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Seeds aren't anchors

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Exposure to a few task-relevant numerical facts (*seed facts*) often improves subsequent numerical estimates. We performed two experiments to investigate the mechanism that produces these seeding effects. In Experiment 1, participants estimated national populations; in Experiment 2, they estimated between-city distances. In both, items were selected so that the actual value of the seed facts (S_A) was, on average, below participants' initial estimates for those items (S_1) and above the initial estimates for the transfer items (T_1). Given this configuration, the *anchoring position* predicts that the postseeding transfer estimates should be greater than the preseeding transfer estimates ($T_2 > T_1$), whereas the *feedback/induction position* predicts the opposite ($T_2 < T_1$). In both experiments, the latter pattern of results emerged, supporting the conclusion that seeds aren't anchors.

Exposure to a few task-relevant numerical facts often influences subsequent numerical estimates. This point has been demonstrated through a method called *seeding the knowledge base*. The typical experiment has three phases: First, participants are presented a set of items and required to estimate the value of a particular quantitative property (e.g., national populations). Next, they learn the actual values of a subset of the items; we call these items *seed facts*. Finally, participants reestimate the values of the items in the initial set. These experiments have demonstrated that the seeding procedure can improve estimation of national populations (Brown & Siegler, 1993, 1996; Experiment 1, below), the latitudes and longitudes of cities (A. Friedman & Brown, 2000a, 2000b; A. Friedman, Kerkman, & Brown, 2001), and the nutritional contents of various foods (Walbaum, 1997). The present study adds between-city distances to the set of quantitative dimensions that have been examined.

These seeding effects raise general issues concerning how people learn from examples and how new information is integrated with existing knowledge. The findings also have obvious educational implications. Understanding the principles that govern revision of quantitative estimates should enable instructors to reduce domain-specific innumeracy by teaching students a small number of well-chosen numerical examples. Seeding effects have been shown to depend on what people already know about the target domain and on the specific identities of the seeds and the transfer items (Brown & Siegler, 1993; A. Friedman & Brown, 2000a, 2000b). Therefore, both theoretical and instructional applications of this method hinge on our ability to predict how seeds will interact with domain knowledge. This, in turn, requires a thorough understanding of the cognitive mechanisms that produce positive seeding effects.

In the present study, we pursued this last goal by comparing predictions that would follow from two plausible, but different, seeding mechanisms: *feedback/induction* and *anchoring* (Brown & Siegler, 1996). In the next sections, we describe these approaches and introduce a variant of the seeding method within which reliance on the two mechanisms would produce different outcomes. These predictions are then tested in two parallel experiments, one dealing with populations and the other with between-city distances.

The Feedback/Induction Position

Prior research has demonstrated that people access two independent sources of knowledge when they generate real-world estimates: mapping knowledge and metric knowledge. *Metric* knowledge is information about the statistical properties of the target dimension—for example, the range, central tendency, and form of the distribution (Brown & Siegler, 1993, 1996). *Mapping* knowledge is the (often nonnumerical) information about particular items in the domain used to order items relative to one another along a target dimension.

People are very skillful at extracting metric information from sets of numbers presented in experimental settings (e.g., Malmi & Samson, 1983; Spencer, 1961). According to the feedback/induction position, the numerical induction process that underlies this ability also produces seeding effects, in two ways. First they provide feedback on the accuracy of preexisting metric beliefs—for example, beliefs about the mean value of the entities on that

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dimension. Second they provide data necessary for inducing more accurate beliefs.

To make this perspective concrete, consider a person in a typical seeding experiment who initially believed that most countries have population around 50 million and who then learns that the actual population of a representative subset of countries is around 25 million. In this situation, the participant is likely to realize that his or her metric beliefs were incorrect and to revise his initial estimates downward for countries whose populations were not presented, as well as for those countries that were. Similarly, someone who believed that countries typically have 10 million people should react to the same set of seeds by revising his mean estimate upward. In both cases, postseed-set estimates should be more accurate than preseed-set estimates.

