Visual search mimics configural processing in human causal learning

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Abstract

Theories of generalization distinguish between elemental and configural stimulus processing, depending on whether stimulus in a compound are processed independently or as distinct entities. Evidence for elemental processing comes from findings of summation in animals, whereas configural processing is supported by experiments that fail to find this effect when similar stimuli are employed. In humans, by contrast, summation is robust and independent of similarity. We show how these results are best explained by an alternative view in which generalization comes about from a visual search process in which subjects process the most predictive or salient stimulus in a compound. We offer empirical support for this theory in three human experiments on causal learning and formalize a new elemental visual search model based on reinforcement learning principles which can capture the present and previous data on generalization, bridging two different research areas in psychology into a unitary framework.

Keywords: generalization, Rescorla-Wagner, configural, summation, elemental, visual search

Introduction

The process of generalization is one of the most studied in the psychology of learning and decision-making. Indeed, from calory intake to escaping from predators, assessing the

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similarity between current and previous situations is a critical process which allows organisms to inform their future behavior and increase their chances of survival and reproduction (Soto & Wasserman, 2010).

Perhaps the most popular paradigm to probe different generalization strategies is the summation procedure. In this procedure, two cues, say A and B, are separately paired with an outcome during a first stage of training and responding to a compound of the two stimuli, AB, is assessed in a final testing phase. A summation effect is obtained if subjects respond more to AB than to each of A or B alone. In human causal learning, an analogous effect is obtained when the compound AB is deemed to be more predictive of an outcome than each of A or B alone (Aydin & Pearce, 1997; Kehoe, Horne, Horne, & Macrae, 1994; Pérez, San Martín, & Soto, 2018; Soto, Vogel, Castillo, & Wagner, 2009; Thein, Westbrook, & Harris, 2008).

The summation effect is readily anticipated by a class of Pavlovian conditioning models called *elemental* (Rescorla & Wagner, 1972). These models assume that subjects represent A and B independently, and that the presence of the compound AB will simply make subjects sum their individual predictions. This additive generalization strategy makes efficient use of the available evidence under the assumption that the two cues are independent causes of the outcome (Pérez et al., 2018).

Configural models take a different approach (Pearce, 1987, 1994), assuming that subjects process and associate whole configurations with the outcomes that follow. Under a configural view, the total responding to a compound AB depends on the similarity between the training configurations A and B, and the testing configuration AB. In the original formulation of this theory, a subject should predict that AB will produce a level of allergy equal to the average allergy of A and B, and no summation should be obtained (Pearce, 1987, 1994).

The evidence on summation has been mixed. In line with an elemental processing view, summation is obtained when A and B are dissimilar, such as when they come from different modalities (e.g., visual and auditory) (Kehoe et al., 1994; Thein et al., 2008), but not when A and B are similar or come from the same modality (Aydin & Pearce, 1995, 1997). In humans, apart from similarity, spatial and temporal contiguity can also impact on the level of summation observed (Glautier, 2002; Glautier, Redhead, Thorwart, & Lachnit, 2010). This evidence has prompted the surge of several models in which the type of processing is assumed to be flexible, depending on the similarity between the elements of a compound (Harris, 2006; McLaren & Mackintosh, 2002; Melchers, Shanks, & Lachnit, 2008; Pérez et al., 2018; Soto et al., 2014a, 2014a; Soto, Quintana, Pérez-Acosta, Ponce, & Vogel, 2015; Thorwart, Livesey, & Harris, 2012; Wagner, 2008).

In a recent series of human studies, however, we failed to obtain evidence of similarity affecting summation. In spite of several manipulations of similarity and contiguity, we observed a consistent and strong summation effect (Pérez et al., 2018). This result suggests that the principles of similarity-based generalization may be different across species. However, our current understanding is that they share much in common (Shepard, 1987). The answer, perhaps, lies in searching for a different principle to unify the animal and human literatures.

The animal literature offers a potential unifying principle to explain these apparent discrepancies. There, evidence for configural processing, including the absence of a summation effect, has been obtained from auto-shaping experiments in pigeons where the animals receive pairings of visual stimuli and food (Aydin & Pearce, 1995, 1997), resulting in the pigeon approaching and pecking at them. Two features of this type of procedure may explain why summation is usually not obtained. First, the proximity of the pigeon to the screen in which stimuli are displayed limits its ability to sample whole stimulus configurations. Moreover, the peck's target is centered on the area dorsalis of the pigeon's retina (Goodale, 1983; Martinoya, Le Houezec, & Bloch, 1984), which is considered a "second fovea" due to its high density of cells. That is, pigeons specifically sample visual information from the pecked area, and they tend to peck on a circumscribed area of the screen displaying visual features predictive of reward (Dittrich, Rose, Buschmann, Bourdonnais, & Güntürkün, 2010; Soto, Siow, & Wasserman, 2012; Wasserman & Anderson, 1974).

These two factors suggest that pigeons may deploy what in the visual search literature is known as a *serial* search process (Wolfe, 2018), in which they sample information from the display until encountering an area previously associated with reward, or *target*, and never sample the rest of the stimulus. If that is so, a reduction in the summation effect is explained not as a consequence of configural processing prompted by the similarity of the components in a compond but rather from limited and inefficient sampling of the stimulus compound. This is in contrast with a *parallel* search process where all stimuli are processed and a summation can be observed. Importantly, in visual search, increasing similarity between target and non-target cues is thought to make search appear more serial (Duncan & Humphreys, 1989).

Our claim in this paper is that tasks and stimuli that promote a serial search strategy will produce behavioral results that mimic configural processing in key generalization designs. Using the summation design, we present empirical evidence in line with this hypothesis from three experiments in humans. To further support our view, we present a computational reinforcement learning model which can capture both the present and previous results usually attributed to configural processing. This work leads to a more parsimonious explanation of the pattern of generalization results obtained across species, and the unification of two seemingly unrelated areas of research in experimental psychology.

Results

Experiment 1

In the three experiments reported here, participants were asked to play the role of an allergist whose goal was to judge the extent to which various drugs, represented by different shapes, caused allergy in a fictitious patient, Mr. X. We used a summation design with two stages (see Figure 1A). In the training stage, participants were presented with different cues and asked to predict the level of allergy produced by them. Two of these cues, A and B, were the target cues associated with allergy. The prediction of the compound AB was tested during a final test stage.

