[Re] Recurrent World Models Facilitate Policy Evolution

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A reference implementation of

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Introduction

Recently, Deep Reinforcement Learning (DRL) has achieved impressive results in a variety of domains, such as video game playing (Mnih et al. [11]) zero-sum games (Silver et al. [12]), and continuous control (Lillicrap et al. [10]). Still, DRL approaches are often brittle, sensitive to small changes in hyperparameters, implementation details and minor environment perturbations. Besides, training performance can widely vary from run to run. Those factors often make reproduction of experimental results challenging (Henderson et al. [6], Irpan [7]).

In addition to its sensitivity, DRL is also known to be sample inefficient, in the sense that it requires huge amounts of environment interactions to obtain good results, even for simple tasks. Model-based reinforcement learning has gained interest to improve sample efficiency. With an accurate and computationally cheap model of the world, the burden of collecting new samples could be considerably alleviated, since the model could, in principle, generate huge amounts of reliable samples, and be used for planning without interacting with the environment. Besides, features provided by a predictive model of the world could constitue relevant inputs to a controller, and ease the optimization process.

Ha and Schmidhuber [3] provided a simple, yet successful model-based reinforcement learning approach. It revolves around a three part model, comprised of:

1. A Variational Auto-Encoder (Kingma and Welling [9]), a generative model, which learns both an encoder and a decoder. The encoder's task is to compress the input images into a compact latent representation. The decoder's task is to recover the original image from the latent representation.
2. A Mixture-Density Recurrent Network (Graves [2]), trained to predict the latent encoding of the next frame given past latent encodings and actions. The mixture-density network outputs a Gaussian mixture for predicting the distribution density of the next latent variable.
3. A simple linear Controller. It takes as inputs both the latent encoding of the current frame and the hidden state of the MDN-RNN given past latents and actions and outputs an action. It is trained to maximize the cumulated reward using the Covariance-Matrix Adaptation Evolution-Strategy (Hansen [4]), a generic gradient-free black box optimization algorithm.

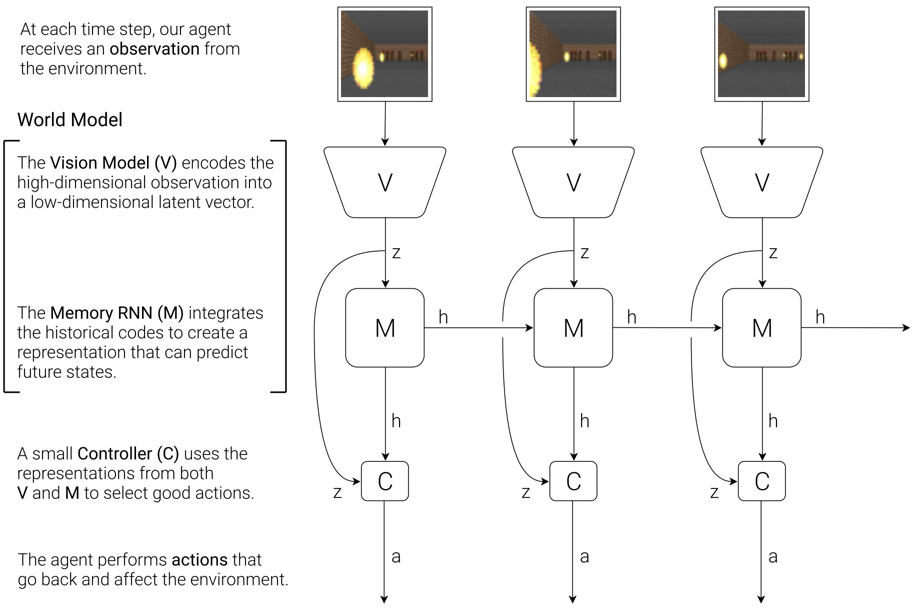


Figure 1: The three parts of the architecture (from the original paper)

On a given environment, the model is trained sequentially as follows:

1. Sample randomly generated rollouts from a well suited *random policy*.
2. Train the VAE on images drawn from the rollouts.
3. Train the MDN-RNN on the rollouts encoded using the encoder of the VAE. To reduce computational load, we trained the MDN-RNN on fixed size subsequences of the rollouts.
4. Train the controller while interacting with the environment using CMA-ES. At each time step, the controller takes as input both the encoded current frame and the recurrent state of the MDN-RNN, which contains information about all previous frames and actions.

