

Brief article

Statistical regularities reduce perceived numerosity

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ARTICLE INFO

Article history:

Received 23 December 2014

Revised 6 September 2015

Accepted 21 September 2015

Keywords:

Statistical learning

Implicit learning

Numerosity estimation

Grouping

Attention

ABSTRACT

Numerical information can be perceived at multiple levels (e.g., one bird, or a flock of birds). The level of input has typically been defined by explicit grouping cues, such as contours or connecting lines. Here we examine how regularities of object co-occurrences shape numerosity perception in the absence of explicit grouping cues. Participants estimated the number of colored circles in an array. We found that estimates were lower in arrays containing colors that consistently appeared next to each other across the experiment, even though participants were not explicitly aware of the color pairs (Experiments 1a and 1b). To provide support for grouping, we introduced color duplicates and found that estimates were lower in arrays with two identical colors (Experiment 2). The underestimation could not be explained by increased attention to individual objects (Experiment 3). These results suggest that statistical regularities reduce perceived numerosity consistent with a grouping mechanism.

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1. Introduction

The visual system is efficient at perceiving numerical information in the environment. For instance, we can quickly approximate the number of items (Ansari, 2008; Dehaene, Dehaene-Lambertz, & Cohen, 1998; Feigenson, Dehaene, & Spelke, 2004). Since number is a discrete measure of unitized items, what determines the unit over which number is computed? The unit of input is flexible and can involve either a discrete item (e.g., one bird), or a set of items (e.g., one flock of birds). The latter is typically determined by explicit grouping cues, such as shared features (Halberda, Mazocco, & Feigenson, 2008; Halberda, Sires, & Feigenson, 2006), categorical memberships (Feigenson, 2008; Halberda & Feigenson, 2008), spatial arrangement (Ginsburg, 1976, 1978), and segmentation (Franconeri, Bemis, & Alvarez, 2009; He, Zhang, Zhou, & Chen, 2009).

The grouping cues not only define the level of input for enumeration, but highlight the relationships among objects, which can in turn shape numerosity perception. For instance, objects connected by lines are underestimated compared to disconnected objects (Franconeri et al., 2009; He et al., 2009). In addition to explicit grouping cues, objects can be associated in other ways. Indeed, relationships among objects are often not immediately available,

but are extracted over repeated experiences. For instance, if an object always appears next to another object over multiple occasions, the joint probability between the two is 1. This reliable co-occurrence effectively associates the objects, without explicit grouping cues.

One mechanism supporting the extraction of regularities is statistical learning (Fiser & Aslin, 2001; Saffran, Aslin, & Newport, 1996; Turk-Browne, Jungé, & Scholl, 2005; Zhao, Al-Aidroos, & Turk-Browne, 2013). Statistical learning extracts probabilistic relationships between objects over space and time, generates implicit knowledge about these relationships (Aslin & Newport, 2012; Perruchet & Pacton, 2006), and allows for chunking of objects (Brady, Konkle, & Alvarez, 2009; Kirkham, Slemmer, & Johnson, 2002; Saffran et al., 1996). An important distinction between statistical learning and grouping is that the knowledge about object co-occurrences is implicit, since observers are not consciously aware of the underlying regularities (Turk-Browne, Scholl, Chun, & Johnson, 2009; Zhao et al., 2013).

Given that regularities facilitate chunking, we hypothesize that statistical learning shapes numerosity perception via implicit grouping. Specifically, exposure to object co-occurrences may lead to the unitization of objects, thus reducing the perceived numerosity. In line with past research showing that ensemble representation diminishes the perceived variability of heterogeneous stimuli (e.g., Burr & Ross, 2008; Dakin, Mareschal, & Bex, 2005; Sweeny, Haroz, & Whitney, 2013), the current study reveals how the visual system processes the complex environment and represents multiple stimuli at once.

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To seek evidence for this hypothesis, we conducted three experiments. Participants estimated the number of colored circles in arrays. Unbeknownst to them, the arrays contained color pairs containing two distinct colors (Experiments 1a and 1b). We examined whether the presence of color pairs reduced numerosity estimates. To test the grouping mechanism, we introduced color duplicates containing two identical colors, and examined if the grouping cue reduced numerosity estimates (Experiment 2). Finally, we tested an alternative explanation by introducing color pop-outs, and examined whether attention to individual objects influenced numerosity perception (Experiment 3).

