Toward a Model of Comparison-Induced Density Effects

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Abstract

A model of the effects of distribution density on evaluations of attribute values is proposed in which biases created by language-expressible magnitude comparisons (e.g., "I waited longer for the bus today than I did yesterday") serve as the mediating mechanism. The biases created by comparisons as well as the mechanisms by which comparison-induced biases could produce density effects are described. Simulation data demonstrate signature characteristics of comparison-induced density effects. An experiment found preliminary evidence in support of the view that some density effects might be comparison-induced.

Density Effects

Evaluations of attribute values such as grades (Wedell, Parducci, & Roman, 1989), taste (Riskey, Parducci, & Beauchamp, 1979), visual velocity (Sokolov, Pavlova, & Ehrenstein, 2000), prices (Niedrich, Sharma, & Wedell, 2001), income (Hagerty, 2000) and so forth often depend upon the density—or frequency—of the distribution from which judged values are drawn (Krumhansl, 1978; Parducci, 1965, 1995). In particular, evaluation functions are typically concave (downward) for positively skewed distributions and convex (concave upward) for negatively skewed distributions. Values drawn from positively skewed distributions are also often judged larger than are values drawn from negatively skewed distributions.

Several explanations for these effects have been proposed. Parducci's (1965) Range-Frequency Theory assumes that people are aware of and use percentile rank information to evaluate attribute values. Range-Frequency Theory explains the finding that evaluation functions are often concave for positively skewed distributions, because the density at the lower end of positively skewed distributions gives low values larger percentile rank scores than they would have had otherwise. The slope of the function becomes shallow at the sparse upper end of the distribution where percentile rank scores increase at a slower rate. The reverse pattern of changes in percentile rank scores in negatively skewed distributions explains the finding that evaluation functions are often convex for negatively skewed distributions.

Haubensak (1992) suggested an alternative explanation for density effects on evaluations of sequentially presented values. He argued that since people do not know the distribution density and range in advance, they tend to assume that early values are typical or average and assign them intermediate verbal labels or category ratings. After these initial labels or category ratings have been assigned, people are obliged to use them consistently. Since early values are most likely to come from the dense portion of skewed distributions, the portion of the range at the dense end of these distributions will be smaller than the portion of the range at the sparse end. To cover the entire range of values the remaining verbal labels or category ratings would have to be assigned asymmetrically.

In this paper, I propose yet another possible explanation for density effects. Namely, that some density effects might be comparison-induced (Choplin & Hummel, 2002). Verbal comparisons will tend to bias values apart in dense regions making the slope of the evaluation function steep and bias values together in sparse regions making the slope of the evaluation function shallow. These biases would make evaluation functions concave for positively skewed distributions and convex for negatively skewed distributions. The assignment of verbal labels or category ratings to these biased values might explain why values drawn from positively skewed distributions are often judged larger than are values drawn from negatively skewed distributions.

I start by reviewing the basic tenets of Comparison-Induced Distortion Theory (Choplin & Hummel, 2002) and describing how comparisons could produce density effects. I present simulation data to demonstrate signature characteristics of comparison-induced density effects and how they differ from density effects produced by other mechanisms. I then describe an experiment in which I found preliminary support for the view that some density effects might be comparison-induced.

Comparison-Induced Distortion Theory

The basic idea behind Comparison-Induced Distortion Theory (Choplin & Hummel, 2002) is that language-expressible magnitude comparisons suggest quantitative values. To investigate the meanings of English age comparisons Rusiecki (1985) gave his participants sentences such as "Mary is older than Jane" and "Martin's wife is older than Ken's wife" and asked them to report the ages they imagined. Rusiecki found considerable agreement in the values imagined by his participants. In response to the comparison "Mary is older than Jane" participants imagined Mary to be 20.2 years on average and Jane to be 17.9 years on average. In response to the comparison "Martin's wife is older than Ken's wife" participants imagined Martin's wife to be 37.2 years on average and Ken's wife to be 33.0 years on average.

Of particular interest to the current discussion, the age differences imagined by Rusiecki's (1985) participants were remarkably similar. Regardless of the particular ages they imagined, participants imagined a difference between the ages of approximately 2 to 5 years (slightly larger for larger values)—not 1 month or 30 years. Inspired by these results, Rusiecki argued that comparisons suggest quantitative differences between compared values. I will henceforth call these quantitative differences "comparison-suggested differences," because they are the differences suggested by comparisons. In the case of age comparisons, for example, Rusiecki's results demonstrate that comparison-suggested differences are approximately 2 to 5 years (for ease of discussion I operationally define the comparison-suggested difference implied by age comparisons to be 3.5 years).

