Reinforcement Learning

—

Exercise 10: RND/ICM

02.07.2024

Alexander Mattick

Fraunhofer IIS

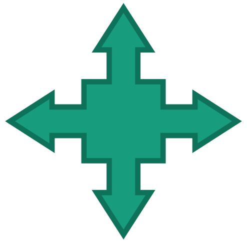
Fraunhofer-Institut für Integrierte Schaltungen IIS

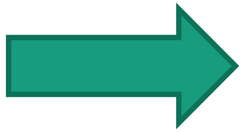
Exploration vs. Exploitation

Exploration vs. Exploitation

Why and How

- Both definitions stem from the same problem:
  - **Exploration**: do things you haven't done before
    (in the hopes of getting even higher reward)
    → increase knowledge
  - **Exploitation**: do what you know to yield highest reward
    → maximize performance based on knowledge





Multi-armed bandits (1-step stateless RL problems)	Contextual bandits (1-step RL problems)	Small, finite MDPs (e.g., tractable planning, model-based RL)	Large, infinite MDPs (e.g., continuous spaces)

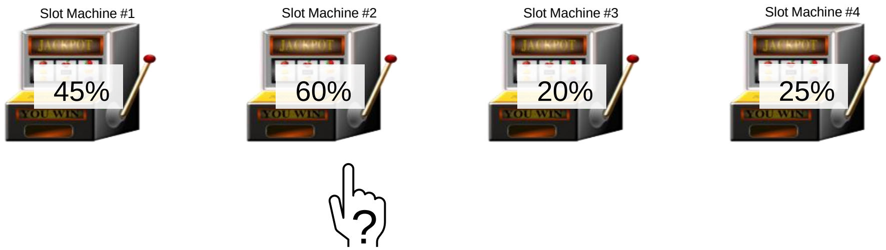
theoretically tractable ⟷ theoretically intractable

(illustration adapted from Sergey Levine's CS285 class from UC Berkeley)

Exploration vs. Exploitation

Multi-Armed Bandits and Regret

- The multi-armed-bandit problem is a classic problem used to study the exploration vs. exploitation dilemma
- Imagine you are in a casino with multiple slot machines, each configured with an unknown reward probability:



- Under the assumption of an infinite number of trials:

→ ***What is the best strategy to achieve highest long-term rewards?***

- Our loss function is the total regret we might have by not select the optimal action up to the time step T:

what we did

per-action regret

$$\mathcal{L}_T = \mathbb{E}\left[\sum_{t=1}^{T}\left(\theta^* - Q(a_t)\right)\right] = \sum_{a\in\mathcal{A}} N_T(a)\Delta_a$$

what we should have been doing

action-selection counter

Fraunhofer IIS

Exploration vs. Exploitation

Straightforward but usually bad: Greedy or ε-greedy

- Greedy may select a suboptimal action forever
  → Greedy has hence linear expected total regret

- ϵ-greedy continues to explore forever
  - with probability $1 - \epsilon$ it selects $a = \arg\max_{a \in \mathcal{A}} Q_T(a)$
  - with probability ϵ it selects a random action

- Will hence continue to select all suboptimal actions with (at least) a probability of $\frac{\epsilon}{|\mathcal{A}|}$
  → ϵ-greedy, with a constant ϵ has a linear expected total regret

- **Option #1: decrease ϵ over course of training might work**
  - It is not easy to tune the parameters

- **Option #2: be optimistic with options of high uncertainty**
  - Prefer actions for which you do not have a confident value estimation yet
    → Those have a great potential to be high-rewarding!
  - This idea is called **Upper Confidence Bounds**

Exploration vs. Exploitation

Upper Confidence Bounds (UCB1)

- Idea: estimate an upper confidence $U_t(a)$ for each action value, such that with a high probability we satisfy

$$Q(a) \leq \hat{Q}_t(a) + U_t(a)$$

- Next, we select the action that maximizes the upper confidence bound:

$$a_t^{UCB} = \arg\max_{a \in \mathcal{A}} [Q_t(a) + U_t(a)]$$

Large $N_t(a)$ → small bound $U_t(a)$ *(estimated value is certain/accurate)*

Small $N_t(a)$ → large bound $U_t(a)$ *(estimated value is uncertain)*

- The vanilla **UCB1** algorithm uses $p = t^{-4}$:

$$U_t(a) = \sqrt{\frac{2 \log t}{N_t(a)}} \quad \text{and} \quad a_t^{UCB} = \arg\max_{a \in \mathcal{A}} Q(a) + \sqrt{\frac{2 \log t}{N_t(a)}}$$

Derived from Hoeffding's Inequality:
$P(\mathbb{E}[X] \geq \bar{X}_t + u) \leq e^{-2tu^2}$

