RL-Course 2025/26: Final Project Report

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February 26, 2026

1 Introduction

The report presents the implementation of three reinforcement learning algorithms by the *WayneGradientzky* team. The algorithms were finally evaluated on the Hockey competition hosted by the Martius Lab. `Hockey` is a 2D-multi-agent, fully observable environment where two agents compete to score goals by hitting a puck into the opponent's goal.
The algorithms implemented are as follows:

- **Task-Driven Model Predictive Control (TDMPC)** by Bartol Markovinović
- **Twin Delayed Deep Deterministic Policy Gradient (TD3)** [5] by Rajinish Aneel Bhatia
- **Soft Actor-Critic (SAC)** [6] by Mohd Khizir Siddiqui

All the implementations are available on the GitHub repository `https://github.com/BartolMarko/HockeyRL`.

2 Temporal Difference Learning for Model Predictive Control (TD-MPC)

Temporal Difference Learning for Model Predictive Control (TD-MPC) [10] is a continuous action space model-based RL algorithm that combines learning a Task-Oriented Latent Dynamics (TOLD) model with trajectory optimization using a variation of the Model Predictive Path Integral (MPPI) method. The TOLD model consists of the following learned components:

- **Latent Encoder**: $z_t = h_\theta(s_t)$ – Encodes the state into a latent representation which captures relevant features for predicting rewards, dynamics, and value.
- **Latent Dynamics**: $z_{t+1} = d_\theta(z_t, a_t)$ – Predicts the next latent state given the current latent state and agent's action. This allows the model to roll out trajectories during planning. For the hockey environment, dynamics model also implicitly predicts opponent's behavior since the opponent's features are part of the state and opponent's actions affect the next state.
- **Reward**: $\hat{r_t} = r_\theta(z_t, a_t)$ – Predicts immediate reward for taking an action in a given latent state.
- **Q-Value Function**: $\hat{Q}_t = Q_\theta(z_t, a_t)$ – Predicts the value of taking an action in a given latent state. Two Q-networks are used to mitigate overestimation bias, similar to TD3.
- **Policy**: $\hat{a_t} \sim \pi_\theta(z_t)$ – Outputs a distribution over actions given the latent state. Policy is used for training the Q-value function and for generating additional trajectories during planning.

Models $h_\theta, d_\theta, r_\theta, Q_\theta$ are jointly trained by minimizing the loss $\mathcal{J}(\theta, \Gamma) = \sum_{i=t}^{t+H} \lambda^{i-t} \mathcal{L}(\theta, \Gamma_i)$ where the objective $\mathcal{L}(\theta, \Gamma_i)$ for each step i consists of reward prediction error, value loss with respect to the TD target, and L2 loss between the predicted next latent state and the encoded actual next state:

$$\mathcal{L}(\theta, \Gamma_i) = c_1 \| r_\theta(z_i, a_i) - r_i \|_2^2 + c_2 \| Q_\theta(z_i, a_i) - (r_i + \gamma Q_{\theta'}(z_{i+1}, \pi_\theta(z_{i+1}))) \|^2 + c_3 \| d_\theta(z_i, a_i) - h_{\theta'}(s_{i+1}) \|_2^2$$

Symbol Γ denotes a trajectory of states, rewards and agent's actions sampled from the replay buffer, λ is a constant that decreases the importance of losses for later steps, γ is the discount factor, and c_1, c_2, c_3 are constants that balance the different loss components. For the Q-value loss and the latent dynamics loss, the target networks θ' are used. Target networks are updated every 2 mini-batch updates with slow-moving averages of the main network parameters to stabilize training. For sampling mini-batches of trajectories, a prioritized experience replay buffer is used, where states are sampled with probability proportional to their TD error. The policy network is trained separately, by minimizing the temporally weighted Q-value objective of the same sampled trajectories: $\mathcal{J}_\pi(\theta) = -\sum_{i=t}^{t+H} \lambda^{i-t} Q_\theta(z_i, \pi_\theta(z_i))$.
To select an action, several iterations of modified MPPI planning are performed. In the first iteration, N random action sequences of length H (horizon) are sampled from the normal distribution $\mathcal{N}(\mu, \sigma)$ and rolled out using the learned dynamics model to obtain future latent states and rewards H steps into the future. Additionally, the policy network is used to generate extra trajectories by rolling out the policy model and adding truncated Gaussian noise. Each trajectory is scored by the discounted sum of predicted rewards and the final Q-value. The top K trajectories are selected and weighted by their exponentiated scores to update μ and σ for the next iteration. After last iteration, a trajectory is sampled from the score weighted multinomial distribution of the final elite set and the first action of that trajectory is executed.

