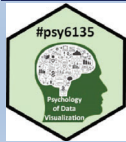
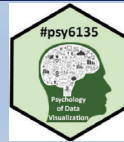


Human Factors Research: How to tell what works



Michael Friendly
Psych 6135

<https://friendly.github.io/6135>



Human Factors

What are the features of:

- humans &
- task characteristics

that affect task performance?

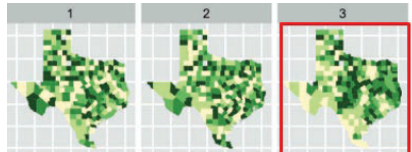


Image: <https://bbpconnect.com.au/event/ozav-seminar-on-human-factors/2020-12-16/>

2

Today's Topics

- Why consider human factors in graphic & information design?
 - Real-world applications
 - Data graphs
- Empirical study of graphs
- Experimental methods
 - Psychophysical methods
 - Eye tracking
 - Computer, web-based experiments
- Visual inference



3

Psychological issues in human factors

The following examples can be analyzed in terms of:

- Sensory (iconic) memory
 - pre-attentive, automatic, feature detection
 - massively parallel, short duration, easily fooled
- Visual attention
 - limited capacity
 - drawn to most salient features (color, motion, ...)
- Top-down processing
 - Goals, expectations

4

Control room display

A control room for a nuclear power plant or electrical system for a large city

- How does visual design support important decisions?
- How to warn or know when something fails?



How many things can the operator attend to at one time?

Find the important **target**

What visual design factors make important **events** salient?

Make it BLINK?

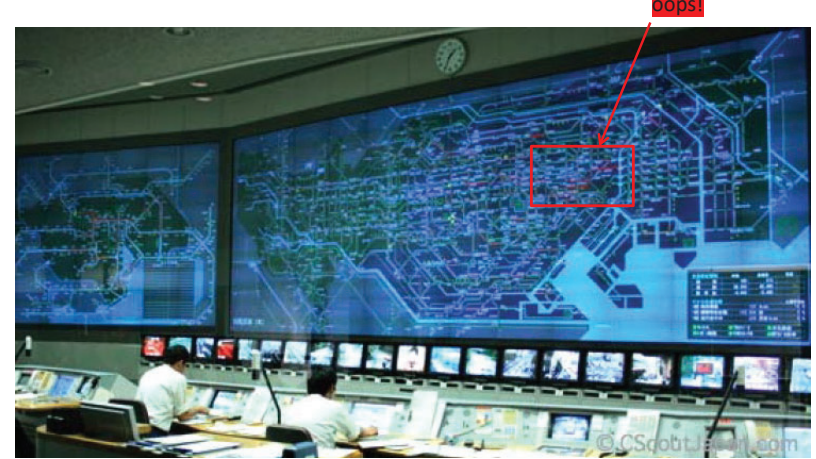
Make it spin

5

Traffic control display

A traffic control system for a large metropolitan city (Tokyo)

- How does visual design support important decisions?
- How to warn or know when something **fails**?
- When is there too much information?



6

Navigation



An early digital navigation display panel, incorporating visual gauges and charts for a variety of functions—combines separate variables into a single display

What visual features make it easier or harder to navigate?

Garmin Txi touchscreen device for a small jet

How does the pilot combine the map view with the heads-up view and all the visual dials?



7

Navigation

A more modern design integrates a wider variety of displays in a touch-screen device

- Are there too many options or features?
- What features demand the most pilot **attention** or distract attention from flying?
- How to study the efficacy of alternative visual display designs?

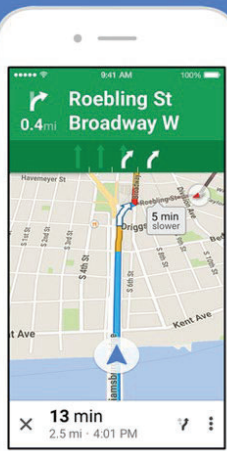


Rockwell-Collins Air King control panel

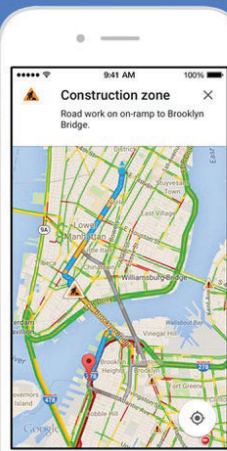
8

Driving Apps

Navigate with ease



Outsmart traffic



- 3D-like display: focus attention on where you are
- Next turn indicator
- Lane assist
- Show alternative routes
- Dynamic traffic notices

9

Financial trading desk

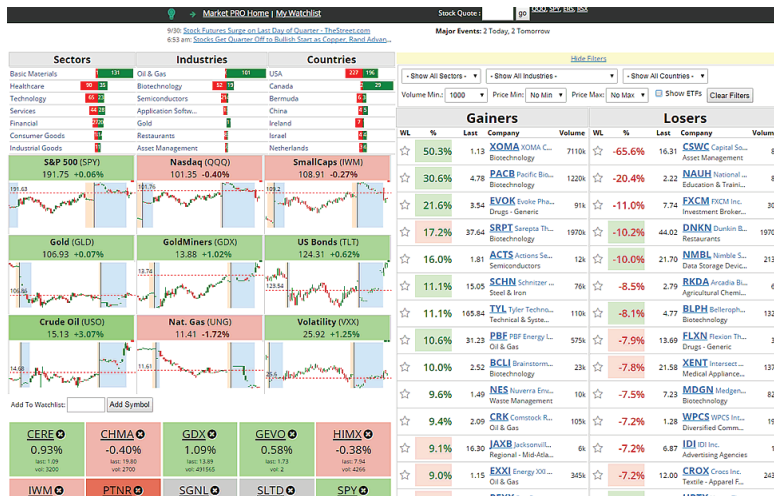


<https://www.varchev.com/en/two-of-the-major-fx-drivers-have-been-removed-whats-next/>

10

Dashboards: Financial trading

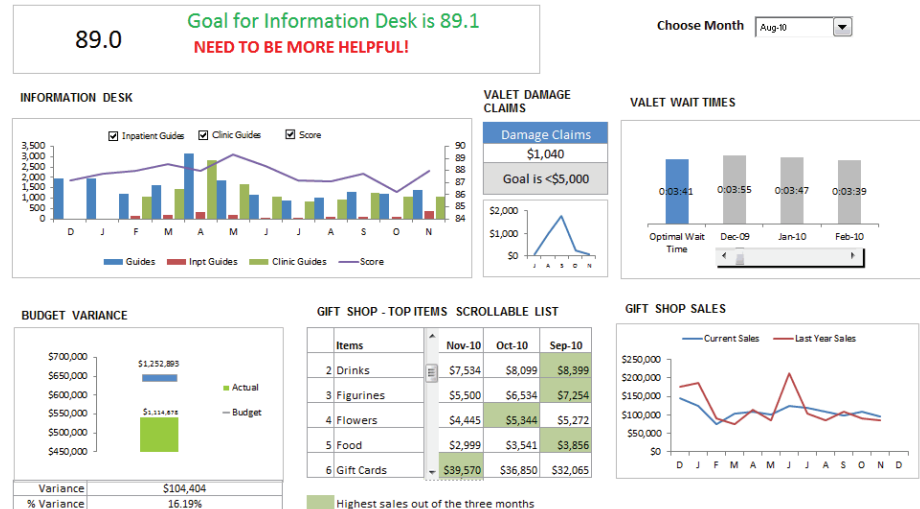
Dashboards combine visual information for decisions on a **single** screen
Good dashboards are: **dynamic**, **interactive**, **customizable**



11

Dashboards: Customer service

Interactive dashboards use sliders, buttons, pick lists, etc.



From: <https://chandoo.org/wp/customer-service-dashboard/>

12

Elements of UI Design

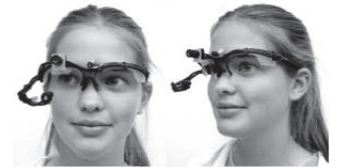
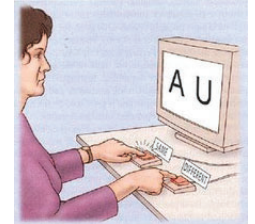
- Input controls
 - Buttons, touch screen?
 - Screen navigation
 - Layout
 - White space
 - Visual hierarchy
 - Content
 - Text, images
- Usability
 - Learnability
 - Efficiency
 - Memorability
 - Avoiding errors
 - User satisfaction

13

Empirical studies of graphs

How can we tell what works?

- Human factors vs. Psychology
- Experimental methods
 - Psychophysical methods
 - Task analysis
- Running graph perception studies
- Some results



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Human factors vs. Psychology

- **Human factors** research often motivated by applied problems in engineering, design, computer science
 - A/B testing (booking.com, Netflix, ...) for features of user interaction
 - navigation controls: pilot testing, flight simulators
- **Psychological** research often motivated by more basic perceptual & cognitive questions.
 - accuracy, RT of judgments of graphs
 - visual search, pattern detection
 - judgments of trend, correlation, etc.

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Psychophysical methods

- Psychophysical methods are used in studies of graphical perception to study the relationship between
 - properties of a **stimulus** (position, length, area, angle, ...)
 - and a **perceived** response (how big? which is greater?)
- Magnitude estimation: rated (0-100) size or %
- Matching – adjust size of B so it is same as A
- Discrimination
 - same/different?
 - which is larger?

