


Graphs:
The art of designing information

"A picture tells a thousand words"

- Lake Blanche

1

Graphs are used to try to tell a story



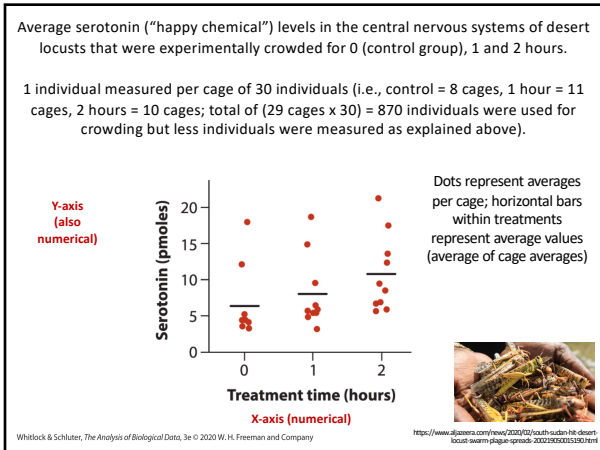
...and to make a point

2

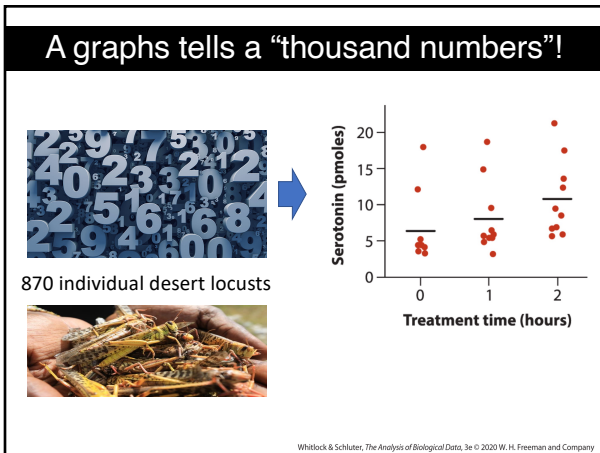
General definition of a graph

- Visual representation of a relationship between two or three variables (and more sometimes).
- Variables can be of any type (e.g., categorical or numerical).
- They commonly consist of two axes: x-axis (horizontal or abscissa) and y-axis (vertical or ordinate).

3



4



5

- Why graphs?**
- Powerful way of summarizing data that is easy to read (i.e., quick and direct).
 - Highlight the most important information (i.e., facilitate communication).
 - Facilitate (summarize) data understanding.
 - Help convince others.
 - Easy to remember (general trends).
 - Aid in detecting unusual features in data.
 - Tell stories.

6

Types of graphs

There are lots of types of graphs! The most commons (and covered in BIOL322) are:

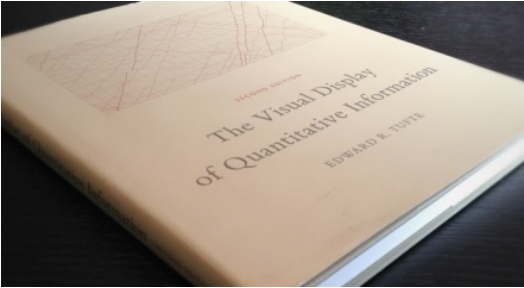
TODAY

- Bar graph
- Pie chart
- Histogram
- Line graph
- Scatter plot
- Strip chart
- Graphs of data distributions (box plots, histograms, violin plot)

7

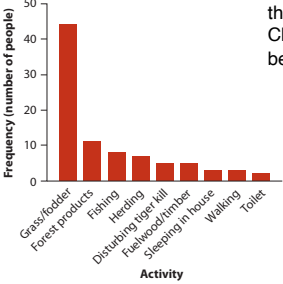
Types of graphs

There are a lots of types of graphs!



8

BAR GRAPH: Vertical or horizontal columns (bars) representing the distribution of a numerical variable against one or more categorical variable.

