SEA-LEAP: Self-adaptive and Locality-aware Edge Analytics Placement

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***Abstract*—Performing near real-time data analytics at the edge requires dealing with issues such as the rapidly growing amount of data, limited resource capacities, and high failure probabilities of edge nodes. To meet SLOs such as service availability, failure resilience, or workload balancing, data replication is of vital importance in this context. Consequently, specific input datasets, requested by on-demand analytics (e.g., object detection), can be present at different locations over time. This can prevent users from exploiting data locality and timely performing decision-making processes. State-of-the-art solutions in the placement of on-demand data analytics at the edge either fail in providing low-latency access to user-requested input data or do not consider data locality. We propose SEA-LEAP (Self-adaptive and Locality-aware Edge Analytics Placement), a framework including a new mechanism for tracking data movements, on top of which we devise a generic control mechanism. SEA-LEAP enables on-the-fly placement of on-demand analytics applications considering the most appropriate dataset location that minimizes overall analytics requests execution time. We conduct experiments using real-world (i) object detection application, (ii) image datasets as input for the application, (iii) obtained benchmarks, and (iv) heterogeneous edge infrastructure using Kubernetes. Experimental results show the ability to efficiently deploy on-demand analytics, and by featuring adaptive data movements, further reducing total latency by 65.85% on average, indicating a promising solution for edge multi-cluster and hybrid environments.**

***Index Terms*—Edge computing, analytics placement, data locality, decision-making processes, data-driven decision.**

I. Introduction

Modern IoT applications such as public safety video surveillance [1], predictive maintenance in smart manufacturing [2], and traffic management in smart cities [3], are characterized by strict latency requirements. Due to the rapidly increasing number of IoT sensing devices, data production is growing exponentially [4], with negative effects on the latency of analytics required by IoT applications. Edge computing, i.e., moving cloud processing closer to data sources, has been proposed as a solution to address these issues [5].

Still, the rapidly growing amount of data produced at the edge affects traditional centralized data collection and processing. Data can be transferred and replicated due to (i) limited storage capacities [6]; (ii) edge failure probabilities [7]; (iii) meeting certain service level objectives (e.g., data loss tolerance [8]); (iv) workload balancing [9]. As a consequence, data can reside in locations different from where they were initially produced. Since exploiting data locality is crucial for low latency analytics, it is important to keep track of data movements for timely placement of analytics applications.

Typical examples are edge video analytics applications. Performing video analytics (e.g., object detection to extract specific information of video frames) close to the source of data (e.g., on edge servers such as traffic cameras or micro data centers) is considered as the killer app for edge computing [10]. For example, video analytics on traffic footages of a specific area could be submitted to detect a suspect's vehicle. However, sampled footage frames from a traffic camera system can be stored at locations different from the source node to ensure fault tolerance, affecting the latency of on-demand analytics. This problem is present in other event-driven scenarios, where critical decision-making processes strongly depend on the timely placement of analytics requests, such as finding lost children or pets [1], and failure prevention in smart manufacturing [2]. Therefore, making self-adaptive analytics placement to the most suitable location is an important step toward improving the overall latency of decision-making processes.

In typical placement strategies for data processing applications available in the literature, researchers focus on traditional centralized data collection and analytics solutions [11], [12], or placing data processing based on resource-cost trade-offs [13], but do not discuss critical latency requirements of such analytics applications. Others propose strategies for latency-aware placement configurations of data stream processing applications [14] and low-latency data management on the distributed edge [15]. Many state-of-the-art approaches for analytics placement address the data locality from aspects such as edge-cloud workload balance [16], resource usage and query accuracy trade-off [17], or the fairness of cloud resource allocation [18]. Still, they do not consider the adaptive placement of on-demand analytics for low-latency access to user-requested data in the distributed edge environment. Data movement tracking and locality-awareness for scheduling on-demand analytics across distributed edge nodes are currently unsolved problems [19], [20].

To ensure efficient placement of on-demand analytics considering data locality and lower analytics execution time, we propose SEA-LEAP, a framework for Self-adaptive and Locality-aware Edge Analytics Placement, featuring:

- **a new architecture**, enabling the exploitation of data locality based on *tracking mechanism* that manages event-triggered registration of edge dataset movements;

- **a generic control mechanism**, allowing on-the-fly adaptation and guided placement of on-demand analytics to node locations storing required input datasets;
- **a placement optimizer**, enabling on-demand analytics placement to the most appropriate dataset location that minimizes overall analytics requests execution time.

We evaluate SEA-LEAP by conducting experiments on (i) real-world video analytics application; (ii) real-world sets of video frames as input for the application; (iii) obtained network and inference benchmarks, and (iv) heterogeneous edge infrastructure using Kubernetes platform. Experimental results show that SEA-LEAP is able to (i) autonomously deploy on-demand analytics requests (e.g., object detection), and by featuring adaptive data movements for certain network and node characteristics, additionally, (ii) reduce the request execution time by 65.85% on average. Our paper advances the state-of-the-art approaches with a generic solution for deploying on-demand analytics while dealing with data locality issues. This can help users and developers to efficiently and timely deploy requested analytics across different edge infrastructures, indicating a promising solution for geo-distributed edge multi-cluster and hybrid environments.

We describe a motivational use case and the importance of data locality in Section II. SEA-LEAP system design is proposed in Section III, while tracking and control parts are detailed in Section IV and Section V, respectively. Section VI shows the experimental setup, while Section VII describes SEA-LEAP evaluation and discussion. Related work is outlined in Section VIII. Section IX concludes the paper.

II. Background

A. Motivational Use Case

We consider the motivational scenario described in Fig. 1. Nowadays, many cities are introducing restrictions on accessing certain areas such as central business districts (CBD), low emission zones for polluting vehicles, or any other roads with a charging system. It often happens that people violate rules either entering without permit or exceeding allowed periods. Our scenario considers a video analytics application that can be queried to find a vehicle suspected of violating traffic rules in captured footages (e.g., by recognizing license plates) in a smart city. This requires placing on-demand analytics requests on edge infrastructure using specific video datasets.

