Predicting Demonstrations' Violence Level Using Qualitative Reasoning

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Abstract. In this paper we describe a method for modeling social behavior of large groups, and apply it to the problem of predicting potential violence during demonstrations. We use qualitative reasoning techniques which to our knowledge have never been applied to modeling crowd behaviors, nor in particular to demonstrations. Such modeling may not only contribute to the police decision making process, but can also provide a great opportunity to test existing theories in social science. We incrementally present and compare three qualitative models, based on social science theories. The results show that while two of these models fail to predict the outcomes of real-world events reported and analyzed in the literature, one model is successful. We believe that this demonstrates the efficacy of qualitative reasoning in the development and testing of social sciences theories.

Keywords: Demonstrations, Social Simulation, Qualitative reasoning

1 Introduction

A violent demonstration, resulting in casualties among its participants, police forces and innocent bystanders, is unfortunately not a rare phenomena. This paper deals with improving the police decision making process, by providing useful predictions as to the potential outcomes of demonstrations, given the specific settings. The hope is to decrease the number of casualties by preventing violence.

In general, there are several technologies that can be used to generate predictions. Agent based simulations [7] require detailed individual cognitive modeling, and furthermore, modeling at the individual participant level is too fine a resolution for useful predictions. Numerical simulation [12] models at an appropriate resolution (global group behavior), but unfortunately requires complete and precise domain information, which is not available here. There exists significant literature on the factors that impact violence during demonstrations, but it mostly reports on partial, macro-level qualitative descriptions of the influencing factors.

In this paper we describe a novel application of Qualitative Reasoning (QR) [10, 3] to modeling and reasoning about potential violence level during demonstrations. QR is a sub-area of AI, which enables reasoning with partial or imprecise numeric information. Using QR, it is possible to draw useful conclusions even with only qualitative representation of data and order values (such as little/medium/large). Thus such modeling

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provides an opportunity to test existing social science theories regarding the influencing factors on the violence level during the demonstrations.

Based on social science research, which provides qualitative information regarding the factors influencing the violence level in demonstrations, we incrementally present and compare three qualitative models of demonstrations. The first two models are based on an extensive research report initiated by Israeli police [2]. The third is our extension of the second model based on sociological consultation. We evaluated the models on four real-life scenarios. The results show that the first two models make incorrect predictions, but the BIU model makes good predictions on the examined test cases.

2 Related Work

Usage of computer simulation is considered to be a leading approach for modeling and reasoning regarding different social phenomena [6]. There are several micro and macro level techniques that enable such modeling, e.g., usage of agent based simulation, cellular automata and system dynamics.

Agent-based simulation is a micro-level approach where by social behaviors are simulated by simulating each individual, and their interactions. By applying agents as an "intelligent" entity we have the ability to model complicated social interactions. Such simulations have been successfully used in modeling crowd behaviors [5, 7], economic phenomena [16], and more. However, it is a bottom-up approach in the sense that to receive a macro-level behavior we must model the micro-level interactions which necessitates detailed individual modeling, and when number of agents is scaled up it may provide significant computational barriers. Furthermore, there are domains such as predicting the likelihood of violence that modeling at the individual participant level may be too high a resolution and even unnecessary.

System dynamics approach [6] is a macro level approach in the sense that it models an entire system. It uses defined stocks, flows and feedback loops to model system behavior. The models are basically sets of differential equations that describe changes in the system. In our domain, such accurate and full definitions are not available.

Qualitative Reasoning (QR) is another macro level approach, allowing modeling and reasoning with partial and imprecise information. It has been used to allow for common-sense reasoning in physics [10, 3]. However, it has also been applied to other branches of science: ecology [13], social science [8], politics [4] etc. However, our use of QR to model and predict the violence level during demonstrations is novel.

Fuzzy Cognitive Maps (FCM) [9] is also a macro level approach which enables causal reasoning using fuzzy directed graphs. Similarly to QR, FCM enables imprecise and qualitative representation of the model. However, the output of FCM is a recommendation on a single action or goal, while QR returns the set of all possible behaviors that the model may manifest.

