

CS 526 Computer Graphics II

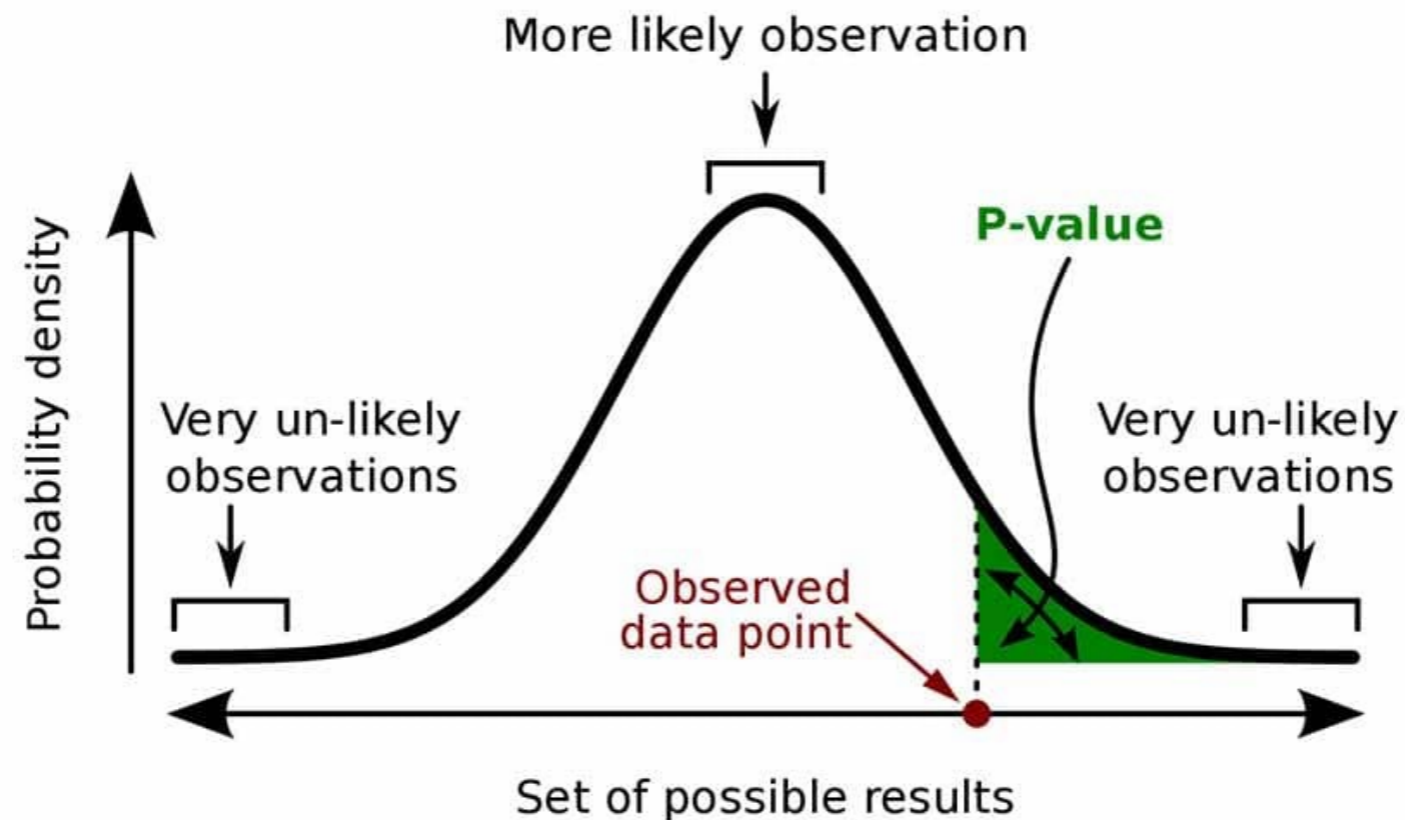
Graphical Inference & applications to Vis evaluation

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UIC CS

How do you know that you're looking at "noise", as opposed to a true data signal?

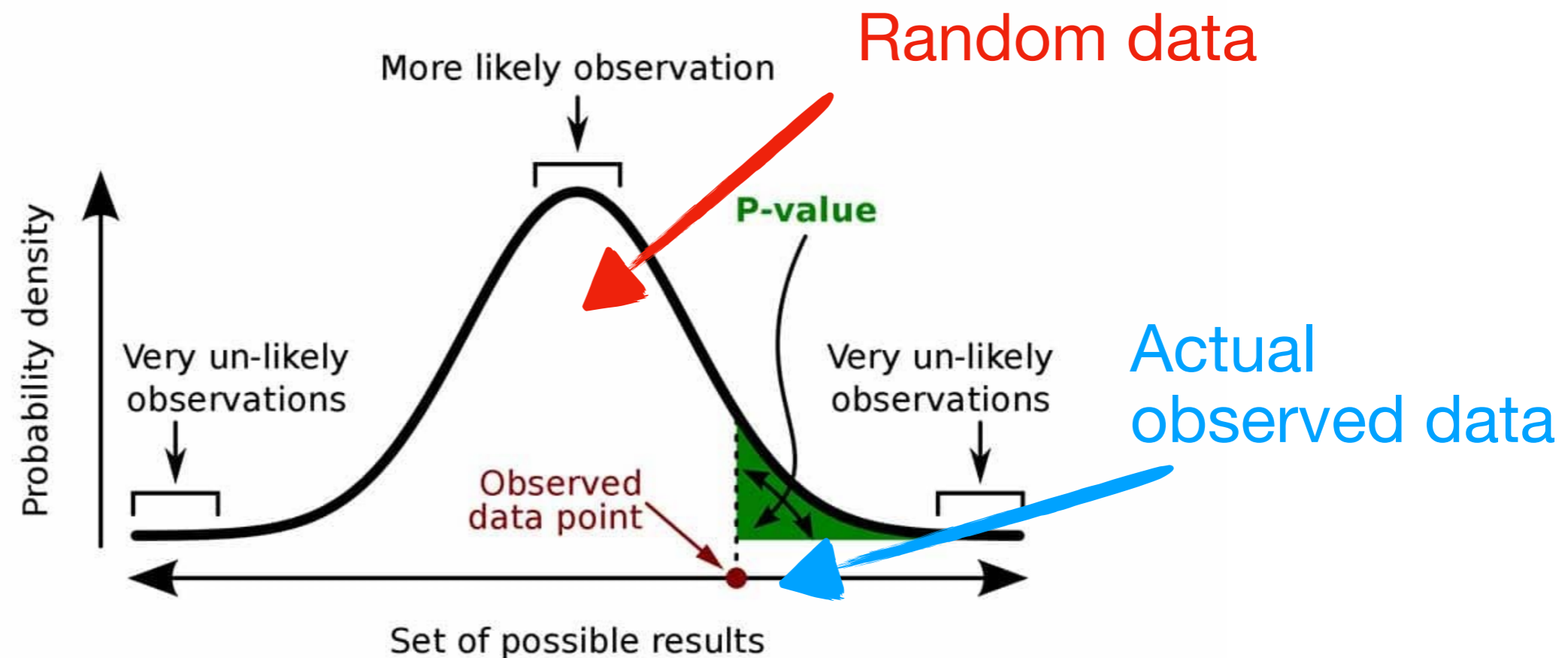
Statistics



A **p-value** (shaded green area) is the probability of an observed (or more extreme) result assuming that the null hypothesis is true.

How do you know that you're looking at "noise", as opposed to a true data signal?

Statistics

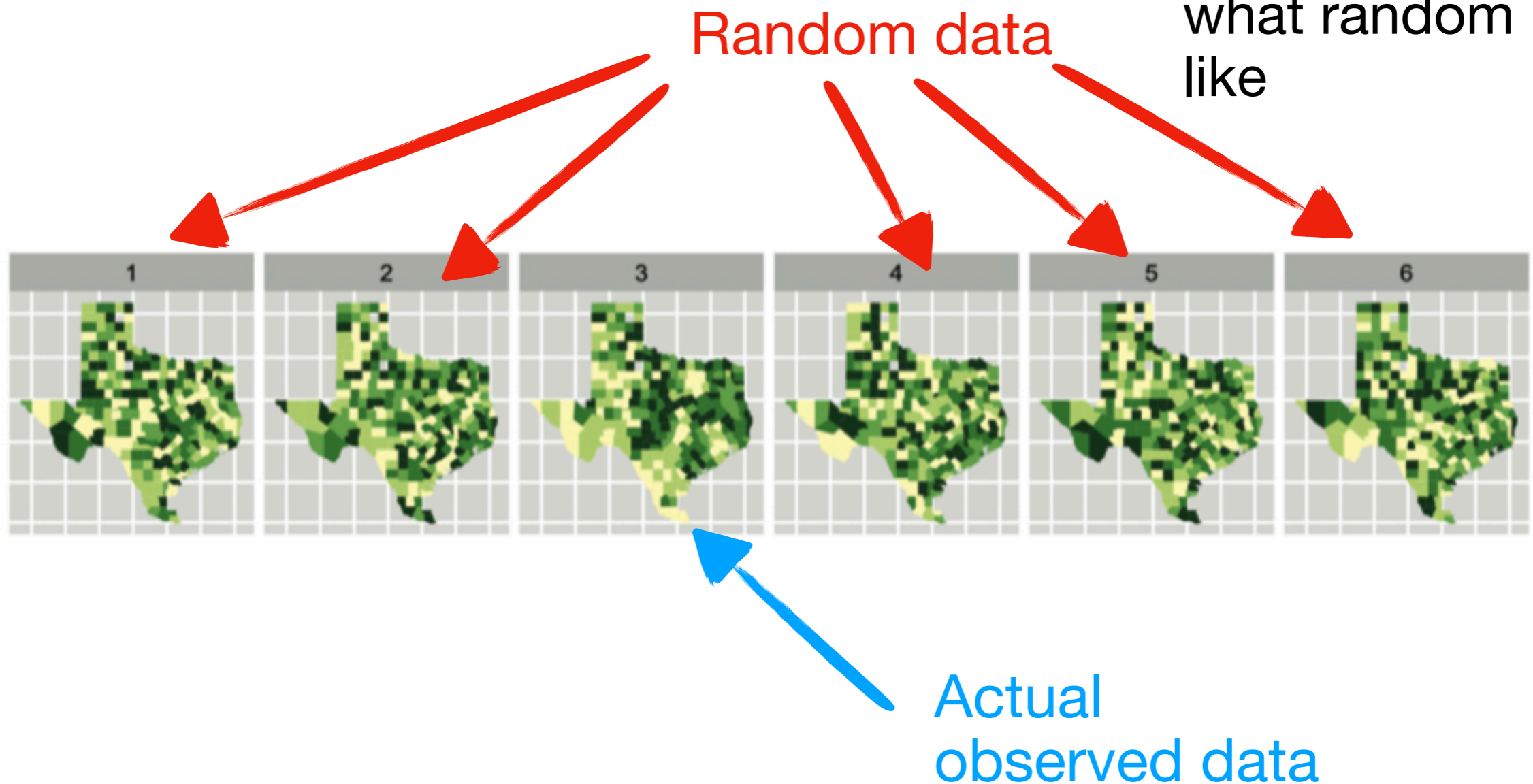


A **p-value** (shaded green area) is the probability of an observed (or more extreme) result assuming that the null hypothesis is true.