However, edge servers can fail to execute analytics services for different reasons such as exceeding capacity, power outages, or network failures [7]. Consequently, in the context of edge servers, it becomes necessary to replicate relevant data and services to other nodes (blue arrows), to meet Service Level Objectives (SLO), e.g., service availability. Based on calculated failure probabilities, some datasets can be regularly replicated (partially or completely) to different locations to avoid data loss or interruption of running analytics services. To meet the low-latency requirements of on-demand analytics [21] (e.g., finding a suspect's vehicle), they should be placed at the same node where the dataset is stored to reduce

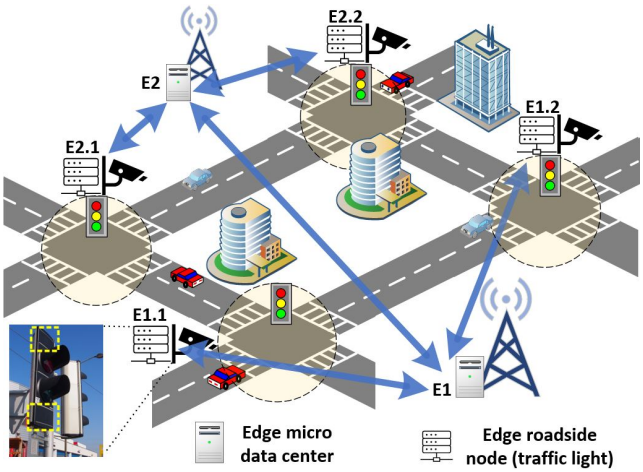


Fig. 1. An example smart traffic scenario to illustrate the problems of (i) tracking dataset movements/replications due to high edge failure probabilities, and (ii) consequently timely placement of future on-demand video analytics.

the impact of network latency. However, in a geographically distributed edge infrastructure, replication causes the required dataset to be present in location(s) different from where it is produced. As a consequence, our challenges are to (i) keep track of datasets, and identify where they are located at a specific time point; (ii) identify which node is the most suitable to reduce the latency of analytics, if the requested dataset is present in multiple locations. Inspired by our InTraSafEd 5G project[1] (Increasing Traffic Safety with Edge and 5G) for improving traffic and pedestrian safety through video analytics, we consider its benefits for running on-demand analytics on heterogeneous edge servers such as Raspberry Pi roadside devices with cameras attached to smart traffic lights.

Definition 1. *On-demand data analytics represents data processing applications that are submitted to a computational infrastructure $\mathcal{I}$ in response to specific user requests $\mathcal{R}$.*

The main characteristics of on-demand data analytics are: (i) they refer to specific input datasets [2], and (ii) they have low-latency requirements [21]. In this work, on-demand data analytics are represented as container-based applications, which can be placed in different nodes of computational infrastructure (as in [22] and [23]). The input of on-demand analytics is a finite dataset that can be stored in different node locations. We focus on a set of sampled video frames generated from video-camera systems.

B. Locality-aware Edge Analytics Placement

Edge computing is a paradigm where computation is performed on edge nodes, deployed near data sources. Edge computing is the key to exploit *data locality*, i.e., processing data closer to its origin, instead of collecting and processing data far from its source [24]. Data locality is considered of paramount importance to meet low-latency requirements of on-demand analytics [25], [26]. However, identifying the

[1] newsroom.magenta.at/2020/01/16/5g-anwendungen-in-wien

correct dataset location to timely perform processing in the distributed edge is a challenging issue due to the regular data transfers and replications. Therefore, we introduce SEA-LEAP, a new framework allowing users and developers to easily deploy on-demand analytics applications without knowing the current location of the required datasets. Once required datasets are located by SEA-LEAP, on-demand analytics are automatically deployed to the most appropriate edge nodes, allowing analytics requests to meet low-latency requirements and significantly improving decision-making processes.

III. SEA-LEAP Design

The design concept of SEA-LEAP is driven by the following properties for on-demand edge analytics placement, namely,

- *Data locality-awareness*: as shown in the motivational scenario, data can regularly change its locations over geographically distributed and heterogeneous edge nodes for different reasons, making it challenging to exploit data locality. Therefore, the framework should be able to keep track of dynamic data movements and enable efficient locality-aware data management.
- *Autonomy*: on-demand analytics requests, as shown in the motivational scenario, often have low-latency requirements, making it difficult to timely identify the node minimizing overall request execution time. For this reason, the framework should be able to (i) find the most appropriate node location for analytics placement and (ii) handle numerous requests on time, with little or no human intervention in the deployment process. To this end, we need to enable autonomous analytics placements.
- *Genericity*: the computational edge infrastructure can be heterogeneous regarding both hardware resources and software configurations. Therefore, the framework design should be generic and applicable to work on top of existing systems by customizing logic of proposed components and services, improving the overall reusability.

Fig. 2 provides an overview of the proposed SEA-LEAP architecture. We envision the on-demand analytics placement scenario based on data locality. We illustrate three main parts:

Edge sites represent sets of geographically distributed edge nodes capable of executing on-demand analytics on data coming from IoT devices. IoT devices constantly generate data, which are transmitted to the edge infrastructure for temporary storage and future analytics.

Tracking mechanism is a component used for event-triggered registration of datasets and for tracking their future movements. It includes a monitoring service and meta-dataset that stores location-related details about datasets, enabling their dynamic tracking in the distributed edge. We focus on datasets with fixed sizes, which are generated, processed, and stored at the edge for future analytics. This is typical in storage-limited edge nodes, since in many cases it is enough to have a subset of data to preserve the analytics accuracy [27].

Control mechanism is a component performing placement of on-demand analytics. It contains two main sub-components: the *meta scheduler* and the *placement optimizer*. The meta

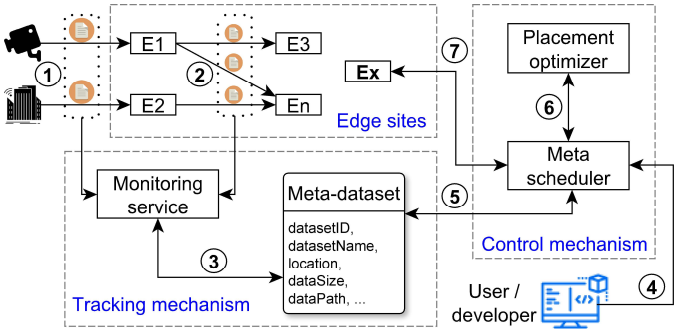


Fig. 2. SEA-LEAP Architecture Overview.

scheduler receives the description of on-demand analytics with the requested dataset name, and communicates with both the meta-dataset and the placement optimizer. The placement optimizer computes the most suitable location for on-demand analytics to minimize overall execution time. Finally, the meta scheduler performs the actual placement to a target node.

