

Representing color and orientation ensembles: Can observers learn multiple feature distributions?

Sabrina Hansmann-Roth

Icelandic Vision Lab, School of Health Sciences,
University of Iceland, Reykjavík, Iceland



Andrey Chetverikov

Icelandic Vision Lab, School of Health Sciences,
University of Iceland, Reykjavík, Iceland
Donders Institute for Brain, Cognition, and Behavior,
Radboud University, Nijmegen, the Netherlands
Cognitive Research Lab, Russian Academy of National
Economy and Public Administration, Moscow, Russia



Árni Kristjánsson

Icelandic Vision Lab, School of Health Sciences,
University of Iceland, Reykjavík, Iceland
School of Psychology, National Research University
Higher School of Economics, Moscow, Russia



Objects have a variety of different features that can be represented as probability distributions. Recent findings show that in addition to mean and variance, the visual system can also encode the shape of feature distributions for features like color or orientation. In an odd-one-out search task we investigated observers' ability to encode two feature distributions simultaneously. Our stimuli were defined by two distinct features (color and orientation) while only one was relevant to the search task. We investigated whether the irrelevant feature distribution influences learning of the task-relevant distribution and whether observers also encode the irrelevant distribution. Although considerable learning of feature distributions occurred, especially for color, our results also suggest that adding a second irrelevant feature distribution negatively affected the encoding of the relevant one and that little learning of the irrelevant distribution occurred. There was also an asymmetry between the two different features: Searching for the oddly oriented target was more difficult than searching for the oddly colored target, which was reflected in worse learning of the color distribution. Overall, the results demonstrate that it is possible to encode information about two feature distributions simultaneously but also reveal considerable limits to this encoding.

Introduction

Although the natural world around us is highly complex and rich in information, it is not random, but composed of regular and structured information. Our visual field often contains a pool of similar objects like the individual leaves on a tree. This redundant information can be compressed and efficiently encoded as an ensemble. Ensemble perception refers to the visual system's ability to reduce and summarize redundant information and extract compressed, statistical information (e.g., average or variance) of groups of features, like the average hue of the leaves on a tree (Alvarez, 2011; Haberman & Whitney, 2012; Whitney & Leib, 2018). Extraction of summary statistics of groups of objects has been successfully shown for various low/midlevel features like orientation (e.g., Miller & Sheldon, 1969; Parkes, Lund, Angelucci, Solomon, & Morgan, 2001), hue (e.g., Maule, Witzel, & Franklin, 2014; Webster et al., 2014), speed and direction of motion (Watamaniuk & Duchon, 1992; Watamaniuk & McKee, 1998; Watamaniuk, Sekuler, & Williams, 1989), or average size (Ariely, 2001; Chong & Treisman, 2003). Moreover, higher level features like the average gaze direction, the average emotional expression or the average head rotation can also be encoded as summary representations (Haberman & Whitney, 2009). Also, subjects may have a reliable representation of the mean of a set without being able

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to reliably recall individual members (Ariely, 2001; Parkes et al., 2001).

In our daily surroundings objects consist of more than one feature and are characterized by their color, shape, orientation, and even more complex material features like gloss or transparency. Combining several features is a necessary step for building object representations (Treisman, 1996, 1998) and to guide attention in general (see Wolfe & Horowitz, 2017, for a review). Given that summary statistics are an efficient way of representing the environment, it is possible that they are also utilized when several features must be analyzed simultaneously. A few studies have already addressed whether observers are able to precisely report summary statistical information from more than one feature domain. Chong and Treisman (2005) presented observers with two sets of stimuli separated either spatially or by color. Observers could successfully extract average information from both sets simultaneously. The results did not differ by whether the relevant set was pre- or postcued. Attarha and Moore (2015) and Attarha, Moore, and Vecera (2014) corroborated these findings, but they also found that when multiple groups of stimuli were presented simultaneously, judgments of mean orientation were less accurate than for sequential presentation. Emmanouill and Treisman (2008) examined the simultaneous statistical representation of multiple dimensions. They presented observers with moving circles varying in size and speed. Observers were instructed to select the set with either the larger size or faster speed. They were either informed before or after the trial whether to judge size or speed. Performance was worse if observers had to attend to both dimensions simultaneously (postcueing condition). These results were replicated using size and orientation. Although performance was worse, the overall results indicate that summary statistical information of multiple features can be represented.

In the real world, however, feature probability distributions are rarely simple enough to be adequately summarized by mean and variance. This point was clearly demonstrated in Girshick, Landy, and Simoncelli (2011) who extracted local orientation distributions from natural images and found a predominance along the cardinal axes over the oblique angles. But it is still unclear whether observers can simultaneously encode information about different feature distributions over and above the mean.

As Chetverikov, Campana, and Kristjánsson, (2017a, 2018) have discussed, groups of objects have a variety of different features that can be represented as probability distributions that can have varied shapes. But only a few studies have addressed whether observers perceive other statistics such as variance, skewness or kurtosis of visual ensembles. Observers

seem to be able to quickly and accurately compute the variability of features (Atchley & Anderson, 1995; Dakin & Watt, 1997). But feature distributions differing in skewness and kurtosis have not been successfully discriminated. Atchley and Anderson (1995) presented observers with four different clouds of moving dots. In an odd-one-out search task, observers successfully detected the dot cloud that had a different mean velocity or a different variance. However, observers were not able to discriminate between distributions based on different skewness or kurtosis. Dakin and Watt (1997) found similar results for orientation distributions. While observers were able to distinguish between distributions with different means or variance, they were unable to discriminate between differently skewed orientation distributions. Morgan, Chubb, and Solomon (2008) and Norman, Heywood, and Kentridge (2015) argued in favor of an explicit mechanism that estimates variance with neurons broadly tuned to low and high levels of variance. In Norman, et al. (2015) observers adapted to a set of Gabor patches with high and low variance in orientation. Perceptual aftereffects were reported in which the perceived variance of subsequent Gabor patches shifted away from the adapting texture. Although these results show that the mean and variance can be extracted from a variety of different distributions, there was no evidence of the perception of other properties of distributions.

Recently Chetverikov, Campana, and Kristjánsson (2016, 2017a, 2017b, 2018) introduced a new approach for studying internal representations of feature distributions, using priming in visual search (Kristjánsson & Campana, 2010). The well-known “priming of pop out” effect involves a decrease in response time after repeated presentation of target and distractor features (Maljkovic & Nakayama, 1994; see Kristjánsson & Ásgeirsson, 2019 for a recent review). Switching the target and distractor features leads to an increase in response time that is even larger than for new target and distractor features (Kristjánsson & Driver, 2008). If a target is blue and distractors are red, search is slowed down more if the target becomes red than if it would switch to green. Chetverikov et al. (2016) used this role-reversal effect to assess the internal representation of orientation distributions by probing the target at different points in feature space, revealing the internal model of the distractor distributions. Their observers saw search displays containing 36 lines drawn from a predefined distribution and observers searched for an oddly oriented line. After a certain number of learning trials with a constant distractor distribution, the target was placed at different probe points within and around the previous distractor distribution. They found that search time was slower when the target feature was suddenly drawn from within the preceding

distractor distribution, compared to when it was drawn from the feature space outside the preceding distractor distribution. Chetverikov et al. were therefore able to use the target as a probe of the learned distractor distribution. Moreover, they found that response times, as a function of the distance between the learned distractor mean and the target, resembled the shape of the distractor distribution. RT functions that followed Gaussian distractor distributions monotonically decreased, and RT functions following uniform distributions consisted of a flat part followed by a linear decrease. Furthermore, their results revealed that the visual system also encodes skewed feature distributions, resulting in skewed RT functions. Observers needed only a few exposures to the distractor distributions to develop an internal feature representation of them, but the minimum number of repeated search displays needed to encode the distribution depended on its complexity. While two to three repetitions were sufficient for a Gaussian or a uniform distribution, observers needed additional learning trials to encode a bimodal distribution (Chetverikov et al., 2017a). Subsequent experiments showed that a minimum number of exemplars (set size in visual search displays) are needed for robust distribution encoding (Chetverikov, Campana, & Kristjánsson, 2017c). Encoding the shape of feature distributions has been shown to occur for both color (Chetverikov et al., 2017b) and orientation (Chetverikov et al., 2016) separately. That is, while the explicit judgments of summary statistics do not seem to reveal any pick-up of more complex distribution properties (e.g., Atchley & Anderson, 1995; Dakin & Watt, 1997), implicit distribution learning during visual search shows that observers implicitly encode the distribution shape, indicating that the method of probing distribution representations may affect the results.