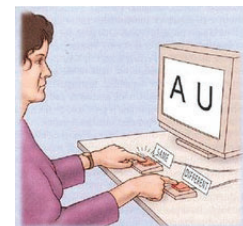
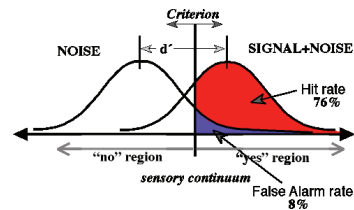


Image:
<http://www.cns.nyu.edu/~david/courses/perception/lecturenotes/psychophysics/psychophysics.html>

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Psychophysical methods: tasks

- Methods of adjustment
 - Adjust intensity of a feature until it is just barely detectable
 - Adjust one stimulus until just noticeably different (JND) than a standard (difference threshold)
- Forced choice tasks
 - Yes/No: On each trial a “signal” is presented or not
 - E.g., light, tone, visual feature, outlier, ...
 - Yes trials vary in some measure of “intensity”
 - Results: # hits, # misses -> d'

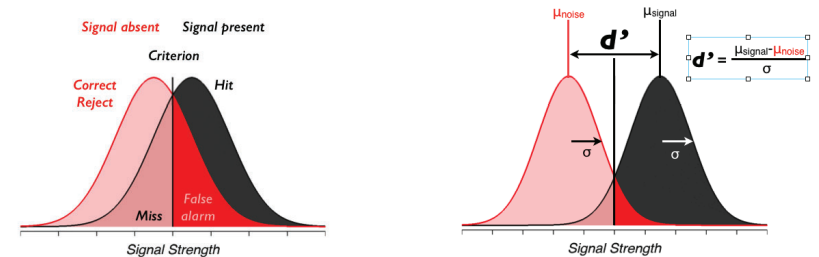


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Signal detection theory

Signal detection theory provides a means to assess performance in forced-choice tasks. It imagines that

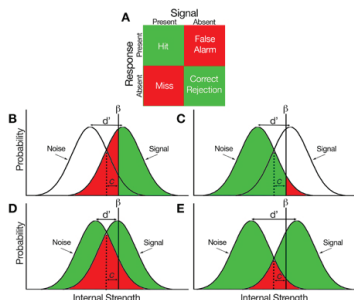
- Stimulus on a given trial evokes a (normal) distribution of internal response
- Subject says “Yes” if that is > criterion; else “No”
- Trials classified as $p(\text{Hit}) = \Pr(\text{“Yes”} | \text{signal})$, $p(\text{FA}) = \Pr(\text{“Yes”} | \text{no signal})$, ...
- Sensitivity = $d' = z(\text{Hit}) - z(\text{FA})$
- But: These depend on observer’s criterion (“bias”)



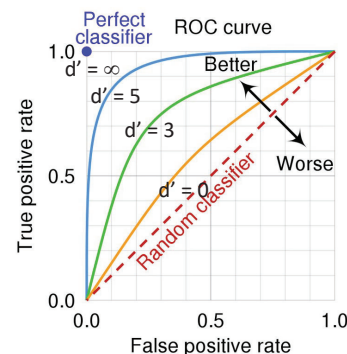
From: Crokerry, P., Campbell, S.G. & Petrie, D.A. The challenge of cognitive science for medical diagnosis. *Cogn. Research* 8, 13 (2023). <https://doi.org/10.1186/s41235-022-00460-z>

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Signal detection theory: measures



d' (sensitivity) = $z(H) - z(FA)$
 β (bias, criterion) = ratio of normals at the value of d'
 c = std distance of criterion from equality



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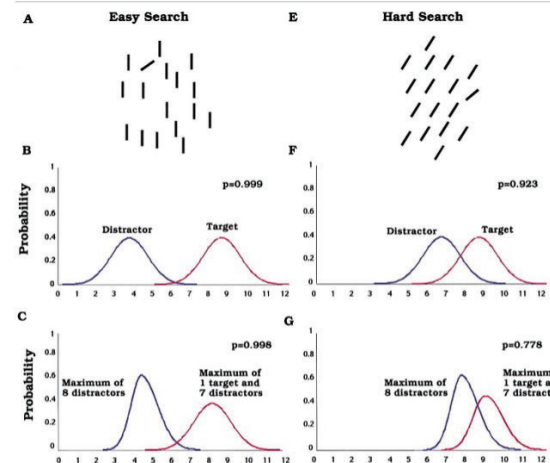
ROC curves: How H & FA vary with constant d'

Area under the curve ($AUC = A'$) often used as a measure

$$0.5 \leq A' \leq 1$$

<https://neuropsychology.github.io/psycho.R/2018/03/29/SDT.html>

SDT: Visual search task



Signal detection theory analysis of a visual search task

Correct detection
 ↑ with difference of target
 ↓ with # of distractors

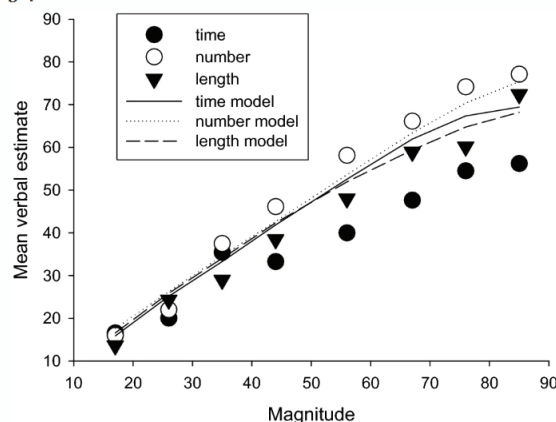
Vergheze, P. (2001). Visual Search and Attention: A Signal Detection Theory Approach, *Neuron*, 31 (4), 523-535, [https://doi.org/10.1016/S0896-6273\(01\)00392-0](https://doi.org/10.1016/S0896-6273(01)00392-0)

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Magnitude estimation: time, number, length

Ogden et al (2020): Verbal estimates of the time (duration), number, or physical length of items presented in visual displays

Fig. 4



Verbal judgments of number (numerosity) are more nearly linear over the range

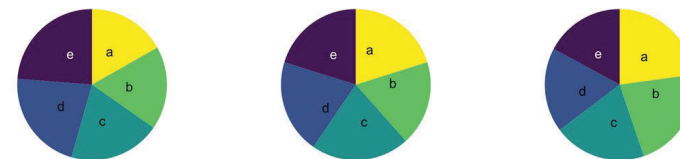
Longer times are underestimated

Ogden, Simmons, & Wearden. Verbal estimation of the magnitude of time, number, and length. *Psychological Research* 85, 3048–3060 (2021). <https://doi.org/10.1007/s00426-020-01456-4>

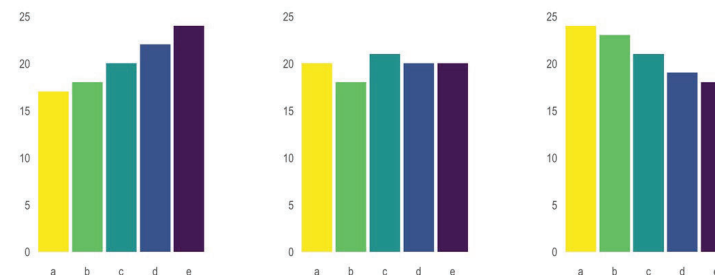
22

Discrimination: Pies vs. bar charts

In each pie chart: Which sector is the largest? Which is the smallest?



Which bar is the largest? Which is the smallest?



Length more accurate than angle

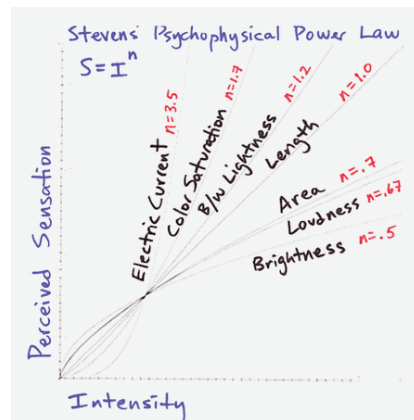
24

Stevens' Power Law

- How does perceived magnitude of a sensation relate to stimulus intensity?
- S. S. Stevens (1957) showed that, for many domains

$$\text{Sensation} \propto \text{Intensity}^p$$

- These provide ways to assess the **accuracy** of **magnitude estimation** for visual encodings
 - length judgments most accurate
 - area: less so
- But: graph perception is not always a matter of estimating magnitudes.



