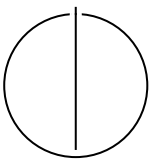
SCHOOL OF COMPUTATION, INFORMATION AND TECHNOLOGY — INFORMATICS

TECHNISCHE UNIVERSITÄT MÜNCHEN

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

Thesis title

Author



SCHOOL OF COMPUTATION, INFORMATION AND TECHNOLOGY — INFORMATICS

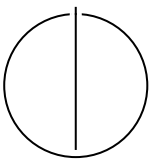
TECHNISCHE UNIVERSITÄT MÜNCHEN

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

Thesis title

Titel der Abschlussarbeit

Author:	Author
Examiner:	Supervisor
Supervisor:	Advisor
Submission Date:	Submission date



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

Acknowledgments

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 (FedNAS). Proposed FedNAS methods differ in their search spaces, targeted clients and optimize for different trade-offs in the FL setting. It is unclear which FedNAS methods are to be used under which circumstances. This Bachelor thesis aims to bring clarity to the field of FedNAS and offers a comprehensive survey and framework analysis of FedNAS methods that aids in selecting FedNAS methods tailored towards a targeted setting.

Federated Learning (FL) is a machine learning method whereby clients collaboratively train a model without sharing their data. This approach enhances the privacy of client data, increases the amount of data available to trainers that would otherwise be locked behind privacy barriers and makes it possible to use massive fleets of devices to train a model [cite Gboard].

NAS aims to automate the laborious architecture engineering process responsible for so many of the advances made in Deep Learning in recent years. In the last ten years, architectures found via NAS occupied the top spot of several benchmarks for 90% of the time [TODO: cite].

Practicioners expect to make use of existing NAS methods in the FL setting to produce architectures that achieve state-of-the-art accuracy. Additionally, a large body of work in NAS has focused on finding smaller, more efficient architectures that still have reasonable accuracy — i.e. architectures ideal for deployment on resource-constrained clients in the FL setting.

However, research in NAS methods has focused on a central NAS setting that relies on assumptions that don't hold for FedNAS [TODO: cite several prominent papers]. [Kai+21] describe the assumptions that need be rethought in the FL setting in detail [TODO: verify] — they include abundance of compute, low latency, relatively consistent latency, high availability of worker nodes and access to the entire dataset and its distribution [TODO: reduce to three most important ones]. This makes most centralized NAS methods unfeasable for direct application as FedNAS. Adopting NAS methods in the FL setting requires adapting them to the FL setting. For example, training a one-shot supernet with a large search space on a set of mobile phones would take weeks or months to complete. Instead, in one appraoch [DLF22], researchers have opted to reduce the compute burden on clients by sending randomly sampled subspaces to

clients for training and applied novel architecture search aggregation techniques. In another [TODO: cite FINCH]. Example: NAS method adapted to deal with non-i.i.d. Example: NAS method made "online" to deal with addition/removal of data

A naive approach to creating a taxonomy for FedNAS might consider a cartesian product of the possible FL settings with NAS methods, but this yields a space relatively sparse of practically relevant combinations.

The increasing amount of papers on this topic leads us to our first research question:
(RQ1) Which FedNAS methods exist?

Reducing training time of a model stands in conflict with Additionally many FedNAS methods are similar and share

Some kind of scoring system for how well FedNAS method for which setting => benchmark?

(RQ2) How can existing FedNAS methods be compared?

To solve RQ2 create a FedNAS taxonmy that uses FL taxonomy + create NAS taxonmy from 1000 papers survey.

(RQ3) Which FedNAS method is suited for which FL setting, what categories of trade-offs become apparent?

on its own:(RQ4) Which trade-off pairings have become apparent?

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 composed of a differing combination of universal components. Most of the approaches 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 existing approaches to applying NAS to FL in this Bachelor's thesis.

Abbreviations

List of Figures

List of Tables

Bibliography

[Avv+25] S. S. P. Avval, N. D. Eskue, R. M. Groves, and V. Yaghoubi. "Systematic review on neural architecture search." In: *Artificial Intelligence Review* 58.3 (Jan. 6, 2025), p. 73. ISSN: 1573-7462. DOI: 10.1007/s10462-024-11058-w.

[DLF22] L. Dudziak, S. Laskaridis, and J. Fernandez-Marques. *FedorAS: Federated architecture search under system heterogeneity*. 2022. arXiv: 2206.11239 [cs.LG].

[Kai+21] P. Kairouz, H. B. McMahan, B. Avent, A. Bellet, M. Bennis, A. N. Bhagoji, K. Bonawitz, Z. Charles, G. Cormode, R. Cummings, R. G. L. D'Oliveira, H. Eichner, S. E. Rouayheb, D. Evans, J. Gardner, Z. Garrett, A. Gascón, B. Ghazi, P. B. Gibbons, M. Gruteser, Z. Harchaoui, C. He, L. He, Z. Huo, B. Hutchinson, J. Hsu, M. Jaggi, T. Javidi, G. Joshi, M. Khodak, J. Konečný, A. Korolova, F. Koushanfar, S. Koyejo, T. Lepoint, Y. Liu, P. Mittal, M. Mohri, R. Nock, A. Özgür, R. Pagh, M. Raykova, H. Qi, D. Ramage, R. Raskar, D. Song, W. Song, S. U. Stich, Z. Sun, A. T. Suresh, F. Tramèr, P. Vepakomma, J. Wang, L. Xiong, Z. Xu, Q. Yang, F. X. Yu, H. Yu, and S. Zhao. *Advances and Open Problems in Federated Learning*. 2021. arXiv: 1912.04977 [cs.LG].

[McM+17] B. McMahan, E. Moore, D. Ramage, S. Hampson, and B. A. y Arcas. "Communication-efficient learning of deep networks from decentralized data." In: *Proceedings of the 20th international conference on artificial intelligence and statistics*. Ed. by Z. J. Singh Aarti. Vol. 54. Proceedings of machine learning research. PMLR, Apr. 2017, pp. 1273–1282.

[Tan+23] A. Z. Tan, H. Yu, L. Cui, and Q. Yang. "Towards personalized federated learning." In: *IEEE Transactions on Neural Networks and Learning Systems* 34.12 (2023), pp. 9587–9603. DOI: 10.1109/TNNLS.2022.3160699.

[Whi+23] C. White, M. Safari, R. Sukthanker, B. Ru, T. Elsken, A. Zela, D. Dey, and F. Hutter. *Neural architecture search: Insights from 1000 papers*. 2023. arXiv: 2301.08727 [cs.LG].

[ZL17] B. Zoph and Q. V. Le. *Neural architecture search with reinforcement learning*. 2017. arXiv: 1611.01578 [cs.LG].

[ZZJ21] H. Zhu, H. Zhang, and Y. Jin. "From federated learning to federated neural architecture search: a survey." In: *Complex and Intelligent Systems* 7.2 (Apr. 2021), pp. 639–657. ISSN: 2198-6053. DOI: 10.1007/s40747-020-00247-z.