UVA | SCHOOL of DATA SCIENCE

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:

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

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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> **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

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

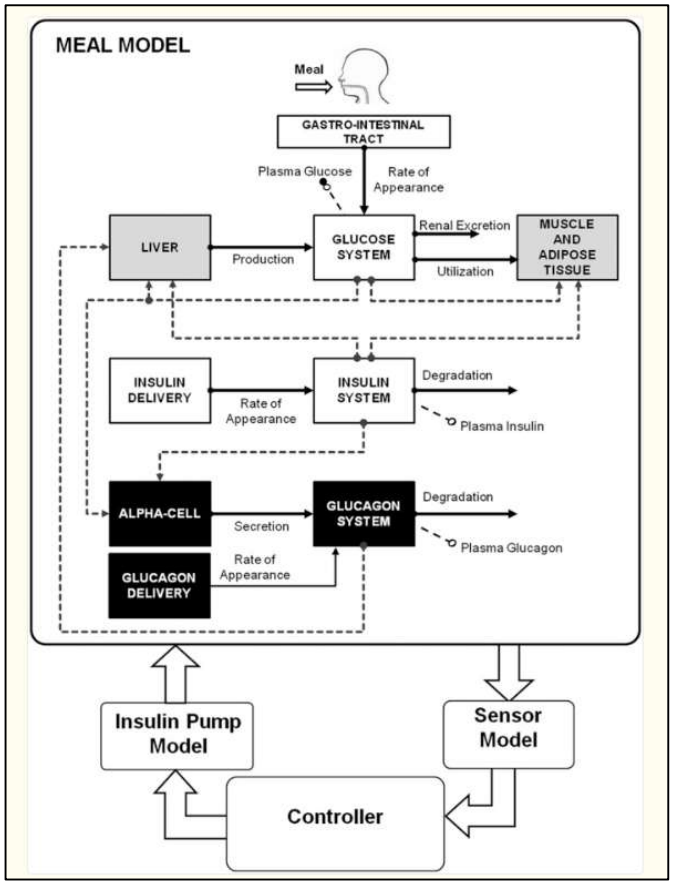
A: Because developing an accurate model can be hard.

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

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:

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

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.

