Count-Based Exploration in Feature Space for Reinforcement Learning

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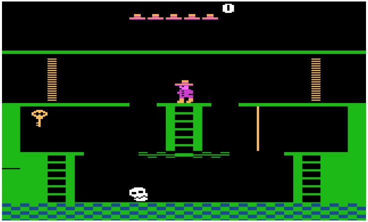
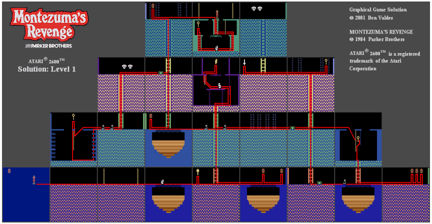
Efficient exploration is still an open problem in MDPs with:

- Large state spaces
- Sparse rewards





Novelty-Based Exploration in Large MDPs

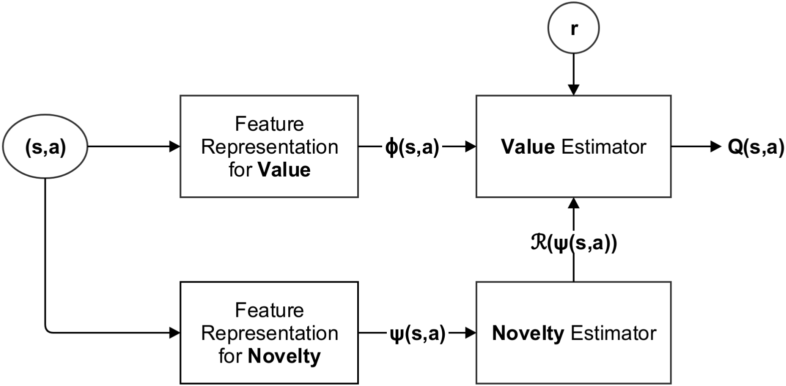
How do you explore efficiently?

- Encourage the agent to visit **novel** states to maximally reduce its uncertainty. How?
- Make your agent **curious about states with novel features**
    1. Choose a feature representation $\psi(s, a)$ of the state space
    2. Compute a visit pseudocount $\hat{N}(\psi)$
    3. Compute a novelty-based exploration bonus:

    $$\mathcal{R}(\psi) \propto \frac{1}{\sqrt{\hat{N}(\psi)}}$$

    4. Add the bonus to the reward r
    5. Train the agent with the augmented reward $r^+ = r + \mathcal{R}(\psi)$

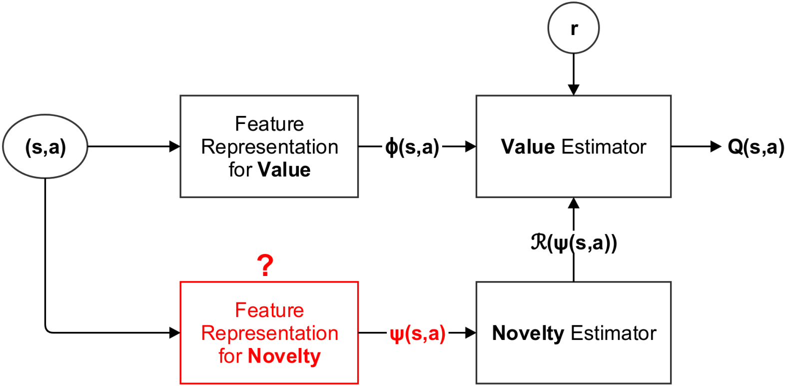
Novelty-Based Exploration in Large MDPs



Feature Representations for Novelty from previous work:

- Context-Tree Switching (CTS) Density Model (Google DeepMind) [1]
- #-Exploration (Berkeley) [4]
- Neural Density Model (Google DeepMind) [3]

