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Part I

Attention and Perception

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1 Unitization of Features Following Extended Training in a Visual Search Task

Denis Cousineau, Chris Donkin, and Étienne Dumesnil

INTRODUCTION

Visual search for a target among foil items has proven to be a complex skill (Shiffrin & Shneider, 1977; Schneider & Shiffrin, 1977). Behavior in this task can be conceptually decomposed into three broad classes of visual subprocesses: (a) recognition of a target; (b) scanning of the display items; and (c) a stopping rule. Factors affecting the stopping rule, which can be categorized as being exogeneous or endogeneous, were examined thoroughly in AuQ1 Donkin, Cousineau and Shiffrin (in preparation; see also Moran, Zehetleitner, Mueller & Usher, 2013), whereas factors influencing scanning processes and whether they produce (almost) flat slope functions were examined in, e.g., Anderson, Heinke & Humphreys, 2010; Egeth, Virzi & Garbart, 1984; Krummenacher, Mueller & Heller, 2001; Triesman, 1986; and Zhang & Luck, 2009. Scanning performance is worse in situations where targets and foils differ on a number of features, and no one feature by itself is indicative of target presence. This situation is usually termed conjunction search, and typically produces response times increasing with the number of items to search through (Wolfe, Cave & Franzel, 1989). For example, a horizontally aligned red rectangle is harder to find when the foils in the display are not only horizontal green rectangles but also vertical red rectangles.

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This leads to point (a) above, target recognition process, which is the focus of this chapter. One factor that may affect target recognition is whether features are processed independently or not. If they are not, one possibility is perceptual unitization of initially unrelated features. As defined by Landy and Goldstone: "when elements co-vary together and their co-occurrence predicts an important categorization, the elements tend to be unitized" (2005, p. 350). In support of unitization in a visual search task, Shiffrin and Lightfoot (1997) carried out an extensive study of a difficult conjunction search task with extended consistent training. Initially, each three-feature stimulus (rectangles with spokes pointing inward) required a comparison time suggestive of three sub-comparisons, one for each feature. Training presumably caused unitization of the features, so that each stimulus could be compared in a single comparison step. Thus, over about thirty sessions

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the search slopes dropped three-fold, from about 270 ms per comparison to about 90 ms per comparison. The slopes remained high and stable thereafter, consistent with serial self-terminating search. Such results suggest unitization learning. Other experiments using consistent training involving conjunction search (such as letter targets and digit foils, or first-half-of-alphabet letter targets, and second-half-of-alphabet letter foils) produced results compatible with unitization of features (e.g., Shiffrin & Schneider, 1977; Wolfe, Cave & Franzel, 1989), although in these cases the underlying feature composition is not easy to infer (see also Cousineau & Larochelle, 2004; Lefebvre, Cousineau & Larochelle, 2008).

The varied results have led investigators to propose a variety of search models incorporating target recognition processes with quite different assumptions. A relevant example is the Guided Search Model, various incarnations of which have been proposed by Jeremy Wolfe (Wolfe, 1994; 2007; Wolfe, Cave & Franzel, 1989; Wolfe & Gancarz, 1996). In this model, the representation of features remains fixed (i.e., no unitization). However, feature diagnosticity is used to determine the order in which items are scanned. A similar example is the Sufficient Feature Model (SFM, Cousineau & Larochelle, 2004) in which feature diagnosticity, learned through exposure to the targets, is used to minimize the number of feature comparisons needed to identify a target. These models assume that feature detection is the main determinant of performance, and as such make certain predictions for response times.

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A second alternative to unitization was proposed in the literature on the redundant-attribute target detection task. Mordkoff and Yantis (1991) suggested that co-occurring features could develop lateral excitatory connections (termed crosstalk) so that the presence of one feature would lower the threshold to detect another feature whose frequency of co-occurrence with the first is high.

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These models do not incorporate unitization or other forms of evolution in feature composition (see Schyns & Murphy, 1994). Targets are localized faster because cues are used (presumably during a pre-attentive phase) in a more rational manner (using diagnosticity; e.g., SFM, Guided Search) or because feature correlations are capitalized on in order to lower thresholds (e.g., crosstalk models).

