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Absolute Identification Is Relative: A Reply to Brown, Marley, and Lacouture (2007)

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N. Stewart, G. D. A. Brown, and N. Chater (2005) presented a relative judgment model (RJM) of absolute identification, in which the current stimulus is judged relative to the preceding stimulus. S. Brown, A. A. J. Marley, and Y. Lacouture (2007) found that the RJM does not predict their finding of increased accuracy after large stimulus jumps, except at the expense of other effects. In fact, the RJM does predict both the core effects and increased accuracy after large jumps (although it underestimates this effect) when better constrained parameters are estimated from the trial-by-trial raw data rather than from summary plots. Further, a modified RJM, in which the stimulus from two trials ago is sometimes used as a referent, provides a better fit.

Keywords: absolute identification, relative judgment

Stewart, Brown, and Chater (2005) presented a relative judgment model (RJM) of absolute identification. In absolute identification, participants are presented with a series of stimuli drawn from a set that varies along a single dimension (e.g., tones varying in their loudness). Stimuli are normally evenly spaced along the dimension. Participants are asked to identify each stimulus with its rank position in the set. Stewart et al.'s RJM differs from previous accounts in assuming that identifications are made without reference to long-term memories of absolute stimulus magnitudes (see also Laming, 1984). Almost all existing models use long-term absolute magnitude information. For example, Thurstonian models represent long-term absolute magnitude information in the positioning of criteria along a perceptual continuum (Durlach & Braida, 1969; Luce, Green, & Weber, 1976; Treisman, 1985). Exemplar models represent long-term absolute magnitude information in the stored stimulus magnitude–stimulus label pairs (Kent & Lamberts, 2005; Nosofsky, 1997; Petrov & Anderson, 2005). Connectionist models represent long-term absolute magnitude information in the mapping between stimulus and response nodes (Lacouture & Marley, 2004). Anchor models represent long-term absolute magnitude information as a memory for anchors at the edges of the stimulus range (Karpiuk, Lacouture, & Marley, 1997; Marley & Cook, 1984).

In the RJM, long-term memories of absolute magnitudes are assumed to be unavailable, and judgment is instead relative to the immediately preceding stimulus. In conjunction with the feedback for the previous stimulus, the difference between the current stimulus and the previous stimulus is used to identify the current stimulus. For example, if the feedback on the previous trial is Stimulus 4 and the current stimulus is 3 response-scale units higher in magnitude, then Stimulus 7 will be given as a response. By assuming that the differences between stimuli are confused and that there is a capacity limit in mapping between stimulus differences and the response scale, the RJM can account for the main phenomena observed in absolute identification (reviewed in detail by Stewart et al., 2005).

Brown, Marley, and Lacouture (2007) presented a more detailed examination of the sequential effects in Lacouture's (1997) experiment involving absolute identification of line length. Although the RJM accounts for the average effects well, Brown et al. claimed that it does not account for the more detailed pattern. Specifically, Brown et al. plotted accuracy on the current trial as a function of the difference between the current stimulus and the previous stimulus (see Figure 1A). There is a small accuracy advantage when the previous stimulus is the same as the current stimulus, and there is a larger accuracy advantage when the difference between stimuli is as large as possible. Brown et al. suggested that this larger advantage is problematic for the RJM. In the RJM, the number of responses represented in the mapping process depends upon the previous feedback and the sign of the difference between the current and previous stimuli (see Stewart et al., 2005, Equations 4 and 5). For example, when Stimulus 1 is followed by Stimulus 10, constant noise in the mapping process produces a large amount of noise in responding, because more possible responses must be represented (Responses 2–10) within the limited capacity. In contrast, when Stimulus 5 is followed by Stimulus 10, fewer responses must be represented (Responses 6–10), and so the constant noise in the mapping process produces less noise in responding. The RJM predicts more noise when there is a big difference between the previous and current stimuli, but Lacouture's (1997) data show increased accuracy—not reduced accuracy—in this situation. This observation led Brown et al. to question whether judgment is always relative.

