Collective action in violent conflicts and other highly uncertain situations

Jeroen Bruggeman and Don Weenink*

January 14, 2022

Abstract

Individuals are reluctant to cooperate for public goods, especially for risky ones that involve violent confrontations where they may get hurt while others freeride on their efforts. Cooperation can be fostered by norms, incentives, reputations, and training for risky situations, which take time to develop and depend on monitoring and reliable information transmission through a group’s network. Nevertheless, untrained amateurs engage in impromptu street fights, rescue victims at disasters, and participate in protests against oppressive regimes, largely without these mechanisms. An Ising model demonstrates that under high uncertainty, agitation by situational turmoil such as aggressing opponents is sufficient to get cooperation started. At a critical level of turmoil, few accidental cooperators entail a burst of cooperation among the rest. If the proportion of unconditional defectors is above a critical threshold, however, bursts do not occur, which is confirmed by video data of street violence. In the end the model is generalized by incorporating the usual mechanisms; it can then explain cooperation without turmoil.

Why would one contribute to a public good if one runs the risk of being exploited by freeriders, especially if one also runs the risk of getting hurt? Police, fire brigades, ambulance staff, and armies specialize in these situations, receive professional training, have leadership, and internalize effective norms. Ordinary citizens who face sudden disasters or violent opponents, in contrast, are less prepared or not prepared at all. Nevertheless, on numerous occasions, citizens save others at disasters, engage in or deescalate

*Jeroen Bruggeman and Don Weenink: Department of Sociology, University of Amsterdam, Nieuwe Achtergracht 166, 1018 WV Amsterdam, Netherlands. Corresponding author: j.p.bruggeman@uva.nl.
street fights, and join protests. For many participants, these situations are unfamiliar, daily routines and norms do not apply, information is incomplete, uncertainty is high, and payoffs are vaguely known at best. In general, high uncertainty makes people less, not more, cooperative [1], which renders cooperation even more puzzling. To explain cooperation for public goods under high uncertainty, we present an Ising spinglass model and apply it to video recorded street fights, where the public good is the defeat of or the defense against opponents.

If people collectively want to help or hurt, they face a dilemma of collective action [2, 3, 4, 5, 6]. To visualize the dilemma, think of two individuals, each with the behavioral options to defect or cooperate [7]. They may both defect, which avoids exploitation but does not yield any public good, and leaves the participants somewhat dissatisfied. Alternatively one individual may cooperate while being exploited by the freeriding other, which yields only half of the public good and results in higher average dissatisfaction. Finally, they may both cooperate at a cost, which maximizes the public good and minimizes average dissatisfaction. Fig. 1 plots the dilemma as a hill that stands in the way to proceed from full defection on the left to full cooperation on the right, with average dissatisfaction [8] on the vertical axis. It is drawn for a group of two and a clique (fully connected network) of five.

The literature presents mechanisms to solve the dilemma centered around individual rewards and punishments, called selective incentives [5]: Norms about (in)appropriate behavior [9] in a given situation, as well as monitoring of the participants [10], and reliable transmission of information (i.e., gossip) through a fairly stable network lead to reputations [11] that feed back through incentives and cooperators breaking ties with or excluding defectors. All of these have to be developed over time, which may not be available at impromptu trouble.

We argue that even without selective incentives, people can cooperate collectively if they are sufficiently agitated by turmoil, for example the sight of victims or provocations by opponents [12]. Turmoil consists of (noisy) signals that agitate individuals who are sensitive to them. This can be due to their awareness of (potential) consequences or opportunities, or can be a physical response. Agitation is manifested by “trembling hands” [13], which means that some participants may accidentally cooperate. We do not assume the presence of initiative takers or leaders, in contrast to well known theories on thresholds [14], cascades [7], and critical mass [15]. If there are initiative takers or leaders [16], however, we can accommodate them in our model, as well as exit as a third behavioral option.

We represent cooperation under uncertainty driven by turmoil by the Ising spinglass model [8, 17, 18, 19, 20, 21, 22, 23], where individuals’ be-
behavioral options (cooperate and defect) correspond to magnetic spins, and turmoil to temperature [24]. An earlier Ising model of cooperation was a two person public goods game [25], which we generalize to groups of any size, and we use payoffs from evolutionary game theory [6], with an extra factor explained below. Whereas spins are generally assigned the value 1 or -1 (and in rare cases 1 and 0), we use asymmetric values 1 and -1/2 for, respectively, cooperation and defection. The reason is that if the public good and the status quo have equal value (are at the same level on the vertical axis in Fig. 1), cooperation yields no more payoff than defection, whereas if defection equals zero, there is no dilemma (only a downward slope to the right). We therefore choose defection’s value halfway between the trivial extremes, and later generalize to variation across individuals.

