ABSTRACT

Now a day, model free algorithm achieve state of the art performance on many RL problems, but the low efficiency of model free algorithm limited the usage. We combine model base RL, soft actor-critic framework, and curiosity. proposed an agent called RMC, giving a promise way to achieve good performance while maintain data efficiency. We suppress the performance of soft-actor critic and achieve state of the art performance, both on efficiency and stability. Meanwhile we can solving POMDP problem and achieve great generalization from MDP to POMDP.

Keywords  RL · Model · POMDP · Curiosity

1 INTRODUCTION

Model-free deep reinforcement learning algorithms shows the power in many challenge domains, from tradition game "go" to moderate robotic control tasks [Henderson et al., 2018]. The combination of reinforcement learning and high-capacity function approximators such as neural networks hold the promise of learning on a lot of decision making and control tasks, but when it comes to real word application, most of these methods have been hindered by three larger challenges [Ha and Schmidhuber, 2018]

First of all, most of current methods are designed to solve the MDP process, but actually problems are seldom follow the MDP assumption in the real world. They are often partially observation states which means you can make decision on current observation only. What make things worth is construct and infer hidden state are significantly hard if possible. The "True state" depend on entire interaction history of the agent, and even rely on domain knowledge. Second, the model-free method suffers from low sample efficiency even some simple tasks need millions of interval with the environment, when it comes to complex decision making problem, the total interval step could easily comes to $10^{10}$, which is inaccessible for most domain except in some really fast simulator.

Third, may methods are often extremely brittle with respect to their hyper-parameters, and they often have so much hyper-parameters need to be tuned. It means we need carefully tuning the parameters, most important, they often suck to local optimal. In many cases they fail to find a reward signal, even when the reward signal is relatively dense, they still fail to find the optimal solution, so often the case we need handcraft the reward function, some researcher design such a complex reward function for each environment they want to solve [Guo, 2017].

In this paper, we propose a different approach to deal with complex tasks with deep reinforcement learning. Although using RNN structure in reinforcement learning problem is not special [Song et al., 2018][Kapturowski et al., 2018]. But, not much effort have been used on combine basic RNN architectures with different brain inspired mechanisms

We investigate a deep-learning approach to learning the representation of states in partially observable tasks, with minimal prior knowledge of the domain. In particular, we propose a new family of hybrid models that combines the strength of both supervised learning and reinforcement learning, training in a joint fashion: The supervised learning component can be a recurrent neural network (RNN) combine with a different head, providing an effective way of learning the representation of hidden states. The RL components a soft actor-critic [Haarnoja et al., 2018a] that learn to optimize the control for maximizing long-term rewards. Furthermore, we design a model together with curiosity

*equal contribution
bond, which leads to better representation and exploration. Extensive experiments on both POMDP and MDP process demonstrate the effectiveness and advantages of the proposed approach, which performs the best among a set of previous state-of-the-art methods.

- First, we employ recurrent neural networks and GRU models to learn the representation of the state for RL. Since these recurrent models can aggregate partial information in the past, and can capture long-term dependencies in the sequence information, their performance is expected to superior to the contextual-window-based approach, which was used in the DQN model of [Mnih et al., 2015].
- Second, in order to best leverage supervision signals in the training data, the proposed hybrid approach combines the strength of both supervised learning and RL. In particular, the model in our hybrid approach is jointly learned using stochastic gradient descent (SGD): in each iteration, the representation of hidden states is first inferred using supervision signals (i.e., next observation and reward) in the training data; then, the Q-function is updated using the SAC that takes the learned hidden states as input. The superiority of the hybrid approach is validated in extensive experiments on a benchmark dataset.
- Third, by jointly training on model and RL algorithm we can get a good representation to capture the underline state, which means we can change the POMDP process to the MDP process.
- Last, to avoid local optimal and encourage our agent to explore more, we add curiosity bond to standard RL objection, which means we use both internal reward and external reward, have a separate reward signal could make our agent capture the reward more easily can find the optimal solution.

2 BACKGROUND

2.1 POMDP

Our problem is searching an optimal policy which maximize our accumulate future reward in Partially Observable Markov Decision Process (POMDP) defined by the tuple $(S, A, P, R, \Omega, O)$ [Hafer et al., 2018]. On the contrary the underlying Markov Decision Process (MDP) is given by tuple $(S, A, P, R)$.

