# Adaptive Aggregation For Federated Learning

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Abstract—In this paper, we present a new scalable and adaptive architecture for FL aggregation. First, we demonstrate how traditional tree overlay based aggregation techniques (from P2P, publish-subscribe and stream processing research) can help FL aggregation scale, but are ineffective from a resource utilization and cost standpoint. Next, we present the design and implementation of AdaFed, which uses serverless/cloud functions to adaptively scale aggregation in a resource efficient and fault tolerant manner. We describe how AdaFed enables FL aggregation to be dynamically deployed only when necessary, elastically scaled to handle participant joins/leaves and is fault tolerant with minimal effort required on the (aggregation) programmer side. We also demonstrate that our prototype based on Ray [1] scales to thousands of participants, and is able to achieve a > 90%reduction in resource requirements and cost, with minimal impact on aggregation latency.

Index Terms—federated learning, serverless, adaptive, aggregation

#### I. INTRODUCTION

Federated Learning (FL) [2], [3] is a mechanism in which multiple parties collaborate to build and train a joint machine learning model typically under the coordination/supervision of a central server or service provider (definition by Kairouz et. al. [2], [3]). This central server is also called an *aggregator*. FL is private by design, because parties retain their data within their private devices/servers; never sharing said data with either the aggregator or other parties. An FL job involves parties performing local training on their data, sharing the weights/gradients of their model (also called a *model update*) with the aggregator, which aggregates the model updates of all parties using a fusion algorithm. The use of *centralized aggregation* is common in FL because of the ease in which various machine learning models (neural networks, decision trees, etc.) and optimization algorithms can be supported.

FL is *typically* deployed in two scenarios: *cross-device* and *cross-silo*. In the cross-silo scenario, the number of parties is small, but each party has extensive compute capabilities (with stable access to electric power and/or equipped with hardware accelerators) and large amounts of data. The parties have reliable participation throughout the entire federated learning training life-cycle, but are more susceptible to sensitive data leakage. Examples include multiple hospitals collaborating to train a tumor/COVID detection model on radiographs [5], multiple banks collaborating to train a credit card fraud detection model, etc. The cross-device scenario involves a large number of parties (> 100), but each party has a small number of data items, constrained compute capability, and limited energy reserve (e.g., mobile phones or IoT devices). They are highly unreliable/asynchronous and are expected to drop

and join frequently. Examples include a large organization learning from data stored on employees' devices and a device manufacturer training a model from private data located on millions of its devices (e.g., Google Gboard [4]).

Increasing adoption of FL has, in turn, increased the need for FL-as-a-service offerings by public cloud providers, which serve as a nexus for parties in an FL job and aggregate/fuse model updates. Such FL aggregation services have to effectively support multiple concurrent FL jobs, with each job having tens to thousands of heterogeneous participants (mobile phones, tablets, sensors, servers) from different organizations and administrative domains. Our experience, in building and operating the IBM Federated Learning (IBM FL) [6], [7] service on our public and private clouds has led us to believe that existing FL aggregation methods have performance, scalability and resource efficiency challenges, primarily due to the use of centralized aggregation.

Performance: Aggregators should not become a bottleneck or a single point of failure in FL jobs. They should be able to store incoming model updates without loss, and have low latency - the time between the arrival of the last expected model update and the completion of aggregation. In the case of a cloud hosted FL aggregation service, said guarantees must hold across all running FL jobs. Most existing FL platforms (IBM FL [7], Webank FATE [8], NVIDIA NVFLARE [9]) are based on a client-server model with a single aggregator per FL job deployed (as a virtual machine or container) in datacenters waiting for model updates. Such platforms are able to easily support multiple concurrent FL jobs, but performance drops as the number of parties increases, especially in crossdevice settings. This is because aggregation throughput is limited by the computational capacity of the largest VM or container (memory and compute, and to a lesser extent, network bandwidth).

**Scalability:** is considered in terms of the number of parties, size of model updates, frequency of updates and (for an FL service) number of concurrent FL jobs. FL platforms using a single aggregator per job only support vertical scalability; nontrivial design using data parallelism and connecting multiple aggregators is necessary for horizontal scalability, especially in cross-device settings. FL jobs involve several rounds, and take an extended period of time, especially with intermittently available parties. Party joins and dropouts are common; so aggregation infrastructure must scale horizontally to support this.

**Resource Efficiency/Cost:** While operating IBM FL and from publicly available FL benchmarks like LEAF [10] and

Tensorflow Federated [11], we have observed that training at the party takes much longer compared to model update fusion/aggregation, resulting in under-utilization and wastage of computing resources dedicated to aggregation. This is a significant problem even in cross-silo settings - active participation is not guaranteed even in cross-silo settings due to competition from other higher priority workloads and variations in data availability. It is further compounded in "crossdevice" deployments, where parties are highly intermittent and do not have dedicated resources for training. In these scenarios, the aggregator expects to hear from the parties eventually (typically over a several hours or maybe once a day). Largescale FL jobs almost always involve intermittent parties – as the number of parties increases, it is extremely hard to expect that all of them participate at the same pace. This results in aggregators having to wait for long periods of time for parties to finish local training and send model updates.