2.1 Network Architecture Changes

Initially, each part of the TOLD model was implemented as an MLP with ELU function [3] as the non-linearity, as described in the original paper. However, this resulted in training instability caused by exploding loss values. To solve this issue, network architectures described in the TD-MPC2 paper [9] were implemented. The activation function was changed to Mish [11], Layer Normalization was added, and latent space was normalized with SimNorm [9]. Furthermore, the Q-value and reward networks were changed to output logits of a softmax distribution over exponentially spaced bins, as described in DreamerV3 [8].

2.2 Adding Ideas from iCEM to the Planning Algorithm

One attempt to improve the planning part of TD-MPC was to implement ideas from the Improved Cross-Entropy Method (iCEM) [12]. These included sampling actions from temporally correlated colored noise instead of independent Gaussian noise, keeping a fraction of the elite set between iterations, including the shifted elite set from previous step into the initial trajectory set of the next iteration, and executing the best action from the final elite set instead of sampling from the score weighted distribution.

2.3 Action Hints – Guiding Planning with Custom Action Sequences

Another idea to improve planning was to replace a part of the initial random action sequences with hand-crafted action sequences that either lead the agent to a future position of the puck or to one of the equidistantly spaced positions in front of the goal. These action sequences were generated with PD control, and the idea was used in conjunction with keeping a fraction of the elite set between planning iterations to potentially preserve exact trajectories that lead to the puck or the goal.

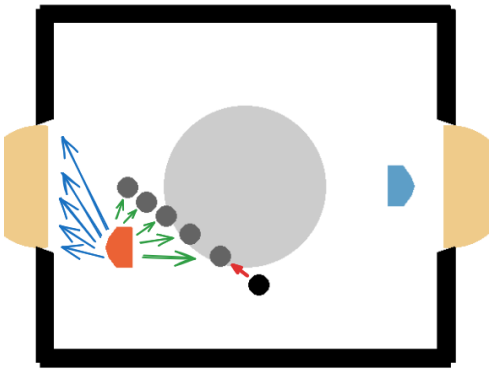


Figure 1: Illustration of action hints

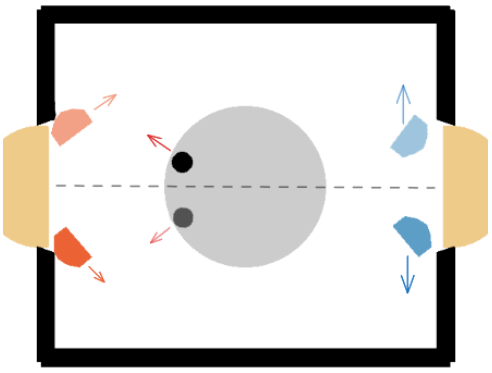


Figure 2: State and action mirroring

2.4 Training Setup and Self-Play

For training, only the terminal (sparse) reward of $+10$ for winning and -10 for losing was used. When adding an episode to the replay buffer, the mirrored episode with respect to the horizontal axis (2) was also added. This doubles the amount of training data and encourages model to learn symmetric strategies.

2.4.1 Training Curriculum

Training is started against only weak and strong bots, and a frozen checkpoint of the model is added to the opponent pool every 100 000 steps, or earlier if win rate against all opponents exceeds 80%. Additionally, 3 TD3 agents with different behaviors are added to the opponent pool after 2 million steps. Maximum opponent pool size is set to 10, and when the pool is full, the oldest frozen checkpoint is removed. This curriculum ensures that the model is exposed to a variety of opponents of appropriate difficulty throughout training. To monitor generalization performance against unseen strong opponents, model was **not trained, but only evaluated** against publicly available SAC agent from last year's competition.

