Rethinking (and challenging) the Ranks of Visual Channels

Reading Group • Friday, March 18, 2022

Graphical Perception: Theory, Experimentation, and Application to the Development of Graphical Methods

WILLIAM S. CLEVELAND and ROBERT McGILL*

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KEY WORDS: Computer graphics; Psychophysics.

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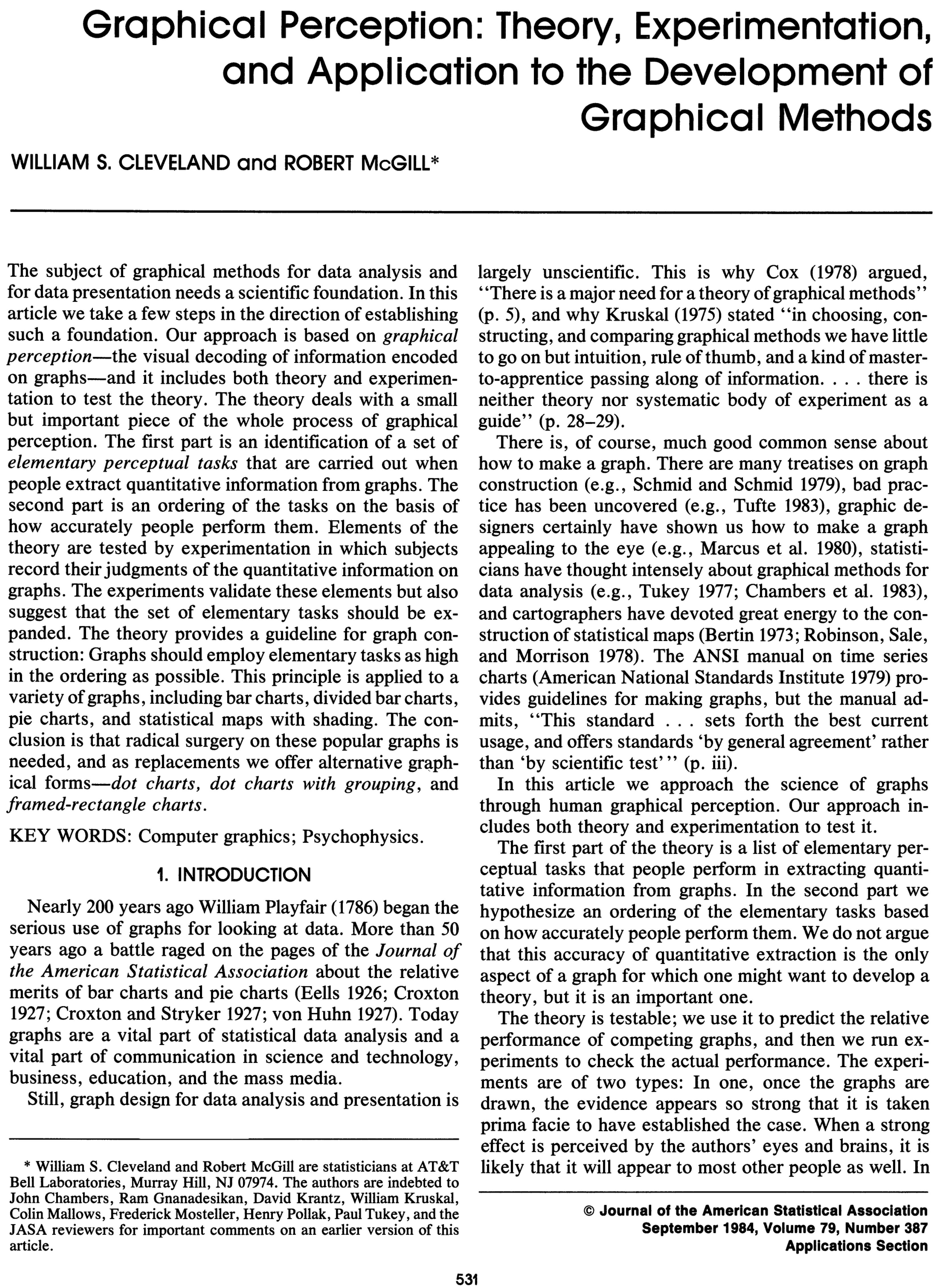

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6. Color luminance → Heatmap

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DEFINITION

Ranking of the most perceptually precise visual channels estimated from two-value ratio judgment tasks for Data Visualization

"What percentage is the smaller value compared to the larger?"

