EFFECTS OF SOCIAL INFLUENCE ON THE WISDOM OF CROWDS

Pavlin Mavrodiev
Chair of Systems Design
ETH Zurich
Kreuzplatz 5, CH-8032 Zurich
pmavrodiev@ethz.ch

Claudio J. Tessone
Chair of Systems Design
ETH Zurich
Kreuzplatz 5, CH-8032 Zurich
tessonec@ethz.ch

Frank Schweitzer
Chair of Systems Design
ETH Zurich
Kreuzplatz 5, CH-8032 Zurich
fschweitzer@ethz.ch

ABSTRACT

Wisdom of crowds refers to the phenomenon that the aggregate prediction or forecast of a group of individuals can be surprisingly more accurate than most individuals in the group, and sometimes – than any of the individuals comprising it. This article models the impact of social influence on the wisdom of crowds. We build a minimalistic representation of individuals as Brownian particles coupled by means of social influence. We demonstrate that the model can reproduce results of a previous empirical study. This allows us to draw more fundamental conclusions about the role of social influence: In particular, we show that the question of whether social influence has a positive or negative net effect on the wisdom of crowds is ill-defined. Instead, it is the starting configuration of the population, in terms of its diversity and accuracy, that directly determines how beneficial social influence actually is. The article further examines the scenarios under which social influence promotes or impairs the wisdom of crowds.

INTRODUCTION

Contrary to popular belief, the wisdom of crowds[1] is a statistical and not a psychological phenomenon. Wisdom, in this context, refers to the aggregate opinion of a population being closer to a true value than most individual opinions. The idea of aggregating over a space of opinions can, in an ergodic fashion, also be applied to aggregating over an individual's own perspectives over time, with the same benefits – i.e. it may yield a more accurate decision making (Rauhut & Lorenz 2011).

However, the wisdom of crowds is not a pure statistical regularity, in the sense that more does not imply better. It necessitates certain conditions, which can be summarised, following (Surowiecki 2005), as diversity and independence of opinions, specialisation in expert knowledge and a mechanism for aggregating individual opinions. From this perspective, the best collective decisions do not rely on consensus building and compromises, but instead on aggregating many heterogeneous views – given enough diversity in opinions, the errors in each of them cancel out until only useful information is left (Surowiecki 2005, p.10).

Diversity has been identified as instrumental in providing creative perspectives to problem-solving, thus avoiding getting stuck in locally suboptimal solutions (Hong & Page 2004). In fact, the "diversity prediction theorem"[2] (Page 2007) shows that diversity weighs as much as individual ability in determining collective accuracy. From a mathematical point of view, diversity is required in order to balance out uncorrelated imperfections in opinions through aggregation. Intuitively, as no single individual is aware of all traits of a given problem at hand, diversity helps people combine their idiosyncratic perceptions so that together they gain a wider perspective. Diversity, however, is not the pinnacle of optimal decision-making. No amount of diversity can help if the population is completely ignorant on a given issue, or if opinions are diverse, but heavily skewed. Thus, the composition of diversity is as important as diversity itself (Bonabeau 2009).

Independence of opinions is another important distinguishing feature of the wisdom of crowds for it either excludes communication, information spreading, learning and social influence processes, such as herding and imitation or limits the effect of such processes should they be present. In this context, it is useful to draw a conceptual difference between wisdom of crowds, as commonly understood, and "collective intelligence". Wisdom of crowds is a quantification of the state currently occupied by a given group, such as an aggregate opinion. Intelligence, pertains to the ability of individuals to learn, to understand, and to adapt to arbitrary external conditions using own knowledge (Leimeister 2010). Collective, describes a group of individuals pooling their intelligence together for a common purpose. As such, collective intelligence can be seen as the mechanism by which groups converge to a certain collective decision, whereas wisdom of crowds is the numerical representation of the said decision. In this paper, we are interested in how the collective intelligence mechanism affects the wisdom of crowds.

Recent empirical evidence has shown that enabling collective intelligence by introducing social influence, can be detrimental to the aggregate performance[3] of a population (Lorenz et al. 2011). By social influence, we under-

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[1]The terms *crowd* and *group* are used interchangeably, as are *opinions* ↔ *estimates* ↔ *judgements* ↔ *beliefs* and *configuration* ↔ *state*.

