EAMQ: Environment-based Adaptive Model Quantization on Federated Reinforcement Learning

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Abstract

Federated Reinforcement Learning (FRL) enables agents to collaboratively train models across distributed environments without sharing raw data. However, existing quantization methods like QuARL, ReLeQ, and VQQL struggle in environments with varying state transitions and rewards, affecting model robustness. In this paper, we introduce Environment-based Adaptive Model Quantization (EAMQ), a method that dynamically adjusts compression ratios based on environmental variability. EAMQ uses a reward-weighted sensitivity analysis to assign lower compression ratios to sensitive parameters in sparse reward environments while applying higher compression in dense reward settings. We also propose a learnable quantization technique that adapts based on a Temporal Difference (TD) loss function. Experiments show that EAMQ outperforms traditional methods across diverse environments, reducing communication and storage costs while maintaining performance, even under heterogeneous conditions.

1 Introduction

Federated Reinforcement Learning (FRL) [7] is a decentralized approach where multiple agents collaboratively train a reinforcement learning model across distributed environments without sharing raw data. FRL has been applied in real-world scenarios such as smart grid management, multi-agent large language models, and the Internet of Things (IoT) [11]. Model quantization, such as QuARL [4], ReLeQ [1], and VQQL [2], have been developed to compress models during reinforcement learning (RL) training in order to reduce the communication and storage costs. However, traditional algorithms perform badly when FRL is applied in environmental heterogeneity situations [3], because they don't consider the influence of the changing environments. Models trained in different environments have different robustness to quantization, models in some environments may be insensitive to higher compression rates, while others rely heavily on accurate parameter representations. In this work, we focus on quantizing model parameters during the training of several FRL functions [3] considering the changing environments. To the best of our knowledge, this is the first effort to apply model quantization specifically in environmental heterogeneity situations.

In this paper, we simulate the packet loss conditions in a Federated Reinforcement Learning (FRL) system and propose a novel model compression algorithm called "Environment-based Adaptive Model Quantization (EAMQ)", inspired by learnable quantization techniques from [6]. Our approach first identifies the sensitivity of model parameters during reinforcement learning training in different environments. Parameters that exhibit significant variation are classified as sensitive and assigned a lower compression ratio, preserving higher precision by quantizing from float32 to int8, while less sensitive parameters are compressed more aggressively, for instance, from float32 to int4. Additionally, we introduce a learnable quantization mechanism that adaptively adjusts the quantization range by

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minimizing the environment-based Temporal Difference loss function which will be adaptively adjusted according to the changing environment. [9].

Our main contributions are as follows: First, we address the impact of environmental heterogeneity on model quantization by developing a compression ratio allocation strategy tailored to different environments. Second, we propose a novel learnable quantization algorithm that dynamically adjusts the quantization range, along with an environment-aware Temporal Difference loss function that accounts for both RL performance and environmental variability. Third, we adapt traditional model quantization algorithms for heterogeneous environments and compare them with our proposed EAMQ algorithm, establishing a new baseline for future research in model quantization under environmental heterogeneity. Fourth, we deployed our FRL algorithm on a real-world wireless distributed system to evaluate its performance, bridging the gap between theoretical analysis and practical application [5].

2 Method

2.1 Reward-Weighted Sensitivity Based on Environment Reward Distribution

To assign adaptive quantization compression rates based on environment reward distribution differences, we calculate a reward-weighted variance for each parameter. The goal is to assign lower compression rates (e.g., float32 to int4) for parameters that are sensitive in sparse reward environments, and higher compression rates (e.g., float32 to int8) for parameters that are less sensitive in dense reward environments. For each environment e, we first compute the average reward across all time steps:

$$R^e = \frac{1}{T}\sum_{t=1}^{T} r_t^e$$

where r_t^e is the reward at time step t in environment e, and T is the total number of time steps. Next, we define the reward sparsity factor α^e for each environment based on the inverse of the average reward:

$$\alpha^e = \frac{1}{R^e + \epsilon}$$

where ϵ is a small constant added to avoid division by zero. A higher α^e indicates a more sparse reward environment, while a lower α^e indicates a dense reward environment. Using the reward sparsity factor α^e, we compute the reward-weighted variance $\text{Var}_R(\theta_k)$ for each parameter θ_k across all environments:

$$\text{Var}_R(\theta_k) = \frac{1}{n}\sum_{e=1}^{E} \alpha^e \cdot (\theta_k^e - \mu_k)^2$$

where θ_k^e is the value of parameter θ_k in environment e, μ_k is the mean value of θ_k across all environments, and E is the total number of environments.

