Abstract—The rapid growth of data generated from Internet of Things (IoTs) such as smart phones and smart home devices presents new challenges to cloud computing in transferring, storing, and processing the data. With increasingly more powerful edge devices, edge computing, on the other hand, has the potential to better responsiveness, privacy, and cost efficiency. However, resources across the cloud and edge are highly distributed and highly diverse. To address these challenges, this paper proposes EdgeFaaS, a Function-as-a-Service (FaaS) based computing framework that supports the flexible, convenient, and optimized use of distributed and heterogeneous resources across IoT, edge, and cloud systems. EdgeFaaS allows cluster resources and individual devices to be managed under the same framework and provide computational and storage resources for functions. It provides virtual function and virtual storage interfaces for consistent function management and storage management across heterogeneous compute and storage resources. It automatically optimizes the scheduling of functions and placement of data according to their performance and privacy requirements. EdgeFaaS is evaluated based on two edge workflows: video analytics workflow and federated learning workflow, both of which are representative edge applications and involve large amounts of input data generated from edge devices.

1. INTRODUCTION

We are living in the big data era where explosive data comes largely from edge devices such as smart phones, and smart home devices. The ubiquitous edge devices can generate 400 Zettabytes of data per year [10]. This big amount of data has presented important challenges to our existing computational infrastructure. The previous cloud-only solution fails to transfer, store or process such vast amounts of data efficiently and cost-effectively. What’s more, many edge applications come with latency and privacy requirements where cloud-only solution falls short. At the same time, edge devices have become unprecedented powerful in both computation and storage, providing new opportunities for the new computing paradigm, “edge computing”.

Contrary to the rapid growth of edge computing, there is a lack of suitable computational infrastructure that supports the unique characteristics of edge applications and edge systems. Edge applications are highly data driven. Most edge applications perform computations based on data collected by IoT devices. For example, the smart home IoT devices collect home metrics through different sensors which is then analysed in the home hub or cloud. Another example would be surveillance systems, where streams of videos are generated from cameras and serves as input data for image processing edge applications. The edge applications uses the IoT devices generated data as input. The edge computational infrastructure should transfer or store the large amount of data generated from IoT devices with care to improve the performance.

Edge applications are also latency sensitive. Due to edge devices’ close interaction with the physical world by sensing and actuating, many edge applications have low latency or even real-time requirement. For example, in autonomous driving, the system’s response time is capped at 100ms [29] for some scenarios such as sensing and processing the surrounding environment which is nearly real time. Another example is for security alarms where the devices are expected to react immediately to detected security issues. The edge computational infrastructure should process the vast amount of data generated from the edge devices and avoid the expensive data transfer latency from edge devices to cloud [25].

Furthermore, edge applications have privacy requirement. Data collected from sensors and edge devices may contain physical world or personal information that is critical to privacy. For example, medical edge devices capture patient-private data and should not be exposed to any unrelated people. Computation that involves private data calls for the data storage and processing to happen on local edge devices to avoid possible data leakage during network transportation and on the cloud.

At the same time, edge systems are highly heterogeneous and highly distributed. From edge to cloud, there are three tiers of resources distributed over IoT devices, edge servers, and cloud datacenters. Within each tier, the resources are also distributed across different geographical areas and administrative domains. An edge system is built upon highly heterogeneous resources. IoT devices, edge servers, and cloud servers are drastically different tiers in the system, whereas within each tier the resources, especially the devices in the IoT tier, are also highly diverse in terms of processors/accelerators, memory/storage, OS/hypervisor, and libraries/runtime.

To better cater to the unique characteristics of edge applications and edge systems, we introduce EdgeFaaS, a function-based distributed computing platform for edge applications.

First, EdgeFaaS allows cluster resources and individual devices to be managed under the same framework and
provides computational and storage resources for functions. The current FaaS platforms such as OpenFaas \cite{14}, OpenWhisk \cite{4}, and AWS Lambda \cite{12} can only run applications on one device or one cluster. Applications cannot exploit both the edge devices' low data transfer cost and the cloud strong computation power. EdgeFaaS can register different clusters and schedule the computation based on the data proximity and latency requirement to different clusters.

Second, it provides virtual function and virtual storage interfaces for consistent function management and storage management across heterogeneous compute and storage resources. For the functions, the locations of input and output data, cluster gateways, all these are virtualized in EdgeFaaS and users do not have direct access. Each function deployment, invocation are conducted through the exposed EdgeFaaS gateway and all the resources are transparent to the user. These help protect the data and function privacy. Besides, it frees users from the hassle of function management and storage management as users do not need to manually participate in distributing functions across heterogeneous computing and storage resources. The manageability of edge computing is improved as function and storage are virtualized and managed by cautiously designed RESTful APIs. Likewise, the storage resources are also virtualized to be transparent to users. Users only get access to their own data through the RESTful APIs and is free from the complexity of storage resource management.

Third, it automatically optimizes the scheduling of functions and placement of data according to their performance and privacy requirements. To fulfill the latency-sensitive feature of edge applications, EdgeFaaS place the functions and data based on data locality to save the data transfer latency from IoT devices to cloud. This feature also satisfies the edge data privacy requirements by storing the device-collected data locally without transferring it to the remote cloud.

We also introduce two representative edge workflows to illustrate the usage of EdgeFaaS. The two workflows are video analytic workflows and federated learning workflows, which are representative of a large portion of today’s edge applications. The video analytic workflow forms a pipeline of continuous video streams generation, motion detection, face detection, face extraction, and face recognition. The whole pipeline involves five stages and uses object storage and message queue for storing the input and output of each stage. The federated learning workflow involves the distributed training on IoT devices and model aggregation on edge and cloud clusters. Each IoT device trains the model locally using the local generated data. It then passes the trained model to edge cluster for aggregation. The edge aggregated model is finally contributed to cloud for final aggregation. Both workflows involve large amounts of data and exhibit the three edge applications characteristics described above.

