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Adaptive Compression for Online Computer Vision: an Edge Reinforcement Learning Approach

Zhaoliang He, Hongshan Li, Zhi Wang, Shutao Xia, Wenwu Zhu

***Abstract*—With the growth of computer vision-based applications, an explosive amount of images have been uploaded to cloud servers that host such online computer vision algorithms, usually in the form of deep learning models. JPEG has been used as the *de facto* compression and encapsulation method for images. However, standard JPEG configuration does not always perform well for compressing images that are to be processed by a deep learning model, e.g., the standard quality level of JPEG leads to 50% of size overhead (compared with the best quality level selection) on ImageNet under the same inference accuracy in popular computer vision models (e.g., InceptionNet and ResNet). Knowing this, designing a better JPEG configuration for online computer vision-based services is still extremely challenging: 1) Cloud-based computer vision models are usually a black box to end-users; thus, it is challenging to design JPEG configuration without knowing their model structures. 2) The "optimal" JPEG configuration is not fixed; instead, it is determined by confounding factors, including the characteristics of the input images and the model, the expected accuracy and image size, etc. In this paper, we propose a reinforcement learning (RL)-based adaptive JPEG configuration framework, AdaCompress. In particular, we design an edge (i.e., user-side) reinforcement learning agent that learns the optimal compression quality level to achieve an expected inference accuracy and upload image size, only from the online inference results, without knowing details of the model structures. Furthermore, we design an *explore-exploit* mechanism to let the framework fast switch an agent when it detects a performance degradation, mainly due to the input change (e.g., images captured across daytime and night). Our evaluation experiments using real-world online computer vision-based APIs from Amazon Rekognition, Face++, and Baidu Vision, show that our approach outperforms existing baselines by reducing the size of images by 1/2 – 1/3 while the overall classification accuracy only decreases slightly; Meanwhile, AdaCompress adaptively re-trains or re-loads the RL agent promptly to maintain the performance.**

***Index Terms*—Edge Computing, Reinforcement Learning, Adaptive Compression, Machine Learning Service**

I. Introduction

With the great success of deep learning in computer vision, this decade has witnessed an explosion of deep learning-based computer vision-based applications. Because of the enormous computational resource consumption for deep learning applications (e.g., inferring an image on VGG19 [2] requires 20 GFLOPs of GPU resource), in today's online computer vision-based applications, users usually have to upload the input images to the central cloud service providers (e.g., SenseTime, Baidu Vision and Google Vision, etc.), leading to a significant upload traffic load.

To reduce the upload traffic load, one should compress the image before uploading it. Though JPEG has been used as the *de facto* image compression and encapsulation method, its performance for the deep computer vision models is not satisfactory. Liu et al. [3] showed that by re-designing the quantization table in the default JPEG configuration, one can compress an image to a smaller version while maintaining the comparable inference accuracy for a deep computer vision model. However, such quantization solutions usually assume the inference model is fixed.

We then raise an intuitive question: to make it practically useful, can we select the JPEG configuration adaptively for different online computer vision-based services, without any prior knowledge of the original model? In this paper, we propose a reinforcement learning-based framework to select JPEG configurations adaptively. In our solution, we tackle the following design challenges.

- *Lack of information about the cloud-based computer vision models.* Previous studies [3]–[5], generally assume that the details of the computer vision models are available so that they can adjust the JPEG configuration according to the model structure, e.g., one can train a model to determine the JPEG configuration by plugging the original computer vision model into it. However, the structural details of online computer vision models are usually proprietary and not open to the users.
- *Different cloud-based computer vision models need different JPEG configurations.* As an adaptive JPEG configuration solution, we target to provide a solution that is adaptive to different online computer vision-based services, i.e., it can *generate* JPEG configuration for different models. However, today's cloud-based computer vision algorithms, based on deep and convolutional computations, are quite hard to understand. The same compression quality level could lead to a different accuracy performance. Some examples are shown in Figure 1: picture 1a and 1b, 2a and 2b are visually similar for human beings, but the deep learning model gives different inference results, only because they are compressed at different quality levels. And such a relationship is not apparent, e.g., picture 3b is highly compressed and looks destroyed comparing to picture 3a, but the deep learning model can still recognize it. This phenomenon is also presented in [6] and commonly seen in adversarial neural network researches [7], [8].
- *Lack of well-labeled training data.* In our problem, one is not provided the well-labeled data on which image should

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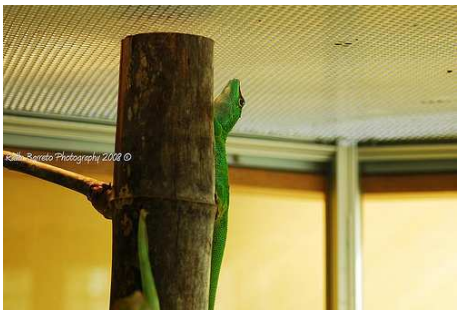
The preliminary version of this paper was published in ACM Multimedia 2019 [1]

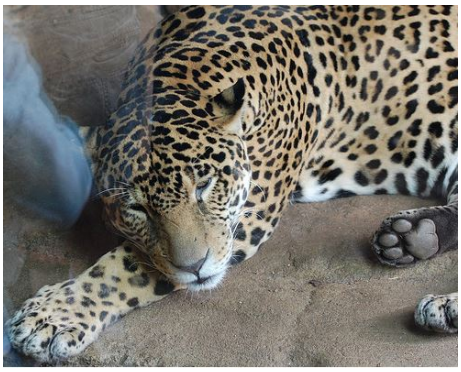
(1a) Q=75
Face++ prediction = [“donut”]

(1b) Q=55
Face++ prediction = [“biscuit”]

(2a) Q=75
Baidu prediction = [“chameleon”]



(2b) Q=55
Baidu prediction = [“electric fan”]



(3a) Q=75
Baidu prediction = [“leopard”]

(3b) Q=5
Baidu prediction = [“leopard”]

Figure 1: The prediction of a deep learning model is not completely related to the input image’s quality, making it difficult to use a fixed compression quality for all images. For image 1a, 1b and 2a, 2b, minor changes cause different predictions though they are visually similar; for image 3a and 3b, the cloud-based model still output correct label from a severely compressed image though they look very different

be compressed at which quality level, as in conventional supervised deep learning tasks. In practice, such an image compression module is usually utilized in an online manner, and the solution has to learn from the images it uploads automatically.

To address the above challenges, we present a reinforcement learning-based solution, called AdaCompress[1], to choose a proper compression quality level for an image to a computer vision model on the cloud-end, in an online manner. This paper is an extension of our earlier conference paper [1], with the following contributions:

▷ We design an interactive training environment that can be applied to different online computer vision-based services. We propose a Deep Q-learning Network-based [9] agent to evaluate and predict the performance of a compression quality level on an input image. In real-world application scenarios, this agent can be highly efficient to run on today’s edge

[1]We open-sourced AdaCompress that works with online computer vision-based APIs at https://github.com/hosea1008/AdaCompress

infrastructures (e.g., Google edge TPU [10], Huawei Atlas 500 edge station [11]).

▷ We build a reinforcement learning-based framework to train the agent in the above environment. The agent can learn to choose a proper compression quality level for an input image after iteratively interacting with the environment by feeding the carefully designed reward that considers both accuracy and data size. We further propose an *explore-exploit* mechanism to let the agent switch between "sceneries". In particular, after deploying the agent, an *inference-estimation-querying-retraining* solution is designed to switch the RL agent intelligently once the scenery changes and the existing running agent cannot guarantee the original accuracy performance.

▷ In this journal extension, we provide more analysis and insights on our design. We notice that the Deep Q-learning Network-based agent's behaviors are various for different input image "sceneries" and backend cloud services. By analyzing the agent's behaviors using Grad-Cam [12], we provide the reasons that the agent chooses a specific compression quality level. We reveal that images containing large smooth areas are more sensitive to compression, while images with complex textures are more robust to compression for computer vision models.

▷ We evaluate our system on representative cloud-based deep learning services, including Amazon Rekognition [13], Face++ [14] and Baidu Vision [15]. We show that our design can reduce the upload traffic load by up to $1/2$ while maintaining comparable overall accuracy. Compared to baseline DeepN-JPEG [3], the overall accuracy of AdaCompress is 8% higher when they have similar compressed image size.

The rest of this paper is organized as follows. We discuss related works in Section II. We present our framework and detailed design in Section III. We present our solution's performance in Section IV and conclude the paper in Section V.

II. Related Works

As online computer vision-based services have become the norm for today's applications [16], [17], many studies have been devoted to improving the cloud-based model execution, including model compression and data compression.

A. Model Compression

Though the accurate term is still for the community to debate, we use "model compression" to represent the studies on *compressing* and *moving* the deep learning models close to users. Many studies tried to compress the deep learning models and deploy them *locally* [18]–[23], i.e., running an alternative "smaller version" of a computer vision model at the user-side, to avoid the image upload so that to improve the inference efficiency. Other studies proposed to run a part of a deep learning model *locally* [24]–[27], by decoupling the deep learning model into different parts, e.g., based on the layers in the deep learning model, so that a part of the inference is done *locally* to save some execution time. However, these solutions usually need to re-train the model using the original dataset of the model, which is not practical for today's online computer vision-based services that are merely a black box to end-users, e.g., in the form of a RESTful API.

B. Data Compression

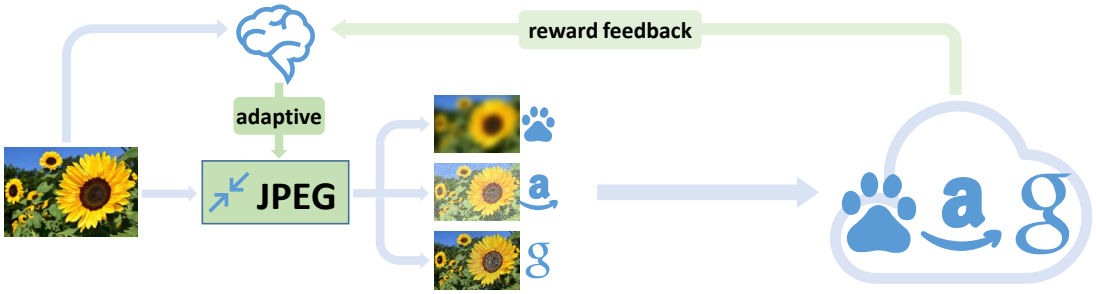
Data compression solutions study how to compress the original data (e.g., a video or image) to be inferred by the cloud-based deep learning model so that less traffic is used to upload the data to improve inference speed. In recent years, researchers found that conventional human visually optimized-based data compression solutions (e.g., JPEG [28], WebP [29] and JPEG2000 [30], etc.) and some recent neural network-based compression solutions [31]–[34] are not usually applicable to deep learning vision models. Liu et al. [3] revealed that the conventional JPEG image compression framework is designed for the Human-Visual System, which is not suitable for the deep neural network, leading to the computer vision model's inference performance degradation. Dodge et al. [35] further discovered that besides the JPEG compression, four types of quality distortions (blur, noise, contrast, and the JPEG2000 compression [30]) can also affect the inference performance of the deep learning models. Delac et al. [6] observed that, in some cases, a high compression quality level does not always reduce the model inference accuracy.

Based on these insights, Robert et al. [4] tried to train the deep neural network from the compressed representations of an auto-encoder. Chao et al. [36] proposed using variable quantization, which is supported by the JPEG standard extension syntax [37] to compress the macroblocks in images. Furthermore, they [38] designed a quantization table based on the observed impact of scale-space processing on the discrete cosine transform (DCT) basis functions for JPEG images, achieving similar inference performance while reducing the image size overhead effectively. Liu et al. [3] proposed DeepN-JPEG that re-designs the quantization table by linking statistical information of defined features and defined quantization values so that the compressed image size is reduced for deep learning models. Chamain et al. [39] proposed a joint optimization of image classification network coupled with the image quantization, achieving image size reduction of JPGE2000 [30] encoded images. Recently, Lionel et al. [5] presented a new type of neural network that infers directly from the discrete cosine transform coefficients in the middle of the JPEG codec. Baluja et al. [40] proposed task-specific compression that compresses images based on the end-use of images.

