COMPUTATIONAL APPLICATIONS TO POLICY AND STRATEGY (**CAPS**)

Session 4 – Model Deployment Evaluation

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Outline

- 1. Auditing Algorithms
- 2. Case: Auditing Google's Search Algorithms
- 3. Auto-Complete and Recommender Algorithms
- 4. Reinforcement Learning
- 5. Failure Modes and Human-in-the-Loop Learning
- 6. Short Case: Determining the Agency of an Aerial Vehicle

1. Auditing Algorithms

Primer's Chief executive, Sean Gourley, said vetting the behavior of this new technology would become so important, it will spawn a whole new industry, where companies pay specialists to audit their algorithms for all kinds of bias and other unexpected behavior.

"This is probably a billion-dollar industry," he said.

1.1 Determining the Type of Audit

| | Interpretable | Not interpretable |
|-----------------------|---------------|-------------------|
| Access to the code | Easy | Difficult |
| No access to the code | Difficult | Hard |

1.2 Challenges of Auditing in Non-Cooperative Environments

- Methods of inquiry are inherently fuzzy
- Results of audit will be imperfect
- Have to make judgement about algorithm based on imperfect information

1.3 Black-Box Testing

```
# example of simple black-box test
# we want to audit the algorithm MathOp that takes two numbers (x, y) as input
and
# performs an unknown mathematical operation on them
MathOp(3, 3)
6 # operation could be x + y or x + 3, or multiple other alternatives
MathOp(3, 2)
5 # operation seems like x + y
MathOp(1, 0)
Error # unclear what the source of the error is, needs further investigation
```

2 Case: Auditing Google's Search Algorithms

How Google Interferes With Its Search Algorithms and Changes Your Results

The internet giant uses blacklists, algorithm tweaks and an army of contractors to shape what you see

2.1 Comparison of Search Results A

| | Joe Biden is | | | • |
|---------------|--------------|------|------------------------------|-----------|
| GOOGLE | | | DUCKDUCKGO | SHOW BING |
| done | | 100% | an idiot | 100% |
| how old | | 100% | creepy | 100% |
| from | | 99% | from what state | 100% |
| running for p | resident | 79% | too old to run for president | 100% |
| he democrat | | 78% | a moron | 94% |
| he running fo | r president | 76% | a liar | 84% |
| toast | | 71% | a joke | 78% |
| a democrat | | 70% | done | 22% |
| | | | a creep | 22% |

2.1 Comparison of Search Results B

| Joe Biden is | | | • |
|--------------------------|------|-----------------------|-----------------|
| GOOGLE | | BING | SHOW DUCKDUCKGO |
| done | 100% | donald trump | 100% |
| how old | 100% | a sen | 78% |
| from | 99% | he done | 78% |
| running for president | 79% | a reclamation project | 71% |
| he democrat | 78% | presidential | 64% |
| he running for president | 76% | a grouper | 58% |
| toast | 71% | going to cure cancer | 58% |
| a democrat | 70% | issues | 58% |

2.1 Comparison of Search Results C

Immigrants are

SHOW DUCKDUCKGO GOOGLE BING a blessing not a burden 100% given shelter 100% increasing taxes 100% entrepreneurs 100% good for the environment 98% law abiding 100% net contributors important 98% 100% more likely to be entrepreneurs 98% tax exempt 100% net contributors 98% entrepreneurs pew 85% treated unfairly 77% funding social security 71% coming from what countries a burden to taxpayers 76% 43%

▼

2.1 Comparison of Search Results C

Immigrants are

| GOOGLE | | DUCKDUCKGO | SHOW BING |
|---------------------------------|------|------------------------------|-----------|
| a blessing not a burden | 100% | animals | 100% |
| entrepreneurs | 100% | dangerous | 100% |
| good for the environment | 98% | less likely to commit crimes | 100% |
| important | 98% | ruining america | 100% |
| more likely to be entrepreneurs | 98% | taking our jobs | 100% |
| net contributors | 98% | good | 84% |
| treated unfairly | 77% | an infestation | 77% |
| coming from what countries | 76% | not criminals | 77% |

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3. Auto-Complete and Recommender Algorithms

How do auto-completion algorithms work?

