

Reducing Regret in Q-Learning with Ensemble Mechanics

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Introduction

Q-learning:

$$Q(s, a) \leftarrow Q(s, a) - \alpha \left(Q(s, a) - \left(r + \gamma \max_{a' \in \mathcal{A}(s')} Q(s', a') \right) \right)$$

ε-greedy:

$$\pi_{\text{act}}(s) = \begin{cases} \arg \max_{a \in \mathcal{A}(s)} Q(s, a) & \text{with probability } 1 - \epsilon \\ \text{uniformly from } \mathcal{A}(s) & \text{with probability } \epsilon \end{cases}$$

Softmax:

Softmax:
$$\pi_{\text{act}}(a \mid s) = \begin{cases} \frac{\exp(Q(s,a)/\tau)}{\sum_{b} \exp(Q(s,b)/\tau)} & \text{probability } \epsilon \\ \mathbf{1}[a = \arg\max_{a' \in \mathcal{A}(s)} Q(s,a')] & \text{probability } 1 - \epsilon \end{cases}$$

VDBE: adaptive π_{act} automatically decrease ϵ in response to environment

$$\delta = r + \gamma \max_{a' \in \mathcal{A}(s')} Q(s', a') - Q(s, a)$$

$$\epsilon \leftarrow \lambda \frac{1 - \exp(-|\alpha\delta|/\sigma)}{1 + \exp(-|\alpha\delta|/\sigma)} + (1 - \lambda)\epsilon$$

Goal: improve VDBE to reduce cumulative regret:

$$R(N) = \underset{\tau \sim \pi_{\text{opt}}}{N} \mathbb{E} \left[\sum_{t \in \tau} r(\hat{s}_t, \hat{a}_t) \right] - \sum_{i=1}^{N} \sum_{t \in \tau_i} r(s_t, a_t)$$

Methodology

Let

$$Q(s, a) = f(\phi(s, a); \mathbf{w})$$
$$\delta_{\mathbf{w}} = \nabla_{\mathbf{w}} \frac{1}{2} \left(Q(s, a) - \left(r + \gamma \max_{a' \in \mathcal{A}(s')} Q(s', a') \right) \right)^{2}$$

Fluctuation energy, where â is action from previous state

$$H(s, \hat{a}) = |Q(s, \hat{a}) - Q'(s, \hat{a})|$$

Then

$$\epsilon \leftarrow \lambda \frac{1 - \exp(-\sum_{\hat{a}} H(s, \hat{a}) / |\mathcal{A}(s)|\sigma)}{1 + \exp(-\sum_{\hat{a}} H(s, \hat{a}) / |\mathcal{A}(s)|\sigma)} + (1 - \lambda)\epsilon$$

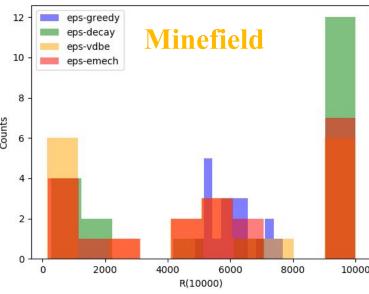
- Baselines: ε -greedy, decaying ε , VDBE, and ensemble-mechanics ε-greedy (aka "Stat Mech") • Python 3.6.8
- Tests: Blackjack (stochastic) from homework; Minefield (nonstochastic) and FrozenLake (stochastic) from Ref. 9
 - SLLL
- **S** = start
- LHLH
- L = land, safe
- LLLH
- $\mathbf{H} = \text{hole/mine}$
- HLLE
- $\mathbf{E} = \text{end}$

Abstract

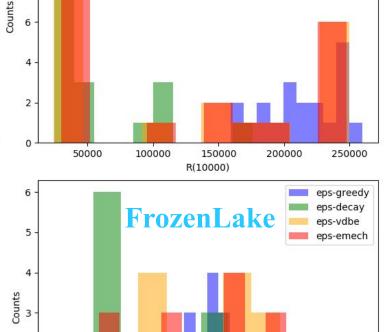
- Reduce speed of convergence (regret) in RL algorithms
- Our algorithm: ε -greedy, but update ε as agent moves through environment according to statistical mechanics
- Compare with three existing RL algorithms
- No improvement but a better *a priori* hyperparameter distribution could help

Results and Analysis

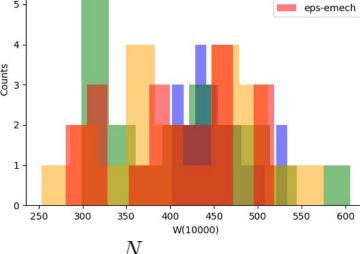
| | | ε-greedy | ε-decay | ε-VDBE | Stat Mech |
|----------------|-----------|----------|---------|--------|-----------|
| Blackjack | Mean | 213744 | 55601 | 127089 | 128443 |
| $R(10^4)$ | Std Error | 6572 | 8898 | 20313 | 20115 |
| Minefield | Mean | 6089 | 6816 | 5350 | 5840 |
| $R(10^4)$ | Std Error | 161 | 920 | 840 | 809 |
| Frozen Lake | Mean | 453 | 407 | 414 | 403 |
| $W(10^4)$ | Std Error | 8.1 | 18.6 | 18.5 | 15.7 |



- Blackjack: high variance, average performance
- Minefield: high variance, decent performance
 - Only nonstochastic environment
- FrozenLake: low variance, bad performance
 - Use cumulative reward W (higher is better):

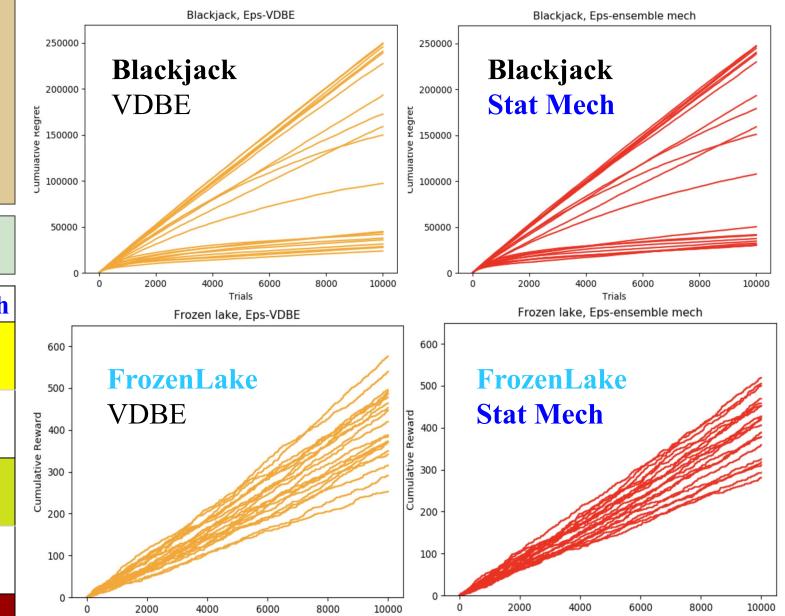


Blackjack



$$W(N) = \sum_{i=1}^{N} \sum_{t \in \tau_i} r(s_t, a_t)$$

Results and Analysis (continued)



Conclusion and Future Work

- Our algorithm ("Stat Mech") performs comparable to VDBE in two environments
- VDBE performs slightly better in one environment
- Used same hyperparameter distribution (a convenient assumption that can be improved) for all tests
 - Future: improve hyperparameter distributions
- Adaptive algorithms underperform nonadaptive in 2/3 tests, possibly due to stochasticity, as noted in Ref. 8
 - Future: formalize stochasticity

References and Acknowledgements

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