

Sampling and uncertainty

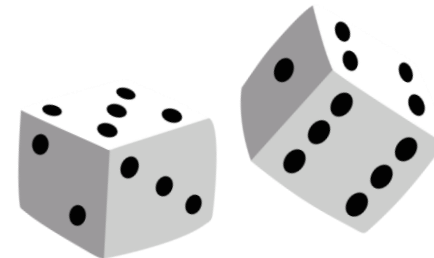
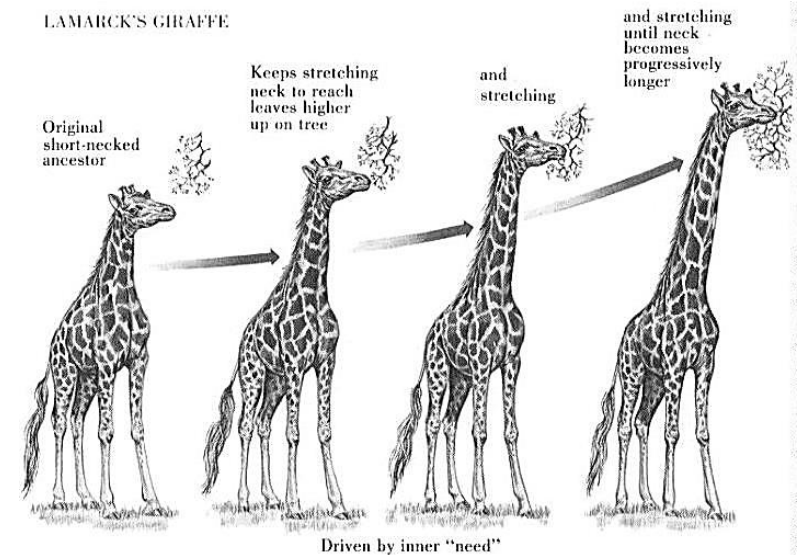
Michael Otterstatter

