# The Robust Beauty of Majority Rules in Group Decisions

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How should groups make decisions? The authors provide an original evaluation of 9 group decision rules based on their adaptive success in a simulated test bed environment. When the adaptive success standard is applied, the majority and plurality rules fare quite well, performing at levels comparable to much more resource-demanding rules such as an individual judgment averaging rule. The plurality rule matches the computationally demanding Condorcet majority winner that is standard in evaluations of preferential choice. The authors also test the results from their theoretical analysis in a behavioral study of nominal human group decisions, and the essential findings are confirmed empirically. The conclusions of the present analysis support the popularity of majority and plurality rules in truth-seeking group decisions.

Human societies rely on groups to make many important decisions. There is a deep-seated belief that groups are more accurate and more just than individuals. This belief is based on the commonsense notion that a group has more problem-solving resources than any individual member because "several heads are better than one." The belief also depends on the assumption that the group process is effective at eliciting and integrating its members' beliefs and preferences. The most popular decision rule in groups of all types is the majority rule. The majority rule has many virtues: It is "transparent" and the easiest of all social decision rules to execute; it is based on a simple principle of equal participation and equal power; it encourages the expression of sincere personal beliefs, rather than conformity; and it yields more effective problem solutions than typical (and sometimes even most accurate) members could achieve. The present article is an exploration of the capacity of the majority rule and the closely related plurality rule to produce accurate judgments.

The majority rule is popular across the full spectrum of human groups from hunter–gatherer tribal societies (Boehm, 1996; Boyd & Richerson, 1985; Wilson, 1994) to modern industrial democracies (Mueller, 1989). Certainly, in ad hoc Western groups, it seems to be the decision rule most frequently adopted to make formal social choices in popular elections,

legislatures, and committees. The second most popular explicit procedure in committees is an autocratic "leader decides" rule (e.g., Smith & Bliege-Bird, 2000). However, when no explicit decision rule is adopted by a group or when a designated leader appears to make the group's decision, the *implicit* decision rule is usually still essentially a majority rule (cf. Davis, 1973, 1982; Kerr, Stasser, & Davis, 1979; Stasser, Kerr, & Davis, 1980). Even when a small group has an explicit rule other than a majority rule, the largest initial faction, that is, the plurality, is usually the ultimate winner (cf. Hastie, Penrod, & Pennington, 1983; Kameda, Tindale, & Davis, 2003; Kerr & Tindale, 2004).

There are several versions of majoritarian rules used in human societies. The most popular version in America is a majority–plurality rule in which the candidate that receives the most votes wins (plurality rule hereinafter). In America, this is the rule that is applied to determine the presidential candidate favored by the popular vote or, more important, the candidate selected to receive each state's electoral college votes. The majoritarian rule, and the focus of much theoretical analysis, is called a Condorcet majority rule after Marie-Jean-Antoine-Nicholas de Caritat Condorcet, the French philosopher who cofounded modern social choice theory (Condorcet majority hereinafter). Under a Condorcet majority rule the candidate who receives more than one half of the votes cast is selected (nb, if there are abstentions, the majority winner can receive less than one half of all possible votes). When there are more than two candidates, all possible two-candidate elections are held, and a Condorcet winner is declared if any candidate wins all the pairwise elections by a simple majority.

When there are only two candidates, majority and plurality yield identical results. However, there are many examples, when there are more than two candidates, in which the majority and the plurality rule do not select the same winners. For example, in the 2000 United States presidential election popular vote, there was no simple majority winner, though Gore was the winner by a plurality rule (there were three candidates who received more than 1% of votes cast: Gore, Bush, and Nader).

It is likely that Gore would also have been the Condorcet winner, but since pairwise elections were not held, there is no way to know this for certain.[1]

One goal of the present analysis is to explore how the performance of the plurality rule and the Condorcet majority rule converge and diverge in ecologically plausible, truth-seeking, group decision tasks. In contrast to the case of political elections, our evaluation assumes that there is a general objective utility to the group decision and that individuals all have the same ultimate preferences. However, when there is preferential conflict, differences in individuals' votes are produced by differences in individual utility functions (e.g., "I would be more satisfied if Gore were president, you would be more satisfied if Bush were president") *and* by differences in knowledge (e.g., "I do not realize it, but Bush would actually provide me with a higher personal utility"). In the present analysis, we focus on the case in which there is no conflict between members with respect to personal preferences, so an outcome that is better for any one member is better for everyone. For example, when a committee of investors decides whether to purchase shares of stock, all members can be assumed to seek the decision that will maximize profits. However, disagreements among members' judgments about which investment will yield the highest profit introduce differences in their choices and votes. Yet, ultimately, in these cases, the best group decision rule is the rule that is most accurate in achieving generally valued outcomes.

It is likely that majority and plurality rules evolved in human society in group foraging situations in which a band of animal or human foragers needed to choose a common direction to search. There is evidence that groups of nonhuman animals make collective decisions in accord with a majority rule (Conradt & Roper, 2003; Seeley & Burhman, 1999) and, as we noted above, it is a popular rule in primordial hunter–gather societies. In the present research, we measure the success of several social decision rules on the basis of the correspondence to reality or accuracy of judgments and decisions rendered by each rule (see Hammond, 1996; Hastie & Rasinski, 1988, for discussions of the correspondence–coherence distinction).

### Accuracy as a Criterion for Good Group Decision Rules

There is a general presumption that groups are more accurate than individual decision makers. This presumption is part of the rationale for the use of group decisions in many human enterprises. One useful characteristic of group judgment and decision strategies is adaptive flexibility in choice of social problem-solving strategies (Hinsz, Tindale, & Vollrath, 1997). For example, some intellectual task performances are best described by a "truth-wins" or "truth supported wins" strategy; these are tasks in which the most competent group members can demonstrate the quality of their superior solutions so that the group tends to choose the best solution generated by any of its members (Laughlin, 1980; Laughlin & Ellis, 1986). Another opportunity for superior group performance occurs when the task is one in which no single member has sufficient information to solve the problem, but different members have the necessary information. In such cases, if information pooling is effective and the group follows a majority or plurality decision rule, the group can solve a problem at which no individual member could succeed (e.g., Stasser, 2003; Stasser & Titus, 1985).

A useful property of the majority rule in truth-seeking tasks is that it encourages the sincere expression of personal beliefs. Imposition of a majority rule can shatter error-prone information cascades by encouraging group members to rely on their personal beliefs rather than conforming to others' opinions. For example, Hung and Plott (2001; see also Anderson & Holt, 1997) created information cascades in a Bayesian judgment task. Each participant in the experiment observed a private information sample from one of two urns. Their task was to identify the source urn from which the sample had been drawn. When early respondents in a sequential judgment task favored one urn, subsequent respondents were likely to ignore the information in their private samples and conform to the prior choices. Ironically, a Bayesian analysis shows that this is what people should do, ignore their own private information and conform to the prior members' opinions. Thus, this task has the insidious property of producing rational but erroneous information cascades when the first members have drawn misleading samples, a condition that occurs on approximately one quarter of the trials under the conditions in Hung and Plott's experiments. However, most important, Hung and Plott demonstrated that when incentives were shifted to reward group accuracy *and* a majority rule was imposed, erroneous cascades were almost completely eliminated.

However, groups rarely outperform their best members (Gigone & Hastie, 1997; Hastie, 1986; Hill, 1982; cf. Steiner, 1972). In the most common group "judgmental tasks," involving uncertainty and inconclusive or delayed feedback about the quality of solutions, groups usually perform at about the level of a typical median member. The modest performance of groups in judgmental tasks is surprising on both intuitive and theoretical grounds. For example, Condorcet's (1785/1994) jury theorem (distinct from his voting paradox) implies that if members of a group are individually able to predict an uncertain outcome at a level better than chance, then a group of sincere voters, relying on a majority decision rule, will approach perfect accuracy, as the number of members increases (cf. Austin-Smith & Banks, 1996; Bottom, Ladha, & Miller, 2002; Grofman & Feld, 1988; Nitzan & Paroush, 1985; Young, 1988). Thus, in theory, the majority rule is a powerful device for amplifying the accuracy of modestly accurate individual judgments. However, decades of research by social psychologists have provided explanations for the less-than-ideal performance of most social groups. "Process loss" saps the resources provided by individual members through coordination failures (Steiner, 1972), social loafing (Latané, Williams, & Harkins, 1979), groupthink (Janis, 1972; Turner & Pratkanis, 1998), and interpersonal competition (McGrath, 1984).