The Anchoring Position

As is implied by its name, the anchoring position holds that people use numerical examples as anchors or reference points. On this view, (1) seeds are stored in memory during a learning phase. (2) At least one seed is retrieved when a participant provides a postseeding estimate for a transfer item. (3) Similarity between the seed and the transfer item determines whether a given seed is retrieved. (4) Estimates for the transfer item are "drawn toward" the retrieved seed(s). Consistent with Assumption 1, participants in seeding experiments typically learn the seeds they have studied (Brown & Siegler, 1993, 1996). Assumption 4 is simply a restatement of the core finding in the anchoring-and-adjustment literature, which is that transfer values tend to move toward anchor values (Tversky & Kahneman, 1974; for recent reviews, see Jacowitz & Kahneman, 1995; Strack & Mussweiler, 1997). Assumptions 2 and 3 are necessary to ensure a nonarbitrary relation between seeds and transfer items; although they have not been tested directly, they do a play a central role in a recent model of reconstructive event dating (Kemp, 1999).

Again, an example is useful. Consider a person who initially believed that 20 million people live in Austria and who then learned the population of Switzerland. If this person were required to estimate Austria's population after learning that of Switzerland, he or she might recall that there are 6.6 million people in Switzerland, recognize that Austria and Switzerland are similar in relevant respects, and infer that Austria's population is similar to Switzerland's. Alternatively, the transfer country might first be compared with a retrieved seed fact, and this comparison could lead to the selective activation of information that supports the conclusion that Austria has a population similar to that of Switzerland (Chapman & Johnson, 1999; Mussweiler & Strack, 1999; Strack & Mussweiler, 1997). In either case, explicit knowledge of Switzerland's population would provide grounds for estimating that there are about 7 million Austrians.

As was noted above, the anchoring position assumes that participants will adjust initial estimates in the direction of anchors. Seed values provide one type of anchor. Thus, when seed values are, on average, larger than people's estimates for other countries were before they encountered the seeds, postseeding estimates for these transfer countries should increase. The opposite pattern should be observed when the seed values are, on average, smaller than the preseeding transfer estimates.

Distinguishing Between Anchoring and Feedback/Induction

As the preceding discussion suggests, both the feedback/induction position and the anchoring position provide plausible accounts for the positive effect of seeds on estimation accuracy. There are, however, two lines of evidence that favor the former over the latter. One was reported in a study of whether seed facts exert lasting influences on estimates of transfer items (Brown & Siegler, 1996). Participants first estimated the populations of 99 countries; next, they learned the actual populations of 24 of the countries; then they estimated the populations of all 99 countries a second time. Four months later, the same participants returned to the laboratory and produced a third set of estimates for the 99 countries.

We expected that specific seed facts would be forgotten during the lengthy retention interval; our interest was in determining whether performance for transfer countries would decline with the delay. The anchoring position predicted that accuracy for the seed countries and accuracy for the transfer countries should decrease in tandem. Within this view, accuracy of estimates is directly linked to the quality of knowledge of reference points. In contrast, the feedback/induction position did not predict a decline. Within this view, people use seeds to revise their metric beliefs, as when thinking "small European countries have fewer people than I would have guessed." Once beliefs are modified, the seeds themselves play no further role in the estimation process. Thus, the feedback/induction position predicted that delayed postseeding estimates would remain more accurate than initial estimates even after the seeds were forgotten.

The prediction of the feedback/induction position proved accurate. Improvement in estimates for the transfer countries was undiminished after the 4-month delay, whereas recall of seed populations was much less accurate than it had been immediately after the seeding procedure.

The second line of support for the feedback/induction position arose in a set of experiments on how seeds affect geographical knowledge (A. Friedman & Brown, 2000a, 2000b). This research indicated that the same seeds could move postseed estimates for some cities toward seed values (assimilation effects) and estimates for other cities away from them (contrast effects). Such findings are incompatible with the anchoring hypothesis (which holds that postseeding estimates consistently move toward the seed [anchor] values or are unaffected by them). However, such findings are entirely consistent with the feedback/induction position.

