CS577 Project Proposal: Multi-Label Medical Image Classification with the MetaTeacher Method

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***Abstract*—This is our team's proposal for the Deep Learning project in the fall of 2023. We have selected this paper to implement and compare our own appilcations of the image classification tasks, from NeurIPS 2022. Our MAIN REFERENCE is: Wang, Z., Ye, M., Zhu, X., Peng, L., Tian, L., Zhu, Y.(2022). MetaTeacher: Coordinating Multi-Model Domain Adaptation for Medical Image Classification.**

I. Description of the Problem

A. Medical Imaging in Healthcare

Medical imaging serves as an essential diagnostic tool, with an increasing volume of data generated due to advancements in healthcare technology. This abundance of data provides an opportunity to develop sophisticated machine learning models. However, the heterogeneity in imaging data, owing to differences in equipment, acquisition protocols, and other factors, introduces challenges in model generalization. Therefore, while we have sophisticated models using deep learning techniques, we continue to struggle with accuracy on new unseen data.

B. Issue of Domain Variability

A significant challenge in medical image analysis is the domain shift. A model trained on imaging data from one institution (source domain) may not generalize well to data from another institution (target domain) due to inherent differences between the two data-sets. This domain discrepancy necessitates the adoption of domain adaptation techniques, aiming to ensure models are robust to such variations.

C. Coordination Among Multiple Models

In scenarios involving multiple models, each trained on different source domains, the challenge is not just adaptation but also effective coordination. The goal is to aggregate the knowledge from multiple models, ensuring optimal performance on the target domain while avoiding pitfalls like negative transfer.

II. Introduction

A. Exploring the MetaTeacher Approach

The paper we have selected introduces the "Metateacher" method- with multiple teachers and one student that keeps giving feedback- proposing a coordinated multi-model domain adaptation approach for medical image classification. The strategy suggests a systematic way to orchestrate domain adaptation among different models. The objective of this project is to thoroughly understand, implement, and evaluate the "MetaTeacher" approach, assessing its viability and effectiveness in addressing domain adaptation challenges in medical imaging. We would also have the opportunity to work on solving this problem on fairly low-power systems (our laptops) which can give us a benchmark of the time and resources required to implement this research in an everyday setting. (Not all hospitals have a high compute power due to cost and location constraints.)

III. Survey of Related Work

For the application of medical image analysis, there seems to be little recognition for teacher-student based domain adaptation methods- even though the structure of a teacher-student model proposes multiple consistencies to solve the unsupervised domain adaptation problem. Upon survey, there are approaches for shallow and deep UDA that involve domain instance weighting and feature transformation– all these methods require source domain data access.

Now, if we use Semi-supervised domain adaptation (SSDA), we are essentially assuming a small number of labeled samples in the target. This can help with achieving better alignment to the domain.

In summary, MetaTeacher proposes a novel framework that combines multi-teacher and one-student models, and introduces a coordinating weight learning method to adapt each teacher in different directions. It boasts a new problem setting: semi supervised multi-source-free domain adaptation for multi-label medical image classification. This approach is different from previous methods used for comparison in the paper.

We are yet to gain more information on the depth of other work that has been done in this area. However, MetaTeacher's accuracy scores are higher than the current state-of-art techniques. This is what is interesting to us and therefore, we shall be working on testing this approach.

IV. Milestones

A. Preliminary Plan

- Acquiring the data: We propose to train and test a basic model on a subset of the public data used in the paper.

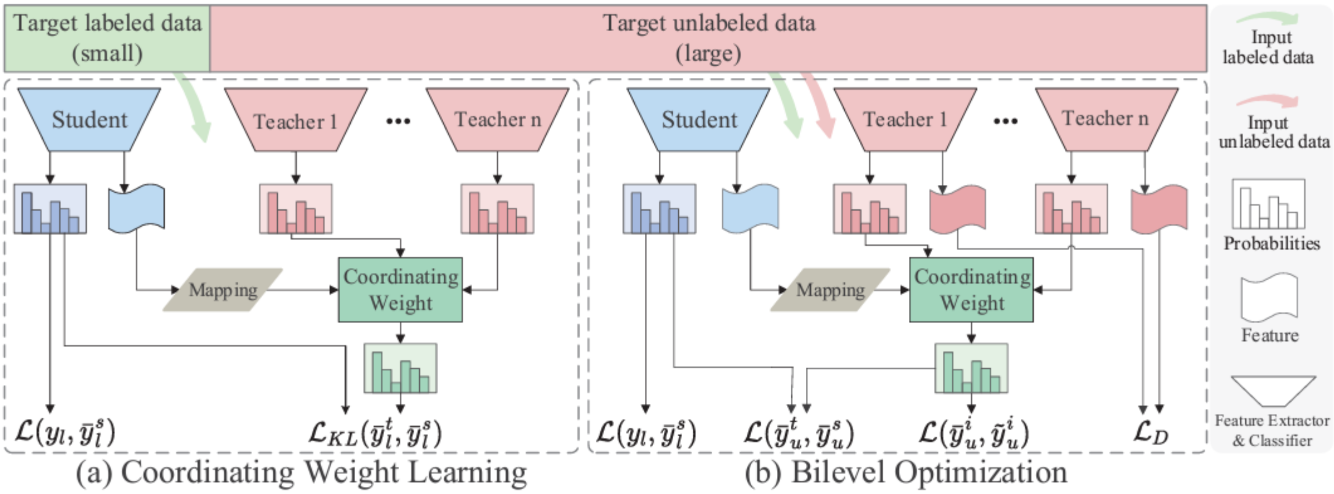

Fig. 1. Diagram of the MetaTeacher architecture, as in paper. (a) Learning the coordinating weight mapping which will be used for updating the teachers. (b)Alternately updating the teacher and student models.

  This would give us an insight to pre-processing and additionally aid in understanding how to create a baseline classifier by applying concepts we have covered in the initial stages of this class (eg. CNN, RNN). Some of the data-sets used:
  - NIH-CXR14 Chest X-Rays
  - MIMIC-CXR X-Rays and Text Reports
  - CheXpert
  - Open-i
- Implementation: For the next few weeks, we will start to break the algorithm down into modules that can be switched out and tuned. We will first begin to build a rudimentary approach to classification.
- Analyzing Performance: We will then essentially compare results and fine-tune our hyper-parameters to see if there is any benchmark speedup we can achieve.

B. Team Contributions and Responsibilities

This section will be updated with every step we take into this project. At present, with respect to this first deliverable:

- Sukhmani: Finding main reference and relevant papers, Project proposal formation on LaTeX, Survey of related work
- Saurabh: Introduction, Planning
- Arpita: Description of the Problem, Goals

References

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