Reducing individuals’ risk sensitiveness can promote positive and non-alarmist views about catastrophic events in an agent-based simulation

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Abstract. We present a cognitive model of opinion dynamics which studies the behavior of a population of interacting individuals in the context of risk of natural disaster. In particular, we investigate the response of the individuals to the information received by institutional sources about the correct behaviors for prevention and harm reduction. The results of our study show that alarmist opinions are more likely to be adopted by populations, since worried people tend to share their points of view more often than other individuals.

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1 Introduction

In the managing of natural disasters, a key passage is represented by the implementation of prevention policies. In particular, to this aim a fundamental task of the official institutions is the correct communication of the proper behaviors the population under risk should adopt before, during and after the catastrophic event in order to minimize its negative consequences.

In the evaluation of a risky situation, several factors, which interact among themselves in complex ways, have to be taken into account. In order to understand which dynamics emerge and how they act in populations vulnerable to natural risks, it is necessary to model these processes and test such models by means of different tools, among them numerical simulations.

In this paper, we are going to address the following research issues, which are the main points for implementing the correct policies for the cases we are dealing with:
– How do individuals process their opinions/beliefs about risky events?
– Which is the role of information from institutional sources with respect to the information an individual collects in his/her social groups (family, friends, colleagues)?
– Which are the collective processes of social influence by which opinions and behaviors spread through the population?
– How much the processes described above are in their turn influenced by the trust the citizens yield to the institutions and by their risk sensitiveness?

In order to answer to the questions above, we have to determine the internal mechanisms of the individuals which drive the opinion dynamics both at microscopic and macroscopic level. In particular, we have to take into account some important factors. Firstly, humans tend to overestimate the risk of catastrophic but unlikely events with respect to more common but less disastrous ones [1]. Secondly, several studies verified that the trust of the individuals towards the sources of information becomes decisive when the available information is little [2,3]. Moreover, it was also observed that considering situations perceived as risky (for instance, OGM-technologies, stocking of radioactive waste, etc.), individuals with higher trust towards official institutions (government, companies, scientists, etc.) repute catastrophic events less probable [4,5]. In short, if we want to model correctly these processes, we have to take into account also these dynamics, together with a more realistic picture of the mental schemes and phenomena by means of which humans elaborate their views and beliefs [6]. The model we have defined and utilized in this work is therefore inspired from the social science point of view to the considerations above. On the other hand, as we are going to show in the next section, it is formally an agent-based opinion dynamics model, close to the Deffuant model [7,8], that is, a continuous-opinion kinetic exchange model [9].

The paper is organized as follows: in the next section we define the model and how it is numerically implemented; in Section 3 we present the results of the simulations and in Section 4 we discuss them; finally, the last section is dedicated to the conclusions and perspectives.

2 The Model

We set a population of $N$ interacting agents. Each agent $i$ is characterized by an opinion $O_i$ about the risky event, i.e., the probability, as estimated by $i$ itself, that the catastrophic event could actually take place. The opinion is an external variable, that is, it can be seen by other individuals. Besides, we define some internal variables to describe the internal state of agents, as well as their mental dynamics. Such internal variables are the risk sensitivity $R_i$, the tendency to inform others $\beta_i$, the trust towards the institution $T_i$ and the trust towards peers $\Pi_i$. In this work, for seek of simplicity we assume that the trust towards the institution is anti-correlated to that towards peers: $\Pi_i = 1 - T_i$. This is a strong but non-unrealistic approximation [10], considering that many people are
suspicious of the “official” communications, trusting more information received by relatives, friends, or even by unknown people on the web.

In Table 1 the variables defining the agent internal and external behavior are summarized, together with their main features.

Table 1. Scheme of the internal and external variables defining the agents.

| Variable | Description         | Notes                     |
|----------|---------------------|---------------------------|
| $O_i$    | Opinion             | Real number $\in [0,1]$; evolving |
| $R_i$    | Risk sensitivity    | Integer $= 0, \pm 1$; constant |
| $\beta_i$| Tendency to communicate | Real number $\in [0,1]$; constant |
| $T_i$    | Trust towards institution | Real number $\in [0,1]$; constant |
| $H_i$    | Trust towards peers | $H_i \equiv 1 - T_i$ |

In this paper we consider a mean-field approach, that is, we put our population on a complete graph: every individual can interact directly with everyone else.