In Step 1, data generated from different IoT sensing devices are transferred to edge nodes, where they can be processed or stored for later analysis. In Step 2, datasets can be moved or replicated to other nodes due to different reasons such as fault tolerance. Any dataset generation as well as its replication or movement are registered and updated constantly within the tracking mechanism (Step 3). For each dataset, current location-related details are stored in a database called *meta-dataset*. Meta-dataset can include information such as dataset id, dataset name, corresponding cluster, location path, and data size. Once a user submits the request description (Step 4), the meta-scheduler initiates the automatic placement adaptation. In Step 5, the meta scheduler extracts the required dataset name and retrieves location-related details of the required dataset from the database. We assume that a user knows the target dataset id or name needed as an input for requested analytics. Some of the proposed solutions include (i) access to a list of already generated and existing dataset names (e.g., based on a dataset catalog explained in Section IV), (ii) a consistent and regulated, easy-to-remember naming of datasets. Considering that (i) required dataset can be present in multiple nodes and (ii) different nodes can comply with analytics requirements (e.g., resource capabilities), in Step 6, the meta scheduler queries the placement optimizer to find the most appropriate location for analytics among node location candidates. Finally, the analytics application is placed to the most appropriate node (Step 7). The proposed SEA-LEAP follows the service-oriented architecture (SOA), featuring multiple parts and services that can be maintained independently. The following subsections describe all proposed parts in detail, while Table I lists the main notations used in our approaches.

IV. Tracking Mechanism

Based on the architectural model, we describe the tracking mechanism. Fig. 3 shows SEA-LEAP agent-based monitoring service, which incorporates an event-triggered registration of

TABLE I
MAIN NOTATIONS AND DEFINITIONS

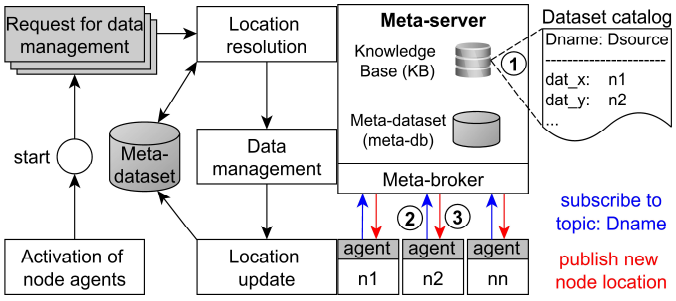
Notation	Description
α	An analytics application that requires input data.
d_{loc}	Variable representing the current dataset location.
d_{name}	Variable representing name of the dataset during the data generation at the data source
dma	A data management action (e.g., replication).
$meta_{db}$	Meta dataset database with location-related info.
KB	A knowledge base containing edge-relevant information.
rcv_{msg}	Variable containing request description for data mgmt.
rcv_f	Description containing the request for analytics placement.
L_{ap}	The most appropriate location for analytics placement.
$\mathcal{L}$	Matrix storing about node candidates for the placement.
$\mathcal{D}$	The set of datasets.
$\mathcal{N}$	The set of locations.
Λ	The set of nodes where dataset d is stored.
$l(n_i, n_j)$	Latency of network connection between n_i and n_j.
$b(n_i, n_j)$	Bandwidth of network connection between n_i and n_j.
$hops(n_i, n_j)$	Number of network hops between n_i and n_j.
$size(d)$	The overall size of a dataset d.
inf_time	An average inference time on a target node.
no_frames	Number of image frames in a target dataset d.

changes of data locations and publish/subscribe based tracking of data movements, while Algorithm 1 shows pseudocode and the concept behind the agent-based monitoring. Regarding the *data locality-awareness* and *autonomy* properties, an autonomous software agent is employed on top of each node, constantly monitoring and acting upon data management events. Location-related details are stored in the meta-dataset database indicating where the datasets are currently available and accessible. The event-triggered data registration mechanism (Fig. 3a) consists of several consecutive phases:

Activation of node agents. Every node has an agent listening to a known port (line 1, Algorithm 1). The *while* loop (line 2) serves one client request for data management action. This phase is executed only once on each node and it is used in all the other phases. The received description of a data management action triggers the following phases.

Request for data management. In this phase, different requests for data management can be initiated (lines 3-4). We define data management as any data manipulation process including (i) generation of a new dataset, (ii) dataset replication or movement. Data management requests employ location-related details about data and can be initiated from (i) meta scheduler (Section V-A), (ii) edge nodes, (iii) edge providers, or (iv) other incorporated mechanisms maintaining edge systems (e.g., load balancing, replication, fault tolerance).

Location resolution. In this phase, based on the target dataset, the location details are either (i) produced for newly generated datasets or (ii) checked in the meta-dataset before further actions. In the first case, a dataset is generated and stored in an edge node. Details about dataset location are saved in the meta-dataset as well as in the dataset catalog (Fig. 3b). Dataset catalog (DC), a lightweight key-value store contains pairs of all generated dataset names and initial locations where they are created (Step 1). It supports the submission of user's analytics request (see Section V), and can be accessed from



(a) Event-triggered data registration (b) Pub/sub based data tracking

Fig. 3. SEA-LEAP monitoring service (a) registration of changes of data location and (b) tracking data movements due to data management events.

meta-server or keeping a synchronized copy locally. In the latter case (ii), the required dataset already exists and meta-dataset is queried, if needed, for retrieving location details.

Data management. In this phase, requested data management action (*dma*) is performed (line 5). Node agents complete data management requests. A trivial example $data_{mgmt}(fetch, dat\_x, n1)$ would fetch dataset dat_x from location $n1$. This phase is designed in a generic way, so it can also be adapted with other data management operations by edge infrastructure providers or deployed edge systems.

Location update. Once the previous data management actions are done, it is required to update new information in the meta-dataset. In this phase, a new connection to the meta database is established and corresponding dataset entries are updated (line 6). Once the database is updated, the source node of the corresponding dataset is notified via the pub/sub (publish/subscribe) channel enabling data movement tracking.

In case of failures, error messages will be returned in each phase. Furthermore, Fig. 3b shows the pub/sub based tracking of data management. First, as shown in the *location resolution* phase, DC stores existing and unique dataset names (Step 1) included in the Knowledge Base (KB). KB represents prior obtained and edge-relevant details such as edge-specific network topology, node characteristics, and analytics benchmarks. They provide a collection of information necessary for analytics placement (explained in Section VII). Edge node locations and produced datasets can be numerous and distributed. Thus, regarding the scalability of the tracking mechanism, the monitoring service includes a pub/sub messaging system in which every edge node $(n_1, n_2, ..., n_n)$ can be subscribed to topics representing dataset names or ids that were initially produced at these nodes (Step 2). Once the dataset location is changed

Algorithm 1 `AgentBasedDatasetRegistration`

1: Listening for data management requests
2: **while** `TRUE` **do** ▷ serving one client request
3: Connect to client
4: $parse(rcv_{msg})$ ▷ analyse received message
5: $data_{mgmt}(dma, d_{name}, d_{loc})$ ▷ data management applied
6: Update $meta_{db}$, setting new node location d_{loc} for given d_{name}
7: Disconnect from client
8: **end while**

in the meta-dataset during the *location update* phase, the meta-broker publishes the change to a specific topic (Step 3). As a result, each node has information about the current location of its datasets, facilitating further edge data management actions. We assume a pub/sub system, such as MQTT (Message Queuing Telemetry Transport), due to its communication scalability and minimum resource requirements [28]. Note that the tracking mechanism is essential for enabling data locality-awareness, while the following control mechanism primarily ensures the self-adaptive and timely placement of edge analytics based on data locality. The scalability of the tracking mechanism will be investigated in future work.

