Encoding target distributions

Perceptual Learning of target probability distributions

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Lokaverkefni til BSc- gráðu í Sálfræði

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Abstract

The goal of this study was to investigate whether people are able to encode the probability distribution of targets in a visual search task and moreover, whether these encoded probabilities affect the strength of priming visual search. Participants saw a set of coloured diamonds with one corner cut off and searched for the diamond with the most distinct colour.The colour of the target diamond was drawn from either a uniform or a normal colour distribution with a predefined mean and variance over the course of separate blocks consisting of 144 trials each. Targets had various distances from the mean of the target colour distribution. Response time could therefore be used to reveal participants' internal probabilistic representations of target colours. We did not see a clear monotonic increase in search time as function of the decreasing probability in the normal distribution, as was expected. However, the results show that difference in response time for different distances between current target and the mean target of the target distribution is dependent on distribution shape. Thus, the results suggest that subjects were able to learn the shape of the target distribution.

Table of contents

1 Visual search

When searching for a particular object in space we engage in visual search. This is a common behaviour and humans normally engage in visual search on a daily basis. From foraging for food to looking for a specific item in a supermarket visual search has been a vital behaviour throught evolutionary history. Evidently, visual search is greatly involved in human life and it‘s exploration can offer a considerable understanding of the visual system.

Our natural environment is extremely rich with different features and colors and therefore searching for relevant information can be cognitivively demanding. Research on visual search has identified two main mechanisms that facilitate search, i.e., suppression of information that is irrelevant to search (i.e. distractors) and enhancement of relevant information (i.e. targets). E.g when looking for a friend in a crowded place you utilize the fact that he is wearing a blue sweater. During search you filter out people wearing sweaters that do not match the color of your friends and your attention is drawn to people wearing sweaters that are similar to your friends in color. This makes searches amongst a complex array of stimuly faster and more efficient (Caputo & Guerra 1998; Awh, Matsukura, & Serences, 2003; Bar et al., 2006). Visual search studies suggest two types of searches: feature and conjunction search.

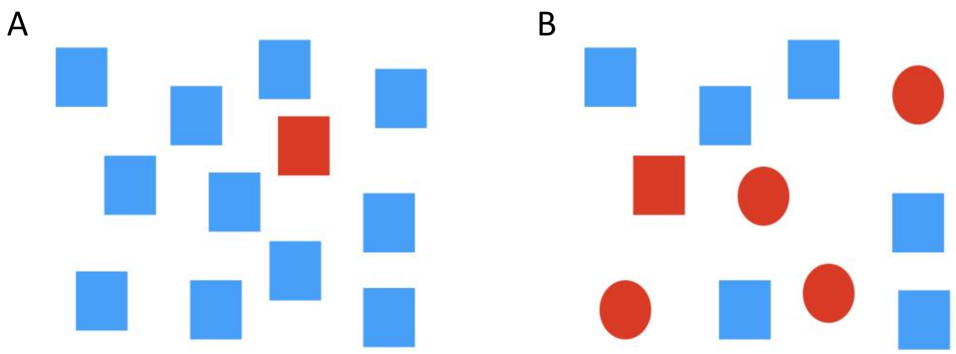

Figure 1. Example of feature and conjunction search task. A) Feature search task, The red box (target) is found easily and ‘‘pops out‘‘ amongst the blue boxes. B) Conjunction search, finding the red box (target) is more demanding and detection time increases.

These two searches differ in their level of processing, were feature search happens at an early preattentive level of processing but conjunction search a later stage where a more focused attention is required. Feature search (Figure 1a) is a rapid analysis of the visual field using parallel processing. In feature search the target differs form the distractors by a simple visual feature (e.g., color, orientation, shape) and a phenomenon refered to as ‘‘pop-out‘‘ occurs where the uniqe visual target can be found rapidly among a set of distractors. Conjunction search (Figure 1b) is a more effortful analysis used when the target shares a feature with all distractors, but differs by a unique combination of features (Treisman, 1985). Visual search experiments usually measure target detectability in terms of response time. In feature search response time and accuracy is independent of the number of distractors. However, in conjuntion search, increasing distractors result in longer response time and is more prone to errors (Treisman & Souther, 1985; Wolfe, 1994).

Studies on visual search have demonstrated that the similarity between distractors affects search time. Treisman (1988) conducted a study where the same target appeared inconsecutive trials but distractors varied. When distractors were heterogeneous response times were longer than when distractors were homogeneous. Additionally, discriminability of targets and distractors appears to have an effect on visual search performance. As target-distrator difference declines search becomes less efficient (Pashler, H. 1987). Repetition of location or particular properties of a target results in faster search (Treisman, 1992). This phenomenom is know as priming.