3 Qualitative Reasoning and Simulation

Qualitative simulation enables reasoning about possible system behaviors that can emerge from an initial world state. The simulation takes as input the initial state of the world which contains a structural description of the model and produces a state transition graph. A final state graph captures the set of all possible behaviors that the model may manifest. It consists of a set of states and the transitions between them (state-transitions). Each state is a possible unique behavior that the model develops, it contains a unique set of values and inequality statements (quantities) which describe the current behavior of the system. State transitions transform one state into another, by specifying the changes in values and in inequality statements. Each state may contain multiple transitions which enables multiple possible developments of the current state. A sequence of states connected by state transitions where each state is the immediate successor of the one before, is called a behavior path.

Each state is composed of a set of quantities. Quantity is the lowest resolution representation for continuous parameters and it is composed of a pair of values: magnitude and derivative. The magnitude represents the amount of quantity and derivative represents the direction of change. The set of possible values is described by Quantity Space (QS) which is a finite and ordered set of landmark values. Changes in the system are defined explicitly by causal relationships. There are two types of casual relationship between quantities, direct $(I+, I-)$ and indirect $(P+, P-)$ influence. Each influence may be positive $(I+, P+)$ or negative $(I-, P-)$ meaning the derivative of the target quantity increases or decreases accordingly.

In each cycle and on each quantity, all influences (direct and indirect) are combined. When positive and negative influences are combined ambiguities may occur. The qualitative simulation considers all the possible combinations thus, when qualitative description is incomplete, it provides a non deterministic prediction.

4 Modeling violence level in demonstration

Knowledge regarding demonstrations is not accurate nor complete. There are many micro-theories in social science regarding the influencing factors on the violence level: Each such theory focuses on a small sub-set of factors. Integrating all of them into a single unified model is real challenge. The Israeli police initiated a comprehensive study to address this challenge, resulting in a report [2] that provides a collection of factors and their influence on the violence level and also on each other. Their goal was to classify and analyze different kinds of demonstrations in order to propose appropriate methods for the police force in dealing with the mass. They studied 102 crowd events (in particular demonstrations) during the years 2000–2003 and interviews with 87 policemen and police officers. They analyzed a variety of factors that may affect violent behavior, as well as relevant literature. This report is a qualitative collection of factors which provide a challenge to the reasoning process. We use this report as a source of knowledge based on which we developed our models and by using qualitative simulation we provide an ability for reasoning regarding potential violence level.

Base Model. The first (*Base*) model was developed based on the report's literature review [2]. It was proposed there as a first attempt at building a baseline, purely based on literature review. According to the Base model the most influential factors on the violence level during the demonstration are (1) the crowd's a-priori hostility towards the police; (2) willingness to pay the personal price (such as willingness to be arrested); (3) low chance for punishment for violent actions (e.g., a belief that police will not respond strongly); (4) group cohesiveness; (5) previous history of violence. All of these increases the level of violence.

Police Model. The second model is an extension of the Base model. Karmeli and Ravid-Yamin [2] significantly expanded the Base model, based on their interviews with police officers and their investigation into 102 demonstrations. In addition to the factors from the Base model, the Police model adds 12 more variables, roughly divided into several groups. *Environmental factors* include weather, time of day, location sensitivity (e.g., for religious reasons), and time of year sensitivity (e.g., Christmas). *Participant factors* include the number of participants, the existence of violent core among the participants, the existence of group leader, and the cohesiveness of the group (e.g., if they all come from a particular ethnic minority). *Procedural factors* include a request for demonstration license, the purpose of the event (emotional or rational), the timing and strength of police intervention.

The research results showed significant relations between these variables and also their impact on the event outcome (the violence level). For example, political or social demonstrations that express protest or support for leader or cause usually end with low level of violence. However, demonstrations with nationalistic flavor that intend to express emotions (letting off steam) are characterized by much more violent outcomes. The research results also showed a relationship between existence of license and united identity: it was found that some united identities tend to apply for a license before the protest while others do not. It was also found that the time of the day has impact on the violence level; more violent demonstrations occur at night than during the day [2]. A graphic representation of the qualitative model is presented in Figure 1. It shows three entities (Population, Nature and Police) and 18 quantities: 6 are of the Base model, and additional 12 listed above.

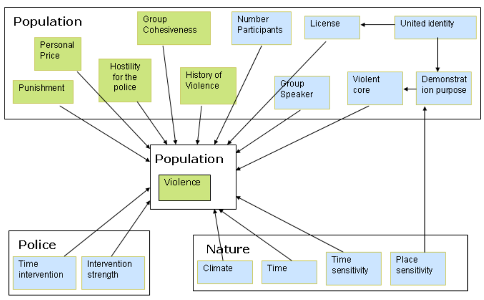

Fig. 1. Police Model: Structure.

