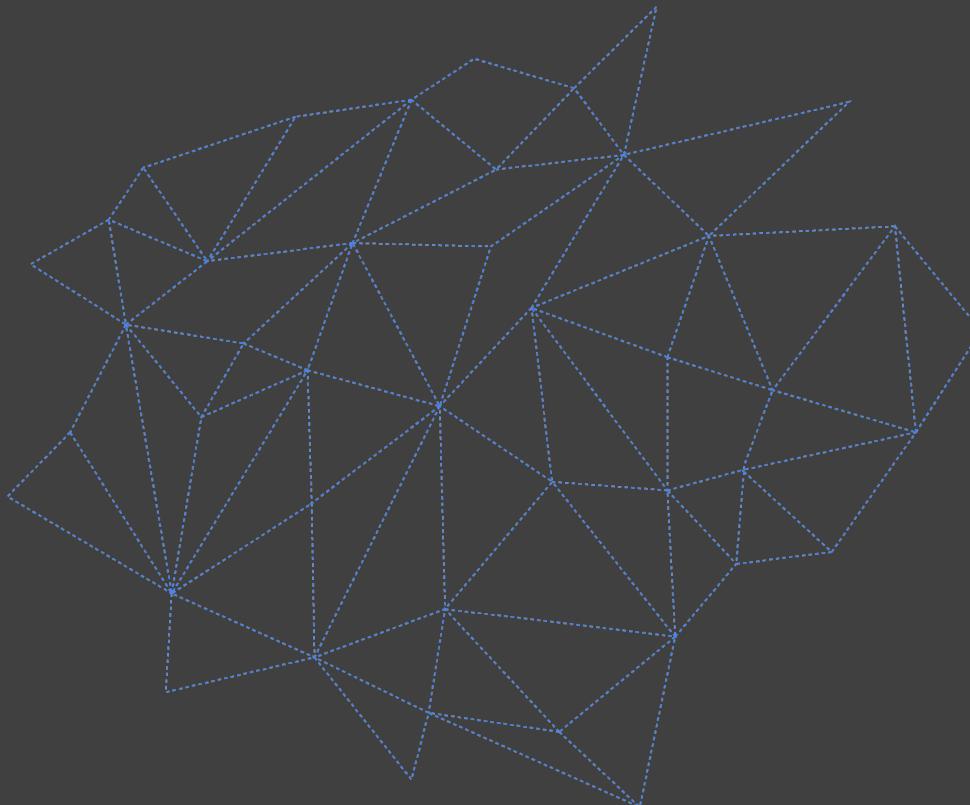


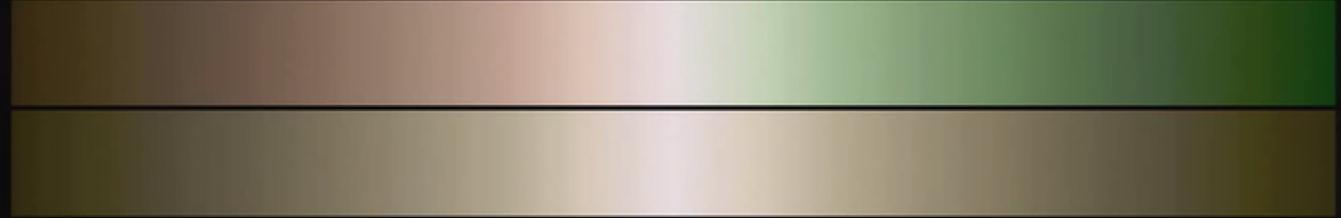
Effective Visualization (Color) Design



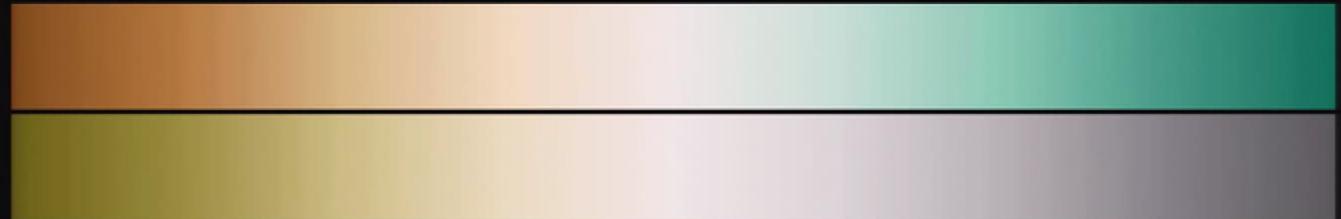
Connor Gramazio
[@ccgramazio](https://twitter.com/ccgramazio)
OVC 2017



confusing palette



color blind safe palette



<https://youtu.be/DjJr8D4Bxjw>

Aim: increase accessibility of theory → practice



Aim: increase accessibility of theory → practice *via application*

(for color)



d3-jnd
gramaz.io/d3-jnd

colorgorical
gramaz.io/colorgorical

d3-cam02
gramaz.io/d3-cam02



d3-jnd
gramaz.io/d3-jnd

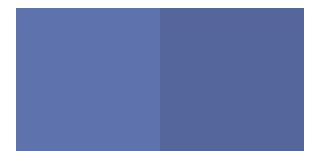


colorgorical
gramaz.io/colorgorical

d3-cam02
gramaz.io/d3-cam02

What does it mean for
visualization design
to be “effective”?

Color Discriminability



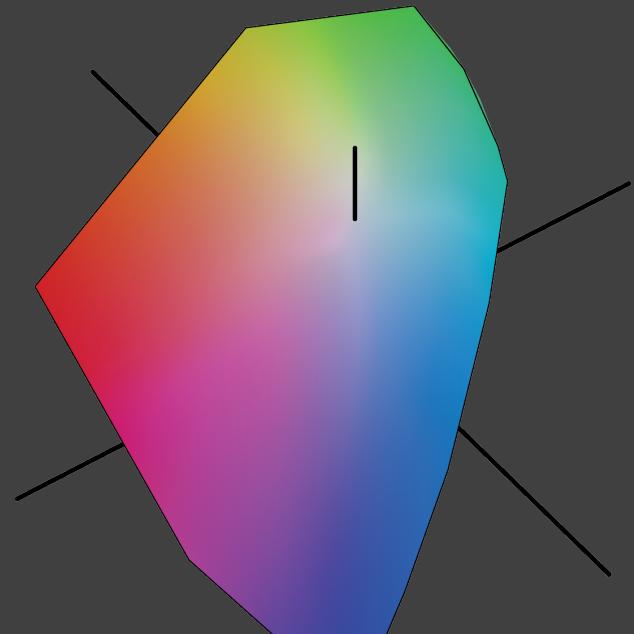
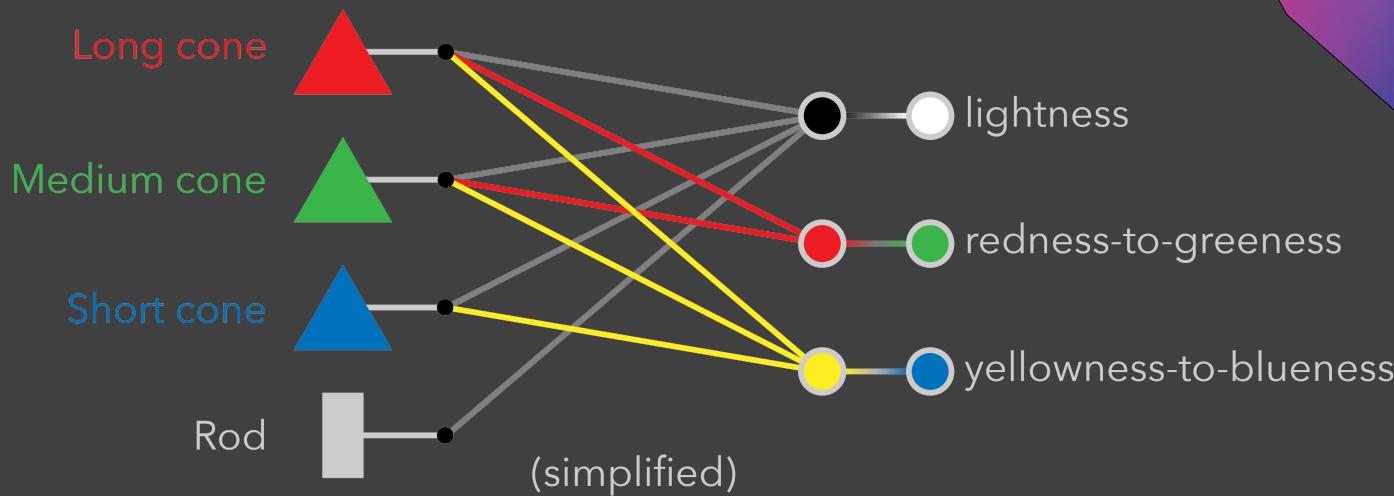
CIELAB perceptual color space

L^* : lightness

a^* : redness-to-greenness

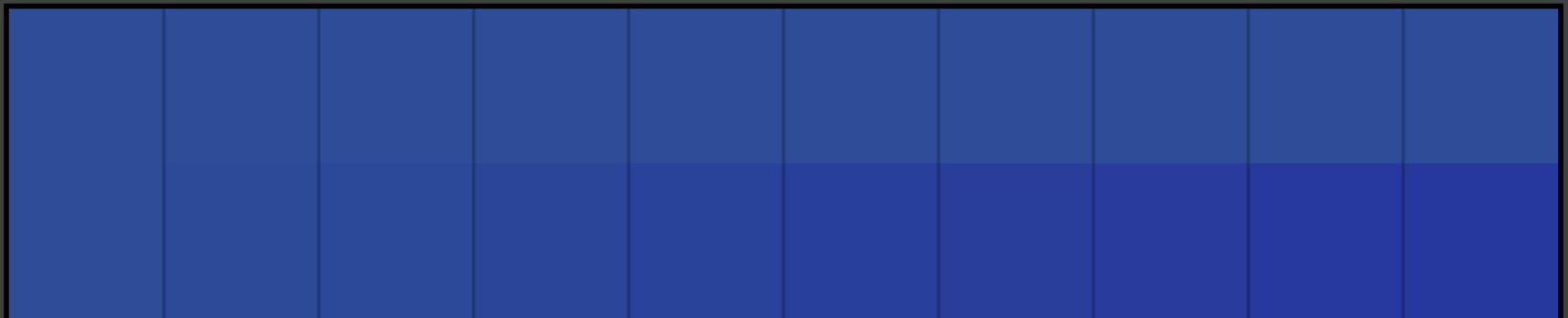
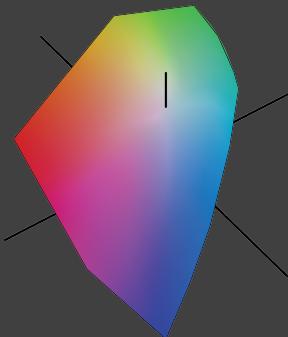
b^* : yellowness-to-blueness

Approximates opponent color processing

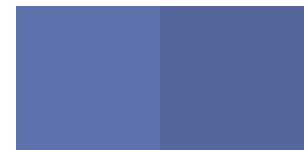


JND: Just Noticeable Difference

Minimum differentiable color distance
→ Many ways (+ papers) to define color JNDs



