Visual Search FREE

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Summary

Visual search is the process of finding things that you are looking for in a world full of things that you are not looking for. Search tasks are ubiquitous. Many are so routine that we do not think of them as search tasks (e.g., Where is the space bar on the keyboard?). Others are more taxing (Where is the cat hiding?) and/or more important (Is there a tumor in this x-ray?). The need for search arises out of limits on the amount of visual input that can be fully processed at one time. Research in this area seeks to understand how observers find the object or objects of search as well as how, when, and why clearly visible targets can be missed by those observers. To understand how visual searches proceed, it is important to describe the forces that guide attention to different objects and locations in the field and to know what is being seen at locations away from the current focus of attention.

Keywords: visual search, attention, capacity limitations, parallel processing, serial processing, features, salience, priming, top-down processing, scene perception

Subjects: Cognitive Psychology/Neuroscience

Introduction

We are continually searching. We only tend to think about visual search as a task when it consumes a noticeable amount of time, but any time we select one stimulus in a visual world containing more than one stimulus, we have committed at least a small act of search. Defined in such sweeping terms, the topic rapidly becomes unwieldy, so we will focus on three broad questions:

1. What are you seeing right now? What are the contents of visual awareness?
2. How do you find what you are looking for? What are the mechanisms of visual search that guide your attention through the visible world?
3. Why do you, not infrequently, miss things that are “right in front of your eyes”? How can you look at something and yet, somehow, not see it?

Figure 1. What do you see as you look at the Pantheon in Rome?

Source: Photograph by the author.

To introduce these questions, look for the girl in the yellow dress in the scene in Figure 1. If you are not viewing this article in too small a format, she was probably relatively easy to find. You may not have noticed her when you first glanced at the image. What were you seeing at that location before the girl in the yellow dress became the object of your search? Surely, you were seeing something. If we assume that you were not attending to the girl, initially, and that you are now, we can define your initial experience as "preattentive" (Egeth, 1977; Neisser, 1967; Wolfe & Utochkin, 2019). If you now direct your attention to the pillars of the Pantheon (We are in Rome.), there is still something visible at the location of the girl. Indeed, as you select other specific items in the scene, the scene remains visible, no matter how vigorously you attempt to focus your attention on one item or one spot (but see Mackworth, 1965). We can call that continuous visible experience the product of "nonselective" visual processing (Wolfe, Vo, et al., 2011). Thus, an initial answer to the question of what you are seeing right now is that you are seeing the output of nonselective processes and the results of selective processing of at least one object or location.

Returning to the girl in the yellow dress, when asked to find her, you did not randomly deploy your attention nor did you start at, say, the upper left of the image and systematically scan left to right and top to bottom. You intelligently deployed your attention to locations in the scene that might hold your target and to items in those locations that had a plausible set of preattentively available features like the yellow color and a girl-like size. You did this quickly and you almost undoubtedly moved your eyes to fixate on the girl as well as moving your attention to her. This encapsulates many of the answers to the second question. Your attention and your eyes are deployed intelligently under the guidance of information that is available preattentively.

Finally, now that you are no longer looking at the image, did you happen to notice the three-legged woman or the single, disembodied leg that appears to be following her? These are creations of the "panorama" setting on the cell phone camera and will be highly visible if you go back to look for them. Quite possibly, you did see these flaws, but it is also possible that you missed them, even though you would like to believe that you would notice a single leg, hopping across the piazza in front of you. You almost undoubtedly fixated on or near these odd objects in the process of finding the girl in the yellow dress. Even if you happened to notice the disembodied leg, we could easily show that other aspects of the image were not registered (Are there any flags present?). In medical image perception, the disembodied leg and three-legged woman would be labeled as "retrospectively visible" (Berlin, 2007; Nodine et al., 2001). They are clearly visible once your attention is directed to them. If this had been a medical image, the one and three-legged figures might qualify as a sort of "incidental finding" (Berge et al., 2020; Schlett et al., 2021); items that you would have wanted to notice, even if your primary task was to look for something else. A tentative answer to the third question about how you could miss something that was right in front of your eyes might be that the nonselective/preattentive characteristics of the one and three-legged figures did not demand attention. You could have selected those items for closer, attentive scrutiny, but if you did not, then, even though they were clearly visible, you did not "see" them in any way that registered their oddity.

Preattentive Vision

In an article about visual search, why start with what happens before search? A classic metaphor for selective visual attention is a spotlight (Posner et al., 1980). Interestingly, the spotlight echoes ancient "extramission" theories of vision that imagined a kind of light or fire coming out of the eye to illuminate what we see (Gross, 1999). The difficulty with a strict spotlight metaphor is that it imagines using attention like a flashlight in an otherwise dark room. In practice, selective attention is more like a rather special flashlight in an illuminated room. It makes it possible to more fully perceive or understand things that would otherwise be merely visible. Since what is merely visible can be used to guide the deployment of the spotlight, it is important to know what that merely visible stuff might be.

The 18th century French philosopher Condillac offers a prescient analysis of this issue in his 1780 book, *La Logique* (Condillac, 1780; Condillac & Albury, 1979), where he asks what would be seen in a brief glimpse of the view out the window of a chateau. He says that, in that brief glimpse, "it is certain that we have seen everything that it contains" but that, in order to have "knowledge of this countryside . . . it is necessary to see each of its parts, one after the other." Without that stage of serial attention, Condillac says that "no one . . . would be . . . able to give an account of what he had seen" (Condillac & Albury, 1979). Condillac neatly anticipates the distinction between an initial, parallel, *preattentive* stage of processing of the whole visual field, followed by a serial stage of sequential processing of its parts (Egeth, 1977; Neisser, 1967; Treisman & Gelade, 1980). However, he was too pessimistic about the preattentive stage. Experiments in the 1970s showed that observers could get some meaning out of scenes after very brief exposures (Biederman, 1972; Biederman et al., 1974; Potter & Faulconer, 1975). After 150 msec, scenes with and without animals produced different evoked potentials (Thorpe et al., 1996) even if the observer didn't necessarily know what animal was present or where it was (Evans & Treisman, 2005). Oliva and colleagues showed that raw image statistics contained semantic information (Oliva, 2005; Oliva &

Torralba, 2001) and it seems likely that nonselective processing of that global information and not fortuitous attention to an animal (or other targets) undergirds this ability. Interesting properties like "navigability" are available after very brief glimpses (Greene & Oliva, 2009). At these short timescales, information about one target can interfere with information about other targets in ways that would not happen under normal, extended viewing. Thus, observers looking for mountain scenes and beach scenes might correctly identify 75% of mountains or beaches but only 55% of scenes with both mountains *and* beaches (Evans, Horowitz, et al., 2011). This result makes a second point. The ability to detect the "gist" of a scene in a brief glimpse is remarkable, but not perfect. Saying that animals can be detected after very brief exposure means that performance is above chance, not that it is perfect; a point that is sometimes lost in popular and even in scientific discussions of what can be seen in the blink of an eye.

Condillac assumed that we would just get some impression of visual stuff from that brief glance. Research on feature search, texture segmentation, and ensemble perception document some details of that impression.

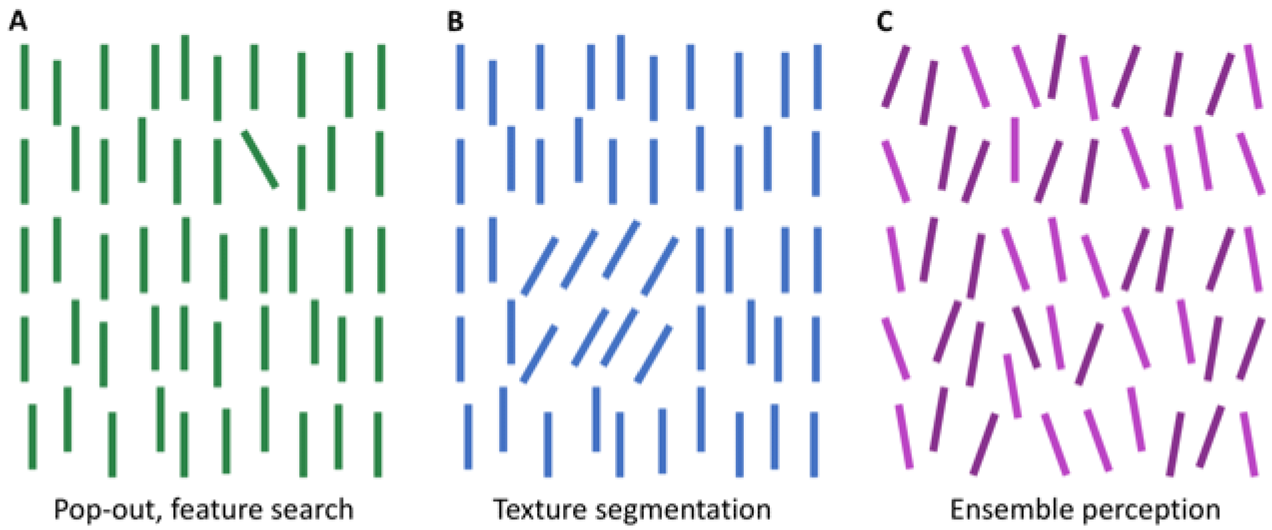

Figure 2. Three phenomena of "preattentive" and/or "nonselective" vision. (A) A single, distinctive item "pop-out." (B) The shape of a region, defined by a distinctive feature, can be rapidly detected. (C) The overall orientation of a group of lines is easy to assess, even though an observer would need to search for a specific line (Is there a vertical line here?)

Figure 2 illustrates our use of these terms. Feature search is the search for a target defined by a single, salient feature. There is a limited set of features for which such search does not feel like a search at all. If the target is present, like the tilted item among vertical items in Figure 2A, it appears to "pop-out" (Egeth et al., 1972; Neisser, 1963). When a region seems to define itself in a similarly immediate manner, we speak of "texture segmentation" (Figure 2B; Beck, 1966, 1982). The rules of texture segmentation are not identical to those for pop-out (Wolfe, 1992). For instance, a region might stand out from its background because it differs in the variation of its elements from the variation in the background (Chubb et al., 1994; Chubb & Landy, 1994). For a review of texture perception, see Victor et al. (2017). Finally, ensemble perception refers to an ability to appreciate the global properties of a set of items (mean, variance, and other properties) without necessarily being explicitly aware of the specific properties of any one element in the array (Ariely, 2001; Chong & Treisman, 2003). This topic is extensively reviewed in Whitney and Yamanashi Leib (2018).

Searching: How Do You Find What You Are Looking for?

You may be perceiving visual "stuff" everywhere and you may be able to respond to the presence of some basic features and some more sophisticated semantic structures in that stuff, but daily life requires that you search for specific items beyond the gist of the scene. As illustrated in the very artificial "scene" in Figure 3, there are at least three factors that might make it impossible to find a target without searching in something like the serial manner, recommended by Condillac.