2. Experiment 1a

The experiment aimed to examine whether regularities reduce numerosity estimates via implicit grouping.

2.1. Participants

Eighty undergraduates (58 female, mean age = 20.7 years, $SD = 2.9$, $N = 40$ in Experiment 1a, and $N = 40$ in Experiment 1b) from University of British Columbia (UBC) participated for course credit. Participants had normal or corrected-to-normal vision, and provided informed consent. All experiments were approved by UBC Behavioral Research Ethics Board.

2.2. Stimuli

Stimuli consisted of ten colored circles (circle diameter subtended 1.4°). The circles were generated from a pool of ten distinct colors (color name = R/G/B values: red = 255/0/0; green = 0/255/0; blue = 0/0/255; yellow = 255/255/0; magenta = 255/0/255; cyan = 0/255/255; gray = 185/185/185; orange = 255/140/0; brown = 103/29/0; black = 0/0/0). Eight circles were randomly assigned for every participant into four 'color pairs'. The remaining two circles were not paired. The single circles ensured that both even and odd numbers were presented in the experiment. The four pairs were grouped into fixed horizontal, vertical, and diagonal configurations (Fig. 1A).

The number of circles in each array ranged from 10 to 20, creating 11 levels of numerosity. An array with 10 circles contained 4 pairs + 2 singles. An array with 11 circles contained 4 pairs + 3 singles (2 singles + 1 single randomly chosen from the 2). An array with 12 circles contained 4 pairs + 2 pairs randomly chosen from the 4 pairs. An array with 13, 14, or 15 circles contained 4 pairs + 2 pairs chosen from the 4 pairs, and 1, 2, or 3 singles, respectively. For 16–20, all pairs were repeated once. In addition, for 17–20, 1, 2, 3, or 4 singles were presented, respectively. Each array was placed on an invisible 5×5 grid (subtending $10.3^\circ \times 10.3^\circ$), with the constraint that each pair neighbored at least one other pair or one single circle. This ensured that statistical learning could not solely be determined by spatial segmentation cues other than co-occurrence. Each level of numerosity was repeated 40 times, resulting in 440 trials (order randomized for every participant).

2.3. Apparatus

In all experiments, participants seated 50 cm from a computer monitor (refresh rate = 60 Hz). Stimuli were presented using MATLAB (Mathworks) and the Psychophysics Toolbox (<http://psycho toolbox.org>).

2.4. Procedure

Participants were randomly assigned to one of two conditions: structured or random ($N = 20$ in each). During exposure, participants in both conditions viewed arrays of colored circles and estimated the number of circles in each array. They were told that each array contained 10–20 circles, and entered their estimate by typing one of 11 keys, with each key corresponding to one number ('~' = 10, '1' = 11, '2' = 12... '9' = 19, '0' = 20). Each array was presented for 500 ms followed by an inter-stimulus interval (ISI) of 500 ms. If the participant responded within the 500 ms presentation time, the next trial appeared after the ISI; otherwise the screen remained blank until response.

In the structured condition, each array contained the pairs and/or single circles. To ensure incidental encoding of regularities, participants were not informed about the pairs. In the random condition, each array was identical to that in the structured condition, except that after the pairs were placed on the grid, their positions were randomly shuffled (Fig. 1A). This eliminated the color pairs, but maintained the spatial layout, the number and the density of the circles.

After completing all estimation trials, participants in the structured condition completed a test phase. In each trial, two sets of circles were presented for 1000 ms, one on the left and one on the right side of the screen. Participants pressed a key to indicate whether the left ('1' key) or right ('0' key) set seemed more familiar. One set was a pair, and the other 'foil' set contained one color from the pair and one color from a different pair. The colors in the foil had never appeared in this spatial configuration. Each pair was tested against two foils: The first foil contained one color from the pair, and the second foil contained its other color. Each pair-foil combination was tested twice, creating 16 trials (order randomized). Because all individual colors were equally frequent during exposure and test, participants could only choose the pair as more familiar if they had learned color co-occurrences. There was no test phase in the random condition since no pairs were presented during exposure.

After test, a debriefing session was conducted, where participants were asked if they noticed any colored circles that appeared with one another. For those who responded yes, we further asked them to specify which colors co-occurred.