We implement and evaluate EdgeFaaS using the open source FaaS platform, OpenFaas \cite{14}. We use the two edge workflows to study the usability of EdgeFaaS. First, we show EdgeFaaS can manage different computation and storage resources. Second, we show how EdgeFaaS schedules the function execution and data storage among different resources to achieve the application requirements. Third, we show how EdgeFaaS can be further extended to run other edge applications.

In summary, the contributions of this work are as follows: 1) we characterize the unique challenges brought by edge applications and the underlying systems; 2) we design and implement EdgeFaaS to address these challenges by providing a unified computing platform; 3) we provide two workflows using EdgeFaaS which can represent a large portion of edge applications; 4) we demonstrate that EdgeFaaS can effectively execute edge workloads to meet edge applications’ requirements.

In the following paper, Section 2 provides a background of edge computing, function-as-a-service, and federated learning. Section 3 provides an overview of the design and implementation of EdgeFaaS. Section 4 introduces the two representative edge workflows. Section 5 evaluates EdgeFaaS based on the two workflows. Section 6 introduces related works and Section 7 concludes the paper.

2. BACKGROUND

2.1. Edge Computing

Edge computing is a computing paradigm that conducts computation close to the data source. With the proliferation of edge devices, even the fast-growing cloud is believed to be inadequate in handling the explosive demand of data collection, transportation and processing. The emerging edge computing, which expands computing infrastructure from the cloud to the computing resources on edge including edge devices, edge servers, and edge clusters \cite{14}, is a promising paradigm to resolve the challenges on the cloud side.

A primary advantage of edge computing is the fast response of applications. The ubiquitous edge devices can generate 400 Zettabytes of data per year \cite{16}. The vast amount of data transportation works have pushed the network to be the bottleneck. Processing such large and fast data in time places a huge burden on the computation resources of cloud data centers. Both the computation and network latencies in the cloud largely slow down applications’ response time, which have pushed computation to move closer to the data source. Doing computation on the ubiquitous edge devices in a scale-out manner can reduce this unnecessary network overhead by processing the data locally to improve the response time.

Edge computing can offload computation to peer edge devices, nearby edge data centers, and farther cloud. All these heterogeneous resources are utilized by edge computing to provide high scalability for different amount of work.

Another key advantage of edge computing is data privacy. Private data like personal video footage and data collected by virtual assistant for model training can be better protected on the edge than in the cloud. One one hand, edge computing allows data to be processed on the user’s own device which can be well protected by different security
features \[2\], \[1\]. On the other hand, it is relatively more difficult to ensure data privacy on shared cloud resources.

Finally, by utilizing the computing and storage resources available on edge, the cost of cloud services can be reduced. More computation are conducted using the edge resources which is weaker and cheaper than cloud services. Users pay less to use powerful cloud resources but in turn can get similar services with acceptable performance.

### 2.2. Function-as-a-Service

Function-as-a-Service (FaaS) is a service-oriented computing model that allows users to run functions without the complexity of building and maintaining the infrastructure.

users define functions and FaaS deploys applications in the unit of sandboxed functions. Functions can be chained to work in a pipelined manner. A function is triggered by function invocation. FaaS quickly and dynamically scales up and down the number of function sandboxes on demand. As soon as a request finishes, its function sandboxes can be shut down to release resources and no state is guaranteed to be preserved.

Compared to the other commonly used service models such as IaaS and conventional PaaS, FaaS has several important benefits. First, FaaS simplifies the development effort. Developers are able to decompose complex applications into smaller and simpler functions which helps reduce the complexity of development and makes debugging easier. The auto-scaling of functions gets easier too. Developers only need to specify a few configuration parameters to tune the auto-scaling without the complexity of changing the infrastructure and deploying more applications manually.

Another advantage of FaaS is the faster initialization. FaaS deploys functions which usually have smaller image sizes compared to entire applications. The functions belonging to the same application can be deployed in parallel to save the initialization time compared to a full-blown application. FaaS also provides better cost effectiveness. Edge devices are increasingly powerful in terms of speed, capability, and capacity. For example, smartphones have equipped with up to 8 core processors, tens of gigabytes of memory and hundreds of gigabytes of storage to cater to the various needs of applications. Finally, FaaS has the benefits of improving resource utilization. Resources are provided to users in a finer-grained unit which can avoid resource being wasted and unutilized for IaaS and PaaS service models. Also, each function requires limited resources and resources can be better divided among different functions.

FaaS platforms typically involves a gateway and a FaaS provider. The gateway provides RESTful APIs such as deploy, invoke, delete operations on functions for users to send requests to the FaaS platform. FaaS provider is a connector to connect the FaaS gateway to the underlying computing platform. Take OpenFaaS for example, it uses Kubernetes as one of the underlying computation platforms and has a faas-netes FaaS provider to connect the FaaS gateway to the Kubernetes. Faas-netes parses the user requests from the gateway and sends them to the Kubernetes for CRUD for Functions, function auto-scaling, invocation of functions, etc.

FaaS typically uses MinIO and S3 services as the external storage to store input and output data of a function. These object stores provide interfaces for easy access to the storage. Take MinIO as an example, it provides putObject, getobject, makeBucket these interfaces for users to create buckets and store and retrieve objects.

### 3. EdgeFaaS

EdgeFaaS manages different resources from IoT tier, edge tier, to cloud tier. Each resource needs to be organized as an OpenFaaS \[14\] resource which exposes a gateway to EdgeFaaS in order to schedule functions to run on the resource. EdgeFaaS provides a unified gateway which could target different platforms using a scheduling mechanism of user’s choice. It implements the same interfaces as OpenFaaS but allows users to run applications using different resources. So whenever an invocation is made or a deployment requested, EdgeFaaS is in the critical-path and acts like a router, picking some most suitable resources for function execution. In order to address the scalability and single point of failure problem, EdgeFaaS can run as a deployment of Kubernetes and utilizes the ReplicaSet provided by Kubernetes to maintain a stable set of replica pods running at any given time. Figure 1 shows the architecture of EdgeFaaS. We will explain each module in details in the following sections. Besides OpenFaaS functions, the resource also needs to have multiple storage backends and monitoring systems deployed. By default, EdgeFaaS uses Minio \[7\] and Prometheus \[10\]. Minio is used to store input, output, and intermediate data and Prometheus is to provide real-time resource usage stats for EdgeFaaS function management.

