A Failure of Collective Intelligence

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***Abstract*—This paper examines the impact of social influence on collective intelligence that causes the divergence of individual decisions from the expected collective decision. An important application of collective intelligence is national election predictions, which may encounter spectacular failures. While experts have provided various explanations, this paper posits that such influence among different types of voters is the primary reason. The 2015 UK Election as a case was studied, which demonstrates that such influence is intrinsic to collective intelligence. This paper then proposes a social influence-based prediction model to remedy these failures. Experiments demonstrate that the new model can account for the existence of such social influence.**

Keywords—collective intelligence, general election prediction, social influence

I. Introduction

Collective intelligence (CI) emerges from the collaboration of many individuals in consensus decision-making problems [1]. Individuals in CI are physically and socially connected, and their opinions are mutually influenced, a phenomenon called social influence [2]. Social influence widely affects the opinion dynamics of CI. It can cause decision convergence or divergence without improved estimation accuracy [3]. Under the social influence, the group can make decisions that none of the members would make individually, which is a phenomenon called emergence [4]. Santos et al. have studied emergence and opinion change in CI in many projects, including opinion change in the 2008 US presidential election [5], emergent border-crossing behavior [6], insider threat in cyberspace [7], emergence in multi-source opinion fusion [8], and Somalia piracy [9]. Their research suggest that nonlinear agent interactions in CI lead to unpredictable behavior from the traditional perspectives such as ensemble methods. Therefore, this paper proposes a new approach to analyzing agent interaction in CI.

This research studies a different type of social influence that causes an individual to change decisions orthogonal to the current group decision. It takes the 2015 UK general election [10] as an example for three reasons: Firstly, there is abundant real-world data. Secondly, it involves rich interactions among different social-economic groups. Thirdly, there are many published pre-election polls and predictions [11]. Most pollster predictions predicted that the Conservative and the Labor would win an equal vote share, but the Conservative won by a seven lead. Many experts explained this failure as a "sampling problem" or from "dishonest participants". However, the authors believe these models are flawed: responsive (those who expressed voting intentions) and nonresponsive (those who did not) voters are treated as two separate groups instead of one unity with interacting members.

Therefore, the authors propose a framework that captures the social influence that responsive voters imposed on non-responsive voters. In particular, the framework divides voters into multiple social-economic groups and measure the social influence of the responsive voters on the non-responsive voters in the same social-economic group based on the campaign topics. Experimental results show that the framework significantly outperforms existing models.

The contributions of this paper are twofold:

- Proposed a social influence model to explain decision divergence phenomenon in a certain collective intelligence problem – national elections modeling. To the best of our knowledge, such a model is the first of its kind.
- Explored several relevant factors to such influence in the election prediction problem, including issue threshold, voter reluctance, and original voting likelihood.

The rest of this paper is organized as follows: Starting with the Background section, we describe the 2015 UK General Election and explain why predictions failed. Next, in our Method section, we propose a data-driven, inter-group influence-based election prediction model. In our Experiments section, we explore several factors that might influence model performance. Lastly, we summarize our contributions.

II. Background

Collective Intelligence originated in 1785 with Condorcet's jury theorem [12]. Levy [13] defines it as "a form of universally distributed intelligence". Individuals in CI interact with one another and influence each other's opinions in the decision-making process, a phenomenon known as social influence. Raven defined social influence [2] as a change in a person's cognition, attitude, or behavior, which has its origin in another person or group. Under social influence, the group may make decisions that none of its members would make individually [13], a phenomenon called emergence [4]. Santos et al. have studied social influence and emergence in [5-9] and conclude that nonlinear agent interactions lead to unpredictable behaviors in CI, which should be modeled from the complex system perspective. This paper proposes a framework based on this idea to explain the failure of election predictions in the 2015 UK election. Social influence in elections is defined as a constituent's change of voting intention under the explicit and implicit influence of other constituents.

