Modeling the Effects of Task-external Status in Small, Task- Oriented, Groups

Roy Wilson*

University of Pittsburgh
rwilson@pitt.edu

Abstract. Several papers and one invited talk at UM2003 suggest a growing interest in both user and group models grounded in social-psychological research. This paper describes a simulation based on the application of a mathematically formulated social-psychological model to small, task-oriented, groups. Also presented is a simple model of influence that captures the phenomenon of "the rich get richer, the poor get poorer". These models are applied to a set of data collected independently, and for a different purpose, by other researchers. The probability that the observed differences across two experimental conditions involving a task-external status manipulation were due to chance alone is 0.138, suggesting a degree of systematicity to the status effect. The possibility that such a model could be deployed in purpose-driven decentralized group modeling is briefly considered.

1 Introduction

It has been suggested that, in building socially aware agents, it may be helpful to model status effects. Recent work has modeled: social collusion [2], and; the formation of social relationships in peer-to-peer networks [1]. Although the importance of status may be obvious, what is less obvious is how to model the interaction of task-external status and task-internal behavior. If it is important that the outcome of group discussions or deliberations be free of the influence of task-external status, it may be useful to have a theory-based model that tracks the emergence of social order within groups.

2 The Models

2.1 Status and Task Participation

The status and task participation model ($STPM$) is based on the body of social psychological research associated with expectation states theory (EST).

> [EST] ... holds that actors' behavior toward others depends on the performance expectations they hold for themselves and for others [and that] ... expectations refer to unobservable states of relational orientation to ... others. [7]

* Many thanks are due the reviewers for their helpful comments.

EST has generated a number of specific, experimentally verified, behavioral predictions that have been applied to educational settings. The $STPM$ gives an account of how stable social orders emerge within task- oriented groups, shaping the distribution of opportunities for group members to contribute to, and influencing the outcome(s) of, group discussion (or, in this paper, group decision).

The $STPM$ describes a cycle. At time T, expectation states enable and constrain the task-internal behavior of members. When actor a addresses actor b, this (probabilistically) induces a social relation R between a and b, denoted aRb. The relation R at time T constitutes a social network. The social network at time T determines the expectation states of the group members at time $T+1$. The cycle then begins again (with possibly updated expectation states).

The $STPM$ is based on a six axioms involving three parameters: π, the probability that the act of a addressing b generates aRb; η, the probability that a task-external status difference between a and b generates aRb; θ, the probability that each observation by some actor z of a communication between a and b generates zRa, zRb, aRz, or bRz. For the simulation experiments described here, $\theta = 0.25$, $\pi = 0.50$, and $\eta = 0.75$.

In EST research, the relation R is generally taken to be dominance or precedence. Actor a is taken to be in a relation of precedence with respect to actor b if actor a routinely takes or is granted the opportunity to contribute to the task. In this study, the relation is precedence. For additional information regarding EST and the $STPM$ axioms, see [11, 7].

2.2 Individual Decision-making

This study is based on a set of $N = 111$ individual, actual, affirmative decisions, each rendered by exactly one of five types of actor (Teacher, Principal, Nurse, Social Worker, and Counselor) and each corresponding to a single case (indexed by c) corresponding to a distinct, actual, elementary school child. For each such case an affirmative decision was reached regarding the following proposition, denoted $A(c)$: The child described by case c *may* have been physically abused by one of its natural parents. These decision data, which reflect only affirmative decisions, were used to construct a probabilistic belief model for each of the five types of actor.

The purpose of the probabilistic belief model is to represent what belief, based on prior experience as encoded in the decision data, each type of actor would form regarding a previously *unseen* case. Each case c is represented by a vector of seven features: family $INCOME$ and $AFDC$ status (namely, whether the family receives Aid For Dependent Children); the child's AGE, SEX, and $ETHNICITY$; $INHOME$, whether a parent lives in the home of the child, and; $OCCUPATION$, the occupation of the school professional that affirmed $A(c)$.[1]

[1] The case data that formed part of the basis for this study were made available (in part) by the National Data Archive on Child Abuse and Neglect, Cornell University, Ithaca, New York. The data from the Substantiation of Child Abuse and Neglect Re-

Using $N = 111$ feature vectors, probabilistic belief models were constructed for each actor type based on the if-then classification rules produced by the machine learning program RIPPER.[2]

The belief of actor a regarding $A(c)$ is denoted by $B_a(c) \in [0, 1]$. $B_a(c) = 0$ signifies that a denies $A(c)$; $B_a(c) = 1$ signifies that a affirms $A(c)$, and; $B_a(c) = 0.5$ signifies that a is epistemically neutral regarding $A(c)$. Hence, $B_a(c)$ is a continuous variable ranging from utter disbelief through neutrality to complete certainty.

