Modeling U.S. Lobbying Industry with Multi-Agent Multi-Armed Bandit Problem

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Motivations

- What is lobbying?
  - This question is simple but answered not clearly in the literature.
- Unexplained phenomenon in lobbying industry.
  - Lobbyists usually lobby to both sides of legislators. (Why?)
    - ★ in terms of their clients' interest.
  - Existing theories don't explain this phenomenon satisfactorily.
    - ★ If the lobbying is simply a process of buying vote, then lobbyists should lobby to only one side of legislators.

New Theory of lobbying

- (Q. Why lobbyists lobby to both sides of legislators?)
- Lobbying is **delegated information acquisition** process.
  - Interest groups hiring lobbyist to acquire information about legislators' position on specific issue.
  - Model this situation as a Multi-Agent Multi-Armed Bandit problem.

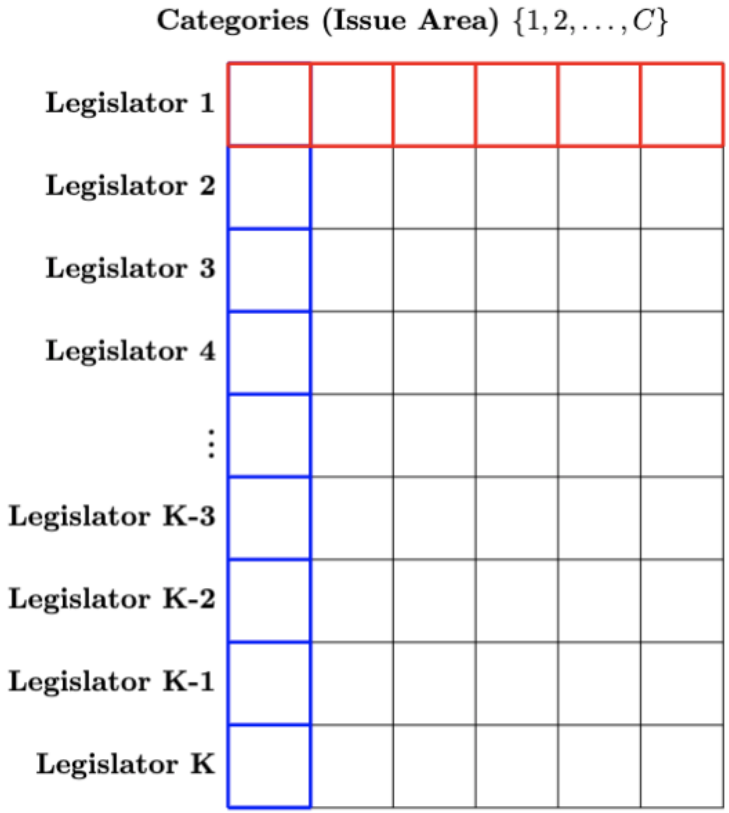
Setting

- $|C| \in \mathbb{N}$ number of issue categories.
- $|J|$ number of interest groups
- Each interest groups $j \in J$ has their own unique category of interest $\phi(j)$
- $|K|$ number of legislators with P_k reward distribution.
- Reward distribution P_k is modeled as a **Categorical distribution** with $|C|$ number of categories.
- Whenever an interest group j interact with a legislator k, they receive $c \in \{1, 2, \ldots, C\}$ sampled from P_k.
- Each interst group j gets reward of $r_j = \mathbb{1}(x_k = \phi(j))$ when j choose legislator k and sampled $x_k \in \{1, 2, \ldots, C\}$ from P_k.
- To maximize the toal reward, interest groups need to find the legislator who are most likely to sample their category of interest.

Bandit Strategy

- Used **Thompson Sampling** algorithm.
- Each interest group j has their own prior belief over $|K|$ number of categorical distributions.
- Keep updating the prior belief using sampled observations from the interaction with legislators.
- After update, choose the best rewarding legislator based on the samples from posterior distributions.
- Use Dirichlet distribution for prior/posterior distribution because it is the conjugate prior of the categorical distribution.

