

SCHOOL OF COMPUTATION,
INFORMATION AND TECHNOLOGY —
INFORMATICS

TECHNISCHE UNIVERSITÄT MÜNCHEN

Master's Thesis in Informatics

**FLOps: Practical Federated Learning via
Automated Orchestration (on the Edge)**

Alexander Malyuk

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TODO

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Submission Date:	15.09.2024

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

Munich, 15.09.2024

Alexander Malyuk

Acknowledgments

Abstract

Kurzfassung

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Abbreviations

This is a list of repeatedly occurring acronyms in the thesis. Abbreviations that are only used once are explained in the text and omitted from this list, to focus on the important ones. This list also includes acronyms that are well known and that are not explicitly explained in the text. For completion they are included here.

Specific Acronyms :

FL Federated Learning
CFL Clustered Federated Learning
HFL Hierarchical Federated Learning
PFL Personalized Federated Learning
MLOps Machine Learning Operations
CI Continuous Integration
CD Continuous Delivery & Deployment
IID Independent and Identically distributed
DP Differential Privacy

Common Acronyms :

AI Artificial Intelligence
ML Machine Learning
DNN Deep Neural Network
LLM Large Language Model
API Application Programming Interface
GUI Graphical User Interface
SLA Service-Level Agreement
CLI Command-Line Interface
IoT Internet of Things
P2P Peer-to-peer

1. Introduction

The number of smart devices has been rapidly growing in the last several years. Improvements in connectivity (Cloud Computing & Internet of Things—IoT), connection speeds (5G), and computing power enable this increasing fleet of edge/mobile devices to generate enormous amounts of data (BigData). Combined with the expansion of AI/ML, this data is a driving factor for current successful workflows and future advancements. This complementing union of technologies plays a key role in elevating various domains, from agriculture and healthcare to education and the security sector, to Industry 4.0 and beyond. Diverse and complex challenges arise from this swiftly evolving landscape. [5]

1.1. Problem Statement

With great access to data comes great responsibility that can be easily exploited. Many of the aforementioned machines are personal user devices or belong to companies and organizations that handle customer or internal resources. These devices store and handle sensitive private data.

In classic (large-scale) Machine Learning, data gets sent from client devices to a centralized server, which usually resides in the cloud. The collected data is used on the server to train ML models or perform inference serving. This approach provides direct access to this sensitive data and the power to trace back its origin, creating a breach of privacy. [25]

Governments and organizations have established laws and regulations to prohibit potential abuse of sensitive data. Examples include the European Parliament regulation to protect personal data [30] or the California Consumer Privacy Act (CCPA) [22]. These measures aim to support cooperation between organizations and nations while protecting trade secrets. However, some laws and regulations prohibit sharing or moving data to other countries or even off-premises. [25]

Ignoring and no longer using this large amount of data would heavily limit current workflows and further developments for many data-dependent and data-hungry technologies. In 2017, a team of Google researchers introduced Federated Learning (FL) as one possible solution to utilize sensitive data while keeping it private. Instead of collecting the data on a server and training ML models centralized, in FL, the model

training occurs directly on the client devices. Afterward, the individually trained models get sent to the server, which combines the collected models into a single shared one. This so-called global model can then be distributed to the clients again for further training cycles. Therefore, FL enables training a shared model on sensitive data while keeping that data secure on the local client devices. [26]

While many researchers are actively engaged in the field of FL, the majority of them are focused on enhancing existing FL components, strategies, and algorithms or devising better ways of doing FL. However, there is a noticeable scarcity of work that concentrates on the crucial aspects of the initial setup, deployment, and usability of FL. We delve into this issue in greater detail in the dedicated background section (2.1.4).

Because FL is a relatively modern technique, it lacks a sophisticated production-grade ecosystem that includes frameworks and libraries that improve ease of use by automating its setup and execution. As a result, contributing to the field of FL or reproducing findings is a task ranging from non-trivial to improbable due to the lack of documented steps regarding setup, deployment, management, and execution. Instead of using a shared set of tools for bootstrapping to make progress on novel work more efficiently, one needs to set up and manage FL from the ground up. Note that a small set of emerging libraries and frameworks exists for FL. Instead of orchestrating FL on real distributed devices, they focus on executing FL algorithms and processes, often via virtual simulations. Not to mention utilizing more advanced techniques to increase productivity that other domains have already been using for several years, such as modern DevOps practices like continuous deployment. We review existing FL tools in detail in the dedicated section (2.1.5).

1.2. Motivation

Building or contributing to a novel FL framework or library focusing on the previously mentioned challenges could soften or entirely alleviate those problems. We are talking about a tool that sees Docker [11] and Kubernetes [21] as role models and strives to be comparable to them but for the discipline of FL. It should specialize in the setup, deployment, component management, and automation, in short, FL orchestration. Allowing researchers, developers, and end-users to set up, perform, reproduce, and experiment with FL in a more accessible way.

The goal of this tool should be to automate and simplify complex tasks, reducing the required level of expertise in various domains, ranging from ML/FL, dependency management, containerization technologies, and automation to orchestration. Such a tool would empower less experienced individuals to participate and contribute to the field of FL. As a result, FL could be adapted and used by more people in more areas.

This tool would streamline and accelerate existing workflows and future progress by utilizing reliable automation to avoid error-prone manual tasks. With its potential to optimize, standardize and unify processes, our envisioned tool could become a significant part of the emerging FL ecosystem, contributing to the development and progress of the entire field.

1.3. Objectives

The motivation allows us to distill the following key objectives for such a tool.

Improve Accessibility

Making FL more accessible by abstracting away and automating complexities, enables more individuals to engage with it. Expanding FL to more areas will increase its usage and user base, raising general interest and relevance for its field, which should aid its development.

Utilize Automation

Automating tedious, error-prone, and repetitive manual tasks necessary to perform FL will free up time and resources for more critical work, leading to further advancements.

Prioritize Tangible Applicability

As we discuss in (2.1.4), FL struggles with a gap between research/virtual-simulation and practical application in real production environments. This tool should focus on being usable in real physical conditions on distributed devices. It should be feasible to incorporate this tool into existing workflows.

Embrace Plasticity

Because FL is such a young field, it faces constant change. Naturally, our tool should welcome change in the form of extendability and adaptability. This tool should be flexible and applicable to a myriad of use cases and scenarios. It should be easy to modify to accommodate evolving needs. Likewise, this tool should profit from existing technologies to offer a higher level of quality than creating everything from square one.

1.4. Contribution

We introduce FLOps to fulfill the objectives above. It enables individuals to use, develop, and evaluate tangible FL. FLOps enriches FL with modern best practices from automation, DevOps/MLOps, and orchestration. FLOps improves accessibility by enabling users without experience in FL, MLOps, or orchestration to do FL and still benefit from these technologies via automated orchestration.

To do FL, users simply provide a link to their ML git repository. Note that this code needs to satisfy some simple structural prerequisites. This repository code gets automatically augmented by FLOps to support FL. FLOps creates a containerized image with all necessary dependencies to do FL training. These images are automatically built and adhere to best practices, ensuring they are as fast and lightweight as possible. FLOps can build these images for multiple different target platforms. Thus, FL components can run on ARM edge-devices like Raspberry Pis or Nvidia Jetsons. FLOps enables FL on all devices that support containerization technologies like Docker [11] or containerd [10]. This approach eliminates the need for tedious device setup and the struggle to configure heterogeneous dependencies to match the necessary requirements for training, thereby streamlining the process and saving time.