Finally, we assign compression rates based on the reward-weighted sensitivity. Parameters with higher reward-weighted variance are assigned lower compression rates (e.g., float32 to int4), while parameters with lower reward-weighted variance are assigned higher compression rates (e.g., float32 to int8).

2.2 Learnable model quantization

Symmetric linear quantization is a widely used data quantization technique [13], where the quantization range is centered around zero, treating positive and negative values symmetrically. In this method, the mapping between original and quantized values follows a linear relationship. However, a key limitation of traditional symmetric linear quantization is that the quantization range is predetermined before quantization. This fixed range may not be optimal for preserving model performance across all data distributions, as it may fail to adapt to the specific characteristics of the data.

In this algorithm, we propose a novel learnable linear quantization that optimizes the quantization range for each data using a loss function called the "environment-based Temporal Difference (TD) loss function," which can be adjusted based on different environments. The formula for this loss function is:

$$L_{\text{total}} = L_{\text{task}} + \lambda_{\text{env}} L_{\text{quant}} + \lambda_{\text{reg}} L_{\text{reg}} \tag{1}$$

Where L_{task} is the standard loss in reinforcement learning (e.g., TD error), L_{quant} is the difference between the original and quantized parameters using discrete cosine distance, and L_{reg} is the regularization term introduced to ensure stable quantization decisions across training iterations.

The regularization term L_{reg} is defined as:

$$L_{\text{reg}} = \sum_k \left(\theta_k^{\text{current}} - \theta_k^{\text{previous}}\right)^2$$

Where $\theta_k^{\text{current}}$ represents the parameter values in the current iteration, and $\theta_k^{\text{previous}}$ represents the parameter values from the previous iteration.

In addition, λ_{env} is a weight dynamically adjusted based on the environment's sensitivity, and λ_{reg} is the weight assigned to the regularization term.

The environment-adaptive weight $\lambda_{\text{env},t}$ is calculated as:

$$\lambda_{\text{env},t} = \alpha \cdot \left(\frac{\delta_t}{\max(\delta)}\right) + \beta \cdot \left(\frac{\Delta G}{\max(\Delta G)}\right) \tag{2}$$

Where δ_t is the TD error at step t, representing the difference between predicted and actual rewards; ΔG is the cumulative reward drop rate across environments; and α and β are hyperparameters to balance between TD error and cumulative reward drop.

3 Experiments

3.1 Experiment Setting

In this experiment, we will first use tabular environments to verify the result of our EAMQ algorithm on quantifying the model in PAvg and QAvg. Next, we evaluate the algorithm's effectiveness in deep reinforcement learning tasks, specifically in DQNAvg. The functions and environment configurations are consistent with those used in [3]. We compare our results against the following baselines: QuARL [4], ReLeQ [1], QFL [12], Fixar [10], FedDQ [8], and VQQL [2]. All model quantization algorithms are evaluated under the same compression ratios for a fair comparison. The original models are in float32 format, and we apply different quantization levels: int16 (50% compression), int8 (75% compression), int6 (81.25% compression), and int4 (87.5% compression). For the 81.25% compression ratio, our EAMQ method quantizes half of the data to int8 and the other half to int4, while the other algorithms quantize all data directly to int6.

In our experiments, we apply quantization to either the Q-table (QAvg) or the policy function (PAvg), using two environments: RandomMDPs and WindyCliffs. To simulate varying degrees of heterogeneity across environments, we introduce the parameter κ. As κ increases, the environments become more diverse, reflecting greater dissimilarity in state transition probabilities and reward distributions. Tables 7, 7, 4, and 6 demonstrate that, across different environments and compression ratios, our quantization algorithm consistently outperforms traditional model quantization methods.

