**Analyse Image Classification**

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# ***Abstract***

*The Hierarchical Temporal Memory (HTM-CLA)—Spatial Pooler (SP) is a neocortical-inspired Cortical Learning Algorithm for learning. Its purpose is to understand the spatial pattern by creating the input's Sparse Distributed Representation code (SDR).Image classification is the process of categorizing and labeling groups of pixels or vectors within an image based on specific rules. It is the most important part of digital image analysis.*

***Keywords:*** *Spatial Pooler*

# Introduction

Over the years, and with the emergence of various technological innovations, the relevance of automatic learning methods has increased exponentially, and they now play a key role in society. This paper aims to change various learning parameters and to find the best fit that shows the image classification and to demonstrate how these parameters influence learning. HTM is based on the biological functions of the brain as well as its learning mechanism. HTM can be described as the theory that attempts to describe the functioning of the neocortex, as well as the methodology that intends to provide machines with the capacity to learn in a human way. (Neto,Peixoto & Brito, 2020)

The neocortex is defined as the portion of the human cerebral cortex from which comes the highest cognitive functioning, occupying approximately half the volume of the human brain. The neocortex is understood by four main lobes with specific functions of attention, thought, perception, and memory. These four regions of the cortex are the frontal, parietal, occipital, and temporal lobes. The frontal lobe’s responsibilities are the selection and coordination of behavior. The parietal lobe is qualified to make decisions in numerical cognition as well as in the processing of sensory information. The occipital lobe, in turn, has a visual function. Finally, the temporal lobe has the functions of sensory as well as emotional processing and dealing with all significant memory. Thus, the algorithm that is presented intends to create a transposition of this portion of the brain, creating a machine with true intelligence. (Ghazanfar & Schroeder, 2006)

The HTM is built based on three of the main characteristics of the neocortex. Thus, it is a system of memory, with temporal patterns and the construction of regions according to a hierarchical structure.

Starting with the first region, the encoder deals with all of the sensory components. This will receive the data in their raw form, converting them into a set of bits that will later be transformed into a Sparse Distributed Representation (SDR). Transposing into the human organism, the SDRs correspond to the active neurons of the neocortex. Thus, a 1 bit represents an active neuron while a 0 bit represents an inactive neuron. This transformation is achieved by transforming the data into a set of bits while maintaining the semantic characteristics essential to the learning process. One of the characteristics that proved to be quite interesting is that similar data entries, when submitted to the encoding process, create overlapping SDRs; that is, with the active bits placed in the same positions. Another important characteristic is that all SDRs must have a similar dimensionality and sparsity (the ratio between the number of bits at 1 and the total number of bits). (Purdy, 2016) A certain percentage of sparsity will result in a system’s ability to handle noise and under-sampling.

The second region, Spatial Pooler (SP), is responsible for assigning the columns according to a fixed number, where each column corresponds to a dendritic segment of the neuron that connects to the input space created by the region described above, the encoder. Each segment has a set of synapses that can be initialized at random, with a permanence value. Some of these synapses will be active (when connected to a bit with value 1) and consequently will be driven in such a way as to inhibit other columns in the vicinity. Therefore, the SP is responsible for creating an SDR of active columns. This transformation follows the Hebbian learning rule that for each input, the active synapses are driven by inhibiting the inactive synapses. The thresholds dictate whether a synapse is active or not.

The third region, Temporal Memory (TM), starts from the result of the previous two, finding patterns in the sequence of SDRs in order to determine a prediction for the next SDR. At the beginning of the process, all the cells of the active column are also active; however, the region TM is responsible for activating a subset of cells of those same columns when a context is predicted. In case there is no forecast, all the cells remain active. The activation of the previously mentioned subsets of cells is carried out because only in this way can the same entry be represented according to different contexts.

Finally, the classifier is the region in which a decoder calculates the overlap of the predicted cells of the SDR obtained, selecting the one with more overlaps and comparing it with the actual value (if known). (Cui, Ahmed, and Hawkins 2016)

An SDR is a vast array of bits with the majority of them turned off (0s) and only a few turned on (1s) (1s). Each SDR represents some meaning since two SDRs are judged to have equivalent meaning if they have several overlapping places on bits. The data is more comparable or the gap between two SDRs is smaller the more bits they share.

# Methods

# Results

Results in this paper show the correlation validation between the input images and also provide the prediction code.New method called ***PredictLabel*** is implemented to predict the label of the image which is imputed by comparing the binarized values of the images.