From: <https://santhoshsoundar.blog/power-law/>

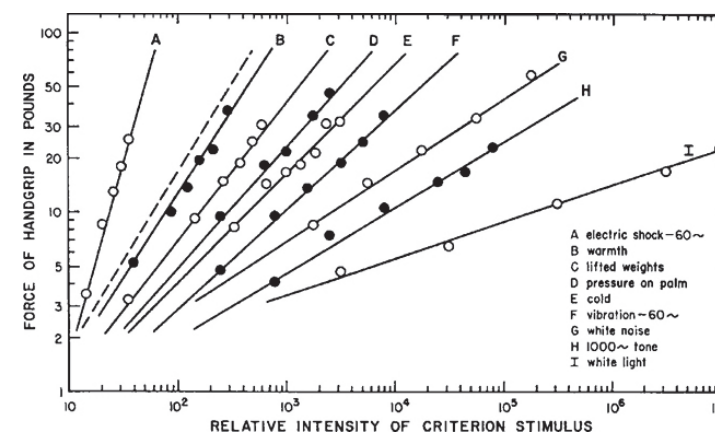
25

Stevens' Power Law: log-log form

The exponential form, $S \sim \text{Intensity}^p$ is more easily understood when both are plotted on log scales, where it is linear

$$\log(S) = p \log(I)$$

p is the multiplier effect of a multiple of Intensity



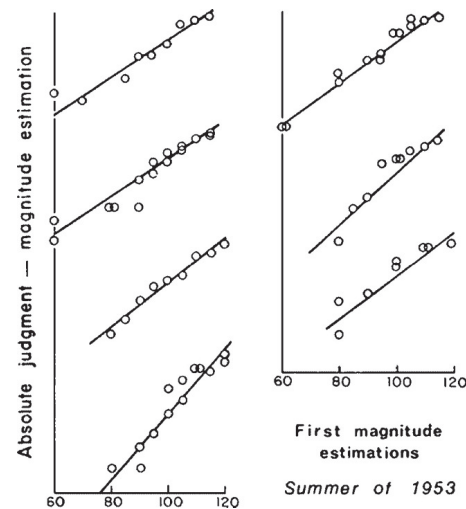
26

Power Law: Origin story

In 1953, S. S. Stevens carried out experiments on magnitude estimation of **loudness** of sounds – measured in db (a log scale)

This graph shows results for 7 individual subjects, offset to show the separate data

The idea of an average slope, p , arose later, as the effect for an **average observer**.



See: (2009) Stevens' Power Law. In: *Sensory Neuroscience: Four Laws of Psychophysics*. Springer, Boston, MA. https://doi.org/10.1007/978-0-387-84849-5_1

27

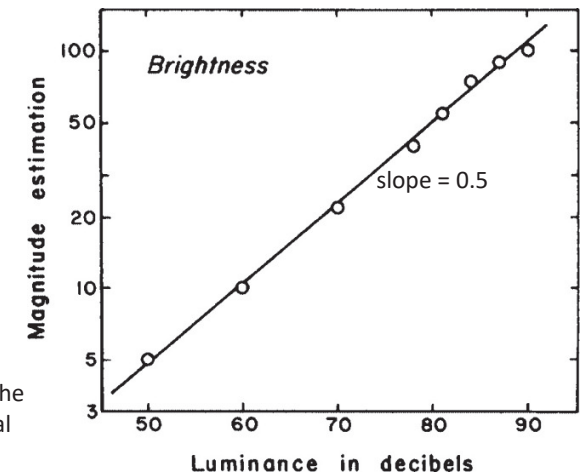
Power Law: Brightness

What about other stimulus domains?

Luminance of a light source could be measured (on a log scale)

Averaging over observers, log of the magnitude estimates was again linear with log intensity.

Stevens (1975) asserted that he had discovered a fundamental law of the relation between physical properties and perception.



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Magnitude estimation & memory

How does **remembered** size relate to **perceived** size?

How does it relate to stimulus intensity?

Kerst & Howard (1984) propose another power law:

$$\text{Sensation} \propto \text{Intensity}^p$$

$$\text{Memory} \propto \text{Sensation}^{p'}$$

therefore

$$\text{Memory} \propto \text{Intensity}^{p \times p'}$$

If $p \approx p'$, the exponent for memory $\approx p^2$

→ remembered area **less** accurate than area itself

Table 1

Power Function Exponents (n) and Correlations (r) for Perceptual and Memorial Estimates of Line Length and Shape Area (Experiment 1)

		Group Data		Median Individual Data	
		Perception	Memory	Perception	Memory
Line Length	n	.93	.84 (.86)	.90	.81 (.81)
	r	.99	.99	.99	.99
Shape Area	n	.77	.61 (.59)	.74	.65 (.55)
	r	.99	.99	.99	.98

Note – Values in parentheses are those predicted by the relation that the memory exponent equals the square of the perceptual exponent.

Kerst & Howard, *Bulletin of the Psychonomic Society* 1984, 22 (6), 517-520

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Visual search tasks

Find a target item among the many distractors in this display

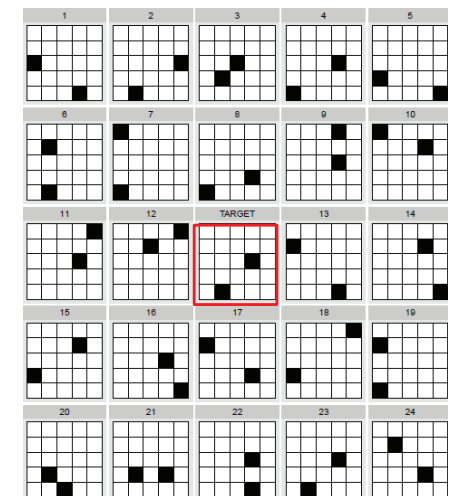


Measure:

- reaction time (RT)
- accuracy (% correct)

Vary:

- # distractors
- # of targets
- complexity (# black squares)
- display format
- ...

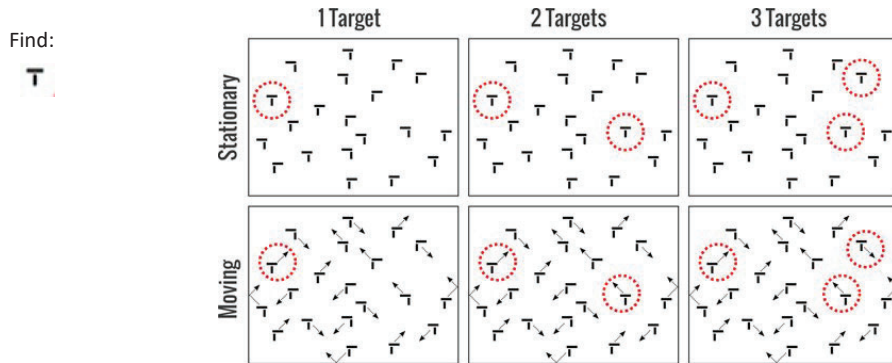


This paradigm is often used in evaluating complex visual displays

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Visual search experiment

Visual search for a diagnostic signal (radiology) can vary with the # of targets and whether these are shown stationary or moving.



The response measure here is % accuracy in detecting a given target.

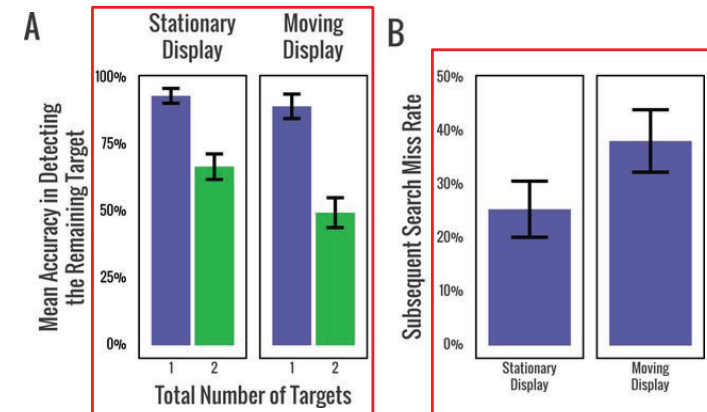
31

Visual search experiment

Results:

Better for 1 target vs. 2, whether moving or not

A 2nd search is less accurate when the target is moving



From: Stothart et al (2018). Satisfaction in motion: Subsequent search misses are more likely in moving search displays. *Psychonomic Bulletin & Review* 25(1):409-415

32

Running graph perception experiments

- Paper & pencil tasks
 - little control of experimental presentation features
 - can't measure RT

- Lab software: run on lab computers

- e-prime (\$\$\$), <https://pstnet.com/>
- matlab (\$) & Psychtoolbox: <http://psychtoolbox.org/>
- PsychoPy – free, open source, see: <http://www.psychopy.org/>



- Web-based

- Survey Monkey / Qualtrics
- Amazon Mechanical Turk



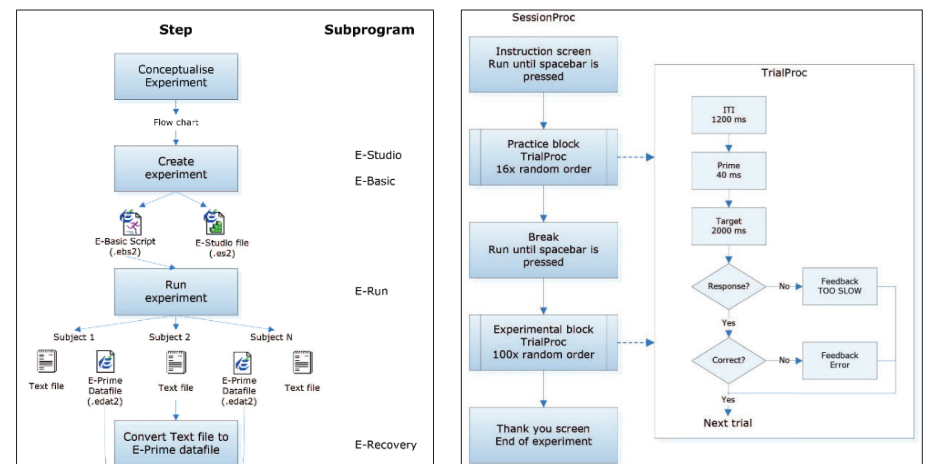
33

e-prime



e prime is a polished software system for designing psychology experiments

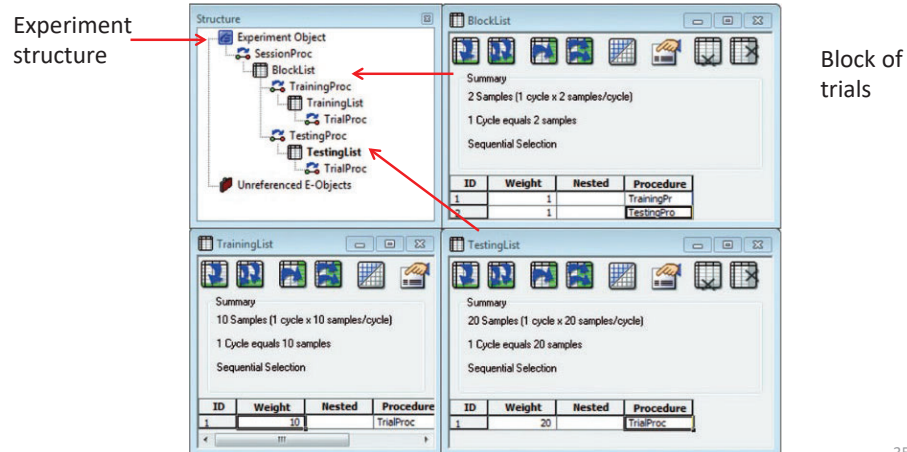
- E-Studio GUI → E-Basic script; E-Run: runs experiments



