An empirical study of the naïve REINFORCE algorithm for predictive maintenance of industrial milling machines

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Abstract

In this empirical study, we document the performance of a simple, early reinforcement learning (RL) algorithm, REINFORCE, implemented for a predictive maintenance problem – an optimal tool replacement policy for a milling machine. We compare a naïve implementation of REINFORCE against the policies of industry-grade implementations (Stable-Baselines3) of three advanced algorithms, namely, Deep Q-Network (DQN), Advantage Actor-Critic (A2C) and Proximal Policy Optimization (PPO). This work is aimed at industrial practitioners not accustomed to the complex hyperparameter tuning often required to get RL to work. Our broad goal was to understand the performance of *untuned* algorithms under various scenarios: (1) simulation tool-wear data (2) real tool-wear data (benchmark IEEE NUAA Ideahouse dataset) (3) added noise levels and a random chance of break-down.

Model performance was measured by how accurately the predictive maintenance agent suggested tool replacement when compared to a deterministic preventive maintenance rule based on the tool-wear threshold. Across variants of the environment, REINFORCE models demonstrated a tool replacement precision of 0.687 against 0.449 for A2C, 0.418 for DQN, and 0.472 for PPO. The F1 scores were 0.609, 0.442, 0.374 and 0.345 respectively. Variability in precision and F1 was lower for REINFORCE by 0.08 and 0.016, when compared to the average of the three advanced algorithms. Comparing the *best model* over 10 rounds of training produced surprisingly larger gaps in performance. REINFORCE precision/F1 stood at 0.884/0.873. The best A2C, DQN and PPO models produced 0.520/0.639, 0.651/0.740 and 0.558/0.580 respectively. Our findings indicate that the computationally lightweight REINFORCE performs significantly well for this particular problem. Consequently, for this particular problem, selecting the naïve REINFORCE could be a more suitable and effective policy generating alternative to more advanced complex algorithms.

For reproducibility, model training and testing code, data and the trained REINFORCE models have been uploaded to https://github.com/Link

Keywords: Predictive maintenance, milling machines, Reinforcement Learning, REINFORCE

Abbreviations

DQN	Deep Q-Network	A2C	Advantage Actor-Critic
PPO	Proximal Policy Optimization	RF	REINFORCE
SS	Single-variable state	MS	Multi-variate state
TP	True positive	TN	True negative
FP	False positive	FN	False negative
RL	Reinforcement Learning	SB3	Stable-Baselines3
PHM	The Prognostics and Health Management Society	*AA*	Advanced Algorithms

1 Introduction

"Plurality should not be posited without necessity" – Of two competing theories, the simpler explanation of an entity is to be preferred
— William of Ockham (1285–1347), *The Occams razor principle*

Milling machines are highly versatile, ubiquitous tools serving a variety of industries. A milling machine removes metal from the work piece by rotating and driving a cutting device into it. Abrasive forces cause tool wear, and optimal tool replacement reduces direct costs and optimizes the machines' downtime. With the 2023 milling machine market valued at USD 68.3 billion (Future Market Insights, 2023), this is an important goal for the industry. The cutting tool experiences multiple types of wear as it cuts through metal. Tool wear depends in several factors such as the cutting speed, force applied to the tool, lubrication and materials of the work piece and cutting tool.

Reinforcement learning (RL) is an artificial intelligence technique inspired by nature. Fig. 1 (Sutton and Barto, 2018) shows the RL learning feedback loop. An actor or "agent" interacts with an environment and learns via "trial-and-error". It acts based on stimuli or feedback received from the environment after performing a certain action. Actions that help in achieving the learning goal receive a reward while actions that do not, are punished. Repeating this loop over thousands of episodes, good actions are "reinforced", thereby building a "policy" that is optimized for that goal. In the case of predictive maintenance for milling machines, the agent is the "planner" with a goal of learning an optimal tool replacement policy. The environment consists of sensors attached to the machine and related information such as job specifications, environment conditions etc.

Introduced in 1992, the REINFORCE algorithm (Williams, 1992) is considered as a basic reinforcement learning algorithm. It is a policy-based, on-policy algorithm, capable of handling both discrete and continuous observation and action domains. In practice the REINFORCE algorithm is considered as a "weak" algorithm and superseded by several algorithms developed since. Most notably the Q-Learning and its deep-neural network version, the DQN (Mnih et al., 2013), followed by Actor-Critic (Mnih et al.,

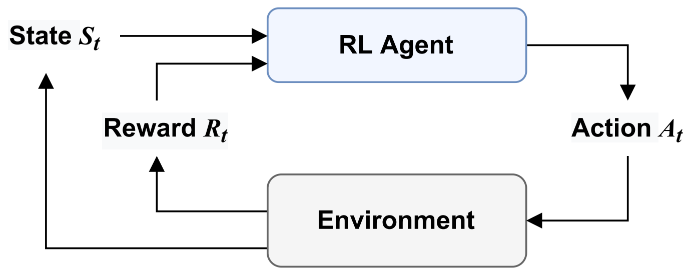


Figure 1: Reinforcement Learning

2016) and one of the most robust modern-day algorithms, the PPO (Schulman et al., 2017).

While most studies on RL algorithms are evaluated on Open AI Gym environments, our experiments cover the predictive maintenance problem using a custom built environment. Also, our study focuses on the earliest RL algorithm, the REINFORCE. This is often neglected by studies, as it is considered an early and weak algorithm. In the industry the milling tool is replaced after a set threshold. We use this “deterministic preventive maintenance" policy as the baseline for comparing the RL algorithm policy.

Our systematic evaluation, based on levels of environment difficulty, different bench-mark data sets and varying noise levels allow a broader, more robust, comparison of the algorithms. We use Particularly, we show that naive Bayes works best in two cases: completely independent features (as expected) and functionally dependent features (which is less obvious), while reaching its worst performance between these extremes. Finally, we conduct statistical tests to ensure a robust statistical-evidence based conclusion.

We also show that, surprisingly, the accuracy of naive Bayes is not directly correlated with the degree of feature dependencies measured as the class-conditional mutual information between the features,. Instead, our experiments reveal that a better predictor of naive Bayes accuracy can be 41 the loss of information that features contain about the class when assuming naive Bayes model, namely , where is the mutual information between features and class under naive Bayes assumption.

This paper is structured as follows. In the next section we provide necessary background and definitions. Section 3 discusses naive Bayes performance for nearly-deterministic dependencies, while Section 4 demonstrates that the "information loss" criterion can be a better error predictor than the strength of feature dependencies. A summary and conclusions are given in Section 5.

1.1 Stable-Baselines3

Stable-Baselines3 Raffin et al. (2021), is Open Source and very popular among the RL community[1]. Stable-Baselines3 was initially based on the Open AI baselines (Dhariwal et al., 2017) and is completely rewritten using PyTorch.

for , implementation s the advanced algorithms – DQN, A2C and PPO and compare its performance to a naïve custom implementation of the REINFORCE algorithm. We use Stable-Baselines3 (SB3), the highly popular and reliable implementations of DQN, A2C and PPO. As of 27-Jun-2023, the REINFORCE was not implemented by Stable-Baselines and we therefore custom implemented a basic version.

1.2 DQN

Deep Q Network (DQN) builds on Fitted Q-Iteration (FQI) (Riedmiller, 2005) and make use of different tricks to stabilize the learning with neural networks: it uses a replay buffer, a target network and gradient clipping.