BCCDC Biostats Session

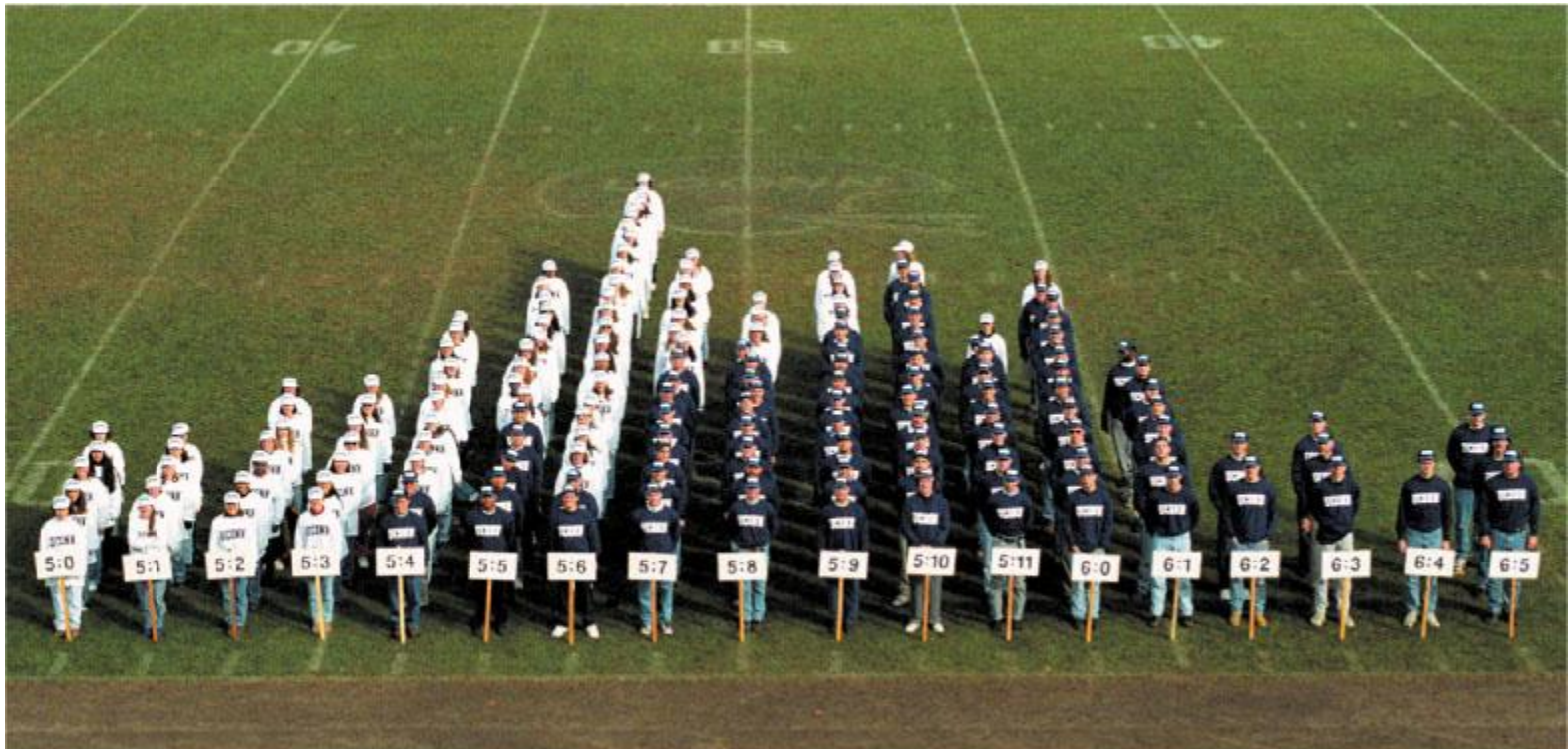
June 7, 2019

- In this session we will discuss
 - concepts of variability and uncertainty
 - how these concepts apply to population sampling
 - how these concepts apply to statistical models

- Two key concepts
 - **Natural variability** – differences between individuals or groups (arising from genetic and/or environmental differences)
 - **Uncertainty** – lack of precise knowledge of characteristics, processes or events (arising from randomness in nature, or incomplete information)



- **Natural variability** is a feature of the natural world, a quantity of interest that we wish to measure



- **Uncertainty** is a nuisance that we wish to remove – however, observations (data) almost always have uncertainty, either because of

- incomplete information or disagreement regarding a *knowable* true value (e.g., measurement error, missing data, etc.)



or,

- inherent unpredictability of an *unknowable* true value (e.g., randomness, complexity, etc.)



- Uncertainty can be reduced by collecting more and better information, but never entirely removed
 - there is always measurement error, even if very small
 - uncertainty due to randomness cannot be reduced

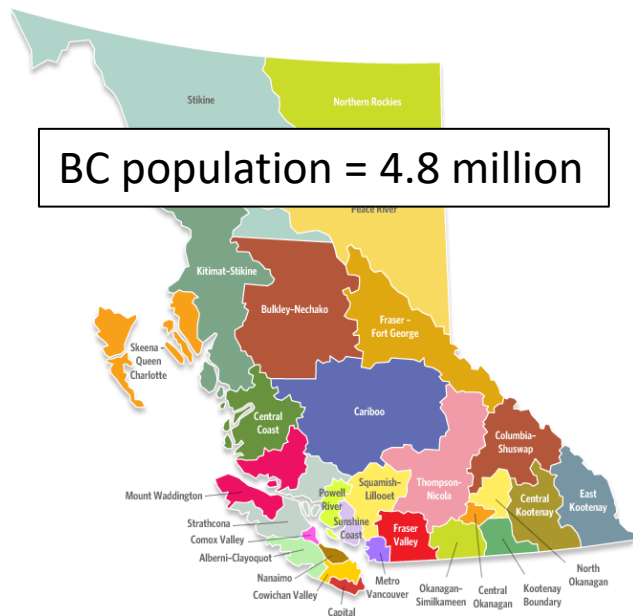


- Typically our goal is to understand health-related phenomena in a large group of individuals (population)
- Two options are available:
 1. observe/measure every individual in the population (**rare**)
 2. use statistics to infer from samples to population (**often**)

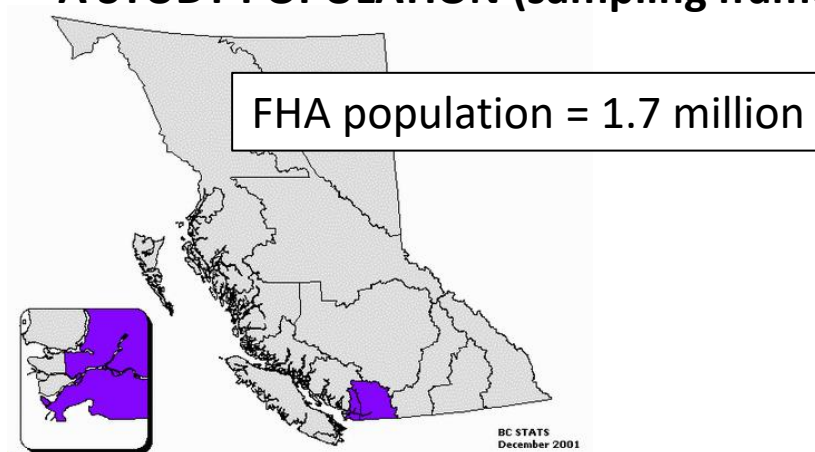


Populations and samples

A TARGET POPULATION



A STUDY POPULATION (sampling frame)