How do you know that you're looking at "noise", as opposed to a true data signal?

What about in visualization?

Need to defined what random looks like



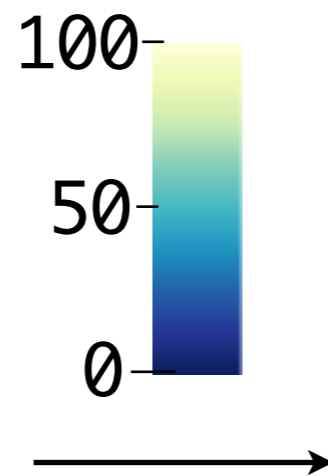
This approach can be used to evaluate visualization designs

Visualizations that afford better ability to detect true signal from “noise” are said to provide higher power

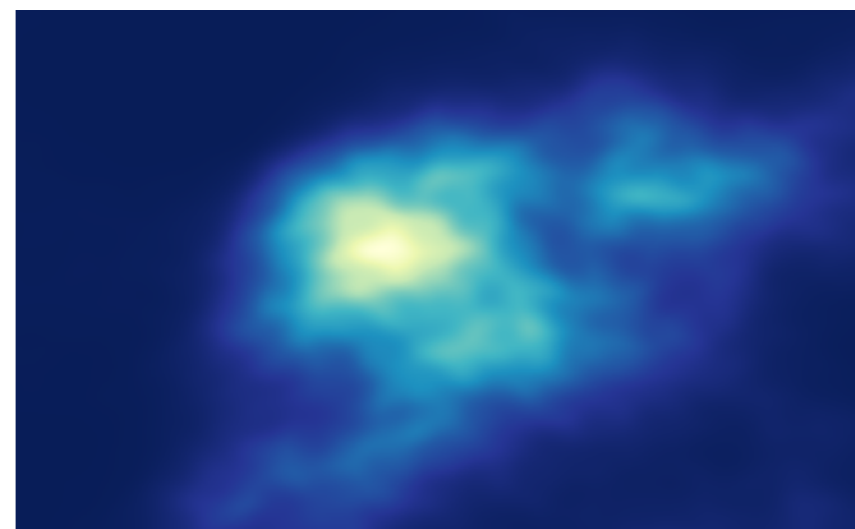
Evaluating colormaps for “graphical inference”

```
1 1 1 0 0 0 0 0 0 0 0 0 0 0 1 1
0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1
0 0 0 0 0 0 1 2 2 3 6 6 4 2 2 4
0 0 0 0 0 4 8 18 15 15 19 26 16 11 10 9
0 0 0 1 14 31 44 51 50 33 28 35 36 32 19 8
1 1 1 1 6 34 66 80 73 52 26 30 30 29 19 12 7
1 1 1 2 10 30 65 79 70 52 39 26 18 13 11 3 3
0 0 0 2 14 28 42 44 47 56 55 29 20 14 7 2 1
0 0 0 2 7 13 19 31 39 37 33 22 15 9 5 2 1
0 0 0 2 7 12 16 27 30 19 10 8 6 4 2 4 3
0 0 1 5 12 20 21 22 11 7 5 3 2 3 3 5 2
0 0 1 6 11 12 14 9 4 3 2 3 5 5 4 6 4
```

scalar field



color map



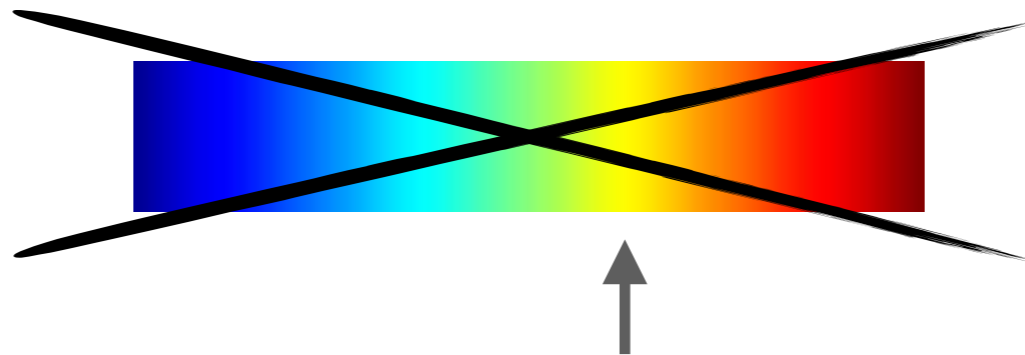
Color encoding guidelines

Smooth &
perceptually
uniform



viridis

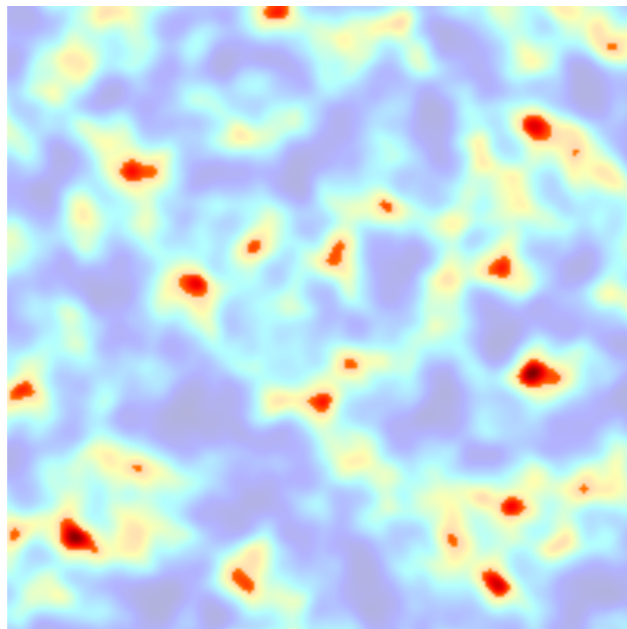
No
color bands



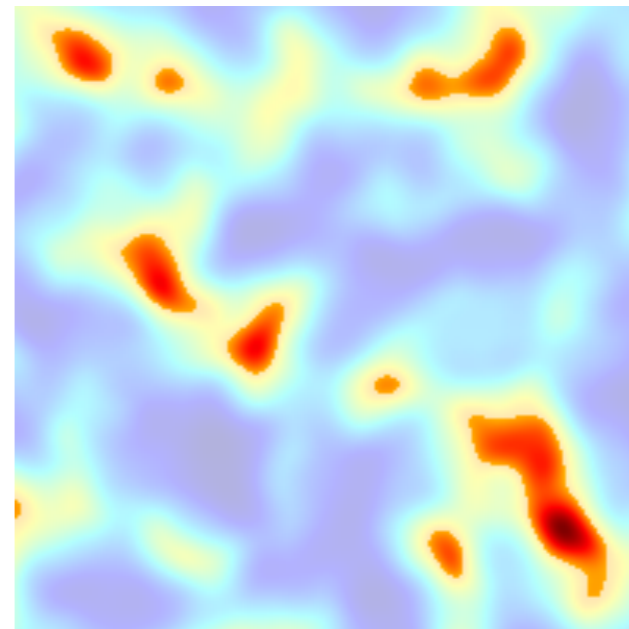
jet

Hypothesis: **color categorization helps** in tasks requiring inference across multiple percepts

Color segments aid the visual system in extracting summary ensemble statistics

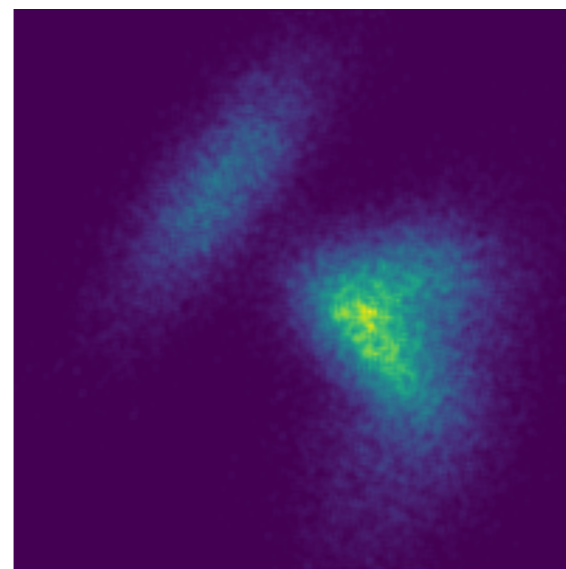
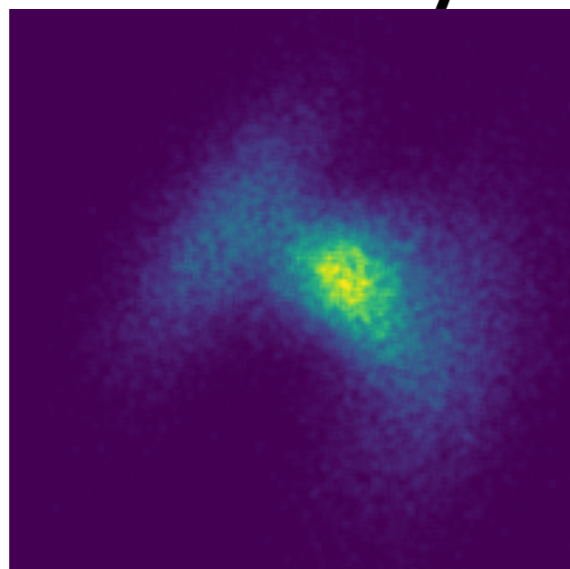


>



Hypothesis: **color categorization helps** in tasks requiring inference across multiple percepts