There have been only a few behavioral tests of the accuracy or adaptive success of group decision rules. The best example of an accuracy test is provided by research conducted by Sorkin and his

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[1] A more dramatic example is provided by the French presidential election in 2002, with nine major candidates, in which Chirac (who won approximately 20% of the popular vote), Le Pen (17%), and Jospin (16%) were the top three candidates. Chirac, the plurality winner, won over Le Pen in a two-candidate runoff election. Though it is probable that Jospin would have easily won over Le Pen in a pairwise election and would have been a strong contender in a two-candidate runoff against Chirac.

colleagues, who studied performance in a visual signal detection task by individuals and small groups with assigned social decision rules (Sorkin, Hays, & West, 2001; Sorkin, West, & Robinson, 1998). Others have manipulated group decision rules in legal decision-making tasks, but these tasks do not permit an analysis of accuracy, as there is no firm criterion for correctness of verdicts (e.g., Davis, Kerr, Atkin, Holt, & Meek, 1975; Hastie et al., 1983; Saks, 1977). In Sorkin's experiments, five- and seven-member groups performed a difficult two-alternative, visual detection task under a simple majority rule, as well as under supermajority and unanimity rules. Groups reliably outperformed individuals, and simple majority rule groups were most accurate on a $d'$ metric for detection sensitivity. However, groups did not perform at the level predicted by an ideal observer model (based on the individual members' levels of accuracy), and Sorkin speculated that some "social loafing" occurred in the groups. In recent theoretical work, Sorkin has argued that the unanimity rule may have advantages when extensive information pooling and deliberation are part of the group decision process (Sorkin, Shenghua, & Itzkowitz, 2004).

Notice that the majority rules introduce an asymmetry into two-alternative decisions when there is a default option ("select 'no signal,' unless a majority votes 'signal'"). Such a default option effectively moves the group decision criterion to more strict levels as the majority quorum increases from simple (one-vote) majority toward unanimity. This means that the types of errors made under the different decision rules are distributed differently between Type I (signal present/no signal present, false alarms) and Type II (no signal/signal present, misses) as the rules change. The $d'$ measure is a useful global accuracy score under these conditions, but it would be a misstatement to say that the simple one-vote majority is most accurate for all possible accuracy scores.

Guarnaschelli, McKelvey, and Palfrey (2000) also tested the accuracy of majority and unanimity decision rules in the context of a simulated jury decision task. Their Bayesian judgment task was an abstract version of the acquit/convict decision addressed by criminal trial juries. Three-person and six-person groups were instructed to infer which of two urns was the source of a sample of colored balls, but the analogy to a jury decision was never made explicit to the subjects. As in Sorkin's signal detection task, the jury decision task creates an asymmetry between the two possible decision options: Innocent (acquit, "presume innocent") is the default, and a quorum (majority or unanimity) is required to defeat the default option and convict the defendant. Thus, accuracy must be assessed conditional on the true state of the world (truly innocent, truly guilty). As might be expected when the true state was innocent (the blue urn had been selected), the unanimity rule had an advantage; when it was guilty, the majority rule had the advantage. Thus, the empirical result is equivocal on the question of global accuracy. Perhaps the most important contribution of the Guarnaschelli et al. study is the result that allowing discussion consistently increased accuracy (straw polls before a final binding vote). Furthermore, their empirical study is an antidote to a previous, controversial article that argued, on the basis of a theoretical model (not behavioral data), that the unanimity rule without discussion was universally inferior to the majority rule (Feddersen & Pesendorfer, 1998).

The present research develops a correspondence-based evaluation of performance accuracy under nine group decision rules (summarized in Table 1). We construct a test bed environment in which simulated groups attempted to choose the best alternative

Table 1
*Nine Group Decision Rules*

| Group decision rule | Algorithm summary | Individual cognitive effort | Social effort |
|---|---|---|---|
| Average winner | Each member estimates the value of each alternative, and the group computes each alternative's mean estimated value and chooses the alternative with the highest mean. | High | High |
| Median winner | Each member estimates the value of each alternative, and the group computes each alternative's median estimated value and chooses the alternative with the highest median. | High | High |
| Davis's (1996) SJS weighted average winner | Each member estimates the value of each alternative, and the group assigns a weighted average value to each alternative (exponential weighting function assigns higher weights to central, shared estimates) and chooses the alternative with the highest weighted average value. | High | High |
| Borda rank winner | Each member ranks all alternatives by estimated value, and the group assigns a Borda rank score to each location (the sum of the individual ranks for each alternative) and chooses the alternative with the lowest (most favorable) score. | High | High |
| Condorcet majority rule | All pairwise elections are held (e.g., 45 for 10 candidates), and the alternative that wins all elections is the Condorcet winner (it is possible for there to be no unique overall winner). | Low | High |
| Majority/plurality rule | Each member assigns one vote to the alternative with the highest estimated value, and the alternative receiving the most votes is chosen. | Low | Low |
| Best member rule | Member who has achieved the highest individual accuracy in estimating alternative values is selected, and this member's first choices become the group's choices. | High | Medium |
| Random member rule | On each trial, one member is selected at random, and this member's first choices become the group's choices. | Low | Low |
| Group satisficing rule | On each trial, alternatives are considered one at a time in a random order; the first alternative for which all members' value estimates exceed aspiration thresholds is chosen by the group. | Medium | Medium |

*Note.* SJS = social judgment scheme.

out of a choice set of 10 alternatives. Members of the simulated groups had judgment policies that enabled each member to estimate a value for each of the 10 alternatives. These individual estimates were then combined with a group decision rule to make a group choice from the set of 10 alternatives. The use of 10 alternatives, rather than a default versus nondefault dichotomous choice, made all of the options equivalent and changed the task from the Sorkin and Guarnaschelli et al. studies of majority rule accuracy. The larger choice set also allowed us to compare the performance of choice rules that would be indistinguishable with smaller (for example, two-candidate) elections.

## Social Choice Theory Analyses of the Goodness of Group Decision Rules

Historically, most theoretical evaluations of group decision rules have focused on preferential conflict resolution and relied on analytical methods to evaluate idealized performance of alternative rules. The focal decision involves differences in individual group members' personal utility functions that lead to conflicting preferences—political elections are the classic example of this situation. Condorcet, Jean Charles de Borda (the other cofounder of modern social choice theory), and other philosophers writing at the time of the French Revolution were concerned with finding a good social choice rule to use in the new French republic. Condorcet favored the simple majority rule, but he discovered that under some conditions, in multicandidate elections, a unique Condorcet majority winner does not exist. Indeed, he showed the majority rule could even produce an intransitive ordering of candidates. Condorcet's "Voter's Paradox" is a demonstration that groups with more than two members who have different but individually rational, stable, transitive preferences could exhibit voting cycles under a majority decision rule. A voting cycle is an intransitivity such that, for example, the group prefers Candidate A over Candidate B, B over C, but C over A; even though any individual member's preferences are completely transitive. Condorcet was disappointed, as he had hoped that a democratic voting system could be proven superior to a monarchy on logical grounds. Instead, he discovered a fundamental flaw in the majority rule.

Voting cycles have been identified in empirical settings, including actual elections and legislatures (e.g., Chamberlin, Cohen, & Coombs, 1984). The paradox was later analyzed extensively by Arrow (1951), who showed that four simple and desirable properties of any democratic system could not be satisfied by any social choice procedure (MacKay [1980] and Saari [2001] provide accessible expositions of Arrow's analysis and its implications; McLean and Hewitt [1994] provide a review of relevant analytical and empirical results).

Although no known voting rule survives the social choice analysis unscathed, there have been many efforts to show that some rules are better than others. Several proofs exist showing the efficacy of the Condorcet majority rule, *if* voters' preferences fit certain constraints. Black (1958) showed that if candidates can be ordered consistently, with different voters' ideal points located on that dimension (each voter's preferences are "single-peaked" on a common dimension, e.g., conservative—liberal for American political candidates), majority cycles will never occur. Sen (1966) proved that more general constraint, "value restriction," on individual preferences would also guarantee no cycles (for every three candidates there is one candidate that no voter ranks in the middle). There are also several empirical studies of actual elections that show potential cycles are rare, given realistic preference orderings of candidates by voters (e.g., Feld & Grofman, 1992; Regenwetter, Adams, & Grofman, 2002; Tsetlin & Regenwetter, 2003).

