Data and Measurement

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Logistics

- Be sure to install `R` and `RStudio` this week!

To R!

Data Foundations

Observations

- **The rows in our data**
- These are the units of analysis, or objects of interest, that we care about.
- Could be comprised of individual entities, such as individual people, animals, etc.
- Could be more aggregate units of analysis: schools, districts, etc.
- Defines the scope and nature of the analysis that will be performed

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- Defines the scope and nature of the analysis that will be performed
- Terminology (often used interchangeably, though sometimes context-dependent):
  - Observation
  - Case
  - Instance
  - Individual
  - Record
  - ...

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  2. For other variables used to make predictions (or for other analyses):
     - Predictors
     - Features
     - Independent Variables
     - Input Variables
     - Covariates

Data Set

- A collection of data is referred to as a data set
- "Clean" or structured data sets typically arranged in tables (a.k.a. data frames)

A Data Set of Classic Books

ID	Title	Author	Year	Cover	Edition	Price
1	Emma	Austen	1815	Paperback	20	5.75
2	Dracula	Stoker	1897	Hardback	15	12.00
3	Ivanhoe	Scott	1820	Hardback	8	25.00
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Variable Types (Mathematical/Conceptual View)

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1. Quantitative/Numeric
   - For characteristics that can naturally be represented by numbers
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2. Categorical/Nominal
   - For characteristics comprised of classes, categories, etc.
   - When used for rigorous analysis, should be a fixed set of possibilities, known as levels (possible categories/values)
   - Sometimes represented as numbers for convenience but should not be treated as such (See Codebooks!)

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  - e.g. Likert scale
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- Indicator/Binary
  - Variable measuring/indicating whether a case belongs to a particular category or not
  - Often coded as 1/0
  - Multi-class categorical variables often transformed into a set of indicator ("dummy") variables for analysis

Variable Types: Conceptual View vs. Computer's View

- Sometimes need to be careful to distinguish between a variable's conceptual/mathematical "type" and its representation/encoding on the computer
- Representation/encoding is how it appears in a data set and is viewed by the computer (i.e. its `class` according to `R`)...
- But its conceptual type determines how it should be analyzed

Variable Types: Conceptual View vs. Computer's View

- For instance, consider a categorical variable that is encoded as numeric/integers:

```
> favorite_color
[1] 1 5 2 6 3 2 1 3 4 2

> class(favorite_color)
[1] "numeric"

> mean(favorite_color)
[1] 2.9
```

Variable Types: Conceptual View vs. Computer's View

- Or a binary indicator that is encoded as character:

```
> won_election
[1] "Yes" "No"  "Yes" "Yes" "Yes" "No"  "No"  "Yes"

> class(won_election)
[1] "character"

> mean(won_election)
[1] NA
Warning message: In mean.default(won_election) :
  argument is not numeric or logical: returning NA

> mean(won_election == "Yes")
[1] 0.625
```

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- A variable comprised of numbers might have such a limited number of values that it makes more sense to treat it as a categorical variable (e.g. election year for a sample of Senators)

Character vs. Factor Variables in R

- Both "character" and "factor" variable types can be used to represent categorical data comprised of strings in R.
- While factors look (and often behave) like character vectors, they are actually stored as integers under the hood (with character labels associated with the unique integers).
- Once created, factors can only contain a pre-defined set of values, known as levels.
- Strings are converted to factor variables by default in many standard functions in R, including `data.frame()`, `read.csv()`, and `read.table()`.
- Behavior of character and factor variables can vary in important ways, so always be aware of your variable class in R!

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"Messy data" is any other other arrangement of the data. "Tidy datasets are all alike, but every messy dataset is messy in its own way."

Key Considerations and Common Challenges

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- Sample
  - Selection/subset of cases from the population that you actually have data on
  - "Sample size" refers to the number cases in the sample
  - Usually a relatively small proportion of the population
  - If the sample is the full population, then it is a "census"

Sampling

- Goal: Usually to understand or find something out about a broad population
- Problem: It can be expensive, impossible, or destructive to collect information on an entire population
- Solution: Sampling, or the act of collecting a sample
- Challenge: External validity (is what you can learn about the sample reflective of the truth about the population?)
- Types of samples (not exhaustive)
  - Simple random sample
  - Convenience samples

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- But downsides to collecting more cases and measuring more variables
  - Costs time and money
  - Adding nonsense variables could make things worse through (a) distraction, (b) computational tractability, (c) adding noise
  - And adding more cases in a nonrepresentative manner will damage external validity

Common Problems

- Data Missingness (variable values missing for some cases)
  - Failure to measure
  - Non-response bias
- Mismeasurement
  - Entry errors or typos
  - Mechanical/natural mismeasurement
- Atypical Values
  - Outliers (quantitative)
  - Sparsity (categorical)
- Inconsistent variable coding
  - Variable unit of measurement
  - Variable type

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- Nonrepresentativeness of bias in the sample could be the result of:
  - Imperfect sampling strategy by the researcher
  - Non-response bias / non-random data missingness
  - Self-selection bias into the sample
- These issues are notoriously thorny in the case of surveys of people
  - e.g. Political polls or surveys

Bonus Slides: Human Discretion with Data

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3. Actualized
   - Precise quantity that is actually measured such that the operational variable can be systematically encoded into data
   - This is what is actually present in the dataset
   - Must decide how to measure the operational variable, in the real world, subject to practical requirements and constraints

Measuring Variables

1. Conceptual
   - Ex. 1 Size
   - Ex. 2 Health
   - Ex. 3 Happiness
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   - Ex. 1 ...
   - Ex. 2 ...
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   - Ex. 3 Self-reported happiness score
3. Actualized
   - Ex. 1 Height measured in feet
   - Ex. 2 Sum of the number of a patient's conditions that are classified as "active" and belong to the reference dictionary of "chronic conditions"
   - Ex. 3 Self-reported level of happiness on a scale of 1 to 10, where 1 denotes "extremely unhappy" and 10 denotes "extremely happy"

The differences are not simply an issue of objectivity vs. subjectivity. Actualized variables can be quite subjective.