FLOps automatically performs FL training based on the user-requested configuration. Users can, for example, specify resource requirements, the number of training rounds, the FL algorithm, the minimum number of participating client devices, and more. During runtime, users can observe this training process via a sophisticated GUI, which allows users to monitor, compare, store, export, share, and organize training runs, metrics, and trained models. FLOps can automatically build inference servers based on the trained model. This inference server can be pulled as a regular image. FLOps can also directly deploy this trained-model image as an inference server.

A multitude of diverse technologies and areas are necessary for FLOps to provide its services. Instead of reimplementing these complex features in a subpar fashion from scratch, we benefit from combining and extending existing solutions and technologies in unique and novel ways. This includes the use of Anaconda [2] and Buildah [6] to manage dependencies and build images. We utilize a pioneering FL framework called Flower [13] to execute the FL training loop. The mentioned runtime observability features are available via a mature MLOps tool called MLflow [27]. Because FL pushes model training to client devices, especially edge devices, we decided to use an orchestrator native to the edge environment. With the help of Oakestra [3], FLOps can deploy and orchestrate its components. FLOps is implemented as an separate addon for Oakestra. Because their interaction is based on general API endpoints and SLAs, FLOps can be modified to support other Orchestrators.

It is noteworthy that these different tools do not natively support each other. FLOps

combines them in unprecedented ways to achieve its goals. As an example, FLOps supports hierarchical FL (HFL), which is not directly supported or offered by Flower. To the best of our knowledge, FLOps is the first work that combines Flower with MLflow and allows HFL, as well as automatically converts ML code into FL enabled containerized images.

As far as we know, the term FLOps, besides being a measurement unit for computer performance (Floating point operations per second), has not been used or applied to FL unlike MLOps has been used to describe DevOps techniques for ML. The goal of this work is to showcase the benefits of utilizing the mentioned techniques and open the doors for future developments for FL.

Besides the end-user perspective, FLOps is intended to be a foundational piece of software that can be easily modified and extended for developers and researchers. We put a lot of effort into writing high quality code, using state of the art libraries and frameworks. FLOps includes many development-friendly features. We enforce proper styling and typing via formatters and linters, including CI. Ready-made extendable multi-platform images and services automate development and evaluation workflows. These images, as well as the entire code, are made available on GitHub [12]. We also added base images with optional development flags to speed up the build and execution times of FLOps so that developers can verify and check their changes more rapidly.

On top of that we also implemented a new CLI tool for Oakestra and FLOps from the grounds up [29]. It is used to interact with Oakestra's and FLOps APIs. Besides that this configurable CLI tool also is capable of visualizing current processes in a human friendly way in real time as well as trigger evaluation runs and other automated tasks like installing necessary dependencies.

1.5. Thesis Structure

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2. Background

As mentioned in the contributions section, FLOps combines and uses a large set of technologies from different disciplines. To properly understand FLOps as a whole and why it combines these techniques, it is necessary to analyze them individually. This enables us to form a common understanding, including critical background knowledge of their benefits and downsides. Only afterward does it make sense to discuss how FLOps merges them to create something new.

This background chapter provides a general overview for each sector and discusses aspects that are necessary for FLOps in greater detail. We start with exploring the field of federated learning. FL is the core task at hand that FLOps aims to optimize. A thorough understanding of this discipline is required to figure out where it has shortcomings. To improve upon these weaknesses, we study the established set of best practices from DevOps and MLOps. Techniques like automation and CI/CD require infrastructure and resources. Orchestration allows us to provision, manage, and deploy such infrastructure and resources. We review the field of orchestration technologies and provide a short overview of Oakestra [3] as the chosen platform. In the final background section, we take a look at and compare a couple of existing pieces of work that resemble FLOps.

2.1. Federated Learning

This section starts with the fundamental building blocks and terminologies of FL, followed by a section showcasing vital supplementary FL concepts. FLOps is orchestrated via Oakestra [3], which uses an unconventional three-tiered structure that allows support for geographical clusters. We have the opportunity to benefit from this unique composition and apply FL to it. To do so, we investigate more advanced concepts in FL, focusing on different FL architectures.

With this solid FL understanding, we review the research landscape of FL. We look at active and popular research directions and point out under-explored aspects, and weak points. Followed by a detailed comparison of existing FL frameworks and libraries. We conclude the section on FL by providing an overview of Flower [13], our FL framework of choice.

We base the majority of the first three subsections (FL basics, supplementary FL concepts, and FL architectures) on the 2022 book ‘Federated Learning - A Comprehensive Overview of Methods and Applications’ [25]. It captures and discusses the history and progress of FL research and state-of-the-art FL techniques (up to 2022).

2.1.1. FL Basics

Note that we assume the reader to be familiar with basic machine learning concepts.

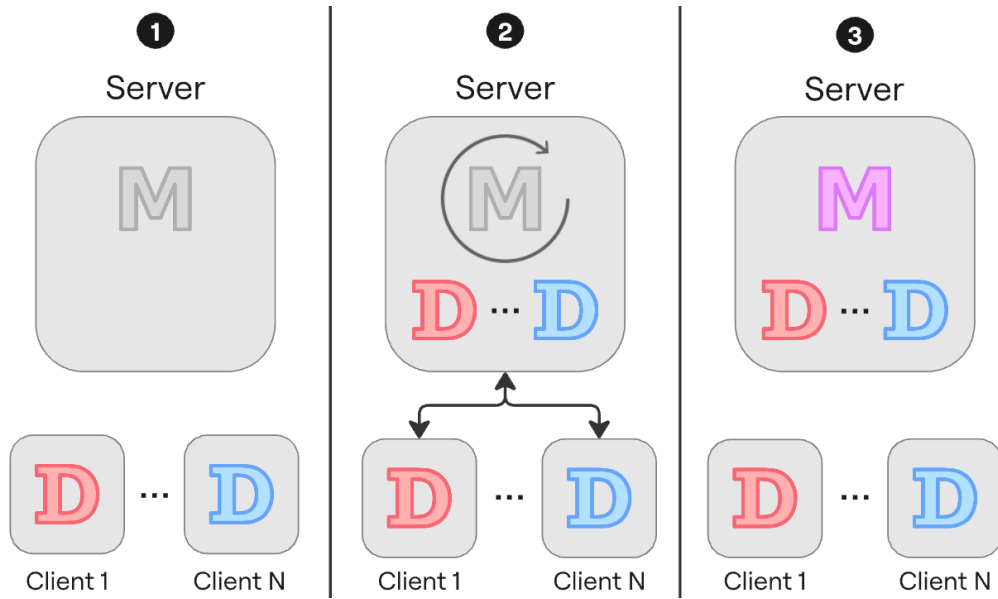


Figure 2.1.: Centralized ML Model Training

Figure 2.1 depicts the classic centralized ML model training process. Starting from (1), where clients have their data (D) and the server hosts the untrained (gray) ML model (M). In (2), the clients send their data to the server. The server can now train the model using data from both clients. (3) depicts the final state after training. (The pink/purple model color represents that both data sources, red and blue, have been used during training.) The client data remains on the server and is exposed to potential exploitation.

As discussed in the introductory chapter, the centralized approach often leads to privacy breaches. FL was introduced to use this lucrative sensitive data on client devices for training ML models while keeping that data private and complying with laws and regulations. Many different algorithms and strategies exist for FL. We focus on the widely used base-case/classic FL algorithm FederatedAveraging (FedAvg) proposed as

part of the original FL paper [26].

