

# The effect of target scarcity on visual foraging

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## Abstract

Previous studies have investigated the effect of target prevalence in combination with the effect of explicit target value on human visual foraging strategies, though the conclusions have been mixed. Some find that individuals have a bias towards high-value targets even when these targets are scarcer whilst other studies find that this bias disappears when those targets are scarcer. In the proposed study, we will test for a bias for scarce targets using standard feature vs conjunction visual foraging tasks, without an explicit value being given. Based on the idea of commodity theory and implicit value, it is hypothesised that participants will show a scarcity bias. The bias will be investigated using a Bayesian statistical model which has been developed for predicting target-by-target foraging behaviours.

## 1 Introduction

Humans and other animals search their environment regularly, looking both for unique items, and for items where there are multiple exemplars

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available (such as berries on a bush). The former situation can be conceptualised as a visual search task where an observer must find a single target type from amongst distractors. The latter is referred to as foraging, in which observers search and collect multiple targets. It is considered an important behaviour given its connection to resource gathering [Bella-Fernández et al., 2021], and has even been argued to be a key behaviour driving human cognitive evolution [Hills et al., 2015, Pretelli et al., 2022]

A number of studies have addressed the factors that influence foraging behaviour. Early work by Dawkins [1971] observed that chicks appear to peck grains in ‘runs’ of one grain type before switching to the other. More recently [Kristjánsson et al., 2014] this behaviour has been studied in humans. When human participants are tasked with collecting multiple target types by sequentially tapping on them during an iPad game, they tend to consecutively select targets of one type in a series of ‘runs’. This is especially the case in relatively difficult ‘conjunction’ searches where the targets are defined by a combination of two features, compared to ‘feature’ searches where just one feature can be used to differentiate targets and distractors. (See Figure 1 for examples of the displays.) This method appears to be more efficient compared to switching between target types [Wolfe et al., 2019].

Target value has been shown to be one of the main factors governing the deployment of visual attention [Wolfe and Horowitz, 2017], and as such, it plays an important role in foraging behaviour. Value can be thought of as either explicit or implicit. An example of explicit value influencing foraging behaviour can be seen in a study by Nityananda and Chittka [2021]. They trained bees to discriminate between artificial flowers, their foraging behaviour was influenced such that they chose the more rewarding flowers (with more sucrose) in higher proportions. In humans, we can also use points and prizes as a way to manipulate explicit value e.g. by tying participant payment to gaining a certain number of points in an experiment. By contrast, implicit values is used to describe situations in which some targets may be more attractive to a forager due to an incidental feature. For example, if some items are more salient than others, they may be selected earlier than those that are not.

One interesting example of implicit value is *scarcity*, where a target type is visually less common in an environment. Brock’s Commodity Theory is a theory from social psychology that suggests that participants may value scarce targets (or other ‘useful things’, including messages and expe-

periences as well as material objects [Brock and Brannon, 1992]) more highly than readily available targets [Brock, 1968]. Empirical evidence for this theory has been found across a range of contexts [Lynn, 1991] (although not all studies have found strong evidence for scarcity biases [e.g. Echelbarger and Gelman, 2017]). A preference for scarce objects could occur because possessing a scarce object may provide a feeling of personal distinctiveness or uniqueness [Lynn, 1991], or because scarcity can be taken as a proxy for other desirable features, such as popularity. However, there may also be more ‘low-level’ explanations for a scarcity preference: for example, it has been argued that participants show stronger sustained attention to scarce resources, leading to more intense evaluation of the item [Sehnert et al., 2014], and therefore perhaps changing behaviour.

Both explicit target value and scarcity have been manipulated in the context of foraging studies. For example, Wiegand and Wolfe [2021] manipulated explicit target value and prevalence and found that participants preferentially selected targets of higher value. However, this effect was modulated by target prevalence: participants no longer showed a preference for the higher-value targets when they had a much lower prevalence than the lower-value targets. In another study, Tagu and Kristjánsson [2022] had participants collect a certain number of points by collecting targets, and the high value targets were rarer than lower-value ones. In contrast to Wiegand and Wolfe [2021], participants tended to select high-value targets earlier than low-value targets, even though the high-value targets were scarcer. Thus, how target scarcity and value interact in human foraging is still unclear. In addition, to the best of our knowledge, there are no previous studies looking at the influence of target scarcity, independent from value, on foraging patterns.

