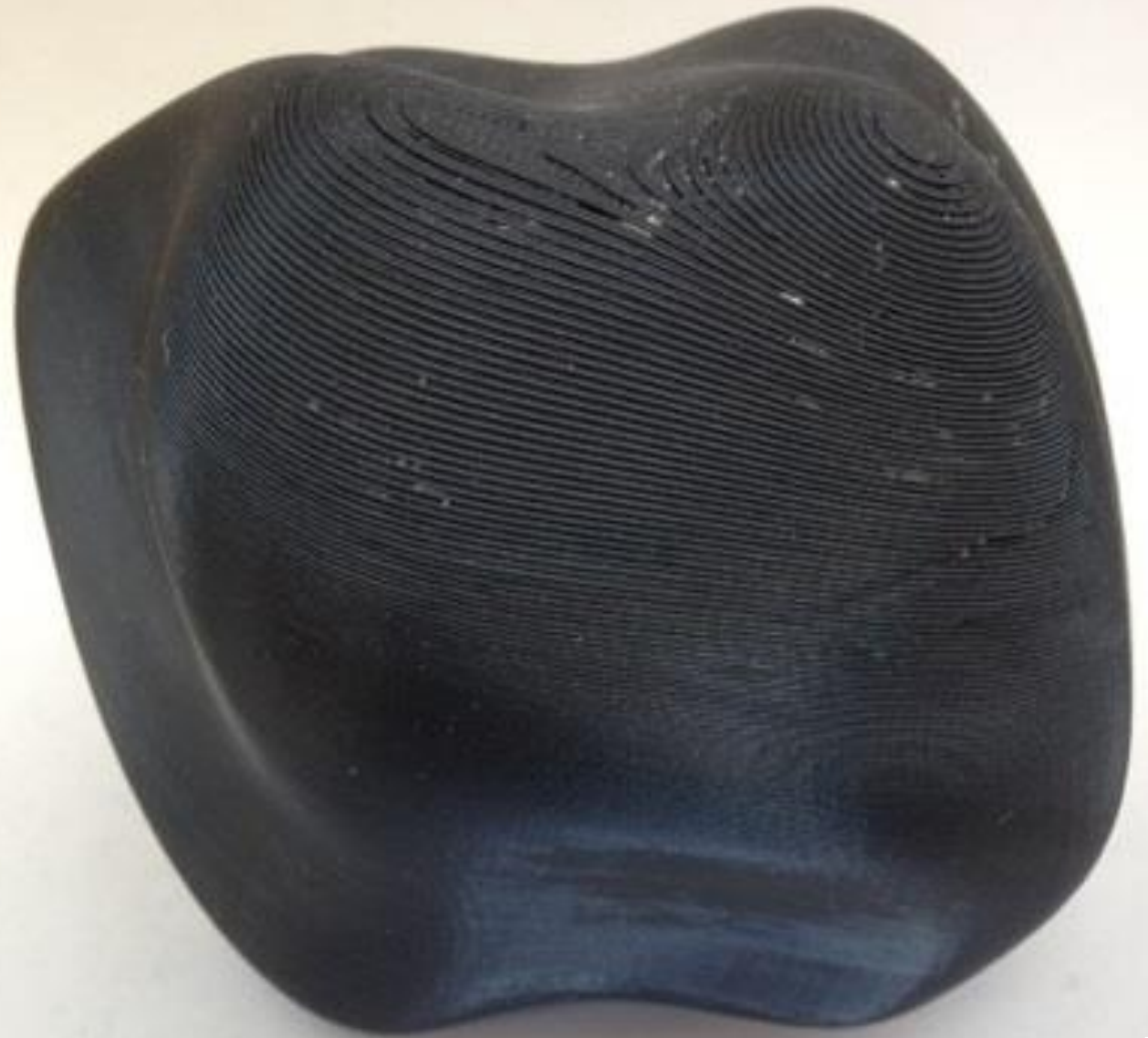


# Single Anchor Sorting of Visual Appearance as an Oriented Graph

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# Outline

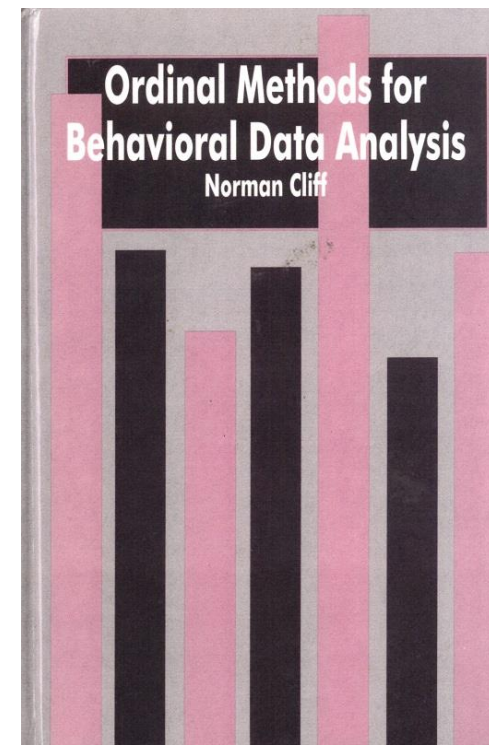
## TL;DR – perceptual similarity as a graph

- Motivation and context
- Ranking stimuli relative to an anchor
- Two experiments
  - Web-based ranking of 3DP complex appearance
  - Laboratory ranking of solid colors
- Representation and analysis
  - Graph in which nodes are stimuli and edges are the rank sequence
  - Thickness of edges is proportional to rank for all observers
  - Rank aggregation using Schulze voting method
- Evaluating models
- Future directions