1.3 REINFORCE

sB-3 dOES NOT IMPLEMENT THE REINFORCE — https://stable-baselines3.readthedocs.io/e

Model Free –> Policy Gradient/Actor-Critic –> REINFORCE) REINFORCE (Monte-Carlo policy gradient)

IEEE NUAA Ideahouse dataset has been used in this paper for the RUL estimation of the milling cutter. Yingguang et al. (2021)

Tool wear modeling is the first step to assist in predicting

Literature search conducted on the Scopus™ and Web Of Science™ did not return any articles for the application of reinforcement learning for predictive

[1]As of 27-Jun-2023, it had 6k+ stars and 424 closed pull requests

maintenance of milling machines. Search strings we tried – ‘‘`reinforcement learning AND tool wear AND maintenance", RL + milling + policy, RL + milling + maintenance, RL + tool wear + policy, RL + tool wear + maintenance"`

Running the search ‘‘`reinforcement learning AND milling AND tool wear"` using the Scopus™ and Web Of Science™ services

Dai et al. (2021) is the only article we found that tackles the

Machine learning methods have been applied for example – Oshida et al. (2023) proposes real-time tool wear detection during the milling process. They use a stacked LSTM encoder-decoder model for anomaly detection.

No results for "reinforcement learning" AND "milling machine" AND "tool wear" - on scopus or wos as of 23-jun-2023 "reinforcement learning" AND "milling machine" - 1 not relevant " *Conference Paper* • Open access "Online Learning of Stability Lobe Diagrams in Milling" Friedrich, J. Torzewski, J. Verl, A.

"reinforcement learning" AND "tool wear" - 10 results

2 Literature Review

Sandeep Varma et al. (2022) - **VERY RELEVANT* Experimental Evaluation of Reinforcement Learning Algorithms – three policy based learning algorithms(PPO, SAC, DDPG) OpenAI Gym on Bipedal Walker, Bipedal Walker Hardcore, Lunar Landing, Mountain Car and Pendulum and (2)A2C on the Atari 2600 environments MuZero on custom 6x6 Go environmen

Velivela and Yarram (2020) - **VERY RELEVANT* Comparison of Reinforcement Learning Algorithms –

Dulac-Arnold et al. (2020) *** An empirical investigation of the challenges of real-world reinforcement learning – Distributional Maximum a Posteriori Policy Optimization (DMPO) [Abdolmaleki et al. 2018a] and Distributed Distributional Deterministic Policy Gradient (D4PG) [(DMPO is an EM-style policy iteration algorithm with a stochastic policy and D4PG is a deterministic policy gradient algorithm) D4PG is a modified version of Deep Deterministic Policy Gradients (DDPG) MPO [Abdolmaleki et al. 2018b] is an RL method that combines the sample efficiency of off-policy methods with the scalability and hyperparameter robustness of on-policy methods – envs cartpole:swingup, walker:walk, quadruped:walk and humanoid:walk tasks from the realworldrl-suite

Duan et al. (2016) cart-pole swing-up, tasks with very high state and action dimensionality such as 3D humanoid locomotion, tasks with partial observations – algorithms: (1) batch alsogs REINFORCE, Truncated Natural Policy Gradient (TNPG) (impoorves RF), Reward-Weighted Regression (RWR) Relative Entropy Policy Search (REPS) Trust Region Policy Optimization (TRPO) Cross Entropy Method (CEM) —- (2) ONLINE algorithms: Deep Deterministic Policy Gradient (DDPG).Compared to batch algorithms, the DDPG algorithm continuously improves the policy as it explores the environment.*OBSERVATION**REINFORCE: Despite its simplicity, REINFORCE is an effective algorithm in optimizing deep neural network policies in most basic and locomotion tasks. Even for high- DOF tasks like Ant, REINFORCE can achieve competitive results. However we observe that REINFORCE sometimes suffers from premature convergence to local optima as noted by Peters Schaal (2008), which explains the performance gaps between REINFORCE and TNPG on tasks such as Walker (Figure 3(a)). By visualizing the final policies, we can see that REINFORCE results in policies that tend to jump forward and fall over to maximize short-term return instead of acquiring a stable walking gait to maximize long-term return. In Figure 3(b), we can observe that even with a small learning rate, steps taken by REINFORCE can sometimes result in large changes to policy distribution, which may explain the fast convergence to local optima.

Henderson et al. (2018) **VERY REINFORCELEVANT Deep Reinforcement Learning that Matters – Peter Henderson* DDPG ACKTR TRPO PPO - ON mujoco envs - HalfCheetah-v1 ,Hopper-v1 , Walker2d-v1 and Swimmer-v1 We investigate the OpenAI baselines implementation of TRPO and DDPG and rllab implementation of TRPO we generally use the OpenAI Baselines2 implementations of the following algorithms: ACKTR (Wu et al. 2017), PPO (Schulman et al. 2017), DDPG (Plappert et al. 2017), TRPO (Schulman et al. 2017). We use the Hopperv1 and HalfCheetah-v1 MuJoCo

(Todorov, Erez, and Tassa 2012) environments from OpenAI Gym (Brock

Ford and Ritchie (2022) - compares DQN A2C AND PPO FOR cognition in sensing systems to the choice of operational radio frequency (RF) mode (active, bistatic receive, electronic surveillance (ES), electronic protection measure (EPM)) for a multi-function RF system (MFRFS) – suggest ppo is best

Dulac-Arnold et al. (2021) taks of real word problem challenges

3 Method

*The methodology explains in detail what the researcher did to undertake the research. Various aspects of the research have to be outlined: The overall structure and operation of the experiment or observational experience. The groups studied in the research including the size of each group and any features of the subjects which may be relevant to the topic being researched. The variables that were changed between groups and the variables measured as a result of the changes. The conditions under which the research was undertaken and any factors or variations in conditions which may have an impact on the results. The methods of data analysis used in order to analyse and collate the results. ***Any limitations of the data collected.* We normalize the tool wear and other state features, $x \in [0,\ 1] \subset \mathbb{R}$. This allows for adding white noise of similar magnitudes across experiments of different data-sets

3.1 RL environment description

3.2 Data description

3.3 Procedure

– training
– selecting the model
– conducting the experiments

3.4 Evaluation method

3.5 Tools

2 different laptops

- why classifction metrics
- why F1beta

3.6 Method - training and testing

3.7 Precision or Recall?

- Precision => low FP => False replacement-action reduced. *** Unnecessary tool replacement reduced. Tool life maximized, down time minimized, production disruption minimized
- Recall => low FN => False declaration of normal operation reduced. Reduce missed replacements. Tool replacements increased. *** Product quality not compromised.