Figure 2.2 shows the basic FL training loop. Note that the number of learners can vary. This and the following figures mainly represent such groups only via two members, to optimize page space. The first differences are the component names. In FL, the server is frequently referred to as an **aggregator** and coordinates the FL processes. Clients are called **learners**. Note that using the terms server and clients in FL is still common. We prefer aggregators and learners because it highlights that these are FL components. This naming choice is also used in FLOps and helps with comprehension because FLOps uses a manifold of components, including non-FL servers and clients. Another difference is that all components must know and possess the ML model locally. They also need to set up their environment for training properly.

Initially, at (1), all models are untrained. At (2), the aggregator starts the first FL training cycle by telling the learners to start their local training. The local training rounds (epochs) are completed at (3). (The 'M's are now colored.) As a reminder, one can split up ML models into two parts. One part is (usually) a static lightweight model architecture that includes layer specification (in DNNs), training configuration, hyper-parameters like learning step sizes, and what loss type or activation function to use. Model weights and biases are the dynamic components of an ML model. A model without them is not useful because weights and biases are what get trained and allow the model to fulfill its intended use, such as prediction, inference, or generation tasks. These weights and biases are the major contributors to a trained model's overall size (space utilization). Because the model architecture is static in classic ML/FL, one can transmit the weights and biases between aggregators and learners instead of the entire trained model. We call everything that gets sent between the learners and aggregators (model) **parameters** and depict it with (P).

In (4), the learners have extracted their model parameters and sent them to the aggregator. The aggregator now has access to these parameters but not the sensitive data used to train them. That is how FL can profit from sensitive data while maintaining its privacy. Note that there are still attack vectors that allow exposing sensitive client information by abusing this parameter-based aggregation process. We briefly discuss this and other FL security aspects later on.

In (5), the server aggregates these collected parameters into new global parameters, which the aggregator applies to its model instance. This aggregation process is also called model fusion. Because learners can be heterogeneous and possess varying amounts of data, some learner updates might be more impactful than others. To respect this circumstance, learners typically also send the number of data samples, they used for training, to the aggregator. That way, the aggregator can prioritize its received updates proportionally. Otherwise, in classic FL aggregation, the mean of the parameters is used for the global model. The result is a **global model** that was trained

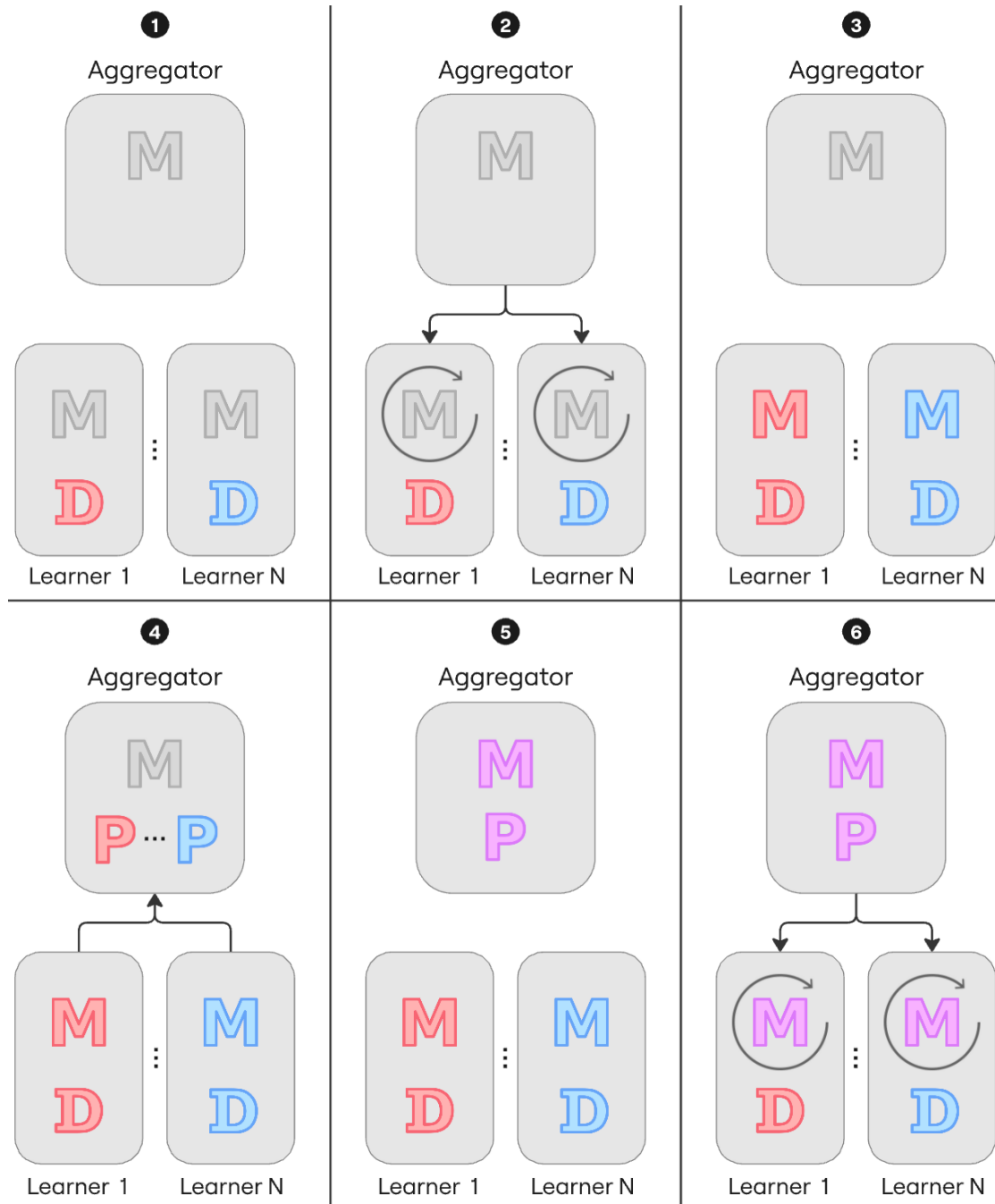


Figure 2.2.: Basic Federated Learning

for one FL cycle.

In (6), the aggregator sends its global parameters back to the learners. The learners apply these parameters to their local model instance to make it identical to the aggregator's global model, thus discarding their locally trained parameters. Now, the FL training loop could terminate, and the learners or servers could use their global model copy for inference, or as depicted in (6), another FL training cycle begins. There can be arbitrarily many FL cycles, similar to conventional training rounds in classic ML. FL training will have to stop, due to time/resource constraints or reaching a satisfying performance. Otherwise, the accuracy and loss will worsen due to overfitting, assuming the available training data is finite and unchanging.

2.1.2. Supplementary FL Concepts

In this subsection, we explore essential supplementary FL concepts to get a better understanding of the field.

FL compared to Distributed Learning

At first glance, FL seems similar to Distributed Learning (DL). Both get used for computationally expensive large ML tasks. To increase convergence times and avoid needing one mighty machine, the computations get distributed among many weaker machines that train individually. Afterward, a global model gets aggregated at the server.

Regarding their differences, the quantity and distribution of training data can be very diverse in FL and might remain unknown throughout training. FL only uses the data that the learners offer. DL starts with full centralized access and control to the entirety of data, before splitting it up among its fixed and predefined clients. Thus, DL does not support the privacy concerns because it has total oversight and control of all data and how to split it up. In FL, the data might be IID or non-IID. Different learners can have varying amounts of data. The number of learners in FL can be very dynamic. Some devices might only join for a few training rounds or crash/fail/disconnect during training.

