On Variant Evolution of Party Competition

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Abstract

Down's (1957) analysis of political ideologies by means of a spatial analogy for political actions suggests that parties' efforts to attract votes leads them to adopt a median position. However, many studies have questioned the result and have many different conclusions. In this study, we model the dynamics of competing parties who make decisions in an evolving environment. We show that there is an essential difference between individual and social learning. This differentiates the result of spatial voting model. We illustrate its consequences by analyzing two variants of computational tools..

Keywords: Voting Model, Genetic Algorithms, Learning, Party Competition

1. Introduction

In recent years there has been an increasing interest in learning and adaptive behaviour including simulation models based on genetic algorithms. A number of studies have pursued a group of models of the economy which are often called "*agent-based*" models. Such models aim to provide an analysis of economy that credible builds on verifiable assumptions about the nature of human agents and institutions in which they work. Many study questions the idea that "*super-rational*" agents can play real, complex economic games as if there was a well-defined unique equilibrium. However, an agent-based model recognises the bounded rationality of human agents and their institutions. A credible alternative to the super-rational game players is a range of models based on the concept of the economy as a number of boundedly rational, adaptive agents interacting through a number of bounded institutions.

Down's spatial theory of elections (1957) has occupied a prominent theoretical status within political science. In elections, voters by observing party ideologies and using the information to make decisions for their votes because voters do not always have enough information to appraise the difference of which they are aware. Therefore, "*the lack of information creates a demand for ideologies in the electorate*" (Downs. 1957). The Downsian idea is that in a two-party system, given certain assumptions, parties converge toward a median position on the continuum of possible voter positions. However, many studies have questioned the result and have many different conclusions.[1] Kollman et al. (1992; 1998) analyzed adaptive parties involved in a spatial voting model. The parties in the model are adaptive, in a sense that they are allowed to modify their positions adaptively in order to gain more votes. The model involves dynamics of competing political parties who make decisions in an learning environment. In particular, there are two types of learning, *individual learning* and *social learning* or called population learning (Vriend, 2002).

In this paper, we will consider a class of two-party competition problem which is a version of Kollman's (1992) spatial voting model. We will argue that the difference between individual and social learning, influenced by the underlying dynamics of learning processes, differentiates the result of voting model.

2. The Model

Consider a model with n-demensional issue space and V voters.[2] Each voter's preferences are represented by two vectors of n integers, which give the voter's ideal positions and strengths on the n issues. A voter's strength on an issue measures the issue's relative importance to the voter. The following notations are used in the model:

y_i^j platform position of party j on issue i

x_{vi} voter v's preferred position on issue i

s_{vi} voter v's strength on issue i.

The utility to a voter from party j's platform, y, is given by:

$$u_j(y^j) = -\sum_{i=1}^{n} s_{vi}(y_i^j - x_{ji})^2$$

We assume that both strengths and ideal points are independently and uniformly distributed. As voter knows his utility from each party platform, he casts a

[1] See for example, Bates (1990), Miller & Stadler (1998) and Coughlin (1990).

[2] See Kollman et al (1992) for details.

ballot for the party with the higher utility. In a series of elections, parties compete for votes by change their platforms. In other words, each party's platform moves in the issue space i.e. an election landscape. For the office-seeking party, their primary goal is to win the election. Therefore, the utility function to a party can be simply defined by:

$$F_j(y) = v(y:x)$$

where, $v(y:x)$ is the number of votes a party receives if it takes platform y and voters' preferred positions x on the n issues. Therefore, each parties attempts get as close to voters' preferred positions and therefore to maximize votes. Parties in search of more votes try to find better platform in terms of voters' preferred positions.

A measure of the goodness called "*centrality*" to evaluate the trajectory of electoral outcomes is employed (Kollman, 1998). The centrality of an outcome, *c(y)*, is the number by which the average voter utility (squared weighted distance) must be multiplied to get the average voter utility of the median, in other words:

$$c(y) = [\sum_j u_j(median)]/[\sum_j u_j(y)]$$

The higher the centrality, the closer the winning candidate is to the weighted centre of voter preferences. We do not attach normative significance to the median as an outcome. With such the measurement, we can compare our simulation outcomes across elections and between learning.

