Finding the Sufficient Condition for the Formulation of Lobbying Industry

Simulative Experiment Using Multi-Agent Multi-Armed Bandit Model

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Motivations

- What is lobbying?
  - What do lobbyists do?
  - Buying vote?
  - Infleunce policy or legislators?
- Answer this question by
  - Finding the sufficient condition that makes lobbying industry.
  - Search for the cause that makes the clients to hire lobbyists.
  - By simulation experiment.

What is lobbying?

- Yun and Preston (2022) define lobbying as **delegated information acquisition** process.
  - Interest groups in lobbying industry hires lobbyists to acquire information about the policy and legislators.
  - Lobbyists are the agents that acquire information about the policy and legislators on behalf of their clients.
- What kind of information are they acquiring?
  - Information that can be used to maximize the political economic goal of the interest groups.

How to Acquire Information?

- By **interaction** with legislators.
  - Campaign contribution
  - Meeting with congressional staffers, etc.
- How to model this interaction?
  - By using Multi-Armed Bandit (MAB) problem.

What is Multi-Armed Bandit[1] (MAB) problem?

- Formulate the exploration-exploitation dilemma problem.
  - Formulate the **exploration-exploitation** dilemma problem.
  - Assume that there are K possible choices (called "arms") for the agent to make.
  - Each arm has a reward probability P_k that is unknown to the agent.
  - Whenever the agent chooses an arm, it receives a reward r_k with probability P_k.
  - The agent choose one of the arms for T times and tries to maximize the total reward.
  - As the agent sequentially choose the arms, the agent builds his own estimate of the reward probability P_k of each arm.
  - In this scenario, the agent keep facing the **exploration-exploitation** dilemma whether to choose the best rewarding arm based on his current estimates (so called "exploitation") or to try another arm to improve the current estimates because the current estimates can be biased (so called "exploration").

[1] Bandit is pejorative name for slot machine because it empties players' pocket

MAB Problem of Interest Groups

- Interest groups face the Multi-Armed Bandit problem when they participate information acquisition process in legislative space.
- There are K number of legislators that interest groups can interact with.
- Each legislator has a reward probability P_k that is unknown to interest groups.
- Interest groups has a limited budget and time constraint to interact with legislators. (Model it as T times of interaction)
- How to balance between exploration and exploitation to find the best fit legislator within this limited chances of interactions? (MAB problem)

Formulation of MAB Problem of Interest Groups

- There exists $C \in \mathbb{N}$ number of categories of interest.
- Assume there are $j \in J$ number of interest groups with $\phi(j) : J \to C$ which represents unique category of interest $\phi(j)$ for each interest group.
- There are K number of legislators with P_k reward distribution.
- P_k is modeled as a **Categorical distribution** with C number of categories. P_k is parameterized by $\mathbf{p_k} = [p_k^{(1)}, p_k^{(2)}, \ldots, p_k^{(C)}]$ where $p_k^{(i)} \in [0, 1], \sum p_k^{(i)} = 1$ with the support of $x_k \in \{1, 2, \ldots, C\}$. (In other words,)
- 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 $r_j^{kn} = \mathbb{1}(x_j^{kn} = \phi(j))$ when j choose legislator k at time t and sampled x_j^{kn} from P_k.
  - In other words, interest group j with $\phi(j) = c$ gets reward of 1 when they sample c from interaction with legislator k.

How to solve MAB problem?

