Psychophysical Scaling Reveals a Unified Theory of Visual Memory Strength

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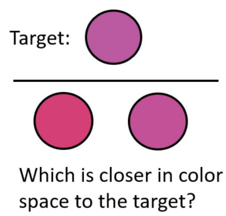
Investigating Visual Memory

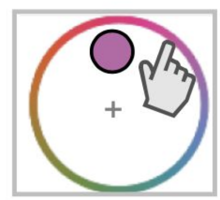
n-AFC Task

- target stimuli is displayed for set encoding time.
- delay of 800 to 5000 ms
- n options are presented from the stimulus space, the subject must choose the one must similar to the target

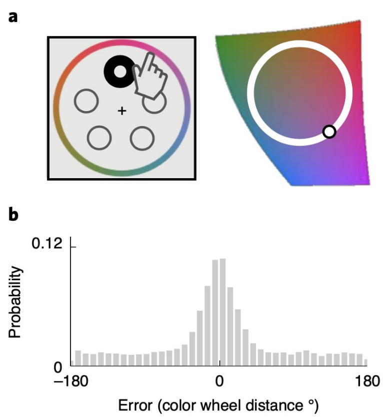


Continuous Response Task

- target stimuli displayed for set encoding time.
- delay of 800 to 5000 ms
- Subject attempts to choose target on continuous stimulus space



Background



- Classically, working memory errors are thought to have two distinct causes
  - Errors caused by limits in number of items that may be stored in working memory present as random guesses
  - Errors caused by a lack of precision in representation, resulting in small deviations from true signal.
- The results shown on the left are often used as evidence for this two-component mixture model of working memory
  - There is a precision distribution around 0, with flat tails on either end.
  - It seems reasonable that the flat tails indicate regions were random guessing was used, and errors near the center are due to a lack of precision in representation of the stimuli.

Figure:

- Subjects were told to pick a target color color from the color wheel, (continuous response task)
- Target presented for 1000ms, and then color wheel presented after 800ms delay

Background

The mixture model for visual memory can fit behavioral data very well, but has some key flaws

1. Requires extensive fine tuning to fit behavioral data well
2. Does not generalize well between different tasks, even within the same stimulus space
3. Does not generalize well between working and long term memory
4. It's not immediately clear how such a system could be instantiated by neuronal populations

Target Confusability Competition:

A Unified Model of Visual Memory Strength

Here a new model is introduced called (Title), or TCC for short.

It aims to address the issues with the mixture models of working memory

While providing deeper insight into the cognitive mechanisms behind visual memory, providing accurate predictions about performance on various memory tasks, and fitting with modern understanding of neuron population coding in the brain.

The key components of the model are first recognizing that similarity between any two stimuli is not linear, and defining a function that captures this, and then building out a standard signal detection framework on top of that.

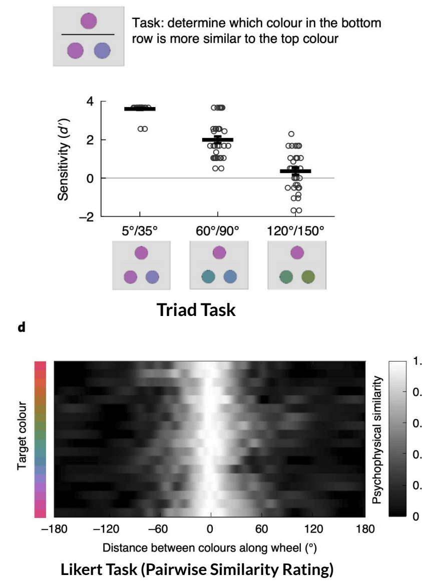
At first we work in just one stimulus space, a percentually evenly spaced circle chose from the CIE L*a*b* color space

Defining the Similarity Function

- The similarity function was determined independently using a variety of perceptual matching tasks **(Right)**

- The triad task data was reconstructed into a continuous measure of similarity using maximum likelihood difference scaling (MLDS).
  - We can notice some non-linearity immediately, subjects are much more sensitive to differences between 5° and 35° (from the target) then between 120° and 130°.