3. Modelling Learning

In this study, the assumptions of perfect information and perfect rationality on the part of parties are relaxed. We model our parties as a class of learning parties. Such the voting model is a dynamic model of elections where party attempts to find a position in the issue space to defeat the opposite party, by choosing a candidate to represent it. The candidates do not have any information about voters' preferences other than vote totals. This implies that parties in the model will not have explicit knowledge of the mean or median position of voters on an issue but have some information. During campaigns, the parties test positions on the voters and receive feedback in the form of vote totals. We assume that voters have perfect information about candidate positions. Hence, these tests are like opinion polls about candidate popularity. The intention is to approximate actual procedures. The procedures themselves are mechanisms for the parties to choose candidate (positions or political platform) it will present to the voters. The only purpose for parties is to win the election.

We model our parties' ability to locate positions with a Genetic Algorithm (GA). There are two basic ways to implement a GA. The first is as a model of social or population learning. Each candidate in the population is characterized by a positions vector (or political platform), which is a binary string of fixed length. In each election, the party chooses a best–to-date candidate positions as coded a binary string, the party's platform is determined and the party's votes total is determined. In every campaign, the population of candidates is modified by applying the genetic operators. The idea is that candidates look around and blend ideas of other candidates that appeared to be successful. The more successful these candidates were, the more likely they are to be selected for this process of blending, where the measure of success is simply the votes total generated by each candidate. Figure 1 show the social learning process with the GA. We call the party *population learning party* (PLP).

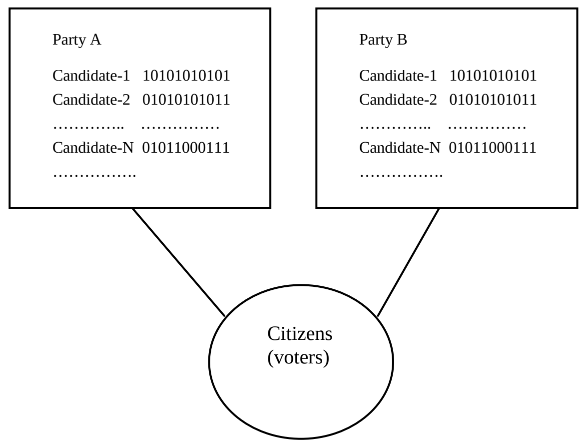

Figure 1 Population Learning Party

The second way to implement a GA is to use it as a mode of individual learning. There is a GA associated with each candidate. Each candidate now has a set of platforms (or a pool of platforms) in mind. Each platform is represented as a string as in population learning, with attached to each a vote measure of its success, i.e. the votes total generated by that platform when it was selected as candidate's platform. There only one of these platforms is used to determine candidate's positions on issues. In this setting, individual GAs are independent of each other and there is no exchange of platforms (or strings) between them. Instead of learning by seeing how well the other candidates with different platforms were doing, a candidate now evaluates how well his/her alternative platforms would have performed. In this respect, the adaptive learning system can be described as ecology of sets of competing platforms or positions on issues. The candidate's knowledge about the voters' preferences is personal and differs from candidate to candidate. Figure 2 shows the individual learning process with the GA. The party is called *individual learning party* (ILP).