- $S$ represent a set of states
- $A$ represent a set of actions,
- $P : S \times A \to \mathcal{P}(S)$ stand for the transition function which maps state-actions to probability distributions over next states $P(s'|s, a)$
- $R : S \times A \times S \to \mathbb{R}$ correspond to the reward function, with $r_t = R(s_t, a_t, s_{t+1})$
- $\Omega$ gives a of observations potentially received by the agent
- $O$ is the observation function mapping (unobserved) states to probability distributions over observations.

Within this framework, the agent acting in the environment according to $a \in A$, the environment changes to a new state following $s' \sim P(\cdot|s, a)$. Next, an observation $o \in O$ and reward $r \sim R(s, a)$ are received by the agent, where the observation may only contain partial information about the underlying state $s \in S$. Thus we additionally defined an Inference model as $q(s_t|o_{\leq t}, a_{< t}) = q(s_t|s_{t-1}, a_{t-1}, o_t)$.

Although there are many approaches suitable for POMDP process, we focus on using recurrent neural networks (RNNs) with back propagation through time (BPTT) to learn a representation that disambiguates the true state of the POMDP. The Deep Q-Network agent (DQN) [Mnih et al., 2015] learns to play games from the Atari-57 benchmark by using frame-stacking of 4 consecutive frames as observations, and training a convolutional network to represent a value function with Q-learning, from data continuously collected in a replay buffer. Other algorithms like the A3C, use an LSTM and are trained directly on the online stream of experience without using a replay buffer. In paper [Song et al., 2018] combined DDPG with an LSTM by storing sequences in replay and initializing the recurrent state to zero during training.

2.2 ENTROPY-REGULARIZED REINFORCEMENT LEARNING

The key idea in reinforcement learning is finding a policy which can maximizes expected future return which we can purposed as in Equation 2:

$$P(\tau|\pi) = \rho_0(s_0) \prod_{t=0}^{T-1} P(s_{t+1}|s_t, a_t) \pi(a_t|s_t)$$ (1)
\[ J(\pi) = \int_{\tau} P(\tau | \pi) R(\tau) = \mathbb{E}_{\tau \sim \pi} [R(\tau)] \]  

Instead of maximizing \( J(\pi) \) directly, we will use a maximum entropy objective [Ziebart, 2010], which is more preferred with stochastic policies by strengthening the objective. With in entropy-regularized framework, along with environment reward our agent gets a bonus reward proportional to the entropy of the policy at each time-step as well. This changes the RL problem to:

\[
\pi^* = \arg \max_{\pi} \mathbb{E}_{\tau \sim \pi} \left[ \sum_{t=0}^{\infty} \gamma^t \left( R(s_t, a_t, s_{t+1}) + \alpha H(\pi(\cdot|s_t)) \right) \bigg| s_0 = s \right]
\]  

(3)

The temperature parameter \( \alpha \) making trade-off between the importance of the entropy term against the environment’s reward. When \( \alpha \) is large, the entropy bonuses play an important role in reward, so the the policy will tend to have larger entropy, which mean the policy will be more stochastic, on the contrary, if \( \alpha \) become smaller, the policy will become more deterministic. It’s obvious we should define a slightly-different value functions in this setting. Now \( V^\pi \) should be changed to include the entropy bonuses as below:

\[
V^\pi(s) = \mathbb{E}_{\tau \sim \pi} \left[ \sum_{t=0}^{\infty} \gamma^t \left( R(s_t, a_t, s_{t+1}) + \alpha H(\pi(\cdot|s_t)) \right) \bigg| s_0 = s \right]
\]  

(4)

And \( Q^\pi \) has to be modified to contain the entropy bonuses as well:

\[
Q^\pi(s, a) = \mathbb{E}_{\tau \sim \pi} \left[ \sum_{t=0}^{\infty} \gamma^t R(s_t, a_t, s_{t+1}) + \alpha \sum_{t=1}^{\infty} \gamma^t H(\pi(\cdot|s_t)) \bigg| s_0 = s, a_0 = a \right]
\]  

(5)

With equation (4)(5), we can draw the connection between \( V^\pi \) and \( Q^\pi \) as:

\[
V^\pi(s) = \mathbb{E}_{a \sim \pi} \left[ Q^\pi(s, a) + \alpha H(\pi(\cdot|s)) \right]
\]  

(6)