# Motivation and Context

*Ordinal Methods for Behavioral Data Analysis* was an interesting read

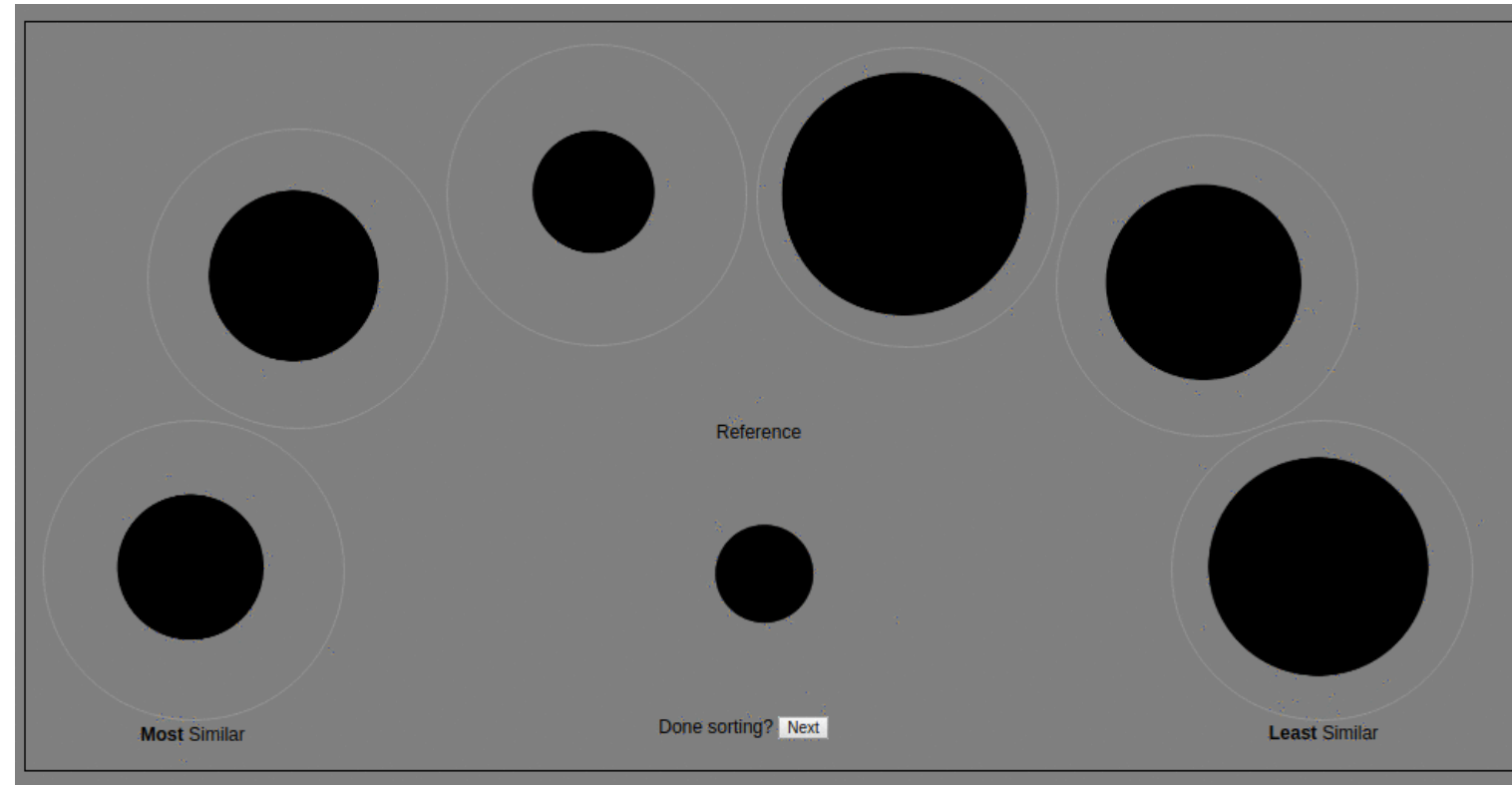
- Even efficient methods of paired-comparison can be time consuming and volunteers may complain
- Interested in rank order methods and metrics
- Perhaps most familiar example in the field, Farnsworth-Munsell 100 hue test
- Engledrum describes ordinal methods and averaging ranks, for a single *-ness*
- Progress made during Michael's summer internship and subsequent collaboration with Gary Meyer:
  - Ludwig, Michael, et al. "Perceptual Appearance Uniformity in 3D Printing." *Electronic Imaging* 2018.8 (2018): 1-12.
- Recent results in web-scale data collection for perceptual metrics:
  - Zhang, Richard et al. "The Unreasonable Effectiveness of Deep Features as a Perceptual Metric", CVPR (2018).



# Anchored Ranking

Rank perceptual similarity relative to a single reference

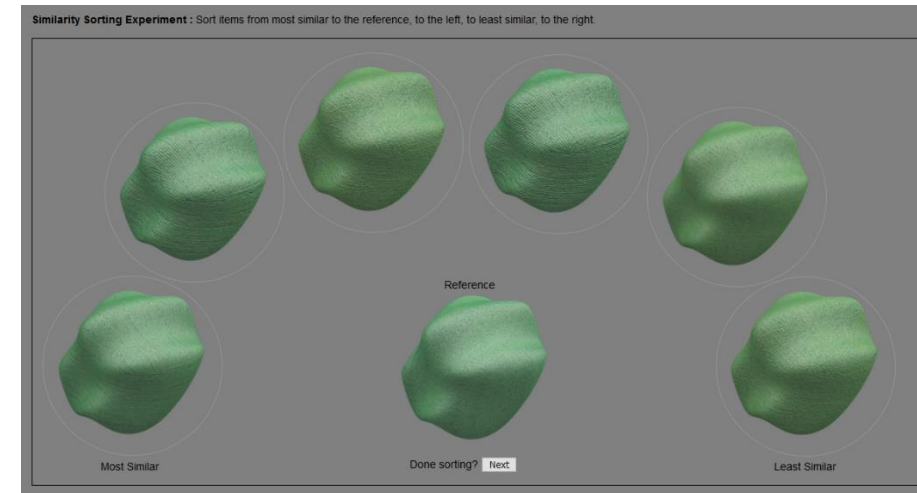
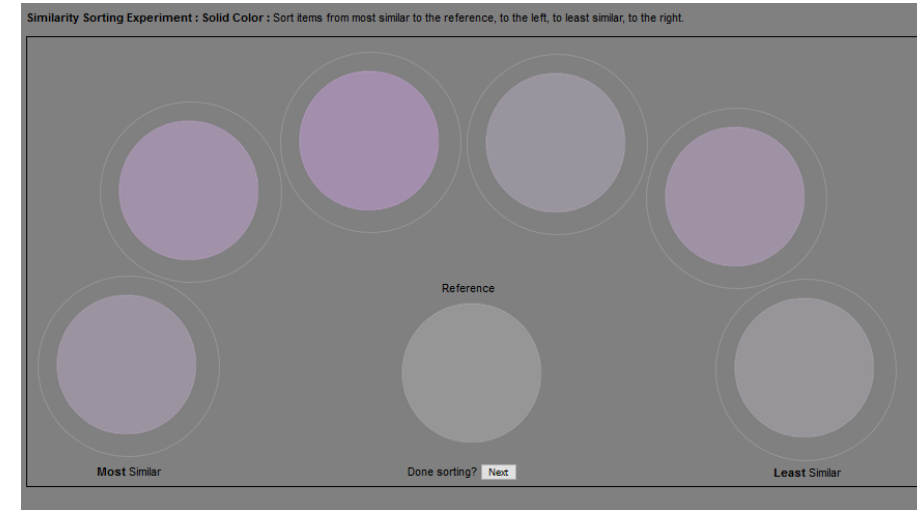
- Simple example varying only the diameter
- Drag-and-drop as interface
- **Center** is reference
- **Left** is most similar
- **Right** is least similar
- Arc layout is used to allow larger stimuli and roughly equal distance for comparisons to reference stimuli



# Two Visual Experiments

In all cases, one reference and six stimuli to sort

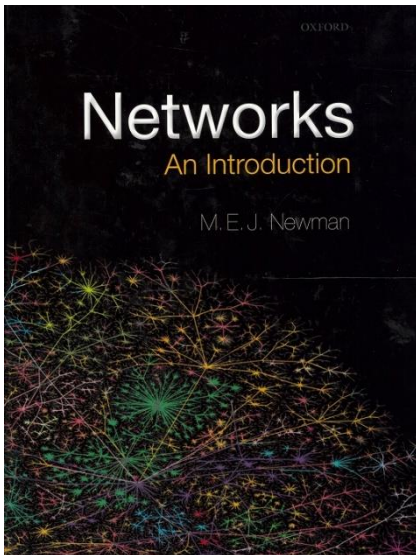
- Solid colors
  - Generated with a target color difference between neighbors
  - Conducted in laboratory with calibrated display and viewing conditions
- Simulated complex appearance of 3D printed blob
  - Generate varying two rendering parameters per sequence
  - Conducted online with unknown displays and viewing conditions
- Both experiments started with two test sequences
  - A Deuteranomic color sampling
  - A sequence of abstract shapes



