Applied Reinforcement Learning for a 2D Shooter Game Environment

World Models, Reward Shaping, and COOM Benchmark

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Outline

Project Overview

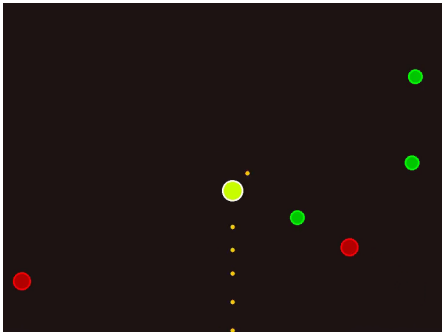
Goal: Train autonomous agents for a 2D top-down shooter game

Challenges:

- Multi-objective optimization (survive, collect, eliminate)
- Continuous state dynamics
- Reactive and strategic decision-making

Approaches:

- Model-free RL: DQN, PPO, SAC
- Model-based RL: World Models (VAE + MDN-RNN)



Environment Details

State Space:

- Agent position & velocity
- Health, cooldown status
- Nearest enemies (relative positions)
- Nearest prizes (relative positions)

Action Space:

- Movement: 5 options (stay, N, S, E, W)
- Shoot: 2 options (fire, hold)
- Direction: 8 options (8 angles)
- Total: $5 \times 2 \times 8 = 80$ combinations

Reward Configurations:

Event	Base	Surv	Aggr
Prize	$+1.0$	$+0.5$	$+2.0$
Kill	$+1.0$	$+0.5$	$+2.0$
Damage	-1.0	-3.0	-0.5
Death	-5.0	-10.0	-3.0

COOM: Continual DOOM

COOM: A Game Benchmark for Continual Reinforcement Learning

Tomilin, Fang, Zhang, Pechenizkiy

NeurIPS 2023 (Datasets and Benchmarks Track)

Key Contribution

First benchmark specifically designed for **continual reinforcement learning** in complex 3D image-based environments with varying objectives and visuals.

Built on: ViZDoom platform

Available:
`https://github.com/hyintell/COOM`

Why Continual RL Matters

Traditional RL: Train on one task, evaluate on same task

Continual RL: Train on sequence of tasks, retain knowledge

Key Challenges:

1. **Catastrophic Forgetting**: Performance on task 1 degrades after training on task 2
2. **Knowledge Transfer**: Can skills from task 1 accelerate learning task 2?
3. **Sample Efficiency**: How quickly can the agent adapt to new scenarios?

Real-world motivation:

- Robots deployed in changing environments
- Game AI that adapts to new levels/mechanics
- Agents that should improve over time, not reset

COOM Scenarios (8 Total)

Combat Scenarios:

- **Run and Gun**: Eliminate enemies with ranged weapons
- **Chainsaw**: Melee combat, seek and chainsaw enemies

Evasion Scenarios:

- **Hide and Seek**: Escape and hide from pursuing enemies
- **Floor is Lava**: Platform navigation to safe zones

Navigation Scenarios:

- **Pitfall**: Traverse tunnels, avoid pits
- **Arms Dealer**: Collect and deliver weapons to locations

Survival Scenarios:

- **Raise the Roof**: Find switches to prevent ceiling crush
- **Health Gathering**: Collect health kits to survive

Each scenario has **default** and **hard** difficulty variants

COOM Task Sequence Types

Cross-Domain (CD): Same objective, different visuals

- Base: Run and Gun scenario
- Modifications: wall textures, enemy types, obstacles, view height
- Tests: visual generalization without goal change

Cross-Objective (CO): Different scenarios entirely

- Sequence: Run and Gun $\rightarrow$ Chainsaw $\rightarrow$ Hide and Seek $\rightarrow$ Floor is Lava $\rightarrow$ ...
- Goal changes drastically: eliminate $\rightarrow$ melee $\rightarrow$ evade $\rightarrow$ navigate
- Tests: skill transfer across fundamentally different tasks

Sequence Lengths: 4-task, 8-task (core), 16-task (extended)

COOM Evaluation Metrics

1. Average Performance

$$\bar{P} = \frac{1}{N} \sum_{i=1}^{N} P_i^{\text{final}} \tag{1}$$

Success rate averaged over all N tasks at sequence end.