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e-prime

Create experiment structure by drag-and-drop in E-Studio
 Stimuli: text, audio, images, video, ...
 Response devices: keyboard, mouse, external devices, ...



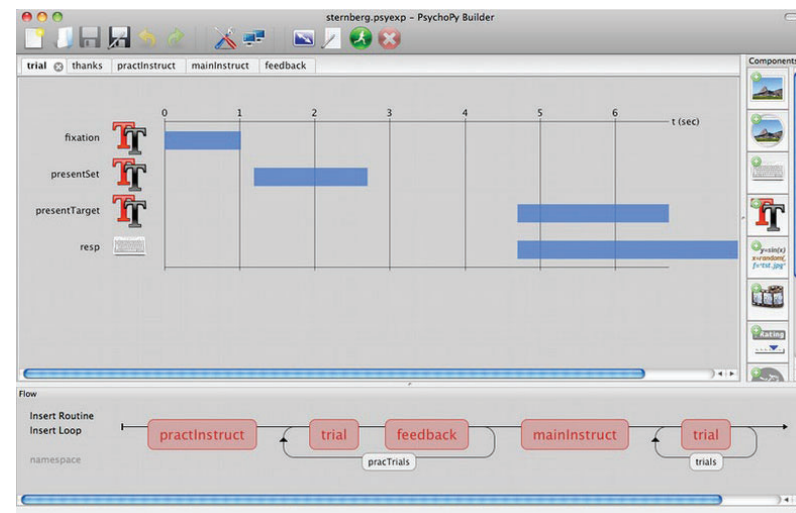
35

PsychoPy



PsychoPy provides a GUI for constructing online experiments
 • Builder interface → python code that runs the experiment

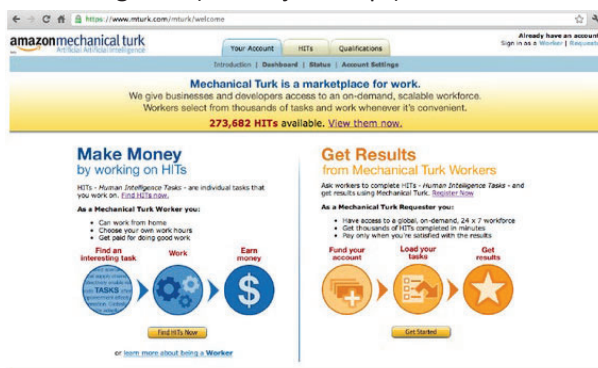
<https://www.psychopy.org/>



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Amazon Mechanical Turk

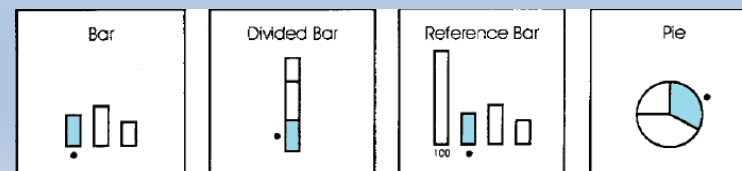
- Web-based experiments, hosted on Amazon servers
 - requester jobs: Human Intelligence Tasks (HITS)
 - worker pool: Turkers, get paid for doing tasks (\$0.01 – 0.10 per item)
 - each cell of a design can be a separate HIT
 - Amazon provides a markup language for presenting text, movies, images, ... (HTML, javascript)



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Studies of Graph Perception

- Early studies
- Elementary perceptual tasks
- Accuracy & reaction time
- Mental processes in graph perception
- Task analysis



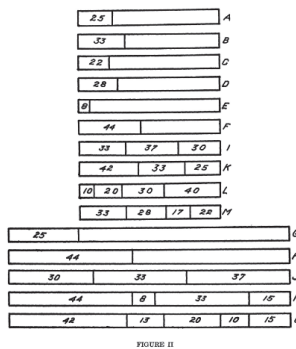
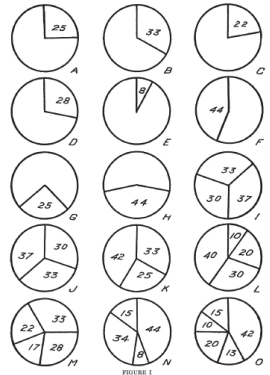
38

Early studies: Circles vs. bars

Eells (1929) studied **magnitude estimation** of proportions of a whole, presented as circles vs. bars

“What number represents the **proportion** for each marked segment?”

51 Circles and Bars for Representing Component Parts 123



Conclusions:

- 1 segment: circles ≈ bars
- >1 segment: circles better than bars

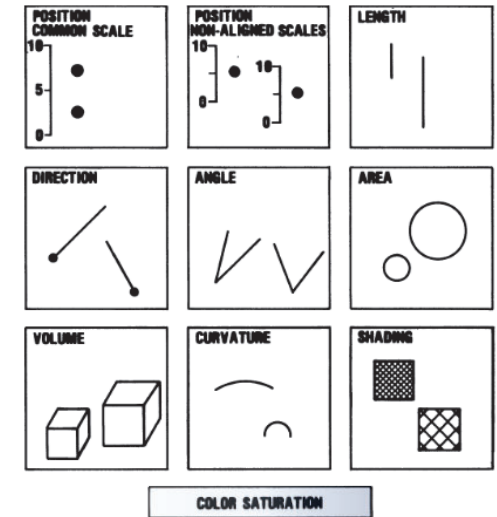
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Graph perception: Elementary perceptual tasks

Cleveland & McGill (1984) proposed that graphical perception could be studied in terms of 10 elementary perceptual tasks involved in most common graphs.

Their study was one of the first modern ones.

It set a standard for magnitude estimation tasks of data graphs



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Cleveland & McGill experiments

Pie charts vs. bar charts – **position-angle** experiment

Elementary perceptual tasks:

- bar chart: position along a scale
- pie chart: angle? area? arc length?

Experiment:

50 graphs (½ pie, ½ bar), random order largest marked ●

“What percent is each of the others?”

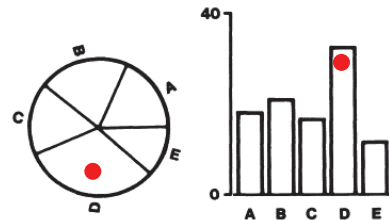
“Make a quick visual judgment”

Response on an answer sheet

Measures:

accuracy: $\log_2(|\text{judged \%} - \text{true \%}| + 1/8)$

bias: judged % - true %

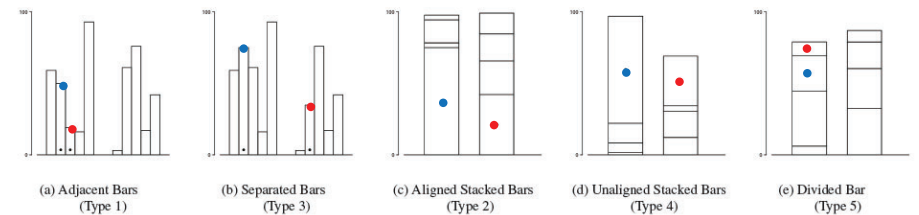


NB: log scale estimates **relative** error; +1/8 handles zero values

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Cleveland & McGill experiments

Bar charts tasks – **position-length** experiment



Experiment:

- 50 graphs, 10 × 5 types
- “What percent is smaller ● of the larger ●?”

Measures:

accuracy: $\log_2(|\text{judged \%} - \text{true \%}| + 1/8)$

bias: judged % - true %

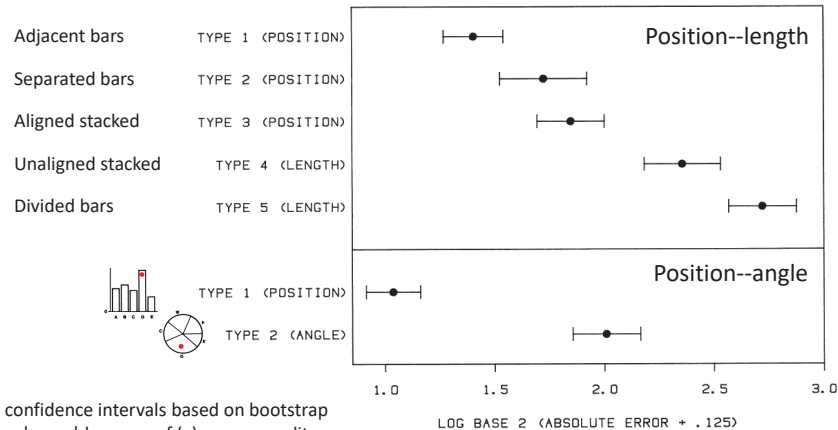
Discussion Q:

- What are the elementary perceptual tasks involved in each of these?
- What is the statistical analysis?

