A Two-Sided Matching Model for Data Stream Processing in the Cloud – Fog Continuum

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Abstract-Latency-sensitive and bandwidth-intensive stream processing applications are dominant traffic generators over the Internet network. A stream consists of a continuous sequence of data elements, which require processing in nearly real-time. To improve communication latency and reduce the network congestion, Fog computing complements the Cloud services by moving the computation towards the edge of the network. Unfortunately, the heterogeneity of the new Cloud - Fog continuum raises important challenges related to deploying and executing data stream applications. We explore in this work a two-sided stable matching model called Cloud - Fog to data stream application matching (CODA) for deploying a distributed application represented as a workflow of stream processing microservices on heterogeneous computing continuum resources. In CODA, the application microservices rank the continuum resources based on their microservice stream processing time, while resources rank the stream processing microservices based on their residual bandwidth. A stable many-to-one matching algorithm assigns microservices to resources based on their mutual preferences, aiming to optimize the complete stream processing time on the application side, and the total streaming traffic on the resource side. We evaluate the CODA algorithm using simulated and real-world Cloud - Fog experimental scenarios. We achieved 11-45% lower stream processing time and 1.3-20% lower streaming traffic compared to related state-of-the-art approaches.

Index Terms—Cloud – Fog computing, computing continuum, matching game algorithm, microservice, data stream processing.

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I. INTRODUCTION

The world is witnessing an exponential growth in the amount of generated data in the presence of pervasive Internet connectivity. Latency-sensitive and bandwidth-intensive data stream processing services, such as live video and video-on-demand streams, are amongst the dominating high velocity traffic generators in today's world. Processing such data streams in nearly real-time [1] requires vast amounts of computational and network resources in proximity of the data sources. However, the high communication penalty for reaching the Cloud data centers significantly hinders the timely processing of the data streams [2], [3]. Fog computing complements the Cloud services by moving the computation towards the edge of network. The extension of the Cloud with distributed micro-data centers (also called cloudlets [4]) and

mobile Edge servers [5] forms the so-called *Cloud – Fog continuum*, which aids the application execution by improving the communication latency and reducing the network congestion.

However, the heterogeneity of the Cloud – Fog continuum raises multiple challenges for executing data stream processing applications [6], including application deployment and resources allocation. Unfortunately, existing works often omit to consider data stream applications with strict latency and bandwidth requirements. It becomes therefore essential to explore models for allocating resources to data stream processing applications in the Cloud – Fog continuum.

We propose a two-sided matching model called *Cloud* – *fOg to Data stream application mAtching (CODA)* to address the problem of deploying data stream processing applications organized as directed acyclic graphs on heterogeneous computing continuum resources. CODA approaches this problem using matching theory principles involving two sets of players:

- Application microservices rank the continuum resources based on their microservice stream processing time (also referred in the following as microservice time);
- *Cloud Fog resources* rank the stream processing microservices based on their residual bandwidth.

The CODA two-sided stable matching model assigns microservices to resources based on their mutual preferences, aiming to optimize the stream processing time on the application side, and the total streaming traffic on the resource side [7].

Hence, the main contributions in this work are:

- A model for quantifying the microservice stream processing time and the residual network bandwidth to a resource;
- A ranking strategy tailored to data stream applications that avoids zero bandwidth surplus;
- A many-to-one matching model that allocates resources based on their capacity to multiple microservices;
- A two-sided stable matching model for allocating Cloud Fog resources to a microservice-based data stream processing application.

The paper has eight sections. Section II surveys the relevant related work. Section III elaborates the model underneath our approach, followed by the CODA matching algorithm in Section IV. Section V describes the stream processing case study application, evaluated using simulation in Section VI. Section VII confirms the simulation in a real-world testbed and Section VIII concludes the paper.

II. RELATED WORK

This section reviews the state-of-the-art in Cloud – Fog resource allocation for data stream processing applications with reduced network streaming traffic.

a) Hierarchical resource allocation: Gupta et al. [8] proposed a hierarchical placement strategy that executes the last microservice of every application in the Cloud and places all its predecessors on the less powerful computational resources in the Cloud – Fog hierarchy. Similarly, Mortazavi et al. [2] presented a novel paradigm called CloudPath computing that enables data stream processing on a progression of Cloud data centers based on their computing and storage capabilities, interposed along the geographical span of the network.

b) Stream processing time reduction: Sharphivand et al. [9] proposed a two-sided matching model for allocating Fog resources to services at the edge of network considering the service response time. The approach improves the user satisfaction and quality of experience using a set of heterogeneous quality of service metrics. Cai et al. [10] also addressed the service response time by defining a placement optimization model for complex event-processing applications on Edge resources. The proposed approximation algorithm deploys the operators on the Edge infrastructure with the lowest predicted delay. Veith et al. [11] proposed a placement strategy called RTR-RP, which uses a greedy strategy to identify the resources that minimize the service response time by reducing the endto-end event latency of a data stream analytic application. This approach decomposes the application in data processing flow patterns such as fork and join, and then distributes it on the Cloud - Fog continuum. Dautov et al. [12] describes a new approach for stream data processing in Fog by supporting run-time clustering of heterogeneous low powered devices. Besides, they utilise horizontal offloading of computational tasks between the Fog devices, which results in reduction of the communication latency by a factor of five compared to the vertical offloading approaches that rely on the Cloud.

c) Streaming traffic reduction: Aral et al. [3] considered the Fog computing characteristics to improve the user experience for latency-sensitive applications. The service placement evaluates the network quality of each Cloud and Fog node with respect to its requirements, in particular the connectivity and bandwidth. Zamani et al. [13] describe a semi-real time data stream processing approach at the edge of the network, which supports stream transformation and analysis from source to destination. The approach leverages an in-network computational model that employs software defined networks to dynamically establish data stream routes that exploit the underutilized computational resources at the Edge.

d) CODA contribution: These works investigate the resource allocation as an optimization problem that minimizes the stream processing time as a main objective, and neglect the streaming traffic. We extend the related approaches by researching a novel resource provisioning approach based on two-sided matching [14] that considers different interests of the involved stakeholders:

- 1) minimization of the stream processing time from the application perspective;
- 2) minimization of traffic considering changes in the data stream rate from the resource provider perspective.

III. MODEL

This section presents a formal model and a set of essential definitions important for this work.

