TUM

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

TUM

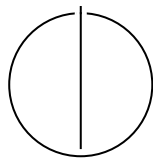## SCHOOL OF COMPUTATION, INFORMATION AND TECHNOLOGY — INFORMATICS

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

Research into NAS has grown rapidly [20] since it was popularized by [23]; consequently, literature on its application to FL has grown. The last survey on NAS applied to FL compared approaches of four papers [22]. 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 [23], 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 [18] 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 [20], [2]) 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. To benefit from the advantages of NAS methods in FL, researchers have started combining them by using NAS in FL [8] [5] [14].

NAS automates the process of engineering neural network architectures for Deep Learning application domains [6]. This saves manual labour compared to the traditional approach driven by a team of experts.

FL is a machine learning method whereby *clients* collaboratively train a model without sharing their local data [15]. FL enables privacy-preserving machine learning on the increasing volume of privacy-sensitive, distributed data and avoids centrally collecting client data.

Using NAS in FL reduces manual effort for practitioners and can be used to mitigate the issues with predefined architectures in FL. Since client data is invisible to practitioners and client data distributions as well as client hardware vary in FL, predefined architectures are often suboptimal. Some NAS methods can be used to tailor architectures to clients and improve FL training effectivenes [9] [16] [21].

Despite the potential, NAS research has focused on the traditional centralised setting as opposed to the FL setting. This makes many NAS methods infeasible for direct application in FL, because centralised NAS can make several assumptions about the search process that do not hold in the FL setting. Each assumption discrepancy creates a *challenge* for using NAS in FL and developers have created *adaptation techniques* for overcoming them. Applying adaptation techniques to NAS methods results in *Federated Neural Architecture Search methods* (FedNAS methods) [8].

For example, one challenge arises from the fact that centralised NAS can assume worker nodes are computationally powerful, whereas clients in most FL settings are not. Since most centralised NAS methods place large computational burdens on worker nodes, practitioners using these NAS methods in FL without modification would experience detrimental search completion times. To combat this, FedNAS developers have created adaptation techniques for reducing the computational burden on individual clients in FedNAS methods [5] [19] [10]. This typically involves reducing the overall computational work and splitting it up into smaller units, which results in a challenge, because the implementation of the resulting FedNAS method tends to be complex.

The subset of challenges faced by FedNAS methods depend on the specific FL setting, which can differ in many aspects [12]. The literature identifies two major classes of FL settings: the *cross-device* class, wherein clients are edge devices, and the *cross-silo* class wherein clients are entire organisations, but even within these classes there is significant variation in the setting parameters. Each FL setting violates centralised NAS assumptions to a different extent, making some challenges more relevant to them than others. For example, for FL settings in the cross-silo class, clients can be expected to be equipped with GPUs, making the challenge described above less relevant.

The literature on adaptation techniques is fragmented and FedNAS methods often lack clarity regarding the targeted FL setting and challenges addressed. As a result, extending and re-using existing techniques remains difficult. This poses a problem for FedNAS developers, since they need to trade off which challenges to address for their targeted FL setting without a clear overview of adaptation techniques that would be useful for that setting. Prior literature surveys [22] [13] [7] summarise FedNAS methods on the whole, but do not dissect them in a manner that allows FedNAS developers to decide on the parts they wish to re-use. To aid the development of new FedNAS methods, we set out to answer our research question:

What challenges arise from different FL settings for FedNAS methods and which adaptation techniques address them in the literature?

To tackle our research question, we conduct a systematic literature review of papers that present FedNAS methods. We employ grounded theory and the methodology from [11]. For our review we consider papers that make modifications to NAS methods motivated by the FL setting.

We define a set of fine-grained parameters to characterise the targeted FL setting of each FedNAS method based on observations of varying setting parameters in the literature. With the help of this characterisation, we identify the violated centralised NAS assumptions and catalog the challenges that arise from them. Next, we extract unrefined adaptation techniques from the FedNAS methods and iteratively refine and merge them to obtain a set of collectively exhaustive adaptation techniques. We analyse how each adaptation technique works towards, against, or does not affect each challenge, and present our findings in the form of a discussion for each adaptation technique and as an overview a table.

Our review aims to support the creation of new FedNAS methods by developers. By identifying the source of challenges and elaborating them, we provide clarity on the expected challenges for a targeted FL setting. Based on the expected challenges, FedNAS developers can use our overview of adaptation techniques to guide the design of new FedNAS methods and decide whether to re-use existing techniques, extend

them or develop new ones.

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 and give an overview of the included literature. In Chapter 4 we highlight the challenges with FedNAS and how they arise from different FL settings. In Chapter 5, we describe the adaptation techniques we found and how they overcome challenges. 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 [12].

2.1 Neural Architecture Search

2.2 Federated Learning

2.3 Federated Neural Architecture Search

3 Method

[TODO: overhaul to include method for identifying challenges and FL settings] - targeted FL setting can be stated directly, indirectly or must be inferred from experimental setup

We use various techniques from [3] and lean on parts of the methodology of [11] to perform a systematic literature review.

