Distracted by Previous Experience: Integrating Selection History, Current Task Demands and Saliency in an Algorithmic Model

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Abstract—Attention can be biased by previous learning and experience. We present an algorithmic-level model of this selection history bias in visual attention that predicts quantitatively how stimulus-driven processes, goal-driven control and selection history compete to control attention. In the model, the output of saliency maps as stimulus-driven guidance interacts with a history map that encodes learning effects and a goal-driven task control to prioritize visual features. We test the model on a reaction-time (RT) data from a psychophysical experiment. The model accurately predicts parameters of reaction time distributions from an integrated priority map that is comprised of an optimal, weighted combination of separate maps. Analysis of the weights confirms selection history effects on attention guidance. The model is able to capture individual differences between participants. Moreover, we demonstrate that a model with a reduced set of maps performs worse, indicating that integrating history, saliency and task information are required for a quantitative description of human attention. Besides, we show that adding intertrial priming effect to the model (as another lingering bias) improves the model’s predictive performance.

Index Terms— Ex-Gaussian distribution, Feature integrated theory, Integrated priority map, Selection history, Self information maximization, Visual attention

I. INTRODUCTION AND RELATED WORK

SELECTIVE visual attention is a brain function that filters irrelevant sensory inputs to facilitate focusing on relevant items. Stimulus-driven and goal-driven mechanisms have traditionally been proposed to control the process of attention guidance. Object saliency and environment features shape the attentional process in a stimulus-driven manner while the goal-driven process is mostly controlled by observer intentions and preferences.

In addition to goal-driven and stimulus-driven contributions also ‘selection history’ can play a significant role in guiding attention toward a specific target [1]. Selection history (as a third mechanism of attentional guidance) comes into play when an object is emphasized just because of previous attendance in the same context [2]. To clarify the distinction between goal-driven guidance and selection history, Theeuwes

argued that selection history is a fast, effortless, and automatic version of attention control while goal-driven selection is slow and effortful [3]. The term ‘selection history’ includes several phenomena that can neither be considered as goal-driven nor as stimulus-driven control, such as lingering effects, statistical learning, emotional and also reward-based biases [4].

One special form of selection history has been investigated in [5]–[7]. These studies combined an associative learning task with a visual search task. The results showed that observers attended more to a stimulus they experienced as response-predictive in the preceding feature discrimination task. To examine to what extent selection history can be suppressed by goal-driven process, Kadel *et al.* [6] tested different goal-driven-influenced modes of task preparations such as pretrial task cuing. As their results showed, attentional biases induced by selection history persisted despite task preparation. Their results show that even with these preparations, selection history still plays a noticeable role in biasing attention towards a formerly experienced target. Wolfe and Horowitz [8] mentioned that not only the three aforementioned contributions but also the scene structure and the relative value of the targets and distractors must be considered in modern visual guidance theories. In Guided Search 6.0 [9] –the latest version of the Guided Search model on visual search and selective attention– these five factors are integrated in a spatial priority map to guide attention.

An integrated priority map was also proposed by Awh *et al.* as a theoretical framework for explaining how selection history and other factors of attention guidance interact [1], [2]. Priority map have been successfully employed by many authors [10]–[15] to explain the result of the processes which shape attention. In a review, Klink *et al.* [12] summarized how goal-driven and stimulus-driven maps in cortex combine with a value-based map in midbrain. This combination results in a priority map for the frontal eye fields. Zelinsky and Bisley [11] speculate about the importance of priority map in relationship with visual working memory and also with the motor system. They also highlighted this map as an appropriate construct for predicting behavior.

Stimulus-driven models of attention were developed early on [16]. These models tend to ignore the effects of selection history, task or training [17]. Itti *et al.* [16] implemented feature integration theory (three feature maps including color, intensity and orientation), winner-take-all, inhibition of return

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and a normalization method to model visual attention in a stimulus-driven manner. This model (or its elaborated version [18]) was subsequently expanded [19], [20]. De Brecht and Saiki [21] showed how Itti and Koch’s model [18] can be implemented by neural networks with biologically realistic dynamics based on data from electrophysiology experiments. This model was also expanded later by integrating motion saliency computation [19]. Itti’s stimulus-driven model was also combined in a goal-driven model [20] to represent the effect of goal-relevance information on attention or eye-movement. Veale *et al.* [14] validated a neural implementation of Itti’s model. In another stimulus-driven model, Bruce and Tsotsos [22] – using self information maximization ($-\log(p(x))$), where x is a feature – proposed a computational model of saliency that is called ‘Attention based on Information Maximization (AIM)’, because attention is attracted by surprising, i.e. potentially informative, regions of an image.

Most of the models reviewed so far were developed to explain data from highly controlled experiments with impoverished artificial stimuli. However, humans deploy their attention in uncontrolled natural settings replete with complex stimuli. Thanks to deep learning advances, there has been recent progress in deep visual saliency models that can process complex natural images [23]. DeepGaze II is a saliency model that predicts where people look using features from a pre-trained convolutional neural network (VGG-19) and a few layers on top that are trained to read out saliency [24]. While these models have near-human performance compared to observers in front of a screen, they mostly explain saliency effects at their current state of development. It will be interesting to include other attentional guidance mechanisms in them, which go beyond the currently presented scene.

Itti and Borji reviewed more than 50 computational stimulus-driven models [17]. Computational models that integrate goal-driven control [25]–[27] are less well researched than saliency models, likely because they require information not available in the stimulus. Some models integrate stimulus-driven and goal-driven signals in attentional guidance [28]. Chikkerur *et al.* [29] used a Bayesian framework to explain how a combination of stimulus-driven and goal-driven attentional guidance work together in cortex.

Previous studies showed that attention can be biased more toward a target feature which was selected in the last trial ([6], [30]–[32]). This effect, known as intertrial priming, is one of the lingering biases attributed to selection history [3]. Selection history has hardly been modelled despite being a well-known phenomenon. Tseng *et al.* [33] implemented a Ratcliff-type diffusion model [34] for a 2-forced-choice task and showed that intertrial priming can affect diffusion model parameters.