A. Stream application

We model a *data stream processing application*:

$$\mathcal{A} = (\mathcal{M}, \mathcal{E}, m_{ t src}, m_{ t snk}, t src, t snk)$$

as a directed acyclic graph (DAG) consisting of:

1) A set of $\mathcal{N}_{\mathcal{M}}$ lightweight interconnected *microservices*:

$$\mathcal{M} = \{ m_i \mid 0 \le i < \mathcal{N}_{\mathcal{M}} \} ;$$

2) A set of *data streams* $data_{ui}$ flowing from an upstream microservice m_u to a downstream microservice $m_i \in \mathcal{M}$:

$$\mathcal{E} = \{ (m_u, m_i, data_{ui}) | (m_u, m_i) \in \mathcal{M} \times \mathcal{M} \};$$

 A source microservice m_{src} processing the data stream produced by src of the application A. The source microservice has no upstream microservices:

$$(m_{\mathtt{src}}, m_i, \mathtt{src}) \in \mathcal{E} \land \not\supseteq (m_i, m_{\mathtt{src}}, _) \in \mathcal{E};$$

 A sink microservice m_{snk} generating the data stream for snk, representing the output of the application A.

$$(m_i, m_{\mathtt{snk}}, \mathtt{snk}) \in \mathcal{E} \land \not\supseteq (m_{\mathtt{snk}}, m_i, _) \in \mathcal{E}.$$

We define a *data stream* using the following triple notation: $data_{ui} = (data_{ui}[x], \lambda_{ui}, Size_{ui})$, where:

- 1) $data_{ui}$ represents a sequence of data stream elements sent between two microservices m_u and m_i , measured in bit;
- data_{ui}[x] is a single data element in the data stream data_{ui}. We assume that m_i recognizes the data elements in the stream data_{ui} by the timestamp and merges the elements in the correct order;
- 3) λ_{ui} represents the ingress data rate that the microservice m_i receives a number of data elements per unit of time from its upstream microservice m_u [15].
- 4) Size_{ui} is the total number of data elements $data_{ui}[x]$ transmitted in a stream $data_{ui}$, where $1 \le x \le \text{Size}_{ui}$.

Proper processing of a data element $data_{ui}[x]$ by a microservice m_i has certain *resource requirements* in terms of the processing load CPU $(m_i, data_{ui}[x])$ (measured in million of instructions (MI)), memory MEM $(m_i, data_{ui}[x])$ and storage STOR $(m_i, data_{ui}[x])$ (measured in MB).

B. Resource model

We define a Cloud – Fog environment as a set of $\mathcal{N}_{\mathcal{R}}$ resources: $\mathcal{R} = \{r_j \mid 0 \leq j < \mathcal{N}_{\mathcal{R}}\}$, where a resource r_j defines its computational power CPU_j (in MI per second), memory size MEM_j, and storage size STOR_j: $r_j = (CPU_j, MEM_j, STOR_j, c_j)$.

We define the *capacity* c_j of a resource r_j as the maximum number of microservices it can host, which relies on its utilization as a threshold [16], [17] that ensures no contention among the microservices [18].

We model the *network channels* between the Cloud – Fog resources as $\mathcal{L} = \{l_{qj} \mid 0 \leq q, j < \mathcal{N}_{\mathcal{R}}\}$, where $l_{qj} = (LAT_{qj}, BW_{qj})$ represents by the round-trip latency LAT_{qj} and network bandwidth BW_{qj} between the resources r_q and r_j . Two interdependent microservices allocated to the same resource have $LAT_{qj} = 0$ and $BW_{qj} = \infty$ [19].

We define a *microservice allocation* as a mapping function $\mu : \mathcal{A} \to \mathcal{R}$ that assigns a microservice m_i to a resource $r_j = \mu(m_i)$. Accordingly, $\texttt{alloc}(r_j)$ represents the list of *microservices* allocated and deployed on each resource r_j :

$$alloc(r_j) = \{m_i \mid \mu(m_i) = r_j\}.$$

C. Ranking methods

The CODA model for matching application microservices to resources uses a two-sided ranking method:

- microservice-side ranking that considers the stream processing time of each microservice;
- resource-side ranking that considers the residual bandwidth to each resource allocated to each microservice.

1) Microservice-side ranking: We define the element processing time $t(m_i, data_{ui}[x], r_j)$ required by a microservice m_i to process the x^{th} element $data_{ui}[x]$ of a stream received by a resource $r_j = \mu(m_i)$ as the sum of three terms:

$$\begin{split} t\left(m_{i}, data_{ui}[x], r_{j}\right) &= \frac{\operatorname{CPU}\left(m_{i}, data_{ui}[x]\right)}{\operatorname{CPU}_{j}} + \\ &+ \frac{data_{ui}[x]}{\operatorname{BW}_{qj}} + \operatorname{LAT}_{qj} \end{split}$$

a) computation time: as the ratio between the computational requirement $CPU(m_i, data_{ui}[x])$ for processing a data element $data_{ui}[x]$ on the microservice m_i and the processing speed CPU_j of the resource r_j ;

b) transmission time: as the ratio between the size of the received data element $data_{ui}[x]$ and the network bandwidth BW_{aj} to $r_j = \mu(m_i)$ [20];

c) latency: as the round-trip time LAT_{qj} between resources r_q and r_j .

The microservice stream processing time $T(m_i, data_{ui}, r_j)$ of a data stream $data_{ui}$ processed by a microservice m_i running on a resource r_j is the sum of its element processing times $t(m_i, data_{ui}[x], r_j)$:

$$T(m_i, data_{ui}, r_j) = \sum_{x=1}^{\text{Size}_{ui}} t(m_i, data_{ui}[x], r_j).$$

Every microservice m_i ranks the resources in a *resource* preference list $RPL[m_i]$ based on the microservice stream

Algorithm 1 Microservice-side ranking algorithm.

Input: $\mathcal{A} = (\mathcal{M}, \mathcal{E}, m_{\texttt{src}}, \overline{m_{\texttt{snk}}, \texttt{src}}, \texttt{snk})$ ▷ Stream application $\begin{array}{l} \mathcal{R} = \{r_j \mid 0 \leq j < \mathcal{N}_{\mathcal{R}}\} & \triangleright \ \text{Cloud} - \text{Fog resource set} \\ \mathcal{L} = \{l_{qj} \mid 0 \leq q, j < \mathcal{N}_{\mathcal{R}}\} & \triangleright \ \text{Cloud} - \text{Fog channel set} \\ \textbf{Output: } \operatorname{RPL}[m_i], \forall m_i \in \mathcal{M} & \triangleright \ \text{Resource preference lists of all microservices } m_i \end{array}$ 1: for all $m_i \in \mathcal{M}$ do ▷ Initialize RPL 2. $\mathtt{RPL}[m_i] \leftarrow \emptyset$ 3: end for 4: for all $m_i \in \mathcal{M}$ do for all $(r_j \in \mathcal{R}) \land (l_{qj} \in \mathcal{L})$ do if $(\text{MEM}(m_i) < \text{MEM}_j) \land (\text{STOR}(m_i) < \text{STOR}_j)$ then \triangleright Check constraints 5: 6: $\operatorname{RPL}[m_i] \leftarrow \operatorname{RPL}[m_i] \bigcup (r_j, \max_{\forall (m_u, m_i)} T(m_i, data_{ui}, r_j))$ 7: $\nabla (m_u, m_i, data_{ui}) \in \mathcal{E}$ 8: \triangleright Add r_j and its microservice time to m_i 's RPL end if 9: end for 10: end for 11: for all $(m_i \in \mathcal{M}) \land (\operatorname{RPL}[m_i] \neq \emptyset)$ do $\operatorname{RPL}[m_i] \leftarrow Sort_T(\operatorname{RPL}[m_i])$ > Sort tuples based on microservice time 13: end for 14: return RPL;

processing time, as presented in Algorithm 1. The resource that guarantees a lower microservice time receives a higher rank. The algorithm first initializes the resource preference lists for each microservice with the empty set in line 1. Thereafter, it filters the resources that do not satisfy the memory MEM $(m_i, data_{ui}[x])$ and storage STOR $(m_i, data_{ui}[x])$ requirements of a microservice (line 6). Afterward, it creates a list of tuples for each microservice m_i that associates the maximum microservice time $T(m_i, data_{ui}, r_j)$ of all upstream microservices m_u of m_i to each resource r_j (line 7). Finally, the algorithm sorts the resource preferences of each microservice based on its microservice time in descending order in line 12.

