An Analysis on Simulation Models of Competing Parties

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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. In recent years there has been an increasing interest in learning and adaptive behaviour including simulation models. Kollman et al (1992:1998) find that adapting parties converge to moderate platforms regardless of the landscape's ruggedness. In this study, we model two computational models of competing parties and show that there is an essential difference between individual and social learning. As a result, the outcome of parties competition under different computational models is different.

1. Introduction

In recent years there has been an increasing interest in learning and adaptive behaviour including simulation models based on genetic algorithms; see for example Ariovic (1994;1995), Birchenhall (1995), Birchenhall and Lin (2002) and Chen (2002) . 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. This 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.

An interesting feature in these systems is their greater ability to adapt to change and robustness to shocks when compared to highly centralised and overly fine tuned systems. It has to be suggested that one of the dangers of analytical approach to such models is reliance on some concept of equilibrium that is not derived from a convincing dynamic process, and thus that reinstate rigid and brittle structures. Moreover, such equilibrium analysis does not help to understand the process of adjustment that characterise the day to day workings of real economies. Computer simulations offer one tool in the study and allow us to regain the vision of an economy as an adaptive and innovative system. The increased interest in various forms of computer simulation models not only reflects the increasing concerns about the definition of rationality or perfect foresight and representative modelling, but also has been due to the flourishing of evolutionary theorizing and the recent fashion of computer innovation and the development of algorithmic techniques. In particular, many fields of artificial intelligence are direct descendants of Darwin's idea, including Evolutionary Computation, Genetic Algorithms, and Genetic Programming. Some advocates consider that computational modelling will inspire and alter how we understand both the physical and social world. Many places use simulation works to assist in the solving of problems, including, theory development, the opening up of new research and agenda and perhaps prediction. There are reasons to believe that the use of computational modelling in building or extending theories in social sciences, particularly in the field of political economy.

In modern politics, political studies have addressed a relationship between a distribution of voters' preferences and party competition both empirically and

theoretically.[1] Down's spatial theory of elections (1957) has occupied a prominent theoretical status within political science. Studies use a notion of ideological distance to develop explanations for observable electoral trends. 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. For example, they do not know in advance what problems the government is likely to face in the future. 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.[2] However, many studies have questioned the result and have many different conclusions. Plott (1967) and McKelvey (1976) have speculated chaotic results are possible. Bates (1990) concluded that while one cannot expect an equilibrium to exist and any outcome can be defeated, the political decisions represent arbitrary outcomes. Coughlin (1990) incorporated various complexities to explain the stable median outcome and believed that the two-party electoral outcomes appear more stable than the chaotic results predict.

This leads studies to revise unrealistic assumptions underlying the spatial voting model to explore equilibrium. 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 evolving environment.

> "*We advocate a new approach to study the dynamics of spatial elections, the use of adaptive artificial agents... Allow us to search previously inaccessible models for patterns of generic behaviour. Our model incorporates most of the assumptions of spatial voting model, with some important exceptions......The unique feature of our approach is the use of boundedly rational agents. (Kollman et al, 1998: 156-57).*"

In addition, Miller & Stadler (1998) found the stability of convergence to a "*strength-weighted*" mean of the voters' preferred positions. Their results also reported some conditions under which other dynamic possibilities occur.

While the introduction of adaptive behaviour in the spatial voting model, there is learning in an interactive setting. In cognitive science, it is clearly understood that the mind obtains much of its power by working in parallel. In fact, various parts of the brain simultaneously respond to information and it is combined results of these

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[1] See Nie, Verba and Petrocik (1976) and Downs (1957).
[2] Downs' model elaborates upon Hotelling's (1929) model of spatial model in which spatial ideas consists of a linear scale running from 0 to 1.

parallel processes that govern the final response. There are two underlying processes, a change in the perception of the underlying environments and a change in these environments themselves. It can generally be the case that the dynamics of learning and those of the underlying forces as such will interact with each other. In a learning problem, there are two types of learning, *individual learning* and *social learning* or called population learning. In the individual learning, an agent learns on the basis of his own experience, whereas in the social learning, learners base themselves on the experience of other players as well. As a result, there is a difference in modeling learning among computational approaches. The effect of forces caused by the difference between individual and social learning will lead to different results when applied as an identical learning algorithm (Vriend, 2000).