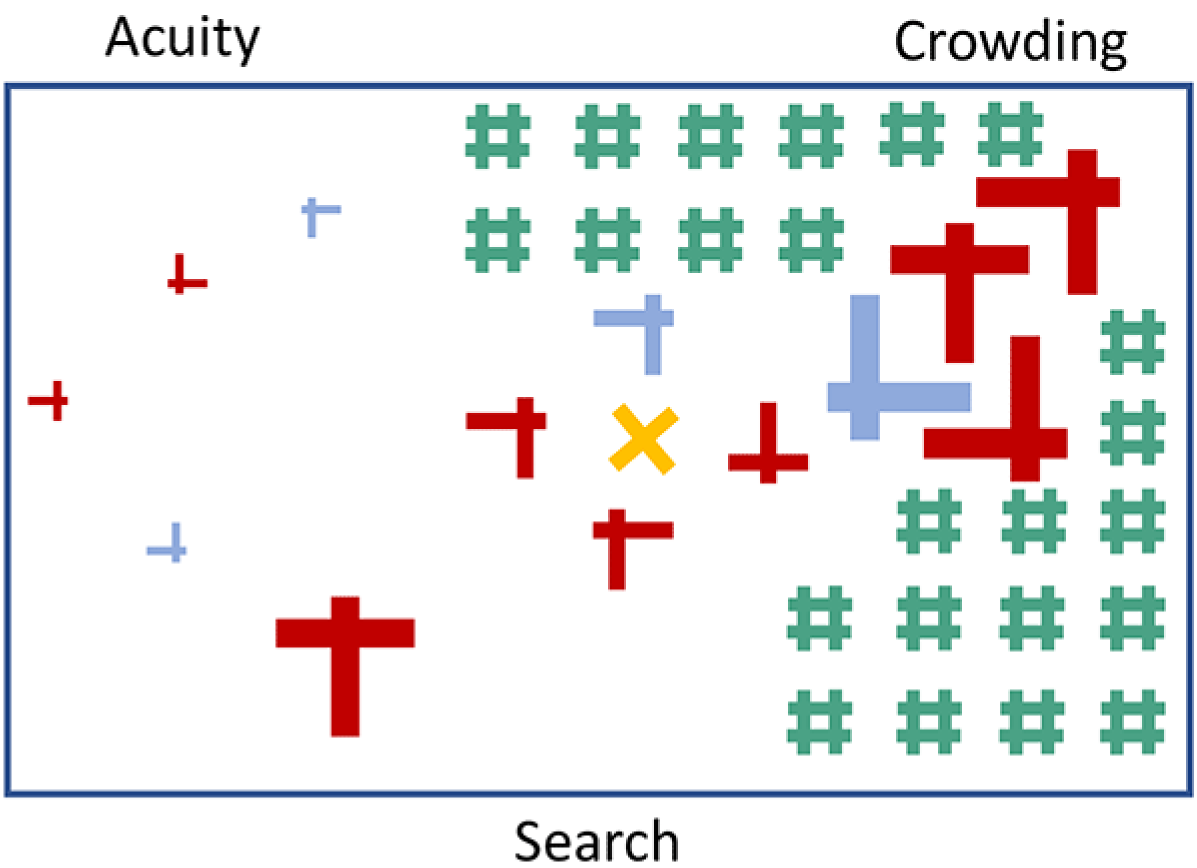

Figure 3. A "scene" that illustrates some of the reasons why we need to search.

Look at the yellow X at the center and find red Ts. You can't find the T at the far left because it is simply too small—an acuity limitation (Westheimer, 1979). It could also be too low in contrast (contrast sensitivity limitation). You can identify the big T at the lower left, while fixating on the X but not the T in the upper right though it is the same size and distance as the identifiable T. Here the problem is "crowding" (Levi, 2008, 2011; Pelli & Tillman, 2008). The target is crowded by the flanking Ls. To find the small or crowded T, you would need to move your eyes. Some argue that this is a central reason for why we need to search (Rosenholtz et al., 2009). For present purposes, the most interesting case involves the four items immediately surrounding the X. Without moving your eyes, you can find the T but the time required to do this task will depend in a linear fashion on the number of relevant distractor items. For this search task, the limiting factor is not crowding or acuity. There are a number of ways to understand and model the need to search in this situation, but one good candidate is to propose, with Condillac, that each item needs to be attended to in a series until the target is found.

Condillac seems to have been thinking of sequential deployments of the eyes (a topic we will turn to in a moment). However, it is clear that, while fixated on the yellow X, one can covertly deploy attention to different portions of the scene. For instance, you could identify the larger of the two collections of greenish "#" items in Figure 3. In the case of the search for the T among Ls, a standard search experiment would involve showing observers (Os) displays containing different numbers of Ls. A display might or might not contain a T. Os could be asked to make a target-present/target-absent response or the T could be present on every trial and Os could be asked to identify some attribute of the target (e.g., does the stem point left or right?) or to localize the T with a mouseclick. If we were to plot the response time (RT) as a function of the number of items (set size), the slope of the RT x set size function in such a task will be in the vicinity of 20–40 msec/item for target present trials and a bit more than twice that for target absent trials (Wolfe et al., 2010). If the items are not subject to significant acuity or crowding constraints, this will be true with or without eye movements (Zelinsky & Sheinberg, 1997). The slope can be considered as an estimate of the rate of processing. How many items per second can be handled? The understanding of that rate will depend on the model of search but for the moment, the important point is that the estimates will be in the range of 20–50 items per second. Since Os make volitional eye movements of only 3–4 per second, that means that several items must be processed during each fixation. Models like Feature Integration Theory (Treisman, 1993; Treisman & Gelade, 1980) and Guided Search (Wolfe, 2021; Wolfe et al., 1989) propose a Condillac-style serial selection of one item after another during a fixation. Other models propose parallel processing of several items at a time during that same fixation (Hulleman & Olivers, 2017; Palmer, 1995; Palmer et al., 2000).

If our processing capacity is limited in a search for a T or, indeed, for most other targets, how do we manage to find things in a reasonable amount of time under most real-world conditions? If you were looking for a street sign, and you could process even as many as 50 items/sec, you would not do well, if every leaf on the trees and every brick in the wall was equally attractive to overt movements of the eyes and/or to covert deployments of attention. There must be well over 1,000 such possible objects of attention on any normal suburban street and you do not have 20,000 msec to find that street name as you drive along.

It is intuitively obvious that deployments of the eyes and/or covert attention are not random. We try to deploy our attention to where we are likely to garner the most useful information (Najemnik & Geisler, 2005). We are guided by the information that is available preattentively. So, in Figure 3, if we were told to search for *red* Ts, we would not bother with the pale blue items (Egeth et al., 1984).

Guidance and the Directing of Attention in Search

Guidance of attention comes in several forms and different models emphasize different aspects. First, it is useful to distinguish between guidance by the properties of the target of the search and guidance by properties of the rest of the scene. The target guides attention in at least two ways, usually labeled top-down and bottom-up. Bottom-up guidance refers to the stimulus-driven summoning of attention, independent of the intentions of the observer. An item that differs from its neighbors will be "salient" and tend to capture attention, if the salient difference is available preattentively. Figure 2A is a relatively trivial example where there is only a single salient item, but a "saliency map" can be generated for any scene (Itti & Koch, 2001) and attention can be directed to the point of highest salience, e.g., by a winner-take-all computation (Koch & Ullman, 1985). There has been much interest over the years in whether some salient stimuli "capture" attention in an essentially involuntary manner (reviewed in Theeuwes et al., 2010). It has been suggested that capture paradigms can be thought of as part of the larger question of how the stimulus shapes a dynamic landscape of salience, with attention drawn to the peaks in that landscape (Lamy, 2021; Luck et al., 2021). For a comprehensive review of models of salience, at least, up to 2013, see Borji and Itti (2013).

Preattentive Features

Not all properties of visual stimulus enter into salience calculations. The Figure 2A experience of "pop-out" (Egeth et al., 1972) will occur if the target is defined by a sufficiently large difference from the neighboring distractors in a basic feature like color, orientation, size, or motion. Smaller difference, even if clearly perceptible, will not summon attention (Foster & Ward, 1991; Nagy & Sanchez, 1990). Large differences can fail to attract attention if the other, distractor items are heterogeneous (Duncan & Humphreys, 1989). Thus, in Figure 2C, the vertical target would be easily found if just one of the tilted orientations was present in the distractors. The distractor heterogeneity of Figure 2C is especially disruptive because the distractors flank the target in orientation space (0 deg. vertical among ± 20 deg.; Wolfe et al., 1992). This is the principle of "linear separability" (Bauer et al., 1996) but see (Vighneshvel & Arun, 2013; Xu et al., 2021). There is evidence that bottom-up salience is based on categorical differences between targets and distractors; e.g., "steep" versus "shallow" rather than 30-deg. versus 60-deg. tilt (Kong et al., 2017; Wolfe et al., 1992; for color, see Yokoi & Uchikawa, 2005).

Not all distinctive visual properties contribute to bottom-up salience calculations. For instance, once attended, it is very easy to tell the difference between an X-junction where two lines cross and a T-junction where one line ends once it reaches another. However, an X-junction surrounded by T-junctions will not summon attention (Wolfe & DiMase, 2003). Much work has been devoted to developing lists of features that do and do not generate salience signals (Treisman, 1986). One version of the list can be found in Wolfe and Horowitz (2017). A more extensive review of the concept of a "preattentive feature" can be found in Wolfe and Utochkin (2019).

Some of the most interesting and unresolved topics in the realm of preattentive guidance of attention have to do with shapes and object identity (Aizenman et al., 2022). It is clear that a star among squares or a circle among triangles will pop-out, even once other features (e.g., orientation, size) are controlled but it is not clear exactly what is popping-out (for some of the best work, see Huang, 2020). Similarly, a face will pop-out among other objects (Hershler & Hochstein, 2005) but it is a matter of debate whether that can be explained in terms of other features or if the "faceness" of the face is preattentively available (Hershler & Hochstein, 2006; Vanrullen, 2006). As another example, visual search for a specific scene among other scenes can be modulated by the space represented in a scene: Is it a near or "reach space" (e.g., breakfast table) or a more extensive view (e.g., kitchen or backyard; Josephs & Konkle, 2019)?

In computer science, one of the great breakthroughs of the past decade or so has been the advent of deep neural networks (DNNs) that can accurately classify thousands of objects (Hassabis et al., 2017; Kriegeskorte & Douglas, 2018). Objects are represented by vectors of thousands of weights in these DNNs. It seems possible that some abstraction from the human equivalent of these networks is available to guide attention (e.g., Yu et al., 2019). This is very different from preattentive features like orientation or color where the assumption is that guidance of attention is based on some coarse, categorical abstraction of the outputs of a relatively limited number of orientation channels (Olzak & Thomas, 1986) or color processes (Witzel & Gegenfurtner, 2018). Still, though the details remain a topic for future research, there is evidence that attention can be guided to types of objects (Guo et al., 2020; Hout et al., 2017). Perhaps an analogy can be made to taste and smell. Taste perceptions are based on four (or five) basic tastes. In olfaction, the search for a small set of basic smells has been largely unsuccessful with our genes coding for thousands of different receptors. Perhaps the salience of a shape cannot be thought of in the same terms as the salience of a color or a size.

Top-Down Guidance and the Search Template(s)

Bottom-up stimulus driven salience is not usually what we are thinking about when we think about performing a visual search in the course of our daily activities. More typically, we are interested in a search for *something*: the cat, the cell phone, or the tumor in the x-ray. These targets of search are very often <u>not</u> the most salient items in the visual field. Indeed, one of the challenges faced by models of search is to explain why attention is not chronically captured and stuck on salient items in the field (e.g., the flashing sign for the pizza shop) when it is important to attend to other aspects of the scene (e.g., the dimly lit child crossing the street). Two approaches to this problem are to propose active inhibition of previously attended items (salient or otherwise; "inhibition of return"; Wang & Klein, 2010) or to propose that salience is transient and, as a guiding signal, fades quite quickly (Donk & van Zoest, 2008).

