Bayesian multi-level modelling for predicting single and double feature visual search

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Abstract

Performance in visual search tasks is frequently summarised by “search slopes” - the additional cost in reaction time for each additional distractor. While search tasks with a shallow search slopes are termed efficient (pop-out, parallel, feature), there is no clear dichotomy between efficient and inefficient (serial, conjunction) search. Indeed, a range of search slopes are observed in empirical data. The Target Contrast Signal (TCS) Theory is a rare example of quantitative model that attempts to predict search slopes for efficient visual search. One study using the TCS framework has shown that the search slope in a double-feature search (where the target differs in both colour and shape from the distractors) can be estimated from the slopes of the associated single-feature searches. This estimation is done using a contrast combination model, and a collinear contrast integration model was shown to outperform other options. In our work, we extend TCS to a Bayesian multi-level framework. We investigate modelling using normal and shifted-lognormal distributions, and show that the latter allows for a better fit to previously published data. We propose running a new fully within-subjects experiment to attempt to replicate the key original findings, with some changes to help distinguish between theories.

Keywords: Visual search, Efficient search, Parallel processing

1. Introduction

Visual search, where participants are asked to find a target within a cluttered scene, has been extensively studied within psychology. Several models have been developed that can generate testable predictions about how different types of distractors and targets affect search efficiency. One of the key distinctions in the field has been between efficient (also referred to as parallel or pop-out) and inefficient (serial) search. These are often studied in the context of the regression slope between the number of distractors and mean reaction time, which has been termed the *search slope*. When the search slope is shallow (usually positive, but occasionally negative e.g. (Rangelov et al., 2017)), the search is called efficient or parallel, and the addition of more non-target distractors has little impact on an observers difficulty in finding a target. When the slope is steeper, each additional distractor has a noticeable impact on increasing difficulty, and the search is described as inefficient or serial. However, the distinction between these types of search is often less clear in real experimental data, with a range of different search slopes being seen for different types of targets and distractors (Duncan and Humphreys, 1989; Cave and Wolfe, 1990; Wolfe, 1998; Liesefeld et al., 2016). Recent work has also attempted to model the variation in search slopes at the boundary between inefficient and efficient search (Liesefeld et al., 2016).

In the current study, we are interested in what has traditionally been termed efficient or parallel search, and the factors that affect search slope in these conditions. Recent work has suggested that for efficient search, there is a logarithmic relationship between distractor set size and reaction time, and that this relationship can be modified by target-distractor similarity (Buetti et al., 2016), providing evidence that search behaviour in parallel search is more complex than has previously been assumed. This observation has formed the basis of the 'Target Contrast Signal (TCS) Theory' (Lleras et al., 2020), which aims to provide a means of predicting observer search slopes for new search arrays by quantifying target-distractor differences. For example, by measuring search slopes for conditions in which the distractors differ from the target along a *single feature* (e.g. colour *or* shape), it has been shown that you can predict search times for arrays in which the target differs from the distractors along two features (e.g., colour *and* shape) which we refer to here as *double feature* search. (Buetti et al., 2019) (but similar paradigms have been known by other names e.g. 'redundant feature search' (Krummenacher and Müller, 2012; Mordkoff and Yantis, 1991)). Here, we aim to replicate and extend this work both theoretically and empirically, to test the generalisability of the TCS model, and to suggest ways in which the TCS model could be modified to generate better predictions.

1.1. Previous Work

Many different forms of visual search models have been proposed. One well developed class of models are the saliency models, which aim to predict eye movements during scene viewing, including visual search. They rest on the assumption that fixations are directed to objects or locations that are most dissimilar to the background or other objects in the visual display (Itti and Koch, 2000; Itti et al., 1998; Koch and Ullman, 1987). While the original saliency model was able to predict fixation allocation in a visual search task above chance (Parkhurst et al., 2002), further research demonstrated that a comparable level of performance could be achieved using a simple central fixation bias heuristic (Tatler, 2007). The saliency models have since been extended and improved (see for example Zhang et al. (2008)): however, the main issue with this family of models remains their limited usability in complex real-life search arrays (Tatler et al., 2011; Koehler et al., 2014), and even in abstract laboratory search arrays (Kotseruba et al., 2020). In addition, in most instances of visual search, the target is clearly defined (i.e. the goal is to find a specific object) and inspecting the most salient areas of the display may in these cases be inefficient. Finally, by focusing on eye movements, these models do not necessarily provide a theoretical framework for the cognitive processes underlying visual search.

Perhaps the most established class of models of visual search are based around Feature Integration Theory (Treisman and Gelade, 1980), which has been modified and extended by Wolfe and colleagues in the Guided Search Model (Wolfe et al., 1989; Wolfe, 2014). These theories have been developed using data from visual search tasks with discrete sets of abstract items. These models combine top-down influences (how closely an item resembles the observer's goal) with bottom-up image properties. For example, if one's goal (top-down processing) is to find a red horizontal bar, all the red and horizontal items in a visual search display will be given greater weight than distractors (e.g. vertical and blue items) in the model. The salience of a given object in the display (how distinctive it is from the surrounding objects) also activates bottom-up processing. For instance, a blue item among red items is ranked higher than red among orange items. In such cases, a salient item can capture attention even without resembling the target. Combining bottom-up and top-down sources of activation generates an activation map which generates a prediction of the order in which stimuli are processed in visual search. Other extensions to these models have been proposed, such as the Dimension Weighting Account, in which saliency weightings are assigned to different target 'dimensions' (e.g. colour or shape), helping to explain results where varying the target dimension within blocks of trials leads to longer reaction times than where the dimension remains consistent within a block (Krummenacher and Müller, 2012). Thus, these models aim to produce a representation of the visual properties of the distractors at each location in the visual field. However, these are predominantly qualitative models, and thus it is difficult to use them to make specific quantitative predictions.