In this paper we introduce an algorithmic-level or ‘mechanistic’ model (in the sense of Marr [35]) to show how stimulus-driven processes, goal-driven control and selection history compete to guide visual attention toward a specific target¹. We operationalize selection history as the effect of training-phase learning on the test phase (see [5]–[7]). The model comprises

a priority map to integrate goal-driven, saliency-based and history-related biases in a winner-take-all manner. Stimulus-driven guidance, feature maps and saliency maps are made based on feature integration theory [36] and self information maximization [22]. Feature-integration theory, developed by Treisman and Gelade [36], posits that separable dimensions (such as shape and color) are processed separately before being integrated on-demand. Using this theory, the proposed model, codes the input into three types of features (color, shape and orientation) and computes a saliency map for each feature dimension with AIM [22]. The model also incorporates the effect of intertrial priming which emphasises the response-relevant feature dimension of the last trial in the current one [37]. Additionally, a history map contributes to the integrated priority map to reflect the effect of selection history and learning in the model. Finally, task-relevant information controls the map integration weights that generate predictions for responses and response times. These integration weights are our model for the goal-driven influences. We test this model on a behavioral database from an experiment by Feldmann-Wüstefeld *et al.* [5]. The model can predict the reaction time distribution parameters for each participant and also across the experimental groups. To find the best fitted distribution on reaction times, several probability density functions are compared minimizing negative log likelihood and the best fitting one –an ex-Gaussian distribution [38]– is used in the model.

The rest of the paper is organized as follows: we review the experiment and explain its details required for a full understanding of the model. We then compare models that differ in the information that enters into the integrated priority map and show that a model with selection history information –on feature level– performs best. We also show that the inclusion of intertrial priming variables lead to an increase of the (approximate) Bayesian model evidence. More information about data analysis and reaction time distributions can be found in Appendix A and B.

II. EXPERIMENTAL DATA

The data used in this study comes from the first experiment of Feldmann-Wüstefeld *et al.* [5]. They investigated the impact of associative learning on covert selective visual attention to examine whether selection history effects generalize from particular features (e.g., ‘blue’ or ‘green’) to the entire color dimension. The experiment consisted of a ‘practice’ and a ‘main’ phase, in which two types of tasks (learning and search) were performed. A central fixation cross was presented on the screen, which was then surrounded by eight different elements on an imaginary circle (Fig. 1). 28 participants were divided randomly into two different groups, namely ‘color group’ and ‘shape group’. They were first naive about their group membership, but had to learn it on a trial and error basis in the practice phase.

In the ‘practice phase’, participants had to learn that either color or shape was the response-relevant dimension in this learning task (see Fig. 1.a). Members of the color group had to report the color of the color singleton (blue or green), whereas

¹A preliminary version of this modeling study has been presented at COGSCI 2021 <https://cognitivesciencesociety.org/cogsci-2021/>.

members of the shape group had to respond to the shape of the shape singleton (triangle or pentagon). They had to use their left hand to press one of two buttons that were placed on the left side of the response pad. Auditory feedback indicated whether they pressed the incorrect key.

In the ‘main phase’ a second visual search task was added, and participants performed both tasks in random order. In the search task (Fig. 1.b), all participants had to search for a shape target and report the orientation of a line presented inside the diamond shaped target. In half of the trials, a response-irrelevant red circle was presented as distractor. Participants used their right hand to press one of two buttons on the right side of the pad to indicate the line orientation (horizontal versus vertical).

The results of this study showed that the history of selection acquired in the learning task affected the participants’ performance in the search task. Reaction time analysis showed that responses in distractor-present trials were slower than in distractor-absent trials, and the distractor cost was larger in color group participants than in participants in the shape group. Concurrently recorded EEG signals also suggested that participants in the color group deployed attention towards the red color distractor, this was not the case for participants in the shape group. Accordingly, the authors suggested that the participants’ history of either shape or color selection in the practice phase had resulted in a selection history bias. Feldmann-Wüstefeld *et al.* had done their study in 4 experiments to examine the influence of task switching. In the first and the second experiments, learning and search trials were intermixed. In experiment three, the tasks were presented block-wise and in the forth one, the tasks were performed on separate days. The results of all experiments demonstrated the presence of selection history effect on attention deployment even when the tasks were done on different days [5]. We decided to use the intermixed presentation trials to model the effect of repeating the response-relevant feature dimension from trial $n-1$ to trial n along with goal-driven, stimulus-driven and selection history influences on attentional control.

We developed a model of this selection history bias in the current study based on the behavioral data from the main phase, which comprises at total of 28672 trials across all participants. More details about the experiment can be found in [5].

Fig. 1. Experiment displays. Learning task (a): Participants in the color group had to respond to the color (green vs. blue) and participants in the shape group had to respond to the shape (pentagon vs. triangle). Search task (b): The orientation (horizontal vs. vertical) of the line embedded in the diamond had to be reported in distractor-absent (left) and distractor-present trial (right).

III. THE ALGORITHMIC MODEL

We first determined which trial parameters affect participants’ RTs by reanalyzing the data from [5]. This served two

purposes: replicated the reported selection history effects with a different analysis method, and determined relevant variables for the more detailed model presented later on. The results of this analysis showed that the group membership – which we modeled as a history map– and also trial types – which were coded into saliency maps– both influence RTs. By ‘trial type’ we mean if the trial is either a learning or a search (distractor-absent, distractor-present) type. For more information about this analysis, see Appendix A. The analysis also showed that switching from one task type to another can affect participants’ RTs and that this effect differs between experimental groups (see Fig. 10). Since the model employs the ex-Gaussian as an RT distribution, we detail in Appendix B how this distribution was chosen based on a model comparison.

We assembled an algorithmic-level model to explain how goal-driven and stimulus-driven influences competitively interact with visual selection history to guide attention toward a specific stimulus. Inspired by the integrated priority map in [2], we used a ‘history map’ reflecting the influence of selection history on current attention deployment, see Fig. 2. Additionally, there is an overall saliency map for stimulus-driven influences. How these maps combine into an integrated priority map is determined by task-dependent weights. Fig. 2 also shows how the output of the integrated priority map is used to predict ex-Gaussian distribution [39] parameters of reaction times (left exit path in the figure) and response likelihoods (the right exit path). Evaluating these response likelihoods and reaction times against participants’ reaction times allows us to fit the model to the experimental data, see (5) below.

