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# The use of recognition in group decision-making

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**Abstract**

Goldstein and Gigerenzer (2002) [Models of ecological rationality: The recognition heuristic. *Psychological Review*, *109* (1), 75–90] found evidence for the use of the recognition heuristic. For example, if an individual recognizes only one of two cities, they tend to infer that the recognized city has a larger population. A prediction that follows is that of the less-is-more effect: Recognizing fewer cities leads, under certain conditions, to more accurate inferences than recognizing more cities. We extend the recognition heuristic to group decision-making by developing majority and lexicographic models of how recognition information is used by groups. We formally show when the less-is-more effect is predicted in groups and we present a study where three-member groups performed the population comparison task. Several aspects of our data indicate that members who can use the recognition heuristic are, not in all but in most cases, more influential in the group decision process than members who cannot use the heuristic. We also observed the less-is-more effect and found that models assuming that members who can use the recognition heuristic are more influential better predict when the effect occurs.
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*Keywords:* Recognition heuristic; Less-is-more effect; Majority rule; Lexicographic model

## 1. Introduction

It is an attractive claim that some level of ignorance can help us make more accurate inferences. From a descriptive point of view, this claim may help explain how we can be functional in a world that we know far from everything about. From a prescriptive point of view, the claim suggests that perhaps we should be relieved from the doomed effort of trying to live up

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to standards of knowledge too high for mere mortals. In order to evaluate this claim, Goldstein and Gigerenzer (2002) proposed the so-called *recognition heuristic* as a model of individual inferences based on incomplete knowledge. Our paper proposes and tests various ways of extending this heuristic to groups.

### *1.1. The recognition heuristic in individuals*

Goldstein and Gigerenzer considered the task of an individual wanting to infer which one of two objects has a larger value on a quantitative dimension of interest, or *criterion*. A popular example is when one wants to infer which one of two cities, say San Diego or San Antonio, has a larger population. The recognition heuristic suggests the following way of making such inferences: "*If one of the two objects is recognized and the other one is not, then infer that the recognized object has the higher criterion value*." It is assumed that it is known that the correlation between recognition and criterion value is positive—if it is known that the correlation is negative, then "larger" would be substituted with "smaller." The strength of this correlation determines the accuracy of the recognition heuristic. When the lack of recognition is systematic, rather than random, the recognition heuristic leads to accurate inferences. However, the recognition heuristic can only be applied if an individual recognizes only one of the two objects—it cannot be applied if the individual has knowledge about both objects. As a consequence, recognizing fewer objects can lead to higher accuracy as the following illustrates. Goldstein and Gigerenzer discuss three Parisian sisters that have to compare the population of $N = 100$ German cities and vary on recognition capacity—the youngest sister recognizes 0, the middle sister 50, and the eldest sister 100 cities. Goldstein and Gigerenzer formally showed that, under a condition we detail in the next section, it is predicted that the middle sister makes accurate population comparisons in 68% of all possible cases, while the eldest sister has an accuracy of 60%.

This effect, called the *less-is-more effect*, was also empirically observed. For example, Goldstein and Gigerenzer (2002) asked American and German students to compare the populations of San Diego and San Antonio, along with other pairs of American cities. Whereas two third of the American students answered this question correctly, all German students correctly inferred that San Diego is more populous—for other between-group comparisons, see Gigerenzer (in press) and Ayton and Önkal (1997). How can it be that judges recognizing fewer cities are more accurate? A possible answer is that Americans could not use the recognition heuristic because they had heard of both cities, while many Germans had not heard of San Antonio and thus could use the recognition heuristic.

The less-is-more effect shows that the recognition heuristic is functional. Goldstein and Gigerenzer (2002) also found that the recognition heuristic is descriptive: In 90% of the inferences in which only one city was recognized, the recognized city was inferred to be more populous. People even seem to stick to the recognition heuristic if they received additional information on a high-validity cue that was in conflict with the recognition heuristic: In another manipulation, participants were first provided with examples of large cities with a soccer team and of small cities with no soccer team. In 92% of the comparisons, however, it was inferred that the recognized city with no soccer team was larger than an unrecognized city with a soccer team. Thus, the recognition information could not be *compensated* by the high-validity soccer-team cue—for more evidence see Gigerenzer (in press); for a critique see Oppenheimer (2003).

### 1.2. Why study the recognition heuristic in groups?

Goldstein and Gigerenzer (2002) showed how the recognition heuristic can exploit the structure of information in the environment in order to make inferences with limited time and information. Our study aims at pushing this approach by extending it to a more complex paradigm, that of a *group* of people making inferences. Linking the approach of fast and frugal heuristics to research on group decision-making promises to make a contribution to both fields.

First, studying if and how recognition is used by groups may further our understanding of the recognition heuristic. The study of groups provides a strong test of the proposition that recognition does play a special role in the process of making inferences. Goldstein and Gigerenzer asked whether recognition is applied in a noncompensatory fashion with respect to other cues; we ask whether recognition is applied in a noncompensatory fashion with respect to other individuals. What happens if a group member who can use the recognition heuristic—like one of the German students in the study described above—has to reach a joint decision with other members who—like one of the American students in this study—recognize both objects? Will the group member, who recognizes only one city be always dominated by group members who recognize both cities, or can this member have greater influence in the group decision process?

Second, studying the recognition heuristic in groups may also enhance our understanding of group behavior. The less-is-more effect is an instance of a family of effects in which decision making is improved by not using all available information. These effects have profound implications for reasoning and decision-making theories as well as practical consequences (Hertwig & Todd, 2003). All these effects, however, refer to individuals. In fact, the established claim in group decision-making is that groups make better decisions when they have more information—for a discussion see Reimer and Hoffrage (2003). Researchers in this field have thus tried to find methods that foster the exchange of information in groups (Larson, Foster-Fishman, & Keys, 1994; Stasser, Stewart, & Wittenbaum, 1995). If the functionality of the recognition heuristic and the less-is-more effect also hold in groups, this may help us understand when and how groups can gain from limiting the amount of information they process. Given the difficulty that group members have pooling and integrating a large amount of information (Winquist & Larson, 1998) it is important to understand in which situations frugal heuristics like the recognition heuristic yield reasonable group decisions and to see if these heuristics are actually used by groups.

To summarize, there are three challenges in the task of furthering the understanding of the recognition heuristic and of the less-is-more effect in groups. First, models must be developed that incorporate recognition information in the group decision process. Second, it has to be formally checked if and under what conditions the less-is-more effect is predicted by these models. Third, it has to be empirically tested how well the models predict group behavior. In this study, we are dealing with exactly these challenges.