Importantly, this feature distribution learning occurred for distractors. This suggests that explicitly attending to the stimuli is not necessary for extracting statistical information. For example, Alvarez and Oliva (2008) encouraged observers to find the centroid of a dot cloud, finding that performance was similar when observers attended to the cloud and when they did not. On the other hand, attention may influence statistical estimates such as of the average or may even bias their estimates (Chong & Treisman, 2005; de Fockert & Marchant, 2008). Thus, attention might be important when more than one feature distribution needs to be encoded. Encoding one feature in the presence of a second feature involves selectively attending to that feature. The nature of encoding more than one feature and the interactions between two features was studied intensively by Garner and colleagues (Garner & Felfoldy, 1970; Garner, 1976, 1978; or see Algom & Fitoussi, 2016 for a review). They distinguished between

integral and separable dimensions. Separable dimensions are features that can be attended to without interference from the unattended feature (e.g., color and shape). Integral dimensions are feature dimensions that the visual system cannot selectively attend to without interference from the second dimension; the two seem to be processed together (e.g., lightness and saturation). Moreover, some dimension pairs are asymmetrical integral, where one dimension can be attended to independently of the other, but not vice versa. It remains an open question, however, whether implicit learning of feature distributions is affected by the presence of a second, irrelevant feature distribution.

Current aims

In the current study, we will address whether observers can learn two probability distributions simultaneously using a search task with lines that have a particular orientation and a particular color drawn from Gaussian or uniform distributions. Observers are instructed to either search for an oddly oriented line or for an oddly colored line making only one of the features task-relevant at a time. Firstly, we expect observer to learn the relevant distribution even in presence of irrelevant features. Thus, we expect search times in the test trials to follow the shape of the distractor distribution as shown in previous experiments (Chetverikov et al., 2016, 2017a, 2017b, 2018). However, although we expect them to learn the features that are currently relevant, we do not know whether they can also learn the irrelevant feature distribution and if so, to what extent (mean, variance, distribution shape).

Material and methods

Overview

Observers performed simple visual search tasks, searching for the odd-one-out target among a 6×6 grid of lines. That target line was distinguishable either by color or orientation. We used a similar design as in Chetverikov et al. (2016, 2017a, 2017b, 2017c) by blocking the trials into learning and test streaks. Test trials were used to probe distribution shape learning. Since only one of the two features was task-relevant, this allows us to investigate the influence of the irrelevant feature distribution on distribution learning. Colors and orientations were drawn from either a Gaussian or a uniform distribution. Distribution characteristics (mean, *SD*, and shape) were held constant during learning streaks. In different condi-

tions we tested the influence of a secondary feature and, moreover, also the possible internal representation of that task-irrelevant feature. The detailed procedure and the design of the stimulus display are described below.

Procedure/task

All participants took part in three experimental sessions lasting about 45 to 60 minutes. These sessions were preceded by an initial training session consisting of 288 blocks. Data from this training session was collected, but is not part of the analysis. Each session consisted of 288 blocks, 72 blocks per condition. Each block consisted of three to four learning trials and a single test trial. Participants searched for the odd-one-out target and indicated its position in a search grid. Participants pressed the up-arrow key if the target was positioned in the upper three rows of the grid, and the down-arrow if the target was positioned in the lower three rows of the search grid. The experiment consisted of four different conditions (see Table 1) with respect to which feature was relevant in the search task (learning: orientation; test: orientation; the conditions were the same for color, but there were also conditions in which the feature switched between learning and test trials). However, observers were not aware of which condition was relevant on a particular trial and whether the current trial was a learning or a test trial. Observers were simply asked to search for the oddest looking line.

Stimulus sets were presented for an unlimited time, but participants were encouraged to respond as quickly and accurately as possible. After the button press the next trial began. Feedback was provided throughout the experiment. If observers made a mistake, the word ERROR appeared on the screen for 1 s. For motivational purposes, participants' performance was scored and their score on the last trial was presented in the upper left corner of the screen. The score was computed as $\text{Score} = 10 + (1 - \text{RT}) \times 10$ for a correct response and $\text{Score} = -|\text{Score}| - 10$ for an error, where RT is the response time in seconds. Individual sessions were interrupted by three breaks, in which the total score was displayed on the screen.

Stimuli

Search displays consisted of 36 colored, oriented lines (Figure 1) that appeared on a 6×6 grid that subtended $17.5^\circ \times 17.5^\circ$ of visual angle on the screen. Individual lines had a length of about 1.4° .

The specific orientation and color of each distractor line were drawn from either a Gaussian or a uniform distribution. Orientation distributions had an SD of 15° (distribution range: 60° ; values outside this range of the

	Learning streak (3–4 trials)	Test trial
Condition 1		
Relevant	color	color
Irrelevant	orientation	orientation
Condition 2		
Relevant	orientation	orientation
Irrelevant	color	color
Condition 3		
Relevant	orientation	color
Irrelevant	color	orientation
Condition 4		
Relevant	color	orientation
Irrelevant	orientation	color

Table 1. Overview of all four different experimental conditions and the relevant and irrelevant features during the learning and test trials. *Notes:* A relevant feature refers to a feature that determines the identity of the target. The target could not be identified through the irrelevant feature.

Gaussian distribution were removed). All parameters were based on previous research using uniform and Gaussian distractor distributions of orientation and color (Chetverikov et al., 2016, 2017a, 2017b). All distractor lines on the test trial were drawn from a Gaussian distribution with an SD of 10° . The color space was based on 48 isoluminant (in DKL color space) hues. Adjacent hues were approximately separated by one average just-noticeable-difference, JND (based on data provided by Witzel, from Witzel & Gegenfurtner, 2013, 2015). That is, the color space was perceptually linearized with respect to the average differences in color discrimination thresholds. This color space has already successfully been used to examine feature distribution learning (Chetverikov et al., 2017b). The color distribution during learning streaks was either uniform or Gaussian with an SD of 6 JND and 3 JND during test trials. The distractor mean was chosen randomly at the beginning of a block and kept constant during a learning streak.

