Model-Based RL

Reinforcement Learning

School of Data Science

University of Virginia

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Agenda

> Model-Free RL

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> World Models

Model Free vs. Model-Based

So far we have looked at model-free approaches

There was no transition model $\boxed{P(s_{t+1}|s_t, a_t)}$

Instead, we *sampled* next state by running action in environment:

$$\boxed{(s_t, a_t) \xrightarrow{\text{environment}} s_{t+1}, r_{t+1}}$$

Reminder about Model-Free RL

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In other cases, we ran a simulator

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In other cases, we ran a simulator

Of course, a simulator might use a model

But the RL agent doesn't know or learn the model

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> **Can’t plan ahead**: it is not possible to simulate rollouts and learn from them

> **Adaptability is challenging**: if environment / reward function changes, a lot of experience is required for learning

> **Lack of interpretability**: value functions and policies can be black boxes

Model-Based RL – General Strategy

Two parts:

1. Learn a **dynamics function** to model observed state transitions $\boxed{P(s_{t+1}|s_t, a_t)}$

2. Use model predictions to learn what **actions** to take (e.g., learn a policy)

Action Selection and Horizon

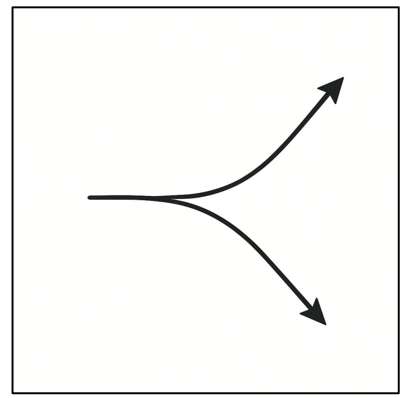
We can use model predictions to learn what **actions** to take

For example, our usual strategy is to maximize return (= expected total discounted reward)

Q: What horizon to use?

Infinite horizon won't work … prediction errors can compound

Instead, we use some planning horizon *H*



Action Selection with Finite Planning Horizon

1. Set planning horizon *H*

2. Generate *K* random action sequences each with length *H, denoted*

$$\mathbf{A}^{(k)} = (a_t^{(k)}, \ldots, a_{t+H-1}^{(k)})$$

3. Use the dynamics model f_θ to predict the future states after taking each action sequence

4. Evaluate the return associated with each candidate action sequence

5. Select the best action sequence

This method is called *random shooting*

Refinement to Action Selection: Replanning

Since our model is imperfect, we might have compounding errors as we plan into the future

We can adopt a *model predictive control* (MPC) approach:

1. At each time step, we perform random shooting or something else

2. Select the best H-step action sequence

3. Only take the first action from the sequence

4. Now replan at the next time step using updated state information

Refinement to Dynamics Model: Ensemble

We are using some model (e.g., a neural network) f_θ to predict the next state

A method for **potentially improving predictions** is to use a set of models $\{f_{\theta_n}\}_{n=1}^{N}$

These can be independently initialized

At inference time: For each candidate action sequence, generate *N* independent rollouts

Average the rewards of the rollouts to select the best sequence

Model-Based RL

Q: Given model-free RL limitations, why don’t we always use a model?

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Q: Given model-free RL limitations, why don't we always use a model?

