RLSB

**Software Engineering for Artificial Intelligence**

# Reinforcement Learning Sustainability Benchmark

**Report v1.0**

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## Abstract

This project explores the energy consumption of deep reinforcement learning (DRL) algorithms and their impact on the environment and business costs. Beginning with the development of Deep Q-Networks (DQN) by DeepMind, numerous algorithms have been proposed to enhance the performance of DRL agents. However, the energy implications of these improvements have not been extensively studied. This project aims to fill this gap by benchmarking the energy consumption and performance of several widely used DRL algorithms.

We train various reinforcement learning algorithms on the same task: Atari 100k, a widely recognized benchmark in the DRL community. The selected algorithms include both value-based methods (such as DQN and RAINBOW) and policy gradient methods (such as REINFORCE with baseline and PPO). Each algorithm is evaluated on 8 different Atari games, with 4 runs per game using different random seeds, to ensure statistically significant results.

To track performance and energy consumption, we utilize Weights and Biases, TensorBoard, and CodeCarbon. The development environment is based on CleanRL, a library that provides single-file implementations of some DRL algorithms, ensuring consistency and reproducibility.

The preliminary version of this report covers the context, goals, and methodological steps of the project. Future sections will present detailed results and analyses of the trade-offs between performance and energy consumption, contributing to a broader understanding of the sustainability implications of DRL technologies.

# Contents

# 1 Context

This project addresses the energy consumption of deep reinforcement learning (DRL) solutions and their impact on the environment and business costs.

Beginning with the resurgence of the field following the development of *Deep Q-Networks* (DQN) by DeepMind in the early 2010s [1][2], there have been a number of algorithm proposals over time that with minor modifications to DQN or using a completely different paradigm (such as policy gradient methods) sought to improve the performance achieved by the learning agent.

Although the performances of the various solutions have been extensively studied and tracked, little effort has been directed toward understanding how the tweaks to the DQN introduced to improve performance impacted energy consumption, or what the cost of the alternative approaches developed was, per se and in comparison with previous solutions.

The motivation behind this project is to fill this gap by evaluating the trade-offs between performance and energy consumption for several widely used deep reinforcement learning (DRL) algorithms. Understanding these trade-offs is crucial for businesses and researchers who aim to optimize both performance and sustainability in their applications. This project aims to provide valuable insights into the energy efficiency of different DRL approaches, enabling informed decisions about their use in various contexts.

To reach this goal we train various reinforcement learning algorithms on the same task, the choice of which is discussed in section 3.2 on page 7. Section 3.1 on the next page describes the selected algorithms, whose choice was made taking into account that DRL algorithms can be devided in two main categories: *value based* (i.e. algorithms based on the approximation of a value function, be it the state-value function or the action-value function) and *policy gradient*. The latter are methods that approximate directly the policy, and includes as a special case the *actor-critic methods*, which approximate simultaneously a policy (said actor) and a value function (said critic).

# 2 Goals

The primary goal of this project is to benchmark the energy consumption and performance of various deep reinforcement learning algorithms. Specifically, we aim to:

1. evaluate the energy consumption of different DRL algorithms when trained on the same task;
2. compare the performance of these algorithms in terms of their ability to achieve high scores on the given task;
3. analyze the trade-offs between performance and energy consumption to identify the most efficient algorithms;
4. provide a comprehensive report that can guide practitioners in selecting the appropriate DRL algorithms based on specific use-case requirements.

By achieving these goals, the project will contribute to the broader understanding of the sustainability implications of deep reinforcement learning technologies.

# 3 Methodological Steps

The methodology used follows from the basic idea of this benchmark: to execute all the algorithms for the same number of environment interactions, so that we can compare the score they achieve and the energy consumption of each one of them. Additionally, a good comparison would be to take the score obtained by the lowest performer in this initial trial and re-train all the algorithms until they reach that score. This would allow us to compare how much time and energy each algorithm requires to achieve the same performance level. Unfortunately, time and resources constraints make retraining all algorithms unfeasible, so we will approximate this second comparison by using the returns from the logging of the training during the first trial. This logging includes the `global_step`, indicating the environment interaction we are at, and the `episodic_return`, which is the return of the episode (i.e., the score on which to compare), as well as all performance and power consumption data up to that point. By analyzing these logs, we will estimate how much time and energy each algorithm would take to reach the score obtained by the lowest performer in the initial trial.

The following sections outline the several key steps involved in the methodology adopted for this project.

## 3.1 Algorithms Selection

As stated, in our benchmark we consider both value-based methods and policy gradient methods. The selected algorithms are chosen to represent a wide range of approaches within both categories.

### 3.1.1 Value-Based Methods

Value-based methods are algorithms based on the approximation of a value function. The following algorithms were considered in this category (but due to time and computational constraints, only a subset of 5 of them were fully trained and evaluated):

- *Deep Q-Network (DQN)*: the first example of success in deep reinforcement learning, will serve as a sort of baseline for our benchmark.
- *RAINBOW* [3]: an advanced method that combines several improvements to the original DQN, that will also be tested individually to assess their individual contributions to energy consumption and performance. These are listed hereafter:
  - Double Q-Learning (Double DQN) [4];
  - Prioritized Experience Replay [5];
  - Dueling Network Architectures [6];
  - Multi-step / N-step Learning [7];
  - Distributional RL [8];
  - Noisy Nets [9];
- *Self-Predictive Representations (SPR)* [10]: a more advanced method introduced in recent research, which leverages self-predictive representations to improve efficiency.

### 3.1.2 Policy Gradient Methods

Policy gradient methods approximate the policy directly and include as a special case the actor-critic methods, which simultaneously approximate a policy and a value function. The algorithms considered in this category are:

- *REINFORCE* [11, Chapter 13]: a basic policy gradient method, or its variant REINFORCE with baseline (also known as Vanilla Policy Gradient, VPG).
- *Proximal Policy Optimization (PPO)* [12]: a popular and efficient policy gradient method that uses a clipped objective to improve training stability.
- *Deep Deterministic Policy Gradient (DDPG)* [13]: an algorithm that combines policy gradients with deterministic policy updates for continuous action spaces.
- *Twin Delayed DDPG (TD3)* [14]: an improvement over DDPG that addresses function approximation errors through various techniques, such as delayed policy updates and target policy smoothing.
- *Soft Actor-Critic (SAC)* [15]: an extension of DDPG that incorporates entropy regularization to encourage exploration. SAC, like TD3, uses two Q-networks to reduce overestimation bias, but it differs by optimizing a stochastic policy instead of a deterministic one. This makes SAC more sample-efficient and stable in continuous control tasks. It is also more easily adapted to discrete action spaces.

- *Data-Regularized Q (DRQ)* [16]: a method that incorporates data augmentation to regularize the training of Q functions, improving performance and stability.

## 3.2 Task Selection

Regarding the task on which to compare the algorithms, there were several suitable candidates: Atari 100k [17], one of the continuous control task of the DeepMind Control Suite, or one of the many other task (besides Atari) included in OpenAI Gymnasium (formerly Gym), and so on. After various tests and research we opted for the Atari 100k benchmark, a discrete task that consists of playing selected Atari games for only 100 000 environment interactions.

The reason for this choice is multifaceted. Atari 100k is a widely used benchmark in the DRL community, the wealth of prior research and baseline results available facilitates a more straightforward validation and comparison of our experimental results with those from other studies and algorithms. It is also well suited for evaluating the performance of almost all popular DRL algorithms, ensuring a comprehensive assessment. Additionally, Atari games provide a range of different challenges, including planning, reaction time, and strategy, making it a robust benchmark for assessing general DRL capabilities.

Moreover, the discrete nature of Atari 100k simplifies the implementation and comparison of algorithms, as continuous control tasks often require additional considerations and modifications. Finally, the 100 000 interactions limit strikes a balance between providing enough data for meaningful evaluation and being computationally feasible within our resource constraints, especially considering the large number of experiments required for each algorithm, as detailed in section 3.3.1.

These factors combined make Atari 100k a practical and effective choice for our benchmark, enabling us to achieve our project goals efficiently.

## 3.3 Experiment Setup

In this section we will address all the decisions made in the setup of the experiments.

### 3.3.1 Number of Runs

In determining how many runs to carry out during the experimentation and testing of a reinforcement learning algorithm, at least two fundamental aspects must be taken into account: the high variance of reinforcement learning, and thus its high susceptibility to randomness, and the evaluation of the generality of the algorithm, which must therefore be tested in several different environments in order to actually prove that it is capable of solving multiple problems and not just be ultra-specialized on a single use-case.

In addressing the first aspect we can refer to the literature to get an idea of how many runs with different seeds are usually performed to alleviate this problem. If in the early days of RL (and not DRL) the number of runs stood at around 100 and in any case did not fall below 30, at least until the introduction of ALE (Arcade Learning Environment) [18] included, with the advent of DRL the number of runs was consistently

reduced to 5 or less because of the high cost in terms of time and resources per run. Although this has been the standard for years, a more recent work [19] has shown that this is the source of a problem. Practitioners use point estimates such as mean and median to aggregate performances scores across tasks to summarize the results of the various runs, but this metrics are not the best way to do so because they ignore the statistical uncertainty inherent in performing only a few runs.

In particular, the study points out that in the case of Atari at least 100 runs per environment are required to obtain robust results, a value that is, however, impractical in reality. To address this, the study recommends using alternative aggregation metrics, such as interquartile means, designed precisely to obtain more efficient and robust estimates and have small uncertainty even with a handful of runs, since they are not overly affected by outliers like the point estimates.

In our case we will be forced to limit ourselves to 4 runs per environment, so we will use, in addition to the more classic and popular metrics such as the point estimates mentioned above, the other metrics suggested in [19]. It should anyway be noted that a low number of runs is a less significant problem for us, since we are not attempting to advance the state of the art performance of DRL algorithms, but have instead a focus on energy consumption and emissions, which should in any case remain constant regardless of the actual learning of the agent, which is instead related to randomness.

With regard to the second aspect, namely, testing the algorithms on a variety of environments to evaluate their generality, Atari 100k once again comes to our aid, being constituted by 26 games. Moreover, the Arcade Learning Environment, built on top of the Atari 2600 emulator Stella and used by gymnasium, includes over 55 games. Unfortunately, again, we do not have the time and/or computational resources to test on all the Atari 100k's 26 games or all the ones available in ALE, so we selected for the benchmark a representative subset of 8 Atari games, trying to choose games that cover a range of difficulties and styles. Obviously, with so few games because of the constraints just mentioned, an exhaustive selection is difficult, but we nonetheless tried to provide a balanced benchmark, ensuring that the selected games cover a range of challenges to effectively evaluate different algorithms, while still not being excessively difficult. This last requirement is due to basic DQN and its more simple extensions, which have some limitations in only 100k interactions (the team that introduced the DQNs trained its model on millions of interactions to achieve interesting results).

Here are the 8 selected games, along with a rationale for their inclusion:

- *Alien* - involves exploration and strategic movement;
- *Amidar* - requires precise movement, quick decision-making and long-term planning;
- *Assault* - a fast-paced shooter testing reflexes and targeting accuracy;
- *Boxing* - visually simple yet requires precise timing and positioning;
- *Breakout* - a control-based game widely studied in RL;
- *Freeway* - simple ruleset, tests quick decision-making and reaction time;

- *Ms. Pac-Man* - emphasizes navigation, evasion, and planning;
- *Pong* - minimalistic, simple and well-understood game used as an RL baseline.

Although Alien and Ms. Pac-Man may appear similar in terms of overall theme, we decided to keep both in our selection due to their differing action space structures. Alien has a more complex movement and shooting action space, while Ms. Pac-Man involves navigation-based control with a different interaction model. Including both allows us to evaluate how reinforcement learning algorithms adapt to environments with distinct control dynamics, rather than just variations in visual style or game mechanics.

So, to summarize, each algorithm will be evaluated on 8 different Atari games, with 4 runs per game using different random seeds, for a total of 32 trainings per algorithm. This approach, with appropriate metrics, ensures that our results are statistically significant and account for the inherent variability in RL training processes.

### 3.3.2 Data Logging and Storage

Collecting comprehensive and accurate data is crucial for evaluating both the performance and energy consumption of the algorithms. We employ several tools and services to ensure robust data collection and analysis.

To track the performance metrics, we use both online and local tools. The online service *Weights and Biases* (wandb) is used for real-time monitoring and storage of experimental data. This platform allows for easy sharing and collaboration, as well as providing powerful visualization and analysis tools. Locally, we use *TensorBoard*, which integrates seamlessly with our training workflows and offers detailed insights into the training process through its rich set of visualizations.

In addition to tracking performance metrics, monitoring energy consumption and emissions is the key aspect of the project. For this we use *CodeCarbon*, a tool designed to measure the carbon footprint of computing activities. As stated in their documentation, this package enables developers to track emissions, measured as kilograms of $CO_2$-equivalents ($CO_2$eq) in order to estimate the carbon footprint of their work. $CO_2$-eq is a standardized measure used to express the global warming potential of various greenhouse gases: the amount of $CO_2$ that would have the equivalent global warming impact. For computing, which emits $CO_2$ via the electricity it is consuming, carbon emissions are measured in kilograms of $CO_2$-equivalent per kilowatt-hour [20]. See this page and section 4.1 for more information on their methodology.

Explained the tools, the metrics we collect through them include:

- *Global Step:* indicates the number of environment interactions during training.
- *Episodic Return:* the score achieved in each episode, providing a measure of the algorithm's performance.
- *Loss(es):* track the optimization process, giving insight into the learning dynamics of the algorithm.

- *Value Estimates:* such as Q-values or value function estimates, offering insight into the agent's decision-making process.
- *Policy Entropy:* measures the randomness in the policy and how much it differs from the previous one, useful for understanding exploration behavior and how much room for improvement is still left.
- *Learning Rate:* the rate at which the model learns, especially if it changes during training.
- *Emissions:* the amount of $CO_2$-eq emitted during training, tracked by CodeCarbon.

Weights and Biases facilitates a coarse aggregation and visualization of these metrics across multiple runs and environments, making it easier to compare results at a first glance and draw some first insights. TensorBoard provide supplementary local visualizations to help diagnose any issues during training and ensure the integrity of the collected data.

By using these tools in tandem, we aim to collect a comprehensive dataset that covers both the performance and energy consumption aspects of the algorithms, ensuring a thorough evaluation aligned with the goals of our project.

### 3.3.3 Development and Execution Environment

The development and execution environment for the project involves both hardware and software. In particular, we have made use of two different hardware setups due to constraints in energy tracking capabilities.

Initially, all configurations and the first fine-tuning of DQN and some other algorithms were performed on a machine with:

- **CPU**: 11th Gen Intel(R) Core(TM) i5-11400F @ 2.60GHz
- **GPU**: NVIDIA GeForce GTX 1050 Ti
- **RAM**: 16GB

However, due to CodeCarbon's lack of support for the GTX 1050 Ti in tracking GPU energy consumption, the main training experiments had to be conducted on a different machine with higher computational power and proper energy tracking support. The second setup consisted of:

- **CPU**: Intel(R) Core(TM) i9-10980XE @ 3.00GHz
- **GPU**: NVIDIA RTX A5000
- **RAM**: 64GB

While the first machine was sufficient for setting up the environment and running initial fine-tuning, this switch to the A5000 GPU in the second setup was necessary to

ensure full compatibility with CodeCarbon and reliable, accurate measurement of energy consumption and carbon emissions during experimentation.

On the software side, after careful considerations and some testing with other alternatives like OpenAI's *Spinning Up*, we chose to base the implementation of the project on *CleanRL* [21]. As the authors states, CleanRL is an open-source library that provides high-quality single-file implementations of Deep Reinforcement Learning algorithms. It provides an environment already complete with most dependencies a project like ours might need (like Gymnasium), has a straightforward codebase, and already integrates tools like Weights and Biases and TensorBoard, that help log metrics, hyperparameters, videos of an agent's gameplay, dependencies, and more.

The single-file implementation philosophy of CleanRL aims to make reinforcement learning research more accessible and reproducible and make the performance-relevant details easier to recognize. By consolidating every algorithm codebase into single files, it simplifies the understanding and modification of algorithms, which is particularly beneficial for both educational purposes and rapid prototyping, even though it comes at the cost of losing modularity and duplicating some code.

We leverage CleanRL's existing implementations where available, tweaking them to meet the specific requirements of our benchmarks. When an implementation for a particular algorithm is not available, we develop it from scratch, trying to adhere to CleanRL's philosophy and implementation principles. This approach ensures consistency and comparability across all tested algorithms.

In the end, the environment for our experiments should be efficient and easily reproducible, facilitating the accurate evaluation of both performance and energy consumption of various deep reinforcement learning algorithms.

### 3.3.4 Atari Environment Configuration

The Atari environment setup follows best practices outlined in [22] for training and evaluating agents in the Arcade Learning Environment (ALE). These decisions were made to ensure a standardized, reproducible, and robust experimental setting. Additionally, we incorporate relevant insights from the ALE documentation to refine our environment configuration. Many of these choices also align with those made in the first works on Deep Q-Networks (DQN), ensuring comparability with early research efforts.

**Preprocessing and Standardization** The preprocessing pipeline ensures consistent input representations across different Atari games, avoiding confounding factors that could skew results. Through the use of appropriate atari wrappers of Stable Baselines v3, the following steps are implemented:

**Frame skipping:** we use `MaxAndSkipEnv(skip=4)`, ensuring that actions are repeated for four frames and the maximum pixel values of consecutive frames are used. This stabilizes the input representation and allows agents to process meaningful changes in the game environment while reducing computational load (the agent can play roughly 4 times more games without significantly increasing the runtime).

**Random no-op initialization:** at the beginning of each episode, a random number (up to 30) of "do nothing" actions are executed (`NoopResetEnv(noop_max=30)`). This prevents deterministic policies from exploiting fixed starting conditions, improving generalization.

**Episodic life and fire reset:**

`EpisodicLifeEnv`: is used to reset the environment after each lost life instead of at the end of the full game. This makes training more efficient by exposing the agent to more starting states per episode.

`FireResetEnv`: is applied in games where a "FIRE" action is required to start (e.g., Breakout), ensuring proper initialization.

**Observation preprocessing:**

- raw RGB images are converted to grayscale and resized to 84×84 pixels (`GrayScaleObservation` and `ResizeObservation`).
- a history of the last four frames is stacked (`FrameStack(4)`) to provide temporal context, compensating for the partially observable nature of the environment.

**Reward clipping:** rewards are clipped between -1 and 1 (`ClipRewardEnv`) to standardize their scale across different games. This makes the algorithms able to work with all games without needing refinements to adapt to particularly high- or low-reward games, while stabilizing training.

**Choice of the Environments Version** The Arcade Learning Environment (ALE) [18] provides multiple versions of Atari environments [23] to address different research requirements and needs. These environments versions encapsulate the preprocessing steps we talked about, each one setting a different default value for them and some other aspects of the games. Two of the most widely used versions are *NoFrameskip-v4* and *v5*. The main distinction between these is the inclusion of *sticky actions* in *v5*, as recommended in [22]. Sticky actions introduce a 25% probability of repeating the previous action, adding stochasticity to the environment to prevent overfitting when training deterministic policies.

In this study, we use the *NoFrameskip-v4* environments [23]. This choice is motivated by several factors. First, *NoFrameskip-v4* ensures fully deterministic execution when a fixed random seed is used, which is crucial for the reproducibility of our experiments. This determinism allows us to conduct controlled comparisons of different algorithms while minimizing the influence of environment stochasticity on performance evaluation. Additionally, since our preprocessing pipeline explicitly applies `MaxAndSkipEnv(skip=4)` to handle frame skipping in a standardized way (as discussed in the previous section), the built-in frame skipping behavior of other environment versions is unnecessary and would introduce redundant processing.

**Table 1:** Comparison between our setup based on NoFrameskip-v4 and ALE v5 environments.

| **Feature** | **NoFrameskip-v4 (Our Setup)** | **ALE v5** |
|---|---|---|
| Frame Skipping | Explicitly set via `MaxAndSkipEnv(skip=4)` | Implicit (default 4) |
| No-op Start | `NoopResetEnv(noop_max=30)` | `NoopResetEnv(noop_max=30)` |
| Episodic Life | `EpisodicLifeEnv` | `EpisodicLifeEnv` |
| Fire Reset | `FireResetEnv` (if needed) | `FireResetEnv` (if needed) |
| Observation Preprocessing | Grayscale + Resize (84x84) + FrameStack(4) | Grayscale + Resize (84x84) + FrameStack(4) |
| Reward Clipping | `ClipRewardEnv` (-1, 1) | `ClipRewardEnv` (-1, 1) |
| Sticky Actions (`repeat_action_probability`) | Not Used (Fixed Action Selection) | Enabled (`0.25`) |

The primary difference between our setup and the *v5* environments is the exclusion of sticky actions. While sticky actions can enhance generalization in long training regimes by preventing the agent from overfitting to deterministic game mechanics, their benefits are less relevant in our setting, where each run is limited to only 100k interactions. Under such a short training horizon, the additional stochasticity introduced by sticky actions would significantly degrade training stability and learning efficiency, leading to noisier performance estimates, thus removing them is not only not problematic, but almost mandatory. Furthermore, the use of sticky actions is not as ubiquitous in the reinforcement learning literature as other preprocessing steps, making their exclusion a reasonable choice also for comparability with prior work.

By structuring our preprocessing pipeline around the NoFrameskip-v4 environments and following the best practices from [22], we ensure that our experimental results are robust, reproducible, and comparable to the large body of prior deep reinforcement learning research. The preprocessing steps applied in our implementation are widely used in reinforcement learning studies and enable fair performance evaluations across different Atari games. Furthermore, the decision to exclude sticky actions aligns with the constraints of our 100k iteration limit, ensuring meaningful training without excessive randomness hindering learning progress. Table 1 show a comparison between our setup and v5.

### 3.3.5 (Hyper)Parameter Configurations

We discuss in this section a set of parameters that influence the experiment setup but not directly the optimization process like hyperparameters do. Regarding the latter, we do discuss here our general approach in their initial setting and optimization, but we delay to section 4, in which we dedicate a section to every algorithm, the details regarding their

fine tuning, so to have a more cohesive and complete presentation. Both parameters and hyperparameters are passed to the script as command-line arguments.

#### Parameters

**Tracking and Logging:** the flag `--track` ensures that training metrics are logged in `wandb`. The project name is set through the flag `--wandb-project-name` (in our case `rlsb`). The tracking in tensorboard is always enabled.

**Device Usage:** `--cuda` enables training on GPU, if this option is available.

**Random Seed:** the `--seed` value to use for this run.

**Video Capture:** the `--capture-video` flag is used to record the gameplay of the agent. We set it to `False`, indicating that video recording of agent behavior is not performed during training, but we enable it during evaluation.

**Model Saving:** the `--save-model` flag is set to `True`, this also automatically starts the evaluation process right after the model is saved.

**Hyperparameters** The hyperparameter selection for all implemented algorithms was primarily based on the configurations used in the original papers introducing each method and, when available, those from the CleanRL implementation. A key consideration across all algorithms was the adaptation of the hyperparameters strictly connected to the number of environment interactions. Since deep reinforcement learning algorithms are typically trained for 5 to 10 million interactions, whereas our study was constrained to 100 000 interactions, certain hyperparameters, such as `learning_starts` and `buffer_size`, required adjustment to ensure appropriate behavior in this limited training setting.

For the baseline Deep Q-Network, the hyperparameters closely matched those from [2] and the CleanRL repository, as both sources used highly similar settings. The main focus of the tuning was the aforementioned adaptation to a reduced number of interactions with the environment.

For the various DQN variants tested, the hyperparameters were initialized using the same configuration employed for the base DQN implementation. The tuning process primarily involved modifying parameters directly associated with the respective architectural or algorithmic tweak while keeping the overall structure as consistent as possible with standard DQN. This approach aligns with the methodology commonly adopted in prior research introducing these modifications, ensuring a fair and controlled comparison. By maintaining a shared foundation across variants, we were able to isolate the impact of each specific enhancement in terms of performance improvements and emissions cost.

### 3.3.6 Evaluation

After completing the training phase, we evaluate the agent by executing 10 episodes in the target environment. During these episodes, we collect the *episodic returns*, which serve as the primary metric for performance assessment.

The evaluation of the DQN-based methods is conducted with a fully deterministic policy, setting $\varepsilon = 0.00$ to disable exploration, ensuring that the agent exploits its learned policy without stochasticity. This allows for a clear assessment of how well the trained model generalizes to unseen episodes. The same is true for SAC (see also the discussion in 4.4.3), while Reinforce and PPO, being on-policy algorithm that optimize a stochastic policy, are evaluated on it, meaning actions are sampled from the learned distribution.

While, to avoid interference with the training process, we disable video recording during it, we enable it during evaluation by setting `capture_video=True`. This provides visual insight into the agent's behavior without incurring the computational overhead during learning.

The collected episodic returns undergo statistical analysis following the methods described in Data Analysis and Visualization. Specifically:

- We apply normalization to the collected data, both **human normalization** and **min-max normalization**, as detailed in 3.4.2.
- Basic statistics are computed on the normalized data, including mean, standard deviation, and median.
- The **interquartile mean (IQM)** is used as a robust estimator, as suggested in prior research.

The evaluation script loads the trained model, initializes a synchronized evaluation environment, and runs the agent for the specified number of episodes. It follows the same preprocessing pipeline used in training, ensuring consistency in observation space and action execution.

## 3.4 Data Analysis and Visualization

A critical part of this project involved consolidating and analyzing the training logs in a consistent and reproducible manner. Although *Weights & Biases* (W&B) and *TensorBoard* can both display metrics across runs, they each have limitations for comparative analysis—particularly when plotting multiple algorithms or combining results with additional metadata (e.g., hyperparameters, emissions data). Consequently, a custom data-processing pipeline was built to generate unified plots and aggregated statistics.

### 3.4.1 Log Collection and Merging

We collected detailed logs for each run: TensorBoard event files (containing metrics such as episodic returns, steps per second, losses, etc.) and W&B logs, which contains all the data of the TensorBoard logs (extrapolated from the uploaded TensorBoard logs), plus some other system related metrics. To work on this data in Python with its scientific tools we employed the `tbparse` library to parse the TensorBoard logs, making modifications to the library where necessary to handle deprecated NumPy types. These parsed logs resulted in two CSV files, one with all the metrics for all the runs, the other containing

additional information about hyperparameters (e.g., learning rate, buffer size, and so forth) from the experimental configuration. We then merged the two files into a single, larger CSV dataset containing all runs from all algorithms.

### 3.4.2 Normalization of Returns

Since the raw episodic returns for Atari games vary widely in scale, a fair and not skewd comparison needed a normalization step. This is one of the reasons that prevented us from directly using tensorboard and wandb plots. We performed two distinct normalization procedures:

**Human-Normalized Returns:** in this approach, for each game, we subtract the score of a random agent and divide by the difference between the human baseline and the random baseline. This is a standard practice in Atari benchmarks to contextualize performance relative to human play. Among the first to use this approach were the authors of [2], from which we took the random policy and professional human player values used for normalization. The formula for obtaining the normalized value is: $x_{\text{norm}} = \frac{x - x_{\text{random}}}{x_{\text{human}} - x_{\text{random}}}$, where $x$ is the agent score, $x_{\text{random}}$ is the random policy score, and $x_{\text{human}}$ is the professional human player score.

**Min-Max Normalization:** a classic min-max scaling (*i.e.*, $x_{\text{norm}} = \frac{x - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}}$) on a per-game basis, where $x_{\text{min}}$ and $x_{\text{max}}$ come from the observed range of returns for that game, over training and evaluation of all algorithms.

These normalized returns facilitate more intuitive cross-game comparisons, ensuring that no single game with unusually high or low rewards dominates the overall analysis. Since the relative comparison between the algorithms is the same with both normalizations, we can use indifferently either one of them based on which one produce a clearer plot.

### 3.4.3 Interpolation and Aggregation

When generating metric curves (such as episodic returns vs. training steps), we needed a consistent $x$-axis across runs. Many runs log metrics at slightly different steps (due to stochastic episode lengths, logging frequencies, etc.). The management of this aspect from both wandb and tensorboard is not ideal or lacking, not always allowing precise control or easy export of aggregated data.

In our pipeline, we therefore:

1. **Filtered by Metric and Run.** We grouped rows in the CSV by a specific tag (e.g., `charts/episodic_return`, `charts/SPS`) and by run.

2. **Interpolated to a Common Grid.** For each subset, we created a uniformly spaced array of steps (i.e., 1000 points from 0 to 100 000). We then applied linear interpolation on each run's time series to ensure all runs aligned on this common step axis.

3. **Computed Statistics.** At each point on the new, shared step grid, we aggregated the interpolated run values to produce statistics such as *mean*, *min–max range*, *standard deviation*, *iqmean* etc.

The interpolation ensures that every run contributes to the curves at the same discrete set of training steps, simplifying the generation of *mean* or *min–max* envelopes. This was crucial for plotting aggregate performance over multiple runs.

