Short Report

PERCEPTION

Learning in the Target Prevalence Effect

Perception
789–798

DOI: 10.1177/0301006618773081
journals.sagepub.com/home/pec
SAGE

Nicholas Hon
Department of Psychology, National University of Singapore, Singapore

Syaheed B. Jabar
Department of Psychology, University of Waterloo, Canada

Abstract
Rare or low prevalence targets are detected less well than counterparts that occur with higher probability. It stands to reason, though, that before such a deficit is apparent, information about a given target's probability of occurrence must be apprehended. In this study, we investigated how much target experience is necessary for target probabilities to be fully acquired and established within mental task representations. A central finding was that different target probability values required approximately the same amount of target sampling to learn. This was true whether learning about target probabilities from a naive start-point (Experiment 1) or when recalibrating from one probability value to another (Experiment 2). We discuss these findings in relation to how mental task representations are modified when new task-relevant information is received and the attentional consequences of such changes.

Keywords
attention, cognition, target detection, target probability

Date received: 23 October 2017; accepted: 30 March 2018

Introduction

Target probability or prevalence is known to affect detection. For example, in visual search, rarely occurring targets are missed more often than more frequently occurring counterparts (Mitroff & Biggs, 2013; Rich et al., 2008; Wolfe, Horowitz, & Kenner, 2005; Wolfe et al., 2007). And even in paradigms that produce high levels of accuracy like simple detection or go/no-go tasks, targets that occur with lower probability are detected more slowly than higher prevalence ones (Dykes & Pascal, 1981; Hon, Yap, & Jabar, 2013). Here, being specifically concerned with the effect of target probability on response times when accuracy is high, we exclusively utilized the simple detection paradigm in the current study.

Corresponding author:
Nicholas Hon, Department of Psychology, National University of Singapore, 9 Arts Link, Singapore 117570.
Email: psyhonn@nus.edu.sg

Much of the work on this target probability effect has focused on unearthing its locus, with several proposals implicating perceptual (Dykes & Pascal, 1981; Jabar & Anderson, 2015; Lau & Huang, 2010; Menneer, Donnelly, Godwin, & Cave, 2010) and response stages (Fleck & Mitroff, 2007). Recently, though, the effect has been demonstrated to have an attentional locus (Hon, Ng, & Chan, 2016; Hon & Tan, 2013), with lower probability targets being disproportionately affected by attentional manipulations even when response and perceptual considerations were held constant. In many studies of the target probability effect, observers are not informed beforehand of the probability values used. As such, in those cases, attentional differences between the different probability targets must have evolved gradually as the various target probabilities were learned and entered into mental task representations. Accordingly, the target prevalence effect (and, in particular, how it develops) is of interest because it may enlighten on the broader issue of how mental task representations are modified by information pertaining to task relevant elements (Hout & Goldinger, 2015). Specifically, the effect is likely able to cast light on how task representations can be modified by the acquisition of information regarding a relevant stimulus' likelihood of occurrence.

What form might learning about target prevalence take? Given the standard observation that the lower the likelihood of occurrence of a target, the slower it is detected, we might predict that initial (i.e., prior to "rarity" being determined) detection of a rare target is quick but becomes increasingly slower as more experience is gained and target probability is estimated, eventually reaching a stable level. This stable level can be taken to represent the point at which target probability information is fully acquired and factored into mental task representations (Hon et al., 2013; La Berge & Tweedy, 1964). Such a pattern is consistent with what would be expected of learning in a general sense (Estes, 1950; Kahana & Wingfield, 2000; Siegel & Allan, 1996).

Previous work has suggested that information about stimulus probabilities can be acquired relatively effortlessly (Estes, 1964; Hasher & Zacks, 1984) and without explicit awareness (Jabar & Anderson, 2015, 2017). Nonetheless, it stands to reason that observers require some level of experience with the relevant stimuli before stimulus probability information can be fully acquired (Ishibashi, Kita, & Wolfe, 2011; Wolfe & Van Wert, 2010).[1] One important task, therefore, is to determine how much target experience is necessary in order to fully learn about a given target's probability of occurrence. Extending this, we might ask whether different target probability values require more or less the same or different amounts of target experience to apprehend. Operationally, this can be framed as whether different target probabilities require experience with a similar or different number of target trials before the stable level of performance is reached. One intuitively appealing possibility is that higher probability targets might, because they are more frequent and appear with greater temporal proximity, produce faster learning, perhaps as consequence of more robust synaptic modifications that might accompany more frequently occurring stimuli (c.f. Hebb, 1949). In such a case, stable levels would likely be reached at different points for different probability values. However, it is also possible that, analogous to learning about physical features (Maljkovic & Nakayama, 1994), different target probabilities require the same amount of target sampling to learn. With this possibility, we would expect stable performance levels to be reached after approximately the same amount of target experience, regardless of probability value used.

