Research Statement

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In general, I am interested in *meta-learning*, *domain adaptation*, and *black-box optimization*, heading toward *lifelong and open-world machine learning systems* with computer-vision orientation. In particular, I am aiming to develop computer vision models that can be continuously optimized with minimal training data or less human supervision and effectively generalize into other domains outside of training distribution. Below, I will review and discuss these research interests.

- ***Meta-learning***: Deep learning algorithms are notorious for learning based on a vast amount of data. However, in many real-world problems, collecting large amounts of data can be costly, time-consuming, or even impossible. Motivated by the research question: *"How can machine learning algorithms learn just based on a small to no labeled set?"*, meta-learning (with the sub-field of few-shot learning and zero-shot learning) aims to develop machine learning algorithms that can generalize effectively based on a small to no amount of labeled support data and extrapolate to unseen tasks efficiently under the same restriction. This setting opens two main approaches for meta-learning: (i) fast learning of a good representation that can generalize well on various domains, and (ii) fine-tuning parameters for a fast adaptation to another task with just a few but effective optimization steps. However, the restriction of training data is a great challenge as it is unable to represent the target object comprehensively under various visual conditions, resulting in a significant difference between the labeled support and unlabeled query sets. In my previous work (Nguyen et al., 2023b), we tackled this challenge by proving that cosine similarity is beneficial in a cross-attention mechanism for computing the correlational map between two sets effectively for the few-shot task. From this work and similar studies (Chen et al., 2019; Hu et al., 2022), I am aiming to explore deeper few-shot learning or zero-shot learning for many vision-related tasks under both generalization and optimization perspectives in my graduate study.
- ***Domain Adaptation***: Classic ML and DL algorithms are often built on the assumption that the training (source) and testing (target) sets are independent and identically distributed. However, this assumption is rarely met in real life, causing overconfidence in the inference that leads to wrong predictions. Addressing the problem, Out-of-distribution (OOD) detection aims to *identify OOD samples (outlier or anomalous) alongside making correct predictions in in-distribution samples from the target set*. Moreover, by identifying outlier samples effectively, continual learning can be further explored to support ML systems in gradually learning new knowledge based on detected OOD samples while preserving information from the learned domains, heading toward lifelong and open-world machine learning systems (Parmar et al., 2023). While the majority of existing approaches for these lines of research focus on image-level tasks, i.e., image classification, I am more concerned with OOD detection for object-level tasks, such as object detection. Based on the previous research works on deep generative models for image-level OOD detection (Liu et al., 2023; Graham et al., 2023), I proposed a framework for object-level OOD detection that utilized the label-conditional diffusion inpainting model as the OOD detector without relying on any fine-tuning effort. Later on, I am interested in exploring further the intersection between domain adaptation and meta-learning in the scope of computer vision.

- ***Black-box optimization for meta-learning/domain adaptation***: Depending on the problem setup, we can *formulate meta-learning and domain adaptation as black-box optimization problems under various constrained conditions that mimic open-world learning settings*, e.g., formulating a few-shot learning model as a black-box function with only small evaluation samples as input and optimal parameters as output. Then, we can build a probabilistic model over the black-box function to either effectively optimize it with low data points or efficiently adapt to another new domain without redundant steps in a derivative-free manner. Bayesian optimization with Gaussian Processes, with the core idea of approximating a surrogate multivariable Gaussian distribution over the objective function and utilizing a simple acquisition function to guide the search for the optimal value (Shahriari et al., 2015), is often an ideal choice for such tasks. The algorithm, well-known for solving black-box optimization problems with minimal evaluation steps, can be utilized to handle domain-shifting tasks in meta-learning and domain adaptation in a data-efficient manner. However, I found that very few studies have explored this line of research to apply BayesOpt for meta-learning and domain adaptation, as they often focus on improving the algorithm from a theoretical perspective. Previously, I stabilized the Gaussian Process to improve the performance of Bayesian Optimization and the Pareto Set Learning model for solving multi-objective black-box optimization (Nguyen et al., 2023a). In my next research stage, I am aiming to explore the integration of black-box optimization algorithms, with Bayesian optimization among them, for improving meta-learning and domain adaptation algorithms.

In summary, I am interested in exploring the potential of meta-learning (few-shot/zero-shot learning) and domain adaptation (OOD detection, continual learning, etc.) for many sophisticated vision tasks. These two lines of research can be well combined in a unified setting, such as few-shot continual learning (Cui et al., 2023) to support AI reasoning and interpreting with human-like performance toward open-world machine learning systems. I am also interested in exploring the connection between (black-box) optimization and machine learning, with Bayesian optimization being one potential solution to support machine learning algorithms under distribution-shift or limited training data. Nevertheless, given any opportunities, I would also like to expand my research into other related tasks in machine learning and AI, not just those aforementioned research works or those limited to computer vision fields.

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