

Scalable Reinforcement Learning via Adaptive Batch Scaling

Jongchan Park*

Hyundai Motor Company

{jcpark11@hyundai.com}

Research Question.

- Why most of reinforcement learning (RL) employ modest batch sizes?
 - Many RL studies adopt **small batch sizes** compared to standard supervised learning (SL).
 - Several studies report that **increasing the batch size** often leads to **diminishing returns** or even **performance degradation** in **RL**[1, 2].

[1] McCandlish, S., Kaplan, J., Amodei, D., and Team, O. D. An empirical model of large-batch training. arXiv preprint arXiv:1812.06162, 2018.

[2] Obando Ceron, J., Bellemare, M., and Castro, P. S. Small batch deep reinforcement learning. Advances in Neural Information Processing Systems, 36:26003–26024, 2023.

Research Question.

- Why most of reinforcement learnings (RL) employ modest batch size?
 - This phenomenon extends even to **scaled RL models**, such as IMPALA[1], SHARSA[2]; they utilize small batch sizes of 32 and 256 respectively.
 - Furthermore, in RL stages for **Large Language Model (LLM)** training, they also utilize notably smaller batch sizes compared to the massive scales employed during SL phases[3, 4].

[1] Espeholt, Lasse, et al. "Impala: Scalable distributed deep-rl with importance weighted actor-learner architectures." International conference on machine learning. PMLR, 2018.

[2] Park, Seohong, et al. "Horizon reduction makes rl scalable." Advances in Neural Information Processing Systems 38 (2026): 8350-8389.

[3] Rafailov, R., Sharma, A., Mitchell, E., Manning, C. D., Ermon, S., and Finn, C. Direct preference optimization: Your language model is secretly a reward model. Advances in neural information processing systems, 36: 53728–53741, 2023.

[4] Guo, D., Yang, D., Zhang, H., Song, J., Zhang, R., Xu, R., Zhu, Q., Ma, S., Wang, P., Bi, X., et al. Deepseek-r1: Incentivizing reasoning capability in llms via reinforcement learning. arXiv preprint arXiv:2501.12948, 2025.

Our Hypothesis.

- We suppose that this stems from the **inherent non-stationary of RL**.
 - An **evolving policy** and the resulting **data distribution shifts** during training create this non-stationary.
 - This non-stationary is **particularly acute during early learning stages**, where rapid policy shifts exacerbate distributional instability.
 - To mitigate these effects, **employing modest batch sizes is often preferred**, as it allows the agent to adapt more fluidly to the non-stationary data stream[1].

[1] Obando Ceron, J., Bellemare, M., and Castro, P. S. Small batch deep reinforcement learning. Advances in Neural Information Processing Systems, 36:26003–26024, 2023.

Our Hypothesis.

- We suppose that this stems from the **inherent non-stationary of RL**.
- We also assume that the **policy and environment will stabilize in late learning phase** which we call '**near-stationary**' phase.

Our Insight.

- We suppose that this stems from the **inherent non-stationary of RL**.
- We also assume that the **policy and environment will stabilize in late learning phase** which we call '**near-stationary**' phase.



Can we leverage the benefits of large batch sizes by increasing them during this near-stationary phase?

Behavioral Divergence.

- We quantify non-stationarity by comparing consecutive policy updates.

