Machine Learning in Conceptual Spaces: Two Learning Processes

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In artificial intelligence, one can classify representations and processes into two layers: The symbolic layer uses abstract symbols and logical formalisms whereas the subsymbolic layer is mainly based on numerical computations. One of the big problems with this dichotomy is the so called symbol grounding problem [4], i.e., the problem of connecting abstract symbols to perception and action. Any solution to this problem has to successfully bridge the gap between symbolic and subsymbolic AI.

The cognitive framework of conceptual spaces [2] provides such a potential bridge by proposing a third layer based on geometric representations. Points in a semantic similarity space correspond to individual objects and observations, whereas convex regions in this space correspond to concepts. Abstract symbols can be grounded by mapping them to regions in a conceptual space whose dimensions are grounded in subsymbolic processing.

Instead of one big gap we are now left with two smaller gaps: Between the subsymbolic and the conceptual layer, and between the conceptual and the symbolic layer. My proposal is to close these two gaps with the use of machine learning. This requires two separate learning processes. Recently, also Gärdenfors has also discussed the need for two learning processes [3].

The first learning process consists in finding the dimensions of the conceptual space. Recent progress in deep learning research has also resulted in neural networks that are able to extract interpretable dimensions from a given data set. Examples include InfoGAN [1] and β-VAE [5]. In my talk, I will present a proposal for using such networks for learning the dimensions of a conceptual space together with first preliminary results.

The second learning process consists in finding meaningful regions in the conceptual space that can be mapped to symbols from the symbolic layer. In my talk, I will argue that almost any machine learning algorithm can be used for this task. An especially promising candidate is the framework of Logic Tensor Networks [6] which can also take into account logical constraints. I will also address the need for a cognitively more plausible approach and propose to develop an incremental clustering algorithm for concept formation.

References

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