3.8 Hyper-parameters for Precision or Recall control

- R1 = +1
- R2 = -1
- R3 = -100 => higher neg. Improve recall. Lower neg. Improve precision
- **LOOK AHEAD PARAM**:
- Training: SB3 - 10 k eps. 3 times. Average their outputs
- Testing:
  - Avg. over 5 rounds.
  - Each round - avg over 40 test cases x 10 test rounds

  - Total: 40 x 10 x 5 = 2000 cases
  - Avgs over: 10 rounds (of 40 cases each) X 5 rounds of **re-trained** SB3 agents = 50 rounds

3.9 Inference

- Training: SB3 is also unstable - show examples of results such as A2C/DQN 0.00
- Training: SB3 is also unstable - SHOW SB3 tensorboard plots
- Training: SB3 is also unstable - EXCEL plots of results over the 10 rounds

4 Network architecture and basic hyper-parameters

soure of ppo implementation details `https://iclr-blog-track.github.io/2022/03/25/ppo-implementation-details/`

source of SB3 network mp : `https://github.com/openai/baselines/blob/ea25b9e8b234e6ee1bca43083f8f3cf974143998/baselines/common/models.py#L75-L103`

4.1 PPO hyperparms

implementation guide source » https://iclr-blog-track.github.io/2022/03/25/ppo-implementation-details/

By default, PPO uses a simple MLP network consisting of two layers of 64 neurons and Hyperbolic Tangent as the activation function. Then PPO builds a policy head and value head that share the outputs of the MLP network. Below is a pseudocode:

4.2 dqn hyperparms

default hyperparms : `https://stable-baselines3.readthedocs.io/en/master/_modules/stable_baselines3/common/policies.html`

	A2C	**DQN**	**PPO**	**REINFORCE**
Network architecture	input dim x [64|Tanh x 64|Tanh] x output dim	input dim x [64|Tanh x 64|Tanh] x output dim	input dim x [64|Tanh x 64|Tanh] x output dim	input dim x [64|ReLU] x output dim
Layers	2	2	2	1
Units	64 x 64	64 x 64	64 x 64	64
Activation	Tanh, Tanh	Tanh, Tanh	Tanh, Tanh	ReLU
Optimizer	RMSprop	Adam	Adam	Adam
Learning rate	0.0007	0.0001	0.0003	0.01
Gamma	0.99	0.99	0.99	0.99

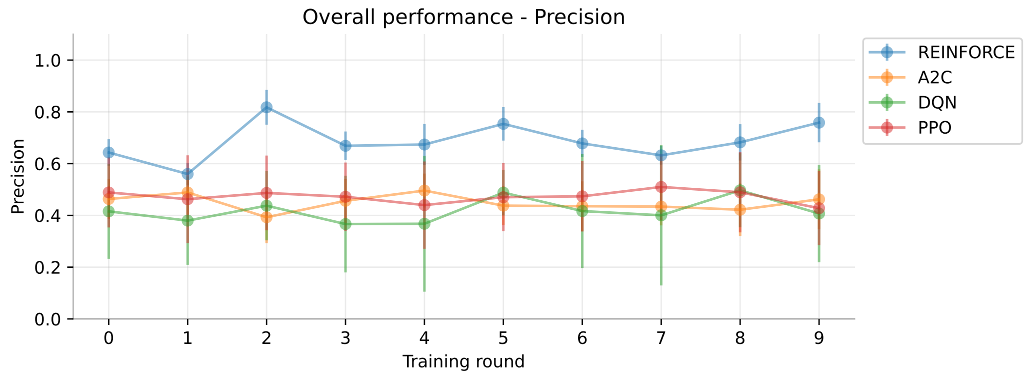
Table 1: Comparing the network architecture and basic hyper-parameters across algorithms

overridden in indiv policies for example SB3 DQN hypoerparms for example were taken from ; Paper: https://arxiv.org/abs/1312.5602, https://www.nature.com/articles/
Default hyperparameters are taken from the Nature paper, except for the optimizer and learning rate that were taken from Stable Baselines defaults