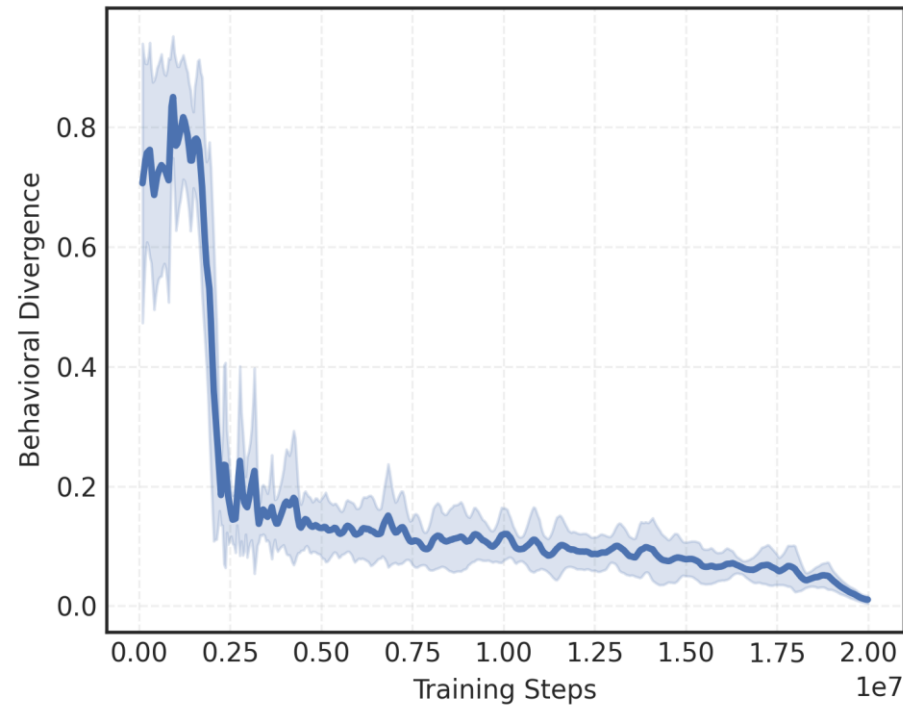
$$\delta_{\pi}(\theta', \theta) := \frac{1}{M} \sum_{i=1}^M \mathbb{I}[\pi_{\theta'}(s_i) \neq \pi_{\theta}(s_i)], \quad s_i \sim \mathcal{B}_{ref}$$

- δ_{π} : Behavioral Divergence (BD).
- $\mathcal{B}_{ref}$: Replay buffer to calculate BD.
- M : Size of $\mathcal{B}_{ref}$.
- $\pi_{\theta'}, \pi_{\theta}$: updated and previous policies respectively.

Behavioral Divergence.

- Figure 1 shows that Behavioral Divergence shrinks as training progress.
- This indicates that the **non-stationarity decreases** over training steps.

Figure 1



Adaptive Batch Scaling (ABS).

- Utilize **small batches** during the **non-stationary early training phase**
 - To maximize gradient update frequency and preserve **plasticity**
- Transition to **larger batches** in the **near-stationary later phase**
 - To ensure **stable convergence**

Adaptive Batch Scaling (ABS).

- ABS dynamically scales batch sizes $|\mathcal{B}|$ by adjusting the rollout length L_{adapt} :