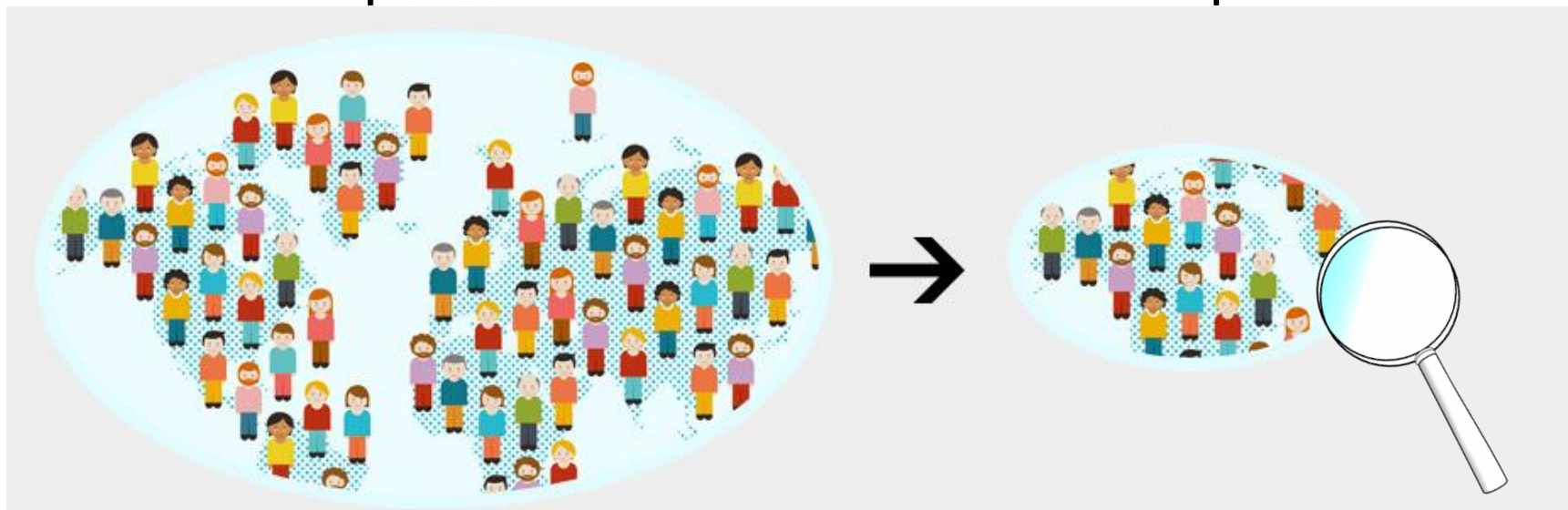
A STUDY SAMPLE



Populations and samples

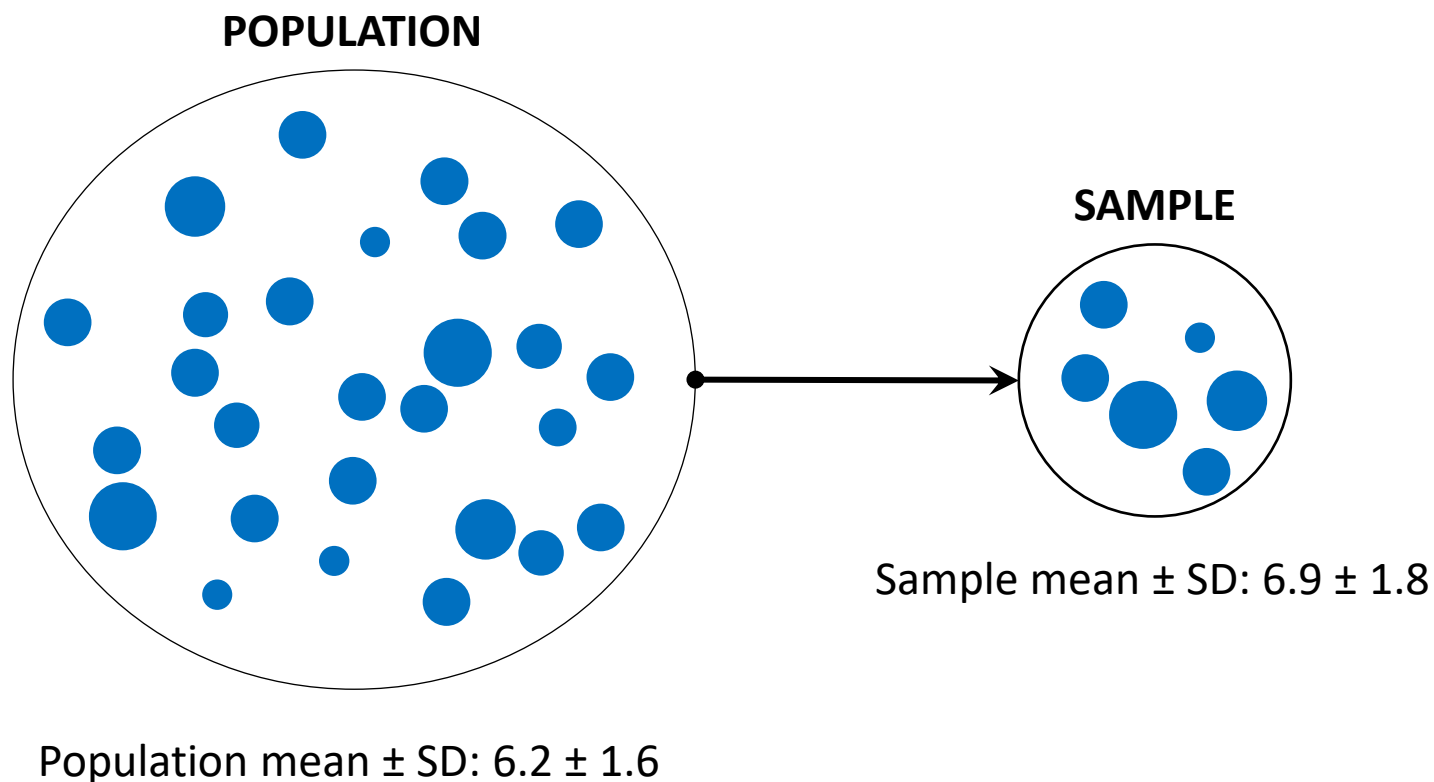
Population

Sample



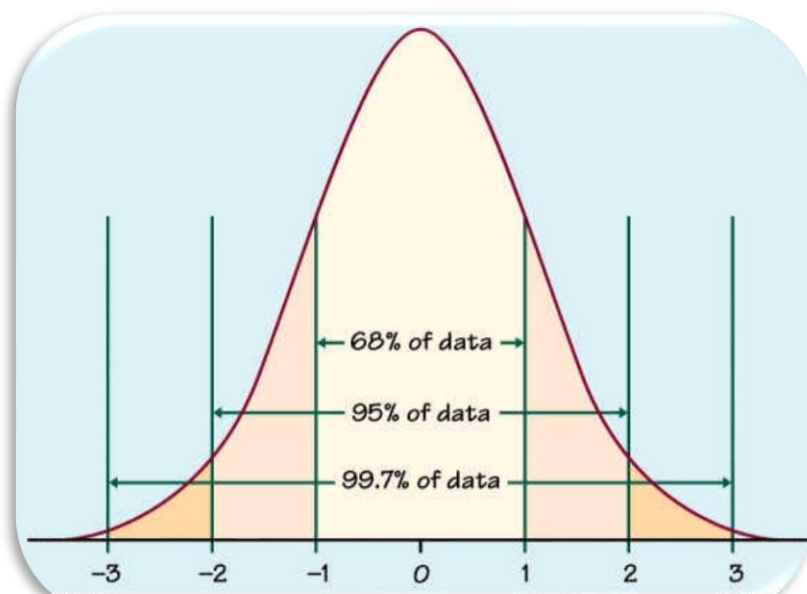
- Taking measurements from population samples has important implications for variability and uncertainty

- Natural variability in a population can be estimated