Specifically, in the next section, we develop models of how recognition information is used by the group—these models make contrasting assumptions about the influence of members that can use the recognition heuristic. All models require that group members have already formed an individual decision first but they differ in how the individual decisions are integrated into one group decision. Note that, in what follows, we assume that the process of making individual inferences is described by the model of Goldstein and Gigerenzer (2002) (see also Appendix A). This model assumes that individuals use the recognition heuristic whenever they can, that is, when they recognize only one object. For a discussion of the relation between the recognition heuristic and the availability heuristic (Tversky & Kahneman, 1973), see Schooler and Hertwig (2004). The model also assumes that individuals guess when they do not recognize either object and that individuals use their general knowledge when they recognize both objects. In line with Goldstein and Gigerenzer (2002) we do *not* assume that no general knowledge is available when one, or no, objects are recognized. The assumption is that individuals do not use any knowledge when they can use the recognition heuristic. Thus, what distinguishes the cases of recognizing only one object and recognizing both objects is that it is assumed that knowledge is used only in the latter case. This knowledge might, or might not, be restricted to name recognition—see also Oppenheimer (2003). These are the assumptions underlying the use of the term "knowledge" in our paper.

## 2. Modeling the impact of group members

How can group members integrate their individual decisions to form a joint group decision on the population comparison task? Dichotomous choice tasks have been extensively studied in psychological research on group decision-making (Hinsz, Tindale, & Vollrath, 1997). This research has revealed that the rule for combining individual inferences that groups prefer depends on task characteristics (Davis, 1992). For example, if a task is *intellective*, that is, if it has a correct solution, which can be demonstrated like in a mathematical task, group behavior often follows a truth-wins scheme, which predicts that the group is correct if one member is correct. In contrast, if a task is *judgmental*, that is, it has no correct solution like when choosing a place to live, or if the correctness can not be demonstrated, groups are more likely to apply some type of a majority rule (Gigone & Hastie, 1997; Laughlin & Ellis, 1986; Sorkin, West, & Robinson, 1998). Because it can hardly be "proven" by any group member what the solution of the population comparison task is, it is reasonable to assume that, in this task, groups integrate individual decisions through a majority rule.

The most common majority rule is a democratic principle that weights individual votes equally and infers that the object with the most overall votes has the highest criterion. According to this simple majority rule, a group combines all individual decisions on the city comparison task irrespective of whether individuals make a recognition-based or a knowledge-based inference. We additionally consider two oligarchic majority rules that model the idea that some members are more influential. Specifically, we also test models which assume that only those individuals contribute to the group decision who (a) can use the recognition heuristic—*recognition-based* majority rule, or who (b) can use knowledge—*knowledge-based* majority rule.

Note that models that use these rules make predictions only when there is no tie among the voters. That is, a group may not always be able to apply these rules. This is a common problem in evaluating psychological models. A model may predict decisions well but may be only applicable to a small number of cases, whereas another model may predict decisions less well but be applicable to more cases. Then, it lies in the eyes of the beholder, which model explains behavior better. In group research, an often used method is to extend models by assuming that groups resolve ties by a proportionality rule (Davis, 1973). In the case of a dichotomous inference task the proportionality rule then reduces to guessing.

When presenting the empirical study, we will report the predictive accuracy of models both with and without guessing. When analytically deriving the models' predictions and relating them to the less-is-more effect, however, we use guessing like in the Goldstein and Gigerenzer model of individual inferences. We do so because the number of inferences for which a decision maker has to guess can strongly affect the predictions for the less-is-more effect. In what follows, we refer to the object inferred to have the larger criterion value by the group as the *group choice*.

*Simple majority rule*: "The group choice is the object inferred to have the larger criterion value by the majority of group members."

The majority of $m$ members, which we symbolize by majority($m$) equals $(m + 1)/2$ if $m$ is odd, and $(m/2 + 1)$ if $m$ is even. For example, in a group composed of three sisters where the youngest and middle sisters have inferred that San Diego is larger than San Antonio, while the eldest sister has inferred that San Antonio is larger than San Diego, the group choice is San Diego. Thus, a three-member group is correct if two or three members are correct. And a two-member group is correct if both members are correct or one member is correct and the guess that resolves the tie is correct. We assume that a guess is correct with probability 1/2. It follows that a single individual is equally accurate when deciding alone and when forming a group with an individual with equal accuracy. This is so because, if $q$ is the common accuracy, the accuracy of the group of two members also equals $q^2 + 2q(1 - q)(1/2) = q$. For more than two equally accurate members, however, the accuracy of the simple majority rule increases as the number of group members increases (Condorcet, 1785; Groffman & Owen, 1986, p. 94).

The simple majority rule assumes that all group members, those that are able to use the recognition heuristic *and* those that are not, have the same impact on the group choice. A sister who recognizes both San Diego and San Antonio and somehow infers that San Diego is larger has equal influence with a sister who infers that San Diego is larger because she does not recognize San Antonio. But if, as Goldstein and Gigerenzer (2002) propose, recognition information has a special role in making inferences, it may be that the second sister has more of a say in the combination of individual inferences. On the other hand, it can also be claimed that members who can use knowledge are more influential because they probably have access to more cues in favor of their position and are judged higher in expertise. Thus, data is needed to evaluate these claims.

### 2.1. Modeling the impact of members who can use recognition heuristic

The first model we discuss is a variant of the simple majority rule. In this restricted majority rule, individuals who recognize both or neither object are ignored.

*Recognition-based majority rule*: "The group choice is determined by the simple majority rule applied to these group members who can use the recognition heuristic."

Consider that two sisters recognize both San Antonio and San Diego, and based on their knowledge infer that San Antonio is larger. The third sister recognizes only San Diego. According to the simple majority rule, the group choice is San Antonio. The prediction, however, of the recognition-based majority rule is that the group choice is San Diego. Thus, according to the recognition-based majority rule, just one individual, who can use the recognition heuristic, can overturn a majority.

The implicit assumption of guessing when no member can use the recognition heuristic may be too strong. For this reason, we also tested the following *lexicographic* model, where the group first attempts to combine the inferences of those members that can use the recognition heuristic, and then to combine the inferences of those members that can use knowledge.

*Recognition-first lexicographic model*: "If there are members who can use the recognition heuristic, the group uses the recognition-based majority rule. If no members can use the recognition heuristic, but there are members who can use knowledge, the group choice is determined by the simple majority rule applied to these group members who can use knowledge."

### 2.2. Modeling the impact of members who can use knowledge

We also construct two models that assume that members who can use knowledge are more influential in the combination of inferences than members who can use the recognition heuristic. The first model assumes that only members who recognize both objects have a say in the combination process. The second model assumes that the members who recognize one object enter the combination process if there are no members who recognize both objects.