However, such proposals all need one to understand the characteristics of the cloud-based deep learning model and have access to the original training dataset, *generating* the appropriate compression schemes. To the best of our knowledge, we are the first to propose an adaptive compression configuration solution that learns the optimal compression quality level to achieve an expected inference accuracy and upload image size, only from the online inference results, without knowing details of the model structures.

In this journal extension, we improve the previous *inference-estimate-retrain* mechanism to cut down the upload image

(a) Conventional solution: fixed user-defined compression quality level



(b) AdaCompress solution: input image and model aware compression

Figure 2: Comparing to the conventional solution, our solution can update the compression strategy based on the backend model feedback

size overhead effectively, add DeepN-JPEG comparative experiment, and amend the manuscript significantly. Especially in the DeepN-JPEG comparative experiment, since Liu et al. [3] evaluated the DeepN-JPEG framework on ImageNet by using four state-of-the-art DNN models (AlexNet [41], VGG [42], GoogLeNet [43] and ResNet [44]) on local edge devices, which are different from online computer vision-based services, for comparison purpose, we implement the DeepN-JPEG framework according to their paper and evaluate the size reduction and accuracy performance using ImageNet and the metrics in Subsection. IV-C on three cloud-based deep learning services (Amazon Rekognition, Face++ and Baidu Vision).

III. Detailed Design

A brief framework of AdaCompress is shown in Figure 2. Briefly, it is a reinforcement learning-based system to train an agent to choose a proper compression quality level c for one image to be compressed by JPEG. We discuss the formulation, agent design, reinforcement learning-based framework, reward feedback, *inference-estimation-querying-retraining* mechanism, and insight of RL agent's behaviors separately in the following subsections. We provide experimental details of all the hyperparameters in Section. IV.

A. Problem Formulation

Without loss of generality, we denote the cloud-based deep learning service as $\vec{y}_i = M(x_i)$ that provides a predicted result list $\vec{y}_i$ for each input image x_i. It has a baseline output $\vec{y}_{\text{ref}} = M(x_{\text{ref}})$ for each reference input image $x \in X_{\text{ref}}$. We use this $\vec{y}_{\text{ref}}$ as the ground truth label. For each image x_c compressed at compression quality level c, the output $\vec{y}_c = M(x_c)$. Therefore, we have an accuracy metric $\mathcal{A}_c$ by comparing $\vec{y}_{\text{ref}}$ and $\vec{y}_c$. In general, we use the top-5 accuracy as the following $\mathcal{A}$, the same as the classification metric of ILSVRC2012 [45].

$$\mathcal{A} = \frac{1}{k}\sum_{k}\max_{j} d(l_j, g_k) \tag{1}$$

$$l_j \in \vec{y}_c, \quad j = 1, ..., 5 \tag{2}$$

$$g_k \in \vec{y}_{\text{ref}}, \quad k = 1, ..., \text{length}(\vec{y}_{\text{ref}}) \tag{3}$$

$$d(x, y) = 1 \text{ if } x = y \text{ else } 0 \tag{4}$$

Where $j = 1, ..., 5$ indicates the prediction labels at the top-5 score, meaning that if any one of the top-5 predicted labels matches the ground truth label $\vec{y}_{\text{ref}}$, it would be regarded as a correct prediction. In general, we cannot get the cloud-based deep learning model's in-layer details (e.g., softmax probabilities) for a cloud-based deep learning service. Therefore we use a binary hard label $d(x, y) \in \{0, 1\}$ to evaluate the accuracy.

We also denote JPEG input images as $f_{ic} = J(x_i, c)$ that for an input image x_i and a given compression quality level c, and it outputs a compressed file f_{ic} at the size of s_{ic}. For a reference compression quality level c_{ref}, the compressed file size is s_{ref}. Besides, the input image from a specific scenery usually belongs to a particular contextual group [46]. For example, in the daytime, the input images are expected to have a bright background, while nighttime images are usually gray-scaled thermal images. Therefore, the agent in one scenery does not need to know all the contextual features in all "sceneries". We formulate this as contextual group $\mathcal{X}$.

Initially, the agent tries different compression quality levels $c_{\min} < c < c_{\max}, c \in \mathbb{N}$ to obtain compressed image x_c

from input image x. To obtain cloud-end recognition results $\{\vec{y}_{\text{ref}}, \vec{y}_c\}$, the agent uploads the compressed image x_c and the reference image x_{ref} to the cloud-end. Comparing the two uploaded instances $\{x_{\text{ref}}, x_c\}$ and cloud-end recognition results $\{\vec{y}_{\text{ref}}, \vec{y}_c\}$, the agent obtains the reference file size s_{ref} and compressed file size s_c, and computes the file compression ratio $\Delta s = \frac{s_c}{s_{\text{ref}}}$ and accuracy metric $\mathcal{A}_c$.

B. RL Agent Design

The RL agent is expected to give a proper compression quality level c for minimizing the file size s_c while keeping the accuracy $\mathcal{A}$. For the RL agent, the input features are continuous numerical vectors, and the expected output is discrete compression quality level c. Therefore we can use the Deep Q-learning Network as the RL agent. But the naive Deep Q-learning Network can not work well in this task because of the following challenges:

- The state space of reinforcement learning is too large. To preserve enough details, we have to add many layers and nodes to the neural network, making the RL agent extremely difficult to converge.
- It takes a long time to train one step in a large inference neural network, making the training process too time-consuming.
- The RL agent starts training from random trials and learns afterward from the reward feedback. When training from a randomly initialized neural network, the reward feedback is very sparse, making it difficult for the agent to learn.

To address these challenges, we use the early layers of a pre-trained neural network to extract the structural information of an input image. This is a commonly used strategy in training a deep neural network [47], [48]. Therefore instead of training a RL agent directly from the input image, we use a pre-trained small neural network to extract the features from the input image to reduce the input dimension and accelerate the training procedure. In this work, we use the early convolution layers of MobileNetV2 [49] as the image feature extractor $\mathcal{E}(\cdot)$ for its efficiency in image classification. The Deep Q-learning Network ϕ is connected to the feature extractor's last convolution layer. We update the RL agent's policy by changing the parameters of the Deep Q-learning Network ϕ while fixing the feature extractor $\mathcal{E}$.

C. Reinforcement Learning-based Framework

In a specific scenery where the user input image x belongs to the contextual group $\mathcal{X}$, we define the contextual group $\mathcal{X}$, along with the backend cloud model M, as the *emulator environment* $\{\mathcal{X}, M\}$ of the reinforcement learning problem.

We formulate the feature extractor's output $\mathcal{E}(J(\mathcal{X}, c))$ as *states* and the compression quality level c as discrete *actions*. In our system, to accelerate training, we define 10 discrete actions to indicate 10 compression quality levels of JPEG ranging from $5, 15, ..., 95$. We denote the *action-value function* as $Q(\phi(\mathcal{E}(f_t)), c; \theta)$ and the optimal compression quality level at time t as $c_t = \text{argmax}_c Q(\phi(\mathcal{E}(f_t)), c; \theta)$ where θ indicates the parameters of the Deep Q-learning Network ϕ. In such reinforcement learning formulation, the training phase is to minimize the loss function $L_i(\theta_i) = \mathbb{E}_{s,c\sim\rho(\cdot)}\Big[\big(y_i - Q(s, c; \theta_i)\big)^2\Big]$ that changes at each iteration i where $s = \mathcal{E}(f_t)$ and target $y_i = \mathbb{E}_{s'\sim\{\mathcal{X},M\}}\big[r + \gamma \max_{c'} Q(s', c'; \theta_{i-1}) \mid s, c\big]$. Especially, r is the reward feedback, and $\rho(s, c)$ is a probability distribution over sequences s and the compression quality level c [9]. When minimizing the distance of *action-value function*'s output $Q(\cdot)$ and target y_i, the *action-value function* $Q(\cdot)$ outputs a more accurate estimation of an action.

Algorithm 1 Training RL agent ϕ in environment $\{\mathcal{X}, M\}$

Initialize replay memory buffer $\mathcal{D}$ to capacity N
Initialize *action-value function* Q with random weights θ
Initialize sequence $s_1 = \mathcal{E}\big(J(x_1, c_1)\big), x_1 \in \mathcal{X}$ and $\phi_1 = \phi(f_1)$
for $t \in 1, 2, \cdots, K$ **do**
  1) Exploration. With probability ϵ:
    $c_t \leftarrow$ a random valid value
  Otherwise:
    $c_t \leftarrow \text{argmax}_c Q\Big(\phi\big(\mathcal{E}(f_t)\big), c; \theta\Big)$

  2) Reward calcuation.
  Compress image x_t at quality c_t to upload
  Receive $(\vec{y}_{\text{ref}}, \vec{y}_c)$ from the cloud service
  $r \leftarrow R(\Delta s, \mathcal{A}_c)$

  3) Gradient decent. Generate c_t, x_{t+1}
  $s_{t+1} \leftarrow s_t$, $\phi_{t+1} \leftarrow \phi\big(\mathcal{E}(f_{t+1})\big)$
  $\mathcal{D} \leftarrow \mathcal{D} \bigcup \{(\phi_t, c_t, r_t, \phi_{t+1})\}$
  if $t \mod T = 0$ and $t \geq T_{\text{start}}$ **then**
    Sample a randomly mini-batch of transitions $(\phi_j, c_j, r_j, \phi_{j+1})$ from memory buffer $\mathcal{D}$
    $y_i \leftarrow r_j + \gamma \max_{c'} Q(\phi_{j+1}, c'; \theta)$
    Compute decay exploration rate
    $$\epsilon \leftarrow \begin{cases} \mu_{\text{dec}} \cdot \epsilon & \text{if } \mu_{\text{dec}} \cdot \epsilon > \epsilon_{\min} \\ \epsilon_{\min} & \text{if } \mu_{\text{dec}} \cdot \epsilon \leq \epsilon_{\min} \end{cases}$$
    Perform a gradient descent step on $\big(y_j - Q(\phi_j, c_j; \theta)\big)^2$ according to [9]
  end if
end for

Different from conventional reinforcement learning, the interactions between the agent and environment are infinite, i.e., there is no signal from the environment telling that an episode has finished. Therefore, we train the RL agent intermittently at a manual interval of T after the condition $t \geq T_{\text{start}}$ guaranteeing that there are enough transitions in the memory buffer $\mathcal{D}$. In the training phase, the RL agent firstly takes some random trials to observe the environment's reaction and decreases the randomness when training afterward. All transitions are saved into a memory buffer $\mathcal{D}$, and the agent learns to optimize its *action* by minimizing the loss function L on a mini-batch from $\mathcal{D}$. The training procedure would converge when the agent's randomness keeps decaying. Finally, the agent's action is based on its historical "optimal" experiences. The training procedure is presented in Algorithm 1.

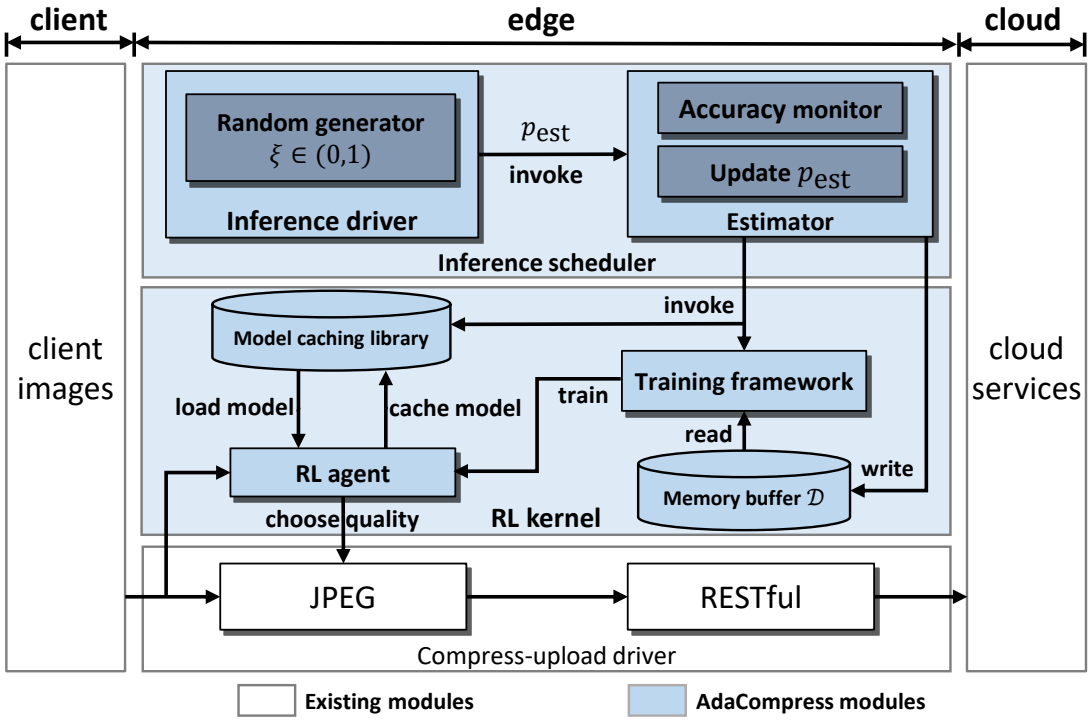


Figure 3: Diagram of AdaCompress architecture

D. Reward Feedback Design

In our solution, the agent is trained by the reward feedback from the environment $\{\mathcal{X}, M\}$. In the above formulation, we define compression rate $\Delta s = \frac{s_c}{s_{\text{ref}}}$ and accuracy metric $\mathcal{A}_c$ at compression quality level c. Basically, we want the agent to choose a proper compression quality level for minimizing the upload image size while remaining acceptable accuracy. Therefore the overall reward r should be in proportion to the accuracy $\mathcal{A}$ while in inverse proportion to the compression ratio Δs. We introduce two linear factors α and β to form a linear combination $r = \alpha\mathcal{A} - \Delta s + \beta$ as the *reward function* $R(\Delta s, \mathcal{A})$.

