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Postdoctoral Researcher @ MBZUAI

Cover Letter for:
Postdoctoral Researcher @ ELLIS Finland

Summary of qualifications. I possess a solid experience in probabilistic machine learning (ML) research, a well-established background in applied mathematics, and a long-standing practical knowledge in programming. I also maintained a strong track-record in both publishing and reviewing for top-tier ML venues—including NeurIPS, ICML, and ICLR—while cultivating national and international collaborations (Brazil, Finland, UAE). Therefore, I am confident I am well-positioned to join ELLIS Institute Finland as a postdoctoral fellow and contribute effectively to its ongoing and future projects.

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., href{https://en.wikipedia.org/wiki/C%C3%A9sar_Camacho}{César Camacho} and href{https://en.wikipedia.org/wiki/Alfredo_Noel_Iusem}{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 href{https://en.wikipedia.org/wiki/Eric_Xing}{Eric Xing} and href{https://en.wikipedia.org/wiki/%C3%89ric_Moulines}{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 emph{approximate Bayesian inference} on large-scale and complex distributions. 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 ref{pp:divergences}. 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? 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).