![Figure 1: EdgeFaaS Architecture](image)

### 3.1. Resource Management

EdgeFaaS manages heterogeneous resources through resource management. Each heterogeneous resource from IoT tier, edge tier, to cloud tier is organized as an OpenFaaS resource. The OpenFaaS resource can be a group of data center nodes forming a kubernetes resource which host OpenFaaS services atop of it or can be a Faasd service,
which is a lightweight version of OpenFaaS, running on a single IoT device. Each OpenFaaS resource exposes a gateway (including Faasd) to EdgeFaaS through which EdgeFaaS deploys functions on the resource to utilize the resource. In this way, EdgeFaaS is able to support different resources. EdgeFaaS uses HTTP to request the RESTful APIs provided by the FaaS framework and object store. In order to support other frameworks and object stores, EdgeFaaS can issue http requests to the RESTful APIs provided by other frameworks and object stores. This way, if resources are organized through other FaaS platforms such as OpenWhisk [4] or AWS Lambda [12], as long as the gateway of the FaaS platform is provided to EdgeFaaS, they can all be managed.

3.1.1. Resource Registration. When a new resource is provided as a resource, users need to register the resource to EdgeFaaS. Each resource is registered through a YAML file containing the resource capability and gateway. All of the fields in the YAML file are shown in Table 1. The name field refers to the resource’s name, it can be IoT, edge, or cloud to illustrate the resource’s nature. Node represents the number of physical nodes in the resource. Memory shows each physical node’s memory capacity. Cpu is the number of CPU logical cores on each physical node. Storage shows the disk size of each physical node. Gpu node shows the number of physical nodes that have GPU installed. Gpu is the number of GPUs each physical node has. Gateway is the OpenFaaS [12] gateway and pwd is the password to authenticate the administrative API Gateway of the OpenFaaS resource. Prometheus is the Prometheus gateway for the resource for monitoring the resource utilization in the system. Minio [7] information includes Minio, which is the MinIO endpoint, miniokey and minioskey, are the AccessKey and SecretKey of MinIO, respectively to authenticate the user privileges. The user should at least have the read and write privileges enabled in order for EdgeFaaS to use the MinIO. The YAML file is parsed and the resource information is stored in memory and backed up in AWS S3 [3]. Each registered resource is assigned a unique resource ID that is returned to the user during resource registration. A resource mapping is maintained to store the resource ID to the resource information mapping. When backed up in S3, all the resources information are stored in the resource_mapping bucket. The resource ID is the object name and the object contains the resource information. All the mappings that EdgeFaaS maintains are backed up in DynamoDB with the mapping-name as the key and content as the value. This is to ensure consistency in case of EdgeFaaS failure or crashes. EdgeFaaS can still get the mappings from DynamoDB and continue scheduling without losing important information. All the resource YAML files are hidden from users to maintain the security of the computing resources.

Upon registration, the resource will be taken into consideration in case of function scheduling and storage allocation. EdgeFaaS utilizes the resource capability of the resource in scheduling applications. For example, the memory size is utilized to determine if the resource has enough memory to run the workflow. The disk storage is used to determine if the resource has sufficient disk space to store input, output or intermediate data. The GPU information is to determine if the resource is suitable for GPU-accelerated workflows. Besides, the gateways of the resource is used by EdgeFaaS to perform operations. The OpenFaaS gateway provides EdgeFaaS the gateway to invoke the function on the resource. The Prometheus gateway helps EdgeFaaS to get the real-time performance and resource usage of the resource. The Minio information can be used to store the data on the resource.

The resource can also be unregistered so that EdgeFaaS removes the resource information and does not consider the resource for scheduling. Once it is unregistered, the resource ID is reused for other resources and the resource mapping is updated both in memory and in S3. In order to unregister a resource, the user has to delete all the functions deployed on the resource and remove all the data stored in the resource. Failure to do these will result in the resource not to be unregistered.

3.1.2. Resource Monitoring. Each resource has a Prometheus [10] service deployed to monitor the resource usages of the resource. The monitoring includes CPU usage, memory usage, I/O bandwidth and GPU usage (if possible). Prometheus also monitors the load distribution of all the nodes that belong to one resource. This information is used for function deployment (Chapter 3.2.1). When doing function deployment decisions, EdgeFaaS fetches the Prometheus resource metrics from each resource and picks out resources that can meet the minimum resource requirement of the function.

3.2. Function Management

A series of functions form an application. Before the functions are created, the user needs to configure the application first. A YAML file with the application’s configuration is provided to configure the application. In the YAML file (Table 2), application is the application’s name which must be unique. Entrypoint is the entript of this application, it must be one of the functions of the application.

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**Table 1: Resource Registration YAML File Fields.**

| Field       | Sample Element                      |
|-------------|-------------------------------------|
| name        | cloud                               |
| node        | 10                                  |
| memory      | 64GB                                |
| cpu         | 32                                  |
| storage     | 512GB                               |
| gpunode     | 8                                   |
| gpu         | 4                                   |
| gateway     | 10.107.30.249:8080                  |
| pwd         | s2TshbDJG4                           |
| prometheus  | 10.107.30.112:30090                 |
| minio       | 10.107.30.112:9000                  |
| miniokey    | minioadmin                          |
| minioskey   | minioadmin                          |

---
deploy_function(ApplicationName string, 
    FunctionName string, FunctionPackage string) (error)

Invoke() invokes an EdgeFaaS function. A function can be invoked synchronously (and wait for the response), or asynchronously. To invoke a function asynchronously, set Sync to False. EdgeFaaS maps EdgeFaaS FunctionName to the candidate resources that have the function created with the candidate_resource mapping. EdgeFaaS can invoke functions on all the candidate resources or on only one of the candidate resources by specifying invokeOne as true. EdgeFaaS executes the invoke function request of OpenFaaS on the resource. The payload of the function is

