UNIVERSITÉ FRANCHE-COMTÉ

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école doctorale sciences pour l'ingénieur et microtechniques SPIM

Titre de la thèse/Thesis title : Supervised-unsupervised deep learning using dense associative memories and classical deep learning processes
Laboratoire d'accueil / Host Laboratory : FEMTO-ST. DISC Dept.
Spécialité du doctorat préparé/Speciality : Computer Science (Informatics)
Mots-clefs / Keywords : Deep Learning. Unsupervised. DAM. Enery function. Stable state

Descriptif détaillé de la thèse / Job description

Scientific framework:

Deep learning is one of the most exciting scientific fields of the decade, it is considered as the spearhead of artificial intelligence. It was successfully applied to many challenging problems such as recognizing images and videos, recognizing speech, disease detection and so-on.

Roughly speaking, supervised deep learning, as it is primarily used, is essentially an approximation process for solving regression and classification tasks, this is based on sample data, using deep neural networks with multiple layers in a feedforward mode.

Gradient optimization algorithms and their variants are usually the heart of these approximations: the gradients are computed by backpropagation technique which is the pillar technique in deep learning architectures. For the deep learning architectures to work well, there must be a huge amount of training data, and the test data must be quite similar to the training data, indeed, the answers are interpolations between training data.

Contrary to human brain, classical deep learning is data hungry and struggles with datasets with medium size, it fails challenges that don't remain close to its core training data and is vulnerable to adversarial attacks. Despite all these drawbacks, supervised deep learning remains an efficient tool when vast amounts of data are available in classification or regression problems. This tool must little by little be enhanced by other approaches.

Alongside supervised learning, there are unsupervised learning approaches. We propose in this PhD project to build novel architectures which mix standard supervised architectures and unsupervised ones, to get the best out of each approach.

Hopfield networks are dense associative memories and are unsupervised networks that are currently experiencing a new interest.

Indeed, contrary to the ancient Hopfield networks [3], [4], modern Hopfield networks have no storage capacity problems and are continuous and differentiable with respect to their parameters, so that they are suitable to be integrated in feedforward classical deep architectures.

Modern Hopfield learning is based on an energy function (Lyapunov function).

In a recent paper [10], the authors proposed a new energy function that is monotone decreasing, allows very high-capacity storage and they deduced an updating learning rule that converges to a stable state (either a fixed state or a cycle). Their work is mathematically rigorously proven. Then, they propose 3 kinds of Hopfield layers that can be integrated into classical deep learning architectures, they also emphasize by experiments, the remarkable performances when integrating such Hopfield layers into classical feedforward deep learning approach. Comparisons with well-known and efficient methods such as LSTM, XGboost or K-means are done.

PhD goal:

The goal of this project PhD is to do the state of the art of the few existing mixed supervised/unsupervised approaches and to propose novel architectures that contribute to this rising theme. The claims must be proved, implementations on significant problems from biology, epidemiology, pharmacology, and physics must be conducted to experimentally compare the proposed architectures and algorithms to well-known classical ones.

Beside originality, efficiency, and robustness of the new architectures with respect to traditional deep learning architectures, the biological plausibility of the proposed process will also be discussed. Indeed, if we compare to human brain, we know that the Hebb's rule implies that changes of the synapse strength should be dependent only on the activities of the local synaptic neurons. In other words, the biological neuron responses are governed by a synapse-change procedure that is physically local and thus describable by local mathematic computation. But supervised training techniques with the backpropagation algorithm, requires massive amounts of labeled data, and a nonlocal learning rule for changing the synapse strengths: the backpropagation technique is biologically implausible.

Conversely, learning with Hopfield nets seems to be more biologically plausible as it is explained in [9]. This last argument contributed to the direction we would like to give to this PhD.

Concretely, after overviewing the state of the art in feedforward approaches and dense associative memory ones, the researcher will:

- Point out the advantages and disadvantages between gradient-based approaches and energy function-based ones.
- Explain the advantage of integrating dense associative memory layers into feedforward architectures and explain how to make this operation in term of tensor (vector) manipulations.
- Prove the claimed results.
- Give the implementation details of the mixed architectures.
- Compare numerically the performance and robustness of the proposed approaches with other approaches proposed in the literature.

  Various datasets from various scientific problems such as Immune Repertoire Classification and on UCI Benchmark Collections [5] must be tested and compared to other methods.

Références bibliographiques / Bibliography

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Profil demandé / Applicant profile

The PhD applicant must have good skills in computer science especially deep learning architectures, machine learning frameworks, high-level programming languages, as well as in applied mathematics particularly numerical approximation methods.

Preferred selection criteria:
- Very good knowledge of deep learning
- Very good-level programmer
- Good skills in numerical algorithms

Personal characteristics:
- Methodical
- Calm

Financement : MESRI Etablissement

Début du contrat : October, 1, 2022
Salaire mensuel brut : 1975€

Direction de la thèse:/ **Thesis Supervisor:** Prof. Jacques Bahi
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Encadrement de la thèse : **co-directeur(s) et co-encadrant(s)**
Co-encadrant : Christophe Guyeux. Professeur

Applicants are invited to submit their application to the PhD supervisors.
Application must contain the following documents:
- CV
- Cover letter
- At least 1 reference letter