V. Control Mechanism

The control mechanism is the cornerstone of SEA-LEAP architecture. The goal is to enable self-adaptive placement of an analytics application α considering a dataset location d_{loc}, based on two actions, namely,

- *GuideMe:* static placement of an analytics application to the source node candidate initially storing the requested dataset. If the input dataset is simultaneously present on multiple locations, the node ensuring the lowest estimated analytics execution time is selected as the target one;
- *FollowMe:* dynamic placement of an analytics application to an alternative node candidate that minimizes overall request execution time. In this case, an adaptive dataset movement from the source to the alternative node is necessary, prior to the analytics placement.

These actions can offer a continuous adaptation of analytics placements in highly distributed and networked edge servers. Both actions rely on two important services of the control mechanism, namely, the *meta-scheduler* and the *placement optimizer*, described in the following.

A. Meta Scheduler

Accessing the dataset locations can be done by storing location details in the meta-dataset (described in Section IV), while placement adaptations are managed on-the-fly within the meta scheduler. We assume that the meta scheduler is accessible, and there can be multiple instances serving. Algorithm 2 describes the meta scheduler life cycle in detail. The scheduler continuously listens for new requests in lines 1-2. Once a user sends an analytics request description, containing details for application execution, its format is checked. If its format is valid (lines 3-5), the meta scheduler extracts information such as the name of the required dataset id and analytics process α (line 6). Next, the meta-dataset is checked and relevant information is retrieved (lines 7-8). If corresponding information exists, the meta scheduler will send details to the placement optimizer (line 9). The output of the placement optimizer represents the node location that guarantees the lowest total latency for the request and it is stored in the L_{ap} (lines 10-11). In case the usage of L_{ap} requires adaptive data movement, the meta scheduler will follow the procedure from Algorithm 1 (lines 12-14). Finally, meta scheduler performs the placement of α in the node L_{ap} (line 15).

Algorithm 2 `MetaScheduler`

1: **while** `TRUE` **do** ▷ loop serving one client's requests
2: $rcv_f \leftarrow waitConnection()$ ▷ waiting for incoming connections
3: **if** $rcv_f = fmt$ **then** ▷ checking the format of analytics request
4: continue
5: **end if**
6: $parse(rcv_f)$ ▷ extracting needed information (d_{name}, α)
7: Create matrix Λ with location-related information about d
8: $\Lambda \leftarrow retrieve(d_{name})$ ▷ retrieving details from $meta_{db}$
9: **if** $\Lambda \neq empty$ **then**
10: $L_{ap} \leftarrow$ `PlacementOptimization`(Λ)
11: Adapt deployment templates with the L_{ap} and other info
12: **if** L_{ap} is not one of the initial location from Λ **then**
13: Replicate dataset d to L_{ap} using Algorithm 1
14: **end if**
15: deploy(R, L_{ap}) ▷ placing analytics to node location L_{ap}
16: **end if**
17: **end while**

B. Placement Optimizer

The goal of the placement optimizer is to find an edge location that minimizes the total latency. It is designed to satisfy users' latency requirements for timely decision-making processes. Total latency is impacted by (i) analytics execution time, that depends on node and dataset characteristics, (ii) data transfer, that is affected by network characteristics.

We consider analytics placement as a minimization problem with latency as an objective. We assume that users can submit requests for executing data analytics applications over different input datasets, whose location is unknown to the user. Computational infrastructure is modeled as a graph $\mathcal{I} = (\mathcal{N}, \mathcal{E})$ (as used in [29]), such that $\mathcal{N}$ is a set of different nodes where applications and datasets can be placed, and $\mathcal{E}$ models the network connections between nodes. For each $(n_i, n_j) \in \mathcal{E}$, with $n_i, n_j \in \mathcal{N}$, we define both latency $l(n_i, n_j)$ and bandwidth $b(n_i, n_j)$ measurements of network connection (Section VI-C).

We also define a set $\mathcal{D}$ of different generated datasets, that can be initially stored in one or multiple nodes $n \in \mathcal{N}$ over a geographical area. In the latter case, we assume that those datasets are always synchronized. Further, each dataset d is defined by its size $size(d)$ and the set $\Lambda(d)$ of nodes where d is stored. Users submit a request $\mathcal{R} = (\alpha, d_{name})$ to $\mathcal{I}$, where α is an analytics application, and d_{name} is the name of input dataset for α. For each $\mathcal{R}$, SEA-LEAP goal is to identify location L_{ap} for α and d that minimizes $\mathcal{R}$ total latency, i.e.,

$$L_{ap} = \arg\min_{\mathcal{L}[i]} (\mathcal{L}[i]^{t_{\mathcal{R}}^{lat}}), \;\; L(\alpha) = L(d). \tag{1}$$

$\mathcal{L}$ is a matrix that contains location candidates with calculated total latency, including a potential data transfer and the analytics execution time on the specific node candidate:

$$TL = t^{mv_d}_{(n_i,n_j)} + t(R, n_j), \tag{2}$$

where n_i initially stores the dataset d ($n_i \in \Lambda(d)$), and n_j is an alternative node candidate ($n_j \in \mathcal{L}(d)$). In case of n_i as the initial candidate, i.e., $n_i = n_j$, then $TL = t(R, n_i)$. Otherwise, we define $t^{mv_d}_{(n_i,n_j)}$ as the time required to send d from n_i to n_j, i.e.,

$$t^{mv_d}_{(n_i,n_j)} = l(n_i, n_j) + hops(n_i, n_j) \cdot \frac{size(d)}{b(n_i, n_j)}, \tag{3}$$

TABLE II
EDGE NODE TYPES USED IN THE EXPERIMENTAL SETUP, TECHNICAL DETAILS AND INFERENCE LATENCY BENCHMARKS FOR EACH NODE TYPE.