Get_function() returns information about the function, including the where the function is deployed and the function specifications. EdgeFaaS maps EdgeFaaS FunctionName to the resources that have the function created using candidate_resource mapping. EdgeFaaS executes OpenFaaS remove function request on each resource. Delete_function() returns the resources that fail to delete the function.

delete_function(ApplicationName string, 
    FunctionName string) (error)

Delete_function() deletes an EdgeFaaS function from all the deployed resources. Users provide the ApplicationName and the FunctionName. EdgeFaaS maps the EdgeFaaS FunctionName to the resources that have the function created using candidate_resource mapping. EdgeFaaS executes OpenFaaS remove function request on each resource.

get_function(ApplicationName string, 
    FunctionName string) (error)

Invoke(ApplicationName string, Sync bool, 
    Payload string, invokeOne bool) (error)

Invoke() invokes an EdgeFaaS function. A function can be invoked synchronously (and wait for the response), or asynchronously. To invoke a function asynchronously, set Sync to False. EdgeFaaS maps EdgeFaaS FunctionName to the candidate resources that have the function created with the candidate_resource mapping. EdgeFaaS can invoke functions on all the candidate resources or on only one of the candidate resources by specifying invokeOne as true. EdgeFaaS executes the invoke function request of OpenFaaS on the resource. The payload of the function is

This tells EdgeFaaS which function should be invoked first to start the application. If multiple entrypoints are given, all the entrypoints will be invoked at the same time to start the application. All the functions of the application together form a dag. EdgeFaaS uses the dag field to store each function’s information. All the function configurations are specified under the dag which is introduced in Section 3.2.2.

### 3.2.1. Function Virtualization

Function virtualization contains two parts: the virtualization of the computing resources and the virtualization of functions. Function virtualization is implemented by creating unique namespace for each computing resource and each function. After the computing resources are registered, EdgeFaaS pools all the computing resources from different resources into what appears to be a single computing resource. In this way, users do not care about what physical resource is running the function but the function is always scheduled to run on the most suitable resource. The virtualization of functions create an isolated namespace for each function. So that each function is allowed to run as if it is in its own private, isolated world. The function can only access the computing resources allocated to the function and cannot see other functions or applications. One function invokes the next function in the application is done through the EdgeFaaS which has the information of the next function and invokes from there. Function virtualization promotes security and is easier for users to use EdgeFaaS. On each OpenFaaS resource, the function is deployed with EdgeFaaS function name. With this EdgeFaaS function name as the key, it is mapped to the computing resource where the function is deployed. The mapping, as introduced in Section 3.1.1, is maintained both in memory and in DynamoDB. The following sections detail how EdgeFaaS rewrites the OpenFaaS to virtualize the functions.

#### TABLE 2: Application Configuration YAML File Fields.

| Field         | Sample Element       |
|---------------|----------------------|
| application   | federatedlearning    |
| entrypoint    | train                |
| dag           | train                |
| name          | firstAggregation     |
| requirements  | train                |
| memory        | 1024MB               |
| gpu           | 0                    |
| privacy       | 0                    |
| affinity      |                      |
| nodetype      | iot                  |
| affinitytype  | data                 |
| reduce        | 1                    |

For FunctionPackage, the code property specifies the location of the .zip file. EdgeFaaS transfers the user provided FunctionName to the EdgeFaaS FunctionName with “ApplicationName.FunctionName” to create unique function names. When users create a function, EdgeFaaS uses the candidate_resource mapping to map the EdgeFaaS FunctionName to the candidate resources that were decided during application configuration. EdgeFaaS builds and deploys the FunctionPackage on the candidate resources using OpenFaaS. The OpenFaaS on the candidate resources provisions an instance of the function and its supporting resources. If the function fails to be created on some resources, create_function() returns error and the failed resource IDs. Besides, the failed resource IDs are removed from the candidate_resource mapping both in memory and S3.

invoke(ApplicationName string, 
    Sync bool, Payload string, invokeOne bool) (error)
appended with the scheduled resource ID which is used in the notify_finish() introduced later. If the function fails to be invoked, the error is returned along with the scheduled resource.

```
list_functions(ApplicationName string) (error)
```

List_functions() lists all the functions of the application. Users provide the ApplicationName. EdgeFaaS uses the stored DAG to get all the functions that belong to the application. With the ApplicationName and the FunctionName, EdgeFaaS further calls get_function() to get each function’s information.

### 3.2.2. DAG Creation

Each function of the application needs to provide the following configuration: 1) `name` which is the name of the function which must be unique within the application; 2) `dependencies` is the previous function’s name. It tells EdgeFaaS which function should be executed before the current function, i.e., the function is dependent on what functions; 3) `requirements` field includes three subfields, `memory`, `gpu`, and `privacy`. `Memory` represents the required memory size of the function, `gpu` is the number of GPUs required, and `privacy` shows if the function needs to be kept private in the IoT device or can be executed in cloud resources. If the privacy requirement is set to 1, the function has the privacy requirement and can only be executed on the IoT devices where the data is generated; Otherwise, it can be executed on cloud resources. By keeping the data on where it is generated and avoiding the data transfer, the data privacy is preserved. 4) `affinity` shows the node affinity of the function. This is the constraint on where the function can run. Three properties decide affinity together: `nodetype`, which can be IoT, edge or cloud; `affinitytype`, which specifies to deploy the function based on the input data location or based on the dependencies function deployed location. It can be either data or function. For data, EdgeFaaS deploys the function based on the input data locality. For function, EdgeFaaS deploys the function based on where the dependencies function is deployed. `reduce` is used to define the map-reduce pattern on how many reduce functions should be invoked. It is introduced in detail in the following section. EdgeFaaS stores the application specifications in a Directed acyclic graph (DAG). The functions are the nodes and the dependencies are the edges. Each application is assigned a unique DAG ID to map to the DAG. The formed DAG is used in the function scheduling where a function is scheduled based on the affinity of its dependent functions or input data which is introduced next in details.