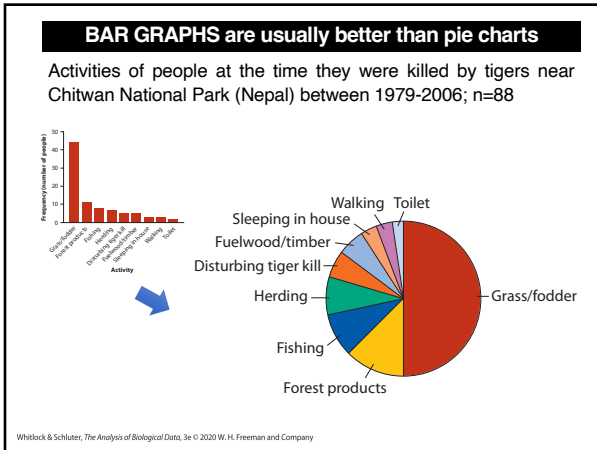


Activities of people at the time they were killed by tigers near Chitwan National Park (Nepal) between 1979-2006; n=88

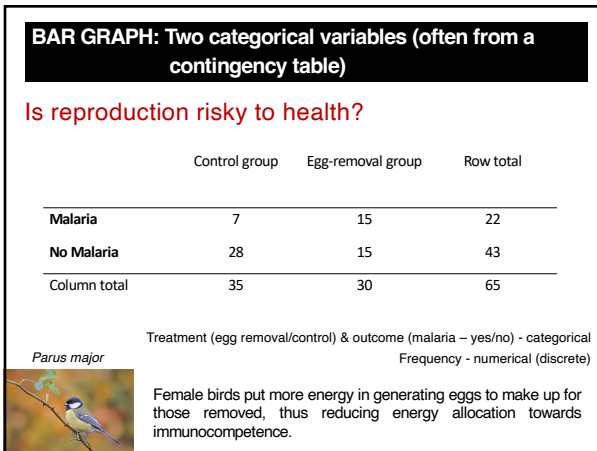
Activity - categorical
Frequency - numerical (discrete)

Whitlock & Schluter, The Analysis of Biological Data, 3e © 2020 W. H. Freeman and Company