Since the focus of this study is collective rather than individual decision-making regarding $A(c)$, it is necessary to somehow determine the collective decision regarding $A(c)$ from the values of $B_a(c)$ where a ranges over each of the five types of actor. This is accomplished by mapping $B_a(c)$ to $desire_a(c)$, the desire of actor a to make the collective decision regarding $A(c)$ that conforms to his/her belief regarding $A(c)$. The desire of actor a to bring about a collective affirmation or denial of $A(c)$ is represented by $desire_a(c) = B_a(c) - 0.5 \in [-0.5, +0.5]$.[3]

If $desire_a(c) < 0$, this signifies that actor a wishes $A(c)$ to be denied by the group; if $0 < desire_a(c)$, this signifies that a wishes $A(c)$ to be affirmed by the group; if $0 = desire_a(c)$, this signifies that a is neutral regarding the group decision. The larger the absolute value of $desire_a(c)$, the stronger the desire of actor a to bring about a collective decision in accord with $B_a(c)$. In short, desire is assumed to be a function of belief.

2.3 Group Decision-making

The collective decision regarding $A(c)$ is modeled as an influence- weighted sum of $desire_a(c)$ over each type of actor a. Real-time simulation is used to generate the values of of $participation(a)$.[4] The collective decision process is described in greater detail below.

3 The Experimental Conditions

Each set of simulation experiments is identified by the distribution of task-external status within the group. Since each member can be assigned any of

ports Project were originally collected by John Doris and John Eckenrode. Funding support for public distribution was provided by a contract (90-CA-1370) between the National Center on Child Abuse and Neglect and Cornell University. Neither the collector of the original data, funding agency, nor the National Data Archive on Child Abuse and Neglect bears any responsibility for the analyses or interpretations presented here.

[2] RIPPER was chosen in order to obtain easily interpretable rules and because of its relatively high level of performance [**?**].

[3] Note that if $B_a(c) = 0$, then $B_a(c) - 0.5 = -0.05$. Likewise, if $B_a(c) = 1$, then $B_a(c) - 0.5 = +0.05$. Since $B_a(c) \in [0, 1]$, $desire_a(c) \in [-0.5, +0.5]$.

[4] The simulation is written in Java using the channel-based process communication provided by the *JCSP* (*Java Communicating Sequential Processes*) library [9].

three task-external status values, there are $3^5 = 243$ possible experimental conditions based solely on task-external status. In this (preliminary) study, only the four conditions in Table 1 are considered. The entries in Table 1 are defined as

Table 1. Experimental conditions for simulations

Experimental condition	Status condition
0	$SC_0 = HMMLM$
2	$SC_1 = HMMMM$
4	$SC_2 = MMMLM$
6	$SC_3 = HMMHM$

follows. In SC_0, actor 0 has $H(igh)$ task-external status, actors 1, 2 and 4 have $M(edium)$ task-external status, and actor 3 has $L(ow)$ task-external status, and so on. The task-external status of each actor is based on: the credentials held by each, and; the amount of resources available to each actor [12].[5]

4 The Quantities of Interest

Each run of the simulation represents one group meeting. In each such run, $addressed(a, b)$, the *number* of times a addressed b is recorded.[6] The value of $addressed(a, b)$ is determined by a pseudo-random number generation process based on the simulation parameters π, η, and θ. Actors communicate dyadically until 376 dyadic communication events have occurred, thereby simulating a meeting of 40 minutes in duration.[7] In turn, a's level of participation during that one meeting is defined as (the proportion)

$$participation(a) = \sum_{b=1}^{5} addressed(a, b) / \sum_{z=1}^{5} \sum_{b=1}^{5} addressed(z, b) \tag{1}$$

A number of experimental and observational studies over a half century suggest that the influence of an actor in a small, task-oriented, group is highly correlated with the quantity of their participation.[8] Those who participate most/least

[5] From a *psychological* social psychology viewpoint, it is quite right to consider personality as a potential determiner of *task-internal* status. From the perspective of *sociological* social psychology [6, pp. ix–xiii], however, it is the task-internal behaviors generated by such personality characteristics that are of interest in explaining the emergence of dominance or precedence structures in small, task-oriented, groups.

