DRIVES

Development and Research on Innovative Vocational Education Skills

U3 DEEP LEARNING AND NEURAL NETWORKS

U3.E8 THE FUTURE TRENDS IN ARTIFICIAL INTELLIGENCE: MACHINE INTELLIGENCE AND THE HIERARCHICAL TEMPORAL MEMORY (HTM)

Artificial Intelligence Technician

March 2021, Version 1

Co-funded by the Erasmus+ Programme of the European Union

The Development and Research on Innovative Vocational Educational Skills project (DRIVES) is co-funded by the Erasmus+ Programme of the European Union under the agreement 591988-EPP-1-2017-1-CZ-EPPKA2-SSA-B. The European Commission support for the production of this publication does not constitute endorsement of the contents which reflects the views only of the authors, and the Commission cannot be held responsible for any use which may be made of the information contained therein.

LEARNING OBJECTIVES

The student is able to

AIT.U3.E7.PC1	Reflect on and analyse the future trends for artificial intelligence.
AIT.U3.E7.PC2	Understand and knows how to define machine intelligence.
AIT.U3.E7.PC3	Understand the HTM approach for unsupervised learning.
AIT.U3.E7.PC4	Compare the different neuron models.
AIT.U3.E7.PC5	Analyse and understand the applications of HTM.

Machine Intelligence, **Artificial Intelligence**, and **Machine Learning** are not synonymous and do not refer to the same concept. These terms are obviously related, but they are not the same.

Artificial Intelligence refers to computer systems that can mimic human cognitive processes or perform tasks previously performed by humans.

Machine learning refers to computer systems that learn from inputs rather than being directed solely by linear programming.

Machine intelligence is a term for specific types of Artificial Intelligence that are becoming more visible as the field progresses.

Computer systems are now capable of performing medical diagnoses, playing chess, understanding limited amounts of speech and natural language, and many other tasks. Although these systems have some degree of Artificial Intelligence, they lack **Machine Intelligence** as they are not grounded in reality.

Machine Intelligence is the result of programming machines with some aspects of human intelligence, such as learning, problem solving, and prioritization.

One can consider **Machine Intelligence** to be a higher evolution of **Machine Learning** that includes prioritization and goals - a starting point on the path to accomplish true AI.

WHAT IS MACHINE INTELLIGENCE?

"Indeed the guiding inspiration of cognitive science is that at a suitable level of abstraction, a theory of natural intelligence should have the same basic form as the theories that explain sophisticated computer systems."

J. Haugeland (1981)

"Intelligence is the computational part of the ability to achieve goals in the world. Varying kinds and degrees of intelligence occur in people, many animals and some machines."

J. McCarthy (2004)

WHAT IS MACHINE INTELLIGENCE?

DRIVES
Development and Research on Innovative Vocational Education Skills

“Any system … that generates adaptive behaviour to meet goals in a range of environments can be said to be intelligent.”

D. Fogel (1995)

“… the ability of a system to act appropriately in an uncertain environment, where appropriate action is that which increases the probability of success, and success is the achievement of behavioral subgoals that support the system’s ultimate goal.”

J. S. Albus (1991)

WHAT IS MACHINE INTELLIGENCE?

DRIVES
Development and Research on Innovative Vocational Education Skills

Machine Intelligence is a different form of intelligence with its own specialties when compared to human intelligence or other animal intelligence.

This field studies the ability of software systems to learn in an identical way to the learning of a human being.

Machine Intelligence is the ability to create machines with a high degree of sophistication and the capacity to operate autonomously in their surroundings, i.e., computer intelligence grounded in reality.

At the end of 2014, Forbes stated: "*Deep Learning and Machine Intelligence Will Eat the World*".

The interesting question is: which changes Machine Intelligence will bring?

"might match or even exceed human intelligence and capabilities on tasks such as complex decision-making, reasoning and learning, sophisticated analytics and pattern recognition, visual acuity, speech recognition and language translation."

Pew Research Center

The interesting question is: which changes Machine Intelligence will bring?

Using all aspects of human intelligence, future AI will provide surprising answers that human beings haven’t considered and it’s even likely to create new business models.

By going a step further, true artificial intelligence will become more distinguishable from automation and machine learning over time, surpassing the human mind in unimaginable ways.

APPLICATION AREAS OF MACHINE INTELLIGENCE

MATHEMATICS

– Dynamic Programming

– Non-linear Dynamic

– Gradient Search Techniques

– Fuzzy Logic

– Markov Processes

– Chaos

– Opinion-Guided Reaction

PSYCHOLOGY

– Conditioned Responses

– Stimulus Reinforcement

BEHAVIOR

– Reactive Behavior (no memory)

– Behavior with Memory

DRIVES
Development and Research on Innovative Vocational Education Skills

REINFORCEMENT LEARNING

– Supervised

– Unsupervised

EVOLUTIONARY LEARNING

– Genetic Algorithms

GRADIENT SEARCH TECHNIQUES

– Temporal Differences

– Reinforcement and Q-Learning

– Neural Networks

Deep Learning attempts to build intelligence based on rules and structural data of human knowledge, solving specific problems for which the system was designed, being very limited in cases not supported in its training environment.

This kind of learning does not offer a response to the question:

How to create a true Artificial Intelligence?

In search for a true Artificial Intelligence, the **Hierarchical Temporal Memory (HTM)** theory arises.

DRIVES
Development and Research on Innovative Vocational Education Skills

The HTM theory can be placed in the area of Machine Intelligence.

HTM is a theory that was born from the idea of creating a true Artificial Intelligence.

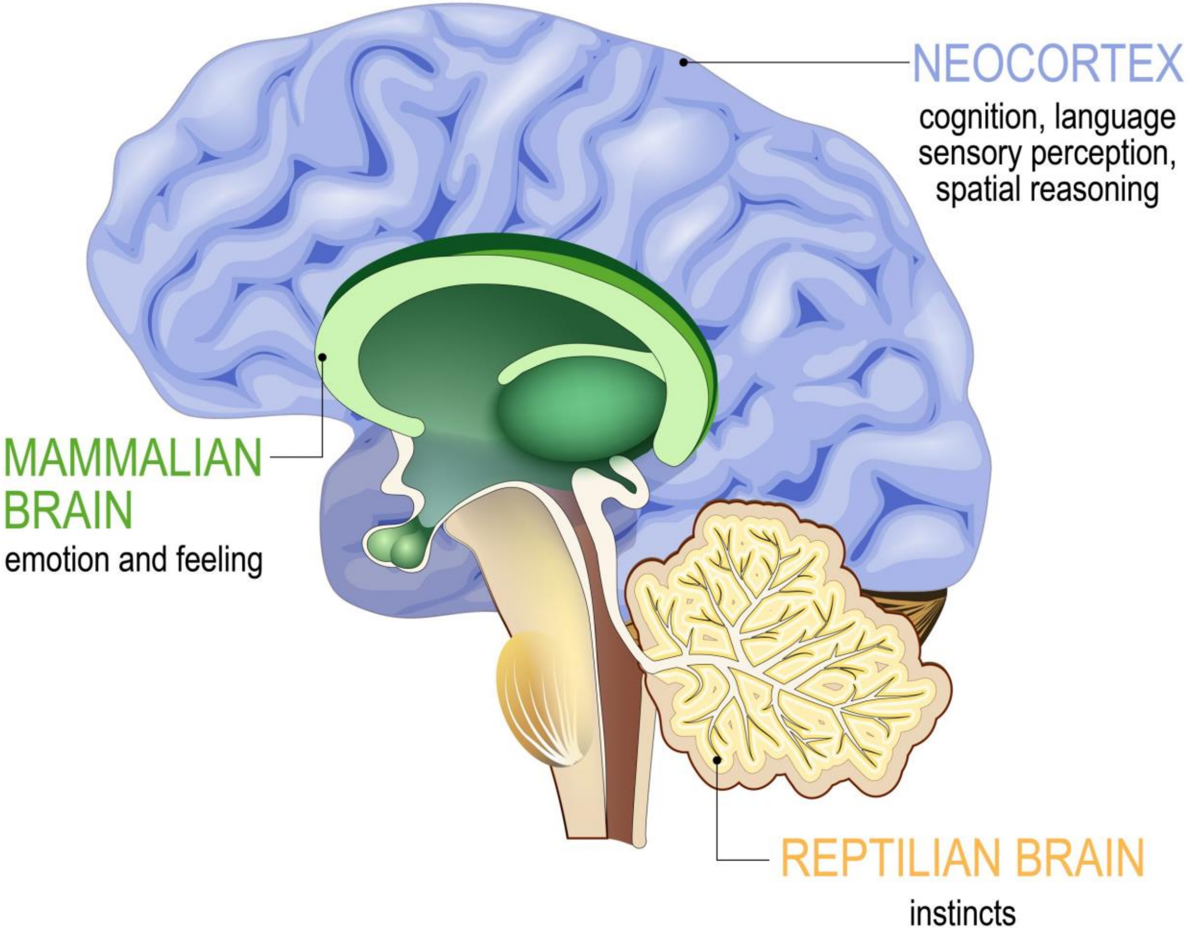
The functioning of the neocortex is the foundation for the HTM theory.