Color Discriminability: Distance in CIELAB



-

-

-

-

Color Discriminability: Distance in CIELAB + size



-

-

-

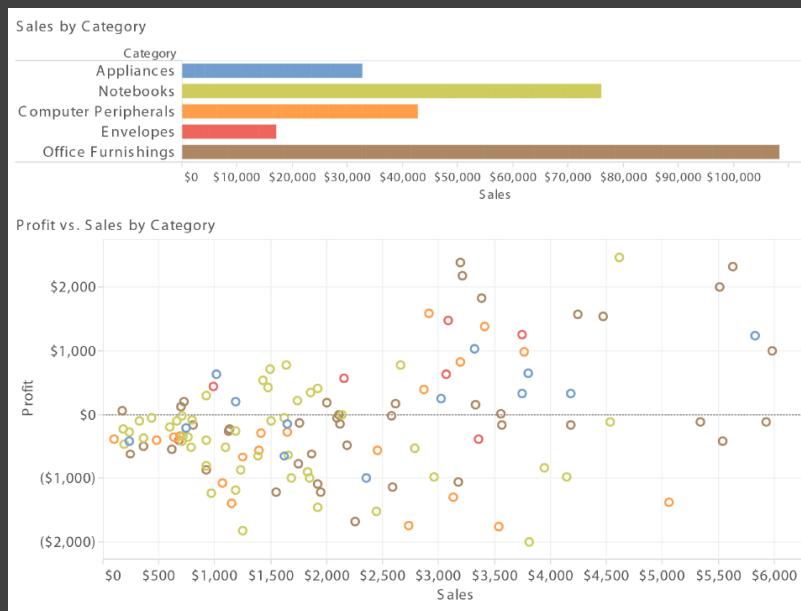
-

JNDs differ with size

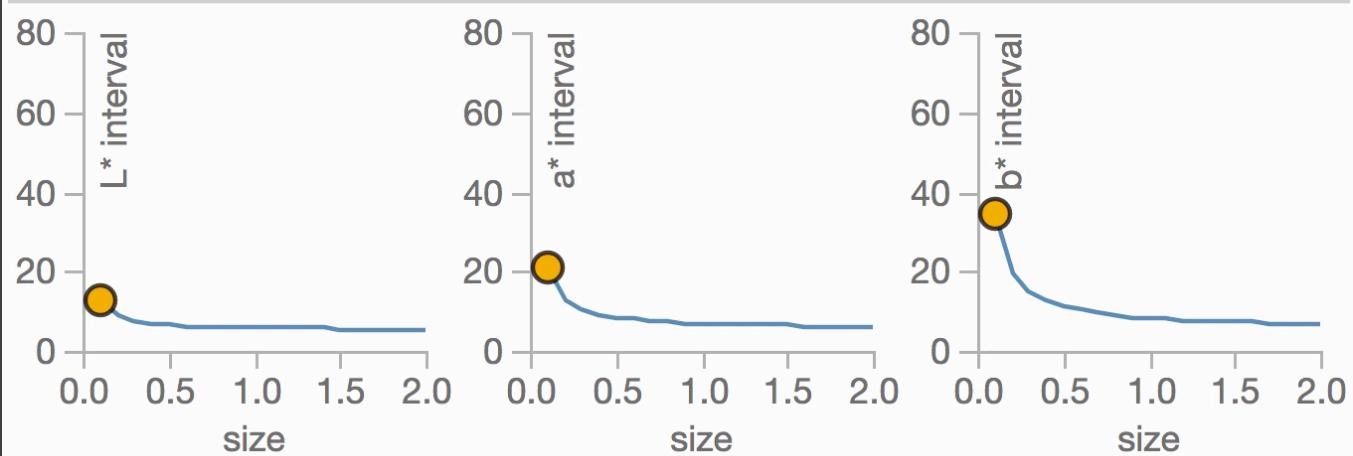
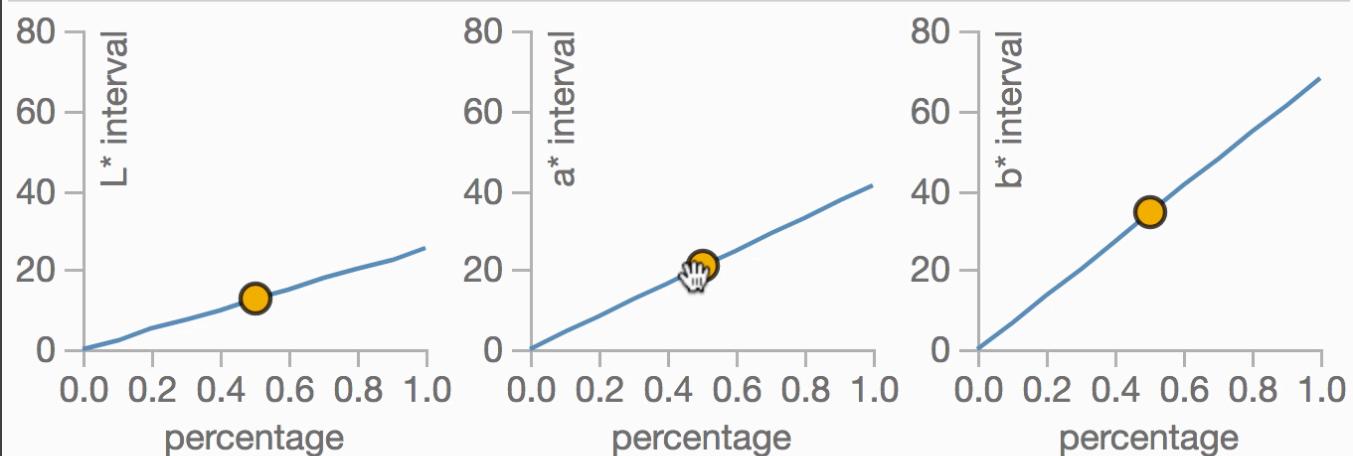
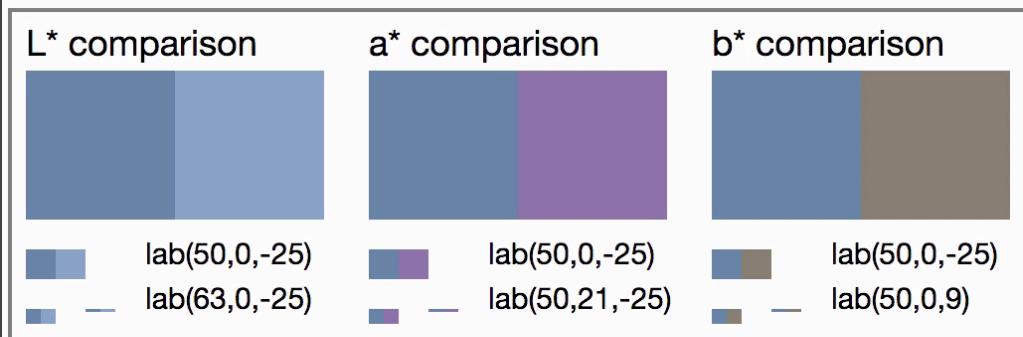
Stone, Albers Szafir, Setlur formalize relation in CIELAB

"An Engineering Model for Color Difference as a Function of Size"
Stone, Albers Szafir, Setlur. 2014. Link @ <https://gramaz.io/d3-jnd>

$$ND(\%, \text{size}) = \{ \Delta L^*, \Delta a^*, \Delta b^* \}$$



Arg: Percent	Arg: Size	ΔL^*	Δa^*	Δb^*
0.5	0.1	12.58	20.74	34.05



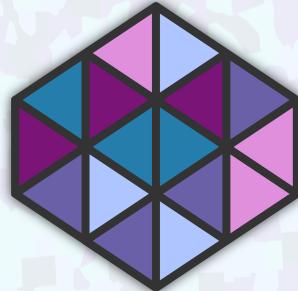
Apply JNDs+size in design?

1. Consider color-encoded area size in the graphic
2. How cautious do you need to be?
(infographic vs. emergency response management)

```
d3.noticeablyDifferent(c1, c2[, percent, size]);
```

```
d3.jndInterval(percent, size); // { l, a, b }
```

d3-jnd
gramaz.io/d3-jnd



colorgorical
gramaz.io/colorgorical

Joint work with
David Laidlaw
Karen Schloss

IEEE VIS 2016

d3-cam02
gramaz.io/d3-cam02

discriminability

What do you do when you
need to make your own
categorical palette?

aesthetic preference

discriminability

Colorgorical
applies color science
to reduce design
boundaries

aesthetic preference

Colorgorical Roadmap

Background

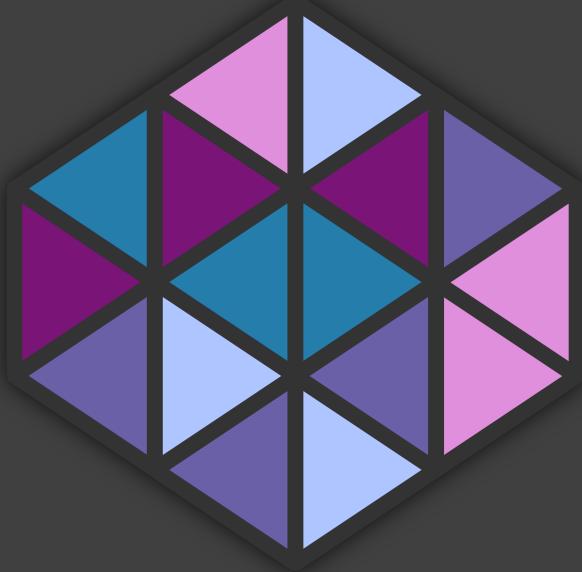
Colorgorical technique

Experiment 1: Does Colorgorical work?

Experiment 2: Colorgorical vs. standards

Colorgorical

Example



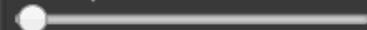
Generate

Number of colors

3

Score importance

Perceptual Distance



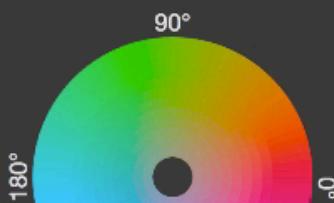
Name Difference



Pair Preference



Select hue filters



Instructions

To generate a palette with n colors, just enter the number of colors you want and click **Generate**. Bigger palettes will take longer than smaller palettes to make. Results will automatically appear when ready.

For greater detail, please consult our [paper](#) or the [source code](#).

Score Importance

Perceptual Distance

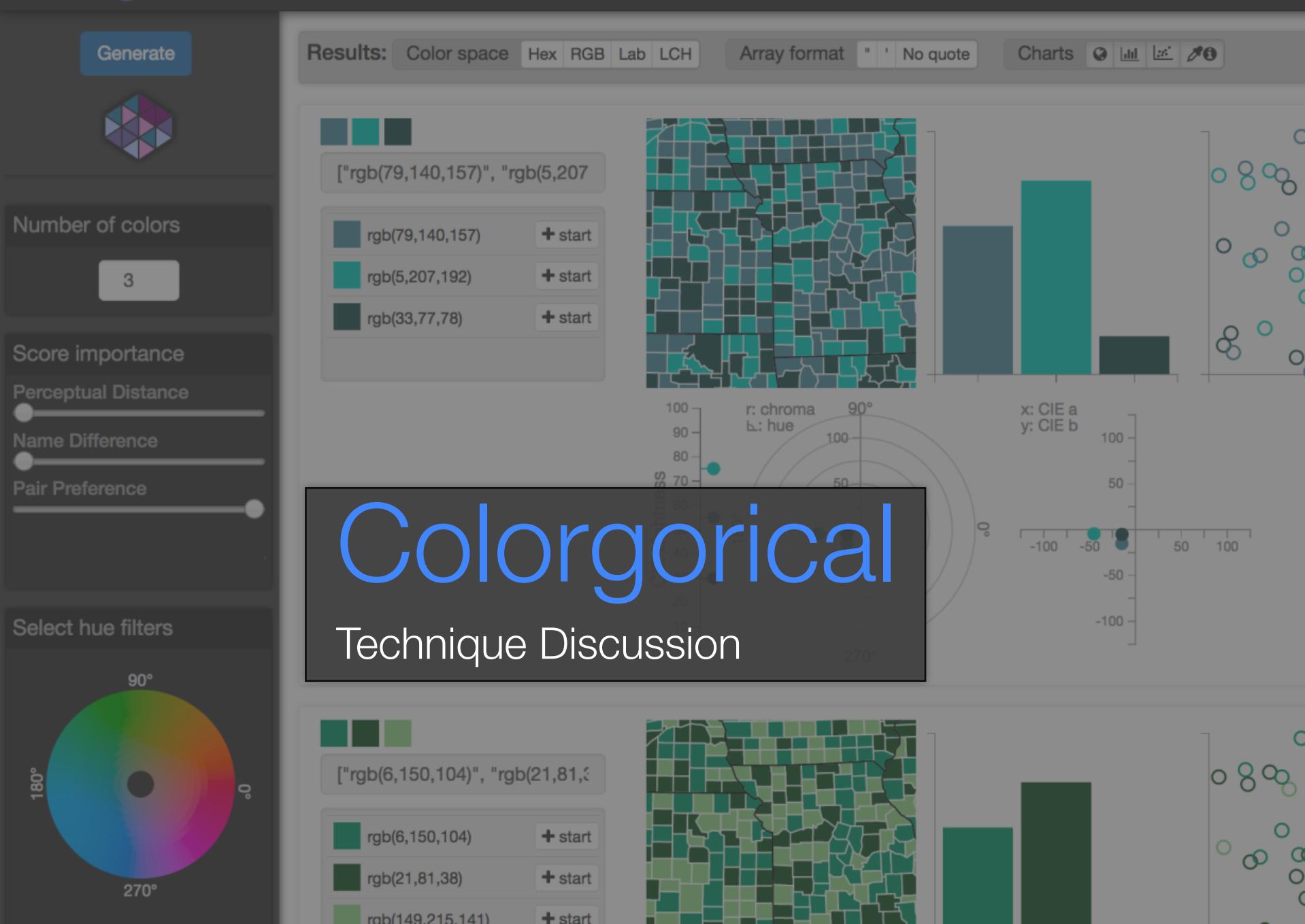
Increasing *Perceptual Distance* favors palette colors that are more easily discriminable to the human eye. To accurately model human color acuity, this is performed using [CIEDE2000](#) in [CIE Lab](#) color space.