Meanwhile, the Bellman equation for \( Q^\pi \) is changing to:

\[
Q^\pi(s, a) = \mathbb{E}_{s' \sim P^\pi, a' \sim \pi} \left[ R(s, a, s') + \gamma \left( Q^\pi(s', a') + \alpha H(\pi(\cdot|s')) \right) \right]
\]  

(7)

\[
= \mathbb{E}_{s' \sim P^\pi} \left[ R(s, a, s') + \gamma V^\pi(s') \right]
\]  

(8)

3 METHOD

Inspired by our brain [Kennedy, 2006], we purposed there are five key elements for intelligence, so-called: Prediction, Curiosity, Intuition, Memory, Inference. In the real world, the full state is rarely observed by the agent. In other words, the Markov property rarely holds in real-world environments and the tasks are often featured incomplete and noisy state information resulting from partial observability. So we reproduce these behaviors within deep learning framework by an RNN based architecture. The structure of our agent contains three parts: RNN, Model head, Intuition head, each part have different role. We use RNN for inference and memory, which means learning \( q(s_t|o_{<t}, a_{<t}) \), as we only will provide \( o_t, a_{t-1} \) as time-step \( t \) instead of \( o_{<t}, a_{<t} \) so it is crucial for RNN store passed information into a hidden state \( s_{t-1} \), we call this process as inference, most important the \( s_t \) both mean hidden state in RNN and it is the state we will use as the input of our RL algorithm. It is hard to say the \( s_t \) is the "true" state which follows MDP property, but we will push the \( s_t \) toward the "true" state by jointly optimize with intuition head and model head(we will discuss future in session 3.4)
The main idea of the model-head is to provide a prediction of future and use the predicted error as curiosity bond. As we all know the understanding and perception of the future is fundamental to human, by putting a model in our agent we can get a better representation of state and avoid stack into local optimal.

As for intuition head, the key function is decision making, we achieve the by using SAC, which based on the actor-critic framework and uses entropy regularization, but we combine the original algorithm with our framework which means it can adapt to the POMDP process having a model and internal reward.

![Overall architecture of our RMC agent](image)

Figure 1: Overall architecture of our RMC agent, there are three main part: RNN, Model head, Intuition head. The RNN cell inference current state from previous state (Memory) and current observation. Model head finish the job of Prediction, curiosity. Intuition head have two sub-head, value head and policy head.

### 3.1 RNN

#### 3.1.1 INFERENCE AND MEMORY

The main function of RNN is providing memory and inference. Due to POMDP process, we can’t use observation at step \( t \) directly to make decision or make prediction, so we need an inference model to encode observation, action to state.

\[
p(s_t | o_{\leq t}, a_{<t}) \Rightarrow p(s_t | s_{t-1}, a_t, s_{t-1})
\]  

(9)

Since the model is non-linear, we cannot directly compute the state posteriors that are needed for parameter learning, but we can optimize the function approximator by backup losses through the RNN cell. Gradients coming from the policy head are blocked and only gradients originating from the Q-network head and model head are allowed to back-propagate into the RNN. We block gradients from the policy head for increased stability, as this avoids positive feedback loops between \( \pi \) and \( q_i \) caused by shared representations.

We will future discuss the choice of backup value loss and model loss in session 3.4. In a word, training RNN with model and value function jointly captures a better representation for state.

#### 3.1.2 INITIALIZE STRATEGY

In order to achieve good performance in a partially observed environment, an RL agent requires a state representation that encodes information about its state-action trajectory in addition to its current observation. The most common way to achieve this is by using an RNN, as part of the agent’s state encoding. To train an RNN from replay and enable it to learn meaningful long-term dependencies, whole state-action trajectories need to be stored in replay and used for training the network. Recent work [Kapturowski et al., 2018] compared four strategies of training an RNN from replayed experience:

- **Zero initialize**: Using a zero start state to initialize the network at the beginning of sampled sequences.
- **Trajectory replay**: Replaying whole episode trajectories.
- **Stored state**: Storing the recurrent state in replay and using it to initialize the network at training time.
- **Burn-in**: Allow the network a ‘burn-in period’ by using a portion of the replay sequence only for unrolling the network and producing a start state, and update the network only on the remaining part of the sequence.
The zero start state strategy’s appeal lies in its simplicity and it allows independent decorrelated sampling of relatively short sequences, which is important for robust optimization of a neural network. On the other hand, it forces the RNN to learn to recover meaningful predictions from an atypical initial recurrent state, which may limit its ability to fully rely on its recurrent state and learn to exploit long temporal correlations. The second strategy, on the other hand, avoids the problem of finding a suitable initial state, but creates a number of practical, computational, and algorithmic issues due to varying and potentially environment-dependent sequence length, and higher variance of network updates because of the highly correlated nature of states in a trajectory when compared to training on randomly sampled batches of experience tuples. [Hausknecht and Stone, 2015] observed little difference between the two strategies for empirical agent performance on a set of Atari games, and therefore opted for the simpler zero start state strategy. One possible explanation for this is that in some cases, an RNN tends to converge to a more ‘typical’ state if allowed a certain number of ‘burn-in’ steps, and so recovers from a bad initial recurrent state on a sufficiently long sequence. We also hypothesize that while the zero start state strategy may suffice in the most fully observable Atari domain, it prevents a recurrent network from learning actual long-term dependencies in more memory-critical domains.

Empirically, this translates into noticeable performance improvements, as the only difference between the pure zero state and the burn-in strategy lies in the fact that the latter unrolls the network over a prefix of states on which the network does not receive updates. The beneficial effect of burn-in lies in the fact that it prevents ‘destructive updates’ to the RNN parameters resulting from highly inaccurate initial outputs on the first few time steps after a zero state initialization. The stored state strategy, on the other hand, proves to be overall much more effective at mitigating state staleness in terms of the Q-value discrepancy, which also leads to clearer and more consistent improvements in empirical performance.

In all our experiments we will be using the proposed agent architecture with replay sequences of length \( l_{\text{train}} = 15 \), with an optional burn-in prefix of \( l_{\text{burn-in}} = 10 \).

### 3.2 MODEL LEARNING (MODEL HEAD)

#### 3.2.1 PREDICTION

Humans have a powerful mental model, when it comes to decision making, although we never doing calculating before every action we take. We knowing the result of our behaviours While the role of the intuition head is to compress what the agent observed at each time frame, we also want to compress what will happens in the future. For this purpose, the role of the model is to predict the future. The model head serves as a predictive model of the future state.

The transition dynamics is \( s' \sim P(s'\mid s, a) \) here we use an function approximator modeled with a feed-forward neural network \( s_{t+1} = \hat{f}_\psi(s_t, a_t) \) to capture the latent dynamic. We predict the change in state \( s_{t+1} - s_t \) given a state \( s_t \) and an action \( a_t \) as inputs. This relieves the neural network from memorizing the input state, especially when the change is small [Kurutach et al., 2018]. Instead of using the \( L_2 \) one-step prediction loss as model loss, here we use \( L_1 \) loss as proposed in [Luo et al., 2018], which also shown to out perform \( L_2 \) loss by our experimental result

\[
L(\psi) = \frac{1}{|D|} \sum_{(s_t,a_t,s_{t+1} \in D)} \|s_{t+1} - \hat{f}_\psi(s_t, a_t)\|_2
\]  

#### 3.2.2 CURIOSITY

There are many types of couriers, but the most fundamental one is the curiosity for things we can’t predict correctly [Loewenstein, 1994], seek a good a model to predict future is almost the origin for science, so it’s an obvious idea we can let our agent predict the future and use the predict error as curiosity bond \( r^i_t = \hat{s}_t - s_t \), or so called curiosity-driven intrinsic reward signal.

In addition to intrinsic rewards, the agent optionally may also receive some extrinsic reward from the environment. Let the intrinsic curiosity reward generated by the agent at time \( t \) be \( r^i_t \) and the extrinsic reward be \( r^e_t \). The policy sub-system is trained to maximize the sum of these two rewards

\[
R(s_t, a_t, s_{t+1}) = \beta \cdot r^i_t + r^e_t \Rightarrow r_t = r^i_t + r^e_t
\]  

In practice we use a parameter \( \beta \) to represent the strength of intrinsic reward, as the learning process continuous, model loss should decay to zero, but this is often not the case, due to the complex environment dynamic, it’s really hard to make perfect prediction if possible. But we can’t let our agent seeding some state all the time, thus we need to decay \( \beta \) to make sure we can have a good policy.
Algorithm 1: RMC AGENT

Input: Initial policy parameters $\theta$
Transition model parameter $\psi$
Q-function parameters $\phi_1$, $\phi_2$
Temperature $\alpha$
Empty replay buffer $D$