The purpose of the present study is to establish whether unitization is altering feature representation in a visual search task. If so, we want to see if the united features are those predictive of classifications, as suggested by Landy and Goldstone (2005). We do this by isolating the recognition processes from the search task by always using a single-item display. Hence, there is no scanning across multiple locations and there is no termination rule. Further, we did not impose temporal pressure. The participant's task was to identify the features perceived. Some of the stimuli were the targets or foils used in a search task that participants performed on sessions that alternated with the present task. The task was made difficult by the presence of masks before and after the stimulus was briefly presented.

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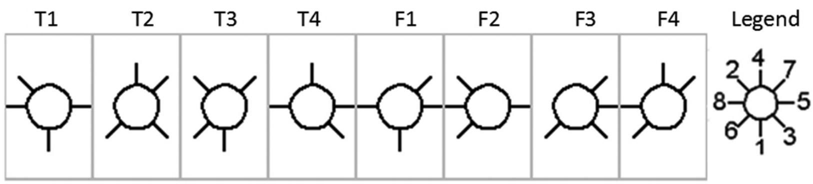
Experiment: The Feature Detection Task

The feature detection task was part of a larger experiment. The participants' main task was a visual search. The possible targets (T1 to T4) and the possible foils (F1 to F4) are shown in Figure 1.1. The visual search task and the visual search results were described in Cousineau and Shiffrin (2004).

These abstract objects were created such that no single feature could signal the presence of a target. However, a conjunction of features could (features 1&2 for targets T1 and T3, or features 3&4 for T2 and T4). Features 1 to 4 will be denoted the *diagnostic features* in what follows (though they were not sufficient in isolation to identify a target).

The visual search task alternated with the feature detection task during the first 30 sessions, for a total of 15 one-hour sessions of training on both tasks (afterwards, the visual search task continued for 44 subsequent hours).



Target and foil composition in the visual search task

Targets					Foils				
T1	1	2	5	8	F1	1	5	7	8
T2	3	4	6	7	F2	2	5	6	8
T3	1	2	6	7	F3	3	5	6	7
T4	3	4	5	8	F4	4	6	7	8

Configurations in the four types of trials

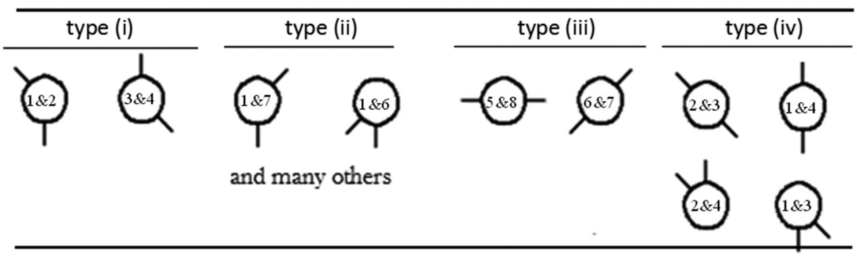


Figure 1.1 (top) Stimuli used in the search task (Cousineau & Shiffrin, 2004), labeled T1 to T4 and F1 to F4 respectively for the four targets and the four foils respectively. The stimuli were actually white on a black background. (middle) Composition of the stimuli in terms of features, using the numbering scheme shown in the legend. (bottom) Examples of two-feature stimuli presented in the four types of trial.

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In what follows, we present only the results of the feature detection task. Also, for brevity, we consider only the last five sessions (even sessions 22 to 30) where performance had reached a plateau, as seen by flat *d*' curves.

Methodology

Six participants (four female) began the experiment. Two of them were excluded from analyses because they dropped out of the experiment early (session 7 and 23; one male). The first author was one of the participants; the rest were paid $7 per hour.

On even-numbered sessions, participants completed the feature detection task. The computer screen was black, in 640 × 480 resolution, at 60 Hz (VGA). A trial started with the presentation of a patch of random dots (33% probability of a pixel being white) for 500 ms sustaining 4° of visual angle vertically and horizontally. Then a test stimulus (32 × 32 pixels; 3.5° of visual angle) was briefly presented, followed by another patch of random dots that remained until the participant gave their response. The test stimulus was initially presented for 33.3 ms, but this duration was reduced to 16.6 ms after session 11 because accuracy was near perfect. The test stimulus was composed of a central circle and one to four features, the features being outward-pointing lines evenly spaced at eight possible orientations (see Figure 1.1 for examples of such stimuli containing two and four features). There exists 162 such items and they were all presented three times per session, for a total of 486 trials per session.

