# Reinforcement Learning

## Sample efficiency I: Model Based Reinforcement Learning (MBRL)

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# Motivation

# RL efficiency

- We usually distinguish between wall-clock efficiency (on-policy PPO) and sample efficiency (off-policy SAC)
- In benchmarks, we usually compare reward with respect to steps or episodes (experiences)
- In RL usually we need a lot of interactions with the environment (order of millions of steps) in order to learn
- When a simulator is available this is usually not a problem, but when interactions are in the real world, it is a problem
- This fact limits the application of RL to real cases

# Sample efficiency

- There can be a lot of reasons where a simulator is not used: Not reliable, not available, too slow, etc.
- Even in cases where simulator is available, it is desirable to learn as fast as possible
- So, we will focus in **sample efficient** methods, that is, methods that allow to learn with fewer interactions with the environment than standard RL algorithms (need less samples)
- Several ways to do that. We will focus today in Model based RL (MBRL) techniques.

# Model based Reinforcement Learning

- RL methods seen until now are **Model-free**
- Model-free methods do not need to previously know or explicitly learn transition probabilities ($P_{s,a}^{s'}$) and reward function ($R(s,a)$)
- Why not?
- Q-values and policies implicitly incorporate transition probabilities

$$\begin{aligned} Q(s,a) &= \mathbb{E}\left[r(s,a) + \gamma \cdot \arg\max_{a'} Q(s',a)\right] \\ &= r(s,a) + \gamma \sum_{s'} P_{s,a}^{s'} \cdot \arg\max_{a'} Q(s',a) \end{aligned}$$

- Also notice that *Experience Replay buffer* has information about transition $(s,a,r,s')$

# Model based Reinforcement Learning

- So, do we need models?
- Benefits of having a model of the world:
  - We can plan
  - We can learn from complete backups instead of samples
  - We can imagine trials and learn from them
  - We can reuse the info to other tasks in same environment
  - Help for Exploration
  - Speed to adapt to changing rewards
  - Speed to adapt to changing dynamics
  - ...
- Goal is sample efficiency

# Model based Reinforcement Learning

- Other reasons to use a model:
  1. To expensive or risky to use real world (f.i. robots)
  2. Simulating complex physical dynamics is too expensive
  3. When interacting with humans
  4. ...

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  4. ...
- So, questions:
  1. What is exactly a model?
  2. How can we learn a model?
  3. How can we take profit of a model?
  4. Which are the problems with models

# Model definition

# What is a model?

## Model Definition

A model is a representation that **explicitly** encodes knowledge about the structure of the environment and task:

- **A transition/dynamics model:**

$$s_{t+1} = f_s\left(s_t, a_t\right)$$

- **A model of rewards:**

$$r_{t+1} = f_r\left(s_t, a_t\right)$$

- In some cases: An inverse transition/dynamics model:

$$a_t = f_s^{-1}\left(s_t, s_{t+1}\right)$$

# What is a model?

- Sometimes we know the ground truth dynamics or rewards. Might as well use them!
- In general not known and **must be learnt**
- This is a supervised learning problem: given a dataset:

$$S_1, A_1 \rightarrow R_2, S_2$$
$$\vdots$$
$$S_{T-1}, A_{T-1} \rightarrow R_T, S_T$$

- learn applying any SL technique.

# About the input to the model

- How do we obtain the data?
  - Random movements before building the model
  - From a initial fixed policy?
  - From Experience Replay while learning?
- Problem of coverage of the dataset!
- RL is interactive, use data collected to improve the model

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- RL is interactive, use data collected to improve the model
- Representation? Guess!... Yes DNNs... but sometimes other approaches as bunch of equations (and determination of parameters) or Gaussian mixtures, etc.
- Remember that model is an approximation (and it can fail!)