There have been a number of visual search studies that have investigated scarcity, focusing on the context of scarce or abundant distractors rather than studying the effect of scarce targets. In one study, where participants searched for a target amongst two types of distractor, the distractor ratio strongly affected behaviour, with participants responding more quickly when one distractor was rarer than the other [Shen et al., 2000]. Similarly, people have been shown to be able to search relatively efficiently for a conjunction target within the smaller group of distractors when one type of distractor is more numerous than the other [Sobel and Cave, 2002]. Attention is therefore directed to the rarer elements of the display, in a manner that might share cognitive similarities to a ‘scarcity bias’.

In previous studies of foraging behaviour, differences between conditions have been studied using aggregate statistics, such as the number of ‘runs’ of a particular target type (i.e. the number of times that target is selected in a row) or the total number of targets found in the longest run. However, these measures have limitations. For example, they can be biased by the spatial layout of the display. They also do not allow us to distinguish between the case where a participant sticks with a particular target because of an inherent bias for that target type, compared to the case where they simply like to stay searching for the same target template, regardless of what the target is. Similarly, with these summary statistics methods, it is not necessarily intuitive to account for imbalances in target numbers in a display, and how we can conclude whether a ‘scarcer’ target is selected more or less often than would be expected by chance.

To be able to more precisely track participant behaviour in these types of foraging tasks, we have developed a generative Bayesian model based on a sampling without replacement procedure. The benefit of this model is that it is able to break down behaviour into a series of cognitive biases, such as a preference for sticking with the same target type, or a preference for selecting a nearby target type, thus overcoming some of the limitations inherent to analyses based on summary statistics. We have successfully demonstrated that our model can account for average patterns of behaviour in a range of human foraging experiments [Clarke et al., 2022b]. In addition, it can make relatively accurate predictions of the next target a given individual will select on a trial [Clarke et al., 2022a]. We therefore think that our model is a powerful tool for studying and understanding the processes underlying human foraging behaviour.

In the current study, participants will search amongst coloured targets and distractors, in feature and conjunction styles of foraging like that of [Kristjánsson et al., 2014]. In the feature task, participants have to distinguish between targets and distractors based on colour. In the conjunction task, both shape and colour will need to be considered in order to differentiate targets and distractors. Participants will take part in some conditions where there are equal numbers of each target types, and other conditions where one target type is more numerous than the other. We have two key aims. Firstly, we will test whether scarcity affects how participants forage. If participants implicitly value the scarcer target more highly, as Brock’s Commodity Theory [Brock, 1968] suggests they would, we expect participants to show a preference for the scarcer target, as measured by the bias

parameter in the generative foraging model. Secondly, we will use the equal target conditions to test the extent to which the results of [Clarke et al., 2022b] generalise to a novel set of data. To date, we have used only secondary data sets, and therefore we will use the registered report format to pre-register specific hypotheses relating to the parameters in our model to test how generalisable previous findings are.

## 2 Planned methods

### 2.1 Participants

We will collect 36 participants, recruited from the University of Essex participant pool. This sample size is justified below in Section 4.4. Informed consent will be collected at the beginning of the study and the participants will be debriefed as to the nature of the study afterwards. Participants will confirm (via self-report) that they have normal or corrected-to-normal vision. Ethical approval for the experiment has been granted by the University of Essex Research Ethics Sub-committee 1 (ETH2223-1093). We anticipate the experiment will take around 30 minutes to complete, and participants will be compensated £5 for their time.

### 2.2 Design

A 2x3 within-subjects design will be used. The first independent variable is the difficulty of the task, with two levels: *feature* and *conjunction* (details of the stimulus manipulation given below). The second independent variable is the ratio of targets of class *A* to *B*, with three levels: target class *A* is *scarce* (5 *A* to 15 *B*); class *B* is *scarce* (15 *A* to 5 *B*) and an *even* ratio (10 *A* to 10 *B*).

