ISSN Number (Print) – 2693-4108
ISSN Number (Online) – 2691-5103

Political Literacy and Partisanship – A Naive Learning Model

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Abstract

Political Partisanship and socio-political behavior are two intertwined attributes of any economic agent. There are several factors that go in to developing partisan principles and political beliefs, but eventually all come under the broader spectrum of social interaction; leading to social learning. Several literatures have provided evidence that this learning phenomenon is not free of biases. The inherent belief system of an individual often creates a screening tool for external information. The present day social-network and media influences are spreading misinformation and rumors that exaggerates partisan beliefs as well as disbeliefs. The paper develops upon the standard DeGroot social learning model (Banerjee et al.) to explore and analyze the nature and impact of such biases over network clusters. The model may then be refined with more psycho-social attributes after gaining experimental evidences.

Keywords: Political literacy, Partisanship, Social learning, DeGroot Model

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Introduction

Studies have provided ample evidence that political partisanship is a key factor influencing socio-political ideologies and attitudes of an individual (Gerber et al. 2010; Barber and Pope 2019). The interactive behavior also becomes generic, encompassing economic perceptions (Lenz 2012) as well as group identification (Greene 2002). But whether the partisanship is pro-social or not, depends heavily on two attributes of an individual: belief system (endogenous) and political information or knowledge (exogenous). There is an obvious interaction between the two variables when it comes to political polarization. The Dunning-Kruger effect is seen to create a knowledge-complex inculcated in the belief-system (Anson 2018; Yu and Han 2023). That is, there exists a distinctive gap between the actual and the perceived political literacy. The paper proposes a naïve agent-based learning model of political literacy. It studies how social learning in terms of political literacy evolves over agent-networks with certain underlying biases.

Political literacy, especially in a democratic setup, stems mostly from political conversations that tend to uplift social-tolerance and agreements over collective problems (Rojas et al. 2005). But such literacy is seldom independent of biases. One of the major causes of information-bias is the highly rising confrontational media penetration (Waisbord 2013). People are regularly exposed to repetitive misinformation over media that lead to rumors (Nyhan and Reifler 2010). In the recent years, social platforms are also driving citizens into partisan-bias over misinformation and hate speech (see Jiang et al. 2019; Heuer et al. 2021; Tran et al. 2022). The studies went deep into analyzing the political content, comments and reactions of the viewers.

On the other hand, the connection between partisanship and affective polarization is getting stronger over time (Iyengar et al. 2012). This context is important because, there seems to be a cyclic relationship between polarized politics, partisanship and political knowledge. If the political setup is democratic, with a larger number of parties; the political knowledge required for unbiased partisanship is consequently higher (Vegetti et al. 2017) as compared to a more polarized system, where the citizens find it easy to gain more knowledge (Suk et al. 2022). But the predisposed and inherent belief-system creates a selective learning environment, where the urge to gain more knowledge that is in line with existing ideologies are higher than those against them (Jerit and Barabas 2012).

It is already established that the knowledge-sphere of the civilians are subject to media infringements and social-discussion and promotion platforms. But the inherent belief-system creates discrimination in accepting information (Uscinski and Parent 2014) as well as being a party to polarized arguments (Kahan and Corbin 2016). People tend to screen out inaccurate information, but that again is influenced by the existing beliefs (Berinsky 2011). So, the paper intends to build upon a learning model taking all such biases with ‘information’ considered as nodal outputs or signals.

Methodology

Initially, we take into account two major contexts of any kind of knowledge, under the social context. Firstly, people learn through exchange of opinions within a group – *Information Aggregation* (Eyster and Rabin 2014). Secondly, the *diffusion model*; where new information is spread amongst an uninformed (or partially informed) group by one or more informed agent (Banerjee et al. 2013). Partisan lines are often targeted by the politicians to infringe upon the belief-system of individuals (Thomas 2018). Hence, the attempt is to incorporate both the sources in the model setup, with a special focus on the later.