Another argument in support of the Condorcet majority rule derives conditions under which the rule is likely to produce maxima or equilibriums in a general social welfare function, calculated from individual voters' utility functions. For example, Orbell and Wilson (1978) showed that under certain conditions (e.g., when the opportunity cost of cooperation is low) the majority rule is effective at finding the social welfare-maximizing equilibrium solution. However, these conditions appear to be rare in actual social conflict situations.

In the present analysis, we treat the Condorcet majority rule and the plurality rule as closely related. However, if all possible candidates are considered simultaneously, the plurality rule is a *scoring rule* in that every candidate is assigned a fixed score, based on the number of voters who ranked it first. This means the plurality rule is not subject to intransitive cycles, as is the Condorcet majority rule. However, the plurality rule is sensitive to changes in the composition of the choice set. For example, adding a third, low-popularity candidate can have dramatic effects on the outcome of an election between two much stronger candidates, as witnessed by the Gore–Bush–Nader result in the 2000 presidential election.

Our research demonstrates that in truth-seeking decision-making groups—in which members have generally adaptive, but not perfect judgment policies—the plurality rule is very likely to select the Condorcet winner if one exists; and one almost always does exist. As we see it, the overriding motivation for voters to select the objectively best outcome acts in a similar manner to constraints on the individual preference functions (proposed by Black, Sen, and others; see previous discussion). Constraints such as single-peakedness and value restriction reduce the rate of pathological outcomes for a rule like the Condorcet majority. Similarly, constraints on preferences introduced by adaptive judgment "functions" for members of a group (that is, all the members perceive some glimmer of the true state of the world) make certain forms of preference conflict very unlikely to occur in truth-seeking groups.

## Group Decision Rules

Four of the group decision rules under examination involve the combination of all individual estimates for each alternative into a score, then the decision rule selects the highest rated alternative. We call these "choice *with* group estimation" algorithms: (a) average winner, in which individual estimates are averaged for each alternative and the alternative with the highest average rating is chosen; (b) median winner, in which the individual estimates are combined with a median estimator for each alternative; (c) social judgment scheme winner, in which a weighted average value is calculated for each alternative according to an exponential weighting scheme proposed by Davis (Davis, 1996; Davis et al., 1997); and (d) Borda count winner, in which each member's rank order of

alternatives is input into summation calculation and the value assigned to each alternative is the sum of the individual rankings.[2]

Five of the group decision rules use individual judgments directly, without first computing a group estimate of the value of each alternative. Because it is not necessary for the group to integrate all individual judgments of every alternative before it renders a decision, these rules are computationally more efficient than choice with group estimation rules. We call these "choice *without* group estimation" algorithms: (e) Condorcet majority rule, all pairwise elections are held, and the alternative that wins all elections is selected, if such a winner exists (otherwise one of the alternatives, that received at least one first-choice vote is selected at random); (f) plurality rule, each member votes for their first-ranked alternative, and the alternative with the most votes is chosen (that is, each member is allotted one equal-weight vote, and the decision rule is to select the choice option that receives the most votes); (g) best member rule, the member with the highest individual accuracy over several previous trials is selected as the group leader, and that member's highest rated alternative is selected on each trial; (h) random member rule, a member is chosen at random from the group, and the group choice is governed solely by that member's judgments; and (i) group satisficing rule, a level of aspiration threshold is set based on prior experience in foraging, then alternatives are considered sequentially, one at a time, and the first alternative that all members estimate to be above threshold is selected (several threshold-setting rules were tested, and the most successful, used here, selected the first alternative that was judged to be one standard deviation above the mean payoff value, for all alternatives).

Performance of the nine group decision rules is evaluated by conducting a simulation in which groups make several thousand choices in the simulated environment, and our evaluation is based on the overall success of each rule in selecting the most valuable alternative on each trial. These methods originated in mathematics and engineering (e.g., Fishman, 1996) and were pioneered in the behavioral sciences by Axelrod (Axelrod & Hamilton, 1981); Payne, Bettman, and Johnson (1993); Fiedler (1996); and Gigerenzer (Gigerenzer, Todd, & the ABC Research Group, 1999) in applications to test the adaptive success of individual decision strategies.

## Monte Carlo Simulation Method

### Basic Simulation

First, we describe the basic structure of our Monte Carlo simulation and then introduce systematic variations of its key parameters to provide specific tests of the performance of social decision rules. The simulation world has two major components, *environmental events,* namely the amount of reward (gain or loss) available at various locations, and *foragers,* whose fitness depends on accurate predictions of the environmental events (Toda [1962] was the inspiration for the present application). The state of an environmental event (reward available) is known only probabilistically to perceivers through proximal, partially valid cues, so each individual faces the adaptive task of aggregating uncertain cue information to infer whether environmental locations are likely to be rewarding or punishing.

To illustrate the basic features of our simulation, we rely on the metaphor of a primitive forager seeking sustenance at locations in an uncertain physical environment. This task represents the essential features of the most general decision problem faced by any organism: which option among a set of candidates to choose, given uncertain information about the payoff contingent on choosing each option. There are many modern analogues of this resource search problem, such as choosing among uncertain financial investments, searching for information or a product on the Internet, or seeking a job or a deal in a market (e.g., Adam, 2001; Bateson & Kacelnik, 1998; Giraldeau & Caraco, 2000; Weitzman, 1979). However, more fundamentally, most everyday decisions under uncertainty can be mapped into this task framework. The front-end individual resource judgment part of the model is a direct implementation of Brunswik's general "Lens Model" framework for perception and judgment (Brunswik, 1955; Cooksey, 1996; Hammond & Stewart, 2001). When the number of options (locations) is reduced to two, the task is identical to the multicue judgment problems that have been central in Gigerenzer's research on adaptive rationality (Gigerenzer & Goldstein, 1996; Gigerenzer et al., 1999).

*Structure of the environment.* Suppose there are 10 locations (for foraging) that differ in potential value. It is a fundamental adaptive problem for a band of foragers to choose a profitable location in which to forage in the uncertain environment. As displayed in Figure 1, in the simulation the profitability of a location can be estimated only imperfectly through three proximal numerical cues with different levels of predictive validity (e.g., a forager could make judgments under uncertainty of a location's value on the basis of information about past success, vegetation, weather, predators, and so forth; or about an investment on the basis of information about past prices, price/earnings, company revenue, and so forth). In the basic simulation, we set up the stochastic features of environmental events as follows. We first generated a random number from a normal distribution $N(0, 30)$ and then designated it as location $j$'s ($j = 1 \ldots 10$) resource value, $Q_j$. However, this value cannot be known directly, revealing itself only imperfectly by three proximal cues. These cues were generated by taking each location's true resource value ($Q_j$) and adding normally distributed error to it, creating a cue value composed of true value + error. In the basic simulation, the normally distributed error terms had standard deviations of 10, 30, and 50, and the cues ($C_1$, $C_2$, $C_3$) differed in validity as predictors of the true value of each patch ranging from .50 to .36. to .26 on a percent-variance-accounted-for metric. As shown in the left portion of Figure 1, the optimal linear combination of these cues for estimation (explaining 78% of the variance of $Q_j$) was the following:

$$Q_j = 0.40C_1 + 0.25C_2 + 0.15C_3. \tag{1}$$

Thus, Equation 1 is the best linear representation of the uncertain environment implemented in the basic simulation, providing a statistical ceiling on accuracy in estimates of each location's value.

