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BRIEF REPORT

Selection and response bias as determinants of priming of pop-out search: Revelations from diffusion modeling

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Abstract

During visual search, both top-down factors and bottom-up properties contribute to the guidance of visual attention, but *selection history* can influence attention independent of bottom-up and top-down factors. For example, *priming of pop-out* (PoP) is the finding that search for a singleton target is faster when the target and distractor features repeat than when those features trade roles between trials. Studies have suggested that such priming (selection history) effects on pop-out search manifest either early, by biasing the selection of the preceding target feature, or later in processing, by facilitating response and target retrieval processes. The present study was designed to examine the influence of selection history on pop-out search by introducing a speed–accuracy trade-off manipulation in a pop-out search task. Ratcliff diffusion modeling (RDM) was used to examine how selection history influenced both attentional bias and response execution processes. The results support the hypothesis that selection history biases attention toward the preceding target's features on the current trial and also influences selection of the response to the target.

Keywords Selection history · Pop-out search · Attention · Priming · Bias

Top-down factors related to task goals (Folk, Remington, & Johnston, 1992; Wolfe, Butcher, Lee, & Hyle, 2003; Yantis, 1998, 2000) and bottom-up factors related to salience (Bundesen, 1990; Müller, Heller, & Ziegler, 1995; Theeuwes, 1992, 1994, 2010; Treisman & Gelade, 1980; Wolfe, Cave, & Franzel, 1989; Yantis, 1993, 2000) modulate attentional selection. Evidence also suggests that *selection history* modulates selection during visual search (Awh, Belopolsky, & Theeuwes, 2012). *Value-driven capture* studies have shown that extrinsic value becomes linked to features, facilitating selection of those features during search (Anderson, Laurent, & Yantis, 2011a, 2011b). *Contextual cuing* studies have revealed that repeating a search context, such as the locations of targets and distractors, speeds search (Chun & Jiang, 1998; Chun & Nakayama, 2000). And *pop-out search* studies have demonstrated that search for a singleton target is facilitated when target and distractor features repeat between trials (e.g., Kristjánsson & Campana, 2010; Lamy, Antebi, Aviani, & Carmel, 2008; Lamy, Carmel, Egeth, & Leber, 2006; Lamy, Yashar, & Ruderman, 2010; Maljkovic & Nakayama, 1994, 1996, 2000).

Maljkovic and Nakayama (1994) observed *priming of pop-out* (*PoP*) by finding faster responses to a singleton target when its distinguishing feature (color) on trial $n-1$ repeated on trial n, even though the color per se was irrelevant. Such effects reveal that selection history biases attention toward information encountered during recent search episodes and, importantly, that history influences visual search even when that history conflicts with the stimulus salience or task goals (Awh et al., 2012).

Although PoP is well-established, several mechanisms have been proposed for the effect. According to *enhanced-salience* or *preattentive* accounts (Becker, 2008; Bichot & Schall, 2002; Maljkovic & Nakayama, 1994, 1996, 2000), encoding the target feature boosts the salience of that feature on the following trial; hence, priming enhances the signal strength. In support of this, Maljkovic and Nakayama found that repetition of noncritical features, such as response features, did not influence PoP. Additionally, Bichot and Schall found that neural activation in areas of the frontal eye fields, which are associated with activation within salience maps, was greater when features repeated. And Becker found that feature repetition sped saccades toward targets and away from fixation, suggesting that selection history influenced early, preattentive visual processes.

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Others have proposed that priming biases attention to select features that are associated with recently encountered targets (Amunts, Yashar, & Lamy, 2014; Lleras, Kawahara, Wan, & Ariga, 2008; Tseng, Glaser, Caddigan, & Lleras, 2014; Yashar & Lamy, 2010; Yashar, White, Fang, & Carrasco, 2017). Thus, the features of a recent target are more likely to be selected on the current trial, but their salience is unchanged. In support of this, Yashar and Lamy (2010; Yashar et al., 2017) found that PoP emerged during feature discrimination tasks requiring focused attention on the target, but not during localization tasks that did not require focused attention, even though the target saliences in both tasks were equivalent. Similarly, Lleras et al. (2008) found that the *distractor preview effect* (*DPE*; Ariga & Kawahara, 2004; Goolsby, Grabowecky, & Suzuki, 2005; Goolsby & Suzuki, 2001)—an intertrial effect in which responding is slower if the target feature has been previewed in a target-absent display—was absent in detection but not in discrimination tasks, presumably because the latter required target selection.

