be expected to have high political ties. Different organizations with similar political/movement goals would tend to have positive ties, although they would also have some elements of competition between them. There obviously has to be some actual mechanism of communication between spatially dispersed elements of the same organization, such as organization newsletters, or telephone calls or e-mail among members. But these actual mechanisms of communication are most often invisible to the protest events researcher, who merely notes that events were organized in five different cities by local chapters of the same organization.

**Relational/social:** Movement organizations may have ties to nonmembers through their members’ ‘other’ social relationships and memberships. These other ties include kinship and friendship, attendance at the same school, membership in the same recreational club or religious congregation, employment at the same workplace, or membership in some secondary association that has no direct relation to the movement. In many cases, these ‘other’ ties become the basis for recruitment into a movement organization or its actions, as well as for increased support for the movement’s opinions (Ohlemacher 1996). Movements whose members have social connections to the larger society through many different social ties are likely to be better able to mobilize support than those that lack such ties. However, as we consider influence models below, it will become apparent that these external ties can have both ‘positive’ and ‘negative’ effects on movement mobilization.

In the work that follows, we will not be able to explore the effects of these different kinds of proximity, but have set up general schemes that should be able to capture the structures that the different kinds of relations would imply.

**Sizes of Networks and Numbers of Actors**

If we are looking at the total numbers of participants in collective action, we often conceive of the network diffusion as reaching down to individual people. But it is well established that most people enter protest movements as parts of relatively cohesive groups, and that whole groups make decisions together about whether to participate in particular actions. This means that it is often most reasonable to think of the ‘actors’ as groups, not individuals. But when this is so, we will then also want to be able to consider the ‘size’ of each of these actors, which is the number of people it mobilizes. Although capturing this complexity in its totality is beyond the scope of this chapter, we will discuss how our models can be modified to deal with group size issues.

**Network Structures and Collective Action**

Network theorists have devoted a fair amount of attention to measuring and categorizing qualitative differences in network structures, as well as quantifying the position of any one actor in a qualitatively-defined network (Knack and Kuklinski 1982; Wasserman and Faust 1995). The same number of ties in a network has
different effects depending upon their distribution, so that star-like structures in
which one central person has links to other actors who have no links to each other
are, for example, quite different from circles in which each actor has exactly two
ties to other actors and all actors are connected. Similarly, cliques can be defined
within larger networks. Unless one wants to stay at the level of the case study,
however, it is difficult to use these concepts in the study of the diffusion of collect-
ive action across a large and complex population. Instead we need to have sum-
mary measures of a movement group’s network ties. In this chapter, we will give
some simple examples of how structural effects can be incorporated, but will not
pursue this dimension in any depth.

The Basic Model

In this model, each actor has a probability \( p_a \) of acting. At each time period, the
actor acts or does not with probability \( p_a \). Thus the number of people who actually
act at each time period varies stochastically around the mean \( N p_a \), where \( N \) is the
number of actors. Each actor’s \( p_a \) may change across time as a function of the past
actions of themselves or others. Elsewhere (Oliver and Myers 2001), we explore
the question of the form of the underlying model for the diffusion of collective
action. Plausible models for mobilization cycles that go up and down are not
straightforward. Collective action always declines, and the question is whether
this should be specified as arising from a natural tendency within actors that
occurs regardless of outside influences, or whether it is a process of outside fac-
tors such as repression. Addressing these questions is beyond the scope of this
chapter. Here, we will simplify the individual decision model and focus only on
the upswing or accelerative phase (Oliver et al. 1985) of a protest cycle, where the
feedback effect from others’ actions is entirely positive. This underlying model
does not produce event distributions that look like real protest cycles, which
always come down again, but it will give us a basis for evaluating network effects.

Models in this chapter are developed using the Stella simulation programme
from High Performance Systems, Inc. The programme has a graphical interface
to represent differential equations. An appealing feature of Stella is that it gen-
ernates a list of the equations implied by the graphical connections. The
programme can handle one- or two-dimensional arrays with sizes constrained only by
the capacity of the computer. The acting probability and other characteristics of each
actor are captured by one-dimensional arrays, while network links and interactor
influences are captured by two-dimensional arrays. The programme accepts hot
links to inputs and outputs, so it is possible to set up a who-to-whom matrix of net-
work linkages in a spreadsheet that can be read by the programme. All of the mod-
els in this chapter could readily be programmed in some other way, but we have
found Stella to be a very useful development tool as it hugely reduces the ratio of
programming to thinking in the process of model development.
For analysis, we have set up several fixed network configurations as well as a random network controlled by a random number generator and can choose between network configurations with a user-controlled switch. For this chapter, the arrays are fixed at size 10, which is large enough to show some of the effects of random variations, but small enough to be manageable in a development phase. Substantively, an $N$ this small could be understood as actions in different cities or by different groups in a movement. Representing a city of a million inhabitants as a matrix would tax our computer systems and be unlikely to be informative. The more reasonable way to proceed for representing large populations is to conceive them as subgroups with varying sizes, where the group’s size is another variable in the model. Such an extension is beyond the scope of this chapter.