2.4.2 Windowed Thompson Sampling Opponent Selection

Since all opponents in the training pool are beatable due to the curriculum, selecting the most challenging opponent seems like a reasonable strategy to maximize learning signal. To do this, the number of wins, draws, and losses against each opponent in the pool was tracked in a sliding window of the last 100 games (in total, not per opponent). Then, win, loss and draw rates of the TD-MPC agent against each opponent were estimated by sampling from a Dirichlet distribution with parameters $\alpha = [\text{wins} + 1, \text{losses} + 1, \text{draws} + 1]$. The opponent where the $loss\_rate + 0.5 * draw\_rate$ is maximized is selected. The intuition behind this is that the problem of choosing the most challenging opponent can be seen as similar to a multi-armed bandit problem, where each opponent is an arm and the reward is 1 for a loss, 0.5 for a draw, and 0 for a win. Using only last 100 episodes accounts for constant change of policy, and Dirichlet distribution was chosen because it is a conjugate prior for the multinomial distribution, which models the outcomes of games against each opponent.

2.5 Experiment Results

All experiment configurations were first run for 3 million steps (or less if unsuccessful), and the best performing experiments were prolonged to 10 million steps. In Figure 3 we see that during all experiments the model quickly learns to defeat the weak bot. However, with the initial bad model architecture, the

win rate against the weak bot plummets after 500 thousand steps, showing the training instability. After fixing the architecture, the model maintains a high win rate against the weak bot. The variations that used iCEM ideas do not generalize well to the validation agent, regardless of the colored noise β parameter. The checkpoint that generalized the best seemed to be the one with action hints trained for 4.3 million steps. This was confirmed with the final tournament results. Additionally, a number of different smaller modifications were tested, such as training with defensive mode, using closeness to goal as an additional reward signal, and using dropout in Q-value networks, but they did not lead to any improvements.

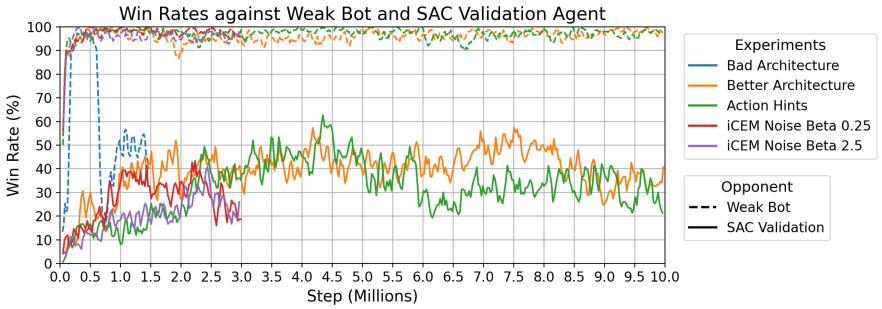


Figure 3: Evaluation win rates against Weak Bot and the SAC validation agent for different experiments

3 Twin Delayed Deep Deterministic Policy Gradient (TD3)

Twin Delayed Deep Deterministic Policy Gradient (TD3) [5] is a model-free, off-policy algorithm for continuous action spaces, improving over DDPG via clipped double Q-learning, delayed policy updates, and target policy smoothing. TD3 maintains two Q-networks (Q_{ϕ_1} and Q_{ϕ_2}) and uses their minimum as the TD target:

$$y = r + \gamma \min_{i=1,2} Q_{\phi_i'}(s', \tilde{a}), \quad \tilde{a} = \pi_{\theta'}(s') + \epsilon, \quad \epsilon \sim \texttt{clip}(\mathcal{N}(0, \sigma), -c, c)$$

Each critic minimizes the squared Bellman error $\mathcal{L}(\phi_i) = \mathbb{E}_{(s,a,r,s')\sim\mathcal{D}}(Q_{\phi_i}(s,a) - y)^2$, while the actor maximizes $J(\theta) = \mathbb{E}_{s\sim\mathcal{D}} Q_{\phi_1}(s, \pi_\theta(s))$ and is updated every 2 critic steps.