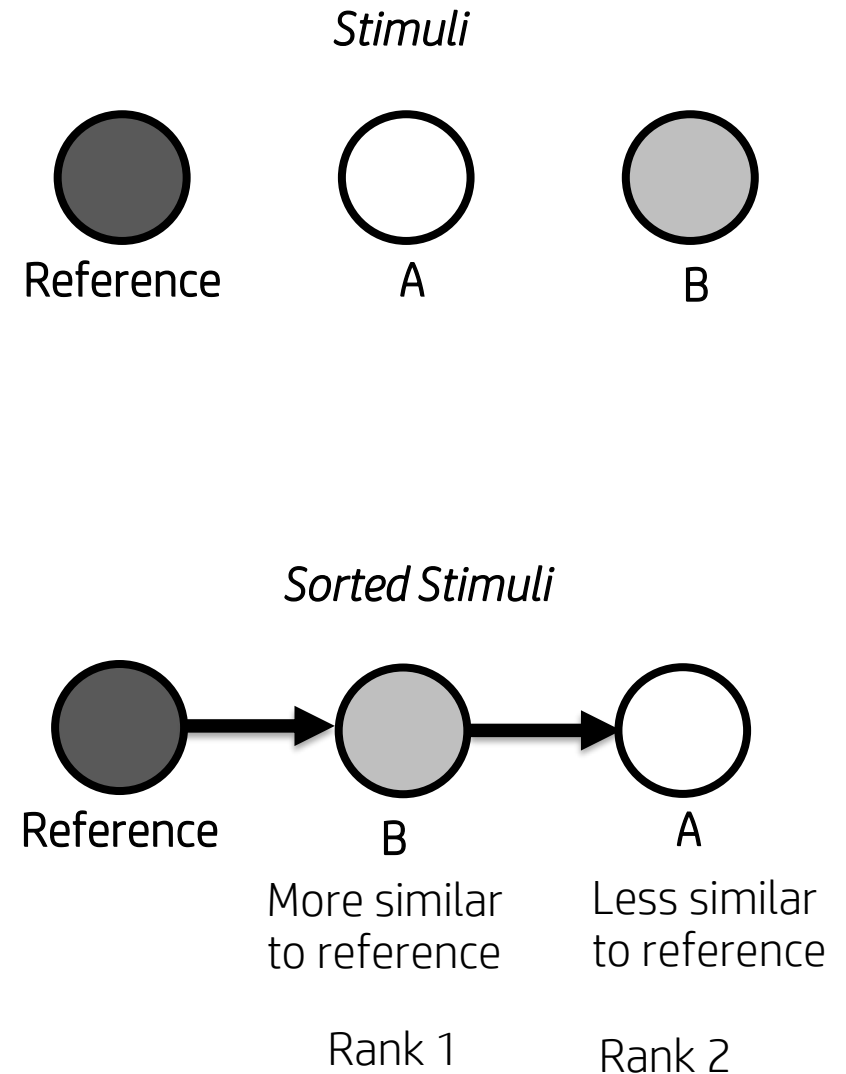
# Graphing Similarity

*Networks: An Introduction* was also an interesting read

- Perceived similarity as a directed graph
  - **Nodes** : stimuli
  - **Edges** : sort sequence neighbors (or rank order)
- In the proceedings referred to as a sort-sequence graph
- For simplicity will show as undirected graph after this slide



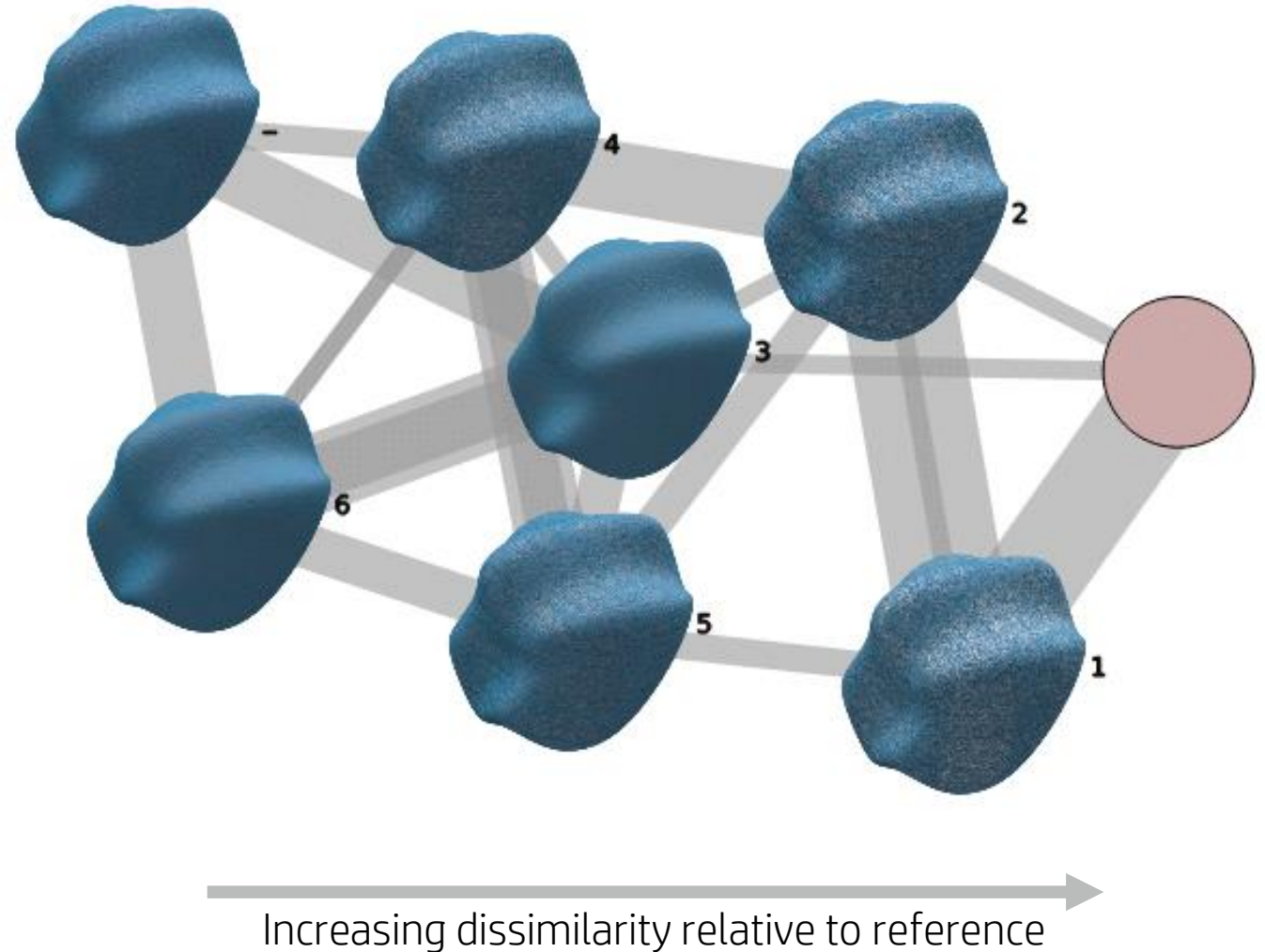
Lots of metrics, tools and concepts in graph theory and network analysis to possibly leverage for perception



# Oriented Graphs

*Establishing a convention for “reading” the graphs*

- Algorithms for graph layout is its own research area
  - D3.js force-directed layout for initial layout
  - Manually orient increasing dissimilarity from left to right
  - Similar to the number line in mathematics and matches the experimental task instructions
- Note “oriented” is not an established term in the terminology of graph theory
- Additional conventions
  - **Dash** or – as label for reference
  - **Period** or . with empty node for “end of graph”

