How Individuals Weigh Their Previous Estimates to Make a New Estimate in the Presence or Absence of Social Influence

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Abstract. Individuals make decisions every day. How they come up with estimates to guide their decisions could be a result of a combination of different information sources such as individual beliefs and previous knowledge, random guesses, and social cues. This study aims to sort out individual estimate assessments over multiple times with the main focus on how individuals weigh their own beliefs vs. those of others in forming their future estimates. Using dynamics modeling, we build on data from an experiment conducted by Lorenz et al. [1] where 144 subjects made five estimates for six factual questions in an isolated manner (no interaction allowed between subjects). We model the dynamic mechanisms of changing estimates for two different scenarios: 1) when individuals are not exposed to any information and 2) when they are under social influence.

Keywords: Estimate aggregation, collective judgment, and social influence.

1 Introduction

The present study examines individuals' mechanisms for revising their estimates in the presence and absence of social influence. How do people weigh their previous estimates while forming new estimates? How do they account for the judgment of others in their next estimate? We base our modeling and estimation work on the data of an experiment by Lorenz et al. [1] where each individual, in 12 groups of 12 people, makes five estimates for six factual questions. Lorenz et al. [1] study different scenarios when individuals do not receive any feedback about others' estimates and when they are given feedback to some degree. Before reviewing their experiment (in Section 2) and presenting our modeling work (in Section 3), we review the key findings of the literature regarding this topic and identify the research questions to which we contribute.

1.1 Aggregation of Individual Estimates

One of the main research areas relevant to our study is the impact of aggregation of individual estimates. In general, individuals aggregate their opinion by averaging

W.G. Kennedy, N. Agarwal, and S.J. Yang (Eds.): SBP 2014, LNCS 8393, pp. 66–73, 2014.

[2, 3]. Although nineteenth century scientists did not trust averaging [3], recent studies have shown that the average of multiple estimates from different individuals is more accurate than the average of multiple estimates from one individual [4-11]. Surowiecki [12] demonstrates that the results of aggregating individual estimates are superior to even those provided by experts.

Averaging increases accuracy, because different individuals' estimates often bracket the true value and thus averaging yields a smaller error than randomly choosing one estimate. Only if significant bias is present across all individuals, and thus the estimates do not bracket the truth, the average would be as accurate as a random estimate [3, 5, 8, 9]. Research shows that averaging ensures that the result has lower variability, lower randomization error, lower systemic error, and converges towards the true forecast [see: 5, 13, 14]. Additionally, averaging not only increases the accuracy, but also some form of averaging is almost nearly optimal. Yaniv [6] notes the "independency of individual" as a central condition for obtaining optimal accuracy, and Hogarth [15] presents that groups containing between 8 and 12 individuals have predictive ability to the optimum. This simple mathematical fact of averaging individual estimates, the so-called "wisdom of crowds", can be easily missed or even if it is seen, it can be hard to accept [12].

1.2 Weighing Process in Aggregation

Research shows that people make decisions by weighing their own opinions with advice from other sources [16]. In the process of giving and receiving advice, individuals discount advice and weigh their own opinions more because they are usually egocentric in revising their opinions and have less access to reasons behind the advisor's view [6, 17, 18]. Harvey and Harries [19] observe a similar behavior in their experiment, where individuals put more weight on forecasts that are their own rather than on equivalent forecasts that are not theirs. In short, differential access to reasons (e.g. advisor's reasons) and egocentric beliefs are the two common causes of overweighing one's own opinions; however, Soll and Mannes [3] show that neither of these two can fully account for the tendency to overweigh one's own reasons.

Yaniv and Milyavsky [20] note that individuals with less information change their opinions based on advice more than more knowledgeable individuals. In their experiment, individuals were less likely to change their initial opinion if they had a strong and formed opinion than others who had not. Additionally, Mannes [21] believes that when individuals recognize the wisdom of crowds and place more weight on their opinions, their revised belief becomes more valid.

