Statistical Learning Affects the Time Courses of Salience-Driven and Goal-Driven Selection

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The present study investigated how statistical regularities present in the display affected the time courses associated with salience-driven and goal-driven visual selection. In two experiments, participants were instructed to make a speeded saccade toward a prespecified target that was presented simultaneously with a distractor among multiple homogeneously oriented background lines. The distractor was presented more often at one location than at all other locations. We found that the statistical regularity regarding the distractor location affected visual selection very early, modulating the time courses associated with both salience-driven and goal-driven selection. These results suggest that statistical learning induces a continuous bias in visual selection, operating above and beyond salience-driven and goal-driven control.

Public Significance Statement
Our visual system is sensitive to statistical regularities in the environment. When exposed to these regularities, humans are able to learn and use them to optimize attentional selection. One way to improve selection is to reduce the influence of irrelevant, yet salient objects in the environment allowing an optimal selection of objects that are task-relevant. In this study, we presented salient distractors more often in one location than in all other locations. By examining speeded eye movements, we show that this statistical regularity regarding the distractor location affected visual selection very early in time modulating the time courses associated with both salience-driven and goal-driven selection.

Keywords: statistical learning, eye movements, salience, visual selection

The complex visual world contains an enormous amount of information. To avoid being overwhelmed, we direct our attention and eyes to those parts that are relevant. Theories of visual selection typically distinguish between bottom-up or salience-driven and top-down or goal-driven control. Selection is considered to be salience-driven when attention and the eyes are guided by salient stimuli, which are stimuli that stand out from their surroundings (see, e.g., Itti & Koch, 2001; Theeuwes, 1991; Yantis & Jonides, 1990). Visual selection is under goal-driven control when selection is guided by knowledge or goals (see, e.g., Baluch & Itti, 2011; Leber & Egeth, 2006). Recently, Awh, Belopolsky,

and Theeuwes (2012) indicated that many findings cannot be explained in terms of the bottom-up and top-down dichotomy (see also Failing & Theeuwes, 2018; Theeuwes, 2018, 2019). For example, the classical priming of pop-out effect as initially demonstrated by Maljkovic and Nakayama (1994) cannot be explained on the basis of bottom-up or top-down mechanisms. Instead, stimuli with a history of being attended elicit a lingering selection bias, suggesting the existence of a third mode of attentional control, which has been labeled as *selection history*. According to this view, selection history affects visual selection independently from both stimulus salience and the goals of an observer and operates through learning. That is, past regularities in search context and selection behavior can be implicitly or explicitly learned and can drive the deployment of attention when these regularities are subsequently encountered again. The influence of selection history has, among others, been demonstrated in studies investigating intertrial priming (Kristjánsson & Campana, 2010; Maljkovic & Nakayama, 1994, 2000), reward (Bucker, Silvis, Donk, & Theeuwes, 2015; Bucker & Theeuwes, 2017; Chelazzi, Perlato, Santandrea, & Della Libera, 2013; Della Libera, Perlato, & Chelazzi, 2011; Failing, Nissens, Pearson, Le Pelley, & Theeuwes, 2015; Failing & Theeuwes, 2014; Hickey, Chelazzi, & Theeuwes, 2010; Preciado, Munneke, & Theeuwes, 2017a, 2017b), and fear conditioning (Nissens, Failing, & Theeuwes, 2017; Schmidt, Belopolsky, & Theeuwes, 2015; see Failing & Theeuwes, 2018 for a review).

Even though traditionally contextual cueing was considered an example of top-down attentional control, in more recent conceptualization it is recognized as a prime example of the role of selection history (see Sisk, Remington, & Jiang, 2019; Theeuwes, 2018, 2019 for reviews). Indeed, in the contextual cueing paradigm, regularities present in the environment result in lingering selection biases. For example, Chun and Jiang (1998) had participants search for a letter *T* among letters *L* in different spatial configurations. Half of the configurations were repeated across blocks while others were completely new. The target was always presented in a consistent location within each repeated configuration. The results demonstrated that the regularity about the spatial relationship between a target and its context influences selection performance (Chun & Jiang, 1998, 1999). That is, when a target appeared consistently in the same location within each repeated configuration, target detection was facilitated compared to when it was presented in a novel configuration. These results show that people have the ability to extract statistical regularities and learn these regularities, which in turn biases subsequent selection behavior.

Recently, it was demonstrated that participants not only learn the regularities regarding the target but also regarding the to-be-ignored distractor (Di Caro, Theeuwes, & Della Libera, 2019; Failing, Feldmann-Wüstefeld, Wang, Olivers, & Theeuwes, 2019; Failing, Wang, & Theeuwes, 2019; Failing & Theeuwes, 2020; Ferrante et al., 2018; Gao & Theeuwes, 2020; van Moorselaar, Theeuwes, & Olivers, 2019; Wang, Samara, & Theeuwes, 2019; Wang, van Driel, Ort, & Theeuwes, 2019; Wang & Theeuwes, 2018a, 2018b, 2018c). Using the well-established additional singleton task, Wang and Theeuwes (2018b, 2018c) had observers search for a target (i.e., a shape singleton) in the presence of an irrelevant salient distractor (i.e., a color singleton). The distractor was presented more often in one specific location (i.e., the high-probability location) than in all other locations (i.e., the low-probability locations). The results showed that performance was strongly affected by the location of the distractor: there was less attentional capture by the distractor when it appeared in the high-probability location than in one of the low-probability locations. Moreover, in those trials in which only the target was presented, responses to the target were slower when it occurred in the high-probability location compared to the low-probability location. Wang and Theeuwes (2018b, 2018c) concluded that statistical learning may result in suppression of the location that is likely to contain a distractor. This idea was also supported by results obtained in an eye-tracking study (Wang, Samara, et al., 2019), which showed that fewer saccades landed at the distractor when it was presented at the high-probability location than at a low-probability location. Moreover, in an EEG study, Wang, van Driel, et al. (2019) found evidence for prestimulus enhanced parieto-occipital alpha power contralateral to the high-probability location, indicating the suppression of this location. In addition to the prestimulus contralateral alpha enhancement, Wang, van Driel, et al. (2019) also reported an early and later distractor positivity (so-called P_D,) indicating spatial suppression of the location during search. Critically, these neural correlates were found regardless of whether a salient distractor, a salient target, or a neutral element was presented at the high-probability location. This pattern of results let Wang, van Driel, et al. (2019) to conclude that through statistical learning the location that is likely to contain a salient distractor is

proactively suppressed. Specifically, it was argued that before display onset, specific locations within the spatial priority map that are likely to contain a distractor are suppressed (see also Ferrante et al., 2018 for similar arguments). This suppression is spatial and feature-blind, and happens regardless of what information is presented at that location.