[2]The theorem states that collective accuracy equals average individual error minus the variance in opinions, i.e. group diversity.

[3]Performance is the pair $\{\mathcal{E}(t), \mathcal{W}(t)\}$. See next section.

stand the pervasive tendency of individuals to conform to the behaviour and expectations of others (Kahan 1997). In separate experiments, Lorenz et al. asked participants to re-evaluate their opinions on quantitative subjects over several rounds and under three information spreading scenarios – no information about others' estimations (control group), the average of all opinions in each round and full information on other subjects' judgements. They found evidence that under the latter two regimes, the diversity in the population decreased, while the collective deviation from the truth increased. This result justified the disheartening conclusion that allowing people to learn about others' behaviours and adapt their own as a response does not always lead to the group acting "wiser"[4]. Rather, as the authors posited, not only is the population jointly convinced of a wrong result, but even the simple aggregation technique of the wisdom of crowds is deteriorated. From a policy-maker's perspective, such groups are, thus, not wise.

Current research has not yet investigated thoroughly the theoretical link between social influence and its effect on the wisdom of crowds. In this paper, we build upon the empirical study in (Lorenz et al. 2011) by developing a formal model of social influence. Our goal is to unveil whether the effects of social influence are unconditionally positive or negative, or whether its ultimate role is mediated through some mechanism, so that the effect on the group wisdom is only indirect. We adopt a minimalistic agent-based model, which successfully reproduces the findings of the said study and gives enough insight to draw more general conclusions. In particular, we confirm that small amounts of social influence lead to faster convergence, however, it is the starting configuration[5] of the population (in terms of its initial diversity and deviation from the truth) that ultimately attribute the net effect of social influence on the wisdom of crowds.

The rest of the paper is organised as follows. The next section reviews the empirical study on which our model is based, together with its main results and the measures used to quantify the collective performance of the groups. The model itself is presented after that. Results and conclusions follow as the last two sections respectively.

THE EXPERIMENT

One of the latest study of the effect of social influence on wisdom of crowds aimed at quantifying how people's opinions are influenced by others and to what extent this influence relates to the aggregate deviation of the group from an objective truth (Lorenz et al. 2011).

The authors recruited 144 subjects among students at ETH Zürich. The subjects were split into 12 experimental sessions, each consisting of 12 participants. During each session the subjects were asked a total of 6 quantitative questions regarding geographical facts and crime

statistics[6]. Each question had to be answered over five time periods. The questions were designed in such a way that individuals were not likely to know the exact answer, but could still formulate educated guesses.

Figure 1 shows the structure of the experiment.
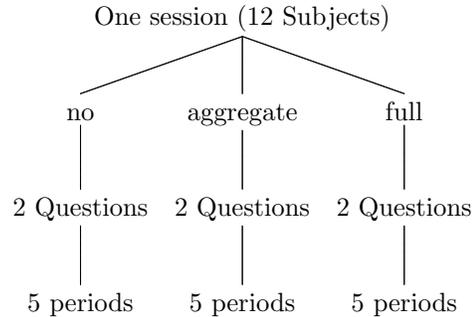
Figure 1. Experiment structure

In the first time period, all subjects responded to the particular question on their own. After all 12 subjects gave their estimations, each had to answer the same question over 4 additional periods for a total of 5 rounds. Three different information conditions were tested regarding the information that participants learnt about the answers of others in the previous time periods. In the "no" information regime, no individual was aware of others' opinions throughout all 5 periods. In the "aggregate" regime, each subjects was provided with the arithmetic average of everyone else's answers in the previous round. Finally, in the "full" information regime, subjects learnt all opinions from all previous rounds so far. In each session, two questions were posed in the no, two in the aggregated, and two in the full information condition. The 12 subjects were randomly assigned to the three information conditions in the beginning of the session.