Still others have suggested that selection history exerts an influence during response selection after a target is selected (Hillstrom, 2000; Huang, Holcombe, & Pashler, 2004; Huang & Pashler, 2005; Thomson & Milliken, 2011, 2013). That is, the visual system verifies whether a selected item is the target by comparing it to recent targets, with retrieval being facilitated if features are repeated. In support of this, Huang et al. (2004) found that repetition of target features interacted with repetition of the response, suggesting that priming influenced postselection response-execution processing.

Additionally, some have proposed that several mechanisms may be influenced by feature priming (e.g., Ásgeirsson, Kristjánsson, & Bundesen, 2015; Kristjánsson & Campana, 2010). For example, Lamy et al.'s (2010; Yashar, Makovski, & Lamy, 2013) *dual-stage account* proposes that selection history influences both selection and retrieval. To support this, Lamy et al. (2010) examined the time course of the interaction between response repetition and target feature repetition observed by Huang et al. (2004), and they found that PoP interacted with response repetition at long but not at short delays. This likely occurred because at short delays there was insufficient time to compare the current to the previous targets. Similarly, Ásgeirsson and Kristjánsson (2011) found Huang et al.'s interaction between target repetition and response priming during inefficient, but not during efficient, search, thus suggesting that at least two stages are affected by visual repetition priming.

Recently, Tseng et al. (2014) examined the mechanisms responsible for PoP and DPE by applying *Ratcliff diffusion modeling* (*RDM*; Ratcliff, 1978, 1981; Ratcliff & McKoon, 2008; Ratcliff & Rouder, 1998; Ratcliff, Van Zandt, & McKoon, 1999) to saccadic response times (RTs) obtained in a pop-out search task. Subjects made saccades toward a color singleton and withheld saccades if no singleton appeared. Tseng et al. found that only the bias parameter (z in RDM and B in Tseng et al., 2014) predicted PoP and the DPE. This parameter reflects a pretrial (presearch) tendency to make saccades toward the previous target color on the current trial; hence, Tseng et al. showed that priming biased attention toward the selection of features associated with recently encountered targets.

RDM assumes that evidence accumulates over time until a response threshold is reached, at which time a decision and a response are made to categorize a stimulus; diffusion models can be adapted to different situations to make predictions about what processes operate during decisions (Voss, Rothermund, Gast, & Wentura, 2013; Voss, Rothermund, & Voss, 2004; Voss, Voss, & Lerche, 2015). Figure 1 illustrates the RDM: A decision process begins at z and continues until the lower boundary (0) or the upper boundary (a) is reached, at which point a response is made and the decision process terminates. The process is noisy, due to momentary influences on the diffusion process.

RDM is defined by several parameters, which relate to different processes. The *upper threshold* (a) is the distance between response thresholds and corresponds to liberal–conservative response criteria. (In my implementation of RDM, the upper boundary is associated with correct responses and the lower boundary with errors.) *Starting point* (z) or *relative starting point* (z_r; Voss et al., 2015) is the pretrial bias toward a response. In the present study, this was bias toward selecting a correct or an incorrect target and response. If responding is unbiased, $z_r = a/2 = .5$. Any difference in z_r between conditions reflects a pretrial influence on decision-making. *Drift rate* (v) is the average rate of evidence accumulation toward a boundary. In the present study, this was evidence accumulation toward a correct response and reflected the efficiency of target processing or

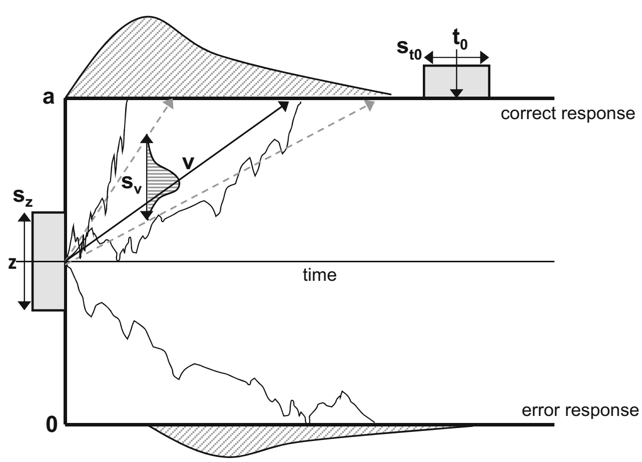

Fig. 1 The Ratcliff diffusion model. The evidence accumulation process starts in each trial from a starting point z within interval s_z. Evidence accumulates in a noisy manner, with a mean drift rate v and intertrial variation s_v. The evidence accumulates until one of two decision thresholds (0, a) is reached, which are separated by the boundary separation a. The response made (correct or error, in this example) is based on whichever boundary is reached first. A nondecision time t_0 with intertrial variation s_{t0} is added to the RT. The predicted RT distributions are depicted outside the thresholds