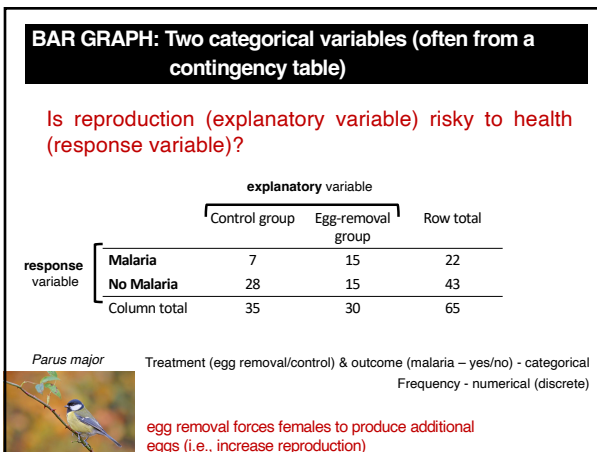
9



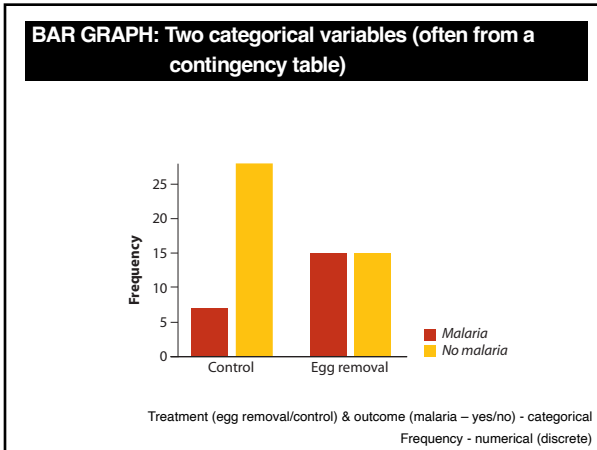
10



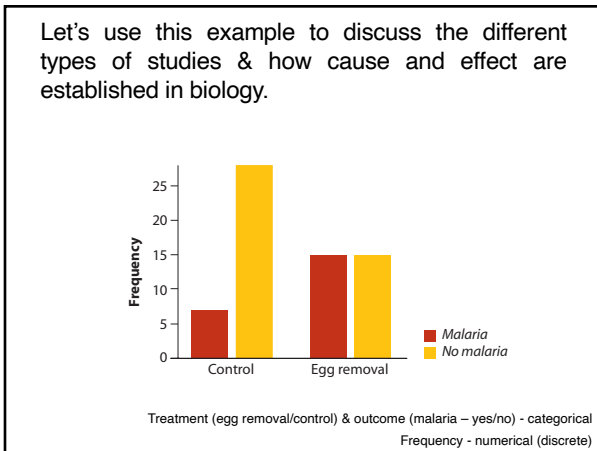
11



12



13



14

Explanatory versus Response variables

- One major use of BioStatistics is to **relate** one variable to another, by examining associations between variables or differences between groups.
- When association between two variables is investigated, a common goal is to assess how well one of the variables, deemed the **explanatory** variable, *predicts* or *affects* (explain) the other variable, called the **response** variable.

15

Explanatory versus Response variables

- One major use of BioStatistics is to **relate** one variable to another, by examining associations between variables or differences between groups.
- When association between two variables is investigated, a common goal is to assess how well one of the variables, deemed the **explanatory** variable, *predicts* or *affects* (explain) the other variable, called the **response** variable.

“Assumed” explanatory power may depend on the type of study:
 [1] **experimental** versus [2] **observational** studies

16

“Assumed” explanatory power may depend on the type of study

Experimental study - Researcher randomly assigns observational units (birds) to different groups (often called treatments), i.e., they control the treatments.

```

    graph LR
      A[Observational units (birds)] --> B[Random assignment]
      B --> C[Control groups]
      B --> D[Egg removal]
      C --> E[Compare the differences between the two groups]
      D --> E
      subgraph Treatments
        C
        D
      end
  
```

17

Explanatory and response variables (experiment)

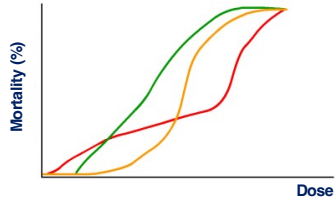
When conducting an experiment (e.g., malaria study in the last slides), the treatment variable (the one manipulated by the researcher) is the **explanatory** variable, and the measured effect of the treatment is the **response** variable.

		explanatory variable		Row total
		Control group	Egg-removal group	
response variable	Malaria	7	15	22
	No Malaria	28	15	43
	Column total	35	30	65

18

Explanatory and response variables (experiment)

Another example of experiment: the administered dose of a toxin in a toxicology experiment would be the **explanatory** variable, and organism mortality would be the **response** variable.



Response to different agents (each one represented by a different color) may vary with increasing dose

<https://toolearn.nlm.nih.gov/htmlversion/module1.html>

19

“Assumed” explanatory power may depend on the type of study

Observational study - Researchers have no control over which observational units fall into which treatment or values of the explanatory variable. Examples:

- Studies on the health consequences of cigarette smoking in humans (unethical to assign smoking and no-smoking treatments to observational units, i.e., people).
- Growth of fish in warm versus cold lakes (observational units, i.e., fish are already in lakes; the research has no control on which fish goes in which lake).

20

Let's take a break - 2 minutes



21

Explanatory and response variables (observational study)

When neither variable is manipulated by the researcher (i.e., observational study; sample of convenience), their association might nevertheless be described by the "effect" of one of the variables (the explanatory) on the other (the response), even though the association itself is not direct evidence for causation.

Whitlock & Schluter, The Analysis of Biological Data, 3e © 2020 W. H. Freeman and Company

22

Explanatory and response variables (observational study)

When neither variable is manipulated by the researcher (i.e., observational study; sample of convenience), their association might nevertheless be described by the "effect" of one of the variables (the explanatory) on the other (the response), even though the association itself is not direct evidence for causation.