The input stage of the model is based on assumptions made by visual search theories such as feature-integration [36] and guided search [9]. The model extracts three types of features (color, shape and orientation) and feature maps –as shown in Fig. 2– are computed. In the next processing step, saliency maps that model the effect of stimulus-driven control on visual attention [40] are formed from the feature maps. Shannon’s measure of Self-Information is applied, similar to Attention Based on Information Maximization [22], to compute saliency maps. Equations (1) and (2) show the actual calculations behind map computation. Feature maps are $M \times N \times K$ vectors where M is the number of trials, N is the number of objects in each trial and K is the number of distinct values that each feature can take on, i.e. we are using 1-out-of- K encoding for the features, with the value 1 indicating which feature value is present. In the current experiment $M = 1024$ (for each participants), $N = 8$ and $K = 4$. Fig. 3 illustrates the method of building feature maps for some example trials. For all trials, we take the feature maps f_i for $i \in \{color, shape, orientation\}$ and compute the self-information X_i :

$$\forall k : X_i[k] = -\log\left(\sum_{n=1}^N f_i[n][k]/N\right) \quad (1)$$

which yields the saliency of all trials $s_i[n]$:

$$\forall n : s_i[n] = X_i \left[\arg \max_k (f_i[n][k]) \right] \quad (2)$$

Fig. 2. An overview of the algorithmic model. The blue arrows show the direction of data flow from visual input to response and gray arrows show the direction of feedback. w_s, w_h, w_t and w_d are model parameters that weigh how strongly different maps enter into the integrated priority map or the RT prediction. w_s is saliency weight with three elements for color, shape and orientation. w_t is intertrial priming weight and also has three elements for color, shape and orientation. w_h is history map weight. w_d is distribution parameters weight and has three elements for μ, σ and τ . B_d is distribution parameters' bias containing B_μ, B_σ and B_τ . The goal-relevant information (on the right side of the figure) helps the model to guide attention to the target location.

where, due to the 1-of-K feature encoding, we can use argmax to pick the self-information corresponding to the current feature value.

Saliency maps s_i are fed into the integrated priority map along with history information (h) to compete in a soft winner-take-all model [1] for the predicted response target. Selection history, the third category of attentional guidance [2], carries the effect of learning (participants learned about color or shape in our experiment) into the priority map (p). To model the priming effect of the last trial on participant' RT, we added another parameter (w_t) to the model. The parameter w_t includes a weight for each feature dimension and it modulates the saliency weights when the maps are combined into the priority map:

$$\forall m, n : p[m][n] = \text{soft max}_n \left(\sum_i ((w_{s_i} + w_{t_i} * t_i[m]) * s_i[m][n]) + w_h * h[m][n] \right) \quad (3)$$

The weights (w_h for history and w_{s_i} for $i \in \{\text{color}, \text{shape}, \text{orientation}\}$) are used to combine the history map and the saliency maps computed from from color, shape and orientation. These weights reflect the influence of the content of the respective map on the integrated priority map for the tasks that the model will be optimized for. In (3) t is a $M \times i$ matrix which carries information from the last trial: in each row of t , a '1' indicates the feature dimension which had to be selected by the participants in the last trial

(see Fig. 4). The softmax function is used to ensure that the winning location receives the most attention while keeping the map interpretable as a probability distribution.

In our model, (3) can be interpreted as the first layer of a (two-layer) neural network. The second layer is a (linear) mapping from the integrated priority map to reaction time distribution parameters:

$$\forall m : d[m] = \sum_{n=1}^N (p[m][n] * w_d) + B_d \quad (4)$$

Where w and B are weights and biases of ex-Gaussian distribution parameters' $d[m] \in (\mu[m], \sigma[m], \tau[m])$ for each trial m .

We also compute a 1-out-of-K representation of the goal-relevant information (g in (5)) (see Fig. 3) which is used for machine-learning the weights with which the history map and the saliency maps are combined in the priority map. Psychologically, we can interpret the role of this as combined guidance of stimulus-driven and history toward the location of the target.

The weights (w_h, w_s, w_t and w_d) for both tasks are determined by maximizing the log of the joint distribution of the reaction times (RT), the goal-relevant information (g) under the distribution predicted by the integrated priority map (p) and eventually the prior distributions over the model

Fig. 3. Feature maps, history map and goal-relevant information for two random trials. We use 1-out-of-K encoding for the feature vectors, i.e. all components but one are zero. The nonzero component indicates the feature value (see the green box). In each row of history map the location of learned feature is marked. In goal-relevant information the location of response-relevant feature is marked.

Fig. 4. Intertrial priming. The priming effect in our model is depicted by solid lines for shape, and dashed lines for color. Attending a particular feature (e.g. triangle shape in trial n-4) primes shape dimension attention in the next trial, here: pentagon in trial n-3. Likewise for color dimension. Line orientation priming is possible too, shown for trial n-2 → trial n-1 (upper orange arrow). Note that shape priming is possible in the color group too if two search trials follow each other (lower orange arrow).

parameters δ :

$$L = \sum_{m=1}^M \log(\text{ExG}(RT[m] | \mu[m], \sigma[m], \tau[m])) + \sum_{m=1}^M \sum_{n=1}^N (\log p[m][n] * g[m][n]) + \delta$$

where ExG is the ex-Gaussian density function. δ is computed as the sum of the logs of the following prior distributions on the parameters:

$$\begin{aligned} w &\sim \mathcal{N}(0.0, 1.0) \\ B_{\mu} &\sim \mathcal{N}(600.0, 100.0) \\ B_{\sigma^2} &\sim \mathcal{N}(75.0, 4.0) \\ B_{\tau} &\sim \mathcal{N}(200.0, 20.0) \end{aligned} \quad (5)$$

Mean and standard deviation of the last three distributions are selected in a way that matches results from similar experiments [5], [6]. To find the weights and biases that maximize the joint probability (5), we draw random initial values from these distributions and then optimize using Python 3.8.8, PyTorch 1.8.1 and Adam optimizer with learning rate 0.1.