HTM is a theory that was born from the idea of creating machines capable of learning based on the way the human neocortex works.

The HTM theory first attempts to biologically describe and understand how the human neocortex - part of the brain involved in perception, cognition, motor skills, among others - works; with this knowledge, it then attempts to convert it into a way of creating intelligent machines that can learn and adapt similarly to the human brain.

Because research into the human neocortex is still incomplete, the HTM theory is, for now, under constant development.

The functioning of the neocortex is the foundation for the HTM theory.



The triune brain theory. *Extracted from https://www.drwealth.com/which-brain-do-you-use-for-investing/*

The human neocortex is a tissue with a surface area of 2600 cm^2 and a thickness of 3-4 mm, containing up to 28 109 neurons and approximately the same number of glial cells - non-neuronal cells that do not produce electrical impulse.

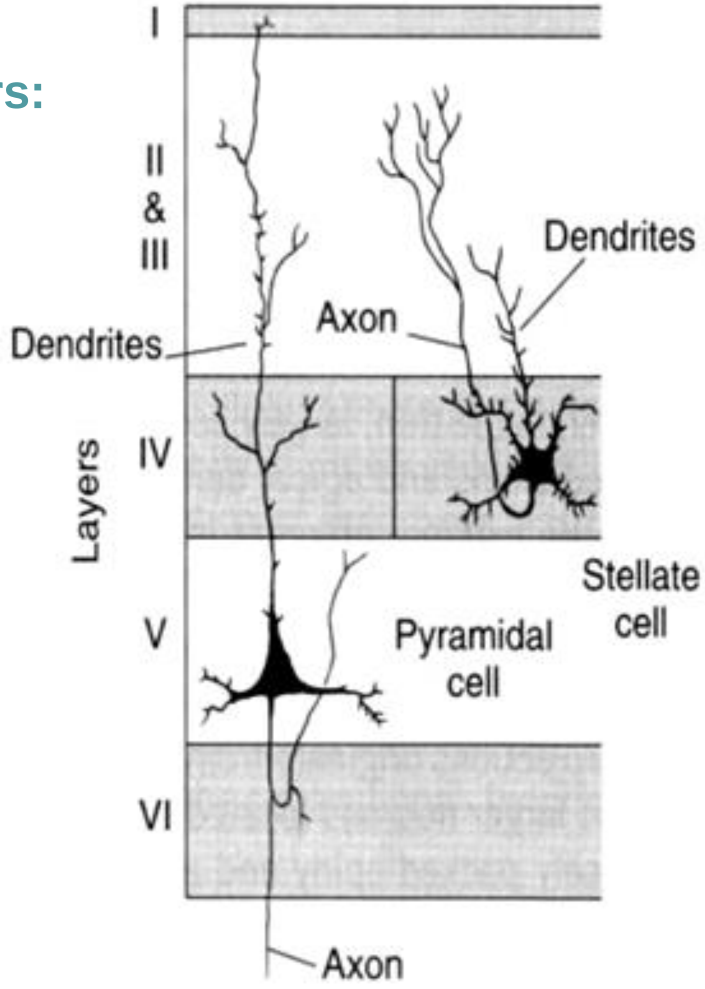
The basic unit of the **neocortex** is the minicolumn, a narrow chain of around 80-100 neurons.

DRIVES
Development and Research on Innovative Vocational Education Skills

The Human Neocortex is organized horizontally into six cellular layers:

I. Molecular layer – mostly neuropil
II. External granular layer – stellate cells
III. External pyramidal layer – small pyramidal cells
IV. Internal granular layer – stellate cells
V. Internal pyramidal layer – large pyramidal cells
VI. Multiform layer – multiple cell types

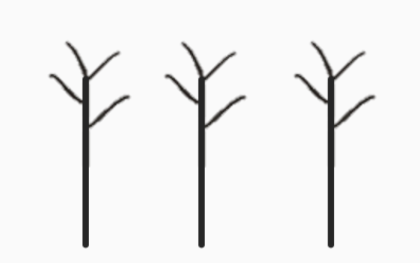
The Human Neocortex is organized vertically into groups of cells linked by synapses across the horizontal laminae.



Layers of the human neocortex. *Adapted from https://epomedicine.com/medical-students/cerebral-cortex-layers-microanatomy-simplified/*

NEOCORTEX

I. Molecular layer – mostly neuropil



It contains very few neurons and cells and is mostly made up of dendrites and axons that extend from lower levels of the neocortex.

II. External granular layer – stellate cells

It is one of the outer layers of the neocortex and is densely packed up with stellate cells and a small number of pyramidal cells, which get their name from the fact that their somas are triangular in shape. It receives input from other areas of the neocortex.

III. External pyramidal layer – small pyramidal cells

It is densely made up of small pyramidal cells and some stellate cells. This layer receives input from other cortical regions and distributes it to other cortical columns.

NEOCORTEX

IV. Internal granular layer – stellate cells

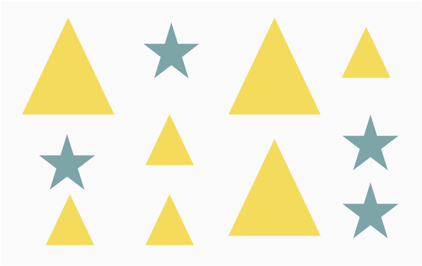
This layer is located deeper within the neocortex and it is solely made up of stellate cells, which receive sensory input and relay it to adjacent neocortex columns.

V. Internal pyramidal layer – large pyramidal cells

This internal layer's pyramidal cells are larger than those in Layer III – Giant pyramidal cells of Betz. This layer distributes to brain stem and spinal cord, being heavily involved in motor movement.

VI. Multiform layer – multiple cell types

This layer is made up of many different types of cells and has a non-homogeneous structure. It receives and integrates information from the brainstem before sending it to the thalamus.



- The **most common excitatory neuron** in the neocortex is the **pyramidal cell.**

- According to Douglas, R. J., and Martin, K. A. (2004), a simple model of cortical processing describes a patch of **superficial pyramidal neurons** that receive **feedforward** excitatory input from **subcortical**, **interareal**, and **intra-areal** sources.

- In addition, pyramidal cells receive **feedback** from **deep pyramidal cells beneath their patch** as well as from **other close patches in the superficial layers**.

- All these **inputs** appear to be **processed** by the **dendrites** of the **superficial pyramids**, which participate in a **selection network** with a soft winner-take-all or soft MAX mechanism, both of which are important elements in many neuronal network models; the **outputs** will also **feedback** to adapt the pattern of vertical smooth **cell activation**.

Furthermore, there are **three** zones of synaptic integration in a neuron:

