Master Project

Distributionally Robust Data-driven Control

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Context: Loosely speaking, in the Distributionally Robust Optimization (DRO) framework, uncertainty is represented through an **ambiguity set**, that is, a family of distributions consistent with the available raw (training) data. Moreover, decisions can be interpreted as a minimax game against "nature", where one optimizes decisions considering the worst possible distribution that is "close enough" to the empirical distribution of the raw data 1). Particularly, the use of the **Wasserstein distance** as a metric to calculate the distance between distributions has proved to be a theoretically interesting and a tractable approach to the DRO problem.

Data-driven control, sometimes called model-free control, entails controlling systems with unknown dynamics directly from their input/output data, bypassing the necessity of the system identification step. Moreover, in recent years, data-driven methods have received an increasing attention from the Control community, mostly due to the new research field at the intersection of Control and Machine Learning. However, many of these data-driven methods for control lack theoretical guarantees as, for example, how does the **out-of-sample** (testing phase) performance compare to the **in-sample** (training phase) performance? Even though the out-of-sample performance can be assessed *a posteriori* (for example, using an unseen test set), theoretical *a priori* bounds are necessary for the understanding and the deployment of these methods on real world systems.

Project goal: combine the field of Distributionally Robust Optimization with data-driven control methods, developing methods for data-driven synthesis of distributionally robust controllers for **stochastic unknown systems**, with **probabilistic guarantees** on their out-of-sample performance. This approach will initially be applied to discrete-time LTI systems, with possible extensions continuous-time and certain classes of non-linear systems, for example.

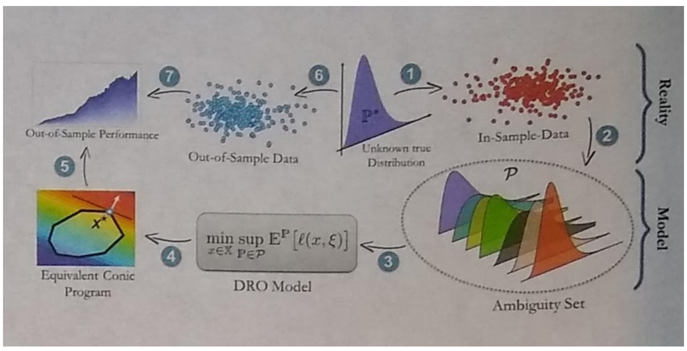

Figure 1: Distributionally Robust Optimization (DRO) framework.