2. Forgetting

$$F_i = P_i^{\text{after\_training\_i}} - P_i^{\text{end\_of\_sequence}} \tag{2}$$

How much performance on task i degrades after subsequent training.

3. Forward Transfer

$$FT_i = \frac{\text{AUC}_{\text{continual}}}{\text{AUC}_{\text{scratch}}} - 1 \tag{3}$$

Training efficiency compared to learning from scratch.

COOM Baseline Results

Method	AP ↑	FGT ↓	FWT ↑
Fine-tuning	0.31	0.58	-0.12
EWC	0.35	0.51	-0.08
PackNet	0.42	0.24	-0.15
ClonEx-SAC	**0.61**	**0.18**	**0.05**

Table: Cross-Objective 8-task sequence

Key Observations:

- Even best method (ClonEx-SAC) shows **18% forgetting**
- Forward transfer is often **negative** (prior tasks hurt!)
- Cross-objective sequences are significantly harder than cross-domain

Continual RL: Open Challenges

What Makes Continual RL Hard?

1. **Catastrophic Forgetting**: Neural nets overwrite old knowledge when learning new tasks
2. **Task Interference**: Skills for one objective may conflict with another
3. **No Clear Task Boundaries**: In deployment, agents don't know when tasks change
4. **Sample Efficiency**: Can't afford to retrain from scratch on each new task

Why World Models Might Help:

- Learned dynamics are more likely to transfer between tasks
- Replay in imagination doesn't require real samples
- Latent space can encode transferable features

Open Problem: No method achieves ¿65% average performance with ¡15% forgetting

Connection to Our Work

Our 2D Shooter vs COOM:

- Multi-objective: survive + collect + eliminate
- Visual observations ($\rightarrow$ World Model VAE)
- Continuous dynamics
- Potential for scenario variations

- 8 COOM scenarios test diverse skills
- ViZDoom visual observations
- 3D navigation
- Cross-domain and cross-objective sequences

Future Work: Apply COOM evaluation framework (AP, FGT, FWT) to test our agents' robustness to environment modifications

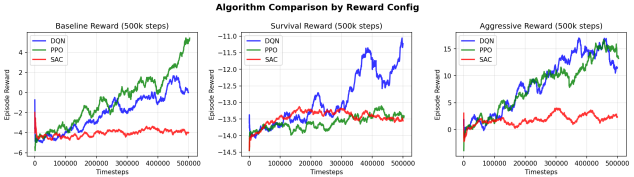
Algorithm Comparison

Key Findings:

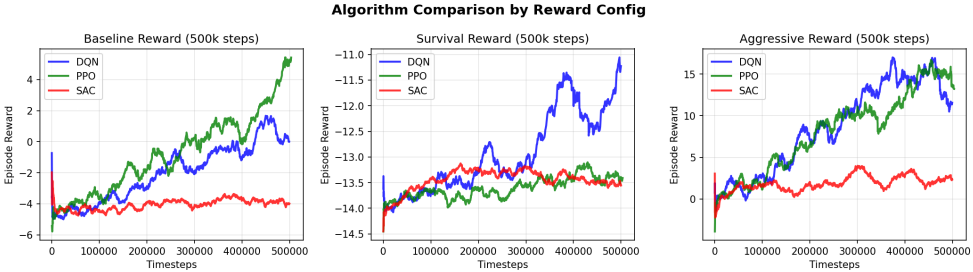
- **PPO** achieves best performance (+38.74)
- **DQN** comparable but more variable
- **SAC** significantly underperforms

Why SAC Failed:

- Action space mismatch
- 12x slower training speed
- Entropy regularization interference

