Adaptive Video Offloading in Mobile Edge Computing

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***Abstract*—By 2022, videos will account for 82% of global Internet traffic. Many camera-based mobile devices, though with limited resources, require ultra low-latency video analytics such as object detection and action recognition. To facilitate these devices with video offloading solutions, Mobile Edge Computing (MEC) is facing several key challenges due to uncertainties associated with the problem. This paper addresses these challenges by proposing a Two-stage Stochastic Program and a novel clustering-based Sample Average Approximation to effectively solve the video offloading problem in uncertain dynamic environments, while satisfying the required latency. The video offloading quality and other offloading decisions are adaptively made to jointly optimize the video quality and migration cost under the consideration of uncertain device mobility.**

I. Introduction

Camera-based mobile devices such as surveillance drones or autonomous vehicles regularly perform video analysis including object detection and action recognition. These devices can choose either to execute the video analysis locally or to offload them to a powerful cloud for processing. However, these solutions can cause significant delay in video processing due to the limited computing resources of the device and the long physical distance to the cloud, respectively [1]. To address this challenge, MEC has been introduced as an emerging solution that enables mobile devices to offload delay-sensitive tasks such as video analytics to physically proximal mini-datacenters, called cloudlets, to improve the quality of service (QoS) [2].

Differing from conventional task offloading, video offloading in MEC brings new challenges. Devices need to compress captured videos by a specific coding ratio before offloading them to the cloudlets. To maximize the performance of video analysis (e.g., object detection accuracy), a higher video quality is beneficial. However, to reduce the latency and satisfy QoS while offloading, a lower video quality should be selected. Moreover, as a device moves and changes its locations, the connected cloudlet for offloading can change frequently, which may trigger a service migration in order to provide a satisfactory service performance (e.g., QoS). Thus, the video offloading solution (including a proper cloudlet and a proper video coding ratio) highly depends on the devices' future mobility which is not deterministic.

To overcome the above challenges, we formulate the Video Offloading Problem (VOP) as a Two-stage Stochastic Program (TSP) model with recourse, called TSP-VOP. Stochastic programming is a promising solution for modeling optimization problems that deal with uncertainty [3]. The goal of TSP-VOP is to find optimal offloading solutions for all mobile devices to offload their videos with minimum migration cost and maximum quality, while other desirable constraints (e.g., latency and energy requirements) are satisfied. However, conventional TSP models require a large number of realizations, called scenarios, to obtain a good representation of the uncertainties for a more accurate estimation. To resolve this issue, we propose a novel Clustering-based Sample Average Approximation Video Offloading Algorithm, called CSAA-VOA, to approximate the expected cost of TSP-VOP with much fewer scenarios. CSAA-VOA guarantees computational tractability by reducing the sample size, while it does not impact the quality of the obtained solutions.

II. Adaptive Video Offloading

Sample Average Approximation (SAA) is a data-driven approach for solving stochastic optimization problems by approximating recourse functions using sampling. Samples are independent and identically distributed (iid) and include a constant number of scenarios. Since the future location of a device is uncertain, a scenario is defined as the locations of the devices. Therefore, different scenarios can be generated to represent the possible new locations of the devices based on their current locations. The rationale behind SAA is that, with sufficient samples and scenarios, the SAA problem (here SAA-VOP) could serve as an accurate proxy for the original problem (here TSP-VOP). Therefore, the optimal solution for the SAA problem is a near-optimal solution for the original problem [3]. Although with larger sample size the solution of SAA problem becomes a more accurate estimate of the original problem, the computational complexity of SAA problem increases at least linearly in sample size.

To reduce the computational complexity of SAA and achieve effectively approximate solutions, we propose a novel Clustering-based Sample Average Approximation Video Offloading Algorithm, called CSAA-VOA. Our approach utilizes K-means clustering to screen out fewer scenarios from a larger set of scenarios for each sample. In doing so, a specific distance metric is required to calculate and compare the (dis)similarity between each pair of scenarios. Since each scenario is composed by two-dimensional coordinates of the devices, CSAA-VOA uses the Euclidean distance function. A scenario which has the minimum distance to the centroid of its cluster is selected as the representative of that cluster. A key property of CSAA-VOA is that it also takes into account the density of the clusters when calculating the sample average function. Since only one scenario is a representative of a cluster, computing the sample average function based on that

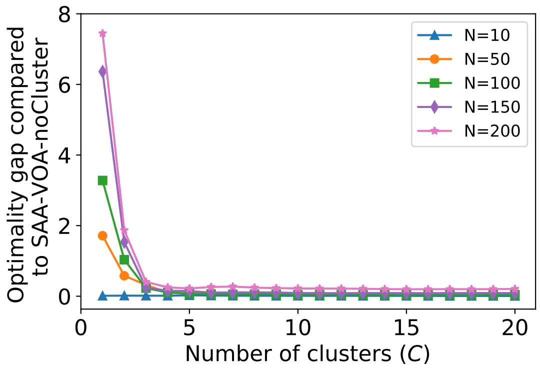

Fig. 1: Optimality gap under different number of devices.

