What Matters for Maximizing Data Reuse In Value-based Deep Reinforcement Learning

Roger Creus Castanyer[1,2], **Glen Berseth**[1,2], **Pablo Samuel Castro**[1,2,3]
{roger.creus.castanyer, glen.berseth}@mila.quebec, psc@google.com

[1]**Université de Montréal**
[2]**Mila – Quebec AI Institute**
[3]**Google DeepMind**

Abstract

A key ingredient for successfully applying deep reinforcement learning to challenging tasks is the effective use of data at scale. Although originally deep RL algorithms achieved this by storing past experiences collected from a synchronous actor in an external replay memory (DQN; Mnih, 2013), follow-up works scaled training by collecting data asynchronously through distributed actors (R2D2; Kapturowski et al., 2018), and more recently by GPU-optimized parallelization (PQN; Gallici et al., 2024). We argue that DQN, PQN, and R2D2 constitute the outer vertices of a graph, whose edges correspond to the addition or removal of various training techniques, and whose interior has thus far remained unexplored. We conduct a thorough empirical study to populate this interior and develop an understanding of the relationship between the uncovered methods. Our empirical analyses demonstrate that maximizing data reuse involves addressing the deadly triad: Q-lambda rollouts for reducing the bias from bootstrapping, the use of LayerNorm for stabilizing function approximation, and parallelized data collection for mitigating off-policy divergence. Our code is publicly available at https://github.com/roger-creus/data-reuse-deep-rl

1 Introduction

A number of works have built on the seminal DQN reinforcement learning agent (Mnih, 2013) to achieve strong performance in complex benchmarks (Hessel et al., 2018), and to provide advances in online representation learning (Castro et al., 2021), exploration (Osband et al., 2016), sample efficiency (Schwarzer et al., 2023), and compute efficiency (Kapturowski et al., 2018). These value-based algorithms leverage previously gathered (off-policy) training data for improved sample efficiency, a distinct advantage over policy-gradient methods that require gathering new (on-policy) data for each update (Sutton & Barto, 2018). Recent GPU-optimization techniques have enabled new environment simulations achieving tens of thousands of steps per second (Matthews et al., 2024; Weng et al., 2022), which can dramatically speed up training.

Despite their advantages, value-based methods face persistent learning challenges due to the "deadly triad" of RL: the interplay between function approximation, bootstrapping, and off-policy learning (van Hasselt et al., 2018). This triad induces severe learning instabilities, particularly when reusing off-policy data, as it amplifies the bias-variance trade-offs inherent to temporal difference (TD) learning. Consequently, value-based algorithms require careful tuning of hyper-parameters, such as small batches, low replay ratios, and large buffers, to ensure stability, making it challenging to scale with more compute (Obando-Ceron et al., 2024).

These issues are more apparent with parallelized data collection, as used by Apex (Horgan et al., 2018), R2D2 (Kapturowski et al., 2018), and PQN (Gallici et al., 2024), which explore asynchronous

and GPU-compiled training setups, necessitating a number of important design choices. For example, R2D2 uses an LSTM (Hochreiter & Schmidhuber, 1997) and prioritized replay (Schaul, 2015), while PQN discards target networks in favor of Layer Normalization (Lei Ba et al., 2016) and eliminates the replay buffer altogether. The learning targets also vary: DQN uses single-step updates (Q(0)), while R2D2 and PQN calculate multi-step updates over full rollouts. These differences illustrate how progress in value-based algorithms span architecture, sampling regimes, and learning objectives. Indeed, these improvements directly address the deadly triad by reducing the reliance on off-policy data (Gallici et al., 2024; Schaul, 2015) or improving function approximation through techniques such as layer normalization.

In this work, we take a data-centric view of the deadly triad in deep RL, systematically tracing the evolution of a representative subset of value-based algorithms. Central to our contributions is the introduction of the **Data Replay Ratio** (DRR), a novel metric that offers a more nuanced understanding of data reuse in value-based methods. This metric forms the basis for optimizing algorithmic efficiency and represents a key highlight of our work.

We conduct a systematic evaluation on subsets of the Arcade Learning Environment (ALE) (Bellemare et al., 2013), exploring algorithmic design choices that interpolate between foundational and modern value-based methods. A high-level summary of this investigation is provided in Figure 6. Our findings outline several promising research directions for advancing scalable on-policy value-based methods and dynamically adjusting the data reuse properties to improve stability and efficiency during training. A more detailed discussion is provided in Appendix F.

2 Data Reuse in Value-Based RL

We introduce the **Data Replay Ratio (DRR)**, a novel metric for analyzing the learning dynamics of value-based algorithms. Unlike the Replay Ratio (RR) commonly used in prior studies (Fedus et al., 2020; D'Oro et al., 2022), the DRR provides a more comprehensive framework for optimizing both sample and compute efficiency.

$$\text{RR} = \frac{\text{num\_grad\_steps}}{\text{train\_frequency}}, \quad \text{DRR} = \text{RR} \cdot \frac{\text{batch\_size}}{\text{num\_envs}}. \tag{1}$$

num_grad_steps controls how many batches to sample from the buffer while *train_frequency* controls how many environment steps are taken between batch samples.

The DRR enables the exploration of alternative scaling strategies, such as increasing batch sizes or parallelizing environment rollouts, rather than solely adjusting the number of gradient steps per experience sample. We note that increasing the number of parallel environments has a similar impact on learning dynamics as decreasing the *train_frequency*, particularly in terms of the data generated per unit of computation. However, increasing parallel environments better aligns with recent advancements in compute-scalable value-based algorithms, as it allows for the efficient generation and consumption of data through massively vectorized environment simulations. Unlike simply reducing the replay ratio, which primarily controls the amount of data reused between updates, increasing parallel environments directly influences the diversity and coverage of data in the replay buffer, thereby affecting the stability and efficiency of learning. The DRR represents the ratio of data used for learning to the new data collected per step.

To address critical gaps in understanding data reuse in value-based algorithms, we pose two central research questions:

RQ1: *What strategies can improve data reuse in high data replay ratio settings, where DQN typically becomes unstable?*

RQ2: *What are the deadly triad considerations that make it difficult to effectively use a high data replay ratio?*

2.1 RQ1: Data Reuse in High Data Replay Ratio Settings

In the original DQN setup, *num_grad_steps* = 1, *train_frequency* = 4, *batch_size* = 32 and *num_envs* = 1, yielding RR $= 0.25$ and DRR $= 0.25 \times \frac{32}{1} = 8$. However, increasing *num_grad_steps* to 2 and reducing *train_frequency* to 1 (resulting in RR $= 2$ and DRR $= 64$) has been shown to destabilize learning entirely (D'Oro et al., 2022; Sokar et al., 2023). Throughout the paper, we refer to these unstable conditions as High Data Replay Ratio (HDRR) settings. With the DRR, we extend this analysis by incorporating batch size and the number of parallel environments into the discussion, allowing for a deeper understanding of how these factors interplay with stability. We hypothesize that DQN's vulnerability to HDRR is tied to its reliance on small batch sizes (susceptible to priming and overfitting) and limited buffer diversity caused by using a single environment instance. Thus, claims about HDRR universally destabilizing DQN are context-dependent and linked to this fragile configuration.

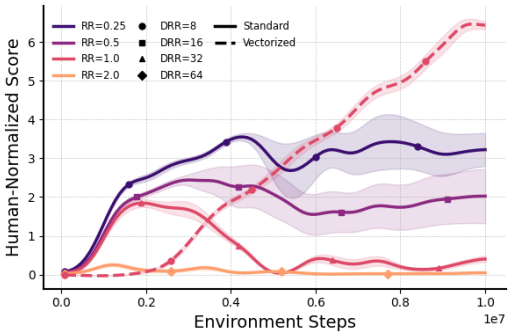


Figure 1: Prior work links high RR to poor performance. We argue this claim is not universal, as RR overlooks key data-centric factors in value-based learning. By adjusting vectorized environments and batch sizes to control the DRR, we replicate failure and success cases at RR=1 using DQN. Our findings suggest high DRR is the primary cause of collapse, and that **DRR can reveal configurations yielding superior performance.**

To overcome these limitations, we introduce algorithmic modifications guided by the DRR, including larger batch sizes, more environments, and improved data regimes that enhance reuse without compromising stability. As shown in Figure 1, DRR-informed design enables stable and high performance configurations even at RR values previously considered unstable. Moreover, we find that DRR, rather than RR alone, more accurately describes the performance collapse observed in high-reuse settings.

2.2 RQ2: Addressing the Challenges of the Deadly Triad

For RQ2, we focus on mitigating challenges posed by the deadly triad (i.e. bootstrapping from off-policy data with neural network function approximators).

First, we explore less biased TD objectives. While Q(0) (Mnih, 2013) remains a widely used method, we hypothesize that its bias can exacerbate poor data reuse, reducing both performance and sample efficiency. To address this, we adopt λ-returns (Peng & Williams, 1994), which incorporates multi-step returns with reduced bias and provide a flexible interpolation of Q(0) and Monte Carlo returns (Sutton & Barto, 2018). We modify the replay buffer to store fixed-length rollouts, allowing the computation of Q(λ) targets from sequences rather than individual transitions (Figure 21).

Secondly, we test Q(λ) in both low and HDRR settings combined with single and parallel environments to mitigate off-policy divergence.

Finally, we explore improved non-linear approximation by means of parameter normalization and re-considering the use of target networks in deep value-based algorithms.

