How can diverse memory improve group decision making?

Hidehito Honda (hitohonda.02@gmail.com)
Department of Psychology, Yasuda Women's University
6-13-1, Yasuhigashi, Asaminami-ku, Hiroshima-shi, Hiroshima, 731-0153, Japan

Itsuki Fujisaki (bpmx3ngj@gmail.com)
Graduate School of Arts and Sciences, The University of Tokyo
3-8-1, Komaba, Meguro-ku, Tokyo, 153-8902, Japan

Toshihiko Matsuka (matsuka@chiba-u.jp)
Department of Cognitive and Information Science, Chiba University
1-33, Yayoi-cho, Inage-ku, Chiba-shi, Chiba, 263-8522, Japan

Kazuhiro Ueda (ueda@gregorio.c.u-tokyo.ac.jp)
Graduate School of Arts and Sciences, The University of Tokyo
3-8-1, Komaba, Meguro-ku, Tokyo, 153-8902, Japan

Abstract

Previous studies have shown that people can make adaptive inferences based on memory-based simple heuristics such as recognition, fluency, or familiarity heuristic. In the present study, we discussed the adaptive nature of memory-based simple heuristics in a group decision making setting. In particular, we examined how the diversity of memory affected group decision making when group members were assumed to make inferences based on the familiarity heuristic. We predicted that, when the group members' memories were diverse, group decision making would become more accurate. To examine this prediction, we conducted a behavioral experiment and computer simulations, and our results generally supported the prediction. We discuss the role of diverse memories in generating adaptive group decision making.

Keywords: group decision making; heuristics; ecological rationality; diversity

Introduction

In research on human judgments and decisions, one of the most studied topics has been the heuristics people use. Previous studies have shown that, although heuristics can produce biases (e.g., Tversky & Kahneman, 1974), they generally result in adaptive judgments and decisions (e.g., Gigerenzer, Todd, & The ABC Research Group, 1999). Some heuristics, such as the availability (Tverky & Kahneman, 1973) or recognition heuristic (Goldstein & Gigerenzer, 2002), are highly related to the nature of an individual's memory. We shall discuss the adaptive nature of memory-based simple heuristics in terms of group decision making.

How do memory-based simple heuristics work in a group decision making setting? Given that individuals can make adaptive judgments and decisions in general based on the memory-based simple heuristics, when each member relies on such heuristics and the group makes a collective decision by, for example, simple majority rule, the group may be able to make good decisions in general. However, as described above, heuristics produce biases. For some situations, biased inferences are enhanced, and group performance may be deteriorated. Thus, although memory-based simple heuristics will enhance group decision making in general, they will also enhance biased group decision making in some cases. Fujisaki, Honda, and Ueda (2018) used computer simulations to show that a group does not always perform well when group members use strategies, which are regarded as generally adaptive in individual usage, because of biases generated by the strategies.

How, then, can the biases of memory-based simple heuristics in a group decision making setting be resolved? Recently, research has discussed how groups can achieve good performance such as wisdom-of-crowds or collective intelligence in terms of group diversity (e.g., Fujisaki et al., 2018; Jönsson, Hahn, & Olsson, 2015; Lorenz, Rauhut, Schweitzer, & Helbing, 2011; Luan, Katsikopoulos, & Reimer, 2012; Mavrodiev, Tessone, & Schweitzer, 2013). In group decision making based on members who use memory-based simple heuristics, if members' memories vary (i.e., memories in group members are diverse), biases generated by heuristics may be resolved.

In the present study, we examined how the diversity of memories in group members works for group decision-making with the following methods. First, we conducted a behavioral experiment about memories of city names. Using these data (i.e., actual memory data), we examined the accuracies of inferences made by hypothetical people who made inferences based on a memory-based simple heuristic. As an inference task, we used binary choice inference problems about population sizes (e.g., "Which city has a greater population size, Tokyo or Chiba?"). For this task, people tend to rely on memory-based simple heuristics such as recognition (Goldstein & Gigerenzer, 2002), fluency (Hertwig, Herzog, Schooler, & Reimer, 2008), or familiarity (Honda, Abe, Matsuka, & Yamagishi, 2011; Honda, Matsuka, & Ueda, 2017; Xu, González-Vallejo, Weinhardt, Chimeli, & Karadogan, 2018). Thus, people's memories will affect the inference processes for this kind of problem. Finally, we constructed a group of such hypothetical people and examined the performance of group decision making.