In sum, studying the effects of social influence on individual decision making is important to evaluate the reliability of their specific predictions. In fact, the internal mechanisms that drive individuals to update their estimates are not fully specified in the literature, especially when they are under social influence. To be more clear, social influence occurs when an individual changes her attitude because of the attitudes of others; that is, when an individual's beliefs, feelings, and behaviors are affected by other people [22].

2 The Experiment

Lorenz et al. [1] ask 144 students to answer six quantitative questions on geographical facts and crime statistics in Switzerland, including (1) population density, (2) border length, (3) the number of new immigrants, (4) the number of murders, (5) the number or rapes, and (6) the number of assaults. The participants were split randomly into 12 experimental sessions, each consisting of 12 participants. Each question was repeatedly answered in five rounds (time periods). The questions were designed in such a way that individuals were not likely to know the exact answer, but could still have some clue. Participants did not interact with each other and the only information they received about the others' estimates was provided by experimental manipulation (no information, aggregated information, and full information) through the software interface. Individuals were also asked about their confidence levels in their first and fifth estimates for each question on a six-point Likert scale (1, very uncertain; 6, very certain). The confidence level values were not provided to the others.

Three different scenarios were tested regarding information exposure, including "no information", "aggregated information", and "full information". In the no information scenario, individuals were not aware of others' estimates and, therefore, the five consecutive estimates were made with no additional information. In the aggregated information scenario, each subject was provided with the arithmetic average of others' estimates in the previous round. Finally, in the full information scenario, individuals received a figure of the trajectories of all others' estimates along with their numerical values from the previous round. For each group, two questions were posed in each information scenario. The order of questions in each information condition was randomized.

Subjects were encouraged to answer questions precisely by offering them financial rewards. Individuals received increasing monetary payments if their estimates fell into the 40%, 20%, or 10% intervals around the truth; otherwise, they received no reward. The correct answer and rewards were disclosed at the end of the experiment to avoid giving away a priori knowledge about the right answer.

3 Modeling

In this study we design two scenarios, no information (No Info) and aggregated information (Aggregated Info), to reproduce the dynamic mechanism of changing estimates, over five estimation making rounds. No Info and Aggregated Info models are discussed in Sections 3.1 and 3.2 respectively. Parameter estimation is then presented in section 3.3.

3.1 No Info Model

We present two alternative models for the No Info scenario. In the first model, estimates are generated anchoring on the initial estimate. In the second one, estimates are generated anchoring on all previous estimates (a weighted average of those).

No Info Model I

The key hypothesis here is that people change their estimates depending on the previous estimates and some random variations, where the higher their initial confidence level is the less variation will be observed in the estimates. Estimate of individual i at round r, $(\hat{E}_i^{(r)})$, $r \in \{1, \ldots, 5\}$, is generated based on the initial estimate (E_{0_i}) and a change rate $(C_i{}^{(r)})$:

$$\hat{E}_i^{(r)} = E_{0_i} + C_i{}^{(r-1)}, \;\; r \in \{1, \ldots, 5\} \tag{1}$$

$C_i{}^{(r)}$ is the rate at which an estimate becomes the next desired estimate (note that $C_i{}^{(0)} = 0$, so $\hat{E}_i^{(1)} = E_{0_i}$). $C_i{}^{(r)}$ is calculated as:

$$C_i{}^{(r)} = DE_i{}^{(r)} - \hat{E}_i^{(r)} \tag{2}$$

Desired estimate $(DE_i{}^{(r)})$ is estimated based on E_{0_i} and some variations $(V_i{}^{(r)})$:

$$DE_i{}^{(r)} = E_{0_i} V_i{}^{(r)} \tag{3}$$

$V_i^{(r)}$ is then generated using a lognormal random variable to change the next desired estimate at each round, $V_i{}^{(r)} = exp(\xi)$ where $\xi \sim \mathcal{N}\left(0, \hat{\sigma}_i^{(r)}\right)$. We hypothesize that $\hat{\sigma}_i^{(r)}$ is a function of individual's initial confidence level (CL_i is between one and six; it is normalized as $CL_i^* = \frac{CL_i - 1}{5}$, so $CL_i^* \in \{0, 0.2, 0.4, 0.6, 0.8, 1\}$). It can be simply assumed that $\hat{\sigma}_i^{(r)}$ is linearly changing in the range of [0,1] based on CL_i^* but the experimental data does not evidence such linearity. We use equation 4 to estimate the functional structure of $\hat{\sigma}_i^{(r)}$,

