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Abstract	Previous studies have shown that people use memory-based simple heuristics in many cases. For example, people use the familiarity heuristic in binary choice inferences, and their inferences based on the familiarity heuristic tend to be highly accurate. That is, by relying on the familiarity heuristic, people can make rational inferences. In the present study, I analyzed how memory constraints, such as forgetting and sensitivity to differences in familiarity, affected the rational use of the familiarity heuristic. In particular, I constructed a familiarity heuristic model based on ACT-R and examined ho memory constraints affected the rational use of the familiarity heuristic sing computer simulations. I found that forgetting boosted the accuracy of the familiarity heuristic, suggesting that the rationality of the familiarity heuristic is enhanced by the "negative" side of memory processes. It was also found that sensitivity to differences in familiarity was not critically related to the rational use of the familiarity heuristic, suggesting that people can take advantage of the rational aspect of the familiarity heuristic regardless of their sensitivity to differences in familiarity.
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How Memory Constraints Boost the Rational Use of the Familiarity Heuristic

Hidehito Honda*

Previous studies have shown that people use memory-based simple heuristics in many cases. For example, people use the familiarity heuristic in binary choice inferences, and their inferences based on the familiarity heuristic tend to be highly accurate. That is, by relying on the familiarity heuristic, people can make rational inferences. In the present study, I analyzed how memory constraints, such as forgetting and sensitivity to differences in familiarity, affected the rational use of the familiarity heuristic. In particular, I constructed a familiarity heuristic model based on ACT-R and examined how memory constraints affected the rational use of the familiarity heuristic using computer simulations. I found that forgetting boosted the accuracy of the familiarity heuristic, suggesting that the rationality of the familiarity heuristic is enhanced by the "negative" side of memory processes. It was also found that sensitivity to differences in familiarity was not critically related to the rational use of the familiarity heuristic, suggesting that people can take advantage of the rational aspect of the familiarity heuristic regardless of their sensitivity to differences in familiarity.

Key words: familiarity heuristic; memory; rationality; memory constraints

Introduction

In the last two decades, one of the most controversial topics in re-

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search on judgment and decision making has been the recognition heuristic (Goldstein & Gigerenzer, 2002). The application of the recognition heuristic to a binary choice inference has the following result: If one of two objects is recognized and the other is not, then infer that the recognized object has the higher value with respect to the criterion (Goldstein & Gigerenzer, 2002, p. 76). For example, consider the following question, "Which city has a larger population, Hiroshima or Shizuoka?" In this problem, the recognition heuristic predicts that a person who recognizes Hiroshima but not Shizuoka will infer that Hiroshima has a larger population. Many researchers have discussed the recognition heuristic from various perspectives such as individual psychological processes (Goldstein & Gigerenzer, 2002; Pachur, Bröder, & Marewski, 2008; Pachur & Hertwig, 2006; Snook & Cullen, 2006; Thoma & Williams, 2013), group decision making (Fujisaki, Honda, & Ueda, 2017; Kämmer, Gaissmaier, Reimer, & Schermuly, 2014; Reimer & Katsikopoulos, 2004), predictions about real-world events (Gaissmaier & Marewski, 2011; Herzog & Hertwig, 2011; Pachur & Biele, 2007; Scheibehenne & Bröder, 2007; Serwe & Frings, 2006), its neural basis (Rosburg, Mecklinger, & Frings, 2011; Volz, Schooler, Schubotz, Raab, Gigerenzer, & von Cramon, 2006), extension of the recognition heuristic to multi-alternative choices (Marewski, Gaissmaier, Schooler, Goldstein, & Gigerenzer, 2010; McCloy, Beaman, & Smith, 2008), and theoretical analyses (Davis-Stober, Dana, & Budescu, 2010; Pleskac, 2007; Schooler & Hertwig, 2005). They have shown that people often use the recognition heuristic, and recognition of the object thus critically affects inference.

People can use the recognition heuristic when they can recognize one of the two objects (e.g., city names). Thus, although the recognition heuristic is widely used when people can recognize one of the two objects, situations where people can use the recognition heuristic is limited. For example, what inference heuristics do people use when they recognize both objects in binary choice inferences? Previous studies have shown that when people recognize both objects, they also use heuristic strategies (e.g., Hertwig, Herzog, Schooler, & Reimer, 2008; Honda, Abe, Matsuka, & Yamagishi, 2011; Honda, Matsuka, & Ueda, 2017; Schooler, & Hertwig, 2005; Xu, González-Vallejo, Weinhardt, Chimeli, & Karadogan, 2018). In the present study, I shall discuss one such heuristic, the *familiarity heuristic*, from theoretical perspectives.