IV. RESULTS AND DISCUSSION

To investigate how selection history and saliency maps quantitatively predict attentional guidance, we tested seven versions of the model. In the first model (M1 in Fig. 5), the history map contains the response-relevant features of the learning phase (blue and green for the color group, triangle and pentagon for the shape group). This model is used as the basis for models M2 to M7, which are altered versions thereof. In M2 the history map includes all color singletons (for participants in the color group) and all shape singletons (for participants in the shape group). Here, the assumption is that the participants have learned response-predictiveness on the dimensional level (color or shape), not on the level of single features (such as green or blue). So not only blue, green, triangle and pentagon but also red and diamond are included. In M3, priming information from previous trials is removed from the model. In M4, we exclude the history map from the model testing the assumption that only goal-driven and stimulus-driven guidance direct attention. In M5, M6 and M7, shape, color and orientation maps are removed to see if all saliency maps are needed to explain the experimental data. To compare these versions of the model, we use a Laplace-approximation to the Bayesian model evidence. We compute a second-order approximation of the marginal log-probability of the data given the different models' assumptions. We employ these log-probabilities for two sets of model comparisons [41]–[43]: fitting one model per participant, and one model per group. In both cases, comparison shows M1 being the most probable, which includes saliency maps, a history map with the features that were predictable during learning and also the effect of the last trial on the current one (as the intertrial priming effect). This model is at least 10^{20} times more probable than the alternatives. For more details about the model evidences see Fig. 5.

Under the assumption that there is at least an approximately linear mapping from the priority map to the reaction time distribution parameters, the model machine-learns to predict the history map weight (w_h), saliency map weights (w_s), inter-trial priming weights (w_t) and also the distribution parameters weights and biases (w_d, B_d) (see Fig. 2). A comparison of the learned weights and their differences between the color group and the shape group is shown in Fig. 6. As one might expect, the color weight is higher in the color group, whereas the shape weight dominates in the shape group. This leads to a stronger influence of the respective saliency map on the contents of the integrated priority map, which is shown in Fig. 7 for a distractor-present trial. In other words, while we assume that saliency is a property of the physical stimulus statistics, the weight with which saliency enters into the integrated priority map can be varied by (learnable) task demands. In Fig. 7 the individual map activations and their weighted combinations are shown in color coding. The color group model's attention is strongly drawn towards the (red) color distractor. In contrast, the shape group model prioritizes the correct target location.

As Fig. 6 shows, the 'history map' has a higher weight (w_h) in the color group than in the shape group: to solve the learning task, the color group model has to rely on the colors

Fig. 5. Model comparison. We computed a Laplace-approximation to the Bayesian model evidence across all participants. The evidences are plotted relative to M7 (the least probable model). Bigger evidence is better. M1, which is called the main model, contains the saliency maps, intertrial priming effect and the history map on response-relevant features. This model scores best. For models descriptions, see the text.

Fig. 6. Map weights. For both color group and shape group, optimal map weights for the first model are shown. A higher weight means a stronger influence of the corresponding map onto the response and reaction time. The hatched parts are the weights modulations by the intertrial priming. Note that the final weight of each saliency map is a sum over the map weight and the priming weight, see (3) and also Fig. 2. Priming modulations on color maps are very small (close to zero) and can be hardly seen. Priming modulation on shape map in color group is negative. The error bars represent the standard deviations of the posterior, i.e. standard errors.

(blue and green) encountered during the practice phase which is reflected in the large weight of the history map. Although these colors could be found in the ‘color map’ as well, there is another color (red) in this map which is task-irrelevant and has to be suppressed, hence the smaller weight of the color map. This is the reason for the increased attention capture by the red distractor in color group members which is reported in [5]. In other words, the presence of a color distractor leads to a down-weighting of dimensional color saliency in favor of a feature-level color representation. For the search task, a high orientation weight is employed by the color group model, since this task can be solved by spotting an orientation singleton.

In contrast, the shape group model can afford to rely mostly on the ‘shape map’, because the items in its history (triangle and pentagon) exist in the ‘shape map’ too (triangle, pentagon and diamond), and there is no shape distractor. Therefore, by using a high shape map weight, both the learning task can be solved and attention can be guided to the shape singleton containing the target in the search task (diamond).

To summarize, the weight of the ‘orientation map’ is larger in the color group than in the shape group, indicating that the

color group model relies on orientation saliency in the search task. However, the shape group model focuses on the ‘shape map’ which is response-relevant in both tasks. Also, the weight of the ‘color map’ was higher in the color group than in the shape group model, since the latter group can ignore color altogether.

All versions of the model except M3 can capture intertrial priming. To see how intertrial priming effect is defined in our model please see Fig.4. Our assumption is that intertrial priming is dimension-specific rather than feature-specific. This is also claimed by Liesefeld *et al.* [44]. In our model, intertrial priming has three weights (w_t) for color, shape and orientation priming. See also (3) and the hatched parts in Fig.6. In the color group the modulatory effect of intertrial priming causes an increased orientation map weight and also a reduction of the shape map weight. The former indicates that the generally high reliance of a color group model on orientation during a search task is amplified during repetition of search task trials. The latter might represent task switching: switching from the search task (reporting orientation embedded in a shape singleton target) to the learning task (reporting colors and not shape singletons) is best accomplished by down-weighting shape features temporarily. Interestingly, for color group participants, there is no priming-driven weight modulation of color map. Irrespective of the previous trial’s type, a color group model relies more on the history map than on the color map to ignore the red distractor. In our opinion, this rules out the alternative hypothesis that longer response times in the color group are induced by task switching efforts only, and not by selection history and the need to suppress the red distractor. This is in agreement with the results of experiments 3 and 4 reported in [5]. In both of these task variants, learning and search task were separated, either block-wise, or by asking participants to perform the tasks on separate days. Search performance of the color group, however, was still affected by their prior selections in the learning task, even though participants now performed only search tasks trials, and task switching no longer occurred.

