

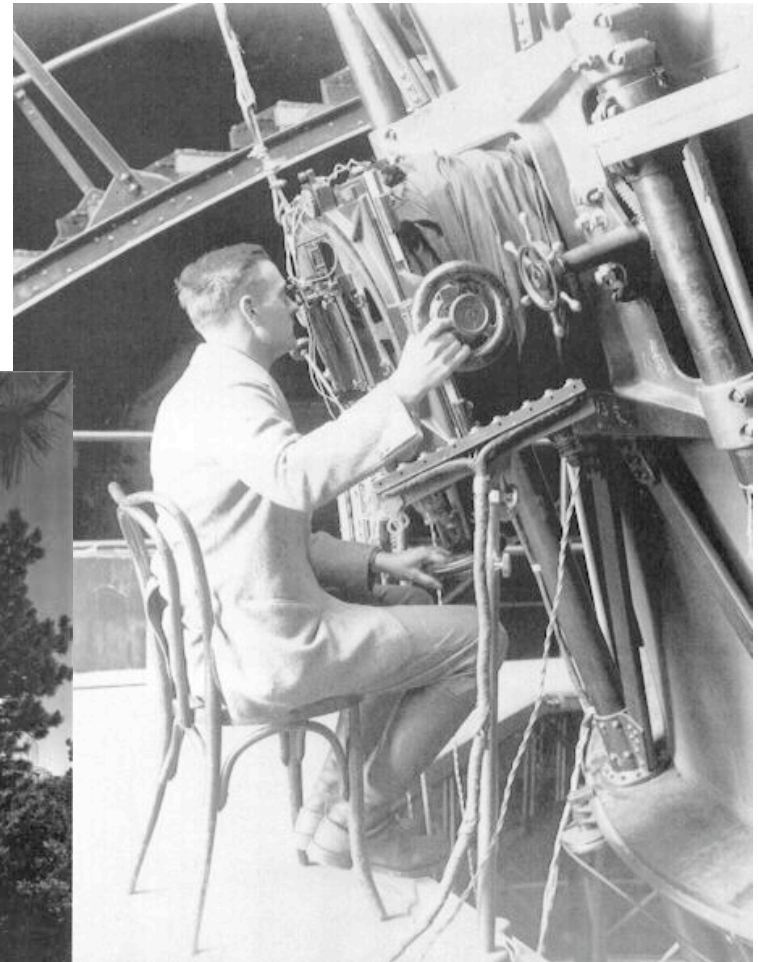
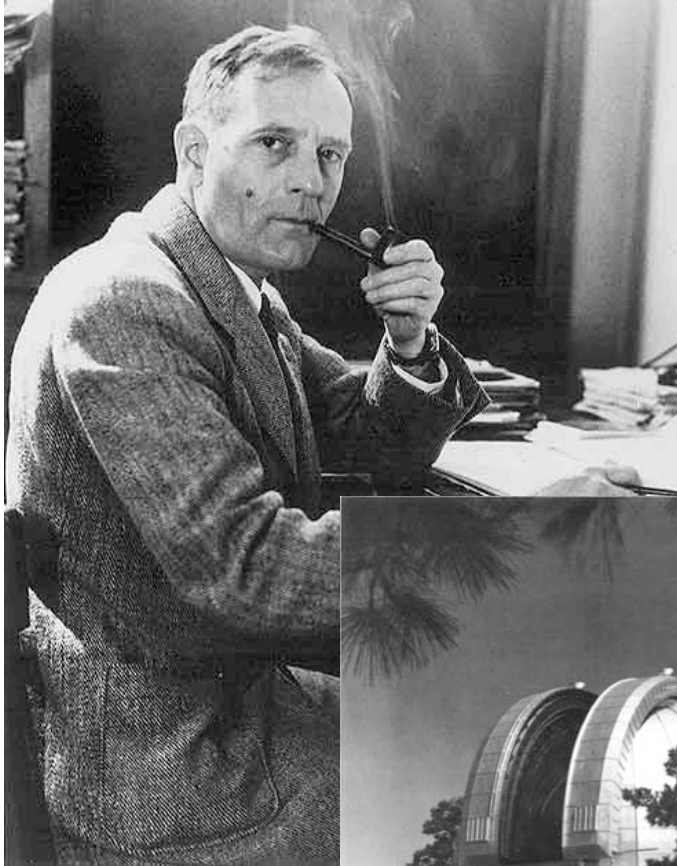
# Exploratory Data Analysis

