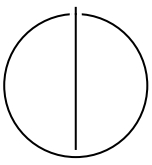
SCHOOL OF COMPUTATION, INFORMATION AND TECHNOLOGY — INFORMATICS

TECHNISCHE UNIVERSITÄT MÜNCHEN

Bachelor's Thesis in Informatics

Adaptation Techniques for using NAS Methods in the FL Setting

Max Coetzee



SCHOOL OF COMPUTATION, INFORMATION AND TECHNOLOGY — INFORMATICS

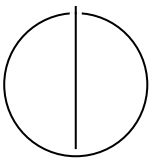
TECHNISCHE UNIVERSITÄT MÜNCHEN

Bachelor's Thesis in Informatics

Adaptation Techniques for using NAS Methods in the FL Setting

Titel

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



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

Munich, Submission date Max Coetzee

Acknowledgments

Abstract

[TODO: overhaul]

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 [8]. It has yielded methods for finding architectures that deal with the challenges imposed by the FL setting.

Research into NAS has grown rapidly [15] since it was popularized by [18]; consequently, literature on its application to FL has grown. The last survey on NAS applied to FL compared approaches of four papers [17]. 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 [18], 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 [13] 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 [15], [1]) and assess whether the underexplored methods are candidates for future research.

Neural Architecture Search

Contents

1 Introduction

Both Neural Architecture Search (NAS) and Federated Learning (FL) have made significant progress independently in the past decade, and both are increasingly adopted in practice. To benefit from the advantages of NAS methods in FL, researchers have started combining them by using NAS in the FL setting.

Neural Architecture Search (NAS) automates the process of engineeering neural network architectures for Deep Learning application domains [3]. This stands in contrast to the traditional, labourious approach to applying Deep Learning. Traditionally a team of domain experts and Deep Learning experts engineer a well-suited architecutre based on expert knowledge and trial-and-error.

NAS does not only reduce manual effort, but can also be used to find architectures that perform better than architectures humans have designed for specific application domains [19] [12] [6] [14].

Federated Learning (FL) is a machine learning method whereby *clients* collaboratively train a model without sharing their data. Weight updates to the shared model are coordinated by a central *server*.

FL was invented by Google to enable privacy-preserving usage of the increasing volume of privacy-sensitive data stored on edge devices. Before FL was invented, it was typical for distributed privacy-sensitive data to either not be used at all for machine learning or it was collected in a central location for training — creating the risk of a major breach by malicious actors.

Although FL was originally targeted towards machine learning on data distributed across edge devices, FL practicioners discovered that FL is also useful for training on distributed data silos (at the organisational level). The former is referred to as *cross-device* FL and the latter as *cross-silo* FL. Both kinds of FL have since been adopted for various ML tasks in production systems by organisations like Google [16], Apple [7] and Owkin [10].

By using NAS in the FL setting, practicioners reap generic benefits of NAS mentioned above as well as benefits specific to the FL setting:

- A large body of work in NAS focuses on finding architectures with minimal inference latency that still have reasonable accuracy [15]. Such lightweight architectures are ideal for deployment on the resource-constrained clients in the cross-device FL setting.

- [8] note that predefined architectures may not be an optimal choice for FL. Since client data is not visible to model developers, a predefined architecture selected by model developers may contain components redundant for generalizing well from certain client data sets.
- Predefined architectures may perform poorly on another prevalent characteristic of the FL setting: data that is not independently and identically distributed (non-i.i.d.).

However, Using NAS in the FL setting is not straightforward. Research on NAS methods has traditionally focused on a centralized setting as opposed to the distributed FL setting. This makes many NAS methods unfeasable for direct application in the FL setting, because NAS methods designed for the centralized setting can make several assumptions about the search process that do not hold in the FL setting (see Table 1). Instead, practicioners need to adapt NAS methods to their FL setting, giving rise to *Federated Neural Architecture Search* [5] (FedNAS) methods.

Assumptions that hold for NAS in the centralized setting, but do not hold for the FL setting, make it challenging to adapt NAS methods to the FL setting. Table 1 illustrates these discreptencies as well as the resulting challenges faced by FedNAS methods. Depending on the FedNAS use case, some centralized assumptions are violated to a larger extent than others. For example, [TODO: illustrate how two different use cases violate a centralized NAS setting to a different degree].