The color and orientation of the target were chosen randomly for each trial. The irrelevant target feature was chosen from within the distractor distribution, and the relevant feature was chosen randomly from a range of values with a minimum and maximum distance from the distractor mean (18–24 JND for color, 60° – 90° for orientation). Choosing the feature of the irrelevant target from within the distractor distribution resulted in a target that was undistinguishable from distractors based on that feature, ensuring that only the relevant distribution in each case defined the target. The learning streak was followed by a single test trial to assess the learning of the distractor distribution. We used nine equally spaced probe points to ensure the uniformity of testing with some random variation around each point. Probe points in color space ranged

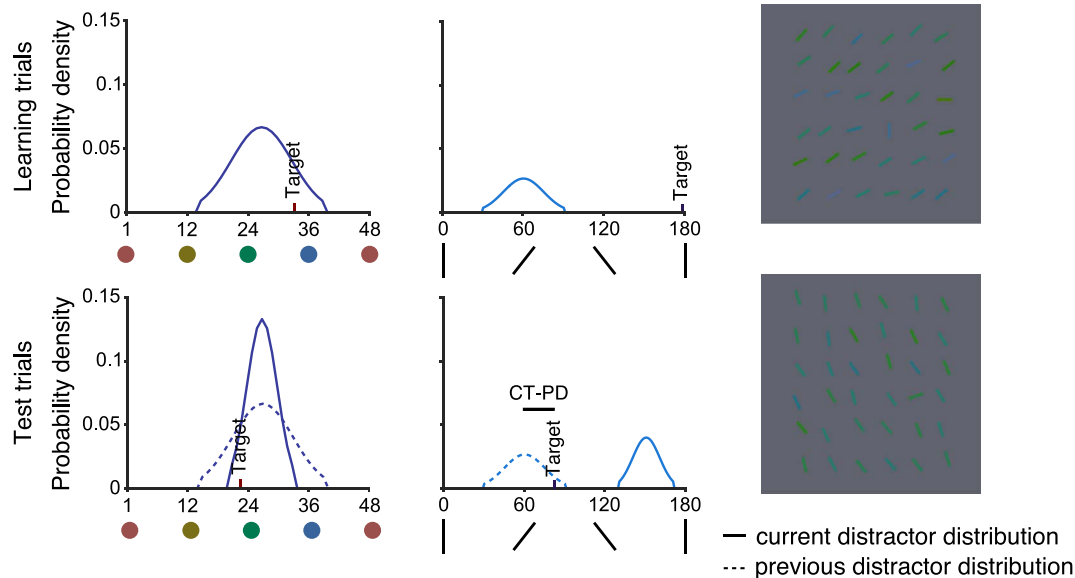


Figure 1. Example of a block in which the distractor distribution of orientation was learned and tested. All features during learning and testing were drawn from a Gaussian distribution. The upper row shows the color and orientation distribution during learning trials and the lower row shows the color and orientation distribution during test trials. The target is distinguishable through orientation only while its color is drawn from within the distractor distribution. The stimulus displays on the right refer to example sets during learning and test trials.

from -24 JND to $+24$ JND relative to previous distractor mean in steps of 6 JNDs with a random value between -3 and 3 added to each probe point. Probe points in orientation space ranged from -80° to $+80^\circ$ in steps of 20° , and a random value between -10° to $+10^\circ$ was added. We refer to this as the current target to previous distractor distance (CT-PD).

The distractor mean during test trials was chosen randomly with the restriction that the target-to-distractor-distance was 18 – 24 JND for color and 60° – 90° for orientation. For the irrelevant feature during the test trial, we used the distribution mean from the learning streak, and the irrelevant feature of the target was again chosen from within the distractor distribution. Figure 1 shows an example of a block where orientation is the task relevant feature on both learning and test trials, and all distractors are drawn from a Gaussian distribution.

Apparatus

All stimuli were displayed on a 24-in calibrated LCD monitor (ASUS, VX248h). The resolution was set to 1920×1080 . All stimuli were displayed using MATLAB (R2016a; MathWorks, Natick, MA) and Psychtoolbox-3 (Brainard, 1997) that ran on a Desktop PC with Windows 10. The screen was color calibrated using a Cambridge Research Systems ColorCal MK2 photometer.

Observers

Ten observers (mean age: 30, five male, five female) participated in the experiment. All observers (except for two authors) were naïve to the purpose of the study and all had normal or corrected-to-normal vision. Participants with red-green color vision deficiencies were excluded through Ishihara plates (Ishihara, 2004) and in a few cases by self-report. They all gave written, informed consent. All experiments were done in agreement with the local ethics committee from the University of Iceland and the Declaration of Helsinki.

Data analysis

Reaction times were log-transformed for the final data analysis. Trials with incorrect responses and the trial immediately following an incorrect response were deleted from the analysis (because of potential posterior slowing). Trials in which search times exceeded the mean response time ± 2 SD were removed. To assess the influence of distribution shape and the effects of repetition within a learning streak, we conducted two-way repeated-measures ANOVAs, with Greenhouse–Geisser corrections, where applicable, after testing for sphericity using Mauchly tests. ANOVAs were conducted in the open source software R (R Development Core Team, 2012) using a random effects model from the *ez* package (Lawrence, 2016). We compared the shapes of the RT CT-PD function using a segmented

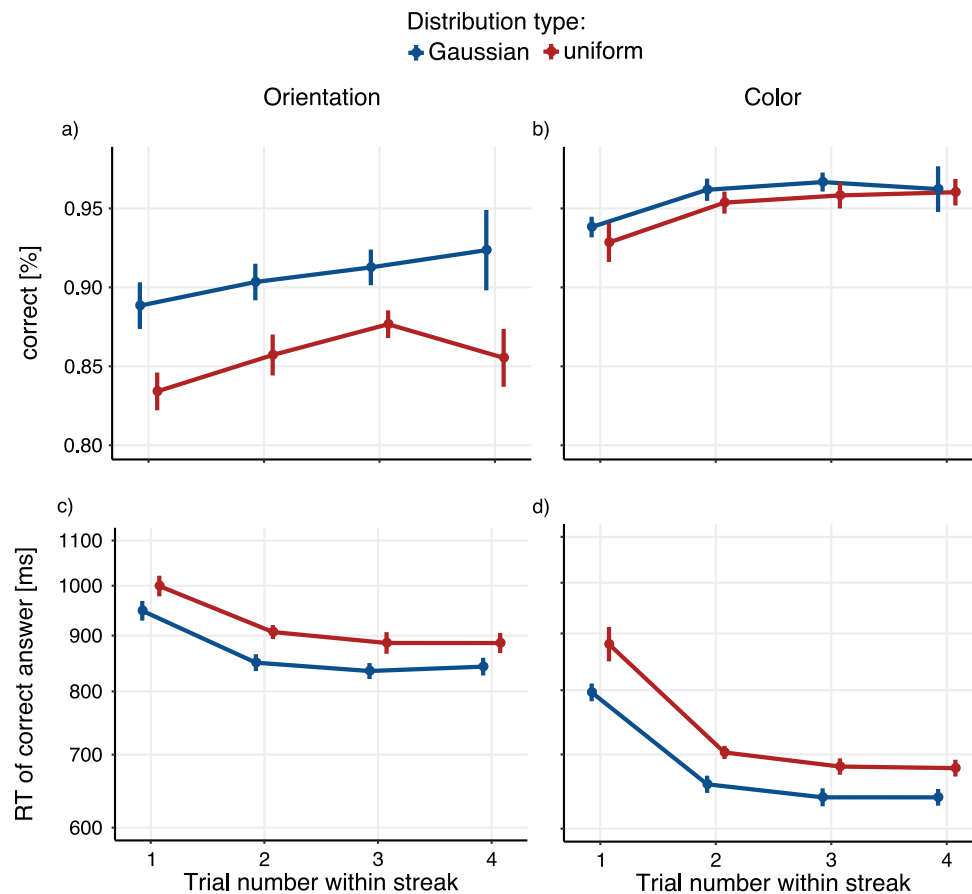


Figure 2. Mean accuracy (upper row) and response time (lower row) across all observers against the trial number within learning streaks and distribution type. (a) and (c) Targets defined by orientation. (b) and (d) Targets defined by color. Error bars correspond to the 95% CI adjusted for within-subject variability (Morey, 2008).

regression in R (Muggeo, 2008). Confidence intervals are presented on the nonlog data, but all statistical tests are done on log-transformed search times.