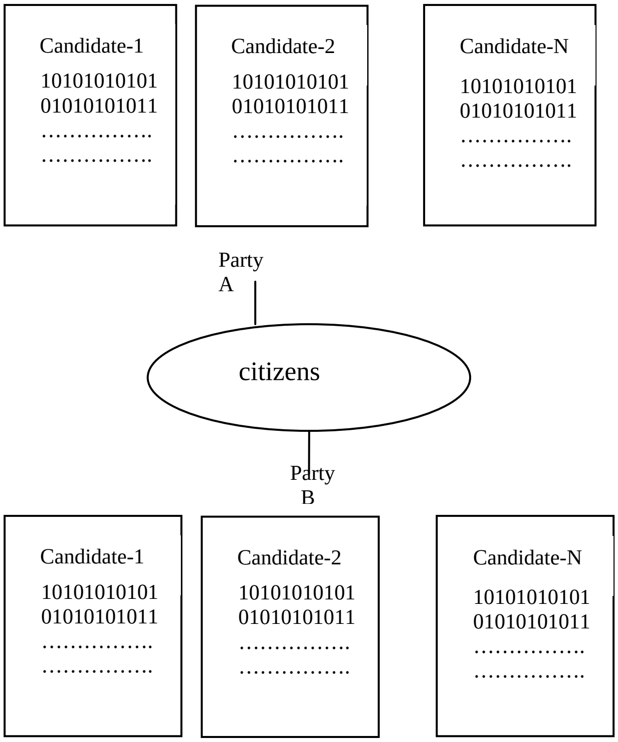

Figure 2 Individual Learning Party

4. The Results

In order to see the implication of the learning model, we simulated experiments based on section 3 described. As mentioned earlier, parties were programmed to compete for votes, office seeking party. The party is seen as a bundle of candidates with positions on issues. Learning model parameter values are shown in Table 1.

Table 1 Learning Model Parameter Values

Parameters	Values
Voter types (V)	251
Number of Issues (n)	15
Positions per issue (k)	7
Strengths (s_{ji})	3

Figure 3 presents the time series of centrality levels for the two algorithms. The vertical axis shows the level of centrality, and the horizontal axis shows the times of elections. They are each based on 100 runs. The periods reported combined with the GA rate of 100 imply that the GA has generated 50 times a new generation in each run. The speed of convergence is quite quickly. Figure 4 presents the level of centrality as the length of the campaign increases from 5 to 30. Increasing campaign length implies that parties or candidates have more information about voters and therefore the level of centrality tends to increase with campaign length. The result is consistent with the result reported by Kollman et al (1992). Turning to the level of centrality for the tow algorithms, as we see they converge to a different level. While in the social learning GA (P.L.), centrality increases over time and converges to around a level of 1, in the individual learning GA (I.L.), centrality converges to around a level of 0.6 (Figure 3). In Figure 4, the centrality of individual learning converges to around a level of 0.7. The two series are generated by exactly the same identical GA for exactly the same identical underlying election model. The classical result is that two competing parties would converge toward a median position for the case in which the parties have complete information. The bounded rational adaptive parties do not use such the information. However, the outcome has been served as a benchmark that helps studies understanding the significance of findings in the models. The results of bounded rational adaptive parties also support the idea of convergence to central regions of the issue space.

Political parties in elections always try to take policy positions which appeal to as many voters as possible. In elections, voters observe party ideologies and using the information to make decisions for their votes. Each party attempts get as close to voters' preferred positions and therefore to maximize votes. As a result, there is an electoral demand depending on how much delivered "*price*" is raised by the ideological distance between party and voters. Hence, two competing parties will be under pressure not only to move closer together to improve votes in their "*competitive region*" but they will also be under pressure to move farther apart to improve votes in their respective "*hinterland*."[3] In population learning, the parties compete in a competitive election, they choose political platforms spatially close to voters' ideal platforms. The population learning parties (PLP) realize that they influence political outcomes through their own platforms; however, they consider that their choice of platforms does not directly affect the other parties' platforms i.e. parties choose platforms spatially close to their ideal platform. As we see in Figure 3, the GA with population learning moves close to the median outcome, the level of centrality approximately to 1, whereas the GA with individual learning converges approximately to 0.6. We argue that the resulting difference depends on how the parties learn.

[3] In this study, the case of abstention is excluded.