- Use **Thompson Sampling** algorithm.
  - Each interest group j has their own prior belief over $\mathbf{p_k}$.
  - Keep updating this prior belief over $\mathbf{p_k}$ using the sampled observations from the interaction with legislators.
  - The Dirichlet distribution is the conjugate prior of the categorical distribution.
    - $f(\mathbf{p_k}|\mathcal{O}) \propto \mathcal{L}(\mathcal{O}|\mathbf{p_k})f(\mathbf{p_k})$ where $\mathbf{p_k} \sim \text{Dirichlet}(\mathbf{D_k})$ with $\mathbf{D_k} = [d_k^{(1)}, d_k^{(2)}, \ldots, d_k^{(C)}] \in \mathbb{R}^C$ and $\mathcal{O}$ represents sampled observations from the interaction with legislators, i.e. $\mathcal{O} = [x_{j,t=1}^{k_1}, x_{j,t=2}^{k_2}, x_{j,t=3}^{k_3}, \ldots]$ where $x_{j,t}^{kt}$ is an observation sampled from the interaction with the legislator k at time t.
    - This is a C dimensional generalization of the Beta conjugate with Bernoulli likelihood.
    - As we did in Beta conjugate, we can update the prior belief by simply adding 1 to d_c when observe $x_j = c \in C$ at each step $t \in T$.
    - In this way of Bayesian update, interest groups can systematically update their prior belief over $\mathbf{p_k}$ based on obsevations from interactions with legislators.
  - After update, choose the best rewarding legislator k based on the samples from posterior distributions $\{f(\mathbf{p_k}|\mathcal{O})|k \in \{1, 2, \ldots, C\}\}$ for the next legislator to interact with.

Validate Thompson Sampling Algorithm

- Let's check whether the Thompson Sampling algorithm can actually find the best rewarding legislator within the limited number of interactions.
- We use the metric called **Regret** to measure the performance of the algorithm for MAB problem.
- $\text{Regret}_t^j \triangleq p_c^* - p_{a_t}^j$ where $c = \phi(j)$ and $p_c^* = \text{argmax}_{k \in K}\{p_1^{(c)}, p_2^{(c)}, \ldots, p_K^{(c)}\}$ and $p_{a_t}^j$ is the cth parameter of P_k when the agent choose the legislator k at time t. a_t represent the action (choice of legislator) taken by the agent at time t.
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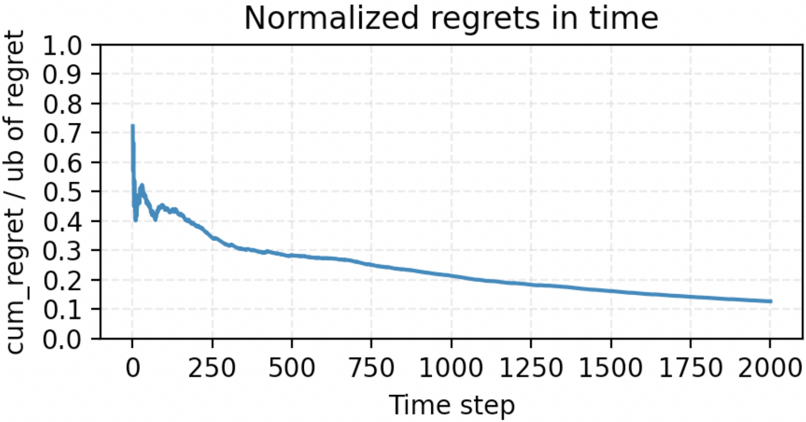
- Regret represents how much the agent could have been done better in terms of the reward if it had chosen the best action.
- Similarly, Cumulative $\text{Regret}_t^c \triangleq \sum_t^T p_c^* - p_{a_t}^j$.
- Agent tries to minimize the cumulative regret for the entire time horizon T.

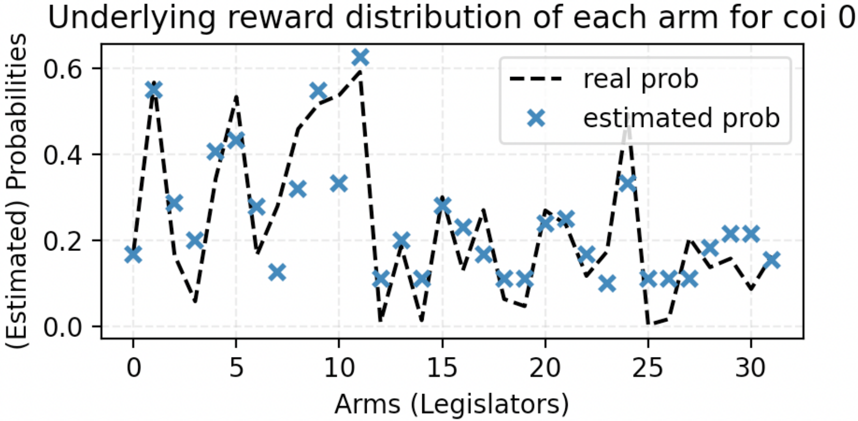
Simulation Results I: Small Search Space