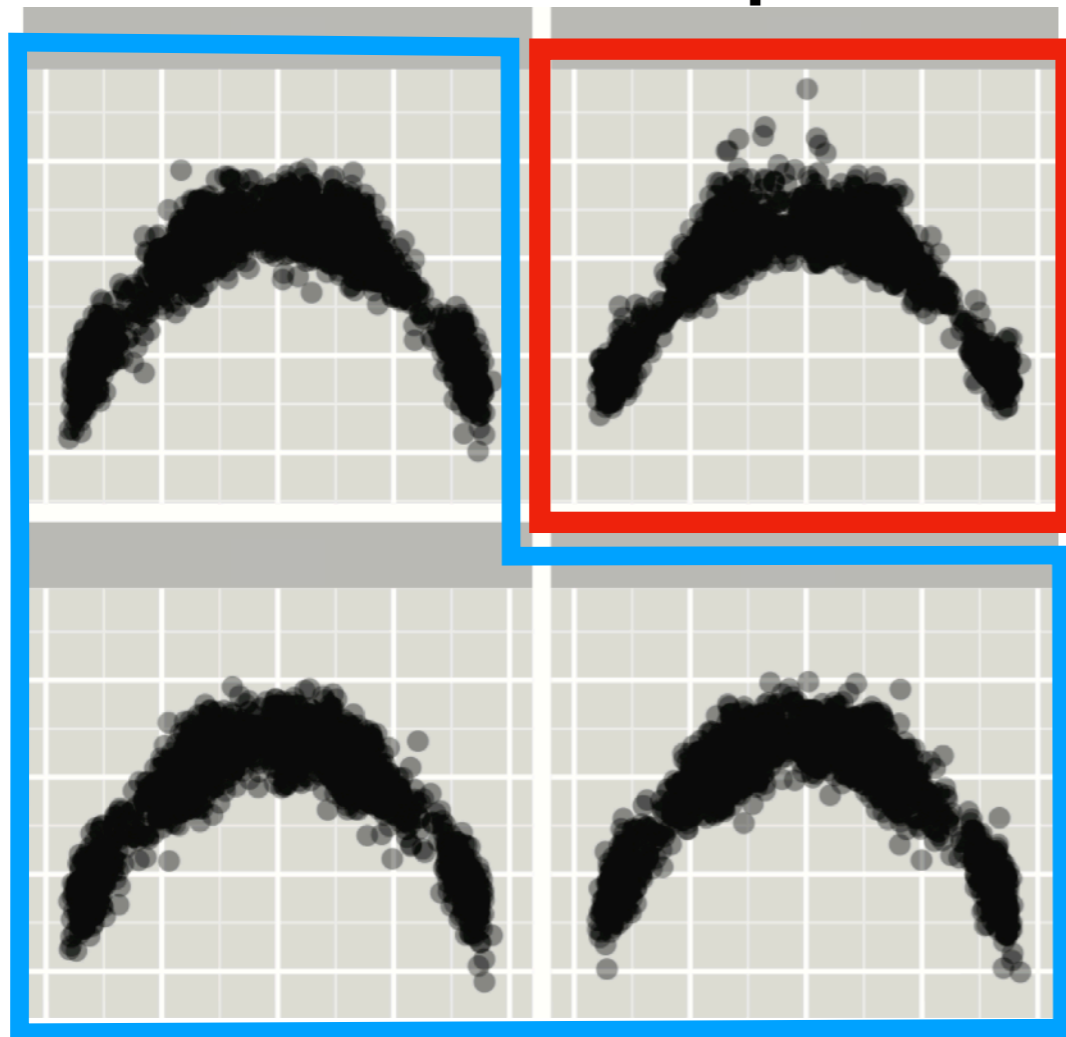
Color segments help compare features that might otherwise be too fuzzy



Model task: Graphical inference

Model task: Graphical inference

Which of the plots does *not* belong?



Model 1:
“Target”

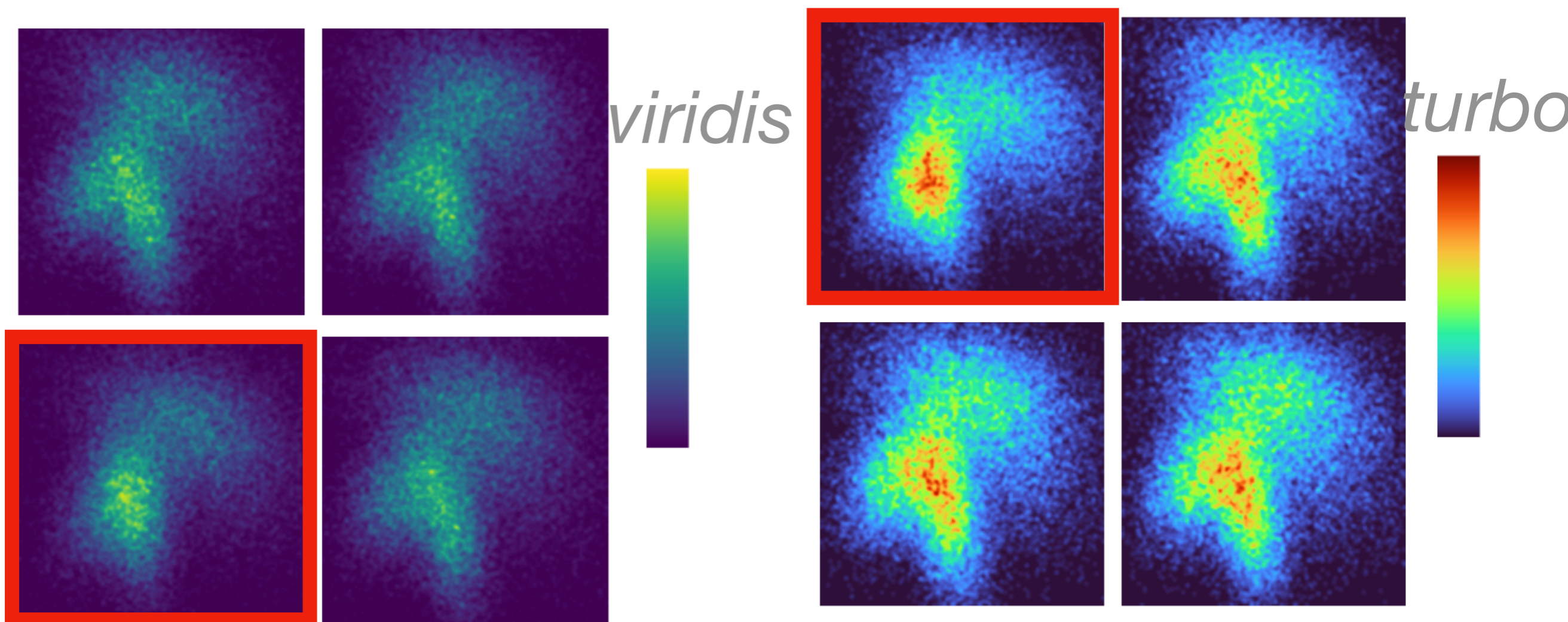
Model 2:
“Decoy”

[Buja et al., 2009]

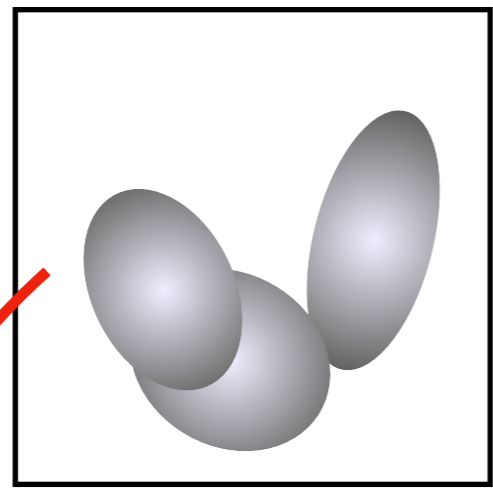
[Wickham et al., 2010]

Model task: Graphical inference

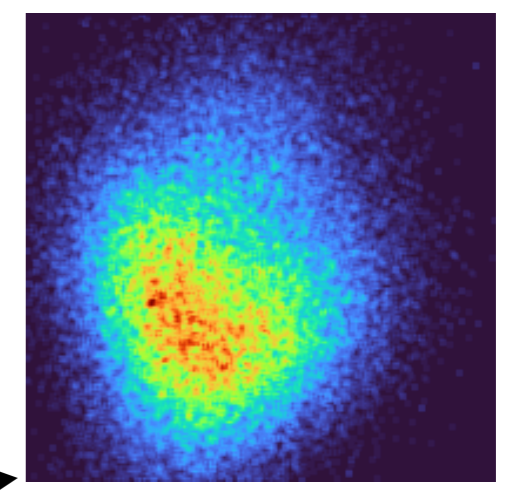
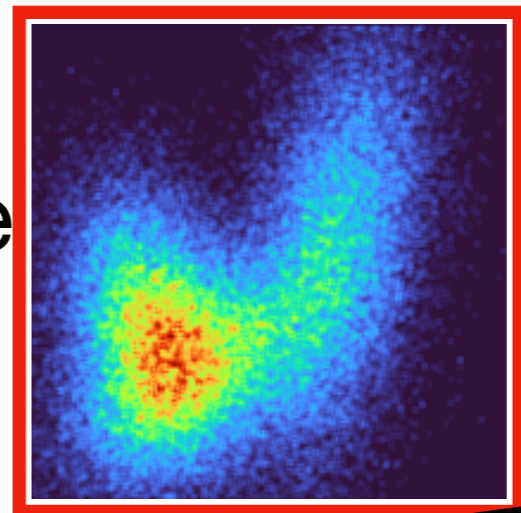
Which of the plots does *not* belong?