$$|\mathcal{B}| = E \cdot L_{adapt}$$

- L_{adapt} in response to the measured Behavioral Divergence δ_π

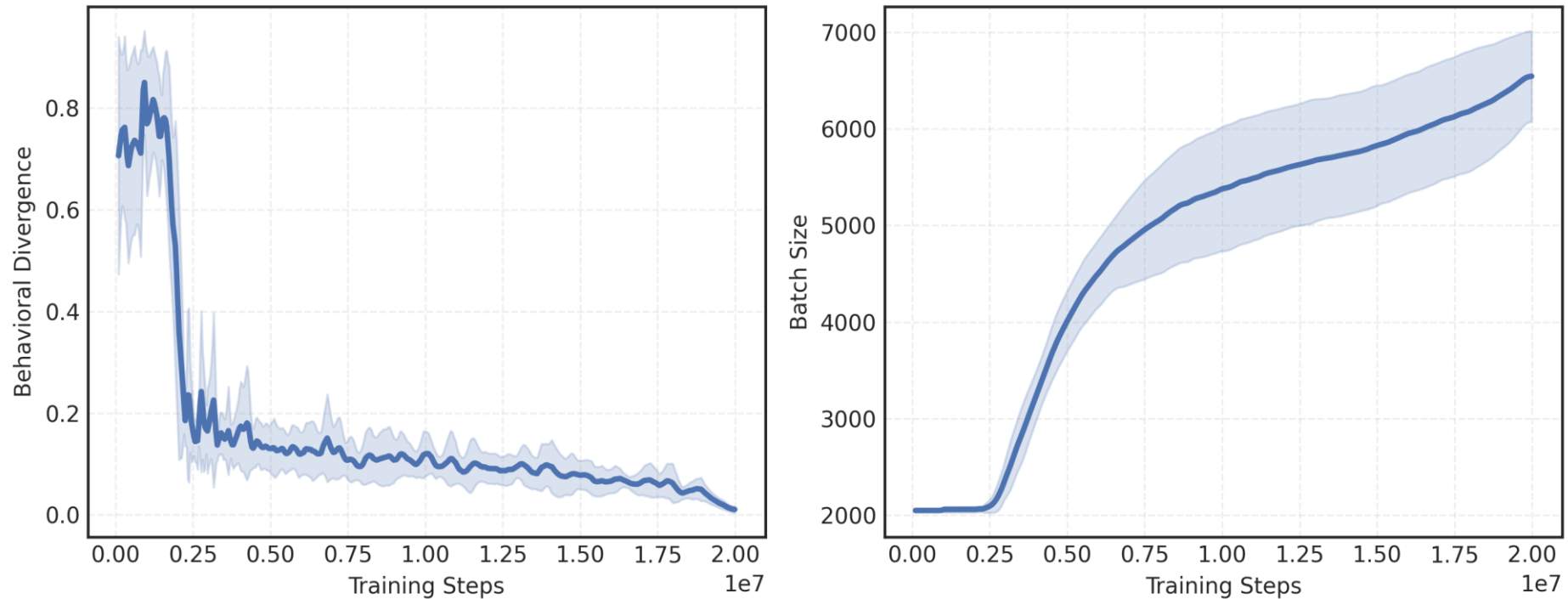
$$L_{adapt} = L_{\max} - \alpha \cdot (L_{\max} - L_{\min}) \quad \alpha = \frac{\log(\delta_{\pi, \text{clipped}} / \delta_{\min})}{\log(\delta_{\max} / \delta_{\min})}$$

- $\delta_{\pi, \text{clipped}} = \text{clip}(\delta_\pi, \delta_{\min}, \delta_{\max})$
- $[\delta_{\min}, \delta_{\max}]$ represents the sensitivity range of the policy change rate

Adaptive Batch Scaling (ABS).

- Figure 2 shows that the batch size of ABS increases inversely with Behavioral Divergence.

