Maximizing LOF As an Objective for Exploration in Reinforcement Learning

Dylan R. Ashley

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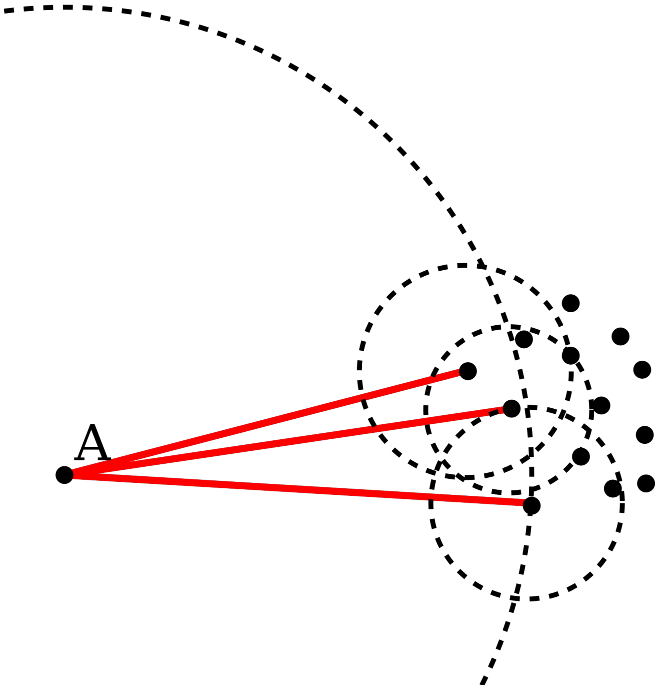
Local Outlier Factor (LOF)

- Compares the density around a point to the density around each neighbour in the point's *k*NN

- LOF ≈ 1 means the point is probably in a cluster

- LOF >> 1 means the point is probably an outlier



Calculating the Local Outlier Factor

$$k\text{-distance}(p) = \max_{q \in k\mathrm{NN}(p)} d(p, q)$$

$$\text{reach-dist}_k(p, q) = \max\{\mathrm{d}(p, q), k\text{-distance}(q)\}$$

$$\mathrm{lrd}(p) = \frac{1}{\frac{1}{k} \sum_{q \in k\mathrm{NN}(p)} \text{reach-dist}_k(p, q)}$$

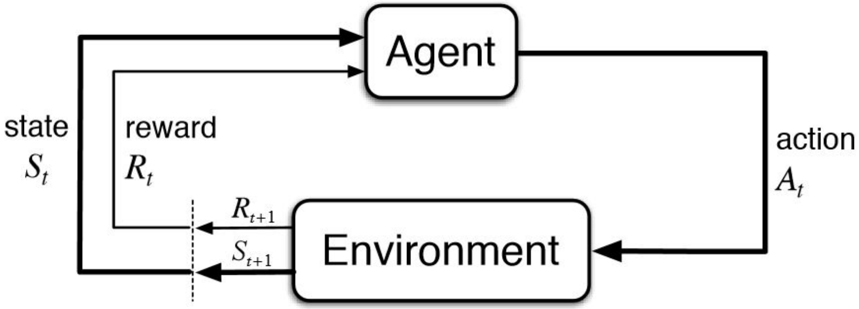
$$\mathrm{LOF}(p) = \frac{\frac{1}{k} \sum_{q \in k\mathrm{NN}(p)} \mathrm{lrd}(q)}{\mathrm{lrd}(p)}$$

Reinforcement Learning

- Models an agent interacting with an environment

- Agent wants to maximize reward signal with later rewards being considered less valuable

- The agent doesn't know about it's environment beforehand and has to explore to learn about it



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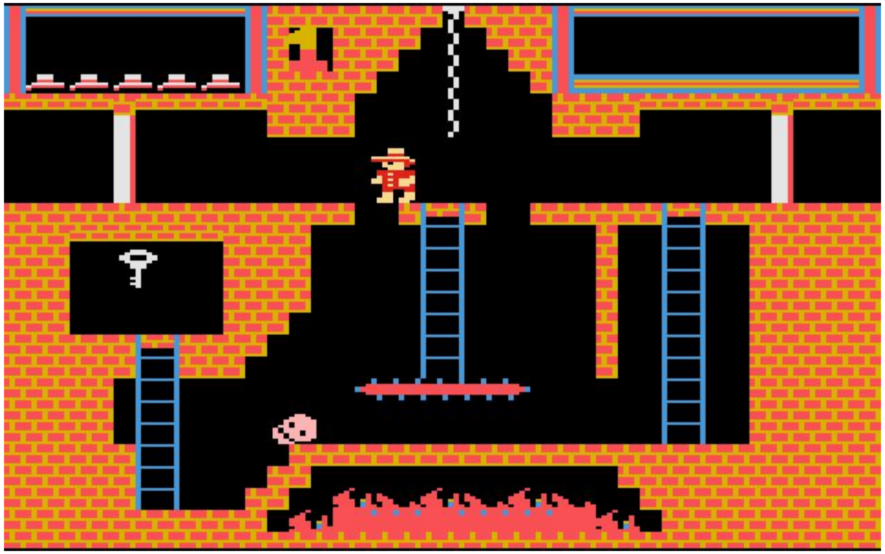
Motivation for Better Exploration

