Scalable Robot Autonomy through Remote Operator Assistance and Lifelong Learning

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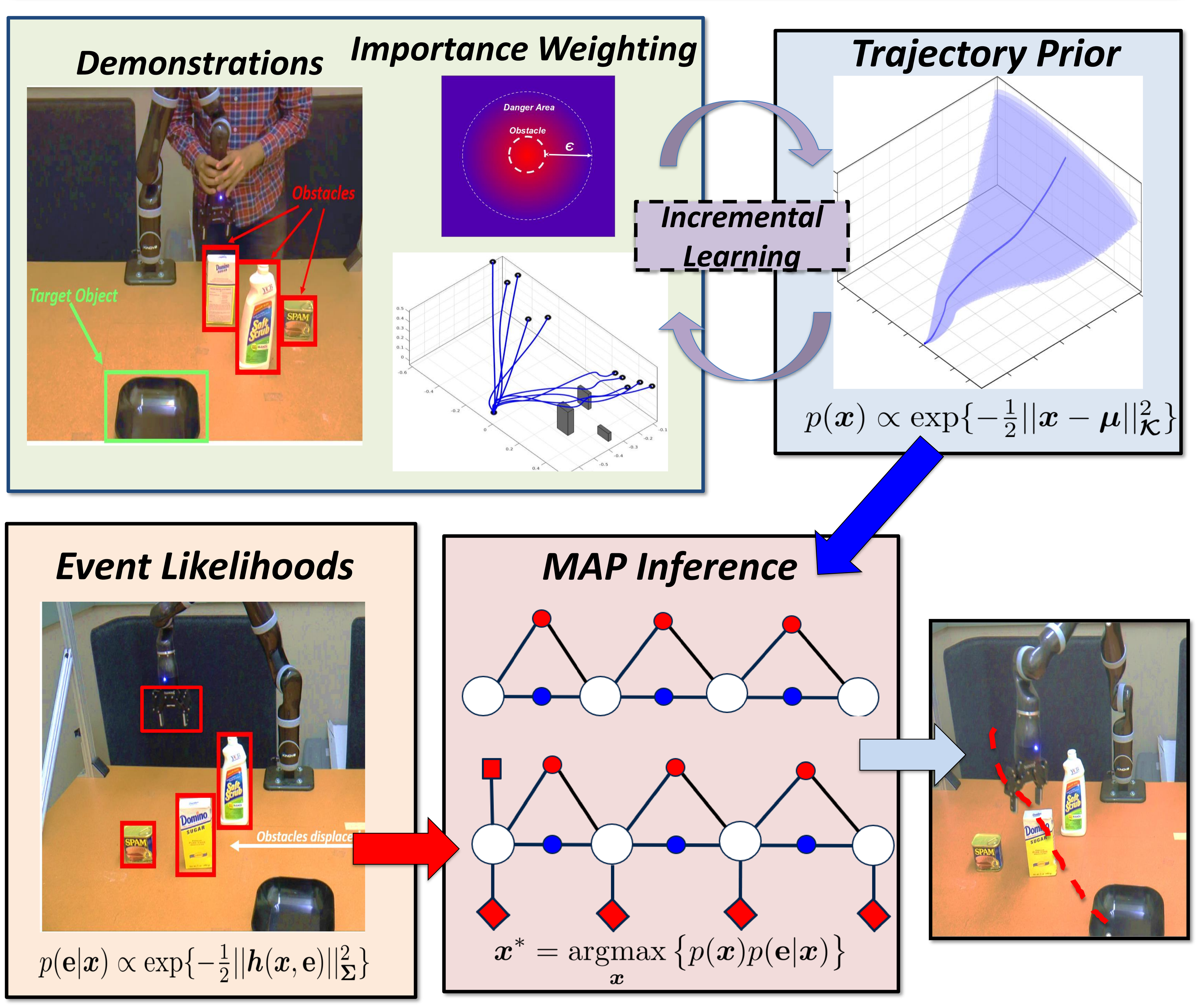
Introduction

