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Mutual Interference Between Statistical Summary Perception and Statistical Learning

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Abstract

The visual system is an efficient statistician, extracting statistical summaries over sets of objects (statistical summary perception) and statistical regularities among individual objects (statistical learning). Although these two kinds of statistical processing have been studied extensively in isolation, their relationship is not yet understood. We first examined how statistical summary perception influences statistical learning by manipulating the task that participants performed over sets of objects containing statistical regularities (Experiment 1). Participants who performed a summary task showed no statistical learning of the regularities, whereas those who performed control tasks showed robust learning. We then examined how statistical learning influences statistical summary perception by manipulating whether the sets being summarized contained regularities (Experiment 2) and whether such regularities had already been learned (Experiment 3). The accuracy of summary judgments improved when regularities were removed and when learning had occurred in advance. In sum, calculating summary statistics impeded statistical learning, and extracting statistical regularities impeded statistical summary perception. This mutual interference suggests that statistical summary perception and statistical learning are fundamentally related.

Keywords

statistical summary representation, ensemble features, visual statistical learning, attention, orientation

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The visual system is remarkably efficient at extracting information that is not directly available in the environment, such as the general properties of objects in a group and the relationships among objects over space and time. For example, when looking out at a classroom, instructors can readily assess the number of students who are present and get a sense of their general level of enthusiasm and comprehension. In addition, throughout the semester, instructors learn which students tend to sit together and where they sit in the room. These two kinds of processing are inherently *statistical*: They involve the aggregation of samples (e.g., the group of students on a given day or an individual student's neighbors over time), as well as the distillation of these samples to statistics (e.g., averages or joint probabilities).

These examples reflect two different types of visual statistical processing that have been identified in past research. One type, statistical summary perception, involves the extraction of summary statistics over sets of objects (Ariely, 2001). In studies of statistical summary perception, observers are briefly presented with an array of objects and asked to discriminate or report a summary statistic, such as mean size (e.g., Ariely, 2001; Chong & Treisman, 2003, 2005). Statistical summary perception occurs for many feature dimensions, including orientation (e.g., Parkes, Lund, Angelucci, Solomon, & Morgan, 2001), spatial position (e.g., Alvarez & Oliva, 2008), speed (e.g., Emmanouil & Treisman, 2008), and facial expression (e.g., Haberman & Whitney, 2007); can be updated continuously over time (Albrecht & Scholl, 2010); and occurs quickly and effortlessly without depending on an explicit tally of, or even knowledge about, the individual objects in a group (e.g., Alvarez & Oliva, 2008; Ariely, 2001).

The other type of visual statistical processing, statistical learning, involves the extraction of relationships among individual objects over repeated experience (Perruchet & Pacton, 2006; Saffran, Aslin, & Newport, 1996; Turk-Browne, Scholl, Chun, & Johnson, 2009). In studies of statistical learning, observers are presented with spatial configurations or temporal

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sequences that, unbeknownst to them, contain regularities in the co-occurrence of features or objects. Statistical learning operates in multiple modalities (Conway & Christiansen, 2005) and over many feature dimensions, including shape (e.g., Fiser & Aslin, 2001), spatial location (e.g., Chun & Jiang, 1998), color (e.g., Turk-Browne, Isola, Scholl, & Treat, 2008), and action (e.g., Baldwin, Andersson, Saffran, & Meyer, 2008); can be observed throughout development (e.g., Kirkham, Slemmer, & Johnson, 2002) and in nonhuman species (e.g., Toro & Trobalón, 2005); occurs only for attended input but proceeds without conscious awareness (Turk-Browne, Jungé, & Scholl, 2005); operates hierarchically (Orbán, Fiser, Aslin, & Lengyel, 2008) but produces flexible representations that transfer between space and time (Turk-Browne & Scholl, 2009); and leads to implicit anticipation of future events and stimuli (Turk-Browne, Scholl, Johnson, & Chun, 2010).