We also investigate how collective action unfolds over time. An influential empirical study of violent confrontations [12] indicated that initially, tension builds up, followed by short bursts of violence committed by small (sub)groups (from a larger and more dispersed group) of individuals in close proximity and with face to face contact [26, 27]. Their targets are often stumbling, outnumbered, or otherwise vulnerable individuals [12, 28]. Other people present on the scene may form an audience or try to deescalate [29, 30, 31] which happens often [32]. Our model predicts the presence/absence of bursts, and makes clear why violence starts in small subgroups despite greater risk.

Cooperation is mostly studied in public goods experiments, where more than half of the participants are conditional cooperators willing to contribute if others do [33], thus conforming to their (weighted) average neighbor in the network [34, 35]. More people do so under high uncertainty [36, 37]. From an evolutionary perspective the heuristic of conformity makes sense in complex situations where uncertainty is high and payoffs are hard to predict [38]. However, not everyone conforms and some tend to defect permanently. In violent situations, people may defect for several reasons. They may be too scared to fight [12], have empathy with their opponents, disagree with violence, i.e. value the public good differently, try to deescalate, or they may have fought but got wounded, were wrestled to the ground, or got exhausted at some point. Our model predicts that if the proportion of unconditional (i.e., temporally steady) defectors is above a critical threshold, there is no burst of cooperation.

The asymmetric Ising model has several advantages over alternatives. It is simple yet individual motivations are multiplex, namely network neighbors, benefits and costs, external stimuli, and random noise. The model can explain cooperation without recourse to the traditional mechanisms, does not depend on assumptions of rationality [15] or (nearly) perfect information of others’ behavior [14], has easily interpretable payoffs, and demonstrates the
effects of network structure on the outcome. Furthermore, it reveals that due
to turmoil, cooperation can get started by accidental cooperators rather than
exceptionally zealous ones, as was already known for the prisoners’ dilemma [13]. Last but not least, it yields new findings on the temporal unfolding of
collective action by distinguishing bursts from fizzles. In the end we argue
how our model can be generalized and incorporate the usual mechanisms with
norms, selective incentives, and reputations, as well as network dynamics and
interpersonal differences of valuations of the public good.

Model

Members of a (fledgling) group can defect, $D$, or contribute, $C$, to the public
good, with $0 < D < C$. Behavioral variable $\sigma_i$ can take the value $\sigma_i = C$
or $\sigma_i = -D$. Before a collective action, everyone defects. Perhaps posing
as a member of a group that confronts opponents is already a dilemma of
itself, but our focus is on the subsequent dilemma of participation in violent
collective action. Network tie $A_{ij}$ means that $i$ is in close proximity of and
pays attention to group member $j$. We assume that attention is reciprocal
(but not necessarily equal), except in simulations of tie disruption. Because
people tend to respond to proportions of their social environment rather than
absolute numbers [7, 39], ties are row-normalized [with $w_{ij} = A_{ij} / \sum_j A_{ij}$
such that $\sum_j w_{ij} = 1$].

We do not assume that individuals know their payoffs in advance, but they
will heuristically and perhaps wrongly distinguish between valuable ($C > D$)
and non-valuable ($C < D$) public goods. When $i$ chooses between $C$ and $D$
amongst $N_C$ cooperators, payoffs for cooperation, $P_C = s(N_C + 1) / n - 1$, and
defection, $P_D = sN_C / n + Q$, with a synergy or enhancement factor $s \geq 1$, are
the same as in evolutionary game theory [6] except for $Q$. This additional
factor $Q$ assures that if $D$ approximates $C$, which means that the outcomes
of defection and cooperation become equally valuable, $P_D$ approximates $P_C$
$[Q = (s/n - 1)(1 - R); R = (C - D)/(C + D); s = s_0 + R$, with a base rate
$s_0 \geq 1$].

The dynamics are modeled by minimizing the following Hamiltonian [40],

$$H = - \sum_{i \neq j} w_{ij} \sigma_i \sigma_j. \quad (1)$$

At the beginning, $H$ is at a local minimum where everybody defects, at
the left hand side of Fig. [1]. The influence of opponents is exerted at the
aggregate level through turmoil, $T$. At stepwise increasing levels of turmoil,
collective (in)action of the focal group is modeled through large numbers of
Monte Carlo steps. For a given level of $T$, at each Monte Carlo step an individual $i$ is randomly chosen. Being a conditional cooperator, $i$ uses the Metropolis algorithm \[40\] to decide how to react to social contacts $j$. First, $H_i = -\sum_j^n w_{ij}\sigma_i\sigma_j$ is calculated; then $i$’s behavior is flipped to its opposite, e.g. from $D$ to $C$, and the calculation is performed again, resulting in $H'_i$. The flip is implemented if $H'_i < H_i$, or with a probability that increases with $T$ [if for a random number $0 \leq c_r \leq 1$, $c_r < \exp(-(H'_i - H_i)/T)$ ] . An implemented flip changes the network neighborhood of everyone connected to $i$. Individuals’ behavior thus depends on social influence ($\sum w_{ij}\sigma_i\sigma_j$), expected benefits and costs (through $C$ and $D$), an external stimulus ($T$), and a portion of randomness ($c_r$).