2.5. Results and discussion

During test, the pairs were chosen over foils for 50.9% of the time, which was not reliably above chance (50%) [$t(19) = 0.28$, $p = .78$, $d = .06$]. During debriefing, 6 participants reported noticing the pairs, but none correctly reported which two specific colors co-occurred. This suggests that participants had no explicit awareness of the color pairs.

To address how regularities influenced numerosity estimation, we calculated errors by subtracting the objective numerosity from the estimated numerosity. Thus, a negative error means underestimation, a positive error means overestimation, and zero means perfect accuracy. We compared the errors across the 11 numerosity levels between the two conditions (Fig. 1B). A 2 (condition: structured vs. random; between subjects) \times 11 (numerosity levels; within subjects) mixed-effects ANOVA revealed a main effect of numerosity levels [$F(10,380) = 199.75$, $p < .001$, $\eta_p^2 = .84$], with greater underestimation as numerosity levels increased. Importantly, there was a main effect of condition [$F(1,38) = 4.87$, $p = .03$, $\eta_p^2 = .11$], with greater underestimation in the structured condition than in the random condition. Moreover, the interaction was reliable [$F(10,380) = 3.83$, $p < .001$, $\eta_p^2 = .09$], with greater underestimation in the structured condition compared to the random condition, at higher levels of numerosity than at lower levels.

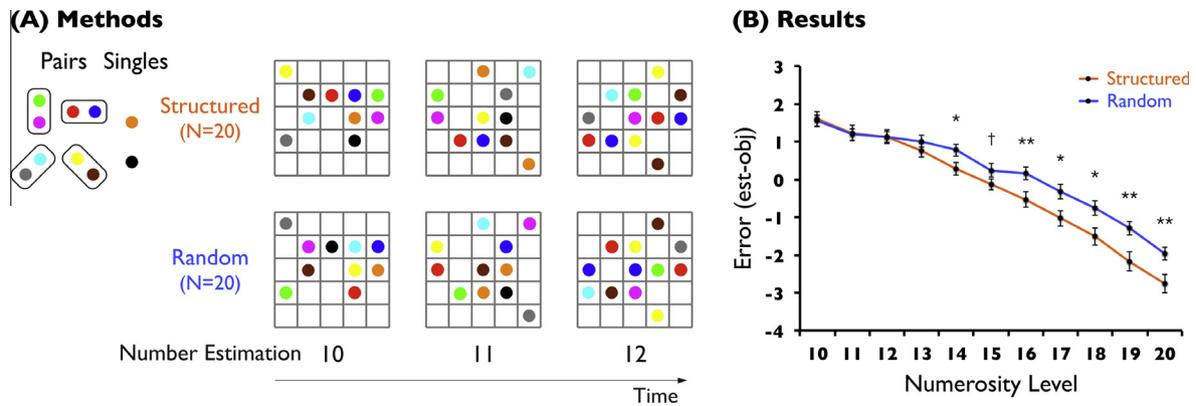


Fig. 1. Experiment 1a. (A) In the structured condition, four color pairs and two single circles were placed on an invisible 5 × 5 grid to generate an array for a given trial. For each array, the number of circles varied from 10 to 20. In the random condition, the positions of colors were randomly shuffled in the grid, removing the pair structure but maintaining the spatial layout of the array. Participants estimated the number of circles in each array. Three sample trials were shown in each condition. (B) Errors were computed (estimated numerosity – objective numerosity). From a two-way ANOVA (structured vs. random conditions × 11 levels of numerosity), there was a main effect of condition, suggesting that the underestimation was significantly greater in the structured condition than in the random condition. The interaction was also reliable, suggesting that the difference between the two conditions was greater for higher levels of numerosity than for lower levels. (Error bars reflect ± 1 SEM; †*p* < .1, **p* < .05, ***p* < .01).

To identify at which numerosity levels the difference was reliable, the errors were compared between the conditions at every numerosity level (Table 1). The errors were significantly different from numerosity level of 16.

The results suggested that exposure to the color pairs reduced the perceived numerosity, in the absence of explicit awareness of the pairs.