Although statistical summary perception and statistical learning have been studied extensively in isolation, their relationship is not yet understood. On the surface, the two processes are different in many respects, including the time scale over which they operate (single exposure vs. repeated exposures) and the types of knowledge they produce (general properties of groups vs. relationships between specific objects within groups). Thus, they might not be related in any meaningful way. However, at a deeper level, the two processes might depend on shared statistical and attentional mechanisms, and thus interact. Such interactions could have beneficial or detrimental consequences for the efficacy of either process. For example, knowledge about statistical regularities reduces visual short-term memory load (Brady, Konkle, & Alvarez, 2009) and may therefore result in more accurate summary estimates. In contrast, if statistical summary perception and statistical learning depend on similar computations, engaging in one process may interfere with the other.

In three experiments, we sought to characterize the relationship between these two forms of visual statistical processing. We examined how computing summary statistics influences statistical learning and how learning regularities influences statistical summary perception. In Experiment 1, participants performed a summary task or one of two control tasks on arrays of oriented lines whose co-occurrences, unbeknownst to participants, exhibited statistical regularities. To assess the effect of statistical summary perception on statistical learning, we examined how calculating the mean orientation of arrays of lines affected performance on a subsequent test of line-pair learning. In Experiment 2, participants performed a summary task on arrays that did or did not contain line pairs. To assess the effect of statistical learning on statistical summary perception, we examined how the presence of pairs affected judgments of mean orientation. In Experiment 3, participants performed a summary task on arrays containing line pairs that had or had not been learned in advance. To obtain converging evidence for an effect of statistical learning on statistical summary perception, we examined how prior learning of the pairs affected judgments of mean orientation.

Experiment 1

The goal of Experiment 1 was to assess whether and how computing the mean orientation of lines in an array would influence the learning of line pairs embedded in the array.

Participants

Fifty-four undergraduates (23 male, 31 female; mean age = 20.0 years) from Princeton University participated for course credit. All participants had normal or corrected-to-normal vision and provided informed consent. The experiment was approved by the institutional review board at Princeton University.

Stimuli

The stimuli consisted of eight black lines oriented at 0°, 15°, 45°, 75°, 90°, 105°, 135°, and 165° (0° = horizontal, 90° = vertical). The eight lines were randomly assigned to four pairs without replacement, and each of the four pairs was assigned to a horizontal (one pair), vertical (one pair), or diagonal (two pairs) configuration (Fig. 1a). These assignments were determined independently for each participant, and remained constant throughout the experiment. In the first phase of the experiment, the lines were presented in arrays. Each array consisted of three pairs whose grand mean orientation was not 90°. These three pairs were overlaid on an invisible 3 × 3 grid, and their positions were pseudorandomly determined. Because of the size of the grid, at least one line in each pair was adjacent to at least one line from a different pair. This arrangement of the arrays ensured that statistical learning could not be facilitated by segmentation cues other than co-occurrence (e.g., grouping). In all conditions, 20% of the arrays contained a duplicate orientation: One line in a randomly selected pair was changed to match the orientation of the other line from that pair.

Apparatus

Participants were seated 70 cm from a Viewsonic CRT monitor (refresh rate = 100 Hz). Stimuli were presented using MATLAB (The Mathworks, Natick, MA) and the Psychophysics Toolbox (Brainard, 1997; Pelli, 1997). The invisible grid on which the line arrays were overlaid subtended 13.6° by 13.6° of visual angle.

Procedure

Participants were randomly assigned to one of three conditions: passive viewing, summary, or control (n = 18 in each condition). The experimental procedure in all conditions consisted of two phases: familiarization and test. During the familiarization phase (Fig. 1b), each participant viewed 100 arrays of lines. Each array was presented for 2,000 ms,