The familiarity heuristic (Honda et al., 2011, 2017; Xu et al., 2018) assumes that people use the familiarity of objects in making inferences: "For two objects A and B, if one of the two objects is more familiar, then infer that this object has the higher value with respect to the criterion." Familiarity is a basic memory processes relevant to recognition (e.g., Yonelinas, 2002; Yonelinas, Otten, Shaw, & Rugg, 2005), and is assumed to be one of the most important components in signal detection theory of memory processes (e.g., Wixted, 2007; Wixted, & Stretch, 2004; Yonelinas, & Parks, 2007). Previous studies have shown that familiarity is involved in a variety of psychological processes, including the mere exposure effect (e.g., Bornstein, 1989; Zajonc, 1968), likelihood judgments (Fox & Levav, 2000), problem solving (Payne, Richardson, & Howes, 2000), implicit learning (e.g., Scott & Dienes, 2010), persuasive processing (Garcia-Marques & Mackie, 2001; Moons, Mackie, & Garcia-Marques, 2009), evaluation (Alter & Oppenheimer, 2008), and relationship comparison task (Shirasuna, Honda, Matsushita, & Ueda, 2020). The familiarity heuristic can be regarded as a generalized model of the recognition heuristic. Both familiarity and recognition heuristics make the same predictions. For inferences when people can recognize one of the two objects, the two heuristics predict that people choose the recognized (that is, more familiar) object. The familiarity heuristic in addition can make predictions for inferences when people recognize both objects. Evidence for the use of the familiarity heuristic in binary choice inference has come from behavioral studies (Honda et al., 2011, 2017; Xu et al., 2018). Experimental studies using ERPs (Rosburg et al., 2011) and theoretical analyses (Dougherty, Franco-Watkins, & Thomas, 2008; Pleskac, 2007) have also shown that familiarity plays an important role in inference processes even when participants use the recognition heuristic.

Honda et al. (2017) discussed the rational nature of the familiarity heuristic. In their analyses, Honda et al. (2017) used behavioral data about familiarities with city names to examine whether a person assumed to make inferences based on the familiarity heuristic could make correct inferences. Honda et al. (2017) showed that use of familiarities in binary choice inferences generally led to accurate (i.e., rational) inferences. However, the following two points remained unclear about the rationality of the familiarity heuristic.

First, the relationship between cognitive constraints and the rationality of the familiarity heuristic remains unclear: Do cognitive constraints attenuate the rationality of the familiarity heuristic? As pointed out above, familiarity is a basic memory process relevant to recognition. Thus, memory constraints such as forgetting may attenuate the rationality of the familiarity heuristic. For example, as a person more easily forgets objects, her/his inferences based on the familiarity heuristic may become more inaccurate. However, this may not be true according to previous findings. Schooler and Hertwig (2005) theoretically analyzed the recognition and fluency heuristics and found that forgetting enhances the rational use of the heuristics: A person who moderately forgets objects can take advantage of the rational nature of the recognition and fluency heuristics. That is, s/he can make more accurate inferences by forgetting. Thus, as in the recognition and fluency heuristics, forgetting may enhance rational use of the familiarity heuristic. This issue has not been examined in previous studies.

Second, previous studies have not examined how sensitivity to differences in familiarity would affect the rational use of the familiarity heuristic. In the use of familiarity heuristic, a person is assumed to discriminate the degrees of familiarity between the two objects. Some people may be highly sensitive to differences in familiarity, and others may not. How do such differences in sensitivity affect the rational use of the familiarity heuristic? Honda et al. (2017) found in their behavioral data that there were large individual differences in the threshold (i.e., how sensitive participants were to the difference between two objects in the use of the familiarity heuristic). However, Honda et al. (2017) did not examine how sensitivity to differences in familiarity affected the rational use of the familiarity heuristic.

In the present study, I theoretically examined the familiarity heuristic with respect to two issues: How do forgetting and sensitivity to differences in familiarity affect the rational use of the familiarity heuristic? To this end, I constructed a computational model of the familiarity heuristic. In particular, I constructed a model of the familiarity heuristic based on ACT-R architecture (Anderson, 2008). By controlling the parameters for memory decay (i.e., the degree of forgetting) and sensitivity to differences in the familiarity of two objects, I theoretically analyzed the two issues.

In the following sections, I shall first explain the model of the familiarity heuristic based on ACT-R, and then report the results of computer simulations.

Model of the familiarity heuristic based on ACT-R

The familiarity heuristic was modeled using ACT-R. The following formalization is based on Schooler and Hertwig (2005), which modeled the recognition and fluency heuristics.