Each participant will participate in all six conditions. Within each condition, there will be six trials, meaning that they will complete 36 trials. Each condition is completed as one block, and the order of blocks will be randomised for each participant.

Before beginning the experiment, each participant will complete a practice trial to familiarise themselves with the procedure: this will be similar to a *feature* trial with an *even* ratio of targets, but using different colours

(black and white for the targets, and 'old lace' and 'thistle' for the distractors) and shapes (all targets and distractors will be triangles). All other feature will otherwise exactly resemble the main experimental trials.

## 2.3 Stimuli

The experiment will be created in PsychoPy-2022.2.4 software. Each trial consists of 40 items on a grey background. These items are organised in a grid but their placement will slightly jittered to create some irregularity, following previous studies [Kristjánsson et al., 2014, Clarke et al., 2022c]. Each trial will include 20 targets and 20 distractors, and their position will be randomised. In the feature task, blue and yellow circles are the distractors whilst green ('lime' will be used as the green colour in all cases) and red circles are the targets. In the conjunction task, red circles and green squares are the distractors whilst red squares and green circles are the targets. Circle targets and distractors will have a radius of 25 pixels, and square targets and distractors will have a width and height of 25 pixels. Examples of the stimuli can be seen in Figure 1.

## 2.4 Procedure

Participants will complete the experiment in a quiet room with normal illumination. The experiment will be conducted on a Dell Optiplex 7050 computer, with screen size 1920 x 1080 pixels (though the targets are placed within a grid of 1000 x 1000 pixels in the centre of the screen). Participants will begin each block by reading instructions telling them which items are the targets for that block. In each trial, they will 'collect' items by clicking on them using a computer mouse. Once a target item is clicked, it immediately disappears from the screen. If a participant clicks on a distractor, the trial will immediately end and it will be restarted (up to a maximum of 5 attempts per trial): this was done to follow the procedure used in previous studies [Kristjánsson et al., 2014, Clarke et al., 2022c]. Trials will end when the participant has clicked on all targets, again following previous work [Kristjánsson et al., 2014, Clarke et al., 2022c]. Participants must complete five valid trials with no mistakes in each condition.

Participants will have their eyes tracked for the duration of the experiment using an SR EyeLink 1000 Plus eyetracker. This data will be made

available for exploratory analysis in the future, but will not be used in the current registered report.

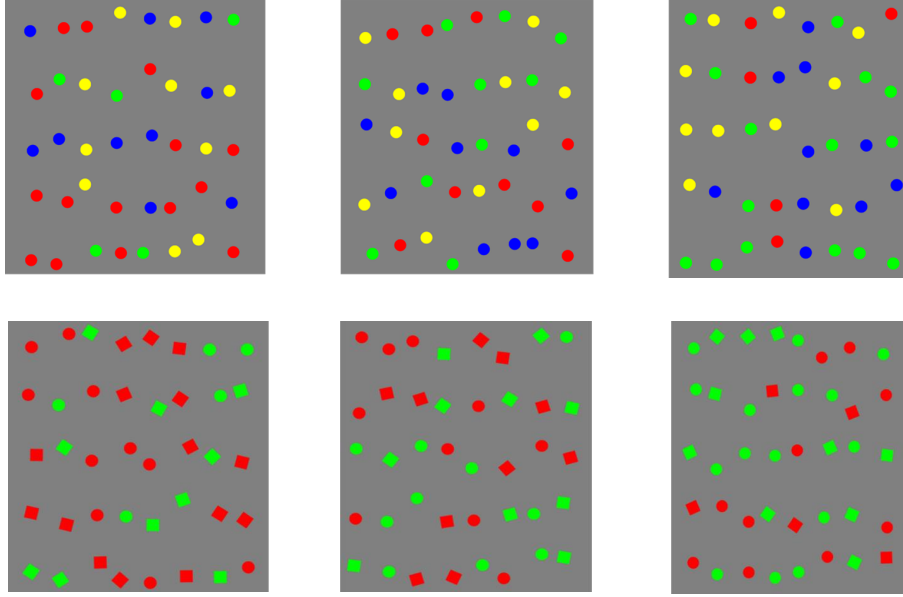


Figure 1: Example stimuli. Top row is stimuli for the feature search, bottom row is for the conjunction search. For feature, from left to right; is scarce green target condition, equal target condition, and scarce red target condition. For conjunction search, from left to right; scarce green circle condition, equal targets condition, and scarce red squares condition.