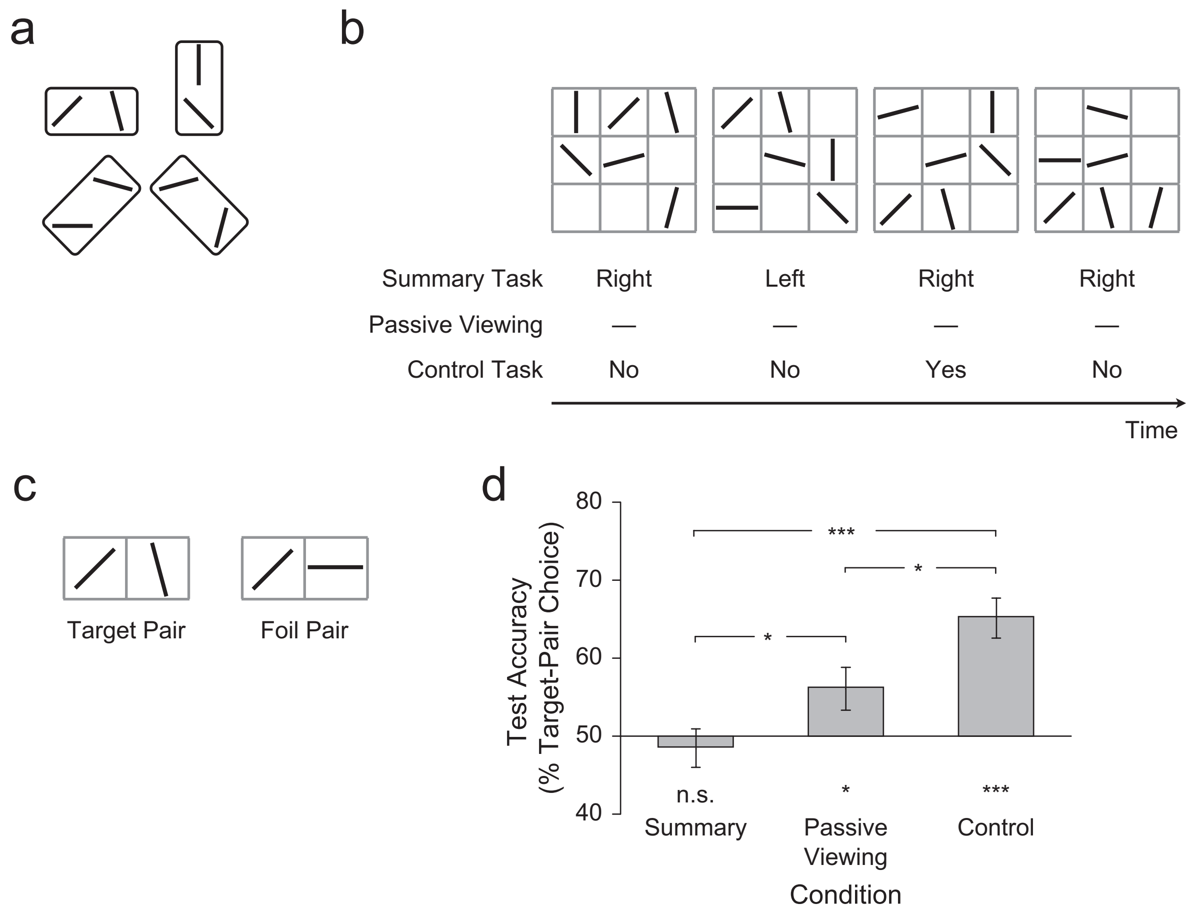

Fig. 1. Design and results for Experiment 1. Eight black lines of various orientations were grouped into four pairs, which were assigned to horizontal, vertical, and diagonal configurations (a). During the familiarization phase (b), arrays of these pairs were presented to participants. In each array, the line pairs were overlaid on a 3 × 3 grid, which was invisible to participants; the pairs' positions on the grid were selected pseudorandomly. Participants in the passive-viewing condition simply paid attention to the arrays; participants in the summary condition indicated whether the mean orientation of all lines in each array fell to the left or right of the vertical meridian; and participants in the control condition indicated whether any orientations had been duplicated in each array. The third illustrated array is an example of an array with a duplicate orientation. During each trial of the test phase (c), participants were presented with two line pairs: a target pair that had been shown multiple times during the familiarization phase and a foil pair that consisted of one line from the same target pair and one line from a different target pair. Participants indicated which pair was more familiar. The graph (d) shows the mean percentage of correct answers during the test phase for each condition. Error bars represent ±1 *SEM*. The asterisks indicate significant differences from chance performance and significant differences between conditions (*$p < .05$; ***$p < .001$).