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The participant was required to answer two questions on each trial. First, they were asked "Was the item a target or not?" This response was not analyzed; it was asked to encourage the participant to use the same recognition process as in the visual search task. In addition, the response keys ("1" for target, "2" for foil, using the numeric keypad) were the same as in the visual search task. They were informed that 97.5% of the objects were not targets (there are only four targets for 162 stimuli). Second, they were asked "What features were presented?" At this moment, participants were given a legend on the side of the display labeling the eight possible features with numbers 1 to 8 (the legend was constant for all trials and all participants). Participants were instructed to indicate all of the features they believed were present in the displayed stimulus. Participants could answer in any order, use backspace to make changes, and ended their response by pressing the "Return" key. Participants were not placed under any time pressure from the experimenter. Figure 1.2 shows a typical feature detection trial.

The four features labeled *diagnostic* are diagnostic in the search task, not in the present feature detection task (in addition, the three naïve participants were uninformed of the existence of diagnostic features; post-experimental discussions indicated that they never noticed their existence). Any difference in processing of these features is therefore a consequence of training in the visual search task.

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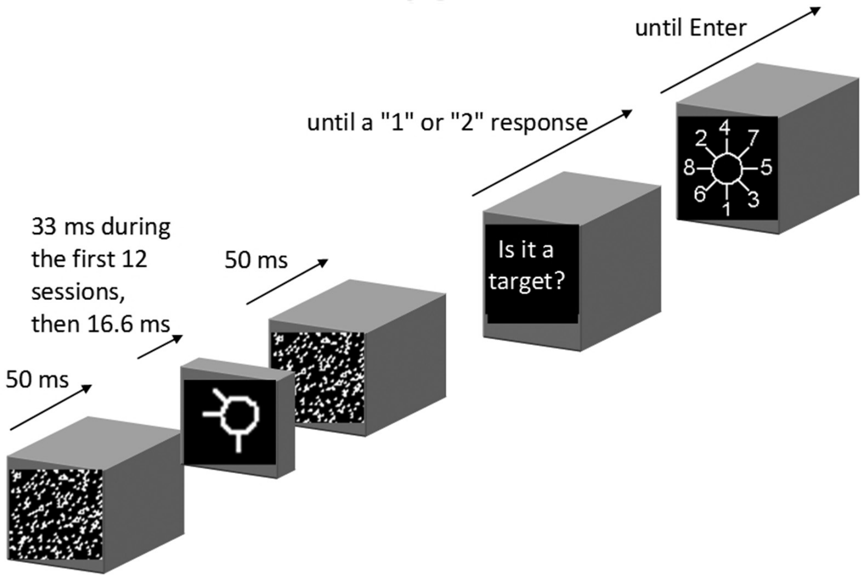

Figure 1.2 Typical trial in the feature detection task.

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Results

All the participants found the task difficult when presentation time was 16.6 ms and were relieved when it was finished. They subjectively reported seeing the stimulus well but they had to concentrate before its impression vanished. This self-report is reminiscent of Sperling's (1960) study of iconic memory. The results show near perfect performance when the stimulus is simple (only one feature) but performance decreases rapidly as the number of features increases. The decrease in the probability of a correct feature recall is mirrored by an increase in incorrectly reported features (hereafter, these results are called hit rates and false alarm [FA] rates, respectively) of about half the magnitude.

We now focus on whether diagnostic features are detected differently than non-diagnostic features. To that end, trials were first divided according to the total number of features presented (*N*). We further selected out four particular types of trials: (*i*) trials in which the pairs of diagnostic features present on targets were seen (i.e., trials displaying the features 1&2 or 3&4); (*ii*) trials where items contained one diagnostic feature along with a non-diagnostic feature (i.e., 1&5, 1&6, . . . 4&8; this type contains 16 different pairs of features all present on one target); (*iii*) trials with pairs of features that were on the targets but in which none was diagnostic (i.e., the features 5&8 and 6&7); and finally (*iv*) trials showing new configurations involving target diagnostic features (trials showing the features 1&3, 1&4, 2&3 or 2&4), non-existent in the visual search task.