The continuous black line in Fig. \[2\] shows the dynamics of a group of conditional cooperators ($n = 5$). Without turmoil, collective action does not start, but at a critical level of turmoil, $T_c$, almost everybody bursts into cooperation, with a maximum at or near $T_c$ ($N_C/n \approx 1$). Cooperation ends when exhaustion sets in, a winner stands out, or others intervene. If there are steady defectors (red line), $T_c$ increases, which is hardly visible in Fig. \[2\] but more pronounced in larger networks, and maximum cooperation decreases. If the proportion of steady defectors reaches a critical level, $p_c$, there is no burst
but a fizzle of gradually increasing cooperation (dashed blue line in Fig. 2) to a lower maximum at a higher level of turmoil. In simulations of cliques, \( p_c \approx 0.34 \), which is scale independent in the size range tested (3 \( \leq n \leq 1000 \)). For the small networks of our empirical study (3 \( \leq n < 10 \)), the estimates fluctuate more strongly around 0.34 than for large networks. When density decreases from 1 to 0.01 (with random tie distributions), \( p_c \) increases by 0.02, hence the critical proportion is nearly density independent. However, if defectors are clustered together, they are less in the way of collective action (higher \( p_c \)) than if they are evenly spread out across the network.

The threshold of agitation (\( T_c \)) increases with network size at a decreasing rate \([24]\) but it also increases with the proportion of steady defectors until \( p_c \) is traversed and there is no \( T_c \) anymore. At \( T_c \), cooperation starts in the smallest clusters of conditional cooperators \([41]\). This bottom up mounting of cooperation is similar to bottom up synchronization in the Kuramoto model \([42]\). The effect of turmoil is non-monotonic (Fig. 2) and the level of cooperation decreases with \( T_b \) beyond \( T_c \), which means that very strong turmoil becomes more confusing and less agitating.

Beyond our empirical study, the payoffs in the asymmetric Ising model can be generalized by relating \( C \) and \( D \) to the symmetric model through a mapping \( \{C, -D\} \rightarrow \{\sigma_0 + \Delta, \sigma_0 - \Delta\} \), with a bias \( \sigma_0 = (C - D)/2 \) with respect to 0, and the two behavioral options symmetrical at each side of \( \sigma_0 \) at an offset \( \Delta = (C + D)/2 \). It can be shown that the asymmetry in \( \sigma \) is equivalent to the symmetric model with an external field \( 2\sigma_0 \) \([24]\); this article also provides a mean field analysis. The bias and offset are in the payoffs through \( R = \sigma_0/\Delta \). If \( \Delta \) is set to a fixed value (0.75 in our examples), decreasing \( \sigma_0 \) makes cooperation less valuable and is equivalent to an increasing threshold of cooperating network neighbors, also in other binary decision models \([7, 14]\). Cooperation can be made more valuable by increasing \( \sigma_0 \), which corresponds to a decreasing threshold of cooperating network neighbors. Initiative takers and leaders \( i \) will have higher \( \sigma_{0,i} \) values than the majority, and in simulations they start cooperating at lower \( T \) and thereby reduce \( T_c \) for the entire group \([41]\). Locally stronger turmoil has the same effect. Anger, ideology, and concerns for reputation \([11, 43, 44]\) may push individuals’ \( \sigma_{0,i} \) upward, whereas an intimidating majority of opponents will pull it downward. To avoid overfitting in our empirical study, however, we set \( \sigma = \{1, -1/2\} \) for all conditional cooperators. For steady defectors, we set their behavior to \( \sigma_i = -D \), irrespective of their reasons.

\footnote{Varying the degree distribution from random to power law does not affect \( T_c \), but making the network sparser decreases \( T_c \), with a smaller effect size than network size has \([41]\).}

Varying the degree distribution from random to power law does not affect \( T_c \), but making the network sparser decreases \( T_c \), with a smaller effect size than network size has \([41]\).
Figure 2: Level of cooperation ($N_C/n$) with increasing turmoil ($T$) in a clique of 5 individuals. The black line depicts the group without steady defectors ($p = 0$), the red line with one steady defectors ($p < p_c$), and the dashed blue line with two steady defectors ($p > p_c$).

**Street violence**

For ethical concerns, collective violence cannot be studied in lab experiments, which also lack the turmoil and the resulting agitation of violent confrontations. Field studies, in contrast, are realistic but cannot be based on a random sample of participants or groups. We obtained 42 videos from websites such as YouTube, LiveLeak, and WorldStarHipHop using search terms with the English keywords “brawl,” “street fight,” and “assault.” This sample is random with respect to temporal unfolding and (sub)group size. Of these clips, 36 are from English-speaking countries (mainly the US and the UK, with one from Canada and one from India); five of the remaining clips are from the Netherlands, and one is from Colombia. We did not observe differences in relevant behavior related to the location of the recording. To keep distracting factors away from our analysis, we excluded clips with professional fighters, long range weapons, protective clothing, a referee, ambush attacks, or youngsters in a school yard. Most of our videos are phone recorded by bystanders and are left-truncated. In all likelihood, there had been already some turmoil that motivated bystanders to start filming. The shortest lasts 30 sec. and the longest nearly 5 minutes (mean 101 sec.; s.d. 59 sec.). Out of a potential 2 x 42 groups, 25 groups attacked a single individual rather than
a group, who on his own could not act collectively, which leaves 59 groups
to examine. Most groups were small, \(2 \leq n < 10\) (mean 3.6) but one had
14 members. The smaller ones were simulated as cliques wherein everyone
could see one another unless there were obstacles or deescalators obstructing
visual contact. Obstruction was simulated by randomly removing \(m\) ties.