FL Variety

Most FL work is focused on end-user/edge/IoT devices. FL is not exclusive to these environments and can be used in conventional cloud environments.

As discussed in the first subsection, FL can train DNNs. One can also apply FL for classic ML models, such as linear models (logistic regression, classification, and more)

or decision trees for explainable classifications. Plentiful FL optimizations, such as custom algorithms and strategies, exist for each mentioned ML variant.

FL can also support horizontal, vertical, and split learning. Horizontal learning can be helpful in scenarios where the available data features are the same but originate from different sources. One use case for horizontal learning is working with patient data from different hospitals that record the same features, such as age and ailment. Vertical learning is practical when different data samples have different feature spaces. In the hospital example, this would mean asking different doctors/experts about the same patients. The patient reports would be about the same individuals but include varying features, such as cardiological metrics or neurological metrics. We omit to discuss split learning due to its complexity that would bloat this thesis.

In case the global model is too general and does not satisfy a learner's individual needs, one can employ personalization. Different personalized FL (PFL) approaches exist. Some take the final trained global model and further train it on local data (fine-tuning). Other techniques train two local models concurrently. The first model gets shared and updated with the global parameters. The second one stays isolated and only gets influenced by local data. For inference a mixture between the global and purely local model can be used. PFL is a deep and growing subfield of FL.

FL Security & Privacy

Secure FL should use secure and authenticated communication channels to prevent messages from being intercepted, read, or impersonated by a man-in-the-middle adversary. To help with that, one should ensure that learners and aggregators are the only actors with access to those messages and can decipher them. There are two kinds of adversaries in FL. Insiders are part of the FL process, such as malicious aggregators or learners. Outsiders try to interfere from beyond the FL system.

A variety of FL threats exist. One example is manipulation, where insiders try to distort the model to their advantage by tinkering with FL components that the attacker can access. The attack goals include polluting the global model to misclassify (Backdoor). If the attack is untargeted (Byzantine), injecting random noise or flipping labels can degrade the model's performance. It is difficult to detect malicious activity because FL can support dynamic or even unknown numbers of learners that can use vastly different non-IID data. It can be unclear if the learner is innocent and simply has access to unusual data or if the learner is adversarial. Another example is if there are no safeguards in place during aggregation. A malicious learner can claim to have used an overwhelming amount of training samples, thus overshadowing other participants and influencing the global model the most. As a result, even very scarce, well-timed attacks in FL can have devastating impact.

Another threat comes from (model) inference, where insiders or outsiders try to extract sensitive information about the used training data. In classic FL, privacy leakage can only occur via inference. Inference attacks try to deduce private information from artifacts that the FL process produces. A large body of ML research exists that focuses on analyzing and protecting against such attacks. There are different subtypes of inference attacks. One example is the membership attack, which tries to find if specific samples were used for training. Another attack is called 'extraction attack', which tries to obtain all training samples. The challenge here is that attackers have easy access to the final model. Malicious insiders can even attack intermediate models. Model inversion attacks are different attack variants in which adversaries query the trained model in peculiar ways to reverse engineer data samples. If the attacker is repeatedly successful, it is possible to deduce the original dataset. Other attacks require malicious aggregators that can trace back the update parameters that the learner provided before aggregating the global parameters.

Fortunately, there exists a growing array of defenses against those threats. It is crucial to pick and combine these defenses wisely based on the use case and environment. One major technique is differential privacy (DP). DP is a complex mathematical framework that is formally proven to work. One can use DP as noise for the dataset or (inference) query. The downside is that DP might reduce the model accuracy significantly.

Secure aggregation is a prominent protection against model inversion attacks. It securely combines individual model parameters into global ones before sending them to the aggregator, which makes re-engineering and backtracking much harder. [19]

2.1.3. FL Architectures

FL comes in two broad structural categories. Cross-silo or enterprise FL gets used in large data centers or multinational companies. Each learner represents a single institution or participating group. There are only around ten to a few dozen learners involved. Cross-silo FL considers the identity of the parties for training and verification. Generally, every individual local update from every learner at every training round is significant. Fallouts and failures of individual learners are serious.

Cross-device FL can include hundreds or millions of devices, primarily edge/IoT devices. One can say that cross-device is the opposite of cross-silo. Due to this great pool of learners, a subset typically gets used per training round. The identities of the participating learners are usually unimportant and get ignored. Due to the nature of these devices and their environments, cross-device FL needs to manage challenges, such as non-IID data, heterogeneous device hardware, different network conditions, learner outages, or stragglers. Various techniques exist to navigate these challenging conditions, including specialized algorithms for aggregation or learner selection. These

strategies can consider bias, availability, resources, and battery life. FLOps focuses on cross-device FL. From now on, when we mention FL, we mean cross-device FL.

As discussed, FLOps wants to benefit from the unique three-tiered Oakestra [3] architecture. Different FL architectures exist to support such large-scale FL environments. The two main challenges for such scenarios are managing a massive number of connections and aggregations and reducing the negative impact of straggling learner updates. The problem with using a single aggregator, as seen in 2.2, is that this single aggregator becomes a communication bottleneck. Additionally, per-round training latency is limited by the slowest participating learner. Thus, stragglers turn into another bottleneck. We discuss four main architectures for large-scale FL.

Clustered FL

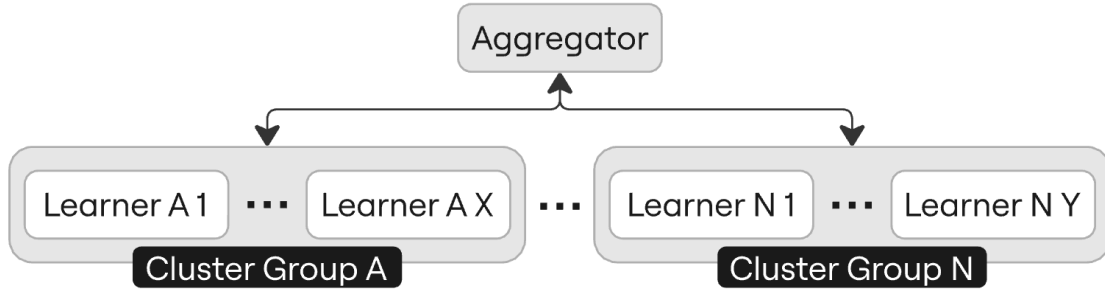


Figure 2.3.: Clustered FL Architecture

Figure 2.3 shows the Clustered FL (CFL) architecture that groups similar learners into clusters. CFL can base clusters on local data distribution, training latency, available hardware or geographical location. The issue of the singular aggregator as a bottleneck persists. The main challenge for CFL is choosing a suitable clustering strategy and criteria for the concrete use case. If the criteria are very biased, the risk arises that updates from preferred clusters will be heavily favored, resulting in a biased global model with bad generalization. Another task is to properly profile the nodes to match them to the correct cluster. For example, the entire cluster suffers if a slow outlier is present in a cluster. Node properties can vary over time, so cluster membership has to be dynamic. One should not overdo profiling. Otherwise, privacy might get compromised.

The benefits of CFL are its ease of implementation, familiar architecture to classic FL, and flexibility to tune clustering/selection dynamically. One can combine CFL with other architectures. A downside of CFL is that a proper clustering strategy is use-case-dependent and challenging to optimize. CFL does not really solve scalability

issues on its own, especially since the clustering overhead becomes critical with larger numbers of nodes.