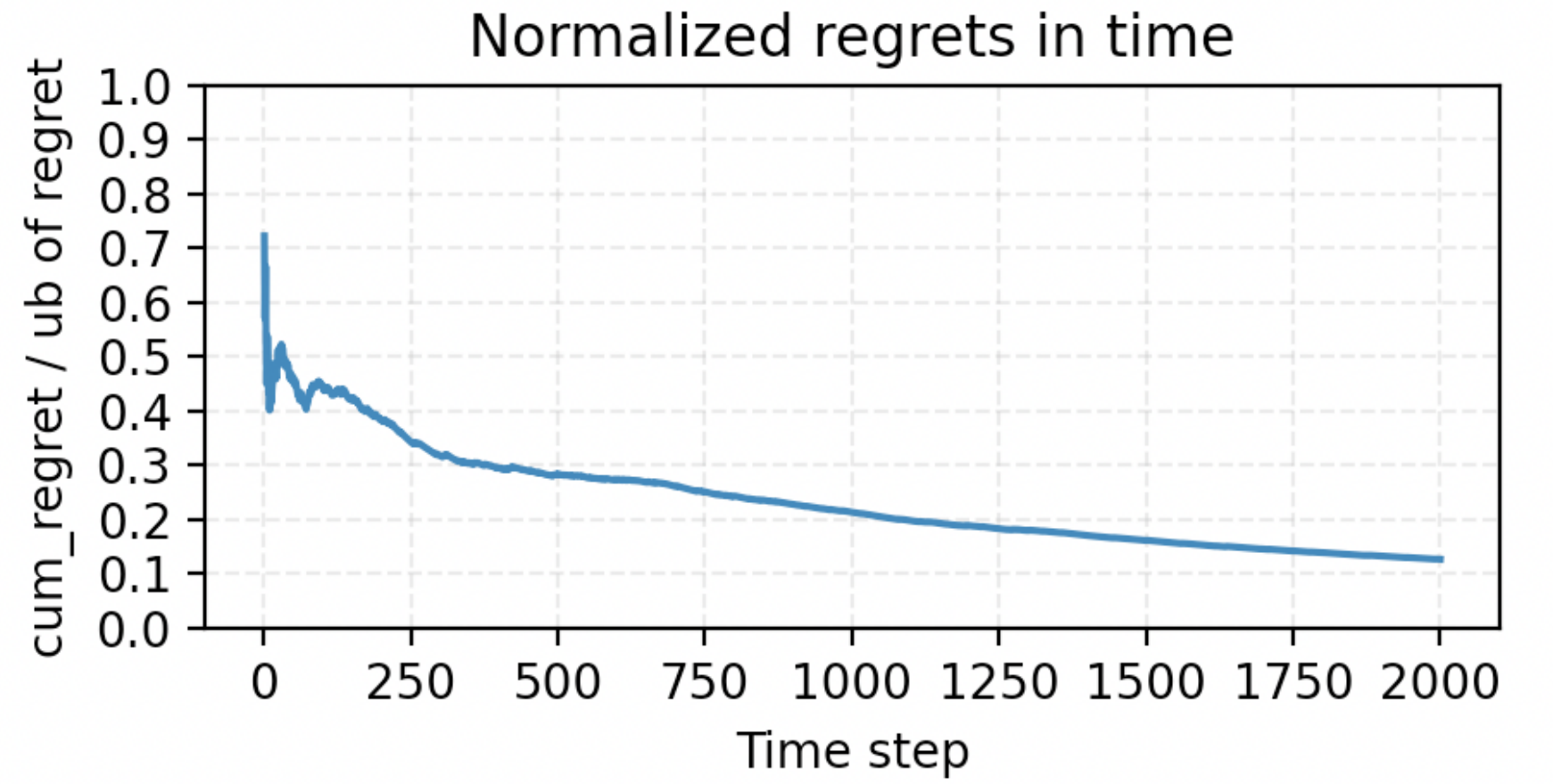
Belief Parameter



- $K \times C$ matrix.
- Starts from flat prior (all entries are 1)
- Add 1 whenever observe c from the interaction with the legislator k.