2.1 Algorithm of the dynamics

Each time step of the simulation is made up of two stages: the institutional communication stage, followed by a round of information exchange among peers. More in depth, the generic $t$-th time step will take place as shown in the following.

Institutional communication - In this first stage the Institution communicates to every player its own risk evaluation $I$. Therefore, every agent processes this information according its opinion and internal variables. Firstly, the player $i$ modifies its old opinion $O_i(t-1) \equiv O_i^o$ following the Deffuant-like [8] rule

$$O_i^o \rightarrow O_i = O_i^o + T_i(I - O_i^o) .$$

Subsequently, $O_i$ is further processed according $i$’s risk sensitivity:

$$O_i \rightarrow \begin{cases} 
\frac{1}{2}(1 + O_i) & \text{se} \quad R_i = +1 \\
O_i & \text{se} \quad R_i = 0 \\
\frac{1}{2}O_i & \text{se} \quad R_i = -1 . 
\end{cases}$$

More precisely, agents with positive risk sensitivity will overestimate the institutional information, agents with negative risk sensitivity will underestimate it, and neutral ones will not process the information further.

Once every individual has elaborated the institutional communication as described above, the information exchange phase will take place.
Information exchange among peers - This second stage is in its turn composed by \( N \) rounds. In each round a couple of agents is picked up at random. Let us call \( i \) and \( j \) the two agents, and \( O_i \) and \( O_j \) their opinions before the interaction, respectively. Now, the probability that player \( i \) (\( j \)) communicates its opinion to the opponent is

\[
P_{i(j)} = \frac{1}{\beta_{i(j)}},
\]

because we assume that given the same opinion the agents with higher tendency to communicate are more likely to speak, but given the same tendency to communicate the more worried agents will also speak more often.

For simplicity, let us consider \( j \) as the “speaker” and \( i \) as the “listener” (the symmetrical interaction where \( i \) is the speaker and \( j \) the listener will take place in the same way). If the speaker decides not to give the listener its opinion (according previous equation, this happens with probability \( 1 - P_j \)), the listener’s opinion \( O_i \) does not change. If instead agent \( j \) actually shares its opinion, agent \( i \) will change its own following another Deffuant-like rule:

\[
O_i \rightarrow O'_i = O_i + \frac{1}{2}(O_j - O_i) \equiv O'_i = O_i + (1 - T_i)(O_j - O_i).
\]

Then, the listener processes further its new opinion again according its risk sensitivity:

\[
O'_i \rightarrow \begin{cases} 
\frac{1}{2}(1 + O'_i) & \text{se } R_i = +1 \\
O'_i & \text{se } R_i = 0 \\
\frac{1}{2}O'_i & \text{se } R_i = -1.
\end{cases}
\]

After \( N \) rounds (so that on average each player has interacted once per time step), the information exchange ends, and the opinions of the agents become their opinions at time \( t \).

Initial conditions - At the beginning of every simulation, the agents are randomly assigned an opinion between 0 and 1, always with uniform distribution. Also the internal variables are randomly distributed, but the distribution is not necessarily uniform, and will be specified in each case. We recall that whilst the opinions evolve, the internal variable are constant in time. The institutional information \( I \), which can be seen as the “opinion” of the Institution, is set at the start of the dynamics and never changes. All the simulation results are averaged over 2000 independent realizations.

Asymmetrical peer interactions - We tested also a slight modification of the algorithm described above: in the information exchange phase, instead of picking up \( N \) times a couple of agents which share their opinions each other, we select \( 2N \) times a couple made up of a fixed speaker (which only communicates its
opinion but does not listen to the opponent’s one) and a fixed listener (which evolves its opinion following the interaction, but does not share its original one). Anyway, the two versions of the model show the very same behavior (apart very small numerical differences), so that in the following we are reporting only the results of the symmetrical interaction model.

3 Results

3.1 Balanced systems

Let us start our review considering a perfectly balanced system: not only all the initial opinions are uniformly distributed in the real interval \([0, 1]\), but also the internal variables \(\{\beta_i, R_i, T_i\}_{i=1,...,N}\) are picked up at random with a uniform probability. Therefore, on average we begin with a neutral population.

First of all, we want to check if a final stationary state can be effectively reached by the system: this is actually the case, as shown in Figure 1. Noticeably, the convergence up to the final state is quite fast: already after very few time steps the average opinion has acquired a stable value.