Here, we investigated the issues set out earlier with two experimental scenarios: Learning about target probabilities from "scratch" (Experiment 1) and recalibrating from one target probability value to another (Experiment 2).

Experiment 1

In this experiment, we investigated how much target experience is necessary to learn a given target's probability of occurrence when beginning from a neutral or naive start-point, mimicking the scenario in typical target probability studies. Here, participants performed four blocks of simple target detection, with each block having a different target probability value. Targets in three of the blocks appeared with what would be considered low probability (accounting for 5%, 10%, or 20% of all trials in those blocks). In the fourth block, targets appeared with what would be considered high probability (targets accounted for 40% of all trials).

Methods

Participants. In total, 28 participants with normal or corrected-to-normal vision from the National University of Singapore contributed complete data sets to this study. The data from one participant were excluded from subsequent analyses owing to poor performance (accuracy < -2.5 standard deviation [*SD*]).

Stimuli. Letter stimuli were utilized in this study, with these being presented in white against a black background. The letters were presented in Courier New font, which, when viewed from a distance of 50 cm, subtended approximately 1.4° of visual angle both vertically and horizontally. All stimuli were presented in the center of the screen. The letter "G" was always the target in the practice blocks, while "W," "T," "S," and "B" were target letters used in the main experimental blocks. Letter-to-probability assignments were equated across participants. Targets were never reused and never formed part of the distractor set. The distractor set comprised the remaining 21 letters of the alphabet, with same set being used for all blocks.

Procedure. Participants observed four 600-trial blocks of serially presented letter stimuli with the objective of detecting occurrences of predefined target letters (one target letter per block). The different blocks had different target probabilities: Targets accounted for 5%, 10%, 20%, or 40% of all trials within a given block. Accordingly, targets accounted for 30 target trials in the 5% block, 60 in the 10% block, 120 in the 20% block, and 240 in the 40% block, with the remaining trials being distractors. Each block was performed in a separate session, with at least 2 days intervening between each session, thereby minimizing the likelihood of "spillover" effects from one session to another. All stimuli, targets and distractors, were presented for 1,000 ms, followed by an 800-ms–long blank frame, and then by the presentation of the next stimulus display. For all blocks, participants made an index-finger button press of the "/" key to indicate detection of a target. No response was made to distractors. Trial order within a block was randomized for each participant, while block order was randomized across participants.

The experimental blocks were preceded by 10 trial practice blocks, in which targets and distractors occurred equally often.

The experiment was controlled by a PC running the E-prime software, with the stimuli were presented on a 24-inch LCD monitor.

Results

Detection accuracy was consistently high across all blocks (40%: 99.6%; 20%: 98.7%; 10%: 98.7%; 5%: 97.7%), as would be expected of a simple detection task involving high visibility

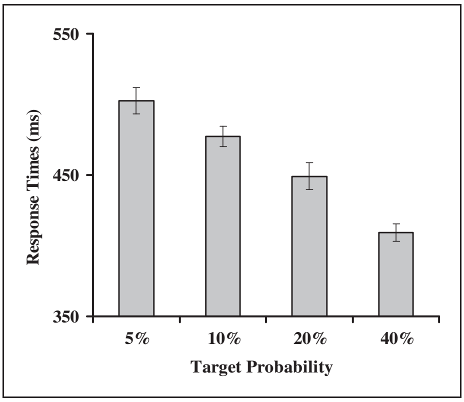

Figure 1. Mean correct RTs to the different probability targets. Error bars indicate 1 SEM. RT = response time; SEM = standard error of the mean.