*Knowledge-based majority rule*: "The group choice is determined by the simple majority rule applied to these group members who can use knowledge."

*Knowledge-first lexicographic model*: "If there are members who can use knowledge, the group uses the knowledge-based majority rule. If no members can use knowledge, but there are members who can use the recognition heuristic, the group choice is determined by the simple majority rule applied to these group members who can use the recognition heuristic."

In sum, in addition to a simple majority rule, we developed two restricted majority models and two lexicographic models. None of the models has any free parameters. All models, except the simple majority model, are noncompensatory and predict that just one individual can overturn a majority. Models, however, differ in which individuals are assumed to have a larger influence in the combination process. Before we test the models empirically, we derive their predictions for the less-is-more effect.

### 2.3. When is the less-is-more effect predicted?

We first define the less-is-more effect—Table 1 lists all relevant symbols. Let $\alpha$ be the *recognition validity*, that is, the probability of a correct inference given that an individual uses the recognition heuristic, and $\beta$ be the *knowledge validity*, that is, the probability of a correct inference given that the individual uses knowledge. Let $f(n)$ be the accuracy as a function of the number of objects recognized, $n$, out of the total number of objects $N$, when $\alpha$ and $\beta$ are fixed—an equation that specifies $f(n)$ is provided in Appendix A. The less-is-more effect is defined as the situation in which there exist $n_1$ and $n_2$ so that $n_1 < n_2$ but $f(n_1) > f(n_2)$. That is, less information ($n_1$) leads to higher accuracy than more information ($n_2$). We call *prevalence*, *p*, of

Table 1
Interpretations of symbols

| Symbol | Interpretation |
|---|---|
| $N$ | Number of objects in population |
| $n$ | Number of objects recognized by a fixed group member |
| $\alpha$ | Recognition validity of fixed group member |
| $\beta$ | Knowledge validity of fixed group member |
| $f(n)$ | Accuracy of fixed group member recognizing $n$ objects, using $\alpha$ and $\beta$ |
| $m$ | Number of group members |
| $p$ | Prevalence of less-is-more effect |
| $g(n)$ (only in Appendix A) | Accuracy of group where each member recognizes $n$ objects and has same $\alpha$ and $\beta$ |

the less-is-more effect the proportion of pairs $(n_1, n_2)$ with $n_1 \neq n_2$ for which the less-is-more effect occurs. The prevalence of the less-is-more effect varies between zero for increasing $f(n)$ and unity for strictly decreasing $f(n)$.

Goldstein and Gigerenzer (2002) discuss the special case of $n_2 = N$, which we call the *strong* less-is-more effect. In the strong less-is-more effect, full recognition information ($N$) is less accurate than partial recognition information ($n_1 < N$). Goldstein and Gigerenzer showed that a necessary and sufficient condition for the strong less-is-more effect for individuals is that the recognition validity is larger than knowledge validity. As an example, they discuss three Parisian sisters that have to compare the population of $N = 100$ German cities. All sisters have $\alpha = .8$ and $\beta = .6$, but they vary on the number of recognized objects: The youngest sister has $n = 0$, the middle sister has $n = 50$, and the eldest sister has $n = 100$. Because $\alpha > \beta$ the strong less-is-more effect is predicted: for the middle sister, $f(50) = .68$, while for the eldest sister $f(100) = .60$. Accuracy for $\alpha = .8$ and $\beta = .6$, interpolated for all $n$, is graphed on Fig. 1.

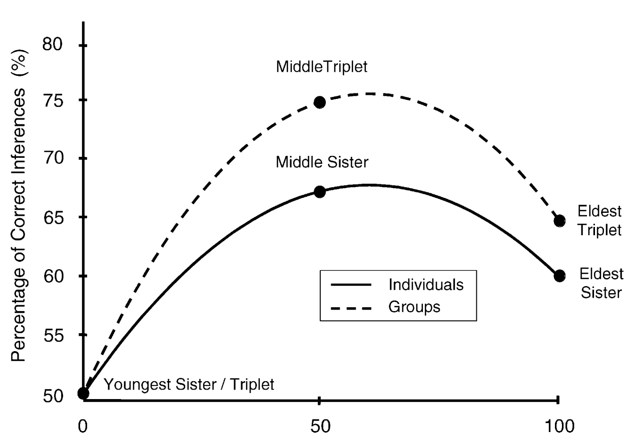


Fig. 1. Predicted accuracy of Parisian sisters and of Parisian triplets that use the simple majority rule, as a function of the number of cities recognized, $n$. All sisters have $\alpha = .8$ and $\beta = .6$ and all sisters in a triplet have the same $n$.

The prevalence of the less-is-more effect for individuals depends on both $\alpha$ and $\beta$. For $\alpha = .8$ and $\beta = .6$, enumeration of all possible cases yields $p = 1/3$. In Appendix A, we formally show that $p$ increases as $\alpha$ increases or $\beta$ decreases and that $p = 0$ if $\alpha \leq \beta$ as long as it is assumed that $\alpha$ and $\beta$ are larger than 1/2.

Fig. 1 also includes the curve of accuracy for *triplets* of girls when their inferences are combined according to the simple majority rule. All three girls in a triplet have $\alpha = .8$ and $\beta = .6$ and equal $n$, that is, triplets are *homogeneous*. On the other hand, $n$ varies from 0 to 100 across triplets. It is also assumed that the recognition and inference processes of any girl are *independent* of these processes for her sisters. That is, whether one girl recognizes a city or not does not influence whether her sisters recognize this city, and which one of two cities one girl infers to be larger does not influence which one of the cities her sisters infer to be larger. Assume that $n = 0$ for the triplet of the three youngest girls, $n = 50$ for the triplet of the three middle girls, and $n = 100$ for the triplet of the three eldest girls. The middle triplet again outperforms the eldest triplet. The effect is also more pronounced compared to the individual case in the sense that the difference in accuracy is larger, ten percentage points versus eight percentage points. The prevalence of the less-is-more effect again equals 1/3.

Fig. 2 shows the curves of accuracy for the same triplets of girls when their inferences are combined according to the restricted majority and to the lexicographic models. Note that for $n = 0$ the predictions of all models coincide because no city is recognized by any sister and the group guesses. For $n = 100$, the predictions of the two lexicographic models and the knowledge-based majority rule coincide because all cities are recognized by all sisters and the group uses the simple majority rule.