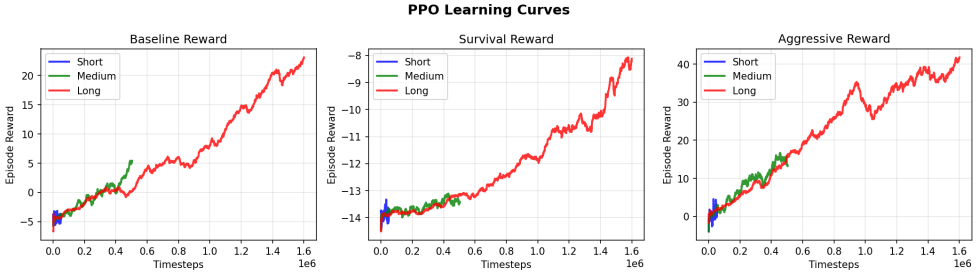


Algorithm Comparison (Detailed)



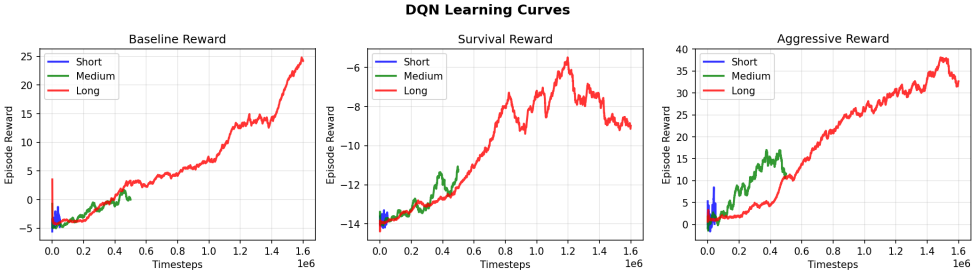
PPO with aggressive rewards achieves +38.74 — SAC underperforms due to action space mismatch

Learning Curves: PPO



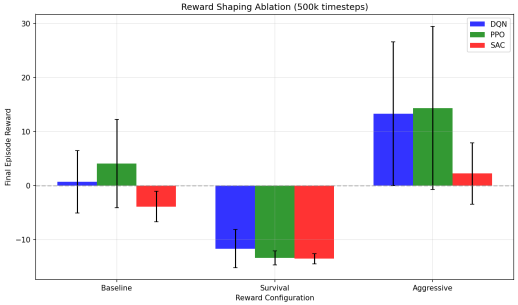
PPO shows stable, monotonic improvement across all configurations

Learning Curves: DQN



DQN shows reward decrease with survival config (sparse rewards)

Reward Shaping Impact



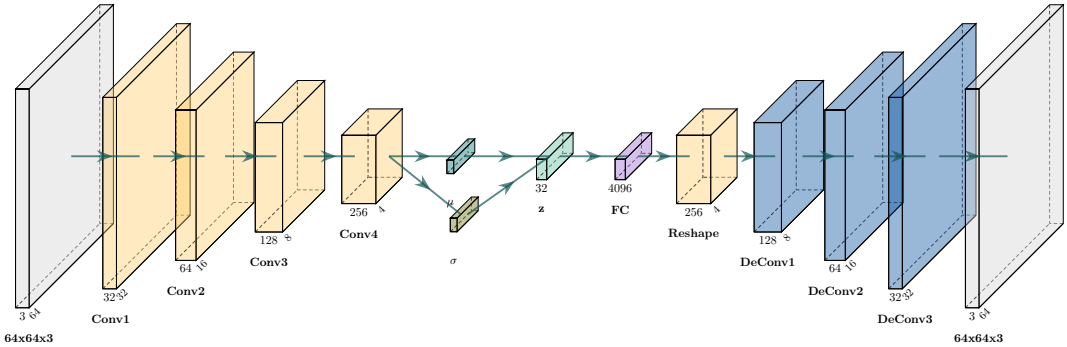
Reward design dominates algorithm choice!