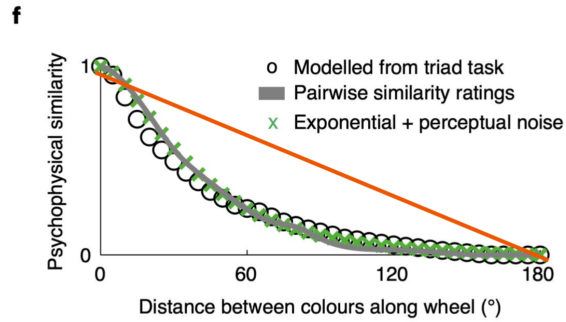
- The likert task directly asks subjects to rate the similarity between pairs of colors from the wheel.



In the triad tasks a target color is shown and subject are asked which is more similar to the one on top

Defining the Similarity Function

- Averaging over the the measured similarity curves for each target, we arrive with the figure to the right.
- Both the pairwise similarity ratings and the triad task model can be well fit with a exponential function with added perceptual noise ($p < .001$)
- This function is the perceptual similarity function for this stimulus space, and forms the basis for the rest of the TCC model
- Under this model there is one empirically derived similarity function belonging to the exponential family for each stimulus space



Similarity function in TCC is a perceptual property of the stimulus space, it does not change depending on subject or memory strength

exponential similarity functions are a very good fit in general.

The similarity function is critical because it tells us how a single target is similar to each other location in the stimulus space.

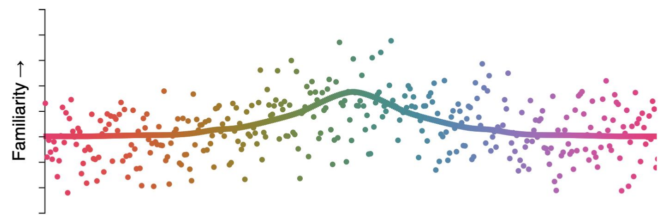
- This not the same metric as perceptual distance, which just ensures even distance between neighbors.
- Mixture models and previous models of working memory tend to assume they are the same metric, which results in a linear similarity function. (cue) which is not supported by the data.

The perceptual noise added here is characterized by a separate perceptual matching task, which I'll talk more about a bit later

- Can clearly see an important effect of it here, causing the similarity function to not be locally exponential at with about 15^{o} , this is because colors may be perceptually confused by individuals when that close is space.

Representing Stimuli Under TCC

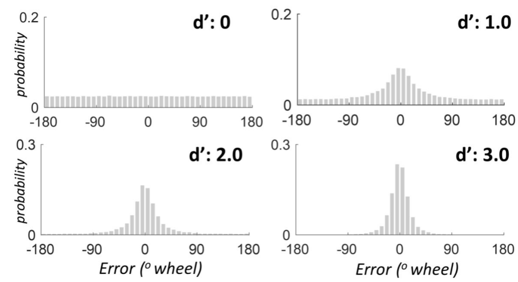
- A stimulus causes a change in overall familiarity centered on the target.
  - Equal to $d' \cdot f(x)$
  - Where d' is a free parameter, (memory strength), and $f(x)$ is the similarity function
- When a subject is asked to perform a n-AFC task (n=360 here), they choose the color that has the highest familiarity after noise.
- If more than one target is presented, encoding can be modelled as
  - $F_{new} = F_{old} + S \circ (d' \cdot f(x))$
  - Where S is the discrete stimuli and F is the overall familiarity function
- The overall magnitude of the noise is irrelevant because of how memory strength is defined.



Will talk about memory strength next

Estimating Memory Strength Parameter, d’