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Note that this subdivision is not exclusive (there could be a trial with features 1&2&4, which would satisfy conditions (*i*) and (*iv*) above). It was made exclusive by looking for conjunctions of diagnostic features seen on targets first (*i*), and if none were present we looked for type (*iv*), type (*ii*) and, finally, type (*iii*). The first condition to apply was tagged to the trial. Finally, when only one feature was presented, the trials were grouped together. There exists a fifth category (with feature pairs 5&6, 5&7, 6&8 and 7&8) but only four stimuli out of 162 had these combinations (and they all had two features in total), so we did not analyze it any further.

The purpose of these types is to have a progression in likelihood of unitization. Indeed, the features in types (*i*) being diagnostic should be unitized according to the Landy and Goldstone (2005) definition. The features in type (*ii*) signal the presence of targets but are not unique to targets, so according to a strict application of the definition, should not be unitized. If on the other hand, a simple appearance of targets is sufficient, then type (*ii*) might lead to unitization. Finally, type (*iv*) should definitely not lead to unitization, as these pairs never occurred during the visual search task.

First Order Accuracies

Hits and false alarms are reported in this section. Hits are computed for each feature characterizing the trial type. So if the response given to stimulus 1&2&4 is 1&2&3, for example, this stimulus is part of type (*i*) trials and we recorded two hits. An FA is recorded when participants incorrectly respond that a feature characterizing the trial type was present (e.g., if to stimulus 1&4, participant responded 1&2&4, the result is one FA in type *i*). Finally, these performances are averaged over all participants for each total number of features.

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Figure 1.3 (top row) shows the hit rates (left) and the FA rates (right) for the final five sessions. In the $N = 1$ condition, performance is perfect (proportion of correct recall, P(*hit*) is above 0.99). As described earlier, as the number of features increases, the probability of correctly reporting them reduces markedly and the probability of falsely reporting an absent feature increases significantly. The decrease in hit rate is as strong as 10% whereas the increase in FA is at worst 4%.

The results are difficult to interpret. For example, the hit rate for the type (*ii*) trials is generally lower than in the other conditions; however, the FA rate is also lower in that condition at $N = 4$. The type (*i*) trials performance seems to be worse when there are two features presented. Finally, there are very few FAs for type (*iii*) trials when N was 3 (and there is no observation possible at length of 4). This last result is surprising as these features (e.g., 5&8) are not diagnostic of targets.

Overall, performance was better for trial types (*i*) and (*iii*). This is also suggested by *d*' obtained from those data and shown in bottom left panel of Figure 1.3. According to a strong unitization view, the type (*i*) trials involving the diagnostic pairs 1&2 or 3&4 should be processed by dedicated