3. Experiment 1b

The restricted response range from Experiment 1a could have caused the estimates close to the bounds (10 and 20) to be biased toward the middle of the response range, artificially compressing the distribution of responses. Thus, this experiment used an expanded response range from 5 to 25, while keeping everything else identical to Experiment 1a.¹

3.1. Results and discussion

During test, the pairs were chosen over foils for 52.5% of the time, which was not reliably above chance (50%) [$t(19) = 1.32, p = .20, d = .30$]. Numerosity estimation errors are plotted in Fig. 2. The two-way ANOVA revealed a main effect of numerosity levels [$F(10,380) = 51.46, p < .001, \eta_p^2 = .58$], a marginal effect of condition [$F(1,38) = 2.99, p = .09, \eta_p^2 = .07$], and a reliable interaction [$F(10,380) = 8.02, p < .001, \eta_p^2 = .17$]. The errors between two conditions became significant from numerosity level of 17 (Table 2). These results replicated the findings in Experiment 1a using an expanded response range.

4. Experiment 2

In Experiment 1a, the color pairs may have served as an implicit grouping cue which caused the underestimation of numerosity. To provide support for this account, we introduced color duplicates (i.e., two identical colors) as a more salient grouping cue.

Table 1

Comparisons of estimation errors in the structured vs. the random conditions at each numerosity level using independent-samples *t*-tests in Experiment 1a.

Numerosity levels	Structured vs. random conditions
10	$t(38) = 0.16, p = .87, d = 0.05$
11	$t(38) = 0.17, p = .87, d = 0.05$
12	$t(38) = 0.04, p = .97, d = 0.01$
13	$t(38) = 1.00, p = .32, d = 0.32$
14	$t(38) = 2.07, p = .04, d = 0.66$
15	$t(38) = 1.69, p = .09, d = 0.53$
16	$t(38) = 2.59, p = .01, d = 0.82$
17	$t(38) = 2.49, p = .02, d = 0.79$
18	$t(38) = 2.52, p = .02, d = 0.80$
19	$t(38) = 2.87, p < .01, d = 0.91$
20	$t(38) = 2.76, p < .01, d = 0.87$

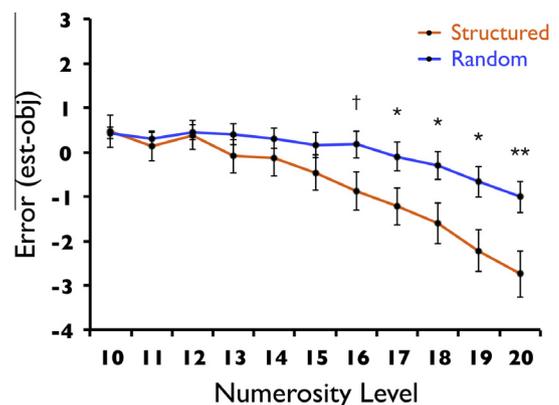


Fig. 2. Experiment 1b. Errors were computed (estimated numerosity – objective numerosity) for each level of numerosity. From a two-way ANOVA (structured vs. random conditions × 11 levels of numerosity), there was a marginal effect of condition, suggesting that the underestimation was marginally greater in the structured condition than in the random condition. The interaction was reliable, suggesting that the difference between the two conditions was greater for higher levels of numerosity than for lower levels. (Error bars reflect ± 1 SEM; †*p* < .1, **p* < .05, ***p* < .01).

4.1. Participants

Forty new undergraduate students (30 female, mean age = 19.5 years, SD = 2.0) from UBC participated for course credit.

¹ We thank an anonymous reviewer for suggesting this experiment.

Table 2

Comparisons of estimation errors in the structured vs. the random conditions at each numerosity level using independent-samples *t*-tests in Experiment 1b.

Numerosity levels	Structured vs. random conditions
10	$t(38) = 0.12, p = .91, d = 0.04$
11	$t(38) = 0.49, p = .63, d = 0.15$
12	$t(38) = 0.18, p = .86, d = 0.06$
13	$t(38) = 1.12, p = .27, d = 0.36$
14	$t(38) = 0.92, p = .36, d = 0.29$
15	$t(38) = 1.26, p = .22, d = 0.40$
16	$t(38) = 1.98, p = .06, d = 0.62$
17	$t(38) = 2.17, p = .04, d = 0.69$
18	$t(38) = 2.36, p = .02, d = 0.75$
19	$t(38) = 2.66, p = .01, d = 0.84$
20	$t(38) = 2.76, p < .01, d = 0.88$

4.2. Stimuli

The stimuli were identical to those in Experiment 1a, except one change: Instead of color pairs, color duplicates (e.g., two red circles) were generated, and four sets of duplicates were grouped into fixed horizontal, vertical, and diagonal configurations (Fig. 3A). Each set contained two circles of the same color. The color values for each set and for the two single circles were drawn from the pool of ten distinct colors as in Experiment 1a.