3.1 Method

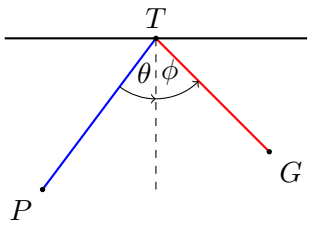
3.1.1 N-Step Returns

Instead of the standard one-step TD target, we use n-step returns to propagate reward signal faster:

$$y = r(s_0) + \gamma r(s_1) + \cdots + \gamma^{n-1} r(s_{n-1}) + \gamma^n q(s_n, \tilde{a}) \tag{1}$$

3.1.2 Custom Opponent and Bank-Shot Reward

We noticed early on that the model did not always manage to learn ricochet (bank) shots, so to help it defend against opponents that hit those shots we introduced a hard-coded opponent that always plays them. Given puck position P, goal position G, and T as the target we must shoot at to reach G. Then T_y is known because that is the boundary and we only need to find T_x. We can assume that $T_x \geq P_x$ and $G_x \geq T_x$. If we assume frictionless walls than $\theta = \phi$.



From $\tan\theta = \tan\phi$ we obtain:

$$T_x = \frac{|T_y - P_y|\, G_x + |T_y - G_y|\, P_x}{|T_y - G_y| + |T_y - P_y|}$$

This agent achieves $\approx 94\%$ win rate against the weak opponent and $\approx 80\%$ against the strong opponent. We also shaped the reward by calculating how aligned the agent's direction was to this direction to encourage the learning agent to prefer shots in this direction.

3.1.3 Layer Normalization

Layer Normalization. Layer normalization normalizes activations across the feature dimension for each sample independently. For a given input vector x, it computes:

$$\texttt{LayerNorm}(x) = \frac{x - \mu}{\sigma + \varepsilon}\,\gamma + \beta$$

where μ and σ are the mean and standard deviation of x, and γ, β are learnable scale and shift parameters. In the RL setting this reduces sensitivity to the scale of inputs and gradients, which can vary dramatically during training. We apply LayerNorm after each linear layer in both actor and critic networks.

3.2 Experiments

3.2.1 Training in Phases (Opponent Scheduling)

Training proceeded in three phases. Phase 1 used only the weak opponent. Phase 2 sampled weak/strong opponents with probabilities 30%/70%. Phase 3 used a mixed pool: 20% weak, 20% strong, 10% custom bank-shot opponent, and 50% from a rolling queue of past checkpoints (self-play). An adaptive opponent selection strategy based on Thompson sampling was evaluated as an alternative but underperformed the manual schedule, as shown in Figure 5.

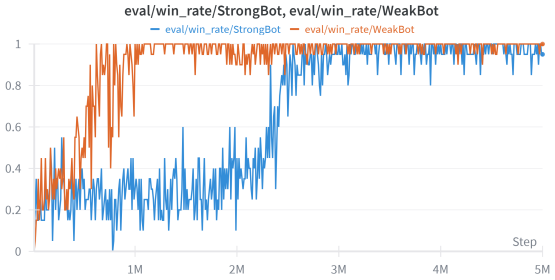


Figure 4: Winrate (trained in phases)

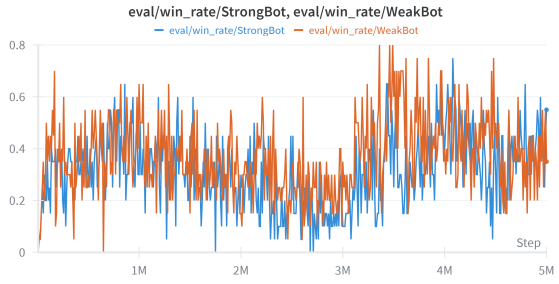


Figure 5: Winrate (trained using Thompson sampling)

3.2.2 Self-Play

Self play was the part of the third phase of training and was implemented by keeping a queue of 50 checkpoints and adding a new checkpoint every 50000 timesteps. This ensured that the model had enough learning experience from each of its previous checkpoints to be able to defeat them.

3.2.3 N-Step Returns, Episode Mirroring and Environment Scheduling

N-step returns and episode mirroring improve the speed of learning as reflected in (Figure 6), compared to one-step TD targets. We chose 3-step for the final training. Environment scheduling (30% SHOOTING_MODE, 70% DEFENSE_MODE) was introduced in Phase 3. Figure 7 shows the win rate when the opponent starts with possession and confirms a clear improvement.