TCS falls under a class of models that take a different approach, in that they focus solely on representing the difference between targets and distractors. For example, in work on eye movement patterns, it has been proposed that performance in inefficient (serial) visual search is mostly determined by the size of the 'functional viewing field', whose size varies as a function of target-distractor similarity (Hulleman and Olivers, 2017). Similarly, work on attention has proposed the notion of 'relative features', where attention is tuned to feature relationships i.e. the appearance of the target relative to distractors in the environment (Becker et al., 2014; Becker, 2010). TCS also has features in common with other models that propose parallel identification of all items in a scene, with diffusion based mechanisms for identifying targets from distractors (Moran et al., 2013, 2016). However, TCS (Lleras et al., 2020) aims to provide a unifying framework that can make quantitative behavioural predictions for visual search based on this general assumption. As such, it is an attractive candidate model for a formal registered replication.

A key assumption of the TCS model is that behaviour is determined by comparing the target template (held in memory) with every element present in the scene in parallel. This allows the visual system to reject peripheral non-targets quickly; the speed at which items are evaluated is determined by how different the item is from the template through an evidence accumulation process (formally, the slope of the logarithmic function is assumed to be inversely proportional to the overall magnitude of the contrast signal between the target and distractor). The model thus focuses on an initial, efficient processing stage of search; if sufficient evidence is not accumulated during this process, the model posits that a second stage is entered, requiring a sequence of eye movements to search for the target in a serial manner. TCS has been successful in predicting a number of empirical results, including search performance in heterogeneous scenes based on parameters estimated in homogeneous scenes, both with artificial stimuli (Buetti et al., 2016; Lleras et al., 2019) and with real-world objects visualised on a computer display (Wang et al., 2017). Table 1 provides an overview of studies investigating the TCS framework to date.

The original version of the TCS model is essentially a (natural) log-linear model in the number of distractors. The full model contains a variable L, which represents the number of different types of distractors present in the display. However, in our paper, we will follow Buetti et al. (2019) and only consider the specific case of $L = 1$, of a target among a homogeneous set of distractors. In this case, the TCS model can be represented in the following way:

$$\hat{RT} = a + D\log(N_T + 1) \tag{1}$$

The intercept, a, corresponds to search arrays in which only the target is present and there are no distractors. N_T is the total number of distractors.

1.2. Rationale for proposed work

While many aspects of the TCS framework have been tested, with extremely promising results, there remains a great deal of scope for verification of some of the key findings to date, and extensions of aspects of the model. In all implementations of TCS so far, predictions of search efficiency (e.g. in heterogeneous scenes) have been made on the average of a group of participants, using data from a different group performing a different task (e.g. searching in homogeneous scenes). Thus, we know that TCS can replicate group-level averages between subjects in search well, but we do not know to what extent it is also able to make predictions at the individual level. This is particularly important given that conclusions based on aggregate data can be different from those that take individual differences into account; in one study where participants searched for a target in an array of randomly oriented line segments, aggregating the data suggested that participants were using a stochastic search model (Nowakowska et al., 2017). However, when considering each participant individually, it became clear that there was a high level of heterogeneity in responses, with some participants performing close to optimally, and others actually performing worse than chance (Nowakowska et al., 2017). Similarly striking variability has also been reported in other search studies (Irons and Leber, 2016, 2018; Clarke et al., 2020).

Taking search time distributions into account is also important for constraining theories of visual search (Wolfe et al., 2010; Liesefeld and Müller, 2020): for example, they have been used to help distinguish between models that make similar predictions at the level of average reaction times (Moran et al., 2016, 2017). Including subject and trial level data into our implementation of the TCS will therefore further aid model development and assumption testing.

We also extend the TCS model into a Bayesian framework, where we begin with existing 'prior' beliefs that are updated with data to give 'posterior' beliefs that can be used for inference (McElreath, 2020). We think this has a number of advantages over frequentist approaches. Perhaps most importantly, Bayesian models are highly flexible. We demonstrate how we are able to specify a model that is able to more accurately represent the distribution of responses (for example, by specifying a response distribution that avoids predicting negative reaction

Reference	Overview
Buetti et al. (2016)	For efficient search with a specific target, there is a logarithmic relationship between distractor set size and reaction time. The steepness of this relationship is modulated by distractor-target similarity, with steeper slopes for more similar distractors.
Wang et al. (2017)	Data from homogeneous search arrays can be used to predict search reaction times in heterogeneous displays containing images of real-world objects, using an equation assuming parallel, unlimited capacity, exhaustive processing, and independence of inter-item processing.
Madison et al. (2018)	Logarithmic efficiency in efficient search cannot be explained by crowding in peripheral vision.
Ng et al. (2018)	Logarithmic efficiency in efficient search cannot be explained by eye movements.
Lleras et al. (2019)	Validation of previous results showing data from homogeneous search arrays can be used to predict reaction times in heterogeneous displays. Distractor-distractor interactions can also facilitate processing when nearby items are similar to each other.
Buetti et al. (2019)	Data from search arrays where the distractors are distinguished from the target by one feature can be used to predict search reaction times in displays with compound stimuli, defined by two features. Reaction times can be predicted using a collinear contrast integration model, which assumes that the overall target-distractor contrast is the sum of the contrasts from the two feature vectors separately.
Lleras et al. (2020)	Full proposal of the Target Contrast Signal Theory, proposing that the initial stage of processing computes a difference signal between each item in the scene and the target template, using this to determine which items in the scene are unlikely to be the target.
Ng et al. (2020)	Attention works in a two stage process, first discarding target-dissimilar distractors in a distributed, parallel way. Focused spatial attention then visits target-similar items at random.
Xu et al. (2021)	Extension of Buetti et al. (2019) to new features (shape and texture), which combine according to a Euclidean metric (orthogonal contrast integration model).