followed by an interstimulus interval of 1,000 ms. In the passive-viewing condition, participants were instructed to simply pay attention to the arrays. This canonical familiarization task (e.g., Fiser & Aslin, 2001) provided a measure of the baseline level of statistical learning. In the summary condition, participants pressed a number key to indicate whether the mean orientation of all lines in each array fell to the left (1) or right (9) of the vertical meridian. This task allowed us to assess the influence of statistical summary perception on statistical learning. In the control condition, participants pressed a number key to indicate whether any orientations had (1) or had not (9) been duplicated in each array. This condition was included as a dual-task control to ensure that any difference in performance between the passive-viewing and summary conditions did not simply reflect the need to perform a secondary task in the summary condition. Five example arrays were presented to participants in all conditions as practice before the familiarization phase began.

After the familiarization phase, all participants completed the same two-alternative forced-choice test phase. On each trial, two pairs of lines were presented side by side for 2,000 ms (Fig. 1c), and participants made an unspeeded response, pressing a number key to indicate whether the left (1) or right (9) pair seemed more familiar. One of these pairs (the target pair) was one of the pairs from the familiarization phase, and therefore had been presented multiple times. The other pair (the foil pair) consisted of one line from that target pair and one line from a different target pair (all lines were presented an equal number of times); thus, the two lines in the foil pair had a much lower probability of having occurred next to each other during the familiarization phase compared with the two lines in the target pair. Each of the four target pairs was tested against two foil pairs: The first foil pair contained one line from the target pair, and the second foil pair contained the other line. Each target-foil comparison was repeated once, so that there were 16 trials in all.[1] The order of test trials was randomized, and the location of the target pair (i.e., on the left or right) was counterbalanced across trials. Because all individual lines in the target and foil pairs were equally frequent during the familiarization phase, participants could choose the target pairs as more familiar only if they had learned which lines had co-occurred during the familiarization phase.

Results and discussion

During the familiarization phase, mean accuracy in the summary condition was 57.8% (SD = 13.0%), which was reliably above chance (50%), $t(17) = 2.53$, $p < .03$, $d = 0.60$. Mean accuracy in the control condition was 81.0% (SD = 12.9%), which was also above chance, $t(17) = 10.17$, $p < .001$, $d = 2.40$.

As shown in Figure 1d, test performance differed across the familiarization conditions. In the passive-viewing condition, the target pair was chosen as more familiar than the foil on 56.3% (SD = 11.7%) of test trials; this level of accuracy was reliably above chance (50%), $t(17) = 2.26$, $p < .04$, $d = 0.53$. This result demonstrates that our procedure can elicit statistical learning, and it provided a baseline for comparison. Mean accuracy in the control condition was 65.3% (SD = 11.0%), also above chance, $t(17) = 5.90$, $p < .001$, $d = 1.39$. This result demonstrates that engaging in a secondary task does not necessarily impair statistical learning, and can in fact improve it, $t(34) = 2.38$, $p < .03$, $d = 0.79$. Critically, mean accuracy in the summary condition was 48.6% (SD = 10.4%), which did not differ from chance, $t(17) = 0.57$, $p = .58$, $d = 0.13$. This level of accuracy was lower than that in the passive-viewing condition, $t(34) = 2.07$, $p < .05$, $d = 0.69$, and the control condition, $t(34) = 4.68$, $p < .001$, $d = 1.56$. Given that the line pairs were learnable in the passive-viewing condition and that performing a secondary task did not interfere with learning in the control condition, these results suggest that statistical summary perception prevents statistical learning.

Although the level of task performance during the familiarization phase was higher in the control condition than in the summary condition, $t(34) = 5.36$, $p < .001$, $d = 1.79$, we think it is unlikely that the difficulty of the familiarization tasks accounts for the differences in statistical learning for at least two reasons: First, passive viewing could be considered the easiest task of all, yet participants in the passive-viewing condition showed less statistical learning than did those in the control condition. Second, if easier familiarization tasks resulted in increased statistical learning, there should have been a positive correlation between performance on the familiarization task and subsequent test performance within each condition; however, this relationship was not reliable in the control condition, $r(16) = .18$, $p = .47$, and was in the wrong direction in the summary condition, $r(16) = -.32$, $p = .20$. In sum, the findings from Experiment 1 provide evidence that statistical summary perception interferes with statistical learning.