E. Inference-Estimation-Querying-Retraining Mechanism

As a running system, we introduce an *inference-estimation-querying-retraining* mechanism to cope with the scenery change in the inference phase, building a system with different components to inferring, capturing the scenery change, then either re-loading or re-training the RL agent based on the performance of the cached model. The overall system diagram is illustrated in Figure 3.

We build up the memory buffer $\mathcal{D}$ and reinforcement learning training kernel based on the compression and upload driver. When the RL training kernel is called, it would load transitions from the memory buffer $\mathcal{D}$ to train the compression quality level predictor ϕ. When the system is deployed, the pre-trained RL agent ϕ guides the compression driver to compress the input image at an adaptive compression quality level c, then uploads the compressed image to cloud-end.

After the AdaCompress is deployed, the input image scenery context $\mathcal{X}$ may change (e.g., day to night, sunny to rainy). When the scenery changes, the older RL agent's compression selection strategy may not be suitable anymore, causing the overall accuracy to decrease. To cope with the scenery change, AdaCompress invokes an estimator with a probability p_{est}. AdaCompress does this by generating a random value $\xi \in (0, 1)$ and comparing it to p_{est}. If $\xi \leq p_{\text{est}}$, the estimator would be invoked. AdaCompress would upload the reference image x_{ref} along with the compressed image x_i to obtain $\vec{y}_{\text{ref}}$ and $\vec{y}_i$, calculate $\mathcal{A}_i$ and save the transition $(\phi_i, c_i, r_i, \mathcal{A}_i)$ to the memory buffer $\mathcal{D}$. The estimator also compares the recent n steps' average accuracy $\bar{\mathcal{A}}_n$ and the initial accuracy threshold $\mathcal{A}_0$. Once the recent average accuracy is lower than the initial accuracy threshold, the estimator would query a RL agent model to replace the current agent model and test the performance of the loaded model. To test the loaded model's performance, the estimator computes the average accuracy $\bar{\mathcal{A}}_n^*$. If $\bar{\mathcal{A}}_n^*$ is still lower than the accuracy threshold, the estimator would invoke the RL training kernel to re-train the agent. Once the estimator discovers that the trained reward is higher than the reward threshold, it would stop the training kernel, cache the trained RL agent, and switch to the normal inference state.

Since the reference image x_{ref} and the compressed image x_i are both needed in the re-training phase, causing a large upload image size overhead, especially when the scenery changes frequently (e.g., day to night, then night to day). To avoid unnecessary upload traffic load in the re-training phase, we build up the model caching library to cache the trained RL agent models. When capturing the scenery change, we firstly query a pre-trained model from the model caching library rather than re-training from scratch.

The *inference-estimation-querying-retraining* mechanism

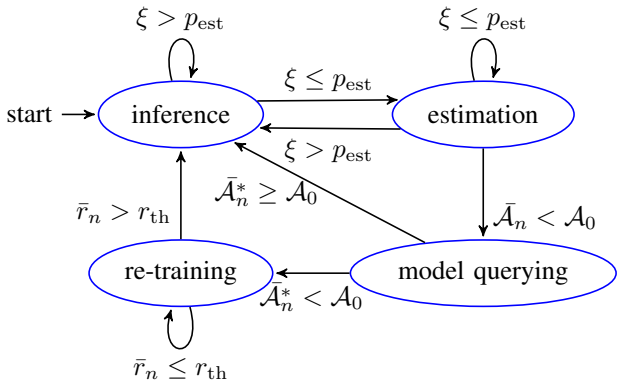


Figure 4: State switching policy

has four states, including inference, estimation, model querying and re-training. AdaCompress switches to these states adaptively. The state switching policy is shown as Figure 4.

1) Inference: Most of the time, AdaCompress runs in this state. In this state, only the compressed images are uploaded to the cloud-end to achieve less upload image size overhead. To keep a stable accuracy performance even the input image scenery changes, the agent would occasionally switch to the estimation state with probability p_{est} since the estimator uploads the reference image to maintain inference accuracy, or remain in the inference state with probability $1 - p_{\text{est}}$.

2) Estimation: In this state, the reference image x_{ref} and compressed image x_i are uploaded to the cloud-end simultaneously to obtain $\vec{y}_{\text{ref}}$ and $\vec{y}_i$ which are used to calculate $\mathcal{A}_i$. In each epoch i, the transition $(\phi_i, c_i, r_i, \mathcal{A}_i)$ is logged in the memory buffer $\mathcal{D}$. When the average accuracy $\bar{\mathcal{A}}_n$ of the latest n steps is higher than the accuracy threshold $\mathcal{A}_0$, the agent would stay in the estimation state with probability p_{est} or switch to the inference state with probability $1-p_{\text{est}}$. Once the average accuracy $\bar{\mathcal{A}}_n$ is lower than the initial accuracy threshold $\mathcal{A}_0$, indicating that the current agent is no more suitable for the current input image scenery, AdaCompress would turn into the model querying state and re-load a new RL agent model from the model caching library.

Therefore, the estimation probability of p_{est} is vital to the whole system. On the one hand, the estimator should be invoked occasionally to estimate the current agent's accuracy for capturing the scenery change on time. On the other hand, the estimator uploads the reference image along with the compressed image. Therefore, the upload image size overhead is greater than the conventional benchmark solution, causing a high upload traffic load.

To achieve trade-off between the risk of the scenery change and the objective of reducing upload traffic load, we design an accuracy-aware dynamic solution. We first define that after running for N steps, the average accuracy of recent n steps is:

$$\bar{\mathcal{A}}_n = \begin{cases} \frac{1}{n}\sum_{i=N-n}^{N} \mathcal{A}_i & \text{if } N \geq n \\ \frac{1}{n}\sum_{i=1}^{n} \mathcal{A}_i & \text{if } N < n \end{cases}$$

With this definition, an intuitive formulation of the change of p_{est} is in inverse proportion of the gradient of $\mathcal{A}$, meaning that when the recent accuracy decreases, the estimation probability p_{est} would increase. We define that $p'_{\text{est}} = p_{\text{est}} + \omega \nabla \bar{\mathcal{A}}$ where ω is a scaling factor. With this recursive formula, we have the general term of $p_{\text{est}} = p_0 + \omega \sum_{i=0}^{N} \nabla \bar{\mathcal{A}}_i$ where p_0 is an initial estimation probability.

3) Model Querying: The model querying state is designed to cope with the scenery change before re-training. It reloads a new RL agent model from the model caching library and tests whether the loaded agent model is suitable for the current scenery by re-calculating the average accuracy. If the new average accuracy $\bar{\mathcal{A}}_n^*$ is higher than the accuracy threshold $\mathcal{A}_0$, indicating that the loaded agent model is suitable for the current scenery, AdaCompress would switch to the normal inference state and use the loaded agent model to infer. Otherwise, AdaCompress would switch to the re-training state and invoke the RL training kernel to re-train a new RL agent for the current scenery.

In this way, AdaCompress is capable to cope with the scenery change in a cached "memory" manner, avoiding re-training the agent model at every scenery change to cut down the upload image size overhead. However, the agent caching strategy would cause a little storage overhead on local edge devices.

4) Re-training: This state is to adapt the agent to the current input image scenery by re-training it with the memory buffer $\mathcal{D}$, which is similar to the training procedure. The re-training phase has finished upon the recent n steps' average reward $\bar{r}_n$ is higher than the user-defined threshold r_{th}. And when the re-training procedure finishes, the memory buffer $\mathcal{D}$ would be flushed, preparing to save new transitions for the re-training of a next scenery change. The trained RL agent model would be cached in the model caching library and be used to switch to the inference state.

F. Insight of RL Agent's Behaviors

In the inference phase, the pre-trained RL agent chooses a proper compression quality level according to the input image's features and the backend service. The reference image is not uploaded to the cloud-end anymore; only the compressed image is uploaded. Therefore, the upload traffic load is reduced. We notice that the RL agent's behaviors are various for different input image "sceneries" and backend cloud services. Therefore we try to make further investigations by plotting the RL agent's "attention map" (i.e., visual explanations why the agent chooses a specific compression quality level).

1) Compression Quality Level Choice Variation: In our experiment, we find that in different cloud-based application environments, the agent's chosen compression quality levels can be quite different. As shown in Figure 5, for Face++ and Amazon Rekognition, the agent's choices are concentrated at around $c = 15$, but for Baidu Vision, the agent's selections are distributed more evenly. The "optimal" compression strategies are different for different backend cloud services. This variation is caused by the interaction between the agent and the backend cloud model in the training phase. Since

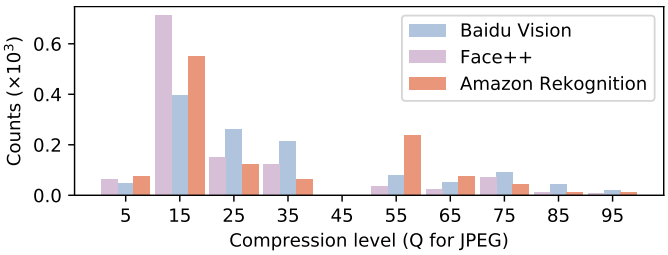


Figure 5: Histogram of RL agent's best compression quality level selection for different cloud services

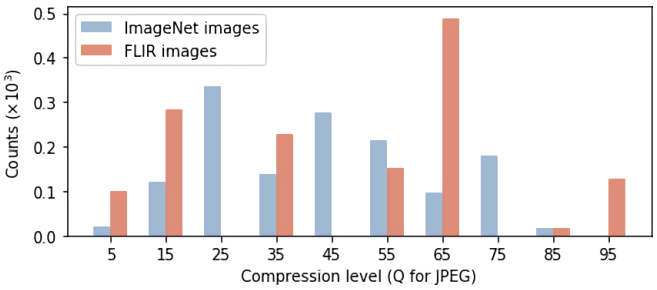


Figure 6: Histogram of RL agent's best compression quality level selection for different input image "sceneries"

the agent's training procedure is based on a specific backend cloud model M_1, for another backend cloud model M_2, the interaction between the agent and M_2 is quite different. Therefore the agent's best compression quality level selection presents variation for different backend cloud models.

Moreover, in our experiment, the agent presents different behaviors when the input image changes from one dataset to another. Figure 6 shows the agent's choices for the same backend cloud model (Baidu Vision) but different image datasets. We prepare two datasets indicating two contextual "sceneries". We randomly sample images from ImageNet [50] whose images are mostly taken in the daytime, to act as a daytime scenery, and randomly select nighttime images from the FLIR Thermal Dataset [51] to form another dataset to act as a nighttime scenery. The histogram shown in Figure 6 points out that, for the ImageNet images, the agent prefers a low compression quality level, but its choices are distributed more evenly. For the FLIR Thermal images, the agent's choices are more accumulated in some relatively higher compression quality levels. We can see that, to maintain high accuracy, when the input image's contextual group $\mathcal{X}$ changes, the agent's compression quality level selection would change as well. This phenomenon presents that the agent can adaptively choose a proper compression quality level based on the input image's features.

