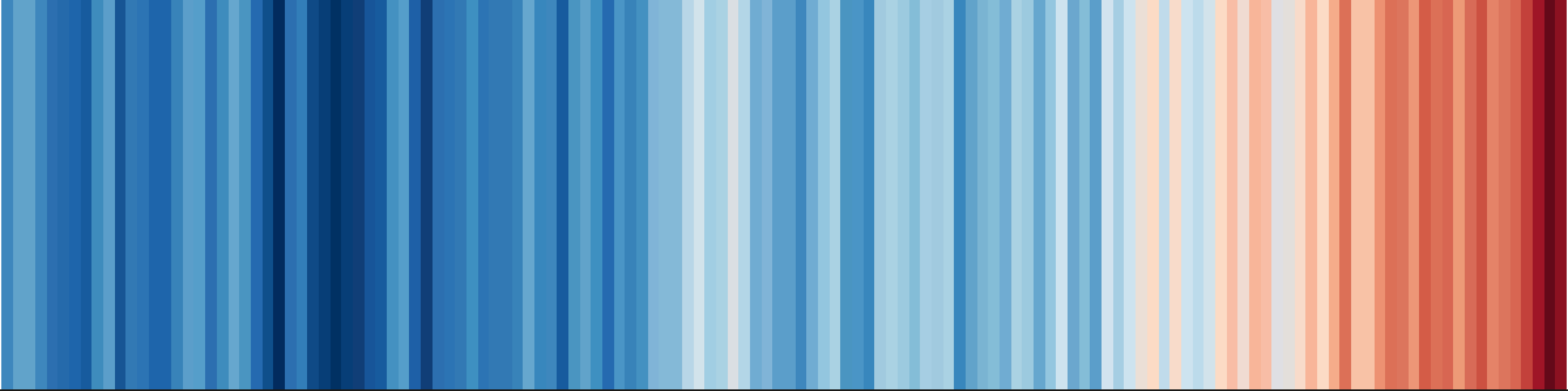
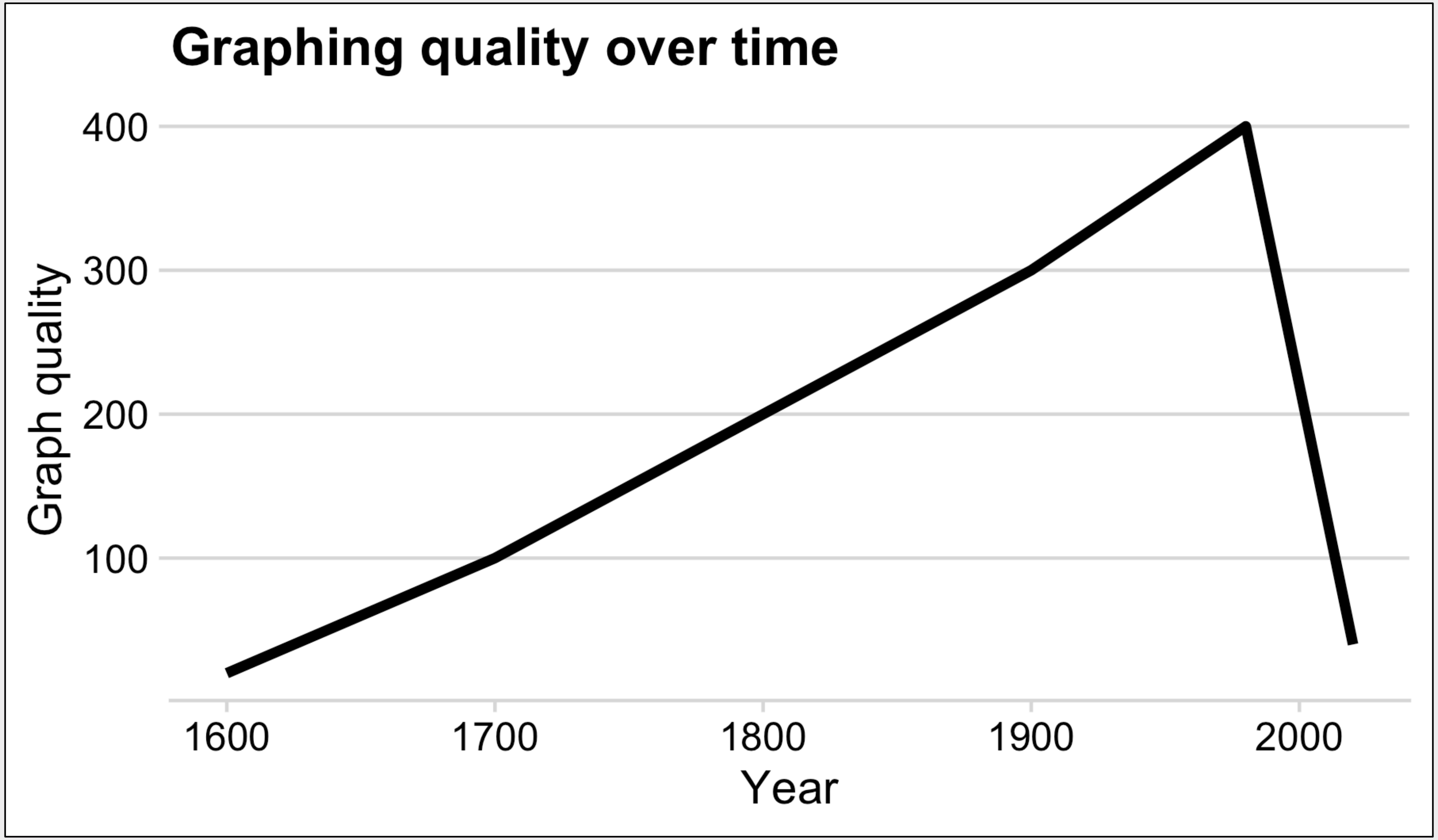


Visualizing information

EMSE 4197 | John Paul Helveston | January 29, 2020


Graphing quality over time
400
300
200
100
Graph quality
1600
1700
1800
1900
2000
Year

“Having word processing software doesn’t make us great writers.”

\- Stephen Few

We don’t write paragraphs like this:

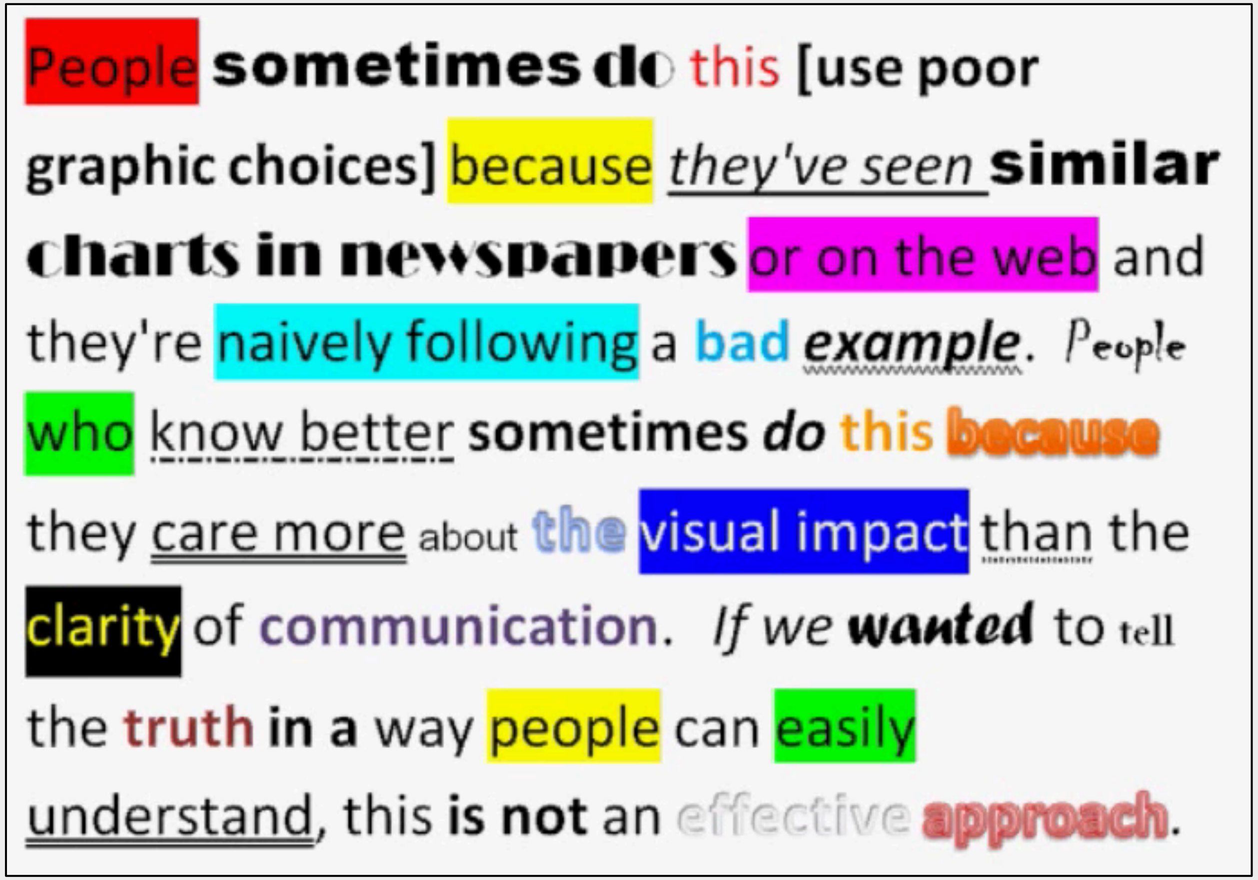

People sometimes do this [use poor graphic choices] because they've seen similar charts in newspapers or on the web and they're naively following a bad example. People who know better sometimes do this because they care more about the visual impact than the clarity of communication. If we wanted to tell the truth in a way people can easily understand, this is not an effective approach.

Image from Few (2012, pg. 227)

So don’t make graphs like this:

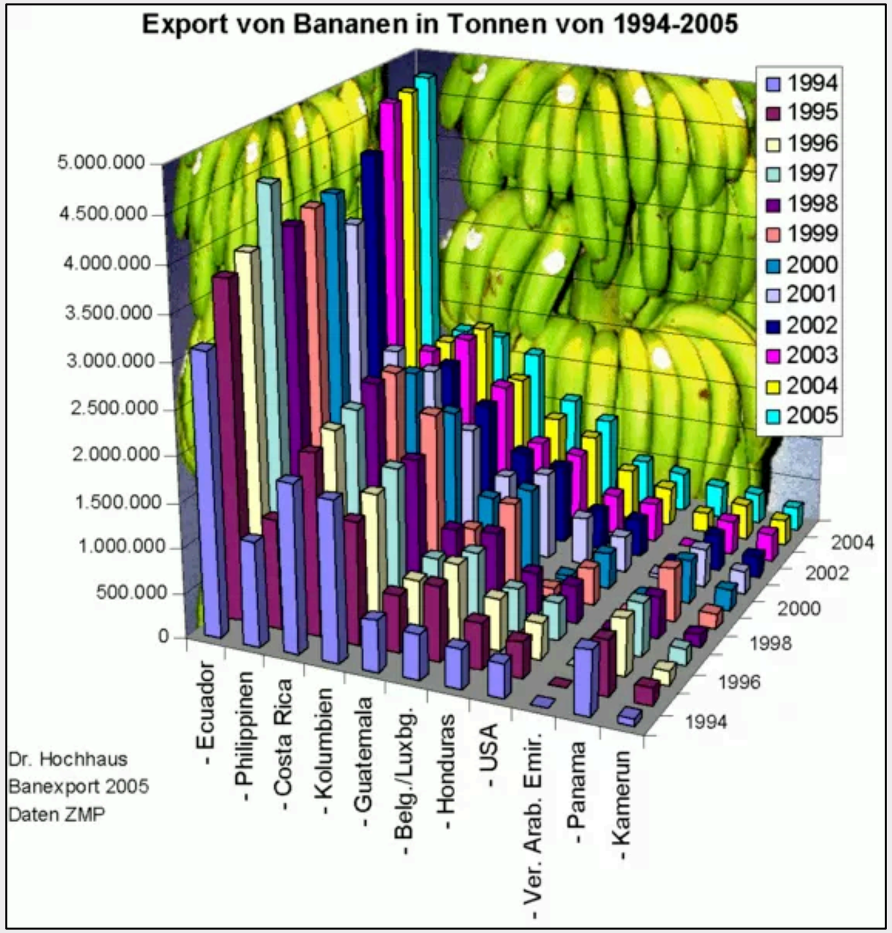
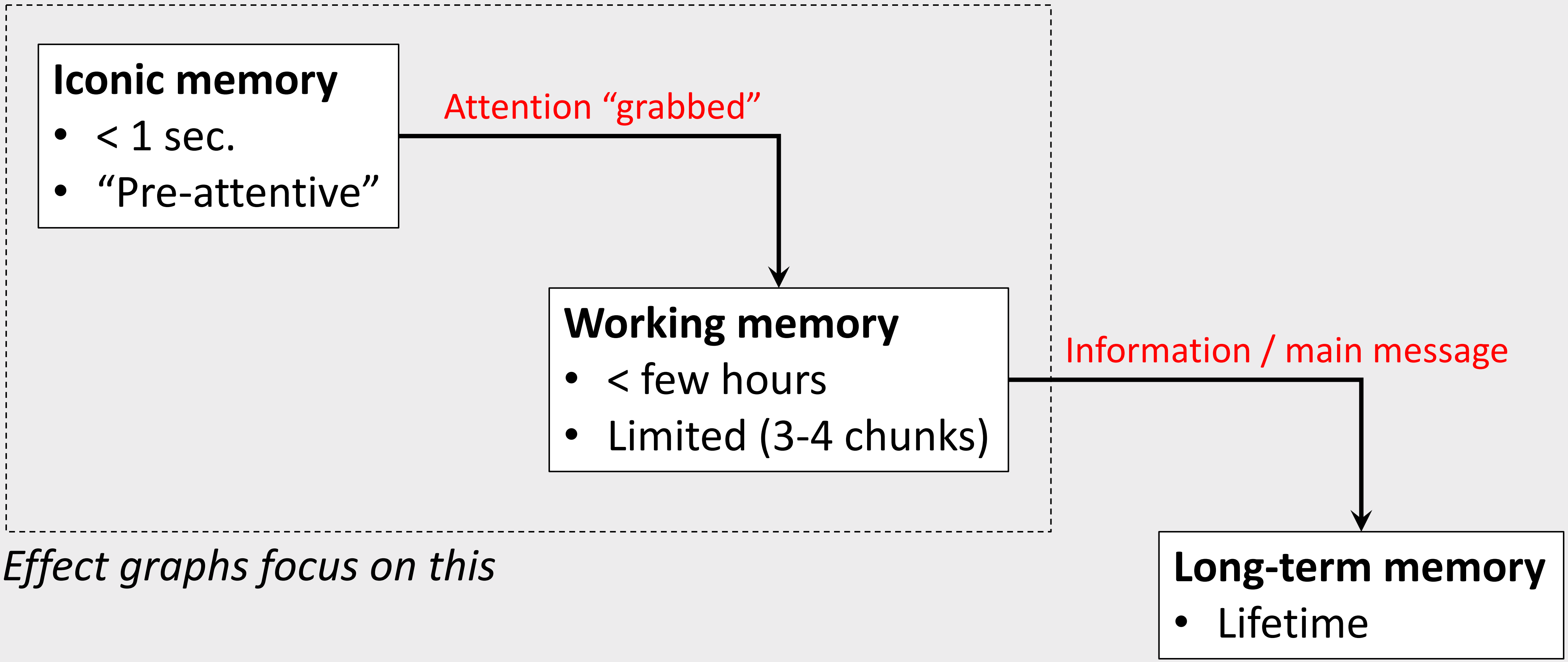


Image from excelcharts.com

Good visualizations optimize for the human visual-memory system

A (very) simplified model of visual-memory system



Two objectives of effective graphs:

1. Grab & direct attention (iconic memory)
2. Reduce processing demands (working memory)

The power of pre-attentive processing

Count all the “5”s:

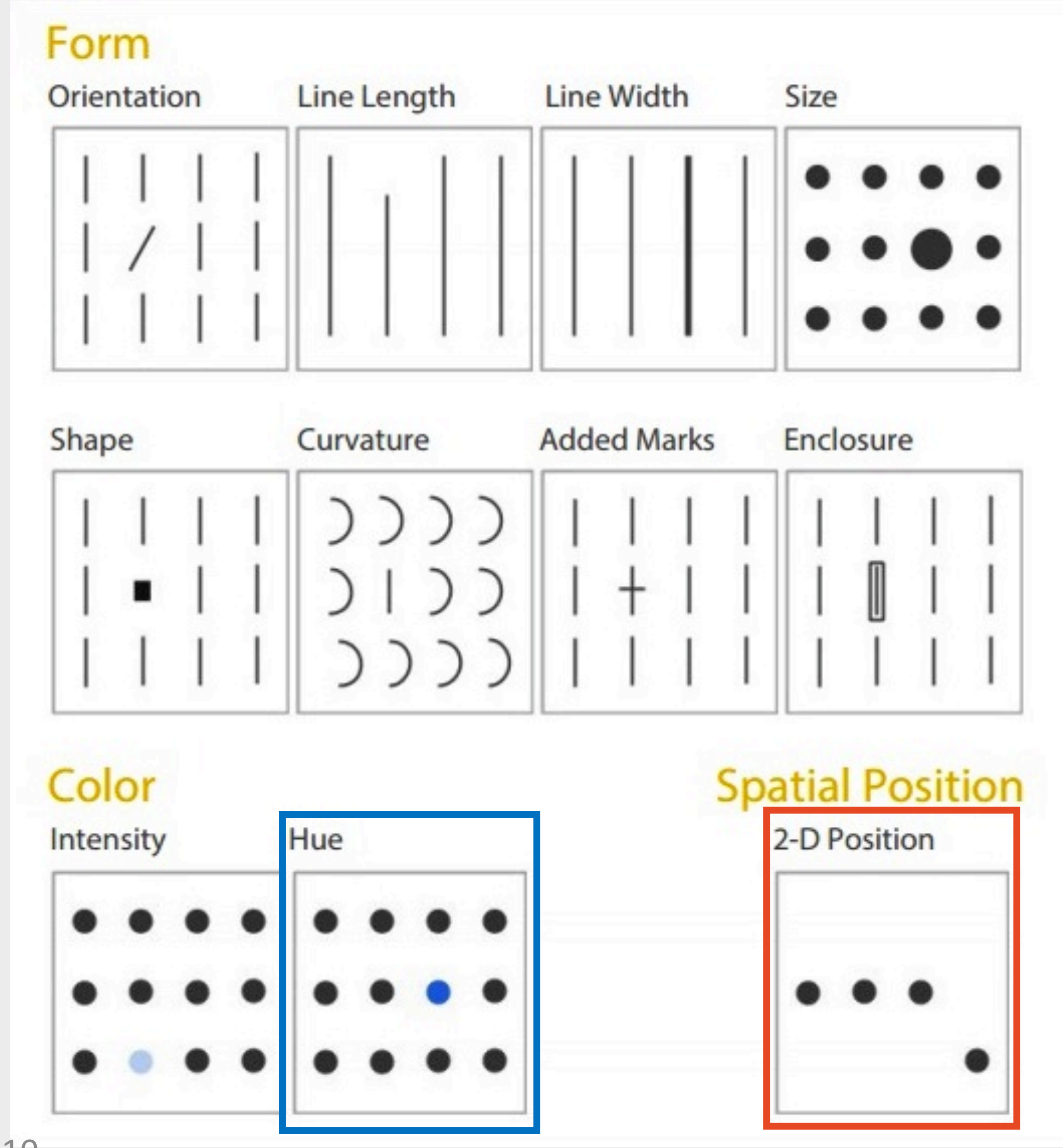
821134907856412043612
304589640981709812734
123450986124790812734
029860192837401489363
123479827961203459816
234009816256908127634
123459087162342015237
123894789237498230192

The power of pre-attentive processing

Count all the "5"s:

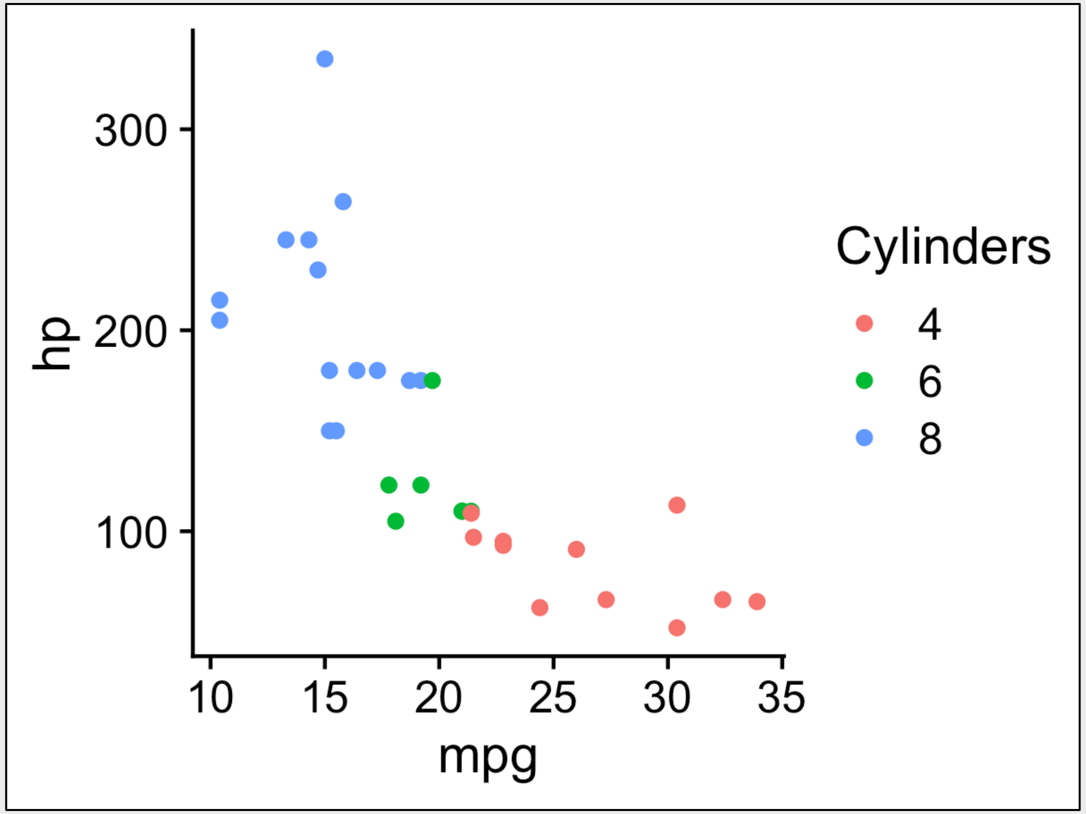
82113490785641204361 2
30458964098170981273 4
12345098612479081273 4
02986019283740148936 3
12347982796120345981 6
23400981625690812763 4
12345908716234201523 7
12389478923749823019 2

Pre-attentive attributes



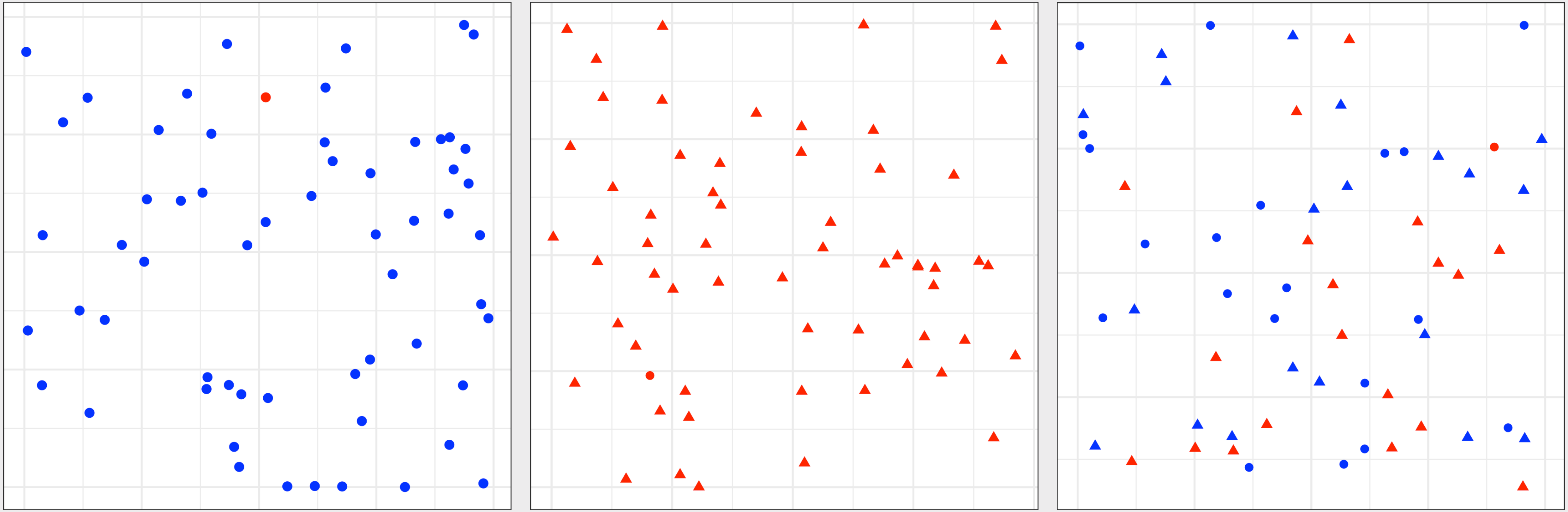
Quantitative data

Categorical data

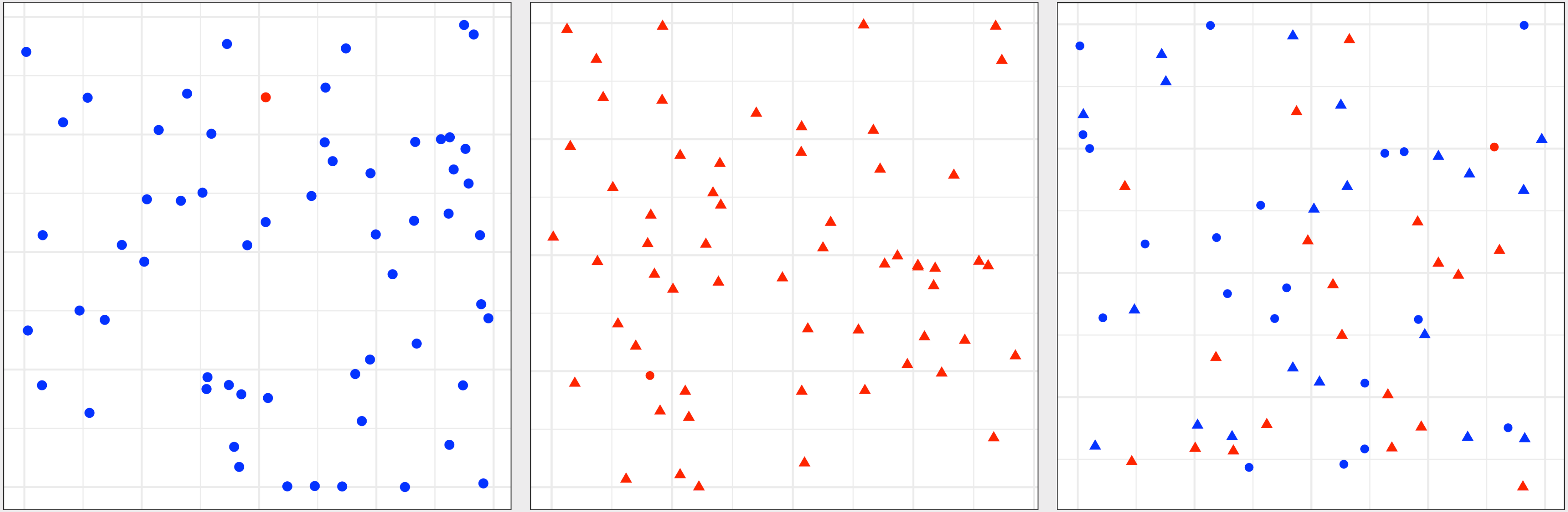


Not all pre-attentive attributes are equal

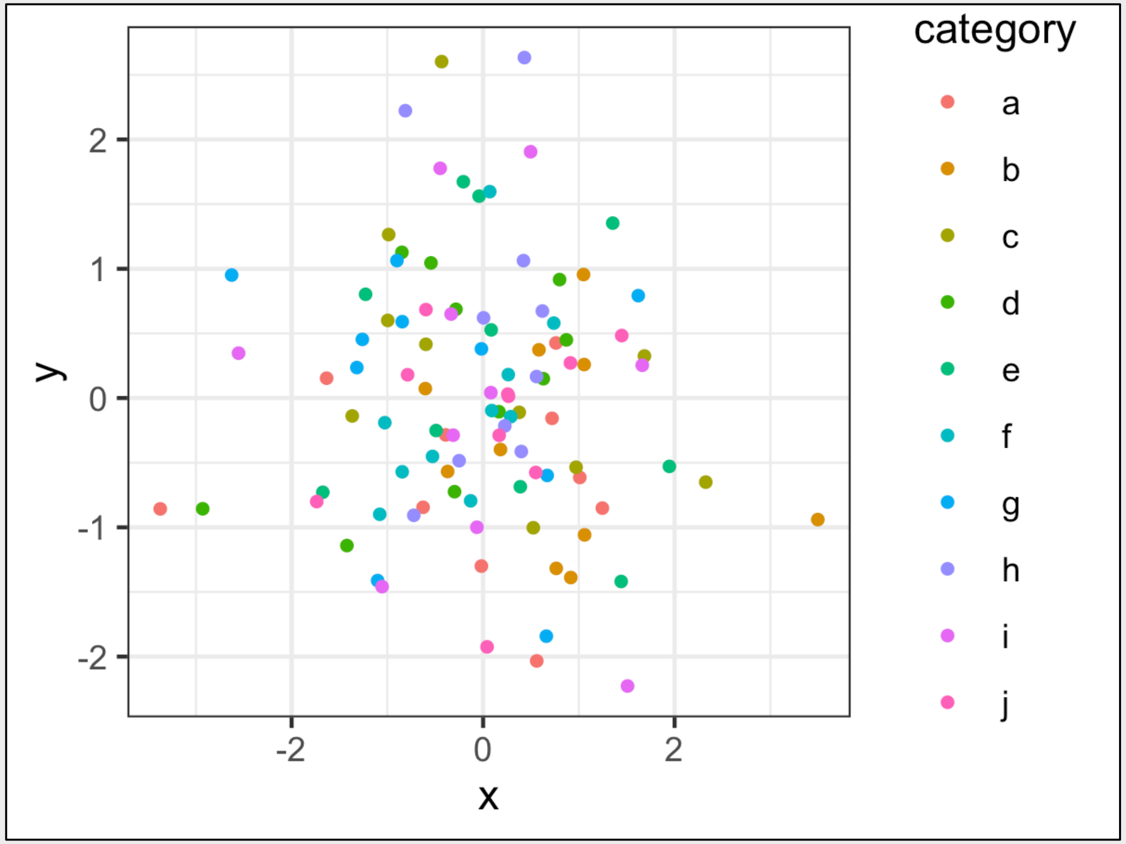
Is there a red dot?

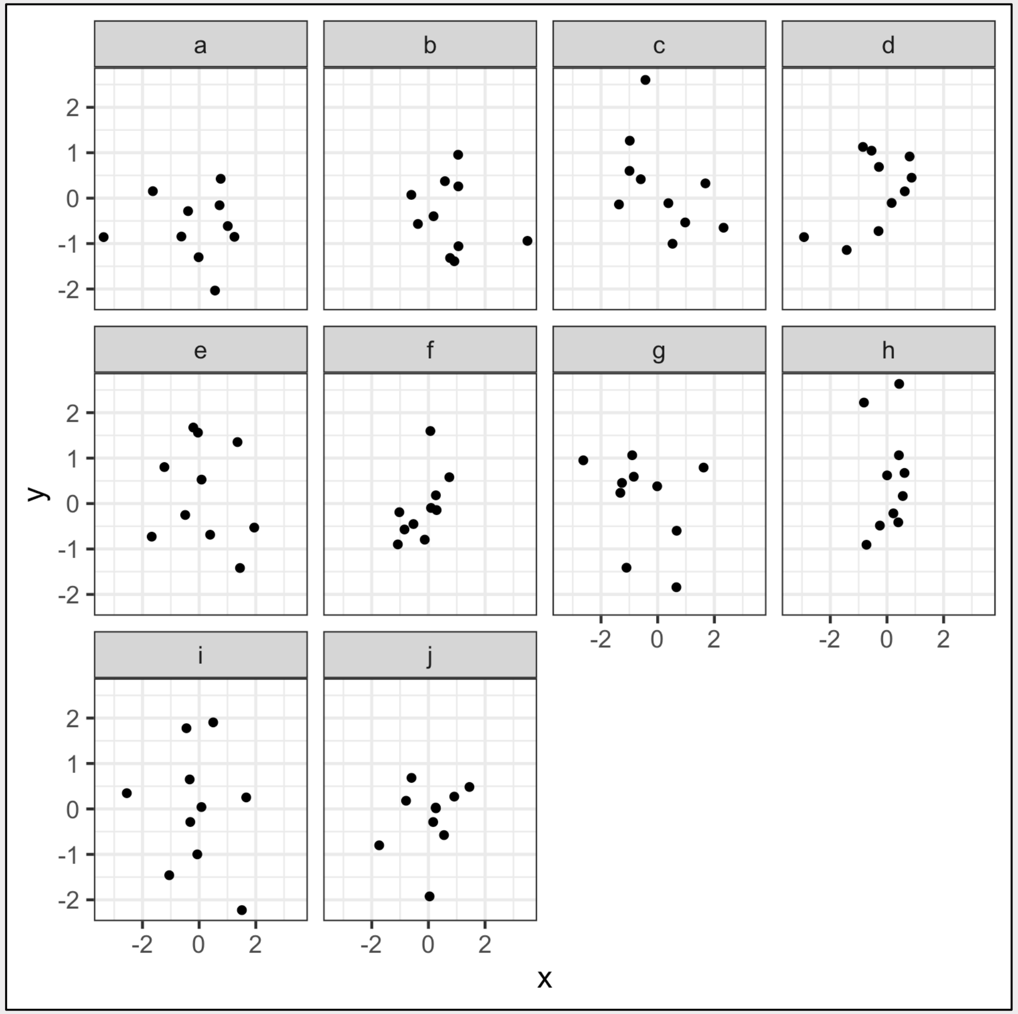


For **categorical data**



Hue > Shape **Less is more**


category
a
b
c
d
e
f
g
h
i
j
y
x
2
1
0
-1
-2
-2
0
2

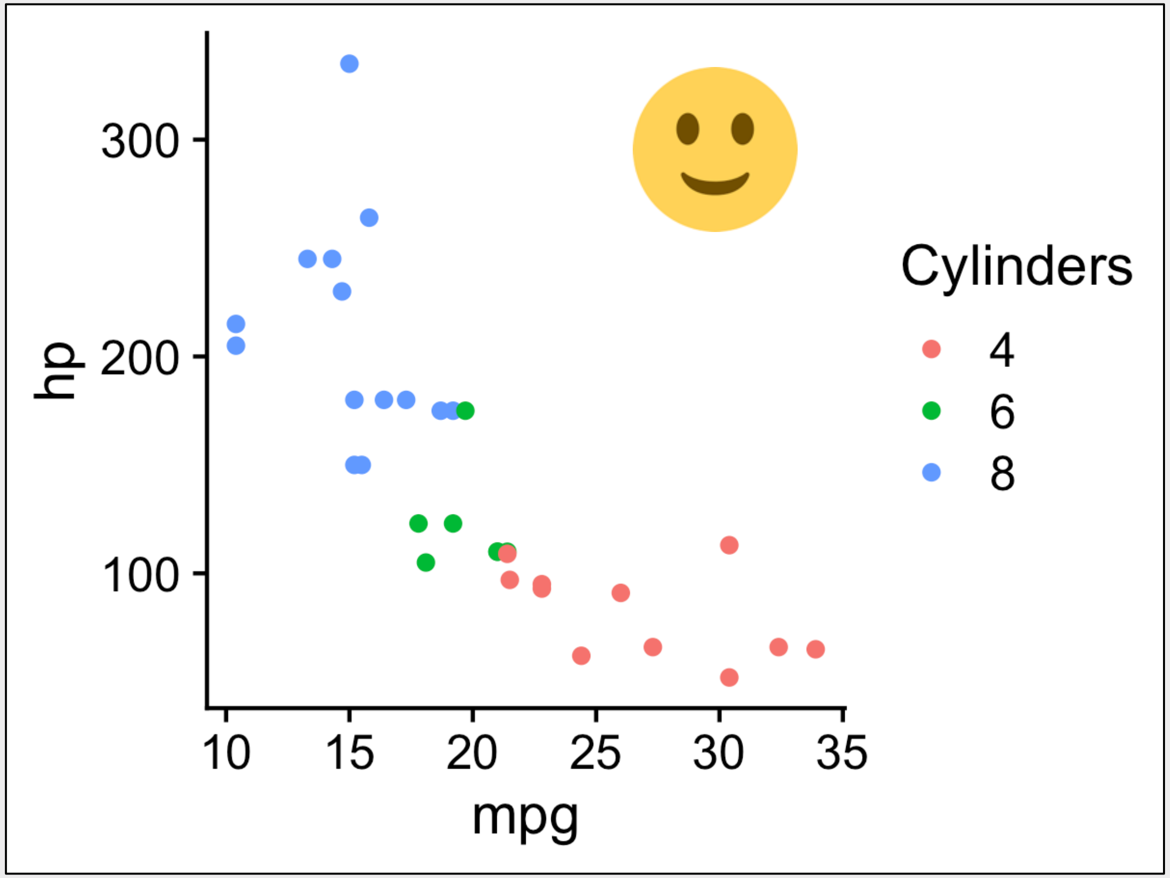

a
b
c
d
e
f
g
h
i
j
y
x

Graph components

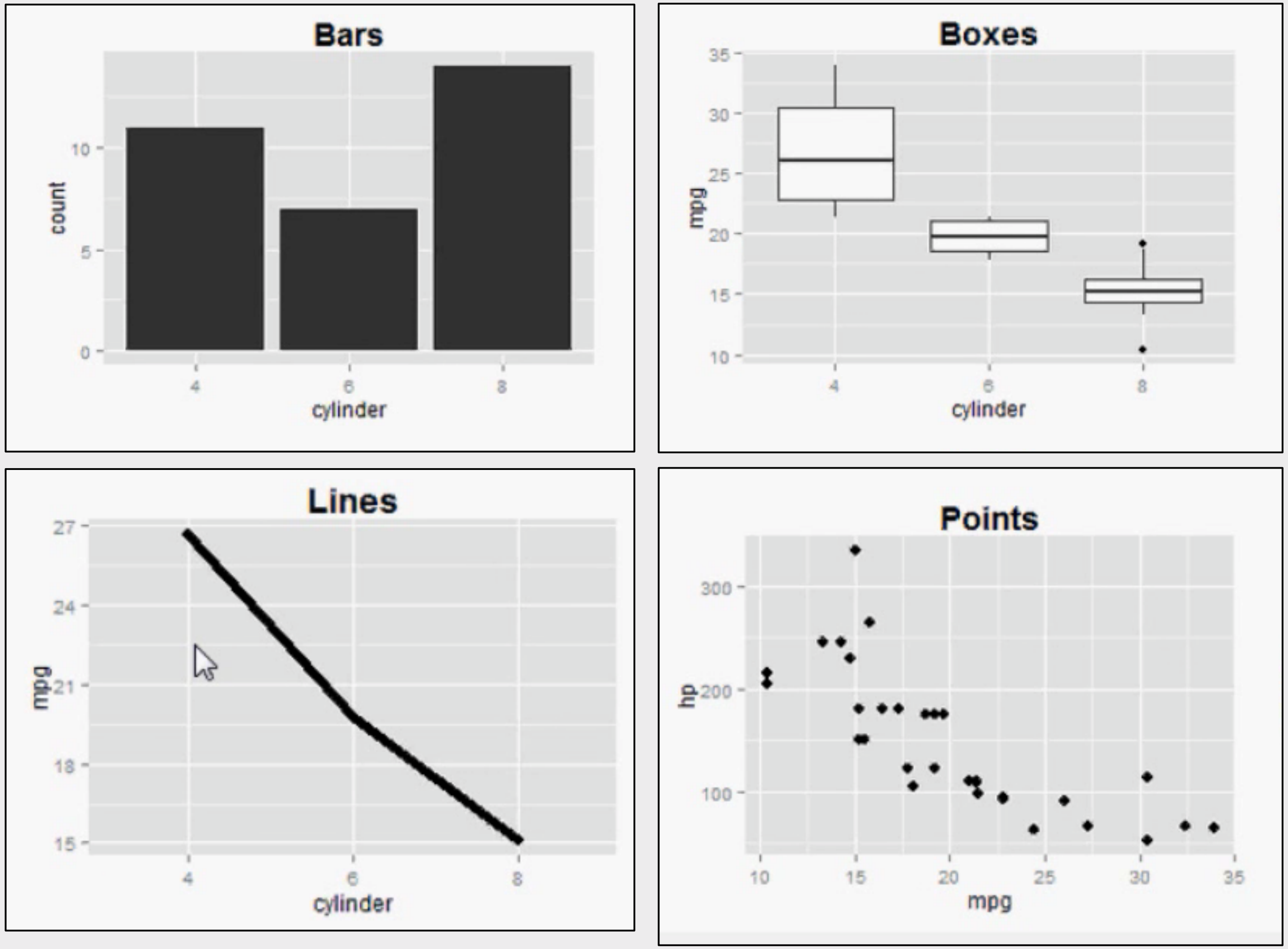
Graph components

1. Geoms:

   points, lines, boxes, bars, etc.



Geoms: geometric shapes used to represent data



Graph components

1. Geoms:

    points, lines, boxes, bars, etc.

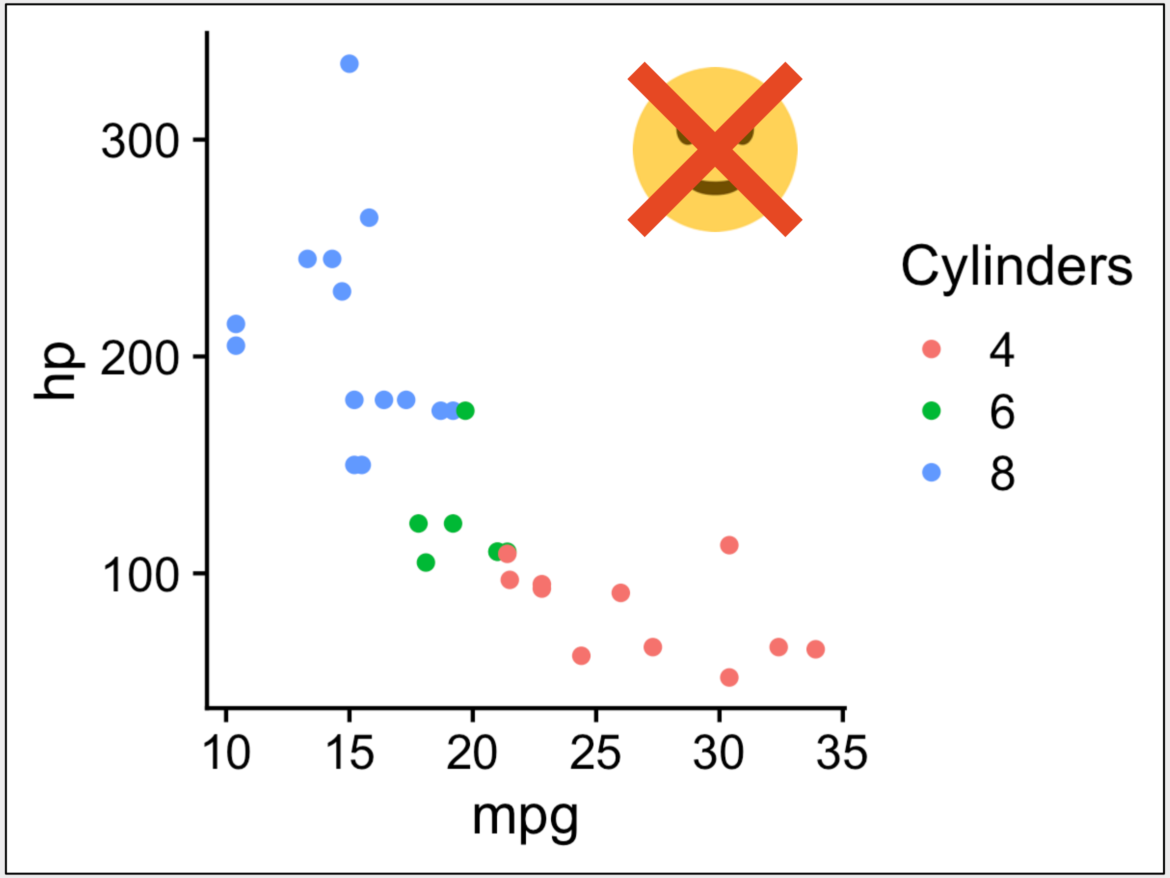
2. Pre-attentive attributes:

    position, color, shape, curvature, etc.

3. Non-data ink:

    scales, grid lines, legend, labels, etc.

<ins>No</ins> “chart junk” (Tufte, 2001)



“*Erase non-data ink.*”
- Edward Tufte

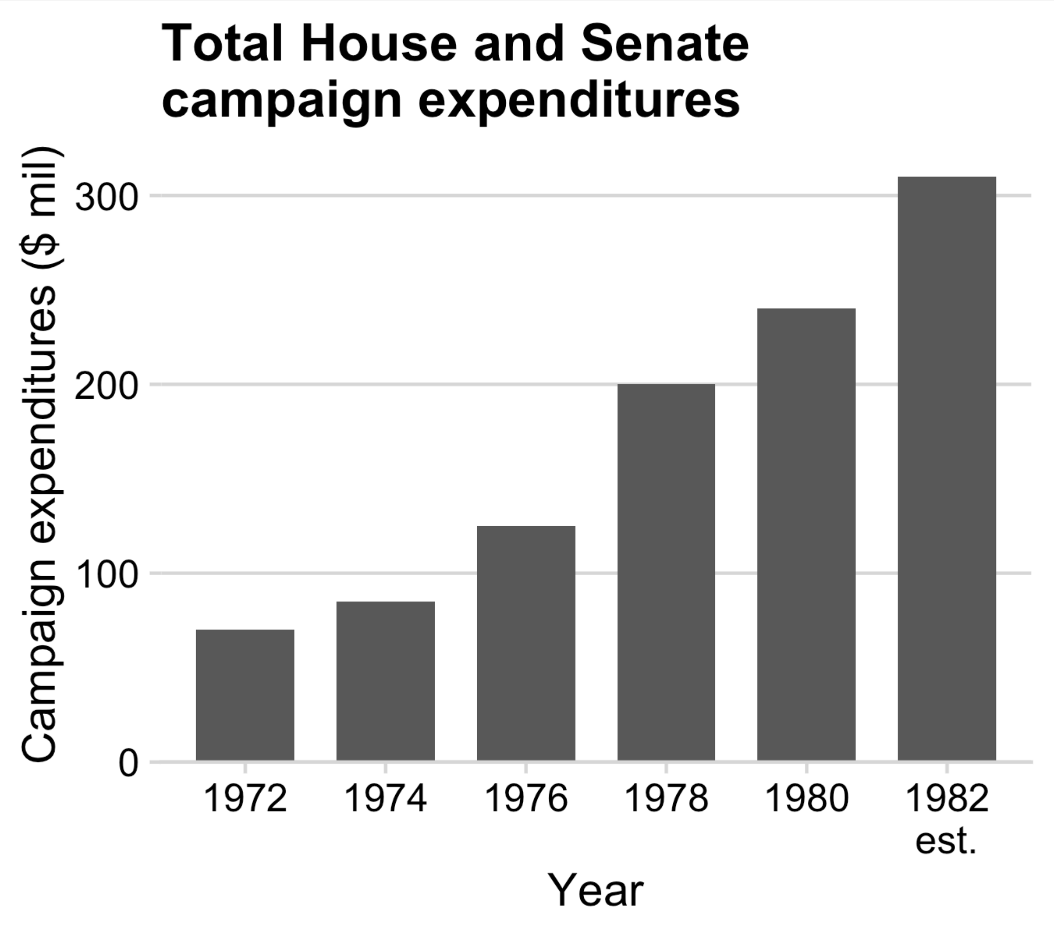


Figure 1.6: `Monstrous Costs' by Nigel Holmes, in Healy, 2018

Lessons from Psychology research

Graphical Perception and Graphical Methods for Analyzing Scientific Data

William S. Cleveland and Robert McGill

Graphs provide powerful tools both for analyzing scientific data and for communicating quantitative information. The computer graphics revolution, which began in the 1960's and has intensified during the past several years, stimulated the invention of graphical methods: types of graphs and types of quantitative information to be shown on graphs (*1–4*). One purpose of this article is to describe and illustrate several of these new methods.

Summary. Graphical perception is the visual decoding of the quantitative and qualitative information encoded on graphs. Recent investigations have uncovered basic principles of human graphical perception that have important implications for the display of data. The computer graphics revolution has stimulated the invention of many graphical methods for analyzing and presenting scientific data, such as box plots, two-tiered error bars, scatterplot smoothing, dot charts, and graphing on a log base 2 scale.

What has been missing, until recently, in this period of rapid graphical invention and deployment is the study of graphs and the human visual system. When a graph is constructed, quantitative and categorical information is encoded, chiefly through position, shape, size, symbols, and color. When a person looks at a graph, the information is visually decoded by the person's visual system. A graphical method is successful only if the decoding process is effective. No matter how clever and how technologically impressive the encoding, it is a failure if the decoding process is a failure. Informed decisions about how to encode data can be achieved only through an understanding of the visual decoding process, which is called graphical perception (*5*).

Cleveland, W. S., & McGill, R. (1985). Graphical perception and graphical methods for analyzing scientific data. *Science*, New Series, 229(4716), 828-833.

