HIERARCHICAL TEMPORAL MEMORY

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Deep Neural Nets

- Deep Neural Nets (DNN) are frameworks for ~~**A**rtificial **I**ntelligence~~
  Assistive **I**ntelligence
- Deep Neural Nets have clocked up incredible successes in many areas, (and continue to do so), however,
  - DNN need thousands if not millions of samples to train on
  - DNN find it hard to adapt to continually changing data and surprises
  - DNN are susceptible to noise and can easily be fooled
- DNN don’t work as our brains do and cannot lead to true AI

HTM

- Hierarchical Temporal memory (HTM) is a theoretical framework for both biological and generalised machine intelligence.

- Based on the latest understanding of the Neocortex

- Only requires a few hundred samples to learn

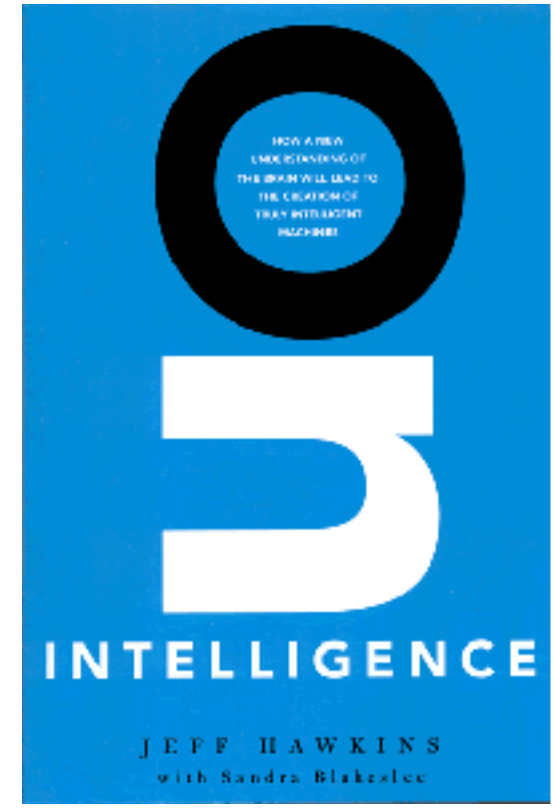
- Learns unsupervised as it goes and easily handles changing data and surprises

- Immune to up to 40% noise

- Opens the way for truely intelligent systems

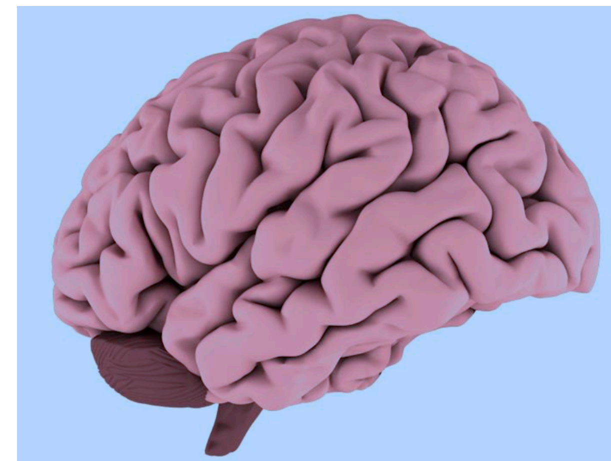
History

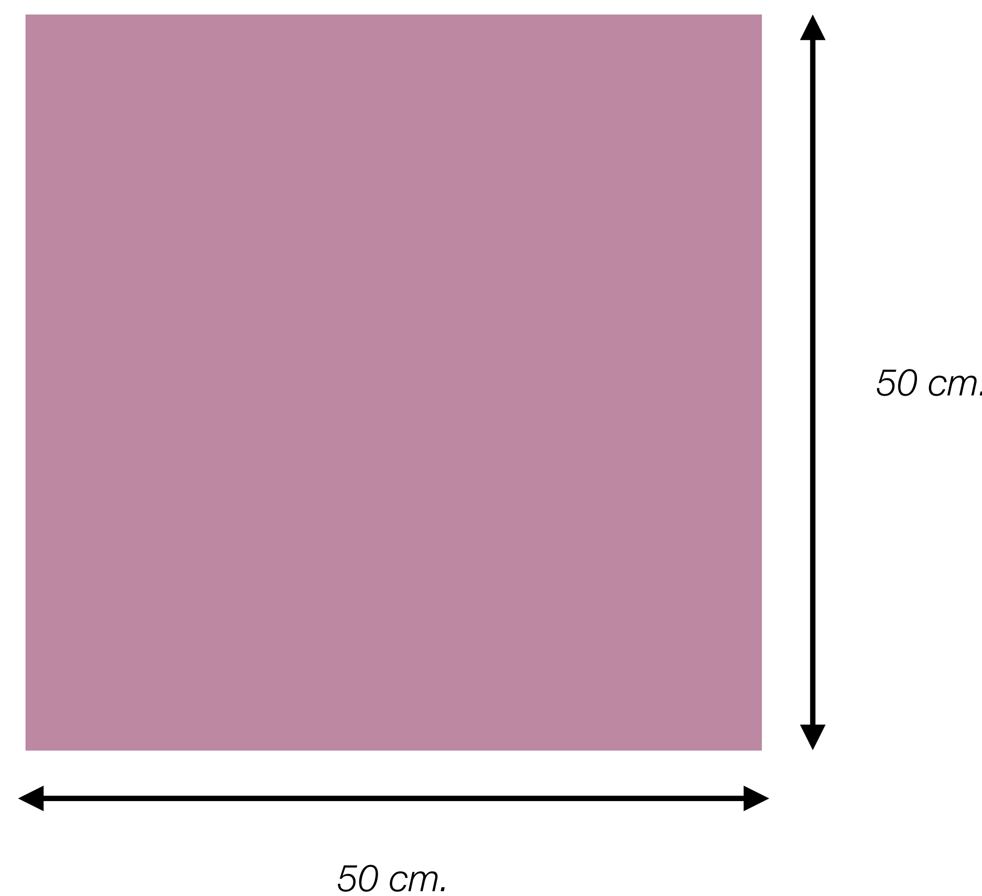
- 2004 “On Intelligence” by Jeff Hawkins & Sandra Blakeslee
  - The core concepts in Hierarchical Temporal Memory (HTM) theory were first described in this book
- 2005 Numenta was established in Redwood City, CA to
  - **Reverse engineer the neocortex**
  - **Apply neocortical theory to AI**
- 2014 NuPIC (**Nu**menta **P**latform for **I**ntelligent **C**omputing) was open sourced under the AGPLv3 license
  - API in Python 2.7, and C++
- Community port to Python 3 (in progress)
- Third Party Implementations in Java, Closure, C#, Javascript…
- HTM is constantly evolving with Numenta’s open research



Neocortex

- Size of a large table napkin (50x50 square centimetres)
- 75% of brain's volume
- 2.5 mm thick
- 30 billion neurons
- Tens of thousands of synapses per neuron
- Sparsely active
  - Only ~ 2% spiking at any one time
- Constantly predicting its inputs
- Learns a model of the world
- Creates behaviours