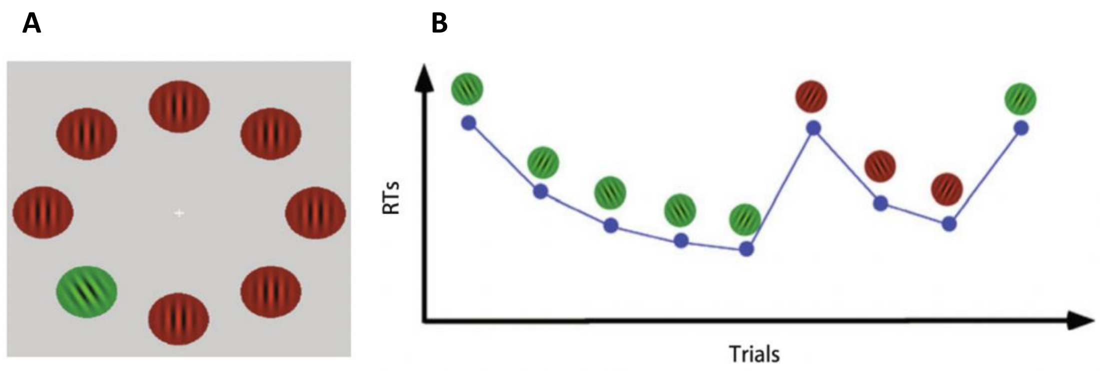

Figure 2. An example of priming in visual search task. A) A visual serch task where subjects find the oddly colored circle indicate whether it is tilted to the right or left. B) Illustration of the changes in response times(RTs) as the target color is either repeated across trials(shown from the left to right), or changed. (Figure taken from Kristjánsson & Campana, 2010)

In a visual search task, when a target feature or spital location is repeated across trials performance gets better versus when the target changes. For example, as seen in Figure 2b search is facilitated as the target color green is repeated across trials. When the target color changes to red search is slowed but then improves as red target color is repeated. Effects of priming have been discoverd in feature search tasks and in conjuntion search as well (Kristjánsson & Wang 2002; Maljkovic & Nakayama, 1994). More recently Kristjánsson & Driver (2008) results suggested that priming effects occur for non-target repetition and that role-reversals impact performance in visual search as well. In role-reversals a target on a trial becomes a distractor on the next and vice-versa. Their study demonstrated that when e.g. a green item that serverd as a distractor on a previous trail becomes a target search time is slower than if the target becomes blue. Later Chetverikov, Campana & Kristjánsson (2016) discovered a way to utilize this phenomenon for studying ensemble representations.

2 Ensemble representation

In our daily life we encounter a stream of visual information, however visual working memory capacities are limited and can only hold a limited amount of information at once. Given the limited capacity of our visual system it is impossible to attend to every visual feature. However, our world is highly structured and contains natural images that are regular (e.g. in color) and predictable (Webster, 1997; Kersten, 1987). This makes it possible to counteract our capacity limitation by exploiting regularities in the world and making inferences from partial data. This ability to compute a summary or statistical representation from multiple measurements has been called ensemble representations. Ariely (2001) found that when looking at a set of different sized spots for 500 ms. Humans can be quite precise in encoding information about mean but storage little information about individual items. Furthermore, research has shown that humans have the ability to encode measures of central tendency for orientation, location but also more complex features like emotions (Ariely, 2001; Haberman, 2007). Research on higher order statistics has suggested that humans can encode the variance of distributions (Norman, Heywood & Kentridge, 2015; Morgan, Chubb & Solomon, 2008) Atchley & Anderson (1995) illustrated that observers could reliably detect differences in mean and variance of moving dots that had particular velocities drawn from particular distributions. However, their study suggested that people are not able to detect differences in either kurtosis or skewness of the distributions. Similarly, research by Dakin & Watt (1997) suggests that the variance of orientation is encoded but not skewness. In sum, research has demonstrated that people can detect the mean and variance of distributions, but it is less clear whether more complex information like kurtosis, skewness and therefore, the distribution shape isencoded.

Chetervikov, Campana & Kristjánsson (2016) used priming to look into higher order statistics like distribution shape. Priming in visual search can reveal implicit expectations. The appearance of a target with unexpected features results in slower RTs but when a target has expected features RT's get faster, RTs can then be used to assess observer's expectations. Furthermore expectations can reveal people's internal representations of stimuli. Acknowledging this Chetverikov, Campana & Kristjánsson (2016) developed a new more precise approach for studying internal ensemble representations by exploiting the effect of role-reversals and ''pop-out'' in visual search. Observers searched for an oddly oriented line among a set of distractors.