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



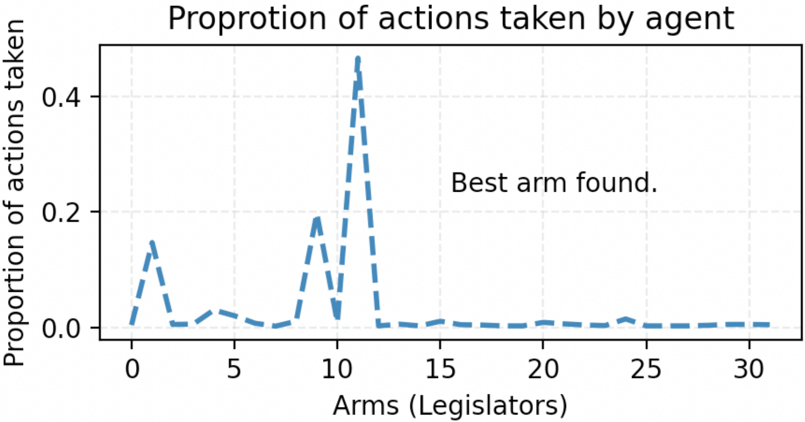
- Total $32 \times 4 = 128$ number of parameters to explore - which is relatively small compared to real world.

Simulation Results I: Small Search Space



- Each x-tick corresponds to $p^c_{k=1}, p^c_{k=2}, p^c_{k=3}, \ldots p^c_{k=32}$ where the agent has a category of interest c
- $K = 11$ is the best rewarding legislator for category c.

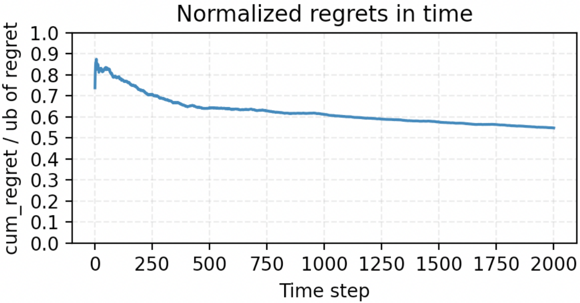
Simulation Results I: Small Search Space



- The agent successfully finds the best rewarding legislator $K = 11$ and exploited it.

Simulation Results II: Large Search Space

- $|K| = 112^2, |C| = 26^3, |T| = 2000.$

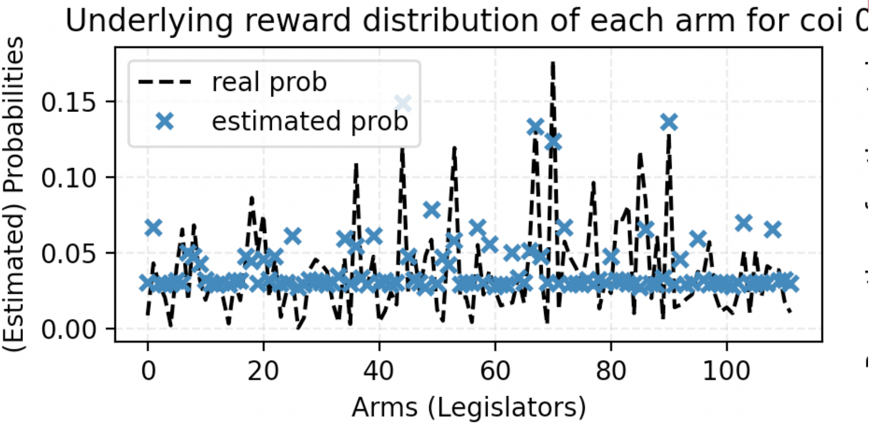


- Total $112 \times 26 = 2912$ number of parameters to explore - which is relatively large compared to the previous case. Hard to explore all the parameters with the same time horizon of $T = 2000$.

[2] Average number of legislators to whome top 10 lobbying firms campaign contribute in 2020.