### 3.4.4 Plot Generation and CSV Output

Following the interpolation and aggregation process, the final step was to produce consistent plots for each metric–algorithm pair. We used `matplotlib` to generate both raster (PNG) and vector (SVG) graphics. Additionally, the aggregated statistics for each plot were saved as a separate CSV file, allowing subsequent combinations of multiple algorithms on a single plot without re-running the entire pipeline.

Overall, this approach provided:

- Fine-grained control over which metrics and runs to include;
- A robust method (interpolation) to align metrics across stochastic training steps;
- Easy export to consistent plots and CSVs for further analysis.

By integrating custom plotting and data analysis with the logs from W&B and TensorBoard, we ensure reproducibility and enable deeper insights into the trade-offs between performance and energy consumption across all tested algorithms.

# 4 Preliminary Results and Findings

This section presents the results obtained from training a subset of the algorithms discussed in section 3.1. The selected algorithms include five DQN-based methods — DQN, Double DQN, Prioritized Experience Replay, Dueling DQN, and C51 — as well as three policy-based methods: REINFORCE, PPO, and SAC. Soft Actor Critic was preferred to DDPG and TD3 because it can simply be seen as a variation that works with a stochastic policy, but is more easily adapted to a discrete action space.

We first describe necessary modifications to the experiment setup, followed by a detailed analysis of each algorithm's performance and emissions. The results are then compared inter-algorithm families and across them.

## 4.1 Experiment Setup Adjustments

During initial training attempts, some adjustments were required to ensure reliable performance and energy tracking. One key reason for this was that employing CodeCarbon as a (next-)real-time emissions tracking tool significantly slowed down training (by a factor of 20 or more). As a result, we opted to record only total emissions at the end of

training rather than tracking them continously. This adjustment allowed us to obtain meaningful comparisons without excessively increasing training time.

In addition to this, on Windows, CodeCarbon's CPU energy tracking relies on the Intel Power Gadget, which has been deprecated for several years. Furthermore, it does not support Intel Performance Counter Monitor (Intel PCM), the official successor to the Power Gadget. In such cases, CodeCarbon switches to a fallback mode, directly quoting from their documentation:

> - It will first detect which CPU hardware is currently in use, and then map it to a data source listing 2000+ Intel and AMD CPUs and their corresponding thermal design powers (TDPs).
> - If the CPU is not found in the data source, a global constant will be applied. CodeCarbon assumes that 50% of the TDP will be the average power consumption to make this approximation.
> - We could not find any good resource showing statistical relationships between TDP and average power, so we empirically tested that 50% is a decent approximation.

This approach should provide reasonable estimates for our project, since most of the workload is on the GPU, while the rest is mostly constant across the algorithms (like the environment simulations). This being said, one instance where this limitation may have had an impact is in tracking the Proximal Policy Optimization (PPO) algorithm, that employs a relatively small neural network but requires more CPU and RAM processing, the latter also explicitly stated to not be tracked satisfactorily by CodeCarbon.

Additionally, Weights & Biases collects system data during training, and while it tracks GPU energy consumption in kWh, it also does not do the same for CPU and RAM. As a result, while we can obtain excellent emissions estimates for the GPU, CPU and RAM energy tracking remains imprecise due to the aforementioned limitations. Consequently, energy consumption analyses must be interpreted with an understanding of these constraints.

## 4.2 DQN-Based Algorithms

We present the results for the five different DQN-based algorithms. Each algorithm is analyzed individually before an overall comparison.

### 4.2.1 Deep Q-Network (DQN Baseline)

**(Hyper)Parameters** Table 2 summarizes the main hyperparameters used for our DQN baseline. `env_id` and `seed` varied across runs (eight Atari games × four seeds), while the rest remained unchanged. Note in particular that `buffer_size` and `learning_starts` have been reduced relative to their usual millions-step values to accommodate the shorter 100k-step regime.

**Table 2:** Key hyperparameters for the DQN baseline. Only `env_id` and `seed` change across runs.

| **Parameter** | **Value** |
|---|---|
| `exp_name` | dqn_atari |
| `seed` | 1..4 |
| `torch_deterministic` | True |
| `cuda` | True |
| `track` | True |
| `wandb_project_name` | rlsb |
| `capture_video` | False |
| `save_model` | True |
| `upload_model` | False |
| `env_id` | e.g. AlienNoFrameskip-v4 |
| `total_timesteps` | 100000 |
| `learning_rate` | 0.0001 |
| `num_envs` | 1 |
| `buffer_size` | 10000 |
| `gamma` | 0.99 |
| `tau` | 1.0 |
| `target_network_frequency` | 1000 |
| `batch_size` | 32 |
| `start_e`, `end_e` | $1.0 \rightarrow 0.01$ |
| `exploration_fraction` | 0.1 |
| `learning_starts` | 1000 |
| `train_frequency` | 4 |

**Hyperparameter Tuning** We began with the *CleanRL* defaults (similar to Mnih et al.'s original DQN [1]) and scaled down parameters tied to a large number of environment interactions. For instance, `buffer_size` was tested at {10k, 20k}, and `learning_starts` at {800, 1000, 2000, 5000}. Empirically, a buffer of 10k and `learning_starts` of 1000 provided the best trade-off between stability and performance in the 100k-step setting. We kep $\tau$ equal to 1 for consistency with the original work. This parameter regulates the update of the target network weights by controlling the interpolation between those of the current Q-network and target network, following the update rule:

$$\vartheta_{\text{target}} = \tau\vartheta + (1-\tau)\vartheta_{\text{target}}$$

where $\vartheta_{\text{target}}$ are the weights of the target network and $\vartheta$ are the ones of the q-network. For $\tau = 1$, the target network is completely overwritten by the Q-network every time it's updated, as done in the original DQN.

**Training Dynamics (Aggregated Over 32 Runs)** Figure 1a shows that episodes usually last in the 3000–4000 step range, but certain runs or environments have early terminations (very short episodes) or extremely long ones (around 8000 steps). Figure 1b indicates that, computationally, training stabilizes at a solid ∼170 steps per second on average, though environment differences introduce some variance.

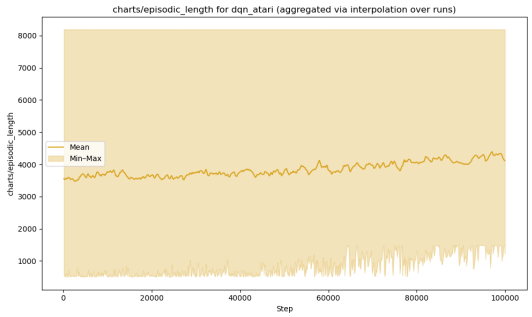
**Q-Values and TD Loss** Figures 1c and 1d show `losses/q_values` and `losses/td_loss`, respectively, across all runs. On average, Q-values increase steadily, suggesting the network's estimates of future returns keep growing with experience. However, the broad min–max band indicates some seeds or games diverge or plateau differently. The TD loss remains small in early training but spikes in certain runs, possibly due to volatile updates from the replay buffer once it's partially filled.

**Episodic Return (Human vs. Min–Max Normalized)** We analyzed the collected episodic returns applying both the human normalization and min–max normalization schemes, as explained in section 3.4.2 on page 16. Figures 2 and 3 aggregate these returns across all 32 runs, while Figures 4 and 5 show per-game curves.

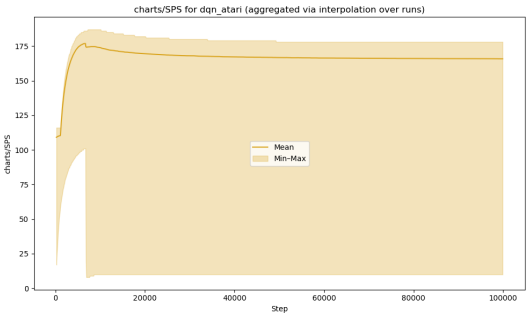
In the human-normalized plot, the mean hovers near zero, occasionally dipping negative due to poor performance on certain games. In the min–max plot, the average climbs from near 0.2 to around 0.4–0.5 by the end, indicating moderate relative progress.

Different environments see dramatically different results: *Freeway* often approaches high normalized scores, while *Pong* and *MsPacman* remain relatively low (especially in the human-normalized scale).

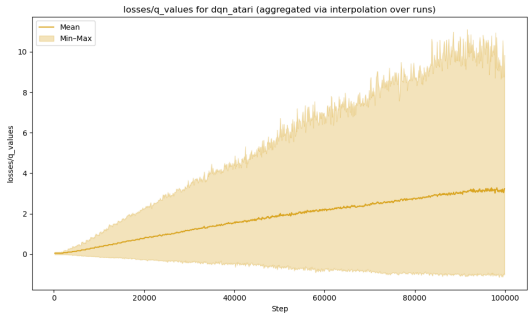
**Emissions** Table 3 presents the aggregated $CO_2$-eq for DQN (over all 32 runs). The mean is about **0.00647 kg**, with a minimum of 0.00616 and a maximum near 0.0070.



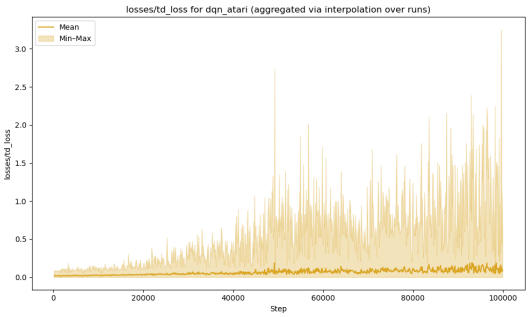

**(a)** *Aggregated episodic length for DQN over 100k steps (interpolation across 32 runs). The mean hovers around 3500–4000 steps, while the min–max envelope extends from near 0 to over 8000.*




**(b)** *Steps per second (SPS) for DQN. After an initial ramp-up, the mean SPS stabilizes around 170–180, with some runs dipping as low as 20 or spiking above 200.*




**(c)** *Estimated Q-values (`losses/q_values`) for DQN (aggregated over 32 runs). The mean Q-value climbs from near 0 up to ∼4–5, while some runs exceed 10.*




**(d)** *TD loss (`losses/td_loss`) for DQN. Losses grow with training, reaching above 3.0 in some runs, reflecting substantial variance near the final stages.*

**Figure 1:** Performance metrics for DQN over 100k steps, aggregated across 32 runs.

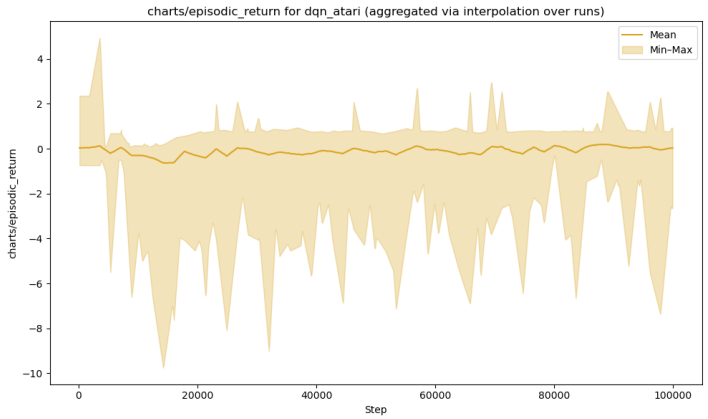



**Figure 2:** Aggregated DQN episodic return (human-normalized) over 100k steps. The shaded region represents min–max variation.

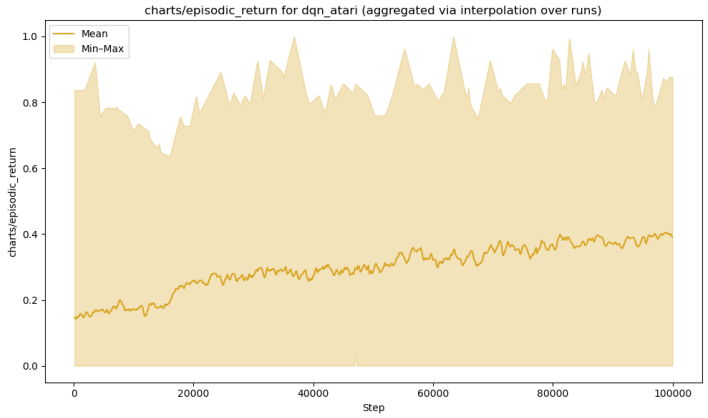



**Figure 3:** Aggregated DQN episodic return (min–max normalized).

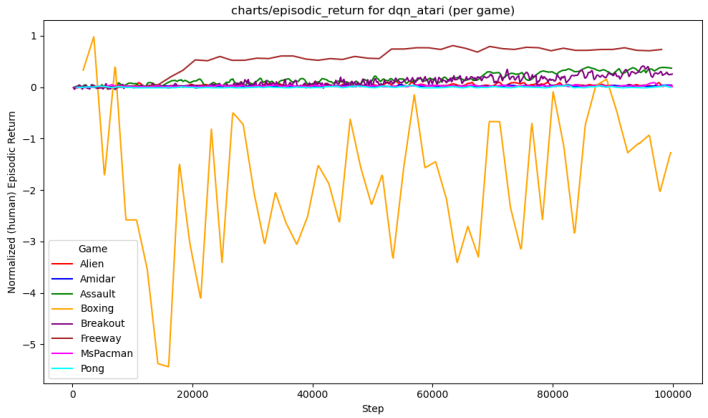



**Figure 4:** DQN returns (human-normalized) by game. Each line aggregates four seeds for that specific environment.

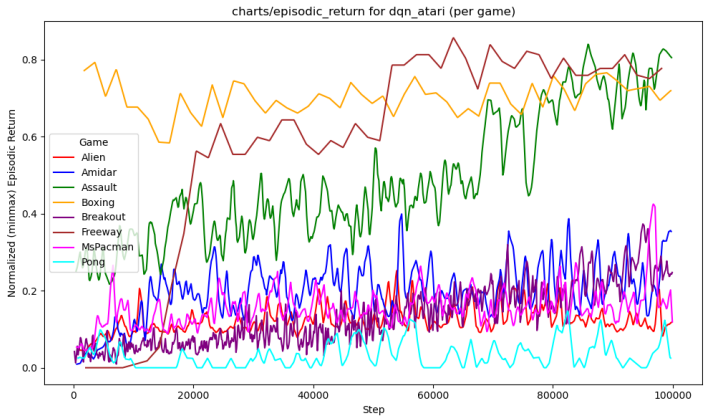



**Figure 5:** DQN returns (min–max normalized) by game.

**Table 3:** Carbon emissions (kg $CO_2$eq) for DQN across 32 runs.

| Algorithm | mean | std | median | q25 | q75 | min | max | iqmean |
|---|---|---|---|---|---|---|---|---|
| DQN | 0.006469 | 0.0002609 | 0.006342 | 0.006296 | 0.006578 | 0.006162 | 0.006997 | 0.006369 |

**Table 4:** Overall final evaluation (10 episodes each) for DQN across all runs.

| Normalization | mean | std | median | q25 | q75 | min | max | iqmean |
|---|---|---|---|---|---|---|---|---|
| **Human** | 0.1353 | 0.7541 | 0.0338 | 0.00072 | 0.398 | -5.024 | 4.738 | 0.1137 |
| **Min–Max** | 0.3802 | 0.3099 | 0.2899 | 0.0969 | 0.7143 | 0.0 | 0.9881 | 0.3426 |

**Evaluation Results** Table 4 aggregates final human-/min–max-normalized returns *over all 32 runs*. A game-by-game breakdown (Table 5) highlights large variability: *Freeway* can exceed 0.7 (human norm) or 0.75 (min–max), while *Boxing* sees a wide range from $-5$ to nearly $+5$ in human norm.

**Observations** In summary:

- **Episodic length** stabilizes around 3500–4000 steps on average, with some extreme runs either terminating quickly or persisting up to 8000 steps.
- **SPS** quickly rises to around 170–180, illustrating the efficiency of the implementation (though some runs are slower).
- **Q-values and TD loss** both exhibit broad variability. On average, Q-values climb steadily to 4–5, but certain runs exceed 10. The TD loss can spike above 3 for some seeds, indicating unstable updates.
- **Returns** show moderate success on easier tasks like *Freeway* and *Boxing*, but remain low in *Pong* or *MsPacman*. Overall, min–max mean is about 0.38, whereas human-normalized is only 0.14 (due in part to highly negative outliers on certain seeds).
- **Emissions** remain modest, at about 0.00647 kg $CO_2$-eq per run. This is unsurprising for a 100k-step setting, but still notable for comparing across algorithms in subsequent sections.

DQN thus provides a baseline—relatively simple and lightweight—to which we will compare Double DQN, Prioritized Experience Replay, Dueling DQN, and C51 in the next subsections, evaluating whether each extension justifies its additional complexity and energy usage.

**Table 5:** Per-game final evaluation for DQN (human- vs. min–max normalized). Each cell aggregates 10 episodes × 4 seeds = 40 total episodes in that game.

| **Game** | **Norm** | **mean** | **std** | **min** | **max** |
|---|---|---|---|---|---|
| Alien | Human | 0.0624 | 0.0752 | 0.0048 | 0.2636 |
| | Min–Max | 0.1607 | 0.1250 | 0.0650 | 0.4950 |
| Amidar | Human | 0.0226 | 0.0138 | 0.00072 | 0.0450 |
| | Min–Max | 0.2005 | 0.1065 | 0.0323 | 0.3733 |
| Assault | Human | 0.3167 | 0.1120 | -0.0262 | 0.4920 |
| | Min–Max | 0.7216 | 0.1703 | 0.2005 | 0.9881 |
| Boxing | Human | -0.4167 | 1.9504 | -5.0238 | 4.7381 |
| | Min–Max | 0.7469 | 0.0635 | 0.5969 | 0.9147 |
| Breakout | Human | 0.3796 | 0.1246 | 0.1096 | 0.6080 |
| | Min–Max | 0.3454 | 0.0987 | 0.1316 | 0.5263 |
| Freeway | Human | 0.7162 | 0.0589 | 0.6419 | 0.8784 |
| | Min–Max | 0.7571 | 0.0622 | 0.6786 | 0.9286 |
| MsPacman | Human | 0.0099 | 0.0120 | -0.0076 | 0.0262 |
| | Min–Max | 0.1047 | 0.0484 | 0.0340 | 0.1702 |
| Pong | Human | -0.0083 | 0.0074 | -0.01 | 0.0233 |
| | Min–Max | 0.0050 | 0.0221 | 0.0 | 0.1 |

### 4.2.2 Double DQN

Double DQN in one of the first and simpler tweak made to DQN. It's simply the adaptation of the Double Q-learning algorithm, initially introduced in a tabular setting, to the Deep Reinforcement Learning setting. Double Q-Learning solves the problem of the maximization bias that afflicts Q-Learning using two different estimations of the action value function when constructing the TD-target: one to chose the action and another to evaluate it. Double DQN does the same thing, starting from DQN. In this environment the natural candidate for a second estimation of the action value function is the target network, so it uses the Q-Network to select the actions, and the target network to evaluate them. Therefore, the only difference in the implementation of the two algorithms is in the update rule. In the tabular case it goes from:

$$Q(S_t, A_t) = Q(S_t, A_t) + \alpha\Big[R_{t+1} + \gamma \max_a Q(S_{t+1}, a) - Q(S_t, A_t)\Big]$$

where the max operator is the cause of the problem, to:

$$Q_1(S_t, A_t) = Q_1(S_t, A_t) + \alpha\Big[R_{t+1} + \gamma Q_2(S_{t+1}, \text{argmax}_a Q_1(S_{t+1}, a)) - Q_1(S_t, A_t)\Big]$$

The roles of $Q_1$ and $Q_2$ can be reversed according to various schedules or rules, and similar approaches have been experimented with in the literature regarding DRL as well, but we have stuck with the original proposal that simply makes use of the target network.

**(Hyper)Parameters** Table 6 shows the main hyperparameters used in our Double DQN implementation. As with the baseline DQN (Section 4.2.1), `env_id` and `seed` vary across the 32 runs (eight Atari games × four seeds), while the rest remain unchanged. In particular, we again set `buffer_size`=10k and `learning_starts`=1000.

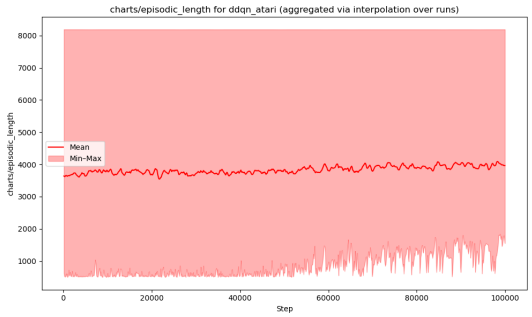
**Hyperparameter Tuning** To isolate the effect of Double DQN, we kept all settings identical to the baseline DQN, simply enabling the Double DQN update scheme. Following [4], we tested higher `target_network_frequency` (in particular the more promising one was 3000, scaled from the 10k–20k range in the original paper), but at 100k steps, performance was comparable or slightly better with 1000, so we retained the lower frequency.

**Training Dynamics (Aggregated Over 32 Runs)** Figure 6 presents key metrics—episodic length, steps per second (SPS), estimated Q-values, and TD loss—aggregated across 32 runs (eight games, four seeds each).

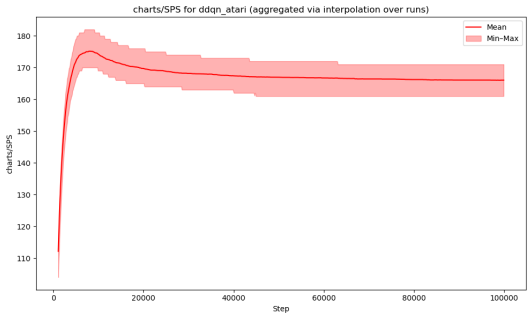
Episodic length and SPS curves are very similar to baseline DQN's (Section 4.2.1). Meanwhile, the mean Q-values grow more modestly than DQN's (which often exceed 4–5 by the end), confirming that Double DQN's approach does mitigate the overestimation (see figure 11 on page 31 for a direct comparison). TD loss remains low overall, though some runs spike above 2.0 near late training.

**Table 6:** Key hyperparameters for Double DQN. Only `env_id` and `seed` change across runs.

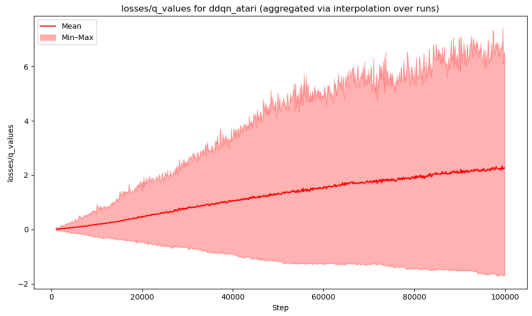
| **Parameter** | **Value** |
|---|---|
| `exp_name` | ddqn_atari |
| `seed` | 1..4 |
| `torch_deterministic` | True |
| `cuda` | True |
| `track` | True |
| `wandb_project_name` | rlsb |
| `capture_video` | False |
| `save_model` | True |
| `upload_model` | False |
| `env_id` | e.g. AlienNoFrameskip-v4 |
| `total_timesteps` | 100000 |
| `learning_rate` | 0.0001 |
| `num_envs` | 1 |
| `buffer_size` | 10000 |
| `gamma` | 0.99 |
| `tau` | 1.0 |
| `target_network_frequency` | 1000 |
| `batch_size` | 32 |
| `start_e`, `end_e` | $1.0 \rightarrow 0.01$ |
| `exploration_fraction` | 0.1 |
| `learning_starts` | 1000 |
| `train_frequency` | 4 |



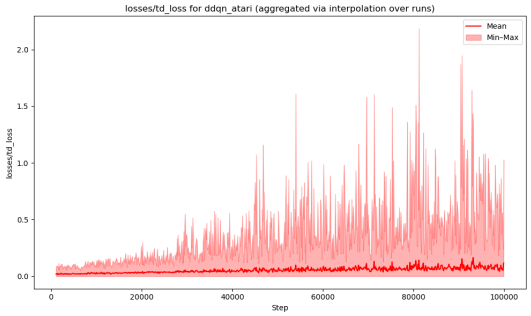

**(a)** Episodic length (`charts_episodic_length`). The mean sits around 3500–4000 steps, min–max ranges from near 0 up to 8000.




**(b)** Steps per second (SPS). After an initial climb near 180, the mean gradually settles around 165–170.




**(c)** Estimated Q-values (`losses/q_values`). The mean climbs from 0 to about 2–3, with upper outliers above 6.




**(d)** TD loss (`losses/td_loss`). Occasional spikes above 2.0 reflect instability on certain seeds.

**Figure 6:** Double DQN training metrics over 100k steps, aggregated over 32 runs.

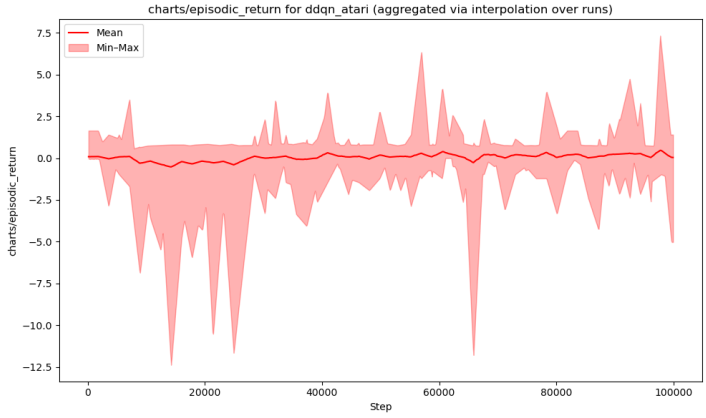



**Figure 7:** Double DQN episodic return (human-normalized), aggregated across 32 runs.

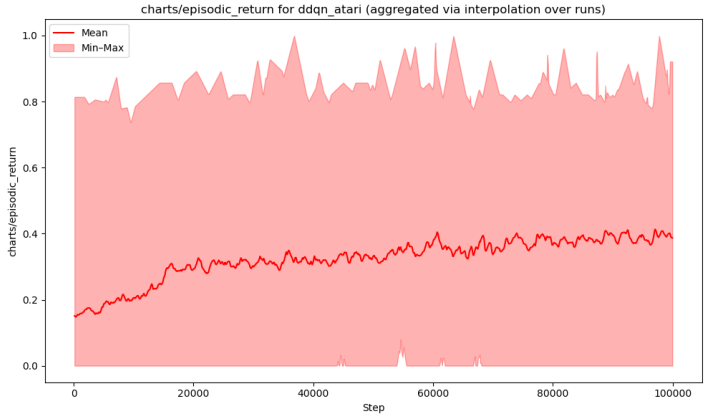



**Figure 8:** Double DQN episodic return (min–max normalized), aggregated across 32 runs.

**Episodic Return (Human vs. Min–Max Normalized)** Figures 7 and 8 show Double DQN's aggregated episodic returns (human- and min–max-normalized, respectively). Figures 9 and 10 break these results down by game.

As in the baseline, *Freeway* can achieve near 0.7–0.8 in human norm, while *Boxing* causes occasional highly negative runs. Min–max normalized returns rise from $\sim 0.2$ to $\sim 0.4$, similar to DQN's overall trajectory.

**Emissions** Table 7 summarizes Double DQN's $CO_2$-eq emissions across 32 runs. The mean is about **0.00667 kg**, slightly above DQN's $\sim 0.00647$.

**Table 7:** Carbon emissions (kg $CO_2$eq) for Double DQN, aggregated over 32 runs.

| Algorithm | mean | std | median | q25 | q75 | min | max | iqmean |
|---|---|---|---|---|---|---|---|---|
| Double DQN | 0.006672 | 0.000282 | 0.006549 | 0.006477 | 0.006755 | 0.006377 | 0.007267 | 0.006565 |

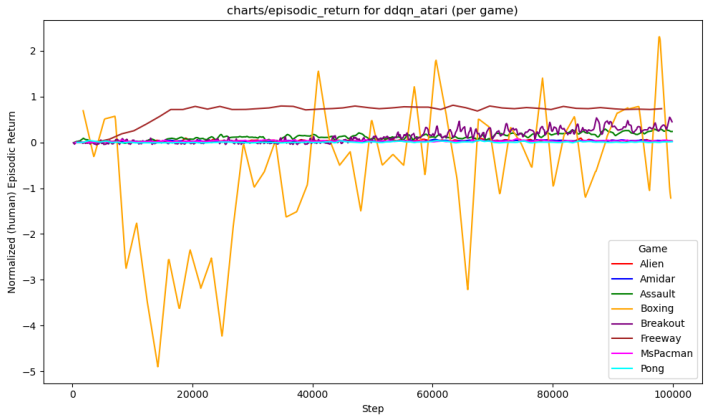



**Figure 9:** Double DQN returns per game (human-normalized). Some large negative dips occur in *Boxing*, while *Freeway* remains relatively high.