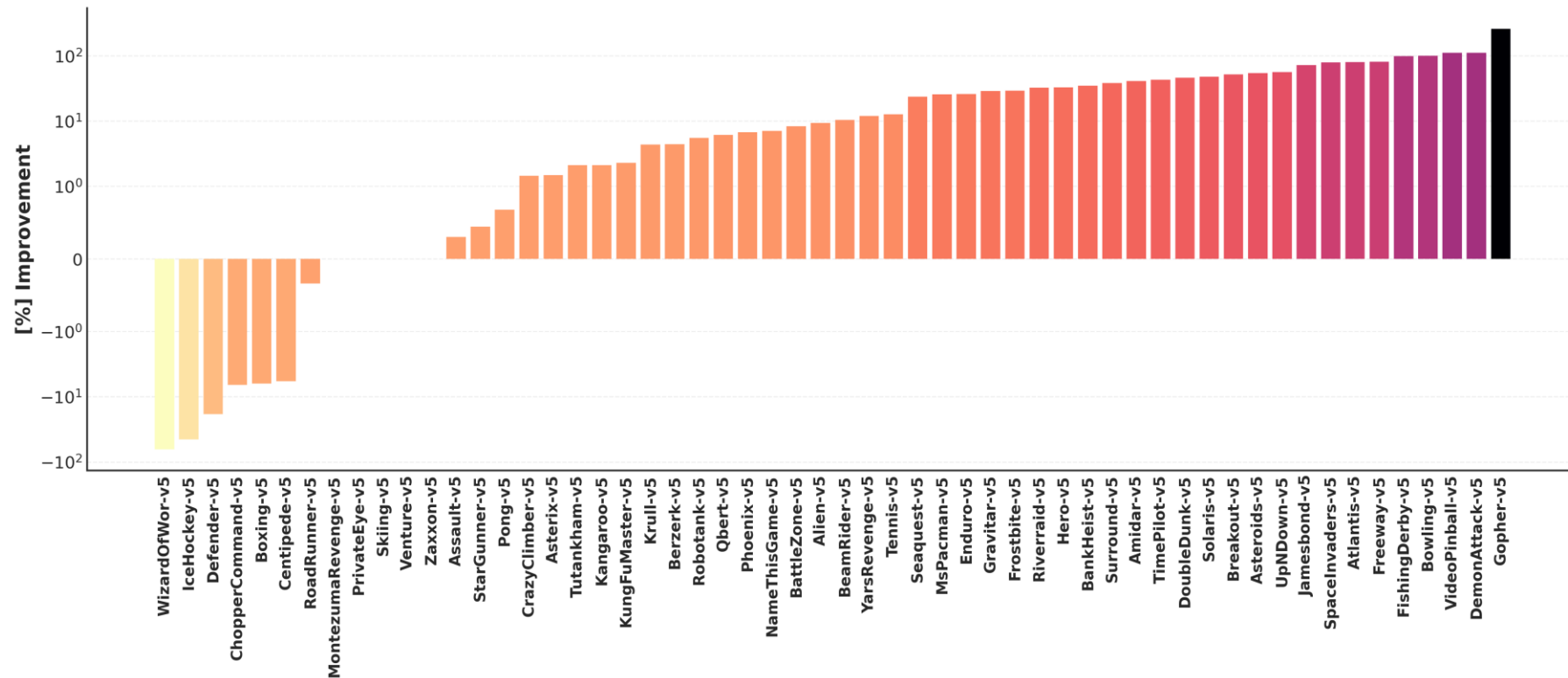
Figure 2



Experimental Results.

- Figure 3 demonstrates that our ABS increases PQN[1] performance across most of the Atari-57 benchmark.

Figure 3

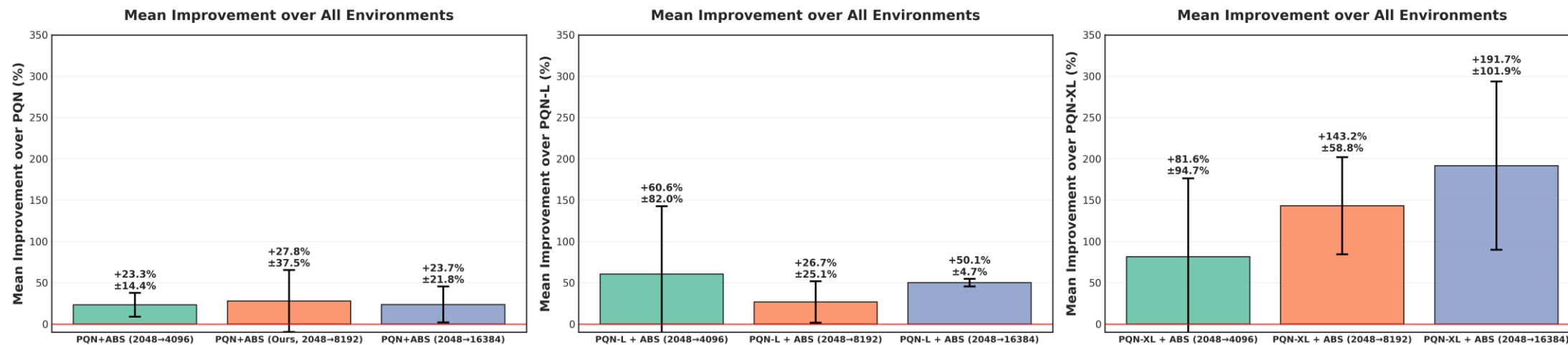


[1] Gallici, M., Fellows, M., Ellis, B., Pou, B., Masmitja, I., Foerster, J. N., and Martin, M. Simplifying deep temporal difference learning. arXiv preprint arXiv:2407.04811, 2024.