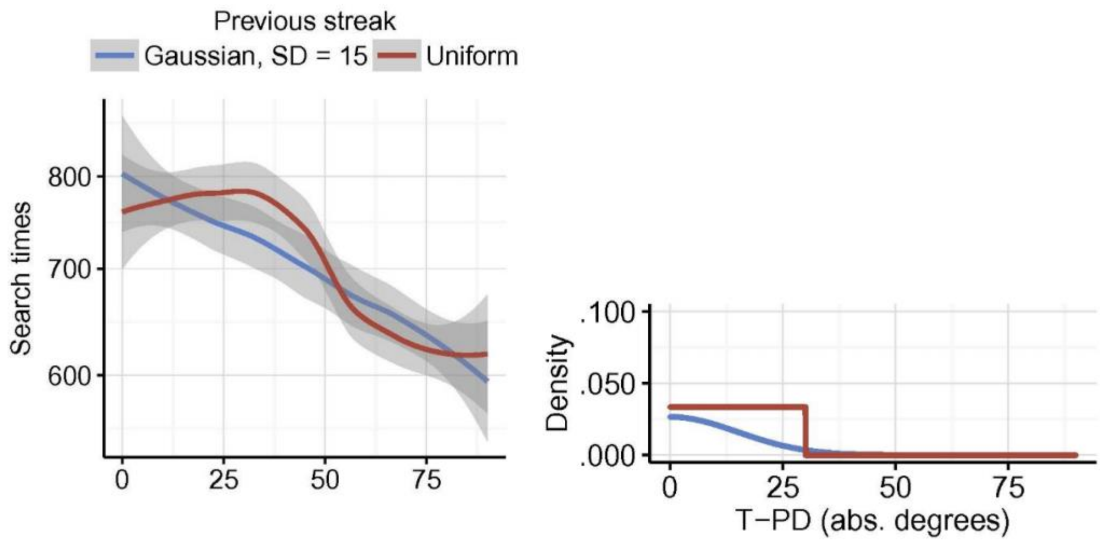

Figure 3. Response times as a function of the distance of the between current target and previous distractors mean. 95% confidance intervals based on local regression fit are shown in the shaded areas (Left). Probability density function of the previous distractor distribution (right) (Figure taken from Chetverikov et al. 2016)

Trials were grouped into blocks, with each block consisting of five to seven trials. During each block, mean, distribution shape (uniform or caussion) and standard deviation of the distractor distribution were held constant. For each trial, distractor orientations were drawn randomly from the current distribution with preset parameters. Observers completed a few learning trials followed by a testing trial were the target was placed at a pre-defined position. During testing trials RTs followed the shape of the preceding distractor distribution (Figure. 3). Therefore, by manipulating the distance between the target and distractor distribution in the previous block they demonstrated that people are able encode the shape of distractor distributions. This pattern has been shown for Normal, uniform, skewed and even bimodal distributions (Chetverikov, Campana, & Kristjánsson 2016; Chetverikov, Campana, & Kristjánsson 2017). To answer the question whether the internal representations of feature distributions generalizes to other features like color, Chetverikov Campana & Kristjánsson (2017) conducted a study to investigate color ensembles using the same approach to assess distractor representations as in their previous research on orientation. Participants looked at a set of colored diamond’s and searched for the diamond with the most distinct color. Forty-eight isoluminant hues from the DKL color space were used, and colors were drawn from either uniform or normal color distribution. Response times followed the same shape as in the preceding distractor color distribution. The results demonstrate that just as for more low-level stimuli such as orientation, the visual system is able to encode the shape of the distractor distribution of colors. However, Tran, Vul & Pashler (2017) recently conducted an experiment on distributional learning of targets. Their results suggests that observers do not implicitly learn complex distributions, and only when distribution is made extremely apparent can observers learn the underlying distribution shape. However, their study differs from the Chetverikov et al. (2017) study in showing only one item (the target) from the distribution at a time. This makes it more difficult to compute a summary or a statistical representation because subjects have to remeber indivudal items and put the into a distribution. In sum previous research on ensemble statistics has indicated observer's ability to encode complex information about feature distributions for distractors, however a number of questions regarding the visual system's ability to extract summary statistics for targets remain to be addressed. Geng, Behrmann (2002, 2005) have shown that people are sensitive to the probabilities in target location. By manipulating the probability of a target appearing in a particular location their research has shown that, when a target has a high probability of appearing at particular location search gets more effecient when the target appears in that location. In this thesis we are investigating the visual system's ability to encode the shape of target distributions. Utilizing Chetverikov Campana and Kristjánsson's approach we conducted a visual search experiment to assess whether target probability for colors is encoded over the course of a block. While Chetverikov et al. (2017) were interested in the encoding of the distractior distribution, our focuss is on the learning of target distribution. The study constists of a small pilot study and one main experiment. The aim of the study is the assess whether priming is affected by the shape of the target distribution. We hypothesize that RTs for uniform target distribution will be same for all distances between the mean color of the distribution and the current target color, since each color has the same probability to appear. And RTs for a normal distribution to reflect the distribution shape: faster searches for highly probable targets and slower searches for less probable target colors.