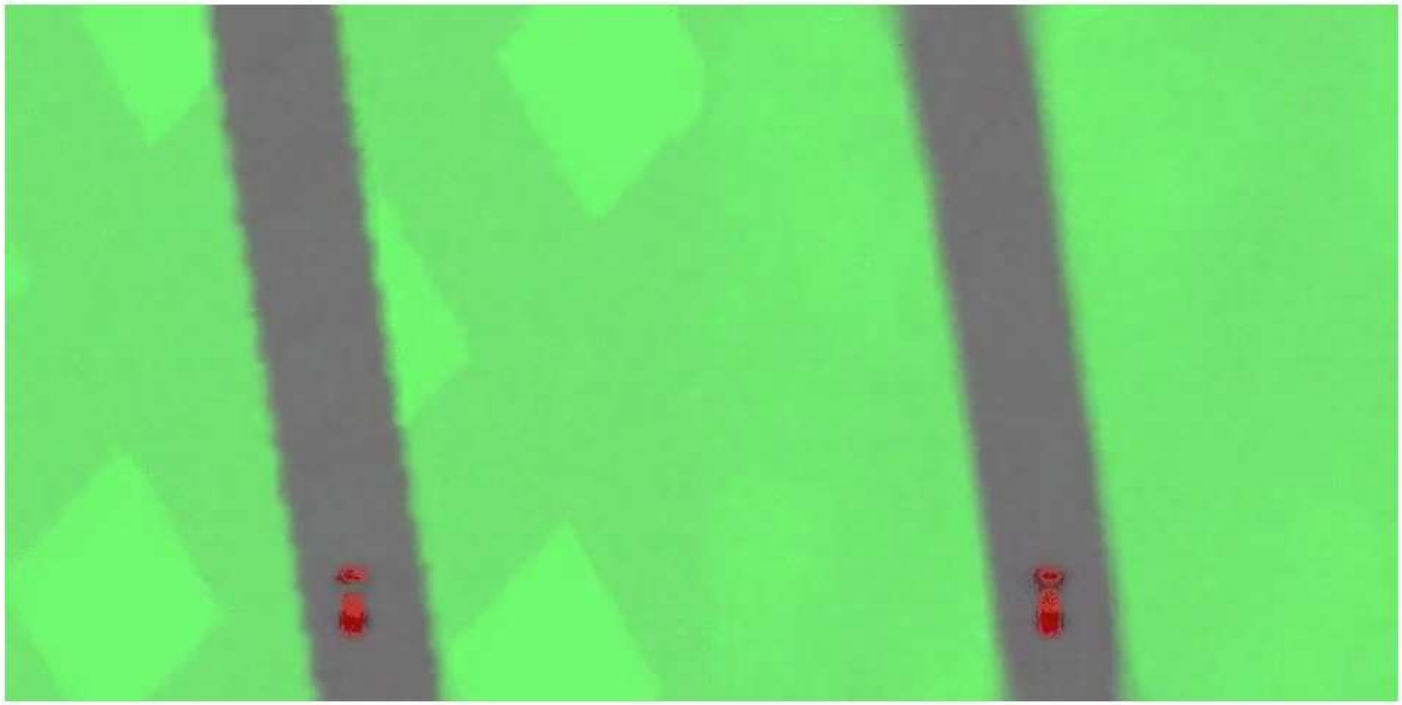
worldmodels.github.io

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

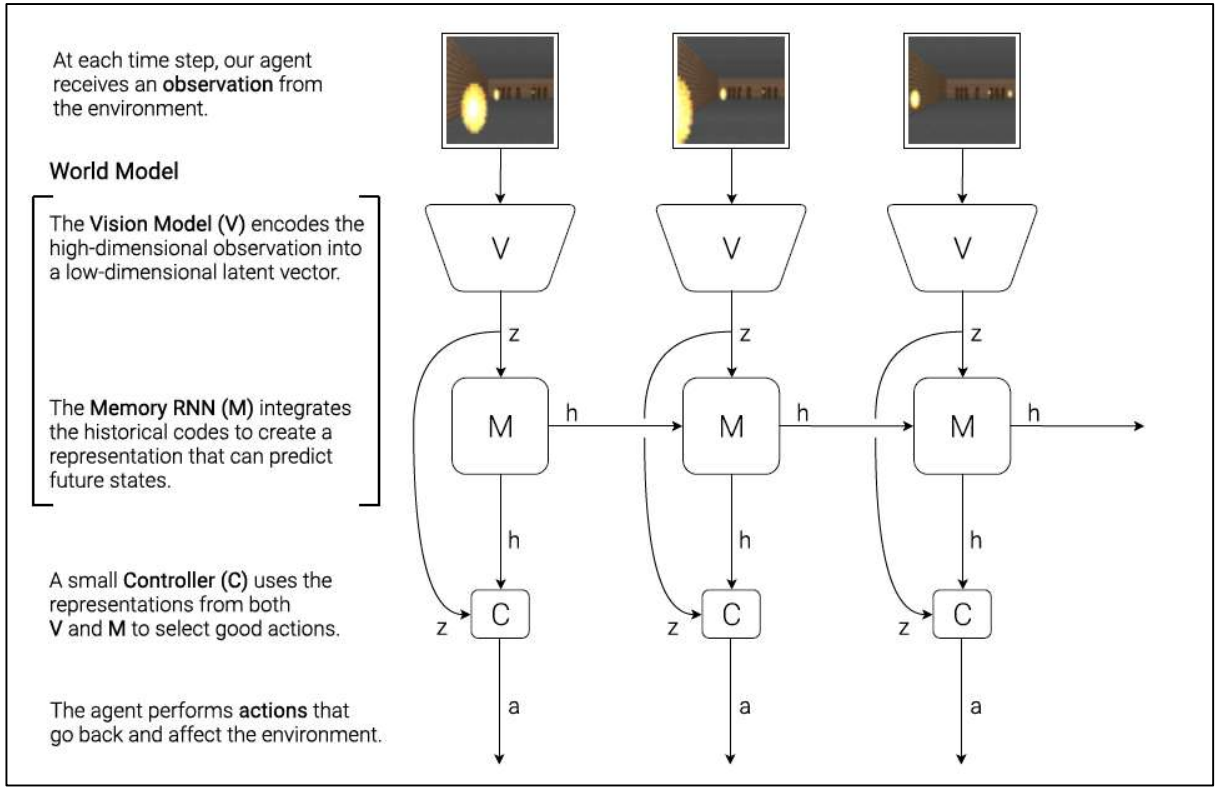


Actual observations from the environment.

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

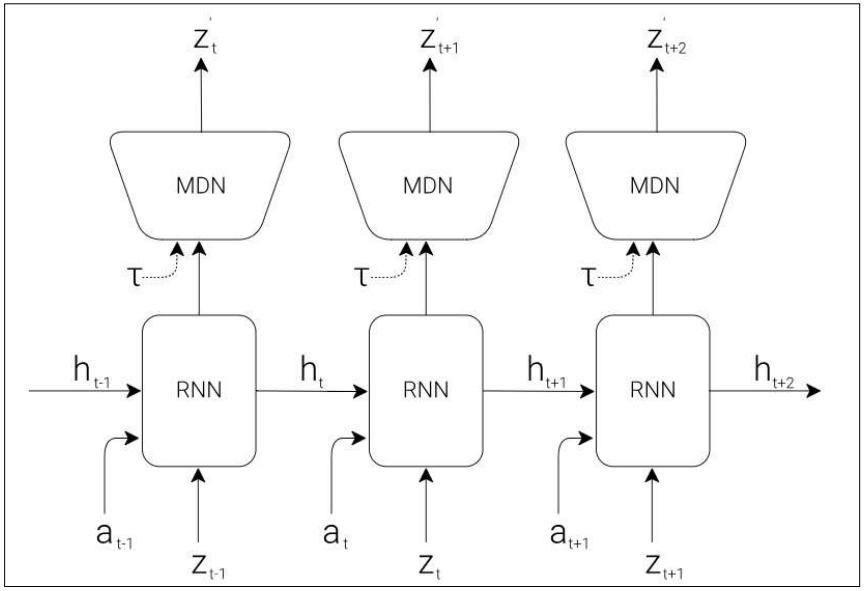
RNN used to model $P(z_{t+1} \mid a_t, z_t, h_t)$

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.



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/