2) Resource-side ranking: We model the residual bandwidth to a resource r_j as the difference between the available bandwidth BW_{qj} and the ingress traffic from an upstream microservice, as defined in the DAG structure of the applications. The ingress traffic is the amount of data per time unit received by a resource r_j allocated to a microservice m_i , which depends on ingress data rate λ_{ui} and data stream $data_{ui}$:

$$\operatorname{ResdBW}_{j}\left(m_{i}, data_{ui}, r_{j}\right) = \operatorname{BW}_{qj} - \sum_{x=1}^{\operatorname{Size}_{ui}} \left(\lambda_{ui} \cdot data_{ui}[x]\right).$$

The resource-side ranking, presented in Algorithm 2, receives as input the resource preference lists $\operatorname{RPL}[m_i]$ ($\forall m_i \in \mathcal{A}$) computed in Algorithm 1, along with the application \mathcal{A} , the resource set \mathcal{R} , and the set of network channels \mathcal{L} . Similarly, the algorithm initializes the *microservice preference list* MPL[r_j] of each resource with the empty set in line 1. Afterward, each resource ranks the microservices in a preference list in line 6 based on its residual bandwidth. Finally, the algorithm sorts the microservice preferences in descending order in line 10 based on the residual bandwidth. Hence, the microservice that offers a lower bandwidth utilization receives a higher rank.

D. Problem definition

Matching theory is a formal framework describing the interactions among interdependent rational entities and forming mutually beneficial relationships over time [21]. The analytical matching theory helps to assign a set of rational entities to one

Algorithm 2 Resource-side ranking algorithm.

 $\overline{\text{Input: } \mathcal{A} = (\mathcal{M}, \mathcal{E}, m_{\text{src}}, m_{\text{snk}}, \text{src}, \text{snk})},$ ▷ Stream app. ▷ Cloud - Fog resource set \triangleright Resource preference lists of all microservices m_i $\mathcal{L} = \{ l_{qj} \mid 0 \leq q, j < \mathcal{N}_{\mathcal{R}} \}$ Output: MPL[r_j], $\forall r_j \in \mathcal{R} \qquad \triangleright M$ ▷ Cloud - Fog channel set \triangleright Microservice preference lists of all resources r_i 1: for all $r_j \in \mathcal{R}$ do ▷ Initialize MPL $MPL[r_j] \leftarrow \emptyset$ 2. 3: end for 4: for all $m_i \in \mathcal{M}$ do $\begin{array}{l} \text{for all } (r_j \in \texttt{RPL}[m_i]) \land (l_{qj} \in \mathcal{L}) \text{ do} \\ \texttt{MPL}[r_j] \leftarrow \texttt{MPL}[r_j] \bigcup (m_i, \texttt{ResdBW}_j) \\ \text{end for} \\ \texttt{PAdd } m_i \text{ and its residual bandwidth to } r_j \text{'s MPL} \end{array}$ 5: 6: 7: 8: end for 9: for all $(r_j \in \mathcal{R}) \land (MPL[r_j] \neq \emptyset)$ do 10: $MPL[r_j] \leftarrow Sort_{ResdBW}(MPL[r_j]) \triangleright Sort tuples based on residual bandwidth$ 11: end for 12: return MPL;

another, typically subject to constraints such as preference lists and capacities [22].

We represent our *resource allocation problem* as a matching game using two finite and disjoint sets of players: 1) the microservices \mathcal{M} of the stream processing application \mathcal{A} , and 2) the Cloud – Fog resources in \mathcal{R} . The game aims to match each microservice $m_i \in \mathcal{M}$ to a resource in $r_j \in \mathcal{R}$ with sufficient capacity that optimizes *two independent goals*: 1) application-specific on one side and 2) resource provider-specific on the other side. The result is a bilateral resource allocation agreement that represents the players' preferences over each other. Section VI-C instantiates this problem on two metrics: 1) *stream processing time* on the application side, and 2) *total streaming traffic* on the resource side.

In a matching game, a microservice $m_i \in \mathcal{M}$ asks for allocation on the first resource r_j in its preference list $\text{RPL}[m_i]$. If r_j has enough capacity c_j and there exists no other preference microservice in its preference list $\text{MPL}[r_j]$, it bids for m_i . If the two sides agree, the microservice m_i holds its demand from the resource r_j and vice versa until the matching completes.

A *valid* resource allocation is (pairwise) stable if it satisfies three properties of a many-to-one matching game [23], [24]:

 Each microservice is allocated to exactly one resource from its preference list:

$$\mu(m_i) \in \mathcal{R} \land |\mu(m_i)| = 1 \land \mu(m_i) \in \mathtt{RPL}[m_i];$$

2) A resource can host multiple microservices that are part of its preference list and within its capacity:

$$\operatorname{alloc}(r_j) \subseteq \operatorname{MPL}[r_j] \subseteq \mathcal{M} \land |\operatorname{alloc}(r_j)| \leq c_j;$$

- 3) The matching does not contain blocking pairs of microservices and resources that prefer matching each other rather than their current assignments [7]. A matching $r_j = \mu(m_i)$ is *not blocking* if the following conditions hold:
 - a) m_i and r_j are currently matched with each other;
 - b) m_i does not prefer another resource to its current matching r_i ;
 - c) r_j does not prefer another microservice to any of its current matching in $alloc(r_j)$.

IV. CODA MATCHING ALGORITHM

Algorithm 3 describes the many-to-one matching-based allocation of microservices to resources. The algorithm receives as input the stream application described as a DAG, the resource preference list RPL of each microservice m_i , and the microservice preference list MPL of each resource r_j , computed by Algorithms 1 and 2. The algorithm outputs a stable matching between microservices and resources $\mu(\mathcal{A}) \subseteq \mathcal{R}$. After initializing the allocation on both sides (lines 1–6), the algorithm loops until it manages to find the appropriate resource allocation matches to all microservices according to their mutual preferences (lines 8–36). In every iteration, it attempts to find a good resource matching for every microservice using several matching states (i.e. State-1, State-2.1, State-2.2), described in the following paragraphs.