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mation from graphs; theory and experimental data are then used to order the tasks on the basis of accuracy. The ordering has an important application: data should be encoded so that the visual decoding involves tasks as high in the ordering as possible, that is, tasks performed with greater accuracy. This is illustrated by several examples in which some much-used graphical forms are presented, set aside, and replaced by new methods.

Elementary Tasks for the Graphical Perception of Quantitative Information

The first step is to identify elementary graphical-perception tasks that are used to visually extract quantitative information from a graph. (By "quantitative information" we mean numerical values

al field that comes without apparent mental effort. We also perform cognitive tasks such as reading scale information, but much of the power of graphs—and what distinguishes them from tables—comes from the ability of our preattentive visual system to detect geometric patterns and assess magnitudes. We have examined preattentive processes rather than cognition.

We have studied the elementary graphical-perception tasks theoretically, borrowing ideas from the more general field of visual perception (*7, 8*), and experimentally by having subjects judge graphical elements (*1, 5*). The next two sections illustrate the methodology with a few examples.

Study of Graphical Perception: Theory

Figure 2 provides an illustration of theoretical reasoning that borrows some ideas from the field of computational vision (*8*). Suppose that the goal is to judge the ratio, r, of the slope of line segment BC to the slope of line segment AB in each of the three panels. Our visual system tells us that r is greater than 1 in each panel, which is correct. Our visual system also tells us that r is closer to 1 in the two rectangular panels than in the square panel; that is, the slope of BC appears closer to the slope of AB in the two rectangular panels than in the square panel. This, however, is incorrect; r is the same in all three panels.

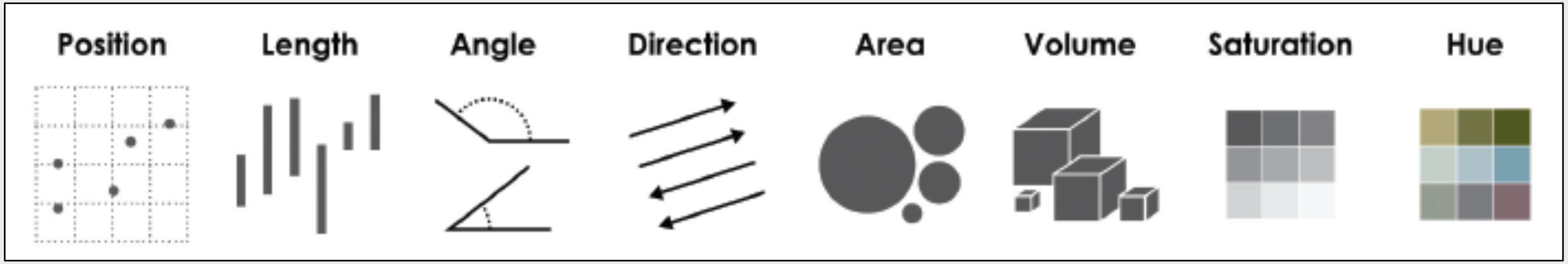
The reason for the distortion in judging Fig. 2 is that our visual system is geared to judging angle rather than slope. In their work on computational theories of vision in artificial intelligence, Marr (*8*) and Stevens (*9*) have investigated how people judge the slant and tilt (*10*) of the surfaces of three-dimensional objects. They argue that we judge slant and tilt as

Table 1. Ordering elementary tasks by accuracy, according to theoretical arguments and experimental results. Graphs should exploit tasks as high in the ordering as possible. The tasks are ordered from most accurate to least.

Rank	Aspect judged
1	Position along a common scale
2	Position on identical but nonaligned scales
3	Length
4	Angle
	Slope (with θ not too close to 0, π/2, or π radians)
5	Area
6	Volume
	Density
	Color saturation
7	Color hue

Cleveland, W. S., & McGill, R. (1985). Graphical perception and graphical methods for analyzing scientific data. *Science*, New Series, 229(4716), 828-833.

Pattern recognition hierarchy:



← More accurate **Less accurate →**

Full disclosure:

Much of the next 50-ish slides are from John Rauser's talk on YouTube

Cleveland’s three visual operations of pattern perception:

- **Estimation**
- Assembly
- Detection

- Discrimination X != Y
- Ranking X > Y
- Ratioing X / Y

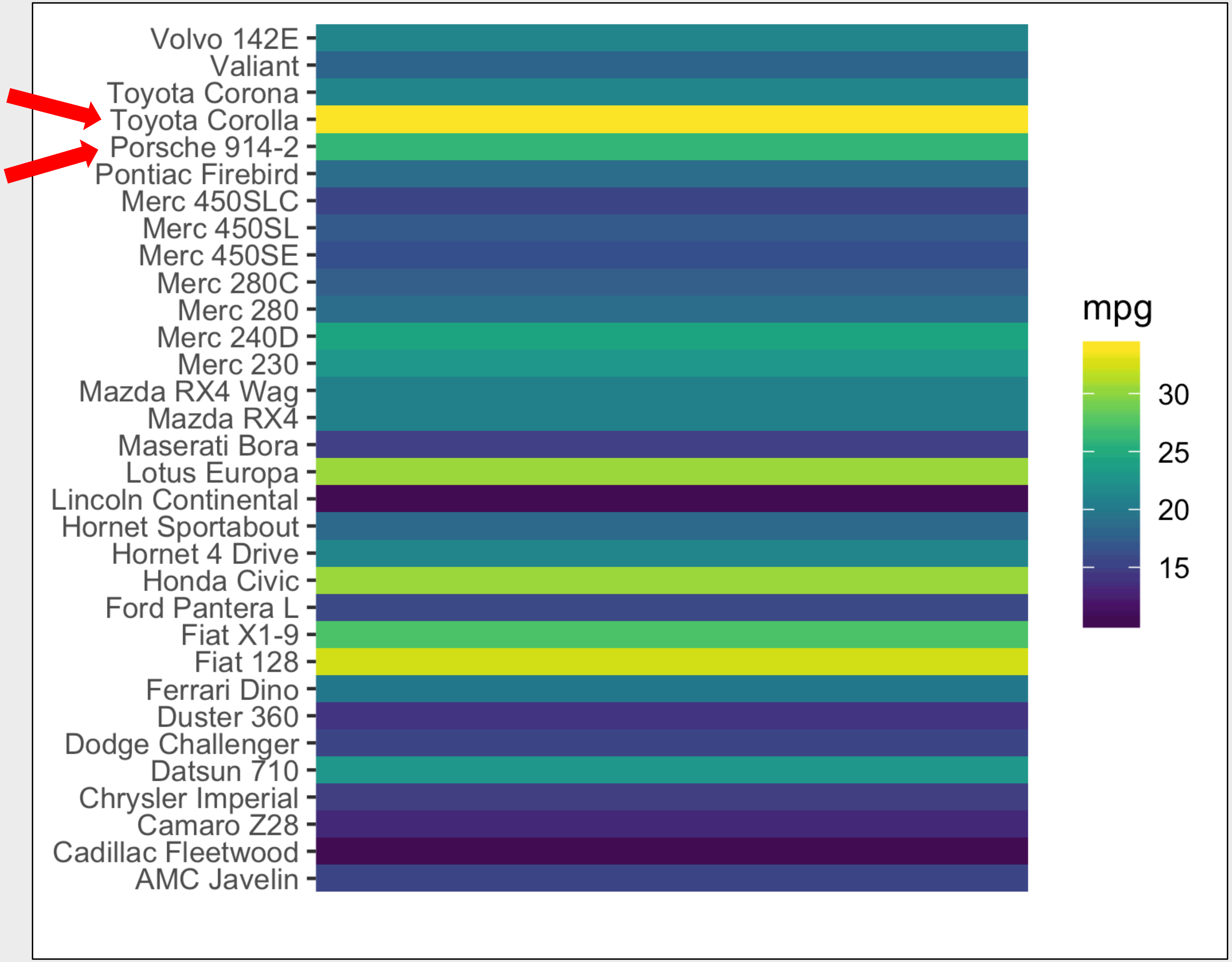
“At the heart of quantitative reasoning is a single question: compared to what?”

- Edward Tufte

1. Position on a common scale
2. Position on non-aligned scales
3. Length
4. Angle
5. Area
6. Color saturation
7. Color hue


luminance
saturation
hue

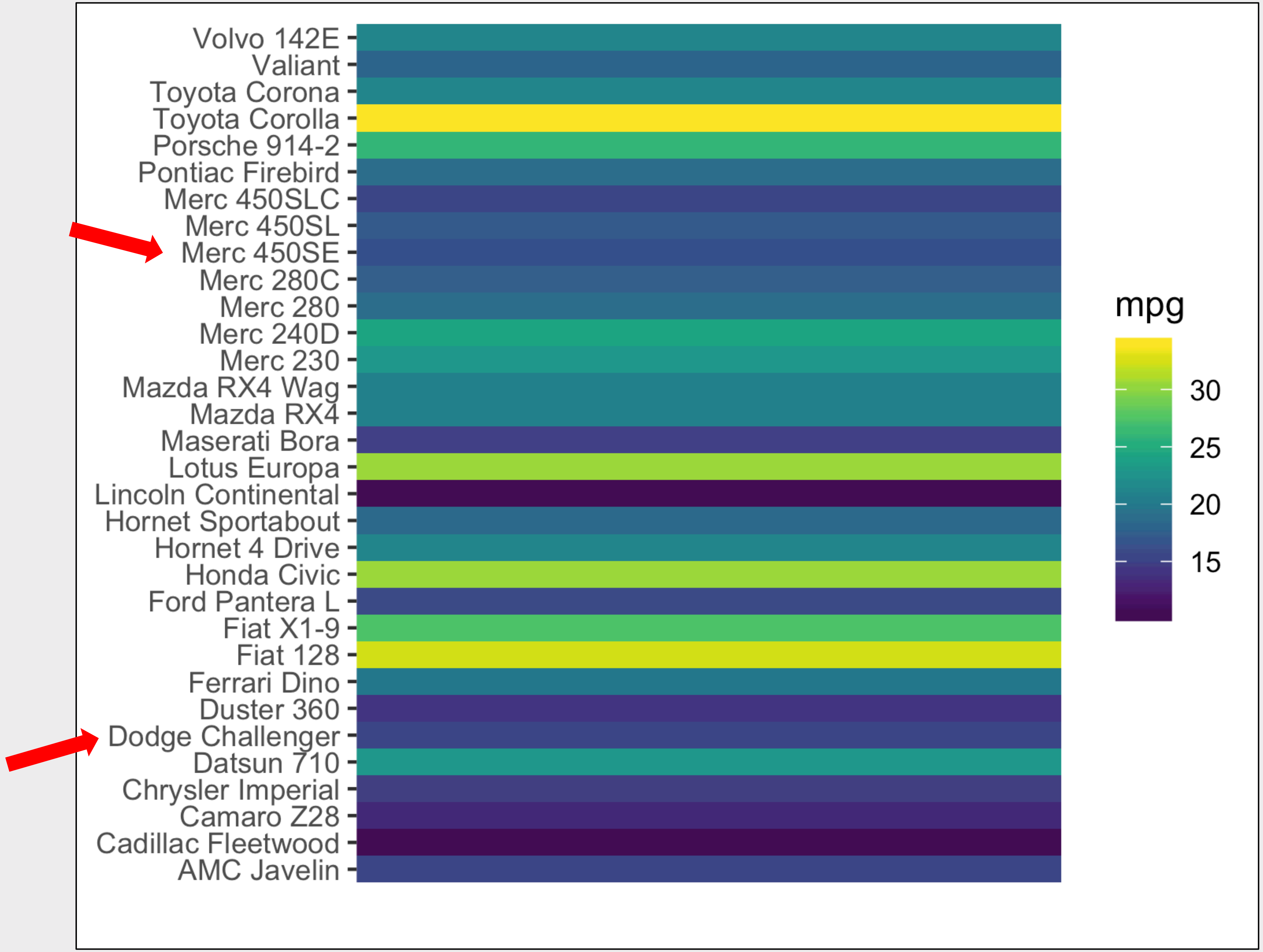
1. Position on a common scale
2. Position on non-aligned scales
3. Length
4. Angle
5. Area
6. Color saturation
7. Color hue



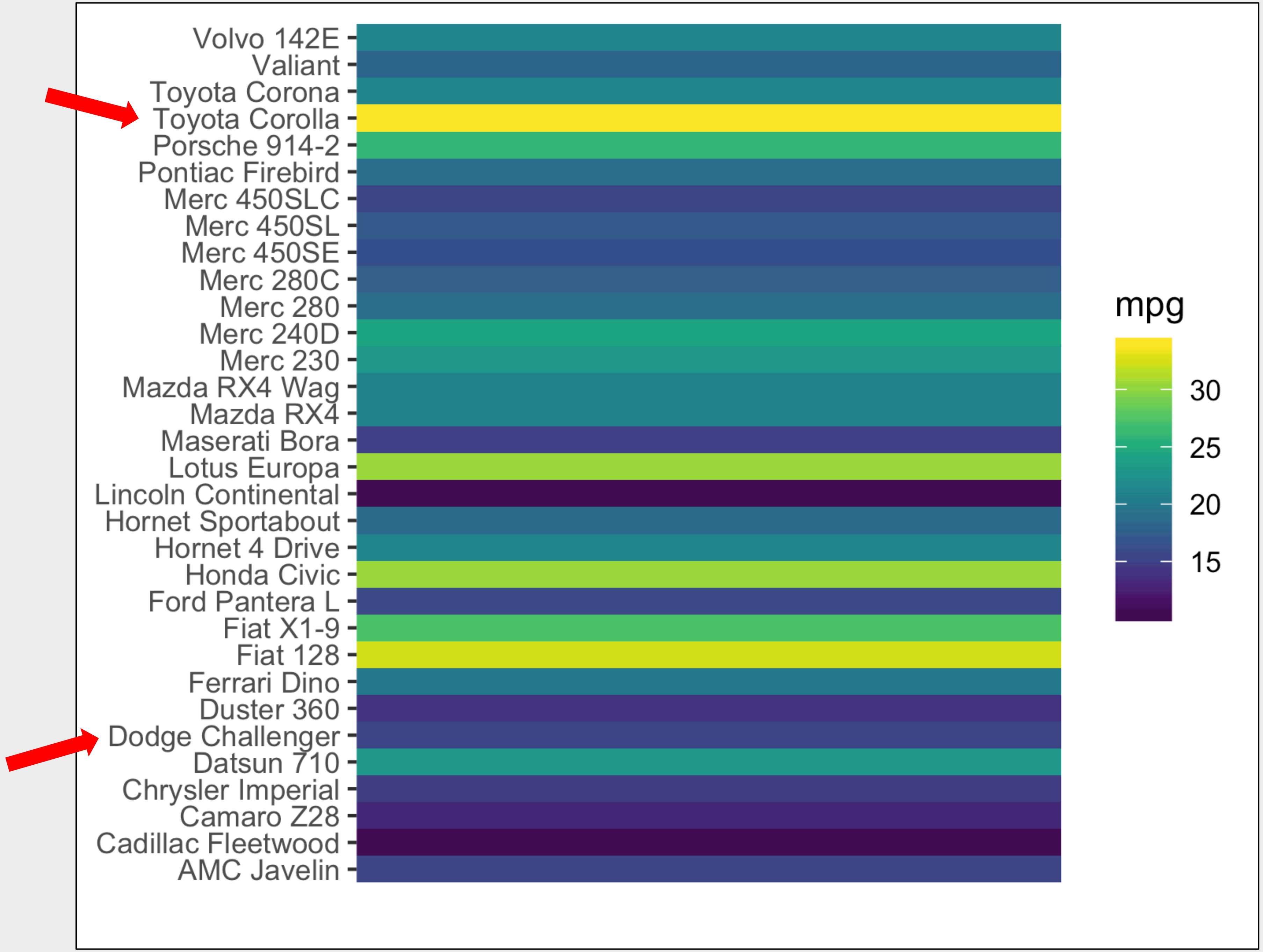
Discrimination?

1. Position on a common scale
2. Position on non-aligned scales
3. Length
4. Angle
5. Area
6. Color saturation
7. Color hue

Discrimination?



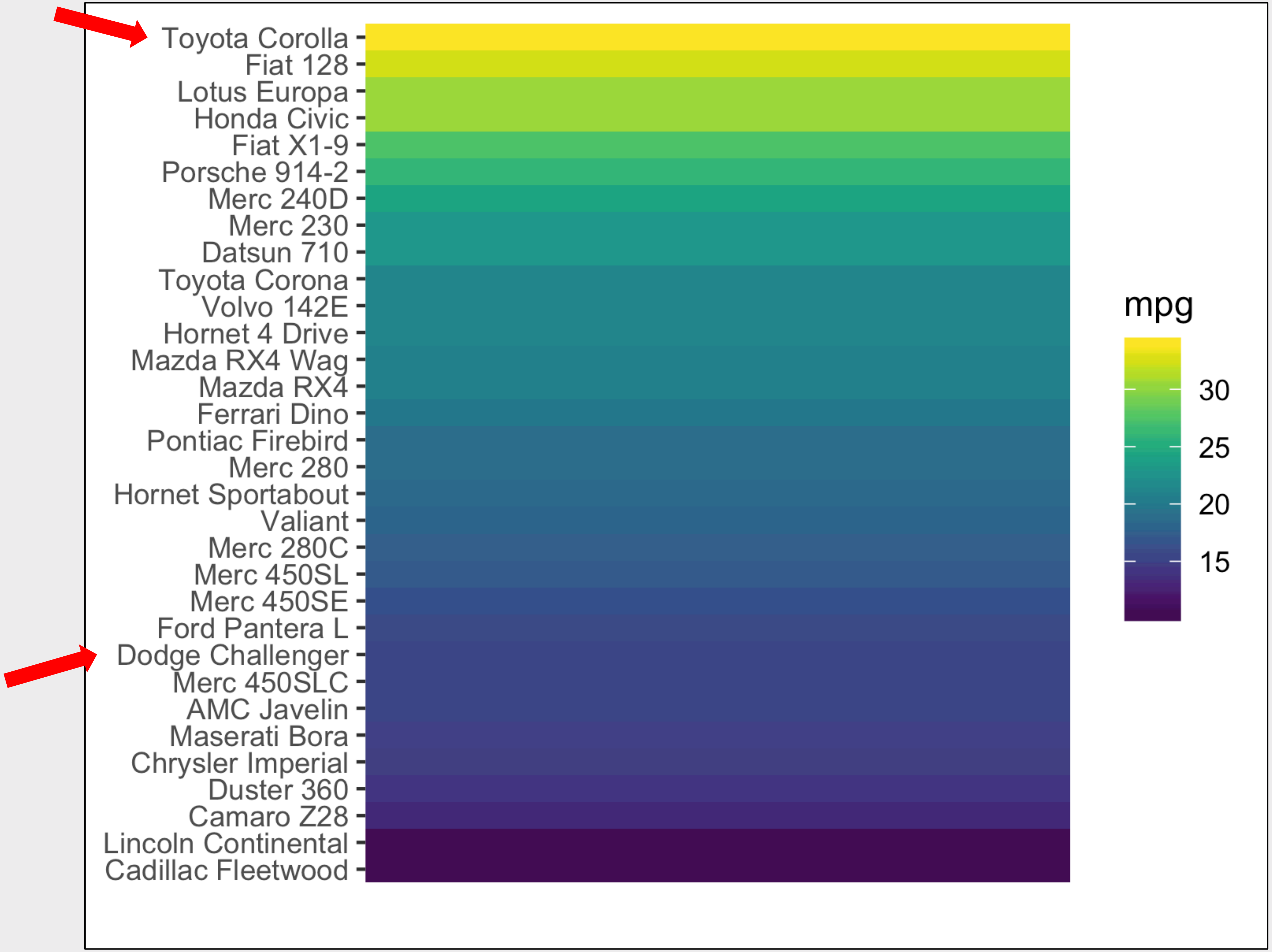
1. Position on a common scale
2. Position on non-aligned scales
3. Length
4. Angle
5. Area
6. Color saturation
7. Color hue



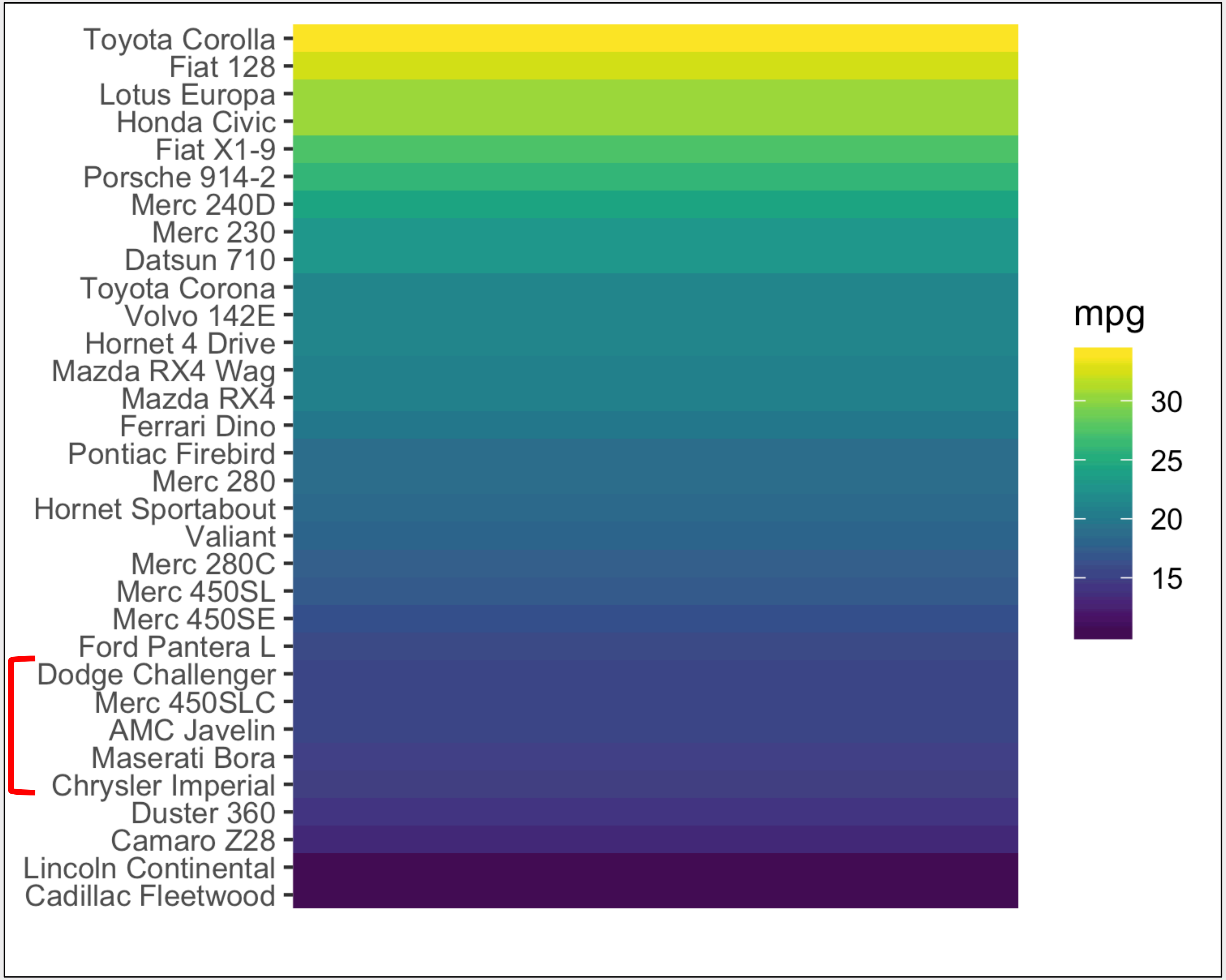
Ranking?

1. Position on a common scale
2. Position on non-aligned scales
3. Length
4. Angle
5. Area
6. Color saturation
7. Color hue

Ranking?

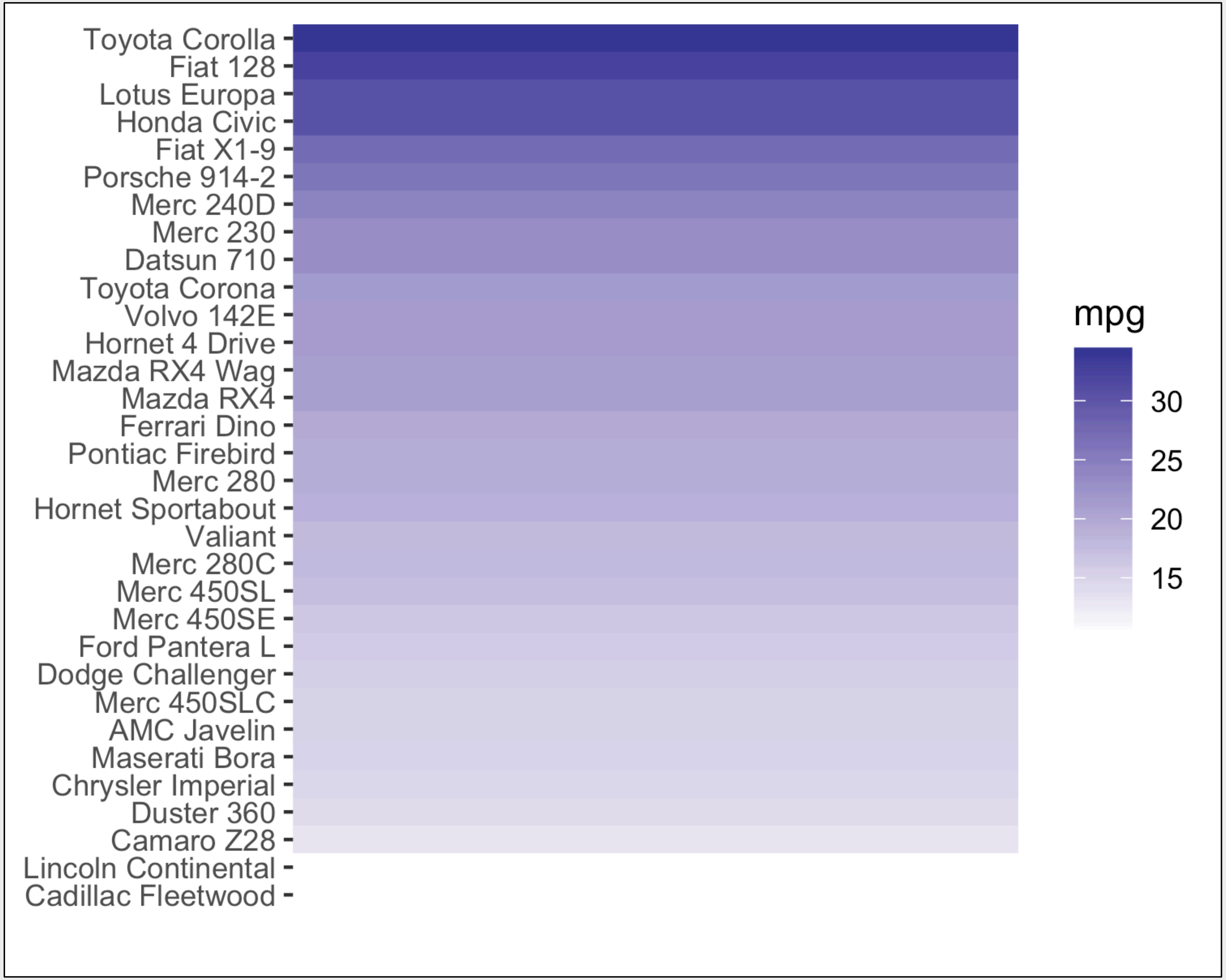


1. Position on a common scale
2. Position on non-aligned scales
3. Length
4. Angle
5. Area
6. Color saturation
7. Color hue

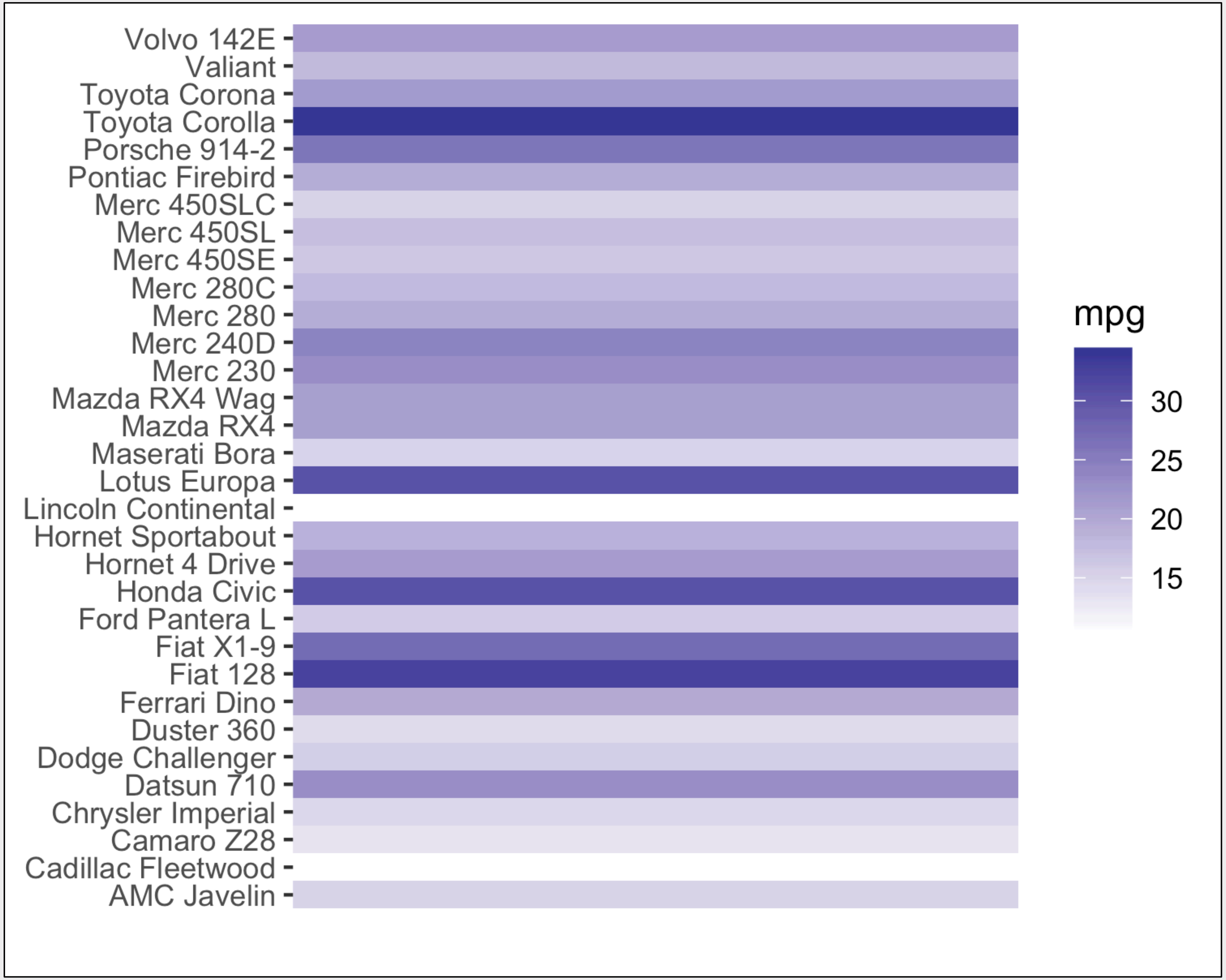


Discrimination?

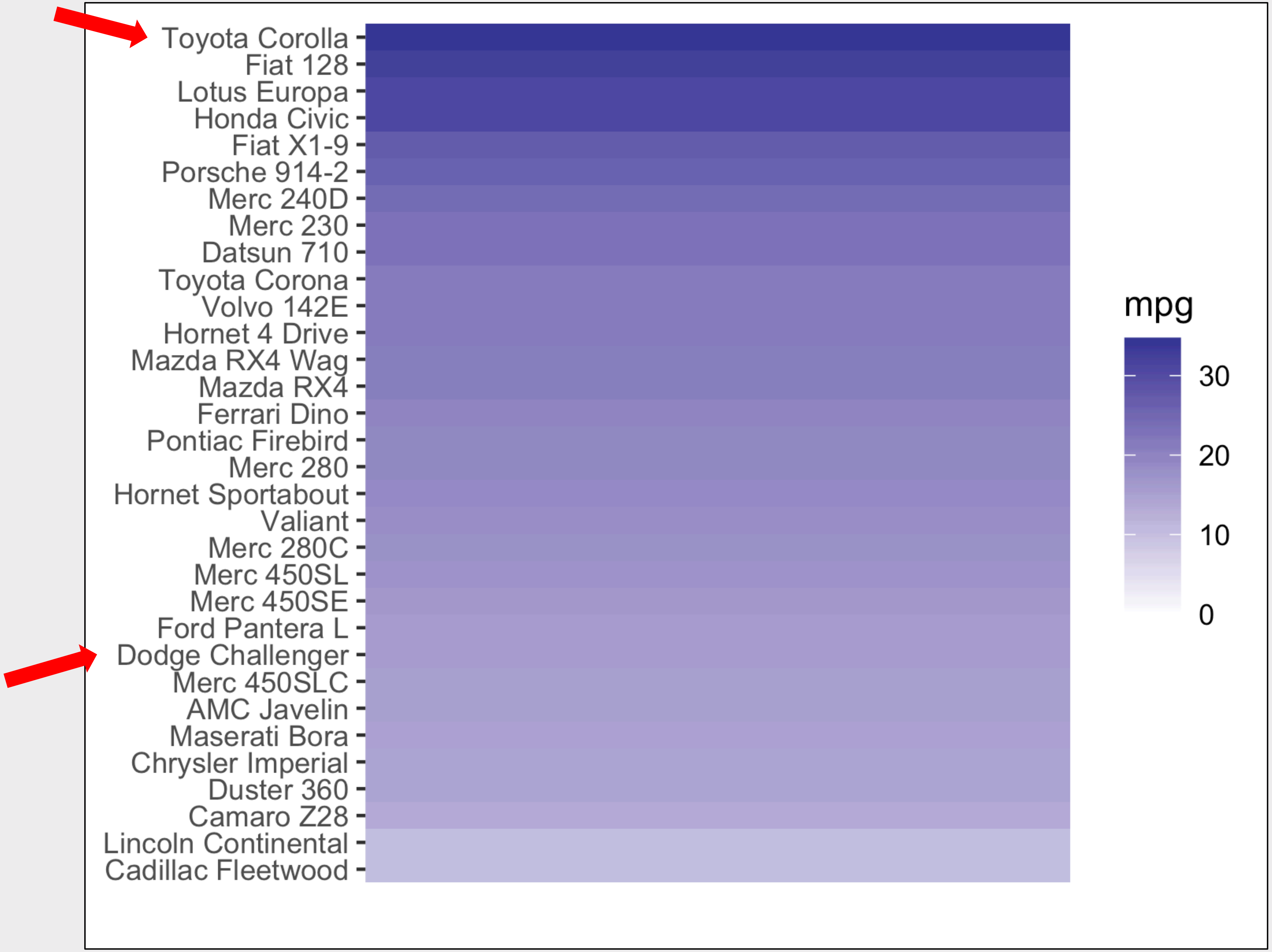
1. Position on a common scale
2. Position on non-aligned scales
3. Length
4. Angle
5. Area
6. Color saturation
7. Color hue



1. Position on a common scale
2. Position on non-aligned scales
3. Length
4. Angle
5. Area
6. Color saturation
7. Color hue



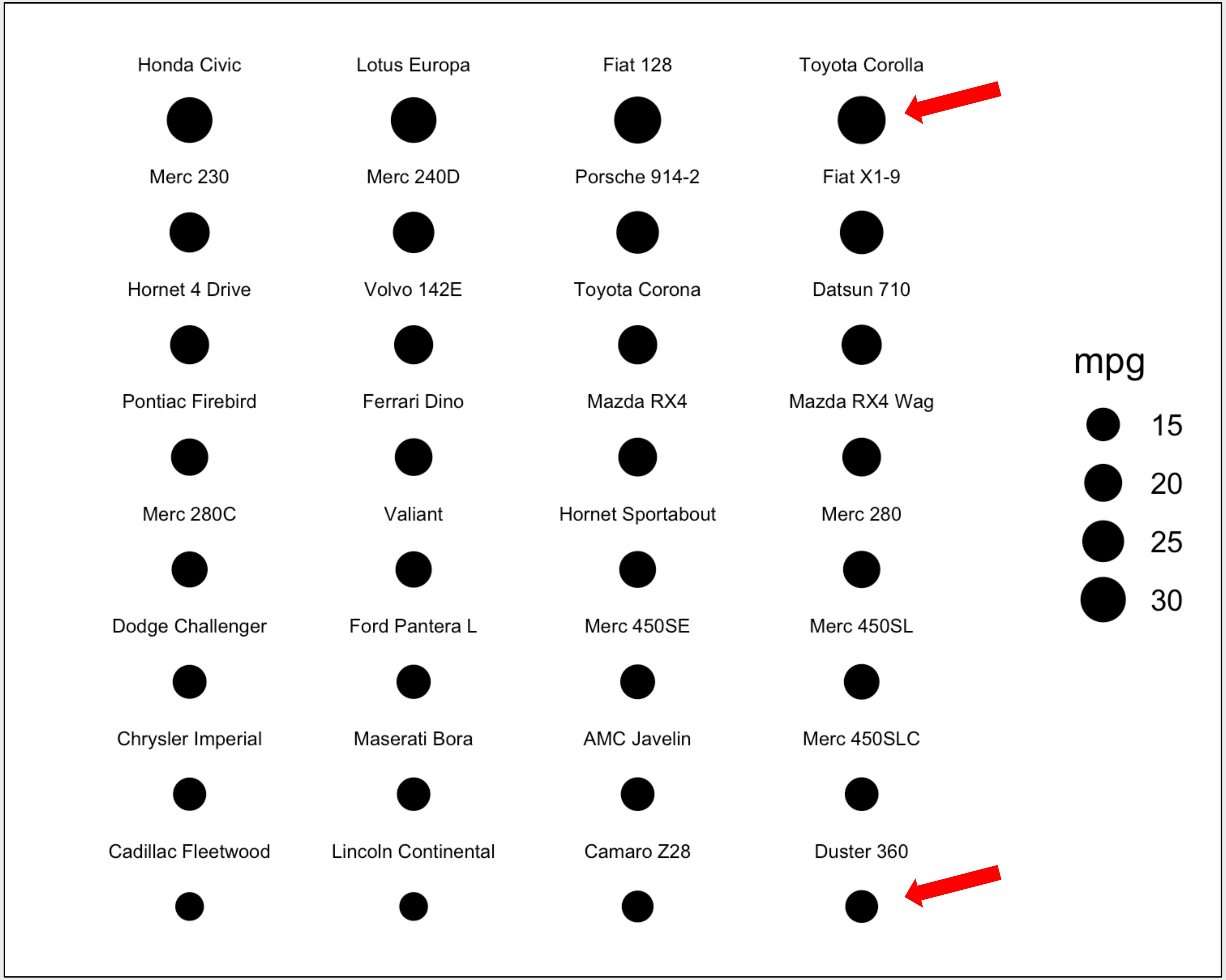
1. Position on a common scale
2. Position on non-aligned scales
3. Length
4. Angle
5. Area
6. Color saturation
7. Color hue



Ratioing?

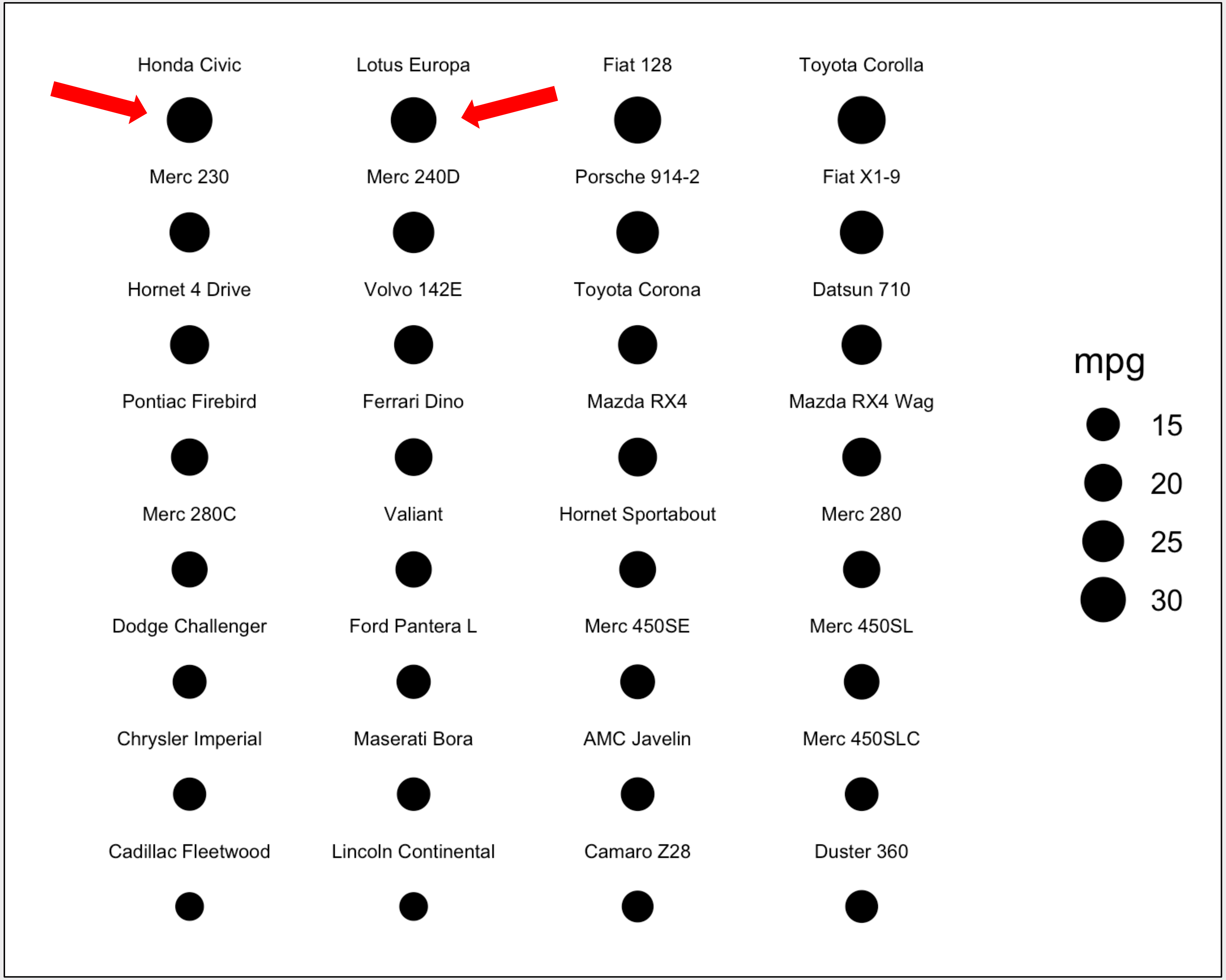
1. Position on a common scale
2. Position on non-aligned scales
3. Length
4. Angle
5. Area
6. Color saturation
7. Color hue

Ratioing?

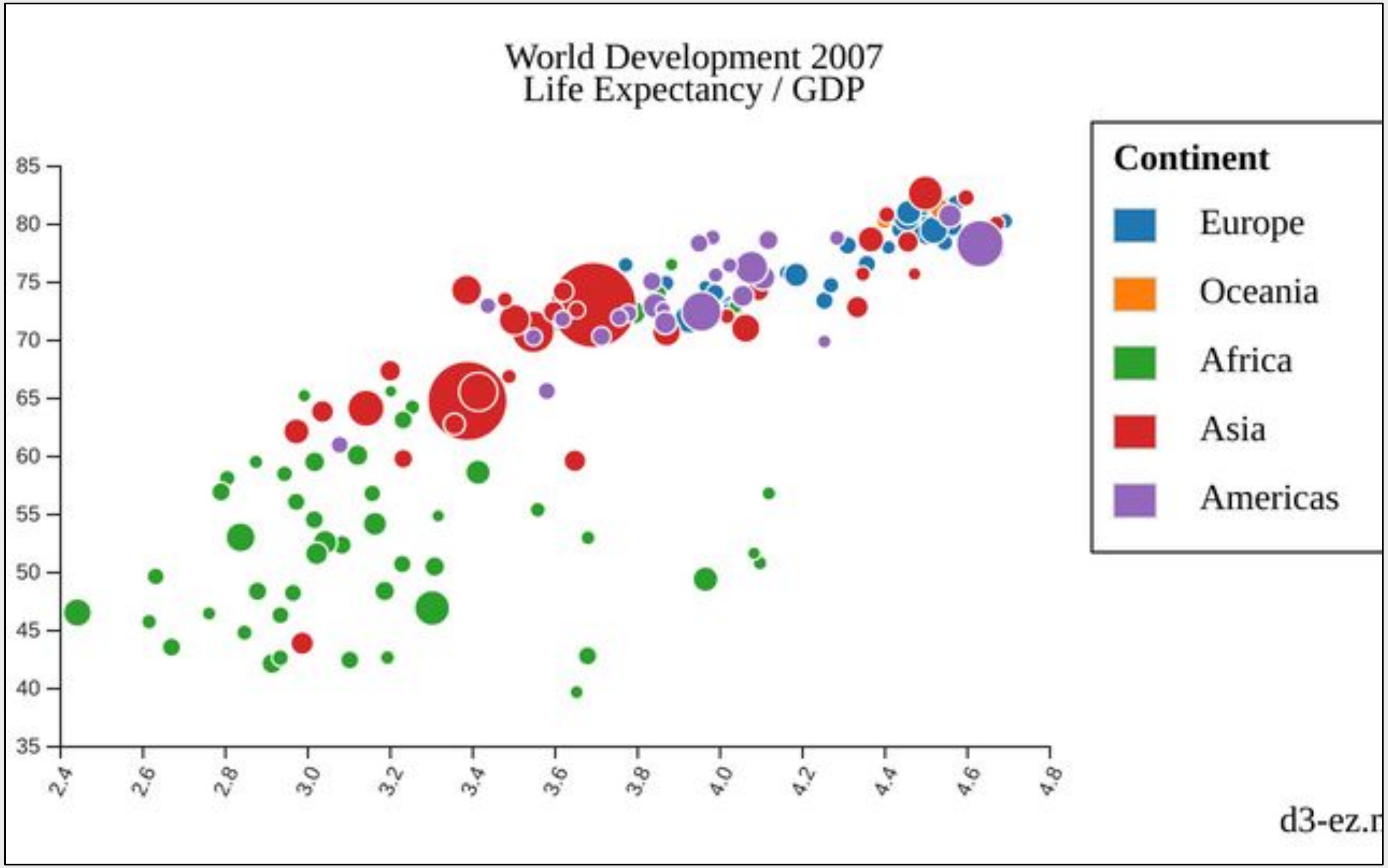


1. Position on a common scale
2. Position on non-aligned scales
3. Length
4. Angle
5. Area
6. Color saturation
7. Color hue

Discrimination?
Ranking?

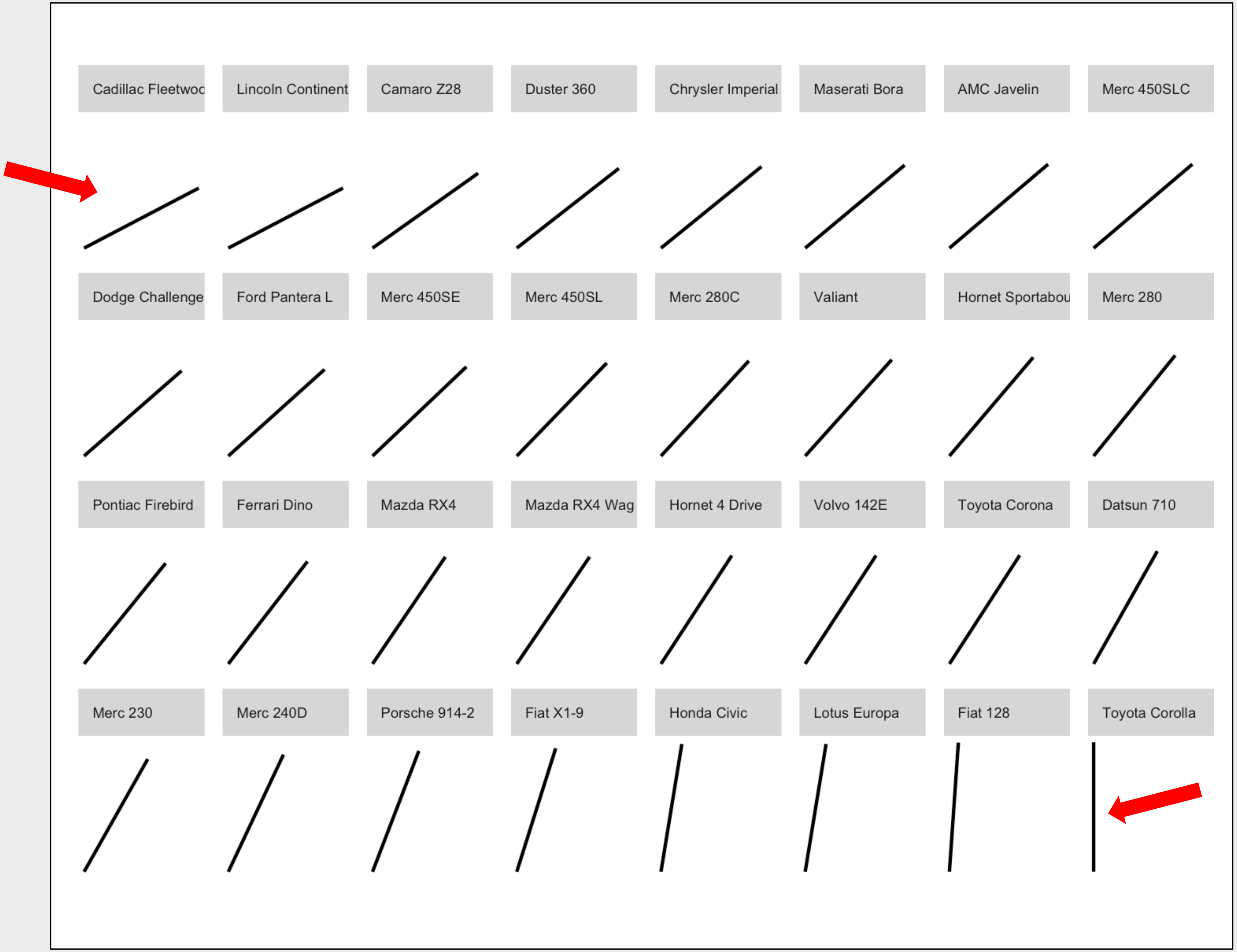


1. Position on a common scale
2. Position on non-aligned scales
3. Length
4. Angle
5. Area
6. Color saturation
7. Color hue



1. Position on a common scale
2. Position on non-aligned scales
3. Length
4. Angle
5. Area
6. Color saturation
7. Color hue

Ratioing?