PROXIMAL

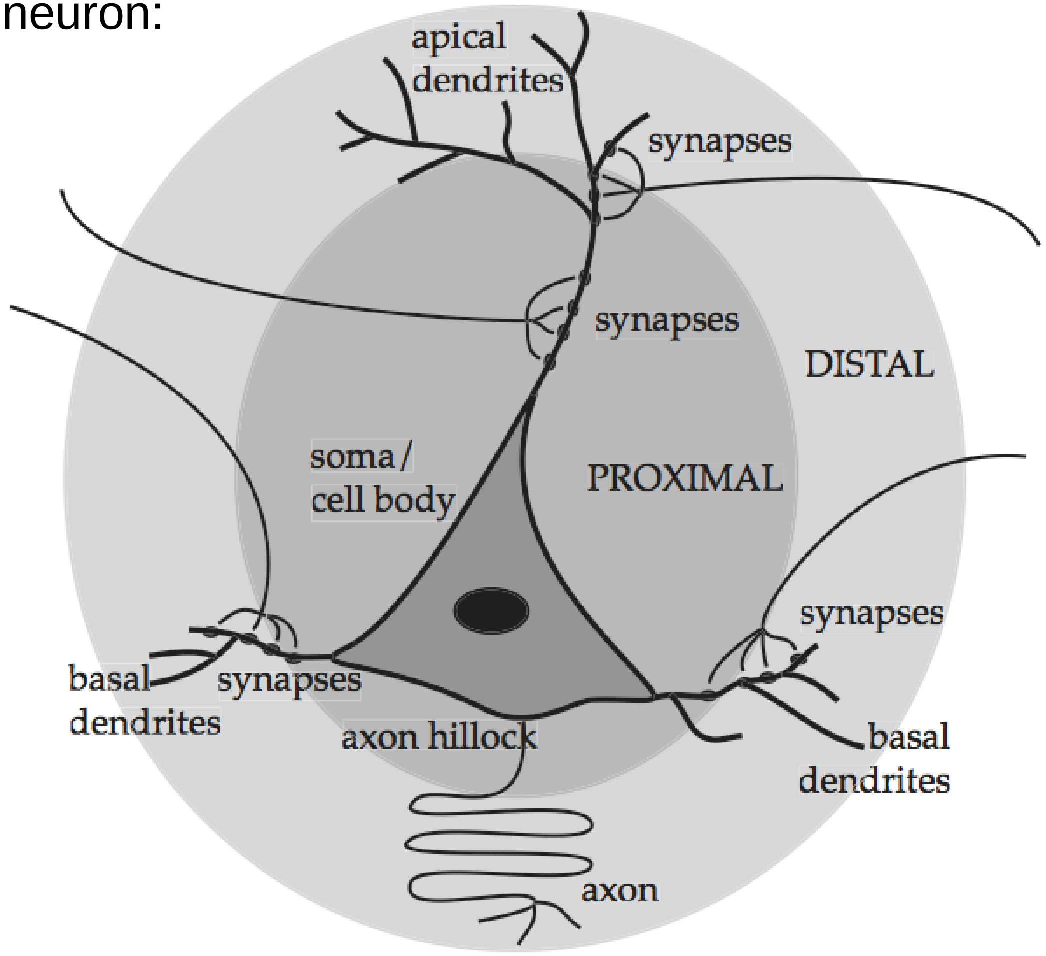
The proximal zone receives feedforward input and is defined as the neuron's basic receptive field response.

BASAL

The basal zone receives contextual input, mostly from nearby cells in the same cortical region, and learns transitions in sequences, indicating that the cell will become active shortly.

APICAL

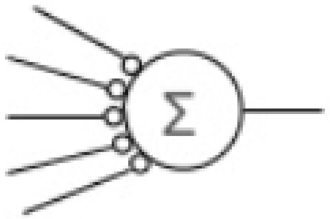
The apical zone receives feedback input, invoking a top-down expectation and acting similarly to a basal dendrite by recognizing patterns and making predictions.



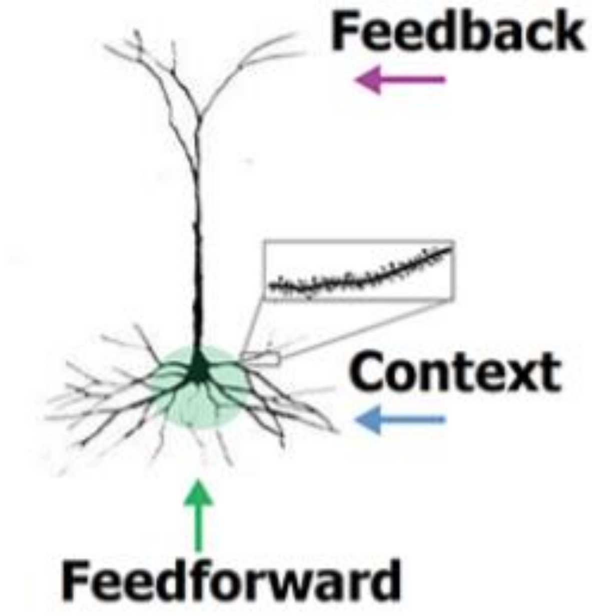
Basic anatomy of a pyramidal cell, *extracted from http://www.tulane.edu/~h0Ward/BrLg/Neuron.html*

DRIVES
Development and Research on Innovative Vocational Education Skills

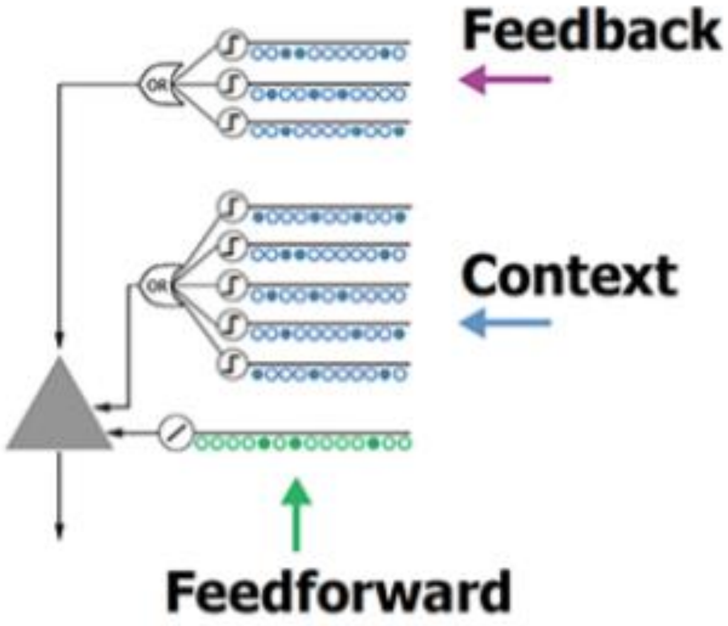
ANN NEURON



HUMAN NEURON



HTM NEURON



ANN neuron, the pyramidal neuron and how the latter is translated into an HTM neuron. *Adapted from Cui, Y., Ahmad, S., & Hawkins, J. (2017).*

DRIVES
Development and Research on Innovative Vocational Education Skills

ANN NEURON

- Few synapses
- No dendrites
- Learns by modifying weights of synapses

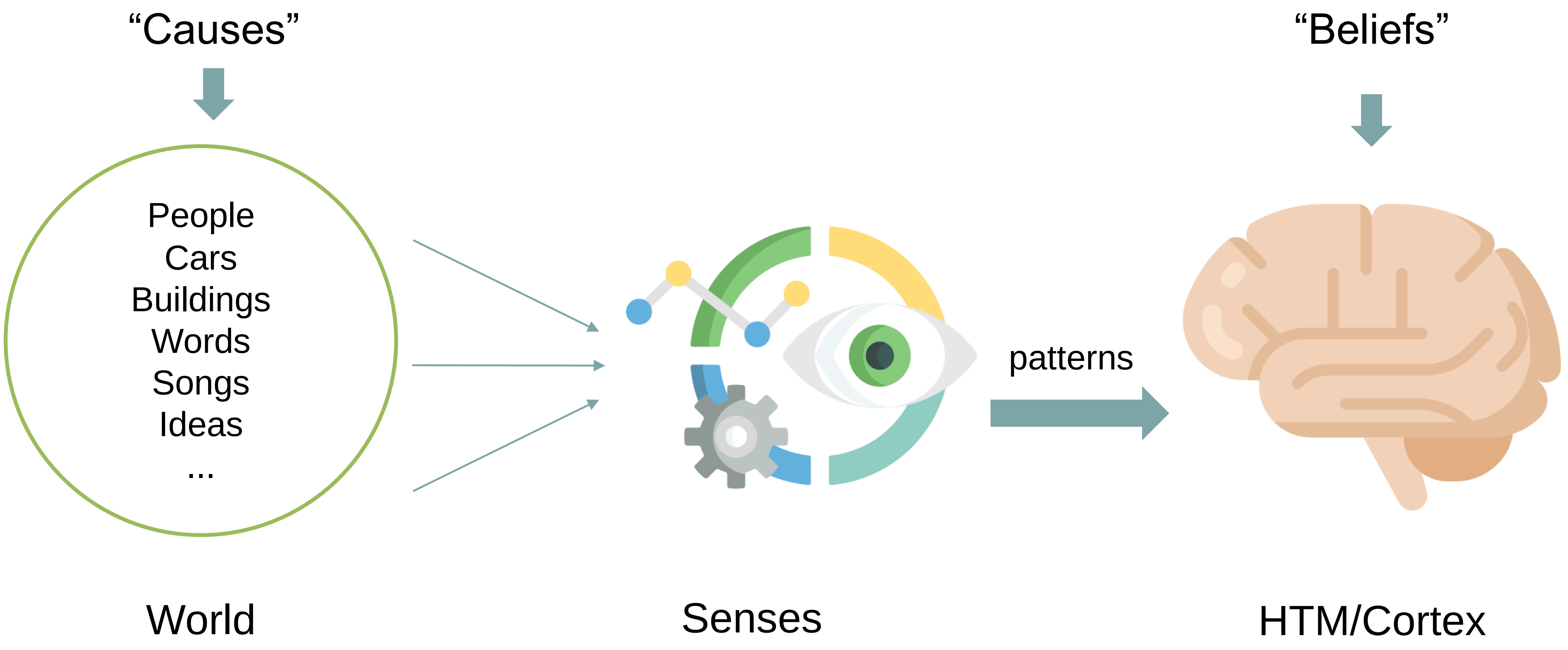
HUMAN NEURON

- Thousands of synapses
- Active dendrites: cell recognizes hundreds of unique patterns
- Learns by growing new synapses