### 3 Data Analysis

We will use the four-parameter generative foraging model proposed by [Clarke et al., 2022b] to analyse the data. The model allows for target-by-target prediction of behaviour during visual foraging [Clarke et al., 2022a] and a benefit of this approach is that it enables us to parameterise the factors that may affect the forager’s choice of targets, such as proximity or a preference for foraging in ‘runs’ of a single target type [Kristjánsson et al., 2014]. The model also contains a ‘class bias’ parameter which detects a

preference for one target type over another type. If item scarcity does make some targets more attractive than others, we should be able to see a difference in this parameter between the *scarce* and *even* conditions.

We have previously shown that the model can detect differences in this parameter between value and no-value conditions of previously collected data [Clarke et al., 2022b, Tagu and Kristjánsson, 2022], and provide justification below (in Section 4.4) that we believe that we can detect small differences in target preference in our experimental design.

### 3.1 A four-parameter model of visual foraging

We model foraging as a process of weighted sampling without replacement. We assume that target items belong to one of two classes ( $A$  and  $B$ ) and details of any distractor items are neglected. In the experiment presented in this manuscript,  $A$  and  $B$  are red and green circles respectively for the feature task, then red squares and green circles for the conjunction task.

The probabilities of each remaining targets item are updated after each selection depending on four parameters defined as follows:

- $b_A = \text{logit}(p_A)$ : the relative attractiveness of items of class  $A$  compared to class  $B$ . Similarly,  $b_B = \text{logit}(p_B)$  is the relative attractiveness of  $B$  over  $A$ . This attractiveness could be due to properties such as low-level salience or reward and value. A value of  $b_A = 0$  ( $p_A = 0.5$ ) corresponds to a situation in which (all else being equal) items from both classes are equally likely to be selected next. The further away this parameter is from zero, the stronger the preference for  $A$  over  $B$  is. In this experiment, we predict that  $b_A$  will be more strongly positive in the case where  $A$  is the scarce target category, and will be more strongly negative when  $B$  is the scarce target category.
- $b_S = \text{logit}(p_S)$ : the preference for selecting an item of the same class as the previously selected item. High values of this parameter will lead to ‘sticky’ behaviour with long runs of the same item class, while low values will lead to switching behaviour in which participants alternate which item class they select.  $b_S \approx 0$  indicates that the class of the previously selected item has little effect on which item will be selected next.



- $\sigma_p$ : this parameter reflects the importance of proximity when selecting the next item. The larger  $\sigma_p$  is, the more heavily weighted selection is to items that are close to the previously selected item.
- $\sigma_d$ : measures relative direction. The larger this parameter is, the larger the preference there is for selecting items that are 'ahead' of the previously selected item. As this parameter becomes more negative, this behaviour flips and there is a preference for selecting items 'behind'.

These four parameters are fit to the data for each experimental condition:  $b_A(k)$ ,  $b_S(k)$ ,  $\sigma_p(k)$  and  $\sigma_d(k)$  where  $k$  is one of  $K$  experimental conditions.

### 3.2 Implementation Details

The model fitting procedure will be the same as Clarke et al. [2022b] with three changes. Firstly, while a multi-level framework will be used to account for the differences between participants, we will not model the correlations between random effects. This is because we previously found relatively weak correlations when modelling similar experiments in Clarke et al. [2022b], and this modification will significantly reduce computational time. Secondly, we have adjusted the manner in which relative distances are calculated in order to account for the fact that the stimulus display is not necessarily square (although we intend in this experiment to use a square display). Finally, we have incorporated the initial selection bias described in Clarke et al. [2022a] into the full model: this allows us to take into account a person's preference for starting each trial in a particular region of the screen (e.g. the centre, or the top left hand corner).