Returning to that deliberate search for *something*, we need to represent that something in our minds in order to search for it. That internal representation is often referred to as a search "template" (Bravo & Farid, 2009; Duncan & Humphreys, 1989). In colloquial speech, the term "template" typically refers to some piece of wood, plastic, or metal that can be traced to create a precise copy of the template's shape. The term is used more metaphorically in search where you could readily search for an “animal” without being able to precisely define a generic animal shape. Moreover, as Figure 4 demonstrates, it is useful to divide the idea of a search template into two components: A “guiding” template and a “target” template. If you look for vowels in Figure 4, you will *guide* your attention to letters, but you may need to match several letters against your *target* template for vowels before you identify the one vowel.

Figure 4. Finding a target like a vowel involves a “guiding template” to restrict your attention to letters and a “target template” that can be interrogated to determine if a specific letter is a vowel.

Similarly, if asked to find the specific hat on the left. You will not guide attention to letters nor are you likely to guide attention to the red or green hats. You will probably guide attention to the sombrero; a reasonable candidate, but your target template will confirm that it is not, in fact, the target.

One way to think about the difference between guiding templates and target templates is to ask how many of each you can use at the same time. The number of guiding templates is severely limited with the primary debate being between a limit of just one at a time (e.g., van Moorselaar et al., 2014) and the possibility of two (e.g., Hollingworth & Beck, 2016) or perhaps something like 1.5 (Carlisle & Woodman, 2019). In any case, the number is small enough to fit into the usual conceptions of the size of visual working memory (Oberauer, 2019; Ort & Olivers, 2020).

Target templates are not limited in the same way. You can probably imagine searching for a specific cat, a dog, any bird, a hammer, a nail, and a board; all at the same time. This is known as “hybrid search”; search for any of several types of targets, held in memory (Schneider & Shiffrin, 1977; Wolfe, 2012). When targets are defined by specific pictures of objects, observers can search for hundreds of targets at the same time (Wolfe et al., 2015). In these hybrid searches, response time (RT) is a linear function of the visible set size—the number of items in the search stimulus—

and a linear function of the *log* of the memory set size—the number of types of targets, held in memory (Wolfe et al., 2015). This is true for object categories (Cunningham & Wolfe, 2014) and for words (Boettcher & Wolfe, 2015), as well as for specific objects (Wolfe, 2012).

The content of templates has been the topic of much work in the first decades of the 21st century; work that overlaps extensively with work on the precision of representations in visual working memory (Bays et al., 2009; Rajsic et al., 2017; Suchow et al., 2014). With regard to search, some of the diversity of ideas and results can be understood if we think about different characteristics for guiding and target templates. Guiding templates tend to be relatively coarse. Thus, when you guide attention to an orientation, you can't guide effectively to precisely 25 deg. from vertical. The guidance is to something more like "tilted, to the right" (Wolfe et al., 1992) and its precision is fairly coarse, when compared to the high precision with which we can assess the orientation of an attended line. This is illustrated in Figure 5. If you search for the 25-deg. target, you will find it quite laborious. Even though the distractors are 15 deg. away from the target in orientation, you can't seem to do better than randomly selecting items. Your guiding template is not helping. However, once you select an item, your target template is adequate to tell you if you have found the target that is not too steep and not too shallow.

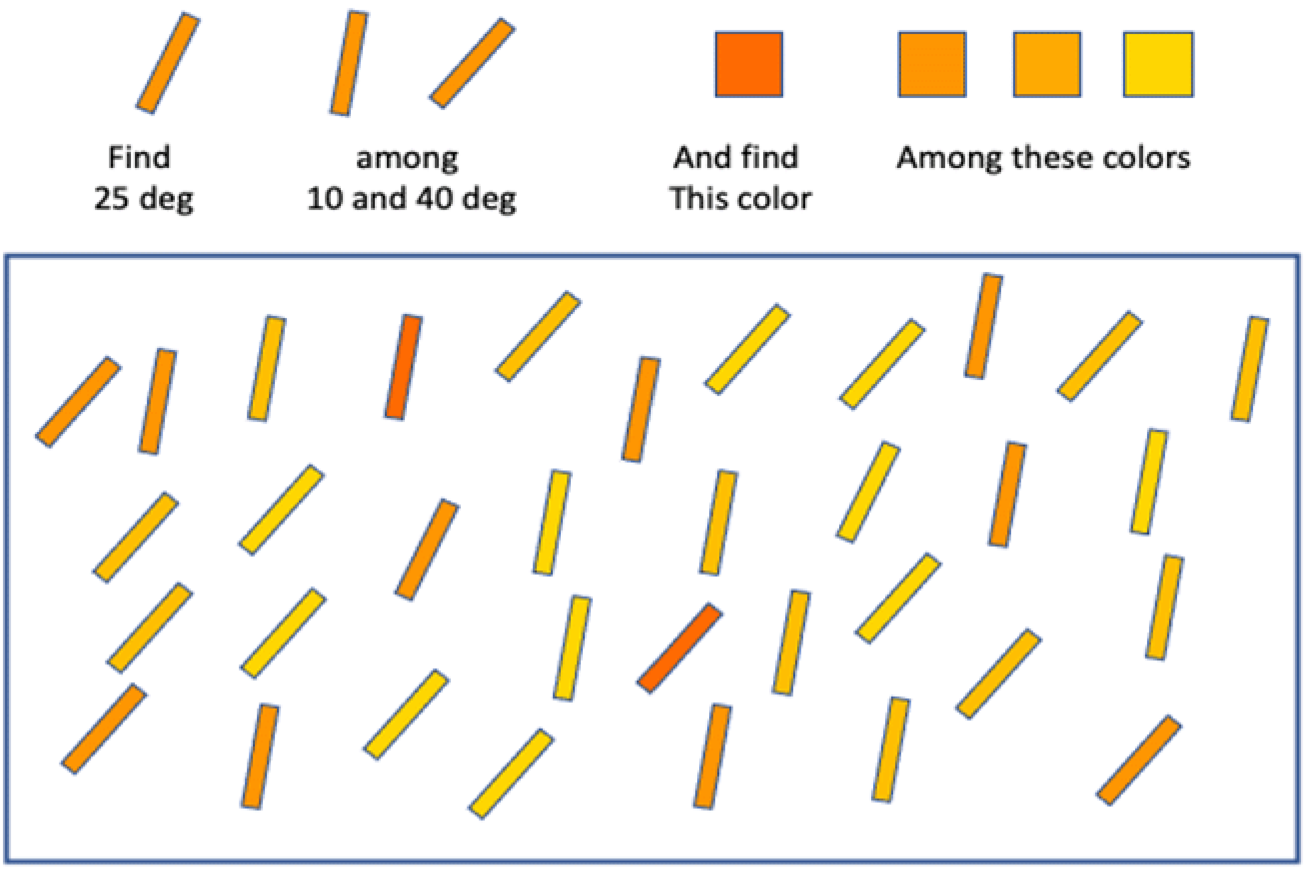

Figure 5. The nature of guiding and target templates: Find the two 25-deg. tilted targets and the two items with the target color.

Figure 5 also illustrates another important characteristic of guiding templates. They are often "relational" in nature (Becker, 2010). If you look for the orange target color, specified in Figure 5, you may well use a template that directs attention to the "reddest" items in the display, even though the target is not red. Once that relational template allows you to select the target, a more precise target template will confirm that it is the correct shade of orange (Kerzel, 2019). In some cases, target template can also be centered to one side of the of the actual target feature. Regan and Beverly (1985) noted, when making fine discriminations, the most useful channels or neurons are not the ones most sensitive to the target. They are the channels, off to one side, whose response changes most dramatically with small changes in the target. Geng and her colleagues have shown similar effects in the composition of templates (Geng et al., 2017; Yu & Geng, 2019) and, indeed, have shown both relational and off-center templates at work in the same task (Yu et al., 2022). The distinction between the role of templates in "guidance-" and "match-decisions" (Yu et al., 2022) is very similar to the distinction between "guiding templates" and "target templates" (Wolfe, 2021). It is possible, but not required, that guiding templates occupy space in visual working memory. In any case, guiding templates and visual representations in visual working memory seem to share some properties and capacity limitations.

History and Priming Effects

What you have searched for in the past has an influence on how you conduct a current search. What we can call "history" effects come in many forms and became an active topic of research in the 2020s (Anderson et al., 2021; Ramgir & Lamy, 2022). Perhaps the most basic form of guidance by history is "priming of pop-out" (PoP; Maljkovic & Nakayama, 1994). In a basic PoP experiment, observers respond to some aspect of a unique, pop-out stimulus in a search display. For example, all the items might be green diamonds. The target in this trial might be a red diamond and the task could be to say if the left or right corner of the red diamond was cut off. This is an extremely easy task. The colors of the target and distractors can switch from trial to trial. Interestingly, RTs are somewhat faster if the preceding search preserved the same target color than if the color changed. This is the basic PoP phenomenon. It is cumulative, being based on the last few trials though the immediately preceding trial has the biggest effect (Maljkovic & Nakayama, 2000). PoP is a widely studied phenomenon that has been replicated with multiple features: e.g., shape (Lamy et al., 2006), orientation (Hillstrom, 2000), and size (Huang et al., 2004).

If more than two colors are involved in the experiment, it is possible to disentangle the effects of repeating the target color or the distractor color. Thus, if one trial had a red target and green distractors, the next might have a red target and blue distractors (distractor change) or a blue target and green distractors (target change). Both target and distractor effects are seen. Some versions of this experiment give a consistently larger role to target change (Wolfe et al., 2003). Others paint a more complex picture; for instance, distractors may have a bigger effect when the target is defined by orientation (Lamy et al., 2013).

PoP can be seen as part of the very large literature on "attentional capture" by salient singletons. The core issue here is whether some stimuli (e.g., abrupt onsets; Rauschenberger, 2003; Theeuwes, 1994; Yantis, 1993; Yantis & Johnson, 1990; Yantis & Jonides, 1990) always, or almost always, grab attention. Without wishing to trivialize the question, it is hard to do better than James Sully (1892), who declared, "One would like to know the fortunate (or unfortunate) man who could receive a box on the ear and not attend to it" (Sully, 1892, p. 146). We would amend the gendered prose but would agree that, if the stimulus is strong enough, it will not be possible to ignore it. Much more can be and has been said (for more comprehensive reviews of attentional capture, see Luck et al., 2021; Theeuwes et al., 2010).

Returning to priming effects, there is wide agreement that the effects are robust and that they can play a role in visual search. However, there is a range of opinions about the extent of that role. Jan Theeuwes has argued for what must be the most expansive view of the role of priming. He titled a 2013 paper with the claim: "Feature-based attention: It is all bottom-up priming" (Theeuwes, 2013).