4 March 2009

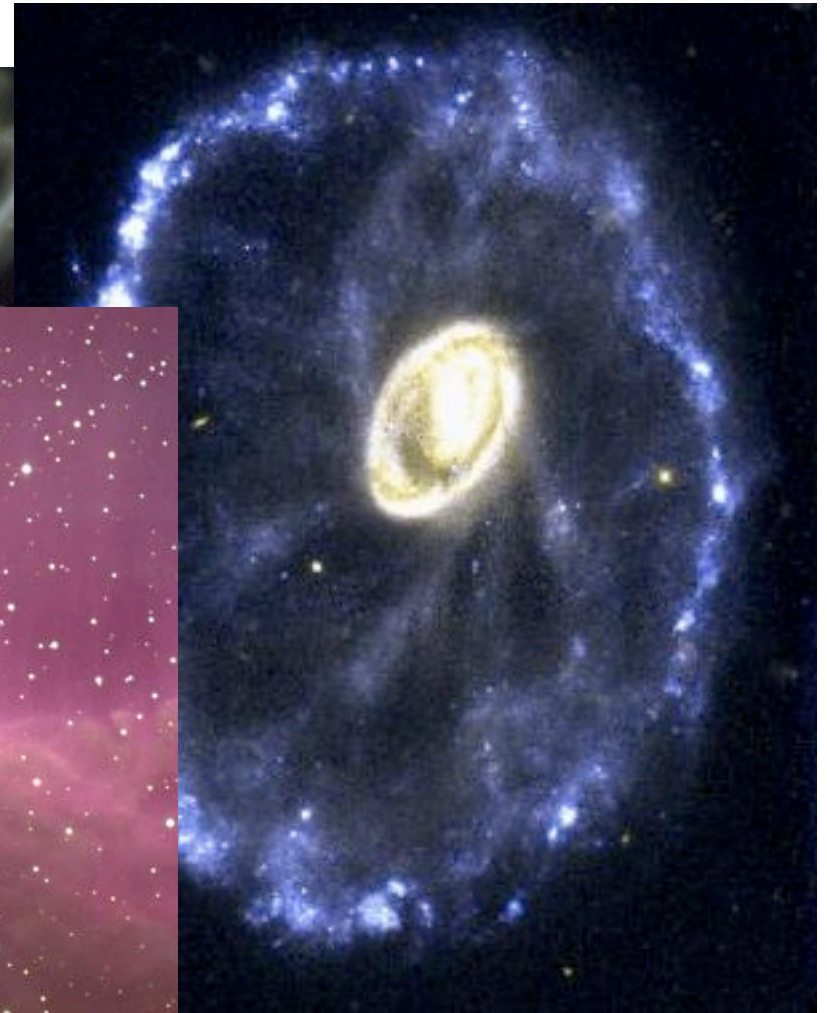
Research Methods for  
Empirical Computer Science  
CMPSCI 691DD