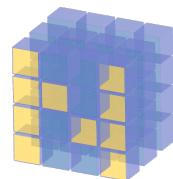
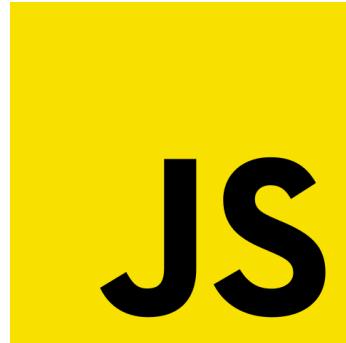
Name Difference

Increasing *Name Difference* favors palette colors that share few common names. This is similar to perceptual distance, but can lead to different results in certain areas of color space. This happens when there are many different names for perceptually close colors (e.g., red and pink are perceptually close but named differently). Colorgorical calculates this using Heer and Stone's [Name Difference function](#), which is built on top of the [XKCD color-name survey](#).

Pair Preference

Increasing *Pair Preference* favors palette colors that are, on average, predicted to be more aesthetically preferable together. Typically these colors are similar in hue, have different lightness, and are cooler colors (blues and greens). *Pair Preference* is based off of [Sullivan and Palmer's](#) [color preference study](#).





NumPy + C functions

Paper, Demo @ <https://gramaz.io/colorgorical>
Source @ <https://github.com/connorgr/colorgorical>

Input: User defined balance

Perceptual Distance

Name Difference

Pair Preference

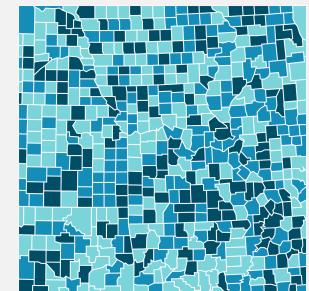
Number of colors



How are these defined?

Colorgorical

Output

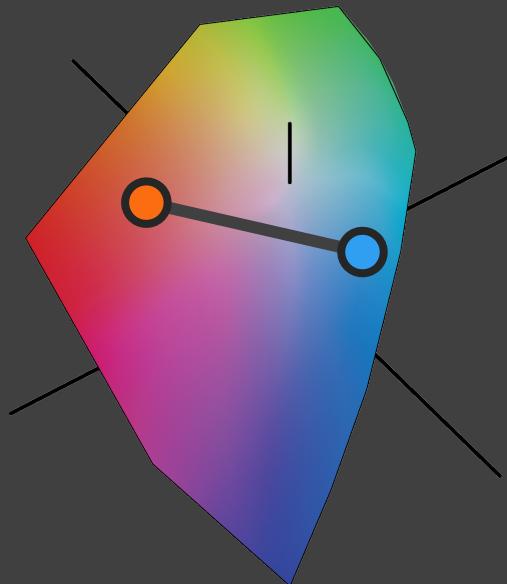


2 Measures of discriminability

Perceptual Distance

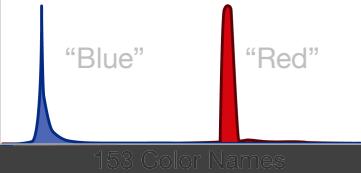


Name Difference



Association
Frequency

Large Color-Name Difference



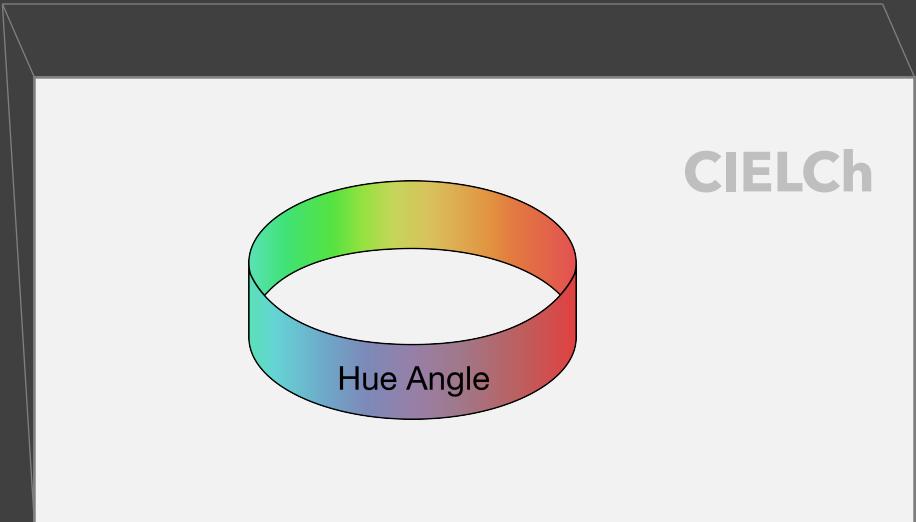
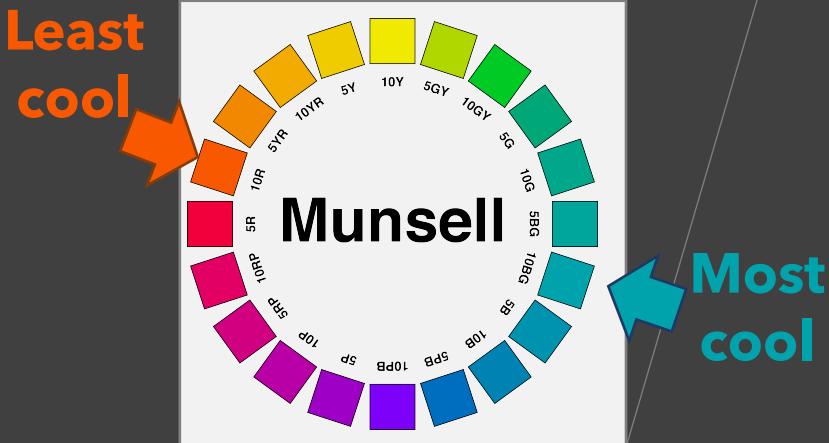
Small Color-Name Difference



Measure of aesthetic preference

Pair Preference

Preferable = "cool" colors with similar hues

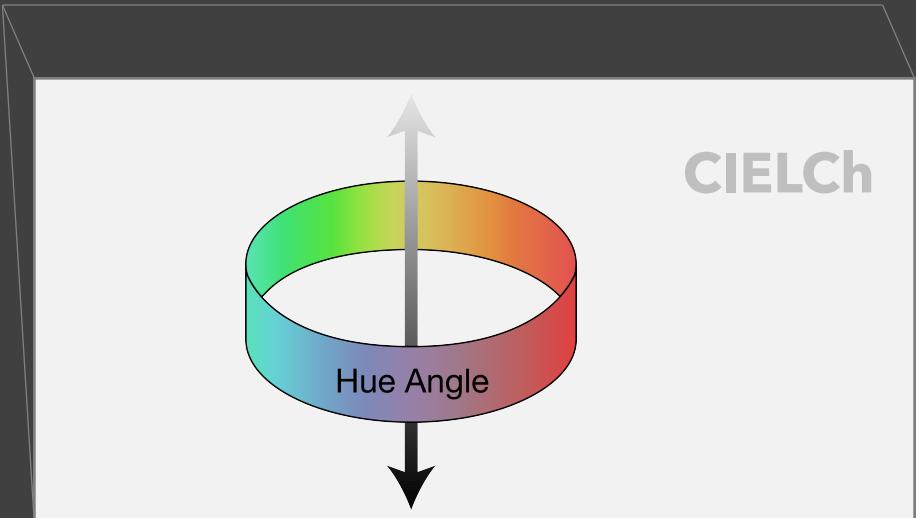
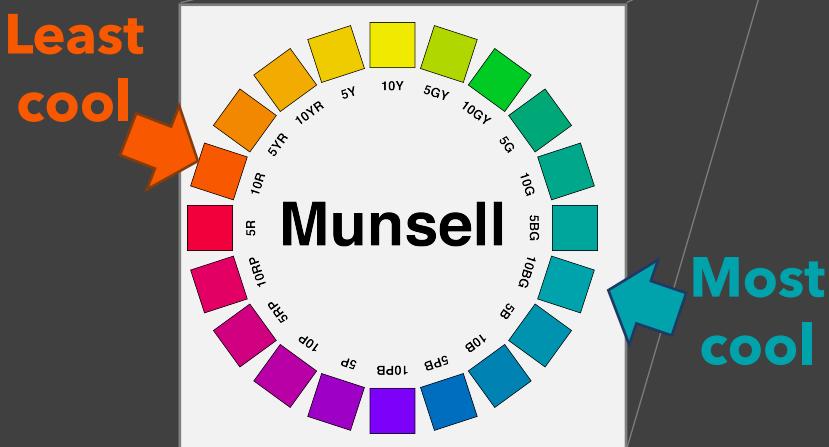


CIELCh

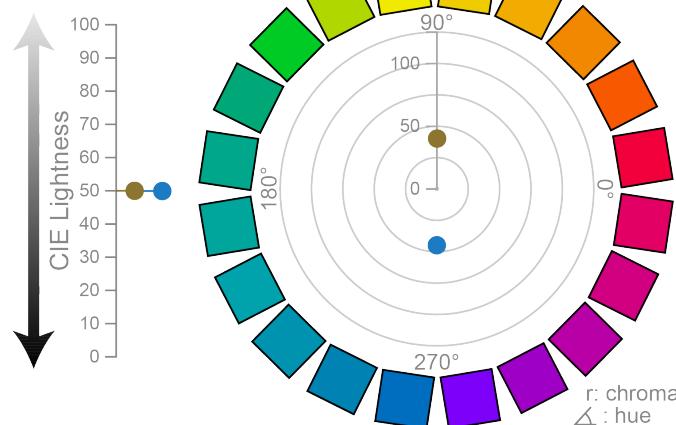
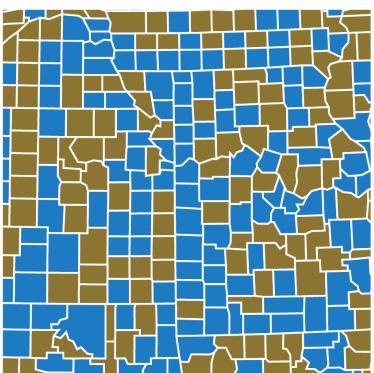
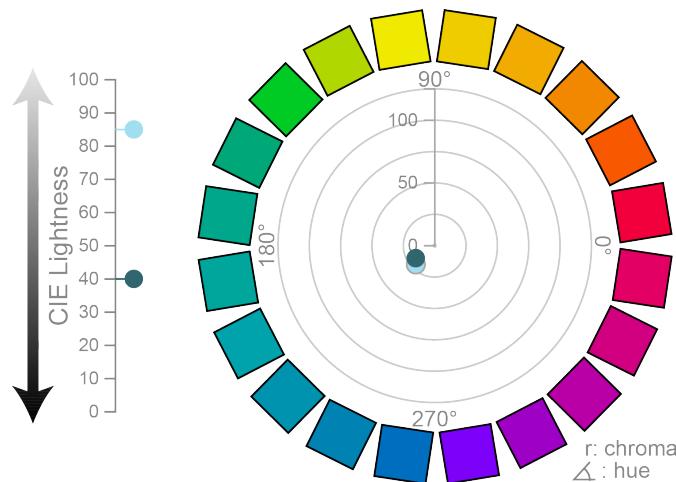
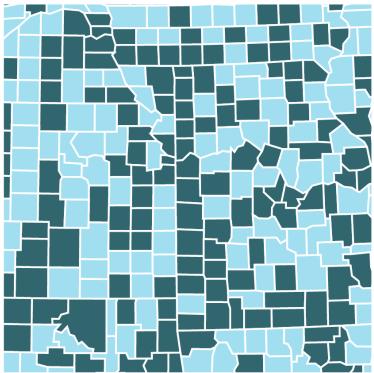
Measure of aesthetic preference

Pair Preference

Preferable = "cool" colors with similar hues and different lightness



Preferable = “cool” colors with similar hues and different lightness



Scoring colors with many slider changes: slider-weighted sum

User defined balance

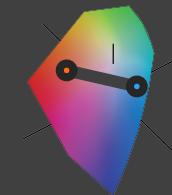
Perceptual Distance

Name Difference

Pair Preference

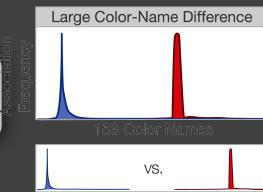
Slider: [0%, 100%]

Perceptual Distance



(c_1, c_2)

Name Difference



(c_1, c_2)

Pair Preference



(c_1, c_2)

+

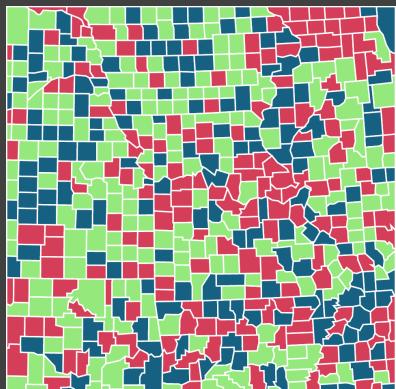
colorPairScore(c_1, c_2)

A palette is only as good as its worst pair.

