Tutorial 10: Generalized Operational Neural Networks

Recent advances in machine learning led to remarkable solutions in many research problems, notably in fields of computer vision, natural language processing and games. This is due to new parallel computing capabilities for scientific computing (Graphical Processing Units–GPUs and distributed computing), the availability of enormous sets of annotated data, and methodological contributions in a family of models called artificial neural networks, and commonly referred to as Deep Learning. Such state-of-the-art models are commonly formed by an enormous number (in the order of hundreds of thousand, or even millions) of parameters which are jointly tuned in an end-to-end optimization process to fit the training data. However, most of research and practical implementations of these powerful learning models exploit a simplistic model for the artificial neuron from early 1960s that can only perform linear transformation (i.e., linear weighted sum), while the topologies used for different tasks are manually optimized based on laborious experimentation requiring expert knowledge (either human expert or expert systems) leading to extremely high computational optimization processes. This is why their learning performance varies significantly depending on the function or the solution space that they attempt to approximate for learning.

Very recently, the Generalized Operational Perceptron (GOP) has been proposed leading to a generalized family of artificial neural networks. GOPs are feedforward neural network architectures that exploit more sophisticated types of artificial neurons for efficiently capturing different types of nonlinearities appearing in different problems. GOPs are based on actual models of biological neurons or neural systems in general that are built from a large diversity of neuron types varying entirely or partially structural, biochemical and electrophysiological properties. With a very compact configuration with few hidden neurons, GOPs have demonstrated superior learning capabilities on many challenging problems where conventional ANNs may fail to learn. A number of methodologies have been also proposed for automatically determining the network's topology, as well as the type of the individual neurons forming each layer of the network. Extensions using skip (or memory) connections and weighted optimization schemes for handling imbalanced classes have been also proposed. Moreover, convergence analysis of GOPs and empirical evidence on a wide range of problems indicate that GOPs can achieve a better generalization performance compared to conventional ANNs. Finally, the most recent ANN model, Operational Neural Networks (ONNs) that are derived from GOPs have achieved remarkable image processing capabilities such as image denoising, syntheses and transformation, that cannot be otherwise achieved by the conventional Convolutional Neural Nets (CNNs) without a "deep" architecture.

Speakers:

Moncef Gabbouj
Tampere University, Finland

Serkan Kiranyaz
Qatar University, Qatar

Alexandros Iosifidis
Aarhus University, Denmark