Results

Performance

During learning trials, search for a target among distractors from the Gaussian distribution was slightly easier than among distractors from the uniform distribution for both features (Figure 2a through d). Observers were faster and more accurate when searching for an oddly colored line among colors drawn from the Gaussian distribution (RT = 730 ms, $SD = 119$, accuracy = 0.96, $SD = 0.02$) than when features were drawn from a uniform distribution (RT = 797 ms, $SD = 148$, accuracy = 0.95, $SD = 0.02$). Search times within a learning streak decreased rapidly after the first repetition (Figure 2b and 2d). A two-factor (distribution shape \times trial number within learning

streak) repeated-measures ANOVA revealed a main effect of distribution shape, $F(1, 9) = 68.9$, $p < 0.001$, $\eta^2 = 0.05$, and a main effect of trial number within learning streaks, $F(1.36, 12.22) = 226.98$, $p < 0.001$, $\eta^2 = 0.3$. We found a small, but significant interaction between the distribution shape and trial number within learning streak, $F(3, 27) = 6.49$, $\eta^2 = 0.003$. Searching for an oddly oriented line yielded similar results. Observers were faster and more accurate when orientations were drawn from a Gaussian distribution (RT = 940 ms, $SD = 166$, accuracy = 0.90, $SD = 0.05$) compared to a uniform distribution (RT = 1002 ms, $SD = 189$, accuracy = 0.86, $SD = 0.06$). Search times also decreased rapidly after the first search trial within a learning streak (Figure 2a and 2c). A two-factor (distribution shape \times trial number within learning streak) repeated-measures ANOVA revealed a main effect of distribution shape, $F(1, 9) = 43.86$, $p < 0.001$, $\eta^2 = 0.03$, and a main effect of trial number in the learning streak, $F(3, 27) = 80.72$, $p < 0.001$, $\eta^2 = 0.084$. We found no significant interactions between the distribution shape and the trial number within learning streaks.

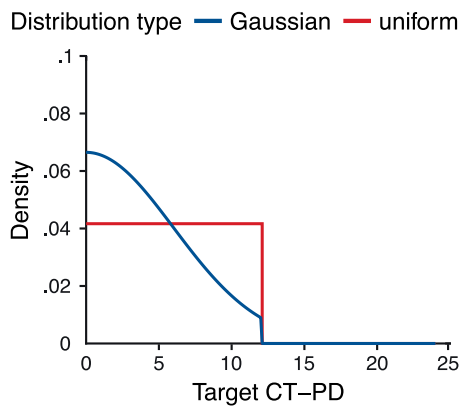


Figure 3. Shape of distractor distributions for color. The two lines correspond to the Gaussian and uniform distractor distribution. Here, we plot only the absolute CT-PD distance since both distributions are symmetrical.

Distribution shape learning

The main goal of the current study was to investigate distractor distribution learning in the presence of a secondary, irrelevant distribution and moreover, to investigate whether any aspects of that irrelevant distribution were also encoded. Previous research has shown (Chetverikov et al. 2016, 2017a, 2017b, 2018) that search times as a function of the distance between the learned distractor mean and the target resemble the shape of the distractor distribution (such as the distributions shown in Figure 3). RT functions that followed Gaussian distractor distributions monotonically decreased while RT functions following uniform distributions consisted of a flat part followed by a linear decrease.

Two main analysis methods have been proven to successfully assess the similarity between the RT functions and the underlying distribution shapes (see Chetverikov, Hansmann-Roth, Tanrikulu, & Kristjánsson, 2019, for an overview of the possible analyses). Firstly, since the Gaussian distractor distribution leads to a monotonic decrease in RT, but the uniform one has a flat part and then a sudden decrease in RT, segmented regression analyses have been used to search for significant changes in the RT function. Previous experiments consistently found a significant breakpoint for the uniform distractor distribution around the “edge” of the distribution whereas there was no breakpoint in the RT functions following a Gaussian distractor distribution. Secondly, RT functions have been tested against models that correspond to actual distribution shapes. Comparing the quality of the fits to the actual data reveals which distribution shape appears most similar to the observed data. If the irrelevant distribution does not hamper the encoding of the relevant one, we expect search times in the test trials to follow the shape of the distractor distribution as

previously shown. However, if the irrelevant distribution is detrimental to the learning of the relevant one, the distinction between the two different distribution shapes might be affected and not even visible anymore. In the following results section, we apply both analysis types to our four different conditions.

Color task

In one quarter of all blocks participants searched for an oddly colored line on both learning and test trials. We expected search times for targets close to the mean of the previous distractor distribution to be slower than search times for targets further away from the mean of the previous distractor distribution (role reversals in visual search). Figure 4a plots search times as a function of the distance between the current target and the previous distractor distribution separately for the two different distractor distribution shapes. Both distribution shapes are reflected in the shape of the RT CT-PD function. Search times for targets within the range of the previous distractor distribution are slower than search times of targets outside the previous distractor distribution. A Gaussian distractor distribution led to a gradual decrease of search times whereas the uniform distractor distribution produced equally slow search times within the range of the distractor distribution and faster search times outside the distractor distribution. A segmented regression confirmed these observations: Search times following the uniform distractor distributions are best described with a two-part linear function with a breakpoint found at around 7 JNDs away from the distribution mean. A Davies test (Davies, 1987) confirmed that the difference between the two slopes was indeed significant, $p < 0.001$ (the Davies test tests the hypothesis that the segmented regression provides a better fit compared to a simple linear model). We tested the slope before and after the breakpoint against zero. The slope, $b = 2.73$, $CI = [-9.72, 15.19]$, of the first part did not differ significantly from zero. The slope after the breakpoint was significantly negative: $b = -11.60$, $CI = [-13.70, -9.51]$. Conversely, search times following a Gaussian distractor distribution did not reveal any significant breakpoints: Davies’ $p > 0.05$. Search times as a function of the target to distractor distance monotonically decreased, and the slope was significantly negative: $b = -9.33$, $CI = [-10.65, -8.01]$.

In addition to the segmented regression we also fitted prespecified models to our data. The prespecified models corresponded to actual distribution shapes: a uniform model with a fixed range of 12 JNDs, a half-Gaussian model with $SD = 6$, a linear model and a “uniform with decrease model,” which contains a flat part within the distribution range and a linear decrease outside the distribution range. Each model includes a