• A user provides the beginning of a search query and the auto-complete algorithm provides the user with a number of suggested alternatives for completing the query

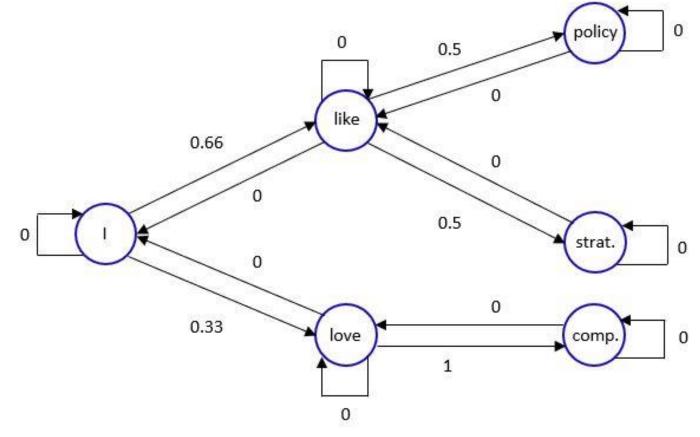
How do recommender algorithms work?

• A user makes a choice among alternatives (movies, items, etc.) and, based on features of the choice, the recommender algorithm generates new alternatives for the user

3.2 Sequential Probabilistic State Transitions

How do auto-completion algorithms work?

• A user provides the beginning of a search query and the auto-complete algorithm provides the user with a number of suggested alternatives for completing the query



CAPS – Session 1 – Model Deployment Evaluation

3.3 Optimal Action Selection Under Uncertainty

How do recommender algorithms work?

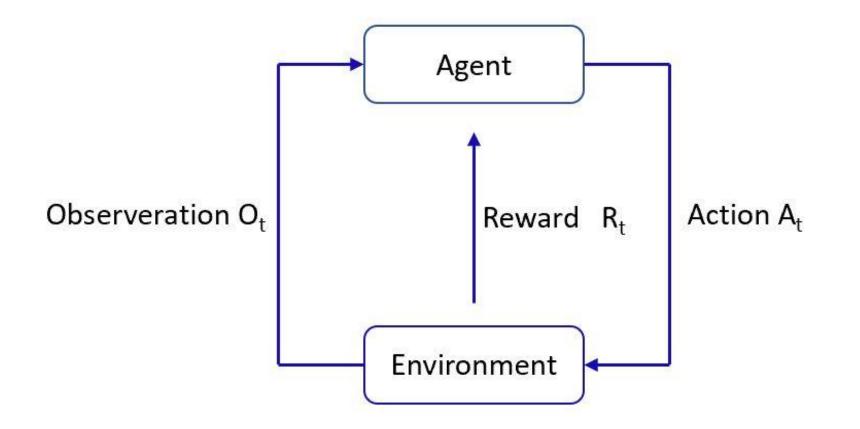
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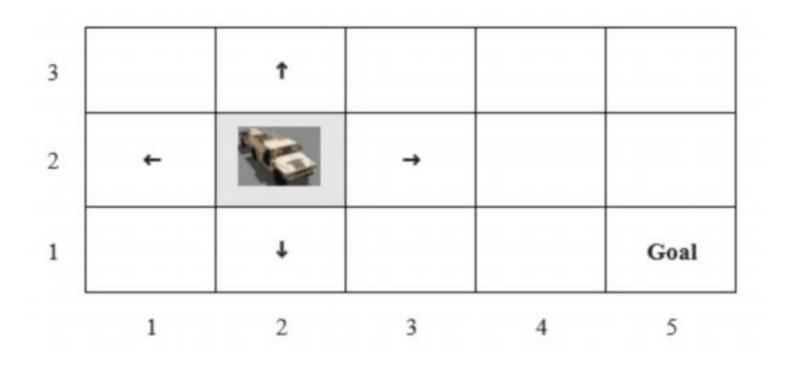
4. Reinforcement Learning

Reinforcement learning is learning what to do—how to map situations to actions—so as to maximize a numerical reward signal. The learner is not told which actions to take, but instead must discover which actions yield the most reward by trying them. In the most interesting and challenging cases, actions may affect not only the immediate reward but also the next situation and, through that, all subsequent rewards. These two characteristics —trial-and-error search and delayed reward—are the two most important distinguishing features of reinforcement learning.

4.1 Markov Decision Processes



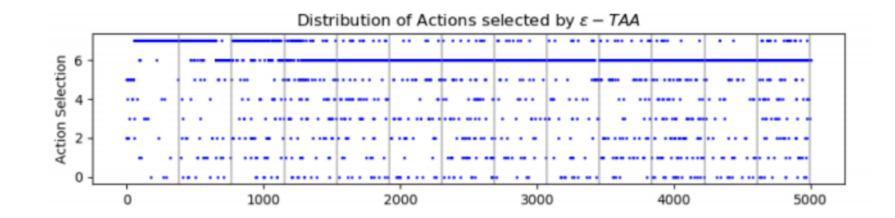
4.2 Simple Reinforcement Learning Example