attentional engagement (Voss et al., 2013). The *nondecision constant* (t_0) is the duration of nondecision processes, such as response execution and encoding. RDM also allows one to model intertrial variability in starting point (s_z), drift rate (s_v), and nondecision processes (s_{t0}). In their adaptation of RDM, Voss et al. (2015) included a *difference in nondecision constant* (d), which is related to response preparation or inhibition.

In the present study, I examined the processes underlying PoP by applying RDM to data obtained in a three-item pop-out search task that required a binary response to the targets (which side of a target was missing). This task allowed for correct and incorrect responses, which were mapped onto the upper and lower thresholds, respectively, and allowed for an examination of whether priming history influenced response execution in addition to attentional selection. Tseng et al. (2014) applied RDM analyses to data obtained in a task that required saccades to targets but no manual response; hence, theirs was more like a detection task.

To examine priming's influences on selection and responding, the study used a speed–accuracy manipulation. In one block, subjects were instructed to favor speed over accuracy, and in another block they were told to favor slow, accurate responding over speed. This manipulation should increase the boundary separation (a) for correct versus incorrect responses under accuracy instructions, due to a more conservative criterion, and should have different influences on the RDM parameters. Following Tseng et al. (2014), if selection history biased attentional selection (z_r), accuracy instructions should promote correct selection and responding to the target, and should result in a larger difference (PoP effect) in z_r [$\Delta z_r = z_r(\text{switch}) - z_r(\text{repeat})$] for accuracy instructions [$\Delta z_r(\text{accuracy}) > \Delta z_r(\text{speed})$]. Second, speed instructions should encourage faster attentional engagement and accumulation of evidence when features repeat than when features switch. This should result in a larger PoP effect (Δv) for speed instructions [$\Delta v(\text{accuracy}) > \Delta v(\text{speed})$]. Third, these countervailing effects *might* result in no observable influence of instructions on PoP for RTs or accuracy, though this is speculation. Finally, if selection history influences response execution, differences in the nondecision parameters (t_0 and d) should be found between the speed and accuracy conditions. In particular, because accuracy instructions promote careful responding, larger differences in both t_0 and d should be observed in the accuracy condition [Δt_0 (accuracy) > Δt_0 (speed) and Δd (accuracy) > Δd (speed)].

Method

Subjects

A power analysis indicated that nine subjects were needed to detect an effect of Cohen's $f = 0.25$ at a power of .80 ($\alpha = .05$). A total of n = 14 University of Scranton undergraduates participated (nine female, five male; two left-handed). The subjects ranged from 18 to 20 years old (M = 18.58 years, SD = 0.90) and reported normal or corrected-to-normal vision. All subjects passed an Ishihra colorblindness test. (Three of the subjects were subsequently removed from the sample; see the Results below.)

Apparatus

The experiment was programmed and presented using E-Prime software (Version 2.0.10242; Psychology Software Tools, 2008) on a Dell 755 computer with a Pentium Core 2 Duo processor with 1.96 GB RAM (2.33 GHz). Subjects sat approximately 60 cm from a Dell E178Fpv monitor with a resolution of 1,024 × 768 running at 60 Hz. A five-button response box was used for responding.

Stimuli

The search displays contained three diamonds (1.1° × 1.1°) appearing on a black background (0.16 cd/m^2; RGB: 0, 0, 0). Each diamond was missing its left or right corner (0.14°), but the missing corner of each diamond was chosen randomly in order not to identify the target. One diamond was a color singleton target, and the other two were homogeneously colored nontargets, with the colors of the target and two nontargets chosen randomly on each trial to be either red (20.44 cd/m^2; RGB: 255, 0, 0) or green (20.62 cd/m^2; RGB: 10, 177, 31). A white cross (25.77 cd/m^2; RGB: 255, 255, 255) appeared throughout each trial in order to maintain fixation. Each diamond appeared at a different one of 12 locations on the circumference of an imaginary ellipse (10° wide × 8° high) centered on the screen (distances between the objects were not equated).

