ABSTRACT

The field of Machine Learning (ML) has advanced considerably in recent years, but mostly in well-defined domains using huge amounts of human-labeled training data. Machines can recognize objects in images and translate text, but they must be trained with more images and text than a person can see in nearly a lifetime. Humans, on the other hand, learn from far fewer examples, generalize well across tasks and modalities, and perform better than machines at most tasks, especially in complex domains. To address this gap, this talk considers active ML methods that integrate and optimize the processes of ML and human labeling. Standard (passive) machine learning involves designing a prediction rule based on randomly selected training data that are labeled by humans. Active ML algorithms automatically and adaptively select the most informative data for labeling so that human time is not wasted labeling irrelevant or trivial examples. The aim is to make ML as efficient and robust as possible, with a minimal amount of human supervision and assistance. The talk describes ongoing theoretical and experimental work in active ML. The focus will be on adaptive crowdsourcing and interactive dataset annotation, two problems at the intersection of computer science and statistics.