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ASSUMPTION

This ranking should hold for different tasks and numbers of marks

QUESTIONS

- Does this ranking hold for other contexts?
- Can we use this ranking as guidelines for Data Visualization?

Rankings

Cleveland & McGill’s Ranking

Position

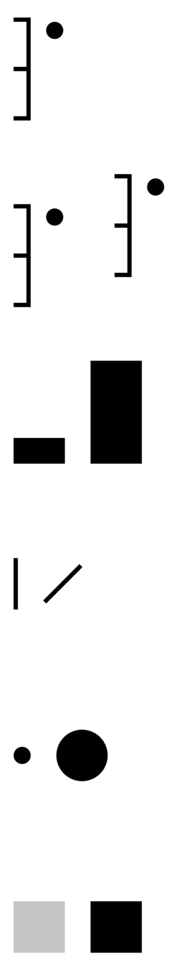
Position

Length

Angle

Area

Color luminance



Rankings

Cleveland & McGill's Ranking vs. Probabilistic Rankings

	BIAS				PRECISION				ERROR OF INDIVIDUAL RESPONSE			
Position |·	Angle	Length	Length	Length	Angle	Area	Area	Area	Angle	Bar	Bar	Bar
Position |· |·	Length	Bar	Bar	Bar	Area	Angle	Bar	Bar	Bar	Angle	Length	Length
Length	Bar	Angle	Lumin.	Lumin.	Lumin.	Lumin.	Angle	Angle	Length	Length	Lumin.	Lumin.
Angle	Lumin.	Lumin.	Angle	Line	Length	Bar	Lumin.	Lumin.	Lumin.	Lumin.	Angle	Area
Area	Area	Area	Line	Area	Bar	Length	Length	Length	Area	Area	Area	Angle
Color luminance	Line	Line	Area	Angle	Line	Line	Line	Line	Line	Line	Line	Line
	2	4	6	8	2	4	6	8	2	4	6	8

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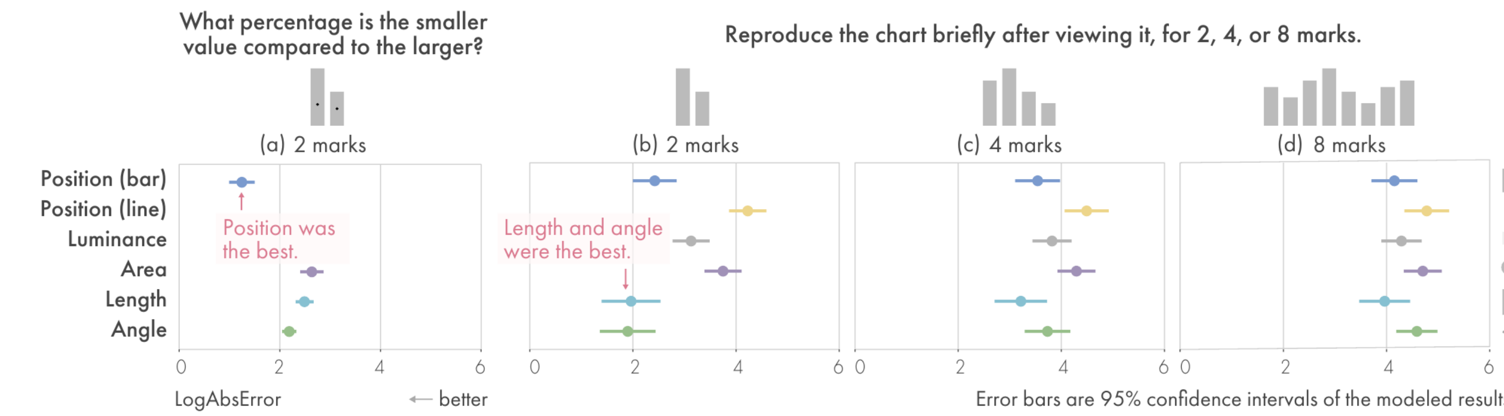