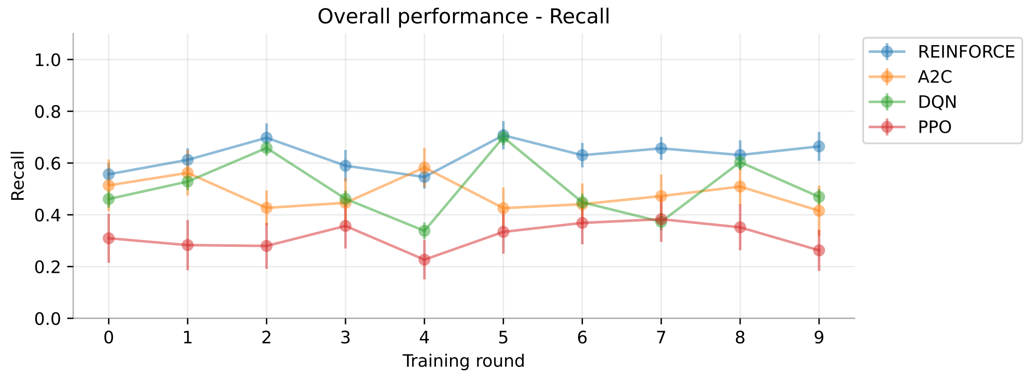
5 Empirical results

5.1 Detailed metrics

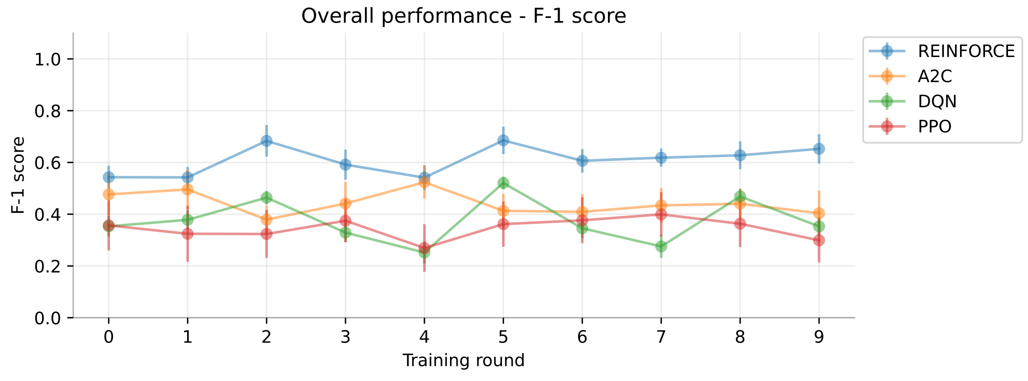
xx



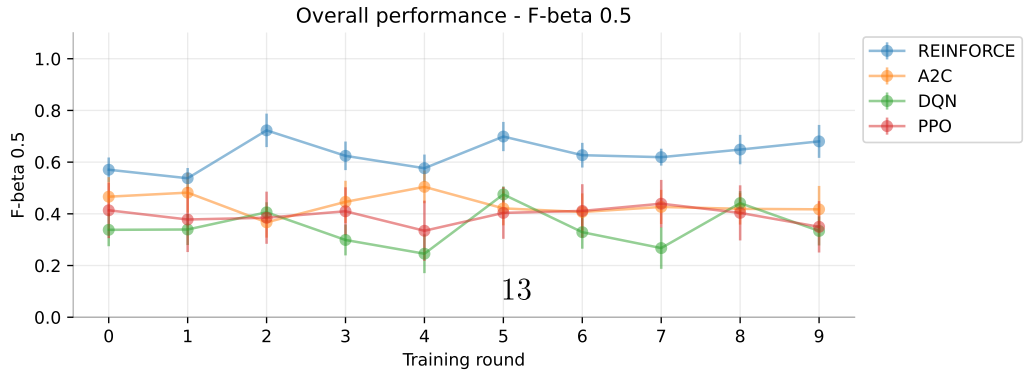
(a) Precision



(b) Recall

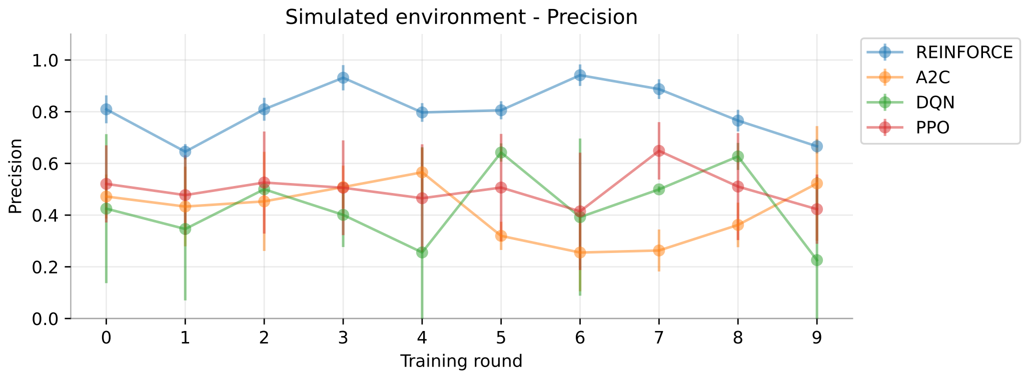


(c) F1-score

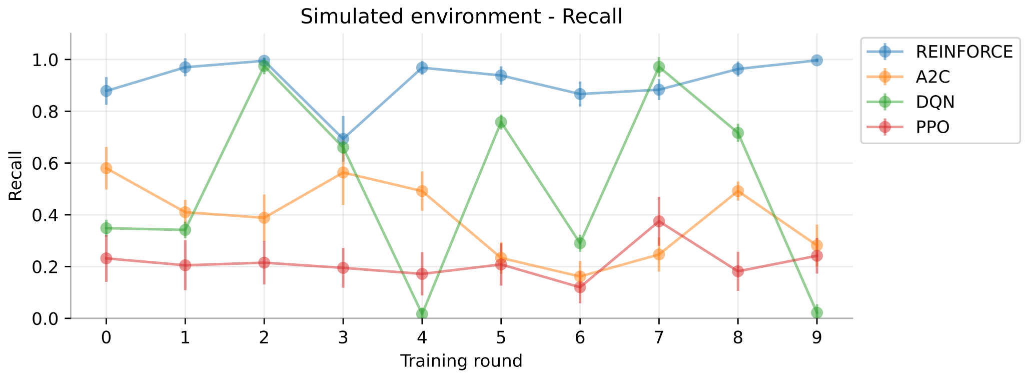


(d) F1-beta (0.5)

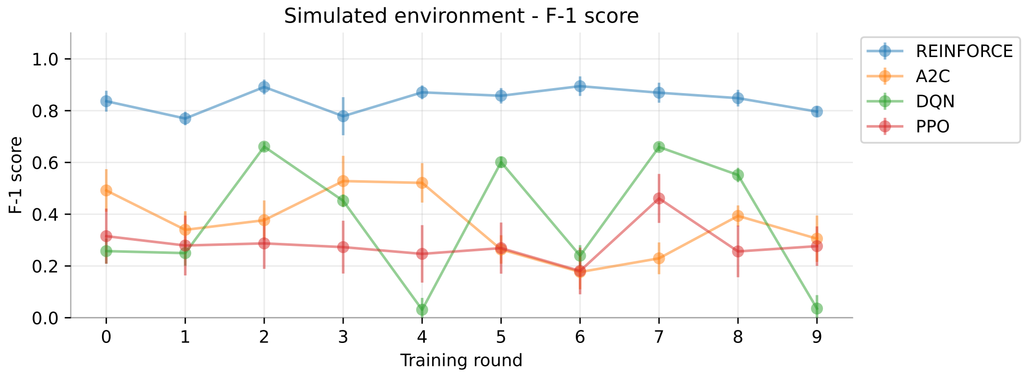
Figure 2: Overall performance – Avg. performance over 10 rounds of model training



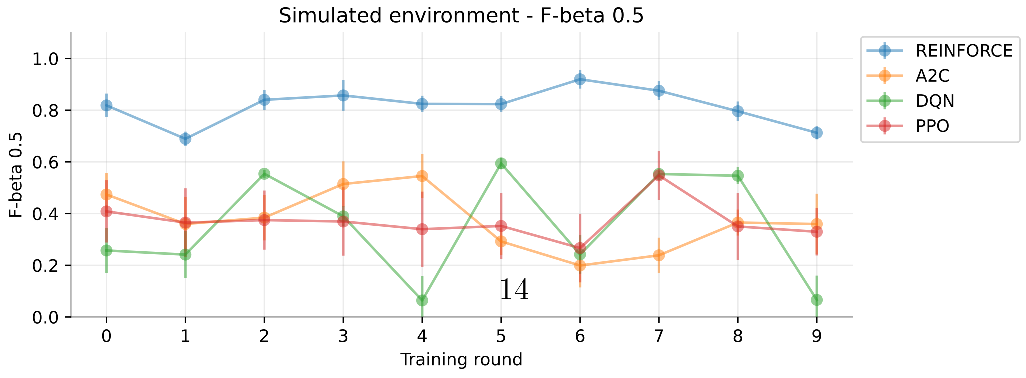
(a) Precision



(b) Recall

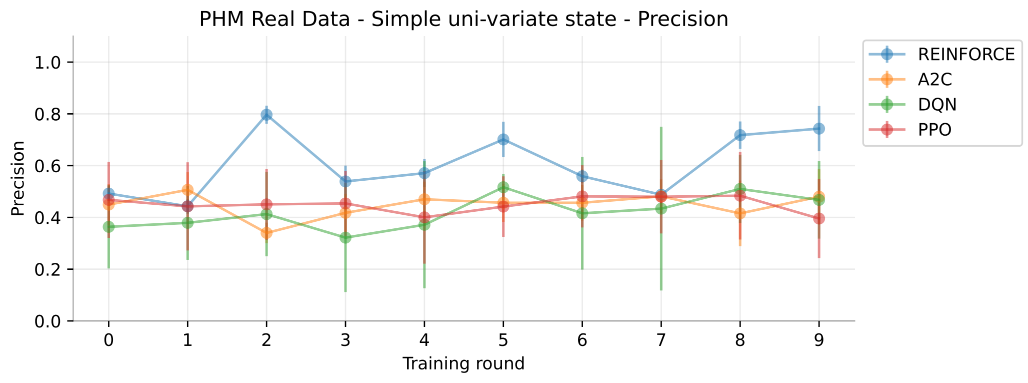


(c) F1-score

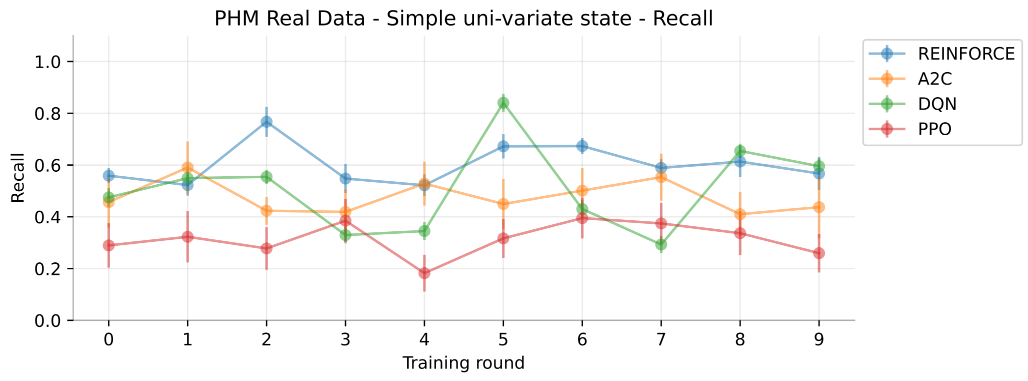


(d) F1-beta (0.5)