- Exploration is a major factor in the learning rate for an agent
- Without proper exploration the agent is liable to miss something important
- Naïve approaches often perform very badly



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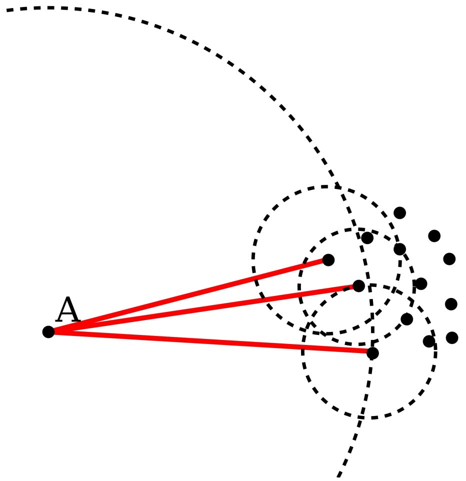
Using the LOF to Guide Exploration

- Reward an RL agent with the LOF of each state or transition it sees and a second agent can learn using the real rewards

- Intuitively this incentivises the agent to find rare states or transitions

- Can combine with random exploration to smooth out the exploration



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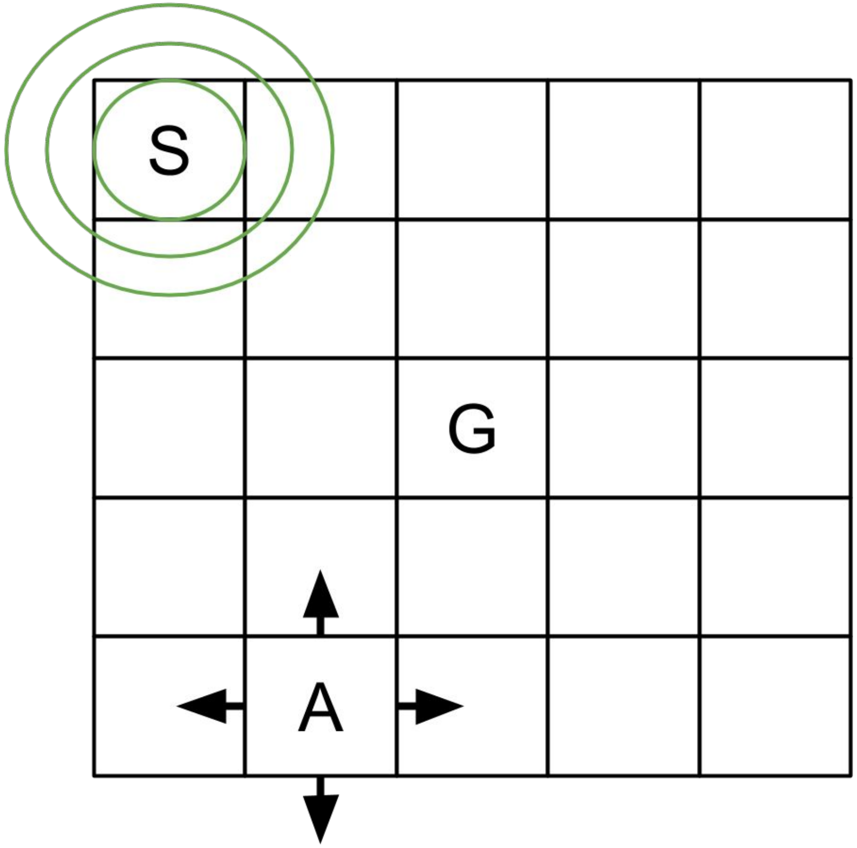
Domain