Experimental Results.

- Figure 4 shows that the mean improvement over each baseline (PQN, PQN-L[1], PQN-XL[1]) across various maximum batch sizes on Atari-10[2]

Figure 4



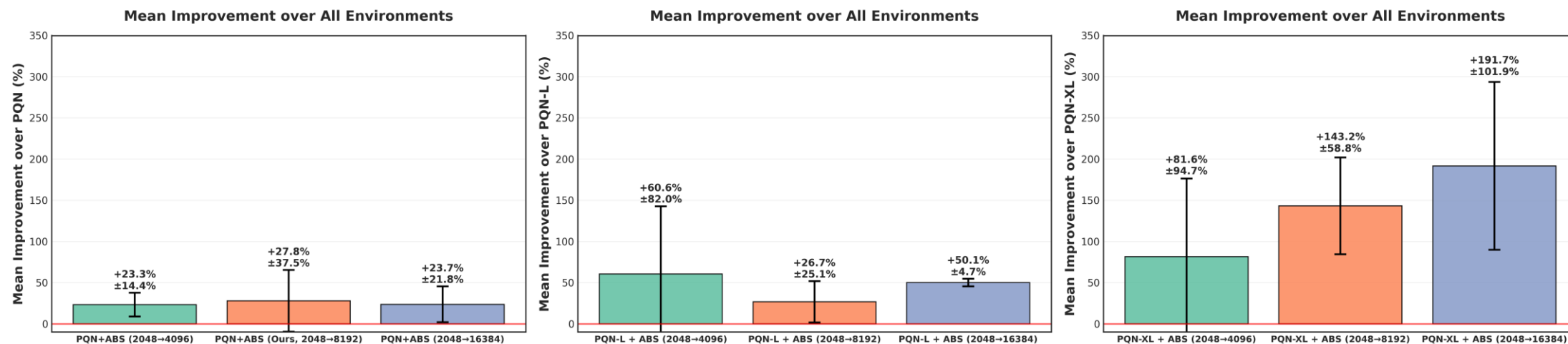
[1] Castanyer, R. C., Obando-Ceron, J., Li, L., Bacon, P.-L., Berseth, G., Courville, A., and Castro, P. S. Stable gradients for stable learning at scale in deep reinforcement learning. arXiv preprint arXiv:2506.15544, 2025.

[2] Aitchison, M., Sweetser, P., and Hutter, M. Atari-5: Distilling the arcade learning environment down to five games. In International Conference on Machine Learning, pp. 421–438. PMLR, 2023.

Experimental Results.

- As **model capacity** and **maximum batch size increase**, the **improvements** yielded by ABS become **more pronounced**.
- For PQN-XL (the largest model), ABS achieves the most substantial gains when scaling the batch size from 2,048 to 16,384 samples.