3 Empirical analyses

Guided by the challenges of the deadly triad and toward maximizing data reuse, we explore three orthogonal axes: (1) the data sampling regime, investigating how parallel data collection impacts the presence of off-policy data in the replay buffer; (2) the use of rollout TD methods, such as Q(λ), to address bootstrapping bias; and (3) improvements to function approximation through normalization

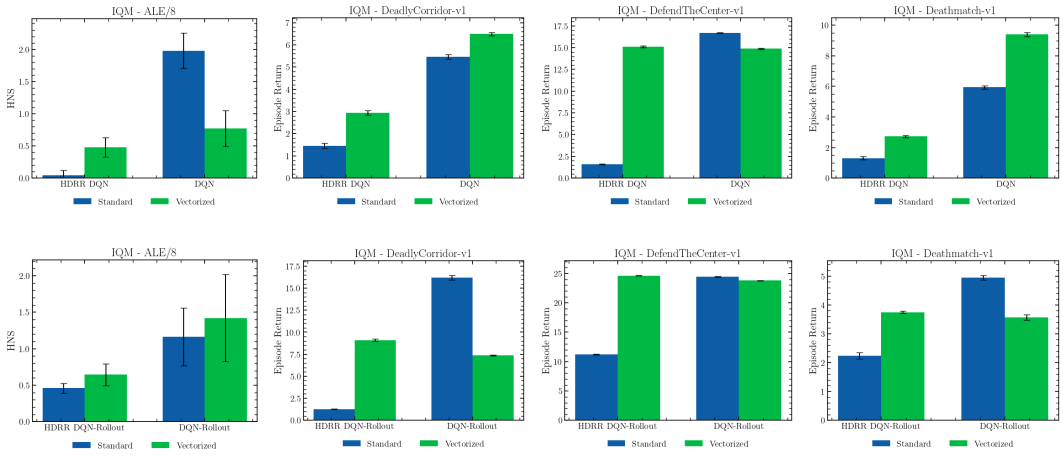


Figure 2: **IQM scores for Q(0) (top row) and Q(λ) (bottom row).**; ALE/8 (left) reports IQM of human-normalized scores over 8 Atari games (100M frames). ViZDoom tasks, *Deadly Corridor*, *Defend the Center*, *Deathmatch*, report IQM episode returns over 10M frames.

and the removal of target networks. These axes yield algorithmic variants that interpolate between DQN, R2D2, and PQN: (1) **Vec-DQN**, which augments DQN with parallel environments (Figure 7); (2) **DQN-Rollout**, which integrates Q(λ) TD estimates into single-environment DQN; (3) **Vec-DQN-Rollout** as the combination of (1) and (2); and (4) **Stable DQN** and **Stable Vec-DQN-Rollout**, incorporating layer normalization and removing target networks. Table 4 provides a complete overview of all algorithmic variants used in our experiments throughout the paper.

3.1 Experimental setup

We conduct our experiments using eight representative games from the Arcade Learning Environment (ALE) benchmark (Bellemare et al., 2013), together with 3 partially-observable tasks from the VizDoom suite (Kempka et al., 2016). Environment details are provided in Appendix C. In addition to reporting accumulated returns during training, our analyses also include the mean, median and interquantile mean (IQM) of the human-normalized scores (HNS) with 95% stratified bootsrap confidence intervals (Agarwal et al., 2021) obtained with 3 independent runs for each experiment configuration. Although it is beyond the scope of our work, we provide a preliminary investigation of data reuse for continuous-action algorithms in Appendix J, as our investigation traces the evolution of value-based algorithms from PQN, which naturally connects to discrete-control algorithms.

3.2 Results

We start by investigating the effect of parallel data collection, focusing on the transition from DQN to Vec-DQN in Figure 6 (right), where the DRR provides a framework for analyzing data reuse properties. As noted in Section 2, DQN typically performs well with a DRR of 8 but experiences learning collapse under HDRR conditions. We investigate whether parallelized data collection can address this issue by designing a training configuration that replicates DQN's data reuse by using parallel environments and larger training batches (see Figure 7). Specifically, we evaluate whether this data regime can mitigate the learning collapse observed in HDRR-DQN. The resulting methods, Vec-DQN, HDRR-DQN, and HDRR-Vec-DQN are illustrated in Figure 20.

In Figure 2, we compare the performance of DQN, HDRR-DQN, Vec-DQN, and HDRR-Vec-DQN. Results indicate that with the simple Q(0) objective, configurations utilizing a single environment instance and small learning batches yield higher aggregated performance.

However, increasing the DRR generally results in diminished performance, with the non-vectorized versions collapsing entirely. Interestingly, vectorized (i.e. parallel) algorithms, which use larger learning batches to mimic the DRR of their equivalent single-environment versions, exhibit greater robustness under HDRR regimes, avoiding complete performance collapse.

These findings suggest that small learning batches induce better optimization, although at the cost of increased sensibility to priming and overfitting. This observation aligns well with the findings by (Obando Ceron et al., 2024). Conversely, larger batches mitigate overfitting by averaging gradients over more diverse data but are more prone to becoming stuck in local minima in the non-stationary optimization process of deep RL.

Next, we explore the use of rollouts to reduce biased updates by using λ-returns. The results shown in Figure 2 suggest that rollout TD methods are more compatible with vectorized environments and larger batch sizes. Importantly, while vectorized algorithms remain more robust under HDRR regimes, the non-vectorized variants also avoid the complete collapse observed when using Q(0). These results suggest that less biased TD objectives, such as λ-returns, have the potential to stabilize the learning dynamics of value-based algorithms and mitigate the risks of collapse under high data reuse settings. The full set of learning curves is presented in Figures 14a and 14b. In Appendix D, we provide a detailed analysis of the learning dynamics induced during training. Our findings reveal notable correlations between several recently proposed learning metrics in deep RL and the HNS. Finally, the work in (Gallici et al., 2024) provided theoretical arguments for the use of LayerNorm

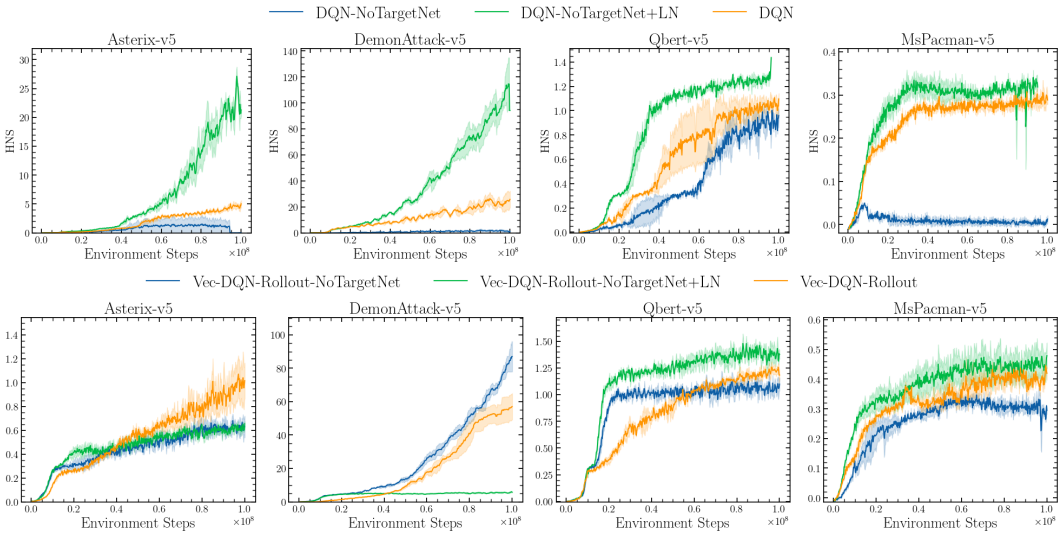


Figure 3: Mean human-normalized scores for target network, online bootstrapping, and online bootstrapping with LayerNorm. **LayerNorm with Q(0)** performs best, showing that improved function approximation can remove the need for target networks. We refer to this variant as **Stable DQN** (see Fig. 6). For $Q(\lambda)$, results vary by environment; e.g., in DemonAttack, bootstrapping without LayerNorm or targets performs best. This suggests that in some cases, **less biased TD methods like $Q(\lambda)$ enable safe bootstrapping from the online network.**

(Lei Ba et al., 2016) to compensate for the instabilities caused by bootstrapping from the online network, thus removing the need for target networks, even when using off-policy data; in their empirical evaluations, however, the authors focused on on-policy settings. We evaluated its impact in off-policy methods in Figure 3, and find that LayerNorm is a viable alternative to target networks, consistent with the findings of (Gallici et al., 2024; Lyle et al., 2024). Our results show significant performance gains in favor of layer normalization compared to the original DQN algorithm, which uses target networks. Notably, DQN with Q(0) experiences a complete collapse in performance when the network is not normalized and target networks are absent (blue lines in Figure 3). The use of Q(λ) returns to estimate the TD targets seems to avoid this collapse (green lines in Figure 3).

This result can be interpreted through the lens of the deadly triad, where improvements in function approximation gained from learned layer normalization result in safer bootstrapping from off-policy data, especially when utilizing highly-biased bootstrapped estimates from Q(0).

4 Closing the triangle

As shown in Figure 6, the parallel version of DQN-Rollout (Vec-DQN-Rollout) is just one step away from PQN (Gallici et al., 2024) and R2D2 (Kapturowski et al., 2018). Building on this connection, we study how these improvements impact parallel data collection, reuse, and overall efficiency. R2D2

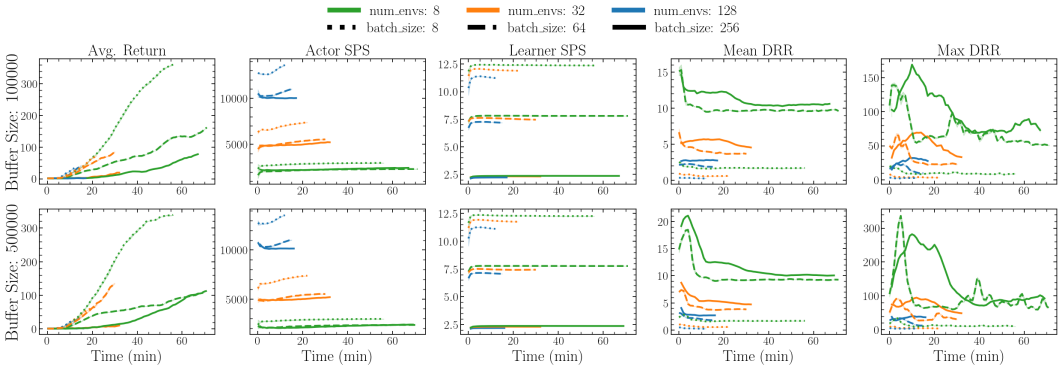


Figure 4: **Asynchronous R2D2 training vs. wall-clock time (40M frames).** 128-actor variants achieve the highest throughput (10k–14k SPS) but suffer from lower DRR and returns, as learners can't keep up with incoming data. 8-actor variants are slower but more sample-efficient; pairing 8 actors with small batches (e.g., 8) yields the best returns under a fixed step budget.

(Kapturowski et al., 2018) was established as the state-of-the-art algorithm in the ALE at the time of its introduction and serves as the basis of the current state-of-the-art algorithms in the ALE such as MEME (Kapturowski et al., 2022) and Agent57 (Badia et al., 2020). In our work, R2D2 emerges as Vec-DQN-Rollout augmented with an LSTM, a prioritized sampling scheme, and distributed training. We provide an implementation of R2D2 that faithfully reproduces the core components of the original method: (i) a recurrent Q-network, (ii) a prioritized replay buffer, and (iii) distributed computation.[1] Further implementation details are available in Appendix H.

In asynchronous training, especially with prioritized replay, DRR isn't analytically tractable. Thus, in R2D2, we empirically track how often each buffer sample is reused during training to estimate DRR, and evaluate performance as a function of this estimate (Figure 4).