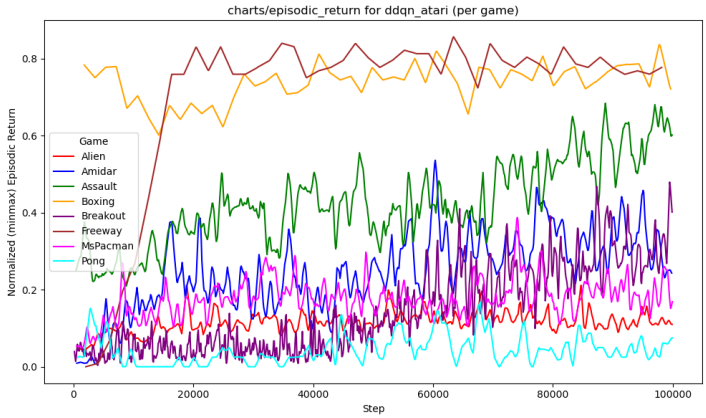



**Figure 10:** Double DQN returns per game (min–max normalized).

**Table 8:** Overall final evaluation (10 episodes each) for Double DQN across 32 runs.

| Normalization | mean | std | median | q25 | q75 | min | max | iqmean |
|---|---|---|---|---|---|---|---|---|
| **Human** | 0.0226 | 1.0083 | 0.0527 | 0.0127 | 0.2871 | -8.5952 | 2.5952 | 0.0894 |
| **Min–Max** | 0.3737 | 0.2854 | 0.2887 | 0.1244 | 0.7054 | 0.0 | 1.0 | 0.3272 |

**Table 9:** Per-game final evaluation for Double DQN (human- vs. min–max normalized). Each row aggregates 40 total episodes (10 per seed).

| Game | Norm | mean | std | min | max |
|---|---|---|---|---|---|
| Alien | Human | 0.0514 | 0.0340 | 0.0094 | 0.1327 |
| | Min–Max | 0.1424 | 0.0565 | 0.0725 | 0.2775 |
| Amidar | Human | 0.0320 | 0.0222 | 0.0127 | 0.0953 |
| | Min–Max | 0.2729 | 0.1708 | 0.1244 | 0.7604 |
| Assault | Human | 0.2310 | 0.1071 | -0.0427 | 0.4103 |
| | Min–Max | 0.5913 | 0.1628 | 0.1754 | 0.8640 |
| Boxing | Human | -1.1607 | 2.4963 | -8.5952 | 2.5952 |
| | Min–Max | 0.7227 | 0.0813 | 0.4806 | 0.8450 |
| Breakout | Human | 0.2666 | 0.1470 | 0.0764 | 0.8738 |
| | Min–Max | 0.2559 | 0.1165 | 0.1053 | 0.7368 |
| Freeway | Human | 0.7213 | 0.0493 | 0.6419 | 0.8784 |
| | Min–Max | 0.7625 | 0.0521 | 0.6786 | 0.9286 |
| MsPacman | Human | 0.0291 | 0.0245 | -0.0037 | 0.0730 |
| | Min–Max | 0.1820 | 0.0986 | 0.0497 | 0.3586 |
| Pong | Human | 0.0100 | 0.0559 | -0.01 | 0.3233 |
| | Min–Max | 0.0600 | 0.1676 | 0.0 | 1.0 |

**Evaluation Results** Table 8 compiles final returns (human-/min–max normalization) aggregated over the 32 runs. Compared to DQN's $\sim$0.135 (human) and $\sim$0.380 (min–max), Double DQN attains 0.023 (human) and 0.374 (min–max). While the min–max average is comparable, the human-normalized mean is noticeably lower due to substantial negative outliers (again, notably *Boxing*).

Table 9 shows the game-by-game breakdown, indicating *Boxing* yields a min of $-8.5952$ and max of 2.5952 in human-normalized scale, dragging down the overall mean. Meanwhile, *Freeway* remains consistently high.

**Comparison with Baseline DQN** Beyond the final statistics, we can compare Q-values and TD loss directly via overlapping curves. Figure 11 on the following page shows the `losses/q_values` for both algorithms, with `ddqn_atari` in red and `dqn_atari` in

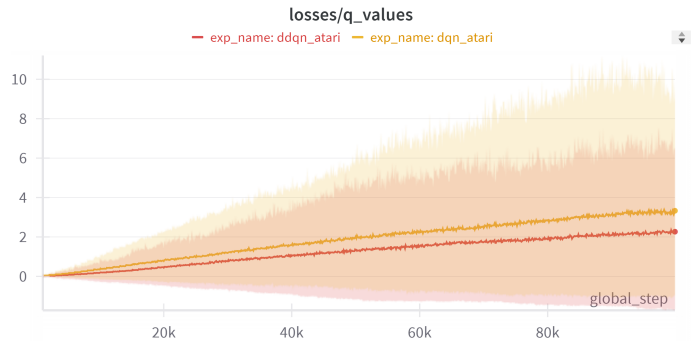



**Figure 11:** Comparison of mean Q-values (with min–max shading) for DQN (gold) vs. Double DQN (red).

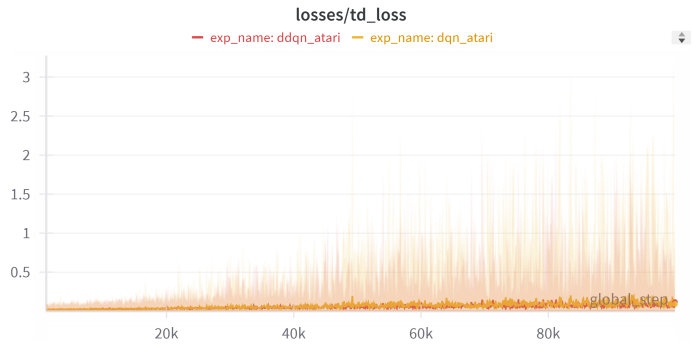



**Figure 12:** Comparison of TD loss for DQN (gold) vs. Double DQN (red). Both remain near 0 for extended periods, though DQN shows slightly higher spikes.

gold; Double DQN's mean Q-values grow more slowly, suggesting less overestimation. Figure 12 indicates TD loss remains similarly small for both, though DQN occasionally spikes higher. The barplot in figure 13 shows the mean emissions side-by-side.

Overall, Double DQN indeed moderates Q-value inflation compared to standard DQN, but under the 100k-step constraint, this reduction in overestimation does not strongly translate into consistently higher final returns.

## Observations

- **Q-values and Losses:** Double DQN's Q-values peak lower than DQN's (about 2–3 vs. 4–5), aligning with the bias-reduction theory. TD losses remain small for both algorithms, with occasional spikes.
- **Performance:** The min–max normalized mean (0.374) is nearly the same as DQN's (0.380), while human-normalized is actually lower (0.023 vs. 0.135) due to certain highly negative runs, especially in *Boxing*.
- **Emissions:** Average $\sim 0.00667\,\text{kg}$ $CO_2$-eq, slightly higher than DQN's $0.00647\,\text{kg}$.

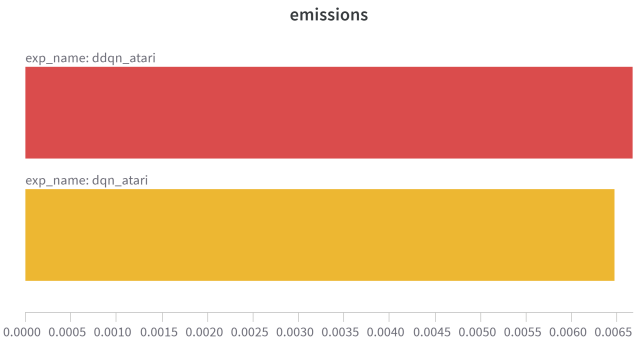



**Figure 13:** Mean emissions of DQN (gold) and Double DQN (red).

Hence, although Double DQN successfully limits Q-value overestimation, its advantage does not fully manifest in higher aggregate returns at 100k steps—indicating that more extensive training or additional refinements may be needed to reap its potential performance gains.

### 4.2.3 Prioritized Experience Replay

In a standard DQN replay buffer, transitions are sampled *uniformly*, giving equal probability to each experience. Prioritized Experience Replay (PER) [5] seeks to allocate more sampling probability to transitions with higher TD error, on the premise that they contain more learning signal for the agent, thus achieving an effect similar to that of prioritized sweeping in the value iteration algorithm for the tabular case. With this focus on "informative" samples, also inspired by biology, PER can potentially accelerate training and reduce sample complexity, especially in long training horizons.

The original paper proposes two primary methods to implement prioritization:

- *Sum-Tree* approach, which stores priority values $p_i$ in a binary tree, allowing for efficient sampling of transitions proportional to $p_i^\alpha$.
- *Rank-Based* approach, which sorts the buffer by TD error magnitude and samples according to rank orders.

We adopt the *sum-tree* variant in our implementation, mirroring the method described in [5] for improved efficiency over naive priority queues. Apart from this change, the underlying DQN hyperparameters (e.g., network architecture, target frequency) remain the same, and we incorporate importance-sampling corrections as recommended to offset the sampling bias introduced by prioritization.

We also explored two implementations of the PER replay buffer—a `numpy`-based (for consistency with the replay buffer used for the other algorithms) and a `torch`-based version. The `numpy` approach proved much slower, so we used the `torch` one in the final runs. It should be noted that even though the other DQN variants use a replay buffer numpy-based, it is the one implemented in Stable Baselines, so it employs

**Table 10:** Key hyperparameters for Prioritized Experience Replay (PER). Only `env_id` and `seed` vary across runs.

| Parameter | Value |
|---|---|
| `exp_name` | per_atari |
| `seed` | 1..4 |
| `torch_deterministic` | True |
| `cuda` | True |
| `track` | True |
| `wandb_project_name` | rlsb |
| `capture_video` | False |
| `save_model` | True |
| `upload_model` | False |
| `env_id` | e.g. AmidarNoFrameskip-v4 |
| `total_timesteps` | 100000 |
| `learning_rate` | 0.0001 |
| `num_envs` | 1 |
| `buffer_size` | 10000 |
| `gamma` | 0.99 |
| `tau` | 1.0 |
| `target_network_frequency` | 1000 |
| `batch_size` | 32 |
| `start_e`, `end_e` | $1.0 \rightarrow 0.01$ |
| `exploration_fraction` | 0.1 |
| `learning_starts` | 1000 |
| `train_frequency` | 4 |

optimizations that our version lacked. For this reason, we assume that using the torch-based implementation does not invalidate direct comparisons.

**(Hyper)Parameters** Table 10 summarizes the key hyperparameters used in our PER implementation. Only `env_id` and `seed` vary across runs (again, eight Atari games $\times$ four seeds $=$ 32 runs), while other settings match those of the baseline DQN (Section 4.2.1) to isolate PER's effects.

**Hyperparameter Tuning** We retained the same settings as baseline DQN (Section 4.2.1) to highlight PER's impact alone, an approach mostly followed by the original authors too. Although [5] suggests lowering the learning rate by a factor of four, our tests at 100k steps with it and other values showed again that $1 \times 10^{-4}$ worked better. Figure 14 compares these rates on *Breakout*, indicating faster convergence at $1 \times 10^{-4}$.

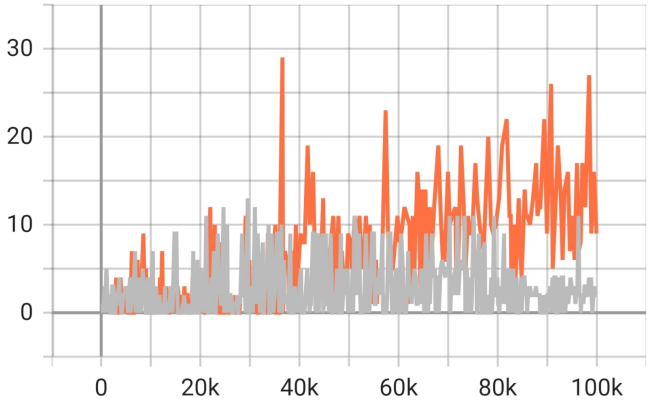



**Figure 14:** Comparison of learning rates for PER on *Breakout*. Orange curve: $1 \times 10^{-4}$ (our final choice). Gray curve: $\frac{1}{4} \times 10^{-4}$ (as per [5]).

**Table 11:** Carbon emissions (kg $CO_2$eq) for PER across 32 runs.

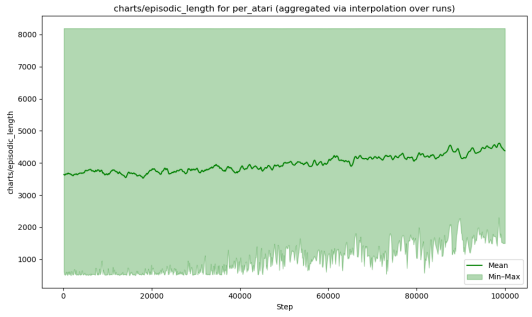
| Algorithm | mean | std | median | q25 | q75 | min | max | iqmean |
|---|---|---|---|---|---|---|---|---|
| PER | 0.007254 | 0.000263 | 0.007146 | 0.007074 | 0.007354 | 0.006935 | 0.007819 | 0.007157 |

**Training Dynamics** Figure 15 on the next page aggregates four key metrics (episodic length, steps per second, Q-values, and TD loss) over 32 runs (eight games, four seeds each). PER shows Q-values approaching or exceeding those of baseline DQN (which typically topped at 4–5). The TD loss is small on average but spikes in certain runs, suggesting that prioritizing high-error samples can exacerbate updates in some episodes.

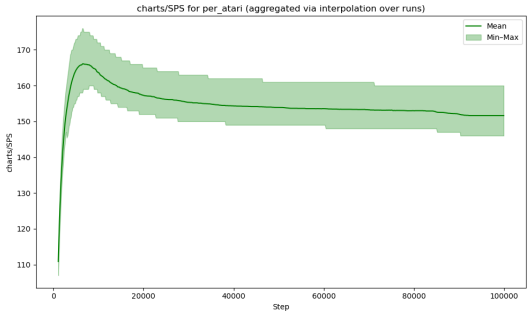
**Episodic Return** Figures 16 (human-normalized) and 17 (min–max) show PER's aggregated episodic returns. The mean in human-normalized scale oscillates around zero, occasionally dipping below $-2$ or $-3$ in some seeds.

**Per-Game Returns** Figures 18 and 19 on page 36 break down the performance by each Atari game (human vs. min–max normalization). We see, for instance, *Freeway* (orange line in min–max) steadily climbing to around 0.7–0.8, while *Alien* can drop below $-3$ in human scale.

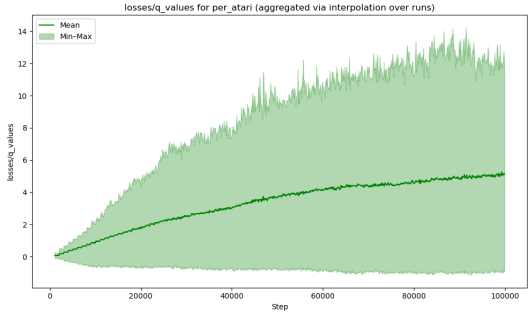
**Emissions.** Table 11 shows the statistics of the emissions of PER, while Figure 20 on page 37 shows a barplot comparing PER's mean emissions ($\approx 0.00725$ kg) to DQN's ($\approx 0.00647$ kg). The overhead of prioritized sampling may partly account for this higher footprint.



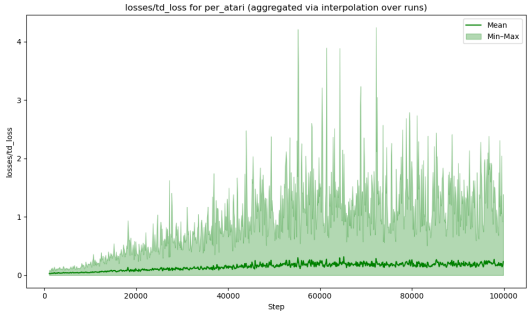

**(a)** Episodic length (`charts_episodic_length`). The mean hovers around 3500–4000, and min–max runs from near 0 up to 8000.




**(b)** Steps per second (SPS). The mean peaks above 170, then gradually declines to 150–160.




**(c)** Q-values (`losses/q_values`). The mean eventually surpasses 4–5, with outliers above 14.




**(d)** TD loss (`losses/td_loss`). Some runs spike above 3–4, showing instability in late training.

**Figure 15:** PER training metrics over 100k steps, interpolated across 32 runs.


**Figure 16:** PER episodic return (human-normalized), aggregated over 32 runs. Negative outliers appear for certain seeds/environments.

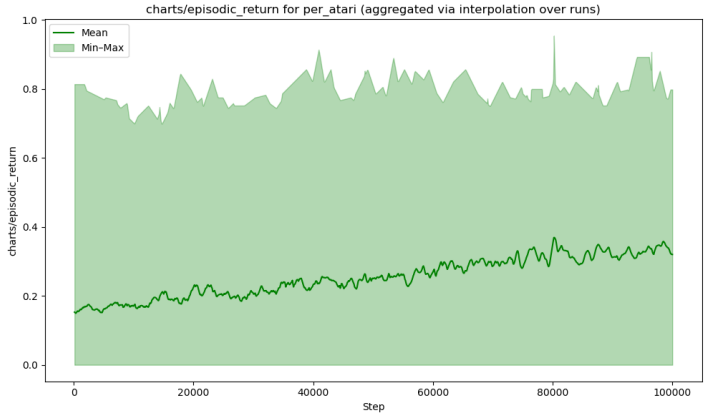



**Figure 17:** PER episodic return (min–max normalized), aggregated over 32 runs.

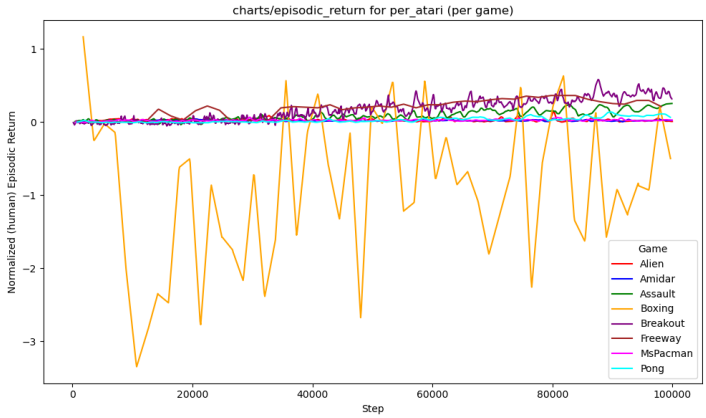



**Figure 18:** PER returns per game (human-normalized). *Alien* (orange) exhibits deep negative dips, while *Freeway*, *Assault*, and *Breakout* stay near or above zero.

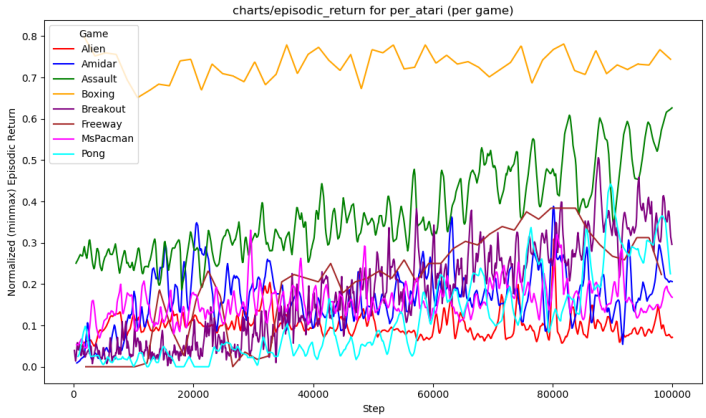



**Figure 19:** PER returns per game (min–max normalized). *Freeway* (gold line) and *Assault* (green) reach 0.7–0.8 near 100k steps.

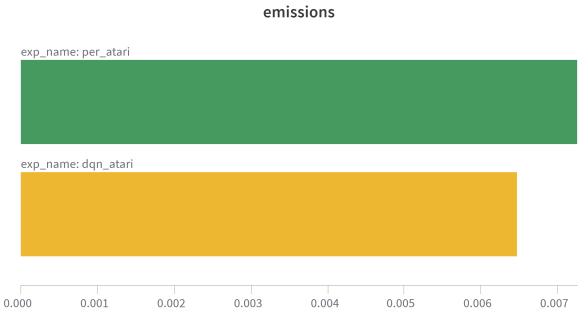



**Figure 20:** Mean emissions comparison: PER (green) at $\sim 0.00725\,\mathrm{kg}$ vs. DQN (gold) at $\sim 0.00647\,\mathrm{kg}$.

**Table 12:** Overall final evaluation (10 episodes each) for PER across 32 runs.

| Normalization | mean | std | median | q25 | q75 | min | max | iqmean |
|---|---|---|---|---|---|---|---|---|
| **Human** | 0.0607 | 1.0170 | 0.0539 | 0.0175 | 0.2541 | -10.2619 | 6.8809 | 0.0813 |
| **Min–Max** | 0.3533 | 0.2695 | 0.2583 | 0.1499 | 0.6265 | 0.0 | 0.9845 | 0.3087 |

**Table 13:** Per-game final evaluation for PER (human- vs. min–max normalized). Each row aggregates 10 episodes × 4 seeds per environment.

| Game | Norm | mean | std | min | max |
|---|---|---|---|---|---|
| Alien | Human | 0.0246 | 0.0315 | -0.0147 | 0.0996 |
| | Min–Max | 0.0978 | 0.0523 | 0.0325 | 0.2225 |
| Amidar | Human | 0.0263 | 0.0220 | -0.0029 | 0.0809 |
| | Min–Max | 0.2288 | 0.1693 | 0.0046 | 0.6498 |
| Assault | Human | 0.2135 | 0.0974 | 0.0232 | 0.3860 |
| | Min–Max | 0.5648 | 0.1480 | 0.2757 | 0.8270 |
| Boxing | Human | -0.6667 | 2.7351 | -10.2619 | 6.8809 |
| | Min–Max | 0.7388 | 0.0890 | 0.4264 | 0.9845 |
| Breakout | Human | 0.3854 | 0.2204 | 0.00997 | 0.9070 |
| | Min–Max | 0.3500 | 0.1746 | 0.0526 | 0.7632 |
| Freeway | Human | 0.4071 | 0.3381 | 0.0 | 0.8446 |
| | Min–Max | 0.4304 | 0.3574 | 0.0 | 0.8929 |
| MsPacman | Human | 0.0338 | 0.0111 | 0.0119 | 0.0515 |
| | Min–Max | 0.2008 | 0.0446 | 0.1126 | 0.2723 |
| Pong | Human | 0.0617 | 0.0682 | -0.01 | 0.2233 |
| | Min–Max | 0.2150 | 0.2045 | 0.0 | 0.7000 |

**Comparison with Baseline DQN.** By final evaluation, PER's overall human-norm mean (0.0607) is lower than DQN's (0.135), and its min–max mean (0.353) lags behind DQN's 0.380. Figure 20 further shows PER's emissions exceed DQN's by $\sim 0.0008\,\text{kg}$ $CO_2$-eq on average, likely due to the overhead from prioritized sampling and somewhat longer average episodes.

**Observations.**

- **Implementation Details:** we used a `torch`-based PER buffer to avoid severe slowdowns in the `numpy` version.
- **Learning Rate:** $\frac{1}{4} \times 10^{-4}$, as suggested in [5], underperformed at 100k steps compared to $1 \times 10^{-4}$ (Figure 14 on page 34).
- **Performance:** PER did not consistently outperform baseline DQN within 100k steps: human-norm mean is 0.0607 vs. DQN's 0.135.
- **Emissions:** PER's overhead leads to slightly higher energy usage (0.00725 kg $CO_2$-eq) than DQN's 0.00647 kg.

In summary, while prioritizing high-error samples can yield benefits in longer training runs, our 100k-step Atari benchmark does not showcase a strong advantage. Further hyperparameter tuning or more extended runs might better reveal PER's strengths.

### 4.2.4 Dueling DQN

The *Dueling DQN* [6] architecture modifies the final layers of the Q-network to separate the estimation of the state-value function $V(s)$ from that of the advantage function $A(s,a)$, defined as $A(s,a) = Q(s,a) - V(s)$. These two *heads*, or *stream* as they are called in the paper, are then combined to yield

$$Q(s,a) = V(s) + (A(s,a) - \mathcal{B})$$

where $\mathcal{B}$ is a sort of "baseline" (see [6] for the details on why this is necessary). The authors of the paper proposed $\mathcal{B} = \max_{a' \in A(s)} A(s,a')$ and $\mathcal{B} = \frac{1}{|\mathcal{A}|} \sum_{a' \in A(s)} A(s,a')$, but mainly experimented with the latter, so we did the same, as did most of the subsequent literature. This approach allows the network to learn which states are valuable (*regardless* of action) and which actions are relatively better than others (*given* a state), stabilizing learning in states where are present various actions with a close value, and improving sample efficiency in many environments.

**(Hyper)Parameters** Because the dueling architecture introduces separate streams for $V$ and $A$, the model ends up with slightly more parameters. We considered reducing the size of the shared layer to keep the overall parameter count equal to the baseline, but the difference was only about 512 neurons, so we retained the original layer size for consistency with the other DQN variants. We also tested whether gradient clipping (as

**Table 14:** Key hyperparameters for Dueling DQN. Only `env_id` and `seed` vary across runs.

| Parameter | Value |
|---|---|
| exp_name | dueling_dqn_atari |
| seed | 1..4 |
| torch_deterministic | True |
| cuda | True |
| track | True |
| wandb_project_name | rlsb |
| capture_video | False |
| save_model | True |
| upload_model | False |
| env_id | e.g. AlienNoFrameskip-v4 |
| total_timesteps | 100000 |
| learning_rate | 0.0001 |
| num_envs | 1 |
| buffer_size | 10000 |
| gamma | 0.99 |
| tau | 1.0 |
| target_network_frequency | 1000 |
| batch_size | 32 |
| start_e, end_e | $1.0 \rightarrow 0.01$ |
| exploration_fraction | 0.1 |
| learning_starts | 1000 |
| train_frequency | 4 |

mentioned in some references) would improve stability, but found no clear benefit here. Finally, we did not combine dueling with Double DQN or PER, as our goal is to isolate the contribution of this single tweak in terms of performance and emissions.

### Training Dynamics

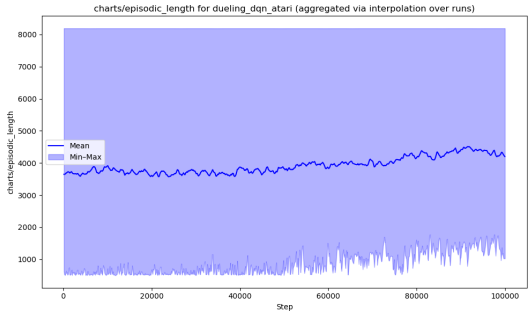
### Episodic Return (Aggregated)

### Per-Game Returns

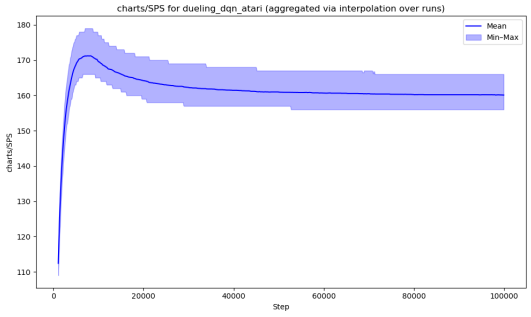
### Emissions

### Evaluation Results

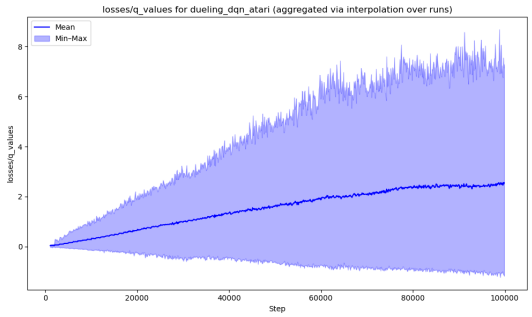
**Comparison with Baseline DQN** In final evaluation, Dueling DQN's *human*-norm mean is 0.1860 vs. DQN's 0.1353, and the *min–max* mean is 0.3849 vs. DQN's 0.3802—so



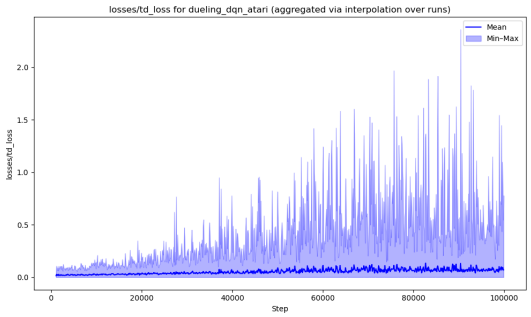

**(a)** Episodic length. The mean hovers around 3500–4000 steps, with min–max from near 0 up to 8000.




**(b)** Steps per second (SPS). After an initial ramp-up near 170, it stabilizes around 155–160.




**(c)** Q-values (`losses/q_values`). The mean grows beyond 4–5, with outliers near 8–10.




**(d)** TD loss (`losses/td_loss`). Some runs spike above 1.5–2.0, showing moderate variability late in training.

**Figure 21:** Dueling DQN training metrics over 100k steps, aggregated over 32 runs.

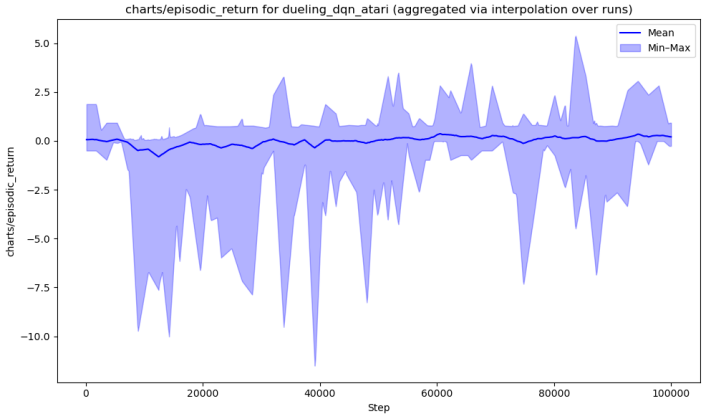



**Figure 22:** Dueling DQN episodic return (human-normalized) over 100k steps. Variance is significant, with some dips below -8.