1) State-1: Each microservice not yet matched to any resource demands the resource r_j with the lowest microservice time, ranked first in its preference list RPL $[m_i]$ (lines 8–10). If the resource r_j has also ranked the microservice first in its preference list MPL $[r_j]$ because of the least bandwidth consumption (line 11), the algorithm creates a matching pair and update the resource $\mu(m_i)$ and the list of microservices alloc (r_j) (lines 12–13).

2) State-2: If the microservice m_i is not the first in the preference list MPL $[r_j]$ (line 15), m_i matches to r_j (lines 16–17). Afterward, the algorithm checks the following two states:

a) State-2.1: If m_i 's allocation to resource r_j exceeds its capacity c_j (line 18), the algorithm removes the allocation $\mu(m_u) = r_j$ with the lowest residual bandwidth in the ranked preference list MPL $[r_j]$ of resource r_j (lines 19–21).

b) State-2.2: If a resource r_j reaches its capacity c_j (line 24), the algorithm identifies the microservice m_u with the lowest residual bandwidth in its allocation list $\texttt{alloc}(r_j)$ (line 25). Afterward, r_j removes all microservices m_s with a lower residual bandwidth than m_u from its preference list MPL $[r_j]$. Similarly, all microservices m_s remove r_j from their resource preference lists $\texttt{RPL}[m_s]$. This avoids deploying microservices with low residual bandwidth on r_j and allows higher ranked microservices in $\texttt{MPL}[r_j]$ to fill its capacity (lines 26–28).

3) CODA complexity: The microservice-side ranking (Algorithm 1) and the resource-side ranking (Algorithm 2) algorithms have complexity of $\mathcal{O}(\mathcal{N}_{\mathcal{M}} \cdot \mathcal{N}_{\mathcal{R}})$, where $\mathcal{N}_{\mathcal{M}}$ is the number of microservices and $\mathcal{N}_{\mathcal{R}}$ is the number of resources allocated to the microservices. Algorithm 3 traverses the microservice m_i 's resource preference list RPL $[m_i]$ that previously ranked all the resources (outputs of Algorithms 1 and 2). Therefore, its worst-case time complexity directly depends on the number of acceptable matches, which is $\mathcal{N}_{\mathcal{M}} \cdot \mathcal{N}_{\mathcal{R}}$. The complexity of the sorting algorithm $Sort_{\text{ResdBW}}$ must consider the maximum capacity of the resources $c_{\max} = \max(c_j) :$ $\forall j \leq \mathcal{N}_{\mathcal{R}}$. Considering the use of a quick-sort algorithm, this leads to a total runtime complexity of Algorithm 3 of $\mathcal{O}(c_{\max} \cdot \log(c_{\max}) \cdot \mathcal{N}_{\mathcal{M}} \cdot \mathcal{N}_{\mathcal{R}})$.

4) CODA trace example: Figure 1 illustrates an example of using Algorithm 3 on five microservices and four resources

Algorithm 3 CODA matching algorithm.



to converge to a stable matching. Each resource has the capacity to allocate at most two microservices. We assume that Algorithms 1 and 2 already created the microservice and resource preference lists (displayed in brackets in Figure 1). Figure 1a shows the matching of the microservice m_1 to the resource r_1 (lines 16–17). Figure 1a also depicts the matching of m_2 to r_4 (ranked highest in each other preference lists) following the State-1 of the algorithm (lines 12-13). Afterward, m_3 matches to r_1 , as shown in Figure 1b (lines 12– 13). In addition, Figure 1b illustrates that the microservices with lower residual bandwidth in the resources preference lists (i.e., not ranked first) demand resources, and thus, m_4 matches to r_4 (lines 16–17). As a consequence, r_1 reaches its total capacity and removes the lower-ranked microservices m_5 and m_4 (with a lower residual bandwidth than m_1) from its preference list (State-2.2). The microservices m_5 and m_4 also remove r_1 from their preference lists (lines 25–28). In the next outer loop iteration (line 8), the remaining microservice m_5 demands its preferred resource r_4 (line 10). Therefore, r_4 and m_5 match one another (lines 16–17), although r_4 already reached its total capacity. This matching is not successful, as the capacity of r_4 is full (State-2.1). However, m_5 has a higher rank than m_4 due to its higher residual bandwidth; therefore, the matching of m_4 to r_4 fails (lines 19–21). As a consequence, r_4 removes m_4 (with lower residual bandwidth





(c) State-2: m_5 matches to r_4 ; State-2.1: r_4 rejects m_4 ; State-2.2: r_4 removes m_4 .



(d) State-2: m_4 matches to r_3 .



than m_5) from its preference list (State-2.2) and m_4 removes r_4 from its preference list too (lines 25–28), as shown in Figure 1c. Finally, Figure 1d shows that the microservice m_4 matches resource r_3 (lines 16–17), as the only resource with enough capacity that prefers it.

V. CASE STUDY: VIDEO STREAM PROCESSING FOR TRAFFIC SIGN CLASSIFICATION

We selected a representative traffic management system case study following road safety inspection concerns. Detecting and recognizing different traffic signs and anomalies in nearly realtime requires fast detection of objects in video frames and embedding the information on the detected objects in video streams at different encoding resolutions and bit rates [25]. Typical examples are broken, covered, worn-out or stolen traffic signs, or incorrectly painted road surface markings [26]. We represent this application as a DAG of seven microservices depicted in Figure 2. Each independent microservice contains a data store and communicates with other microservices through a lightweight HTTP interface [27].

1) Encoding microservice: receives and encodes the raw video stream in high resolution and bitrate near to the vehicles



Fig. 2: Traffic sign classification in video stream applications.

equipped with multiview-cameras. We use for this purpose the ffmpeg software suite [28] with the H.264 video codec for encoding, transcoding and packaging of the video streams.

2) Framing microservice: utilizes OpenCV to produce still frames from different video scenes [29].

3) Low-accuracy inference microservice: identifies features in the video stream, such as traffic signs on the road. The microservice uses TensorFlow core version 2.3.0 for Python v3.7.4 to train a convolutional neural network with nine layers on localized signs from 50,000 video frames of 43 different traffic sign classes. Every frame contains a traffic sign used for training and testing the neural network. This microservice aims for a low classification accuracy of 70%.

4) High-accuracy inference microservice: uses a machine learning model [30] capable of accurate inference when the low-accuracy microservice has a poor confidence. We use the same convolutional neural network with nine layers to classify the signs in the same video frames as for the low-accuracy inference until reaching a 90% accuracy.

5) Analysis microservice: updates and retrains the multiclass classification model to learn from newly collected data [31]. This microservice is the upstream of the highaccuracy inference and transcoding microservices and requires a barrier to synchronize the received data.