Node label	Node type	CPU	RAM	# of nodes	Edge TPU	Inference/frame [ms]
A	Raspberry Pi 4	Quad-core Cortex-A72 (ARMv7) at 1.5GHz	4GB	2	yes	17.81
B	Raspberry Pi 4	Quad-core Cortex-A72 (ARMv7) at 1.5GHz	4GB	1	no	250.74
C	Raspberry Pi 3 B+	Quad-core Cortex-A53 (ARMv7) at 1.4GHz	1GB	8	no	500.62

where $hops(n_i, n_j)$ is the number of hops between n_i and n_j. Further, we define $t(R, n_j)$ as the estimated time required to complete analytic request $R(\alpha, d)$ on node n_j, i.e.,

$$t(R, n_j) = inf\_time(n_j) \cdot no\_frames(d), \tag{4}$$

where $inf\_time(n_j)$ is an average inference time per frame, and $no\_frames(d)$ is the corresponding number of frames in target dataset d (see Section VI-C).

Algorithm 3 describes the placement optimizer. First, two data structures are created to store location candidates for analytics placement (lines 1-2): $\mathcal{L}$, containing a total estimated latency, and $\mathcal{L}_{KB}$, which stores potential candidates retrieved from KB if they satisfy certain conditions, e.g., nodes with better inference time compared to the source node(s) (line 3). Next, each node containing the requested dataset (line 4) will initially become a candidate for placing the required analytics (lines 5-7). Then, even if the required dataset is present on multiple nodes, the placement depends on the total latency of each candidate (line 6). In lines 8-12, we calculate total latency for each new candidate, since due to the heterogeneity of the infrastructure it is possible to achieve a lower total latency on a node with more resources, despite the data transfer (line 10). Consequently, the most appropriate node location L_{ap} is the one offering the lowest total latency (line 14), returned in line 15. We consider three scenarios: (i) the dataset is stored on a single node with the lowest estimated analytics latency; (ii) the dataset is stored on multiple and heterogeneous nodes, therefore the most powerful will run the analytics; and (iii) edge node(s) storing the required dataset do not have resources to meet latency requirements, thus, the dataset will be placed to a node which minimizes overall request execution time.

Theorem 1. *SEA-LEAP complexity is* $O(n \cdot m + k)$.

Algorithm 3 `PlacementOptimizer`

Input: Set of nodes storing req. dataset Λ
Output: The most appropriate location L_{ap}
1: Create matrix $\mathcal{L}$ forming location candidates with est. total latency
2: Create matrix $\mathcal{L}_{\mathcal{KB}}$ for potential location candidates from KB
3: $\mathcal{L}_{\mathcal{KB}} \leftarrow KB(n_{type} > \Lambda(n_{type}))$ ▷ retrieving alternative candidates
4: **for** each $n_{init} \in \Lambda$ **do**
5: Add node n_{init} to $\mathcal{L}$
6: Calculate $TL(n_{init})$ for the initial node using (4)
7: $\mathcal{L}(n_{init}, TL) \leftarrow TL(n_{init})$
8: **for** each $n_{new} \in \mathcal{L}_{\mathcal{KB}}$ **do**
9: Add node n_{new} to $\mathcal{L}$
10: Calculate $TL(n_{new})$ for new nodes locations using (2), (3) and (4)
11: $\mathcal{L}(n_{new}, TL) \leftarrow TL(n_{new})$
12: **end for**
13: **end for**
14: $L_{ap} \leftarrow \mathcal{L}_i$ with minimum total latency ▷ Compute L_{ap} using (1)
15: Return L_{ap}

Proof. SEA-LEAP complexity is determined mainly by `MetaScheduler` and `PlacementOptimizer`. `MetaScheduler` complexity (see Algorithm 2) depends on `PlacementOptimizer` (see Algorithm 3), since all other lines have complexity $O(1)$. The for loop (line 4) from Algorithm 3 iterates over the set of node locations Λ that simultaneously store the requested dataset. Entering the inner for loop in line 8, it iterates over each new node location candidate and calculates the estimated total latency in line 10, resulting in complexity of $O(n \cdot m)$, where n is the number of the initial node candidates, and m is the number of alternative node candidates. Next, searching the candidate with the lowest total latency in line 14 has the complexity of $O(k)$, where k is the total number of node candidates. Other lines are $O(1)$, resulting in the overall complexity of $O(n \cdot m + k)$. □

$O(n \cdot m + k)$ is acceptable in our context, since n is expected to be small due to limited edge capacities and m is limited to (i) nodes whose types match the types from KB benchmarks and (ii) nodes that have lower inference time per frame than initial nodes from the set Λ.

VI. EXPERIMENTAL SETUP

SEA-LEAP is implemented using Python, while the experimental evaluation of the proposed SEA-LEAP architecture uses Kubernetes for deploying analytics applications. Our emulation-based evaluation is based on real traces and using RuconLiveLab, our physical edge infrastructure consisting of 11 Raspberry Pi (RPi) single-board computers, available in three different configurations (see Table II).

A. Implementation Details

We first introduce technologies used for the experimental evaluation of SEA-LEAP. Considering the deployment of analytics applications, many researchers and industries are revealing nowadays the rapid adoption of Kubernetes orchestration platform [22], [23], relying on master-worker architecture. The master node is, in our scenario, responsible to assign a container-based analytics application to one of the available nodes in the corresponding cluster. Containerized applications are typically using Docker, a container platform used to build and isolate applications with a relevant stack of services. Here, to deploy an analytics application to edge nodes, a docker image has to be included in the Kubernetes manifest, i.e., deployment file, typically defined in YAML (Fig. 5).

B. Target Application

We consider as our target application object detection, a typical video analytics processing in which an input set of

video frames is analyzed. Analytics output is a list of detected objects with confidence levels and their positions on the image. We assume that edge keeps only a limited number of frames, e.g., sampling an industry-standard frame rate of 30fps and filtering only frames with significant changes or object movements, due to the limited capacity of edge nodes and efficient bandwidth usage [10].

In this experimental setup, we used the computation logic from our real-world application InTraSafEd 5G, used to perform object detection analytics to increase traffic and pedestrian safety with edge and 5G in the city of Vienna. The application runs a quantized version of SSD MobileNet v2 model [30], a lightweight and pre-trained convolutional neural network (CNN) based object detection. We dockerized the object detection logic and expose it as a service running in a container. Docker images for all node types, with and without edge TPU attached (Coral USB Accelerator enabling high-performance neural network inference), are available on the Docker hub repository[2], while the SEA-LEAP implementation is accessible on the GitHub repository[3]. Further, we used a PostgreSQL database running in a docker container to store metadata, i.e., location-related details about existing datasets.