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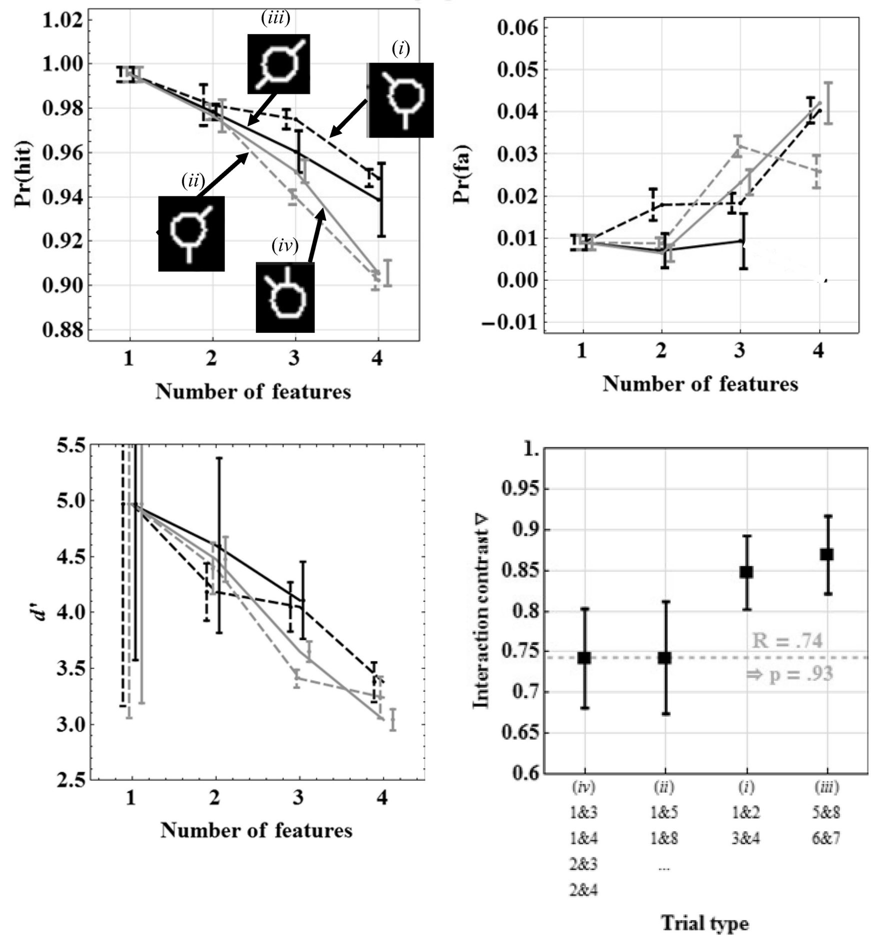

Figure 1.3 (top left) Proportion of hits as a function of the total number of features presented, and as a function of type of trials (*i* to *iv*). (top right) Proportion of FAs, using the same format as above. The points at 1, showing only one feature, are not part of any configuration and are arbitrarily connected. The stimuli shown in the insets are possible examples of two-feature stimuli. (bottom left) *d*' computed from the upper panels. (bottom right) The stimulus interaction contrasts as a function of type of trials (*i* to *iv*) computed from all the trials showing two, three or four features. Error bars shows 95% confidence intervals.

detectors and therefore (a) have better performance than trials involving conjunctions of non-diagnostic features (type *iii*); (b) there should not be any differences in hits for the trials where the diagnostic pairs are absent, e.g., types (*ii*) and (*iii*); and finally (c), FA should be lower for type (*i*) than for type (*ii*). As we will see next, similarities between (*i*) and (*iii*) are also present when performing model fitting.

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A Model of Unitization

To further examine the results, we applied a model of unitization to the data. The model assumes a strong version of unitization, one by which unitization results in a dedicated process that can detect pairs of features independently of the process used to register single features. Let U denote the probability that the pair is identified correctly using the unitization-based process and let p denote the probability that a single feature is identified without this process. We define the following shortcuts:

$$Pr_{AB} = Pr\,(R_A \;\&\; R_B \mid S_A \;\&\; S_B)$$
$$Pr_{Ab} = Pr\,(R_A \;\&\; M_B \mid S_A \;\&\; S_B)$$
$$Pr_{aB} = Pr\,(M_A \;\&\; R_B \mid S_A \;\&\; S_B)$$
$$Pr_{ab} = Pr\,(M_A \;\&\; M_B \mid S_A \;\&\; S_B)$$

where S_A is the presence of feature A; R_A is to respond that feature A is present; and M_A is to miss the presence of A.

From the model, we have the following expected probabilities:

$$Pr_{AB} = U + (1 - U)p^2$$
$$Pr_{Ab} = Pr_{aB} = p(1 - p)(1 - U)$$
$$Pr_{ab} = (1 - p)^2(1 - U)$$

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Best-fitting parameters are obtained through log-likelihood (log(£)) maximization (Cousineau, Brown and Heathcote, 2004). Search was performed using simulated annealing (Ingber, 1993). We fitted four different U parameters, U_1 to U_4, one for each of the trial types described earlier. Also, we used two different p values, p_{High} for diagnostic features (1 to 4) and p_{Low} for non-diagnostic features (5 to 8). So we have in total six free parameters to accommodate accuracies in 16 different cells (the four types *i* to *iv* and the four observed proportions of response Pr_{AB} to Pr_{ab}). We allowed U_4 to be free; according to a strict view of unitization, this parameter should be estimated to zero as the features in type (*iv*) trials are not predicting any responses, never being seen in the visual search task, and therefore no unitization should occur.