The notion that suppression operates on locations within the spatial priority map before the stimulus is presented suggests that salient information can be discarded before attention is directed to that location (see also Gaspelin, Leonard, & Luck, 2015, 2017). This type of selection can be contrasted with reactive suppression that suggests that suppression operates later in time and only after attention first was directed to that location (Won, Kosoyan, & Geng, 2019). In other words, attention is first captured, disengaged, and then the location is immediately suppressed. For example, regarding the additional singleton paradigm, Theeuwes (2010) argued that it is possible that disengagement of attention from the salient distractor is so fast that there are virtually very little (or no) costs of the presence of the salient distractor (i.e., basically no attentional capture). This notion of rapid disengagement is similar to Moher and Egeth's (2012) "search and destroy" hypothesis showing that participants that were instructed to inhibit an object with a particular color, could only do so after attending to the location of the to-be-ignored color.

In the current study we used a paradigm that allowed us to precisely uncover the dynamic processes of attentional activation and suppression. Similar to previous studies participants were confronted with displays containing particular statistical regularities. We measured eye movements, which allowed us to uncover how statistical learning affected visual selection from the earliest responses to those occurring later in time. The measurement of eye movements does not only provide temporal information but also information concerning which stimulus has actually been overtly selected, making it possible to precisely pinpoint when specific selection processes occur. Indeed, in order to investigate the time courses of salience-driven and goal-driven processes, Donk, van Zoest, and colleagues (Donk & van Zoest, 2008; Siebold, van Zoest, & Donk, 2011; Siebold & Donk, 2014; Silvis & Donk, 2014; Van Zoest & Donk, 2005, 2006, 2008; van Zoest, Donk, & Theeuwes, 2004) have used eye movement measurements to explicitly address the question when salience-driven and goal-driven control contribute to selection behavior. In their modified oculomotor capture paradigm, participants were required to make a speeded eye movement toward a prespecified target (e.g., a left-tilted line singleton) that was presented simultaneously with one distractor (e.g., a right-tilted line singleton) and multiple homogenously oriented background lines. Typically, the relative salience of target and distractor was varied across conditions and saccadic selection performance was analyzed in relation to saccadic latency. The findings from these studies showed that both stimulus-driven and goal-driven processes affect visual selection but dominate during different time windows, with the former operating early in time and the latter operating in a late time window.

In order to uncover how statistical learning affects the time course of overt attentional selection, we used a paradigm similar to that used by Donk and van Zoest (2008). In this paradigm, participants were asked to make a single eye movement to a predefined target (e.g., a left-tilted line singleton) in a search display consisting of one target (e.g., a left-tilted line singleton), one distractor (e.g., a right-tilted line singleton),

and multiple background lines (e.g., either left-tilted or right-tilted line singleton). By manipulating the orientation of the background lines, the salience of the target was either high (salient target condition) or low (nonsalient target condition) relative to the salience of the distractor. This paradigm allows to separately investigate the time courses of salience-driven and goal-driven selection by comparing selection performance across saccade latency between the salient target and the nonsalient target condition. Any difference between these two conditions in the proportions of eye movements toward the target is indicative of salience-driven selection because the target is salient in one and nonsalient in the other condition. Differences between these conditions in the proportions of eye movements toward the most salient singleton provide evidence for goal-driven selection because the most salient singleton is the target in one and the distractor in the other condition. In order to investigate how statistical learning affects salience-driven and goal-driven selection, the distractor was presented at different locations in the visual field but occurred more often at one location (high-probability location) than at all other locations (low-probability locations) inducing the possibility of statistical learning.

If suppression is basically proactive, we expect to see a difference very early in time between trials in which the distractor was presented at the high-probability location and low-probability locations, changing the time course of salience-driven selection. If suppression is reactive, we expect that the effects of statistical learning may occur later in time, affecting primarily goal-driven selection.

Experiment 1

In Experiment 1, we investigated how the statistical regularity regarding the distractor location influenced the dynamic processes of oculomotor selection associated with salience-driven and goal-driven control. Observers were instructed to make a speeded saccade to a prespecified target among one distractor and multiple background lines. The target was either more salient or less salient than the distractor in the search display, which allowed us to discriminate between the effects of salience-driven and goal-driven control. To induce statistical learning, the distractor was presented more often in one location than at all other locations. If distractor suppression is proactive, early salience-driven selection should be modulated by the distractor location. Alternatively, if suppression is reactive, the distractor location should primarily affect the late time course of oculomotor selection related to goal-driven selection.

Method

Participants. Based on the reported effect size of $\eta_p^2 = .74$ in (Wang & Theeuwes, 2018a) for the major manipulation of the distractor's spatial regularities, a sample size of at least 18 was required to obtain a power of .95 with $\alpha = .01$ (using G*Power 3.1, Faul, Erdfelder, Lang, & Buchner, 2007). However, the present study investigates how distractor location affects the time courses of overt salience-driven and goal-driven selection, which may not result in the same effect size as reported in Wang and Theeuwes (2018a) who used reaction time (RT) measures and different analyses. Given this, we adopted a sample size of 20, which was

well above the estimate derived from Wang and Theeuwes (2018a). Twenty healthy students from the Vrije Universiteit Amsterdam participated in this experiment (14 women, age: 18–24, $M = 20.5$). Participants either received course credits or got paid for their time. They reported normal or corrected-to-normal vision. The experiment was approved by the Ethical Committee of the faculty of Behavioral and Movement Sciences of the Vrije Universiteit Amsterdam. Before the experiment, all participants gave informed consent in accordance with the Declaration of Helsinki.

Apparatus and stimuli. The experiment was conducted in a dimly lit and sound-attenuated room. The stimuli were presented on a 21″ LCD monitor (Samsung 2233RZ) with a 1680 × 1050 pixel resolution and a 120 Hz refresh rate. Eye movements were recorded using the Eyelink 1000 (SR Research) with a temporal resolution of 1 ms and a spatial resolution of .01°. The experiment was programmed using OpenSesame Version 3.2.8 (Mathôt, Schreij, & Theeuwes, 2012) with the Psychopy backend (Peirce, 2007) and Pygaze (Dalmaijer, Mathôt, & Van der Stigchel, 2014). The monitor was located at eye level 70 cm from chinrest. An automatic algorithm detected saccades using minimum velocity and acceleration criteria of 35°/s and 9,500°/s², respectively.