An important component of the experiment was the reward structure. Participants received individual awards depending on their deviations from the correct answer – reward-bearing deviations were defined as 10%, 20% and 40% intervals around the truth. The rewards were provided at each round, so that individuals were motivated to make optimal decisions at all times. However, the correct answer and rewards were disclosed at the end of the experiment to avoid giving away a-priori knowledge about the truth. This reward structure eliminated the benefits of strategic considerations, such as misleading or cooperating with others, because it did not affect individuals' payments – subjects had incentives to use only their own knowledge and interpretation of others' opinions to find the truth.

As we mentioned above, a requirement for quantifying the wisdom of crowds is a suitable aggregation measure. Ideally, an aggregated measure would indicate the most central opinion in the population. For

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[4]Wiser, in the numerical sense of the wisdom of crowds.
[5]Configuration is the pair $\{\mathcal{E}(t), \mathcal{D}(t)\}$. See next section.

[6]Example: What is the population density of Switzerland?

opinion distributions that are Gaussian-like, the simple unweighted arithmetic average may be a good choice. There are other averaging methods, which could perform better in special cases (Genest & Zidek 1986, Dawid et al. 1995, Hegselmann & Krause 2005). The opinion distributions in the experiment were found to be heavily right-skewed with a majority of low estimates and a minority spread on a fat right tail, much like log-normal distributions. The skew made the arithmetic average inappropriate as a measure of centrality, since it was closer to the truth than individuals' first estimates in only 21.3% of the cases. However, taking the natural logarithm of the estimates, resulted in a more bell-shaped distribution. Consequently, the arithmetic average of the log-transformed opinions (which equals the logarithm of the geometric mean of the original data) performed much better – it was closer to the true value than individuals' first estimates in 77.1% of the cases. This provided a justification for log-transforming all opinions over all sessions before further analysis[7].

Three main quantities were used to evaluate the aggregate performance of the crowd – "collective error", "group diversity" and "wisdom of crowds indicator". Let N be the number of individuals and $x_i(t)$ be the answer of individual i in round t. The collective error, $\mathcal{E}(t)$, is defined as the squared deviation of the average opinion in round t from the true value, $\mathcal{T}$. Since all x_i's were log-transformed, the arithmetic average is $\langle \ln x(t) \rangle$[8], which equals the logarithm of the geometric mean of the original data, thus the collective error in period t equals:

$$\mathcal{E}(t) = (\ln \mathcal{T} - \langle \ln x(t) \rangle)^2 \qquad (1)$$

The group diversity in period t, $\mathcal{D}(t)$, is the variance of the opinion distribution:

$$\mathcal{D}(t) = \frac{1}{N} \sum_{i=1}^{N} (\ln x_i(t) - \langle \ln x(t) \rangle)^2 \qquad (2)$$

Finally, the wisdom of crowds indicator, $\mathcal{W}(t)$, measures how much deviation from the most central estimate is needed to encompass, or bracket, the true value. More precisely, $\mathcal{W}(t) = \max\{i | \hat{x}_i(t) \leq \mathcal{T} \leq \hat{x}_{N-i+1}(t)\}$, where $\hat{x}_i$'s are the original (i.e. not log-transformed) *sorted* opinions. The indicator has a maximum of $N/2$ when the truth lies between the most central estimates (or is the most central estimate) and a minimum of zero when the truth is outside the range of all estimates.

The experiment demonstrated that even trace amount of social influence, in terms of knowledge about others' opinions, has a negative effect on the wisdom of crowds. This is manifested via three effects: "Social influence", "Range reduction" and "Self-confidence" effect. The first leads to convergence of opinions, i.e., reduction of group diversity, without improving the collective error

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[7]The authors in fact took the logarithm of the original estimates divided by the true values, so that answers across different questions could be compared

[8]The notation $\langle X \rangle$ stands for $(1/N) \sum_{i=1}^{N} X_i$

significantly. Range reduction reveals that the core range of estimates needed to enclose the true value gradually increases (i.e. the wisdom of crowds indicator decreases, meaning that the true value becomes less central in the distribution of opinions), while at the same time the distribution becomes narrower due to the social influence effect. As a result, the crowd slowly converges to a wrong value. Finally, the self-confidence effect demonstrates that individuals become increasingly confident in their opinions, whereas concurrently the group converges away from the truth. The authors concluded that social influence undermines the wisdom of crowds, as the population collectively drifts away from the truth with increasing confidence.