4.3. Procedure

Participants were randomly assigned to either the structured condition or the random condition ($N = 20$ in each). The exposure phase in the structured condition was identical to that in Experiment 1a, except that sets of color duplicates were presented in each array instead of color pairs. In the random condition, the positions were randomly shuffled as in Experiment 1a, which removed the duplicate set structure, but maintained the spatial layout, the number and the density of the circles (Fig. 3A). There was no test phase, since statistical learning was not examined.

4.4. Results and discussion

As in Experiment 1a, the errors were derived by subtracting the objective numerosity from the estimated numerosity, and compared across the 11 numerosity levels between the two conditions (Fig. 3B). A 2 (condition: structured vs. random; between subjects) \times 11 (numerosity levels; within subjects) mixed-effects ANOVA revealed a main effect of numerosity levels [$F(10,380) = 355.20, p < .001, \eta_p^2 = .90$], with greater underestimation as numerosity levels increased. Although there was no main effect of condition [$F(1,38) = 1.26, p = .27, \eta_p^2 = .03$], the interaction remained reliable [$F(10,380) = 5.32, p < .001, \eta_p^2 = .12$], with greater underestimation in the structured condition compared to the random condition, at higher levels of numerosity than at lower levels. Moreover, the errors became significant from numerosity level of 18 (Table 3).

These results suggested that sets of identical colors reduced the perceived numerosity, providing support for the grouping mechanism of color pairs in Experiment 1a.

5. Experiment 3

An alternative explanation for the underestimation was that the regularities could draw attention to specific objects in the array, therefore limiting the input over which numerosity was computed (Zhao et al., 2013). To test this account, we induced attention to individual objects in the arrays and examined whether this produced underestimation.

5.1. Participants

Fifty new undergraduates (36 female, mean age = 20.0 years, $SD = 2.7$) from UBC participated for course credit.

5.2. Stimuli

The stimuli consisted of the same colored circles as in Experiment 1a, but there was no pairing or grouping of colors in the arrays. As before, the number of circles in each array ranged from 10 to 20. Each numerosity level was repeated 20 times, resulting in 220 trials (order randomized for every participant).

5.3. Procedure

Participants were randomly assigned to one of two conditions: pop-out or uniform ($N = 25$ in each). In the pop-out condition, most circles in each array were in one color, while two remaining circles were in a different color (Fig. 4A). The color values were randomly drawn from the pool of ten colors in Experiment 1a. The two distinct circles created a pop-out effect, drawing attention to themselves (Bacon & Egeth, 1994; Treisman & Gelade, 1980). The two color oddballs were randomly positioned in each trial. In the uniform condition, all circles in each array were in the same color.

5.4. Results and discussion

The errors were again derived by subtracting the objective numerosity from the estimated numerosity, and compared across the 11 numerosity levels between the two conditions (Fig. 4B). Using a 2 (condition: pop-out vs. uniform; between subjects) \times 11 (numerosity levels; within subjects) mixed-effects ANOVA, we found a main effect of numerosity levels [$F(10,480) = 148.18, p < .001, \eta_p^2 = .76$], suggesting that there was greater underestimation as numerosity levels increased. There was no main effect of condition [$F(1,48) = 1.16, p = .28, \eta_p^2 = .02$], or interaction [$F(10,480) = 0.20, p = .99, \eta_p^2 = .004$].

The results suggested that the presence of color pop-outs did not influence numerosity estimation. Thus, this finding was inconsistent with the explanation that directing attention to individual objects in the array resulted in the underestimation of numerosity.

6. General discussion

This study examined how regularities in terms of object co-occurrences shape numerosity perception. Numerosity estimates were reliably lower in arrays containing color pairs than in random arrays (Experiments 1a and 1b), and also lower in arrays containing color duplicates (Experiment 2). When attention was drawn to individual objects in the array using color pop-outs, numerosity estimation was not influenced (Experiment 3). The results suggested that regularities reduced perceived numerosity, which was consistent with a group mechanism, and could not be explained by attention to individual objects.