### 3.2.3. Function Scheduling

Based on resource registration and application configuration, when a function is first created, EdgeFaaS can filter out the resources that are not suitable and picks out resources that are most suitable to run the functions. Two-phase scheduling is utilized for function scheduling. In phase one, EdgeFaaS filters out the resources that do not meet the function requirements.

Two requirements are used here, privacy requirement and resource requirement. First, if the function sets the privacy as 1, the function can only be created on the IoT devices where the input data is generated. Second, based on the Prometheus resource monitoring, if the resource does not have sufficient memory, CPU, or GPU resources for the function, the resource is filtered out. All the remaining resources are stored in a candidate_resource mapping with the application name plus the function name as the key and the candidate resource IDs as the value.

In phase two, EdgeFaaS provides the following scheduling policies that further helps to decide the best candidate resources. Scheduling based on data locality, EdgeFaaS schedules the functions to be created on the closest user-defined resource to the input data from the candidate resources. For example, for a fl-pipeline workload, when the input data is generated from the IoT devices, the first function with nodetype set as IoT is co-located where the input data is generated.

The `reduce` item in the application YAML file decides how many instances of the next function is getting deployed. The `reduce` item can be set as 1 or auto. If the reduce is 1, there is only one instance gets deployed on the closest edge resource to all the IoT devices. If the reduce is set as auto, EdgeFaaS automatically finds the closest resource to each IoT device of the previous function and deploys on each resource. The number of instance deployed in not fixed. EdgeFaaS also offers easy to use interface for users to implement their own scheduling policies.

```
schedule(request FunctionCreation) []int
```

Schedule() is the interface to implement the scheduling policy. FunctionCreation struct is the input which contains the essential information used to create a function, such as the application name, function name, data object urls, etc. The returned array is an array of resource IDs that gets the function created. The interface is shown below.

### 3.3. Storage Management

#### 3.3.1. Storage Virtualization

Storage virtualization virtualizes the storage backend of each resource. Storage virtualization is implemented by creating unique namespace for each storage resource. EdgeFaaS provides a unified interface to user which can be used to store the data used by the functions across distributed, heterogeneous storage resources. Users do not know where the data is actually stored but can access and store the data through the EdgeFaaS. This provides user easy-to-use interfaces that are similar to commonly used object stores.

Each resource provides its local storage as the EdgeFaaS storage. It is using MinIO by default to organize the local storage. For other storage, they can also provide the gateway and RESTful APIs to EdgeFaaS in order to use the storage. EdgeFaaS virtualizes all the resources’ storage and provide
a unified interface for users to access different storage resources. An application’s data reside in the application’s name space, and different applications’ datasets are isolated from one another. The following sections introduce all the interfaces provided by EdgeFaaS for users to manage the storage of input, output and intermediate data.

```go
create_bucket(ApplicationName string, BucketName string) (error)
```

Create_bucket() creates a new EdgeFaaS storage bucket. Bucket names should follow the S3 bucket naming rules [33]. EdgeFaaS transfers the user provided BucketName to the EdgeFaaS BucketName with "ApplicationName + BucketName" to create unique bucket names. EdgeFaaS executes Minio MakeBucket request to create the bucket on the resource. A bucket map is created to record the mapping between the EdgeFaaS BucketName and the resource ID. Another application_bucket mapping is created to track all the buckets that are created for the application. The bucket names in the mapping is the original BucketNames provided by the user. Both mappings are synchronized on S3 with the bucket map and application_bucket mapping as the bucket names. Bucket map uses EdgeFaaS BucketName as the object name and resourceID as the object value. Application_bucket mapping uses application name as the object name and a list of bucket names that belong to this application as the object contents.

```go
delete_bucket(ApplicationName string, BucketName string) (error)
```

Delete_bucket() deletes an EdgeFaaS storage bucket. EdgeFaaS uses the EdgeFaaS BucketName as the key of the bucketmap to get the resource that has the bucket. EdgeFaaS executes Minio RemoveBucket request to remove the bucket from Minio. All objects in the bucket must be deleted before the bucket itself can be deleted. After the bucket is deleted, the bucket map and the application_bucket mapping are both updated.

```go
list_buckets(ApplicationName string) (BucketName []string, error)
```

List_buckets() returns a list of all the buckets created for the application. EdgeFaaS uses the application_bucket mapping to get all the buckets created for the application and return their original BucketNames created by the user.

```go
put_object(FilePath string, ApplicationName string, BucketName string) (string)
```

Put_object() adds an object to a bucket. If EdgeFaaS receives multiple write requests for the same object simultaneously, it overwrites all but the last object written. Based on the EdgeFaaS BucketName, EdgeFaaS searches for the resource that has the bucket using the bucket map. With the resource, EdgeFaaS executes Minio FPutObject request to upload the object to Minio. The FilePath is the path to the file to be uploaded. The uploaded object name is the file name of the last tier FilePath hierarchy. Each successfully uploaded object is given a url to user where user can use to access the data. The url is formatted as "application_name/bucket_name/resource_ID/object_name".

```go
get_object(object_url string, FilePath string) (error)
```

Get_object() retrieves object from EdgeFaaS storage. The ObjName is the object name stored in Minio. The FilePath is the local path to download the object to. EdgeFaaS uses the EdgeFaaS BucketName to get the resource from the bucket map. It then executes Minio FGetObject request to download the object from Minio to local FilePath.

```go
delete_object(ObjName string, ApplicationName string, BucketName string) (error)
```

Delete_object() deletes an object from EdgeFaaS storage. EdgeFaaS uses the EdgeFaaS BucketName to get the resource. It then executes Minio RemoveObject request to delete the object using the ObjName from Minio.

```go
list_objects(ApplicationName string, BucketName string) (error)
```

List_objects() returns all the objects in a bucket. EdgeFaaS uses the EdgeFaaS BucketName to get the resource. It then executes Minio ListObjects request to list the objects recursively from Minio bucket.

3.3.2. Data Placement. EdgeFaaS uses function locality to decide where the data is placed. For example, when data is generated from IoT devices, the data is stored on IoT devices based on data locality. For other intermediate data, if the data volume is large, it is stored where the data is generated to save the data transfer latency. For functions running on other clusters to access the data, the functions need to be redeployed on the resource where the data is located. This locality-based data placement policy is shown to provide the best performance which is evaluated in Section 5.