Whitlock & Schluter, The Analysis of Biological Data, 3e © 2020 W. H. Freeman and Company

23

Explanatory and response variables (observational study)

Divorce rate in Maine
correlates with
Per capita consumption of margarine (US)

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
Divorce rate in Maine (Divorces per 1000 people (US Census))	5	4.7	4.6	4.4	4.3	4.1	4.2	4.2	4.2	4.1
Per capita consumption of margarine (US Pounds (USDA))	8.2	7	6.5	5.3	5.2	4	4.6	4.5	4.2	3.7

Correlation: 0.992558

Permalink - Mark as interesting - Not interesting <http://www.vigen.com/vigen/correlation/9-1203>

24

Independent versus dependent variables = explanatory versus response variables, respectively

Strictly speaking, if one variable depends on the other, then neither is independent, so we rather say **explanatory** and **response** (e.g., in Whitlock and Schluter).

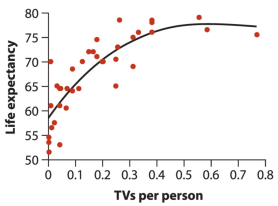
Sometimes you will hear variables referred to as "**independent**" and "**dependent**". These are the same as **explanatory** and **response** variables, respectively.

25

Independent versus dependent variables = Explanatory versus response variables, respectively

Strictly speaking, if one variable depends on the other, then neither is independent, so we rather say **explanatory** and **response** (e.g., in Whitlock and Schluter).

Sometimes you will hear variables referred to as "**independent**" and "**dependent**". These are the same as **explanatory** and **response** variables, respectively.



Life expectancy

TVs per person

Regardless whether the association is causal, the expected explanatory variable goes in the X-axis and the expected response variable goes in the Y-axis.


Whitlock & Schluter, The Analysis of Biological Data, 3e © 2020 W. H. Freeman and Company

26

Back to BAR GRAPHS: two categorical variables

Is reproduction risky to health?

		explanatory variable		Row total
		Control group	Egg-removal group	
response variable	Malaria	7	15	22
	No Malaria	28	15	43
Column total		35	30	65



Parus major

Treatment (egg removal/control) & outcome (malaria – yes/no) - categorical
Frequency - numerical (discrete)

27

Back to BAR GRAPHS: two categorical variables

Is reproduction risky to health?
Not so clear from this bar graph

Treatment	Malaria (Frequency)	No malaria (Frequency)
Control	7	25
Egg removal	15	15

Treatment (egg removal/control) & outcome (malaria – yes/no) - categorical
 Frequency - numerical (discrete)

28

BAR GRAPHS (stacked = mosaic graph): Two categorical variables

Is reproduction risky to health? Much clearer now!

Treatment	No malaria (Relative frequency)	Malaria (Relative frequency)
Control	0.8	0.2
Egg removal	0.5	0.5

Treatment (egg removal/control) & outcome (malaria – yes/no) - categorical
 Frequency - numerical (discrete)

Whitlock & Schluter, The Analysis of Biological Data, 3e © 2020 W. H. Freeman and Company

29

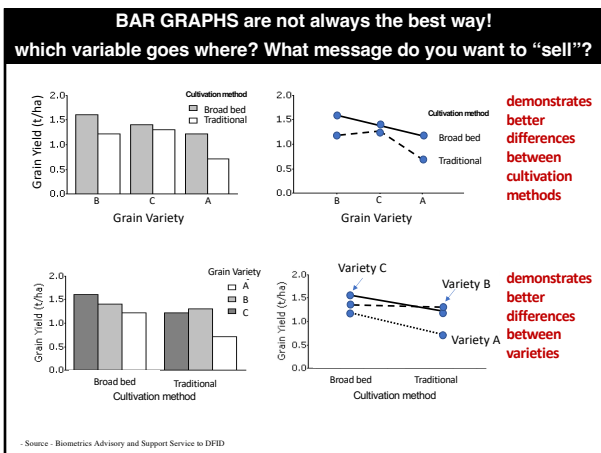
BAR GRAPHS are not always the best way!
 (these graphs are based on the same data)