2) Attention Map Variation: To make insight investigations, we plot the importance map of a chosen compression quality level. We leverage a conventional visualization algorithm, Grad-Cam, to observe the Deep Q-Learning Network-based agent's interest when choosing compression quality levels. Grad-Cam is a widely used effective solution to present the importance map of a deep neural network by calculating the gradients of each target concept and backtracking to the final convolution layer. In this work, we plot the RL agent's attention map by Grad-Cam in Figure 7.

notation	value	notation	value
c_{ref}	75	K	1000
$\epsilon_{\min}$	0.02	p_0	0.2
γ	0.95	ω	-3
μ_{dec}	0.99	T	5
r_{th}	0.45	n	10

TABLE I: Experiment parameter

In our investigations, we find that in different environments $\{\mathcal{X}, M\}$, the RL agent selects compression quality levels based on the visual textures of different regions in the image. As shown in Figure 7, picture 1a – 1d are some pictures which the agent chooses to compress aggressively. The agent selects low compression quality levels based on the complex texture of the images. On the contrary, for pictures 2a – 2d, the agent chooses relatively higher compression quality levels to preserve more details since its interest falls on some smooth regions. Especially for 1a and 2a, for picture 1a, the agent chooses a low compression quality level based on the rough central region though there are smooth regions around it, for picture 2a, the agent chooses a relatively higher compression quality level based on the surrounding smooth region rather than the central region.

IV. Evaluation

In this section, we present AdaCompress's behaviors and effectiveness by some real-world experiments.

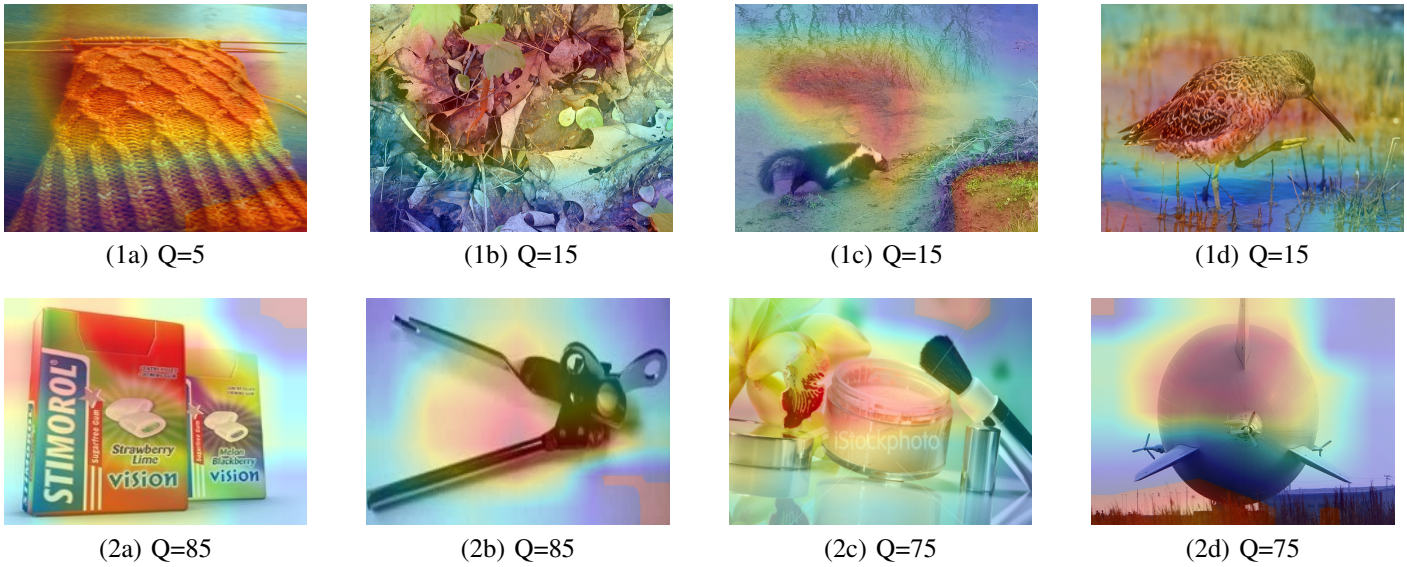
A. Experiment Setup

We carry out real-world experiments to verify our solution's performance. We use a desktop PC with an NVIDIA 1080ti graphic card as the edge infrastructure. For the cloud-based deep learning services, we choose Baidu Vision, Face++ object detection services and Amazon Rekognition. In the experiments, we use two datasets mentioned before in Subsection. III-F. The ImageNet dataset indicates daytime scenery, and the FLIR Thermal Dataset indicates nighttime scenery. Some important hyperparameters in our experiments are given in Table I.

B. Dataset

We use two datasets, the ImageNet dataset and the FLIR Thermal Dataset. The ImageNet dataset is a Large-Scale Hierarchical Image, in which each node of the hierarchy is depicted by hundreds and thousands of images. Its images are mostly taken in the daytime. Therefore we use it as a daytime scenery. Usually, a surveillance camera captures colored pictures in the daytime and gray-scaled thermal images in the night. Therefore we choose a thermal image dataset to act as a nighttime image dataset. The FLIR Thermal Dataset is such a dataset having more than 14000 images collected by thermal sensors.

We use the ImageNet dataset in size reduction and accuracy performance experiment, DeepN-JPEG comparative experiment and end-to-end latency simulation experiment. Moreover,



(1a) Q=5 (1b) Q=15 (1c) Q=15 (1d) Q=15

(2a) Q=85 (2b) Q=85 (2c) Q=75 (2d) Q=75

Figure 7: Visualization of the importance map for the RL agent to choose a compression quality level

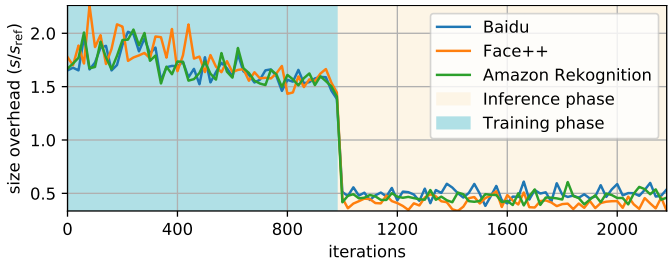


Figure 8: Size overhead in the training and inference phase

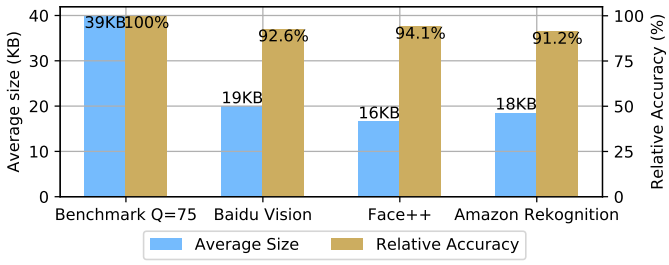


Figure 9: Average size and relative accuracy on different cloud services

we use ImageNet and the FLIR Thermal Dataset alternately to simulate the scenery change in the *inference-estimation-querying-retraining* mechanism experiment.

C. Metrics

The default compression quality level for JPEG is usually 75 [52], [53]. Therefore we regard this as a reference value $c_{\text{ref}} = 75$ of the conventional benchmark.

In our experiments, we measure the compressed and reference image's file size to obtain the compression rate Δs. Since we do not have the real ground truth label of an image, we use the output $\vec{y}_{\text{ref}}$ from a reference image as the ground truth label, and calculate the relative top-5 accuracy $\mathcal{A}$ as the accuracy metric. The formula of $\mathcal{A}$ is presented in Subsection. III-A.

D. Upload Image Size Overhead

Figure 8 presents the upload traffic load of the training and inference phase. To be more intuitionistic, we plot the size overhead $\frac{s}{s_{\text{ref}}}$ as the y-axis where s is the real upload size of AdaCompress and s_{ref} is the benchmark upload size. Therefore $y \geq 1$ means that our solution uploads more data then benchmark, and $y < 1$ means the compression rate of AdaCompress. From Figure 8, we can see that as the training procedure runs, the upload image size decreases because the RL agent learns to choose better compression quality levels to upload less data. In the training phase, to train the agent while remaining a convincing recognition result, AdaCompress has to upload the original image along with the compressed image to the cloud-end, obtaining the real result and the reward feedback. Therefore the upload traffic load is even higher than the conventional solution. But once the training phase has finished, the upload traffic load is lower than the benchmark. As shown in Figure 9, in the inference phase, AdaCompress's upload size is only 1/2 of the benchmark's.

E. Size Reduction and Accuracy Performance

Figure 9 presents the compression performance in the inference phase for each cloud service. We test AdaCompress on Face++, Baidu Vision and Amazon Rekognition. Comparing to the benchmark compression quality level, our solution can reduce the upload size by more than 1/2 for all tested cloud services, meanwhile maintain the relative accuracy that only decreases about 7% on average, proving the efficiency of our design.

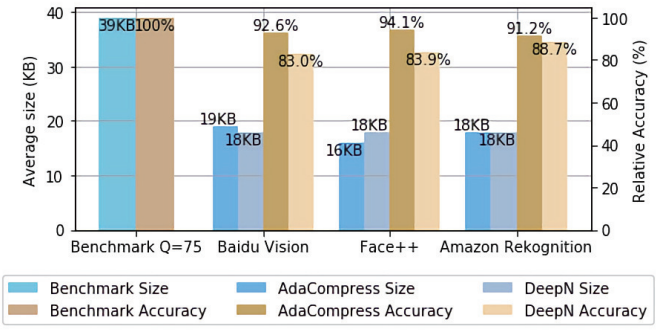


Figure 10: Comparative compression performance between DeepN-JPEG and AdaCompress

F. DeepN-JPEG Comparative Experiment

Figure 10 presents a comparison performance between DeepN-JPEG and AdaCompress for each cloud service. As we can see, both DeepN-JPEG and AdaCompress cut down the upload size overhead more than 1/2. However, for all tested cloud services, AdaCompress's accuracy is higher than DeepN-JPEG's slightly. Compared with DeepN-JPEG's average accuracy is about 85% on three cloud services, AdaCompress achieves a better average accuracy of 93%. In a word, comparing to the DeepN-JPEG framework, AdaCompress presents a similar size reduction performance but achieving higher inference accuracy for online computer vision-based services.

AdaCompress compresses images in a more adaptive manner rather than DeepN-JPEG. (i.e., the explanation why AdaCompress achieves a better accuracy). As shown in Figure 11, for picture 1a, compared to DeepN-JPEG, AdaCompress compresses the image at a more aggressive compression quality level of 15, reducing upload size overhead. On the contrary, for picture 2a of Figure 11, DeepN-JPEG compresses the image with the same quantization table, but AdaComperss chooses a relatively higher compression quality level to preserve more details so that the backend deep learning model can still recognize the picture. Compared with DeepN-JPEG compresses all images with the same quantization table, AdaCompress chooses a low compression quality level for picture 1a and a relatively higher compression quality level for picture 2a based on the features of the input image.

Comparing to DeepN-JPEG, AdaCompress has two advantages and one disadvantage as following:

- AdaCompress and DeepN-JPEG both decrease the upload size overhead more than 1/2, but AdaCompress maintains higher inference accuracy.
- For different "sceneries" or cloud services, DeepN-JPEG compresses images with the same quantization table, while AdaCompress makes a more proper compression strategy adaptively.
- DeepN-JPEG re-designs the quantization table *locally*, while AdaCompress needs to upload reference images and compressed images to the cloud-end in the training phase, leading some upload size overhead at the beginning.

G. Adaptively Cope With the Scenery Change

To evaluate the efficiency of the *inference-estimation-querying-retraining* mechanism, we feed AdaCompress with a combined dataset whose first 2000 images from FLIR Thermal images, the next 3000 images randomly sampled from ImageNet and the last 2000 images from FLIR Thermal images. We adapt AdaCompress's current RL agent to FLIR nighttime scenery by training it on the FLIR dataset, and run AdaCompress on the combined dataset, observing AdaCompress's behaviors upon the scenery changes at step 2000 and 5000.