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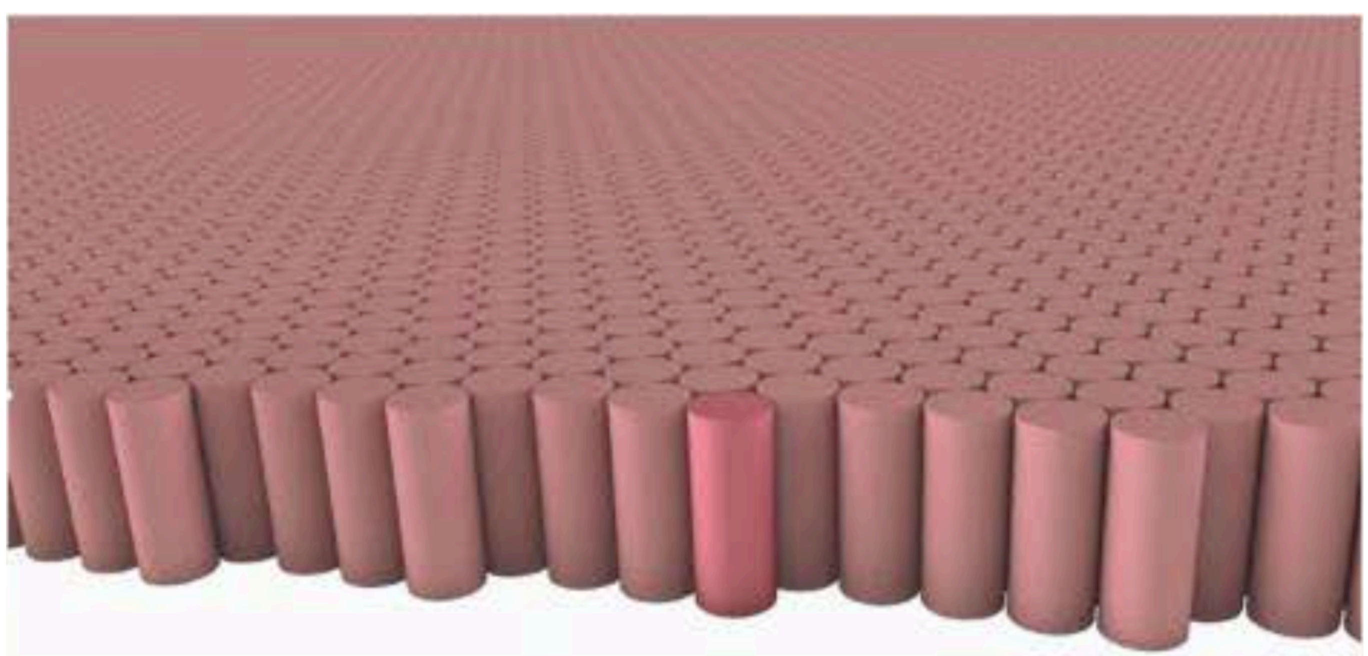
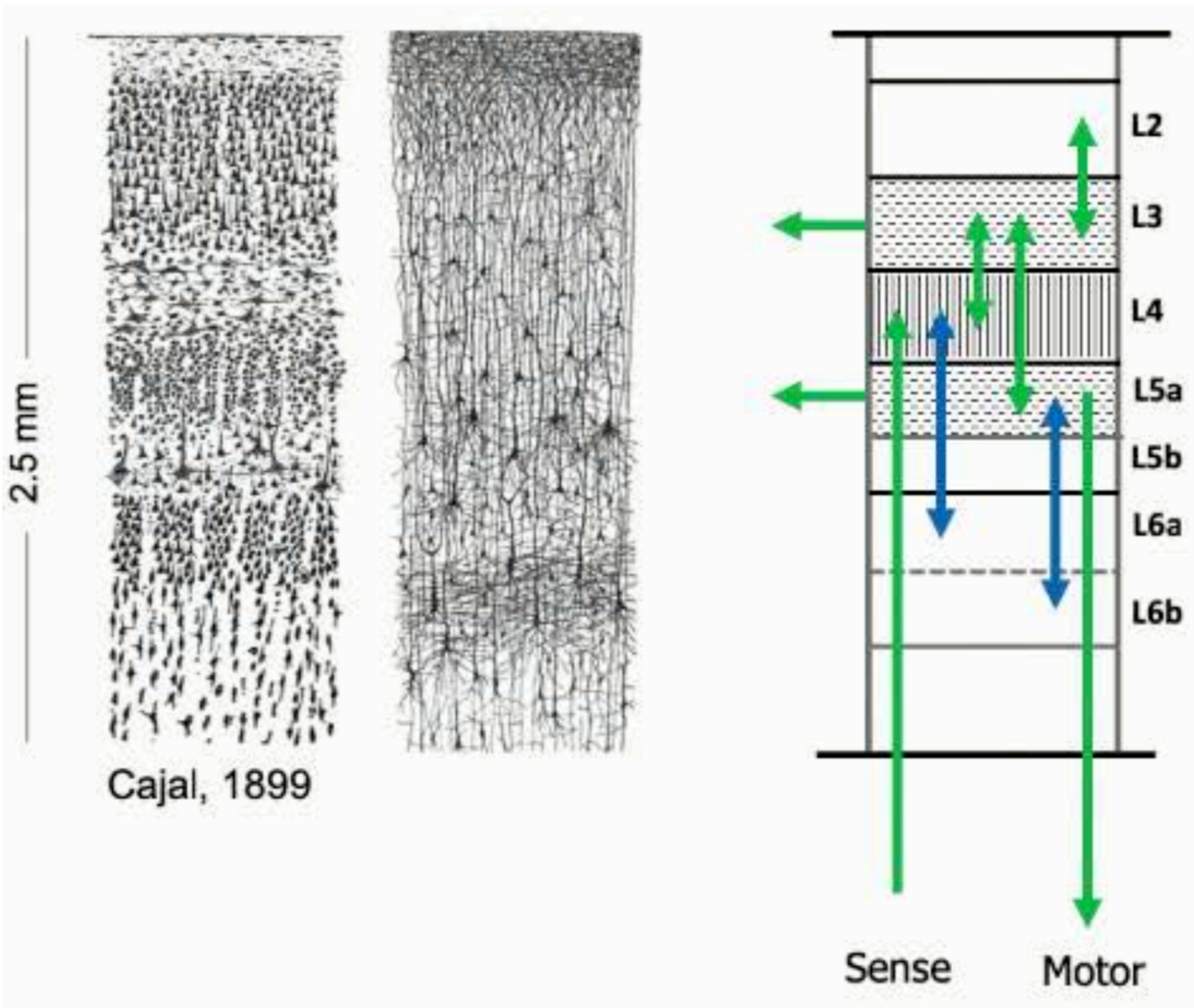
Neocortex Cortical Columns

- All areas in the neocortex look the same, so they must perform the same basic function
- What makes one region visual and an another touch is what is connected to them
- The basic unit of replication is a cortical column ($1mm^2$)
  - So logically, it must be the basic unit of computation



Cortical Column



Dozens of neuron types

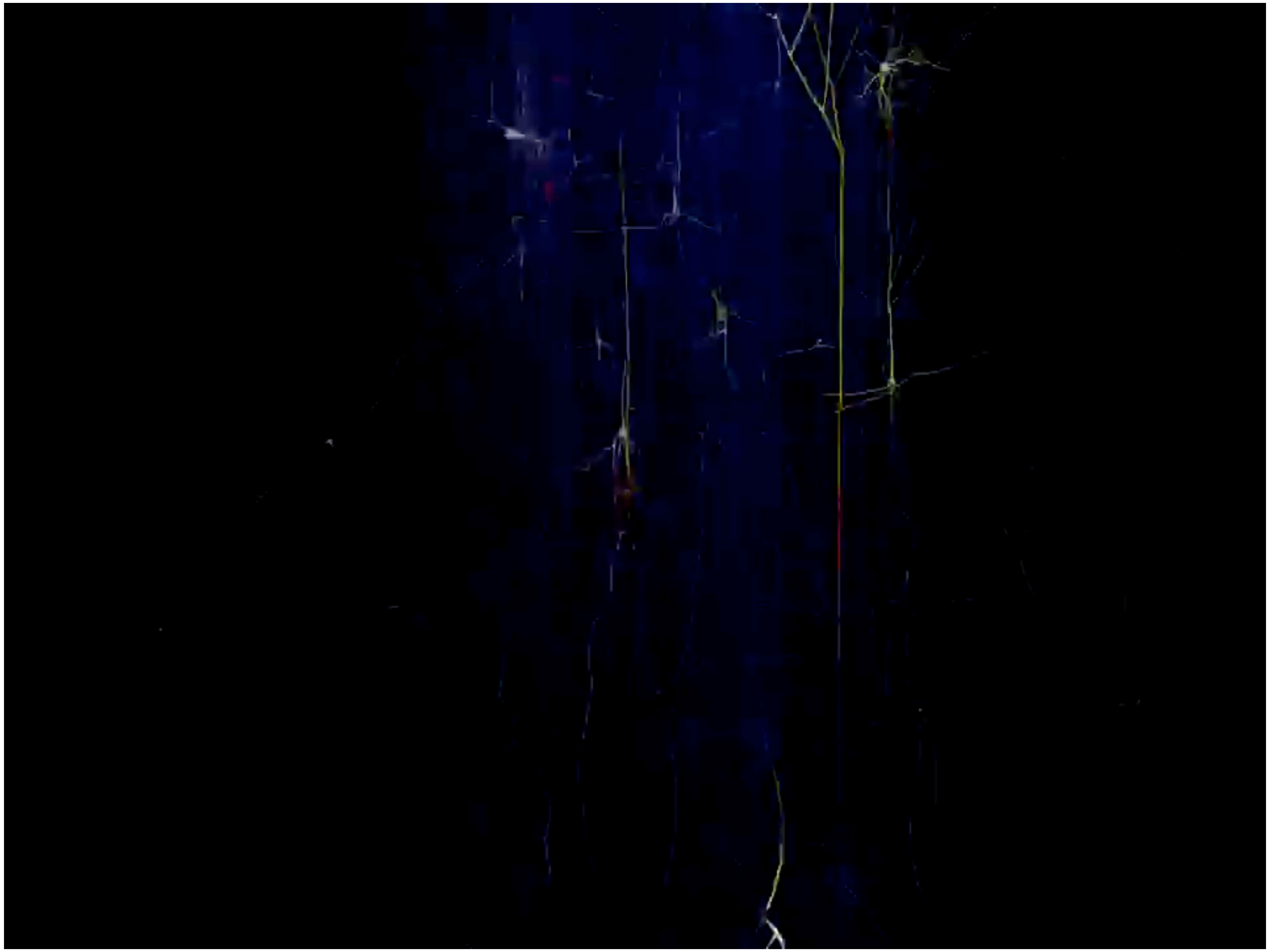
Organised into layers

Vertical local projections cross all layers

Horizontal inter-column long distance projections in some layers

- Cortical Columns are complex
- So whatever the column does must also be complex
- And whatever the column does, so does the neocortex.