Hierarchical FL



Figure 2.4.: Hierarchical FL Architecture

Figure 2.4 depicts the hierarchical FL (HFL) architecture. In HFL, the root aggregator delegates and distributes the aggregation task to intermediate aggregators. Note that HFL can have multiple layers of intermediate aggregators. Each intermediate aggregator and its connected learners resemble an instance of classic FL. After aggregating an intermediate model, the intermediate aggregators send their parameters upstream to the root aggregator. The root combines the intermediate parameters into global ones and sends them downstream for further FL rounds.

This structure requires significant modifications to the underlying FL architecture. The proper design and implementation, as well as the assignment of learners to aggregators, determine the success of one’s FL setup. For example, if too many learners are attached to a given aggregator, that aggregator becomes a bottleneck. If too few learners are assigned, the intermediate aggregated model can get very biased, and the infrastructure resource and management costs become unjustified for the small number of learners. A management overhead arises with more components, including handling fault tolerance, monitoring, synchronizing, and balancing. Bad synchronization can amplify straggler problems. Balancing refers to combining and harmonizing intermediate parameters to get a good global model.

The benefits of HFL are its dynamic scalability and load balancing. One can easily add or remove intermediate aggregators and their connected learners. Due to this distribution of load and aggregation, each aggregator, including the root, is less likely to face bottleneck issues. One can combine HFL with CFL, where each intermediate aggregator is responsible for one or multiple clusters. The downsides of HFL are communication and management overheads. More components lead to more transmitted messages.

These messages all need to be secured and encrypted. With more components and nodes, adversaries can take advantage of more possible backdoors.

Decentralized FL

Decentralized FL does not require a central aggregator. Instead, it operates on a peer-to-peer basis via a blockchain. That way, the centralized communication bottleneck gets resolved. The blockchain represents the global model. Learners train in parallel. Each locally trained update gets a version. Based on this version, random clients are chosen for aggregation. The results get appended to the blockchain, and the model version is incremented. FLOps does not use this kind of FL, so we keep this part short.

Asynchronous FL

This architecture allows learners to train continuously and push their updates to the aggregator once they are finished. This method eliminates stragglers and dropout problems because a training round does not need to wait or handle outliers and timeouts. A new issue of staleness arises when updates are merged into the global model that took a very long time to complete. Such an update used a now outdated version of the global model. As a result, the global model is partially reverted to an older state. Asynchronous FL can be combined with other architectures.

2.1.4. FL Research

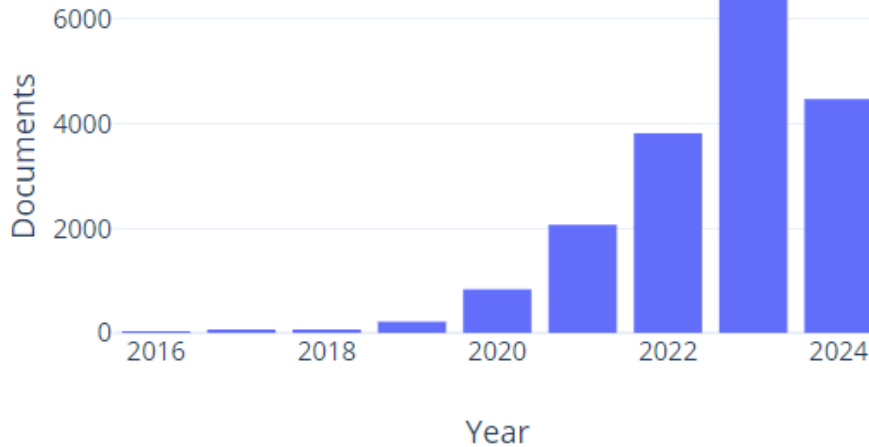


Figure 2.5.: Evolution of FL Publications

Figure 2.5 shows the exponential growth of FL documents since 2016. (This data comes from searching for "federated learning" in article title, abstract or keywords via Scopus [33].) Note that we based the idea for this graph on [32] and we used a different query with the latest available data.

Before we started working on FLOps we wanted to find research gaps in the fields of ML at the edge, specifically FL. In total we have read and examined 47 papers in detail. 26 papers were focused on FL. Additionally, we consulted several articles, joined and participated in discussion forums, and completed a couple of payed courses [34]. Discussing each paper in detail would heavily bloat this thesis. We present key and meta findings instead.

During our reading we created and incrementally updated a database where we noted down specific properties of each paper. These properties include, one or multiple categories the paper fits in, the initial problems or challenges the authors tried to resolve, their contributions, results, limitations, and envisioned future work. We also noted down what ML or FL frameworks or libraries they used. Note that these properties are based on our own subjective analysis instead of extracting them directly from the paper verbatim.

Table 2.1 depicts a subset of the FL papers we analyzed. It shows the contributions, limitations, and future work properties that we documented. Note that we explicitly decided to use an abbreviated format instead of verbose sentences to optimize the limited space. One can inspect the remaining FL papers in the appendix A.

These tables should provide a good impression of the individual papers we examined. To get a better understanding of the research field of FL as a whole we look for patterns and trends. We utilize the documented properties for this.

2. Background

ID	Contributions	Limitations & Future Work
[1]	A novel selection and staleness-aware aggregation strategy. Analysis of resource wastage and the impact of stragglers. A smart participation selection based on learner availability.	Privacy or security were not considered. Evaluations are based on classic datasets (MNIST, CIFAR-10), which do not reflect real non-IID data. Only homogeneous resources were assumed. Use of a simple linear regression model for availability prediction. More sophisticated alternatives exist. Factors such as battery level, bandwidth, and user preferences should also be considered for availability prediction.
[20]	A novel cluster-based secure aggregation strategy for diverse nodes. Clustering based on processing score & GPS information/latency leads to better throughput and reduces false-positive dropouts. A new additive sharing-based masking scheme that is robust against dropouts.	All participants are assumed to be honest. Malicious users were not considered. The aggregator might become a bottleneck, which can be resolved via HFL (with cluster heads). Image classification was the only evaluated ML task.
[39]	An FL caching scheme including novel algorithms and architecture. Utilization of an AI training model that considers user history.	A convergence analysis was not provided. For further security and privacy improvements, blockchain-empowered FL should be investigated.
[28]	Analysis of the impact of pre-training ML models for FL initialization compared to the common random approach. Findings show pre-trained model superiority.	It is challenging to get a pre-trained model if the necessary data is not available or private. Using pre-trained models can lead to biases. Only a specific (warm-start) initialization strategy was considered.
[23]	A novel incentive/resource-based allocation schema that utilizes game theory. Learners with more data are more valuable and they can compete for higher participation rewards. Multiple model owners compete for cluster heads with the most data.	The effects of social networks and their impact on worker's cluster selection decisions should be researched. Malicious workers were not considered.
[8]	Synergy of asynchronous and synchronous FL via asynchronous tiers, which is able to handle stragglers.	The tiers all update the server individually. Further improvements are possible via HFL with intermediate cluster heads to do the aggregation. Additional security could be applied at these cluster heads.

