Wisdom of Crowds versus Groupthink: learning in groups and isolation

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Mayo-Wilson, Conor, Kevin Zollman, and David Danks. "Wisdom Of Crowds Versus Groupthink: Learning In Groups And In Isolation." International Journal Of Game Theory 42.3 (2013): 695-723.

Overview

- Compare learning ability of networked agents to isolated agents
- Multi-armed bandit problem
- 6 different approaches
  - Simulated Annealing
  - Epsilon Greedy
  - Delta-Epsilon
  - Reinforcement learning
  - Weighted Reinforcement learning
  - Upper Confidence Bound
- **Hypothesis: No significant difference between networked and isolated agents in a general case.**

Agenda

1. Introduction to Multi-armed bandit problem
2. Overview of the 6 methods
3. Summarize the experiment
4. Evaluate the results
5. Discuss future work
6. Review and Conclude

Multi-armed Bandits

- Colloquial slot machine name: “one-armed bandit”
- Agent pulls one “arm” and receives reward
- Reward is independent of other arms
  - Typically also random
- Regret defined as (possible reward – actual reward)
- Agent’s goal is to maximize reward and minimize regret
  - Achieve by alternating exploration and exploitation
- Agents in paper seek to find optimal reward
- Let’s look at an example

Rosin, Christopher. "Multi-Armed Bandits With Episode Context." Annals Of Mathematics & Artificial Intelligence 61.3 (2011): 203-230.

Multi-armed Bandit example

	Arm 1	Arm 2	Arm 3
First Pass	Reward = 1	Reward = 1	Reward = 0
Second pass	Reward = 1	Reward = 2	Reward = 0
Best choice?	✗	✓	✗
Actual reward	P(1) = 1.0	P(1) = 0.5 P(2) = 0.5	P(0) = 0.9 P(1000) = 0.1
Actual best	✗	✗	✓

Bounded rationality

- Limitation on decision making ability
- Make the best decision based on information available in the time allotted [Jones]
- Large subset of Computing problems
  - Example, Multi-armed bandit problem
  - All information => trivial solution

Jones, Bryan. “Bounded Rationality” Northwestern University Press. (1999) Accessed via web on November 5, 2014.

Agenda

1. Introduction to Multi-armed bandit problems
2. **Overview of each of 6 methods**
   1. Epsilon Greedy
   2. Sigma Epsilon
   3. Reinforcement Learning
   4. Weighted Reinforcement Learning
   5. Simulated Annealing
   6. Upper Confidence Bound
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Epsilon Greedy

- Pick a best action most of the time and explore remainder
- P(a = best) : $1 - \varepsilon$
- P(a = random) : ε
- "Best" is action with highest expected reward
- Pro:
  - Focus on exploitation
  - Also guaranteed to search
- Con:
  - Very slow exploration compared to other methods
  - Continues to explore after finding true optimal

Delta Epsilon

- Uses a set of “favorite arms”
- Choose best with $1 - (\partial + \varepsilon)$ probability
  - $P(a = \text{best}) : 1 - (\partial + \varepsilon)$
  - $P(a = \text{random}) : \varepsilon$
  - $P(a = \text{favorite}) : \partial$
- Pro:
  - Same as Epsilon Greedy
  - Better approximates human decision making
- Con:
  - Set of favorites may not be optimal
    - Could perform very bad

Reinforcement Learning

- Agent seeks to maximize cumulative reward
- Choose based on ratio of reward
  - P(a) = R_a / R_t
  - R_a is the expected reward for action a.
  - R_t is the total reward of all actions
- Pro:
  - Great exploration of search space
- Con:
  - Very slow when all rewards are similar
  - Will still explore even when the “best” is found
    - Optimal arm just has highest selection probability