Source code and best-fitting parameters for the modified model are available from http://www.stewart.psych.warwick.ac.uk/

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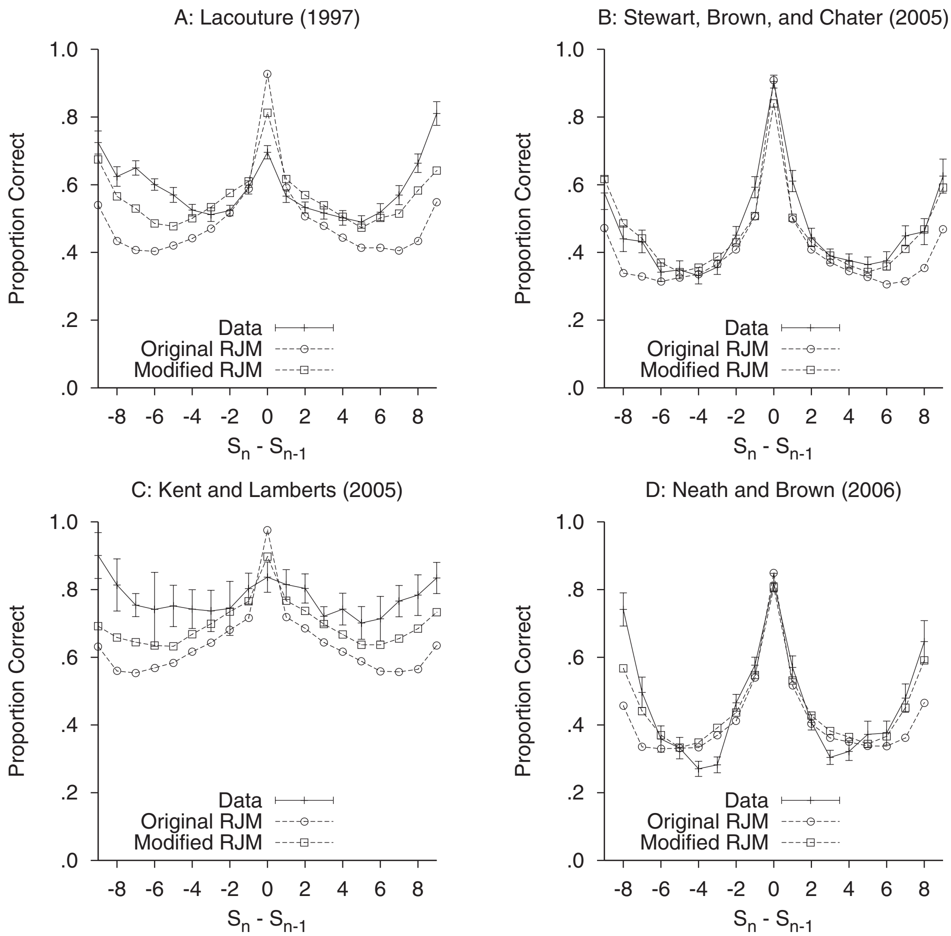

Figure 1. Accuracy plotted as a function of the difference in ranks of the current and previous stimulus. Data (solid line) are from (A) Lacouture (1997); (B) Stewart, Brown, and Chater (2005); (C) Kent and Lamberts (2005); and (D) Neath and Brown (2006). Error bars are standard error of the mean. Predictions of the relative judgment model (RJM) are shown as dashed lines.

Extension to Other Data Sets

I have examined three other data sets (see Table 1) and repeat Brown et al.'s (2007) analysis in the other panels of Figure 1. Kent and Lamberts (2005) used a task in which the distance between two dots was identified (a task very similar to the identification of line lengths used by Lacouture, 1997). Stewart et al. (2005) and Neath and Brown (2006) used absolute identification of the frequency of pure tones. The same qualitative pattern can be seen in all of the data sets. There is an accuracy advantage for stimulus repetitions and for the largest jump sizes compared with intermediate jump sizes. Finding this pattern in data from four different laboratories (Lacouture's, Kent's, Stewart's, and Neath's) with two different continua (length and pitch) shows it is reliable, and I would tentatively suggest that this effect be included in the set of benchmark phenomena that any absolute identification model should explain. The relative ordering of performance on stimulus repetitions and the largest jump sizes differ among data sets. Performance is better for large jumps in Lacouture's (1997) data set (by .070) and Kent and Lamberts's data set (by .029), but