Simulation Results I: Small Search Space

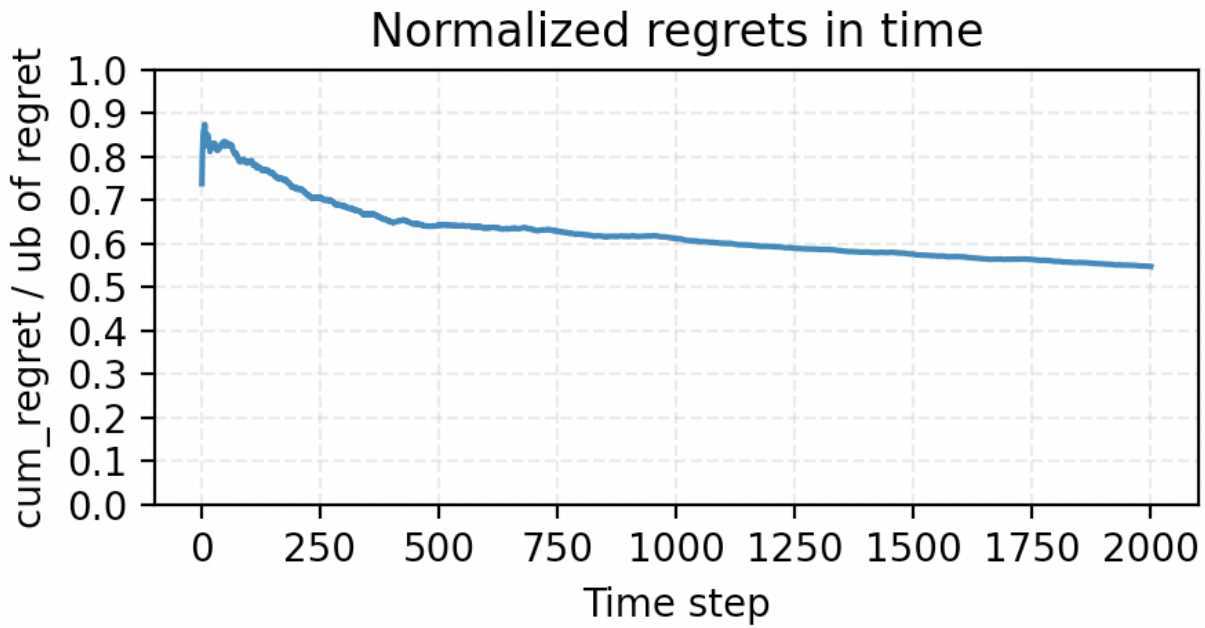
- $|K| = 32, |C| = 4, |T| = 2000$.



- Total $32 \times 4 = 128$ number of parameters to explore - which is relatively small compared to real world.

Simulation Results II: Large Search Space

- $|K| = 112$[1], $|C| = 26$[2], $|T| = 2000$.



- Total $112 \times 26 = 2912$ number of parameters to explore - which is relatively large compared to the previous case. Hard to explore all the parameters with the same time horizon of $T = 2000$.

[1] Average number of legislators that top 10 lobbying firms campaign contribute in 2020. (From Lobbying Disclsoure Act dataset)

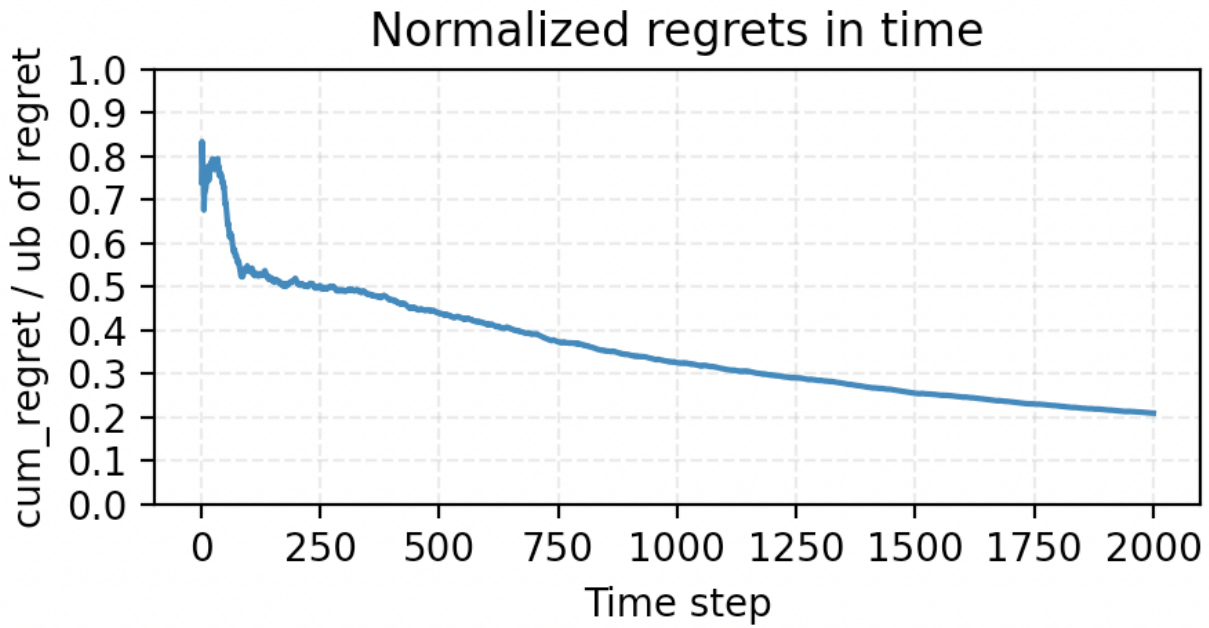
[2] Average number of issue codes for each client in 2020. (From Lobbying Disclsoure Act dataset)