Palette score: how would a new color c change palette P 's score?

$$\begin{aligned}\text{paletteScore}(c, P) \\ = \min(\text{colorPairScore}(c, p_i) \ \forall p_i \in P)\end{aligned}$$

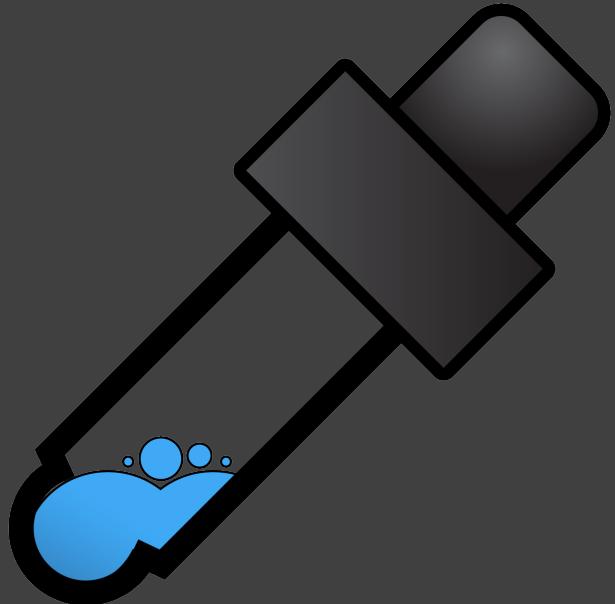
Discriminability



Aesthetic Preference



Colorgorical sampling procedure



Perceptual Distance

Name Difference

Pair Preference

Number of colors

Colorgorical

Preferable first color

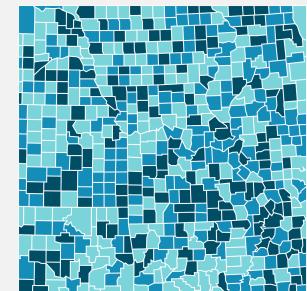


$i+1$ colors:



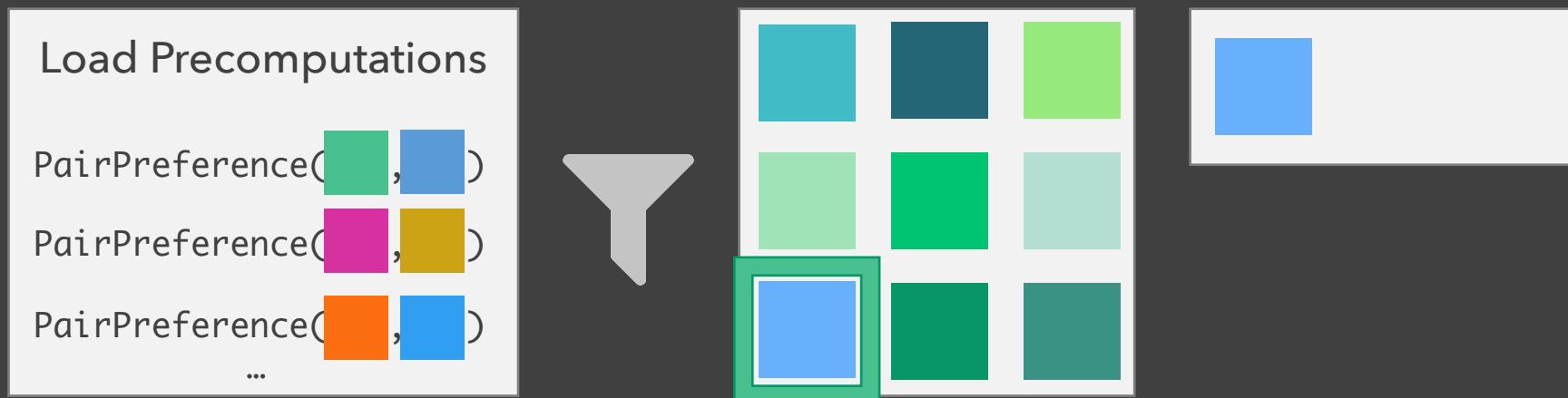
Colorgorical makes 10

↓
Return:
most
preferable



Step 1: Colorgorical chooses 1st color

Goal: choose a color that exists in highly preferable pairs



Step 2: Colorgorical chooses $i+1$ colors

User defined balance

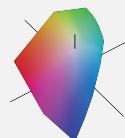
Perceptual Distance

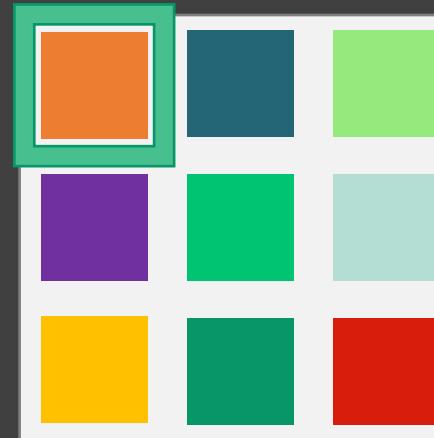
Name Difference

Pair Preference

paletteScore \forall
remaining CIELAB

paletteScore(c , 

$\forall c \in$ 



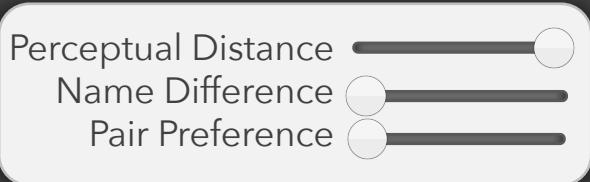
Repeat as
needed...

Experiment 1

How do Colorgorical settings map onto
human discriminability & preference?

Exp. 1: Settings → Human Judgement?

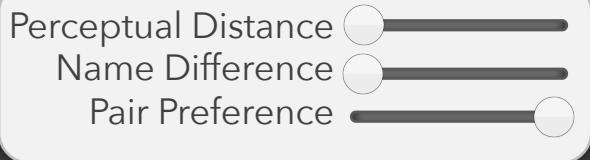
User defined balance



User Behavior

?

Low error



?

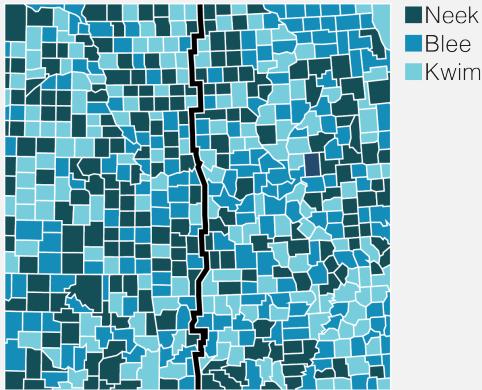
High preference ratings

Task: crowdsourced on MTurk

Discriminability

More "Neek": left or right?

Response: Error



Preference Rating

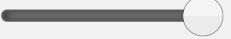
Is color combination preferable?

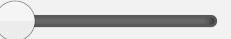
Response: Rating [-100,100]

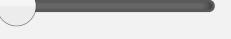


Exp. 1: Settings → Human Judgement?

User defined balance

Perceptual Distance 

Name Difference 

Pair Preference 



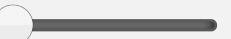
User Behavior

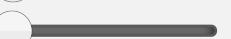
Low error

3-color: $\text{range}(r) = [0.697, 0.887]$

5-color: $\text{range}(r) = [0.898, 0.945]$

8-color: $\text{range}(r) = [0.731, 0.838]$

Perceptual Distance 

Name Difference 

Pair Preference 



High preference ratings

3-color: $\text{range}(r) = [0.897, 0.971]$

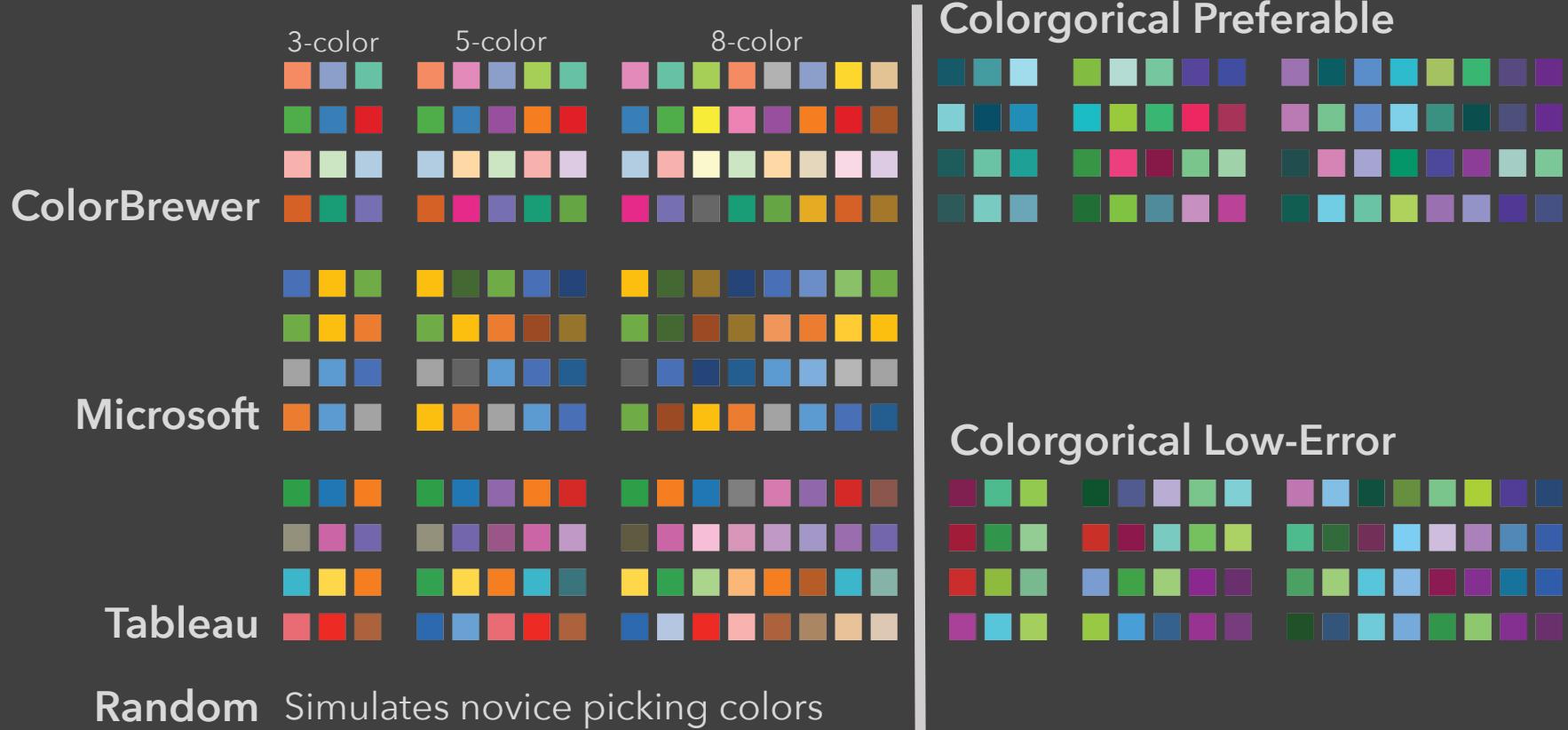
5-color: $\text{range}(r) = [0.412, 0.570]$

8-color: $\text{range}(r) = [0.751, 0.891]$

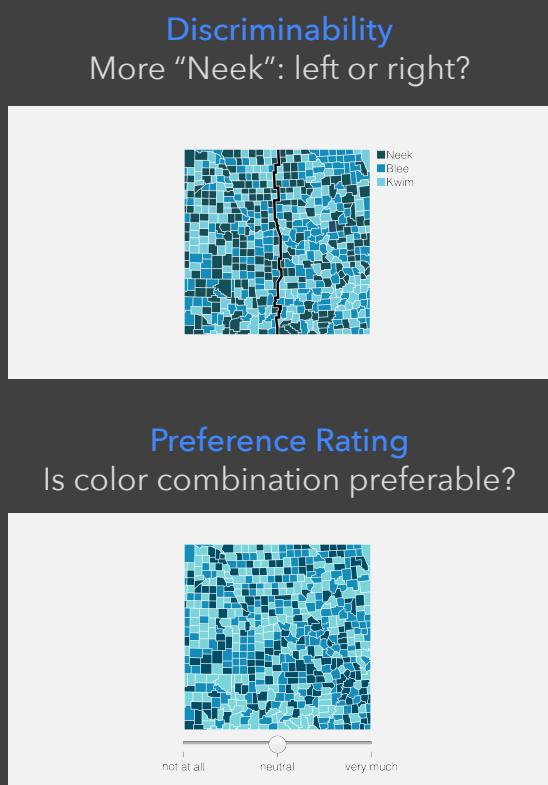
Experiment 2

How does Colorgorical compare to industry standards?