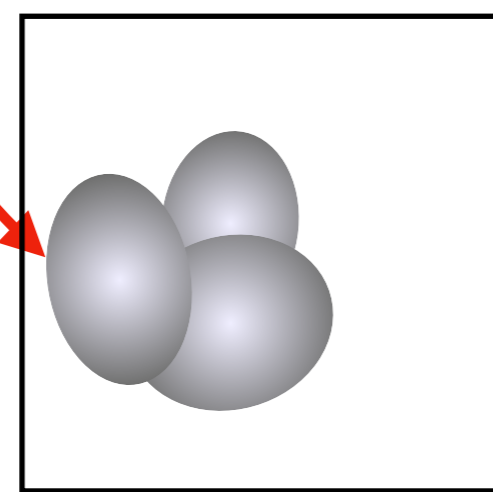
Target model



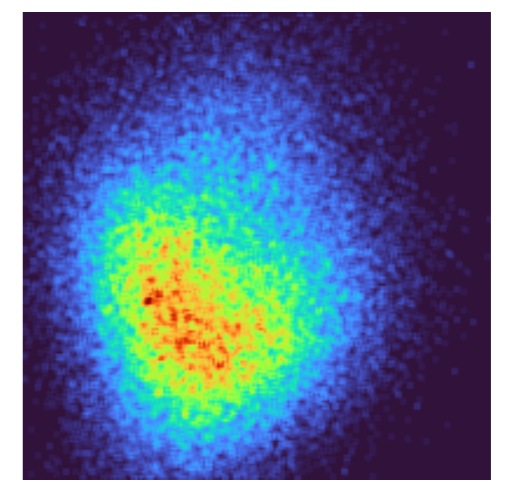
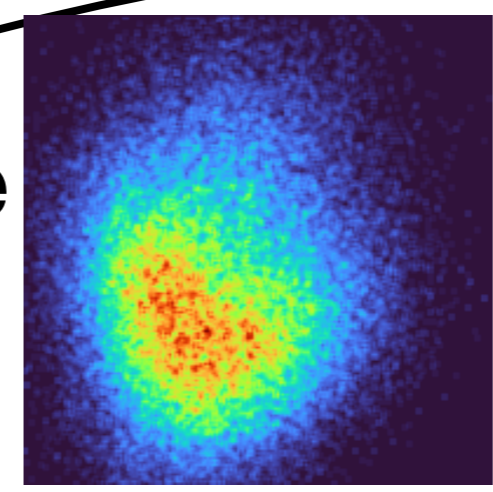
sample



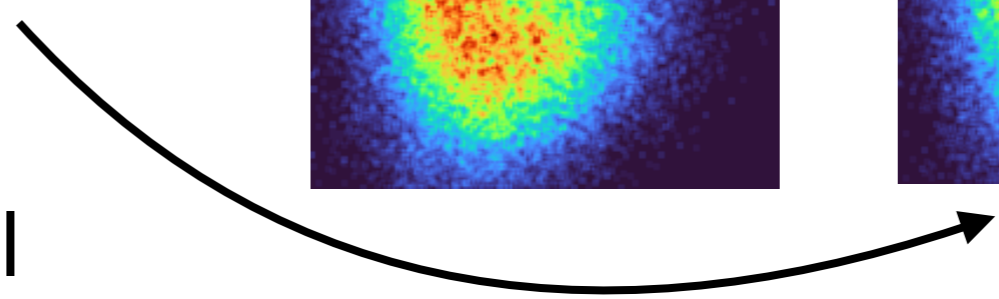
perturb
Gaussians



sample

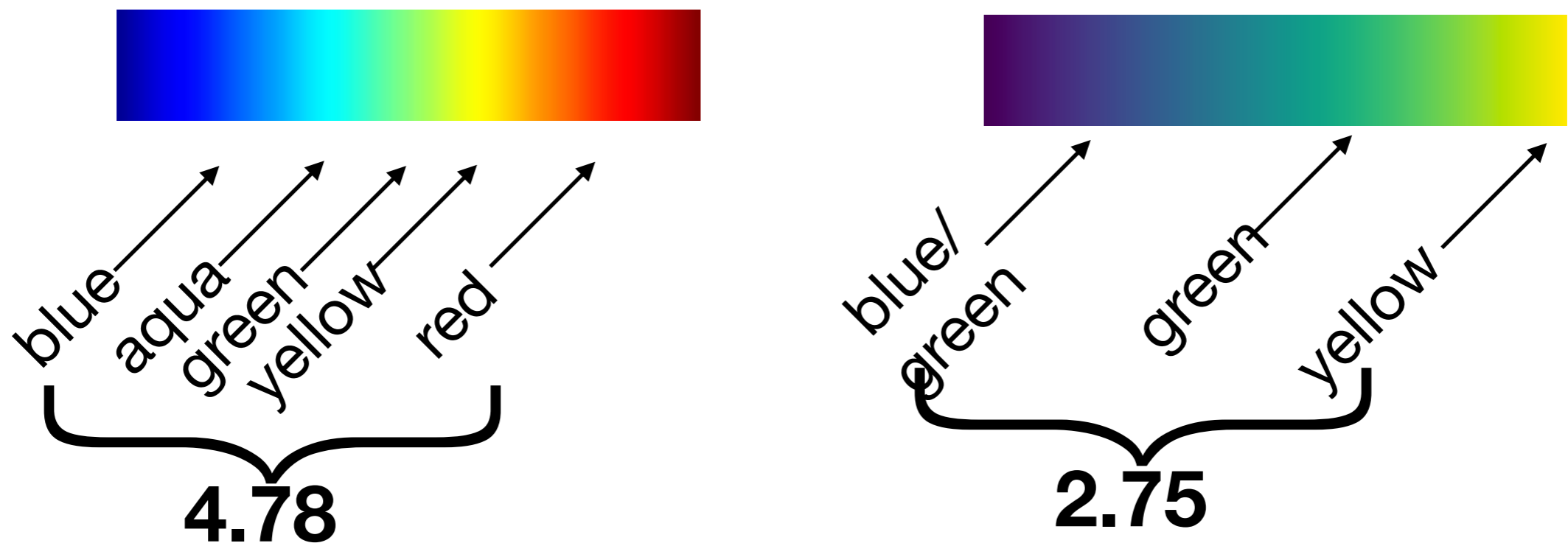


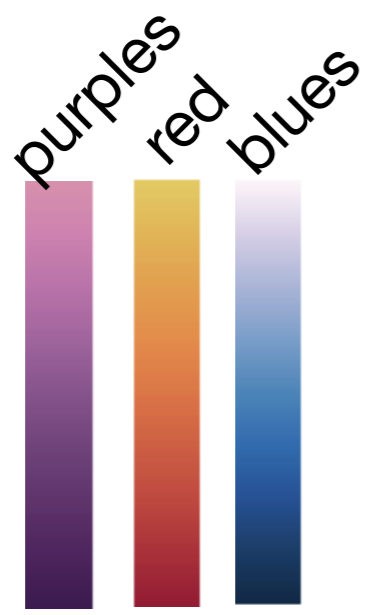
Decoy model



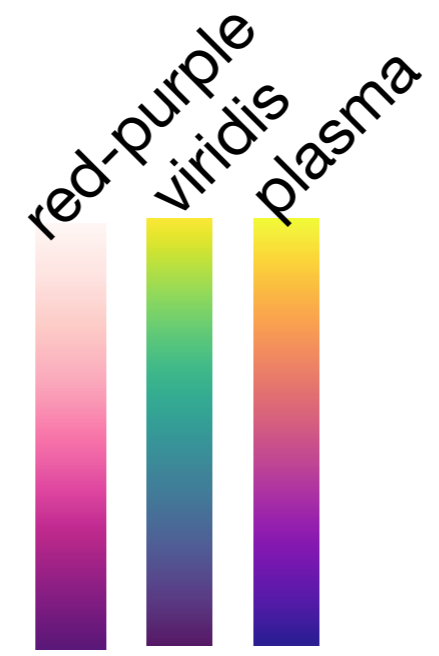
Measuring color categorization tendency

Color name variation: count the number of distinct color names in a continuous ramp [Heer & Stone]