$$\hat{\sigma}_i^{(r)}(CL_i^*, \alpha, \beta, \gamma) = \gamma[\beta + (1 - CL_i^{*\alpha})(1 - \beta)], \;\; \{\alpha, \beta, \gamma\} \in \mathbb{R} \tag{4}$$

α, β, and γ are control parameters (to be estimated) where: $\alpha > 0$ controls the convexity shape of the function (linear function if $\alpha = 1$); $0 \le \beta < 1$ controls the intersect of $\hat{\sigma}_i^{(r)}$ at $CL_i^* = 1$, e.g. $\left\{\hat{\sigma}_i^{(r)}(CL_i^* = 1) = 0 \middle| \beta = 0\right\}$; and $\gamma > 0$ controls the intersect of $\hat{\sigma}_i^{(r)}$ at $CL_i^* = 0$, e.g. $\left\{\hat{\sigma}_i^{(r)}(CL_i^* = 0) = 1 \middle| \gamma = 1\right\}$.

No Info Model II

In the second model, individuals take into account all previous estimates for making estimates rather than only their initial estimate as a pivot point. $\hat{E}_i^{(r)}$, estimate of individual i at round r, is a linear combination of weighted previous estimates $(E_i^{(j)})$, j^{th} previous estimate made by individual i, ($j < r$ and $j \in \{1, \ldots, 4\}$). Also, weights $(\widehat{W}^{(j)})$ are assigned to estimates of previous rounds, j^{th} previous estimate. $\hat{E}_i^{(r)}$ is calculated as shown in equation 5.

$$\hat{E}_i^{(r)} = \frac{\sum_2^r E_i^{(r-1)} \widehat{W}^{(r-1)}}{\sum_2^r \widehat{W}^{(r-1)}}, \;\; r \in \{2, \ldots, 5\} \tag{5}$$

3.2 Aggregate Info Model

In this model, individuals are affected by social influence as they are given the group average ($GA^{(r)} = \frac{1}{12}\sum_{i=1}^{12} E_i^{(r)}$) of the previous round. The main idea is that individuals make estimates based on a weighted average of their own estimates and the group average. Individuals also consider the group average based on two variables: degree of compliance DC_i (how much they rely on the opinion of others) and threshold T_i (e.g. they do not take into account the group average when it is T_i times bigger/smaller than their own estimate). The degree of compliance ($0 \leq DC_i \leq 1$), defines whether the individual is willing to follow the group estimate and is based on CL_i^*:

$$DC_i = \vartheta[\zeta + (1 - CL_i^{*\eta})(1 - \zeta)]$$
$$\text{where, } \{\eta, \zeta, \vartheta\} \in \mathbb{R} \text{ and } \eta > 0,\ 0 \leq \zeta < 1,\ 0 < \vartheta \leq 1 \quad (6)$$

Defining $E_i^{(j)}$ and $\widehat{W}^{(j)}$ as same as in the No Info model II, $\hat{E}_i^{(r)}$ is calculated as:

$$\hat{E}_i^{(r)} = DC_i * GA^{(r-1)} + (1 - DC_i) * \frac{\sum_2^r E_i^{(r-1)} \widehat{W}^{(r-1)}}{\sum_2^r \widehat{W}^{(r-1)}} \quad (7)$$

We design five hypotheses to study the structural form of DC_i and T_i on estimates as: H_1: fixed DC_i without T_i, H_2: fixed DC_i and fixed T_i, H_3: fixed DC_i and variable T_i ($T_i = \rho + \omega CL_i^*, \{\rho, \omega\} \in \mathbb{R}$), H_4: variable DC_i and fixed T_i, H_5: variable DC_i and variable T_i. The results of F-tests show that H_5 has less error and variance. Note that in equation (7), $DC_i = 0$ if the group average is T_i times bigger/smaller than individual's estimate.