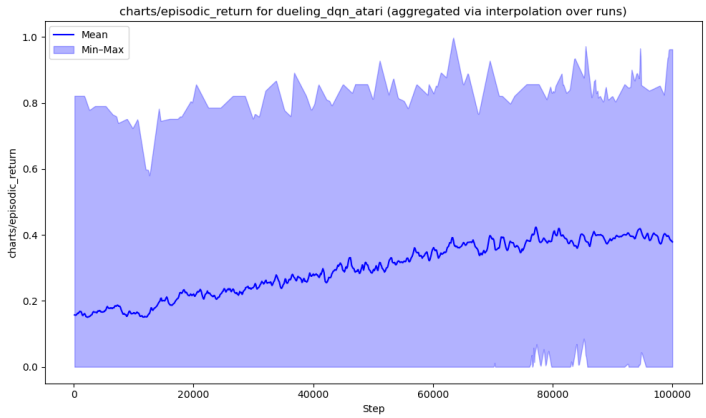



**Figure 23:** Dueling DQN episodic return (min–max normalized) aggregated over 32 runs.

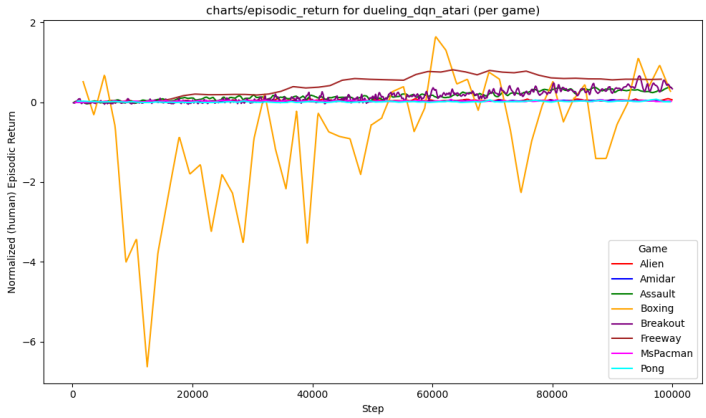



**Figure 24:** Dueling DQN returns per game (human-normalized). *Boxing* (orange) experiences deep negative dips, while *Freeway* and *Assault* can reach higher normalized scores.

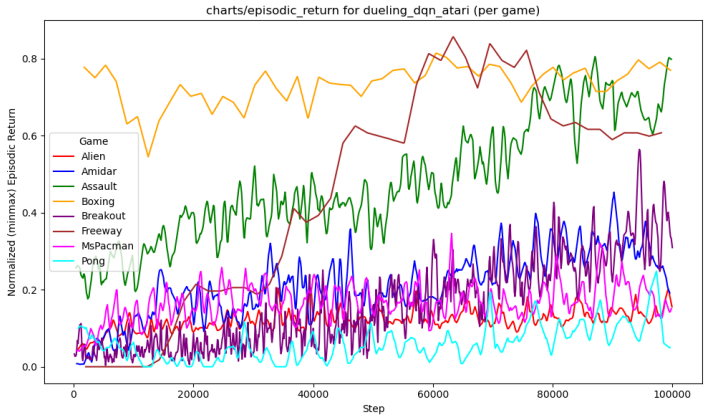



**Figure 25:** Dueling DQN returns per game (min–max normalized). *Freeway* (gold) and *Assault* (green) often exceed 0.7.

**Table 15:** Carbon emissions (kg $CO_2$eq) for Dueling DQN across 32 runs.

| Algorithm | mean | std | median | q25 | q75 | min | max | iqmea |
|---|---|---|---|---|---|---|---|---|
| Dueling DQN | 0.006893 | 0.0002901 | 0.006742 | 0.006672 | 0.007002 | 0.006617 | 0.007478 | 0.0067 |

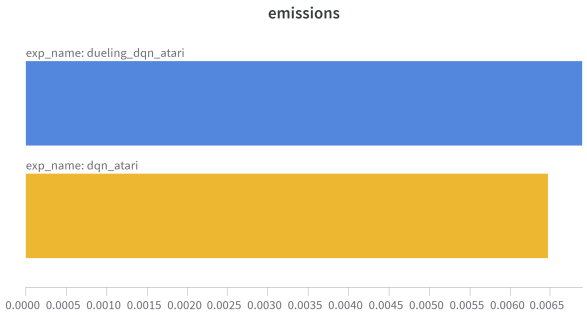



**Figure 26:** Mean emissions comparison: Dueling DQN (blue) at $\sim 0.00689$ kg vs. DQN (gold) at $\sim 0.00647$ kg.

**Table 16:** Overall final evaluation (10 episodes each) for Dueling DQN across 32 runs.

| Normalization | mean | std | median | q25 | q75 | min | max | iqmean |
|---|---|---|---|---|---|---|---|---|
| **Human** | 0.1860 | 0.5258 | 0.0402 | 0.0148 | 0.3530 | -1.9286 | 3.5476 | 0.1020 |
| **Min–Max** | 0.3849 | 0.3056 | 0.2632 | 0.1100 | 0.7448 | 0.0 | 0.9523 | 0.3454 |

**Table 17:** Per-game final evaluation for Dueling DQN (human- vs. min–max normalized).

| Game | Norm | mean | std | min | max |
|---|---|---|---|---|---|
| Alien | Human | 0.0398 | 0.0346 | -0.0072 | 0.1493 |
| | Min–Max | 0.1231 | 0.0574 | 0.0450 | 0.3050 |
| Amidar | Human | 0.0372 | 0.0193 | 0.0235 | 0.0935 |
| | Min–Max | 0.3127 | 0.1482 | 0.2074 | 0.7465 |
| Assault | Human | 0.3200 | 0.0985 | 0.1057 | 0.4684 |
| | Min–Max | 0.7266 | 0.1498 | 0.4010 | 0.9523 |
| Boxing | Human | 0.1190 | 1.3282 | -1.9286 | 3.5476 |
| | Min–Max | 0.7643 | 0.0432 | 0.6977 | 0.8760 |
| Breakout | Human | 0.4020 | 0.2904 | -0.0565 | 1.0066 |
| | Min–Max | 0.3632 | 0.2300 | 0.0 | 0.8421 |
| Freeway | Human | 0.5372 | 0.3162 | 0.0 | 0.7770 |
| | Min–Max | 0.5679 | 0.3342 | 0.0 | 0.8214 |
| MsPacman | Human | 0.0265 | 0.0204 | 0.00018 | 0.0736 |
| | Min–Max | 0.1713 | 0.0823 | 0.0654 | 0.3613 |
| Pong | Human | 0.0067 | 0.0185 | -0.01 | 0.0567 |
| | Min–Max | 0.0500 | 0.0555 | 0.0 | 0.2 |

we see a small positive difference on average. However, *Boxing* outliers (some runs exceed 3.5, others dip below $-1.9$) inflate the variance. Meanwhile, emissions at $\sim 0.00689$ kg $CO_2$-eq are higher than DQN's $\sim 0.00647$ but remain lower than some other variants (e.g. PER at 0.00725).

#### Observations

- **Architecture Impact:** The *dueling* approach separates state-value and advantage, intending to stabilize updates in states where action choices matter less.
- **Network Size:** We kept the same shared layer size as DQN, adding only a modest number of extra parameters.
- **Performance:** The final mean in human normalization (0.1860) is higher than baseline DQN's 0.1353, though min–max (0.3849 vs. 0.3802) is only slightly larger.
- **Emissions:** Dueling DQN uses $\sim 0.00689$ kg $CO_2$-eq, more than DQN's 0.00647 but less than PER's 0.00725.

### 4.2.5 Categorical DQN (C51)

#### (Hyper)Parameters

**Innovation: Distributional RL** Categorical DQN (**C51**) [8] models $Q(s, a)$ as a discrete probability distribution over possible returns, using `n_atoms` support points that span the interval $[v_{\min}, v_{\max}]$. By capturing more than a single expected value, C51 can potentially improve learning stability and performance, especially in risk- or variance-sensitive tasks.

**Hyperparameter Tuning** We adopted CleanRL's `c51_atari` configuration with 51 atoms, $v_{\min} = -10$, $v_{\max} = 10$, and a learning rate of $2.5 \times 10^{-4}$. While we tested alternative rates, this default proved effective over only 100k steps.

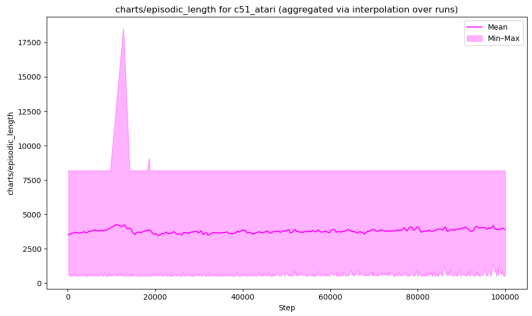
We also experimented with `target_network_frequency` values of 1k, 5k, and 10k to see if less frequent updates might reduce overhead. Ultimately, 1k provided a good balance of stable returns and moderate emissions, aligning with other DQN-based variants.

**Training Dynamics** Figure 27 shows that certain runs produce extremely long episodes (Figure 27a, subfloat a), while the overall `SPS` curve (subfloat b) hovers around 140–150 later in training, slightly lower than baseline DQN's $\sim$ 160. The training loss (subfloat c) descends from near 4.0 to 2.0, while distributional `q_values` (subfloat d) broaden significantly.

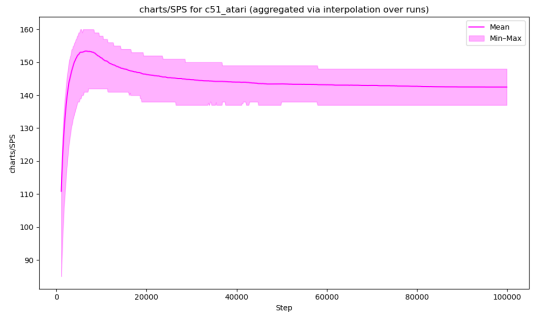
**Episodic Return (Aggregated)** Due to extreme negative performance in certain games, such as *Boxing*, the human-normalized return (Figure 28) often falls below -1. In min–max (Figure 29), the mean approaches $\sim$ 0.25–0.30 by 100k steps.

**Table 18:** Key hyperparameters for the C51 algorithm. Only `env_id` and `seed` vary across runs.

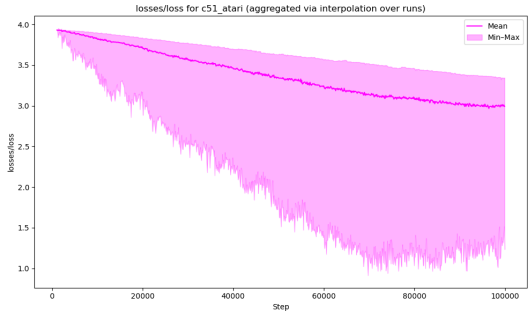
| Parameter | Value |
|---|---|
| `exp_name` | c51_atari |
| `seed` | 1..4 |
| `torch_deterministic` | True |
| `cuda` | True |
| `track` | True |
| `wandb_project_name` | rlsb |
| `capture_video` | False |
| `save_model` | True |
| `upload_model` | False |
| `env_id` | e.g. AlienNoFrameskip-v4 |
| `total_timesteps` | 100000 |
| `learning_rate` | 0.00025 |
| `num_envs` | 1 |
| `n_atoms` | 51 |
| `v_min` | -10 |
| `v_max` | 10 |
| `buffer_size` | 10000 |
| `gamma` | 0.99 |
| `target_network_frequency` | 1000 |
| `batch_size` | 32 |
| `start_e`, `end_e` | $1.0 \rightarrow 0.01$ |
| `exploration_fraction` | 0.1 |
| `learning_starts` | 1000 |
| `train_frequency` | 4 |



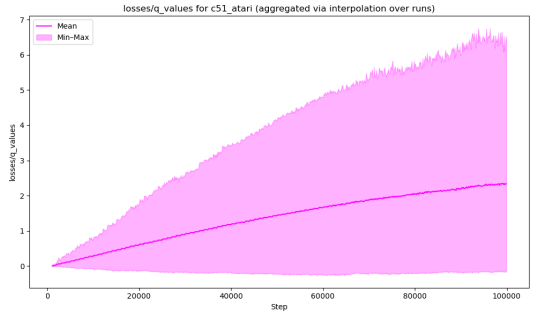

**(a)** Episodic length (`charts_episodic_length`). The mean is $\sim$ 3500–4000, while min–max occasionally spikes above 8000 or even 17500 in some runs.




**(b)** Steps per second (SPS). Mean peaks around 160–170, then slowly converges near 140–150.




**(c)** Overall loss (`losses/loss`). The mean steadily declines from about 4.0 toward near 2.0 by the end of training.




**(d)** Q-values (`losses/q_values`). The mean climbs from near 0 to $\sim$ 4–5, with outliers reaching 6–7.

**Figure 27:** C51 training metrics over 100k steps, aggregated (via interpolation) across 32 runs.

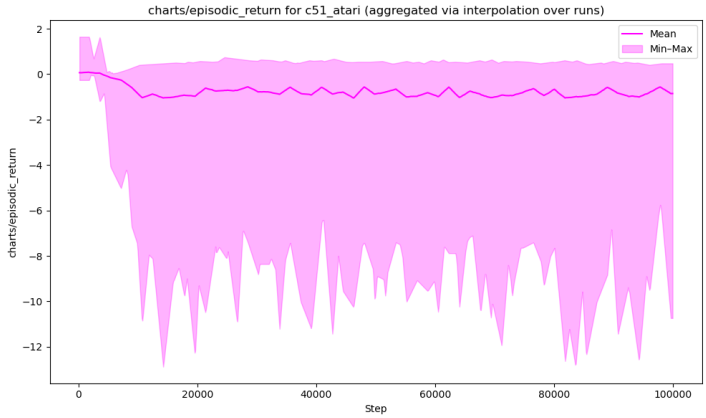



**Figure 28:** C51 episodic return (human-normalized), aggregated over 32 runs. Negative scores dominate, especially due to *Boxing*'s steep dips below -10.

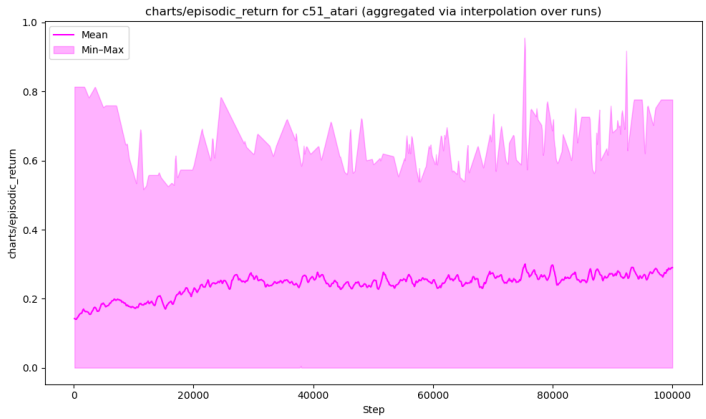



**Figure 29:** C51 episodic return (min–max normalized). The mean grows toward 0.25–0.30, indicating moderate performance relative to each game's min–max range.

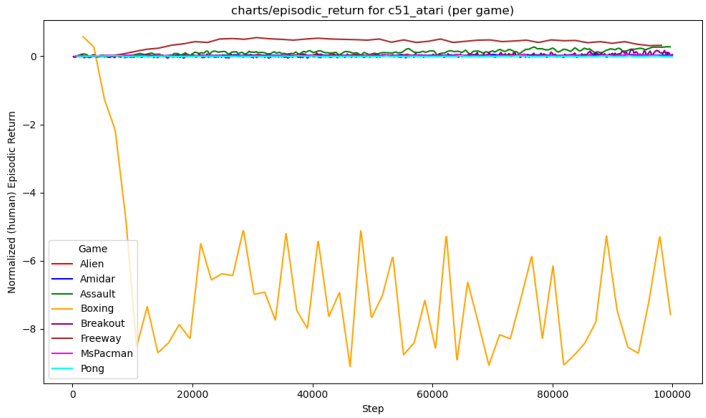



**Figure 30:** C51 returns per game (human-normalized). *Boxing* (orange) can plunge below -12, dwarfing improvements in other games.

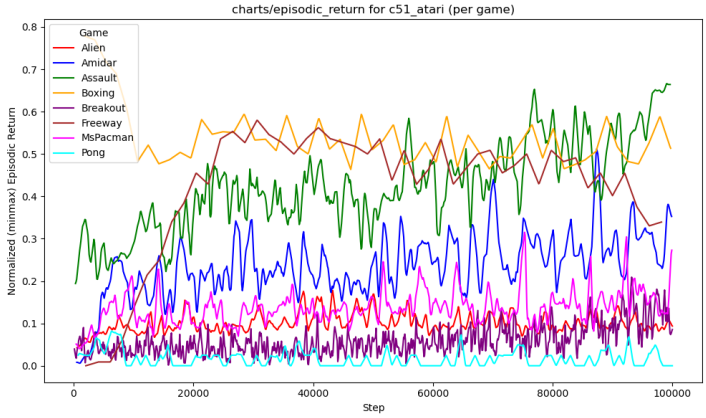



**Figure 31:** C51 returns per game (min–max normalized). *Assault* (green) climbs above 0.5, while *Pong* (cyan) remains near zero.

**Table 19:** Carbon emissions (kg $CO_2$eq) for C51 across 32 runs.

| Algorithm | mean | std | median | q25 | q75 | min | max | iqmean |
|---|---|---|---|---|---|---|---|---|
| C51 | 0.007750 | 0.0003042 | 0.007655 | 0.007489 | 0.008099 | 0.007410 | 0.008257 | 0.007679 |

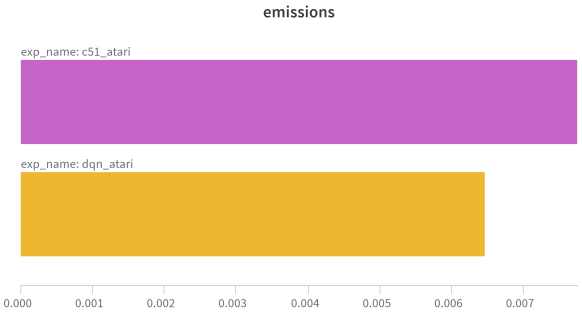



**Figure 32:** Mean emissions: C51 (magenta) at $\sim 0.00775$ kg vs. DQN (gold) at $\sim 0.00647$ kg.

### Per-Game Returns

**Emissions** C51's mean emissions near 0.00775 kg exceed DQN's 0.00647 kg. Distributional overhead (computing 51 probability "atoms") likely increases GPU usage.

### Evaluation Results

**Comparison with Baseline DQN** Overall, C51's human-normalized final mean is **-1.0811**, pulled down by severe negative performance in *Boxing* (around $-9.39$). Even ignoring that outlier, other titles do not significantly outperform baseline DQN's 0.1353. In min–max scale, C51's 0.2503 is also lower than DQN's 0.3802. Emissions, by contrast, are higher ($\sim 0.00775$ kg vs. DQN's 0.00647), reflecting the overhead of computing a 51-atom return distribution each update.

### Observations

- **Distributional Advantage:** Although distributional RL can better capture risk or reward variance, 100k steps may be insufficient to realize its full potential.

**Table 20:** Overall final evaluation (10 episodes each) for C51 across 32 runs.

| Normalization | mean | std | median | q25 | q75 | min | max | iqmean |
|---|---|---|---|---|---|---|---|---|
| **Human** | -1.0811 | 3.2862 | 0.0 | -0.0132 | 0.0418 | -12.8810 | 0.7770 | 0.00684 |
| **Min–Max** | 0.2503 | 0.2568 | 0.2005 | 0.0 | 0.4419 | 0.0 | 0.8270 | 0.13997 |

**Table 21:** Per-game final evaluation for C51 (human- vs. min–max normalized). Each row aggregates 40 total episodes (10 per seed).

| Game | Norm | mean | std | min | max |
|---|---|---|---|---|---|
| Alien | Human | -0.0149 | 0.0127 | -0.0343 | 0.00635 |
| | Min–Max | 0.0321 | 0.0211 | 0.0 | 0.0675 |
| Amidar | Human | 0.0336 | 0.0153 | 0.00431 | 0.0678 |
| | Min–Max | 0.2851 | 0.1181 | 0.0599 | 0.5484 |
| Assault | Human | 0.1994 | 0.1467 | -0.0262 | 0.3860 |
| | Min–Max | 0.5434 | 0.2229 | 0.2005 | 0.8270 |
| Boxing | Human | -9.3869 | 2.6728 | -12.8810 | -4.7857 |
| | Min–Max | 0.4548 | 0.0870 | 0.3411 | 0.6047 |
| Breakout | Human | 0.1478 | 0.2072 | -0.0565 | 0.4751 |
| | Min–Max | 0.1618 | 0.1641 | 0.0 | 0.4211 |
| Freeway | Human | 0.3632 | 0.3688 | 0.0 | 0.7770 |
| | Min–Max | 0.3839 | 0.3899 | 0.0 | 0.8214 |
| MsPacman | Human | 0.0189 | 0.0176 | -0.0057 | 0.0483 |
| | Min–Max | 0.1410 | 0.0707 | 0.0419 | 0.2592 |
| Pong | Human | -0.01 | $5.27 \times 10^{-18}$ | -0.01 | -0.01 |
| | Min–Max | 0.0 | 0.0 | 0.0 | 0.0 |

- **Performance:** Human-norm is $-1.0811$ vs. DQN's 0.1353, with many games remaining near/below zero. Min–max is 0.2503 vs. 0.3802.
- **Emissions:** C51 uses $\sim 0.00775\,\text{kg}$ $CO_2$-eq, higher than DQN's 0.00647, likely due to distributional overhead.
- **Target Network Frequency:** Testing 1k, 5k, and 10k found 1k gave decent stability and moderate power usage.

In summary, C51 did not outperform the baseline DQN in this 100k-step Atari benchmark, though distributional RL may yield advantages over longer runs or with additional tuning.

## 4.3 Overall Comparison of DQN-Based Algorithms

In this section, we synthesize the results of all five DQN-based algorithms:

- **Baseline DQN** (no additional tweaks)
- **Double DQN** (mitigating Q-value overestimation)
- **Prioritized Experience Replay (PER)** (sampling transitions by TD-error priority)
- **Dueling DQN** (separating state-value from advantage)
- **C51** (distributional RL with a categorical return distribution)

We compare them on two axes: final performance (evaluated in both human- and min–max-normalized scales) and carbon emissions.

**Aggregated Final Returns and Emissions** Table 22 compiles the final evaluation means from Sections 4.2.1, 4.2.2, 4.2.3, 4.2.4, and 4.2.5. We list each method's mean episodic return under both normalization schemes, along with its mean carbon footprint. For completeness, we include standard deviations (`std`) and other statistics where relevant.

### Performance Discussion

- **Dueling DQN** achieves the highest human-norm mean (0.1860), though min–max is only slightly above baseline DQN (0.3849 vs. 0.3802). Its moderate overhead in computations yields emissions of 0.00689 kg, just above baseline.
- **Double DQN** has a low human-norm mean (0.0226) but a reasonably strong min–max mean (0.3737). Some games suffer from negative outliers (e.g. *Boxing*), but overall it matches baseline DQN in relative scale.

**Table 22:** Overall final evaluation and emissions for DQN-based algorithms. Human-/min–max-normalized performance are the global means across 32 runs (8 games, 4 seeds). Emissions are reported in kg $CO_2$-eq. Lower or negative human-norm means indicate below-human performance on average (e.g. in *Boxing*), whereas higher min–max means imply better relative scores.

| | **Final Episodic Return (Mean)** | | **Emissions** |
|---|---|---|---|
| **Algorithm** | **Human Norm** | **Min–Max** | **(kg $CO_2$-eq)** |
| **DQN (baseline)** | 0.1353 | 0.3802 | 0.00647 |
| **Double DQN** | 0.0226 | 0.3737 | 0.00667 |
| **PER** | 0.0607 | 0.3533 | 0.00725 |
| **Dueling DQN** | 0.1860 | 0.3849 | 0.00689 |
| **C51** | −1.0811 | 0.2503 | 0.00775 |

- **PER** does not strongly outperform DQN in short (100k-step) training, scoring 0.0607 human-norm and 0.3533 min–max, with slightly higher emissions (0.00725 kg). Prioritizing TD errors may show more benefit in longer runs.
- **C51** exhibits the largest negative dip on human-norm (−1.0811), largely due to extreme results in *Boxing* and a few other titles, but obtains 0.2503 in min–max. It also has the largest emissions (0.00775 kg) among these five, reflecting the overhead of a distributional approach with 51 "atoms."
- **Baseline DQN** remains a strong reference point. Though not best in any single metric, it has decent performance across games (especially 0.3802 in min–max), while keeping the lowest carbon footprint (0.00647 kg).

Table 23 extends the previous summary (Table 22) by including the interquartile mean (IQM) [19] for each of the three metrics:

- **Human-Normalized Returns** (mean and IQM)
- **Min–Max Normalized Returns** (mean and IQM)
- **Emissions (kg $CO_2$-eq)** (mean and IQM)

Recall that IQM is a robust estimator of central tendency, averaging only the middle 50% of data points (between the 25th and 75th percentiles), thus mitigating the impact of extreme outliers.

### Discussion.

- **Human-Norm vs. IQM.** Some methods (*e.g.*, Double DQN, C51) exhibit a large discrepancy between the mean and IQM in human-normalized returns, indicating a handful of extreme outliers (often due to specific games like *Boxing*).

**Table 23:** DQN-Based Algorithms: Final Returns (Human & Min–Max Norm) *vs.* Emissions, including both Mean and Interquartile Mean (IQM). Data are aggregated over 32 runs (8 Atari games × 4 seeds). Negative human-norm means can stem from poor performance in certain games (e.g. *Boxing* with highly negative scores).

| | Human-Norm Return | | Min–Max Return | | Emissions ($\mathbf{kg\,CO_2}$) | |
|---|---|---|---|---|---|---|
| **Algorithm** | **Mean** | **IQM** | **Mean** | **IQM** | **Mean** | **IQM** |
| **DQN** | 0.1353 | 0.1137 | 0.3802 | 0.3426 | 0.00647 | 0.00637 |
| **Double DQN** | 0.0226 | 0.0894 | 0.3737 | 0.3272 | 0.00667 | 0.00656 |
| **PER** | 0.0607 | 0.0813 | 0.3533 | 0.3087 | 0.00725 | 0.00716 |
| **Dueling DQN** | 0.1860 | 0.1020 | 0.3849 | 0.3454 | 0.00689 | 0.00678 |
| **C51** | −1.0811 | 0.00684 | 0.2503 | 0.1400 | 0.00775 | 0.00768 |

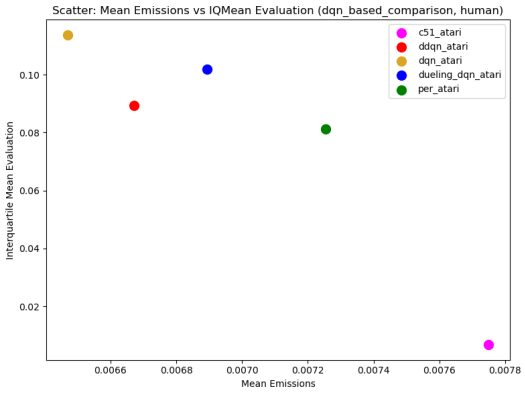
- **Dueling DQN.** Its mean is highest in human-norm (0.1860), but the IQM (0.1020) is closer to baseline DQN's 0.1137, suggesting moderate overall gains once outliers are downweighted.
- **C51's Negative Mean.** With −1.08 in human-norm, C51 suffers from severely negative outliers; however, its IQM (0.00684) sits just above zero, reflecting that most runs or games are not quite so disastrous outside *Boxing*.
- **Emissions Overhead.** Distributional (C51) and prioritized (PER) methods do have higher carbon costs (around 0.0077 kg and 0.00725 kg, respectively) than vanilla DQN (0.00647 kg). The IQM for emissions shows a similar trend (0.00768 and 0.00716 vs. 0.00637).