Industry Standard Comparisons



Exp. 2 Design: Same task as Exp. 1



N=20/size

3 palette sizes



3 5 8

6 palette sets

4 versions/set

4 repetitions (discriminability)

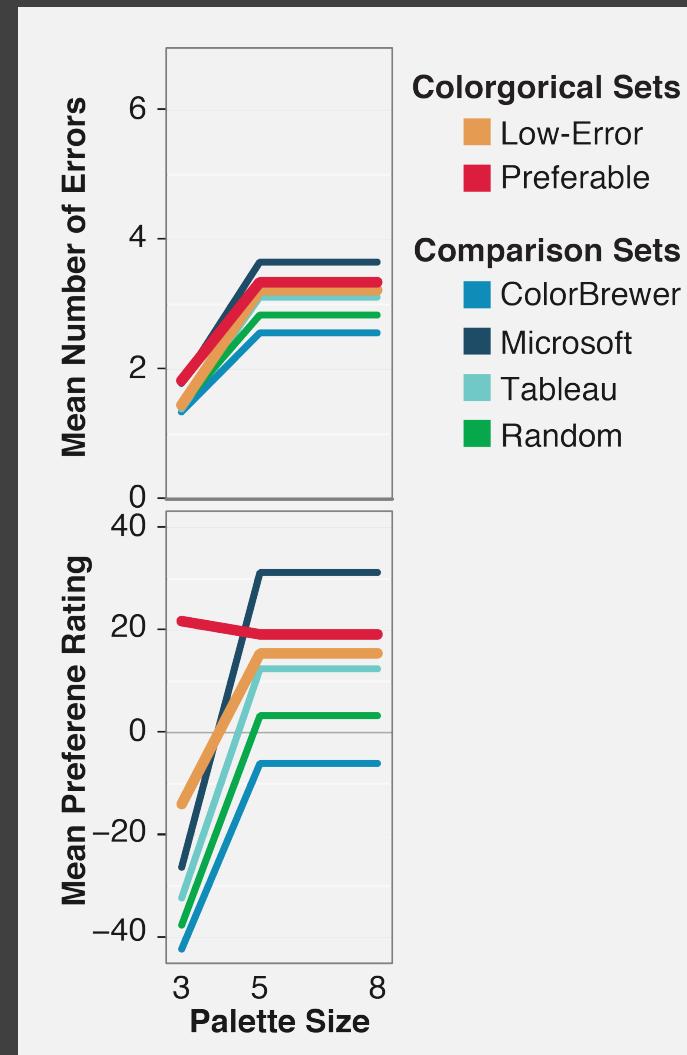
= 24 preference trials

= 96 discriminability trials

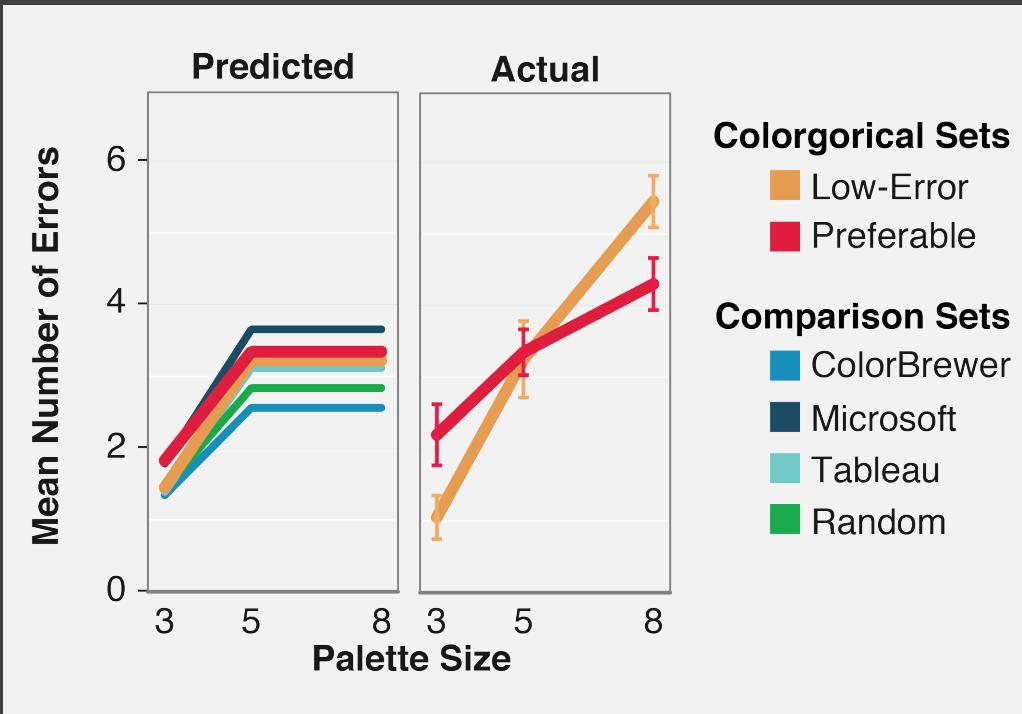
Experiment 2 Prediction

Based on linear regressions
trained with Exp. 1 data

Experiment 2 Colorgorical
palettes chosen anew



Discriminability error-rate: Colgorical

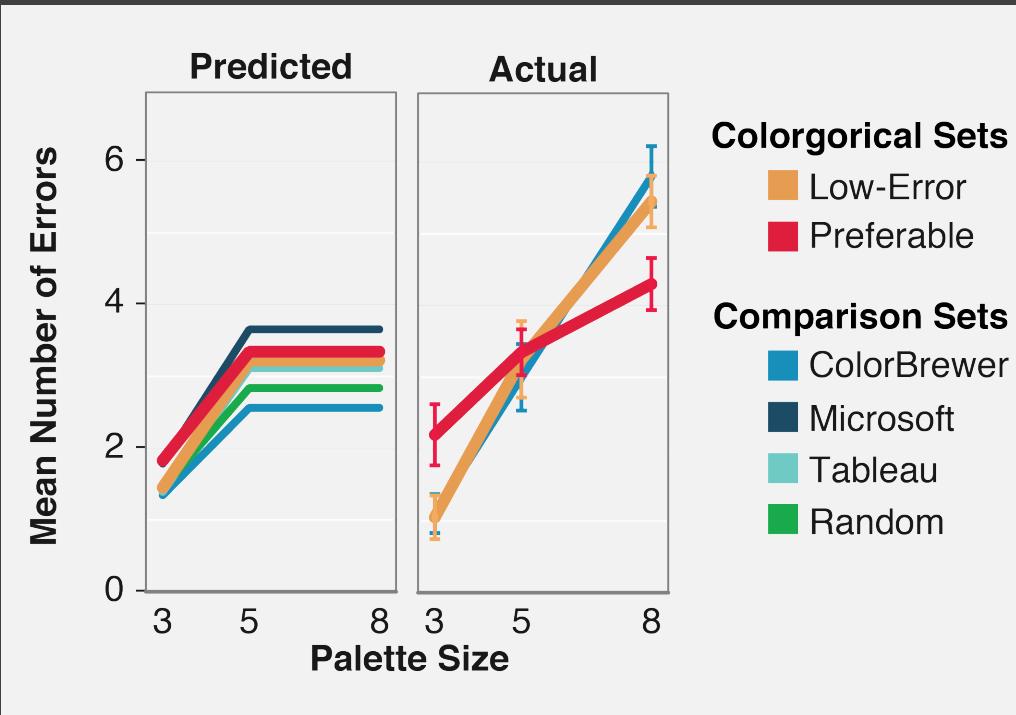


Prediction:
Colgorical is
comparably
discriminable

Error: # incorrect out
of 16

Bars: standard error

Discriminability error-rate

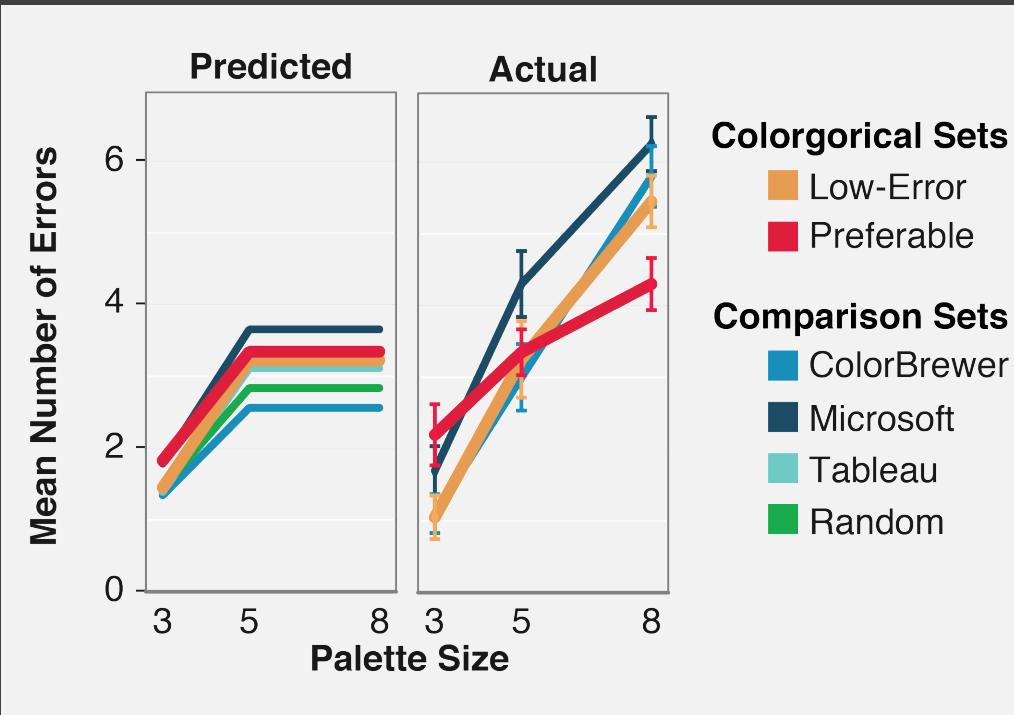


Prediction:
Colorogrical is
comparably discriminable

Error: # incorrect out of 16

Bars: standard error

Discriminability error-rate

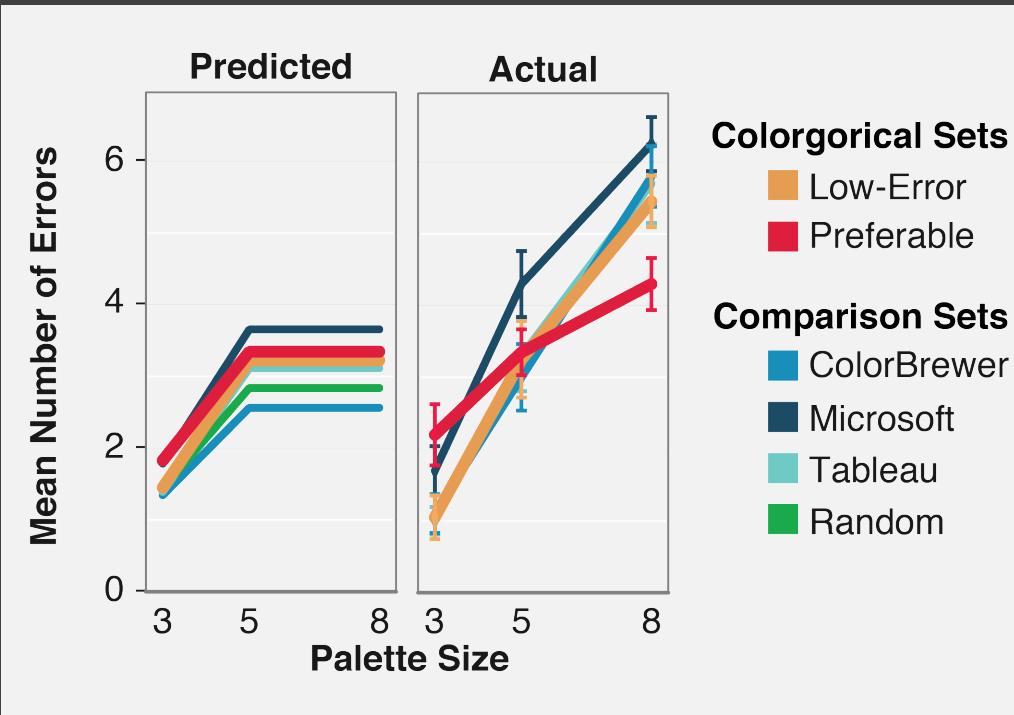


Prediction:
Colorgorical is
comparably discriminable

Error: # incorrect out of 16

Bars: standard error

Discriminability error-rate

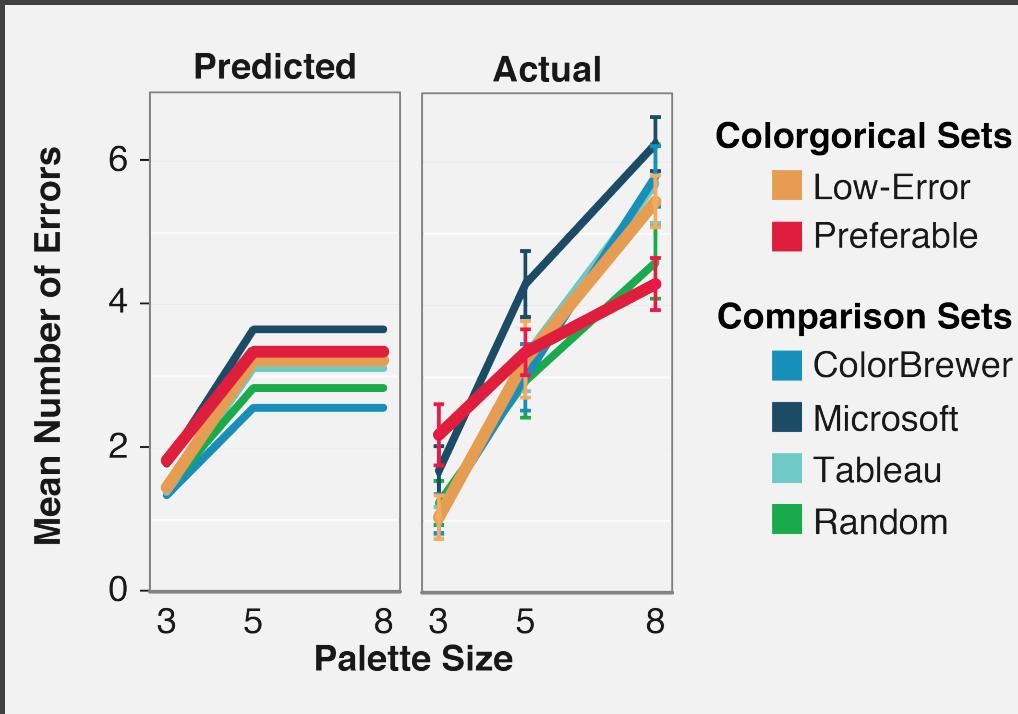


Prediction:
Colorgorical is