  - This ensures that we always keep exploring
  - But we select the optimal action much more often as $t \to \infty$

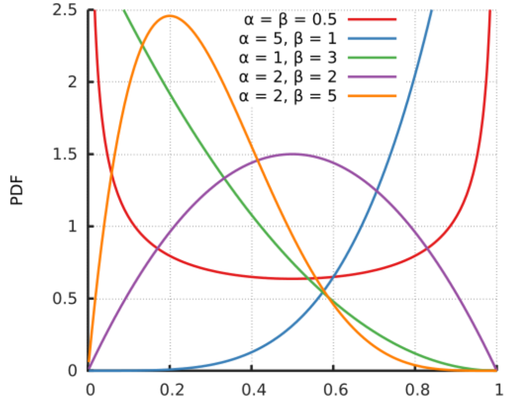
Exploration vs. Exploitation

Probability Matching via Thompson Sampling

We can also try the idea of directly sampling the action

- Select action a according to probability that a is the optimal action (given the history of everything we observed so far):

$$\pi_t(a|h_t) = P[Q(a) > Q(a'), \forall a' \neq a|\, h_t]$$
$$= \mathbb{E}_{r|h_t}\left[\mathbb{I}\left(a = \arg\max_{a\in\mathcal{A}} Q(a)\right)\right]$$



Probability matching via Thompson Sampling:

1. Assume $Q(a)$ follows a Beta distribution for the Bernoulli bandit
   - As $Q(a)$ is the success probability of θ
   - Beta(α, β) is within $[0,1]$,and α and β relate to the counts of success/failure
2. Initialize prior (e.g., $\alpha = \beta = 1$ or something different/what we think it is)
3. At each time step t we sample an expected reward $\hat{Q}(a)$ from the prior Beta(α_i, β_i) for every action
   - We select and execute the best action among the samples: $a_t^{TS} = \arg\max_{a\in\mathcal{A}} \hat{Q}(a)$
4. With the newly observed experience we update the Beta distribution:

$$\alpha_i \leftarrow \alpha_i + r_i \mathbb{I}[a_t^{TS} = a_i]$$
$$\beta_i \leftarrow \beta_i + (1 - r_i)\mathbb{I}[a_t^{TS} = a_i]$$

Exercise Sheet 10

Bandits

Prediction-based Exploration in Deep RL

ICM and RND

Exploration in Deep RL

Intrinsic Rewards as Exploration Bonuses

- Instead of $r(s,a)$ we provide $r^+(s,a) = r(s,a) + \mathcal{B}\big(N(s)\big)$

  decreases with $N(s)$

- We can give this to any model-free agent!
- A general formulation looks like this:

$$r_t = r_t^e + \beta \cdot r_t^i$$

  - β is a hyperparameter that adjusts the balance between exploitation and exploration
  - r_t^e is called the extrinsic reward form the environment at time t
  - r_t^i is called the intrinsic reward, i.e., the exploration bonus at time t

- The intrinsic reward is/can be inspired intrinsic motivation[1] and we can transfer those findings to RL too:
  1. Discovery of novel states
  2. Improvement of the agent's knowledge about the environment

[1] *Pierre-Yves Oudeyer and Frederic Kaplan: How can we define intrinsic motivation? 8th Intl. Conf. Epigenetic Robotics*

Prediction-based Exploration

Predicting Models: Forward Dynamics

- Idea of the **forward dynamics prediction model**:
  - The agent learns a parameterized function f_θ such that:

$$f_\theta : (s_t, a_t) \rightarrow s_{t+1}$$

  - Derive a reward bonus based on the prediction error of the dynamics model

$$e(s_t, a_t) = \| f(s_t, a_t) - s_{t+1} \|_2^2$$

    - Large prediction error: high bonus (as we encountered something unusual/unknown)
    - Low prediction error: low bonus (as we have seen this coming)
  - Our agent uses all the experience samples (s_t, a_t, s_{t+1}) collected so far and retrains its prediction model as it interacts with the environment

Prediction-based Exploration

Predicting Forward Dynamics

Deep Predictive Models[1]

- Predicting high-dimensional state spaces (images) can become very difficult
- Train a forward dynamics model in an encoding space ϕ (train an autoencoder):

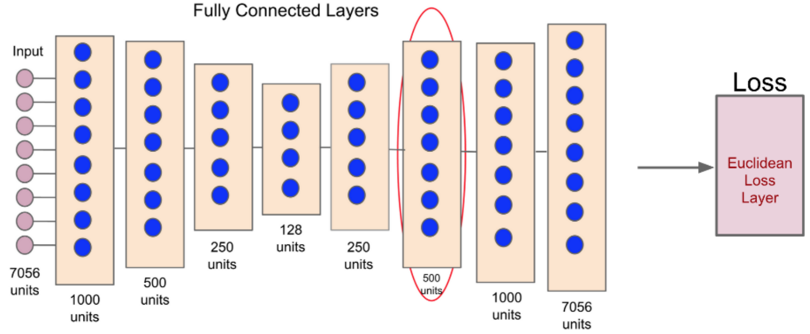
$$f_\phi : (\phi(s_t), a_t) \rightarrow \phi(s_{t+1})$$