Altogether, adding the IQM metric helps to highlight the presence of large outliers in short 100k-step runs. Dueling emerges as a modest improvement on baseline DQN once extreme seeds are downweighted, whereas C51 and PER do not yet exhibit strong benefits for the added cost in short training scenarios.

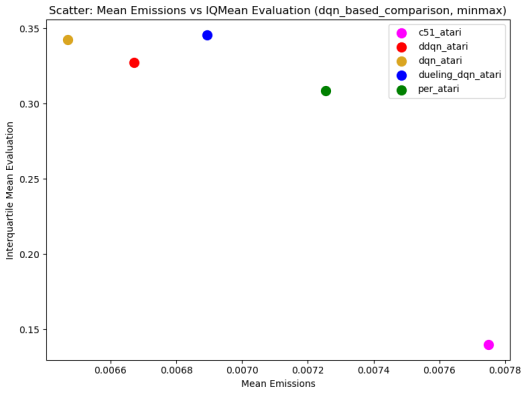
**Scatter Plots of Emissions vs. Performance** To visually depict the trade-off between carbon footprint and final performance, Figures 33 and 34 show scatter plots of `Mean Emissions` on the x-axis against (*i*) the `IQMean` or (*ii*) the `Mean` of final evaluation on the y-axis. We plot both the human-normalized and min–max normalized variants:

**Game-by-Game Observations** When looking individually per environment:

- **Boxing** heavily skews human-normalized averages for PER and especially C51, yielding strongly negative means. Dueling or Double DQN often handle *Boxing* more stably.
- **Freeway** is comparatively easier, so all variants converge to near-human or above. PER and Dueling both score well here.

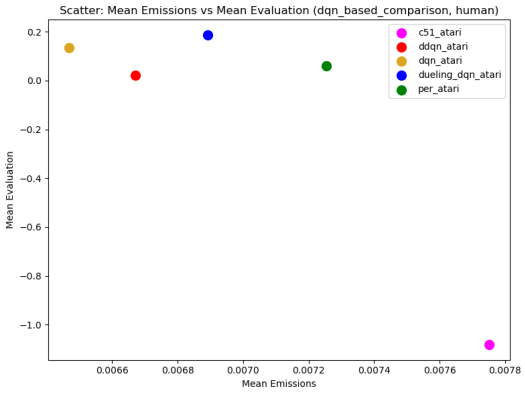



**(a)** Human Norm: Mean Emissions vs. IQMean Evaluation

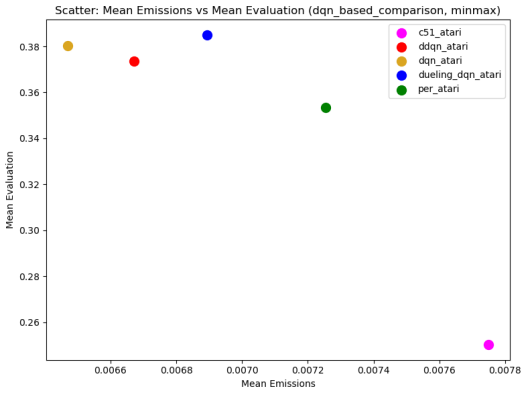



**(b)** Min–Max: Mean Emissions vs. IQMean Evaluation

**Figure 33:** Scatter: Mean Emissions vs. Interquartile Mean (IQM) final evaluation, for DQN-based algorithms. C51 (magenta) appears far to the right (highest emissions) and near the bottom in human norm, though it's closer in min–max. DQN and Double DQN cluster with relatively low emissions.



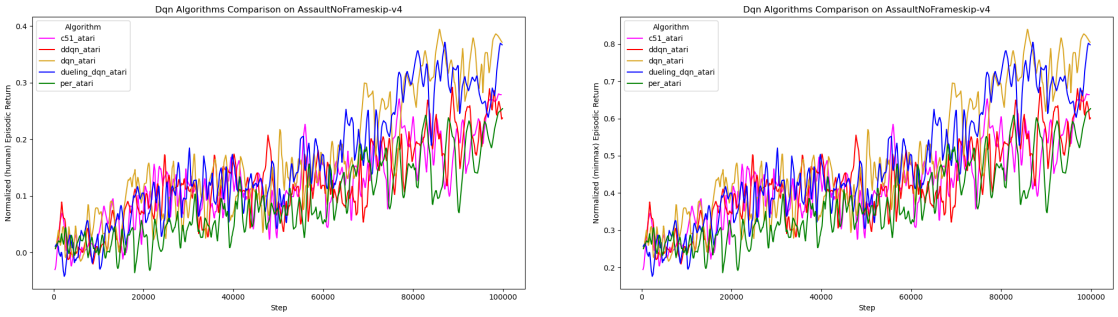

**(a)** Human Norm: Mean Emissions vs. Mean Evaluation




**(b)** Min–Max: Mean Emissions vs. Mean Evaluation

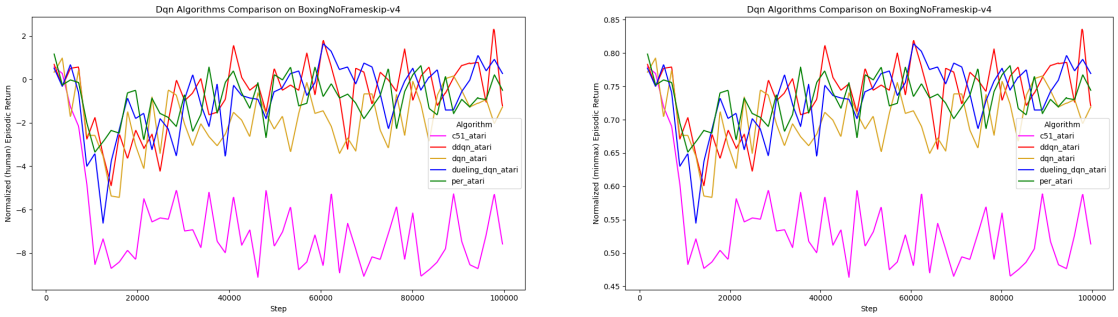
**Figure 34:** Scatter: Mean Emissions vs. Mean final evaluation, for DQN-based algorithms. Again, C51 (magenta) is an outlier with higher emissions and negative (human) or low (min–max) returns. Dueling (blue) has moderate emissions and the highest human-norm performance.

- **Assault** sees moderate or high min–max normalized returns across the board; distributional methods like C51 can do fairly well in some seeds, but not enough to beat DQN or Dueling on average.




**(a)** Human Norm: Assault **(b)** Min–Max: Assault

**Figure 35:** Comparison of DQN-based algorithms on **Assault**, showing human-normalized (**left**) and min–max normalized (**right**) final returns over 100k steps. Distributional methods (e.g. C51) can excel in some seeds but not enough to surpass Dueling/DQN on average.

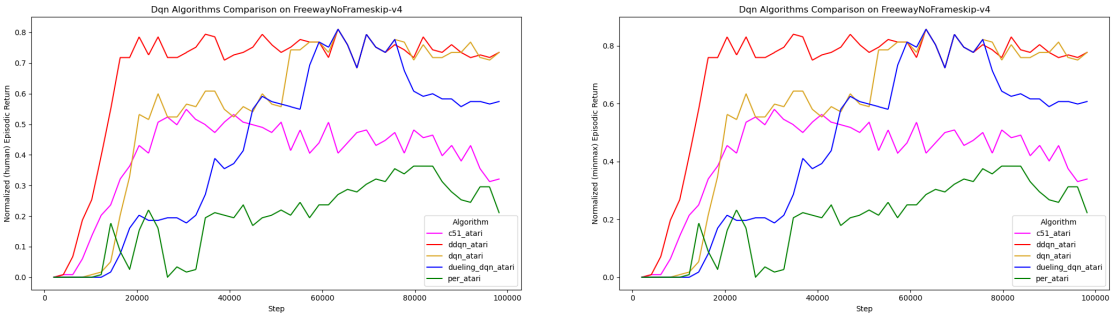



**(a)** Human Norm: Boxing **(b)** Min–Max: Boxing

**Figure 36:** Comparison of DQN-based algorithms on **Boxing**. The human-normalized scale (**left**) highlights large negative dips, especially for C51 and PER. Min–max normalized (**right**) shows moderate ranges for most algorithms.

**Emissions and Efficiency** As indicated by both Table 22, Table 23, and the scatter plots (Figures 33–34), **C51** has the highest mean emissions ($\sim 0.00775\,\text{kg}$), while **PER** also exceeds baseline levels at $0.00725\,\text{kg}$. **DQN** remains the lowest ($0.00647\,\text{kg}$). In short 100k-step training, the benefits of distributional or prioritized approaches do not fully emerge, whereas their computational overhead (and hence emissions) is quite tangible.

**Emissions Barplot** Finally, Figure 38 illustrates a direct barplot comparison of the average emissions (with error bars for standard deviation) for the five methods.




**(a)** Human Norm: Freeway **(b)** Min–Max: Freeway

**Figure 37:** Comparison of DQN-based algorithms on **Freeway**. All methods converge relatively quickly to near-human or above. PER and Dueling typically perform strongly on this environment.

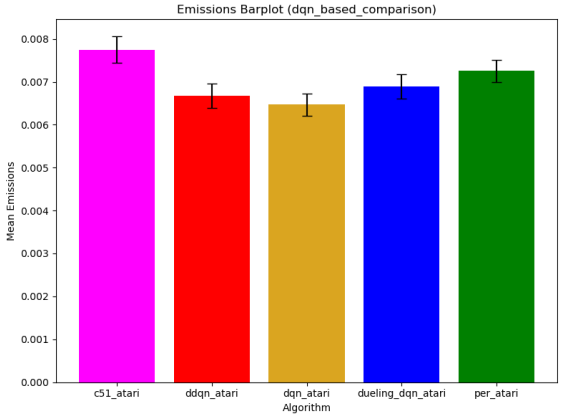



**Figure 38:** Emissions Barplot (DQN-based Comparison). C51 (magenta) leads with $\sim 0.0078\,\text{kg}$, while DQN (gold) is at the low end (0.00647).

## Key Takeaways

- **Dueling DQN** shows the best human-norm mean (0.1860), or second-best min–max (0.3849). Its overhead is modest.
- **Double DQN** is cheap in energy and helps curb Q-value inflation, but does not necessarily raise final returns in short runs (0.0226 human, 0.3737 min–max).
- **PER** is also more costly (0.00725 kg) with only slight gains in 100k steps, suggesting PER's advantage might need longer training to appear.
- **C51** is the outlier in both emissions and negative returns (human), though its IQM is far less extreme, indicating that only a few seeds/games are catastrophic.
- **Baseline DQN** remains a viable option at 100k steps, balancing decent performance and the lowest emissions of the five variants.

## 4.4 Policy-Based Algorithms

This section presents results for the three policy gradient methods.

### 4.4.1 REINFORCE

**Table 24:** Key hyperparameters for the REINFORCE algorithm. Only `env_id` and `seed` vary across runs.

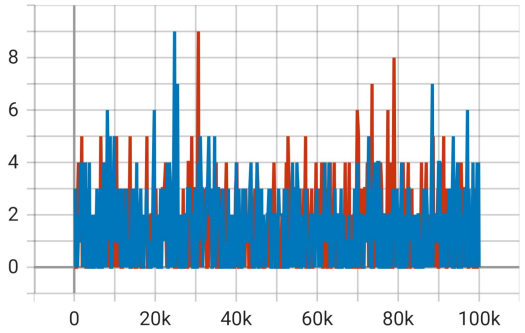
| Parameter | Value |
|---|---|
| `exp_name` | reinforce_atari |
| `seed` | 1..4 |
| `torch_deterministic` | True |
| `cuda` | True |
| `track` | True |
| `wandb_project_name` | rlsb |
| `capture_video` | False |
| `save_model` | True |
| `env_id` | e.g. AmidarNoFrameskip-v4 |
| `total_timesteps` | 100000 |
| `learning_rate` | 0.00025 |
| `num_envs` | 1 |
| `gamma` | 0.99 |

#### (Hyper)Parameters

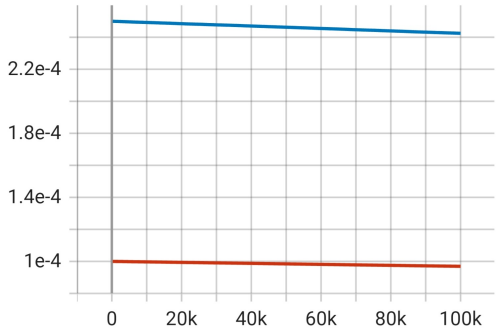
**Learning-Rate Tuning** We tested two primary learning rates ($1 \times 10^{-4}$ vs. $2.5 \times 10^{-4}$), each with a slight annealing schedule over the 100k steps. Ultimately, $2.5 \times 10^{-4}$ converged more reliably in short-run experiments, as illustrated in Figure 39. Removing reward clipping made no difference, likely because we already normalize returns. However, even the better LR sees limited improvements in just 100k steps, reflecting the high variance of REINFORCE.

**Aggregated Returns** Figures 40 show the aggregated episodic returns (mean ± min–max envelope) for *human-normalized* and *min–max normalized* scales:

- **Human norm** typically hovers around zero—some seeds spike up to +4 or +5, others dip to -2 or -3.
- **Min–max norm** plateaus around 0.15–0.20, but occasionally climbs near 0.8 in certain runs.

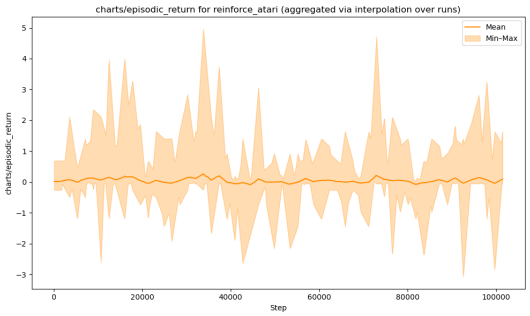



**(a)** Episodic Return (Raw) for Two LRs

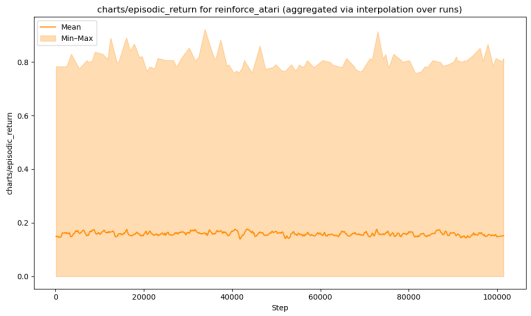



**(b)** Learning Rate Schedules

**Figure 39: REINFORCE LR Tuning.** Two learning rates ($1 \times 10^{-4}$ in red, $2.5 \times 10^{-4}$ in blue) both with minimal decay. The higher LR eventually performed better, although volatility remained high.




**(a)** Human-Normalized Returns (Aggregated)

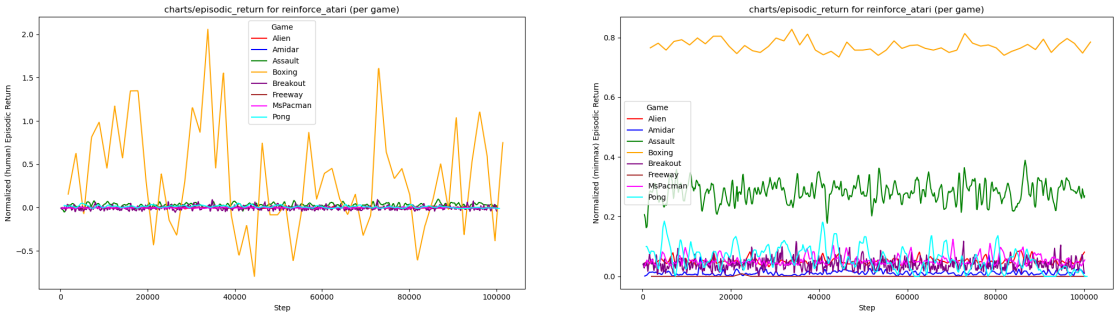



**(b)** Min–Max Returns (Aggregated)

**Figure 40: REINFORCE: Aggregated Episodic Returns.** Strong variance across seeds/games yields a wide min–max band in both normalizations. Mean in human norm often oscillates near zero, while min–max hovers around 0.15–0.20.

**Per-Game Breakdown** Figure 41 displays the same returns (human & min–max) but *separated by environment*:

- **Boxing** can show positive or negative extremes in human-norm, while **Freeway** remains almost trivial (zero or near zero).
- **Assault** (green in min–max) can reach $\sim 0.4$ in certain seeds, outpacing many other tasks.




**(a)** Per-Game: Human Norm

**(b)** Per-Game: Min–Max Norm

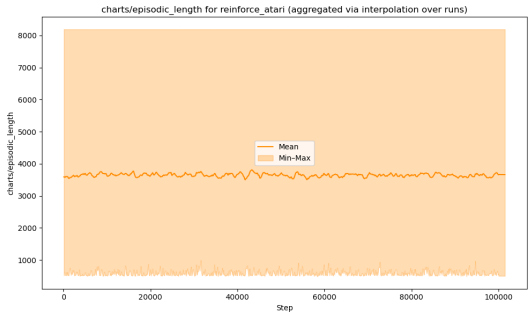
**Figure 41: REINFORCE: Returns by Environment.** Some runs on *Boxing* or *Assault* achieve higher peaks, while *Freeway* is essentially flat. Variance remains high across multiple seeds.

**Training Metrics** We log additional metrics in Figures 42–43. The steps per second (SPS) quickly rises above 150, the episodic length averages around 3500–4000 steps, and the `losses_loss` curve fluctuates significantly from positive to negative. The learning rate chart verifies the slight linear decay from $2.5 \times 10^{-4}$ to roughly $2.4 \times 10^{-4}$ by 100k steps.

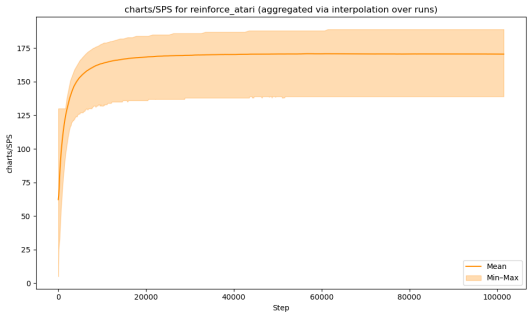
**Evaluation and Emissions** Table 25 consolidates final performance and emissions across 32 runs (8 Atari games $\times$ 4 seeds). Mean human-norm returns are about 0.026 (with large variance), and min–max is $\sim 0.154$. Energy usage is $0.00676\,\mathrm{kg\,CO_2}$ on average, slightly above baseline DQN (0.00647).

## Discussion

- **Pure Policy Gradient Variance:** Without baselines or actor-critic structure, REINFORCE's updates rely entirely on full returns. In just 100k steps, this approach shows wide fluctuations, as seen in the loss and returns.
- **LR Choice:** $2.5 \times 10^{-4}$ is preferable to $1 \times 10^{-4}$ within these short runs, but neither rate fully stabilizes the performance.

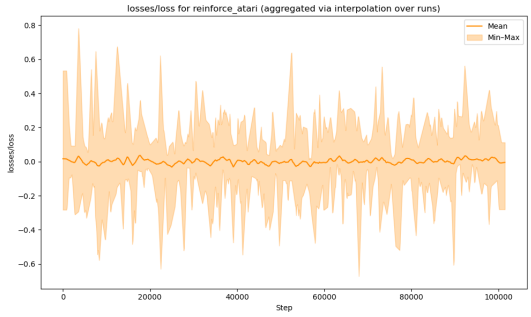



**(a)** Episode Length

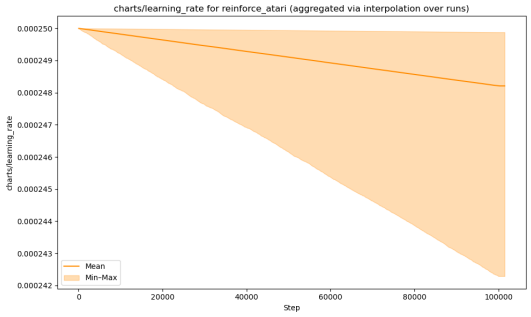



**(b)** Steps Per Second (SPS)

**Figure 42: REINFORCE: Episode Length and Throughput.** The average length stabilizes near 3800–4000 steps; min–max can exceed 7000–8000 in some seeds. SPS plateaus around 150–170.




**(a)** Policy Loss (raw)




**(b)** Learning Rate (Minimal Decay)

**Figure 43: REINFORCE: Loss and Learning-Rate Curves.** The loss exhibits large swings across runs due to high-variance returns, while the LR only drifts from $2.5 \times 10^{-4}$ down to $\sim 2.4 \times 10^{-4}$.

**Table 25:** REINFORCE: Final Evaluation and Emissions (Means and Ranges). High variance is evident in the negative minimum (Boxing) and moderate positive maximum (2.83).

| | **Human Norm** | **Min–Max** | **Emissions** |
|---|---|---|---|
| Mean | 0.0259 | 0.1544 | 0.00676 |
| Std | 0.3549 | 0.2515 | 0.00056 |
| Min | -2.4048 | 0.0 | 0.00614 |
| Max | 2.8333 | 0.8527 | 0.00760 |

- **Emissions and Overhead:** REINFORCE's simpler forward pass keeps emissions at 0.00676 kg, somewhat above the 0.00647 kg for DQN but below distributional or PER methods ($\sim$ 0.0072–0.0078).
- **Longer-Horizon Potential:** Theoretical convergence may require millions of steps. Practical setups usually adopt actor-critic or baseline modifications to reduce variance and accelerate learning in fewer steps.

### 4.4.2 Proximal Policy Optimization (PPO)

**Table 26:** Key hyperparameters for PPO. Only `env_id` and `seed` vary across runs. Note that `num_envs`=8 collects experience from 8 parallel environments each rollout.

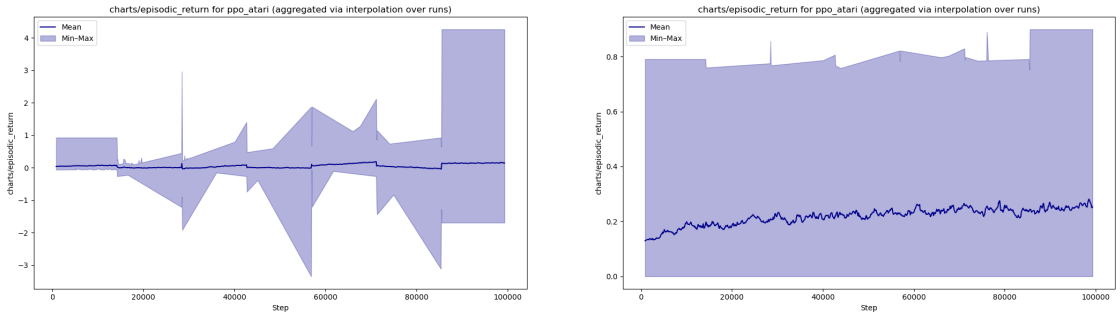
| Parameter | Value |
|---|---|
| `exp_name` | ppo_atari |
| `seed` | 1..4 |
| `torch_deterministic` | True |
| `cuda` | True |
| `track` | True |
| `wandb_project_name` | rlsb |
| `capture_video` | False |
| `save_model` | True |
| `env_id` | e.g. AlienNoFrameskip-v4 |
| `total_timesteps` | 100000 |
| `learning_rate` | 0.00025 |
| `num_envs` | 8 |
| `num_steps` | 128 |
| `anneal_lr` | True |
| `gamma` | 0.99 |
| `gae_lambda` | 0.95 |
| `num_minibatches` | 4 |
| `update_epochs` | 4 |
| `norm_adv` | True |
| `clip_coef` | 0.1 |
| `clip_vloss` | True |
| `ent_coef` | 0.01 |
| `vf_coef` | 0.5 |
| `max_grad_norm` | 0.5 |
| `target_kl` | None |
| `batch_size` | 1024 |
| `minibatch_size` | 256 |
| `num_iterations` | 97 |

### (Hyper)Parameters

**Overview and Settings** We follow the default *CleanRL* [21] PPO hyperparameters, with `clip_coef` $= 0.1$ (a bit lower than the usual 0.2). Each iteration processes $8 \times 128 = 1024$ steps, giving $\sim 97$ updates across 100k total steps. We keep standard GAE [**schulman:gae**] for advantage estimation. Importantly, `anneal_lr=True` implements a **substantial** linear decay of the learning rate from $2.5 \times 10^{-4}$ down toward zero by the end of training, as seen in Figure 47.

**Aggregated Returns** Figures 44 depict the episodic returns (mean $\pm$ min–max) for both **human** and **min–max** normalization across 32 total runs (8 games, 4 seeds each):

- **Human norm** (Fig. 44a): The average meanders near zero, with large negative dips (below $-2$) and a few positive spikes (above $+4$).
- **Min–max norm** (Fig. 44b): The mean gradually hovers around 0.2–0.3, with some seeds spiking up to 0.8 or higher.

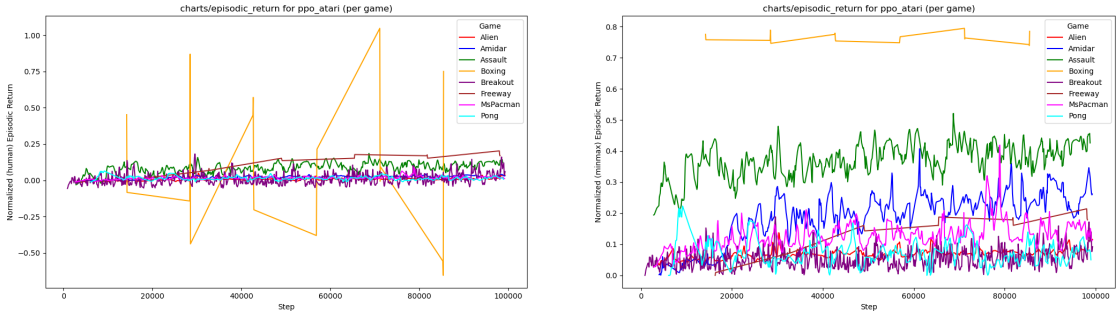



**(a)** Human-Normalized (Aggregated) **(b)** Min–Max Normalized (Aggregated)

**Figure 44: PPO: Aggregated Episodic Returns.** The broad shaded area shows high variance among runs/games. The mean remains around zero in human norm but reaches 0.2–0.3 in min–max.

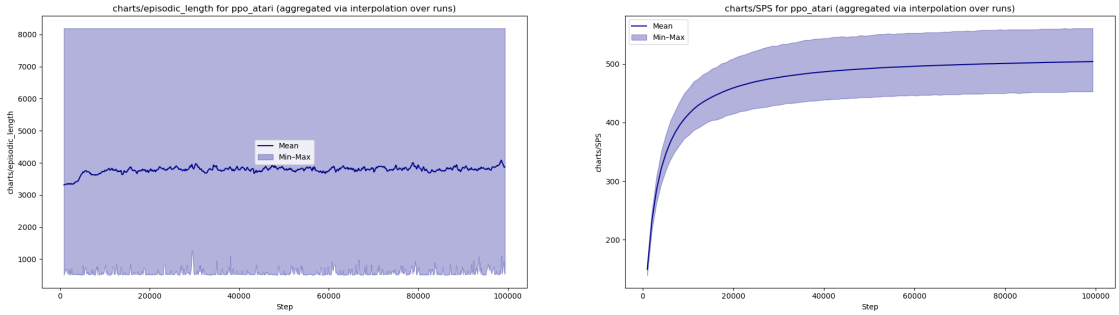
**Per-Game Returns** Figure 45 shows these returns for each environment:

- **Boxing** (orange) occasionally leaps above $+1$ or below -1 in human norm, with big shifts in min–max as well.
- **Assault** (green) can exceed 0.4 in min–max.
- Some runs in **Breakout** or **Freeway** remain near zero.




**(a)** Per-Game: Human Norm **(b)** Per-Game: Min–Max Norm

**Figure 45: PPO: Returns by Environment.** Notable extreme spikes/dips appear in *Boxing* (orange) and occasionally *Assault* or *Breakout*.




**(a)** Episode Length **(b)** Steps per Second (SPS)

**Figure 46: PPO: Episode Length & Throughput.** The mean ep-length hovers near 3500–4000 steps, with some runs dropping below 1000 or spiking above 7000. Meanwhile, parallel envs let SPS exceed 400 or 500.