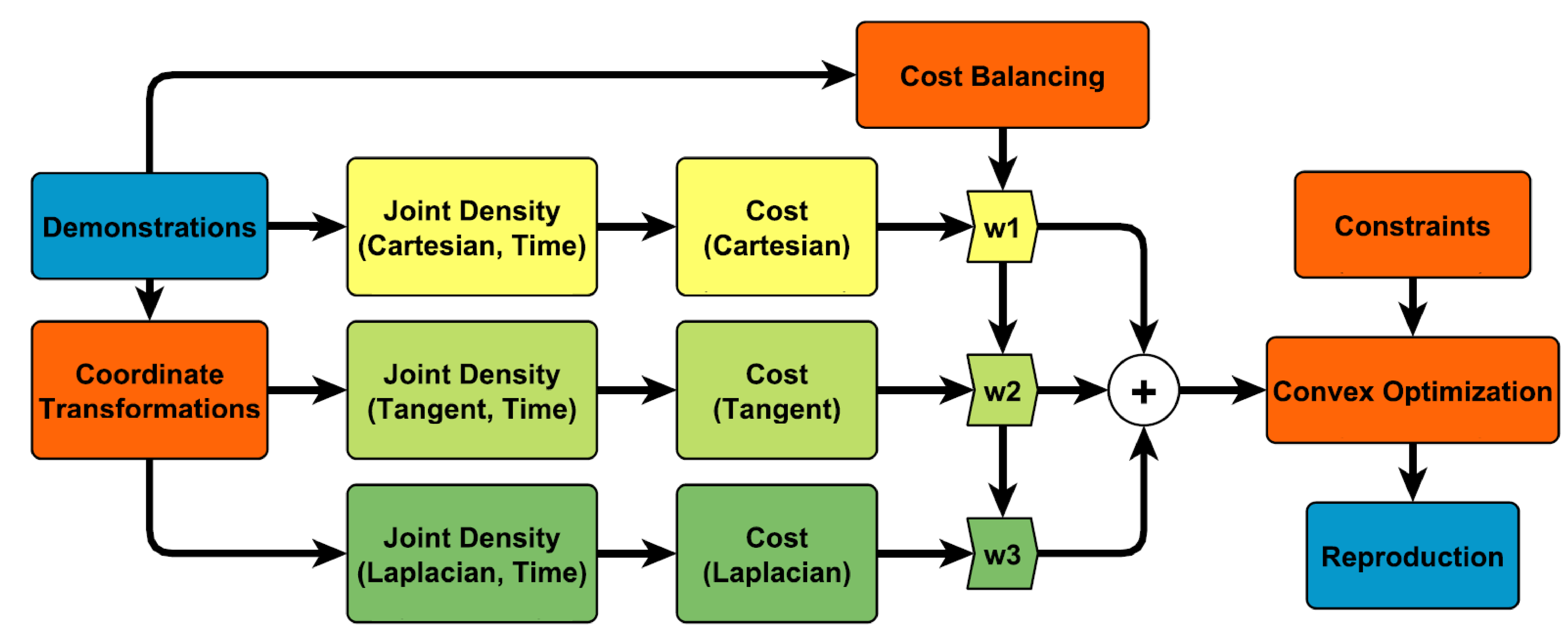
To operate in unstructured environments and allow end-user customization, robots must possess the ability to learn new skills from demonstrations. We present three research thrusts in skill learning: (a) learning generalizable robot skills, (b) learning simultaneously in multiple coordinate systems, and (c) benchmarking skill learning algorithms from an end-user perspective.