The search displays comprised a homogenous group of background line segments and two singletons, one target, and one distractor, with different orientations (see Figure 1). All elements were white (RGB color space in decimal code: 255, 255, 255) on a black background (RGB color space in decimal code: 0, 0, 0). The orientations of target and distractor singletons were held constant during the experiment at 30° tilted to the left and 30° tilted to the right, respectively, for one half of the participants and the other way around for the other half. The background lines were tilted 5° to the left in half of the trials and 5° to the right in the other half of the trials which resulted in a salient target condition with the background lines tilted in the opposite direction of the target, and a nonsalient target condition with the background lines
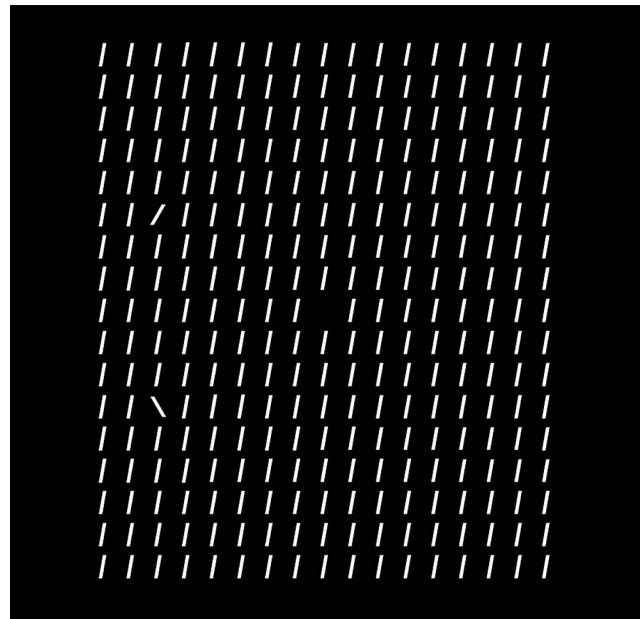

Figure 1. Example of a search display.

tilted in the same direction as the target. All elements in the display were arranged in a 17 * 17 rectangular matrix with a raster height of 17.13° and width of 14.31°. Elements had an approximate length of 0.75° and an approximate width of 0.13°. The singletons could be presented in six potential locations, which were placed on an imaginary circle with a radius of 6.14° centered at central fixation. One of these locations was designated as the high-probability location, implying that the distractor was presented with a probability of 65% at that location and with a probability of 7% at each of the remaining locations, the low-probability locations. The target was evenly presented at one of five locations that was not occupied by the distractor. One of the six potential locations was randomly selected as the high-probability location for each participant and fixed throughout the task. This resulted in the following distribution of participants across the six possible high-probability locations (with locations numbered clockwise starting from Location 1 at the middle-top location): Location 1: five participants; Location 2: four participants; Location 3: four participants; Location 4: three participants; Location 5: three participants; Location 6: one participant. The circular angle between the two singletons could either be 60°, 120°, or 180°.

Design and procedure. Calibration of the eye tracker was performed before the experiment. Each trial started with a self-paced drift correction (0.28°). Subsequently, a small circular fixation point (0.1°) was presented at the center of the screen for 1,000 ms, followed by the search display for 1,500 ms. The task was to make a speeded eye movement toward the prespecified target and ignore the distractor. A visual warning message was presented when participants did not move their eyes to either the target or the distractor within 1,500 ms. The main experiment consisted of 1,000 trials. The distractor was presented at the high-probability location in 650 trials and at a low-probability location in 350 trials (70 trials for each of the 5 low-probability locations). All trials were fully randomized and then split into 20 blocks of 50 trials, implying that the number of trials for each condition varied across blocks. Before the experiment, 20 trials were randomly selected from the full pool of experimental trials and used for practice. Feedback concerning response latency and accuracy was provided at the end of each block. Participants were free to take a brief break after each block of trials. Target salience (salient target and nonsalient target) and distractor location (high-probability location and low-probability location) were randomly varied within the experiment. The location designated as the high-probability location was randomly chosen from the six potential locations for each participant. The orientations of the target and distractor singletons were held constant for each participant and were counterbalanced across participants. To probe awareness, participants were asked to indicate which one of the six locations they thought contained the distractor more often and how confident they were about their answer (scaled from 1 to 7) at the end of the experiment (see for a similar procedure Wang & Theeuwes, 2018b).

Data analysis. Eye-tracking events were extracted using custom-written python code (Van Rossum, 2007). Saccades were detected using automatic detection by the Eyelink system. The initial saccade was categorized as landing on the target or the distractor if its endpoint was within 2.4° of visual angle of the particular target or distractor position. Trials were excluded if the initial saccade did not land within the defined boundaries around the target or the distractor. Trials with initial saccade latencies below 80 ms or above 600 ms were also excluded from further analyses.

Two types of analysis were conducted. First, we performed a repeated-measures ANOVA on the mean proportions and the mean saccade latencies of eye movements directed toward the target with target salience (salient target, nonsalient target) and distractor location (high-probability location, low-probability location) as within-subject factors. We conducted an additional analysis in which we examined the mean proportions and mean saccade latencies of eye movements directed toward the target as a function of target location (high-probability location vs. low-probability location) for those trials in which the distractor was presented at a low-probability location. Subsequently, to examine the time courses of selection performance, the proportions of the eye movements directed to the target (p[target]) and those directed to the most salient singleton (p[salient singleton]) were separately analyzed as a function of saccade latency using the SMART method (van Leeuwen, Smeets, & Belopolsky, 2019). A moving Gaussian window between 140 and 500 ms (step size 1 ms and $\sigma = 10$ ms) was used to create weighted smoothed time series. Please note that the presence of a difference in p(target) between the salient and nonsalient target conditions is indicative of salience-driven control as the conditions only differed in the relative salience of target and distractor. In a similar vein, the difference in p(salient singleton) between salient and nonsalient target conditions indicates the extent to which selection was under goal-driven control. It is important to note that the singleton denoted as the salient singleton varied in dependency of target salience. That is, the salient singleton was the target in the salient target condition whereas it was the distractor in the nonsalient target condition. Therefore, the differences between the smoothed time series of salient target and nonsalient target trials derived from p(target) and p(salient singleton) reveal the temporal influences of salience-driven and goal-driven control respectively. To investigate how distractor location affects salience-driven selection performance, we calculated the difference curve between the time series of the proportions of saccades toward the target in the salient target condition and the nonsalient target condition separately for the low- and high-probability location conditions. The resulting difference curves in both distractor location conditions were subsequently compared using a weighted paired sample t tests for each sample of the smoothed time series. We used cluster-based permutation testing to control for multiple comparisons: for each comparison, trial labels were shuffled between conditions to construct smoothed time series. This procedure was repeated a thousand times for each participant (1,000 permutations, see van Leeuwen et al., 2019 for further details). We calculated the effect size by comparing the average data of each cluster (i.e., averaging data points within the time window of the significant cluster for each participant) between conditions. To examine the effect of distractor location on goal-driven selection performance, similar analyses were conducted on the time series of p(salient singleton).