Table 1
Experimental Details for the Four Data Sets

Authors	Stimulus	No. participants	No. trials
Neath and Brown (2006)	Pure tone frequency	60	134
Kent and Lamberts (2005), Experiment 1	Dot separation	3	4,000
Lacouture (1997), Experiment 1	Line length	48	620
Stewart, Brown, and Chater (2005), Experiment 1, Set Size 10 Condition	Pure tone frequency	40	840

performance is better for repetitions in Stewart et al.'s data set (by .303) and Neath and Brown's (2006) data set (by 0.127).

Relation to Other Effects

Increased accuracy on stimulus repetitions can be seen in other summary plots of the data. For example, when accuracy plotted as a function of stimulus is parameterized by the number of trials since a stimulus repetition (e.g., Petrov & Anderson, 2005; Rouder, Morey, Cowan, & Pfaltz, 2004; Siegel, 1972; Stewart et al., 2005), very high accuracy is observed when stimuli are repeated (i.e., at 0 trials since a repetition). This shows that the advantage for repetitions is seen for all stimuli. When d' (a measure of the confusion between adjacent stimuli), plotted as a function of stimulus, is parameterized by the difference between the current and previous stimulus, higher d' is observed when the current and previous stimuli are similar (e.g., Stewart et al., 2005), although the effect is sometimes small or null (e.g., Luce, Nosofsky, Green, & Smith, 1982; Nosofsky, 1983; Purks, Callahan, Braida, & Durlach, 1980).

Increased accuracy after large stimulus jumps can also be seen in other summary plots of the data. For example, when accuracy or d' is plotted as a function of stimulus, a bow is observed with better performance for the smallest and largest stimuli (see Stewart et al., 2005, for a review of the bow effect). Because the largest jumps are necessarily between the smallest and largest stimuli, high accuracy for the smallest and largest stimuli is linked with high accuracy for the largest jumps. The bow effect in accuracy can be attributed, in part, to the restricted opportunity to make mistakes at the edges of the stimulus range. Increased accuracy after large jumps can also be attributed to this restricted opportunity to make mistakes. When the error in responding is plotted as a function of the current stimulus and the previous stimulus, assimilation of the current response to the previous stimulus is seen for all stimulus combinations (see Stewart et al., 2005, for a review of assimilation and contrast effects). The amount of assimilation is roughly a constant proportion of the difference between the current stimulus and the previous stimulus. However, assimilation is reduced for the largest stimulus jumps, and this is directly linked to the increase in accuracy for the largest jumps.

Fits of the RJM

To examine whether the RJM predicts the effect in Figure 1, I have fitted the RJM to each data set. Because the trial-by-trial raw data were available, I have estimated the model's parameters separately for each participant by maximizing the likelihood of the response on each trial using the Nelder–Mead (Nelder & Mead, 1965) simplex algorithm. This method is exactly equivalent to fitting the full conditional (upon all previous stimuli) confusion matrix. (This method should be preferred to fitting summary data, because the raw data will constrain the parameters better and prevent the model fitting summarized effects at the expense of other, unsummarized effects.) For each participant, I used the best fitting parameters to plot accuracy as a function of stimulus difference. Figure 1 shows these predictions averaged across participants (dashed line marked with circles).

The RJM captures the qualitative pattern of increased accuracy for stimulus repetitions and for large stimulus jumps. However, for Lacouture's (1997) and Kent and Lamberts's (2005) data sets, the original model overestimates accuracy after repetitions and underestimates accuracy after large jumps. The overestimation in accuracy after stimulus repetitions occurs because the RJM predicts very little noise in responding when stimuli are repeated. As described above, the underestimation in accuracy after large stimulus jumps occurs because a large number of responses must be represented within the limited mapping capacity when there is a large stimulus jump, and this leads to more noise in responding. For Stewart et al.'s (2005) and Neath and Brown's (2006) data sets, the RJM provides a much better quantitative fit. The model captures the high accuracy after stimulus repetitions well, although it still underestimates accuracy after large stimulus jumps.