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 essential difference between individual and social learning, influenced by the underlying dynamics of learning processes, differentiates the result of spatial voting model.

II. The Model

Consider a model with *n*-demensional issue space and *V* voters.[3] 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.[4] As voter knows his utility from each party platform, he casts a 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

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[3] See Kollman et al (1992) for details.
[4] This assumption that voter ideal points are uniformly distributed does not necessarily imply regularity. While a relatively small number of voters are generated in a large space, central limit theorems and the like are not appropriate.

election. Therefore, the utility function to a party can be simply defined by:[5]

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

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. Each possible platform is perceived as a physical location and its corresponding vote total against rivalry platform is perceived as an elevation. Parties in search of more votes try to find points of higher elevation (better platform in terms of voters' preferred positions) on the landscape.[6]

Following Kollman's work, a measure of the goodness called "*centrality*" to evaluate the trajectory of electoral outcomes is employed. With such the measurement, we can compare the model analytically to other models and compare our simulation outcomes across elections and between learning. 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.

III. 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 spatial voting model is a dynamic model of elections where the incumbent party is fixed and the challenger party attempts to find a position in the issue space to defeat the incumbent, 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

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[5] The functional form can be different according to party's types and other elements, for example ambitious or ideological party. See Kollman et al (1992).

[6] Landscape may take several different environments depending on voters' preferences. To realize how voters' preferences influence electoral landscapes and platform changes, the distribution of preferences is relevant. Therefore, the question comes to how to identify characteristics of voters' preferences. Kollman et al (1992) suggest one plausible set of characteristics i.e. strengths across issues. They then consider three types of correlations between ideal points and strengths, centrist, extremist and uniform.
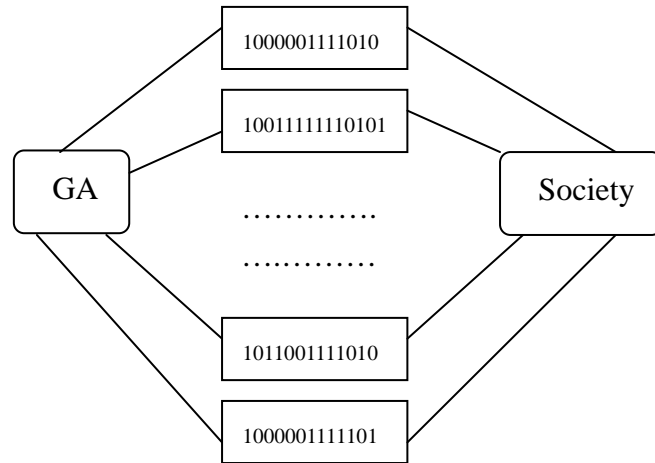
challenger party tests positions on the voters and receives feedback in the form of vote totals. We assume that voters have perfect information about candidate positions. Hence, these tests are like opinion polls about candidate popularity. The intention is to approximate actual procedures. The procedures themselves are mechanisms for the challenger party to choose candidate (or positions) it will present to the voters against the incumbent party.

We model our parties' ability to locate positions with a Genetic Algorithm (GA). Excellent introductions to GAs are available elsewhere.[7] Holland's (1992) stress on exploiting the best among tested options and views adaptation as a search process. The use of the term "*string*" to refer to a sequence of zeros and ones, e.g. 010110, we can approximate any search space by a set of strings of appropriate length. In a simple form, the GA works as follows. Set up a mapping from the problem space to a set of S of strings of length N, together with a function that returns the "*fitness*" of any given string, with the understanding that the algorithm will attempt to increase fitness. Establish a population P of K strings drawn at random from the set S. Then, iterate the following processes: reproduction, crossover and mutation, with some convergence or other stopping rule. Dawid (1996) and Riechmann (1998) are good starting point when interpreting a GA as model of learning.

As there is learning in an interactive setting, one dimension is how level of learning is modeled. The essential difference between social learning and individual learning, influenced by the underlying dynamics of learning processes, will differentiate the result of spatial voting model. Then 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. Before an election to be held, there are campaigns for the party to test candidates' popularity and receives feedback in the form of vote totals. In every campaign, the population of candidates is modified by applying the genetic operators: reproduction, crossover and mutation. The idea is that candidates look around and blend ideas of other candidates that appeared to be successful. The more successful these rules 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.

