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Evidence for and against a simple interpretation of the less-is-more effect

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Abstract

The less-is-more effect predicts that people can be more accurate making paired-comparison decisions when they have less knowledge, in the sense that they do not recognize all of the items in the decision domain. The traditional theoretical explanation is that decisions based on recognizing one alternative but not the other can be more accurate than decisions based on partial knowledge of both alternatives. I present new data that directly test for the less-is-more effect, coming from a task in which participants judge which of two cities is larger and indicate whether they recognize each city. A group-level analysis of these data provides evidence in favor of the less-is-more effect: there is strong evidence people make decisions consistent with recognition, and that these decisions are more accurate than those based on knowledge. An individual-level analysis of the same data, however, provides evidence inconsistent with a simple interpretation of the less-is-more effect: there is no evidence for an inverse-U-shaped relationship between accuracy and recognition, and especially no evidence that individuals who recognize a moderate number of cities outperform individuals who recognize many cities. I suggest a reconciliation of these contrasting findings, based on the systematic change of the accuracy of recognition-based decisions with the underlying recognition rate. In particular, the data show that people who recognize almost none or almost all cities make more accurate decisions by applying the recognition heuristic, when compared to the accuracy achieved by people with intermediate recognition rates. The implications of these findings for precisely defining and understanding the less-is-more effect are discussed, as are the constraints our data potentially place on models of the learning and decision-making processes involved.

Keywords: recognition heuristic, less-is-more effect.

1 Introduction

Perhaps the simplest heuristic proposed within the "fast and frugal" approach to understanding human decision making developed by Gigerenzer, Todd, and the ABC Group (1999) is the recognition heuristic (Goldstein & Gigerenzer, 2002). It applies to the common decision-making situation in which a decision maker must choose between two presented alternatives on the basis of some criterion. The recognition heuristic assumes that, when decision makers recognize one of the alternatives, but not the other, they choose the recognized alternative. Thus, if a decision maker is asked whether Frankfurt or Paderborn has the greater population, and has only heard of Frankfurt, then Frankfurt will be chosen based on recognition.

The recognition heuristic has been widely studied, both empirically and theoretically. Empirically, the use of the recognition heuristic under various experimental manipulations has been studied for questions including the population of cities, the length of rivers, the age of famous people, and so on (e.g., Bröder & Eichler, 2006; Hoffrage, 2011; Oppenheimer, 2003; Pohl, 2006). Theoretically, there has been work at both the algorithmic level in Marr's (1982) hierarchy, studying how the recognition heuristic can be integrated with process models of related elements of cognition such as memory (e.g., Erdfelder, Küpper-Tetzel, & Mattern, 2011; Pleskac, 2007), and at the computational level, studying its optimality properties with respect to different decision-making environments (e.g., Davis-Stober, Dana, & Budescu, 2010; Katsikopoulos, 2010; Smithson, 2010). The usefulness of the recognition heuristic as a means of making decisions has also been studied in a number of applied contexts, including predicting the winners of sporting competitions (e.g., Herzog & Hertwig, 2011; Pachur & Biele, 2007; Scheibehenne & Bröder, 2007; Serwe & Frings, 2006), political elections (Gaissmaier & Marewski, 2011), consumer choice (Hilbig, 2014; Oeusoonthornwattana & Shanks, 2010), and choosing stock market portfolios (Andersson & Rakow, 2007; Borges, Goldstein, Ortmann, & Gigerenzer, 1999). A relatively recent series of three special issues on the recognition heuristic in this journal provides an excellent survey (Marewski, Pohl, & Vitouch, 2010, 2011a, 2011b), including many of the articles cited above, as well as the reflections, evaluations, and perspectives of those who developed the heuristic (Gigerenzer & Goldstein, 2011).

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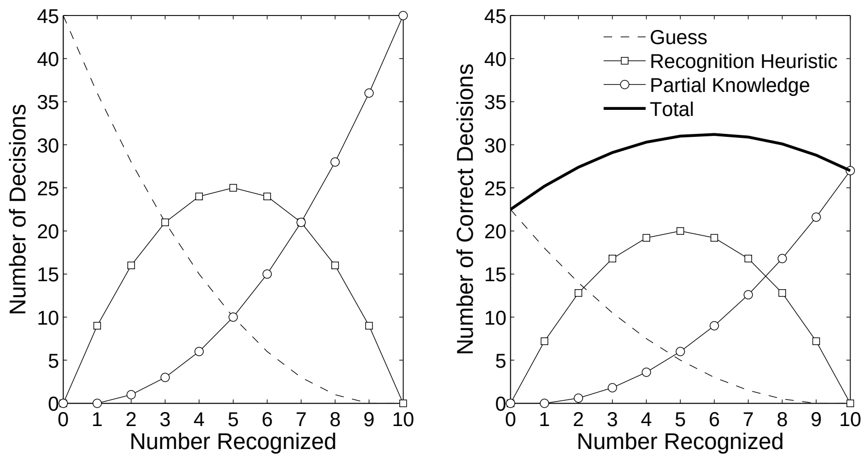
Figure 1: The intuition underlying the less-is-more effect. The left panel shows the number of decisions out of a total of 45 made by guessing, recognition, and partial knowledge as the number of recognized alternatives increases from 0 to 10. The right panel shows the number of correct decisions made by guessing, recognition, and partial knowledge, assuming accuracy rates of 0.5, 0.8, and 0.6 respectively. The total number of correct decisions is shown by the solid line, and peaks when 6 out of 10 alternatives are recognized.



One interesting prediction based on the use of the recognition heuristic is the "less-is-more" effect (Goldstein & Gigerenzer, 2002). The premise is that it is possible that the decisions made by the recognition heuristic (applicable when only one alternative is recognized) could be more accurate than decisions made on the basis of partial knowledge (applicable when both alternatives are recognized). When this assumption is met, people who recognize all of the alternatives will have a lower overall accuracy than at least some people who do not recognize all of the alternatives. Knowing less about the alternatives leads to the more accurate decisions, and this is coined the less-is-more effect.

Formal analyses proving the less-is-more result were provided originally by Goldstein and Gigerenzer (2002), and have been carefully analyzed and generalized by Katsikopoulos (2010) and Smithson (2010). An important generalization has involved considering the potential role of recognition memory in the recognition heuristic, and its impact on predictions about the less-is-more effect. In this paper, I consider only the original statement of the effect, which assumes that recognition memory is perfect, and provides the simplest framework for analysis. The key intuition of these formal analyses—which Katsikopoulos (2010, p. 249) terms the *accurate heuristics* explanation, to distinguish it from other possibilities involving recognition memory—is that, if recognition is more accurate than knowledge, some ignorance (non-recognition) is needed so that recognition can be applied to improve overall accuracy.

Figure 1 attempts to convey the accurate heuristics explanation in a concrete way, considering the case where there are 10 alternatives, and so $\binom{10}{2} = 45$ comparisons. The left panel shows how many of these 45 comparisons are made by guessing (when neither alternative is recognized), by using the recognition heuristic (when one alternative is recognized), and by using partial knowledge (when both alternatives are recognized) as the number of recognized alternatives increases from 0 to 10. When none of the alternatives are recognized, every decision must be made by guessing. When all of the alternatives are recognized, every decision must be made using partial knowledge. Between these extremes, a number of decisions are made by the recognition heuristic, with its use peaking when exactly half the alternatives are recognized.

The right-hand panel of Figure 1 considers the number of *correct* decisions. This depends on the total number of decisions being made by guessing, recognition, and partial knowledge, and by the accuracy of each of those methods. To demonstrate the less-is-more effect in Figure 1, it is assumed that recognition is 80% accurate, partial knowledge is 60% accurate, and guessing is 50% accurate. The individual lines now show the number of correct decisions, which is simply the total number of decisions made by each method, scaled by the accuracy of each method. Thus, the guessing line is exactly half as high in the right-hand panel compared to the left hand panel. Because it is assumed recognition is more accurate than partial knowledge, the inverse-U-shaped recognition line is not shrunk to the same extent as the partial knowledge line. The net result of these differences is seen in the total number of correct decisions, shown by the bold line, which simply sums the number of correct decisions across all three cases. This line is non-monotonic, and peaks when 6 alternatives are recognized. This is the less-is-more effect. Total accuracy is highest when some number of alternatives is not recognized.