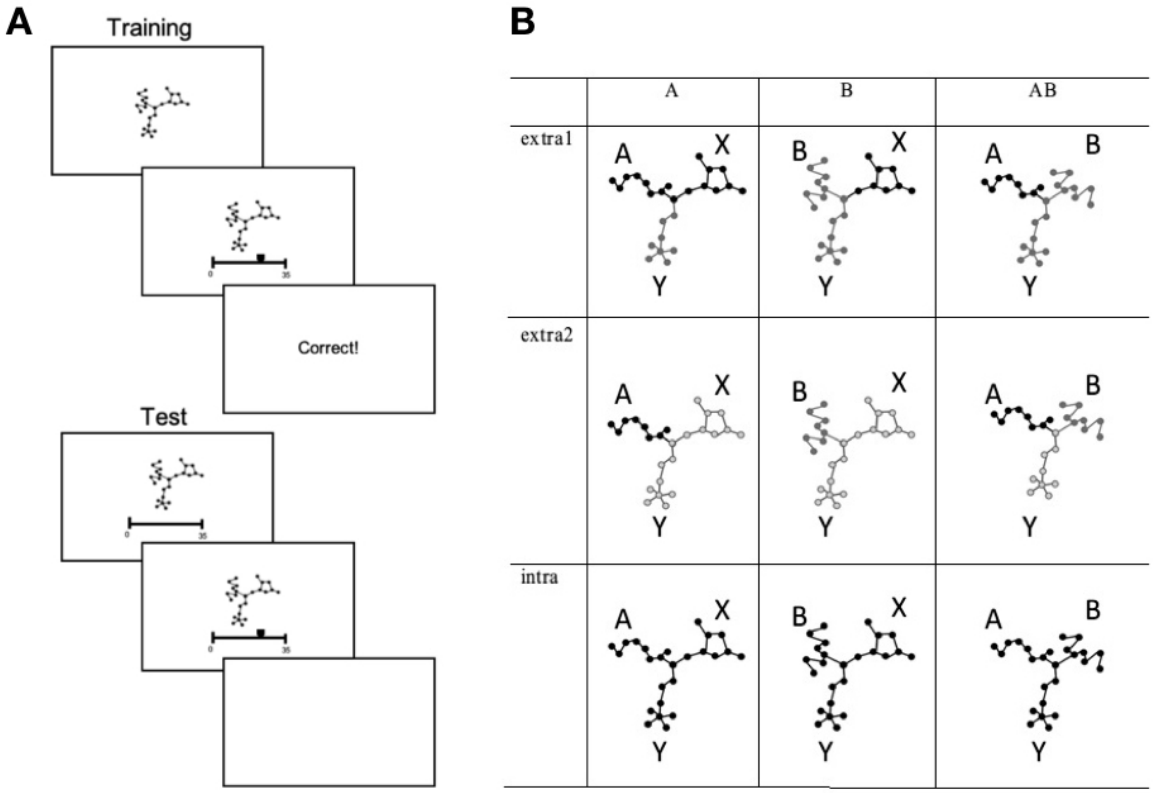

Figure 1. (A) Stimuli used in Experiment 1. Each stimulus was formed by a central point which extended in three different components. Target cues A and B were accompanied by two other non-target cues, X and Y. The compound AB was accompanied by one of the non-target stimuli X or Y. All compounds were presented in three different planar orientations, so that each component was equally likely to appear in one of three positions. (B) During training, in each trial participants observed one cue and were subsequently asked to rate the level of allergy they thought would be produced by it, in a scale from 0 to 35. After an inter-stimulus interval, feedback was presented (correct, if the prediction was correct; incorrect, if the prediciton was incorrect). During the test phase, the cues were presented as in training, but now the compound AB was added in some trials. The predictions were assessed in the same way as in training, but no feedback was given during this stage.

Our hypothesis in Experiment 1 was that a task in which the target cues must be searched sequentially in the stimulus configuration is more akin to the situation of pigeon auto-shaping, and should lead to less summation if similarity between target and non-target cues is increased. To this end, a configuration of three cues was presented in all trials, so that each trial included one target and two non-target cues. As shown in Figure 1B, all stimuli consisted of three cues joined at a central point. In training trials, A and B were presented together with the non-target cues X and Y, and in testing trials both of them were presented with one of the non-target cues. To make spatial position irrelevant, we rotated the stimuli across trials, so that each cue was presented in each of the three possible spatial positions within the configuration

We manipulated the similarity of the three cues within a configuration in three different groups. Group *intra* included cues that varied only in shape (i.e., intra-dimensional differences, see Figure 1B). We expected very inefficient search with stimuli composed of the same features (points and lines) and differing only in spatial arrangement (Wolfe, 2018) and consequently low summation. For the two *extra* groups, cues varied both in shape and in color (i.e., extra-dimensional differences). In group *extra1*, A and B had different color (black vs. gray), but the colors were shared with the non-target cues X and Y (one of them black and the other gray, see top-left stimulus in Figure 1B). This means that although A and B can be easily distinguished, they are not easily distinguishable from the non-target cues. This high similarity between target and non-target cues should produce inefficient search and low summation. Finally, in group *extra2*, A and B had different color (black vs. gray), and they also differed in color with the non-target cues X and Y (light gray with black contours, see Figure 1B). In this case, we anticipated efficient sampling of all cues and a stronger summation effect.

The results of Experiment 1 are shown in Figure 2B. To analyze these data, we ran a 2(group) x 3(cue) mixed ANOVA with group as between-subject and cue as within-subject factors. We found a significant main effect of cue ($F(2, 110) = 16.54, p < .01$) and group ($F(2, 55) = 3.79, p = .03$). More importantly, we found a significant difference in the summation effect between the groups ($F(4, 110) = 4.00, p < .01, \eta^2 = .13, 90\% CI[.02, .20]$). Consistent with a visual search approach, the significance of this interaction effect was due to a difference in scores for the compound in groups *intra* and *extra2* ($t(177.48) = 4.54, p < .001, D = 0.71, 95\%\, CI[0.06, 1.36]$).

The results of this experiment agree with our hypothesis that stimulus similarity affects the summation effect via visual search strategies. Unlike the results of our previous studies (Pérez et al., 2018; Soto et al., 2009), we find for the first time that humans can show little to no summation if the right conditions are in place. We also found that an important driver of this effect was the similarity between targets and non-targets (Duncan & Humphreys, 1989), rather than the similarity between the targets A and B—as would be anticipated by contemporary learning models (Harris, 2006; McLaren & Mackintosh, 2002; Soto et al., 2014b; Thorwart et al., 2012; Wagner, 2008).

A

Training	Test
Stimuli	
AXY+	**AXY**
BXY+	**BXY**
CXY-	**ABX**
DXY-	**ABY**
	CXY
	DXY

B

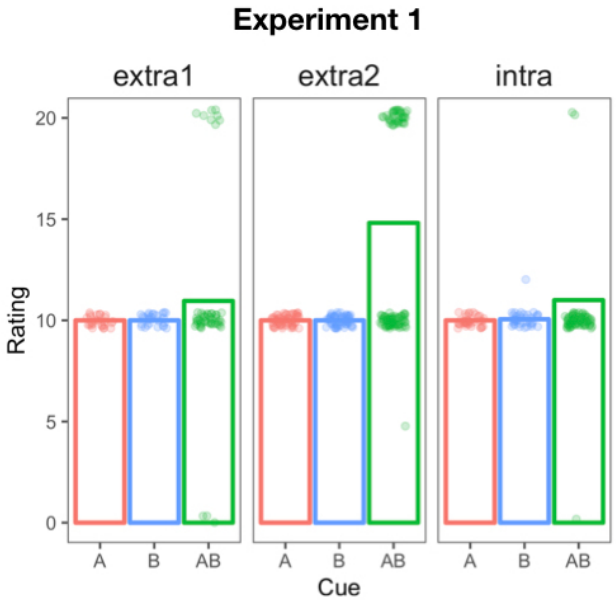

Figure 2. **Design and results of Experiment 1**. Letters denote cues, represented by different chemical shapes that can cause different levels of allergy to a fictitious patient. Each cue is represented by a capital letter. Cues A and B were the target cues, whereas X and Y were non-target cues. Cues C and D were fillers included to test if participants learnt during the training phase. (A) In Experiment 1, all cues were followed (+) or not followed (-) by the same level of allergy (10 points of allergy out of a total of 35).