HTM NEURON

- Thousands of synapses
- Active dendrites: cell recognizes hundreds of unique patterns
- Learns by modeling the growth of new synapses

HIERARCHICAL TEMPORAL MEMORY

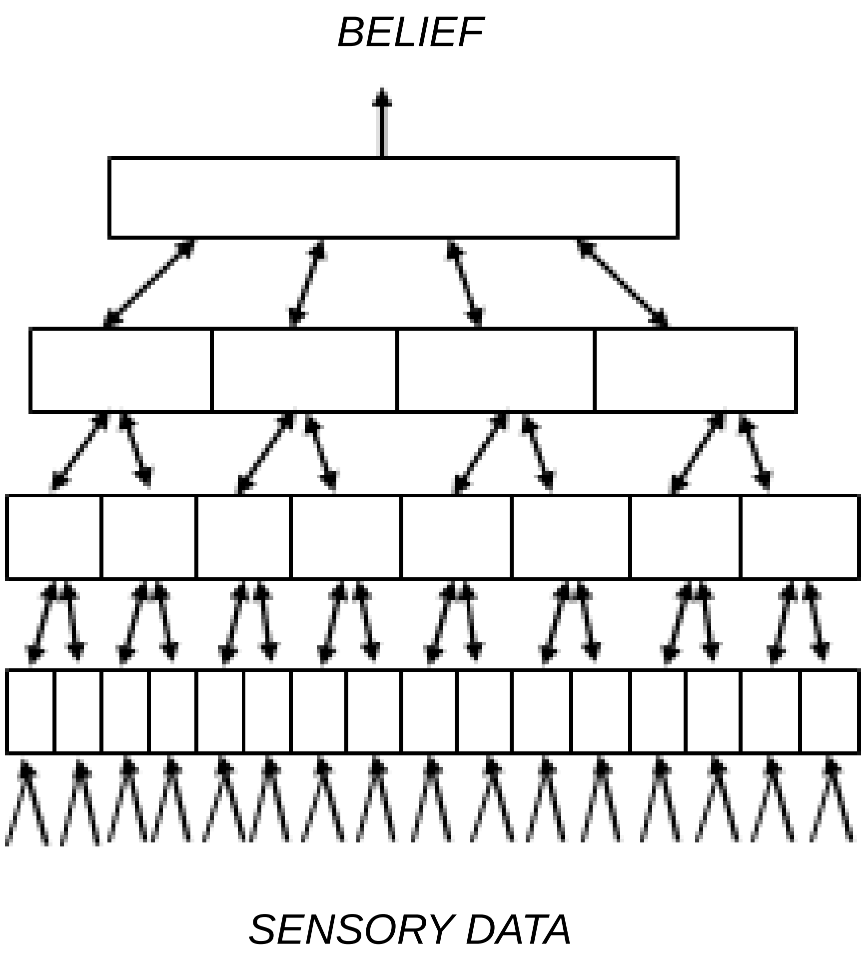


The HTM theory uses a **hierarchy of memory nodes** and is built based on **three** neocortical features:

it is a **memory system** generating **temporal patterns** with the input given, and

its regions are organized in a **hierarchical structure**.

All nodes/neurons in the regions use the same learning and inference algorithms, with the only difference being the information gained during the learning phase.



Each node:

- Discovers causes of its input
- Passes beliefs up
- Passes predictions down
- Stores common sequences
- Changing sensory data forms stable beliefs at top
- Stable beliefs at top form changing sensory predictions

DRIVES
Development and Research on Innovative Vocational Education Skills

Encoder is the first region of HTM and is responsible for the algorithm's **sensory action** – similar to human sensory organs. Its main function is to **receive raw data** and convert it into a **binary vector**.

Although this first region **should not be assumed as part of the HTM algorithm**, it is **required** in order to create a **Sparse Distributed Representation (SDR)**!

corresponds to the **active neurons** of the neocortex and is represented as an **array of bits**, with bit **1** representing an **active neuron** and bit **0** representing an **inactive neuron**.

The mechanism of **transforming** the **raw data** into a **set of bits** must preserve the **semantic characteristics** of the data in order to ensure a **successful learning process**.

When **similar data entries** are submitted to the encoding process, they should generate **overlapping SDRs**, i.e., the 1s and 0s should have a high percentage of overlap when the input is similar.

Another important feature of SDRs is their **similar dimensionality** and **sparsity** (ratio between the number of 1 bits and the total number of bits).

A sparsity percentage of around 2% results in a better system's ability to handle **noise**, **undersampling**, and **overfitting**.

The next region is called the **Spatial Pooler** and is responsible for **assigning mini-columns**, where each of them corresponds to a **dendritic segment of the neuron**. This process is in charge of forming the proximal dendritic connections.

⇩

A **mini-column connects** to a local area of the **input vector** created by the **Encoder** region and has a set of synapses that can be initialized at random, with a permanence value.

A **mini-column** is composed by many cells, where each one of them share the same proximal dendritic connections to the input space.

DRIVES
Development and Research on Innovative Vocational Education Skills

ACTIVATION

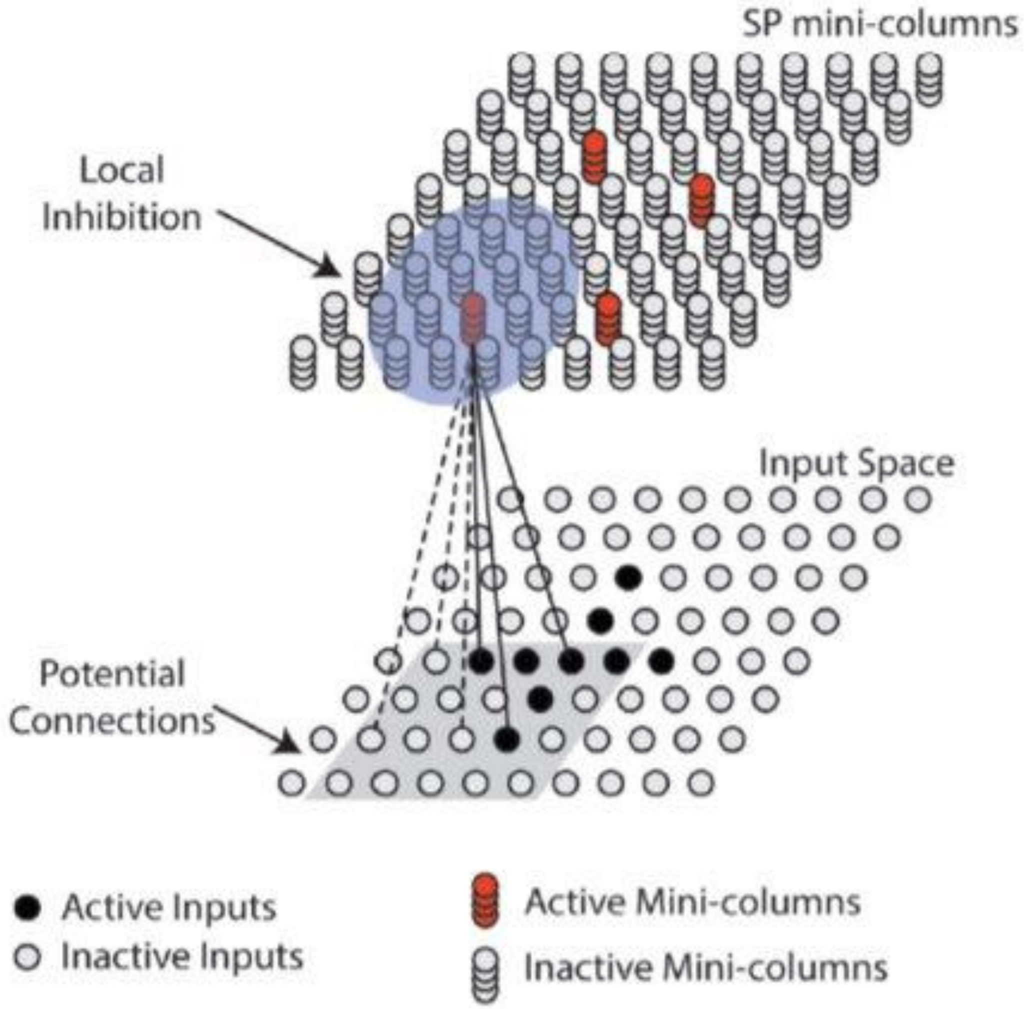
Some of these columns will become **active** when their synaptic permanence value exceeds a stimulus threshold; when the **mini-column** is **connected** to a **1 bit** (overlapping), **the synapses become active**, increasing their permanence value.