BIU Model. The third model is our own novel extension of the Police model. Based on interviews with social and cognitive scientists, as well as additional literature surveys, we added four additional variables, and updated 19 influences (relations) among the variables. The added factors are: (1) maintenance of order; (2) participants anonymity (indicates whether the participants believed they could be recognized); (3) participants' visual cohesiveness (such as similarly-colored clothes among football fans); and (4) the presence of light. The resulting QR model is shown in Figure 2.

We provide here several examples for updated influences. First, we updated the influence of police's intervention strength, thus instead of direct impact on violence level as in the Police model, it impacts the participants' belief that they may be punished, and their hostility for the police. In BIU model, high intervention strength increases participants' hostility for the police and increases the participants' chance for punishment. However, low intervention strength just decreases the participants' chance for punishment without a change in hostility for the police factor. Another example is that existence of group speaker and existence of license increase the maintenance of order, which decreases the violence level. In contrast, in the Police model, license and group speaker variables had a direct influence on the violence level. Moreover, for the variable *number participants*, we no longer allow direct influence on the violence level as in Police model, but instead have it influence the participants' anonymity level ("the more participants around me the less recognizable I am"). Another example of addition to the BIU model is: participants visual cohesiveness has an impact on group cohesiveness, it actually increases the sense of belonging to the same group.

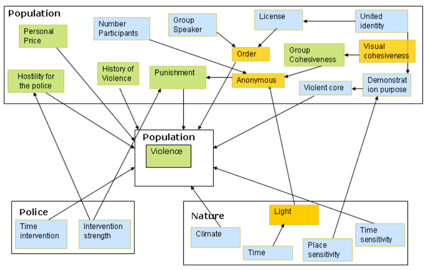

Fig. 2. BIU Model: Structure

5 Models Evaluation

We compare these models on four real-life scenarios. These are cases for which we had a detailed description along with an analysis [2]. The first three are well known events which where extensively analyzed and described [2, 11, 15, 14], and ended with tragic outcomes. The last event was a calm one-hour protest (which we video-taped and analyzed), involving about 100 people, which ended without any confrontation. The results show that the Base model and Police model failed to provide correct prediction on one or more of the test-cases, while the BIU model provides good results.

The first event is the Heysel Stadium Disaster which occurred in 1985 [11]. It was the 1985 European cup final, Liverpool vs. Juventus which was a very tragic and violent event with many casualties. According to Lewis [11] who analyzed this event, one of the reasons for this violent outcome is the police's lack of intervention to prevent the developing violence.

The second event is the Los Angeles Riots which occurred in 1991. This was also a very violent event with many casualties, with 55 killed people and over 2000 injured. Useem [15] who analyzed this event, argued that the police were not properly organized and did not react on time with appropriate force to prevent the eruption, but for the six hours from the beginning of the event, police did little to prevent it which allowed the violent core to grow.

The third event is the London Riot Disaster which occurred in 1990 [14]. As opposed to the previous two events, here the police used enormous force against the protests without distinguishing between anarchists and peaceful marchers. The marchers, with nowhere to go to escape had to fight back. What started as a peaceful protest turned to a very violent event with many casualties.

The last event is a Petach Tikva protest occurred in 2009. In 2009, several children from the Ethiopian community in Petach Tikva were not assigned to schools by time summer vacation was over. This was due, according to some opinions, to racial prejudice against these children. Consequently, approximately 100 people got together in the city square to protest. The incident began calmly and also ended without any violence.

For the evaluation of the QR models, we implemented the models in GARP, a QR engine which enables building and simulating qualitative models and was successfully used in many domains [13, 1]. GARP takes as input an initial setting of the world state (partial state information is acceptable) and produces a simulation state-transition graph. Each sequence of states, following transitions from the initial state and ending with a different outcome state is a possible system trajectory—a possible sequence of qualitative state changes that may occur given the initial state, and the qualitative dynamics specified. The end state in of each such path is where the system dynamics allow no further evolution (i.e., the system is stable). Taking the value of the outcome variables (in our case, violence level) in these final states allow categorical predictions.