Experiment 2

To test our visual search hypothesis further, in Experiment 2 we used the same stimuli as group *intra* of Experiment 1, but assigned different outcome values to cues A and B in different groups (see Figure 3A). Group *intra* was a replication of the same group from the previous experiment. Group *intra2*, by contrast, involved two different outcome values: 10 points of allergy for cue A and 8 points of allergy for cue B. As in the previous experiment, we expected participants to score the compound AB in group *intra* as producing 10 points of allergy, so that no summation should be observed in this group. By contrast, to the extent that our stimulus manipulation prompts a serial visual search strategy, participants in group *intra2* should score the compound AB as producing either 8 or 10 points of allergy, indicating that they have responded in accord with the value of only one of the two single components. We also expected a null, or very weak summation effect for group *intra2* under these conditions.

Figure 3B presents the results of Experiment 2. As expected for group *intra*, participants scores for A, B and AB did not differ ($F(2, 77) = 1.48, p = .24$), replicating the absence of a summation effect found in Experiment 1. By contrast, we found a significant difference between these cues in group *intra2* ($F(4, 76) = 529.24, p < .0001$). More importantly, group *intra2* scored the compound AB as giving around 10 points of allergy,

A

Training	Test
Stimuli	
AXY→10	**A**XY
CXY→0	**B**XY
DXY→0	**AB**X
Group *intra1*: **B**XY→10	**AB**Y
Group *intra2*: **B**XY→8	CXY
	DXY

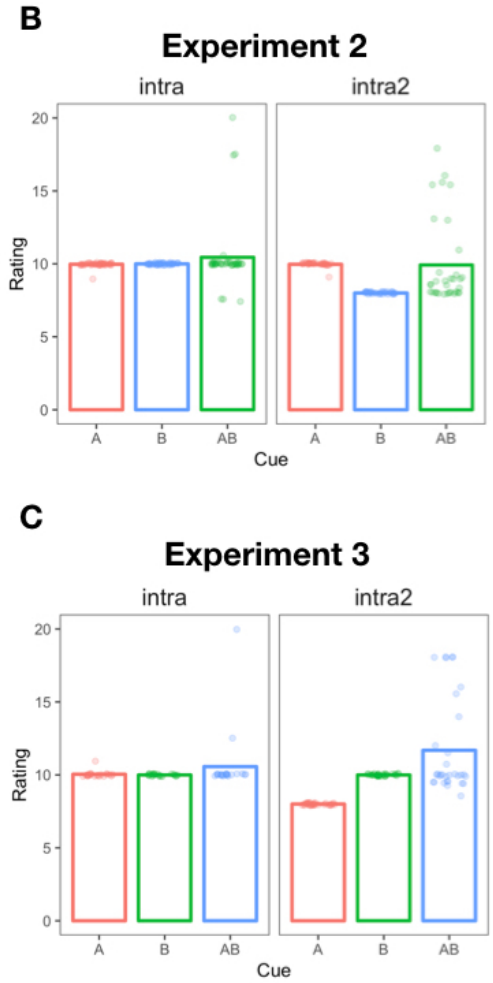

Figure 3. **Design and results of Experiments 2 and 3**. (A) In Experiment 2, cues were followed by different levels of allergy, which are represented by the numbers shown next to each of them. The only difference between Experiments 2 and 3 was the assignment of allergy levels to cues A (AXY) and B (BXY) in group *intra2*: in Experiment 3 the outcomes of A and B were swapped so that they predicted 8 and 10 points of allergy, respectively. (B) Average ratings given to each cue during the test. Individual ratings for each test trial are shown in dots.

and this value did not differ from the value assigned to A ($t(32) = -0.09, p = .92, D : -0.07\ 95\% CI[-0.38, 0.52], BF_{01} = 5.35$).

Note that even though the average rating for AB in group *intra2* was 10 points of allergy (95% CI $[9.19, 10.48]$) the mode of scores was 8, and most participants in this group predicted that the compound would cause near 8 points of allergy—the level caused by B during training. In fact, 43% (15 subjects) gave scores to AB between 7 and 9 points of allergy, while only 17% (6 subjects) scored AB between 9 and 11 points. The rest of participants gave scores higher than 11 points to the compound, and only one participant showed full summation (18 points of allergy).

While these data offer additional support for an elemental visual search process against an elemental view, they do not allow us to completely rule out configural processing, as a high proportion of participants scored the compound AB between 8 and 10 points, which is the "average" effect that configural models of learning would predict (Pearce, 1987, 1994).

Experiment 3

To rule out configural theory as an explanation for our data, in Experiment 3 we kept everything as in Experiment 2, except that the values produced by the components A and B in group *intra2* were swapped. If the properties of stimulus B attract participants' attention during a search process, the majority of participants should give a higher rating to the compound AB (closer to 10 rather than 8) in response to the compound presentation. By contrast, the same averaging effect found in Experiment 2 is anticipated by configural theory (i.e., between 8 and 10 points).

The results of Experiment 3 are shown in Figure 3C. As expected, we found no difference between the ratings to A, B and AB in group *intra*, ($F(1, 42) = 1.41, p = .26$), replicating the lack of summation in group *intra* of Experiment 2. In group *intra2*, participants rated AB as producing near 11 points of allergy (mean=$11.69, 95\% CI[10.39, 12, 99]$), a value higher than the score to AB in Experiment 2 ($t(62.13) = 2.30, p = .03$). However, the mode of scores was again equal to the outcome predicted by B (10 points of allergy). Moreover, the distribution of scores showed that the majority of participants (15 participants, 66% of the sample) scored the compound AB as producing between 9 and 11 points of allergy while only 2 participants (5% of the sample) scored the compound as producing between 7 and 9 points of allergy. This change in the distribution of scores from Experiment 2 to Experiment 3 confirms our hypothesis that the compound AB is rated as equal to the outcome predicted by one of the cues forming the compound.

Taken together, the three studies reported here provide empirical evidence for the hypothesis that inefficient visual search strategies mimic configural processing in the summation design. We believe that a similar process of serial search might underlie many results from the animal learning literature which are usually interpreted as arising from configural processing. In the next section we formalize this hypothesis in a reinforcement learning model and show through simulations how many patterns of results taken as evidence for configural processing can be captured by this new elemental visual search approach.