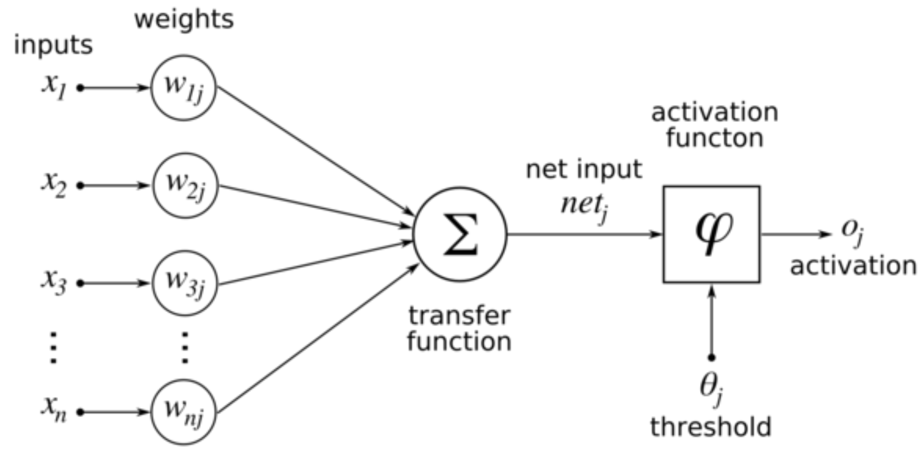
Visualisation



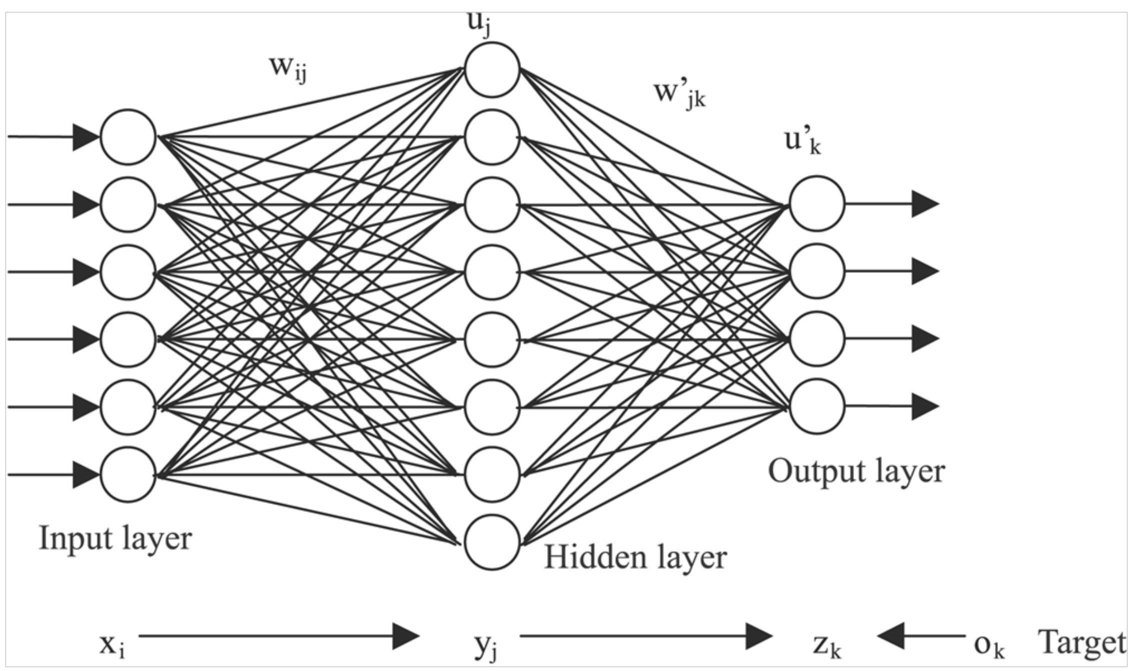
Cajal Blue Brain Project - http://cajalbbp.cesvima.upm.es/

- Tries to model all aspects of the neuron

Deep Neural Net Neuron



- Based on the 1957 concept of the Perceptron



- Learning is by adjusting the synaptic weights
- Real neurons are not like this

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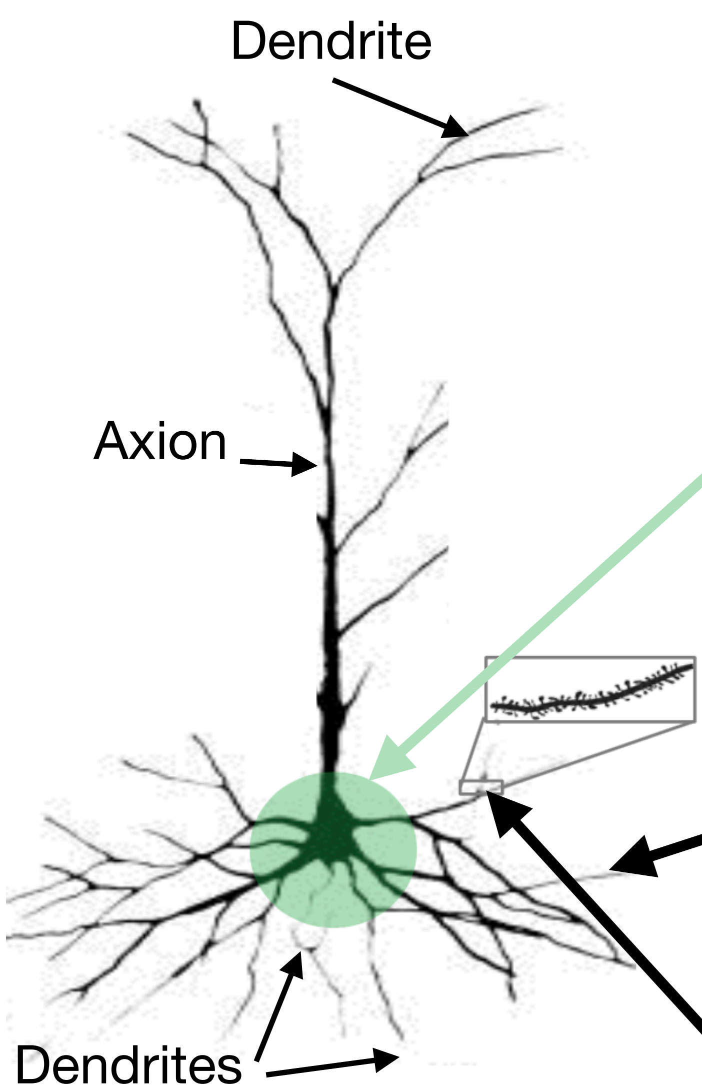
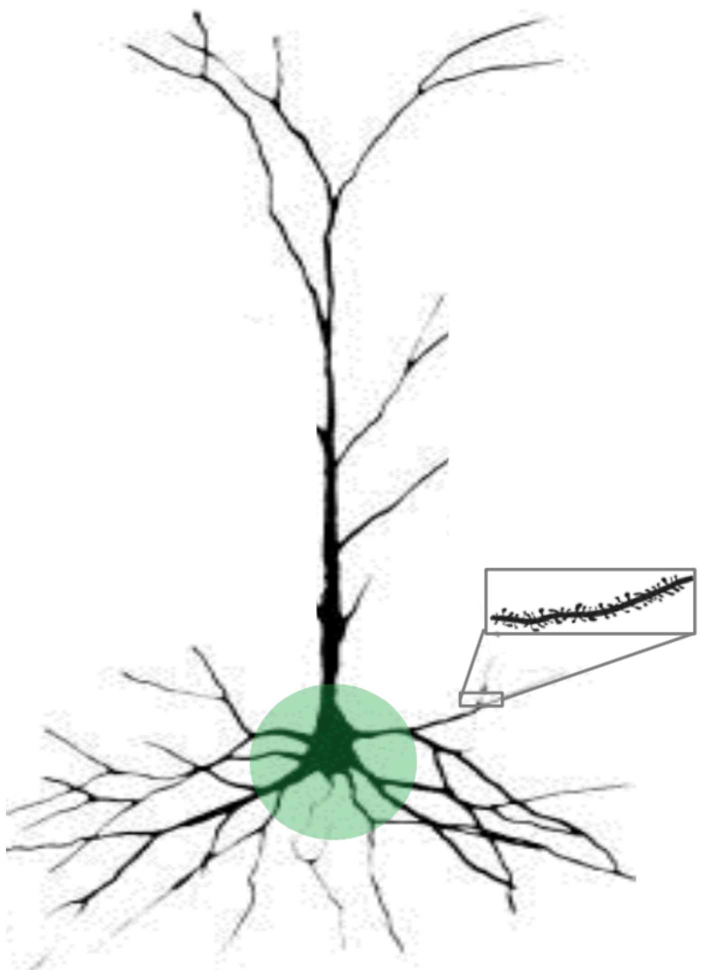
Real Neuron