# Edwin Hubble

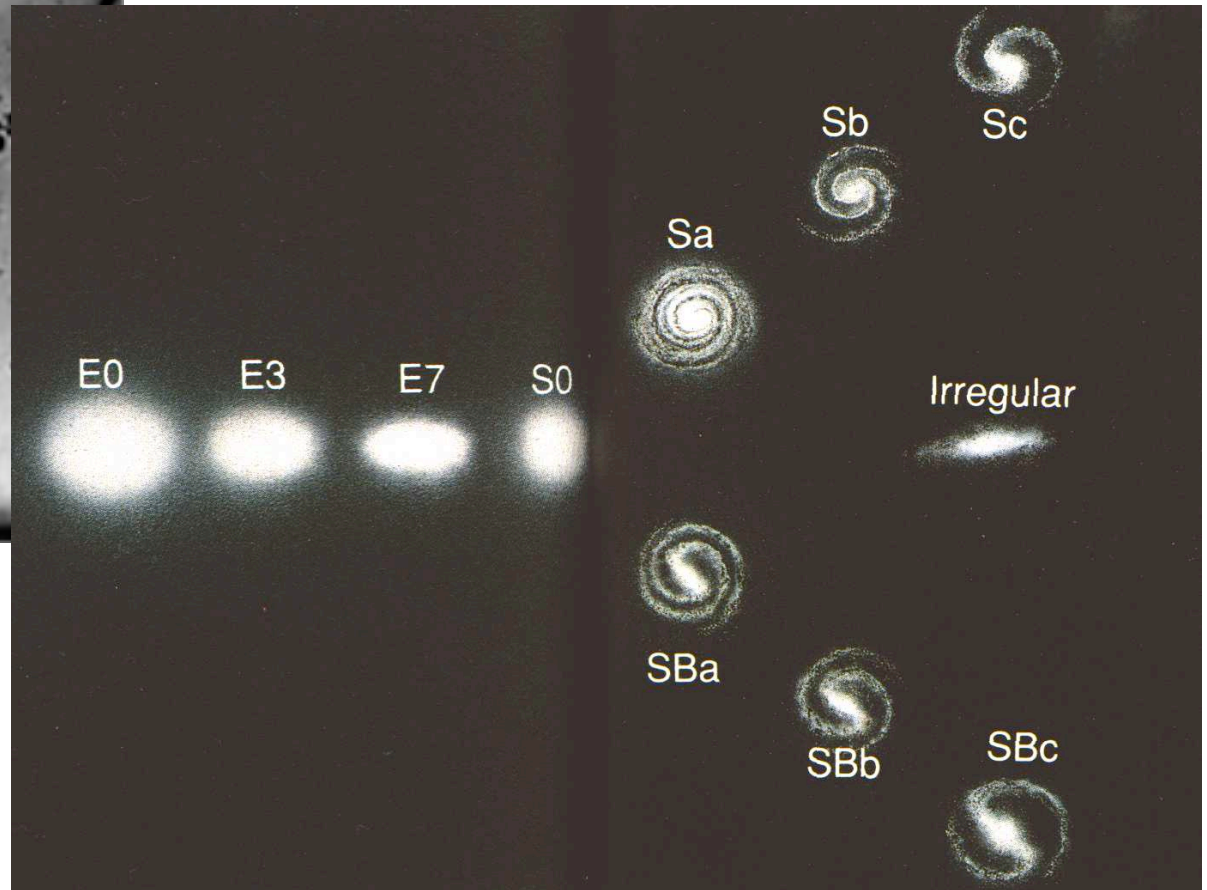
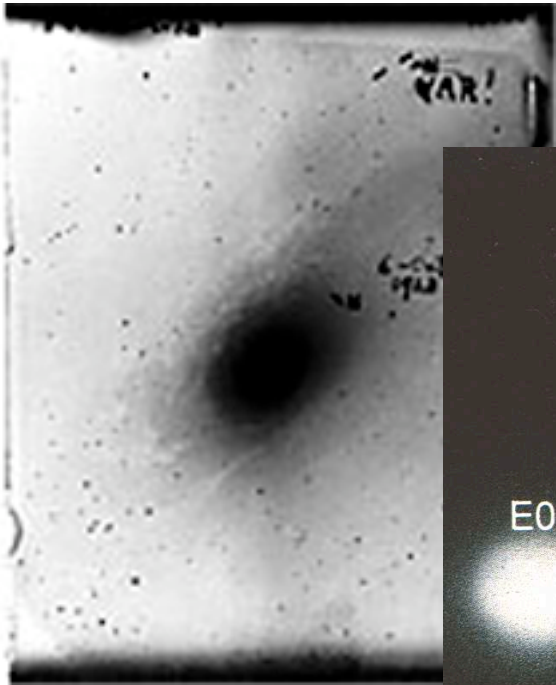