Procedures

Subjects were informed that they would see three diamonds, one of which was a different color, and their task was to indicate whether its left or the right corner of one was missing. Subjects pressed the left key on the response box for the left corner and the right key for the right corner. Subjects were informed that the colors of the diamonds and the missing corner were both chosen randomly, so the target color and the missing corner were uncorrelated.

Subjects completed the task in two conditions: (1) In a *speed-instruction* condition, subjects were asked to respond quickly and not to worry about errors. (2) In an *accuracy-instruction* condition, subjects were encouraged to be as accurate as possible, even if that meant responding more slowly. The speed and accuracy conditions were blocked and counterbalanced for order across subjects. In both conditions each subject completed a practice block of 32 trials, followed by eight blocks of 96 trials each; all blocks were separated by self-paced breaks.

Each trial began with a fixation display of a white cross for 500 ms. Next, the search display was presented for 2,000 ms or until the subject had responded. The next trial began after a 100-ms delay. If a subject responded incorrectly or took longer than 2,000 ms to respond, a 500-Hz tone was played during the delay.

Results

The data from two subjects were excluded due to error rates above 30%. One additional subject was excluded due to making no errors in at least one condition, resulting in poor model fit. Analyses were conducted on the remaining $n = 11$ subjects. For the RT analyses, only trials with correct responses on both the current and preceding trials were used, which resulted in the removal of 11.4% of trials. For the error analyses, only trials with a correct response on the preceding trial were used. The data in the speed and accuracy conditions were sorted on the basis of the target and nontarget colors in trial $n-1$ and trial n, to create a *repeat* condition (colors repeated) and a *switch* condition (colors switched). Each subject's mean RT (M_{RT}) and percentage of errors were calculated for each condition. The M_{RT}s and percent errors averaged over all subjects appear in Table 1.

Response times

A 2 (Instructions: speed vs. accuracy) × 2 (Transition: repeat vs. switch) repeated measures analysis of variance (ANOVA) on M_{RT} (Fig. 2) revealed a main effect of instructions [$F(1, 10) = 14.40$, $MSE = 15{,}452.07$, $p = .004$, Cohen's $f = 1.20$], due to faster responding in the speed condition. The effect of transition was also significant [$F(1, 10) = 48.15$, $MSE = 5{,}323.94$, $p < .001$, $f = 2.19$], because of a PoP effect of 153 ms [118, 187]. The interaction was nearly significant [$F(1, 10) = 3.64$, $MSE = 692.87$, $p = .085$, $f = 0.60$], with the PoP effect being larger in the accuracy condition [$F(1, 10) = 43.11$, $p < .001$, $f = 2.07$] than in the speed condition [$F(1, 10) = 42.90$, $p < .001$, $f = 2.07$].

Table 1 Mean RTs, *SD*s, and percent errors, as a function of switch and repeat condition and speed and accuracy condition

Condition	Between-Trial Transition	M_{RT}	*SD*	%Error
Speed	Switch	758 [740, 776]	130	11.29%
	Repeat	620 [603, 638]	72	8.22%
	Overall	689 [630, 748]	100	9.80%
	PoP	138 [120, 155]		3.10%
Accuracy	Switch	915 [898, 933]	170	3.81%
	Repeat	747 [730, 765]	104	2.01%
	Overall	831 [772, 890]	134	2.90%
	PoP	168 [150, 185]		1.80%

Values in brackets are the 95% confidence limits based on the within-subjects error term (Eq. 2; Hollands & Jarmasz, 2010)

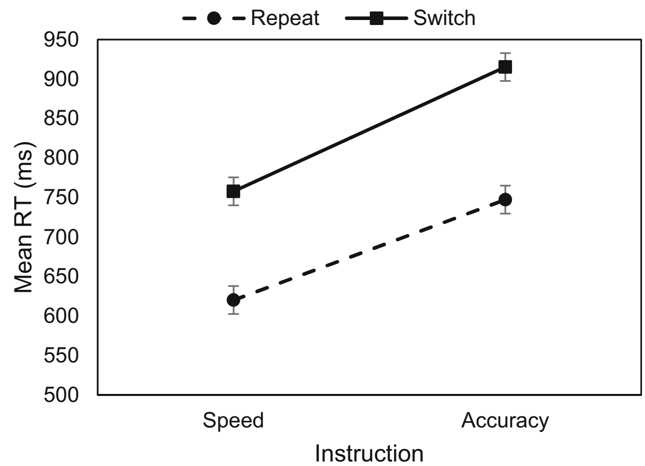

Fig. 2 Mean RTs in the Instruction × Transition design. Error bars show the 95% confidence limits based on the within-subjects error term (Eq. 2; Hollands & Jarmasz, 2010)