A clear trade-off emerges: neither very low (blue dotted) nor very high (green solid) DRRs yield optimal performance. Adjusting environment count, batch size, and buffer size can improve DRR and sample efficiency, but beyond a point, higher DRR leads to performance collapse. This effect

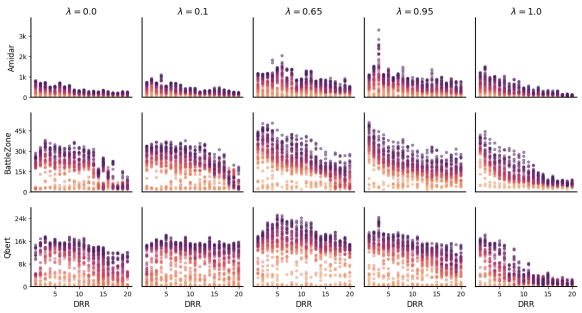


Figure 5: **PQN scores vs. DRR (200M frames)**. Rows: ALE games; columns: λ values. The x-axis varies update epochs (DRR proxy), and the y-axis shows achieved scores. Shade darkens with training progress.

[1] Our implementation is available at https://github.com/roger-creus/data-reuse-deep-rl

generalizes across all value-based methods we tested. The challenge is to maintain learning quality even as DRR increases.

We also evaluate PQN under varying data reuse. PQN trains only on-policy batches from parallel environments, discarding data after a set number of updates, akin to PPO (Schulman et al., 2017). Here, DRR is exactly equal to the number of training epochs per batch.

As with R2D2, PQN exhibits a DRR trade-off: too few epochs hurt sample efficiency; too many cause collapse. This bell-shaped pattern is prominent in games like Qbert ($\lambda = 0.65$).

Biased TD targets amplify HDRR failures. PQN avoids full collapse due to large batches, but performance still drops at high DRR. Lower λ (e.g., 0.0 or 0.1) leads to greater degradation under HDRR. More balanced targets ($\lambda = 0.65$ or 0.95) are safer. Monte Carlo returns ($\lambda = 1.0$) cause the sharpest decline, implying that both TD bias and variance shape the DRR-performance trade-off.

HDRR sensitivity is environment-specific. In BattleZone, performance decays almost monotonically with DRR, while in Amidar and Qbert the drop is milder, suggesting environment-dependent learning dynamics warrant deeper study.

Finally, we benchmark PQN and R2D2 on Atari-10, a reliable proxy for the full ALE suite (Aitchison et al., 2023; Gallici et al., 2024). See Appendix I for detailed results.

5 Conclusion

In this work, we revisited advancements in value-based deep RL algorithms since the introduction of the canonical DQN algorithm, focusing on the data reuse properties that distinguish this class of algorithms. Considering the issues of the deadly triad, we proposed modifications to value-based algorithms by redefining the data regime and introducing the Data Replay Ratio (DRR) as a more precise measure of sample efficiency compared to the commonly used Replay Ratio (RR). Unlike the RR, the DRR quantifies the usage of each individual data point during training.

Using the DRR, we proposed a data sampling regime that mimics the characteristics of the original DQN implementation but incorporates larger training batches and parallel environments. Our goal was to alleviate the issues of the deadly triad by achieving more stable bootstrapping from off-policy data. We defined two RQs to drive our empirical study and be able to tackle the deadly triad from a data-centric perspective, concretely by studying larger training batches, parallel data collection, less biased TD methods and normalized networks.

Our results indicate that while larger batches trade off the performance benefits associated with the higher variance of smaller batches (Obando Ceron et al., 2024), they offer increased robustness to overfitting. Furthermore, less biased TD methods, such as Q(λ) in place of Q(0), generally improve data reuse and task performance. Finally, our empirical evidence supports the use of normalized networks as a viable alternative to target networks, even in off-policy training scenarios, aligning with the theoretical findings of (Gallici et al., 2024).

Crucially, our study facilitates a clearer mapping of modern developments in value-based algorithms and their interconnections. To this end, we release an open-source implementation of the R2D2 algorithm[2], which emerged naturally in our framework as Vec-DQN-Rollout with the addition of an LSTM network, prioritized sampling, and asynchronous computation. We benchmarked R2D2 alongside PQN, a recent, simple, yet effective on-policy value-based algorithm, on multiple subsets of the ALE including the Atari-10 (Aitchison et al., 2023).

As advances in the software and hardware used to train deep networks continue to progress, RL researchers are empowered to tackle problems of increasing complexity with ever-growing models. Our investigation has highlighted that, even in these modern and large-scale settings, the canonical deadly triad continues to prove a central challenge to overcome. In order to develop robust and reliable agents, it is crucial that we develop a deep understanding of the challenges and trade offs that

[2] https://github.com/roger-creus/data-reuse-deep-rl

accompany training under these settings. Our work, which takes a data-centric perspective, is a step towards developing this understanding.

A Supplementary Diagrams

This section presents additional diagrams referenced throughout the main paper. These visualizations are intended to support and clarify key concepts and experimental setups discussed in the study.

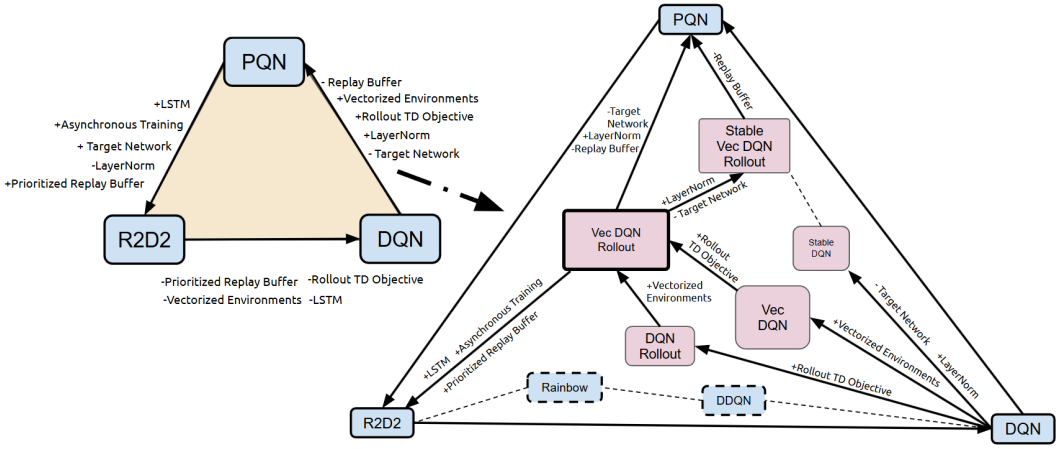
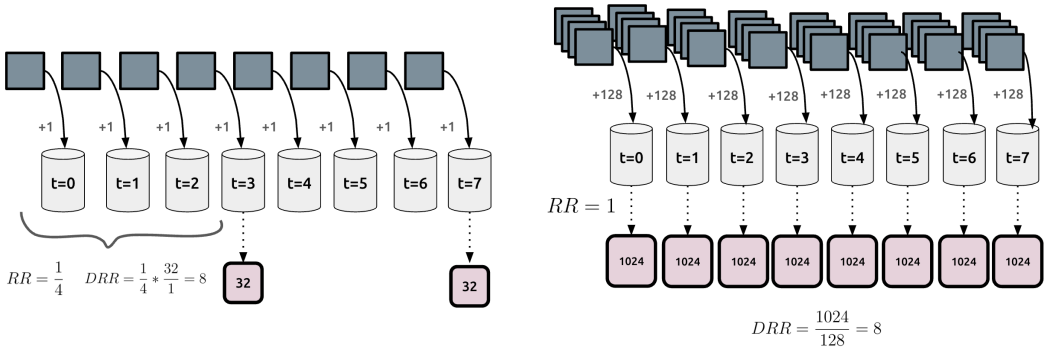


Figure 6: **Conceptual overview of our study**. Modern developments in value-based deep RL algorithms constitute the outer vertices of a graph where edges correspond to adding/removing techniques. We systematically trace the evolution of this algorithmic family from the canonical DQN algorithm by means of a composable exploration of data-centric training techniques. Table 4 provides a complete overview of all algorithmic variants used in our experiments throughout the paper

.



(a) DQN

(b) Vec-DQN

Figure 7: **Illustration of the Data Replay Ratio induced by different data sampling configurations**. Gray squares represent environment observations, where *Vec-* denotes vectorized (parallel) environments contributing observations to a shared buffer. Red squares represent learning batches.

B Background

Our work builds on the evolution from DQN (Mnih, 2013) to more compute- and sample-efficient value-based algorithms. This progression addresses key challenges in deep RL: improving data reuse, stabilizing learning, and mitigating the deadly triad: the instability arising from the combination of **bootstrapping**, **off-policy learning**, and **function approximation** (Sutton & Barto, 2018).

B.1 Bootstrapping Bias and Multi-Step Returns

Bootstrapping updates value estimates using prior estimates, introducing bias that can destabilize training. DQN (Mnih, 2013) uses one-step TD targets Q(0), while modern methods like R2D2 (Kapturowski et al., 2018) and Rainbow (Hessel et al., 2018) adopt n-step returns to balance bias and variance.

Q(λ) (Peng & Williams, 1994; 1996) has shown promise even in regimes previously considered unstable (Kozuno et al., 2021), but its off-policy use is challenging due to stale updates. Mitigation strategies include importance-weighted corrections (Retrace (Munos et al., 2016)) and periodic recomputation of targets (Daley & Amato, 2019). Recently, PQN (Gallici et al., 2024) introduced a lightweight alternative using λ-returns on parallel on-policy rollouts, bypassing replay buffers. We extend these approaches by analyzing multi-step TD methods across varying data reuse regimes.

B.2 Off-Policy Learning and Data Reuse

Off-policy learning is a central challenge in deep RL, as it enables better sample efficiency but also induces instability due to distributional shift (Sutton & Barto, 2018; van Hasselt et al., 2018). DQN leverages an experience replay buffer, which allows the agent to reuse past experiences for training (Mnih, 2013). Several extensions on the replay buffer, such as prioritized experience replay (Schaul, 2015) and distributed replay schemes (Horgan et al., 2018; Kapturowski et al., 2018), have improved DQN's learning efficiency by biasing sampling toward informative transitions. However, maximizing data reuse introduces new challenges. While increased data reuse improves efficiency in supervised learning, excessive reuse in RL often leads to training collapse (Kumar et al., 2020; D'Oro et al., 2022; Sokar et al., 2023).

B.3 Neural Network Function Approximation

The third challenge of the deadly triad arises from the use of deep neural networks as non-linear function approximators in value-based RL. Unlike learning with linear models, function approximation errors are often unstructured, rendering deep RL particularly susceptible to overestimation bias, representation collapse, and catastrophic forgetting (Baird et al., 1995; Tsitsiklis & Van Roy, 1996; Sutton & Barto, 2018; van Hasselt et al., 2018). DQN partially mitigates these issues with target networks, which stabilize bootstrapping updates by maintaining a slowly updated copy of the Q-network, and recent works have explored alternative stabilizers (Bhatt et al., 2019).