The agent-based model introduced below reproduces the social influence and range reduction effects in an artificial population under the no- and aggregate-information scenarios and, based on this framework, we will show that the decline of crowd wisdom cannot be imputed to social influence alone.

THE MODEL
Consider a population of N individuals, each possessing a continuous opinion $x_i(t)$ at time t. We posit that the opinion of agent i evolves according to the following process:

$$\frac{d}{dt} x_i(t) = \alpha_i \left(\langle x(t) \rangle - x_i(t) \right) + \beta_i \left(x_i(0) - x_i(t) \right) + D \xi_i(t) \qquad (3)$$

The first term represents coupling to an individual's environment. We refer to it as "social influence". In the aggregate regime, people are only aware of the arithmetic average of all opinions, so they try to converge to that value with a given sensitivity α_i: it corresponds to the perceived strength of social influence affecting the i–th individual.

The second term models individual's tendency to uphold their original opinions. We refer to it as "individual conviction", and its strength is given by the parameter β_i.

The third term corresponds to the fact that individuals may change their opinion because they incorporate other information (known *ex ante*), they previously disregarded. This term does not come from interactions, but originates purely from internal mechanisms. Then, $\xi_i(t)$ is Gaussian white noise with unit variance. D is the corresponding noise intensity.

From a physicist's point of view, this dynamics resembles Brownian particles interacting in a mean-field scenario (Schweitzer Frank 2007). In social psychology, we can also see Eq. (3) as a formalisation of Lewin's heuristics that the individual action is a function of idiosyncratic perception of available information and the influence of a "field", that is the influence of their environment (Sansone et al. 2004).

With these basic ingredients set-up, we investigate numerically the evolution of the collective error, $\mathcal{E}$, group

diversity, $\mathcal{D}$, and the wisdom of crowds indicator, $\mathcal{W}$, as it depends on the $\{\alpha, \beta\}$ parameter space. In the simplest case, we take $\alpha_i = \alpha$ and $\beta_i = \beta$.

RESULTS

For all simulations, we used the Heun/Euler method with a constant time-step $\Delta t = 0.01$:

$$x_i(t + \Delta t) = x_i(t) + \Delta t \alpha(\langle x(t)\rangle - x_i(t)) +$$
$$+ \Delta t \beta(x_i(0) - x_i(t)) + D\sqrt{\Delta t}\ \text{GRND}$$

GRND is a Gaussian random number whose mean equals 0 and standard its deviation is one. The noise intensity, $D = 10^{-3}$.

To test dependence on the initial configuration, two different starting populations were sampled from log-normal distributions with means, $\mu_1 = -3$, $\mu_2 = -2.9$, and variances, $\sigma_1^2 = \sigma_2^2 = 0.72^9$. A noise intensity of 0.001 for the stochastic term, thus, ensures that the impact of the noise is small, yet present.

Each simulation was run for $N = 100$ agents and $T = 3000$ time steps. The latter ensures that the population eventually reaches a steady-state, where $dx_i(t)/dt = 0$. The equilibrium is attained when the perceived social influence driving an individual's opinion away from its initial value equals the strength of individual conviction trying to keep the individual at its original estimate.

No-information Regime

The *no-information regime* is recovered by setting $\alpha = 0$. Eq. (3) then becomes:

$$\frac{d}{dt}x_i(t) = \beta\left(x_i(0) - x_i(t)\right) + D\xi(t) \tag{4}$$

This is a standard Orstein-Uhlenbeck process, whose solution is formally given by:

$$x_i(t) = x_i(0)e^{-\beta t} + x_i(0)\left(1 - e^{-\beta t}\right) + D\int_0^t e^{\beta(s-t)}\xi_i(s)ds$$

Therefore the time average of the individual estimates, $\overline{x_i(t)}$, drifts towards $x_i(0)$ for large t.

