# Count-Based Exploration in Feature Space for Reinforcement Learning

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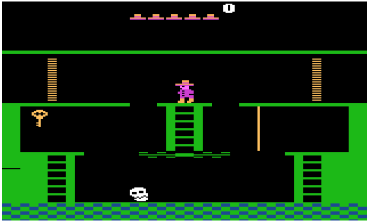
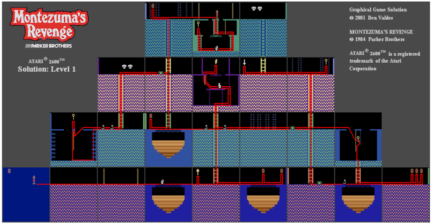
# The Exploration/Exploitation Dilemma

Efficient exploration is still an open problem in MDPs with:

- Large state spaces
- Sparse rewards





# Novelty-Based Exploration in Large MDPs

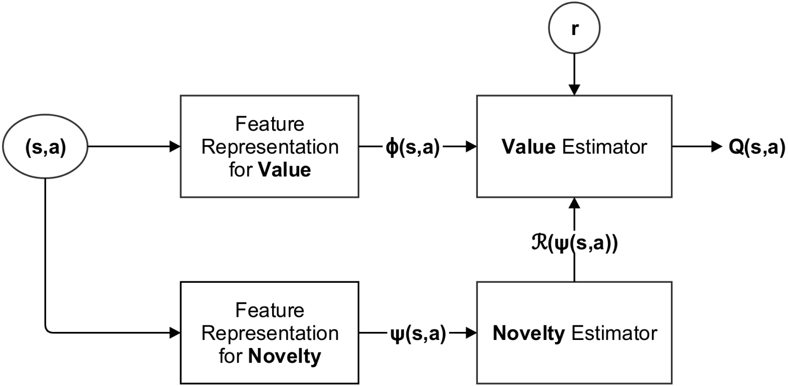
How do you explore efficiently?

- 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:

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

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

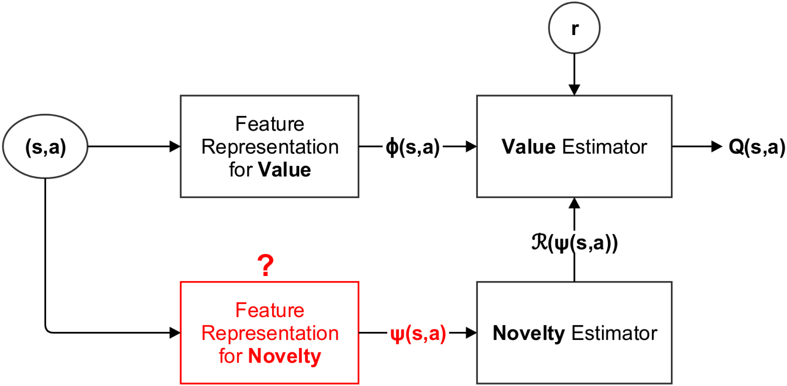
# Novelty-Based Exploration in Large MDPs


r
(s,a)
Feature Representation for **Value**
ϕ(s,a)
**Value** Estimator
Q(s,a)
ℛ(ψ(s,a))
Feature Representation for **Novelty**
ψ(s,a)
**Novelty** Estimator

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]

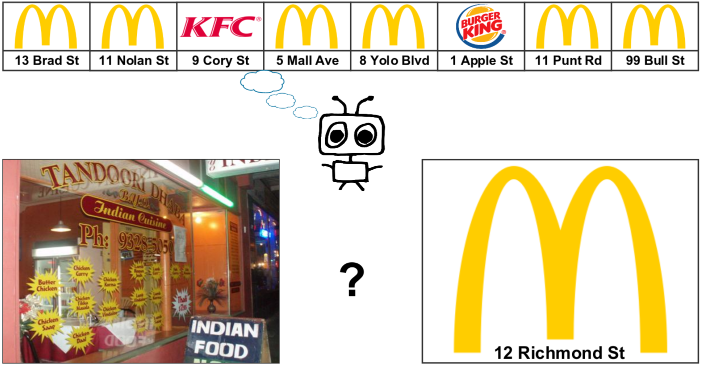
# Novelty-Based Exploration in Large MDPs