INHIBITION

Inhibition is introduced **within the surrounding columns**, resulting in only a **small fraction** of the **spatial pooler mini-columns** being **active** in a **local area**. **Active synapses** will have their **permanence value increased**, while **inactive synapses** will be inhibited, **decreasing** their **permanence value**.

During the learning process, the **mini-columns** will recognize the **important features** of the **spatial input**, which means that **different columns** will be **more sensitive** to **certain features** of the input space.

A **boost factor** can also be applied to **each column** differently in order to **multiply a column's overlap score prior** to the **inhibition** phase, allowing **fewer active columns** to express themselves and **increasing the granularity** with which the SP region recognizes the input space.



Synaptic connections between the Encoding and the Spatial Pooler regions, transforming the input space into an SDR.
Adapted from Cui, Y., Ahmad, S., and Hawkins, J. (2017).

DRIVES
Development and Research on Innovative Vocational Education Skills

Hence, the **output** of the **Spatial Pooler** region displays an **SDR of active columns**.

⇩

This representation will be the **input** for the next region, **Temporal Memory**, which is in charge of **receiving** and **learning** the **previous SDR** as well as attempting to **predict** the next active columns – **the next spatial pattern**.

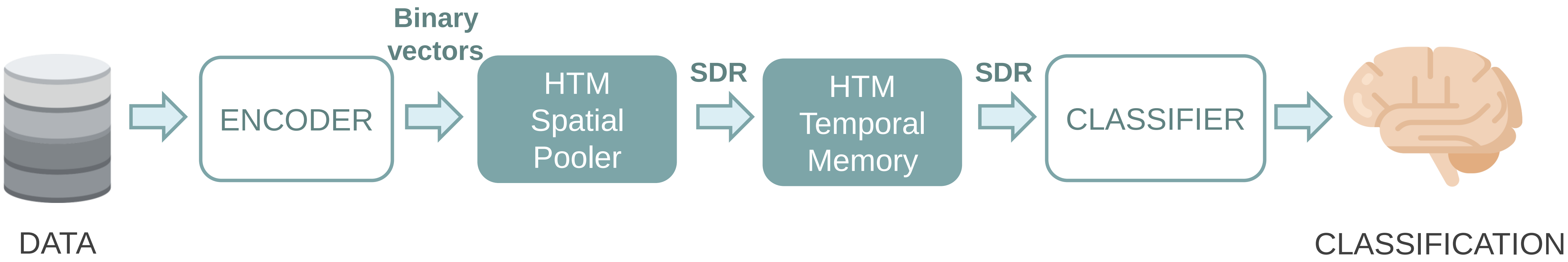
1. **Prior** to **learning**, when the **algorithm** is **unable** to **predict** the **next time step** because there are no cells in a predictive state, **all** the **cells** of the **active columns** **remain** **active** – a process known as **bursting**. However, a winner-cell is chosen randomly or by the lowest amount of distal connections.

2. **After** the **learning**, the **algorithm** is capable of **predicting only** a **cell within a mini-column** – this allows the algorithm to **understand the temporal context** of an input even if it contains the same mini-columns active. As the algorithm learns, it will forget sequences that it hasn't seen in a while.

   The **predictive state** of a **cell** within this region is determined by the **number of distal connections** it has with **other cells** that are **active at the time**; if the cell is active in the next timestamp, it was correctly predicted.

3. A **classifier region** is used to **decode** and **calculate** the **overlap** of the **predicted cells** of the **SDR** obtained by the TM region, **relative to the actual input**, in order to obtain the results predicted by the algorithm. As a result, this layer **outputs** a **predicted distribution of all classes**.

An **end-to-end HTM system** consists of an **encoder**, the **HTM spatial pooler**, the **HTM temporal memory**, and an **SDR classifier**.

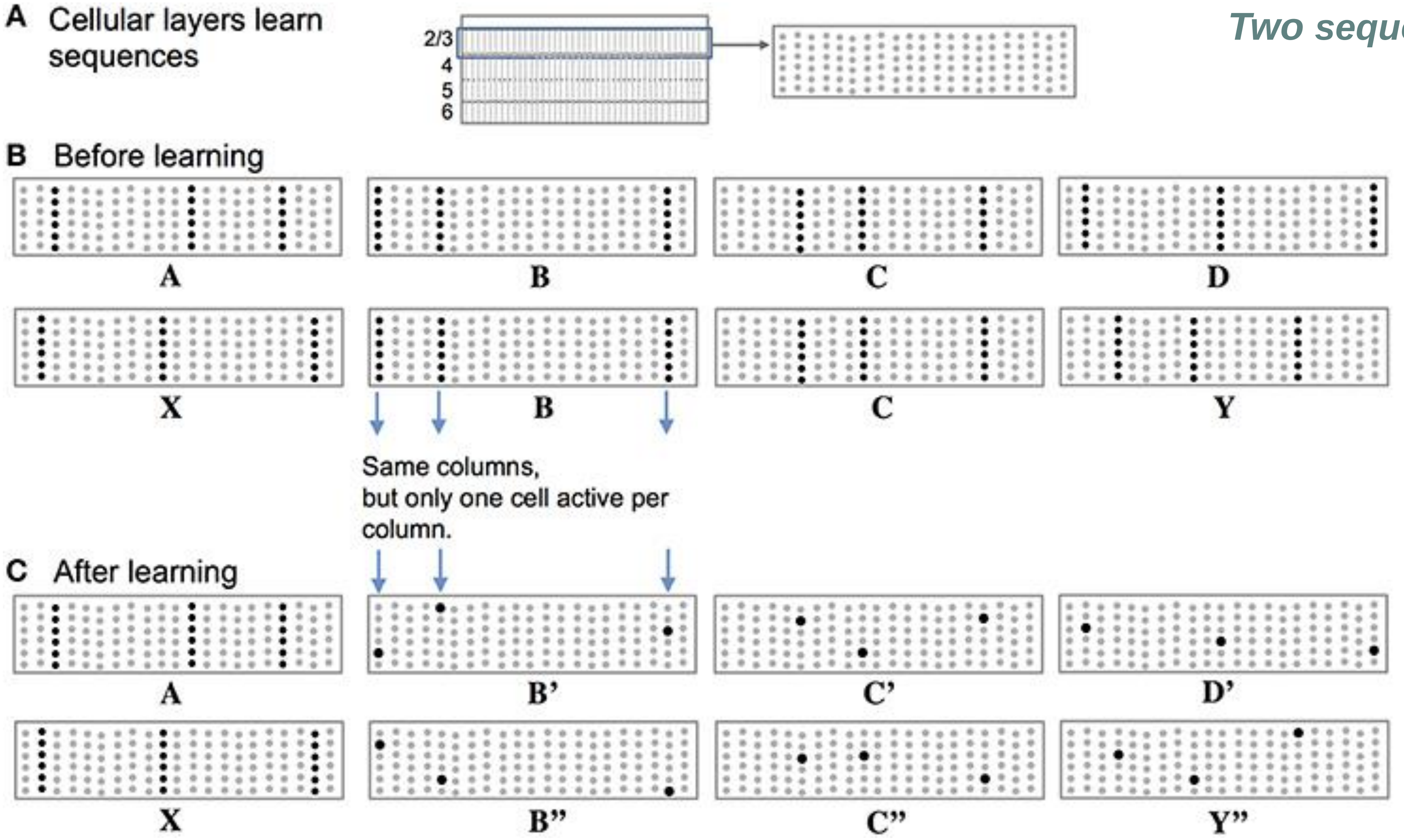


DRIVES
Development and Research on Innovative Vocational Education Skills

Computational Properties:

- **On-line learning**
- **High order representations**
  For example sequences "ABCD" vs. "XBCY"
- **Multiple simultaneous predictions**
  For example "BC" predicts both "D" and "Y"
- **Fully local and unsupervised learning rules**
- **Extremely robust**
  Tolerant to >40% noise and faults
- **High Capacity**

DRIVES
Development and Research on Innovative Vocational Education Skills



Two sequences "ABCD" and "XBCY"

Representing sequences in cortical cellular layers.