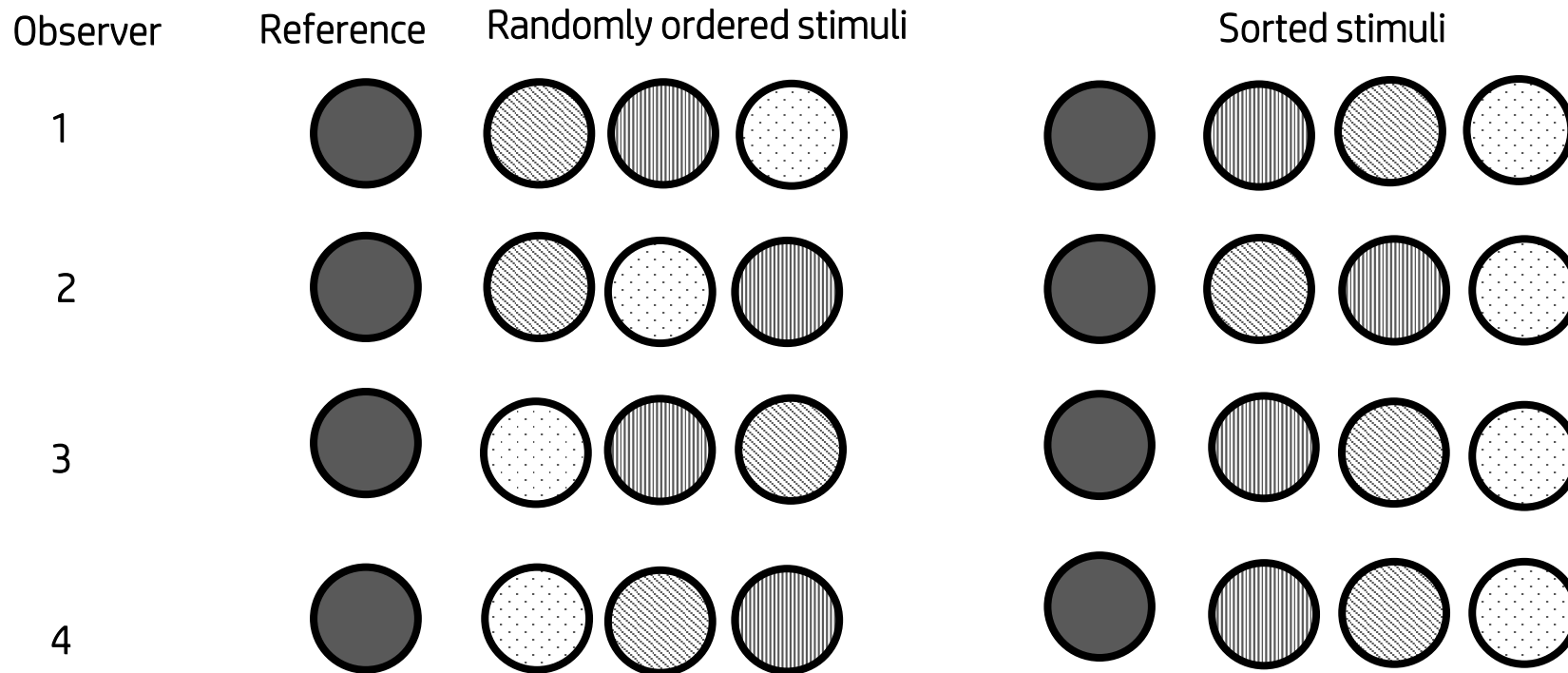




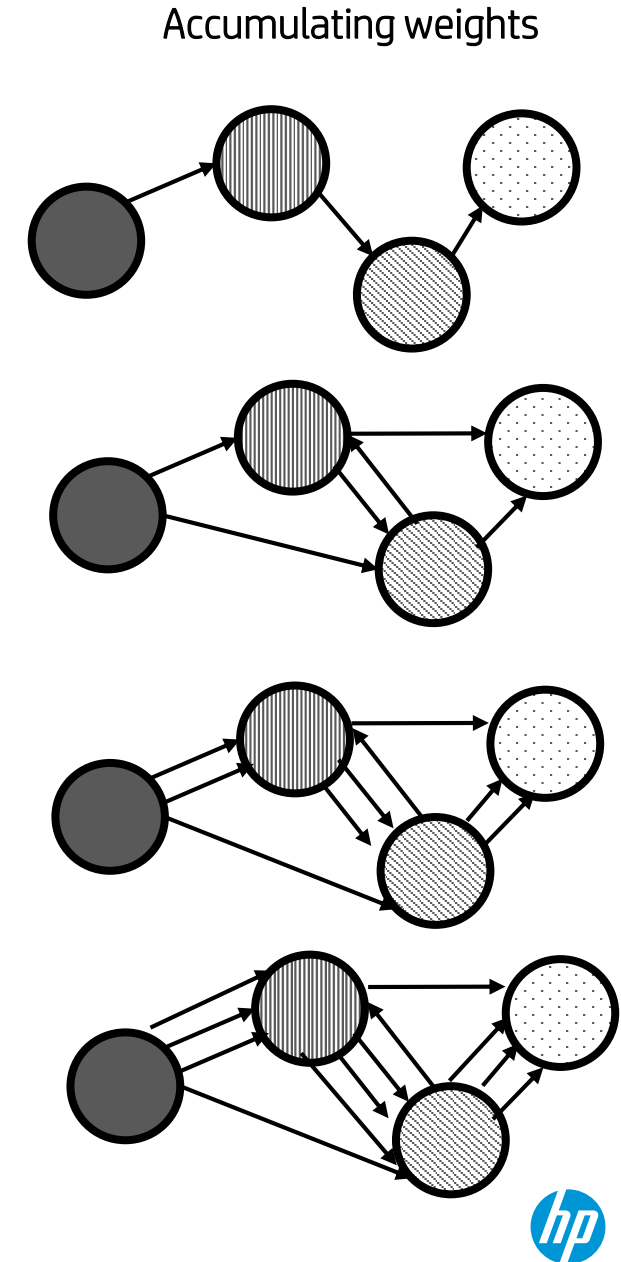
# Weighted Graph

*Consider using when the dissimilarity matrix just looks like a table of numbers*

- Thickness is proportional to number of times a node rank order occurs



For each observer, connect corresponding neighboring ranks.  
Convert number edges to thickness. Above pattern fills only an example set of stimuli.