4.3 Specifying a Multi-Armed Bandit

| Action | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|----------|-----|-----|-----|-----|-----|-----|-----|-----|
| Mean | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 |
| Variance | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 |

4.4 Epsilon-Greedy Action Selection

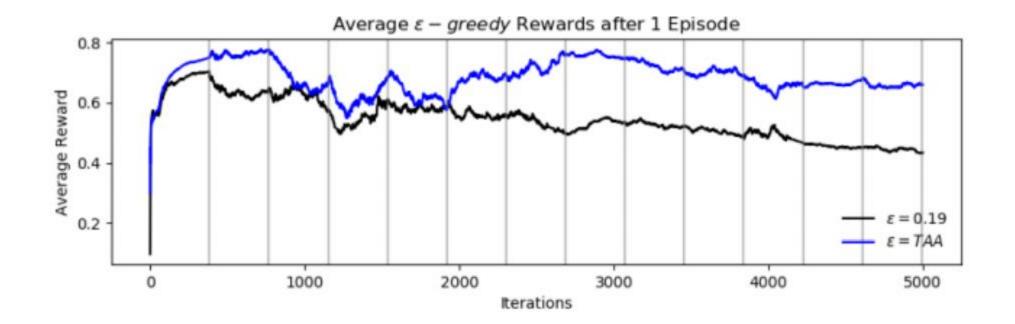


a

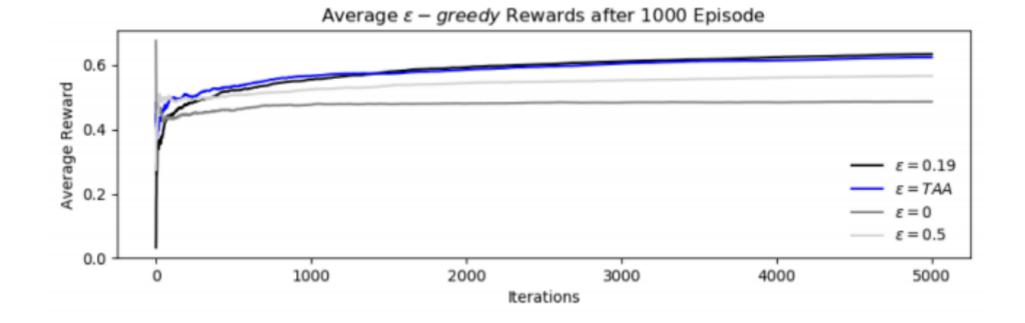


Distribution of Actions selected by $\varepsilon - 0.19$

4.4 Epsilon-Greedy Rewards



4.4 Epsilon-Greedy Rewards after 5000 Episodes



5. Failure Modes and Human-in-the Loop Learning

Reinforcement learning is a powerful technique but it comes with many unexpected failure modes that we often need human supervisors to fix.

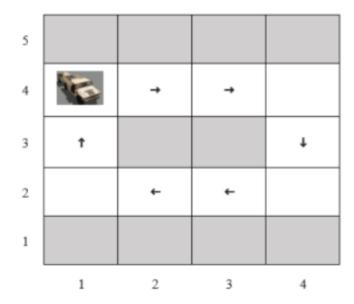
In this section, as an exercise, we look at two of these failure modes and discuss how humans can fix them.

We look at reward gaming and negative side effects.

5.1 Reward Gaming

Reward Gaming

> Agent exploits an unintended loophole in the reward specification, to get more reward than deserved

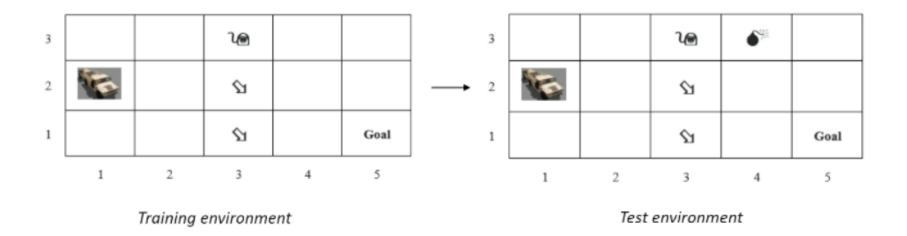


- > Desired outcome: clockwise completion of race
- > Arrows are checkpoints associated with a reward of 3

5.2 Negative Side Effects

Negative Side Effects

> Reward function does not fully capture all the properties of the test environment



- > Desired outcome: reach goal state
- > \Im (spotted by enemy) = -1, \Im (bad terrain) = -3, \clubsuit (land mine) = -100, **Goal** = 10

5. Short Case: Determining the Agency of an Unknown AV