Brown et al. (2007) also presented fits of the RJM to the Lacouture (1997) data set. Brown et al. used the best fitting parameters for Lacouture's data presented in Stewart et al. (2005). With these parameters, the RJM fails to predict increased accuracy after large stimulus jumps. These parameters were estimated by fitting the model to a summary plot of the error in responding on the current trial as a function of the lag and magnitude of preceding stimuli (see Lacouture, 1997, Figure 5), to demonstrate that the model could predict the summary pattern. However, as Stewart et al. acknowledged, fitting only the summary data does not constrain some of the model parameters well, because information in the raw data is discarded in the summary. The fits to raw data presented above should be preferred because they constrain the parameters better.

Brown et al. (2007) also presented fits using a modified parameter set, which they obtained by fitting the RJM to several summary plots, including the plot in Figure 1. In the RJM, a random variable representing the response is partitioned into response categories by a set of criteria (see Stewart et al., 2005, Equations 6 and 7). The spacing of all of the criteria is controlled by a single c parameter. The value of this parameter was smaller in Brown et al.'s fit, which shrank the criteria toward the center of the response scale. This had the effect of increasing accuracy for the smallest and largest stimuli, because more of the response scale fell within these categories. In turn, this allowed the model to predict increased accuracy after large stimulus jumps because these jumps necessarily finished on the smallest or largest stimulus. However, Brown et al. found that this modified parameter set caused the model to fail to predict the smooth bow seen when d' between adjacent stimuli was plotted as a function of stimulus rank. All of the fits to raw data presented in the current article do predict a smooth bow in d', although they do underestimate the bow (as Stewart et al., 2005, consider in detail, p. 896).

As a follow-up to Brown et al.'s (2007) investigation of criteria placement, I ran an additional set of model fits in which each criterion's location was a separate free parameter, instead of constraining all of the criteria with the single c parameter as in the original RJM. Allowing the criteria to vary independently produced only a slightly better fit to the data (the improvement in fit was not significant). In fact, the free criteria took almost exactly the same values as when they were constrained by the c parameter. Stewart et al. (2005) presented a related finding. They found that allowing the criteria to vary freely to maximize accuracy (rather than the fit to the data) did not increase accuracy. Together, these two findings support Stewart et al.'s assumption that the criteria in the RJM are optimally located to maximize response accuracy (or information transmission).

A Simple Modification of the RJM

Thus far, I have shown that the sequential effects found by Brown et al.'s (2007) more detailed analysis of Lacouture's (1997) data are robust and occur in three other data sets. I have also shown that the original RJM does predict increased accuracy after large stimulus jumps when parameters are estimated by fitting data at the trial-by-trial level, rather than from a single summary plot. However, the RJM does still underestimate the accuracy after large stimulus jumps, particularly for Lacouture's (1997) and Kent and Lamberts's (2005) data sets. Also, for these two data sets, the RJM does overestimate accuracy when stimuli are repeated. In the remainder of this article, I will show that two simple modifications of the RJM provide a much better quantitative fit. First, a parameter that was fixed in the original model will be allowed to vary. Second, I will assume that judgment is sometimes relative to the stimulus two trials ago instead of one trial ago.

Stimulus Repetitions

The discrepancy between Stewart et al.'s (2005) and Brown et al.'s (2007) data sets (in which there is a large advantage for stimulus repetitions) and Lacouture's (1997) and Kent and Lamberts's (2005) data sets (in which the advantage for stimulus repetitions is smaller) is seen in other data sets. For example, Petrov and Anderson (2005), Rouder et al. (2004), and Siegel (1972) found a large accuracy advantage for stimulus repetitions. Luce et al. (1982) and Nosofsky (1983) found that d' was only slightly higher when the current and previous stimuli were similar (although the difference was significant), and Purks et al. (1980) found no difference. These results are not necessarily inconsistent: An increase in accuracy on stimulus repetitions could be caused by movement of criteria within a Thurstonian framework away from the previous stimulus, resulting in increased accuracy but unchanged d' (see Purks et al., 1980).