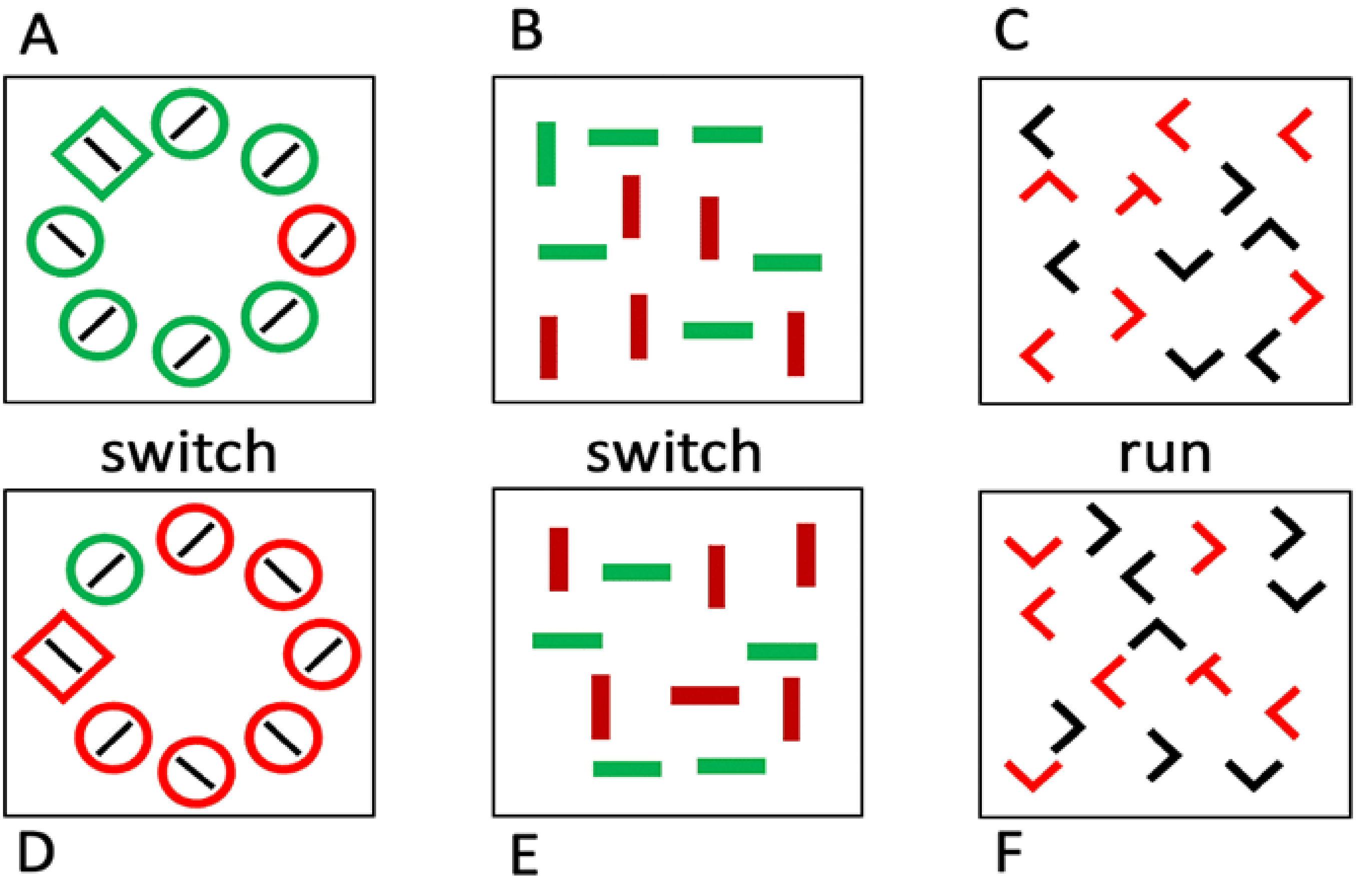

Figure 6. Varieties of priming experiments. (A) Feature singleton. In the next trial (D), the color "switches." (B) Conjunction. In the next trial (E), the target *identity* switches. (C) Inefficient search for a T. In the next trial (F), the irrelevant color remains the same (Run).

The experiments supporting this claim often use stimuli like those shown in Figures 6A and 6D. Here, Os might be asked to give the orientation of the line in the color singleton or to give the orientation of the line in the diamond and ignore the singleton (Theeuwes, 1991, 1992). In those experiments, it is very hard not to attend to the singleton even though it is not the target. The attention capturing effect of the singleton is stronger when the singleton repeats in color. Even in these experiments involving a salient singleton, there is some debate about whether all of the effects attributed to top-down guidance are actually attributable to priming. When Lamy and Kristjánsson (2013) looked at the data, they concluded "that priming accounts for considerable portions of effects attributed to top-down guidance, but that top-down guidance can be independent of intertrial priming."

Do history effects like priming have their effects on the entirety of a search or just on its beginning? For example, what is the role of priming in a conjunction search like Figure 6B (Find the green vertical item)? In this case, models like Guided Search (Wolfe, 2021) would argue that observers guide attention to green and vertical in a top-down manner. The maximalist priming account would argue that what looks like top-down guidance is actually priming of the next green vertical target by the last green vertical target. If that were true, then primed conjunction search should be more efficient than unprimed. That is, the slope of the RT × set size functions in conjunction searches should be shallower when the conjunction search is primed by a repeated target than when it is not. Several studies have looked at priming with conjunction stimuli mostly using variations of the stimuli shown in Figures 6B and 6E. Observers are looking for a conjunction that can be, for example, green vertical on one trial (Figure 6B) and red horizontal on another (Figure 6E). Reliable priming effects are found. In most cases, these have been additive with set size (Geyer et al., 2006; Hillstrom, 2000; Kristjánsson et al., 2002). RTs are shorter if the target repeats, but the slope of the RT × set size function remains unchanged. Becker and Horstmann (2009) did find a change in slopes and produced eye-tracking data to argue that priming was producing attention guidance.

This conjunction experiment is quite different from the singleton search experiment because the target of search is changing. In effect, observers are performing a fairly simple, "hybrid" search (Wolfe, 2012) for either of two targets; green vertical or red horizontal. This may produce priming. It also may produce substantial task switching costs. This can be seen in the very large differences between RTs on Run and Switch trials; on the order of 100s of msec in Becker and Horstmann (2009), for example, compared to 10s of msec in typical feature singleton priming experiments (Figures 6A and 6D). It is unclear, therefore, if the priming effects in these experiments really tell us about the general role of priming in search. It is, in fact, also unclear whether the maximalist priming position is realistic. Imagine that you are looking for a red ball in a child's bedroom. It is obvious that there are many possible objects of attention and it is obvious that you do not treat them all as plausible candidates for attention in this search. You guide your attention to red and round and to objects of a plausible size. This self-evident guidance occurs even if the previous searches have been for the child's blue towel or for any of many things that are not red or round or ball-sized.

A less maximalist position would be that priming guides search. Figures 6C and 6F show an approach to this question that uses a task that does not involve task switching. Observers are asked to categorize the orientation of the stem of the one T among Ls. This is an inefficient search. In a standard guided version of the task, observers might be told that the target was always red. In this case, they would search preferentially through the red items and the slope of the RT x set size function would be shallower than it would be if the target color was not known (Egeth et al., 1984). In the priming version, the color of the T changes randomly from trial to trial and is irrelevant to the task of identifying the orientation of the T. Priming occurs in this condition. Run trials are faster than Switch trials. However, the slope does not differ between run and switch (Wolfe et al., 2022). Wolfe et al. propose that priming is a transient form of guidance (as is bottom-up salience; Donk & Soesman, 2010). It seems to guide the first deployment of attention, but, perhaps, not much beyond that.

The source of this type of guidance does not need to be the previous trials of a search task. Though it is a separate literature, essentially the same type of priming appears to occur if visual working memory is loaded with the feature (e.g., remember this green color). If the observer carries out a search task while the feature is being held in working memory, attention will be guided to items with that feature, even though the search task is presented to the observer as being unrelated to the memory task (Hollingworth & Luck, 2009; Oberauer, 2019; Olivers et al., 2011; van Moorselaar et al., 2014).

In priming and working memory effects, history works by guiding attention to features of the target (or, potentially, away from distractors). Another class of history effect is based on properties of the scene that contains that target. Chun and Jiang introduced the idea of contextual cueing at the end of the 20th century (Chun, 2000; Chun & Jiang, 1998, 1999). In a standard contextual cueing experiment, observers search for a target like the Ts in Figures 6C and 6F. Unbeknownst to the observers, some of the displays repeat over the course of the experiment and others do not. Observers come to respond more quickly to repeated displays than the unrepeated even though, when tested subsequently, they have little or no measurable ability to discriminate repeated from unrepeated displays. The paradigm is of interest as an example of the ability to implicitly/automatically extract statistical regularities from the environment. The effect can be seen with real scenes, not just with random sets of distractors (Brockmole & Henderson, 2006; Castelhano et al., 2019; Oliva et al., 2004).

Particularly, with scenes, since they are remembered so well (Konkle et al., 2010; Standing et al., 1970), there has been debate about whether contextual cueing is truly implicit (Vadillo et al., 2015) because the distinction between implicit and explicit is a continuum and not a strict dichotomy. Probably, the best answer is that there are both implicit and explicit components to the effects of scene repetition on visual search (Ramey et al., 2019). It is obvious that explicit memory for a scene could guide search. If you walk into the ice cream shop, again, your explicit memory may guide your eyes to the list of flavors. At the same time, there is good evidence for guidance by repetition history, even if you don’t have measurable memory for the scene.

As with priming, there is some question about whether contextual cueing is a form of guidance. If it was a form of guidance, one might expect that contextual cueing would make search more efficient. Operationally, it should reduce the slope of the RT × set size function for cued scenes compared to uncued. Kunar et al. (2006) found that contextual cueing was additive with set size and they raised the possibility that it was a product of response stage effects (Schankin et al., 2011), while others argue for an effect occurring earlier in processing (Geyer et al., 2010). Chun and Jiang (1998) had observed reduced search slopes in their original work. In a useful review of the issue, Jiang et al. (2018) raise the possibility that only a few items near the target are relevant to the contextual cueing effect and that, as a result, the set size manipulation is irrelevant. Another possibility is that, like priming and bottom-up salience, implicit contextual cueing might be relatively transient, having its effects at the beginning of each search, rather than guiding attention throughout a search. In any case, Jiang et al. (2018) hold that a preponderance of the evidence (especially the electrophysiological evidence) favors an early locus for the effect and a true guiding role for contextual cueing.

Location probability learning is related to, but not the same as, contextual cueing (Geng & Behrmann, 2002; Hong et al., 2022; Jiang et al., 2013). In location probability learning, targets are more frequent in some parts of the visual field than in others and observers come to respond more quickly to items in that part of the field. As with contextual cueing, there has been a debate about whether this form of guidance is implicit or explicit. The point is debatable because it is hard to prove that someone is *not* aware of something (Giménez-Fernández et al., 2020). At the present, the preponderance of evidence suggests that location probability learning can be implicit, even if it is not always implicit (Golan & Lamy, 2022; Jiang et al., 2018). Location probability learning is part of a family of statistical learning effects in visual search, reviewed in (Theeuwes et al., 2022).