The following weakly informative priors will be used.

$$b_A, b_B \sim \mathcal{N}(0, 1) \tag{1}$$

$$b_S \sim \mathcal{N}(0, 1) \tag{2}$$

$$\sigma_p \sim \mathcal{N}(15, 4) \tag{3}$$

$$\sigma_d \sim \mathcal{N}(0, 3) \tag{4}$$

These are based on applying the model to data from previous related experiments [Clarke et al., 2022b]. An LKJ prior will be used for the random effect structure [Lewandowski et al., 2009]. Importantly, we use the same set of priors for both the *equal* and *scarce* experimental conditions.

Models will be fit using R [R Core Team, 2021] and Stan [Stan Development Team, 2020] (full details of the software environment will be included in supplementary materials). The model fit will be checked to ensure that  $\hat{r} < 1.01$  and the traceplots will be visually inspected to check convergence.

Applying sophisticated modelling to new data can sometimes lead to unexpected problems. Such issues can sometimes be easily solved by using a different set of priors, or some other change to how the model is implemented. If we find ourselves in this situation, we will transparently document all changes from our original plan in our supplementary materials.

### 3.3 Data Exclusion

The following criteria will be used for data inclusion/exclusion:

- Data from terminated trials (due to selecting a distractor) will not be analysed.
- Any trial containing an inter-target selection time of more than five seconds will be removed.

We will only analyse data from participants who have at least five trials of data for each condition after the above criteria are applied. We will collect enough data to ensure we have 36 participants for the final analyses after data exclusion criteria are applied.

## 4 Hypotheses

### 4.1 The Effect of Scarcity

Our main hypothesis [H1] is that participants will show a preference for selecting scarce targets. As preferences to select one target class over another may also differ due to visual salience, we will take  $b_A(equal)$  as our baseline condition and compare this to  $b_A(scarce_A)$  and  $b_A(scarce_B)$ .

We will test this hypothesis by examining the posterior distributions (given the data  $D$ ) for the difference between these parameters: if both

$$Pr(b_A(scare_A) - b_A(equal) > 0 | D) > 0.99 \quad (5)$$

$$Pr(b_A(equal) - b_A(scarce_B) > 0 | D) > 0.99 \quad (6)$$

are true, marginalising over the *feature* and *conjunction* conditions, then we will conclude in favour of our hypothesis. We will also use the same procedure to measure the effect of scarcity in the *feature* and *conjunction* conditions separately, although we have no specific hypothesis about the size or direction of potential effects.

If we do not find strong evidence in favour of our hypothesis, we will carry out exploratory analysis to a) investigate if one of the counterbalanced conditions shows a scarcity effect but not the other and/or b) investigate the extent to which it holds in a subset of participants. If there is a range of scarcity effects across different participants, we will explore whether these are correlated with the other parameters in our model.

In the unlikely event that we are unable to achieve a good model fit using the full four parameter model, we will fit a simpler ‘sampling without replacement’ model which ignores the spatial components of the model [Clarke et al., 2022b].

## 4.2 Secondary Hypotheses around model fit

We will also test a number of secondary hypotheses to test the extent to which the results of [Clarke et al., 2022b] generalise to a novel set of data:

H2 : If our *feature* vs. *conjunction* manipulation shows a similar effect as that seen in [Kristjánsson et al., 2014] and [Clarke et al., 2022c], we expect to see a larger value for  $b_S$  in the *conjunction* condition compared to the *feature* condition. This will be investigated by examining the posterior distribution for a difference between feature and conjunction conditions using the same procedure as above.

H3 : We predict there will be a large ( $\sigma_\rho > 10$ ) proximity bias in both conditions. Previous work has shown values of around  $\sigma_\rho = 20$  are typical. We expect the effect of proximity to be larger in the *feature* condition, based on findings from [Kristjánsson et al., 2014] and

[Clarke et al., 2022c] (as analysed in [Clarke et al., 2022b]). This will be investigated in a similar manner to [H2].