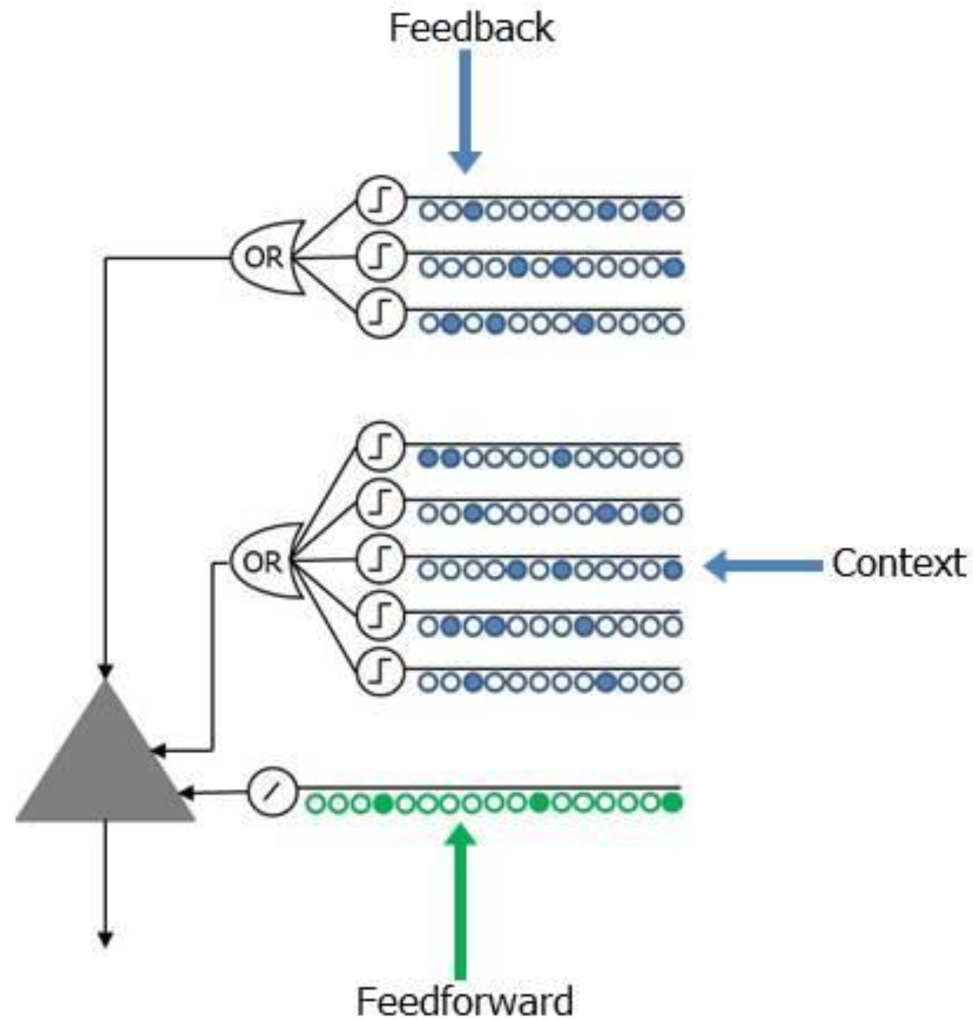


- 5K to 30K excitatory synapses on the dendrites
    - 10% proximal can cause **neural** spike
    - 90% distal cannot cause neural spike

- Distal dendrites are pattern detectors
    - 8-15 co-active, co-located synapses will generate a **dendritic** spike
        - this puts the cell into a depolarised, or “predictive” state
    - Depolarised neurons fire sooner, inhibiting nearby neurons.

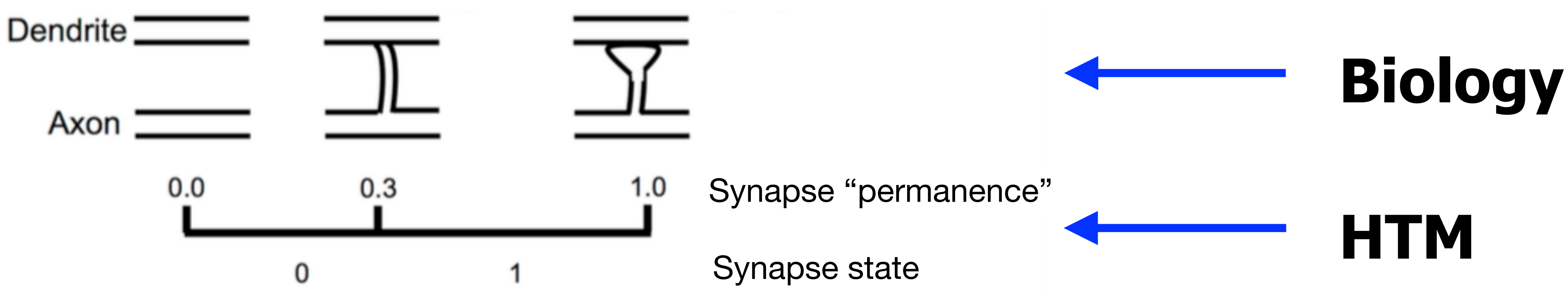
HTM Neuron





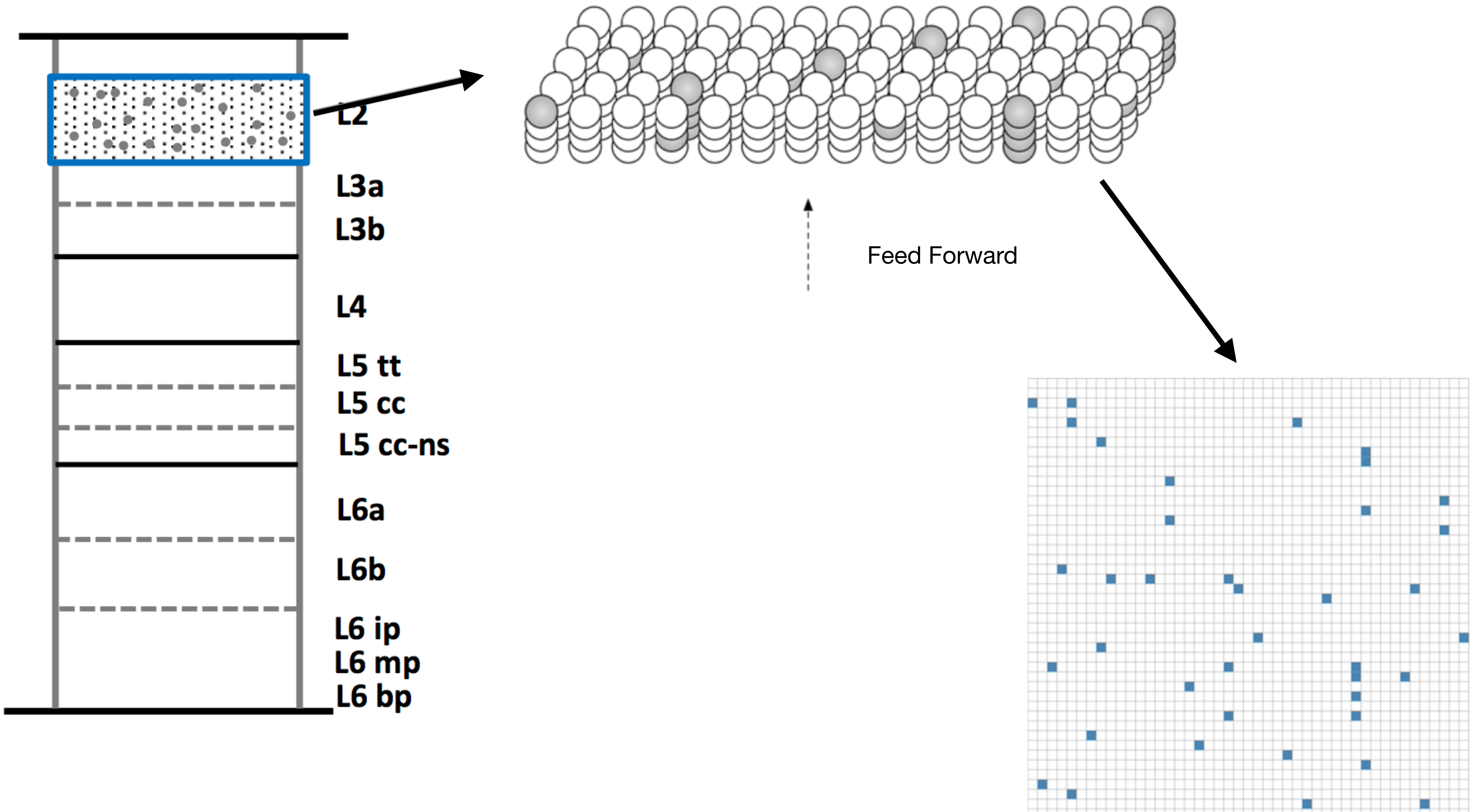
- HTM neurons don’t attempt to model all aspects of biological neurons
- Only those that are essential for the informational aspects of the neocortex.
- HTM neuron state depends on the position and number of activated synapses - **not on a sum of weights**