Results

The upper panels of Figure 2 (solid lines) show the mean proportions and mean saccade latencies of eye movements to the target as a function of target salience and distractor location. An
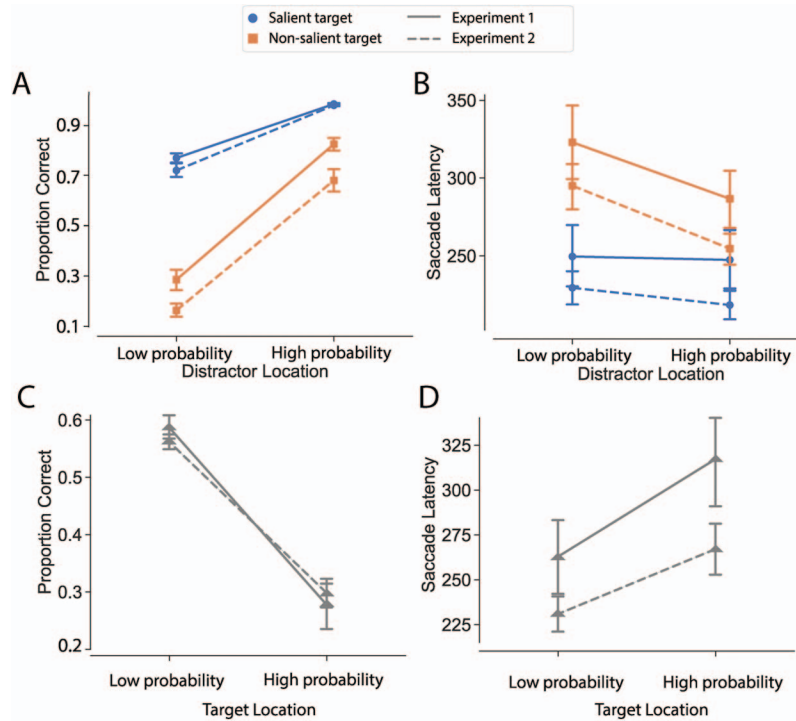
Figure 2. Mean proportions and mean saccade latencies in Experiments 1 (solid lines) and 2 (dashed lines). Mean proportions (A) and mean saccade latencies (B) of eye movements toward the target as a function of target salience (salient, nonsalient) and distractor location (high probability, low probability) in Experiments 1 (solid lines) and 2 (dashed lines). Mean proportions (C) and mean saccade latencies (D) of eye movements toward the target as a function of target location (high-probability, low-probability) for only those trials in which the distractor was presented at a low-probability location in Experiment 1 (solid lines) and 2 (dashed lines). Error bars represent ±1 the standard error of the mean. See the online article for the color version of this figure.

ANOVA on the mean proportions of eye movements to the target with the variables target salience (salient target and nonsalient target), and distractor location (high-probability location and low-probability location) showed significant effects of target salience, $F(1, 19) = 277.4$, $p < .001$, $\eta_p^2 = .94$ and distractor location, $F(1, 19) = 90.1$, $p < .001$, $\eta_p^2 = .83$. There was also a significant interaction between Target Salience and Distractor Location, $F(1, 19) = 85.88$, $p < .001$, $\eta_p^2 = .82$ indicating that the effect of target salience was larger for the low-probability than for high-probability location trials, $t(19) = 9.27$, $p < .001$, $d = 2.07$. An ANOVA on the mean saccade latencies of eye movements to the target[1] showed significant main effects of target salience, $F(1, 19) = 67.93$, $p < .001$, $\eta_p^2 = .78$ and distractor location, $F(1, 19) = 15.94$, $p < .001$, $\eta_p^2 = .46$. Moreover, these effects were qualified by a significant interaction between Target Salience and Distractor Location, $F(1, 19) = 17.18$, $p < .001$, $\eta_p^2 = .47$ indicating that the effect of target salience was larger for the low-probability than for high-probability location trials, $t(19) = 4.15$, $p < .001$, $d = 0.93$. The lower panels of Figure 2 (solid lines) show the mean proportions and mean saccade latencies of eye movements to the target as a function of target location (high-probability location vs. low-probability location) for those trials in which the distractor appeared in a low-probability location. Planned comparisons showed that participants committed more errors, $t(19) = 10.19$, $p < .001$, $d = 2.28$ and responded slower, $t(19) = 4.46$, $p < .001$, $d = 1.00$

when the target was presented at the high-probability location than when the target was presented at the low-probability location.

Figure 3 shows the time courses of p(target) as a function of target salience separately for the low-probability location condition (A) and the high-probability location condition (B). The results indicate that in both the low- and the high-probability location condition, participants performed better when searching for a salient target than for nonsalient one early in time (see Figure 3), which is evident from the presence of one significant cluster in the low-probability location condition (140~240 ms, $p < .001$, $t_{cluster}(19) = 17.62$, $d_{cluster} = 3.94$) and two significant clusters in the high-probability location condition (140~290 ms, $p < .001$, $t_{cluster}(19) = 7.08$, $d_{cluster} = 1.58$; 320 ~ 350 ms, $p = .002$, $t_{cluster}(19) = 2.51$, $d_{cluster} = 0.56$). Figure 3C depicts the differences curves for p(target) between the salient target and the nonsalient target conditions obtained in the low-probability condition and the high-probability condition. The results show that selection perfor-