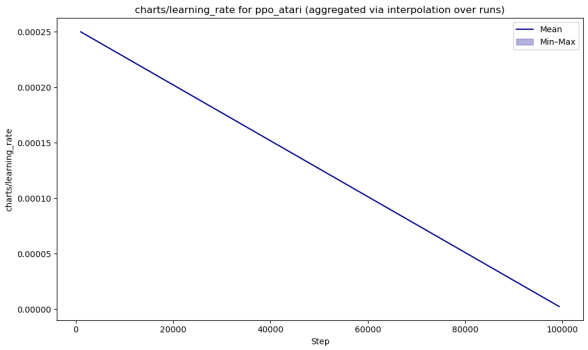
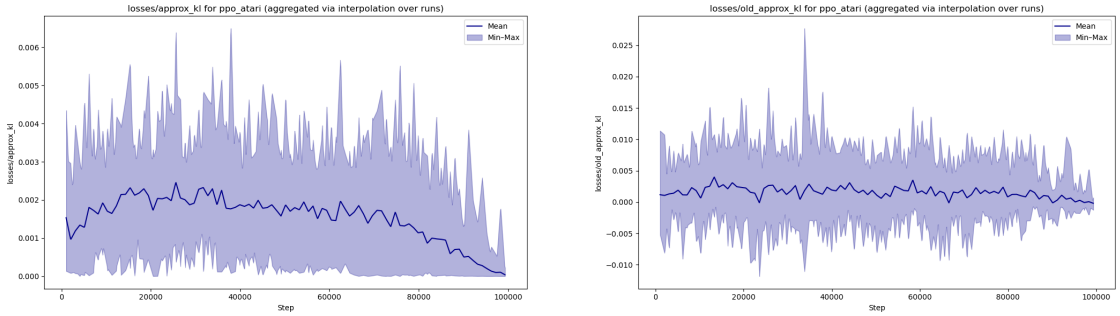
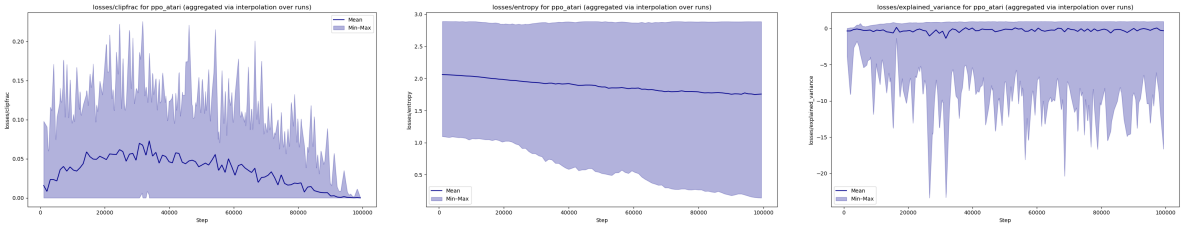



**Figure 47: PPO: Learning Rate Decay.** The LR anneals linearly from $2.5 \times 10^{-4}$ down to near 0 over 100 000 steps, a steep slope that can reduce update magnitudes near the end.



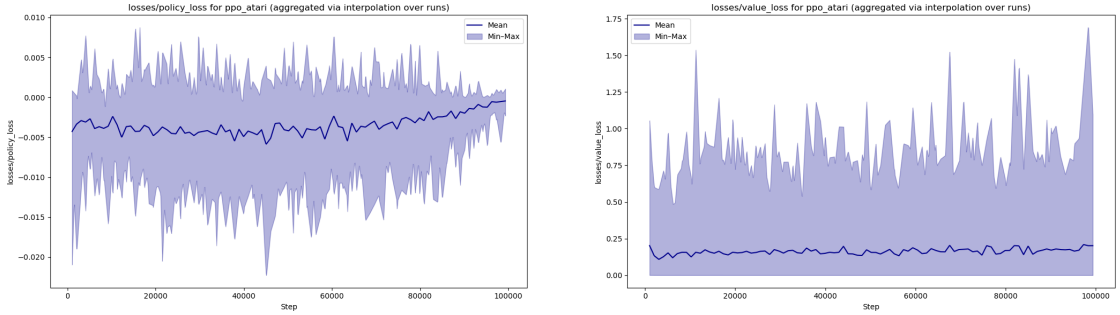

**(a) Approx KL** **(b) Old Approx KL**

**Figure 48: PPO: KL Divergences vs. Training Steps.** Both metrics hover near 0.001–0.003 for most of training, though spikes appear. The old KL is centered around 0 but can jump above +0.02 or dip below -0.01.




**(a) Clip Fraction** **(b) Entropy** **(c) Explained Variance**

**Figure 49: PPO: Additional Diagnostics (ClipFrac, Entropy, Explained Variance).** (a) Clip fraction often spikes above 0.1 early, then drops under 0.01 by 100k steps. (b) Entropy declines from about 2.0 to below 1.5 in some runs, indicating the policy becomes more deterministic. (c) Explained variance remains near or below 0 for many runs, suggesting the value function struggles to capture returns in some seeds.




**(a) Policy Loss** **(b) Value Loss**

**Figure 50: PPO: Policy and Value Losses.** **(a)** The policy loss fluctuates around slightly negative values (often between $-0.01$ and 0.0), with occasional positive spikes up to $\sim 0.005$. **(b)** The value loss remains around 0.1–0.3 on average but can exceed 1.0 in some runs (max reaching over 1.5). This large min–max spread indicates variability across seeds and environments, while the mean stays comparatively stable.

**Additional Training Metrics** Alongside returns, we log episode length, throughput (SPS), learning rate, KL divergences, and further diagnostic losses:

**Evaluation and Emissions** Table 27 summarizes PPO's final returns (human/min–max) and mean $CO_2$ usage. Interestingly, PPO emits only $\sim 0.00288\,\text{kg}$ $CO_2$ on average—significantly lower than the typical 0.006–0.007 range of DQN-based runs. Parallel sampling and shorter GPU usage per environment step likely contribute to this efficiency.

**Table 27:** PPO: Final Evaluation (Mean) & Emissions. Negative dips mainly from *Boxing* or *Breakout*.

| Metric | Mean | Std | Min / Max |
|---|---|---|---|
| Human-Norm Return | 0.077 | 0.563 | (-5.02 / 3.31) |
| Min–Max Return | 0.248 | 0.271 | (0.0 / 0.9643) |
| Emissions ($\text{kg}\,CO_2$) | 0.00288 | 0.00039 | (0.00244 / 0.00369) |

## Discussion

- **Performance Variability:** Some runs stay near zero, while others occasionally spike above +1 or +2 in human norm. The min–max scale averages around 0.25, but can exceed 0.8 in certain seeds/games.
- **Low Emissions:** PPO's parallel rollout approach (8 envs) plus relatively fast updates yield the lowest carbon footprint among tested algorithms so far.
- **Clipping Coef = 0.1:** A smaller clipping range might limit the policy's rate of change, which, combined with the large LR anneal, can hamper final performance in only 100k steps.
- **KL Divergence and LR Decay:** As `learning_rate` decays to near zero, the approximate KL metrics (Fig. 48) and clip fraction (Fig. 49(a)) both trend downward, suggesting slower policy updates and fewer ratio violations.
- **Policy / Value Losses:** The policy loss typically hovers around slight negative values (Fig. 50a), reflecting how PPO's objective is calculated relative to advantage. Value loss (Fig. 50b) shows moderate means but large max spikes, implying some seeds or games exhibit abrupt divergences in state-value estimation.
- **Entropy Decline and Value Modeling:** Steady entropy decay (Fig. 49(b)) shows the agent becomes more selective, while negative dips in explained variance (Fig. 49(c)) indicate the baseline network sometimes fails to track returns accurately, perhaps due to limited training steps or high variability.

Overall, PPO in 100k-step Atari remains highly variable, but it demonstrates notably *lower emissions* than the DQN-based methods, albeit with modest average returns in this short training regime.

### 4.4.3 Soft Actor-Critic (SAC)

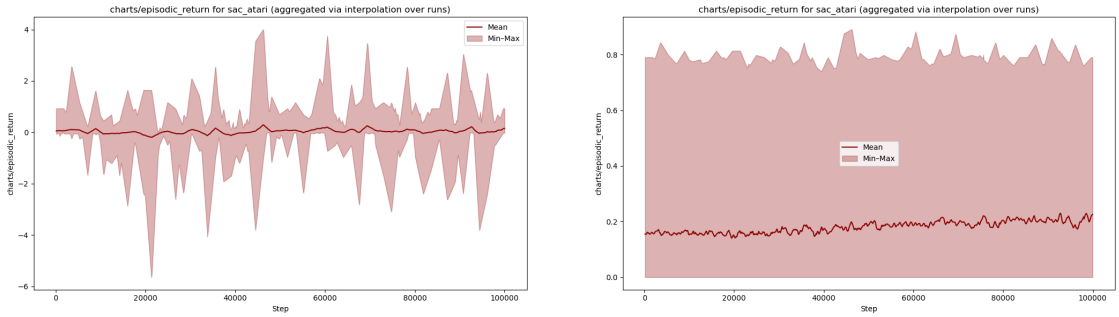
**Table 28:** Key hyperparameters for SAC. Only `env_id` and `seed` vary across runs.

| Parameter | Value |
|---|---|
| `exp_name` | sac_atari |
| `seed` | 1..4 |
| `torch_deterministic` | True |
| `cuda` | True |
| `track` | True |
| `wandb_project_name` | rlsb |
| `capture_video` | False |
| `save_model` | True |
| `env_id` | e.g. AlienNoFrameskip-v4 |
| `total_timesteps` | 100000 |
| `buffer_size` | 20000 |
| `gamma` | 0.99 |
| `tau` | 1.0 |
| `batch_size` | 64 |
| `learning_starts` | 1000 |
| `policy_lr` | 0.0003 |
| `q_lr` | 0.0003 |
| `update_frequency` | 4 |
| `target_network_frequency` | 1000 |
| `alpha` | 0.2 |
| `autotune` | True |
| `target_entropy_scale` | 0.89 |

#### (Hyper)Parameters

**Overview and Settings** This SAC implementation derives from `sac_atari` in *CleanRL*, tailored to a 100k-step budget. Key adjustments include a replay buffer of 20k, `learning_starts`=1000, and `target_network_frequency`=1000 for target Q updates. We enable `autotune` for $\alpha$, letting the algorithm optimize its entropy coefficient dynamically based on a target entropy of $\sim 0.89$.

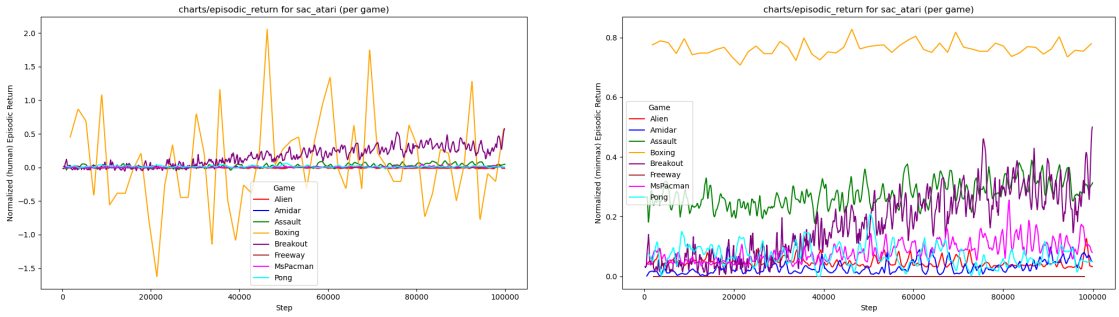
**Aggregated Returns** Figures 51 illustrate the mean $\pm$ min–max episodic returns, both human- and min–max-normalized. The short 100k horizon yields considerable variance, with some runs dropping below -4 in human norm.




**(a)** Human-Normalized (Aggregated) **(b)** Min–Max Normalized (Aggregated)

**Figure 51: SAC: Aggregated Episodic Returns.** Notice the swings below -4 in the human norm, while min–max remains mostly under 0.8.

**Per-Game Returns** Figure 52 breaks down performance by environment, showing that *Boxing* significantly skews the human-norm mean downward. Meanwhile, *Breakout* and *Assault* achieve moderate positive scores.



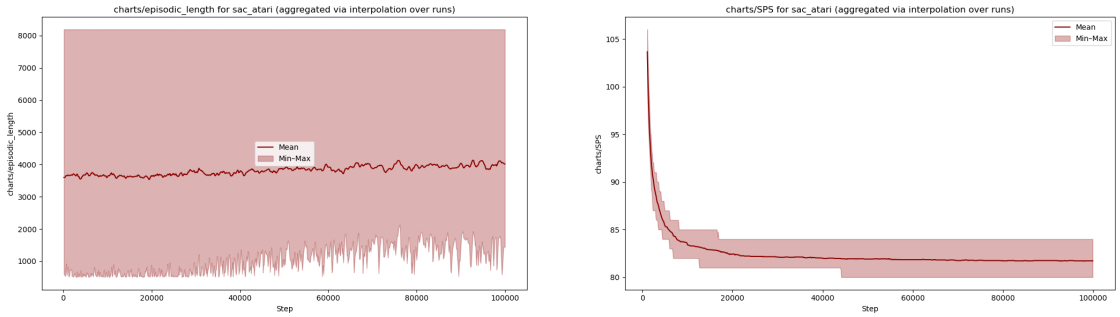

**(a)** Per-Game: Human Norm **(b)** Per-Game: Min–Max Norm

**Figure 52: SAC: Returns by Environment.** *Boxing* can dip below -20 in some runs, while *Pong* remains near -0.01 (human norm).

**Episode Length and SPS** Figure 53 shows the episode length and steps-per-second (SPS). The average ep-length hovers near 3800–4000, while SPS drops from over 100 at start to 80 by 20k steps, stabilizing thereafter.

**Actor Loss and Temperature ($\alpha$)** Figures 54 and 55 detail how the policy updates and the learned entropy coefficient evolve:

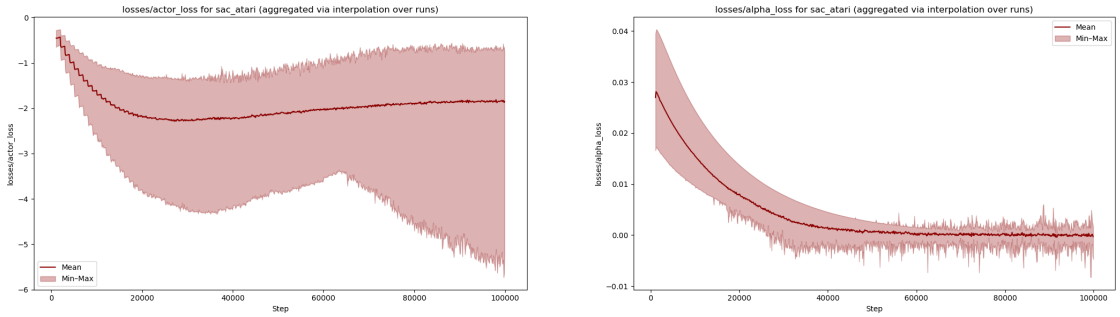
- **Actor Loss**: Initially around -1.0, quickly dips to about -3 by 10k steps, then recovers to near -2.
- **Alpha Loss**: Falls below 0.01 around 30k steps, indicating fewer gradient corrections to $\alpha$.




**(a)** Episode Length **(b)** Steps per Second (SPS)

**Figure 53: SAC: Episode Length & Throughput.** Min–max ranges from under 1000 to over 7000 steps, while SPS levels around 80 after initial decay.

- $\alpha$ **Parameter**: Exhibits a U-shaped curve, dropping to $\approx 0.1$ then climbing above 0.3. Some runs exceed 1.0 near the end, showing high exploration in later training.




**(a) Actor Loss** **(b) Alpha Loss**

**Figure 54: SAC: Actor and Alpha Losses.** The actor loss bottoms out near -3 by ∼10k steps, while alpha loss decays from 0.03 to near 0.0.

**Q-Function Losses and Values** SAC uses two Q-functions (QF1, QF2) to mitigate overestimation and stabilize training. Figures 56–57 showcase their losses and value estimates:
Both QF1 and QF2 exhibit moderate *mean* losses (generally below 3), but the min–max band can spike drastically, especially after ∼40k steps. The Q-function value estimates likewise climb, with some seeds surpassing 80–100 near the end, which can indicate overestimation or genuinely high return states.

**Evaluation and Emissions** Table 29 reports final performance after 100k steps and average $CO_2$ emissions. Large negative outliers in *Boxing* produce a mean human-norm score of $-1.10$, while *Breakout* and *Assault* partially offset this. Emissions at $\sim 0.015$

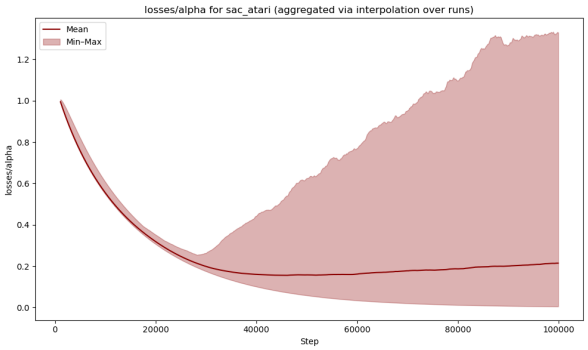
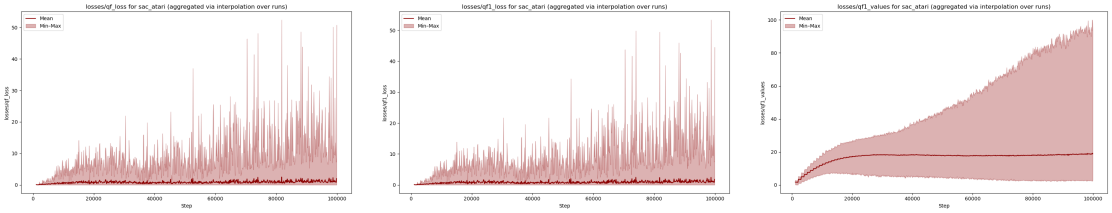
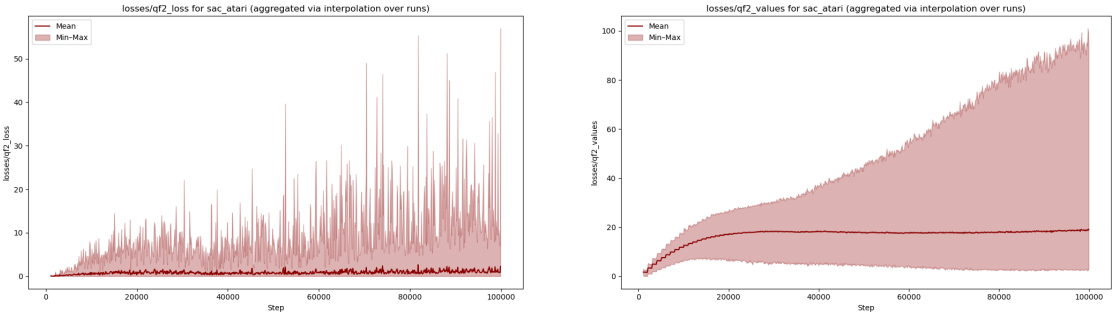



**Figure 55: SAC: Learned $\alpha$ Over Time.** After dipping to 0.1 around 30k steps, some runs climb above 1.0, while the mean lands near 0.3 at 100k.



**(a) QF Loss (combined)** **(b) QF1 Loss** **(c) QF1 Values**

**Figure 56: SAC: QF1 Metrics.** Mean QF1 losses remain below 3, but min–max spikes reach 50+ post-40k steps. QF1 values rise from near 0 to about 20 in the mean, with outliers above 80.



**(a) QF2 Loss** **(b) QF2 Values**

**Figure 57: SAC: QF2 Metrics.** Similar to QF1, QF2 losses show large spikes up to 50+ in some runs, and QF2 values climb from below 10 to 20 in the mean, reaching 100 in certain seeds by 100k steps.

kg $CO_2$ exceed PPO's $\sim 0.003$ but remain in line with other off-policy setups requiring more frequent updates.

**Table 29:** SAC: Final Evaluation (Mean) & Emissions.

| Metric | Mean | Std | Min | Max |
|---|---|---|---|---|
| Human-Norm Return | -1.10 | 4.43 | -23.36 | 0.93 |
| Min–Max Return | 0.227 | 0.254 | 0.00 | 0.83 |
| Emissions ($\mathrm{kg\,CO_2}$) | 0.01545 | 0.00033 | 0.01495 | 0.01610 |

### Discussion

- **High QF Variance:** QF1 and QF2 both show substantial spikes in loss and inflated value estimates, suggesting partial overestimation or instability in certain seeds—common in off-policy algorithms with short training horizons.
- $\alpha$ **U-Shape:** After initially dropping to enhance exploitation, many runs ramp $\alpha$ back up above 1.0, indicating renewed exploration strategies late in training.
- **Performance Skew:** Negative *Boxing* results dominate the human-norm average, but *Breakout* and *Assault* exhibit moderate positive returns, illustrating the algorithm's uneven game-to-game performance in only 100k steps.
- **Emissions:** Frequent gradient steps (update frequency = 4) and maintaining two critics lead to higher carbon costs ($\sim 0.015$ kg) compared to simpler on-policy methods, though still modest in absolute terms.

Overall, SAC demonstrates potential for improvement in some Atari tasks under 100k interactions but also exhibits high variance in Q-function estimates and a complex $\alpha$ schedule. Longer training or more conservative Q-network updates may mitigate these spikes and produce steadier performance across seeds.

## 4.5 Overall Comparison of Policy Gradient Algorithms

In this section, we compare the three policy gradient–based algorithms tested in our benchmark: **PPO** (on-policy with a clipped objective), **REINFORCE** (a basic Monte Carlo policy gradient), and **SAC** (an off-policy method with automatic entropy tuning). Each algorithm was trained for 100 000 steps on the same 8 Atari games, with 4 random seeds per game, producing 32 runs per algorithm. We examine both their *final performance* (human-normalized and min–max normalized returns) and *carbon emissions* over the course of training.

**Table 30:** Overall human-normalized returns (aggregated) for policy gradient algorithms.

| Algorithm | Mean | Std | Min | Max | IQM | Median |
|---|---|---|---|---|---|---|
| PPO | 0.077 | 0.563 | -5.02 | 3.31 | 0.0173 | 0.0163 |
| REINFORCE | 0.026 | 0.355 | -2.40 | 2.83 | -0.0039 | -0.0029 |
| SAC | -1.100 | 4.428 | -23.36 | 0.93 | 0.0085 | 0.0045 |

**Final Evaluation Performance: Human-Normalized.** Table 30 summarizes the aggregated human-normalized returns over all 8 environments for each algorithm (mean, std, etc.).
By this metric, **PPO** shows the highest mean value (0.077), albeit with large variance (0.563). **REINFORCE** follows at 0.026, while **SAC** has a negative average ($-1.10$), strongly influenced by its very poor performance on *Boxing* (see Section **??** for details). Notably, the interquartile mean (IQM) for all three algorithms is near zero or slightly negative, reflecting that the short 100k-step horizon yields limited gains in some games. SAC's extreme negative outliers in *Boxing* pull its mean well below zero, even though it attains moderate success in *Assault* and *Breakout*.

**Final Evaluation Performance: Min–Max Normalized.** A similar pattern emerges when we switch to min–max normalization, as shown in Table 31.

**Table 31:** Overall min–max normalized returns (aggregated) for policy gradient algorithms.

| Algorithm | Mean | Std | Min | Max | IQM | Median |
|---|---|---|---|---|---|---|
| PPO | 0.248 | 0.271 | 0.00 | 0.964 | 0.1523 | 0.1204 |
| REINFORCE | 0.154 | 0.252 | 0.00 | 0.853 | 0.0291 | 0.0393 |
| SAC | 0.227 | 0.254 | 0.00 | 0.826 | 0.1477 | 0.1105 |

Here, **PPO** leads with a mean of 0.248, slightly outperforming **SAC** (0.227). **REINFORCE** remains lower on average (0.154). Interestingly, SAC's min–max maximum (0.826) is in line with PPO's (0.964), suggesting some of its runs achieve decent returns in certain games, offset by very low or zero returns in others.

**Emissions and Energy Consumption.** In addition to performance, our benchmark tracks **carbon emissions** (kg $CO_2$) during training (Fig. 58). Table 32 shows the mean emissions for each algorithm aggregated over all 32 runs:
**PPO** exhibits the lowest emissions, averaging $\sim 0.0029$ kg $CO_2$ per run, whereas **SAC** is by far the highest ($\sim 0.0154$ kg). **REINFORCE** lands in the middle at $\sim 0.0068$ kg. These differences likely arise from:

- *REINFORCE*: Simpler architecture, but it replays from scratch each episode (Monte Carlo), incurring moderate overhead.

**Table 32:** Average carbon emissions (kg $CO_2$) for policy gradient algorithms over 100k steps.

| Algorithm | Mean | Std | Min | Max |
|---|---|---|---|---|
| PPO | 0.00288 | 0.00039 | 0.00244 | 0.00369 |
| REINFORCE | 0.00676 | 0.00056 | 0.00614 | 0.00760 |
| SAC | 0.01545 | 0.00033 | 0.01495 | 0.01610 |

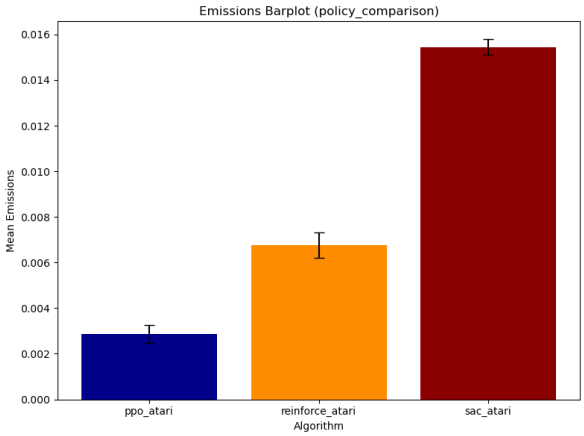
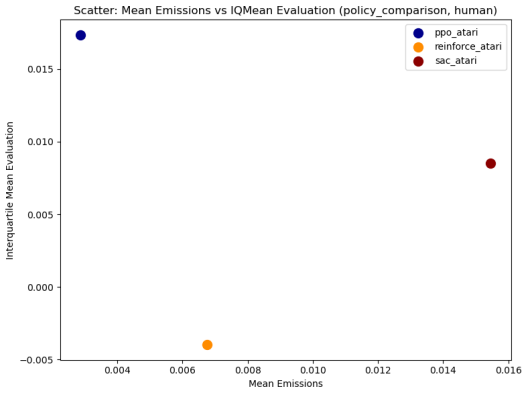



**Figure 58: Policy Algorithms: Mean Emissions (kg $CO_2$).** Error bars show the standard deviation across 32 runs.

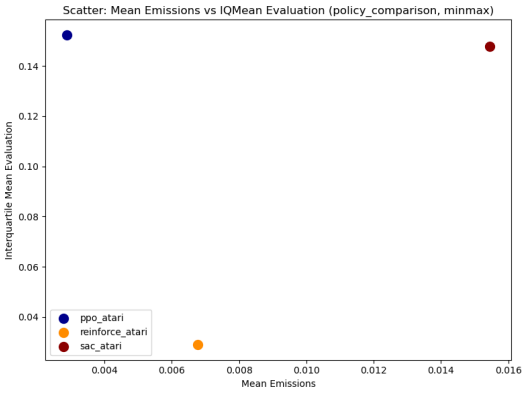
- *PPO*: On-policy sampling plus parallel environments yield a relatively fast throughput, reducing total compute time.
- *SAC*: Off-policy approach with frequent gradient updates, two Q-networks, and autotuning overhead results in higher GPU usage.

**Performance vs. Emissions** Beyond the aggregated returns and raw carbon footprints, it is also informative to visualize the **trade-off** between *mean emissions* (kg $CO_2$) and *performance* (mean or IQM). Figures 59 and 60 combine these metrics under both human-normalized and min–max normalization.
*Observation.* - In all four scatter plots, **PPO** (blue) occupies the *lowest emissions* regime ($\approx$ 0.003 kg $CO_2$) yet achieves higher or comparable returns than the others. - **SAC** (red) clearly emits more ($\approx$ 0.015 kg), placing it on the far right of each scatter, while its performance can be strong (especially in mean min–max) or moderate (IQM), depending on the metric. - **REINFORCE** (orange) sits in between for emissions ($\approx$ 0.007 kg) but remains near zero or negative in human-normalized returns. Overall, these visualizations underscore a **trade-off**: although SAC can sometimes compete in raw performance, its significantly higher carbon footprint may not be ideal for short 100k-step benchmarks.