The model approximates the reaction time distribution parameters (μ, σ, τ) very well (as can be seen in Fig. 8). To quantify how close the model-predicted distributions are to the best fit to the data, we evaluate an approximation to the Kullback–Leibler (KL) divergence [41]:

$$KL(p||q) = \int p(RT) \log \left(\frac{p(RT)}{q(RT)} \right) dRT \quad (6)$$

$$\approx \frac{1}{M} \sum_{m=1}^M \log p(RT_m) - \frac{1}{M} \sum_{m=1}^M \log q(RT_m)$$

where RT_m is the reaction time in trial m , $p(RT)$ and $q(RT)$ are model-predicted and best-fit distributions respectively. For both color and shape group RTs, we find $KL(p||q) \leq 10^{-4}$ which is very close to the minimal possible value of zero.

V. CONCLUSION

The presented model shows how saliency, selection history and goal-driven demands collaborate in guiding visual attention. The model implements the idea that selection history

Fig. 7. Map activations in distractor-present search task trials for a color group (a) and a shape group (b) participant model. To visualize these activations the weighted value of each map is used as a color code: $((w_{s_i} + w_{t_i}) * s_i)$ for each saliency map (i) and $(w_h * h)$ for history map. See Fig. 2 for variable names. Warmer colors indicate higher activations. Individual weighted map activations are integrated in the final priority map and attention is guided to the location with the highest feature activity. See (3) for a computational description.

Fig. 8. Ex-Gaussian distributions of reaction times. Best fits to the data (red) and model predicted distributions (green) for participants in the color group. Shape group model predictions fit comparably well.

plays an important role in attention guidance as claimed in [5]. We compared different versions of the model and the results show that the one which includes selection history (long-learned selection preferences and also intertrial priming), beside stimulus-driven and goal-driven control, is best suited for a quantitative description of the behavioral (RT) results. This paper is our first effort to model selection history as an attentional mechanism. To make the model more comprehensive, we plan the following future steps: since previous experiments on selection history effects were done with impoverished stimuli and simple participant responses, we planned to run an experiment in natural or semi-natural (virtual reality) environments. The data obtained in richer environments will likely require an extension of the model, in particular with respect to stimulus representation and response capability. Second, our model successfully implements an integrated priority map [2], [45]. To determine if this integrated priority map approach is indeed the best description of human behaviour, future research needs to investigate non-integrated alternatives. The search for such alternatives might be facilitated if we knew what the attentional system is actually trying to achieve on a quantitative level. This is a question situated on the ‘computational level’ [35]. Therefore, we intend to build a computational model in a Bayesian/optimal feedback control framework for both ideal and non-ideal observer-actors. Stochastic evidence accumulation approaches – that

have been applied in some other models such as Race Models [46] and Drift Diffusion models [39] – might be useful to this end. Besides, to have dynamical version of the model, we are building a dynamical priority map which is updating over time. Importantly, our model does not yet include an explicit reinforcement learning component. Participants did learn the tasks from negative reinforcement only. Our model captures participants’ behaviour after this reinforcement learning phase is completed, which was determined by a high enough performance level (see [5]). We agree that it would be interesting to model this first phase in future work, too. Another interesting avenue of investigation, which would help in constraining the model, would be the addition of physiological variables. For example, adding EEG signals to disentangle processes of target selection and distractor suppression would shed further light on attentional guidance processes.

APPENDIX A STATISTICAL ANALYSIS OF REACTION TIMES

We analyzed reaction times (RT) binarized at their grand (population) mean across all trial types and participants. While this is a fairly coarse analysis, it should reveal strong effects of experimental manipulations. Thus, we model the probabilistic dependence of these binarized times on different variables with Bayesian networks. The variables we consider are group membership, trial type or both. By group membership we mean either ‘color group (CG)’ or ‘shape group (SG)’, i.e. whether participants had to categorize either color or shape singletons in the practice phase of the experiment.

Evaluating a network with both trial type and group membership as conditioners of reaction time, one can see the joint effect, (see Fig. 9.a and 9.b). Although both groups are slower in distractor-present trials, color group participants are less probable to have reaction times smaller than the grand mean. This may be a selection history effect: these participants learned to respond to color, and they are consequently more distracted by a color distractor.

To see how ‘intertrial priming effect’ is reflected in behavioral data, we conducted another analysis (see Fig. 10). Here, we wanted to know if switching from one trial to another

Fig. 9. Reaction time analysis. The Bayesian network shows the tested dependencies between experimental variables (group membership and trial types) and reaction times. The bar chart shows the probability of having a reaction time less than the grand mean. Error bars represent the standard error of the mean. Trial type has a strong effect on reaction time. Color group participants are more distracted by a color singleton than shape group members.

impacts the probability of having RT less than mean and additionally if this impact differs between groups. As the bar charts in (Fig. 10.b) show, participants are faster when the trial type is duplicated (i.e., the current trial (trial n) is the same as the last one (trial $n-1$)). Switching between learning and search trials always causes delays in responding and it is especially noticeable in distractor-present trials when the last trial is a learning trial. Considering the group membership as another RT conditioner, we see that the above mentioned observation is more pronounced in color group (see bar charts in Fig. 10.b):

$$P(RT \leq \text{mean} | T_n = \text{distr. pres.}, T_{n-1} = \text{learn.}, \quad (7) \\ | \text{group memb.} = CG) = 0.29$$

where N is the number of trials in these condition and T is trial type. This probability is 0.35 for shape group. These reduced probabilities might be due to attending the distractor in both groups. However, the reduction is stronger in the color group, where the (color) selection history is activated by the previous (T_{n-1}) learning trial. In other words, responding to the color in a learning trial increases the chance of being distracted by the red distractor in the subsequent search trial, and thus responding to a shape singleton takes longer.

APPENDIX B REACTION TIME DISTRIBUTION

Reaction time measurements have been widely employed in psychological experiments to analyze behavioral responses to well-defined tasks. Psychologists agree that there are three

Fig. 10. Reaction time analysis after adding intertrial priming variables : a) the network models dependencies between RT, trial types and group membership. N is the number of trials, trial n is the current trial and trial $n-1$ is the previous trial. b) the probability of having RT less than or equal to the grand mean is shown on the bar-charts based on the group membership, current trial type and last trial type. RT probability reduction (mean RT increase) is particularly strong for color group members when a learning trial is followed by a distractor-present trial, possibly because their selection history is activated. Error bars represent the standard error of the mean.

main types of reaction times: simple reaction times, recognition reaction times, choice reaction times and also some more forms such as discrimination reaction times and decision reaction times that come from combining varieties of experimental tasks [47].