Figure 1. Social Learning

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[7] These include Holland's original exposition Holland (1982, 1992), Goldberg's classic tutorial Goldberg (1989), Michaleqicz (1996) general survey of evolutionary programs and the popular Mitchell (1996). A brief summary is presented in Birchenhall (1995).

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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 rule 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. By applying the GA operators on the set of platforms, the platforms which have been more successful recently are more likely to be chosen as those platforms have been more propagated in the set of platforms. In a sense, a platform will become dominant in the pool if it has been more successful in the past and therefore gets more progeny. As a result, the probability of this platform being chosen is higher than that of the other platforms being chosen in the pool. The 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.

Figure 2. Individual Learning
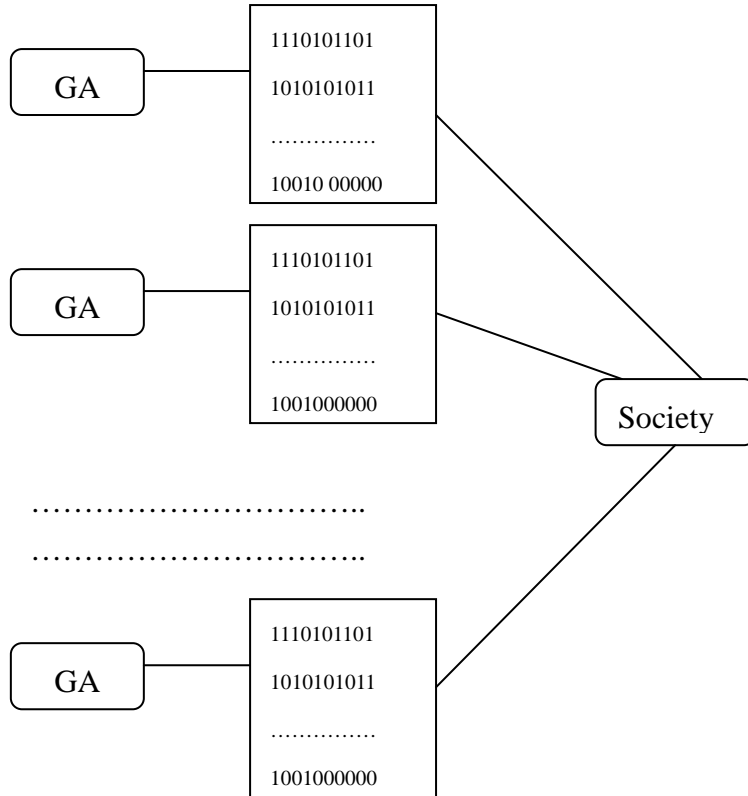
IV. Simulation Design and Results

In order to see the implication of the learning model, we simulated experiments based on section III 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. Prolonging runs did not add new development. The speed of convergence is quite quickly, and the result also consists with the result reported by Kollman et al (1992).

