

# Principles Of Hierarchical Temporal Memory - Foundations Of Machine Intelligence

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## 0.1 Context

## 0.2 Learned in this study

## 0.3 Things to explore

## 1 Overview

### 1.1 Why will machines intelligence be based on cortical principles?

- The cortex uses a common learning algorithm
- The cortical algorithm is incredibly adaptable
- It has a network effects: hardware and software efforts will focus on the most universal/generic solution

## 2 Cortical facts

Sensory systems:

- Retina
- Cochlear
- Somatic

Patterns of action potential, firing of neural fibers.

The brain deals with patterns.

The neocortex learns a model from fast changing sensory data. With the model, it can generate

- predictions
- anomalies
- actions

The neocortex learns what is called a **sensory-motor model** of the world.

The brain is a sheet of cells which is remarkably uniform.

It is organized as a hierarchy.

Within a level of the hierarchy are cellular layers.

Within those layers there's an organisation called mini-columns.

At the *end* are neurons.

Learning is about modifying synaptic weights, but also about degeneration/neogenesis of synaptic connections.

## 3 Cortical theory (HTM)

### 3.1 Overview

1. Hierarchy of identical regions

2. Each region learns sequences (time-based patterns)
3. Stability increases going up the hierarchy if input is predictable
4. Sequences unfold going down

## 3.2 Questions

- What does a region do?
- What do the cellular layers do?
- How do neurons implement this?
- How does this work in hierarchy?

## 3.3 Cellular layers

1-6 layers, 2 to 3 layers of feed forward (2-3-4) and 2 layers of feedback (5-6)

Each layer is implementing a type (variation) of a common sequence memory algorithm

Layers 2-3-4 are doing inference

Layer 5 is doing motor behavior

Layer 6 is doing attention

The input to a particular region arrives at the layer 4 (L4) and then projects to L3 which then projects down to the lower layer of the hierarchy

The motor behavior is also passed in at the same time

Thus, what is received is the information that is perceived as well as the recent behaviors of the body

L4: Learns sensory-motor sequences

If the layer is able to predict properly the sequence, it forms a stable representation that is passed onto L3 if it is unable to predict, it passes through the change to L3

L3: Learns high-order sequences

## 3.4 The neuron

### 3.4.1 Biological neuron

10% of the synapses are close to the cell body

Feedforward input

Added linearly

Generate spikes

2 regions

Basal dendrites (bottom, close to the cell)

Apical dendrites (top, far from the cell)

They are non-linear

Dendritic action potentials depolarize soma

### 3.4.2 HTM neuron

Feedforward

Linear summation

Binary activation

Distal synapses

Modeled as a set of coincidence detector

Threshold coincidence detectors

Puts the cell in a predicted state

### 3.4.3 Biological synapses

Learning is mostly formation of new synapses  
Synapses are low fidelity

### 3.4.4 HTM synapses

Scalar permanence  
Binary weight

## 3.5 Sparse distributed representations (SDRs)

Called *The language of intelligence*

Many bits (thousands)  
Few 1's, mostly 0's  
Each bit has semantic meaning  
Learned

## 3.6 SDR properties

1. Similarity  
shared bits = semantic similarity
2. Store and compare  
store indices of active bits  
subsampling is OK
3. Union membership  
can ask "is this pattern part of the union?"

A cell can recognize many unique patterns on a single dendritic branch

A cell activates from dozens of feedforward patterns  
It predicts its activity in hundreds of contexts

## 3.7 Learning transitions

1. Feedforward activation
2. Inhibition which generates sparse cell activation
3. Formation of connections with nearby cells which were previously active cells (give them the ability to predict future activity)

If a pattern is input, many cells will indicate that they predict to be activated next

It can predict A-B, A-C, A-D

This is known as a first order sequence memory

It cannot learn A-B-C-D vs X-B-C-Y

Mini-columns turn this into a high-order sequence memory

## 3.8 Forming high-order representations

If there is no prediction, all cells within a column become active

If there is a prediction, only the predicted cells will become active (the other will be inhibited)

## 3.9 HTM temporal memory (aka cellular layer)

Converts input to sparse activation of columns  
Recognizes and recalls high-order sequences

### 3.9.1 Desirable traits

- Continuous learning
- High capacity
- Local learning rules
- Fault tolerant
- No sensitive parameters
- Semantic generalization

## 4 Research roadmap

### 4.1 Applications using HTM high-order inference

```
graph LR;
  0[Data] --> 1[Encoder]
  1 --SDR--> 2[HTM high-order sequence memory]
  2 --> 3[Predictions<br/>Anomalies]
```

## 5 Thoughts on machine intelligence

- Cortical (HTM)
- ANNs (deep learning)
- AI (Watson)

|                               | Cortical                                               | ANNs             | AI                    |
|-------------------------------|--------------------------------------------------------|------------------|-----------------------|
| Premise                       | Biological                                             | Mathematical     | Engineered            |
| Data                          | Spatial-temporal<br>Behavior                           | Spatial-temporal | Language<br>Documents |
| Capabilities                  | Prediction<br>Classification<br>Goal-oriented behavior | Classification   | NL Query              |
| Valuable?                     | Yes                                                    | Yes              | Yes                   |
| Path to machine intelligence? | Yes                                                    | Probably not     | No                    |

## 6 See also

## 7 References

- Video: <https://www.youtube.com/watch?v=6ufPpZDmPKA>
- Slides: <http://www.slideshare.net/numenta/2014-10-17-numenta-workshop>