Resource-aware Federated Data Analytics in Edge-Enabled IoT Systems

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Abstract

The importance of processing data gathered by Internet-of-Things (IoT) devices is becoming increasingly vital for extracting valuable insights and facilitating informed decision-making across various applications (Atzori, Iera, and Morabito 2010). Machine Learning (ML) and Deep Learning (DL) techniques (Dargan et al. 2019) have emerged as valuable tools for processing data and extracting insights from data. These models are usually trained on extensive datasets and offer solutions to complex tasks that are challenging to program manually. However, training these models is resource-intensive, involving substantial data pre-processing (e.g., data cleaning, data reduction, etc.) and compute resources. To overcome the resource limitations of IoT devices, Edge computing (EC) (ETSI 2014) emerged as a solution that brings computation closer to the data source, reducing latency and communication costs compared to the traditional cloud-based data processing. However, EC faces its own resource limitations, therefore, necessitating careful resource management decisions. Given the distributed nature of IoT data, resource constrains of IoT devices, and privacy concerns of IoT users, distributed machine learning techniques and more recently distributed Federated Learning (FL) (Konečnỳ et al. 2016a,b) have emerged as a key technology in extracting knowledge from these data. FL delegates the model training task to the IoT devices themselves. Each IoT device performs a small amount of training and communicates only the model parameters of its locally trained neural network to a central location. These parameters are then averaged to ensure knowledge is shared among all IoT devices. This process avoids the transmission of raw data, thereby introducing an immediate layer of privacy. Reliable and efficient orchestration of FL in dynamic, heterogeneous, and resource constrained IoT systems remains a challenge. Heterogeneous data sources, different modalities of data collected/generated by IoT devices, dynamics of the IoT system and different quality-of-service requirements in different IoT applications makes data pre-processing and model training more complex for such systems. System heterogeneity and the range of devices involved can impact the performance of trained models. On the other hand, it is crucial to consider the inter-dependency between the data pre-processing and machine learning model training, as they both affect the overall performance of the machine learning model. Furthermore, continuous generation of data in IoT devices necessitates simultaneous pre-processing and training, ensuring that new data entering the system is promptly processed and made usable by the ML model. Specially, in a resource constrained environment like IoT systems, it is critical to make optimal decisions on **how much resources to allocate pre-processing** and **how much to allocate to model training**, and which specific combination of pre-processing and learning should be selected. This talk first, provides an overview of some initial steps we took towards developing federated data pre-processing in IoT environments (Mahanipour and Khamfroush 2023b,a), and then a visionary overview of potential research problems related to developing an integrated resource-aware and QoS-aware data pre-processing and model training system is provided.

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