Knowledge Distillation for Mobile Edge Computation Offloading

CHEN Haowei, ZENG Liekang, YU Shuai, CHEN Xu
(School of Data and Computer Science, Sun Yat-sen University, Guangzhou, Guangdong 510006, China)

Abstract: Edge computation offloading allows mobile end devices to execute compute-intensive tasks on edge servers. End devices can decide whether the tasks are offloaded to edge servers, cloud servers or executed locally according to current network condition and devices' profiles in an online manner. In this paper, we propose an edge computation offloading framework based on deep imitation learning (DIL) and knowledge distillation (KD), which assists end devices to quickly make fine-grained decisions to optimize the delay of computation tasks online. We formalize a computation offloading problem into a multi-label classification problem. Training samples for our DIL model are generated in an offline manner. After the model is trained, we leverage KD to obtain a lightweight DIL model, by which we further reduce the model's inference delay. Numerical experiment shows that the offloading decisions made by our model not only outperform those made by other related policies in latency metric, but also have the shortest inference delay among all policies.

Keywords: mobile edge computation offloading; deep imitation learning; knowledge distillation

DOI: 10.12142/ZTECOM.202002006

http://kns.cnki.net/kcms/detail/34.1294.TN.20200529.1853.002.html, published online May 29, 2020

Manuscript received: 2019-12-01

Citation (IEEE Format): H. W. Chen, L. K. Zeng, S.Yu, et al., "Knowledge distillation for mobile edge computation offloading," *ZTE Communications*, vol. 18, no. 2, pp. 40 – 48, Jun. 2020. doi: 10.12142/ZTECOM.202002006.

1 Introduction

Nowadays more and more end devices are running compute-intensive tasks, such as landmarks recognition apps in smartphones[1], vehicles detection apps used for traffic monitoring in cameras[2], and augmented reality apps in Google Glass. The advantages of executing compute-intensive tasks on end devices are twofold. On the one hand, most data, such as images, audios and videos, are generated at end devices. Compared with sending these data to the cloud server, processing data locally on end devices can avoid time-consuming data transmission and reduce heavy bandwidth consumption. On the other hand, some tasks are sensitive to latency and the execution result can be out of date if being late. In some cases (e.g., face recognition applications), high latency can result in poor user experience. If computation tasks are offloaded to the cloud, the unreliable and delay-significant wide-area connection can be problematic. Hence, executing compute-intensive tasks on end devices is a potential solution to lower end-to-end latency.

However, compared with cloud servers, the computing resources of end devices are very limited. Even a smartphone's computing capability is far weaker than a cloud server, not to mention the Google Glass and cameras. It turns out that exe-

This work was supported in part by the National Science Foundation of China under Grant No. 61972432 and the Program for Guangdong Introducing Innovative and Entrepreneurial Teams under Grant No. 2017ZT07X355.

cuting compute-intensive tasks on end devices may result in high computation latency. In addition, end devices often have energy consumption restrictions; for example, most smartphone users do not want a single app to consume too much power. Thus, it is unwise to execute tasks on end devices indiscriminately.

Recently, edge computing has emerged as a new paradigm different from local execution and cloud computing, and has attracted more and more attention. The European Telecommunications Standards Institute provided a concept of multi-access edge computing (MEC)[3]. In the MEC architecture, distributed edge servers are located at the network edge to provide computing capabilities and IT services with high bandwidth and real-time processing. Edge servers become the third offloading location of compute-intensive tasks in addition to end devices and cloud. However, due to edge servers' restricted computing capability, they cannot completely take place of cloud servers. Many factors, including available computation and communication resources, should be taken into consideration when making offloading decisions. To tackle this challenge, in this paper, we design a computation offloading framework which jointly considers computation and communication and dynamically makes optimal offloading decisions to minimize the end-to-end execution latency.

Recent advances in deciding offloading strategies focus on learning-based methods. YU et al.[4] propose to "imitate" the optimal decisions of traditional methods by deep imitation learning (DIL), where DIL[5] uses instances generated from human's behaviors to learn the decision strategies in specific environments. DIL enjoys two advantages compared with traditional methods[6] and deep reinforcement learning methods[7]. First, inference delay of DIL is much shorter than that of traditional methods especially when the amount of input data is large (as shown in our experiment in Section 5). Second, DIL has higher accuracy in imitating optimal offloading decisions compared with approaches based on deep-reinforcement-learning (DRL).

However, the DIL model is built upon deep neural network (DNN), which is compute-intensive and typically requires high inference latency. On this issue, model compression[8] is proposed, and knowledge distillation (KD) is one of the solutions[9]. The idea behind KD is similar to transfer learning. KD not only effectively reduces the size of the neural network and improves the inference efficiency, but also improves the accuracy in the case where training samples are insufficient and unbalanced, which may appear in DIL training phase. Hence, we believe that applying KD can benefit the deployment of DIL model.

In this article, we leverage the emerging edge computing paradigm and propose a framework based on DIL and KD, which jointly considers available computation and communication resources and makes fine-grained offloading decisions for end devices. The objective of the proposed framework is to minimize the end-to-end latency of compute-intensive tasks on end devices. We use offloading decision instances to train our DIL model offline and compress the model to a lightweight one by KD online for quickly making near-optimal offloading decisions.

The rest of this article is organized as follows. We briefly review related works in Section 2. We explain how to build a DIL model and use it in computation offloading decisions in Section 3. Then we describe how to use KD to further optimize the performance of the DIL model in Section 4. Numerical experiment results are shown in Section 5. At last we discuss some future directions and conclude in Section 6.