1. Set target parameters equal to main parameters $\overline{\theta} \leftarrow \theta$, $\overline{\phi}_1 \leftarrow \phi_1$, $\overline{\phi}_2 \leftarrow \phi_2$
2. while not converge do
   for each environment step do
      $a_t \sim \pi_\theta(a_t|s_t)$ // Sample action from the policy
      $s_{t+1} \sim p(s_{t+1}|s_t, a_t)$ // Sample transition from the environment
      $D \leftarrow \cup \{(o_t, s_t, a_t, r(s_t, a_t), o_{t+1}, s_{t+1})\}$ // Store the transition in the replay pool
   end
   for each gradient step do
      $\{(s, a, r, s', d)\}_{i=1}^B \sim D$ // Randomly sample a batch of transitions
      Compute model loss $L(\psi)$ from equation (10)
      $\psi \leftarrow \psi - \lambda_\psi \nabla_\psi L(\psi)$ // Update model parameter
     Compute value loss $L(\phi)$ from equation (14)
      $\phi \leftarrow \phi - \lambda_\phi \nabla_\phi L(\phi)$ // Update value parameter
      Compute policy loss $L(\theta)$ from equation (19)
      $\theta \leftarrow \theta - \lambda_\theta \nabla_\theta L(\theta)$ // Update policy parameter
      Compute temperature loss $L(\alpha)$ from equation (21)
      $\alpha \leftarrow \alpha - \lambda_\alpha \nabla_\alpha L(\alpha)$ // Update temperature parameter
      $\overline{\phi}_i \leftarrow \rho \overline{\phi}_i + (1 - \rho)\phi_i$, for $i \in \{1, 2\}$ // Update target network weights
   end
3.3 INTUITION HEAD

Function approximators is used for both the soft Q-function and the policy. Instead of running evaluation and improvement to convergence, we alternate between optimizing both networks with stochastic gradient descent. We will consider two parameterized soft Q-function $Q_{\phi_1}$, $Q_{\phi_2}$ and a tractable policy $\pi_\theta$. The parameters of these networks are $\phi$ and $\theta$.

3.3.1 LEARNING Q-FUNCTIONS

The Q-functions are learned by MSBE minimization, using a target value network to form the Bellman backups. They both use the same target, like in TD3, and have loss functions:

$$L(\phi_i, D) = \mathbb{E}_{(s, a, r, s', d) \sim D} \left[ (Q_{\phi_i}(s, a) - (r + \gamma(1 - d)V_{\phi_{\text{targ}}}(s')))^2 \right]$$ (12)

As for target value network, we can obtain it by polyak averaging the value network parameters over the course of training. It not hard to rewrite the connection equation between value function and Q-function as follows:
The value function is implicitly parameterized through the soft Q-function parameters via Equation 14. We use clipped double-Q like TD3 [Fujimoto et al., 2018] and SAC [Haarnoja et al., 2018a] for expressing the TD target, and takes the minimum Q-value between the two approximators. So the loss for Q-function parameters is:

$$L(\phi_i, D) = E_{s \sim D} \left[ Q_{\phi_i}(s, a) - \left( r + (1 - d)(\min_{i=1,2} Q_{\phi_i}(s, a)) - \alpha \log \pi(a|s) \right) \right]^2$$

(15)

The update makes use of a target soft Q-function, that are obtained as an exponentially moving average of the soft Q-function weights, which has been shown to stabilize training. Importantly, we do not use actions from the replay buffer here: these actions are sampled fresh from the current version of the policy.

### 3.3.2 LEARNING THE POLICY

The policy should, in each state, act to maximize the expected future return plus expected future entropy. That is, it should maximize

$$V^\pi(s) = E_{a \sim \pi} [Q^\pi(s, a) + \alpha H(\pi(a|s))]$$

(13)

$$= E_{a \sim \pi} [Q^\pi(s, a) - \alpha \log \pi(a|s)]$$

(14)

The target density is the Q-function, which is represented by a neural network and can be differentiated, and it is thus convenient to apply the reparameterization trick instead, resulting in a lower variance estimate, in which a sample from $\pi_\theta(a|s)$ is drawn by computing a deterministic function of state, policy parameters, and independent noise. Following the authors of the SAC paper [Haarnoja et al., 2018b], we use a squashed Gaussian policy, which means that samples are obtained according to

$$\tilde{a}_\theta(s, \xi) = \tanh (\mu_\theta(s) + \sigma_\theta(s) \odot \xi), \quad \xi \sim \mathcal{N}(0, I)$$