3 Experiment 1

The first experiment was a small pre-experiment to test some initial parameters, like set size, mean search time for each distance and whether target probability would be encoded over the course of a block.

3.1 Methods

3.1.1 Participants

Four Participants (3 men and 1 woman, age M=23.8) took part in a two session experiment, each session lasting about 25 minutes with the interval of at least 1 day between the sessions. Participants signed informed consent and did not receive payment for participation. All participants were pre-screened for color blindness using Ishiara plates.

3.1.2 Apparatus and Procedure

Participants sat in a darkened room in front of a 24-inch Asus VX248h display with a refresh rate of 60 Hz, 1920x1080 pixel resolution and a viewing distance of 57 cm. The software used to run the experiment was MATLAB 2016a using the Psychophysics Toolbox 3. The task was an odd-one out visual search. Participants viewed a set of either four or 12 diamonds which all had one corner cut off (Figure 6). The sessions were counterbalanced so that one half of participants did the set of 4 diamonds first and other half did the set of 12 diamonds first. The position of each diamond was selected randomly each trial based on an invisible underlying 6x6 grid. 48 isoluminant hues arranged in the Derrington, Kraufskopf, and Lennie (DKL) color space were used for the study (Figure 4). Adjacent hues on the DKL color space are separated by one just-noticable-difference (JND) unit, accordingly to data provided by Witzel and Gegnefurtner (2013, 2015) on group-average JNDs.

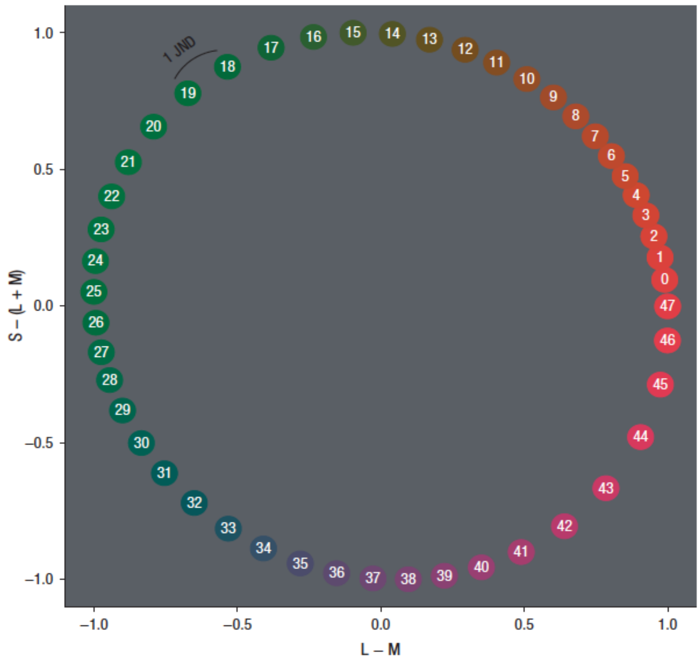

Figure 4. Hues arrenged in the Derrington, Kraufskopf, and Lennie (DKL) color space. Adjacent hues are separated by one just-noticable-difference (JND) unit (Figure taken from Chetverikov et al. 2017)

The task was to find the diamond (target) with the color that differed most from the others (distractors) and report the position of the cut-off corner, using the arrow keys on the keyboard (left/right, top/bottom). The experiment had 12 blocks and each block consisted of 144 trials. Stimuli appeared on the screen and lasted until the observer made a response. During each block (144 trials) the parameters of the distractor and target distribution (mean, SD and shape) were held constant. For each block the target distribution mean was selected randomly among a set of six equally spaced colors in the DKL-color space (Colors 0, 8, 16, 24, 32 and 40 in Figure 4).

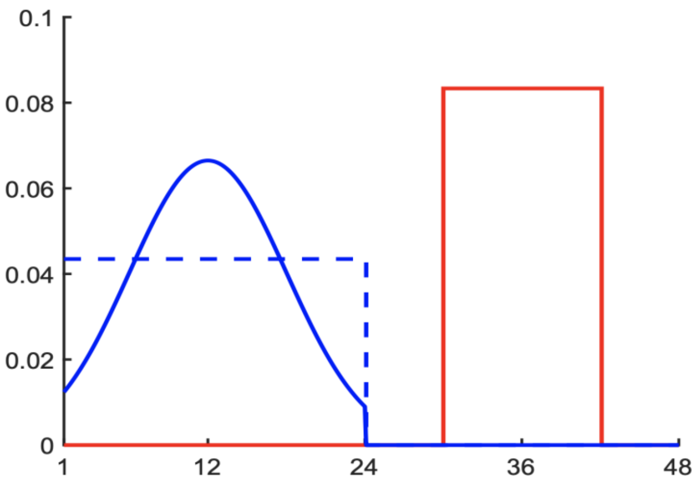

Figure 5. An example of how target color and distractor colors are selected. The *x*-axis represents the probability of a target accuring. The *y*-axis represents colors in the DKL-color space. The target distribution mean is 12(left curve), the target color for each trial is then randomly drawn from that distribution where the probability for each color corresponds to the shape of the normal distribution curve. The distractor distribution mean is 36 (right curve),as the uniform curve showes, all distractor colors have the same probability to appear