- Normalize the prediction error at time T by the maximum error so far:

$$\bar{e}_t = \frac{e_t}{\max_{i \leq t} e_i}$$

- Define the extrinsic reward accordingly (C is a decay parameter):

$$r_t^i = \left(\frac{e_t(s_t, a_t)}{t \cdot C} \right)$$



- The autoencoder can be trained upfront using images collected randomly or trained along with the policy and being updated steadily.

[1] Stadie, Levine, Abbeel: Incentivizing Exploration in Reinforcement Learning with Deep Predictive Models. 2015.

Fraunhofer IIS

Prediction-based Exploration

Predicting Forward Dynamics

Intrinsic Curiosity Module (ICM)[1]

- Instead of an autoencoder ICM trains the state space encoding $\phi(s_t)$ with a self-supervised *inverse dynamics* model

- Motivation:
  - Predicting s_{t+1} given (s_t, a_t) is not always easy as many factors in the environment cannot be controlled/affected by the agent
  - Popular example: imagine this tree with leaves
  - Such factors should not be part of the encoded state space as the agent should not base its decision based on these factors

- Solution: Learn an inverse dynamics model g:

$$g\colon \big(\phi(s_t), \phi(s_{t+1})\big) \rightarrow a_t$$

- The feature space then only captures those changes in the environment related to actions that the agent takes, and ignores the rest

learn to explore in Level-1

explore faster in Level-2

[1] *Deepak Pathak et al.: Curiosity-driven Exploration by Self-Supervised Prediction. ICML 2017.*

Fraunhofer IIS

Prediction-based Exploration

Predicting Forward Dynamics

Intrinsic Curiosity Module (ICM)[1], given

- a forward model f with parameters θ_F
- an inverse dynamics model g with parameters θ_I
- and an observation (s_t, a_t, s_{t+1})

$$\hat{a}_t = g(\phi(s_t), \phi(s_{t+1}); \theta_I)$$
$$\hat{\phi}(s_{t+1}) = f(\phi(s_t), a_t; \theta_F)$$
$$r_t^i = \frac{\eta}{2}\left\|\hat{\phi}(s_{t+1}) - \phi(s_{t+1})\right\|_2^2$$

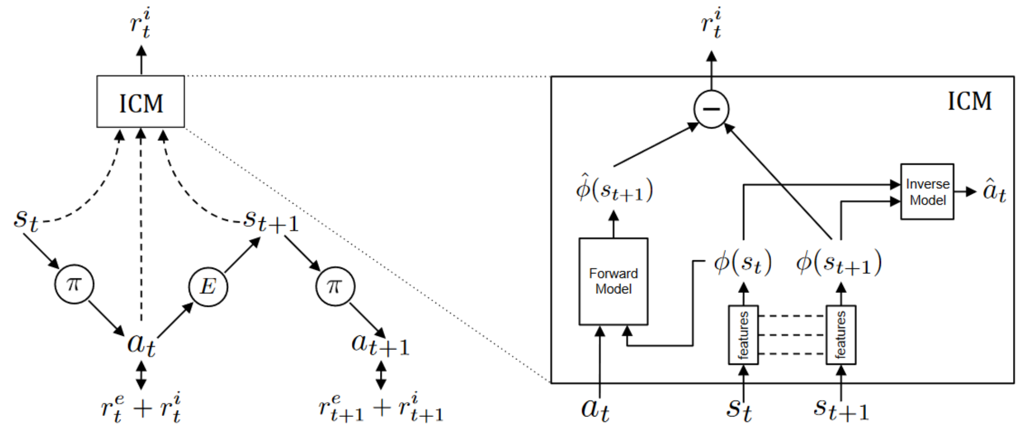
- The policy is jointly optimized as a whole:

if actions are discrete: softmax ML under multinomial distribution

$$\min_{\theta_P, \theta_I, \theta_F}\left[-\lambda \mathbb{E}_{\pi(s_t;\theta_P)}\left[\textstyle\sum_t r_t\right] + (1-\beta)L_I + \beta L_F\right]$$

policy gradient loss

$$L_F\left(\phi(s_t), \hat{\phi}(s_{t+1})\right) = \frac{1}{2}\left\|\hat{\phi}(s_{t+1}) - \phi(s_{t+1})\right\|_2^2$$



[1] *Deepak Pathak et al.: Curiosity-driven Exploration by Self-Supervised Prediction. ICML 2017.*

