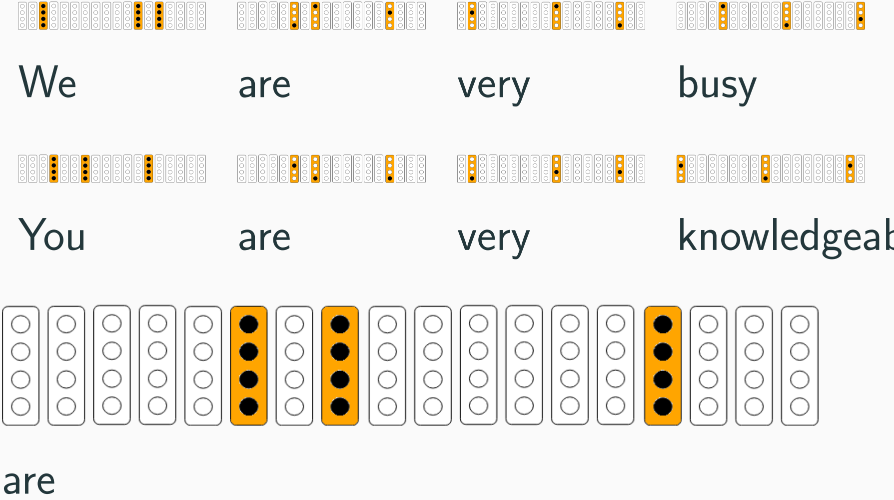


very

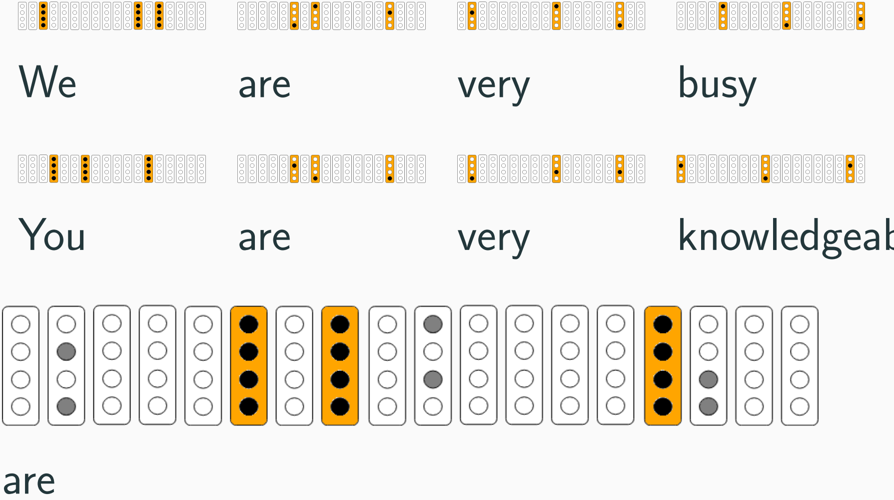


knowledgeab

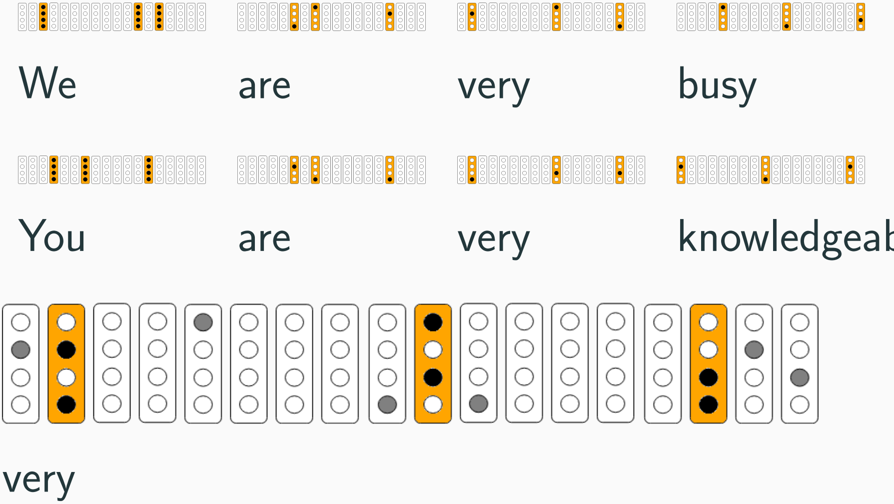
# Temporal Memory - Example I



# Temporal Memory - Example I



# Temporal Memory - Example I



# 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

# Content

# Biology

# Biology

- The Neocortex is only a part of the brain

- The Neocortex is only a part of the brain
- The smallest computational units are called 'Cortical Columns'