The curve of the recognition-based majority rule is concave and symmetric around $N = 50$ and thus the strong less-is-more effect is predicted. The prevalence of the less-is-more effect

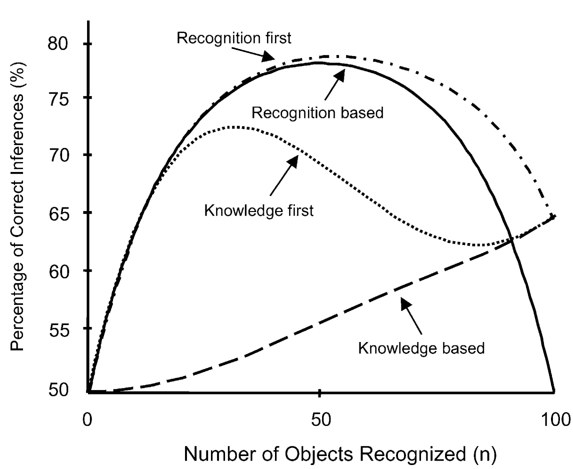


Fig. 2. Predicted accuracy of Parisian triplets that use the recognition-based and knowledge-based majority rules, as well as the recognition-first and knowledge-first lexicographic models, as a function of the number of cities recognized, $n$. All sisters have $\alpha = .8$ and $\beta = .6$ and all sisters in a triplet have the same $n$.

equals 50/101. If the triplet uses the knowledge-based majority rule, the situation is different. The curve of the knowledge-based majority rule is increasing and thus the strong less-is-more effect is not predicted and the less-is-more effect has zero prevalence. More generally, we prove the following in Appendix A.

*Result*: Assume a homogeneous group where the recognition and inference processes of members are independent given criterion. The following statements hold.

(i) If the group uses the simple majority rule, the strong less-is-more effect is predicted if and only if $\alpha > \beta$ and $p$ equals the prevalence of the effect for one member.
(ii) If the group uses the recognition-based majority rule, the strong less-is-more effect is predicted, and $p = N/[2(N+1)]$ for even $N$ and $p = (N-1)/(2N)$ for odd $N$.
(iii) If the group uses the knowledge-based majority rule, the strong less-is-more effect is not predicted, and $p = 0$.

The homogeneity and independence assumptions are not necessary for all parts of this result. For example, the simple majority model can predict the strong less-is-more effect for heterogeneous groups as long as recognition validity is greater than knowledge validity for all members. This prediction can also be derived if independence is replaced with the weaker assumption that all members contribute positively to group accuracy. Note that as $N$ increases, $N/[2(N+1)]$ and $(N-1)/(2N)$ tend to 1/2. That is, when there is a large enough number of objects and the group uses the recognition-based majority rule, the less-is-more effect is predicted half of the time—in practice, $p > .45$ for $N > 10$, and $p \approx 1/2$ for $N = 100$.

The accuracy curves of the lexicographic models in Fig. 2 have more complicated shapes and we do not have general results. We do know, however, that both models predict less-is-more effects, as for example the strong less-is-more effect. For the recognition-first lexicographic model, accuracy is maximized at $n = 53$ and exceeds accuracy at $n = 100$ by fourteen percentage points. For the knowledge-first lexicographic model, accuracy is maximized at $n = 33$ and exceeds accuracy at $n = 100$ by seven percentage points.

Surprisingly, the effect is *more* prevalent when members who can use knowledge are more influential (.64) than when members who can use recognition are more influential (.32). This is driven by the curve of the knowledge-first model decreasing for $n$ between 33 and 53 and the curve for the recognition-first model increasing in this range. This happens because, in that range of $n$, it becomes increasingly more likely that a member recognizes only one rather than two objects; see Appendix A for the relevant formulas. It thus becomes more likely that the group forms a larger recognition-based majority, and this decreases the accuracy of the knowledge-first model and increases the accuracy of the recognition-first model.

## 3. Method

Since Goldstein and Gigerenzer (2002) found that the recognition heuristic described individual inferences well in the population comparison task, we also used this task so that we could study how individual recognition processes interact with group decision processes. The details are as follows.

### *3.1. Participants and compensation*

Ninety participants (forty-six female and forty-four male, mean age of 23.2 years) were recruited from the Free University of Berlin, Germany. Each participant attended two approximately hour-long sessions, one week apart. A fixed amount of eighteen euros was received for participation in both sessions, plus three euro-cents per correct inference made on the second session, with a maximum compensation of 21.15 euros.

### *3.2. Design and procedure*

In the first session, participants were first individually asked which of forty American cities they recognized. These cities are provided in Table 2. The responses allowed us to determine the parameters $n$ and $\alpha$ for each individual. Specifically, $\alpha$ was estimated as the proportion of correct inferences each individual would make if they used the recognition heuristic for all these pairs of cities where only one city was recognized. For example, for an individual who recognized San Diego but not San Antonio, the inference made for this pair of cities would count as correct. Then, participants were asked to perform the population comparison task for all pairs of cities that were both recognized. The parameter $\beta$ was estimated as the proportion of correct responses for these pairs.

The averages of the individual parameter estimates of the first session were $\alpha = .72$ and $\beta = .65$. It is not trivial that we came up with such values for there is no a-priori reason to suppose that the situation $\alpha > \beta$ ever occurs in the real world—only Goldstein and Gigerenzer (2002) have observed this before. We then chose fifteen cities, which are italicized in Table 2, so that the average $\alpha$ (.81) and $\beta$ (.58) of the individuals were as close as possible to .8 and .6, respectively. We chose fifteen cities so that it would be possible to perform the population comparison task on all possible 105 pairs, in one hour.

A test of the less-is-more effect in groups requires groups with approximately equal average $\alpha$ and $\beta$ but different average $n$. For this reason, the eighty-four participants who returned for the second session were grouped into twenty-eight groups of three so that the variability of the average $n$ across groups was reasonably high, $SD = 9.5$, while the variability in the average $\alpha$

Table 2
The forty cities used in the first session; italicized are the fifteen cities used in the second session

| Cities | | | |
|---|---|---|---|
| 1. New York | 11. San Jose | 21. Portland | 31. Oakland |
| 2. Los Angeles | 12. *Indianapolis* | 22. *Oklahoma City* | 32. *Omaha* |
| 3. Chicago | 13. *San Francisco* | 23. Tucson | 33. Minneapolis |
| 4. Houston | 14. *Jacksonville* | 24. Las Vegas | 34. *Miami* |
| 5. *Philadelphia* | 15. Columbus | 25. Long Beach | 35. *Wichita* |
| 6. Phoenix | 16. Austin | 26. Albuquerque | 36. Pittsburgh |
| 7. San Diego | 17. Milwaukee | 27. *Kansas City* | 37. Arlington |
| 8. *Dallas* | 18. *Washington* | 28. *Fresno* | 38. Cincinnati |
| 9. *San Antonio* | 19. *El Paso* | 29. Atlanta | 39. Toledo |
| 10. Detroit | 20. Charlotte | 30. Sacramento | 40. *Raleigh* |

