Summary of qualifications. I have a solid experience in probabilistic machine learning (ML) research [4][1][3], a strong background in applied mathematics, and a long-standing practical knowledge in programming. In particular, I can competently write deep learning programs based on `Jax` and `PyTorch`, and I am both interested and knowledgeable about approximate Bayesian inference and large-scale numerical computations. Besides, I have a consistent track of collaborative work on culturally diverse environments—both nationally and internationally (Brazil, Finland, and the UAE). In this context, I believe I am well-positioned to contribute effectively as a postdoctoral researcher at the Technical University of Denmark in Søren Hauberg's group.

The past and the present

A short biography. I was born in the island of Florianópolis, in Brazil. During my teenage years, I was deeply engaged in academic olympiads, in which I consistently ranked among the best in the country in both mathematical and chemistry competitions. Upon coming of age, I was invited for a fully-funded undergraduate scholarship at the Getulio Vargas Foundation's School of Applied Mathematics, a recently created institution spearheaded by some of the most prominent Brazilian mathematicians, e.g., César Camacho and Alfredo Iusem. After four years, I finished my bachelor's degree in Data Science with a near-perfect GPA. A year later, due to my scientific productivity and consistent academic excellence, I also successfully defended both my master's and doctoral's theses on Applied Mathematics. Following this, I have spent several months contributing to risk management and engineering projects in the sports betting and retail industries at rapidly growing Brazilian startups. Then, I returned to academia as a postdoctoral associate at MBZUAI in the UAE—a fast-paced and AI-first university with a prestigious faculty body, including Eric Xing and Éric Moulines—, where I am working on the analysis and design of approximate inference algorithms through the lens of amortized sampling.

Research experience. During my PhD, my research focused on algorithmic and theoretical improvements for Generative Flow Networks (GFlowNets), which are a class of models for amortized sampling on discrete and compositional spaces (e.g., graphs and sentences—which can be built by adding atomic components, such as edges and tokens, to a fixed initial state). From a theoretical viewpoint, I designed PAC-Bayesian generalization bounds, delineated the expressivity, and studied divergence-based learning objectives for GFlowNets. Drawing on the derived theory, I developed distributed and streaming algorithms for large-scale approximate Bayesian inference on discrete posteriors. My research has appeared at the top-tier ML venues (e.g., NeurIPS, ICML).

Professional experience. I have also worked for approximately two years—during and after my PhD—as an analytics engineer at tech startups. Throughout this period, I built web APIs, deployed them in cloud-based services, and maintained them for internal and external users. During this period, I learned about software engineering and project management, and I also greatly sharpened my communication skills for a non-technical audience.

Fitness to the position

Alignment in research interests. Bayesian statistics provides a principled and pragmatic framework for learning from data. At its core, Bayes's rule naturally implements a belief update mechanism based on noisy information. Nonetheless, the research community still struggles to efficiently incorporate Bayesian principles into modern deep learning systems. With this in mind, identifying and mitigating the challenges constraining the efficient implementation of Bayesian methods has been a major driver of my research. As exact Bayesian inference is computationally intractable, I have both studied and worked during the past few years on understanding the Bayesian framework and devising effective tools for carrying out *approximate Bayesian inference* on large-scale and complex distributions [1] [2] [5] [3]. Notably, these methods amount to minimizing a divergence (distance) function from a family of tractable distributions to a target measure, having an inherently geometrical interpretation [3]. As such, I also have a growing interest in differential geometry—Riemannian manifolds, logarithmic and exponential maps, curved exponential families—, which is a mathematically coherent approach for cleanly characterizing these problems.

What lies ahead? My goal as a postdoc at Søren Hauberg's group will be to understand and mitigate the limitations of approximate Bayesian methods applied to deep learning—through the lens of differential geometry. I am also eager to work with students, aid with teaching, assist with grant-writing, and engage in further academic activities (e.g., reading groups, presentations).

[1] T. da Silva, A. Souza, L. Carvalho, S. Kaski, D. Mesquita, "Embarrassingly Parallel GFlowNets", ICML, 2024.

[2] T. da Silva, D. de Souza, D. Mesquita, "Streaming Bayes GFlowNets". NeurIPS, 2024.

[3] T. da Silva, E. Silva, D. Mesquita, "On Divergence Measures for Training GFlowNets", NeurIPS, 2024.

[4] T. da Silva, E. Silva, R. Alves, A. Souza, V. Garg, S. Kaski, D. Mesquita "When do GFlowNets learn the right distribution?", ICLR, 2025. Also, SPIGM@ICML 2024 workshop.

[5] T. da Silva, O. Rivasplata, A. Souza, S. Kaski, V. Garg, D. Mesquita, "Generalization and Distributed Learning of GFlowNets", ICLR, 2025.

[6] T. da Silva, E. Silva, D. Heider, S. Kaski, D. Mesquita, A. Ribeiro, "Human-aided discovery of ancestral graphs", under review, 2024. LatinX@NeurIPS workshop. Also available on arxiv.