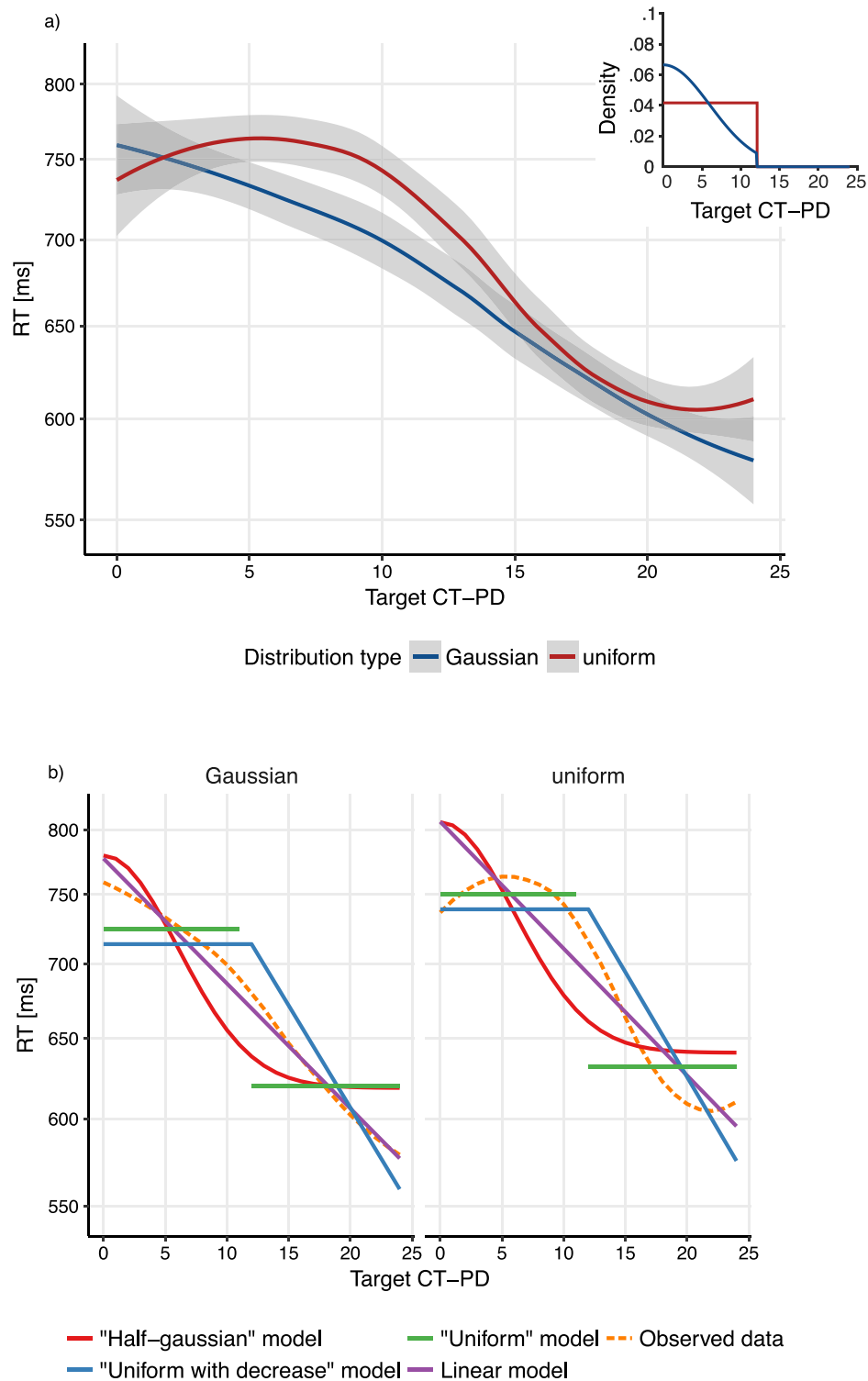


Figure 4. Search time in test trials of condition one, where color was the relevant feature in both the learning and the test trials. (a) Mean response time across all participants during test trials against the distance between the target and the previous distractor mean. Response times include only blocks in which color was the relevant feature on both learning and test trials. Gray areas show the 95% CIs based on fitted loess functions. Each fitted line corresponds to one particular distribution shape. (b) Observed data and modelling fits using maximum likelihood estimation. Observed data are plotted in orange, and the best fit of different models to the observed data is plotted in red, green, purple, and blue.

Gaussian-distributed error term (see Chetverikov et al., 2017b, for equations for the models). We fitted the different models to our data and obtained the best fitting parameters using Maximum Likelihood Estimation and used the Bayesian Information Criterion for comparison. Figure 4b shows participants data and the resulting fits. Following a Gaussian distribution, the best fit we obtained was with the linear model ($BIC = 418.18$), followed by the “uniform with decrease model” ($\Delta BIC = 24.81$). We also fitted the same models to individual participants. Following the Gaussian distribution, the best fit was provided by the linear model ($N = 6$ subjects) and for four subjects the uniform with decrease model provided better fits. Following a uniform distribution, the best fits were obtained with the “uniform with decrease” model ($BIC = 515.33$), followed by the linear model ($\Delta BIC = 2.78$). When the models were fitted for individual subjects, the best fit was provided by the “uniform with decrease” model ($N = 6$ subjects) and for four subjects the linear ($N = 3$) or the uniform ($N = 1$) model provided better fits.

Orientation task

In another quarter of all blocks, participants searched for an oddly oriented line during both learning and test trials. The performance on the orientation task was worse than for color search. Average search times on test trials for the orientation search were 916 ms, $CI = [906, 926]$, while for the oddly colored target they were 743 ms, $CI = [736, 750]$. As in the color search, we expected search times for targets close to the mean of the previous distractor distribution to be slower than search times for targets further away from the mean of the previous distractor distribution. Figure 5a plots search times as a function of the distance between the current target and the previous distractor distribution separately for the two different distractor distribution shapes. Figure 5a shows that both distribution shapes are reflected in the shape of the RT CT-PD function. Search times of targets within the range of the previous distractor distribution were slower than search times of targets outside the previous distractor distribution. A Gaussian distractor distribution led to a gradual decrease of search times whereas the uniform distractor distribution produced equally slow search times within the range of the distractor distribution and faster search times outside the distractor distribution. A segmented regression and modeling analyses confirmed these observations.

The segmented regression showed that search times following the uniform distractor distributions are best described with a two-part linear function. A breakpoint was found around 19 degrees away from the distribution mean. A Davies test confirmed that the difference

between the two slopes was indeed significant, $p = 0.047$. We tested the slope before and after the breakpoint against zero. The slope, $b = 2.49$, $CI = [-2.37, 7.71]$, of the first part did not differ significantly from zero. The slope after the breakpoint was significantly negative: $b = -1.00$, $CI = [-1.59, -0.42]$. Search times following a Gaussian distractor distribution did not reveal any significant breakpoint: Davies test: $p > 0.05$. Search times as a function of the target to distractor distance monotonically decreased. The slope was significantly negative: $b = -0.95$, $CI = [-1.53, -0.38]$.

As previously described for color, we compared prespecified models to actual distribution shapes in our results. We used a uniform model with a fixed range of 30° , a half-Gaussian model with $SD = 15$, a linear model and a “uniform with decrease model,” which contains a flat part within the distribution range and a linear decrease outside the distribution range. Each model includes a Gaussian-distributed error term. We fitted the different models to our data and obtained the best fitting parameters using Maximum Likelihood Estimation and used the Bayesian Information Criterion for comparison. Figure 5b shows participants’ data and the resulting fits. Following a Gaussian distribution shape, both the linear ($BIC = 1096.05$) and the “uniform with decrease” model ($BIC = 1096.04$) provided equally good fits ($\Delta BIC = 0.0039$). We also fitted the same models to individual participants, and for the majority of subjects a Null model provided the best fit ($N = 7$). This suggests that for a majority of participants the orientation search was difficult and did not yield distribution shape learning, or that the results for individual participants contain too much noise. Following a uniform distribution, the best fit was provided by the “uniform with decrease” model ($BIC = 920.44$), followed by the linear model ($\Delta BIC = 2.45$). However, fitting these models to individual participants revealed that again most participants yielded best fits with a Null model ($N = 8$), that does not presume any distribution shape learning.

Distribution shape learning of the irrelevant feature

On 50% of trials the relevant feature for the search task switched from the learning streak to the test trial. The odd-one-out stimulus was an oddly oriented line during the learning streak but was an oddly colored line on the test trial and vice versa. This was a crucial aspect of our design since it allowed us to assess whether observers implicitly learned the statistics of the *irrelevant* feature distribution. Figure 6a shows the response times plotted against the distance between the target on the test trial and the mean of that feature distribution on the learning trials. Figure 6 contains