(17)

The reparameterization trick allows us to rewrite the expectation over actions (which contains a pain point: the distribution depends on the policy parameters) into an expectation over noise (which removes the pain point: the distribution now has no dependence on parameters):

$$E_{a \sim \pi} [Q^\pi(s, a) - \alpha \log \pi(a|s)] = E_{\xi \sim \mathcal{N}} [Q^\pi(s, \tilde{a}_\theta(s, \xi)) - \alpha \log \pi_\theta(\tilde{a}_\theta(s, \xi)|s)]$$

(18)

To get the policy loss, the final step is that we need to substitute $Q^\pi$ with one of our function approximators. The same as in TD3, we use $Q_{\phi_1}$. The policy is thus optimized according to

$$L(\theta) = E_{\xi \sim \mathcal{N}} [Q_{\phi_1}(s, \tilde{a}_\theta(s, \xi)) - \alpha \log \pi_\theta(\tilde{a}_\theta(s, \xi)|s)]$$

(19)

### 3.3.3 LEARNING $\alpha$

As it proposed in [Haarnoja et al., 2018b], for the purpose of improving performance, we lean the temporal parameter $\alpha$ by minimizing the dual objective as well:

$$\alpha^*_T = \arg\min_{\alpha_T} E_{a_t \sim \pi^*_T} [-\alpha_T \log (\pi^*_T(\alpha_T|s_T; \alpha_T)) - \alpha_T H]$$

(20)
Prior give us tools to achieve this, as shown in 
[Boyd and Vandenberghe, 2004], approximating dual gradient descent is a way to achieve that. Because we use a function approximator and it is impractical to optimizing with respect to the primal variables fully, we compute gradients for $\alpha$ with the following objective:

$$L(\alpha) = E_{a \sim \pi_t} \left[ -\alpha \log \pi_t(a_t | s_t) - \alpha H \right]$$  \hspace{1cm} (21)

The final algorithm is listed in Algorithm[1]. The method alternates between collecting experience from the environment with the current policy and updating the function approximators using the stochastic gradients from batches sampled from a replay pool. Using off-policy data from a replay pool is feasible because both value estimators and the policy can be trained entirely on off-policy data. The algorithm is agnostic to the parameterization of the policy, as long as it can be evaluated for any arbitrary state-action tuple.

### 3.4 BETTER REPRESENTATIONS

When we talk about parameters update, there are several options, first of all, there are three types of loss, and three are four kinds of networks, we list them with the update option in Table[1].

Table 1: Different update option for different head, Option means we can choose True or False, the first column list all the parameters on the contrary, the head of table list all the losses, there is no such called RNN loss, cause all the losses are coming from three heads, so the second column is all False, but how should we update RNN cell with losses coming from is undecided. We can choose different update option.

| Parameters \ loss | RNN | Model | Value | Policy |
|------------------|-----|-------|-------|--------|
| RNN              | False | Option | Option | Option |
| Model            | False | True  | False | False |
| Value            | False | False | True  | False |
| Policy           | False | False | False | True  |

It’s obvious we have to update each head according to their own loss, and it won’t make any sense if we back-propagate loss from one head to another head, thus our question become which part of loss should we back-propagate into RNN, in order to understand this question, in many prior papers they choose a method arbitrary, we will analyses different way to address this problem.

Gradient coming from the policy head are blocked and only gradients originating from the value head and model head are allowed to back-propagate into the RNN, We block gradients from the policy head for increased stability, as this avoids positive feedback loops between $\pi$ and $q_i$ caused by shared representations.

We hypothesise by jointly training on model loss and intuition loss, we can get a better representation, cause for POMDP, we sim to find a $s_t$ enough to predict next state, which is what we did by training RNN on model loss, Meanwhile we need a powerful intuition, and the state is correlate to value as well, so we can combine two parts and get a better representation, we further give the experimental result to prove our theory in session[4.3].

### 4 EXPERIMENT

In order to test our agent, We designed our experiments to answering the following questions:

1. Can RMCSAC be used to solve challenging continue control problems? How does our agent compare with other methods when applied to this problems, with regard to final performance, computation time, and sample complexity?
2. Can RMCSAC handling POMDP process, how well does it deal with the absence of information, and how well does it generalize.
3. We optimize RNN on model loss and intuition loss jointly, does this really help us improve performance.
4. We add curiosity bond and model head on our agent, does this parts give us a more powerful agent.

