NEURINF: Neuroinspired Informatics Special session at Cognitive 2017, Athens

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***Abstract*—Since the initial model of the perceptron proposed in 1957, artificial neural networks have ignited great interest in the scientific community as an alternative to the classical Von Neumann's model. Fifty five years later, Deep Neural Networks (DNNs) have become the state-of-the-art method in many supervised or reinforcement learning tasks. Neuroinspired models obtain the best performance on challenges that are efficiently solved by the human brain. On the other hand, the biological plausibility of DNNs is debatable. Finding neural networks architectures that are both biologically inspired and efficient at solving challenging problems is a very active field of research, and the motivation for this special session.**

I. Introduction

Deep Neural Networks (DNNs) have achieved unprecedented performance in numerous supervised learning challenges [1]. Thanks to their large number of parameters (typically of the order of a billion connection weights), they are able to absorb huge amounts of data and capture an efficient representation of the problem at hand. More recently, they have been used in combination with reinforcement learning to beat top Go players in the world [2].

The success of DNNs have questioned far beyond the communities of machine learning and computer vision [3], and the growing interest of major industries in this technology shows how big the impact is on our society. Following this trend, and considering its strong roots with neural networks, the community of neuroinspired computing is benefiting from an unprecedented stand. In this context, it is also essential to insist on the diversity of these methods and the associated problems.

Fundamentally, neural network methods have in common the fact they consider a mix of linear and nonlinear operators, where linear ones are typically data-driven whereas nonlinear ones are arbitrarily chosen. They historically find their roots in mimicking the brain, even if a vast proportion of researchers refute this connection in their proposed models. The problems addressed are numerous: supervised learning, unsupervised learning, reinforcement learning, associative memories, prediction...

It is undeniable that neural networks are of particular interest when facing problems for which humans are reputably good at and no other method obtain good performance. Thus, sharing connections with the brain from its fundamental unit – the neuron –, and from its more high level abilities (such as plasticity, feedforward and feedback connections, memory effects,...), an increasing number of researchers consider modern neural networks as a renewal of Artificial Intelligence (A.I.).

There are still many open questions to be addressed, and the research on neuroinspired computing for A.I. is most probably at its beginning. The purpose of this special session is to gather works related to different problems and different neuroinspired architectures, in order to confront them and better understand their similarities and controversies.

II. Problems and corresponding architectures of neural networks

In computer vision, there are classically four problems at hand: indexing, search, unsupervised and supervised learning. Each of this problem comes with well-known models of neural networks to solve it.

A. Indexing and search

Indexing consists of being able to test whether some collection of signals (typically vectors) denoted by $\mathcal{X}$ contain a query element $\mathbf{x}$. Of course, the challenge of the problem lies in proposing efficient solutions, since a trivial algorithm is to review each element in $\mathcal{X}$ independently from the others. In search, the problem consists in retrieving the element in $\mathcal{X}$ which is the closest (given some metric) to the query element $\mathbf{x}$.

Associative memories provide solutions to this problem. They are devices that are able to store elements then recall them in presence of noise and/or erasures. Most prominent models are the celebrated Hopfield neural network [4] and the Willshaw-Palm model [5] and its recent extensions [6].

B. Unsupervised learning

Unsupervised learning is an interesting field of research considering the fact it is one where no solution available today is on par with the human brain. The idea is to partition a collection of signals $\mathcal{X}$ into coherent subsets, where coherence is typically defined by the variance obtained using some metric.

Here again, neural networks have proposed solutions. The most prominent model is Kohonen maps [7], and more recently autoencoders [8].

C. Supervised learning

Supervised learning is one of the most active field of research in machine learning, due to its numerous direct applications. In supervised learning, the idea is to infer some functional f given a finite set of examples $(\mathbf{x}, f(\mathbf{x}),$ for $\mathbf{x}$ in some collection $\mathcal{X}$.

In this domain, perceptrons [9] and multi-layer perceptrons have remained a preferred method for a long time. Today, DNNs and in particular Convolutional Neural Networks (CNNs) [10] in vision have become the state-of-the-art.

D. Related problems and architectures

Obviously there are hundreds of other problems and corresponding architectures. For the purpose of this special session, it is important to consider Recurrent Neural Networks (RNNs) [11]. RNNs are devices that are able to learn time series and then perform prediction. In the context of computer science, they are now used to infer algorithms and grammars [12].

III. Outline of the special session

In this special session, the authors present their work on neuroinspired algorithms. Multiple problems are considered: incremental learning, indexing, robustness towards computation faults, optimizing and predicting.

The first paper "Incremental Face Recognition by Tagged Neural Cliques" [13] investigates the problem of one-shot incremental learning. The authors demonstrate the efficiency of an innovative scheme mixing feature extraction and associative memories.

The second paper "Finding All Matches in a Database using Binary Neural Networks" [14] tackles the problem of efficiently indexing pieces of information in neural networks, enabling the retrieval of multiple ones from partial probes. The authors are particularly interested in the case of nonuniform databases.

In the third paper "A Study of Deep Learning Robustness Against Computation Failures" [15], the authors tackle the question of the robustness of DNNs towards component failures in electric circuits. Interestingly, they show how a good choice of some hyperparameters can greatly accommodate these errors.

Next paper is "Sparse Clustered Neural Networks for the Assignment Problem" [16]. Usually, neural networks are trained using optimization routines, but in this case the authors are interested in solving an optimization problem with neural networks. Namely they approximately solve the assignment problem.

The final paper "An Intrinsic Difference Between Vanilla RNNs and GRU Models" [17] investigates the abilities of recurrent neural networks to retain long-term dependencies in learning sequences. In particular, the authors explain that the commonly used arguments of vanishing gradients computation are not valid, and that the reason lies in more intrinsic properties of the underlying mathematical models.

The problems addressed in this special session are numerous, yet their solutions share the common idea of neuroinspired algorithms. This special session is thus an ideal opportunity to discuss the future of artificial neural networks.

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