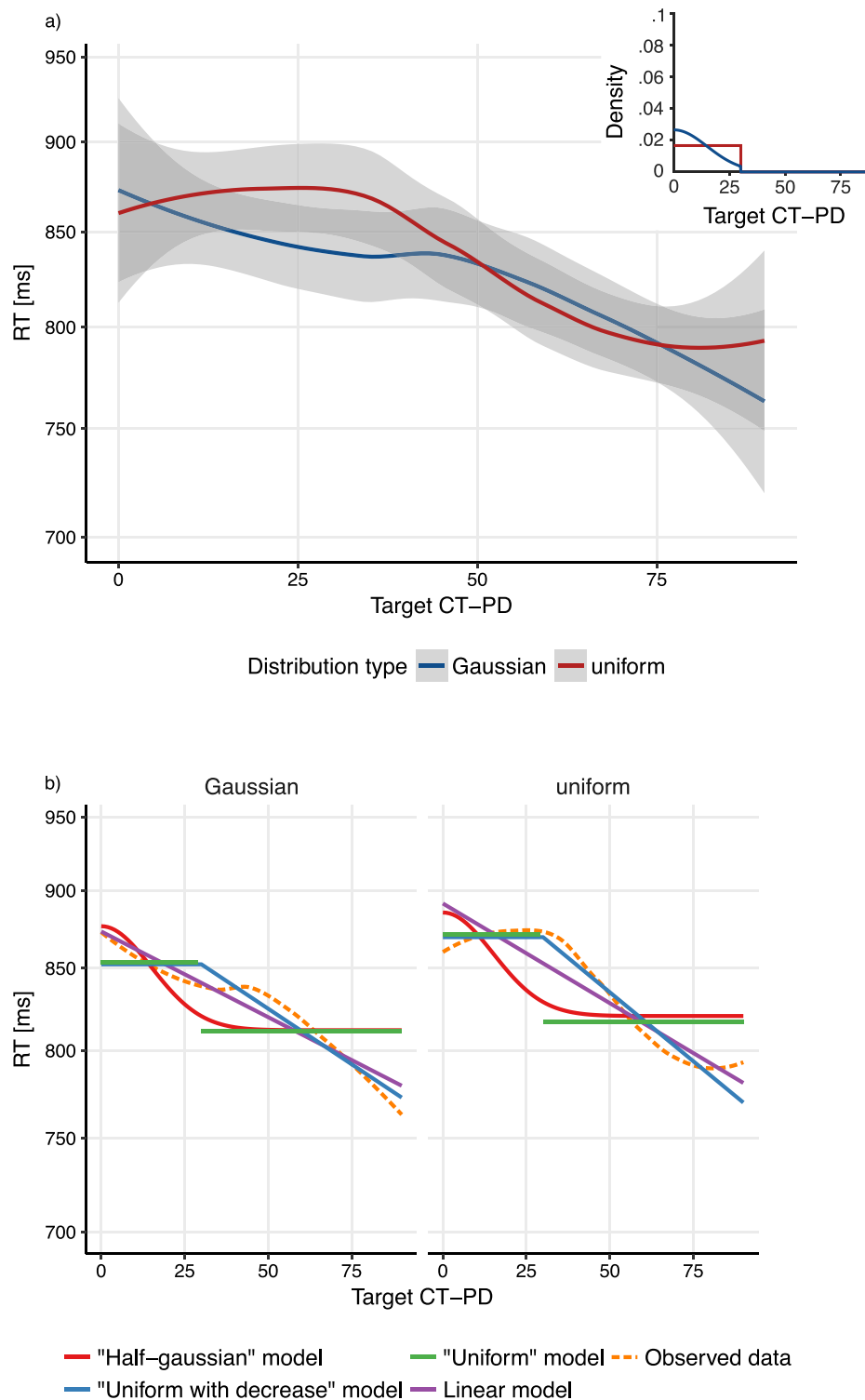


Figure 5. Search times in test trials of condition two. Response times include only blocks where orientation was the relevant feature both on learning and test trials. (a) Mean response time across all participants during test trials against the distance between the target and the previous distractor mean. Gray areas show the 95% CIs based on fitted loess functions. Each fitted line corresponds to one particular distribution shape. (b) Observed data and modelling fits using maximum likelihood estimation. Observed data are plotted in orange, and the best fit of different models to the observed data is plotted in red, green, purple, and blue.

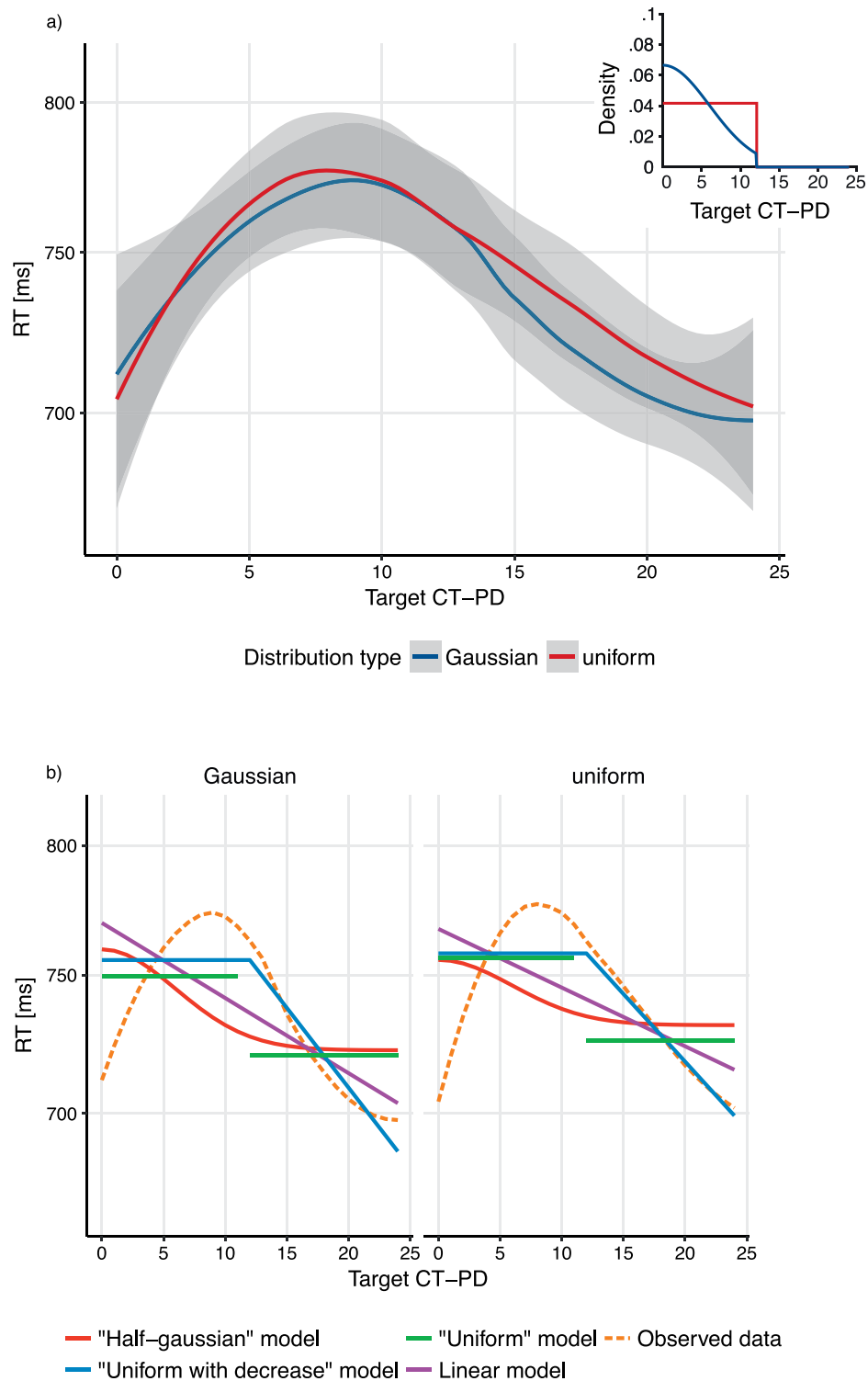


Figure 6. Search times in test trials of condition three where orientation was the relevant feature in the learning streak, and color was the relevant feature during the test trial. Response times include only blocks in which color was the relevant feature during testing but preceded by learning streak in which orientation was the relevant feature (condition three in Table 1). (a) Mean response time across all participants during test trials against the distance between the target and the previous mean of the color distribution. Gray areas show the 95% CIs based on fitted loess functions. Each fitted line corresponds to one particular distribution shape. (b) Observed data and modelling fits using maximum likelihood estimation. Observed data are plotted in orange, and the best fit of different models to the observed data is plotted in red, green, purple, and blue.

only trials of condition three where participants searched for an oddly oriented line during learning streaks and for an oddly colored line during test trials. Overall search times for targets within the range of the previous distractor distribution were slower than search times of targets outside the previous distractor distribution. However, participants also responded faster when the target was close to the mean of that feature distribution in the preceding learning streak.