Lobbyist as a Solution to Explore a Large Search Space

- Introduce new $l \in L$ arms which represent lobbyists.
- Each lobbyist arm has its own belief parameter matrix.
- Interest groups can choose to use a lobbyist or not.
- **Pros:** Interest group can take advantage of the lobbyist's knowledge of the legislators' reward distribution. This distribution could be less biased because many interest groups can collectively update the lobbyist's parameters.
- **Cons:** Interest group can not update its own distribution. This means that the interest group can not learn from its own experience.

Simulation III: Large Search Space with Lobbyist

- $|K| = 112, |C| = 26, |T| = 2000, |J| = 5^3, |L| = 1.$

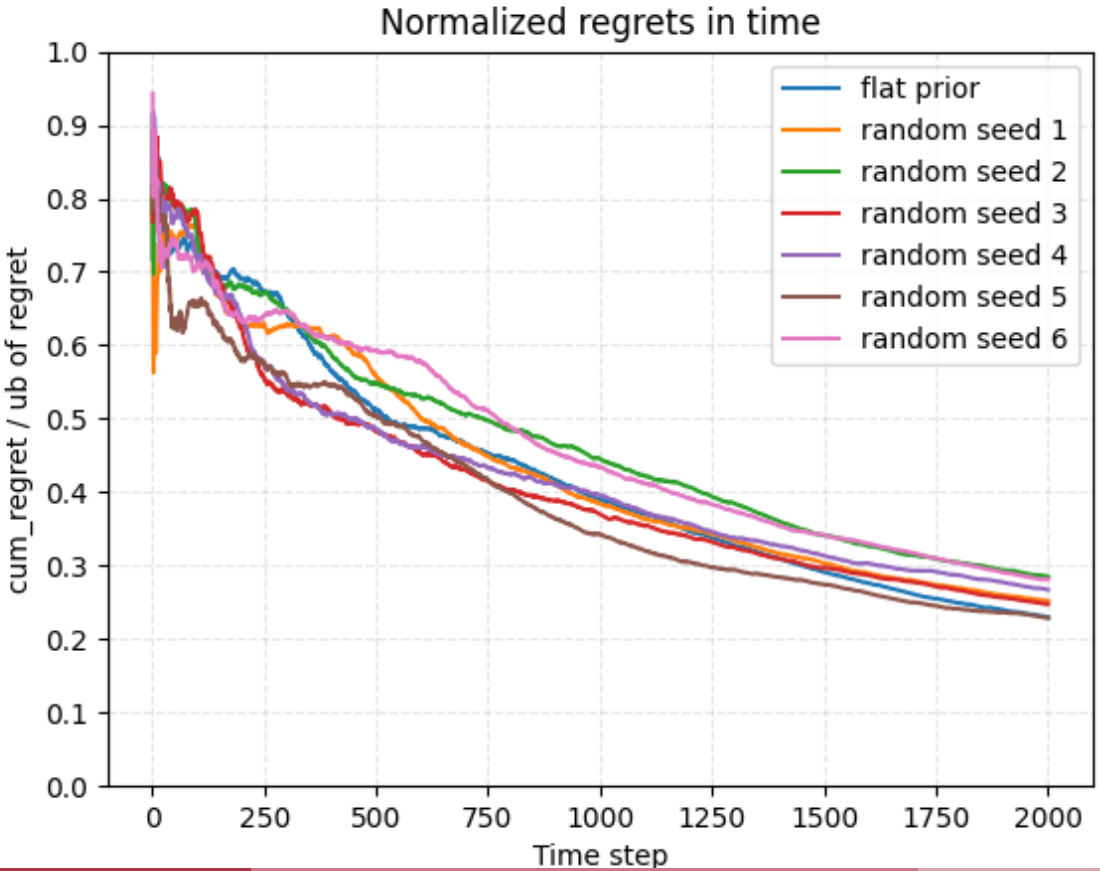


- With a lobbyist and 5 interest groups with a common category of interest, it achieves 0.2 of the lowest normalized regret (< 0.55 w/o lobbyist).
- This suggests that lobbyist can help interest groups to explore the search space more efficiently.