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[2] The highest ranking or lowest sum wins; for example, suppose there are three members who rank Alternative A, 2nd, 4th, and 5th in a set of 10 alternatives, Alternative A's Borda count would be $2 + 4 + 5 = 11$; (nb, the highest possible ranking count in this example would be 3, which would occur if all members ranked the same alternative 1st). Saari (2001) argues that the Borda count has advantages over other social choice procedures; Black, 1958, provides an historical introduction to the Borda count rule.
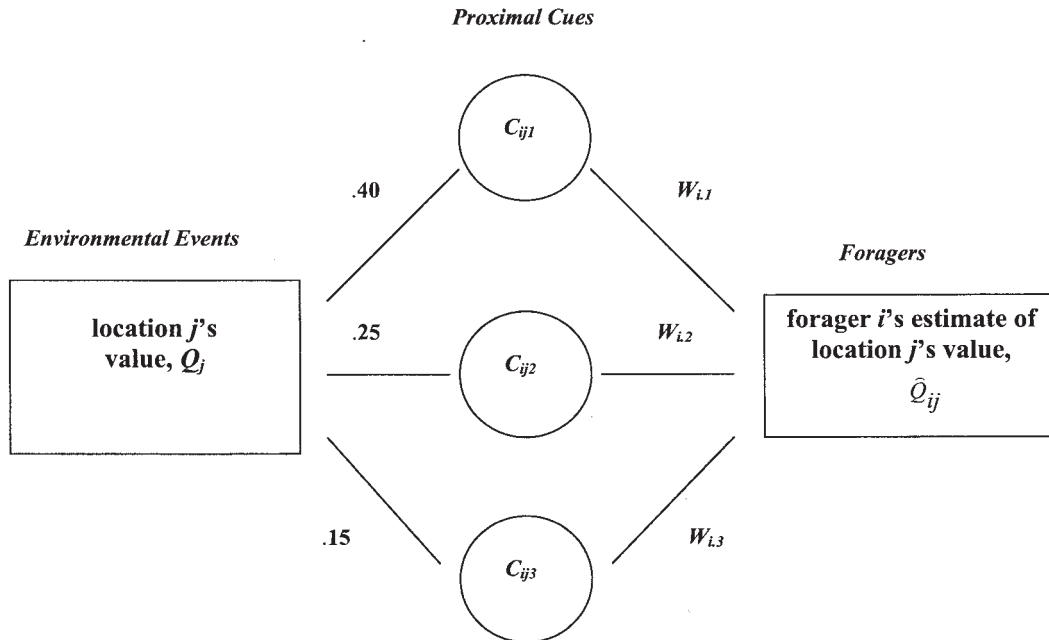
*Figure 1.* Structure of the basic simulation test bed.

*Foragers.* As evident from the discussion above, the *adaptive goal* for each individual "forager" is to combine the cues, in the same manner as the optimal linear combination rule, to yield an estimate of each location's profitability. Such an individual estimation process, called a *judgment policy,* can be represented by how the person weights the three proximal cues to form an estimate. Our simulation implemented this feature by assigning judgment policies to foragers at random as follows (see the right portion of Figure 1). Member $i$'s estimation of location $j$'s profitability is expressed ($i$ = member, $j$ = location, and $k$ = cue)

$$\text{estimated } Q_{ij} = w_{i,1} C_{ij1} + w_{i,2} C_{ij2} + w_{i,3} C_{ij3}, \quad (2)$$

where $w_{i,1}$ is the weight forager $i$ gives to Cue 1 in estimation; $C_{ij1}$ is Cue 1's value revealed to member $i$ about location $j$. Each *perceived* cue value, $C_{ijk}$, has two components: a true value ($C_{jk}$), which is common to all members, plus an environmental-perceptual error ($e_{ijk}$), associated uniquely with each member $i$'s perception of the cue ($C_{ijk} = C_{jk} + e_{ijk}$). The error component, $e_{ijk}$, was generated randomly from $N(0, 20)$ in the basic simulation. Thus, the model allows for perceptual errors—cue values are not perceived veridically—and different judges will make different errors. (One key question in the present research concerns the extent to which different group decision rules damp or correct for unsystematic errors in members' perceptions and judgments.)

Expressing a forager's estimation process as $\Sigma w_{i,k} c_{ijk}$, the most important element is the weighting scheme, the $w_{i,k}$s in the individual forager's judgment policy used to aggregate the three proximal cues. We relied on Dawes's (1979; see also Brehmer & Joyce, 1988) observation that, in judgment under uncertainty tasks such as the one in our simulations, people appear to use simplified linear aggregation rules. Instead of using optimal weights (for example, Equation 1), people judge as though they rely on approximate weights and often on equal weights, getting the predictive "direc-

tion" right, but only approximating relative cue importance. (Dawes [1979] also demonstrated that such "improper linear models" achieve levels of accuracy comparable to optimal linear aggregation rules in many situations; see also Gigerenzer et al., 1999, for analyses of other simplified estimation rules.)

Dawes's conclusion implies that most people would weight the three cues approximately equally in aggregation. On the basis of this reasoning, our simulation used the following procedure in the implementation of $w_{i,k}$s. For each member of the foraging group, we generated three random numbers and then standardized them so that their sum equaled 1. The standardized fractions determined that member's judgment policy. Thus, the modal judgment policy under this procedure is equal cue weighting, (.33, .33, .33), but there is considerable variation in individual cue weighting rules. The important point is that a modal forager's estimates in the basic simulation are not statistically optimal but, on average, are based on equal cue weights.

*Evaluating group aggregation algorithms.* Given a group of foragers who are able to judge each location's profitability, we are now ready to combine these individual estimates into a social choice by means of the nine group decision rules described earlier (see Table 1). To evaluate performance of the group decision rules, we relied on two efficiency indices in the basic simulation. Our first index is the difference in actual profitability between the chosen and the best location on each trial (best location's $Q$ – chosen location's $Q$). This index represents *opportunity loss* (missed profit) accruing from the choice. Our second index is the squared value of the first index; the squared opportunity loss penalizes larger losses more severely relative to small losses. The second index reflects the adaptive principle that a small opportunity loss may be tolerable, whereas a large one is not, which is often the case in animal and human foraging in which a large loss means ruin or even extinction (Bateson & Kacelnik, 1998; Yden-

berg, 1998). Table 2 also reports a third measure based on the percentage of trials on which each group aggregation algorithm correctly chose the best location across the 100 trials. Finally, because of its significance in the traditional social choice analyses, we report a measure of Condorcet efficiency, the percentage of trials on which each rule selected the Condorcet winner (calculated only on trials on which there was a unique winner).

In the basic simulation, each foraging team was given 100 foraging trials. Thus, these performance indices were averaged over the 100 opportunities, yielding a mean per-trial opportunity loss index for each team for the various group aggregation algorithms we tested. We repeated this procedure for 1,000 groups (each with 100 foraging trials) in the simulation and calculated overall average performance for each of the nine group decision rules.

The best member and satisficing rules required special treatment, because both depended on information from performance on the trials to instantiate the rules. The 100-trial block was used to calculate values to select the best member for the best member rule. We simply identified the member with the overall best performance on an individual opportunity loss score and let that member serve as the best member. We calculated individual opportunity loss scores on the basis of each member's highest estimated location on each of the 100 trials; that is, each member's

first choice location's value ($Q$) was subtracted from the best location's $Q$ to calculate the member's opportunity loss index. The satisficing rule-stopping criterion was selected to maximize group performance. Several criterion-setting rules were tried, and the most successful was based on the theoretical standard deviation for the locations' profit values (used to generate profit values by the simulation). The first location encountered, in a random sample sequence, that was estimated to have a value one standard deviation or more about the mean value *by all members*, was selected on each trial. If no location was "satisfactory," a location was chosen at random on that trial (this occurred on less than 3% of the trials).

### Results of the Basic Simulation

Recall that we have two types of group aggregation algorithms, with and without group estimation, differing in the amount of computation required to calculate the group choice. Some algorithms (e.g., averaging, median rule) require groups to aggregate members' individual estimates for each of 10 locations first, before they can yield a final group choice. Other algorithms (e.g., majority rule, best member rule) do not have an aggregation phase and simply operate only on members' first choice preferences (or a limited number of preferences). In the basic simulation, we exam-