The work on contextual cueing can be seen as part of a broader set of studies of “repeated search.” Unsurprisingly, there is evidence that a second search through the same scene is faster than the first (Korner & Gilchrist, 2007; Wolfe, Alvarez, et al., 2011). However, there is a puzzle in the repeated search literature. There are fairly dramatic circumstances where extensive repetition does not make search more efficient, even if it does make it faster. For example, Wolfe et al. (2000) had observers search through the identical arrays of letters multiple (>350) times. These were arrays of three or six letters so observers had certainly memorized the arrays after a few repetitions. Nevertheless, their RT data suggest that they were performing the same inefficient search on the nth trial that they performed on the first. Given perfect memory, why did observers need to search at all? The answer appears to be that access to even a well-learned memory takes time and, with a relatively small set size, it was faster to do the visual search again from the start than to rely on the memory (Kunar et al., 2008). If the search task is made harder, observers are more likely to use memory, once they learn the display (Hout & Goldinger, 2010; Solman & Smilek, 2012).

Measuring search efficiency with real scenes is difficult because it is very difficult to specify the set size of a scene. Perhaps the best that can be done is to measure the “effective set size”—the number possible target items divided by the number of targets present (Neider & Zelinsky, 2008; Wolfe, Alvarez, et al., 2011). Working in virtual reality can help because the objects can be controlled (Beitner et al., 2021; Li et al., 2016). Still, while standard RT × set size functions cannot be generated, it is possible to measure the development of the memory that can guide search in repeated search settings. Vo and Wolfe (2012) reported that effective memory was seen when observers searched for an object the second time in a scene. Explicit efforts to memorize displays seem to be less effective than implicit learning (Helbing et al., 2020). Hollingworth (2012) did related experiments and did find effects of a preview task on subsequent visual search. As with the repeated search experiments, there is no doubt that previews or memorization tasks will produce memory traces. The actual influence of memory on repeated search behavior probably depends on whether there are other routes that get to a response more quickly. One such route is "scene guidance," to which we will turn shortly.

One more form of guidance by history should be mentioned. The reward structure of a task can guide attention (Anderson et al., 2011; Anderson & Yantis, 2013). Reward produces effects like priming (Kristjansson et al., 2010). If Os are rewarded for red, for example, attention will tend to be captured by subsequent red items, even if their color is now irrelevant to the task. Related to that point, this sort of guidance by reward can migrate between tasks. So, if a target is rewarded in a conjunction task, its features will continue to be primed in feature search, for example (Lee & Shomstein, 2014). Reward effects are quite robust. In attentional capture tasks, reward can trump history (Marchner & Preuschhof, 2018) and the effects of reward can be seen in a foraging context, as well (Wiegand & Wolfe, 2021; Wolfe et al., 2018; Zhang et al., 2017).

Not everything works. The reward findings might suggest that simply paying Os to find targets might be a remedy for miss errors in socially important search tasks, but at least one effort to show this failed (Chantland & Becker, 2018). Reward effects seem to be primarily attached to targets, not distractors (Hickey et al., 2011). There is some question about whether target locations can be rewarded or only their features. Inter-trial, priming-style effects can be based on position (Hickey et al., 2014). Longer term, contextual-cueing-style effects of location-based rewards are not readily produced (Won & Leber, 2018) unless observers are explicitly aware of the reward contingency (Sisk et al., 2020). Finally, while reward works, pairing a feature with loss does not seem to work (Becker et al., 2020). Overall, reward appears to be a real but, perhaps, modest source of guidance.

Scene Guidance

In contrast to the guiding effects of history, guidance by the structure and contents of scenes is a massive source of guidance in the real world. The only excuse for its omission from earlier theories of visual search (e.g., Wolfe, 1994; Wolfe et al., 1989) is that those theories were based on the available search data, most of which involved search for targets in random arrays of items on uniform backgrounds. In virtually any of the search tasks of daily life, most of the current visual field will be ignored on the basis of what is known about the scene. Under most circumstances, there is simply no point in looking for light switches on the floor or for pigeons in the kitchen.

There were some early efforts to study search in scenes. Titchener (1924) and Ruckmick (1926) introspected presciently about the process of finding items in cluttered scenes. Kingsley (1932) reported on eye movements while observers viewed photographs; albeit, without an eye tracker. By the late 1950s, eye trackers were used to study search in aerial imagery (Enoch, 1959a, 1959b) and medical images (Thomas & Lansdown, 1963; Tuddenham & Calvert, 1961). However, the real roots of the modern study of scene guidance probably lie in the work of Biederman and his colleagues (Biederman et al., 1973, 1982, 1983). Their 1973 paper showed that search was markedly slower when a scene was scrambled by dividing it into six squares and shuffling those into disordered 3 × 2 arrays. Even though the basic content of the scene was still interpretable, the disruption of its structure made search harder.

More subtle manipulations of scenes support division of scene guidance into two major categories. Biederman borrowed the jargon of linguistics to talk about scene "syntax" and "semantics" (Biederman, 1977; Biederman et al., 1982). Semantics refers to where things belong in a meaningful scene. A toothbrush can be in many places but it makes more semantic sense if it is in the bathroom, near the sink (Davenport & Potter, 2004; Hwang et al., 2011). Scene syntax describes where it is structurally plausible for objects to be. A toothbrush, floating in midair, violates scene syntax even if it floats near the sink (Vo & Henderson, 2009). Henderson and Ferreira (2004) give a particularly clear account of the parallels between language and scene processing. Vo and Wolfe (2013a) looked at EEG responses to violations of scene semantics or syntax and found that the timing of scene semantics or syntax signals looked like the timing for the analogous effects in language. It remains a matter of speculation whether this reveals a deep tie between language and scenes (Võ, 2021).

In some cases, scene guidance is based on quite general information about scenes; what can be called a knowledge of a scene schema (Henderson et al., 2007; Pereira & Castelhano, 2014). So, for example, if one's task is to find humans, even the first eye movement in a novel scene is likely to take gaze toward targets, if they are present, because people can very rapidly grasp the rough layout of a scene and direct the eyes toward the ground plane, where humans are most likely to be (Ehinger et al., 2009). In other cases, scene guidance is something more like a form of episodic memory. The structure of the scene guides attention to the known/remembered location of a target item. Castelhano and Heaven (2011) showed that learned associations between an object and a location could guide attention even if the object was in a semantically inconsistent location. The scene guidance didn't need to make sense. The scene just needed to be informative.

As shown in Figure 7 (redrawn from Experiment 4 of Wolfe, Alvarez, et al., 2011), there is a distinction between a general understanding of a scene and episodic knowledge about where to find specific items in that scene. This is the distinction between becoming generally familiar with the kitchen and episodic memory for where a specific item (e.g., the toaster) is located. In this study, Os searched twice for each of 15 objects in a single scene. The presentation order was random, so the lag between the first and second searches for a specific target could be anywhere between 1 and 29 trials. RTs as a function of the average positions are plotted. For instance, the red circles mark the 11th object in order of first appearance. On average it appeared in ~13th of 30 positions for the first time and in the ~26th position when it appeared for the second time. The purple circles show that RT improves modestly as Os search repeatedly for different items through the same scene, while the green diamonds show a much more marked decrease in RT when an item became the target for a second time.

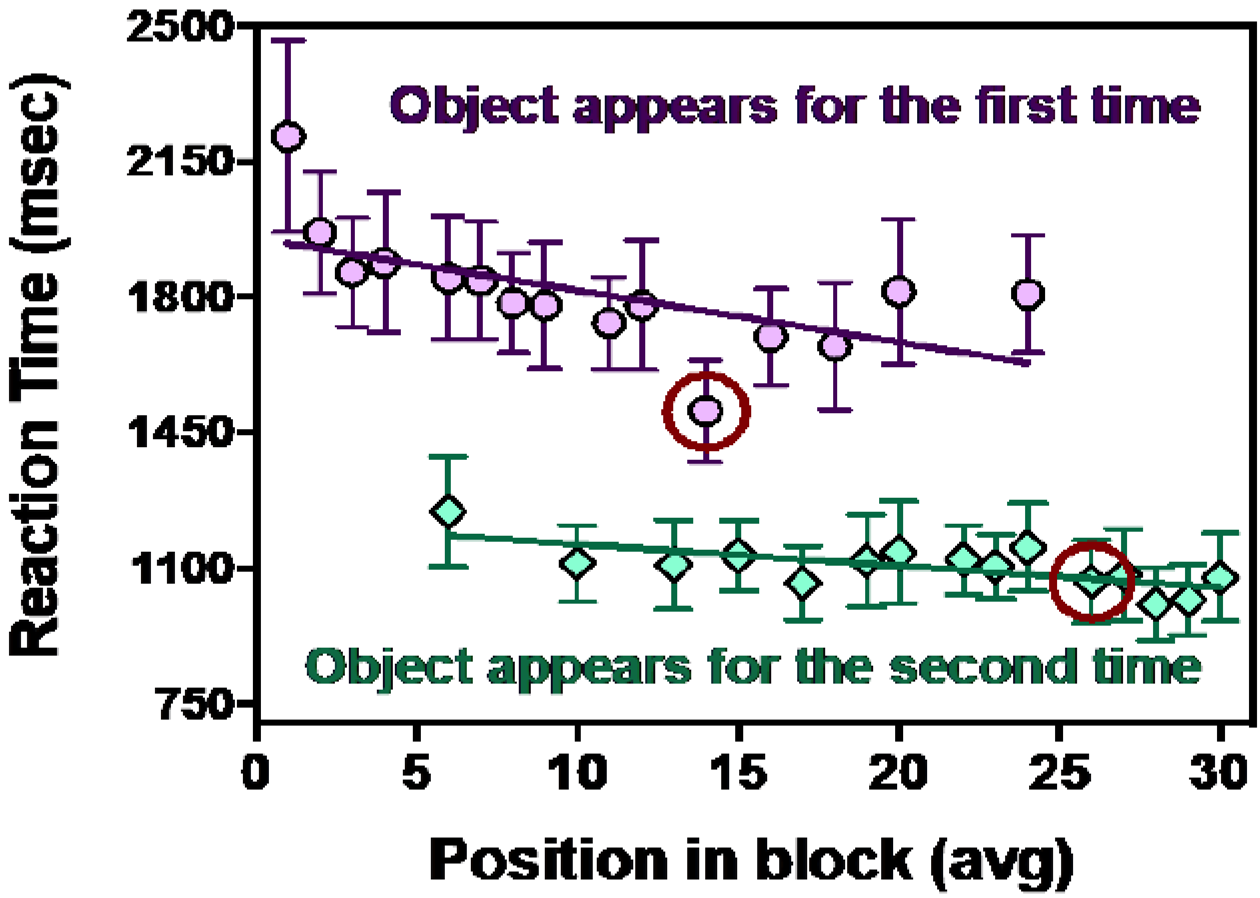

Figure 7. Os search 30 times through the same scene, twice for each of 15 objects. While there is some improvement simply as a function of repeated search through the scene, the dramatic drop in RT occurs when an item is repeated as a target.

Source: Figure redrawn from Exp 4 of Wolfe, Alvarez, et al. (2011).

Simply repeating the scene may matter less because the observer already gets the bulk of schematic scene guidance on the first appearance of that scene. However, once the target is repeated, search can make use of the episodic memory of the position of that target in the present scene (Vo & Wolfe, 2013b). Simply attempting to memorize the scene produces far less of this episodic benefit than does actively searching for the target (Vo & Wolfe, 2012).