through representative samples and *measures of variation*



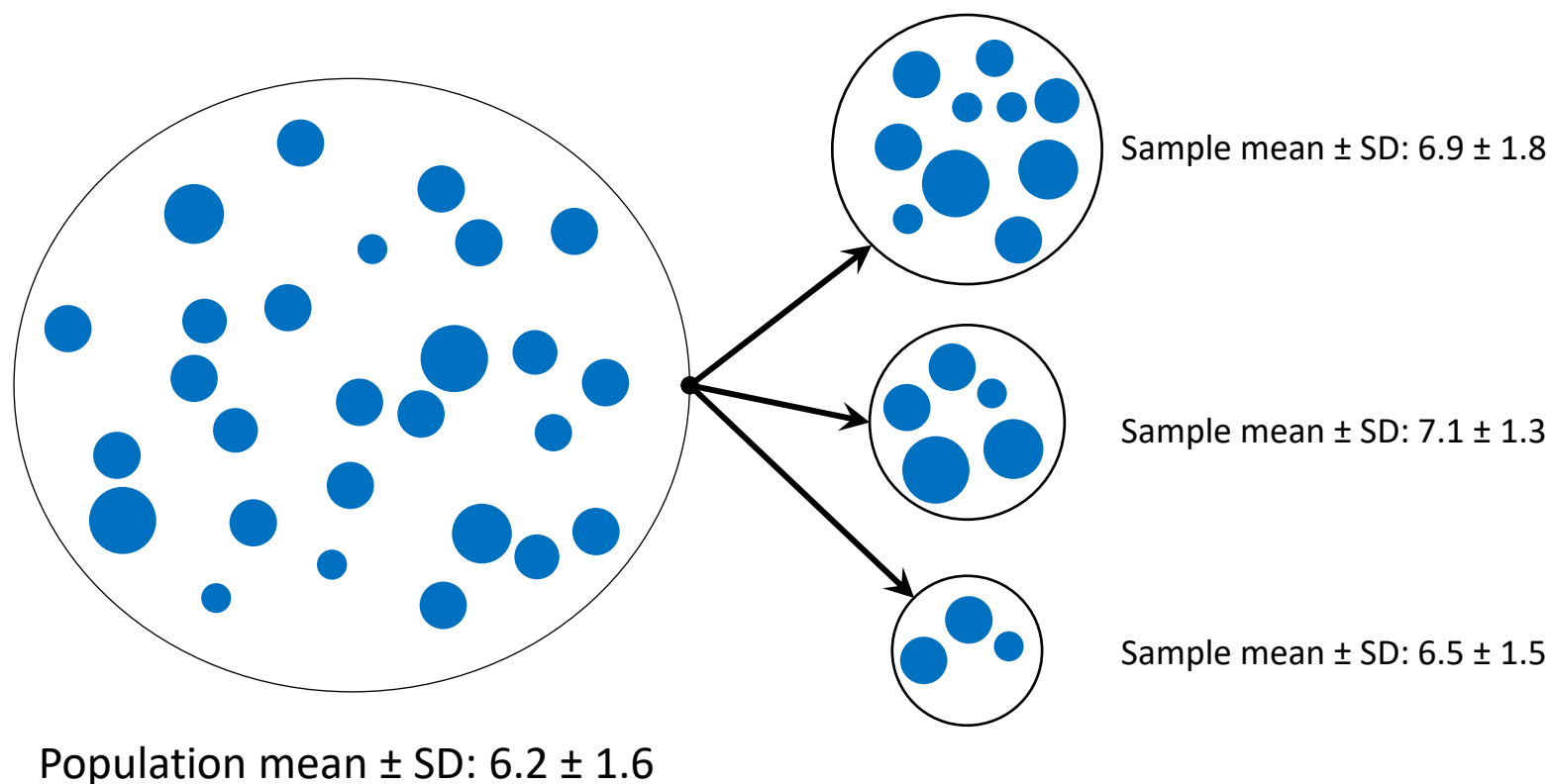
- **Variance:** how spread out data are in a sample (or in a population)
 - average squared deviation of data points from the mean
- **Standard deviation:** spread of data around the mean in a sample (or a population)
 - square root of variance