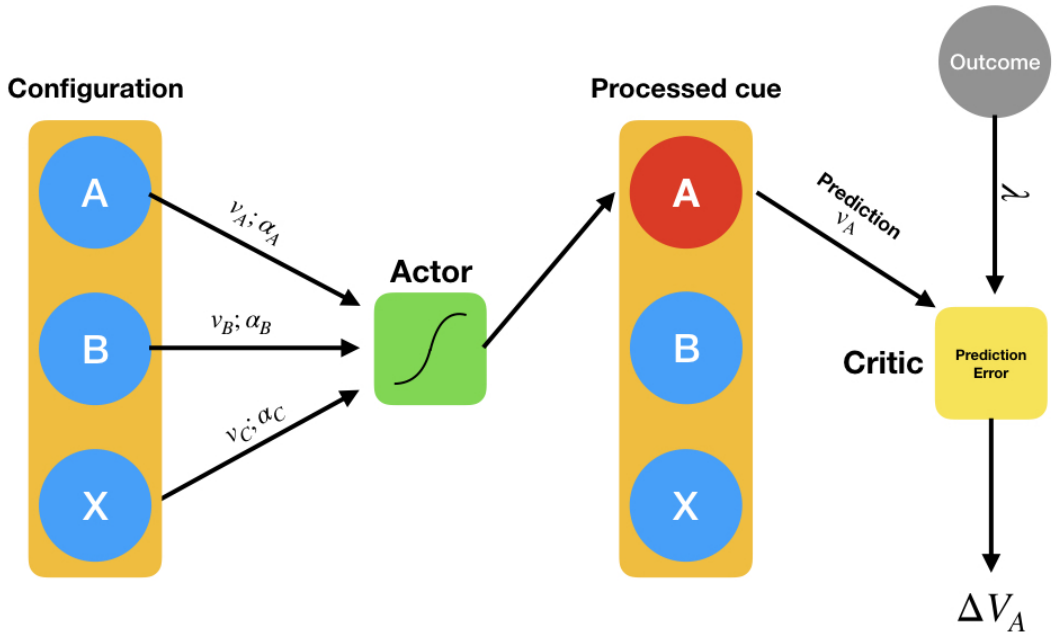

Figure 4. **An elemental visual search model.** On each trial where the agent is presented with a compound of cues that predict an outcome, the actor samples one of the cues according to their current value and salience. In this example, the compound AB is presented and the unique cue X is represented by the subject for this particular combination of stimuli. For illustrative purposes, cue A has been sampled by the actor in this trial. Once the actor has sampled the cue, the critic updates the value according to a prediction error rule. Only the value of the sampled cue A is updated for the following trial. The model assumes that the agent represents an additional unique cue for each one of the possible combinations of cues (for example, if the compound of three cues ABC is presented, we assume that there is an additional unique cue represented for each possible pair—AB, AC, BC—and the compound of three cues—ABC).

An elemental visual search model

The model offered here is related to the actor-critic model from the reinforcement learning literature (Maia, 2010; O'Doherty et al., 2004). One system, the critic, learns the values of each cue according to a prediction-error rule (see Methods section) so that if the actual outcome during a trial is higher than the value predicted by the cue presented in that trial, the value of the cue is increased (and viceversa). An additional system, the actor, samples a single cue in the compound to be processed as a function of its current value and salience (the higher the value of salience, the most likely the cue is to be sampled). Importantly, when a compound of more than one cue is presented, the subject represents an additional, *unique cue*, which follows the same rules as any other cue in the compound (Wagner & Rescorla, 1972).

Summation

We start by simulating the conditions of autoshaping in pigeons. To this end, we assume that both components predict the same outcome value and have equal saliencies. The results of this simulation are shown in the right panel of Figure 5A. The EVS model correctly predicts the failure to find a summation effect when an inefficient search strategy is adopted. This is in keeping with the results reported by Rescorla and Coldwell in pigeons (see left panel of Figure 5A) (1995). Intuitively, during the test phase the actor sometimes samples the unique cue that is only represented in the testing phase, which tends to bring down responding to AB compared to the elements A and B.

In a second set of simulations, we investigated the predictions of the EVS model when cue B predicts a lower outcome value than A, trying to match the conditions of Experiment 2. The model correctly predicts the pattern of results of Experiment 2 (see Figure 5B). The model also replicates our finding that responding to AB would be closer to B than to A. Lastly, we tried to match the conditions of Experiment 3 by reversing the roles of A and B, so that B predicts a higher outcome value than A. Again, the EVS model correctly captures the pattern of behavior observed in this experiment, in that responding to AB should be closer to the outcome predicted by B, and higher than in Experiment 2 (see Figure 5C).

Differential summation

Using pigeon auto-shaping, Pearce and colleagues (1997) found that responding for an ABC compound was weaker when the three cues were separately paired with a reward (A+, B+, C+) than when the cues were paired with the same reward, but in compounds (AB+, AC+, BC+) (see Figure 6, left panel). Figure 6 (right panel) shows how the EVS model correctly predicts this result. In the case of single-cue training, at the end of training ABC is comprised of four unique cues with very low predictive values (.05 each, by assumption), whereas the same ABC compund is comprised of the same four unique cues, some of which have been represented by the agent during training and have therefore acquired higher predictive values than in the case of single-cue training. During the presentation of ABC during the test, the actor sometimes sample these higher-valued unique cues. Consequently,

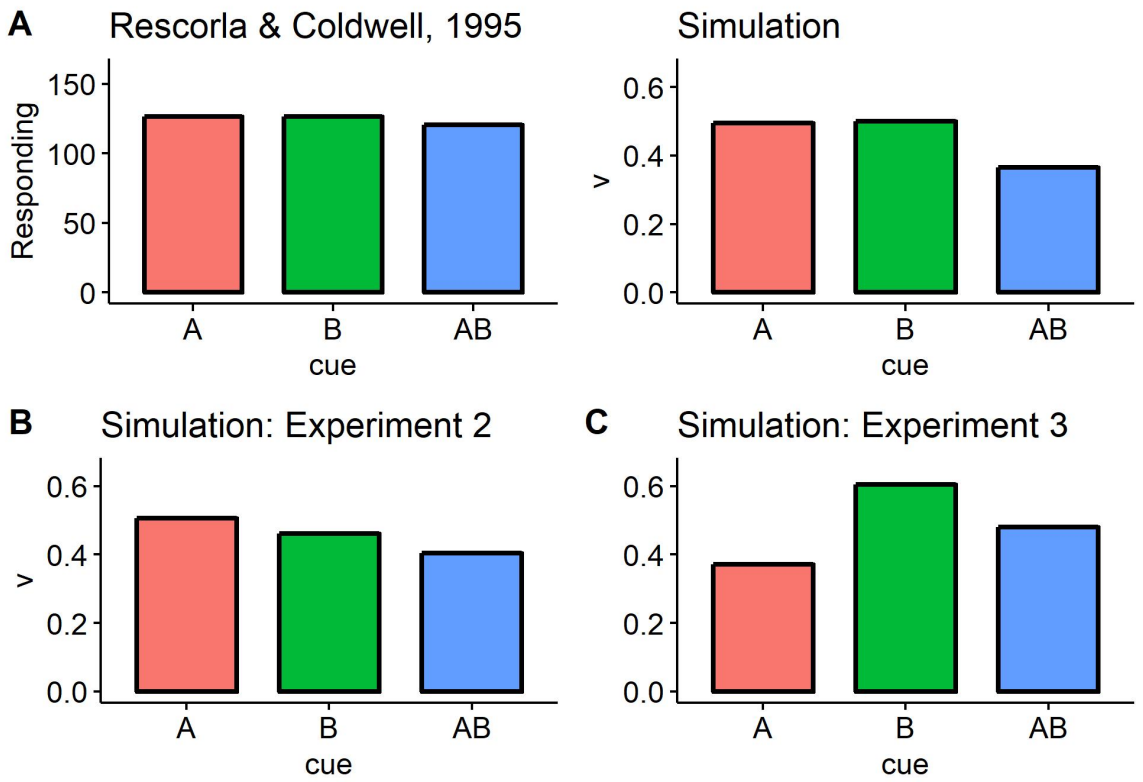

Figure 5. (A) Simulations of the EVS model for different summation designs. (A) The left panel shows the results obtained by Rescorla and Coldwell (1995) using pigeon autoshaping. The right panel shows the simulations of the model assuming that the saliencies of A and B are equal. (B) Results of a simulation of Experiment 2, where the salience of B is assumed to be higher than that of A, but B predicts a lower outcome value. (C) Results of a simulation of Experiment 3, where the salience of B was higher than that of A but the outcome value predicted by B was higher than the value predicted by A.

subjects tend to respond more to the compound ABC after compound training than after single-cue training.