In thinking about scene guidance, it is important to address two extreme accounts. One would be that scene guidance is simply a version of bottom-up stimulus salience. After all, simple salience does account for some amount of the variance in where the eyes go under free-viewing conditions (Itti & Koch, 2001). However, scene semantics explains variance that salience does not capture (Henderson, 2007; Henderson et al., 2007). In fact, semantics can be seen as trumping salience in some scene search tasks (Hayes & Henderson, 2019; Spotorno & Tatler, 2017).

A semantic analog of a salience map has been developed by Henderson and Hayes (2017). They took scenes and divided them up into an array of small circular tiles. They then had observers rate the meaningfulness of each patch. The patches were small enough that you could not typically tell what was being shown but a blank patch of color would get a lower rating than something with a lot of contours. The ratings can be pooled to create a "meaning map" that is intended to be a semantic analog of a saliency map. Obviously, meaning maps do not capture all of scene guidance. They conspicuously lack information about scene layout, for example, though, in subsequent work, Henderson's group has shown that, as would be expected, guidance can be based on a combination of meaning and surface information (Peacock et al., 2021). Salience maps and meaning maps are correlated with each other. Still, Henderson and Hayes (2018) found that meaning maps accounted for variance in fixations beyond what could be accounted for by salience, though this claim has been disputed (Pedziwiatr et al., 2021). In one effort to distinguish between salience and meaning, Hayes and Henderson altered patches in a scene using a transformation "designed to remove the meaning of an image region while preserving its image features" (Hayes & Henderson, 2022). They found that meaning maps were sensitive to this manipulation while salience models ignored it.

Local salience and meaning clearly have their limits in explaining important visual searches in scenes. For example, a radiologist might be asked to search a chest x-ray for signs of pneumonia. That pneumonia, if present, is almost undoubtedly not going to be among the more salient items in the x-ray. Pneumonia shows up as something like a subtle fogginess in the lung. Blood vessels, bones, the heart, and so forth will all be more salient. Nor would a meaning map, based on ratings of isolated small patches, reveal much. Still, scene guidance is at work in such tasks. One way to see this is by eye tracking radiologists of different levels of expertise (Krupinski, 1996). A standard finding in such search tasks is that experts spend less time, make fewer eye movements, and cover less of the image than do novices. The presumed reason is that expertise has taught the experts where *not* to look based on an understanding of the scene that is clearly distinct from the signals measured by salience or local meaning. Deep learning networks can learn these skills as well (e.g., Rajpurkar et al., 2018) and it is an interesting question whether humans and machines are using similar principles to search.

Scene Search Beyond Static 2D Images

Before concluding this look at scene guidance, it is worth noting that research in the lab does not capture the richness of real-world search tasks and that, as a result, important factors in search may be relatively understudied. Most research on scenes involves search through static images on a computer screen. Search in real-world scenes differs in many ways, some of which might be quite fundamental (Võ et al., 2019).

1. Real-world scenes typically fill the visual field. As a result, head movements become important in ways that they are not in most laboratory work (Hardiess et al., 2008; Sanders & Donk, 1996). The rise of Virtual Reality technology is making search experiments in a 360-deg. world more practical (Bennett et al., 2021; Hadnett-Hunter et al., 2019; Helbing et al., 2020).

2. Real-world scenes are not as composed as most scene stimuli. Convenience has led to the use of sets of scenes in which very neat, unoccupied, upper middle-class indoor spaces are overrepresented and/or where objects of interest tend to lie toward the center of the image. This latter factor probably contributes to the center bias seen in eye tracking studies with scenes (Berga et al., 2019; Chakraborty et al., 2022) though center bias may simply reflect a tendency to center the eyes in the orbit and to point the head at the screen (or the relevant part of the world). That, alone, will tend to produce fixations toward the center of an image (Tatler, 2007).
3. There is also a bias toward indoor scenes with multiple objects of more or less the same size. We rarely ask subjects to look for a mountain peak on one trial and for rocks on the path on the next, even though sequences of search tasks like this would be standard in normal life.
4. Real-world scenes do not typically pop-up with no context. You are not in the kitchen at one moment and in the farm yard at the next. More typically, you have been in the kitchen for a while when it occurs to you to look for the carving knife. Again, the rise of VR research makes it practical to spend time in an environment, performing multiple searches (Helbing et al., 2020).
5. Many real-world searches involve interactions with the relevant stimuli, as in searching by hand through the Lego bin (Hout et al., 2022; Sauter et al., 2020; Solman et al., 2012).
6. Many, if not most, real-world searches involve a mobile observer, moving through the scene. From looking for your keys to looking for cyclists while driving (Robbins & Chapman, 2018), the observer is dealing with a continually changing scene. Indeed, searchers are often deliberately changing the search scene by changing the points of view. This is true of important artificial scenes, too, such as scrolling through 3D volumes of image data in, for example, medical CT images (Drew, Vo, et al., 2013; Kelahan et al., 2019; Venjakob & Mello-Thoms, 2015) or changing magnification in search of very large images such as aerial imagery (Ehinger & Wolfe, 2016), mammography (Øynes et al., 2020), or viewing microscope slides in pathology (e.g., Randell et al., 2013).
7. The real world is not a purely visual stimulus but most of the time, search research is limited to the visual domain, though there is a body of multisensory search research (e.g., Flanagan et al., 1998; Fujisaki et al., 2006; Matusz & Eimer, 2011; Orchard-Mills et al., 2013; Smith et al., 2020).
8. In the real world, individual differences, especially in the form of experience with specific settings (my kitchen vs. yours), are likely to make a major difference in search.
9. Relatedly, scene-specific memories may serve an outsized role in real-world search (Draschkow & Võ, 2016; Kristjánsson & Draschkow, 2021).

Does this mean that laboratory studies of scenes, to say nothing of search through random arrays of geometric or alphanumeric items, have been a waste of effort? The situation is probably not so dire. Imagine that you are walking down the street, looking for your cat. In the next second of this search, the rules governing the deployment of attention in this real-world situation are probably quite similar to those in the lab. The RT for the overall cat search, however, is unlikely to be usefully explained as the sum of anything like a collection of RT × set size functions. The overall RT will be shaped by factors like your walking speed that would have no counterpart in a standard lab search task. Nevertheless, were you suddenly to be deprived of the forms of guidance, you would not readily find your cat. Imagine searching for the cat without a guiding template directing your attention to cat-sized objects or without scene guidance guiding you away from cat-sized clouds. At the same time, a model, based exclusively on research on static 2D images, will not predict the course or success of your search.

Artificial "Scenes" in the Real World

Modern civilization has created a range of important search tasks that involve artificial scenes. Probably the largest body of research in this area concerns search of medical images (for reviews, see Alexander et al., 2020; Samei & Krupinski, 2018; Waite et al., 2019, 2020; Wolfe, 2016; Wu & Wolfe, 2019). Other artificial scenes include those created for x-ray baggage screening (for a review, see Donnelly et al., 2019), fingerprint identification (Hicklin et al., 2019), air traffic control (Fraga et al., 2021; Remington et al., 2000; Sivagnanasundaram et al., 2016), and others. Many of these artificial tasks present challenges that do not exist in the "real-world," even in the artificial, real world of urban or indoor scenes. As an illustrative example, consider volumetric imagery in medicine (Williams & Drew, 2019). These are imaging modalities like computerized tomography (CT), magnetic resonance, or ultrasound that create 3D volumes of data; a virtual set of "slices" through the tissue being examined. Of course, the real world presents a three-dimensional space to a searcher, but it is a different type of 3D space. Objects can be seen at a variety of distances, though a nearer object may occlude a more distant one. In volumetric imagery, the observer typically "moves" through a stack of locally correlated but essentially 2D images, a viewing situation that does not happen in the natural world. Eye tracking studies have found that observers adopt distinct strategies for searching through a volume of image data (Aizenman et al., 2014; Drew, Vo, et al., 2013; Venjakob & Mello-Thoms, 2015; Wen et al., 2016; Williams & Drew, 2017) but much more needs to be done before we can claim to understand how humans perform these searches and, importantly, how humans *should* perform these searches.

Prevalence Effects

A characteristic of many of the socially important search tasks such as medical or security screening is the very low prevalence of actual "targets." Fortunately, there are very few airline passengers who are trying to get threat objects past security. Similarly, breast and lung cancers, while obviously very important to find, are rare in screening populations (Lee et al., 2016). It has long been known that low prevalence (e.g., in vigilance tasks; Colquhoun & Baddeley, 1967) has an impact on human decision-making. This is related to the more general problems humans have in properly accounting for the "base rate" when making choices (Bar-Hillel, 1980). Over the past two decades quite a substantial literature has examined the effect of prevalence in visual search; both in the lab and under more real-world conditions (reviewed in Horowitz, 2017).

The central finding of the prevalence literature is that false negative/miss errors rise at low prevalence (Wolfe et al., 2005). This is generally accompanied by a decrease in false-alarm errors. This is the hallmark of a criterion shift in signal detection terms (Hautus et al., 2021). Indeed, in early work in the radiology literature, it was noted that d' and/or the area under the Receiver Operating Characteristic (ROC) curve Area Under the Curve (AUC) didn't change at low prevalence (Gur et al., 2003; Kundel, 1982). This was regarded as useful evidence that laboratory studies at high prevalence could be used to inform us about clinical performance at low prevalence (Obuchowski, 2004) and, indeed, if d', AUC, and related measures are the measures of interest, it has been repeatedly shown that prevalence effects are minimal (e.g., Wolfe & van Wert, 2010).

However, if the false negative/miss error rate is the measure of greatest interest, as it might be in cancer or threat detection settings, then prevalence effects look like more of a problem and one that proves to be resistant to various easy fixes (Wolfe et al., 2007). Prevalence effects, seen as an increase in missed targets, have been reported in the case of radiologists performing breast cancer screening (Evans et al., 2013), cytopathology technicians reading cervical cancer (Pap smear) stimuli (Evans, Tambouret, et al., 2011; Evered, 2017), airport security officers (Wolfe et al. 2013), experts matching fingerprints (Growns & Kukucka, 2021), and lifeguards at the pool (Schwebel et al., 2007).

Because such expert observers are a limited resource, most of the work on prevalence effects in search has involved nonexpert observers. Mitroff et al. (2014) found a productive middle-ground between experts and laboratory research when they gained access to data from a handheld game, "Airport Scanner," that is based on airport baggage screening. This platform has provided them with literally billions of trials and has allowed them to look at miss rates for "ultra rare" stimuli (Mitroff & Biggs, 2014) and to test other effects that would not be possible in the lab or in the field (Biggs et al., 2014).

Fleck and Mitroff (2007) thought that the laboratory prevalence effect might be a motor error. If Os were overwhelmingly responding "target absent," they might develop a tendency to hit "absent" even when the target was present. Motor errors are real. However, a number of studies show that prevalence effects persist when the motor errors are counteracted (Lau & Huang, 2009; Rich et al., 2007; van Wert et al., 2009). In a different sort of motor error, Solman et al. (2014) found that Os could fail to notice a target, even if they "dragged" that target off of an on-screen pile with a computer mouse.

