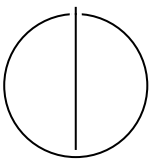
SCHOOL OF COMPUTATION, INFORMATION AND TECHNOLOGY — INFORMATICS

TECHNISCHE UNIVERSITÄT MÜNCHEN

Bachelor's Thesis in Informatics

Adaptation Techniques for using NAS Methods in the FL Setting

Max Coetzee



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Titel

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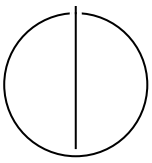

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Munich, Submission date Max Coetzee

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

Research into NAS has grown rapidly [17] since it was popularized by [20]; consequently, literature on its application to FL has grown. The last survey on NAS applied to FL compared approaches of four papers [19]. 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 [20], 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 [15] 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 [17], [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, 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 [5]. 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 [21] [14] [7] [16].

Federated Learning (FL) is a machine learning method whereby clients collaboratively train a model without sharing their data. Clients train a shared model on their local data and coordinate weight updates to the shared model via a central server.

FL was originally invented by Google to enable the usage of the increasing volume of privacy-sensitive data stored on edge devices, but distributed data silos (at the organisational level) containing privacy-sensitive data have become another use case. The former is referred to as the *cross-device* FL setting and the latter as the *cross-silo* FL setting. Before FL, it was typical for both kinds of 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. FL has been adopted for various ML tasks in production systems by organisations like Google [18], Apple [8] and Owkin [12].

By using NAS in the FL setting, practicioners not only benefit from the generic benefits of NAS mentioned above, but from several advantages specific to the FL setting:

- A large body of work in NAS focuses on finding smaller architectures with reduced inference latency that still have reasonable accuracy [17]. Such lightweight architectures are ideal for deployment on the resource-constrained clients in the cross-device FL setting.

- [9] 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.).

Using NAS in the FL setting is not straightforward. Research on NAS methods focuses on a centralized setting as opposed to the distributed FL setting. This makes most NAS methods unfeasable for direct application in the FL setting, because NAS methods designed for the centralized setting can make several assumptions about the architecture search process that do not hold in the FL setting.

Each assumption that does not hold for architecture search process in the FL setting, but holds for the centralized training process, results in a class of challenges related to the discreptancy. Table 1 shows the discreptencies in assumptions about the training environment between the centralized and FL setting.

In the FL setting, several assumptions made in the centralized do not hold NAS methods can make assumptions about the training process that simplifies

When used in a centralized setting, NAS methods can assume i) that worker nodes have high availability, ii) that worker nodes have access to the same amount of computational resources iii) that worker nodes have similar low ii) that the entire training dataset can be accessed, iii) that the distribution of the training data can be inferred, etc. These assumptions do not hold for the FL setting, making most NAS methods unfeasable for direct application in the FL setting. Instead, practicioners need to adapt NAS methods to the FL setting, giving rise to what we shall call *FedNAS* methods.

FedNAS methods face a set of challenges similar to the challenges faced by performing FL in general. Following is a list of previously identified challenges [11] [9] [3] [1]:

1. **Client Hardware Heterogeneity**: The variance in computational resources available to clients is large. The variance tends to be particularily pronounced in the cross-device setting.

   For many use cases in the cross-device setting, a large variance in the amount of computational resources available to clients and variance in the amount and distribution of data on clients can be expected. This makes it challenging to use conventional NAS methods that would expect each client to be able to run the same amount of the architecture search. Some clients may not be able to contribute to searching architectures that are computationally demanding, while

others may sit idle waiting for slower devices to finish a communication round. may not be able to contribute, because they have too little data.

2. **Client Data Heterogeneity**: - Unbalanced Data - Non-I.I.D. Data
3. **Model Fairness**: - bias As the aforementioned challenge notes, clients in the cross-device setting are data and resource heterogenous. Clients with more compute resources may participate in communication rounds more often, biasing the shared models towards their data.
4. **Client's Limited Networking Capabilities**: Some NAS methods train large supernetworks. To train a supernetwork in FL, weight updates for the supernetwork need to be sent from each client. This poses a challenge for the cross-device setting, clients have high network latency and low bandwith.
5. **Client's Limited Hardware**: Clients in the cross-device FL setting typically do not have enough computation resources to train large neural networks.
6. **Client Selection**: - some clients contribute more than others, but only using them leads to bias -> how to trade off which client to select during communication round

   clients contribute different amounts of information towards training the shared model, it's hard to select the right clients for a communication round and select clients that will be available for the next communication round
7. **Privacy of Client Data**: - Architecture parameters can leak things about the data, how to mitigate attack?
8. **Fault-Tolerance**: - invidual client failures, network failures clients are not always available and stragglers need to be dealt with
9. **Selecting The Location where the Search Happens**:

As [19] and [6] note, FedNAS is an inherently multi-objective optimization problem. Each FedNAS method employs several *adaptation techniques* dependant on a) the type of NAS method it adapts and b) the class of challenges the FedNAS method aims to overcome. For example, naively using a supernet-based NAS method in the cross-device FL setting by having each client train the entire supernet, would result in detrimental completion times. This embodies the computational efficiency challenge class, and one FedNAS method [4] overcomes it by *adapting* the subnet sampling process of X NAS method, such that only subnets within the client's training budget get selected for training.

- scenarios for which a FedNAS method exists that suits a problem Practicioners use existing FedNAS methods to solve a problem.

create new FedNAS methods, either to adapt new NAS methods to the FL setting or to adapt NAS methods in new ways to overcome different sets of challenge classes. To this end, it is useful to use existing literature on FedNAS methods and avoid re-inventing adaptation techniques for overcoming each of the challenge classes. A considerable amount of literature on FedNAS methods has appeared in recent years, resulting in a large number of novel adaptation techniques. Unfortunately, adaptation techniques are scattered throughout the increasingly large volume of FedNAS literature, putting a burden on researchers intersted in re-using them for new FedNAS methods.

There have been prior literature surveys on FedNAS methods [19] [10] [6]. [19] 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. [10] gives a brief overview of the FedNAS landscape at the time, highlighting the major contributions each FedNAs method has made. [6] 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.

Prior literature surveys only analyze a fraction of the FedNAS literature. [19] and [10] are limited by the small amount of FedNAS literature available at the time. The volume of proposed FedNAS methods has grown substantially since. [6] only analyzes FedNAS methods that make use of multi-objective optimization (MOO), thereby excluding a large share of the literature.

None of the prior literature surveys provide a consolidated body of knowledge that can inform researchers on adaptation techniques used by FedNAS methods. [19] and [10] only analyse and summarise FedNAS methods on the whole. [6] analyses how MOO is used within FedNAS methods. The prior surveys do not identify individual adaptation techniques responsible for overcoming sets of challenge classes.

- users can pick FedNAS method for their use case - researcher can create new, better FedNAS methods Adaptation techniques are composable design patterns extracted from the FedNAS literature that make it easy to compose new FedNAS methods suited towards new tasks.

Extracting the adaptation techniques used by FedNAS methods and organising them into a single consolidated body of knowledge, would allow researchers to easily make use of this knowledge to compose new FedNAS methods tailored to overcoming a specific set of challenge classes relevant to them. This leads us to our research question:

(RQ) **How and which challenge classes do adaptation techniques described in the literature overcome?**

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

1. **Literature Selection:** We follow the guidelines and flow diagrams provided by PRISMA 2020 [13] 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 taxonomy that gives researchers an overview of the FedNAS landscape through the lens of adaptation techniques. Our discussions on each adaptation technique helps researchers find and choose adaptation techniques relevant to their problem.

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.

Abbreviations

List of Figures

List of Tables

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