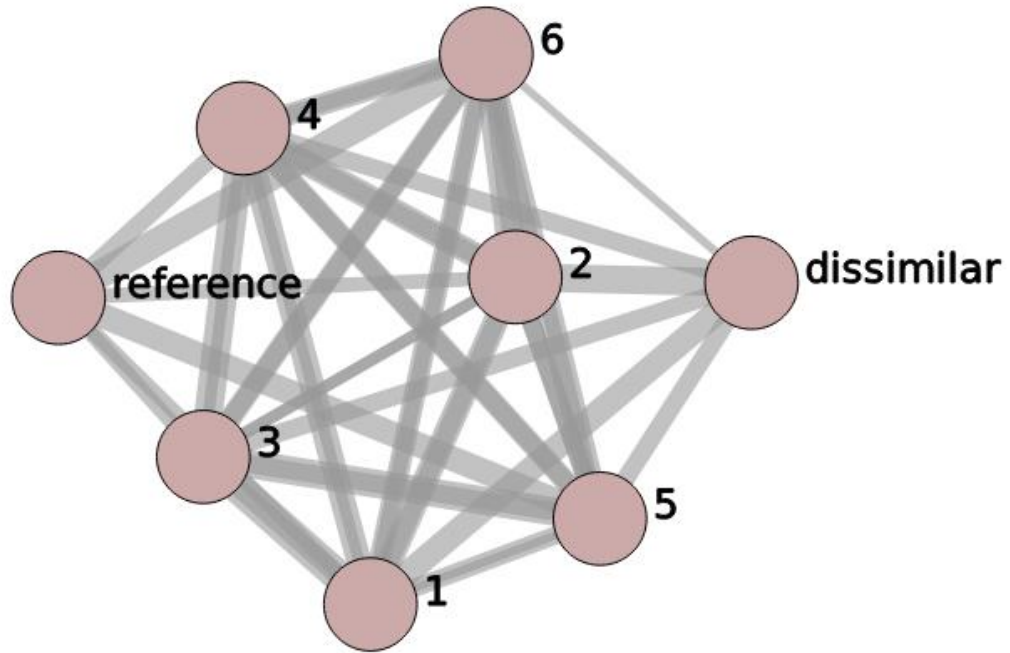




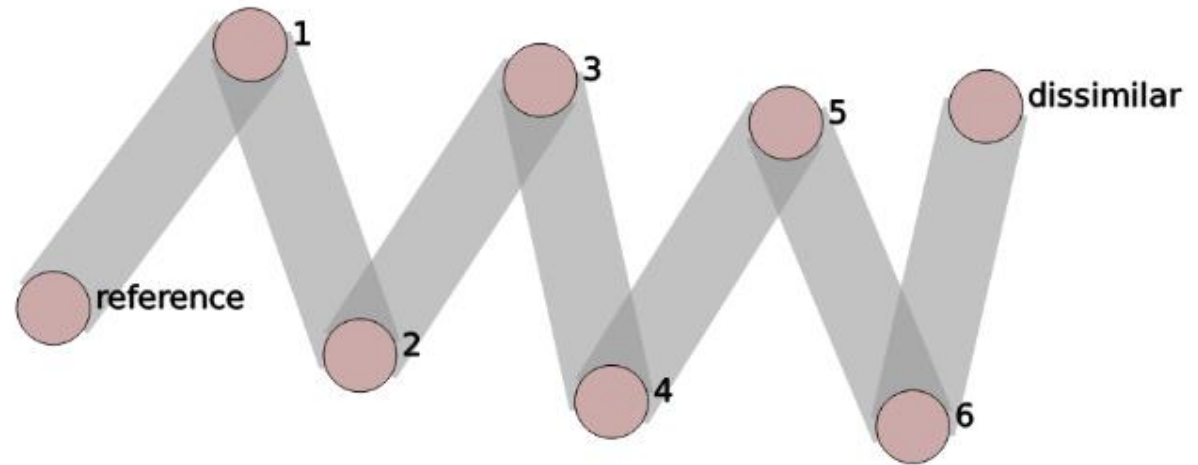
# Computational Graphs

*Graphs that can be directly simulated and used for comparison purposes*

Two examples shown below, other processes and models possible.  
But a useful example of one pair of generative endpoints.



Uniform random sorting

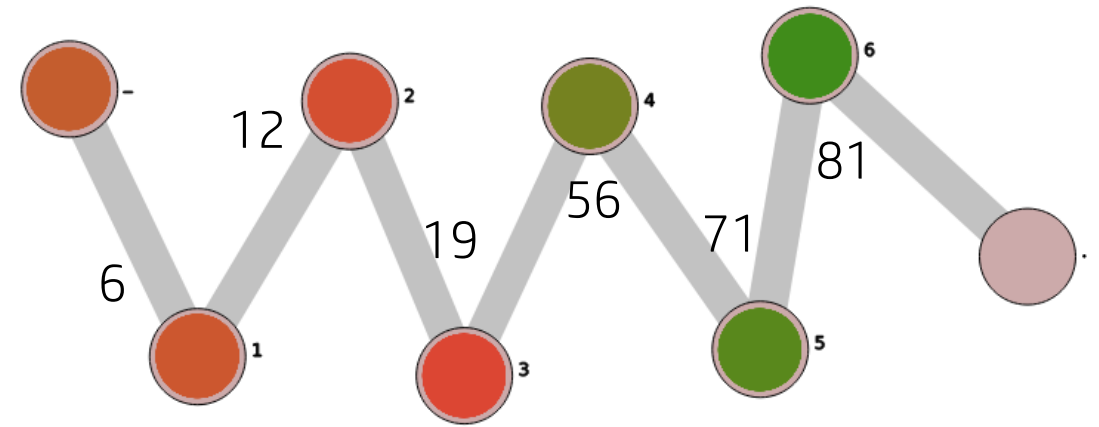
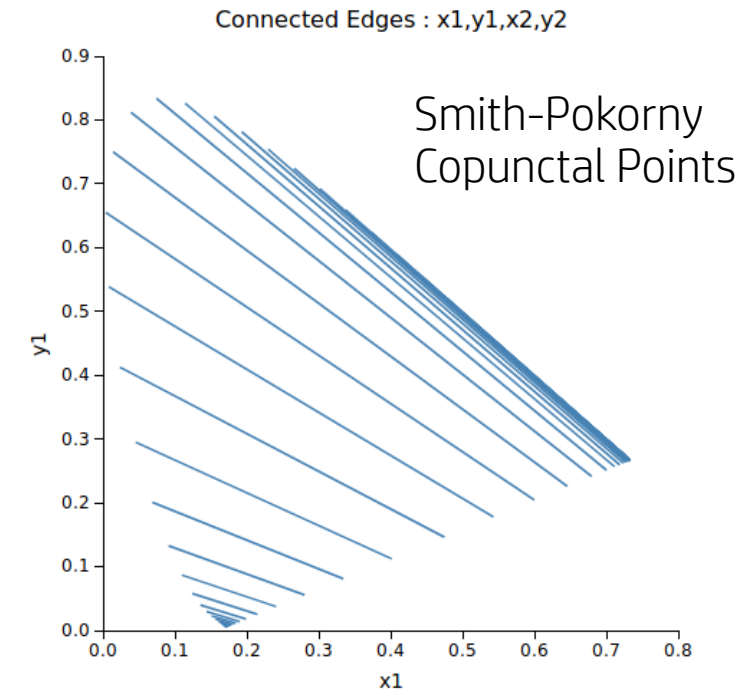


Perfect order sorting

# Test Sequence One: Deuteranopic Confusion Colors

*Ramp of equal luminance solid colors from a reddish to a greenish color*

- 70% of 150+ participants provided a sort in perfect agreement based on  $\Delta E^*_{ab}$  assuming sRGB as display, shown at bottom right
- 23% of participants had only within-color term disagreements (i.e. only oranges out of order or only greens)
- 7% of participants have cross-color term disagreement (i.e. mixing oranges & greens)
- The above 7% can be deuteranopic or 'adversarial' (I've estimated ~4% adversarial rates for past experiments)