Table 2

*Performance of Each Group Decision Rule for the Simulation Test Bed (N = 1,000 100-Hunt Trials)*

| Group decision rule | Opportunity loss | | Squared opportunity loss | | Best alternative picked % | Condorcet efficiency (% picking the Condorcet winner) |
|---|---|---|---|---|---|---|
| | M | SD | M | SD | | |
| *5-member groups* | | | | | | |
| With group estimation (continuous or rank) | | | | | | |
| Averaging | −4.27 | 1.03 | 87.59 | 32.71 | 65.8 | 91.3 |
| Median | −4.73 | 1.08 | 102.22 | 35.85 | 64.8 | 90.0 |
| Davis's (1996) SJS[a] | −6.00 | 1.28 | 146.56 | 48.34 | 62.3 | 82.8 |
| Borda rule | −4.51 | 1.03 | 95.07 | 33.05 | 65.0 | 94.4 |
| Without group estimation | | | | | | |
| Condorcet majority (unique winner only) | −4.43 | 1.10 | 93.54 | 34.69 | 65.7 | |
| Condorcet majority (all) | −4.65 | 1.10 | 99.54 | 35.94 | 64.8 | |
| Majority/plurality | −4.80 | 1.06 | 105.88 | 35.95 | 64.2 | 93.7 |
| Best member | −5.29 | 0.88 | 120.87 | 30.15 | 62.7 | 75.3 |
| Random member | −7.00 | 1.31 | 186.19 | 52.99 | 57.8 | 73.9 |
| Group satisficing | −6.45 | 1.35 | 179.52 | 66.19 | 59.5 | 81.5 |
| *12-member groups* | | | | | | |
| With group estimation (continuous or rank) | | | | | | |
| Averaging | −3.92 | 0.90 | 75.79 | 26.19 | 67.4 | 92.0 |
| Median | −4.13 | 0.94 | 82.23 | 28.34 | 67.0 | 91.4 |
| Davis's (1996) SJS[a] | −4.63 | 1.01 | 98.66 | 33.27 | 65.9 | 87.5 |
| Borda rule | −3.99 | 0.89 | 77.96 | 26.46 | 67.0 | 92.9 |
| Without group estimation | | | | | | |
| Condorcet majority (unique winner only) | −4.02 | 0.90 | 79.33 | 26.80 | 67.0 | |
| Condorcet majority (all) | −4.03 | 0.90 | 79.77 | 27.13 | 66.9 | |
| Majority/plurality | −4.15 | 0.92 | 83.36 | 27.77 | 66.7 | 91.6 |
| Best member | −4.76 | 0.76 | 102.71 | 24.96 | 64.6 | 72.6 |
| Random member | −7.09 | 1.22 | 189.44 | 52.31 | 57.6 | 70.0 |
| Group satisficing | −4.75 | 1.00 | 106.19 | 35.97 | 64.2 | 85.4 |

[a] The social judgment scheme (SJS) estimate is an average of all members' quantitative judgments, with each judgment weighted by its centrality in the distribution of all judgments (see Davis, 1996, for the specific calculations).

ined performances of these decision algorithms for two different group sizes, namely 5- or 12-person groups.

Table 2 displays mean performances of the nine group decision rules. As can be seen from the table, aggregation algorithms with group estimation (top half of the table) tend to perform better than algorithms without group estimation (bottom half) on all measures of performance. It is not surprising that the averaging rule is overall winner on adaptive success measures, as the rule is essentially an additive linear algorithm operating in an environment in which cues to resources are linearly related to true resource values. We report two Condorcet winner evaluations, one calculated on only the trials (97%) in which there was a unique winner and the other calculated across all trials by means of picking a winner from the tied top candidates when there was no unique winner (the second calculation is used in all comparisons with other rules). In general, the more computationally demanding algorithms—averaging, median, Borda, and Condorcet winner—outperform the simpler algorithms.

The plurality rule stands out for its high level of achievement, given its simplicity. This rule is fast and frugal in terms of necessary computations (operating only on members' first preferences), and its performance is comparable to much more computationally demanding algorithms, such as the averaging, median, and Borda rules. It even outperforms the social judgment scheme-aggregation rule, which is a continuous scale analog of majority aggregation (Davis, 1996; Davis et al., 1997). These conclusions hold for both 5-person and 12-person groups.

Another important result is that the plurality rule also beats the best member rule, whose choices adhere most closely to those of the optimal cue utilization equation (Equation 1). Recall that in our simulation, the modal members' judgment policy is a nonoptimal, equal cue-weighting combination rule. The observed superiority of plurality rule to the best member rule is reminiscent of Dawes's (1979) conclusion concerning "the robust beauty of *improper* linear models," but at the group rather than the individual, decision-making level.

The Condorcet winner has been central in analyses of preferential social choice, and it is interesting to observe its performance in an accuracy-based test. It performs quite well, placing third behind the Borda and the ecologically rational averaging rule. It is also instructive to see that the Borda and plurality rules achieve comparable and high levels of Condorcet efficiency, picking the unique Condorcet winner about 95% of the time when there is one.

### Testing the Generality of the Initial Findings

In the following, we vary several key parameters of the basic simulation to systematically examine the robustness of the comparative success of the plurality rule. In this extended simulation, we focus on five of the original nine algorithms (average winner, Condorcet winner, best member rule, random member rule, and plurality rule) and compare their performance under a wide range of simulation parameters. As the two group sizes and the two efficiency measures used in the basic simulation yielded qualitatively parallel results, the extended simulation examines the performance of 12-member groups only on the mean opportunity loss index.

*Cue validity.* A key parameter of the stochastic environment is the degree of predictive validity of three proximal cues for esti-

mating the criterion (profitability of a location). In the basic simulation, we set up the validity of the three cues so that the proportions of variance in the criterion explained by the best cue, the second best cue, and the worst cue were 50%, 36%, and 26%, respectively (Equation 1).

What if we vary the relative validity of the three proximal cues systematically? Are the group decision rules affected differentially by changes in relative cue validity? In the extended simulation, we kept the predictive validity of the best cue constant (explaining 50% of the variance), while changing the validity of the other two cues systematically. Figure 2A displays mean opportunity losses of the four decision rules under different levels of cue validity. The abscissa represents discrepancy in predictive validity between the best and the worst cue in terms of the ratio of explained variance. The 1.9 point on the abscissa corresponds to the original cue structure used in the basic simulation (1.9 = 50%/26%).

Figure 2A shows that, compared with the other two algorithms, the average winner and the plurality rule perform in a similar manner. In a sense, the plurality rule may serve as a computationally economical substitute for the averaging rule in group decision making.

Second, the superiority of the plurality rule over the best member rule, observed in the basic simulation, diminishes and is eventually reversed with increasing differences in cue validity. For example, when the best–worst cue ratio is 3.4 (that is, the worst cue explains only 15% of the variance in the criterion, whereas the best cue explains 50%), the best member rule outperforms the plurality rule. Recall that the best member's judgment policy will be closer to the optimal equation than a modal member's judgment policy. The plurality rule performs at a level closer to the modal member than the best member rule, and the difference between best member and modal member increases as the differences between optimal best cue and worst cue weights increase. Thus, with the increase in discrepancy of predictive validity between the best and worst cues, the best member rule has an increasing advantage over the plurality rule (and average winner rule).[3]

*Performance with incomplete information.* The simulation so far has assumed complete information for each member; each forager had access to information about all three cues for all 10 locations. What if each forager has access to cue information about only a subset of the 10 locations? These incomplete information cases represent the classic rationale for group decisions: If each member has only part of the information necessary to solve a problem and different members have nonshared information, then several heads are almost certainly better than one. To examine this issue, we introduced a new situation in which information on each location was available to each forager with a probability less than unity. Each forager produces estimates for a subset of 10 locations, and the group as a whole must operate on incomplete individual inputs. Figure 2, panels B and C, shows results from two such incomplete information situations, in which the probability of individual accessibility to each location is set at 0.8 or 0.6, (in