6) Transcoding microservice: converts the video in different resolutions and bitrates, and prepares it for delivery. We again use the ffmpeg software suite with the H.264 video codec for transcoding the video streams.

7) Packaging and delivery microservice: provides the transcoded video stream together with the detected signs in the format required by the drivers. This microservice is the downstream of analysis and transcoding microservices, and uses a barrier to synchronize the data received from its upstream microservices.

We used the Phoronix test suite [32] to benchmark the application microservices on a set of heterogeneous devices integrated in our testbed, described in Section VII. Afterward, we identified the requirements of the encoding, transcoding, packaging and inference microservices based on the average

TABLE I: Application resource requirements per microservice.

	CPU	MEM	Storage	$data_{ui}$	λ_{ui}	
	$[MI] \cdot 10^3$	[MB]	[GB]	[MB]	[/s]	
encoding	30 - 40	300 - 500	1 - 5	0.1 - 10	0.2 - 40	
framing	1 - 5	100 - 300	0.5 - 2	0.1 - 10	0.2 - 40	
low-accuracy inf.	5 - 20	200 - 500	0.5 - 2	0.1 - 10	0.2 - 40	
high-accuracy inf.	30 - 40	300 - 500	3 - 5	0.1 - 10	0.2 - 40	
analysis	10 - 20	100 - 300	1 - 3	0.1 - 10	0.2 - 40	
transcoding	5 - 40	200 - 500	0.5 - 5	0.1 - 10	0.2 - 40	
packaging	10 - 20	100 - 300	1 - 2	0.1 - 10	0.2 - 40	

device utilization in terms of MI, memory, storage, $data_{ui}$ (in MB) and ingress data rate (in [/s]). We summarize the video stream processing application requirements in Table I.

VI. SIMULATION-BASED EVALUATION

We implemented the CODA matching-based resource allocation in *Python v.3.7.4* using the *matching* library [33]. The script required to run the CODA model is available in the GitHub code repository¹. We utilize the *iFogSim* simulator [8] to perform the evaluation on a simulated Cloud – Fog environment.

A. Resource setup

Table II displays the simulated Cloud – Fog computing environment divided in three hierarchical tiers based on their computation, storage and networking capabilities. We used the Phoronix test suite benchmark [32] to measure the performance of each resource and then use it in the simulation. The measured computational CPU power of the resources is in the range $20\,000\,\text{MIPS} - 100\,000\,\text{MIPS}$.

1) Cloud data center: simulates instances equivalent to m5a.8xlarge of Amazon EC2, based on the 32-core AMD[®] EPYC 7571 processor with a clock frequency of 2.1 GHz. We select the m5a.8xlarge instance as it provides a good balance of computation, memory and network resources, suitable for executing data stream processing [34].

2) Fog-tier-2: simulates processing gateways (ISP GW) and cellular Base Transceiver Stations (BTS) available within Internet Service Providers (ISP) networks. We simulate the configuration based on the Alcatel-Lucent Ultimate Wireless Packet Core with 28-core Intel[®] Xeon Platinum 8175 and base clock frequency of 2.5 GHz [35].

3) Fog-tier-1: simulates resources co-located with the WiFi transceivers based on an eight-core Intel[®] Core^(TM) i7-7700 CPU at 3.60 GHz equivalent configuration, widely used for data stream processing at the consumer premises [36].

4) Interconnection network: simulates various Ethernet, wireless LAN, and 4G/LTE interfaces. We assume that gigabit switches interconnect the Cloud data centers and the Fog resources. As the Cloud interconnection network multiplexes the streaming traffic of multiple instances, the throughput to the Cloud data center is lower than to the Fog resources because of the shared bandwidth. Hence, we chose a bandwidth BW in the range 200 Mbit s⁻¹ – 1000 Mbit s⁻¹ and a latency in

¹https://github.com/SiNa88/CODA

TABLE II: Simulated Cloud – Fog infrastructure.

	Cloud	Fog-tier-2	Fog-tier-1
CPU [MIPS] $\cdot 10^3$	100	$\{80,75\}$	{20,30}
Memory [GB]	128	{64,32}	{8,16}
Storage [GB]	1200	{250,128}	{16,64}
BW [Mbit/s]	200	{200,500}	1000

the range 3 ms - 100 ms for interconnecting the Cloud and Fog resources. We derived these values from the maximum achievable bandwidth and the effective downlink throughput measured using the iPerf3 tool [37], [38] (see Table II).

B. Experimental design

We designed two sets of experiments according to the characteristics of the video stream processing application.

1) CPU experiment: varies the requirement in the range of $\{10000, 20000, 30000, 40000\}$ (MI) by bounding the data element to $data_{ui}[x] = 10 \text{ MB}$, which is the largest data element supported by the simulated communication protocol.

2) Data experiment: varies the data element size $data_{ui}[x]$ transferred between microservices in the range $\{0.1, 1, 5, 10\}$ MB, with a CPU requirement of 15000 MI.

C. Performance metrics

We compare the performance of our CODA method against related works based on two metrics.

1) Stream processing time: on the resources $\mu(\mathcal{A}) \subseteq \mathcal{R}$ is the completion time of the application m_{snk} microservice:

$$C(\mathcal{A},\mathcal{R}) = C(m_{\mathtt{snk}},\mathcal{R}),$$

where the completion time of a microservice m_i is the maximum completion time of all its upstream microservices $C(m_u, \mathcal{R})$ plus its microservice stream processing time $T(m_i, data_{ui}, r_i)$ on the allocated resource $r_i = \mu(m_i)$:

$$C\left(m_{i},\mathcal{R}\right) = \begin{cases} T\left(m_{\text{src}}, \text{src}, r_{j}\right), & m_{\text{src}} = m_{i};\\ \max_{\forall \left(m_{u}, m_{i}, \atop data_{u}\right) \in \mathcal{E}} \end{cases} \left\{C\left(m_{u}, \mathcal{R}\right)\right\} + T\left(m_{i}, data_{ui}, r_{j}\right), m_{\text{src}} \neq m_{i}; \end{cases}$$

2) Total streaming traffic: aggregates the traffic across all network channels. We define the streaming traffic on a network channel l_{qj} as the ratio of all the data elements $data_{ui}[x]$ streaming between the resources $r_q = \mu(m_u)$ and $r_j = \mu(m_i)$ allocated to two interdependent microservices and the bandwidth BW_{qj} of a channel between the two resources:

$$Str_Traf\left(\mathcal{A},\mathcal{R}\right) = \sum_{\substack{\forall (m_u,m_i,data_{ui}) \in \mathcal{E} \\ \land \ l_{qj} \in \mathcal{L}}} \frac{\sum_{x=1}^{\mathtt{Size}_{ui}} \left(\lambda_{ui} \cdot data_{ui}[x]\right)}{\mathtt{BW}_{qj}}$$

D. Related work comparison

We conduct the performance comparisons against three state-of-the-art approaches divided in two categories.