Many distributions have been used to describe RT in neurocognitive and psychological research. In [48], the Gamma distribution is used to model PEBL (Psychology Experiment Building Language) Go/No-Go tests, with the primary motivation that RTs can be modeled better with a right-skewed distribution. In another study, inverse Gaussian (Wald) is used in a theoretical analysis of psychophysical parameters in a 2AFC design [49] with the assumption that if RT is the time needed for an evidence accumulation to reach a fixed boundary—similar to Brownian diffusion process—it is distributed as an inverse Gaussian. Another popular distribution is the Recinormal [50] which is introduced in LATER model to describe psychological decision making processes [51], [52].

We tried to find the best fitting distribution model for the reaction times in our data by testing the following distribution types against each other by approximate Bayesian model comparison: Gaussian, Gamma, inverse Gamma, inverse Gaussian, Recinormal and exponential Gaussian(ex-Gaussian). We fitted the distributions on each participant's RT and also on aggregates defined by group memberships and trial types. We then compared the negative log likelihoods, which showed that the best fit is achieved with an ex-Gaussian. For illustration, Fig. 11 shows the different densities (red lines) fitted to one

Fig. 11. Distribution functions fitted on RT datasets for a random participant. Ex-Gaussian fits best.

Fig. 12. Distribution comparison using -log likelihood score, lower is better. Distributions are fitted on individual participants data and on group-based data (all color group participants and all shape group participants). The best distribution is Ex-Gaussian, followed by inverse Gaussian.

of the participant's RT data (histograms). Visual inspection indicates that the ex-Gaussian provides the best fit. For a quantitative comparison we computed each distribution's parameters that minimized the sum of negative log likelihood scores (participants-based and also group-based). These scores are depicted in Fig. 12, lower is better. The best fits are ex-Gaussian and inverse Gaussian models respectively. To fit the distributions on data we used Python 3.8.8 and PyTorch 1.8.1.

The ex-Gaussian distribution is a convolution of Gaussian and exponential distributions, see e.g. [39]. It has three parameters: μ , σ and τ that are the mean and standard deviation of the Gaussian component and the mean of the exponential component, respectively. The mean and the variance of this distribution are $\mu + \tau$ and $\sigma^2 + \tau^2$.

Response times are not distributed normally [53]. Because of their long tail on the right, RT distributions might have an exponential component. Christie and Luce [54] and also McGill [55] therefore proposed that RT distributions are a convolution of two components. For an ex-Gaussian distribution to arise, one of them has to have an exponential distribution. The above mentioned authors had opposite beliefs about the source of this exponential component: Christie and Luce mentioned that decision time is exponentially distributed but McGill related that to movement response. Hohle [56] also

tried to show that the RT distribution is a convolution of a normal and exponential components by auditory RT experiments.

The ex-Gaussian has been popular recently in psychological research. In [57] several distributions are fitted on behavioral data of three visual search tasks. The best fits all have an exponential component and the ex-Gaussian is one of those. Ex-Gaussian parameters can even be useful in evaluating attention disorders [58], [59]. More research on ex-Gaussian parameters analysis can be found in [60], [61].

REFERENCES

- [1] J. Theeuwes, "Goal-driven, stimulus-driven, and history-driven selection," *Current Opinion in Psychology*, vol. 29, pp. 97–101, 2019. doi: 10.1016/j.copsyc.2018.12.024
- [2] E. Awh, A. V. Belopolsky, and J. Theeuwes, "Top-down versus bottom-up attentional control: a failed theoretical dichotomy," *Trends in Cognitive Sciences*, vol. 16, no. 8, pp. 437–443, 2012. doi: 10.1016/j.tics.2012.06.010
- [3] J. Theeuwes, "Visual Selection: Usually Fast and Automatic; Seldom Slow and Volitional," *Journal of Cognition*, vol. 1, no. 1, pp. 1–15, 2018. doi: 10.5334/joc.13
- [4] M. Failing and J. Theeuwes, "Selection history: How reward modulates selectivity of visual attention," *Psychonomic Bulletin and Review*, vol. 25, no. 2, pp. 514–538, 2018. doi: 10.3758/s13423-017-1380-y
- [5] T. Feldmann-Wüstefeld, M. Uengoer, and A. Schubö, "You see what you have learned. Evidence for an interrelation of associative learning and visual selective attention," *Psychophysiology*, vol. 52, no. 11, pp. 1483–1497, 2015. doi: 10.1111/psyp.12514
- [6] H. Kadel, T. Feldmann-Wüstefeld, and A. Schubö, "Selection history alters attentional filter settings persistently and beyond top-down control," *Psychophysiology*, vol. 54, no. 5, pp. 736–754, 2017. doi: 10.1111/psyp.12830
- [7] D. T. Henare, H. Kadel, and A. Schubö, "Voluntary control of task selection does not eliminate the impact of selection history on attention," *Journal of Cognitive Neuroscience*, vol. 32, no. 11, pp. 2159–2177, 2020. doi: 10.1162/jocn_a_01609
- [8] J. M. Wolfe and T. S. Horowitz, "Five factors that guide attention in visual search," *Nature Human Behaviour*, vol. 1, no. 3, pp. 1–8, 2017. doi: 10.1038/s41562-017-0058. [Online]. Available: <http://dx.doi.org/10.1038/s41562-017-0058>
- [9] J. M. Wolfe, *Guided Search 6.0: An updated model of visual search*. Psychonomic Bulletin & Review, 2021, vol. 28, no. 4. ISBN 1342302001859
- [10] J. H. Fecteau and D. P. Munoz, "Salience, relevance, and firing: a priority map for target selection," *Trends in Cognitive Sciences*, vol. 10, no. 8, pp. 382–390, 2006. doi: 10.1016/j.tics.2006.06.011
- [11] G. J. Zelinsky and J. W. Bisley, "The what, where, and why of priority maps and their interactions with visual working memory," *Annals of the New York Academy of Sciences*, vol. 1339, no. 1, pp. 154–164, 2015. doi: 10.1111/nyas.12606
- [12] P. C. Klink, P. Jentgens, and J. A. M. Lorteije, "Priority maps explain the roles of value, attention, and salience in goal-oriented behavior," *Journal of Neuroscience*, vol. 34, no. 42, pp. 13 867–13 869, 2014. doi: 10.1523/jneurosci.3249-14.2014
- [13] R. M. Todd and M. G. Manaligod, "Implicit guidance of attention: The priority state space framework," *Elsevier*, vol. 102, pp. 121–138, 2017. doi: 10.1016/j.cortex.2017.08.001
- [14] R. Veale, Z. M. Hafed, and M. Yoshida, "How is visual salience computed in the brain? Insights from behaviour, neurobiology and modeling," *Philosophical transactions of the Royal Society of London. Series B, Biological sciences*, vol. 372, no. 1714, 2017. doi: 10.1098/rstb.2016.0113
- [15] L. Chelazzi, J. Eščinová, R. Calletti, E. L. Gerfo, I. Sani, C. D. Libera, and E. Santandrea, "Altering spatial priority maps via reward-based learning," *Journal of Neuroscience*, vol. 34, no. 25, pp. 8594–8604, 2014. doi: 10.1523/JNEUROSCI.0277-14.2014
- [16] L. Itti, C. Koch, and E. Niebur, "A model of saliency-based visual attention for rapid scene analysis," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 20, no. 11, pp. 1254 – 1259, 1998. doi: 10.1109/34.730558
- [17] L. Itti and A. Borji, "Computational models: Bottom-up and top-down aspects," 2015. [Online]. Available: <http://arxiv.org/abs/1510.07748>