H4 : We predict we will see a negative effect of relative direction, although this effect will likely be weak (around -1) with considerable variation between individuals. In order to test this hypothesis, we will calculate whether 99% of the posterior distribution for the relative direction parameter is negative.

H5 : We predict that we will be able to make more accurate target-by-target predictions for the *feature* condition compared to the *conjunction* condition, similar to our findings in Clarke et al. [2022a]. This is because it is easier to predict on a target-by-target basis if the proximity bias is stronger.

### 4.3 Planned exploratory analyses

If a new version of our model has been released by the time we have collected our data, we will also present results using this (in supplementary material).

We would also be willing to test alternative models proposed by other researchers if appropriate.

### 4.4 Justification of Sample Size

We use a simulation approach to justify our sample size. In short, we can use our generative model of visual foraging to simulate data for a given set of parameters. Based on the results from [Clarke et al., 2022b] we will set  $b_S = 1$  (i.e.,  $p_S = 0.73$ ) with  $\sigma_p = 20$  and  $\sigma_d = -2$ . For the *equal* condition, we made both target types equally likely ( $b_A = 0$ ), while in the *scarce* condition we assumed a small preference for the less common target type of  $p_A = 0.6$  (i.e.,  $b_A = 0.405$ ). This effect was chosen so that it was somewhat smaller than the effect of explicit value found in data from [Tagu and Kristjánsson, 2022] of 0.75. It is also similar to the target preference seen in [Clarke et al., 2022c]: in this experiment, there was no specific experimental manipulation or hypothesis regarding a bias for one target or another, so we would expect this to be a reasonable minimal effect size of interest.

We simulated 36 participants, each completing five trials per condition (the minimum amount of data we expect to collect: in most cases, we expect that each participant will complete six trials per condition). While five trials may seem a relatively small amount, we have shown previously that good parameter estimates can be recovered with as little as one trial of data in a similar task [Clarke et al., 2022b]. The parameters for the random effect structure were again based on results from [Clarke et al., 2022b] (see Supplementary Materials for full details and code). We then fit the four-parameter foraging model to these simulated data, the results of which can be seen in Figure 2. We can clearly detect the bias towards the less common target type in the scarce condition, as well as recovering the correct values for the other parameters.