TABLE I. VOTING INTENTION BY ELECTORATE PROFILE FROM RESPONSIVE VOTERS

Voting Intention		Age				Social Class				Region				
	Total	*18-24*	*25-34*	*35-64*	*65+*	*AB*	*C1*	*C2*	*DE*	*Scotland*	*Wales*	*North*	*Midlands*	*South*
Weighted base	1157	90	160	614	292	348	341	217	250	117	66	279	291	404
Conservative	33%	21%	29%	30%	46%	43%	33%	29%	25%	13%	16%	27%	42%	41%
Labour	36%	51%	40%	36%	26%	29%	38%	32%	45%	22%	34%	51%	36%	29%
Other Party	31%	28%	31%	34%	28%	28%	29%	39%	30%	55%	50%	22%	22%	30%

National elections are an important application of collective intelligence. Election polls are conducted before elections regardless of their impact on the final voting result [14]. Scientific polling was introduced in the 1936 US election [15]. Polling methods include random calls on landlines and cell phones, mail-in or in-person surveys in households, online surveys, and a mixture of these methods. Hillygus [16] identified several challenges: sampling error, non-sampling error, respondent's honesty, and the volatile mind. Sanders [17] argued that election prediction was relatively accurate. However, polls failed in many elections such as the 2015 UK general election. This failure has many explanations. including nonresponsive and dishonest conservatives and elderly, over-represented labors and youth, and a late swing. However, these explanations cannot reveal the reason for the intention change of certain voters.

The authors also found that pollsters either ignored non-responsive voters or estimated their intentions with their historical voting intentions, which causes nonresponsive bias [18]. Even if they considered nonresponsive voters, pollsters ignored their opinion change under social influence from responsive voters with the publication of their intentions. The authors propose a framework to prove that the exclusion of social influence is the true cause of their failures.

III. METHOD

This section first explains the failure of prediction model made by a public research company called ICM (https://www.icmunlimited.com/wp-content/uploads/2016/03/2015_final_poll_FINAL.pdf). Next, it proposes a social influence-based model.

A. Baseline Election Prediction Model

ICM conducted a final poll on May 7, 2015, by calling random landline and cell phone numbers and collected 2023 samples. For each respondent, ICM surveyed his/her demographic profile, 2010 vote, voting intention, vote likelihood and political issues he/she cares. However, to protect respondent privacy, ICM only published summary data, which contain a pairwise relationship of voting intention with four profile variables (gender, age, social class, and region) and the 2010 vote. Within 2023 respondents, 1157 respondents are responsive voters that expressed voting intentions. TABLE I lists the relationship between the intention and profile.

For the responsive voters, several variables are defined. Let v be the **Voting Intention** with three states: Conservative (***Con***), Labour (***Lab***) and Other Party (***Other***). Let v^i be the event that variable v takes i^{th} state, where $i \in [1,3]$. Similarly, let a be **Age** which has four states: "***18-24***", "***25-34***", "***35-64***" and "***65+***". Let a^m be the event that a takes m^{th} state, where $m \in [1,4]$. Let sc be **Social Class** with four states: ***"AB", "C1", "C2"*** and ***"DE".*** Let sc^n be the event that sc takes n^{th} state, where $n \in [1,4]$. Let r be the variable **Region** with five states: ***"Scotland", "Wales", "North", "Midlands"*** and ***"South".*** Let r^q be the event that r takes q^{th} state, where $q \in [1,5]$.

Each value represents the conditional probability of some voting intention given a state of one profile. The authors compute the responsive voter's intention as follows: The conditional probability of one variable given voting intention is computed from this table. Then the conditional independence relationship is assumed, and the conditional probability of voting intention given all variables is computed per (1).

$$P(v^i|a^m, sc^n, r^q) \propto P(a^m, sc^n, r^q|v^i)P(v^i)$$
$$\cong P(a^m|v^i)P(sc^n|v^i)P(r^q|v^i)P(v^i) \quad (1)$$

For the nonresponsive voters, their voting intentions were estimated by ICM via their 2010 vote history with 50% discount without any explanation. ICM did not include those who said they would certainly not to vote, which took up 7% (144/2023) of respondents. TABLE II lists nonresponsive voters' 2010 votes, indicating that the discounted nonresponsive voters with 2010 vote records consist of 15% (0.5*188/639) of all nonresponsive voters. Therefore, the nonresponsive voters contribute to 15% shares of votes. The conditional probability of the 2010 vote given a profile for the nonresponsive voters is computed as follows:

TABLE II. 2010 VOTE OF NONRESPONSIVE VOTER

		2010 Vote		
	Total	*Con*	*Lab*	*LibDem*
Weighted Base	2023	443	370	273
Don't know	300 15%	56 13%	41 11%	46 17%
Refused	195 10%	20 5%	14 4%	11 4%