2 Related Work

2.1 Computation Offloading Strategies

To achieve lower latency or energy, mobile end devices usually choose to offload tasks to the cloud or edge servers. However, due to the complexity of network conditions in practice, for different devices at different times, the optimal computation offloading decisions are different. It is difficult to find this optimal decision in real time. Traditional computation offloading strategies are mostly based on mathematical modeling. Researchers in Ref. [6] study the computation offloading problem in multi-user MEC environment. They firstly prove that finding the best offloading strategies in multi-channel and multi-user condition is NP-hard. Then they model this problem as an offloading game and design a distributed approach to reach the Nash equilibrium. The authors in Ref. [10] study offloading video objects detection tasks to cloud server. In Ref. [10], a big YOLO model is deployed in cloud while a lite YOLO model is deployed at end devices. Many factors such as bit rate, resolution and bandwidth are considered and the offloading problem is formulated into a multi-label classification problem. A near-optimal solution is found by an iteration approach and it successfully achieves higher accuracy in video objects detection. The main disadvantage of mathematical modeling methods is that they are so complicated that they may cause non-negligible inference delays and are difficult to be deployed in MEC network.

One of the typical compute-intensive tasks is DNN inference, on which many researchers study specialized computation offloading strategies. KANG et al.[11] propose Neurosurgeon framework for DNN offloading. Neurosurgeon divides DNN into two parts. One part runs at end devices and the other runs at the cloud. This method reduces the calculation at end devices, and tries to find a balanced point between computation and transmission. Neurosurgeon evaluates the latency of each DNN layer by regression models offline, and uses these models to calculate the best divided point online tailored to end devices' performance and bandwidth.

Recently, some researchers introduce DRL to find computation offloading strategies. In this case, the latency or energy consumption serves as agents' reward. The authors in Ref. [7]

consider a condition of vehicular networks based on software defined network and jointly optimize networking, caching, and computer resource by a double-dueling Deep-Q-Network. The main drawback of DRL-based approaches in computation offloading is that the offline training and online inference takes many overheads. To tackle this challenge, we propose to utilize DIL for computation offloading, the training cost and inference latency of which are significantly lower than those of DRL.

2.2 Deep Imitation Learning and Knowledge Distillation

DIL refers to training agents to imitate human's behaviors by a number of demos. Compared with DRL, training and inference time of DIL is much shorter. The authors in Ref. [4] build an edge computation offloading framework based on DIL. However, since DIL is based on DNN, if the size of DNN grows too large, it may still result in high inference delay. On this issue, we use Knowledge Distillation to compress the DIL model.

KD is firstly proposed in Ref. [9], where the authors show that small DNNs can achieve approximately high accuracy as large DNNs with relatively less inference latency. This motivates us to compress the models to reduce inference delay with tiny accuracy loss. In KD, a large DNN is trained on a large training set and a lite DNN is trained on a small training set whose labels are the output of large DNN after "softened".

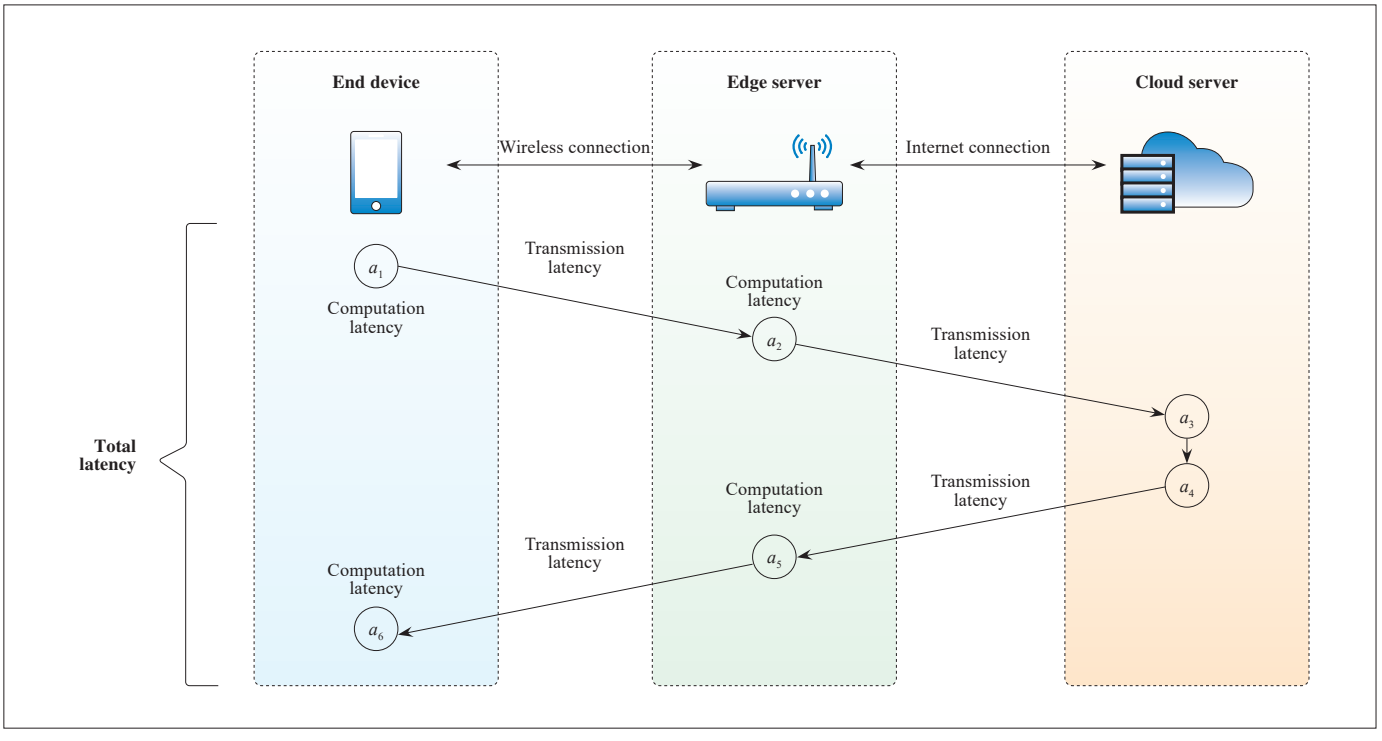
In our work, we compress our DIL model through KD to further reduce the inference delay, and improve the model's performance when training samples are missing and unbalanced.