![Fig. 1. Time behavior of the average opinion of a system of \(N = 1000\) agents for totally non-alarmist, neutral and highly alarmist institutional information. Completely balanced population: initial opinions, trust towards institution, tendency to speak and risk sensitivity randomly assigned with uniform distributions.](image)

Afterwards, it is important to understand how the populations responds to the institutional inputs, that is, how the final average opinion behaves as a function of the institutional information. This is shown in Figure 2.

As it is easy to see, the system shows to be more alarmist than the institution for appeasing information, but results less alarmed if instead the official information is worrying. However, these results exhibit another interesting asymmetry: the value \(I^*\) of the institutional information for which the response of
Fig. 2. Behavior of the final average opinion as a function of the institutional information for a system of $N = 1000$ agents. Completely balanced population: initial opinions, trust towards institution, tendency to speak and risk sensitivity randomly assigned with uniform distributions. Linear fitting parameters: intercept $\simeq 0.33$, slope $\simeq 0.43$.

the population is equal to the input is not $\bar{I} = 0.5$, as one could expect since the system is balanced, but larger (more precisely, we have here $I^* \simeq 0.58$): this counterintuitive outcome (in favor of alarmist opinions) is due to the fact more alarmist people share their opinions more often than non-alarmists, so that worried messages have more chances to spread throughout the entire population.

We have also to notice that in any case consensus is not reached: in the final state it does not happen that every individual has an opinion equal to the average, but that there is a final stationary opinion distribution, as shown in Figure 3. As it is easy to see, the median opinions are less common in the final configuration, especially when the system ends up in an alarmist state. In general, even though on average the population has a well-defined view about the risk, there are always many contrarians which oppose the majority’s opinion.

### 3.2 Unbalanced systems

In this subsection we investigate what happens when the system is not balanced, that is, in case the distributions among agents of the internal variables are not uniform (equivalently, their average is not equal to their median value). In particular, we studied the behavior of the system by varying the average risk sensitivity and trust towards the institution.

**Varying trust, balanced risk sensitiveness** Let us start with the case of systems in which the risk sensitiveness is again uniformly distributed among agents, while the trust towards the institution has an unbalanced distribution. More precisely, each player $i$ is assigned with probability $P_T$ a trust $T_i$ uniformly distributed between 0.5 and 1 (high trust), and with probability $1 - P_T$ a trust
$T_i$ uniformly distributed between 0 and 0.5 (low trust). Therefore, the average trust is

$$\langle T \rangle = \frac{1 + 2P_T}{4}. \quad (6)$$

It is worth to notice that as $P_T$ is tuned from 0 to 1, $\langle T \rangle$ goes from 0.25 to 0.75.

Fig. 3. Final opinion distribution for totally balanced systems of $N = 1000$ agents with institutional information equal to 0.10 (left) and 0.80 (right).

Fig. 4. Behavior of the final average opinion as a function of the unbalance probability $P_T$ of the trust towards the institution for systems of $N = 1000$ agents, balanced risk sensitiveness, and two different values of the institutional information. Linear fitting parameters: a) $I = 0.20$, intercept $\simeq 0.54$ and slope $\simeq -0.21$; b) $I = 0.80$, intercept $\simeq 0.70$ and slope $\simeq -0.03$. 
In Figure 4 we show how by varying the average trust towards the institution a population responds to the official input. Understandably, when the institution communicates a non-alarmist message ($I = 0.20$), increasing the trust means decreasing the final average opinion. On the other hand, when the input is alarmist ($I = 0.80$), we would expect the opposite effect: in fact, in this case the system is much less sensitive to the trust, indeed the final average opinion is almost constant with respect to $P_T$ (what is more, it slightly decreases with $P_T$ increasing).

**Varying risk sensitiveness, balanced trust** Here we analyze the opposite case where trust towards the institution is uniformly distributed, but risk sensitiveness is not. In particular, every player $i$ is assigned the neutral risk sensitiveness ($R_i = 0$) with probability $1/3$, a positive risk sensitiveness $R_i = +1$ with probability $2P_R/3$, and a negative one with probability $2(1-P_R)/3$. Therefore, the average risk sensitiveness is

$$\langle R \rangle = \frac{2P_R - 1}{3}.$$  

(7)

In this way, as $P_T$ varies from 0 to 1, $\langle R \rangle$ goes from $-1/3$ to $1/3$.