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[3] We experimented with other manipulations of the statistical structure of the simulated environment, specifically, manipulating average cue intercorrelations. However, these variations had no effects on the relative performance of the group decision rules, so we do not report them in detail here.
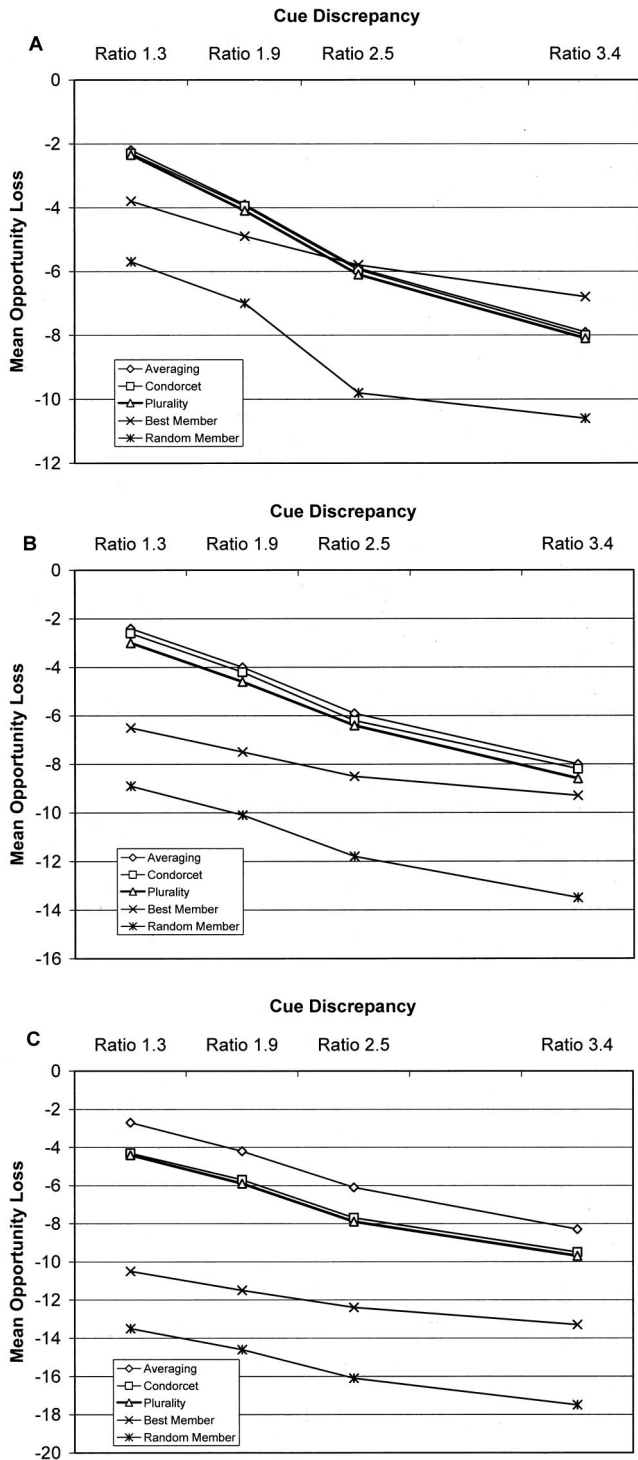
**Cue Discrepancy**



**Cue Discrepancy**



**Cue Discrepancy**



*Figure 2.* Performance of group decision rules as a function of judgment cue validity (cue discrepancy; best/worst cue ratio in terms of explained variance). A: Complete information, $p = 1.0$. B: Incomplete information, $p = .08$. C: Incomplete information, $p = .6$.

other words, on average, each member has information only about 8 or 6 of the full choice set of 10 locations).

First, compared with the other two decision rules, the average winner, plurality, and Condorcet winner rules behave very similarly under incomplete information conditions. Second, missing information has a larger detrimental impact on the best member rule than on the plurality rule. Compared with the complete information case (see Figure 2A), the best member rule degrades rapidly with increases in missing information, whereas the plurality, Condorcet winner, and the average winner rules are affected only slightly. This implies that the plurality rule performs the information-pooling function effectively at a collective level by relying on foragers' first preferences. Finally, however, when information becomes very incomplete (0.6 levels), the voting rules (plurality, Condorcet winner) fall behind the ecologically rational averaging rule. It is obvious how the averaging rule serves such an information-pooling function statistically, but the fact that the same result can be achieved by the far simpler majority algorithm is important and nonobvious. Again, this illustrates that the plurality rule can serve as a computationally efficient substitute for the averaging rule in group decision making under uncertainty.

*Distributions of resources in the environment.* In the original simulation, we generated locations' profitability values randomly from a normal distribution. Normality is a reasonable first hypothesis about actual uncertain environments, but what if the profitability distribution is skewed? The most extreme (and adaptively most challenging) case of a skewed environment would be a "barren" environment in which only one location is profitable, whereas the other nine locations are not. We examined performance of the five aggregation algorithms under such a barren environment, while manipulating the other parameters in the same manner as described above.

The results from previous tests were replicated under the barren environment. Briefly, the averaging rule and the plurality rule function in a similar manner. The plurality rule (and the averaging rule as well) beats the best member rule, as long as discrepancy in cue validity is not extreme. Furthermore, incompleteness of information enhances the superiority of the plurality rule over the best member rule even more dramatically in the barren environment than it does in the richer environment. In a barren environment, incomplete information is often fatal to the functioning of the best member rule, whereas it is less detrimental to the plurality rule.

## A Behavioral Study of Nominal Groups of Human Decision Makers

The computer simulation studies supported our hypothesis that the plurality rule is both economical in computational terms and achieves high levels of accuracy in adaptive group decision making under uncertainty. This result is in line with the empirical finding that majority aggregation can often summarize actual group decision outcomes well, especially when some uncertainty is associated with the decision and/or task environment (see Kameda, Tindale, & Davis [2003] for a review of group decision-making studies conducted in industrialized societies such as the United States and Japan; see Boehm [1996] for a review of ethnographic data on group decision making in primordial societies).

Although these two lines of findings converge nicely under the adaptation theme, there still remain some gaps between our com-

puter simulation results and the empirical group decision-making literature. One important limit may derive from the artificiality of individual judgments used in our computer simulation. In the simulation, we generated individual judgments using a Brunswikian framework to evaluate various group aggregation algorithms. Our method of generating individual judgment policies ($w_{i,k}$'s in Equation 2) was inspired by an empirical finding in behavioral decision making, yet artificiality in simulating the individual judgment process may have biased our conclusions. It would be desirable if we could use *actual* individual judgments under uncertainty as inputs to group decision making algorithms. For this reason, we collected data from human research participants who actually made a series of judgments and choices under uncertainty. We then formed nominal groups by resampling individuals from this data set and compared the performance of four group decision rules in the same manner as in the Monte Carlo simulations. It is important to note that we did not study actual interacting groups; rather we used individual human judgments in place of our individual judgment simulation and relied on computer-created nominal groups to study the effects of alternate group decision rules.

## Collection of Behavioral Data

*Participants.* Participants were 129 (82 male and 47 female) undergraduate students enrolled in introductory psychology classes at Hokkaido University, Hokkaido, Japan. Participants were paid contingent on their performances in the experiment ($M = 382$ yen, $SD = 200$ yen; approximately 120 yen $= \$1$ US).

*Experimental task.* The experimental task was based on the Brunswikian framework used in the computer simulations. Participants made a series of judgments and choices under uncertainty in which the state of environmental event (profitability of a company) was known only stochastically by means of three statistical cues. Two kinds of environmental structure were created: one with a small cue-validity discrepancy and the other with a larger discrepancy. The former is the original environment implemented in the basic Monte Carlo simulation in which the ratio of the best and worst cues in terms of explained variances was 1.9. The latter is one of the environments examined in the extended simulation in which the best and worst cue ratio is 3.4. (The best linear representation of this second environment is given by $Q = 0.50C_1 + 0.20C_2 + 0.10C_3$.) The two environmental structure conditions were introduced to verify that cue discrepancy had the same impact on performance of group aggregation algorithms based on human judgments as had been observed in the Monte Carlo simulations (cf. Figure 2A).

*Procedure.* The experiment was run individually on laboratory computers. On arrival, participants were randomly assigned to one of the two cue conditions mentioned above (low cue discrepancy vs. high cue discrepancy). The experiment had three phases. In the first phase, participants were asked to choose the "most profitable company" out of 10 on the basis of three statistical cues provided for each company (analogous to forage "locations" in the original simulation). As in the simulation studies, perceived cue values for each company could be different for each participant because of perceptual errors, although true cue values were held identical across participants. Participants were told that their experimental payment would be contingent on choice accuracy.

There were 50 such choice trials in total. After each choice, participants were informed whether the choice was correct, along with their cumulative reward up to that trial.

In the second phase, we asked participants to report on their judgment strategies used to integrate cue information during the first phase. Five strategy alternatives were provided: equal cue weighting (Dawes, 1979); take-the-best strategy (Gigerenzer et al., 1999); weighted additive (regression) strategy; configural weighting (e.g., Mellers, 1980); or any other strategy described by the participant. In all experimental conditions, the most common strategy was described as equal cue weighting, followed by unequal-weight regression-like additive rule, and then configural-weighting rules. Among the explicit responses offered to participants, the take-the-best strategy was selected least frequently.

In the third phase of the experiment, participants were provided only one company's cue information on each trial and asked to estimate its profitability numerically. There were 30 such estimation trials. Participants were again instructed that their experimental payment would be contingent on the accuracy of their estimates (no performance feedback, however, was provided during the estimation phase).