Neural Learning



- In HTM neurons, learning is modelled by the growth of new synapses or removal of unused synapses as in biological neurons
- This learning occurs by incrementing or decrementing the synapse "permanence".
- A synapse is **disconnected** for a permanence **under** the threshold
- A synapse is **connected** for a permanence **over** the threshold
- **Learning is making or breaking synapses, not adjusting synaptic weights as in DNNs**

HTM Cortical Column



Sparse Distributed Representation (SDR)

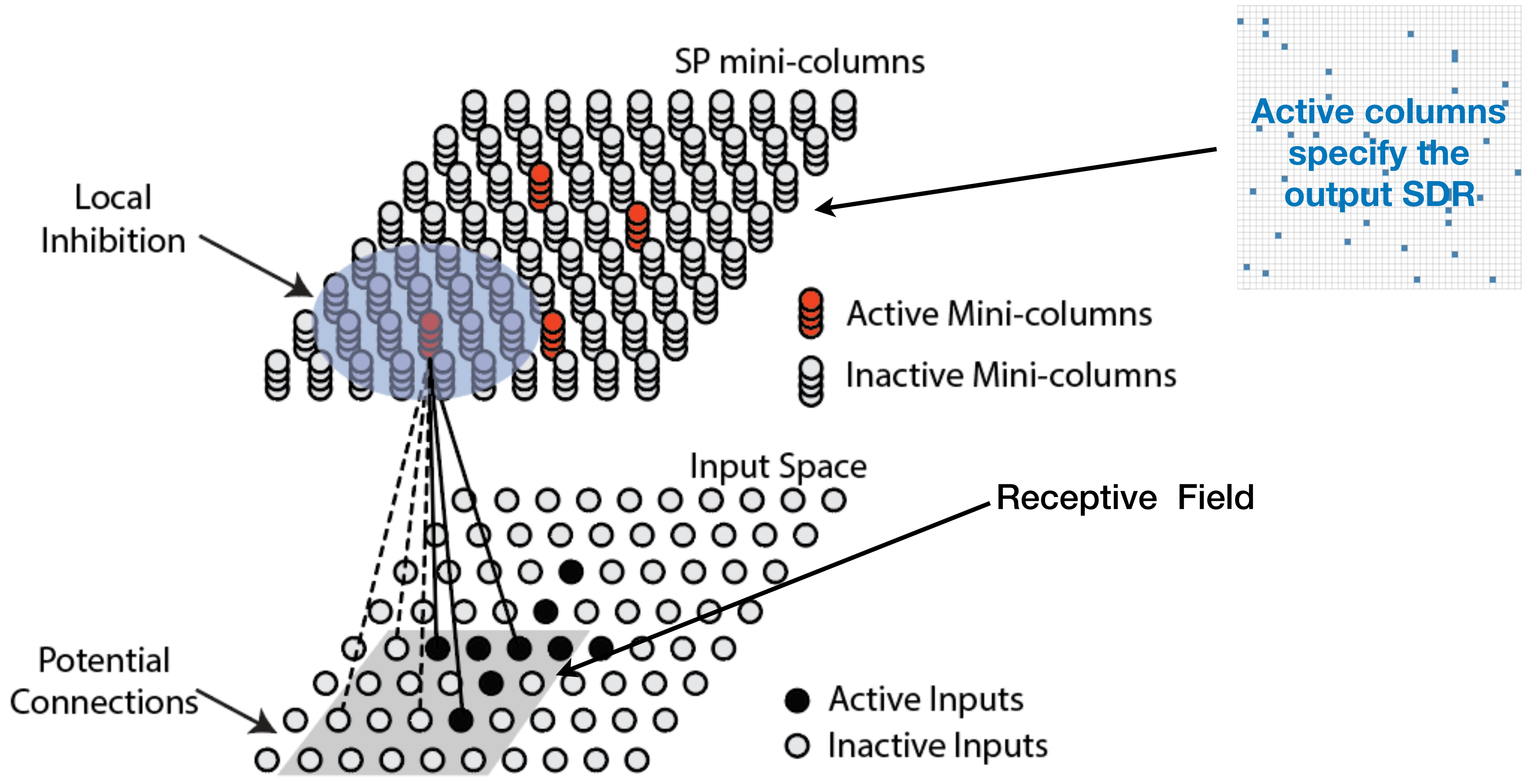
Sparse Distributed Representations

- SDRs are how brains solve the problem of representing knowledge
- Each bit has semantic meaning
- Extremely high capacity. For 2048 bit vector and 2% are set, we have >> 10^{84} unique patterns
- Fixed sparseness

```
0100000000000000000000001000000000000000000000000000000000000000000010000..........01000
0000000010000000000000001000000000000000000000000001000000000000000010000..........00000
                        ↑                                          ↑
```

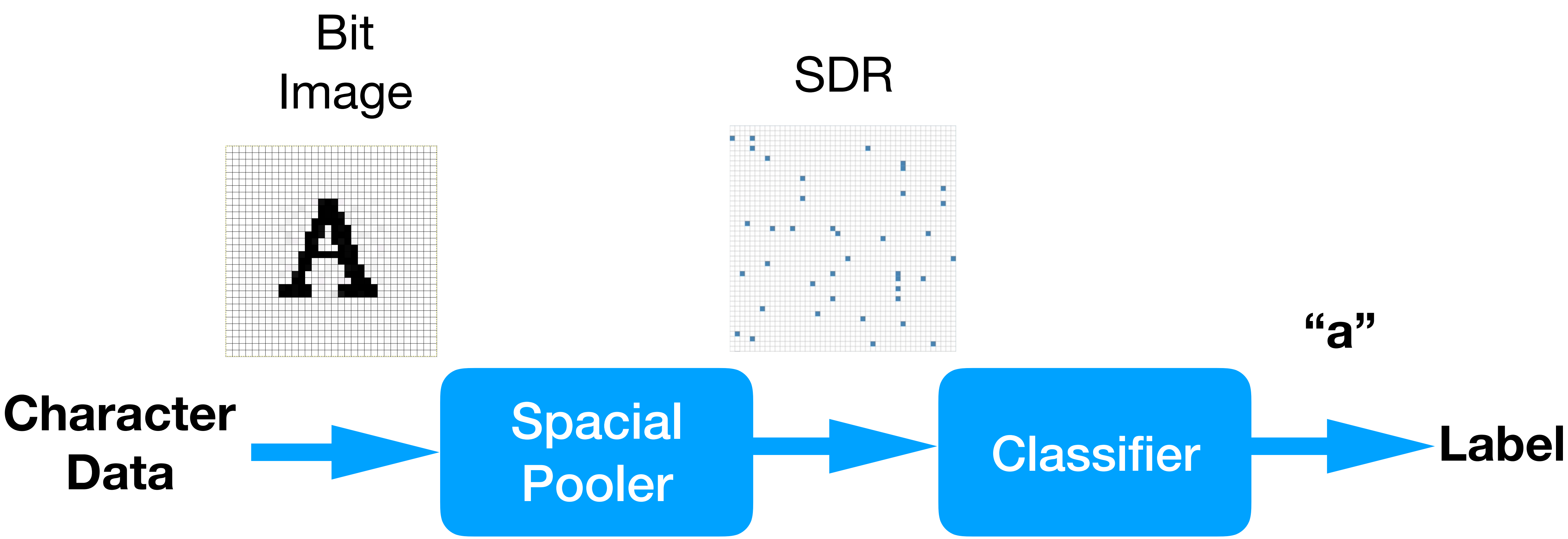
- Two representations with shared bits have some shared semantic information
- Comparing two representations is as simple as taking the intersection of the two indices sets.
- SDRs are inherently fault-tolerant and noise tolerant.
- Can check for existence of an SDR in a union