Figure 4



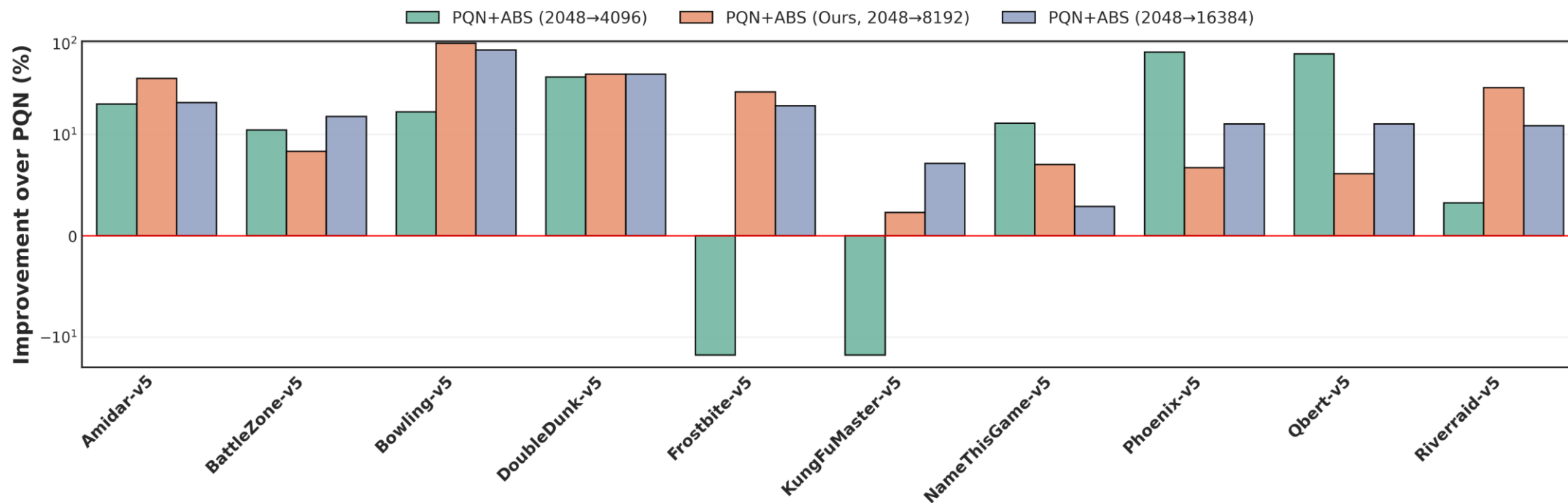
Conclusion.

- **Core Insight:** RL's inherent non-stationarity stabilizes in the later phase, allowing the effective use of larger batch sizes.
- **Proposed ABS:** Automatically scales up the batch size as behavioral divergence shrinks, avoiding early-stage performance drops.
- **Scalable RL Contribution:** Maximizes training efficiency for large-scale RL models, enabling more effective and scalable training.

Appendix.

- Figure 5 shows the detailed improvement of PQN+ABS in Figure 4 (Left) on the Atari-10 environments