1. Position on a common scale
2. Position on non-aligned scales
3. Length
4. Angle
5. Area
6. Color saturation
7. Color hue

Discrimination?
Ranking?

1. Position on a common scale
2. Position on non-aligned scales
3. Length
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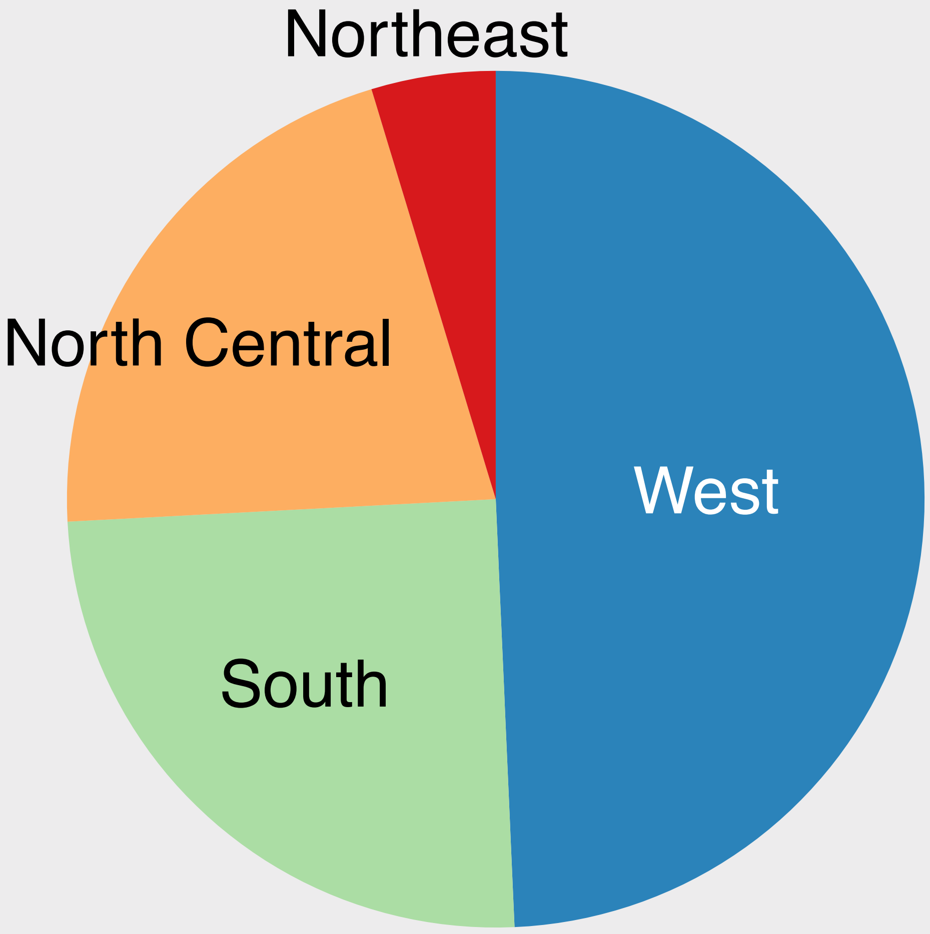
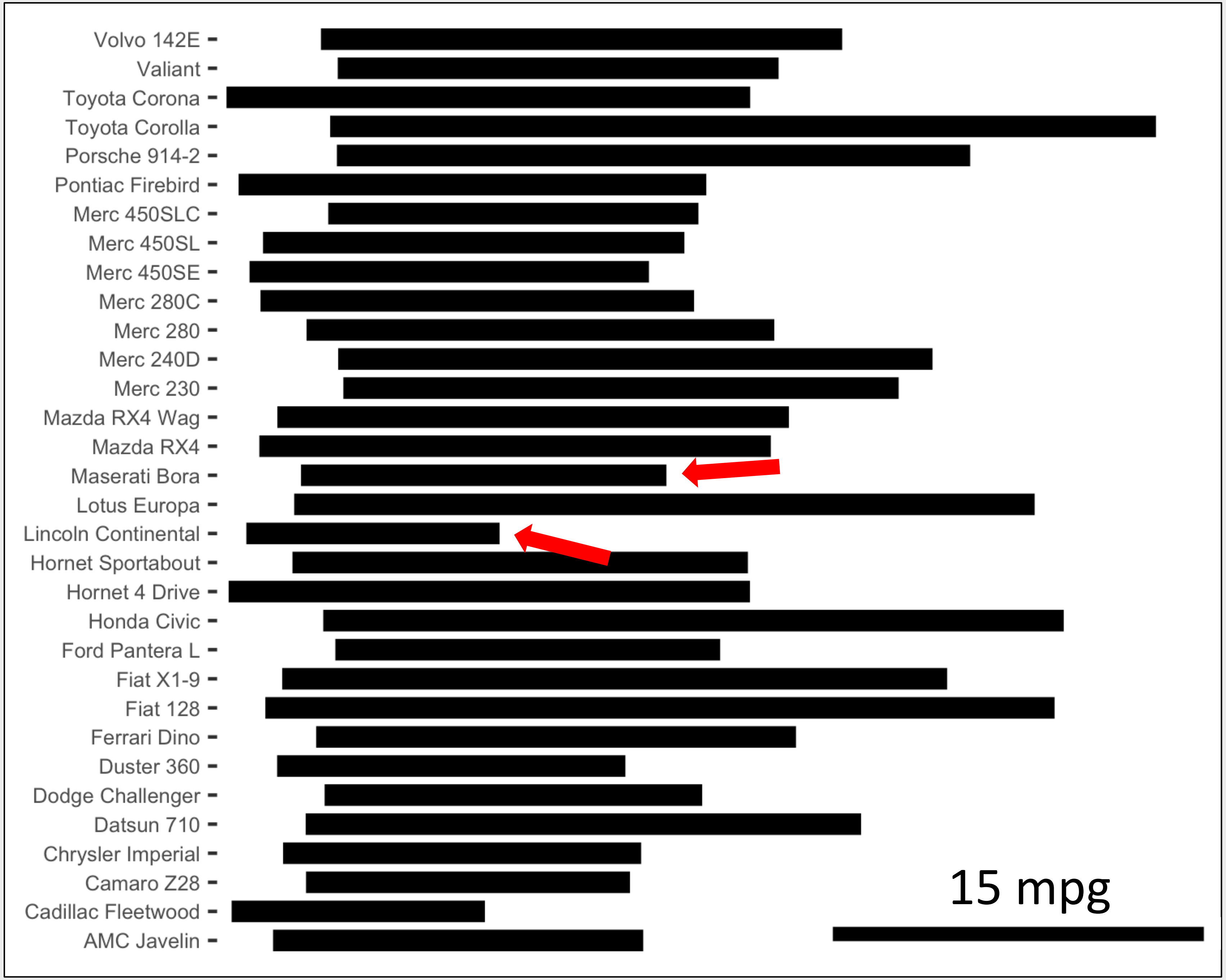
7. Color hue

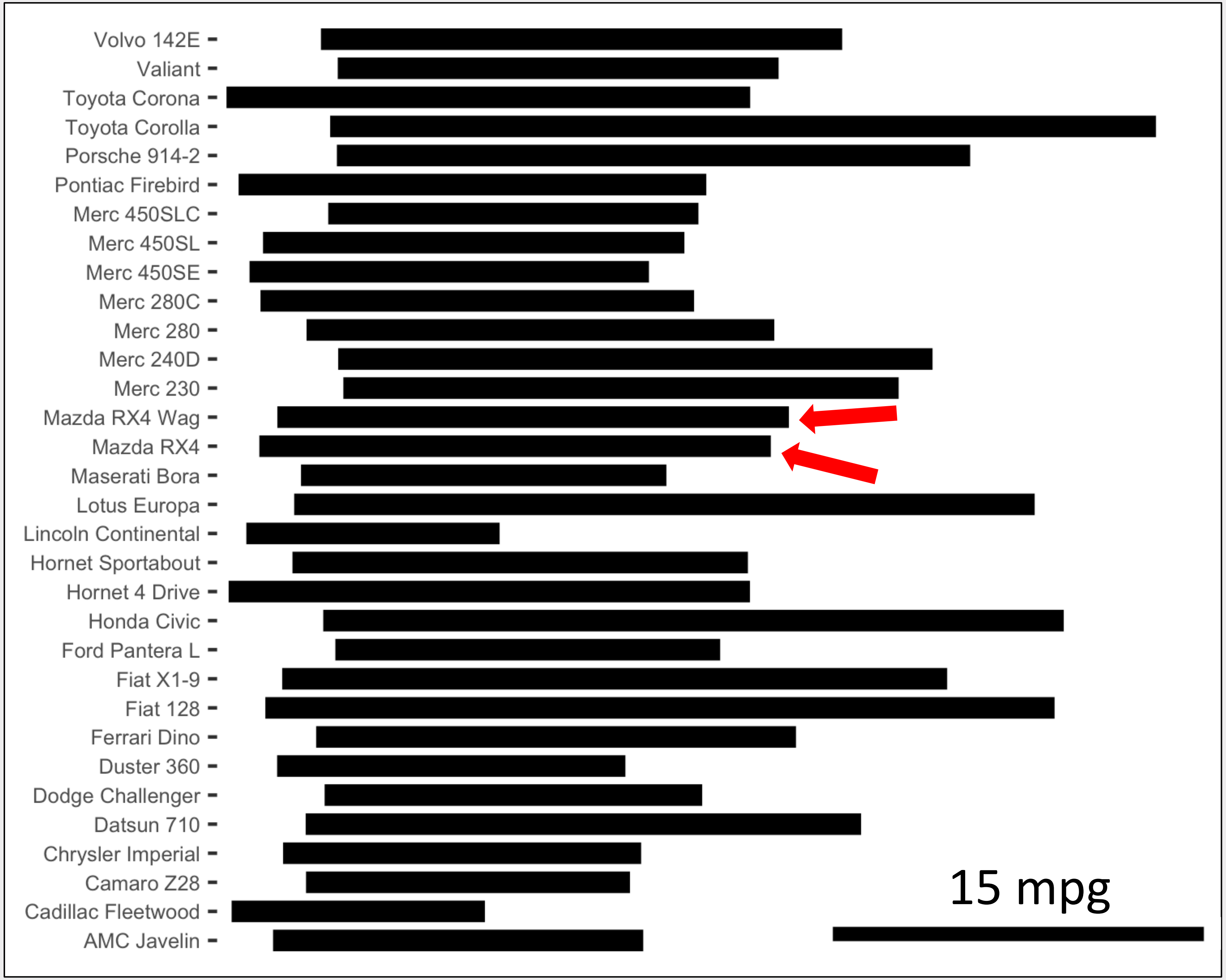


1. Position on a common scale
2. Position on non-aligned scales
3. Length
4. Angle
5. Area
6. Color saturation
7. Color hue



Ratioing?

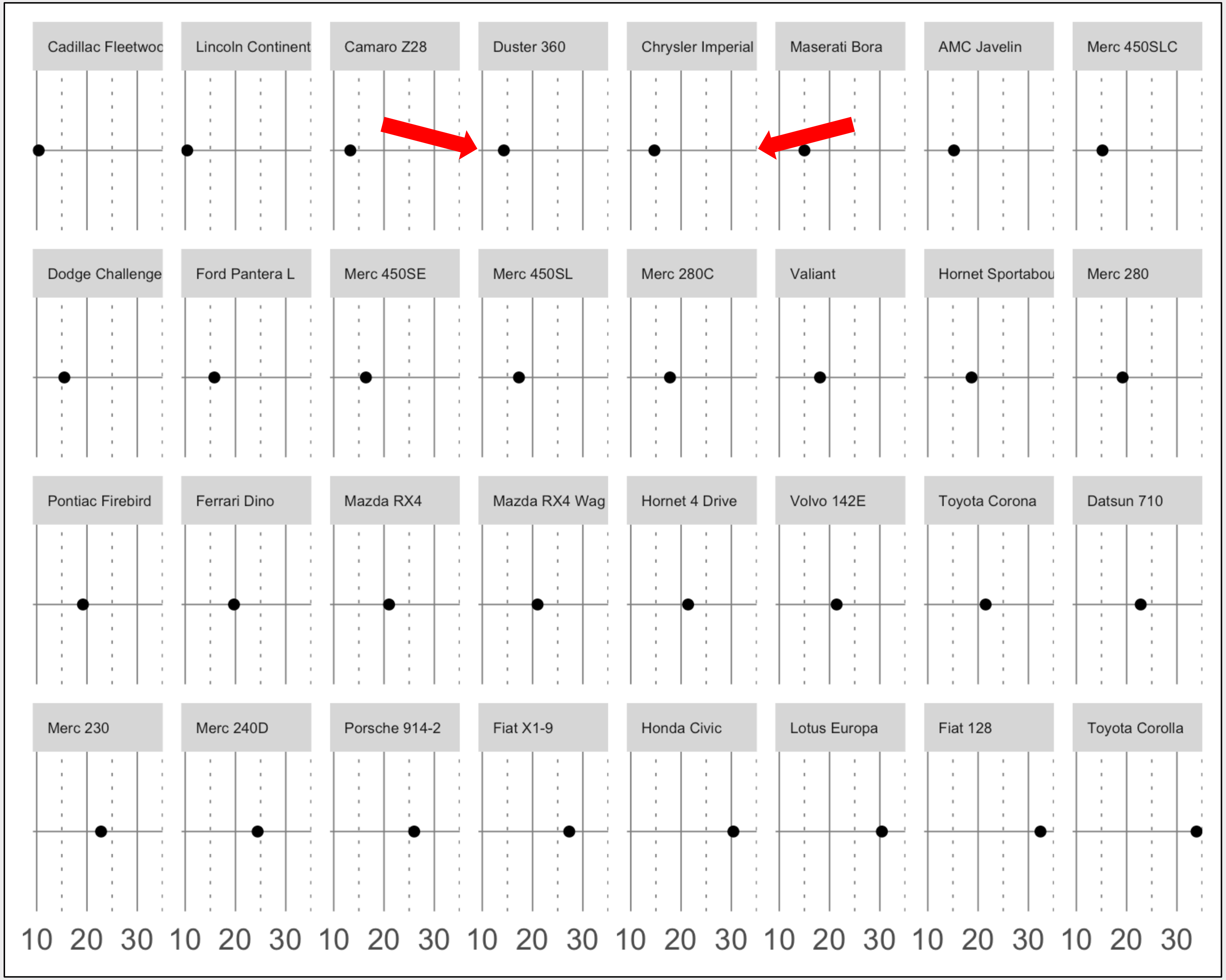
1. Position on a common scale
2. Position on non-aligned scales
3. Length
4. Angle
5. Area
6. Color saturation
7. Color hue



Discrimination?

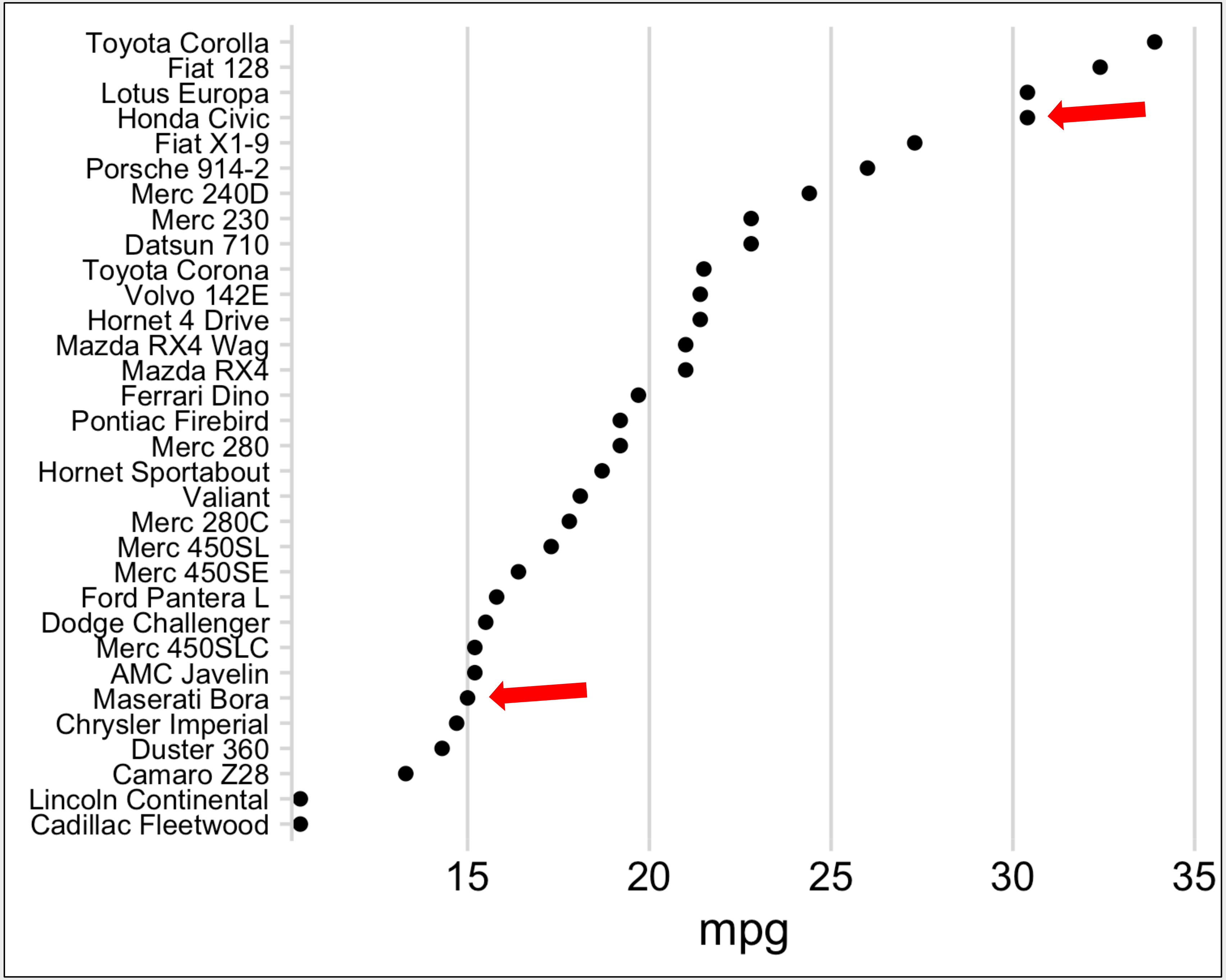
Ranking?

1. Position on a common scale
2. Position on non-aligned scales
3. Length
4. Angle
5. Area
6. Color saturation
7. Color hue



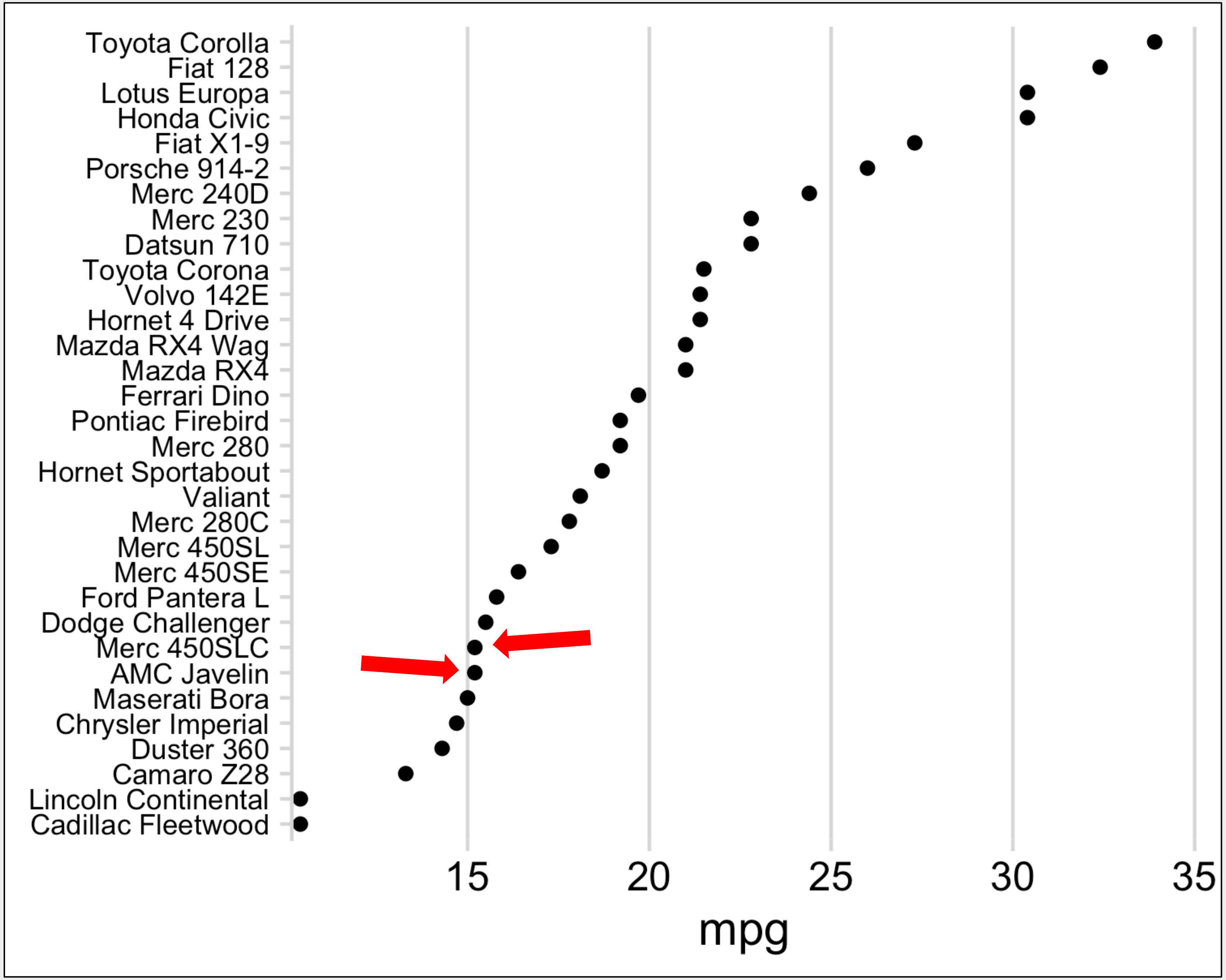
Discrimination?
Ranking?

1. Position on a common scale
2. Position on non-aligned scales
3. Length
4. Angle
5. Area
6. Color saturation
7. Color hue



Ratioing?

1. Position on a common scale
2. Position on non-aligned scales
3. Length
4. Angle
5. Area
6. Color saturation
7. Color hue

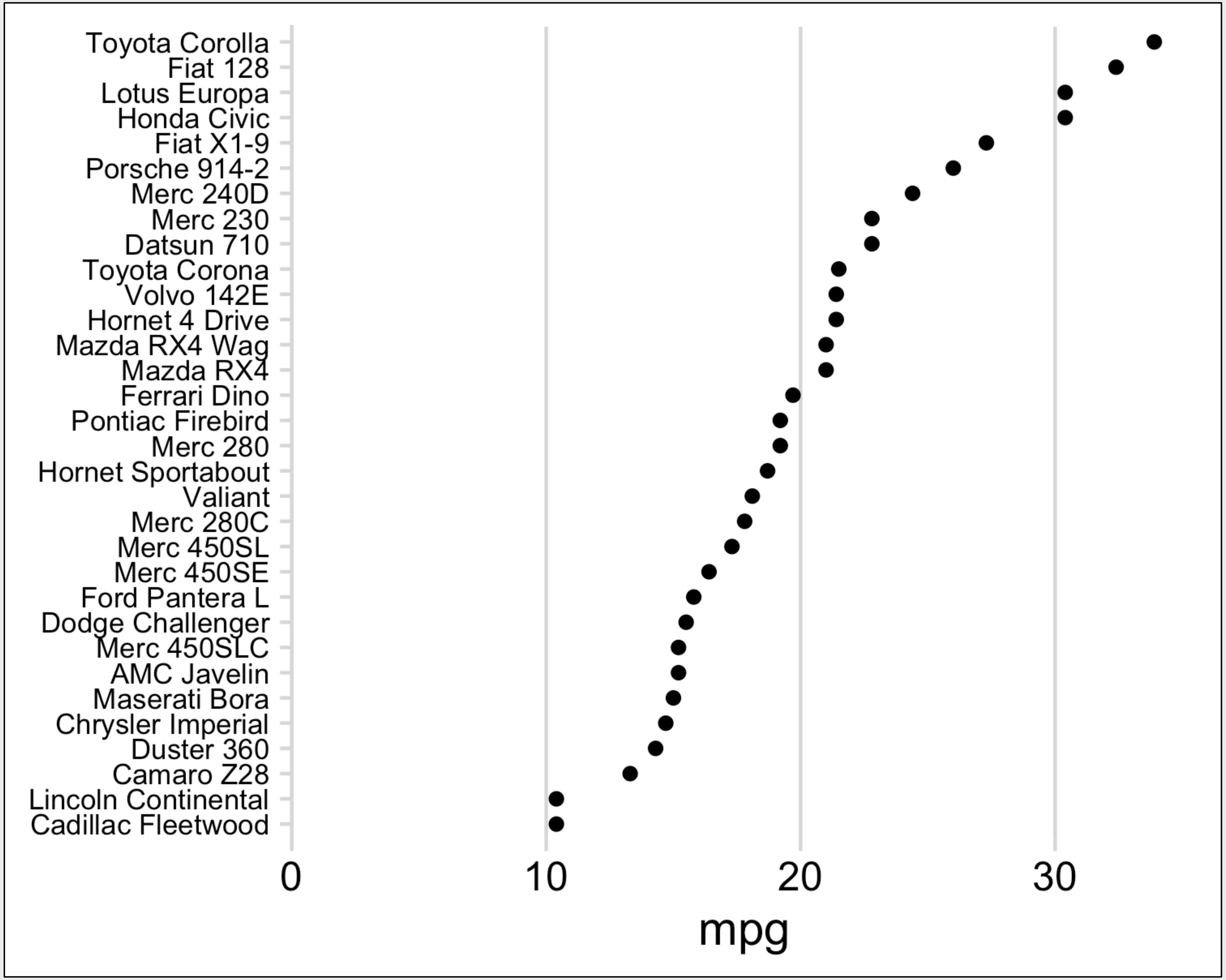


Discrimination?
Ranking?

1. Position on a common scale
2. Position on non-aligned scales
3. Length
4. Angle
5. Area
6. Color saturation
7. Color hue

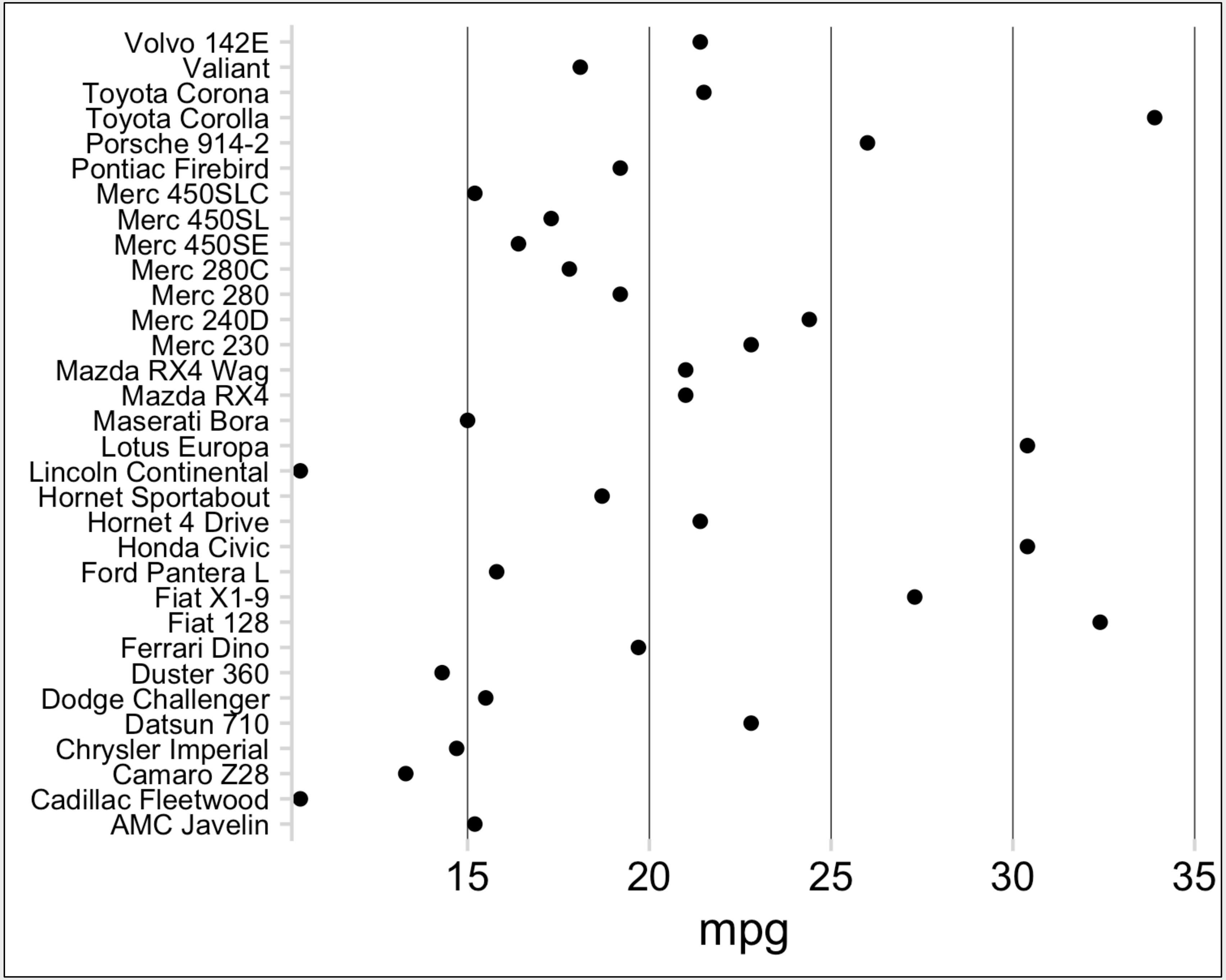
No need to scale to 0:

- Lowers resolution
- Isn't needed for accurate ratioing



1. Position on a common scale
2. Position on non-aligned scales
3. Length
4. Angle
5. Area
6. Color saturation
7. Color hue

Ordering still crucial



Cleveland's three visual operations of pattern perception:

- Estimation
- **Assembly** → The grouping of graphical elements
- Detection

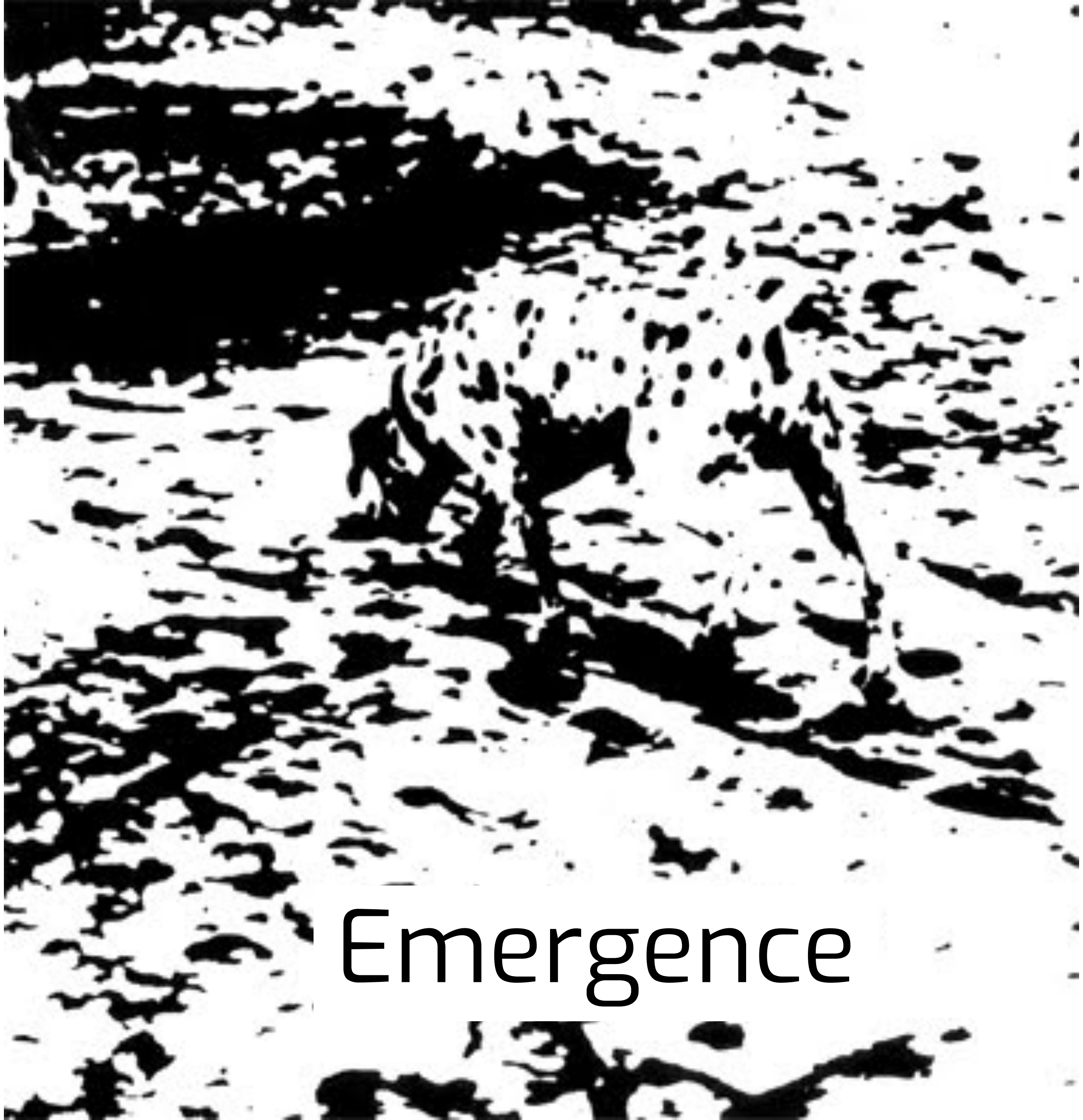
Gestalt Psychology

The whole has a reality that is entirely separate from the parts

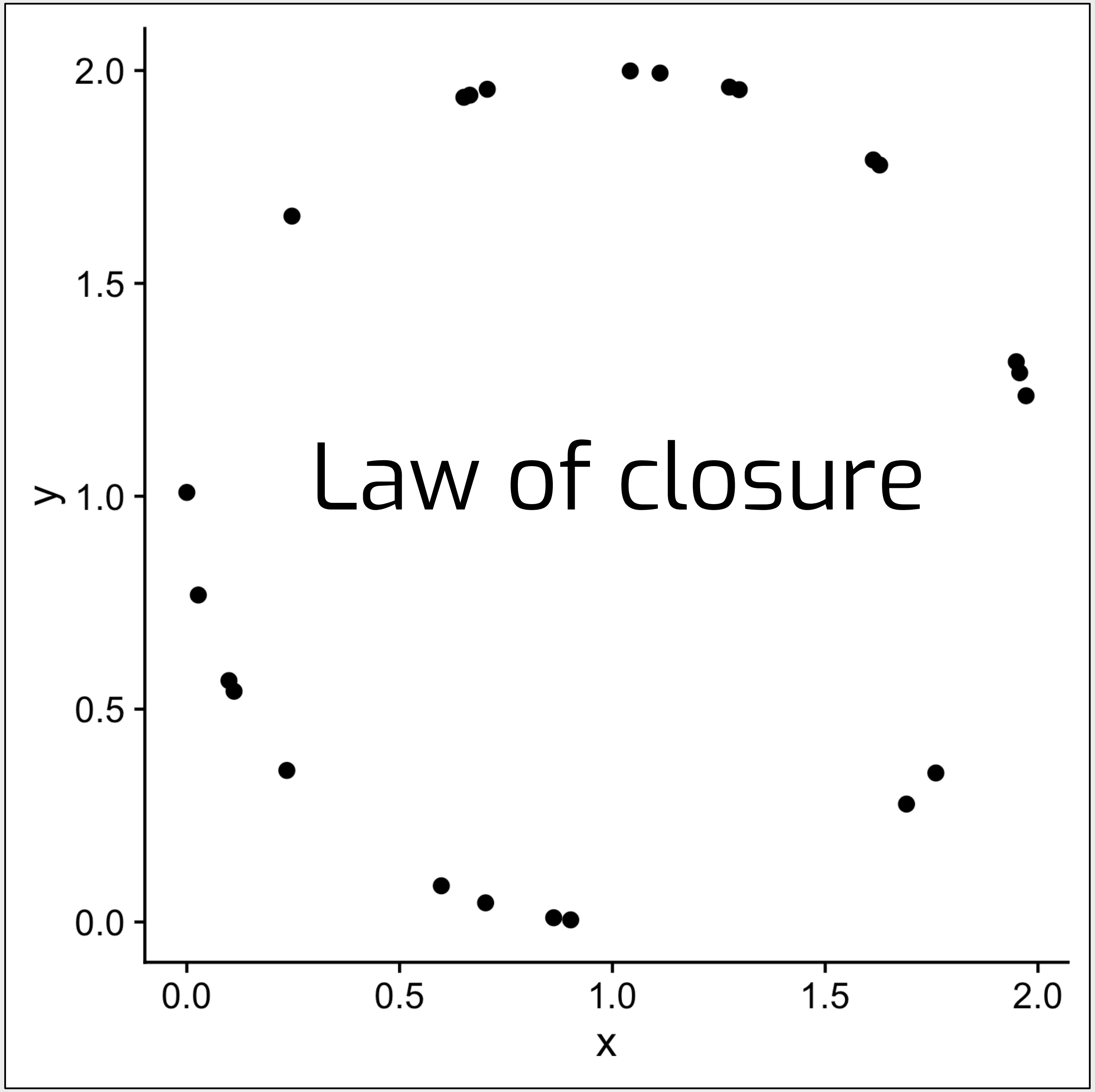
WWF

Reification

Formula 1

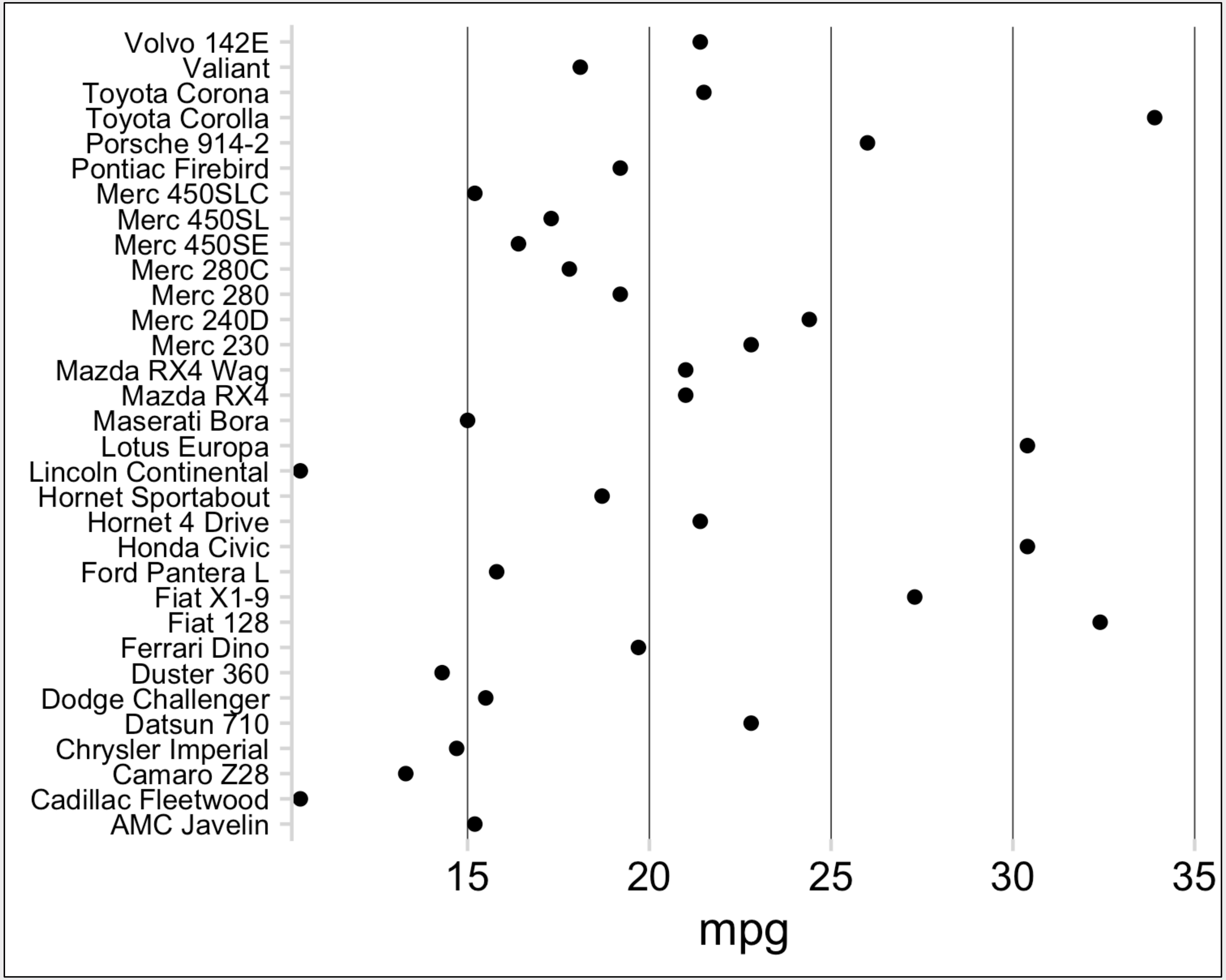

Emergence

x	y
1.972	1.236
1.112	1.994
0	1.009
0.665	1.942
0.235	0.356
0.247	1.658
1.275	1.961
0.702	0.045
1.76	0.35
1.691	0.277
1.628	1.778
1.957	1.29
0.111	0.542
0.902	0.005
0.598	0.085
1.613	1.79
1.298	1.955
0.651	1.937
1.949	1.316
0.099	0.567
0.862	0.01
0.027	0.768
0.706	1.956
1.042	1.999



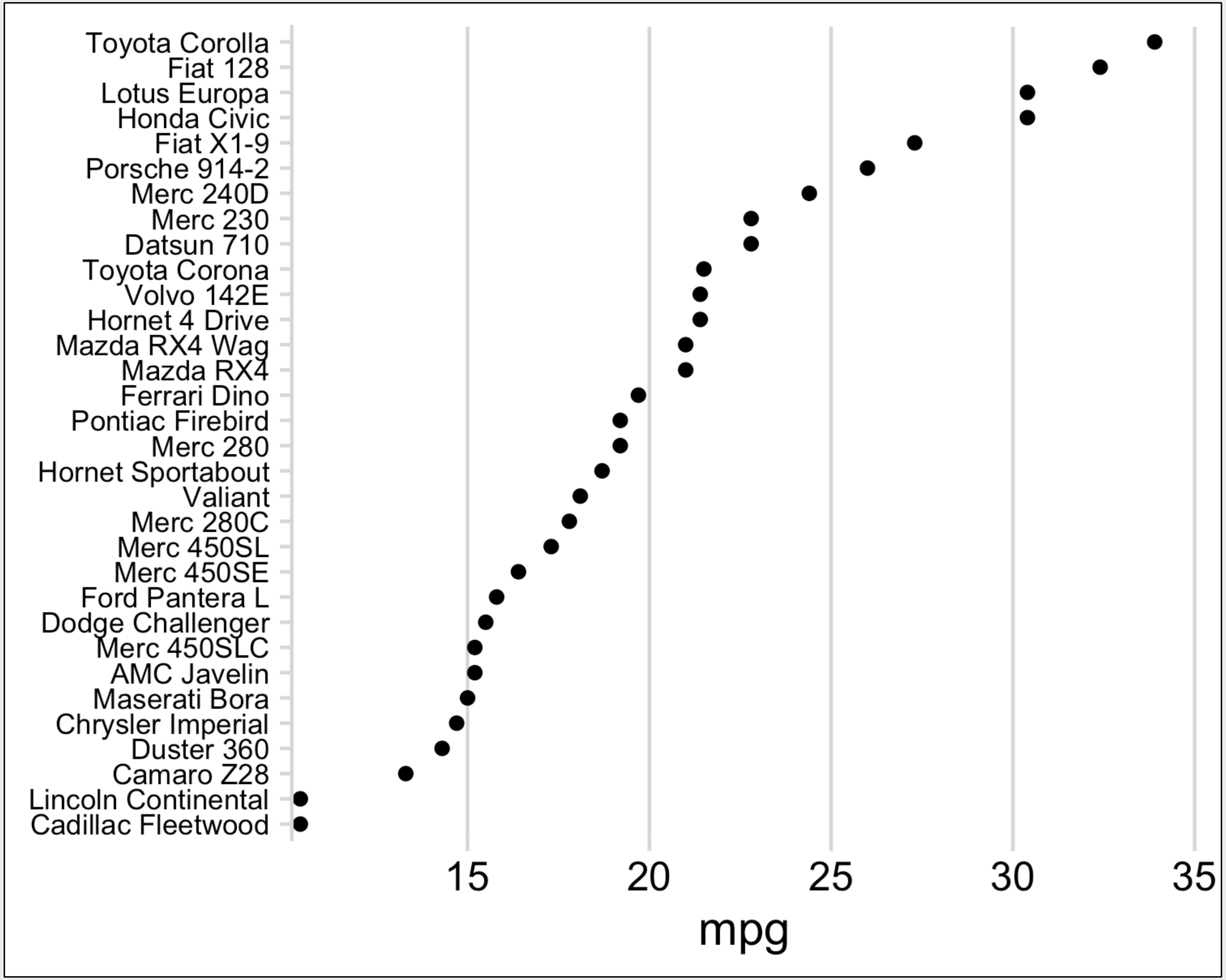
Prägnanz

We strongly prefer to interpret stimuli as regular, simple, and orderly


Volvo 142E
Valiant
Toyota Corona
Toyota Corolla
Porsche 914-2
Pontiac Firebird
Merc 450SLC
Merc 450SL
Merc 450SE
Merc 280C
Merc 280
Merc 240D
Merc 230
Mazda RX4 Wag
Mazda RX4
Maserati Bora
Lotus Europa
Lincoln Continental
Hornet Sportabout
Hornet 4 Drive
Honda Civic
Ford Pantera L
Fiat X1-9
Fiat 128
Ferrari Dino
Duster 360
Dodge Challenger
Datsun 710
Chrysler Imperial
Camaro Z28
Cadillac Fleetwood
AMC Javelin
15
20
25
30
35
mpg