**Single-
hue**



**Multi-
hue**

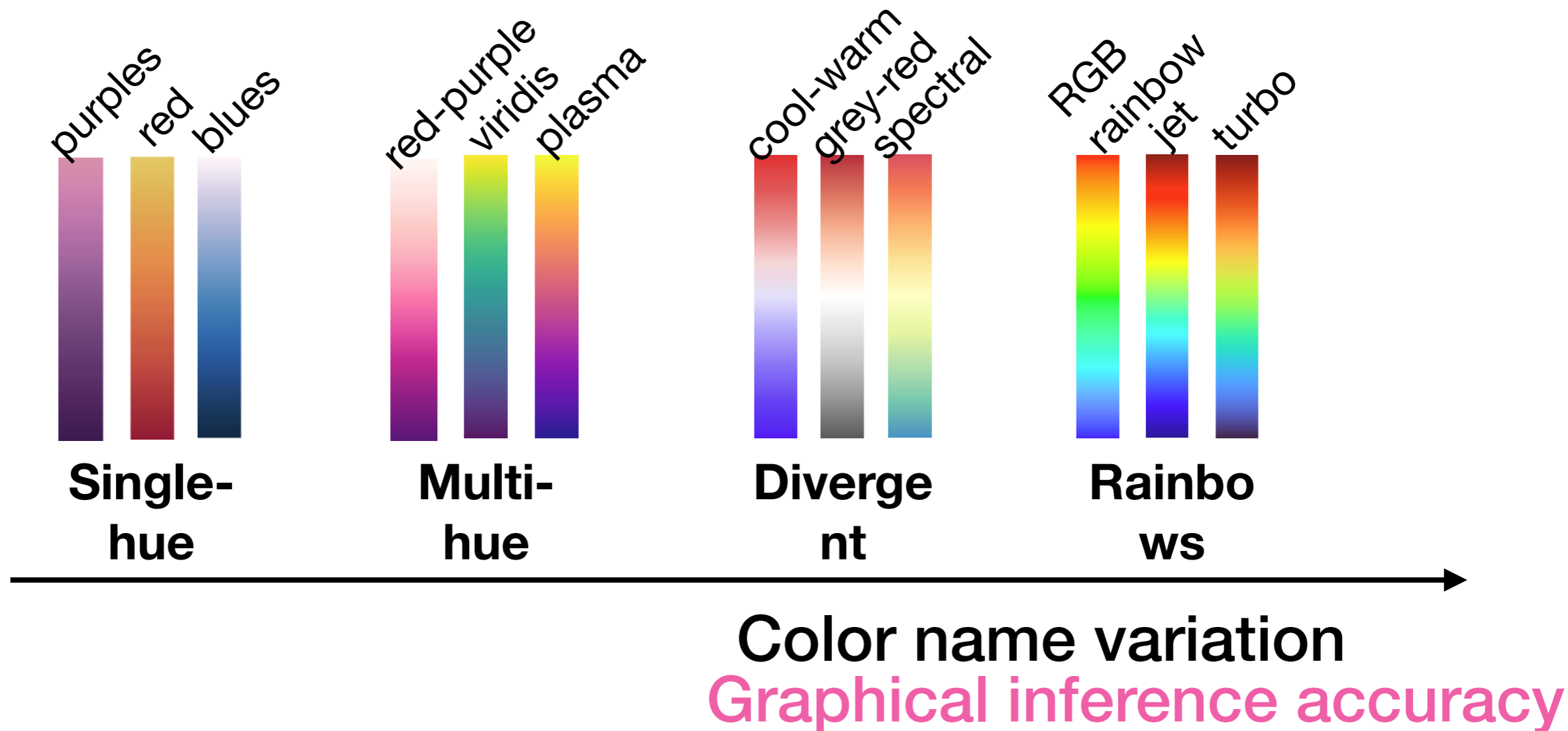


**Diverge
nt**

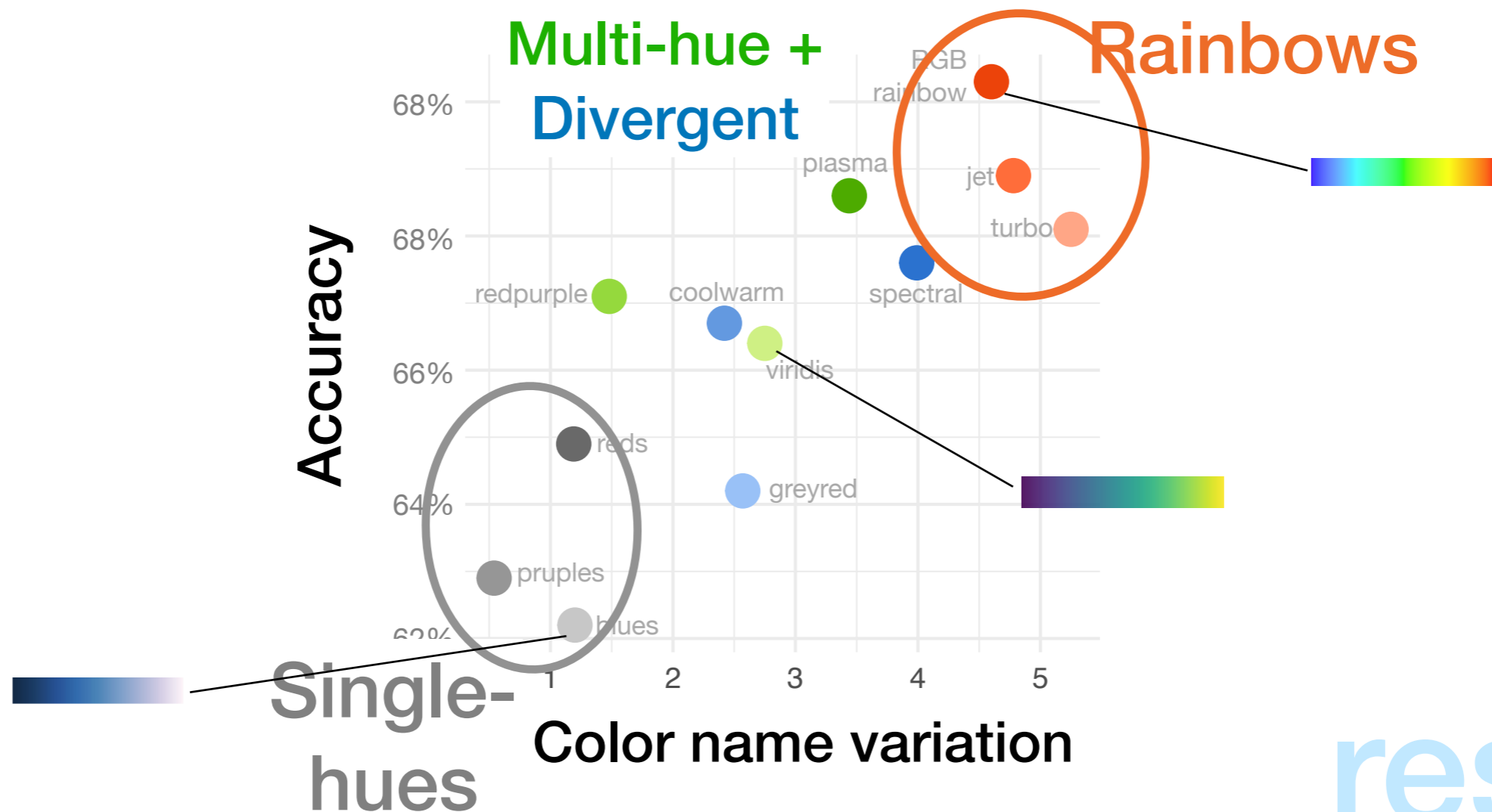


**Rainbo
ws**

H1: colormaps with higher name variation will enable more accurate graphical inference



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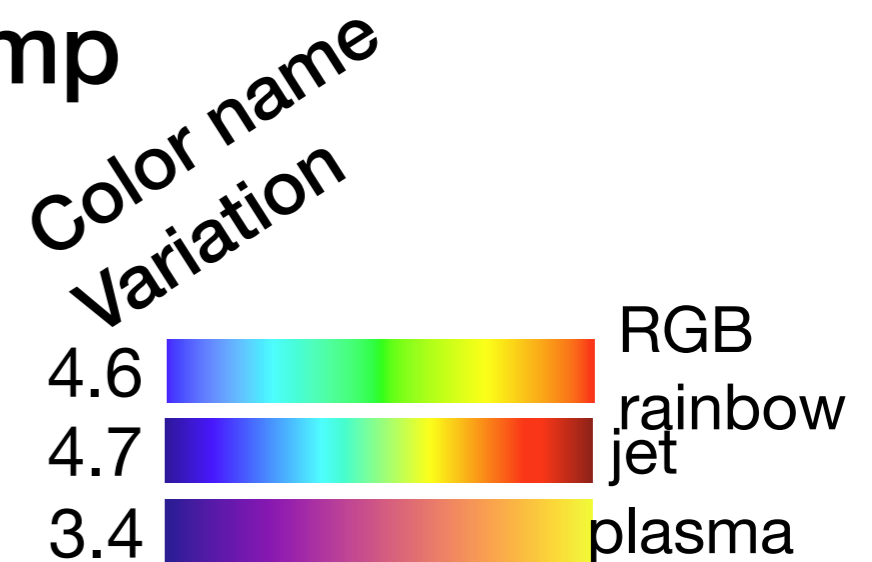
results

H1: colormaps with **higher name variation** will enable more accurate graphical inference



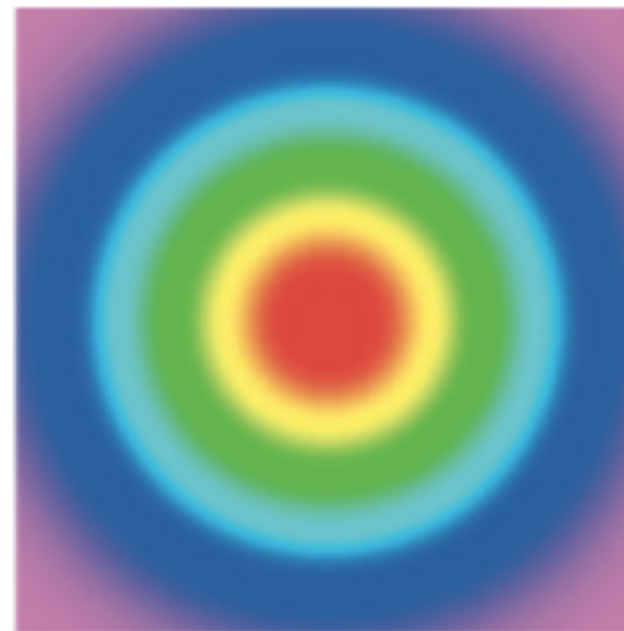
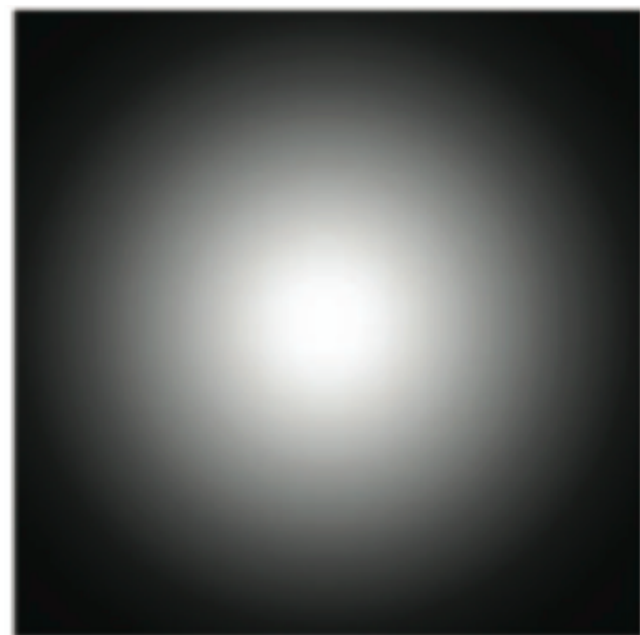
Accuracy linearly correlated with number of distinctly nameable colors in the ramp

“Colorful” maps perform better



results

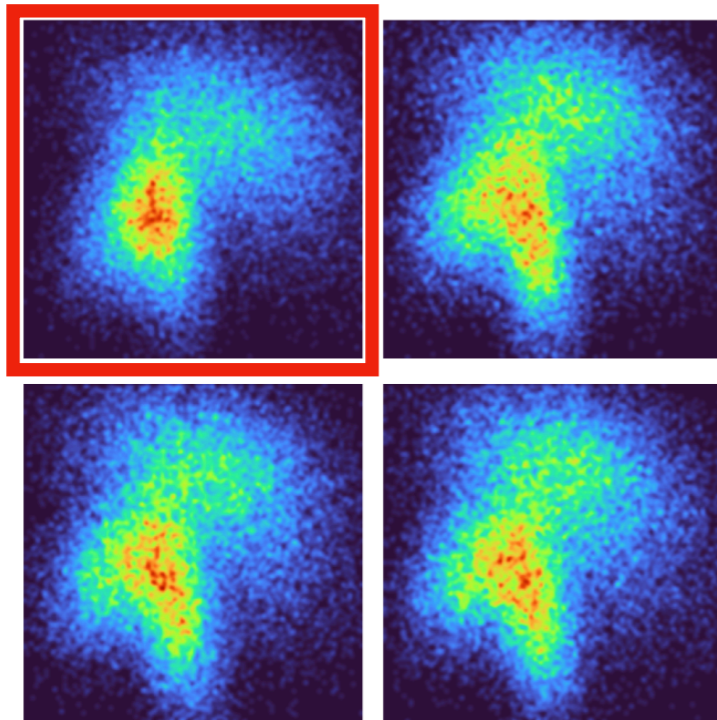
H2: color bands can cause people to infer false features



[Borland and Russell, 2007]

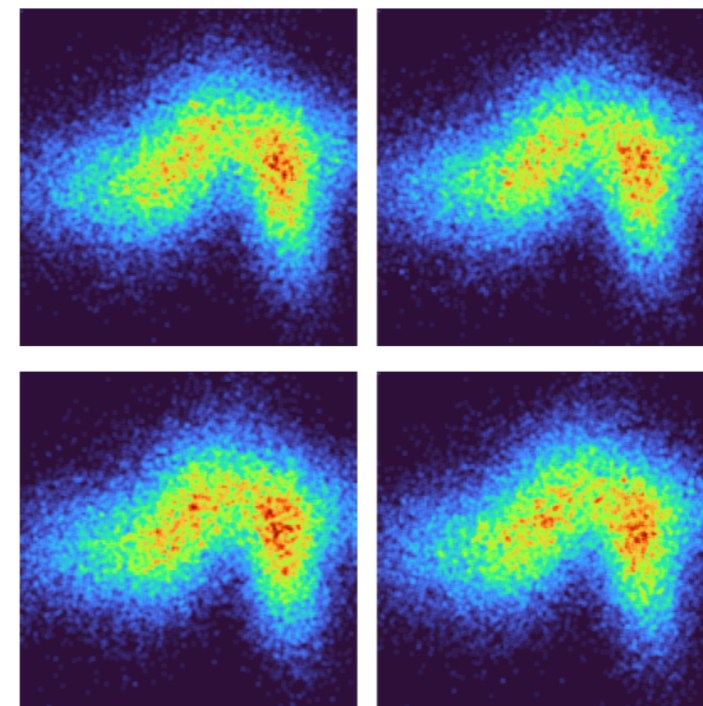
H2: color bands can cause people to infer false features

Do colorful maps trick people into reporting false differences?



