The Birth of Lobbyists: A Multi-Agent Multi-Armed Bandit Modeling of U.S. Lobbying Industry

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Abstract

What is lobbying? This paper provides an answer to this question by modeling the lobbying industry with a multi-agent multi-armed (MAMA) bandit problem. In this MAMA bandit problem, bandits (which represents clients who hire lobbying firms) interact with arms (which represents legislators) to explore the unknown payoff of each legislator (arm) to maximize their rewards.

1 Introduction

What is lobbying in the United States? This simple question has been asked for a long time, but there is no clear answer with agreement among scholars. For example, *vote-buying* theories argue that lobbying is to buy votes in legislation (Grossman and Helpman, 1994), however, the theory doesn't explain why the average price of vote is too cheap compared to the expected return from lobbying. Besides, *persuasion* theories argue that lobbying is to persuade legislators to change their positions on legislation (Young and David, 1951; Bauer et al., 2017; Milbrath, 1984), however, this theory couldn't explain the empirical findings that people often lobby already like-minded legislators those who don't need any more persuasions.

This paper, above all other theories, aims to simulatively prove *Reverse Information Theory on Lobbying (RIF)* (Yun and Johnston, 2022) which explains lobbying as a *delegated information acquisition process*. According to RIF, every legislator has a different level of authority over different issue areas but clients lack an understanding of which legislator has which authority over which issue areas. Therefore, they hire lobbyists (or lobbying firms) to acquire information related to their business. For example, Waymo LLC., an autonomous vehicle company reported they hired a lobbying firm, Holland & Knight LLP., to acquire information on Build Back Better Act provisions on autonomous vehicles[1]. To Waymo, keep tracking the development of Build Back Better Act will be costly and lack an expertise on analyzing complicated legal articles and politics behind it. Therefore, they hire highly specialized lobbying firm who has its own expertise on policy development on the issue area of autonomous vehicle. The lobbying firm Holland & Knight also has NAVYA Inc., a self-driving solutions company as its client, along with General Motors (GM) and Toyota. Seeing this, we can infer that Holland & Knight has a specialized knowledge on legislative space on automobile industry and companies hire them as their lobbying firm to delegate their information acquisition process.

RIF (Yun and Johnston, 2022) argues that a group of clients who share the similar interests has an incentive to delegate their information acquisition process to a certain lobbying firm which has expertise on their issue areas of interest. To support this perspective, this paper models the lobbying

[1] `https://lda.senate.gov/filings/public/filing/0fe5096c-adc4-486a-93fe-7d8b99b823b5/print/`

industry as a multi-agent multi-armed (MAMA) bandit problem. The main reason of modeling the lobbying industry as a MAMA bandit problem is that the lobbying industry is a network of agents (clients) and arms (legislators) and the agents interact with legislators to maximize their rewards. This fits to how the MAMA bandit problem is formulated.

To model the U.S. lobbying industry as MAMA bandit problem, I model legislators as arms and companies as agents. This is an abstraction of U.S. lobbying industry where the companies explore the best rewarding legislators related to their business. However, they don't know which legislators give the best reward to them *a priori*. Rather, they need to deterimine how strategically explore and interact with which legislator to maximize their rewards.

In addition, this paper models the rewards distribution of arms as categorical distribution to incorporate varying level of authorities of legislators over different issue areas. For example, Sen. Gary Peters may have a higher level of authority on issues related self-driving cars compared to the issue area of aviation because he's a chair of Senate sub-committee on *surface transportation*. Therefore, we can expect Waymo will acquire more reward from interacting with Gary Peters compared to interacting with Sen. Kyrsten Sinema who's a chair of Senate sub-committee on aviation. To model this varying authorities over different issue areas, this paper assumes each agent has its own predefined categories of interest and gets the highest reward when it matches with the legislator's distribution of authority.