**Contributions:** The core technical contribution of this paper is the design, implementation and evaluation of a flexible parameter aggregation mechanism for FL – AdaFed, which has the following novel features:

- AdaFed reduces state in aggregators and treats aggregators as serverless functions. In many existing FL jobs, every aggregator instance typically acts on a sequence of inputs and produces a single output. State, if present, is not local to the aggregator instance and may be shared by all aggregators. Such state is best left in an external store, and consequently aggregators can be completely stateless and hence, serverless. AdaFed is therefore scalable both with respect to participants effective for cross-silo and cross-device deployments, and with respect to geography single/hybrid cloud or multicloud.
- AdaFed leverages serverless technologies to deploy and tear down aggregator instances dynamically in response to participant model updates, thereby supporting both intermittent and active participants effectively. There is no reason to keep aggregators deployed all the time and simply "awaiting input".
- AdaFed is efficient, both in terms of resource utilization with support for automatic elastic scaling, and in terms of aggregation latency.
- AdaFed is reasonably expressive for programmers to easily implement scalable aggregation algorithms. AdaFed is implemented using the popular Ray [1] distributed computing platform, and can run arbitrary Python code in aggregation functions, and use GPU accelerators if necessary.
- Increased FL job reliability and fault tolerance by reducing state in aggregators, eliminating persistent network connections between aggregators, and through dynamic load balancing of participants.
- AdaFed supports widely used FL privacy preserving and security mechanisms

#### II. BACKGROUND: FL AGGREGATION

## Aggregator Side

## Participant Side

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Participant Side RECV (m^{(r)}) from aggregator Local model x^{(r,1)} \leftarrow m^{(r)} for k \in \{1,2,\ldots,\tau\} do Compute local stochastic gradient g_i(x^{(r,k)}) x^{(r,k+1)} \leftarrow \text{OPTIMIZER}(x^{r,k}, -g_i(x^{(r,k)}), \eta^{(r)}) end Compute local model update \Delta^{(r,l)} \leftarrow x^{(r,\tau)} - x^{(r,1)} SEND \Delta^{(r,l)} to aggregator
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**Algorithm 1:** Generalized FedAVG [3]

An aggregator typically coordinates the entire FL job. The parties, aided by the aggregator, agree on the model architecture (ResNet, EfficientNet, etc), optimizer to use (SGD, Adam, AdaGrad, etc.) and hyperparameters to be used for the FL job (batch size, learning rate, aggregation frequency etc.). The aggregator is responsible for durably storing the global model and keeping track of the FL job. We illustrate FL using the most common algorithm used for neural networks and gradient descent based machine learning models – FedAvg [3]. For FedAvg (Algorithm 1), the aggregator selects a random subset  $S^{(r)} \subset S$  of parties for every round r. The aggregator initializes the global model  $m^1$  using the same process as if the job is centralized (i.e, either randomly or from existing pre-trained models). At each round, the aggregator transmits the global model  $m^{(r)}$  to  $S^{(r)}$ . Once a party receives  $m^{(r)}$ , it uses  $m^{(r)}$  to make  $\tau$  training passes on its local dataset.  $\tau$  is the aggregation frequency. It then computes the local gradient update after  $\tau$  passes,  $\triangle^{(r,l)}$ , and transmits the same to the aggregator. The aggregator in FedAvg then computes the weighted average of all gradient updates  $-\frac{1}{N}\sum_{i\in\mathcal{S}^{(r)}}n_i\triangle_i^{(r)}$  to compute the global gradient update  $\triangle^{(r)}$  and update the global model (for the next round)  $m^{(r+1)}$ . This process proceeds for a set number R of rounds or until the aggregator has determined that the model has converged. The term  $n_i$ in the weighted average is the number of training samples at party i and N is the total number of training samples involved in the round, i.e.,  $N = \sum_{i \in \mathcal{S}^{(r)}} n_i$ .

**Associativity of Aggregation:** Since the number of participants typically varies between FL jobs, and within a job (over time) as participants join and leave, horizontal scalability of FL aggregation software is vital. *Horizontally scalable* aggregation is only feasible if the aggregation operation is associative – assuming  $\oplus$  denotes the aggregation of model updates (e.g., gradients)  $U_i$ ,  $\oplus$  is associative if  $U_1 \oplus U_2 \oplus U_3 \oplus U_4 \equiv (U_1 \oplus U_2) \oplus (U_3 \oplus U_4)$ . Associativity is the

property that enables us to exploit data parallelism to partition participants among aggregator instances, with each instance responsible for handling updates from a subset of participants. The outputs of these instances must be further aggregated. In the case of FedAvg,  $\sum_{i\in\mathcal{S}^{(r)}}n_i\triangle_i^{(r)}$  is associative because addition is associative, and the most computationally intensive because each  $\triangle_i^{(r)}$  involves millions of floating point numbers. A common design pattern in parallel computing [15] is to use tree-based or hierarchical aggregation in such scenarios, with a tree topology connecting the aggregator instances. The output of each aggregator goes to its parent for further aggregation.

## III. ADAFED: DESIGN AND IMPLEMENTATION

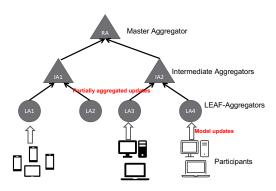


Fig. 1. Hierarchical/Tree-based Aggregation

AdaFed, as its name suggests, adapts to the mechanics of a specific FL job. When a job's aggregation function is associative, as it is in most FL jobs, AdaFed leverages data parallelism to spawn several aggregation "entities/instances" per FL job and arranges them in a tree based (hierarchical) overlay. Tree-based overlays are a common distributed computing pattern in publish-subscribe [16] and stream processing [17]. This enables aggregation to scale to support thousands of parties. However, using "statically deployed" (always on) overlays, while advantageous in high throughput stream processing, is not suitable for FL.

Consequently, AdaFed has a programming model whose goal is to reduce state in aggregators and to decouple aggregator instances. This enables said instances to execute as serverless functions, which are spawned only when model updates arrive, and are torn down when parties are busy training (no updates available to aggregate). An aggregation function instance can be triggered once a specific number of model updates are available; or multiple instances can be triggered once the expected number of model updates for the current FL round are available. Once a model aggregation round is complete and the fused model is sent back to the parties, all aggregator functions exit until the next round, thereby releasing resources.