As there is no social influence in this regime, agents do not have incentives to deviate from their original opinions nor information on which to base such deviations, up to small random fluctuations. In this sense, the population can be considered static (Figure 2).

In Figure 2, a simulation of two populations with $\{\mathcal{E}_1(0) = 0.01, \mathcal{D}_1(0) = 0.72\}$ and $\{\mathcal{E}_2(0) = 0.018, \mathcal{D}_2(0) = 0.72\}$ demonstrates that in the long-term neither group significantly deviates from its initial accuracy and heterogeneity. Note that the actual value of the truth, $\ln\mathcal{T}$, is irrelevant, since of interest is only the initial "correctness" of the crowd, $\mathcal{E}(0)$.

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[9] μ and σ^2 refer to arithmetic average and variance of the log-transformed estimates respectively.
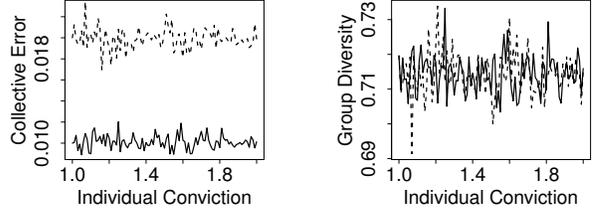
Figure 2. Simulation of Eq. (4). The aggregate measures, $\mathcal{E}$ and $\mathcal{D}$, fluctuate around their starting values. Left: $\mathcal{E}(0) = 0.018$ (dashed), $\mathcal{E}(0) = 0.01$ (solid). Right: $\mathcal{D}(0) = 0.72$. Simulation parameters: $D = 10^{-3}$.

Analogous result is obtained for the long-term value of $\mathcal{W}$.
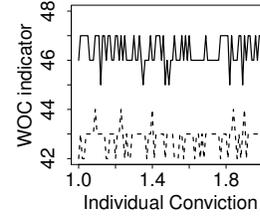
Figure 3. The Wisdom of Crowds indicator for the two populations from Figure 2 (same line styles). Long term behaviour is random fluctuations around $\mathcal{W}_1(0) = 46$ (solid line) and $\mathcal{W}_2(0) = 42$ (dashed line). Simulation parameters: $D = 10^{-3}$.

We conclude that in the absence of information other than one's own judgement, groups do not tend to deviate significantly from their original state, i.e. the wisdom of crowds is constant.

Aggregate Information Regime

In the aggregate information regime agents observe the average of all estimates, which is equivalent to a mean-field scenario. Averaging Eq. (3) over the whole population yields:

$$\frac{d\langle x(t)\rangle}{dt} = \beta\left(\langle x(0)\rangle - \langle x(t)\rangle\right) + \frac{D}{\sqrt{N}}\langle\xi(t)\rangle$$

which is again an Ornstein-Uhlenbeck process, with solution:

$$\langle x(t)\rangle = \langle x(0)\rangle e^{-\beta t} + \langle x(0)\rangle\left(1 - e^{-\beta t}\right) +$$
$$+ \frac{D}{\sqrt{N}}\int_0^t e^{\beta(s-t)}\langle\xi(s)\rangle ds \tag{5}$$

hence, the arithmetic average is approximately constant with fluctuations around its starting value, $\langle x(0)\rangle$.