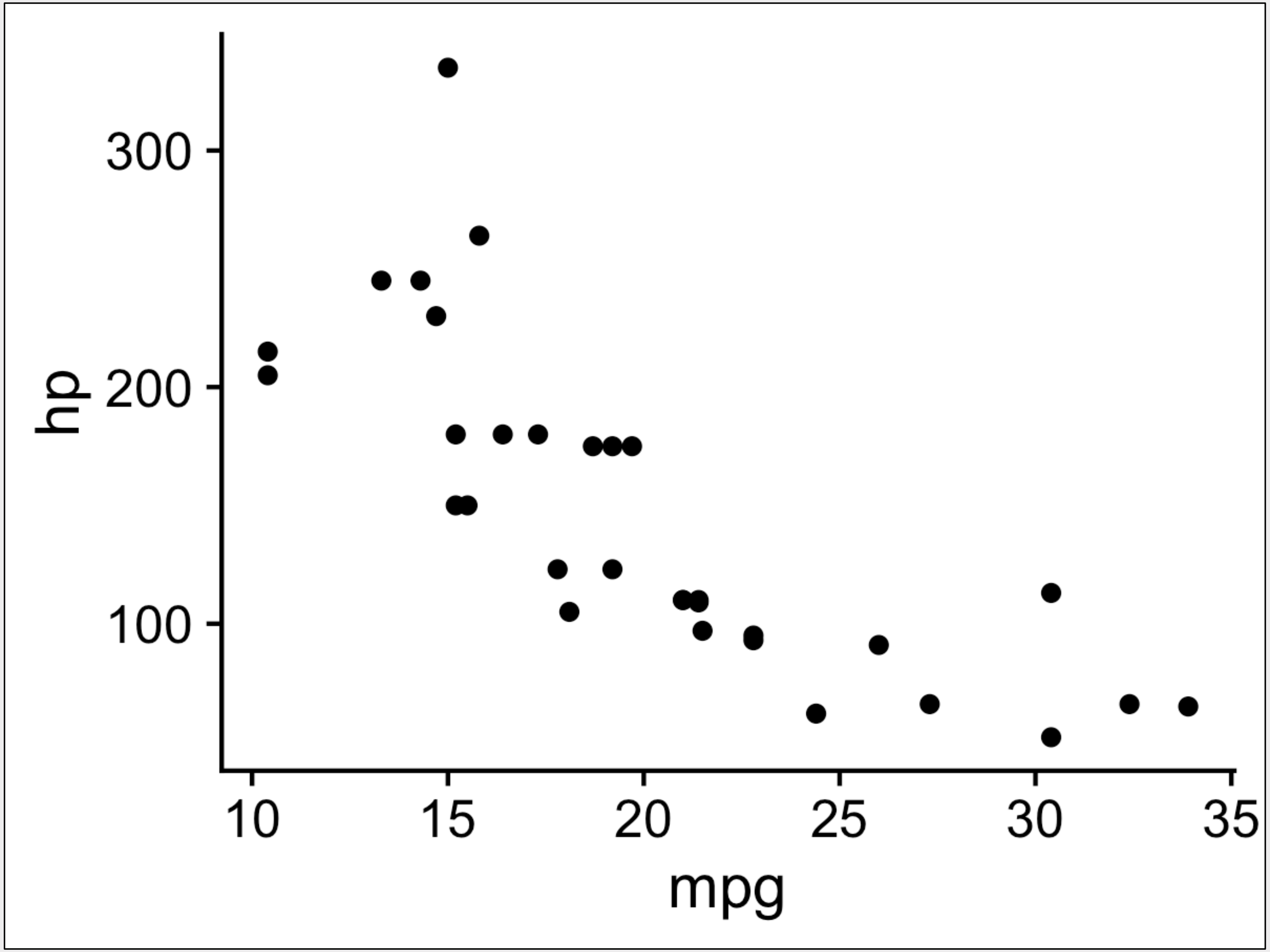
Law of continuity

We will group together objects that follow an established direction



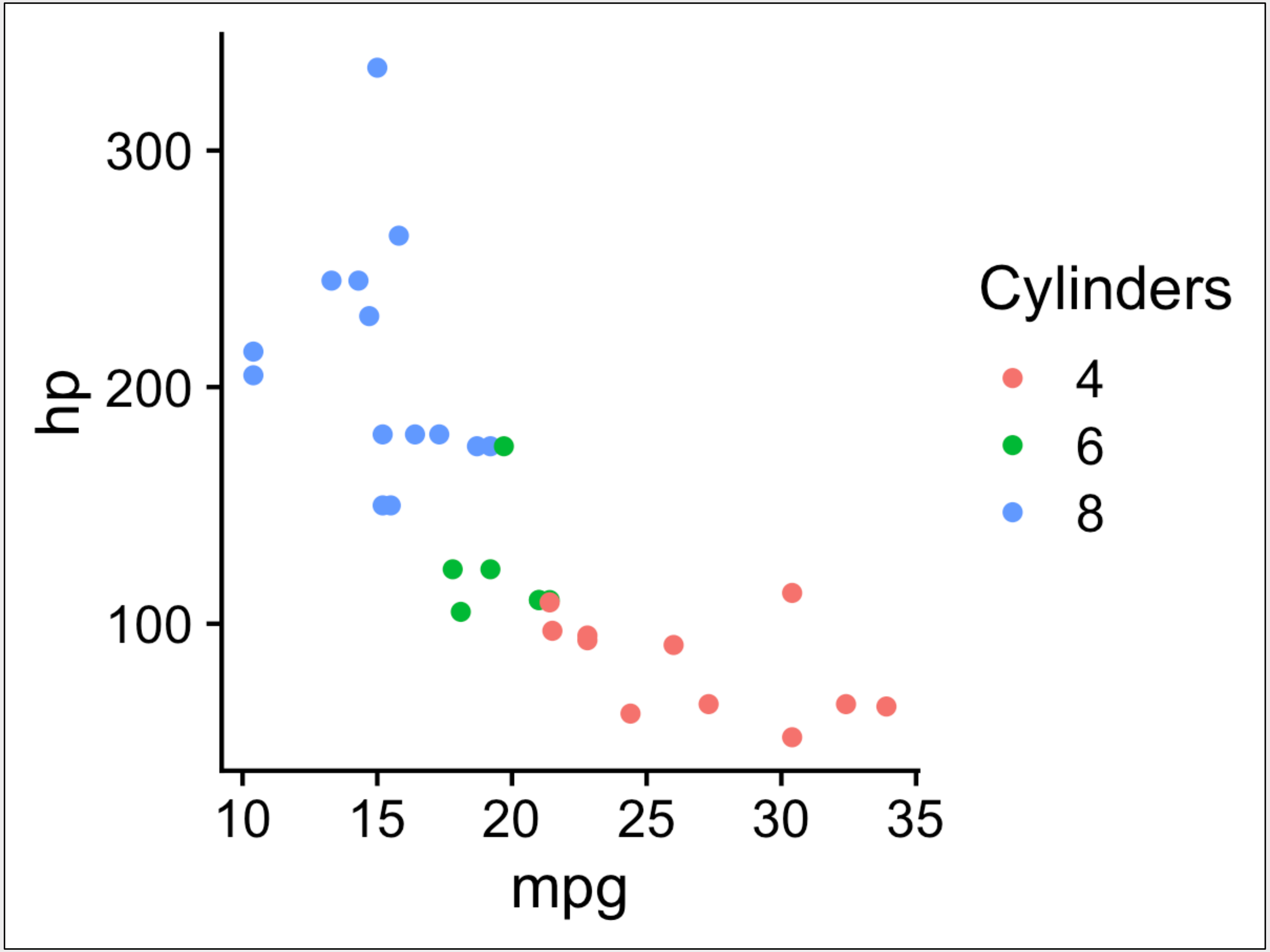
Law of continuity

We will group together objects that follow an established direction



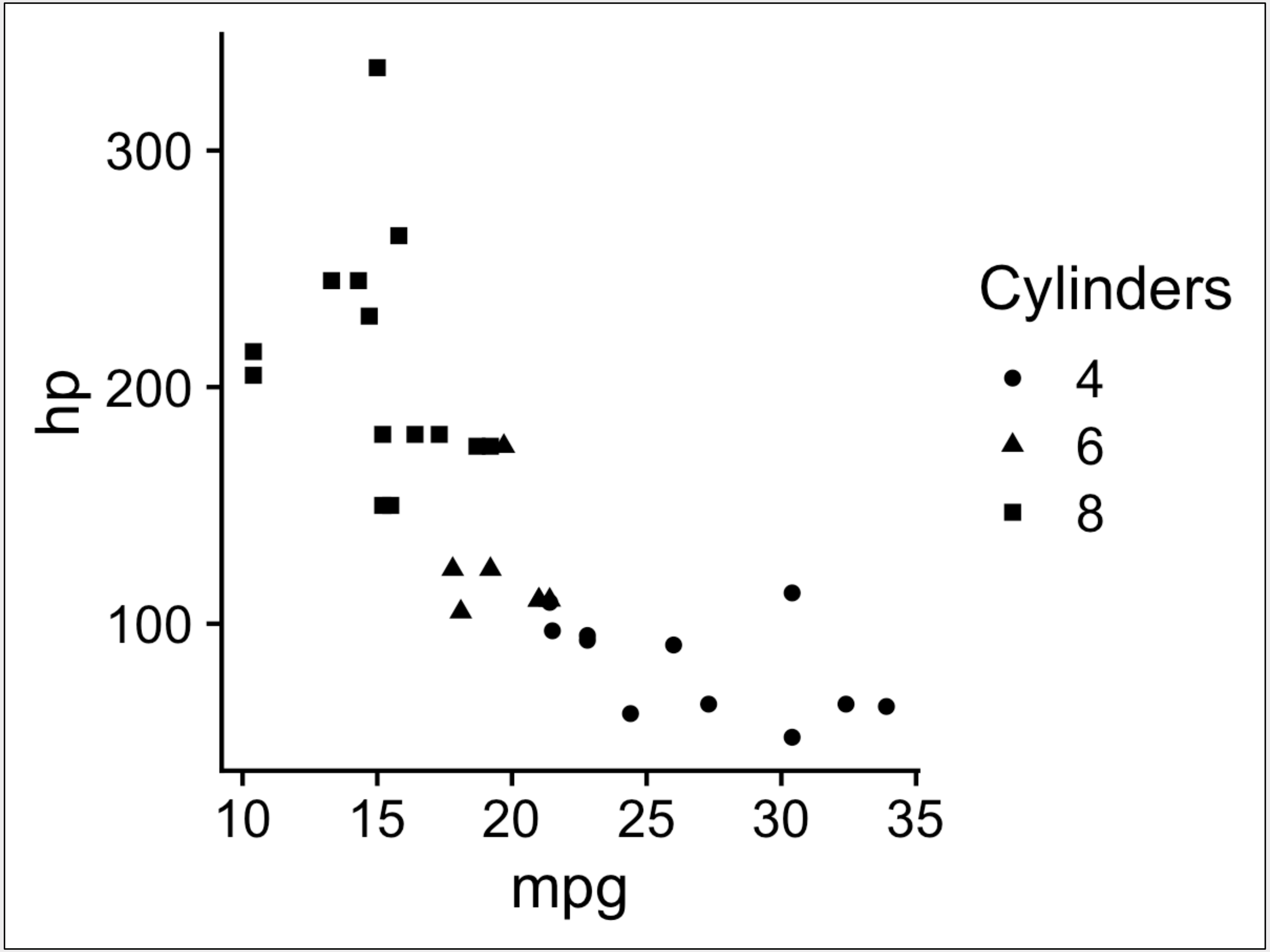
Law of similarity

We tend to see elements that are physically *similar* as part of the same object



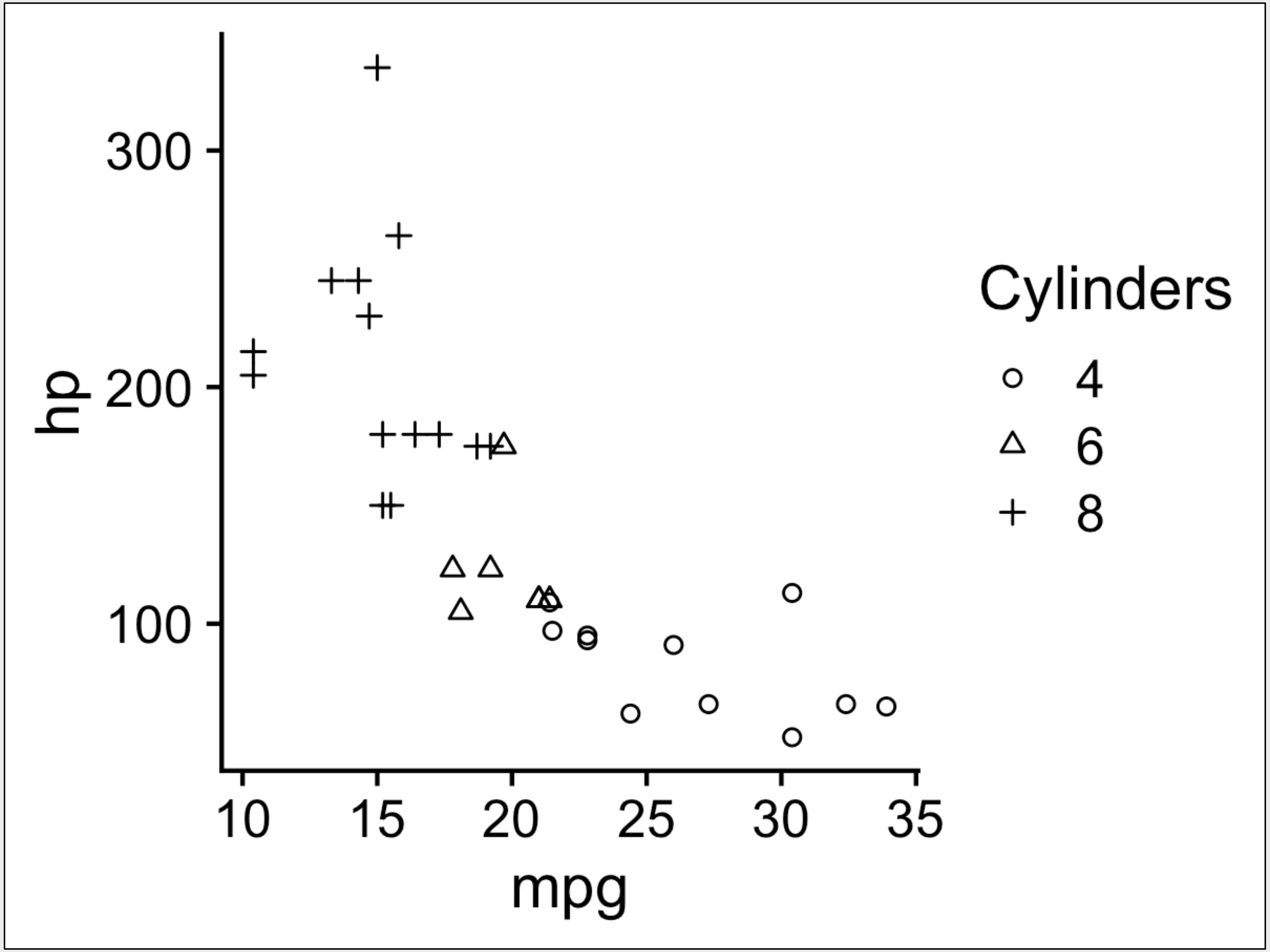
Law of similarity

We tend to see elements that are physically *similar* as part of the same object



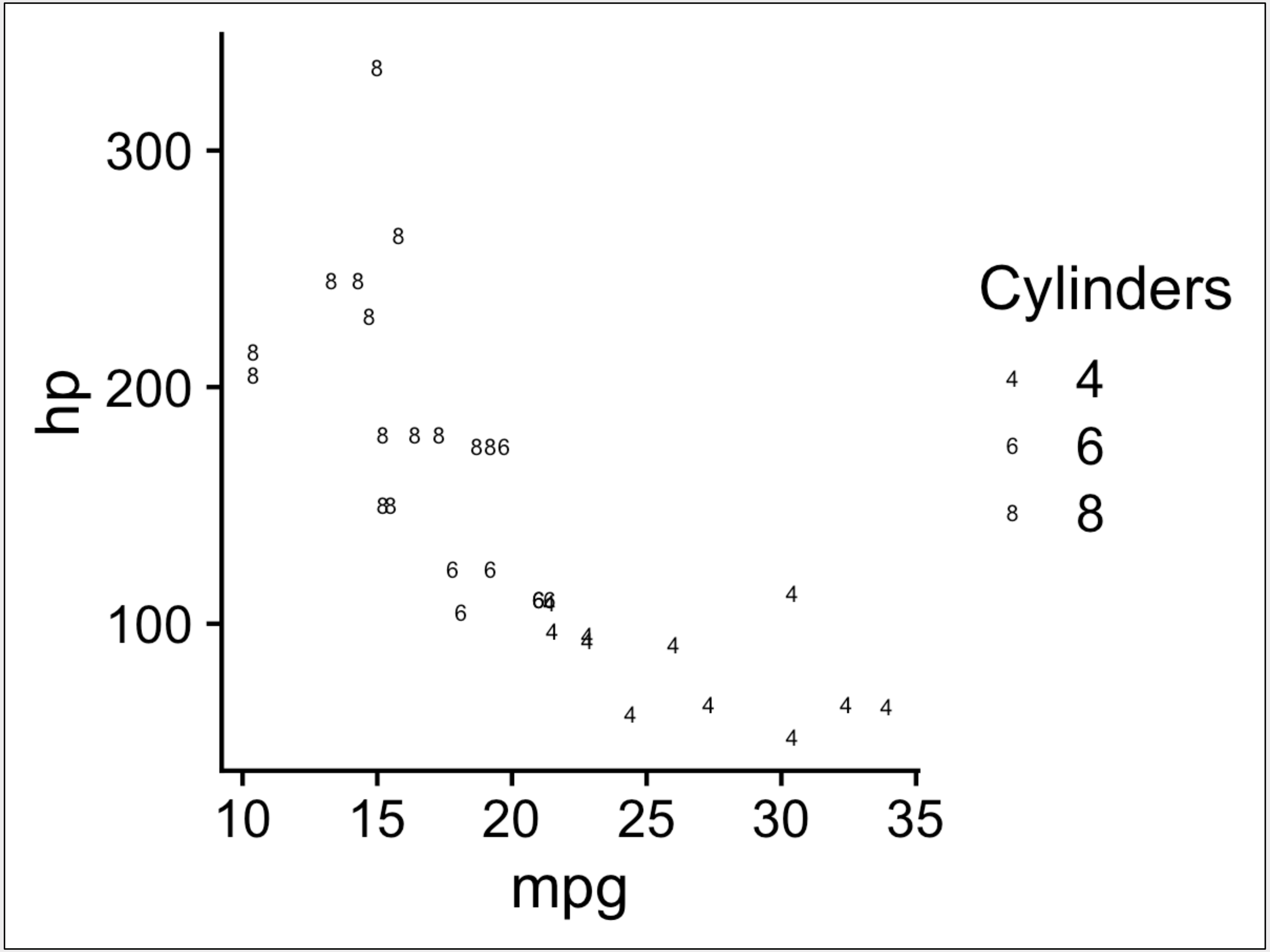
Law of similarity

We tend to see elements that are physically *similar* as part of the same object



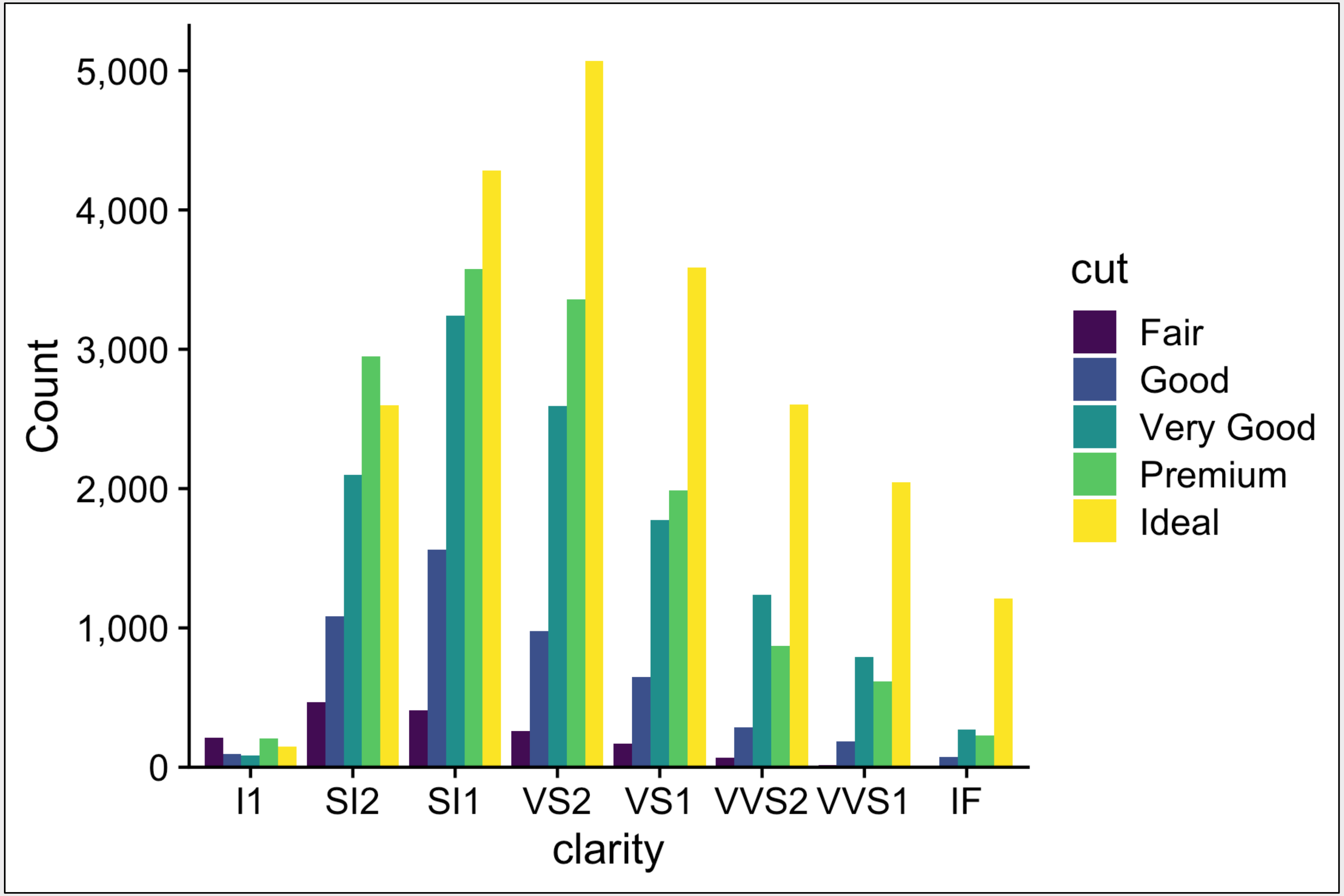
Law of similarity

We tend to see elements that are physically *similar* as part of the same object



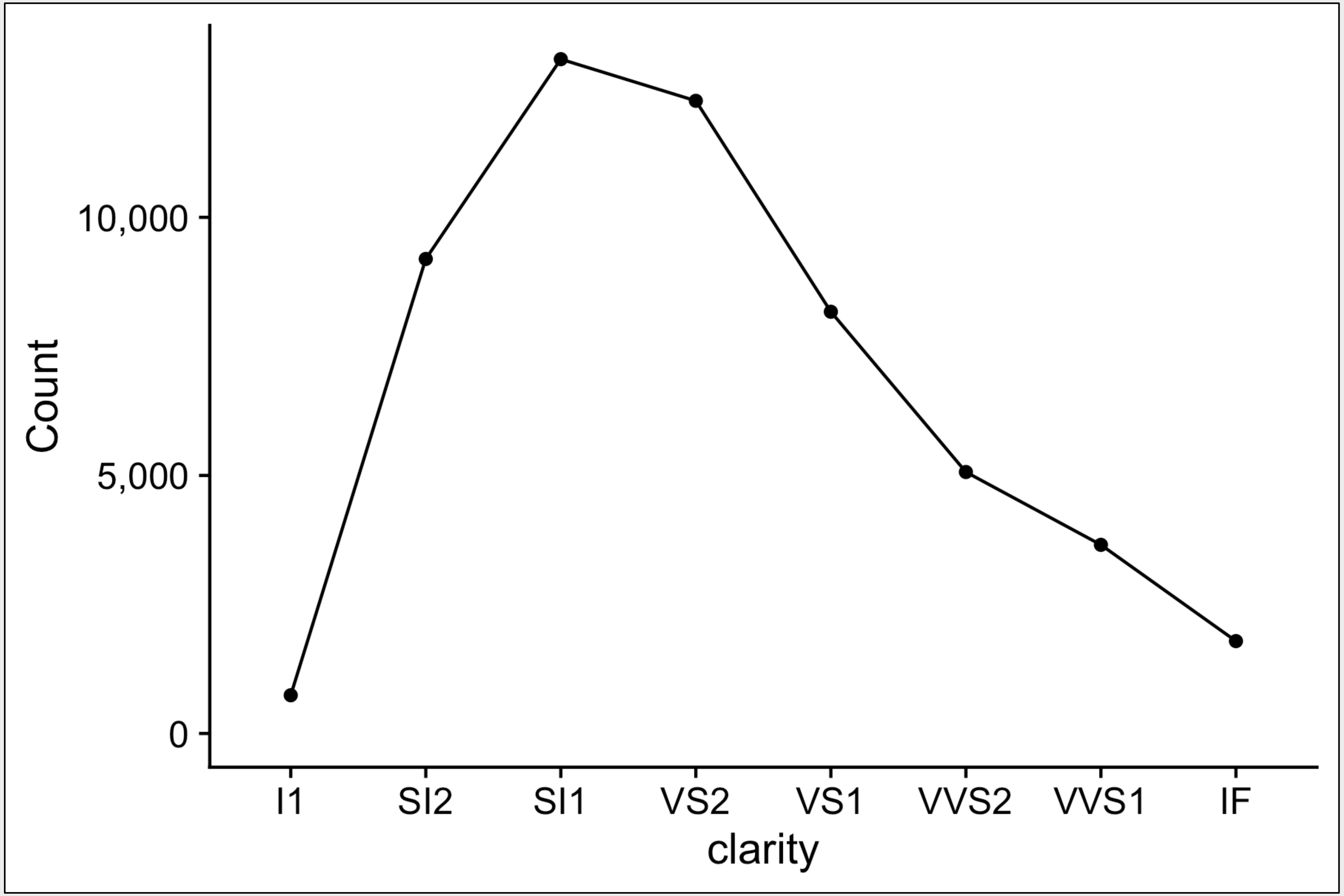
Law of proximity

We tend to see elements that are physically *near* each other as part of the same object



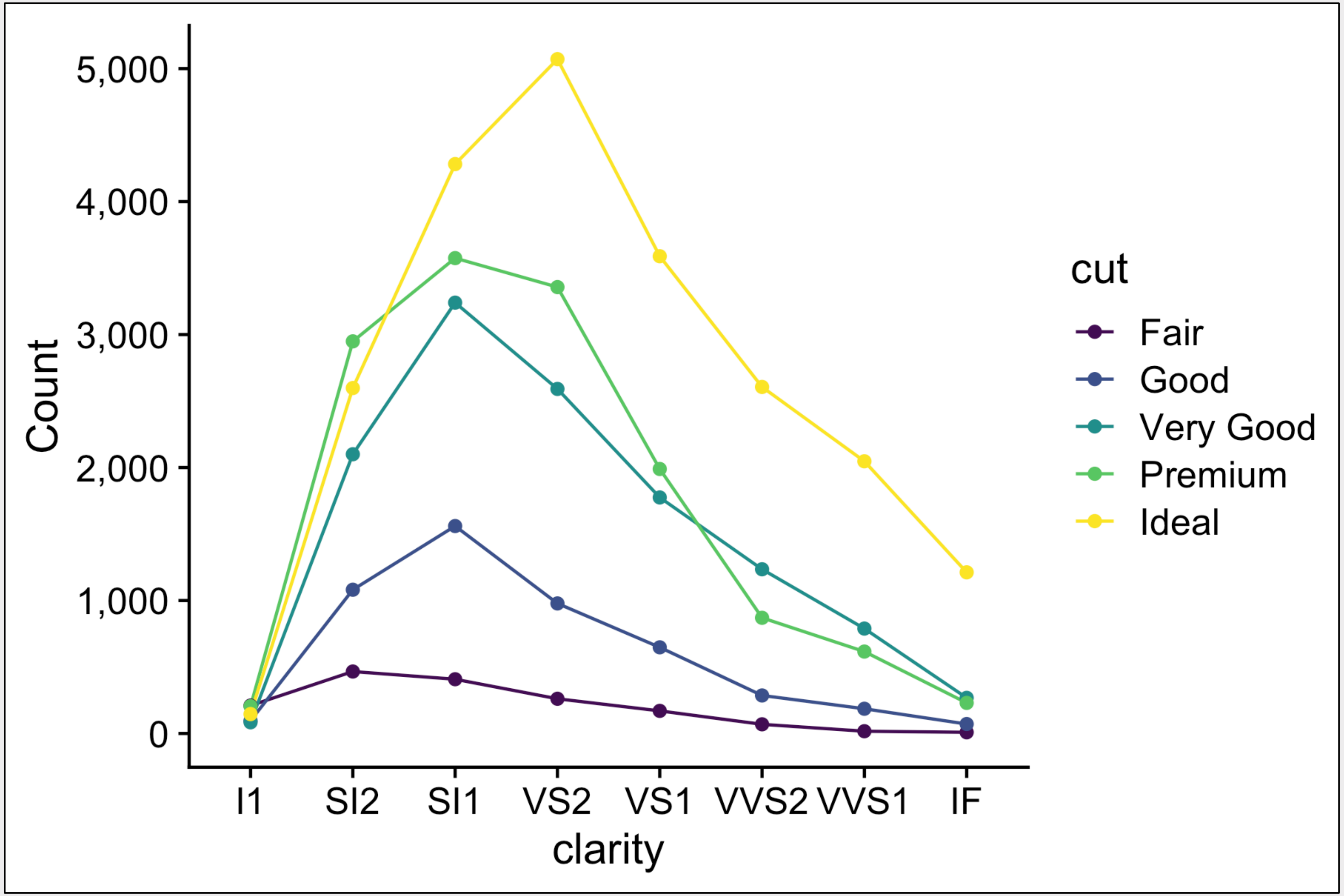
Law of proximity

We tend to see elements that are physically *near* each other as part of the same object



Law of proximity

We tend to see elements that are physically *near* each other as part of the same object



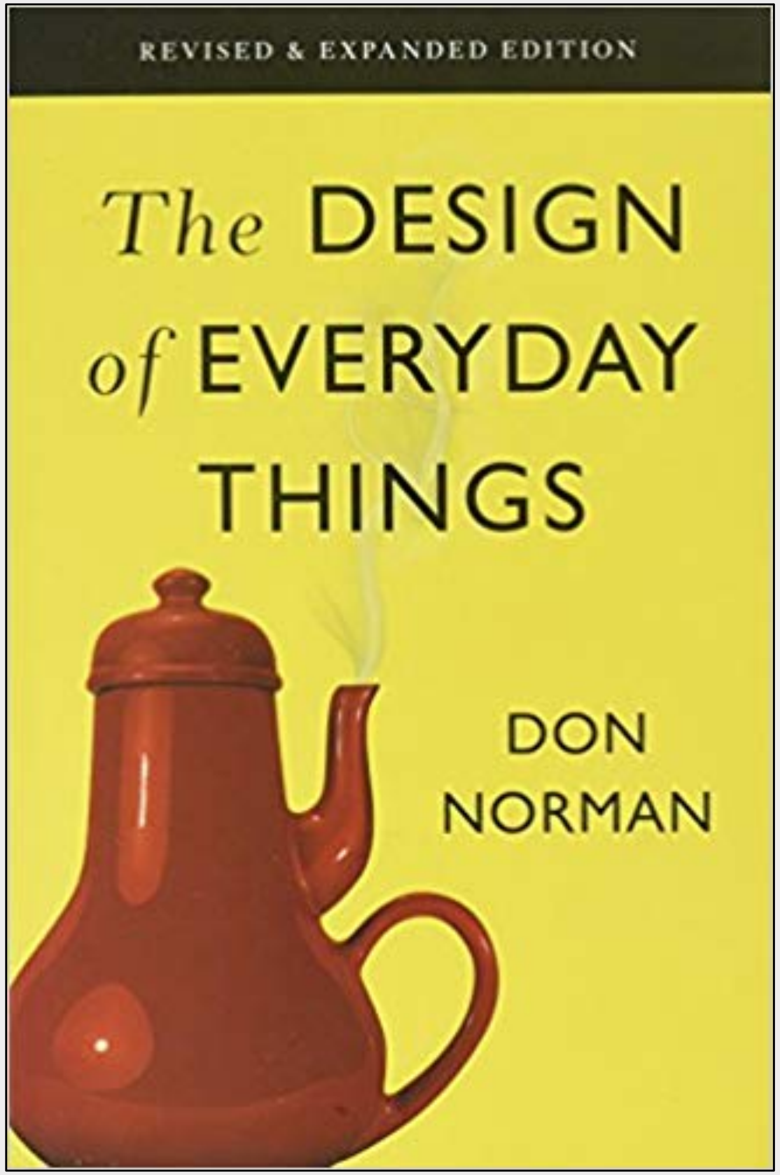
Cleveland’s three visual operations of pattern perception:

- Estimation
- Assembly
- **Detection**

Norman door (n.):

1. A door where the design tells you to do the opposite of what you're actually supposed to do.

2. A door that gives the wrong signal and needs a sign to correct it.

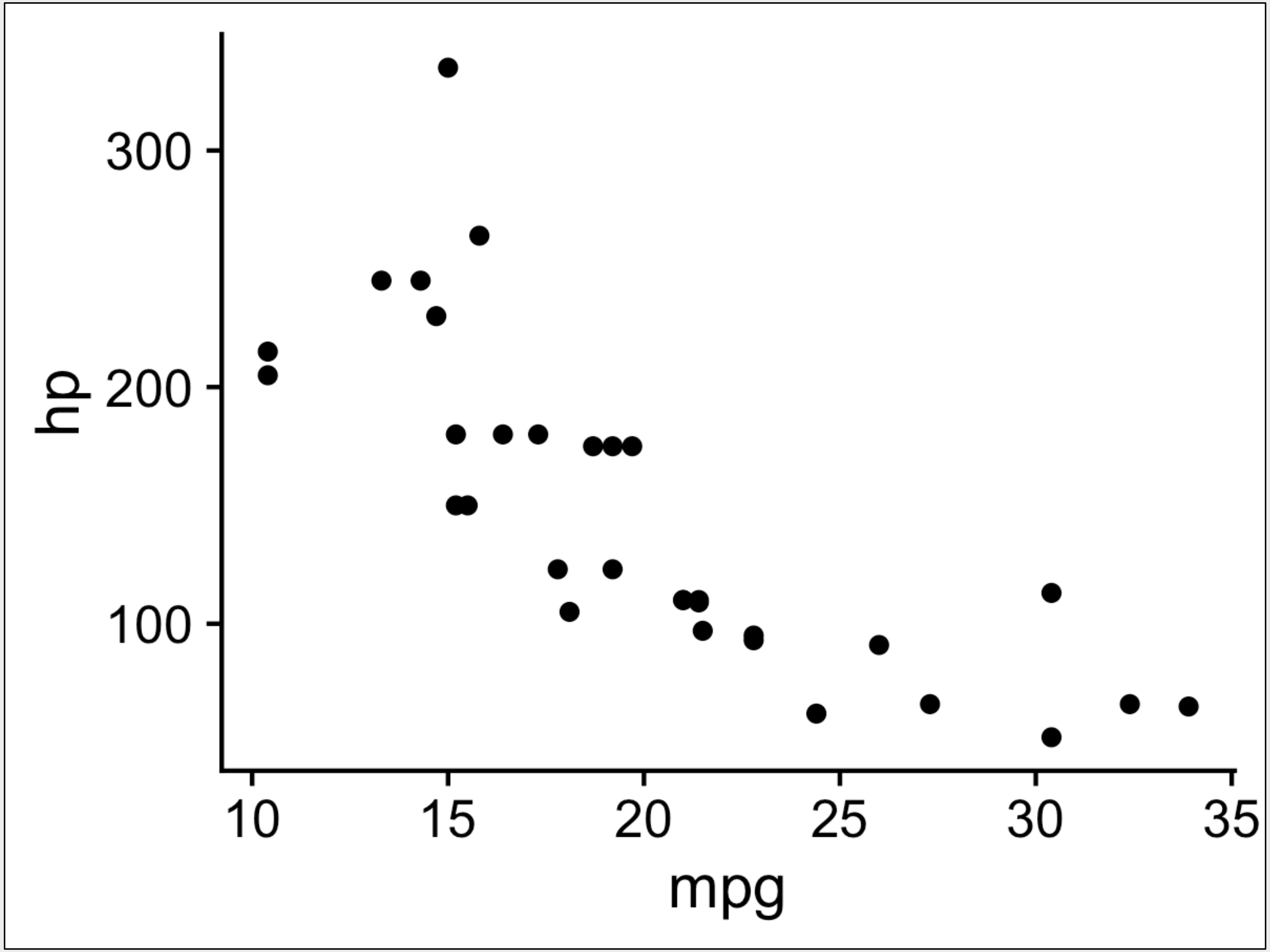


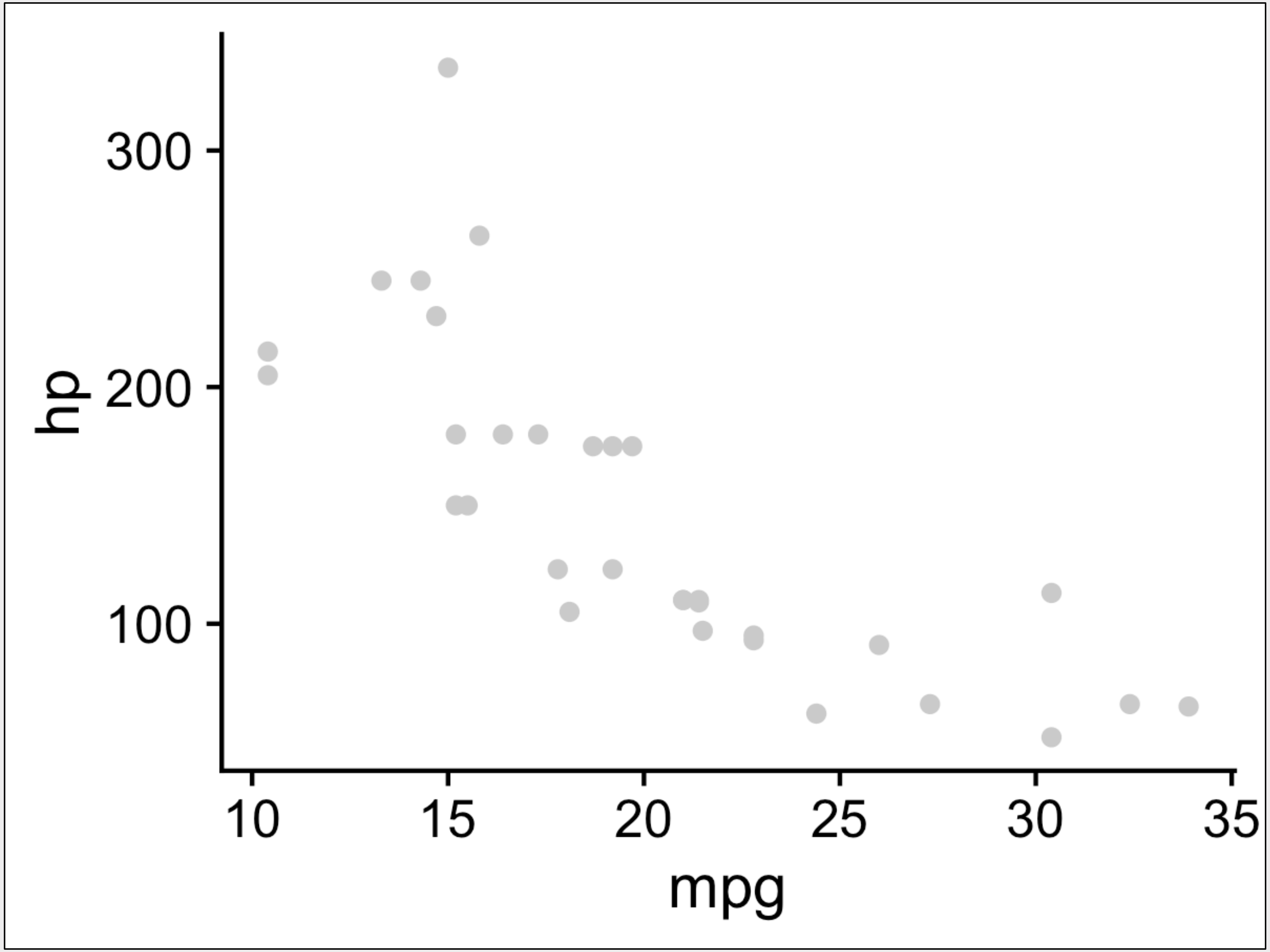
Norman door

Non-Norman door

Cleveland’s three visual operations of pattern perception:

- Estimation
- Assembly
- **Detection** → Recognizing that a geometric object encodes a physical value


300
200
100
hp
10
15
20
25
30
35
mpg


300
200
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hp
10
15
20
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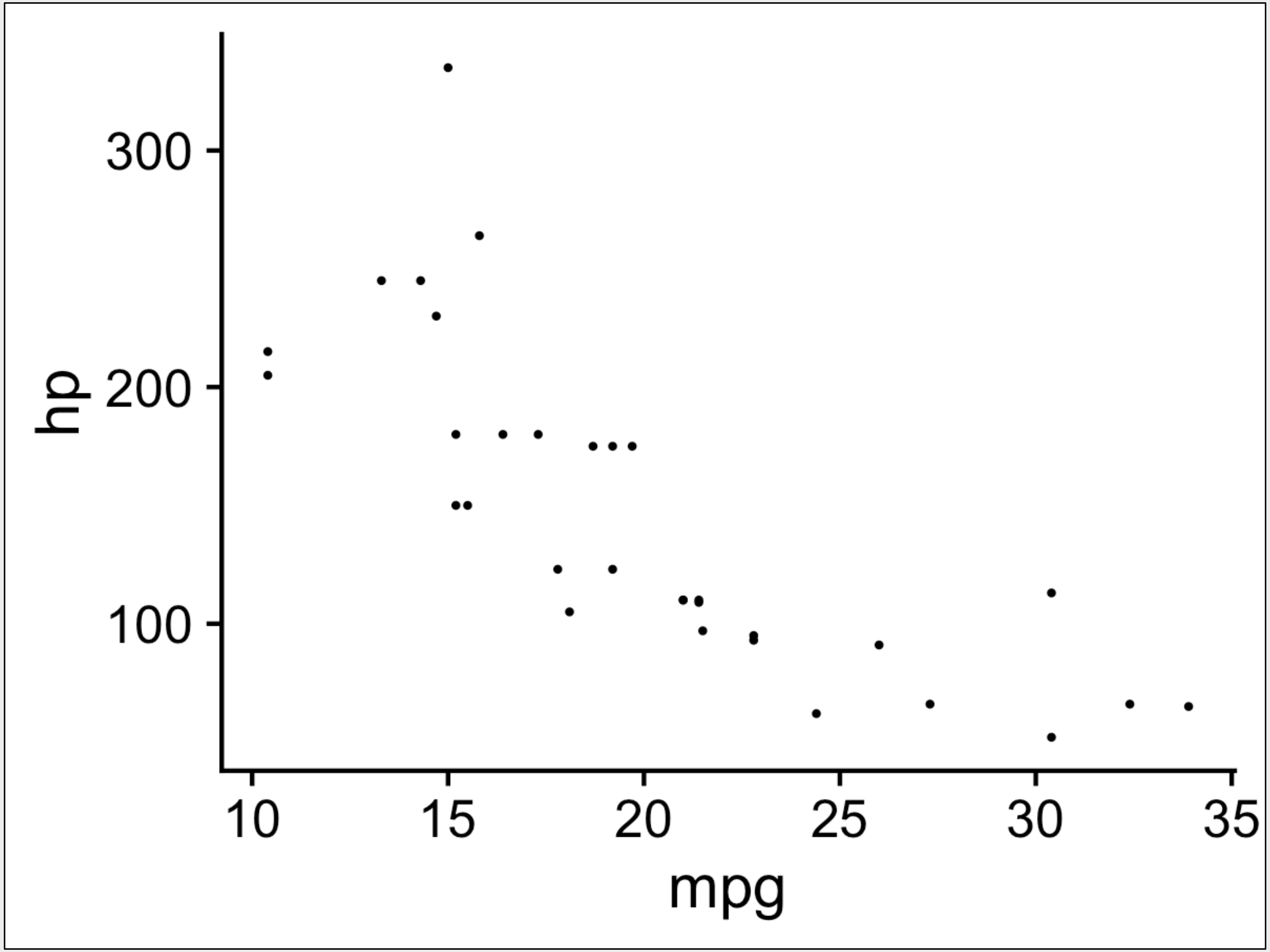
mpg


300
200
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hp
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15
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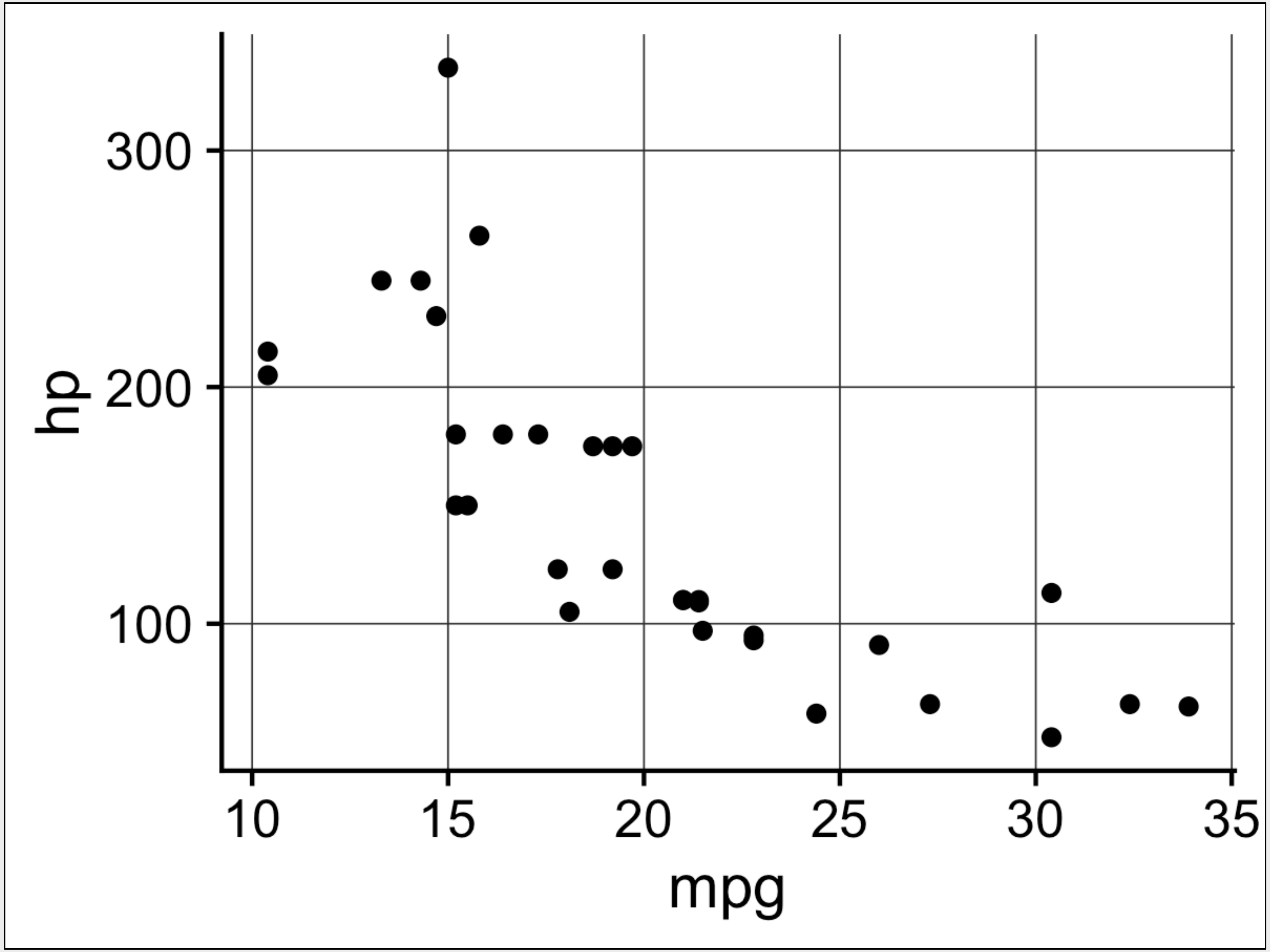
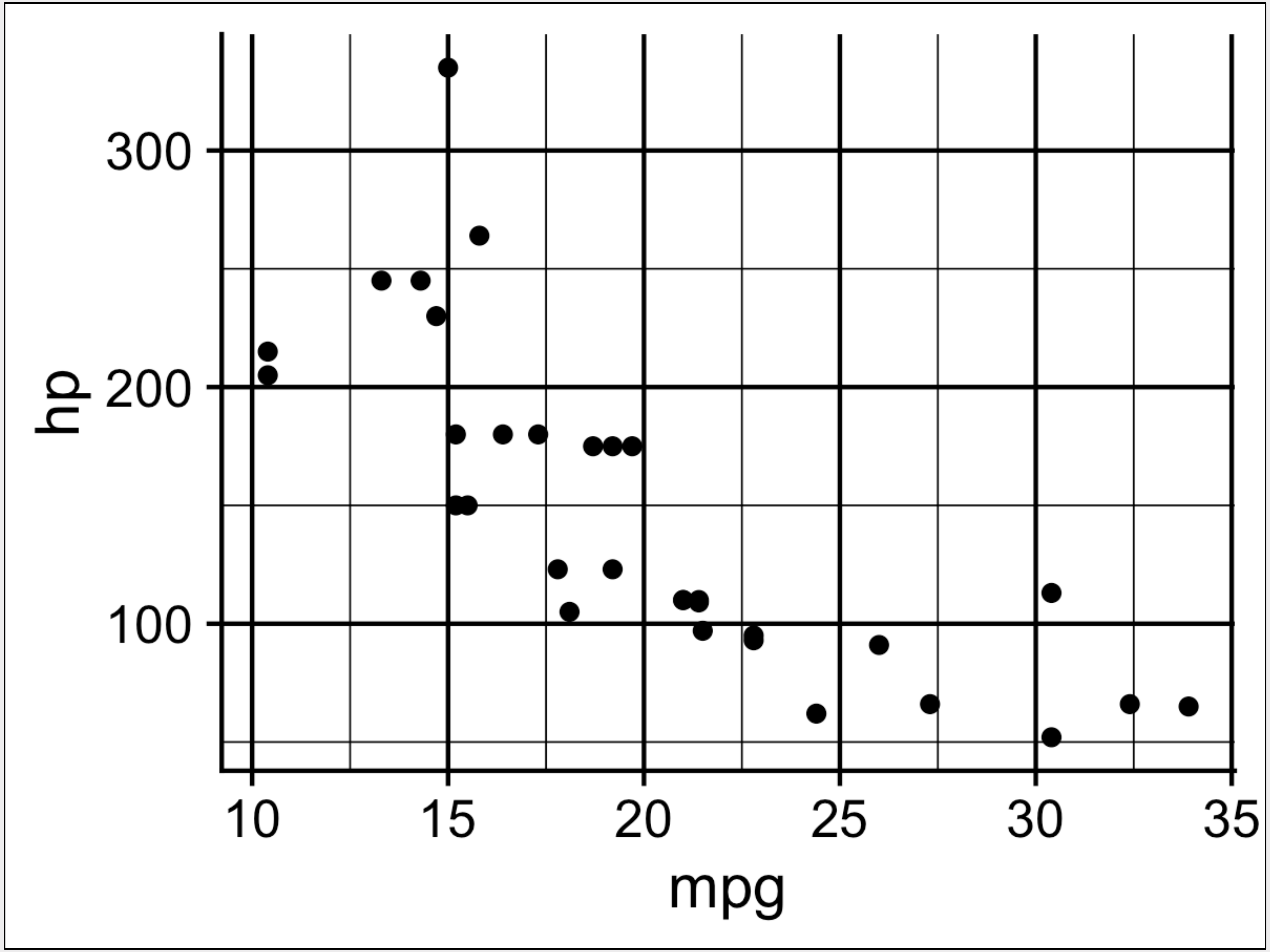
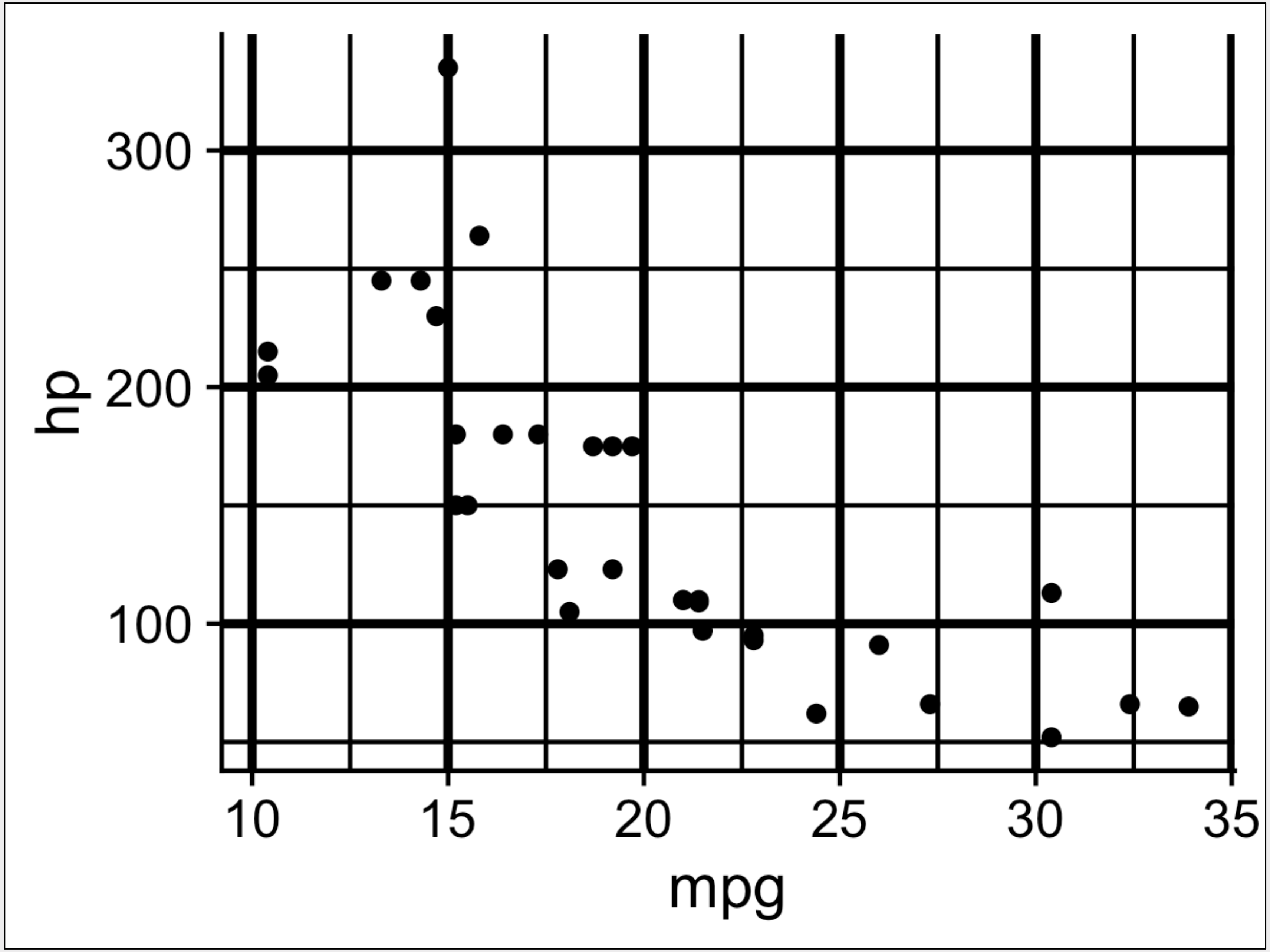
mpg