Combined Learning from Demonstration & Motion Planning

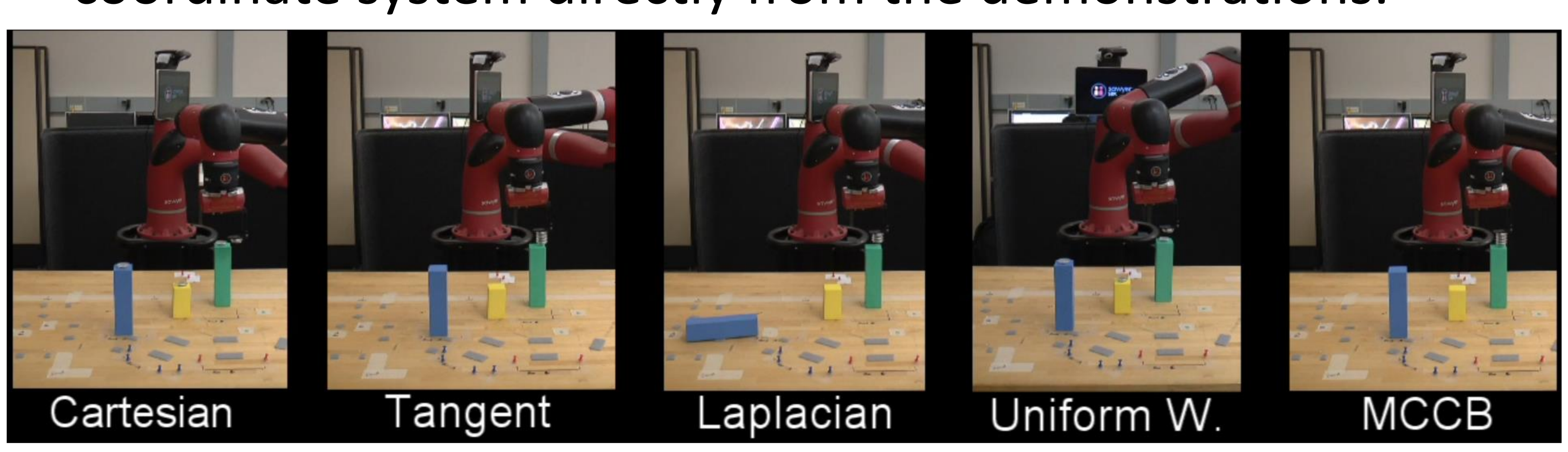


- CLAMP finds trajectories which are ***optimal*** in terms of demonstrations and ***feasible*** in the reproduction scenario.
- ***Importance weighting*** in trajectory prior learning enables learning from demonstrations provided in clutter.
- ***Incremental learning*** allows skill improvement as more demonstrations become available.

Automated Multi-Coordinate Cost Balancing



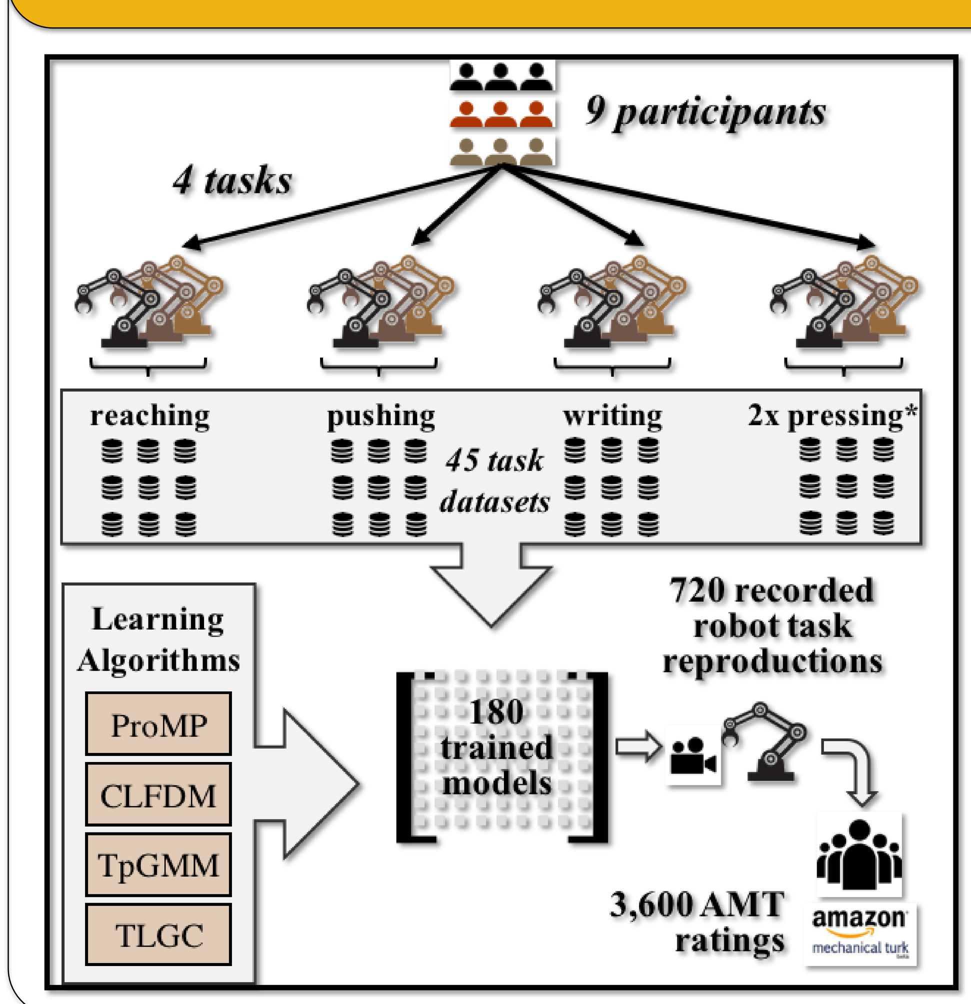
- Encodes demonstrations *simultaneously* in ***multiple differential coordinates.***
- **Blended cost function** incentivizes conformance to the norm while considering *expected variance*.
- Learns to ***balance the relative influence*** of each coordinate system directly from the demonstrations.



