Ph.D. in Information Technology
Thesis Defense

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At 2:30 p.m.
Carlo Erba, Edificio 7

Bernardo CAMAJORI TEDESCHINI– XXXVII Cycle

COOPERATIVE MACHINE LEARNING METHODS IN DISTRIBUTED SYSTEMS
Supervisor: Prof. Barbara Monica Nicoli

Abstract:

Cooperative learning and inference in multi-agent systems (MAS) are increasingly pivotal in addressing the complexities and dynamic demands of modern technological environments. Spanning domains from robotics and internet of things (IoT) to telecommunications and healthcare, these collaborative strategies enhance the robustness and adaptability of systems handling intricate or resource-intensive tasks. This thesis explores innovative approaches in both centralized and decentralized frameworks, focusing on optimizing system performance through advanced machine learning (ML) methods. The goal is to introduce novel methods that expand the capabilities of MAS in practical scenarios, ensuring efficient, scalable, and privacy-aware solutions that adapt dynamically to changing conditions and maintain high performance among varied and unpredictable environmental factors.

The thesis is divided into two main parts, each dedicated to analyzing one of the two key components of a MAS: learning and inference. In the first part of the thesis, the focus is on cooperative learning which is investigated in graph-aware centralized machine learning (C-ML), privacy-preserving decentralized machine learning (D-ML), and non-stationary learning frameworks. For graph-aware learning, we considered the tasks of data association (DA) and cooperative positioning (CP) in vehicular networks, where exploiting a logical graph structure enables the handling of non-linear distributions and scalable architectures. When data exchanged between agents is private or sensitive, D-ML algorithms can be used to exchange only model parameters or latent features, reducing the disclosure of privacy information. In this context, we proposed a real platform for performing decentralized and fully-decentralized learning in medical and IoT networks. In particular, we studied federated learning (FL) algorithms in asynchronous learning processes and FL weighted averaged consensus (WAC) techniques for serverless learning in non-independent and identically distributed (IID) conditions with heterogeneous devices. In the presence of resource-constrained devices, we proposed decentralized split learning (SL) algorithms that iteratively distribute the computational burden of training among agents. Finally, whenever agents are in the presence of highly-dynamic environments and non-stationary distributions of data, multi-agent reinforcement learning (MARL) algorithms can be adopted.
In the thesis, we developed a novel MARL algorithm for performing implicit cooperative positioning (ICP) in vehicular networks, where passive objects (or targets) are exploited to refine the agents' state estimate.

After having investigated techniques for cooperative learning, in the second part of the thesis, we turned our attention to cooperative inference, where we studied efficient and reliable techniques for the tasks of non-line-of-sight (NLoS) identification, static and mobile position in next-generation cellular networks. The agents, i.e., the base stations (BSs) in this case, estimate and compress the channel into a latent representation which is subsequently adopted for sensing. For NLoS identification, we proposed an anomaly detection scheme which efficiently evaluates the likelihood of channel samples of belonging to the line-of-sight (LoS) normal distribution. On the contrary, for static positioning, we presented a cooperative inference scheme for efficiently combining latent features. In particular, in LoS conditions, the BSs cooperatively localize the user equipment (UE) by fusing latent features, whereas in NLoS conditions, the BSs perform independently positioning. Finally, for mobile positioning, we first proposed a novel Bayesian neural network (BNN) algorithm for estimating the full uncertainty of predictions in real-time.

Then, we integrated this uncertainty into tracking filters, optimally combining the fingerprint-based likelihood functions of different BSs in out of distribution (OoD) areas.

In conclusion, this thesis presents a comprehensive exploration of cooperative learning and inference strategies within MASs, offering scalable and adaptive solutions across a diverse range of technological domains. By integrating advanced ML techniques with the implicit complexities of cooperative environments, we have developed robust models that significantly enhance both the precision and reliability of various application areas, ranging from vehicular and IoT networking to healthcare and cellular systems. These innovative approaches not only demonstrate the practical benefits of cooperative strategies but also highlight the potential for future advancements in data-driven technologies.

PhD Committee

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