The target color was then drawn randomly from either a uniform distribution or a normal distribution with the range of 24 JND and a standard deviation equal to 6 JND's. The distractor distribution mean was set to the opposite side in color space to the target mean (target distribution mean and distractor distribution mean always differed by 24 JND's) and colors were always drawn from a uniform distribution with the standard deviation of 2 JND's. Participants had unlimited decision time but were asked to respond as accurately and quickly as they could. For motivational purposes participant received feedback during the experiment. When a participant answered incorrectly the word ''ERROR'' appeared on the middle of the screen for 1s before the next trial. In the upper left side of the screen participants received information on the current trial number, total number of trials and a live feedback on their score, appearing green for fast and accurate response and red for errors and slow response time (Figure 6).

Figure 6. An example of a trial with a set size of four: one target (pink diamond) and three distractors (all other diamonds), as well as participants feedback during the experiment.

3.2 Data analysis

Mean seach time was calculated for each subject. RTs that deviated from participants overall mean by +/-2 standard deviations were exluded from the data. This was done to exclude trials were subjects made unusual slow responses or pressed the button twice by accident. For the RT analysis wrong responses were excluded. We expected a post-error slowing effect and therefore, responses that followed a wrong response were excluded as well.

4 Results.

In the pilot-study we tested whether set size would have an affect on search performance and if target probability would be encoded over the course of a block. If subjects can learn the target distribution we expected RT‘s for the uniform distribution to be flat and RT’s for the normal distribution to increase monotonically as the distance between target and the mean of the current target distribution increases (so called CT-CTM distance).

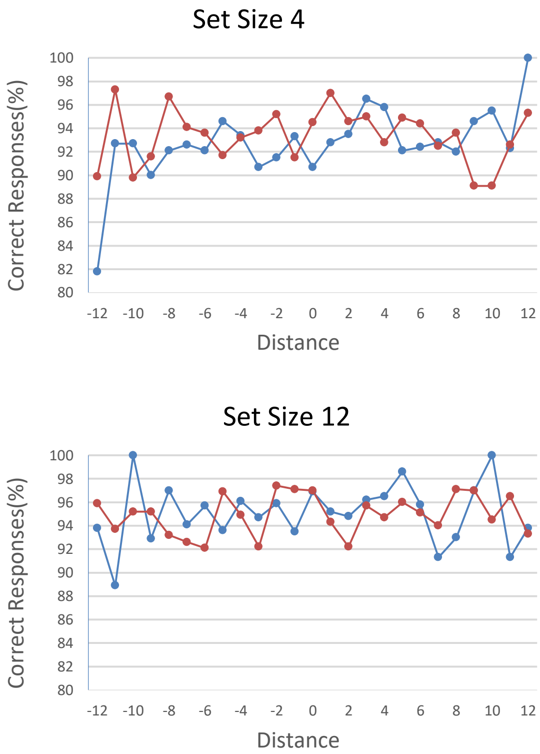

Figure 7. Mean precentage of correct responses as a function of CT-CTM distance and distribution type (Normal vs uniform) for set sizes 12 and 4. The *x*-axis shows distance between the current target and the mean target of the target distribution (We will refer to this as CT-CTM distance in the rest of the paper). Error bars are omitted due to the small number of data points.

As shown in Figure 7 the mean precentage of correct responses is scattered and did not follow the anticipated pattern. For both set sizes, the precentage of correct responses did not seem to depend on the CT-CTM distance, and there is no noticeable differences in mean percentage of correct responses between a normal and uniform distribution, for either set size. Overall performance was high so the task did not appear to be too difficult.