# What did Hubble see?





# What did Hubble see?



# Hubble's Law

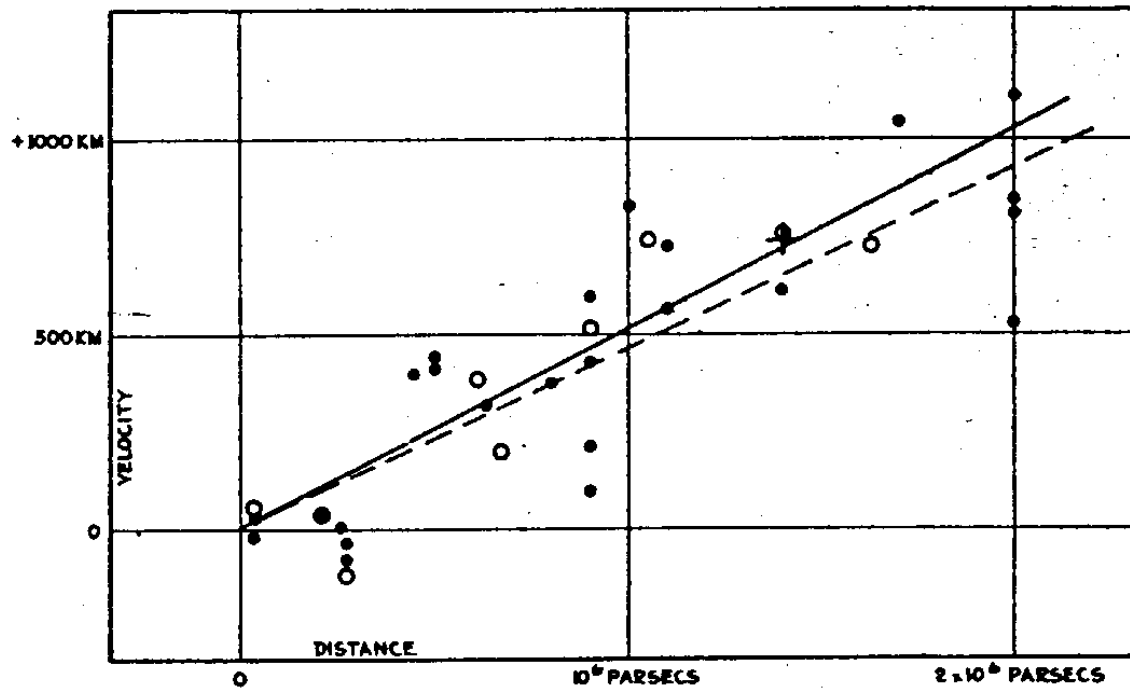


FIGURE 1

$$V = H_0 r$$

Where:

$V$  = recessional velocity

$H_0$  = Hubble constant

$r$  = distance (mpc)

E. Hubble (1929). A relation between distance and radial velocity among extra-galactic nebulae.

*Proceedings of the National Academy of Sciences* 15(3).