Figure 4 presents the level of centrality as the length of the campaign increases from 5 to 30. As mentioned earlier, during a campaign, the parties or candidates test their current platforms on votes, receive feedback in the form of vote total, and alter their platforms to improve vote total. Therefore, increasing the length campaign implies that parties or candidates have more information about voters. Consisting with the result reported by Kollman et al (1992), the level of centrality tends to increase with campaign length.
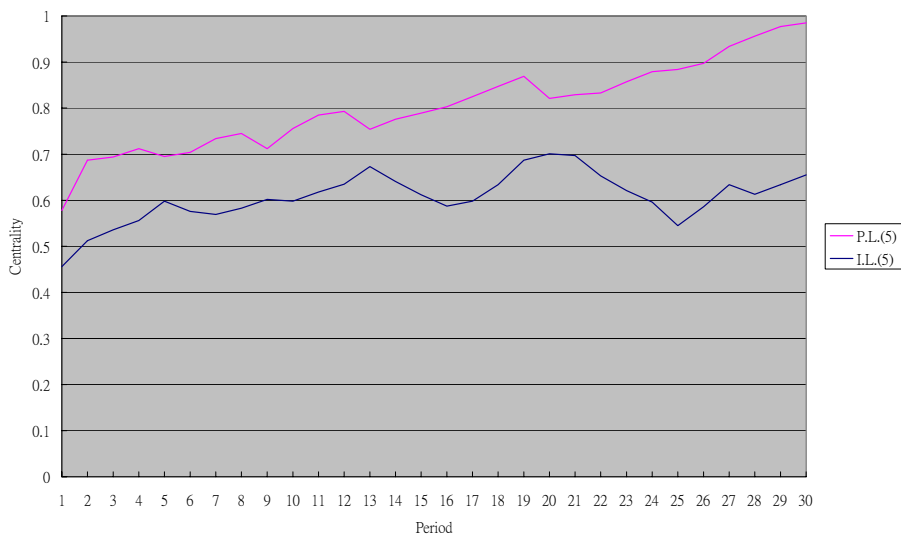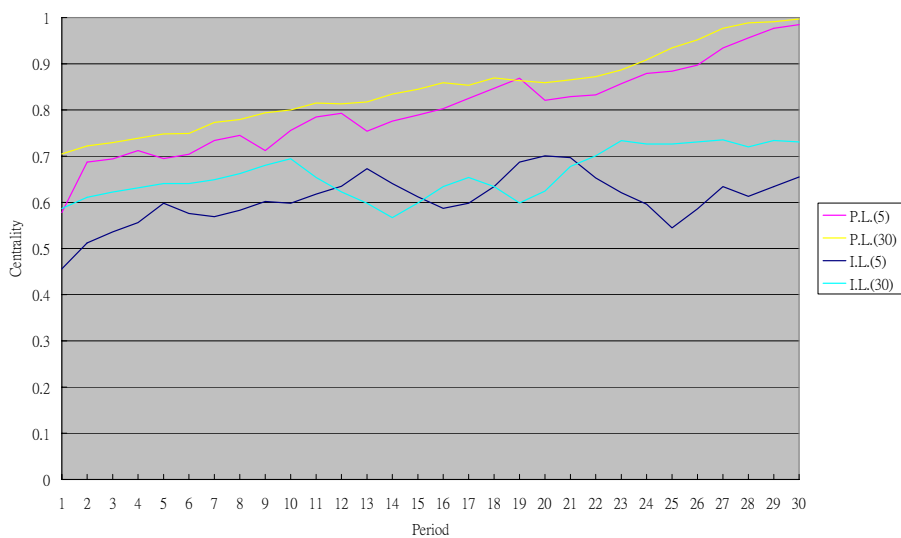
Figure 3 Evolution of Centrality

Figure 4 Evolution of Centrality: Length 5 and 30

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 0.9, in the individual learning GA (I.L.), centrality converges to around a level of 0.6 with zigzagging walk (Figure 3). In Figure 4, the centrality 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, "*political externalities*" are raised by the ideological distance between party and voters.[8] 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.*"[9] As we see in Figure 3, the GA with population learning moves close to the median outcome, the level of centrality approximately to 0.9, whereas the GA with individual learning converges approximately to 0.6, with a zigzagging walk between 0.5 and 0.65. We argue that the resulting difference depends on how the parties learn.

In the population 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 for the party representative 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 be 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 vote total generated by a specific platform is not influenced by the platforms that are used in other campaigns. The platforms do not compete with this

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[8] Political externalities are losses in well-being that occur when voters do not obtain their most-preferred outcomes.
[9] In this study, the case of abstention is excluded.

individual candidate's platforms in the individual learning processes. 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. In other words, the dynamics of learning and the dynamics of the political forces as such interact in a different way with each other in the two variants of the GA. This explains the different results generated by the two GAs. 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.

X. Conclusion

While political outcome in the literature under the Downsian's spatial voting tradition appears polymorphous, we show how political parties learn will differentiates the outcome of parties competition. There is a difference between an individual learning and a social learning algorithm. 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 hinterland outcome. In other words, we must pay attention on learning variant to explanation the results based on computational models. We do not argue whether or when people tend to learn by social or individual approach. In addition, we do not argue that this difference between population and individual learning is easily observed, or, it has an important role in an actual process. This leaves to cognition science and it is indeed an empirical argument. Simply, in this study, the general conclusion is that there is an essential difference between individual and social learning. We illustrate the difference, in this study, by modeling two variants of learning GA and report such the result.

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