[6] The abstractness of the $STPM$ and the rudimentary nature of the simulation engine is such that there is no mechanism for modeling the dependence of $addressed(a, b)$ upon c.

[7] The number 376 is a normalized value derived from observational data presented in [8].

[8] For a brief review of this literature, see [11].

in a small, task-oriented, group generally have the most/ least influence. Not all participation, however, is influential.[9]

I adopt a "rich get richer, poor get poorer" view of influence in relation to participation with

$$influence(a) = participation(a)^2 / \sum_{z=1}^{5} participation(z)^2. \tag{2}$$

Note that the values of $influence(a)$ obtained via equation (2) preserve the order relations that exist among the values of $participation(a)$.

For each experimental condition in Table 1, the simulation consists of 100 batches of 20 independent runs. Each batch provides a sample mean for the population parameter $participation(a)$. Regardless of how $participation(a)$ is distributed, the Central Limit Theorem implies that the sample means are themselves normally distributed about $\mathcal{E}[participation(a)]$, the expected (or mean) value of $participation(a)$.

$CD(c)$, the collective decision of a task-oriented group concerning $A(c)$, is modeled as follows.

$$CD(c) = \begin{cases} 0 \text{ if } \sum_{a=1}^{5} influence(a) \cdot desire_a(c) \leq 0 \\ 1 \text{ otherwise} \end{cases}$$

$CD(c) = 0$ signifies that $A(c)$ is denied; $CD(c) = 1$ signifies that $A(c)$ is affirmed. Since $influence(a)$ is a random variable, so too is $CD(c)$. Under each experimental condition, the estimated expected value of $CD(c)$ is

$$\hat{\mathcal{E}}[CD(c)] = \sum_{a=1}^{5} desire_a(c) \cdot \hat{\mathcal{E}}[influence(a)] \tag{3}$$

4.1 Intermediate Values

Table 2 gives the estimated value of, and confidence limits for, the expected value of $participation(a)$ along with $\hat{\mathcal{E}}[influence(a)]$, the estimated expected value of $influence(a)$. The latter is computed from equation (2) by replacing $participation(a)$ with its estimated expected value.[10]

Within each experimental condition, the values of $\hat{\mathcal{E}}[participation(a)]$ are ordinally consistent with the predicted outcomes: participation is positively correlated with status rank. Moreover, as can be determined by comparing confidence intervals, a number of these differences in estimated expected participation are statistically significant at the $\alpha = 0.05$ level. *Across* experimental conditions,

[9] An obvious limitation of the model is that the *quality* of participation is not considered, a task for future work: As noted by a reviewer, assessing the quality of participation is no easy task.

[10] Although the expected value of the LHS of equation (2) is not strictly equal to the expected value of the RHS, for reasons of expediency I estimate $\mathcal{E}[influence(a)]$ as if it were, ignoring bias.

Table 2. Participation and Influence

Experimental condition	Actor a	Lower limit	$\hat{\mathcal{E}}[participation(a)]$	Upper limit	$\hat{\mathcal{E}}[influence(a)]$
0	0	0.2381	0.2399	0.2417	0.2858
	1	0.1996	0.2011	0.2027	0.2009
	2	0.1986	0.2005	0.2024	0.1997
	3	0.1514	0.1527	0.1541	0.1158
	4	0.1976	0.1996	0.2017	0.1979
2	0	0.2387	0.2405	0.2422	0.2896
	1	0.1880	0.1900	0.1921	0.1808
	2	0.1838	0.1859	0.1879	0.1730
	3	0.1864	0.1886	0.1909	0.1781
	4	0.1866	0.1888	0.1910	0.1785
4	0	0.2083	0.2103	0.2124	0.2210
	1	0.2089	0.2110	0.2130	0.2225
	2	0.2077	0.2098	0.2119	0.2199
	3	0.1508	0.1524	0.1539	0.1161
	4	0.2081	0.2101	0.2121	0.2206
6	0	0.2281	0.2298	0.2315	0.2628
	1	0.1755	0.1773	0.1791	0.1564
	2	0.1754	0.1774	0.1795	0.1566
	3	0.2311	0.2330	0.2348	0.2701
	4	0.1740	0.1760	0.1780	0.1541