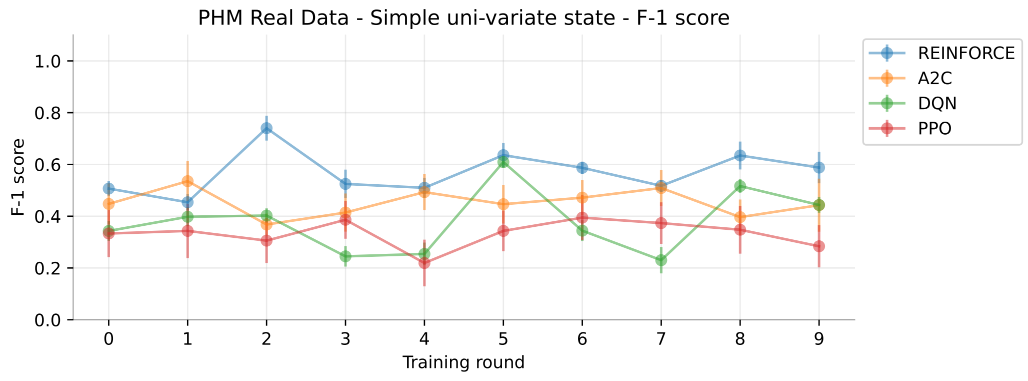
Figure 3: Simulated environment – Avg. performance over 10 rounds of model training



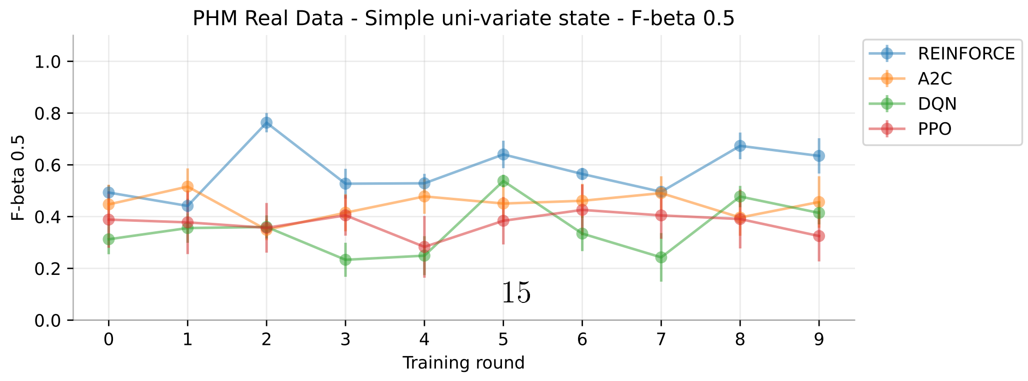
(a) Precision



(b) Recall

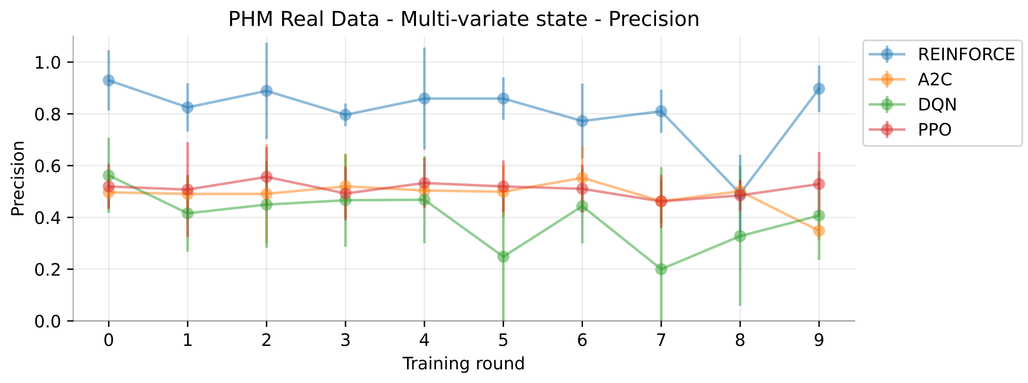


(c) F1-score

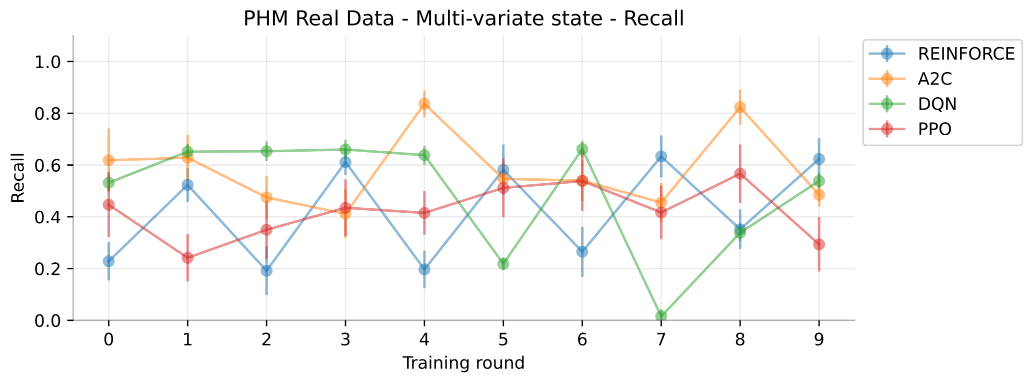


(d) F1-beta (0.5)

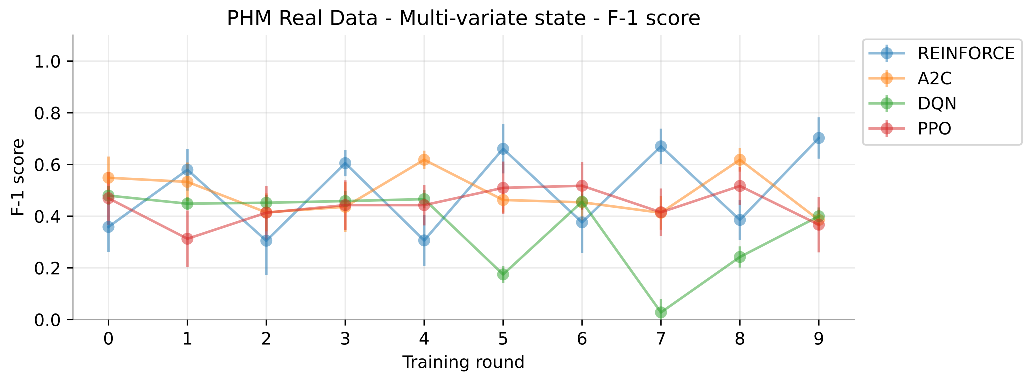
Figure 4: Singe-variable state environment – Avg. performance over 10 rounds of model training