![Fig. 5. Behavior of the final average opinion as a function of the unbalance probability $P_R$ of the risk sensitiveness for systems of $N = 1000$ agents, balanced trust towards the institution, and two different values of the institutional information.](image)

Linear fitting parameters: **a)** $I = 0.20$, intercept $\simeq 0.12$ and slope $\simeq 0.56$; **b)** $I = 0.80$, intercept $\simeq 0.43$ and slope $\simeq 0.50$.

In Figure 5 we show the behavior of the final average opinion as a function of the risk sensitivity unbalance $P_R$, again for an alarmist institutional information ($I = 0.80$) and a non-alarmist one ($I = 0.20$). As expected, $\langle O_{\text{fin}} \rangle$ increases linearly as the population increases its global risk sensitiveness, in the same way for different values of $I$. 
3.3 Beyond the mean-field topology

In the previous subsections we focused our study on systems in mean-field approximation, that is, populations acting on complete graphs. Then, it is also worth to understand how a change in topology affects the outcome of the model. In order to do that, we considered the following four networks:

a - a one-dimensional ring of $N = 1000$ nodes with connections to second-nearest-neighbors (so that each agent is linked to four other individuals);

b - an Erdős-Rényi random network of $N = 1000$ nodes with probability of existence of a link $p = 0.1$;

c - a Watts-Strogatz small-world network [11], generated from the ring defined above with rewiring probability $p_r = 0.05$;

d - a real network of $N = 1133$ users of the e-mail service of the University of Tarragona, Spain [12], which can be approximated for high degrees with a scale-free network network with exponent $\simeq 2$.

As it results clear from Figure 6, the influence of the topology is negligible, meaning that the relevant effects are due to other factors, in particular the internal variable distributions, as we are going to discuss in the next section.

4 Discussion

In this work we have simulated the dynamics of a population subject to risk of natural disasters. Each agent gets information about the level of the risk, that is, on the probability that a catastrophic event can actually take place, from an institutional source and by exchanging opinions and ideas with other agents, adopting an opinion as a consequence of the interactions with the institution and peers. The individuals process the information according to their mental attitudes and inclinations: in particular, we considered three internal features: the trust towards the institutional sources (anticorrelated to the trust towards peers), the risk sensitiveness and the tendency to communicate.

The main results we have obtained in our simulations are the following. First of all, we observe that in general the global final average opinion is more alarmist than the institutional message when the latter is reassuring, and vice versa. This is due to the presence of agents with low trust towards the institution, which act as “contrarians” in any situation.

Secondly, also in balanced populations (that is, populations where trust, risk sensitiveness and tendency to communicate are uniformly distributed), in the final state there is an asymmetry in favor of the alarmist opinions: this happens because an alarmist agent will share its opinion more often than a non-alarmist one with the same tendency to communicate.

Concerning the role of the internal variables, it is worth to notice that the risk sensitiveness is more influencing than the trust towards the institution:
indeed, by varying the distribution of the former the final average opinion results much more affected than by changing the latter. Therefore, according to these results, when the institution transmits appeasing messages, if we want that the population follows the official indication, it would be better to act on the risk sensitiveness of the citizens than on their trust.

Finally, we have checked that the topology on which the dynamics takes place is substantially irrelevant for the final fate of the system: this is not a complete novelty, since there are some social dynamics processes which were experimentally shown to be independent from the details of the networks [13].
5 Conclusions and perspectives

In this paper, we have applied a computational approach to the study of collective risk evaluation processes. While we know, for example, that individuals in many situations tend to overestimate the risk of catastrophic events, little we know about the collective effects of those biases. We have simulated the joint effect of institutional communication with individual opinion exchange, showing how social interaction modifies the effects of institutional communication in a complex way. Individuals, exchanging opinions under a similarity bias, can polarize against institutional messages and reduce their effectiveness. Our simulations also highlighted the prevalent role of risk sensitiveness with respect to trust, independently of connectivity. Alarmist opinions prevail in the model because they incite agents to share more. Risk sensitivity, thus, is much more effective as an intervention target with respect to risk perception.

In the future, we plan to extend these results and to validate them. For validation ex ante, natural experiments could be searched for, that is, empirical studies where individuals are exposed to experimental and control conditions by policy choices, nature, or other factors outside the control of the investigators. On the other hand, validation ex post would benefit from a cross-methodologically approach, hybridizing simulation with experiments, online or in the laboratory.

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