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Exposé — Bachelor's Thesis

Adaptation Techniques for using NAS Methods in the FL Setting

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Contents

1	Problem Statement	3
2	Objectives	5
3	Explanation of Terms	5
3.1	Neural Architecture Search (NAS)	5
3.2	Centralised NAS	6
3.3	Federated Learning	6
3.4	FL system parameters	6
3.5	Federated Neural Architecture Search (FedNAS)	6
3.6	Adaptation technique	6
4	Research Approach	6
4.1	Data Collection	6
4.2	Data Analysis	7
5	Structure	8
6	Expected Results	10
	References	10

1 Problem Statement

Engineering the architecture of a neural network for a Deep Learning application is traditionally done by a team experts via a process of trial and error. To reduce the amount of manual labour involved in this process, researchers invented *Neural Architecture Search* (NAS) [2] methods and improved them over the past decade. NAS methods employ diverse strategies to automatically search for a neural network architecture for a given Deep Learning application.

Independantly, but in parallel to NAS, researchers developed a distributed machine learning approach called *Federated Learning* (FL) [11] in response to growing concerns about data privacy. In FL, *clients* collaboratively train a model without sharing their local data. This enhances the privacy of clients' data by ensuring FL model trainers can not view clients' data and client data is not collected at a central location where a single breach could expose the data of all clients.

Engineering neural network architectures in FL is as labour-intensive as in centralised Deep Learning, therefore practitioners¹ have started investigating the use of NAS methods in FL [5] [1] [10], creating *Federated Neural Architecture Search methods* (FedNAS methods) [5]. FedNAS methods also provide a potential alternative to selecting a fixed architecture upfront — a so-called *preddefined architecture*. Predefined architectures can lead to slow training convergence and poorly performing models in FL, because practitioners can not view the clients' data and client hardware capabilities vary. Practitioners may therefore select a predefined architecture that contains components irrelevant for generalising well from client data sets or select an architecture that trains slowly on some clients. Work has already been done that shows the use of NAS methods can mitigate these issues [6] [12] [13].

The approach used by most FedNAS methods — and on which we focus in this thesis — is to take NAS methods developed in a centralised setting and use them for FL. However, this requires modifying the NAS method for the FL setting, because many assumptions that hold for the search process in centralised NAS do not hold for FedNAS. These assumption discrepancies result in *challenges* for using centralised NAS methods in FL, and practitioners have created *adaptation techniques* for overcoming them. For example, the FedNAS method *FedorAS* [1] makes use of the centralised NAS method *SPOS* [3], but runs into the following challenge caused by the fact that centralised NAS can assume worker nodes are connected via low latency, high-bandwidth links, whereas clients in FL are not: sending the parameters of the entire supernet used in *SPOS* to each client would take an infeasible amount of time. Instead *FedorAS* adapts *SPOS* such that only a small, sampled subspace of the supernet is sent to each client

¹In this thesis, *practitioners* refers to both users and developers of FedNAS methods.

for training and evaluation.

The relevant subset of challenges faced by these kinds of FedNAS methods depends on the configuration of FL system parameters [8]. System parameters include average hardware capabilities of clients, average network latency of clients, the number of participating clients etc. For example, in the so-called *cross-silo setting*, clients can be expected to be equipped with GPUs, making challenges caused by low-end hardware in FL less relevant.

Practitioners adapting a centralised NAS method to FL with a specific set of FL system parameters in mind must decide which challenges to prioritise and which adaptation techniques to implement, but the literature does not offer clear advice for these design decisions. The incurred challenges are scattered throughout the literature, the adaptation techniques used to address them are often not presented in isolation and many FedNAS papers do not clearly state the targeted FL system parameters. As a result, practitioners struggle to assess the usefulness of existing adaptation techniques for their targeted FL system parameters and risk selecting ineffective techniques or selecting techniques for addressing a challenge that are known to worsen another.

