CS466- Project Report

A Two-Sided Matching Approach for Distributed Edge Computation Offloading

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Introduction

The Internet of Things (IoT) has seen a rapid expansion in recent years, with billions of mobile devices being connected to wireless networks. This results in an immense amount of data and computation, which requires high resource consumption. To address this issue, cloud computing has been proposed as a solution that offloads computation tasks from mobile devices to remote cloud centers. However, this approach has its limitations, such as excessive latency due to the long propagation distances.

To overcome the limitations of cloud computing, Mobile Edge Computing (MEC) has been proposed as an alternative technology. MEC offloads latency-sensitive computation tasks from mobile devices to the network edge, such as access points (AP) or base stations (BS), that are physically proximal to the mobile devices. By doing so, MEC significantly reduces transmission latency and energy consumption, making it an effective solution for handling low-latency requirements in 5G mobile communication systems and IoT.

Many works have been undertaken to study the joint radio and computation resources allocation for MEC, with a focus on energy minimization for mobile devices. A variety of energy-efficient joint radio and computation resource allocation problems have been studied. However, most of these studies only consider a single AP (MEC server) with homogeneous resources, and as a result, they neglect the heterogeneity of resources that exist in real-world scenarios. In reality, there are multiple APs (MEC servers) with varying resource sizes and functions. Hence, users must select the appropriate APs for task offloading based on their requirements and network situation. Therefore, a more practical approach that considers the heterogeneity of resources is necessary.

Another issue that needs to be addressed is that most existing solutions to resource allocation problems in MEC require complete knowledge of the network, which results in significant signaling overhead. However, in real-world scenarios, distributed schemes with local information and independent computing are necessary in the case of multiple MEC servers. Hence, more attention needs to be given to developing distributed resource allocation solutions that use local information to minimize signaling overhead while maximizing system performance.

In conclusion, while MEC has shown promising results, there are still some important issues that need to be addressed. These include the heterogeneity of resources and distributed schemes with local information and independent computing for MEC systems with multiple APs. Addressing these issues will lead to the development of more practical and efficient MEC systems that can cater to the increasing demands of IoT and 5G mobile communication systems.

System Model

Consider a multi-user MEC system, consisting of K users and M APs, where each AP is integrated with a MEC server, as shown in Fig. 1.

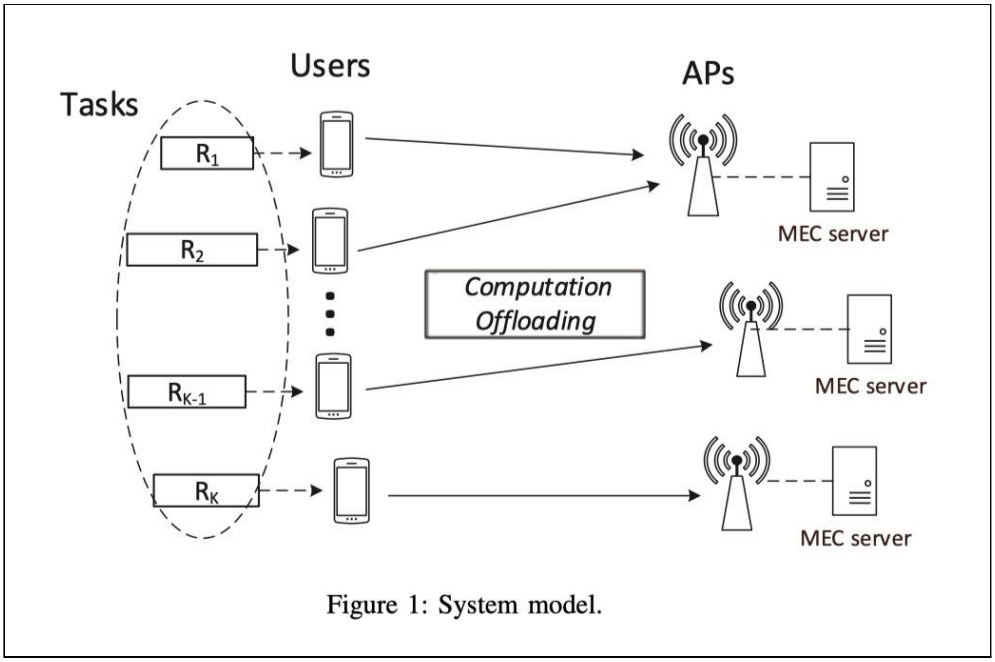


Figure 1: System model.