The underestimation was most pronounced at higher numerosity levels. This could be driven by the fact that each pair was presented twice in each array at levels above 15. From an information theoretic perspective, such repetition of pairs introduces redundancies that make the information more compressible (Brady et al., 2009). The compressed input may cause underrepresentation of the number of objects, leading to underestimation.

Alternatively, the repetition of pairs may alter the unit of input for enumeration. Specifically, exposure to reliable co-occurrences between two objects may result in the unitization of the objects.

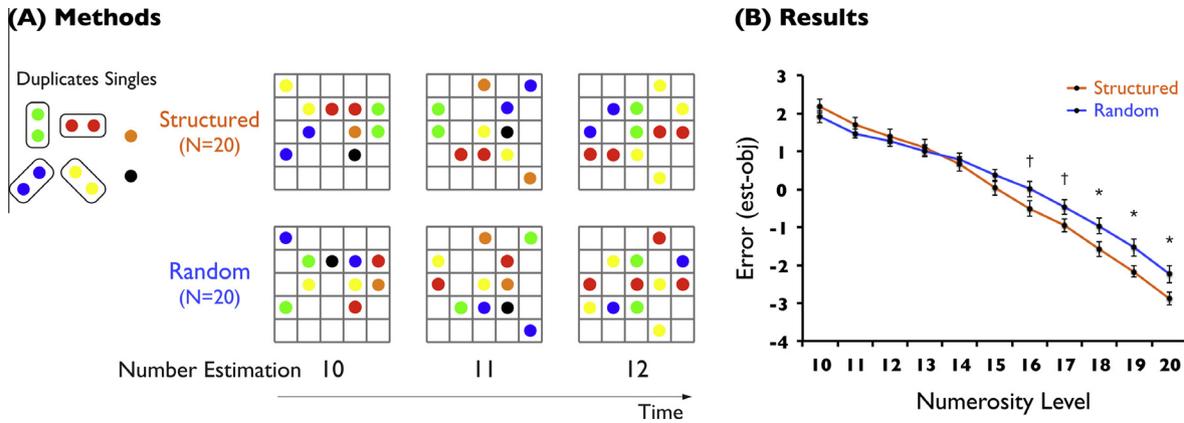


Fig. 3. Experiment 2. (A) Each array in the structured condition contained four sets of color duplicates (e.g., two red circles) and two singles, whereas the circles in the random condition were shuffled. For each array, the number of circles varied from 10 to 20. Participants in both conditions estimated the number of circles in each array. Three sample trials were shown in each condition. (B) Errors were computed (estimated numerosity – objective numerosity). Although there was no main effect of condition, the interaction remained reliable, suggesting that the difference between the two conditions was greater for higher levels of numerosity than for lower levels. (Error bars reflect ± 1 SEM; $^{\dagger}p < .1$, $^*p < .05$). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 3
Comparisons of estimation errors in the structured vs. the random conditions at each numerosity level using independent-samples *t*-tests in Experiment 2.

Numerosity levels	Structured vs. random conditions
10	$t(38) = 1.15, p = .26, d = 0.36$
11	$t(38) = 1.02, p = .31, d = 0.32$
12	$t(38) = 0.49, p = .63, d = 0.15$
13	$t(38) = 0.32, p = .75, d = 0.10$
14	$t(38) = 0.45, p = .65, d = 0.14$
15	$t(38) = 1.42, p = .16, d = 0.45$
16	$t(38) = 1.78, p = .08, d = 0.56$
17	$t(38) = 1.78, p = .08, d = 0.56$
18	$t(38) = 2.09, p = .04, d = 0.66$
19	$t(38) = 2.35, p = .02, d = 0.74$
20	$t(38) = 2.29, p = .03, d = 0.72$

For instance, an array of 16 circles may be represented either as 16 discrete circles, 8 units of pairs, or a combination of both. Since both types of units were present in the array, perceived numerosity could be a weighted sum of both, and thus the resulting numerosity representation is less than the total numerosity.