Plasticity loss and primacy bias in deep RL networks have been a barrier to improving algorithms (Nikishin et al., 2022). Proposed solutions include periodic network resets (Nikishin et al., 2022; Sokar et al., 2023), weight pruning (Obando-Ceron et al., 2024a), and auxiliary penalties to prevent feature rank collapse (Kumar et al., 2020).

Layer normalization (Lei Ba et al., 2016) has been shown to improve training stability by addressing distributional drift in network activations (Lyle et al., 2024). PQN (Gallici et al., 2024) eliminates target networks entirely in favor of LayerNorm and achieves competitive performance without the need for a replay buffer.

A more comprehensive discussion of our work in relation to existing research can be found in Appendix E.

C Evaluation Details

In this paper, we use subsets of the Arcade Learning Environment (ALE) (Bellemare et al., 2013) for our experiments. For evaluating the research questions, we use 8 representative games from ALE. To benchmark the most promising algorithmic variations identified in this study, alongside modern baselines such as PQN (Gallici et al., 2024) and R2D2 (Kapturowski et al., 2018), we use the Atari-10

subset (Aitchison et al., 2023). This subset comprises 10 games chosen for their strong correlation with evaluation results on the full set of 57 ALE games.

- **Eight representative ALE games**: Breakout, SpaceInvaders, Asterix, Pong, Qbert, DemonAttack, Seaquest, MsPacman
- **Atari-10**: Amidar, Bowling, Frostbite, KungFuMaster, RiverRaid, BattleZone, DoubleDunk, NameThisGame, Phoenix, Qbert

All experiments were conducted on a single-GPU setup using an NVIDIA RTX 8000, 12 CPU workers, and 50GB of RAM. DQN experiments required approximately 10 hours to complete 40 million environment steps in the ALE using single-environment settings. In contrast, vectorized DQN variants and PQN reduced training time to approximately 2 hours under the same compute configuration.

D Learning Dynamics

We investigate the learning dynamics of the different value-based algorithms evaluated in Figures 2 and 2 by measuring several recently proposed learning metrics to uncover their relationships with the downstream task performance. These metrics include the emergence of dead neurons, computed as dormant neurons with $\tau = 0$ (Sokar et al., 2023; Nikishin et al., 2022), policy churn (Schaul et al., 2022), and representation rank (Kumar et al., 2020). The results are shown in Figure 19 and indicate that while there are some interesting correlations between learning metrics from different recent works, none result in a significantly strong relationship with HNS. Notable relations include:

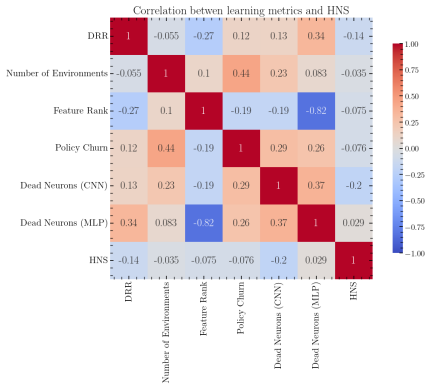


Figure 8: Correlation matrix with statistics aggregated over the 8 ALE environments used throughout the paper. This analysis captures linear relationships between widely used learning metrics, providing insights into the learning dynamics of deep RL algorithms.

- Higher DRR generally leads to worse performance, increased policy churn, a decrease in the rank of the representations (which causes a loss of the network's expressivity) (Kumar et al., 2020), and more dead neurons, especially in the penultimate fully-connected layer of the networks.
- Using a higher number of environments (i.e., also implying larger batch sizes) drastically reduces the number of dead neurons in the representations, at the cost of a slight increase in dead neurons in the convolutional layers. This allows the network to learn higher-rank representations. Notably, larger batches increase policy churn, which can help with exploration but also makes updates more unstable, as the greedy policy varies more abruptly.
- Feature rank does not seem to have a significant relation with HNS, though it is strongly (negatively) correlated with the presence of dead neurons in the representations. The appearance of dead neurons significantly diminishes the rank of the representations.

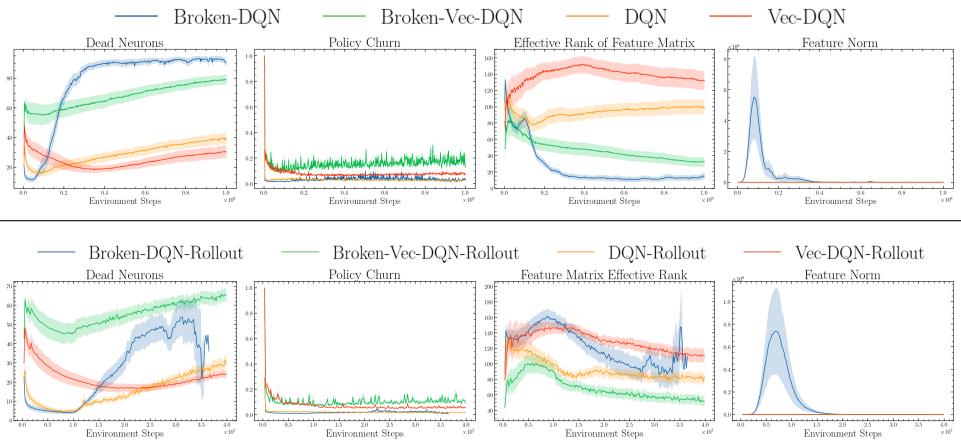


Figure 9: Learning dynamics during training for the algorithms evaluated in the RQs.

- Policy churn is correlated with several other metrics, as larger batches induce more churn, but also more dead neurons. However, the aggregate of all results indicates that there is no strong relationship between churn and HNS.
- Interestingly, dead neurons in the convolutional layers occur less frequently than in the penultimate fully-connected layer, but when they do appear, they have a more severe impact on task performance. This underscores the importance of improving the expressivity of convolutional architectures in online deep RL and empirically justifies the widespread adoption of the residual architecture, such as the Impala CNN (Clark et al., 2024; Castro et al., 2018), in recent literature. This architecture has shown significant performance gains across benchmarks in deep RL, despite the lack of rigorous studies explaining why.

We present the learning dynamics during training in Figure 9, which provide several insightful observations:

- HDRR leads to an increase in the number of dead neurons during training. Additionally, it results in a collapse of the representation rank, particularly when using Q(0) for optimization. In contrast, Q(λ) proves to be a more robust objective, helping to prevent this feature rank collapse.
- HDRR also causes a significant increase in the norm of the representations, especially in the early stages of training, which negatively impacts performance. Notably, this effect is mitigated when using larger training batches.
- Larger training batches tend to increase policy churn, resulting in more abrupt changes in the greedy policy. This not only affects the actions chosen during training but also influences the bootstrapping targets, thereby impacting the stability of the TD targets. This could explain the observed performance loss compared to smaller batches.

E Discussion

The Deadly Triad in deep RL

The concept of the deadly triad, comprising function approximation, bootstrapping, and off-policy learning, has long been recognized as a potential source of instability in reinforcement learning algorithms (Sutton & Barto, 2018). This combination, when not managed carefully, can lead to divergence in value estimates and erratic learning behavior even with linear function approximators (Tsitsiklis & Van Roy, 1996; Baird et al., 1995).

Function approximation, particularly with complex architectures like deep neural networks, inherently introduces approximation errors. When bootstrapping is applied to these approximations, any errors

are compounded across iterations, exacerbating divergence issues (Zhang et al., 2021; Van Hasselt et al., 2018). Off-policy learning further complicates this picture because the data distribution under which the agent learns may differ substantially from that induced by its current policy (Kozuno et al., 2021). This divergence between data and policy has been a key focus in reinforcement learning research, motivating the development of techniques aimed at stabilizing learning while leveraging the benefits of off-policy data (Munos et al., 2016; D'Oro et al., 2022).

Deep reinforcement learning algorithms, such as Deep Q-Network (DQN) (Mnih, 2013) and its various extensions, have made significant progress in addressing the deadly triad. These algorithms incorporate mechanisms like experience replay (Li et al., 2021), target networks (Zhang et al., 2021), and carefully tuned update rules that help mitigate the instability typically induced by the triad (Schwarzer et al., 2023).

Despite these advances, the deadly triad remains a critical area of investigation in reinforcement learning research (Van Hasselt et al., 2018; Nauman et al., 2024a; Hussing et al., 2024). The interplay between theoretical insights and empirical evaluations continues to drive progress toward more robust and reliable algorithms (Gallici et al., 2024). Recently, (Gallici et al., 2024) propose PQN, a purely on-policy value-based algorithm that explicitly deals with the cornerstone challenges of the deadly triad and achieves great performance empirically. PQN includes LayerNorm layers (Lei Ba et al., 2016) to stabilize function approximation, multi-step λ-returns to reduce the bootstrapping bias, and computes gradient updates only with on-policy data.

Parallel Reinforcement Learning

Parallel reinforcement learning (RL) has played a central role in scaling up learning processes by enabling faster data collection and more efficient policy updates. In these settings, multiple agents (actors) interact with environment replicas concurrently, with their experiences aggregated, either synchronously or asynchronously, to update a central learner. This decoupling improves sample efficiency, reduces temporal correlations, and accelerates convergence.

Parallel policy gradient algorithms often employ the actor-learner architecture. Asynchronous Advantage Actor-Critic (A3C) (Mnih et al., 2016) was a seminal work in this direction, showing that multiple asynchronous actor threads, each interacting with its own environment instance, can reduce sample correlation and improve exploration without requiring experience replay. A synchronous variant, A2C (Sutton & Barto, 2018), collects trajectories from parallel environments and performs batched updates to stabilize learning.

Later, asynchronous PPO variants combined PPO's clipped surrogate objective with parallel experience generation. IMPALA (Importance Weighted Actor-Learner Architecture) (Espeholt et al., 2018) scaled this further by decoupling acting and learning entirely: many CPU-based actors generate trajectories and send them to a GPU-based learner. To address the off-policy nature of the resulting data, IMPALA applies a V-trace correction to ensure stable learning.

These approaches share several key ideas:

- **Parallel data collection:** Multiple actors generate diverse trajectories in parallel, reducing variance in policy gradient estimates.
- **Actor-Learner architecture:** A central learner aggregates and applies gradient updates based on batches from distributed workers.
- **On-policy vs. off-policy trade-offs:** While A3C and A2C are fundamentally on-policy, IMPALA handles off-policy corrections arising from asynchronous updates.