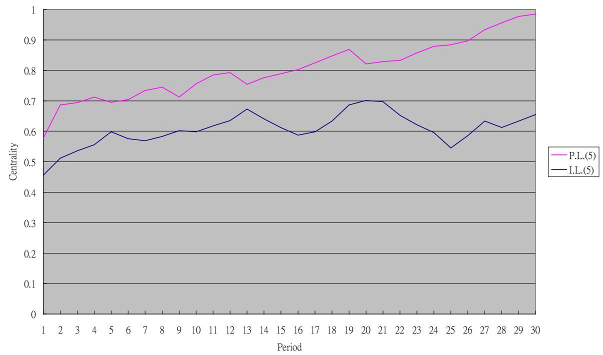

Figure 3 Evolution of Centrality

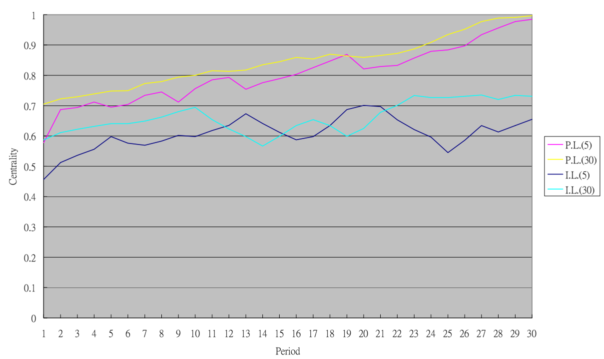

Figure 4 Evolution of Centrality: Length 5 and 30

In the social learning, each candidate is characterized by its own position platform (see Figure 1). The more a candidate's vote total, the more likely he/her platform selected (or favored) by the party and therefore the more likely the candidate selected to represent the party in an election. Whenever when the party move farther (left or right) from the median position, this happens to be the other party with the median position that has a more vote total and therefore the party with median position is more likely to selected for reproduction. As a result, the population of candidates tends to converge to the median platform. However, in the individual learning, the political platforms that compete with each other in the learning process do not interact with each other in the same election environment. In any given campaign, a candidate actually applies only one of his/her platforms (see Figure 2). Therefore, the learning effect does not affect the learning process because the vote total generated by that platform is not influenced by the platforms that are used in other campaigns. Candidates in social and individual learning only try to improve their own vote total and their learning is based on a different set of observations. The dynamics of learning i.e. dynamics of the political forces as such interact in a different way with each other in the two variants of the GA result in the different outcomes. To sum up, in the environment of population learning, we have the median outcome. In the environment of individual learning, we have the "*apart*" outcome.

5. Conclusion

The competing parties under electoral pressure move not only closer together but also farther apart each other. In equilibrium, it is resulted from the two opposite forces. Interestingly, the social learning leads to the classical outcome i.e. median outcome; the individual learning leads to the "apart" outcome.

6. References

[1] Bates, R. 1990. "Macropolitical Economy in the Field of Development." In *Perspectives on Positive Political Economy*, ed. James Alt and Kenneth Shepsle. New York:Cambridge University Press.
[2] Coughlin, P. 1990. "Majority Rule and Election Models." *Journal of Economic Surveys* 3:157-88.
[3] Downs, A. 1957. *An Economic Theory of Democracy*, New York: Harper & Row.
[4] Hamilton, W. D. (1970). "Selfish and spitful behaviour in an evolutionary model." *Nature* 228: 1218-1220.
[5] Hotelling, H., 1929. "Stability in Competition." *Economic Journal* 39:41-57.
[6] Kollma, K., J.H. Miller & S.E. Page 1992. "Adaptive Parties in Spatial Elections", *The American Political Science Review* Vol. 86, No. 4:929-37.
[7] Kollma, K., J.H. Miller & S.E. Page 1998. "Political Parties and Electoral Landscapes." *British Journal of Political Science* 28:139-58.
[8] Miller, J. H. and P. F. Stadler. 1988. "The Dynamics of Locally Adaptive Parties under Spatial Voting." *Journal of Economic Dynamics and Control* 23:171-189.
[9] Vriend, N. J. 2000. "An illustration of the essential difference between individual and social learning, and its consequences for computational analyses." *Journal of Economic Dynamics and Control* 24: 1-19.