For both distractor distributions we found a significant breakpoint at around 8 JND (uniform distractor distribution) and 4 JND (Gaussian distractor distribution). A Davies test confirmed that the difference between the two slopes was indeed significant, $p < 0.001$ for both the uniform and the Gaussian distributions. We tested the slopes preceding and following the breakpoint against zero. Following a uniform distribution, the slope, $b = 7.84$, $CI = [-3.52, 19.20]$, of the first part did not differ significantly from zero. The slope following the breakpoint was significantly negative: $b = -4.45$, $CI = [-7.17, -1.90]$.

Following a Gaussian distribution, the slope, $b = 8.49$, $CI = [1.00, 15.98]$, of the first part was significantly positive, and the slope after the breakpoint was significantly negative: $b = -8.49$, $CI = [-11.72, -5.27]$. During learning streaks the color of the lines was irrelevant to the search task, but participants responded faster when the target on the test trials had a color very similar to the mean color of the lines in the learning streak, indicated by the drop in search time close to 0 in Figure 5b (Note that this preceding distribution was not the distractor distribution, since color was not the relevant feature).

Fitting our prespecified models revealed that for a small subset of participants ($N = 4$) the “uniform with decrease” model provided the best fit for both distribution shapes (Gaussian: $BIC = 688.19$; uniform: $BIC = 583.19$), whereas for the remainder of participants ($N = 6$) the null model yielded the best fit, showing that the distribution shape of the irrelevant feature during learning was not encoded (Figure 6).

Figure 7a plots the response time of all test trials where the oddly oriented line was the odd-one-out target, but the test trial was preceded by searches where the oddly colored line was the odd-one-out. The segmented regression did not reveal any significant breakpoints for any of the two distribution shapes: Davies test $p > 0.05$. Following a Gaussian distribution, search times as a function of the target to distractor distance also did not significantly decrease: $b = -0.095$, $CI = [-0.66, 0.47]$. However, we found a significant negative slope for the uniform distribution: $b = -0.61$, $CI = [-1.11, -0.11]$.

Fitting our prespecified models revealed that for all participants except one, the null model yielded the best fit for both distribution shapes (Gaussian: $BIC =$

152.69, uniform: $BIC = -12.48$), showing that the distribution shape of the irrelevant feature during learning was not encoded (Figure 7b).

Discussion

We investigated whether observers would be able to learn a probability distribution of stimulus features in the presence of another, task-irrelevant feature distribution, and whether this task-irrelevant distribution would also be encoded. To this end, we used the feature-distribution learning paradigm introduced by Chetverikov et al. (2016) with stimuli that combined two different features, color and orientation.

The most important result is that feature distribution learning occurs even in the presence of a secondary irrelevant feature. We also found that the color distribution was encoded more precisely than the orientation distribution. Note that this was only noticeable when the models were fitted on individual subjects' data while the group-level performance was similar. This probably reflects the addition of color. Oddly colored lines were apparently more salient than oddly oriented lines in our task and distributions of distractor orientations could seemingly not be processed without interference from the color distribution similar to the description of integral feature dimensions by Garner and colleagues (Garner & Felfoldy, 1970; Garner, 1976, 1978). Integral dimensions are often dimensions that are processed together, but as Garner noted, this is not the case for color and orientation. We therefore speculate that better distribution learning for color reflects that color was more salient than orientation in our paradigm.

Our task was identical to previous orientation search tasks that have revealed learning of distractor distributions (Chetverikov et al., 2016, 2017a, 2017c), except that the color of the lines varied. In these previous experiments the distractor lines were all white. The color differences in the present experiment may have made orientation search more difficult (Figure 8 shows examples of different search displays with homogeneous and inhomogeneous line colors). In agreement with this hypothesis, search times on learning trials were indeed faster in Chetverikov et al. (2016); $RT = 820$ ms, $SD = 106$) than in our experiment ($RT = 940$ ms, $SD = 166$), although comparisons between different studies must be made with caution because of different samples and testing conditions.

Additionally, on a subset of trials we tested participants' learning of the irrelevant feature distribution by switching the relevant target feature between the learning and test trials. This allowed us to assess whether participants also encoded information about

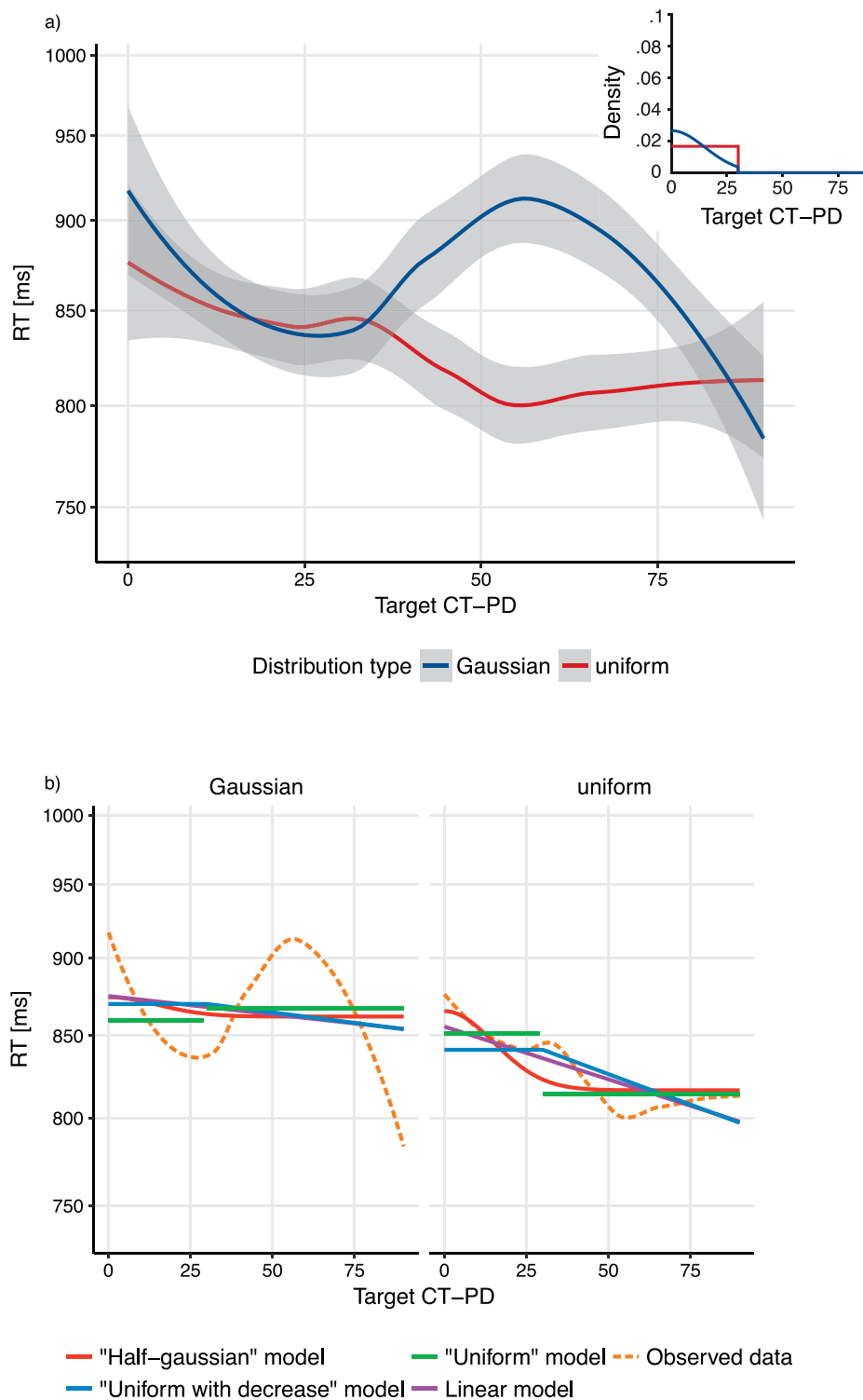


Figure 7. Search times in test trials of condition four, in which color was the relevant feature in the learning streak and orientation was the relevant feature during the test trial. (a) Mean response time across all participants during test trials against the distance between the target and the previous distractor mean. The two colors (red and blue) correspond to the two different distribution shapes. Gray areas show the 95% CIs based on fitted loess functions. (b) Observed data and modelling fits using maximum likelihood estimation. The observed data is plotted in orange, and the best fit of different models to the data is plotted in red, green, purple, and blue.