For normally distributed data,
mean and SD determine data
intervals



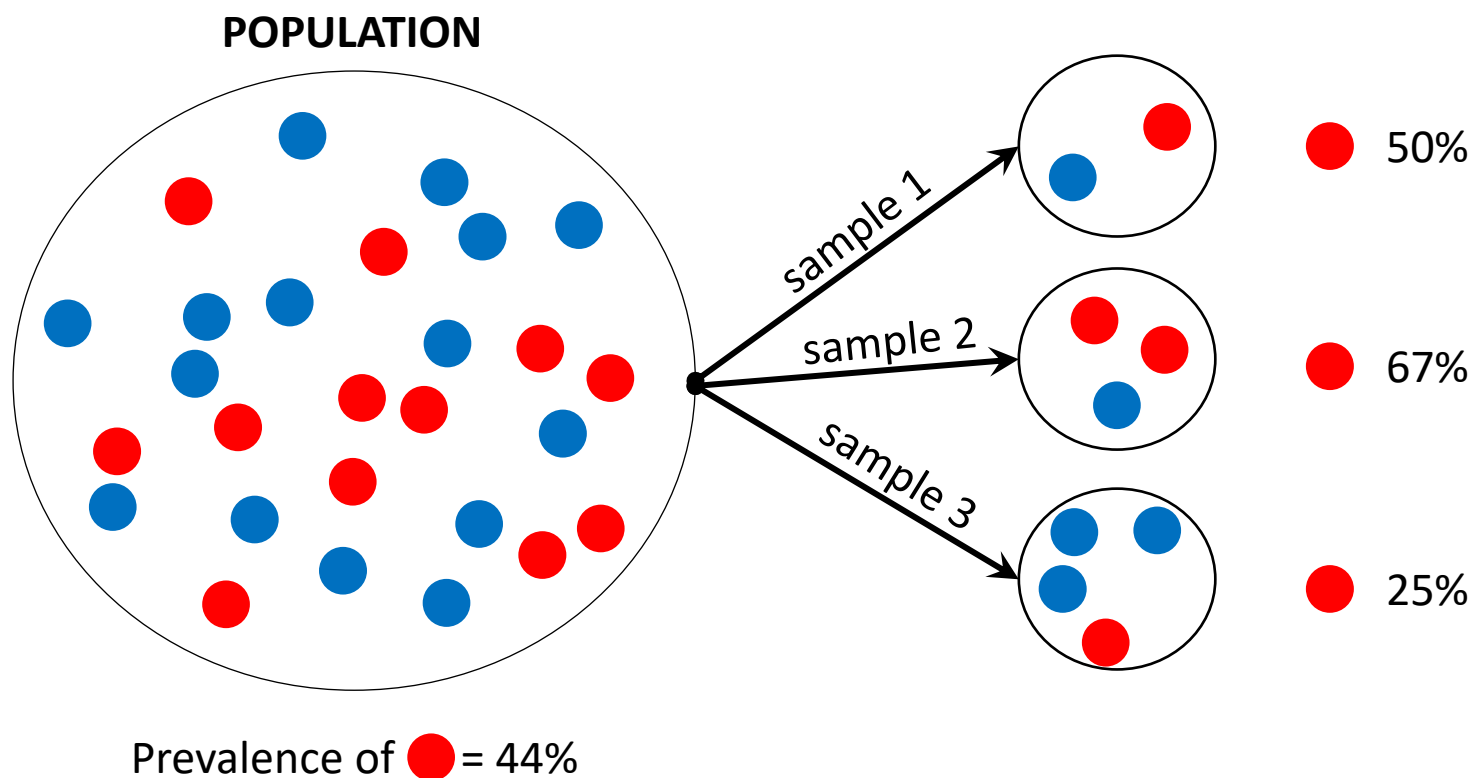
Standard deviations from the mean

- Can we reduce natural variability in our data?
- If we increase our sample size, does that change our measures of variation?