In this scenario, each user is assigned a separate channel to offload their data to edge clouds without interference. Partial offloading is allowed, which means that each user can execute a portion of their computation task locally while the rest is offloaded to an access point (AP) simultaneously. The channel is assumed to be quasi-static, which means that it remains constant during each offloading period but varies in different periods.

The number of CPU cycles required to compute 1 bit of input data for user k is denoted by C(k), while R(k) represents the total input data that user k needs to execute. The variable $\ell(k,m)$ represents the number of computation input bits offloaded from user k to AP m, where $0 \leq \ell(k,m) \leq R(k)$, and the remaining part of the computation $(R(k)-\ell(k,m))$ is executed locally by user k. The local CPU frequency of user k, measured by the number of CPU cycles per second, is denoted by Fk, while fk,m represents the computational speed assigned by AP m to user k

Problem Formulation

First, we introduce a set of binary variables { x k,m } which are related to AP section and can be written as

$$x_{k,m} = \begin{cases} 1, & \text{if user } k \text{ offloads computation to AP } m, \\ 0, & \text{otherwise.} \end{cases} \quad (1)$$

We assume that each user k can offload computation task to at most one AP, which is expressed as

$$\sum_{m=1}^{M} x_{k,m} \leq 1, \quad \forall k. \quad (2)$$

Matching Based Distributed Algorithm

P1 is the joint resource allocation problem and the two variables x and ℓ are coupled. So we attempt to obtain a suboptimal solution by solving the problem in two steps, and each step solves one of x and ℓ. The first step is to solve the optimal computation offloading bits ℓ_*. The second step is to solve the user-AP association x_* under given ℓ_* by applying matching theory.
Both the two steps can be implemented in a distributed manner.

Distributed Offloading Data l∗

Firstly, we solve the optimal ℓ ∗ . We denote t_k^{loc} and $t_{k,m}^{off}$ as the time used for local computing of user k and the time that user k spends for offloading computation task to AP m, respectively. Since the local computing and offloading can be performed concurrently, the delay of user k for executing the total R_k bits data can be expressed as

$$t_{k,m} = \max\{t_k^{\text{loc}}, t_{k,m}^{\text{off}}\}.$$

The delay of local computing for each user k can be given by

$$t_k^{\text{loc}} = (R_k - \ell_{k,m})C_k/F_k.$$

The offloading time consists of three parts: the uplink transmission time, the execution time at AP m, and the downlink feedback time from the AP.
The optimal offloaded data can be described as a piecewise function:

$$t_{k,m} = \begin{cases} t_k^{\text{loc}} & 0 \leq \ell_{k,m} \leq \ell_{k,m}^*, \\ t_{k,m}^{\text{u}} + t_{k,m}^{\text{c}} + t_{k,m}^{\text{d}} & \ell_{k,m}^* \leq \ell_{k,m} \leq R_k. \end{cases}$$

The minimal offloading time can be obtained through the following equation:

$$t^*_{k,m} = \frac{R_k C_k}{F_k}\left(1 - \frac{C_k}{\frac{F_k}{r^{\mathrm{u}}_{k,m}} + \frac{C_k F_k}{f_{k,m}} + C_k + \frac{\alpha_{k,m} F_k}{r^{\mathrm{d}}_{k,m}}}\right)$$

Distributed User-AP Association x*

We apply the two-sided matching theory to the association problem, which allows each network node to decide their individual actions based on local information. In this section, we first formulate the association problem as a two-sided matching game. Then we present a matching algorithm which can find a stable matching.