Let hv be the **2010 vote** with three states: ***Con, Lab,*** and ***LibDem***. Let hv^i be the event that hv takes i^{th} state, where $i \in [1,3]$. Let ev be the estimated voting intention, which has three values and let ev^k be the event that ev takes k^{th} state, where $k \in [1,3]$. Let v' be the **Voting Intention** of a nonresponsive voter with three answers: "Will not vote", "Don't know" and "Refused". Let v'^j be the event that v' takes j^{th} state, where $j \in$

[1,3]. Then the profile is correlated with the 2010 vote per (2) and (3).

$$P(hv^i, a^m, sc^n, r^q | v'^j) \cong P(hv^i|v'^j)P(a^m|v'^j)P(sc^n|v'^j)P(r^q|v'^j) \quad (2)$$

$$P(hv^i|a^m, sc^n, r^q) = \frac{\sum_{v'} P(hv^i, a^m, sc^n, r^q|v'^j)P(v'^j)}{P(a^m, sc^n, r^q)} \quad (3)$$

The ICM then computed the weighted average voting intentions of responsive and nonresponsive voters and predicted 34% for the Conservative and 35% for the Labor.

B. Social Influence-Based Election Prediction Model

This subsection details a social influence-based election prediction model. It first models the voting intention of responsive voters. Then, it models intention change of nonresponsive voters under the social influence of responsive voters.

1) Modeling Published Election Prediction

TABLE III lists some issues a constituent may consider based on the ICM survey. TABLE IV lists each major party's pledge for some issues based on the theory of issue voting [19-21], where +1 means "superior," 0 means "neutral" and -1 means "inferior". Then the voting intentions of responsive voters based on issues are computed as follows:

Let isu be a binary variable representing an issue. Let isu^j be the event that isu takes j^{th} state, where $j \in [1,2]$. Two isu states have two meanings: For a party, isu^1 means that this issue will be improved while isu^2 means the opposite; For a nonresponsive voter, isu^1 means that isu will be considered isu^2 means the opposite. Let $si(v^i, isu)$ be variable *score* with three values: -1,0, and 1, which means the party v^i's pledge score for the issue, which impacts the likelihood of each issue benefiting an average voter according to (4).

$$P(isu^1|v^i) = \begin{cases} 0.2, if\ si(v^i, isu) = -1 \\ 0.5, if\ si(v^i, isu) = 0 \\ 0.8, if\ si(v^i, isu) = 1 \end{cases} \quad (4)$$

The responsive voters' intentions and their influences on the campaign issues are calculated in four steps. The first step computes their profiles based on TABLE I. The second step computes the conditional probability of voting for a party given a responsive voter's profile based on TABLE III. The third step computes an issue's state distribution given the vote state distribution based on TABLE IV. The fourth step computes the probability of each issue being beneficial to an average voter given the current prediction per (4), which is noted as $E(isu)$.

2) Modeling Nonresponsive Voter and Social Influence

This subsection first models the nonresponsive voters' intention, then models social influence and finally models the nonresponsive voters' change of intention under social influence. For a group of nonresponsive voters, the probability of considering an issue is calculated as follows: Firstly, the conditional probability of isu^2 given some state of one profile variable is calculated from TABLE III in (5.1), (5.2) and (5.3). Secondly, the conditional probability of one profile state given isu^1 is computed in (6.1), (6.2) and (6.3). The conditional probability of one profile state given isu^2 is calculated similarly. Thirdly, the conditional independence relationship is assumed, and the conditional probability of joint profile state given isu^1 and isu^2 is calculated in (7.1) and (7.2). Next, the conditional probability of isu state given joint profile variables is calculated based on the Bayes Rule in (8.1) and (8.2). Lastly, we normalized these conditional probabilities.