There is empirical evidence both for (e.g., Frosch, Philip Beaman, & McCloy, 2007; Goldstein & Gigerenzer, 2002; Reimer & Katsikopoulos, 2004) and against (e.g., Boyd, 2001; Dougherty, Franco-Watkins, & Thomas, 2008; Pohl, 2006) the less-is-more effect. A good review of the empirical evidence is provided by Pachur (2010, see especially Table 1 and Figure 2). There is also some empirical evidence for extensions of the less-is-more effect to choices that involve more than two alternatives (Frosch et al., 2007), and predictions of less-is-more effects in collective group decision-making (Reimer & Katsikopoulos, 2004). Theoretically, the less-is-more effect has been integrated with cognitive models of recognition, within both standard signal detection theory (Pleskac, 2007) and multinomial processing tree (Erdfelder et al., 2011) frameworks. The extended theoretical assumption of imperfect recognition memory—which seems very plausible in many experimental and real-world situations—complicates the analysis of the less-is-more effect in interesting ways, and basic properties of the accurate heuristics explanation no longer hold (see Katsikopoulos, 2010, pp. 250–255)..

As Beaman, Smith, Frosch, and McCloy (2010) note, the less-is-more prediction is "surprising", and so provides a strong test of the theory from which it is derived (Roberts & Pashler, 2000). This means, in turn, that theoretical and empirical evidence for and against the less-is-more effect is used rhetorically to support or attack the recognition heuristic in particular, and fast and frugal heuristic approaches in general. Of course, the recognition heuristic alone does not imply a less-is-more effect, so failure to find the effect does not imply that the heuristic is not used.

Against this background, the aim of this paper is to test the use of the recognition heuristic, and the existence of the less-is-more effect, based on new empirical evidence. The next section describes experimental data designed to examine both questions in a direct way, using a task in which participants judge which of two cities is larger for cities in four different countries, and indicate whether or not they recognize the cities. The data are then analyzed in two ways. The first analysis is at a group level, testing whether the recognition heuristic is followed, and how its accuracy compares to the decisions based on partial knowledge. The second analysis is at an individual level, examining how the accuracy of individual participants changes as function of their different recognition rates. These two analyses suggest different conclusions, but I reconcile them by examining limitations in the assumption that the recognition heuristic provides equally accurate decisions for all people.

2 Experiment

A total of 225 participants—all students in a large undergraduate class at the University of California, Irvine—provided data from the experiment. The experimental task presented participants with pairs of cities, and required them to indicate which city they believed had the larger population, and whether or not they recognized each city. The task was repeated for each of four countries, and participants were free to choose in which order they completed both the countries, and the comparisons within the countries.

The countries were Germany, the United States, Italy, and the United Kingdom. The cities were the 82 most populous from the set of German cities reported by Gigerenzer and Goldstein (1996, Appendix), and the 74 United States cities, 48 most populous Italian cities, and 66 United Kingdom cities reported by Lee and Zhang (2012). One fewer German city and one fewer Italian city was used than was available in the complete set, to give an even number, and enable unique presentation of each city in paired comparisons.

The empirical data were collected over three years as part of a class requirement. In each of the three years, 12 different versions of the task were constructed—selecting different city pairs at random subject to the constraint each city was presented exactly once—and participants completed the version corresponding to their birth month. If a participant did not complete any comparison within a country, all of their data for that country were discarded. This was done because a number of key measures, including a participant's recognition rate for a country, rely on complete data.

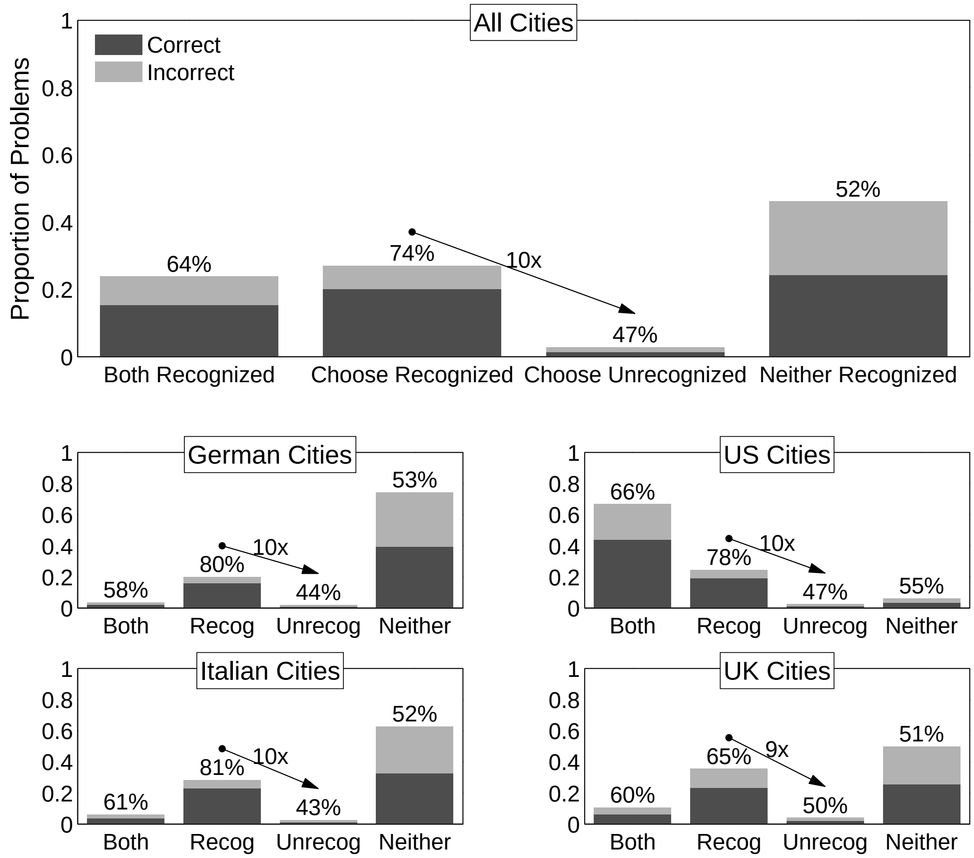
3 Results

I analyze the data to examine the less-is-more effect from two different perspectives. First, I present a group-level analysis, which produces results consistent with the effect. Then, I present an individual-level analysis, which produces results inconsistent with the effect. Consequently, I present an additional analysis that attempts to reconcile the group-level and individual-level results.

3.1 Group-level analysis

A group-level analysis is shown in Figure 2. The main panel considers all of the answers given by all participants to all of the comparisons for all countries. The four bars divide the city pairs into those cases where both cities were recognized, where one city was recognized and was chosen as the most populous, where one city was recog-

Figure 2: The main panel shows the number and accuracy of the four possible classes of decisions in judging which of two cities has the larger population. The problems are divided according to whether both cities were recognized ("both recognized"), one city was recognized and was chosen ("choose recognized"), one city was recognized but the unrecognized one was chosen ("choose unrecognized"), or neither city was recognized ("neither recognized"). The overall height of each bar corresponds to the proportion of all decisions that belonged to that class. The darker and lighter areas within bars indicate how many of these decisions were correct and incorrect, respectively. The label above each bar gives the overall percentage of correct decisions so that, for example, the accuracy of decisions when neither city is recognized is close to 50% consistent with guessing. The arrow indicates how many times more often the "chosen recognized" rather than "chosen unrecognized" class occurred, and so measures how many times more often decisions followed the recognition heuristic. The four sub-panels show the same information, for each country separately.



nized but the unrecognized city was chosen as the most populous, and where neither city was recognized. Each bar is sub-divided into a darker area representing correct choices, and a lighter area representing incorrect choices. The accuracy rate is displayed as a percentage above each bar. The four sub-panels in Figure 2 show exactly the same analysis for each country separately.