Choplin and Hummel (2002) proposed a model of attribute evaluation in which magnitude comparisons (like those investigated by Rusiecki, 1985) bias evaluations of magnitude values. In particular, they suggested that evaluations of magnitude values might be vulnerable to bias whenever values differ from the values suggested by comparisons. For example, if the actual age difference between two people were 1.5 years (i.e., less than the comparison-suggested difference of 3.5 years), then a comparison would tend to bias evaluations of their ages apart—toward a difference of 3.5 years. The younger person would be evaluated younger than she or he would have been evaluated otherwise and the older person would be evaluated older than she or he would have been evaluated otherwise. If the actual age difference between two people were 5.5 years (i.e., more than the comparison-suggested difference of 3.5 years), then a comparison would tend to bias evaluations of their ages together—again toward a difference of 3.5 years. The younger person would be evaluated older than she or he would have been evaluated otherwise and the older person would be evaluated younger than she or he would have been evaluated otherwise.

Formally, the comparison-suggested value of the smaller of two compared values (E_S; E for Expected) and the comparison-suggested value of the larger of two compared values (E_L) can be calculated from the comparison-suggested difference, D:

$$E_S = S_L - D \tag{1a}$$

$$E_L = S_S + D \tag{1b}$$

where S_L and S_S (S for Stimulus values) are the values of the larger and smaller values unbiased by comparisons respectively. Represented values are assumed to be a weighted mean of the values unbiased by comparisons and the comparison-suggested values:

$$R_S = wE_S + (1-w)S_S \tag{2a}$$

$$R_L = wE_L + (1-w)S_L \tag{2b}$$

where w is the relative weights of the two values, is bound between 0 and 1, and is constrained so as to prevent impossible values (e.g., negative years or sizes of geometric figures) from being represented. For example, assuming a comparison-suggested difference, D, of 3.5 years, a comparison between a 22-year old and a 28-year old would bias evaluations of their ages toward each other. If the weight given to comparison-suggested values were .2, then the represented age of the 22-year old would be 22.5 years and the represented age of the 28-year old would be 27.5 years. That is, the age of the 22 year old would be evaluated, i.e., treated, as if it were half a year older and the age of the 28 year old would be evaluated as if it were half a year younger.

Comparisons Might Create Density Effects

Comparison-induced biases like those just described might produce density effects. Consider, for example, the positively skewed distribution of ages presented in Figure 1 which might be approximately representative of the ages of students in a typical undergraduate classroom. Filled-in arrows represent biases created by comparisons between values that are closer together than the comparison-suggested difference and that are, therefore, biased apart by comparisons. Outlined arrows represent biases created by comparisons between values that are farther apart than the comparison-suggested difference and that are, therefore, biased together by comparisons. Values in dense regions (i.e., 18 – 22 years in Figure 1) are more likely to be closer together than the comparison-suggested difference and as a result comparisons will more likely bias evaluations apart. Values in sparse regions (i.e., 22 – 28 years) are more likely to be farther apart than the comparison-suggested difference and as a result comparisons will more likely bias evaluations together. I propose that this difference in the effects of comparisons within dense regions versus the effects of comparisons within sparse regions might produce comparison-induced density effects.

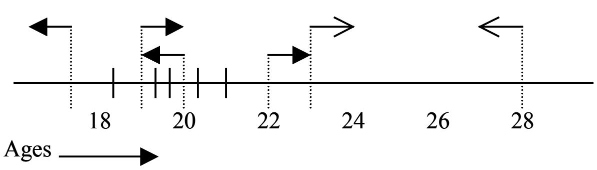

Figure 1: Comparison-induced biases that might occur in a positively skewed distribution of ages.

Modeling Density Effects

To model comparison-induced density effects, Comparison-Induced Distortion Theory requires several assumptions. First, an operational definition of the comparison-suggested difference (D) is required. In the preceding sections, for example, an adequate operational definition of the difference suggested by age comparisons was obtained from Rusiecki's (1985) study in which he queried his participants as to the differences they imagined. Alternatively, an adequate operational definition might be obtained from common real-world differences.