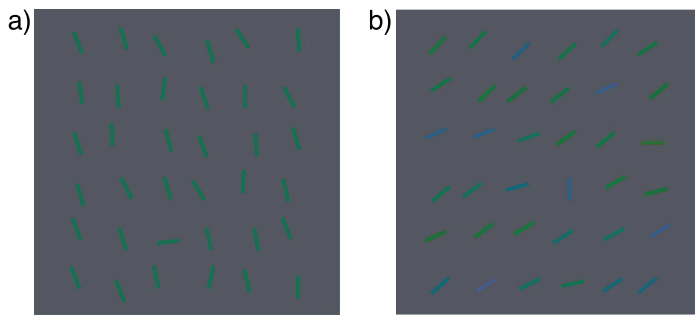


Figure 8. Example of a stimulus set (a) with only a single color and (b) with colors drawn from a Gaussian distribution but orientation is the relevant feature (condition two and three).

that irrelevant feature distribution. For example, consider the case when observers search for an oddly oriented line during learning trials and the color of the lines was constantly drawn from the same color distribution with a mean color of green similar to the search display in Figure 8b. This color distribution defines both the distractor and target colors. For color we found significant breakpoints using a segmented regression. For the Gaussian distribution we even found a positive slope for small CT-PD distances, indicating that search times were lower for colors close to the mean of the previous distribution and far away from the distribution mean. Participants found the oddly colored line faster when the color of the line was similar to the mean color of the lines during learning trials. During learning trials, participants were repeatedly exposed to the same average line color (green in our hypothetical example). These faster search times on the test trials might therefore be a result of priming. The mean of a Gaussian distractor distribution corresponds to the color that is the most probable color in stimulus set. This suggests that participants were primed by the repeated exposure to the same average color green, and if on a subsequent trial the target was distinguishable from its green color, participants responded faster than for a different color. Observers were also faster when the target was furthest away from the previous distribution mean. In that case the target color was very different from the distribution mean on the learning trials. But in that case the distractors were close to the previous mean. Given that the difference between target and distractor mean varied between 18 and 24 JND (in color space), the distractors on the test trials in our hypothetical example would most likely be greenish if the target color was far away. This means that although color was not relevant during the preceding learning trials, some statistical information was still encoded. However, this information was associated both with the target and the distractors, presumably resulting in either target priming or distractor priming (Kristjánsson & Driver, 2008).

Bronfman, Brezis, Jacobson, and Usher (2014) and Ward, Bear, and Scholl (2016) showed that during a modified version of the Sperling partial report task (Sperling, 1960), subjects reported letters of cued rows, but were also able to recall the color diversity of noncued rows. They concluded that participants still encode statistical information like color diversity even in the absence of focal attention. Although it is unclear whether the representation of the colors was conscious, these findings clearly demonstrate an ability for representing summary statistical information of colors outside the focus of attention and even with only a coarse representation of individual items (Ward et al., 2016). However, in both studies, judging the color diversity was part of the task, and participants might have split their attention between the different rows of colored letters. Conversely, in our study, participants were unaware of the structure of the experiment (learning and test trials). And although only orientation was task relevant in this part of the experiment, we still found learning of the average color of the lines, indicating that even in the absence of attention and task relevance, information about ensemble statistics can be processed and represented.

Conversely, our data shows that the irrelevant orientation distribution was not encoded. For the encoding of the relevant distribution of distractor orientation, we found worse learning at the individual-level analysis compared to color. It is therefore unlikely that the orientation distribution is encoded if it is not relevant to the search task.

Our results also seem to indicate that the unicolored oddly oriented line pops out more easily than the oddly oriented line among differently colored lines. Previous research has shown that extracting summary statistical information from sets of stimuli is easier during pop-out searches that presumably involve more global attention. Chong and Treisman (2005) combined two different tasks: Participants initially performed either serial search (closed circle among open ones) or parallel search (open circle among closed ones). In a subsequent task, observers were presented with two test circles and either performed a member identification task or a mean discrimination task. They judged which test circle corresponded to the mean size of the circles, and in the member identification task, they decided which test circle had been presented at a particular location on the screen. The results showed that performance on the mean discrimination task was better if it was preceded by a parallel search task that allows more global attention than a serial search task. Performance in the member identification task was, on the other hand, better if it was preceded by a serial search task that requires more local attention. Consistent with this, De Fockert and Marchant (2008) found that attention can bias average size estimates.

If the colored lines prevent parallel search and participants instead have to apply more local attention and serially search for the target, this may inhibit the distribution learning. Similar to the results earlier described by Chong and Treisman (2005), orientation distribution learning might have been affected by locally applied attention which was needed to find the target. Although research has shown that attention is not a necessary prerequisite for ensemble perception, attention does, however, modulate summary statistical representations (see also Haberman & Whitney, 2011). Our results therefore may suggest that attention also modulates learning of more complex properties of feature distributions.

Search times for an oddly colored target were similar to those in our previous experiment with color singletons (Chetverikov et al., 2017b). Speculatively, this suggests that search for a color pop-out was not affected by the orientation of the lines and the oddly colored line popped-out independently of its orientation. Mean RT's during learning trials were even faster than in Chetverikov et al. (2017b). However, the task in the previous work was different since we only asked participants about the position of the target. In Chetverikov et al. (2017b) the task was to find the target and then report its shape.

Overall, our results show that distribution learning in the presence of other features is possible. However, they also reveal that distribution learning differs between the two tested features. Seemingly, the colored lines prevented the oddly oriented target from immediately popping out, and observers were therefore unable to encode information about the irrelevant feature distributions. How more complex object properties are encoded that actually consist of multiple components like the color and the transmittance of a transparent object remains to be studied.

Conclusions

Our results show that feature distribution learning can occur in the presence of a secondary feature. But the results also highlight how distribution learning is modulated by the salience of the items. More specifically, if the colored lines prevent parallel search and participants instead have to apply more local attention and serially search for the target, distribution learning is diminished. Attention also seems to modulate more complex distribution learning. Although only a single feature was relevant for the search, we still found learning of some summary statistical information of the color of the lines, indicating that even in the absence of attention and relevance, statistical information can be represented. It remains to be studied whether other

combinations of features would yield similar results. Other feature distributions that do not influence pop-out or saliency might be encoded without interference from a secondary feature if the features are separable (Garner & Felfoldy, 1970; Garner, 1976, 1978). Moreover, how multiple feature distributions interact for integral features that are processed together like lightness and saturation or lightness and hue remains an open question.

Keywords: ensemble perception, statistical learning, perceptual learning, perceptual organization

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Corresponding author: Sabrina Hansmann-Roth.

Email: sabrina@hi.is.

Address: Icelandic Vision Lab, School of Health Sciences, University of Iceland, Reykjavík, Iceland.

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