Count-Based Exploration in Feature Space for Reinforcement Learning

J. Martin  S. Narayanan S.  T. Everitt  M. Hutter

Research School of Computer Science
Australian National University

SURL workshop, ECML PKDD
September, 2017
The Exploration/Exploitation Dilemma

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:

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

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

13 Brad St  11 Nolan St  9 Cory St  5 Mall Ave  8 Yolo Blvd  1 Apple St  11 Punt Rd  99 Bull St

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

- Different flavours
- Different drinks menu

- Same flavours
- Same drinks menu

12 Richmond St
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?
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 $\phi$-Exploration Bonus Algorithm ($\phi$-EB)

**Require:** $\beta$, $t_{\text{end}}$

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

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

Compute joint feature probability $\rho_t(\phi) := \prod_{i}^{M} \rho^i_t(\phi_i)$

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

Update each probability $\rho^i_{t+1}$ with observed feature $\phi_i$

**end for**

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

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

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

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 $\theta_t$

**end while**

**return** $\theta_{t_{\text{end}}}$

J. Martin, S. Narayanan S., T. Everitt, M. Hutter  Count-Based Exploration in Feature Space for Reinforcement Learning 9 / 13
Empirical Evaluation

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Score</th>
<th>Frames</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Montezuma</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sarsa-$\phi$-EB</td>
<td>1169.2</td>
<td>2745.4</td>
</tr>
<tr>
<td>Sarsa-$\epsilon$</td>
<td>0.0</td>
<td>399.5</td>
</tr>
<tr>
<td>DDQN-PC</td>
<td>86.4</td>
<td>3459</td>
</tr>
<tr>
<td>A3C+</td>
<td>0</td>
<td>142</td>
</tr>
<tr>
<td>TRPO-Hash</td>
<td>445</td>
<td>75</td>
</tr>
<tr>
<td><strong>Venture</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DDQN-PC</td>
<td>1500.0</td>
<td>1e8</td>
</tr>
<tr>
<td>A3C+</td>
<td>1500.0</td>
<td>1e8</td>
</tr>
<tr>
<td>TRPO-Hash</td>
<td>1500.0</td>
<td>1e8</td>
</tr>
</tbody>
</table>

J. Martin, S. Narayanan S., T. Everitt, M. Hutter  Count-Based Exploration in Feature Space for Reinforcement Learning 10 / 13
Trained $\phi$-EB agent playing Atari

Switch to dedicated video-player, if flash fails to load video.
Marc G. Bellemare, Sriram Srinivasan, Georg Ostrovski, Tom Schaul, David Saxton, and Rémi Munos.  
Unifying count-based exploration and intrinsic motivation.  

Jarryd Martin, Suraj Narayanan S., Tom Everitt, and Marcus Hutter.  
Count-Based Exploration in Feature Space for Reinforcement Learning.  

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