For the deep reinforcement learning environment, we quantify the Deep Q-Network (DQN) in two scenarios: Acrobot and CartPole. The performance of DQNAvg is evaluated over 20 episodes. The curve illustrates the generation objective value, which represents the averaged performance across 10 environments with newly generated state transitions. A higher objective value indicates better performance. Our results demonstrate that EAMQ outperforms other model quantization algorithms in terms of overall performance across these environments.

3.2 Ablation Study and Analysis

In this section, we conducted ablation experiments to evaluate the effectiveness of our proposed algorithms. Figures 2a and 2b demonstrate that at a compression ratio of 81.25%, applying a

Table 1: Q-Avg over RandomMDPs for different compression ratios under $\kappa = 0.4$ and $\kappa = 0.6$ larger κ indicates environments with larger environment heterogeneity. The number stands for the average cumulative reward of the algorithm, higher is better

	$\kappa = 0.4$				$\kappa = 0.6$			
Compression Rate	50%	75%	81.25%	87.5%	50%	75%	81.25%	87.5%
QPI	27.88	25.99	23.23	20.89	27.48	25.29	23.03	20.79
QuARL	29.01	26.17	25.33	21.34	28.01	26.07	25.33	21.34
ReLeA	26.58	25.52	24.12	22.99	26.58	24.52	23.02	21.19
VAQL	28.89	27.05	26.33	23.22	27.88	26.15	25.47	23.12
VOQL	29.87	28.57	27.91	23.21	28.86	27.47	26.92	25.25
EAMQ	34.05	33.80	32.15	30.82	34.14	32.80	31.80	30.80

Table 2: P-Avg over WindyCliffs at a compression ratio of 81.25% under $\kappa = 0.6$ and $\kappa = 0.8$ in an FRL system with a high packet loss wireless network.

	$\kappa = 0.6$				$\kappa = 0.8$			
Loss package Rate	50%	70%	80%	90%	50%	70%	80%	90%
No quantization	106.52	95.51	93.11	90.08	10.58	10.72	9.21	9.19
ReLeA	116.52	113.51	104.13	102.05	15.58	14.72	11.91	10.21
VAQL	122.77	116.05	105.31	103.01	28.01	25.95	24.47	23.02
VOQL	121.17	114.51	109.98	105.02	20.06	17.07	14.82	14.15
EAMQ	135.57	133.05	127.14	121.87	31.05	27.28	25.19	23.48

Table 3: P-Avg over RandomMDPs for different compression ratios under $\kappa = 0.4$ and $\kappa = 0.6$ larger κ indicates environments with larger environment heterogeneity. The number stands for the average cumulative reward of the algorithm, higher is better

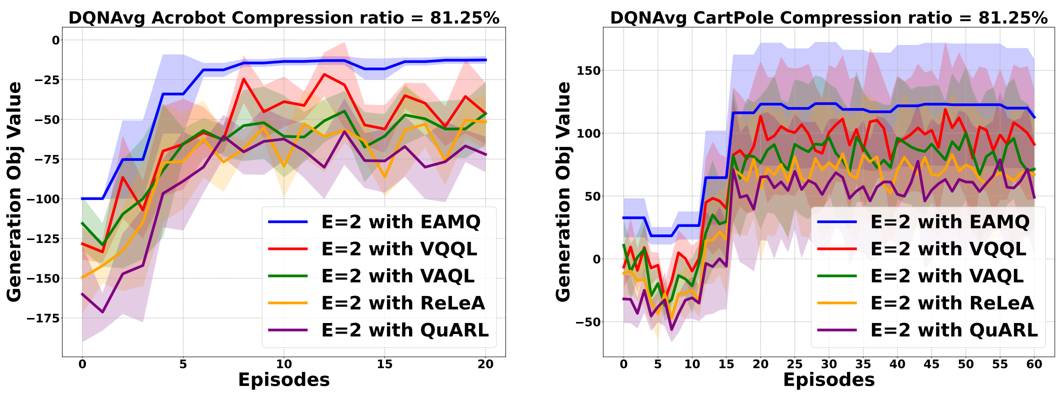
	$\kappa = 0.4$				$\kappa = 0.6$			
Compression Rate	50%	75%	81.25%	87.5%	50%	75%	81.25%	87.5%
QPI	25.18	24.89	22.21	20.81	26.48	22.29	21.03	19.79
QuARL	26.21	25.16	24.32	21.24	28.01	26.07	25.03	21.04
ReLeA	26.52	25.51	24.11	23.98	25.58	24.82	23.00	20.19
VAQL	27.82	26.05	25.39	24.21	28.01	25.95	24.47	23.02
VOQL	28.17	27.51	26.98	25.22	28.06	27.07	26.82	25.15
EAMQ	33.58	32.07	30.15	29.83	32.14	31.81	30.79	29.80