What the observer knows about the situation is important. It has been suggested several times that if low prevalence is a problem, perhaps observers should be told that the prevalence is higher than it actually is. Such false feedback does have effects in the lab (Schwark et al., 2012) and radiologist expectations can be manipulated to change response criteria (Littlefair et al., 2016; Reed et al., 2011, 2014). However, it is unclear whether "lying" to the observer is a practical, long-term solution (Larson, 2011; Wolfe, 2011). There may be other ways to manipulate expectation. Lau and Huang (2009) show that what Os think about prevalence matters less than what they have experienced. Case by case/trial by trial feedback matters in many different contexts (Boutis et al., 2010; Growns & Kukucka, 2021; Lyu et al., 2021; Weatherford et al., 2020) so it is possible that a period of high prevalence testing with feedback might have persistent effects on a subsequent period of low prevalence without feedback (as might be the case in the clinic), though such effects might be small (Papesh et al., 2018). One clever idea forces Os to identify the most target-like item on each trial, turning a low prevalence task into something like a 100% prevalence task (Taylor et al., 2022). That does greatly reduce false negative errors, though, if one imagines marking one location as suspicious in each mammogram or carry-on bag, someone would still need to decide which of those possible targets are, in fact, real targets.

Eye Movements and the Functional Visual Field

As was discussed in the context of Figure 3, it is possible to search by covertly deploying attention or by overtly moving the eyes. Many laboratory visual search studies focus on covert search either by the use of brief display presentations (usually less than 200 ms), which are too short for useful eye movements (e.g., Gibson & Jiang, 1998; Horstmann, 2002; for a review, see Palmer et al., 2000), or by training participants to hold fixation and suppress saccades during search. Interestingly, if acuity and crowding effects do not shape the results, laboratory search tasks can result in similar performance with or without eye movements (Klein & Farrell, 1989; Zelinsky & Sheinberg, 1997). Given the choice, participants prefer to make eye movements, even if those eye movements are not strictly necessary (Motter & Simoni, 2008). Eye movements are a form of motor activity that even the laziest among us do not avoid. Under normal circumstances in the real world, most of our searches undoubtedly involve both overt eye movements and covert deployments of attention. In the world of research, how one understands visual search can depend on whether one gives primacy to movements of the eyes or if one treats covert deployments as primary with eye movements serving to handle limits imposed by the spatial inhomogeneity of the visual system.

Overt movements of the eyes and covert deployments of attention are closely related. Covert attention is typically deployed to the target of the next saccade before the eyes arrive at that new fixation point (Kowler et al., 1995; for a review, see Kowler, 2011) and though attention can be deployed away from the point of fixation, under most real-world conditions, covert attention probably remains in the vicinity of the current overt fixation, if only because that is where the resolution is the best. Given those facts, it is not unreasonable to use the pattern of eye movements as the dependent measure of interest and to declare the goal of visual search modeling to be the prediction of the sequence of eye movements. Perhaps, the most vigorous proponent of this view is Greg Zelinsky (for a clear oculomotor supremacy argument and review, see Zelinsky et al., 2020).

It is worth quoting a piece of Zelinsky et al. (2020) because it nicely states the oculomotor argument and then allows us to point to a complication.

> Researchers who choose to adopt oculomotor dependent measures in their studies of search are often reminded that eye movements and shifts of spatial attention are not the same thing. We get it . . . for researchers interested in the mechanism of attention, the debate over the exact relationship between eye movements and shifts of spatial attention is important and lives on . . . However, for the majority of cognitive scientists this debate is over, as indicated by the explosive growth in the use of oculomotor measures of attention over the last decade (Findlay, 2004). This widespread embrace of oculomotor measures reflects a realization that eye movements are highly correlated with shifts of attention, even in the laboratory. (pp. 235–236)

The complication has to do with the nature of a fixation. The eye tracker gives us a point of fixation. Obviously, the observer is processing more than that single pixel. There is some region around fixation within which you can perform some visual function; for instance, choosing the destination of the next eye movement in a visual search or identifying the target of that search. The region is referred to as the Useful Field of View (Ball et al., 1988) or the Functional Field of View (FVF; Sanders, 1970); the terms refer to more or less the same idea. We will use FVF.

The FVF is often talked about as if it were a "thing" of some fixed size, but a moment's introspection—with the help of Figure 8—will tell you that the FVF will be very task dependent. We will discuss this matter and then return to the role of eye movement data in the study of visual search.

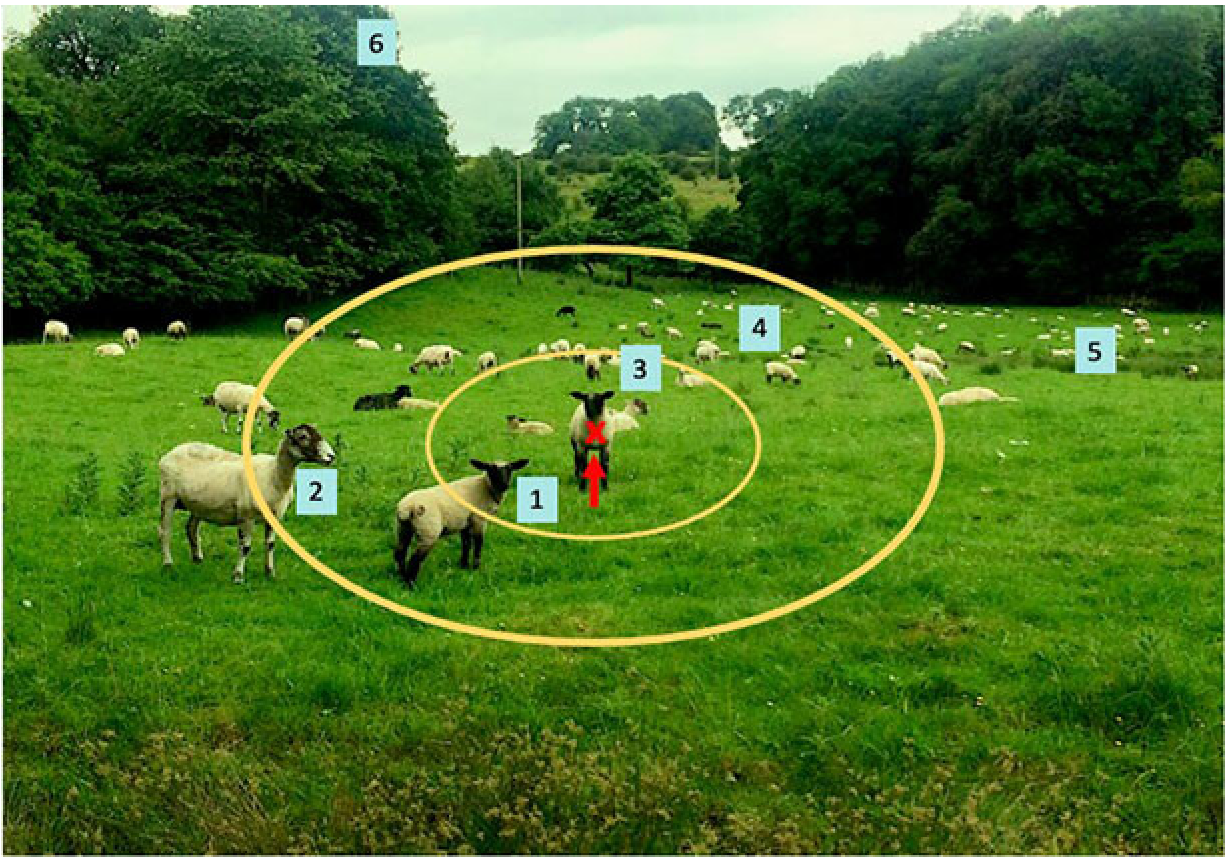

Figure 8. If you are searching for black-headed sheep, different functional visual fields (FVFs) can be defined around the X for different aspects of the task.

Suppose you are fixated on the red X and you are looking for black-headed sheep. There is an FVF surrounding that X that would allow you to identify the black-headed sheep at (1) and, probably, at (2), and, perhaps, to program the next saccade to fixate on one of them. More physically distant sheep, forming smaller images on the retina, might be identified within a retinotopically much smaller FVF. Thus, the sheep below the (3) is identifiable as black-headed from the fixation at X. The target sheep at (4), while inside that larger FVF, is not identifiable. Suppose, having found sheep 1–4, you were trying to decide where to fixate next. Now, information from within a retinotopically much larger FVF would identify the area around (5) as a promising source of possibly black-headed sheep while the equidistant (6) would not be a useful destination for the eyes. From fixation on the X, you cannot resolve sheep at (5) but you could prioritize the area as one potentially containing targets. A gaze shift to (1), (2), or (3) would be a target acquisition saccade. A saccade to (5) would be a searching saccade. One might borrow language from the foraging literature and refer to targeting saccades as "exploitation" saccades and searching saccades as "exploration" saccades (Stephens & Krebs, 1986).

The sequence of eye movements over an image or a scene forms a scanpath (Noton & Stark, 1971a, 1971b). These have been used as data in the study of visual search with increasing frequency as eye tracking technology has become easier to use. Medical image perception provides an interesting use case. Kundel and colleagues (1978) used scanpaths to classify radiologists' reading errors. They identified "search" errors as cases where the eyes never landed on the target (e.g., a mass in the lung). "Recognition" errors occurred if the eyes landed on the target but left after less than 500 msec total viewing time (1,000 msec in mammograms). Finally, "decision" errors were defined by cases where the target was scrutinized but not identified as a target. Returning to Figure 8, suppose that an observer fixated at the X but failed to report the black-headed sheep at (1). What kind of error was that? It could be a search error, because the eyes did not land on that sheep, but it could also be classified as a recognition error since that sheep could have been recognized from fixation at location X. The answer depends on what is happening inside the FVF(s) around location X and it seems hard to imagine an answer that would not involve understanding what covert attention was doing. Explaining the sequence of saccades is a worthy goal for modeling but a full account of visual search will be a story of a complex dance of overt and covert partners.

Because attention and eye movements are locked in this close relationship, in most search tasks, response times can be almost perfectly correlated with the number of fixations and fixation durations Hulleman and Olivers (2017). To a first approximation, saccades occur about four times per second so, if the RT is, say, 750 msec, the observer will have made about three saccades. Researchers disagree about what goes on during those three fixations. Imagine three search trials that each produce an RT of 750 msec to successfully find the target among 3, 12, and 50 distractors, respectively. The difficulty of the search task can be quantified in how many distractors can be handled per second. In those terms, the 3-distractor task is the hardest because only three items are handled in 750 msec compared to the 12 in the next task which is, itself, harder than the task with 50 distractors. A model like the FVF-based model of Hulleman and Olivers (2017) would understand the differences in difficulty in terms of the size of the FVF. The 3-distractor task would require an FVF that could only cover a single item at a time. The 12-distractor task would have a bigger FVF that could handle about four items (×3 fixations = 12), while the 50-distractor task would allow a still bigger FVF. A model like Guided Search (Wolfe, 2021) would argue that the 3-distractor task required fixation on each item, perhaps due to an acuity or crowding limitation. Items in the 12-distractor task could be identified using covert attention deployed from item to item at a rate of ~60 msec/item. In the 50-distractor task, Guided Search would propose that most items did not need to be identified at all. They could be rejected preattentively or, phrased differently, attention could be guided to a subset of about 12 possible targets.

As has been quite typical in search models, both of these accounts ignore the possibility that the fixation duration and, thus, the number of fixations per second could vary. However, studies have shown that there is variability in fixation durations (e.g., Hooge & Erkelens, 1996, 1998) especially in search for complex stimuli like face photographs (Horstmann et al., 2019). In general, as the target becomes more similar to the distractors, fixation durations increase (Becker, 2011; Shen et al., 2003).