The videos were coded using Noldus Observer XT 14 software. Clips
were played at half speed many times over, and one of us discussed the
coding of each with one or two assistants. The assistants were unaware of
the theoretical expectations. Each of 406 individuals was coded for belonging
to a focal, opponent, or third-party group. Their behavior was interpreted
and represented on the time line.

We coded violence when force was used against another’s body (punching,
slapping, kicking, hitting, stomping) and/or when another person’s body was
forcefully moved (by pushing, shoving, dragging, wrestling, holding, etc.).
Collective violence implies at least two fighting focal group members. For a
burst of violence we require that at least half of a group participated (Fig. 2),
or both individuals did in a dyad, and they started fighting less than 2
seconds after the first, with a 5% margin.\(^2\) In the videos it was not possible
to distinguish leaders from initiative takers, but we noticed individuals who
started violence on their own.

We subsumed the following behaviors of members of the opponent group
under turmoil for the focal group: aggressing, including fighting gestures;
pulling off clothing (jackets or vests); pulling up pants; pointing towards op-
ponents; provocative gesturing with fingers or hands (as an invitation to en-
gee); bending forward toward opponent; encroaching (invading opponents’
personal space through using or damaging objects belonging to them); teas-
ing such as lightly hitting or ridiculing; and, violence. We also included stum-
bling and falling, because vulnerability tends to agitate opponents \([12, 28, 45]\)
as well as approaching the focal group in the context of confrontational ten-
sion, which under normal circumstances would not provoke. We calculated
the total level of turmoil from the beginning of the clip until a focal group’s
maximum participation in violence by the duration of each instance of tur-
moil and multiplying it by the number of individuals involved.

Deescalation was coded as follows \([29]\): open-handed gestures in the di-
rection of other individuals; waving arms to stop or dampen in the direction
of others; touching or patting; guiding a person away; pulling people apart;
and, putting one’s body in between opponents. Other reasons and causes for
not participating in violence could be distraction by deescalator(s), spatial

\(^2\)The requirement that \(N_C \geq 0.5n\) is based on simulations of small networks just above
\(p_c\), but in large networks with \(p \geq p_c\), \(N_C < 0.5n\).
constraints blocking the way, spatial distance, or harm inflicted by opponents. Everyone who for whatever reason did not participate in violence was considered a defector with respect to the collective goal of attack or defense.

A plausible alternative explanation of the onset of collective action is synchrony of motion [12, 46], which yields a feeling of oneness among group members [47], and a stronger willingness to fight and take risks for group mates [48]. To measure the degree of synchronization, we counted the number of synchronous pairs in a group with respect to simultaneous aggressing or moving towards or away from opponents, and dividing the score by the maximum possible number of pairs.

Ethics

The use of videos for research purposes poses distinct ethical challenges, largely due to the nonanonymous content of the videos. However, ethical guidelines for digital spaces tend to be less restrictive [49], with the consent of the participants being less stringent for data acquired from the public domain, including the Internet. While our video corpus is open to use and inspection by other researchers upon request, we require that they take the same measures to ensure the anonymity of the persons portrayed as we did.

Results

Of the 59 groups considered, there were 23 groups where violence started in a burst, 15 groups where violence was collective without a burst, and 21 cases of violence by a single group member. Turmoil preceded all collective violence with one exception, where two individuals suddenly assaulted a passive victim. The critical level of turmoil \( (T_c) \) for bursts is case-specific and depends on group size, both in absolute numbers and relative to the size of the opponent group, and on the proportion of steady defectors. Also the use of weapons has an effect.

Simulations point out that smaller (sub)groups burst into action at lower turmoil than larger groups [41], and lower levels are of course reached earlier. Bursts developed in 13 (37%) of the 35 smallest groups (dyads and triads, i.e. fully connected triples) and in 10 (42%) of the 24 larger groups. In bursts, the correlation between group size and turmoil is 0.53. The size-turmoil pattern is slightly disturbed by dyads more often facing a larger opponent group and therefore less likely to fight collectively than triads, which in turn are more robust in general [50]. As a matter of fact, larger groups always defeated smaller opponent groups (made them flee or work
Figure 3: Proportion of steady defectors ($p$) in groups without a burst (0) and with a burst (1) of violence. The vertical line is the predicted threshold that separates the two sets of groups ($p = 0.34$).

them to the ground) with only one exception.

