02323 Introduction to Statistics

Lecture 7: Simulation-based statistics

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Overview

Overview

Motivation

- Many (most?) relevant statistics ("computed features") have complicated sampling distributions. One might want to do statistical inference for, e.g.:
  - The median
  - Quantiles in general, or perhaps IQR $= Q_3 - Q_1$
  - The coefficient of variation
  - Any non-linear function of one or more input variables
  - (The standard deviation)
- The distribution of the data itself may be non-normal, complicating the statistical theory for even the simple mean.
- We may hope for the magic of the CLT (Central Limit Theorem).
- But: We never *really* know whether the CLT is good enough in a given situation - simulation can tell us!
- Requires: Use of a computer with software that can do simulations. R is a super tool for this!

What is simulation really?

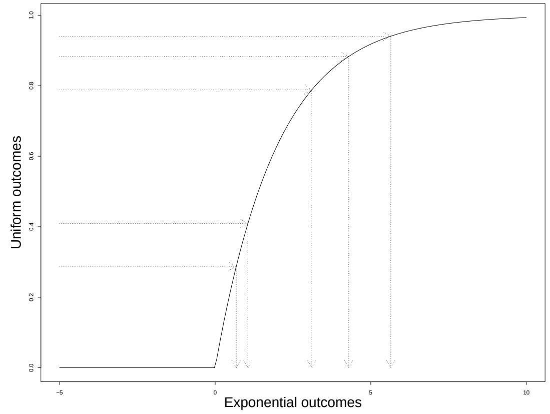
- (Pseudo) random numbers are generated using a computer.
- A random number generator is an algorithm that can generate x_{i+1} from x_i.
- The resulting sequence of numbers appears random.
- Requires a "starting point" called a *seed*.
- Basically, the uniform distribution is simulated in this manner, and then:

Theorem 2.51: All distributions can be extracted from the uniform

If $U \sim \text{Uniform}(0,1)$ and F is a distribution function for any probability distribution, then $F^{-1}(U)$ follows the distribution given by F.

Example: The exponential distribution with $\lambda = 0.5$:

$$F(x) = \int_0^x f(t)dt = 1 - e^{-0.5x}$$



In practice, in R

Many distributions are ready for simulation, for instance:

`rbinom`	The binomial distribution
`rpois`	The Poisson distribution
`rhyper`	The hypergeometric distribution
`rnorm`	The normal distribution
`rlnorm`	The log-normal distributions
`rexp`	The exponential distribution
`runif`	The uniform distribution
`rt`	The t-distribution
`rchisq`	The χ^2-distribution
`rf`	The F-distribution

Example: Area of plates

A company produces rectangular plates. The length of a plate (in meters), X, is assumed to follow a normal distribution $N(2, 0.01^2)$. The width of a plate (in meters), Y, is assumed to follow a normal distribution $N(3, 0.02^2)$. We are interested in the area of the plates, which is given by $A = XY$.

- What is the mean area?
- What is the standard deviation of the area?
- How often do such plates have an area that differs by more than 0.1 m^2 from the targeted 6 m^2?
- (The probability of other events?)
- Generally: What is the probability distribution of the random variable A?

Example: Area of plates, solution by simulation

```r
k = 10000 # Number of simulations
X = rnorm(k, 2, 0.01)
Y = rnorm(k, 3, 0.02)
A = X*Y

mean(A)
```

[1] 6

```r
var(A)
```

[1] 0.0025

```r
mean(abs(A - 6) > 0.1)
```

[1] 0.044

Overview

Propagation of error

Must be able to find:

$\sigma^2_{f(X_1,\ldots,X_n)} = \text{Var}(f(X_1,\ldots,X_n))$

We already know:

$$\sigma^2_{f(X_1,\ldots,X_n)} = \sum_{i=1}^{n} a_i^2 \sigma_i^2 \quad \text{if} \quad f(X_1,\ldots,X_n) = \sum_{i=1}^{n} a_i X_i \text{ (and independence)}$$

Method **??**: For non-linear functions, if $X_1,\ldots,X_n$ are independent,

$$\sigma^2_{f(X_1,\ldots,X_n)} \approx \sum_{i=1}^{n} \left(\frac{\partial f}{\partial x_i}\right)^2 \sigma_i^2$$

Example: Area of plates (continued)

We used a simulation method in the first part of the example.