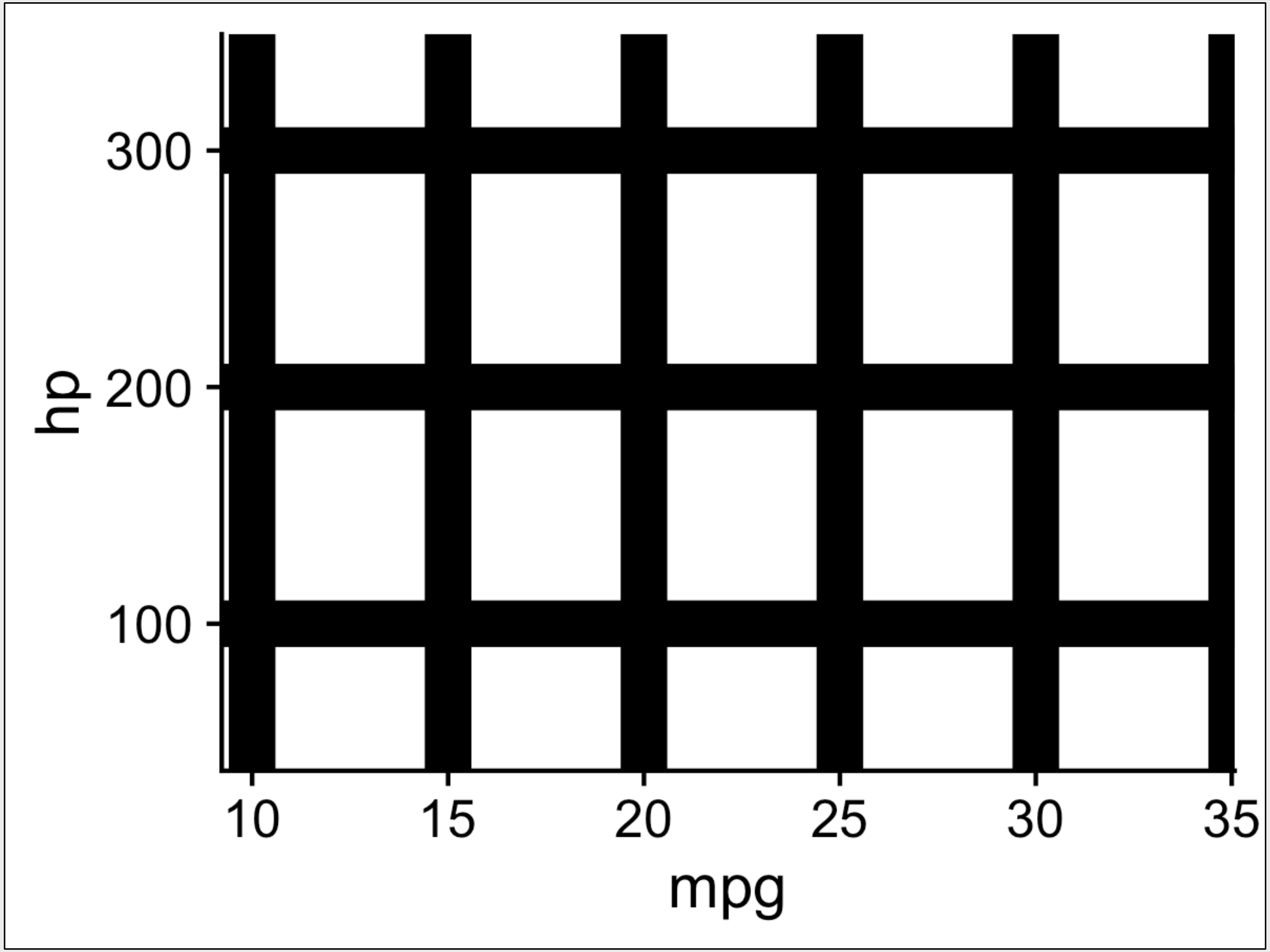


300
200
100
hp
10
15
20
25
30
35
mpg

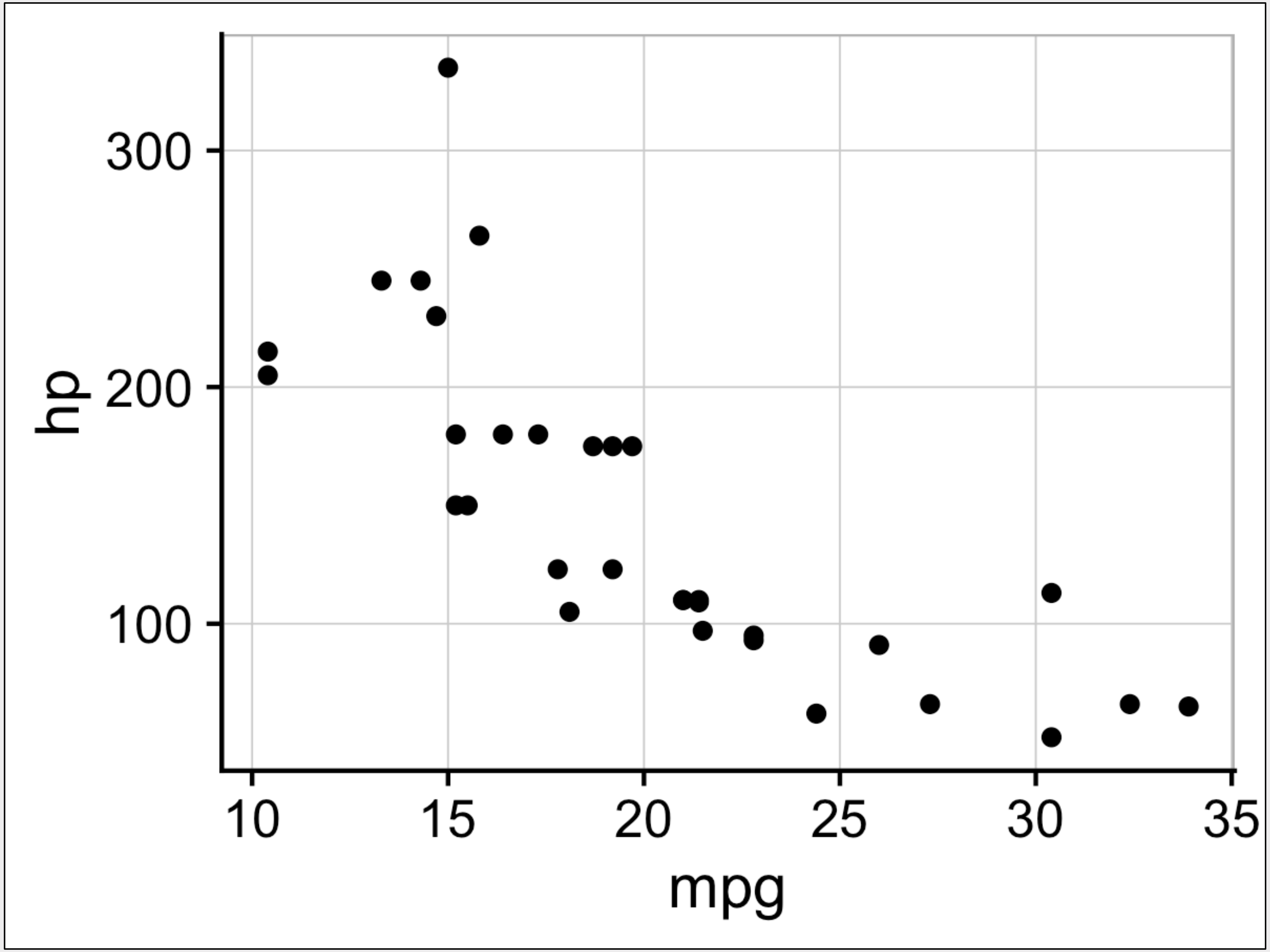

hp
300
200
100
10
15
20
25
30
35
mpg


300
200
100
hp
10
15
20
25
30
35
mpg

The Hermann Grid illusion



“*Above all else, show the data*”
- Edward Tufte


300
200
100
hp
10
15
20
25
30
35
mpg

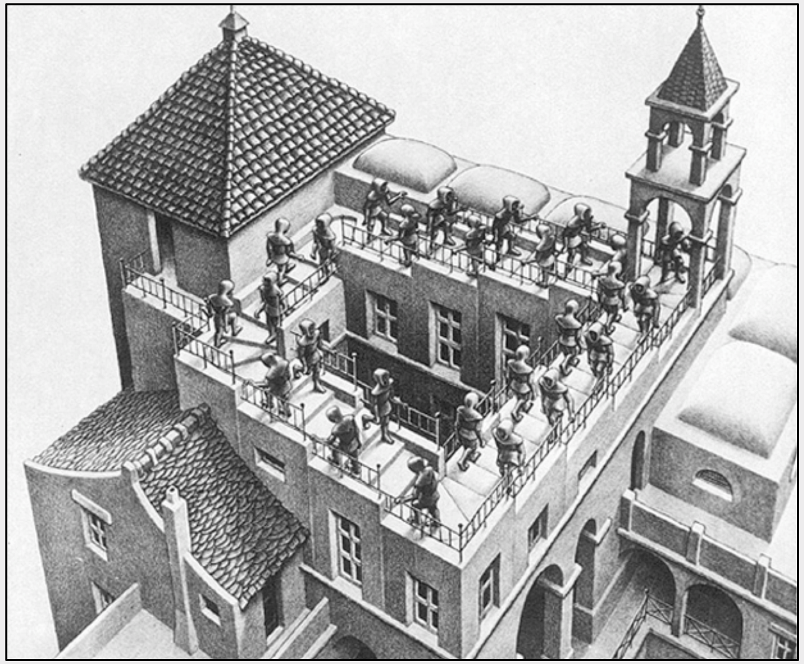
10 lessons from research on visual perception

1. Don’t make 3D plots
2. Don’t use pie charts for proportions
3. Don’t stack bars
4. Don’t lie
5. Do rotate and sort categorical axes
6. Do eliminate legends & directly label geoms
7. Don’t use pattern fills
8. Don’t use red & green together
9. Do remove chart chunk
10. Do consider tables for small data sets

*...most of the time

Don't: 3D plots

1) Humans are not that good at distinguishing 3D space

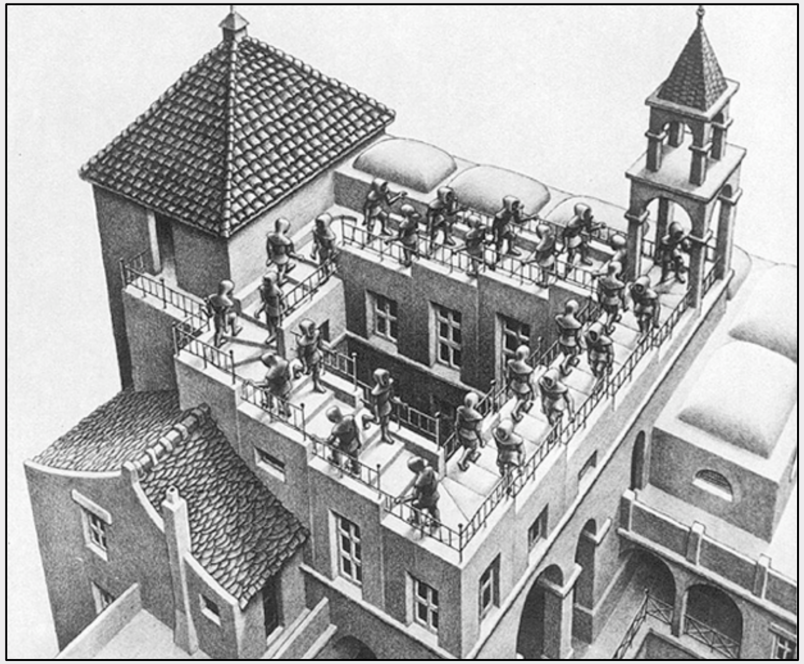


M.C. Escher (1898-1972)
Upstairs and Downstairs
(1960; lithography)

https://en.wikipedia.org/wiki/Penrose_stairs

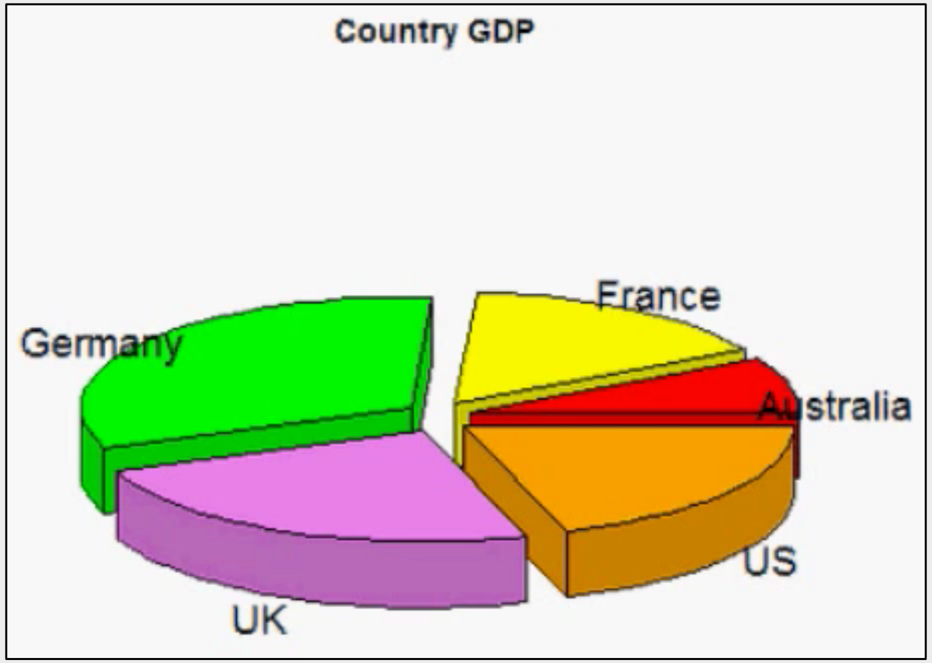
Don't: 3D plots

1) Humans are not that good at distinguishing 3D space



M.C. Escher (1898-1972)
Upstairs and Downstairs
(1960; lithography)

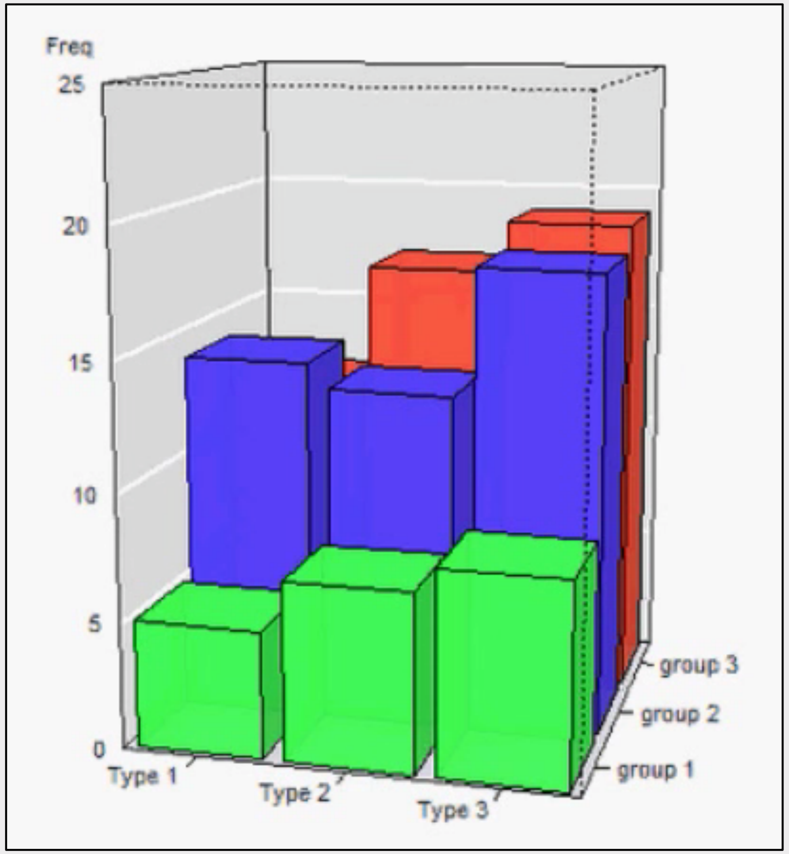
Ink proportions != true proportions



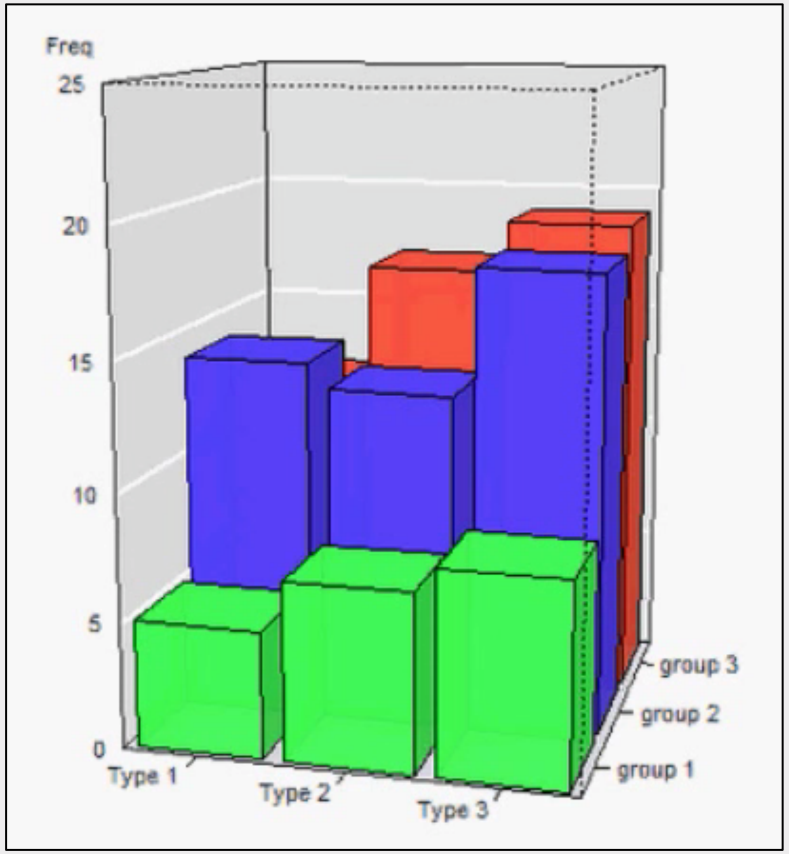
https://en.wikipedia.org/wiki/Penrose_stairs

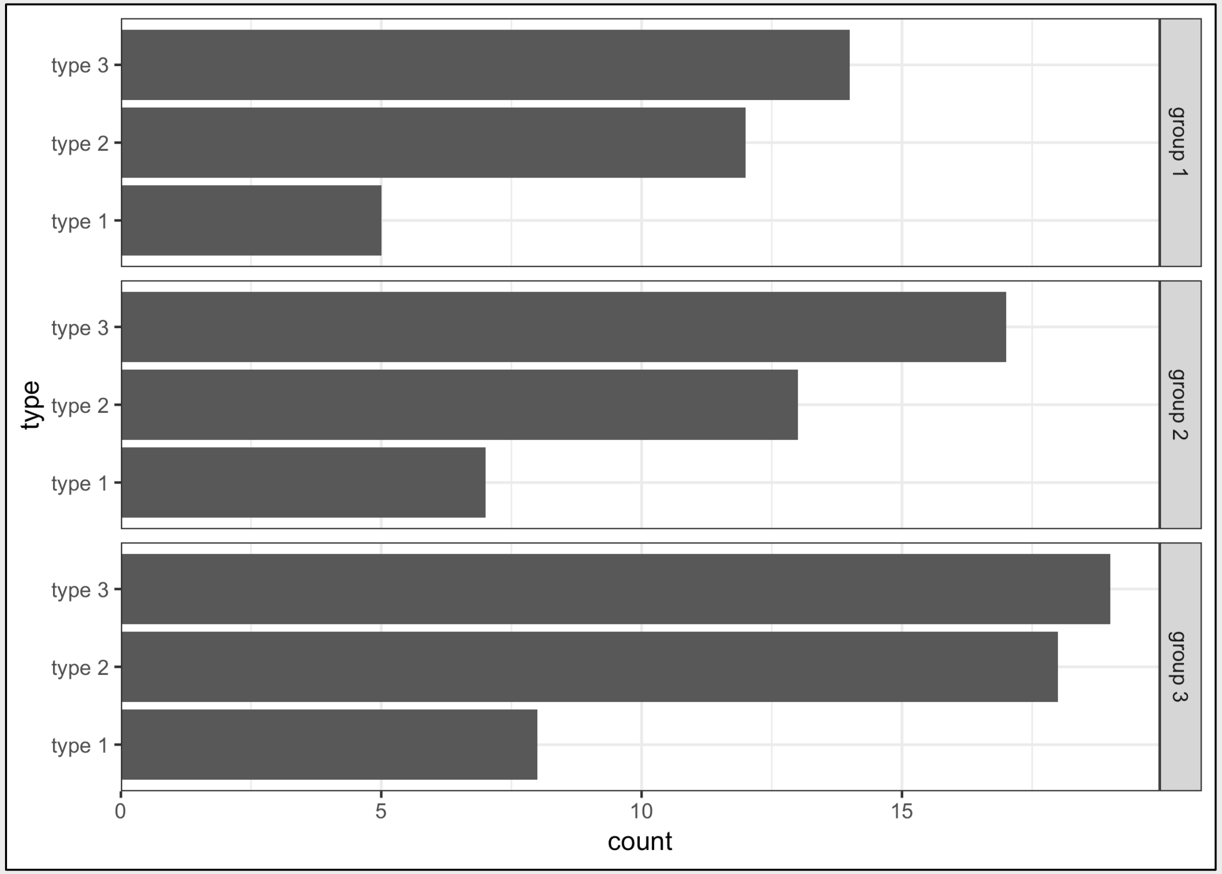
Don't: 3D plots

2) Occlusion: geoms are obscured



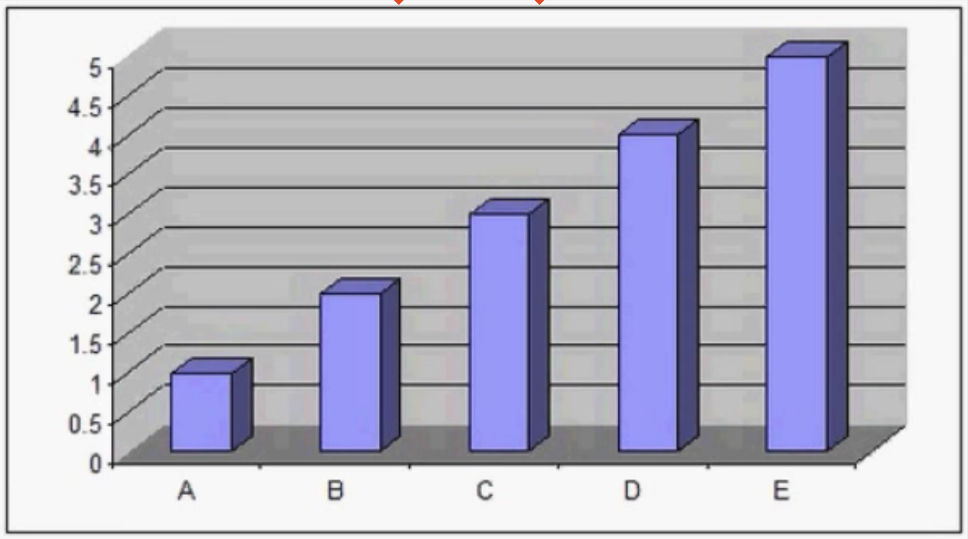
A better alternative to 3D: **faceting**

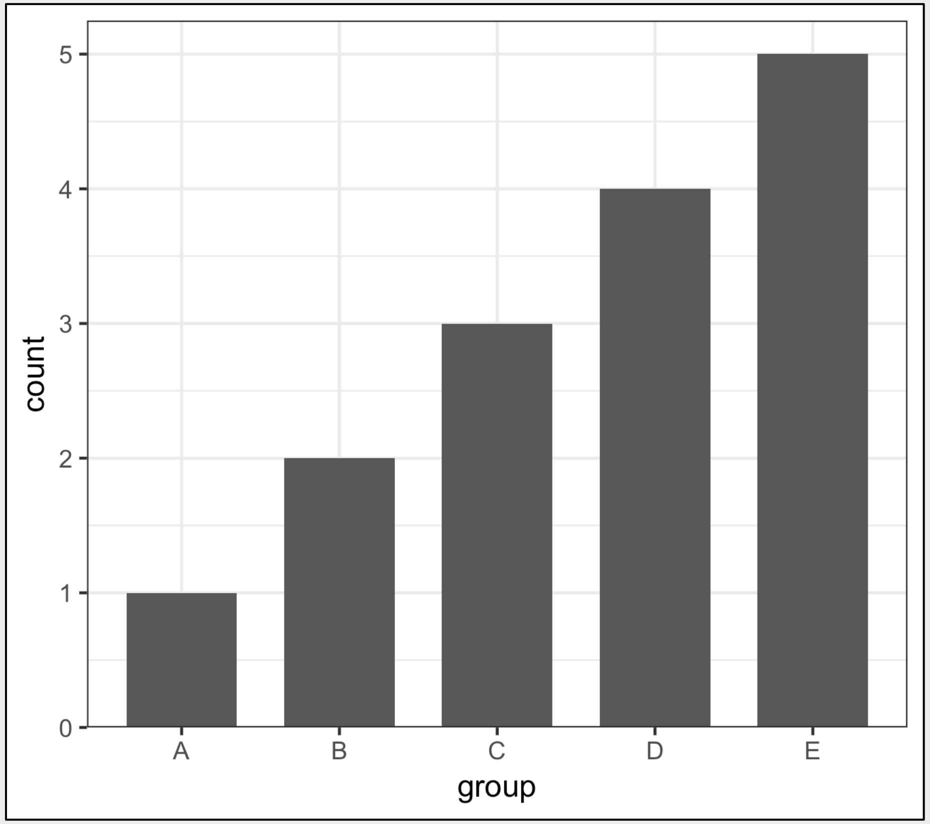




Don't: 3D plots

3) The third dimension distracts from the data
(this is what Tufte calls "chart junk")





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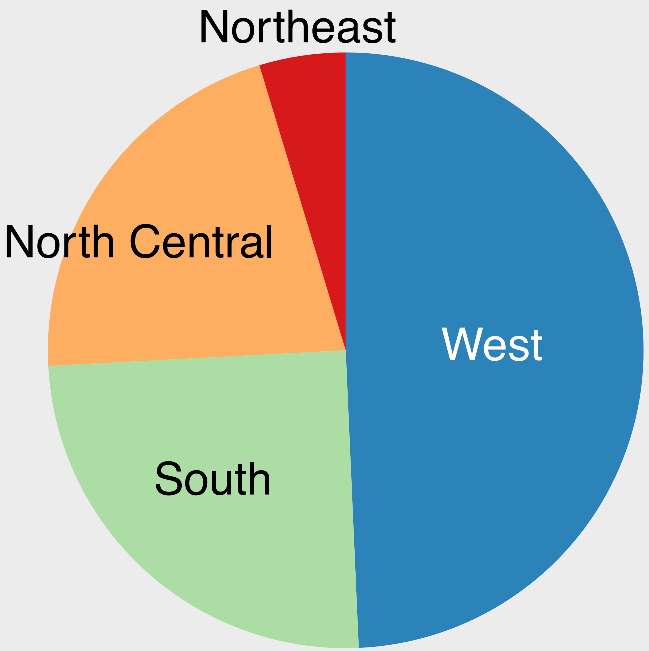
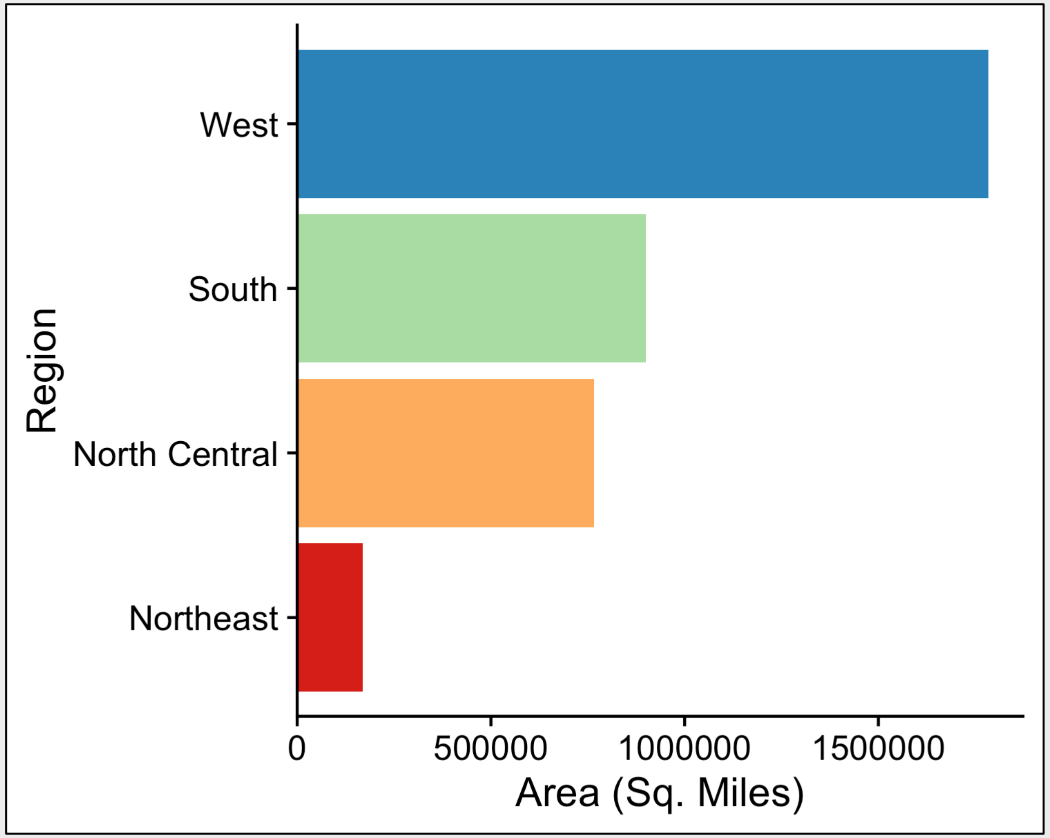
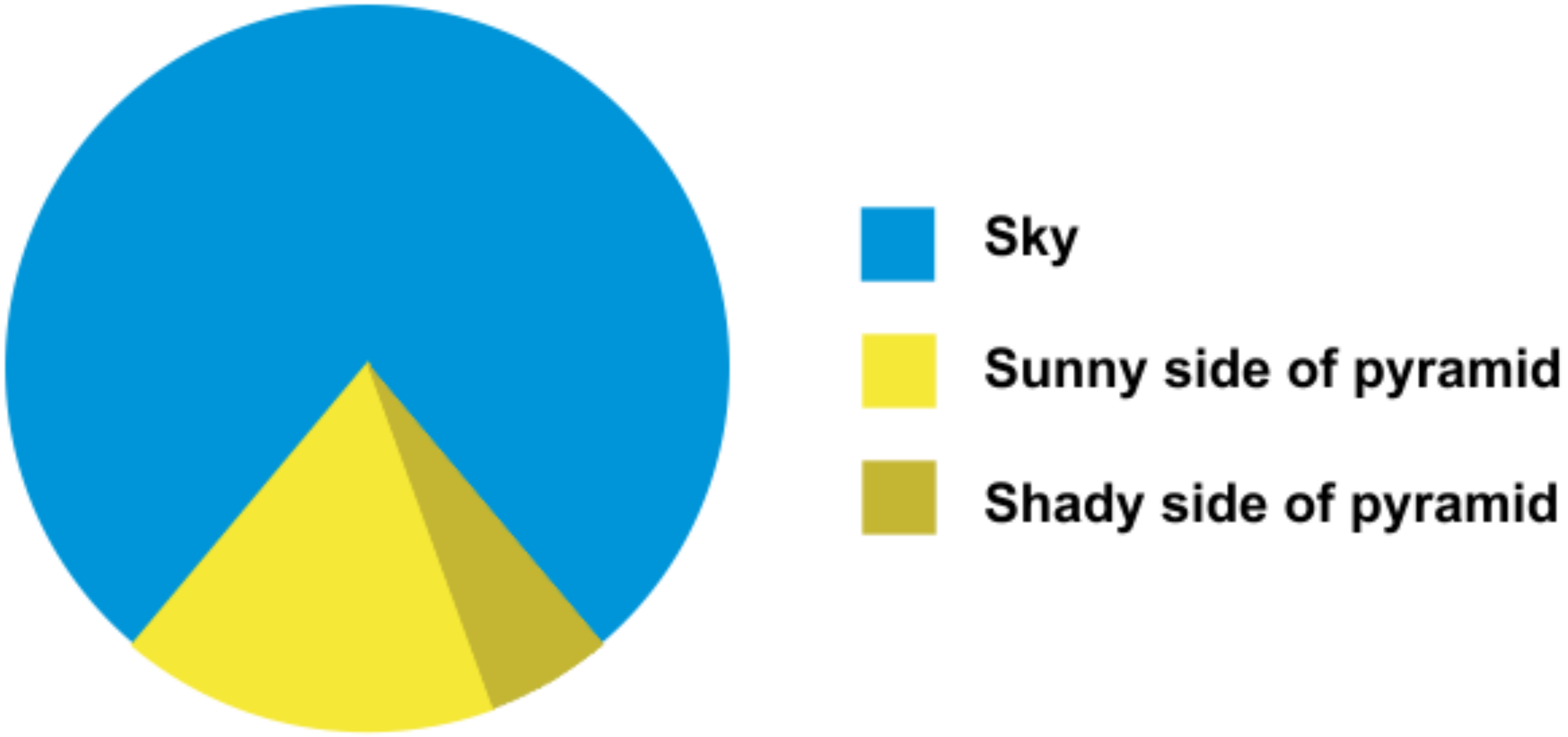
10. Do consider tables for small data sets

*...most of the time

“Pie charts are the information visualization equivalent of a roofing hammer to the frontal lobe”
- Coda Hale


Northeast
North Central
West
South


West
South
North Central
Northeast
Region
0
500000
1000000
1500000
Area (Sq. Miles)


Sky
Sunny side of pyramid
Shady side of pyramid

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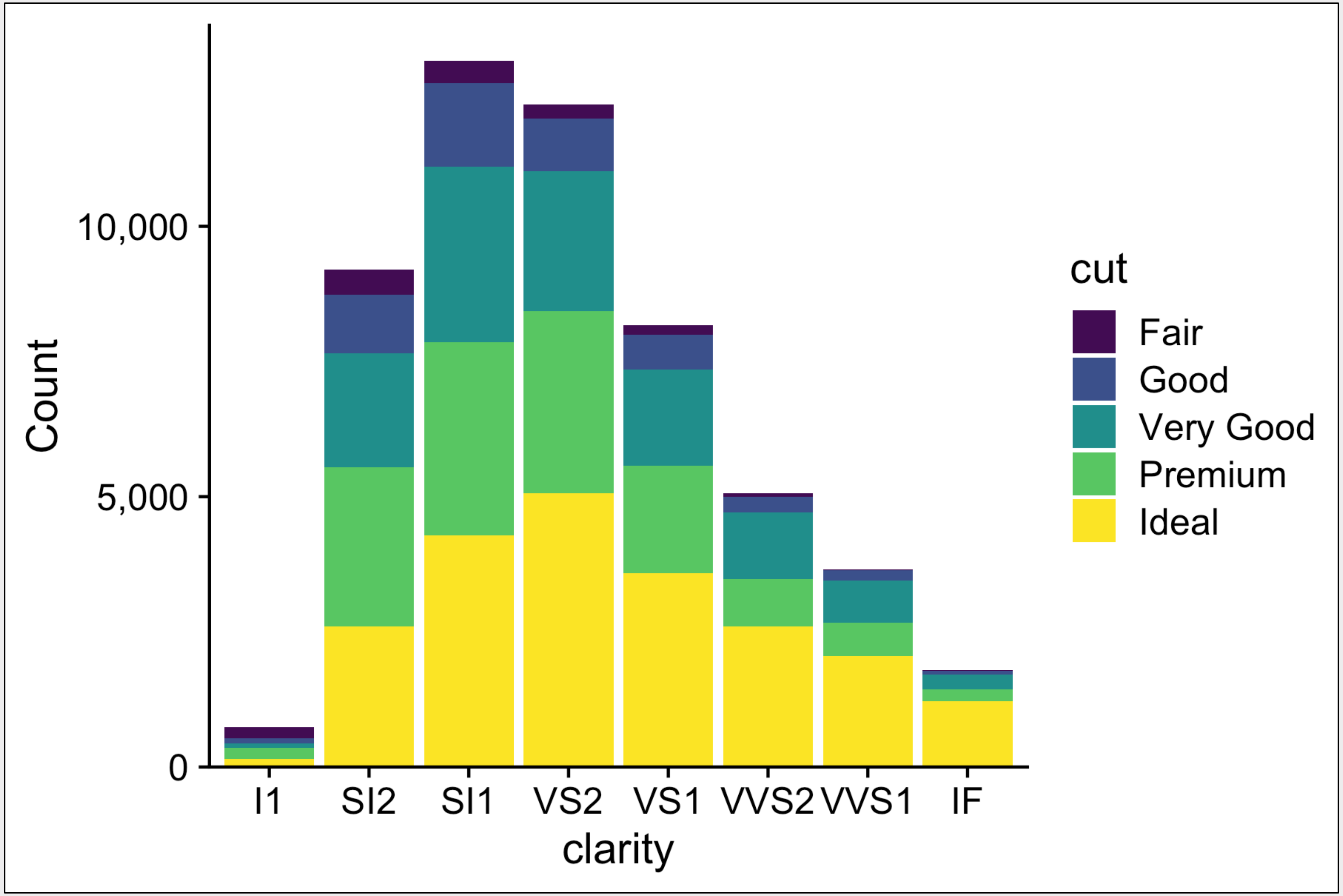
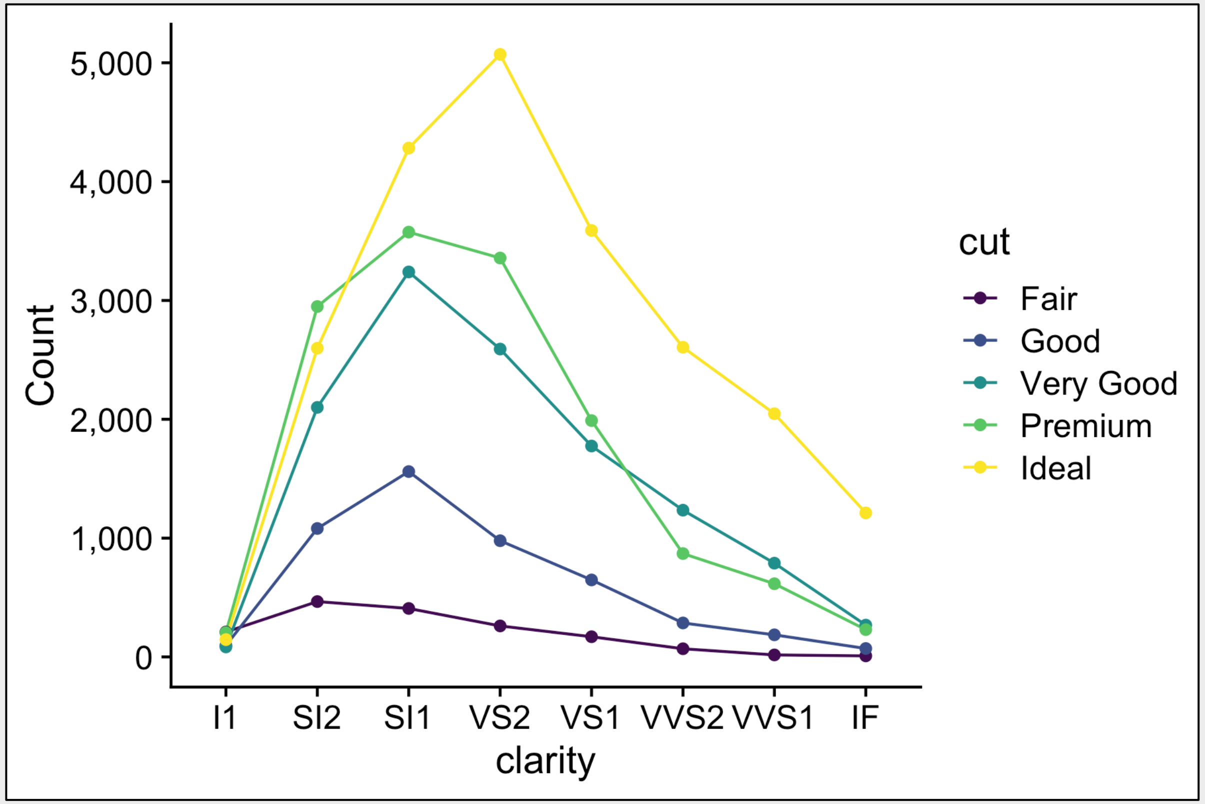
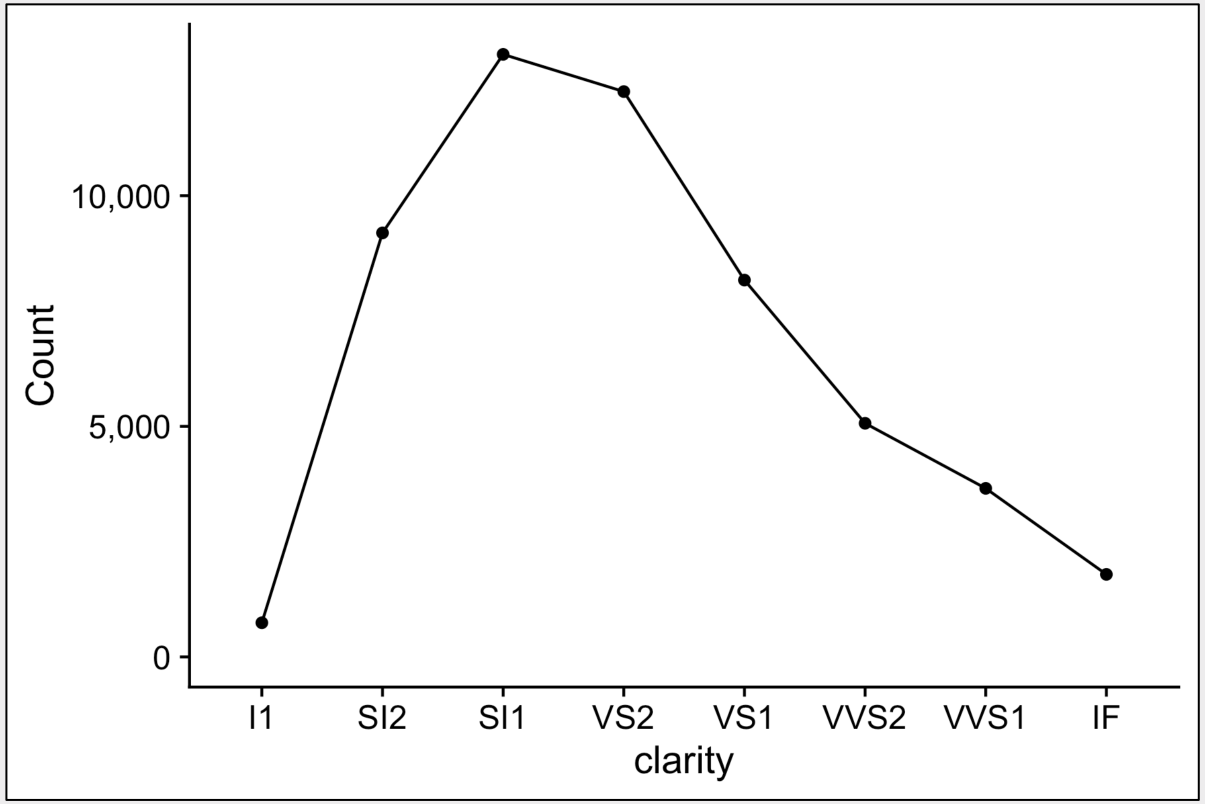
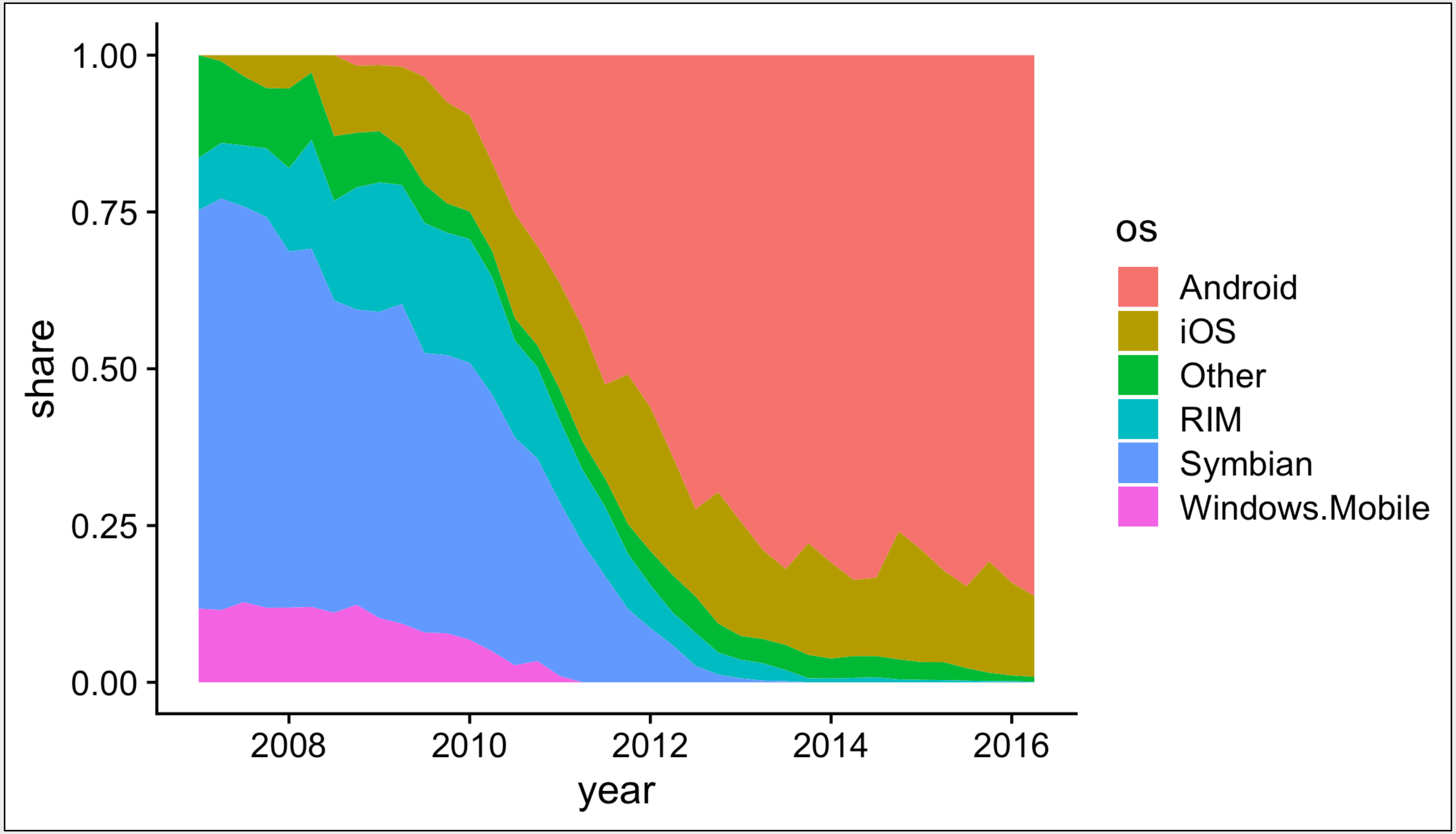