3 Edge Computation Offloading by Deep Imitation Learning

3.1 System Model

We study the problem of making fine-grained offloading decisions for a single end device user. A compute-intensive task A on end device needs to be executed. We firstly split task A into some subtasks, following Ref. [12]. Each subtask can be denoted by a tuple $a_t = (t, \varepsilon_t, d_t, d_{t+1})$. Task A can be seen as a set of all subtasks a_t. And ε_t represents the computation complexity of the t-th subtask (usually in central processing unit (CPU) cycles). All of the computation complexity forms a set $E = \{\varepsilon_t | t \in [0, |A|)\}$. The d_t denotes the size of input data of the t-th subtask (usually in bytes). When t=0, d_0 represents the size of input data of task A. d_{t+1} denotes the size of output data of the t-th subtask, and is also the input data size of the $(t+1)$-th subtask. When $t=|A|$, $d_{|A|}$ represents output size data of task A. Sizes of all data flow jointly form the set $D = \{d_t | t \in [0, |A|+1)\}$.

As shown in **Fig. 1**, during the runtime of the mobile end device, a wireless connection with an edge server is established, and the edge server maintains a connection with the cloud server through the Internet. When a computation task in the end device needs to be executed, it will be divided into some subtasks. Each subtask can choose to be executed locally on end device or sent to the edge server. When the edge server receives a requirement of execution of a subtask, it can decide whether to execute it locally on edge server or further send it to cloud server. Execution of a subtask leads to compu-



▲Figure 1. Subtasks are offloaded to end device, edge server and cloud server respectively.

tation latency, which depends on the profile of end device and edge server and the computation complexity of subtasks E. If two adjacent subtasks are offloaded to different locations, transmission latency will also occur, which mainly depends on the bandwidth between end device, edge server and cloud server and transmission data size D. In this paper, due to the strong computing capability of the cloud server, cloud computation latency is far less than the transmission latency. Hence, when the subtask is offloaded to cloud server, the computation latency can be ignored and only the transmission latency is concerned.

3.2 Problem Formulation

When a computation task needs to be executed, end devices split it into some subtasks and evaluate computation complexity E and transmission data sizes D of all subtasks. We can leverage the method introduced in Ref. [12] to evaluate E and D. Then all subtasks, E, D and the computing capability of the end device (denoted by p_1) are sent to edge server; p_1 can be measured in CPU frequency (in Hz). The edge server measures the bandwidth between the end device and edge server (denoted by b_1) and the bandwidth between the edge server and cloud server (denoted by b_2). Factors mentioned above and the computing capability of edge server (denoted by p_2) jointly form the description of current offloading requirement $S = (E, D, p_1, p_2, b_1, b_2)$. The edge server is responsible for making offloading decisions of each subtask according to S.

For each subtask a_t, its offloading decision is represented by $I_t \in \{0, 1, 2\}$. $I_t = 0, 1, 2$ indicates that subtask a_t is executed at end device, edge server or cloud server respectively. Offloading decision of the whole task A is given by $I = \{I_t | t \in [0, |A|)\}$. Obviously, $|I| = 3^{|A|}$. The offloading problem turns into finding the offloading decision I with the shortest end-to-end latency according to given S.

Now we compute the end-to-end latency of a specific I. As we have discussed, end-to-end latency can be divided into computation latency and transmission latency. Let L^t_{exec} denote the computation latency of t-th subtask. When $I_t = 0, 1$, the subtask is executed at end device or edge server, hence $L^t_{exec} = \varepsilon_t / p_1$ or $L^t_{exec} = \varepsilon_t / p_2$, respectively. When $I_t = 2$, as mentioned in Section 3.1, computation latency at cloud server is ignored, hence $L^t_{exec} = 0$. Given S and offloading decision I, computation latency of the whole task A is:

$$L_{exec}(S, I) = \sum_{t=0}^{|A|-1} L^t_{exec} . \tag{1}$$

Let L^t_{trans} represent the data flow size between t-th and (t-1)-th subtask. When data are transmitted between end device and edge server, $L^t_{trans} = d_t / b_1$, and when data is transmitted between edge server and cloud server, $L^t_{trans} = d_t / b_2$. Note that the data at the beginning of the whole task are input by the end device, and the final output destination is also the end device, thus we can assume that I_{-1} and $I_{|A|}$ are always 0. Given S and offloading decision I, transmission latency of the whole task A is:

$$L_{trans}(S, I) = \sum_{t=0}^{|A|} L^t_{trans} . \tag{2}$$

Our goal is to find the offloading decision I^* with the shortest end-to-end latency, which is:

$$I^* = \text{argmin}_I \left(L_{exec}(S, I) + L_{trans}(S, I) \right) . \tag{3}$$

So far, we have formulated computation offloading problem to an end-to-end latency minimization problem. By changing the parameter of argmin to energy, we can switch optimization objective to the energy consumption. Let S represent the description of offloading requirement, I represent the offloading decision, $R_{exec}(S, I)$ be the energy consumption of computation and $R_{trans}(S, I)$ be the energy consumption of transmission. Then the best offloading decision I^* is: $I^* = \text{argmin}_I (R_{exec}(S, I) + R_{trans}(S, I))$. If it is required to optimize latency and energy simultaneously, we can set the parameter of argmin to a weighted sum of latency and energy.