Now, given two specific measurements of X and Y, $x = 2.00$ m and $y = 3.00$ m: What is the variance of $A = XY$, using the error propagation law?

Example: Area of plates (continued)

The variances are:

$$\sigma_1^2 = \mathsf{Var}(X) = 0.01^2 \text{ and } \sigma_2^2 = \mathsf{Var}(Y) = 0.02^2$$

The function and its derivatives are:

$$f(x,y) = xy,\ \frac{\partial f}{\partial x} = y,\ \frac{\partial f}{\partial y} = x$$

So the result becomes:

$$\begin{aligned} Var(A) &\approx \left(\frac{\partial f}{\partial x}\right)^2 \sigma_1^2 + \left(\frac{\partial f}{\partial y}\right)^2 \sigma_2^2 \\ &= y^2\sigma_1^2 + x^2\sigma_2^2 \\ &= 3.00^2 \cdot 0.01^2 + 2.00^2 \cdot 0.02^2 \\ &= 0.0025 \end{aligned}$$

Propagation of error - by simulation

Method **??**: Error propagation by simulation

Assume that we have actual measurements $x_1, \dots, x_n$ with known/assumed error variances $\sigma_1^2, \dots, \sigma_n^2$.

1. Simulate k outcomes of all n measurements from assumed error distributions, e.g. $N(x_i, \sigma_i^2)$: $X_i^{(j)}$, $j = 1 \dots, k$.
2. Calculate the standard deviation directly as the observed standard deviation of the k simulated values of f:

$$s_{f(X_1,\dots,X_n)}^{\text{sim}} = \sqrt{\frac{1}{k-1}\sum_{i=1}^{k}(f_j - \bar{f})^2}$$

where

$$f_j = f(X_1^{(j)}, \dots, X_n^{(j)})$$

Example: Area of plates (continued)

Actually, in this example, one *could* deduce the variance of A theoretically:

$$\begin{aligned} \mathsf{Var}(XY) &= \mathsf{E}\left[(XY)^2\right] - [\mathsf{E}(XY)]^2 \\ &= \mathsf{E}(X^2)\mathsf{E}(Y^2) - \mathsf{E}(X)^2\mathsf{E}(Y)^2 \\ &= \left[\mathsf{Var}(X) + \mathsf{E}(X)^2\right]\left[\mathsf{Var}(Y) + \mathsf{E}(Y)^2\right] - \mathsf{E}(X)^2\mathsf{E}(Y)^2 \\ &= \mathsf{Var}(X)\mathsf{Var}(Y) + \mathsf{Var}(X)\mathsf{E}(Y)^2 + \mathsf{Var}(Y)\mathsf{E}(X)^2 \\ &= 0.01^2 \times 0.02^2 + 0.01^2 \times 3^2 + 0.02^2 \times 2^2 \\ &= 0.00000004 + 0.0009 + 0.0016 \\ &= 0.00250004 \end{aligned}$$

Example: Area of plates (continued)

Three different approaches:

1. The simulation based approach.
2. A theoretical derivation.
3. The analytical, but approximate, error propagation method.

The simulation approach has a number of crucial advantages:

1. It offers a simple tool to compute many other quantities than just the standard deviation. (The theoretical derivations of these could be much more complicated than what was shown for the variance).
2. It offers a simple tool to use any other distributions than the normal, if we believe that they reflect reality better.
3. It does not rely on linear approximations of the true non-linear relations.