How can memory diversity be generated? Given that the present study used city names as stimuli, we predicted that constructed memories about city names (e.g., recognitions of or familiarities with city names) were more dissimilar (i.e., diverse) between people in different areas than between those in the same area. Based on this consideration, we recruited participants from two areas (Tokyo and Osaka).

In the following section, we shall report two studies: a behavioral experiment and a computer simulation.

Study 1: Behavioral experiment

We conducted a behavioral experiment about memories of 30 cities in Japan. We examined whether recognitions and familiarities regarding the 30 cities differed depending on the area participants lived in and analyzed the memory diversity.

Method

Participants We recruited participants in their 30s and 50s from two areas, Tokyo and Osaka, with the following definitions: first, they were born in Tokyo (or Osaka); second, they had lived in Tokyo (or Osaka) for more than 20 years in total; and third, they had been living in Tokyo (or Osaka) during the past five years. As a result, we recruited 99 people in their 30s in the Tokyo area (M_{age} = 35.48, SD_{age} = 2.76, n_{female} = 49), 101 people in their 50s in the Tokyo area (M_{age} = 54.74, SD_{age} = 2.51, n_{female} = 50), 99 people in their 30s in the Osaka area (M_{age} = 35.15, SD_{age} = 2.92, n_{female} = 50), and 101 people in their 50s in the Osaka area (M_{age} = 53.92, SD_{age} = 2.89, n_{female} = 51). In total, 400 Japanese participated in the experiment.

Tasks, materials, and procedure We conducted a recognition task and measurement of familiarity. In the recognition task, participants were presented with a city name and answered whether they knew the city. When participants knew the presented city, they were also asked about their level of familiarity with the city. They answered this question using a scale labeled "I know only the name" on the far left and "I know a lot" on the far right. This rating was recorded with 100 points ranging from 1 (I know only the name) to 100 (I know a lot) depending on the familiarity level. In these two tasks, we used 30 Japanese cities based on Honda et al. (2017). 15 of the 30 cities were from the difficult list, and the other 15 were from the easy list (see Appendix for the specific city names). The definition of "difficulty" for the list lies in the difficulty of binary choice inferences about population size (Honda et al., 2017). Since memory-based heuristics in group decision making can work differently depending on the inference problems (see Fujisaki et al., 2018), we used these 30 cities. We conducted the two tasks on the Internet. Each city name was presented individually. The presentation order of the 30 cities was randomized for each participant.

Results and discussion

First, we examined the similarities of memories. In this examination, we calculated Spearman's correlation coefficient for familiarity ratings between two participants. We used the correlation coefficient as the criterion of similarity for memories between the two participants. We examined the differences in similarities as functions of area and age. As Table 1 shows, we examined the distributions of correlation coefficients in 10 pairs of participants each for easy and difficult lists. For example, in the "Tokyo30s–Tokyo30s" pair, since there were 99 participants in their 30s in the Tokyo area, there were 4851 (99 × 98 / 2) pairs at most. In some cases (14 out of 800[400 participants × 2 lists]), participants provided the same familiarity ratings for 15 cities in a list. For this case, we excluded the data since we could not calculate correlation coefficients.

Table 1 shows the distributions of correlation coefficients as a function of pair type. For each pair, we estimated a 95% confidence interval of the mean based on bootstrapping using 5000 simulations. Familiarity ratings between two participants became more similar in pairs of individuals from the same area than different areas, supporting our prediction. In contrast, we did not find a specific trend of similarity in terms of the age difference.