#### A. Associativity $\rightarrow$ Tree-based Aggregation

Associativity enables us to partition parties among aggregator instances, with each instance responsible for handling updates from a subset of parties. The outputs of these instances

must be further aggregated. A tree topology connects the aggregator instances. The output of each aggregator goes to its parent for further aggregation. We have determined that it is possible to split any associative FL aggregation operation into leaf and intermediate aggregators as illustrated by Figure 1. A leaf aggregator implements logic to fuse raw model weight updates  $U_i$  from a group of k parties to generate a partially aggregated model update  $U_k$ . For example, in the case of FedAvg [18], [19] this function would take  $k_i$  gradient update vectors and return the weighted sum  $S_i = \sum_{1,...,k_i} n_i \triangle_i^{(r)}$  of these vectors, along with the number of data items processed so far  $\sum_{1,...,k_i} n_i$ . An intermediate aggregator implements logic to further aggregate partially aggregated model updates  $(U_k)$ , in stages, to produce the final aggregated model update  $(U_F)$ . In the case of FedAvg, this function would aggregate (add up) multiple  $(S_i)$ . If all expected model updates have arrived from  $\mathcal{S}^{(r)}$ parties, the intermediate aggregator would have thus calculated  $\sum_{1,...,|\mathcal{S}^{(r)}|} n_i \triangle_i^{(r)}$  and  $N = \sum_{1,...,|\mathcal{S}^{(r)}|} n_i$ , from which the aggregated gradient update  $\triangle^{(r)}$  is calculated per Algorithm 1 at the root/master aggregator (Figure 1).

Establishing a tree-based aggregation topology as in Figure 1 starts by identifying the number of parties that can be comfortably handled by an aggregator instance. This is dependent on (i) size/hardware capability (CPU/RAM/GPU) of the instance (server or VM or container) and its network bandwidth, and (ii) the size of the model, which directly determines the size of the model update and the memory/compute capabilities needed for aggregation. Assuming that each instance can handle k participants, a complete and balanced k-ary tree can be used.  $\lceil \frac{n}{k} \rceil$  leaf aggregators are needed to handle n participants; the tree will have  $O(\lceil \frac{n}{k} \rceil)$  nodes.

While a tree-based FL aggregation overlay is conceptually simple, it does involve significant implementation and deployment effort for fault tolerant aggregation. Typically, aggregator nodes are instantiated using virtual machines (VMs) or containers (e.g., Docker) and managed using a cluster management system like Kubernetes. These instances are then arranged in the form of a tree, i.e., each instance is provided with the IP address/URL of its parent, expected number of child aggregators, credentials to authenticate itself to said parent and send aggregated model updates. Failure detection and recovery is typically done using heartbeats and timeouts, between each instance, its parents and children. Once faults happen, the aggregation service provider should typically take responsibility for recovering the instance, and communicating information about the recovered instance to its children for further communications. Things become complicated when an instance fails at the same time as one of its parent or child instances. Another issue, common in distributed software systems, that arises in this scenario is network partitions. In summary, to implement hierarchical aggregation the traditional way [15], any aggregation service has to maintain dedicated microservices to deploy, monitor and heal these aggregation overlays.

## B. "Idle Waiting" in Static Tree Aggregation

Even if some technologies like Kubernetes pods and service abstractions are able to simplify a few of these steps, a more serious problem with tree-based aggregation overlays is that aggregator instances are "always on" waiting for updates, and this is extremely wasteful in terms of resource utilization and monetary cost. To handle FL jobs across thousands of parties, aggregation services including AdaFed must support intermittent parties effectively. Given that, for every round, parties may send model updates over an extended time period (hours), aggregators spend the bulk of their time waitin. Idle waiting wastes resources and increases aggregation cost. A tree-based aggregation overlay compounds resource wastage and cost.

Re-configuring tree-based aggregation overlays is also difficult. This is needed, for example, when midway through a job, a hundred (or a thousand) participants decide to join. Supporting them would require reconfiguration at multiple levels of the aggregation overlay. Reconfigurations are also necessary to scale down the overlay when participants leave. Thus, elasticity of aggregation is hard to achieve in the static tree setting.

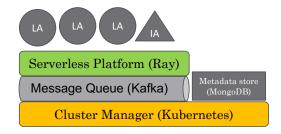


Fig. 2. AdaFed System Architecture. Aggregators are executed as serverless functions.

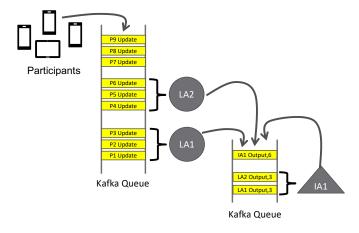


Fig. 3. AdaFed - Illustration of stepwise serverless aggregation

#### C. Using Serverless Functions

AdaFed takes associativity one step further. AdaFed mitigates issues with aggregation overlays by avoiding the construction of *actual/physical* tree topology. Instead, AdaFed

uses serverless functions chained together with message queues to realize a *logical* tree topology. AdaFed executes both leaf and intermediate aggregation operations as serverless/cloud functions. These functions are executed in containers on a cluster managed by Kubernetes, which multiplexes multiple workloads and enables the cluster to be shared by multiple FL jobs and/or other workloads. Also, since there is no static topology, more (or less) aggregator functions can be spawned depending on the number of parties (model updates), thereby handling party joins/leaves effectively. The challenge in executing aggregation as serverless functions, which are ephemeral and have no stable storage, is to manage state - that of each aggregation entity, intermediate aggregation outputs, inter-aggregator communications and party-aggregator communications. We also note that splitting aggregation into leaf and intermediate functions makes the logic simpler. It is also possible to have a single serverless function that can operate on both raw updates and partially fused updates; doing that will increase the complexity of the function.