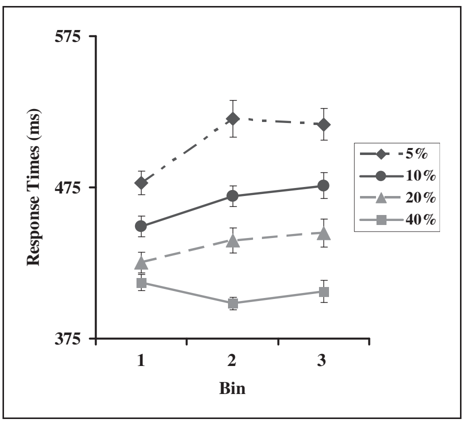

Figure 2. Mean correct RTs to the different probability targets as a function of target bin. The first bin contained the first 10 targets, with the second bin containing the next 10 targets, and so on. Error bars indicate 1 SEM. RT = response time; SEM = standard error of the mean.

stimuli that are presented at a slow rate. Figure 1 presents the average response times (RTs) for the different blocks. A one-way analysis of variance (ANOVA) revealed a significant effect of probability, $F(3,78) = 55.19$, $p < .001$. Simple effects tests revealed that subsequent probability values were significantly different from each other (paired t tests, all ps $< .005$).

To assess the amount of target experience required to acquire target probability information, we partitioned our targets into three different bins: first 10 targets, second 10 targets, and third 10 targets.[2] Figure 2 depicts these data. A fully within Block (5%, 10%, 20%, 40%) $\times$ Bin (first, second, third) ANOVA revealed significant main effects of block, $F(3, 78) = 62.66$, $p < .001$, and bin, $F(2, 52) = 15.16$, $p < .001$, and a significant Block $\times$ Bin interaction, $F(6, 156) = 8.13$, $p < .001$. Because we were interested in the acquisition of the respective target probabilities, we performed independent one-way ANOVAs on the data from each block. We found that these were significant for all blocks, 40%: $F(2, 52) = 4.40$, $p = .017$; 20%: $F(2, 52) = 4.69$, $p = .013$; 10%: $F(2, 52) = 10.12$, $p < .001$; 5%: $F(2, 52) = 18.43$,

$p < .001$. Simple effects tests revealed that for the 5%, 10%, and 20% blocks, the RTs from the first bin were significantly faster than the second, 5%: $t(26) = 5.25$, $p < .001$; 10%: $t(26) = 2.99$, $p = .006$; 20%: $t(26) = 2.17$, $p = .04$, with no difference between the second and third bins (all $ps > .24$). For the 40% block, however, we found the reverse pattern, with the first bin being slower than the second, $t(26) = 3.59$, $p = .001$, but, again, with no difference between the second and third bins ($p = .17$). These data suggest that stable levels of performance, our indicator that target probability information is fully established within task representations, occur after fairly similar amounts of target experience regardless of probability value.

Now, the 40% condition clearly produced a different pattern of results from the other conditions. One possibility is that this reflects the difference between violating and fulfilling initial expectations. Performance benefits are generally observed when expectations are fulfilled (Geng & Behrmann, 2005), while expectancy violations are typically associated with performance costs (Tzelgov, Henik, & Berger, 1992). Given that our paradigm broadly categorizes stimuli into two classes, targets and distractors, it is possible that observers initially expect the two classes to occur equiprobably (i.e., each occurring 50% of the time). On this view, the pattern observed for the 5%, 10%, and 20% conditions might reflect a violation of this initial expectation, while the pattern observed in the 40% condition might reflect the fulfillment of such (as 40% is reasonably close to 50%). An alternative possibility is that the results of the 40% condition reflect priming effects, which have been observed in search tasks (Godwin et al., 2016). For example, priming of physical features appears to reach its peak after a given feature has been encountered five to eight times in close temporal proximity (Maljkovic & Nakayama, 1994). Similarly, targets in the 40% condition appeared close in time to each other (on average, once every 2.5 trials). Such close temporal proximity may have resulted in one target instance (perceptually) priming another, with this effect peaking after several consecutive close-in-time exposures, thus explaining the initial improvement in performance and the subsequent asymptote. This would not have been the case for the other conditions, where targets were separated by much larger temporal intervals. Although we do not engage this issue beyond presenting these possibilities, we nonetheless employed a design, in Experiment 2, that allowed us to circumvent issues relating to perceptual priming and expectations.