Next, we analyzed the similarity of memories in terms of ecological rationality (Gigerenzer & Todd, 1999). In this analysis, a participant was assumed to make inferences based on her/his memory as follows: s/he was presented with a pair of cities and made binary choice inference about population size (i.e., inferred which city had a greater population size). In making inferences, s/he used memory-based simple heuristics. We assumed that s/he used the familiarity heuristic (Honda, et al, 2011, 2017; Xu, et al., 2018). In this heuristic, s/he inferred that the more familiar city had the larger population size. In Honda et al. (2017), for the inference in pair x, person i's decision (D) is defined as follows:

$$D_i(x) = c_i(FA_{iL} - FA_{iS}) \quad (1)$$

where FA_{iL} and FA_{iS} represent familiarities for the larger and smaller cities in pair x, and c_i represents the scaling parameter. This scaling parameter for each person was selected so that the maximum or minimum value of D became 1 or −1. This model predicts that, when $D(x)$ is larger than 0 and satisfies the decision threshold (i.e., $D[x]$ > decision threshold), person i infers that the larger city has the larger population and that, when it is smaller than 0 and satisfies the decision threshold (i.e., $-D[x]$ > decision threshold), person i infers that the smaller city has the larger population. In pairs in which participants could recognize only the larger (or smaller) city, $D(x)$ was set as 1 (or −1) so that they choose the larger (or smaller) city. This choice is consistent with the recognition heuristic (Goldstein & Gigerenzer, 2002), indicating that the familiarity heuristic model can explain inference patterns predicted by the recognition heuristic.

We then examined how accurate people's memory-based inferences were and discussed the diversity of memory from this perspective. In this examination, we set two criteria, validity and discrimination rates (Gigerenzer & Todd, 1999). The validity rate is defined as follows:

$$V = \frac{H_c}{H_c + H_i} \quad (2)$$

where H_c (or H_i) denotes the number of pairs for which a person can use heuristic (i.e., $D[x]$ exceeds the decision threshold) and heuristic-based inference resulted in the correct (or incorrect) inference. That is, the validity rate means the accuracy of the familiarity heuristic. In contrast, the discrimination rate means the proportion of pairs in which a person can use the familiarity heuristic.

We calculated the validity and discrimination rates for all 105 pairs in difficult and easy lists for each participant. In this calculation, we set the decision threshold as 0.3 based on the empirical findings in Honda et al. (2017). Figure 1 shows the distributions of validity and discrimination rates for the two lists. We conducted 2 (area; Tokyo and Osaka) × 2 (age; 30s and 50s) ANOVA for the two criteria (i.e., validity and discrimination rates) and the two lists, respectively.

As for the validity rate, in the difficult list, a significant main effect of area was observed [$F(1, 388) = 111.49$, $p < .001$, $\eta^2 = 0.223$], indicating that the familiarity heuristic by participants from the Tokyo area would have led to more accurate inferences (M_{Tokyo}= 0.680, M_{Osaka} = 0.488). No significant main effect of age [$F(1, 388) = 0.09$, $p = .77$, $\eta^2 = 0.00$] or interaction [$F(1, 388) = 0.95$, $p = .33$, $\eta^2 = 0.00$] was observed. In the easy list, a significant main effect of area was observed [$F(1, 382) = 8.09$, $p = .005$, $\eta^2 = 0.223$], indicating that the familiarity heuristic by participants from the Osaka

Table 1. Distribution of correlation coefficients for familiarity rating. The range (95% confidence interval) was estimated by bootstrapping with 5000 simulations.