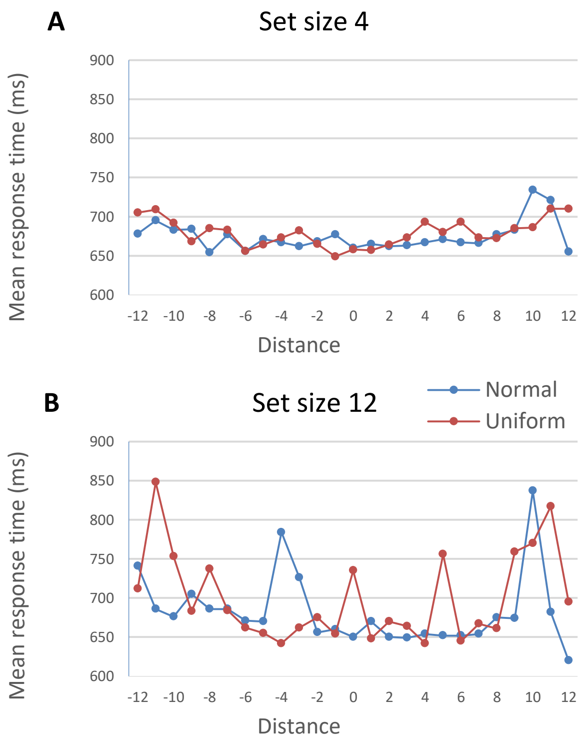

Figure 8. A) Mean response time for correct answerer's as a function of CT-CTM distance and distribution type (normal vs uniform) for set size 4. B) Mean response time for set size 12. Error bars are omitted due to the small number of data points.

Overall response times were mainly flat for the small size and soemwhat irrelegular for the larger set size and did not seem to be effected systematically by the CT-CTM distance(Figure 8). Additionally, no difference between distribution shape was found for the mean response time for either of the set sizes. For both, accuracy and response time, thedistribution type did not seem to have an effect on performance. For this reason the first experiment was discontinued after collecting the data of four participants and a new modified version of the experiment was developed. Given that participants performance was generally high, a ceiling effect could have diminsihed the contribution of the two different distribution types. Therefore, in a modified version of the first experiment we decided to decrease the presentation time and reduce the set size, to potentially observe lager priming effects.

5 Experiment 2

To try to get a larger priming effect in Experiment 2 displays fewer items than in Experiment 1. We also changed the presentation time of items to be shorter to try avoid a possible ceiling effect in performance observed in Experiment 1.

5.1 Method

5.1.1 Participants

Ten participants (4 men and 6 woman; mean age = 24.2) were included in the second experiment. The experiment was devided into two sessions and each session lasted about 40 minutes. The minimum interval between sessions was one day. Participants gave written, informed consent and did not receive payment for participation. All participants were pre-screened for color blindness using Ishihara plates.

5.1.2 Procedure

The task and stimuli were identical to the first experiment except for the following modifications: Instead of varying the set size between sessions, it was held constant at only three items (two distractors and one target). Stimuli were presented on the screen for only 250ms. participants were tested on a normal and a uniform target distribution separately in different sessions. Conditions were counterbalanced so that half of participants did the uniform distribution in the first session and the normal distribution in the second, and vice versa for the other participants. All participants completed a training block before testing, which involved 144 trials.

5.1.3 Data analysis

Data processing was identical to the one in the first experiment except that additonally each block was split into two halfs to analyse the process of learning the probability of targets. We anticipated that it will take a set of trials to encode the target distribution and therefore the strength of the distribution shape on priming could differ at the beginning and the end of the block. Three-way repeated-measures ANOVA tests with Greenhouse-geisser correction was performed to analyse both response time and accuracy. ANOVAS were conducted using SPSS version 23.

5.2 Results

We investigated whether participants priming strength was affected by the target distributionif the distribution shape was encoded during the block. We expected RT‘s for the uniform distribution to be flat since all colors had the same probability to appear. For the normal distribution, the probability monotonically decreases as the target shifts away from the target distribution mean. Therefor we expect RT’s for the normal distribution to decrease monotonically as the distance between the target and the mean of the target distribution decreases. We except that it might take subjects several trials to learn the distribution characteristics. To investigate the effect of Learning over time we divided each block into two halves’ by splitting them at the 72nd trial. The overall mean response time was 570ms. Overall accuracy was about 86% which is lower than in the first experiment. Therefore, the ceiling effect found initially was reduced in this modified version of the first experiment.

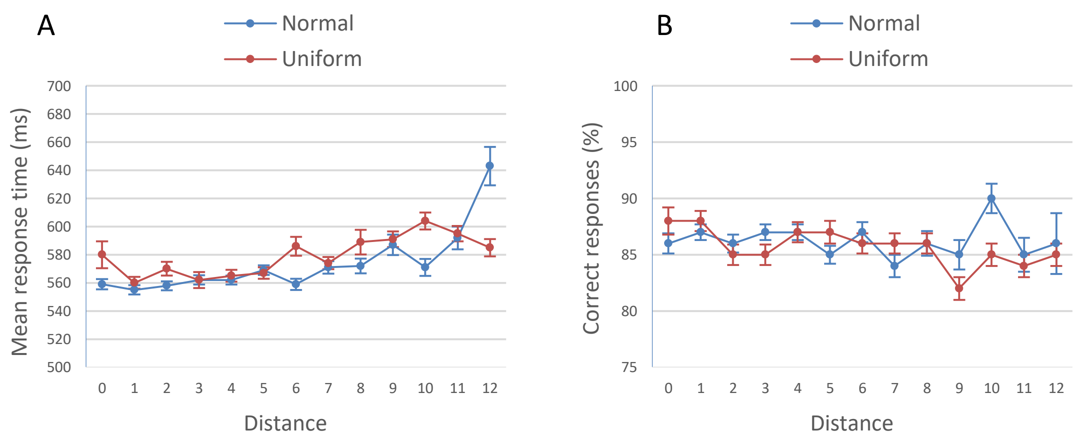

Figure 9. A) Mean response time as a function of CT-CTM distance and distribution shape(normal vs. uniform) and B) mean precentage of correct responses as a function of CT-CTM distance and distribution type.