$$P(isu^2|a^m) = 1 - P(isu^1|a^m) \quad (5.1)$$

$$P(isu^2|sc^n) = 1 - P(isu^1|sc^n) \quad (5.2)$$

$$P(isu^2|r^q) = 1 - P(isu^1|r^q) \quad (5.3)$$

$$P(a^m|isu^1) = \frac{P(isu^1|a^m)P(a^m)}{P(isu^1)} \quad (6.1)$$

$$P(sc^n|isu^1) = \frac{P(isu^1|sc^n)P(sc^n)}{P(isu^1)} \quad (6.2)$$

$$P(r^q|isu^1) = \frac{P(isu^1|r^q)P(r^q)}{P(isu^1)} \quad (6.3)$$

$$P(a^m, sc^n, r^q|isu^1) = P(a^m|isu^1)P(sc^n|isu^1)P(r^q|isu^1) \quad (7.1)$$

TABLE III. ISSUE

Issue	Total	Age				Social lass				Region				
		18-24	*25-34*	*35-64*	*65+*	*AB*	*C1*	*C2*	*DE*	*Scotland*	*Wales*	*North*	*Midlands*	*South*
benefits cut	0.57	0.54	0.63	0.59	0.47	0.57	0.56	0.58	0.56	0.6	0.42	0.63	0.54	0.56
tax rises	0.46	0.5	0.55	0.48	0.32	0.47	0.47	0.52	0.4	0.53	0.27	0.46	0.45	0.48
squeezed living standards	0.52	0.54	0.56	0.57	0.37	0.5	0.53	0.54	0.5	0.6	0.4	0.52	0.53	0.51
government deficit	0.49	0.38	0.49	0.53	0.47	0.56	0.5	0.49	0.4	0.48	0.46	0.44	0.52	0.51
future of the NHS	0.81	0.86	0.78	0.83	0.75	0.78	0.83	0.83	0.79	0.85	0.83	0.79	0.81	0.8
smaller party holding government to ransom	0.40	0.27	0.34	0.43	0.46	0.44	0.38	0.38	0.41	0.41	0.38	0.41	0.4	0.4

TABLE IV. PARTY POLICY

Party\issue	NHS	Benefit	Tax	Deficit
Conservative	£8bn above inflation +1	Extend right to buy; 30hr of free childcare -1	30hr minimum wage no tax -1	Be running a surplus +1
Labour	£2.5bn -1	Raise minimum wage; access to childcare +1	rise mansion tax; no rise on many taxes +1	Cut deficit -1
Other Party	£3-8bn 0	Guarantee education funding; control immigration 0	No tax on minimum wage; increase tax-free allowance 0	Balance budget 0

TABLE V. HIDDEN INFLUENCE-BASED VOTING INTENTION FOR NONRESPONSIVE VOTER

Hidden Influence-Based Voting Intention Algorithm	
1	set vote of nonresponsive voter $v_{nr}^i = 0, \forall i \in [1,3]$
2	for each group of nonresponsive voters with certain profile combination $p = \langle a^m, sc^n, r^q \rangle$
3	compute their original distribution of v as v_p
4	set vote likelihood change $vlc_p = 0$, vote change $vc_p = 0$
5	for each isu in $\{benefit, tax, deficit, NHS\}$
6	compute their expected probability of each isu as isu_p^1
7	compute probability difference $dt = P\left(isu_p^1\right) - E(isu)$
8	if $dt > isu\_th$
9	$vlc_p += dt$
10	if $si(v^1, isu) > si(v^2, isu)$
11	if $v_p^1 > v_p^2$, then $vc_p^1 += 1.5dt, vc_p^2 -= dt, vc_p^3 -= 0.5dt$
12	else $vc_p^1 += 1.5dt \cdot dc, vc_p^2 -= dt \cdot dc, vc_p^3 -= 0.5dt \cdot dc$
13	else if $si(v^1, isu) < si(v^2, isu)$
14	if $v_p^1 < v_p^2$, then $vc_p^2 += 1.5dt, vc_p^1 -= dt, vc_p^3 -= 0.5dt$
15	else $vc_p^2 += 1.5dt \cdot dc, vc_p^1 -= dt \cdot dc, vc_p^3 -= 0.5dt \cdot dc$
16	$\forall i \in [1,3], vc_p^i = \max\left(0, \min\left(1, vc_p^i\right)\right)$, update vote distribution $v_p'^i = v_p^i + vc_p^i$ and normalize v'_p
17	compute profile p density $d(p)$
18	update vote likelihood $vl'_p = vl_{org} + vlc_p$
19	$\forall i \in [1,3], v_{nr}^i += v_p'^i \cdot d(p) \cdot vl'_p$
20	normalize and return $v_{nr}^i, \forall i \in [1,3]$

$$P(a^m, sc^n, r^q | isu^2) = P(a^m | isu^2) P(sc^n | isu^2) P(r^q | isu^2) \quad (7.2)$$

$$P(isu^1 | a^m, sc^n, r^q) \propto P(isu^1) P(a^m, sc^n, r^q | isu^1) \quad (8.1)$$

$$P(isu^2 | a^m, sc^n, r^q) \propto P(isu^2) P(a^m, sc^n, r^q | isu^2) \quad (8.2)$$