**Training Throughput and Runtime** A key factor driving these energy differences is **training speed**, often measured in *Samples per Second* (SPS). Figure 61 compares the

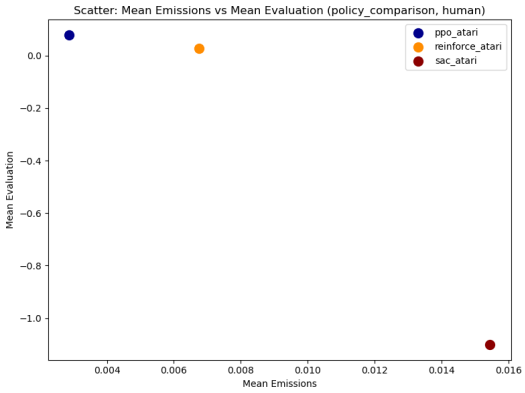



**(a) IQM (Human)**

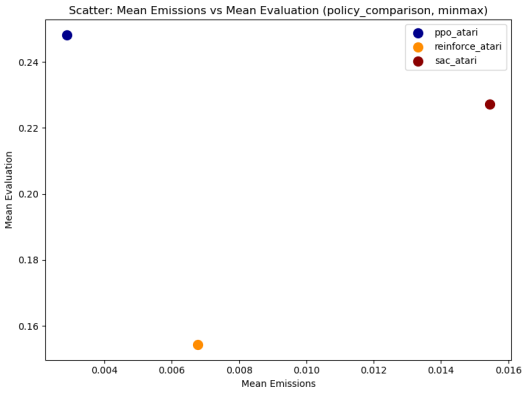



**(b) IQM (Min–Max)**

**Figure 59: Mean Emissions vs. Interquartile Mean (IQM) Return.** Each point corresponds to one algorithm's aggregated final performance (IQM) against its mean carbon emissions. **(a)** uses human-normalized returns, while **(b)** is min–max normalized.




**(a) Mean (Human)**




**(b) Mean (Min–Max)**

**Figure 60: Mean Emissions vs. Mean Return.** Similar to Fig. 59, but plotting the average (mean) final performance in human **(a)** vs. min–max **(b)** normalization.

SPS curves for PPO, SAC, and REINFORCE across the 100k interactions. Meanwhile, Table 33 lists the total wall-clock time for all 32 runs (8 games × 4 seeds).

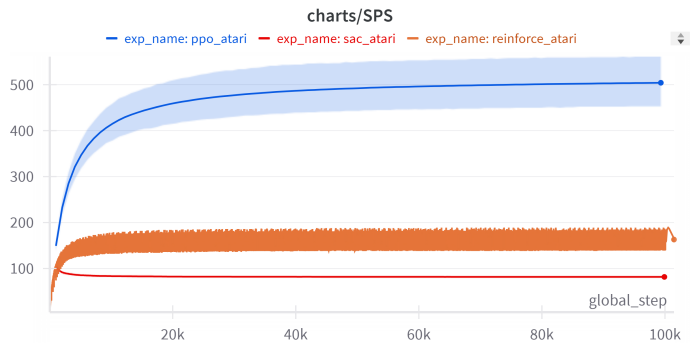



**Figure 61: Combined SPS Curves for PPO, SAC, and REINFORCE.** PPO rapidly climbs above 400–500 SPS, while SAC settles around 100–120, and REINFORCE around 150–200. Shaded areas (if visible) indicate min–max across seeds.

**Table 33:** Total wall-clock time for 32 runs (8 games × 4 seeds) per algorithm.

| Algorithm | Total Training Time |
|---|---|
| PPO | 2 h 25 m 08 s |
| REINFORCE | 5 h 53 m 23 s |
| SAC | 11 h 28 m 23 s |

*Commentary.* - **PPO** easily attains the highest SPS ($\sim 500$), completing all runs in just over 2.4 hours. This efficiency helps keep its emissions the lowest. - **SAC**'s off-policy updates and dual Q-networks produce a low SPS ($\sim 100$), causing an 11.5-hour total runtime and the highest carbon footprint. - **REINFORCE**, despite simpler logic, often hits $\sim 150$ SPS, finishing around 5.9 hours. Its overhead partly stems from lower data efficiency (Monte Carlo returns) and non-parallel sampling.

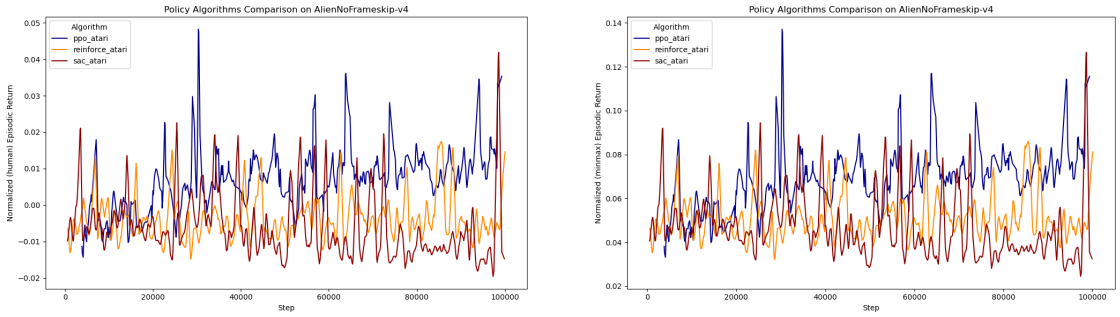
**Synthesis** Putting it all together:

- **PPO** emerges as the most *energy-efficient* approach, yielding good (and sometimes top) performance while taking the shortest total runtime ($\approx$ 2.4h). It also leads in many environments, particularly *Amidar*, *Assault*, *Freeway*, and *MsPacman*.
- **SAC** can match or exceed PPO in certain tasks (*Breakout*, *Alien*), but suffers from a long training time and high emissions due to frequent gradient updates and dual Q-networks. Its negative outliers in *Boxing* also drag down the overall human-norm mean.

- **REINFORCE** sits in the middle for carbon usage ($\approx 0.007$ kg $CO_2$), but lags behind significantly in final returns, highlighting the difficulty of pure Monte Carlo methods within 100k steps.

Hence, for *short-horizon* Atari training, **PPO** stands out as the best balance of performance and sustainability, while **SAC** demands substantially more compute resources for often modest gains—except in specialized games like *Breakout*, where it excels.

**Per-Game Observations** To illustrate performance trends for **PPO**, **REINFORCE**, and **SAC**, each of the eight Atari games is now presented with a paired set of plots. One subfigure shows the human-normalized returns over 100 000 steps, while the other displays the corresponding returns under **min–max normalization**, which rescales each environment's returns based on its observed minimum and maximum. This dual presentation clarifies differences that might be obscured by large raw score ranges.
**Alien.**




**(a) Human Norm** **(b) Min–Max Norm**

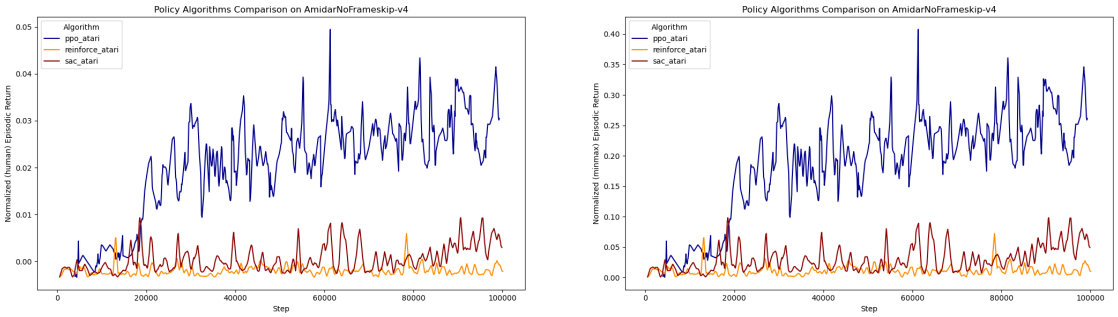
**Figure 62: Alien.** (**a**) Under human normalization, PPO (blue) and SAC (red) periodically reach 0.04–0.05, while REINFORCE (orange) lingers near 0.0. (**b**) Min–max scaling places PPO's peaks around 0.12–0.14, with SAC following closely by 100k steps, and REINFORCE near 0.04–0.08.

*Commentary.* Figure 62 shows that the numeric range under min–max is larger (up to 0.14) than in human norm (up to 0.05), yet the relative ordering (PPO $\approx$ SAC $>$ REINFORCE) remains similar.

**Amidar.**
*Commentary.* In Figure 63, the difference is more dramatic in min–max space, where PPO nears 0.35 vs. $\approx 0.05$ in human norm.

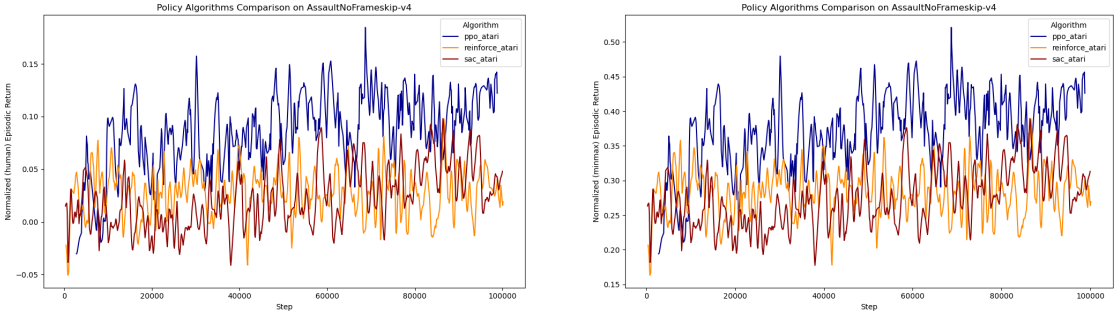
**Assault.**
*Commentary.* PPO leads in both scales, with a clearer margin under min–max (0.50 vs. 0.35).

**Boxing.**
*Commentary.* Figure 65 highlights how an environment's large or small absolute score range can drastically alter the min–max scale.



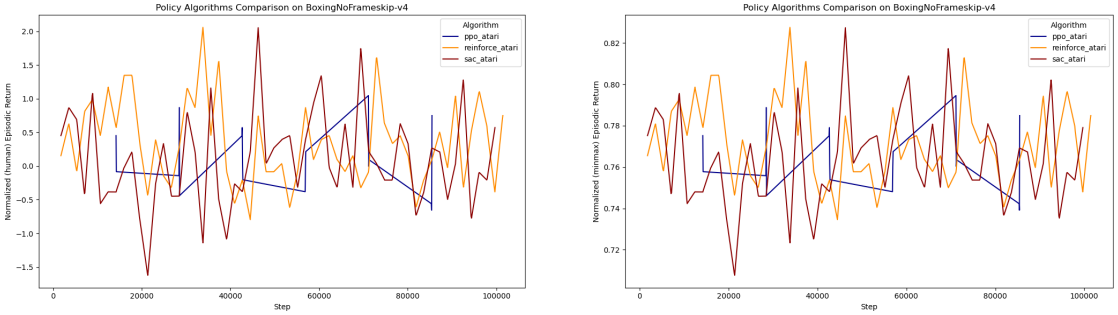

**(a) Human Norm** **(b) Min–Max Norm**

**Figure 63: Amidar.** (**a**) PPO (blue) rises above 0.03, while SAC (red) and REINFORCE (orange) stay under 0.01. (**b**) Min–max scaling reveals PPO crossing 0.30, whereas SAC/REINFORCE remain below 0.1.




**(a) Human Norm** **(b) Min–Max Norm**

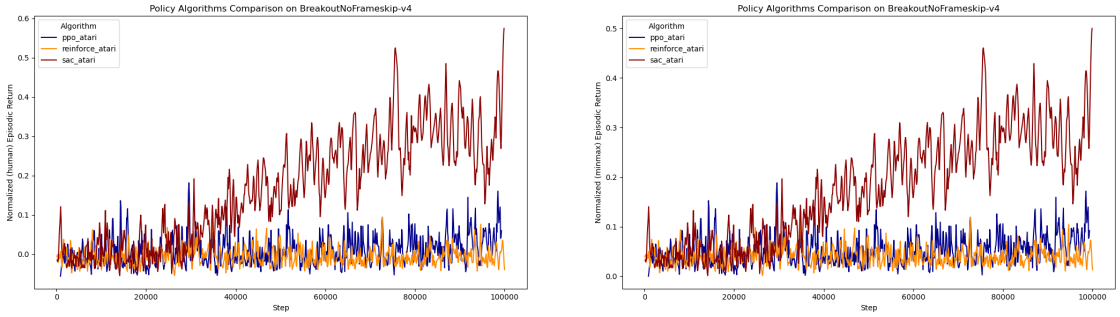
**Figure 64: Assault.** (**a**) PPO (blue) approaches 0.15–0.18, while SAC (red) remains near 0.05–0.10. (**b**) Min–max scaling finds PPO around 0.30–0.50, SAC 0.20–0.35, and REINFORCE (orange) near 0.20–0.30.




**(a) Human Norm** **(b) Min–Max Norm**

**Figure 65: Boxing.** (**a**) All three exhibit wild swings in human norm (e.g., REINFORCE from -1.5 to +2). (**b**) Min–max compresses those swings to $\sim$ 0.72–0.82.

**Breakout.**

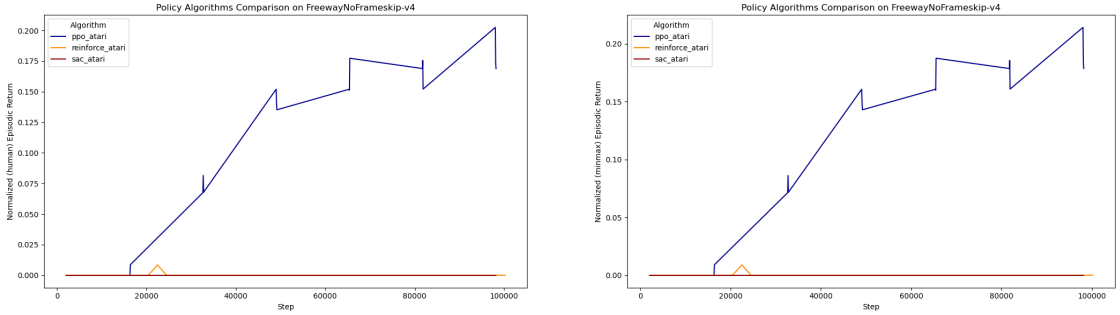



**(a) Human Norm** **(b) Min–Max Norm**

**Figure 66: Breakout.** (**a**) SAC (red) surpasses 0.4–0.5, well above PPO (blue) or REINFORCE (orange). (**b**) Min–max confirms SAC reaching above 0.5, while PPO stays near 0.2.

*Commentary.* In Breakout, **SAC** is the clear winner under both normalizations, though the gap appears even larger in min–max form.

**Freeway.**




**(a) Human Norm** **(b) Min–Max Norm**

**Figure 67: Freeway.** (**a**) PPO (blue) climbs to $\sim$ 0.18–0.20, while SAC (red) and REINFORCE (orange) remain near 0.0. (**b**) Min–max also shows PPO at $\sim$ 0.20, with the others near 0.0.

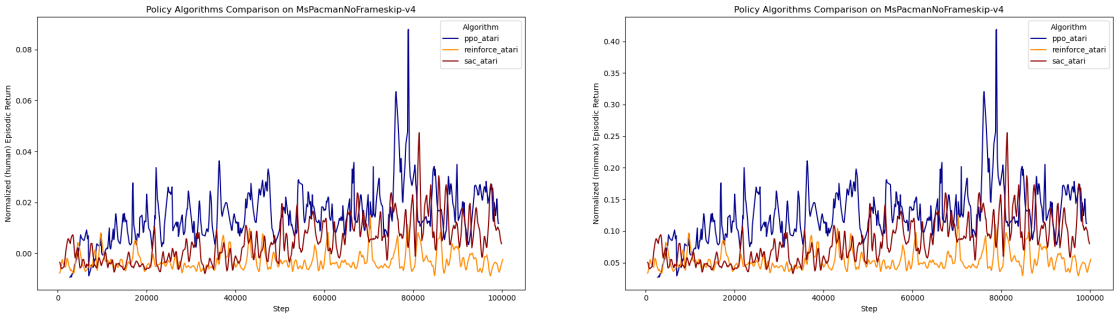
*Commentary.* Figure 67 illustrates how SAC and REINFORCE barely register on either scale, as PPO's partial success reveals a bigger raw score gap.

**MsPacman.**

*Commentary.* Figure 68 underscores **PPO**'s lead in MsPacman, while SAC remains behind, and REINFORCE barely improves.

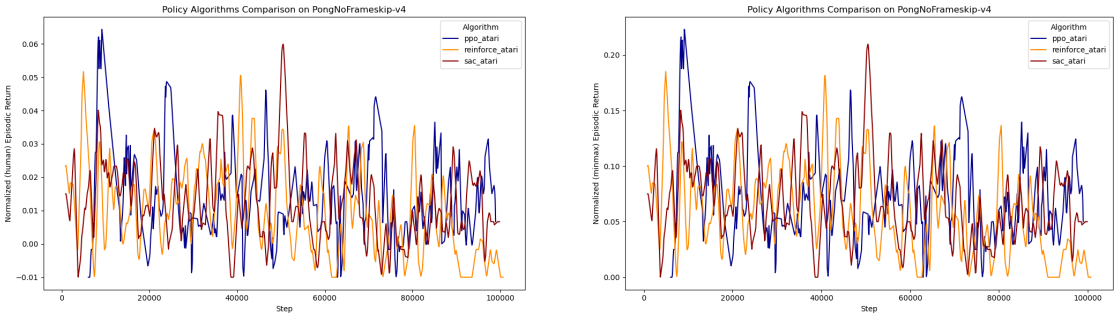
**Pong.**

*Commentary.* In *Pong*, Figure 69 reveals no substantial improvement by PPO, SAC, or REINFORCE, regardless of the normalization scheme.




**(a) Human Norm** **(b) Min–Max Norm**

**Figure 68: MsPacman.** (**a**) PPO (blue) peaks near 0.08 by 80k steps, SAC (red) stays in 0.03–0.05, REINFORCE (orange) below 0.02. (**b**) Min–max scales these results, yielding PPO at $\sim 0.35$–$0.40$ vs. SAC $\sim 0.15$–$0.20$, and REINFORCE $< 0.10$.




**(a) Human Norm** **(b) Min–Max Norm**

**Figure 69: Pong.** (**a**) All three methods fluctuate around 0.0–0.06 in human norm. (**b**) Min–max normalizes that to about 0.0–0.2.

**Overall Combined Takeaways.** Our analysis across both human-normalized and min–max normalized returns reveals consistent trends among the three algorithms. Across all eight Atari games, **PPO** generally achieves the highest or near-highest returns—especially in *Amidar*, *Assault*, *Freeway*, and *MsPacman*—demonstrating robust performance over the 100k-step benchmark. In contrast, while **SAC** excels notably in *Breakout* (and sometimes in *Alien*), it exhibits greater variability, struggling in environments such as *Freeway* and *Pong* and showing high volatility in *Boxing*. **REINFORCE** consistently underperforms, with only occasional spikes (as seen in *Boxing*), which highlights the challenges of employing pure Monte Carlo policy gradients within this limited interaction horizon.

Moreover, while the two normalization schemes yield different numerical scales—reflecting, for example, that large raw score ranges in *Boxing* are compressed under min–max—the relative ranking among the algorithms remains largely similar. Overall, these findings underscore **PPO** as the most consistently successful policy gradient method in our study, with **SAC** showing pockets of promise amid higher variance, and **REINFORCE** trailing significantly in most tasks.

## 4.6 Overall Algorithm Comparison

We now bring together all eight algorithms from our benchmark—five value-based methods (*DQN, DDQN, DuelingDQN, PER, C51*) plus three policy-gradient methods (*REINFORCE, PPO, SAC*)—to provide a unified comparison of their final performance, carbon emissions, training runtime, and throughput (SPS).

### 4.6.1 Final Evaluation Performance

Tables 34 and 35 summarize the aggregated performance (mean, std, min, max, median, IQM) for each algorithm under both **human** and **min–max** normalization, respectively. These results extend the single-family comparisons made earlier to the full set of eight algorithms.

**Table 34:** Overall final returns (human-normalized) for all algorithms.

| Algorithm | Mean | Std | Min | Max | IQM | Median |
|---|---|---|---|---|---|---|
| C51 | -1.0811 | 3.2862 | -12.88 | 0.7770 | 0.0068 | 0.0000 |
| DDQN | 0.0226 | 1.0083 | -8.5952 | 2.5952 | 0.0894 | 0.0527 |
| DQN | 0.1353 | 0.7541 | -5.0238 | 4.7381 | 0.1137 | 0.0338 |
| DUELING_DQN | 0.1860 | 0.5258 | -1.9286 | 3.5476 | 0.1020 | 0.0402 |
| PER | 0.0607 | 1.0170 | -10.2619 | 6.8809 | 0.0813 | 0.0539 |
| PPO | 0.0775 | 0.5632 | -5.0238 | 3.3095 | 0.0173 | 0.0163 |
| REINFORCE | 0.0259 | 0.3549 | -2.4048 | 2.8333 | -0.0039 | -0.0029 |
| SAC | -1.1000 | 4.4278 | -23.3571 | 0.9286 | 0.0085 | 0.0045 |

**Table 35:** Overall final returns (min–max normalized) for all algorithms.

| Algorithm | Mean | Std | Min | Max | IQM | Median |
|---|---|---|---|---|---|---|
| C51 | 0.2503 | 0.2568 | 0.0 | 0.8270 | 0.1400 | 0.2005 |
| DDQN | 0.3737 | 0.2854 | 0.0 | 1.0000 | 0.3272 | 0.2887 |
| DQN | 0.3802 | 0.3099 | 0.0 | 0.9881 | 0.3426 | 0.2899 |
| DUELING_DQN | 0.3849 | 0.3056 | 0.0 | 0.9523 | 0.3454 | 0.2632 |
| PER | 0.3533 | 0.2695 | 0.0 | 0.9845 | 0.3087 | 0.2583 |
| PPO | 0.2481 | 0.2712 | 0.0 | 0.9643 | 0.1523 | 0.1204 |
| REINFORCE | 0.1544 | 0.2515 | 0.0 | 0.8527 | 0.0291 | 0.0393 |
| SAC | 0.2272 | 0.2536 | 0.0 | 0.8258 | 0.1477 | 0.1105 |

*Observation.* From these tables, we see that among the *value-based* algorithms, DuelingDQN, DQN, and DDQN often exhibit the highest mean or IQM returns, while *PER* and *C51* sometimes trail behind or show higher variance (especially in human-norm with large negative outliers). For the *policy* group, SAC yields strong results in some tasks but is heavily penalized in others (e.g., *Boxing*), resulting in negative or near-zero means in human norm. PPO remains moderate, whereas REINFORCE lags in final average.

### 4.6.2 Emissions and Runtime

Figure 70 compares the average emissions (kg $CO_2$) for all 8 algorithms, along with standard deviation error bars. Table 36 then lists each method's total wall-clock time to complete 8 games $\times$ 4 seeds $=$ 32 runs.

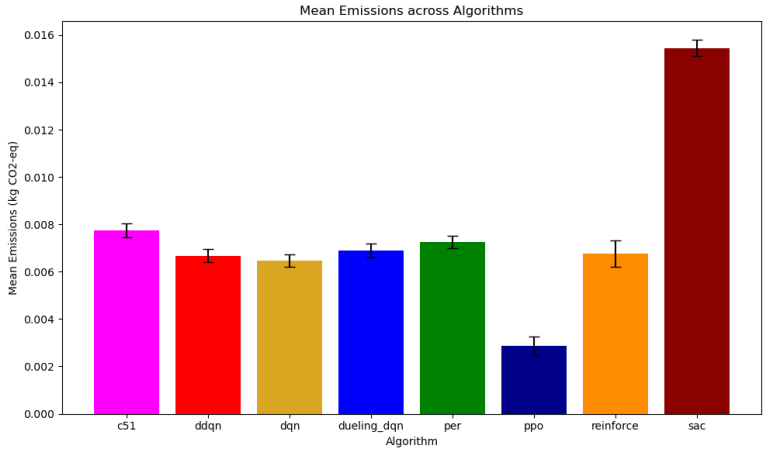



**Figure 70: Mean Emissions for All 8 Algorithms**, with standard deviation bars. SAC stands out at nearly 0.015 kg $CO_2$ on average, while PPO is notably lower than any of the DQN-based methods.

*Commentary.*

**Table 36:** Total runtime (hh:mm:ss) over 32 runs per algorithm.

| Algorithm | Total Time |
|---|---|
| DQN | 5h 46m 54s |
| DDQN | 5h 55m 17s |
| PER | 6h 26m 58s |
| DUELING_DQN | 6h 08m 02s |
| C51 | 6h 51m 23s |
| REINFORCE | 5h 53m 23s |
| PPO | 2h 25m 08s |
| SAC | 11h 28m 23s |

- **SAC** demands the longest runtime (over 11.4 hours) and, as seen in Figure 70, produces the highest average emissions.
- **PPO** completes all runs in just 2.4 hours, with the lowest $\sim 0.003$ kg $CO_2$.
- **Most DQN variants** cluster around 5–7 hours total, with emissions $\sim 0.006$–$0.008$ kg $CO_2$, well above PPO but significantly below SAC.

### 4.6.3 Samples per Second (SPS) Comparison

Another measure of algorithmic efficiency is how many environment interactions each method can process per second. Figure 71 plots the aggregated SPS curves for all eight algorithms over 100k steps.

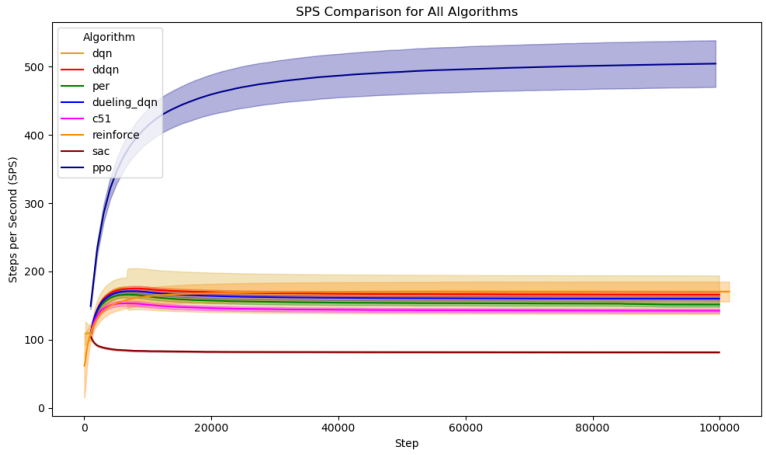
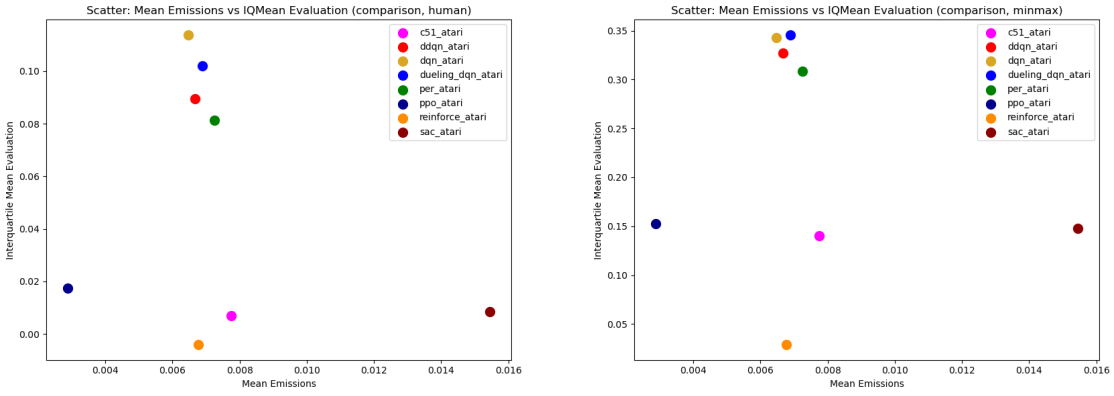



**Figure 71: SPS Comparison for All Algorithms**. PPO (blue line/shade) surpasses 500 SPS (mainly due to the parallel environments), while DQN variants group around 150–200, REINFORCE near 150, and SAC remains under 100. Shaded regions represent min–max or std across seeds.

*Analysis.* - **PPO** quickly ramps up to $\sim$ 500 SPS, dwarfing the $\sim$ 100–200 range of the DQN algorithms plus REINFORCE. - **SAC**, consistent with its high runtime/emissions, lingers around 80–100 SPS. - Minor differences exist among the DQN variants (e.g., PER may have a slightly heavier overhead due to priority calculations, etc.).

### 4.6.4 Performance vs. Emissions (Scatter Plots)

To visualize how each algorithm trades off *emissions* and *performance*, we plot the **mean carbon footprint** ($x$-axis) against final evaluation ($y$-axis). Figures 72 and 73 each contain two subplots, one for **human-normalized** and one for **min–max normalized** performance. We show both **IQM** (i.e. interquartile mean) and **mean** returns in separate figures.