1. **Literature Selection:** We follow the guidelines and flow diagrams provided by PRISMA 2020 [17] for inclusion and exclusion of papers and perform forward and backwards citation searching. We identify 58 papers that present FedNAS methods. Each paper contains one or more FedNAS methods.

2. **Unrefined Adaptation Technique Extraction:** Once the set of included papers is fixed, we perform open coding on each FedNAS method to extract unrefined adaptation techniques. Any modification to a NAS method that is explicitly motivated by the federated setting is treated coded as one unrefined adaptation technique.

3. **Adaptation Techniques Coneceptualization:** We iteratively refine and merge unrefined adapatation techniques in an axial coding step to obtain a coherent set of adaptation techniques that are mutually exclusive and collectively exhaustive. Unrefined adaptation techniques with conceptually highly-similar mechanisms are merged into a single representative adaptation technique.

4. **Categorise Adaptation Techniques:** After merging, in a second axial coding step, we cluster adaptation techniques based on a) the FedNAS challenges they address and b) the conceptual similarity of their mechanisms. As a result, we obtain a taxonomy of adaptation techniques.

5. **Discuss FedNAS Challenges for Adaptation Techniques:** We discuss how each adaptation technique works towards, against, or does not affect overcoming each of FedNAS challenges.

6. **Produce Table Overviews:** Finally, we create two tables that practicioners can use to make decisions about FedNAS methods for their use case.

The first table contains a coded vector of effects over the FedNAS challenges for each *FedNAS method*. The effects per FedNAS method are the result of the effects of its adaptation techniques in aggregate. Practicioners can use this table to decide which FedNAS method suits their use case or if their use case would benefit from a new FedNAS method.

The second table table contains a coded vector of effects over the FedNAS challenges for each *adaptation technique* based on the prior discussion. If practicioners need to create new FedNAS methods, they can use this table to choose existing adaptation techniques relevant to the set of FedNAS challenges they need to address for their use case.

3.1 Reviewed Literature

add some overview and statistics about the literature

4 Challenges for FedNAS

Assumption in Centralised Setting	Reality in FL Setting	Resulting FedNAS Challenge Description	FedNAS Challenge Name
Worker nodes' hardware is homogeneous.	Clients' hardware varies significantly. More pronounced in the cross-device setting than the cross-silo setting.	FedNAS methods need to be heterogeneity-aware; otherwise, the search will be delayed by low-end devices or leave high-end devices waiting in idle most of the time.	Hardware Heterogeneity
Worker nodes communicate over high-bandwidth, low-latency links.	Clients typically communicate with the central server over high-latency and low-bandwidth connections.	FedNAS must be communication-efficient; otherwise, exchanging model weights and architecture parameters becomes a bottleneck during the search process.	Limited Networking Capabilities
Worker nodes are high-end machines with powerful CPUs, GPUs, and large amounts of RAM.	Clients are edge devices with few computational resources.	The computational burden placed on clients by a NAS method needs to be adjusted such that the architecture search takes place within an acceptable time frame. This can involve splitting up computational work, usually done on single worker nodes, amongst multiple clients, making the implementation complex.	Limited Computational Resources
Training data is gathered at a central location.	Training data is distributed unevenly across clients	Since some clients have more data than others, FedNAS methods must ensure that these clients are not overrepresented in the searched architecture.	Unbalanced Client Data

The training data is drawn from the same distribution.	Each client draws training data from their own distribution.	FedNAS methods need to be robust with respect to non-i.i.d. data, which makes evaluating and ranking candidate architectures noisier than in the centralised setting.	Non-I.I.D. Training Data
Worker nodes are equally available.	Some clients are more frequently available than others.	FedNAS methods must prevent the search from being dominated by the most frequently available clients; otherwise, the resulting architecture will be biased towards them.	Variable Client Availability
All worker nodes participate in each iteration.	Only a subset of clients participates in each iteration of the search.	FedNAS methods must ensure that a realistic sample of the client population is represented in the architecture search and address high-variance performance estimates, as candidate architectures are evaluated on changing subsets of clients.	Client Participation
Worker nodes are inside the same trust domain.	All participating parties (i.e. the central server and clients) can consider another potentially malicious.	FedNAS methods must address attacks from participating parties, such as architecture parameter poisoning during the search process.	Security
Worker nodes consistently participate in the search process.	Clients can drop out of a communication round at any time, and completion times of epochs vary.	FedNAS methods need to handle client dropouts and stragglers, since interrupted or delayed evaluations of candidate architectures can slow down or destabilise the search process.	Client Reliability

Model accuracy is more important than model resource consumption in selecting architectures.	Model accuracy needs to be traded for model resource consumption in selecting architectures.	Models trained in FL tend to be deployed on the same resource-constrained clients they are trained on. Therefore FedNAS methods need to optimise the architecture of the trained model w.r.t. resource constraints.	Model Resource Constraints

Table 4.1: Discrepancies between NAS in the centralised setting and the FL setting and the resulting FedNAS challenges. *Worker nodes* perform the architecture search in the centralised setting, whereas a *server* and *clients* perform the search in the FL setting. The challenges are based to some extent on previously identified challenges in the FL setting in general [15] [12] [4] [1].

5 Adaptation Techniques

5.1

6 Discussion

7 Conclusion

Abbreviations

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