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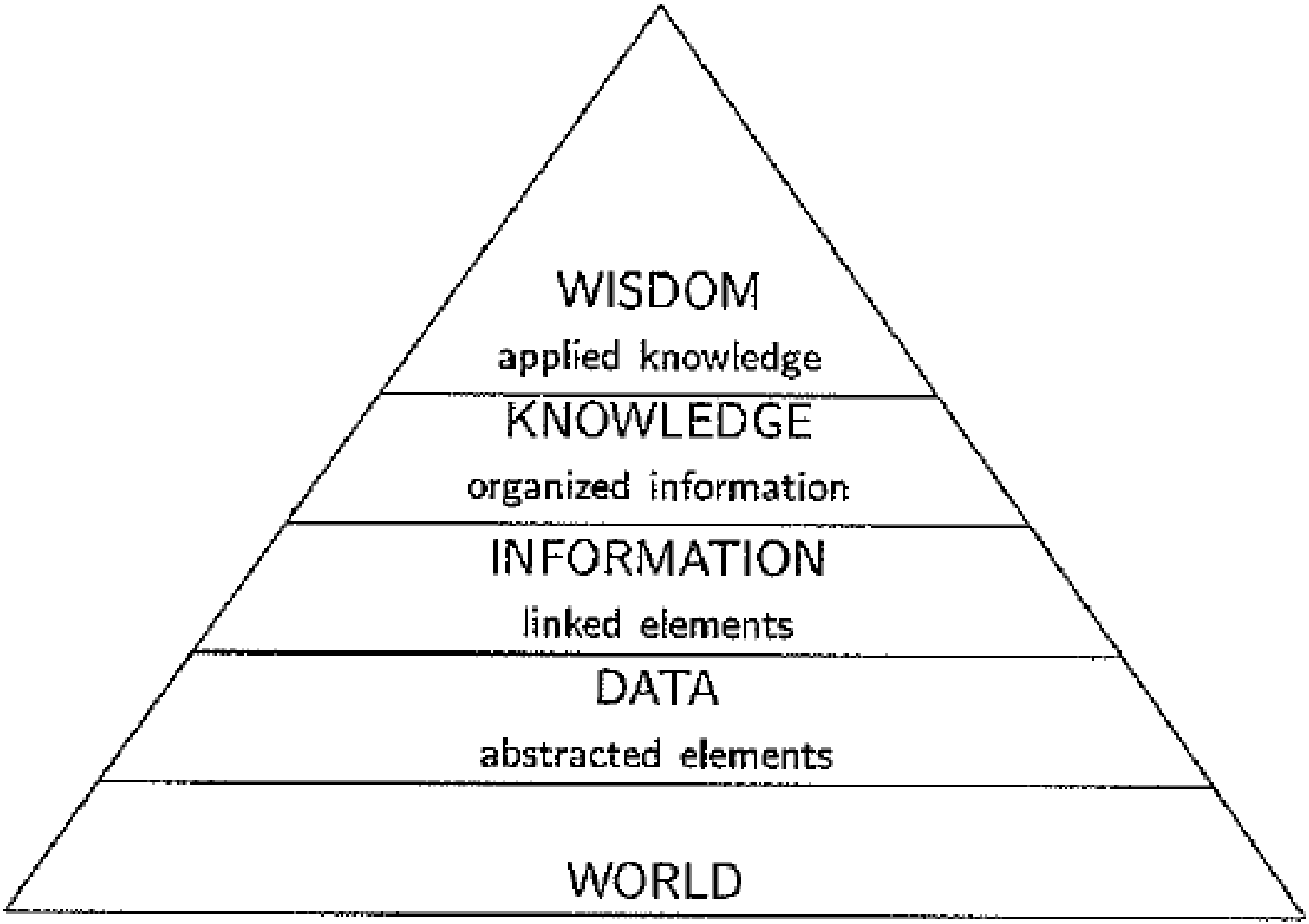
- Establishing validity of measurement is often subjective
- Andrew Gelman: "the #1 neglected topic in statistics is measurement."


WISDOM
applied knowledge
KNOWLEDGE
organized information
INFORMATION
linked elements
DATA
abstracted elements
WORLD

A Day in the Life of a Data Scientist

According to 2016 survey of data scientists, this is the breakdown of time spent on different tasks:

- Data Collection: 19%
- Cleaning and Organizing Data: 60%
- Building Training Sets: 3%
- Mining Data for Patterns: 9%
- Refining Algorithms: 4%
- Performing Other Tasks: 5%

Install R and RStudio!!!