Table 1: An overview of work on the Target Contrast Signal Theory. The key paper for our replication is highlighted.

times) with a relatively complex model structure, that can be fit to a relatively small amount of pilot data: something that would be challenging within a frequentist framework. We also believe that Bayesian models offer very intuitive methods for model testing and comparison and straightforward interpretation of results, and we hope that this manuscript can act as a demonstration of these benefits, showing how they can be applied to real scientific questions beyond the simplified examples often found in textbooks or tutorials.

In the current manuscript, we focus on replicating and extending findings from Buetti et al. (2019). In their study, participants searched for a target in a scene of homogeneous distractors (see Figure 1). First, parallel search efficiency (measured by the logarithmic search slope) was estimated for cases where the distractors varied from the target in one dimension: either colour (e.g. a cyan target being searched for in either yellow, blue or orange distractors) or shape (e.g. a semicircle target in either circle, diamond or triangle distractors). New participants then searched for the same targets in displays where the distractors were compounds, differing from the target in both colour and shape (e.g. searching for a cyan semicircle in either blue circles, orange diamonds or yellow triangles). The logarithmic search slopes in the initial experiments were then used to predict the logarithmic slopes and reaction times using a number of models. The authors found that the best model was a 'collinear contrast integration model' where the distinctiveness scores were summed along each attribute in the unidimensional experiments, creating an overall contrast score that was used for compound stimuli predictions. In our registered replication, we will attempt to verify the conclusions of Buetti et al. (2019), that the collinear contrast integration model does indeed offer the best characterisation of contrast signal combinations in visual search within the TCS framework.

We begin by verifying the analysis of Buetti et al. (2019). We then describe our proposed replication study, showing with pilot data how we are able to extend their model of how multi-dimensional contrasts are calculated, both by incorporating a multi-level design to predict within-subjects effects and by utilising a Bayesian generalised linear model framework to better represent the distribution of responses (e.g. avoiding predicting negative reaction times, accounting for uncertainty in model predictions).

2. The Target Contrast Model

We first describe the original Target Contrast Model, as presented in Buetti et al. (2019) and verify that we can succesfully replicate the original analysis

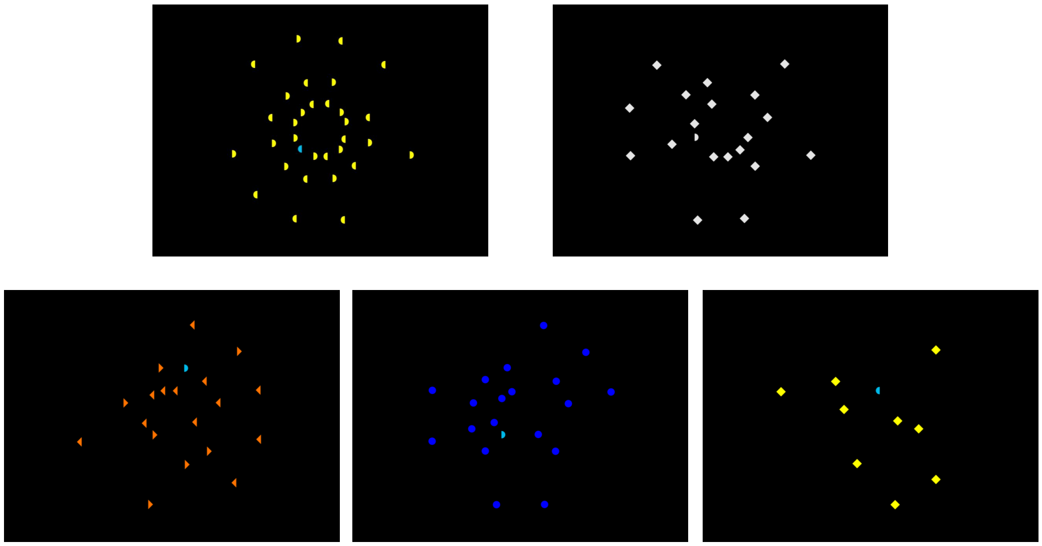

Figure 1: Example stimuli from Buetti et al. (2019) Top left: Expt 1A. Here, the target is a blue semicircle within a set of homogeneous (yellow semicircle) distractors. Top right: Expt 1B. The target is a grey semicircle in circular grey distractors. Bottom left: Expt 2A. The target is a blue semicircle in orange diamond distractors. Bottom middle: Expt 2B. The target is a blue semicircle in dark blue triangle distractors. Bottom right: Expt 2C. The target is a blue semicircle in yellow circular distractors.

(both using frequentist modelling and Bayesian modelling; see *Supplementary Materials).*

2.1. TCS modelling overview

In Experiment 1a of Buetti et al. (2019), participants searched for a cyan semicircle target among blue, yellow or orange semicircular distractors i.e. they searched for a target that differed from the distractors by a *single feature* (colour). The experiment was then repeated (1b) using a different single feature (shape, with participants searching for the semicircular target within triangle, circle or diamond distractors). In Experiments 2a, 2b and 2c, participants again searched for a cyan semicircle, but this time, the distractors differed in both shape and colour. We will refer to these conditions as *double features*. Note, unlike in standard conjunction searches, in this paradigm, the distractors are all identical with respect to these features (i.e, orange triangles). Examples of all these stimuli are shown in Figure 1. Buetti et al. (2019) also carried out a replication of their basic results using slightly different target and distractor stimuli (Experiments 3 and 4).

The *Target Signal Contrast* theory is built around a linear model for predicting mean reaction times from the logarithm of the number of distractors (see Equation 1). In particular, the TCS theory allows us to predict the value of the logarithmic slope, $D_{\mathrm{c,s}}$, in this condition based on the corresponding D_i in the single feature search experiments.