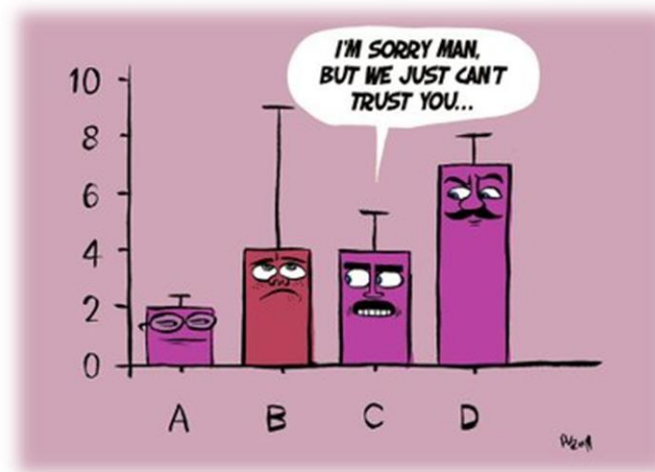


Populations and samples

- However, samples do not necessarily behave alike, or exactly like the population -- hence, we have **sampling error** and *measures of uncertainty*

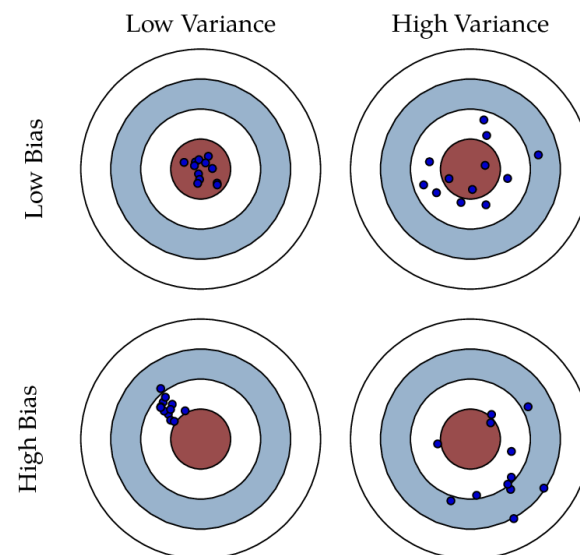
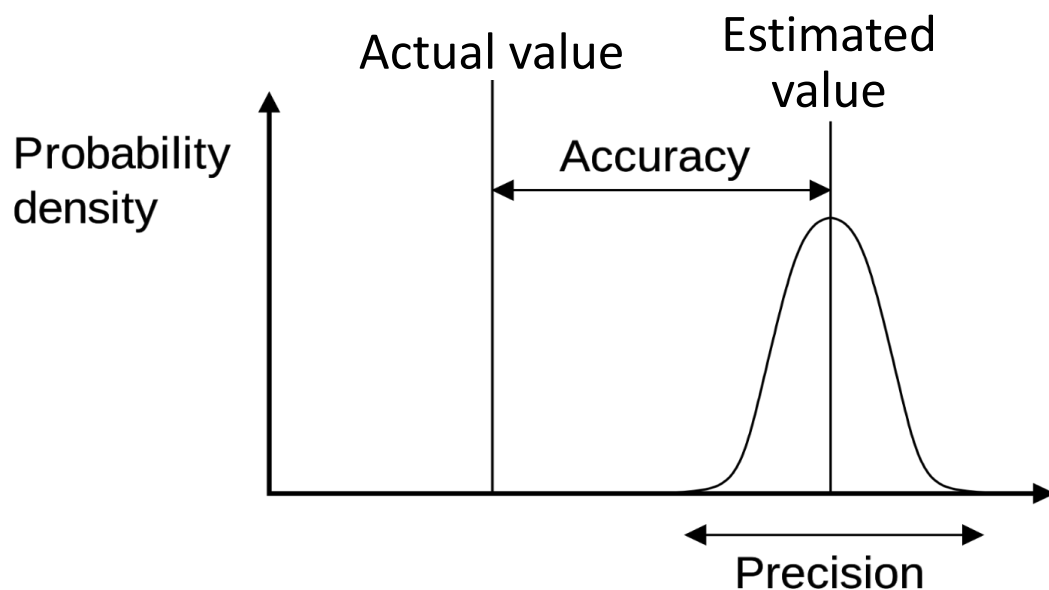


