Learning networks for complex interconnections

Decebal Constantin Mocanu[1], Georgios Exarchakos[1], Antonio Liotta[1]
[1] Eindhoven University of Technology, Electrical Engineering, Electro-Optical Communications Group
Contact: {d.c.mocanu; g.exarchakos; a.liotta}@tue.nl

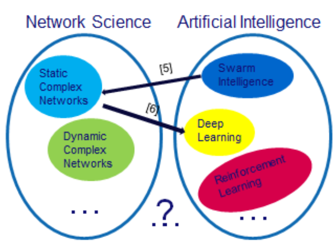
1. Introduction

Nowadays, science is mainly done using the traditional reductionism paradigm [1]. It attempts to explain the behaviour of any system by zooming over and understanding at different levels all its components. These yield to have very specialized persons in any subfield of science, but to have fewer people to study the systems as a whole. With this approach, somewhere on the way, the whole picture is lost. This was hinted millenniums ago by Aristotle in Metaphysics: "*The whole is more than the sum of its parts*". Mathematically, Aristotle's statement cannot be true, but it may be that we do not have knowledge on all systems' elements. To overcome these limitations the modern complex systems paradigm tries to study the systems and the interactions between them as a whole, making use of network science (a multi-disciplinary field across mathematics, physics, sociology, and computer science).

2. Real-world open questions

Following this vision, we tried to solve difficult open questions in areas such as communication networks and computer vision using artificial intelligence or network science, e.g.: simultaneously classification and prediction of human activities [2]; redundancy reduction in wireless sensors networks [3]; estimating the quality perceived by users in image/video network services with no prior knowledge [4].

3. A theoretical breakthrough: the synergy between network science and artificial intelligence



Even when successful in real-world problems, still, all of the above solutions may be affected by scalability issues at some level. Thus, we pioneered the theoretical study of the synergy between network science and artificial intelligence [1] (left image) to enlarge the scalability bounds of both fields. Firstly, we conceived a fully decentralized and stochastic centrality metric inspired by swarm intelligence [5]. We showed how, for instance, a Facebook application running in a decentralized way on each user device would be able to compute the importance of all 1 billion users in less than 9 seconds. Secondly, we showed how neural networks inspired by network science may handle higher dimensional data (few orders of magnitude more) than their counterparts at no cost in performance or speed [5].

4. Conclusions

In the big picture, all of these fruitful achievements represent just a drop in the ocean. One limitation of them is the static setting. As next steps, we will tackle this limit by considering dynamic settings.

References

[1] D.C. Mocanu*, "On the synergy of network science and artificial intelligence",* ***25th*** **International Joint Conference on Artificial Intelligence** (IJCAI), New York, USA, 2016.

[2] D.C. Mocanu, H. Bou Ammar, D. Lowet, K. Driessens, A. Liotta, G. Weiss, K. Tuyls: "*Factored Four Way Conditional Restricted Boltzmann Machines for Activity Recognition* ", **Pattern Recognition Letters**,2015.

[3] D.C. Mocanu , M. Torres Vega, A. Liotta: "*Redundancy reduction in wireless sensors via centrality metrics*", Proc. Of **IEEE ICDMW**, Atlantic City, USA, 2015.

[4] D.C. Mocanu , G. Exarchakos, A. Liotta: "*Deep Learning for objective QoE assessment of 3D images*", **IEEE International Conference on Image Processing** (ICIP), Paris, France, 2014.

[5] D.C. Mocanu, G. Exarchakos, A. Liotta: "*Shades of strengths in complex networks*", **Nature** (in preparation), 2016.

[6] D.C. Mocanu, E. Mocanu, P. Nguyen, M. Gibescu, A. Liotta: "*A topological insight into restricted Boltzmann machines*", **Machine Learning Journal**, ECML-PKDD 2016 special track (under review), 2016.