2.1.1. *Calculating the intercept, a, and the logarithmic slope parameter, D_i*

Experiments 1a and 1b and 3a and 3b were used to calculate the logarithmic slope parameter D_i. In all experiments, the number of distractors varied, allowing the data to be used to fit a log-linear model for reaction times, where reaction times increase logarithmically with N_T, the number of distractors (see Equation 1). In the original model the error distribution was assumed to be normal. Thus the results of Experiments 1 and 3 were used to calculate D_i, for each type of distractor. When colour varied, we will refer to D_c, for $c = 1,2,3$. Similarly for shape we will denote this (D_s), and the compound features are denoted as ($D_{c,s}$).

Fitting the model specified in Equation 1 to the data, we obtain the values for D_c and D_s given in Table 2. As can be seen, the more similar the distractors are to the target, the steeper the slope parameter is.

feature	D_c	feature	D_s
blue	76.8	triangle	141.1
yellow	16.0	diamond	77.2
orange	9.8	circle	62.1

Table 2: A table of D_i values for Experiment 1a and 1b. See *Supplementary Materials* for full values for all experiments.

2.1.2. *Estimating $D_{c,s}$, the logarithmic slope parameter for compound features*

In the context of the current experiments, the core idea of TCS theory is that we can estimate the (natural) logarithmic slope parameter for a double feature visual search from the slopes parameters in the two independent single feature searches i.e., $D_{c,s} = f(D_c, D_s)$. Buetti et al. (2019) tested three different models for predicting D for compound colour-shape stimuli. The best feature guidance model (Equation 2) suggests that when the target and lures differ in two dimensions, participants will choose to attend to whichever feature dimension is the most discriminable (i.e. has the smallest D value):

$$D_{\mathrm{c,s}} = \min\left(D_{\mathrm{c}}, D_{\mathrm{s}}\right) \tag{2}$$

The orthogonal contrast combination model instead suggests that independent feature dimensions comprise a multidimensional space, where an object can be described by the overall vector in this space, and thus $\mathrm{D}_{\mathrm{c,s}}$ can be represented as:

$$D_{\mathrm{c,s}} = \frac{1}{\sqrt{(\frac{1}{D_{\mathrm{c}}})^2 + (\frac{1}{D_{\mathrm{s}}})^2}} \tag{3}$$

Finally, the collinear contrast integration model also assumes independence of feature dimensions, but assumes that while the visual features create a multidimensional space, the contrast between them is unidimensional. As D is assumed to be inversely proportional to contrast, the equation can be written as follows:

$$\frac{1}{D_{\mathrm{c,s}}} = \frac{1}{D_{\mathrm{c}}} + \frac{1}{D_{\mathrm{s}}} \tag{4}$$

Buetti et al. (2019) found that with their dataset, the collinear contrast integration model was best able to predict $D_{c,s}$ from D_c and D_s, with $R^2 = 0.915$. We verified we were able to replicate this result using the dataset available on OSF (https://osf.io/f3m24/)[1] and using the exclusion criteria originally applied; see Figure 2 (left panel) and *Supplementary Materials* for details. We show that we are able to do this using both the frequentist modelling approaches used in the original paper, and using Bayesian modelling.

2.1.3. Estimating a, the intercept parameter for compound features

As a is the intercept of the model, it represents how long observers take to find a target when $N_T = 0$, i.e., there are no distractors. As such, it should be independent of both shape and colour, and can be thought of as the role of non-search processes (such as motivation, motor preparation etc.) that influence reaction time. In Buetti et al. (2019), a was calculated for each sub-experiment. Here, we follow that method in order to replicate their results exactly.

2.1.4. Estimating mean reaction times

Finally, we can use Equation 1 to predict mean reaction times. As can be seen in Figure 2 (centre panel), these predictions are essentially identical to the empirical RT results: $R^2 = 0.93\%$.

[1] downloaded on 28th August 2020

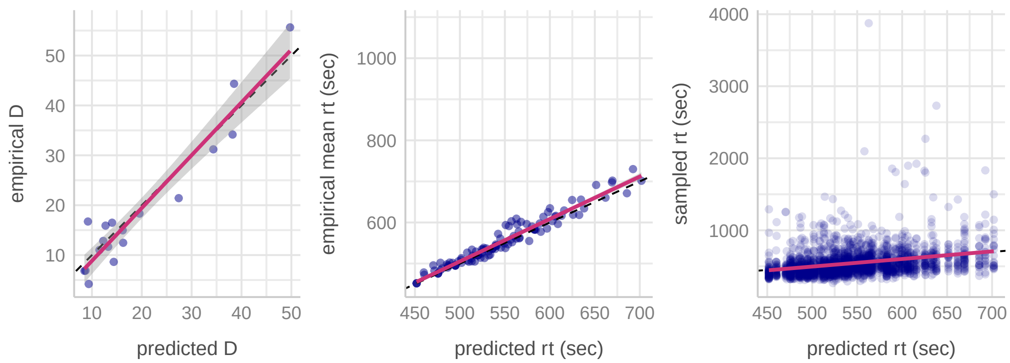

Figure 2: (left) The collinear method for calculating D offers a good prediction. (centre) Using the TCS to predict reaction times. (right) Each dot now represents a randomly sampled reaction time from an observer. Note that there is greater spread in the data points here, due to the fact that there will be trial-to-trial variability due to target position, inter-item distances, observer differences and so on.

2.1.5. Discussion

While TCS theory offers a good prediction of search slopes and corresponding mean reaction times for double feature search, there are two related limitations. Firstly, it is unable to account for individual differences between observers, only the changes to the sample average. Secondly, it cannot account for the distribution of reaction times over multiple trials. Figure 2 (right panel) shows clearly that these factors generate high levels of variability within the individual trial-level data. To address these issues, we propose adapting TCS to make use of multi-level modelling techniques. Multi-level models allow us to take into account the hierarchical structure of the data (i.e. that each participant completes multiple trials) in a way that does not require averaging, meaning that we are able to model participant variability as well as group-level effects (Gelman and Hill, 2006).