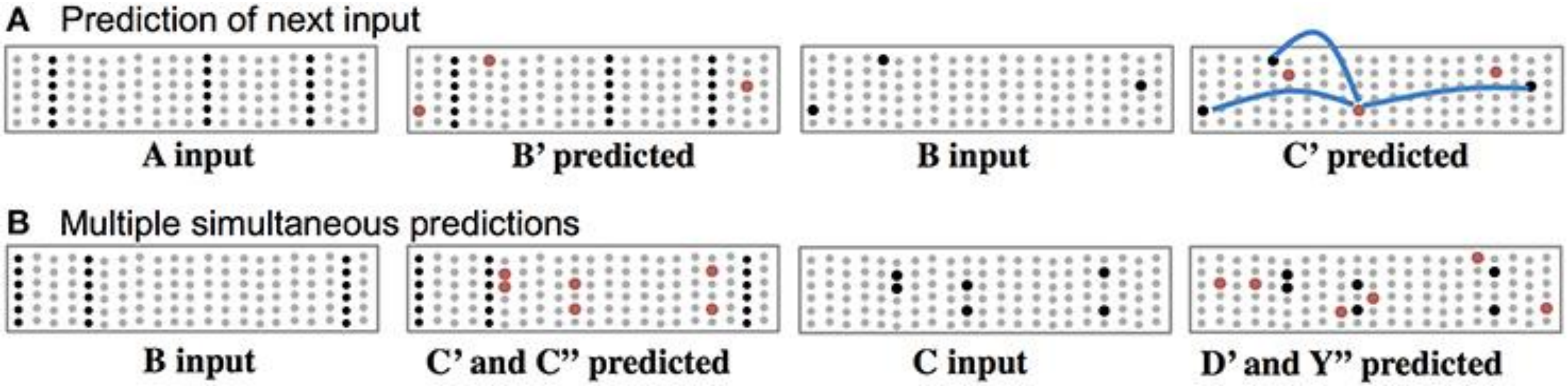
(A) The panels show part of one cellular layer of the neocortex and only show 21 mini-columns with 6 cells per column.

(B) Each sequence element invokes a sparse set of mini-columns, only three in this illustration. All the cells in a mini-column become active if the input is unexpected, which is the case prior to learning the sequences.

(C) After learning the two sequences, the inputs invoke the same mini-columns but only one cell is active in each column, labeled B′, B″, C′, C″, D′, and Y″. Because C′ and C″ are unique, they can invoke the correct high-order prediction of either Y or D.

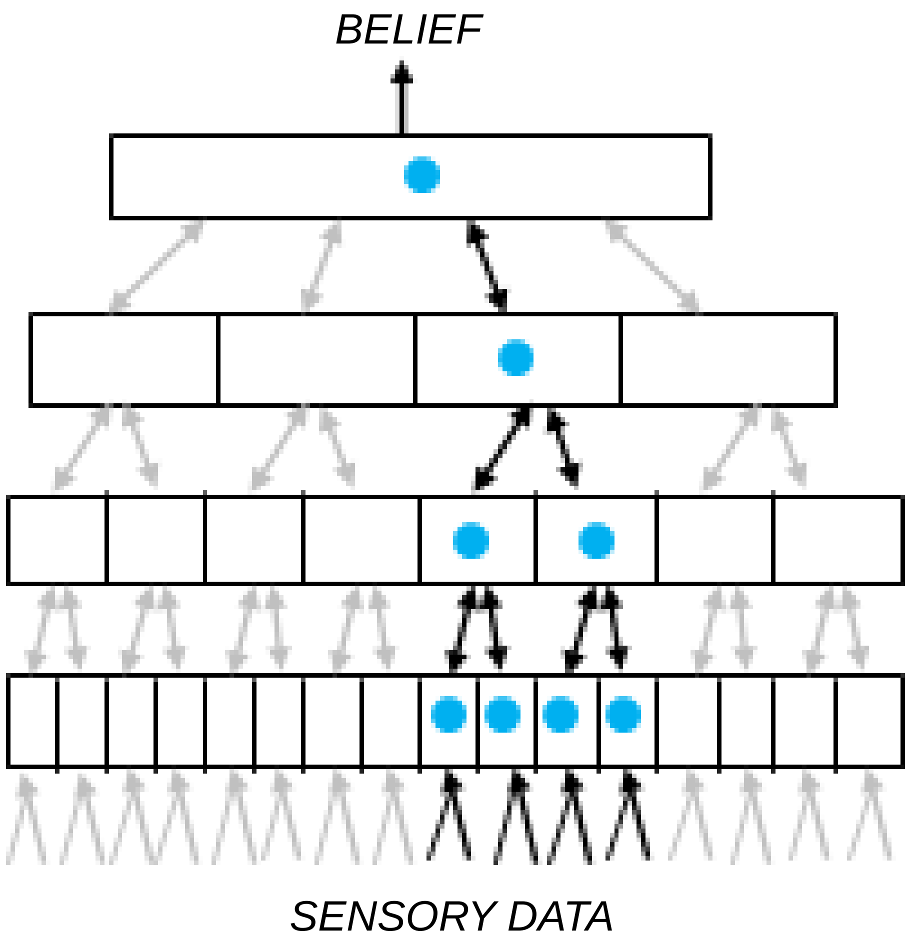
Extracted from Hawkins, J., & Ahmad, S. (2016).

Two sequences "ABCD" and "XBCY"