		Difficult list			Easy list		
		95% confidence interval			95% confidence interval		
Pair	Area	Lower bound	Mean	Upper bound	Lower bound	Mean	Upper bound
Tokyo30s–Tokyo30s	Same	0.197	0.205	0.212	0.191	0.199	0.207
Tokyo30s–Tokyo50s	Same	0.213	0.218	0.223	0.228	0.233	0.238
Tokyo50s–Tokyo50s	Same	0.234	0.241	0.248	0.283	0.290	0.297
Osaka30s–Osaka30s	Same	0.435	0.442	0.448	0.269	0.277	0.284
Osaka30s–Osaka50s	Same	0.471	0.475	0.479	0.251	0.256	0.261
Osaka50s–Osaka50s	Same	0.512	0.518	0.523	0.233	0.241	0.248
Tokyo30s–Osaka30s	Different	0.176	0.181	0.187	0.038	0.044	0.050
Tokyo30s–Osaka50s	Different	0.174	0.179	0.184	0.007	0.012	0.018
Tokyo50s–Osaka30s	Different	0.175	0.181	0.186	0.018	0.023	0.029
Tokyo50s–Osaka50s	Different	0.177	0.182	0.187	-0.004	0.001	0.007

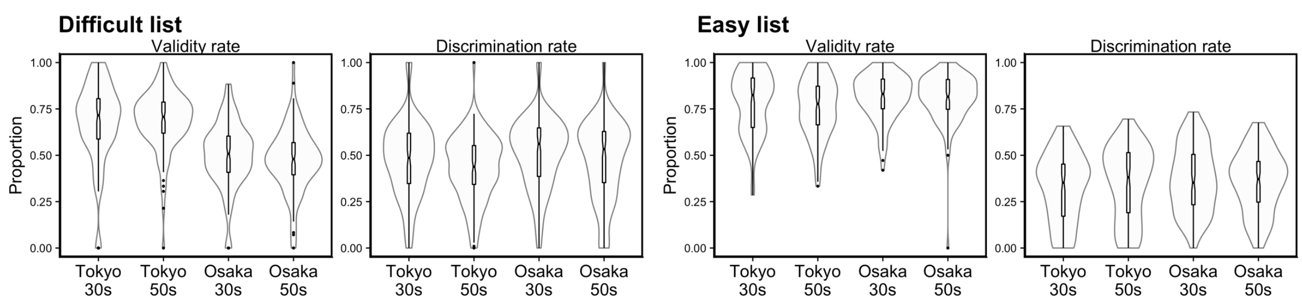

Figure 1. Validity and discrimination rates of the familiarity heuristic.

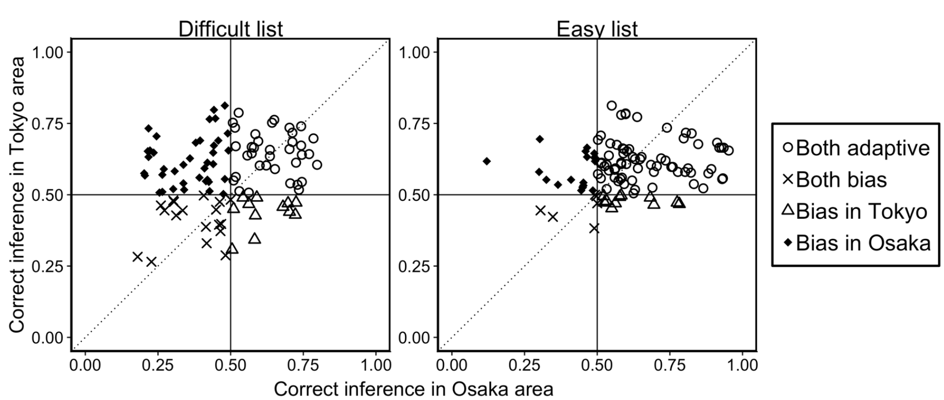

Figure 2. Proportions of correct inferences for Osaka's and Tokyo's participants. Each point denotes the proportion of correct inferences for each inference problem [i.e., there are 105 (15 × 14 / 2) points in each list].

area would have led to more accurate inferences (M_{Tokyo}= 0.771, M_{Osaka} = 0.814). No significant main effect of age [$F(1, 382) = 0.99$, $p = .32$, $\eta^2 = 0.00$] or interaction [$F(1, 382) = 0.32$, $p = .57$, $\eta^2 = 0.00$] was observed.