Prior literature surveys [14] [9] [4] only summarise FedNAS methods on the whole and do not focus on isolated, re-usable adaptation techniques. Additionally, prior surveys are limited by the FedNAS methods available at the time or exclude a large share of the FedNAS literature due to their chosen focus. As a result, prior surveys don't provide an exhaustive overview of adaptation techniques and do not help practitioners assess the usefulness of existing adaptation techniques for their targeted FL system parameters. Since prior surveys do not solve the problem mentioned in the previous paragraph, we pose the following research question help with the adaptation of NAS methods to FL:

What challenges arise when adapting centralised NAS methods to FL, how is the relevance of challenges influenced by FL system parameters and how do adaptation techniques in the literature overcome these challenges?

To tackle our research question, we conduct a systematic literature review of papers that present FedNAS methods which modify centralised NAS methods in response to 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 catalogue the challenges that arise from them. Next, we extract unrefined adaptation techniques from the FedNAS methods and iteratively refine

and merge them (similar to [7]) 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, as well as an overview table.

Our review aims to support the adaptation of centralised NAS methods to FL. To this end we make the following contributions:

1. We create an overview of challenges arising from assumption discrepancies between centralised NAS and FedNAS

By identifying the source of challenges and elaborating on them, we provide clarity on the expected challenges for a targeted FL setting. Based on the expected challenges, FedNAS practitioners can use our overview of adaptation techniques to guide the design of new FedNAS methods and determine whether to re-use existing techniques, extend them, or develop new ones.

2 Objectives

The primary objective of this thesis is to provide an overview of techniques used to adapt centralised NAS to FL, spawning the following sub-objectives:

1. Catalogue the assumptions that hold for centralised NAS, but are violated in FedNAS and to what extent these assumptions are violated based on FL system parameters.
2. Describe the challenges arising from the mismatch in assumptions between centralised NAS and FedNAS.
3. Catalogue the adaptation techniques used to overcome these challenges.

3 Explanation of Terms

3.1 Neural Architecture Search (NAS)

Traditionally, the neural network architecture for an applying Deep Learning effectively are designed by a team of domain and Deep Learning experts. In NAS, the architecture is automatically searched by continuously evaluating the performance of candidate architectures and updating the architectures with high performance for a given task, dataset, and constraints.

3.2 Centralised NAS

3.3 Federated Learning

FL is a machine learning approach in which multiple *clients* collaboratively train a shared model while keeping training data local to the clients. A central *server* coordinates *communication rounds* with the clients, wherein each client trains the model for several epochs locally and finally sends gradient updates to the server for aggregation into the shared model.

3.4 FL system parameters

FL setting vs system parameters

- number of clients - degree of variance in hardware of clients - average networking latency of clients - average computing power of clients - degree of data imbalance between clients - availability of clients

3.5 Federated Neural Architecture Search (FedNAS)

3.6 Adaptation technique

An adaptation technique is a modification to a centralised NAS method that is explicitly motivated by making the NAS method feasible for FL.

For example, letting each client train a supernet of a centralised NAS method in a cross-device setting would lead to detrimental search completion times, because the having each client train the entire supernet, works for the cross-silo FL setting [HAA21], it does not translate to the cross-device setting. Clients in the cross-device setting are generally less powerful, and such a training scheme would result in detrimental completion times. Instead, in one FedNAS method [DLF22], researchers have opted to reduce the computational burden on clients by only sampling and training subnets within the client’s training budget.

4 Research Approach

We take a qualitative research approach in the style of the CDML paper.

4.1 Data Collection

We obtain the set of literature relevant to our review by searching the abstract, title and keywords of literature in Scopus [TODO: cite] with the search string "federated learning

neural architecture search" and include literature that presents a FedNAS method that uses a centralised NAS method explicitly modified for FL. We exclude literature that (i) designs FedNAS methods from scratch, (ii) performs only hyperparameter optimisation, (iii) or does not provide sufficient methodological detail to extract adaptation techniques.

We extend this initial set of literature by recursively adding literature from the references of the literature that meets our inclusion and exclusion criteria until we obtain a set of literature for which no new literature can be added.