[3] Average number of clients that top 10 lobbying firms has for one issue area in 2020

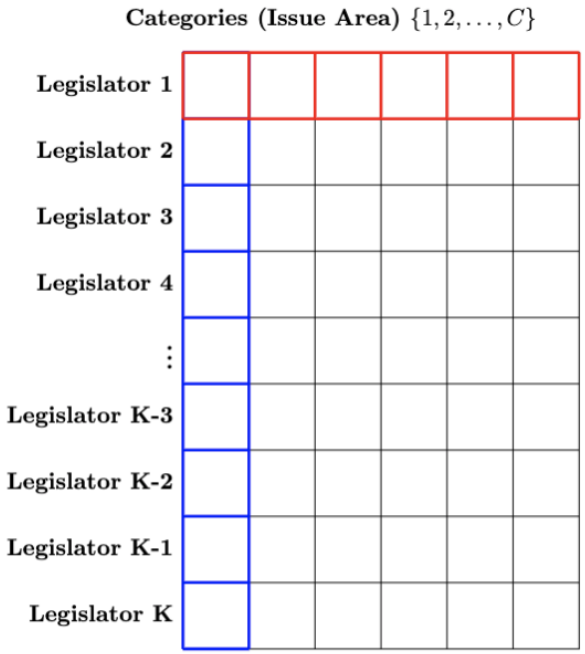
Expertise of Lobbyist

- Regret plot of the simulation with lobbyist with **flat prior** and **random prior**.
- Regardless of the expertise of the lobbyist, the agents (IGs) use lobbyist for collaboration and successfully solve the large search space problem.



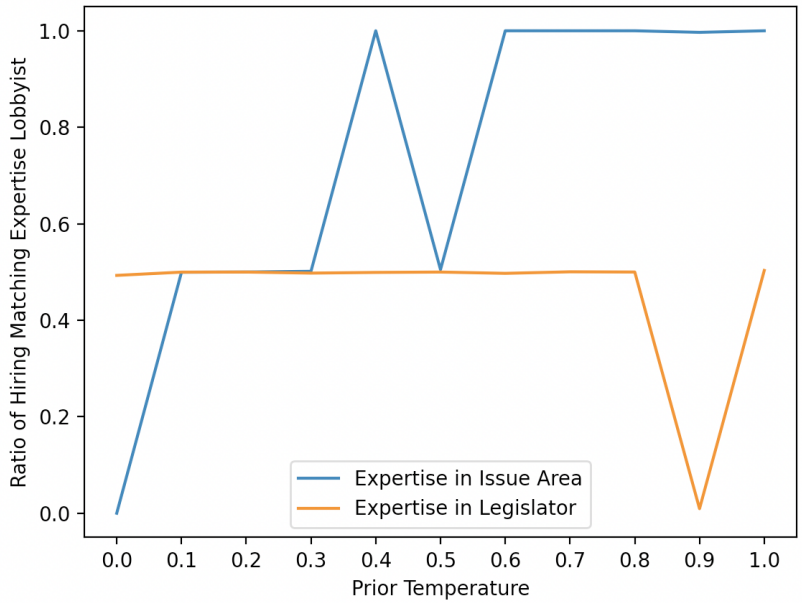
Two Different Types of Expert Knowledge

- In reality, IGs who share the same topic of interest tend to hire the same lobbyist. (**specialization**)
- **Expertise in a Legislator**: Knowing the reward distribution of a specific legislator. (Red)
- **Expertise in an Issue Area**: Knowing the reward distribution of a specific issue area across legislators. (Blue)



Simulation IV: Condition for Specialization

- $|K| = 112, |C| = 26, |T| = 2000, |IG| = 10, |L| = 2.$



- Tested two different conditions for specialization.
- The result shows that the lobbying industry is more specialized when the lobbyist has expertise in an issue area across all the legislators rather than having expertise in a specific legislator across all issue areas.
- This explains why lobbyist campaign contribution to legislators of both sides.

Limitation

- Simulated with hypothetical reward distribution of legislators.
  - How to get good representation of legislators' reward distribution?
- Modeled each interest group's category of interest as one dimension which is orthogonal to other categoires.
  - In reality, it's multiple dimension with correlated categories.
- Intentionally simplified the lobbying industry due to the computational limit.
  - In reality, $70,000$ interest groups and $20,000$ lobbyists are registered in the US lobbying industry.