Count
10,000
5,000
0
I1
SI2
SI1
VS2
VS1
VVS2
VVS1
IF
clarity
cut
Fair
Good
Very Good
Premium
Ideal


5,000
4,000
3,000
2,000
1,000
0
Count
I1
SI2
SI1
VS2
VS1
VVS2
VVS1
IF
clarity
cut
Fair
Good
Very Good
Premium
Ideal


10,000
5,000
0
Count
I1
SI2
SI1
VS2
VS1
VVS2
VVS1
IF
clarity

Exception



1.00
0.75
0.50
0.25
0.00
share
2008
2010
2012
2014
2016
year
os
Android
iOS
Other
RIM
Symbian
Windows.Mobile

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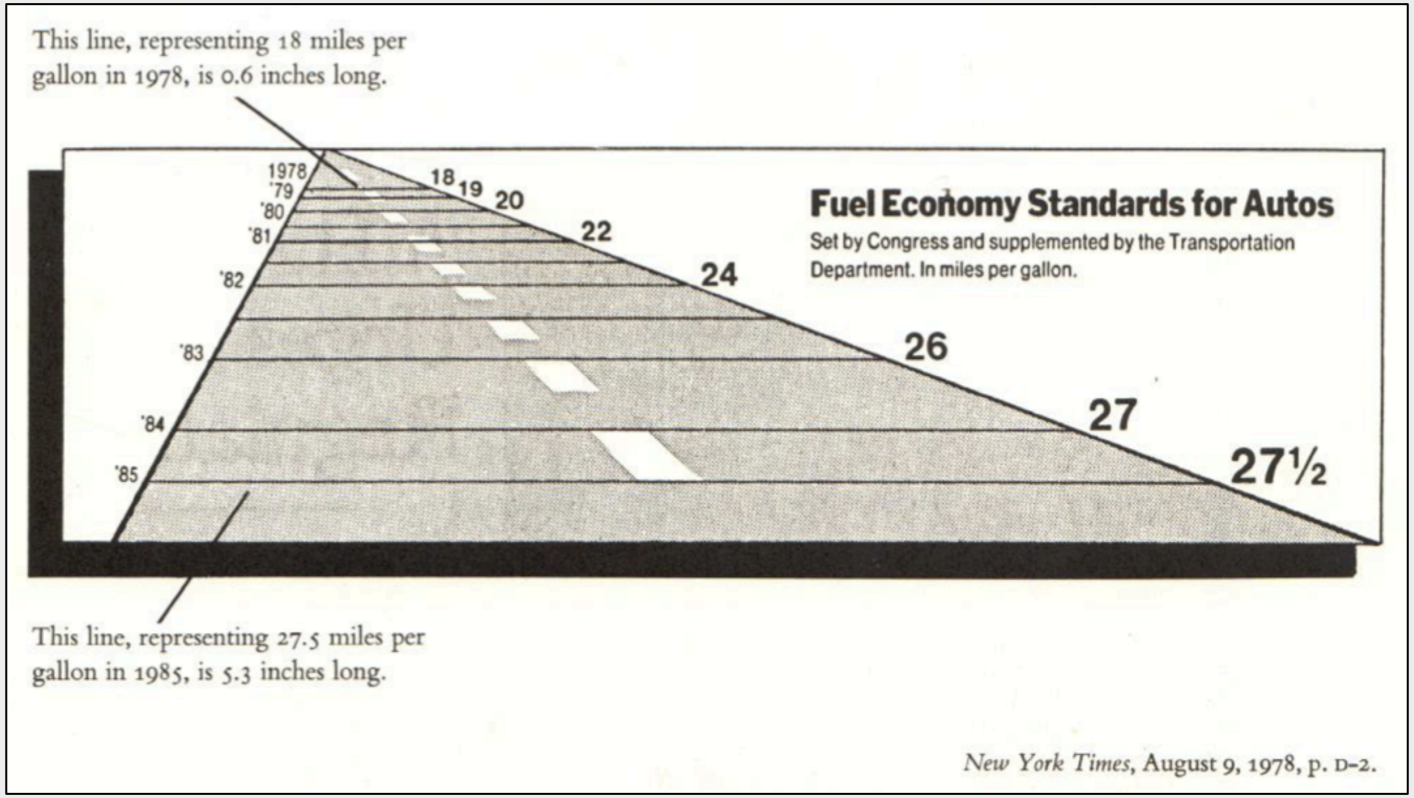
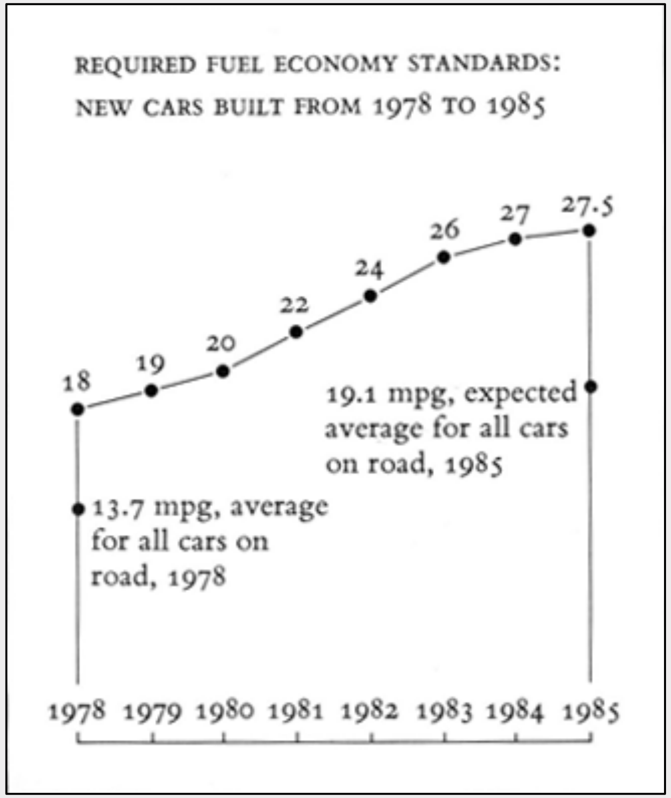
$$\text{"Lie Factor"} = \frac{\text{Size of effect shown in graphic}}{\text{Size of effect in data}} = \frac{\frac{5.3 - 0.6}{0.6}}{\frac{27.5 - 18}{18}} = \frac{7.83}{0.53} = 14.8$$





Edward Tufte (2001): *The Visual Display of Quantitative Information*, 2nd Edition, pg. 57-58

Do: Start bar charts at 0

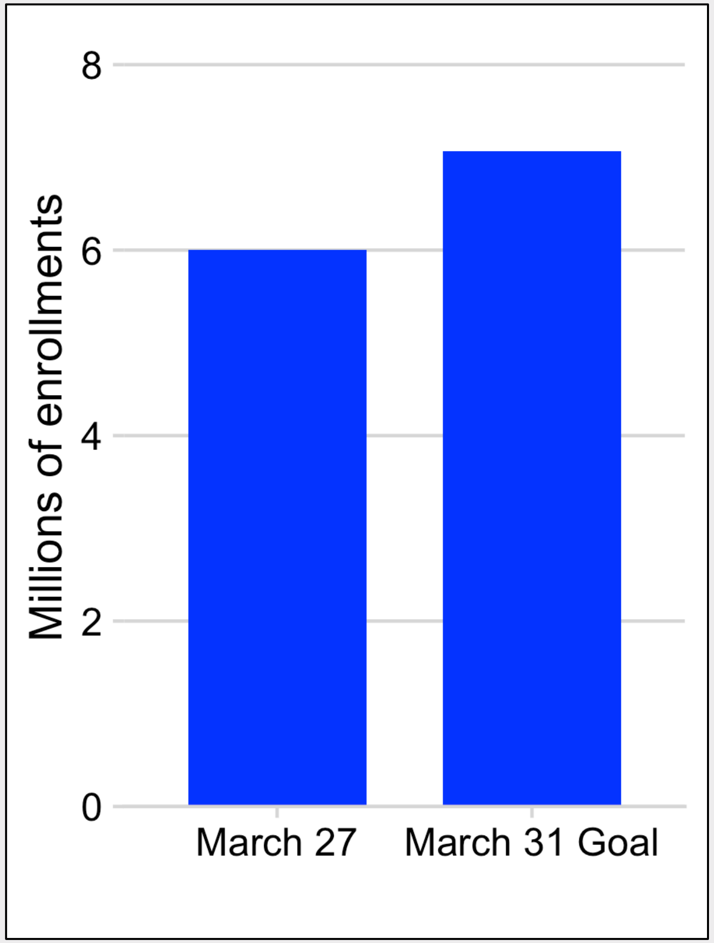


Image from http://livingqlikview.com/the-9-worst-data-visualizations-ever-created/

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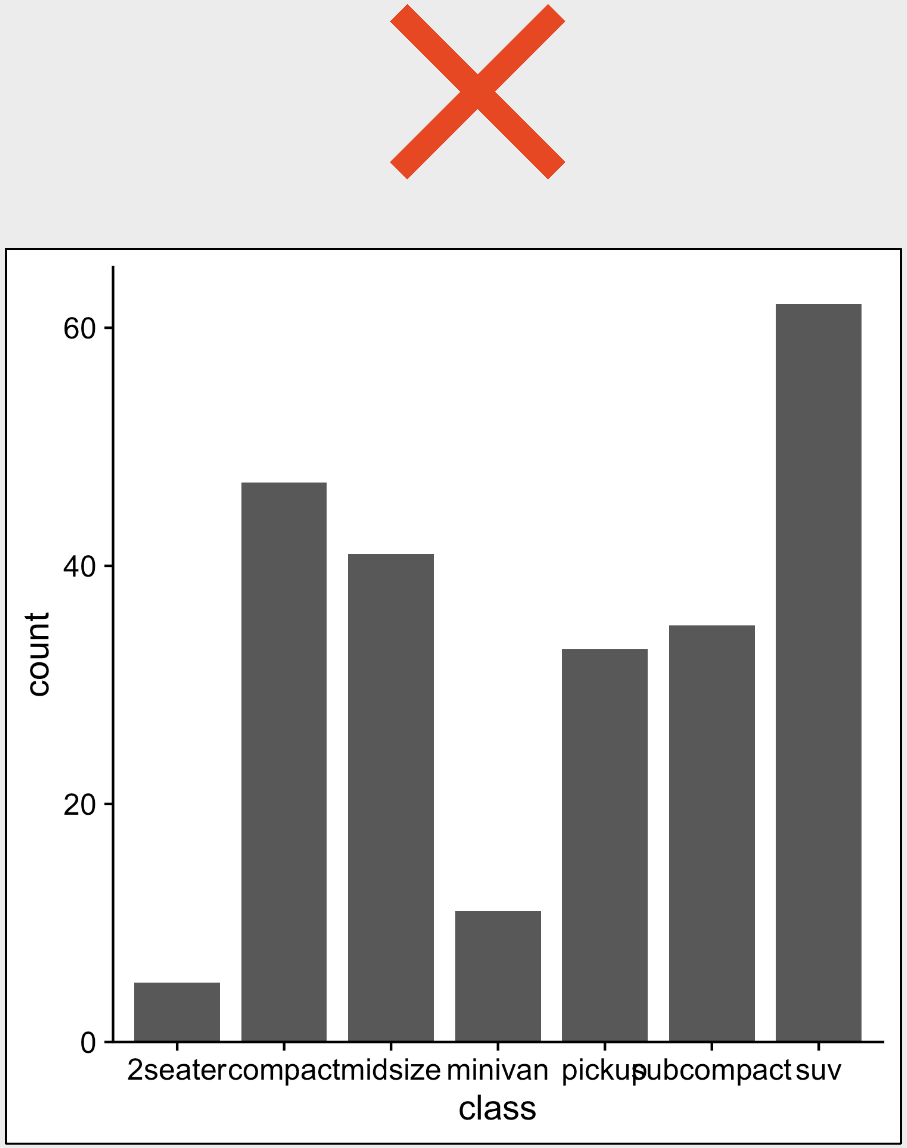
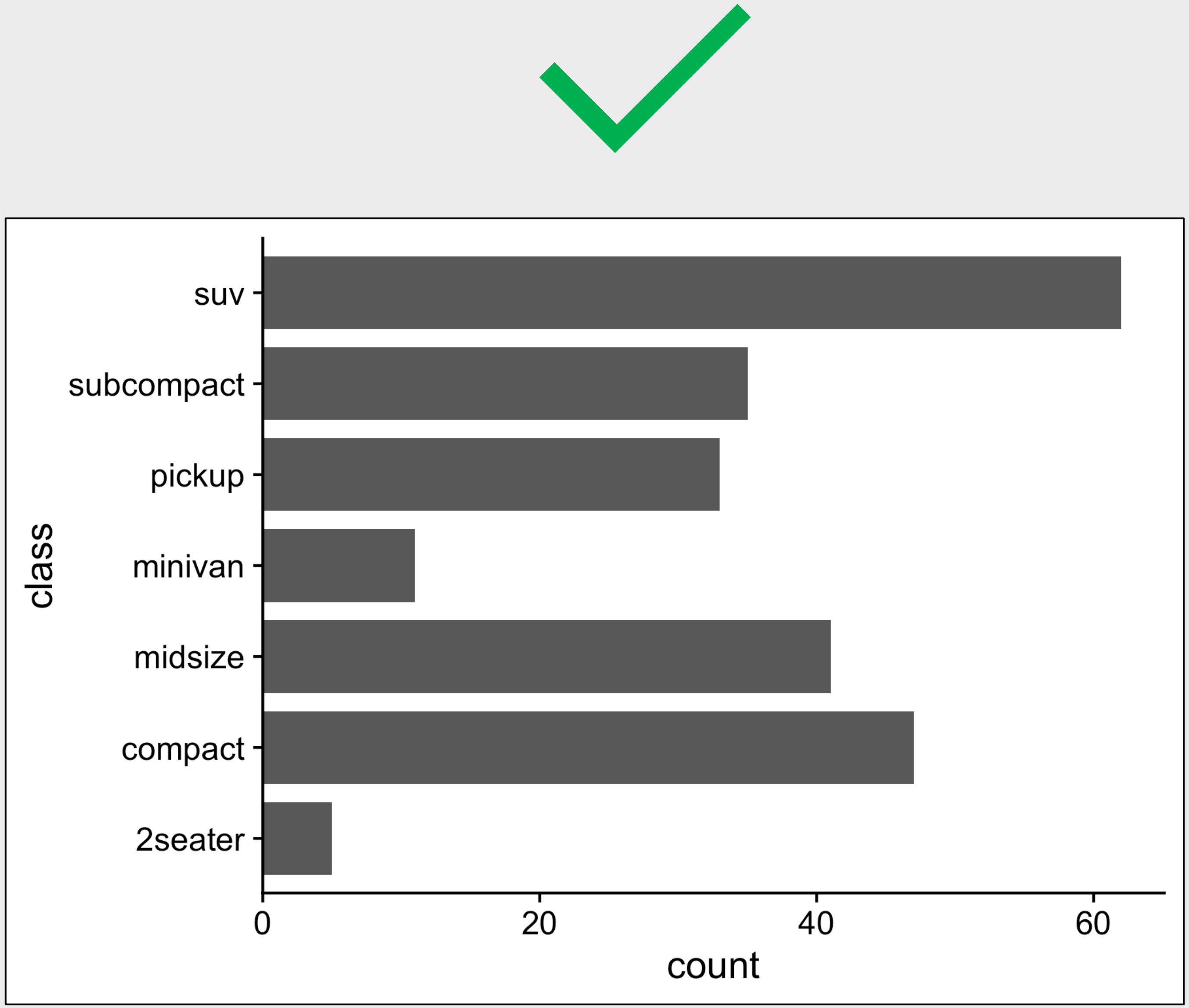
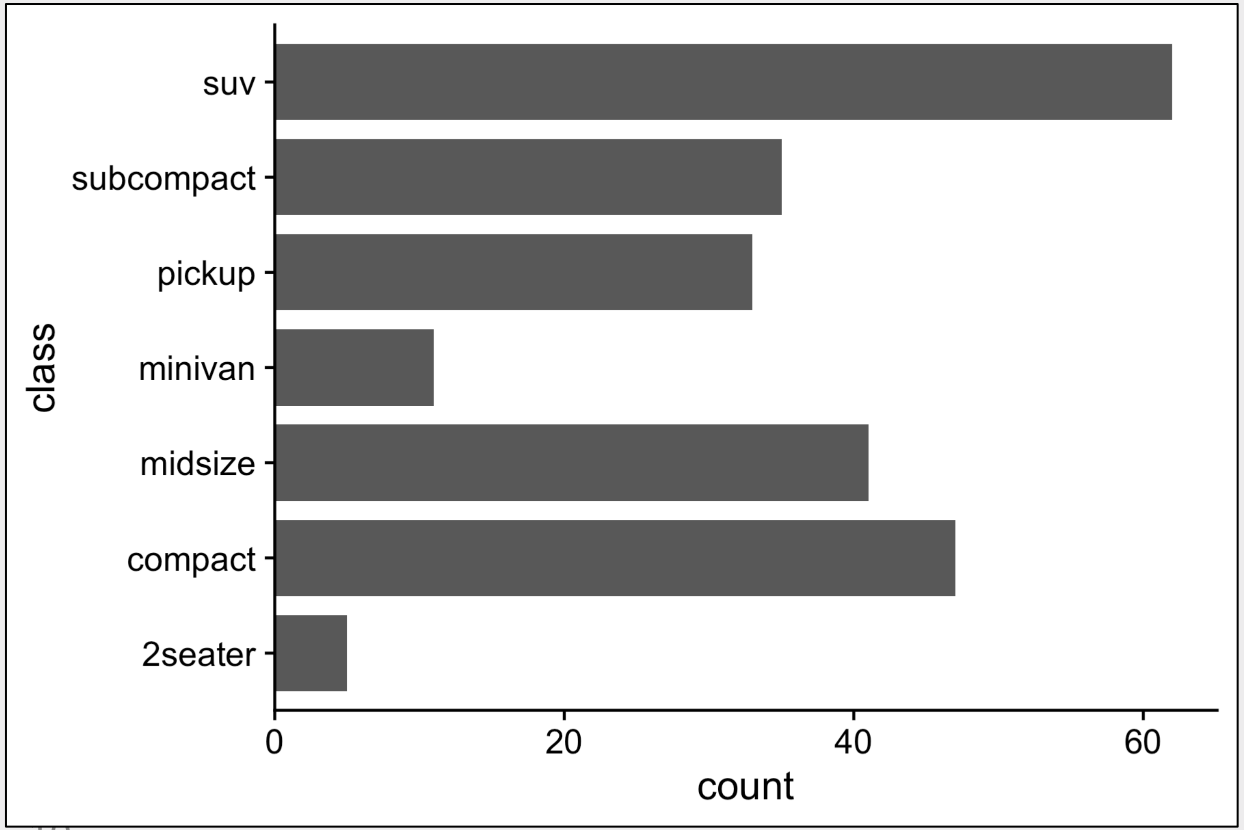

count
60
40
20
0
2seater
compact
midsize
minivan
pickup
subcompact
suv
class

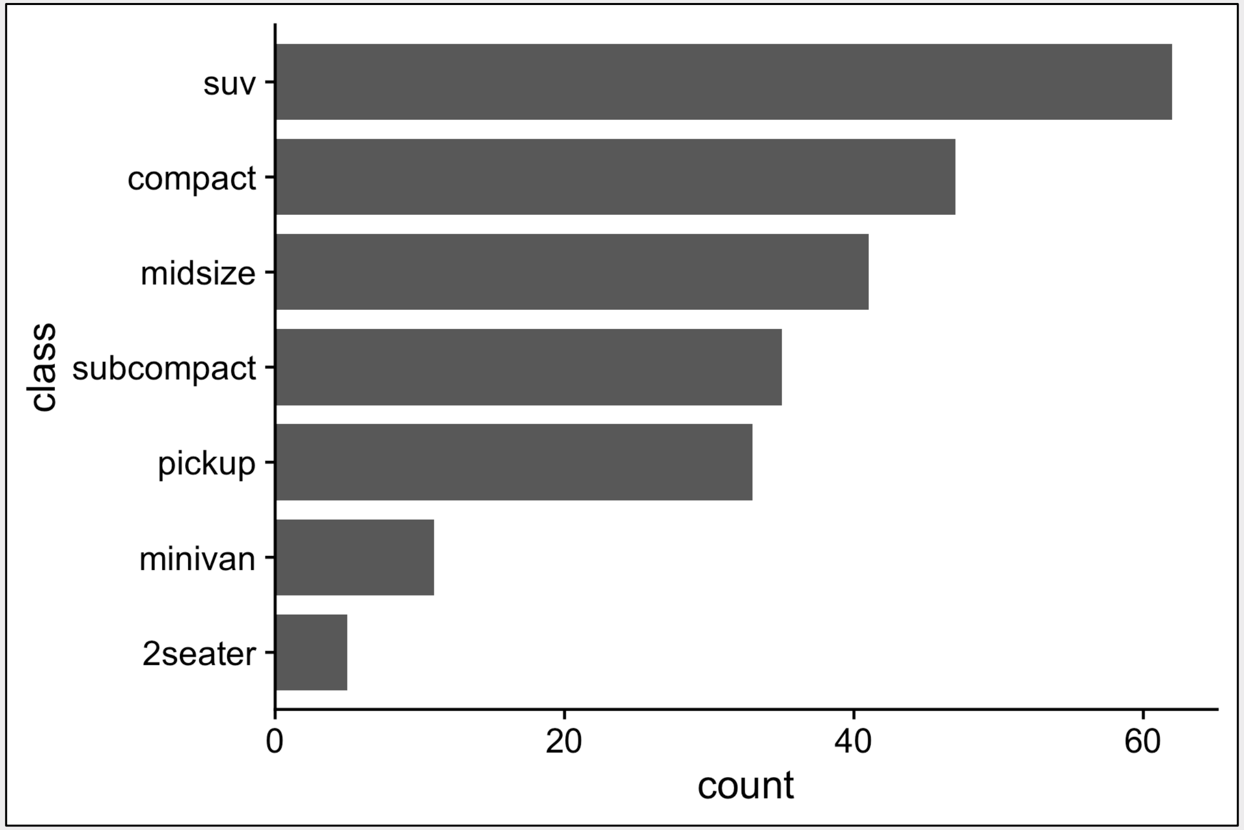

class
suv
subcompact
pickup
minivan
midsize
compact
2seater
0
20
40
60
count

Default ordering is almost always wrong

Ordered by alphabet



Ordered by count



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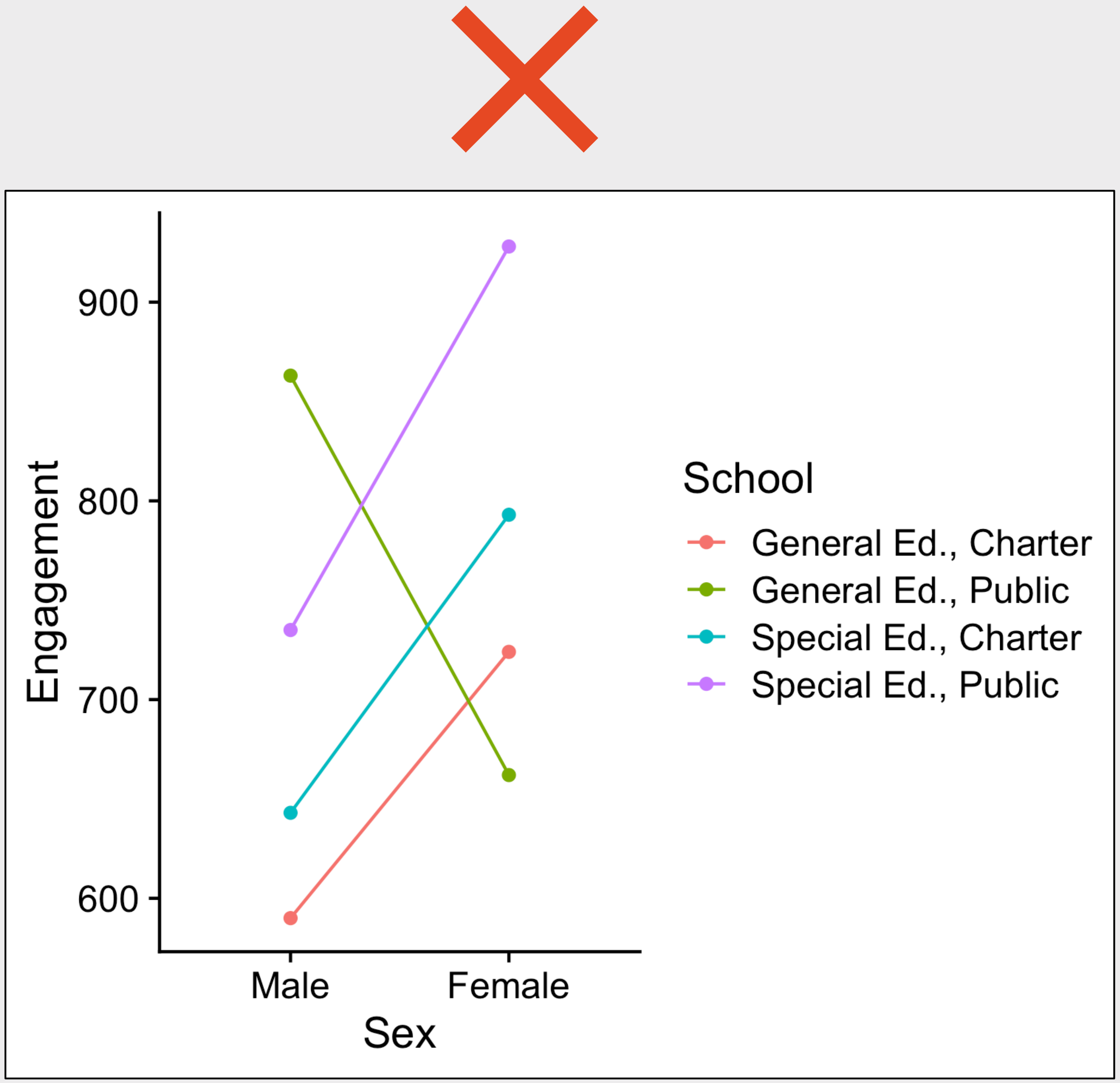
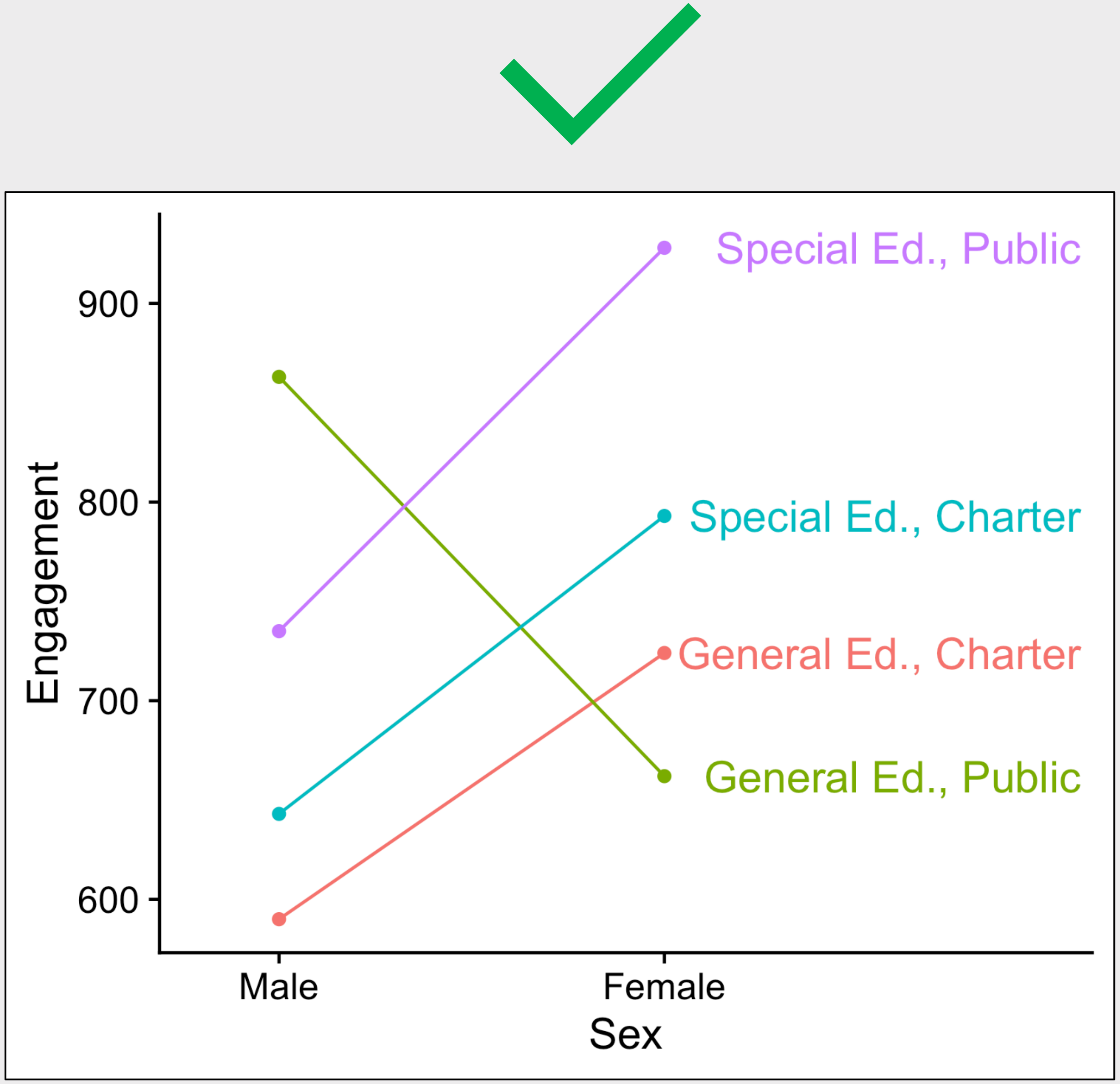

900
800
700
600
Engagement
Male
Female
Sex
School
General Ed., Charter
General Ed., Public
Special Ed., Charter
Special Ed., Public


900
800
700
600
Engagement
Male
Female
Sex
Special Ed., Public
Special Ed., Charter
General Ed., Charter
General Ed., Public

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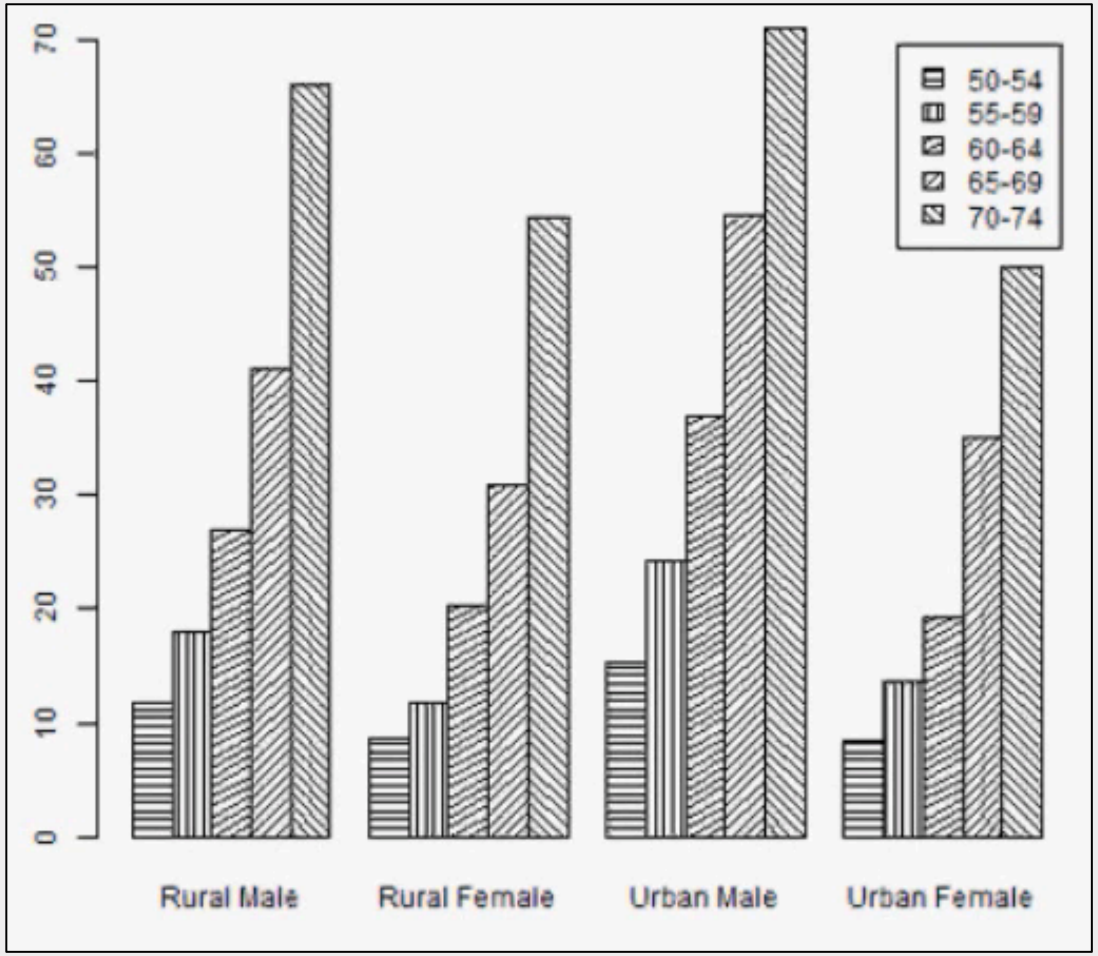
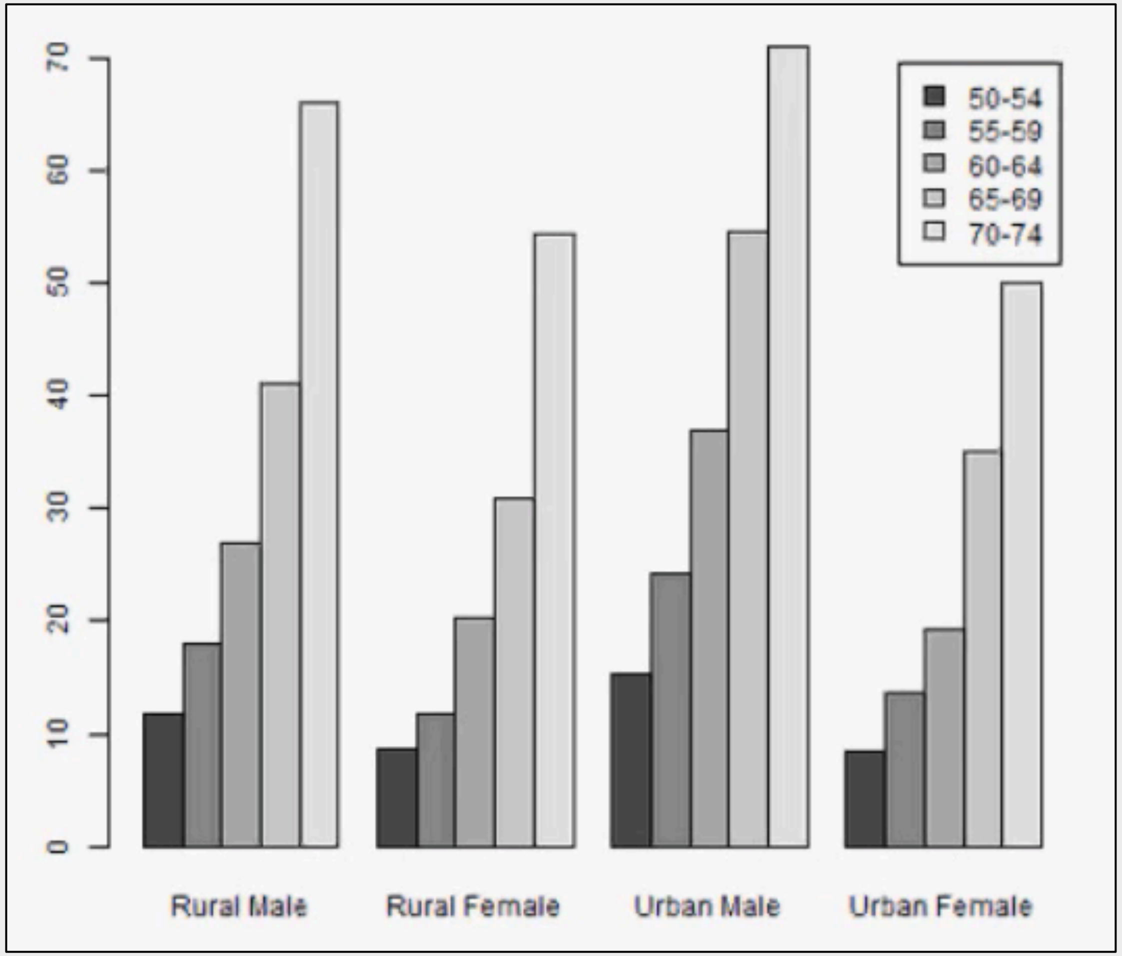
4. Don’t lie
5. Do rotate and sort categorical axes
6. Do eliminate legends & directly label geoms
7. Don’t use pattern fills
8. Don’t use red & green together
9. Do remove chart chunk
10. Do consider tables for small data sets

*...most of the time

Don't use pattern fills


0
10
20
30
40
50
60
70
50-54
55-59
60-64
65-69
70-74
Rural Male
Rural Female
Urban Male
Urban Female


0
10
20
30
40
50
60
70
50-54
55-59
60-64
65-69
70-74
Rural Male
Rural Female
Urban Male
Urban Female

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7. Don’t use pattern fills
8. Don’t use red & green together
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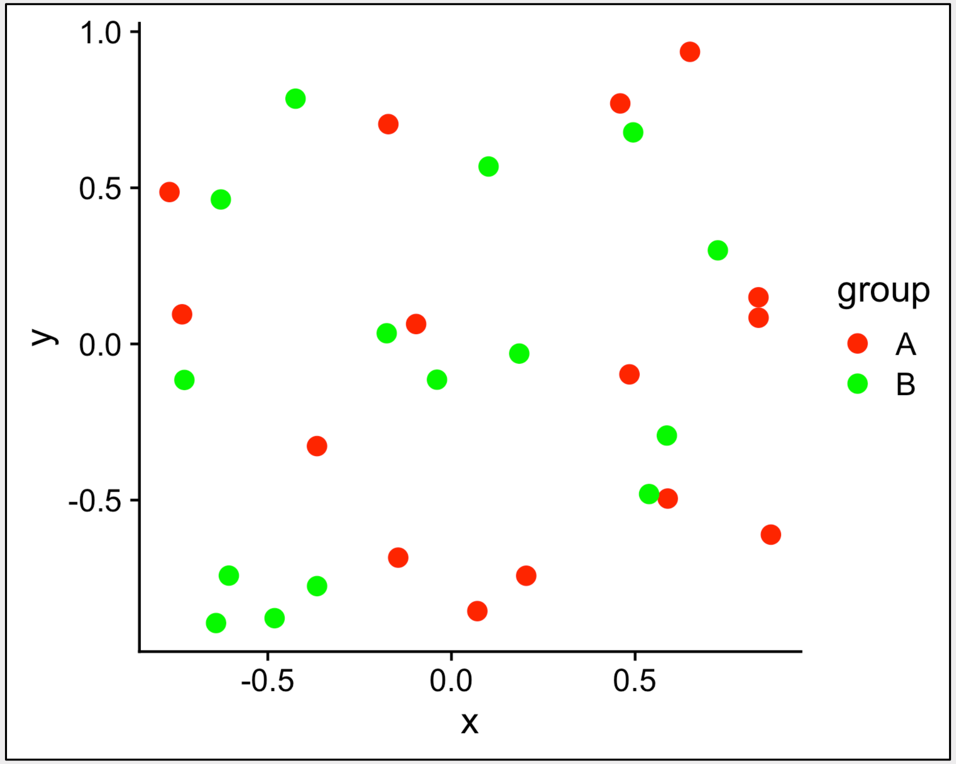
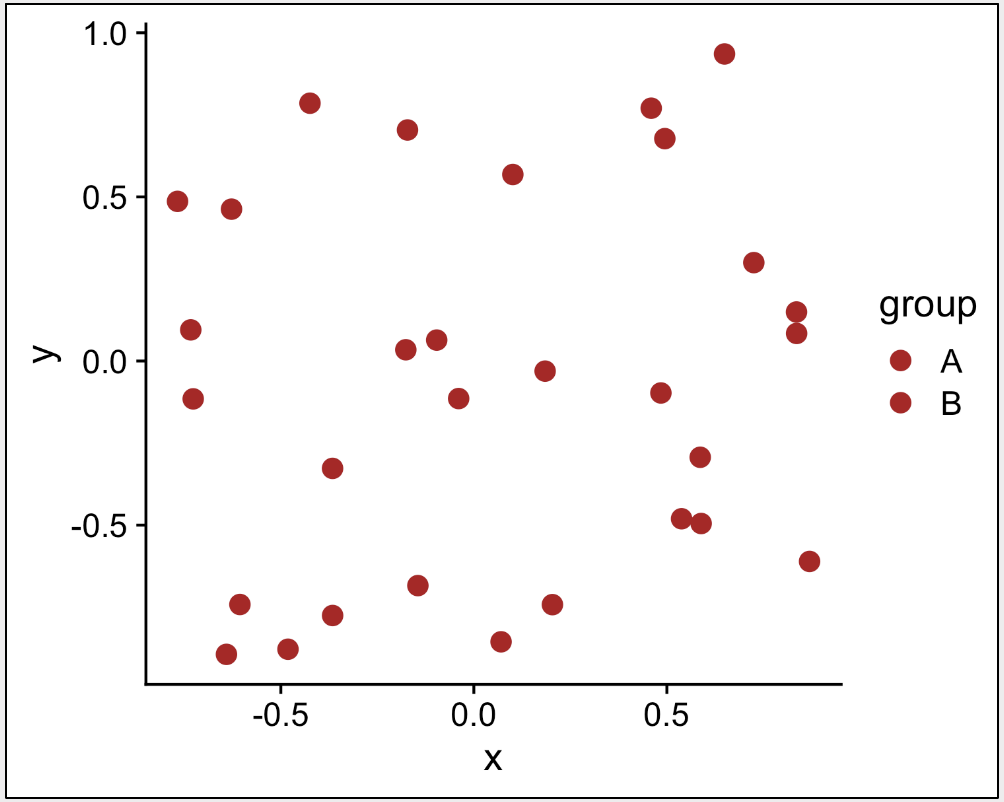
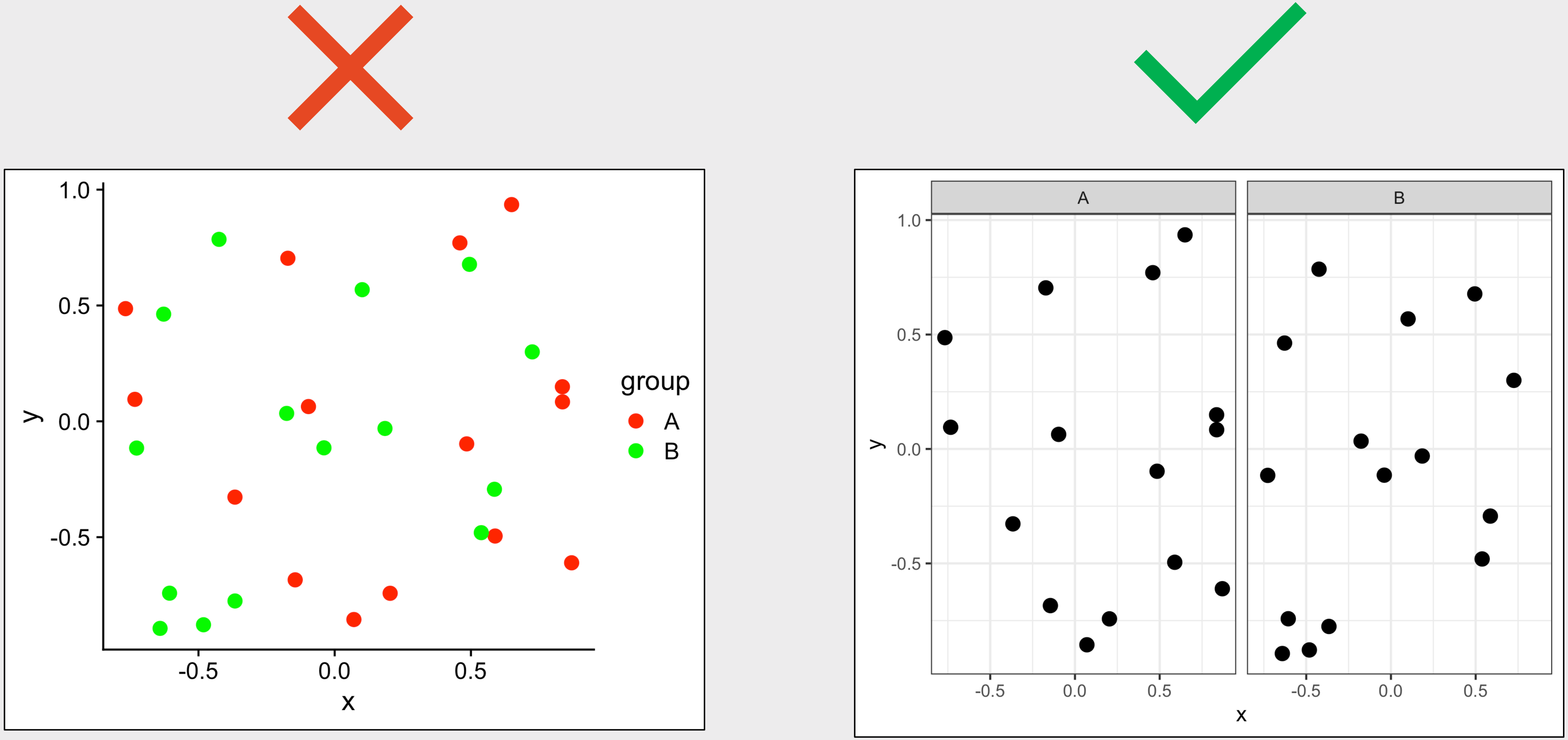
*...most of the time