4.2 Data Analysis

We follow a qualitative research approach in the form of a systematic literature review. In our review, we develop a conceptual model that links violated centralised NAS assumptions to resulting challenges for adapting a centralised NAS method to FL, and the adaptation techniques used to overcome these challenges as follows:

1. **Challenges arising from Assumption Discrepancies:** We first define challenges that arise for using centralised NAS methods in FL, because of assumptions that hold for centralised NAS, but not for FL.
2. **Influence of FL System Parameters on Challenges:** We then classify the influence FL system parameters on the relevance of challenges as either "low" or "high". We derive our classification by collecting the FL system parameters
3. **Unrefined Adaptation Technique Extraction:** 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 initially coded as one unrefined adaptation technique.
4. **Adaptation Techniques Conceptualization:** We iteratively refine and merge the unrefined adaptation techniques (similar to [7]) to obtain a coherent set of adaptation techniques. Unrefined adaptation techniques with conceptually highly-similar mechanisms are merged into a single representative adaptation technique.
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. **Table Overview:**

Finally, we create a table that researchers can use to make design decisions about the techniques they wish to use to adapt a NAS method to FL.

The table contains a coded vector of effects over the FedNAS challenges for each *adaptation technique* based on the prior discussion. 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.

1. **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 Structure

1. Introduction (3 pages)

What is the motivation behind this thesis? What is the relevance of this thesis? What problem does this thesis try to solve? What kind of approach does this thesis take to solve that problem? How is the thesis structured?

2. Background (6 pages)

What background knowledge is required to understand this thesis?

2.1 Neural Architecture Search (2.5 pages)

What is NAS used for and how does it work? What is a NAS method? What are the origins of NAS? What environment are NAS methods typically developed in?

2.2 Federated Learning (2.5 pages)

What is Federated Learning? What was it designed for and how does it work?

2.3 Federated Neural Architecture Search (0.5 pages)

How do FedNAS methods relate to NAS and FL? What are the origins FedNAS methods and how have they been developed over the last couple of years?

3. Method (5 pages)

How does this thesis aim to achieve the objectives described in Section 2?

- 3.1 Reviewed Literature (2 *pages*) Will include visualisations that break down the included literature for the reader.
Which literature is included in the review?
- 3.2 Methodology (3 *pages*)
How is the literature analysed? Which methodology is employed and how?
4. **Challenges with Adapting Centralised NAS methods to FL** (10 *pages*):
 - 4.1 Assumption Discrepancies between NAS and FedNAS (3 *pages*)
How do centralised NAS and FedNAS differ? How does this difference manifest in different assumptions?
 - 4.2 Adaptation Challenges (4 *pages*)
How do FL system parameters influence challenges faced for adapting centralised NAS methods to FL?
 - 4.3 Influence of FL system parameters on Challenges (3 *pages*)
Which FL system parameters influence the degree to which a challenge is relevant? Which FL system parameters are relevant and which ones are not?
5. **Adaptation Techniques** (25 *pages*)
What adaptation techniques are described in the literature? What can we learn from these adaptation techniques that we can use for adapting NAS methods to FL in the future? For which FL system parameter configuration was each adaptation technique developed? How do adaptation techniques work towards, against, or do not affect overcoming each of the challenges relevant to that FL system parameter configuration?
 - 5.1 Adaptation Technique 1 (1 *page*)
Description of the refined adaptation technique, the FedNAS methods that use it and a discussion on how it overcomes challenges.
 - 5.2 Adaptation Technique 2 (1 *page*)
 - 5.3 ...
 - 5.4 Adaptation Technique 20 (1 *page*)
 - 5.5 Overview (5 *pages*) A large overview table that makes it easy to see which adaptation techniques are beneficial for overcoming which challenges at a glance.

6. **Discussion** (2 pages)

What do our findings indicate for the future of adapting centralised NAS methods to FL? How can researchers and practitioners use these contributions when adapting centralised NAS methods to targeted FL system parameters?

7. **Conclusion** (1 page)

What is the answer to the thesis' research question, and what are the main contributions?

... pages in total.

6 Expected Results

1. Catalogue of challenges that arise when adapting centralised NAS methods to FL.
2. An overview of FL system parameters that influence the relevance of a challenge.
3. A catalogue of adaptation techniques extracted from FedNAS methods with an in-depth discussion of the challenges they overcome.
4. An overview of adaptation techniques that developers can use to see which adaptation challenges overcome which challenges to what extent at a glance.

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