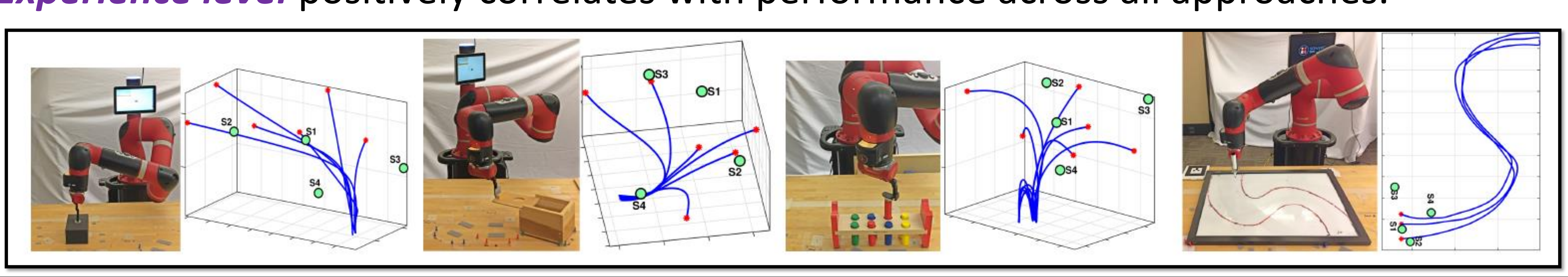
	Single Coordinate			Multi-Coordinate	
	Cartesian	Tangent	Laplacian	Uniform W.	MCCB
Handwriting		✓ ✓	✓ ✓	✓	✓
Picking		✓			✓
Pressing	✓				✓
Pushing			✓		✓

Orange => most important coordinate, green => best performance

Benchmarking Skill Learning from Demonstration



- ***Crowdsourced evaluation*** of statistical (TpGMM) [1], dynamical system (CLF-DM) [2], geometric (TLGC) [3], and probabilistic (ProMP) [4] approaches on **four different tasks**.
- ***Best performance***: Tasks with **constrained direction of the motion** (e.g., *writing*): TLGC; Tasks with **positional constraints** (e.g. *reaching*): ProMP and TpGMM; Generalization to **starting locations closer to the target**: CLF-DM and TLGC.
- ***Experience level*** positively correlates with performance across all approaches.



[1]] S. Calinon. A tutorial on task-parameterized movement learning and retrieval. Intelligent Service Robotics, 9(1):1–29, 2016.
[2] S.M. Khansari-Zadeh and A. Billard. Learning control Lyapunov function to ensure stability of dynamical system-based robot reaching motions. Robotics and Autonomous Systems, 62(6):752–765, 2014.
[3] S.R. Ahmadzadeh, M. A. Rana, and S. Chernova. Generalized cylinders for learning, reproduction, generalization, and refinement of robot skills. In Robotics: Science and systems, volume 1, 2017.
[4] A. Paraschos, C. Daniel, J. R. Peters, and G. Neumann. Probabilistic movement primitives. In Advances in neural information processing systems, pages 2616–2624, 2013.

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