Grain Variety	Broad bed (t/ha)	Traditional (t/ha)
B	1.5	1.2
C	1.4	1.3
A	1.3	0.8

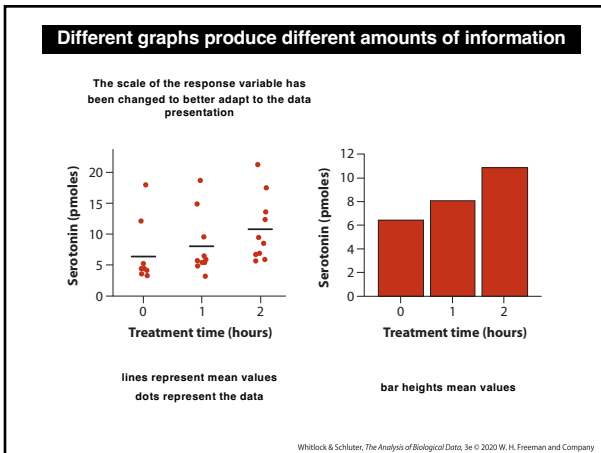
Traditional (continuous, non-spaced) Broad bed (spaced)

Source - Biometrics Advisory and Support Service to DFID

30



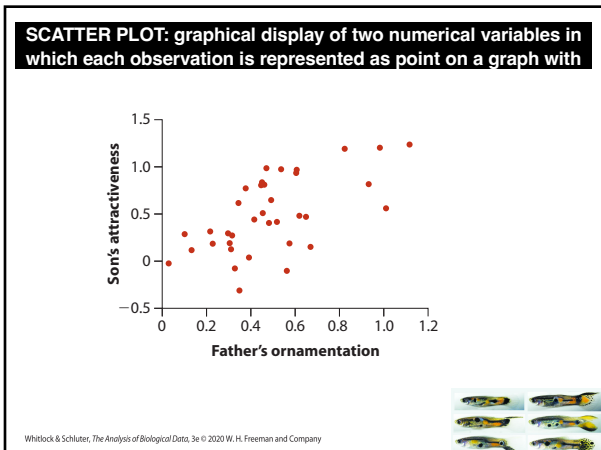
31



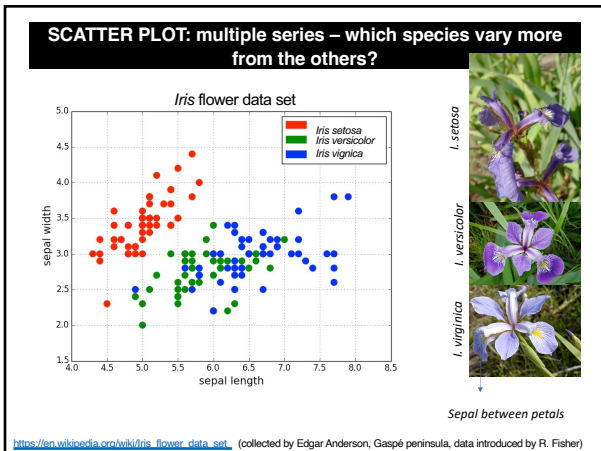
32



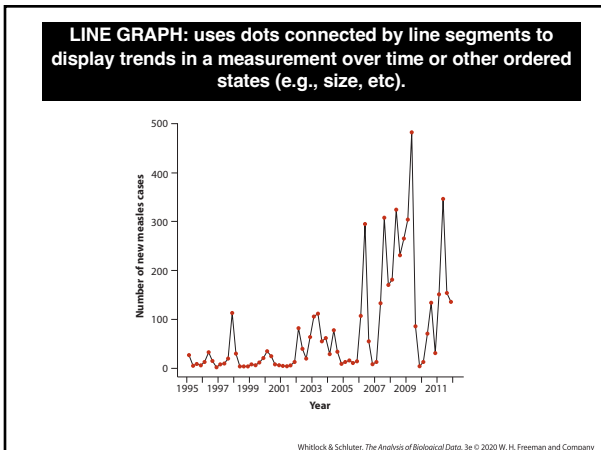
33



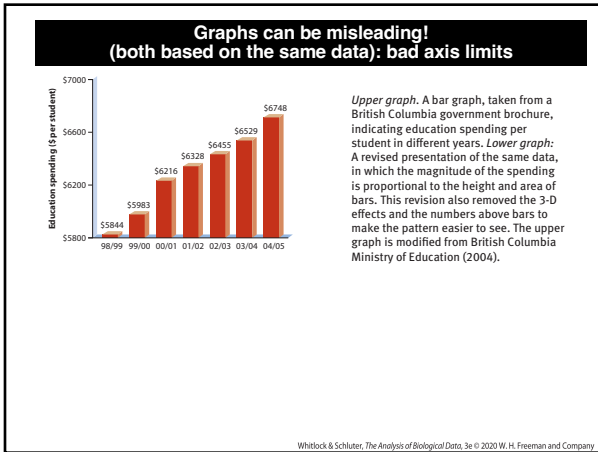
34



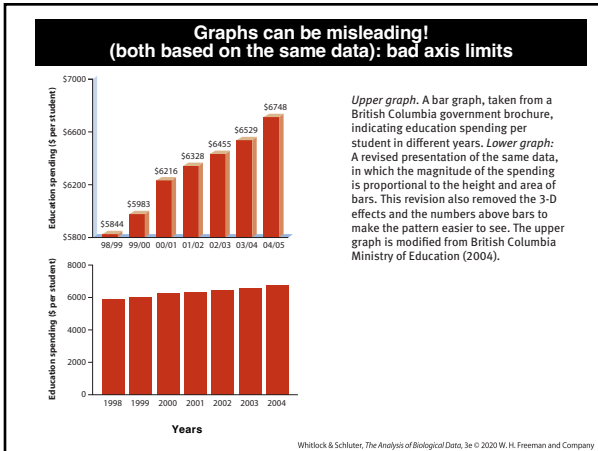
35



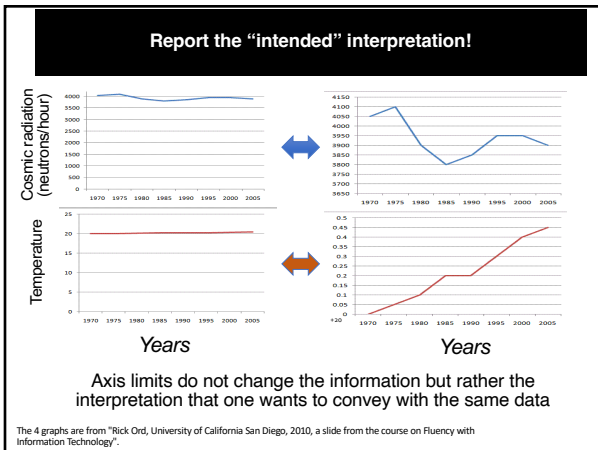
36



37



38



39

Graphs:
The art of designing information

“A picture tells a thousand words”

- Lake Blanche

40

Next lecture: How to build frequency distributions and introduction to descriptive (or summary) statistics

41

Rules of Data visualization
(asynchronous component of lecture 3)

42

How to Make a Good Plot

1. Show the data.
2. Make patterns easy to see.
