An increasing amount of algorithms are made available on the Web - exemplary fields are computer vision or in natural language processing (NLP). Here, researchers publish their prototypes as code to adhere to the goal of "reproducible research" or wrap them as Web services to enable direct access. Such algorithms can be used to solve diverse complex tasks, which might require pipelines of algorithms to generate hypotheses.

Finding eligible algorithms is difficult, as interfaces usually vary and only textual descriptions are available. In addition to the problem of discovery, multiple algorithms might be eligible for a single step of the pipeline and, thus, multiple constructed pipelines are seemingly redundant. There is, however, a high probability that there is no single "correct" pipeline for all problem instances. A pipeline of algorithms thus might work well for tweets but not for news articles.

In our work, we thus present approaches to two general challenges: We first develop a framework for automatically discovering eligible pipelines for tasks on the Web and therefore build on tools and methods developed for the Semantic Web. We then enable to learn highly adaptive and well-performing pipelines based on reference data sets, where we distinguish between centralized and decentralized decision-making. We therefore formalize the problem as specialization of the well-known Reinforcement Learning framework and integrate techniques from Statistical Relational Learning. We apply our approaches to medical assistance- as well as NLP tasks, where we conduct different empirical evaluations to show their suitability.