A person's familiarity with an object (e.g., a city name) will increase as s/he encounters the object more. Furthermore, the time when s/he encounters the object is an important factor in forming familiarity. For example, if a person encountered an object yesterday, its familiarity may be high. However, if s/he encountered the object 100 days before, its familiarity may be low. In the present model, I assume that the familiarity with an object may be represented as follows.

$$F_i = B_i + \sum_j S_{ji} \tag{1}$$

$$B_i = \ln\left(\sum_{j=1}^{n} t_j^d\right) \tag{2}$$

F_i represents the familiarity with object i. This corresponds to activation level in the ACT-R model (Schooler & Hertwig, 2005). The level of familiarity is formed by the environmental pattern of occurrence (i.e., record). B_i, the base-level of strength of record, is determined by how frequently and recently one encountered the object in the past. B_i is calculated from the following factors: (1) How many times (n) a person encountered the object i in the past, (2) the j^{th} encounter occurred t_j time units in the past, and (3) d, which represents a decay parameter capturing the amount of forgetting in declarative memory (typically, d is set at -0.5). An example calculation is as follows: Imagine two people, Ms. X and Mr. Y. Ms. X encountered the city name "Hiroshima-shi" 100 and 400 days ago, while Mr. Y encountered it 10, 50, 100, 200, and 250 days ago. In these cases, the base-level strength of record is calculated as follows:

Ms. X: $\ln\,(100^{-0.5}+400^{-0.5}+600^{-0.5})=-1.66$
Mr. Y: $\ln\,(10^{-0.5}+50^{-0.5}+100^{-0.5}+200^{-0.5}+250^{-0.5})=-0.37$

As equation (1) shows, the level of familiarity depends on the contextual factor represented by the second term. Following Schooler and Hertwig (2005), I did not assume the influence of contextual factors in detail in the present study.

The present familiarity heuristic model assumes that a person recognizes (or unrecognizes) an object depending on the level of familiarity. In particular, the probability of recognition of object i, R_i, is defined as follows:

$$R_i = \frac{1}{1+e^{-(F_i-\tau)/s}} \tag{3}$$

where s captures momentary and permanent fluctuations in the activation level of record i, and τ is a parameter called the retrieval criterion[1].

Based on the assumptions of the familiarity heuristic in the binary choice inference about population size implemented in Honda et al. (2017), a person is assumed to make an inference under the following three cases:

Case 1: Inference based on recognition
When one of the two cities is recognized and the other is not, s/he infers that the recognized object has the larger population.
Case 2: Inference based on the level of familiarity
When the two cities are recognized and difference in familiarity between the two cities is sufficiently large (i.e., the difference is above the threshold), s/he infers that the more familiar city has the larger population.
Case 3: Random guess
When both cities are not recognized (Case 3-a) or the two cities are recognized and the difference in familiarity between two cities is insufficiently large (i.e., the difference is below the threshold, Case 3-b), s/he makes a random guess (chooses one of the two cities randomly).

Computer simulations

Basic procedure

I conducted computer simulations with the following two steps.
Step 1: Construction of the historical record of a person's encounters with city names
First, I constructed a historical record of the simulated person's encounters with city names across her/his life. According to the nature of familiarity, a person's familiarity with city names should positively correlate with the number of encounters with city names in their daily lives. Thus, I examined the frequencies of appearance of city names in a newspaper using the database for *Asahi-Shinbun*. I counted the number of appearances (from January 1, 2010, to December 31, 2018) of the 50 cities used in the present computer simulations in Kurazo 2 (the database for

Table 1. City data in the simulation studies.

City name	Population	Frequency in database	City name	Population	Frequency in database
Yokohama-shi	3,724,844	30,724	Utsunomiya-shi	518,594	10,793
Osaka-shi	2,691,185	15,062	Matsuyama-shi	514,865	2,931
Nagoya-shi	2,295,638	7,887	Higashiosaka-shi	502,784	902
Sapporo-shi	1,952,356	4,643	Nishinomiya-shi	487,850	2,762
Fukuoka-shi	1,538,681	4,204	Matsudo-shi	483,480	4,780
Kobe-shi	1,537,272	5,156	Ichikawa-shi	481,732	4,006
Kawasaki-shi	1,475,213	13,603	Oita-shi	478,146	761
Kyoto-shi	1,475,183	6,959	Kurashiki-shi	477,118	869
Saitama-shi	1,263,979	13,748	Kanazawa-shi	465,699	1,660
Hiroshima-shi	1,194,034	4,281	Fukuyama-shi	464,811	658
Sendai-shi	1,082,159	23,537	Amagasaki-shi	452,563	1,101
Chiba-shi	971,882	12,150	Machida-shi	432,348	3,430
Kitakyushu-shi	961,286	2,349	Nagasaki-shi	429,508	1,861
Sakai-shi	839,310	1,972	Fujisawa-shi	423,894	4,684
Niigata-shi	810,157	13,655	Toyota-shi	422,542	870
Hamamatsu-shi	797,980	8,789	Takamatsu-shi	420,748	1,131
Kumamoto-shi	740,822	2,325	Toyama-shi	418,686	3,244
Sagamihara-shi	720,780	6,289	Kashiwa-shi	413,954	5,191
Okayama-shi	719,474	1,477	Gifu-shi	406,735	858
Shizuoka-shi	704,989	12,961	Yokosuka-shi	406,586	4,638
Funabashi-shi	622,890	5,620	Hirakata-shi	404,152	601
Kagoshima-shi	599,814	1,240	Miyazaki-shi	401,138	885
Kawaguchi-shi	578,112	4,019	Toyonaka-shi	395,479	787
Hachioji-shi	577,513	4,121	Okazaki-shi	381,051	603
Himeji-shi	535,664	685	Ichinomiya-shi	380,868	381

Note. In searching the database, I limited the database to newspapers in the east of Japan.