Second, because the number of comparisons people could hypothetically articulate as well as the sequences in which they could hypothetically articulate them is—in most cases—indefinite, assumptions about which comparisons get articulated are required. Almost any comparison scheme would produce density effects. Comparing each value to the value presented one item back, for example, would produce density effects. In the modeling presented below, I assumed that the to-be-judged item is only compared to one other item. Additionally, I assumed two constraints on the selection of this comparison item: the similarity between the to-be-judged item and candidate comparison items and the sequence in which values were presented. Although these assumptions were optional, I utilized them because they are psychologically realistic and they have a long history in models of categorization and the psychology of judgment (see, for example, Haubensak, 1992; Nosofsky & Palmeri, 1997; Smith & Zarate, 1992).

To model the constraint of similarity on the selection of comparison items, I (along with Shepard, 1987) assumed that similarity is an exponentially decreasing function of the distance between item values. For every recently presented item j, it's similarity to i, the to-be-judged item, (η_{ij}) is calculated as:

$$\eta_{ij} = e^{-cd_{ij}} \quad (3)$$

where c is a sensitivity parameter and d_{ij} is the weighted distance between i and j in similarity space across all relevant dimensions weighted by the importance of each dimension (see, for example, Nosofsky & Palmeri, 1997).

To model the constraint provided by the sequence in which items are presented, I calculated the activation (a_{ij}) of each candidate comparison item j as:

$$a_{ij} = M_j \eta_{ij} \quad (4)$$

where M is the memory strength of exemplar j and is given by: $M_j = \alpha^{t(i) - t(j)}$ where α represents the memory decay on each trial and is bound between 0 and 1 and where t(i) and t(j) are the trials on which i and j were presented respectively (see Nosofsky & Palmeri, 1997). Selection of the item to which the to-be-judged item is compared could be accomplished a number of different ways. The choice axiom might be used to make selection stochastic. In the simulations below, maximum activation (a_{ij}) was used to make selection deterministic.

Simulation Using Artificial Values

The purpose of this simulation was to demonstrate how the model proposed above might create density effects and to point out signature characteristics of comparison-induced density effects that differentiate them from density effects created by other mechanisms. To demonstrate how the model presented above would create density effects, a computer-generated sequence of 500 values drawn from a log-normal distribution was created from equations 5 and 6.

$$V_{normal} = \sqrt{-2 \log R_1} \sin(2\pi R_2) \quad (5)$$

$$V_{\log-normal} = e^{\sigma V_{normal}} \quad (6)$$

where R_1 and R_2 are random, computer-generated values between 0 and 1. Equation 5 produced a normally distributed sequence and Equation 6 changed that sequence into a log-normally distributed sequence. To skew the log-normal distribution, σ was set at .9.

To model recall of the item to which the to-be-judged item was compared, the parameter α, representing memory decay, was arbitrarily set at .985 thereby minimizing memory losses. The parameter c, representing sensitivity to differences, was set at 0.3. Within the sequence, the second value was compared to the first value; the third value was compared to whichever of the first or the second value had the highest activation (a; see Equation 4); the fourth value was compared to whichever of the first, second, or third value had the highest activation, and so forth. In these simulations, only the most recent 7 values were candidates for comparison. Recalled values were biased by the comparison on the trial on which they were judged, but were not biased further by subsequent comparisons.

To model comparison-induced distortions, the comparison-suggested difference, D, was set at 0.38 and the weight given the comparison-suggested values, w, was .5. As suggested in Figure 1, values from the dense region were more likely to be compared to values that were less than a comparison-suggested difference away than were values from the sparse region. The values that were smaller than 1.5 (the dense lower region) were most similar to a value that was less than a comparison-suggested difference away 86.1% of the time (329/382). By contrast, the values that were larger than 1.5 (the sparse upper region) were most similar to a value that was less than a comparison-suggested difference away 40.2% of the time (47/117).

The results are presented in Figure 2. Generated values are plotted along the horizontal axis. The value of each item is plotted on the vertical axis. The filled-in squares represent comparison-biased values and the outlined circles represent unbiased values.

