

Flow Matching Predictive Control with Constraints

Master Thesis

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Introduction and Problem Description

Flow Matching (FM)[2, 3] is a modern generative modeling framework that has achieved state-of-the-art performance across diverse domains, including image, video, audio, and biological structures. The core principle of FM is to learn a continuous transformation, or "flow," that maps a simple source probability distribution (e.g., Gaussian noise) to a complex target data distribution. This transformation is defined by a time-dependent vector field, which is modeled by a neural network. The network is trained using a simple regression objective to learn the instantaneous velocities of data points along trajectories from the source to the target distribution. In essence, the goal of Flow Matching is to learn a vector field whose flow generates a probability path from the source to the target distribution as shown in the Fig.1. In this thesis, the objective is to use Flow Matching to generate trajectories for robotic systems. As Flow Matching is a type of generative model, it can produce diverse and novel trajectories but these trajectories might not be safe or feasible for real-world robotic systems. Therefore, as a next step you need to incorporate Model Predictive Control (MPC) with safety constraints into the Flow Matching framework which ensures that the generated trajectories are safe and feasible for robotic applications.

Thesis Goals

The primary objective of this thesis is to develop and evaluate a novel control framework based on Flow Matching. The scope of this work encompasses the following key tasks:

- **Literature Review and Dataset Generation:** Familiarize with the D4RL (Datasets for Deep Data-Driven Reinforcement Learning) simulation framework [1]. Generate an expert dataset to be used for training the Flow Matching model.
- **Framework Adaptation:** Analyze the existing Diffusion Predictive Control with Constraints (DPCC) framework [4]. The core task is to adapt this framework by replacing its Diffusion Model component with a Flow Matching approach. The source code for DPCC is available at <https://github.com/ralfroemer99/dpcc>.
- **Implementation and Extension:** Implement the new algorithm on robotic manipulator environments from D4RL. After successful validation, extend the framework to a different domain, such as drone control, and evaluate its performance.

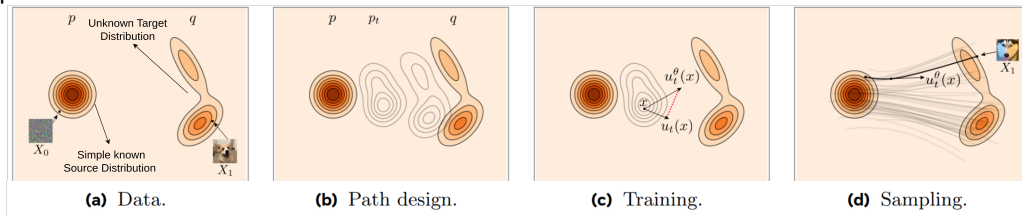


Figure 1: The Flow Matching blueprint. (a) The goal is to find a flow mapping samples X_0 from a known source or noise distribution p into samples X_1 from an unknown target or data distribution q . (b) To do so, design a time-continuous probability path $(p_t)_{0 \leq t \leq 1}$ interpolating between $p := p_0$ and $q := p_1$. (c) During training, use regression to estimate the velocity field u_t known to generate p_t . (d) To draw a novel target sample $X_1 \sim q$, integrate the estimated velocity field $u_t^\theta(X_t)$ from $t = 0$ to $t = 1$, where $X_0 \sim p$ is a novel source sample.

References

- [1] Fu, J., Kumar, A., Nachum, O., Tucker, G., and Levine, S. *D4RL: Datasets for Deep Data-Driven Reinforcement Learning*. 2020. arXiv: [2004.07219](https://arxiv.org/abs/2004.07219) [cs.LG].
- [2] Lipman, Y., Chen, R. T., Ben-Hamu, H., Nickel, M., and Le, M. “Flow matching for generative modeling”. In: *arXiv preprint arXiv:2210.02747* (2022).
- [3] Lipman, Y., Havasi, M., Holderrieth, P., Shaul, N., Le, M., Karrer, B., Chen, R. T., Lopez-Paz, D., Ben-Hamu, H., and Gat, I. “Flow matching guide and code”. In: *arXiv preprint arXiv:2412.06264* (2024).
- [4] Römer, R., Rohr, A. von, and Schoellig, A. P. “Diffusion Predictive Control with Constraints”. In: *arXiv preprint arXiv:2412.09342* (2024).