We illustrate AdaCompress's behaviors in Figure 12. The x-axis indicates steps, and the reference line indicates the scenery change. We plot AdaCompress's overall accuracy and the estimation probability p_{est}. At the bottom of Figure 12, we also plot the scaled upload size of AdaCompress and benchmark solution to illustrate the upload size overhead.

From Figure 12, we can see that AdaCompress can adaptively update the estimation probability p_{est}. When the overall accuracy decreases, AdaCompress would increase the estimation probability, trying to capture the scenery change. When the overall accuracy is stable and high enough, the estimation probability p_{est} decreases to reduce transmission.

Upon the first image scenery changes (i.e., night to day) shown as the first reference line in Figure 12, comparing to the earlier steps, the accuracy decreases dramatically and the estimation probability p_{est} raises to determine whether the scenery changes. The accuracy keeps dropping in the following steps, indicating that the current RL agent is no more suitable for the current input scenery. At the moment, AdaCompress should switch to the model querying state and re-load a new RL agent model from the model caching library. However, there is no model except the current RL agent at that time. Therefore, AdaCompress starts to re-train at once to adapt the RL agent to the current scenery. In the re-training phase, AdaCompress uses the reference image's prediction label $\vec{y}_{\text{ref}}$ as the output result. Therefore the accuracy $\mathcal{A}$ and p_{est} are locked to 1. After finishing re-training the agent in the daytime scenery, the trained agent is cached in the model caching library. In the following steps, sometimes the accuracy decreases accidentally, and the estimation probability p_{est} also raises. The accuracy is not lower than the accuracy threshold $\mathcal{A}_0$. Therefore the re-training phase would not be triggered again until the second image scenery changes.

Upon the second image scenery changes (i.e., day to night) shown as the second reference line in Figure 12, like the first scenery change, the accuracy decreases and p_{est} raises, indicating that the current RL agent is no more suitable again. AdaCompress switches to the model querying state at once and re-loads a new RL agent model (the initial model trained on the FLIR Thermal images) from the model caching library. When using the new agent in this scenery, the accuracy stops decreasing and maintains more than the accuracy threshold, indicating the current RL agent is suitable for the current scenery.

From Figure 12, we can also observe the upload size overhead in different phases. In the re-training phase, Ada-

(1a) Origin Image (Q=75)
Baidu prediction = ["parrot"]

(1b) AdaCompress (choose Q=15)
Baidu prediction = ["parrot"]

(1c) DeepN-JPEG
Baidu prediction = ["parrot"]

(2a) Origin Image (Q=75)
Baidu prediction = ["cake"]

(2b) AdaCompress (choose Q=65)
Baidu prediction = ["cake"]

(2c) DeepN-JPEG
Baidu prediction = ["fossil"]

Figure 11: Comparative compressed images of DeepN-JPEG and AdaCompress

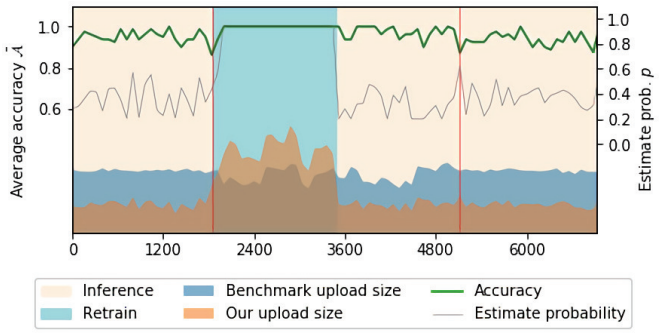


Figure 12: AdaCompress's reactions upon scenery change

Compress uploads more data than the conventional benchmark. But in the inference phase, AdaCompress's upload size is only half of the benchmark's. Especially once the second image scenery changes, AdaCompress achieves a low upload traffic load by re-loading a suitable RL agent model rather than re-training from scratch.

H. End-to-End Latency Simulation

Comparing to the conventional solution that uploads the image directly, in our solution, the image is passed to the RL agent firstly to estimate the compression quality level. Running this RL agent brings extra latency to the whole system. In this subsection, we evaluate the overall latency overhead.

We compute compressed file size for batches of images, and test the RL agent's inference time and the latency of uploading such compressed images. We test the average inference latency on 1000 ImageNet images and simulate the network bandwidth as 27.64 Mbps according to the global average fixed broadband upload speed [54] in Feb. 2019, to verify the end-to-end latency performance. The latency comparison is listed in Table II.

	Benchmark	AdaCompress
Average upload size	42.68 KB	18.46 KB
Inference latency	0 s	2.09 ms
Transmission latency	12.35 ms	5.34 ms
Overall latency	12.35 ms	7.43 ms

TABLE II: Latency between image upload and inference result feedback

Our solution brings in inference latency to the end-to-end latency, but the transmission latency is low by reducing the upload file size. In today's network architecture where the edge infrastructure's computational power is increasing significantly [55], [56], we can use the computing power of the edge infrastructure in exchange for the reduction of upload traffic load and transmission latency.

V. Conclusion

To reduce the upload traffic load of deep learning applications, most researchers focus on modifying the deep learning model, but this does not apply to the industry because the backend deep learning model is usually inaccessible to users. We present a heuristic solution using a reinforcement learning agent to decide the proper compression quality level for each image according to the image's features and the backend service. Our experiment results show that for different backend deep learning cloud services and different input image "sceneries", using different compression strategies can significantly reduce the upload file size overhead while keeping

comparable accuracy. Moreover, we design the *inference-estimation-querying-retraining* mechanism to cope with the input image scenery change and make a proper compression strategy for the current scenery. Our experiment results show that once the scenery changes, the mechanism would either reload a pre-trained agent or re-train a new agent intelligently to achieve low upload image size overhead while maintaining the inference accuracy.

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Dear Editors,

We would like to submit the enclosed manuscript entitled "Adaptive Compression for Online Computer Vision: an Edge Reinforcement Learning Approach," which we wish to be considered for publication in IEEE Transactions on Multimedia. No conflict of interest exists in the submission of this manuscript, and the manuscript is approved by all authors for publication.

This paper is an extension of our previous publication in Proceedings of ACM Multimedia 2019 (https://arxiv.org/pdf/1909.08148.pdf). We have significantly improved the conference version (9 pages) into this journal version (13 pages), with the following significant extensions.

1. We have significantly improved the AdaCompress framework, to provide more generality and robustness of the whole design. First, to improve AdaCompress' efficiency upon re-train (e.g., upon scenery change), in this extension, we have introduced a new inference-estimation-querying-retraining mechanism to avoid unnecessary iteration during the re-train phase by letting the framework "re-use" a historical cached model (the new Figure 3 shows the updated AdaCompress architecture). Second, to incorporate the new mechanism into the original AdaCompress framework, we have re-designed the state switching policy, with a newly added state "model querying" (the new Figure 4 shows the updated state switching policy). More details are provided in Subsection. III-E.

2. We have provided more solid motivation and evidence for our design. In particular, the new Figure 6 shows the different performance of the same backend model (e.g., Baidu Vision), under different input datasets (e.g., ImageNet and FLIR), as shown in the new Figure 12. These new insights provide more solid evidence for our design. More details are provided in Subsection. III-F.

3. We have also significantly improved our evaluation of the design. We have implemented baseline DeepN-JPEG[1], and show that our design has much higher accuracy than DeepN-JPEG when they both compress the input images to the same level, as shown in the new Figure 10. More details are provided in the new Subsection. IV-F.

4. We have also improved the related works, to include more recent related studies in this area.

Last but not least, we have also improved the presentation of the whole paper.

We sincerely appreciate your consideration of our manuscript, and we look forward to receiving comments from the reviewers.

Thank you and best regards.

Yours sincerely,
Authors

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AdaCompress: Adaptive Compression for Online Computer Vision Services

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ABSTRACT

With the growth of computer vision based applications and services, an explosive amount of images have been uploaded to cloud servers which host such computer vision algorithms, usually in the form of deep learning models. JPEG has been used as the *de facto* compression and encapsulation method before one uploads the images, due to its wide adaptation. However, standard JPEG configuration does not always perform well for compressing images that are to be processed by a deep learning model, e.g., the standard quality level of JPEG leads to 50% of size overhead (compared with the best quality level selection) on ImageNet under the same inference accuracy in popular computer vision models including InceptionNet, ResNet, etc. Knowing this, designing a better JPEG configuration for online computer vision services is still extremely challenging: 1) Cloud-based computer vision models are usually a black box to end-users; thus it is difficult to design JPEG configuration without knowing their model structures. 2) JPEG configuration has to change when different users use it. In this paper, we propose a reinforcement learning based JPEG configuration framework. In particular, we design an agent that adaptively chooses the compression level according to the input image's features and backend deep learning models. Then we train the agent in a reinforcement learning way to adapt it for different deep learning cloud services that act as the *interactive training environment* and feeding a reward with comprehensive consideration of accuracy and data size. In our real-world evaluation on Amazon Rekognition, Face++ and Baidu Vision, our approach can reduce the size of images by 1/2 – 1/3 while the overall classification accuracy only decreases slightly.

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CCS CONCEPTS

• **Networks** → *Network components*; • **Computer systems organization** → *Real-time systems.*

KEYWORDS

edge computing;reinforcement learning;data compression;online computer vision services

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1 INTRODUCTION

With the great success of deep learning in computer vision, this decade has witnessed an explosion of deep learning based computer vision applications. Because of the huge computational resource consumption for deep learning applications (e.g., inferring an image on VGG19 [37] requires 20 GFLOPS GPU resource), in today's computer vision applications, users usually have to upload the input images to the central cloud service providers (e.g., SenseTime, Baidu Vision and Google Vision, etc.), leading to a significant uploading traffic burden. For example, a picture taken by a cellphone at the resolution of 3968×2976 when saved as JPEG format at the default compression level, has a size up to 3MB.

To reduce the upload traffic, it is straightforward that an image should be compressed before one uploads it. Though JPEG has been used as the de facto image compression and encapsulation method, its performance for the deep computer vision models is not satisfactory, because JPEG was originally designed for human vision system. Liu et al. [27] showed that by modifying the *quality level* in the default JPEG configuration, by retraining it on the original dataset, one can compress an image to a smaller version while maintaining the inference accuracy for a fixed deep computer vision algorithm. We then raise an intuitive question: to make it practically useful, can we improve the JPEG configuration adaptively for different cloud computer vision services, without any pre-knowledge of the original model and dataset?

Our answer to this question is a new learning-based compression methodology for today's cloud computer vision services. We tackle the following challenges in our design.

- **Lack of information about the cloud computer vision models.** Different from the studies [15, 27, 42], in which the computer vision models are available so that one can adjust the JPEG configuration according to the model structure or retrain the parameters in it, e.g., one can greedily search a gradient descent to reach an optimal compression level in JPEG. In our study, however, the details of the online cloud computer vision model are inaccessible.
- **Different cloud computer vision models need different JPEG configurations.** As an adaptive JPEG configuration solution, we target to provide a solution that is adaptive to different cloud computer vision services, i.e., it can *generate* JPEG configuration for different models. However, today's cloud computer vision algorithms, based one deep and convolutional computations, are quite hard to understand. The same compression level could lead to totally different accuracy performance. Some examples are shown in Figure 1, picture 1a and 1b, 2a and 2b are visually similar for human beings, but the deep learning models give different inference results, only because they are compressed at different quality levels. And such relationship is not apparent, e.g., picture 3b is highly compressed and looks destroyed comparing to picture 3a, but the deep learning model can still recognize it. This phenomenon is also presented in [7] and commonly seen in adversarial neural network researches [10, 43].
- **Lack of well-labeled training data.** In our problem, one is not provided the well-labeled data on which image should be compressed to which quality level, as in conventional supervised deep learning tasks. In practice, such an image compression module is usually utilized in an online manner, and the solution has to learn from the images it uploads automatically.