# Hubble's Law

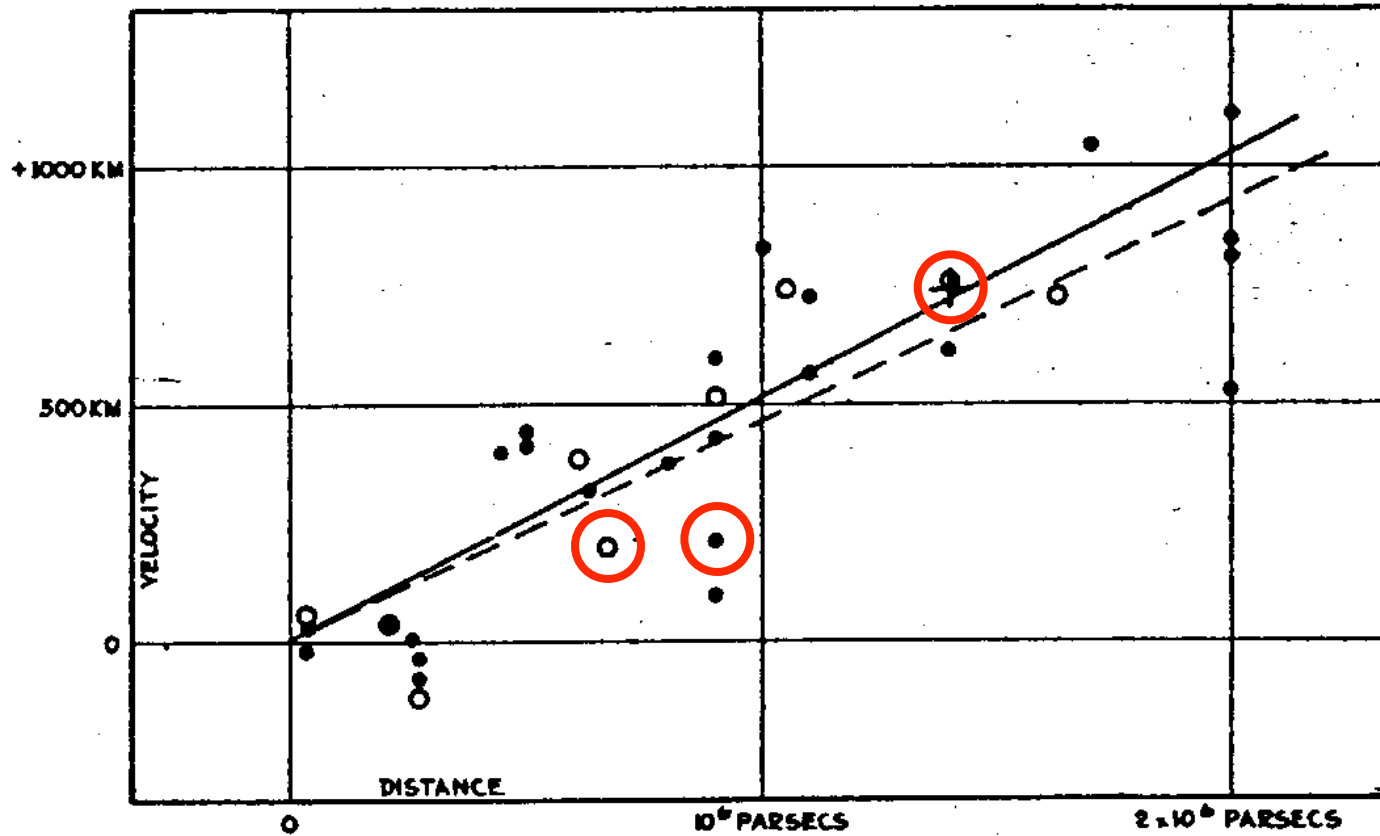
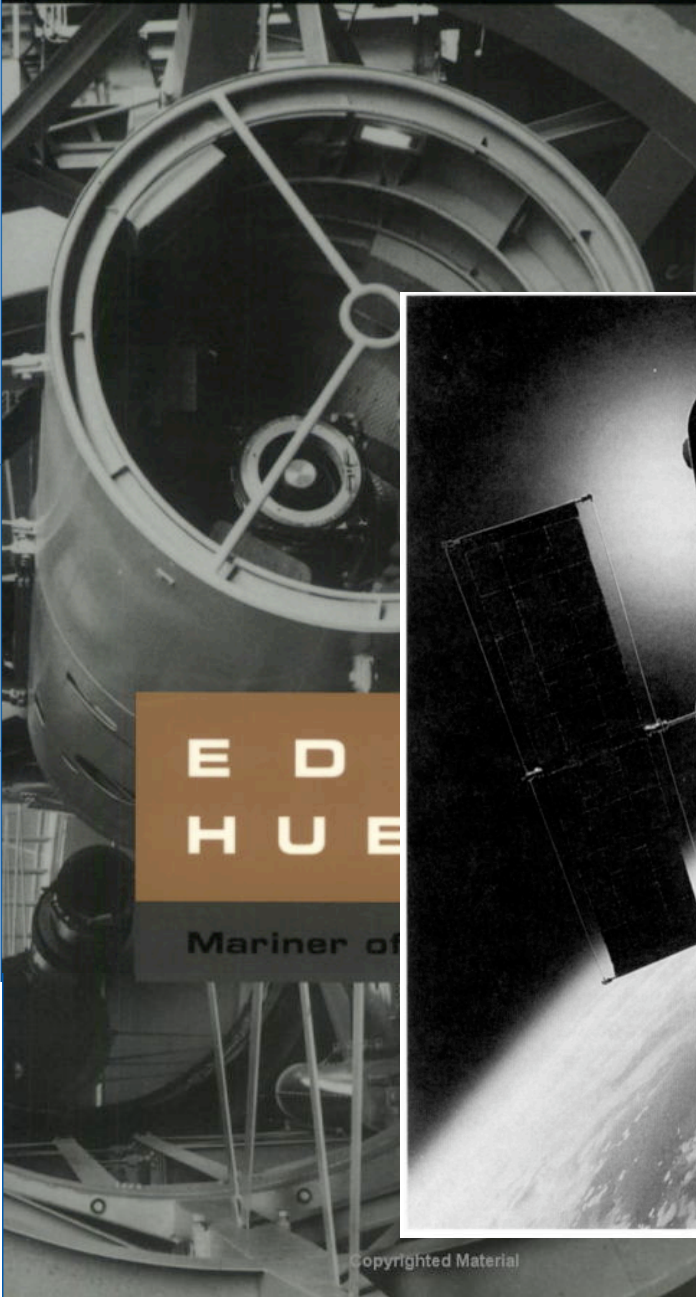