## Nominal Group Analysis

With the individual human judgment data, it is now possible to evaluate performance of the group decision rules by forming nominal groups. Here, we focus on individual *choice* data collected in the first phase of the behavioral experiment. For each of the two cue conditions, we randomly composed 1,000 nominal groups by a resampling procedure and evaluated performances of three aggregation algorithms: the plurality rule, the best member rule, and the random member rule. To reduce participants' cognitive load, we did not ask them to provide profitability estimates for 10 companies in the initial choice phase. Instead, we asked only for their top preferences on each of 50 trials. (As individual, per-company judgments are not available, the average winner cannot be implemented in this analysis.)

Figure 3, panels A and B, displays results of the nominal group analysis (5-person groups and 12-person groups, respectively) in the small cue-discrepancy environment. Recall that participants made 50 choices over time. In Figure 3, we summarized these 50 choice opportunities into 10 blocks and plotted mean performance of the group decision rules for each block.

It is obvious that participants improved in accuracy over time. For example, in 5-person groups (see Figure 3A), mean opportunity loss by the random member rule (a benchmark strategy of randomly picking one member's individual preference as the group's choice) was reduced from $-10.6$ in the first block to $-3.8$ in the last block.

How did such individual learning in the uncertain environment affect performances of the plurality rule versus the best member rule? As can be seen from Figure 3A, the superiority of the plurality rule to the best member rule was firmly established in the early trial blocks. After the second block, the plurality rule yielded a smaller mean opportunity loss than the best member rule, except for turbulence in Block 8. This tendency is accentuated in 12-person groups, as shown in Figure 3B. These patterns replicate the results of the Monte Carlo simulation (see Table 2).
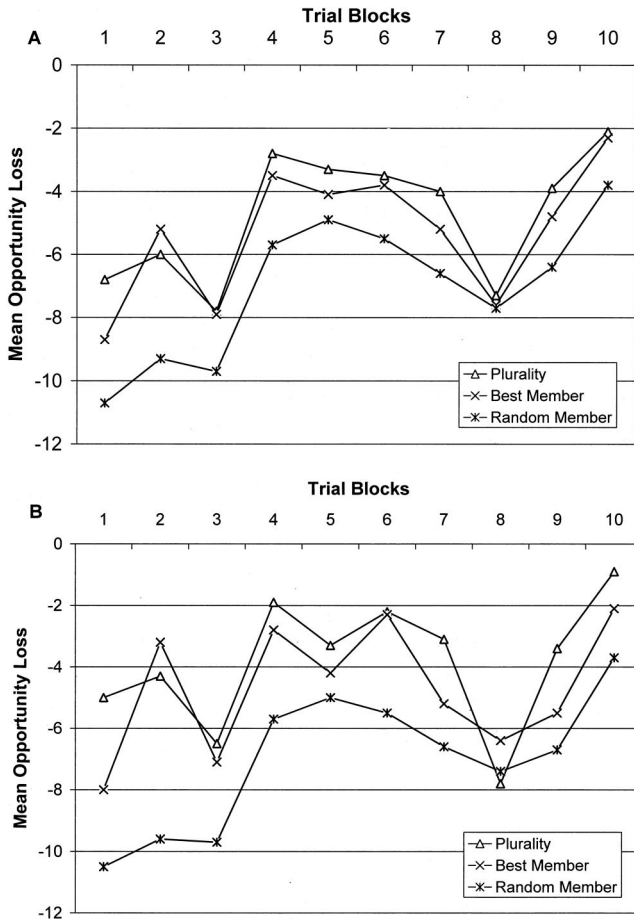
*Figure 3.* Performance of nominal decision making groups as a function of experience making judgments in a small cue-discrepancy environment. A: 5 members. B: 12 members.

most participants reported relying on equal cue-weighting policies. Besides calculating subjective self-reports, we also calculated a quantitative judgment policy for each participant by regression analysis of the estimation data collected in the last phase of the experiment. Average beta weights, summarizing impact of the three cues, were .31, .25, and .26 in the small cue-discrepancy environment and .22, .30, and .26 in the large cue-discrepancy environment. These patterns were statistically different from the optimal linear regression weights but indistinguishable from an equal cue-weighting rule. Together with the parallel performance patterns of group aggregation algorithms described earlier, these results provide more empirical evidence for the plausibility of the assumptions underlying our Monte Carlo simulation.

## General Discussion

The Marquis de Condorcet initiated a long-running evaluation of the quality of majority rule decisions with two monumentally important conclusions. The bad news was stated in his voting paradox: The majority rule cannot satisfy absolutely elementary criteria for coherent, decisive social choice procedures. The good
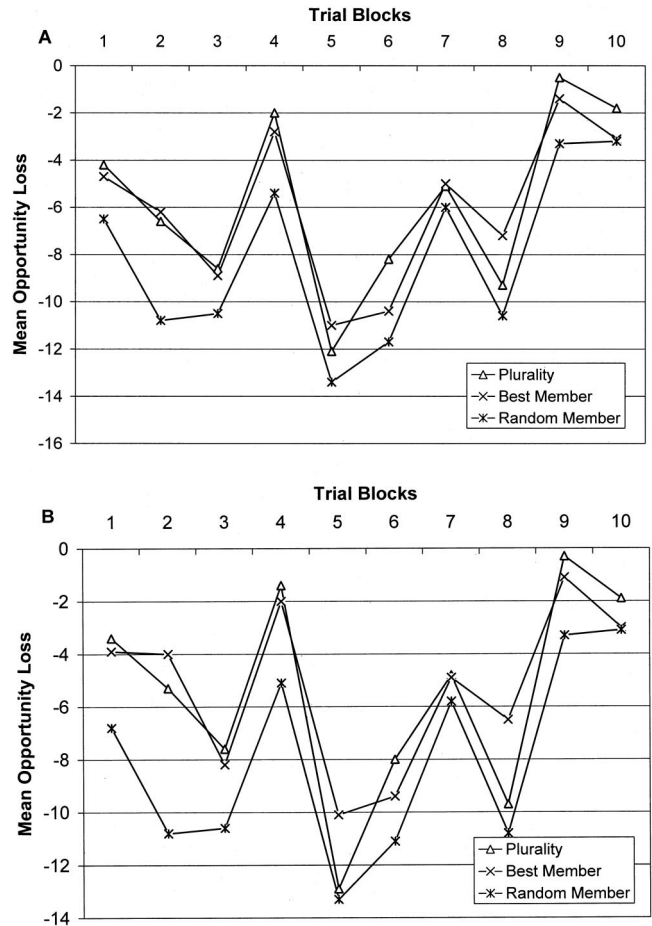
We next turn to the large cue-discrepancy environment. Figure 4, panels A and B, displays results of a nominal group analysis. As can be seen from the graphs, performance of the plurality rule and the best member rule was much closer here, in contrast to the small cue-discrepancy environment examined above. The plurality rule outperformed the best member rule in only 6 of 10 blocks. This pattern is again qualitatively consistent with the original simulation results in that the superiority of the plurality rule to the best member rule was gradually lost and could be even reversed in large cue-discrepancy environments (cf. Figure 2A).

### Individual Judgment Policies

The nominal group analysis in which we used actual human judgments yielded results comparable to those we obtained in the computer simulation studies. This suggests that the assumptions underlying our computer simulations approximate the patterns of actual human judgments under uncertainty.

One of the central assumptions in the Monte Carlo simulation was that the modal member judgment policy could be captured by an equal cue-weighting integration process. As noted above,



*Figure 4.* Performance of nominal decision making groups as a function of experience making judgments in a large cue-discrepancy environment. A: 5 members. B: 12 members.

news was stated in his jury theorem: The majority rule can enhance the accuracy of "above chance accurate" group members, and under some conditions, it could approach perfect levels of accuracy. Condorcet and later analysts relied on mathematical derivations of the implications of the majority rule to evaluate its usefulness under relatively limited conditions. What is new in the present analysis is our use of a stochastic simulation method that yields new results concerning the comparative accuracy of the majority rule and its robustness across variations in environmental conditions.

Both computer simulations and a nominal group analysis that used actual human judgments revealed that, among frugal algorithms, the plurality rule is adaptively the most efficient across a wide range of environmental variations. Two comparisons, in particular, provide strong evidence for the "robust beauty of majority rule."