Assumption in Centralized Setting	Reality i
Assumption in Centralized Setting	Reality i
Worker nodes' hardware is homogeneous.	Clients' hardware varies significantly. More pronoun
Every worker node can access all training data.	Clients can only a
Training data is gathered at a central location.	Training data is distribu
The training data is drawn from the same distribution.	Each client draws training d
Worker nodes are equally available.	Some clients are more fre
"Worker nodes communicate over high-bandwidth, low-latency links.	Clients typically communicate with the cent
Worker nodes are high-end machines with powerful CPUs, GPUs and large RAM.	Clients are edge devices wit
All worker nodes participate in each iteration.	Only a subset of clients par
Worker nodes are inside the same trust domain.	All participating parties (i.e. the central server an
Worker nodes reliably take part in the search process.	Clients can drop out of a communication round

Table 1.1: Discreptencies between NAS in the centralised setting and the FL setting and the resulting FedNAS challenges. *Worker nodes* perform the architecture search in the centralized setting. A *server* and *clients* perform the search in the FL setting.

FedNAS practicioners need to choose which set of challenges to address for their particular use case, since a) the relevance of overcoming challenges depends on the degree to which each of the centralized NAS assmptions are violated and b) overcoming one challenge typically comes at the expense of neglecting others. For example, consider a use case in which a certain set of clients have a lot of useful data, but constantly drop out of communication rounds. Practicioners can choose to prioritize either avoiding delays due to stragglers or waiting for stragglers to ensure model fairness.

FedNAS practicioners have diverse use cases for FedNAS methods and can choose from a wide variety of subsets of challenges to overcome. Consequentially, a growing body of FedNAS methods has been created by practicioners. To this end an overview of FedNAS methods would be useful to practicioners, since it would help practicioners find FedNAS methods for their use case or aid them in reusing knowledge for creating new FedNAS methods. However, no such overview exists.

Researchers have already conducted several literature surveys on FedNAS methods [17] [9] [4]. [17] is an early survey that characterises FedNAS methods on the whole. The survey differentiates FedNAS methods into offline vs. online architecture search and single- vs. multi-objective methods. [9] gives a brief overview of the FedNAS landscape at the time as part of larger survey into combining NAS and Hyperparameter Optimization. It highlights the major scientific contributions each FedNAS method has made. [4] provides an overview of how multi-objective optimizaiton can be integrated into FL in general and includes sections that discuss how this is done specifically for FedNAS methods.

Existing literature surveys only analyze a fraction of the FedNAS literature. [17] and [9] are limited by the small amount of FedNAS literature available at the time. The volume of proposed FedNAS methods has grown substantially since. [4] only analyzes FedNAS methods that make use of multi-objective optimization, thereby excluding a large share of the literature.

None of the existing literature surveys identify individual techniques employed by FedNAS methods and analyze how they deal with FedNAS challenges. We introduce the term *adaptation techniques* to refer to these techniques. For example, naively using a supernet-based NAS method in the cross-device FL setting by allowing all clients to evaluate any candidate architecture, regardless of the computational footprint, would signficantly lengthen the search process, because low end devices end up evaluating computationally expensive architectures. This embodies the client heterogeneity challenge, and one FedNAS method [2] overcomes it by using the following adaptation technique: The subnet sampling method of X NAS method is adapted, such that only subnets within the client's training budget get selected for training.

None of the existing literature surveys identify adaptation techniques used by FedNAS methods and analyze how they overcome FedNAS challenges. [17] and [9] only

analyse and summarise FedNAS methods on the whole. [4] only analyses how multi-objective optimization is used within two [TODO: verify] FedNAS methods. This leaves adaptation techniques scattered throughout the literature and makes it hard for practicioners to re-use them for creating new FedNAS methods and decide which adaptation techniques could be useful for their use case.