Experiment 2

Is the interference between statistical summary perception and statistical learning unidirectional, or does statistical learning also interfere with statistical summary perception? We hypothesized that the relatively poor summary-task performance in Experiment 1 might be attributable to the existence of statistical regularities in the line arrays. Even if they were not ultimately learned, these regularities might have engaged statistical learning, which in turn might have interfered with statistical summary perception. The goal of Experiment 2 was to assess how the presence of line pairs in the arrays used in Experiment 1 influenced judgments of mean line orientation.

Participants

Twenty new undergraduates (9 male, 11 female; mean age = 20.6 years) from Princeton University participated for course credit. All participants had normal or corrected-to-normal vision and provided informed consent. The experiment was approved by the institutional review board at Princeton University.

Stimuli, apparatus, and procedure

The line stimuli and apparatus were identical to those of Experiment 1. Participants were randomly assigned to one of two conditions: structured or random (n = 10 in each condition). The structured condition consisted of a familiarization phase and a test phase that were identical to those of the summary condition in Experiment 1. In the familiarization phase, three of the four line pairs (Fig. 2a) were selected for each array and overlaid pseudorandomly on an invisible 3 × 3 grid. Two participants in this condition were not able to complete the test phase because of technical issues, so we used their data from the familiarization phase only. The random condition also included a familiarization phase, which was the same as the familiarization phase in the structured condition except for one critical difference: After three pairs of lines were selected for each array and placed on the grid, the positions occupied by the lines were randomly shuffled (Fig. 2b). Shuffling the positions of the lines in each array eliminated spatial regularities in the arrangement of line orientations. There was no test phase in the random condition because no pairs were presented during the familiarization phase.

It is important to consider whether shuffling the locations of lines, in addition to eliminating spatial regularities, led to other differences in the line arrays that could have affected statistical summary perception. One possible difference could have been caused by the manner in which the grids were generated: On each trial, three of the four pairs were selected for

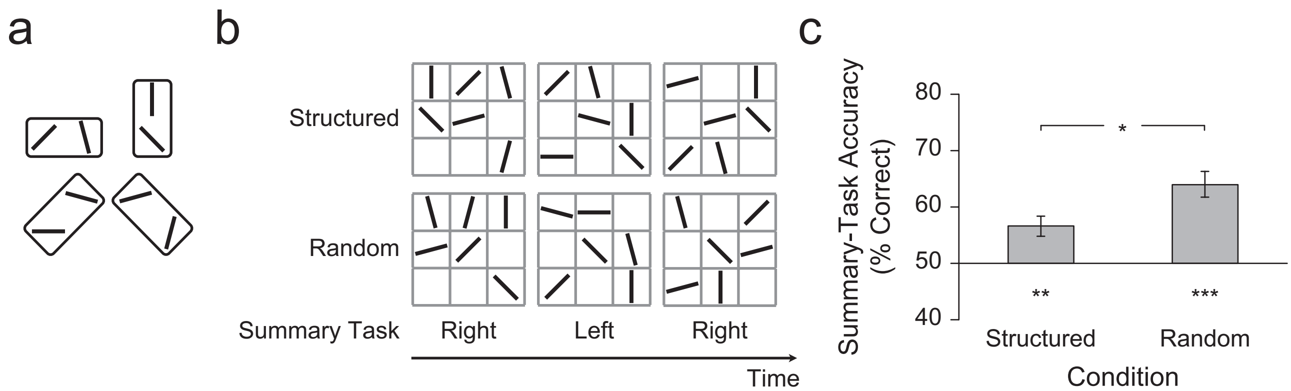

Fig. 2. Design and results for Experiment 2. Eight black lines of various orientations were grouped into four pairs as in Experiment 1 (a). During the familiarization phase (b), arrays of three line pairs were overlaid on an invisible 3 × 3 grid; the pairs' positions on the grid were selected pseudorandomly. In the structured condition, line pairs were overlaid on the grid in accordance with their assigned configurations (horizontal, vertical, or diagonal). In the random condition, the positions of lines in each display were randomly shuffled among occupied cells on the grid. Participants in the two conditions performed a summary task, in which they indicated whether the mean orientation of all lines in each display fell to the left or right of the vertical meridian. The graph (c) shows the mean percentage of correct responses on the summary task for each condition. Error bars represent ±1 *SEM*. The asterisks indicate significant differences from chance performance and significant differences between conditions (*$p < .05$; **$p < .01$; ***$p < .001$).