Experiment 2

In Experiment 1, we observed that, starting from a naive start-point, different target probabilities require approximately the same amount of target sampling to learn. In this experiment, we assessed whether a similar pattern would be observed when one is required to recalibrate from one target probability value to another. Here, participants performed two 600-trial long blocks of simple target detection. Although continuous from the viewpoint of the participant, each block comprised two equal-length segments (300 trials each), with the target probability value transitioning from low to high (10%–40%) or high to low (40%–10%) across the segments. In operational terms, we were interested in how much target sampling is necessary for a posttransition performance asymptote to be reached.

It is worth mentioning that the lengthy experience with one probability value prior to the transition allowed us to control what the observer might expect for the critical posttransition trials: Expectations for the posttransition portion would be largely determined by the experiences of the pretransition segment. In addition, by keeping the target constant across transitions, we minimized the likelihood that perceptual priming would affect the critical posttransition trials as observers would already have had extensive experience with the target in the pretransition segment.

Methods

Participants. In total, 26 participants with normal or corrected-to-normal vision from the National University of Singapore participated in this study.

Stimuli. This experiment utilized the same stimulus and presentation parameters as those in Experiment 1.

Procedure. Participants observed two 600-trial long blocks of serially presented letter stimuli with the objective of detecting occurrences of predefined target letters (one target letter per block). Although continuous from the viewpoint of the participant, each block actually comprised two separate 300-trial segments, with each segment having a different target probability value. Target probability either transitioned, across segments, from high (targets accounting for 40% of all trials in the segment) to low (targets accounting for 10% of all trials in the segment) or vice versa. These are designated as *40–10* and *10–40* blocks, respectively. Detection was indicated with an index-finger button-press response of the "/" key. Trial order within a block was randomized for each participant, while block order was counterbalanced across participants.

Results

Detection accuracy was high for both transition types ($10\%_{10–40}$: 97.8%; $40\%_{10–40}$: 99.1%; $10\%_{40–10}$: 96.0%; $40\%_{40–10}$: 99.1%).

To assess the amount of target experience required to acquire target probability information, we partitioned the critical data into three different bins: Last 10 pretransition targets (Last PRE),[3] first 10 posttransition targets (first POST) and second 10 posttransition targets (second POST). These bins were emphasized because they would give an indication of stabilized performance with the "old" probability value (Last PRE) along with the changes to performance accompanying the transition to a "new" value (first and second POST bins). Figure 3 depicts these data. A fully within two transition type (10–40, 40–10) × bin (first, second, third) ANOVA revealed *only* a significant disordinal interaction, $F(2,50) = 78.377$, $p < .001$, suggesting that the effect of moving from low to high and from high to low probability was of equal magnitude, albeit in opposite directions.

Independent one-way ANOVAs conducted on the different transition types were significant for both 10–40, $F(2,50) = 51.254$, $p < .001$, and 40–10 versions, $F(2,50) = 32.336$, $p < .001$. Simple effects tests revealed significant differences between the Last PRE and first POST bins for both transition types, 10–40: $t(25) = 7.026$, $p < .001$; 40–10: $t(25) = 6.188$, $p < .001$, but no differences between first and second POST bins for either transition type. Taken together, this suggests that performance to the new target probability stabilized within the span of one bin, with this being true whether one moved from high to low probability or vice versa. It is worth noting that a similar pattern is observed when recalibration is studied in visual search tasks (Sha, Remington, & Jiang, 2017). This suggests that learning about target probability occurs in the same way, even when different paradigms are used.

Discussion

In this study, we investigated the amount of target sampling required for target probability to be estimated and factored into behavior-governing task representations

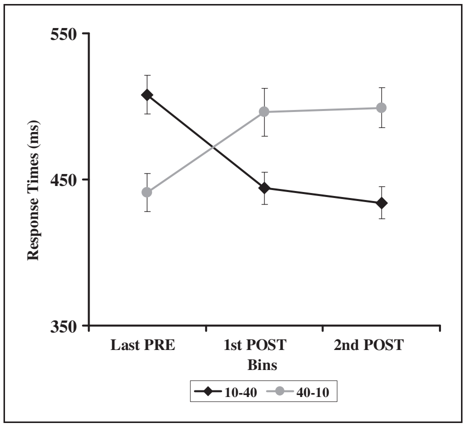

Figure 3. Mean correct RTs to the last pretransition (PRE) and the first two posttransition (POST) bins for the two transition types. Each bin comprised 10 consecutive target trials. Error bars indicate 1 SEM. RT = response time; SEM = standard error of the mean.