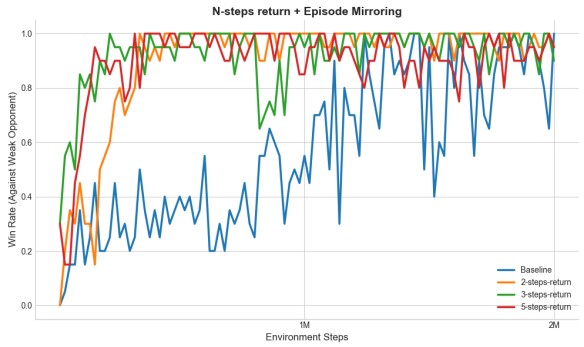


Figure 6: Win rate vs. past checkpoints (n-step returns)

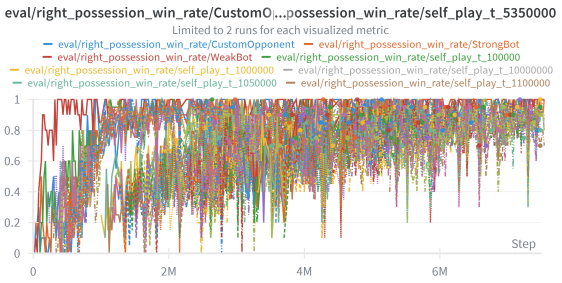


Figure 7: Win rate when opponent starts with possession using environment scheduler

3.2.4 Bank-Shot Reward

The bank-shot preference reward visibly shifts puck density toward the walls (Figures 8, 9), confirming that the agent learned to incorporate ricochet shots into its strategy.

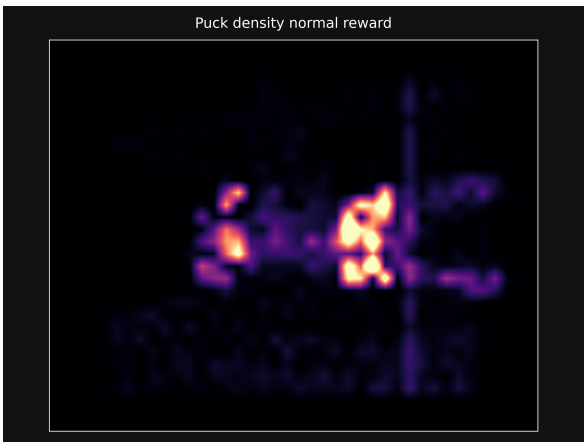


Figure 8: Puck density — standard reward

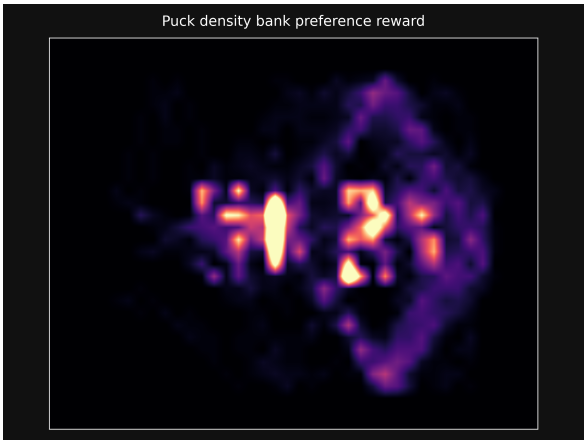


Figure 9: Puck density — bank-shot preference reward

3.2.5 Layer Normalization

LayerNorm converged faster against the fixed bots (Figure 10) but hurt generalization during self-play: the agent progressively drew against all previous checkpoints (Figure 11) rather than maintaining dominance, so it was excluded from the final model.