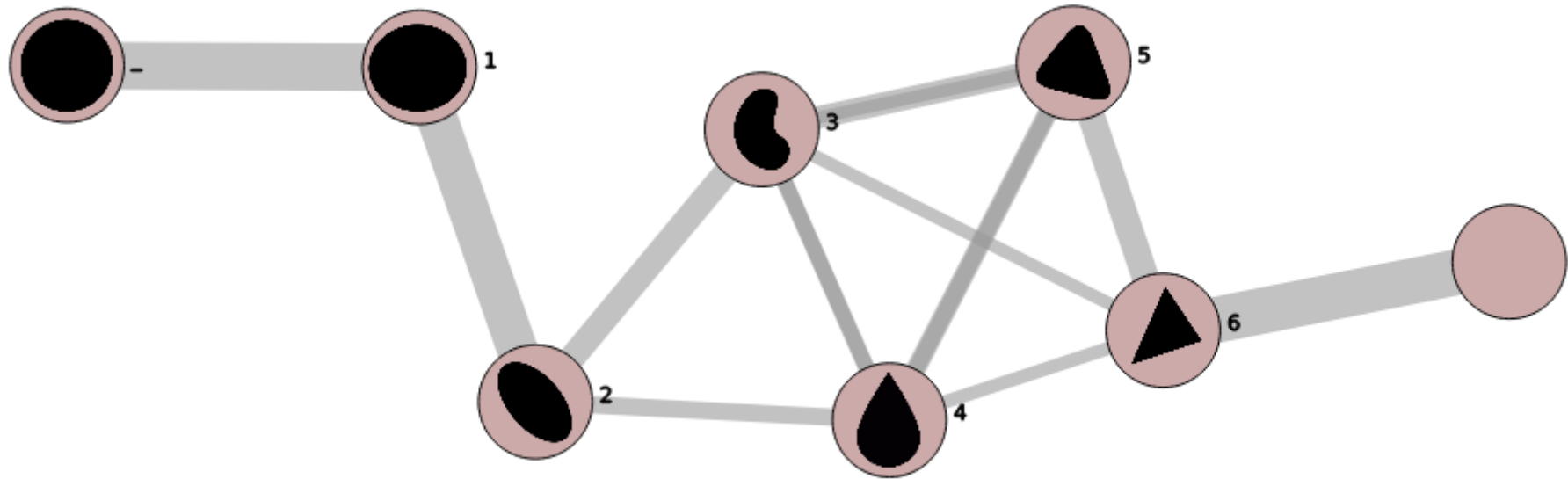


Larger numbers above are  $\Delta E^*_{ab}$  w.r.t. the reference.

# Test Sequence Two: Simple Shape Sequence

*Ramp of solid black shapes from circular to triangular*

This test (and the previous) are useful for assessing instructional clarity and/or identifying adversarial participants



# Rank Aggregation

*Schulze voting method or widest path*

number of voters	order of preference
5	ACBED
5	ADECB
8	BEDAC
3	CABED
7	CAEBD
2	CBADE
7	DCEBA
8	EBADC

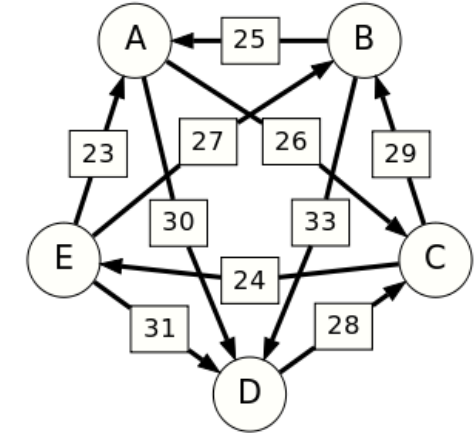
45 voters provide rank preferences for 5 candidates



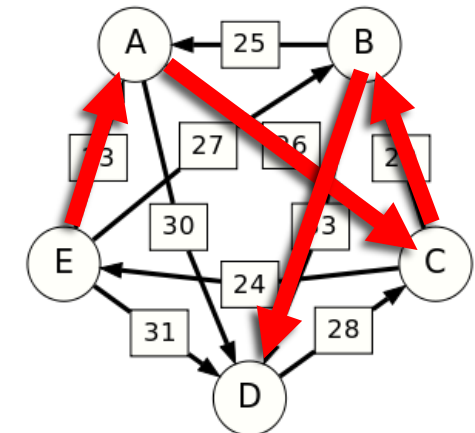
Matrix of pairwise preferences					
	$d[*, A]$	$d[*, B]$	$d[*, C]$	$d[*, D]$	$d[*, E]$
$d[A, *]$		20	26	30	22
$d[B, *]$	25		16	33	18
$d[C, *]$	19	29		17	24
$d[D, *]$	15	12	28		14
$d[E, *]$	23	27	21	31	



Directed preference graph



Variant of Floyd–Warshall algorithm



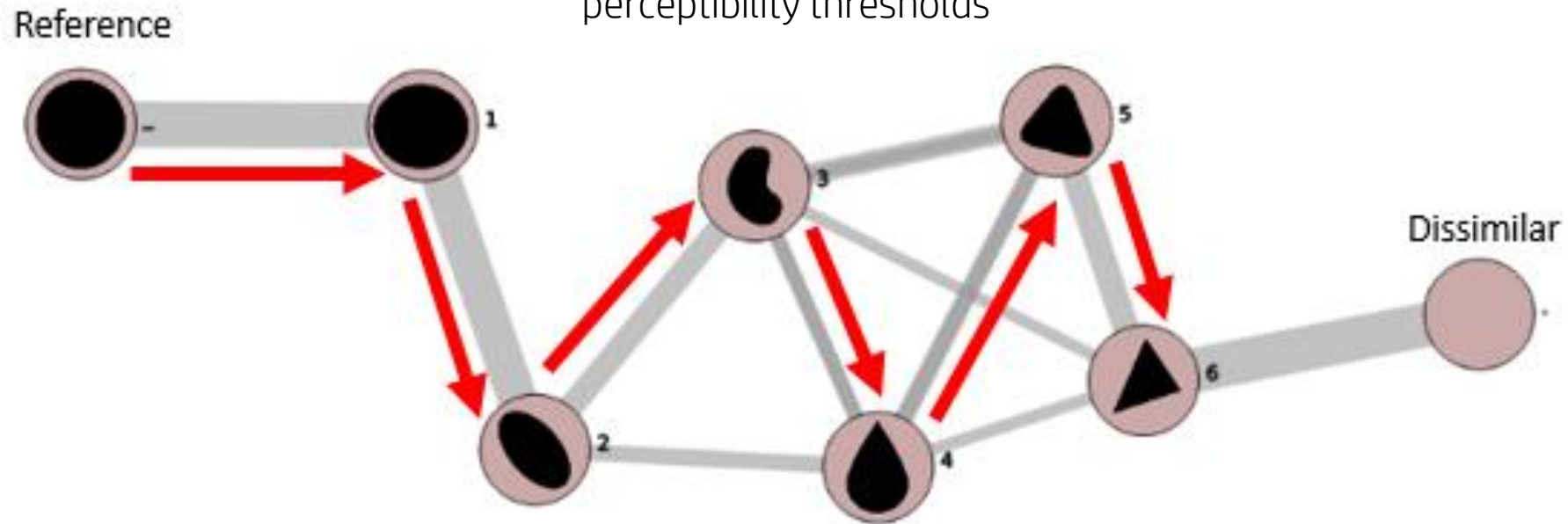
Aggregated rank or widest path is shown as red sequence

Graphics on this slide are from  
[https://en.wikipedia.org/wiki/Schulze\\_method](https://en.wikipedia.org/wiki/Schulze_method)

# Test Sequence Two: Simple Shapes Widest Path

*Circle, ellipse, bean, tear drop, rounded triangle and finally triangle*

Variations here are likely due to multiple cognitive sorting criteria, and not approaching perceptibility thresholds

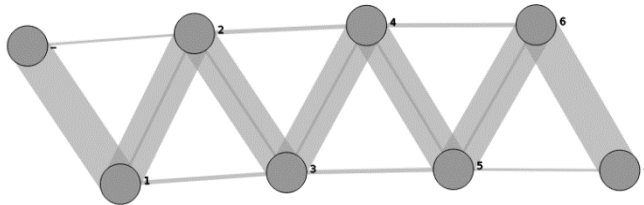
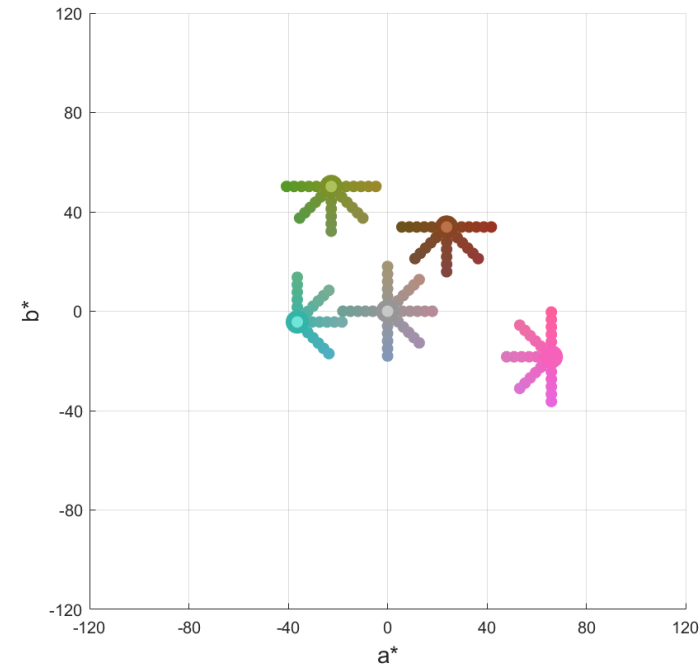


The inverse ordering of this path (the “wrongest path”) is of interest as a possible method for outlier detection.