# About the input to the model

- I know. I said state and action:

$$s_{t+1} = f_s(s_t, a_t)$$

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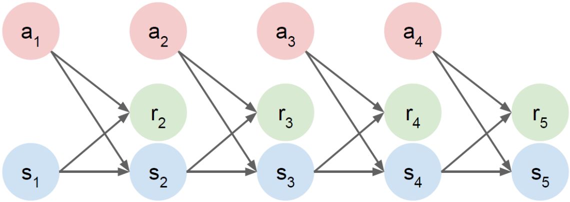
- ... but in some cases not possible or desirable
- Usually three options:
  - States
  - Observations
  - Latent States

# Input is state

- Usually we use a DNN to predict next state.

$$s_{t+1} = f_s\left(s_t, a_t\right), r_{t+1} = f_r\left(s_t, a_t\right)$$



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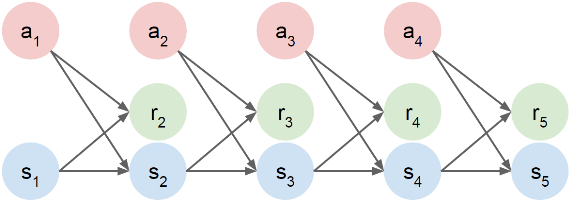


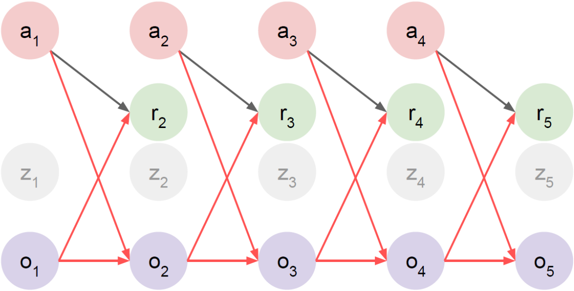

Practical trick: typically better to predict the derivative (change in $s$), and then integrate to obtain $s_{t+1}$

$$s_{t+1} = s_t + f(s_t, a_t)$$

# Input is observation

- In some cases, agent has Partial Observability and no access to true state

$$o_{t+1} = f_s\left(o_t, a_t\right), r_{t+1} = f_r\left(o_t, a_t\right)$$

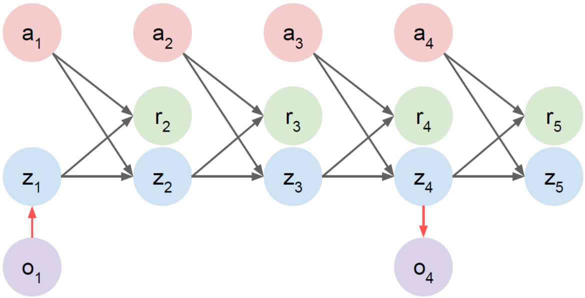


# Input is latent state

- In some cases, observation is too complex to do predictions (f.i from pixels of an image)

$$z_{t+1} = f_s(z_t, a_t), r_{t+1} = f_r(z_t, a_t)$$

$$z_t = Enc(o_t) , \quad o_t = Enc^{-1}(z_t) = Dec(z_t)$$




Nice interactive paper on latent space

# What does the model predict?

- Models that return the **expectation of next state**
- Goal: estimate model $\mathcal{M}_\eta$ from experience $\{S_1, A_1, R_2, \ldots, S_T\}$ that computes function $f(s, a) = r, s'$
- Pick loss function (e.g. mean-squared error), and find parameters $\eta$ that minimise empirical loss
- This would give an expectation model If $f(s, a) = r, s'$, then we would hope

$$s' \approx \mathbb{E}\left[S_{t+1} \mid s = S_t, a = A_t\right]$$

$$r \approx \mathbb{E}\left[R_{t+1} \mid s = S_t, a = A_t\right]$$

# Three kinds of uses

- Expectation models can have disadvantages:
  - Imaging that a (high-level) action randomly goes left or right past a well
  - The expectation model might interpolate and put you in the wall
- Alternative can be **stochastic models** (also known as generative models), that is, returns probability of being in one state.

$$\hat{R}_{t+1}, \hat{S}_{t+1} = \hat{p}\left(S_t, A_t, \omega\right)$$

  where $\omega$ is a noise term
- Stochastic models can be chained, even if the model is non-linear - But they do add a lot of noise