$\hat{\mathcal{E}}[participation(a)]$ by the highest status individual(s) is not uniform. Experimental condition 2 has the least status differentiation and actor 0 has the highest participation across the four experimental conditions considered. Although the differences between the proportions are small in absolute terms, a number of the differences in the estimated expected value of participation *across* experimental conditions are statistically significant at the $\alpha = 0.05$ level. As predicted, status matters in relation to participation.

5 Findings

The question now is whether differences in influence lead to systematic differences in the collective decision outcomes. The expected number of negative and affirmative collective decisions under each experimental condition, shown in Table 3, were obtained from equation (3) based on values of $desire_a(c)$ (not shown here) and the values of $\hat{\mathcal{E}}[influence(a)]$ shown in Table 2.[11] Table 3, which is computed using equation (3), suggests that actor 0 (of type School Principal) and actor 3 (of type Teacher) hold opposing beliefs regarding some cases, so that a change in their relative task-external status leads, via a change in their

[11] Since the status distributions across experimental conditions differ only with respect to actors 0 and 3, only the status of those actors is displayed in Table 3.

Table 3. Collective Decisions regarding $A(c)$ over all c

Experimental condition	Actor 0 status	Actor 3 status	Total such that $\hat{\mathcal{E}}[CD(c)] = 1$	Total such that $\hat{\mathcal{E}}[CD(c)] = 0$
0	H	L	44	67
2	H	M	49	62
4	M	L	47	64
6	H	H	56	55

participation and influence, to a change in the number of affirmative collective decisions.

The smallest number of affirmative decisions occurs in experimental condition 0. That is increased if: the task-external status of actor 3 is raised to M or H, or; the task-external status of actor 0 is lowered to M. With respect to experimental conditions 2 and 4, the largest effect is obtained by raising the status of actor 3 rather than simply lowering the status of actor 0. As indicated via experimental condition 6, raising the task-external status of actor 3 from L to H counteracts the high task-external status of actor 0.

For each pair of experimental conditions shown in Table 3, the null hypothesis of equal proportions (of affirmative and negative decisions) was evaluated using Fisher's two-sided exact test (which is a more precise cousin of the χ^2 test) [4, pp. 307]. Out of a series of pairwise comparisons, the smallest p-value of 0.138 is obtained when comparing experimental conditions 0 and 6. So, although there is a systematic difference in the number of the number of affirmative collective decisions obtained in conditions 0 and 6, it is not enough to generate a statistically significant difference.[12]

The discussion thus far has focused entirely on how variations in *individual* status affect the collective decision. Another way of considering the situation is to ask how the weight given to case features varies with experimental condition, which in this paper reduces to the status distribution. Since the feature values associated with each case are, with the probable exception of ethnicity, objective characteristics, a shift in the distribution of influence *may* amount to a change in the importance accorded to these features by the group.

From the data in Table 3, $P_0 = 44/111 = 0.396$ and $P_6 = 56/111 = 0.505$. A shift in the status of actor 3 from L to H is associated with a greater number of expected affirmative collective decisions. To help understand this shift, a logistic regression was performed with the $\hat{\mathcal{E}}[CD(c)]$ as the dependent variable and $INCOME$, $AFDC$, AGE, SEX, $ETHNICITY$, $INHOME$ as the explanatory variables. Since the point is to understand the shift as a function of the a group property, the task-external status composition, the feature $OCCUPATION$ is not included. A logistic regression was performed because

[12] It appears, based on Krippendorff's α, that the level of agreement amongst the actors is not high enough to explain the lack of statistical significance of Fisher's test.

the $\hat{\mathcal{E}}[CD(c)]$ is a binary variable, a situation for which a linear regression is generally inappropriate.