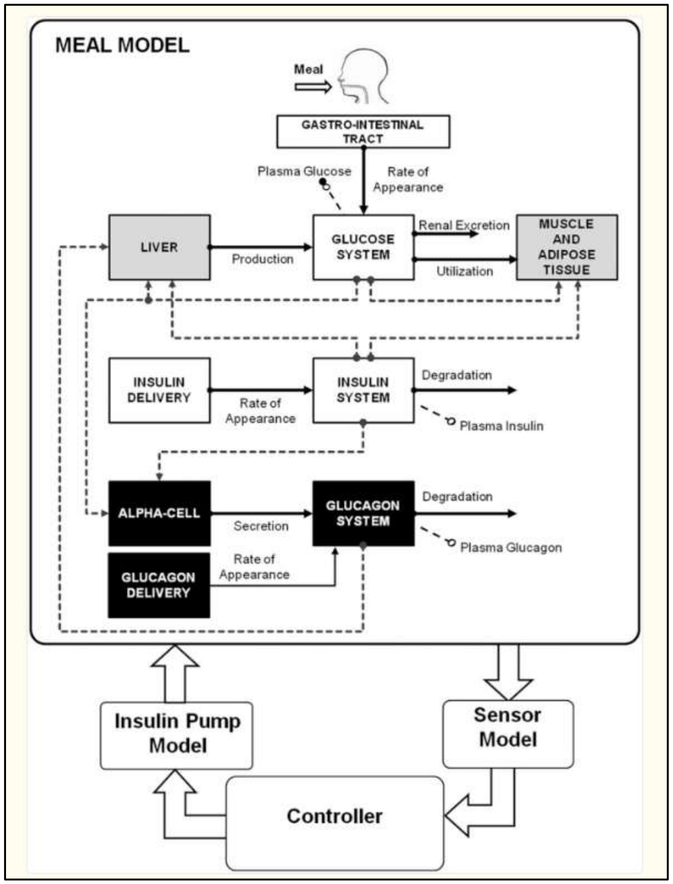
A: Because developing an accurate model can be hard.

$$x_1[k+1] = \theta_1 u[k-1] + \theta_2 u[k] + \theta_3 u[k+1] + \theta_4 x_1[k-1] + \theta_5 x_1[k] + \theta_6 x_2[k] + \theta_0$$

Individualization of pharmacological anemia management using reinforcement learning☆

Adam E. Gaweda[a,*], Mehmet K. Muezzinoglu[b], George R. Aronoff[a], Alfred A. Jacobs[a], Jacek M. Zurada[b], Michael E. Brier[a,c]

Model-Based RL: Diabetes Simulator



▸ J Diabetes Sci Technol. 2014 Jan;8(1):26–34. doi: 10.1177/1932296813514502

The UVA/PADOVA Type 1 Diabetes Simulator

New Features

Chiara Dalla Man [1], Francesco Micheletto [1], Dayu Lv [2], Marc Breton [2], Boris Kovatchev [2], Claudio Cobelli [1,✉]

The model of glucose kinetics is described by,

$$\begin{cases} \dot{G}_p = EGP - U_{ii} - k_1 \cdot G_p(t) + k_2 \cdot G_t(t) & G_p(0) = G_{pb} \\ \dot{G}_t = -U_{id}(t) + k_1 \cdot G_p(t) - k_2 \cdot G_t(t) & G_t(0) = G_{pb}\frac{k_1}{k_2} \end{cases}$$

World Models

World Models

A *world model* (David Ha, Jürgen Schmidhuber, 2018) is a learned model of the dynamics:

$$\boxed{(s_t, a_t) \rightarrow s_{t+1}, r_{t+1}}$$

Useful for:

> Predicting next state

> Planning

> Imagining possible futures without taking the actions in real environment.
Critical when it would be dangerous or costly to try the actions in real world.