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Cleveland & McGill experiments

Cleveland & McGill summarized these experiments in this figure, comparing absolute error in the tasks in these two experiments.



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Heer & Bostock: MTurk experiments

- Replicated Cleveland & McGill T1—T5, T6 (angle)
- Added **area** judgment tasks:
 - T7: Bubble chart
 - T8: Center-aligned rectangles
 - T9: Treemap

Task:
“What % is area A of area B?”

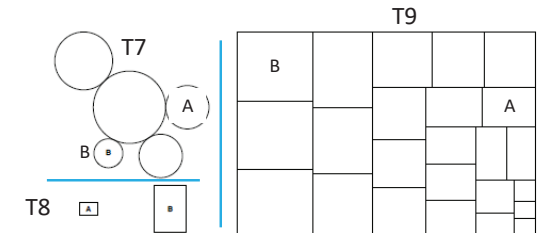


Figure 2: Area judgment stimuli. Top left: Bubble chart (T7), Bottom left: Center-aligned rectangles (T8), Right: Treemap (T9).

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Heer & Bostock: results

Results largely confirmed Cleveland & McGill (1984) with respect to relative order
The area judgment tasks are shown to give even larger errors

Details:

H & B use a **between-S** design, $n=50$ per chart type, 10 charts of each type

$10 \times 7 = 70$ separate HITs (each S responds to 1 chart)

Response: **type in a #** (% of smaller)

This graph of these results is a great model for data display

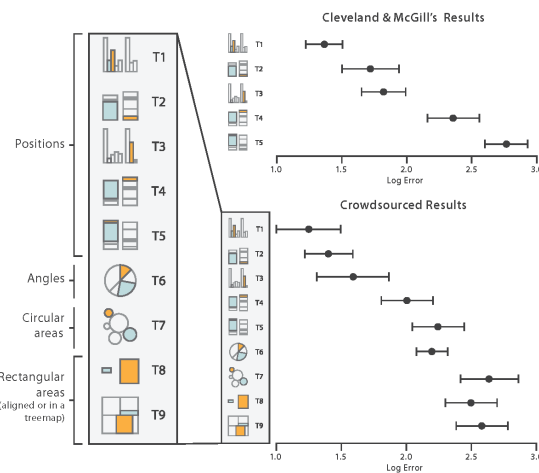


Fig. 5.8 from: Munzner, *Visualization Analysis & Design*

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Heer & Bostock: results

Other findings:

For a given graph type, judgments are most accurate when the true difference is **extreme**

Also: **Asymmetric**, peak at ~55%

The within-graph effect is larger than the differences between graphs

Discussion Q:

What are some problems with this graph?

How could it be improved?

Reduce prominence of grid lines
Direct labels
Different point shapes

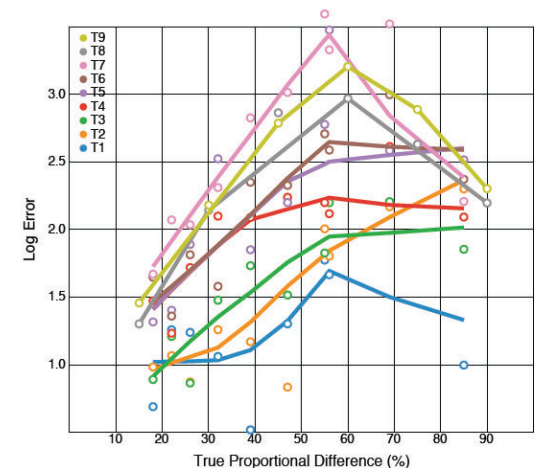


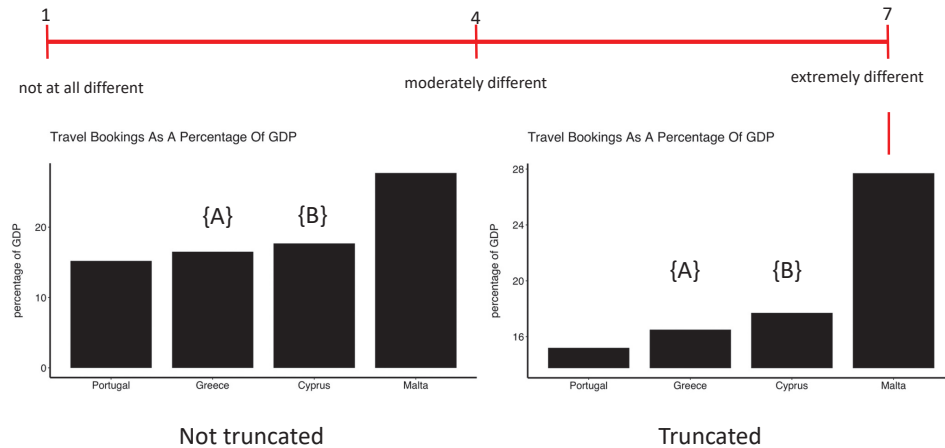
Figure 3: Midmeans of log absolute errors against true percentages for each proportional judgment type; superimposed are curves computed with *lowess*.

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Effect of truncation in bar charts

An Mturk experiment to assess the effect of **Y-axis truncation** on relative judgements

How do bookings to {A} compare to bookings to {B}?



Yang et al., Truncating Bar Graphs Persistently Misleads Viewers, *Journal of Applied Research in Memory and Cognition*, 2021, <https://doi.org/10.1016/j.jarmac.2020.10.002>

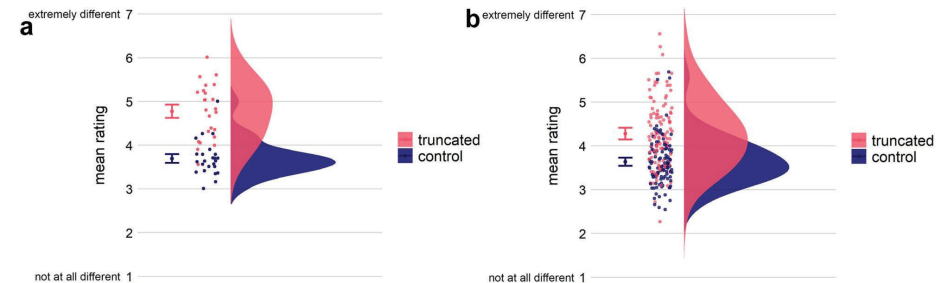
47

Effect of truncation in bar charts

Design: Within-S, each subject saw 20 control bar graphs and 20 truncated bar graphs

Study 1: No warning (n=24)

Study 2: Subjects warned that some graphs might be misleading (n=109)



This graph form ("raincloud plot") combines density estimates, data dots & CIs
Study 2 tests an interpretation based on task **mental set** / instructions

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Simkin & Hastie: accuracy and RT

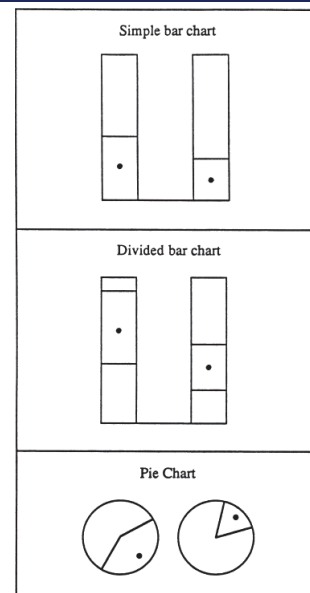
Problems with Cleveland & McGill study:

- Assessing accuracy-only omits consideration of **speed of judgment** – should also measure reaction time
- "Elementary perceptual tasks" give no insight into the **cognitive processes** used by observers to perform these judgments.

Simkin & Hastie used computer-controlled experiments to measure both accuracy & RT

- Three types of stimuli x 30 of each = 90 trials
- Discrimination task**: Which is larger?
- Judgment task**: What % is smaller of the larger?

Analyses: Separate ANOVAs of discrimination RT, judgment RT and errors in each task



Simkin & Hastie (1987), An Information-Processing Analysis of Graph Perception, *JASA*, **82**, 454-465

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Simkin & Hastie: processing stages

They propose that tasks using various graph types can be understood in terms of **elementary mental processes**:

- anchoring**: segment a component to serve as a standard for comparison
- scanning**: visual sweep across a distance in a graph
- projection**: send a ray from one point to another
- superimposition**: mentally move elements to a new, overlapping location
- detection**: detect difference in size of two components

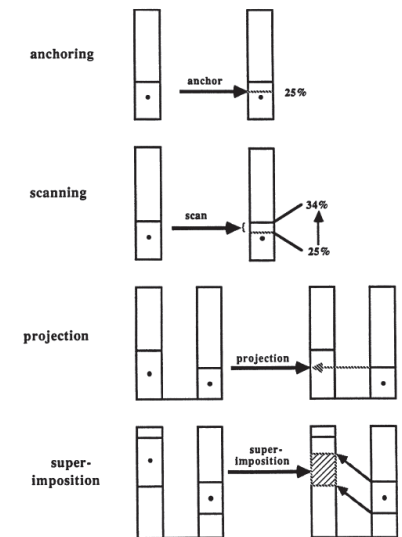


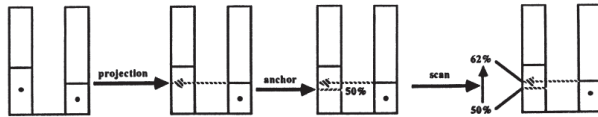
Figure 2. Schematic Summaries of Proposed Elementary Mental Processes That Can Be Combined to Explain Performance in the Experimental Tasks.