10% of males and 1% of females are color blind





Facets can be used to avoid color altogether



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Before

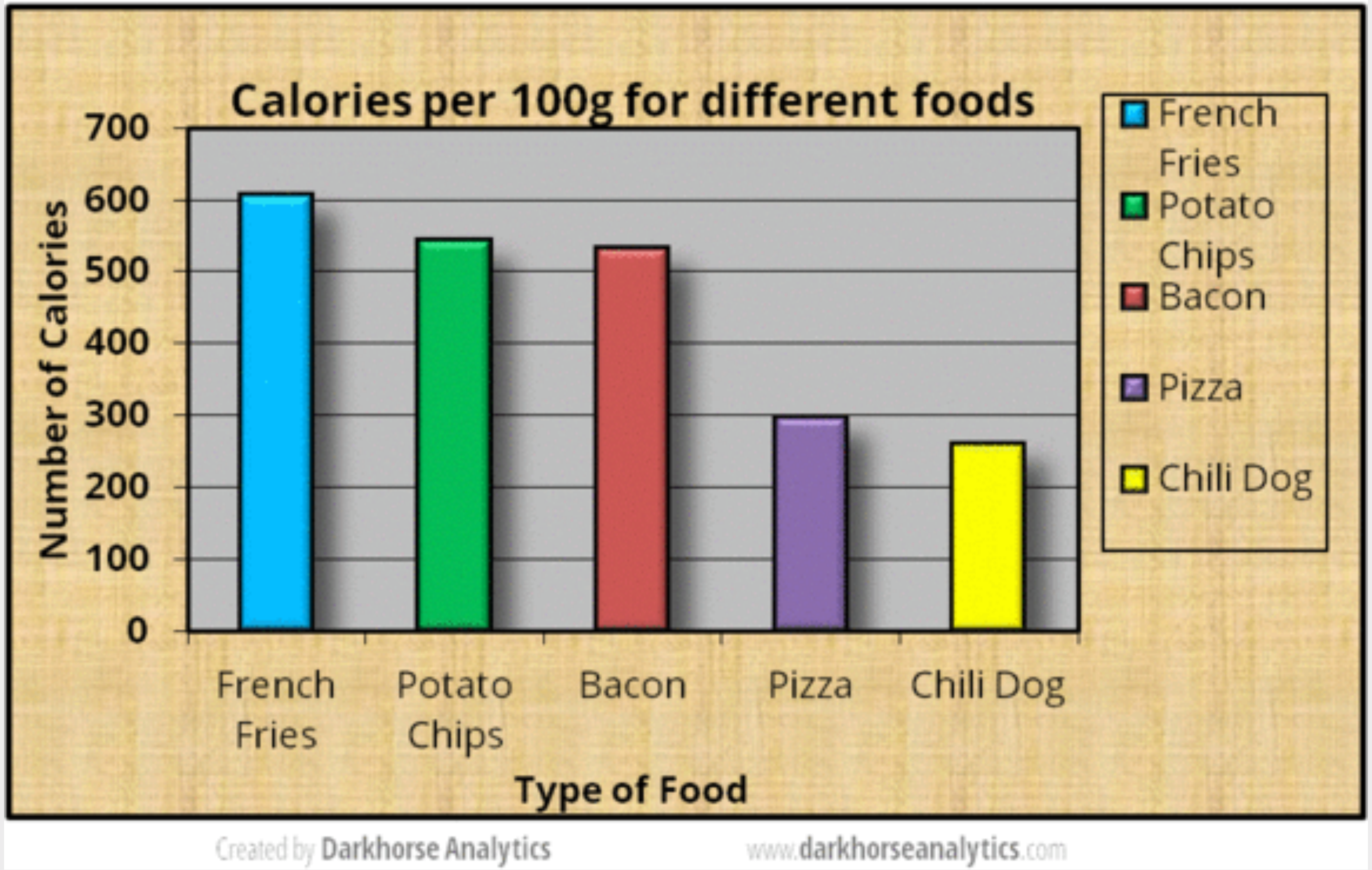

Figure 24.1: From Data Looks Better Naked by Darkhorse Analytics

Figure 24.1: From Data Looks Better Naked by Darkhorse Analytics

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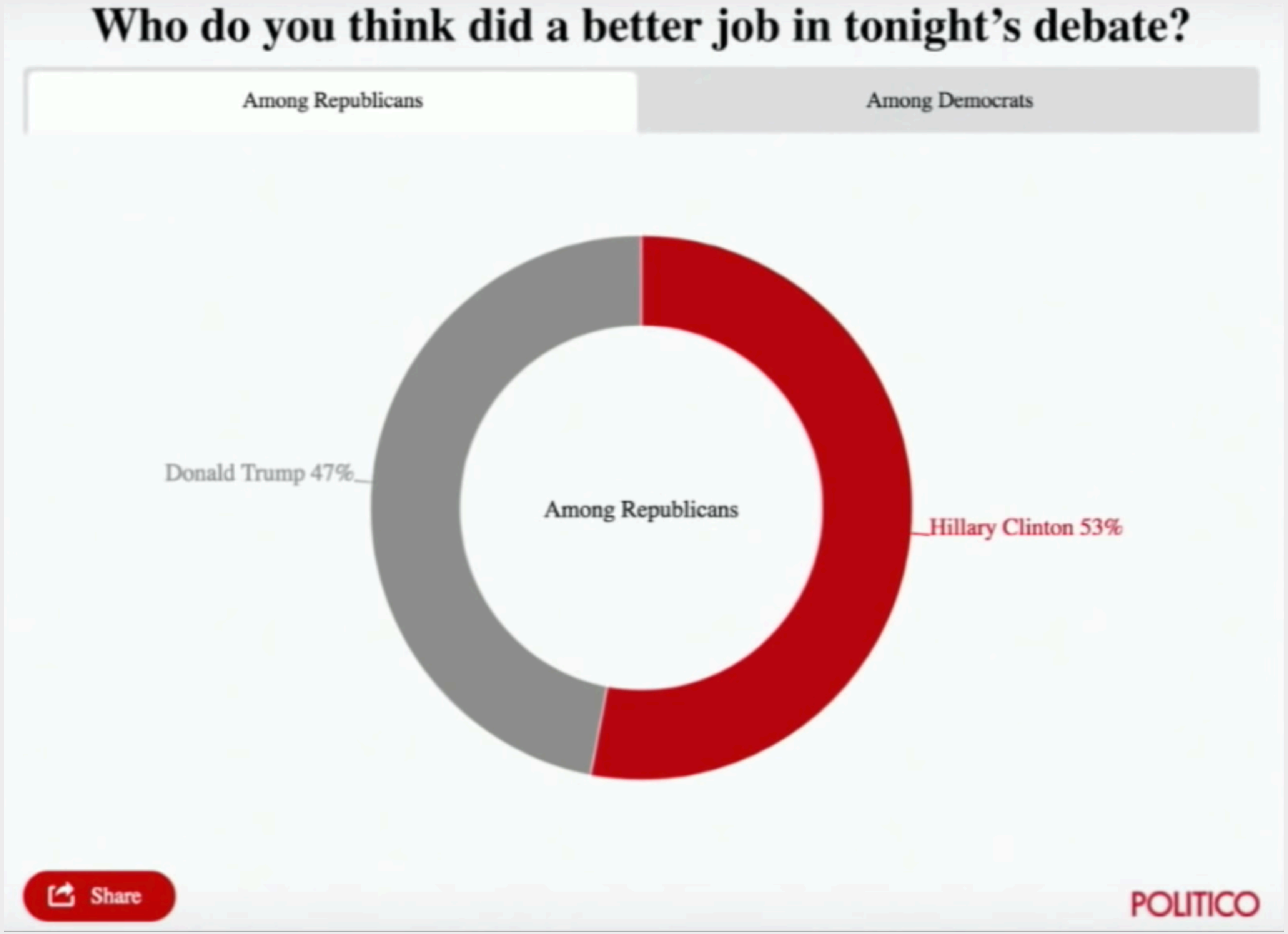
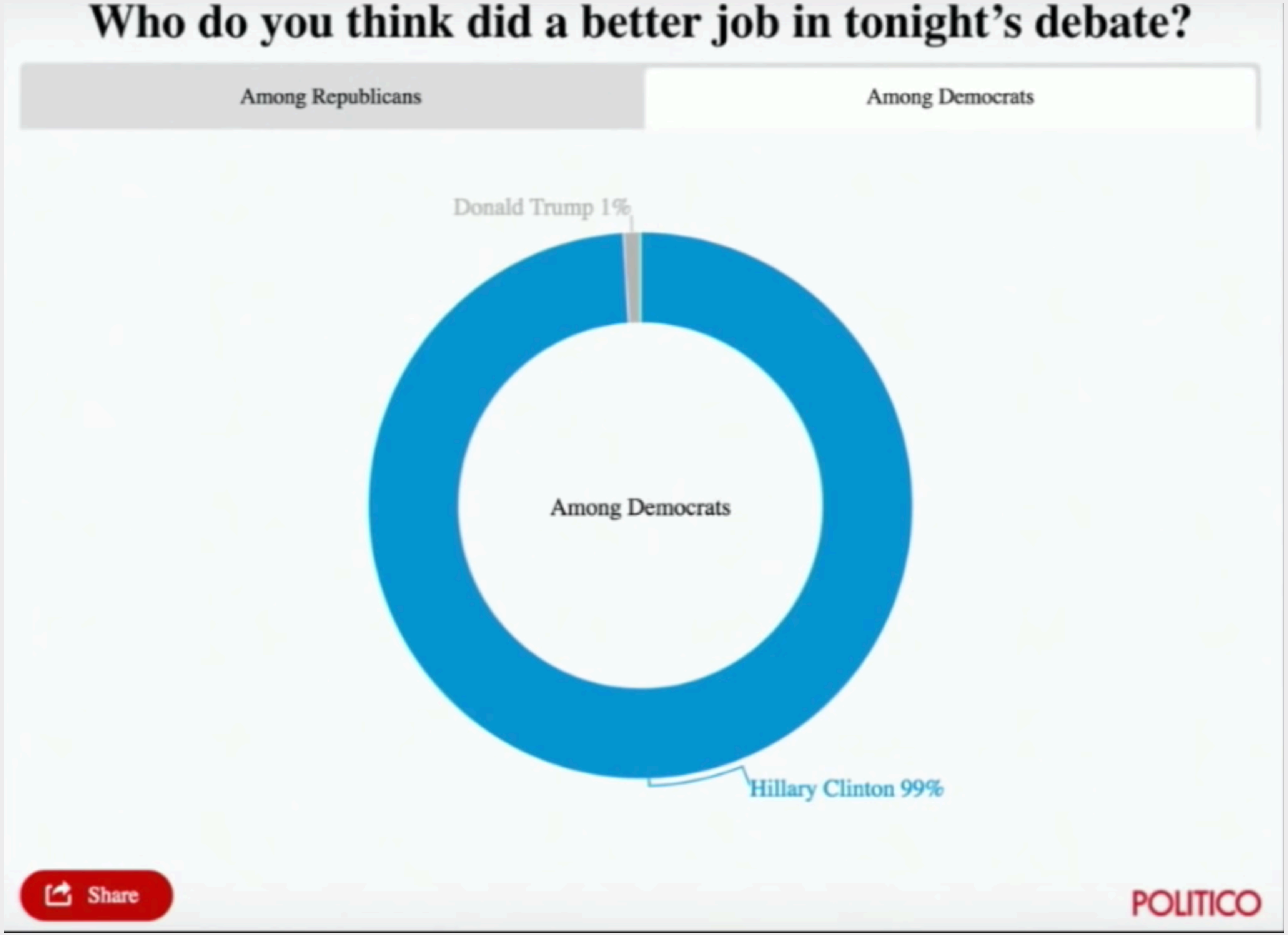

Who do you think did a better job in tonight's debate?
Among Republicans
Among Democrats
Donald Trump 47%
Among Republicans
Hillary Clinton 53%
Share
POLITICO


Who do you think did a better job in tonight's debate?
Among Republicans
Among Democrats
Donald Trump 1%
Among Democrats
Hillary Clinton 99%
Share
POLITICO

Who do you think did a better job in tonight's debate?

	Clinton	Trump
Among democrats	99%	1%
Among republicans	53%	47%

Two objectives of effective graphs:
1. Grab & direct attention (iconic memory)
2. Reduce processing demands (working memory)

Graph components:
1. Geoms:
   - points, lines, boxes, bars, etc.
2. Pre-attentive attributes:
   - position, color, shape, curvature, etc.
3. Non-data ink:
   - scales, grid lines, legend, labels, etc.
4. No chart junk!

Pattern recognition hierarchy:
- Position on a common scale
- Position on non-aligned scales
- Length
- Angle
- Area
- Color saturation
- Color hue

Cleveland's three visual operations of pattern perception:
1. Estimation:
   - Discrimination X != Y
   - Ranking X > Y
   - Ratioing X / Y
2. Assembly:
   - The grouping of graphical elements
   - Prägnanz: We strongly prefer to interpret stimuli as regular, simple, and orderly
3. Detection:
   - Recognizing that a geometric object encodes a physical value
   - Above all else, show the data

10 lessons* from research on visual perception:
1. Don't make 3D plots
2. Don't use pie charts for proportions
3. Don't stack bars
4. Don't lie
5. Do rotate and sort categorical axes
6. Do eliminate legends & directly label geoms
7. Don't use pattern fills
8. Don't use red & green together
9. Do remove chart chunk
10. Do consider tables for small data sets

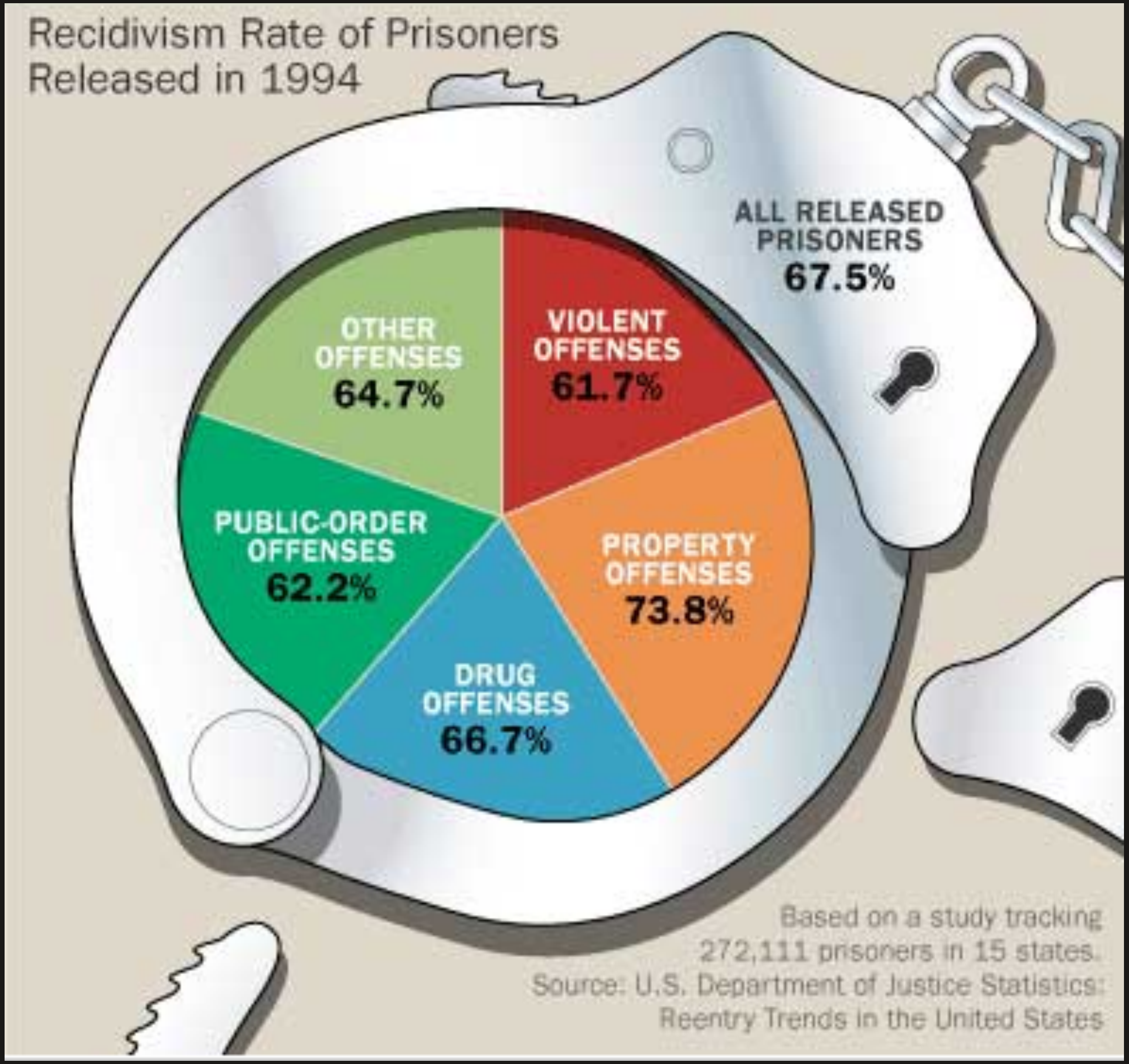
*most of the time

Your turn

1) Identify the following:
   - The geoms
   - The pre-attentive attributes
   - Where the graphic falls on Cleveland's pattern recognition hierarchy

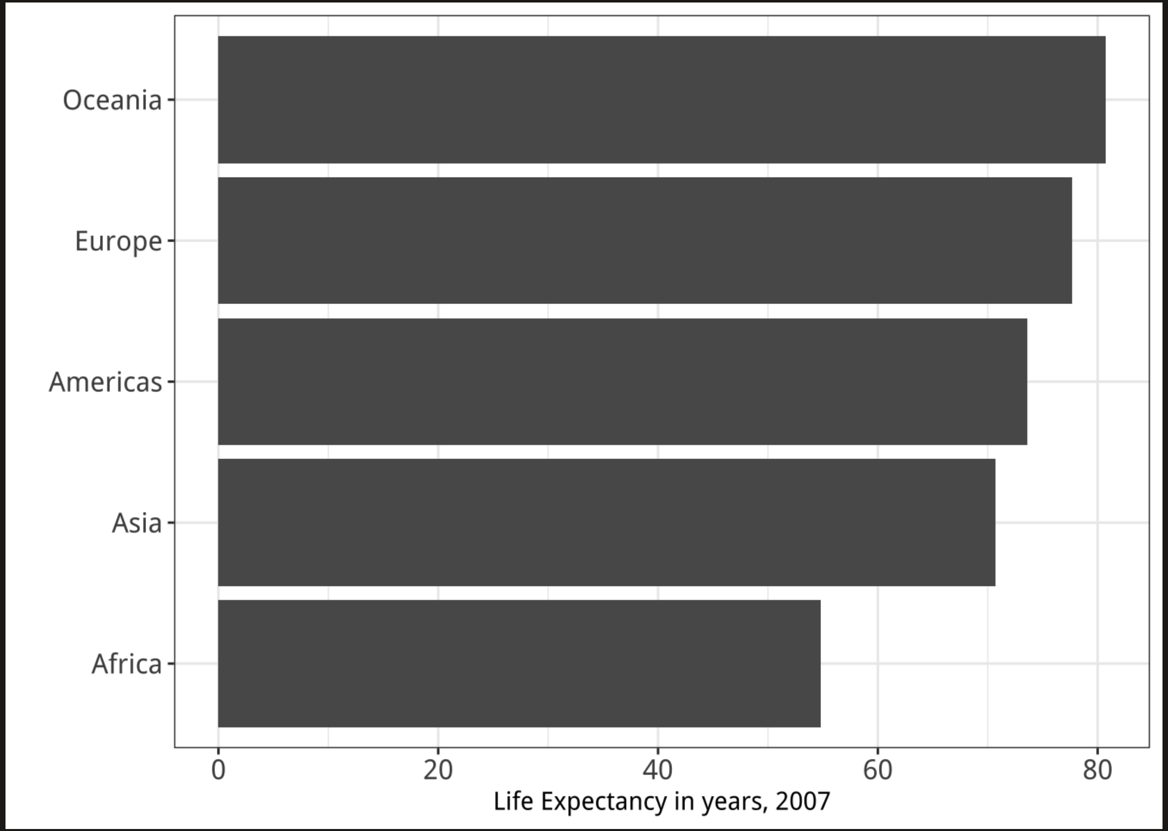
2) Identify the design rules that are broken (if any)

3) Suggest at least two improvements



https://people.howstuffworks.com/prison4.htm

Figure 1.4 in Healy, 2018



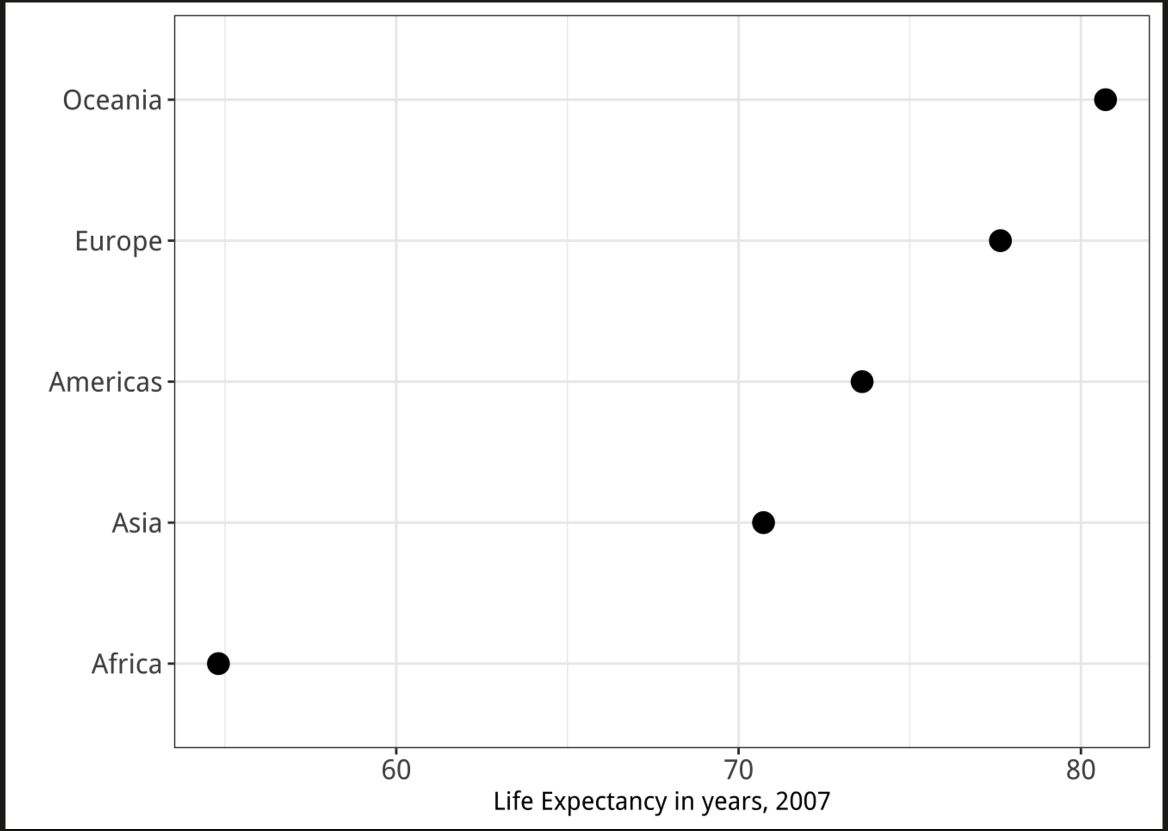
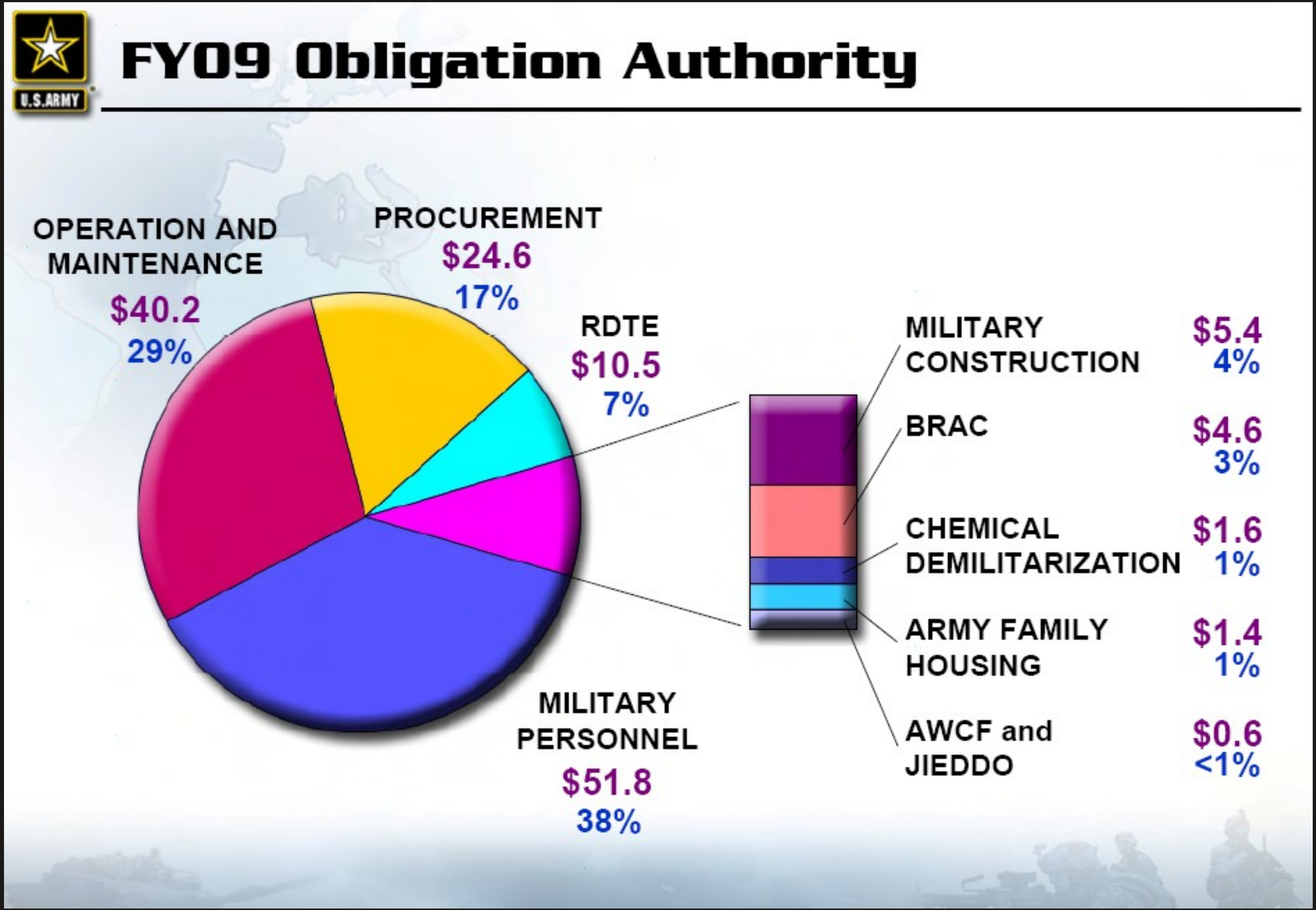
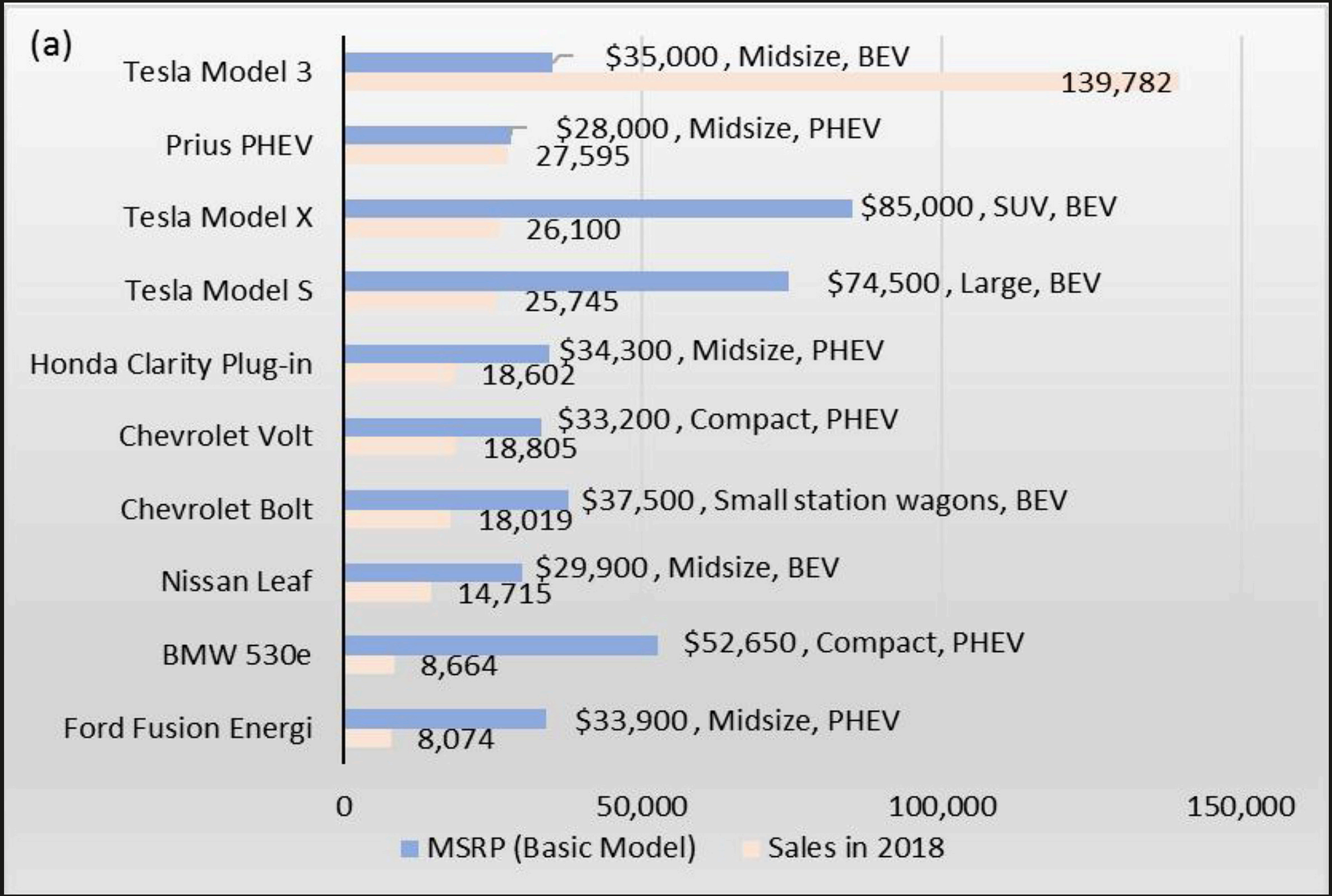


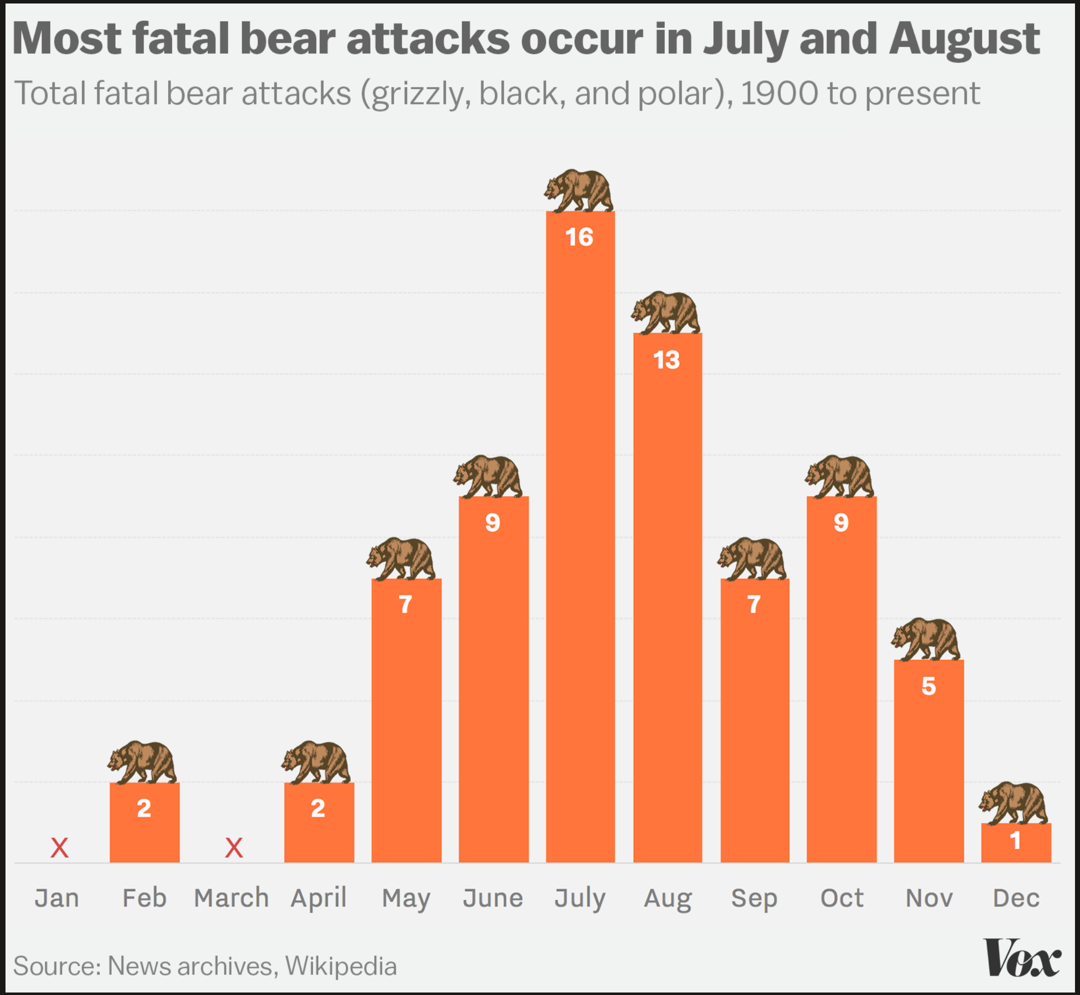
Figure 1.4 in Healy, 2018

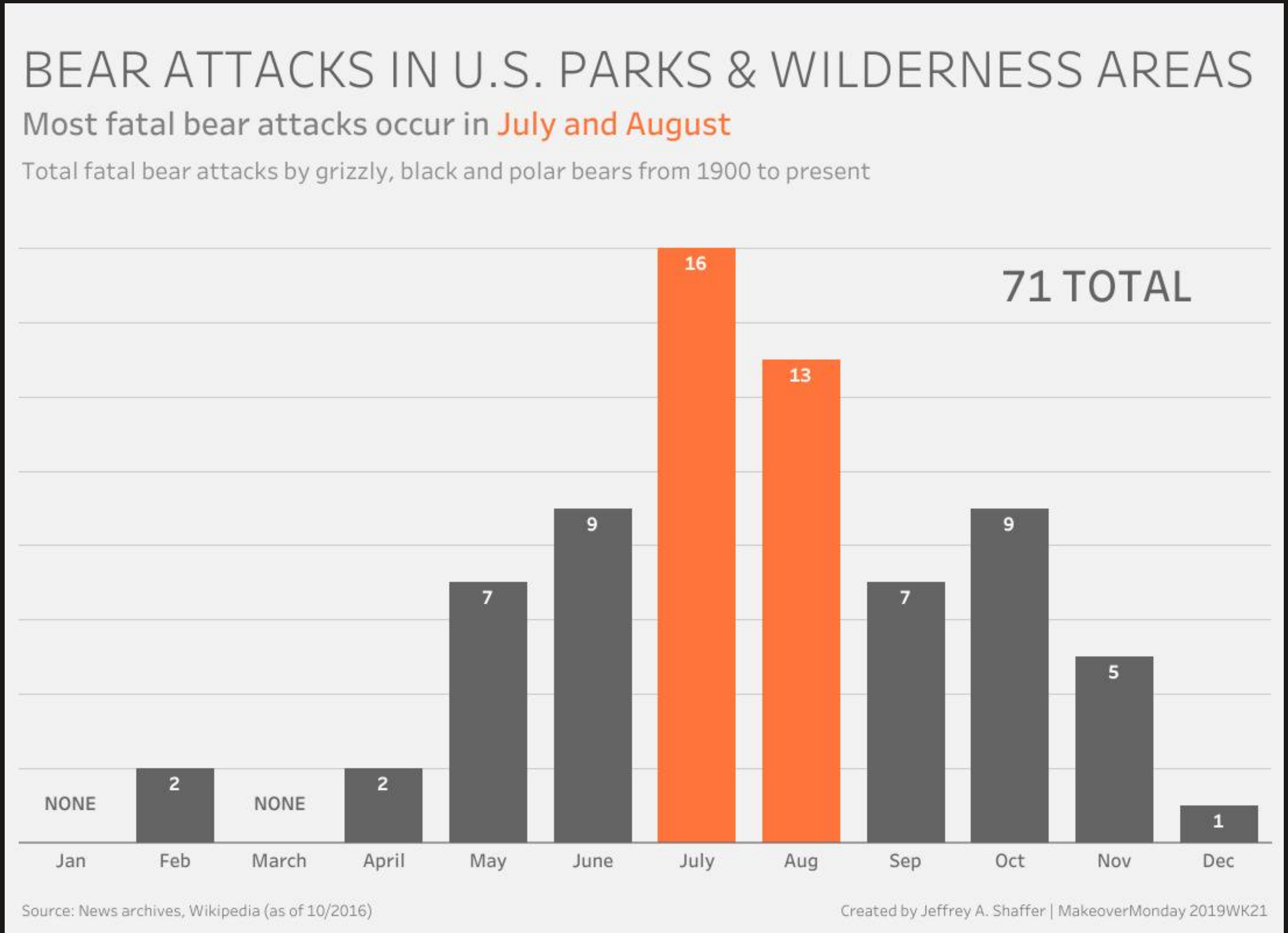


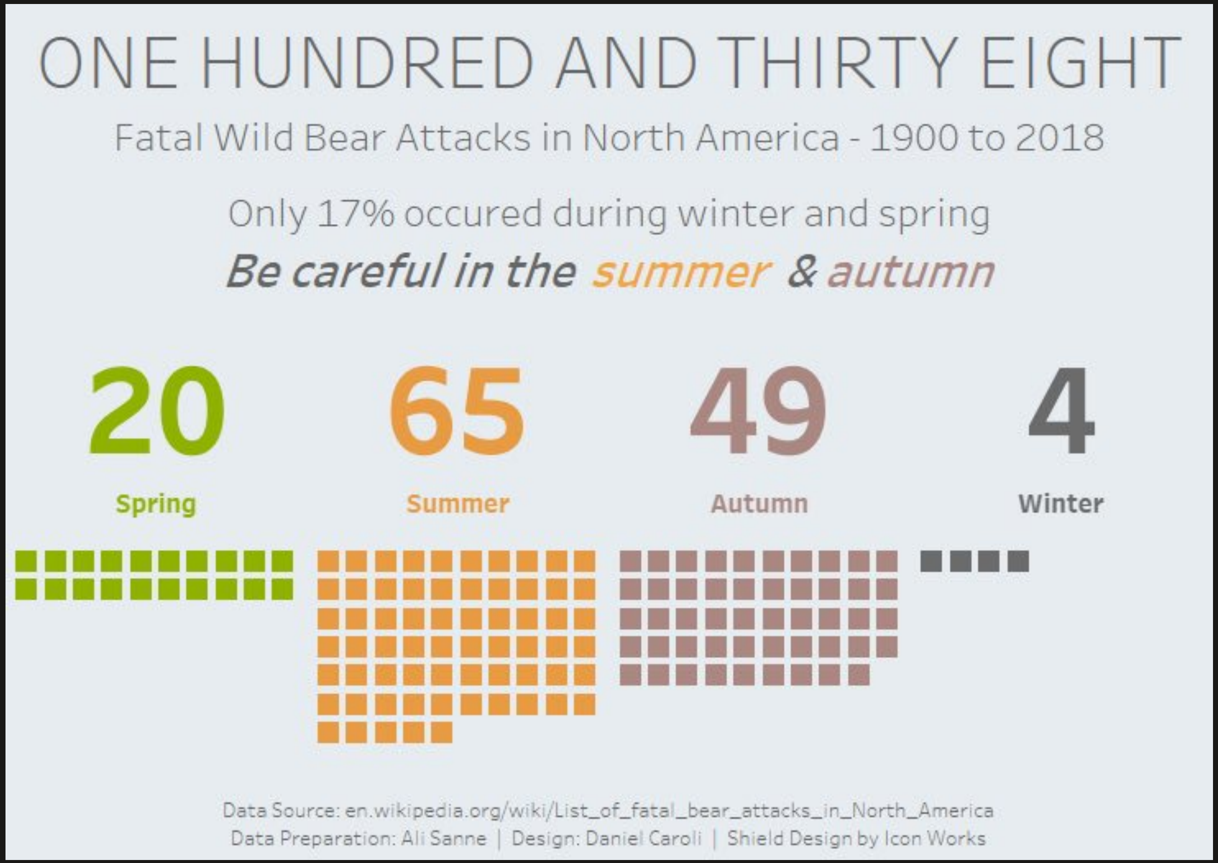
http://www.wallstats.com/blog/down-the-rabbit-hole-of-the-pentagon-graphics-machine/

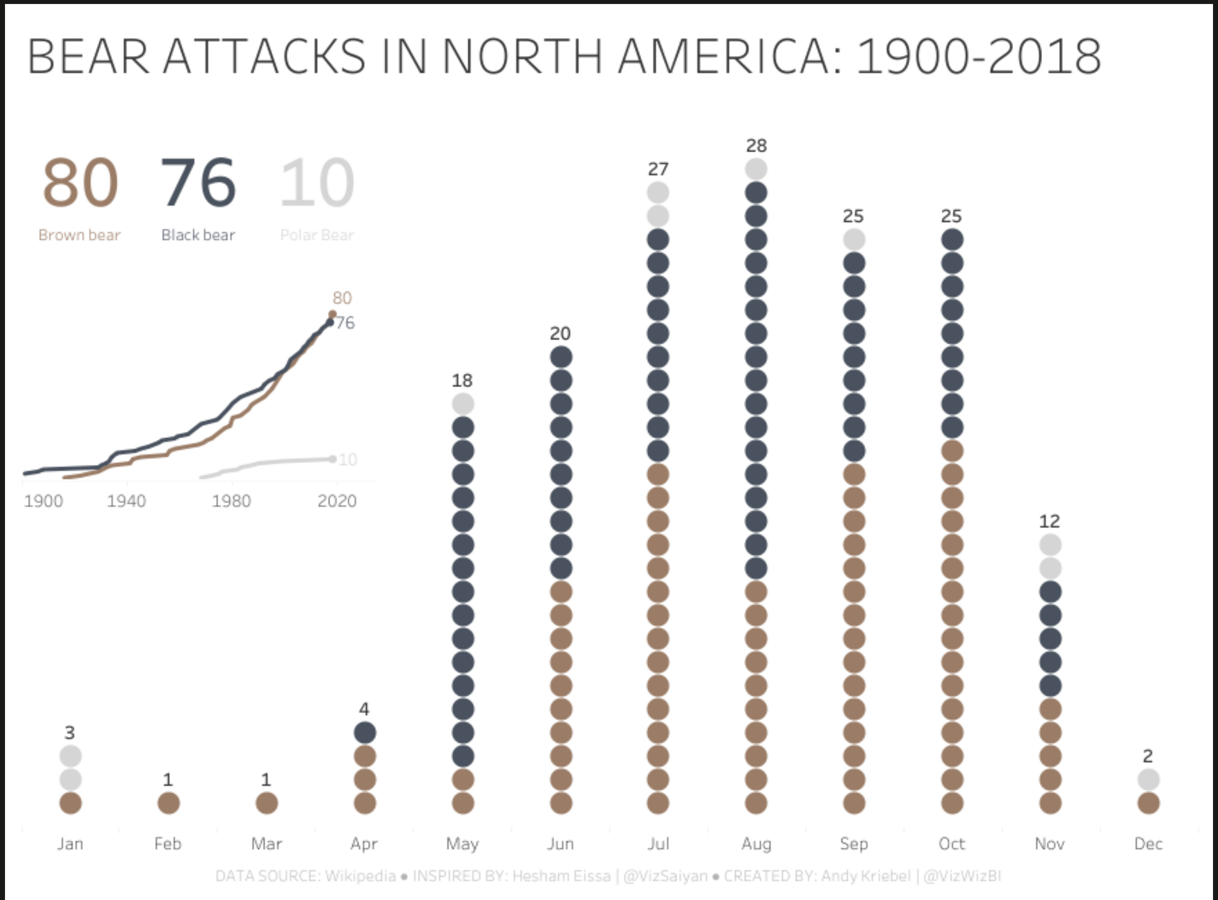


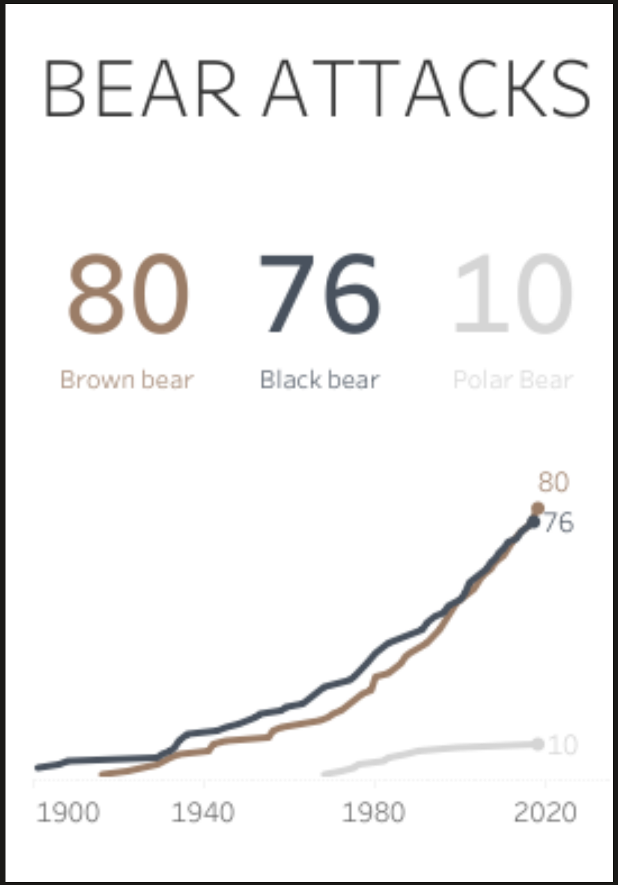
Ou et al., 2019 "Light-duty plug-in electric vehicles in China: An overview on the market and its comparisons to the United States"

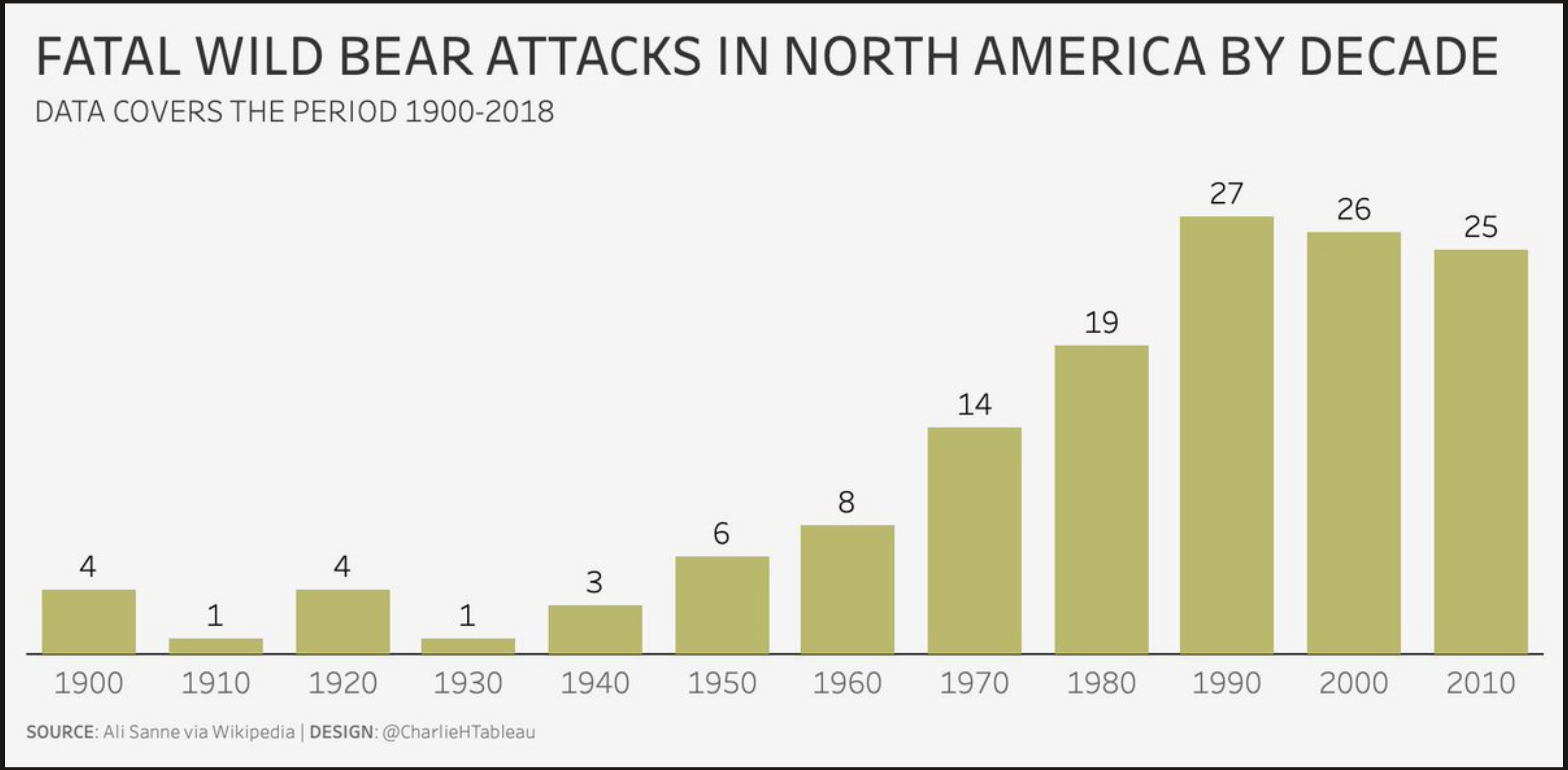

Most fatal bear attacks occur in July and August
Total fatal bear attacks (grizzly, black, and polar), 1900 to present
X
2
X
2
7
9
16
13
7
9
5
1
Jan
Feb
March
April
May
June
July
Aug
Sep
Oct
Nov
Dec
Source: News archives, Wikipedia
Vox


BEAR ATTACKS IN U.S. PARKS & WILDERNESS AREAS
Most fatal bear attacks occur in July and August
Total fatal bear attacks by grizzly, black and polar bears from 1900 to present
71 TOTAL
NONE
2
NONE
2
7
9
16
13
7
9
5
1
Jan
Feb
March
April
May
June
July
Aug
Sep
Oct
Nov
Dec
Source: News archives, Wikipedia (as of 10/2016)
Created by Jeffrey A. Shaffer | MakeoverMonday 2019WK21