50% true positives

No
discernible
difference
between
images

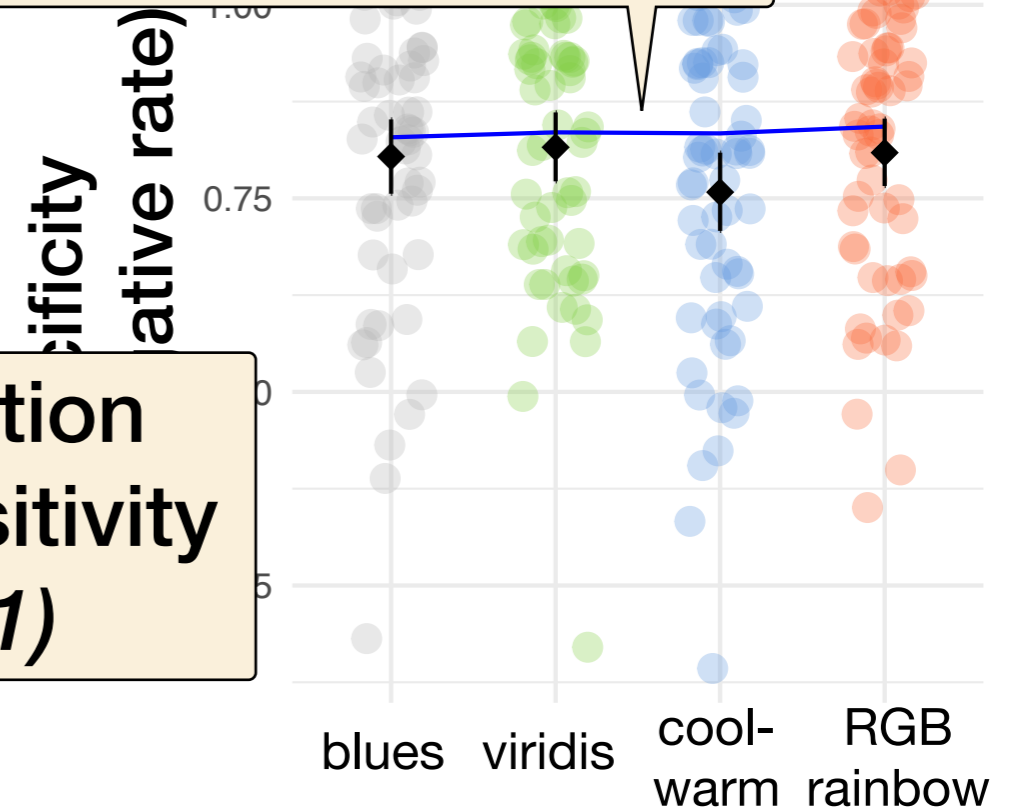
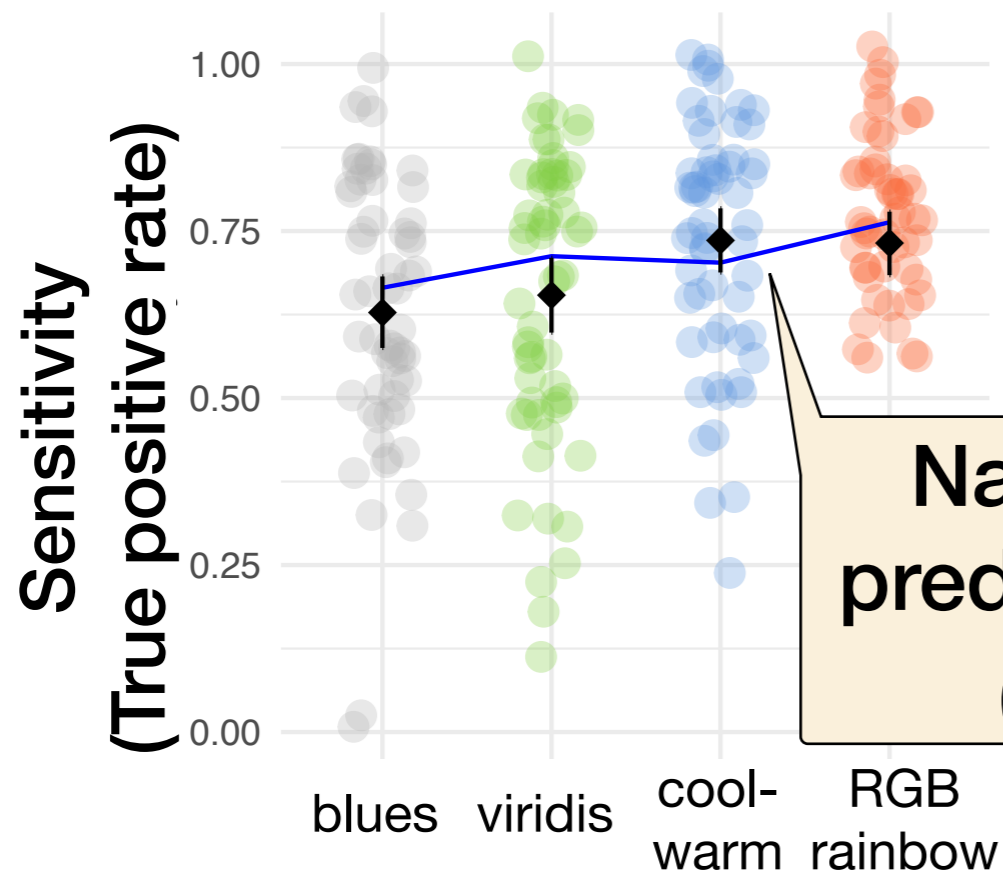


**50% true negatives
(i.e., no decoys)**

No
discernible
difference
between
images

H2: color name variation correlates negatively with

Color name variation does *not* predict specificity



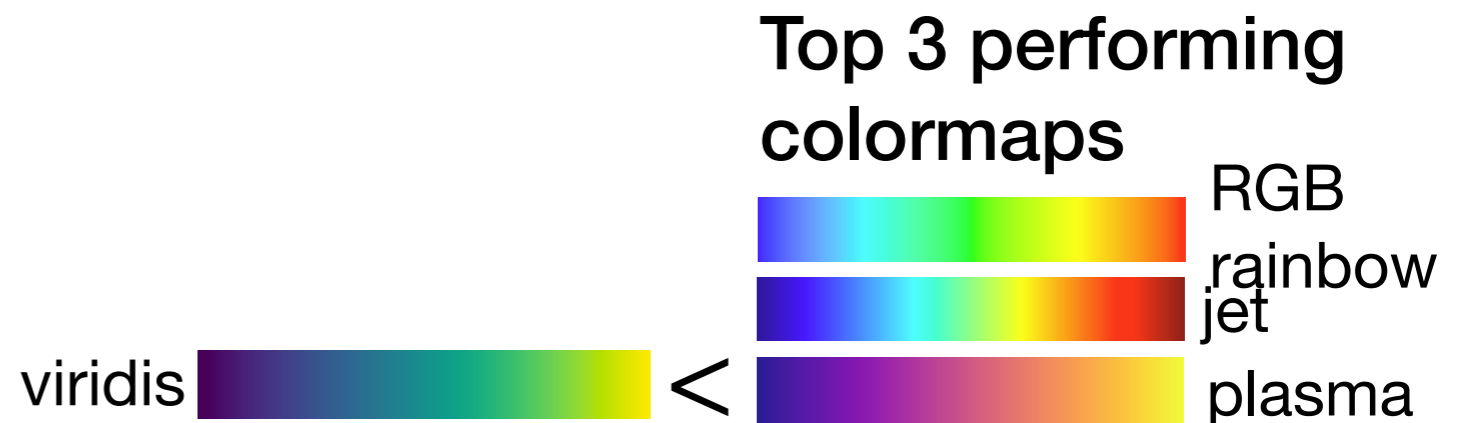
H2: color name variation
correlates negatively with specificity



Participants were no more likely to report false model differences when viewing a rainbow

Colorfulness improves sensitivity

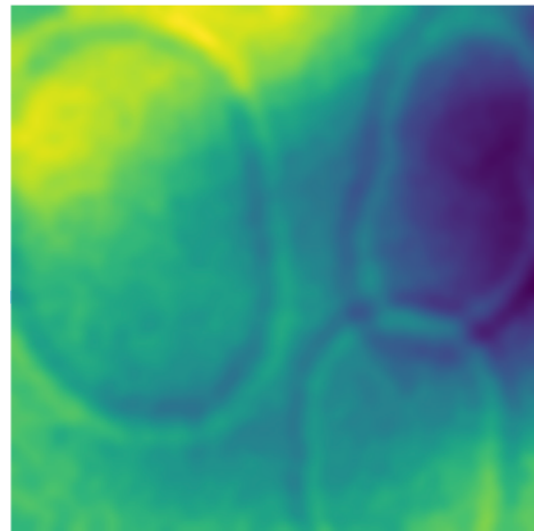
Color name variation
predicts performance in
graphical inference



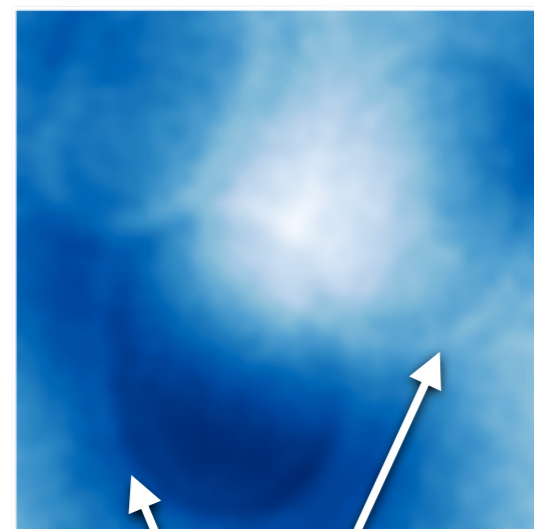
Traditional perceptual properties (e.g., uniformity, lightness monotonicity) don't seem to affect inference