the array; given that two of the four pairs had diagonal configurations, at least one diagonal pair was selected. Because each array was composed of three pairs and had to include one diagonal pair, only lines from diagonal pairs could occupy the center cell. Specifically, if the diagonal pair was placed such that neither of its lines occupied the center cell, there was no way to place a line from a horizontal or vertical pair in the center cell without preventing the third pair from being placed on the grid. Because of this constraint, only the four orientations in the diagonally configured pairs could occupy the center cell in the structured condition. However, because the positions of lines were shuffled, all eight of the orientations could appear in the center cell in the random condition.

The different spatial distribution of orientations across conditions could not have influenced performance in the summary task for two reasons. First, because lines were shuffled only among occupied cells in the random condition, the center cell of the grid was equally likely to contain a line in the structured and random conditions. Second, because orientations were randomly assigned to pairs and the mean orientation varied randomly across trials, the orientation of the line in the center of the grid was not differentially informative about the mean orientation between the two conditions. Indeed, an analysis of our stimuli revealed that the center of the grid was equally likely to contain a line whose orientation matched the mean orientation in the structured (38.2%) and random (37.4%) conditions, $t(18) = 0.21$, $p = .83$, $d = 0.03$.

Results and discussion

As in the summary condition of Experiment 1, participants in the structured condition did not express statistical learning in the test phase (mean accuracy = 43.8%, SD = 19.5%), $t(7) = 0.91$, $p = .39$, $d = 0.32$.

As shown in Figure 2c, statistical summary perception was affected by the presence of regularities. In the structured condition, mean accuracy in the summary task was 56.6% (SD = 5.8%), which was reliably above chance (50%), $t(9) = 3.63$, $p < .01$, $d = 1.15$. In the random condition, mean accuracy in the summary task was 64.0% (SD = 7.2%), which was also above chance, $t(9) = 6.12$, $p < .001$, $d = 1.94$. Critically, performance was reliably better in the random condition than in the structured condition, $t(18) = 2.51$, $p < .03$, $d = 1.12$. These results indicate that the mere presence of statistical regularities can impair statistical summary perception even if statistical learning is not successful, and thus suggest a possible dissociation between the detection of regularities and their longer-term retention.

Experiment 3

In Experiment 2, we found that statistical summary perception was hampered by the presence of regularities. We interpret this finding as evidence that statistical learning was engaged by the regularities and interfered with statistical summary perception. To seek converging support for the conclusion that statistical learning interferes with statistical summary perception, we manipulated the engagement of statistical learning in a different way in Experiment 3. The goal of this experiment was to assess whether learning the line pairs in advance would disengage statistical learning during the summary task and thus prevent regularities from impairing statistical summary perception.

Participants

Thirty new undergraduates (13 male, 17 female; mean age = 20.4 years) from Princeton University participated for course credit. All participants had normal or corrected-to-normal vision and provided informed consent. The experiment was approved by the institutional review board at Princeton University.

Stimuli, apparatus, and procedure

The line stimuli and apparatus were identical to those used in Experiments 1 and 2. Participants were randomly assigned to one of two conditions: learned or novel (n = 15 in each condition). Both conditions consisted of three phases: preexposure, summary, and test (Fig. 3a). During the preexposure phase, participants in both conditions performed the control task from the familiarization phase in Experiment 1, indicating whether each line array contained a duplicate orientation. In the learned condition, the arrays contained line pairs (as in the structured condition of Experiment 2), whereas in the novel condition, the arrays contained no pairs (as in the random condition of Experiment 2). On the basis of the results from the control task in Experiment 1, we expected to observe robust statistical learning for line pairs in the learned condition in Experiment 3.