# How to learn a policy with a model

# Three kinds of uses

- (Wang et al. 19) did a classification and comparison of MBRL algorithms. (web here)

  target caption

- They classify MBRL approaches in three different approaches:
  1. Model Predictive Control (MPC) inspired
  2. Learn from simulated (imagined/hallucinated) trials
  3. End-to-end approaches

Subsection 1

## MPC-like methods

# Model Predictive Control (MPC) [1]

- Helps to improve the policy:
  1. Plan *whole trial* from step $s_t$ using the world model
  2. Execute only *first action*
  3. (get data to update the model and the policy)
  4. Return to 1 if not ended experience
- Why?

# Model Predictive Control (MPC) [1]

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- Why?
- Things can go wrong specially in stochastic environments or bad model
- Widely used in robotics and Control systems

# PETS Example (1)

- Probabilistic Ensembles with Trajectory Sampling (PETS) is an example of MPC-like approach (Chua et. al 18)
- Authors Cite two kinds of uncertainty in models:
  - *Aleatoric uncertainty* which is the inherent stochasticity of the environment
  - *Epistemic uncertainty* which reflects the model's confidence regarding different input state-actions.
- To solve aleatory uncertainty they propose to use **probabilistic neural networks** as models that output parametrizes gaussian distributions over the next state and reward
- They are trained using negative log likelihood of the true next state under the distribution predicted by our model

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- Planning is done by generating different trajectories until the horizon allowed is reached
- They propose a trajectory sampling method that combines, by bootstrapping, the actual model of the ensemble that will be used in the prediction of one step.
- From all trajectories, the best one is selected and *only the first action* is executed
- Learning of the policy is done using cross entropy method (CEM)
- Achieve good in several domains in few trials (but more clock-time), specially in stochastic environments!
- Competitive results

Subsection 2

## Learning from simulated trials

# Learn from simulated trials [2]

- Idea: Instead of learning only from experiences in the environment, use the model to generate trials and learn from them!
  1. Choose action from current state and observe results
  2. Update the policy using this data
  3. Update the model with data collected
  4. Simulate trial with the model
  5. Update the policy with results from simulated data
  6. Return to 1!
- Some people use word *simulated*, others *imagined* or, when talking about visual states, *hallucinated*
- Some example methods:
  - Dyna
  - World Models paper
  - Model Based Policy Optimization (MBPO)

# Dyna (Sutton 90)

- Based on Q-learning before DNNs. Sample based (not whole trajectories)

**Tabular Dyna-Q**

Initialize $Q(s,a)$ and $Model(s,a)$ for all $s \in \mathcal{S}$ and $a \in \mathcal{A}(s)$
Loop forever:
(a) $S \leftarrow$ current (nonterminal) state
(b) $A \leftarrow \varepsilon$-greedy$(S, Q)$
(c) Take action $A$; observe resultant reward, $R$, and state, $S'$
(d) $Q(S,A) \leftarrow Q(S,A) + \alpha\big[R + \gamma \max_a Q(S',a) - Q(S,A)\big]$
(e) $Model(S,A) \leftarrow R, S'$ (assuming deterministic environment)
(f) Loop repeat $n$ times:
    $S \leftarrow$ random previously observed state
    $A \leftarrow$ random action previously taken in $S$
    $R, S' \leftarrow Model(S,A)$
    $Q(S,A) \leftarrow Q(S,A) + \alpha\big[R + \gamma \max_a Q(S',a) - Q(S,A)\big]$

# Dyna (Sutton 90)

- Can be done better
- Random exploration of experiences is not optimal
- Let's sample the experiences stored according to the imprecision on the prediction (Bellman error!)
- Ring a bell?
- Prioritized sweeping (Moore, Atkenson, 93)

# Prioritized sweeping (Moore & Atkenson, 93)

**Prioritized sweeping for a deterministic environment**

Initialize $Q(s, a)$, $Model(s, a)$, for all $s, a$, and $PQueue$ to empty

Loop forever:

(a) $S \leftarrow$ current (nonterminal) state

(b) $A \leftarrow policy(S, Q)$

(c) Take action $A$; observe resultant reward, $R$, and state, $S'$

(d) $Model(S, A) \leftarrow R, S'$

(e) $P \leftarrow |R + \gamma \max_a Q(S', a) - Q(S, A)|$.