Value-based methods have also benefitted significantly from parallelization. Distributed DQN variants such as APEX (Distributed Prioritized Experience Replay) (Horgan et al., 2018) and R2D2 (Recurrent Experience Replay in Distributed RL) (Kapturowski et al., 2018) use many actors to generate experience stored in a centralized replay buffer. The learner samples from this buffer, often with prioritization, to update the Q-network.

Recently, methods such as PQN (Parallel Q-Networks) (Gallici et al., 2024) and its variants have demonstrated that it is possible to achieve strong performance using purely on-policy data collection, even in value-based settings. In PQN, multiple actors each generate trajectories in parallel across distinct environment instances. These rollouts are then aggregated into a single large batch of on-policy experience, which is used to perform multiple gradient updates, similar to the minibatch and multi-epoch optimization procedure in PPO. After completing several epochs of training on this batch, the data is discarded, and a new set of rollouts is collected, with no persistent replay buffer or experience reuse.

Despite the lack of off-policy data reuse, PQN still achieves strong sample efficiency and competitive performance. This finding is central to the motivation behind our work: we investigate what fundamental factors enable such efficiency in the absence of replay and explore whether value-based algorithms like PQN can be extended to support more effective data reuse. In particular, we seek mechanisms that allow more gradient steps per data point without suffering from the empirical collapse typically observed in off-policy value-based methods when data is overused.

Learning Dynamics Under High Data Reuse

A number of studies have identified several factors that impede effective data reuse in deep reinforcement learning. For example, the phenomenon of *dying neurons*, in which a large fraction of ReLU-activated neurons become inactive over time, has been reported as a significant barrier to sustained learning (Sokar et al., 2023). Concurrently, *representation collapse*, often measured by a decrease in the rank or diversity of internal features, further restricts a network's ability to capture new information and thus hinders data reuse (Lyle et al., 2024; Kumar et al., 2020). These issues limit the network's effective capacity by reducing the richness of the learned representations, ultimately leading to poorer generalization on novel data.

In addition to neuron inactivation and representational bottlenecks, *loss of plasticity* has emerged as a central challenge, where a network's ability to adapt to new data distributions gradually deteriorates (Nikishin et al., 2022). Research has shown that beyond the well-known problem of catastrophic forgetting, deep RL agents may also struggle to update their parameters effectively when overexposed to a fixed data distribution. Interventions such as plasticity injection (Nikishin et al., 2022; D'Oro et al., 2022) have been proposed to maintain plasticity by periodically reinitializing or perturbing less active units. These approaches indicate that a more dynamic strategy is needed to preserve the network's learning capability, which motivates our investigation into alternative metrics like the Data Replay Ratio (DRR) to capture the true impact of data reuse on learning dynamics.

What matters for maximizing data reuse

Our main contribution is the introduction of the Data Replay Ratio (DRR), a metric that offers a more faithful characterization of the effective data utilization in deep reinforcement learning experiments. We demonstrate that DRR captures important aspects of learning dynamics that are overlooked by the more commonly used Replay Ratio (RR). In particular, we present empirical scenarios in which different configurations, despite having identical RR values, lead to significantly different learning behaviors, which are accurately distinguished by their DRR values (see Figure 1).

Crucially, by modifying data-centric settings such as the number of parallel environments, batch size, and replay buffer capacity, we can induce variations in DRR while keeping RR constant. This allows us to isolate the effects of data reuse from other confounding factors. We observe that increasing the number of parallel environments and using larger batch sizes tends to mitigate the harmful effects of overfitting and priming in high-DRR regimes.

Additionally, DRR provides an accurate characterization of data reuse even in asynchronous settings, where the interaction between the actor and learner processes does not follow a fixed learning schedule. Instead, the rate at which data is generated and consumed varies dynamically, making traditional metrics less reliable. Our experiments with R2D2 in Figure 4 reveal key factors that

influence DRR fluctuations in highly asynchronous and parallelized environments, providing insights into how data reuse evolves under such conditions.

Progress in value-based deep reinforcement learning

Recent advancements in value-based deep reinforcement learning RL have introduced a variety of new algorithms aimed at training agents to achieve superior performance in complex benchmarks. Many of these approaches address different orthogonal challenges in existing methods, leading to improvements in sample efficiency, stability, and generalization.

BBF (Schwarzer et al., 2023) enhances learning efficiency by incorporating dynamic schedules for key hyperparameters, such as the discount factor and n-step return, alongside self-predictive representations. These innovations enable BBF to achieve state-of-the-art sample efficiency, as demonstrated in the Atari100k benchmark. Similarly, BRO (Nauman et al., 2024b) improves sample efficiency in continuous control tasks by selectively scaling the critic's architecture in an actor-critic framework and applying layer normalization to the critic. Additionally, BRO incorporates mechanisms for optimistic exploration to enhance learning stability.

Further architectural innovations have been introduced by Simba (Lee et al., 2024), which leverages dynamic observation normalization, residual connections, and layer normalization to facilitate more efficient parameter scaling. Beyond architectural improvements, recent works such as ReDo (Obando-Ceron et al., 2024b) focus on fundamental learning dynamics in value-based RL. ReDo specifically addresses the issue of dormant neurons by identifying and pruning them throughout training, resulting in sparser models that benefit from a simplicity bias, leading to improved generalization and sample efficiency.

The evolution of value-based RL methods can also be seen in the lineage from DQN (Mnih, 2013) to Rainbow (Hessel et al., 2018), and subsequently to Agent57 (Badia et al., 2020) and MEME (Kapturowski et al., 2022). These later approaches leverage learned meta-controllers to dynamically select policies for data collection. MEME further improves sample efficiency by integrating trust regions and multi-step returns with Q(λ), while also eliminating the need for a target network. However, both Agent57 and MEME are computationally expensive and currently lack accessible open-source implementations, limiting their practical adoption.

F Future Work

Our study reveals several promising research directions to tackle the learning challenges identified:

Interconnections of normalization, bootstrapping instability, and temporal difference (TD) bias: Our findings suggest that while target networks can be replaced with layer normalization when using Q(0), removing them in favor of Q(λ) provides stability without performance loss. This aligns with the empirical insights of (Kapturowski et al., 2022), where MEME optimizes a soft Q(λ) objective without target networks, relying on bootstrapping from the online network.

Advancing on-policy value-based algorithms: Develop methods that combine the compute efficiency of parallel algorithms without large replay buffers (like PQN) while efficiently leveraging the theoretical off-policy learning properties of value-based algorithms.

Batch size and DRR scheduling in value-based deep RL: Gain a deeper understanding of how batch size and DRR affect performance. Explore how dynamically adjusting batch size, and consequently DRR, during training can balance the increased variance and exploration benefits of smaller batches with the stability, robustness, and improved sample reuse efficiency offered by larger batches. This opens the door to adaptive scheduling strategies that optimize data reuse and performance throughout learning.

Open-source implementations of state-of-the-art algorithms: Provide open-source implementations of competitive algorithms like MEME and Agent57. In this work, we release an open-source

implementation of R2D2[3], featuring a recurrent Q network with an LSTM module, a prioritized replay buffer, and high-throughput asynchronous training. Since MEME and Agent57 are built on the R2D2 infrastructure, our implementation serves as a foundation for further open-source development of these algorithms. Additionally, it enables the analysis of DRR properties in asynchronous settings, facilitating a better understanding of these algorithms.

Improving convolutional architectures: Address the emergence of dormant neurons in convolutional layers, which our results show that significantly influence the task performance of value-based algorithms. This may explain the empirical success of adopting the ImpalaCNN residual architecture in deep RL (Castro et al., 2018; Clark et al., 2024). Further investigation is needed to understand the performance gains offered by different convolutional architectures such as squeeze-and-excitation networks (Hu et al., 2018), which have been utilized in algorithms like MEME.

G Limitations

The Data Replay Ratio (DRR) offers a more informative measure of data reuse in deep value-based algorithms than the traditional Replay Ratio (RR), capturing performance degradation more accurately in high-reuse regimes. However, fully characterizing data-centric scaling laws requires considering additional factors beyond DRR.

Notably, different configurations can yield the same DRR, for instance, by proportionally scaling *num_envs* and *batch_size*, yet result in distinct learning dynamics and performance. Larger batch sizes, in particular, influence stability, variance, and exploration in ways not captured by DRR alone (Obando Ceron et al., 2024). Moreover, evaluation depends on the experimental budget: fixing the number of environment steps means larger batch settings require fewer gradient updates, while fixing the number of updates leads to larger batches consuming more total data, and both affect comparability.

In this work, we propose DRR as a practical metric to guide data-centric scaling in value-based RL. While helpful, DRR should be interpreted alongside other design factors when generalizing across diverse training regimes.

H R2D2 Open Source Implementation

R2D2 (Kapturowski et al., 2018) trains a recurrent Q-function using an LSTM network to extract representations that capture historical information. To train with off-policy data, R2D2 introduces a burn-in strategy to recover from stale LSTM states in the replay buffer. Additionally, R2D2 operates in a distributed setting, similar to using parallel environments but with the added complexity of asynchronous communication.

The state-of-the-art performance of R2D2 reported by (Kapturowski et al., 2018) required 1e10 environment steps and 2M gradient updates, taking few days to complete the training program thanks to the extensive compute resources used. Note that a single-environment implementation of DQN (Mnih, 2013) can achieve better performance than R2D2 given a fixed budget of environment interaction steps (e.g. 200M frames) but it can take up to 4 full days of training (Castro et al., 2018). The latter illustrates the trade-off between sample-efficiency and wall-clock time in the asynchronous settings mentioned in the paper.

Similar to the original R2D2 implementation, we use batches of 64 rollouts during training, containing rollouts of length 80, along with a burn-in period of 40 steps. (Kapturowski et al., 2018) reported an approximate speed of 65k simulation steps per second for data collection and 5 learning steps per second. In contrast, our best-performing R2D2 configuration achieves around 5k steps per second for data collection and 7 learning steps per second, likely resulting in a significantly higher DRR than the original implementation.

[3] https://github.com/roger-creus/data-reuse-deep-rl

A significant difference between our implementation of R2D2 compared to the original one in (Kapturowski et al., 2018) (other than the available computational resources used during training) is the multi-step TD method used for computing target returns. In our work, we used λ-returns due to consistency reasons as that is the same objective we use for all other discovered rollout algorithms (e.g. DQN-Rollout, Vec-DQN-Rollout, PQN). (Kapturowski et al., 2018) used n-step returns instead (Sutton & Barto, 2018).

Table 1: Hyperparameters for R2D2.