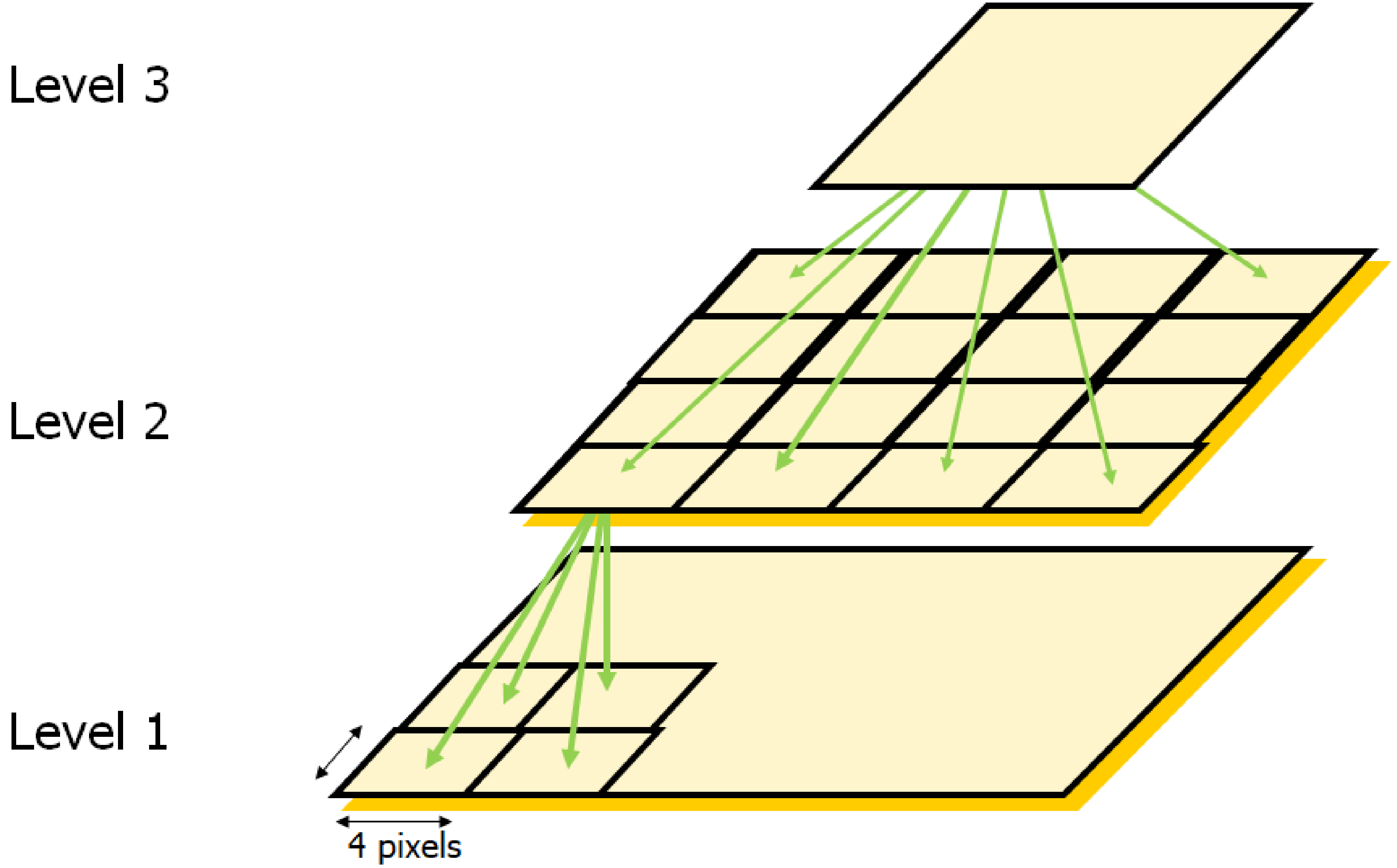


Basal connections to nearby neurons predict the next input.
(A) Using one of the sequences, both active cells (black) and depolarized/predicted cells (red) are shown. The first panel shows the unexpected input A, which leads to a prediction of the next input B′ (second panel). If the subsequent input matches the prediction then only the depolarized cells will become active (third panel), which leads to a new prediction (fourth panel). The lateral synaptic connections used by one of the predicted cells are shown in the rightmost panel.
(B) Ambiguous sub-sequence “BC” (which is part of both ABCD and XBCY) is presented to the network. The first panel shows the unexpected input B, which leads to a prediction of both C′ and C″. The third panel shows the system after input C. Both sets of predicted cells become active, which leads to predicting both D and Y (fourth panel).
Extracted from Hawkins, J., & Ahmad, S. (2016).

WHY IS HIERARCHY IMPORTANT?



1. Shared representations lead to generalization and efficiency.
2. The HTM hierarchy corresponds to the spatial and temporal hierarchy of causes in the world.
3. Belief propagation techniques ensure that all nodes quickly reach mutually compatible beliefs.



Simple HTM vision system (32x32 pixel). *Adapted from Numenta.*

HIERARCHICAL TEMPORAL MEMORY *VS* *DEEP LEARNING*

Hierarchical Temporal Memory	Deep Learning
Relies on on-line learning – continuous learning - in which the network gradually and continuously adapts to new input	Relies on a training set for learning. After the learning, the algorithms stop learning new inputs, making predictions based on the cases in the training dataset.
It doesn't require batches of new inputs to keep up with new data since it adopts a continuous learning process	It requires batches of new inputs for new training sessions, in order to keep up with new data
The learning rules are local to each neuron, in both space and time, without the need for a global objective function	All the neurons are trained to meet a global objective function

HIERARCHICAL TEMPORAL MEMORY *VS* *DEEP LEARNING*

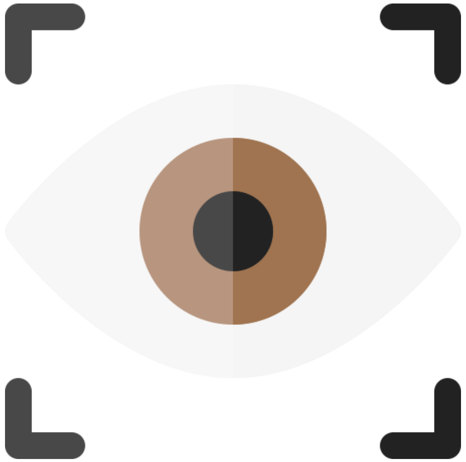
HTM	Deep Learning
No data preprocessing needed (e.g. data normalization)	Requires data preprocessing
The use of sparse distributions	The use of dense layers of neurons
There is no hyperparameter tuning in HTM networks, making them robust to a wide range of problems	Most machine learning algorithms require a hyperparameter tuning optimization for each specific task

HIERARCHICAL TEMPORAL MEMORY APPLICATIONS

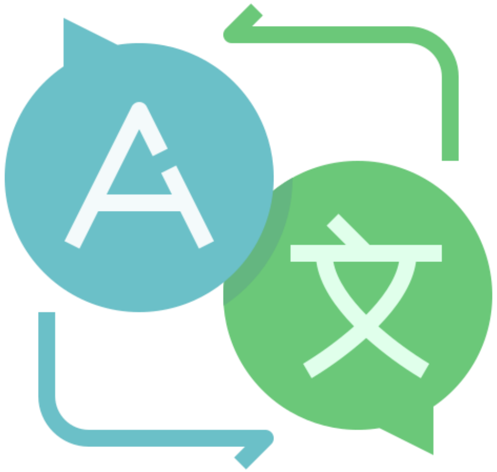
Current **HTM applications** are typically centered on **Anomaly Detection**, which is useful for a wide range of applications such as:

- Fraud Detection;
- Geospatial Tracking;
- Preventative Maintenance;
- Traffic Patterns;
- Network and Server Monitoring;
- Among Others.

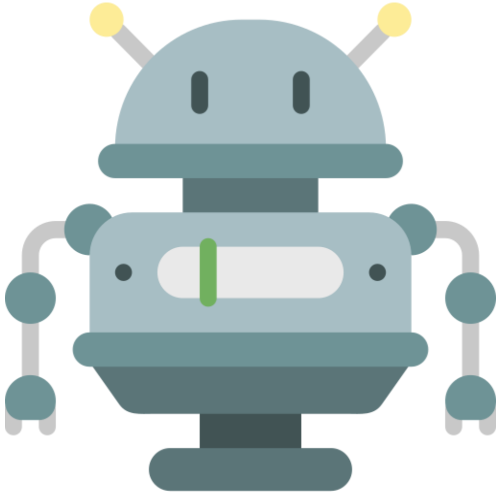
HIERARCHICAL TEMPORAL MEMORY APPLICATIONS