Table 4: Q-Avg over WindyCliffs for different compression ratios under $\kappa = 0.6$ and $\kappa = 0.8$ larger κ indicates environments with larger environment heterogeneity. The number stands for the average cumulative reward of the algorithm, higher is better

	$\kappa = 0.6$				$\kappa = 0.8$			
Compression Rate	50%	75%	81.25%	87.5%	50%	75%	81.25%	87.5%
QPI	125.18	124.89	122.21	120.81	126.48	122.29	121.03	119.79
QuARL	126.21	125.16	124.32	121.24	128.01	126.07	125.03	118.01
ReLeA	126.52	125.41	124.01	123.68	125.58	124.82	123.02	119.09
VAQL	127.81	126.15	125.09	123.19	128.01	125.95	124.47	123.02
VOQL	128.87	127.53	126.08	125.02	128.06	127.07	126.82	125.05
EAMQ	133.96	132.07	130.15	129.83	133.65	131.81	130.79	129.81

Table 5: P-Avg over WindyCliffs for different compression ratios under $\kappa = 0.6$ and $\kappa = 0.8$ larger κ indicates environments with larger environment heterogeneity. The number stands for the average cumulative reward of the algorithm, higher is better

	$\kappa = 0.6$				$\kappa = 0.8$			
Compression Rate	50%	75%	81.25%	87.5%	50%	75%	81.25%	87.5%
QPI	125.18	124.89	122.21	120.01	126.08	122.19	121.93	119.39
QuARL	126.21	125.16	124.32	21.44	128.01	126.07	125.03	121.04
ReLeA	126.52	125.51	124.11	123.08	125.58	124.72	123.91	121.29
VAQL	127.82	126.05	125.39	124.01	28.01	25.95	24.47	23.02
VOQL	128.17	127.51	126.98	125.12	28.06	27.07	26.82	25.15
EAMQ	139.58	132.07	131.15	131.89	32.14	31.81	30.79	29.80



(a) DQNAvg in Acrobot environment

(b) DQNAvg in CartPole environment

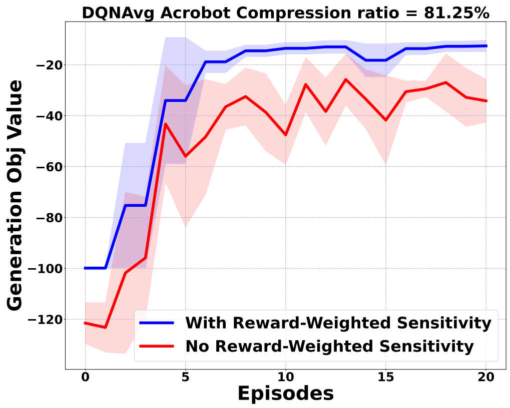
Figure 1: Performance of DQNAvg in different environments. The y-axis shows the cumulative reward of the agents. E=2 means the agents' models are averaged every 2 episodes. Different colors show the performance of the algorithm after quantification by different quantization algorithms, the standard error (a measure of variability or uncertainty) is depicted as a shadow around the line, with the shadow width being 1.65 times the standard error.

uniform compression ratio across all data yields inferior results compared to utilizing Reward-Weighted Sensitivity for adaptive compression allocation, as shown in Figure 7, our learnable model quantization method significantly outperforms traditional symmetric linear quantization.