Table 2.1.: A Subset of the FL Papers considered for FLOps

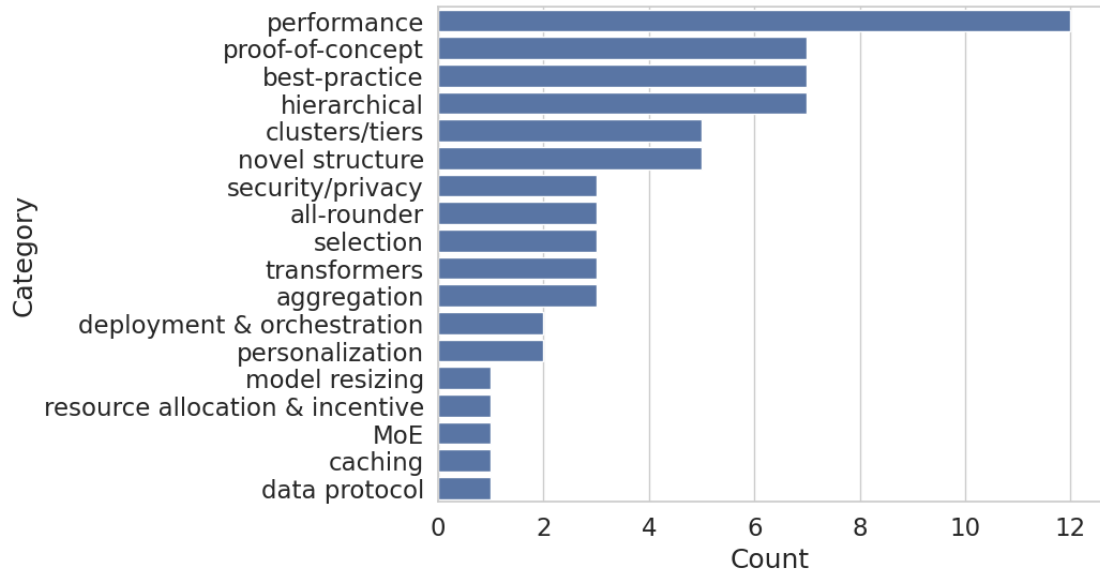


Figure 2.6.: FL Paper Categories

Figure 2.6 shows the different found categories and their distribution. The majority of our papers were focused on performance, trying out new concepts, finding best practices, and exploring different FL architectures. Only two papers focused on deployment and orchestration.

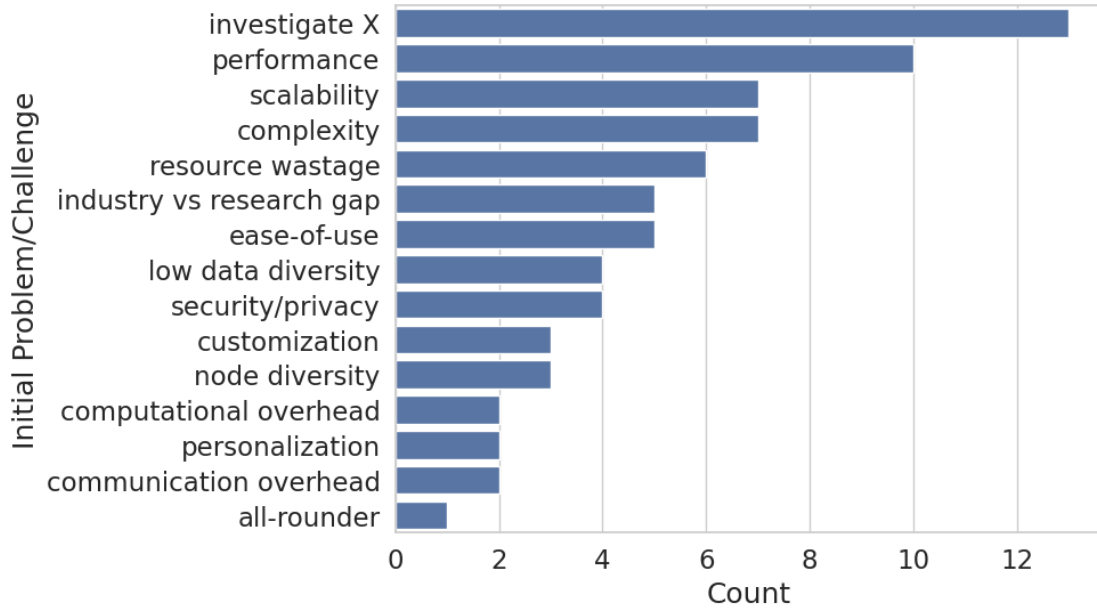


Figure 2.7.: Targeted Problems & Challenges of FL Papers

A similar trend can be seen in figure 2.7. The primary focus is on investigating new concepts or improving existing bottlenecks, with regards to their performance, scalability, and complexity. We point out that several papers aimed to narrow the gap between industry and research or to make FL easier to use. This ease of use seems to focus on improving already configured and working FL setups.

2. Background

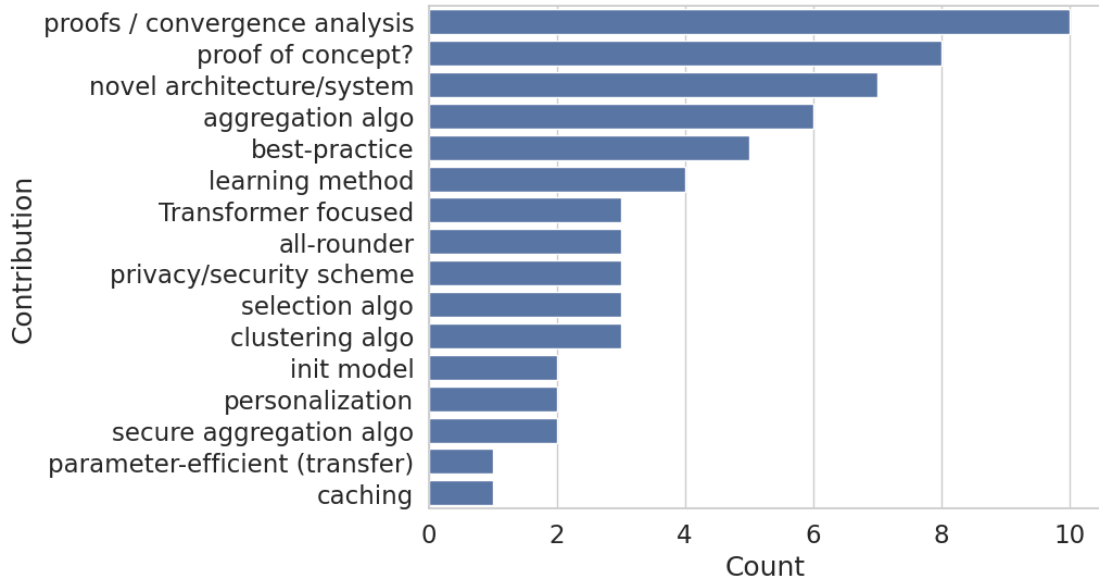


Figure 2.8.: FL Paper Contributions

This is indicated by the main contributions seen in figure 2.8. This chart is dominated by mathematical and conceptual proofs that novel architectures and algorithms work as proposed. Contributions do not seem to focus on improving the initial setup, deployment, and configuration processes.

