SCHOOL OF COMPUTATION, INFORMATION AND TECHNOLOGY — INFORMATICS

TECHNISCHE UNIVERSITÄT MÜNCHEN

Bachelor's Thesis, Master's Thesis, ... in Informatics

Thesis title

Author

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I confirm that this bachelor's thesis, master's thesis, . . . is my own work and I have documented all sources and material used.

Munich, Submission date Author

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Abstract

Applying techniques from Neural Architecture Search (NAS) to Federated Learning (FL) has been fruitful (remove) in recent years. The combination was identified as a promising research (remove) direction by [Kai+21]. It has yielded methods for finding architectures that deal with the challenges imposed by the FL setting.

Research into NAS has grown rapidly [Whi+23] since it was popularized by [ZL17]; consequently, literature on its application to FL has grown. The last survey on NAS applied to FL compared approaches of four papers [ZZJ21]. Since then, we have identified approximately 50 new papers. This motivates a new systematic survey of the landscape to identify progress and gaps in the literature.

In this thesis, we propose a map of the literature landscape based on the FL challenges they address. We achieve this by systematically evaluating the literature and identifying which challenge it solves.

We refer to the FL challenges described in [McM+17], i.e., non-IID data, limited communication, client heterogeneity, privacy of client data, and break them down into smaller subchallenges — each subchallenge being associated with a pattern in the literature. We include personalized FL [Tan+23] as an additional subchallenge that was not originally posited, but has since drawn the community's attention.

We then analyze how the subchallenges are addressed and focus on the contribution of the used NAS method towards overcoming the subchallenge. For each subchallenge, we keep track of the NAS types used (following [Whi+23], [Avv+25]) and assess whether the underexplored methods are candidates for future research.

Neural Architecture Search

Contents

1 Introduction

Applying Neural Architecture Search (NAS) methods to Federated Learning (FL) is an emerging field of study under active investigation. NAS aims to automate the laborious architecture engineering responsible for so many of the advances made in Deep Learning in recent years. NAS methods have discovered unknown architectures that perform better than handcrafted ones — in several fields of research NAS has produced architectures that improved upon the performance of the state-of-the-art. Federated Learning (FL) is a machine learning method whereby clients collaboratively train a model without sharing their data. This approach aims to enhance the privacy of client data and make training possible where it would otherwise not be due to large data transfer costs. Practicioners expect to make use of NAS methods in the FL setting to achieve state-of-the-art performance. Additionally, NAS methods may be particularily well-suited in finding lightweight architectures by optimizing for both performance and latency — i.e. architectures ideal for deployment in a resource-constrained FL environment. Unfortunately, many NAS methods make assumptions that do not hold in the FL setting. Therefore applying NAS methods in the FL setting requires modification. It is a matter of ongoing research how NAS methods are to be adopted to the FL setting and many different approaches have been suggested.

In fact, over the last 5 years more than 50 papers on the topic have appeared. In most cases, making use of NAS for FL requires designing a framework or system with many components suited to the given use case. The variation between different frameworks and approaches is large, but they tend to be compose of a differing combination of universal components. Most of the approaches in the papers have some degree of overlap in the components they use to apply NAS to the FL setting, with components depending on the challenges of the targeted use case. It is unclear what the most widely used components are, how different components are beneficial towards certain goals and how exactly these components should be defined. Identifying these components along with the direction in which they push a system could allow future research to more easily compose existing components into systems for specific use cases. Furthermore, clarity on the segmentation of a system into components could allow reasoning about the comparison of two systems more effectively.

We therefore propose a detailed analysis of the 50 research papes in order to find these components.

Abbreviations

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