3.3 Parameter Estimation

No Information Model

The maximum likelihood estimation is used to estimate parameters so that the model optimally fits the experimental data. The results of the parameters' estimation are shown in Table 1. Comparison of the two models indicates that although they do not significantly differ in variability, model II provides a better fit with the experimental data.

Table 1. Parameters estimated in No Info models

No Info, model I		**No Info, model II**	
Parameter	Estimation (95% CI)	Parameter	Estimation (95% CI)
α	2.07 (2.05-2.09)	$W^{(2)*}$	0.33 (0.27-0.40)
β	0.80 (0.75-0.91)	$W^{(3)}$	0
γ	1.06 (1.05-1.07)	$W^{(4)}$	0

* $W^{(j)}$ is weight of j^{th} previous estimate. $W^{(1)} = 1$.

Aggregated Information Model

Parameters are estimated using the maximum likelihood estimation. Given estimated ρ and ω as 5 and 3 respectively, individuals' threshold T_i to follow the group average varies between 5 and 8 with respect to their confidence level. Table 2 shows parameters estimated in the Aggregated Info model.

Table 2. Parameters estimated in Aggregated Info model

Aggregated Info			
$\widehat{W}^{(j)}$		$\boldsymbol{DC_i}$ **parameters**	
Parameter	Estimation (95% CI)	Parameter	Estimation (95% CI)
$\boldsymbol{W^{(2)}}$*	0.21 (0.14-0.22)	η	1.25 (0.59-1.90)
$\boldsymbol{W^{(3)}}$	0	ϑ	0.54 (0.51-0.60)
$\boldsymbol{W^{(4)}}$	0	ζ	0

* $W^{(j)}$ is weight of j^{th} previous estimate. $W^{(1)} = 1$

4 Discussion

In this study we aim to understand how individuals weigh previous estimates of their own in presence and absence of social influence. We first modeled the No Info scenario where individuals were not aware of others' estimates. Two models were tested for this scenario—in model I individuals rely only on their initial estimate while in model II they take into account all previous estimates rather than only their initial estimate. Our analysis shows that Model II provides a better fit with the experimental data. The main difference between the No Info model II and the Aggregated Info model is that in the Aggregated Info model each subject was provided with the arithmetic average of others' estimates in the previous round, in other words, individuals were affected by social influence.

We show that in both scenarios, the initial estimate has no significant influence on the final estimate, which is not consistent with Mannes's [21] findings. One reason for this could be the best guess efforts are the most updated ones for individuals and not their initial ones. Another reason could be that individuals do not know the true value and as they also do not receive any feedback about others' estimates, they change their ideas based on their more recent thoughts.

Our results also show that when individuals are not affected by social influence they use one and two previous estimates to generate new estimates, where the two previous estimate has lower weight, 0.33 (0.27-0.40). When they are affected by social influence, they still use only one and two previous estimates and the two previous estimate has lower weight 0.21 (0.14-0.22). Comparison between those situations reveals that the weight of the two previous estimate is lower when individuals are given the group average—they tend to make a combination of their own estimates and of the others. To do so individuals consider two variables, threshold and degree of compliance as functions of their confidence level, to include estimates of others in their next estimate. Our analysis reveals that individuals have a threshold of about 6.5

(they do not take into account the group average when it is 6.5 times bigger or smaller than their own estimate), to consider the group average as significant. This result is in close accordance with Yaniv's study [20].

One of our major limitations in this study is the small sample size of the experimental data. The precision and accuracy of our estimates can be potentially improved as larger data are analyzed. Future research can also apply our models in different settings to test the robustness of the findings. Analysis of inconsistencies of research findings such as the influence of initial estimate on the final estimate could be also another research work.