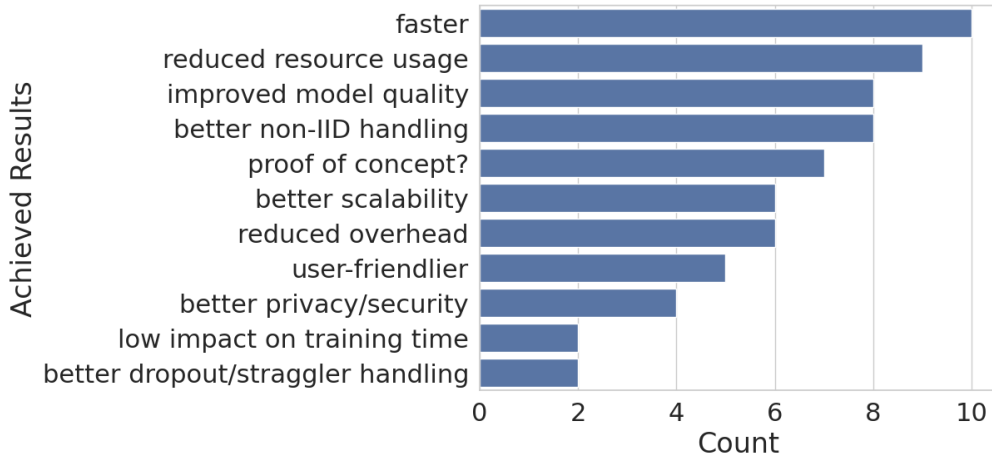


Figure 2.9.: Achieved Results of FL Papers

This finding is mirrored in the achieved results. Figure 2.9 shows that these contribu-

tions lead to better efficiencies in terms of speed, resource utilization, training results, and handling of heterogeneous data. Note that we based these properties on the results and contributions the authors mentioned themselves as well as on our own conclusions.

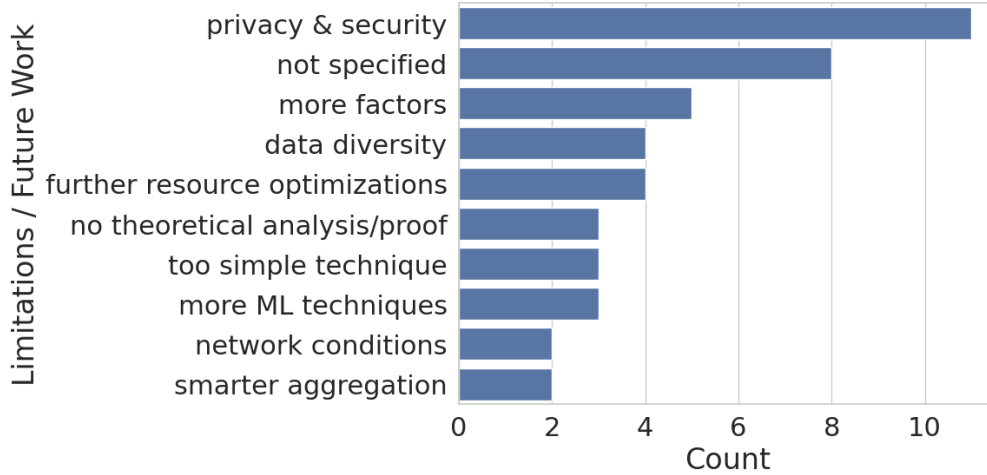


Figure 2.10.: Limitations & Future Work of FL Papers

Our perception is once more reflected in figure 2.10. The focal point, if specified, is on improving privacy, security, further performance optimizations, or adding support for more ML use cases. Even the future focus is not on optimizing accessibility, usability, or the mentioned initial vital steps.

Because we assigned these properties subjectively and our sample size of papers is rather small, we compare our findings so far with the total number of published works about FL. We use the same method to gather the data as for 2.5.

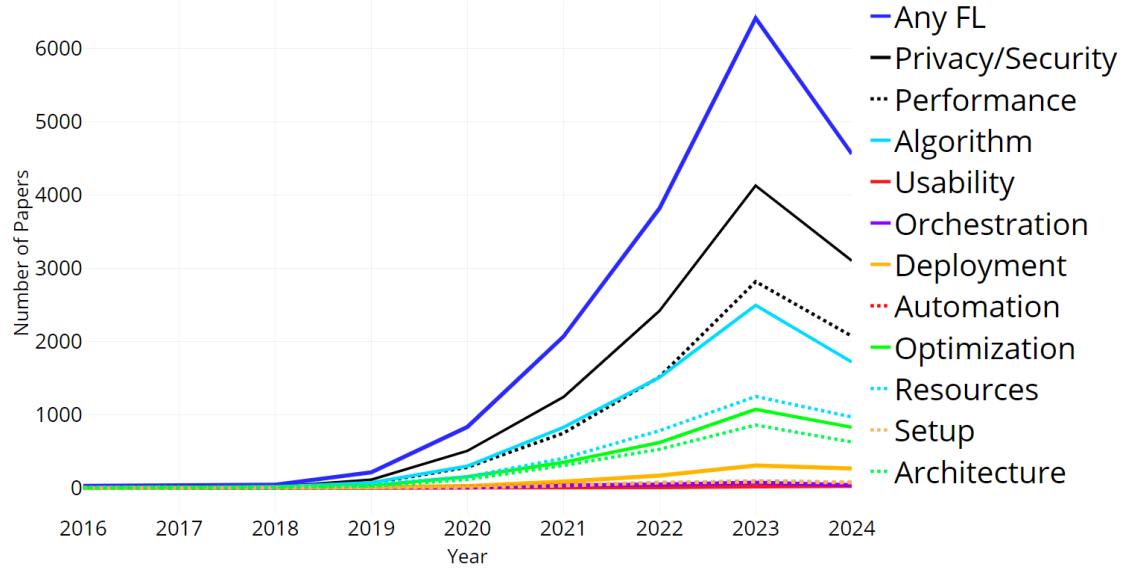


Figure 2.11.: Evolution of FL Publications based on Keywords

Figure 2.11 shows how many works have been published in FL with specific keywords that match our custom categories. The global results paint a similar picture as our samples. The most popular topics in FL are either related to privacy/security, performance, or algorithms. Only a very small portion of FL papers are focused on usability, automation, orchestration, or other initial steps.

It seems that researchers assume others to have already working FL environments, and motivate their readers to optimize them based on their findings instead of replicating and configuring such an FL setup initially. These tendencies can also be seen when inspecting what ML and FL frameworks and libraries the authors mentioned they used in our examined papers.

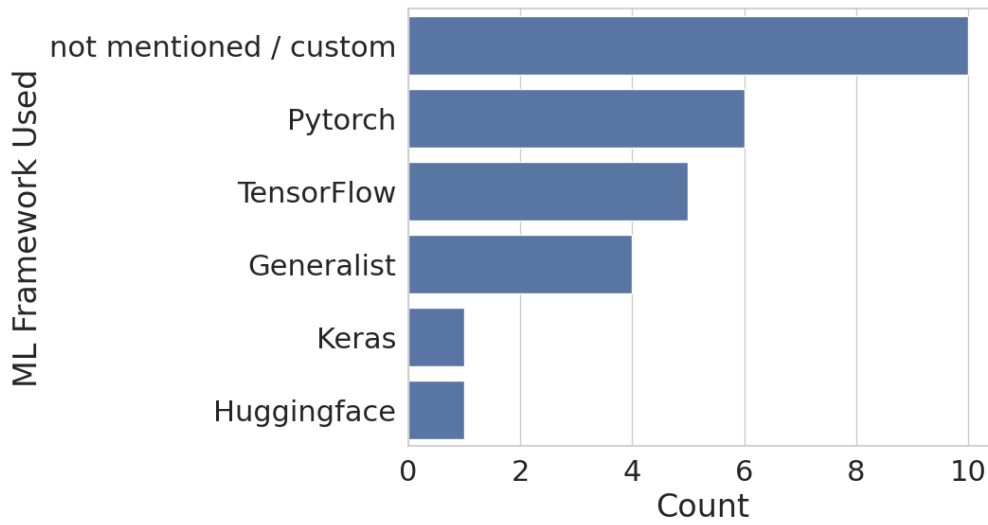


Figure 2.12.: Distribution of mentioned ML Frameworks in FL Papers

Figure 2.12 shows that the majority of authors did not explicitly state what ML framework or library they used for their work. Many researchers used Pytorch and TensorFlow.