Algorithm 1 Two-Sided Matching Based Resource allocation Algorithm

Input: ${\mathcal{P}_k}^{(t)}$, ${\mathcal{P}_m}^{(t)}$, $\forall k, m$.
Initialize: $t = 1$, $\mu^{(1)} \triangleq \{\mu(k)^{(1)}, \mu(m)^{(1)}\}_{k\in\mathcal{K}, m\in\mathcal{M}} = \emptyset$, $F_m^{\mathrm{res}(1)} = F_m$, $\zeta_m^{(1)} = \emptyset$, $\forall k, m$.
$t \to t+1$,
For $\forall k$, update $\mathcal{P}_k^{(t)}$ according to given $\mu(m)^{(t-1)}$.
For $\forall k$, select the most preferred m in its ${\mathcal{P}_k}^{(t)}$.
while $k \notin \mu(m)^{(t)}$ and ${\mathcal{P}_k}^{(t)} \neq \emptyset$ **do**
  if $F_m^{\mathrm{res}(t)} < \ell_{k,m} C_k$ **then**
    The users ranked lower than k in current matching $\mu(m)^{(t)}$ form ${\mathcal{P}'_m}^{(t)} = \{k' \in \mu(m)^{(t)} \mid k \succ_m k'\}$.
    $j_{lp} \leftarrow$ the least preferred $k' \in {\mathcal{P}'_m}^{(t)}$.
    while $({\mathcal{P}'_m}^{(t)} \neq \emptyset) \bigcup (F_m^{\mathrm{res}(t)} < \ell_{k,m} C_k)$ **do**
      $\mu(m)^{(t)} \leftarrow \mu(m)^{(t)} \setminus j_{lp}$, ${\mathcal{P}'_m}^{(t)} \leftarrow {\mathcal{P}'_m}^{(t)} \setminus j_{lp}$.
      $F_m^{\mathrm{res}(t)} \leftarrow F_m^{\mathrm{res}(t)} + \ell_{j_{lp},m} C_{j_{lp}}$.
    end while
    if $F_m^{\mathrm{res}(t)} < \ell_{k,m} C_k$ **then**
      $j_{lp} \leftarrow k$.
    end if
  else
    $\mu(m)^{(t)} \leftarrow \mu(m)^{(t)} \bigcup k$, $F_m^{\mathrm{res}(t)} \leftarrow F_m^{\mathrm{res}(t)} - \ell_{k,m} C_k$.
  end if
end while
$\zeta_m^{(t)} = \{j \in {\mathcal{P}_m}^{(t)} \mid j_{lp} \succ_m j\} \bigcup \{j_{lp}\}$.
for $j \in \zeta_m^{(t)}$ **do**
  ${\mathcal{P}_j}^{(t)} \leftarrow {\mathcal{P}_j}^{(t)} \setminus m$, ${\mathcal{P}_m}^{(t)} \leftarrow {\mathcal{P}_m}^{(t)} \setminus j$.
end for
Output: $\mu^{(t)}$.

Implementation

The following values of variables were used for the simulation.

- Number of APs, M = 3
- Number of Users, k ∈ [10, 15, 20, 25, 30]
- The local CPU frequency, $F_k \in [400,500]$ MHz
- Data size of each user, $C_k \in [500,1500]$ cycles/bit
- BIts of each user, $R_k \in [50,80]$ kb
- Computational speed of the edge cloud assigned by AP m to user k, $F_{k,m} \in [3,15]$ GHz
- CPU cycles of AP, $F_m \in [50,100]$ MHz/slot
- Uplink transmission rates, $R_{ukm} \in [0.7,1.2]$ Mbp/s
- Downlink transmission rates, $R_{dkm} \in [2,5]$ Mbp/s
- Out-input ratio of the offloaded data, $\alpha_{km} = 0.2$

We have implemented the above algorithm in a python program. The first step was to initialize the values of the network variables as mentioned above by using the uniformly distributed random function. The random variables are generated once for all possible values of k and the same is used throughout.

The first step was to compute the optimal amount for bits that has to be offloaded by every user k to an AP m so that the latency of bits computed locally and those which are computed at the AP have similar latencies. This ensures that the total computation time remains a minimum. This was done using the formula for $L_{k,m}$ mentioned in the previous section.