2.2. A multi-level TCS

Switching from a linear regression model to a multi-level model will allow us to compute D for each participant, while simultaneously estimating the trial-to-trial variance. We also switch from a frequentist to Bayesian framework, as this allows us to naturally account for the uncertainty in the model's predictions. However, switching from linear regression to a multi-level model raises the problem of which distribution to use for modelling reaction times. Using a normal distribution is unlikely to be satisfactory, as it is unable to account for the skew frequently seen in reaction time distributions, and also allows the possibility of negative reaction times. We can account for both of these problems by using a log-normal distribution. We will also test whether a slightly more complex extension of this model, the shifted lognormal model (which allows the distribution to be offset to the right i.e. mimicking the patterns seen in reaction time data, where valid responses begin at around 100ms) offers any improvement in model fit. Note that a Wald, or inverse Gaussian distribution, would also be a reasonable distribution choice for this data given that TCS is based on a diffusion process e.g. (Moran et al., 2013), and this distribution has been argued to be psychologically more plausible (e.g. Kieffaber et al. (2006), though see Matzke and Wagenmakers (2009)): we chose not to use this distribution as it often leads to computational issues, which would make it harder for others to reproduce or build on our approach later.

3. Hypotheses

We plan an experiment to test the extent to which the original results in Buetti et al. (2019) replicate and generalise, using our new modelling approach.

3.1. Proposed Modifications to Experimental Design

In order to better test the above, and increases sensitivity, we propose to make the following changes to the experiment described in Buetti et al. (2019):

1. **Within-subjects design.** This modification should give us greater power to detect differences between different models, as well as allowing us to investigate how individual differences in the single-feature task might explain differences in the double-feature task.

2. **Increase target-distractor similarity.** If the distractors are a very different colour from the target, they may not distinguish well between different contrast models. We will therefore run a version of the experiment where the target is a red semicircle, with distractors being either orange, purple or pink.

3.2. Registered Hypotheses

1. **Shifted lognormal model.** We hypothesise that a shifted lognormal model will give the best fit to our single-feature data, when compared to a lognormal and a normal model.

2. **Log-linear effect of N_T.** We will test the TCS model assumption that N_T has a log-linear effect by testing models with and without the log of this term. We expect that this will confirm the results previously seen in papers testing TCS i.e. that the log-linear approach will be best.

3. **Contrast model comparisons.** We will test the hypothesis proposed by (Buetti et al., 2019): specifically, that the *collinear contrast integration model* outperforms the *best feature guidance*, and *orthogonal contrast combination models* for the calculation of D, by calculating and comparing the mean absolute prediction error for each model.

4. **Reaction time predictions.** We will further test the hypothesis proposed by (Buetti et al., 2019) by testing which model gives the best prediction at the trial-by-trial RT level.

We will test each of these hypotheses by calculating the marginal likelihood of the relevant models, and then calculating the posterior probabilities. This will give us a probability for each model that represents the likelihood that the model gives the best prediction. We will consider there to be evidence for one model over the others if a given model has a probability above 90%. We will consider there to be strong evidence for one model over the others if that model has a posterior probability above 99%. This approach is most appropriate for our model: other measures of model fit, such as AIC, require an assumption of flat priors (which is not valid for multi-level models) and are based on point estimates (which is not valid for Bayesian models) (McElreath, 2020).

3.3. Planned Explorations

We plan to investigate the effect of individual differences in this paradigm: to what extent performance in the single-feature task can predict performance in the double-feature task for a given individual (Buetti et al. (2019) were not able to investigate this due to the between-subjects design of their study). We plan to do this by specifying a more complex random effects structure for the model, that allows for individual differences across different slopes for different features. This allows us to then study the random effect correlation structure. However, given these models can be challenging to fit, we will do this in an exploratory manner after carrying out our formally registered analysis.

One of the benefits of using a multi-level modelling approach is that it is relatively easy to extend to incorporate other factors that may contribute to reaction times, such as eccentricity and inter-item distance, which may help to explain behaviour further. To demonstrate this, we will also run exploratory analyses including a factor for which ring the target is in to assess whether this improves model fit or affects any of the conclusions that can be drawn from the model.

3.4. Pilot Experiment

Full details of a pilot experiment with $n = 4$ participants (960 trials each) using our proposed analyses can be found in *Supplementary Materials*. This suggests that even with a small sample, we can convincingly demonstrate H1 and H2. However, more data will be required to discriminate between the models, particularly for H4. Given that our methods are within-subject, we have reduced the number of trials per condition compared to Buetti et al. (2019) (12 in our pilot study, 20 in our proposed, compared to 40 in theirs). It is therefore possible that the increased noise in our estimated D single-feature parameters will make it more difficult to predict double-feature Ds accurately. However, we think this is unlikely to be the case as we can see that even in a small amount of pilot data, we can verify H3, with the collinear model having the lowest mean absolute prediction error.

4. General Methods

4.1. Sample Size: Participants and Trials

We plan to test 40 participants during the experiment. Our pilot experiment shows that H1 and H2 are easily demonstrated with 10 times less data, and Buetti et al. (2019) used 20 participants per experiment. Our sample size will therefore be in line with previous work testing H3 and H4. Ethical approval for the study was granted by the University of Aberdeen (application number PEC/4677/2021/2).

Our pilot study above suggests that just 12 trials per condition may be sufficient to fit our models. To be conservative, we propose using 20 in our experiment. We have demonstrated that using just half the data (20/40 trials per condition) from Buetti et al. (2019) makes no difference to our computational verification (see *Supplementary Materials*).