References

1. Lorenz, J., et al.: How social influence can undermine the wisdom of crowd effect. Proceedings of the National Academy of Sciences of the United States of America 108(22), 9020–9025 (2011)
2. Budescu, D.V., Rantilla, A.K.: Confidence in aggregation of expert opinions. Acta Psychologica 104(3), 371–398 (2000)
3. Soll, J.B., Mannes, A.E.: Judgmental aggregation strategies depend on whether the self is involved. International Journal of Forecasting 27(1), 81–102 (2011)
4. Rauhut, H., Lorenz, J.: The wisdom of crowds in one mind: How individuals can simulate the knowledge of diverse societies to reach better decisions. Journal of Mathematical Psychology 55(2), 191–197 (2011)
5. Herzog, S.M., Hertwig, R.: The Wisdom of Many in One Mind: Improving Individual Judgments With Dialectical Bootstrapping. Psychological Science 20(2), 231–237 (2009)
6. Yaniv, I.: The benefit of additional opinions. Current Directions in Psychological Science 13(2), 75–78 (2004)
7. Yaniv, I.: Receiving other people's advice: Influence and benefit. Organizational Behavior and Human Decision Processes 93(1), 1–13 (2004)
8. Larrick, R.P., Soll, J.B.: Intuitions about combining opinions: Misappreciation of the averaging principle. Management Science 52(1), 111–127 (2006)
9. Soll, J.B., Larrick, R.P.: Strategies for Revising Judgment: How (and How Well) People Use Others' Opinions. Journal of Experimental Psychology-Learning Memory and Cognition 35(3), 780–805 (2009)
10. Wright, G., Rowe, G.: Group-based judgmental forecasting: An integration of extant knowledge and the development of priorities for a new research agenda. International Journal of Forecasting 27(1), 1–13 (2011)
11. Lee, M.D., Zhang, S., Shi, J.: The wisdom of the crowd playing The Price Is Right. Memory & Cognition 39(5), 914–923 (2011)
12. Surowiecki, J.: The wisdom of crowds: why the many are smarter than the few and how collective wisdom shapes business, economies, societies, and nations, 1st edn., vol. xxi, p. 296. Doubleday, New York (2004)
13. Bonaccio, S., Dalal, R.S.: Advice taking and decision-making: An integrative literature review, and implications for the organizational sciences. Organizational Behavior and Human Decision Processes 101(2), 127–151 (2006)

14. Hourihan, K.L., Benjamin, A.S.: Smaller Is Better (When Sampling From the Crowd Within): Low Memory-Span Individuals Benefit More From Multiple Opportunities for Estimation. Journal of Experimental Psychology-Learning Memory and Cognition 36(4), 1068–1074 (2010)
15. Hogarth, R.M.: Note on Aggregating Opinions. Organizational Behavior and Human Performance 21(1), 40–46 (1978)
16. Gino, F., Moore, D.A.: Effects of task difficulty on use of advice. Journal of Behavioral Decision Making 20(1), 21–35 (2007)
17. Krueger, J.I.: Return of the ego–Self-referent information as a filter for social prediction: Comment on Karniol (2003)
18. Yaniv, I., Kleinberger, E.: Advice taking in decision making: Egocentric discounting and reputation formation. Organizational Behavior and Human Decision Processes 83(2), 260–281 (2000)
19. Harvey, N., Harries, C.: Effects of judges' forecasting on their later combination of forecasts for the same outcomes. International Journal of Forecasting 20(3), 391–409 (2004)
20. Yaniv, I., Milyavsky, M.: Using advice from multiple sources to revise and improve judgments. Organizational Behavior and Human Decision Processes 103(1), 104–120 (2007)
21. Mannes, A.E.: Are We Wise About the Wisdom of Crowds? The Use of Group Judgments in Belief Revision. Management Science 55(8), 1267–1279 (2009)
22. Reed-Tsochas, F., Onnela, J.P.: Spontaneous emergence of social influence in online systems. Proceedings of the National Academy of Sciences of the United States of America 107(43), 18375–18380 (2010)