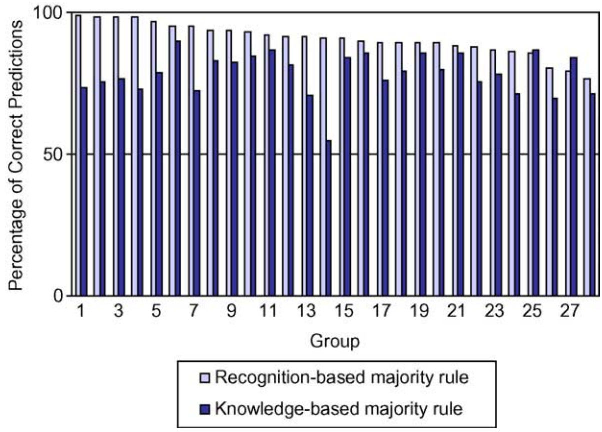


Fig. 3. Match between observed and predicted group choices for the recognition-based and the knowledge-based rules, for each individual group, without guessing. Groups are ordered according to the match of the recognition-based rule.

and $\beta$ across groups was reasonably low, $SD = 5.9$. This procedure allowed us to identify seven pairs of groups that had approximately equal average $\alpha$ and $\beta$ but different average $n$. Two groups were considered having equal average $\alpha$ and $\beta$ if these averages differed by at most .03. This threshold was chosen as the smallest one for which slightly higher averages did not increase the number of pairs.

Groups performed the population comparison task as follows. Members sat around a table so that everybody could see the computer screen where all pairs of cities were presented randomly. Groups discussed and after coming to a joint decision, one group member had to mark the decision on a paper—all members took turns at doing this in a clockwise fashion. Then, the experimenter pressed the corresponding key and the next pair appeared on the screen. There was no opportunity to correct answers afterwards. There was no feedback during this session—or after the first session—but groups were told that three euro-cents would be paid to each group member per correct group choice after the session was over.

## 4. Evaluating the models

How well do the models predict the group choices? Unless stated otherwise, for each model, we averaged, across groups, the number of cases to which the model can be applied. All groups together made a total of $28 \times 105 = 2940$ inferences. The simple majority rule can be applied to 2798 inferences and 84% of its predictions agree with the group choices. Fig. 3 graphs the predictive accuracy of the two restricted majority rules. Groups are ordered according to the predictive accuracy of the recognition-based rule and the bars indicate the percentage of cases in which the group choice matched the prediction of the models when these were applicable. Overall, the knowledge-based majority rule can be applied to 2091 inferences and 78% of its predictions agree with the group choices. The recognition-based majority rule can be applied to somewhat less choices, 1775, but its predictions agree with the observations in an impressive

90% of these cases. Recall that Goldstein and Gigerenzer (2002) found that the recognition heuristic accurately predicted individual choices in 90% of cases as well.

By construction, the lexicographic models can be applied to more choices than the restricted majority rules—the recognition-first model can be applied to 2796 choices and the knowledge-first model can be applied to 2709 choices. Predictive accuracy does not change much with the order by which the group attempts to form a majority. If it is first attempted to form a recognition-based majority, the predictions agree with observations in 84% and this drops to 82% if it is first attempted to form a knowledge-based majority. There were no strong differences in the ease of the items to which the five models could be applied. The average absolute differences in population rank between the two cities of a pair ranged from 5.1 to 5.7 and did not strongly deviate from the average difference of 5.3 for all possible pairs.

If the models are applied to all choices, that is, if guessing is included, choices are described best by the simple majority model (82%) and by the recognition-first (83%) and the knowledge-first (81%) models, followed by the recognition-based (74%) and the knowledge-based rules (70%), which have to guess more often. These predictions overall suggest that some type of majority rule describes well how groups combine individual inferences. The question then becomes *which* members participate in the formation of the majority: those that use the recognition heuristic, those that use knowledge, or both?

Overall, the data was described well by the simple majority rule which resolves ties by guessing and assumes that the group members form their individual inferences as described by Goldstein and Gigerenzer (2002). But, more specifically, the predictive accuracy of the simple majority model is better when majority consists of members that can use the recognition heuristic rather than knowledge. Group choices deviated much more often from the simple majority rule when the majority consisted of members who could use knowledge than when the majority consisted of members who could use the recognition heuristic. Note that these cases are exclusive. Agreement with the majority rule was in 77% of the 1051 choices in which the majority was formed by members who could use their knowledge, and in 96% of the 1379 choices in which the majority was formed by members who could use the recognition heuristic. This behavior is functional since groups were more accurate when the majority consisted of members that could use the recognition heuristic (.85) than when the majority had to base their inference on knowledge (.63).

The above constitute indirect evidence for the following claim: *It is the members that use the recognition heuristic that are more influential in the process of combining judgments*. By analyzing some special cases, we found more direct evidence for this claim—in most of the cases where recognition-based criteria are in conflict with knowledge-based criteria, the recognition-based criteria seem to be preferred by groups.

### *4.1. Do members who can use recognition heuristic have more impact?*

In order to evaluate this claim more directly, we additionally analyzed those cases in which *both* the recognition-based and the knowledge-based models could be applied. For example, both models are applicable when there is one member recognizing both, one member recognizing one, and one member recognizing zero cities. Overall, there are 1023 such cases. In 85% of those cases the two models made identical predictions—this happens, for example, when member(s) who can use knowledge and member(s) who can use the recognition heuristic make the same inference. In these cases the percentage of correct predictions is very high, 94% on the average.

What happens in the 15% of cases for which the two models make contrasting predictions? These 154 cases may be of one of three different types: (a) two members can use their knowledge and one member can use the recognition heuristic—34 cases; (b) one member can use knowledge and two members can use the recognition heuristic—75 cases; and (c) one member can use knowledge, one member can use recognition, and one member has to guess—45 cases. We had a closer look on each of these three types of situations.

#### *4.1.1. Two members can use knowledge*

Consider the situation where two members recognize both cities and infer that a certain city is larger while the third member recognizes the other city. Surprisingly, the single individual seems to *trump* the majority more often than not: In 59% of these cases, the group choice matches the inference suggested by the recognition heuristic. Note that the knowledge-based majority rule and the knowledge-first lexicographic model, as well as the simple majority model, predict 0%. A probability-matching scheme like the proportionality rule would predict 33%. These data are more consistent with the recognition-based majority rule and the recognition-first lexicographic model.