This picture is made more complicated by the presence of some very short fixations. When a fixation is on the order of 100 msec, it will not affect the destination of the next fixation because the next saccade has already been planned and initiated on a neuronal level and cannot be stopped (Caspi et al., 2004). Indeed, in most circumstances, attention has already been deployed to that next fixation location ~50 msec before the eyes arrive (Kowler et al., 1995). Nevertheless, information relevant to a search can still accumulate during even a short fixation and can influence the destination of the saccade *after* the next saccade (Findlay et al., 2001). In free viewing paradigms, these short fixations may reflect the failure of the saccade to land exactly where it was desired. They are frequently followed by short corrective saccades that bring the previously intended saccade target closer to the fovea (Wu et al., 2010). It may be useful to think of fixation duration in search as being under "mixed control" (Godwin et al., 2017). There is a default fixation duration which can be set strategically, based on the expected search difficulty of the search task. That duration is modulated, to some extent in an online manner, with the current fixation exerting an effect on the next saccade destination.

Eye movements become increasingly useful as visual search tasks and stimuli become more complex. Using RT to uncover search mechanisms becomes difficult in scenes where it is essentially impossible to meaningfully define the set size. As a consequence, eye movement data have been central to most of the work on scene search and scene guidance (e.g., Boettcher et al., 2018; Koehler & Eckstein, 2017; Peacock et al., 2019; Vo & Wolfe, 2015). Eye movements have been critical in understanding more complex task with a search component like the making of a peanut butter sandwich (Hayhoe et al., 2003) or the processing of copying a pattern by moving objects in virtual reality (Draschkow et al., 2021). A central finding in these and related studies is that participants would rather use repeated acts of search than use their memory to store even just two or three task instructions at a time.

When Is It Time to Stop Searching?

Visual search tasks are often described in terms of finding what you are looking for. If you need to find that phone-charging cable, search ends when you find it. But what if you don't find the cable? Obviously, you do not search forever. When do you stop? The classic answer in models like the original forms of Feature Integration Theory (Treisman & Gelade, 1980) and Guided Search (Wolfe et al., 1989) was to propose a serial, exhaustive search. Observers attended to each item. If none of the items proved to be the target, then it was time to quit. This required that each rejected distractor be marked in some fashion. Inhibition of return (IOR) was proposed as a mechanism for this distractor marking (Klein, 1988; Posner & Cohen, 1984).

This account can't be correct in its simple form. If we return to Figure 4, search for a specific hat would end after the hats were examined. It would not be necessary to attend to each of the letters. Thus, one could propose ending search after an exhaustive search through a relevant subset of stimuli. That modification is made implausible by evidence that IOR does not robustly label each attended distractor as rejected (Horowitz & Wolfe, 1998, 2003), though IOR does play an important role as a "foraging facilitator" (Klein & MacInnes, 1999), preventing perseveration on single, salient items (Klein, 2009; MacInnes et al., 2014).

Subsequent to this work, theories of search termination have proposed that a signal of some sort accumulates; ending search when that signal reaches a quitting threshold (e.g., Hawkins and Heathcote (2021); Wolfe & van Wert, 2010) or increasing the probability of quitting probabilistically over time (Moran et al., 2013). Setting this threshold has been modeled as an adaptive process: lower the threshold after successful target absent trials, raise the threshold after a miss error (Chun & Wolfe, 1996). Such models do quite well in estimating error rates and quitting times but there are issues that remain unresolved. Most notably, the adaptive threshold mechanism works well enough when observers are performing many instances of the same search in the lab. However, in the real world, you need to be able to stop that search for a phone-charger cable at a sensible time without having performed the same search, with feedback, dozens of times in a row. One may imagine that a form of adaptive learning occurs over the course of a lifetime, but no one has shown this. One might predict that quitting times would be longer or searches would be less accurate in these "one-off" real-world searches than they would be if the search was repeated as in a laboratory, but, again, this experiment has not been done.

Hawkins and Heathcote (2021), while not writing about search, raise the possibility that we need a second quitting threshold in search. Search can be seen as a series of decisions about the identity of items. Those decisions can be modeled as drift diffusion or similar processes where information accumulates toward a threshold that would confirm the item's identity (Ratcliff, 1978; Schall, 2019). Suppose, however, that the evidence accumulation is slow and meandering. If no answer is forthcoming, it must be possible to move on to the next item. Hawkins and Heathcote (2021) propose a diffusion model that includes an accumulating quitting signal that can end the analysis of an item when that signal reaches its threshold.

Figure 9. A "mixed hybrid" search in which you are asked to look for instances of two specific target types and two categorical target types.

Figure 9 illustrates how this could play out in visual search. Figure 9 is a "mixed hybrid search" (Wolfe et al., 2017). In a hybrid search, as defined in "Top-Down Guidance and the Search Template(s)," Os search for multiple target types. In mixed hybrid search, some targets are specific: this knob and these skates in Figure 9. Other target types are categorical: here, any cup and any fruit. This search will be essentially unguided (Vickery et al., 2005) and it will take longer to identify a cup or a fruit than to identify a specific item. Importantly, for present purposes, Os will be more likely to miss a categorical target (Did you find *both* cups?). Given that each item in the search display is roughly equally likely to attract attention, why is this? The answer may be that, in some cases, Os attended to a cup but reached Hawkins and Heathcote's item-level quitting threshold before the cup was identified. They moved on to other items and missed the cup. At present, this is a hypothesis and is mentioned here to point out the complexity of quitting rules in search. If you searched Figure 9 and you are now reading this, you figured out how to quit the search as a whole, even without finding any fruit.

Missing What Is Right in Front of Our Eyes

The elevated rate of missed categorical targets in mixed hybrid search is one example of an interesting general problem. How and why do we miss clearly visible targets, even when we are actively searching for them? As noted, there is no reason to think that categorical targets are attended to and/or fixated on less reliably than the specific targets. In this experiment, they are unambiguously identifiable. Nevertheless, they are missed at a higher rate. Outside of the lab, errors of this sort are often what people are interested in explaining. Why do radiologists miss cancers that are "retrospectively visible" on subsequent examination of the images (Bird et al., 1992; Jang et al., 2020; Mello-Thoms et al., 2002)? Why are threats missed at airport security screening (Albert et al., 2020; Biggs et al., 2018)? For that matter, why are clearly visible typos missed when we proofread our work? In driving, errors of this sort are sometimes called “Looked but failed to see” (LBFTS) errors (Hills, 1980) since drivers often offer a version of that expression at the scene of an accident: I looked to the left but I just didn’t “see” that cyclist.

Accounting for LBFTS errors can serve as something of a review of the topic of visual search. Suppose that one was performing the mixed hybrid task of Figure 9. First, in the spirit of Condillac, you will have the impression of seeing something at all locations at once. However, Os do not experience Condillac’s patchwork of colors and shapes. They experience their best guess about the current state of the world. In this case, that would be a screen full of identifiable objects. Helmholtz would have called this an example of “unconscious inference” (Helmholtz, 1924). A more modern description might speak of a process of Bayesian “predictive coding” generating “the hypothesis with the highest posterior probability” (Hohwy et al., 2008). Next, Os would search through this set of objects. In this case, this is a relatively slow task that will produce RT × set size slopes of about 100 msec/item (Wolfe et al., 2017). Imagine, the observer is fixated on the clock. From that position, the functional visual field probably permits identification of the clock and 3–4 of the surrounding objects. However, in a 250 msec fixation, Os will only be able to process 2–3 of the objects. In experiments with simple Ts and Ls (Wu & Wolfe, 2022) and complex mammograms (Wolfe et al., 2021), we have found that the chance that the next fixation goes to the target is only about 50% even when the target is within a degree or two of current fixation. It is clearly possible to fixate on or near an object and yet fail to process it before moving the eyes to the next location.

The search in Figure 9 is largely unguided, but most search tasks are guided. This allows “misguidance” to contribute to LBFTS errors. This may be most clearly seen in cases of “inattentional blindness” like the famous Simons and Chabris (1999) gorilla experiment. There, Os who were attending to the white shirted team in a ball game, frequently failed to report a large black gorilla even though the eyes must have fallen on or near that gorilla. Fixated near the gorilla, we can imagine them being guided to a few white objects and, for the purposes of gorilla detection, being misguided away from the shaggy black object. In a medical image search version of this experiment, radiologist observers failed to report a big shaggy black gorilla while searching for small, round white lung nodules (Drew, Vo, & Wolfe, 2013). Misguidance probably played a role here as well.

Many LBFTS errors involve relatively rare targets: rare “incidental findings” in medicine, rare cyclists in the wrong place on the road. Even the typo is rare in a document composed of largely correctly spelled words. In mixed hybrid search, error rates are dramatically increased when the categorical targets are rare (Wolfe et al., 2017). Low prevalence makes Os more conservative, less inclined to report a target as present. This can be seen as a raised decision boundary in a diffusion process. It also makes Os more willing to abandon a search, a lower quitting threshold (Wolfe & van Wert, 2010). As result, Os will be more likely to miss a low prevalence target.

Each of these factors is an aspect of normal search behavior. The failure to identify every item near fixation is a response to fundamental limits on processing speed. Misguidance is the flip side of the guidance that makes it possible to attend to intelligently in a crowded world. A criterion shift in response to low prevalence is an adaptive way to avoid too many false positive responses.

Finally, the job of the system is to deliver the most plausible account of the current state of the external world in the face of the impossibility of fully processing all of the input from that world. Taken together, these factors virtually guarantee that there will be occasions when the object of search will not be found, even though it is “right in front of your eyes.” It is important to remember that, most of the time, these same processes allow us to find what we are looking for or to confirm with reasonable certainty that it is not present.

Limitations

A reader who has made it to this point in this article will probably be thinking that the article is as long as (and perhaps longer than) it needs to be. A reader, working in the field, may feel that there is a lot that has been left out or merely alluded to. Notably, there has been no systematic review of models of search. For reviews of, at least, parts of that literature, see, for example, Borji and Itti (2013), Moran et al. (2016), Yang et al. (2002), and Zelinsky et al. (2020). Some of the notable models, in addition to those already mentioned, would include these: Duncan and Humphreys (1989), Huang (2021), Huang and Pashler (2007), Liesefeld et al. (2019), Miconi et al. (2016), Rangelov et al. (2012), Rosenholtz et al. (2012), Schwarz and Miller (2016), Yu et al. (2019), Zelinsky et al. (2013), Zhang et al. (2015) . . . with apologies to other models that should have been mentioned.

We have also said almost nothing about the neural basis of search (for reviews, see Buschman & Kastner, 2015; Eimer, 2014; Reynolds & Chelazzi, 2004; Schall, 2019; Scolari et al., 2014; Treue, 2014). And there are other topics that were largely ignored like foraging for multiple instances of a target (Bella-Fernández et al., 2021; Kristjánsson et al., 2019, 2020; Wolfe, 2013) or the effects of age in development and later life (Couperus et al., 2011; Gil-Gómez de Liaño et al., 2020; Ólafsdóttir et al., 2016; Wiegand & Wolfe, 2017, 2018).

Many other topics received useful treatment in Nobre and Kastner’s (2014) magisterial *Oxford Handbook of Attention*. Somewhat different reviews of this material are found in Wolfe (2018, 2020).

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