3. Display magnitudes honestly.
4. Draw graphics clearly.

© 2020 W.H. Freeman and Company

43

How to Make a Bad Plot

1. Hide the data.
2. Make patterns hard to see.
3. Display magnitudes dishonestly.
4. Draw graphics unclearly.

© 2020 W.H. Freeman and Company

44

Mistakes in displaying data
Mistake 1. Hide the data

45

Mistake 1: Hide the data

How to hide data:

- Provide only statistical summaries.
- Over-plotting.

How to reveal data:

- Present all data points, while allowing all to be seen.

© 2020 W.H. Freeman and Company

46

Not Showing Data, Just Summaries

This plot hides the variation within positions.

Mean heights of NBA players by position

Position	Mean Height (inches)
G	~75
G/F	~78
F	~80
F/C	~81
C	~82

© 2020 W.H. Freeman and Company

47

Not Showing Data, Over-Plotting

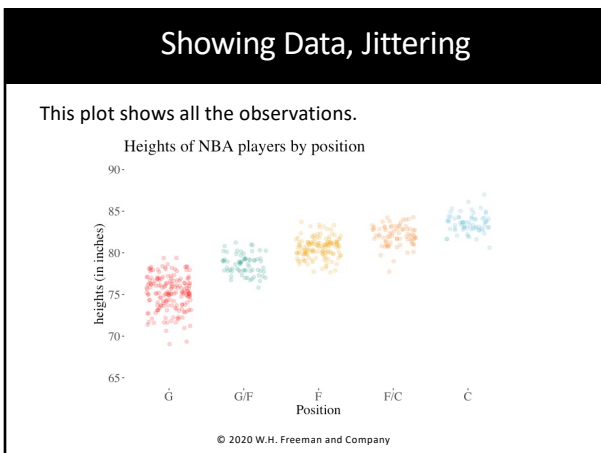
This plot hides the density of observations.