1) Cloud: uses only Cloud data centers for an application:

a) Heterogeneous Earliest Finish Time – only Cloud (HEFT-oC): deploys all microservices on the Cloud and selects the proper Cloud instances using a bottom ranking approach to optimize the stream processing time [39].

2) Cloud and Fog: uses a combination of Cloud data centers and Fog resources.

a) Response Time Rate with Region Patterns (RTR-RP): [11] minimizes the stream processing time by analyzing the data flow patterns to deploy the microservices on the Fog resources that offer the shortest stream processing time. The Cloud data center only hosts the microservices that do not fit on the Fog devices due to resource and network requirements.

b) CloudPath: [2] optimizes the stream processing time on a progression of Cloud data centers and Fog resources. CloudPath organizes the data centers in a multi-tier topology, and identifies first resources in the lowest tier (closest to the data src) that meet the application requirements. If such resources are not available, it checks in the upper layers until it finds appropriate allocation resource.

E. Simulation results

Figures 3 and 4 illustrate the relation between the stream processing time and the total streaming traffic by increasing the computation and communication loads.

1) CPU experiment:

a) Stream processing time: Figure 3a shows that CODA reduces the stream processing time by 22%, 12%, and 15% compared to RTR-RP, HEFT-oC and CloudPath. The related methods allocate Cloud resources to the last microservices residing farther away from the data src in the application DAG, which explains this result. RTR-RP allocates the Cloud resource to the snk microservice, which increases stream processing time, as the data needs to travel at least twice between the Cloud and the Fog-tier-1.

b) Total streaming traffic: Figure 3b shows that CODA reduces the average streaming traffic by 5%, 8% and 7% compared to RTR-RP, HEFT-oC and CloudPath by allocating resources in the Fog-tier-2 instead of Cloud virtual machines. As the data element size does not vary during the simulation, the streaming traffic does not change for microservices with different CPU requirements.

2) Data experiment:

a) Stream processing time: Figure 4a shows that CODA reduces the stream processing time by 8%, 9.7% and 11% compared to RTR-RP, HEFT-oC and CloudPath for different data element sizes. Unlike the other approaches, CODA considers the network bandwidth and the data element in its microservice-side ranking to find matches that reduce the streaming traffic, and consequently the processing time.

b) Total streaming traffic: Figure 4b shows that HEFToC and CloudPath generate higher streaming traffic than CODA and RTR-RP for small data elements. As the data element increases, the streaming traffic gradually saturates the network channels, and the related approaches perform almost equally well. CODA reduces the streaming traffic up to 2.3% compared to the related methods by considering the data element in its resource-side ranking.

VII. REAL TESTBED EVALUATION

To validate the simulation results, we analyze in this section the CODA performance on a real experimental testbed.



Fig. 3: Simulated video application stream processing time and total traffic comparison for different CPU requirements.



Fig. 4: Simulated video application stream processing time and total traffic for different data element sizes.

A. Carinthian Computing Continuum

We deployed a real testbed at the University of Klagenfurt named *Carinthian Computing Continuum* (C^3) [40] that aggregates heterogeneous resources in three hierarchical categories [41], as depicted in Figure 5.

1) Cloud data center: consists of virtualized instances provisioned on-demand from the Amazon Web Services (AWS), located at the geographically closest European data center in Frankfurt (Germany). We selected the m5a.xlarge general purpose instance powered by AMD EPYC 7000 processors at 2.5 GHz and up to 10 Gbit s^{-1} network bandwidth as the most suitable instance for our case study.

2) Fog-tier-2: comprises resources from two providers, Exoscale [42] and University of Klagenfurt, thanks to their low round-trip communication latency ($\leq 7 \,\mathrm{ms}$) and high bandwidth ($\leq 10 \,\mathrm{Gbit \, s^{-1}}$). University of Klagenfurt provides a private Cloud infrastructure (PCI) using OpenStack v13.0 and Ceph v12.2 with support for block and S3-compatible object storage. The computing optimized instances are of type large running Ubuntu 18.04 LTS, as described in Table III. 3) Fog-tier-1: comprises five NVIDIA Jetson Nano (NJN), three Raspberry Pi-3 B+ (RPi3B+), and 32 Raspberry Pi-4 single-board computers (RPi4). We installed Raspberry Pi OS (version 2020-05-27) on all RPis and Linux for Tegra (L4T) operating system on NJN resources. A managed layer-3 HP Aruba switch interconnects the Fog-tier-1 resources. The switch has 48 1 Gbit s⁻¹ ports, a latency of 3.8 µs and an aggregate data transfer rate of 104 Gbit s⁻¹. The Fog-tier-1 has a Fog/Edge Gateway System (EGS) as the entry point to the other resources available in this tier. The EGS has a twelve-core AMD Ryzen Threadripper 2920X processor at 3.5 GHz and 32 GB of RAM, running Ubuntu 18.04 LTS. It supports 1 Gbit s⁻¹ Ethernet and dual band PCIe WiFi 5 (802.11ac) network connections.

We installed a Docker engine 19.03 on all resources and containerized each microservice in Ubuntu 18.10 Docker official image. The minimal scripts to create and run the containerized microservices on the resources is available in the GitHub code repository¹.



Fig. 5: The C^3 testbed architecture.

TABLE III: The C^3 testbed configuration.

		Cloud	Fog-tier-2	Fog-tier-1			
	Instance / Device	AWS m5a.xlarge	Exoscale Large PCI Large	EGS	NJN	RPi4	RPi3B+
	CPU type	AMD EPYC 7000	Intel Xeon	AMD Ryzen	Tegra X1 and	ARM	ARM
			Platinum 8180	2920	ARM Cortex A57	Cortex 72	Cortex 53
	CPU clock [GHz]	2.5	3.6	3.5	1.43	1.5	1.4
	Memory [GB]	32	8	32	4	4	1
	Storage [GB]	1,000	256	1,000	64	64	64
	BW [Mbit/s]	27	65	813	450	800	330

B. Experimental design

We evaluated CODA compared to the related HEFT-oC, RTR-RP and CloudPath methods using the video stream processing application for traffic sign classification, described in Section V. We processed a raw video stream of $9 \,\mathrm{s}$ and $45 \,\mathrm{MB}$ in size that includes the traffic signs. We designed two sets of experiments according to the application characteristics.

1) CPU experiments: investigate the impact of CPU requirements for transcoding the raw video segment. We considered four encoding and transcoding bit rates of $\{200, 1500, 3000, 6500, 20000\}$ kbit s⁻¹, corresponding to resolutions of $\{180, 576, 720, 1440, 2160\}$ pixels. We further considered two machine learning models with 70% and 90% accuracy for the inference microservices with different CPU requirements. We fixed the size of the data element to 2560 kB.

2) Data experiments: compare the different methods using data element sizes in the range: $data_{ui}[x] \in$ $\{35, 300, 420, 1350, 2560\}$ kB, which correspond to different video frame sizes obtained by using five different qualities. We fixed the video resolution to 2160p.