In order to give a qualitative portrayal of differences in the relative importance accorded to the explanatory variables under experimental conditions 0 and 6, I construct a visualization of how $P\{\hat{\mathcal{E}}[CD(c)] = 1\}$, the probability that $\hat{\mathcal{E}}[CD(c)] = 1$, changes in response to a unit change in a single (*standardized*) explanatory variable when all other such explanatory variables are regarded as fixed.

As indicated by Figure 1, the value of ΔP (an abbreviation for $P\{\hat{\mathcal{E}}[CD(c)] = 1\}$) depends on the value of P . I am interested in the values of ΔP when $P = P_0$ and $P = P_6$.[13]

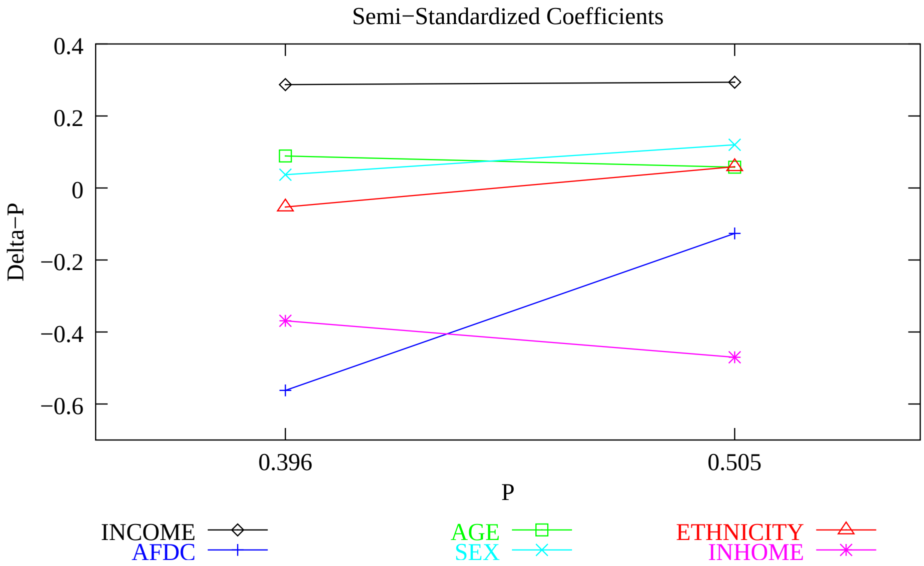

Fig. 1. $\Delta P\{\hat{\mathcal{E}}[CD(c)] = 1\} = f(\sigma, P)$

For experimental condition 0, P is most sensitive to change in $AFDC$. The point associated with $AFDC$ is furthest away from 0 and is negative, indicating that change in $AFDC$ reduces P. A smaller reduction in P results from change in $INHOME$, followed closely by a positive change in P due to $INCOME$. The effects of AGE, SEX and $ETHNICITY$ are relatively small as indicated by the proximity to the line $\Delta P = 0$.

[13] The plot of ΔP is based on *semi-* standardized (logistic) regression coefficients (termed semi-standardized because the outcome variable is *not* standardized). ΔP lies in the interval $[-1, 1]$ and represents the maximum possible change in P that can result from a change of one standard deviation in a particular explanatory variable. For a full discussion of semi-standardized coefficients in logistic regression, see [5].

For experimental condition 6, P is most sensitive to change in $INHOME$. The point associated with $INHOME$ is furthest away from 0 and is negative, indicating that change in $INHOME$ reduces P. $INCOME$ exerts a lesser, positive, influence on P, while the effect of $AFDC$ is negative and approximately half the magnitude of that exerted by $INCOME$. Once again, the effects of AGE, SEX, and $ETHNICITY$ are relatively small.

Whereas P is relatively more sensitive to changes in $AFDC$ and $INHOME$ under both experimental conditions, their ordering is different. Raising the status of actor 3 to that of actor 0 in experimental condition 6 reverses the importance assigned by the group to $AFDC$ and $INHOME$ under experimental condition 0. In effect, the importance assigned by the group to these explanatory variables depends on the task-external status distribution within the group.