#### D. Party-Aggregator Communication

This is done using a distributed message queue (Kafka). Kafka is a topic-based message queue offering standard publish/subscribe semantics. That is, each queue has a "name" (i.e., pertains to a "topic"), and multiple distributed entities can write to (publish) and read from (subscribe to) it. Kafka enables us to set a replication level per queue, which ensures durability of messages between the aggregator instances and parties. For each FL job (with an identifier JobID, two queues are created at deployment time - JobID-Agg and JobID-Parties. Only aggregator instances (serverless functions) can publish to JobID-Agg and all parties subscribe to it. Any party can publish to JobID-Parties but only the aggregator instances can both publish to and read from it. This ensures that model updates sent to JobID-Parties are private and do not leak to other parties. When the job starts, the aggregator publishes the initial model on JobID-Agg; parties can then download the model and start training. At the end of each job round, parties publish their model updates to JobID-Parties. Inter-Aggregator Communication, is also handled using Kafka. Partially fused model updates are published by aggregation functions into Kafka, and can trigger further function invocations.

## E. Aggregation Trigger

For serverless functions to execute, they must be triggered by some event. AdaFed provides several flexible and configurable triggers. The simplest ones trigger an aggregation function for every k updates published to JobID-Parties, or every t seconds. For FL jobs that use a parameter server strategy for model updates, it is possible in AdaFed to implement the update logic as a serverless function and trigger it every time an update is published by a party. Other custom triggers involve the periodic execution of any valid Python code (also as a serverless function) which triggers aggregation. Custom triggers are vital to handling FL jobs involving intermittent

parties. As an illustration, consider an FL job where each round is successful if 50% of parties send model updates within 10 minutes. The aggregation trigger here could be a serverless function, invoked every minute, to count the number of parties that have responded and perform partial aggregation through leaf aggregators; aggregation is complete when at least 50% of the parties have responded. Another FL job may require that aggregation waits for at least 10 minutes and considers the round successful if at least 50% of parties have responded. In this case, the job would contain a configuration parameter that triggers aggregation after 10 minutes.

## F. End-to-End Illustration

As illustrated in Figure 3, a set of parties decide to start an FL job through existing private communication channels. "Matchmaking" or inducing parties to join an FL job is out of scope of this paper and AdaFed. We assume that this set of parties is convinced of the benfits of FL and want to collaborate. While forming a group, they also decide things like model architecture, model interchange format and hyperparameters (initial model weights, batch size and learning rate schedule, number of rounds, target accuracy and model update frequency). AdaFed then assigns a JobID to this job, creates metadata pertaining to the job (including party identities and hyperparameters), updates its internal data structures, instantiates two Kafka queues - JobID-Agg and JobID-Parties. A serverless function is triggered to publish the initial model architecture and weights on JobID-Agg. The FL job also specifies the triggering function. Then the first round of training starts at the parties' local infrastructure using the model downloaded/received from JobID-Agg.

Once local training is complete, parties send model updates to JobID-Parties. The trigger (serverless) function executes, and if it determines that an aggregation has to be initiated, triggers a leaf or intermediate aggregator. They pull inputs from JobID-Parties and publish their outputs to the same. This process continues as model updates arrive. When an aggregator function determines that all parties have sent their updates, the round is finished and the updated model published to JobID-Agg. Then the next round starts.

Job termination criteria may be different depending on the type of the FL job, as discussed earlier. A time-based or a quorum-based completion criterion may be also used.

## G. Durability

Aggregation checkpointing for fault tolerance determines how frequently the aggregator checkpoints its state to external stable storage. While this is needed for traditional FL platforms, AdaFed does not use checkpointing. If the execution of a serverless aggregation function fails, it is simply restarted. All aggregator state (updates from parties, partially fused models, etc) is durably stored in message queues. This aspect of AdaFed is vital to understanding AdaFed's resource usage; we observe that the resource overhead of using message queues is equal to that of checkpointing using cloud object stores in single/hierarchical aggregator schemes.

## H. Implementation and Elastic Scaling

We implement AdaFed using the popular Ray [1] distributed computing platform. Ray provides several abstractions, including powerful serverless functions (Ray remote functions). We explored a couple of alternate implementations, including KNative [20] and Apache Flink [21], and settled on Ray because it provides arbitrarily long serverless functions, is well integrated with common Python libraries (numpy, scikit-learn, Tensorflow and PyTorch) and provides the freedom to use accelerators if necessary. Ray's internal message queue could have been used in lieu of Kafka, but we found Kafka to be more robust. Aggregation triggers are implemented using Ray, and support typical conditions on JobID-Parties (receipt of a certain number of messages, etc.), but are flexible enough to execute user functions that return booleans (whether aggregation should be triggered or not).

Our implementation using Ray executes on the Kubernetes cluster manager. Ray's elastic scaler can request additional Kubernetes pods to execute serverless functions, depending on how frequently aggregation is triggered. It is also aggressive about releasing unused pods when there are no model updates pending. When aggregation is triggered, groups of model updates are assigned to serverless function invocations. Each invocation is assigned 2 vCPUs and 4GB RAM (this is configurable). If there are insufficient pods to support all these invocations, Ray autoscales to request more Kubernetes pods. This also enables AdaFed to handle large scale party dropouts and joins effectively. Only the exact amount of compute required for aggregation is deployed – overheads to spawn tasks on Kubernetes pods and create new pods are minimal, as demonstrated in our empirical evaluation.

It is also vital to ensure that model updates are not consumed twice by aggregation functions. When aggregation is triggered for a model update in a Kafka queue, it as marked using a flag. The flag is released only after the output of the function is written to Kafka. If the aggregation function crashes, Ray restarts it, thereby guaranteeing "exactly once" processing and aggregation semantics.