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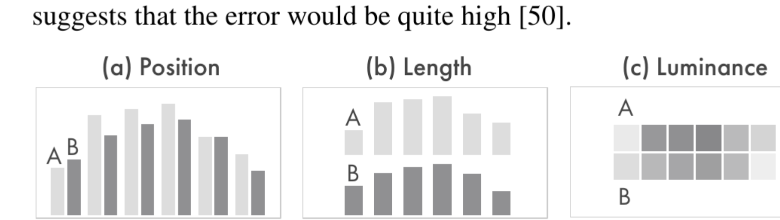

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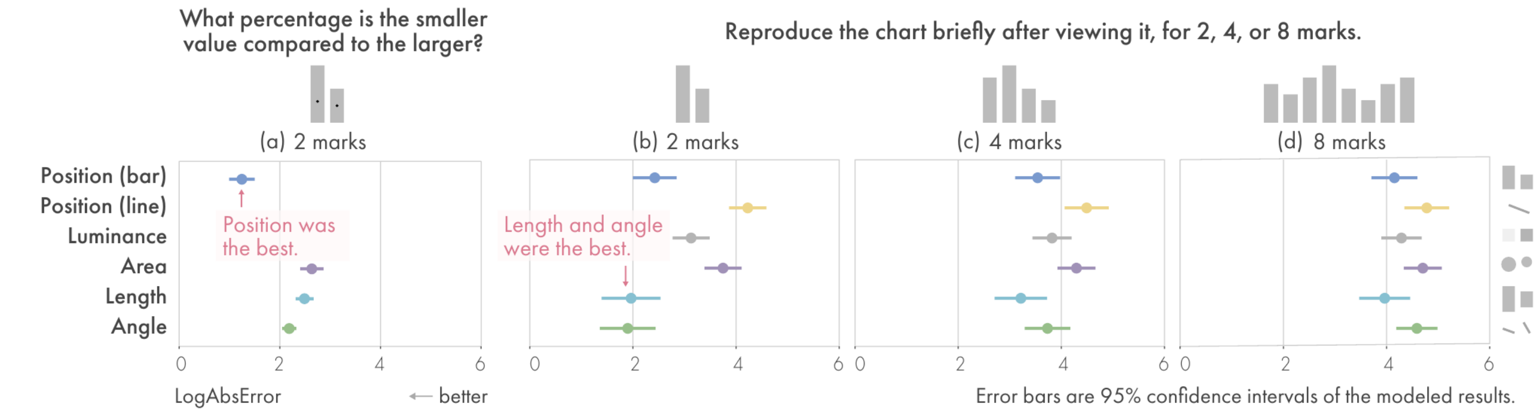

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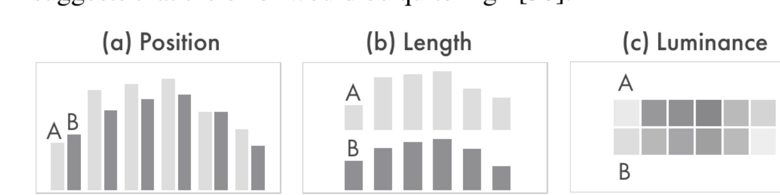