- [18] L. Itti and C. Koch, "A saliency-based search mechanism for overt and covert shifts of visual attention," *Vision Research*, vol. 40, no. 10-12, pp. 1489–1506, jun 2000. doi: 10.1016/S0042-6989(99)00163-7
- [19] D. F. Ramirez-Moreno, O. Schwartz, and J. F. Ramirez-Villegas, "A saliency-based bottom-up visual attention model for dynamic scenes analysis," *Biological Cybernetics*, vol. 107, no. 2, pp. 141–160, 2013. doi: 10.1007/s00422-012-0542-2
- [20] J. Tanner and L. Itti, "A top-down saliency model with goal relevance," *Journal of Vision*, vol. 19, no. 1, p. 11, 2019. doi: 10.1167/19.1.11
- [21] M. de Brecht and J. Saiki, "A neural network implementation of a saliency map model," *Neural Networks*, vol. 19, no. 10, pp. 1467–1474, 2006. doi: 10.1016/j.neunet.2005.12.004
- [22] N. D. B. Bruce and J. K. Tsotsos, "Saliency, attention, and visual search: An information theoretic approach," *Journal of Vision*, vol. 9, no. 3, pp. 1–24, 2009. doi: 10.1167/9.3.5
- [23] A. Borji, "Saliency prediction in the deep learning era: Successes, limitations, and future challenges," 2019. [Online]. Available: <https://arxiv.org/abs/1810.03716>
- [24] M. Kümmerer, T. S. A. Wallis, and M. Bethge, "DeepGaze II: Reading fixations from deep features trained on object recognition," 2016. [Online]. Available: <http://arxiv.org/abs/1610.01563>
- [25] V. Navalpakkam and L. Itti, "Modeling the influence of task on attention," *Vision Research*, vol. 45, no. 2, pp. 205–231, 2005. doi: 10.1016/j.visres.2004.07.042
- [26] A. D. Hwang, E. C. Higgins, and M. Pomplun, "A model of top-down attentional control during visual search in complex scenes," *Journal of Vision*, vol. 9, no. 5, pp. 1–18, 2009. doi: 10.1167/9.5.25.A
- [27] A. Borji, D. N. Sihite, and L. Itti, "What/where to look next? Modeling top-down visual attention in complex interactive environments," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 44, no. 5, pp. 523–538, 2014. [Online]. Available: <http://ilab.usc.edu/>
- [28] A. Kimura, D. Pang, T. Takeuchi, K. Miyazato, J. Yamato, and K. Kashino, "A stochastic model of human visual attention with a dynamic Bayesian network," 2008. [Online]. Available: <http://arxiv.org/abs/1004.0085>
- [29] S. Chikkerur, T. Serre, C. Tan, and T. Poggio, "What and where: A Bayesian inference theory of attention," *Vision Research*, vol. 50, no. 22, pp. 2233–2247, 2010. doi: 10.1016/j.visres.2010.05.013
- [30] V. Maljkovic and K. Nakayama, "Priming of pop-out: I. Role of features," *Memory and Cognition*, vol. 22, no. 6, pp. 657–672, 1994. doi: 10.3758/BF03209251
- [31] G. Kristjánsson, Á. Arní, Campana, "Where perception meets memory: A review of repetition priming in visual search tasks," *Attention, Perception, & Psychophysics*, vol. 72, pp. 5–18, 2010. doi: 10.3758/APP.72.1.5
- [32] J. Theeuwes and E. van der Burg, "On the limits of top-down control of visual selection," *Attention, Perception, and Psychophysics*, vol. 73, no. 7, pp. 2092–2103, 2011. doi: 10.3758/s13414-011-0176-9
- [33] Y. C. Tseng, J. I. Glaser, E. Caddigan, and A. Lleras, "Modeling the effect of selection history on pop-out visual search," *PLoS ONE*, vol. 9, no. 3, 2014. doi: 10.1371/journal.pone.0089996
- [34] R. Ratcliff, "A theory of memory retrieval," *Psychological Review*, vol. 85, no. 2, pp. 59–108, 1978. doi: 10.1037/h0021465
- [35] D. Marr, *Vision: A Computational Investigation into the Human Representation and Processing of Visual Information*. W. H. Freeman and Company, 1982. ISBN 0-7167-1284-9
- [36] A. M. Treisman and G. Gelade, "A feature-integration theory of attention," *Cognitive Psychology*, vol. 12, no. 1, pp. 97–136, 1980. doi: 10.1016/0010-0285(80)90005-5
- [37] J. Theeuwes and M. Failing, *Attentional Selection: Top-Down, Bottom-Up and History-Based Biases (Elements in Perception)*. Cambridge: Cambridge University Press., 2020. ISBN 9781108891288
- [38] D. Matzke and E. J. Wagenmakers, "Psychological interpretation of the ex-gaussian and shifted wald parameters: A diffusion model analysis," *Psychonomic Bulletin and Review*, vol. 16, no. 5, pp. 798–817, 2009. doi: 10.3758/PBR.16.5.798
- [39] R. D. Luce, *Response times: Their role in inferring elementary mental organization*. Oxford University Press, 1986.
- [40] C. Koch and S. Ullman, "Shifts in selective visual attention: Towards the underlying neural circuitry," *Human Neurobiology*, vol. 4, no. 4, pp. 219–227, 1985. doi: 10.1007/978-94-009-3833-5
- [41] C. M. Bishop, *Pattern Recognition and Machine Learning*. Springer, 2006. ISBN 9780387310732