C. Real-world testbed results

1) CPU experiments:

a) Stream processing time: Figure 6a shows that CODA reduces the stream processing time by 11%, 28% and 33% compared to RTR-RP, HEFT-oC and CloudPath. CODA performs the video encoding on Fog-tier-1 resources (NJN and RPi4), and enables video transcoding and high-accuracy inference on the EGS. The RTR-RP and CloudPath methods tend to allocate resources from Fog-tier-2 (i.e. Exoscale Large, PCI Large) with higher communication latency and similar computing performance to EGS. Lastly, HEFT-oC utilizes the AWS m5a.xlarge instances with high computing performance but limited measured bandwidth of 27 Mbit s⁻¹.

b) Total streaming traffic: Figure 6b shows that all methods except CloudPath exhibit similar performance as the data element size increases. CloudPath introduces up to 16% higher streaming traffic than CODA because it allocates Fog-tier-1 and Cloud resources, which require the data to traverse more network channels from the src. CODA deploys encoding microservices onto Fog-tier-2 resources closer to the data src and hence, the raw video stream traverses less network channels with lower streaming traffic.

2) Data experiments:

a) Stream processing time: Figure 7a shows that CODA outperforms RTR-RP, HEFT-oC, and CloudPath by 37%, 16%, and 45% on average by deploying microservices on resources closer to the application data src and snk. CODA reduces the stream processing time by performing the video encoding on the NJN and RPi4 devices. This considerably reduces the streaming traffic, as the encoded video is significantly smaller for the same data element size. HEFT-oC generates the highest stream processing time by transferring a raw video stream from the src to the m5a.xlarge instance in the AWS data center. Finally, RTR-RP and CloudPath show similar performance because they use more distant Fog-tier-2 resources for encoding, despite performing the machine learning training on the computationally-efficient EGS device.

b) Total streaming traffic: Figure 7b shows that CODA reduces the streaming traffic by 1.3%, 1.4% and 16% on average compared to RTR-RP, HEFT-oC and CloudPath. CODA reduces the streaming traffic by allocating microservices to





Fig. 6: Real video application stream processing time and total traffic for different bitrates.

resources in the Fog-tier-2 layer with lower stream processing time. In contrast, CloudPath requires the data stream to traverse more network channels towards the data snk, which generates higher streaming traffic.

3) Conclusion: The real testbed evaluation confirms the simulation. Surprisingly, the benefits of CODA to the stream processing application are even higher compared to the three related methods due to the higher latency and lower bandwidth difference between the Fog-tier-1, Fog-tier-2 resources and the Cloud instances within the C^3 testbed.

VIII. CONCLUSIONS AND FUTURE WORK

We introduced CODA, a novel approach for allocating heterogeneous Cloud – Fog computing resources to data stream processing applications, described as DAGs. CODA applies a two-sided stable matching model that enables manyto-one assignment of application microservices to resources based on specific ranking strategies. The microservices rank the continuum resources based on their microservice stream processing time. On the other side, resources rank the stream processing microservices based on their residual bandwidth.

Fig. 7: Real video application stream processing time and total traffic for different frame sizes.

A two-sided stable matching model assigns microservices to resources based on their mutual preferences, aiming to optimize the complete stream processing time on the application side and the total streaming traffic on the resource side. We evaluated CODA based on a video stream processing application for traffic sign classification using comprehensive simulation combined with a real Cloud – Fog experimental testbed deployment. The results demonstrate that CODA achieves 11-45% lower stream processing times and 1.3-20% lower streaming traffic than three state-of-the-art approaches. In the future, we plan to further improve our results by analyzing Nash equilibrium while processing the data streams in the Cloud – Fog computing continuum.

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REFERENCES

- [1] Phu Lai, Qiang He, Mohamed Abdelrazek, Feifei Chen, John Hosking, John Grundy, and Yun Yang. Optimal edge user allocation in edge computing with variable sized vector bin packing. In *International Conference on Service-Oriented Computing*, pages 230–245. Springer, 2018.
- [2] Seyed Hossein Mortazavi, Mohammad Salehe, Carolina Simoes Gomes, Caleb Phillips, and Eyal de Lara. Cloudpath: A multi-tier cloud computing framework. In *Proceedings of the Second ACM/IEEE Symposium* on Edge Computing, pages 1–13, 2017.
- [3] Atakan Aral, Ivona Brandic, Rafael Brundo Uriarte, Rocco De Nicola, and Vincenzo Scoca. Addressing application latency requirements through edge scheduling. *Journal of Grid Computing*, pages 1–22, 2019.
- [4] Eva Marín-Tordera, Xavi Masip-Bruin, Jordi García-Almiñana, Admela Jukan, Guang-Jie Ren, and Jiafeng Zhu. Do we all really know what a fog node is? current trends towards an open definition. *Computer Communications*, 109:117–130, 2017.
- [5] Sami Kekki, Walter Featherstone, Yonggang Fang, Pekka Kuure, Alice Li, Anurag Ranjan, Debashish Purkayastha, Feng Jiangping, Danny Frydman, Gianluca Verin, et al. Mec in 5g networks. *Sophia Antipolis, France, ETSI, White Paper*, 2018.
- [6] Marcos Dias de Assuncao, Alexandre da Silva Veith, and Rajkumar Buyya. Distributed data stream processing and edge computing: A survey on resource elasticity and future directions. *Journal of Network* and Computer Applications, 103:1–17, 2018.
- [7] Sarder Fakhrul Abedin, Md Golam Rabiul Alam, SM Ahsan Kazmi, Nguyen H Tran, Dusit Niyato, and Choong Seon Hong. Resource allocation for ultra-reliable and enhanced mobile broadband iot applications in fog network. *IEEE Transactions on Communications*, 67(1):489–502, 2018.
- [8] Harshit Gupta, Amir Vahid Dastjerdi, Soumya K Ghosh, and Rajkumar Buyya. ifogsim: A toolkit for modeling and simulation of resource management techniques in the internet of things, edge and fog computing environments. *Software: Practice and Experience*, 47(9):1275–1296, 2017.
- [9] Nafiseh Sharghivand, Farnaz Derakhshan, and Lena Mashayekhy. Qosaware matching of edge computing services to internet of things. In 2018 IEEE 37th International Performance Computing and Communications Conference (IPCCC), pages 1–8. IEEE, 2018.
- [10] Xinchen Cai, Hongyu Kuang, Hao Hu, Wei Song, and Jian Lü. Response time aware operator placement for complex event processing in edge computing. In *International Conference on Service-Oriented Computing*, pages 264–278. Springer, 2018.
- [11] Alexandre da Silva Veith, Marcos Dias de Assunçao, and Laurent Lefevre. Latency-aware placement of data stream analytics on edge computing. In *International Conference on Service-Oriented Computing*, pages 215–229. Springer, 2018.
- [12] Rustem Dautov and Salvatore Distefano. Stream processing on clustered edge devices. *IEEE Transactions on Cloud Computing*, 2020.
- [13] Ali Reza Zamani, Mengsong Zou, Javier Diaz-Montes, Ioan Petri, Omer Farooq Rana, Ashiq Anjum, and Manish Parashar. Deadline constrained video analysis via in-transit computational environments. *IEEE Transactions on Services Computing*, 2017.
- [14] Mahsa Ehsanpour, Siavash Bayat, and Ali Mohammad Afshin Hemmatyar. An efficient and social-aware distributed in-network caching scheme in named data networks using matching theory. *Computer Networks*, 158:175–183, 2019.
- [15] Tianchu Zhao, Sheng Zhou, Xueying Guo, Yun Zhao, and Zhisheng Niu. Pricing policy and computational resource provisioning for delay-aware mobile edge computing. In *ICCC*, pages 1–6, 2016.
- [16] Ying Mao, Jenna Oak, Anthony Pompili, Daniel Beer, Tao Han, and Peizhao Hu. Draps: Dynamic and resource-aware placement scheme for docker containers in a heterogeneous cluster. In 2017 IEEE 36th International Performance Computing and Communications Conference (IPCCC), pages 1–8. IEEE, 2017.
- [17] Georg Birkenheuer, André Brinkmann, Hubert Dömer, Sascha Effert, Christoph Konersmann, Oliver Niehörster, and Jens Simon. Virtual supercomputer for hpc and htc. *Joint workshop of the GI / ITG specialist* groups on "der GI/ITG Fachgruppen Betriebssysteme und KuVS", pages 37–50, 2008.
- [18] Donald Firesmith. Virtualization via containers, 2017. https://insights. sei.cmu.edu/sei_blog/2017/09/virtualization-via-containers.html.