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[1] As can be seen in Figure 2A, a large proportion of saccades (.984) was made towards the salient target when the distractor was located at the high-probability location. Accordingly, there were only a few saccades directed towards the distractor location in this condition. Three out of 20 participants did not make any eye movements to the distractor when it was located at the high-probability location. For this reason, we only analyzed the mean saccade latencies of eye movements towards the target.
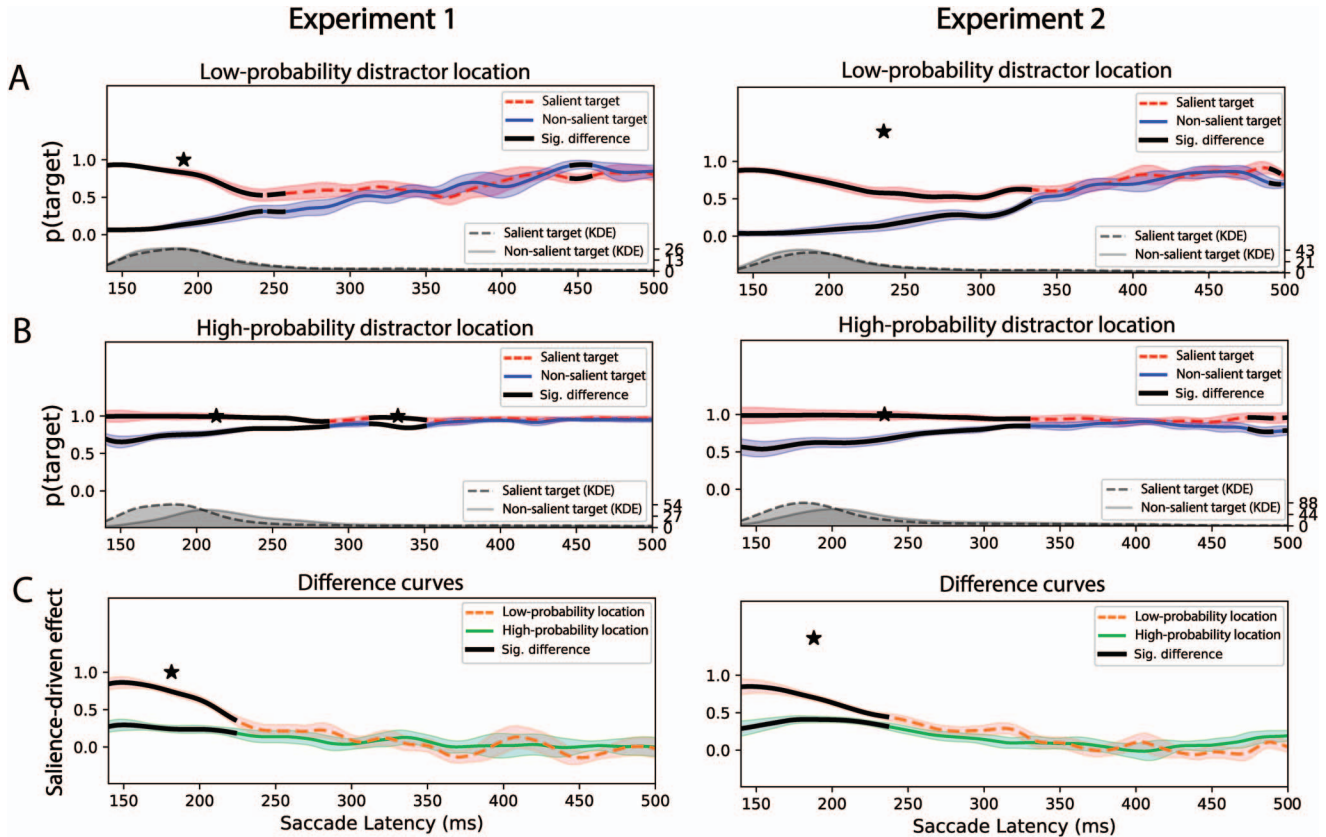
Figure 3. The time courses of the proportions of eye movements toward the target (*p*[target]) in Experiments 1 (left panels) and 2 (right panels). The panels show *p*(target) smoothed as a function of saccade latency separately for salient-target (red [dashed] line) and non-salient-target (blue [solid] line) trials when the distractor is presented in the low-probability location (A) and when the distractor is presented in the high-probability location (B). The lower left panel (C) depicts the difference curve obtained in the low-probability trials (orange [dashed] line) and high-probability trials (green [solid] line). Asterisks indicate significant clusters after cluster-based permutation testing. The shaded area around the lines shows the weighted 99% confidence intervals. The kernel density estimations below the smoothed time series show the estimated trial number per millisecond. See the online article for the color version of this figure.

mance is less affected by salience in the high-probability condition than in the low-probability condition as indicated by a significant cluster in the early time window (140~220 ms, $p < .001$, $t_{cluster}$ (19) = 8.98, $d_{cluster}$ = 2.01, Figure 3C).

Figure 4 shows the time courses of the *p*(salient singleton) as a function of target salience separately for the low-probability (A) and the high-probability (B) location condition. The results show that when the distractor was presented in the low-probability location, there was a significant cluster in a late time window (375~500 ms, $p < .001$, $t_{cluster}$ (19) = 4.99, $d_{cluster}$ = 1.12) indicating that *p*(salient singleton) was higher when this singleton was the target compared to when it was not (Figure 4A). We also found a significant cluster in the early time window (210~260 ms, $p = .007$, $t_{cluster}$ (19) = 4.09, $d_{cluster}$ = 0.92), showing that *p*(salient singleton) was smaller when this singleton was the target compared to when it was not. It is important to note that in the low-probability location condition, the target was presented at the high-probability location on 7% of trials. Given that targets presented at that location were less likely to be selected (see Figure

2C), we reanalyzed the time courses of the *p*(salient singleton) as a function of target salience for the low-probability location excluding those trials in which the target was presented at the high-probability location. With these trials removed, the results showed that the early bias favoring the distractor in the low-probability location condition was no longer present ($p = .19$) while the further time courses remained unchanged.

When the distractor was presented in the high-probability location, the proportion was higher in the salient target condition than in the nonsalient target condition throughout the whole time window (140~500 ms, $p < .001$, $t_{cluster}$ (19) = 25.56, $d_{cluster}$ = 5.72, Figure 4B). Figure 4C depicts the differences curves for *p*(salient singleton) between the salient target and the nonsalient target conditions obtained in the low-probability condition and the high-probability condition. The results show that selection performance is primarily affected by distractor location between 140 to 440 ms ($p < .001$, $t_{cluster}$ (19) = 13.65, $d_{cluster}$ = 3.05, Figure 4C).