- Repeatedly sampling a population generates a distribution of values (means, for example)
 - **Standard error:** the SD of this distribution; a measure of uncertainty or *precision*
 - **Confidence intervals:** interval of this distribution within which a sample statistic will fall (e.g., sample mean falls within this interval 95% of the time)



Measures of uncertainty

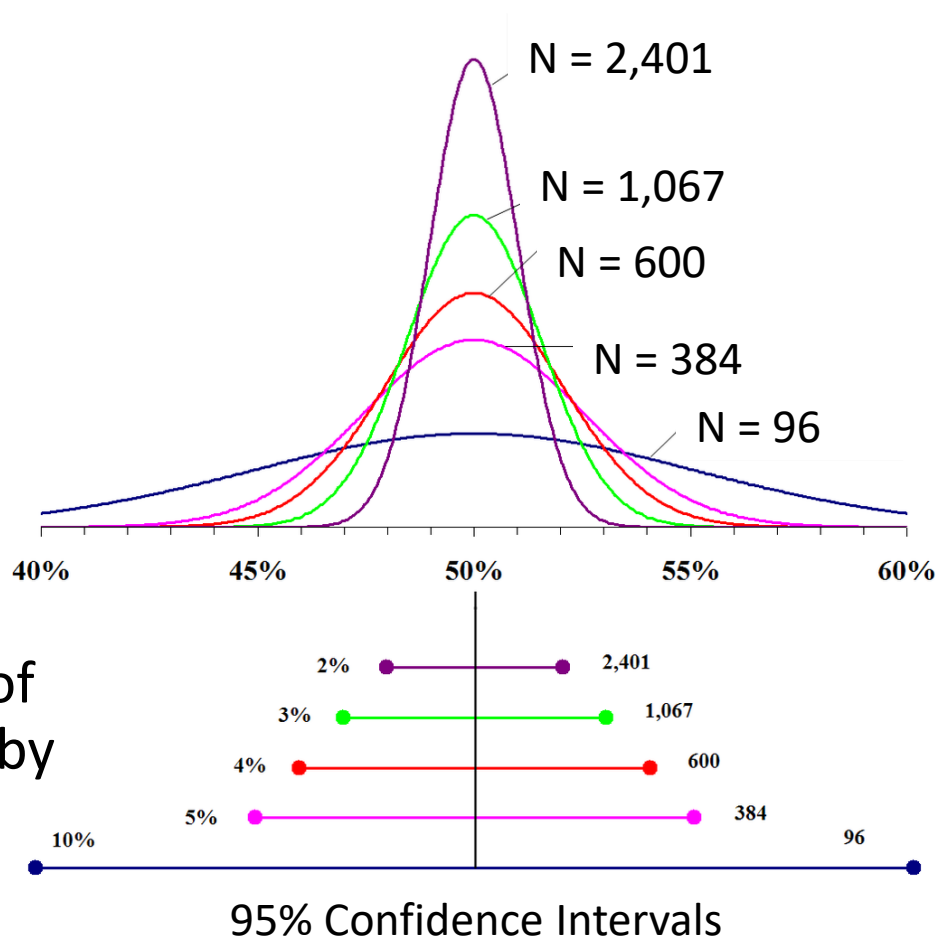
- Note that measures of uncertainty reflect the *precision* of study results, not necessarily the *accuracy*

