INTRODUCTION

"Introdução"

Nowadays, modelling intelligent complex systems uses two main paradigms, commonly referred to as Symbolism and Connectionism, as basic guidelines for achieving your goals of creating intelligent machines and understanding human cognition. These two approaches depart from different positions, each advocating advantages over the other in reproducing intelligent activity. The traditional symbolic approach argues that the algorithmic manipulation of symbolic systems is an appropriate context for modelling cognitive processes. On the other hand, connectionists restrict themselves to brain-inspired architectures and argue that this approach has the potential to overcome the rigidity of symbolic systems by more accurately modeling cognitive tasks that can only be solved, in the best case, approximately. Years of experimentation with both paradigms lead us to the conclusion that the solution lies between these two extremes, and that the approaches must be integrated and unified. In order to establish a proper link between them, much remains to be researched.

If in the 1980s the discussion of intelligence was placed at the distinct poles of the symbolists and connectionists, today the connectionists are divided by the reductionist arguments of the structuralists. For this structuralist current, the failure of the symbolists was due to the fact that their models despised brain architecture, and therefore connectionism must continue to explore more deeply the structural aspects of the thinking organ. In this project, the connectionist and structuralist aspects are approached, respectively, through the paradigm of artificial neural networks and realistic models of the brain, within the area called Computational Neuroscience. Through our models, we investigate ancient questions of Artificial Intelligence regarding the understanding of computability aspects of the human mind.

In this project we will continue with the study and implementation of Deep Neural Networks (RNPs), which have been used to solve artificial intelligence problems, in areas such as: automatic speech (or voice) recognition, image recognition and treatment, natural language processing, bioinformatics, among many others.

Our previous experience, both in the development of research in the field of artificial neural networks and general distributed processing and its technological applications, as well as in the pursuit of realistic models of brain biology, allows us to mature in the same direction of multidisciplinary research.

"Justificativas"

In recent years, as RNPs have been used very successfully in various data analysis tasks. In 2011, for the first time, the use of RNP learning methods enabled the achievement of the best performance of a human being in a competition to solve visual pattern

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recognition problems. These techniques are being used a lot for a solution of various computational intelligence problems.

"Objetivos"

We will study the problem of pattern recognition in data with Deep Neural Networks. We will be experimenting with parametric model adjustment on pattern recognition problems such as image analysis and natural language processing.

"Metas"

- Study of the algorithms that make up the Deep Neural Networks technique.
- Study of problems that benefit from the use of these RNP techniques.
- Experimentation with the parametric adjustment of the model to obtain performs well on data pattern recognition issues.
- Publication and dissemination of the results of our work.

"Método"

We will use Neuronal Networks with deep learning techniques to perform data analysis. RNPs are a class of machine learning algorithms that use a multilayer cascade with nonlinear processing units for feature extraction into a dataset. Each successive layer receives the output signal from the previous layer as input signal. These networks may use supervised or unsupervised learning techniques. They can learn multiple levels of representations that correspond to different levels of abstraction.

"Resultado Esperado"

We hope to obtain results that represent advances in understanding the Deep Neural Network method and how to perform parametric model adjustments to automatically recognize patterns in problems such as image processing and natural language processing.

1 BOLTZMANN MACHINES

Here we begin by explaining the theory behind Boltzmann Machines

1.1 Boltzmann Machines

Boltzmann Machines (BM) are a type of stochastic neural networks (SNN) where the connections between units are symmetrical $w_{ij} = w_{ji}$ [HERTZ]. This kind of stochastic neural networks are capable of learning internal representation and to model an input distribution. Boltzmann Machines were named after the Boltzmann distribution. Due to its stochatics behaviour, the probability of the state of the system to be found in a certain configuration is given by previous mentioned distribution [HERTZ]. According to [MONTUFAR, 2018], BM can be seen as an extension of Hopfield networks to include hidden units.

Boltzamann Machines have visible and hidden units. The visible units are linked to the external world and they correspond to the components of an observation. On the other hand, the hidden units do not have any connection outside of the network and model the dependencies between the components of the observations [FISCHER, 2012]. In BM, there is no connection restriction, this means that every unit, visible or hidden, can be connected to every other unit as in a complete graph, this pattern is not mandatory as some of the connections may not exists depending on the network layout.

Training Boltzmann Machines means finding the right connection between the units.

Boltzmann Machines (BM) are stochastics neural networks with symmetric connections, i.e., $w_{ij} = w_{ji}$. Boltzmann Machines use the Boltzmann distribution to determine the probability of the state of the system of the network. BM ressambles the Hopfield networks with the inclusion of hidden units. Finding the right connections between the hidden units without knowing it from the training patterns what the hidden units represent is part of the solving the Boltzmann Machine problem.

Units x_i in BM are split into two kinds: visible and hidden units. The visible units have connection to the outside world and are the units that receive the data input. On the other hand, the hidden units do not have any connection to the outside of the network and they are resposible to find the data relation from the input. In a BM, the connections between units can be complete or not. Regardless of how the connections are, every connection in a BM is symmetric.

BM are made of stochastics units x_i which each of them can assume a binary value with a certain probabily as follows:

(2)

$$x_i = 1 \quad withprobabilityg(h_i), 0withprobabi$$