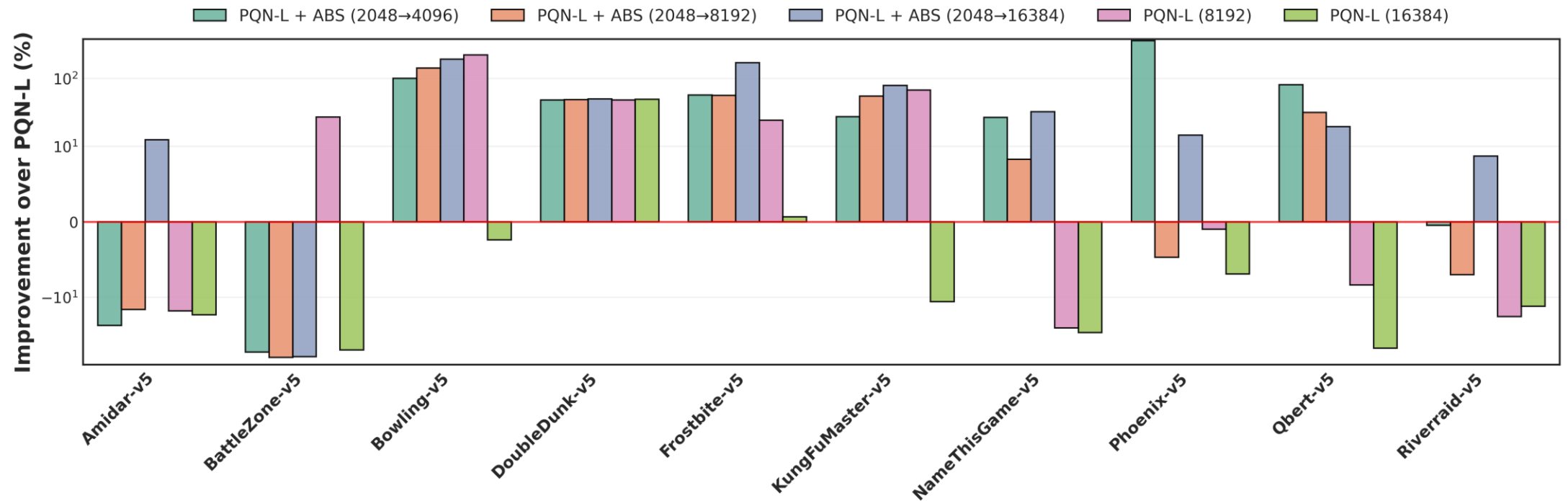
Figure 5



Appendix.

- Figure 6 shows the detailed improvement of PQN-L+ABS in Figure 4 (Center) on the Atari-10 environments

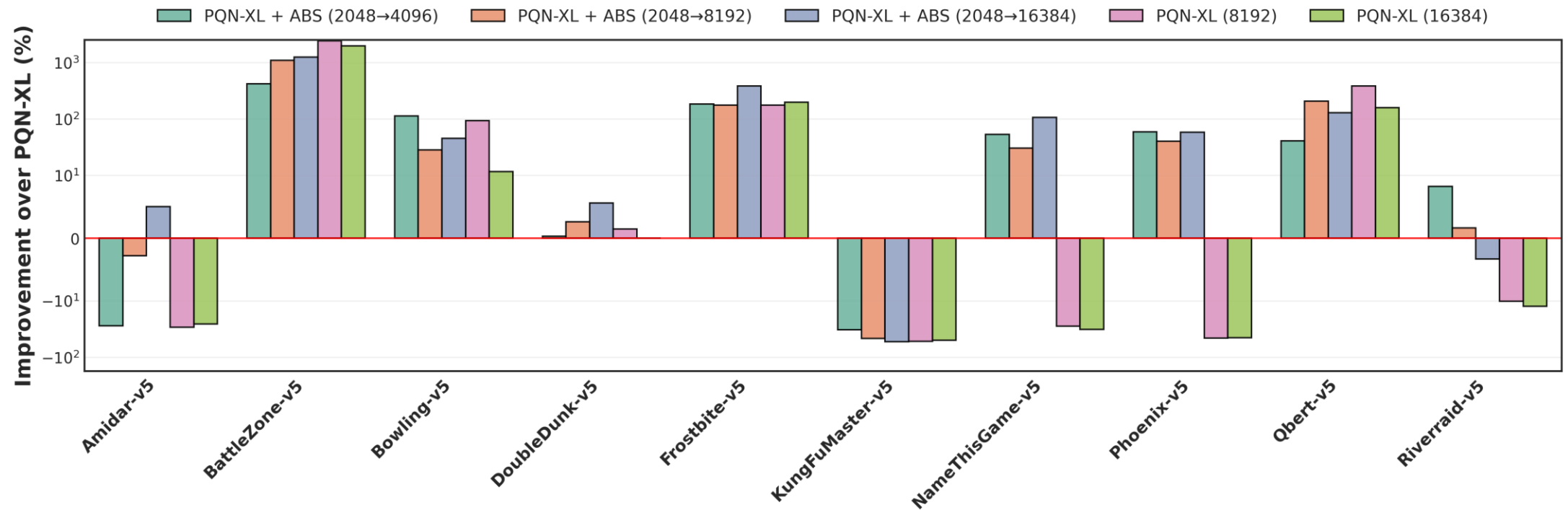
Figure 6



Appendix.