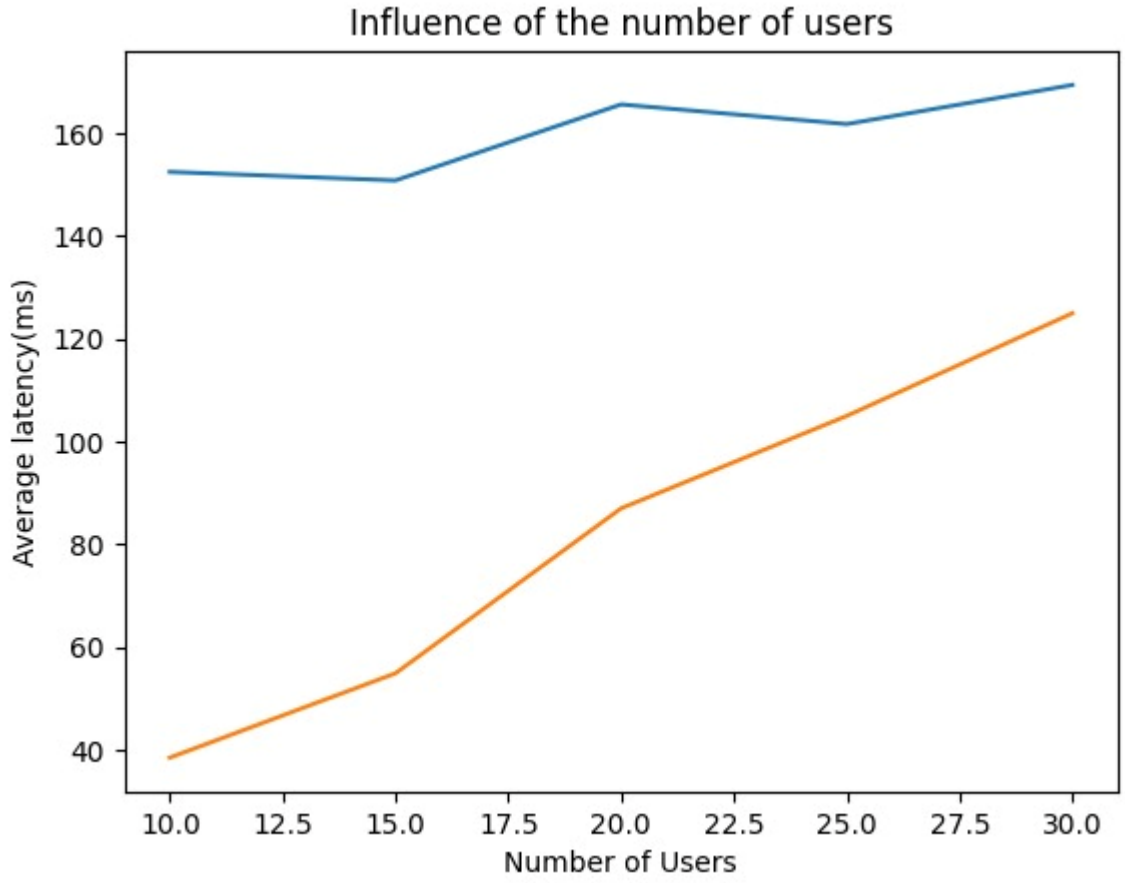
The next step was to map the users to the corresponding AP to which the data will be offloaded. The preference profile for each user and each AP is required to perform this step. To perform the mapping for every user its preferred AP is selected and checked if resources are available in that particular AP. If it is available then bits are offloaded. If the bits are not available then the preference of the AP is checked and depending on the position of the user, other users are dropped to accommodate the current user. This process is followed until all users have their offloaded or no APs are available. From the mapping thus obtained the average latencies of users is found.

In order to evaluate the performance of the proposed algorithm, we also consider the local computing scheme and a heuristic algorithm for a comparison purpose. In the local computing scheme, all users adopt local computing for their tasks. In the heuristic scheme, all users are ranked in a decreasing order according to the data-size of the tasks R_k and offload each entire task R_k to an AP in this order until this AP's computational capacity is fulfilled and then offload to another AP. If all APs are fulfilled, the rest R_k's are executed locally.

The results from the above algorithms were plotted to compare their performance. The first comparison was to compare average latency with the changing in the number of users present in the

system. The second graph was to compare the results of average latency changes compared with the edge cloud computation capacity.

Results



The above graph represents the results obtained from the comparison of the local only computing and the two sided offloading approach. It gives the average latencies of the two approaches to differing number of users in the system.
Here orange line represents the two sided approach and blue line represents local only approach. From the graph above, we can see that the average latency for the case all computation is done locally is pretty much constant. For the case where some bits of the computation are offloaded to the AP, the average latency is consistently lesser than that of local computation. The latency for this case slowly goes up as the number of users increases naturally owing to increased bandwidth requirements and limited computing resources resources available at the AP.

References

H. Bao and Y. Liu, "A Two-Sided Matching Approach for Distributed Edge Computation Offloading," 2019 IEEE/CIC International Conference on Communications in China (ICCC), 2019, pp. 535-540, doi: 10.1109/ICCChina.2019.8855906.