We did, however, also look at these inferences that cannot be predicted by the recognition-based majority rule and the recognition-first lexicographic model. These comparisons do not seem to be more difficult than those that could be accounted by the models: the difference in population rank between the two cities is practically the same—on the average 4.3 for correct predictions and 4.2 for incorrect predictions. Rather, the models fail when one of three particular cities—Jacksonville, San Antonio, El Paso—was an alternative. Some of these cases might mostly reflect an inconsistency with the recognition heuristic as a description of individual inferences, as opposed to an inconsistency with the assumptions on combining those inferences: The city of El Paso was recognized by the single individual but not chosen by the group in six cases. It is plausible that El Paso is recognized as a relatively small city and thus the individual choice is also that El Paso is the smaller city, contrary to the prediction of the recognition heuristic.

#### *4.1.2. Two members can use recognition heuristic*

What happens when two members recognize only one city while the third member recognizes both cities and infers that the city that is not recognized by the other two members is larger? In 76% of these cases the group choice matched the suggestion of the recognition heuristic.

Thus, in agreement with the assumption that members who can use the recognition heuristic are more influential in the combination process, it is not so likely that an individual who can use knowledge overturns a majority of two group members who can apply the recognition heuristic. We, however, also took a closer look at the eighteen cases where this happened. Many of these cases are due to two particular groups making inferences in which two particular cities are involved. Overall, these cases involved only five cities whereas the cases in which the group choice was in accordance with the recognition heuristic referred to eleven cities. Furthermore, just two cities—Fresno and Raleigh—were involved in five cases each. Consistently, nine cases referred to just two groups and one of these groups contributed three Fresno cases and the other group contributed four Raleigh cases.

Inspecting the group discussions suggests that the Fresno and Raleigh cases were extraordinary. For example, when two members recognized Indianapolis but not Fresno, the third member stated that "he was 99% sure that Fresno was more populous." In other cases, arguments were used instead of confidence: An individual who recognized both Raleigh and Oklahoma City managed to convince two members who only recognized Oklahoma City by arguing that Raleigh is a state capital and that it is in the East Coast which is densely populated. Thus, we observed cases, in which recognition was used in a compensatory manner, that is, in which one group member who could use knowledge overturned a majority of two group members who could use the recognition heuristic. However, these cases were rare and restricted to few groups that made inferences on particular cities.

#### *4.1.3. One member can use knowledge and/or one member can use recognition*

In the third type of situation where the recognition-based and knowledge-based models make contradictory predictions, one member recognizes both cities and makes the opposite inference from a second member who can use the recognition heuristic. Also, the third member does not recognize any city. Here, groups chose in accordance with the recognition heuristic in 61% of the cases. We also looked for patterns underlying the 39% of cases in which the group choice agreed with the members who could use their knowledge. However, in contrast to the two situations described before, we did not find any systematic patterns.

What happens if two members recognize zero cities? In a similar vein, if two members did not recognize either city while the third member recognized only one city, the group choice matched the suggestion of the recognition heuristic in 78% of 106 cases. In 27 cases where two members did not recognize any city and the third member recognized both cities, the match between group choice and the choice of the third member dropped to 58%.

In sum, we found that members who can use the recognition heuristic are usually more influential in the process of combining inferences than members who can use their knowledge. First, when guessing was ignored, the predictive accuracy was 90% for the recognition-based rule and 78% for the knowledge-based rule. When guessing was included, these percentages were 74% and 70%, respectively. The differences were smaller for the lexicographic models, but again in favor of the recognition-first as opposed to the knowledge-first model. Note also that the simple majority model described the data better when the majority consisted of members who could use the recognition heuristic than when the majority consisted of members who could use knowledge.

Second, more direct evidence comes from the finding that in the cases in which both the recognition-based and the knowledge-based models can be applied, but make contradictory predictions, the recognition-based model described the data better. Across 154 discriminating cases, the group choices matched the predictions of the recognition-based majority rule almost twice as often as those of the knowledge-based majority rule—65% versus 35%. More specifically, one member who could use recognition heuristic more often than not seemed to win over one member (61%) as well as two members (59%) who could use knowledge, while the reverse pattern occurred less often—39% and 24%, respectively. The final piece of evidence comes from the predictions of the less-is-more effect.

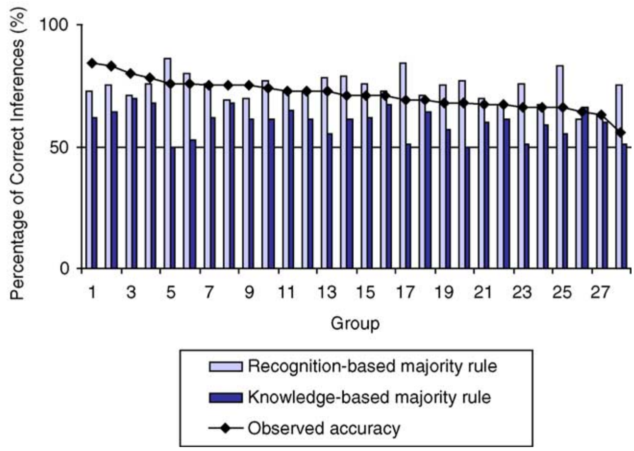


Fig. 4. Observed and predicted group accuracies for the recognition-based and the knowledge-based rules, for each individual group, with guessing. Groups are ordered according to observed accuracy.

### *4.2. Did the less-is-more effect occur and which models capture it?*

The less-is-more effect can be investigated by looking at group accuracies rather than at group choices. Note that these two measures do not necessarily correlate perfectly. For example, assume that there are two choices to be made and the group makes one correct and one incorrect choice. A model that says that the group choice is the opposite from what it actually is has 0% match rate but predicts perfectly the group accuracy of 50%.

On Fig. 4, we graph the observed group accuracies—groups are ordered in decreasing order of these observations. In addition, the figure shows the predictions of group accuracies according to the restricted majority rules—for the formal details of the derivations see Appendix A. On average, the groups made accurate decisions in 71% of all choices. The average of the predictions of the recognition-based models matched this well, from 74% to 77%, while the average of the predictions of the knowledge-based models was lower than observed, from 60% to 64%.

We have seven pairs of groups with approximately equal average $\alpha$ and $\beta$ but different average $n$. As is indicated by the observed accuracies in Table 3, in five pairs the group with smaller average $n$ had higher accuracy. This is the first empirical demonstration that the less-is-more effect occurs in groups.

How well can the models predict when the effect occurs and when it does not? Note that the formal result we stated above does not apply because it assumes homogeneous groups. For example, note that because homogeneity is violated, the knowledge-based rule can also predict less-is-more effects. Thus, we use the predictions graphed in Fig. 4. The recognition-first lexicographic model and the recognition-based majority rule correctly predict whether the effect occurs or not in all seven cases. On the other hand, the knowledge-based majority rule and the simple majority rule make six correct predictions, and the knowledge-first lexicographic model makes five correct predictions.

