PhD offer

Distributed Machine Learning for IoT applications

**Project Description:**

IoT applications will become one of the main sources to train data-greedy machine learning models. Until now, IoT applications were mostly about collecting data from the physical world and sending them to the Cloud. Google’s *federated learning* already enables mobile phones, or other devices with limited computing capabilities, to collaboratively learn a machine learning model while keeping all training data locally, decoupling the ability to do machine learning from the need to store the data in the cloud. While Google envisions only users’ devices, it is possible that part of the computation is executed at other intermediate elements in the network. This new paradigm is sometimes referred to as *Edge Computing* or *Fog Computing*. Model training as well as serving (provide machine learning predictions) are going to be distributed between IoT devices, cloud services, and other intermediate computing elements like servers close to base stations as envisaged by the *Multi-Access Edge Computing framework*. This approach provides at least three benefits.

1. **Reduce network load.** According to recent estimates, there are 7 billions IoT devices deployed in the world. This number should increase by a factor 3 by 2025. Routing the raw data traffic generated by these devices to a few data-centers will not be feasible. It is required to extract relevant features as close as possible to the locations where data is generated.

2. **Reduce latency.** ML models will be used by IoT devices to take actions in the physical world. Future wireless services for connected and autonomous cars, industrial robotics, mobile gaming, augmented and virtual reality have strict latency requirements, often below 10 ms and below 1ms for what is now called the tactile internet. A key element to satisfy such constraints is to run these services closer to the user, directly on IoT devices. Edge computing also ensures that applications are not disrupted in case of limited or intermittent network connectivity.

3. **Preserve privacy.** Data captured by IoT devices can contain sensitive or private information. Pre-processing at the edge can make sure that sensitive information is removed or aggregated with data from other devices to preserve user’s profile.

The goal of this PhD thesis is to investigate how both learning tasks and prediction services can be effectively distributed across different elements in the network, taking into account computation/communication constraints.
Hosting groups:
NEO and Epione teams (Inria Sophia Antipolis) - Accenture Labs (Sophia antipolis). The groups are located in the tech Park of Sophia Antipolis and in Nice, in the French Riviera.

During the project the candidate will:
• Design new distributed learning algorithms with a particular focus on communication constraints;
• Study analytically their performance and guarantees;
• Implement distributed machine learning algorithms using libraries like PyTorch;
• Participate to the activity of Accenture Labs, interact with research and engineering personnel;
• Interact with Inria students and researchers, and participate to teams’ scientific.

Required competences:
Competences in probability, statistics, optimization, and mathematical modeling are essential (Master level). Solid programming and IT skills are necessary (Python, bash, version control systems), along with strong communication abilities.

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• Mehdi Mohammadi, Ala Al-Fuqaha, Sameh Sorour, Mohsen Guizani, Deep Learning for IoT Big Data and Streaming Analytics: A Survey, IEEE Communications Surveys & Tutorials, 2018
• Lorenzo Valerio, Andrea Passarella, Marco Conti, A communication efficient distributed learning framework for smart environments, Pervasive and Mobile Computing 41 (2017) 46–68