To illustrate, in one experiment (A. Friedman & Brown, 2000b, Experiment 1), participants first estimated the latitudes of cites in Canada, the United States, and Mexico. Then they learned the actual latitudes of Tijuana (33º) and Chihuahua (29º). Finally, they generated a second set of latitude estimates. Postseeding estimates for the Mexican cities shifted northward toward values for the seed countries, whereas postseeding estimates for the U.S. and Canadian cities shifted northward away from them. Apparently, the participants reacted to the seeds by first updating their beliefs about the latitude of the U.S.–Mexican border and then revising their metric beliefs about the latitudes of other locations in a way that maintained ordinal relations among regions.

Overview of the Present Study

In brief, we have found that delay periods have differing effects on seed and transfer items and that seeding produces contrast effects on some items and assimilation effects on others. We believe that both findings support the feedback/induction hypothesis and that both are inconsistent with the anchoring position. However, there are other ways of interpreting these data. For example, results of the long-term recall study are consistent with a hybrid position that assumes that seeds can be used as anchors and that they also can support the assessment and revision of underlying metric beliefs. On this view, participants might have revised their metric beliefs during the learning phase, used the seeds to anchor their estimates during the immediate postseeding test, and then relied on appropriately revised metric knowledge when generating their estimates during the delay test. In a similar vein, an anchoring advocate might argue that latitude estimation is not representative of other real-world estimation tasks. This is because the functional categories (i.e., geographical regions) are mutually exclusive, and as a result, a shift in estimates for one region necessitates a shift in adjacent regions. Thus, the contrast effects observed in the latitude estimation studies could be limited to rigidly structured domains.

In light of such alternatives, and given the intuitive appeal of the anchoring position, we felt that other types of evidence were required to discriminate between the anchor and the feedback/induction positions. To this end, we devised a variant of the seeding paradigm that generated clearly contrasting predictions and was not subject to the types of objections that might be leveled at the evidence previously available. We used this new approach in the two experiments reported below.

In both experiments, seed sets were selected so that the actual value of seed items (S_A) would be greater than the preseeding estimates for items in the transfer set (T_1) but less than the preseeding estimates for the items in the seed set (S_1)—that is, $T_1 < S_A < S_1$. In this situation, the anchoring and feedback/induction positions make opposite predictions. To the extent that anchoring influences postseeding estimates for transfer items (T_2), they should be drawn *toward* the actual value of the seed items, relative to the initial estimates for the same items ($T_2 > T_1$). In contrast, the feedback/induction position predicts that these estimates will move *away* from the seeds ($T_2 < T_1$).

The logic for these predictions is relatively straightforward. First, consider the logic underlying the anchoring predictions. Seeding experiments present participants with a more complex situation than does the typical anchoring study. However, there is evidence that people respond to multiple anchors as if they were responding to a single anchor with a value equal to the average of the presented facts (Pohl, 1996; Switzer & Sniezek, 1991). Thus, if participants use seeds as anchors, postseeding estimates should be drawn toward the seed values, even if more than one seed is presented.

The best way to understand the feedback/induction prediction is by example. Consider a person who first estimates the population of 96 countries, then learns the actual populations of 10 of these countries, and finally provides a second set of estimates for the 86 transfer countries and the 10 seed countries. Suppose that this person's initial estimates averaged 60 million for the seed countries (S_1) and 20 million for the transfer countries (T_1) and that the actual average population for the seed countries was 35 million (S_A). While learning the actual populations of the seed countries, this person should come to realize that his or her initial estimates for the seed countries were too large. In turn, this should lead to the conclusion that the initial estimates for the transfer countries were also too large. Having arrived at this conclusion, it would make sense to decrease previous estimates. More generally, if the seeds provide participants with feedback about the accuracy of their metric beliefs, then participants should adjust their estimates downward when the seeds indicate that the initial estimates tended to be too large (i.e., when $S_A < S_1$), and they should move them upward when the seeds indicate that the initial estimates tended to be too large (i.e., when $S_1 < S_A$).[1]

In summary, the anchoring hypothesis and the feedback/induction hypothesis provide two plausible explanations for the seeding effects observed in prior experiments. In this article, we report two experiments designed to provide a direct test of these positions. In both, we selected seeds whose actual values fell between participants' initial estimates of their values and their initial estimates for the transfer items. Under these conditions, the feedback/induction hypothesis predicts that postseeding transfer estimates should shift away from the anchors' values, and the anchoring hypothesis predicts the opposite.