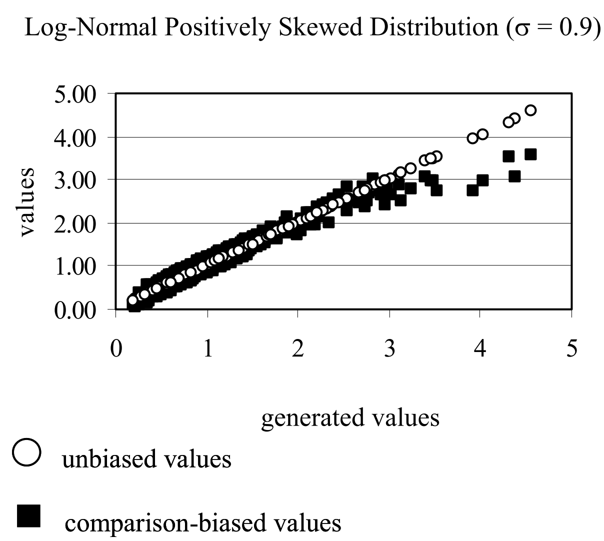

Figure 2: Simulation Results.

As shown in Figure 2, comparisons between each value and the most recent similar value created biases. Consistent with previous research using category ratings as the dependent measure, these biases produced a concave evaluation function. Seemingly contrary to previous research, however, comparisons had a tendency to bias values downward instead of upward.

This seeming contradiction can be reconciled by noting that category ratings depend not only upon representations of values but also upon the function mapping representations to category ratings. A number of functions could produce high category ratings. For example, if people were to use the range of values to make category ratings as proposed by Volkmann (1951), then even if comparisons biased representations in one direction (perhaps, as measured by reproduction), category ratings could be biased in the other direction (see Biernat, Manis, & Kobrynowicz, 1997).

To demonstrate this possibility, range scores (i.e., [value on trial t minus smallest value up to trial t] divided by [largest value up to trial t minus smallest value up to trial t]) were calculated from the comparison-biased values. The results—after the initial 35 trials in which the range was established—are plotted in Figure 3. Filled-in squares represent comparison-biased range scores. The range transformation makes comparison-biased values comparable to the predictions of Range-Frequency Theory and so range-frequency compromise values (with the weight given to frequency set at .35) are also plotted in Figure 3 and represented as outlined triangles (see Parducci, 1965). The comparison-biased range scores mirrored the unbiased range-frequency compromise scores, suggesting that in some cases the effects of density on people's category ratings might be comparison-induced.

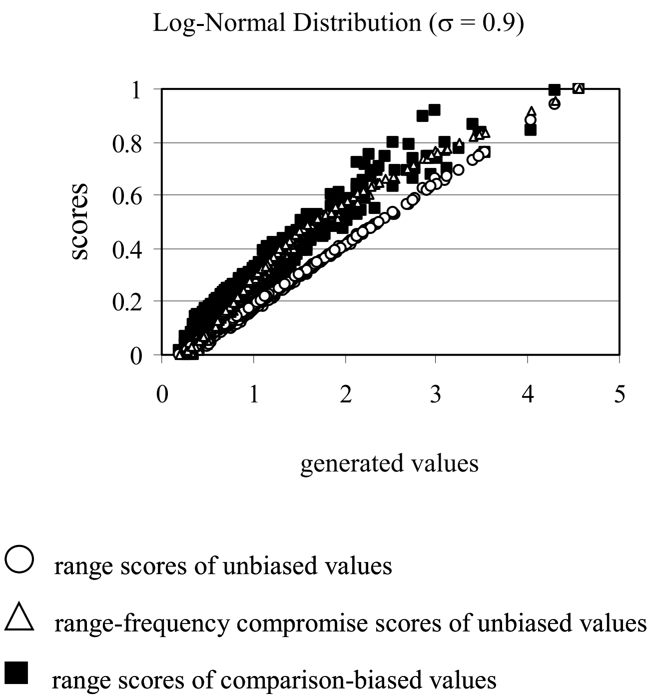

Figure 3: Simulation Data. Range scores on comparison-biased values mirror Parducci's (1965) range-frequency compromise scores.

Mirroring range-frequency compromise scores, the generated values in this simulation had comparison-biased range scores that were larger than their unbiased range scores 97.4% (487/500) of the time. I have successfully fit the model of comparison-induced density effects presented here to the results of several published density effect studies (e.g., Riskey et al., 1979) under the assumption that the comparison-biased represented values are mapped to category ratings using Volkmann's (1951) range function.