Asahi-Shinbun). Table 1 shows the data in the present study. These 50 cities ("*shi*") were the top 50 cities in their population sizes among all Japanese cities.

Based on the data of the frequencies of the city names in the newspaper, I operationally defined the probability of encountering city name *i*, *P(i)*, on any given day as follows.

$$P(i) = \frac{f_i}{30724} \times c \qquad (4)$$

wherein f_i is the total number of citations for the city i, 30,724 is the number of citations of "Yokohama-shi," the most cited city, and c is a scale parameter. In the present study, I set $c = 0.8$. That is, the (highest) probability of encountering the city name "Yokohama-shi" was 0.8,[2] and the (second highest) probability of encountering the city name "Osaka-shi" was 0.39. According to these encountering probabilities, the historical record for city i was created. In particular, I set the historical time window as the past 5000 days, and a person was assumed to encounter city i with the probability $P(i)$ on each day. Based on the created historical record, I calculated the familiarity for city i using equations (1) and (2). Since I created the historical record with this probabilistic method, the number of patterns in the historical record is huge. Thus, I created 1000 simulated people with different historical records for each city name.

Step 2: Binary choice inference about population sizes based on the familiarity heuristic

Second, the simulated person answered binary choice inference problems based on the familiarity heuristic (as to the specific inference processes, see the section "Familiarity heuristic model based on ACT-R"). S/he answered the all of the pairs among the 50 cities in Table 1 (i.e., 1,225 pairs).

Parameter settings

As described in the Introduction, the goal of the present study was to examine how forgetting and sensitivity to differences in familiarities were related to the rational use of the familiarity heuristic. To this end, I assigned the following parameter settings. For the examination of forgetting, I controlled the decay parameter d in equation (2) and took 101 values from −1 (i.e., more forgetting) to 0 (i.e., less forgetting) by increments of 0.01. For the examination of sensitivity to differences in familiarity, I controlled the threshold (i.e., the least difference in familiarity between the two objects that the simulated person can discriminate) and took five values, 0 (i.e., the simulated person can discriminate any difference; i.e., highly sensitive), 0.1, 0.2, 0.5, and 1.0 (i.e., less sensitive).

I conducted computer simulations for all possible combinations of parameters (i.e., $101 \times 5 = 505$) for the 1000 simulated people. In the following result sections, I reported the average of the 1000 simulated people (i.e., the mean proportion of correct inferences) as the inference for each parameter setting.

Results and discussion

Rational analyses of the heuristics

In the following sections, I report the results of computer simulations. In particular, the analyses of the familiarity heuristic were conducted in terms of accuracy and applicability (i.e., a person can use the familiarity heuristic for the inference). The accuracy is the basic criterion for the rational analysis of a heuristic. That is, this criterion regards a heuristic as rational if using the heuristic results in high accuracies of inferences. However, the accuracy of the heuristic may not be sufficient in rational analyses of heuristics: Heuristics that lead to highly accurate inferences may not be useful if people can rarely use them. In the present binary choice inferences, when the simulated person cannot use the familiarity heuristic, s/he was assumed to make a random guess (i.e., probability of correct inference is 0.5), suggesting that low applicability of the familiarity heuristic may adversely affect inference performance. Thus, I also examined the applicability of the familiarity heuristic and examined how forgetting and sensitivity to differences in familiarity between two cities were related to the applicability of the familiarity heuristic. These policies were based on previous analyses (e.g., Gigerenzer & Goldstein, 1999;

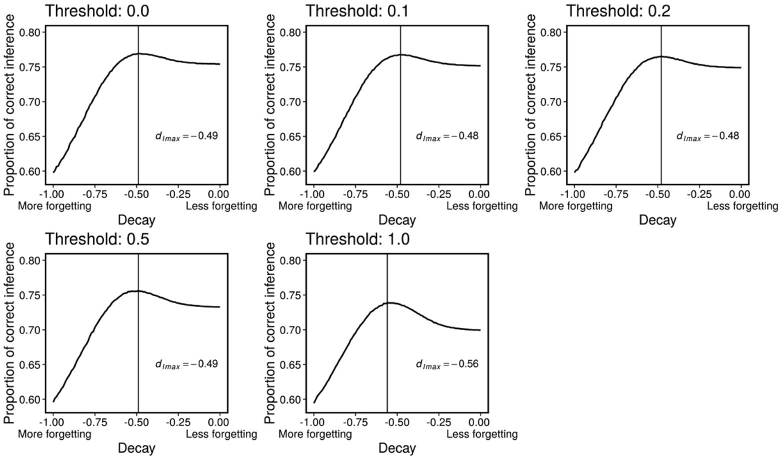

Figure 1. Proportion of correct inferences as a function of decay parameter. Each figure shows a different threshold. d_{Imax} indicates the value of the decay parameter for which the proportion of correct inferences was the highest (the solid line).