Parameter	Value
num_envs	32
buffer_size	1,000,000
batch_size	64
rollout_length	80
start_e	1
end_e	0.01
exploration_fraction	0.1
learning_rate	2.5e-4
learning_starts	80,000
λ	0.65
gamma	0.99
tau	1.0
target_network_frequency (learner steps)	500
burn_in_lstm_length	40
per_eta	0.9
per_alpha	0.9
per_beta	0.6

I Benchmark

We evaluate the best-performing R2D2 configuration in Figure 4 and PQN on both the 8 representative ALE games used throughout the paper and the Atari-10 suite (Aitchison et al., 2023), training for the standard 200M environment steps (see Appendix C for details). We also include the DQN-NoTarget+LN variant, referred to as Stable DQN in Figure 6, which demonstrated superior performance among the Q(0)-based methods (see Figure 3). This evaluation, summarized in Table 2, provides valuable context for comparing the performance of various value-based baselines. Additionally, we provide the benchmark results in the Atari-10 in Table 3. In the 8 representative ALE

Table 2: Scores on the 8 representative ALE games (200M frames)

Environment	PQN	DQN-NoTarget+LN	R2D2
Asterix	**331,062**	226,677	9,000
Breakout	**518,46**	393,62	422,89
DemonAttack	171,992	**976,311**	50,912
MsPacman	**4,480**	2,609	2,734
Pong	**20.86**	**20.74**	**20.55**
Qbert	**22,900**	18,683	14,841
Seaquest	**54,489**	10,803	20,770
SpaceInvaders	**30,427**	2,522	11,341
DRR	2	8	~ 4
Training Time (hours)	2.69	26.34	20.07

games, PQN outperforms the other algorithms in 6 out of the 8 environments and is approximately nine times faster to train. These results position the newly proposed PQN algorithm as a highly competitive and efficient baseline for advancing value-based deep RL. For R2D2, the differences between our results and those reported by (Kapturowski et al., 2018) can be attributed to variations in the training budget (200M vs. 1e10M frames) and the number of computational resources used (32 vs. 256 CPU actors). The results on the Atari-10 benchmark (Aitchison et al., 2023) are presented in Table 3. Notably, our R2D2 implementation achieves the highest performance in 3 games of the Atari-10 despite differences in compute availability, while PQN and DQN-NoTarget+LN achieve the best results in 5 and 2 games, respectively.

Table 3: Atari-10 scores (200M frames)

Environment	PQN	R2D2	DQN-NoTarget+LN
Amidar	1,409	**1,614**	1,063
BattleZone	58,140	**68,000**	29,340
Bowling	**60.86**	49.75	41.81
DoubleDunk	-8.48	**3.00**	-19.39
Frostbite	4,058	4,650	**7,712**
KungFuMaster	19,114	26,200	**26,880**
NameThisGame	**18,784**	2,540	11,877
Phoenix	**71,933**	4,116	22,629
Qbert	**22,900**	18,683	14,841
Riverraid	**24,985**	7,830	16,618
DRR	4	4	8
Training Time (hours)	2.69	24.07	26.34

J Extended Evaluation in Continuous Control Tasks

For this study, our choice of DQN, PQN, and R2D2 is directly motivated by the recent introduction of PQN, a value-based algorithm designed to be sample-efficient and stable while entirely avoiding the use of a replay buffer, thus disallowing data reuse. Interestingly, despite PQN being theoretically off-policy, there is no strong justification for completely discarding the replay buffer. This observation naturally motivates our exploration: can we improve over PQN by explicitly reintroducing and controlling data reuse?

To assess the generality of our claims beyond discrete-action environments, we conducted additional experiments in continuous control domains using SAC (Haarnoja et al., 2018), TD3 (Fujimoto et al., 2018), and DDPG (Lillicrap et al., 2015) across the standard benchmarks of Hopper, Walker2d, and Humanoid, averaging the results over 3 independent runs. These experiments serve two main purposes:

- Validate whether the core phenomenon observed in our main analysis, namely that high data reuse (HDRR) degrades learning performance, extends to continuous control settings.
- Test the explanatory power of DRR versus RR in these domains, and whether the learning collapse under HDRR is similarly observed and mitigated by appropriate data regimes (e.g., larger batch sizes, more parallel environments).

Interestingly, TD3 exhibits a strong capacity for data reuse, benefitting from training configurations that lead to higher DRR values. However, interpreting the learning dynamics remains challenging. For instance, in the Humanoid environment, high DRR (HDRR) settings with vectorized environments and large training batches perform similarly to low DRR settings with small training batches. Conversely, the vectorized version with small batches performs as poorly as the non-vectorized version with larger batches. Despite these variations, the configuration with the highest DRR generally yields the best performance for TD3 across these environments. This observation motivates further investigation into the effects of delayed updates and double clipping mechanisms in TD3, which may help maximize data reuse.

For SAC and DDPG, the results are inconclusive and highly dependent on the specific environment. As mentioned earlier, the main focus of our paper is to trace the algorithmic decisions that led to the development of modern algorithms like PQN, which deploy deep value-based methods in purely on-policy settings, achieving strong performance across various baselines. In doing so, we specifically targeted discrete control problems. However, the findings presented in this section also provide valuable insights that can inspire future research on purely on-policy and highly regularized algorithms for continuous control tasks.

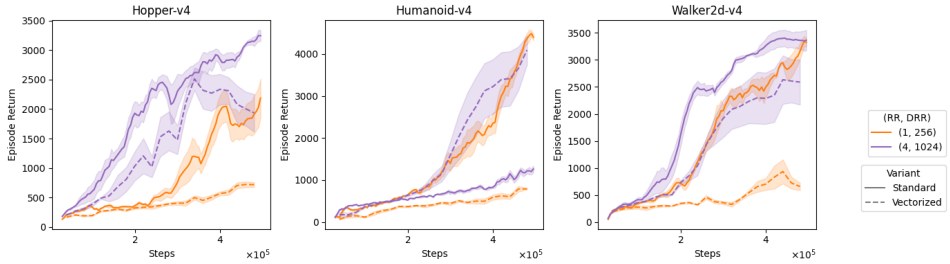


Figure 10: DRR vs. performance in TD3 across the Hopper, Walker2d, and Humanoid environments.

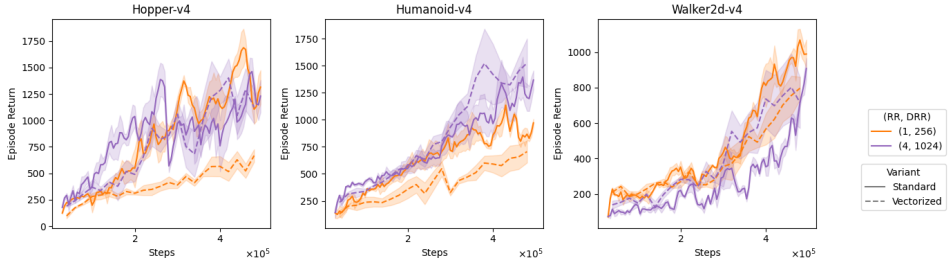


Figure 11: DRR vs. performance in DDPG across the Hopper, Walker2d, and Humanoid environments.

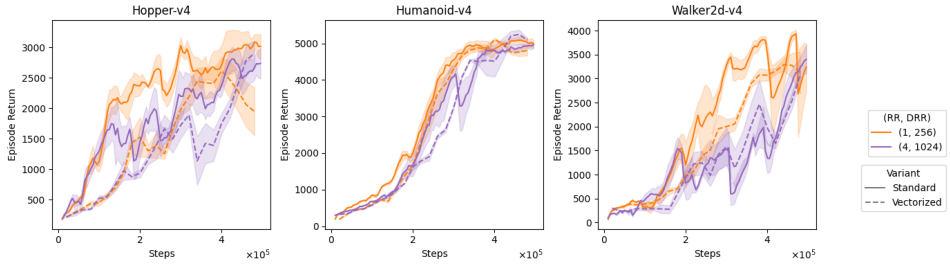


Figure 12: DRR vs. performance in SAC across the Hopper, Walker2d, and Humanoid environments.

Figure 13: DRR vs. performance in continuous control tasks (Hopper, Walker2d, Humanoid) for different algorithms: TD3, DDPG, and SAC.

K Algorithmic Variants

Alg.	Vec.	Tgt	LN	TD	Replay	DQL	LSTM
DQN	✗	✓	✗	Q(0)	✓	✗	✗
Double DQN	✗	✓	✗	Q(0)	✓	✓	✗
Rainbow	✗	✓	✗	N-step	✓	✓	✗
PQN	✓	✗	✓	Q(λ)	✗	✗	✗
R2D2	✓	✓	✗	N-step	✓	✓	✓
DQN-Rollout	✗	✓	✗	Q(λ)	✓	✗	✗
Stable-DQN-Rollout	✗	✗	✓	Q(λ)	✓	✗	✗
Vec-DQN	✓	✓	✗	Q(0)	✓	✗	✗
Stable-Vec-DQN	✓	✗	✓	Q(0)	✓	✗	✗
Vec-DQN-Rollout	✓	✓	✗	Q(λ)	✓	✗	✗
Stable-Vec-DQN-Rollout	✓	✗	✓	Q(λ)	✓	✗	✗

Table 4: Component-wise configuration of the value-based algorithms studied in this work, covering both architectural and algorithmic dimensions. Abbreviations: **Vec.** = Vectorized (multi-environment training), **Tgt** = Target Network, **LN** = Layer Normalization, **TD** = Temporal Difference Target, **Replay** = Replay Buffer, **DQL** = Double Q-Learning, **LSTM** = Long Short-Term Memory.

L PQN Hyperparameters

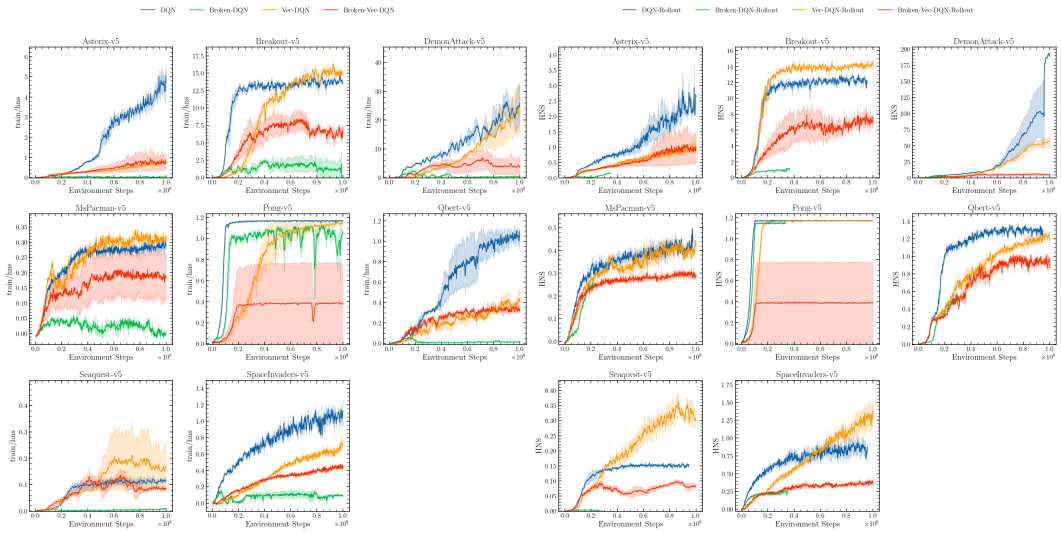
We use the implementation of PQN provided in CleanRL[4] and the hyperparameters proposed by (Gallici et al., 2024).