The results concerning awareness showed that 11 participants chose the wrong location. Of the nine participants who indicated
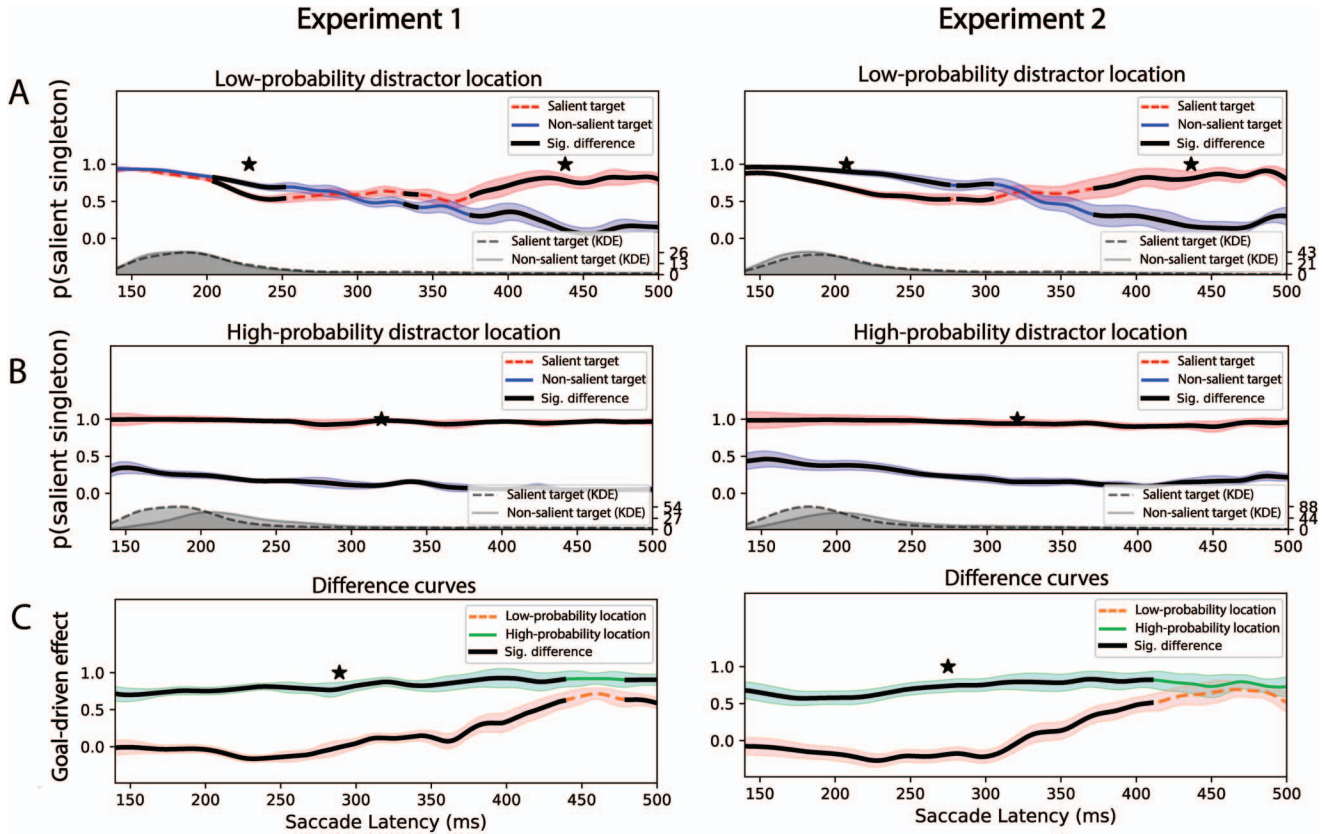
Figure 4. The time courses of the proportions of eye movements toward the most salient singleton (*p*[salient singleton]) in Experiments 1 (left panels) and 2 (right panels). The panels show *p*(salient singleton) smoothed as a function of saccade latency separately for salient-target (red [dashed] line) and nonsalient-target (blue [solid] line) trials in the low-probability (A) and the high-probability (B) location condition. The lower left panel (C) depicts the difference curve obtained in the low-probability trials (orange [dashed] line) and high-probability trials (green [solid] line). Asterisks indicate significant clusters after cluster-based permutation testing. The shaded area around the lines shows the weighted 99% confidence intervals. The kernel density estimations below the smoothed time series show the estimated trial number per millisecond. See the online article for the color version of this figure.

the correct location, only three participants were sure about their answer (i.e., a confident rating higher than 4), whereas six participants were not. We included awareness as a between-subjects variable in the analysis of the mean proportions and the mean saccade latencies. Participants who correctly indicated the location were categorized as the aware group while others were categorized as the unaware group. There was no effect of awareness, nor any interaction with the other variables, suggesting that the awareness of the high-probability location did not alter the results (all *p*s > 0.32).

Discussion

The results of Experiment 1 show that eye movements were initiated faster toward the target when the distractor was presented at the high-probability location relative to the low-probability location. Speed–accuracy trade-off cannot account for this effect as participants also performed better when the distractor was presented at the high-probability location as compared to the low-probability location. In contrast, eye movements were initi-

ated slower and were directed less likely toward the target when the target was presented at the high-probability location as compared to the low-probability location. These findings are in line with previous research showing that the high-probability location was suppressed through statistical learning (Wang, Samara, et al., 2019; Wang & Theeuwes, 2018a, 2018b).

Importantly, and consistent with proactive suppression, by tapping into the time course of visual selection, the present study shows that distractor location already exerted its effect in the earliest possible time window, as evident from the reduced salience-driven effect in the high-probability relative to the low-probability location condition (see Figure 3C). Additionally, we also find that the goal-driven effect was modulated from the earliest responses until about 440 ms after the presentation of the display. Even though the salience-driven time courses differ substantially from the goal-driven time courses (see Panel C in Figures 3 and 4), it is important to note that all time courses are derived from the same data set. The difference curves depicting *p*(target) against saccade latency is indicative of the time course of

salience-driven control for the underlying curves only differ with regard to whether the target was salient or not. The difference curves plotting p(salient singleton) against saccade latency indicate the time course of goal-driven control for the underlying curves only differ with respect to whether the salient singleton was the target or the distractor. Taken together, these results suggest that statistical learning modifies the earliest responses of selection, which is consistent with the idea that the high-probability location was suppressed proactively (Wang, van Driel, et al., 2019).

It is important to note that the manipulation of distractor location in Experiment 1 did not only affect the probability that a distractor was presented at specific locations but also the probability of the target. In each trial, the target was equally often presented at one of the five locations unoccupied by the distractor. Because of this, the target was presented less often at the high-probability location than at the other five locations. In other words, the target was presented at the high-probability location with a probability of 7% and at each of the five low-probability locations with a probability of 18.6%. Indeed, the results of several studies have shown that the presence of a statistical regularity in the target position may have a profound effect on performance (Chun & Jiang, 1998, 1999). Accordingly, it is possible that the effects we reported were not due to the fact that the distractor was presented more often at the high-probability location but because the target was presented less often at that location. Even though this is a concern, a recent study specifically addressed this issue and showed that that suppression of the distractor location was unaffected by statistical regularities regarding the target position (Failing, Wang, et al., 2019). Yet, to ensure that this is not a concern in the present study, we ran a second experiment similar to Experiment 1 but now the target was presented equally often at each of the six potential locations.

Experiment 2

To address the possibility that the time course modulations found in Experiment 1 were caused by statistical regularities in the target position, we used exactly the same task as in Experiment 1 except that the target was now equally often presented at each location. If the observed effects in Experiment 1 were due to the statistical regularities regarding the target rather than the distractor, the effects should no longer be present in Experiment 2. Alternatively, the results should resemble those of Experiment 1.

Method

Participants.   To counterbalance both the high-probability location and the orientation of the target and distractor, we increased our sample size to 24. Twenty-four healthy students from the Vrije Universiteit Amsterdam participated in this experiment (22 women, age: 18–27, $M = 20.42$). Participants either received course credits or got paid for their time. They reported normal or corrected-to-normal vision. The experiment was approved by the Ethical Committee of the faculty of Behavioral and Movement Sciences of the Vrije Universiteit Amsterdam. Before the experiment, all participants gave informed consent in accordance with the Declaration of Helsinki.

Apparatus and stimuli.   The apparatus and stimuli were the same as in Experiment 1, except that the target was equally likely

to be presented at each of the six locations. Specifically, in the trials in which the distractor was presented in the high-probability location, targets were equally likely assigned to the other five locations. In contrast, in the trials in which the distractor was presented in one of the low-probability locations, the target was located more often at the high-probability location than at one of the other four locations. We adopted this change to compensate for the smaller number of target occurrences in the high-probability location so as to ensure that overall the target occurred equally often at each of the six locations.

Design and procedure.   The design and procedure were equal to those of Experiment 1 with the exceptions that the high-probability location was now fully counterbalanced over participants. Participants finished 20 blocks of 60 trials each.