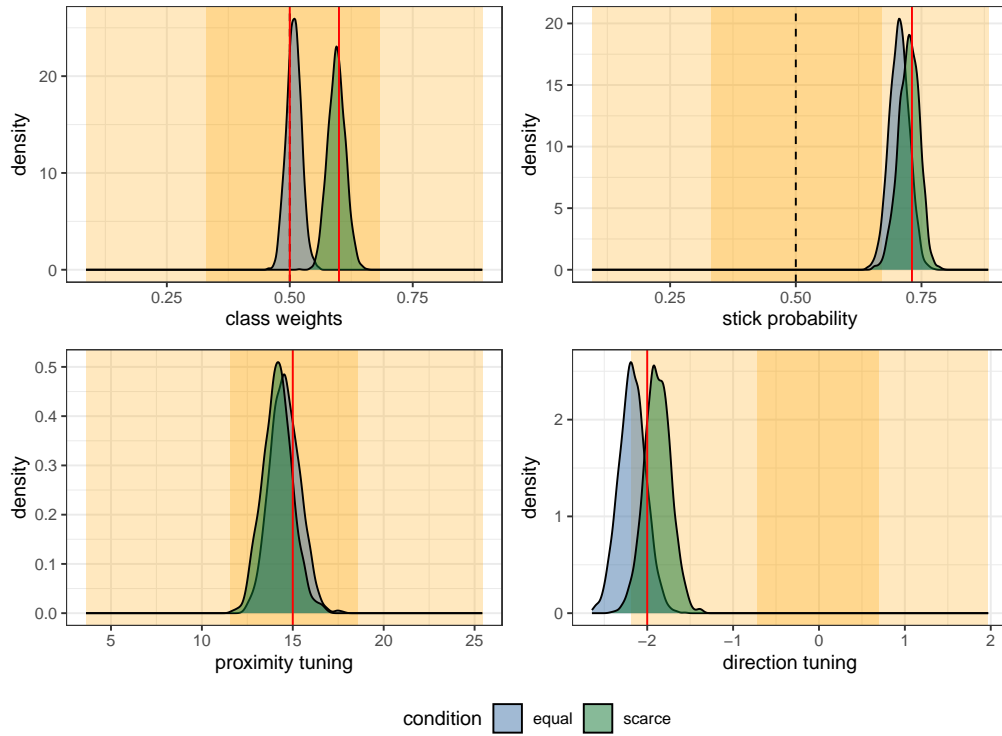


Figure 2: Posterior probabilities after fitting the model to the simulated data. The grey-shaded background areas represent the prior distribution (53% and 97% HPDIs). Red lines indicate the parameter values used in the simulation.

## 4.5 Pilot Results

Pilot data was taken from 3 female participants, each performing 5 trials in all 6 conditions. When applying [Clarke et al., 2022b]’s model, we see in the  $p_S$  parameter a replication of [Kristjánsson et al., 2014]’s findings; participants tended to stick to one target type more in the conjunction tasks compared to the feature tasks. In the  $p_A$  parameter, there is a slight preference for scarce targets in the conjunction task (see Figure 3). We can also see a proximity bias of approximately the expected size, although no real suggestion of a directional bias (although previously we have found this is a rather small effect). Overall, the pilot data shows that in a small number of participants, the effects seen are generally in line with our hypotheses.

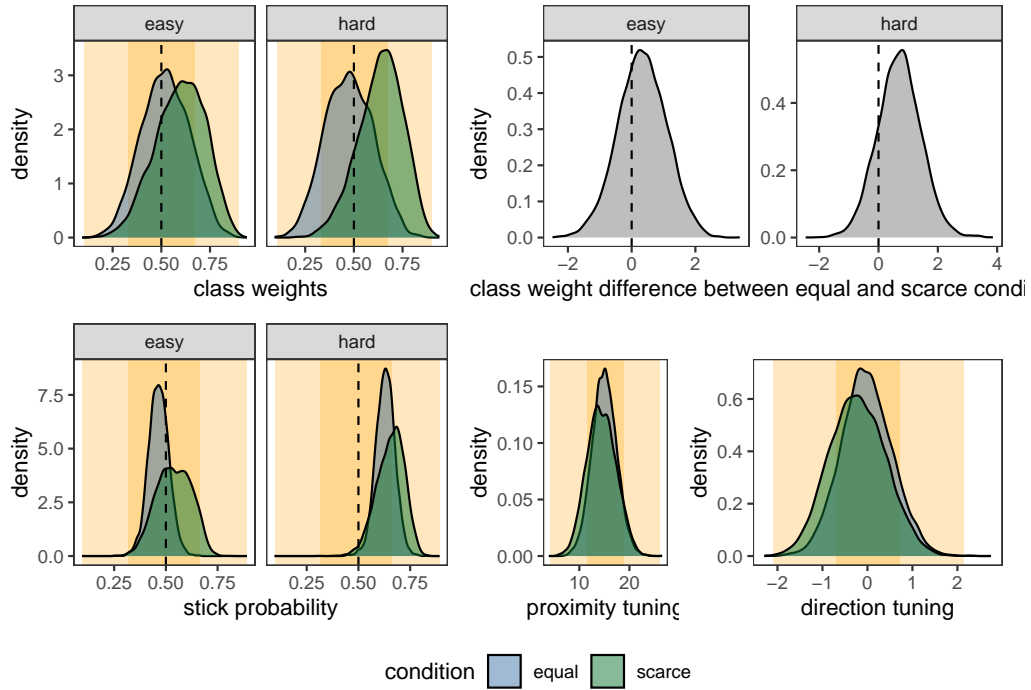


Figure 3: Posterior probabilities after fitting the model to the pilot data. The grey shaded background areas represent the prior distribution (53% and 97% HPDIs). (top left) Posterior distribution for  $p_A$ . (top right) Posterior distributions for the difference between the *scarce* and *equal* conditions. (bottom) Posterior distributions for the other model parameters.

## 5 Results

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## 6 Discussion

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