Finally, we have carried out a simulation experiment to estimate the confidence intervals on the mean when sampling from a log-normal distribution. We defined our distribution to have a mean-log of 6.135 and a standard deviation of 0.32. These values were loosely based on the distributions of reaction times in Buetti et al. (2019). The results are shown in Figure 3. Based on these simulations, we find that a sample of $n = 20$ leads to a 95% confidence interval that is

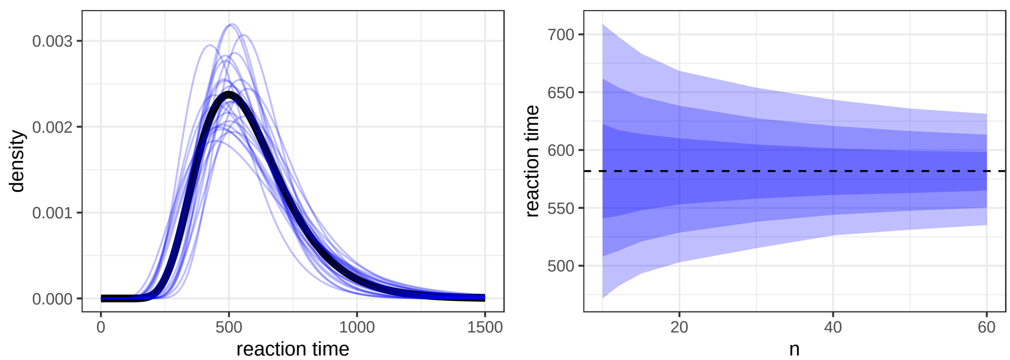

Figure 3: (left) The dark line shows the distribution we sampled from. The blue lines show distributions fitted to different samples of 20 data points. (right) Plot showing how the distribution of sample means vary with n. Shaded regions indicate the 50%, 80% and 95% confidence intervals.

approximately 1.4 times larger than $n = 40$. We feel this is a suitable compromise given we will be collecting our data within-subjects.

4.2. Stimuli

The targets and distractors are randomly assigned to the display based on an invisible grid. Within each quadrant of the screen, there are three 'spokes' each with four possible target positions (starting from the centre of the screen and moving outwards), creating 36 different target positions in total, in three concentric circles. A small amount of jitter is added to each possible position to make the target locations less predictable.

Distractor and target types: we will replicate the distractor types used in Buetti et al. (2019), apart from that we will change one distractor colour (from blue to pink) to allow us to discriminate better between different models of the data (see above). There are six single-feature conditions (purple, orange and pink distractors and triangle, circle and diamond distractors) and nine double-feature conditions (all possible pairings of the single-feature conditions). The target is always a red semicircle, except in the trials where the distractors are single-feature shapes (triangles, circles and diamonds) in which case the target is a white semicircle.

Set sizes: we will run all the distractor set sizes used in Buetti et al. (2019) (1, 4, 9, 19 and 31). We will also run target-only 'zero distractor' trials (60 in total, with 12 being the white semicircle target and the remainder the red semicircle target).

The experiments were programmed in PsychoPy and Pavlovia (Peirce et al., 2019). Stimuli were pre-made to generate search array images with 1920×1080 resolution.

4.3. Procedure

Participants will complete the experiment in the laboratory, sitting at a viewing distance of 45cm from the screen (viewing distance will be fixed by using a chin rest). They will view a fixation cross before viewing a search array: they will press the space bar to continue to the trial. Participants will be told to search for the target among distractors (either a red semicircle or a white semicircle, depending on the block) and report if the semicircle target points to the left or right, by pressing either the left or right button on a button box (Cedrus RB-540). They will first complete 16 practice trials where they will receive feedback immediately after completing each trial. In the real experimental trials, participants will receive feedback on their average accuracy and reaction time after each block of 320 trials. Participants will complete 5 blocks of trials (1600 trials overall i.e. 320 trials in each of 5 experiments, consisting of 5 set sizes x 3 distractor conditions x 20 repeats + 20 zero distractor trials). The trials where the distractors are single-feature shapes (i.e. the target is a white semicircle - Experiment 1b in Buetti et al. (2019)) will all appear in one block (which will appear at a randomly selected position within the experiment). All other trials (where the target is red semicircle) will be fully randomised i.e. all different conditions will be completely intermixed. This approach will be taken as TCS requires the participant to have a well-defined target template in mind in order to compare this to the stimuli in the display. Thus, participants will be cued to search for the relevant target at the beginning of each block.

In both the practice and experimental trials, the search display will always remain on screen until a response is made, or until 5 seconds had passed.

4.4. Data Pre-processing

Only participants who complete the full experiment will be considered candidates for inclusion in the data analysis. We will apply the same inclusion criteria as the original paper: participants will only be included if their search accuracy is over 90% and their average response time is not smaller or larger than two standard deviations from the group average response time.

For participants included in the analysis, we will apply the data cleaning used in the pilot data analysis i.e. *removing incorrect trials* and removing the top and bottom 1% of their data.

4.5. *Analysis Plan*

All analysis will be carried out using R (vx.xx)[2], brms (v.xx.xx) and rStan (vx.xxxx) As discussed above, we will use a mixed-effect models with either normal, lognormal or shifted lognormal distributions.

Please see the analysis of our pilot data for a full implementation of our analysis pipeline, including all code (available on Github at `https://github.com/scienceanna/TCS_Bayesian`).

5. Results

All 40 participants had accuracy over 90% (minimum 93.1%). One participant had an average response time (1100ms) over two standard deviations from the group average response time (781ms) and was removed. Incorrect trials were then removed, and the data was trimmed (only including response times between the 1% and 99% quantiles) leaving us with 39 participants completing a total of 59,587 trials.

All Bayesian models were fit to the new data using exactly the same procedure[3] as the pilot data presented in the Stage One review process. All models converged with WHAT CRITERIA DO WE WANT TO SAY HERE? $\hat{R}$

5.1. *Hypothesis 1: Shifted-lognormal model*

Our first hypothesis concerns which distribution best fits the single feature response time data. We fit multi-level models with a i) normal, ii) lognormal, and iii) shifted-lognormal distribution. The models all used the same model formula that estimated search slopes in terms of $\log N_t$ for each feature. Maximal random effect structures where used.