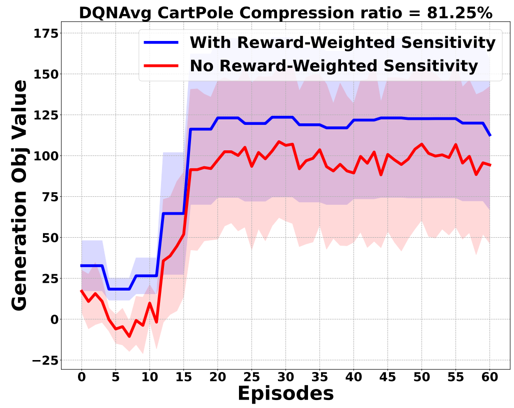
Table 2 demonstrates that FRL performance declines in high packet loss networks due to information loss during communication, a significant challenge in real-world IoT systems [10]. We implemented our algorithm in a real wireless distributed system, controlling the packet loss ratio to simulate communication loss between agents in different environments. Results show that our model quantization algorithm enhances FRL robustness in poor network conditions, highlighting both the effectiveness and efficiency of our approach.

4 Conclusion and Future Work

In this paper, we introduced Environment-based Adaptive Model Quantization (EAMQ) to tackle the challenges of model quantization in heterogeneous environments within Federated Reinforcement Learning (FRL). EAMQ uses reward-weighted sensitivity and a learnable quantization method to adapt compression rates based on the environment, ensuring strong performance across different scenarios. Our experiments show that EAMQ outperforms traditional methods, reducing communication costs while preserving or improving model effectiveness. We hope our algorithm will encourage further exploration of Federated Reinforcement Learning model quantization in heterogeneous environments, as a promising and innovative direction for advancing model compression techniques.



(a) DQNAvg in Acrobot environment



(b) DQNAvg in CartPole environment

Figure 2: Performance of DQNAvg in different environments. We compare the performance in the same compression ratio between we not using Reward-Weighted Sensitivity analysis and using Reward-Weighted Sensitivity analysis

Table 6: P-Avg over WindyCliffs for different compression ratios under $\kappa = 0.6$ and $\kappa = 0.8$ larger κ indicates environments with larger environment heterogeneity. The number stands for the average cumulative reward of the algorithm, higher is better

	$\kappa = 0.6$				$\kappa = 0.8$			
Compression Rate	50%	75%	81.25%	87.5%	50%	75%	81.25%	87.5%
QPI	125.18	124.89	122.21	120.01	26.08	22.19	21.93	19.39
QuARL	126.21	125.16	124.32	21.44	26.01	26.07	25.03	21.04
ReLeA	126.52	125.51	124.11	123.08	25.58	24.72	23.91	21.29
VAQL	127.82	126.05	125.39	124.01	28.01	25.95	24.47	23.02
VOQL	128.17	127.51	126.98	125.12	28.06	27.07	26.82	25.15
EAMQ	139.58	132.07	131.15	131.89	32.14	31.81	30.79	29.80

Table 7: Q-Avg and P-Avg over RandomMDPs for different compression ratios under $\kappa = 0.4$ and $\kappa = 0.6$, the result we use Learnable model quantization or directly using Symmetric linear quantization

	$\kappa = 0.4$				$\kappa = 0.6$			
Compression Rate(Q-Avg)	50%	75%	81.25%	87.5%	50%	75%	81.25%	87.5%
Linear quantization	26.17	26.07	25.01	21.21	25.86	24.47	22.02	21.15
EAMQ(ours)	33.58	32.07	30.15	29.83	32.14	31.81	30.79	29.80

	$\kappa = 0.4$				$\kappa = 0.6$			
Compression Rate(P-Avg)	50%	75%	81.25%	87.5%	50%	75%	81.25%	87.5%
Linear quantization	29.17	28.07	28.01	22.21	27.86	26.47	26.02	24.15
EAMQ(ours)	34.05	33.80	32.15	30.82	34.14	32.80	31.80	30.80

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A Algorithm

B Detail of Q-Avg function

B.1 Q-Avg Algorithm in Federated Reinforcement Learning

In this paper, we apply the Q-Avg algorithm, a variant of the Q-learning algorithm adapted for Federated Reinforcement Learning (FRL). Q-Avg is designed to address the challenges of training multiple agents across distributed and heterogeneous environments by periodically averaging the Q-value updates from each agent. This approach aims to reduce communication costs and improve the overall performance of the system in scenarios with varying environment dynamics.