Spacial Pooler



- Creates SDRs from N dimensional bit array inputs using Hebbian learning
- Learning is continuous
- Each cell in a column receives the same input
- Same input will generate the same unique SDR
- Preserves semantic similarity

Example - Character Reader



Demo - Character Reader

3 Training Fonts

Times New Roman 0123456789
ABCDEFGHIJKLMNOPQRSTUVWXYZ
abcdefghijklmnopqrstuvwxyz

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144 Testing Fonts

Chalkduster 0123456789

ABCDEFGHIJKLMNOPQRSTUVWXYZ

abcdefghijklmnopqrstuvwxyz

Courier New Bold Italic 0123456789

ABCDEFGHIJKLMNOPQRSTUVWXYZ

abcdefghijklmnopqrstuvwxyz

Comic Sans MS 0123456789

ABCDEFGHIJKLMNOPQRSTUVWXYZ

abcdefghijklmnopqrstuvwxyz

Apple SD Gothic Neo 0123456789

ABCDEFGHIJKLMNOPQRSTUVWXYZ

abcdefghijklmnopqrstuvwxyz

HERCULANUM 0123456789

ABCDEFGHIJKLMNOPQRSTUVWXYZ

ABCDEFGHIJKLMNOPQRSTUVWXYZ

Xingkai 0123456789

ABCDEFGHIJKLMNOPQRSTUVWXYZ

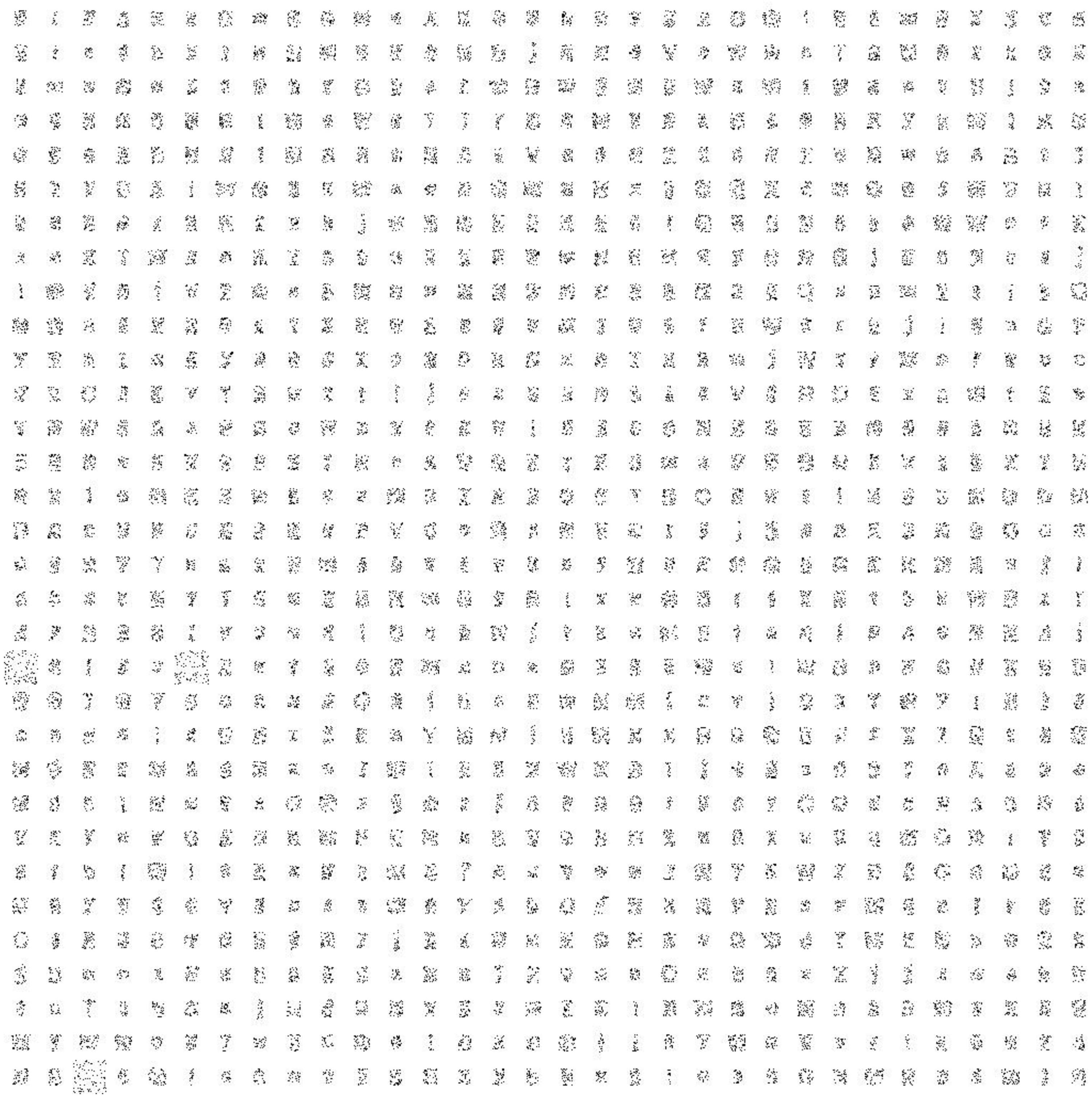
abcdefghijklmnopqrstuvwxyz

SnellRoundhand 0123456789

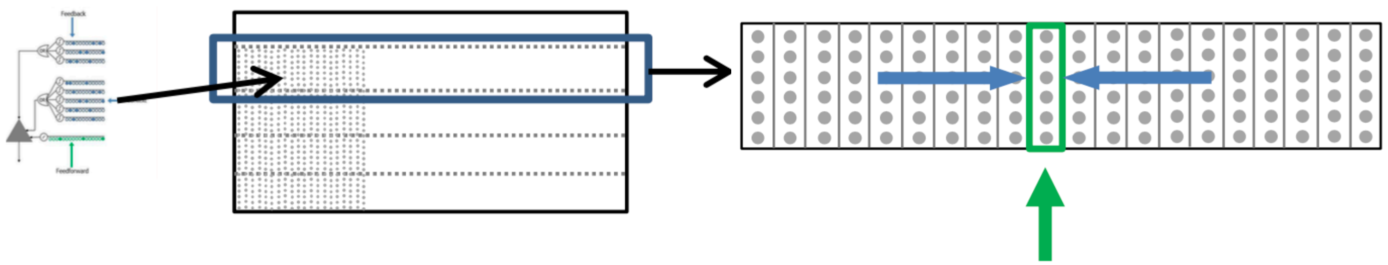
ABCDEFGHIJKLMNOPQRSTUVWXYZ

abcdefghijklmnopqrstuvwxyz

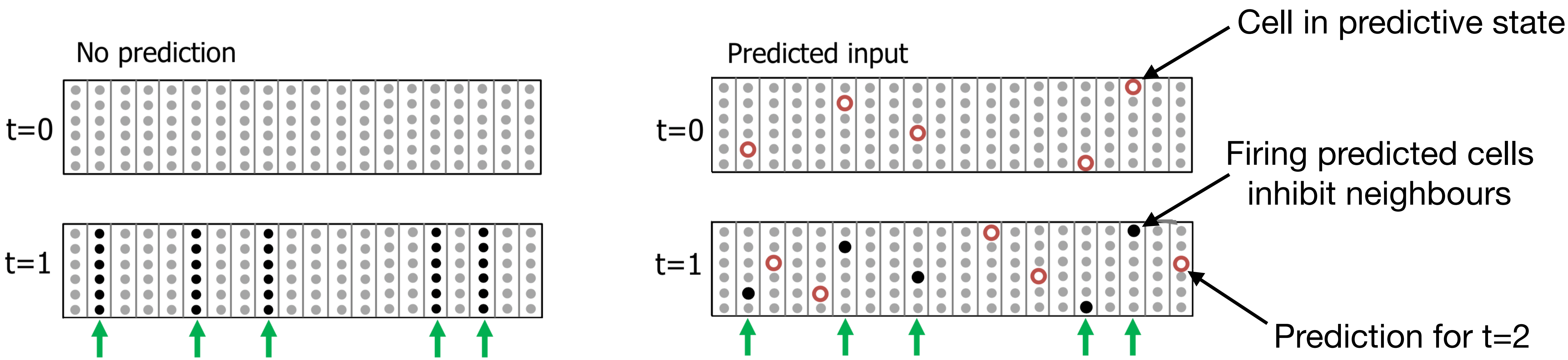
Character Reader Receptive Fields



Temporal (or Sequence) Memory



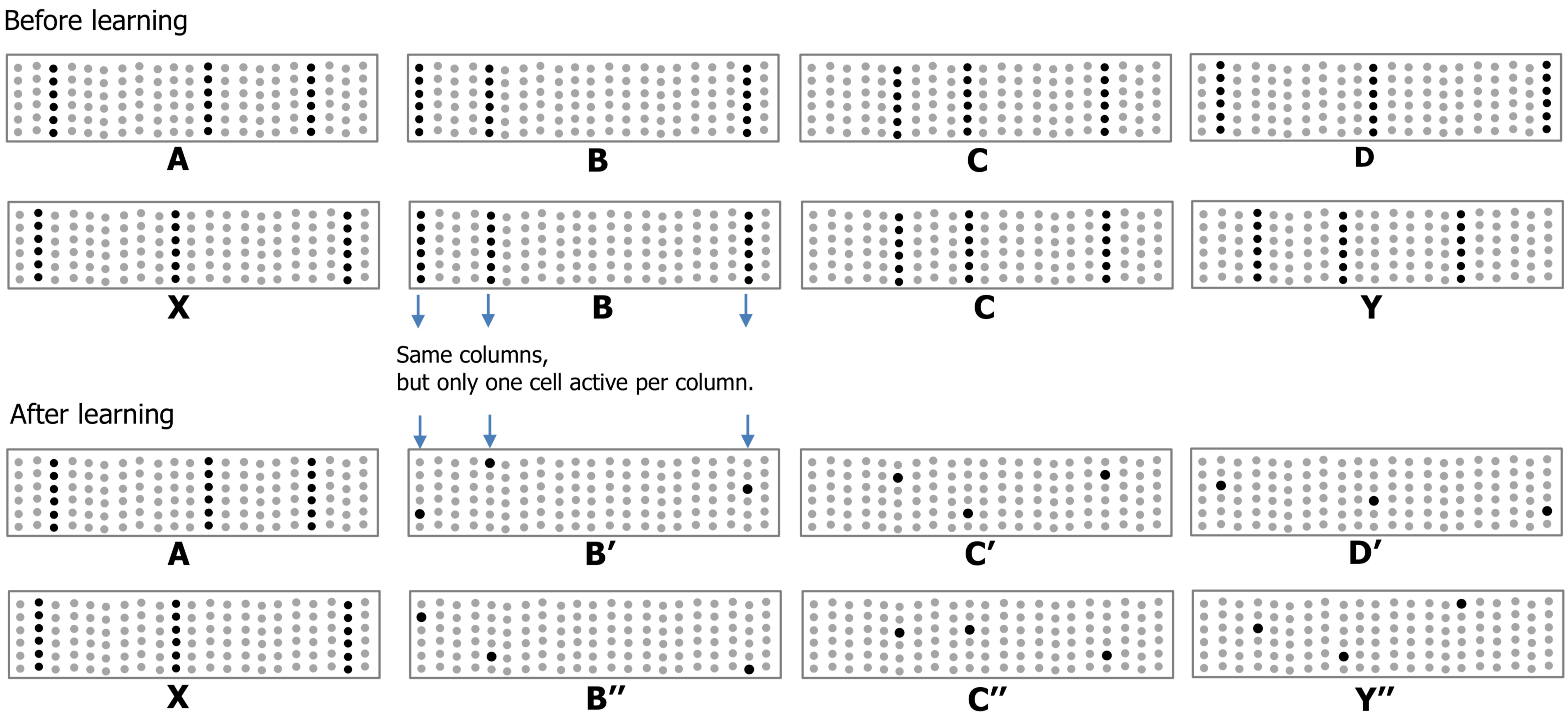
- Neurons in a mini-column learn same FF receptive field.
- Neurons forms distal connections to nearby cells.



- Learns sequences of SDRs and makes predictions of what the next input SDR will be
- Learns higher order sequences: “ABCD” vs “XBCY”
- Makes simultaneous predictions: “BC” predicts “D” and “Y”
- Extremely robust (40% noise and fault tolerant)
- Learning is unsupervised and continuous