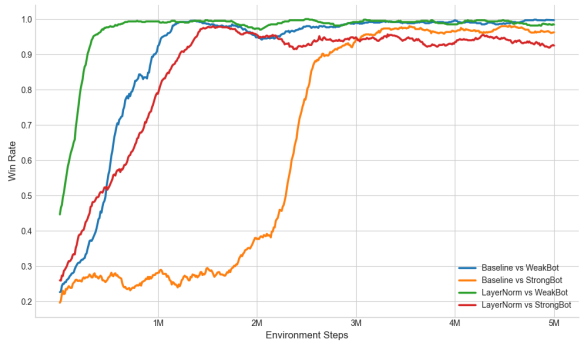


Figure 10: Win rate: baseline vs. LayerNorm

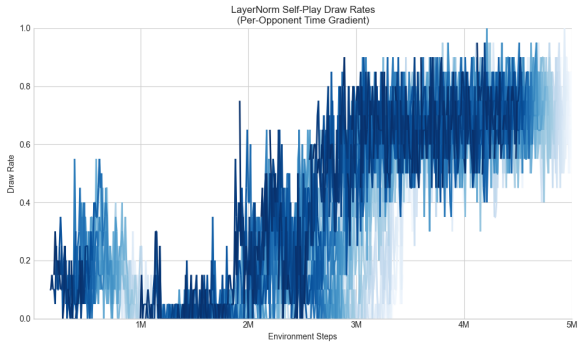


Figure 11: Draw rate of LayerNorm vs. past checkpoints

4 Soft-Actor Critic (SAC)

Soft-Actor Critic (SAC) [6] is an off-policy, model-free algorithm and forms a bridge between stochastic policy optimization and DDPG-style approaches. It incorporates an entropy term in the objective to encourage exploration as a trade-off against reward maximization. The two Q-functions are trained with the following target value:

$$y = r + \gamma \left(\min_{i=1,2} Q_{\phi_i'}(s', a') - \alpha \log \pi_{\theta'}(a'|s') \right), \quad a' \sim \pi_\theta(\cdot|s') \tag{2}$$

Similar to TD3, the critic is updated by following squared Bellman error:

$$\mathcal{L}(\phi_i) = \mathbb{E}_{(s,a,r,s') \sim \mathcal{D}} (Q_{\phi_i}(s,a) - y)^2 \tag{3}$$

The actor is updated to maximize the expected Q-value plus the entropy term:

$$J(\theta) = \mathbb{E}_{s \sim \mathcal{D}, a \sim \pi_\theta(\cdot|s)} \left[\alpha \log \pi_\theta(a|s) - \min_{i=1,2} Q_{\phi_i}(s,a) \right] \tag{4}$$

Later, the authors of [7] propose an automatic entropy coefficient tuning method. The temperature α is optimized to match a target entropy $\mathcal{H}_t$ by minimizing the following loss:

$$\mathcal{L}(\alpha) = \mathbb{E}_{a \sim \pi_\theta(\cdot|s)} \left[-\alpha \log \pi_\theta(a|s) - \alpha \mathcal{H}_t \right] \tag{5}$$

We use $\mathcal{H}_t = -\dim(\mathcal{A}) = -4$ as the target entropy, where $\dim(\mathcal{A})$ is the dimensionality of the action space.

4.1 Method

4.1.1 Parallelized Environment Simulation

To speed up data collection, we used 16 environments in parallel when collecting experience in replay buffer. Each environment is reset with different seed and starting side to ensure diversity of experience. This improves sample efficiency and allows the agent to learn from wider range of states and actions.

4.2 N-Step Prioritized Experience Replay with Episode Mirroring

To introduce far-sightedness into the learning process, we implemented n-step returns in the TD target, which allows the agent to propagate reward signals more quickly through the state space. We also use a prioritized experience replay [13] buffer which samples transitions based on their TD-error magnitude, giving more importance to new and informative experiences. The combination of n-step returns and prioritized replay helps the agent learn more efficiently by focusing on transitions that have a greater impact on learning. Furthermore, similar to the other methods from the team, every experience stored in the replay also creates a mirrored experience by flipping the required state and action components.

4.3 Self-Play and League Training

The training process is divided into 4 steps:

1. We, first, train the agent against the environment WeakBot and StrongBot. When the agent reaches a 85% win-rate against these opponents, we proceed to the next stage.

2. In second step, we train the agent against its past checkpoints. The checkpoints are collected every 150 parallel-environment steps. The self-play pool is used to sample opponent with a probability $p = 0.7$ and the remaining $p = 0.3$ is assigned to uniformly sample from the fixed opponents. When sampling from the self-play pool, we use a Prioritized Self-Play Sampler [15] which samples opponent based on modified win-rate, giving more importance to competitive opponents.