Algo	Aggr	Base	Surv
PPO	**+38.74**	+21.96	−8.80
DQN	+33.95	+19.42	−8.77
SAC	+1.49	−5.02	−13.73

Why Aggressive Works:

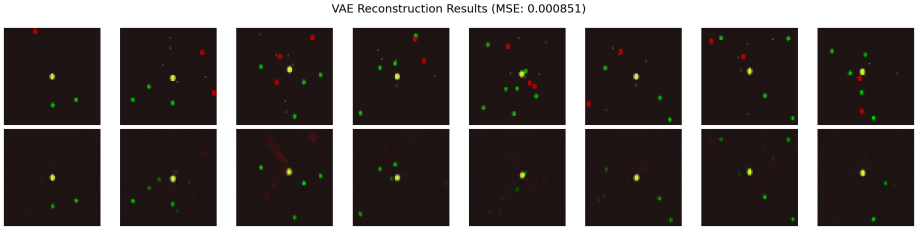
- Stronger positive signals
- Reduced death penalty → exploration
- Higher time penalty → active play

VAE Architecture (Full)



Encoder: Conv2D (32→64→128→256) → FC → μ, σ (32 dims each)
Decoder: FC → ConvTranspose2D (256→128→64→32→3)
Loss: BCE reconstruction + $\beta\cdot$ KL divergence

VAE Reconstruction Quality



Top row: Original game frames — **Bottom row:** VAE reconstructions

MSE: 0.00085 — Entities, colors, and positions accurately preserved!

World Models Architecture

Vision Model (VAE):

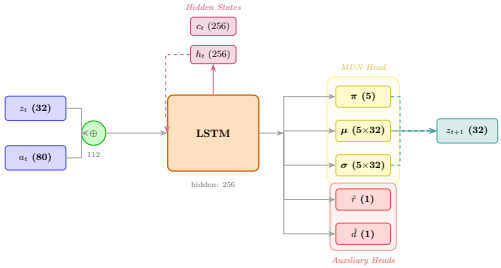
- Input: 64×64 RGB frames
- Output: 32-dim latent z
- Loss: BCE + KL divergence

Memory Model (MDN-RNN):

- LSTM with 256 hidden units
- MDN output for $P(z_{t+1}|z_t, a_t)$
- Predicts: reward, done

Controller (PPO):

- Input: $[z_t, h_t]$ (288 dims)



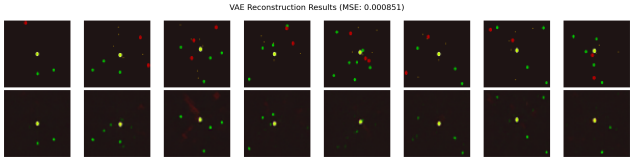
VAE: MSE vs BCE Loss

Problem with MSE:

- Blurry reconstructions
- Washed-out colors
- MSE ≈ 0.015

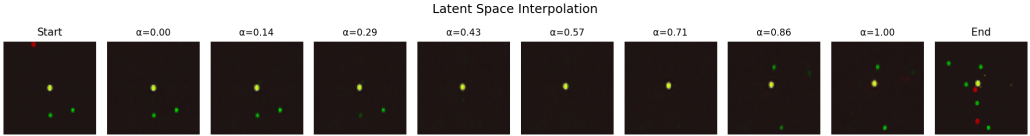
Solution with BCE:

- Sharp reconstructions
- Correct entity colors
- **15$\times$ improvement**
- MSE ≈ 0.001



VAE Reconstruction with BCE Loss (MSE: 0.00085)

Latent Space Properties



Smooth interpolation between game states $\Rightarrow$ well-structured latent space

$$z_\alpha = (1 - \alpha) \cdot z_{\text{start}} + \alpha \cdot z_{\text{end}}$$

MDN-RNN: Sigma Hacking Problem

The Problem:

$$-\log p(z|\mu,\sigma) = \frac{(z-\mu)^2}{2\sigma^2} + \log\sigma + \text{const} \tag{4}$$

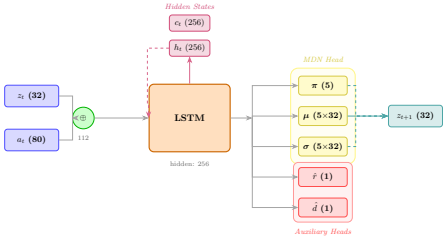
As $\sigma \to 0$ with $\mu \to z$, loss $\to -\infty$

Metric	**Value**	**Status**
Min sigma	0.0012	OK
Latent MSE	0.0016	Good
Reward correlation	**0.08**	FAILED
Predicted rewards	$[-0.017, +0.034]$	Near-zero!