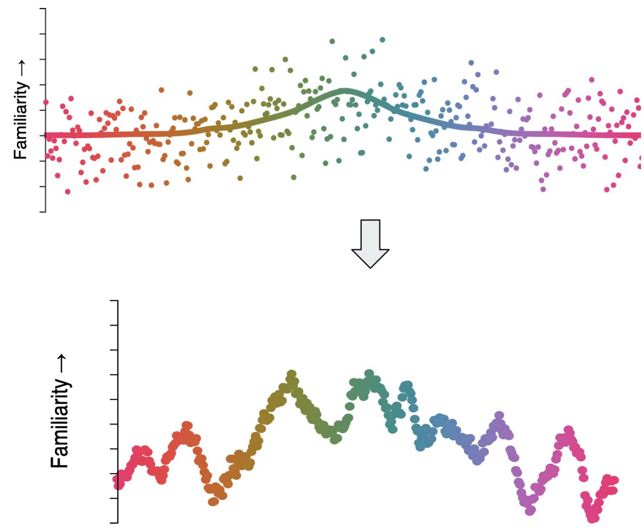
- The memory strength parameter (d’) is the one free parameter in the TCC model.
    - This parameter can also be estimated empirically, and should be constant for a given stimulus space
- d’ is measured in standard deviations of the noise distribution
    - Note that this makes the actual magnitude of the noise variance irrelevant
- We can fit a TCC model to n-AFC data with arbitrary n simply by adjusting d’, and the model should generalize to any other task employing the same stimulus space.



- This is an extremely high bias model, making a lot of assumptions about the underlying nature of memory
- It basically saying we can scale this one parameter, d’, and represent any visual memory task in any stimulus space.
- d’ is really a measure of signal to noise ratio, but can simply be thought of as the amplitude of the similarity functions if the variance in noise is set to 1.

Perceptual Matching to Smooth Noise

- Intuitively, it makes little sense that perceptually adjacent stimuli may have very different familiarities due to random noise.
  - i.e. it is implausible that the noise at nearby locations in stimulus space is not correlated
- A obvious solution to this is to smooth the noise, preventing drastic changes between nearby stimuli
- Data from a separate perceptual matching task is used to choose how much to smooth noise, so no new parameter is introduced



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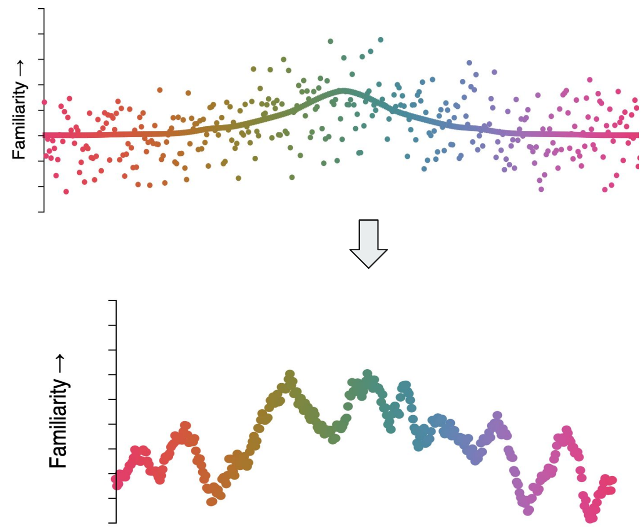
- However the smoothing doesn’t really add much extra anyway, since there usually averaging over multiple trials / targets

Perceptual Matching to Smooth Noise

- Subjects were asked to pick which color matched a target out of 60 colors covering the whole color wheel
  - Used to construct perceptual correlation matrix
- In TCC, the amount of shared variance in the noise between any two colors is how often colours at that distance are confused in the perceptual matching task
  - $p(x) = C_x / C_0$,
  - x is number of degrees two colors are apart on the color wheel
  - C_x is the average correlation between colors x degrees apart



- The model really is quite simple, so I just wanted to go through a quick demo since it makes thing very clear (I think)
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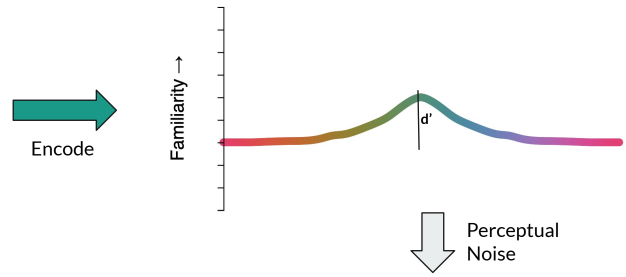
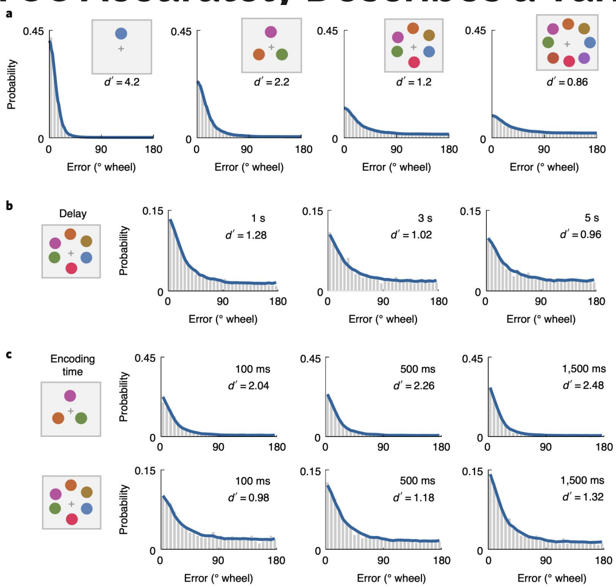
TCC Recap