FIGURE 1

GALE E. CHRISTIANSON

Copyrighted Material



ED  
HUE

Mariner of

Copyrighted Material



**“The tool that is so dull that  
you cannot cut yourself on it  
is not likely to be sharp enough  
to be either useful or helpful.”**

– John W. Tukey





# Random variables

- The “embarrassingly dogmatic misnomer”
- They are neither *random*, nor are they *variables*
- A random variable is...
  - a function that maps from *instances* to *scales*
  - the numeric result of a non-deterministic experiment
- They can be distinguished from “fixed variables” whose value can be set or predetermined before the experiment
- They are not the individual values (e.g., 5.92), but rather the *process* of assigning value to instances or (colloquially) the set of values so assigned

# Examples

- *Recall* of an IR system, given query, corpus, and designated relevant documents
- *Size and speed* of code produced by a compiler, given source and a target processor
- *Number of database rows returned*, given an anytime query processor, query, database, and time
- *Lines of code written*, given an assignment, language, development environment, and programmer

## Notes

- The objects of study are usually the systems that enable random variables (e.g., IR systems), rather than the instances that the measures are on (e.g., queries).
- What we define as a random variable for a particular experiment can change as we discover deterministic and causal relationships in a given system

# Representation of data instances

- *i.i.d. instances* are commonly assumed
  - Independent — Knowing something about one instance tells you nothing about another
  - Identically distributed — Drawn from the same probability distribution
- Examples?
  - Queries in TREC data
  - Programs in SPEC benchmarks
  - Data sets in UCI repository
- Some alternatives
  - Time series  
(e.g., users submitting sets of slightly modified queries)
  - Relational  
(e.g., router performance embedded in a network)

# Populations and samples

- A population is a specified set of instances
  - An actual finite set of instances (e.g., the UCI data sets for machine learning research)
  - A generalization of an actual finite set (e.g., the set of all data sets that might be produced by a particular simulator in infinite time)
  - A purely hypothetical set which can be described mathematically (e.g., the set of all correct Java programs)
- Samples are finite subsets of populations