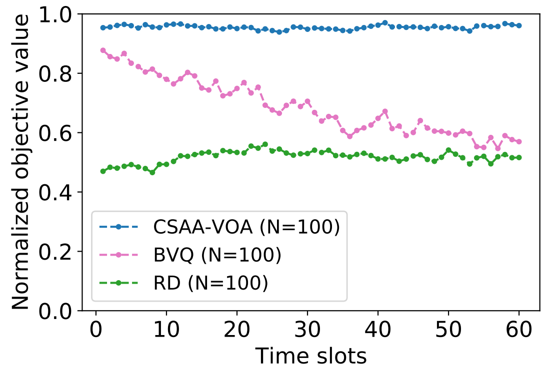

Fig. 2: Comparing CSAA-VOA with other offloading solutions.

will deviate from the original expectation with all scenarios and hence become ineffective.

III. Performance Evaluation

Since CSAA-VOA is a clustering-based approach, it is necessary to study the effectiveness and impacts of clustering. Therefore, we compare our proposed CSAA-VOA with the traditional SAA algorithm (called SAA-VOA) that no clustering technique is applied. We consider different number of clusters for CSAA-VOA and evaluate the results in terms of the optimality gap that is calculated as the difference between the obtained upper and lower bounds. The results in Fig. 1 show that the optimality gap of CSAA-VOA becomes tighter as the number of clusters increases considering different number of devices, which means the offloading solution by our CSAA-VOA becomes a better estimation of the original TSP-VOP problem. This is due to the fact that using more scenarios in calculating the sample average function, the corresponding optimality gap of our CSAA-VOA gradually converges to the optimality gap of the SAA-VOA.

To further evaluate the impact of uncertain device mobility on the obtained offloading solutions of our CSAA-VOA, we simulate a real-time movement trace with a duration of 60 consecutive time slots (the length of each time slot is set to 1 minute) and compare the results with the following offloading strategies:

- **Best Video Quality (BVQ)**: At each time slot, each device is greedily assigned a cloudlet which enables offloading its video chunk with the maximum video coding ratio to keep the highest quality for the videos.
- **Random (RD)**: At each time slot, each device is randomly assigned a cloudlet to offload its video chunk.

To enable tractable analysis, we normalize the objective values into $[0, 1]$. The value of 1 here means the best solution that all devices offload their video chunks with the highest quality (no video compression) while there is no migration. Fig. 2 shows the obtained normalized values for 100 devices. Clearly, the RD strategy leads to an average performance (i.e., the normalized objective values remain at about 0.5) over time due to its arbitrary policy. As for BVQ strategy, the objective value dramatically decreases as the devices move. This is because that BVQ only optimizes the video coding ratio part at each current time slot while the possibly incurred migration cost at the next time slot is not considered. Thus, BVQ approach leads to higher migration costs and lower objective values. However, our CSAA-VOA significantly outperforms these approaches and achieves stably higher objective values over the entire time duration. This is due to the fact that CSAA-VOA finds the optimal assignment solution of the SAA-VOP for the devices at each time slot by taking their possible future movements into account. In other words, our CSAA-VOA minimizes the overall sum of the negative video coding ratios at each current time slot and the expected recourse cost (comprised by the sum of negative video coding ratios and migration costs) at the next time slot.

To sum up, the experimental results show that CSAA-VOA efficiently solves VOP and finds near-optimal offloading solutions, considering uncertain movements of devices.

IV. Conclusion

In this paper, we studied the video offloading problem in MEC to minimize migration cost and maximize video quality while the device mobility in the future are unknown. Motivated by such uncertainty, we formulated the problem as a two-stage stochastic program. Since our stochastic optimization problem is computationally intractable, we developed a clustering-based SAA algorithm, CSAA-VOA, to obtain efficient scenario reduction, while the quality of results is not impacted. Through extensive experiments, the results have demonstrated the effectiveness and stability of our proposed algorithm in video offloading problem in MEC.

References

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