**Baseline Model with No Communication**

For baseline comparisons, we begin with a group of $N$ actors who have no awareness of each other. Each group may randomly emit an action. We tally the plot of all actions. Initially, we have all actors with the same low probability. Because actors do not influence each other, this probability does not change. Because of its random component, each iteration of this model produces a slightly different outcome plot. Figure 8.1 shows plots of the baseline model for a system of 10 actors. Even though there is a constant probability of action, because it is a random model, there are varying numbers of actors at any given time, and the plot exhibits a spiky sawtooth form with waves typical of protest event plots. The cumulative count, however, shows a different story: in a purely random model with a constant probability, the total rises essentially linearly with time. We will be using the total counts across five periods in subsequent models because they damp out some of the random variations of one-period counts. These five-period counts are roughly equivalent to the kinds of patterns you would get if you aggregate daily event counts to weeks, or weekly counts to months. This is shown in the bottom panel of Fig. 8.1. Note that this purely random process generates cycles and even small diffusion-like S-curves in the cumulative count.

To model information diffusion effects, we have to provide some specification of how one actor’s probability of acting is affected by the actions of others. Here, we will assume that the tendency to repeat this action is a function of how many others are doing it. Although verbal theorists can relax into vague discussions of positive effects, and even quantitative empirical researchers can just specify a regression coefficient on the lag of prior action, when we write a mathematical model, we have to say exactly how we think people respond to others’ actions, and this is not at all clear from empirical research. Shall we assume that others’ actions always increase our own probabilities, no matter what? And, if so, in what functional form? Linearly in a power relationship? With rising and then falling marginal returns? Or should we assume that actors respond not to the absolute level of others’ actions, but to whether it is increasing or not? The former assumption, that
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No feedback, $p = 0.05$

![Graph showing cumulative probability over time with annotations]

Fig. 8.1. Random processes produce apparent cycles. Top panel is number of events per time period, bottom panel is 5-period moving average (used in other models).

actors respond to the level of others’ actions, would arise if there is an accelerating production function or if actors’ behaviour is principally determined by influence or imitation processes. However, in the long run, such models produce unanimous action in which everyone is protesting with certainty forever, something that never happens. The latter assumption, that actors respond positively to the increase in others’ actions, and negatively to decreases, would arise from an S-shaped production function that first rises then falls, which seems consistent with an underlying process in which initial action obtains benefits, but there are declining marginal returns to action after it has been at a given level for some time. Our initial work with this second model indicates that, while interesting, it produces volatile results that are very sensitive to initial conditions, which makes
it unsuitable as a platform for investigating network effects. For this reason, we use models employing the first assumption in this chapter.

The model we use assumes that actors respond to the total level of others’ action in a diffusion-like fashion. The basic formulas for this model are: \( p_t = \text{probability of acting at time } t \); \( n = \text{number of actors} \); a random process determines whether each actor actually acts on a given trial; \( n - 1 = \text{recent total number of actions across all actors within the past } k \text{ trials at time } t \); and \( k \) is the number of trials considered.

The algorithm for changing the probability of action as a function of past actions is

\[
p_t = p_{t-1} \left(1 + w_t \right) \frac{(kn - r_{t-1})}{r_{t-1}} / n,
\]

where \( w_t \) is a weighting coefficient on the feedback term. Actors simply respond to the total of others’ actions, which means that “full information” is assumed so that there are no network effects. This simple model produces an S-shaped growth in the probability until a probability of 1.0 is reached, when it stabilizes if everyone acting. The weighting factor determines how quickly this happens; if the weighting factor is small enough relative to the time span of the model, the probabilities may remain essentially unchanged for the duration of the model. The distribution of current action exhibits random variation around an S-shaped rise until unanimous action is reached; unanimous action is an absorbing state. The cumulative distribution is S-shaped until unanimity is reached, and thenceforth rises linearly. In Fig. 8.2 we show examples of the effect of feedback from others’ actions in this algorithm. The plot of cumulative protests clearly shows the S-shaped growth pattern diagnostic of a diffusion process in the first phase, until unanimous action is achieved, and then it becomes a linear curve like any other constant-probability model. We have parameterized the baseline model so that it has a low level of action if there is no feedback and a relatively rapid rise toward unanimity if there is 100 per cent feedback through all possible network ties. This will give us a backdrop against which to consider the effects of various network constructs. The upper panel shows the current action rate as well as the cumulative event count and the probability for a homogenous group in which everyone’s initial probability is 5 per cent and the feedback weight is 0.005. We also provide two variants of the initial probability of action. In the homogenous case, all actors begin with a 5 per cent probability of acting; in the heterogeneous case, actor 1 has a 40 per cent chance of acting, while the other nine actors each have a 1 per cent chance. The average probability is about the same in the two cases. The lower panel compares the homogeneous and heterogeneous cases for the full feedback and zero feedback models. When there is no feedback, the heterogeneous group has slightly more action, due to the one high-probability actor. When there is full feedback, the heterogeneous group reaches unanimous action a little more slowly than the homogenous group.