C. Input Datasets

We evaluate proposed approaches using datasets typically used in computer vision analytics applications such as object detection and recognition [24]. To perform a complete evaluation, we select datasets of a different average size of image files, which allows having a wide diversity in terms of resolution, dimensions, and color depth. The main characteristics of datasets are presented in Table III. For each dataset, we show the average size-frame ratio (γ) calculated as $\gamma(d) = size(d)/no\_frames(d)$, impacting SEA-LEAP placement optimizer (explained in Subsection VII-B).

Dataset *Intrasafed* comes from the InTraSafEd 5G project, containing sampled video frames from the chosen Vienna's intersection used for the real-time detection of critical situations and to support drivers in avoiding accidents. The frames are taken by traffic cameras and show critical situations where objects like pedestrians, cyclists, and pets, can appear in drivers' blind spots when turning on intersections.

Dataset *Penn-Fudan* comes from an image database used for object detection and recognition on areas around campus and streets around University of Pennsylvania and Fudan University [31]. Selected frames represent various image qualities and angles of captured objects (pedestrians, bikes, and cars).

Datasets *Sherbrooke* and *René-Lévesque* come from the cameras monitoring different intersections, used for detecting and tracking multiple objects of various types in outdoor urban traffic surveillance [32]. Selected image frames represent different camera angles and resolutions, namely, a low camera monitoring cars, trucks, and pedestrians moving at an intersection (*Sherbrooke*) and a high camera covering three intersections with cars and bikes (*René-Lévesque*).

[2]https://hub.docker.com/r/ilujic/inference-arm32v7/

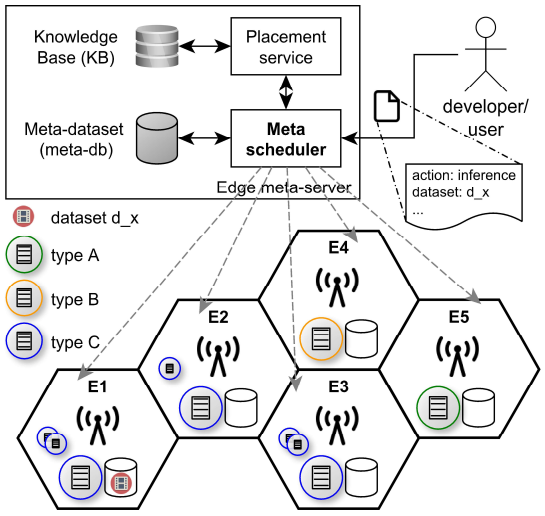
[3]https://github.com/lujic/sea-leap

TABLE III
MAIN CHARACTERISTICS OF DATASETS.

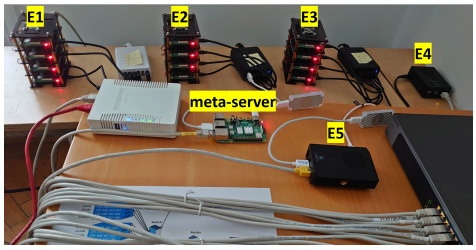
Dataset name	Frames	Size [MB]	Size/frame [MB]	Dimensions
Intrasafed	600	91.4	0.15	1280x720
Penn-Fudan	60	25.2	0.42	various
Sherbrooke	1800	154	0.09	800x600
René-Lévesque	3600	1011.8	0.28	1280x720

D. Testbed Configuration

In the experimental setup, we emulated a real-world system from our InTraSafEd 5G project, where node communication is handled by TU Wien's MQTT broker, communicating to distant edge nodes deployed on traffic lights near a short-range cellular base station. Emulating and extending this real-world scenario, Fig. 4 shows our testbed configuration as well as an initial setup based on different edge sites (E1-E5). Edge sites represent small cells in a cellular network, featuring short-radius coverage of a small cell base station (as used in [29]), providing specific network connection types. Each site can contain one or multiple edge clusters, where in our setup contains multi-node (i.e., E1 and E3 including 3-node clusters, E2 including 2-node cluster) and single-node (i.e., E4 and E5) Kubernetes clusters. Edge meta-server represents a more reliable node (e.g., edge micro data center), able to communicate with edge nodes within different sites. Meta-scheduler receives from a user the description of an analytics



(a) The emulation-based scenario and network topology.



(b) Edge infrastructure overview.

Fig. 4. Testbed configuration.

TABLE IV
NETWORK LATENCY AND BANDWIDTH BENCHMARK (VIENNA'S SUBURB).

Network type	Latency [ms]	Bandwidth [Mbps]
3G	247.92	8.81
4G	23.44	41.43
5G	13.83	66.55

request with a specific dataset.

We evaluate our emulation-based approach with the containerized analytics application, where as a baseline, we measured inference times on the real-world datasets using our physical edge nodes, as described in Table II. For each node type we show the average inference time per single image. Results are averaged over 100 image frames for statistical significance, since by adding more images the differences in inference time show a deviation of $39\mu s$ on average. These results are saved in the KB, which is used by Algorithm 3 for selecting the node which minimizes the latency of edge analytics placement. Further, Table IV shows different latency and bandwidth measurements obtained using standard *iperf* application. The representative values are weighted averages of bandwidth collected on different network types in a suburb area of Vienna from the InTraSafEd 5G project and will be used in our placement optimizer (Section VII-B).

VII. SEA-LEAP EVALUATION

A. Static Placement Evaluation

Based on the *GuideMe* action (Section V), the SEA-LEAP placement optimizer will enable the execution of the user's request on a node storing the required dataset, i.e., without considering alternative candidates (considered in Section VII-B). In the case of multiple locations storing the dataset, a node showing better performances (node type with a lower inference benchmark observation) will be prioritized. Otherwise, the algorithm will randomly select one of them. However, to enable the analytics execution on a target node using the requested dataset, the meta-scheduler needs to add a set of placement-specific details into a Kubernetes deployment file.