- 5x5 Gridworld with single start and goal state
- Observations drawn from truncated Gaussian centered at current state scaled to cell size leading
- Empirically learnable with simple RL methods

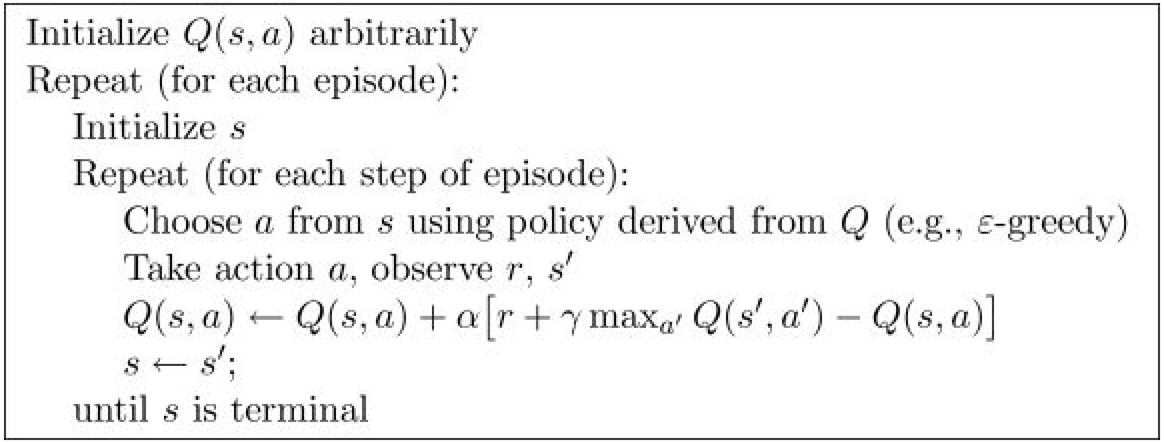


Algorithms

- Q-learning with tile coding as function approximation

- Well known algorithm that learns the value of taking an action based on the state the agent is currently in

- Note that tile coding is actually optimal for this domain



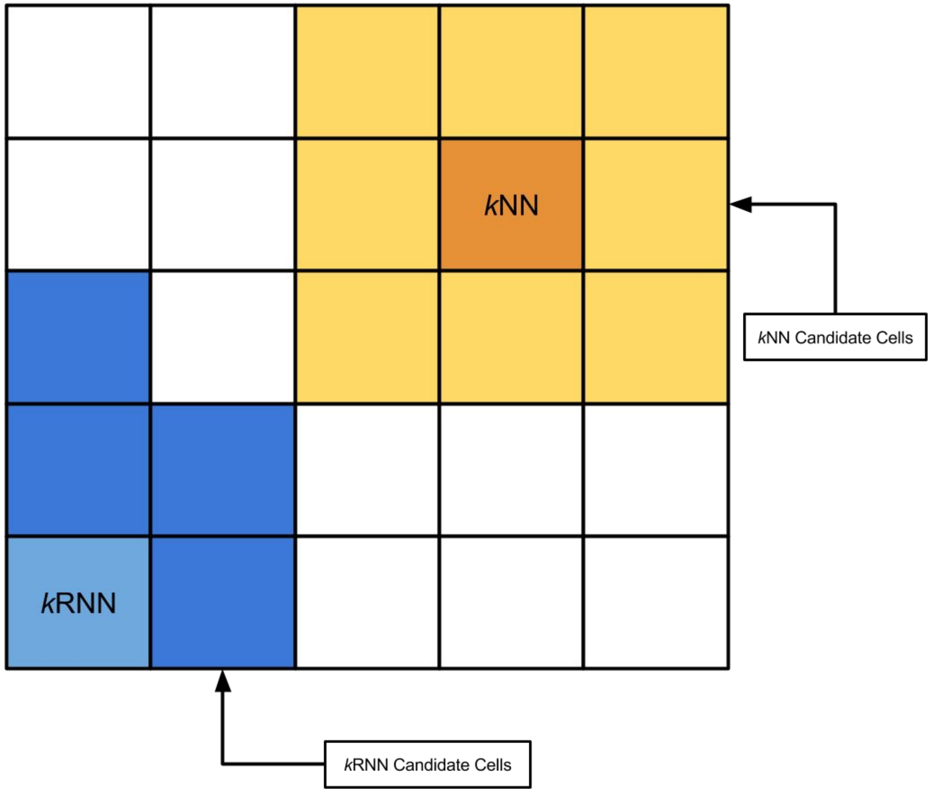
```
Initialize $Q(s, a)$ arbitrarily
Repeat (for each episode):
    Initialize $s$
    Repeat (for each step of episode):
        Choose $a$ from $s$ using policy derived from $Q$ (e.g., $\varepsilon$-greedy)
        Take action $a$, observe $r$, $s'$
        $Q(s, a) \leftarrow Q(s, a) + \alpha\big[r + \gamma \max_{a'} Q(s', a') - Q(s, a)\big]$
        $s \leftarrow s'$;
    until $s$ is terminal
```