Contrary to the no-information case, allowing for social interactions can lead the group to different end states, depending on the strengths of social influence and individual conviction. A parameter sweep in α and β reveals the complete picture.
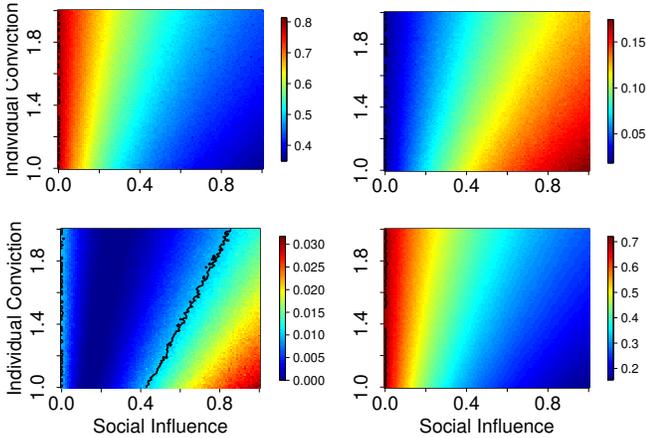
Figure 4. Ambiguous effect of social influence on the collective error ($\mathcal{E}$). Top-left: $\mathcal{E}(0) = 0.8$, $\ln \mathcal{T} = -2$, $\langle \ln x(t) \rangle = -2.9$. Top-right: $\mathcal{E}(0) = 0.02$, $\ln \mathcal{T} = -3.14$, $\langle \ln x(t) \rangle = -3$. Bottom-left: $\mathcal{E}(0) = 0.01$, $\ln \mathcal{T} = -2.9$, $\langle \ln x(t) \rangle = -3$. The group diversity for the previous three cases is the same and shown in the bottom-right, with $\mathcal{D}(0) = 0.72$. Black contour lines indicate regions where the collective error equals its starting value. Simulation parameters: $D = 10^{-3}$.

In Figure 4 we have displayed the long-term collective errors (top-left, top-right, bottom-left) and group diversity (bottom-right) for three different starting configurations. The group diversity behaves almost the same for all three cases, hence we have shown it for the top-left population. Not surprisingly, agents tend to conglomerate around a common opinion in the presence of social influence (Figure 4, bottom-right), regardless of the starting configuration. We note also that individual conviction acts in the opposite way – it maintains diversity in the group by reducing the perceived strength of social influence.

Figure 4 also illustrates the opposing effects between social influence and individual conviction – the colour transition from blue to red regions and vice versa. This struggle is present in all starting configurations, however, its polarity is equivocal. In the top-left plot, stronger individual conviction is in the group's detriment, for the long-term collective error increases with β for any fixed α. Individual conviction is beneficial in all other cases – the net effect is dependent on the initial state of the population.

Further, we note that the collective error grows if $\langle \ln x(0) \rangle > \ln(\mathcal{T})$, as shown in the top-right. The reason is that the geometric mean strictly increases when $x_i(t)$ is driven by Eq. 3[10]. Figure 5 provides an intuition for this claim.

The top-right case in Figure 4 essentially represents a scenario where social influence not only does not improve the aggregate performance of the population, but can
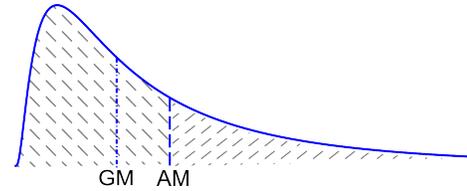
Figure 5. Rightward motion of the geometric mean (GM). The geometric mean equals the median (i.e. the 50th percentile) for log-normal distributions. However, since agents are coupled to the arithmetic mean (AM) and AM is greater than GM, at any given time there will be more mass moving to the right (negative-sloped stripes) than to the left (positive-sloped stripes). As a result the GM will strictly increase until agents reach equilibrium.

significantly increase its inaccuracy, reducing the group diversity at the same time.

Similar fate awaits the group even if $\langle \ln x(0) \rangle < \ln(\mathcal{T})$, albeit for reduced parameter range. In the bottom-left scenario, the aggregate opinion of the population starts from a relatively accurate state, and ends up with a larger long-term collective error for values of (α, β) to the right of the second 0.01 contour line. In effect, these two configurations reproduce the negative effect that social influence has been shown to have in empirical studies. In particular, Lorenz et al. describe their "social influence effect" as diminishing diversity in groups without improving their accuracy, which is precisely our finding here. Therefore, despite the opposing effect of individual conviction, for any non-zero strength of social influence, the population ends up at a worse long-term state than the one it started from.

Interestingly, other configurations exist where social influence brings a clear advantage. Consider the relatively inaccurate initial population in the top-left. Virtually for the whole parameter range, the end collective error is lower than that in the beginning. Even more, with the weakest individual conviction and strongest social influence, the agents actually converge to the most accurate long-term state.