(operationalized here as the reaching of a stable level of performance). A notable finding here was that, with due consideration to the paradigm used in a given experimental setting, different target probabilities required similar amounts of target experience to acquire.[4] That this was observed both when learning about probabilities from a naive start-point and when recalibrating from one probability value to another speaks to the generality of this observation.

As lower target probabilities are generally associated with longer intervals or a greater number of nontargets intervening between target events (Mackworth, 1970), it is possible that target probability might be estimated purely on the basis of these. Our data speak against this view. If probability estimation was determined solely by sampling a specific number of nontarget events, we would, given that the average number of intervening nontarget events doubled with each successive lower probability value, expect asymptotes to be reached at predictably different points for the different conditions. Nonetheless, it is worth considering the contribution of the intervals (or nontarget events) between targets. We speculate that initial estimates of target probability may be generated on the basis of target-to-target intervals or nontarget events. However, we propose that actual target experience is required for these estimates to be "confirmed" and entered into task representations. A similar idea has been raised with respect to task-switching: Even when switching is predictable, task representations cannot be reconfigured without experiencing the appropriate task-relevant stimulus (Rogers & Monsell, 1995).

As mentioned in the Introduction section, the target probability effect appears to have an attentional locus, with lower probability targets requiring more attentional resources in order to accurately detect (Hon & Tan, 2013). The current data suggest that this attentional difference develops gradually as learning about a target's probability of occurrence produces changes to task representations. This begs the question of what happens to task representations when one learns that a given target is rare. Endogenous, goal-directed attentional control is generally thought to operate in the following manner: Behaviorally relevant information is held in higher order task representations, with control said to be exerted as these higher order representations influence the operations of other mental systems that deal with the more specific aspects of task execution (Corbetta & Shulman, 2002; Kastner & Ungerleider, 2000). For example, if a target for a particular block of trials is the letter "A," then higher order task representations will preactivate, throughout the length of the block, perceptual processors that are sensitive to this letter, such that matches between incoming stimuli and this perceptual target template are facilitated (Desimone & Duncan, 1995). We speculate that, when one learns that a target does not occur particularly often, the level of sustained top-down control over task-related systems may be reduced. This may occur for reasons of cognitive or metabolic economy: It may be uneconomical to sustain high levels of mental and neural activity for something that does not occur very often. The consequence of this would be a reduced level of preactivation of target templates or response plans related to the task at hand. Thus, when the rare target appears, greater online attentional guidance is needed for accurate detection.

Finally, our results suggest that the rare target deficit is likely to comprise (at least) two stages—an initial stage in which one learns about the given target's probability of occurrence and a postlearning stage in which the effect of target rarity on behavior is at its most stable and pronounced. We propose that, going forward, it may be wise to consider the individual contributions of these two stages, instead of simply relying on summary values like overall block or condition means that might conflate the two. Furthermore, it would certainly be of interest to ascertain what factors, if any, might influence the length of each stage. For instance, future research might focus on whether the fully blown deficit can be forestalled or delayed by impeding learning in the initial stage.

Acknowledgement

The authors would like to thank Alwyn Ng for helping with the data collection.

Declaration of Conflicting Interests

The author(s) declared no potential conflict of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) received no financial support for the research, authorship, and/or publication of this article.

Notes

1. It is, of course, possible to give participants explicit instructions about target probabilities, but such instructions appear to have only a marginal influence on behavior above and beyond that contributed by direct learning/experience (Ishibashi et al., 2011; Lau & Huang, 2010).
2. We equated the total number of trials in each block, in part to ensure that each session lasted the same amount of time. A consequence of this is that each block had a different number of targets (see Methods section). We limited our analysis to the first 30 targets because the 5% block only comprised 30 targets.
3. The Last PRE bin for the 40–10 block was the twelfth 10-target bin for 40% condition, while the Last PRE bin for the 10–40 condition would have been the third 10-target bin for the 10% condition.
4. Stabilized performance was achieved in the second 10-trial bin in Experiment 1, but within the first 10-trial POST bin in Experiment 2. It is important to note that the two experiments used different paradigms. Thus, it seems likely that, although stability for different probability values will be reached after a similar a number of target trials in a given paradigm, this number may differ depending on the specific paradigm adopted.

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