(f) if $P > \theta$, then insert $S, A$ into $PQueue$ with priority $P$

(g) Loop repeat $n$ times, while $PQueue$ is not empty:

  $S, A \leftarrow first(PQueue)$

  $R, S' \leftarrow Model(S, A)$

  $Q(S, A) \leftarrow Q(S, A) + \alpha\left[R + \gamma \max_a Q(S', a) - Q(S, A)\right]$

  Loop for all $\bar{S}, \bar{A}$ predicted to lead to $S$:

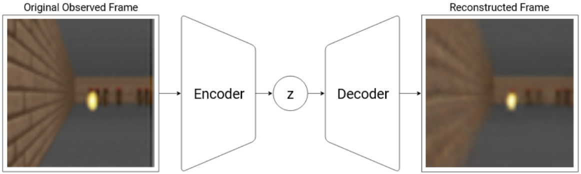
    $\bar{R} \leftarrow$ predicted reward for $\bar{S}, \bar{A}, S$

    $P \leftarrow |\bar{R} + \gamma \max_a Q(S, a) - Q(\bar{S}, \bar{A})|$.

    if $P > \theta$ then insert $\bar{S}, \bar{A}$ into $PQueue$ with priority $P$

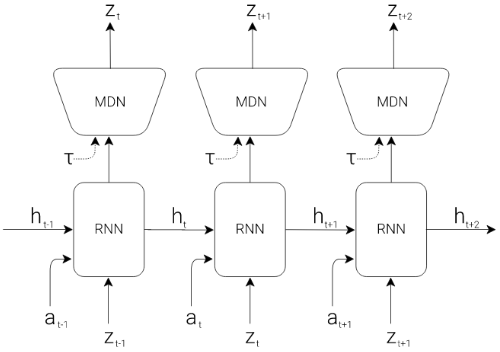
# World Models 1 (Ha & Schmidhuber, 18)

- A more modern paper with nice interactive web.
- Learn from pixels. To decrease dimensionality, creates a latent representation of observations.
- Latent representation is learnt using Variational Auto Encoder (VAE) before training the policy



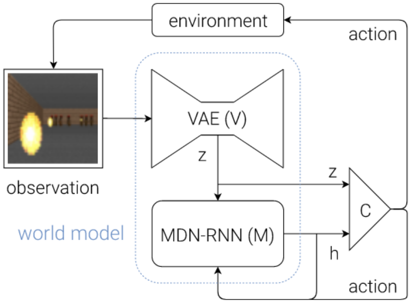
# World Models 2 (Ha & Schmidhuber, 18)

- A model in the latent space is learnt using RNNs and Mixture Density Network (generative model of state controlled with noise and temperature)
- Model is trained collecting 10,000 rollouts from a random policy.



# World Models 3 (Ha & Schmidhuber, 18)

- Finally CEM is used to train the policy
- At this point Model is only used as features to help the learning of the policy



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- So, if we have a model, can we use to learn a policy without going to the true environment?
- That is what they call *learning in a Dream*
- Problems they found were about transfer of the policy to true environment
- Model was not perfect and policy take profit of that to increase *dreamed reward*
- Solved increasing noise in MDN
- Illustrative exploration in WM

# Model Ensemble TRPO (Kurutahc et al. 18)

- (ME-TRPO) Learn an ensemble of Models and train a policy (with TRPO) collecting episodes from all of them
- When performance of policy does not increase for most of the ensembles, go back to env. for more data

**Algorithm 2** Model Ensemble Trust Region Policy Optimization (ME-TRPO)

Initialize a policy $\pi_\theta$ and all models $\hat{f}_{\phi_1}, \hat{f}_{\phi_2}, \ldots, \hat{f}_{\phi_K}$.
Initialize an empty dataset $\mathcal{D}$.
**repeat**
    Collect samples from the real system $f$ using $\pi_\theta$ and add them to $D$.
    Train all models using $\mathcal{D}$.
    **repeat** ▷ Optimize $\pi_\theta$ using all models.
        Collect fictitious samples from $\{\hat{f}_{\phi_i}\}_{i=1}^{K}$ using $\pi_\theta$.
        Update the policy using TRPO on the fictitious samples.
        Estimate the performances $\hat{\eta}(\theta; \phi_i)$ for $i = 1, \ldots, K$.
    **until** the performances stop improving.
**until** the policy performs well in real environment $f$.