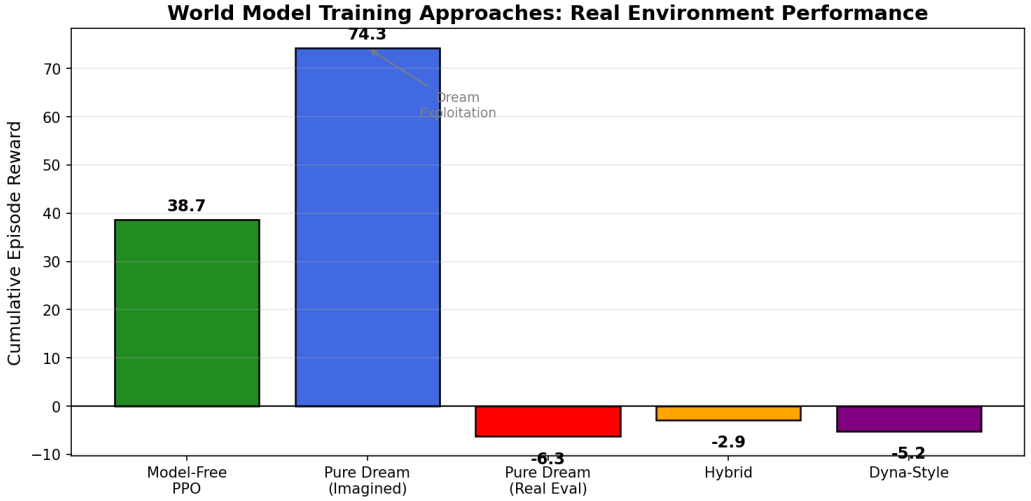
Root cause: Random policy data $\to$ sparse rewards $\to$ predict mean (zero)

Training Approaches

Approach	Method	Real Reward
Pure Dream	Train on predicted rewards (MDN)	−5.2 (Failed)
Hybrid	Real rewards + VAE observations	−2.9 (Poor)
Dyna-Style	**Interleaved Real + Dream**	**−4.9 (Most Stable)**



Dream Exploitation: A Critical Warning



Key Finding: $+74.3$ in imagination $\rightarrow$ -6.3 in reality

World Model: Lessons Learned

Why World Models Underperformed Here:

1. **Information Bottleneck**: VAE compresses $64 \times 64 \times 3 \rightarrow 32$ dims, losing precise values
2. **Useless Hidden State**: MDN-RNN trained on random data = 256 dims of noise
3. **Dream Exploitation**: Agent finds adversarial actions that maximize predicted (not real) rewards
4. **Wrong Use Case**: Environment already provides structured state—no need for vision

When World Models Excel:

- Pixel-only observations (Atari, DMC)
- Sample efficiency critical (expensive simulators)
- Complex dynamics requiring prediction

Summary

Model-Free RL:

- PPO with aggressive rewards: **+38.74** (best overall)
- Reward shaping $>$ algorithm choice
- SAC struggles with discrete actions (12x slower)

World Models:

- VAE with BCE: excellent visual reconstruction (MSE 0.001)
- Dream Exploitation: +74 in imagination $\rightarrow$ -6.3 in reality
- Dyna-style fixes exploitation but limited by information loss
- Best WM result: **-5.18** (vs +38.74 model-free)

Key Insight: World Models shine for pixel-only envs; structured state $\rightarrow$ model-free wins

Future Work

1. **State-based World Model**: Learn dynamics on structured state, not pixels
2. **DreamerV3 Implementation**: Symlog rewards, ensemble disagreement
3. **Shorter Imagination Horizons**: 15-50 steps instead of 500
4. **COOM-style Continual Learning**: Test catastrophic forgetting
5. **Sample Efficiency Study**: Compare wall-clock time to performance

Thank you! Questions?

References

- Tomilin et al., "COOM: A Game Benchmark for Continual RL," NeurIPS 2023
- Ha & Schmidhuber, "World Models," arXiv 2018
- Hafner et al., "Mastering Atari with Discrete World Models," ICLR 2021
- Schulman et al., "Proximal Policy Optimization," arXiv 2017