Weighted Reinforcement Learning

- Same as Reinforcement learning with a weighted function
- P(a) = $f\,(\,R_a\,)\,/\,f\,(\,R_{\mathrm{t}}\,)$
  - Where f () is a function that increases with time
  - Weights recent actions more strongly than distant actions
- Pro:
  - Over time, probabilities greatly favor optimal actions
- Con:
  - Depending on weights, might exploit too fast
    - Agent would choose non optimal action
  - Difficult to determine the exact weighting factor

Simulated Annealing

- Similar to hill climbing with multiple restarts
  - Over time “cool” the problem so we widen our search space
  - $P(r_{cur}, r_{next}, T)$
    - r_{cur} is the reward of the current arm.
    - r_{next} is the expected reward of the next arm.
    - T is the temperature of the system
- Pro:
  - Settles on a single answer
- Con:
  - Temperature is the dampening factor
    - Too high and system will never exploit
    - Too low and system will find local (not global) maximum

Hasani, Keramat, Svetlana A. Kravchenko, and Frank Werner.
"Simulated Annealing And Genetic Algorithms For The Two-Machine Scheduling Problem With A Single Server."
International Journal Of Production Research 52.13 (2014): 3778-3792.

Upper Confidence Bound

- Also known as Confidence Interval
- Statistically measure how well the agent is doing.
- Over time the confidence increases
  - Statistical certainty of level of performance.
- Pro:
  - Minimize regret after each “play”
    - Each “play” involves a sample from all arms
  - Self describing level of fitness
    - Useful for mathematical comparisons
- Con:
  - Requires a huge number of samples for each round
    - Difficult to break down search space

Mitchell, Tom. *Machine Learning*. McGraw-Hill Publications. March 1 (1997)

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Math Notations

- Our learning problem is defined as { Ω, *A* , *O*, *p*}
  - Ω is the finite set of states of the world
  - A is a finite set of actions
  - O is a finite set of non-negative outcomes (rewards)
  - p is the probability of obtaining a particular award based on an action

$$p = \{p(* \mid a, \omega)\}_{a \in A, \omega \in \Omega}$$

Math Notations

- A Strategic Network is defined as $S = \{G, M\}$
  - G is the network (group) of agents
  - M is the method used by the agents
- Focus on networks S applied to learning problems that are:
  - Non-trivial
    - Same history of actions could lead to different states
  - Difficult
    - No action guaranteed to succeed
    - Little to no certainty of optimality

Experiment

- Mathematically state each learning method
- Evaluate networked and isolated agents
  - Comparing each method to themselves
  - Show any performance difference
- Hypothesis: No significant difference between networked and isolated agents in a general case.

RL vs RL

UCB vs UCB

wRL vs wRL

εG vs εG

∂ε vs ∂ε

SA vs SA

Experiment

- How to define convergence in bounded rational problem?
  - Define individual metrics
    - Isolation Consistency (*IC*)
      - Agent converges to optimal while in isolation
    - Universal Consistency (*UC*)
      - Agent converges to optimal while in an arbitrary network
        - Could be similar or foreign agents
  - Define the same but for groups!
    - Group Isolation Consistency (*GIC*)
      - One agent uses the strategy *M* and all agents converge
    - Group Universal Consistency (*GUC*)
      - All agents use strategy *M* and all converge

Individual Consistency

- Some implementations satisfy for all 6 methods
  - Does not need to be all!
  - We are looking for the existence of consistency in the methods
    - Not necessarily the robustness
- Consider the case of ε Greedy.
  - Small values of ε will converge
  - Large values will explore too often and shift the average away from the optimal return

Universal Consistency

- UC methods will always be IC
  - Just separate the connections in the grouping
- Not all IC methods are UC
- Consider ε Greedy strategies again
  - Experiment with rate $\frac{1}{n^{x/y}}$
    - x = number of actions observed
    - y = number of actions performed
  - In isolation that is $\frac{1}{n}$
  - In networks that becomes $\frac{1}{n^2}$
    - Too small to ensure optimality
- ε Greedy is IC but not UC