## I. Expressivity and Security

The programming model of AdaFed and its implementation using Ray enables us to support a wide variety of FL aggregation algorithms. Associativity is a pre-requisite for aggregation scalability; and any associative algorithm can be programmed using AdaFed. Most FL aggregation algorithms, including FedAvg/FedSGD [4], FedProx [22], FedMA [23], Mime [25], Scaffold [26], FedPA [27], FedPD [28] and FedDist [24] are associative. In the rare case that the aggregation algorithm is not associative, AdaFed still uses serverless functions to spawn the single aggregator instance and does so with a Docker container of the maximum size (configurable) supported by the underlying Kubernetes cluster. The size and number of aggregator instances, as well as the number of parties handled by any single instance are configurable, enabling AdaFed to support FL jobs with varying participation.

Furthermore, none of the design choices of AdaFed has any impact on FL privacy mechanisms used. Transport layer encryption (TLS) used to transmit model updates in existing FL platforms can be used to send updates to Kafka in AdaFed. Updates are decrypted by the aggregation function reading them from Kafka. AdaFed is oblivious to any noise added by parties for differential privacy. And the fact that functions in AdaFed can execute most Python code means that aggregation of homomorphically encrypted model updates (using appropriate libraries) is also feasible.

#### IV. EVALUATION

In this section, we evaluate the efficacy of AdaFed, by first comparing AdaFed against a centralized aggregator setup common in several FL frameworks like IBM FL [7], FATE [8] and NVFLARE [9]. We demonstrate how such single aggregator setups have difficulties when scaling beyond 100 participants. We then demonstrate how a static hierarchical (tree) overlay of aggregator instances can help with the scalability issue, but is ineffective from a resource consumption, utilization, cost and elasticity perspectives.

#### A. Metrics

Given that aggregation depends on whether the expected number of model updates are available, we define aggregation latency as the time elapsed between the reception of the last model update and the availability of the aggregated/fused model. When compared to a static tree deployment of aggregator instances, serverless functions are dynamically instantiated in response to model updates. Deployment of serverless functions takes a small amount of time (< 100 milliseconds) and elastic scaling of a cluster in response to bursty model update can also take 1-2 seconds. Consequently, the overhead of aggregation in AdaFed will usually manifest in the form of increased aggregation latency. It is measured for each FL synchronization round, and the reported numbers in the paper are averaged over all the rounds of the FL job. We want aggregation latency to be as low as possible. Scalability, or the lack thereof, of any FL aggregation architecture, also manifests in the form of increased aggregation latency when the number of parties rises. We therefore evaluate (i) efficiency by examining whether serverless functions increase the latency of an FL job, as perceived by a participant, (ii) scalability by examining the impact of the number of parties on latency, (iii) adaptivity/elasticity, by examining the impact of parties joining midway on latency.

We evaluate *resource efficiency*, by measuring resource consumption (in terms of the number and duration of containers used for aggregation), resource (CPU and memory) utilization and projected total cost. We execute both hierarchical aggregation and AdaFed using containers on Kubernetes pods in our datacenter, and measure the number of *container seconds* used by an FL job from start to finish. Container seconds is calculated by multiplying the number of containers used with the time that each container was used/alive. This

includes all the resources used by the ancillary services, including MongoDB (for metadata), Kafka and Cloud Object Store. Measuring *container seconds* helps us use publicly available pricing from cloud providers like Microsoft Azure to project the monetary cost of aggregation, in both cases, and project cost savings. We also report average CPU and memory utilization, averaged over the entire FL job.

## B. Experimental Setup

Aggregation was executed on a Kubernetes cluster on CPUs, using Docker containers. For IBM FL, the container used for the single aggregator was run on a dedicated server with 16 CPU cores (2.2 Ghz, Intel Xeon 4210) and 32GB of RAM. Each container for hierarchical or serverless aggregation was equipped with 2 vCPUs (2.2 Ghz, Intel Xeon 4210) and 4 GB RAM. For hierarchical/tree aggregation, each instance was encapsulated using the Kubernetes service abstraction. Parties were emulated, and distributed over four datacenters (different from the aggregation datacenter) to emulate geographic distribution. Each party was also executed inside Docker containers (2 vCPUs and 4 GB RAM) on Kubernetes, and these containers had dedicated resources. We actually had parties running training to emulate realistic federated learning, as opposed to using, e.g., Tensorflow Federated simulator.

We select three real-world federated learning jobs – two image classification tasks from the Tensorflow Federated (TFF) [11] benchmark and one popular document classification task. From TFF [11], we select (i) CIFAR100 dataset which can be distributed over 10-10000 parties, with classification performed using the EfficientNet-B7 model and the FedProx [22] aggregation algorithm and (ii) iNaturalist dataset which can be distributed over 10-9237 parties, with classification performed using the InceptionV4 model and FedProx [22] aggregation algorithm. Thus, we consider two types of images and two models of varying sizes. We do not consider other workloads from TFF because they involve less than 1000 parties. For additional diversity, we consider a third workload using the VGG16 [32] model and FedSGD [4] aggregation algorithm on RVL-CDIP [33] document classification dataset. Each job was executed for 50 synchronization rounds, with model fusion happening after every local epoch. For all scenarios, the datasets were partitioned in a realistic non-IID manner.

## C. Aggregation Latency and Scalability

First, we consider a scenario where the number of parties remains constant throughout the FL job, for all synchronization rounds, i.e., once the job starts, no parties join or leave. From Figure 4, we observe that a centralized single aggregator setting does not scale to a large number of parties, as average aggregation latency increases significantly – almost linearly. This is because of both constrained compute/memory capacity at the single aggregator and constrained network bandwidth needed to transfer/load model updates for aggregation. Figure 4 also illustrates that the increase in aggregation latency is