This modeling points out several signature characteristics of comparison-induced density effects that differentiate them from density effects produced by other mechanisms (e.g., range-frequency compromise). The comparison-induced biases in this simulation depended solely upon the model's knowledge of the comparison-suggested difference (D), the importance of the comparison (w), and the value retrieved for comparison. The model has no knowledge of the density of the distribution or of the percentile ranks of values and so the percentile ranks of values do not affect the model's judgments on individual trials. Rather, density affects aggregate data, because values in dense regions are more likely to be compared to values that differ from them by less than a comparison-suggested difference (and less likely to be compared to values that differ from them by more than a comparison-suggested difference) than are values in sparse regions. By contrast, Range-Frequency Theory assumes that people have implicit knowledge of percentile rank information and use that knowledge in making judgments on individual trials. Due to this difference, Range-Frequency Theory predicts that density effects ought to be observable on individual trials and Comparison-Induced Distortion Theory predicts that they ought not to be.

Experiment

The purpose of this experiment was to investigate whether the signature characteristics of comparison-induced density effects demonstrated in the modeling presented above could be observed empirically. Participants imagined that they were spending 25 days in rural Minnesota during the middle of winter and had to rely upon public transportation. The length of time they had to wait for the bus varied each simulated day and they indicated how aversive the wait would be. Half of the participants judged wait times drawn from a negatively skewed distribution and the other half judged wait times drawn from a positively skewed distribution.

Method

Participants. Seventy-three people volunteered to participate after being approached by the experimenter on the University of California, Los Angeles campus or in the surrounding community (36 in the positively skewed condition and 37 in the negatively skewed condition).

Materials and Procedure. A random sequence of 10 wait times drawn from a negatively skewed (7, 10, 13, 16, 16, 16, 19, 19, 19, and 19 minutes) or a positively skewed (7, 7, 7, 7, 10, 10, 10, 13, 16, and 19 minutes) distribution was created for each participant. Each participant's sequence was presented twice. An initial sequence of 5 days was inserted at the start of the sequence to control for primacy effects, introduce participants to the range of values they would see in the experiment, and to measure participants' baseline evaluations prior to being exposed to the density manipulation. The wait times on these 5 days were 7, 19, 13, 19, and 7 respectively and were the same for all participants. On each simulated day (simulated within a single session), the experimenter verbally told participants how long the fictitious wait for the bus was that day. Participants indicated how aversive they imagined that wait would be using a line-analogue measure in which they placed a tick at the spot along the line that was analogous to how aversive the wait was (see Schifferstein & Frijters, 1992). A stop mark on the left-hand side of the line was labeled 0=not bad and a stop mark on the right-hand side of the line was labeled 10=extremely bad. The 25 lines were presented on a single, one-page experimental handout and labeled Day 1 through Day 25.

Results and Discussion

To reduce variance caused by idiosyncratic reactions to wait times, participants' judgments during the initial sequence were used as a baseline. Each participant's judgments on trials 6 through 25 were divided by the average of her or his judgments on trials 4, 5, and 6.

Distribution density effects were revealed by differences between judgments in sparse regions versus differences between judgments in dense regions. Among participants whose wait times were drawn from the negatively skewed distribution, the difference between judgments of 7-minute wait times and judgments of 13-minute wait times (i.e., the sparse region) was reliably smaller than the difference between judgments of 13-minute wait times and judgments of 19-minute wait times (i.e., the dense region), $t(36) = 3.99$, $p < .01$. Among participants whose wait times were drawn from the positively skewed distribution, the difference between judgments of 7-minute wait times and judgments of 13-minute wait times (i.e., the sparse region) was approximately the same size as the difference between judgments of 13-minute wait times and judgments of 19-minute wait times (i.e., the dense region), $t < 1$. A 2 (distribution) x 2 (region) Mixed-Factors ANOVA found that this interaction was significant [$F(1,71) = 6.11$, $MSE = 0.22$, $p = .01$].

Because the initial sequence of 5 days inserted at the start of the experiment introduced participants to the entire range of wait times and was the same for all participants, Haubensak's (1992) model is not a viable model of the observed density effects (but note that the density effects observed in this experiment were smaller than the density effects often observed). Range-Frequency Theory and Comparison-Induced Distortion Theory remain as viable models of the observed density effects.