50

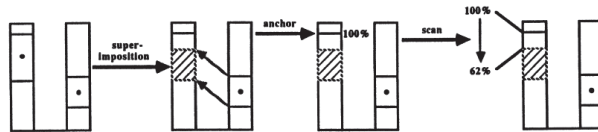
Simkin & Hastie: processing stages

Analysis of the three graph types in terms of proposed elementary mental processes

bar chart
(position)



divided bar
(length)



pie chart
(angle)

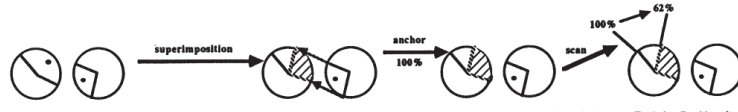


Figure 7. Proposed Sequence of Elementary Mental Processes to Explain Performance in the Comparison Judgment Task for Position (top panel), Length (middle panel), and Angle (bottom panel).

NB: If these processes are **sequential**, RTs should reflect **additive** components
AFAIK, this idea has not been tested or explored.

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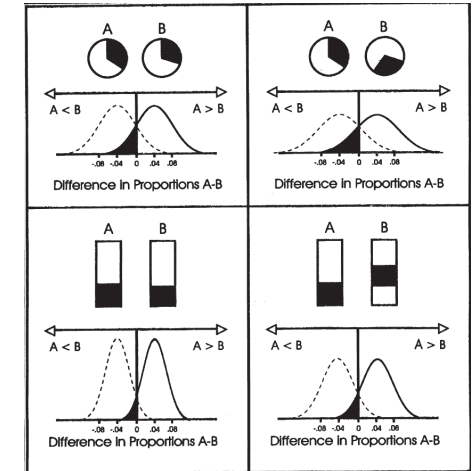
Hollands & Spence: Discrimination analysis

How do people make decisions about which is **larger** from different visualizations?

- aligned vs. not aligned
- pie vs. bar chart

Hollands & Spence propose an incremental estimation model to account for **speed** of processing:

- each stimulus evokes a distribution of a psychological response of "size"
- the response ($A > B$?) is determined by the separation and overlap between the two distributions
- less overlap \rightarrow faster response



Hollands, J. & Spence, I. (2001). The discrimination of graphical elements. *Applied Cognitive Psychology*, 15, 413-431.

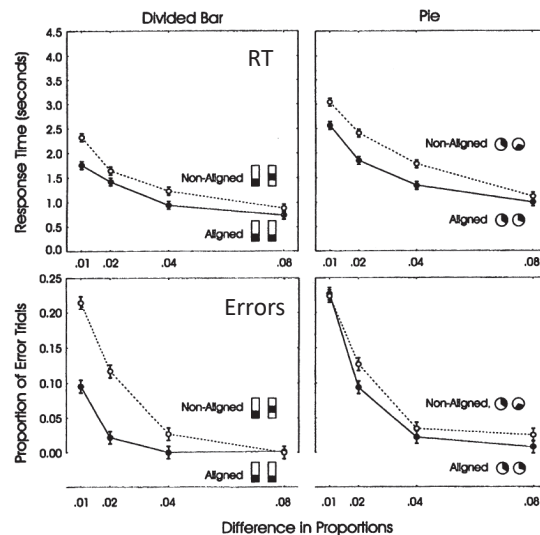
52

Hollands & Spence: results

Experiment 1

- RT \downarrow as $\Delta p \uparrow$
- RT < for aligned vs. non-aligned
- RT < for divided bars vs. pies

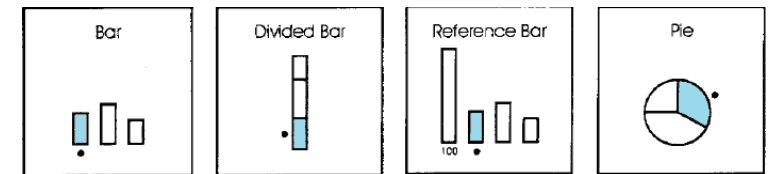
Similar pattern for errors



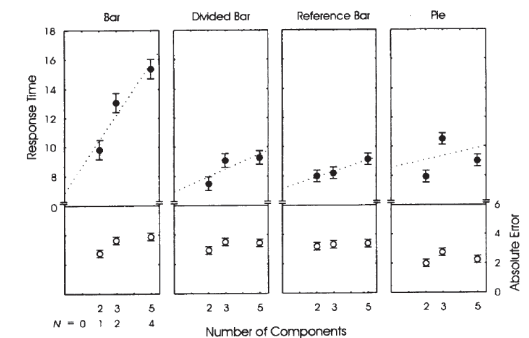
53

Are pies ever better?

What **percent** is the indicated region of the **total**?



Other experiments by Holland & Spence (1992, 1998) show that this judgment task is hardest for separated bars and **easiest for pie charts**



Hollands, J. & Spence, I. (1998). Judging Proportion with Graphs: The Summation Model. *Applied Cognitive Psychology*, 12, 173-190

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More pie studies: Skau & Kosera

Infographics use many variations of the basic pie chart to show part-whole relations
What properties do people use in making judgments: Angle, area, arc length?

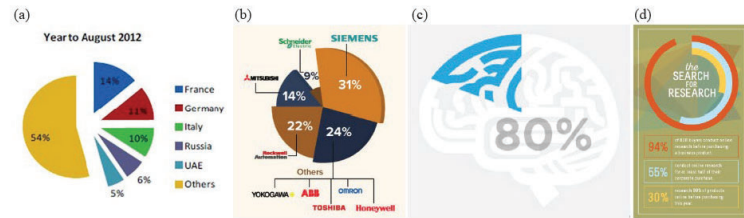
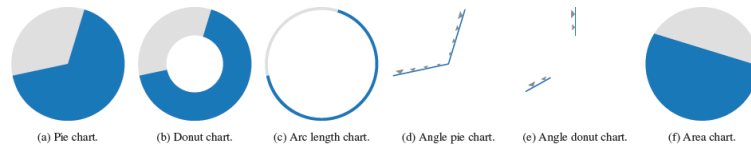


Figure 3: A sampling of pie and donut charts used in infographics, taken from examples found on Visual.ly [Vis15]. (a) exploded pie chart, (b) chart with varying segment radii, (c) pie chart constructed with an icon, and (d) nested donut chart.

Variations of these designed to test accuracy of part-whole judgments

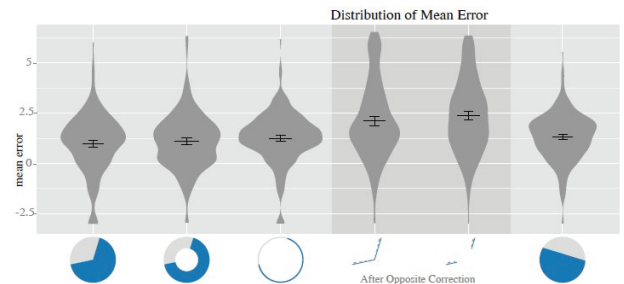


Skau & Kosara (2016), Arcs, Angles, or Areas: Individual Data Encodings in Pie and Donut Charts, EuroVis.

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More pie studies: Skau & Kosera

Little difference among these, except for plots showing only angle

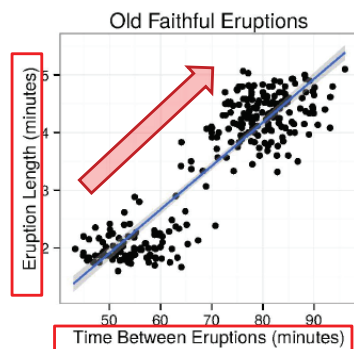


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Task analysis

Another cognitive approach is to study the visual/mental steps a viewer takes in trying to answer a question based on a graph. Sometimes uses "protocol analysis"

Q: What is the relationship between the length of the eruption and the time between eruptions for Old Faithful?



Mental steps:

1. **Understand** the Q: identify "length of eruption" & "time between eruptions" as things to search for in the graph.
2. **Look** at axis labels: See Y: "Eruption length"; X: "Time between Eruptions"
3. **Scan** data: See "Y increases as X increases"
4. **Answer** the Q: As the time between eruptions increases, the length of the eruption seems to increase.
5. **Notice**: Hmm, something weird here!

Illustration from VanderPlas (2015), *Perception in statistical graphics*, PhD thesis, Iowa State U

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Eye-tracking studies

Where do people look when viewing graphic displays?