Figure 2 presents two important results. The first is that *when participants are able to apply the recognition heuristic, they almost always do*. The total height of the "choose recognized" bar compared to the "choose unrecognized" bar measures how often participants chose the recognized rather than unrecognized city for those pairs where only one is recognized. The main panel shows that the recognized city is 10 times more likely to be chosen overall, and this result is consistently seen for the individual countries. The second result is that *the recognition heuristic leads to more accurate decisions than ones based on partial knowledge of the cities*. The "both recognized" bar represents those comparisons where both cities are recognized, and the accuracy of these decisions is the accuracy based on partial knowledge. The "choose recognized" bar represents comparisons where the choice made is consistent with applying the recognition heuristic, and the accuracy of these decisions is the accuracy of the heuristic. Overall, the recognition heuristic is 74% accurate, compared to 64% when both cities are recognized. The same superior accuracy for the recognition heuristic is found in all four of the countries. It is a large superiority of around 20% for the German and Italian cities, around 10% for United States cities, and around 5% for United Kingdom cities.

The superior accuracy of decisions consistent with using the recognition heuristic was found to apply not just in aggregate for each country, but at the level of individual participants.[1] Combining the decisions each participant made across all of the countries, 96% were more accurate in making "choose recognized" than "both recognized" decisions. Exactly the same result was found when each country for each participant was considered separately, under the restriction that at least 5 decisions were required to estimate the accuracy rate as a proportion. Once again, 96% of these individual participant-by-country sets of decisions showed greater accuracy for "choose recognized" than "both recognized" decisions.

These results are highly consistent with the less-is-more effect, and its theoretical underpinnings, at least under the assumption of perfect recognition memory. The basic finding is that people make more accurate decisions when they make a choice consistent with the recognition heuristic than when they recognize both cities. It is also clear, in the city domains considered, that people almost always make choices consistent with the recognition heuristic when this is possible. Thus, both the empirical finding of differences in accuracy, and the proposed mechanism for this difference in terms of applying the recognition heuristic, are found in the group-level analysis of the data.

3.2 Individual-level analysis

While the group-level analysis provides evidence for the use of the recognition heuristic, and for its accuracy relative to the use of knowledge, it does not take the same form as the standard presentation of the less-is-more effect. The standard form closely follows the right-hand panel of Figure 1, by relating the recognition rates of people to their accuracies in making decisions. The less-is-more effect, stated in these terms, implies that there are people who recognize fewer cities but are more accurate than people who recognize more cities. Goldstein and Gigerenzer (2002, Figure 2) caricature the less-is-more effect in this way, by imagining younger, middle, and older sisters who have low, medium, and high recognition rates respectively, and making the prediction that the middle sister will make the most accurate decisions.

Figure 3 presents this analysis for the current data. The main panel considers every set of country questions completed by individual participants, showing by circular markers the accuracy and recognition rate of that participant. A trend line based on binning is overlaid. The sub-panels repeat this analysis for each of the countries separately, so that the main panel is simply the superimposition of the four sub-panels. It is clear that there are large individual differences in both recognition rates and accuracy, as well as overall effects for the different countries, with United States cities being more often recognized than for the other countries. Despite this variation in both recognition and accuracy, however, there is no evidence that accuracy changes as an inverse-U-shaped function with recognition. The distribution of accuracy over people—and the averages shown by the trend lines—appears to be very similar at all levels of recognition, perhaps with a slow linear increase in accuracy with recognition.

The Appendix presents a formal Bayesian statistical analysis that bears out these conclusions. The key findings are based on Bayes factors, which quantify the relative evidence data provide for two or more alternative models (Kass & Raftery, 1995). The data provide at least 15 times more support for a model that assumes a linear increase in accuracy with recognition, when compared to a quadratic model that makes inverse-U-shaped predictions consistent with the less-is-more effect.[2] The data also provide overwhelmingly more support for the linear model than for alternative models that that assume accuracy is constant, or that accuracy is consistent with guessing. Thus, I conclude that there is evidence for a linear relationship between accuracy and recognition, rather than evidence for an inverse-U-shaped relationship. I note that the failure to find an inverse-U-shaped curve relating accuracy to recognition appears to be consistent with the majority of previous data sets conveniently displayed in Pachur (2010, Figure 2).

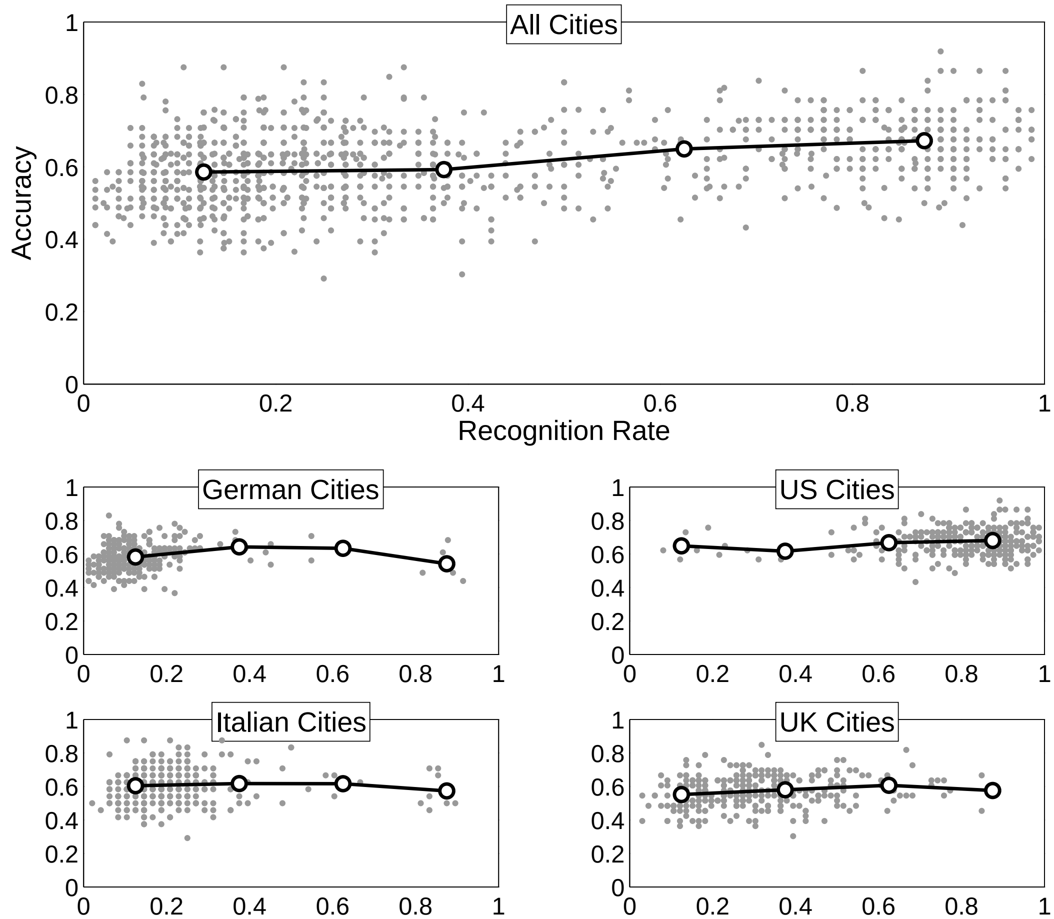
3.3 Reconciling the group and individual analyses

One way to reconcile the group-level analysis (indirectly) in support of the less-is-more effect with the individual-level analysis (directly) failing to support the effect, is to consider a basic assumption in the original analysis. Goldstein and Gigerenzer (2002, p. 80) were clear that an assumption underlying the prediction of the standard less-is-more effect is that "the recognition validity alpha and the knowledge validity beta remain constant as the number of cities recognized, varies." A number of authors have pointed out that his is a strong assumption that seems unlikely to be met (Beaman et al., 2010; Pachur, 2010;

[1] I thank Konstantinos Katsikopoulos for suggesting these analyses.

[2] The appendix presents two analyses that support this conclusion. One is based on relatively general specifications of the alternative relationships being considered between recognition and accuracy. The other analysis is based on stronger assumptions about the alternative relationships, including predictions about the size and nature of the less-is-more effect more tightly matched to the underlying theory and previous empirical findings.

Figure 3: The main panel shows the number of cities recognized and accuracy for each participant as a small circular marker. The larger markers connected by the line show the trend in the relationship between recognition and accuracy. The four panels below show the same information for each country separately.



