Linearized Laplacian Approximation for Meta Acquisition functions

Shivam Pamdey
200938

Anshuman Barnwal
200259

Mohan Krishna
200590

Varada Agarwal
201086

Tejas Chikoti
200296

Abstract

This project would proposes the LLAMA technique to boost the efficiency of active learning by incorporating Laplace linearization into an improved approximate calculation of Probabilistic Predictive Distributions (PPD). In the context of acquisition functions vital for guiding active learning systems in selecting informative samples, our method provides a computational shortcut using closed form when compared to traditional Monte Carlo (MC) sampling used for approximating marginalization over posterior.

1 Introduction

Active learning traditionally relies on acquisition functions that acquire samples from a pool of (unlabelled) data by optimizing over scores like predictive entropy, variation ratios, BALD, BatchBALD, EPIG that inherently marginalize over posterior of models that are practically done using methods like MC sampling, which can be computationally demanding and limit scalability. Our approach utilizes Laplace's approximation of linearising models to approximate the posterior distribution which when combined with optimum approximations of likelihoods, yields an approximation of a closed-form Gaussian expression for PPD that are directly used by acquisition functions.

Our method reduces the need for iterative sampling and lowers computational overhead. The Gaussian approximation derived through linear Laplace facilitates predictive distribution generation without multiple stochastic evaluations. The experiments will be rigorously evaluated on diverse image datasets 4.

2 Possible Extensions

In extending this work, we aim to integrate warm start methods into active learning for expedited training when acquiring new labeled points. Leveraging continual learning techniques, we seek to avoid training models from scratch, enabling the discard of previously trained data points and mitigating training time, computational costs, and data storage concerns.

We also propose optimizing the acquisition cost calculation process through possibly cluster-based strategies. We intend to establish a mapping between data points and the acquisition function output domain, utilizing clustering techniques and continually updating clusters until reaching a critical mass that significantly alters them, triggering a re-clustering process.

Furthermore, we will explore avenues to integrate unlearning with active learning to simulate continual learning with domain shifts, facilitating adaptation within the constraints of continual learning settings.

3 Timeline

04 Feb - 10 Feb	Derivation of Laplace's Approximation of posterior distribution of subnets; Derivation of approximate closed form of posterior predictive of subnets for classification problems
11 Feb - 17 Feb	Datasets and architecture decisions, environment setup and Implementation of model posterior and posterior predictive calculation on 4
03 Mar - 09 Mar	Implementation of multiple acquisition functions using closed form of posterior and probit's approximation, experimentation
10 Mar - 16 Mar	Iterating over feedback and improvements by incorporating suggestions from professor and literature review on account of lacking performance
17 Mar - 23 Mar	Inclusion of furthur improvements like warm-start and integration of unlearning with active learning to a robust continual learning system

4 Specifications

- Gal et al. [2017]: This paper defined the problem statement; The approximate posterior $q^*(\omega)$ have been shown to be used for all acquisition functions which is intractable, and Monte Carlo approximation has been used for score using Monte Carlo Dropout.
- Daxberger et al. [2022]: This paper demonstrates inference over a small subset of model weights in order to obtain accurate predictive posteriors. This can be directly used to obtain the approximate posterior $q^*(\omega)$.
- Datasets to be used: MNIST and ISIC 2016 Melanoma detection as used by Gal et al. [2017]

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