TABLE V lists the proposed social influence computation algorithm (Algorithm 1). The intuition is that if certain group considers some issue that will not be sufficiently improved based on the prediction, this group will be more likely to vote for the party that has the best policy on this issue. It contains three variables: issue threshold isu_th in line 8, intention change discount dc in line 12 and 15, and original vote likelihood vl_{org} in line 18. Variable isu_th represents a positive threshold value for difference dt between expected and predicted probability of isu being improved for profile group p, and it will impact their intention only when dt becomes greater than the isu_th. Variable dc represents a nonresponsive voter's reluctance to change voting intention in the later of two situations: 1) when an electorate prefers party A and party A's pledge on isu is better; and 2) when an electorate prefers party A, but party A's pledge on isu is worse. Variable vl_{org} represents original vote likelihood of a nonresponsive voter.

This algorithm computes the profile density $d(p)$ of each profile group p as follows: It first computes the profile distribution of all respondents. Next, it computes the profile distribution of responsive voters. Thirdly, it computes the profile distribution of nonresponsive voter from these two distributions in TABLE VI. Lastly, it derives a joint profile distribution per (9).

$$P(a^m, sc^n, r^q) = P(a^m) P(sc^n) P(r^q) \quad (9)$$

TABLE VI. WEIGHTED VOTE SHARE PREDICTION OF RESPONSIVE AND NONRESPONSIVE VOTERS

Weighted Vote Share Prediction Algorithm	
1	load all voters' distribution for a, sc, r: $dist(a), dist(sc), dist(r)$
2	load split ratio for a, sc, r: $sp(a), sp(sc), sp(r)$
3	load updated vote likelihood vl'_p for each profile group p
4	set responsive and nonresponsive voter weights $wt1 = wt2 = 0$
5	for each a^m
6	for each sc^n
7	for each r^q
8	$wt1 += P(a^m) sp(a^m) P(sc^n) sp(sc^n) P(r^q) sp(r^q)$
9	$wt2 += (P(a^m)(1 - sp(a^m)) P(sc^n)(1 - sp(sc^n)) P(r^q)(1 - sp(r^q))) vl'_p$
10	set responsive vote weight $w = \frac{wt1}{wt1 + wt2}$
11	load predicted vote of responsive and nonresponsive voter: v_r, v'_{nr}
12	compute weighted vote $v_w^i = w v_r^i + (1 - w) v_{nr}'^i, \forall i \in [1,3]$

TABLE VII. PROFILE DISTRIBUTION OF NONRESPONSIVE VOTER

variable\state index	1	2	3	4	5
a	0.2	0.19	0.46	0.14	
sc	0.22	0.28	0.25	0.25	
r	0.0	0.04	0.25	0.28	0.35

Finally, the proposed framework computes the weighted responsive and nonresponsive voters' intentions by their population size and vote likelihood in TABLE VII.

IV. EXPERIMENTS

This section first explores three variables: issue threshold, discount, and original vote likelihood. It then examines the prior distribution and split ratio.

A. Parameter Variation

This subsection tests different issue thresholds ranging from 0.05 to 0.5 at 0.05 intervals, discounts ranging from 0.1 to 2.0 at 0.1 intervals, and original vote likelihood ranging from 0.1 to 0.5 at 0.1 intervals. Their combinations result in 1000 experiments. Each experiment extracts nonresponsive voter's intention v_{nr}, weighted voting intention v_w, and compute distance d between v_w and true vote share distribution v_{tr} per (10).

$$d = \sum_{i=1}^{2} \left| v_w^i - v_{tr}^i \right| \quad (10)$$

Fig. 1 illustrates the relationship between the nonresponsive voters' intentions and parameter variations: Firstly, when isu_th increases, Con vote share first increases then decreases, and Lab vote share changes in the opposite direction. Secondly, when dc grows, Con vote share increases, and Lab vote shares decreases. Finally, the vote share does not change when vl_{org} increases.