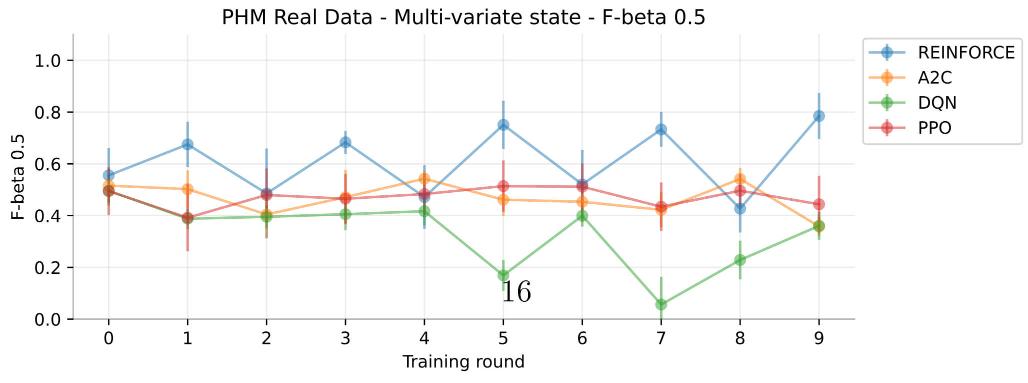
(a) Precision



(b) Recall



(c) F1-score



(d) F1-beta (0.5)

Figure 5: Multi-variate state environment – Avg. performance over 10 rounds of model training

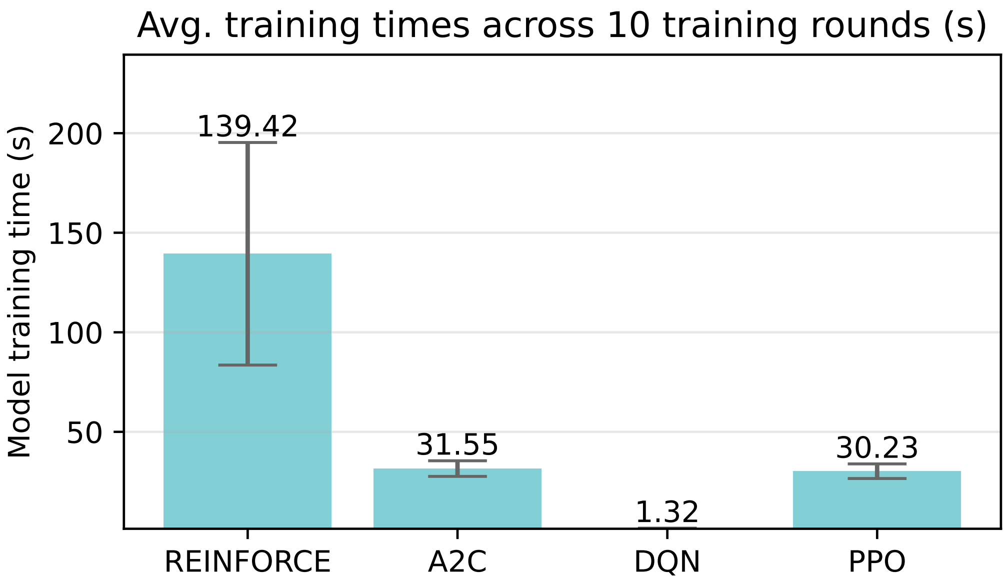


Figure 6: Training time. Across 10 rounds and all environment variants.

	REINFORCE				A2C				DQN				PPO			
Environment	Prec.	Recall	F1	F0.5	Prec.	Recall	F1	F0.5	Prec.	Recall	F1	F0.5	Prec.	Recall	F1	F0.5
Simulated - No noise	0.842	0.878	0.838	0.834	0.424	0.451	0.423	0.421	0.426	0.674	0.471	0.410	0.504	0.200	0.271	0.360
Simulated - Low noise	0.777	0.929	0.834	0.796	0.465	0.423	0.409	0.427	0.421	0.338	0.270	0.283	0.482	0.236	0.296	0.369
Simulated - High noise	0.798	0.940	0.851	0.816	0.358	0.281	0.256	0.272	0.447	0.519	0.380	0.360	0.514	0.207	0.286	0.382
PHM C01 SS - No noise	0.478	0.363	0.400	0.439	0.501	0.500	0.493	0.496	0.472	0.807	0.568	0.490	0.440	0.417	0.387	0.395
PHM C01 SS - Low noise	0.507	0.311	0.332	0.383	0.503	0.598	0.535	0.513	0.393	0.502	0.351	0.317	0.522	0.338	0.388	0.448
PHM C01 SS - High noise	0.693	0.562	0.579	0.623	0.266	0.282	0.267	0.262	0.458	0.525	0.400	0.384	0.456	0.369	0.372	0.400
PHM C04 SS - No noise	0.751	0.878	0.784	0.757	0.487	0.442	0.449	0.463	0.439	0.684	0.472	0.411	0.500	0.510	0.469	0.473
PHM C04 SS - Low noise	0.662	0.756	0.672	0.657	0.409	0.455	0.428	0.416	0.411	0.500	0.370	0.341	0.488	0.280	0.324	0.386
PHM C04 SS - High noise	0.611	0.713	0.620	0.598	0.518	0.607	0.552	0.530	0.358	0.451	0.325	0.294	0.428	0.262	0.286	0.333
PHM C06 SS - No noise	0.830	0.726	0.754	0.792	0.517	0.509	0.507	0.511	0.360	0.309	0.256	0.258	0.409	0.248	0.275	0.321
PHM C06 SS - Low noise	0.205	0.279	0.228	0.212	0.510	0.577	0.530	0.516	0.434	0.266	0.266	0.296	0.417	0.181	0.232	0.294
PHM C06 SS - High noise	0.709	0.843	0.759	0.726	0.316	0.324	0.311	0.308	0.449	0.518	0.400	0.375	0.388	0.222	0.265	0.317
PHM C01 MS - No noise	0.835	0.652	0.656	0.716	0.461	0.444	0.397	0.404	0.384	0.558	0.393	0.348	0.513	0.383	0.416	0.460
PHM C04 MS - No noise	0.739	0.255	0.359	0.494	0.498	0.589	0.490	0.470	0.323	0.209	0.160	0.168	0.499	0.393	0.421	0.457
PHM C06 MS - No noise	0.864	0.356	0.469	0.616	0.501	0.713	0.578	0.527	0.489	0.705	0.529	0.479	0.523	0.488	0.485	0.498

Table 2: Model performance comparison all variants of the environments, over 10 rounds of training.