EXPERIMENT 1

Participants estimated the populations of the 96 countries, learned the actual populations of 10 of these, and then provided a second set of estimates for all 96. As was noted above, the anchoring and feedback/induction positions make different predictions only when S_A falls between T_1 and S_1. To maximize the frequency with which this would happen, we selected seed countries that had relatively large populations but that elicited population estimates that were even larger. On the basis of pilot data, we expected that the participants would often generate S_1 estimates that were larger than S_A, and T_1 estimates that were smaller than S_A. For reasons outlined above, we were particularly interested in learning how those participants whose first estimates conformed to this *split* pattern would respond to the seed facts.

Method

Materials. The stimulus set used in this experiment consisted of 96 country names (mean population = 49.11 million; median = 15.6 million; standard error = 14.9; skew = 6.5). This represented an almost complete listing of the world's 100 largest countries at the time. Recent events compelled us to exclude the Soviet Union, Yugoslavia, and East Germany, and the United States was excluded because it served as an example. The full set of countries, along with their 1992 populations, can be found in Brown and Siegler (1993, Table 1). The seed countries are listed in Table 1.

Procedure. This experiment included four tasks. First, participants rated their knowledge of each of the 96 test countries, using a scale from 0 (*no knowledge*) to 9 (*a great deal of knowledge*). This task was conducted to familiarize the participants with the stimulus set and with the data collection procedure. Second, participants were asked to estimate each country's current population. Third, they proceeded through four rounds of a study–test procedure; in each round, they were presented the actual populations of 10 seed countries and tested on each of them. Fourth, the participants provided a second set of estimates for all 96 countries. In all phases, country names were presented one at a time, in a unique random order, at the center of a computer-controlled video display; all responses were typed at the computer's keyboard.

Participants. Thirty Carnegie Mellon University undergraduates participated in this experiment. Some received course credit for their cooperation; others were paid. The procedure lasted approximately 1 h.

Table 1
Seeds Used in Experiments 1 and 2, Along With Actual and Median Estimated Values

Seed	Quantity: Actual	Quantity: Estimated*
Experiment 1		
Mexico	85.4†	120.0
Great Britain	57.5	75.0
Spain	39.2	50.0
Poland	38.2	50.0
South Africa	40.6	43.0
Argentina	32.3	45.3
Canada	26.1	142.5
Romania	23.9	25.5
Iraq	17.8	28.9
Australia	17.3	53.0
Mean	37.8	63.3
Median	35.3	50.0
Standard error	6.5	12.2
Experiment 2		
Beijing, China	5138‡	8550
Los Angeles, United States	5588	10000
Rio de Janeiro, Brazil	5681	10250
Cape Town, South Africa	5782	7000
Tokyo, Japan	6034	8050
Manila, Philippines	6677	9500
Buenos Aires, Argentina	6857	9250
Honolulu, United States	7452	10000
Mean	6151	9075
Median	5908	9375
Standard error	273	399

*Median values derived from pilot data. †In millions. ‡Distance in miles from Paris, France.

Results and Discussion

For each participant, medians were computed for the preseeding estimates for the 86 transfer countries (T_1) and for the postseeding estimates for those countries (T_2), and the 10 seed countries (S_1). In addition, separate rank-order correlations were computed between the actual populations and the preseeding and postseeding estimates for the transfer and seed countries. These rank-order correlations provided an index of mapping accuracy. A measure called *order of magnitude error* (OME), which converts estimation error to a percentage of an order of magnitude, provided the main measure of metric accuracy (Brown & Siegler, 1992, 1993; Nickerson, 1981). On this measure, the lower the score, the closer the participant's estimate to the actual population. A separate OME value was computed for each estimate according to the following equation:

$$\text{OME} = |\log_{10}(\text{estimated value/actual value})|.$$

Mean OMEs were computed for preseeding and postseeding performance on seeding and transfer countries for each participant.