4. EDGEFAAS WORKFLOWS

Two representative edge workflows were implemented using EdgeFaas, an end-to-end video analytics workflow, and a federated learning workflow. The two workflows help illustrate the usability of EdgeFaas. The two workflows have distinct behaviors in both I/Os and computation. Figure 2 and Figure 3 show the workflow logics.

The video workload is a pipeline of stages vertically distributed from IoT to cloud tiers. Data is processed stage by stage. The computation involves video and image processing and several different machine learning algorithms. It is representative of the reality of a considerable portion of edge applications. Many edge applications such as autonomous
driving, retail and security system involve video analytics workflow as an essential part to serve the real-time needs of consumers. The real-time streamed raw videos are processed by the edge applications consisting of multiple stages to finally transform into meaningful messages. Some other workflows such as LiDAR mapping applications process large and continuous data streams of 3D topographic data points of object’s surfaces generated by LiDAR [17] is also following the pipeline style.

The federated learning workload has wide distribution within each tier, in addition to vertical distribution. Different stages work in a map-reduce style where the training phase is like map procedure where the models is being trained on the IoT devices. The aggregation phase is like reduce procedure where each trained model is aggregated and reduced to a single model. The federated learning workflow is largely used in autonomous driving, smart manufacturing, and smart health. Some other workflows such as Geo-location based online mobile games such as Pokemon Go [9] generate small and frequent GPS data as well as video footage for AR (augmented reality) visualization is also following the map-reduce style.

4.1. Video Analytics.

The video analytics workflow (Figure 2) implements an end-to-end pipeline from when a video stream is generated to when the final video analytics result is stored. The workflow consists of six stages: video generator, video processing, motion detection, face detection, face extraction and face recognition. Each stage’s output is fed as the input of the next stage.

The video stream generator continuously generates live videos and streams the videos to video processing stage. Video processing stage chunks them into groups of pictures (GoP) using FFmpeg [9]. These GoPs serve as an input of motion detection. Motion detection detects motion within each picture and only outputs the pictures that contain motions. The motion detection function uses OpenCV [8] to do inter-frame comparison. Note that within a GoP, if a picture is detected with motion, all the following pictures are considered to contain motion. The generated pictures serve as input of face detection. Face detection detects the faces in the pictures using Single Shot MultiBox Detector (SSD) [30] and selects images containing faces as the output. These pictures are used as the input for face extraction. Face extraction uses dlib [5] to extract face features from the picture and passes to the last stage, face recognition. Face recognition first uses a ResNet-34-based [24] pre-trained model to encode each detected face and then uses k-nearest neighbors (k-NN) to classify the faces. The final outputs are the images that are marked with identities. The stages are chained together using pipeline workflow logic.

Comparing the six stages, the first stage involves more I/Os since it needs to process and store the entire video stream. The second stage serves as a filter for the last three stages. The last three stages, however, employs more machine learning algorithms and are more computation intensive. Among them, face recognition is the most computation intensive since it involves two steps of computation algorithms (deep learning inference and k-NN classification).

EdgeFaaS scheduler schedules this workflow follows the YAML file listed in source code [1]. The first function video-generator is deployed where the video is generated on each IoT device. Video-processing is deployed to the closest edge resource to where each video-generator is deployed. Motion-detection is deployed to the closest edge resource to where each video-processing is deployed, i.e, it is co-located on the same resource as video-processing. Face-detection is deployed to the closest cloud resource to where each motion-detection is deployed. Face-extraction and face-recognition co-locate to the same cloud resource where face-detection is deployed. This YAML file configuration is evaluated in Section 5.

4.2. Federated Learning.

Federated learning is a learning paradigm that allows many edge workers to collaboratively train a shared model using their local data [31]. After performing local training for a pre-defined number of iterations, each worker contributes to the training of the shared model by sending their local model updates to the aggregator. The aggregator server receives the weights from all the workers and performs averaging on the received weights. The aggregator uses the federated averaging algorithm [31], which performs averaging of all the weights from the edge workers. The aggregator server then sends the shared model back to each of the edge workers. After receiving the aggregated weights from the aggregator, each worker then updates their local model with this shared model. Federated learning allows users to create a shared global model without putting training data in a central location. This can help reduce the response time of an application by saving the data transfer time and avoid the privacy issue of transferring the data to a central location. Federated learning is being used in Google assistant, autonomous vehicles and hospitals [11].

We choose two-level aggregation for the workflow where the aggregation phase involves two steps. The first step is to aggregate the training models on edge data centers. Each aggregation only takes some of the training models from the training phase. This step then forwards the partially aggregated models to the cloud and do a complete aggregation. This two-level aggregation has two benefits: first, it better mimics the real-world scalable and distributed edge computing model containing different tiers of resources. Second, it further reduces the response time of the application by saving the data transfer time from the previous one-phase
The workflow involves three stages. The first stage works on the IoT devices where distributed IoT devices train local data on the devices to preserve user privacy for a pre-defined number of iterations. The input data for the first stage is the local dataset and a pre-trained model. After the training is done, each IoT device contributes their locally trained model to an aggregator, the second stage. The first-level aggregator, which resides in the edge data centers, receives the weights of the model that each IoT device has trained locally and performs averaging on the received weights. It takes the trained models from the first stage as input and outputs the aggregated model to the third stage. The second-level aggregator then sends the averaged weights further to the cloud cluster and the third stage conducts another aggregation. This aggregation creates the shared model, combining the weights from all the edge aggregators and send the shared model back to the edge workers. After receiving the averaged weights from the cloud aggregator, each worker then updates their local model accordingly based on the shared model. The whole workflow is depicted in Figure 3. In the workflow, the model is LeNet-5 ([27]) and the input dataset is MNIST database ([21]).