Reversing a conditioned inhibitor

Pearce and Wilson ran an experiment which included a negative patterning design of the form A+, AB- in a first phase, and rewarded presentations of B alone in a second phase (B+). In contrast to an elemental theory which would predict B to recover its predictive value so that responding to AB should be higher than A or B alone, Pearce and Wilson observed that responding to AB during test was indeed lower (see Figure 7, left panel). This result is also anticipated by the EVS model (see Figure 7, right panel). During the first stage, A acquires more value than B and the unique cue represented for AB. During the second stage, B acquires more value. During the final test with AB, however, the actor still samples the unique cue, whose value has not changed during the second phase, staying at a

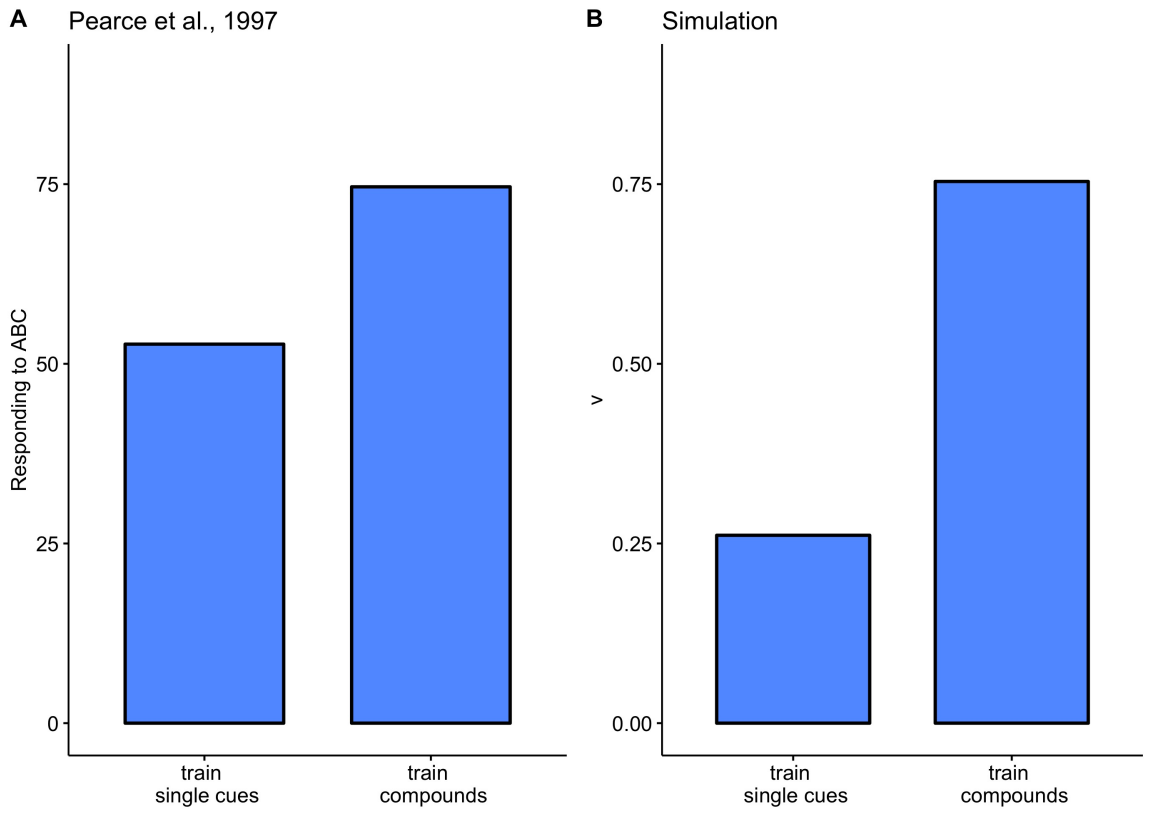

Figure 6. Simulations of a EVS model for a differential summation design. Left panel. Results obtained by Pearce and colleagues (1997) in pigeon autoshaping. The bars show the responding to the compound ABC after training with the single cues A, B and C or after training with the compounds AB, BC, and AC. Right panel. Simulations of the EVS model for the same design.

low level. Responding to AB is therefore lower than to either A or B.

Negative patterning

In another experiment in pigeons, Pearce and Redhead (1993, Exp. 1) found that subjects mastered a negative patterning discrimination (A+ AB-) easier than the same discrimination with an added redundant stimulus (AC+ ABC-). Figure 8A shows the results obtained by these authors in pigeons. The left panel shows the results observed after training with A+ and AB-; the right panel shows the results observed after training AC+ and ABC-. Given that the similarity between A and AB is lower than that of AC and ABC, an elemental approach anticipates that it will be easier for agents to master the discrimination in the group that is trained with A and AB separately than in the group trained with AC and ABC as compounds. Configural models, by contrast, correctly predicts this result (Pearce, 1987, 1994).