Fig. 2 illustrates the relationship between distance d and three parameters. The figures in the first row indicate an optimal isu_{th} of 0.3; The figures in the second row indicate an optimal vl_{org} of 0.1; The figures in the third row indicate an optimal dc of 0.7. When all three parameters take their optimal values, the smallest distance of 0.033 is reached. In addition, as isu_th increases, the distance first drops and then rises when discount equals 0.5. However, when discount equals 1.0 and 1.5 and vote likelihood becomes larger, the distance first drops, then rises, later drops and rises again as isu_th increases. This trend reflects the impact of isu_th on social influence, which dramatically increases prediction difficulty. However, dc affects social influence differently. With a low isu_th, distance first drops and then rises as dc increases. However, with a high isu_th, dc does not influence distance. This implies that dc only counts when the nonresponsive voters are sensitive to issue gaps and that they prefer the original choices.

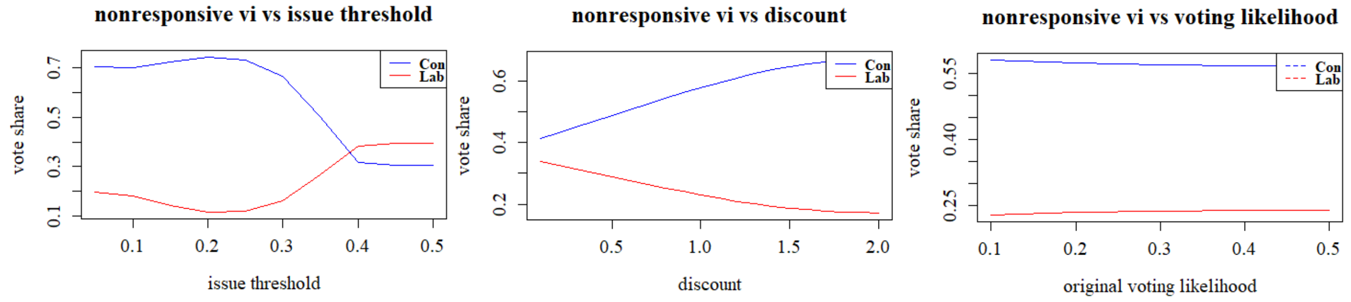

Fig. 1. Nonresponsive vote share vs three parameters

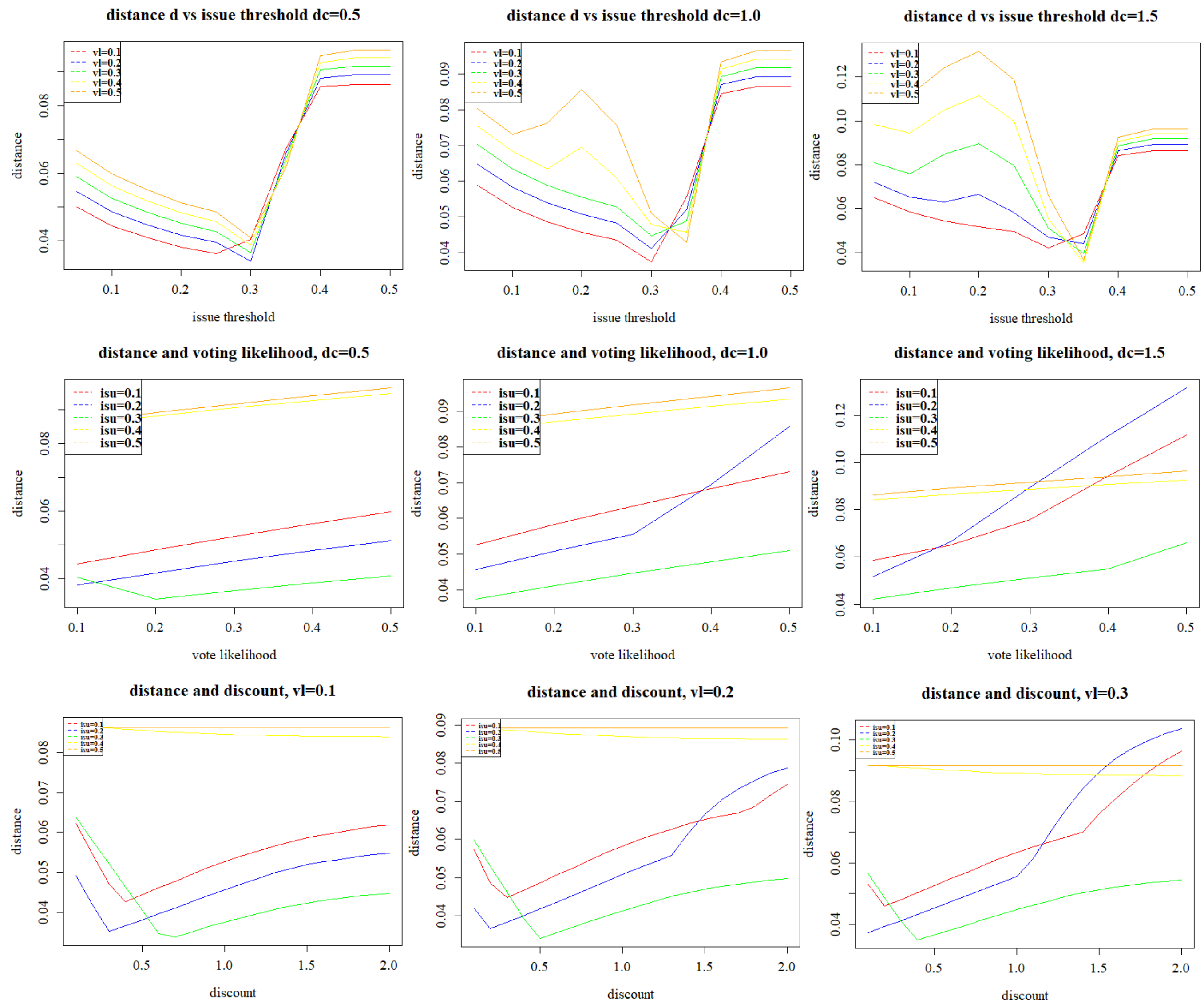

Fig. 2. Distance vs three parameters

This subsection demonstrates the complex relationship between social influence and three variables, which explains the failure of ICM's method that separately models the responsive and the nonresponsive voter.

B. Profile Change and Split Change

This subsection compares the proposed model with the ICM baseline under various profile and split settings. It first explores profile change. Then it explores the change of split. Lastly, it combines these changes.