Metric and mapping performance. The data presented in Table 2 indicate that the participants' general pattern of performance was much like that observed in past studies (Brown, Cui, & Gordon, 2000; Brown & Siegler, 1992, 1993). Performance initially was quite poor in an absolute (metric) sense and moderately good in a relative (mapping) sense. Also, consistent with prior results, the seeding procedure produced a substantial improvement in absolute accuracy but had little effect on relative accuracy.

To be specific, the mean preseeding OME for the transfer countries was .54, and the postseeding mean was .40 [$t(29) = 4.09, p < .001$]. In contrast to this large improvement in metric accuracy, the average rank-order correlation between estimated and actual populations decreased slightly, although significantly, from .40 to .35 [$t(29) = 2.48, p = .02$]. As was expected, given the extensive practice on the seed populations, postseeding estimates were much more accurate than preseeding estimates. OME decreased from .43 to .07 [$t(29) = 10.13, p < .0001$], and the correlation between estimated and actual populations increased from .17 to .82 [$t(29) = 9.93, p < .0001$]. These data indicate that the participants learned the seed populations during the learning phase.

In prior studies, we found that the information provided by the seed sets determined the direction and magnitude of metric adjustments. In particular, those participants who initially overestimated the populations of the transfer countries reduced the magnitude of their post-

Table 2
Mean Accuracy Measures (Median Estimated Value, Mean Order of Magnitude Error [OME], and Mean Rank-Order Correlation Between Actual Value and Estimated Value) With Standard Errors for Pre- and Postseeding Responses Elicited by Transfer and Seed Items in Experiments 1 and 2

	Estimate				OME				Rank-Correlation			
	Preseeding		Postseeding		Preseeding		Postseeding		Preseeding		Postseeding	
Items	*M*	*SE*	*M*	*SE*	*M*	*SE*	*M*	*SE*	*M*	*SE*	*M*	*SE*
						Experiment 1						
Transfer	34.82	7.22	17.17	1.24	.54	.04	.40	.02	.40	.02	.35	.03
Seed	76.96	9.47	33.48	1.13	.43	.04	.07	.01	.17	.04	.82	.04
						Experiment 2						
Transfer	10,411	2,391	3,462	187	.28	.04	.20	.02	.83	.02	.84	.03
Seed	15,138	5,965	5,966	71	.27	.05	.05	.02	.38	.04	.55	.07

seeding estimates, and those who initially underestimated increased their postseeding estimates. The strength of this tendency was measured by computing the correlation between the median of the initial estimates for the seed countries and the difference between medians for initial and final estimates for the transfer countries. Replicating prior results, this correlation was strongly negative ($r = -.76$).

Analysis of target data patterns. The primary aim of this experiment was to determine how participants would react to seeds when their initial estimates for the transfer items were, on average, less than the actual value for the seed items and when their initial estimates for the seed items were greater than the actual value of the seed items (i.e., $T_1 < S_A < S_1$). As it turned out, 19 of the 30 participants displayed this target *split* pattern. Of the 19 who showed the desired pattern, 14 produced postseeding transfer estimates that were smaller than their preseeding estimates; 4 increased their estimates following the seeding procedure, and 1 displayed no change ($p < .02$, by a one-tailed sign test). The mean of these 19 participants' median population estimate for the transfer countries decreased 29%, from 23.1 million to 16.5 million [$t(18) = 3.67$, $p < .01$].Thus, Experiment 1 produced a robust contrast effect of the type predicted by the feedback/induction mechanism, rather than the assimilation effect predicted by anchoring.

EXPERIMENT 2

The participants in Experiment 2 estimated the distances between Paris, France and 60 target cities. They then learned actual distances between Paris and 8 seed cities within the set. Finally, they reestimated the distances between Paris and the other 60 cities. We collected these data for two reasons. First, we hoped to demonstrate the applicability of the seeding approach to a task on which participants already possess reasonably accurate knowledge. We chose distance estimation because people have a good sense of the relative ordering of between-city distances and some sense of the absolute distances (Hirtle & Mascolo, 1991).