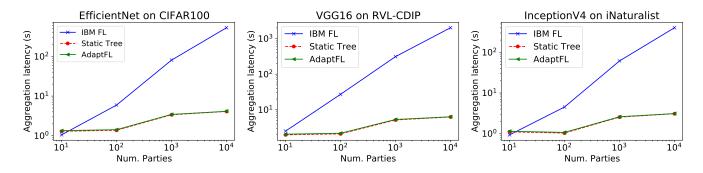


Fig. 4. Aggregation Latency (s) - time taken for aggregation to finish after the last model update is available

| # parties | Static Tree (s) | Serverless (s) | $\frac{Static\ Tree}{Serverless}$ |
|-----------|-----------------|----------------|-----------------------------------|
| 100       | 4.58            | 1.57           | 2.92×                             |
| 1000      | 12.46           | 4.34           | $2.87 \times$                     |
| 10000     | 15.59           | 4.82           | $3.23 \times$                     |

Fig. 5. Effect of 20% party joins on aggregation latency (seconds). EfficientNet-B7 on CIFAR100 using FedProx aggregation algorithm.

| # parties | Static Tree (s) | Serverless (s) | $\frac{Static\ Tree}{Serverless}$ |
|-----------|-----------------|----------------|-----------------------------------|
| 100       | 10.59           | 4.29           | $2.47 \times$                     |
| 1000      | 17.6            | 6.45           | $2.73 \times$                     |
| 10000     | 26.82           | 7.4            | $3.62 \times$                     |

Fig. 6. Effect of 20% party joins on aggregation latency (seconds). VGG16 on RVL-CDIP using FedSGD aggregation algorithm.

much more gradual for both static tree overlays and AdaFed (which uses serverless functions), enabling these architectures to scale to larger FL settings. In fact, for both static tree and AdaFed, latency increases only by  $\approx 4 \times$  when the number of parties increases  $1000 \times$ . This trend is due to the data parallelism inherent in both the static tree and AdaFed.

From an efficiency standpoint, we observe that the aggregation latency is similar between static tree and AdaFed, within 4% of each other, with aggregation latency of AdaFed being slightly higher than that of the static tree overlay. This is because using serverless functions does not reduce the number of aggregation steps; it merely avoids having to keep the aggregators provisioned and alive when they are not needed. We used runtime profiling to determine that the slight (up to 4%) increase in aggregation latency over the static tree is primarily due to cold starts when functions are started; the other minor factor is the latency due to the aggregation trigger. Thus, we observe that the runtime overhead of using and triggering serverless functions is minimal.

## D. Adaptivity/Elastic Scaling for Party Joins

Next, we illustrate how AdaFed can handle parties joining in the middle of the job with minimal impact on aggregation latency. For this, we consider a single synchronization round, and increase the number of parties by 20%. Figures 5,6 and 7 illustrate the aggregation latency when 20% more parties send model updates during the synchronization round. For these

| # parties | Static Tree (s) | Serverless (s) | $\frac{Static\ Tree}{Serverless}$ |
|-----------|-----------------|----------------|-----------------------------------|
| 100       | 20.64           | 7.5            | 2.75×                             |
| 1000      | 36.64           | 10.66          | $3.44 \times$                     |
| 7000      | 59.78           | 13.45          | $4.44 \times$                     |

Fig. 7. Effect of 20% party joins on aggregation latency (seconds). InceptionV4 on iNaturalist using FedProx aggregation algorithm.

experiments, we only illustrate static tree based overlays and AdaFed. This is because Section IV-C has already demonstrated that centralized aggregators do not scale to handle large numbers of parties; the effect of party joins is similar - aggregation latency increases almost linearly w.r.t number of parties joining. Serverless aggregation in AdaFed needs no overlay reconfiguration, while static tree aggregation needs to add more aggregator instances and reconfigure the tree. This manifests as a significant increase in aggregation latency  $(2.47 \times \text{ to } 4.62 \times)$ . This is due to the fact that the number of serverless function invocations depends on the aggregation workload, and partially aggregated updates can be stored in message queues. However, with a tree overlay, new aggregator nodes have to be instantiated and the topology changed. Thus, although both static tree and serverless aggregation methods are elastic, using serverless functions provides significantly better outcomes.

## E. Resource Consumption & Cost

We compare AdaFed with static tree aggregation in terms of resource usage. Although the single aggregator deployment (e.g., using IBM FL) has much lower resource requirements when compared to AdaFed, it has significantly higher latency and does not scale. So, we do not consider it in the experiments in this section. We first illustrate the resource consumption of experiments where parties participate actively (as defined in Section II). Figures 8,9 and 10 tabulate the resource usage for the three workloads, in terms of container seconds and CPU/memory utilization. This data illustrates the real benefits of using serverless aggregation, with > 85% resource and cost savings for the EfficientNet-B7/CIFAR100/FedProx job, > 90% for VGG16/RVL-CDIP/FedSGD and > 80% for InceptionV4/iNaturalist/FedProx. These savings are significant and are a direct result of the adaptivity of AdaFed, by

|         |             |        | ,           |        | Cost      | Avg. CPU    | ` /    | Avg. Memor  |        |
|---------|-------------|--------|-------------|--------|-----------|-------------|--------|-------------|--------|
| Parties | Static Tree | AdaFed | Static Tree | AdaFed | Savings % | Static Tree | AdaFed | Static Tree | AdaFed |
| 10      | 1723        | 228    | 0.46        | 0.06   | 86.96%    | 12.31%      | 82.95% | 46.54%      | 73.35% |
| 100     | 2653        | 351    | 0.71        | 0.09   | 87.32%    | 17.09%      | 83.08% | 20.89%      | 72.89% |
| 1000    | 22340       | 2951   | 6.01        | 0.79   | 86.86%    | 10.99%      | 83.52% | 17.23%      | 72.87% |
| 10000   | 298900      | 40849  | 80.46       | 11     | 86.33%    | 10.61%      | 84.27% | 18.66%      | 75.39% |