As mentioned above, the lack of an exhaustive overview of FedNAS methods, the adaptation techniques they use and how these adaptation techniques overcome FedNAS challenges, leads us to our research question:

(RQ) **How do adaptation techniques described in the literature deal with FedNAS challenges?**

To answer our research question, we perform a systematic literature review of adaptation techniques used by 58 FedNAS methods and their effects on overcoming FedNAS challenges. We divide our approach into 5 steps:

1. **Literature Selection:** We follow the guidelines and flow diagrams provided by PRISMA 2020 [11] for inclusion and exclusion of papers and perform forward and backwards citation searching. Each paper contains one or more FedNAS methods.

2. **Adaptation Technique Extraction:** Once the set of included papers is fixed, we analyse each paper individually, extracting the adaptation techniques it uses and summarising them.

3. **Merge Highly-Similar Adaptation Techniques:** We then merge conceptually highly-similar adaptation techniques into a single representative adaptation technique.

4. **Categorise Adaptation Techniques:** After merging, we categorise the adaptation techniques based on conceptual similarity and deliver a taxonomy of adaptation techniques.

5. **Map FL Challenge Types onto Adaptation Techniques:** Next, we discuss how each adaptation technique works towards, against, or does not affect overcoming each of the FL challenge classes and provide a table with an overview as an end result.

Our review organizes the n extracted adaptation techniques into a single consolidated body of knowledge that gives FedNAS practicioners an overview of the FedNAS landscape through the lens of adaptation techniques. Compared to existing surveys,

our review is exhaustive of the FedNAS landscape at this point in time. Additionally, our discussions on each adaptation technique helps practicioners find and choose FedNAS methods relevant to their use case or construct new FedNAS methods by re-using appropriate adaptation techniques.

In chapter 2 we cover the background required for this thesis and related work. In chapter 3 we describe the method with which we conduct our literature review in detail. In chapter 4 we explain our process of including FedNAS literature and give an overview of the included FedNAS literature. In chapter 5 we present our taxonomy of adaptation techniques and explain the effect of adaptation techniques on challenge classes. In Chapter 6 we conduct a discussion about our work. Chapter 7 contains our conclusion.

2 Background and Related Work

NAS is contained entirely in the 5th step of the FL pipeline as described in [8].

3 Method

1. **Literature Selection:** We follow the guidelines and flow diagrams provided by PRISMA 2020 [11] for inclusion and exclusion of papers and perform forward and backwards citation searching. Each paper contains one or more FedNAS methods.

2. **Adaptation Technique Extraction:** Once the set of included papers is fixed, we analyse each paper individually, extracting the adaptation techniques it uses and summarising them.

3. **Merge Highly-Similar Adaptation Techniques:** We then merge conceptually highly-similar adaptation techniques into a single representative adaptation technique.

4. **Categorise Adaptation Techniques:** After merging, we categorise the adaptation techniques based on conceptual similarity and deliver a taxonomy of adaptation techniques.

5. **Map FL Challenge Types onto Adaptation Techniques:** Next, we discuss how each adaptation technique works towards, against, or does not affect overcoming each of the FL challenge classes and provide a table with an overview as an end result.

4 Reviewed Literature

5 Adaptation Techniques

6 Discussion

7 Conclusion

Abbreviations

List of Figures

List of Tables

Bibliography

[1] 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.

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

[3] T. Elsken, J. H. Metzen, and F. Hutter. "Neural architecture search: A survey." In: *Journal of Machine Learning Research* 20.55 (2019), pp. 1–21.

[4] M. Hartmann, G. Danoy, and P. Bouvry. *Multi-objective methods in Federated Learning: A survey and taxonomy*. 2025. arXiv: 2502.03108 [cs.LG].

[5] C. He, M. Annavaram, and S. Avestimehr. *Towards Non-I.I.D. and invisible data with FedNAS: Federated deep learning via neural architecture search*. 2021. arXiv: 2004.08546 [cs.LG].

[6] A. Howard, M. Sandler, B. Chen, W. Wang, L.-C. Chen, M. Tan, G. Chu, V. Vasudevan, Y. Zhu, R. Pang, H. Adam, and Q. Le. "Searching for MobileNetV3." In: *2019 IEEE/CVF international conference on computer vision (ICCV)*. Los Alamitos, CA, USA: IEEE Computer Society, Nov. 2019, pp. 1314–1324. DOI: 10.1109/ICCV.2019.00140.