In our design, the meta-scheduler already stores different deployment templates that will be adapted with a specific set of information such as the node location, appropriate container image of the analytics application, and the dataset path on the target node (using *hostPath* as a volume). A simple example of an adapted deployment file is showed in Fig. 5. Based on specific lines from this description (i.e., the one including keyword *nodeName*), a distant master node will know where to place the analytics application in its cluster using the default scheduler. Beforehand, the edge meta-server is created as a single-node Kubernetes cluster and enabled to communicate to multiple clusters, using so-called Kubernetes configuration files with needed details (e.g., IP addresses of master nodes from our testbed edge sites). Followed by a meta-scheduler command to process a certain input dataset on the exposed analytics application, the obtained results can be forwarded back to a user. That said, the proposed SEA-LEAP meta-scheduler is designed as a new service that can be used on top

```
...
spec:
  containers:
  - name: inference
    image: inference-notpu:latest
    ports:
    - containerPort: 5000
    volumeMounts:
    - mountPath: /data
      name: input-data
  volumes:
  - name: input-data
    hostPath:
      path: /data
      type: Directory
  nodeName: E1-m01
```

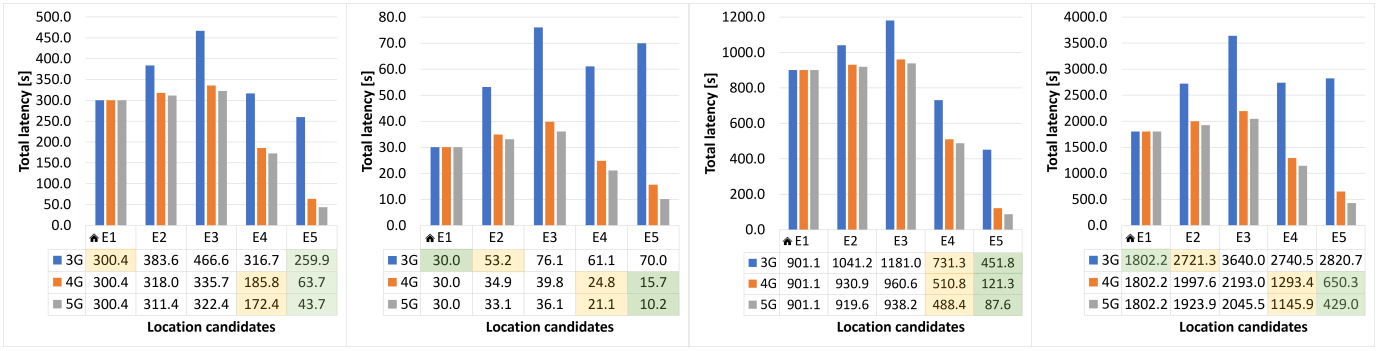
Fig. 5. SEA-LEAP deployment YAML file example.

of existing schedulers as a feature in different edge scenarios that require data locality-aware analytics placement.

B. Adaptive Data Movement Evaluation

In this experiment, we want to evaluate the *FollowMe* action (Section V), SEA-LEAP placement optimizer will consider alternative location candidates different than the initial node storing the required dataset, and select the option with the lowest total latency. Thus, the placement algorithm estimates the total latency (based on details from KB) including the transfer of requested data from the source to an alternative location. Fig. 6 shows the results of the SEA-LEAP placement optimizer applied to each dataset from Table III. In this representative example, the source node location of a dataset is set to the edge site E1. For that reason, the source location from E1 represents at the same time an initial candidate for analytics placement. Other alternative candidates will include additional network latency due to needed dataset transfer. Green and yellow shaded locations show first and second-best candidates, respectively.

For dataset *Intrasafed* (Fig. 6a), the selected appropriate node location for analytics placement in each network type results in moving the dataset from the source node storing the dataset. In all cases of 3G (low), 4G (medium), and 5G (high) network conditions, we can decrease the total latency by 13.47%, 78.81%, and 85.46%, respectively, by moving the dataset to a candidate location in E5. For dataset *Penn-Fudan* (Fig. 6b), in low network conditions the selected appropriate node location for analytics placement will be in the source location storing the dataset, while for medium and high network conditions the total latency becomes 47.77% and 66.14% lower by moving dataset to an alternative location candidate. At the same time, even in the scenarios where the most appropriate location cannot host the analytics application or the dataset for different reasons (e.g., limited capacity, high failure probability), selecting the second-best candidate can still achieve 17.44% and 29.70% lower total latency by selecting a location candidate in E4, for medium and high network conditions, respectively. For dataset *Sherbrooke* (Fig. 6c), for all network types, moving dataset can bring 49.86% (3G), 86.54% (4G), and 90.28% (5G) lower latency



(a) Intrasafed (b) Penn-Fudan (c) Sherbrooke (d) René-Lévesque

Fig. 6. SEA-LEAP placement calculation of node location candidates in different edge sites, driven by *GuideMe* and *FollowMe* actions. It is based on network connection benchmarks from a real-world edge location. For all cases, the source location of the dataset is set to E1.

than in the source location initially storing the dataset. The dataset *René-Lévesque* (Fig. 6d) with the largest number of frames and overall size can benefit from better network conditions, achieving 63.92% and 76.20% lower total latency for medium and high bandwidth availability, respectively.

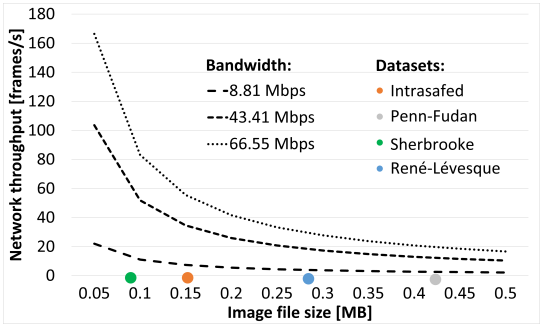
C. Discussion

The results show twofold benefits of the proposed SEA-LEAP, namely, (i) it enables an autonomous placement of analytics requests, and (ii) it allows the self-adaptation to data locality by considering both network and node candidate characteristics. For example, although node types A and B from our experimental setup have respectively 28x and 2x lower inference time per frame compared to the source node type C (Fig. 4), additional transfer of data does not bring benefits if lower bandwidth is available, for specific datasets.

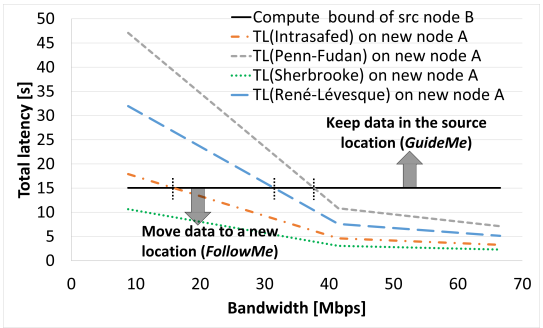
Despite different network characteristics of different edge sites, the network performance will depend on the available network bound of a node location storing the dataset. As described in Section V-B, the total latency of placing analytics to new location candidates will be also impacted by other factors such as network latency, number of hops, analytics execution time, and the size of the dataset. Still, based on the experimental results, moving the dataset to another location we can reduce total latency by 65.85% on average. To determine these specific cases, Fig. 7 shows the SEA-LEAP placement decision rule and which aspects have strong impacts on it. Estimated total latency of analytics placement is largely affected by two main aspects, namely, network bound (available bandwidth) and compute (node performance) bound.