Table 3
Seven pairs of groups with approximately equal average $\alpha$ and $\beta$

| | Pair | | | | | | |
|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| Average *n* | | | | | | | |
| Smaller *n* | 9.0 | 10.3 | 11.3 | 11.3 | 9.3 | 10.7 | 8.0 |
| Larger *n* | 12.0 | 12.0 | 13.0 | 12.3 | 12.3 | 12.0 | 9.7 |
| Average $\alpha$ | | | | | | | |
| Smaller *n* | .79 | .78 | .88 | .72 | .68 | .79 | .77 |
| Larger *n* | .79 | .81 | .87 | .70 | .66 | .81 | .79 |
| Average $\beta$ | | | | | | | |
| Smaller *n* | .60 | .64 | .64 | .61 | .62 | .58 | .53 |
| Larger *n* | .58 | .62 | .66 | .60 | .64 | .60 | .54 |
| Observed accuracy | | | | | | | |
| Smaller *n* | .83 | .73 | .78 | .67 | .66 | .67 | .56 |
| Larger *n* | .75 | .69 | .75 | .63 | .64 | .73 | .66 |
| Simple majority rule | | | | | | | |
| Smaller *n* | .78 | .78 | .81 | .71 | .69 | .72 | .71 |
| Larger *n* | .73 | .75 | .78 | .68 | .71 | .74 | .79 |
| Recognition based | | | | | | | |
| Smaller *n* | .75 | .73 | .76 | .67 | .67 | .70 | .75 |
| Larger *n* | .70 | .71 | .69 | .63 | .61 | .72 | .83 |
| Recognition first | | | | | | | |
| Smaller *n* | .77 | .77 | .81 | .71 | .68 | .72 | .76 |
| Larger *n* | .74 | .76 | .78 | .67 | .66 | .76 | .84 |
| Knowledge based | | | | | | | |
| Smaller *n* | .64 | .65 | .68 | .61 | .59 | .60 | .51 |
| Larger *n* | .61 | .64 | .68 | .60 | .66 | .61 | .55 |
| Knowledge first | | | | | | | |
| Smaller *n* | .70 | .70 | .70 | .63 | .64 | .64 | .63 |
| Larger *n* | .62 | .65 | .68 | .61 | .67 | .63 | .65 |

Average $n$, $\alpha$, $\beta$, observed accuracy, and predicted accuracies are reported for both groups and all models.

We also considered how well the models capture the magnitude of the effect or its inversion. This is indexed by the sum of absolute values of the differences between observed and predicted accuracies in the two groups. The recognition-first lexicographic model again outperformed the other models, with the index equaling twelve percentage points. The index equaled fifteen, nineteen, twenty-four, and thirty-six percentage points for the simple majority, recognition-based majority, knowledge-first lexicographic, and knowledge-based majority rule, respectively.

## 5. Conclusions

Goldstein and Gigerenzer (2002) investigated how individuals can use the recognition heuristic and exploit the structure of the environment in order to make inferences with limited time and information. We pushed this approach to a more complex paradigm, that of a group of people making a joint inference. In doing so, we developed models of how individual inferences are combined, derived and tested their predictions, and predicted and tested when the less-is-more effect occurs in groups.

What did we learn from this work? First, in analogy to Goldstein and Gigerenzer showing that recognition is applied in a noncompensatory fashion with respect to other cues, we showed that—in most of the cases—recognition was applied in a noncompensatory fashion with respect to other individuals: When both recognition-based and knowledge-based models could be applied but made different predictions, recognition-based criteria captured the group choice in 65% of cases. This behavior was also functional because the groups performed better when their choices matched the prediction of the recognition heuristic. Second, we provided theoretical analyses and empirical data that contradict the established claim in group decision-making that groups always make better decisions when they have more information—see Reimer and Hoffrage (2003) for a discussion. Overall, it appears that the recognition heuristic interacts with group decision-making processes in a way that can again lead to the less-is-more effect, and that this interaction can be modeled in a simple fashion, for example, by the recognition-based majority rule and the recognition-first lexicographic model.

Future directions of this research could investigate the processes by which a group manages to exploit the recognition information. For example, it may be that group members who can use the recognition heuristic when forming an individual decision are more influential in the group decision process because they make their decision faster and are more confident. Moreover, those group members may be at an advantage because they can justify their decision by using a simple but strong argument—one city must be smaller because they do not even recognize the name of this city.

Another future direction could be to investigate tasks other than simple magnitude estimations. The recognition heuristic is a recent model, but there has already been research in domains like sport (Andersson, Ekman, & Edman, 2003) or election forecasting (Zdrahal-Urbanek & Vitouch, 2004).

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## Appendix A

Goldstein and Gigerenzer (2002) have shown that an individual who recognizes $n$ out of $N$ objects can use the recognition heuristic with probability $r(n) = 2n(N - n)/[N(N - 1)]$, knowledge with probability $k(n) = n(n - 1)/[N(N - 1)]$, and has to guess with probability $u(n) = (N - n)(N - n - 1)/[N(N - 1)]$. Thus, the following holds for individual accuracy.

$$f(n) = r(n)\alpha + k(n)\beta + u(n)\left(\frac{1}{2}\right). \tag{1}$$

*Prevalence of less-is-more effect for individuals*: Assuming $\alpha, \beta > 1/2$, we show that $p$ increases in $\alpha$ and decreases in $\beta$ if $\alpha > \beta$ and that $p = 0$ if $\alpha \leq \beta$.

If we let $n$ vary continuously, $f'(n) = [(-4\alpha + 1 + 2\beta)n + (2\alpha - 1)N + 1/2 - \beta]/[N(N-1)]$, and $f''(n) = (-4\alpha + 1 + 2\beta)/[N(N-1)]$. The second derivative is negative for $\alpha > \beta$ and $\alpha > 1/2$ because $-4\alpha + 1 + 2\beta = (1 - 2\alpha) + 2(\beta - \alpha)$. Thus, $f(n)$ is concave with the maximum being achieved at $n^* = -[(2\alpha - 1)N + 1/2 - \beta]/(-4\alpha + 1 + 2\beta)$. Because $f(n)$ is concave, $p$ decreases in $n^*$. Also, $n^*$ decreases in $\alpha$ and decreases in $\beta$, and thus $p$ increases in $\alpha$ and decreases in $\beta$.

If $\alpha = \beta$, the first derivative reduces to $(N - n - 1/2)(2\beta - 1)/[N(N-1)]$, which, if $\beta > 1/2$, is positive for $n < N$, and thus $f(n)$ is increasing and $p = 0$. Increasing $\beta$ also increases $f'(n)$ for $n > 0$, and thus again $p = 0$.