[7] A. Ji, B. Bandyopadhyay, C. Song, N. Krishnaswami, P. Vashisht, R. Smiroldo, I. Litton, S. Mahinder, M. Chitnis, and A. W. Hill. *Private federated learning in real world application – a case study*. 2025.

[8] 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].

[9] S. Khan, A. Rizwan, A. N. Khan, M. Ali, R. Ahmed, and D. H. Kim. "A multi-perspective revisit to the optimization methods of Neural Architecture Search and Hyper-parameter optimization for non-federated and federated learning environments." In: *Computers and Electrical Engineering* 110 (2023), p. 108867. ISSN: 0045-7906. DOI: https://doi.org/10.1016/j.compeleceng.2023.108867.

[10] M. Oldenhof, G. Ács, B. Pejó, A. Schuffenhauer, N. Holway, N. Sturm, A. Dieckmann, O. Fortmeier, E. Boniface, C. Mayer, A. Gohier, P. Schmidtke, R. Niwayama, D. Kopecky, L. Mervin, P. C. Rathi, L. Friedrich, A. Formanek, P. Antal, J. Rahaman, A. Zalewski, W. Heyndrickx, E. Oluoch, M. Stößel, M. Vančo, D. Endico, F. Gelus, T. Boisfossé, A. Darbier, A. Nicollet, M. Blottière, M. Telenczuk, V. T. Nguyen, T. Martinez, C. Boillet, K. Moutet, A. Picosson, A. Gasser, I. Djafar, A. Simon, Á. Arany, J. Simm, Y. Moreau, O. Engkvist, H. Ceulemans, C. Marini, and M. Galtier. *Industry-scale orchestrated federated learning for drug discovery*. 2022. arXiv: 2210.08871 [cs.LG].

[11] M. J. Page, J. E. McKenzie, P. M. Bossuyt, I. Boutron, T. C. Hoffmann, C. D. Mulrow, L. Shamseer, J. M. Tetzlaff, E. A. Akl, S. E. Brennan, R. Chou, J. Glanville, J. M. Grimshaw, A. Hróbjartsson, M. M. Lalu, T. Li, E. W. Loder, E. Mayo-Wilson, S. McDonald, L. A. McGuinness, L. A. Stewart, J. Thomas, A. C. Tricco, V. A. Welch, P. Whiting, and D. Moher. "The PRISMA 2020 statement: an updated guideline for reporting systematic reviews." In: *BMJ* 372 (2021). DOI: 10.1136/bmj.n71. eprint: https://www.bmj.com/content/372/bmj.n71.full.pdf.

[12] E. Real, A. Aggarwal, Y. Huang, and Q. V. Le. "Regularized evolution for image classifier architecture search." In: *Proceedings of the thirty-third AAAI conference on artificial intelligence and thirty-first innovative applications of artificial intelligence conference and ninth AAAI symposium on educational advances in artificial intelligence*. AAAI'19/IAAI'19/EAAI'19. Honolulu, Hawaii, USA: AAAI Press, 2019. ISBN: 978-1-57735-809-1. DOI: 10.1609/aaai.v33i01.33014780.

[13] 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.

[14] M. Tan and Q. Le. "EfficientNetV2: Smaller models and faster training." In: *Proceedings of the 38th international conference on machine learning*. Ed. by M. Meila and T. Zhang. Vol. 139. Proceedings of machine learning research. PMLR, July 2021, pp. 10096–10106.

[15] 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].

[16] T. Yang, G. Andrew, H. Eichner, H. Sun, W. Li, N. Kong, D. Ramage, and F. Beaufays. *Applied federated learning: Improving google keyboard query suggestions*. 2018. arXiv: 1812.02903 [cs.LG].

[17] 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.

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

[19] B. Zoph, V. Vasudevan, J. Shlens, and Q. V. Le. "Learning transferable architectures for scalable image recognition." In: *2018 IEEE/CVF conference on computer vision and pattern recognition (CVPR)*. Los Alamitos, CA, USA: IEEE Computer Society, June 2018, pp. 8697–8710. DOI: 10.1109/CVPR.2018.00907.