Modeling Lobbying Industry with Multi-Agent Multi-Armed Bandit

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Abstract

What is lobbying? In this work, I model the lobbying industry with a multi-agent multi-armed bandit problem. Under this setting, I provide supportive evidence for the argument that explains lobbying as a delegated information acquisition process. First, I show that interest groups can successfully explore a large legislative space by delegating information acquisition process to lobbyists. Second, I show that lobbyists become specialized when lobbyists have expert knowledge on a specific issue area across multiple legislators. Those resulsts provide supportive evidence why interest groups have incentives to delegate information acquisition process to lobbyists and why lobbyists in real world interact with both sides of the legislators in terms of interest of their clients.

1 Introduction

What is lobbying? This simple question has been asked in different literatures but there is no clear answer with agreement among scholars. For example, *vote-buying* theory argues that lobbying is to buy votes in legislation (Grossman and Helpman, 1994). However, this theory doesn't explain why the average price of vote is too cheap compared to the expected return of lobbying. As another example, *persuasion* theory argue that lobbying is to persuade legislators to change their positions on legislation close to the position of the lobbyists (Young and David, 1951; Bauer et al., 2017; Milbrath, 1984). However, this theory doesn't explain why lobbyists lobby already like-minded legislators those who don't need any persuasions.

Apart from these theories, this work provides a supportive evidence why interest groups have incentives to delegate information acquisition process to lobbyists. By modeling the lobbying industry with a multi-agent multi-armed bandit problem, I simulatively show that interest groups can successfully explore a large legislative space by delegating information acquisition process to lobbyists.

In addition, simulation results show that lobbyists become specialized when lobbyists have expert knowledge on a specific issue area across multiple legislators. This result provides a supportive evidence why lobbyists in real world interact with both sides of the legislators with respect to the interest of their clients.

2 Multi-Agent Multi-Armed Bandit Problem

In lobbying industry, interest groups need to specify which legislator have a highest potential power to influence the issue area of their interest. To do so, they need to interact with different legislators to explore the potential expected rewards from each legislator. However, total chances of exploration is limited and interest groups need to decide whether to keep exploring or exploiting the best legislator they have already explored at each timestep. This situation can be modeled by multi-armed bandit problem which formalizes the exploration–exploitation dilemma.

2.1 Categorical Multi-Armed Bandit Problem

Since legislators have varying level of authorities over different issue areas, I model this situation by categorical multi-armed bandit problem. There exists $|J|$ number of interest groups $\{1, 2, \ldots, J\}$, $|K|$ number of legislators $\{1, 2, \ldots, K\}$, $|C|$ number of categories of interset $\{1, 2, \ldots, C\}$ and $|T|$ number of timesteps $\{1, 2, \ldots, T\}$. Then each interst group $j \in J$ has its own category of interest $\phi(j) \in C$ and each legislator $k \in K$ has a categorical distribution $\mathrm{Cat}(\mathrm{C}, \mathbf{p_k})$ where $C = \{1, 2, \ldots, C\}$ and $\mathbf{p_k} = [p_k^{(1)}, p_k^{(2)}, \ldots, p_k^{(C)}]$. Whenever an intesrest group j interact with the k-th legislator, they sample $X_k \in C$ from $\mathrm{Cat}(\mathrm{C}, \mathbf{p_k})$. If the sampled category X_k matches with the category of interest of the interest group, i.e. $X_k = \phi(j)$, it gets the reward of $r_j^k = \mathbb{1}(x_j^k = \phi(j))$.

2.2 Thompson Sampling as a Bandit Strategy

Let's assume that each interest group hold a prior belief over the categorical distribution of each legislator. Since Dirichlet distribution is conjugate prior of categorical distribution, I model the prior belief of each interest group j over the categorical distribution of the k-th legislator as $\mathrm{Dir}(C, \alpha_{jk})$ where $\alpha_{\mathbf{jk}} = [\alpha_{jk}^{(1)}, \alpha_{jk}^{(2)}, \ldots, \alpha_{jk}^{(C)}]$. At each timestep $t \in T$, interest group j choose the k-th legislator to interact with and sample $X_k^t \in C$ from $\mathrm{Cat}(\mathrm{C}, \mathbf{p_k})$. Then the interest group j updates its prior belief over $\mathrm{Cat}(\mathrm{C}, \mathbf{p_k})$ by adding 1 to $\alpha_{jk}^{(X_k^t)}$. After update, the interest group j chooses the next legislator k_{t+1} to interact with by sampling $\hat{\mathbf{p}}_\mathbf{1}, \hat{\mathbf{p}}_\mathbf{2}, \ldots \hat{\mathbf{p}}_\mathbf{K}$ from $\mathrm{Dir}(C, \alpha_{\mathbf{j1}})$, $\mathrm{Dir}(C, \alpha_{\mathbf{j2}}), \ldots, \mathrm{Dir}(C, \alpha_{\mathbf{jK}})$ and choose $k_{t+1} = \underset{K}{\mathrm{argmax}}\{\hat{p}_1^{(\phi(j))}, \hat{p}_2^{(\phi(j))}, \ldots, \hat{p}_K^{(\phi(j))}\}$. In this way the interest group j can systematically update its prior belief and balance the exploration and exploitation by randomness of sampling from Dirichlet distribution. This strategy is called *Thompson sampling* (Thompson, 1933).

2.3 Validation of Thompson Sampling Strategy

To validate the effectiveness of Thompson sampling strategy,

3 Large

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.

3.1 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.

3.2 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.

4 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?".

References

Bauer, R. A., de Sola Pool, I., and Dexter, L. A. (2017). *American Business and Public Policy*. Routledge.

Grossman, G. M. and Helpman, E. (1994). Protection for Sale. *American Economic Review*, 84(4):833–850.

Jedor, M., Perchet, V., and Louedec, J. (2019). Categorized bandits. In Wallach, H., Larochelle, H., Beygelzimer, A., d'Alché-Buc, F., Fox, E., and Garnett, R., editors, *Advances in Neural Information Processing Systems*, volume 32. Curran Associates, Inc.

Kaufmann, E., Koolen, W., and Garivier, A. (2018). Sequential test for the lowest mean: From thompson to murphy sampling.

Milbrath, L. (1984). *Washington Lobbyists Survey, 1956-1957*. ICPSR (Collection : En ligne). Inter-university Consortium for Political and Social Research.

Thompson, W. R. (1933). On the likelihood that one unknown probability exceeds another in view of the evidence of two samples. *Biometrika*, 25(3/4):285–294.

Young, R. and David, T. (1951). The governmental process: Political interests and public opinion. *The ANNALS of the American Academy of Political and Social Science*, 278(1):200–201.

5 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`