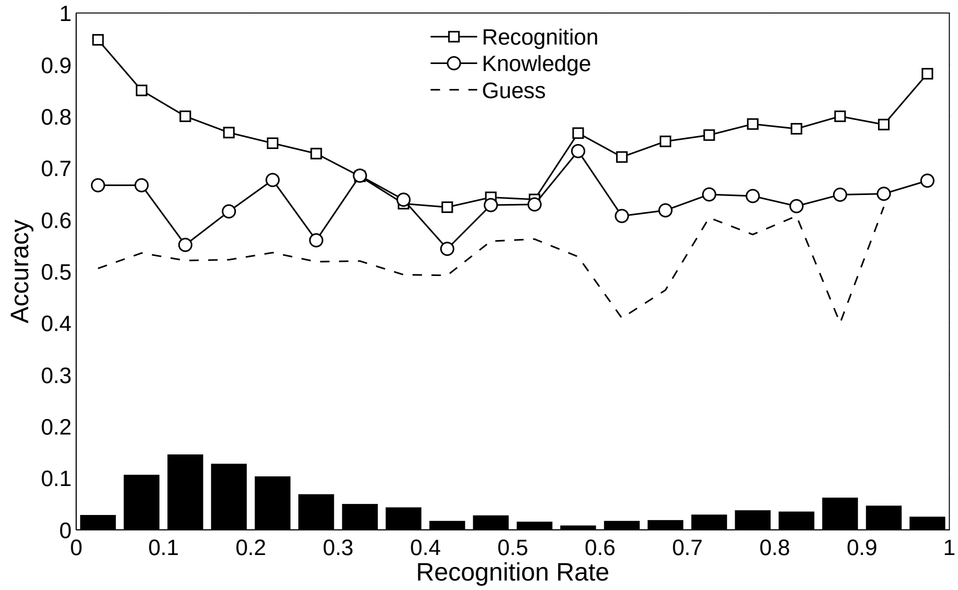
Pachur & Biele, 2007; Smithson, 2010). Figure 4 tests this assumption directly, by presenting an analysis of how the accuracy of recognition, knowledge, and guessing decisions change as a function of individual-level recognition. These curves were found by considering all of the participants who, for a set of country questions, had a recognition rate in a small range, and calculating the proportion of correct decisions they made for comparisons where they recognized one city (recognition), both cities (knowledge), or neither city (guess).[3] The relative number of participants in each recognition range is shown by the histogram at the bottom of Figure 4

The accuracy of guessing is variably estimated for high levels of recognition (because these participants have to guess relatively rarely), but is consistent with an expected value around 0.5 across the entire range of recognition. The statistical analyses presented in the appendix find strong evidence that accuracy of guessing is constant over changes in recognition rate, but is slightly higher than the chance rate of one-half.

The accuracy of knowledge-based decisions is variably estimated for low levels of recognition, but appears to be consistently around 0.6 and 0.7 across the entire range of recognition. The statistical analyses presented in the appendix find that the data provide the most evidence for accuracy being constant with respect to recognition rate, although more complicated relationships, such as a gradual linear increase, cannot be ruled out. If the constant relationship holds, it would constitute an interesting finding, because it is not consistent with the reasonable prediction that people who know more cities make more accurate decisions choosing between those cities they know. A previous finding is that people who know more items are more accurate in choosing between those cities they recognize (Pachur, 2010), which has a natural interpretation in terms of those people being generally more intelligent, and so knowing more answers, or using their partial knowledge

[3] The statistical analyses in the appendix present each of these curves separately, and so are able to display error bars without visual clutter.

Figure 4: The pattern of change in the accuracy of recognition (squares), knowledge (circles), and guessing (dashed line), in choosing the larger city, for individuals with different recognition rates. The bars show the distribution of individuals over the recognition rates.



better. The evidence for constancy of the knowledge curve in Figure 4 is inconsistent with these findings and interpretations.

Most importantly, however, Figure 4 clearly shows the accuracy of recognition based decisions changes as a function of the underlying recognition rate. At very high and very low levels of recognition, accuracy is around or above 0.9. At intermediate levels of recognition, accuracy is between about 0.6 and 0.7. The statistical analyses presented in the appendix show that the data provide strong evidence for this conclusion. In particular, Bayes factors provide strong evidence for a quadratic, rather than linear or constant, relationship between recognition-based decisions and the recognition rate. This non-monotonic U-shaped change is a clear violation of the assumption of constant accuracy. It is also inconsistent with previous analyses that have focused on the possibility of a linear relationship, and not considered non-monotonic relationships, by relying on correlation coefficient measures of the association between the accuracy of recognition-based decisions and recognition rates (Pachur, 2010).

The U-shaped relationship is easily and intuitively interpreted. It means that people who recognize very few cities in a country tend to recognize the large cities, and so decisions consistent with the recognition heuristic will tend to be very accurate. Similarly, people who recognize almost all the cities in a country tend only not to recognize a few of the smallest cities, and so the decisions they make that are consistent with the recognition heuristic will also tend to be very accurate. The dip in the accuracy of recognition decisions for people with moderate recognition rates for a country means that, when a person knows about half the cities, those cities recognized follow the city populations less closely. These people do not simply recognize the largest 50% of cities. Instead, recognition is more loosely related to city population, and so decisions consistent with the recognition heuristic will only sometimes be correct. In effect, it is the exactness or looseness of the relationship between the decision criterion and recognition that the accuracy of the recognition heuristic measures.

The change in the accuracy of recognition decisions naturally reconciles the contrasting results from the group-level and individual-level analyses. Figure 4 shows that, overall, recognition decisions are more accurate than those based on knowledge. At worst, the accuracy of decisions consistent with the recognition heuristic falls to the level the knowledge decisions show throughout. Thus the overall difference in accuracy observed in the group-level analysis makes sense. For the individual-level analysis, however, Figure 4 shows that for recognition levels corresponding to knowing very few or very many cities—those cases in which recognition heuristic is applicable relatively less often—the accuracy of decisions consistent with the recognition heuristic is high. Thus, the decrease in accuracy for high and low recognition rates, which generates the less-is-more effect in the standard analysis presented in Figure 1, does not eventuate. Guessing is equally accurate, and knowledge is equally accurate, but decisions consistent with the recognition heuristic are less accurate for recognition levels where it can often be applied, but more accurate for recognition levels where is can be less often applied. The net result of this relationship between frequency of use and accuracy of use is that overall accuracy does not change as function of recognition rate. A geometric intuition for this reconciling explanation is that the U-shaped curve for the accuracy of recognition decisions "undoes" the inverse-U-shaped curve predicted by the less-is-more effect. The two nearly cancel each other to produce the gentle linear relationship between accuracy and recognition rate observed in Figure 3.

4 Discussion

The analyses and reconciliation presented here show that it is important to be precise about what is meant by the less-is-more effect. Goldstein and Gigerenzer (2002, p. 83) distinguished between three different versions of the less-is-more effect, and these versions have been influential in subsequent theorizing (e.g., Pachur, 2010; Smithson, 2010). Smithson (2010, p. 232) provides a concise summary of the three versions: "One comparing more and less knowledgeable agents, another comparing performance in different domains, and a third comparing performance as an agent learns new items."

The first of these versions can be interpreted as claiming that accuracy based on recognition is greater than accuracy based on knowledge. This interpretation is consistent with the finding, for example, that Londoners are more accurate than New Yorkers in choosing Detroit as having a larger population than Milwaukee (see Gigerenzer & Goldstein, 2011, p. 101). The group-level analysis presented here tests this version, since it examines average performance of a group of people for questions where recognition can and cannot be used. The results for these data, summarized in Figure 2, are consistent with this version of the less-is-more effect, since they show decisions consistent with the recognition heuristic to be more accurate than those made in situations where the recognition heuristic cannot be applied.

The second version of the less-is-more effect can be interpreted (loosely) as claiming that individuals who recognize many items will be more accurate than individuals who recognize a moderate number. This interpretation is the one made by the standard account of the effect, especially in the graphical form presented by Goldstein and Gigerenzer (2002, Figure 2). The individual-level analysis presented here tests this version, since it examines the relationship between levels of recognition and accuracy over individuals. The results, summarized in Figure 3, are inconsistent with this version of the less-is-more effect, since they do not show the predicted non-monotonic inverse-U shape relationship.