6 Related Work

Recent work on social collusion models how relationships are linguistically constituted on the basis of interpersonal characteristics [2]. Although power is identified as an important, longer-term, dimension of social relations, it is not explicitly modeled. The chief aim of the work described here is to predict the influence of actors, an attribute correlated with power.

In a study of cooperation in peer to peer networks, the authors observe that free-riding is less an economic, and more a social-psychological, issue [1]. Their work describes an adaptive agent that models user interests and the social relationships amongst users using reinforcement learning techniques. Like the work on social collusion, the work on peer cooperation focuses on the emergence of interpersonal relations. In contrast, the work described here focuses on how task-external status (often a matter of stereotyping) conditions (but does not determine) the emergence of social order in a small, task-oriented, group. The work described here may be complementary to that on peer-to-peer networks.

In the initial presentation of results obtained from the $STPM$, attention focused primarily on inequality of participation and the correlation of status and participation as a function of θ, π, and η over a wide range of values [7]. Whether differences due to status were statistically significant was not addressed. In [**?**], the $STPM$ was used to explore inequality of participation and the correlation of status and participation, but over a small region of the (θ, π, η) parameter space. Several statistical tests were performed, but influence was not modeled.

7 Summary

This paper describes a simulation approach to the study of task- external status effects in small, task-oriented, groups, It is the first work I know of where influence is modeled as a function of participation. Although status differences were statistically significant in one comparison at only the $\alpha = 0.138$ level, this does suggest that collective decision- making sometimes depends in part on the status of group members *before* they begin deliberating. Although it is important to examine the behavior of the $STPM$ simulations under a wider set of parameters, it is equally important to augment the bare notion that actor a addresses b with a representation of socio-linguistic and other behavior.

Attention has recently been drawn to possibility of decentralized user models in which user data fragments are dispersed among various devices, services and agents. In distance education, it is important that task-external status differences not shape discussion or deliberation outcomes. It may, then, be useful to regard the $STPM$ (and other models) as a special sort of data, a template, useful for requesting and interpreting data pertaining to interaction in a small, task-oriented, group.

References

1. Bretzke, H., Vassileva, J.: Motivating cooperation on peer-to-peer networks. In: User Modeling 2003, Proceedings of the 9th International Conference, Johnstown, PA (2003) 218-227
2. Cassell, J., Bickmore, T.: Negotiated collusion: Modeling social language and its relationship effects in intelligent agents. *User Modeling and User-Adapted Interaction* **13** (2004) 89-132
3. Cohen, William: Fast Effective Rule Induction. In: Machine Learning, Proceedings of the 12th International Conference, Lake Tahoe, CA (1995)
4. Collett, D.: *Modeling binary data.* Chapman and Hall, Boca Raton, FL (2003)
5. Kaufman, R.: Computing effects in dichotomous logistic regression: A variety of standardized coefficients. *Social Science Quarterly* **77** (1996) 90-109
6. Lawler, E. J., Markovsky, B.: Sociological social psychology: A preface. In Lawler, E. J., Markovsky, B. eds.: *Social psychology of groups: A reader.* JAI Press, Greenwich, CT (1993)
7. Skvoretz, J., Fararo, T.J.: Status and participation in task groups: A dynamic network model. *American Journal of Sociology* **101** (1996) 1366-1414
8. Smith-Lovin, L., Skvoretz, J. V., Hudson, C. G. : Status and participation in six-person groups: A test of Skvoretz's comparative status model. *Social Forces* **64** (1986) 992-1005
9. Welch, P. H. , Austin, P. D.: Java Communicating Sequential Processes (JCSP) Library, Release Candidate 4. University of Kent, Canterbury England (2003)
10. Wilson, R.: Simulating classroom interaction using communicating process architecture. In: Proceedings of the 2001 International Conference on Parallel and Distributed Processing Techniques and Applications, Las Vegas, NV (2001)
11. Wilson, R.: Modeling task-oriented discussion groups. In: Proceedings of the 9th International Conference, UM2003, Johnstown, PA (2003) 248-257
12. Wright, E. O.: The comparative project on class structure and class consciousness. *Acta Sociologica* **32** (1989) 3-22