comparably discriminable

Error: # incorrect out of 16

Bars: standard error

Largely no significant difference in error rates

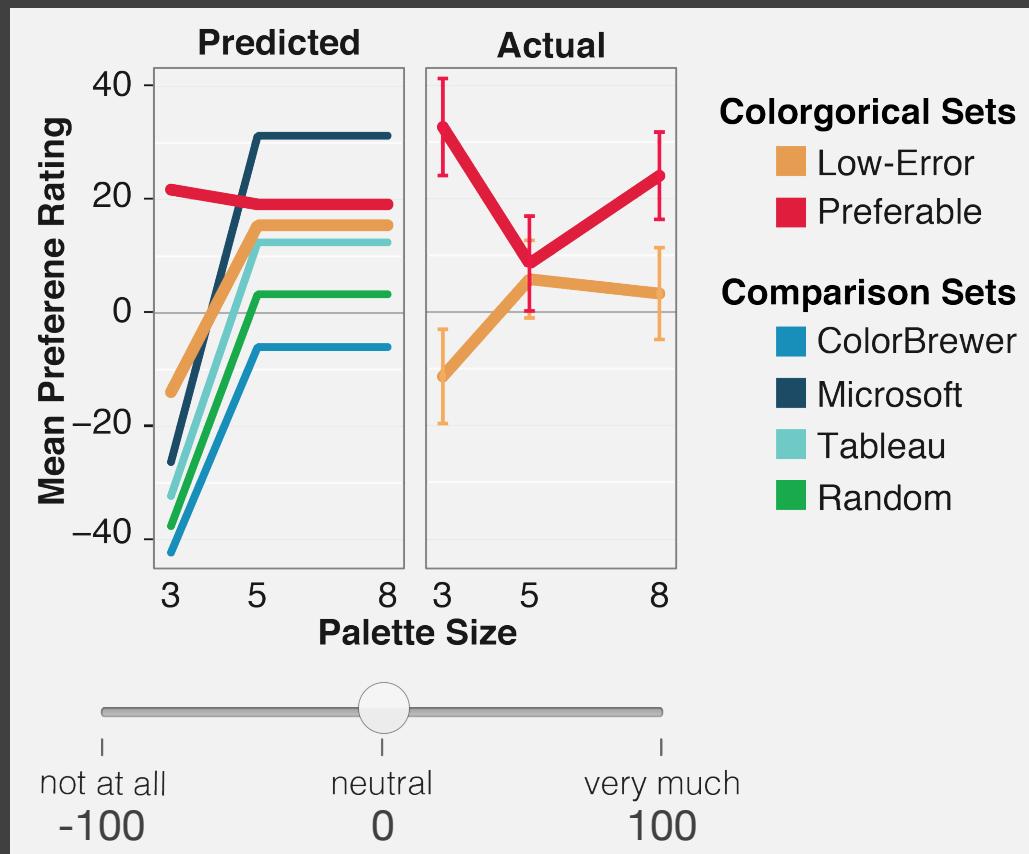


Prediction:
Colorgorical is
comparably discriminable

Error: # incorrect out of 16

Bars: standard error

Preference ratings

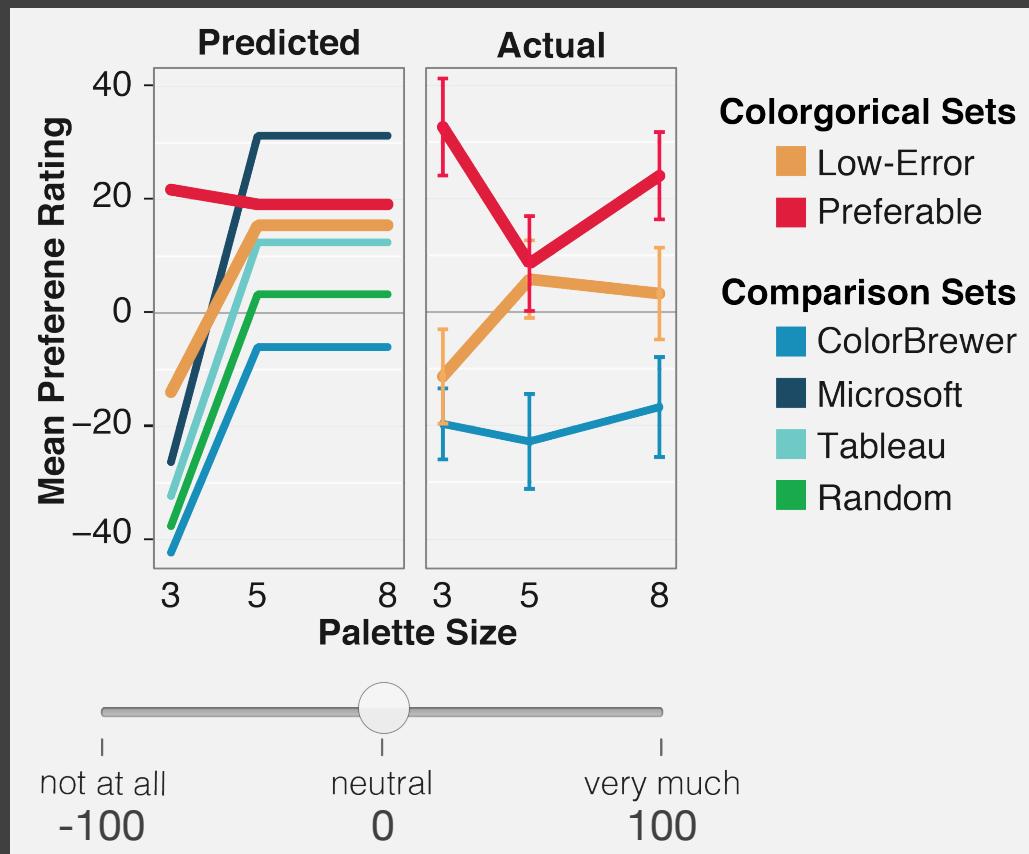


Prediction

Colorgorical is typically more preferable

Bars: standard error

Preference ratings

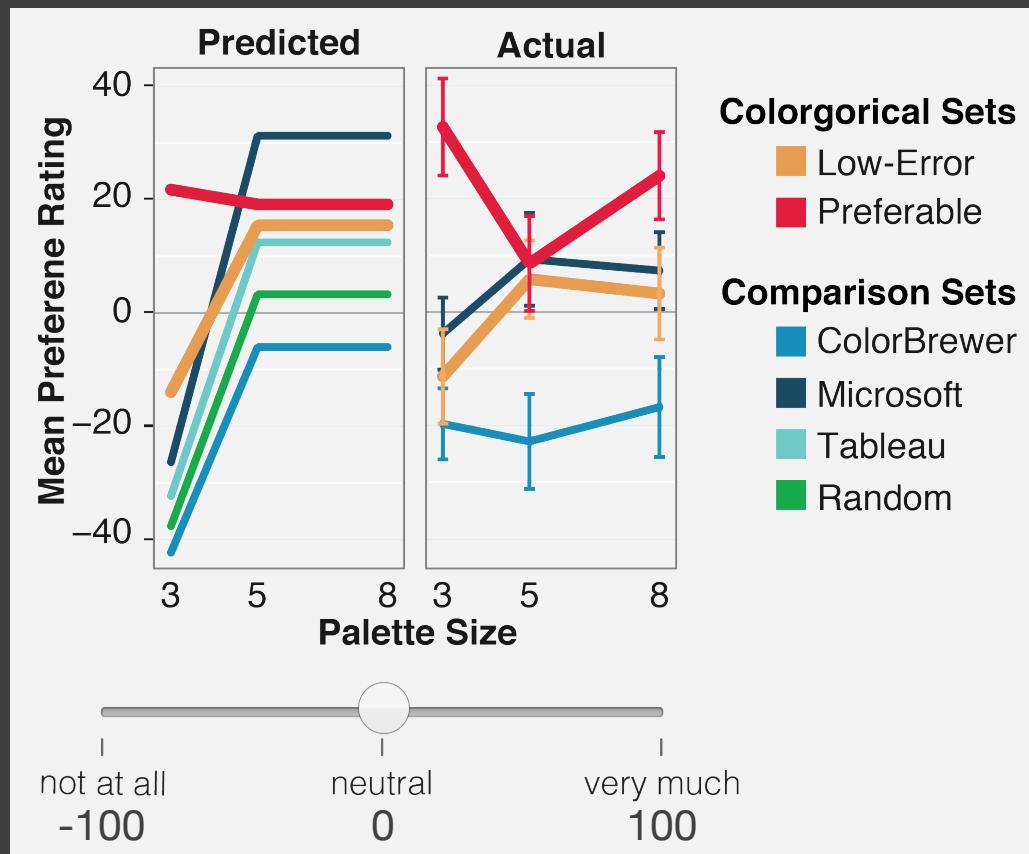


Prediction

Colorgorical is typically more preferable

Bars: standard error

Preference ratings

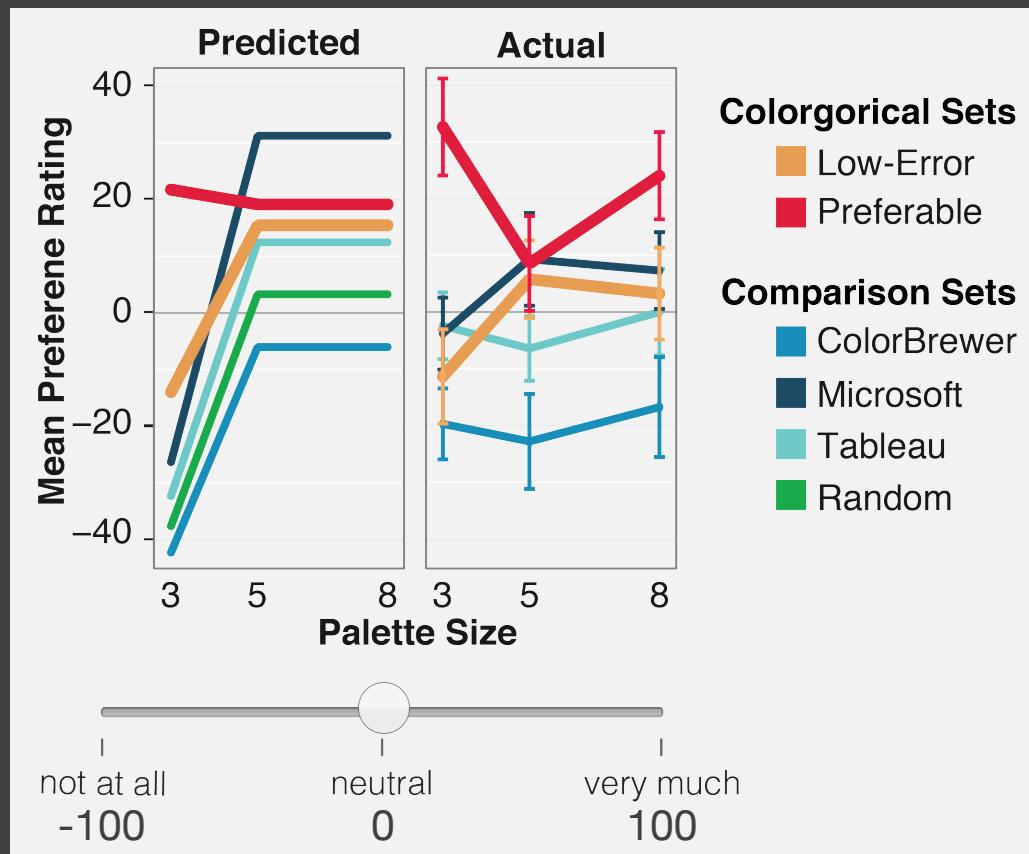


Prediction

Colorgorical is typically more preferable

Bars: standard error

Preference ratings

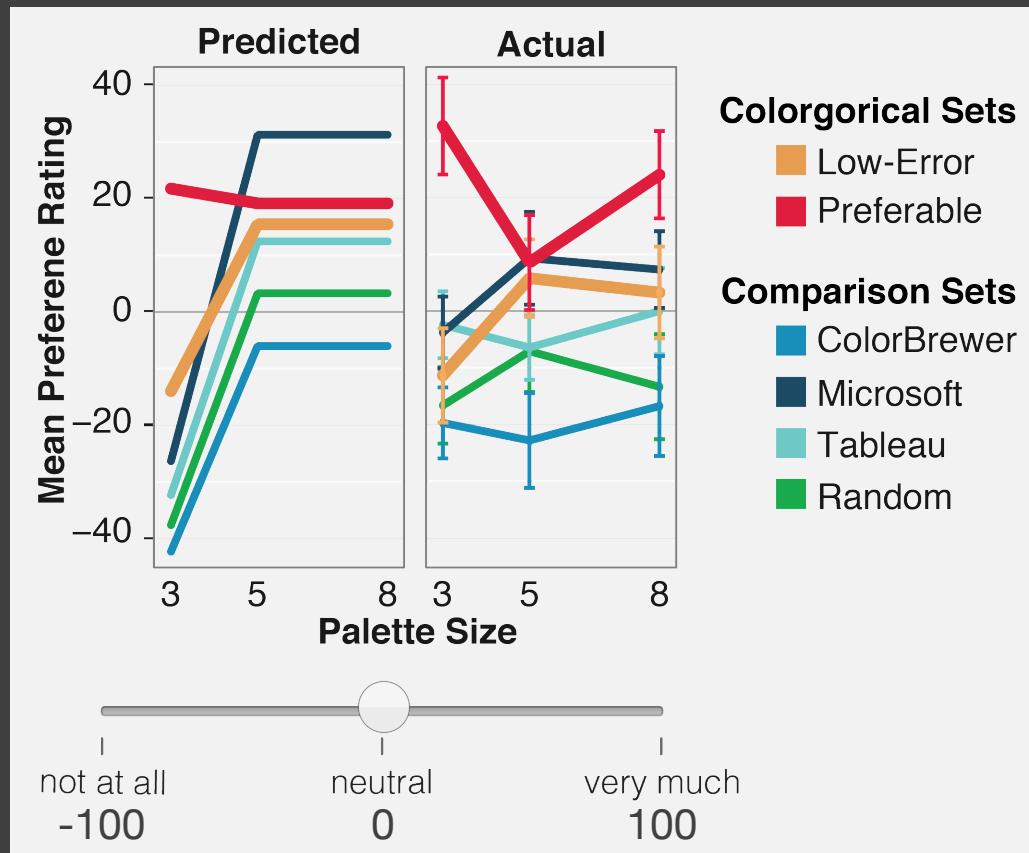


Prediction

Colorgorical is typically more preferable

Bars: standard error

Cologorical-Preferable more, -Low-Error sometimes more

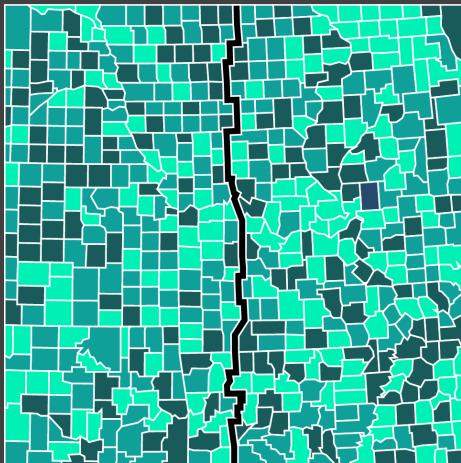


Prediction

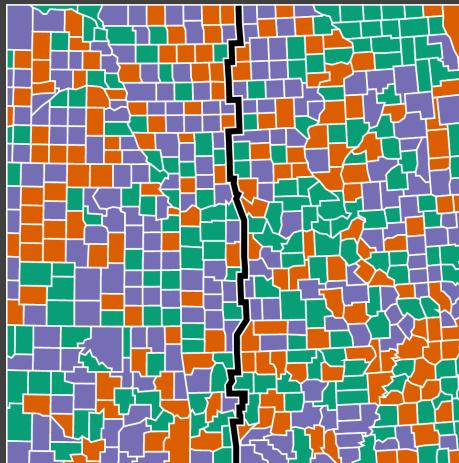
Colorgorical is typically
more preferable

Bars: standard error

Colorgorical is comparably effective.



Colorgorical