Heights of NBA players by position

Position	Height Range (inches)
G	~68 - 79
G/F	~76 - 82
F	~78 - 85
F/C	~78 - 85
C	~81 - 88

© 2020 W.H. Freeman and Company

48



49

Mistakes in displaying data

Mistake 2. Making patterns hard to see

50

Mistake 2: Making Patterns Hard to See

How to hide patterns:

- Make one plot and call it good.
- Use unreasonable scales.
- Arrange factors nonsensically.

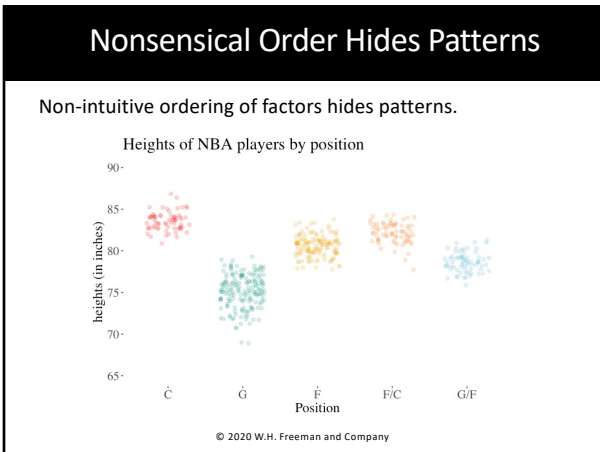
How to reveal patterns:

- Explore multiple potential plots.
- Use appropriate scales.
- Arrange factors meaningfully.

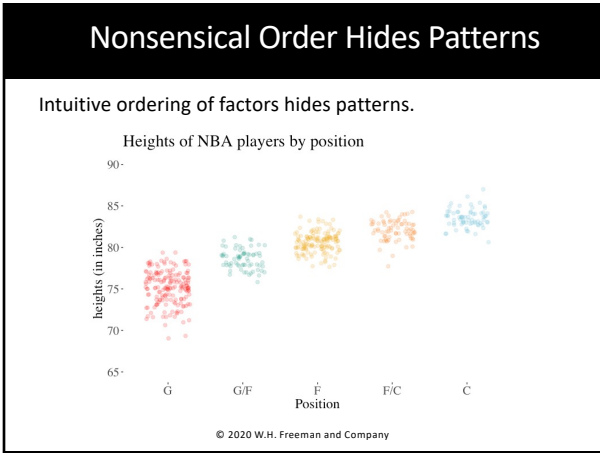
Arrange in order for ordinal, by mean for nominal.

© 2020 W.H. Freeman and Company

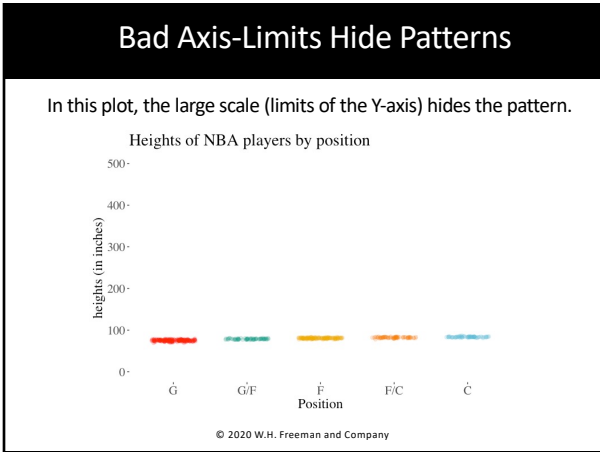
51



52



53



54