After each of these models had been fit to the data, leave-one-out (LOO) model comparison was used to calculate posterior probabilities for each. The results of this procedure allocated $\sim 100\%$ of the weight to the shifted-lognormal model, so we can conclude that it is the best distribution (out of the three we tested[4]) to use for modelling response times in this paradigm. This model is shown in Figure 4.

[2]Version numbers will be recorded upon completion of final analysis.

[3]the only departure was an increase in samples in the bridgesampling procedure from xxxx to xxxx. Based on advice given in the Stan forums

[4]See discussion for wald, weilbull, etc

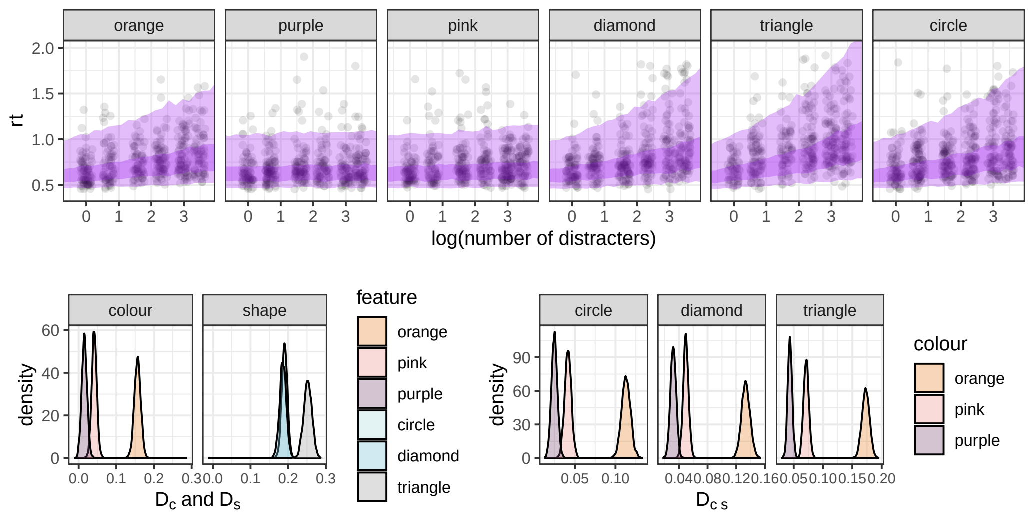

Figure 4: (*top*)The shifted-lognormal model fits for the single-feature data. / Data points show a random sample of 10% of the individual trials from our experiment. Shaded region shows the 53% and 97% HPDI for the fixed-effect component of the shifted-lognormal model (loglinear in N_T). (*bottom*) Values for D_c, D_s and $D_{c,s}$ from the shifted lognormal model. These are comparable to traditional search slopes, except that our model has a log-log relationship between the number of distractors and response times.

5.2. *Hypothesis 2: log-linear effect of* N_T

We then used the same methods to verify that using $\log N_T$ for the search slope does indeed give a better fit to the data than simply using N_T. The results are again conclusive with $\sim 100\%$ of the model weight being assigned to the model that is log-linear in N_T.

5.3. *Hypothesis 3: Contrast Model Comparison*

Now that we have confirmed that the shifted-lognormal multilevel model (with a log-linear effect of N_T) is indeed the best fit to the data we will extract the search slopes for each feature. These are summarised in Table 3 and Figure 4. We can see that we have successfully obtained a range of values for both D_c and D_s. As with Buetti et al. (2019) we find that the values for D_s are larger than D_c: search slopes for colour features are easier than shape. **Anna please check/expand!**

We now combine the *single-feature* search slopes, D_c and D_s, to predict the *double-feature* conditions ($D_{c,s}$) using Equations 2, 4 and 3 above. The results are summarised in Figure 5. We find that while the collinear contrast model has the

feature	D_c	95%HDCI	feature	D_s	95%HDCI
orange	0.161	[0.144 , 1.110]	triangle	0.258	[0.237 , 0.849]
pink	0.039	[-0.061 , 0.053]	diamond	0.190	[0.174 , 1.168]
purple	0.019	[0.005 , 0.537]	circle	0.188	[-0.065 , 0.202]

Table 3: A summary of the posterior estimates of D_c and D_s values from our Experiment.

highest R^2 (0.922, compared to $R^2 = 0.883$ for best feature, and $R^2 = 0.915$ for orthogonal contrast), the orthogonal contrast model is the most accurate, both in terms of mean absolute error (0.165, compared to 0.185 for best feature and 0.271 for collinear) and having a regression slope closest to 1 (0.999 compared to 0.748 and 1.48). Therefore, Hypothesis 3 does not hold: orthogonal contrast rather than collinear contrast offers the best prediction of search slopes in the double-feature condition.

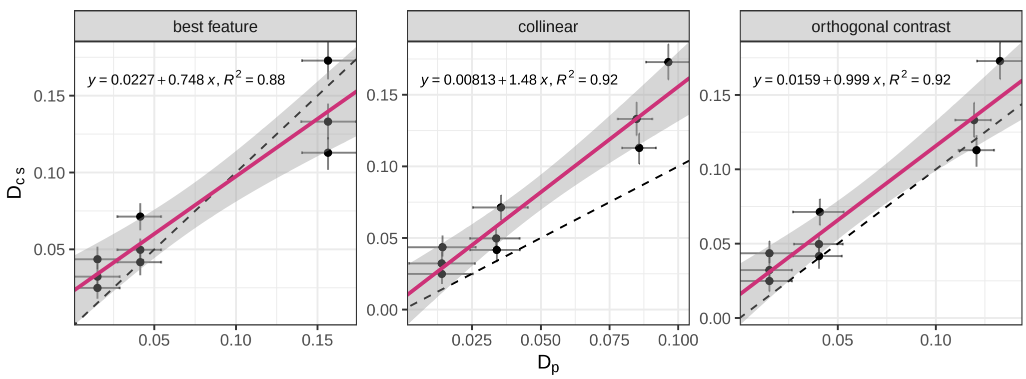

Figure 5: Predicting $D_{c,s}$ from D_c and D_s. The x-axis shows our predictions, D_p, using the best feature, collinear contrast, and orthogonal contrast models.