Honda et al., 2011, 2017).

Inference performance

First, I shall report inference performances. In Figure 1, the proportion of correct inferences is shown as a function of the decay parameter, and each graph shows the result for different threshold levels. d_{Imax} indicates the value of the decay parameter for which the proportion of correct inferences was the highest (the solid line). One of the most intriguing findings was that a simulated person who forgets "moderately" showed the highest inference performance. That is, loss of information by forgetting enhances the accuracy of the familiarity heuristic. This finding is basically consistent with that in Schooler and Hertwig (2005), wherein "moderate" forgetting bolsters the accuracies of inferences in recognition and fluency heuristics.

In Figure 2, the mean proportion of correct inferences by merging decay values is shown. It was found that as the simulated person became

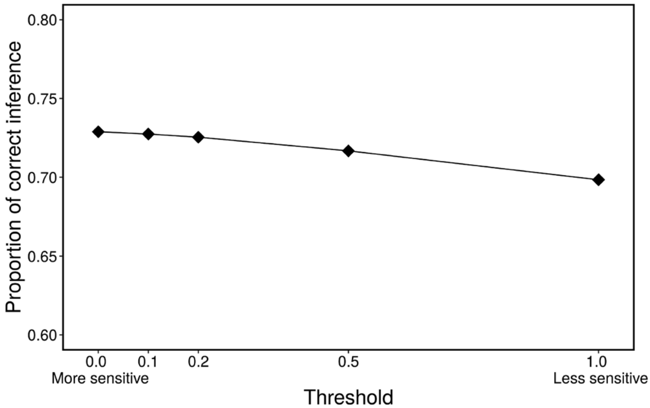

Figure 2. Proportion of correct inferences as a function of the threshold. For each threshold value, the inference performance was merged with the decay parameter.

more sensitive to differences in familiarity, s/he showed better inference performances. However, note that the effect of threshold on inference performance was relatively small: The difference in performance between the highest (0.729 at threshold 0.0) and lowest (0.699 at the threshold 1.0) was 0.03. In contrast, the difference in performance between the highest and lowest resulting from controlling the decay parameter was more than 0.1 (see Figure 1). These results imply that the sensitivity to differences in familiarity does not play as important a role in inference performance as does forgetting.

Applicability of the familiarity heuristic

Next, I shall report the applicability of the familiarity heuristic. In Figure 3, the application rate is shown as a function of the decay parameter, and each graph shows the result for a different threshold level. d_{Amax} indicates the value of the decay parameter for which the application rate was the highest (the solid line). Generally, as the simulated person became "less forgetting," the application rate increased. However, note

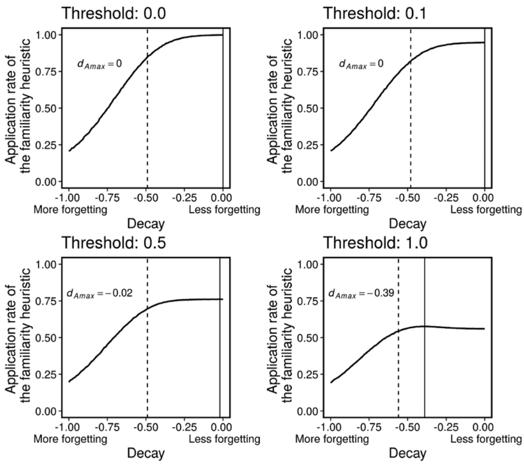

Figure 3. Application rate of the familiarity heuristic (i.e., proportion of pairs for which the simulated person could use the familiarity heuristic) as a function of the decay parameter. Each figure shows a different threshold level. d_{Amax} indicates the value of the decay parameter for which the application rate was the highest (the solid line). The dotted line indicates the value of the decay parameter for which the proportion of correct inferences was the highest (i.e., d_{Imax} in Figure 1).