3. Next, we train the agent against the fixed opponents of first step along with best checkpoints from different previous experiments. One can find more details in the repository [1].

4. The last step of training is to play in self-play mode again.

4.4 Experiments

4.4.1 Replay Buffer

We use $1.5M$-sized replay buffer and PER buffer to evaluate the effect of sampling probability. In Figure 13, we can see that the agent sampling with PER buffer (orange) learns slower but has a more stable curve and achieves higher win-rate against fixed opponents compared to the agent trained with uniform sampling (green).

4.4.2 Self-Play and League Training

We can see the effect of self-play with Prioritized Self-Play Sampler in Figure 12, where the win-rate of the sampled opponents quickly reduces, indicating that the agent is learning strategies and not outright defeated. Both, self-play and league training changes where the agent receives the puck and in what direction is it hit. After defeating the fixed opponents, the agent is able to hit the puck with hotspots in both the walls and (unfortunately) dead areas such as the center line (Figure 14). After training the agent with self-play and league training, the puck heatmap shows the agent has perfected the bank-shot and also taken a preference of bottom wall (Figure 15). This mirrors the TD3's bank-shots 9 without using such hand-crafted reward. Such behavior emphasizes the importance of entropy-regularized exploration for diverse and goal-focused tactics in the environment.

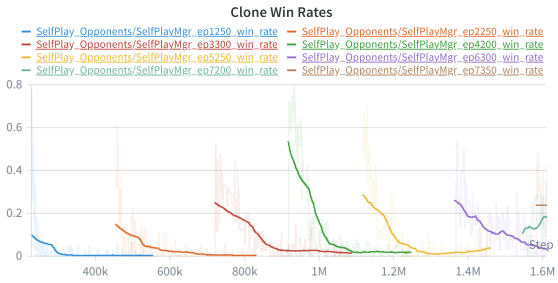


Figure 12: Prioritized Self-Play Sampler motivates learning from competitive opponents, and their win-rates reduce in effect. Note: the win-rate of opponent is lower when the agent win-rate is high.

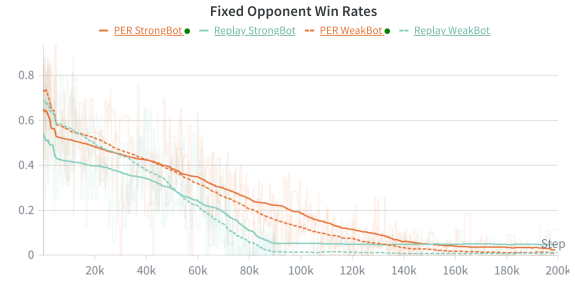


Figure 13: Win rates of fixed opponents when training agents with different buffer types. Note: A lower opponent win-rate is higher win-rate for the agent.

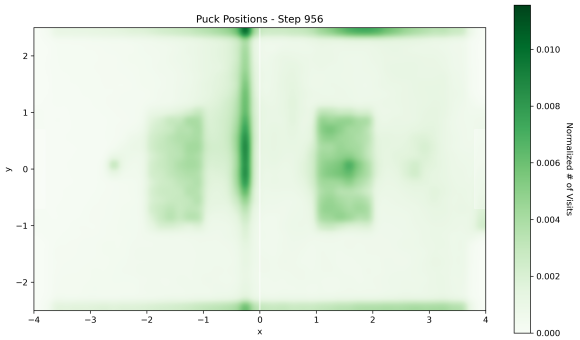


Figure 14: Heatmap of puck positions after training against fixed opponents.

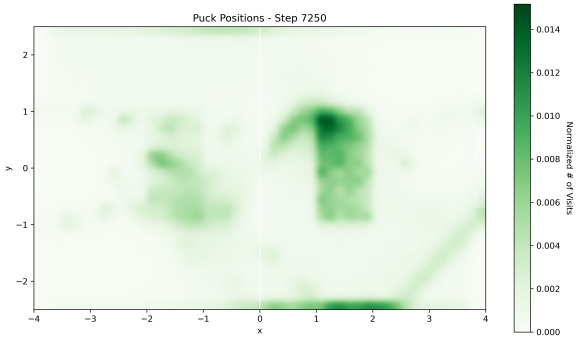


Figure 15: Heatmap of puck positions after 4 types of training.