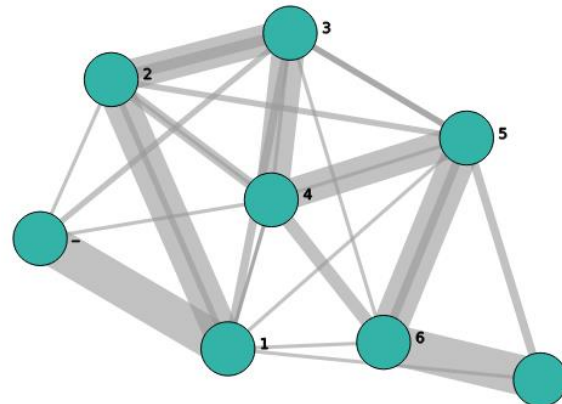
# Solid Color Sorting

*Sorting is easy enough, repetitions are feasible*

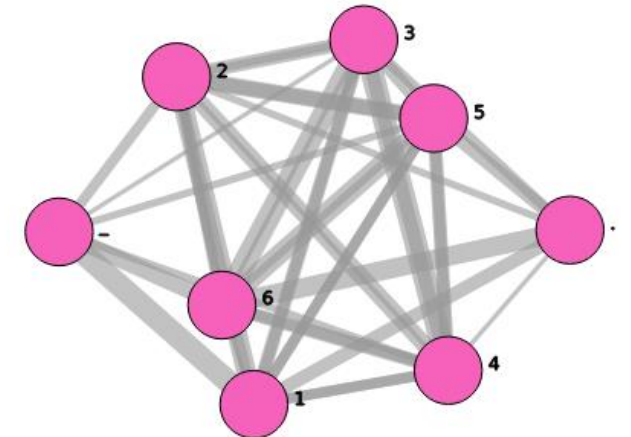
- Five nominal centroids : olive, brown, pink, teal and gray
- 25 different directions (in sRGB gamut)
- Four  $\Delta E^*_{ab}$  step sizes : 3, 2, and 1
- Use sRGB display in dark surround, four observers
- Reference is centroid
- Rank sequence is relative to stimulus set that is monotonic with color difference



$1 \Delta E^*_{ab}$  : all grays, all trials



$1 \Delta E^*_{ab}$  : all teals, all trials



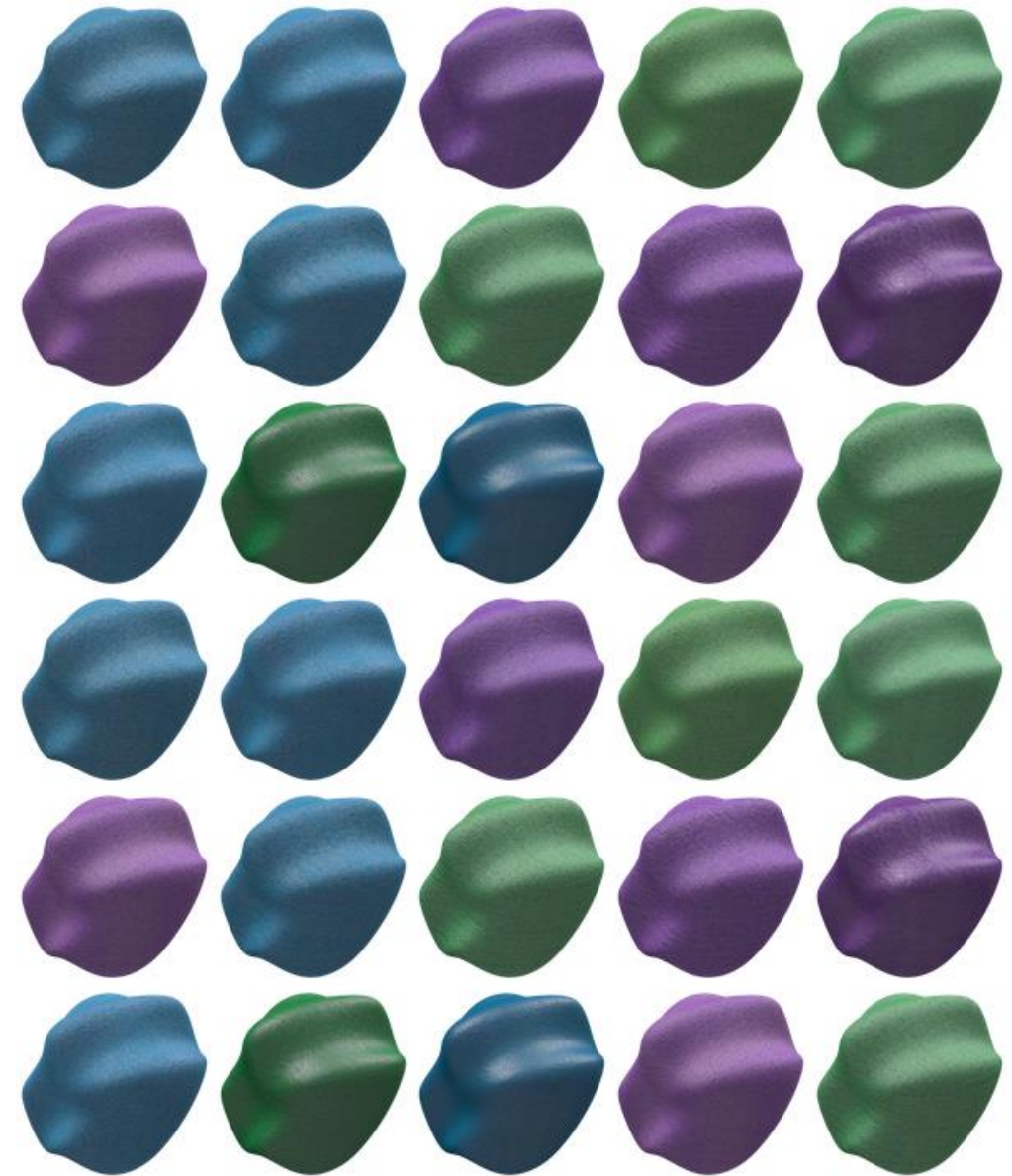
$1 \Delta E^*_{ab}$  : all pinks, all trials



# Sorting Complex Appearance

*Add subtitle*

- HP MultiJetFusion or MJF 3D printed tiles were scanned using an X-Rite TAC 7
- Resulting AxF<sup>tm</sup> or Appearance Exchange Format data post-processed to magnify or diminish one or more rendering parameters
- Qualitatively the diffuse color, gloss, roughness and graininess
- Generate 30 sequences that have bivariate or two parameter variations in the rendering
- Randomly select 6 sequences for each observer as an all volunteer web-based experiment



Blob object via the X-Rite Pantora<sup>TM</sup> software with acknowledgements to Prof. Roland W. Fleming's design