A three-way ANOVA was run to examine the effect of distribution shape, CT-CTM distance and the effect learning over time on response time. To investigate observes ability to encode targed probability we analysed mean search time as a function of the distance between target distribution mean and target color. Figure 9a showes the mean response time for each CT-CTM distance. Response time is longer in the uniform condition for most distances. Search times from the normal distributions increased as a function of the distance between the current target and the target distribution mean while mean response time in the uniform condition are more flat (Figure 9a). A three-way ANOVA did not show a significant main effect for distribution shape, $F(1, 9) = .096$, $p > .05$. However, we found a main effect for CT-CTM distance, $F(3.447, 31.024) = 8.285$, $p < .05$, and the interaction effect between CT-CTM and distribution shape $F(3.511, 31.596) = 3.47$, $p < .05$ was significant as well. The main effect of learning over time was non-significant, $F(1, 9) = .03$, $p > .05$, and the three-way interaction between distribution shape, CT-CTM distance and the effect of learning over time was non-significant $F(3.014, 27.122) = 2.01$, $p > .05$ as well.

A three-way ANOVA with the same factors was then run to examine the effect on accuracy. Figure 9b shows the mean accuracy for each CT-CTM distance. One line does not appear higher than the other, and the Normal and Uniform lines show a similar scattered trend. The Figure does not indicate an effect of distribution shape on accuracy in responses. The three-way ANOVA did not reveal a main effect for distribution shape, $F(1, 9) = 1.57$, $p > .05$, or CT-CTM distance,$F(4.789, 43.179) = 2.2$, $p > .05$. The interaction effect between CT-CTM and distribution shape was non-significant $F(4.251, 38.255) = .971$, $p > .05$. However, there was a significant main effect was for learning, $F(1, 9.) = 6.47$, $p < .05$. Indicating a difference in mean percentage of correct responses in the two halves' in each block. Accuracy in the second experiment was lower than in the first experiment. Overall the accuracy for targets drawn from a normal distribution did not differ between the first and the second half of the blocks: 86% in the first 72 trials and 86.7% in the last 72 trials. Results for targets drawn from a uniform distribution revealed similar results: Overall accuracy was at 84.9% in the first half and 86.4% in the second half.

6 Discussion

Experiment 1 did not show any signs of probability learning. For both, accuracy and response time, the distribution type did not seem to have an effect on performance. In Experiment 2 we did not see a clear monotonic increase in search time as a function of the decreasing probability in the normal distribution as expected. However, results show that difference in response time for different distances between current target and the mean target of the target distribution is dependent on distribution shape. Previous studies have suggested that subjects can learn information about the shape of distributions (Chetverikov, Campana, & Kristjánsson 2016; Chetverikov, Campana, & Kristjánsson 2017). Chetverikov et al. (2017) Showed that subjects can encode the actual shape of the distribution of colors. Our study investigated whether subjest can learn the distribution shape for targets, whereas Chetverikov et al. (2017) focus was on distractors. Additionally, our experiment differs from theirs in having small set size with only one item of the distribution at a time (the target), while the Chetverikot et al. (2017) had large set size with 36 items. Our experiment also had more trials each block so subjects did have longer time to learn the distribution shape. The goal of this research was to assess whether priming is affected by the shape of target distribution, we did that by observing if subjects were able to learn the distribution shape of target colors over the course of a block. Analyzing accuracy, results did not show a effect of distribution shape or CT-CTM distance on subjects accuracy. This could stem from the fact that subjects are high in accuracy overall, and a tendency to give a right anwer regardless of response time. We expected RTs for a uniform target distribution to be flat, since each color had the same probability to appear, and RTs for a normal target distribution to reflect faster searches for highly probable targets and slower for less probable targets. The results do not clearly demonstrate that observers were able to learn the distribution shape of target colors over the course of a block. In particular RT's did not increases monotonically with increasing distance between the target and of the mean of the target distribution. However, the results do give some evidence for the learning of distribution shape. In Figure 9a the line for the uniform distribution tends to be flatter while the line for the normal distribution shows an increase in RT‘s for the least probale targets. This can be interpreted as a sign of probability distribution learning. In addition, our results show a interaction between distribution shape and CT-CTM distance. This means that the difference in response time for different CT-CTM distances depends on the distribution shape. This may be considered a further validation of probability learning and that priming is indeed affected by the shape of the target distribution. Nevertheless the magnitute of our evidence should be taken in consideration before making any strong speculations. Tran et al. (2017) research only found a sign of distribution shape learning for distributions that could be discretized and when the distribution was made extremely apparent. Our study is similar to theirs in that only one item of the distribution is shown at a time (the target). For further study on target probability learning, having a more apparent distribution and only using binned distribution could result in stronger evidence for probability learning.