Such a positive outcome is also achieved in the bottom-left plot. Up to a certain limit, increasing the social influence leads the population to better stationary states[11] (dark blue regions), while decreasing the diversity at the same time. Considering these cases now, one can rightly conclude the opposite – social influence is beneficial to the average accuracy of crowds.

Turning our attention now to the wisdom of crowds indicator, $\mathcal{W}$, we plot its long-term behaviour for the two of the three starting configurations in Figure 4.

The population in the left plot is the same as in Figure 4, top-right. Naturally, as the long-term collective error always increases with social influence, the distribution of estimates moves farther from the true value and gets

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[10]Thus $\ln x(t) = \ln \mathrm{GM}$ always increases with time. This result can be derived analytically.

[11]Better in the sense of lower collective error.
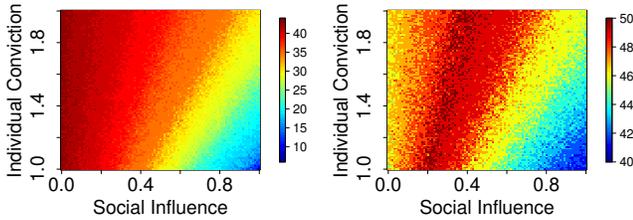
Figure 6. Simulated long-term value of the Wisdom of Crowds indicator. Left: $\mathcal{W}(0) = 43$, $\mathcal{E}(0) = 0.02$. **Right:** $\mathcal{W}(0) = 46$, $\mathcal{E} = 0.01$. **Both:** $\langle \ln x(t) \rangle = -3$, $\mathcal{D}(0) = 0.72$. **Simulation parameters as in Figure 4**

more homogeneous at the same time. As a result, the range of estimates needed to bracket the truth strictly increases, which explains why $\mathcal{W}$ ends up always lower than in the beginning. Moreover, the strength of social influence accelerates the said drift of this group, and in turn decreases further the long-term $\mathcal{W}$ (blue region). The same behaviour can be observed in the right plot of Figure 6 (right-half of plot only), which is the configuration from Figure 4, bottom-left – social influence leads the group away from the truth and decreases its wisdom, as measured by $\mathcal{W}$. In effect, what we have described above is the "range reduction effect" found in (Lorenz et al. 2011) – the truth is displaced to peripheral regions of the opinion distribution and the group becomes narrowly centred around a wrong value. As a consequence, a social planner who takes a unique advise, represented by the aggregate opinion of the group, is likely to be misled.

As with the collective error, we find that social influence can also be beneficial for the wisdom of crowds indicator. In Figure 6, right, $\mathcal{W}$, actually grows with the strength of the social interactions, and achieves the maximum value of $N/2$ (darkest red region). So, despite the loss of heterogeneity in estimates, due to the favourable initial conditions the long-term aggregate opinion of the group ends up closer to the true value (i.e. the collective error decreases) for moderate amounts of social influence. As a result the distribution of opinions is narrowly centred around the truth – the crowd is "wiser".

Explaining these ambiguous effects of social influence on $\mathcal{E}$ and $\mathcal{W}$ is one of our main results. It is not the case that social influence is inherently "good" or "bad", and that one should attribute group performance directly to it. Rather its impact is modulated by the starting state of the group, in terms of $\mathcal{E}(0)$ and $\mathcal{D}(0)$. Awareness of the latter could allow us to determine ex-ante whether stronger social interactions are favourable or not. In addition, the counter effect of individual conviction could be used to remedy those populations that started from an unfavourable state; by implementing measures, which promote individuals' self-confidence at the expense of social influence.

CONCLUSION

This paper set out to study the relationship between the collective wisdom of a group, and the social influence among the individuals constituting it. In particular, we aimed at explaining the ambiguous role of social influence, which in some circumstances bears a positive effect on the wisdom of crowds, and in others a negative one. This is a pressing question as social interactions are practically ubiquitous – crowds are embedded in social contexts, which invariably couple the individuals within them. Democracies assume and rely on extensive public discussions to form opinions and create policies. Our behaviour as consumers, investors, voters, etc., is influenced by discussions with, friends, colleagues and experts (among others). From a policy-maker's perspective, this question translates to whether a government can reliably harness the wisdom of crowds subject to heavy social influence (Coleman & Blumler 2011). Unravelling the mechanisms (if any) by which social influence positively or negatively affects the wisdom of crowds, becomes then important for evaluating the trustworthiness of crowd predictions.