Sequence Prediction

Sequences A-B-C-D vs. **X-B-C-Y**



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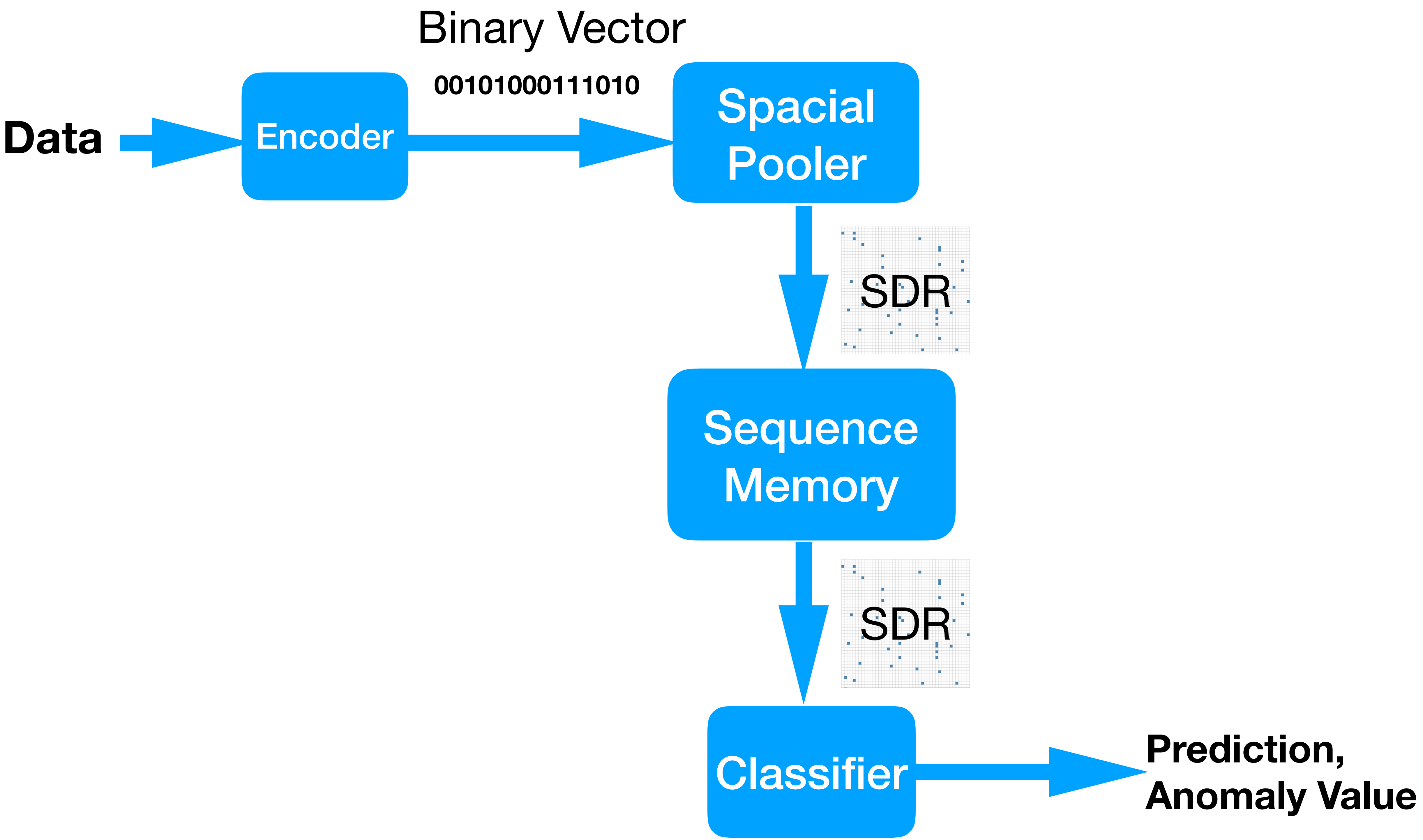
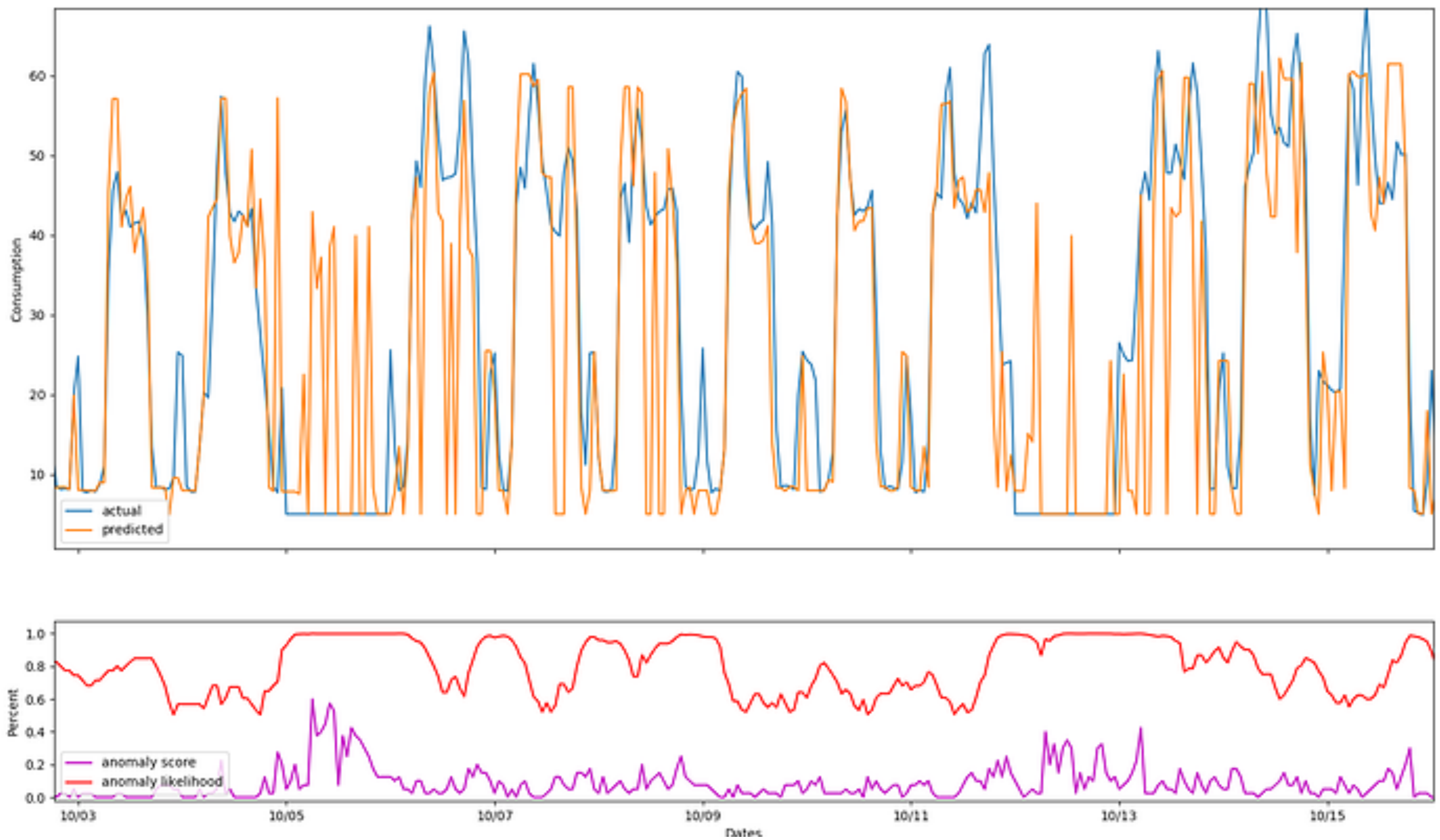
Anomaly Detection



Demo - Anomaly Detection



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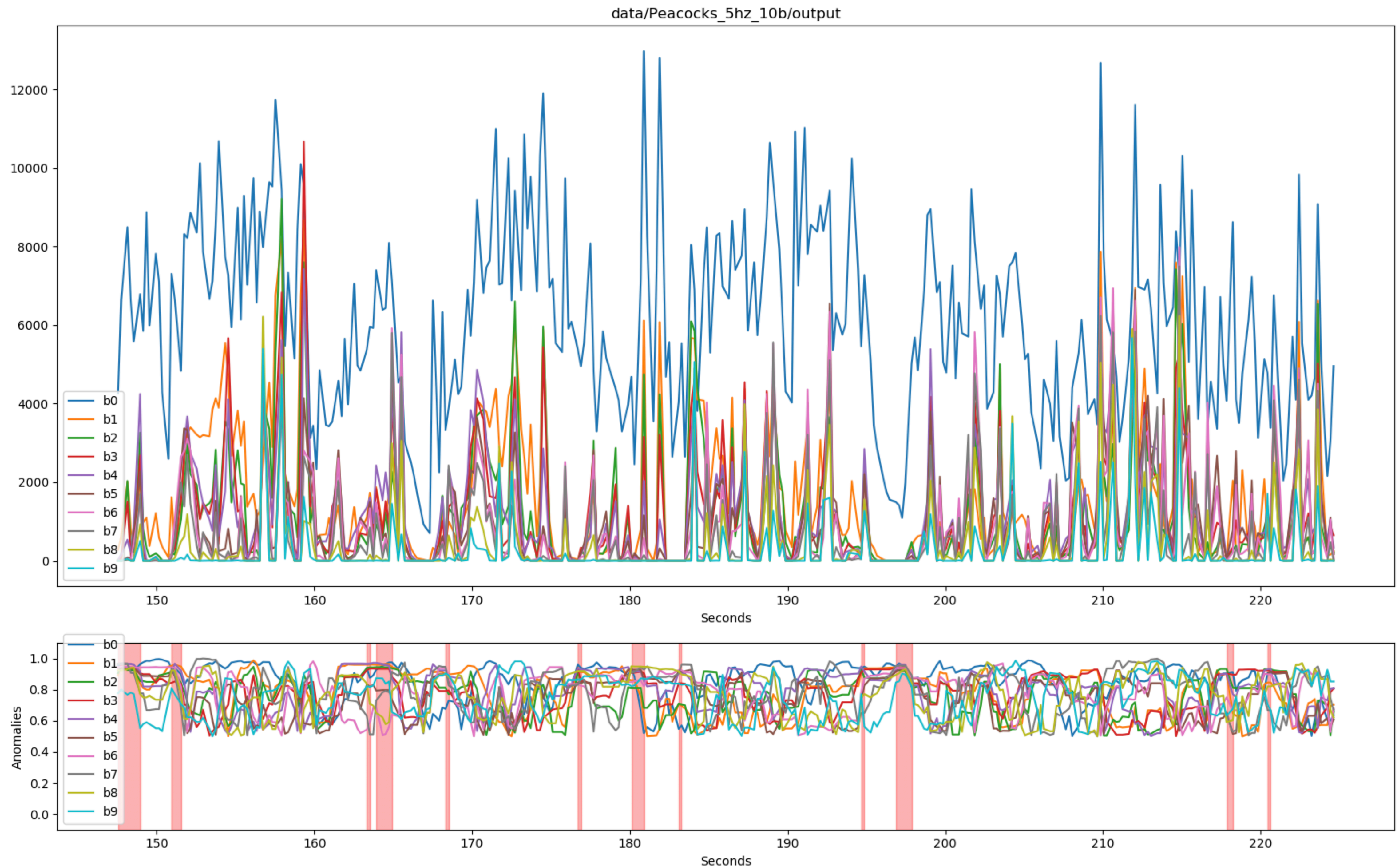
Demo - Music Critic



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Commercial Applications

http://grokstream.com/

http://www.cortical.io/

https://intelletic.com/

Links

- https://numenta.com/

- https://numenta.org/

- HTM School: https://www.youtube.com/channel/UC8-ttzWLgXZOGuhUyrPlUuA

- https://www.datasciencecentral.com/profiles/blogs/off-the-beaten-path-htm-based-strong-ai-beats-rnns-and-cnns-at-pr

Slides and Demos

- https://github.com/fcr/python_meetup_htm_slides

Questions?