The data presented here do not directly address the third version of the less-is-more effect, involving changes in performance over time. To test this version longitudinal data, tracking the accuracy of people as they learn to recognize items over time, are required.

The reconciliation of the group-level and individual-level analyses suggested here—hinging on the systematic and interpretable change in the accuracy of the recognition heuristic over different levels of individual recognition—is useful for a number of reasons reasons. The reconciliation highlights the difference between the first and second versions of the less-is-more effect. It is possible for recognition-based to be more accurate than knowledge-based decision-making overall, without implying that there are individuals who use recognition more often who are more accurate than individuals using knowledge. In fact, one way of summarizing the main result is that three conditions are needed for the standard less-is-more effect, without the complication of considering recognition memory. One condition is that people must often follow the recognition heuristic when it is possible to do so. The data provide compelling evidence this condition is met. A second condition is that the accuracy of decisions following the recognition heuristic must be greater than the accuracy of decisions based on partial knowledge. The data also show this condition being satisfied in each country domain considered, as well as overall, and for the vast majority of individuals, both per country, and over all countries. The third condition, however, is that the accuracies of the recognition-based and knowledge-based decisions must be constant with respect to the recognition rate. It is this condition that is not satisfied by the data, and the violation explains the lack of an individual-level less-is-more effect.

A more general contribution of examining the accuracy of recognition-based, knowledge-based, and guessing-based decisions for different levels of recognition is to provide empirical constraints to guide theorizing and model development. The empirical regularities evident in Figure 4 are non-trivial. The accuracy of decisions made when both alternatives were recognized seems not to change with a person's level of recognition. Thus, it does not appear that people who know more cities are more intelligent or knowledgeable, because they are not able to make better decisions when they know both cities. The implication for theories and models of individual differences in the current task is that mechanisms such as memory capacity or decision bias need to be carefully included, so that they do not predict improved knowledge-based performance for people with higher levels of recognition. Similarly, the accuracy of guessing appears to be constant around one-half across all recognition levels. This is intuitive, but it would also have been plausible to expect, for example, an increase in guessing accuracy for people with higher recognition levels, again on the grounds they are more intelligent, and so more able to make educated guesses.

Most importantly, the relationship between the accuracy of recognition-based decision-making and the level of recognition, evident in Figure 4, provides a strong constraint on theorizing. It is clear that the decisions made by following the recognition heuristic are, at least in some situations, not equally accurate for all levels of recognition. The possibility of non-constancy was anticipated theoretically in general terms by a number of authors (e.g., Goldstein & Gigerenzer, 2002; Katsikopoulos, 2010; Pachur, 2010; Smithson, 2010). Goldstein and Gigerenzer (2002) conducted simulations to examine whether constancy was a necessary condition for the less-is-more effect. Pachur (2010) examined the possibility of non-constancy by measuring correlations in existing data sets, and showed the consequences of these correlations by simulation. The empirical regularities found in the data, however, are different. In particular, they reveal a non-monotonic relationship between recognition rate and the accuracy of recognition-based decisions that cannot be expressed by linear correlations.

For these reasons, I think the analysis of how recognition-based accuracy changes with recognition rate provides a new sort of empirical evidence that should be an especially valuable guide for model development. It is possible to give an interpretation of the shape of the recognition accuracy curve in Figure 4, which shows that very low and very high recognition levels permit the most accurate use of recognition. One explanation for the increase in recognition-based accuracy at low recognition rates is that people learn about cities in a way that depends on their populations. Each of the countries considered here has a small number of cities that are much larger than the others, and if these are learned first, people with very low recognition rates will be be very likely only recognize these cities, making their use of the recognition heuristic very accurate. This sort of interpretation relates to the sequences with which people learn to recognize items over time. Such an explanation is more difficult to apply to the increased accuracy of recognition-based decision making for high recognition rates, since there are many cities with similar small populations. Additional empirical evidence would be useful for replicating the increase in recognition-based accuracy for high levels of recognition that is evident in the main panel of Figure 4.

A weakness of the current data is that they rely on the use of different countries to ensure sufficient variation in individual recognition rates to test the less-is-more effect. It is an established experimental manipulation in the literature on the less-is-more effect to change countries in order to induce changes in recognition rates within individuals, as when US and German residents are asked about both US and German cities (e.g., Goldstein & Gigerenzer, 2002). Nonethelss, a narrow interpretation of the preconditions for evaluating the less-is-more effect articulated by (Gigerenzer & Goldstein, 2011) could challenge the current data, claiming that the combination of countries means there is no unitary "reference class" of items over which recognition and accuracy measures are established. I think, however, that the current data do usefully address the existence and nature of the less-is-more effect, for two reasons. First, the failure to find the less-is-more effect in the individual-level analysis—in the sense of a failure to find decrease in accuracy for individuals with very high levels of recognition—is almost entirely driven by the US country data. It is clear from Figure 3 that most the the cases of individuals with high recognition rates come from comparing US cities, and that there is no systematic and discernible decrease in accuracy for individuals with high recognition rates in these comparisons, as required by a substantive interpretation of the less-is-more effect. In this sense, the US country data provide evidence against the less-is-more effect in a way that does meet reference class preconditions. Secondly, and most generally, I think the reference class conception does not need to be applied narrowly to test the less-is-more effect in useful ways. All of the countries in the data set have the key properties that recognition-based decisions are more accurate than those based on partial knowledge, and that the decisions people make are consistent with the recognition heuristic. These are the key theoretical elements underpinning the standard accurate heuristics exposition of the less-is-more effect. The data clearly show, however, that accuracy does not decrease at high levels of recognition, which is what a theoretically interesting and empirically meaningful less-is-more effect predicts. My reconciling analysis suggests this is because the accuracy of recognition-based decisions is not constant, but varies in an interpretable way. Thus, I think the data have both the properties needed to test the less-is-more effect, and the richness to allow for an analysis that furthers our theoretical understanding.

5 Conclusion

The recognition heuristic makes a compelling contribution to the general case for fast and frugal heuristic accounts of human decision making. It is simple and plausible, and presents a concrete way in which a heuristic following an environmental regularity can generate impressively accurate decisions. The data provide strong evidence for people making decisions consistent with this heuristic. The less-is-more effect is a surprising prediction derived from the recognition heuristic by making some simple assumptions. The data, suggest, however, that these assumptions are too simple. The accuracy of the recognition heuristic, for the city domains considered, is not constant over the level of recognition in the way required for the standard account of the less-is-more effect to emerge. Instead, the accuracy of the recognition heuristic varies in systematic and interpretable ways.

Future work should focus on developing models of decision-making that explicitly tackle the issues of how the environment supplies the information that drives recognition and learning. To the extent that the regularities evident in Figure 4 are replicable and generalizable, models need to be consistent with the relationship between the accuracy of recognition-based and knowledge-based decisions and recognition rate. The challenge is to understand and model how people encounter and recognize items in their environment, and the consequences of these interactions and abilities for the performance of recognition-sensitive decision heuristics.

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Appendix

This appendix presents the details of the statistical inferences reported in the main text. The first analyses test whether the relationship between accuracy and recognition at the individual level, as presented in Figure 3, follows the inverse-U-shape predicted by the less-is-more effect. The second analyses test the patterns of change in the accuracy recognition-based, knowledge-based, and guessing-based decisions for different recognition rates, as presented in Figure 4.

5.1 Individual-level relationship between accuracy and recognition

The relevant data are the counts of k_i^{a} accurate decisions out of n_i^{a} questions, and k_i^{r} recognitions out of n_i^{r} cities, made by the ith individual. From these data, it is natural to consider underlying accuracy θ_i^{a} and recognition θ_i^{r} rates, defined as $k_i^{\mathrm{a}} \sim \mathrm{Binomial}\big(\theta_i^{\mathrm{a}}, n_i^{\mathrm{a}}\big)$ and $k_i^{\mathrm{r}} \sim \mathrm{Binomial}\big(\theta_i^{\mathrm{r}}, n_i^{\mathrm{r}}\big)$.