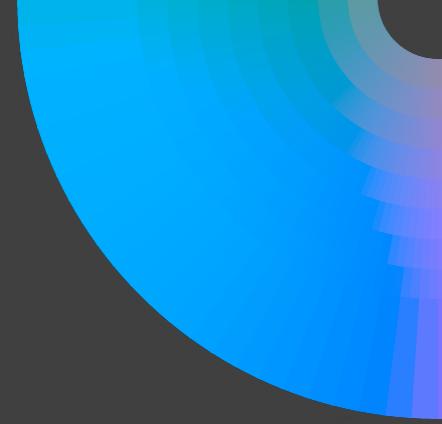
ColorBrewer

Similar levels of discriminability

Typically more preferable

→ See paper for more findings

Colorgorical Summary



Colorgorical Contributions

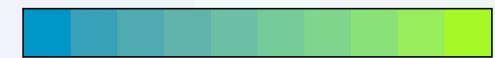
1. User-defined discriminability vs. preference
 2. Δ sliders -> Δ discriminability and preference
 3. Comparable to industry standards
- Reduces design expertise requirements to make palettes

d3-jnd
gramaz.io/d3-jnd

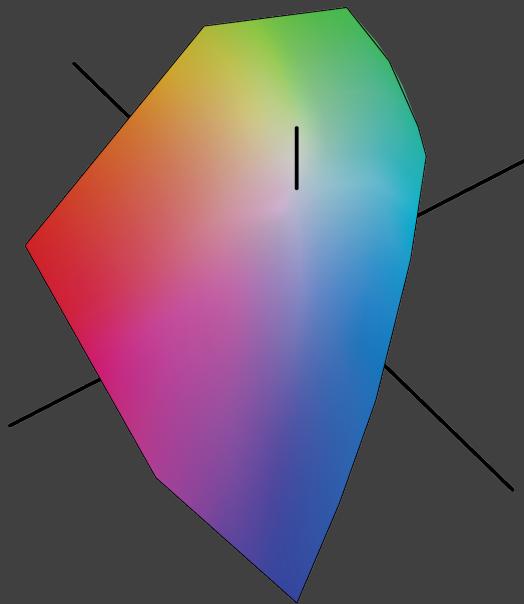
colorgorical
gramaz.io/colorgorical



d3-cam02
gramaz.io/d3-cam02



Perceptual color goal: approximation



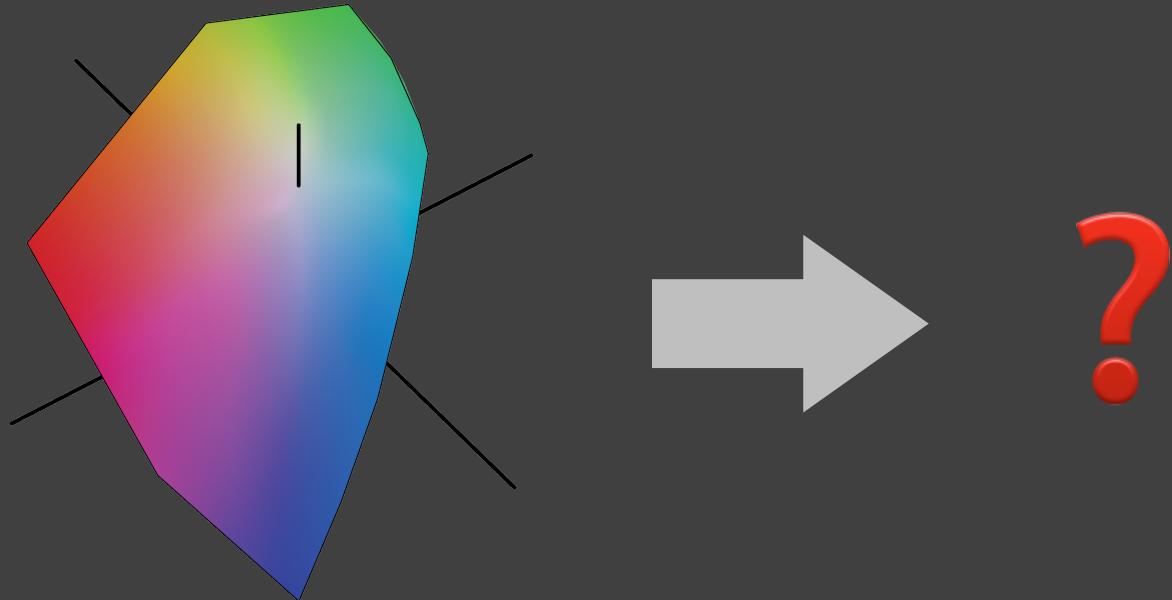
Perceptual uniformity:

$$\Delta E = \sqrt{\Delta L^2 + \Delta a^2 + \Delta b^2} = \odot$$

In reality, CIELAB ΔE is

$$\sqrt{\left(\frac{\Delta L'}{k_L S_L}\right)^2 + \left(\frac{\Delta C'}{k_C S_C}\right)^2 + \left(\frac{\Delta H'}{k_H S_H}\right)^2 + R_T \frac{\Delta C'}{k_C S_C} \frac{\Delta H'}{k_H S_H}}$$

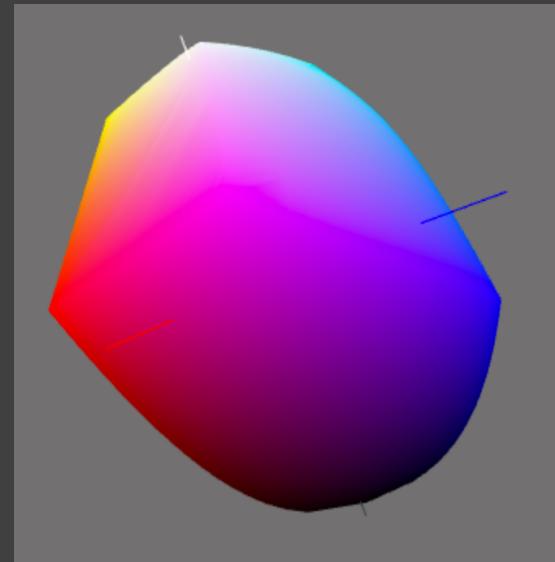
How can we change color spatiality to better model human color perception?