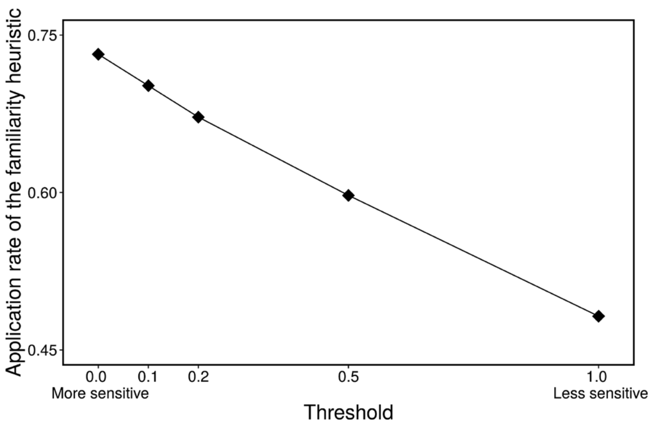

Figure 4. Application rate as a function of the threshold. For each threshold value, the application rate was merged with decay parameters.

the relationship between d_{Amax} (the solid line) and d_{Imax} (the dotted line) in Figure 3. Although the application rate rose linearly at first, the increase rate diminished. At d_{Imax}, the increase rate was nearly at the end point of "linear rise," suggesting that the application rate at d_{Imax} was sufficiently high. That is, even if the decay parameter became higher than d_{Imax}, the resulting increase in the application rate was relatively small.

Figure 4 shows the application rate as a function of the threshold value. In this figure, the mean proportion by merging decay values is shown. As is apparent (and as is expected from the features of the threshold), as the simulated person became less sensitive to differences in familiarity, the application rate decreased.

Closer analyses (1): Why does memory decay boost the accuracy of the familiarity heuristic?

In the preceding section, I reported that memory decay enhanced the accuracy of the familiarity heuristic. What is the mechanism underlying this? Memory decay can produce the following differences in inference processes (see "Model of the familiarity heuristic based on ACT-R"): The familiarity heuristic assumes that a person makes an inference based on recognition when s/he can recognize one of the two city names (Case 1). When a person more easily forgets city names, it is predicted that opportunities to make inferences based on recognition will increase. Likewise, memory decay will also affect the proportion of random guesses due to the inability to recognize both city names (Case 3-a). That is, memory decay will increase the proportions of Cases 1 and 3-a at the same time. In other words, memory decay can have simultaneously opposed effects (i.e., boosting and deteriorating inference performances at the same time). Furthermore, memory decay will also affect the proportion of Case 2: It is predicted that opportunities to make inferences in Case 2 will decrease when a person more easily forgets city names. In addition, Honda et al. (2017) showed based on behavioral data that inferences based on familiarity (Case 2) were less accurate than those based on recognition

(Case 1). Accordingly, memory decay changes the relationship of the proportions of Cases 1, 2, and 3-a, and these three cases have different effects on inference performance (i.e., boosting or deteriorating accuracies). Based on these considerations, I analyzed the following two points as a function of memory decay: The differences in proportions of Cases 1, 2, and 3-a in inferences and a comparison of the accuracies between inferences based on recognition (Case 1) and on familiarity (Case 2).

Figure 5 shows the predicted proportions of the three cases as a function of memory decay. This proportion was calculated as follows:[3] The recognition rates for the 50 cities could be calculated using equation (3). Then, for each pair, the predicted proportions of the three cases were calculated. For example, in a pair of Cities X (the larger city) and Y, the recognition rates are 0.8 and 0.6, respectively. For this pair, the predicted proportions of the three cases are:

Case 1: $0.8\times(1-0.6)+(1-0.8)\times0.6=0.44$
Case 2: $0.8\times0.6=0.48$
Case 3-a: $(1-0.8)\times(1-0.6)=0.08$

With this procedure, I calculated the proportions of the three cases for each pair and simulated person, and Figure 5 provides the mean values of the proportions for each decay value. Figure 6 shows the proportion of correct inferences based on recognition (Case 1) and familiarity (Case 2). As to inferences based on recognition, I calculated the predicted proportion of correct inferences. For example, in the above case of cities X and Y, the predicted proportion of correct inference is:

$$\frac{0.8\times(1-0.6)}{0.8\times(1-0.6)+(1-0.8)\times0.6}=0.72$$

I calculated the predicted proportion of correct inferences for each pair and simulated person and took the median value as the representative value for each decay value.[4] For inferences based on familiarity, I examined whether such inferences resulted in correct inferences for each

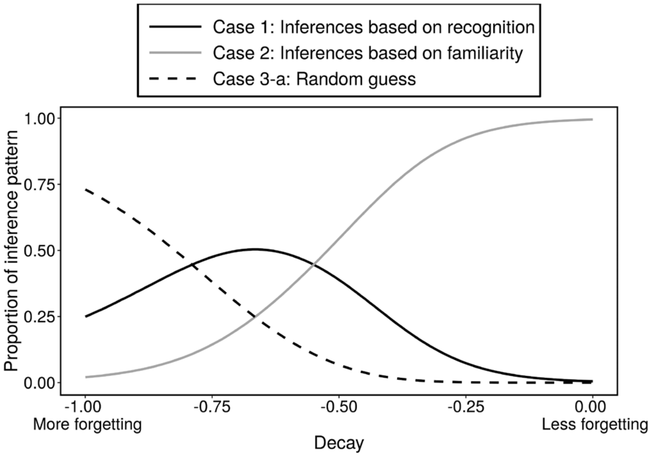

Figure 5. Predicted proportions of the three cases in inferences as a function of memory decay.