4.4.3 Failed Experiments

The above experiments yielded the best results, but we also tried a few more ideas which didn't work out, such as:

1. **Munchausen RL** [14] - This method adds a scaled log-policy to the immediate reward to favor decisive policies with larger gaps. However, in our experiments, it constantly failed to generalize and led to worse performance.

2. **Exploration** - We experimented with different exploration strategies, namely Ornstein-Uhlenbeck noise, Random-Network Distillation [2], Gaussian Noise, Uniform Noise, and Pink Noise [4]. Most of the strategies conflicted with the entropy term in the SAC objective, and did not lead to improvements. We settled on using Pink Noise, which is temporally correlated and encourages exploration of action sequences. It enables $\sim 70\%$ more states for us compared to the Gaussian noise.

These experiment results are omitted for brevity, but can be found on the GitHub repository [1].

5 Discussions and Conclusion

5.1 Comparison of algorithms - Tournament

To compare our agents, we chose all promising checkpoints of each algorithm and evaluated them in a tournament together with WeakBot and StrongBot. The number of agents in the tournament was 25 and each agent played 1500 matches, with one match consisting of 4 episodes. The tournament used the Placket-Luce model to rank the agents and matchmaking algorithm based on the Gauss-Leaderboard score, same as in the official final tournament.

Table 1: Comparison of the best checkpoints of each algorithm in our tournament

Rank	Agent	μ	σ	Score
1	td3_bank_pref_rollout_3_mirroring_10M_177k	38.20	1.65	33.25
2	tdmpc2_action_hints_4_3M	33.60	1.57	28.90
14	sac-v4-pink-6-step-per-env-defence	26.51	1.55	21.86
23	StrongBot	3.94	2.18	-2.60
25	WeakBot	0.66	2.21	-5.96

Summary of the tournament results shown in Table 1 shows that the best TD3 checkpoint significantly outperforms all other agents. It is followed by TDMPC with action hints. The fact that StrongBot and WeakBot are ranked 23rd and 25th respectively confirms that all three algorithms are able to consistently defeat the baseline bots.

6 Bonus - Additional Team Agent

We attempted to additionally improve the best TD3 agent by combining it with a defensively specialized TD3 agent. The defensive agent was trained without the +10 reward for winning, instead only with -10 reward for losing, combined with the puck closeness reward. It was trained against the best TD3 checkpoints only on the improved version of the defensive environment mode where the puck is initially directed towards the agent's goal, but with a higher probability of hitting the corners of the goal. The idea was to use the defensive agent when the puck starts is in the opponent's half and switch to the main TD3 agent when the puck was caught by the agent. This approach was submitted to the official tournament under our team name.

A Appendix: External Code and AI Coding Assistance

- **Bartol Markovinović (TD-MPC):** Used the original TD-MPC codebase from `https://github.com/nicklashansen/tdmpc` as starting point for the implementation. To get the code initially working on the hockey environment, completely new training script was implemented and the implementation had to be adapted to variable episode lengths, which included adapting loss calculations and replay buffer sampling. For improving the architecture, some parts of the code were adapted from the TD-MPC2 codebase `https://github.com/nicklashansen/tdmpc2`. The rest of the code was implemented from scratch. Regarding AI usage for coding, only Github Copilot smart autocompletion was used.
- **Rajinish Aneel Bhatia (TD3):** Used the OpenAI TD3 implementation from `https://github.com/openai/spinningup` for the base algorithms and PER, OU noise was taken from RL as-

signments, Pink noise was taken from `https://github.com/martius-lab/pink-noise-rl`, the rest was coded from scratch. AI was not used for coding.

- **Mohd Khizir Siddiqui (SAC):** The implementation is based on clean-rl continuous action space SAC implementation `https://www.github.com/vwxyzjn/cleanrl`. Pink noise usees the pink noise generator from `https://github.com/martius-lab/pink-noise-rl`. Most of the code is done from scratch unless, otherwise attributed in the codebase with individual components. Regarding AI usage for coding, Github Copilot was used for tag autocompletion and boilerplates, but not for logic and design of the code.

Note: TD3 and SAC both use the N-Step Returns but were implemented independently by the respective authors, without sharing code.

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