As for the discrimination rate, in the difficult list, a significant main effect of age was observed [$F(1, 396) = 5.32$, $p = .02$, $\eta^2 = 0.01$], indicating participants in 30s could have potentially used familiarity heuristic more often than those in 50s (M_{30s}= 0.499, M_{50s} = 0.454). No significant main effect of area [$F(1, 396) = 3.30$, $p = .07$, $\eta^2 = 0.01$] or interaction [$F(1, 388) = 0.02$, $p = .89$, $\eta^2 = 0.00$] was observed. In the easy list, no significant effects were observed [main effect of age, $F(1, 396) = 0.11$, $p = .75$, $\eta^2 = 0.00$; main effect of area, $F(1, 396) = 1.76$, $p = .19$, $\eta^2 = 0.00$; interaction, $F(1, 388) = 1.01$, $p = .32$, $\eta^2 = 0.00$].

The above analyses indicated that, although similarities of familiarity ratings and the nature of ecological rationality differed depending on the areas, ages were not generally related. Thus, in the following analyses, we merged the data between the two generations.

Next, we analyzed the accuracy of the familiarity heuristic for each inference problem. Figure 2 shows the relationship of correct inference between the two areas. Each figure includes 105 points, each of which shows the proportion of correct inference for each problem. Depending on the relationships about inference adaptivity (i.e., proportions of correct inferences were above the chance level [0.5] or not), we named pairs "Both adaptive," "Both bias," "Bias in Tokyo," and "Bias in Osaka." If the participants in the two areas show the same adaptivity or bias, each point will lie on the diagonal line (i.e., proportions of correct inferences correspond with each other). However, as is apparent in the figure, this was not true; the proportions of correct inferences varied depending on the areas, and the relationship of correct inferences between the two areas was not strong (in the difficult list, $r = 0.18$, $p = .07$; in the easy list, $r = 0.19$, $p = .05$). Furthermore, there were nonnegligible cases of "Bias in Tokyo" or "Bias in Osaka," indicating that participants in each area showed opposite direction of inference accuracy.

Altogether, we found that accuracy of the familiarity heuristic varied depending on the participants' profiles. In particular, the area (i.e., Tokyo or Osaka) was highly related to the accuracy of the familiarity heuristic, indicating that ecological rationality of memory differed depending on the area participants were from. Thus, constructed memory in the two areas were diverse.

Study 2: Computer simulations

We conducted computer simulations about group decision making based on the behavioral experiment data. We constructed hypothetical groups that comprised participants in the behavioral experiment, and the groups made inferences about population. Then, we compared group performance in terms of diversity of group members (i.e., members from only Tokyo or Osaka or members from a mixture of Tokyo and Osaka).

Method

Group construction We set group size at 5, 10, 20, or 50. In constructing a group, we randomly selected group members from participants in the behavioral experiment. Groups were constructed from a single area (i.e., participants from only Tokyo or Osaka) and both two areas (i.e., mixture of participants from Tokyo and Osaka).

Group decision making We set the following hypothetical group decision making situation. Group members made binary choice inferences about population size. They were presented with a pair of cities and made binary choice inference about population size (i.e., inferred which city had a greater population size). Here, each member was assumed to make inferences based on the familiarity heuristic, and the group made decisions based on simple majority rule (Hastie & Kameda, 2005; Sorkin, Hays, & West, 2001). According to previous assumptions (Fujisaki et al., 2018), when a member could not make an inference (i.e., her/his inference did not exceed the decision threshold), s/he did not participate in the group decision making. Furthermore, when a group could not make decisions (i.e., an equal number of members chose different cities), the group randomly chose one city.

Procedure The group made decisions for all 105 inference problems for the two lists. For each parameter setting (i.e., group size or diversity of group members), we constructed, in total, 5000 different groups based on random selection of members. We regarded the average of proportion of correct inference in the 5000 groups as the group performance in each parameter setting.