This paper conjectures incentive of hiring lobbying firm increases as the size of the exploration space increases. For example, if there exists a large number of legislators, companies will be more incentivized to hire lobbying firms to delegate their exploration due to the limited budget to explore all the legislative space. Unlike companies, lobbying firms have a large group of clients who share the similar interests who pay them to explore the legislative space. Therefore, they can specialize in the exploration of certain issue-oriented legislative space and acquire more information related to those issue areas.

To prove this conjecture simulatively, this paper incorporates a special multi-agents setting which allows agents to delegate their exploration to lobbying firms. In detail, after every round of playing with arms, agents can choose to delegate their exploration to other agents who have already explored the better reward to them. To enable this, this paper provides a special arm to each agent on every round. Except the initial round, all agents get provided with the best rewarding arm to them from the pool of learned arms' distribution of all agents. This arm represents "delegation" and agents who chose that delegating arm will get the reward following the action of the agent who is the master of that arm. However, since this delegation always give the benefit to agents, the reward from this special arm will be discounted with proper hyperparameter. Then total sum of discounted rewards will be conferred to the delegated agents. This resembles the situation where the lobbying firm is the master of the delegation arm and the client is the agent who delegates its exploration to the lobbying firm. Then the discount factor represents the cost of hiring the lobbying firm.

In summary, this paper models the U.S. lobbying industry with categorized bandit problem where agents can delegate their exploration to other agent. By doing so, this paper expects to simulatively prove that more number of agents tend to choose delegation as the number of legislators and the number of categories increase, which corresponds to the situation where agents have more large space to explore.

2 Multi-Agent Multi-Armed (MAMA) Bandit Problem

This section aims to show that MAMA bandit problem can plausibly represents the U.S. lobbying industry with interactions between companies, legislators and lobbying firms with some institutional features that can explain the lobbying as a delegated information acquisition process.

2.1 Vanilla Multi-Armed Bandit Problem

Vanilla multi-armed bandit problem is assuming a single agent playing with K number of arms and the reward of each arm $X_{k\in[K]}$ is modeled as a Bernoulli distribution $X_k \sim \text{Bernoulli}(\theta_k)$. If we assume that the agent played kth arm n times, sum of rewards $Y_k = \sum_{i=1}^{n} X_k \sim \text{Binomial}(n, \theta_k)$ because the sum of Bernoulli random variables is Binomial. Then our goal is to infer $p(\theta_k|y_k)$ which represents the posterior distribution of θ_k given the observed rewards y_k. Intuitively, this represents the learned experience of the agent about the payoff of kth arm. Most widely used method to find the posterior distribution $p(\theta_k|y_k)$ is *Thomposon sampling* (Thompson, 1933), that uses the $\mathrm{Beta}(\alpha, \beta)$ distribution as the prior which is conjugate for the Binomial likelihood $p(y|\theta_k)$. Formally speaking,

$$
\begin{aligned}
p(\theta_k \mid y_k) \propto p(y \mid \theta)p(\theta) &= \left(\begin{array}{c} n \\ y \end{array} \right) \theta^y (1-\theta)^{n-y} \frac{1}{B(\alpha,\beta)} \theta_k^{\alpha-1}(1-\theta_k)^{\beta-1} \\
&\propto \theta_k^{y_k+\alpha-1}(1-\theta_k)^{n-y_k+\beta-1} \\
&\propto \mathrm{Beta}(y_k+\alpha, n-y_k+\beta) \\
&\propto \mathrm{Beta}(\text{number of success} + \alpha, \text{number of failure} + \beta) \qquad (1)
\end{aligned}
$$

(1) implies that by adding 1 to the α when we get a reward from $\mathrm{Bernoulli}(\theta_k)$ and otherwise by adding 1 to β, we can update the posterior distribution $p(\theta_k \mid y_k)$.