The proportions of steady defectors in burst (mean = 0.19; s.d. = 0.21) and non-burst groups (mean = 0.49; s.d. = 0.27) are box-plotted in Fig 3 (Welch test $t = 4.796; p = 6.411 \times 10^{-6}; \text{df} = 54.76$). Despite the simplicity of the model, with the same $C$ and $D$ values as in earlier non-empirical papers [24, 41], the predicted critical threshold ($p_c = 0.34$) separates the bursts from the non-bursts quite well. Although this threshold also holds true for empirical triads, simulations of triads do predict wrongly that one steady defector poses an obstacle to a burst of collective action by the other two, which is refuted by 4 of our cases. Consistent with Fig. 2, there was more turmoil preceding collective violence in the non-burst cases (16.6 versus 14.5 for bursts on average).

We now focus on the 21 groups where violence was committed by a single member; 13 thereof are dyads. In 11 of these 21 groups, one or few deescalators in the focal group successfully prevented participants from using violence. In 2 groups, members of the opponent group were able to avoid collective violence by hampering focal group members from joining the fight. In 2 dyads, the participants were separated by their opponents and could not adjust their actions to each other any longer, leaving them to either fight on their own or flee. All these outcomes are consistent with the Ising model once interrupted ties and/or steady defectors are simulated. In 4 of the 6
remaining groups, opponents carried knives, a machete, a bat, or looked too intimidating even unarmed, which apparently lowered $\sigma_0$ in the focal groups. In the last 2 groups, members took turns attacking a fallen victim instead of using violence simultaneously, perhaps confident that they were in control (low uncertainty; high $\sigma_0$). Because we took the same $\sigma_0$ values for all conditional cooperators, variations of these values are below the resolution of our simple model, though.

An interesting alternative explanation is synchrony of motion [12, 47, 48]. Although in 21 out of 23 bursts, some degree of synchronization (10.8 on average) preceded collective violence, there were 18 cases in which synchronization (9.6 on average) was not followed by collective violence. In some of the latter cases, synchrony turned out to be a deceptive performance composed of blustering and aggrandizing [51] without commitment to fighting. This does not imply that synchronization is unimportant, just that it does not predict collective violence.

**Discussion and conclusion**

The simple Ising model is now a century old [52] and has been applied to a wide range of problems [53, 54], to which we add the dilemma collective action. It explains cooperation parsimoniously, based on agitation without recourse to rationality, initiative takers, reputations, norms, feedback through selective incentives, or reliable information passing through the network. The Ising model provides new insights in the temporal pattern of cooperation under uncertainty by predicting a critical threshold of steady defectors that distinguishes a burst of collective action from a fizzle, and is supported by the data. The model also explains why violent groups are often small, or are small subgroups of larger groups, whereas larger groups have a better chance to win at lower individual costs. Small (sub)groups have a lower critical threshold of turmoil, and in a confrontation with opponents, lower levels are reached first. Whether the magnitude of turmoil predicts the intensity of violence remains a question for future studies. We also investigated if synchronous action precedes violence, but it turned out that synchronization precedes both collective and solitary violence, and cannot predict either of these outcomes. Synchronization may still be important to increase solidarity, though.

This study has several limitations. Because we selected the videos for violence, we cannot be certain that turmoil is its cause. When investigating the videos, however, we observed time and again that people reacted violently to provocations, hence it seems quite plausible that turmoil triggers violence.
indeed. Our measurements underestimated turmoil because the videos are left-truncated and depend on camera angle and vision width, thus we erred on the safe side. Another limitation is in the simulated Ising model. Despite well-predicting the threshold of steady defectors, it miss-classified triads with one steady defector as non-bursts, which was refuted by four triads. In future studies it is important to expand the number and diversity of cases, to code videos by different people, and to complement field studies by ethically responsible lab experiments. Perhaps one day, the time consuming coding can be done accurately by AI.

Here we applied the Ising model to violence, but it can also be applied to other uncertain encounters. Its dynamics are entirely consistent with temporal patterns of protests [55], which break out more often if (rumors say that) a government or its police are weakened [56, 57], analogous to vulnerable individuals in our data. Interestingly, as most groups look for a justified reason to attack, some of our group members provoked opponents in order to be reciprocally provoked, such that the start of violence could be othered. Some groups in other studies generated their own turmoil, for example by a rapid increase in online messaging [58], whereas autocrats censor social media to keep turmoil below the critical level. The model seems also applicable to spontaneous lynchings [59], as well as to helping victims under uncertainty [32]. It is even applicable to other species, for example quorum sensing and cooperating microbes [60], as well as buffalo herd bulls chasing away lions [61].