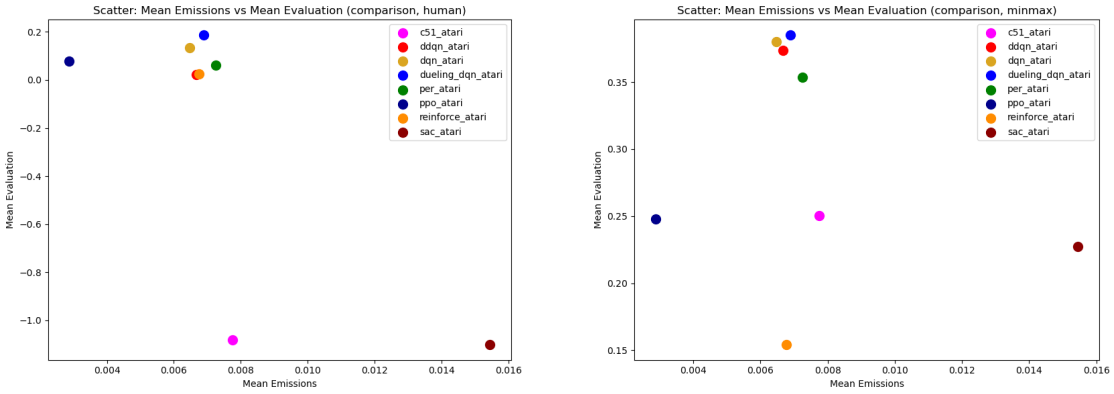



**(a) IQM (Human)** **(b) IQM (Min–Max)**

**Figure 72: Mean Emissions vs. IQM Evaluation for All 8 Algorithms. (a)** Human-normalized IQM vs. mean emissions. **(b)** Min–max–normalized IQM vs. mean emissions. Points are labeled by algorithm (`c51`, `ddqn`, `dqn`, `dueling_dqn`, `per`, `ppo`, `reinforce`, `sac`).

*Observation.* Across these four plots:

- **PPO** (blue point) sits at the far left ($\approx 0.003$ kg $CO_2$), with moderate returns in both IQM and mean. It is the most *energy-efficient*.
- **SAC** (red point) is the rightmost outlier ($\approx$ 0.015–0.016 kg $CO_2$), with widely varying performance depending on the metric.
- **DQN-based variants** (C51 in pink, DDQN in red, DQN in gold, Dueling_DQN in dark blue, PER in green) cluster in the $\sim$ 0.006–0.008 range of mean emissions. Some, e.g. *DQN* or *DuelingDQN*, achieve higher IQM or mean than others.
- **REINFORCE** (orange) lies around $\sim$ 0.007 emissions but yields relatively low returns under both human-norm and min–max.




**(a) Mean (Human)** **(b) Mean (Min–Max)**

**Figure 73: Mean Emissions vs. Mean Evaluation for All 8 Algorithms.** **(a)** Human-normalized mean returns vs. emissions. **(b)** Min–max normalized mean returns vs. emissions.

Overall, these scatter plots underscore that **PPO** provides a strong balance of moderate/high returns with minimal carbon cost, while **SAC** can yield decent scores but at a high energy expense. The DQN-family methods vary: some (like DuelingDQN) approach or exceed PPO's performance, but typically with 2–3× the emissions.

### 4.6.5 Per-Game Details

To better understand how each algorithm performs on individual Atari environments, we collected **episode-level data** for each run, providing per-game final returns (human or min–max normalized) and per-game mean emissions. Table 37 below shows a **small extract** of these environment-level results for reference:

**Table 37:** Example snippet of per-game returns (human norm) and emissions for selected environments. Full details for all games and normalizations appear in Appendix **??**.

| Env | Algorithm | Human Return (Mean) | $CO_2$ (Mean) | IQM |
|---|---|---|---|---|
| AlienNoFrameskip-v4 | C51 | -0.0149 | 0.00779 | -0.0113 |
| AlienNoFrameskip-v4 | PPO | 0.0103 | 0.00292 | 0.0084 |

A full breakdown for every environment (Alien, Amidar, Assault, ..., Pong) and each algorithm is included in **Appendix ??**, where we present the entire CSV data you provided (see the attached code block). We also provide environment-specific line plots of episodic returns (Figures Y1–Y8) for readers who wish to explore how training evolves in detail.

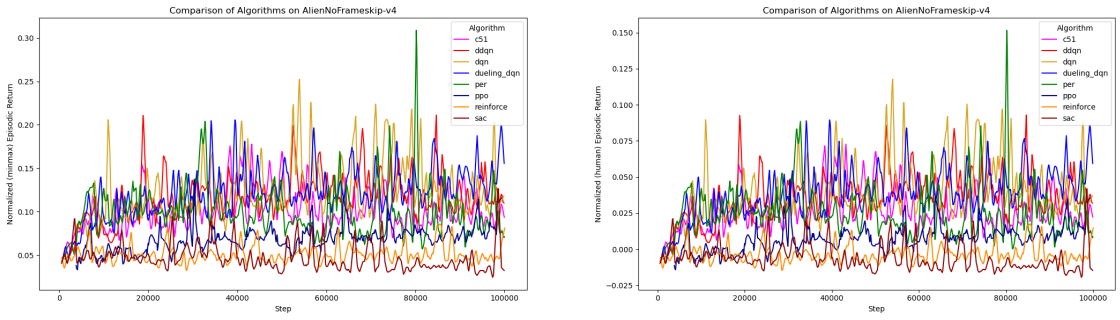
**Interesting Outliers** Here we highlight two outliers:

- **Boxing:** Some algorithms (SAC, REINFORCE) show large negative outliers in the human norm, though min–max compresses them.
- **Freeway:** PPO significantly outperforms DQN and other policy methods at just 100k steps, showing a near-monotonic climb.

### 4.6.6 Per-Environment Episodic Returns (All Algorithms)

In this section, we display the over-time training curves (up to 100k steps) for *all eight* algorithms on each of the eight Atari environments under study, using both **min–max** and **human** normalization for the episodic returns. We discuss notable patterns in each environment below.

**AlienNoFrameskip-v4**




**(a) Min–Max Norm** **(b) Human Norm**

**Figure 74: Alien:** Episodic returns for C51 (pink), DDQN (red), DQN (gold), DUELING_DQN (dark blue), PER (green), PPO (navy blue), REINFORCE (orange), and SAC (dark red).

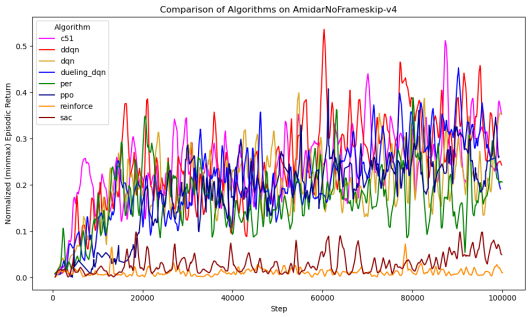
*Commentary.* `DDQN` (red) and `DQN` (gold) often spike above 0.15–0.20 in min–max, whereas `PPO` (blue) remains near 0.10–0.15. `SAC` (dark red) lingers lower but sometimes climbs late, `REINFORCE` (orange) generally stays near the bottom, and `C51` (pink) shows moderate oscillations. Under human norm, the range compresses to near 0.0–0.1 for many runs.

**AmidarNoFrameskip-v4**

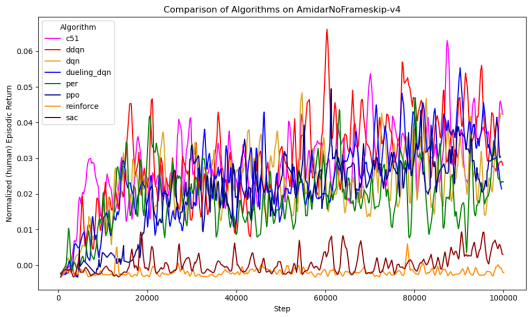
*Commentary.* `DDQN` (red) and `Dueling_DQN` (dark blue) surpass 0.4–0.5 near 80k steps in the min–max figure, while `C51` (pink) occasionally peaks around 0.5. `PPO` (blue) is more steady, around 0.2–0.3. `SAC` (dark red) and `REINFORCE` (orange) stay below 0.1. Under human norm, the overall scale is 0.0–0.06 for most algorithms, revealing smaller raw rewards in Amidar.

**AssaultNoFrameskip-v4**

*Commentary.* `Dueling_DQN` (dark blue) and `DQN` (gold) climb toward 0.8–0.85 late in training (min–max). `PPO` (blue) approaches 0.7, while `reinforce` (orange) remains under 0.4. `C51` (pink) gradually ascends but ends around 0.6. Under human norm, the spread condenses to 0.0–0.4, consistent with higher raw scores in Assault.

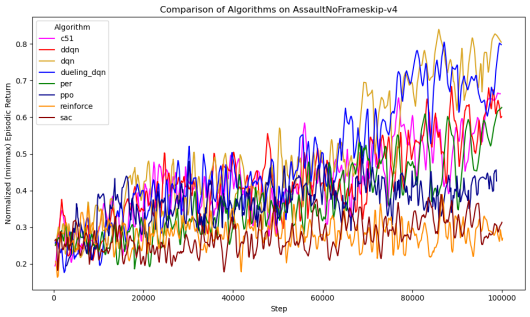



**(a) Min–Max Norm**

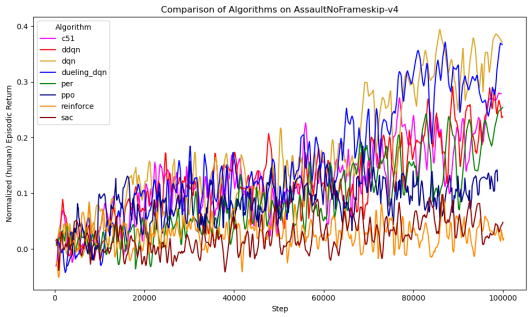



**(b) Human Norm**

**Figure 75: Amidar:** Episodic returns across 100k steps.



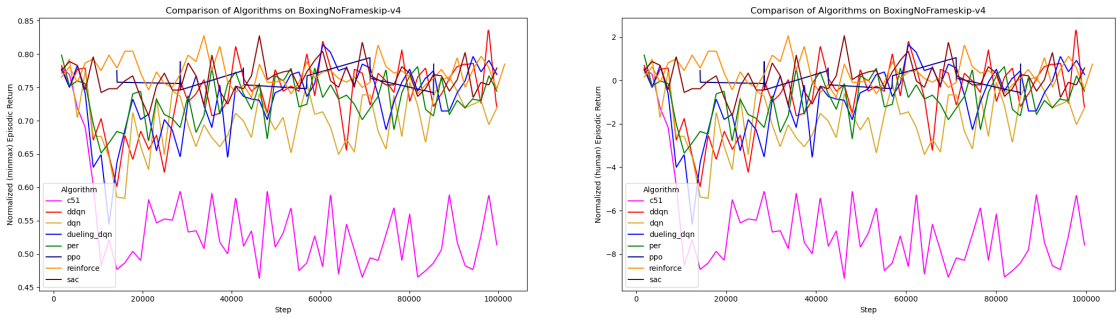

**(a) Min–Max Norm**




**(b) Human Norm**

**Figure 76: Assault:** Episodic returns across 100k steps.

### BoxingNoFrameskip-v4

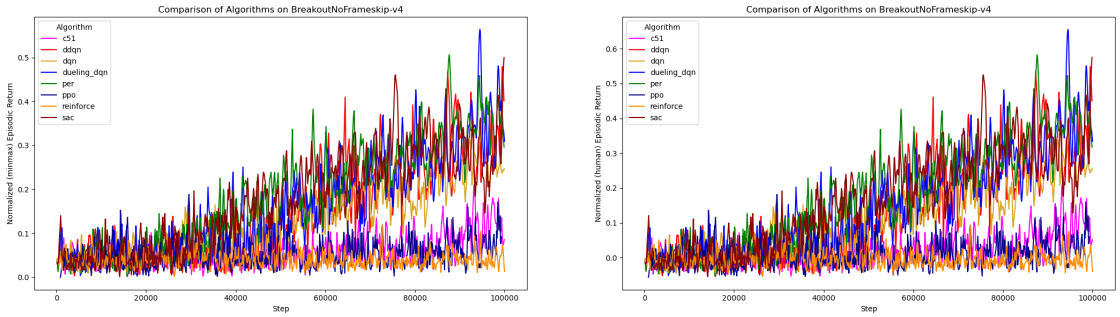



**(a) Min–Max Norm** **(b) Human Norm**

**Figure 77: Boxing:** Episodic returns across 100k steps.

*Commentary.* Min–max values bunch around 0.5–0.8, with `DDQN` (red) sometimes near 0.8. `C51` (pink) hovers 0.55–0.65. Meanwhile, in human norm, `C51` and `Reinforce` see large negative dips below -5.0, showing how Boxing's limited raw score range drastically affects the human scale. `PPO` (blue) and `Dueling_DQN` (dark blue) stay near 0.0–1.0 in that scale.

### BreakoutNoFrameskip-v4



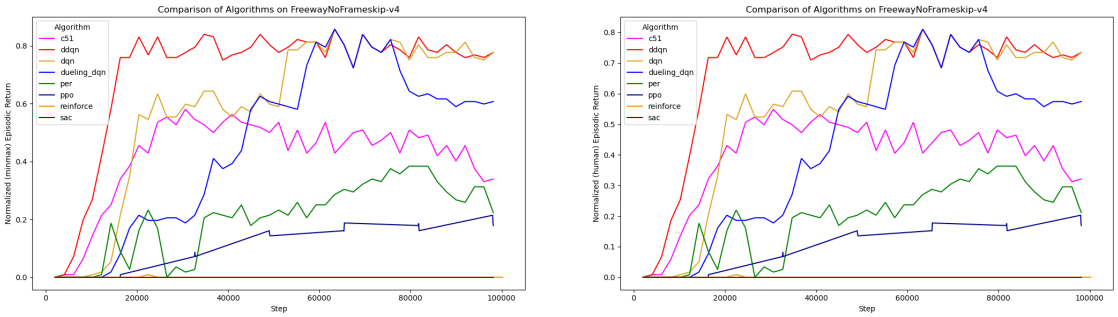

**(a) Min–Max Norm** **(b) Human Norm**

**Figure 78: Breakout:** Episodic returns across 100k steps.

*Commentary.* `SAC` (dark red) excels around 60k–100k steps, surpassing 0.5 in min–max and 0.4–0.5 in human norm. `PPO` (blue) lags near 0.2, and `DQN` (gold) settles around 0.2–0.3. `Reinforce` (orange) stays near or below 0.1. Breakout highlights **SAC**'s potential for strong late-game performance, albeit at a higher computational cost (§4.6).

### FreewayNoFrameskip-v4

*Commentary.* Here, `DDQN` (red) rapidly climbs to 0.85+ in min–max by 15k steps, with `C51` (pink) and `DQN` (gold) following suit. `PPO` (blue) only reaches 0.6, `PER` (green) hits 0.3, while `Reinforce` (orange) and `SAC` (dark red) remain near 0.0. In human norm,

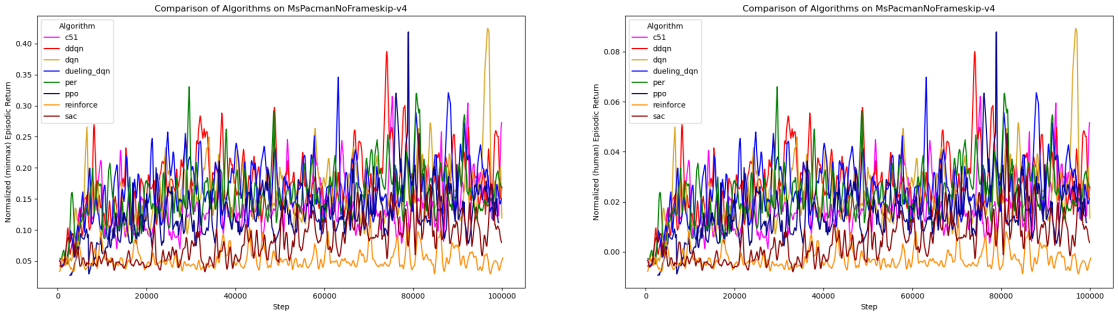



**(a) Min–Max Norm** **(b) Human Norm**

**Figure 79: Freeway:** Episodic returns across 100k steps.

these large raw scores translate to 0.3–0.8 for the top algorithms, reflecting that Freeway has a high reward potential even early in training.

### MsPacmanNoFrameskip-v4



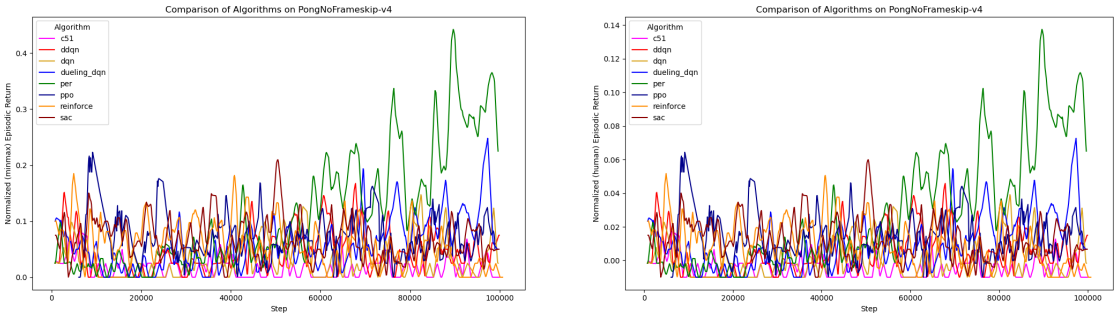

**(a) Min–Max Norm** **(b) Human Norm**

**Figure 80: MsPacman:** Episodic returns across 100k steps.

*Commentary.* No single algorithm dominates strongly, but `dqn` (gold) and `ddqn` (red) occasionally spike above 0.25 in min–max, while `reinforce` (orange) remains near 0.0–0.1. `PPO` (blue) hovers around 0.15–0.20, with `c51` (pink) also in that range. Under human norm, the entire scale is fairly tight ( 0.0–0.08) due to MsPacman's moderate raw reward potential within 100k steps.

### PongNoFrameskip-v4

*Commentary.* `PER` (green) occasionally spikes near 0.3–0.4 in min–max, `DQN` (gold) has mid-range fluctuations, `PPO` (blue) and `Reinforce` (orange) remain under 0.2 for most runs. `SAC` (dark red) never climbs above 0.1. Because Pong's raw scoring can be small or negative, the human norm figure is mostly 0.0–0.1. None of the algorithms achieve the large positive returns that DQN-based methods have historically reached with much longer training.




**(a) Min–Max Norm** **(b) Human Norm**

**Figure 81: Pong:** Episodic returns across 100k steps.

**Summary of Environment-Level Comparisons** These per-environment plots reinforce the observations from our aggregate metrics (Section 4.6). Notable highlights:

- **Freeway**: Some DQN variants (DDQN, DQN) rapidly approach near-maximum scores, overshadowing `PPO` and `SAC`.
- **Breakout**: `SAC` outperforms others late in training.
- **Boxing**: Min–max compression vs. large negative swings in human norm accentuates how the raw score range shapes these normalizations.
- **Amidar, Assault, Alien**: DuelingDQN and DQN often do well, while `PPO` is typically moderate, and `SAC` or `Reinforce` can lag behind.

Overall, each game's reward structure significantly influences how algorithms evolve over 100k steps, corroborating the broader performance–emissions findings in Section 4.6.

### 4.6.7 Summary

Bringing all eight algorithms together reveals distinct trade-offs among performance, emissions, and runtime:

- **PPO** remains the overall most energy-efficient method, finishing runs $\sim$ 2.4h total. Its final returns are decent, though certain DQN variants can match or exceed it in specific tasks.
- **SAC** can excel (e.g. *Breakout*) but has the highest emissions and slowest SPS, taking over 11h to finish.
- **DQN-based variants** occupy a middle ground in both carbon footprint ($\sim$ 0.006–0.008 kg $CO_2$) and total runtime (5–7h). Some, like DUELING_DQN, achieve strong mean returns.
- **REINFORCE** similarly runs about 6h total, but yields lower performance than DQN methods or PPO in most tasks.

Hence, if one's priority is *high performance* but with minimal compute cost, **PPO** or select DQN variants might be ideal. **SAC** offers potential but requires significantly more energy for short 100k-step training. These findings highlight a clear *trade-off* between performance and sustainability. **PPO** is the most energy-efficient overall, while certain DQN variants can overtake it in raw performance yet emit 2–3× more $CO_2$. **SAC** incurs the greatest overhead, offset by its strengths in a few tasks like *Breakout*. In Section 5, we discuss the broader implications of these results for real-world deployments and future research directions.

# 5 Implications of the Results

In this section, we interpret the findings from Section 4 in light of practical concerns such as deployment costs, carbon footprints, and sustainability requirements. We also consider how short-horizon benchmarks (100k steps) might shape our broader understanding of deep RL performance.

## 5.1 General Observations

Overall, our results show that:

- **Value-based** (DQN-family) methods (DQN, DoubleDQN, PER, DuelingDQN, C51) typically converge to moderate or high returns on several environments (e.g., *Freeway*, *Boxing*), but face stability challenges in some tasks (e.g., *Pong*, *MsPacMan*).
- **Policy-based** algorithms produce more varied performance: `PPO` reliably achieves competitive returns with lower emissions, whereas `SAC` can outperform others in a few environments (*Breakout*) but runs more slowly and emits significantly more $CO_2$.
- **Short 100k-step horizon** constrains the potential for improvement, so many advanced techniques (e.g., Rainbow combinations, PER, etc.) do not show clear benefits over simpler methods within this limited training budget.

As a consequence, while these results confirm certain known trends—e.g., *DoubleDQN* mitigates Q-value overestimation, *PER* can accelerate training if allowed enough steps—the practical impacts at 100k steps are muted.

## 5.2 Energy Efficiency vs. Performance Trade-Off

A central theme of this work is the **trade-off** between achieving higher returns and incurring greater computational cost and carbon emissions. Our measurements reveal that:

- **SAC** consistently has the highest carbon footprint (on average $\sim 0.015\,\mathrm{kg\,CO_2}$), in part due to its off-policy updates and dual Q-network overhead, even though it sometimes outperforms other algorithms in late-stage learning.
- **PPO** exhibits the *lowest* emissions (around $0.0029\,\mathrm{kg\,CO_2}$) and shortest runtime ($\sim 2.4$ hours total for 32 runs) but generally places only mid-to-high in final returns, depending on the environment.
- Most **DQN-based methods** lie in the middle ($\sim 0.006$–$0.008\,\mathrm{kg\,CO_2}$ on average), with total runtimes of around 5–7 hours for 32 runs.

Hence, the classic adage of "no free lunch" holds: **SAC** can deliver strong scores on certain games but at a large computational and environmental cost, while **PPO** is impressively lean and still achieves respectable performance. For tasks where top-tier scores are not essential, a lower-emission method like PPO or DQN might suffice.

## 5.3 Practical Implications for AI Sustainability

For organizations aiming to balance *performance* with *sustainability*:

1. **Hardware Selection:** Using GPUs that CodeCarbon or W&B can track precisely (e.g., recent NVIDIA lines) greatly improves the accuracy of energy estimates. CPU usage is more difficult to capture reliably on certain OS/hardware combos.
2. **Short-Horizon Benchmarks:** Although many RL advances were proposed under multi-million-step training, the 100k-step regime can highlight efficiency differences relevant to real-world scenarios where time or resources are limited.
3. **Algorithm Choice:** If a moderate level of performance is acceptable, adopting **PPO** significantly lowers emissions while reducing training time. If the highest possible return is mandatory and the environment's raw reward range suits it (e.g., *Breakout*), **SAC** might be worth its higher carbon cost.

This interplay of performance vs. overhead suggests that sustainability-conscious applications should carefully weigh the marginal returns gain from more computationally intense algorithms, especially if those gains only appear after 500k or 1 million steps.

## 5.4 Limitations and Future Work

A few constraints shape our interpretation:

**Limited Training Steps (100k).** Many popular DRL algorithms (Rainbow, distributional expansions, multi-step returns, etc.) truly shine beyond the 1 million–step mark. Our 100k-limit test can understate these methods' potential.

**Restricted Environment Selection.** Although we tested 8 Atari games across 4 seeds (32 runs per algorithm), the full ALE suite has 55+ games. A broader set might reveal different rank orders, especially for highly complex tasks.

**Approximate CPU/RAM Tracking.** Due to Windows Intel Power Gadget deprecation and partial fallback modes, our CPU and RAM usage data rely on either TDP approximations or coarse telemetry from W&B. GPU tracking is more accurate, but the total system-level emissions remain an estimate.

**Stochastic Variation.** With only 4 seeds per environment, some especially negative outliers (Boxing's large negative dips for certain seeds) can skew the aggregated means, though we mitigate this with IQM as recommended in [19].

Future work might extend training to 1–5 million steps for each method to see if advanced techniques eventually surpass simpler baselines in both performance and energy efficiency. Additionally, exploring specialized hardware or *hybrid HPC* could reveal new ways to reduce DRL's carbon footprint.

# 6 Conclusions

In this final section, we synthesize the findings and propose next steps.

## 6.1 Summary of Findings

- **Baseline DQN** attains moderate performance across most environments, emitting $\sim 0.0065\,\mathrm{kg\,CO_2}$ on average over 100k steps. DoubleDQN reduces Q-value overestimation but does not yield a clear improvement in final returns at this short horizon.
- **PER** overhead raises emissions slightly ($\sim 0.00725\,\mathrm{kg\,CO_2}$), yet the 100k-step limit masks much of its usual advantage in accelerating learning.
- **DuelingDQN** and **C51** each show environment-specific benefits (e.g., *Boxing*, *Freeway*), but their aggregated returns remain similar to or slightly exceeding baseline DQN, with comparable runtime/emissions.
- **PPO** stands out as the most "eco-friendly," completing runs in only 2.4 hours for all seeds/games combined and emitting a mere $0.0029\,\mathrm{kg\ CO_2}$. It achieves respectable performance across many environments.
- **SAC** occasionally dominates a few tasks (*Breakout*) but exhibits the highest energy cost ($0.015\,\mathrm{kg\,CO_2}$), slow throughput (80–100 SPS), and large variance in returns.

## 6.2 Final Thoughts on Energy-Efficient Reinforcement Learning

The tension between *advanced techniques* and *computational overhead* emerges as a core challenge in DRL. Under a short 100k-step regime, simpler methods (PPO, baseline DQN) often provide a better ratio of performance to carbon cost, while fancier algorithms—like SAC or distributional DQN variants—struggle to gain a decisive edge before the run ends.

In realistic production or industry settings with limited time/budget for model tuning, prioritizing algorithms that quickly converge to adequate performance can yield significant energy savings. On the other hand, high-level research or competitive RL benchmarks often push beyond millions of steps, letting advanced methods eventually surpass simpler ones in raw returns.

## 6.3 Future Research Directions

Several pathways could extend this project:

**Longer Training Horizons.** Repeating these experiments at 1–5 million steps would clarify how advanced DQN tweaks or policy gradient expansions (Rainbow, TD3, etc.) surpass simpler baselines given more time. One might track the exact moment (in interactions) at which these enhancements repay their higher emissions.

**Wider Environment Coverage.** Our 8 chosen games reasonably sample different Atari mechanics, but including the full 26 Atari 100k or 55+ ALE tasks could reveal whether certain algorithms generalize better to more varied or obscure games.

**Alternative Normalizations.** In addition to "human" and "min–max" returns, some tasks might benefit from scoreboard-based normalization (comparing to public baselines) or reward shaping to unify the scale across tasks more strictly.

**Real-Time Emissions Minimization.** One future direction might involve *dynamic resource scheduling* or *carbon-aware training*, adjusting GPU usage or frequency if real-time energy prices or carbon intensities fluctuate throughout the day. This idea merges RL with HPC resource management for a truly "green AI."

**Hybrid CPU–GPU Profiling.** Finally, a more robust toolchain for CPU and RAM tracking (e.g., Intel PCM on Linux) would help produce more accurate system-level carbon footprints, especially for on-policy methods that rely heavily on CPU-based data collection.

With these possible directions in mind, we hope that the insights gained from our 100k-step experiments can foster a broader conversation on *energy-efficient deep RL*, balancing performance with real-world sustainability needs.

**Comments on RL Algorithm Choice in Contemporary Applications.** Recent studies and industry practices have highlighted that the choice of reinforcement learning (RL) algorithm may not critically affect final outcomes in settings where human supervision is employed. For instance, early work in RL fine-tuning for large language models (LLMs) often utilized Proximal Policy Optimization (PPO) due to its robust performance and ease of integration with human feedback. However, subsequent investigations found that simpler methods, such as Vanilla Policy Gradient (VPG), yield comparable results with a lower computational overhead and easier implementation [**raffel:exploring_rl_for_llms**, **ouyang:ppo_vpg_comparison**]. Similarly, in emerging frameworks like DeepSeek, preliminary reports suggest that the specific choice of RL algorithm may be less decisive than originally assumed—with experimental results showing negligible differences in performance across various RL methods, although further systematic experimentation is required to substantiate these claims [**deepseek:blog**, **zhang:rl_in_deepseek**]. This trend implies that, for many practical applications, selecting a more energy-efficient or computationally economical algorithm (e.g., VPG over PPO) might be preferable without incurring significant performance penalties.

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