To address the above challenges, we present a deep reinforcement learning (DRL) based solution, AdaCompress, to choose the proper compression level for an image to a computer vision model on the cloud, in an online manner. We open-sourced[1] our JPEG configuration module that works with today's cloud computer vision APIs upon acceptance of this paper. In particular, our contributions are summarized as follows:

- First, we design an interactive training environment that can be applied to different computer vision cloud services at different times, then we propose a deep Q neural network agent to evaluate and predict the performance of a compression level on an input image. In real-world application scenarios, this deep Q neural network can be highly efficient to run on today's edge infrastructures (e.g., Google edge TPU [14], Huawei Atlas 500 edge station [21]).
- Second, we build up a reinforcement learning framework to train the deep Q network in the above environment. By feeding the agent with carefully designed reward comprehensively considering accuracy and data size, the agent can learn to choose a proper compression level for an input image after iteratively interacting with the environment. To make the solution adaptive to the changing input images, we propose an explore-exploit mechanism to adapt the agent to different "scenery" online. After deploying the deep Q agent, an inference-estimate-retrain mechanism is designed to restart the training procedure once the scenery changes, and the existing running Q agent cannot guarantee stable accuracy performance.
- Finally, we provide analysis and insights on our design. We analyze the Q network's behavior by introducing Grad-Cam [36], and we explain why the Q network chooses a specific compression level, and provide some general patterns. Generally speaking, images that contain large smooth areas are more sensitive to compression, while the images with complex textures are more robust to compression when shown to deep learning models. We evaluate our system on some most popular cloud deep learning services, including Amazon Rekognition [2], Face++ [11] and Baidu Vision [5], and show that our design can reduce the uplink traffic load by up to 1/2 while maintaining comparable overall accuracy.

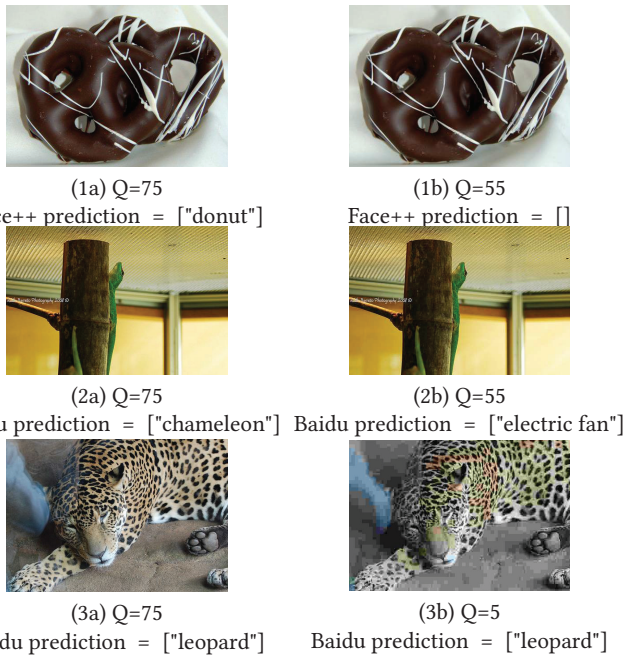
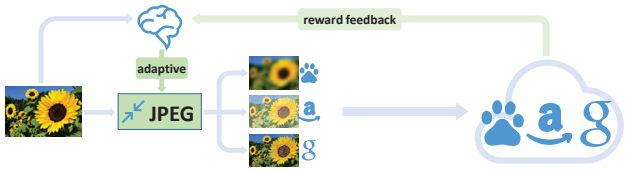


Figure 1: The prediction of a deep learning model is not completely related to the input image's quality, making it difficult to use a fixed compression quality for all images. For image 1a, 1b and 2a, 2b, minor changes cause different predictions though they are visually similar; for image 3a and 3b, the cloud model still output correct label from a severely compressed image though they look very different

The rest of this paper is organized as follows. We present our framework and detailed design in Sec. 2. In Sec. 3 we present our solution's performance. We discuss related works in Sec. 4 and conclude the paper in Sec. 5.

[1] https://github.com/hosea1008/AdaCompress

(a) Conventional solution:
fixed user-defined compression level



(b) AdaCompress solution:
input image and model aware compression

Figure 2: Comparing to the conventional solution, our solution can update the compression strategy based on the backend model feedback

2 DETAILED DESIGN

A brief framework of AdaCompress is shown in Figure 2. Briefly, it is a DRL (deep reinforcement learning) based system to train an agent to choose the proper quality level c for one image to be compressed by JPEG. We will discuss the formulation, agent design, reinforcement learning framework, reward feedback, and retrain mechanism separately in the following subsections. We will provide experimental details of all the hyperparameters in Sec. 3.

2.1 Problem formulation

Without loss of generality, we denote the cloud deep learning service as $\vec{y}_i = M(x_i)$ that provides a predicted result list $\vec{y}_i$ for each input image x_i, and it has a baseline output $\vec{y}_{\text{ref}} = M(x_{\text{ref}})$ for all reference input $x \in X_{\text{ref}}$. We use this $\vec{y}_{\text{ref}}$ as the ground truth labels, and for each image x_c compressed at quality c, we have $\vec{y}_c = M(x_c)$. Therefore, we have an accuracy metric $\mathcal{A}_c$ by comparing $\vec{y}_{\text{ref}}$ and $\vec{y}_c$. To be general, we use the top-5 accuracy as the following $\mathcal{A}$, the same as the classification metric of ILSVRC2012 [29].

$$\begin{aligned}\mathcal{A} &= \sum_k \min_j d(l_j, g_k) \\ & l_j \in \vec{y}_c, \quad j = 1, \ldots, 5 \\ & g_k \in \vec{y}_{\text{ref}}, \quad k = 1, \ldots, \text{length}(\vec{y}_{\text{ref}}) \\ & d(x, y) = 1 \text{ if } x = y \text{ else } 0\end{aligned}$$

Where $j = 1, \ldots, 5$ indicating the prediction labels at top-5 score, $k = 1, \ldots, \text{length}(\vec{y}_{\text{ref}})$ means that if anyone of the top-5 predicted labels matches one of the predictions from $\vec{y}_{\text{ref}}$, it is regarded as a correct prediction. To be general, we stipulate that for a cloud deep learning service, we cannot get the deep model's in-layer details (e.g., softmax probabilities) therefore we use a binary hard label $d(x, y) \in \{0, 1\}$ to evaluate the accuracy.

We also denote JPEG input images as $f_{ic} = J(x_i, c)$ that for an input image x_i and a given compression quality c, it outputs a compressed file f_{ic} at the size of s_{ic}, for a reference compression level c_{ref}, the compressed file size is s_{ref}. Besides, images input from a specific location usually belong to a particular contextual group. For example, in an indoor scenery, the user input is less likely to have the images of the ocean, airplanes, and dolphins but more likely to have furniture and so on. Therefore, the agent at one place does not need to know all the contextual features in all places. We formulated this as contextual group $\mathcal{X}$. This contextual grouping concept is also discussed in [18].

Initially, the agent tries different compression level $c_{\min} < c < c_{\max}, c \in \mathbb{N}$ to obtain compressed image x_c from input image x, and an image compressed at a reference level c_{ref} is also uploaded to the cloud to obtain $\vec{y}_{\text{ref}}$. Comparing the two uploaded instances $\{x, x_c\}$ and cloud recognition results $\{\vec{y}_{\text{ref}}, \vec{y}_c\}$, we can have the reference file size s_{ref} and compressed file size s_c and therefore the file compression ratio $\Delta s = \frac{s_c}{s_{\text{ref}}}$ and accuracy metric $\mathcal{A}_c$.

2.2 DRL agent design

The DRL agent is expected to give a proper compression level c that minimizing the file size s_c while keeping the accuracy $\mathcal{A}$. For the DRL agent, the input features are continuous numerical vectors, and the expected output are discrete quality levels c, therefore we can use DQN (Deep Q Network) [28] as the DRL agent. But naive DQN can't work well in this task because of the following challenges:

- The state space of reinforcement learning is too large, and to preserve enough details, we have to add many layers and nodes to the neural network, making the DRL agent extremely difficult to converge.
- It takes a long time to train one step in a large inference neural network, making the training process too time-consuming.
- DRL starts training from random trials, and starts learning after it found a better reward feedback. When training from a randomly initialized neural network, the reward feedback is very sparse, making it difficult for the agent to learn.

To address these challenges, we use the early layers of a well-trained neural network to extract the structural information of an input image. This is a commonly used strategy in training a deep neural network [12, 30]. Therefore instead of training a DRL agent directly from the input image, we use a pre-trained small neural network to extract the features from the input image to reduce the input dimension and accelerate the training procedure. In this work, we use the early convolution layers of MobileNetV2 [34] as the image feature extractor $\mathcal{E}(\cdot)$ for its efficiency in image classification and lightweight. The Q network ϕ is connected to the feature extractor's last convolution layer, therefore the output of $\mathcal{E}$ is the input of ϕ. We update the RL agent's policy by changing the parameters of Q network ϕ while the feature extractor $\mathcal{E}$ remains fixed.

2.3 Reinforcement learning framework

In a specific scenery where the user input x belongs context group $\mathcal{X}$, we define the contextual information $\mathcal{X}$, along with the backend cloud model M, as the *emulator environment* $\{\mathcal{X}, M\}$ of the reinforcement learning problem.

Based on this insight, we formulate the feature extractor's output $\mathcal{E}(J(\mathcal{X}, c))$ as *states*, and the compression quality c as discrete *actions*. In our system, to accelerate training, we define 10 discrete actions to indicate 10 quality levels of JPEG ranging from 5, 15, ..., 95. We denote the *action-value function* as $Q(\phi(\mathcal{E}(f_t)), c; \theta)$, then the optimal compression level at time t is $c_t = \text{argmax}_c Q(\phi(\mathcal{E}(f_t)), c; \theta)$ where θ indicates the parameters of Q network ϕ. In such reinforcement learning formulation, the training phase is to minimize a loss function $L_i(\theta_i) = \mathbb{E}_{s,c\sim\rho(\cdot)}\left[\left(y_i - Q(s, c; \theta_i)\right)^2\right]$ that changes at each iteration i where $s = \mathcal{E}(f_t)$, and $y_i = \mathbb{E}_{s'\sim\{\mathcal{X},M\}}\left[r + \gamma \max_{c'} Q(s', c'; \theta_{i-1}) \mid s, c\right]$ is the target for iteration i, r is the feedback reward and $\rho(s, c)$ is a probability distribution over sequences s and quality level c [28]. When minimizing the distance of the action-value function's output $Q(\cdot)$ and target y_i, the action-value function $Q(\cdot)$ outputs a more accurate estimation of an action. In such formulation, it is similar to DQN problem but not the same. Different from conventional reinforcement learning, the interactions between the agent and environment are infinite; there is no signal from the environment telling that an episode has finished. Therefore, we train the RL agent intermittently at a manual interval of T after the condition $t \geq T_{\text{start}}$ guaranteeing that there are enough transitions in the memory buffer $\mathcal{D}$. In the training phase, the RL agent firstly takes some random trials to observe the environment's reaction, and we decrease the randomness when training. All transitions are saved into a memory buffer queue $\mathcal{D}$, the agent learns to optimize its action by minimizing the loss function L on a minibatch from $\mathcal{D}$. The training procedure will converge as the agent's randomness keeps decaying. Finally, the agent's action is based on its historical optimal experiences. The training procedure is presented in Algorithm 1, we list the parameters in Sec. 3.

Algorithm 1 Training RL agent ϕ in environment $\{\mathcal{X}, M\}$

Initialize replay memory queue $\mathcal{D}$ to capacity N
Initialize action-value function Q with random weights θ
Initialize sequence $s_1 = \mathcal{E}\big(J(x_1, c_1)\big), x_1 \in \mathcal{X}$ and $\phi_1 = \phi(f_1)$
for t = 1, K **do**
  With probability ϵ select a random compression level c_t otherwise select $c_t = \text{argmax}_c Q\Big(\phi\big(\mathcal{E}(f_t)\big), c; \theta\Big)$
  Compress image x_t at quality c_t and upload it to the cloud to get result $(\vec{y}_{\text{ref}}, \vec{y}_c)$ and calculate reward $r = R(\Delta s, \mathcal{A}_c)$
  Set $s_{t+1} = s_t$, generate c_t, x_{t+1} and preprocess $\phi_{t+1} = \phi\big(\mathcal{E}(f_{t+1})\big)$
  Store transition $(\phi_t, c_t, r_t, \phi_{t+1})$ in $\mathcal{D}$
  if t mod T == 0 and $t \geq T_{\text{start}}$ **then**
    Sample random minibatch of transitions $(\phi_j, c_j, r_j, \phi_{j+1})$ from memory buffer $\mathcal{D}$
    Set $y_i = r_j + \gamma \max_{c'} Q(\phi_{j+1}, c'; \theta)$
    Decay exploration rate $\epsilon = \begin{cases} \mu_{\text{dec}} \cdot \epsilon & \text{if } \mu_{\text{dec}} \cdot \epsilon > \epsilon_{\min} \\ \epsilon_{\min} & \text{if } \mu_{\text{dec}} \cdot \epsilon \leq \epsilon_{\min} \end{cases}$
    Perform a gradient descent step on $\big(y_j - Q(\phi_j, c_j; \theta)\big)^2$ according to [28]
  end if
end for

2.4 Feedback reward design

In our solution, the agent is trained by the reward feedback from the environment $\{\mathcal{X}, M\}$. In the above formulation, we defined compression rate $\Delta s = \frac{s_c}{s_{\text{ref}}}$ and accuracy metric $\mathcal{A}_c$ in compression quality c. Basically, we want the agent to choose a proper compression level that minimizing the file size while remaining acceptable accuracy, therefore the overall reward r should be in proportion to the accuracy $\mathcal{A}$ while in inverse proportion to the compression ratio Δs. We introduce two linear factors α and β to form a linear combination $r = \alpha\mathcal{A} - \Delta s + \beta$ as the reward function $R(\Delta s, \mathcal{A})$.