5.4. *Hypothesis 4: Reaction Time Predictions*

Our final hypothesis concerns how well the different feature combination models perform when we have to predict reaction times. We find very little difference between the three methods in terms of LOO model weights: 0.294 for best feature, 0.341 for collinear and 0.365 for orthogonal contrast.

5.5. *Discussion*

Our results allow us to confirm Hypothesis 1 and 2. We also find that using the best fitting model leads us to favour the orthogonal contrast model over collinear.

Our interpretation of the null/neutral results in the prediction of reaction times is that the differences in predictions from the three contrast combination methods are small relative to the (i) individual differences between participants and (ii) trial-to-trial variability. These will be further explored below in our *Planned Explorations* section.

6. Planned Explorations

6.1. Individual Differences

We start this exploratory analysis looking at how the D_c and D_s values vary from participant to participant. From Figure 6(*left*) we can see that there is considerable variation between observers - in fact, the variation from one observer to the next is often larger than the variation across features. To investigate this further we calculted the correlations betwen each of the features (we calcualted Pearson's r for each sample from our posterior, which gives us a full posterior distirubtion for the correlations). We can see in Figure 6(*right*) that while both the D_c and D_s are correlated within feature classes (~ 0.75), there is no correlation from any of the colour features to any of the shape features. While it is not possible to determine whether this pattern us caused by differences in colour v shape features, or by the block structure used in our experiment[5], either way, this is an intrguing result. (To be discussed further in the General Discussion.)

The individual differences for the *double-feature* conditions are much less pronounced - these conditions are easy and the search slopes are quite close to flat (how to summarise? oh, and CHECK this!) and hence, the correlations are all much weaker, presumably due to range restriction. THIS IS ALL SPITT BALLINGYAYYAYA

Given these results, it is perhaps unsurprising that our analysis for Hypothesis 4 leads to a neutral result between the three contrast combination methods. Perhaps taking these individual differences into account when we predict the RTs will lead to an improved power to discriminate between the models.

6.2. Target Eccentricity

Does taking target location into account help with the reaction time predictions?

[5] blame the reviewer! probably best not

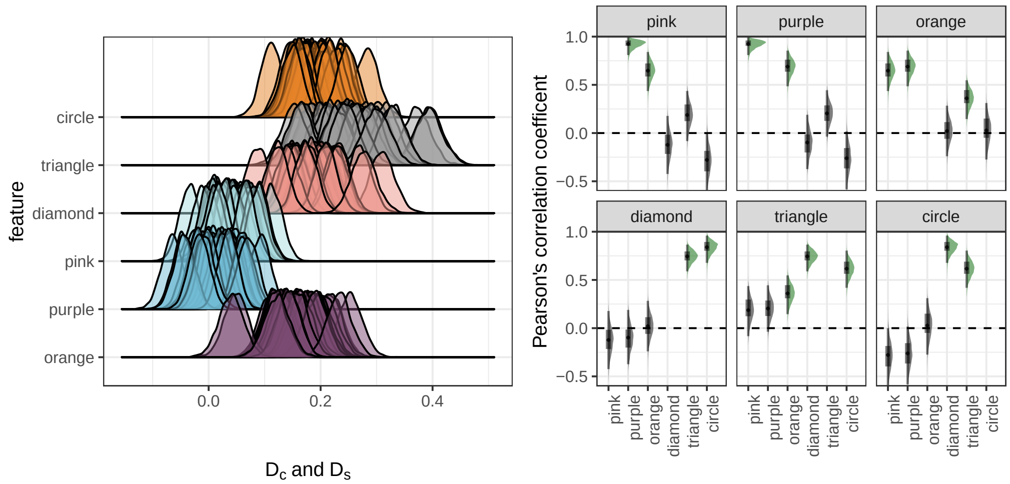

Figure 6: Individual differences in D_c and D_s. (*left*) Posterior probability distributions for D_c and D_s for each individual. (*right*) Estimated correlations between each of the D_c and D_s.

7. General Discussion

We have two main conclusions from our registered analysis. The first relates to how reaction times should be modelled and the calculation of search slopes. In much of the literature on visual search (cite some examples), mean reaction times are modelled using a simple linear model $\bar{y} = bN_T + a$. The b coefficients are often referred to as "search slopes" and are often treated as measurements of theoretical important ¡HOW TO PHRASE PROPOPERLY?¿. The results presented above indicate that a shifted-lognormal model that is loglinear in N_T offers a much better fit to the data.

This result isn't particularly novel. For example, Buetti et al. (2019) use $\log N_T$ when computing their search slopes (also see CITE STUFF). In terms of reaction time distributions, researchers have looked at which distribution offers the best fit to empirical response times in visual search before. For example, Palmer et al. (2011) compared ex-Gaussian, ex-Wald, Gamma, and Weibull distributions and found that the distributions with exponential components offer a better fit to the data. Our results are in linear with this, we opted to use a shifted-lognormal distribution in our analysis above for pragmatic reasons (INSERT NOTE HERE). In most situations we would expect it to be difficulty to distinguish between these different distributions. Also see (Wolfe et al., 2010). It is also worth mentioning more sophisticated methods make use of drift-diffusion papers (cite some examples) (cite some of the papers outlining why these models can be difficult).

Despite these previous findings, the use of linear search slopes is still prevalent in the visual search literature (can we find any examples? Do we want to name names?). We recommend that other researches make use of these more sophisticated models when calculating search slopes. Our work shows that these choices of distribution can influence results and conclusions

say something about correlations/. can cite Clarke et al. (2020)

Conflict of interest

The authors declare that they have no conflict of interest.

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