5. EVALUATION

We evaluate EdgeFaaS against the two workflows discussed in Chapter 4. Three types of resources, IoT, edge and cloud, are configured for the experiments (Figure 4). Table 3 shows the specifications of the resources. For IoT tier, we use eight Raspberry Pi 4B+. Each Raspberry Pi is a standalone cluster running faasd [22] (version 10.62.0.1) as the serverless platform. We have two edge clusters. Each edge cluster includes one edge server. Each edge cluster runs an OpenFaaS (gateway version 0.18.18, faas-netes version 0.12.3) deployment with Kubernetes (version 1.18.9) cluster as the backend. For the cloud tier, we have one cloud cluster with ten cloud nodes. Each cloud node is equipped with four GeForce RTX 2080 Ti GPU to accelerate the computation. MinIO (version 2022-04-16T04-26-02Z) and Prometheus (version 2.35.0) are deployed on Kubernetes, both use local storage as the persistent storage.

From Figure 4, we can see geographically, IoT tier and edge tier are close to each other. In particular, four Raspberry Pis and one edge server form a set and are within the same network. The two sets of IoT clusters and edge cluster are far from each other. The cloud tier is far from all the edge tier and IoT tier and is not within the same network as the other tiers. The network RTT from IoT clusters 1 to edge server 1 is 5.7ms and from edge server 1 to cloud is 43.4ms. The network RTT from IoT clusters 2 to edge server 2 is 0.6ms and from edge server 2 to cloud is 4.7ms. EdgeFaaS is set up in the cloud tier. For video analytics workflow, we evaluate the performance of the workflow with different partition points of the workflow. For federated learning workflow, we illustrate how EdgeFaaS automates

1. Faasd is a lightweight version of OpenFaaS which runs on a single node
the deployment process to distribute functions to the desired resource.

5.1. Video Analytics Workflow

We use the first set of IoT tier and edge tier and the cloud tier for the evaluation. Of the six stages described in Chapter 4.1, video generator uses a Raspberry Pi camera to take 1080p real-time videos. Each video is 30 seconds long. The video is then streamed to edge tier or cloud tier for further processing.

5.1.1. Performance Breakdown. We break down the latency of the video analytics workflow to figure out where the performance overhead comes from when running on different resources.

**Data Size Variations** - Figure 5 shows the data size of each stage’s output data. Video generator generates 30-second 92MB of video file which is the largest output data. After video processing, groups of pictures are also generated at a large size. Note that, the output of the video processing is the zip file of a group of pictures. The number of pictures in a group is equal to the frame per second (fps) of the video. The fps of the video is 24 here. So the output data of video processing is a zip file of 24 pictures which is much smaller than the original video file. For the following stages, each stage only generate a single picture as the output data and remains small in data size. This shows the transmission of different input data to different tiers plays a critical role in end-to-end performance.

**Communication Latency** - Figure 6 shows when Edge-FaaS chooses different stages to compute on different tiers, the latency to upload the output data of this stage to edge tier or to cloud tier. It shows that uploading the video file of size 92MB to cloud tier at video generator stage takes the longest communication time 92.7s at a uploading bandwidth of 7.39 Mbps. While to upload to the edge tier, it takes only 8.5s. For the following stages, the communication latency to cloud tier reduces but is still slightly larger than uploading the output to edge tier. This corresponds to the size of each stage’s output data, which is also the input of the next stage.

**Computation Latency** - Figure 7 shows the computation latency of each stage on different tiers. For stages face detection, face extraction, and face recognition, the computation are accelerated on GPU on cloud tier. For each stage, cloud tier executes faster than edge tier. For example, for face detection, cloud tier takes 0.113s while edge tier takes 0.433s.

**End-to-end Latency** - Figure 8 shows the total latency required by running the workflow on the cloud tier and edge tier starting from the video processing stage (video generator stage runs on the IoT devices). Cloud tier takes 96.7s while
edge tier takes 12.1s. From the above analysis, we know most of the latency of cloud tier comes from the output data transfer at the video generator stage. While for edge tier, although the computation takes longer than cloud tier, it benefits from the data proximity and saves the network transmission overhead.

5.1.2. Computation Partitioning. The analysis in Chapter 5.1.1 indicates that there exist interesting points within the video analytics workflow to partition the pipeline between edge tier and cloud tier. After the partition point, we schedule the computation to cloud tier. Figure 8 shows the end-to-end latency breakdown when choosing different partition points. X-axis illustrates different partition points. If partition at the video generator and video processing stages, data transfer dominates the end-to-end latency, which is consistent with our observation in Chapter 5.1.1 that the data size is the largest at the early stage of the video analytics workflow. Partitioning at the latter stages provides better performance since the workflow can minimize the data transfer overhead, while taking advantage of the cloud tier to execute the more compute heavy stages at the cloud tier.

Of all the partition points, partitioning at motion detection achieves the best end-to-end latency of 11.5s. In particular, partition point at video generator is cloud only solution while partition point at face recognition is edge only solution. EdgeFaaS chooses to schedule the first stage, video generator on IoT tier (running other stages on IoT tier takes much longer computation time compared to running on the other two tiers) and the middle three stages, video processing, motion detection, and face detection, on edge tier while the latter two stages, face extraction, and face recognition on cloud tier based on input data size variations to achieve the best performance as illustrated in Figure 9. EdgeFaaS improves the workflow end-to-end latency by 7.4X compared to cloud only solution and by 5% compared to edge only solution.

5.2. Federated Learning Workflow

For federated learning workflow, we illustrate a use case on how EdgeFaaS can be utilized to help with the resource scheduling. Figure 3 shows the workflow of the use case. We use both sets of the IoT devices and edge servers for this experiment. In this use case, Raspberry Pi cameras take pictures of handwritten characters and federated learning trains the Lenet5 model in order to recognize the handwritten characters. We would like each Raspberry Pi to train the local MNIST dataset [21] on its own for privacy purpose and then send the trained model to the closest edge server for first aggregation. After the first aggregation is done on the edge tier, the models are sent to the cloud tier for the second aggregation.