The summary phase was identical in the learned and novel conditions, and was the same as the familiarization phase of the structured condition in Experiment 2: Participants estimated the mean orientation of arrays containing line pairs. In the learned condition, the pairs in the summary phase were identical to those in the preexposure phase, whereas in the novel condition, the pairs were constructed from the lines that had been unpaired in the preexposure phase. In other words, the only difference between the learned and the novel conditions was that participants in the learned condition had the opportunity to learn the pairs during the preexposure phase, whereas participants in the novel condition could begin learning the pairs only during the summary phase. In the test phase, participants in both conditions completed a two-alternative forced-choice test of statistical learning (as in Experiment 1).

Results and discussion

Participants in the learned condition expressed robust statistical learning in the test phase (mean accuracy = 67.5%, SD = 12.9%), $t(14) = 5.22$, $p < .001$, $d = 1.35$. Participants in the novel condition did not show statistical learning (mean accuracy = 50.8%, SD = 18.7%), $t(14) = 0.17$, $p = .87$, $d = 0.04$. These results are fully consistent with those of Experiment 1: Reliable statistical learning occurred when regularities were present during the control task (learned condition), but not when they were present only during the summary task (novel condition).

As shown in Figure 3b, statistical summary perception was affected by whether participants had been able to learn regularities in advance. In the learned condition, mean accuracy in the summary task was 65.9% (SD = 7.9%), which was reliably above chance, $t(14) = 8.34$, $p < .001$, $d = 2.15$. In the novel condition, mean accuracy in the summary task was 58.6% (SD = 8.0%), which was also above chance, $t(14) = 4.15$, $p < .01$, $d = 1.07$. Critically, performance was reliably better in the learned condition than in the novel condition, $t(28) = 2.60$, $p < .02$, $d = 0.95$.

This result replicates and extends the findings from Experiment 2, in which summary-task performance was impaired by the possibility of statistical learning. In that experiment, the manipulation of statistical learning relied on differences in the arrays over which participants made summary judgments (i.e., arrays in the structured condition contained pairs, but arrays in