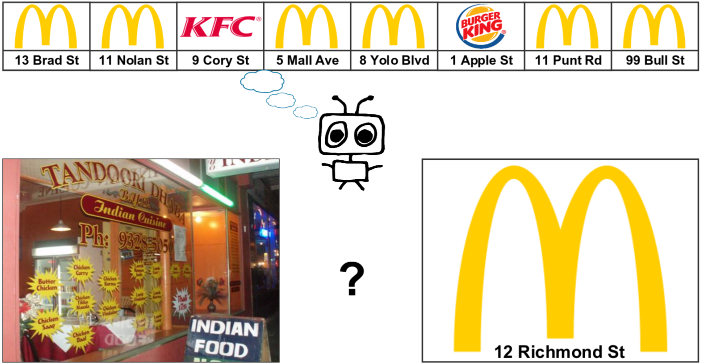
Novelty-Based Exploration in Large MDPs



Problem:

- **Which feature representation is appropriate for measuring the novelty of a state?**
- Previous works do not justify their choices

Which features are relevant when measuring novelty?

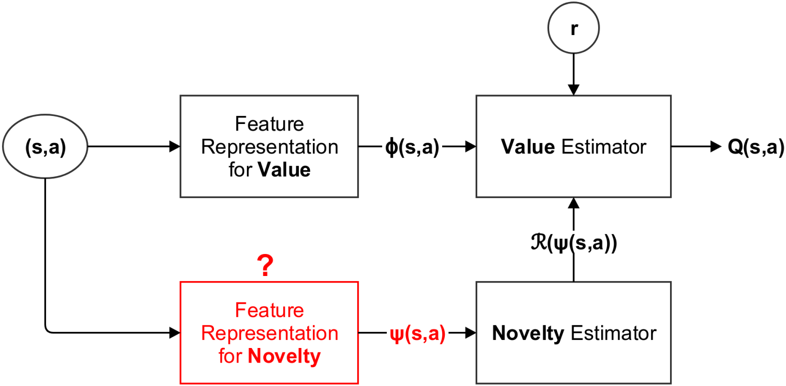


- Different flavours
- Different drinks menu

- Same flavours
- Same drinks menu

Irrelevant features: Wallpaper, Parking, Lighting, Floorspace, Address...

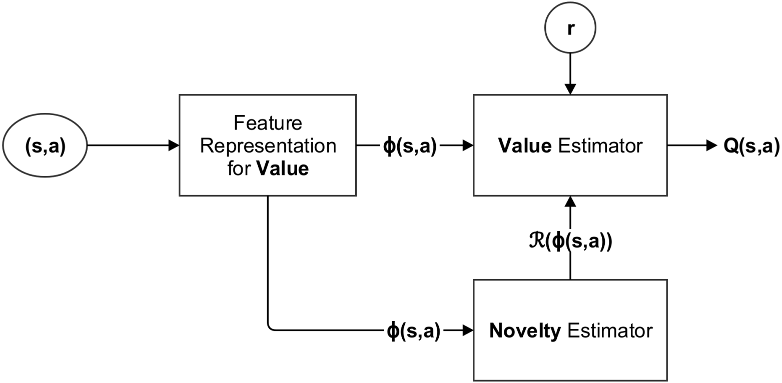
Previous Works do not use Value-Relevant Features



Problem:

- In this architecture, the feature representation used for novelty estimation may not capture **value-relevant features**
- So which features are relevant for maximising value?

The ϕ-Exploration Bonus Algorithm (ϕ-EB)



- Our novelty estimator assigns a high exploration bonus to states that have **novel, value-relevant features**
- Our ϕ-**Exploration Bonus** algorithm is simpler and less computationally expensive than previous approaches

The ϕ-Exploration Bonus Algorithm (ϕ-EB)

Require: β, t_{end}

while $t < t_{\text{end}}$ **do**

Observe r_t and features $\phi(s)$ for the current state s

Compute joint feature probability $\rho_t(\boldsymbol{\phi}) := \prod_i^M \rho_t^i(\phi_i)$

for i in $\{1,\ldots,\text{M}\}$ **do**

Update each probability ρ_{t+1}^i with observed feature ϕ_i

end for

Recompute joint probability $\rho_{t+1}(\boldsymbol{\phi}) := \prod_i^M \rho_{t+1}^i(\phi_i)$