Naive subject



Tasks
1. Continuous report task
    a. Subject will report highest familiarity color
2. n-AFC task
    a. Subject will choose option closest in perceptual space to highest familiarity color

TCC Accurately Describes a Variety of Data



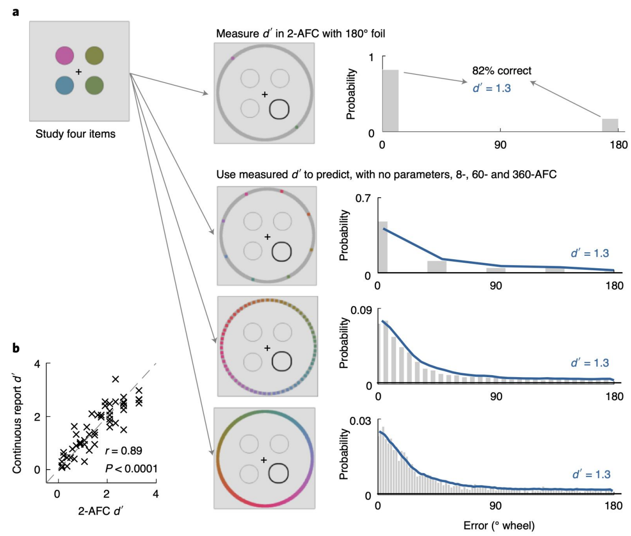
- Fitting a TCC model to each of the conditions shown to the left result in a good fit to experimental data, despite only having one free parameter.

TCC Generalizability

- A TCC model can be fit using a single foil in a 2-AFC task, e.g. asking whether a stimuli at 0° or 180° degrees perceptual difference is more similar to the target

- The resulting **d'** is the same a for any other set of stimuli in the space for an n-AFC task.

- This show an inherent robustness in TCC that is not shared by classical mixture models of visual memory



Simply saying the model can fit the data well isn't the best proof of its correctness, so let's see if we can make predictions using a fit TCC model.

Explain this figure more clearly .

- A mixture model would fail completely at this, on this 2afc subject would be perfect at all times except for the small percentage of random guesses.

FROM PAPER
If these models were correct, it should not be possible for TCC to make such accurate predictions across tasks using a single d′ and no free parameters.

The fact that TCC can make such accurate predictions has important theoretical and clinical implications, as it shows that measuring d′ with one set of foils is sufficient to understand memory response distributions—there is no separate concept of 'precision' that is being missed in such tasks.

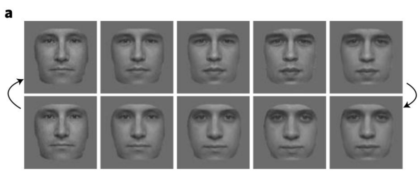
Moving Beyond Color Space

- TCC can be applied to any stimulus space, for both working and long term memory.