In our empirical study, people were agitated to cooperate by turmoil, but in general, they can be agitated by a broader range of stimuli. A case in point is the urgency of the public good to be achieved or protected, for example the global climate. A group consensus or a leader’s imposition of the collective goal may lead to the establishment of prosocial norms (indexed $q$), which can be represented by additional terms $-h_q \sum \mu_{q,i} \sigma_i$ in Eq. 1, with $h_q$ an increasing function of $N_q$ norm maintainers and $\mu_{q,i} \geq 0$ increasing with norm internalization by $i$. If the norm is sufficiently strong (internalized or $N_q$ large enough), cooperation can start by a weak stimulus ($T < T_c$) or none at all ($T = 0$), in a gradual manner instead of a burst, and foster ongoing cooperation. Norms also preclude a great deal of situational uncertainty (at low $T$) but they cannot prevent the decline of cooperation at high $T$, and come at additional costs for the maintainers and punished defectors. If the maintainers act collectively, the cost per individual decreases [62], and the second order dilemma is completely solved if sanctioning is centrally organized [63, 64, 65], and is paid through taxation or fines. Punishment can have unintended consequences, however, for example when severely punished individuals suffer great losses, whereafter they may decide to leave the group.
In general, rewards and punishments as well as psychological factors and different valuations of the public good can be implemented in the model in terms of $\sigma_{0,i}$ and payoffs, and kinship or friendship can be expressed as tie strength.

Further, when individuals find themselves more often in similar situations, they learn, which is easier in smaller groups where they have a larger influence on their payoffs [66]. Some change their decision rule, or strategy, and turn into unconditional defectors [67] who exploit other group members by maximizing their individual payoff, instead of maximizing the group’s payoff. From then on these learners minimize $H_i = \sum_j w_{ij}(-D\sigma_j)$, and one could model the entry of this strategy (probabilistically) at subsequent Monte Carlo steps. Deescalators value violence negatively, either from the beginning or when someone gets hurt, and try to minimize $H_i = -\sum_j w_{ij}(-D\sigma_j)$. Network dynamics can be dealt with during the Monte Carlo steps, for example by a chance that a cooperator disconnects from a defector [68].

Along with situational uncertainty, or turmoil, there can be endogenous uncertainty in the information that participants $i$ have about $j$’s behavior, i.e. when reputation $r_{ij}$ is tainted with noise and bias [69]. At each Monte Carlo step when $j$ decides, gossip about $j$ spreads into the network with a chance $p_t$ at each transmission that it does not make it to the next individual, and a chance $p_e$ that the gossip is incorrect. Group members $i$ then assess $j$’s reputation on the basis of received gossip by taking a (weighted) average of the gossips and, if they are connected to $j$, their personal observation of $j$ [70]. They decide by the Metropolis algorithm applied to $H_i = -\sum_k w_{ik}\sigma_i r_{ik}$, with $j$ in the index $k$ of some $i$. If reputations are free of error ($r_{ij} = \sigma_j$), for example in small cliques, Eq. [1] is recovered. The important message is that among conditional cooperators, erroneous reputations get cooperation started more easily (in fewer Monte Carlo steps) but once collective action has been mounted, noise lowers the average level of cooperation.

These elaborations point out that the usual mechanisms of cooperation, as well as network dynamic and individual differences, can all be expressed in the Ising model, thereby making it suitable as a general approach to collective action. In this first empirical application, we showed that it can explain dynamics of street violence, and in all likelihood, many more discoveries lay ahead.

**Author contributions**

JB made the asymmetric Ising model; wrote the software and the paper. DW collected, interpreted, and analyzed the data.
Acknowledgement

We thank David van der Duin and Marly van Bruchem for their assistance in coding the videos. DW is supported by ERC grant nr.683133.

Data and code availability

All data files, the R script used to produce plots from coded video data, and a Fortran script for simulations of the Ising spinglass are available at https://osf.io/f25nq/. A Supplementary Information document is available from JB upon request.

References

[1] Kappes, A. et al. Uncertainty about the impact of social decisions increases prosocial behaviour. *Nature Human Behaviour* 2, 573–580 (2018).
[2] Gavrilets, S. Collective action problem in heterogeneous groups. *Philosophical Transactions of the Royal Society B* 370, 20150016 (2015).
[3] Hardin, G. The tragedy of the commons. *Science* 162, 1243–1248 (1968).
[4] Ostrom, E. A general framework for analyzing sustainability of social-ecological systems. *Science* 325, 419–422 (2009).
[5] Olson, M. *The Logic of Collective Action: Public Goods and the Theory of Groups* (Harvard University Press, Harvard, 1965).
[6] Perc, M. et al. Statistical physics of human cooperation. *Physics Reports* 687, 1–51 (2017).
[7] Watts, D. J. A simple model of global cascades on random networks. *Proceedings of the National Academy of Sciences* 99, 497–502 (2002).
[8] Galam, S., Gefen, Y. & Shapir, Y. Sociophysics: A new approach of sociological collective behaviour. *Journal of Mathematical Sociology* 9, 1–13 (1982).
[9] Fehr, E. & Fischbacher, U. The nature of human altruism. *Nature* 425, 785 (2003).
[10] Rustagi, D., Engel, S. & Kosfeld, M. Conditional cooperation and costly monitoring explain success in forest commons management. *Science* 330, 961–965 (2010).
[11] Nowak, M. A. & Sigmund, K. Evolution of indirect reciprocity. *Nature* 437, 1291–1298 (2005).
[12] Collins, R. *Violence: A Micro-Sociological Theory* (Princeton University Press, Princeton, NJ, 2008).
[13] Dion, D. & Axelrod, R. The further evolution of cooperation. *Science* 242, 1385–1390 (1988).
[14] Granovetter, M. Threshold models of collective behavior. *American Journal of Sociology* 83, 1420–1443 (1978).
[15] Marwell, G. & Oliver, P. The Critical Mass in Collective Action (Cambridge University Press, Cambridge, MA, 1993).