Second, we wanted to determine whether the seed-driven contrast effect observed in Experiment 1 could be replicated and extended to a new domain. To this end, we presented the participants with large seed items that had been overestimated in the pilot study. As in Experiment 1, our expectation was that many participants would produce a split response pattern, with the true value of the seed set above their average estimate for the transfer countries but below their average estimate for the seed countries (i.e., $T_1 < S_A < S_1$). As before, we were interested in whether the postseeding transfer estimates produced by these participants would shift toward the seed values, as the anchoring position predicts, or away from them, as the feedback/induction position predicts.

Method

Materials. The 60 cities that served as stimulus items in this experiment were selected for being well known and widely distributed across the globe. As in the population estimation studies, the to-be-estimated values spanned a large range of magnitudes. London, England was the closest city to Paris (215 miles); Sydney, Australia was the most distant (10,544 miles). Mean distance between the target cities and Paris was 3,947 miles (median = 4,124 miles). Because care was taken to select cities from around the globe, distances were quite variable (standard error = 345.47) and fairly symmetric (skew = 0.47). The 8 cities selected from this set to serve as seeds are listed in Table 1.

Procedure. With a few differences, the procedure followed in Experiment 2 was identical to that followed in Experiment 1. One difference was that there was no initial knowledge-rating task. A second difference was that the participants responded to 60 items, rather than to 96, in the preseeding and postseeding estimation tasks. Third, 8 seeds, rather than 10, were studied during the four learning blocks. Fourth, on each trial, the participants were presented with a phrase (e.g., "Distance between PARIS and SINGAPORE"), rather than with a country's name. Fifth, the distance between Paris and Pittsburgh was used as an example in the instructions.

Participants. The 28 participants were drawn from the Carnegie–Mellon undergraduate participant pool; none had participated in previous real-world estimation studies. Each of them was tested individually and received course credit or money in return. Sessions lasted approximately 45 min.

Results and Discussion

As in Experiment 1, four median estimates, four correlations between estimated and actual distances, and four OME means were computed for each participant.

Metric and mapping performance. As is illustrated in Table 2, initial between-city distance estimates were more accurate than the population estimates in Experiment 1. This was true for measures of both metric accuracy (mean preseeding transfer OME = .28) and mapping accuracy (mean rank correlation between actual distance and preseeding estimated distance for transfer cities = .86).

Nonetheless, participants in this experiment responded to the seeds in much the same way as their counterparts in Experiment 1. Exposure to the seeds increased metric accuracy [mean postseeding OME for the transfer items = .20; $t(27) = 2.67, p < .02$], but it had little impact on the already high mapping accuracy [mean correlation between the actual distance and the postseeding estimates for the transfer cities = .88; $t(27) = 1.91, .10 > p > .05$]. Again, the postseeding estimates for the seed cities were more accurate than the preseeding estimates. In this case, OME dropped from .27 to .05 [$t(27) = 4.38$, $p < .0001$], and the mean correlation between estimated and actual distances increased from .38 to .55 [$t(27) = 2.67, p > .02$].

It is unclear why the participants did not come to a better understanding of the relative distances of the eight seed cities. It could be that the range of distances was too narrow to warrant a careful encoding of the actual distances. Nonetheless, exposure to the seeds did produce reliable seeding effects on the transfer countries, which means that the participants must have attended to the facts and learned something about them. Moreover, these participants responded to distance seeds in the same way that others have responded to population seeds. Participants who initially overestimated the distances tended to decrease their estimates after they studied the seed facts, and those who initially underestimated the distances tended to increase their estimates. This resulted in a negative correlation between initial median estimates for the seed countries and the difference between initial and final median estimates for the transfer countries ($r = -.49$, p < .01). Moreover, the correlation increased to $-.79$ when a single outlier was removed.

Analysis of data from split participants. Of the 28 participants, 15 produced estimates that conformed to the split pattern (i.e., $T_1 < S_A < S_1$) needed to test the competing predictions of the anchoring and feedback/induction positions. As in Experiment 1, the prediction that followed from the feedback/induction position proved accurate. Postseeding estimates for the transfer cities were reliably smaller than preseeding estimates [3,728 vs. 3,285 miles; $t(14) = 2.17, p < .05$]. Of the 15 *split* participants, 10 produce this pattern of change, 3 produced the opposite pattern, and 2 displayed no change ($p < .05$, by a one-tailed sign test).