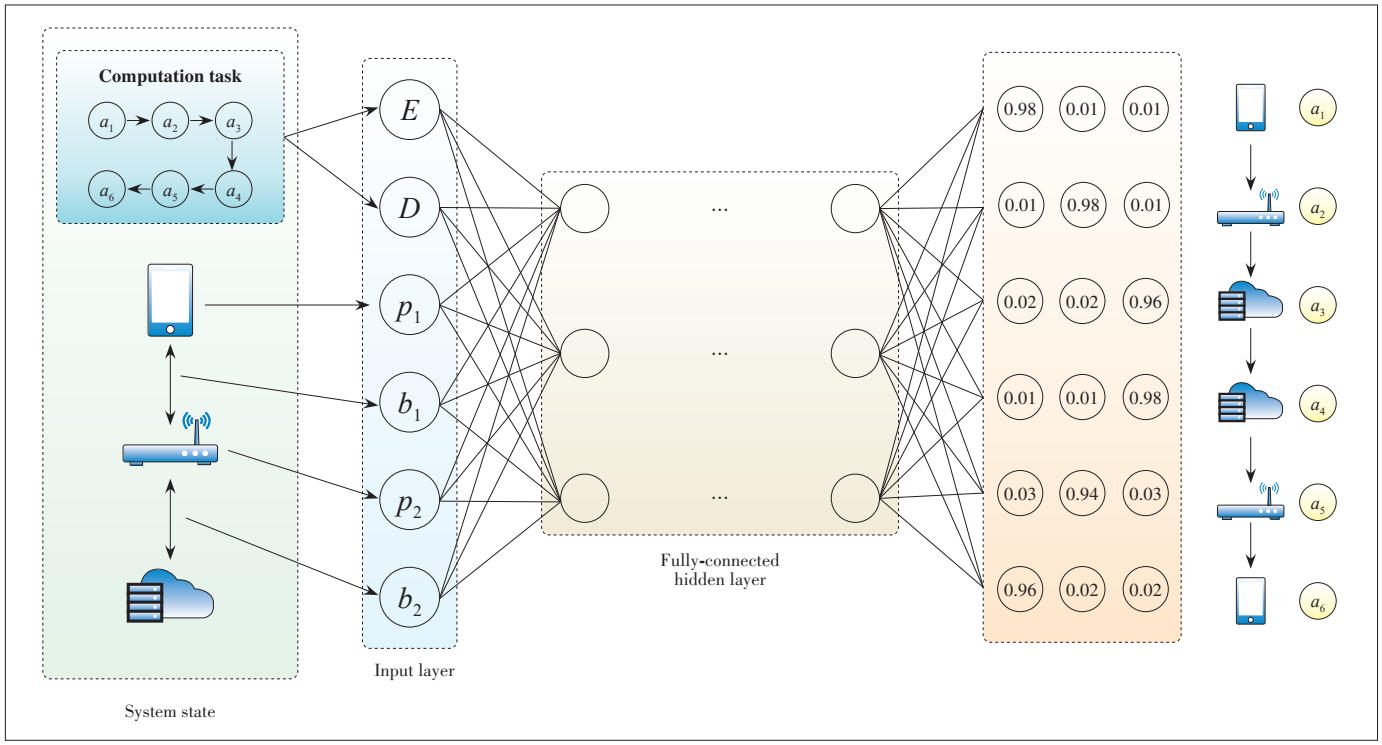
3.3 Deep Imitation Learning for Offloading

The above minimization problem can be considered as a combinatorial optimization problem. Existing technologies such as traditional offloading algorithms or reinforcement learning are difficult to solve such problems efficiently. Hence, we apply DIL to deal with it. Finding the best offloading decision I^* can be formulated to a multi-label classification problem[13]. Decision I is a set of $|A|$ labels and the three values of I_t corresponding to three classes. The idea of DIL is to use a DNN to learn the mapping from S to the best offloading decision I^*. To this end, offloading requirement S can serve as features of input samples and I^* serves as the real labels of samples, as shown in **Fig. 2**.

DIL for offloading consists of three phases described as follows:

1) Generate training samples offline. DIL is supervised learning and it needs a number of features labels pair (S, I^*). The feature S can be obtained by collecting the actual offloading task requirement, or randomly generating features based on the distribution of various parameters in the actual offloading task requirement. Since labels I^* are generated offline, some expensive non-real-time algorithms can be applied. In addition, performance of our DIL model is limited by the quality of labels, and only the labels with high accuracy can ensure highly accurate DIL model. Note that the size of decision space is $3^{|A|}$. In summary, when $|A|$ is small, we can use an exhaustive approach to obtain the optimal offloading decision by searching the whole decision space. When $|A|$ is large, we solve this problem as integer programming problem by existing efficient solvers such as CPLEX.

2) Train DIL model offline. We train a DNN model to learn



▲ **Figure 2. Deep imitation learning model for edge computing offloading. Given the offloading requirement $S=(E, D, p_1, b_1, p_2, b_2)$ as the input, the deep imitation learning model can output the offloading decision $I^* = (a_1, a_2, a_3, a_4, a_5, a_6)$.**

the mapping from S to I^*. In this multi-label classification problem, the output of DNN consists of predictions of $|A|$ labels. Each prediction has three possibilities corresponding to three values of I_t. Hence the output layer of DNN has $3 \times |A|$ neurons and the activation function is SoftMax. All hidden layers are full connected layers.

3) Make offloading decisions online. After our DIL model is trained, it is deployed to edge server to make offloading decisions online. Experiment shows that the efficiency of DIL model inference is higher than baseline models.

DIL is based on learning. DIL's performance is closely related to the training samples. If the training samples are diverse, DIL model can deal with more conditions, i.e., it becomes more robust. If training samples contain offloading requirement under the conditions with fluctuation of wireless channels, DIL model can learn how to make a good decision under these conditions. In practice, training samples are from actual offloading requirement. The fluctuation of the wireless channels is also covered.

After the DIL model is trained, we should consider where the DIL model is deployed for online inference. Same as the computation tasks, DIL model can be deployed on end devices, edge server or cloud server. However, if DIL model is deployed on the cloud server, the wide-area connection will become an unstable factor. To ensure model's performance, we expect that the inference result of DIL model can be obtained with a low and predictable delay. Hence, even though the computing capability of cloud server is much stronger, it is not recommended to deploy DIL model on cloud server. In addition, since having all model inference workload on end device may lead to high energy consumption, we believe that edge server is a better place for DIL model deployment.