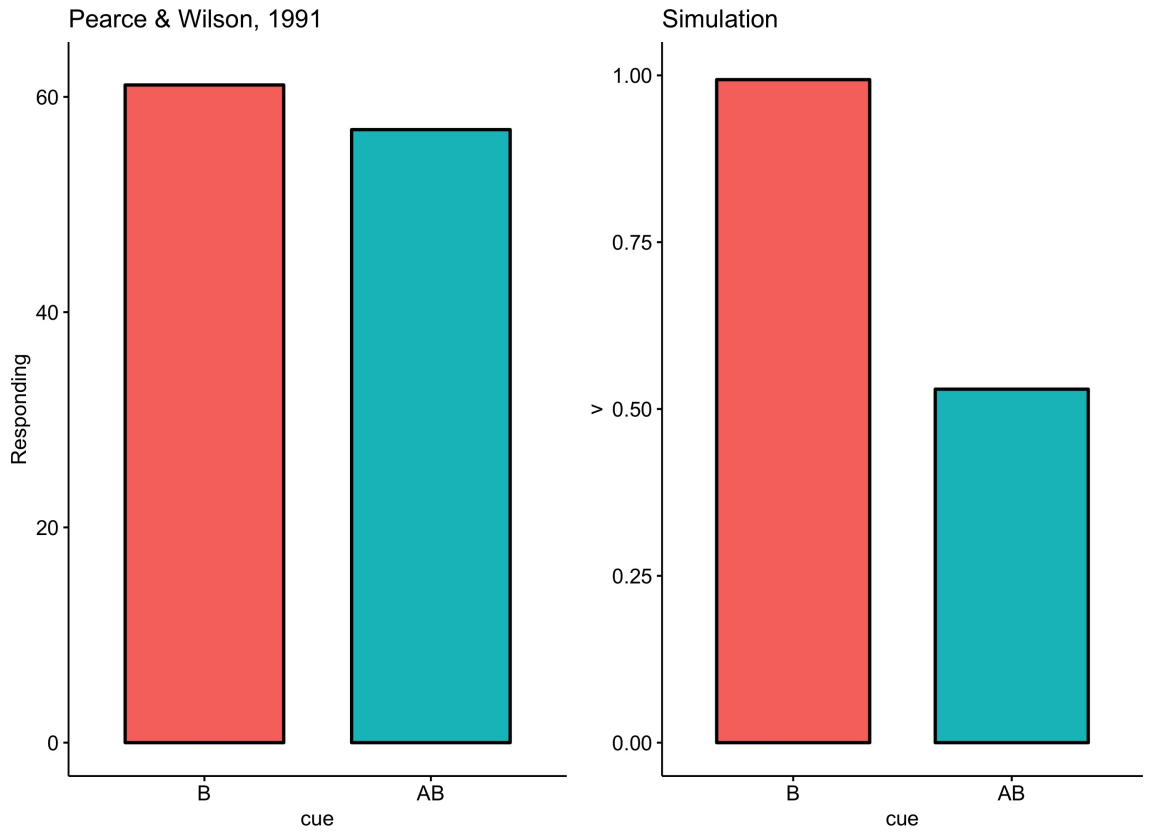

Figure 7. Simulations of a EVS model for Experiment 3 of Pearce and Wilson (1991). The experiment comprises a first phase where A is rewarded and the compound AB is not (A+, AB-). In the second phase B is rewarded in isolation. The left panel shows the original data obtained by these authors. Simulations of the EVS model are shown in the right panel.

Figure 8B shows the results of the simulations of these two negative patterning designs. The left panel shows the predictive value of A, and AB during training with a A+, AB- discrimination; the right panel shows a similar simulation for a AC-, ABC- design. The results of this simulation are reasonably in keeping with those obtained by Pearce and Redhead (1993): the difference in value between A and AB is higher than that between AC and ABC, and the order of values also follows the one obtained by these authors.

Discussion

In this paper, we have presented empirical and computational evidence supporting the hypothesis that many results from the learning literature usually thought to support configural processing of stimuli can be also explained by an alternative elemental view in which the learning process is governed by a critic that, combined with an actor's visual search mechanism, determines the cues that subjects sample and update during each training episode. We argued that task conditions fostering inefficient serial search on the stimulus compound are easily met by visual auto-shaping in pigeons, which explains the ease with

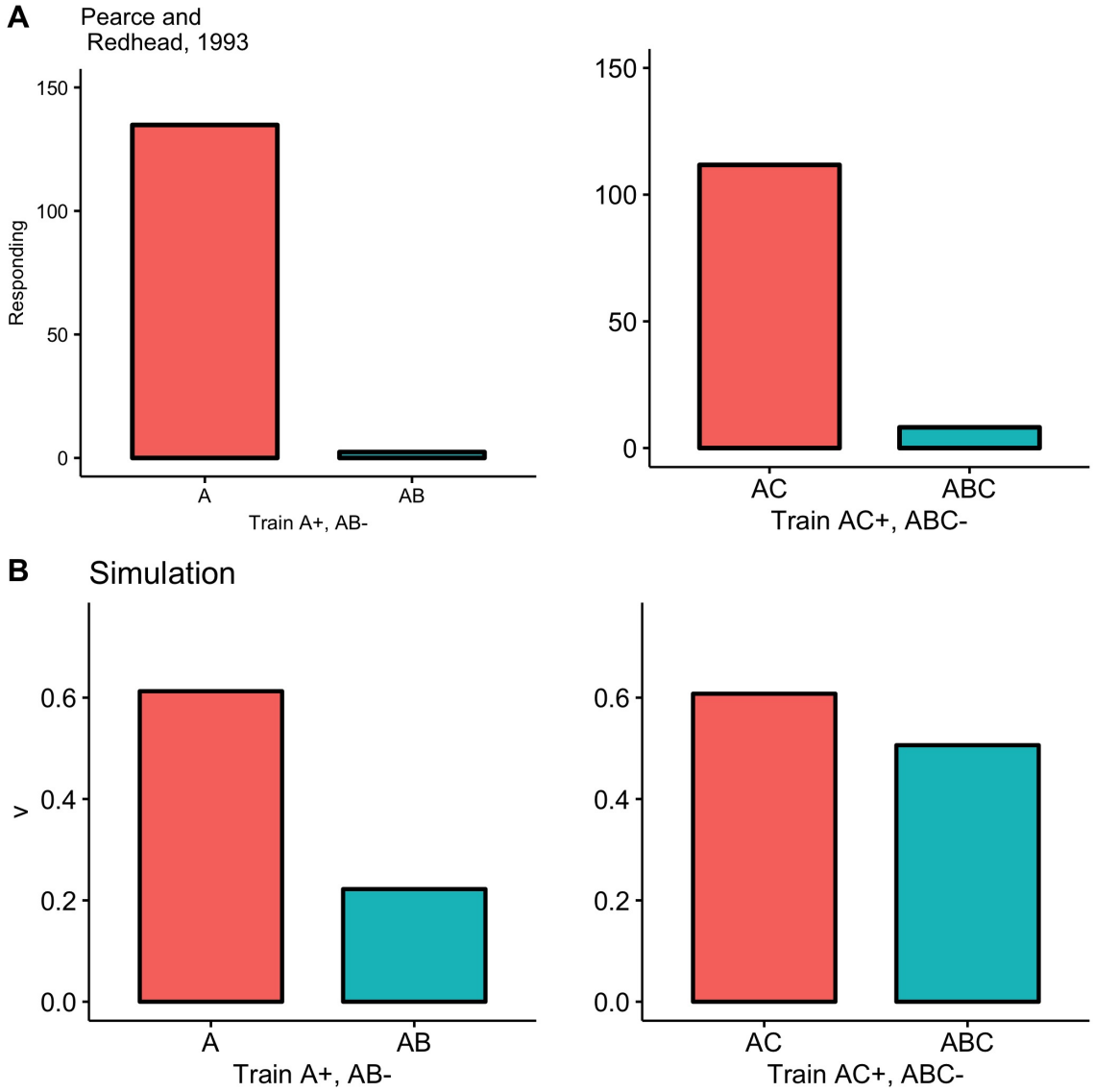

Figure 8. Simulations of the EVS model for a negative patterning design. (A) Data obtained by Pearce and Redhead (1993) in pigeons. The left panel shows responding to the compound to A and AB at the end of training after a discrimination with rewarded trials of A and non-rewarded trials with AB (A+, AB-). The right hand panel shows responding to the compounds AC and ABC at the end of training after a discrimination with rewarded trials of AC and non-rewarded trials with ABC (AC+, ABC-). (B) Simulations of the EVS model for a group trained on the A+, AB- discrimination (left panel) and for a group trained on the AC+, ABC- discrimination.

which lack of summation is found using such a procedure. We also suggested that such conditions are more difficult to meet in human causal learning with visual stimuli, which explains our inability to reduce the summation effect through stimulus manipulations in previous studies (Pérez et al., 2018).