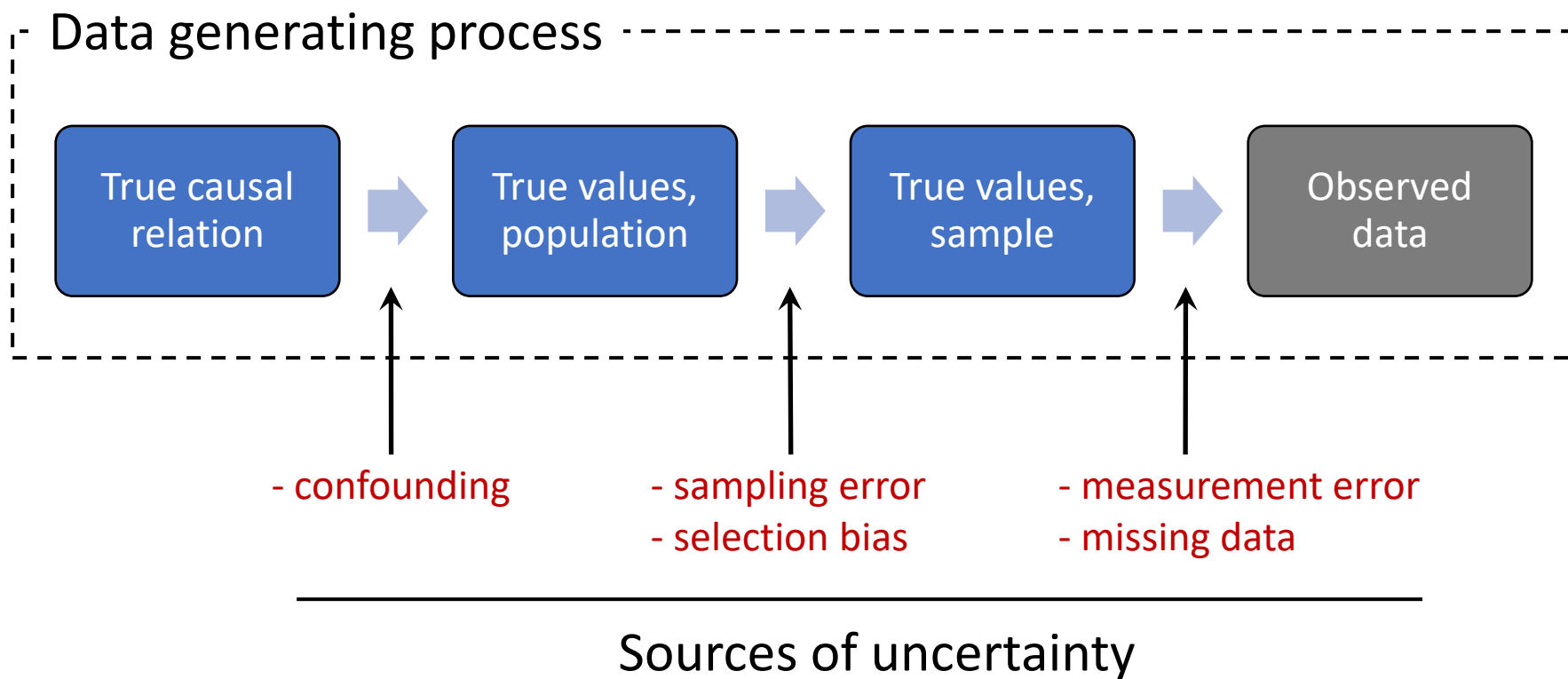


- A poorly designed study could generate very precise estimates that are completely wrong

We can see how uncertainty is reduced when more information is collected

- Certainty that true (population) value is near observed (sample) value depends on sample size
- In order to reduce sampling uncertainty (95% CI) by a factor of 2, we must increase sample size by a factor of 4





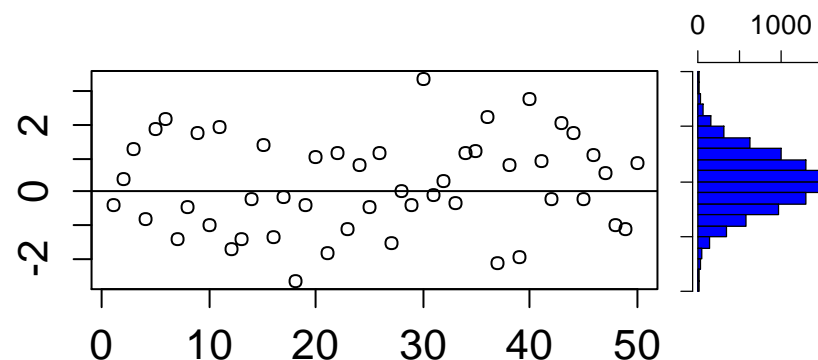
- Recall that in **general linear models**, the error term (ε) captures so-called 'unexplained variation'

intercept predictor

$$Y = \alpha + \beta_1 X_1 + \varepsilon$$

response slope error ('residual')

The diagram shows the equation $Y = \alpha + \beta_1 X_1 + \varepsilon$. Blue arrows point from labels to terms: 'intercept' to α , 'predictor' to X_1 , 'response' to Y , 'slope' to β_1 , and 'error ('residual')' to ε .



These errors (residuals) are assumed to be normally distributed

- Early linear regressions were used to study positions of astronomical bodies and variation was due to measurement error, for which the Normal distribution is appropriate
- In later applications, particularly in biology, variation in measurements arose from both uncertainty and natural variability; hence, error term commonly includes any 'unexplained variation'



- Recall that in **generalized linear models** (e.g., Poisson regression), no error term is specified

$$y_i \sim \text{Poisson}(\mu_i)$$

$$E(y_i/x_i) = \log(\mu_i) = \alpha + \beta x_i$$

- But that the expected variance around our observations y comes directly from the underlying distribution
 - For example, in Poisson regression variance of y_i should be equal to the mean μ_i
- As with general linear models, the observed error can be a 'catch all' of uncertainty (randomness, measurement error) and natural variability

- Two related concepts, natural variability and uncertainty, generate measureable variation in our data
 - some of this variation is interesting (differences between individuals), but some is a nuisance that may or may not be reducible
- Samples are often used to study populations and this presents us with both natural variability and uncertainty
 - the two sources of variation have differing measures and interpretations
- In statistical modeling using GLMs or GLIMs, observed variation is usually captured in a 'catch all' of both natural variability and uncertainty
 - Knowing there are multiple sources of variation helps in the understanding of these models and what is actually explained