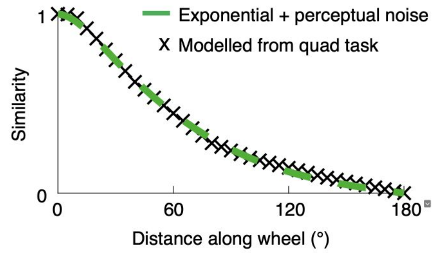
- Color was chosen initially because approximate perceptually equidistant color spaces are well formalized, e.g. CIE L*a*b*

- TCC was applied to two other stimulus spaces
    - A working memory task on continuous set of faces
    - A long term memory task involving colored objects

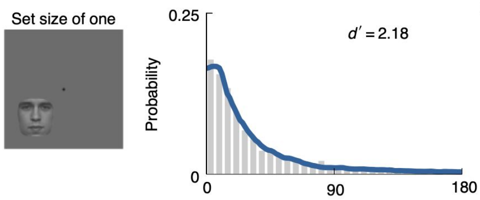
TCC Generalizes to Other Stimuli Domains

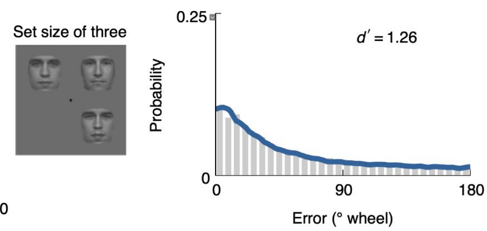


Samples from continuous face space



Empirically determined similarity function from perceptual matching task. Notice that while still exponential, this similarity function is different from that of the color space.





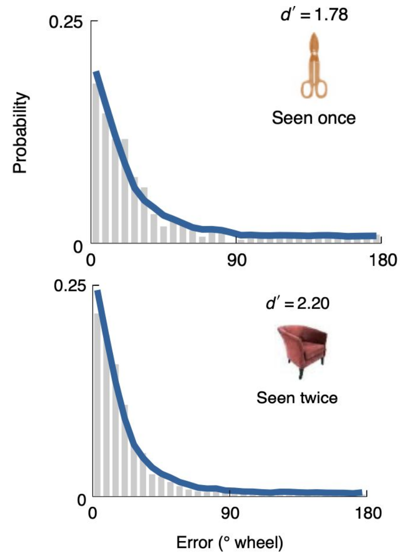
For target set sizes 1 and 3 TCC fits the observed data very well ($P < .001$ for both cases)

This demonstrates TCC's generalizability to other stimuli domains.

- TCC accounts for data across multiple stimulus spaces. As long as the perceptual similarity space of the stimuli is accurately measured using psychophysical scaling (see Supplementary Discussion), TCC's straightforward signal detection account, with only a single d′ parameter, accurately captures the data.
-

TCC Generalizes to Other Memory Systems

- Subjects were shown blocks of 40 colored items, with each item appearing either once or twice
- They were then asked to report the color of a grayscale item from the block after a delay
- Designed to show that TCC generalizes to longer term memory, not just working memory
- The similarity function for this task is assumed to be the same as that for color



Once again, TCC is able to fit the observed behavioral data ($p < .001$ for both cases).

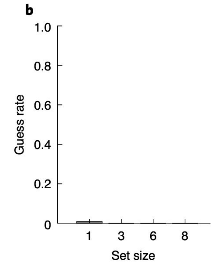
Long term memory task

- TCC naturally fits data from both visual working memory and long-term memory with the same underlying similarity function and signal detection process applicable across both memory systems.

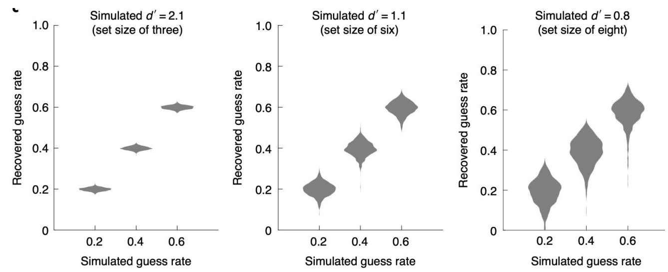
- Note in case of question about same d' s (from paper)
    - *Note that long-term memory performance in this task probably depends on a two-part decision: item memory and source memory (for example, the object itself and then its colour). This two-part decision is related to the processes of recollection and familiarity and probably introduces heterogeneity in memory strength into the colour memory reports. Here, where item memory was consistently strong and colour memory was the main factor, this did not affect the fits of TCC, but in other data where heterogeneity in the strength of item memory was greater, variability in d' between items would probably need to be accounted for.*