Better approximate: CIECAM02-UCS

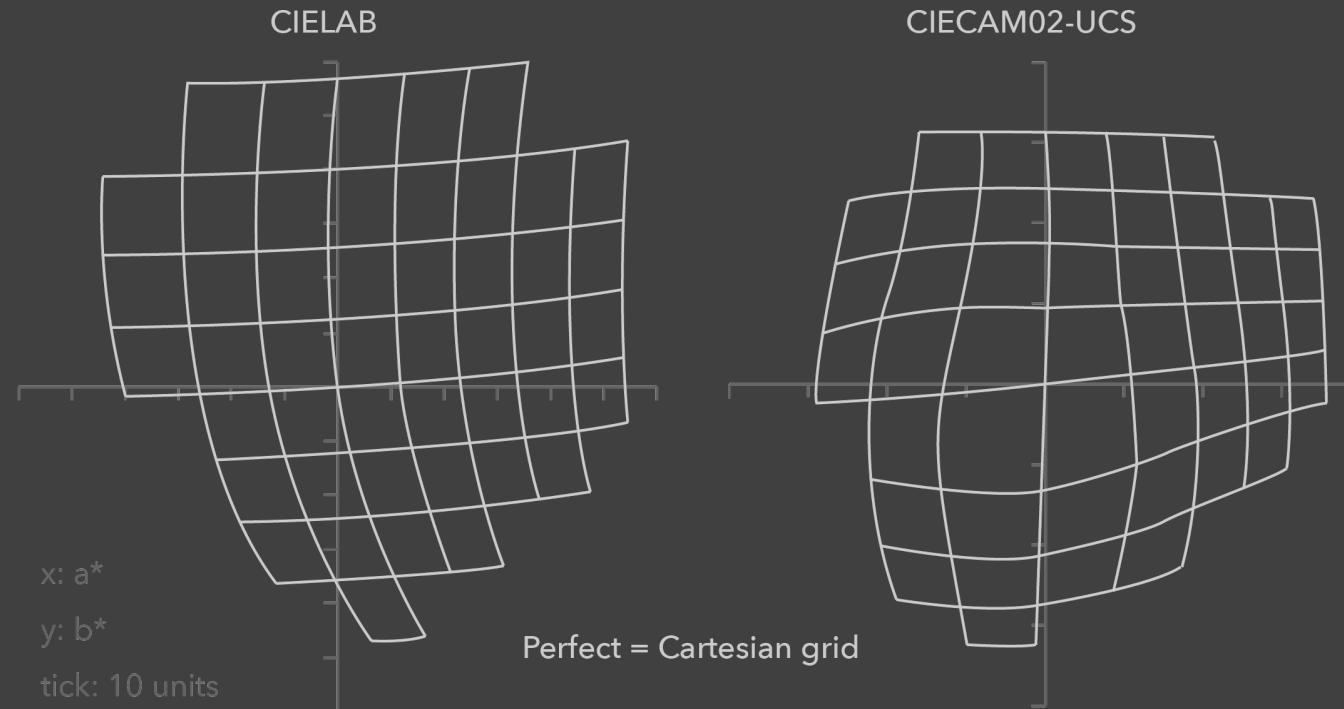
CAM02: Color Appearance
Model 2002
UCS: Uniform Color Space

J^* : Lightness
 a^* : redness-to-greenness
 b^* : blueness-to-yellowness



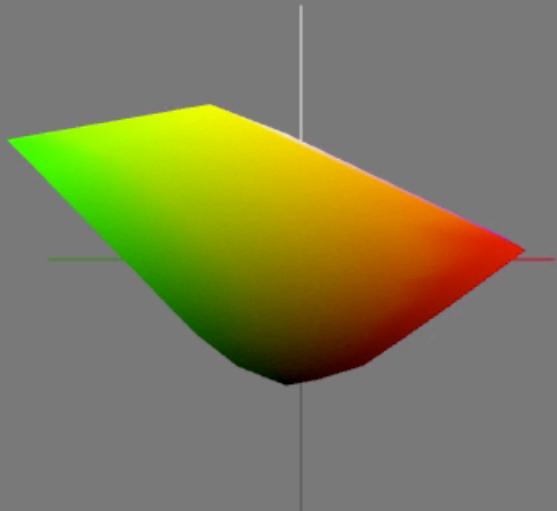
(CAM02 assumptions listed online)

Better approximate: CIECAM02-UCS

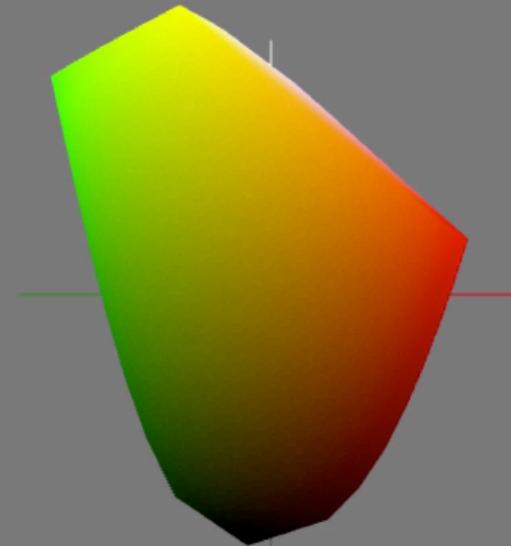


How do these color spaces compare?

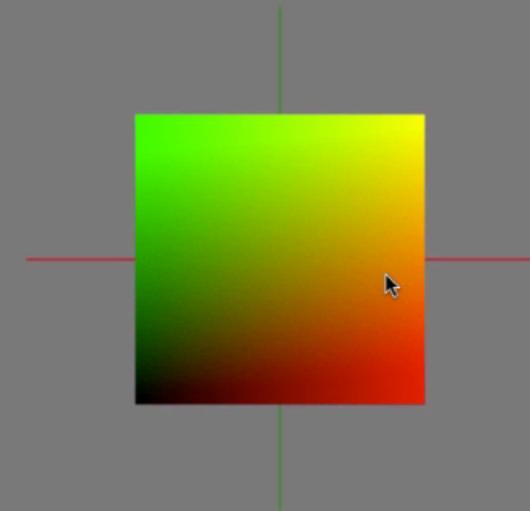
CIELAB



CAM02-UCS



RGB Cube



How do these color spaces compare?

white to blue



CAM02-UCS
CIELAB
RGB

DeepSkyBlue to DarkOrange



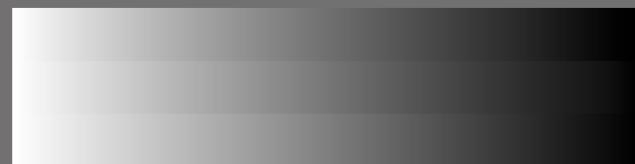
CAM02-UCS
CIELAB
RGB

red to blue



CAM02-UCS
CIELAB
RGB

white to black



CAM02-UCS
CIELAB
RGB

d3-cam02 functions

d3.jab(J, a, b[, opacity])

d3.jab(specifier)

d3.jab(color)

// lightness, chroma, hue

d3.jch(J, C, h[, opacity])

d3.jch(specifier)

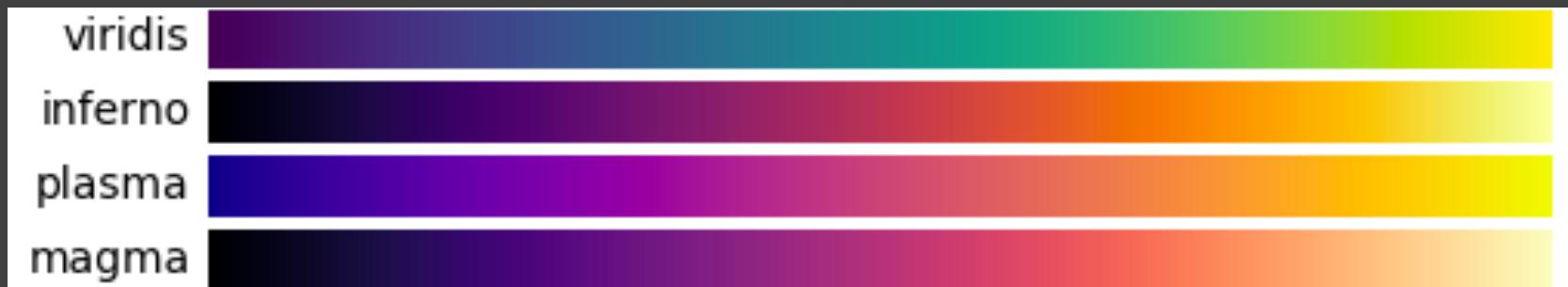
d3.jch(color)

Caveat: evaluation needed

CAM02-UCS validated in color science

Lack of formal evaluation for visualization

But: matplotlib uses CAM02-UCS! So, precedent!



Wrap Up

Just Noticeable Differences

Look at distance for discriminability, but also size

Colorgorical

Effective automation of color palette design with customizable appearance

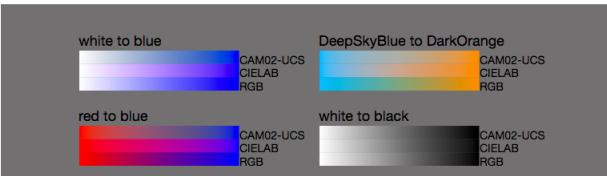
CIECAM02-UCS

Use perceptual spaces knowledgeably;
Consider other options for versatility

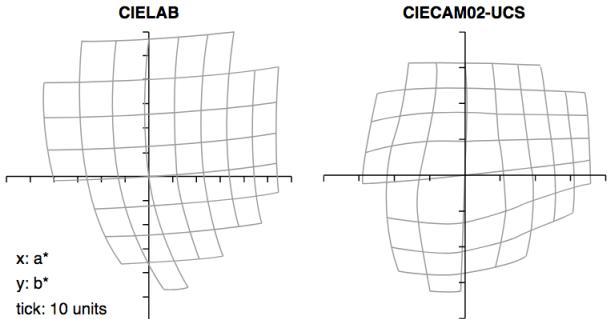
Each project has lots of online documentation + resources

CIECAM02-UCS vs. CIELAB ↗

Perhaps the most common perceptually uniform color space that is currently used by designers is CIELAB color space characterized with CIE Standard Illuminant D65. If you've ever used d3.lab, you've used this color space. So how does CIECAM02-UCS differ from CIELAB? Maybe the best way is to see color interpolation differences:



As evident, even though CAM02-UCS and CIELAB are both perceptually uniform approximations, they define color in different ways. Also note how each compares to RGB, which is not perceptually grounded. You can see the asymmetry between CIELAB and CIECAM02-UCS in Li, Cui, and Luo's plot comparing uniformity results using colors from the Optical Society of America, where more grid-like meshes reflect greater perceptual uniformity.



CIELAB and CIECAM02-UCS comparison reconstructed from Li, Cui, and Luo 2006 [6]. Non-skewed grids reflect perceptual uniformity. Data based on fitting perceptually uniform colors as determined by the Optical Society of America.

So, is it worth using CIECAM02-UCS instead of CIELAB? As with most design decisions, there isn't a definite answer. Although CIECAM02 gives a more uniform approximation, it is unclear what the actual magnitude of difference would be on average for online audiences given the diaspora of displays that an audience could use. But, greater precision never hurts either. Ultimately, by even considering perceptual uniform spaces to begin with you are taking a step in the right direction, regardless of which you select.

Examples ↗

[Interactive CIECAM02 and CIECAM02-UCS color picker](#)

Further reading ↗

Citations

1. [Wikipedia entry on CIECAM02 color](#)
2. Stone, Szafir, Setiur. "An Engineering Model for Color Difference as a Function of Size," *22nd IS&T Color and Imaging Conference*. 2014.
3. [Wikipedia entry on LMS color space](#)
4. Luo and Li. "CIECAM02 and its recent developments," *Advanced Color Image Processing and Analysis*. 2013.
5. [Wikipedia entry on color difference \(ΔE or DE\)](#)
6. Luo, Cui, and Li. "Uniform Colour Spaces Based on CIECAM02 Colour Appearance Model," *Color Research & Application*. 2006.

Other useful links

Open source is necessary to bridge the divide, **but think about accessibility, too.**



Thanks!

🐦 @ccgramazio
🔗 <https://gramaz.io>

d3-jnd: <https://gramaz.io/d3-jnd>

Colorgorical: <https://gramaz.io/colorgorical>

d3-cam02: <https://gramaz.io/d3-cam02>