It should also be noted that average postseeding transfer estimate (3,285 miles) was considerably smaller than the value of even the smallest of the seed distances (i.e., Beijing, 5,138 miles). This fact is important because it rules out *selective anchoring* as a possible explanation for the shifts observed in this experiment. The selective anchoring view holds that seeding effects are produced by anchoring and that the postseeding shifts occur because participants, for some reason, chose to anchor on only the smallest of the seed facts. At the extreme, participants might adopt the smallest anchoring value as the response for all transfer items. If so, one would expect the postseeding transfer estimates to be very close in value to the magnitude of the smallest seed value. The results of Experiment 1 are not inconstant with this interpretation; the smallest seed was Australia, with its population of 17.3 million, and the mean of the median postseeding transfer estimates for participants who produced the split pattern was 16.5 million. It is, however, difficult to imagine any plausible version of the selective anchoring position that could produce the pattern of results obtained in the present experiment. Not only did the postseeding transfer estimates move away from the seed values, rather than toward them, but the average postseeding transfer estimate was some 2,000 miles smaller than it would have been if the participants had given the smallest of the seed values in response to all of the transfer items.

In summary, the findings of Experiment 2 indicate that seeding can produce a marked improvement in metric accuracy even when participants already possess reasonably accurate understanding of the to-be-estimated values. The findings also indicate that the seeding procedure is applicable to distance estimation, as well as to the previously studied population and latitude estimation tasks. These findings increase our confidence that seeding is capable of fostering numeracy in a variety of domains, both ones in which prior relevant knowledge is sparse or inaccurate and ones in which it is more substantial.

GENERAL DISCUSSION

The results of the present study help us to understand the mechanisms through which seeding exercises its effects. As was noted above, prior studies indicated that seeding effects persist even after the particular seed facts are forgotten (Brown & Siegler, 1996). Prior findings also indicated that both assimilation and contrast effects can arise in the same set of postseeding estimates (A. Friedman & Brown, 2000a, 2000b).

The present study provided a direct contrast between predictions of the feedback/induction and the anchoring positions. It yielded quite conclusive support for the feedback/induction position. Specifically, in both experiments, those participants whose initial estimates produced the split pattern (i.e., $T_1 < S_A < S_1$) adjusted their mean estimates for transfer countries downward after encountering evidence that their initial estimates for the seed facts were too large. Such a data pattern, in which estimates move away from the anchor, should not occur by the logic of the anchoring position.

Thus, three lines of evidence now support the claim that a feedback/induction mechanism produces seeding effects. This mechanism rests on fundamental intellectual abilities: detecting patterns over sets of examples, representing an abstracted pattern as generalized knowledge, and transferring the abstracted pattern to novel instances. Moreover, both mnemonic and processing considerations favor the feedback/induction approach. As was noted above, we have previously demonstrated that metric knowledge extracted from seed facts is retained better than the seed facts themselves (Brown & Siegler, 1996). The memory advantage enjoyed by the metrics makes sense when one considers that each presentation of a seed fact provides participants with an occasion to update and rehearse their metric knowledge. For example, in Experiment 1, each of the 10 seed facts was presented four times during the study phase. This means that the participants had 40 chances to consider the metric implications of the seed facts, but only 4 chances to learn each seed. Moreover, if participants generate their post-seeding estimates by mapping a relative value onto the updated dimension, the subsequent application of this metric knowledge should impede forgetting.

The processing advantage associated with the feedback/induction approach derives from two general classes of estimation strategies: reconstructive strategies and mapping strategies.[2] Reconstruction of a real-world quantity involves searching memory for potentially relevant facts (i.e., seeds), assessing the relation between the retrieved seed facts and the target item, drawing a plausible inference, and determining whether the inferred value meets confidence and precision criteria. If the criteria are not met, it also involves iterating through the retrieval–inference–evaluation cycle (Brown, 1990; Collins & Michalski, 1989; Kemp, 1999). In contrast, the mapping approach requires participants only to assess the relative magnitude of an item along the target dimension and then to select a value from the appropriate portion of the response range.