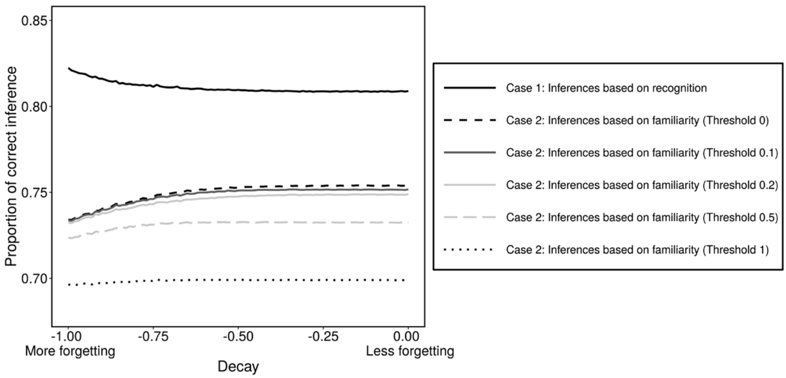

Figure 6. Proportion of correct inferences by Cases 1 and 2 as a function of memory decay.

pair and simulated person and calculated the mean proportion of correct inferences.

According to these findings, the mechanism of why forgetting boosts accuracies of the familiarity heuristic can be interpreted as follows: The proportion of Case 3-a was extremely small around $d = 0.5$, suggesting that the simulated person made few random guesses. In addition, s/he made recognition or familiarity-based inferences with similar proportions. Then, as is apparent in Figure 6, inferences based on recognition led to more accurate inferences than those based on familiarity. Too much forgetting leads to an increase in inferences by random guessing, and too little forgetting leads to decreases in inferences based on recognition, which are more accurate than those based on familiarity. With "moderate" forgetting (i.e., the decay parameter is around 0.5), the proportion of random guesses can sufficiently decrease for a person to more often take advantage of inferences based on recognition, which are more accurate than those based on familiarity.

Closer analyses (2): The relationship between correct inferences and sensitivity to differences in familiarity

As described before, the sensitivity to differences in familiarity (i.e., threshold) was critically related to the application rate of the familiarity heuristic. This result indicates that the number of opportunities where a person can take advantage of the rational familiarity heuristic decreases as s/he becomes less sensitive to differences in familiarity. Given the nature of the threshold, this is understandable. However, note that the deterioration of inference performance with changes in the threshold was relatively small (see Figure 2). In order to examine why these ostensibly contradictory phenomena occurred, I examined the relationship between correct inferences by Case 2 and sensitivity to the difference in familiarity between two city names.

Figure 7 shows the proportion of correct inferences by Case 2. In this figure, the proportion of correct inferences by Case 2 is shown as a function of the difference in familiarity between two cities. Here, results at five decay parameters are reported. As is apparent, the accuracy of the familiarity-based inferences increased as the difference in familiarity between two cities increased regardless of the decay level. Thus, this

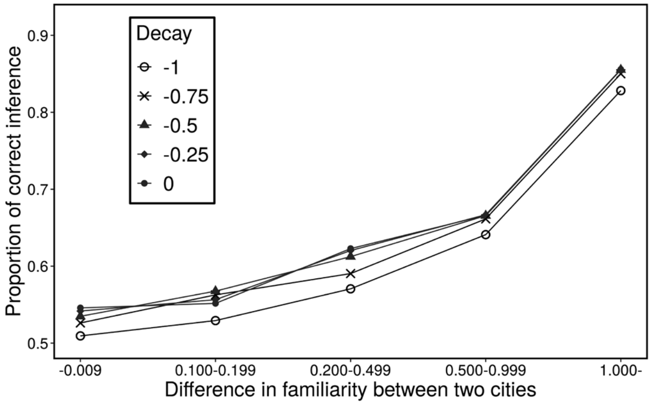

Figure 7. Proportion of correct inferences by the familiarity in Case 2 as a function of differences in familiarity.

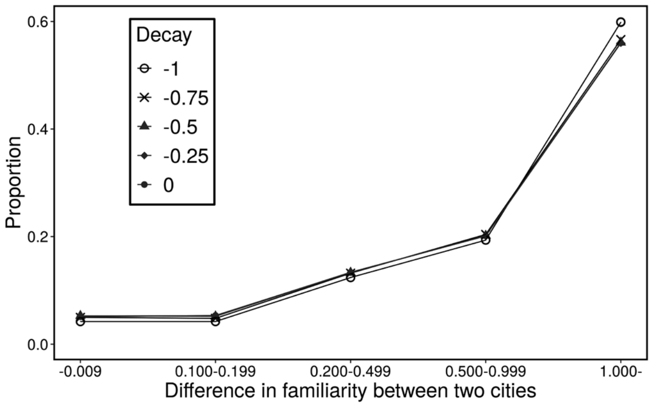

Figure 8. The distribution of differences in familiarity between two cities.

result indicates that people can take greater advantage of the rationality of familiarity-based inferences as the difference in familiarity between the two cities increases. What then is the distribution of the difference in familiarity between the two cities? Figure 8 shows the distributions for the five decay levels shown. The most intriguing point is that around

60% of the difference values exceeded 1.0 regardless of the decay parameters. These results indicate that when a person encounters binary choice inference problems and recognizes both city names, the difference in familiarity between the two cities would be sufficiently large in many cases. Given that the familiarity-based inference is highly accurate when the difference in familiarity between two cities exceeds 1.0 (see Figure 7), a person can take advantage of the rationality of familiarity-based inferences in many cases even if s/he is not so sensitive to differences in familiarity.

