Humans are exceptionally good at acquiring skills by performing tasks and adapting them to novel scenarios. For example, a tennis player learns to hit a forehand by practicing how to hit to a few different regions of the court. However, the player does not need to hit every single point in the court to be able to do it when he needs to.

In the same fashion, robotic applications should be able to learn to perform a general task, and exploit that ability to generalize to new related tasks. A recent proposed solution to this generalization problem for motor control is Dynamic Movement Primitives (DMP). This method is able to learn a general skill from a few samples, and extend the solution to other tasks that are achievable by similar motions. However, they only generalize to one specific kind of motion.

In this study, I propose to investigate a methodology for further generalization of DMP. To do so, I will bring together techniques used in the robotics and machine learning literature. If we assume that there is some underlying structure to the set of parameters that give rise to the DMPs that achieve these variations of a given movement, we may be able to identify it and exploit it to obtain a model by which complete DMPs can be produced, on-demand, given only a description of the task. In order to model the structure of the space containing such DMPs, it is necessary to account for the existence of possibly non-linear intersecting manifolds.

The method I will investigate generates a number of DMPs for solving a set of related motor problems, and identifies a number of DMPs and their structure in the space of parameters. Then, these structures (manifolds) will be separated in case of intersection by ML techniques, such as low rank alignment (LRA). Intersections in the space of solutions may occur when different tasks can be executed via a same movement or, in this case, a same or similar DMP. It is important to realize when this is the case in order to create specialized prediction models, one per identified manifold, capable of generating DMP parameters given a task. Each manifold would be learned via a mixture model, that serves as a predictor of the parameters of an appropriate DMP given a task to be accomplished. Given a description of a of a novel task, then, the only thing to do would be to identify to which manifold this task belongs and use the appropriate mixture model to generate the corresponding trajectory.

As a result of this project, I expect to be able to combine methods for identifying mixed manifolds with predictive mixture models in order to generate new DMP parameters for solving novel tasks. To evaluate the results I will present novel targets to the system and measure how well those predicted motor solutions effectively accomplish a novel task.

To compare this type of accuracy, I will contrast the predicted behavior against those directly generated by learning specific DMPs.

I will also evaluate the computational cost of generating new DMPs via this type of predictive model and compare it with that of constructing a new solution from scratch.

I will carry out experiments in physically accurate simulators such as Gazebo or V-REP. If time permits, I will also test my results on the uBot.

At the end of the project, I will present to my readers a detail report analyzing the different techniques I needed to master to work on this project, how they all fit together under a single framework and the results I obtained.

Since this methodology has not been thoroughly researched as a potential solution to the generalization of DMPs, if my results are promising enough, I will also submit a paper to a prestigious conference such as AAAI or ICRA

This project brings together techniques from both the machine learning and robotics literature. To the best of my knowledge, the limitations to generalization of DMPs is an unsolved problem. Addressing it by using predictive models to analyze the underlying manifold of the solution space, seems like a sound approach which has not been thoroughly explored.

My proposed methodology is a novel approach that makes use of machine learning techniques to address an issue in robotics.