In the original RJM, a stimulus was identified as repeated whenever the magnitude of perception of the difference between the current stimulus and the previous stimulus was less than a criterion value χ (see Stewart et al., 2005, Equation 5). χ was assumed to be fixed at half the stimulus spacing in Stewart et al.'s (2005) model fitting. Stewart et al. suggested that the discrepancy between data sets described above could be captured by allowing the χ parameter to vary (p. 905). A smaller value of χ represents a greater difficulty in identifying (or reluctance to identify) stimulus repetitions. For this reason, I allow χ to vary in the second set of fits.

Large Stimulus Jumps

Siegel's (1972) data and Stewart et al.'s (2005) data showed that not only is there an advantage when the current stimulus (S_n) is the same as the previous stimulus (S_{n-1}), but there is also a smaller advantage when the current stimulus is the same as the stimulus two trials back (S_{n-2}). One possible explanation that Stewart et al. put forward (p. 904) is that people sometimes judge S_n against S_{n-2} instead of against S_{n-1}. Stewart and Brown (2004) presented some evidence that is particularly suggestive of this possibility. They showed that people were very accurate in a binary categorization task if a recent stimulus was nearer to the category boundary than the current stimulus. In this situation, relative judgment of the current stimulus against the recent stimulus allows participants to determine the correct category. For example, if the previous stimulus is in the low category and the current stimulus is perceived as lower in magnitude, then the current stimulus must also be in the low category. Stewart and Brown found that when S_{n-2} was nearer to the boundary than was S_n, accuracy was high and unaffected by S_{n-1}. This strongly suggests that participants categorized S_n by comparing it with S_{n-2} instead of with S_{n-1}.

In the second set of fits, I assume that, on trials when S_{n-2} is much nearer to S_n than S_{n-1} is, S_n is sometimes judged relative to S_{n-2} instead of to S_{n-1}. For example, if the sequence of stimuli is $S_{n-2} = 9$, $S_{n-1} = 1$, $S_n = 10$, I assume that S_n is compared with S_{n-2} and not with S_{n-1}. In these fits, I define *much nearer* at half of the stimulus range. Using S_{n-2} only when it is much nearer represents the assumption that it is easier and preferable to compare S_n with the relatively strong trace of S_{n-1} than with the relatively weaker trace of S_{n-2}. Revised equations are given in the Appendix.

Modified RJM Fit

The procedure for fitting this modified version of the RJM was the same as described above. Figure 1 shows these predictions averaged across participants (dashed line marked with squares). In comparison with the original RJM fits, the fits of the modified RJM predict a greater accuracy advantage after large stimulus jumps and a smaller accuracy advantage after stimulus repetitions, producing a better overall fit to the data. For Stewart et al.'s (2005) and Neath and Brown's (2006) data sets, the model's fit to the data is good, although the model slightly underestimates accuracy for repetitions and overestimates accuracy for large jumps in Neath and Brown's data.

For Lacouture's (1997) and Kent and Lamberts's (2005) data, the modified model comes much closer to capturing the pattern in the data, although it still overestimates accuracy on stimulus repetitions and underestimates accuracy after large stimulus jumps. Each of these deficits can be addressed by further modification of the model. First, to address the overestimation in accuracy after stimulus repetitions, a second, independent source of noise can be added to the model (e.g., perceptual noise, Stewart et al., 2005, p. 897, or noise in representing the difference between stimuli, $D^{C}_{n,n-1}$), allowing a closer fit to be obtained. Second, to address the underestimation in accuracy after the largest jumps, the RJM can be extended so that stimuli on trials further back in the sequence can be used to judge the current stimulus. Ultimately, one could extend the RJM so that any previous stimulus could be used. This would effectively turn the model into an exemplar model of absolute identification and introduce long-term representation of magnitudes into the model. The RJM and the absolute magnitude models could be viewed as opposite ends of a continuum, with only very short-lived magnitude representations at the relative judgment end and very long-lived magnitude representations at the absolute judgment end. In practice, extending the model to use S_{n-1} most of the time, S_{n-2} sometimes, and S_{n-3}

rarely allows the model to predict higher accuracy after large stimulus jumps.