Algorithms (continued)

- Use a grid for *k*NN to prevent having to check all data points in *k*NN search

- Increases overhead and slows early *k*NN computation in exchange for faster later *k*NN computation

- No change in worst case time complexity



Performance Metric

$$\sigma = \sqrt{\frac{\sum_{i=1}^{|S|} \left(V_{S_i} - \overline{V} \right)^2}{|S| - 1}}$$

- Standard deviation of state visitations

- Minimizing means a more even exploration of the world

- Penalizes linear increase in distance to mean superlinearly

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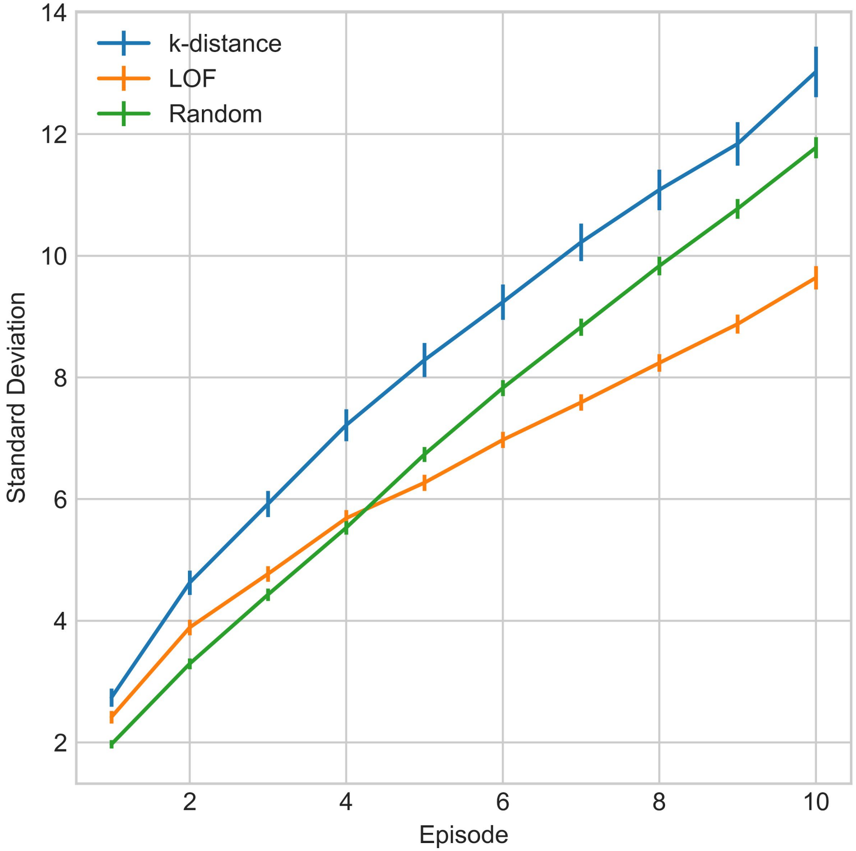
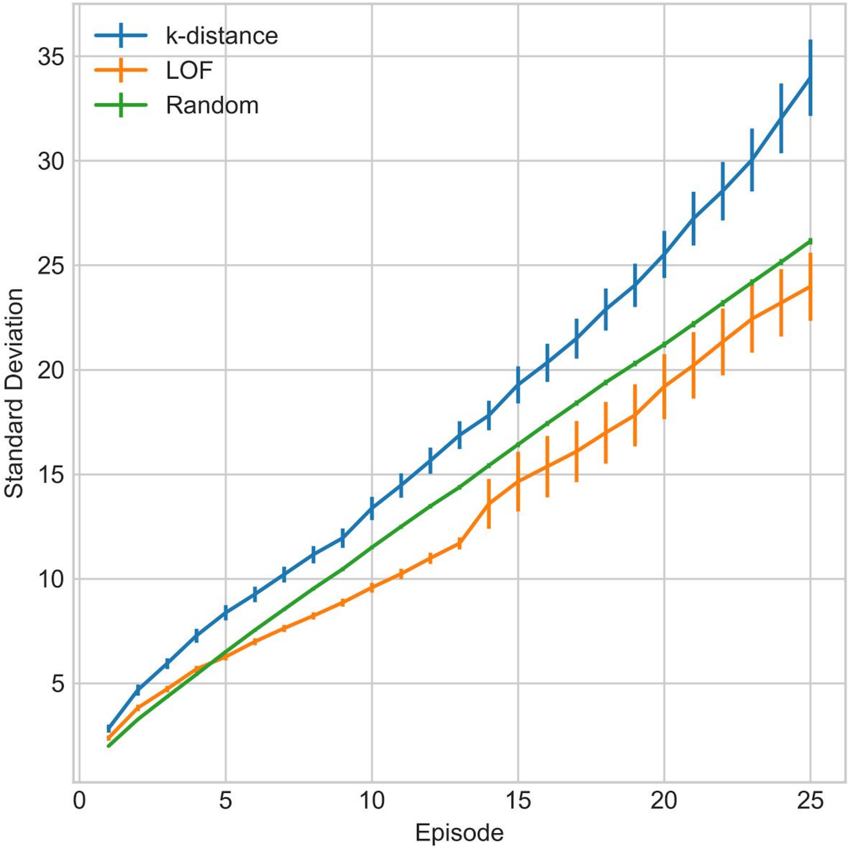
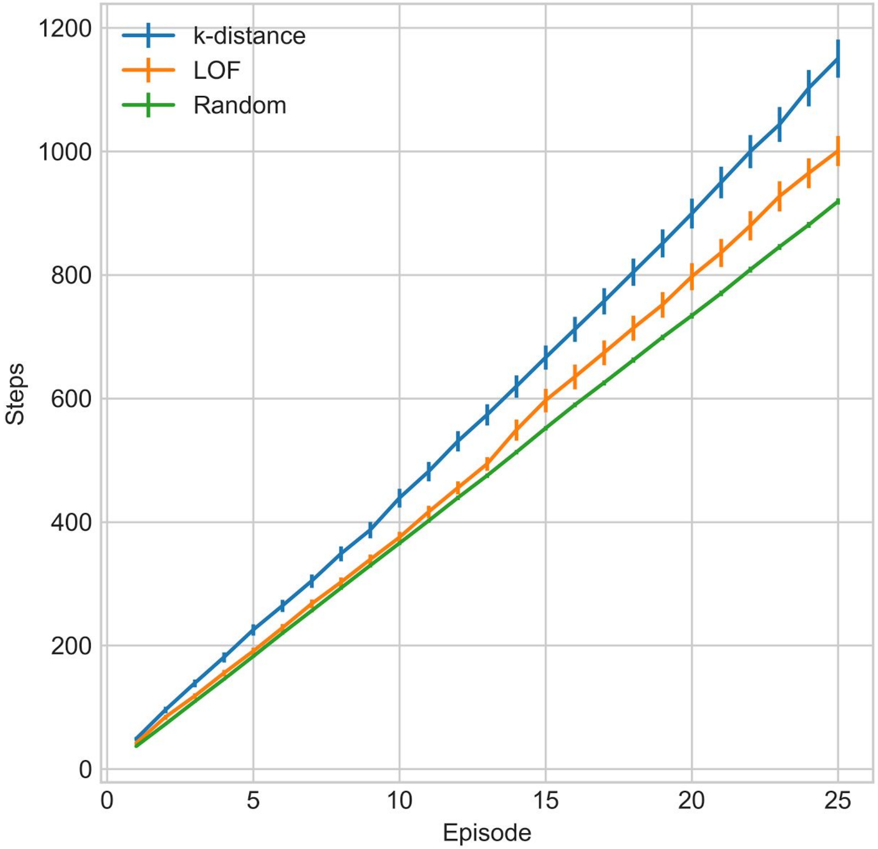
Experimental Results



Experimental Results (continued)





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Discussion

Pros

- Since it’s just a reward signal it can be used with any RL algorithm
- Natively handles a continuous space
- Can handle a changing environment by storing only the last *n* states or transitions

Cons

- Have to store states or transitions
  - If you only store the last n this is viable for the long term
- Doesn’t natively handle identical observations
  - Clipping values may be possible without incurring too severe a penalty
- *k*NN is quite expensive
  - There are cheaper approaches that haven’t been considered for this project because of complexity

References

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- http://web.stanford.edu/class/cs234/images/header2.png
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