5.2 Super models metrics

	REINFORCE				A2C				DQN				PPO			
Environment	Prec.	Recall	F1	F0.5	Prec.	Recall	F1	F0.5	Prec.	Recall	F1	F0.5	Prec.	Recall	F1	F0.5
Simulated - No noise	0.897	0.960	0.926	0.908	0.500	1.000	0.667	0.556	0.505	0.980	0.667	0.560	0.669	0.430	0.518	0.597
Simulated - Low noise	0.960	0.945	0.952	0.957	0.516	1.000	0.680	0.571	0.500	0.980	0.662	0.554	0.633	0.460	0.530	0.586
Simulated - High noise	0.922	0.990	0.955	0.935	0.503	1.000	0.669	0.558	0.504	0.990	0.668	0.559	0.569	0.355	0.434	0.505
PHM C01 SS - No noise	0.889	0.995	0.939	0.908	0.586	0.625	0.603	0.592	0.647	0.970	0.776	0.693	0.543	1.000	0.703	0.597
PHM C01 SS - Low noise	0.988	0.765	0.861	0.932	0.499	0.995	0.664	0.554	0.504	0.990	0.668	0.559	0.623	0.740	0.675	0.643
PHM C01 SS - High noise	0.850	0.970	0.905	0.871	0.521	0.680	0.588	0.546	0.505	0.985	0.668	0.560	0.520	0.725	0.604	0.551
PHM C04 SS - No noise	0.811	1.000	0.895	0.842	0.536	0.645	0.583	0.554	0.501	0.965	0.660	0.554	0.579	0.895	0.702	0.622
PHM C04 SS - Low noise	0.798	0.980	0.879	0.829	0.556	0.665	0.603	0.573	0.734	0.990	0.843	0.774	0.546	0.660	0.596	0.565
PHM C04 SS - High noise	0.708	0.840	0.767	0.730	0.521	0.835	0.641	0.563	0.511	0.985	0.672	0.565	0.517	0.820	0.633	0.558
PHM C06 SS - No noise	1.000	0.895	0.944	0.977	0.520	0.680	0.587	0.545	0.935	0.975	0.954	0.942	0.587	0.650	0.615	0.597
PHM C06 SS - Low noise	0.943	0.795	0.861	0.908	0.501	1.000	0.668	0.557	0.961	0.725	0.826	0.901	0.552	0.370	0.438	0.497
PHM C06 SS - High noise	0.821	0.845	0.831	0.825	0.540	0.755	0.628	0.572	0.980	0.960	0.969	0.976	0.521	0.615	0.564	0.537
PHM C01 MS - No noise	0.827	0.995	0.903	0.856	0.500	1.000	0.667	0.556	0.505	0.985	0.668	0.560	0.512	0.595	0.549	0.526
PHM C04 MS - No noise	0.910	0.425	0.577	0.738	0.500	1.000	0.667	0.556	0.501	0.975	0.662	0.555	0.501	0.635	0.558	0.522
PHM C06 MS - No noise	0.934	0.865	0.896	0.918	0.500	1.000	0.667	0.556	0.969	0.600	0.741	0.863	0.497	0.690	0.577	0.526

Table 3: Super Models: Best models selected over 10 rounds of training.

5.3 Overall summary performance

	Precision		Recall		F1-score		F1-beta score	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
A2C	0.449	0.088	0.480	0.084	0.442	0.070	0.436	0.071
DQN	0.418	0.185	0.504	0.032	0.374	0.035	0.348	0.058
PPO	0.472	0.144	0.316	0.087	0.345	0.091	0.393	0.105
REINFORCE	0.687	0.059	0.629	0.051	0.609	0.050	0.631	0.052

Table 4: Model performance summary - averaged over all environment.

5.4 Simulated environment

	Precision		Recall		F1-score		F1-beta score	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
A2C	0.416	0.120	0.385	0.073	0.363	0.072	0.373	0.082
DQN	0.432	0.184	0.510	0.031	0.374	0.034	0.351	0.056
PPO	0.500	0.178	0.215	0.081	0.285	0.099	0.370	0.122
REINFORCE	0.806	0.040	0.915	0.038	0.841	0.035	0.816	0.037

Table 5: Model performance summary - averaged over simulated environments.

5.5 Real data – simple uni-variate environment

	Precision		Recall		F1-score		F1-beta score	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
A2C	0.447	0.077	0.477	0.091	0.452	0.072	0.446	0.070
DQN	0.419	0.179	0.507	0.032	0.379	0.036	0.352	0.057
PPO	0.450	0.146	0.314	0.082	0.333	0.087	0.374	0.102
REINFORCE	0.605	0.046	0.603	0.046	0.570	0.041	0.576	0.040

Table 6: Model performance summary - averaged over PHM-2010 environments with simple single-variable environment.

5.6 Real data – complex multi-variate state

	Precision		Recall		F1-score		F1-beta score	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
A2C	0.487	0.086	0.582	0.075	0.488	0.063	0.467	0.065
DQN	0.399	0.204	0.491	0.032	0.361	0.035	0.332	0.060
PPO	0.512	0.107	0.422	0.107	0.441	0.096	0.472	0.096
REINFORCE	0.813	0.119	0.421	0.079	0.495	0.090	0.609	0.101

Table 7: Model performance summary - averaged over PHM-2010 environments with complex multi-variate environment.

5.7 Hypothesis testing

$$\left.\begin{aligned} H_0 &: \mu_{RF} - \mu_{AA} = 0, \\ H_a &: \mu_{RF} - \mu_{AA} > 0, \end{aligned}\right\} \qquad \forall \;\; AA \in [A2C, DQN, PPO] \tag{1}$$

	p Value			t Statistic		
Metric	RF $\overset{H_a}{\underset{H_0}{\geqq}}$ A2C	RF $\overset{H_a}{\underset{H_0}{\geqq}}$DQN	RF $\overset{H_a}{\underset{H_0}{\geqq}}$PPO	RF $\overset{H_a}{\underset{H_0}{\geqq}}$ A2C	RF $\overset{H_a}{\underset{H_0}{\geqq}}$DQN	RF $\overset{H_a}{\underset{H_0}{\geqq}}$PPO
Overall (1500 samples)						
Precision	4.31E-126	2.17E-109	2.81E-106	25.071	23.170	22.804
Recall	4.20E-35	3.37E-16	4.36E-150	12.522	8.206	27.650
F1 score	1.99E-64	1.46E-88	5.29E-155	17.364	20.634	28.160
Simulated environment (300 samples)						
Precision	3.20E-98	1.69E-63	2.65E-81	25.611	19.032	22.427
Recall	8.12E-104	2.56E-41	1.57E-264	26.665	14.558	62.541
F1 score	9.60E-134	8.56E-99	2.96E-242	32.402	25.719	56.575
PHM Real data - Simple uni-variate state (900 samples)						
Precision	2.27E-32	7.29E-31	9.95E-31	12.082	11.770	11.742
Recall	1.27E-16	1.55E-06	8.19E-71	8.357	4.821	18.607
F1 score	1.94E-19	4.67E-34	2.19E-67	9.121	12.423	18.098
PHM Real data - Complex multi-variate state (300 samples)						
Precision	1.64E-60	3.34E-54	7.88E-59	18.451	17.207	18.122
Recall	2.69E-10	2.69E-02	9.68E-01	-6.425	-2.219	-0.041
F1 score	7.27E-01	1.44E-08	1.35E-03	0.349	5.748	3.220

Table 8: One-tail t-test - Ho: No difference in metrics. Ha: REINFORCE metric > Advanced algorithm metric

5.8 Training times

6 Environment description

6.1 simulated data

(Dašić, 2006). eq 16 from the paper parameters b0, b1, b2 and a under the form of a complex power-exponential regression equation power functions as approximating functions of cutting tool wear, we proposed is powerexponential function form

tool flank wear VB

$$VB = a \cdot t^{b_1} \cdot e^{b_2 \cdot t} \Big|_{t=t_0}^{t=t_1}$$

b0 -2.4941 b1 0.3342 b2 0.03147 a 0.08257 Determination of Complex Power- Exponential Regression Equation for Functional Dependence between Tool Wear and Cutting Time for Cutting Speed v=79.2 [m/min] Parameter calculation b0, b1 and b2 of the linear regression for the mentioned example is consisted in the solving of the normal system equation (12) with the following shape:

