ABSTRACT

Machine learning algorithms are increasingly deployed in applications that have high-stake impacts on people and it is crucial to ensure the reliability of such ML systems. My research considers reliability in two categories: reliability in machine metrics and reliability in human metrics. In this talk, I will discuss recent results that address reliability challenges in both metrics and exciting future directions towards building end-to-end reliability, from machines to humans. I will discuss my work towards building reliability in machine metrics, especially when we train a model on large-scale distributed systems. When we utilize thousands of distributed nodes for computing, there can be slow nodes, unresponsive nodes, or bit flips that can degrade the overall computation time and accuracy of the output. I will introduce coded computing. I developed MatDot codes that meet the fundamental limit and solve the longstanding intellectual problem of computing matrix multiplication reliably. In collaboration with the Oak Ridge National Lab, we implemented this theoretical breakthrough into a practical parallel matrix multiplication algorithm, 3D SUMMA, bringing coded computing closer to HPC practitioners. I ask a novel question that has significant practical impacts: how do we learn a fair model when data has missing values? Even though there are numerous fairness intervention methods in the literature, most of them require a complete training set as input. In practice, data can have missing values, and data missing patterns can depend on group attributes. We derive a fundamental limit that shows that simply applying fair ML methods after data imputation is insufficient and there is no universally fair imputation method for different downstream learning tasks. I propose a decision-tree-based approach that can learn a fair model by incorporating data imputation and learning into a single algorithm. I apply the algorithm on education datasets and show that it outperforms state-of-the-art fair ML methods. Further, I discuss the downstream effects of fair decisions in the context of education. Finally, I will tie these together and present my research vision for building reliable machine learning systems.