Errors

A 2 (Instructions) × 2 (Transition) repeated measures ANOVA on errors revealed a main effect of instructions [$F(1, 10) = 28.18$, $MSE = 0.0018$, $p < .001$, $f = 1.68$], due to fewer errors in the accuracy condition. The effect of transition was again significant [$F(1, 10) = 16.96$, $MSE = 0.0004$, $p = .002$, $f = 1.30$], showing a PoP effect of 2.40%. The interaction was not significant [$F(1, 10) = 1.67$, $MSE = 0.0003$, $p = .225$, $f = 0.54$], though the PoP effect was larger in the speed condition.

Diffusion model analysis

Correct responses were assigned to the upper boundary and errors to the lower boundary of the model (Fig. 1). The RT distributions for correct and error responses were entered into a diffusion-model analysis using fast-dm (Voss & Voss, 2007; Voss et al., 2015), with parameters being estimated separately for each subject. Drift rate (v), nondecision constant (t_0), response execution bias (d), and starting point (z_r) were estimated in each Instruction × Transition condition. Other parameters (a, s_v, s_{zr}, s_{t0}) were estimated separately for the speed and accuracy conditions but were held constant across the repeat and switch conditions. Chi-square optimization was used for the estimation (criterion = 4). The computing time was 8,616.68 s ($M = 783.33$, $SD = 664.87$). Table 2 provides the parameter estimates averaged over the 11 subjects.

The parameters held constant across transitions (a, s_v, s_{zr}, and s_{t0}) were compared between the accuracy and speed

Table 2 Means and standard deviations of estimates for the diffusion model parameters

Instruction	Transition	a		z_r		v		t_0		d		s_{zr}		s_v		s_{t0}	
		M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Speed	Switch	1.28	0.32	.467	.071	1.76	0.50	0.452	0.036	– .040	.110	.288	.134	1.19	0.68	0.193	0.083
	Repeat	–	–	.330	.104	3.21	1.10	0.407	0.040	.053	.103	–	–	–	–	–	–
Accuracy	Switch	1.89	0.32	.469	.072	2.56	0.59	0.502	0.098	.004	.123	.266	.136	1.09	0.54	0.129	0.090
	Repeat	–	–	.591	.212	2.82	1.18	0.404	0.093	– .154	.250	–	–	–	–	–	–

If a parameter was fixed across conditions, the value is presented only in the top row

conditions. As predicted, a difference in boundary separation (a) was apparent between the speed and accuracy conditions [$t(10) = 6.23$, $SE = 0.098$, $p < .001$ (two tailed), $d = 1.88$], suggesting that the subjects were more conservative when accuracy was stressed. No other differences were statistically significant [*t*s < 1.42, *p*s > .187].

The parameters allowed to vary by instruction and transition (v, t_0, d, and z_r) were entered into separate 2 (Instructions) × 2 (Transition) repeated measures ANOVAs, the results of which are reported in Table 3. For starting point (z_r), the effect of instructions was significant and, importantly, the interaction was significant, resulting from a positive effect ($\Delta z_r = .122$) in the accuracy condition [$F(1, 10) = 13.23$, $p = .005$, $f = 1.15$], as compared to a negative effect ($\Delta z_r = -.137$) in the speed condition [$F(1, 10) = 5.36$, $p = .043$, $f = 0.73$]. For drift rate (v), the effect of transition was significant, due to greater drift (faster evidence accumulation) for repeat ($M = 3.018$) than for switch ($M = 2.160$) trials. Importantly, the interaction was also significant, shown by a significant effect ($\Delta v = -1.45$) in the speed condition [$F(1, 10) = 30.84$, $p < .001$, $f = 1.76$], as compared to a nonsignificant effect ($\Delta v = -0.27$) in the accuracy condition [$F(1, 10) = 1.02$, $p = .335$, $f = 0.32$]. For nondecision time (t_0), the effect of transition was significant, with a smaller nondecision time for repeat trials ($M = 0.406$) than for switch trials ($M = 0.477$). This nearly interacted with instructions, with a larger difference in the accuracy condition [$\Delta t_0 = 0.098$; $F(1, 10) = 9.54$, $p = .011$, $f = 0.98$] than in the speed condition [$\Delta t_0 = 0.045$; $F(1, 10) = 70.25$, $p < .001$, $f = 2.64$]. For response execution bias (d), the interaction was significant, because of a negative PoP effect ($\Delta d = -.093$) for speed instructions [$F(1, 10) = 15.53$, $p = .003$, $f = 1.24$] but a positive effect ($\Delta d = .158$) for accuracy instructions [$F(1, 10) = 4.77$, $p = .054$, $f = 0.69$].