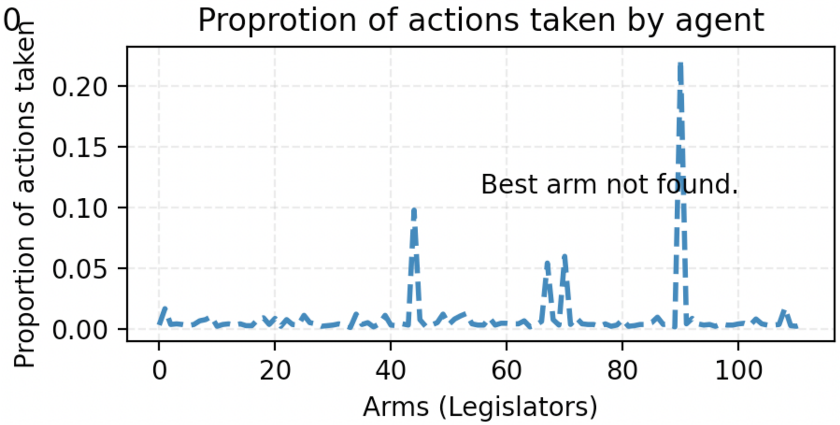
[3] Average number of issue codes appearing in each lobbying report in 2020.

Simulation Results II: Large Search Space



- Each x-tick corresponds to $p^c_{k=1}, p^c_{k=2}, p^c_{k=3}, \ldots p^c_{k=112}$ where the agent has a category of interest c
- $K = 68$ is the best rewarding legislator for category c.
- Most of the legislators are not explored properly.

Simulation Results II: Large Search Space



- The agent failed to find the best rewarding legislator $K = 68$ and exploited the worse rewarding legislator $K = 90$ mostly.

How to Explore a Large Search Space?

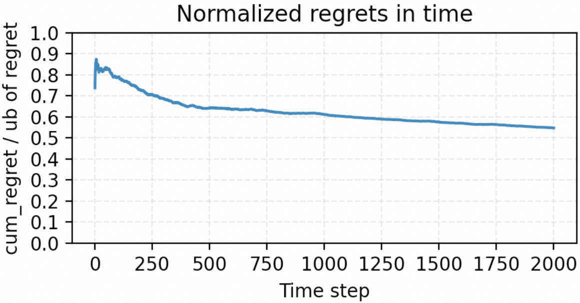
- From the previous two simulations, we've seen that interest groups fail to find the best rewarding legislator in a large search space.
- If we accept the setting that the MAB with large search space plausibly model the exploration-exploitation dillema that the real world interest groups face, how do they solve this large search space problem?
- **Conejcture:**
  - Interest groups use lobbyists to successfully explore the large search space.
  - A lobbyist has multiple interest groups as their clients so they can explore more legislators than a single interest group since the resources are concentrated from multiple clients.
- **Hypothesis:**
  - Interest groups can successfully explore the large search space by concentrating their resources to their hired lobbyist to delegate the exploration of legislative psace.

How to Introduce Lobbyist into MAB formulation?

- Introduce new $l \in L$ arms which represent lobbyists.
- Each lobbyist arm l has a set of parameters of Dirichlet distribution for each legislator $\{D_k^l | k \in 1, 2, \ldots, K\}$ as same as any other interset groups.
- Allow any interest groups to choose any lobbyists at each step.
- If an interset group choose to use a lobbyist, the interest group determine with which legislator to interact based on the current posterior distributions of the lobbyist.
- After getting observation from the chosen legislator, the interest group update the parameter of the lobbyist's parameter of Dirichlet distribution, not its own.
  - **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

- $|K| = 112^4, |C| = 26^5, |T| = 2000, |L| = 1.$



- 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 $T = 2000$.

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Knowledge Finding Strategy in this Project

- 1. Model a simulative enviroment by mimicking the real world.
- 2. Assume that the simulative enviroment closely approximate the real world enviroment and statistically verify hypothesis of interst using simulations.

Benifit of this theory

- Encompasses influence theory as well because to influence, you first need to know influence whom.

Implications

- provides criticism over Expertise vs. Connections (Is It Whom You Know or What You Know? An Empirical Assessment of the Lobbying Process)