[16] Oberschall, A. The manipulation of ethnicity: from ethnic cooperation to violence and war in Yugoslavia. Ethnic and Racial Studies 23, 982–1001 (2000).

[17] Walter, J. & Barkema, G. An introduction to Monte Carlo methods. Physica A 418, 78–87 (2015).

[18] Castellano, C., Fortunato, S. & Loreto, V. Statistical physics of social dynamics. Reviews of Modern Physics 81, 591 (2009).

[19] Dorogovtsev, S., Goltsev, A. & Mendes, J. Critical phenomena in complex networks. Review of Modern Physics 80, 1275–1335 (2008).

[20] Stauffer, D. & Solomon, S. Ising, Schelling and self-organising segregation. European Physical Journal B 57, 473–479 (2007).

[21] Jones, F. L. Simulation models of group segregation. The Australian and New Zealand Journal of Sociology 21, 431–444 (1985).

[22] Callen, E. & Shapero, D. A theory of social imitation. Physics Today 27, 23–28 (1974).

[23] Weidlich, W. The statistical description of polarization phenomena in society. British Journal of Mathematical and Statistical Psychology 24, 251–266 (1971).

[24] Bruggeman, J., Sprik, R. & Quax, R. Spontaneous cooperation for public goods. Journal of Mathematical Sociology 44, 1–9 (2020).

[25] Adami, C. & Hintze, A. Thermodynamics of evolutionary games. Physical Review E 97, 062136 (2018).

[26] Cialdini, R. B. & Goldstein, N. J. Social influence: Compliance and conformity. Annual Review of Psychology 55, 591–621 (2004).

[27] McDoon, O. S. Who killed in Rwanda’s genocide? Micro-space, social influence and individual participation in intergroup violence. Journal of Peace Research 50, 453–467 (2013).

[28] Nassauer, A. Situational Breakdowns: Understanding Protest Violence and other Surprising Outcomes (Oxford University Press, Oxford, 2019).

[29] Levine, M., Taylor, P. J. & Best, R. Third parties, violence, and conflict resolution: The role of group size and collective action in the microregulation of violence. Psychological Science 22, 406–412 (2011).

[30] Phillips, S. & Cooney, M. Aiding peace, abetting violence: Third parties and the management of conflict. American Sociological Review 70, 334–354 (2005).

[31] Weenink, D., Dhattiwala, R. & van der Duin, D. Circles of peace. a video analysis of situational group formation and collective third-party intervention in violent incidents. British Journal of Criminology (2021).

[32] Philpot, R., Liebst, L. S., Levine, M., Bernasco, W. & Lindegaard, M. R. Would I be helped? Cross-national CCTV footage shows that intervention is the norm in public conflicts. American Psychologist 75, 66–75 (2020).
[33] Chaudhuri, A. Sustaining cooperation in laboratory public goods experiments: A selective survey of the literature. *Experimental Economics* 14, 47–83 (2011).

[34] Blau, P. *Exchange and Power in Social Life* (Transaction Publishers, New Brunswick, 1964), 2nd 1986 edn.

[35] Toelch, U. & Dolan, R. J. Informational and normative influences in conformity from a neurocomputational perspective. *Trends in Cognitive Sciences* 19, 579–589 (2015).

[36] Wu, J.-J., Li, C., Zhang, B.-Y., Cressman, R. & Tao, Y. The role of institutional incentives and the exemplar in promoting cooperation. *Scientific Reports* 4, 6421 (2014).

[37] Morgan, T., Rendell, L., Ehn, M., Hoppitt, W. & Laland, K. The evolutionary basis of human social learning. *Proceedings of the Royal Society of London B* 279, 653–662 (2012).

[38] Van den Berg, P. & Wenseleers, T. Uncertainty about social interactions leads to the evolution of social heuristics. *Nature Communications* 9, 2151 (2018).

[39] Friedkin, N. E. & Johnsen, E. C. *Social Influence Network Theory: A Sociological Examination of Small Group Dynamics* (Cambridge University Press, Cambridge, MA, 2011).

[40] Barrat, A., Barthelemy, M. & Vespignani, A. *Dynamical Processes on Complex Networks* (Cambridge University Press, New York, 2008).

[41] Bruggeman, J. & Sprik, R. Cooperation for public goods under uncertainty. *Lecture Notes in Computer Science* 12140, 243–251 (2020).

[42] Arenas, A., Díaz-Guilera, A. & Pérez-Vicente, C. J. Synchronization reveals topological scales in complex networks. *Physical Review Letters* 96, 114102 (2006).