7 Conclusions

Our results from the second experiment reveal that some information of the target distribution might be encoded. However, we did not see a clear monotonic increase in search time a function of the decreasing probability in the normal distribution. Only the smallest probability (at the edge of the distribution) showed a clear increase in search time. Overall, participants seemed to respond faster for more probable targets and slower for the least probable target color. In order to strengthen general priming it was required to introduce a more difficult task

References

Alvarez, G. A., & Oliva, A. (2008). The representation of simple ensemble visual features outside the focus of attention. *Psychological science*, *19*(4), 392-398.

Ariely, D. (2001). Seeing sets: Representation by statistical properties. *Psychological science*, *12*(2), 157-162.

Awh, E., Matsukura, M., & Serences, J. T. (2003). Top-down control over biased competition during covert spatial orienting. *Journal of Experimental Psychology: Human Perception and Performance*, *29*(1), 52.

Bar, M., Kassam, K. S., Ghuman, A. S., Boshyan, J., Schmid, A. M., Dale, A. M., ... & Halgren, E. (2006). Top-down facilitation of visual recognition. *Proceedings of the national academy of sciences*, *103*(2), 449-454.

Caputo, G., & Guerra, S. (1998). Attentional selection by distractor suppression. *Vision research*, *38*(5), 669-689.

Chetverikov, A., Campana, G., & Kristjánsson, Á. (2016). Building ensemble representations: How the shape of preceding distractor distributions affects visual search. *Cognition*, *153*, 196-210.

Chetverikov, A., Campana, G., & Kristjánsson, Á. (2017). Rapid learning of visual ensembles. *Journal of vision*, *17*(2), 21-21

Geng, J. J., & Behrmann, M. (2005). Spatial probability as an attentional cue in visual search. *Perception & psychophysics*, *67*(7), 1252-1268.

Haberman, J., & Whitney, D. (2007). Rapid extraction of mean emotion and gender from sets of faces. *Current Biology*, *17*(17), R751-R753.

Kersten, D. (1987). Predictability and redundancy of natural images. *JOSA A*, *4*(12), 2395-2400.

Kristjánsson, A., Wang, D., & Nakayama, K. (2002). The role of priming in conjunctive visual search. *Cognition*, *85*(1), 37-52.

Kristjánsson, Á., & Campana, G. (2010). Where perception meets memory: A review of repetition priming in visual search tasks. *Attention, Perception, & Psychophysics*, *72*(1), 5-18.

Kristjánsson, Á., & Driver, J. (2008). Priming in visual search: Separating the effects of target repetition, distractor repetition and role-reversal. *Vision Research*, *48*(10), 1217-1232.

Maljkovic. V., & Nakayama. K. (1994). Priming of pop-out: I. Role of features. Memory & Cognition, 22(6), 657-672.

Morgan, M., Chubb, C., & Solomon, J. A. (2008). A ‘dipper’function for texture discrimination based on orientation variance. *Journal of Vision*, *8*(11), 9-9.

Norman, L. J., Heywood, C. A., & Kentridge, R. W. (2015). Direct encoding of orientation variance in the visual system. *Journal of vision*, *15*(4), 3-3.

Pashler, H. (1987). Target-distractor discriminability in visual search. *Perception & Psychophysics*, *41*(4), 285-292.

Tran, R., Vul, E., & Pashler, H. (2017). How effective is incidental learning of the shape of probability distributions?. *Royal Society open science*, *4*(8), 170270.

Treisman, A. (1985). Preattentive processing in vision. *Computer vision, graphics, and image processing*, *31*(2), 156-177.

Treisman, A. (1988). Features and objects: The fourteenth Bartlett memorial lecture. *The quarterly journal of experimental psychology*, *40*(2), 201-237.

Treisman, A. (1992). Perceiving and re-perceiving objects. American Psychologist, 47(7), 862. Webster, M. A., & Mollon, J. D. (1997). Adaptation and the color statistics of natural images.

Treisman, A., & Souther, J. (1985). Search asymmetry: a diagnostic for preattentive processing of separable features. *Journal of Experimental Psychology: General*, *114*(3), 285.

Wolfe, J. M. (1994). Guided search 2.0 a revised model of visual search. *Psychonomic bulletin & review*, *1*(2), 202-238.