The study considers the DeGroot model as the basis that takes into account both the foresaid social learning mechanisms (DeGroot 1974). The standard DeGroot model (DeMarzo et al. 2003) and the generalized DeGroot model (Banerjee et al. 2021) are then carefully altered to accommodate certain special biases amongst the agents. Experimental studies have shown that the actual information acquiring system is closer to the DeGroot model (henceforth called as DGM) than the conventional Bayesian network system (see Corazzini et al. 2012; Chandrasekhar et al. 2020). Furthermore, partisanship is rarely driven or shaped on a short-term basis. An aggregation of micro political ideologies goes on to define a nation in the long run. DGM provides the advantage to cater to the long term aggregation, consistent with Golub and Jackson 2010. The DGM learning model has also been extended to setups where participating agents do not guarantee complete or perfect recall (Molavi et al. 2017). This seems more practical, in the sense that partisanship, as an ideology may be a long term affair; but specific political facts over the timeline are not necessarily kept in mind by the general mass.

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The generalized DGM (henceforth called as GDGM) accounted for two groups – informed and uninformed agents. Here, the model is adapted to accommodate four kind of respondents – informed or politically literate with a rational inclination to provide the knowledge (informed-vocal I_v), people who are vocal but do not put forward opinion (informed-silent I_s), people who are uninformed and silent (uninformed-silent U_s), and people who are uninformed but provide biased opinion (uninformed-vocal U_v). Each agent is represented as a node in a graph and all silent agents are put into the uninformed category at the initial stage. Once the model is experimentally extended, the inherent signal-bias may be analyzed. Moreover, an agent may interpret 'no-signal' as indicative information too. Political knowledge and also affiliation are much more sensitive than other issues. So, the model also takes care of the bias arising out of wilful secrecy.

The Network Design

The network builds upon the standard DGM (henceforth called SDGM) with '***n***' number of agents (where ***n*** is finite). The agents are plotted as nodes in a weighted and complete graph ***G***. Every edge is a static communication path between any two agents ***(i, j)***. Self-loops are allowed against common intuition. The case where one creates and manipulates partisan principles for oneself; without being influenced by any external stimuli, seems not a practical point of view. But as information pass on, all clusters will have intra and inter communication channels that will impact the initial nodes too. Refer to Figure 1 to picture the information flow mechanism with an arbitrary value of $n = 5$.

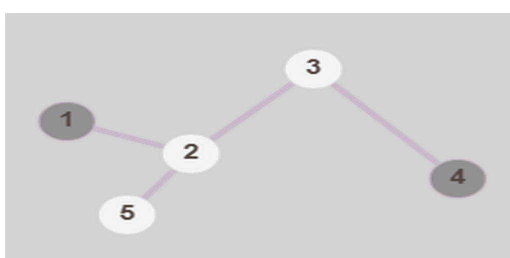

Fig. 1. Graph denoting information flow ($n = 5$)

The grey cells indicate I_v and I_s (without correction) and the white cells indicate U_v or U_s (without correction), at any point in time t_i. Assume that the grey cells are the agents holding the political opinion y_i^t and the white cells are the agents holding null opinion ϕ. It is assumed that when an opinion is passed on to the direct neighbor, it remains unbiased with the error term ε following a Gaussian distribution $N(0, \sigma^2)$. Hence, the equation follows:

$$y_i^0 = P + \varepsilon_i \qquad (1)$$

Where P is the generic political information y_i may receive at time $\boldsymbol{t = 0}$. It must be noted that at $t = 0$, only a finite number of agents '*a*' receive an information P, with $\boldsymbol{a < n}$ is a necessary condition. In the next time period, only the direct neighbors learn about the information P and cease to possess a null value. Each agent assigns a weight *'w'* to the information-authenticity of the neighbor and upgrades his/her own information before passing it on to his/her direct neighbor/s. The nodes are updated based on the weighted average of all the information received. Let the modified node at time *'t'* beM_i^t.

$$y_i^{t+1} = \begin{cases} \phi & if\ M_i^t = \emptyset \\ \dfrac{\sum_{m \in M^t} y_m^t w_{ij}}{\sum_{m \in M^t} w_{ij}} & if\ M_i^t \neq \emptyset \end{cases}$$

Refer to Appendix 1 for an intuitive guideline about the information flow mechanism and the general assimilation rule. In appendix 1, it is assumed that there are no $\boldsymbol{I_s}$ or $\boldsymbol{U_v}$ agents in the network. In other words, if an agent is informed about a political issue, he/she will pass on the same without any secret motive. Similarly, if the agent is uninformed, he/she will remain silent. Eventually, all nodes are informed without any bias; hence, they all approach a finite, real number limiting value. To understand whether the limiting 'opinion' value is an efficient estimator or not, the product of the summation of the weighted variance of the total set η must be computed.

$$var\ (y^{\infty}) = \sum_{i \in \eta} w_i(\eta)^2\, \sigma^2 \qquad (2)$$

Assume $t^m\ (\eta)$ to be the time when the final information exchange takes place in a specific network. Now, since the GDG model profiles for linear operators, then $x_i^{t^m}$ for all i, must be a linear combination of x_j^0 for $j \in \eta$. Starting at $t^m\ (\eta)$, the process follows SDGM because every agent has an information-signal. So, the limit is the weighted average of the initial signals, if the matrix is aperiodic and irreducible.