2.5 Inference-estimate-retrain mechanism

As a running system, we introduce a running-estimate-retrain mechanism to cope with the scenery change in the inference phase, building a system with different components to inference, capturing scenery change, then retraining the RL agent. The overall system diagram is illustrated in Figure 3.

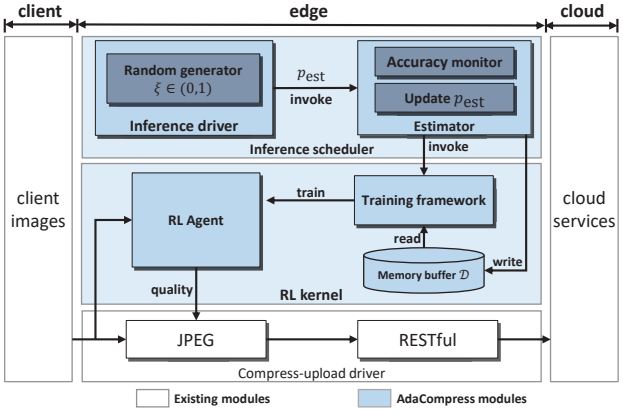


Figure 3: Diagram of AdaCompress architecture

The system diagram is shown in Figure 3. We build up the memory buffer $\mathcal{D}$ and RL (reinforcement learning) training kernel based on the compression and upload driver. When the RL kernel is called, it will load transitions from the memory buffer $\mathcal{D}$ to train the compression level predictor ϕ. When the system is deployed, the pre-trained RL agent ϕ guides the compression driver to compress the input image with an adaptive compression quality c according to the input image, then uploads the compressed image to cloud.

After the AdaCompress is deployed, the input images scenery context $\mathcal{X}$ may change. (e.g., day to night, sunny to rainy), when the scenery changes, the older RL agent's compression selection strategy may not be suitable anymore, causing the overall accuracy decreases. To cope with this scenery drifting issue, we invoke an estimator with probability p_{est}. We do this by generating a random value $\xi \in (0, 1)$ and compare it to p_{est}. If $\xi \leq p_{\text{est}}$ the estimator is invoked, AdaCompress will upload the reference image x_{ref} along with the compressed image x_i to fetch $\vec{y}_{\text{ref}}$ and $\vec{y}_i$ and therefore calculates $\mathcal{A}_i$, and save the transition $(\phi_i, c_i, r_i, \mathcal{A}_i)$ to the memory buffer $\mathcal{D}$. The estimator will also compare the recent n steps' average accuracy $\bar{\mathcal{A}}_n$ and the earliest average accuracy $\mathcal{A}_0$ in memory

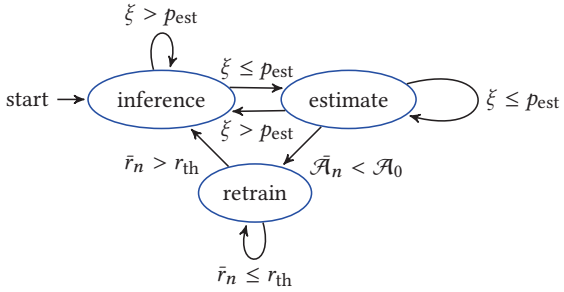


Figure 4: State switching policy

$\mathcal{D}$, once the recent average accuracy is much lower than the initial average accuracy, the estimator will invoke the RL training kernel to retrain the agent. And once the estimator discover that the trained reward is higher than a threshold, it will stop the training kernel, returning to normal inference state.

Basically, AdaCompress will adaptively switch itself between three states. The switching policy is shown as Figure 4.

2.5.1 ***Inference:*** For most times, AdaCompress runs in this state. In this state, only the compressed images are uploaded to the cloud to achieve minimum uploading traffic load. To keep a stable accuracy performance even the input scenery changes, the agent will occasionally switch to estimation state with probability p_{est}, meanwhile remains inference state with probability $1 - p_{\text{est}}$.

2.5.2 ***Estimate:*** In this state, the reference image x_{ref} and compressed image x_i are uploaded to the cloud simultaneously to fetch $\vec{y}_{\text{ref}}$ and $\vec{y}_i$ and therefore $\mathcal{A}_i$. In each epoch i the transition $(\phi_i, c_i, r_i, \mathcal{A}_i)$ is logged in a memory buffer $\mathcal{D}$. Once the average accuracy $\bar{\mathcal{A}}_n$ of the latest n steps is lower than the average accuracy $\mathcal{A}_0$ of the earliest n steps in the memory buffer $\mathcal{D}$, indicating that the current agent is no more suitable for the current input scenery, AdaCompress will switch into retrain state and invoke the RL training kernel. Otherwise, it remains estimate state with probability p_{est} or switches back into inference state with probability $1 - p_{\text{est}}$.

Therefore, the estimating probability p_{est} is vital to the whole system. On the one hand, the estimator should be invoked occasionally to estimate the current agent's accuracy, so that to retrain the agent on time once the scenery changes; on the other hand, the estimator will upload the reference image x_{ref} along with the compressed image, therefore the upload size is greater than the conventional benchmark solution, causing higher traffic load.

To trade-off between the risk of scenery changes and the objective of reducing upload traffic, we design an accuracy-aware dynamic p_{est} solution, we first define that after running for N steps, the recent n steps' average accuracy is:

$$\bar{\mathcal{A}}_n = \begin{cases} \frac{1}{n}\sum_{i=N-n}^{N} \mathcal{A}_i & \text{if } N \ge n \\ \frac{1}{n}\sum_{i=1}^{n} \mathcal{A}_i & \text{if } N < n \end{cases}$$

With this definition, an intuitive formulation of the changes of p_{est} is in inverse proportion of the gradient of $\mathcal{A}$, meaning that when the recent accuracy is going down, we should increase the estimation probability p_{est}. We formulate that $p'_{\text{est}} = p_{\text{est}} + \omega\nabla\bar{\mathcal{A}}$ where ω is a scaling factor. With this recursive formula, we have the general term of p_{est} with an initial estimation probability p_0 is $p_{\text{est}} = p_0 + \omega\sum_{i=0}^{N}\nabla\bar{\mathcal{A}}_i$.

2.5.3 ***Retrain:*** This state is to adapt the agent to the current input image scenery by retraining it with the memory buffer $\mathcal{D}$, which is similar to the training procedure. The retrain phase finishes upon the recent n steps' average reward $\bar{r}_n$ higher than a user-defined threshold r_{th}. And when the retrain procedure finishes, the memory buffer $\mathcal{D}$ will be flushed, preparing to save new transitions for the retraining of a next scenery drift.

2.6 Insight of RL agent's behavior

In the inference phase, the pre-trained RL agent predicts a proper compression level according to the input image's feature. The reference image is not uploaded to the cloud anymore; only the compressed image is uploaded, therefore, the upload traffic is reduced. We noticed that the RL agent's behavior are various for different input dataset and backend cloud services, we try to take further investigations by plotting the RL agent's "attention map" (i.e., visual explanations of why the agent chooses a quality level).

2.6.1 ***Compression level choice variation:*** In our experiment, we found that in different cloud application environments, the agent's final chosen compression qualities can be quite different. As shown in Figure 5, for Face++ and Amazon Rekognition, the agent's choices are concentrated at around $c = 15$, but for Baidu Vision, the agent's choices are distributed more evenly. Therefore, the optimal compression strategy should be different for different backend cloud services. This variation is caused by the interaction between the agent and the backend model in the training phase. Since the agent's training procedure is based on a specific backend cloud model M_1, for another cloud model M_2, the interaction between the agent and M_2 is quite different. Therefore the agent's compression level choice presents variation for different backend cloud models.

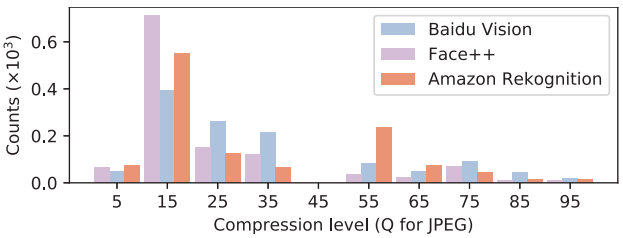


Figure 5: Histogram of RL agent's best compression level selection for different cloud services

Moreover, in our experiment, the agent presents different behavior when the input images change from one dataset to another. Figure 6 shows the agent's choices for a same backend model (Baidu Vision) but different image datasets. We prepare two datasets indicating two contextual scenery. We randomly sample images from ImageNet [33] whose images are mostly taken in the daytime, to act as a daytime scenery, and we randomly select nighttime images from DNIM [44] to form another dataset to act as a nighttime scenery. The histogram shown in Figure 6 points out that, for the ImageNet images, the agent prefers a lower compression level, but its

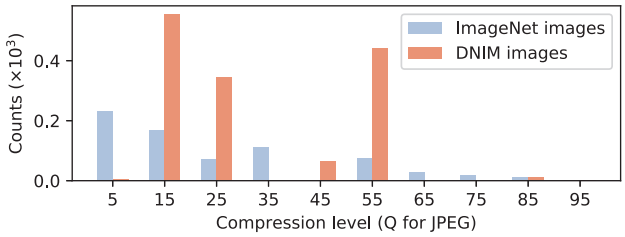


Figure 6: Histogram of RL agent's best compression level selection for different scenery image inputs

choices are distributed more evenly. For DNIM images, the agent's choices are more accumulated in some relatively high compression qualities. We can see that, to maintain high accuracy, when the input image's contextual group $\mathcal{X}$ changes, the agent's compression level selection changes as well. This phenomenon presents that the agent can adaptively choose a proper compression level based on the input image's features.

2.6.2 ***Attention map variation:*** To take insight investigation, we plot the importance map of a chosen compression quality. We do so by introducing a conventional visualize algorithm, Grad-Cam, to observe the Q prediction network's interest when choosing compression levels. Grad-Cam is a widely used solution to present the importance map of a deep neural network, it is done by calculating the gradients of each target concept and backtracking to the final convolution layer. In this work, we plot the RL agent's attention map by Grad-Cam in Figure 7.

In our investigation, we found that in different environment $\{\mathcal{X}, M\}$, the Q agent picks up compression qualities based on the visual textures of different regions in the image. As shown in Figure 7, picture 1a – 1d are some pictures that the agent chooses to compress highly, the agent selects lower compression qualities based on the complex texture of the images. On the contrary, for pictures 2a – 2d, the agent chooses higher compression qualities to preserve more details, and the agent's interest falls on some smooth regions. Especially for 1a and 2a, in picture 1a, the agent chooses a low compression level based on the rough central region though there are smooth regions around it, and in picture 2a, the agent chooses a relatively higher compression level based on the surrounding smooth region rather than the central region.

3 EVALUATION

In this section, we present AdaCompress's behavior and effectiveness by some real-world experiments.