However, it is not enough to know whether a demonstration might be violent; in a sufficiently complex model, all three possible values will have at least one state transition path leading to them. Instead, our goal is also estimate the likelihood of different outcomes. Such knowledge may provide a sufficient addition to the decision making process of the police force. To do this, we use the received state-graph as an input and based on this developed graph we calculate the likelihoods of different outcomes as follows: we count the number of behavior paths that lead to a specific violence level and divide it by the total number of paths.

To initialize the test cases, we utilized the information appearing in their descriptions in the literature. We initialized only the quantities for which we had explicit information; qualitative simulation can work with such partial information.

Results. First we want to explore whether the models correctly predict the results of the test cases. For the Heysel Stadium Disaster, the Base model and the Police models predict 100% high violence and 0% low and no violence, and the BIU model predict 96% high violence, 3% low violence and 1% no violence. For the Los Angeles Riots, the Base model and the Police models predict similar outcomes: 66% high violence and 34% no violence. The BIU model predicts for the same event 99% high violence and 1% low violence. For the London Riot Disaster Base model predict 66% high violence and 34% no violence, the Police model predicts 80% high violence and 20% no violence. The BIU model for the same event predicts 57% high violence, 30% low violence and 13% no violence. For the Petach Tikva Protest which was a calm demonstration, in contrast to the other events, the Base model predicts 100% of no violence, Police model predict **66%** high violence and 34% no violence, and the BIU model predicts 5% high violence, 78% low violence and 17% of no violence.

The results demonstrate that Base model and BIU model made a successful prediction in all examined test cases. However, The Police model provide a poor results in prediction of Petach Tikva Protest where the demonstration as it occurred in real life was a peaceful protest while Police model predicts 66% of high violence outcome.

In the following experiment we want to demonstrate the use of QR for hypothetical changes to the police intervention strength. Lewis [11] who analyzed the Heysel stadium disaster concluded that police did too little to prevent the rioting. Similar conclusion was also presented by Useem [15] who analyzed the LA riots. However, Stott and Drury [14], who analyzed the London riots, concluded that police used too much force, and that this was one factors in the tragical outcome. Based on these conclusions, if the police would act differently the events could end differently. Thus, we want to examine the presented model's prediction in *what if* scenarios.

Table 1 presents the experiment results. As before the first column corresponds to the examined test case. The second column corresponds to recommended police intervention strength. Then we present the models predictions for each possible outcome: no violence, low violence and high violence. Below of each experiment, we presented whether the recommended reaction changed the model's prediction.

The results demonstrate that Basic model and Police model failed in providing correct prediction while the BIU model provided good results. The failure of the Base model is not surprising, since the Base model not accounts for the factor of police intervention strength therefore there are no change in the model's predictions.

Exp.	Recommended Change	Model Outcome	**Basic Model**	**Police Model**	**BIU Model**
Exp1	Increase strength [11]	High violence	100%	66%	83%
		Low violence	0	0	6%
		No violence	0	34%	10%
	Change/No-Change		No-Change	**Change**	**Change**
Exp2	Increase strength [15]	High violence	66%	66%	87%
		Low violence	0	0	3%
		No violence	34%	34%	10%
	Change/No-Change		No-Change	No-Change	**Change**
Exp3	Decrease strength [14]	High violence	66%	80%	19%
		Low violence	0	0	45%
		No violence	34%	20%	36%
	Change/No-Change		No-Change	No-Change	**Change**

Table 1. Experiments results: changed police intervention strength

6 Summary and Future Work

In this paper we described a method for modeling and reasoning about social behavior of large groups, and applied it to the problem of predicting potential violence during demonstrations. We used qualitative reasoning (QR) techniques, which to our knowledge have never been applied for modeling crowd behaviors, nor in particular demonstrations. Based on social science research, we incrementally presented and compared three QR models for predicting the level of violence in demonstrations: A Base model, Police model and BIU model. We evaluated these models on four real life test cases scenarios. The results show that BIU model makes good predictions on the examined test cases even where the others fail.

In our future work we plan to expand our model to account for bidirectional influences (feedback loops). For example, in the BIU model the "hostility for the police" quantity increases the violence level. However, increasing the violence level has no impact on hostility. We believe that such expansion is necessary to provide a more accurate prediction. Also, in our future work, we plan to provide a statistical analysis of the developed state-graph and enables reasoning regarding the developed process and not only regarding the final outcome. The third direction is to expand our evaluation process by test our model on additional real-life test cases.

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