2.2 Adopting Categorized Bandit

2.1 models the payoff of each arm as Bernoulli distribution. However, this paper models the payoff of each arm as categorical distribution. This is to represent each legislator's varying level of authority over different issue areas. To model this varying level of authority over different issue areas, this paper models the payoff of each arm as categorical distribution. This scenario is recognized under the name of *categorized bandit* and Kaufmann et al. (2018) generalizes *Thomposon sampling* (Thompson, 1933) and introduces *Murphy Sampling* to solve the categorical bandit problem. However, this solution doesn't consider the case of each agent having ordered preference over different categories. In the lobbying industry, it's common that clients have ordered preference over different issue areas. Therefore, the reward should be maximized when the ordered preference of each agent aligns with the categorical distribution of the legislator. In this context, Jedor et al. (2019) introduces a new algorithm called *CatSE* to solve the categorized bandit problem under the assumption of ordered preference of each agent. Therefore, this paper will use this algorithm to solve the categorized bandit problem.

2.3 Multi-Agent Multi-Armed (MAMA) Bandit Problem

Simply creating multiple agents doesn't make it a meaningful multi-agent problem because the agents are not interacting with each other. To plausibly abstractize the U.S. lobbying industry, this paper assumes a special institutional structure where agents can delegate their exploration to other agents. To implment this, this paper provides a special arm to each agent on every round. Except the initial round, all agents get provided with the best rewarding arm to them from the pool of learned arms' distribution of all agents. This arm represents "delegation" and agents who chose that delegating arm will get the reward following the action of the agent who is the master of that arm. However, since this delegation always give the benefit to agents, the reward from this special arm will be discounted with proper hyperparameter. Then total sum of discounted rewards will be conferred to the delegated agents. This resembles the situation where the lobbying firm is the master of the delegation arm and the client is the agent who delegates its exploration to the lobbying firm. Then the discount factor represents the cost of hiring the lobbying firm.

This paper expects that agents who have more biased preference over specific category will be eventually be the master of the delegation arm. This is because the agents who have more biased preference over specific category will be more likely to choose the arm that has the highest reward for them. This represents the U.S. lobbying industry where the lobbyists are specialized in specific issue areas and the clients delegate their exploration to those specialized lobbyists.

2.4 Purely Simulative Environment and Claim of the Paper

In this paper, I focus on the varying equalibrium across the different hyperparmeters that deterimines the number of legislators, number of categories and discount factors for delegation. If the number of legislstors are very small, the incentive of delegation is weak because the exhaustive exploration is possible. However, if the number of legislators are sufficiently large, the incentive of delegation is strong because the exhaustive exploration is impossible and benefits from the delegation become more significant. To explore the emergence of lobbyists within the framework of exploitation and exploration dillemma with regard to the size of the exploration space, this paper purely relies on the simulation without involving any empirical data. However, by observing the change of the equalibrium of the system with varying number of legilsators and issue areas, this paper aims to prove that lobbyists emerge when the number of legislators and number of issue categories are sufficiently large.

3 Summary of the Proposal and Future Directions

This paper aims to reproduce the emergence of lobbyists in a simulated environment. To do so, it's required to implement (1) categorized bandit (Jedor et al., 2019) and (2) institutional feature that enables delegation. After implementation, this paper will simulate the system and observe (1) stability of the practice of delegation among agents and (2) distributional characteristics of agents who keep delegated by other agents.

The biggest motivation to adopt this simulative approach is to prepare a computational environment that can model the different behavioral and institutional features that different theories of lobbying highlight. Once this simulative environment is prepared, we can gradually build up and test the different theories of lobbying in this simulation environment. Moreover, although this paper doesn't plan to involve any empirical data, this simulative environment can be equipped with the empirical data to more closely approximate the U.S. lobbying industry. For example, we can use the actual bill sponsor information to model the varying authorities of legislators over different issue areas. Also, we can use the actual lobbying data to model the varying preferences of clients over different issue areas. In conclusion, by preparing this computational environment, researchers will be able to test different theories on lobbying in a simulative environment. By doing so, this paper expects to facilitates agreement among scholars on answer to the question - "What is lobbying?".

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4 Further Directions

- Use Dirichlet distribution for arms (Need Boojum distribution, a conjugate prior of dirichlet distribution)
- Check this article for Boojum distribution `https://arxiv.org/abs/1811.05266`