Algorithm 1 Gradient Descent for Quantization Range Optimization with Regularization and Environment Sensitivity

Require: Initialized quantization ranges $S = \{S_1, S_2, \ldots, S_m\}$, learning rate η, number of iterations T, λ_{reg}, λ_{env}.

Initialize parameters S_k for each parameter k
for each iteration $t = 1 \to T$ **do**
    Compute task loss L_{task}
    Quantize parameters using current quantization ranges S_k
    Compute quantization loss L_{quant}
    Compute regularization term:

$$L_{\text{reg}} = \sum_k \left(\theta_k^{\text{current}} - \theta_k^{\text{previous}}\right)^2$$

    Compute total loss:

$$L_{\text{total}} = L_{\text{task}} + \lambda_{\text{env}} L_{\text{quant}} + \lambda_{\text{reg}} L_{\text{reg}}$$

    for each parameter S_k **do**
        Compute gradient $\frac{\partial L_{\text{total}}}{\partial S_k}$
        Update quantization range:

$$S_k \leftarrow S_k - \eta \frac{\partial L_{\text{total}}}{\partial S_k}$$

    end for
end for
Return optimized quantization ranges S

Q-Value Averaging: In each environment, agents independently learn Q-values by interacting with the environment. After a set number of episodes, the Q-value updates from each agent are transmitted to a central server where the **Q-Avg** algorithm computes the averaged Q-values across all participating agents. This ensures that all agents benefit from each other's learning experiences, even in environments with heterogeneous state transitions and reward functions. The Q-Avg formula is given by:

$$Q_{\text{avg}}(s, a) = \frac{1}{N} \sum_{i=1}^{N} Q_i(s, a) \tag{3}$$

where N is the number of agents, $Q_i(s, a)$ is the Q-value of agent i for state s and action a, and $Q_{\text{avg}}(s, a)$ represents the averaged Q-value after aggregation.

Handling Heterogeneous Environments: One of the key advantages of Q-Avg is its ability to handle heterogeneous environments. In standard reinforcement learning, models are trained in homogeneous environments, but in FRL, agents operate in environments with different state transition dynamics and reward structures. To address this, Q-Avg adapts by incorporating the agents' experiences across diverse environments. This allows agents to generalize better to new environments and ensures robustness in learning.

Communication Efficiency: A major challenge in FRL is the communication overhead due to frequent parameter updates. Q-Avg mitigates this by reducing the frequency of communication between agents and the server, only averaging the Q-values after a predefined number of episodes. By doing so, Q-Avg minimizes the communication costs while still benefiting from collaborative learning across agents.

Algorithm Overview: The overall steps of the Q-Avg algorithm can be summarized as follows:

1. **Initialization:** Each agent initializes its Q-table $Q_i(s, a)$ and begins interacting with its local environment.

2. **Learning:** Each agent updates its Q-values using the standard Q-learning update rule:

$$Q_i(s,a) \leftarrow Q_i(s,a) + \alpha \left(r + \gamma \max_{a'} Q_i(s', a') - Q_i(s,a) \right) \tag{4}$$

where α is the learning rate, r is the reward, and γ is the discount factor.

3. **Averaging:** After a fixed number of episodes, each agent sends its updated Q-values to the central server, which computes the average Q-values:

$$Q_{\text{avg}}(s,a) = \frac{1}{N} \sum_{i=1}^{N} Q_i(s,a) \tag{5}$$

4. **Update:** The central server sends the averaged Q-values $Q_{\text{avg}}(s,a)$ back to the agents, which update their Q-tables accordingly.
5. **Reiteration:** The process continues, with agents periodically sending their updated Q-values for averaging and receiving the averaged Q-values from the server.

Advantages

- **Collaborative Learning:** Q-Avg enables agents to leverage the experiences of other agents, improving overall learning performance in federated environments.
- **Scalability:** The algorithm scales efficiently with the number of agents, as the Q-value averaging process is simple and communication is minimized.
- **Adaptability:** Q-Avg is well-suited to handle heterogeneous environments, making it robust in real-world scenarios where environment dynamics vary between agents.