4 Knowledge Distillation for Model Compression

Since our DIL model is based on compute-intensive DNN execution, the inference latency could be high due to the limited computing capability of edge servers. We hope that the DIL model running on the edge server is lightweight and the model inference delay is minimized. Towards that, a potential solution is to put the three phases mentioned above into edge server to train a DIL model based on small DNN locally on edge server. However, it raises two problems. First, limited by the number of parameters, the learning capability of a small DNN is insufficient. Compared with large DNN, it may cause loss of accuracy and make performance worse. Second, in the phase of generated demo offline, training samples are obtained by collecting the actual offloading task requirement or randomly generated based on distribution of various parameters in the actual offloading task. However, the service area of an edge server is highly limited. Compared with the samples collected by cloud server, samples collected by edge server may be not enough and unbalanced. This further incurs the accuracy and

performance of small DNN. To this end, directly training a lightweight DIL model on edge server is not practical[15].

The authors in Ref. [9] proposed KD, which can be used for DNN compression. This technology helps us transfer the knowledge from a large DNN to a small DNN. When the training samples are inadequate and unbalanced, accuracy of the DNN trained by KD is higher than that of the DNN directly trained on samples. Large DNN is called the "teacher" and small DNN is called the "student". Back to our offloading problem, we can leverage the strong computing capability of cloud server and a number of samples to train a large DNN with high accuracy to serve as the teacher, and then transfer the knowledge learned by large DNN to small DNN which is deployed to edge server by KD, achieving low inference delay and small scale with tiny loss of accuracy, as shown in **Fig. 3**.

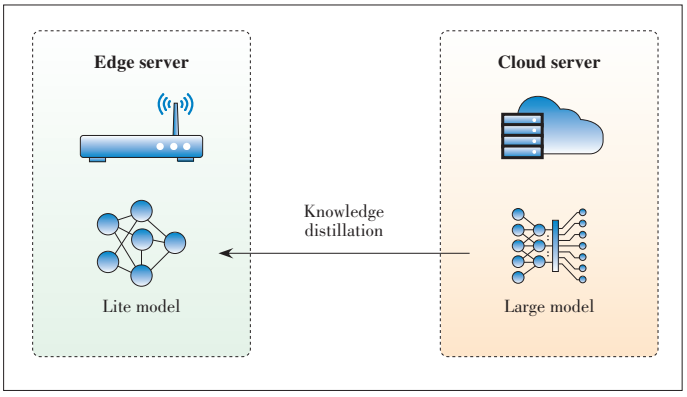
KD can be applied to any neural networks whose output layer is activated by SoftMax; in other words, the networks are used for solving classification problem. In KD, we train two networks, the teacher network and the student network. Training the teacher network is the same as training conventional network, and training the student network is also similar. The only difference is that the initial labels of student network before training are from the teacher network's trained labels, rather than from the training dataset.

In some cases, teacher network's trained labels may be very small and close to zero (e.g., $< 10^{-3}$), which is nearly the same as the original one-hot encoded labels and remains difficult for student network to learn the differences between labels. To alleviate this problem, we amplify the differences by further "softening" the labels. Let p_i be the probability of the *i-th* class predicted by the teacher, and q_i is the softened probability corresponding to p_i. We slightly change the form of the softening formula in Ref.[9] to compute q_i:

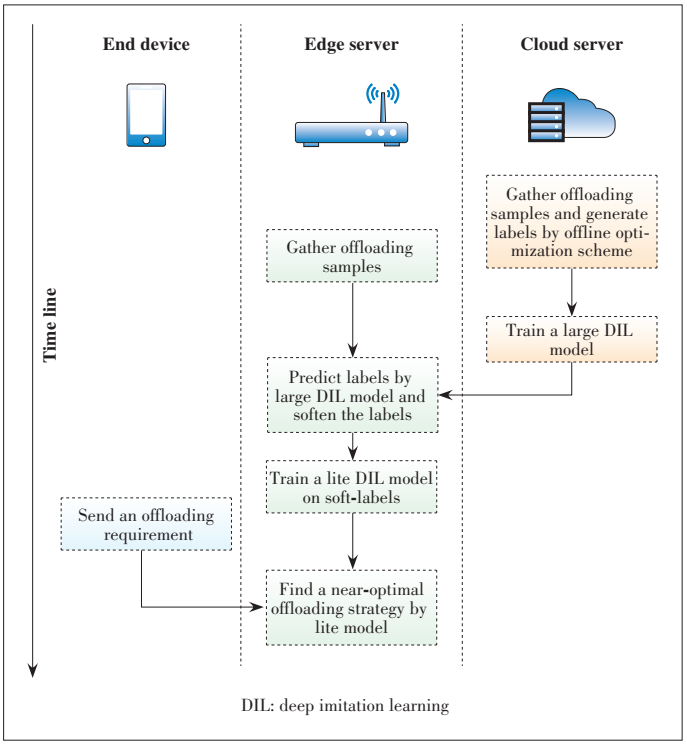
$$q_i = \frac{\exp\left(\frac{\ln(p_i)}{T}\right)}{\sum_{j=1}^{C}\exp\left(\frac{\ln(p_j)}{T}\right)}, \quad (4)$$

where C is the total number of classes, in our offloading problem C=3. T is a tunable hyper-parameter with the constraint $T \geqslant 1$. If T=1, $q_i = p_i$. The labels will be softer with higher T. For instance, if original label is $(0.999, 2 \times 10^{-4}, 3 \times 10^{-6})$, when T=5, the softened label will be (0.71, 0.20, 0.09); when T=10, the softened label will be (0.53, 0.28, 0.19). In the following experiment we set T=5. Back to the offloading problem, we use a teacher network trained at cloud server to predict labels of the training set obtained by edge server. Then soften these labels by the formula mentioned above and train student network by softened labels at edge server.

We show the complete flowchart of our DIL offloading framework with KD in **Fig. 4**.