In Experiment 1, we showed that when task conditions foster inefficient visual search, it is possible to reduce the summation effect by increasing stimulus similarity. We also showed that, as would be predicted from the visual search literature (Duncan & Humphreys, 1989), not only similarity between the two target stimuli, but also similarity of target and non-target cues produces a reduction in the summation effect. In Experiments 2 and 3, we showed that when similar cues were used, producing no summation effect, responding to the compound AB depended strongly on responding to only one of the cues, as it would be expected from an inefficient serial search strategy rather than from configural stimulus processing.

To further test this visual search hypothesis, we formalized a computational model, the EVS model, that implements our assumptions about the processes involved in these experiments. The model borrows concepts from the reinforcement learning literature, and in particular from the actor-critic model (Maia, 2010; O'Doherty et al., 2004; Sutton & Barto, 1998). The critical assumption of the actor-critic model is the deployment of two different systems that contribute to each other so that the agent can choose which options are best to maximize reward in the long run. The EVS model follows a similar approach. One system, the critic, deploys an elemental learning algorithm as presented by Wagner and Rescorla (1972). What distinguishes our model from the ones offered in the learning literature is that an additional system, the actor, samples cues according to their current value and salience, factors that have been demonstrated to prompt sampling in the visual search literature (Anderson, Laurent, & Yantis, 2011; Parkhurst, Law, & Niebur, 2002). The actor, therefore, biases the critic to update the value of only one of the cues in each trial.

Our model can also capture a number of additional phenomena from the learning literature (see Supplemental Material for simulations). External inhibition, for example, in which there is less responding to a compound AB than to the single element A after training A to predict an outcome, is anticipated because during the test with AB the subject sometimes sample B and the common cue for AB, both of which have low value, bringing down responding to AB compared to A. Incidentally, Pavlov had a similar interpretation for this phenomenon (Pavlov, 1927).

The EVS model also anticipates cue-competition phenomena. In a blocking procedure, for example, after having trained A to predict an outcome, AB is trained in compound during a second stage and responding to B is weaker compared to a group that has not undergone the first stage with A. In the EVS model, the second stage produces a visual search process in which the added cue B is sampled only in a low proportion of trials as a consequence of the higher predictive value of A at the start of the second stage (Kamin, 1969; Mackintosh & Turner, 1971). Compared to a group that has not undergone the first stage of training, responding to B will be lower, and blocking follows. Likewise, when compounds are presented during training the sampling mechanism of the EVS model makes it so that, for the same amount of training, each cue is sampled only half the time it would have been

processed during training with either of the single cues alone; the sequential search process will then explain why training compounds brings about less responding to each cue than training the cues in isolation (overshadowing; Mackintosh (1976)).

Regardless of the generalizability of the EVS model, the empirical and computational results in this paper demonstrate how results that are usually interpreted in favor of configural processing may be better explained as a consequence of elemental processing combined with visual search strategies. Our work thus bridges two seemingly unrelated areas of experimental psychology and leads to a more parsimonious explanation of the results of experiments across species, and the discovery of new principles underlying the generalization of learning.

Methods

Experiment 1

Participants. 86 undergraduate students from Florida International University participated in Experiment 1. Participants did not have previous experience with the experimental procedure and were tested simultaneously and in the same room. The procedures were approved by the Institutional Review Board at Florida International University. Participants were randomly assigned to one of three groups: *intra* ($n_{intra} = 27$), *extra1* ($n_{extra1} = 28$) and *extra2* ($n_{extra2} = 31$). The final number of participants in Experiment 1 was $n_{intra} = 18$, $n_{extra1} = 13$, $n_{extra2} = 27$.

Materials. Participants were tested in Windows (c) computers running Psychopy (Peirce, 2007) 1.75. Responses were recorded from standard PC keyboards.

Procedure. Participants were presented with a task in which they were asked to play the role of an allergist that had to predict the levels of allergy caused by different drugs in a hypothetical patient, Mr. X (see Figure 1B) (Pérez et al., 2018; Soto et al., 2009). During training, one or two drugs were presented as different abstract shapes (see Figure 1), and participants were required to give an assessment of the level of allergy that each drug would cause in Mr. X in a scale of 0 to 35. Two trials per each cue were presented during the testing stage.

Groups differed in the similarity between cues in the display (see Figure 1A). Each stimulus was created from three different cues that "branched out" from a central point. Among these branches, only one of them represented the target cue associated with either allergy or no allergy during training. The other two branches were non-target cues that could not predict the presence or absence of allergy. During the test, the compound AB was comprised by two target branches together with an additional non-target cue. In group *intra*, all these "branches" were of the same color (black), but differed in shape. In group *extra1*, A and B differed in color (grey and black), but they shared color with the non-target cues (X and Y, one grey and one black). In group *extra2*, the target cues were the same as in group *extra1*, but now the background stimuli had a distinctive color as well. In all groups, A and B, which predicted allergy, shared color with cues C and D, which predicted no allergy. Thus, all participants, regardless of group, had to attend to shape. Color, on the other hand, was irrelevant to solve the discrimination.

Experiment 2

Participants. 75 undergraduate students from Florida International University were randomly assigned to one of two groups ($n_{intra} = 40, n_{intra2} = 35$) and were compensated with course credit for their participation. The final number of participants per group was therefore $n_{intra} = 40$, $n_{intra2} = 33$.

Materials. Participants were tested as described for group *intra* of Experiment 1 using Windows (c) computers running Psychopy (Peirce, 2007) 1.82.4.

Procedure. The procedure was the same as described for group *intra* of Experiment 1, with only one exception: In group *intra2*, stimulus B was associated with 8 points of allergy during training (see Figure 4).

Experiment 3

Participants. 80 undergraduate students from Florida International University were randomly assigned to one of two groups ($n_{intra} = 42, n_{intra2} = 38$) and were tested under the same conditions of Experiment 2. Twenty six participants failed to meet the inclusion criteria and were discarded from the statistical analysis. The final number of participants per group was $n_{intra} = 22$, $n_{intra2} = 32$.

Materials. Participants were tested in the same way as in Experiment 2.

Procedure. The procedure was the same as in Experiment 2. Only the outcomes of A and B were interchanged in group *intra2*. The outcome assigned to A was 10 while a value of 8 was assigned to B.

Exclusion criteria

Following the procedure of our previous study on summation (Pérez et al., 2018), participants that failed to score on average 10 (+/-3) points of allergy to cues that predicted allergy and 0 (+3) points of allergy to cues that did not predict allergy, were left out from the analysis.