It may be that the RJM is not capturing some aspects of the judgment process in Lacouture's (1997) and Kent and Lamberts's (2005) data sets. Some additional length cues may have been available in these experiments: In Kent and Lamberts's experiment, the edges of the screen were just visible after a little time to dark adapt. In Lacouture's experiment, distance between each response key and the home key was 101 mm, 2 mm longer than Stimulus 9 and 13 mm shorter than Stimulus 10. The (constant) stimulus width (20 mm) was similar in length to the shorter stimulus lengths (33 mm, 38 mm, . . .). Relative judgment of stimuli against these additional length cues (rather than against the previous stimulus) would reduce accuracy after stimulus repetitions and improve accuracy for the longest and shortest stimuli, which in turn would also improve accuracy for the largest jumps (which are between the longest and shortest stimuli). However, Luce et al. (1982) and Purks et al. (1980) found large edge effects and small repetition effects using tones differing in loudness. Additional contextual cues were probably not available in these experiments because they were conducted in soundproof chambers. So the availability of additional contextual cues is probably not the sole cause of the difference between Neath and Brown's (2006) and Stewart et al.'s (2005) data sets and Kent and Lamberts's and Lacouture's data sets.

Finally, I note that, in addition to capturing the effects considered here, the modified RJM predicts the effects considered by Stewart et al. (2005): limits in information transmitted, bows in accuracy and d', set size effects, sequence manipulation effects, and assimilation to the previous stimulus and contrast to those further back.

Conclusion

Brown et al. (2007) have drawn attention to a pattern of conditional accuracy that I have found to be robust in three other data sets: Accuracy is higher after stimulus repetitions or very large jumps compared with intermediate jumps. Here I have shown that the original RJM can capture this qualitative pattern, although it overestimates accuracy after repetitions and underestimates accuracy after large jumps. Exploring modifications suggested by Stewart et al. (2005), I presented a modified RJM—that maintains the hypothesis that judgment is relative—that can capture these effects more fully. The direct experimental test of the relative judgment hypothesis presented by Stewart et al. strongly supports the idea that absolute identification is relative, and the data reviewed here are compatible with the relative judgment hypothesis.

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(*Appendix follows*)

Appendix

The Modified RJM

When S_{n-2} is much nearer to S_n than S_{n-1} is, S_{n-2} is used as the base for relative judgment. Equations 1 and 2 implement this and replace Equations 4 and 5 from Stewart et al. (2005).

$$R_n = \left\{ \begin{array}{ll} F_{n-1} + \dfrac{D^C_{n,n-1}}{\lambda} + \rho_{n-1}L & \mathit{if} |S_n - S_{n-1}| \leq |S_n - S_{n-2}| + \dfrac{N}{2} \\ F_{n-2} + \dfrac{D^C_{n,n-2}}{\lambda} + \rho_{n-2}L & \mathit{if} |S_n - S_{n-1}| > |S_n - S_{n-2}| + \dfrac{N}{2} \end{array} \right\} \quad (1)$$

$$\rho_{n-\mathrm{i}} = \left\{ \begin{array}{cc} N - F_{n-i} & \mathit{if}\, D^C_{n,n-i} > +\chi \\ 1 & \mathit{if} - \chi \leq D^C_{n,n-i} \leq +\chi \\ F_{n-i} - 1 & \mathit{if}\, D^C_{n,n-i} < -\chi \end{array} \right\} \quad (2)$$

When S_{n-2} is used as the base for judgment, the difference between S_n and S_{n-2} is assumed to be estimated and is confused with recently encountered differences $D_{n,n-1}, D_{n-1,n-2}, \ldots$

$$D^C_{n,n-2} = \alpha_0 D_{n,n-2} + \sum_{i=1}^{n-2} \alpha_i D_{n-i,n-i-1} \quad (3)$$

In the modified model, generalization on the response scale is assumed to be exponential, not Gaussian, as in the original model. Thus, $\boldsymbol{L}$ in Equation 1 is the double exponential or Laplace distribution, with mean 0 and scale parameter χ. There are good precedents for assuming exponential generalization (Shepard, 1957), and the exponential function provides a better fit for 80% of participants across the four data sets modeled here. Note that similar fits to the Figure 1 data are obtained if Gaussian generalization is retained.

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