To answer (1) we compare the performance of our agent with other method in session[4.1] To answer (2) we purposed a modified mujoco environment so-called flicker mujoco, which follows the POMDP process, we will discuss the details.
of the environment and the experiment setting in session 4.2. With regard to (3)(4), we addressed ablation study on our algorithm in session 4.3 testing how does different update scheme and network design influenced the performance.

The results shows overall our agent outperform baseline with a large margin, both in terms of learning speed and the final performance. The quantitative results attained by our agent is our experiments also compare very favorably to results reported by other methods in prior work, indicating that both the sample efficiency and the final performance of our agent on these benchmark tasks exceeds the state of art.

### 4.1 MUJOCO

The goal of this experimental evaluation is to understand how the sample complexity and stability of our method compares with prior off-policy and on-policy deep reinforcement learning algorithms. We compare our method to prior techniques on a range of challenging continuous control tasks from the OpenAI gym benchmark suite. Although the easier tasks can be solved by a wide range of different algorithms, the more complex benchmarks, such as the 21-dimensional Humanoid, are exceptionally difficult to solve with off-policy algorithms. The stability of the algorithm also plays a large role in performance: easier tasks make it more practical to tune hyper-parameters to achieve good results, while the already narrow basins of effective hyper-parameters become prohibitively small for the more sensitive algorithms on the hardest benchmarks, leading to poor performance [Gu et al., 2016].

We compare our method to deep deterministic policy gradient (DDPG) [Lillicrap et al., 2015], an algorithm that is regarded as one of the; proximal policy optimization (PPO) [Schulman et al., 2017], a stable and effective on-policy policy gradient algorithm; and soft actor-critic (SAC) [Haarnoja et al., 2018a], a recent off-policy algorithm for learning maximum entropy policies. We additionally compare to twin delayed deep deterministic policy gradient algorithm (TD3) [Fujimoto et al., 2018].

We conducted the robotic locomotion experiments using the MuJoCo simulator [Todorov et al., 2012]. The states of the robots are their generalized positions and velocities, and the controls are joint torques. Under actuation, high dimensionality, and non-smooth dynamics due to contacts make these tasks very challenging. To allow for reproducible and fair comparison, we evaluate all the algorithm with similar network structure, for off-policy algorithm we use a two layer feed-forward neural network of 400 and 300 hidden nodes respectively, with rectified linear units (ReLU) between each layer for both the actor and critic, for on-policy algorithm we use a 64 hidden nodes feed-forward neural network, we use the parameters with is shown superior in prior work [Henderson et al., 2018] as the comparison of our agent. Both network parameters are updated using Adam [Kingma and Ba, 2014] with a learning rate of $10^{-4}$, with no modifications to the environment or reward.

Figure 2 compares five individual runs with both variants, initialized with different random seeds. RMCSAC performs much more better, shows that our agent significantly outperforms the baseline, indicating substantially better stability and stability. As evident from the figure, with jointly training and internal reward, we can achieve stable training. This becomes especially important with harder tasks, where tuning hyperparameters is challenging.

It shows our agent outperform other baseline method with a large marginal, indicate both the efficiency and stability of method is superior.

### 4.2 FLICKER MUJOCO

So now we need to test our agent on POMDP process, we establish a new environment called Flickering Mujoco, it change classic Mujoco benchmark to POMDP environment. such that at each time-step, the screen is either fully revealed or fully obscured with probability $p = 0.5$. Obscuring frames in this manner probabilistically induces an incomplete memory of observations needed for Mujoco to become a POMDP.

#### 4.2.1 RESULT

Now we face choices, previous works deal POMDP with deep network with a long history of observations but as a nature of RMC, we use a recurrent network trained with a single observation at each timestep. The results in this section show that our method outperform previous work [Wang et al., 2019].

As it is shown in Figure 2f. Our agent outperform standard SAC combine with frame stack, our agent performs well at this task even when given only one input frame per time-step. RMC successfully integrates information through time. Our agent are capable of integrating noisy single-frame information through time to detect events. Thus, given same length of history, the recurrent net can better adapt at evaluation time if the quality of observations changes.
Figure 2: (a) to (e) are the training curves on continuous control benchmarks, RMC agent performs consistently across all tasks and outperforms both on-policy and off-policy methods in the most challenging tasks. (f) shows the normalized score for training on Flicker mujoco with $p = 0.5$.