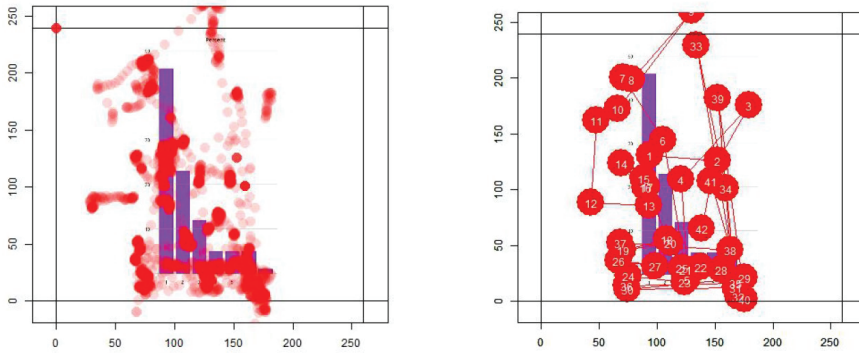
Eye-tracking hardware allows recording of **gaze fixation points** over time
Eye-tracking software allows some visual analysis



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Viewing a bar chart

This 2016 study by Trent Fawcett was a basic test of this methodology. Uses R and the [saccades](#) package. There is also: [gazePath](#), [emov](#) and more...



Gaze fixation points with a scatterplot and transparency to show density

Gaze fixation points showing the temporal sequence of saccades

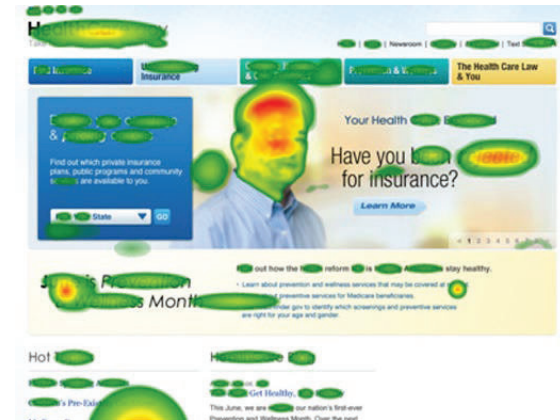
Fawcett, T. "The Eyes Have It: Eye Tracking Data Visualizations of Viewing Patterns of Statistical Graphics" (2016). <https://digitalcommons.usu.edu/gradreports/787>

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Viewing web pages

This methodology is now well developed, particularly for viewing web pages

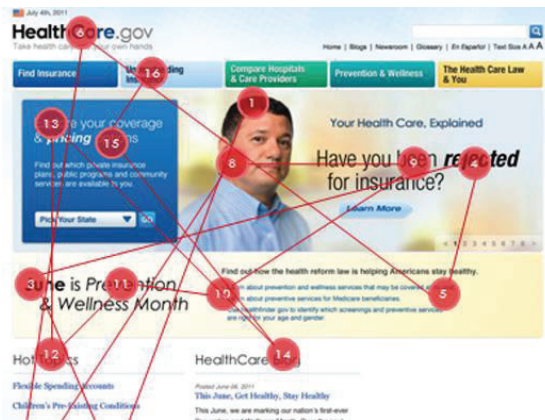
This illustration uses heatmap colors to show density of gaze locations



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Viewing web pages

This illustration shows a path of eye-movement locations in viewing the same web page

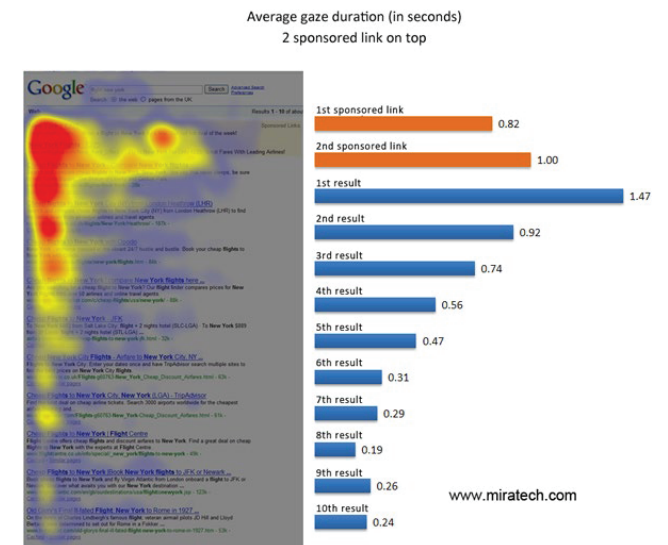


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Viewing web pages

This method is widely used to evaluate effectiveness & \$ for ads on web pages

Online vendors do numerous such studies



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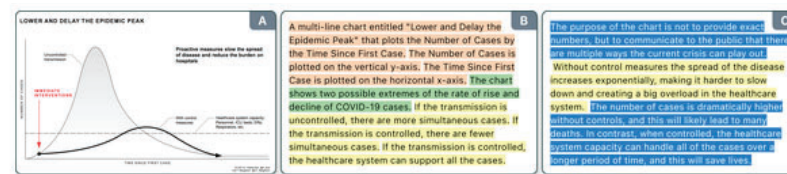
Accessibility of data visualization

- Graph design
 - Design for color deficiencies
 - Favor direct labels over legends
- Assistive technology
 - Data sonification: map data to sounds
 - Screen readers: turn text into speech
- Text, titles, captions
 - Web: use alt-text
 - PPT: embed descriptive text in images
 - Papers: use better titles and captions

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Accessibility of graph captions

Lundgard & Satyanarayan (2022) studied how graph captions affect understanding, particularly for disabled (blind) viewers



Long Description

Visualizations like "Flatten the Curve" (A) efficiently communicate critical public health information, while simultaneously excluding people with disabilities [11, 28]. To promote accessible visualization via natural language descriptions (B, C), we introduce a four-level model of semantic content. Our model categorizes and color codes sentences according to the semantic content they convey.

How to design figure captions / alt-text to better communicate what is to be shown?

Accessible Visualization via Natural Language Descriptions, <http://vis.csail.mit.edu/pubs/vis-text-model>

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Accessibility of graph captions

They present a model of 4 levels of description and their semantic content

#	LEVEL KEYWORDS	SEMANTIC CONTENT	COMPUTATIONAL CONSIDERATIONS
4	contextual and domain-specific	domain-specific insights, current events, social and political context, explanations	contextual knowledge and domain-specific expertise (perceiver-dependent)
3	perceptual and cognitive	complex trends, pattern synthesis, exceptions, commonplace concepts	reference to the rendered visualization and "common knowledge" (perceiver-dependent)
2	statistical and relational	descriptive statistics, extrema, outliers, correlations, point-wise comparisons	access to the visualization specification or backing dataset (perceiver-independent)
1	elemental and encoded	chart type, encoding channels, title, axis ranges, labels, colors	access to the visualization specification or rasterized image (perceiver-independent)

Mortality rate is plotted on the vertical y-axis from 0 to 15%. Age is plotted on the horizontal x-axis in bins: 10-19, 20-29, 30-39, 40-49, 50-59, 60-69, 70-79, 80+.

For low income countries, the average life expectancy is 60 years for men and 65 years for women. For high income countries, the average life expectancy is 77 years for men and 82 years for women.

The low income countries are more scattered than the high income countries. There is a visible gap between high and low income countries, indicated by the Income-Age Divide line.

People living in low-income countries tend to have a lower life expectancy than the people living in high-income countries, likely due to many societal factors, including access to healthcare, food, other resources, and overall quality of life.

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Study design

- Stimuli:
 - chart types (bar, line, scatter)
 - topics (academic, business, journalism)
 - difficulty (easy, medium, hard)
- Subjects: 90 sighted, & 30 blind (proficient with a screen reader).
- Task: rank the usefulness of 4 descriptions (Levels 1-4) for understanding

"Suppose that you are reading an academic paper about how life expectancy differs for people of different genders from countries with different levels of income. You encounter the following visualization. [Table 3.C] Which content do you think would be most useful to include in a textual description of this visualization?"

Read the paper to see the scope and content of this type of research

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BrailleR package

- Improve access to graphs for blind users
 - `Describe()`: quick description of a graph
 - `VI()`: visual inspection of a graph
 - `MakeAccessibleSVG()`: create webpages a user can explore by using arrow keys & basic navigation buttons

```
basicPlot <- ggplot(iris, aes(Sepal.Length, Sepal.Width)) +  
  geom_point()  
Describe(basicPlot)
```

Output:

A `geom_point` layer created with the `ggplot2` framework

General Description:

A scatter plot shows the relationship between two variables by plotting a symbol for each observation at the coordinates for the two variables.

There's a lot more here. Check out:

<https://rdrr.io/cran/BrailleR/f/vignettes/BrailleR.Rmd>

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Visual inference

- To what extent can visual display of real data, against a background of random data, be used as a **substitute** for standard statistical inference?

One of these plots doesn't belong. Which one??

Six choropleth maps of cancer deaths in Texas, darker colors = more deaths.

Can you spot which of the six plots is made from a **real** dataset vs. simulated under the null hypothesis of **spatial independence**?



From: Wickham et al. (2010) Graphical Inference for Infovis, *IEEE Trans. Visualization & Computer Graphics*, Vol. 16, No. 6, 972-979.