## Biology

- 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

# Learning

- Only statistical

# Learning

- Only statistical
- Based on Prediction and Inference

# Learning

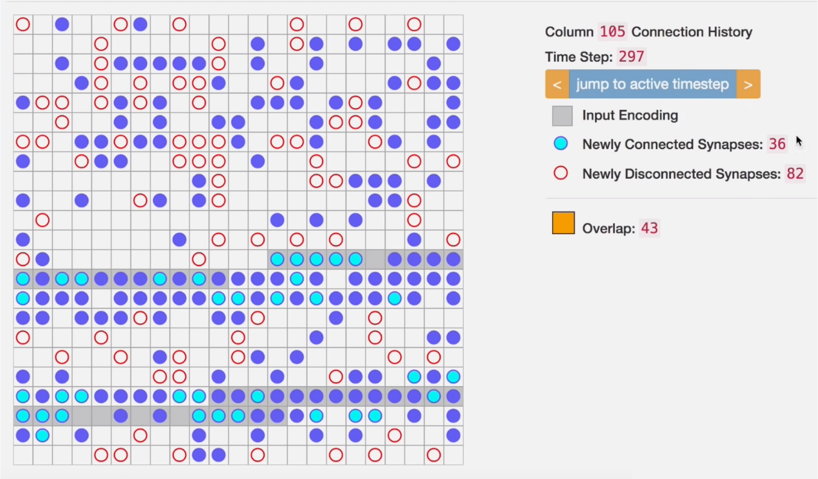
- Only statistical
- Based on Prediction and Inference
- Spatial and Temporal patterns

## Learning

- 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
- Form predictions based on previous inputs
- 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!

# Content

# 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 efficiacy).

## Implications - Brain Parameters

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

## Implications - Brain Parameters

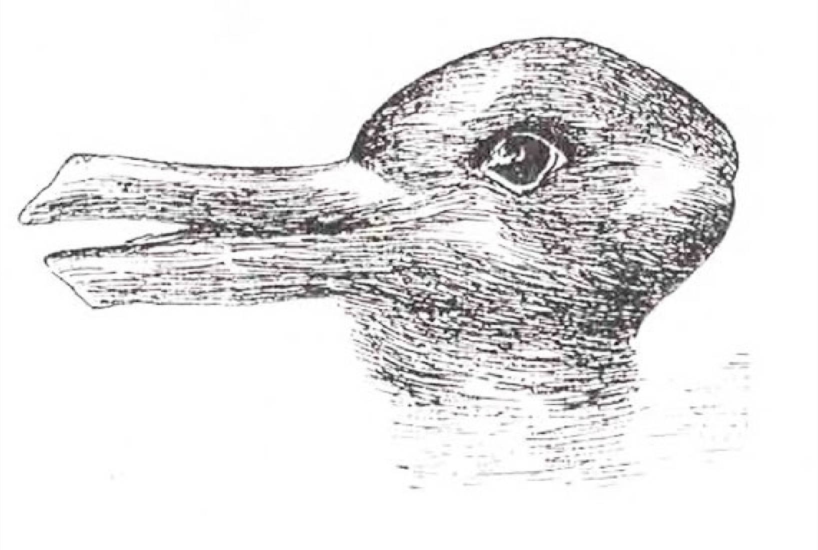
There is also a varying threshold for the spatial pooler activations.

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 - Inhibition in the Visual System

# Implications - Top-Down Processing I

Yuo cna porbalby raed tihs esaliy desptie teh msispeillgns.

# 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 Irqai 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 - Cached Thought

This fully explains the fallacy of cached thought, among others.

# Implications - Meaning

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

# 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

Content mainly from [1]

# Sources ii


- J. Hawkins, S. Ahmad, S. Purdy, and A. Lavin, "Biological and machine intelligence (bami)." Online release 0.5 (March 2017), 2017.
- 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.
- 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.

# Sources vi

H. Gray, “Gray754.”
https://en.wikipedia.org/wiki/File:Gray754.png, 1918.
**Accessed 2019-08-24.**

# End

# Cortical Column

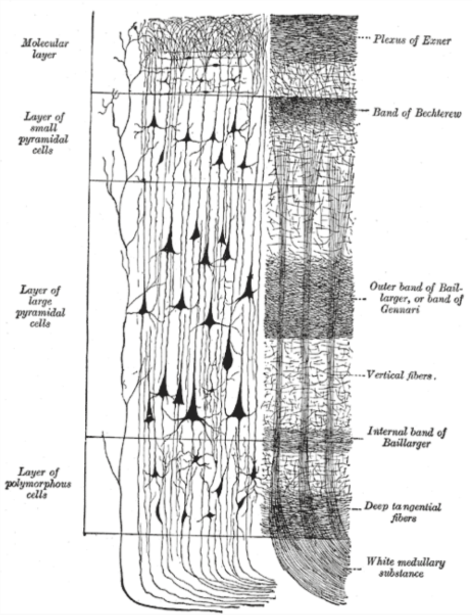



Image from [11]

# Cortical Column II