SLBO (Luo et al. 19) variation that separates learning Model from policy and train models on differences (derivative)

# Model Based Policy Optimization (Janer et al. 19)

- After analysis of error in MBRL they conclude that collecting whole trajectories and learning from them lead to accumulate error
- MBPO proposes a Dyna-like procedure for sampling and learn, with with SAC added
- You can take larger samples because you learn not from episodes but from transitions

**Algorithm 2** Model-Based Policy Optimization with Deep Reinforcement Learning

1: Initialize policy $\pi_\phi$, predictive model $p_\theta$, environment dataset $\mathcal{D}_{\text{env}}$, model dataset $\mathcal{D}_{\text{model}}$
2: **for** $N$ epochs **do**
3:     Train model $p_\theta$ on $\mathcal{D}_{\text{env}}$ via maximum likelihood
4:     **for** $E$ steps **do**
5:         Take action in environment according to $\pi_\phi$; add to $\mathcal{D}_{\text{env}}$
6:         **for** $M$ model rollouts **do**
7:             Sample $s_t$ uniformly from $\mathcal{D}_{\text{env}}$
8:             Perform $k$-step model rollout starting from $s_t$ using policy $\pi_\phi$; add to $\mathcal{D}_{\text{model}}$
9:         **for** $G$ gradient updates **do**
10:             Update policy parameters on model data: $\phi \leftarrow \phi - \lambda_\pi \hat{\nabla}_\phi J_\pi(\phi, \mathcal{D}_{\text{model}})$

Subsection 3

## End-to-end approaches

# End-to-end approaches [3]

- Accumulating errors are a source of problems in MBRL (example)
- Previous approaches only use first action (MPC) or use ensembles or small rollouts (Dyna like) to diminish the problem

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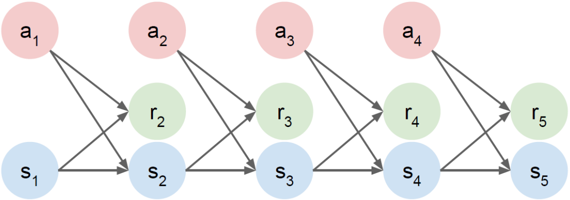
- Accumulating errors are a source of problems in MBRL (example)
- Previous approaches only use first action (MPC) or use ensembles or small rollouts (Dyna like) to diminish the problem
- But wait, lets look in detail a imagined episode (assuming sequence is generated using the model)




- Notice that $s_5 = f(f(f(f(s_1, a_1), a_2), a_3), a_4)$

# End-to-end approaches

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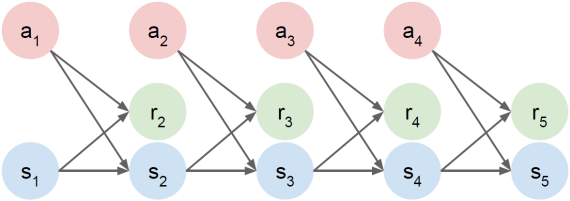