Figure 3: (a) When trained on normal games (MDPs) and then evaluated on flickering games (POMDPs), RMC performance degrades more gracefully than SAC. Each data point shows the average percentage of the original game score over all 5 games in Figure 2. (b) we testing six different update scheme on HalfCheetah-v2, it clearly shows update RNN on model loss, value loss and block policy loss get the best result. (c) with different $\beta$ the agent perform different when the beta is very small, it become hard to exploring for difference policy but if the beta is too large the policy is near random, right scale of beta could lead to fast and fruitful converge.
4.2.2 GENERALIZATION PERFORMANCE

We ask ourselves an interesting question: Can RMC agent which is trained on a standard MDP generalize to a POMDP at evaluation time? To answer this question, we evaluate RMC agent and SAC trained on standard mujoco over the flickering equivalents of all games. Figure 3a shows our agent captures more of its previous performance than SAC across all levels of flickering. We conclude that RMC have a certain degree of robustness against missing information, even trained with full state information.

4.3 ABLATION STUDY

4.3.1 THE IMPACT OF DIFFERENT TRAINING METHOD

As shown in Table 2, we have at most six different kinds of update scheme. Figure 3b shows how learning performance changes when the update schemes are changed. For scheme 4-6, the policy becomes nearly random, and consequently fails to exploit the reward signal, resulting in substantial degradation of performance. For scheme 2, the value function is enhanced with the capacity of RNN so the model learns quickly at first, but the policy then becomes nearly deterministic, leading to poor local minimal due to the lack of adequate exploration and worse state representation, as for scheme 3, due to the weak capacity of the value function, although the representation of the state maybe better, still it can not achieve awesome performance. With scheme 1, the model balance exploration and exploitation, model head make sure the state is good enough to predict next state, and push the POMDP process to MDP process by back-propagate model loss into RNN. At the same time, value head can adjust representation and achieve amazing capacity by jointly optimize RNN with model head. Just like our brain has two different kinds of thinking pattern, so-called intuition and reasoning, our agent can take advantage of joint optimization, by learning a representation of state from observation both for predict and decision making.

4.3.2 THE IMPACT OF CURIOSITY STRENGTH

Table 2: All valid update schemes

| scheme | Model | Value | Policy |
|--------|-------|-------|--------|
| 1      | True  | True  | False  |
| 2      | False | True  | False  |
| 3      | True  | False | False  |
| 4      | True  | True  | True   |
| 5      | True  | False | True   |
| 6      | False | True  | True   |

As we discuss in session 3, the model head can provide a prediction of the future in the meantime provide curiosity bond and a better representation, we already analyzed the influence of model update and shown that jointly training can improve performance, but how about curiosity part what if we only training jointly but set $\beta$ to zero(remove internal) To test the design of our algorithm, we choose update scheme 1, which has been shown to be superior in the previous experiment, and change the scale of $\beta$ As illustrate in figure 3c, when we set $\beta$ to zero, the model can’t explore well so both the sample efficiency and final score is obscured. If we use a huge $\beta$, the internal reward influenced the agent too much, so it’s hard to utilize external reward and the policy become nearly random.

Theoretical speaking, with the learning process going on and on the model loss will become smaller and smaller until zero, so beta won’t have much impact at the end, and all the different choices will lead to a similar final policy, but in practice due to the stochastic environment, the model loss almost never be zero, so we decay the $\beta$ from large to small, make our agent explore more at the beginning, and exploited more at the end, leading to fast learning at the beginning and stable learning at the end.

5 CONCLUSION

We found that the impact of RNN and jointly training goes beyond providing the an agent with memory. Instead, also serves a role not previously studied in RL, potentially by enabling better representation learning, and thereby improves performance even on domains that are fully observable and do not obviously require memory.

Empirically results show that RMCSAC outperforms state-of-the-art model-free deep RL methods, including the off-policy SAC algorithm and the on-policy PPO algorithm by a substantial margin. provide a promising avenue for improved robustness and stability. Meanwhile with the memory and inference functionality of our agent, we can solve POMDP problem as well, which shell light to real-world applications Further exploration including methods that incorporate stochastic transition function (e.g. deep plan net[Hafner et al., 2018], world model[Ha and Schmidhuber, 2018]) and more theoretic analyze.
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