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Table 1.1 shows the best fit along with the values of the best-fitting parameters. The first point to mention is that there is no significant difference between the two p parameters (all tests are based on individual data of the participants, significance is established using a likelihood ratio test; Hélie, 2006). Hence, the model does not suggest that the diagnostic features are processed with a higher accuracy than non-diagnostic features. Second, we note that participant A is different from the three other participants. This finding was also found in the visual search task where it was established that this participant was almost perfectly following a serial self-terminating process to locate targets (Cousineau & Shiffrin, 2004).

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Table 1.1 Best-fit and best-fitting parameters for the 6-parameter model of unitization presented in the text applied to accuracies of the last 5 sessions in the detection task.

	Participant			
	A	**B**	**C**	**D**
log(£)	–121.6	–134.8	–596.8	–635.6
PLow	0.98	.98	.90	.89
PHigh	0.99	.98	.90	.89
U_1	0.57	.50	.50	.41
U_2	.00	.05	.00	.03
U_3	0.34	.84	.95	.79
U_4	0.70	.07	.19	.00

More importantly, for the remaining three participants, the parameter U_4 is not significantly different from zero (all significance > .15). This finding is in line with unitization, as the features seen in these trials were not predicting target presence or absence in the visual search task. More surprising, though, is the fact that all U_3 parameters are different from zero (all significance < .01) whereas all U_2 parameters are not different from zero (all significance > .70). We tried various starting values to see if the best fit could locate a solution away from zero for U_2, but with no success.

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In sum, using a model-based approach, we again find a dichotomy between types (*i*) and (*iii*) trials, and types (*ii*) and (*iv*) trials. The result was expected with regard to type (*iv*) but (*iii*) was unexpected given a strict definition of unitization. The results are clearer here (and significant) because all the analyzed probabilities are conditional on two features being presented; in the previous section, FAs required that one feature be absent but reported as being present.

Second-Order Accuracies

The above results are based on model fitting and so are susceptible to local minima. In what follows, we show that the unitization model can be reframed into a non-parametric version. As the results will show, we will again have a dichotomy between the trial types (*i*) and (*iii*) on one side, and trial types (*ii*) and (*iv*) on the other.

In order to accomplish this, we turn to a second-order contrast. Using the same shortcuts as in the previous section, we can consider the following aggregates: (a) the sum of Pr_{AB}, Pr_{Ab}, Pr_{aB} and Pr_{ab}. It is easy to see that the result is 1 (as it covers all possible responses to two features). (b) We can consider an interaction contrast (denoted ∇ in the following) with

$$\nabla = Pr_{AB} - Pr_{Ab} - Pr_{aB} + Pr_{ab}.$$

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This interaction contrast is similar to the ones proposed by Shaw (1978; Mulligan & Shaw, 1980) except that her contrasts were "response-based" (the response was constant but the stimuli presented were either present or absent) whereas the present interaction contrast is "stimulus-based" (the stimulus presented is constant but the responses given are either "present" or "absent"). The computation of these contrasts is also reminiscent of Townsend's mean interaction contrast and survivor interaction contrast (see e.g., Townsend & Nozawa, 1995; Fific, Townsend & Eidels, 2008).

To see the relevance of this contrast in our current analyses, we examine the unitization model (assuming a single p for all features) when the contrast is computed:

$$\begin{aligned}
\nabla &= Pr_{AB} - Pr_{Ab} - Pr_{aB} + Pr_{ab} \\
&= U + (1 - U)p^2 - 2p(1 - p)(1 - U) + (1 - p)^2(1\text{-}U) \\
&= U + (1 - U)(p^2 - 2p + 2p^2 + 1 - 2p + p^2) \\
&= U + (1 - U)(1 - 2p)^2 \\
&= U + (1 - U)\mathrm{R} \\
&= R + (1 - R)\mathrm{U}
\end{aligned}$$

in which $R = (1 - 2p)^2$ is like a reliability parameter: if p is .5 (responding randomly), then R is zero; if p is 1, then R is 1 (we exclude the possibility that $p < .5$). For a constant R, this function is linear with U. In particular, as the trial type (*iv*) should have no unitization, U_4 should be zero, and when U is zero, the above contrast reduces to $\nabla = R$. Further, given a value of R, it is trivial to infer a value of p.