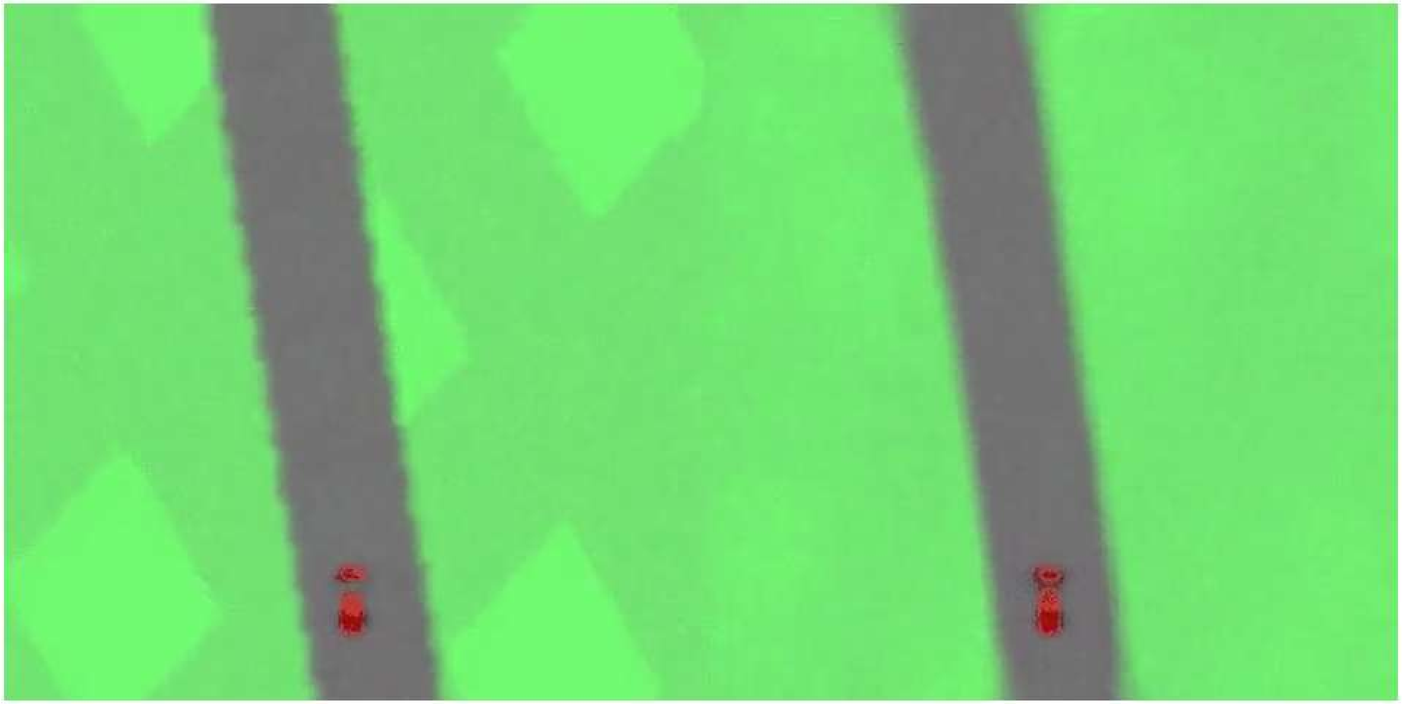
worldmodels.github.io

World Models – Classic Model

From Ha & Schmidhuber paper, architecture has three parts:

VAE (encoder)	Compress high-dim obs (e.g., images) into a low-dim latent space
MDN-RNN	Learn to predict next latent state, given current latent state, action
Controller	“Small” policy network that decides actions in latent space