Table 3 Results of repeated measures ANOVAs on starting point (z_r), drift rate (v), nondecision time (t_0), and response execution biases (d)

Parameter	Effect	$F(1, 10)$	*MSE*	*p*	*f*
z_r	Instructions	8.22	0.023	.017	0.91
	Transition	0.08	0.007	.784	0.09
	Instructions × Transition	11.65	0.016	.007	1.08
v	Instructions	0.36	1.269	.562	0.19
	Transition	26.34	0.307	<.001	1.62
	Instructions × Transition	8.29	0.458	.016	0.91
t_0	Instructions	1.62	0.004	.232	0.40
	Transition	17.62	0.003	.002	1.33
	Instructions × Transition	3.09	0.002	.109	0.56
d	Instructions	4.54	0.016	.059	0.67
	Transition	0.77	0.015	.400	0.28
	Instructions × Transition	10.12	0.017	.010	1.01

Each mean z_r was compared to .5 (unbiased decisions). For repeat trials, the starting point was significantly less than .5 for speed instructions [$t(10) = -5.39$, $SE = 0.031$, $p < .001$ (two-tails), $d = 1.62$] and nonsignificantly greater than .5 for accuracy instructions [$t(10) = 1.43$, $SE = 0.060$, $p = .183$ (two-tails), $d = 0.43$]. For switch trials, the starting point was nonsignificantly less than .5 for speed instructions [$t(10) = -1.52$, $SE = 0.022$, $p = .159$ (two-tails), $d = 0.46$] and for accuracy instructions [$t(10) = -1.41$, $SE = 0.022$, $p = .188$ (two-tails), $d = 0.42$].

Model fit

Fits were examined graphically. Predicted RT and error distributions were generated for each subject and each condition using the construct-samples routine in fast-dm (Voss & Voss, 2007; Voss et al., 2015). Each subject's model parameters were used to generate separate data sets of $N = 1{,}000$ trials. A total of 11 (Subjects) × 2 (Instructions) × 2 (Transition) data sets were generated, for a total of 44,000 trials.

First, the observed (empirical) proportions of correct responses and M_{RT}s in each of the four conditions were compared against the predicted proportions of correct responses and M_{RT}s (Voss, Rothermund, & Brandtstädter, 2008; Voss et al., 2013; Voss et al., 2004; Voss et al., 2015). Figure 3 plots the predicted values against the empirical values for all subjects in all conditions. Points lie close to the line of perfect congruency, suggesting good fits of the diffusion model and no bias in the predicted data.

Second, quantile–probability (Q–P) plots were constructed by plotting the .1, .3, .5, .7, and .9 RT quantiles for the empirical and predicted distributions against the proportions of