In a recent experiment (Lorenz et al. 2011), participants were given a guessing task, where an objective true value had to be approached. Each individual updated their estimate for several rounds based on (i) no information about others' judgements, (ii) the average estimation of the population or (iii) full information about everyone else's estimates. The study found that under the last two scenarios the wisdom of crowds is weakened, which speaks for the negative effects of social influence.

In this paper, we introduced a simple model that reproduces the results of the no- and aggregate-information scenarios in said study. The model consists of a population of agents endowed with a minimum set of cognitive abilities. The agents continuously revise their estimations, based on individual conviction (their belief in own estimations) and social influence (from the rest of the population). We focused on the long-term dynamics of three indicators measuring the performance of the population: (i) the collective error, (ii) group diversity and (iii) wisdom of crowds indicator once equilibrium has been reached.

We have demonstrated that groups whose initial average opinion is relatively far from the truth in general benefit from stronger social influence. The effect occurs because the stationary value the aggregated opinion tends to (i.e. the geometric mean in our case), and the convergence speed to this value, increase with the strength of social influence, which in turn reduces the collective error in the long-term. In other words, promoting extended communication and exchange of views is more likely to help those crowds that start off relatively wrong.

The effect of social influence, however, is detrimental to groups with a relatively accurate initial configuration and thus suffer from an increased drift in the aggregated opinion. In these cases, the initially small collective error quickly reduces to zero, but then continues to increase

even beyond its starting value, due to the persistent motion of the geometric mean. For such groups, small to moderate amounts of information exchange are thus more beneficial.

Finally, other initial conditions exist, where even traces of social influence leads to deterioration in the long-term collective error. This is the main finding of (Lorenz et al. 2011), which is referred to as "social influence" effect.

The above discussion applies analogously to the wisdom of crowds indicator, the quantification of how far the median estimate of the population is from the truth. We have found starting configurations which lead groups to be less *wise*[12] in the long-term, for any amount of social influence, i.e. the so-called "range reduction" effect from (Lorenz et al. 2011); and configurations where groups end up wiser in the presence of moderate social influence.

Based on these observations, our main result is that social influence in the aggregate-regime does not directly influence the wisdom of crowds. Rather it is the starting configuration of the population, in terms of its collective error and group diversity, which determines the long-term benefits or harms of social influence. The result gives insight into how crowds can be driven to different states by modulating the strength of social influence. For example, given some intuition about how inaccurate the crowd initially is, we suggest that a policy-maker may either promote social influence processes in a population or increase individual conviction to counter undesired group influence in order to steer the group prediction into more optimal long-term states.

It is important to stress that this result is applicable only when individuals do not possess knowledge about the objective truth[13], nor do they learn or receive information that can lead them towards it. In other words, there is no feedback between an agent's opinion, at any given time, and their distance from the truth. Consequently, social influence through coupling to the mean affects relevant system-wide properties (the geometric mean in our case), but not the collective error or wisdom of crowds indicator. As a topic for further research, we hypothesise that even using different modelling approaches to social influence (e.g. model the full-information regime in (Lorenz et al. 2011) or couple only to those deemed "experts"), our result qualitatively holds, as long as no feedback between the objective truth and agents performance is present.

The current model assumes the existence of an objective truth, and ignores learning, which is not the case in many real-world situations (e.g. financial markets, political polls, etc.). However, individuals in our model do no possess perfect knowledge of the truth, and the latter is only present in the form of the distribution of initial guesses. Consequently, by definition the collective error

and the wisdom of crowds indicator are driven solely by interactions and information dissemination within the group. The true value is needed *ex-post* to quantify the current state of the population. Therefore, our proposition that it is the crowd's starting configuration that ultimately determines the effect of social influence can be generalised to these scenarios as well.

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[12]Wise, in the sense of the wisdom of crowds indicator.
[13]Except for idiosyncratic knowledge that forms initial opinions.