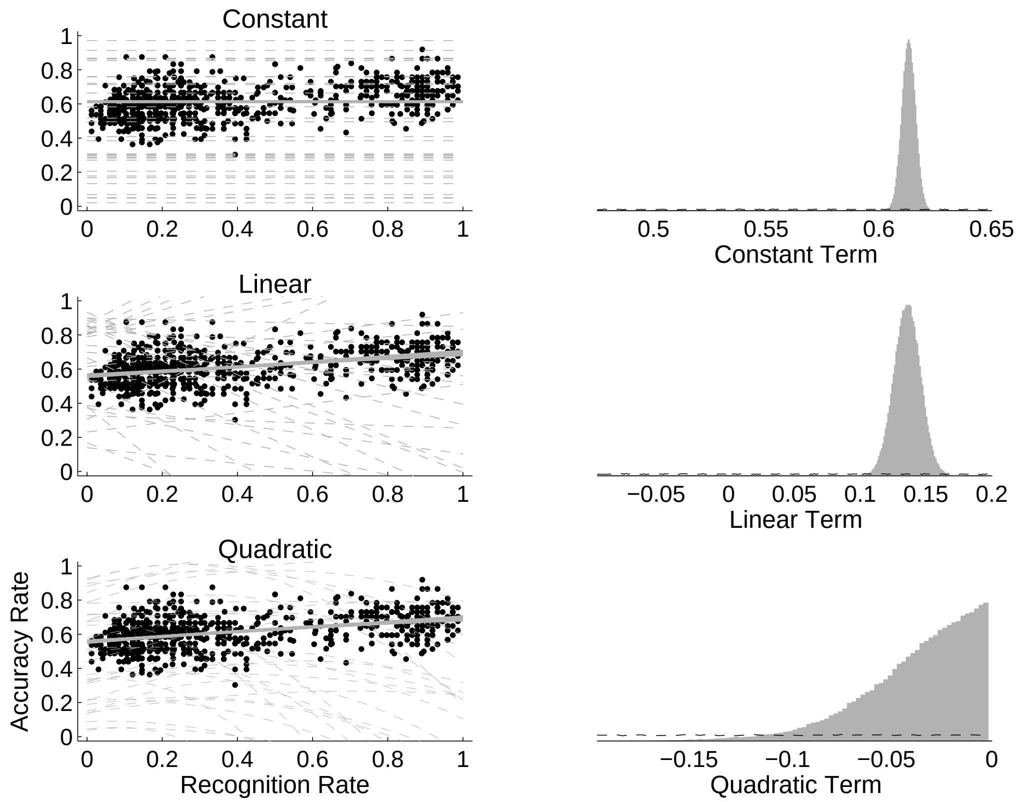
I consider four interesting statistical models of the relationship between θ_i^{a} and θ_i^{r}, corresponding to different psychological interpretations of the relationship between accuracy and recognition rate. The first model simply assumes people *guess* all their answers, independent of their recognition rates. The second assumes that people have some *constant* rate of accuracy, independent of their recognition rates. The third assumes a linear relationship, so that accuracy increases or decreases with recognition rate. The fourth assumes a inverse-U-shaped relationship, in the form of a *quadratic* with a negative quadratic coefficient, as predicted by the less-is-more effect.

I formalize these models—which in a Bayesian analysis requires formalizing both the likelihood function and priors on parameters, since both express theoretical assumptions (Vanpaemel & Lee, 2012)—as

$$
\begin{aligned}
&\mathcal{H}^{\mathrm{g}}:\ \theta_i^{\mathrm{a}} = \frac{1}{2},\\
&\mathcal{H}^{\mathrm{c}}:\ \theta_i^{\mathrm{a}} = c_1,\ c_1 \sim \mathcal{U}\big(0,1\big),\\
&\mathcal{H}^{\mathrm{l}}:\ \theta_i^{\mathrm{a}} = b_2\theta_i^{\mathrm{r}} + c_2,\ b_2 \sim \mathcal{N}\big(0,1\big),\ c_2 \sim \mathcal{U}\big(0,1\big),\\
&\mathcal{H}^{\mathrm{q}}:\ \theta_i^{\mathrm{a}} = a_3\left(\theta_i^{\mathrm{r}}\right)^2 + b_3\theta_i^{\mathrm{r}} + c_3,\ a_3 \sim \mathcal{TN}^{-}\big(0,1\big),\\
&\qquad\ b_3 \sim \mathcal{N}\big(0,1\big),\ \ c_3 \sim \mathcal{U}\big(0,1\big).
\end{aligned}
$$

The priors were chosen by inspecting prior predictive distributions, and choosing combinations that corresponded to reasonable expressions of the different alternative relationships between recognition and accuracy being tested. In particular, the quadratic coefficient was constrained to

Figure 5: The left-hand panels show the prior predictive (broken lines) and posterior predictive (solid lines) distributions for the constant (top), linear (middle), and quadratic (bottom) models of the relationship between accuracy and recognition rate. The right-hand panels show the prior (broken line) and posterior (solid histogram) distribution for the parameters corresponding to the constant (top), linear (middle), and quadratic (bottom) terms that allow for the estimation of Bayes factors between the models using the Savage-Dickey density ratio method.



be negative, corresponding to the prediction of the less-is-more effect of an inverse-U-shaped function.

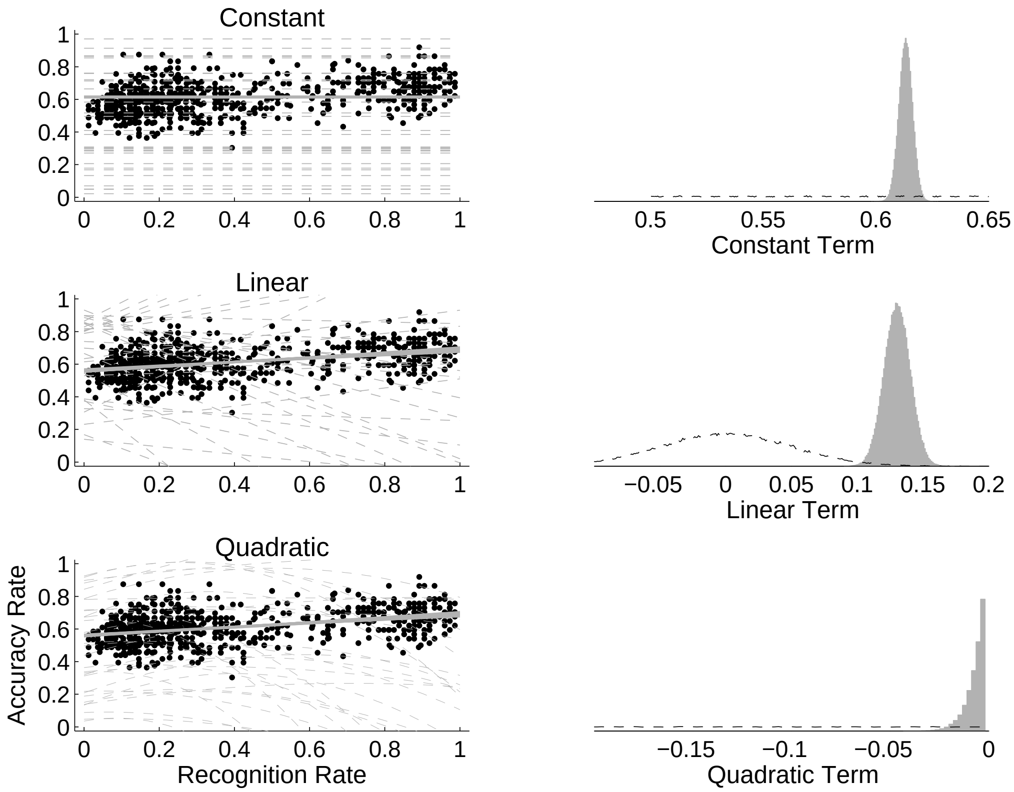
All four of these models were implemented as graphical models in JAGS (Plummer, 2003), which allows for Bayesian inference using computational sampling methods (see Lee & Wagenmakers, 2013, for an introduction to Bayesian graphical models aimed at the cognitive sciences), and applied to the data shown in Figure 3. The results are based on 3 chains of 50,000 posterior samples collected after 1000 discarded "burn in" samples for all 4 models, with the standard $\hat{R}$ statistic used to check the convergence of the chains (Brooks & Gelman, 1997).