Results and discussion

First, we examined the performance in the single-area group (i.e., group members comprised participants from only Tokyo or Osaka). Figure 3 shows results of computer simulations. This shows the proportion of correct inferences for 105 inference problems each in the difficult and easy lists. Our findings can be summarized with the following three points. First, when individuals showed accurate inferences on average (i.e., proportion of correct inferences exceeded the chance level), group decision making enhanced accurate inferences. Second, when individual inference showed biases on average (i.e., proportion of correct inferences fell below the chance level), group decision making deteriorated accurate inferences (see Osaka performance in the difficult list). Third, and most importantly, individual performance did not always predict the better boost of group decision making. See the group performance in the easy list. At the individual level, members in Osaka showed more accurate inferences than those in Tokyo (see group size 1 in Figure 3). Intuitively, the group that comprises Osaka members seemed to show better group performance than that comprising Tokyo members since participants in Osaka showed more accurate inferences at the individual level. However, this was not true, and the group of participants from Tokyo performed better than the group of participants from Osaka. This counter-intuitive phenomenon may occur because of the biases (Fujisaki et al., 2018). Regarding the problems wherein people have bias (i.e., mean proportion of correct inference lies below the chance level [0.5] at the individual level), group decisions deteriorate accurate inferences, and the mean proportion of correct inferences reaches 0 as the number in the group increases. Actually, out of the 105 problems on the easy list, the proportion of biased problems for participants in Osaka was 0.234, and that for participants in Tokyo was 0.162. Thus, although participants in Osaka showed more accurate inferences on average, they also showed more biases. Thus, in group decision-making, inaccurate inferences were enhanced for more inference problems in Osaka than in Tokyo, and a counter-intuitive phenomenon occurred.

Next, we examined the performance of decisions in groups whose members were diverse (i.e., mixture of participants). Figure 4 shows the performance of decisions for these groups. The x-axis indicates the proportion of members from Tokyo (i.e., 1 – the proportion is the proportion of members from Osaka). Thus, the values 0 and 1 indicate that the group includes members from only a single area (i.e., the values correspond to those in Figure 3 in each parameter setting). On the difficult list, the proportion of correct inferences in groups was boosted as the proportion of members from Tokyo increased. Since individual inferences in participants from Osaka were not accurate (i.e., their inferences were almost chance level), members from Tokyo boosted accurate inferences. On the easy list, the findings were highly intriguing. The peak of the group performance did not lie in the endpoint (i.e., group comprised members from a single area) but in the group that comprised members from the two areas. That is, when the group included diverse members, the group reached the highest performance.

In sum, we found that, when memories of group members were diverse, collective decisions by the group could be more accurate in some decision situations (e.g., when making collective decisions for the inference problems on the easy list).

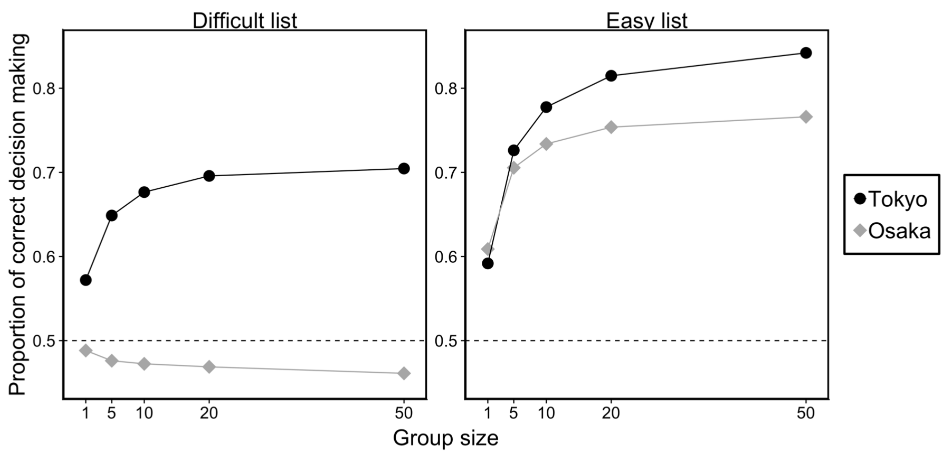

Figure 3. Performance of group decision making (i.e., proportions of correct inferences for 105 inference problems on the difficult and easy lists) in the group whose members were from a single area (i.e., Tokyo or Osaka). Group size 1 indicates the mean proportions of correct inferences in individual inferences. The dotted line indicates the chance level of inferences.