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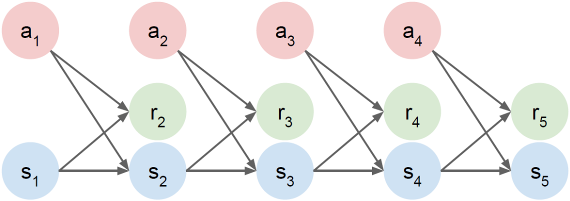
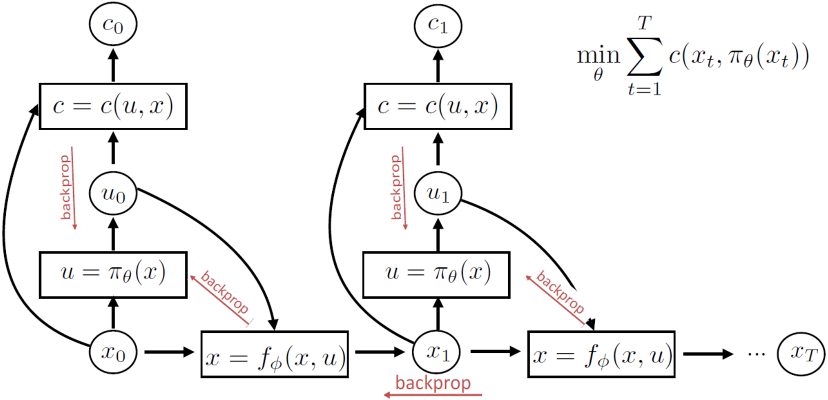



- Also notice that $f$ is a DNN (usually)
- So, you can apply back-propagation from any state backwards to the initial state in order to learn the model!
- This is called *Back-propagation through time* (BTT)

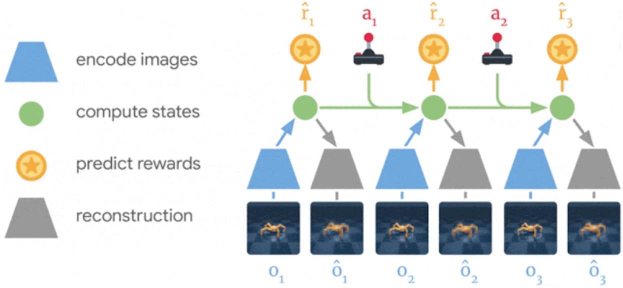
# End-to-end approaches




1. run base policy $\pi_0(\mathbf{u}_t|\mathbf{x}_t)$ (e.g., random policy) to collect $\mathcal{D} = \{(\mathbf{x}, \mathbf{u}, \mathbf{x}')_i\}$
2. learn dynamics model $f_\phi(x, u)$ to minimize $\sum_i ||f_\phi(x_i, u_i) - x'_i||^2$
3. backpropagate through $f_\phi(x, u)$ into the policy to optimize $\pi_\theta(\mathbf{u}_t|\mathbf{x}_t)$
4. run $\pi_\theta(\mathbf{u}_t|\mathbf{x}_t)$, appending the visited tuples $(\mathbf{x}, \mathbf{u}, \mathbf{x}')$ to $\mathcal{D}$

# End-to-end approaches: DREAMER

- Dreamer algorithm (evolution of previous Planet)




- Learns on latent space
- Uses BTT to learn the models (they call multi-step prediction)

# DREAMER

- Other things not in image:
  - It uses RNN to deal with partial observability
  - Used TD($\lambda$) to learn the policy
  - Use stochastic models to solve aleatoric uncertainty

# DREAMER

- Other things not in image:
  - It uses RNN to deal with partial observability
  - Used TD($\lambda$) to learn the policy
  - Use stochastic models to solve aleatoric uncertainty
- Lately, they have proposed Dreamer v2 (Haffner et al. 20) that claim it's better than Rainbow in Atari Games
- In general End-to-end approaches have problems with local minima and gradient vanishing (similar problems than RNNs)

Subsection 4

## Conclusions

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- Different ways to deal with uncertainty in models
- Learning the policy and the model is done at the same time
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- Different ways to deal with uncertainty in models
- Learning the policy and the model is done at the same time
- (Wang et al. 19) did a classification and comparison of MBRL algorithms (web here)
- They do reduce number of interaction with the env.
- ... but usually don't achieve model-free methods performance

# Do models help in another way?

- Other uses:
  - Classical planning and learning a policy (Monte Carlo Tree search and uses in AlphaGo, Muzero, etc.)
  - Help to explore better the domain Plan2Explore
  - As auxiliary loss
  - Transfer between RL tasks
  - ...