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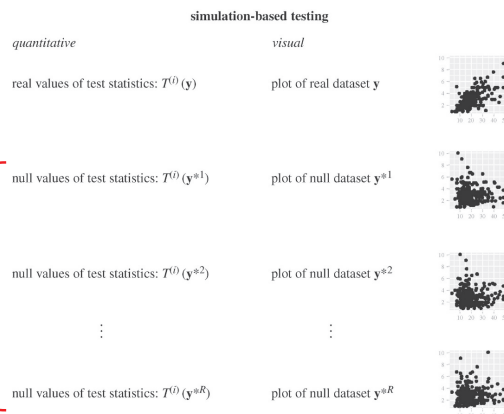
Visual inference: Lineup protocol

Buja et al. (2009) propose an analogy between standard statistical inference and visual inference based on human observers

Lineup protocol:

- Generate $n-1$ decoys (null data sets).
- Make plots of the decoys, and randomly position a plot of the true data.
- Show to an impartial observer. Can they spot the real data?

With $n=19$ decoys, a correct decision by chance would have $p=1/20 = 0.05$



From: Buja et al. (2009), Statistical inference for exploratory data analysis and model diagnostics. *Phil. Trans. R. Soc. A*, **367**, 4361–4383

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Visual inference: Lineup protocol

This graphic table makes the comparison more direct:

	Conventional inference	Lineup protocol
Hypothesis	$H_0 : \beta = 0$ vs $H_1 : \beta > 0$	$H_0 : \beta = 0$ vs $H_1 : \beta > 0$
Test statistic	$T(y) = \frac{\hat{\beta}}{se(\hat{\beta})}$	$T(y) =$
Sampling Distribution	$f_{T(y)}(t);$	$f_{T(y)}(t);$
Reject H_0 if	Actual T is extreme	Actual plot is identifiable

From: Majumder, Hofmann & Cook (2013) Validation of Visual Statistical Inference, Applied to Linear Models, *JASA*, 108:503, 942-956, DOI: 10.1080/01621459.2013.808157

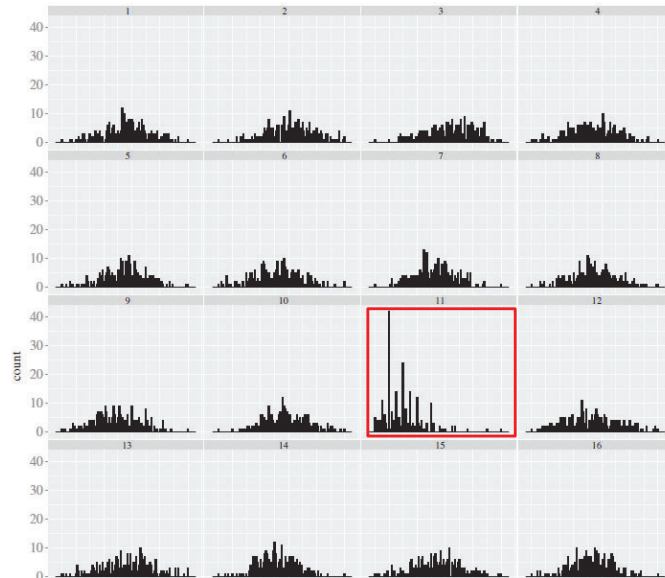
70

Frequency distribution of tips at restaurants.

Which one is the real data?
What features lead you to this conclusion?

Panel 11:

- Skewed
- Multiple peaks
- Outliers



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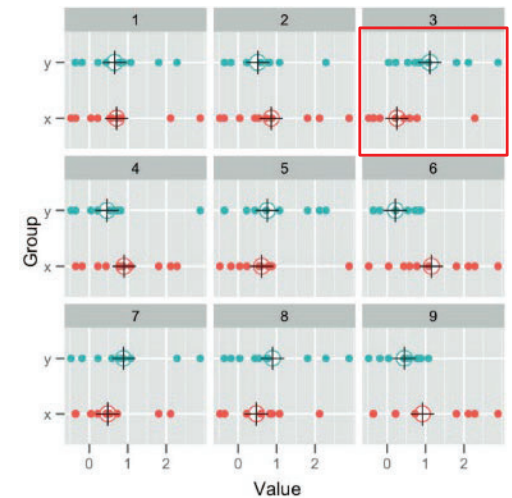
Visual t-test

For each data set, the observations are shown as points and the group means as crosses.

The accused (real data) is hidden amongst eight innocents.

Can you spot him?

Panel 3: a larger difference among the group means



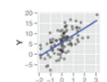
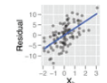
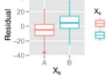
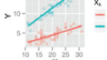
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Visual tests for linear models

This idea can be extended to visual inference for a wide range of hypotheses in linear models.

Main idea: Numerical test → Visual test

Table 3. Visual test statistics for testing hypotheses related to the model $Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \beta_3 X_{i1} X_{i2} + \dots + \epsilon_i$

Case	null hypothesis	Statistic	Test statistic	Description
1	$H_0 : \beta_0 = 0$	Scatterplot		Scatterplot with least square line overlaid. For null plots we simulate data from fitted null model.
2	$H_0 : \beta_k = 0$	Residual plot		Residual vs X_k plots. For null plots we simulate data from normal with mean 0 variance $\hat{\sigma}^2$.
3	$H_0 : \beta_k = 0$ (for binary X_k)	Boxplot		Boxplot of residuals grouped by category of X_k . For null plots we simulate data from normal with mean 0 variance $\hat{\sigma}^2$.
4	$H_0 : \beta_k = 0$ (interaction of continuous and binary X_k)	Scatterplot		Scatterplot with least square lines of each category overlaid. For null plots we simulate data from fitted null model.

From: Majumder et al (2013) Validation of Visual Statistical Inference, Applied to Linear Models, JASA

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Visual inference: Power

Some statistical tests have greater **power** to detect a non-null effect

What can be said about the power of different graphical methods for visual inference?

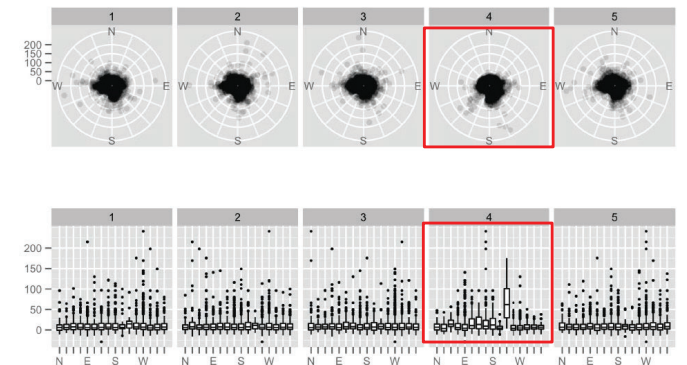
Graphs of wind direction and arrival delays for incoming flights to Phoenix airport.

1: polar scatterplot, delay=radius, wind=angle

2: boxplots of delay grouped by angle

Which is easier?

Which is the real data?

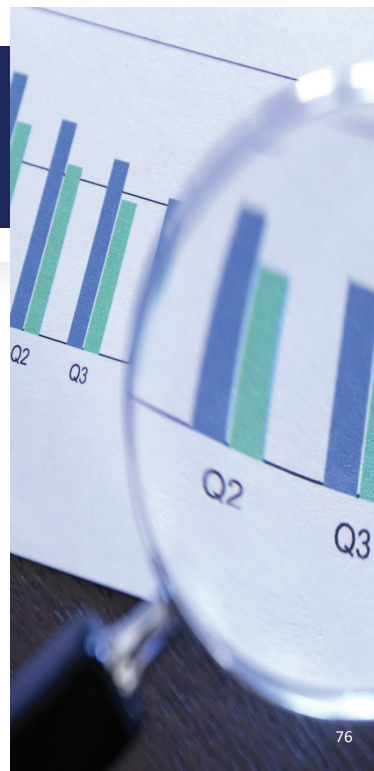


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Visual inference: Discussion

What can we learn from this approach?

- To what extent can visual inference substitute for numerical statistical inference?
- How to study this more?
 - How many observers to declare some effect “significant”
 - Can we use this paradigm to study observer differences?
 - Can we use this to study the effectiveness of different graph types or forms?

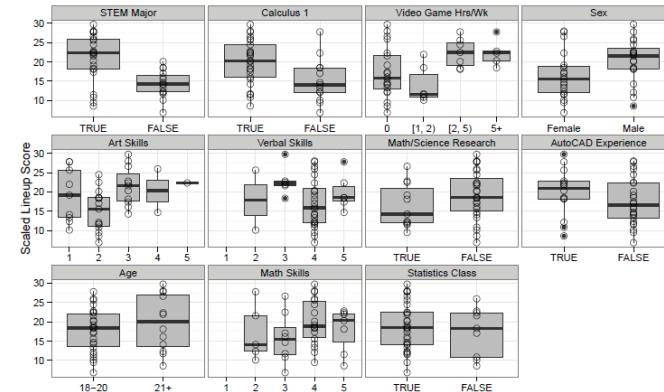


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Online studies: Demographics

It is relatively easy to conduct online studies of graph perception.

- For validity & comprehensibility of results, it is often crucial to examine possible **demographic variables** that relate to the outcome



What was the effect of various subject variables on outcome in a lineup task?

Various demographic variables are ordered here by the effect size for differences among various groups.

When several visual displays are compared, important to consider interactions – some people may do better with some displays.

from VanderPlas (2015), *Perception in statistical graphics*, PhD thesis, Iowa State U, Fig. 4.5

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Discussion questions

- Why is human factor research in graphics useful & important?
 - How can it make a difference?
- What methods are available to study this?
 - What is the task?
 - How to measure “performance”?
- What have we learned?
- How to go forward?

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