## Plurality Versus Averaging

First, the plurality rule and the average winner strategy consistently performed in a similar manner, even though the underlying computations are very different for the two algorithms. Variations of key parameters in the simulation, such as discrepancy in cue validity, degree of information completeness, skewness in environmental events, and different group sizes had essentially the same effects on the performance of both aggregation rules. Although at a computational level averaging and plurality voting are obviously different, at an abstract level they share some performance characteristics. Both have an additive character in that every member's contribution is summed up in the central aggregation process. The plurality rule precedes the summation with an individual "winner take all" computation that puts all the weight on the favored alternative. This could be viewed as a weighted-average-like computation, but with extreme weights (0s and 1s). While the first-step computation in the average winner strategy is an equal-weight calculation, the similar performance of the two rules leads us to emphasize the analogical correspondence between them.

One essential functional similarity that leads the two rules to mimic one another is that both effectively "cancel out" random errors in the environment. To illustrate, suppose for the moment that individual judgment policy is optimal as expressed in Equation 1. Then, as long as environmental and perceptual errors are unsystematic, averaging of individual *estimates* provides an unbiased estimate of the true target value (profitability of a location in the foraging domain). The same error cancellation function is also served by the plurality aggregation of individual first preferences, as unsystematic errors that happen to bias one member's preferences are unlikely to be shared with others members. Thus, unsystematic perceptual errors can be reduced by both rules, though the error-reduction process occurs on different levels of measurement for the two procedures (at an interval scale level for the average winner vs. at an ordinal scale level for the plurality rule).

Another, less obvious functional similarity between the two rules involves the information-pooling function. Both the average winner and the plurality rule were only slightly affected by missing information. Even if a substantial amount of information was missing, both rules did not degrade much, compared with other rules (see Figure 2, panels B and C). Under the average winner rule, such robustness against missing information is readily understandable. Even when information about a candidate is missing for some members, the mean of individual estimates still provides a reliable, unbiased estimate of the target value (location profitability). The average winner rule effectively pools whatever information is available to members. Our finding that a similar information-pooling function is achieved by the plurality rule, which operates only on members' first preferences, is not intuitively obvious and is theoretically and practically important.

Given these essential functional similarities, plurality aggregation serves as a computationally more frugal substitute for averaging in group decision making under uncertainty. Whenever averaging yields an adaptive group choice, the plurality rule serves as its fast-and-frugal counterpart.

## Plurality Versus Best Member

In most actual decision-making situations, usually the group aggregation algorithms *with* group estimation are impractical in terms of procedural costs; choice strategies that are cognitively less demanding are the only viable options in many situations. The plurality rule and the best member rule are the most representative social decision rules in the world of practical decision making. Indeed, in the social choice tradition (Arrow, 1951; Mueller, 1989), the two rules are pitted against each other (as democratic vs. autocratic regimes) in terms of logical coherence. However, how do these two rules compare from an *adaptive* perspective? This question could be answered analytically, if no environmental uncertainty were involved in the decision setting (some example derivations are available from the authors). However, in an uncertain environment, as represented by the Brunswikian framework, analytical solutions would be formidable.

Thus, we conducted Monte Carlo computer simulations to systematically vary key parameters. The results showed that, even if modal members' judgment policies were nonoptimal in the statistical sense, the plurality rule outperformed the best member rule under a wide range of parameter values. The only exception to this observation is in a complete-information case in which the cue discrepancy is quite high. Under these conditions, the best member rule yielded substantially better performances than the plurality rule (see the 3.4 point in Figure 2A). However, we believe that this reversal may be of little significance in real decisions. First, as we discussed earlier, the assumption of complete information is usually violated in the everyday world. As is evident in Figure 2, panels B and C, the plurality rule performs well under incomplete information conditions, consistently outperforming the best member rule.

Our simulation assumed that individual judgment policies were unresponsive to the environmental cue structure, with the modal policy being equal cue weighting. However, this assumption may be unrealistic if the discrepancy in cue validities is extreme. Individuals do recognize dramatic differences in cue validities and should adjust their judgment policies to unequal weight algorithms. For example, what if modal individuals shift their policy from equal cue weighting to take-the-best strategy? Under the large cue discrepancy conditions, the take-the-best strategy is close to the statistically optimal linear combination (cf. Gigerenzer et al., 1999). Then, the plurality rule, which is good at handling unsystematic errors, should perform close to the best member rule.

Indeed, nominal group analysis using actual human judgments provided some support for this speculation. Even in the large-cue discrepancy condition (corresponding to the 3.4 case in Figure 2A), the plurality rule performed as well as the best member rule. This suggests that the adaptive efficiency of the plurality rule may be even more robust in actual decision making than in our simulations.

### The Condorcet Majority Winner

The Condorcet winner has been central in social choice analyses of the performance of group decision rules. It is not a practical rule; we know of no actual decision-making groups that attempt to apply it, but it has served as the standard against which other voting and scoring rules have been measured, in theory and in practice of political elections (cf. Regenwetter, Adams, & Grofman, 2002; Regenwetter, Marley, & Grofman, 2002). Our simulation provides a first test of its performance against an accuracy criterion, and it fares well, being beaten only slightly by the Borda and averaging rules. It is also instructive that the Borda and plurality rules track the behavior of the much more computationally demanding Condorcet winner calculations, matching it on approximately 95% of the trials in which there was a unique winner.

### Conclusions

In this article, we have explored the performance of fast-and-frugal group decision rules with stochastic simulations and a nominal group analysis under a Brunswikian model of the environment-judgment system. Although we believe that the Brunswikian framework is a useful research paradigm to represent key features of decision making under uncertainty, the paradigm can be enriched further by incorporating other adaptively critical environmental elements. One such element may be environmental instability. For example, the archeologist Potts (1996) argued that ecological instability, including climate changes, fluctuations in food sources, and other survival-relevant conditions, was a fundamental condition of early hominid evolution. Environmental instability is also an essential feature in the modern society, in which technologies, economies, and cultures are changing rapidly.

The present study assumed an uncertain but stationary environment. However, if temporal instability of the environmental structure is indeed realistic and adaptively significant, we need to systematically study these conditions. For example, if the environmental structure changes over time, an individual judgment policy effective at time $t$ may be maladaptive at time $t + 1$. Such instabilities will provide a challenging test for the adaptive value of the majority rule. How various group decision rules will perform in unstable environments is an open question. Is a majority rule still adaptive in an uncertain and nonstationary environment (cf. Boyd & Richerson, 1985; Henrich & Boyd, 1998; Kameda & Nakanishi, 2002, 2003)? How is individual learning reflected in group adaptation to environmental shifts (Busemeyer & Myung, 1992; Camerer, 1999; Massey & Wu, 2003)?

Another theoretical issue concerns motivational aspects in group decision making. In this article, we focused only on cognitive aspects of decision making and assumed no special role for members' motivation; we essentially assumed that members are equally motivated to provide good individual estimates. Although this assumption is reasonable in individual decision making in which one's fate is contingent solely on one's own decisions, it may not always be the case in group decision making. When individuals' inputs are pooled collectively, "social loafing" in which some members free ride on others' efforts often degrades group performance. In the context of group decision making, members' involvement in exhaustive information search and demanding deliberations may not be guaranteed. What happens to group performance if we add individual information search and voting costs to the social decision system (Kameda & Nakanishi, 2002, 2003; Kameda, Takezawa, & Hastie, 2003)?

One of the most fundamental problems in social decision making is the question of how to aggregate people's judgments or preferences into a collective choice. Social choice theorists (Arrow, 1951; Mueller, 1989) have approached this issue from the logical perspective; a group aggregation rule that potentially yields logical incoherence (e.g., intransitivity, deadlocking) in decisions is regarded as unacceptable. In contrast, we took an adaptive perspective in evaluating group decision rules and found that the majority rule, although not perfect in terms of logical coherence (e.g., Condorcet voting paradox), nonetheless supports robust adaptively viable decisions under uncertainty. Perhaps, the "robust beauty of the majority rule" explains its wide popularity in modern as well as primordial societies. When exploring the Northwest Territory in 1805, Captain Clark used the majority rule to decide where to set his winter camp (Ambrose, 1996; Moulton, 2003). Everyone in the expedition, including servants and native guides, had an equal vote in the majority rule decision. This social choice procedure may have been adaptive as well as fitting the democratic ideals he cited in his personal diary of the expedition.

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