After updating metric information, it is a relatively simple matter to produce new sets of estimates that are consistent with current beliefs, at least when people rely on the mapping strategy. All that is required is that new numerical values be appropriately assigned to the response range. However, if participants were to treat seeds as anchors, they would have to persist with (or adopt) a reconstructive strategy that is demanding but does not necessarily produce accurate responses. Given these options, it seems that there would be little motivation to use seeds as anchors, even when they can be recalled.

At this point, data and theory allow us to conclude that seeds aren't anchors. This conclusion raises an interesting question: If seeds aren't anchors, can anchors profitably be viewed as seeds? To understand this question, it is necessary to consider how anchoring effects are produced in the laboratory. Many experimental demonstrations of anchoring involve quantitative dimensions about which metric knowledge is sparse. Few people, for example, have a good sense of the populations of most countries. The procedure within such experiments tends to pose participants with initial questions that include an anchor that serves as a comparison point (e.g., "Is the population of Kenya less than or equal to 75 million?"). Then, participants are asked to provide a related quantitative estimate without the anchor present (e.g., "What is the population of Kenya?"). The standard finding is that later estimates are larger following a "high" anchor (e.g., 75 million) than a "low" one (e.g., 15 million).

In such anchoring experiments, the "uninformative" comparison values actually may be highly informative, at least for participants who have limited relevant metric knowledge (Grice, 1975; Schwarz, 1996). Such participants may use anchors as they use seed facts—as sources of metric information that indicate the magnitude of reasonable numerical estimates. More generally, participants may respond to potentially informative anchor values in several ways: They could adopt the anchor value as an answer, integrate it with prior knowledge, or reject it completely (Brown, 2000). Prior metric knowledge, confidence in that knowledge, and beliefs about the experimental situation all seem likely to influence participants' responses to anchor values.

Note that the anchor-as-seeds interpretation provides a fundamental reconceptualization of the anchoring effect. Anchoring effects have been viewed as biases, inevitable and unfortunate by-products of processes evoked when people compare a target value with a reference value (Chapman & Johnson, 1999; Mussweiler & Strack, 1999; Pohl & Eisenhauer, 1997; Tversky & Kahneman, 1974). In contrast, the present approach recasts anchors as potentially useful numerical information and assumes that these values are processed in much the same way as other quantitative facts. On this view, what differentiates anchors from seeds is the absence of an explicit indication that the anchor is informative.

Although the anchors-as-seeds approach is still being developed, we believe that it holds promise. For example, it correctly predicts the relation between domain knowledge and anchoring (Wilson, Houston, Etling, & Brekke, 1996): People with greater knowledge of a domain are less influenced by the size of anchors, because plausible anchors provide no new information. The account also explains why comparison questions produce anchoring effects when the comparison item (e.g., Kenya) differs from the item that appears in the follow-up estimation question (e.g., Somalia; Beck & Carlson, 1998). In this case, the anchor provides information about the correct metric to be used when estimating national populations. Of course, further research is required to directly assess the validity of this extension of our approach and to determine whether there are anchoring effects that cannot be explained by it. Nonetheless, the account suggests that the metrics-and-mapping framework and the feedback/induction mechanism may well apply across a broad range of numerical estimation tasks.

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NOTES

1. There are, of course, six ways to configure the three values S_A, S_1, and T_1. However, the two positions make identical predictions when S_A is greater than S_1 and T_1 (i.e., $S_1 < T_1 < S_A$ and $T_1 < S_1 < S_A$) or when S_A is less than S_1 and T_1 (i.e., $S_A < S_1 < T_1$, and $S_A < T_1 < S_1$); in the former case, both positions predict, $T_1 < T_2$, and in the latter case, both predict $T_2 < T_1$. In this article, we focused on only one of the two configurations, which places S_A between S_1 and T_1. We did this for the sake of expository simplicity but assume that the $S_1 < S_A < T_1$ configuration would produce comparable results.

2. In the context of event dating, W. J. Friedman, 1996, refers to these two classes as "location-based" and "distance-based" strategies, respectively.

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