Range-Frequency Theory assumes that people have implicit knowledge about the percentile ranks of stimulus values and use that knowledge to judge stimulus values on particular trials. It, therefore, predicts density effects on individual trials. By contrast, Comparison-Induced Distortion Theory assumes that comparisons produce the same biases regardless of the type of distribution from which values are drawn (as long as D, w, and the values to which they are compared remain constant). It predicts density effects not on individual trials, but rather only in the aggregate and it does so only because the values to which judged values are compared differ across distributions.

The predictions of Range-Frequency Theory and Comparison-Induced Distortion Theory were tested by concentrating on differences between successive wait times of 3 minutes. At 3-minute differences the stimulus one back will likely be the most similar recent value, although occasionally the identical value 2 trials back may be the most similar recent value. To-be judged values drawn from the negatively skewed distribution were preceded by a value that was 3 minutes away 41.5% of the time (292/703). Of these to-be-judged values, 69.9% (204/292) were larger than 13, i.e., were in the dense region, and 14.7% (43/292) were smaller than 13, i.e., were in the sparse region. The to-be-judged values drawn from the positively skewed distribution were preceded by a value that was 3 minutes away 40.6% of the time (278/684). Of these to-be-judged values, 72.7% (202/278) were smaller than 13, i.e., were in the dense region, and 12.2% (34/278) were larger than 13, i.e., were in the sparse region.

Contrary to the predictions of Range-Frequency Theory and consistent with the predictions of Comparison-Induced Distortion Theory, differences between successive judgments (when actual differences were 3 minutes) were not correlated with differences in percentile rank. These correlations were not significant for descending ($r = .065$, $F < 1$) or ascending ($r = -.030$, $F < 1$) pairs from the positively skewed distribution or for descending ($r = -.047$, $F < 1$) or ascending ($r = -.050$, $F < 1$) pairs from the negatively skewed distribution.

Consistent with the predictions of Comparison-Induced Distortion Theory and not predicted by Range-Frequency Theory, the differences between judgments of successive wait times that were different by 3 minutes were biased apart, i.e., larger than their rightful proportion of 25% of the range (using participants' responses on trials 4, the large end of the range, and 5, the small end of the range, as the baseline). The differences between judgments of values that differed by 3 minutes were 33.2% of the range on average (SD = 25.1%) in the positively skewed distribution [which was significantly larger than their rightful proportion of 25%, $t(277) = 5.46$, $p < .01$] and were 44.6% of the range on average (SD = 49.6%) in the positively skewed distribution [which was also significantly larger than their rightful proportion of 25%, $t(291) = 6.77$, $p < .01$]. Further analyses did not find differences between the two distributions or between regions within the two distributions, or interactions between them. The differences between judgments of values that differed by 6, 9, and 12 minutes did not differ from their rightful proportions of the range (all t's < 1), perhaps because more similar recent items were recalled instead.

General Discussion

A model of distribution density effects in which verbal comparisons such as "I waited longer for the bus today than I did yesterday" create the observed biases was proposed.

Modeling demonstrated that comparisons might produce density effects. An experiment found preliminary empirical support for this proposal.

Future research will investigate density effects using reproduction dependent measures and investigate the predicted disassociation between representations of values (perhaps as measured by reproduction, see Figure 2) and category ratings (see Figure 3, Biernat et al., 1997). Future work will also investigate effects of distribution density on recall of values from memory. Comparison-Induced Distortion Theory predicts density effects on recall of values from memory and Range-Frequency Theory does not (see Choplin & Hummel, 2002, for a discussion).

Although in my view many density effects are likely to be comparison-induced, I do not assume that all density effects are comparison-induced. Density effects observed when all values are presented simultaneously in ascending or descending order (e.g., Wedell et al., 1989) strike me as cases where density effects are particularly likely to be categorization-induced as Parducci (1965) suggested. Additionally, even if density effects are found to be comparison-induced, the equations used to formalize Range-Frequency Theory will likely still provide a useful heuristic for predicting effects of density on judgment.

Conclusions

Some density effects might be comparison-induced. Comparisons of values in dense regions will tend to bias values away from each other, while comparisons of values in sparse regions will tend to bias values toward each other. These biases could produce density effects.

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