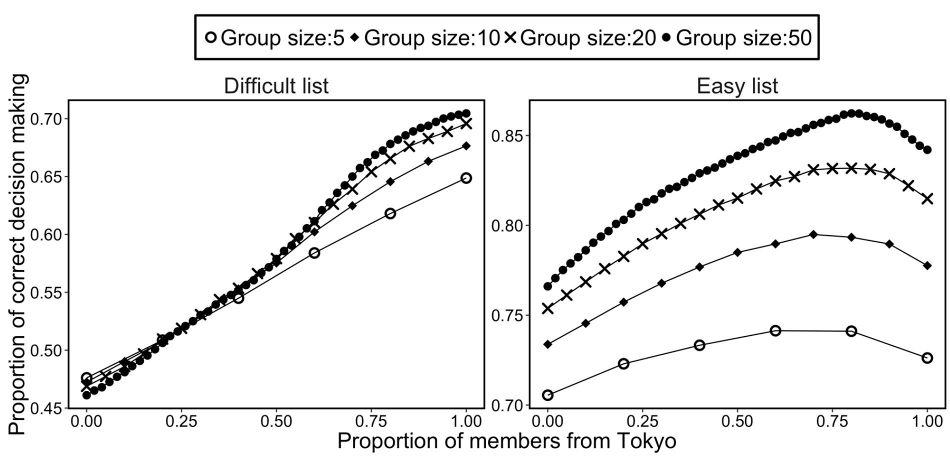

Figure 4. Performance of group decision making (i.e., proportions of correct inferences for 105 inference problems on the difficult and easy lists) in the group whose members were from two areas (i.e., Tokyo or Osaka).

General discussion

Through a behavioral experiment and computer simulations, we found that diverse memories in group members enhanced accurate group decision making.

How was the effect of member diversity generated? The key was the biases. As Figure 2 shows, participants in each area had unique biases (i.e., “Bias in Tokyo” and “Bias in Osaka” in Figure 2). In the mixed group, these biases could be improved by members from different areas, leading to accurate inferences.

Finally, we note the following two points about the difference in the adaptive nature of inferences between individual and group decision making levels. First, adaptive heuristics at the individual level do not indicate that such heuristics also boost accurate inferences in group decision making (see Figure 3 regarding the easy list) since adaptive heuristics are accompanied by some biases. That is, group decision making can boost both accurate and inaccurate inferences. Second, such problems in group decision making can be resolved by the diversity of inferences. In the present study, we showed that diversity in memories could remedy individual biases. Diverse memories can produce different inferences even when people use the same heuristic. That is, people make inferences using superficially “different” strategies. This is basically consistent with previous findings that diverse inference strategies used by group members can boost group decision making (Fujisaki et al., 2018). These findings suggest that diversity in inferences plays a key role in improving biases produced by individual inferences.

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Appendix

The two lists used in the present study. We used these lists based on Honda et al. (2017).

Easy list	Difficult list
Yokohama-shi	Kawaguchi-shi
Osaka-shi	Machida-shi
Nagoya-shi	Kohriyama-shi
Sapporo-shi	Takasaki-shi
Kobe-shi	Tsu-shi
Kyoto-shi	Sasebo-shi
Fukuoka-shi	Hachinohe-shi
Hiroshima-shi	Matsumoto-shi
Sendai-shi	Hitachi-shi
Chiba-shi	Yamaguchi-shi
Niigata-shi	Takaoka-shi
Hamamatsu-shi	Imabari-shi
Kumamoto-shi	Miyakonojo-shi
Okayama-shi	Ogaki-shi
Kagoshima-shi	Ashikaga-shi