Fig. 8. EfficientNet-B7 on CIFAR100 using FedProx aggregation algorithm. Active Participants. Resource usage and projected cost, using container cost/s of 0.0002692 US\$ (source Microsoft Azure [34])

| Num.<br>Parties | Tot. contained<br>Static Tree |       | Proj. Total<br>Static Tree |      | Cost<br>Savings % | Avg. CPU<br>Static Tree | \ /    | Avg. Memor<br>Static Tree | y Util. (%)<br>AdaFed |
|-----------------|-------------------------------|-------|----------------------------|------|-------------------|-------------------------|--------|---------------------------|-----------------------|
| 10              | 1953                          | 162   | 0.53                       | 0.04 | 91.73%            | 13.17%                  | 91.98% | 47.01%                    | 84.36%                |
| 100             | 3078                          | 234   | 0.83                       | 0.06 | 92.4%             | 10.75%                  | 90.22% | 20.27%                    | 82.01%                |
| 1000            | 25250                         | 1992  | 6.8                        | 0.54 | 92.11%            | 13.86%                  | 92.92% | 22.9%                     | 85.82%                |
| 10000           | 337830                        | 30303 | 90.94                      | 8.16 | 91.03%            | 12.36%                  | 89.25% | 22.96%                    | 82.89%                |

Fig. 9. VGG16 on RVL-CDIP using FedSGD aggregation algorithm. Active Participants. Resource usage and projected cost, using container cost/s of 0.0002692 US \$ (source Microsoft Azure [34]

|      | Tot. containe<br>Static Tree |       | , ,   |       | Cost<br>Savings % | Avg. CPU<br>Static Tree |        | Avg. Memor<br>Static Tree |        |
|------|------------------------------|-------|-------|-------|-------------------|-------------------------|--------|---------------------------|--------|
| 10   | 2365                         | 389   | 0.64  | 0.1   | 83.55%            | 10.86%                  | 91.86% | 49.73%                    | 82.25% |
| 100  | 3354                         | 548   | 0.9   | 0.15  | 83.65%            | 14.17%                  | 91.18% | 21.71%                    | 83.49% |
| 1000 | 30545                        | 5144  | 8.22  | 1.38  | 83.16%            | 10.87%                  | 91.77% | 23.12%                    | 83.43% |
| 9237 | 420870                       | 68307 | 113.3 | 18.39 | 83.77%            | 13.44%                  | 91.01% | 21.33%                    | 82.49% |

Fig. 10. InceptionV4 on iNaturalist using FedProx aggregation algorithm. Active Participants. Resource usage and projected cost, using container cost/s of 0.0002692 US \$ (source Microsoft Azure [34]

| Num.<br>Parties | Tot. contained<br>Static Tree |       | Proj. Total<br>Static Tree |      | Cost<br>Savings % | Avg. CPU<br>Static Tree | ` /    | Avg. Memor<br>Static Tree |        |
|-----------------|-------------------------------|-------|----------------------------|------|-------------------|-------------------------|--------|---------------------------|--------|
| 10              | 634                           | 272   | 0.17                       | 0.07 | 99.28%            | 10.58%                  | 81.3%  | 42.67%                    | 75.26% |
| 100             | 576                           | 385   | 0.16                       | 0.1  | 98.89%            | 11.97%                  | 79.77% | 12.17%                    | 74.77% |
| 1000            | 10516                         | 1113  | 2.83                       | 0.3  | 99.82%            | 11.41%                  | 81.06% | 11.05%                    | 74.15% |
| 10000           | 105021                        | 18741 | 28.27                      | 5.05 | 99.7%             | 10.25%                  | 81.09% | 10.29%                    | 74.71% |

Fig. 11. EfficientNet-B7 on CIFAR100 using FedProx aggregation algorithm. Intermittent participants updating over a 10 minute interval for every synchronization round. Resource usage and projected cost using Container cost/s of 0.0002693 US \$ (source Microsoft Azure [34]).

deploying aggregator functions only when needed. Resource wastage due to static tree can also be observed from the CPU/memory utilization figures, which are consistently low for static tree because aggregator instances are idle for long periods. We also observe that, while compute resources needed for aggregation increase with the number of participants for both static tree and serverless aggregation, the amount of resource and cost savings remains fairly consistent. We use Microsoft Azure's container pricing for illustrative purposes only; pricing is similar for other cloud providers.

We stress that the experiments in Figures 8,9 and 10 are *conservative*; they assume active participation. That is, parties have dedicated resources to the FL job, parties do not fail in the middle of training, and training on parties for each round starts immediately after a global model is published by the aggregator. In realistic scenarios, parties (e.g., cell phones or laptops or edge devices) perform many functions other than model training, have other tasks to do and can only be expected to respond over a period of time (response

timeout). Depending on the deployment scenario, this can be anywhere from several minutes to hours. Figures 11,12 and 13 demonstrate that resource and cost savings are huge (> 99%) when response timeout is set to *a modest* 10 minutes per aggregation round. Real world FL jobs typically use higher response timeouts and will thus reap enormous benefits. Thus, our experiments reinforce our confidence that serverless aggregation can lead to significant resource and cost savings with minimal overhead.

#### V. RELATED WORK

Parallelzing FL aggregation using a hierarchical topology has been explored by [4], though the design pattern was introduced by and early work on datacenter parallel computing [15]. While [4] uses hierarchical aggregation, its programming model is different from AdaFed. Its primary goal is scalability and consequently, it deploys long lived actors instead of serverless functions. AdaFed aims to make FL aggregation resource efficient, elastic in addition to being

| Num.<br>Parties |                |            | 1 3         |             | Cost<br>Savings % | Avg. CPU<br>Static Tree | ` /             | Avg. Memor      |                  |
|-----------------|----------------|------------|-------------|-------------|-------------------|-------------------------|-----------------|-----------------|------------------|
|                 |                |            |             |             |                   |                         |                 |                 |                  |
| 10              | 33043<br>33037 | 258<br>385 | 8.9<br>8.89 | 0.07<br>0.1 | 99.21%<br>98.88%  | 13.23%<br>14.12%        | 87.06%<br>84.2% | 46.98%<br>10.3% | 82.11%<br>81.56% |
| 1000            | 510039         | 2975       | 137.3       | 0.8         | 99.42%            | 14.46%                  | 85.77%          | 10.69%          | 81.7%            |
| 10000           | 5700030        | 40884      | 1534.45     | 11.01       | 99.28%            | 10.91%                  | 84.27%          | 12.08%          | 80.86%           |