▲**Figure 3. Compress model by knowledge distillation to get a lightweight model deployed to edge server.**



▲**Figure 4. Complete flowchart of our edge offloading framework based on DIL and KD.**

5 Evaluation

5.1 Evaluate Large DIL Model Performance

In this section, we set up a numerical experiment to evaluate the performance of DIL model described in Section 3. We consider that an MEC network consists of an end device user and an edge server connected by wireless connection, meanwhile the edge server connects to cloud server via the Internet[16]. We assume that the compute-intensive task A on end device is divided into 6 subtasks, which is $|A|$=6. If the number of subtasks of some computation tasks is not 6, we can merge some subtasks or insert empty subtasks to make the number of subtasks 6. The computation complexity of each

subtasks ε_t (measured in CPU cycles) is in the interval of $[0, 2\,000] \times 10^6$, following uniform distribution. Sizes of data transmission between subtasks follow uniform distribution with $d_t \in [0,10]$ MB, like the setting in Ref.[14]. In addition, we assume that the computing capability of end device and edge server (both measured by CPU frequency in Hz) is in the intervals of $[100, 1\,000]$ MHz and $[500, 5\,000]$ MHz respectively, both following the uniform distribution. The bandwidth between end device and edge server and the bandwidth between edge server and cloud server are uniformly distributed in $b_1 \in [0, 2]$ MB/s and $b_2 \in [0, 3]$ MB/s respectively. We randomly generate 100 000 samples offline to train DIL model and 10 000 testing samples for testing.

Our DIL model is based on a DNN with 5 hidden layers. All hidden layers are full connected layers and consist of 256 neurons. The number of parameters in the whole DNN is 1.6 million. Activation function of hidden layers is RELU and output layer is activated by SoftMax. To evaluate the performance of our DIL based offloading framework, we consider some baseline frameworks listed follow:

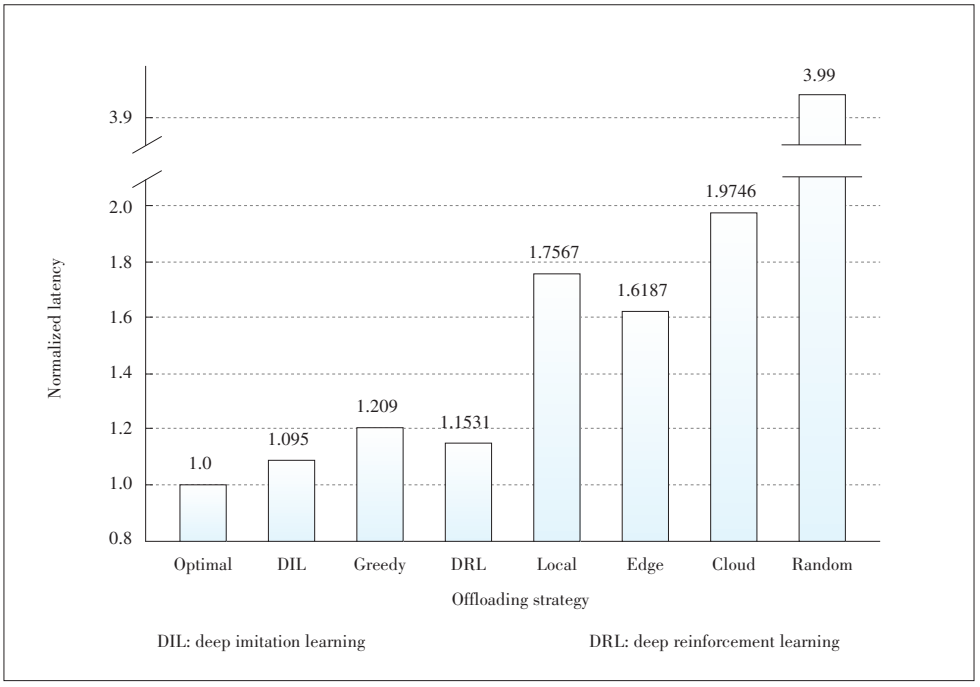
1) Optimal. Exhaustive method: For each sample, search the whole $3^{|A|}$ decision space, compute the latency described in Section 3.2 and choose the offloading decision with minimal latency. Note that this minimal latency is the lower bound in the decision space. Hence, this decision is bound to be optimal.

2) Greedy. For each sample, find the offloading location one by one for each subtask to minimize the computation and transmission latency of current subtask.

3) DRL. Offload framework based on deep reinforcement learning. Features of samples serve as environment and offloading decisions serve as actions. The opposite number of latency acts as reward. The deep Q network is similar to that in Ref. [7].

4) Others. Local: The whole task is executed on end device, which is for any t, $I_t = 0$; Edge: All subtasks are executed on edge server, which means $I_t = 1$; Cloud: All subtasks are offloaded to cloud server, which is $I_t = 2$; Random: Randomly choose offloading location for each subtask, that is to say, I_t are randomly chosen from {0, 1, 2}.

Fig. 5 shows the normalized latency of the DIL model and baseline frameworks with the latency of optimal decision are normalized to 1.0, and then the latency of decision made by our DIL model is 1.095, with an increase less than 10%. Experiment results show that our model outperforms other baseline frameworks. Note that latency of "Edge" is less than "Local" and "Cloud", which indicates that edge server can certainly improve the compute-intensive tasks in end-to-end latency. At last, latency of "Random" is far higher than others, this is because randomly choosing offloading location will cause high transmission latency, which is expectable.



▲**Figure 5. Normalized end-to-end latency of offloading decisions made by our DIL model and baselines.**

5.2 Evaluate Knowledge Distillation Performance

As mentioned in Section 4, we should compress our DIL model before deploying it to edge server and deal with the situation in which training samples on edge server are insufficient and unbalanced. We call our compressed model "KD-DIL" for short. In this section, we assume the CPU cycles of subtasks are uniformly distributed in $\varepsilon_t \in [500, 1\,500] \times 10^6$. Sizes of transmission data between subtasks are in $d_t \in [3, 8]$ MB, following uniform distribution. The distribution range of ε_t and d_t is reduced by half compared with that in Section 5.1. Distributions of other parameters remain the same. In order to simulate the case in which training samples are insufficient, we only generate 1 000 samples for training in this section, reduced by 99% compared with that in Section 5.1. Testing samples remain the same as that in Section 5.1.