Implementation details: Normalization

init

reset

reward function

degradation model as exponential

$$H(t) = 1 - D_0 - \mathrm{e}^{(at^b)}, \tag{2}$$

where, D_0 is the initial degradation state while a and b are wear-rate coefficients that depend on the effect of temperature, vibration and other system stress parameters

$$X(m,n) = \left\{ \begin{array}{ll} x(n), & \text{for } 0 \leq n \leq 1 \\ x(n-1), & \text{for } 0 \leq n \leq 1 \\ x(n-1), & \text{for } 0 \leq n \leq 1 \end{array} \right\} = xy$$

$$R_t = \begin{cases} 0, & \text{if } U(s_t) = U(s_{t+1}) = 0 \\ -1.0, & \text{if } U(s_t) = 0, U(s_{t+1}) = 1 \\ R_{ff}, & \text{if } U(s_t) = 1 \end{cases} \tag{3}$$

6.2 SS

```
def _get_observation(self, index):
next_state = np.array([
self.df['time'][index],
self.df['tool_wear'][index]
], dtype=np.float32)

return next_state
```

6.3 MS

```
def _get_observation(self, index):
next_state = np.array([
self.df['tool_wear'][index],
self.df['force_x'][index],
self.df['force_y'][index],
self.df['force_z'][index],
self.df['vibration_x'][index],
self.df['vibration_y'][index],
self.df['vibration_z'][index],
self.df['acoustic_emission_rms'][index]
], dtype=np.float32)

return next_state

# Machine data frame properties
self.df = df
self.df_length = len(self.df.index)
self.df_index = 0

# Milling operation and tool parameters
self.wear_threshold = wear_threshold
self.max_operations = max_operations
self.breakdown_chance = breakdown_chance
self.add_noise = add_noise
self.R1 = R1
self.R2 = R2
self.R3 = R3
self.reward = 0.0
```

6.4 main env

```
env = MillingTool_SS_NT(df_train, WEAR_THRESHOLD_NORMALIZED, MILLING_OPERATIONS_
```

6.5 test env

```
env_test = MillingTool_SS_NT(df_test, WEAR_THRESHOLD_ORG_NORMALIZED, MILLING_OPE
```

7 The core elements of the 4 algorithms

The core elements of the 4 algorithms. (Graesser and Keng, 2019)

REINFORCE: Paper (Williams, 1992)

$$\nabla_\theta J(\pi_\theta) = \mathbb{E}_t \left[\, R_t(\tau)\ \nabla_\theta \ln \pi_\theta(a_t|s_t)\,\right] \tag{4}$$

DQN: Learning Q-function in DQN. Paper (Mnih et al., 2013). Implementation notes: "*SB3 says:* Deep Q Network (DQN) builds on Fitted Q-Iteration (FQI) and make use of different tricks to stabilize the learning with neural networks: it uses a replay buffer, a target network and gradient clipping"

$$Q^\pi(s,a) = r + \gamma \max_{a'} Q^\pi(s',a') \tag{5}$$

A2C: Actors learn parameterized policy π_θ using the policy-gradient as shown in Equation 6. "*SB3 says:* A synchronous, deterministic variant of Asynchronous Advantage Actor Critic (A3C). It uses multiple workers to avoid the use of a replay buffer.". Paper (Mnih et al., 2016)

$$\nabla_\theta J(\pi_\theta) = \mathbb{E}_t \left[\, A_t^\pi \; \nabla_\theta \ln \pi_\theta(a_t|s_t) \, \right] \tag{6}$$

Where the advantage function $A_t^\pi(s_t, a_t)$ measures how good or bad the action is w.r.t. policy's average, for a particular state using Equation 7

$$A_t^\pi(s_t, a_t) = Q^\pi(s_t, a_t) - V^\pi(s_t) \tag{7}$$

PPO: " *SB3 says:* The Proximal Policy Optimization algorithm combines ideas from A2C (having multiple workers) and TRPO (it uses a trust region to improve the actor). The main idea is that after an update, the new policy should be not too far from the old policy. For that, ppo uses clipping to avoid too large update.". Paper (Schulman et al., 2017)

$$J^{CLIP}(\theta) = \mathbb{E}_t \left[\, min(r_t(\theta) A_t^{\pi_{\theta_{old}}}, clip(r_t(\theta), 1-\epsilon, 1+\epsilon) A_t^{\pi_{\theta_{old}}}) \right] \tag{8}$$

8 The REINFORCE algorithm

Three key features of any RL algorithm:

1. Policy: π_θ = Probablities of all actions, given a state. Parameterized by θ

2. Objective function:

$$\max_\theta J(\pi_\theta) = \mathop{\mathbb{E}}_{\tau \sim \pi_\theta} [R(\tau)] \tag{9}$$

3. Method: Way to udate the parameters = Policy Gradient

8.1 Policy gradient numerical computation

1. Plain vanilla:

$$\nabla_\theta J(\pi_\theta) = \mathbb{E}_{\tau \sim \pi_\theta} \left[\sum_{t=0}^{T} R_t(\tau) \; \nabla_\theta \ln \pi_\theta(a_t|s_t) \right] \tag{10}$$

2. With Monte Carlo sampling and approximation: $\nabla_\theta J(\pi_\theta) \approx [\, \sum_{t=0}^{T} R_t(\tau) \; \nabla_\theta \ln \pi_\theta(a_t|s_t) \,]$

3. With baseline: $\nabla_\theta J(\theta) \approx [\, \sum_{t=0}^{T} (R_t(\tau) - b(s_t)) \; \nabla_\theta \ln \pi_\theta(a_t|s_t) \,]$

4. Where, baseline does not change per time-step, it is for the entire trajectory

5. One baseline option: V^π - leads to Actor-Critic algorithm

6. Simpler option: Average returns over trajectory: $b = \frac{1}{T} \sum_{t=0}^{T} R_t(\tau)$

Algorithm

9 Discussion

9.1 Precision or Recall?

- Precision => low FP => False replacement-action reduced. *** Unnecessary tool replacement reduced. Tool life maximized, down time minimized, production disruption minimized
- Recall => low FN => False declaration of normal operation reduced. Reduce missed replacements. Tool replacements increased. *** Product quality not compromised.

limitiongs of the slecting model for evaluation

Raffin et al. (2021) – quote from paper - intro section – "A major challenge is that small implementation details can have a substantial effect on performance often greater than the difference between algorithms (Engstrom et al., 2020). It is particularly important that implementations used as experimental baselines are reliable; otherwise, novel algorithms compared to weak baselines lead to inated estimates of performance improvements"

DPO paper - Rafael Rafailov May-2023 — Direct Preference Optimization: Your Language Model is Secretly a Reward Model

5.2 Instability of Actor-Critic Algorithms We can also use our framework to diagnose instabilities with standard actor-critic algorithms used for the RLHF, such as PPO. We follow the RLHF pipeline and focus on the RL fine-tuning step outlined in Section 3. We can draw connections to the control as inference framework [18] for the constrained RL problem outlined in 3. We assume a parameterized model and minimize This is the same objective optimized in prior works [45, 35, 1, 23] using the DPO-equivalent reward for the reward class of In this setting, we can interpret the normalization term in as the soft value function of the reference policy . While this term does not affect the optimal solution, without it, the policy gradient of the objective could have high variance, making learning unstable. We can accommodate for the normalization term using a learned value function, but that can also be difficult to optimize. Alternatively, prior works have normalized rewards using a human completion baseline, essentially a single sample Monte-Carlo estimate of the normalizing term. In contrast the DPO reparameterization yields a reward function that does not require any baselines.

10 Conclusion

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