General discussion

In the present study, I analyzed how memory constraints affected the rational use of the familiarity heuristic. In particular, I proposed a familiarity heuristic model using ACT-R to examined how forgetting and sensitivity to differences in familiarity affected the accuracy of the familiarity heuristic. The present findings are summarized as follows.

First, it was found that memory decay affected the rationality of the familiarity heuristic. In particular, a simulated person who "moderately" forgets objects made the most accurate inferences. Thus, to a certain extent forgetting boosts the rational features of the familiarity heuristic. Second, sensitivity to the difference in familiarity between two objects was critically related to the applicability of the familiarity heuristic: As is expected from the nature of the threshold, a simulated person who was more sensitive to the difference in familiarity could use the familiarity heuristic more often. However, the sensitivity did not critically affect the accuracy of the familiarity heuristic. That is, people can take advantage of the rational aspect of the familiarity heuristic regardless of their sensitivity to differences in familiarity. Third, as to the mechanism underlying why forgetting boosts the accuracy of the familiarity heuristic, moderate forgetting causes opportunities for random guessing due to lack of recognition to sufficiently decrease, allowing the person to take advantage of recognition-based inferences, which are more accurate than familiarity-based inferences, in more opportunities. As a result, a person who forgets "moderately" can make more accurate inferences under the familiarity heuristic. Fourth, as to the mechanism for why people who are relatively insensitive to differences in familiarity can take advantage of the rational aspect of the familiarity heuristic, it was found that when the simulated person encountered two objects (i.e., city names) and recognized both objects, the difference in familiarity between the two objects was in many cases sufficiently high. Furthermore, as the difference in familiarity increased, familiarity-based inferences became more accurate. Therefore, people can use the familiarity heuristic regardless of their sensitivity to differences in familiarity in many cases, and their inferences based on the familiarity heuristic are highly accurate.

The preset findings are basically consistent with the previous findings in Schooler and Hertwig (2005). They found that forgetting boosted the accuracy of the recognition and fluency heuristics. The present findings provide further evidence that memory constraints do not necessarily cause memory-based simple heuristics such as recognition, fluency, and familiarity heuristics to deteriorate but can enhance the rational aspect of such heuristics. It is also noteworthy that sensitivity to differences in familiarity was not critically related to the rationality of the familiarity heuristic. Given that sensitivity to differences in familiarity is closely related to individual differences in the usage of the familiarity heuristic (see Figure 4 of the applicability of the familiarity heuristic), then regardless of their sensitivity to differences in familiarity, people can take advantage of the rational nature of the familiarity heuristic.

In conclusion, the relationship between memory constraints and the rational use of the familiarity heuristic can be understood theoretically: Forgetting boosts the accuracy of the familiarity heuristic, and sensitivity to the difference in familiarity between two objects is not critically related to the rational use of the familiarity heuristic. Ostensibly, memory constraints such as forgetting are the negative side of cognitive processes. However, the present findings provide evidence that people can exploit such "negative" sides of memory to make rational inferences. I therefore believe that the present findings make a substantial contribution to understanding the relationship between cognitive constraints and rational heuristic usage.

Footnotes

[1] The two parameters τ and s were estimated using the behavioral data in Honda et al. (2017). The estimates for τ and s were 1.36 and 0.64, respectively, which were used in the present simulations. In Schooler and Hertwig (2005), the estimated values of τ and s based on behavioral data were 1.44 and 0.73, respectively, and these values were used in their computer simulations. Thus, the two parameter values used in the computer simulations were highly analogous in the present and previous studies.

[2] In the simulation studies on the recognition and fluency heuristics reported in Schooler and Hertwig (2005), the probability of encountering the largest city, Berlin, was 0.73. Based on this value, we set the scale parameter c at 0.8 in the present study.

[3] Here, Case 3-b (i.e., random guess upon indiscriminability of familiarity between two cities) was included in Case 2, and I examined how such random guesses affected the accuracies of the familiarity heuristic (see Figure 6). In this calculation, only the recognition was involved (i.e., the threshold for the difference in familiarity was irrelevant in this calculation).

[4] The distribution of the predicted proportions of correct inferences was negatively skewed. Hence, the median is appropriate as the representative value in this case.

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