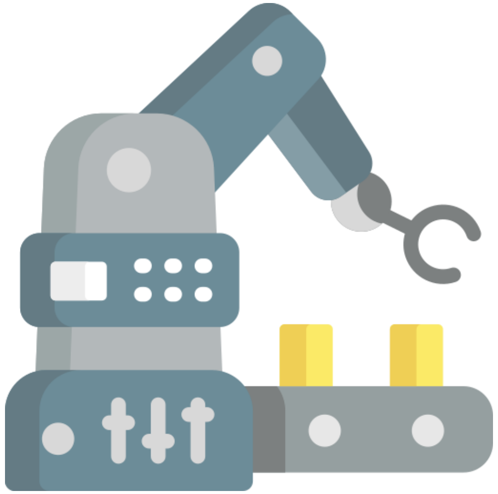
VISION



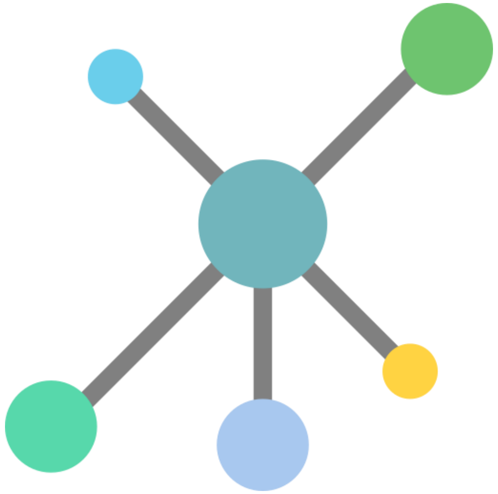
LANGUAGE



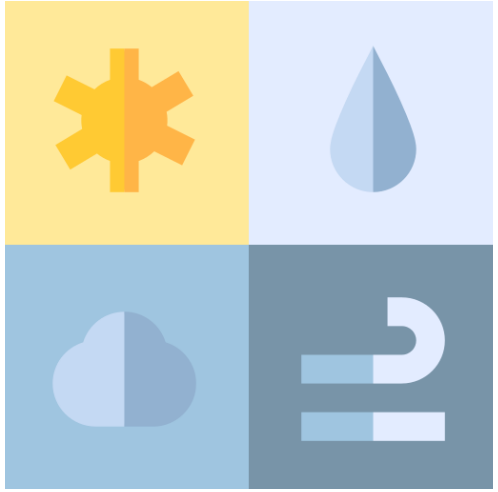
ROBOTICS



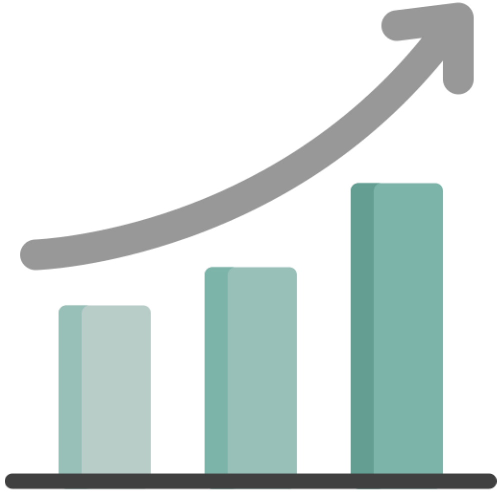
MANUFACTURING



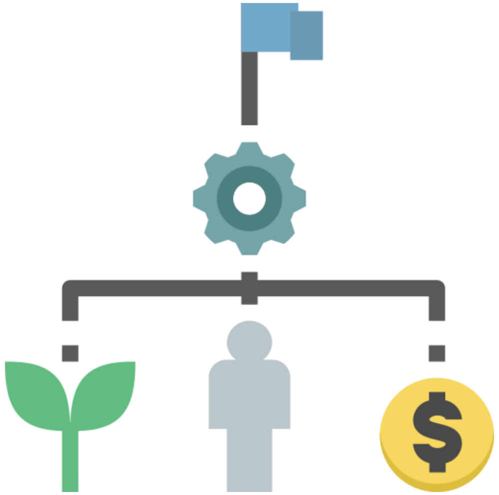
NETWORK MODELING



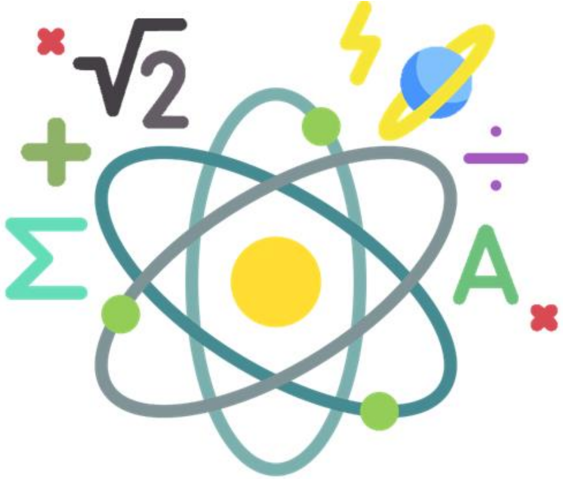
WEATHER PREDICTION



BUSINESS AND MARKET MODELING



RESOURCE EXPLORATION



MATH AND PHYSICS

- **Machine Intelligence**, **Artificial Intelligence**, and **Machine Learning** are obviously related, but they do not refer to the same concept.

- **Machine Intelligence** studies the ability of **software systems** to **learn** in an **identical way** to the learning of a **human being**. It is the result of programming machines with some aspects of human intelligence, such as learning, problem solving, and prioritization.

- The **HTM theory** was born from the idea of creating a true Artificial Intelligence and can be placed in the area of Machine Intelligence.

- The functioning of the **neocortex** is the foundation for the **HTM theory**.

- The basic unit of the **neocortex** is the **mini-column**.

- The **Human Neocortex** is organized **horizontally** into **six cellular layers**.
- The **most common excitatory neuron** in the neocortex is the **pyramidal cell.**
- The HTM theory is built based on **three** neocortical features: it is a **memory system** generating **temporal patterns** with the input given, and its regions are organized in a **hierarchical structure**.
- An **HTM** is composed by three regions: **encoder**, **spatial pooler** and **temporal memory**.
- **HTM** relies on on-line learning – **continuous learning** - in which the network gradually and continuously adapts to new input, not requiring batches of new inputs to keep up with new data.
- **HTM** uses **sparse** distributions.

REFERENCES

Legg, S., & Hutter, M. (2007). Universal intelligence: A definition of machine intelligence. *Minds and machines*, *17*(4), 391-444.

Taylor, A. S. (2009, April). Machine intelligence. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (pp. 2109-2118).

Fogel, D. B. (2006). *Evolutionary computation: toward a new philosophy of machine intelligence* (Vol. 1). John Wiley & Sons.

Haugeland, J. (1981). Mind Design: Philosophy, Psychology. *Artificial Intelligence*, *2*, 282-306.

https://www.forbes.com/sites/quora/2019/11/15/what-exactly-is-machine-intelligence/

https://www.techopedia.com/definition/33706/machine-intelligence

https://www.pewresearch.org/internet/2018/12/10/artificial-intelligence-and-the-future-of-humans/

http://www.forbes.com/sites/anthonykosner/2014/12/29/tech-2015-deeplearning-and-machine-intelligence-will-eat-the-world/

REFERENCES

Mountcastle, V. B. (1997). The columnar organization of the neocortex. *Brain: a journal of neurology*, *120*(4), 701-722.

Rockland, K. S., & Ichinohe, N. (2004). Some thoughts on cortical minicolumns. *Experimental Brain Research*, *158*(3), 265-277.

Cui, Y., Ahmad, S., & Hawkins, J. (2017). The HTM spatial pooler—A neocortical algorithm for online sparse distributed coding. *Frontiers in computational neuroscience*, *11*, 111.

Cui, Y., Ahmad, S., & Hawkins, J. (2016). Continuous online sequence learning with an unsupervised neural network model. *Neural computation*, *28*(11), 2474-2504.

Douglas, R. J., & Martin, K. A. (2004). Neuronal circuits of the neocortex. *Annu. Rev. Neurosci.*, *27*, 419-451.

Hawkins, J., & Ahmad, S. (2016). Why neurons have thousands of synapses, a theory of sequence memory in neocortex. *Frontiers in neural circuits*, *10*, 23.

Hawkins, J., Ahmad, S., & Cui, Y. (2017). A theory of how columns in the neocortex enable learning the structure of the world. *Frontiers in neural circuits*, *11*, 81.

Ahmad, S., & Hawkins, J. (2015). Properties of sparse distributed representations and their application to hierarchical temporal memory. *arXiv preprint arXiv:1503.07469*.

Hawkins, J., & Ahmad, S. (2016). Why neurons have thousands of synapses, a theory of sequence memory in neocortex. *Frontiers in neural circuits*, *10*, 23.

Xie, L., Yang, K., & Gao, X. (2016). Multi-object recognition by optimized hierarchical temporal memory network. *Optik*, *127*(19), 7594-7601.

Maltoni, D. (2011). Pattern recognition by hierarchical temporal memory. *Available at SSRN 3076121*.

Lewis, M., Purdy, S., Ahmad, S., & Hawkins, J. (2019). Locations in the neocortex: a theory of sensorimotor object recognition using cortical grid cells. *Frontiers in neural circuits*, *13*, 22.

http://www.tulane.edu/~h0Ward/BrLg/Neuron.html

REFERENCE TO AUTHORS

Diana Ferreira

- PhD student in Biomedical Engineering
- Research Collaborator of the Algoritmi Research Center

iD 0000-0003-2326-2153

Regina Sousa

- PhD student in Biomedical Engineering
- Research Collaborator of the Algoritmi Research Center

iD 0000-0002-2988-196X

José Machado

- Associate Professor with Habilitation at the University of Minho
- Integrated Researcher of the Algoritmi Research Center

iD 0000-0003-4121-6169

António Abelha

- Assistant Professor at the University of Minho
- Integrated Researcher of the Algoritmi Research Center

0000-0001-6457-0756

Victor Alves

- Assistant Professor at the University of Minho
- Integrated Researcher of the Algoritmi Research Center

0000-0003-1819-7051

REFERENCE TO AUTHORS

This Training Material has been certified according to the rules of **ECQA – European Certification and Qualification Association.**

The Training Material was developed within the international job role committee **"Artificial Intelligence Technician":**

UMINHO – University of Minho (https://www.uminho.pt/PT)

The development of the training material was partly funded by the EU under Blueprint Project DRIVES.

DRIVES

Development and Research on Innovative Vocational Education Skills

Thank you for your attention

DRIVES project is project under **The Blueprint for Sectoral Cooperation on Skills in Automotive Sector**, as part of New Skills Agenda.

The aim of the Blueprint is **to support an overall sectoral strategy and to develop concrete actions to address short and medium term skills needs.**

Follow DRIVES project at:

More information at:

www.project-drives.eu

Co-funded by the Erasmus+ Programme of the European Union

The Development and Research on Innovative Vocational Educational Skills project (DRIVES) is co-funded by the Erasmus+ Programme of the European Union under the agreement 591988-EPP-1-2017-1-CZ-EPPKA2-SSA-B. The European Commission support for the production of this publication does not constitute endorsement of the contents which reflects the views only of the authors, and the Commission cannot be held responsible for any use which may be made of the information contained therein.