Heuristic: maximize colormap's curve length in LAB space (*details in paper*)

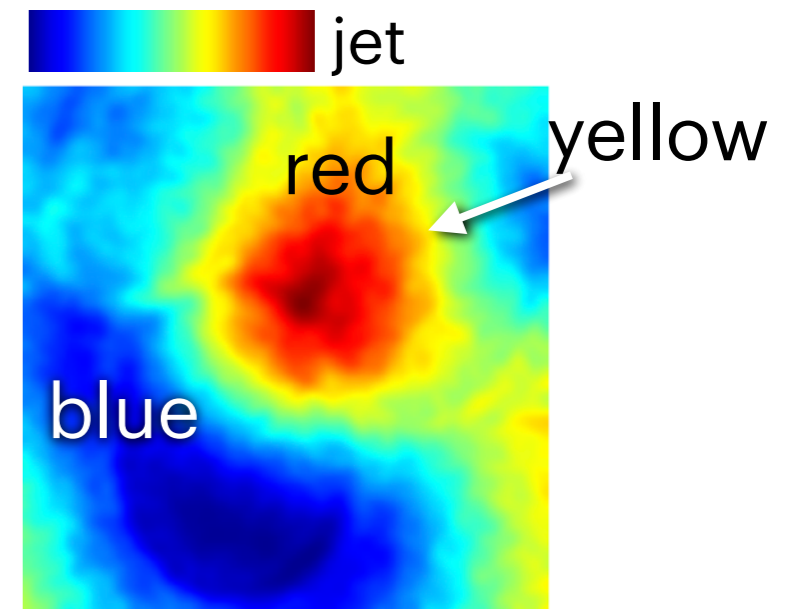
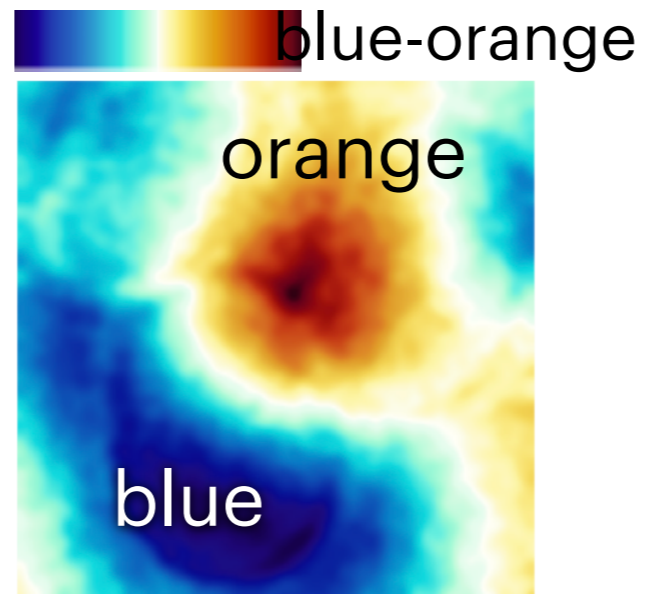
Hypothesis: Rainbows (and other colorful maps) are useful for highlighting global, distributional features



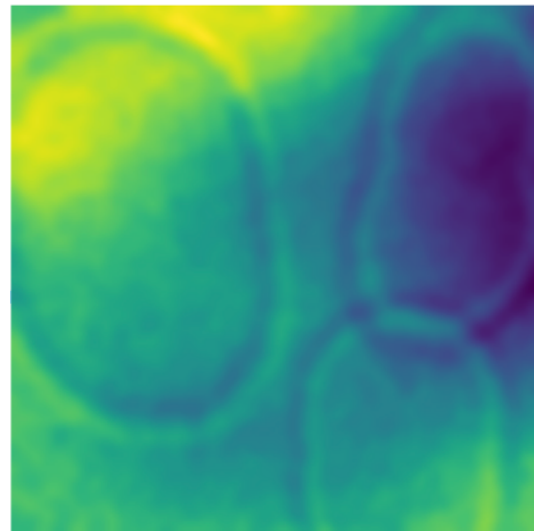
The cost: "local" features become less visible



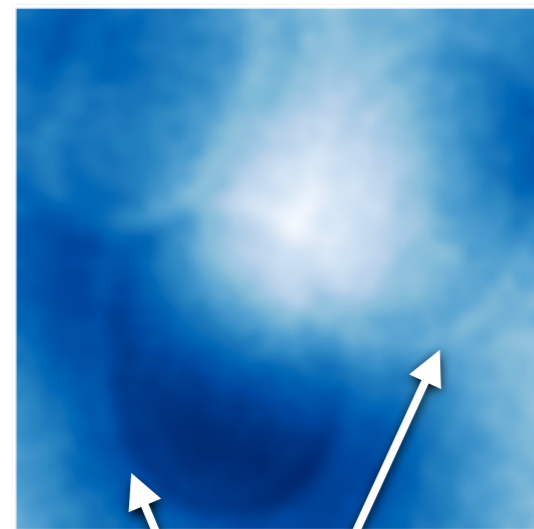
Oh, beans!



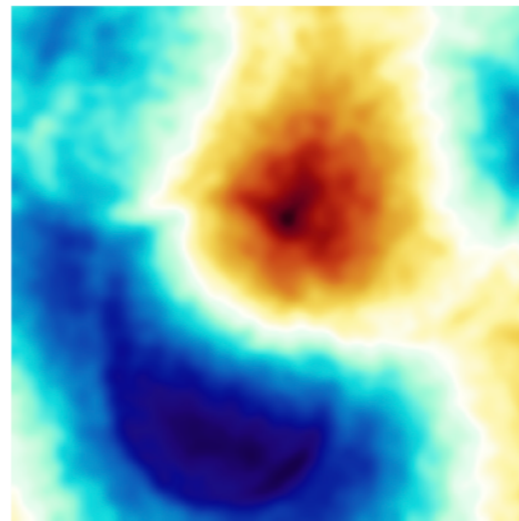
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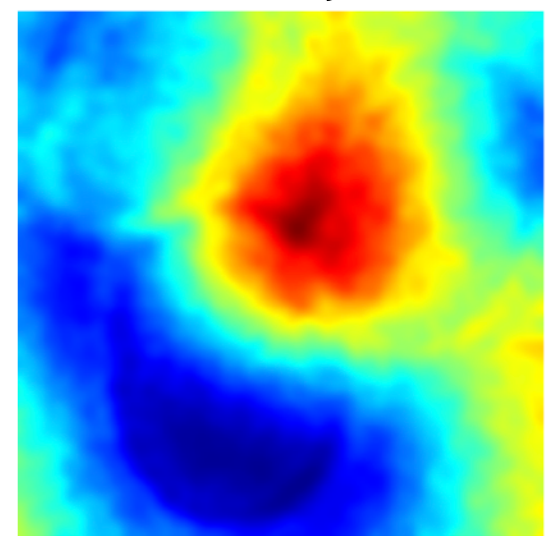
The cost: “local” features become less visible



blue-orange



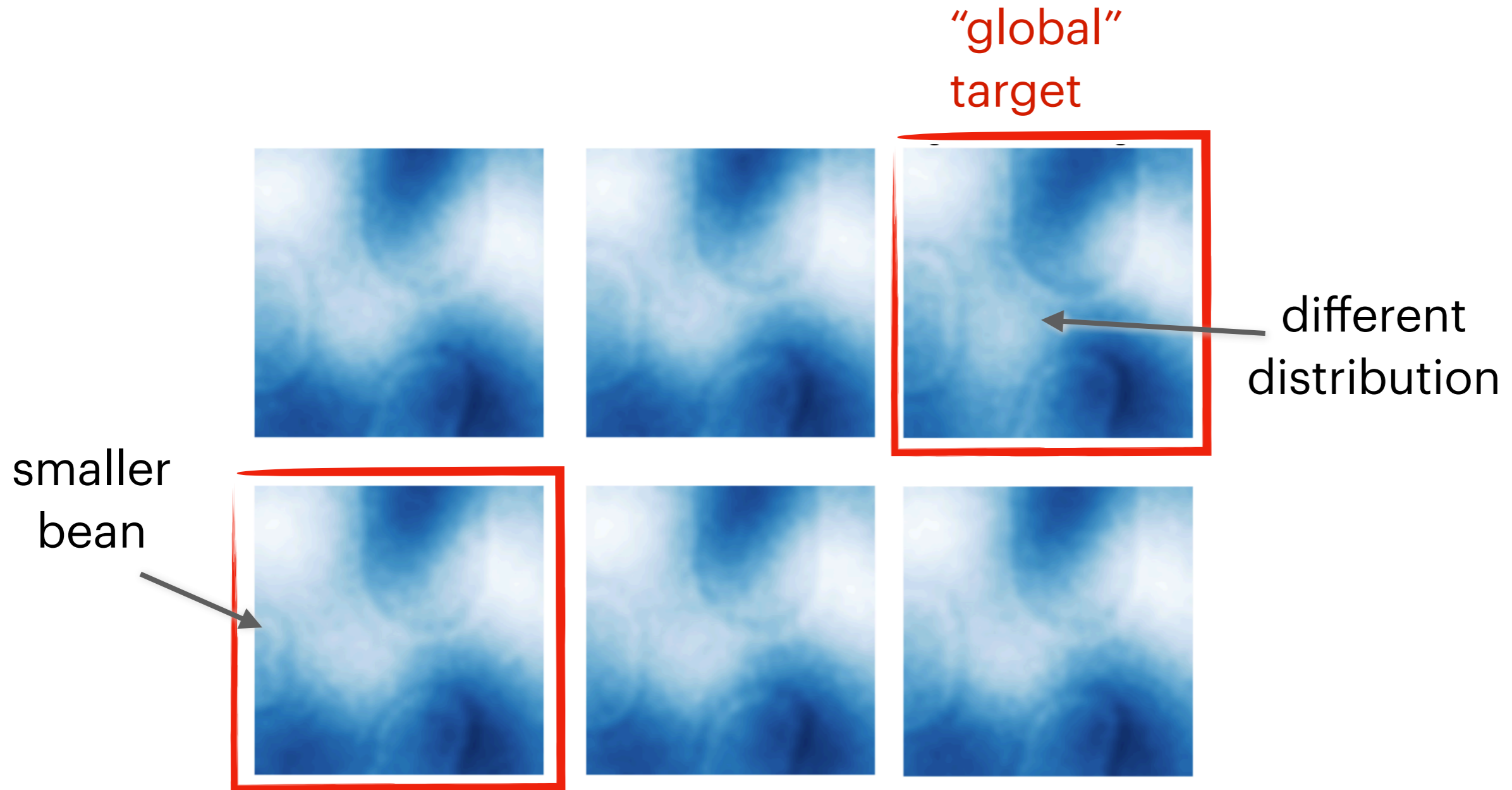
jet



← fewer colors ————— more “colorful”

How do we test this empirically?