Compute the ϕ-pseudocount $\hat{N}_t^{\phi}(s) := \dfrac{\rho_t(\boldsymbol{\phi})(1-\rho_{t+1}(\boldsymbol{\phi}))}{\rho_{t+1}(\boldsymbol{\phi})-\rho_t(\boldsymbol{\phi})}$

Compute the exploration bonus $\mathcal{R}_t^{\phi}(s,a) := \dfrac{\beta}{\sqrt{\hat{N}_t^{\phi}(s)}}$

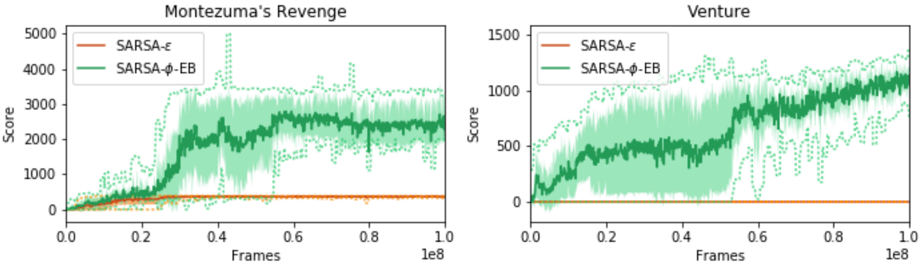
Add the bonus to the reward $r_t^+ := r_t + \mathcal{R}_t^{\phi}(s,a)$

Pass $\phi(s)$, r_t^+ to RL algorithm to update $\boldsymbol{\theta}_t$

end while

return $\boldsymbol{\theta}_{t_{\text{end}}}$

Empirical Evaluation



	Venture	**Montezuma**
Sarsa-ϕ-EB (100M)[2]	1169.2	2745.4
Sarsa-ϵ (100M)	0.0	399.5
DDQN-PC (100M)[1]	86.4	**3459**
A3C+ (200M)[1]	0	142
TRPO-Hash (200M)[4]	445	75

Trained ϕ-EB agent playing Atari

Summary

The ϕ-Exploration Bonus algorithm:

- A new count-based optimistic exploration algorithm for RL
- Feasible in **high-dimensional** state spaces
- **Simpler** and **cheaper** than competitive methods
- Near **state-of-the-art results** across the ALE

- Our ϕ-pseudocount measures uncertainty/novelty by exploiting the **same features used for value function approximation**

Outlook

- Use with **nonlinear** function approximation
- Combination with Deep RL algorithms

Further Reading I

Marc G. Bellemare, Sriram Srinivasan, Georg Ostrovski, Tom Schaul, David Saxton, and Rémi Munos.
Unifying count-based exploration and intrinsic motivation.
CoRR, abs/1606.01868, 2016.

Jarryd Martin, Suraj Narayanan S., Tom Everitt, and Marcus Hutter.
Count-Based Exploration in Feature Space for Reinforcement Learning.
In *Proceedings of the 26th International Joint Conference on Artificial Intelligence*. AAAI Press, 2017.

Georg Ostrovski, Marc G. Bellemare, Aäron van den Oord, and Rémi Munos.
Count-based exploration with neural density models.
CoRR, abs/1703.01310, 2017.

Further Reading II

Haoran Tang, Rein Houthooft, Davis Foote, Adam Stooke, Xi Chen, Yan Duan, John Schulman, Filip De Turck, and Pieter Abbeel.
#Exploration: A study of count-based exploration for deep reinforcement learning.
CoRR, abs/1611.04717, 2016.

Contact

- **Email:** mail@jarrydmartin.com
- **Paper Title:** Martin et. al. "Count-Based Exploration in Feature Space for Reinforcement Learning" (2017)
- **Available at:** IJCAI-17 proceedings, arxiv

- **Shameless self-promotion:** This was my MSc dissertation, I am currently applying for **PhDs** and **Research Internships**. Hire me!