Results

The upper panels of Figure 2 (dashed line) show the mean proportions and mean saccade latencies of eye movements to the target as a function of target salience and distractor location. An ANOVA on the mean proportions of eye movements to the target with the variables target salience (salient target and nonsalient target), and distractor location (high-probability location and low-probability location) showed significant effects of target salience, $F(1, 23) = 150.86$, $p < .001$, $\eta_p^2 = .87$ and distractor location, $F(1, 23) = 104.73$, $p < .001$, $\eta_p^2 = .82$. There was also a significant interaction between Target Salience and Distractor Location, $F(1, 23) = 80.39$, $p < .001$, $\eta_p^2 = .78$, Figure 2A indicating that the effect of target salience was larger for the low-probability than high-probability location trials, $t(23) = 8.97$, $p < .001$, $d = 1.83$. A subsequent ANOVA on the mean saccade latencies of eye movements to the target showed significant main effects of target salience, $F(1, 23) = 73.69$, $p < .001$, $\eta_p^2 = .76$ and distractor location, $F(1, 23) = 36.14$, $p < .001$, $\eta_p^2 = .61$. Moreover, these effects were qualified by a significant interaction between Target Salience and Distractor Location, $F(1, 23) = 16.48$, $p < .001$, $\eta_p^2 = .42$, Figure 2B indicating that the effect of target salience was larger for the low-probability than for high-probability location trials, $t(23) = 8.19$, $p < .001$, $d = 1.67$. The lower panels of Figure 2 (dashed line) show the mean proportions and mean saccade latencies of eye movements to the target as a function of target location (high-probability location vs. low-probability location) when the distractor appeared in the low-probability location. The planned comparisons showed that participants committed more errors, $t(23) = 11.51$, $p < .001$, $d = 2.35$ and responded slower, $t(23) = 5.11$, $p < .001$, $d = 1.04$ when the target was presented at the high-probability location than when the target was presented at the low-probability location.

Figure 3 (right panels) shows the time courses of p(target) as a function of target salience separately for the low-probability (A) and the high-probability (B) locations. The results indicate that in both the low- and the high-probability location conditions, participants performed better at searching for the salient target than for the nonsalient one early in time ($p < .001$), which is evident from the presence of a significant cluster in the low-probability location condition (140 ~ 330 ms, $p < .001$, $t_{cluster}(23) = 11.10$, $d_{cluster} = 2.27$) and a significant cluster in the high-probability location condition (140 ~ 330 ms, $p < .001$, $t_{cluster}(23) = 7.26$, $d_{cluster} = 1.48$). Figure 3C (right panel) depicts the differences curves for the

p(target) between the salient target and the nonsalient target conditions obtained in the low-probability condition and the high-probability condition. The results show that selection performance is less affected by salience in the high-probability condition than in the low-probability condition as indicated by a significant cluster in the early time window (140~240 ms, $p < .001$, $t_{cluster}$ (23) = 7.49, $d_{cluster}$ = 1.53).

Figure 4 (right panels) shows the time courses of p(salient singleton) as a function of target salience separately for the low-probability (A) and the high-probability (B) locations. The results show that when the distractor was presented in the low-probability location, there was a significant cluster in a late time window (375~500 ms, $p < .001$, $t_{cluster}$ (23) = 3.96, $d_{cluster}$ = 0.81) indicating that the p(salient singleton) was higher when this singleton was the target compared to when it was not (Figure 4A right panel). We also found a significant cluster in the early time window (140~275 ms, $p < .001$, $t_{cluster}$ (23) = 7.95, $d_{cluster}$ = 1.62) signifying that p(salient singleton) was smaller when this singleton was the target compared to when it was not. However, a reanalysis on the time courses of p(salient singleton) as a function of target salience for the low-probability location excluding those trials in which the target was presented at the high-probability location showed that the early bias favoring the distractor in the low-probability location condition was no longer present. Instead, an inverse bias favoring the target was found in a time window ranging from 245~280 ms ($p = .028$, $t_{cluster}$ (23) = 2.09, $d_{cluster}$ = 0.43).

When the distractor was presented in the high-probability location, the proportion was higher in the salient target condition than in the nonsalient target condition throughout the whole time window (140~500 ms, $p < .001$, $t_{cluster}$ (23) = 20.27, $d_{cluster}$ = 4.14, Figure 4B right panel). Figure 4C (right panel) depicts the differences curves for p(salient singleton) between the salient target and the nonsalient target conditions obtained in the low-probability condition and the high-probability condition. The results show that selection performance is primarily affected by distractor location between 140 to 420 ms ($p < .001$, $t_{cluster}$ (23) = 13.14, $d_{cluster}$ = 2.68).

The results concerning awareness showed that 16 participants chose the wrong location. Of the eight participants who indicated the correct location, five participants were sure about their answer (i.e., a confident rating higher than 4), whereas three participants were not. We included awareness as a between-subjects variable for the analysis of the mean proportions and the mean saccade latencies. Participants who correctly indicated the location were categorized as the aware group while the others were categorized as the unaware group. There was no effect of awareness, nor any interaction with other variables, suggesting that the awareness of the high-probability location did not alter the results (all ps > 0.16).

Discussion

The results of Experiment 2 are similar to those previously reported by Failing, Wang, et al. (2019), indicating that distractor location affected performance even when the target was equally often presented at the high-probability location as at either one of the other locations. This demonstrates that the effects found in Experiment 2 were truly related to the location of the distractor

rather than of the target. The results are also remarkably similar to those obtained in Experiment 1. Distractor location affected performance in the earliest possible time window indicating that distractor location suppression modified performance instantaneously even to the extent that the influence of salience was strongly reduced. Moreover, like in Experiment 1, the effect of distractor location continued across the further time window such that it also modulated goal-driven selection.

General Discussion

The present study investigated how the selective suppression of a distractor location affected the time courses of salience-driven and goal-driven visual selection. The results of Experiment 1 showed that the effect of distractor location occurred very early, modulating the time courses of both salience-driven and goal-driven control. Importantly, the modulating effects of spatial suppression were already present in the earliest possible responses. The results of Experiment 2 were similar to those of Experiment 1, even when the target occurred equally often at each of the possible distractor locations. Together these results are in line with previous findings (Wang & Theeuwes, 2018b, 2018c) and consistent with the idea of proactive suppression (Wang, van Driel, et al., 2019), showing that distractor suppression of the high-probability location induced by statistical learning exerts its effects at the very beginning, influencing not only early salience-driven selection, but also goal-driven selection occurring in a later time window.