- [42] D. Barber, *Bayesian Reasoning and Machine Learning*. Cambridge: Cambridge University Press, 2012. ISBN 9780511804779
- [43] D. M. Endres, E. Chiovetto, and M. A. Giese, "Model selection for the extraction of movement primitives," *Frontiers in Computational Neuroscience*, vol. 7, p. 185, 2013. doi: 10.3389/fncom.2013.00185
- [44] H. R. Liesefeld, A. M. Liesefeld, S. Pollmann, and H. J. Müller, "Biasing allocations of attention via selective weighting of saliency signals: behavioral and neuroimaging evidence for the Dimension-Weighting Account," in *In T. Hodgson (Ed.), Processes of Visuospatial Attention and Working Memory*. Springer, 2019. ISBN 9783642209246
- [45] J. Theeuwes, L. Bogaerts, and D. van Moorselaar, "What to expect where and when: how statistical learning drives visual selection," *Trends in Cognitive Sciences*, vol. 26, no. 10, pp. 860–872, 2022. doi: 10.1016/j.tics.2022.06.001. [Online]. Available: <https://doi.org/10.1016/j.tics.2022.06.001>
- [46] J. T. Mordkoff and S. Yantis, "An Interactive Race Model of Divided Attention," *Journal of Experimental Psychology: Human Perception and Performance*, vol. 17, no. 2, pp. 520–538, 1991. doi: 10.1037/0096-1523.17.2.520
- [47] R. Harald Baayen and P. Milin, "Analyzing reaction times," *International Journal of Psychological Research*, vol. 3, no. 2, p. 12, 2017. doi: 10.21500/20112084.807
- [48] M. Santhanagopalan, M. Chetty, C. Foale, S. Aryal, and B. Klein, "Modeling neurocognitive reaction time with gamma distribution," *Proceedings of the Australasian Computer Science Week Multiconference*, 2018. doi: 10.1145/3167918.3167941
- [49] J. V. Stone, "Using reaction times and binary responses to estimate psychophysical performance: An information theoretic analysis," *Frontiers in Neuroscience*, vol. 8, 2014. doi: 10.3389/fnins.2014.00035. [Online]. Available: <http://journal.frontiersin.org/article/10.3389/fnins.2014.00035/abstract>
- [50] M. D. P. Martin and Fermin, "A theory of reaction time distributions," Tech. Rep., 2008.
- [51] R. H. S. Carpenter, "Oculomotor procrastination," *Eye Movements: Cognition and Visual Perception*, eds D. F. Fisher, R. A. Monty and J. W. Senders (Hillsdale, NJ: Lawrence Erlbaum), pp. 237–246, 1981. doi: 10.4324/9781315437415-19
- [52] I. Noorani and R. H. Carpenter, "The LATER model of reaction time and decision," *Neuroscience and Biobehavioral Reviews*, vol. 64, pp. 229–251, 2016. doi: 10.1016/j.neubiorev.2016.02.018
- [53] R. Whelan, "Effective analysis of reaction time data," *Psychological Record*, vol. 58, no. 3, pp. 475–482, 2008. doi: 10.1007/BF03395630
- [54] L. Christie and R. D. Luce, "Decision structure and time relations in simple choice behavior," *The bulletin of mathematical biophysics*, vol. 18, pp. 89–112, 1956.
- [55] W. J. McGill, "Stochastic latency mechanisms," in *D. Luce (ed.), Handbook of Mathematical Psychology*, John Wiley & Sons., pp. 1–309, 1963.
- [56] R. H. Hohle, "Inferred components of reaction times as functions of foreperiod duration," *Journal of Experimental Psychology*, vol. 69, no. 4, pp. 382–386, 1965. doi: 10.1037/h0021740
- [57] E. M. Palmer, T. S. Horowitz, A. Torralba, and J. M. Wolfe, "What are the shapes of response time distributions in visual search?" *Journal of Experimental Psychology: Human Perception and Performance*, vol. 37, no. 1, pp. 58–71, 2011. doi: 10.1037/a0020747
- [58] S. L. Hwang-Gu, Y. C. Chen, S. H. Y. Liang, H. C. Ni, H. Y. Lin, C. F. Lin, and S. S. F. Gau, "Exploring the variability in reaction times of preschoolers at risk of attention-deficit/hyperactivity disorder: An ex-Gaussian analysis," *Journal of Abnormal Child Psychology*, vol. 47, no. 8, pp. 1315–1326, 2019. doi: 10.1007/s10802-018-00508-z
- [59] S. L. Hwang Gu, S. S. F. Gau, S. W. Tzang, and W. Y. Hsu, "The ex-Gaussian distribution of reaction times in adolescents with attention-deficit/hyperactivity disorder," *Research in Developmental Disabilities*, vol. 34, no. 11, pp. 3709–3719, 2013. doi: 10.1016/j.ridd.2013.07.025
- [60] D. C. Osmon, D. Kazakov, O. Santos, and M. T. Kassel, "Non-Gaussian Distributional Analyses of Reaction Times (RT): Improvements that Increase Efficacy of RT Tasks for Describing Cognitive Processes," *Neuropsychology Review*, vol. 28, no. 3, pp. 359–376, 2018. doi: 10.1007/s11065-018-9382-8
- [61] N. Dias, *Eye-Tracking Measures of Attentional Bias in Cocaine*. UT GSBS Dissertations and Theses (Open Access). Paper 446., 2014.