In what follows, assume a homogeneous group with $m \geq 2$ members, each with accuracy $f = f(n)$, where members recognize objects and make inferences independently of each other.

*Proof of main result*.

(i) Let $X$ be the number of individuals that make a correct inference. $X$ is a binomial random variable with parameters $m$ and $f$. For the simple majority model, group accuracy, $g = g(n)$, is increasing in $X$. Thus, for fixed $m$, $g$ increases as $f$ increases because it is more likely that $X$ increases as $f$ increases. It follows that the results for the strong less-is-more effect and the prevalence of less-is-more effects for a single individual also hold for the group.

(ii) Let $R$ be the number of individuals that can use the recognition heuristic, and $X_R$ the number of these individuals that make a correct inference. $R$ is a binomial random variable with parameters $m$ and $r(n)$, and $X_R$ is a binomial random variable with parameters $R$ and $\alpha$.

For the recognition-based majority model, when $m$ is fixed, $g$ is increasing in $r(n)$ since it is more likely that there are more voters when $r(n)$ is larger and the *Condorcet jury theorem* (Condorcet, 1785; Groffman & Owen, 1986, p. 94) states that the accuracy of a majority increases with the number of voters. Note that it is assumed that $\alpha > 1/2$. Furthermore, the strong less-is-more effect is predicted for $r(n) = 2n(N-n)/N(N-1)$ because it is concave and symmetric in $n$. Thus, the strong less-is-more effect is predicted. This prediction does not require $\alpha > \beta$.

Thus, group accuracy $g(n)$ is concave and symmetric in $n$ and, for discrete $n$, achieves its maximum at $N/2$ when $N$ is even and at $(N-1)/2$ and $(N+1)/2$ when $N$ is odd. It follows that, for even $N$, the number of pairs $(n_1, n_2)$ with $n_1 \neq n_2$ for which the less-is-more effect is predicted equals $(N/2) + 2[1 + \cdots + (N/2 - 1)]$. This is so because the number of $n_2$ for which the less-is-more effect is predicted when $n_1 = N/2$, equals $N/2$, and this number decreases by one as $n_1$ increases or decreases by one. Computing this sum, dividing with the total number of $(n_1, n_2)$ pairs, $N(N+1)/2$, and simplifying yields $p = N/[2(N+1)]$. The derivation is similar for odd $N$.

(iii) Similar arguments hold for the knowledge-based majority model. The difference is that group accuracy is now increasing in the probability $k(n)$ that a member can use knowledge, and $k(n) = n(n-1)/[N(N-1)]$ which is increasing in $n$.

In what follows, $c(m, i)$ symbolizes the number of ways in which $i$ objects can be chosen, without replacement, out of $m$ objects, $(m!)/(m-i)!\,(i!)$

*Group accuracy predictions*: Let $F(i)$ be the probability of exactly $i$ members being accurate *and* the group, using the simple majority model, being accurate. Based on the arguments in the proof of ($i$), $F(i) = c(m, i)\, f(n)^i\, (1 - f(n))^{m-i}$ for $i \geq$ majority($m$), except for $i =$ majority($m$) when $m$ is even, in which case $F(i) = c\,(m, i)\, f(n)^i (1 - f(n))^{m-i}(1/2)$. Then the following holds for the group accuracy of the simple majority model.

$$g(n) = \sum_{i=\text{majority}\,(m),\ldots,m} F(i). \tag{2}$$

Group accuracy for the recognition-based majority model is derived similarly. The difference is that first we need to determine the probability that $r$ out of the $m$ members can use the recognition heuristic and then the probability that the majority of these $r$ members make the correct inference. If $A(i)$ is the probability of exactly $i$ members, using the recognition heuristic, being accurate *and* the group, using the recognition-based majority model, being accurate, then $A(i) = c(r, i)\, \alpha^i\, (1-\alpha)^{r\text{-}i}$ for $i \geq$ majority($m$), except for $i =$ majority($r$) when $r$ is even, in which case $A(i) = c(r, i)\, \alpha^i\, (1 - \alpha)^{r-i}(1/2)$. Thus, the group accuracy of the recognition-based majority model is given by the following.

$$g(n) = \sum_{r=1,\ldots,m} [c(m, r) r(n)^r (1 - r(n))^{m-r}] \sum_{i=\text{majority}(r),\ldots,r} A(i) + (1 - r(n))^m \left(\frac{1}{2}\right). \tag{3}$$

The same reasoning applies to the knowledge-based majority rule with $k(n)$ playing the role of $r(n)$ and $\beta$ playing the role of $\alpha$. If $B(i) = c(k, i)\beta^i (1 - \beta)^{k-i}$, except for $i =$ majority($k$) when $k$ is even, in which case $B(i) = c(k, i)\, \beta^i (1 - \beta)^{k-i}(1/2)$, the following holds:

$$g(n) = \sum_{k=1,\ldots,\, m} [c(m, k) k(n)^k (1 - k(n))^{m-k}] \sum_{i=\text{majority}(k),\ldots,k} B(i) + (1 - k(n))^m \left(\frac{1}{2}\right). \tag{4}$$

The equations for the lexicographic models are derived by combining the logic of (3) and (4). For the recognition-first model, there are two events to be considered: first, there are members who can use the recognition heuristic—then, (3) without the guessing term applies—second, there are no such members—then, a version of (4) applies which takes into account that members who cannot use knowledge have to be guessing. The guessing terms for the whole group is adjusted as well since guessing now occurs only if all members guess. Thus, we have the following:

$$g(n) = \sum_{r=1,\ldots,m} [c(m, r) r(n)^r (1 - r(n))^{m-r}] \sum_{i=\text{majority}(r),\ldots,r} A(i) + \sum_{k=1,\ldots,m} [c(m, k) k(n)^k$$
$$g(n)^{m-k}] \sum_{i=\text{majority}(k),\ldots,k} B(i) + g(n)^m \left(\frac{1}{2}\right). \tag{5}$$

The same reasoning applies to the knowledge-first model with $k(n)$ playing the role of $r(n)$ and $\beta$ playing the role of $\alpha$.

$$u(n) = \sum_{k=1,\ldots,m} [c(m, k) k(n)^k (1 - k(n))^{m-k}] \sum_{i=\text{majority}(k),\ldots,k} B(i) + \sum_{r=1,\ldots,m} [c(m, r) r(n)^r$$

$$\times u(n)^{m-r}] \sum_{i=\text{majority}(r),\dots,r} A(i) + u(n)^m \left(\frac{1}{2}\right). \tag{6}$$

Eqs. (2)–(6) were used to generate the idealized curves in Fig. 2. The predictions of the models for the empirical data were generated by similar equations with the observed $\alpha$, $\beta$, and $n$ for each group member—the only differences were due to the parameters varying across members.

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