Group Consistencies

- Similar idea to Individual and Universal Consistency
- If Network is GUC then any single agent is GIC
- Not always true for the reverse
  - Consider ∂ε with sub-optimal favorite actions
    - Group may do very well but individual agents will not
- In general, GUC is to GIC as UC is to IC

Isolated vs Networked

- "Rational network of irrational individuals"
  - Paradox state
  - At least one IC individual in network
    - Broadcasts optimal choice to all others
    - Network settles on optimal action
- "Irrational network of rational individuals"
  - Conflicting information between individuals
  - Same problem we saw with ε Greedy and Universal Consistency

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Results

- Several of the methods lack Universal Consistency
  - ε and RL methods
  - This means they also lack Group Universal Consistency
- There are exceptions to the general case
  - Contextual information is hugely important
- Independent Consistency and Group consistency need not coincide
- Learning methods all have strengths and weaknesses like anything else
  - Here some are better for isolation while others favor the performance of groups
- Group Learning is not necessarily more accurate!

The winner is: UCB

- None of the methods hold up against all criteria
  - UCB meets both IC and UC
    - Less promising in GIC and GUC
- Seems to hold up to math models the best
- The devil is in the details
  - Implementations vary and there may be more factors
  - Would need to study other applications on a case by case basis

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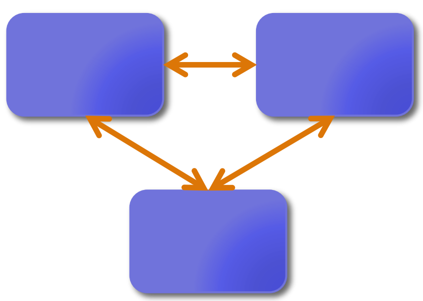
Future Work and Opportunities

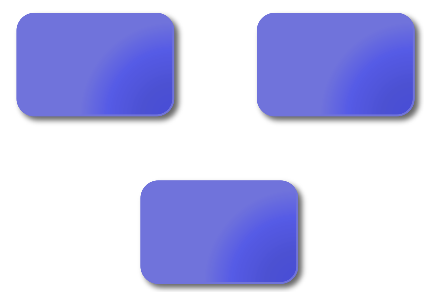
- Implementation
  - Can we be successful even without proof
    - Heuristics could be something we use for performance
- Incorporate real world data and testing
  - Theory is helpful but real data has new set of challenges
    - Quality of data and ability of methods to filter bad data
- Confidence Intervals look very promising
  - Implementations vary
- Expand analysis to other problem domains
  - Plenty of other Bounded Rational problems to study
  - Including the adversarial Bandit problem

Challenges

- Upper Confidence Bound misleading performance
  - Each "round" requires a sample of all arms
  - A UCB "round" is much more computationally complex than εG
    - Intuitively we would expect a greater knowledge gain
- Downplay of unconnected groups
  - Focus on connected only



Test consistency of Groups



Test individual variance?

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Review

- 6 Different Learning methods
- Compared across 4 criteria
- None stand out as a general solution
    - Authors choose Upper Confidence Bound as a top performer in the general case
- Need to test with real world data to verify model
- Expand analysis to more domains

Conclusion

- Takeaways
  - Information transfer is difficult to accomplish in general form
  - Careful implementation details would bypass many difficulties
    - Dynamic programming
    - Use of heuristics
- Real world disconnect
  - There exists optimal policy
  - Finite number of actions to that policy
  - Can’t write that policy without exploring all actions and states
    - Still limited by physical hardware for complex problems.

References

- Mayo-Wilson, Conor, Kevin Zollman, and David Danks. "Wisdom Of Crowds Versus Groupthink: Learning In Groups And In Isolation." International Journal Of Game Theory 42.3 (2013): 695-723.
- Rosin, Christopher. "Multi-Armed Bandits With Episode Context." Annals Of Mathematics & Artificial Intelligence 61.3 (2011): 203-230.
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Thank you

Questions?