Alternatively, if the MDN-RNN is good enough at modelling the environment, the controller can be trained directly on simulated rollouts in the dreamt environment.

Methods

Reproducibility of the original results

We reproduced the authors results on the CarRacing environment (Brockman et al. [1]). We only used the paper description, and took the same hyperparameters as the original paper, unless stated otherwise below, or originally unspecified. We did not use any original sources, and we did not contact the authors. The exact training procedure is detailled below.

Data generation

The original paper started by generating rollouts using a random policy interacting with the environment. The policy was not specified. In our experiments we tested two types of policies. The first policy generates independant standard normal actions at each step. The second policy generates actions according to a discretized brownian motion, with a discretization parameter of $\frac{1}{50}$. This means that each component of the action (the action is three dimensional) is generated as

$$a_{t+1}^k = a_t^k + \frac{1}{\sqrt{50}}\varepsilon_t^k$$

where the ε's are i.i.d. standard normal random variables. The data samples generated by the first policy lack diversity, and the car only moves in a very restricted area of the track. The samples generated by the second policy, on the other are much more diverse, and were consequently used for the next stages of training. The original paper generated 10,000 rollouts. For our replication, we generated 1,000 rollouts, to reduce the computational load.

Variational auto-encoder (VAE) training

The VAE is trained following the training procedure of the original paper, on the rollouts previously generated. The model is the same as the one detailled in the paper. The first 600 rollouts are used as a training set, and the next 400 as a validation set. The VAE is optimized using Adam (Kingma and Ba [8]) with default hyperparameters, learning rate 10^{-3}, $\beta_1 = 0.9$, $\beta_2 = 0.999$. Since the dataset is quite large, validation is perfomed each time a fifth of the dataset has been processed. Each step of validation is performed on 200 samples of the validation dataset. The learning rate is halved each time the validation performance has not improved for 5 consecutive evaluations. Training is stopped when the validation performance has not improved for 30 consecutive evaluations. Training was performed on a single Quadro GP100 GPU, with 16Go of RAM.

Mixture Density Recurrent Neural Network (MDN-RNN) training

Similarily the MDN-RNN is trained following the original paper procedure. The model is the same as the one detailled in the paper. The training splits are the same as for the VAE, and evaluations are also performed using the same schedule. The network is trained and validated on subrollouts of length 32. RMSprop (Tieleman and Hinton [13]) is used to optimize the MDN-RNN, with a learning rate 10^{-3}, and $\alpha = 0.9$. The learning rate schedule and early stopping policy of the VAE training are used without any modification. Training was performed on a single Quadro GP100 GPU, with 16Go of RAM.

Controller training with CMAES

Finally, the controller is trained using the Covariance Matrix Adaptation Evolution Strategy (Hansen [4]), using the python library pycma (Hansen, Akimoto, and Baudis [5]). As in the original paper, the controller is a linear network that takes as inputs the concatenation of the output of the VAE and the hidden layer of the MDN-RNN. For a set of parameters of the controller, the loss function is obtained by averaging the returns from 16 rollouts of length at most 1000. The population size used for CMAES is 64, and an initial standard deviation of 0.1 is used. Rollouts are executed parallelly, on 64 threads, with models sharing 8 V100 GPUs.

