Society-Oriented Developments of Machine Learning: Challenges and Opportunities

Witold Pedrycz

Department of Electrical & Computer Engineering
University of Alberta, Edmonton, Canada
wpedrycz(at)ualberta.ca

Abstract

Over the recent years, we have been witnessing numerous achievements of Artificial Intelligence and Machine Learning (ML), in particular. We have seen highly visible accomplishments encountered in the domains of natural language processing and computer vision impacting numerous areas of human endeavours. Being driven inherently by the technologically advanced learning and architectural developments, ML constructs are highly impactful coming with far reaching consequences; just to mention autonomous vehicles, health care, imaging, decision-making processes in critical areas, among others.

We advocate that the design and analysis of ML constructs have to be carried out in a holistic manner by identifying and addressing a series of central and unavoidable societal quests. The key challenges on the list of interest concerns interpretability, energy awareness (being also lucidly identified on the agenda of green AI), efficient quantification of quality of ML constructs, and privacy. The credibility of ML models and credibility of their results are also of concern to any critical application. The above stated quests are highly intertwined and exhibit direct relationships with the computational end of ML.

The talk elaborates on the above challenges, offers definitions and identifies the linkages among them. In the pursuit of coping with such challenges, we advocate that Granular Computing can play a pivotal role offering a sound conceptual environment and realizing algorithmic development. An essential role of information granularity is identified. We advocate that the credibility (confidence) of results produced by ML constructs is inherently expressed in the form of information granules; several development scenarios are revisited including those involving constructs in statistics (confidence and prediction intervals), probability (Gaussian process models), and granular parameters (supported by fuzzy sets techniques).

As detailed studies, we discuss the ideas of federated learning (emphasizing a way in which data privacy becomes addressed) and knowledge transfer (by demonstrating on how a thoughtful and prudently arranged knowledge reuse supports energy-aware ML computing). Knowledge distillation leading to model compression is also studied in the context of transfer learning.