Fig. 12. VGG16 on RVL-CDIP using FedSGD aggregation algorithm. Intermittent participants updating over a 10 minute interval for every synchronization round. Resource usage and projected cost using Container cost/s of 0.0002693 US \$ (source Microsoft Azure [34]).

| Num.    | n.   Tot. container seconds |        | Proj. Total cost US\$ |        | Cost      | Avg. CPU Util. (%) |        | Avg. Memory Util. (%) |        |
|---------|-----------------------------|--------|-----------------------|--------|-----------|--------------------|--------|-----------------------|--------|
| Parties | Static Tree                 | AdaFed | Static Tree           | AdaFed | Savings % | Static Tree        | AdaFed | Static Tree           | AdaFed |
| 10      | 34365                       | 509    | 9.25                  | 0.14   | 98.52%    | 13.49%             | 87.75% | 51.13%                | 84.17% |
| 100     | 34358                       | 588    | 9.25                  | 0.16   | 98.29%    | 11.08%             | 87.08% | 11.88%                | 83.72% |
| 1000    | 734456                      | 17700  | 197.72                | 4.76   | 97.59%    | 11.59%             | 89.09% | 10.1%                 | 87.28% |
| 9237    | 6783036                     | 206883 | 1825.99               | 55.69  | 96.95%    | 11.43%             | 88.55% | 11.19%                | 84.4%  |

Fig. 13. InceptionV4 on iNaturalist using FedProx aggregation algorithm. Intermittent participants updating over a 10 minute interval for every synchronization round. Resource usage and projected cost using Container cost/s of 0.0002693 US \$ (source Microsoft Azure [34]).

scalable; and use off-the-shelf open source software like Ray, Kafka and Kubernetes.

Another closely related concurrent work is FedLess [35], which predominantly uses serverless functions for the training side (party side) of FL. FedLess is able to use popular serverless technologies like AWS Lambda, Azure functions and Openwhisk to enable clients/parties on cloud platforms perform local training and reports interesting results on using FaaS/serverless instead of IaaS (dedicated VMs and containers) to implement the party side of FL. It also has the ability to run a single aggregator as a cloud function, but does not have the ability to parallelize aggregation, and does not seem to scale beyond 200 parties (with 25 parties updating per FL round, per [35]). Our work in AdaFed has the primary goal of parallelizing and scaling FL aggregation. Fedless [35] also does not adapt aggregation based on party behavior, and it is unclear whether parties on the edge (phones/tablets) can train using FedLess.

A number of ML frameworks – Siren [36], Cirrus [37] and the work by LambdaML [38] use serverless functions for centralized (not federated) ML and DL training. Siren [36] allows users to train models (ML, DL and RL) in the cloud using serverless functions with the goal to reduce programmer burden involved in using traditional ML frameworks and cluster management technologies for large scale ML jobs. It also contains optimization algorithms to tune training performance and reduce training cost using serverless functions. Cirrus [37] goes further, supporting end-to-end centralized ML training workflows and hyperparameter tuning using serverless functions. LambdaML [38] analyzes the cost-performance trade-offs between IaaS and serverless for datacenter/cloud hosted centralized ML training. LambdaML supports various ML and DL optimization algorithms, and can execute purely using serverless functions or optimize cost using a hybrid serverless/IaaS strategy. AdaFed differs from Siren, Cirrus and LambdaML in significant ways - Distributed ML (in Siren, Cirrus and LambdaML) is different from FL. Distributed ML involves centralizing data at a data center or cloud service and performing training at a central location. In contrast, with FL, data never leaves a participant. FL's privacy guarantees are much stronger and trust requirements much lower than that of distributed ML.

The term "serverless" has also been used to refer to peerto-peer (P2P) federated learning, as in [12]-[14]. In such systems, aggregation happens over a WAN overlay and not in a datacenter. The first step involves establishing the overlay network, by following existing technologies like publish/subscribe overlays, peer discovery, etc [16], [17]. The next step involves establishing a spanning tree over the P2P overlay, routing updates along the spanning tree and aggregating at each node on the tree. Gossip based learning, [14] does not construct overlays but uses gossip-based broadcast algorithms to deliver and aggregate model updates in a decentralized manner. While these techniques are scalable and (in the case of gossip algorithms) fault tolerant, they do require either (i) that the model be revealed to more entities during routing, or (ii) homomorphic encryption [39] which can be challenging both from a key agreement and model size explosion standpoints, or (iii) differential privacy [40] which reduces model accuracy in the absence of careful hyperparameter tuning.

#### VI. CONCLUSIONS AND FUTURE WORK

In this paper, we have presented AdaFed, a system for adaptive serverless aggregation in federated learning. We have described the predominant way of parallelizing aggregation using a tree topology and examined its shortcomings. We have demonstrated how serverless/cloud functions can be used to effectively parallelize and scale aggregation while eliminating resource wastage and significantly reducing costs. Our experiments using three different model architectures, datasets and two FL aggregation algorithms demonstrate that the overhead of using serverless functions for aggregation is minimal, but resource and cost savings are substantial. We also demonstrate that serverless aggregation can effectively adapt

to handle changes in the number of participants in the FL job.

We are currently working to extend this work in two directions: (i) increasing the dependability and integrity of aggregation using trusted execution environments (TEEs) and (ii) effectively supporting multi-cloud environments by using service mesh (like Istio) to find the best aggregator function to route a model update.

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