Dealing with Ambiguities in Data, Learning and Perception

Nearly all real-world image understanding problems are inherently ambiguous. Often, predictive systems do not model this ambiguity and do not consider the possibility that there can be more than just a single outcome for a given problem. This leads to sub-par performance on ambiguous tasks as a learnt model has to account for all possibilities with one answer. This talk discusses three typical sources of confusion that render tasks not optimally solvable with a single unique prediction. We analyze three principled and general approaches of dealing with ambiguity. The first method allows the algorithm to predict multiple instead of one single answer. This is a pragmatic way of dealing with ambiguity: instead of deciding for an exclusive outcome for a given problem, we enable the system to list several possibilities. The second part describes an alternative way to deal with uncertain predictions. Often human perception can provide additional information about a task or application that an intelligent system or robot might have not recognized. Building on the paradigm of human-machine interaction, enabling communication between the system and a user can improve predictions on the example of semantic segmentation. The last approach explicitly models the underlying probability distribution that makes a problem ambiguous by making use of marginal conditional distributions. Building on the idea of autoregressive distribution estimators, it can learn complex distributions of natural images without supervision, which can be used for tasks such as in-painting, denoising or anomaly detection.