Table 5: Hyperparameters for PQN.

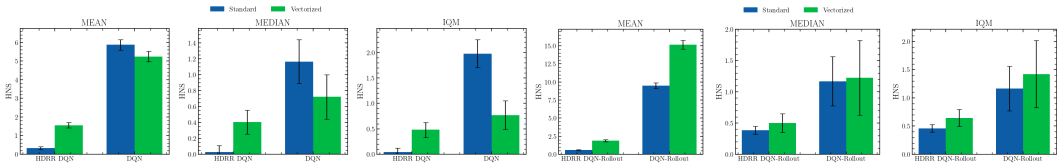
Parameter	Value
learning_rate	2.5e-4
num_envs	128
num_steps	32
anneal_lr	True
gamma	0.99
num_minibatches	32
update_epochs	2
max_grad_norm	10.0
start_e	1
end_e	0.01
exploration_fraction	0.10
λ	0.65

[4] https://github.com/vwxyzjn/cleanrl/blob/master/cleanrl/pqn_atari_envpool.py

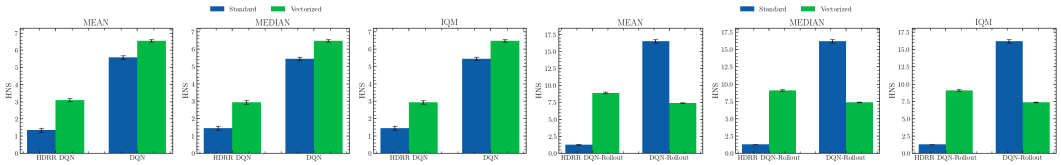
M Learning Curves



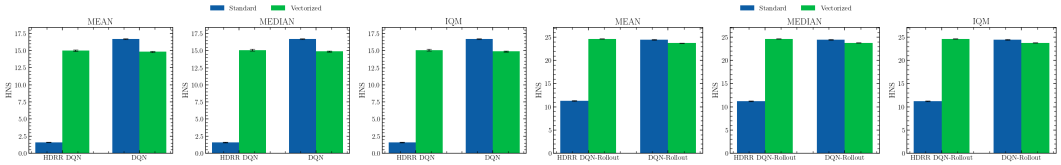
(a) Q(0) (b) Q(λ)



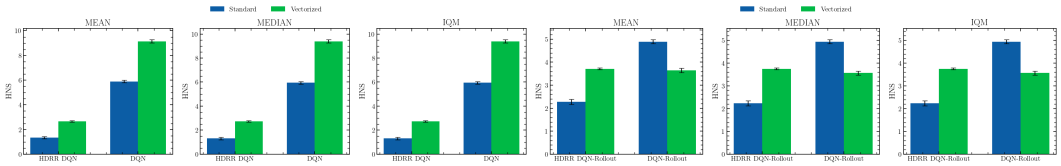
(a) ALE/8 - Q(0) (b) ALE/8 - Q(λ)



(a) DeadlyCorridor - Q(0) (b) DeadlyCorridor - Q(λ)



(a) DefendTheCenter - Q(0) (b) DefendTheCenter - Q(λ)



(a) Deathmatch - Q(0)

(b) Deathmatch - Q(λ)

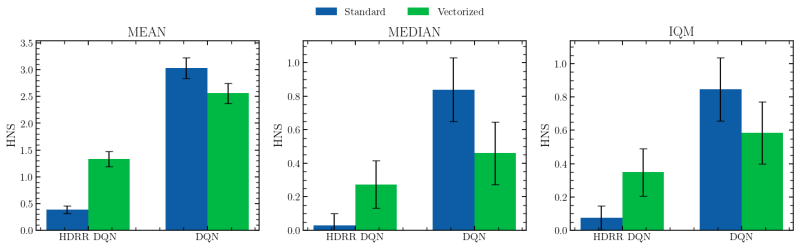
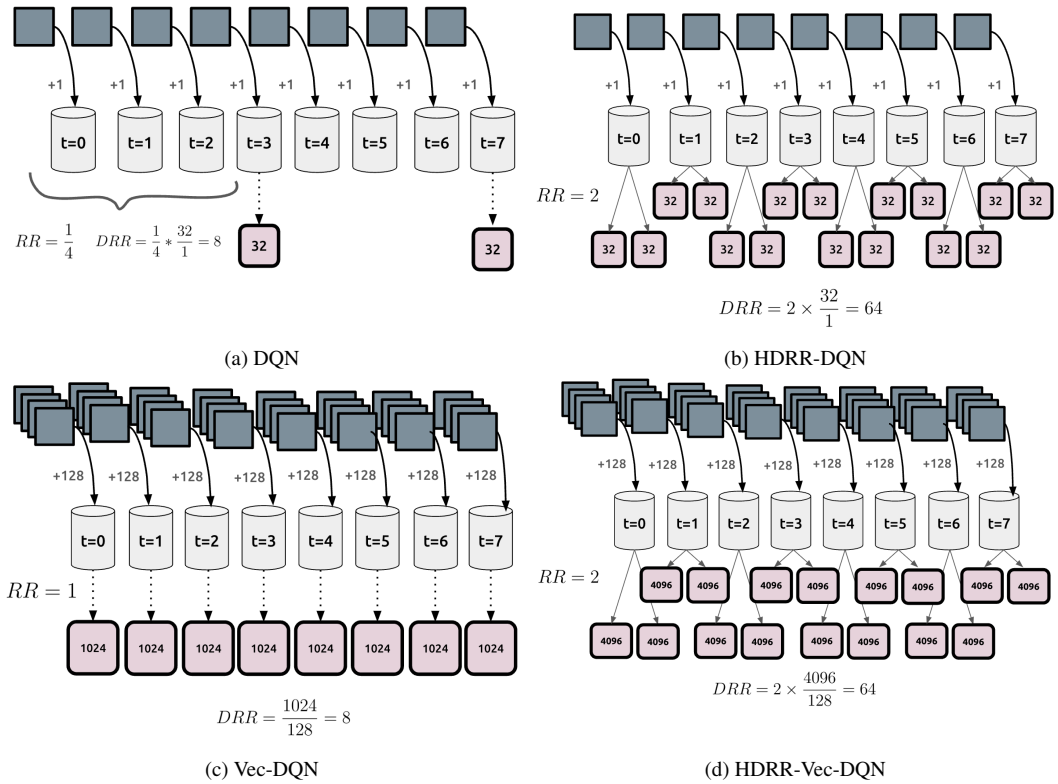


Figure 19: Evaluation of Double DQN (DDQN) in Atari10. While DDQN is designed to mitigate the TD bootstrapping bias and potentially improve data reuse, our results for DDQN show similar behavior to the DQN results in Figure 2. Specifically, small batch sizes remain highly sensitive to HDRR settings, often resulting in complete collapse. This issue can be mitigated by using vectorized environments and larger batch sizes. However, smaller batches can offer performance improvements due to their high variance updates, which may facilitate better exploration within the parameter space.

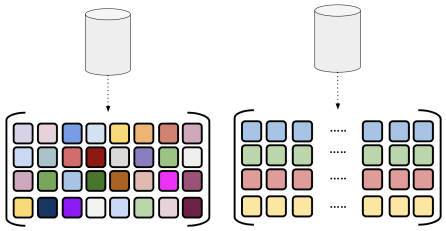


(a) DQN (b) HDRR-DQN

(c) Vec-DQN (d) HDRR-Vec-DQN

Figure 20: Illustration of the DRR across different data sampling configurations. Gray squares represent environment observations, where *Vec-* denotes multiple environments contributing observations to a shared buffer. Red squares depict learning batches.

N Diagrams



(a) Q(0) (b) Q(λ)

Figure 21: Different data sampling procedures when training with Q(0) vs Q(λ).

O Broader Impact

This paper presents work whose goal is to advance the field of Machine Learning. There are many potential societal consequences of our work, none which we feel must be specifically highlighted here.

References

Rishabh Agarwal, Max Schwarzer, Pablo Samuel Castro, Aaron C Courville, and Marc Bellemare. Deep reinforcement learning at the edge of the statistical precipice. *Advances in neural information processing systems*, 34:29304–29320, 2021.

Matthew Aitchison, Penny Sweetser, and Marcus Hutter. Atari-5: Distilling the arcade learning environment down to five games. In *International Conference on Machine Learning*, pp. 421–438. PMLR, 2023.

Adrià Puigdomènech Badia, Bilal Piot, Steven Kapturowski, Pablo Sprechmann, Alex Vitvitskyi, Zhaohan Daniel Guo, and Charles Blundell. Agent57: Outperforming the atari human benchmark. In *International conference on machine learning*, pp. 507–517. PMLR, 2020.

Leemon Baird et al. Residual algorithms: Reinforcement learning with function approximation. In *Proceedings of the twelfth international conference on machine learning*, pp. 30–37, 1995.

Marc G Bellemare, Yavar Naddaf, Joel Veness, and Michael Bowling. The arcade learning environment: An evaluation platform for general agents. *Journal of Artificial Intelligence Research*, 47: 253–279, 2013.

Aditya Bhatt, Daniel Palenicek, Boris Belousov, Max Argus, Artemij Amiranashvili, Thomas Brox, and Jan Peters. Crossq: Batch normalization in deep reinforcement learning for greater sample efficiency and simplicity. *arXiv preprint arXiv:1902.05605*, 2019.

Pablo Samuel Castro, Subhodeep Moitra, Carles Gelada, Saurabh Kumar, and Marc G Bellemare. Dopamine: A research framework for deep reinforcement learning. *arXiv preprint arXiv:1812.06110*, 2018.

Pablo Samuel Castro, Tyler Kastner, Prakash Panangaden, and Mark Rowland. Mico: Improved representations via sampling-based state similarity for markov decision processes. *Advances in Neural Information Processing Systems*, 34:30113–30126, 2021.

Tyler Clark, Mark Towers, Christine Evers, and Jonathon Hare. Beyond the rainbow: High performance deep reinforcement learning on a desktop pc. *arXiv preprint arXiv:2411.03820*, 2024.

Brett Daley and Christopher Amato. Reconciling λ-returns with experience replay. *Advances in Neural Information Processing Systems*, 32, 2019.