3.1 Experiment setup

We carry out real-world experiments to verify our solution's performance. We used a desktop PC with an NVIDIA 1080ti graphic card as the edge infrastructure. For the cloud deep learning services, we choose Baidu Vision, Face++ object detection service, and Amazon Rekognition. In the experiments, we use two datasets mentioned before in Sec.2.6, ImageNet dataset indicating daytime scenery and DNIM dataset indicating nighttime scenery. Some important hyperparameters in our experiments are given in Table 1.

notation	value	notation	value
c_{ref}	75	K	1000
ϵ_{min}	0.02	p_0	0.2
γ	0.95	ω	-3
μ_{dec}	0.99	T	5
r_{th}	0.45	n	10

Table 1: Experiment parameter settings

3.2 Metrics

In industry, the default compression quality for JPEG is usually 75 [26, 31], we regard this as a typical value $c_{\text{ref}} = 75$ of the conventional industry benchmark.

In our experiments, we measure the compressed and original image's file size to obtain the compression rate Δs. Since we don't have the real ground truth label of an image, we use the output from a reference image $\vec{y}_{\text{ref}}$ as the ground truth label, and calculate the relative top-5 accuracy $\mathcal{A}$ as the accuracy metric, the formula of $\mathcal{A}$ is presented in Sec. 2.1.

3.3 Upload size overhead

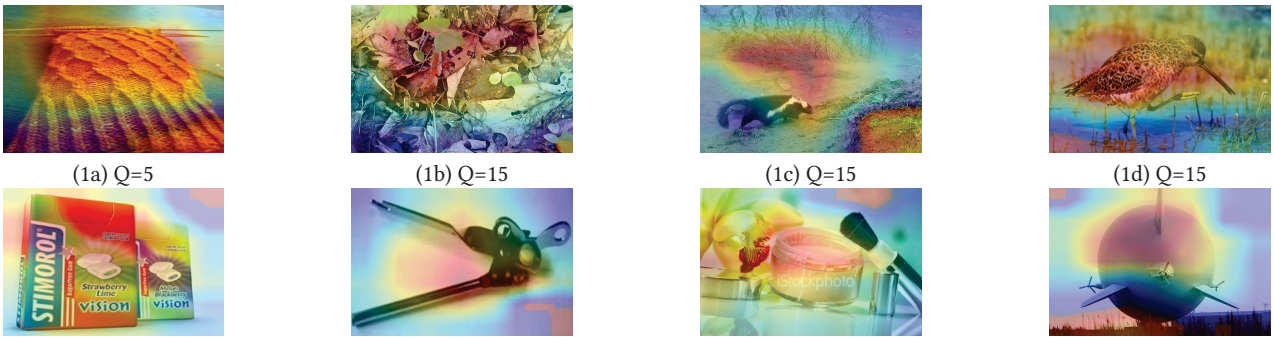
Figure 8 presents the upload traffic load of the training and inference phase, to be more intuitionistic, we plot the size overhead $\frac{s}{s_{\text{ref}}}$ as the y-axis where s is the real upload size of AdaCompress, s_{ref} is the benchmark upload size, therefore $y \geq 1$ means that our solution uploads more data then benchmark, and $y < 1$ means the compression rate of AdaCompress. From Figure 8 we can see that as the training procedure runs, the uploaded size is decreasing because the DRL agent is learning to choose better quality levels to upload less data. In the training phase, to train the agent while remaining a convincing recognition result, we have to upload the original image to the cloud to get the real result, along with the compressed image to obtain reward feedback, therefore the upload traffic load is even higher than the conventional solution. But once the training phase finished, the upload traffic is much lower than the benchmark. As shown in Figure 9, in the inference phase, AdaCompress's upload size is only 1/2 of the benchmark's.

3.4 Size reduction and accuracy performance

Figure 9 presents the compression performance in the inference phase for each cloud service. We tested AdaCompress on Face++, Baidu Vision and Amazon Rekognition, comparing to the conventional compression level, for all tested cloud services, our solution can reduce the upload size by more than 1/2, meanwhile, the relative accuracy, indicated by brown bars, only decrease about 7% on average, proving the efficiency of our design.

3.5 Adaptive retrain upon scenery change

To evaluate the efficiency of the inference-estimate-retrain mechanism, we feed AdaCompress with a combined dataset whose first 720 images from DNIM night images, the later 2376 images randomly sampled from ImageNet. We adapt AdaCompress's current DRL agent to DNIM night scenery by training it on DNIM dataset, then we run AdaCompress on the combine dataset, observing AdaCompress's behavior upon the scenery change at step 720.



(1a) Q=5 (1b) Q=15 (1c) Q=15 (1d) Q=15

(2a) Q=85 (2b) Q=85 (2c) Q=75 (2d) Q=75

Figure 7: Visualization of the importance map for the RL agent to choose a compression quality

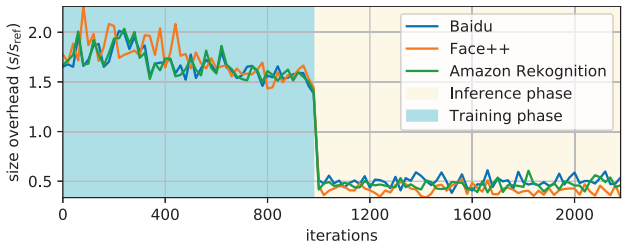


Figure 8: Size overhead in training and inference phase

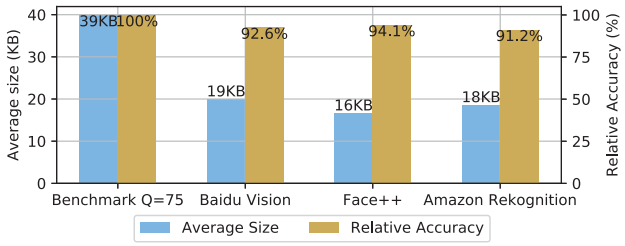


Figure 9: Average size and relative accuracy on different cloud services

We illustrate AdaCompress's behavior in Figure 10, the x-axis indicates steps, the vertical red line with a Δ mark on x-axis means the dataset change(i.e. scenery change). We plot AdaCompress's overall accuracy as the green line and the estimating probability p_{est} as the gray line. At the bottom of Figure 10, we also plot the scaled uploading data size of AdaCompress and benchmark solution to illustrate the upload data size overhead in the inference phase.

From Figure 10 we can see that AdaCompress can adaptively update the estimation probability p_{est}, usually, when the overall accuracy decreases, AdaCompress will increase the estimation probability, trying to catch the scenery change. When the overall accuracy is stable and high enough, the estimation probability p_{est} decreases to reduce transmission.

Upon the data scenery change shown as the vertical red line in Figure 10, comparing to the earlier steps, the accuracy decreases dramatically and therefore p_{est} raises to determine whether scenery changes, the accuracy keeps dropping in the following estimations.

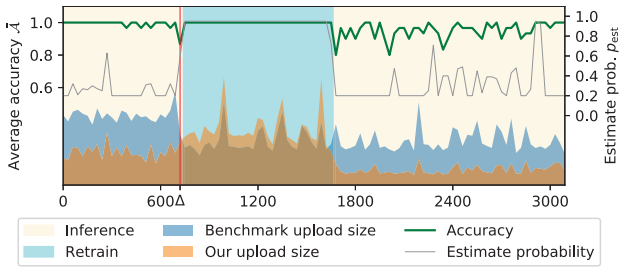


Figure 10: AdaCompress's reaction upon scenery change

Therefore, AdaCompress starts to retrain, to adapt the RL agent into the current scenery. The retrain steps are shown as the light-blue region in Figure 10. In the retrain phase, AdaCompress always uses the reference image's prediction label $\vec{y}_{\text{ref}}$ as the output result, therefore the accuracy $\mathcal{A}$ and p_{est} is locked to 1. After finishing retraining the agent in the new scenery, in the following iterations, sometimes the accuracy decrease accidentally, the estimation probability p_{est} also raises to get more samples, but the accuracy is not lower than the initial average accuracy $\mathcal{A}_0$ of this scenery, therefore the retrain phase will not be triggered again.

From Figure 10 we can also observe the uploading file size overhead in different phases, we can see that in retrain phase, AdaCompress uploads more data than the conventional benchmark, but in inference phase, AdaCompress's upload data size is only half of the benchmark's.

3.6 End-to-end latency simulation

Comparing to the conventional solution that uploads the image directly, in our solution, the image is passed to the DRL agent first to estimate the compression level. Running this DRL agent brings extra latency to the whole system. In this subsection, we evaluate this latency overhead.

We tested the DRL agent's inference time and compressed file size for batches of images, and simulate the latency of uploading such compressed images. We test the average inference latency from 1000 ImageNet images and simulate the network bandwidth as 27.64 Mbps according to the global average fixed broadband

upload speed [38] in Feb. 2019 to verify the end-to-end latency performance. The latency comparison is listed in Table 2.

	Benchmark	AdaCompress
Average upload size	42.68 KB	18.46 KB
Inference latency	0 s	2.09 ms
Transmission latency	12.35 ms	5.34 ms
Overall latency	12.35 ms	7.43 ms

Table 2: Latency between image upload and inference result feedback

Our solution brings in inference latency to the end-to-end latency, but the transmission latency is much lower by shrinking the upload file size. In today's network architecture where the edge infrastructure's computational power is increasing significantly [20, 35], we can use the computing power of the edge infrastructure in exchange for the reduction of upload traffic and transmission latency.

4 RELATED WORKS

As cloud-based computer vision services have become the norm for today's applications [1, 22], many studies have been devoted to improving the cloud-based model execution, including model compression and data compression.

4.1 Model compression

Though the accurate term is still for the community to debate, we use "model compression" to represent the studies on *compressing* and *moving* the deep learning models close to users. A number of studies tried to compress the deep learning models and deploy them *locally* [3, 4, 13, 16, 17, 23], i.e., running an alternative "smaller version" of a computer vision model at the user end, to avoid the image upload, so that to improve the inference efficiency. Other studies proposed to run part of a deep learning model locally [9, 19, 24, 25], by decoupling the deep learning model into different parts, e.g., based on the layers in the deep learning model, so that a part of the inference is done locally to save some execution time. However, these solutions usually need to *re-train* the model, using the original dataset of the model, which is not practical for today's cloud computer vision services that are merely a black box to end-users, e.g., in the form of a RESTful API.

4.2 Data compression

Data compression solutions study how to compress the original data (e.g., a video or image) to be inferred by the cloud deep learning model, so that less traffic is used to upload the data to improve inference speed. Conventional data compression solutions (e.g., JPEG, WebP, JPEG2000 etc.) and some recent neural network based compression solutions [32, 39–41] are initially designed for human vision systems. In recent years, researchers start to found that the human visually optimized data compression solutions are not usually applicable to deep learning vision systems. Delac et al. [7] observed that, in some cases, higher compression level does not always deteriorate the model inference accuracy, and in some cases, even improves it slightly. Dodge et al. [8] further discovered that besides the JPEG compression, four types of quality distortions: blur, noise, contrast, and JPEG2000 compression can also affect the performance in deep learning inference.

Based on these insights, Robert et al. [42] tried to train the neural network from the compressed representations of an auto-encoder. Liu et al. [27] proposed DeepN-JPEG that provides a JPEG quantization table learned from the dataset so that the compressed image size is reduced for deep learning models. Recently, Lionel et al. [15] present a new type of neural network that inference directly from the discrete cosine-transform (DCT) coefficients in the middle of the JPEG codec. Baluja et al. [6] proposed task-specific compression that compresses images based on the end-use of the image.

However, such proposals all need one to understand the characteristics of the cloud-end deep learning model and have access to the original training dataset, to generate the appropriate color space and/or compression schemes. To the best of our knowledge, we are the first to propose an adaptive compression configuration solution that learns the deep learning model by itself.

5 CONCLUSION AND FUTURE WORK

To reduce the upload traffic load of deep learning application, most researchers focus on modifying the deep learning model, but this does not apply to the industry because the backend deep model is usually inaccessible for users. We present a heuristic solution using a deep learning agent to decide the proper compression quality for each image, according to the input image and backend service. Our experiments show that for different backend deep learning cloud services and different input image scenery, using different quality selection strategy can significantly reduce the upload file size while keeping comparable accuracy. Based on this work, some possible future orientations can focus on the following: 1) In some regularly change scenery (e.g., daytime and nighttime, etc.), one can design an agent caching strategy, to cache an agent for a specific scenery and use it again when a similar scenery arrives rather than retrain from scratch. 2) By introducing transfer learning and knowledge distillation, an agent could learn from another nearby agent to accelerate its training.

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