

# DmpBbo: A versatile Python/C++ library for Function Approximation, Dynamical Movement Primitives, and Black-Box Optimization

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## Software

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## General overview

Dynamical movement primitives (DMPs) (A. J. Ijspeert, Nakanishi, & Schaal, 2002, A. Ijspeert, Nakanishi, Pastor, Hoffmann, & Schaal (2013)) are one of the most popular representations for goal-directed motion primitives in robotics. They are also often used as the policy representation for policy improvement in robotics, a particular form of reinforcement learning. `dmpbbo` provides five software modules for the representation and optimization of dynamical movement primitives. These five modules are:

- `dynamicalsystems/`, various dynamical systems representing for instance exponential decay or spring-damper systems (standalone module).
- `functionapproximators/`, various function approximators such as Gaussian process regression, radial basis function networks, and Gaussian mixture regression (standalone module).
- `dmp/`, implementation of dynamical movement primitives, where various dynamical systems and function approximators in the first modules can be easily exchanged to get DMPs with different properties.
- `bbo/`, implementations of several stochastic optimization algorithms for the optimization of black-box cost functions (standalone module)
- `dmp_bbo/`, applies black-box optimization to the parameters of a DMP (depends on all other modules)

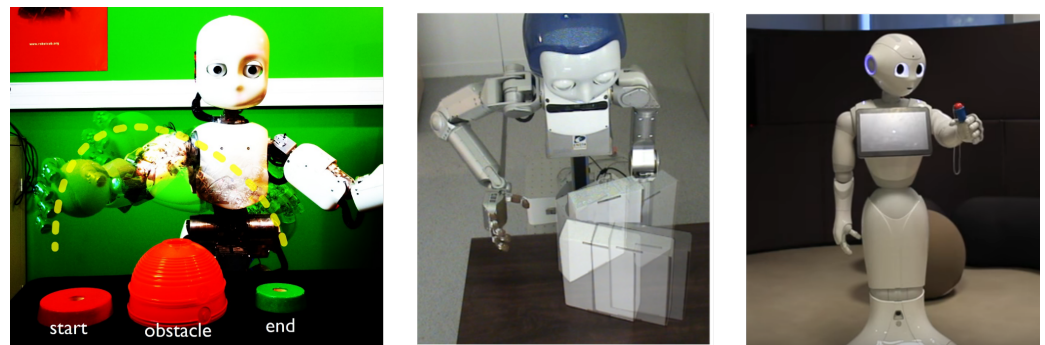
`dmpbbo` provides both a real-time C++ implementation, as well as an implementation in Python for non-roboticists.

`dmpbbo` is accompanied by an extensive tutorial on the motivation for dynamical movement primitives, and their mathematical derivation.

## Advanced features

Several more advanced features implemented in `dmpbbo` are:

- Contextual dynamical movement primitives, which can adapt to variations of tasks (Stulp, Raiola, Hoarau, Ivaldi, & Sigaud, 2013)
- Dynamical movement primitives with gain schedules (Buchli, Stulp, Theodorou, & Schaal, 2011)



**Figure 1:** Overview

- Unified models for function approximators (Stulp & Sigaud, 2015)
- Covariance matrix adaptation in black-box optimization, which enables automatic exploration tuning (Stulp, 2012)

## Applications

This library and its predecessors were used in the following scientific publications (Stulp, 2012, Stulp et al. (2013), Stulp, Herlant, Hoarau, & Raiola (2014), Stulp & Sigaud (2015)). The images below are snapshots of robotic applications where ‘dmpbbo’ was used. And here a list of videos:

- <https://www.youtube.com/watch?v=R7LWkh1UMII>
- <https://www.youtube.com/watch?v=MAiw3Ke7bh8>
- [https://www.youtube.com/watch?v=jkaRO8J\\_1XI](https://www.youtube.com/watch?v=jkaRO8J_1XI)
- [https://www.youtube.com/watch?v=i\\_JBRojCqcc](https://www.youtube.com/watch?v=i_JBRojCqcc)

Robot names and credits in order of appearance: iCub (Photo by ISIR), MEKA (Photo by ENSTA ParisTech), Pepper (Photo by SoftBank)

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