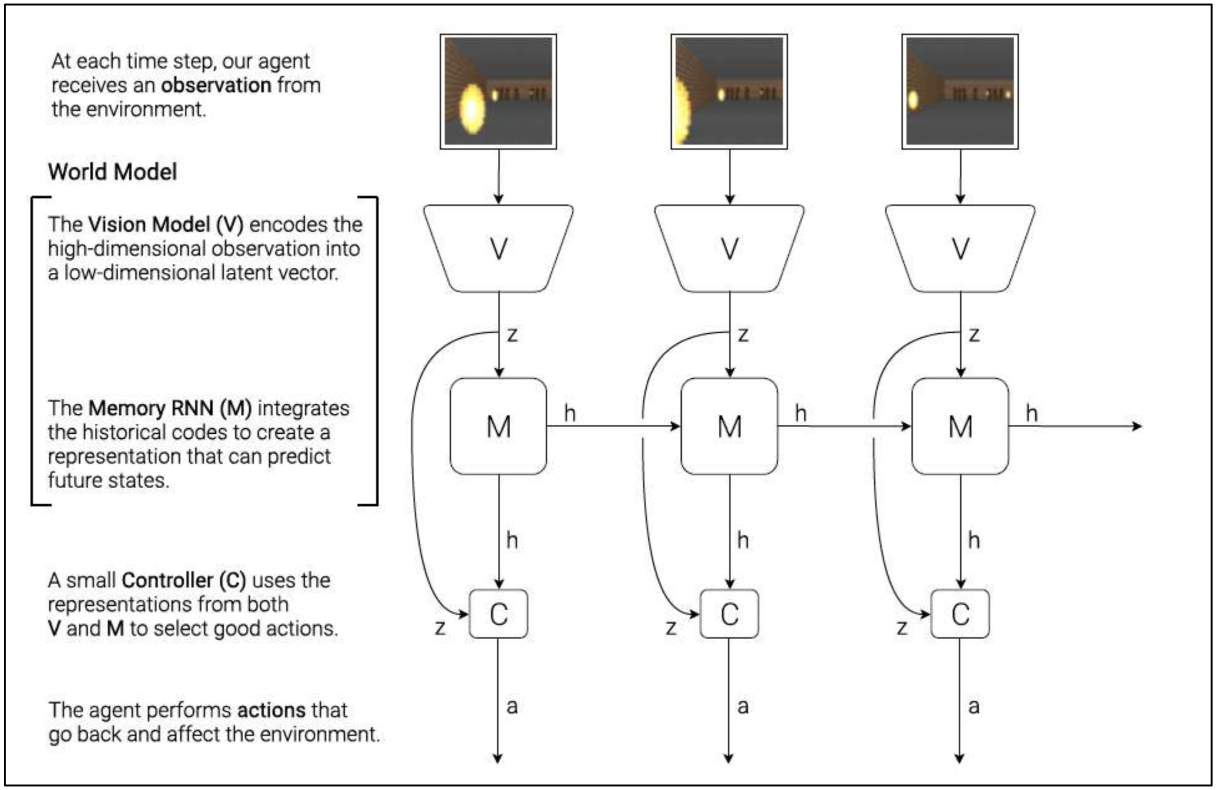
Car Racing Experiment - Image Encoding



Actual observations from the environment. What gets encoded into z_t.

World Model with Images

David Ha, Jürgen Schmidhuber, 2018



MDN-RNN

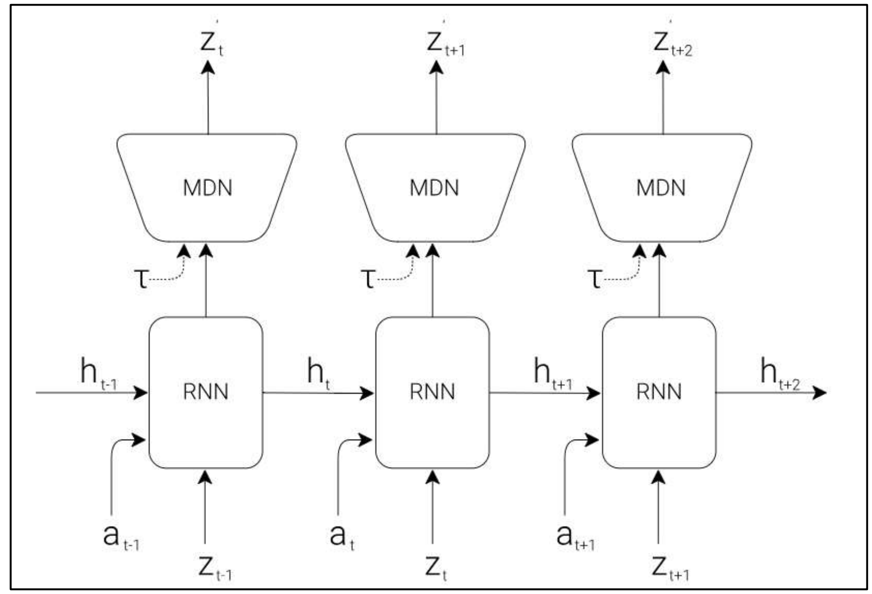
Predicts next latent state as density function $p(z)$