# Examples

## Populations

## Actual data samples

---

All possible  
IR queries

The TREC 2005  
HARD queries

All possible programs  
written in Java

The SPECjvm98  
benchmarks

All Java programmers  
active in 2005

Students taking  
CMPSCI 320 in Fall 2005

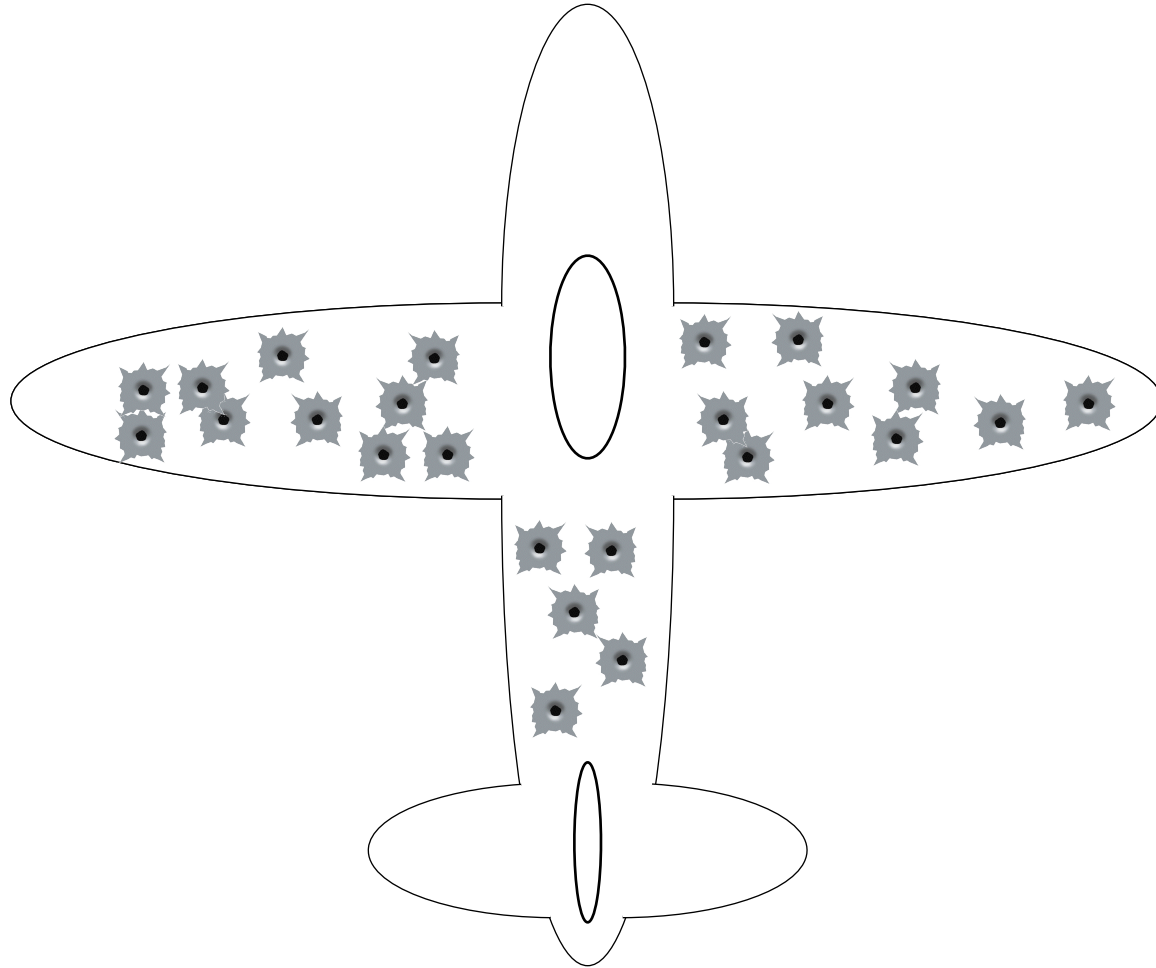
The SPECjvm98  
benchmarks

A subset of  
the benchmarks

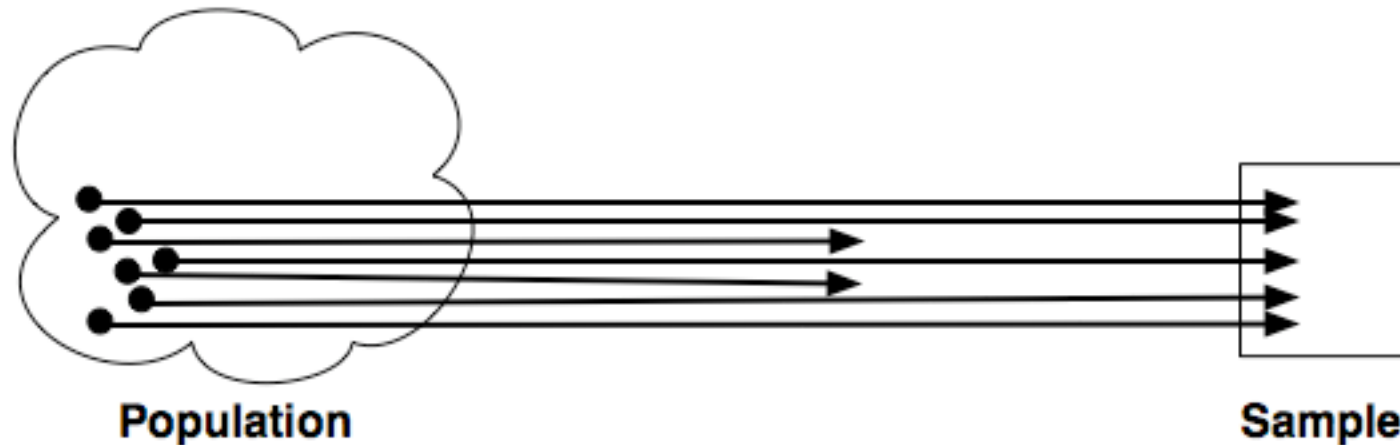
# Four stages of defining a sample

- The ***target population***  
(e.g., all computer programs)
- The ***sampling frame***  
(all programs written in Java or C++)
- The ***selected sample***  
(all programs written by CS undergraduate students in 200-level courses at UMass)
- The ***actual sample***  
(all programs actually turned in)