Select the visualization that doesn't belong (aka lineup test)

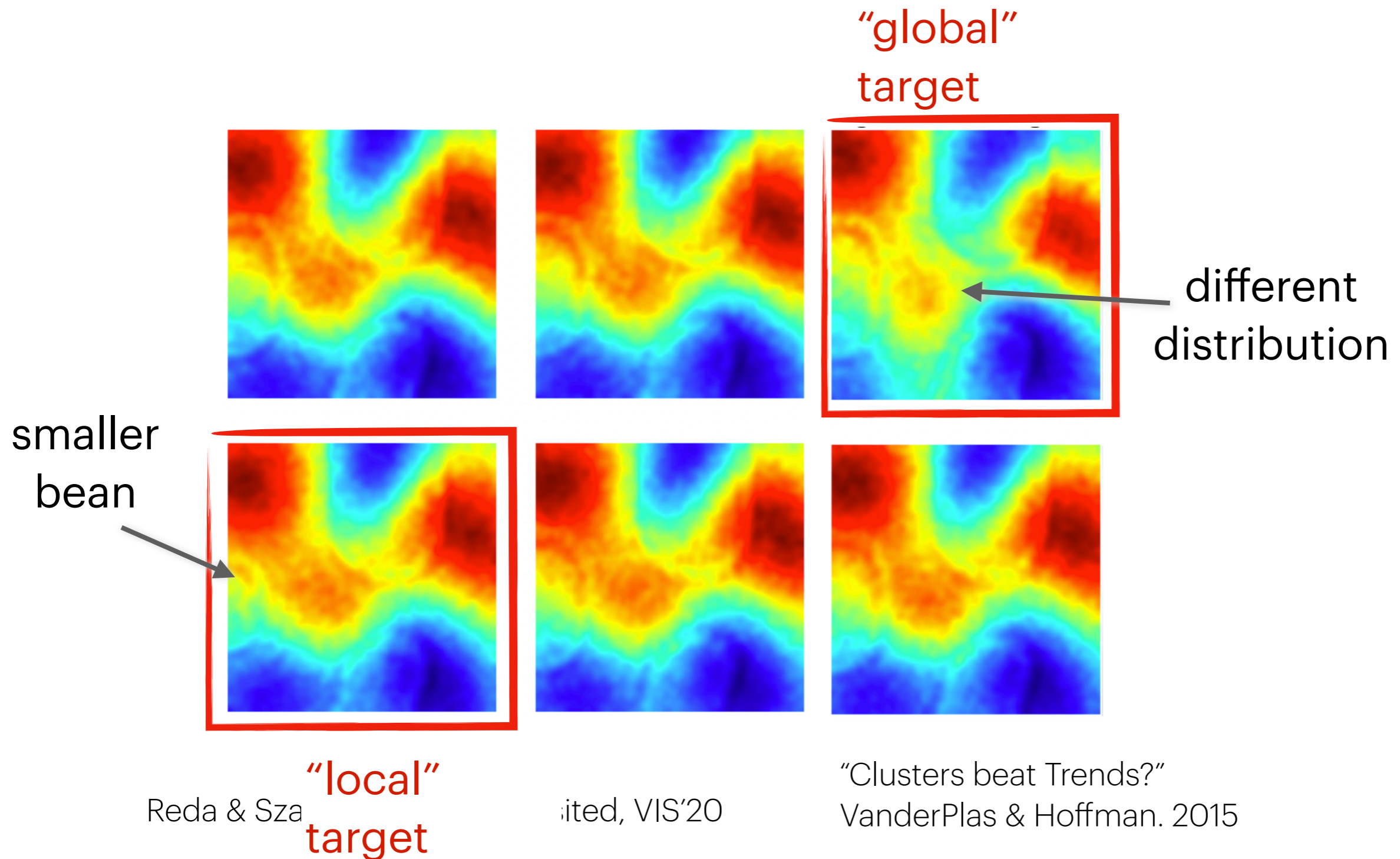


Reda & Sz
“local” target
vs Revisited, VIS’20

“Clusters beat Trends?”
VanderPlas & Hoffman. 2015

How do we test this empirically?

Select the visualization that doesn't belong (aka lineup test)



Expectation

more likely to see differences in "beans" (*local features*)

50-50 chance

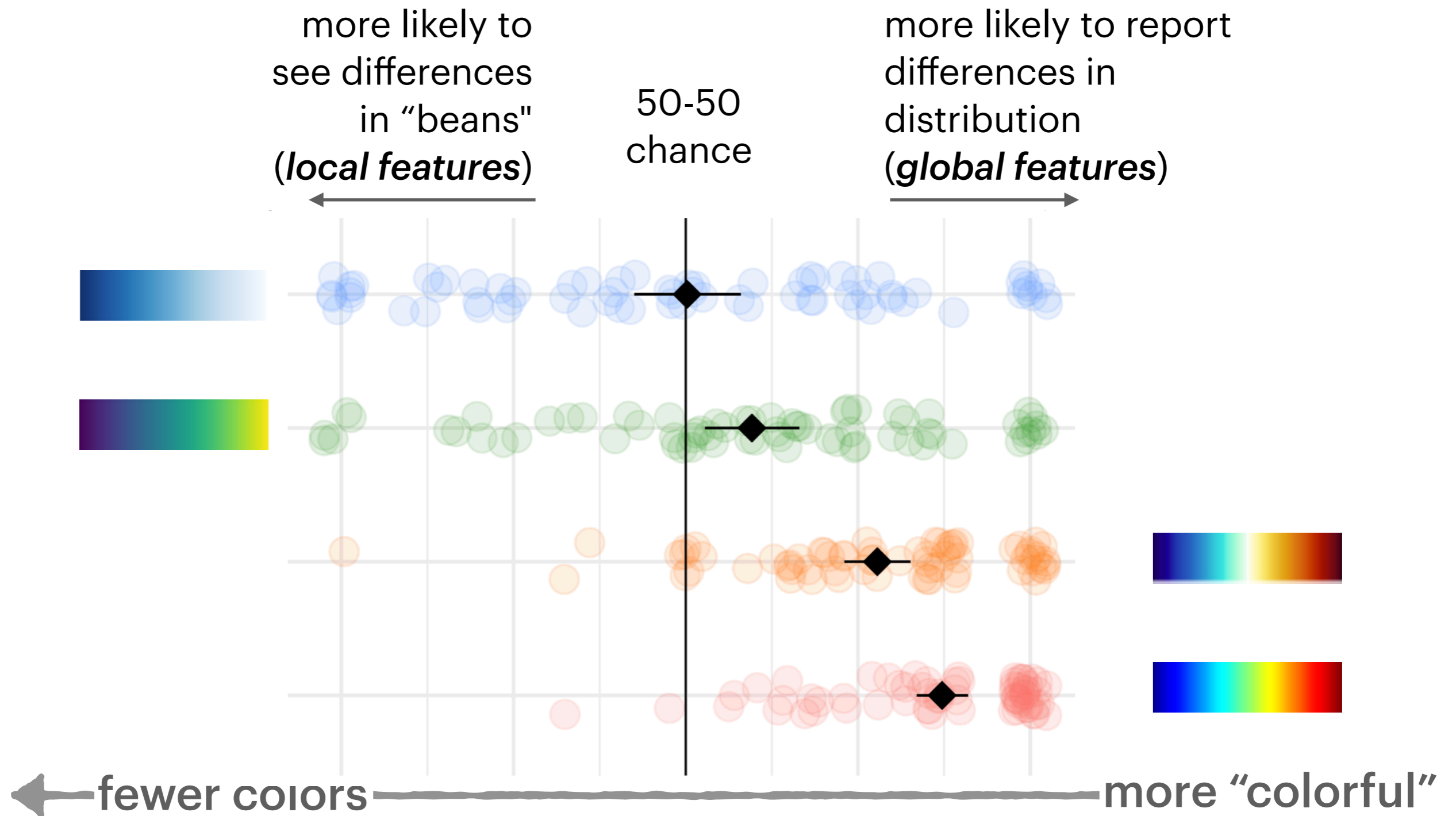
more likely to report differences in distribution (*global features*)



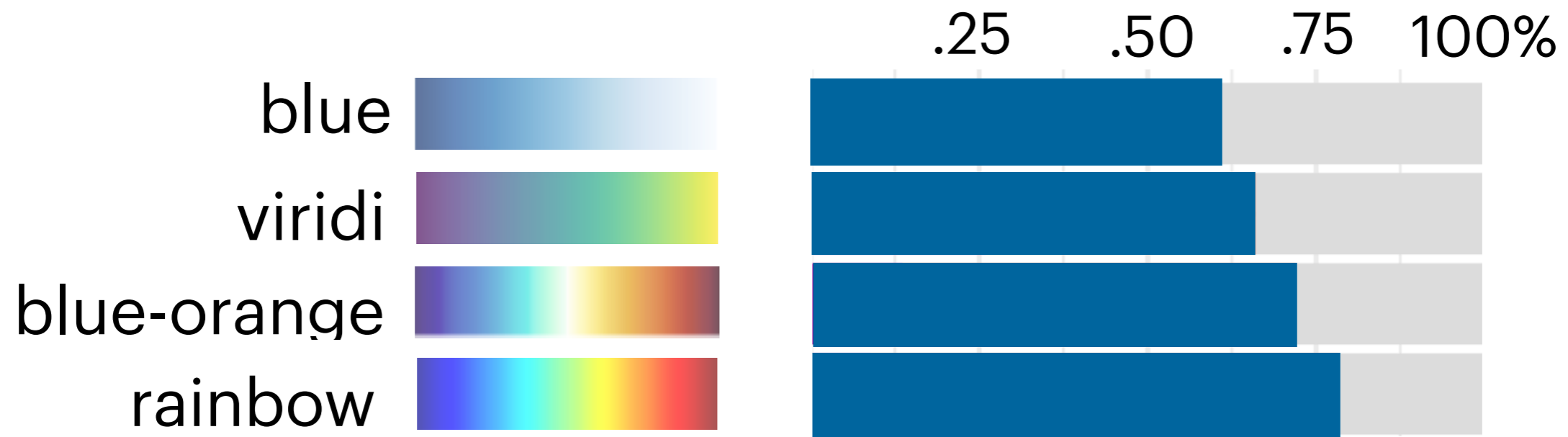
← fewer colors

more "colorful" →

Results



Results (overall sensitivity)



More colorful designs afford better sensitivity (**rainbow is best overall**)

Results (bias)