**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?

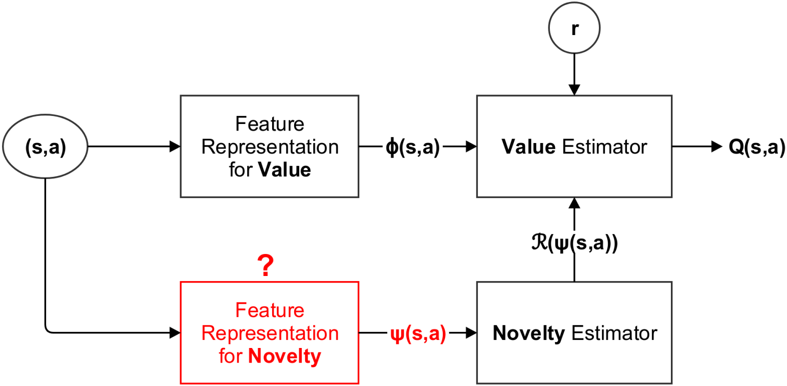


- Different flavours
- Different drinks menu

- Same flavours
- Same drinks menu

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

# Previous Works do not use Value-Relevant Features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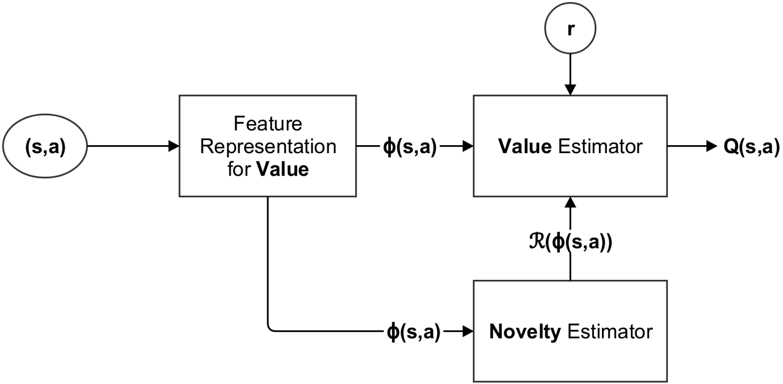
Feature Representation for **Novelty**
ψ(s,a)
**Novelty** Estimator

**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 $\phi$-Exploration Bonus Algorithm ($\phi$-EB)

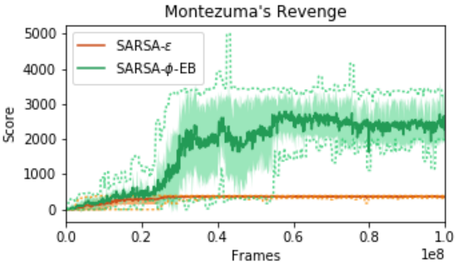


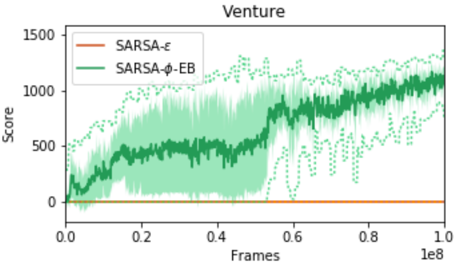
- Our novelty estimator assigns a high exploration bonus to states that have **novel, value-relevant features**
- Our $\phi$-**Exploration Bonus** algorithm is simpler and less computationally expensive than previous approaches

# 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 $\rho_t(\boldsymbol{\phi}) := \prod_i^M \rho_t^i(\phi_i)$
      for i in $\{1,\ldots,M\}$ do
          Update each probability $\rho_{t+1}^i$ with observed feature $\phi_i$
      end for
      Recompute joint probability $\rho_{t+1}(\boldsymbol{\phi}) := \prod_i^M \rho_{t+1}^i(\phi_i)$
      Compute the $\phi$-pseudocount $\hat{N}_t^{\phi}(s) := \frac{\rho_t(\boldsymbol{\phi})(1 - \rho_{t+1}(\boldsymbol{\phi}))}{\rho_{t+1}(\boldsymbol{\phi}) - \rho_t(\boldsymbol{\phi})}$
      Compute the exploration bonus $\mathcal{R}_t^{\phi}(s,a) := \frac{\beta}{\sqrt{\hat{N}_t^{\phi}(s)}}$
      Add the bonus to the reward $r_t^+ := r_t + \mathcal{R}_t^{\phi}(s,a)$
      Pass $\boldsymbol{\phi}(s)$, $r_t^+$ to RL algorithm to update $\boldsymbol{\theta}_t$
  end while
   return $\boldsymbol{\theta}_{t_{\text{end}}}$
```

# Empirical Evaluation





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

# Trained $\phi$-EB agent playing Atari

Switch to dedicated video-player, if flash fails to load video.

# 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.