The results of this analysis are shown in Figure 5. The left-hand panels show the data, in the form of proportions of recognized cities and accurate decisions for each individual, as in Figure 3. The solid overlaid lines show the posterior distribution of the constant, linear, and quadratic models. The broken lines show samples from the prior predictive distribution of each model.

The histograms in the right-hand panels show the posterior distributions over the key coefficient parameters in each of the models. These are the c_1 constant term in the constant model, the b_2 slope term in the linear model, and the a_3 quadratic term in the quadratic model. The broken lines show the prior distributions for these coefficients. A standard Bayesian method, known as the Savage-Dickey method, for finding Bayes factors between nested models involves the ratio of prior to posterior densities at critical values of the parameter that reduces the more complicated model to its nested special case (Lee & Wagenmakers, 2013; Wetzels, Grasman, & Wagenmakers, 2010). Thus, for example, the Bayes factor for comparing the constant model to the guessing model is the ratio of the prior to posterior density of the coefficient c_1 at the value $c_1 = \frac{1}{2}$.

Using this method, and approximating the posterior densities with Normal distributions, the log Bayes factors were estimated to be greater than 50 in favor of the constant model over the guessing model, and for the linear model over the constant model. This is overwhelming evidence. The crucial log Bayes factor between the linear and quadratic models was estimated to be 2.75, which means the data provide about 15 times more evidence for the lin-

Figure 6: The left-hand panels show the prior predictive (broken lines) and posterior predictive (solid lines) distributions for the modified constant (top), linear (middle), and quadratic (bottom) models of the relationship between accuracy and recognition rate. The right-hand panels show the prior (broken line) and posterior (solid histogram) distribution for the parameters corresponding to these modified constant (top), linear (middle), and quadratic (bottom) terms that allow for the estimation of Bayes factors between the models using the Savage-Dickey density ratio method.



ear than the quadratic model. I interpret this as moderately strong evidence.

An anonymous reviewer suggested that an additional analysis should be done, using a quadratic model that more closely reflected the predictions of the less-is-more effect and, in particular, predicted the peak in the curve to be at very high values of the recognition rate near 90%. To implement this suggestion, I conducted a second version of the analysis, using more informative priors on the parameters for the constant, linear, and quadratic models. The intention was that these priors would capture additional theory that—while not formally stated in the literature—could reasonably be inferred from interpreting the theory underlying the less-is-more effect and findings from previous relevant data. This additional theory serves to simplify the models, make their predictions more precise, and allow the data to provide potentially more decisive evidence for-and-against the models (Vanpaemel & Lee, 2012).

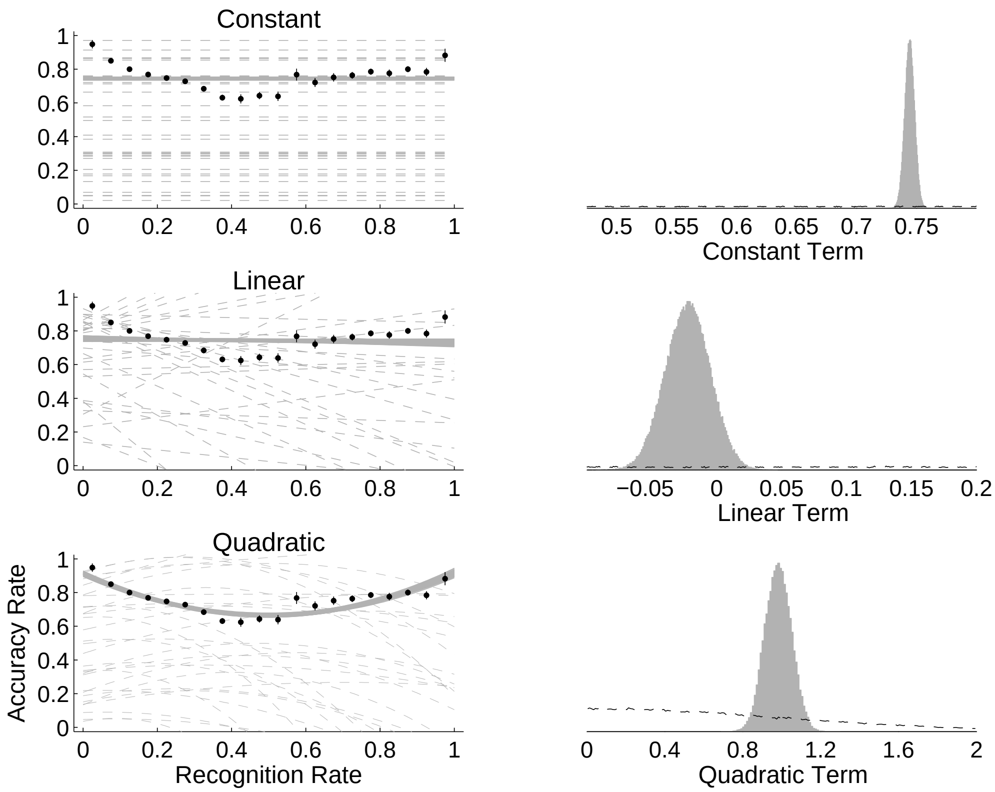
Once again, the exact prior distributions were largely determined by inspecting prior predictive distributions. For the quadratic model, standard results from the quadratic formula were also applied so that he peak would be near 90% recognition. These considerations resulted in the new models[4]

$$\begin{aligned}
\mathcal{H}^{c'} &: \ \theta_i^{\mathrm{a}} = c_1', \ c_1' \sim \mathcal{U}\big(0.5, 0.75\big), \\
\mathcal{H}^{l'} &: \ \theta_i^{\mathrm{a}} = b_2'\theta_i^{\mathrm{r}} + c_2', \ b_2' \sim \mathcal{N}\big(0, \frac{1}{0.05^2}\big), \\
&\quad\ c_2' \sim \mathcal{U}\big(0.5, 0.75\big), \\
\mathcal{H}^{q'} &: \ \theta_i^{\mathrm{a}} = a_3'\,(\theta_i^{\mathrm{r}})^2 + b_3'\theta_i^{\mathrm{r}} + c_3', \ a_3' \sim \mathcal{U}\big(-0.3, 0\big), \\
&\quad\ b_3' \sim \mathcal{N}\big(-1.8a_3', \frac{1}{0.05^2}\big), c_3' \sim \mathcal{U}\big(0.5, 0.75\big).
\end{aligned}$$

The results of this analysis are shown in Figure 6. The left-hand panels again show the data, the solid overlaid lines show the posterior distribution of the constant, linear, and quadratic models, and the broken lines show samples from the prior predictive distribution of each model. The

[4]Note that I parameterize Normal distributions in terms of means and precisions, to be consistent with their implementation in JAGS, so that, for example, $\mathcal{N}\big(0, \frac{1}{0.05^2}\big)$ is a Normal distribution with a mean of zero and standard deviation of 0.05.

Figure 7: The left-hand panels show the prior predictive (broken lines) and posterior predictive (solid lines) distributions for the constant (top), linear (middle), and quadratic (bottom) models of the relationship between the accuracy of recognition-based decisions and recognition rate. The right-hand panels show the prior (broken line) and posterior (solid histogram) distribution for the parameters corresponding to these constant (top), linear (middle), and quadratic (bottom) terms that allow for the estimation of Bayes factors between the models using the Savage-Dickey density ratio method. The error bars in the left-hand panels show one standard error for the binomial proportions.



histograms in right-hand panels show the posterior distributions over the key coefficients in each of the models, allowing the estimation of Bayes factors.