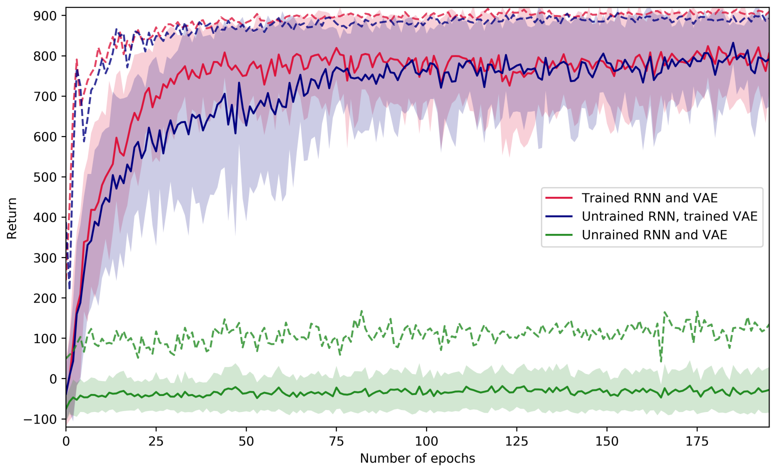
Results

Reproducibility

On the CarRacing-v0 environment, results were reproducible with relative ease. The model achieved good results on the first try, relatively to the usual reproducibility standards of deep reinforcement learning algorithms (Irpan [7], Henderson et al. [6]). Our own implementation reached a best score of 895, below the 906 reported in the paper, but much better than the second best benchmark reported which is around 780. Results are further detailled in the tables and fig.??. Fig.?? displays the learning curves of CMAES in the three considered setups. Solid lines represent the mean performance and standard deviation of the population, while dashed line represent the maximal performance. At test time, we select the best performing element of the CMAES population.

Additional experiments

We wanted to test the impact of the MDN-RNN on the results. Indeed, we observed during training that the model was rapidly learning the easy part of the dynamic, but mostly failed to account for long term effects and multimodality.



In the original paper, the authors performed an ablation study, and compared their results with a model without the MDN-RNN. They obtained the following scores:

Method	Average score
Full World Models Ha and Schmidhuber [3]	906 ± 21
without MDN-RNN Ha and Schmidhuber [3]	632 ± 251

Still, we wanted to investigate this question even more. We also trained the controller, but with an untrained MDN-RNN instead of the trained one (we kept it at its random initialization values). Similarily, we tried training a controller with both an untrained MDN-RNN and an untrained VAE. Surprisingly, controllers trained with untrained recurrent models achieve results close to the values of the original controller, while controllers with both untrained VAE and MDN-RNN achieves very low performance.

Method	Average score
With a trained MDN-RNN	895 ± 79
With an untrained MDN-RNN	866 ± 69
With untrained MDN-RNN and VAE	131 ± 66

It seems that the training of the MDN-RNN does not significantly improve the performance. Our interpretation of this phenomenon is that even if the recurrent model is not able to predict the next state of the environment, its recurrent state still contains some crucial information on the environment dynamic. Without a recurrent model, first-order information such as the velocity of the car is absent from individual frames, and consequently from latent codes. Therefore, strategies learnt without the MDN-RNN cannot use such information. Even a random MDN-RNN still holds some useful temporal information, which is enough to learn a good strategy on this problem.

Conclusion

We reproduced the paper "World Models" on the CarRacing environment, and made some additional experiments. Overall, our conclusions are twofold:

- The results were easy to reproduce. It probably means that the method on this problem does not only achieve high perforance but is also very stable. This is an important remark for a deep reinforcement learning method.

- On the CarRacing-v0 environment, it seems that the recurrent network only serves as a recurrent reservoir, enabling access to crucial higher order information, such as velocity or acceleration. This observation needs some perspective, it comes with several interrogations and remarks:

  – (Ha et al. 2018) reports good results when training in the simulated environment on the VizDoom task. Without a trained recurrent forward model, we cannot expect to obtain such performance.
  – On CarRacing-v0, the untrained MDN-RNN already obtains near optimal results. Is the task sufficiently easy to alleviate the need for a good recurrent forward model?
  – Learning a good model of a high dimensional environment is hard. It is notably difficult to obtain coherent multi modal behaviors on long time ranges (i.e. predicting two futures, one where the next turn is a right turn, the other where it is a left turn). Visually, despite the latent gaussian mixture model, our model doesn't seem to overcome this difficulty. Is proper handling of multi modal behaviors key to leveraging the usefulness of a model of the world?

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