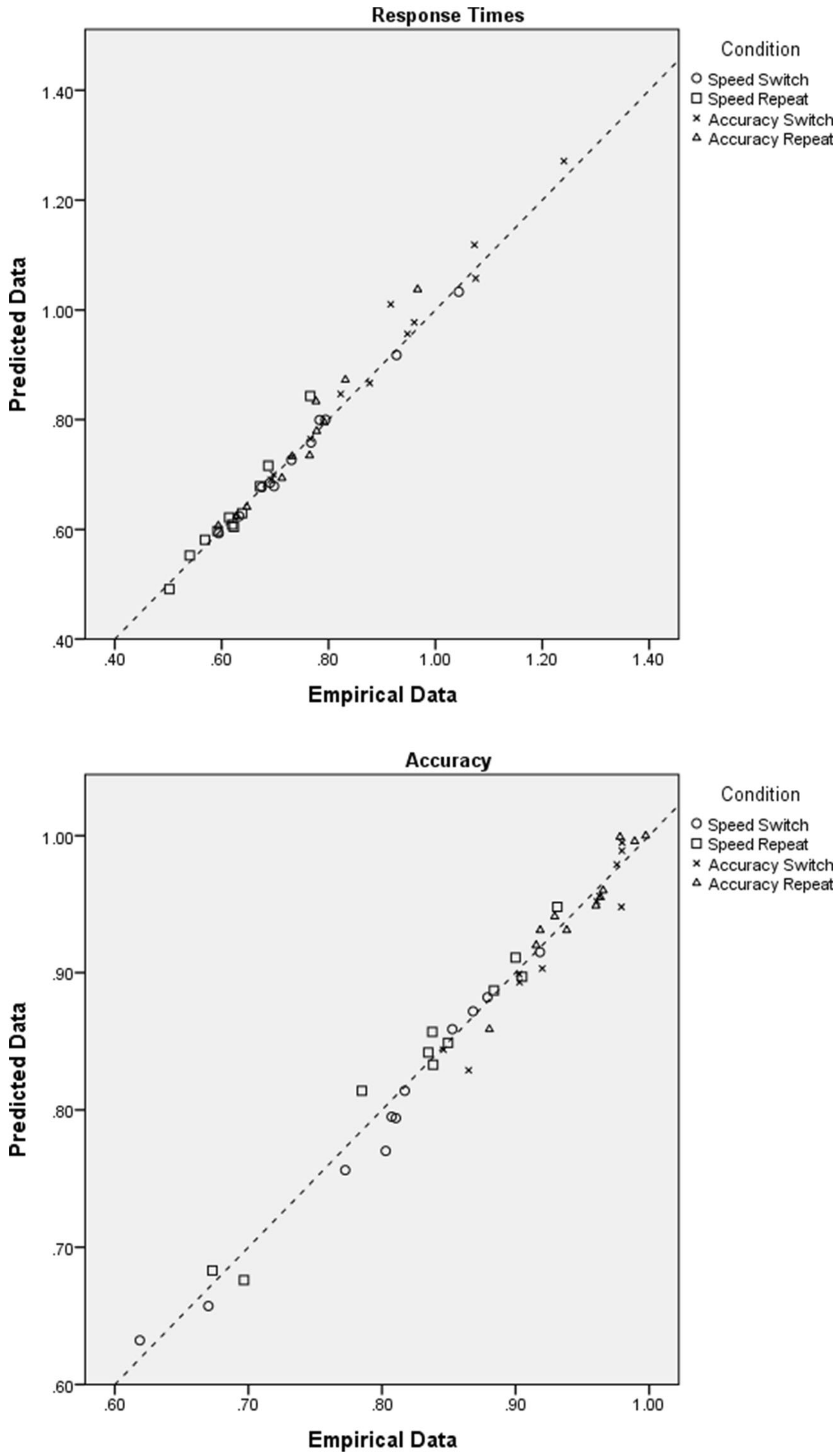

Fig. 3 Individual model fits. The figure displays the relationship between the empirical statistics and the predicted statistics on the basis of fits of the diffusion model. Each symbol represents the mean of a single subject in a single experimental condition. The top panel shows mean RTs, and bottom panel shows proportions correct

correct and incorrect responses (Voss et al., 2015; see Ratcliff, 2002; Ratcliff & Smith, 2010, for explanations of Q–P plots). Figure 4 shows the overall Q–P plot for the experiment, with the empirical quantiles denoted by the digits 1–5 and the predicted quantiles from the diffusion model indicated by lines. As can be seen in the plot, the accuracy of the diffusion model was quite high, with close correspondence between the empirical and predicted quantiles. In short, on the basis of graphical inspection of the empirical and predicted statistics, the diffusion model fit the data quite well.