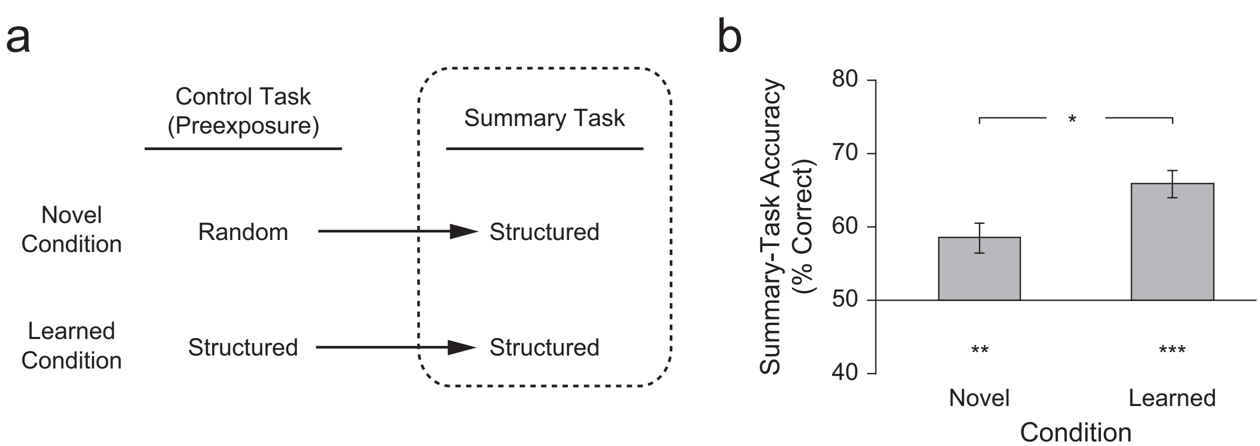

Fig. 3. Design (a) and results (b) for Experiment 3. Eight black lines of various orientations were grouped into four pairs. During the preexposure phase, arrays of these line pairs were overlaid on an invisible 3 × 3 grid; in the novel condition, lines in these arrays were randomly shuffled among occupied positions on the grid, whereas in the learned condition, the lines were structured into assigned configurations (horizontal, vertical, or diagonal). In both conditions, participants' task was to detect duplicate orientations in the arrays. During the summary phase, participants in both conditions viewed arrays containing the line pairs from the preexposure phase of the learned condition (which were new to participants in the novel condition) and judged the mean orientation of the lines in each array. The graph shows the mean percentage of correct responses on the summary task for each condition. Error bars represent ±1 *SEM*. The asterisks indicate significant differences from chance performance and significant differences between conditions (*p < .05; **p < .01; ***p < .001).

the random condition did not). In Experiment 3, we observed a similar decrement in summary-task performance when learning was possible, despite the fact that the stimuli in the summary phase were identical in the learned and novel conditions. Regularities, which appeared in both conditions, impaired statistical summary perception only in the novel condition—that is, when they had not been learned in advance and thus engaged statistical learning for the first time.

General Discussion

The goal of this study was to examine the relationship between two kinds of statistical processing that have previously been studied in isolation. Statistical summary perception and statistical learning appear to be separate kinds of processing, operating over different time scales and resulting in different kinds of knowledge. However, both processes require aggregating and distilling sensory evidence, and they may therefore interact. Indeed, we found mutual interference between statistical summary perception and statistical learning: Computing the mean orientation of lines impeded statistical learning of line pairs in Experiment 1, and learning about line pairs impeded statistical summary perception in Experiments 2 and 3.

One potential explanation for this bidirectional interference is that statistical summary perception and statistical learning depend on shared statistical computations. Specifically, computing the mean value in a feature dimension might rely on the same process as updating a probability matrix about object co-occurrences. Thus, statistical summary perception may directly interfere with the calculation of probabilities, and statistical learning may directly interfere with the calculation of summary statistics.

Alternatively, statistical summary perception and statistical learning might change the currency of the visual system, prioritizing summary-level representations and individual-level representations, respectively. Thus, summary representations may serve as the primary input to statistical learning during statistical summary perception, weakening learning about specific relationships among individual objects.[2] In turn, statistical learning may be implicitly engaged by these relationships, limiting the set of individual objects over which summary statistics can be computed.

These changes in how visual information is represented could be mediated by requirements for different spatial scales of attention. Statistical summary perception is more accurate when attention is distributed globally, whereas the identification of individual objects is more accurate when attention is directed locally (Chong & Treisman, 2005). Because regularities in our study were defined over individual objects, a global scale of attention during the summary task of Experiment 1 could have blocked statistical learning. According to this explanation, impaired summary task performance in Experiments 2 and 3 might have resulted from a detrimental shift to a more local scale of attention. Future research is needed to evaluate the intriguing possibility that the presence of task-irrelevant regularities can attract local attention.

The known consequences of statistical learning for other cognitive processes are largely beneficial; such consequences include facilitated object-label learning (Graf Estes, Evans, Alibali, & Saffran, 2007), speeded object categorization (Turk-Browne et al., 2010), and increased visual short-term memory capacity (Brady et al., 2009). In contrast, the current findings reveal a novel cost of statistical learning for statistical summary perception. Uncovering the nuanced ways in which statistical learning interacts with other aspects of cognition may help to elucidate how statistical learning works.

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Declaration of Conflicting Interests

The authors declared that they had no conflicts of interest with respect to their authorship or the publication of this article.

Notes

1. Each target pair was presented twice as often as each foil pair during the test phase; this procedure raised the possibility that learning of the target pairs would occur during the test. However, because the test phase was identical in all conditions, learning during the test cannot explain the differences in performance between conditions. Moreover, results did not indicate that learning occurred during the test phase: Performance did not improve between the first and second halves of the test phase (56.3% vs. 57.2%), $t(53) = 0.31$, $p = .76$, $d = 0.05$.

2. According to this currency hypothesis, statistical learning may occur when summary statistics themselves contain regularities, such as when the temporal sequence of mean orientations is structured.

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