A surprising finding in Experiments 1a and 1b was that regularities reduced numerosity estimation during exposure, and yet, learning of the regularities was not expressed at test. In fact, no

participant was explicitly aware of the regularities based on debriefing. This finding is consistent with two emerging phenomena: First, statistical learning occurs without conscious intent and generates implicit knowledge about the regularities (Brady & Oliva, 2008; Fiser & Aslin, 2001; Kim, Seitz, Feenstra, & Shams, 2009; Zhao et al., 2013); and second, statistical learning interferes with ensemble perception such as the mean (Zhao, Ngo, McKendrick, & Turk-Browne, 2011) and the number (Zhao, Goldfarb, & Turk-Browne, submitted for publication). However, interference cannot explain underestimation because it would produce greater error variability in the estimates, rather than a specific direction in the error. Given the implicit nature of statistical learning, one explanation for the current finding is that the color pairs were detected to some extent during exposure, but this nascent learning was so weak that it was not robustly expressed in the subsequent explicit choice between the pair and the foil. This further highlights a possible dissociation between the online detection of regularities and the long-term retention of regularities in memory.

The current findings are significant in several ways. We found a novel consequence of statistical learning on numerosity perception. Unlike explicit grouping cues, object co-occurrences may serve as a grouping cue that reduces perceived numerosity. Even

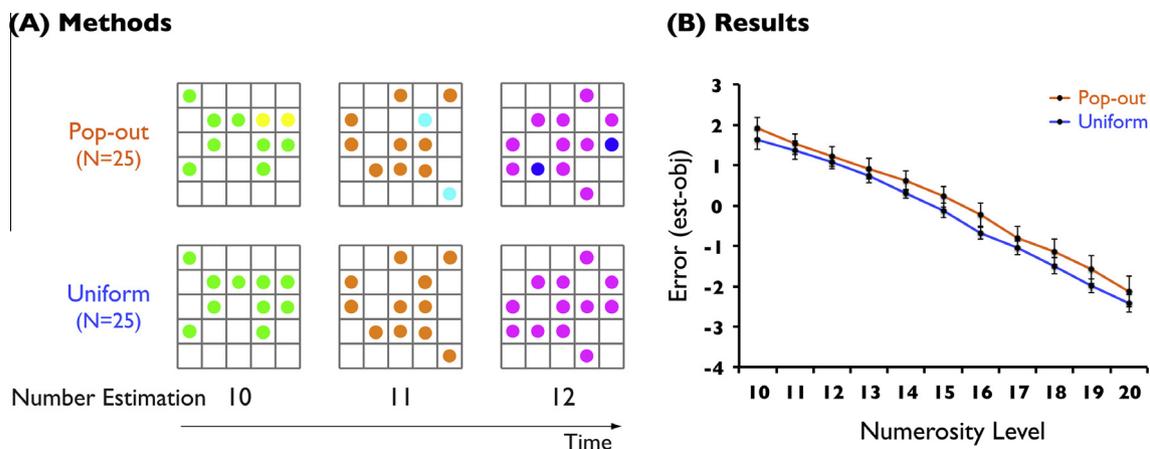


Fig. 4. Experiment 3. (A) In the pop-out condition, each array contained two distinct circles which were in a different color from the other circles. In the uniform condition, all circles were the same color. (B) Errors were computed (estimated numerosity – objective numerosity). There was no main effect of condition, or interaction. (Error bars reflect ± 1 SEM).

without the explicit awareness of regularities, the underestimation was as large as that when a salient grouping cue was present. Moreover, the study further elucidates the directionality of the interference between statistical learning and ensemble perception (Zhao et al., 2011; Zhao et al., submitted for publication). Finally, the study suggests that regularities may cause an under-representation of the information in the environment, rendering the visual world perceptually more manageable, contributing to the so-called Grand Illusion (Noë & O'Regan, 2000).²

Acknowledgments

For helpful conversations, we thank Nick Turk-Browne, Brian Scholl, Jim Enns, Darko Odic, Judy Fan, and the Zhao Lab. We also thank Yu Luo and Manjot Khosah for assistance with data collection. This work was supported by NSERC Discovery Grant (RGPIN-2014-05617 to JZ), the Canada Research Chairs program (to JZ), and the Leaders Opportunity Fund from the Canadian Foundation for Innovation (F14-05370 to JZ).

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² We thank an anonymous reviewer for raising this point.