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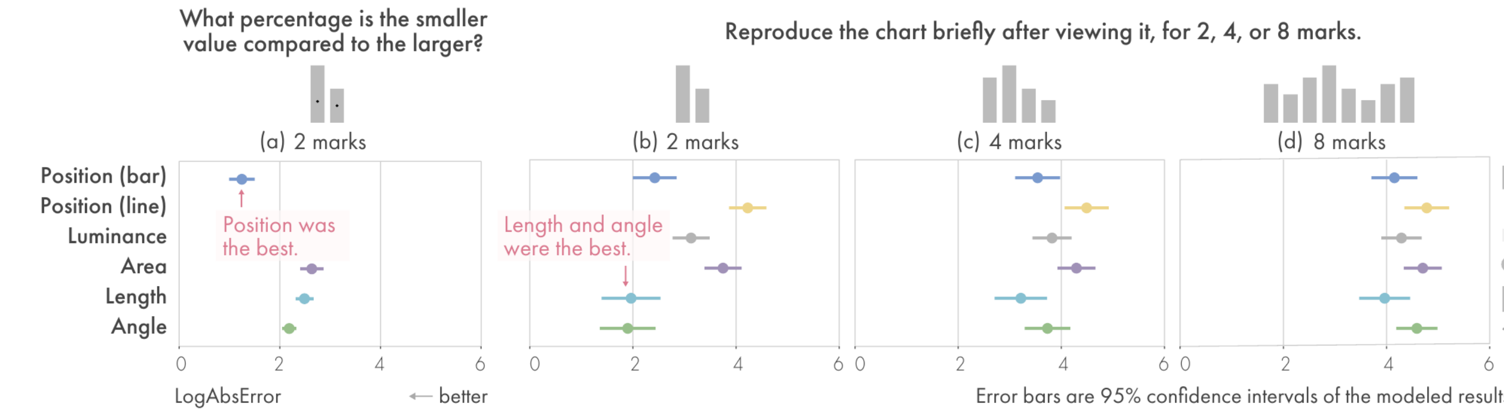

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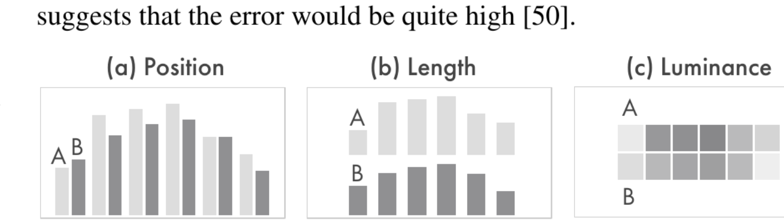

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Steve Franconeri
@SteveFranconeri

Replying to @domoritz @fumeng_yang and 2 others

'Consider' is a good term for the moment, this ranking is not ready for implementation. The paper challenges the existing ranking method, but more work is needed using more realistic tasks before generating concrete guidelines.

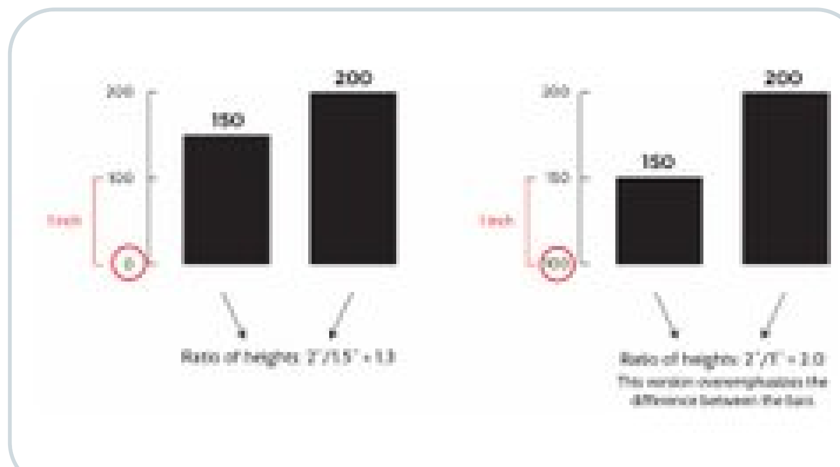
5:51 PM · Oct 23, 2021

4 Reply Cop...

Explore what's happening ...

Jon Schwabish
@jschwabish

I'm still on team 'bar charts start at zero' and here's an image that shows my mathematical reasoning. 📊 📊 📊



2:51 PM · Mar 10, 2022

90 Reply Co...

Read 2 replies

Steve Haroz 📊 👁 🧠
@sharoz

Replying to @jschwabish

If you want to take the "bar charts start at 0" stance, fine! But multiple papers have failed to find any difference between interpretation of bar charts and dot/line charts. So, you should have the same view there.

3:09 PM · Mar 10, 2022

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Read 1 reply

Thanks!

Some chart types/visual encodings are more "precise", based on asking people to judge a ratio between two values. The authors asked people to reproduce up to 8 values. Cleveland & McGill's ranking did not hold. The rankings are distinct for a different task, metrics, and numbers of marks.