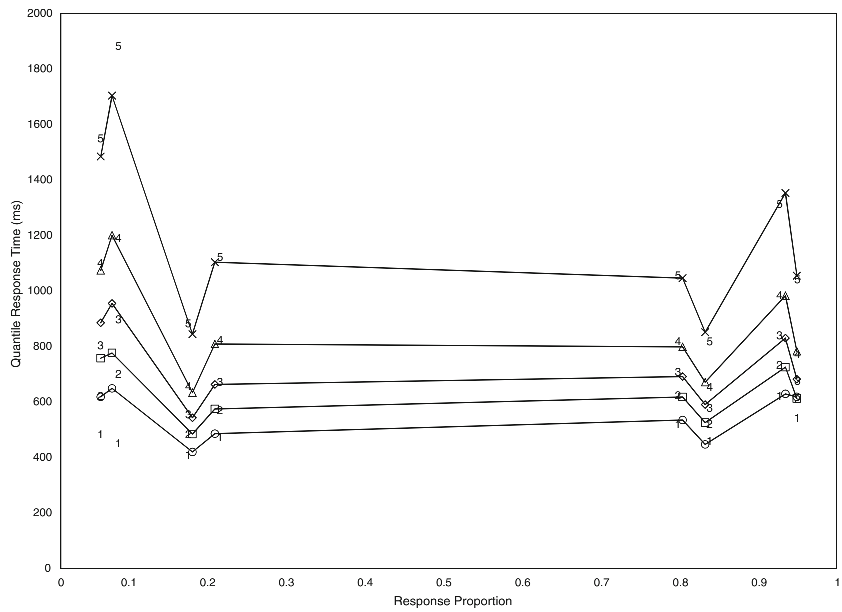

Fig. 4 Quantile–probability plot. The digits 1–5 represent the observed quantile RTs (averaged over all subjects), and the points on the lines are the predicted quantile RTs from fits of the diffusion model

Discussion

This study used a speed–accuracy manipulation in a pop-out search task along with diffusion modeling to examine how selection history biased attentional selection and response execution. Accounts of intertrial priming have proposed that selection history increases feature salience, biases selection, or facilitates response execution, and some have proposed that more than one process is affected by priming. Previously, Tseng et al. (2014) used RDM and found that selection history biased selection of the items most likely to be the target on the current trial. The present study required manual responses to targets—in line with other PoP studies—and using RDM examined how selection history biased response execution in addition to attentional selection. The results supported the predictions made earlier.

First, Δz_r was larger following accuracy instructions, suggesting that a preference for accurate responding increased priming's influence on attentional selection of the likely target—that is, increased the bias to select the most recent target's feature. Second, Δv was greater following speed instructions, suggesting that a preference for fast responding promoted efficient processing of recent target features—whether or not those features distinguished the target on the current trial. Finally, both Δt_0 and Δd were larger for accuracy instructions, suggesting that a preference for accuracy increased the reliance on previous encounters with targets while executing the current response.

These results are consistent with selection history affecting at least two processes: (1) attentional selection of the most recent target's features, and (2) postselection responding. That selection history biased attention toward the target feature can be seen in the PoP effects on z_r and v and the influence of the speed–accuracy manipulation on Δz_r and Δv, because z_r and v reflect bias to select a target and the efficiency of target processing, respectively. Section history's effect on response execution can be seen in the PoP effects and speed–accuracy interactions for t_0 and d. Because t_0 and d are assumed to reflect response execution and bias, respectively, the priming effects on t_0 and d indicate that selection history influenced postselection decisions.

These countervailing effects resulted in no difference in PoP for M_{RT}s between the speed and accuracy instructions, which shows a benefit of diffusion modeling and the analysis of full RT distributions (e.g., ex-Gaussian; Kristjánsson & Jóhannesson, 2014). Analyses of M_{RT}s alone might obscure underlying processes, so by utilizing modeling, the contributions of specific processes can be uncovered. Indeed, modeling may begin to uncover the relationship between bottom-up, top-down, and selection history processes on visual search and selective attention. Although the RDM analyses used in this study suggest that priming influenced both attentional selection and response execution, the results do not rule out the possibility of selection history enhancing the salience of the preceding target color (preattentive account). Neither the experimental manipulations nor the RDM analysis were set up to examine this additional mechanism that may underlie PoP.

In short, the results add to those of studies supporting the position that at least two mechanisms are affected by selection history (e.g., Ásgeirsson et al., 2015; Kristjánsson, 2009; Kristjánsson & Campana, 2010; Kristjánsson, Ingvarsdóttir & Teitsdóttir, 2008; Lamy et al., 2010; Yashar et al., 2013). Importantly, the present study is one of only two that have used diffusion modeling to examine selection history's influence on search. The results replicated and extended those of Tseng et al. (2014) by showing that selection history biased postperceptual response processes in addition to attentional selection. Indeed, the results support those obtained by Ásgeirsson et al. (2015), who modeled search performance on the basis of the assumptions of Bundesen's (1990) theory of visual attention, and concluded that priming influences at least two mechanisms. Thus, during visual search, selection history biases attention to select the likely target, while also biasing retrieval of the most probable response.

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