Our KD-DIL model is still based on DNN consisting of full connect layers. There are only 2 hidden layers in DNN with 32 neurons in each layer. The number of parameters of the whole DNN is about 10 000, reduced by 99.375% compared with that in Section 5.1. The following baseline models are used for evaluating the performance of our KD-DIL model.

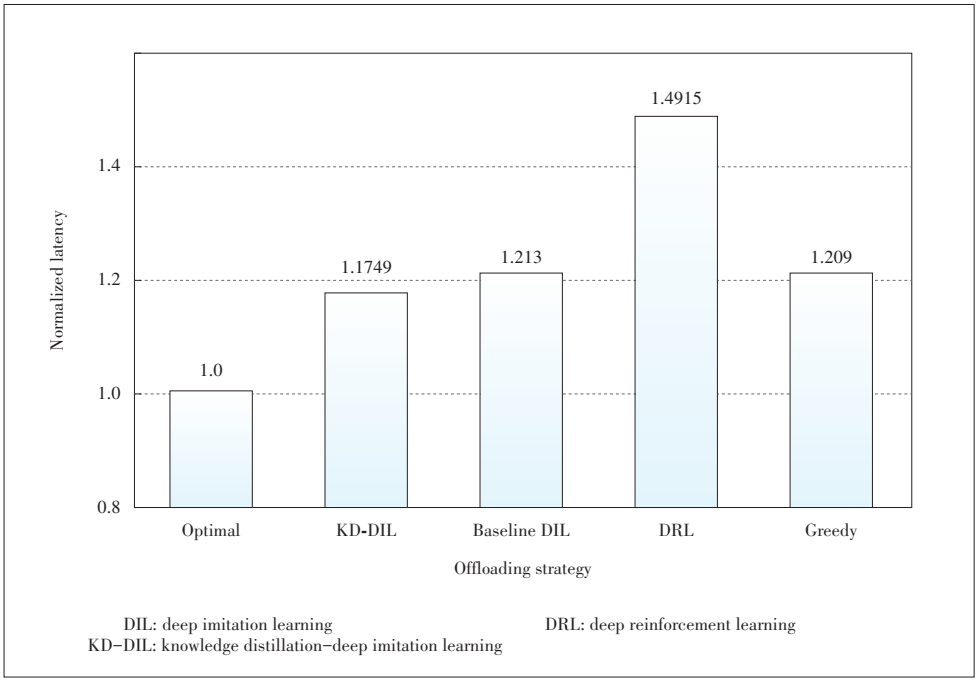
1) Baseline DIL: This DIL model is based on the DNN which is same as that in KD-DIL. The difference is that Baseline DIL

is directly trained on the training set described above without applying KD described in Section 4.

2) DRL: Deep reinforcement learning based on DQN. The difference between this and DRL model in Section 5.1 is that it is trained on training set with 1 000 samples described above instead of that with 100 000 samples described in Section 5.1.

3) Greedy: Same as Greedy in Section 5.1.

Fig. 6 shows the normalized latency of KD-DIL models and baseline models. Again, the latency of optimal decision is normalized to 1.0. It shows that our KD-DIL model still outperforms baseline models. Note that the performance of DRL has a sharp decreasing compared that in Section 5.1 because of the change of training set. It is further shown that when the number and distribution of training samples are changed, the accuracy loss of our KD-DIL model is relatively small.



▲**Figure 6. Normalized KD-DIL model and baselines when using a small training set.**

▼**Table 1. Inference delay of all models**

Model Name	KD-DIL	Large DIL	DRL	Greedy	Optimal
Normalized Delay	0.17	0.51	119.72	1.00	122.54

KD-DIL: knowledge distillation-deep imitation learning
DIL: deep imitation learning
DRL: deep reinforcement learning

At last, **Table 1** shows the normalized inference delay of all models with delay of "Greedy" being normalized to 1.00, since the greedy method is the typical method for computation offloading. We measure the delay of making 100 000 decisions of all the models, and divide this delay by 100 000 to get the average delay of each decision. As shown in Table 1, compared with the large DIL model, the inference delay of KD-DIL model decrease by 63% (0.17/0.51). Table 1 shows that the inference delay of the Greedy approach is slightly higher than DIL model. As described in Section 5.1, the Greedy approach finds deployment place for each subtask by iterations. The number of iterations equals to that of subtasks. In practice, the number of subtasks may be much higher than 6, so the inference delay of the Greedy approach may become correspondingly higher.

Lastly, the inference of the optimal approach and DRL is hundreds of times that of our DIL models. Because optimal apply exhaustive method, high inference delay is expectable. While making decisions by DRL, we treat each strategy as an action and end-to-end latency as reward. We calculate each action's reward to find the highest reward, which needs many times of DNN inference. Hence, the delay of DRL inference is much higher than DIL.

6 Future Work and Conclusions

Flowcharts of subtasks can be represented by directed acyclic graph (DAG) known as computation graph. In computation graph, nodes denote subtasks, edges denote data flow and directions of edge represent data transmission directions. DNN can also be regarded as a computation graph. In many programming frameworks dedicated to deep learning, such as TensorFlow, the concept of computation graph is applied. Offloading a computation graph in MEC network to optimize end-to-end latency is a difficult problem. The subtasks flowchart studied in this article has a list structure. In our future work we will focus on how to modify our work to adapt to DAG.

In this article, we have studied fine-grained edge computing offloading framework. In the situation in which an end device wirelessly connects to an edge server, compute-intensive tasks can choose to be executed at end device, edge server or cloud server. We first review existing edge offloading framework including mathematic model method (game theory) and reinforcement learning. Then we provide model of computing task and describe the execution process of a task. Offloading problem is formulated into a multi-label classification problem and is solved by a deep imitation learning model. Next, in order to deal with the insufficient and unbalanced training sample, we apply knowledge distillation to get a lightweight model with tiny accuracy loss, making it easier to be deployed to edge serv-

er. Numerical experiment shows that the offloading decisions made by our model have the lowest end-to-end latency and the inference delay of our model is the shortest, and after knowledge distillation we successfully reduce the inference delay by 63% with tiny accuracy loss. At last we briefly discuss some future directions of edge computation offloading.