Overall, Q-Avg offers a simple yet effective solution for federated Q-learning, particularly in scenarios where communication costs and environment diversity are key challenges.

C Detail of P-Avg function

C.1 P-Avg Algorithm in Federated Reinforcement Learning

In this paper, we utilize the **P-Avg** algorithm, a federated averaging approach specifically designed for policy-based reinforcement learning in distributed environments. P-Avg focuses on averaging policy parameters across multiple agents, allowing them to collaboratively improve their policies while interacting with heterogeneous environments. This method is particularly useful for handling policy gradients in Federated Reinforcement Learning (FRL), where agents work in diverse environments and need to share their policy updates efficiently.

Policy Averaging: The core idea of P-Avg is to periodically average the policy parameters from each agent to form a global policy. Each agent learns its local policy by interacting with its environment, and after a set number of episodes, the policies are shared with a central server for averaging. The **P-Avg** update rule is as follows:

$$\pi_{\text{avg}} = \frac{1}{N} \sum_{i=1}^{N} \pi_i \tag{6}$$

where N is the number of agents, π_i represents the policy parameters of agent i, and π_{avg} is the averaged policy after aggregation. This global policy is then distributed back to the agents for further updates.

Handling Environmental Heterogeneity: P-Avg is particularly effective in **heterogeneous environments**, where each agent operates in a different environment with its own dynamics and reward structures. Since each agent learns a policy suited to its local environment, averaging these policies helps agents generalize across different environments. This approach ensures that all agents benefit from each other's experiences, improving the robustness of the global policy.

Policy Gradient Updates: In P-Avg, each agent updates its local policy parameters using the **policy gradient** method. For each agent i, the policy is updated using the following rule:

$$\theta_i \leftarrow \theta_i + \alpha \nabla_{\theta_i} J(\theta_i) \tag{7}$$

where θ_i are the policy parameters for agent i, α is the learning rate, and $\nabla_{\theta_i} J(\theta_i)$ is the policy gradient computed based on the agent's experience. After a fixed number of updates, the local policies are shared and averaged, as described earlier.

Algorithm Overview: The overall process of P-Avg can be summarized as follows:

1. **Initialization:** Each agent initializes its policy parameters π_i and begins interacting with its local environment.
2. **Policy Update:** Each agent updates its policy using the policy gradient method:
$$\theta_i \leftarrow \theta_i + \alpha \nabla_{\theta_i} J(\theta_i)$$
where θ_i are the policy parameters, and $J(\theta_i)$ is the objective function.
3. **Averaging:** After a predefined number of episodes, each agent sends its updated policy parameters π_i to the central server, which computes the averaged policy:
$$\pi_{\text{avg}} = \frac{1}{N} \sum_{i=1}^{N} \pi_i$$
4. **Update:** The central server sends the averaged policy π_{avg} back to the agents, which update their local policies accordingly.
5. **Reiteration:** The process repeats, with agents periodically sending their policy updates for aggregation and receiving the averaged policy from the server.

Communication Efficiency: Like Q-Avg, P-Avg reduces communication costs by minimizing the frequency of parameter exchanges between agents and the server. Instead of continuously transmitting policy updates, agents only communicate their policies after a set number of episodes, reducing the overall communication overhead in large-scale distributed systems.

Advantages

- **Collaborative Learning:** P-Avg enables agents to share and combine their policies, leveraging the collective knowledge from diverse environments.
- **Adaptability to Heterogeneous Environments:** By averaging policies across agents working in different environments, P-Avg improves the generalization of policies to unseen or diverse conditions.
- **Scalability:** The algorithm scales efficiently with the number of agents, as policy averaging is computationally lightweight and reduces the need for frequent communication.

Overall, P-Avg provides a scalable and efficient solution for policy-based reinforcement learning in federated settings, particularly when agents operate in environments with varying dynamics and reward structures.