# Why is sampling difficult?



# Sampling problems



- The *target population*
- The *sampling frame*
- The *selected sample*
- The *actual sample*

# Random sampling in CS

- Random sampling isn't easy in CS
- ...but it's not easy in most sciences
- Answer isn't to give up, but to consider how to get closer to the ideal
  - Define the ideal population
  - Identify sources of bias in sampling and in subsequent steps of sample definition
  - Remove or mitigate as many sources of bias as possible
- Modify your confidence in your ability generalize based on your assessment of the match between your actual sample and your desired population



# Types of scales

- **Categorical, discrete, or nominal** — Values contain no ordering information (e.g., multiple-access protocols for underwater networking)
- **Ordinal** — Values indicate order, but no arithmetic operations are meaningful (e.g., "novice", "experienced", and "expert" as designations of programmers participating in an experiment)
- **Interval** — Distances between values are meaningful, but zero point is not meaningful. (e.g., degrees Fahrenheit)
- **Ratio** — Distances are meaningful and a zero point is meaningful (e.g., degrees K)

# Data transformations

- Downgrading type (e.g., interval to ordinal)
- Shifting intervals
  - Tukey's “ladder of powers”:  $\text{trans} = \text{original}^{(1-b)}$
  - E.g.:  $-2 \rightarrow \text{original}^3$ ,  $0.5 \rightarrow \sqrt{\text{original}}$ ,  $2 \rightarrow 1/\text{original}$
- Combining several variables
  - Normalize measurements  
(e.g., Simsek & Jensen 2005, normalized to optimal)
  - Remove unwanted factors  
(e.g., remove file read times from total compile times)
  - Consider relation of two variables  
(e.g., Kirkpatrick & Selman, vertex/edge ratio)

# Exploratory data analysis

- “Exploratory data analysis (EDA)... employs a variety of techniques to...
  - maximize insight into a data set;
  - uncover underlying structure;
  - extract important variables;
  - detect outliers and anomalies;
  - test underlying assumptions;
  - develop parsimonious models; and
  - determine optimal factor settings”
- “The EDA approach is precisely that — an approach — not a set of techniques, but an attitude/philosophy about how a data analysis should be carried out.”

# Why EDA?

- Data analysis tools are typically used for
  - Hypothesis testing
  - Parameter estimation
- Graphics tools are typically used for presentation
- However, much of the quality of scientific work is determined by the quality of the hypotheses and models used by the researcher
- Can data analysis help suggest hypotheses?

# Resources

- Books
  - *Exploratory Data Analysis*, Tukey, (1977)
  - *Data Analysis and Regression*, Mosteller and Tukey (1977)
  - *Interactive Data Analysis*, Hoaglin (1977)
  - *The ABC's of EDA*, Velleman and Hoaglin (1981)
- Software
  - Data Desk (Data Description)
  - Fathom (Keypress)
  - XGobi (AT&T Research)



# Exploratory Data Analysis



Copyright © 2009, 2015 David Jensen.

Except where noted, this material is licensed under a Creative Commons Attribution-NonCommercial-ShareAlike 4.0 International License.

<http://creativecommons.org/licenses/by-nc-sa/4.0/>

All content not licensed under a Creative Commons license has all rights reserved, and you must request permission from the copyright owner to use this material.

Material not licensed under a Creative Commons License is:

- Images on pp. 2–8, 17
- Text on pp. 8, 21

For related context, please see the following paper:

Jerod Weinman, David Jensen, and David Lopatto. 2015. Teaching Computing as Science in a Research Experience. In *Proceedings of the 46th ACM Technical Symposium on Computer Science Education (SIGCSE '15)*. ACM, New York, NY, USA, 24-29. <http://dx.doi.org/10.1145/2676723.2677231>

Other slides in this series may be found here: <http://dx.doi.org/11084/10002>