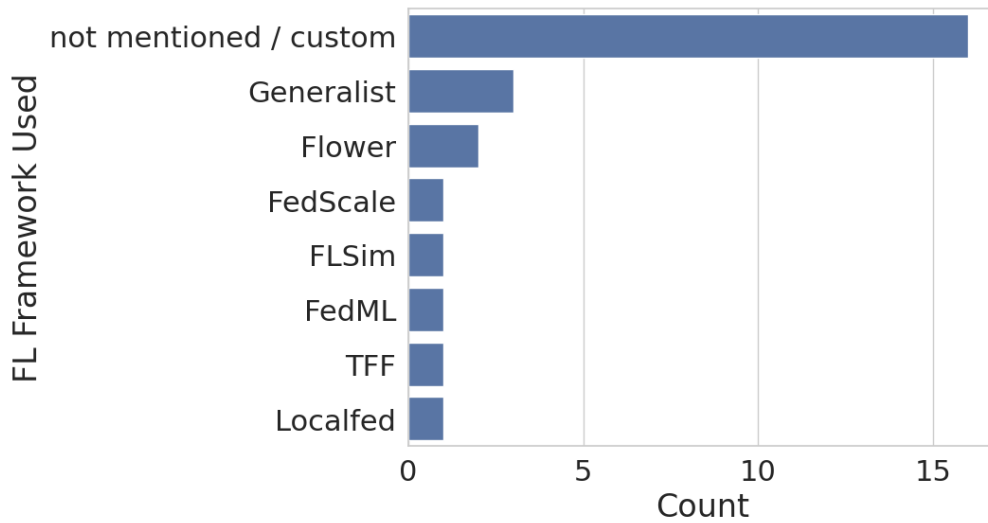


Figure 2.13.: Distribution of mentioned FL Frameworks in FL Papers

Figure 2.13 shows that FL researchers very rarely mention what FL frameworks they use for their work.

It is noteworthy that it is a lot more common for authors to mention what ML framework they used than what FL framework they used.

Possible reasons for this might be that ML as a field is a lot older, more sophisticated, widespread, and established. The same applies for ML frameworks. On the other hand, FL is a very young sub-field of ML research, thus FL frameworks are still in their infancy.

Therefore, FL researchers might be using FL frameworks but due to the early-stage of the framework the researchers might not deem it important to explicitly point out that they used them. Another possible explanation is, that FL researchers are experts in FL and are able to setup, configure FL from the ground up by themselves.

Either way, this lack of transparency makes reproducing or extending their work difficult if not infeasible.

This gap in FL research motivated the creation of FLOps.

2.1.5. FL Frameworks & Libraries

TODO

2.1.6. Flower

2.2. Machine Learning Operations

2.2.1. DevOps

2.2.2. MLOps

2.2.3. MLflow

2.3. Orchestration

2.3.1. Fundamentals

2.3.2. ML Containerization & Orchestration

2.3.3. Oakestra

2.4. Related Work

3. Requirements Analysis

3.1. Overview

3.2. Proposed System

3.2.1. Functional Requirements

3.2.2. Nonfunctional Requirements

3.3. System Models

3.3.1. Scenarios

3.3.2. Use Case Model

3.3.3. Analysis Object Model

3.3.4. Dynamic Model

4. System Design

5. Object Design

6. Evaluation

6.1. Rationale

6.1.1. Chosen Experiments

6.2. Experimental Setup

6.2.1. Monolith

6.2.2. Multi-Cluster

6.2.3. Evaluation Procedure

6.3. Results

6.3.1. Basics

6.3.2. Image Builder

6.3.3. Different ML Frameworks/Libraries & Datasets

6.3.4. Multi-cluster & HFL

7. Conclusion

7.1. Limitations & Future Work

7.1.1. Federated Learning via FLOps

7.1.2. Complementary Components & Integrations

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Appendices

A. Additional FL Research Paper Analysis

The following two tables (A.1, A.2) refer to the omitted FL papers that we examined for FLOps. The main part can be found here (2.1).

Table A.1 shows the first half of the remaining FL papers and table A.2 depicts the second half. When there is no content (-) in the "Limitations & Future Work" column that means that the authors did not mention any explicitly and that we did not notice anything specifically.

ID	Contributions	Limitations Future Work
[16]	Improved an existing PFL algorithm that used clustered models (but discarded all but one in the end). A novel idea to improve performance by using these cluster models as experts in a MoE (Mixture of Experts) setup.	-
[35]	Analysis of drift that occurs due to different learner speeds Novel ideas eliminating that drift.	This work does not consider hierarchical structures, clusters/tiers, or privacy/security.
[17]	Efficiency improvements for privacy-preserving ML techniques for hierarchically distributed structures. Different data partitions and distributions, such as vertical and non-IID, were considered.	Written in 2019. Many other newer papers have investigated HFL security/privacy further.
[7]	A benchmark for federated settings, especially FL, with implementations and datasets.	Outdated benchmark from 2019. When we tried to use it, we encountered many errors and problems, such as broken dependencies, failing example code, and more.
[4]	Proof-of-concept that demonstrates that FL can be deployed and used in hierarchical architectures that fulfill specific industry standards.	The findings and experiments are very basic. Further topics such as diverse network conditions, heterogeneous data, and resources should be investigated.
[37]	Accelerated and improved FL training and the aggregation algorithm via a hierarchical structure and ML momentum.	Security, privacy, and challenging network conditions were not considered.
[15]	Analysis of LLM behavior in FL when using different numbers of learners.	Due to its proof-of-concept nature, this work only features simple experiments that yield few new insights.
[14]	A novel approach to finding and sharing information between FL components and discovering learners. This work uses MQTT with semantic URIs representing the clients' properties, including their resources.	It is a very short paper. The experiments are only simulated. This work's approach was not extensively compared to classic or novel techniques.

Table A.1.: Additional FL Papers considered for FLOps - Part I

ID	Contributions	Limitations Future Work
[9]	Analysis of HFL benefits for security. A novel secure aggregation method and hierarchical DP for HFL.	The number of (online) clients per zone has to be small. Further privacy improvements should be investigated.
[18]	Introduction of distributed adaptive FL model pruning.	Privacy and security were not considered. Further optimizations are possible, primarily focused on GPUs.
[31]	Analysis of the use of transformers in FL compared to other architectures. Findings show that transformers are excellent and should be preferred for FL.	Further investigations are required on how transformers behave with other, latest FL algorithms and privacy/security schemas.
[40]	A scalable edge-only (serverless) FL framework. It utilizes synchronous training and promises rapid integration, prototyping, and deployment.	Planned improvements for this framework include resource optimizations like model compression and quantization and adaptive aggregation strategies based on network conditions, resources, and data diversity. The framework assumes P2P without addressing diverse network conditions. It does not consider security or privacy. The evaluation only checked image classification tasks.
[38]	This paper is likely the first to combine PFL with HFL in a three-tiered structure. It proves mathematically that its approach works and converges. This work includes many interesting insights regarding HPFL.	-
[36]	Analysis of the effects of different global/local update frequencies. A new algorithm to determine global aggregation frequency instead of using the common static one.	Diverse resource usage should be investigated.
[24]	A combination of FL with transfer-learning on Transformers. A parameter efficient (PE) learning method to adapt pre-trained Transformer Foundation Models (FMs) in FL. A novel PE adapter that modulates all pre-trained Transformers layers, enabling flexible early predictions.	-

Table A.2.: Additional FL Papers considered for FLOps - Part II