References

[1] YAP K H, CHEN T, LI Z, et al. A comparative study of mobile-based landmark recognition techniques [J]. IEEE intelligent systems, 2010, 25(1): 48 – 57. DOI: 10.1109/mis.2010.12
[2] JIANG J C, ANANTHANARAYANAN G, BODIK P, et al. Chameleon: scalable adaptation of video analytics [C]//2018 Conference of the ACM Special Interest Group on Data Communication. Budapest, Hungary, 2018: 253 – 266. DOI: 10.1145/3230543.3230574
[3] Multi-access edge computing-standards for MEC [EB/OL].(2019-11-04)[2020-01-05]. https://www.etsi.org/technologies-clusters/technologies/multi-access-edge-computing
[4] YU S, CHEN X, YANG L, et al. Intelligent edge: leveraging deep imitation learning for mobile edge computation offloading [J]. IEEE wireless communications, 2020, 27(1): 92 – 99. DOI:10.1109/mwc.001.1900232
[5] ZHANG T H, MCCARTHY Z, JOW O, et al. Deep imitation learning for complex manipulation tasks from virtual reality teleoperation [C]//2018 IEEE International Conference on Robotics and Automation (ICRA). Brisbane, Australia, 2018: 1 – 8. DOI:10.1109/icra.2018.8461249
[6] CHEN X, JIAO L, LI W Z, et al. Efficient multi-user computation offloading for mobile-edge cloud computing [J]. ACM transactions on networking, 2016, 24(5): 2795 – 2808. DOI:10.1109/tnet.2015.2487344
[7] HE Y, ZHAO N, YIN H X. Integrated networking, caching, and computing for connected vehicles: a deep reinforcement learning approach [J]. IEEE transactions on vehicular technology, 2018, 67(1): 44 – 55. DOI: 10.1109/tvt.2017.2760281
[8] BA L J, CARUANA R. Do deep nets really need to be deep? [EB/OL].(2014-10-11) [2020-01-05]. https://arxiv.org/abs/1312.6184
[9] HINTON G, VINYALS O, DEAN J. Distilling the knowledge in a neural network [EB/OL].(2015-03-09)[2020-01-10]. https://arxiv.org/abs/1503.02531
[10] RAN X, CHEN H, ZHU X, et al. Deep decision: A mobile deep learning framework for edge video analytics [C]//IEEE INFOCOM 2018-IEEE Conference on Computer Communications. IEEE, 2018: 1421 – 1429
[11] KANG Y P, HAUSWALD J, GAO C, et al. Neurosurgeon: collaborative intelligence between the cloud and mobile edge [J]. ACM SIGARCH computer architecture news, 2017, 45(1): 615 – 629. DOI:10.1145/3093337.3037698
[12] CUERVO E, BALASUBRAMANIAN A, D-KCHO, et al. MAUI: Making smartphones last longer with code offload [C]//Proceedings of the 8th International Conference on Mobile Systems, Applications, and Services. San Francisco, USA, 2010: 49 – 62
[13] TSOUMAKAS G, KATAKIS I. Multi-label classification [J]. International journal of data warehousing and mining, 2007, 3(3): 1 – 13. DOI: 10.4018/jdwm.2007070101
[14] YOU C S, ZENG Y, ZHANG R, et al. Asynchronous mobile-edge computation offloading: energy-efficient resource management [J]. IEEE transactions on wireless communications, 2018, 17(11): 7590 – 7605. DOI: 10.1109/twc.2018.2868710
[15] ZHOU Z, CHEN X, LI E, et al. Edge intelligence: paving the last mile of artificial intelligence with edge computing [EB/OL]. (2019-05-24)[2020-01-05]. DOI:10.1109/JPROC.2019.2918951
[16] CHEN X, PU L, GAO L, et al. Exploiting massive D2D collaboration for energy-efficient mobile edge computing [J]. IEEE wireless communications, 2017, 24(4): 64 – 71. DOI:10.1109/MWC.2017.1600321

Biographies

CHEN Haowei received the B.S. degree in computer science from the School of Data and Computer Science, Sun Yat-sen University (SYSU), China in 2020. He is working towards the master's degree in the School of Data and Computer Science, SYSU. His research interests include mobile deep computing, edge intelligence and deep learning.

ZENG Liekang received the B.S. degree in computer science from the School of Data and Computer Science, Sun Yat-sen University, China in 2018. He is currently pursuing the master's degree with the School of Data and Computer Science, Sun Yat-sen University. His research interests include mobile edge computing, deep learning, and distributed computing.

YU Shuai received the Ph.D. degree from Pierre and Marie Curie University (now Sorbonne Université), France, in 2018, the M.S. degree from Beijing University of Post and Telecommunications, China, in 2014, and the B.S. degree from Nanjing University of Post and Telecommunications, China, in 2009. He is now a post-doctoral Research Fellow at the School of Data and Computer Science, Sun Yat-sen University. His research interests include wireless communications, mobile computing and machine learning.

CHEN Xu (chenxu35@mail.sysu.edu.cn) is a full professor in Sun Yat-sen University, China, and the vice director of National and Local Joint Engineering Laboratory of Digital Home Interactive Applications. He received the Ph.D. degree in information engineering from The Chinese University of Hong Kong in 2012, and worked as a post-doctoral research associate at Arizona State University, USA from 2012 to 2014, and a Humboldt Scholar Fellow at Institute of Computer Science of University of Goettingen, Germany from 2014 to 2016. He is currently an area editor of *IEEE Open Journal of the Communications Society*, an associate editor of the *IEEE Transactions Wireless Communications*, *IEEE Internet of Things Journal* and *IEEE Journal on Selected Areas in Communications (JSAC) Series on Network Softwarization and Enablers*.