D Detail of DQNAvg function

D.1 DQNAvg Algorithm in Federated Reinforcement Learning

The **DQNAvg** algorithm is an adaptation of the standard Deep Q-Network (DQN) for Federated Reinforcement Learning (FRL) environments, where multiple agents learn independently in distributed environments and periodically share their model parameters with a central server for aggregation. DQNAvg is particularly useful in continuous action spaces, where learning a robust policy across heterogeneous environments is crucial for improving performance while reducing communication costs.

Deep Q-Network (DQN): DQN is a model-free reinforcement learning algorithm where a neural network is used to approximate the Q-values $Q(s, a)$ for each state-action pair. The network is trained to minimize the difference between the predicted Q-values and the target Q-values, which are based on the Bellman equation:

$$Q(s,a) \leftarrow Q(s,a) + \alpha \left(r + \gamma \max_{a'} Q(s', a') - Q(s,a) \right) \tag{8}$$

where α is the learning rate, γ is the discount factor, r is the reward, and s', a' represent the next state and action, respectively.

Averaging Q-Networks: In DQNAvg, each agent trains its own local Q-network based on its interactions with the environment. After a certain number of episodes, the local Q-networks are sent to the central server, where they are aggregated to form a global Q-network. This global Q-network is then distributed back to the agents for further training, ensuring that agents benefit from the experiences of others.

The aggregation of Q-networks follows a simple averaging scheme:

$$Q_{\text{avg}}(s,a) = \frac{1}{N} \sum_{i=1}^{N} Q_i(s,a) \tag{9}$$

where N is the number of agents, $Q_i(s, a)$ represents the Q-values of agent i, and $Q_{\text{avg}}(s, a)$ is the averaged Q-value for each state-action pair after aggregation.

Handling Environmental Heterogeneity: DQNAvg is designed to handle **heterogeneous environments**, where each agent operates in an environment with different state-transition dynamics and reward functions. By averaging the Q-values across agents, DQNAvg ensures that the global Q-network reflects experiences from diverse environments, improving the generalization of policies to new and unseen conditions.

The key advantage of this approach is that agents can learn robust policies even in environments with varying dynamics, as the averaging process incorporates knowledge from multiple sources.

Experience Replay: Each agent in DQNAvg uses an **experience replay buffer** to store past transitions, which are sampled randomly to break the correlation between consecutive experiences. The Q-network is updated using mini-batches of experiences from the replay buffer, ensuring more stable and efficient learning.

Algorithm Overview: The main steps of the DQNAvg algorithm can be summarized as follows:

1. **Initialization:** Each agent initializes its Q-network Q_i and its experience replay buffer.
2. **Learning:** Each agent interacts with its local environment, updates its Q-network using the DQN update rule, and stores experiences in the replay buffer:

$$Q_i(s,a) \leftarrow Q_i(s,a) + \alpha \left(r + \gamma \max_{a'} Q_i(s', a') - Q_i(s,a) \right)$$

3. **Averaging:** After a fixed number of episodes, each agent sends its Q-network Q_i to the central server. The server computes the average Q-network as:

$$Q_{\text{avg}}(s,a) = \frac{1}{N} \sum_{i=1}^{N} Q_i(s,a)$$

4. **Update:** The averaged Q-network Q_{avg} is sent back to all agents, which update their local Q-networks accordingly.
5. **Reiteration:** The process continues with agents periodically sending their Q-networks for aggregation and receiving the averaged Q-network for further training.

Communication Efficiency: To reduce communication overhead, DQNAvg only averages Q-networks after a predefined number of episodes. This minimizes the frequency of model transmissions, significantly lowering communication costs in federated settings, especially when applied to large-scale environments.

Advantages:

- **Collaborative Learning:** DQNAvg allows agents to leverage the experiences of others, enabling faster and more robust learning in distributed environments.
- **Adaptability to Heterogeneous Environments:** By averaging Q-values across diverse environments, DQNAvg ensures that the global model can generalize to a wide range of conditions.
- **Reduced Communication Costs:** The periodic averaging of Q-networks ensures that communication is minimized, making DQNAvg well-suited for large-scale federated learning applications.

Overall, DQNAvg extends the traditional DQN approach to a federated learning framework, allowing multiple agents to collaborate and learn efficiently across diverse environments while reducing communication costs and improving policy generalization.

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