Pierluca D'Oro, Max Schwarzer, Evgenii Nikishin, Pierre-Luc Bacon, Marc G Bellemare, and Aaron Courville. Sample-efficient reinforcement learning by breaking the replay ratio barrier. In *Deep Reinforcement Learning Workshop NeurIPS 2022*, 2022.

Lasse Espeholt, Hubert Soyer, Remi Munos, Karen Simonyan, Vlad Mnih, Tom Ward, Yotam Doron, Vlad Firoiu, Tim Harley, Iain Dunning, et al. Impala: Scalable distributed deep-rl with importance weighted actor-learner architectures. In *International conference on machine learning*, pp. 1407–1416. PMLR, 2018.

William Fedus, Prajit Ramachandran, Rishabh Agarwal, Yoshua Bengio, Hugo Larochelle, Mark Rowland, and Will Dabney. Revisiting fundamentals of experience replay. In *International conference on machine learning*, pp. 3061–3071. PMLR, 2020.

Scott Fujimoto, Herke Hoof, and David Meger. Addressing function approximation error in actor-critic methods. In *International conference on machine learning*, pp. 1587–1596. PMLR, 2018.

Matteo Gallici, Mattie Fellows, Benjamin Ellis, Bartomeu Pou, Ivan Masmitja, Jakob Nicolaus Foerster, and Mario Martin. Simplifying deep temporal difference learning. *arXiv preprint arXiv:2407.04811*, 2024.

Tuomas Haarnoja, Aurick Zhou, Pieter Abbeel, and Sergey Levine. Soft actor-critic: Off-policy maximum entropy deep reinforcement learning with a stochastic actor. In *International conference on machine learning*, pp. 1861–1870. Pmlr, 2018.

Matteo Hessel, Joseph Modayil, Hado Van Hasselt, Tom Schaul, Georg Ostrovski, Will Dabney, Dan Horgan, Bilal Piot, Mohammad Azar, and David Silver. Rainbow: Combining improvements in deep reinforcement learning. In *Proceedings of the AAAI conference on artificial intelligence*, volume 32, 2018.

Sepp Hochreiter and Jürgen Schmidhuber. Long short-term memory. *Neural Comput.*, 9(8): 1735–1780, November 1997. ISSN 0899-7667. DOI: 10.1162/neco.1997.9.8.1735. URL https://doi.org/10.1162/neco.1997.9.8.1735.

Dan Horgan, John Quan, David Budden, Gabriel Barth-Maron, Matteo Hessel, Hado Van Hasselt, and David Silver. Distributed prioritized experience replay. *arXiv preprint arXiv:1803.00933*, 2018.

Jie Hu, Li Shen, and Gang Sun. Squeeze-and-excitation networks. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 7132–7141, 2018.

Marcel Hussing, Claas Voelcker, Igor Gilitschenski, Amir-massoud Farahmand, and Eric Eaton. Dissecting deep rl with high update ratios: Combatting value overestimation and divergence. *arXiv e-prints*, pp. arXiv–2403, 2024.

Steven Kapturowski, Georg Ostrovski, John Quan, Remi Munos, and Will Dabney. Recurrent experience replay in distributed reinforcement learning. In *International conference on learning representations*, 2018.

Steven Kapturowski, Víctor Campos, Ray Jiang, Nemanja Rakićević, Hado van Hasselt, Charles Blundell, and Adrià Puigdomènech Badia. Human-level atari 200x faster. *arXiv preprint arXiv:2209.07550*, 2022.

Michał Kempka, Marek Wydmuch, Grzegorz Runc, Jakub Toczek, and Wojciech Jaśkowski. Vizdoom: A doom-based ai research platform for visual reinforcement learning. In *2016 IEEE conference on computational intelligence and games (CIG)*, pp. 1–8. IEEE, 2016.

Tadashi Kozuno, Yunhao Tang, Mark Rowland, Remi Munos, Steven Kapturowski, Will Dabney, Michal Valko, and David Abel. Revisiting peng's q (lambda) for modern reinforcement learning. In *International Conference on Machine Learning*, pp. 5794–5804. PMLR, 2021.

Aviral Kumar, Rishabh Agarwal, Dibya Ghosh, and Sergey Levine. Implicit under-parameterization inhibits data-efficient deep reinforcement learning. *arXiv preprint arXiv:2010.14498*, 2020.

Hojoon Lee, Dongyoon Hwang, Donghu Kim, Hyunseung Kim, Jun Jet Tai, Kaushik Subramanian, Peter R Wurman, Jaegul Choo, Peter Stone, and Takuma Seno. Simba: Simplicity bias for scaling up parameters in deep reinforcement learning. *arXiv preprint arXiv:2410.09754*, 2024.

Jimmy Lei Ba, Jamie Ryan Kiros, and Geoffrey E Hinton. Layer normalization. *ArXiv e-prints*, pp. arXiv–1607, 2016.

Ang A Li, Zongqing Lu, and Chenglin Miao. Revisiting prioritized experience replay: A value perspective. *arXiv preprint arXiv:2102.03261*, 2021.

Timothy P Lillicrap, Jonathan J Hunt, Alexander Pritzel, Nicolas Heess, Tom Erez, Yuval Tassa, David Silver, and Daan Wierstra. Continuous control with deep reinforcement learning. *arXiv preprint arXiv:1509.02971*, 2015.

Clare Lyle, Zeyu Zheng, Khimya Khetarpal, James Martens, Hado van Hasselt, Razvan Pascanu, and Will Dabney. Normalization and effective learning rates in reinforcement learning. *arXiv preprint arXiv:2407.01800*, 2024.

Michael Matthews, Michael Beukman, Benjamin Ellis, Mikayel Samvelyan, Matthew Jackson, Samuel Coward, and Jakob Foerster. Craftax: A lightning-fast benchmark for open-ended reinforcement learning. *arXiv preprint arXiv:2402.16801*, 2024.

Volodymyr Mnih. Playing atari with deep reinforcement learning. *arXiv preprint arXiv:1312.5602*, 2013.

Volodymyr Mnih, Adria Puigdomenech Badia, Mehdi Mirza, Alex Graves, Timothy Lillicrap, Tim Harley, David Silver, and Koray Kavukcuoglu. Asynchronous methods for deep reinforcement learning. In *International conference on machine learning*, pp. 1928–1937. PmLR, 2016.

Rémi Munos, Tom Stepleton, Anna Harutyunyan, and Marc Bellemare. Safe and efficient off-policy reinforcement learning. *Advances in neural information processing systems*, 29, 2016.

Michal Nauman, Michał Bortkiewicz, Piotr Miłoś, Tomasz Trzciński, Mateusz Ostaszewski, and Marek Cygan. Overestimation, overfitting, and plasticity in actor-critic: the bitter lesson of reinforcement learning. *arXiv preprint arXiv:2403.00514*, 2024a.

Michal Nauman, Mateusz Ostaszewski, Krzysztof Jankowski, Piotr Miłoś, and Marek Cygan. Bigger, regularized, optimistic: scaling for compute and sample-efficient continuous control. *arXiv preprint arXiv:2405.16158*, 2024b.

Evgenii Nikishin, Max Schwarzer, Pierluca D'Oro, Pierre-Luc Bacon, and Aaron Courville. The primacy bias in deep reinforcement learning. In *International conference on machine learning*, pp. 16828–16847. PMLR, 2022.

Johan Obando-Ceron, João GM Araújo, Aaron Courville, and Pablo Samuel Castro. On the consistency of hyper-parameter selection in value-based deep reinforcement learning. *arXiv preprint arXiv:2406.17523*, 2024.

Johan Obando Ceron, Marc Bellemare, and Pablo Samuel Castro. Small batch deep reinforcement learning. *Advances in Neural Information Processing Systems*, 36, 2024.

Johan Obando-Ceron, Aaron Courville, and Pablo Samuel Castro. In deep reinforcement learning, a pruned network is a good network. *arXiv preprint arXiv:2402.12479*, 2024a.

Johan Obando-Ceron, Aaron Courville, and Pablo Samuel Castro. In value-based deep reinforcement learning, a pruned network is a good network. *arXiv preprint arXiv:2402.12479*, 2024b.

Ian Osband, Charles Blundell, Alexander Pritzel, and Benjamin Van Roy. Deep exploration via bootstrapped dqn. *Advances in neural information processing systems*, 29, 2016.

Jing Peng and Ronald J Williams. Incremental multi-step q-learning. In *Proceedings of the International Conference on Machine Learning*, 1994.

Jing Peng and Ronald J. Williams. Incremental multi-step q-learning. *Machine Learning*, 22(1): 283–290, 1996.

Tom Schaul. Prioritized experience replay. *arXiv preprint arXiv:1511.05952*, 2015.

Tom Schaul, André Barreto, John Quan, and Georg Ostrovski. The phenomenon of policy churn. *Advances in Neural Information Processing Systems*, 35:2537–2549, 2022.

John Schulman, Filip Wolski, Prafulla Dhariwal, Alec Radford, and Oleg Klimov. Proximal policy optimization algorithms. *arXiv preprint arXiv:1707.06347*, 2017.

Max Schwarzer, Johan Samir Obando Ceron, Aaron Courville, Marc G Bellemare, Rishabh Agarwal, and Pablo Samuel Castro. Bigger, better, faster: Human-level atari with human-level efficiency. In *International Conference on Machine Learning*, pp. 30365–30380. PMLR, 2023.

Ghada Sokar, Rishabh Agarwal, Pablo Samuel Castro, and Utku Evci. The dormant neuron phenomenon in deep reinforcement learning. In *International Conference on Machine Learning*, pp. 32145–32168. PMLR, 2023.

Richard S Sutton and Andrew G Barto. *Reinforcement learning: An introduction*. MIT press, 2018.

John Tsitsiklis and Benjamin Van Roy. Analysis of temporal-diffference learning with function approximation. *Advances in neural information processing systems*, 9, 1996.

Hado van Hasselt, Yotam Doron, Florian Strub, Matteo Hessel, Nicolas Sonnerat, and Joseph Modayil. Deep reinforcement learning and the deadly triad. *arXiv [cs.AI]*, December 2018.

Hado Van Hasselt, Yotam Doron, Florian Strub, Matteo Hessel, Nicolas Sonnerat, and Joseph Modayil. Deep reinforcement learning and the deadly triad. *arXiv preprint arXiv:1812.02648*, 2018.

Jiayi Weng, Min Lin, Shengyi Huang, Bo Liu, Denys Makoviichuk, Viktor Makoviychuk, Zichen Liu, Yufan Song, Ting Luo, Yukun Jiang, et al. Envpool: A highly parallel reinforcement learning environment execution engine. *Advances in Neural Information Processing Systems*, 35:22409–22421, 2022.

Shangtong Zhang, Hengshuai Yao, and Shimon Whiteson. Breaking the deadly triad with a target network. In *International Conference on Machine Learning*, pp. 12621–12631. PMLR, 2021.