Implications of TCC: No More Objective Guessing

- Provides evidence against working memory having a fixed size.
- While items far from the target stimuli are sometimes chosen, this is due to the stochastic nature of the model, not because of a failure to represent the target, or varying memory strength.
- To be sure TCC would have captured objective guessing if present, a mixture of TCC and a uniform distribution (guessing) was also fitted to experimental data **(b)**
- To show that the mixture would recover guessing if present, it was also fitted to simulated data with guessing added **(c)**



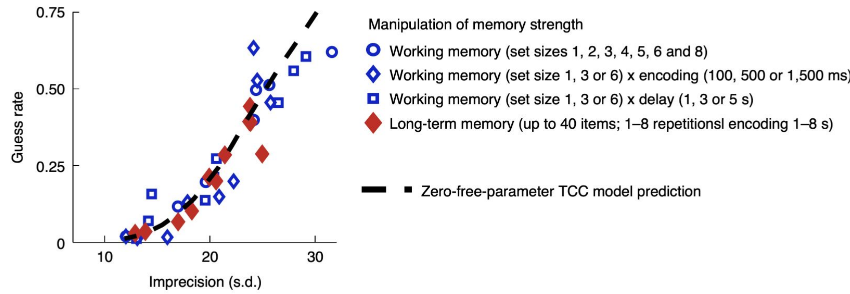
On experimental data, the contribution of the guessing component of the mixture model if always 0



Besides being a unifying framework

- On simulate data, we can see that the mixture model works, It would utilize a two part TCC and random guessing mixture if it was the true model of the data.
- However, on real data, the random guesser goes sadly unused.
- This rounds back to the central claim, there are not two psychological states of memory.

Mixture Models are Unnecessarily Complex



- The two major characteristics of a mixture model of guessing and precision are show for all tasks in the paper.
- While mixture models may cover a large parameter space, they tend to be constrained to the same line of the TCC model prediction
- The TCC model fits as well or better, with less variability, and is thus a stronger model of the underlying memory processes

The currently dominant conception of memory arises from mixture models claiming that memory varies in at least two psychologically distinct ways: the precision of memory and the number of represented items (modelled as the guess rate). TCC makes a strong counter prediction: that if the stimulus space, and thus psychophysical similarity function, is held constant, memory report distributions vary in only one way (that is, memory strength). Thus, TCC claims that the particular manipulation (encoding, set size or delay) used to change memory strength should not selectively change one mixture model parameter or another (for example, encoding changing the precision or high set sizes affecting only the guess rate, and so on), but that both should always change together. To visualize this, we show a state– trace plot of mixture model parameters across a wide range of manipulations of working memory (from the current paper) and long-term memory (from miner et al.31), with one point per condition. We find that despite the huge number of different ways we vary memory strength, all of the points lie on a single line, consistent with only a single parameter being varied, and that this line is extremely well predicted by the zero-free-parameter prediction of TCC. TCC can only predict an extremely small part of the possible space that the mixture model can predict, and only a very particular relationship between the two mixture model parameters, and the data from all of these conditions land on this line. This provides strong evidence against mixture models measuring two distinct parameters and in favour of the TCC conception of memory.

Relating TCC to Neuronal Population Codes

- Critical feature of TCC is the use of the similarity function as the basis for memory encoding

- This similarity function is naturally understood using models of population coding.

- All stimuli that are far away from target are approximately equally similar could be due to very low overlap in population of neurons encoding those stimuli

- TCC model provides an important bridge between levels of understanding.

- They do talk quite a bit about how TCC makes sense in the context of neuro population coding, but they didn't really due experiments to that point, its more of an "it could be this way" sort of thing

- Though it does make sense, if you think about encoding information into a network you'd expect to end up with the sort of error predicted under TCC, due to overlapping representations

Conclusion

- TCC provides a very simple one parameter model that generalizes across a wide range of visual memory tasks
- It unifies fragmented models of memory in a way that provides deeper understanding of underlying cognitive processes
- It provides a framework for future investigation into visual working memory

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- It unifies fragmented models of memory in a way that provides deeper understanding of underlying cognitive processes
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Q/A