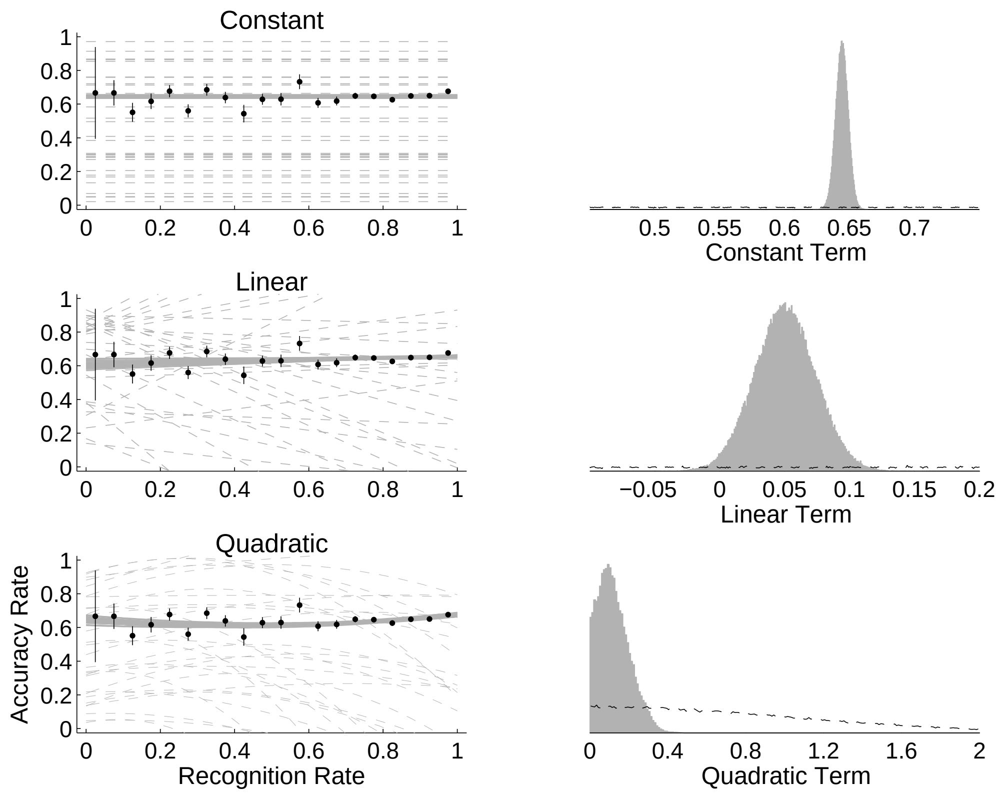
The log Bayes factors for these modified models were estimated to be greater than 50 in favor of the modified constant model over the guessing model, and for the linear model over the constant model. This is overwhelming evidence. The log Bayes factor between the modified linear and modified quadratic models was estimated to be 4.72, which means the data provide about 100 times more evidence for the modified linear than the modified quadratic model. I interpret this as strong evidence. In short, the modified models using prior distributions that made stronger theoretical assumptions, especially about the nature of the less-is-more effect, led to the same conclusions as the original analysis.

Intuitively, these analyses provide evidence that the relationship between accuracy and recognition rate is well captured by a gently increasing linear relationship, and that there is no evidence for the non-monotonicity of accuracy via a decrease at high levels of recognition, even when considering a quadratic model specifically designed to predict such a decrease.

5.2 Changes in accuracy with recognition

Figure 4 shows the accuracy recognition-based, knowledge-based, and guessing-based decisions, as a function of (binned) recognition rates. I examine whether these data provide evidence for guessing, constant, linear, or quadratic relationships using essentially the same methodology used to examine the relationship between individual-level accuracy and recognition. The same $\mathcal{H}^{\mathrm{g}}$, $\mathcal{H}^{\mathrm{c}}$, and $\mathcal{H}^{\mathrm{l}}$ models were used, but the $\mathcal{H}^{\mathrm{q}}$ model was modified to test U-shaped, rather than inverse-U shaped quadratics, in order to test for the apparent increase in accuracy with high and low recognition rates for recognition-based decisions. This change in the model was achieved simply by truncating to positive values of the quadratic coefficient, so that $a_3 \sim \mathcal{TN}^+(0, 1)$.

Figure 8: The left-hand panels show the prior predictive (broken lines) and posterior predictive (solid lines) distributions for the constant (top), linear (middle), and quadratic (bottom) models of the relationship between the accuracy of knowledge-based decisions and recognition rate. The right-hand panels show the prior (broken line) and posterior (solid histogram) distribution for the parameters corresponding to these constant (top), linear (middle), and quadratic (bottom) terms that allow for the estimation of Bayes factors between the models using the Savage-Dickey density ratio method. The error bars in the left-hand panels show one standard error for the binomial proportions.

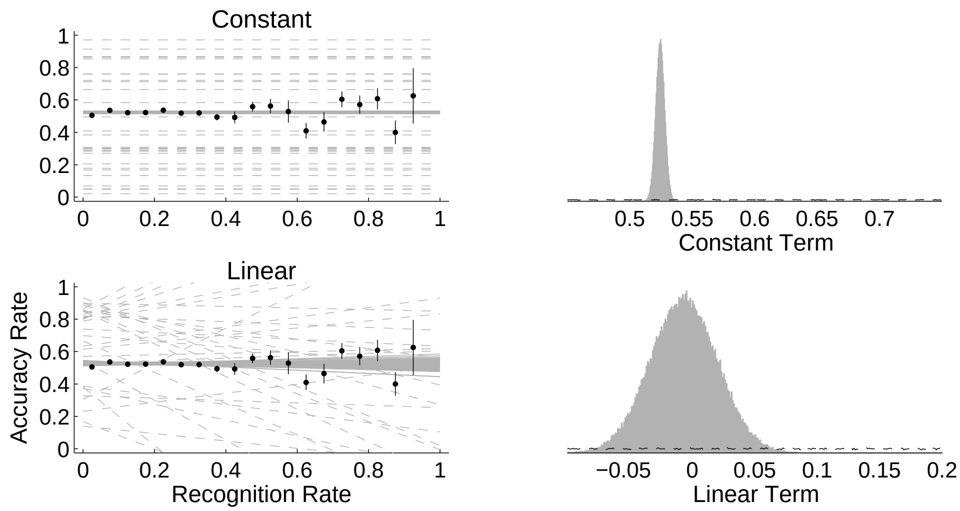


The results for this analysis for decisions consistent with recognition are shown in Figure 7. The log Bayes factors for the constant over the guessing model, and for the quadratic over all of the other three models, are all greater than 50. The log Bayes factor for the constant over the linear model is 3.22. More importantly, though, the data provide evidence for an above-guessing constant accuracy rather than a linear relationship between accuracy and recognition, if only constant or monotonic relationships are considered. They, however, provide overwhelming evidence for a non-monotonic quadratic model over the monotonic alternatives. Intuitively, the posterior distributions in Figure 7 show that it is not definitively clear that the linear coefficient is not 0, but it is clear the quadratic term is not. I conclude that the data provide evidence for a non-monotonic relationship between the accuracy of recognition-based decisions and recognition rate, with greater accuracy at high and low levels of recognition.

The results for knowledge-based decisions are shown in Figure 8. The log Bayes factor for the constant over the guessing model is greater than 50. The log Bayes factors for the constant over the linear and quadratic model are 1.45 and 1.31, respective. Thus, the data provide evidence for the constant model. This evidence is overwhelming when considering the guessing model as an alternative, but weak in relation to the linear and quadratic models. My conclusion is that the constant model is favored by the current data, but the possibility of linear or more complicated relationships remains, and additional evidence—most obviously in the form of additional data—would be valuable.

The results for guessing-based decisions are shown in Figure 9. The log Bayes factor for the constant over the guessing model is again greater than 50, but the log Bayes factor favoring the constant over the linear model is about 3.6. This means the data provide about 30 times more evidence for a constant rather than linear relationship. Because of the strength of this evidence, there is no need to report the results for the quadratic model. Overall, I interpret the results as showing that the accuracy of guessing-

Figure 9: The left-hand panels show the prior predictive (broken lines) and posterior predictive (solid lines) distributions for the constant (top) and linear (bottom) models of the relationship between the accuracy of guessing-based decisions and recognition rate. The right-hand panels show the prior (broken line) and posterior (solid histogram) distribution for the parameters corresponding to these constant (top) and linear (bottom) terms that allow for the estimation of Bayes factors between the models using the Savage-Dickey density ratio method. The error bars in the left-hand panels show one standard error for the binomial proportions.



based decisions is constant over recognition rate, but a little higher than the chance accuracy of one-half.