Overall the results of the current study provide compelling evidence for the claim that the suppression of the high-probability location through statistical learning operates in a proactive fashion (Wang, van Driel, et al., 2019). Our results show that distractor location already influences salience-driven visual selection from the earliest responses on. If there had been reactive suppression (after display onset) there should be activation instead of suppression at the earliest responses and only later in time there should be a gradual buildup of suppression (Won et al., 2019). The notion of reactive suppression is similar to the "search and destroy" hypothesis (Moher & Egeth, 2012), which claims that feature suppression is only possible after attending the location of a feature that needs to be ignored. Our interpretation is also different from the *signal suppression hypothesis* of Luck and colleagues (Gaspelin et al., 2015; Sawaki & Luck, 2010, 2014). Even though according to this hypothesis under certain conditions (referred to as the "feature search mode," Bacon & Egeth, 1994) there can be proactive suppression of salient irrelevant singletons, the underlying mechanism is different from what we argue here. According to the signal suppression hypothesis, an irrelevant singleton automatically generates a priority signal which has been called an *attend-to-me* signal (Sawaki & Luck, 2010). When engaged in feature search (searching for a specific feature instead of searching for a singleton), this attend-to-me signal is proactively suppressed. However, unlike the signal suppression hypothesis, here we argue that the location-based proactive suppression prevents the generation of an attend-to-me signal (see also Wang & Theeuwes, 2018c). Note that this type of proactive suppression is not feature-based (as is the signal suppression hypothesis) but can only be location-based. We assume that within the spatial priority map of selection, the high-probability location is proactively suppressed

such that it no longer competes for attention (see also Kong, Li, Wang, & Theeuwes, 2020).

It is important to note that a recent study of Wang and Theeuwes (2020) showed that the feature suppression as conceived by Gaspelin et al. (2015; Gaspelin & Luck, 2018) can only be found when heterogeneous displays are used consisting of a few (usually 4) nonsalient elements. It is likely that when these types of displays are used, participants engage in serial search, which allows feature-based suppression (see also Kerzel & Burra, 2020, for a similar argument). In the current experiments, both target and distractor were highly salient and stood out from the background as the local feature contrast (which refers to how different an item is from nearby items, see Nothdurft, 1993) was high.

The statistical regularity regarding distractor location also affected goal-driven selection, as evident from the observed differences in the goal-driven time courses between the high-probability and the low-probability location condition (see Figure 4C). Moreover, this difference was already evident in the earliest responses, suggesting that distractor suppression of the high-probability location allowed observers to correctly ignore the presence of a very salient distractor and move their eyes to the target very early on. Previous studies on the time course of visual selection have repeatedly shown that goal-driven control typically occurs in long-latency responses only (but see Hollingworth, Matsukura, & Luck, 2013), suggesting that this type of control takes time to become operational (Godijn & Theeuwes, 2002; Hochstein & Ahissar, 2002; Sagi & Julesz, 1985; Van Zoest & Donk, 2008; van Zoest et al., 2004). This suggests that even though distractor suppression allowed performance to become goal-driven early on, this was probably not caused by the operation of the slow (volitional) top-down mechanism typically regarded as responsible for goal-driven selection. Together the overall modulation of salience-driven and goal-driven selection by distractor location strongly suggests that the statistical regularity of distractor location biases selection above and beyond salience and goals. The location that contains a distractor more often is proactively suppressed through statistical learning and competes less for attention than other locations, invoking a continuous bias in selection.

In both experiments we found evidence that in the low-probability condition, early on fewer saccades were made toward the most salient singleton when this singleton was the target compared to when it was the distractor (see Figure 4A). This result seems surprising given previous findings showing that fast saccades tend to be directed toward the most salient singleton, irrespective of it being the target or the distractor (Donk & van Zoest, 2008, 2011; Godijn & Theeuwes, 2002; Van Zoest & Donk, 2004, 2005; Van Zoest et al., 2004). The observed difference cannot be attributed to the influence of goal-driven control as fewer rather than more eye movements were made to the target. One viable explanation for this bias is related to the location of the target. In the low-probability condition, the target was sometimes presented at the high-probability location (i.e., in 7% of the trials in Experiment 1 and in 20% of the trials in Experiment 2). If the high-probability location was indeed proactively suppressed, any singleton presented at that location should compete less for attention (Desimone & Duncan, 1995), leading to a selection bias favoring the other singleton, even if it was the distractor. Indeed, our results show that when the target was presented at the high-probability location (see Figure 2C and D) both the mean proportions and

mean saccade latencies of eye movements to the target were lower than when the target was presented at a low-probability location. Wang and Theeuwes (2018a, 2018b; see also: Failing, Wang, et al., 2019) described a similar effect showing that in trials without a distractor, responses to the target were slower when the target appeared in the high-probability location than in the low-probability location. More importantly, our results show that if trials in which the target was presented at the high-probability location were excluded from our analyses, the early bias favoring the distractor over the target was no longer present. This suggests that suppression of the high-probability location is proactively applied regardless of whether a target or a distractor is presented at that location.

Even though the results are much in line with the idea that the high-probability location was proactively suppressed leading to a reduced salience effect when the distractor was presented at that location, it is also possible that, instead, the low-probability locations were enhanced. That is, it is possible that distractors presented at low-probability locations led to a larger salience effect due to the fact that these trials were rare. Indeed, various studies have shown that rare events capture attention more than frequent events (e.g., Sauter, Liesefeld, & Müller, 2019; Schönhammer & Kerzel, 2018). In this sense, distractors presented at low-probability locations can be considered as rare events leading to enhanced capture and subsequently to a larger effect of salience. There are several reasons, however, why it is unlikely. First, both experiments show that target detection was worse when the target was presented at the high-probability location compared to the low-probability locations. Critically, this result was only obtained for trials in which the distractor was presented at a low-probability location. If our findings were to be explained by the notion that rare events capture attention, one would not have expected any difference in target detection performance between the high- and low- probability locations. Second, the results obtained in the low-probability location condition are very similar to those obtained in earlier studies (Donk & van Zoest, 2008, 2011; Van Zoest & Donk, 2008; van Zoest et al., 2004), suggesting that it was the high-probability location rather than the low-probability locations that modulated performance. Finally, our results are very much in line with those previously obtained by Wang and Theeuwes (2018a, 2018b, 2018c), which showed reduced attentional capture by distractors at the high-probability location and underperformance of target selection when the target was presented at this location.

Together, the findings of the current study provide further support for the idea that the spatial priority map of selection (Awh et al., 2012) does not only receive salience-driven and goal-driven inputs but also inputs related to selection history, representing a third mode of attentional bias. Within the map, selection priority is determined by the integrated spatial weights calculated based on the contributions of salience-driven, goal-driven, and selection history. The results of the present study suggest that selection history leads to statistical learning, which in turn may cause a lingering suppression of the high-probability location. Importantly, this suppression operates instantaneously and influences selection in addition to salience and goals, biasing selection across its full time course. The present study is the first to show that this pervasive effect of distractor suppression modulates the time

course of selection even to the extent that salience-driven control becomes less effective and goal-driven control is enhanced.

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