Prediction-based Exploration

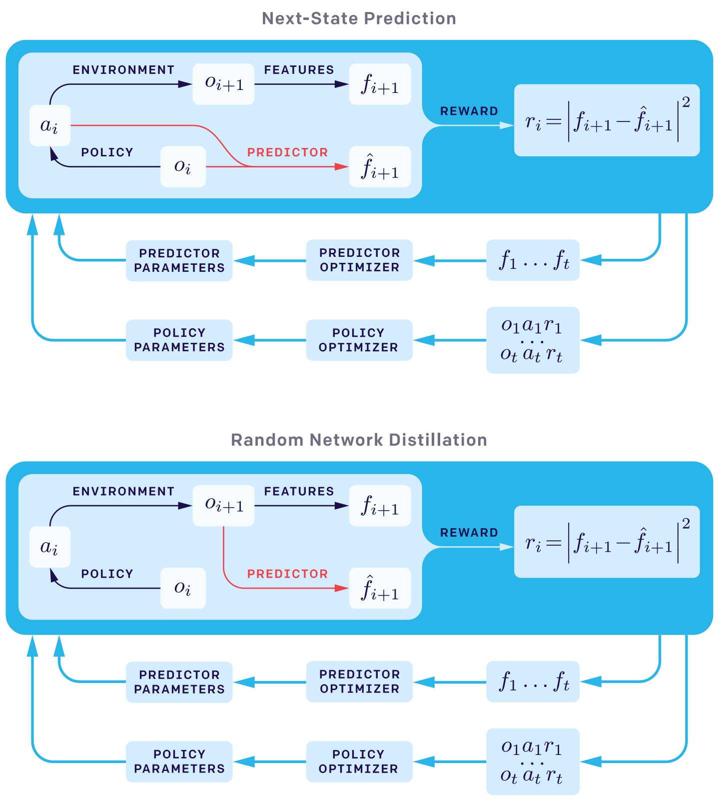
Prediction Models: Random Networks

Random Network Distillation (RND)[1,2]

- Similar idea: predict something that is independent from the main task
- We use two neural networks:
  1. A randomly initialized but **fixed** neural network to transform a state into a feature space: $f(s_t)$
  2. A network $\hat{f}(s_t;\theta)$ that we train to predict the same features as the fixed network

  → We want $\hat{f}(s_t;\theta) = f(s_t)$
- Intuition: Similar states have similar features
  - And if we have already seen them, we should also have a lower error on predicting them!
- We use an exploration bonus: $r^i(s_t) = \left\|\hat{f}(s_t;\theta) - f(s_t)\right\|_2^2$

Comparison of Next-State Prediction with RND



[1] Yuri Burda et al.: Exploration by Random Network Distillation. ICLR 2019.
[2] https://openai.com/blog/reinforcement-learning-with-prediction-based-rewards/

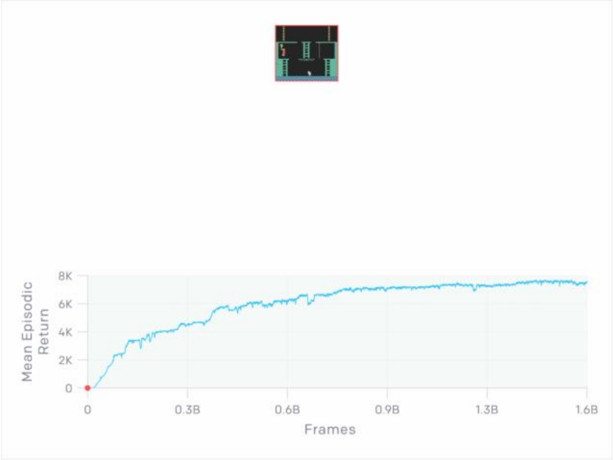
Prediction-based Exploration

Random Network Distillation

Random Network Distillation (RND)

- Advantage of synthetic prediction problem:
  - The fixed network makes the prediction target deterministic (bypassing issue #2)
  - It is inside the class of functions that the predictor can represent (bypassing issue #3) if the predictor and the target network have the same architecture.

- Results:
  - RND works well for hard-exploration problems
    → maximizing RND bonus finds half of the rooms in Montezuma's Revenge
  - Normalization is important! The scale of the rewards is tricky to adjust given a random network as prediction target
    → Normalize by a running estimate of standard deviations of intrinsic return
  - Non-episodic settings work better, especially in cases without extrinsic rewards (the return is not truncated at *game over* and intrinsic return can spread across multiple episodes)



[1] https://openai.com/blog/reinforcement-learning-with-prediction-based-rewards/

Exercise Sheet 11

ICM and RND

Thank you for your attention!

Fraunhofer IIS

Fraunhofer-Institut für Integrierte Schaltungen IIS