We show in Figure 1.3 (bottom right panel) the interaction contrast computed for three participants (we excluded participant A, who we know is processing the display with a different approach). As seen, for two conditions, trial types (*ii*) and (*iv*), there is no difference in the interaction contrast. As U_4 has no reason to show unitization, we get an estimate of R from the vertical axis (0.74) from which we deduce that p is .93. This result is very consistent with model fits reported in Table 1.1 (average p is .923 across all three participants).

For the third time, and using a non-parametric approach, we find two clusters of trial types (*i* and *iii* vs. *ii* and *iv*). We discuss their implications with regard to unitization next.

Discussion of the Results

The strict view of unitization put forth by Landy and Goldstone (2005): "When elements co-vary together *and their co-occurrence predicts an important categorization*, the elements tend to be unitized" (our emphasis) is not entirely supported by the results. The above definition would lead to only type (*i*) trials to benefit from it. But we find that both types (*i*) and (*iii*) are enhanced.

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Instead of assuming a strict version of unitization, we could assume a weaker version in which any co-occurrence of features pairs with a target-present response improves their processing. But then, the fact that type (*ii*) trials do not benefit from training in visual search is bizarre. It suggests that the diagnostic features are not (con)fused with non-diagnostic features. For example, with the first target (composed of 1&2&5&8), 1&2 is given a special status, as is 5&8, but not 1&5 (1&5 and 5&8 are equally frequent on targets and on foils).

The only difference between these two pairs is a frequency difference: 5&8 is present on two targets (and on two foils) whereas 1&5 is present on only one target (and on one foil). So alternatively, the above definition could be rephrased as "When elements co-vary together *and their co-occurrence predicts itself co-occur with an important categorization*, the elements tend to be unitized". With this reformulation, the pair 5&8 would be more frequently reinforced than the pair 1&5. The present formulation "flattens" internal representations: the category response ("target") is not on a different level than the features. Instead, all of them are given equal status, and co-occurrences with category response is not different from other forms of co-occurrences. Category response would be a mere "label", an additional "feature". Further experimentation is needed to examine the ontological status of category labels.

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Taken together, the results go against a strict view of unitization. We note that the *U* parameters are moderate (0.5 to 0.8) so unitization processes may not be fully in place. We don't know how many sessions would be required to further consolidate this route, and maybe the present 15 sessions of visual search are not enough. Nevertheless, differential treatments of the features are evidenced here and so perhaps we analyzed a behavior that might be an intermediate stage, preluding deeper changes to occur.

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General Discussion

Before turning to a more general discussion of the results, we highlight a few points. First, the stimulus-based interaction contrasts turned out to be a nice tool to examine the results. It is interpretable and contrasts four measures of accuracy into one. By comparison, *d*' measures (from signal detection theory; Green and Swets, 1966) were less clear, owing to the fact that FAs were difficult to analyze. More interestingly, this contrast provided a visual tool which is non-parametric, but strongly motivated by a model.

Second, the results show that skills acquired in a visual search task transfer to a different task. However, an open question remains as to whether transfer only occurs when face validity is maintained (here, participants were asked on every trial of the feature detection task whether the stimulus was a target or not; not surprisingly, they are 99.0% correct, but the base rate of a non-target is 97.5%).

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With the present methodology, we were able to explore one facet of the skill involved in visual search, namely target recognition. We did this in a setting in which stopping rule and scanning behavior are absent, considerably simplifying the behavior to describe.

Explaining what is occurring during recognition/classification/decision is most central for our inquiry. The notion of unitization pops to mind. However, as it stands, a strict model of unitization is not supported by the data. The fact that co-occurrences seemed to play a role in the result is one indication that crosstalk could be the mechanism responsible for unitization. However, it is not clear why crosstalk would not benefit type (*ii*) as much as type (*i*) trials. Finally, it is difficult to consider prioritization models here as response times cannot be collected in this paradigm. Yet, prioritization coupled with limited capacity could possibly accommodate the results and thus contribute to the debate.

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