Fig. 7a shows the relation between the average image file size and network throughput. We see that the higher the bandwidth, the higher is the network bound for transferring a certain number of images for a specific dataset. However, this relation does not hold for the compute-bound of a specific node candidate in this context. This is because the target inference application resizes each input frame to the same dimension due to performance reasons. Since resizing does not affect the accuracy of object detection, the average inference per frame (i.e., compute-bound) will stay the same, independent of the dimension or size of a single image frame. As a consequence, the computation time for a specific node type will depend exclusively on the number of input image frames.

For example, in Fig. 7b, the number of input image frames for each dataset is set to 60, while the initial candidate for analytics placement is a source node type B, and only alternative node candidates with lower inference time per frame are considered, i.e., node type A. The solid black line represents the compute-bound of the source node B as the baseline, i.e., the total latency of running requested analytics on the dataset in the source location is equal to $\sim 15s$ ($60 \cdot 250.74ms$).



(a) Network bound



(b) Placement decision

Fig. 7. SEA-LEAP placement decision. Subfigure (a) shows network bounds for various image file sizes. Subfigure (b) shows a borderline of placing analytics between the source node B and a new node A, among different datasets (60 frames) and available bandwidths with two hops.

Dashed lines represent the estimated total latency of running the analytics on the datasets in alternative node candidates, including data transfer over different network characteristics with two hops. Depending on the available bandwidth in the source location, the self-adaptive SEA-LEAP placement optimizer will decide whether to place analytics to (i) the initial location storing the dataset (*GuideMe*) for all results above the baseline, or (ii) a new location where the dataset is also moved (*FollowMe*) for all results below the baseline. Our self-adaptive solution shows that considering data locality in edge analytics placement can significantly improve overall analytics requests execution time, and thus impacting the timely placement of on-demand analytics applications.

D. Assumptions and Limitations

The SEA-LEAP placement optimizer estimates total latency for initial and alternative candidate locations based on prior obtained and managed edge-related details such as network characteristics (e.g., network types and number of hops between edge sites) and analytics benchmarks on node types. Also, we assume in our setup that edge nodes have access to existing docker images of analytics applications. Still, we partially address these issues by designing SEA-LEAP parts as generic services, which can be easily extended to consider (i) other analytics applications, (ii) different network topologies and characteristics, (iii) new datasets, and (iv) additional conditions for filtering location candidates for analytics placement.

In the proposed solution, a centralized edge meta-server represents a single point of failure, which could affect SEA-LEAP reliability. Also, in the current version, we assume a network of edge servers managed by trusted infrastructure providers that control access to edge computing resources. Data security and privacy issues are delegated to the trusted infrastructure. Even though accessing metadata via the meta-scheduler or through the tracking mechanism already provides access control, we believe that additional protection measures could be taken, especially in contexts where security is critical (e.g., in use cases with sensitive information).

VIII. Related Work

Analytics placement. Analytics placement at the edge has been discussed in several recent works. In [12], the authors propose a service-oriented resource management framework for fog computing focusing on service reliability. The paper [13] proposes EdgeEye, a service enabling the development and execution of video analytics. EdgeBox [11] is an architecture to improve automatic event detection in edge near real-time video analytics. However, these works limit placement to a specific cloud/edge location. Authors in [24] discuss the decentralized and federated edge infrastructure, focusing on a scalable approach to perform data collection and video analytics at the edge. Still, these approaches do not consider data locality and adaptive analytics placement.

Data management. Current data management approaches adopt storage services configured toward centralized data aggregation [33] or geo-distributed data storage [34]. The work [35] surveys existing solutions for IoT data management. In [10], the relationship between resource availability and accuracy of video analytics are investigated, without considering data locality. In [19], Firework system is described facilitating distributed data processing, considering only specific locations.

Latency-aware scheduling. The work [36] addressed the offloading of computation-intensive tasks on edge nodes as an optimization problem. The proposed scheduling approach minimizes latency by static offloading of dependent tasks according to input data. In [14] latency-aware placement of data stream analytics applications is proposed, while [15] performs low-latency data management over geo-distributed and heterogeneous edge infrastructures. We focus on a latency-aware placement of on-demand analytics using data locality.

Data locality. The exploitation of data locality has been considered by other works in literature. For example, [20] discuss the concept of Semantic Cache, which employs a caching technique for edge analytics while reducing latency compared to cloud-only inference. In [37], the spatio-temporal locality of analytics is used to improve workload balancing between edge and cloud servers. Other works for analytics placement exploit data locality considering the edge-cloud workload balance perspectives [16], the trade-off between the resource usage and query accuracy [17], or the fairness of cloud resource allocation [18]. However, these works either do not consider the autonomous placement of on-demand analytics or focus on different aspects than minimizing requests execution time. We bridge these gaps by considering data locality in the self-adaptive placement of on-demand edge analytics.

IX. Conclusions and Future Work

Edge computing allows the execution of latency-sensitive analytics close to data sources. However, executing on-demand analytics brings critical challenges to (i) identify locations of requested input datasets, and (ii) determine the target computational node where analytics must be deployed to minimize user requests execution time. We propose SEA-LEAP (Self-adaptive and Locality-aware Edge Analytics Placement) framework to address the aforementioned issues.

SEA-LEAP includes a mechanism for tracking data movements on top of which we propose a generic control mechanism featuring meta-scheduler and placement optimizer. Our solution allows on-the-fly placements of on-demand analytics considering data locality and minimizing the request execution time by performing adaptive data movements. We evaluate SEA-LEAP by considering on-demand video analytics application using our physical edge infrastructure and obtained benchmarks. Results show benefits for users and developers, automating the placement of analytics requests and reducing the total latency by 65.85% on average for certain network and node characteristics. We believe that SEA-LEAP is a valuable step towards data locality-aware placements of on-demand analytics for edge multi-cluster or hybrid environments.

In the future, we plan to consider the single point of failure of the meta-scheduler, proposing a solution to improve scalability and reliability of meta-scheduler, i.e., by using

multiple instances and implementing replication strategies of meta-dataset. We also plan to investigate the scalability of the tracking mechanism by experimenting different edge storage technologies such as Ceph, Minio, or other object storage technologies. Finally, we plan to further investigate the privacy and the data protection of SEA-LEAP.

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