Expose: Framework for Transfer Learning in Neuroimaging

Alpay Yilmaz

March 5, 2022

1 Problem

Machine learning, especially with deep neural networks, continues to gain importance in today's times. Neuroimaging is one section where machine learning gains relevance. Data available from MRI scan's enables many use cases by using machine learning not possible before, e.g. automatic disease classification from MRI scans.

For research with machine learning, a large sample size with uniform data is needed. This is not always the case because of small datasets or different institutions using different scanners/methods of obtaining and recording data which leads to heterogeneous data.

To circumvent the problem of limited and non uniform data, transfer learning is used. Transfer learning focuses on storing knowledge gained while solving one problem and applying it to a different but related problem [6]. Transfer learning approaches have shown to considerably increase performance while still using limited data [8].

But transfer learning for neuroimaging introduces problems. By using transfer learning problems like overfitting or catastrophic forgetting [1] can occur, which have not yet been solved for neuroimaging data. To find a setup that works for a specific dataset/target and/or develop algorithms to solve these problems of transfer learning for neuroimaging, researchers systematically compare different transfer learning algorithms on a variety of different datasets and transfer learning scenarios.

Finding the circumstances where transfer learning works best is time consuming and difficult to reproduce.

2 Goals

To make finding the circumstances where transfer learning works best easier and more straight forward, we propose a framework for transfer learning on neuroimaging data.

The proposed framework should be a Python library using PyTorch. By abstracting several key layers necessary for transfer learning and parameterizing relevant attributes, this framework should accelerate development and increase ease of use while maintaining flexibility and adaptability for research.

3 Related Work

To understand the problem, we will look at multiple research papers on transfer learning and transfer learning frameworks. Much research exists in the field of transfer learning frameworks and should give insight on how a transfer learning framework could look like.

The first one is a comprehensive survey on transfer learning [10]. This survey give us an overview on transfer learning in general, attempts to connect and systematize the existing transfer learning research studies, as well as to summarize and interpret the mechanisms and the strategies of transfer learning in a comprehensive way, which may help us have a better understanding of the current research status and ideas.

One example of research with transfer learning using MRI scans as input is "A Deep Learning-Based Framework for Automatic Brain Tumors Classification Using Transfer Learning" [4]. In it the authors conducts three studies using the proposed framework to classify brain tumors such as meningioma, glioma, and pituitary.

Another research by Armin W. Thomas et al [5] is concentrating on systematically evaluating transfer learning for the application of deep learning models to the decoding of cognitive states (e.g., viewing images of faces or houses) from whole-brain functional Magnetic Resonance Imaging (fMRI) data.

An example of a review for transfer learning in imaging is "Transfer Learning in Magnetic Resonance Brain Imaging: A Systematic Review" [7]. The aim of this review is to identify research directions, gaps in knowledge, applications, and widely used strategies among the transfer learning approaches applied in MR brain imaging.

One example of a transfer learning framework is Co-Transfer [9]. Co-Transfer proposes a new semi-supervised inductive transfer learning framework. Co-Transfer first generates three TrAdaBoost classifiers for transfer learning from the source domain to the target domain, and meanwhile another three TrAdaBoost classifiers are generated for transfer learning from the target domain to the source domain, using bootstraped samples from the original labeled data.

Another framework is EigenTransfer [3]. EigenTransfer proposes a general framework to tackle a variety of transfer learning problems, e.g. cross-domain learning, self-taught learning, etc. The basic idea is to construct a graph to represent the target transfer learning task.

FedHealth is a transfer learning framework for wearable healthcare [2]. FedHealth performs data aggregation through federated learning, and then builds relatively personalized models by transfer learning.

4 Study Project

The study project should contain the following tasks:

4.1 Literature Review for transfer learning

First, we will do a literature review on current transfer learning methods for neuroimaging data. Furthermore, we should look at the current application of these methods in neuroimaging and identifying open research questions regarding transfer learning for neuroimaging data.

4.2 Literature Review for Frameworks

Next we will do a literature review on frameworks for machine learning on images. This should give us an understanding in the creation of well designed frameworks. We should also research existing transfer learning frameworks shown in section "Related Work". Furthermore, analysing the structure of PyTorch, a machine learning framework for Python, should provide us with insight for framework design.

4.3 Documentation of current workflow

Another task is the documentation of the current workflow, which we will use as a basis for the framework creation. We will examine the current machine learning techniques, and focus on transfer learning by using PyTorch. We will take existing code, which is used for transfer learning in neuroimaging, and document all relevant steps.

4.4 Propose Abstractions/Abstraction layers

Next we will document the possible abstractions and abstraction layers. We can use an existing unfinished toolbox for transfer learning in neuroimaging by Marc-Andre Schulz as a baseline. We will identify the current structure of the toolbox and possible problems.

4.5 Evaluation

Evaluation of the framework is an important part of the master thesis. For the evaluation we have multiple possibilities, each with different trade-offs. Some examples include comparing LoC and code complexity with and without using the framework. Another possible method could be a questionnaire for users, though we are limited in available developers. In the study project we should analyse possible methods of evaluation and compare them to each other.

References

[1] Xinyang Chen, Sinan Wang, Bo Fu, Mingsheng Long, and Jianmin Wang. Catastrophic forgetting meets negative transfer: Batch spectral shrinkage for safe transfer learning. *Advances in Neural Information Processing Systems*, 32, 2019.

[2] Yiqiang Chen, Xin Qin, Jindong Wang, Chaohui Yu, and Wen Gao. Fedhealth: A federated transfer learning framework for wearable healthcare. *IEEE Intelligent Systems*, 35(4):83–93, 2020.

[3] Wenyuan Dai, Ou Jin, Gui-Rong Xue, Qiang Yang, and Yong Yu. Eigentransfer: a unified framework for transfer learning. In *Proceedings of the 26th Annual International Conference on Machine Learning*, pages 193–200, 2009.

[4] Arshia Rehman, Saeeda Naz, Muhammad Imran Razzak, Faiza Akram, and Muhammad Imran. A deep learning-based framework for automatic brain tumors classification using transfer learning. *Circuits, Systems, and Signal Processing*, 39(2):757–775, 2020.

[5] Armin W. Thomas, Ulman Lindenberger, Wojciech Samek, and Klaus-Robert Müller. Evaluating deep transfer learning for whole-brain cognitive decoding, 2021.

[6] Lisa Torrey and Jude Shavlik. Transfer learning. In *Handbook of research on machine learning applications and trends: algorithms, methods, and techniques*, pages 242–264. IGI global, 2010.

[7] Juan Miguel Valverde, Vandad Imani, Ali Abdollahzadeh, Riccardo De Feo, Mithilesh Prakash, Robert Ciszek, and Jussi Tohka. Transfer learning in magnetic resonance brain imaging: A systematic review. *Journal of Imaging*, 7(4), 2021.

[8] Karl Weiss, Taghi M Khoshgoftaar, and DingDing Wang. A survey of transfer learning. *Journal of Big data*, 3(1):1–40, 2016.

[9] Zhe Yuan and Yimin Wen. A new semi-supervised inductive transfer learning framework: Co-transfer. *arXiv preprint arXiv:2108.07930*, 2021.

[10] Fuzhen Zhuang, Zhiyuan Qi, Keyu Duan, Dongbo Xi, Yongchun Zhu, Hengshu Zhu, Hui Xiong, and Qing He. A comprehensive survey on transfer learning. *Proceedings of the IEEE*, 109(1):43–76, 2021.