For profile age, the prior probability of one age group is increased and that of another age group is decreased by 5% in a trial. Then, the percentage of the responsive voters in one age group is increased and the percentage of the responsive voters in another age group is decreased by 10% in a trial. Lastly, both prior and split of one age group are modified in a trial. Fig. 3 illustrates two models' distances to the true vote share distribution. The x-axis represents a prior/split change for each age group combination. For example, the first bin "18/25" means "increase prior distribution of age group 18-24 and decrease prior distribution of age group 25-34 by 5%" in the first group of trials. The y-axis is the distance between predicted vote share and true vote share for both proposed methods and baseline method.

This figure shows several results: 1) In all thirty-six trials, the proposed method significantly outperforms the baseline. 2) For both methods, prior/split change combinations "25/18", "35/18", "65/18" have better prediction accuracy, which verifies expert explanation of overrepresented young people in favor of Labour. 3) Increasing the split ratio of responsive voters for age group 65+ yields better performance, which verifies the expert explanation of "people who declined voting are more likely to vote for Conservative."

The experiments on the profile of social class and region give similar results. In short, the divergence of individual decisions and the final collective intelligence depend on population distribution.

V. Conclusion

This paper studied the impact of social influence on the divergence of decisions in a collective intelligence problem. Under the social influence, the individual decision may diverge, and collective performance becomes unpredictable in these collective intelligence problems. Even though it only studied the emergent outcome of the 2015 UK general election, the proposed model will be applied to other collective intelligence problems in the future work.

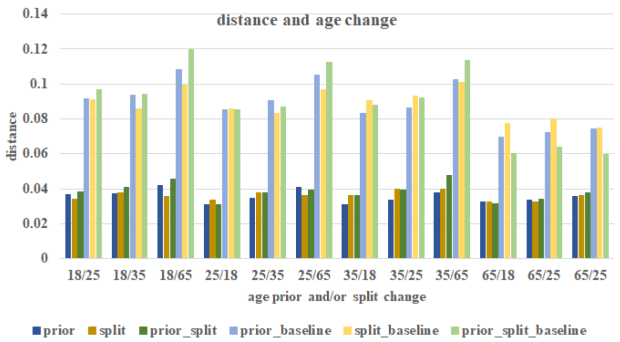

Fig. 3. Distance vs age change

VI. Acknowledgments

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