In order to utilize EdgeFaaS, user first provides the application configuration yaml file (source code 2). User first deploys the first function, Train, using the affinity provided in the yaml file. In the yaml file, the nodetype for Train is iot, the nodelocation is data and the reduce is auto. Based on this, EdgeFaaS deploys Train on the IoT tier where the input data is located. Because each Rapsberry Pi takes pictures of the handwritten character as the input data, each train function is deployed on the same Raspberry Pi with the reduce set as auto.

For the FirstAggregation, user specifies the affinity with nodetype as edge, nodelocation as function, and reduce as...
6. RELATED WORKS

Previous research efforts have focused a lot on offloading computation from edge to cloud and pay special attention to finding the offloading point. Neurosurgeon [25] automatically partitions DNN computation between edge and cloud based on the intermediate data size of DNN networks. Likewise, MAUI [20] profiles each application and predicts when to partition the computation. EdgeAI [28] partitions DNN networks and resize the DNN models to achieve the best offloading performance. Computation partitioning is a good way to decide on when to schedule functions on cloud and when to schedule functions locally and works best when large amount of data is transferred across functions. For other edge applications where intermediate data is not big or the privacy requirement is more of a concern such as federated learning, computation partitioning may not be suitable. EdgeFaaS provides a federated computing platform to not only partitions computation based on performance requirement but can also schedule functions based on storage requirements and privacy requirements.

Some other research works aim at building unified cloud and edge serverless computation platforms. CSPOT [36] is a FaaS platform which executes functions across heterogeneous devices ranging from servers in the cloud to resource-constrained IoT devices. CSPOT encapsulates Linux executables in containers to provide function distribution and isolation. It introduces an append-only storage abstraction Woof to persist and share function state and to record the execution logs. To provide better portability, NanoLambda [23] is a followup work on CSPOT. It proposed to allow executing python-based functions on microcontrollers with the help of a resource optimized python interpreter. NanoLambda schedules functions to suitable locations based on latency requirements during function distribution. However, NanoLambda does not follow the dynamic changes of system loads and communication latency to reschedule functions.

FaDO [35] designs an orchestrator to load balance FaaS requests to different resources and provides a unified storage interface for users to access the object storage deployed on the resource. For function management, FaDO does not provides a layer of abstraction to manage the functions. Also, by simply load balancing the FaaS requests, it violates the data-driven and privacy requirements of edge applications. EdgeFaaS on the other hand, schedules functions based on data locality. Also, FaDO requires users to use the storage interface to place the data on different resources. This breaks the virtualization of storage services. On the other hand, EdgeFaaS decides on the data placement and users do not know where the data is actually stored.

DFaaS [18] proposes a decentralized FaaS architecture to autonomously balance the traffic load across edge nodes. The serverless platform does not consider cloud resources and the scheduling is mainly based on the traffic load. In comparison, EdgeFaaS proposes a federated serverless platform to virtualize IoT, edge and cloud computation and storage resources. Besides, the scheduling of EdgeFaaS

| application: | federatedlearning |
|-------------|------------------|
| entrypoint: | train            |
| dag:        |                  |
| - name:      | train            |
| - dependencies: |              |
|   affinity: |                  |
|     nodetype: | iot              |
|     nodelocation: | data  |
|     reduce: | auto            |
| - name:      | firstaggregation |
| - dependencies: |              |
|   affinity: |                  |
|     nodetype: | edge             |
|     nodelocation: | function |
|     reduce: | auto            |
| - name:      | secondaggregation |
| - dependencies: |              |
|   affinity: |                  |
|     nodetype: | cloud            |
|     nodelocation: | function |
|     reduce: | 1               |

Source code 2: Federated Learning Workflow Configuration Yaml File Snippet
considers the performance requirement, data locality and privacy requirement of the functions.

Some other works focus on function placement of edge computing. Kaustabha et al. [22] present a microservice scheduling and migration algorithm for edge computing. It places the microservice to the closest edge data centers and when user moves, the microservice is migrated to the nearest edge data center to the user’s new location. EdgeFaaS also includes a function placement policy which chooses the closest resource of the user specified type. EdgeFaaS manages resources including IoT devices, edge data centers and cloud. In comparison, this paper does not consider the heterogeneous resources but considering only edge data centers resources. However, it also places microservices to the nearest resource to save latency which confirms that our function placement policy fulfills the latency-sensitive nature of edge applications.

Auction-based approach [13] requires application developers to bid on resources to decide function placement on resources. This approach fails to virtualize the resources and leaves the scheduling process to the application developer. Decentralized [19] proposes a framework for efficient dispatching of stateless tasks to different resources based on response time and fairness. It fails to consider the data locality and privacy requirement of functions.

Other related works accelerates FaaS workflows by optimizing FaaS computation platforms. Faastlane [26] provides lightweight thread-level isolation to accelerate FaaS workflows. SAND [14] utilizes application-level sandboxing and hierarchical message bus to provides a low-latency, more resource efficient serverless platforms. Both works are intended for Faas platforms utilizing one resource. However, EdgeFaaS extends existing serverless platforms to manage various resources and schedule functions to the most suitable resources transparently.

7. CONCLUSION

We are living in big data era where vast amount of data is generated daily from everyday use of search engines, social media, e-commerce, and smart phones. To save the communication overhead of the data transfer and to alleviate the computation stress on the cloud side, computation and storage of data has been pushed to the edge. This thesis presents EdgeFaaS, a federated serverless computing platform for edge applications. It allows edge applications to utilize various resources, including IoT, edge and cloud using the convenient function-based abstraction. It virtualizes functions and storage so that different resources are managed by EdgeFaaS and different functions can be scheduled to the most suitable resources. Besides the development of EdgeFaaS, this thesis developed two workflows, video analytics workflow and federated learning workflow, to illustrate the usage of EdgeFaaS. EdgeFaaS deploys video analytics workflow to different computation tiers to achieve the best performance based on the data size variations. It improves the workflow end-to-end latency by 7.4X compared to cloud only solution and by 5% compared to edge only solution.

For federated learning workflow, EdgeFaaS deploys the workflow based on a use case study that follows the data locality to preserve data privacy.

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