- [19] Vincenzo De Maio and Dragi Kimovski. Multi-objective scheduling of extreme data scientific workflows in fog. *Future Generation Computer Systems*, 106:171 – 184, 2020.
- [20] Narges Mehran, Dragi Kimovski, and Radu Prodan. Mapo: A multiobjective model for iot application placement in a fog environment. In *Proceedings of the 9th International Conference on the Internet of Things*, pages 1–8, 2019.
- [21] Siavash Bayat, Yonghui Li, Lingyang Song, and Zhu Han. Matching theory: Applications in wireless communications. *IEEE Signal Processing Magazine*, 33(6):103–122, 2016.
- [22] David Gale and Lloyd S Shapley. College admissions and the stability of marriage. *The American Mathematical Monthly*, 69(1):9–15, 1962.
- [23] Franz Diebold, Haris Aziz, Martin Bichler, Florian Matthes, and Alexander Schneider. Course allocation via stable matching. *Business & Information Systems Engineering*, 6(2):97–110, 2014.
- [24] Henry Wilde, Vincent Knight, and Jonathan Gillard. A novel initialisation based on hospital-resident assignment for the k-modes algorithm. arXiv preprint arXiv:2002.02701, 2020.
- [25] Siniša Šegvić, Karla Brkić, Zoran Kalafatić, and Axel Pinz. Exploiting temporal and spatial constraints in traffic sign detection from a moving vehicle. *Machine vision and applications*, 25(3):649–665, 2014.
- [26] S Šegvić, K Brkić, Z Kalafatić, V Stanisavljević, M Ševrović, Damir Budimir, and I Dadić. A computer vision assisted geoinformation inventory for traffic infrastructure. In 13th International IEEE Conference on Intelligent Transportation Systems, pages 66–73. IEEE, 2010.
- [27] Samodha Pallewatta, Vassilis Kostakos, and Rajkumar Buyya. Microservices-based iot application placement within heterogeneous and resource constrained fog computing environments. In *Proceedings of the 12th IEEE/ACM International Conference on Utility and Cloud Computing*, pages 71–81, 2019.
- [28] Anatoliy Zabrovskiy, Christian Feldmann, and Christian Timmerer. Multi-codec dash dataset. In *Proceedings of the 9th ACM Multimedia Systems Conference*, pages 438–443. ACM, 2018.
- [29] Framing a video. https://gist.github.com/SiNa88/ c85d8cfac641918c6de8b4f31d8cdc22. [Online; accessed 12-March-2021].
- [30] Ganesh Ananthanarayanan, Victor Bahl, Landon Cox, Alex Crown, Shadi Nogbahi, and Yuanchao Shu. Video analytics-killer app for edge computing. In Proceedings of the 17th Annual International Conference on Mobile Systems, Applications, and Services, pages 695–696, 2019.
- [31] Johannes Stallkamp, Marc Schlipsing, Jan Salmen, and Christian Igel. Man vs. computer: Benchmarking machine learning algorithms for traffic sign recognition. *Neural networks*, 32:323–332, 2012.
- [32] Phoronix test suite benchmarking platform, and automated testing. https://www.phoronix-test-suite.com/. [Online; accessed 12-March-2021].
- [33] Henry Wilde, Vincent Knight, and Jonathan Gillard. Matching: A python library for solving matching games. *Journal of Open Source Software*, 5(48):2169, 2020.
- [34] Xiangbo Li, Mohsen Amini Salehi, Yamini Joshi, Mahmoud K. Darwich, Brad Landreneau, and Magdy A. Bayoumi. Performance analysis and modeling of video transcoding using heterogeneous cloud services. *IEEE Trans. Parallel Distrib. Syst.*, 30(4):910–922, 2019.
- [35] The Alcatel-Lucent Ultimate Wireless Packet Core. https://images.tmcnet.com/online-communities/ngc/pdfs/ The-Alcatel-Lucent-Ultimate-Wireless-Packet-Core.pdf. [Online; accessed 12-March-2021].
- [36] Atlas 500 ai edge station (model: 3000). https://e.huawei.com/en/ products/cloud-computing-dc/atlas/atlas-500. [Online; accessed 12-March-2021].
- [37] iperf the ultimate speed test tool for tcp, udp and sctp. https://iperf.fr/. [Online; accessed 12-March-2021].
- [38] Wuyang Zhang, Jiachen Chen, Yanyong Zhang, and Dipankar Raychaudhuri. Towards efficient edge cloud augmentation for virtual reality mmogs. In *Proceedings of the Second ACM/IEEE Symposium on Edge Computing*, pages 1–14, 2017.
- [39] Haluk Topcuoglu, Salim Hariri, and Min-you Wu. Performance-effective and low-complexity task scheduling for heterogeneous computing. *IEEE* transactions on parallel and distributed systems, 13(3):260–274, 2002.
- [40] The carinthian computing continuum. https://c3.itec.aau.at/.
- [41] Dragi Kimovski, Roland Mathá, Josef Hammer, Narges Mehran, Hermann Hellwagner, and Radu Prodan. Cloud, fog or edge: Where to compute? *IEEE Internet Computing*, 2021.
- [42] European cloud hosting. https://www.exoscale.com/.