Approximated as mixture of Gaussians

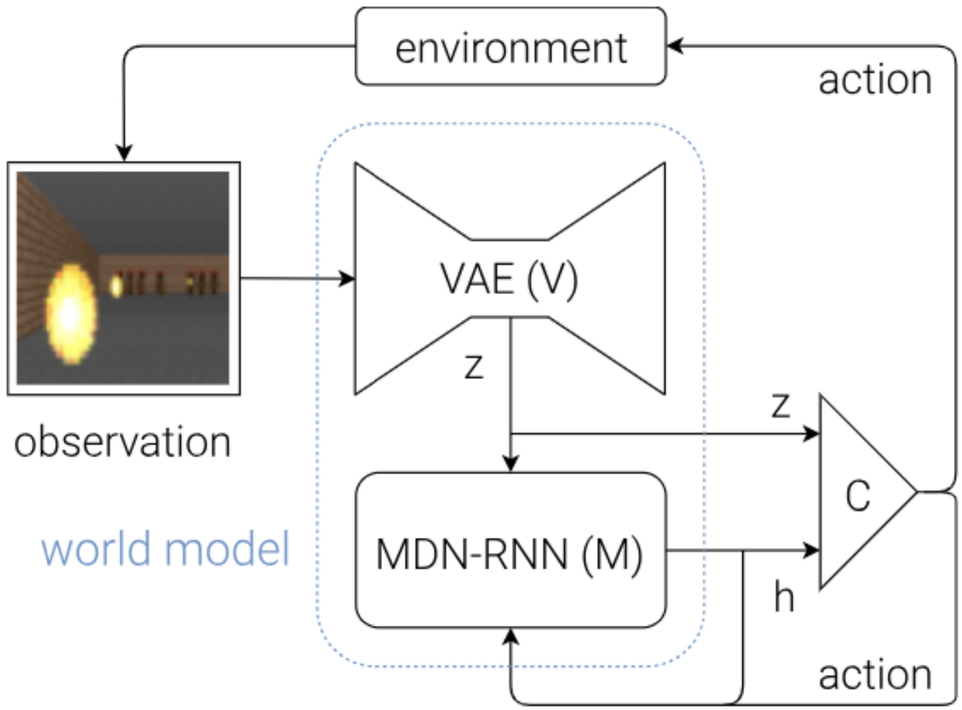
RNN used to model $P(z_{t+1} \mid a_t, z_t, h_t)$

where a_t denotes the action
h_t is the hidden state
τ is the *temperature* for controlling uncertainty

MDN component outputs parameters of mixture distn.



Putting the Pieces Together



Flow diagram of our Agent model. The raw observation is first processed by V at each time step t to produce z_t. The input into C is this latent vector z_t concatenated with M's hidden state h_t at each time step. C will then output an action vector a_t for motor control. M will then take the current z_t and action a_t as an input to update its own hidden state to produce h_{t+1} to be used at time $t+1$.

Car Racing Experiment - Procedure

1. Collect 10,000 rollouts from a random policy.
2. Train VAE (V) to encode each frame into a latent vector $z \in \mathcal{R}^{32}$.
3. Train MDN-RNN (M) to model $P(z_{t+1} \mid a_t, z_t, h_t)$.
4. Evolve Controller (C) to maximize the expected cumulative reward of a rollout.

Learning in a Dream

We have seen the procedure for training a simple policy to solve tasks

Can train the agent insides its “dream” environment

Then transfer policy back to actual environment

Explore the paper and interactive demo:

https://worldmodels.github.io/