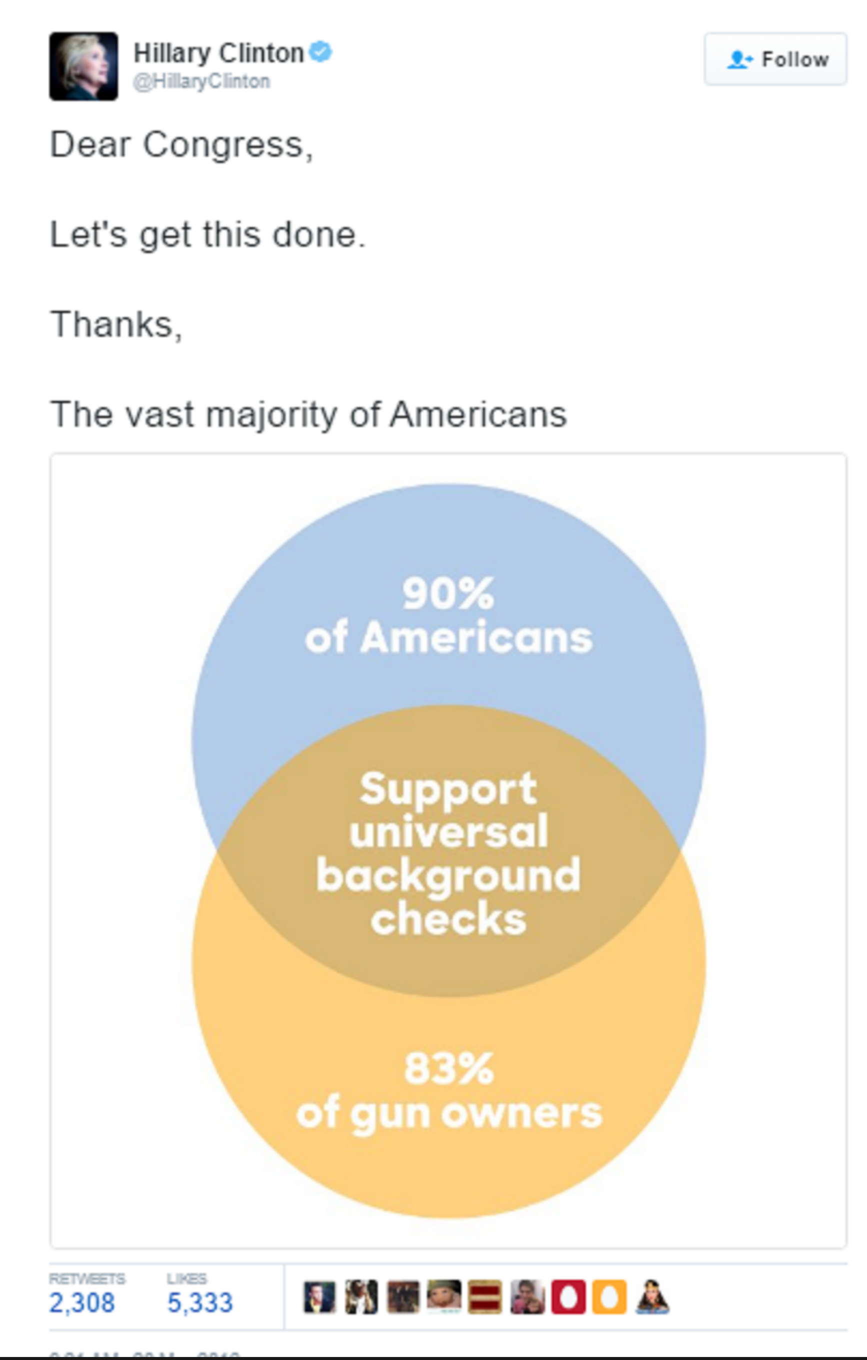

ONE HUNDRED AND THIRTY EIGHT
Fatal Wild Bear Attacks in North America - 1900 to 2018
Only 17% occured during winter and spring
Be careful in the summer & autumn
20
Spring
65
Summer
49
Autumn
4
Winter
Data Source: en.wikipedia.org/wiki/List_of_fatal_bear_attacks_in_North_America
Data Preparation: Ali Sanne | Design: Daniel Caroli | Shield Design by Icon Works

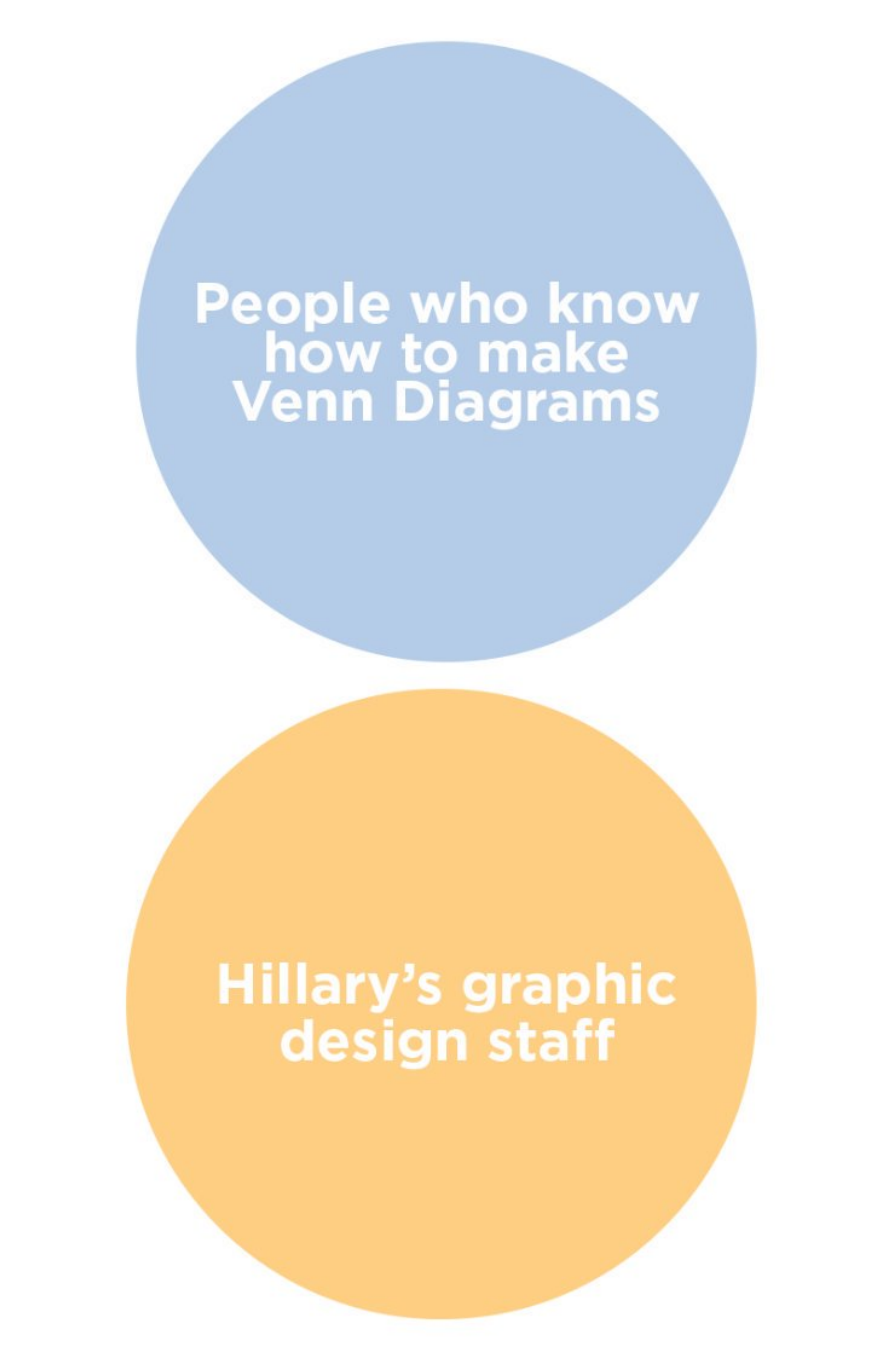

BEAR ATTACKS IN NORTH AMERICA: 1900-2018
80
Brown bear
76
Black bear
10
Polar Bear
1900
1940
1980
2020
3
1
1
4
18
20
27
28
25
25
12
2
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
DATA SOURCE: Wikipedia ● INSPIRED BY: Hesham Eissa | @VizSaiyan ● CREATED BY: Andy Kriebel | @VizWizBI

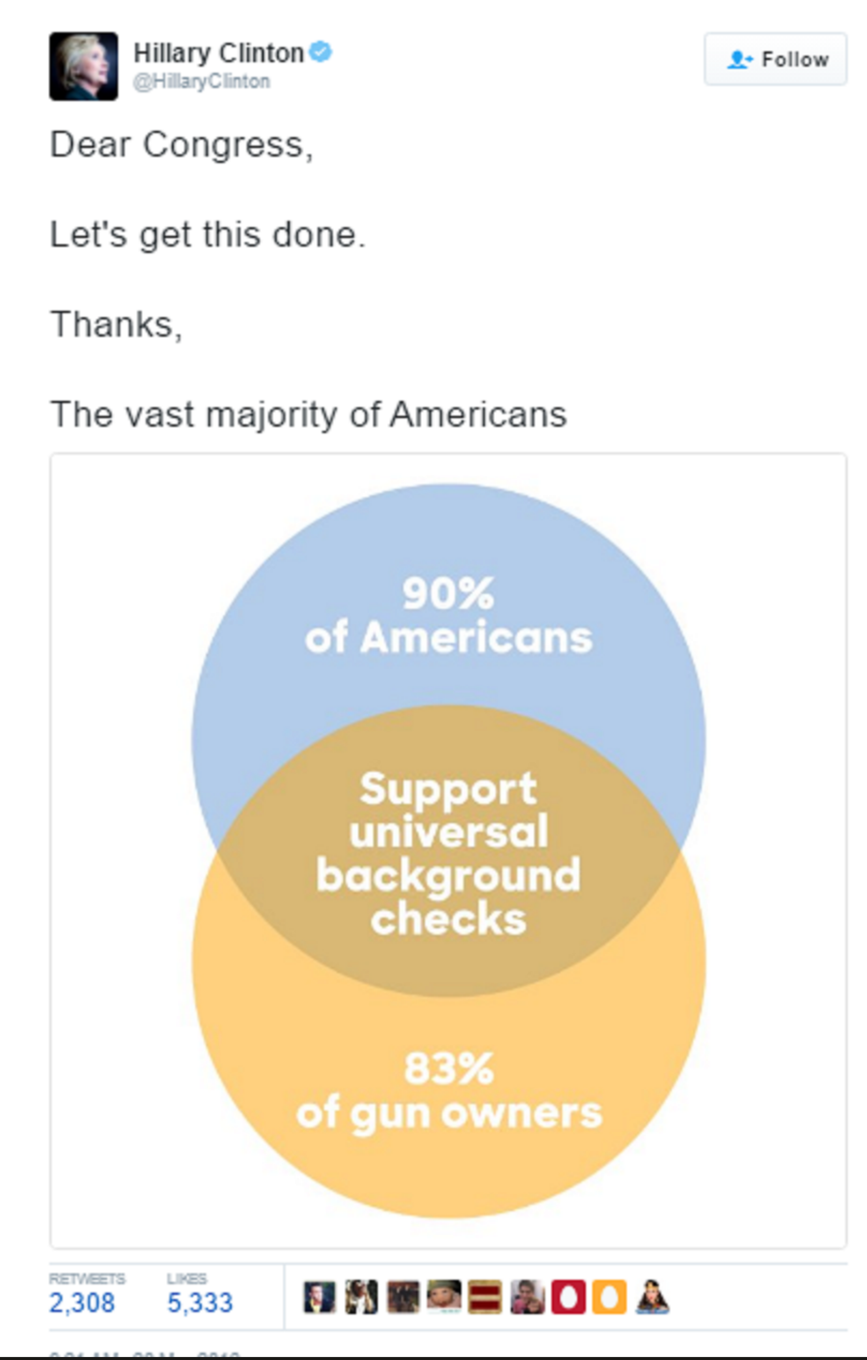

BEAR ATTACKS
80
Brown bear
76
Black bear
10
Polar Bear
80
76
10
1900
1940
1980
2020


FATAL WILD BEAR ATTACKS IN NORTH AMERICA BY DECADE
DATA COVERS THE PERIOD 1900-2018
4
1
4
1
3
6
8
14
19
27
26
25
1900
1910
1920
1930
1940
1950
1960
1970
1980
1990
2000
2010
SOURCE: Ali Sanne via Wikipedia | DESIGN: @CharlieHTableau

Extra Slides


Hillary Clinton
@HillaryClinton
Follow
Dear Congress,
Let's get this done.
Thanks,
The vast majority of Americans
90% of Americans
Support universal background checks
83% of gun owners
RETWEETS
2,308
LIKES
5,333


People who know how to make Venn Diagrams
Hillary's graphic design staff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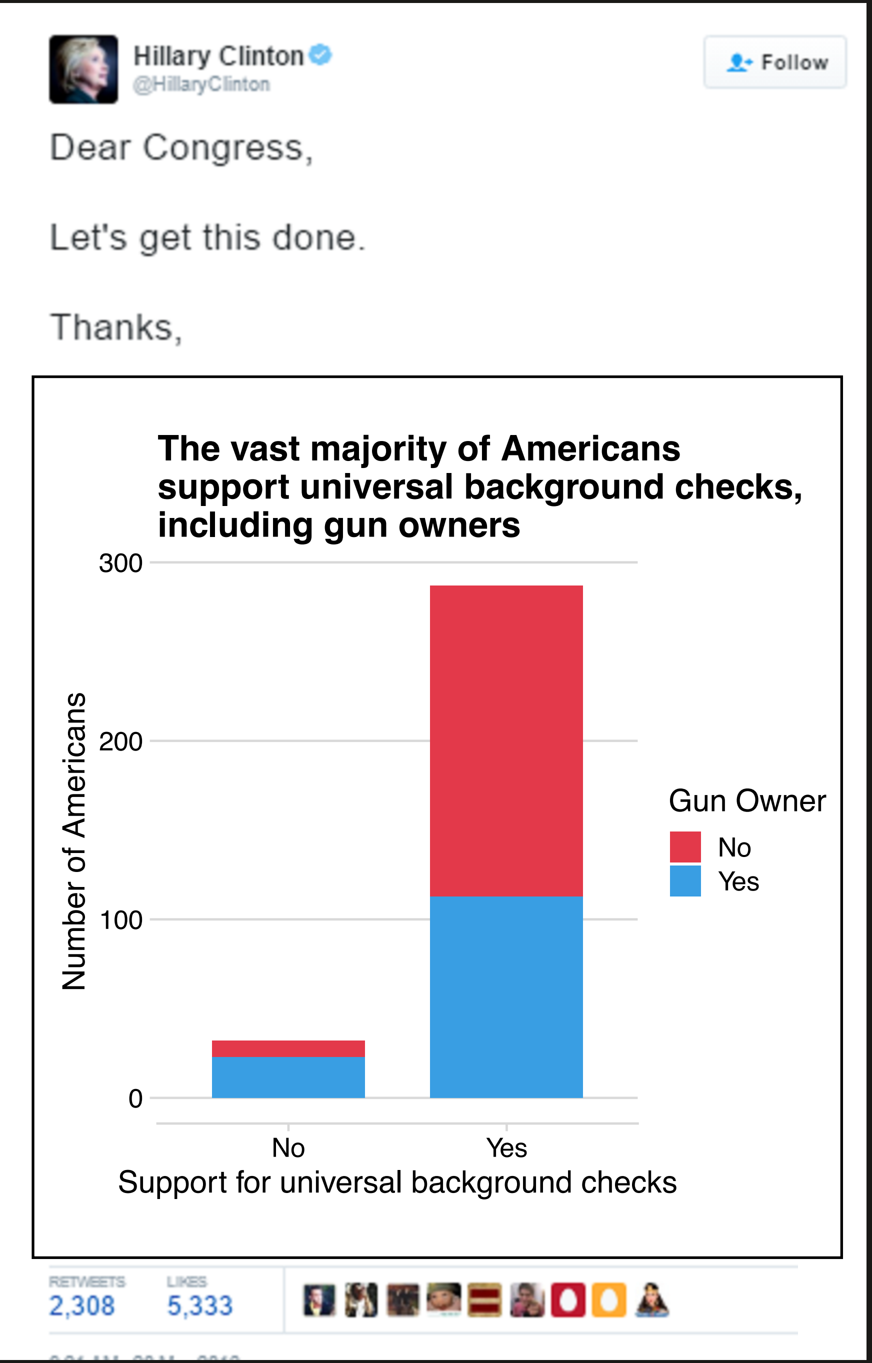
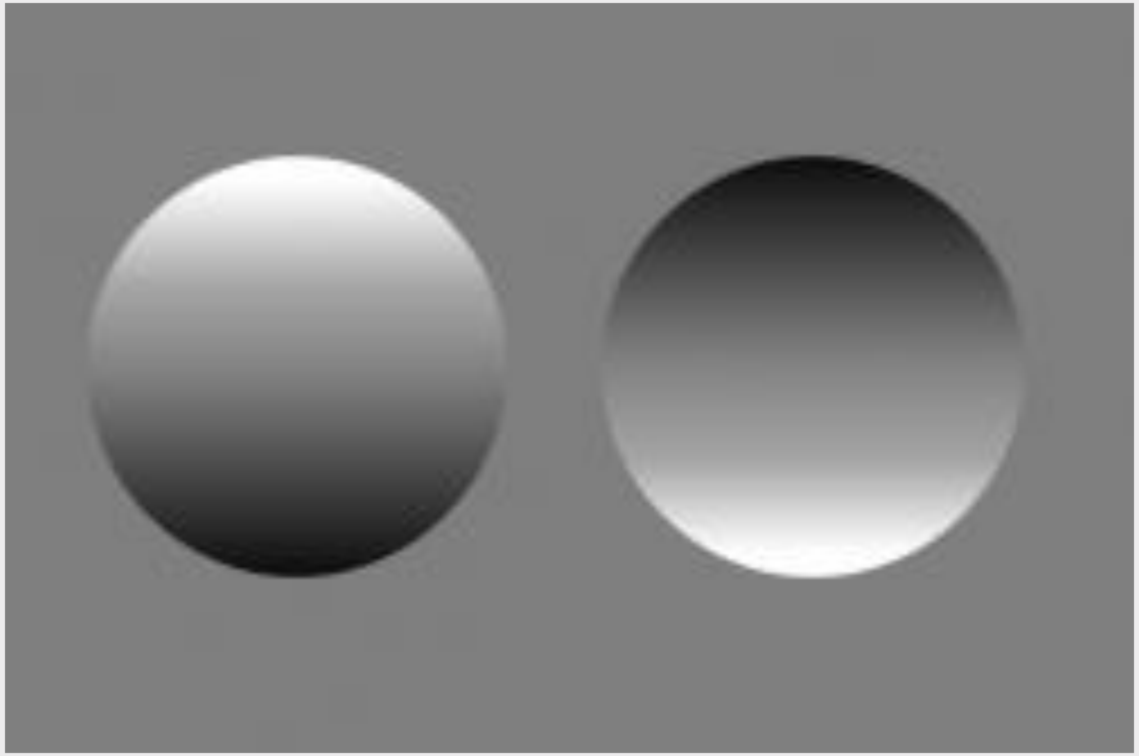
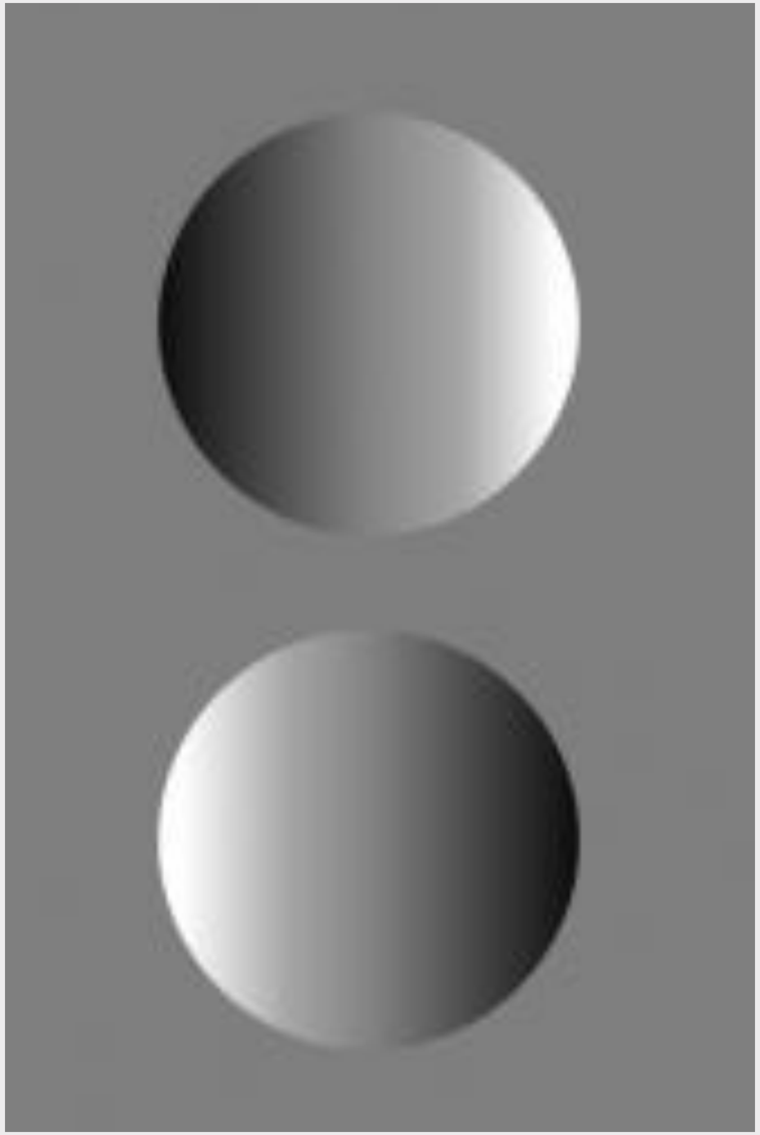

Hillary Clinton
@HillaryClinton
Follow
Dear Congress,
Let's get this done.
Thanks,
The vast majority of Americans support universal background checks, including gun owners
Number of Americans
300
200
100
0
No
Yes
Support for universal background checks
Gun Owner
No
Yes
RETWEETS
2,308
LIKES
5,333





Do: Consider using *graphs* instead of *tables*

Table 5
Regression Coefficient for weighted U.S. and China models in the WTP space.

Attribute	Coef.	Model 1: MNL U.S.	Model 1: MNL China	Model 2: MXL U.S.	Model 2: MXL China
Price	μ	0.052 (0.002)***	0.033 (0.002)***	0.066 (0.003)***	0.039 (0.002)***
Powertrain type (base = CV)					
HEV	μ	−1.176 (1.611)	4.882 (1.917)	−0.418 (1.585)	4.962 (1.992)
	σ	–	–	0.188 (4.664)	19.403 (7.723)
PHEV10	μ	0.027 (1.782)	−1.291 (2.069)	0.822 (1.796)	−1.748 (2.098)
	σ	–	–	2.197 (5.428)	6.055 (8.872)
PHEV20	μ	1.695 (1.751)	−1.242 (2.031)	3.207 (1.734)	−2.245 (2.074)
	σ	–	–	8.664 (5.719)	4.041 (6.792)
PHEV40	μ	2.650 (1.774)	0.930 (2.023)	3.304 (1.741)	0.380 (2.039)
	σ	–	–	7.141 (5.466)	9.108 (6.179)
BEV75	μ	−20.137 (1.978)***	−6.032 (2.088)***	−18.453 (1.934)***	−7.627 (2.365)***
	σ	–	–	4.175 (6.232)	29.843 (7.417)***
BEV100	μ	−19.496 (1.984)***	−8.151 (2.144)***	−18.947 (1.965)***	−10.377 (2.286)***
	σ	–	–	1.898 (5.368)	8.600 (7.340)
BEV150	μ	−13.691 (1.959)***	1.305 (2.050)	−12.727 (1.959)***	0.616 (2.075)
	σ	–	–	10.486 (6.061)	6.973 (6.406)
Brand (base = German)					
American	μ	8.188 (1.289)***	−10.574 (1.560)***	7.432 (1.268)***	−7.612 (1.687)***
	σ	–	–	0.665 (3.439)	19.299 (5.866)***
Japanese	μ	0.934 (1.289)	−18.098 (1.689)***	−0.577 (1.289)	−15.169 (1.790)***
	σ	–	–	11.765 (3.508)***	23.666 (5.941)***
Chinese	μ	−19.008 (1.550)***	−9.674 (1.509)***	−19.848 (1.666)***	−6.049 (1.691)***
	σ	–	–	8.078 (4.173)	34.541 (6.544)***
S. Korean	μ	−9.510 (1.398)***	−19.361 (1.725)***	−10.412 (1.378)***	−17.774 (2.124)***
	σ	–	–	12.335 (3.850)***	54.771 (6.171)***
Cost and performance					
PHEV fast-charge	μ	3.944 (1.330)***	7.615 (1.565)***	3.331 (1.335)	7.567 (1.653)***
	σ	–	–	8.882 (4.396)	20.119 (5.449)***
BEV fast-charge	μ	3.343 (1.478)	6.662 (1.599)***	0.030 (1.821)	6.428 (1.668)***
	σ	–	–	26.237 (3.871)***	11.567 (5.360)
Operating cost	μ	−1.598 (0.106)***	−3.214 (0.242)***	−1.626 (0.104)***	−3.467 (0.267)***
	σ	–	–	0.076 (0.247)	3.275 (0.968)***
Acceleration time	μ	−1.172 (0.255)***	−4.651 (0.299)***	−1.269 (0.293)***	−4.878 (0.319)***
	σ	–	–	5.766 (0.880)***	3.359 (0.949)***
LL:		−3425.6	−6788.8	−3373.1	−6720.9
Null model LL:		−4360.5	−7487.3	−4360.6	−7487.3
AIC:		6883.3	13609.6	6808.3	13503.8
McFadden R^2:		0.21	0.09	0.23	0.10
Adj. McFadden R^2:		0.21	0.09	0.22	0.10
Num. of Obs:		5760	6720	5760	6720

Standard errors of estimates are presented in parenthesis. Coefficient units are USD $1000. * ⩽0.05. ** ⩽0.01. *** ⩽0.001.

Helveston, J. P., Y. Liu, E. M. Feit, E. Fuchs, E. Klampfl, J.J. Michalek (2015) “Will subsidies drive electric vehicle adoption? Measuring consumer preferences in the U.S. and China.” *Transportation Research Part A: Policy and Practice*, 73, 96–112.

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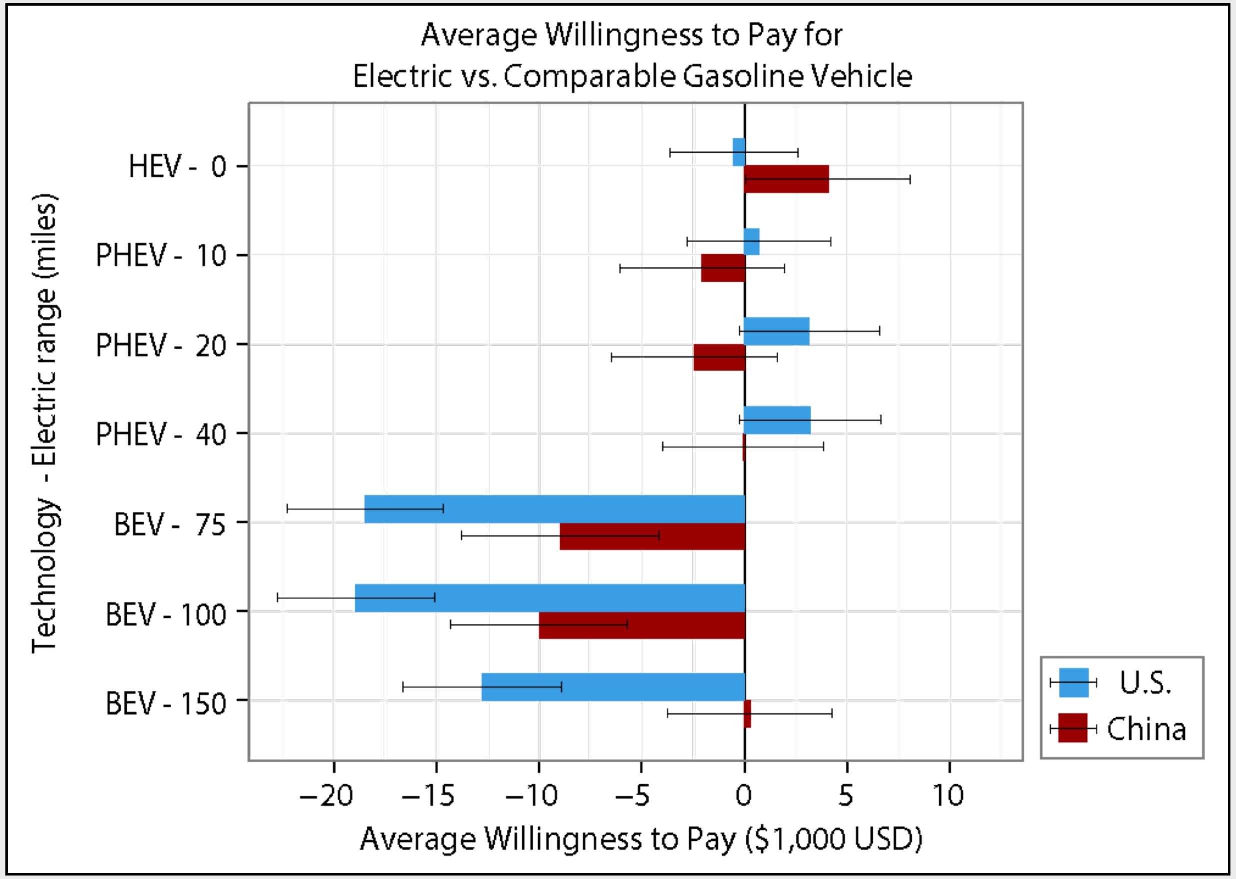

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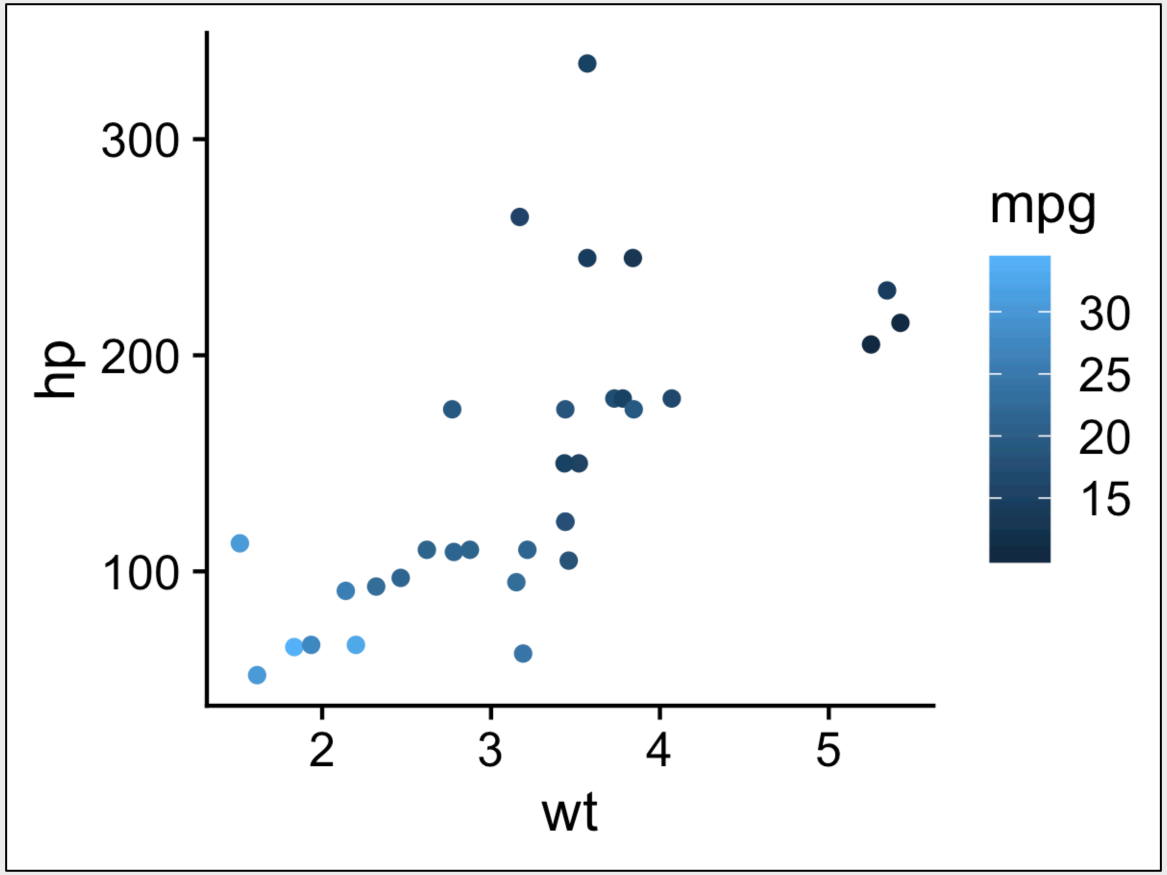
Gradient:

Change in <u>continuous</u> variable



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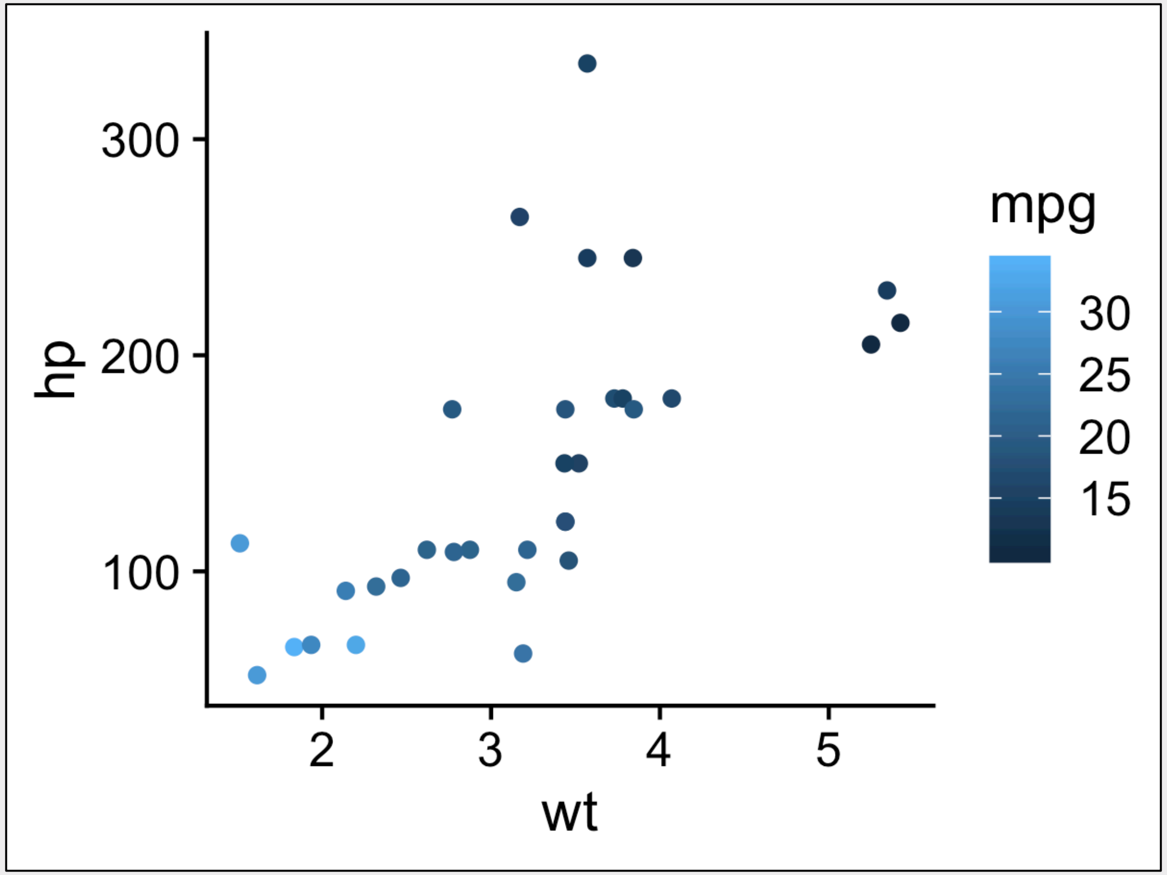
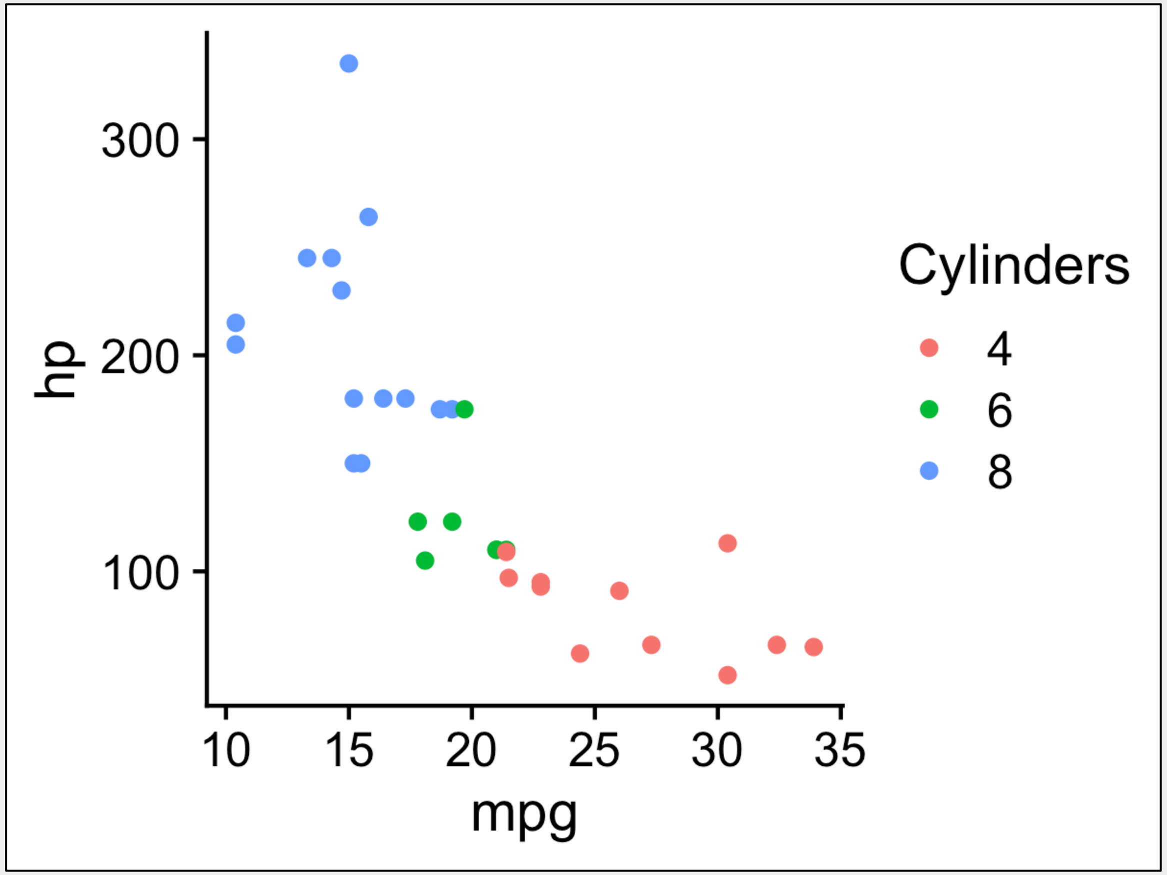


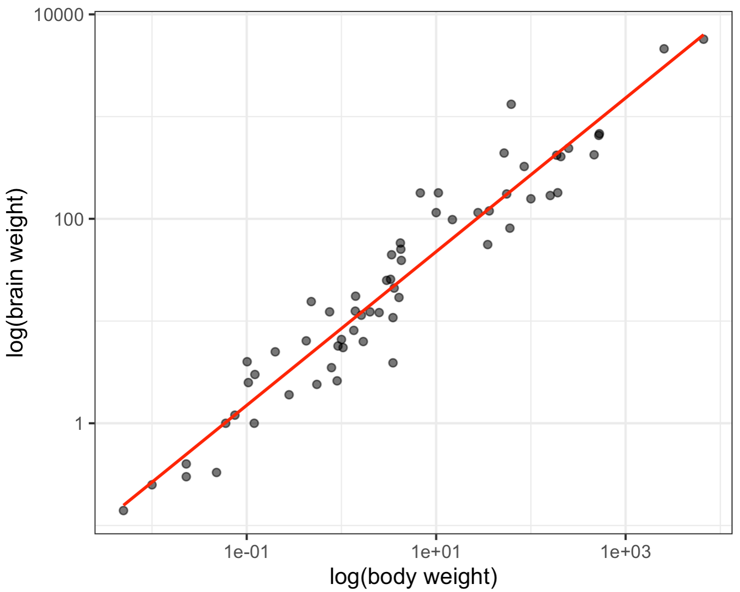
Discrete:
Identify (a few) categorical variables



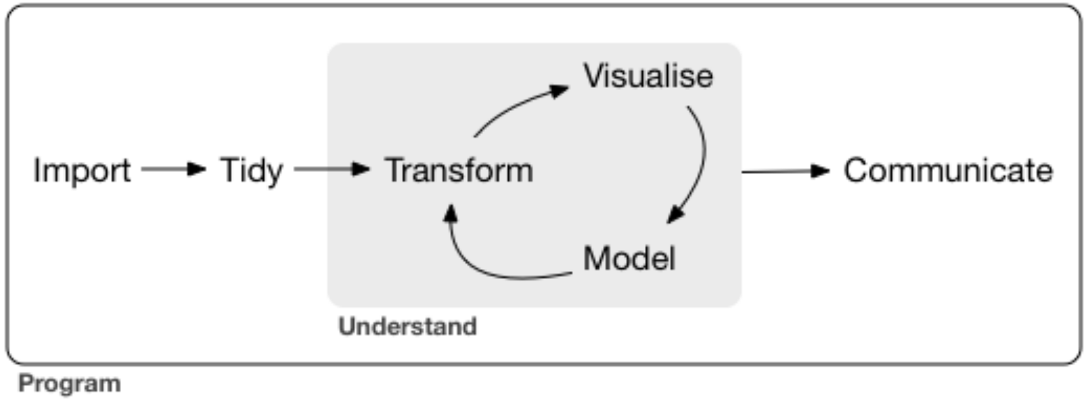
Tables:
Data organized into rows and columns

Mammal	Body (kg)	Brain (g)
Arctic fox	3.385	44.5
Owl monkey	0.48	15.5
Mountain beaver	1.35	8.1
Cow	465	423
Grey wolf	36.33	119.5
Goat	27.66	115

Graphs:
Visual representation of information in tables



Diagrams:
Visual representation of a process



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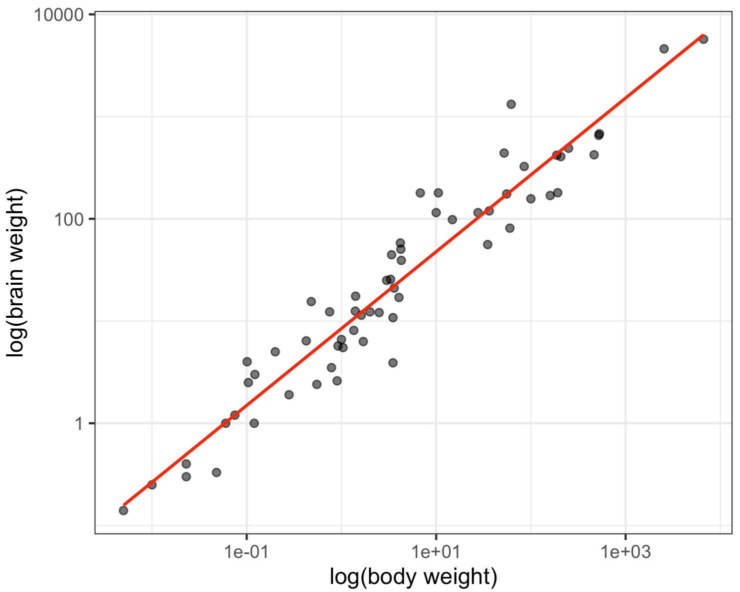

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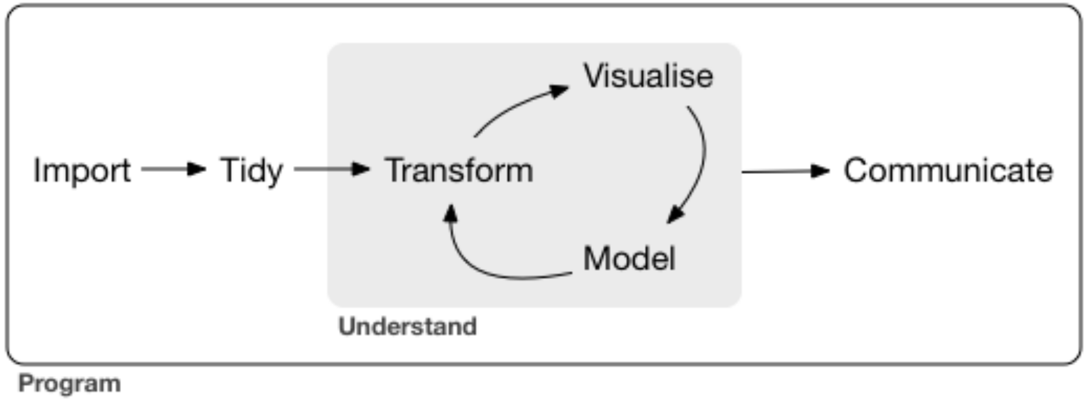
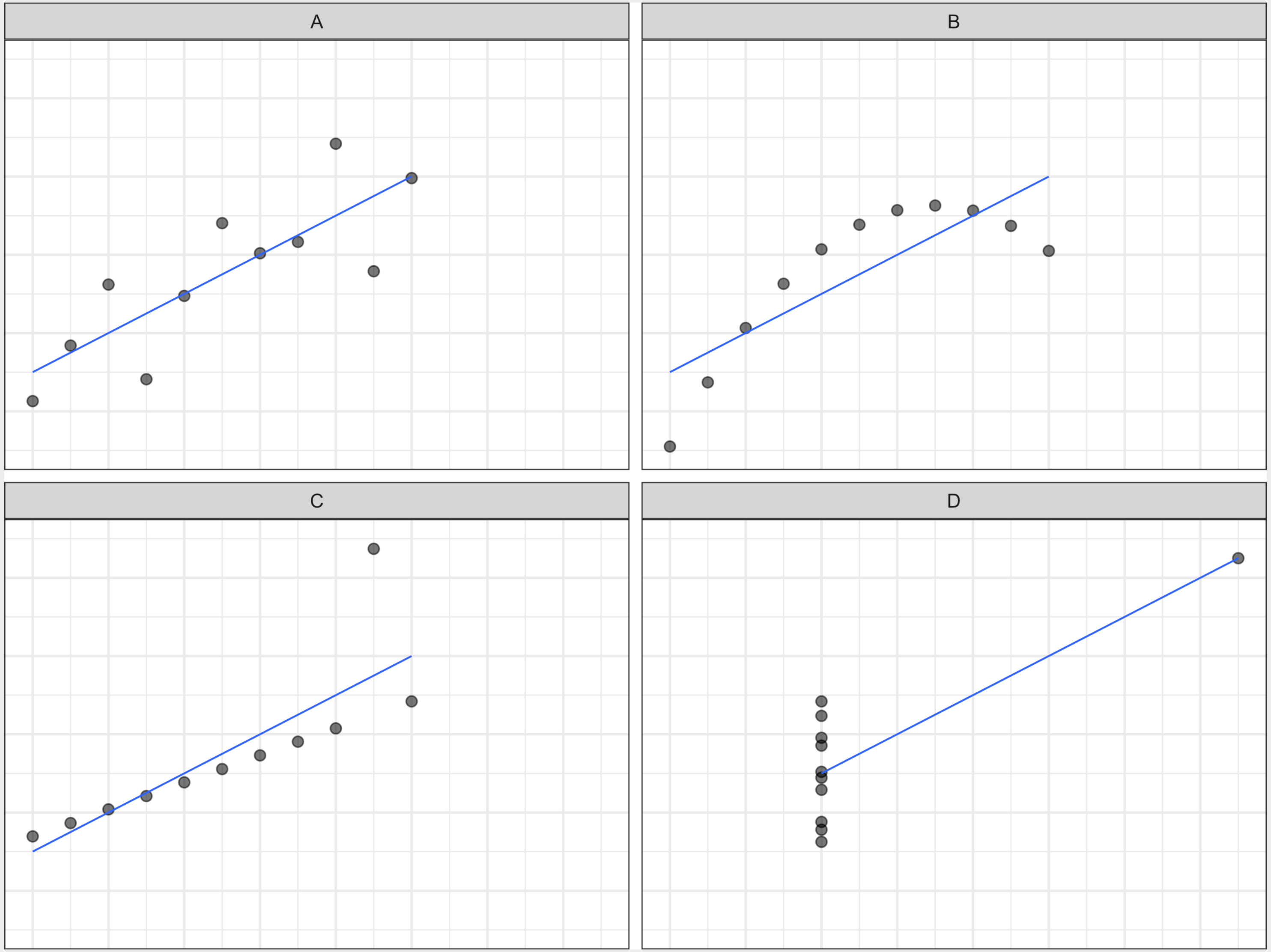


"Visualizing data helps us think[1]"

	A		B		C		D	
	x	y	x	y	x	y	x	y
	10	8.04	10	9.14	10	7.46	8	6.58
	8	6.95	8	8.14	8	6.77	8	5.76
	13	7.58	13	8.74	13	12.74	8	7.71
	9	8.81	9	8.77	9	7.11	8	8.84
	11	8.33	11	9.26	11	7.81	8	8.47
	14	9.96	14	8.1	14	8.84	8	7.04
	6	7.24	6	6.13	6	6.08	8	5.25
	4	4.26	4	3.1	4	5.39	19	12.5
	12	10.84	12	9.13	12	8.15	8	5.56
	7	4.82	7	7.26	7	6.42	8	7.91
	5	5.68	5	4.74	5	5.73	8	6.89
Sum:	99	82.51	99	82.51	99	82.5	99	82.51
Mean:	9	7.5	9	7.5	9	7.5	9	7.5
St. Dev:	3.3	2	3.3	2	3.3	2	3.3	2

1. Stephen Few (2009, pg. 6)

“Visualizing data helps us think[1]”



1. Stephen Few (2009, pg. 6)