[43] Papachristos, A. V. Murder by structure: Dominance relations and the social structure of gang homicide. *American Journal of Sociology* 115, 74–128 (2009).

[44] Gould, R. V. Collective violence and group solidarity: Evidence from a feuding society. *American Sociological Review* 63, 356–380 (1999).

[45] Weenink, D. Frenzied attacks: A micro-sociological analysis of the emotional dynamics of extreme youth violence. *British Journal of Sociology* 65, 411–433 (2014).

[46] McNeill, W. H. *Keeping Together in Time: Dance and Drill in Human History* (Harvard University Press, Cambridge, MA, 1995).

[47] Fischer, R., Callander, R., Reddish, P. & Bulbulia, J. How do rituals affect cooperation? *Human Nature* 24, 115–125 (2013).

[48] Swann Jr., W. B., Gómez, A., Huici, C., Morales, J. & Hixon, J. G. Identity fusion and self-sacrifice: arousal as a catalyst of pro-group fighting, dying, and helping behavior. *Journal of Personality and Social Psychology* 99, 824–841 (2010).

[49] Mihe, E.-J., Mitchell, C. & de Lange, N. *Handbook of Participatory Video* (AltaMira Press, Walnut Creek, CA, 2012).

[50] Simmel, G. The number of members as determining the sociological form of the group. *American Journal of Sociology* 8, 1–46 (1902).
[51] Trivers, R. *Deceit and Self-Deception: Fool Yourself the Better to Fool Others* (Allen Lane, London, 2011).

[52] Kobe, S. Ernst ising 1900-1998. *Brazilian Journal of Physics* **30**, 649–654 (2000).

[53] Parisi, G. Spin glasses and fragile glasses: Statics, dynamics, and complexity. *Proceedings of the National Academy of Sciences* **103**, 7948–7955 (2006).

[54] Stein, D. L. & Newman, C. M. *Spin Glasses and Complexity* (Princeton University Press, Princeton, NJ, 2013).

[55] Gonzalez-Bailón, S., Borge-Holthoefer, J., Rivero, A. & Moreno, Y. The dynamics of protest recruitment through an online network. *Scientific Reports* **1**, 1–7 (2011).

[56] Skocpol, T. *States and Social Revolutions: A Comparative Analysis of France, Russia and China* (Cambridge University Press, Cambridge, UK, 1979).

[57] Tufekci, Z. *Twitter and Tear Gas: The Power and Fragility of Networked Protest* (Yale University Press, New Haven, 2017).

[58] Johnson, N. F. *et al.* New online ecology of adversarial aggregates: Isis and beyond. *Science* **352**, 1459–1463 (2016).

[59] Beck, E. M. & Tolnay, S. E. The killing fields of the Deep South: The market for cotton and the lynching of blacks, 1882-1930. *American Sociological Review* **55**, 526–539 (1990).

[60] West, S. A., Diggle, S. P., Buckling, A., Gardner, A. & Griffin, A. S. The social lives of microbes. *Annual Review of Ecology, Evolution, and Systematics* **38**, 53–77 (2007).

[61] Estes, R. *The Behavior Guide to African Mammals* (University of California Press Berkeley, London, UK, 1991).

[62] Oliver, P. Rewards and punishments as selective incentives for collective action. *American Journal of Sociology* **85**, 1356–1375 (1980).

[63] Sigmund, K., De Silva, H., Traulsen, A. & Hauert, C. Social learning promotes institutions for governing the commons. *Nature* **466**, 861–863 (2010).

[64] Baldassarri, D. & Grossman, G. Centralized sanctioning and legitimate authority promote cooperation in humans. *Proceedings of the National Academy of Sciences* **108**, 11023–11027 (2011).

[65] Güürerk, Ö., Irlenbusch, B. & Rockenbach, B. The competitive advantage of sanctioning institutions. *Science* **312**, 108–111 (2006).

[66] Burton-Chellew, M. N. & West, S. A. Payoff-based learning best explains the rate of decline in cooperation across 237 public-goods games. *Nature Human Behaviour* **5**, 1330–1338 (2021).

[67] Andreozzi, L., Ploner, M. & Saral, A. S. The stability of conditional cooperation: beliefs alone cannot explain the decline of cooperation in social dilemmas. *Scientific Reports* **10**, 1–10 (2020).

[68] Gallo, E. & Yan, C. The effects of reputational and social knowledge on cooperation. *Proceedings of the National Academy of Sciences* **112**, 3647–3652 (2015).
[69] Hilbe, C., Schmid, L., Tkadlec, J., Chatterjee, K. & Nowak, M. A. Indirect reciprocity with private, noisy, and incomplete information. *Proceedings of the National Academy of Sciences* **115**, 12241–12246 (2018).

[70] Sommerfeld, R. D., Krambeck, H.-J. & Milinski, M. Multiple gossip statements and their effect on reputation and trustworthiness. *Proceedings of the Royal Society B* **275**, 2529–2536 (2008).