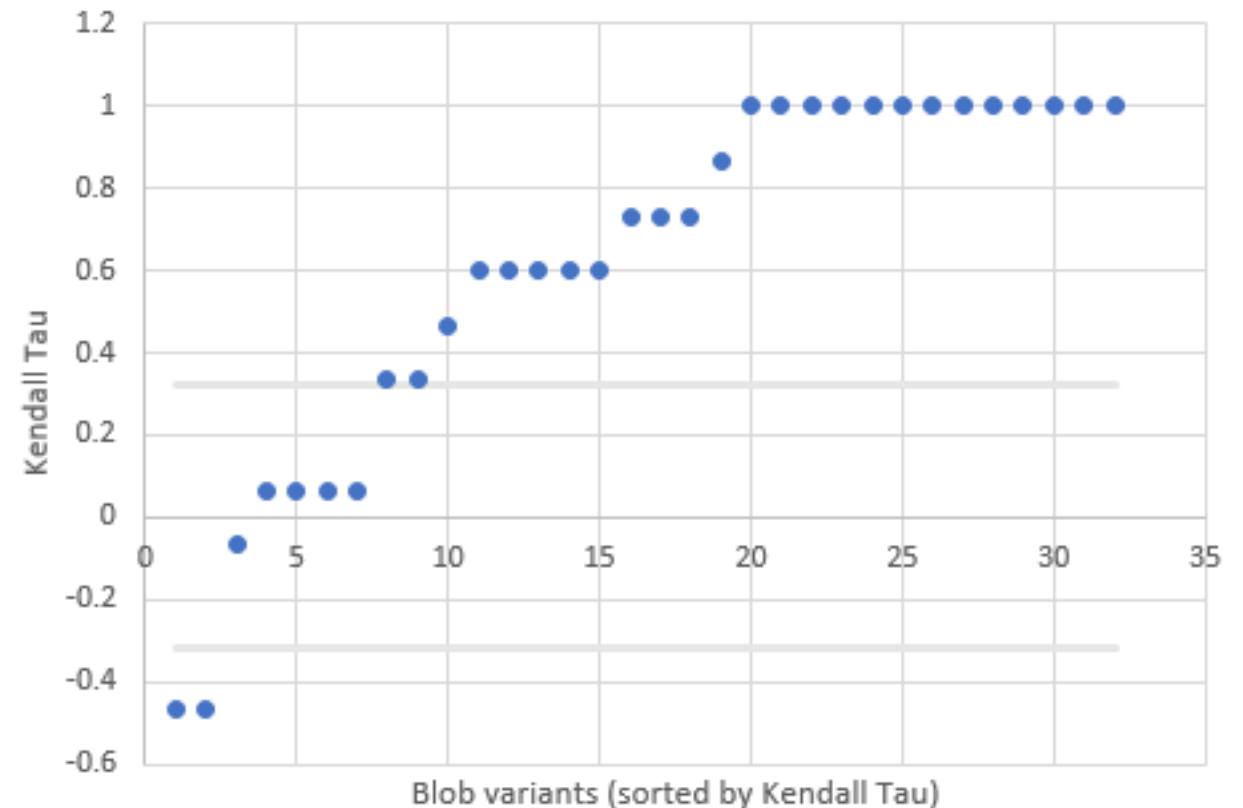


# Evaluating Models

*How good is simply using  $\Delta E^*_{ab}$ ?*

- Use variant a of Kendall's Tau or  $T_a$  to compare aggregated observer ranks versus the rank order as predicted by average pixel  $\Delta E^*_{ab}$ 
  - Simple baseline model for future comparisons
- Sort the sequences by  $T_a$  and plot the resulting ordered trails
- The gray bars are the plus/minus 1 standard deviation for a “random ranker”
- Roughly 2/3rds have  $T_a$  value of  $> 0.6$

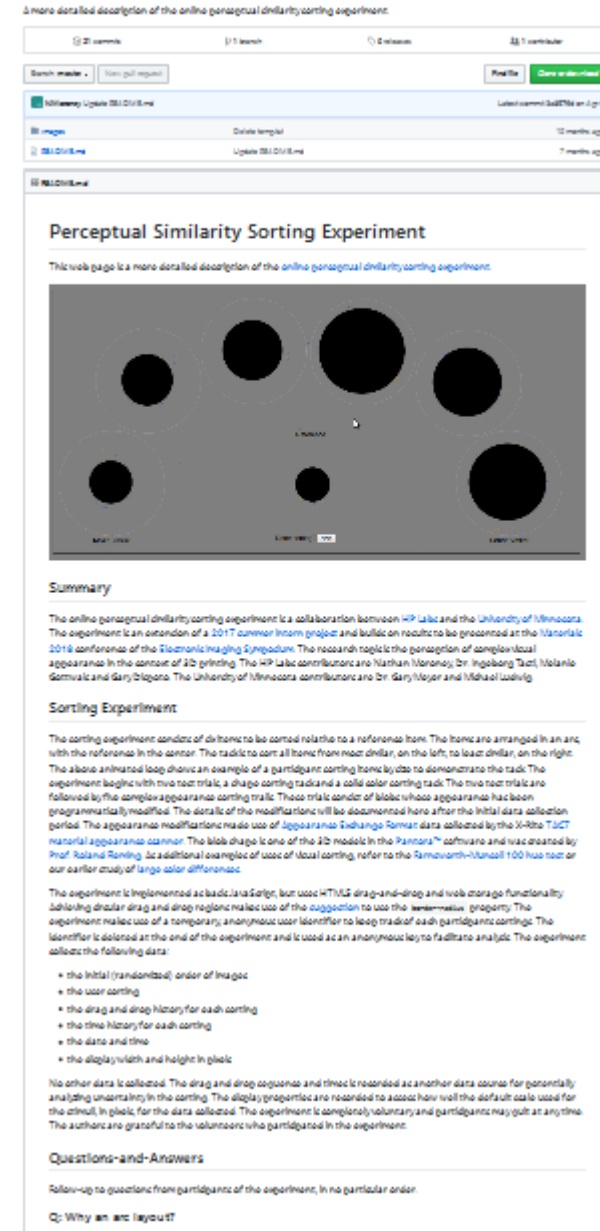
Blob Apperance: Mean  $\Delta E^*_{ab}$  vs Kendall Tau



# Future Directions

*Obligatory plug for a related web site*

- Graph-based similarity analysis; kernels and classification
- Using the rank data directly, in fact this is something Michael has done
  - Ludwig, Michael, et al. "An appearance uniformity metric for 3D printing." *Proceedings of the 15th ACM Symposium on Applied Perception*. ACM, 2018.
- A focused investigation of color differences at the extremes of large gamut displays
- For JND situations, implement a “logistic” ranker for comparison purposes
- Revisit our large color difference experimental sorting data from CIC22
- All data is accessible on public github page
  - <https://github.com/NMoroney/SimilaritySorting>



# Summary

*Now would be a good time to think of a question or two*

- Sorting stimuli with respect to a single anchor can be represented as an oriented weighted directed graph
- Rank aggregation can be performed using the Schulze voting method or the widest-path graph algorithm
- Model ranks can be compared to aggregated ranks using Kendall's Tau a or  $T_a$
- Graph visualizations can be used to supplement dissimilarity matrices and tabular data
- Ranking can also be simulated, i.e. random or perfect
- $\Delta E^*_{ab}$  of 1 ranges from nearly perfect sorting for grays to nearly random sorting for pinks
- Average pixel  $\Delta E^*_{ab}$  provides a baseline prediction of MJF 3D print appearance with  $2/3^{\text{rds}} T_a \geq 0.6$
- Thanks!





keep reinventing