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Correcting for Information biases

There are two primary corrections needed as per the biases observed in the literature section – Opinion leadership bias and misinformation bias. The opinion leadership bias refers to whether people are prone to gaining information based on collective learning, i.e. assigning (more or less) equal weights to all the nodes, or the whole or part of the set η, favors few distinctive nodes (or individuals) as political opinion leaders. The boundary values of the variance in Equation 2 are given as:

$$\sigma^2/\grave{\eta} \leq var\,(y^\infty) \leq \sigma^2 \qquad (3)$$

Let ὴ be number of nodes out of η who are political opinion leaders, assumed to get the first information signals; information from them are given all the weights. It is elaborated in the experimental setup that such opinion leaders are mostly a single agent in a given network. The closer the variance is to the upper bound, the more efficient is the estimator. On the other hand, opinion leadership bias will pull the value close to the lower bound. The weights $\boldsymbol{w_i}$ are specifically interpreted by Voronoi networks where each set $\acute{\upsilon}_i$ is associated with the informed node *i* and all other nodes closer to *i* in terms of path length. If $G_{ij} = 0$, then there exists no connection between *i* and *j*.

Misinformation bias relates to the presence of I_s and/or U_v agents in the network. It is assumed that uninformed agents, who are vocal about an issue, are actually misinformed about the issue. And similarly, the informed agents, who are silent about an issue, can have a dominance of secrecy or they feel that they are less informed than actual. It is always difficult to put control on the Dunning-Kruger effect in practice. So any future experiment has to rely upon the findings of Shino and Smith 2022 that knowledgeable voters are more likely to put their votes early in the day, as against the others who waits till the end. This approach screens in the I_s agents into the opinion network and the model can test the impacts they put in their opinions in a social setup. The U_v agents may be identified by the answers they give to questions pertaining to specific ideologies of the parties they do not associate themselves with.

Proposed Experimental Design – Indian Context

Governing a democratic country becomes tougher under the context of misinformation. Partisan identity was seen to be more influential than policy arguments when it comes to political participation and voting decisions in multi-party democracy (Bankert et al. 2017; Colombo and Kriesi 2017). Hence, it becomes exceedingly important to understand how partisanship evolves under such a setup. In Indian context, prominent clusters must be identified where partisanship directly influences how people obey political hierarchies and how they adhere to social norms (Puthillam and Kapoor 2021).

Deeper studies are quite sparse in India – the largest democracy; although it is evident that there is an all-pervasive rise in misinformation where partisans are keener towards online news items, with a higher proneness to accepting them with an inherent bias (Neyazi et al. 2021). Badrinathan 2021 identified that controlled media literacy had insignificant impact on the people's ability to screen out misinformation. Parties often use celebrity-promotional campaigns to create partisan bias. It was noticed that sportsperson endorsing a party tends to get more favoritisms with people posing more trust on them as they represent the country at large (Mothilal et al. 2022). But the pattern of information flow and subsequent political literacy with the inherent biases are still fuzzy in India.

To understand the nuances of the information flow and the consequent adaption, the panel may be observed over their political literacy through anti-partisan issues, their exposure to their immediate neighbors' opinion and the weights they attach to the respective opinions, their perceived influence on their succeeding neighbors, their exposure to political media content, and their likelihood to accept an opposite viewpoint. The responses may be supervised with three experimental parameters – whether they give more importance to some opinion leaders (belief dictatorship as per GDGM), the timings of their two consecutive votes (as a benchmark for keenness towards political knowledge) and their acceptance to experimental political news (partisan or anti-partisan behaviour).

The agents (individuals in general) must be considered to be geographically clustered. It must be noted that without each agent being physically close, it is not possible to link the nodes either directly or indirectly; the population of each panel, in general, will be too high for the resulting experiment. If there exists an opinion leader, or there is a particular pattern in the flow of structured or unstructured information; it will be difficult to tap the four distinct nodes in terms of social behaviour.

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