Statistical analyses

Statistical analyses were performed using the R programming language (Version 3.4.3; R Core Team, 2017) under RStudio (RStudio Team, 2015), using the packages *BayesFactor* (Version 0.9.12.2; Morey & Rouder, 2015), *bootES* (Version 1.2; Gerlanc & Kirby, 2015), *dplyr* (Version 0.7.4; Wickham, Francois, Henry, & Müller, 2017), *ggplot2* (Version 2.2.1; Wickham, 2009), *ggpubr* (Version 0.1.6; Kassambara, 2017) and *lme4* (Version 1.1.15; Bates, Mächler, Bolker, & Walker, 2015). For all the pre-planned comparisons we calculated a Welsh *t*-test and included Cohen's D, along with a 95% confidence interval on this estimate, as a measure of effect size. When reporting interactions between factors, we computed η^2 and a 90% confidence interval on this estimate. The reliability of the results was contrasted

against the usual criterion of $\alpha = .05$. All scripts and materials for this paper can be found at www.github.com/omadav/seq_search

The EVS model

Our model assumes a *critic* that learns according to a prediction-error algorithm, where the predictive value or *associative strength* of stimulus i in trial n , v_i^n, is updated in accord with Equation 1

$$v_i^{n+1} = v_i^n + \alpha_i \beta(\lambda^n - v_i^n) \tag{1}$$

, where α and β are learning rate parameters ($\alpha \in [0, 1], \beta \in [0, 1]$) which represent how much the subject updates the value of cue i in trial n and λ^n is an indicator function that takes the value one if a reward is presented in trial n and zero if the reward is not presented ($\lambda \in \{0, 1\}$). This algorithm assumes that the change in the associative or predictive value of stimulus i is determined by the difference between the observed outcome and the current outcome expected from that stimulus.

The next step is formulating the type of elemental representation that is brought about when compound of stimuli are presented to the agent. Assuming that the actual stimuli presented by the experimenter are the only cues represented by the agent, and that compounds are simply comprised of the same components is problematic, as such a model cannot account for the fact that animals learn non-linear discriminations in which elements and compounds are differentially rewarded. For this reason, we follow a previous model offered by Wagner and Rescorla (1972). Under this model, any component can activate its own elemental representation and acquire its own predictive value in accord with Equation 1, but the modification concerns how the agent represents cues in isolation and in compound. When a stimulus is presented in compound with other stimulus, this model assumes that an additional element enters into an association with the outcome, and that this *unique-cue* element follows the same learning algorithm as in Equation 1.

Three important aspects of this unique cue are worth noting. First, the addition of a cue representing the compound does not imply that subjects process stimuli in a configural manner. The key property of configural processing is whether or not the representation of a given cue, like A, is "context-specific" (Wagner, 2008), changing when A is presented alone versus when it is presented in compound with other stimuli. This is not the case for the Wagner-Rescorla model. In a summation design, A and B are still represented and processed elemntally, and a summation effect is still predicted by the model.

Second, the unique cue is usually interpreted as an internal representation of a compound. However, this interpretation is not necessary in the present application. As long as visual cues are presented in close proximity during compound trials (i.e., either overlapping or close to one another), it is possible for the subject to sample visual information in some areas of the display that are unique to compound trials (e.g., line intersections), which makes the compound trial different to a single cue trial.

Third, the unique cue is not necessary to explain results from simple summation experiments, like those presented in this paper. This aspect of the model is only important for the explanation of more complex designs, like the non-linear discriminations just mentioned. To illustrate this point, take one of the cardinal results suggesting a configural type of processing, the negative patterning design (Myers, Vogel, Shin, & Wagner, 2001). Under this design, each component A and B is rewarded in isolation, but the compound AB is not (A+,B+,AB-). Given the above equations, it is relatively clear that an agent should never be able to solve this problem under an elemental-type of representation; that is, it should never learn to respond less to AB than to each of A or B alone. Given the assumption that predictions are summed linearly ($v_{Total} = v_{AB} = v_A + v_B$), the presentation of AB should always produce a summation effect. And yet animals are able to solve this problem and respond less to AB than to either of A and B (see also Saavedra (1975)). However, the assumption of an additional unique cue is able to correctly predict these data. Assume, for example, that a unique cue X is active whenever the compound AB is presented, but inactive when A and B are presented in isolation. This is equivalent to A+, B+ and ABX- training, which, according to the Wagner and Rescorla model, implies that X will acquire negative predictive value. If the salience of X is high enough so as to counteract the positive predictions of A and B together, the discrimination is readily solved.

To model our agent's visual search process, in addition to the critic learning the value of a cue according to Equation 1 we assume an additional system, the actor, which searches in the stimulus array for a single stimulus to process. We model this actor through sampling from a multinomial distribution with parameter $\mathbf{p} = [p_1, p_2, ..., p_k]$ where k is the number of stimuli presented in a given training or testing trial. In line with the visual search literature where both higher salience (α) (Parkhurst et al., 2002) and higher predictive value (v) (Anderson et al., 2011) increase the probability of a stimulus capturing attention, we assume that the probability of stimulus i being processed is given by a softmax function incorporating both of these factors (Sutton & Barto, 1998):

$$p_i = \frac{\exp\left(\eta \alpha_i \left|v_i\right|\right)}{\sum\limits_j \exp\left(\eta \alpha_j \left|v_j\right|\right)} \tag{2}$$

, where η is a decisiveness or *temperature* parameter that determines the extent to which the actor is biased to sample cues with low salience or predictive value ($j = [1, 2, ..., i, ...k]$). We use the absolute value of v, since cues with high inhibitory strength (negative v) should command more attention than other cues in a given array (Parkhurst et al., 2002). The operation of this model is presented in Figure 4.

For all the simulations in this paper, we assume that the salience of the unique cues is equal to the salience of the target cues, that is, $\alpha_{target} = \alpha_{nonTarget}$, and that the order of presentations of different trial types in an experiment is random. The former assumption—that the salience of the cues presented and the unique cues represented by the subject in compound trials are equal—is an assumption generally held by Pearce (1994, 2002) in his modelling of configural theory and is the one that, unless otherwise noted, we follow in all the subsequent simulations in this paper.

To allow the actor to sample cues with low predictive value we set the temperature parameter η to 30 and the initial predictive value of each cue, both target and unique cues, v_i, $i \in [1, ..., k]$, to 0.05. Unless otherwise noted, the value of λ was set to 1 for reinforced trials and to zero for non-rewarded trials. We ran 80 simulations for each experimental design. The values shown in the following figures are the average values across all simulations.

Summation. To mimic the conditions of pigeon auto-shaping, we first set the values of ($\alpha_A = \alpha_B = .4$). To account for the fact that B is more salient in Experiment 2, we set the value of α_A to .4 and the value of α_B to .5. A value of .4 was also set to the unique cue X ($\alpha_X = .4$). To account for different outcome values predicted by each cue, we set $\lambda_A = 1 > \lambda_B = .95$. To replicate the conditions of Experiment 3, we swapped the values of λ so that $\lambda_A = .95, \lambda_B = 1$.

Negative patterning. It is relatively clear that when the actor of the EVS model is highly exploratory, solving the negative patterning problem would be particularly difficult, as there needs to be less sampling of unique cues that have a low value during training. We therefore tested if our model would predict this behavioural pattern assuming a low exploratory agent ($\eta = 5$) for which the unique cue for the compound ABC is more salient than the other cues ($\alpha_A = \alpha_B = .4 < \alpha_X = .7$, where X is the unique cue for the compound ABC).

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