- Figure 7 shows the detailed improvement of PQN-XL+ABS in Figure 4 (Right) on the Atari-10 environments

Figure 7



Appendix.

Algorithm 1 PQN with Adaptive Batch Scaling (ABS)

Input: Initial parameters θ , environment count E , update frequency K , thresholds $\delta_{\min}, \delta_{\max}$, bounds $L_{\min}, L_{\max}$.

while $t < T_{\text{total}}$ **do**

 If $t \pmod{K} == 0$, set $\theta_{\text{old}} \leftarrow \theta$.

Step 1: Data Collection

 Collect trajectories for L_{adapt} steps using E environments and policy π_{θ} .

$t = t + (E \times L_{\text{adapt}})$

Step 2: Policy Update

for $epoch = 1$ **to** N_{epochs} **do**

 Sample mini-batches from the collected trajectories.

 Update θ by minimizing PQN loss.

end for

Step 3: Adaptive Scaling

if $t \pmod{K} == 0$ **then**

 Sample reference batch $\mathcal{B}_{\text{ref}}$ of size M from the collected trajectories.

 Calculate behavioral divergence:

$$\delta_{\pi} = \frac{1}{M} \sum \mathbb{I}[\pi_{\theta}(s) \neq \pi_{\theta_{\text{old}}}(s)], \quad s \sim \mathcal{B}_{\text{ref}}$$

 Calculate L'_{adapt} based on δ_{π} (Eq. 4).

 Smooth update: $L_{\text{adapt}} \leftarrow (1 - \alpha)L_{\text{adapt}} + \alpha L'_{\text{adapt}}$

end if

end while

PQN w/ ABS

Parameter	Value
<i>General Hyperparameters</i>	
Total Timesteps	2×10^7
Num. Environments	128
Frame Stack	4
Sticky Action Probability	0
Life Information	False
Learning Rate	2.5×10^{-4}
Base Steps per Rollout ($L_{\min}$)	32
Discount Factor (γ)	0.99
Mini-batches	4
Update Epochs (N_{epochs})	2
Max Grad Norm	10.0
Exploration ($\epsilon_{\text{start}} \rightarrow \epsilon_{\text{end}}$)	$1.0 \rightarrow 0.001$
Exploration Fraction	0.10
Q-Learning λ	0.65
<i>Adaptive Rollout Hyperparameters</i>	
Adapt Rollout	True
Rollout Range ($L_{\min}, L_{\max}$)	[16, 64]
Adapt Frequency (K)	50 iterations
Policy Change Thresholds ($\delta_{\min}, \delta_{\max}$)	[0.05, 0.95]
Schedule Type	log

PQN-L/XL w/ ABS

Parameter	Value
<i>General Hyperparameters</i>	
Total Timesteps	2×10^7
Num. Environments	128
Frame Stack	4
Sticky Action Probability	0
Life Information	False
Learning Rate	2.5×10^{-4}
Anneal LR	False
Base Steps per Rollout ($L_{\min}$)	32
Discount Factor (γ)	0.99
Mini-batches	4
Update Epochs (N_{epochs})	2
Max Grad Norm	10.0
Exploration ($\epsilon_{\text{start}} \rightarrow \epsilon_{\text{end}}$)	$1.0 \rightarrow 0.001$
Exploration Fraction	0.10
Q-Learning λ	0.65
<i>Multi-Skip Network Architecture</i>	
Use Multi-Skip Residual MLP	True
MLP Hidden Size	512
MLP Layers	5
Layer Normalization	True
Activation Function	ReLU
CNN Channels	(64, 128, 128)
<i>Adaptive Rollout Settings</i>	
Adapt Rollout	True
Rollout Range ($L_{\min}, L_{\max}$)	[16, 128]
Adapt Frequency (K)	50 iterations
Policy Change Thresholds ($\delta_{\min}, \delta_{\max}$)	[0.05, 0.95]
Schedule Type	log