Overview

1. Introduction to simulation - what is it really?
   - Example: Area of plates
2. Propagation of error
3. Parametric bootstrap
   - Introduction to bootstrap
   - One-sample confidence interval for any feature
   - Two-sample confidence interval assuming any distributions
4. Non-parametric bootstrap
   - One-sample confidence interval for any feature
   - Two-sample confidence interval

Bootstrapping

Bootstrapping exists in two versions:

1. Parametric bootstrap: Simulate multiple samples from the assumed (and estimated) distribution.
2. Non-parametric bootstrap: Simulate multiple samples directly from the data.

Example: Confidence interval for an exponential mean

Assume that we observed the following 10 call waiting times (in seconds) in a call center:

$$32.6, 1.6, 42.1, 29.2, 53.4, 79.3, 2.3, 4.7, 13.6, 2.0$$

From the data, we estimate

$$\hat{\mu} = \bar{x} = 26.08 \text{ and hence: } \hat{\lambda} = 1/26.08 = 0.03834356$$

Our distributional assumption:

The waiting times come from an exponential distribution.

What is the confidence interval for μ?

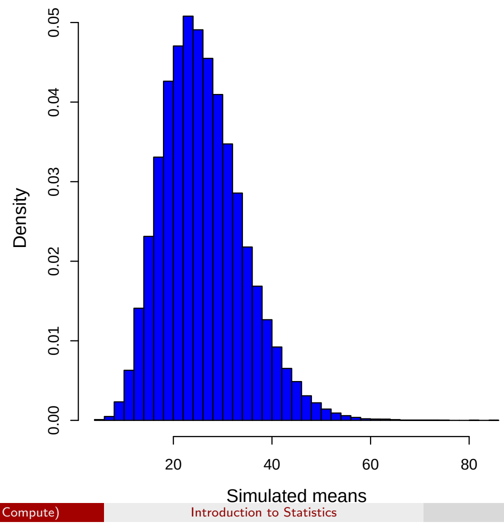
Based on previous knowledge in this course: We don't know!

Example: Confidence interval for an exponential mean

```r
# Number of simulations
k <- 100000

# Simulate 10 exponentials with the 'right' mean k times
sim_samples <- replicate(k, rexp(10, 1/26.08))

# Compute the mean of the 10 simulated observations k times
sim_means <- apply(sim_samples, 2, mean)

# Find relevant quantiles of the k simulated means
quantile(sim_means, c(0.025, 0.975))

##  2.5% 97.5%
##    13    45
```

Example: Confidence interval for an exponential mean

```r
# Make histogram of simulated means
hist(sim_means, col = "blue", nclass = 30, main = "", prob = TRUE, xlab = "Simulated means")
```



Example: Confidence interval for an exponential median

Assume that we observed the following 10 call waiting times (in seconds) in a call center:

$$32.6, 1.6, 42.1, 29.2, 53.4, 79.3, 2.3, 4.7, 13.6, 2.0$$

From the data we estimate

$$\text{Median } = 21.4 \text{ and } \hat{\mu} = \bar{x} = 26.08$$

Our distributional assumption:

The waiting times come from an exponential distribution.

What is the confidence interval for the median?

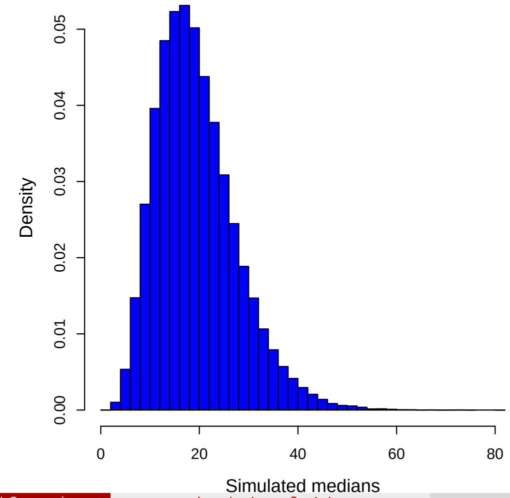
Based on previous knowledge in this course: We don't know!

Example: Confidence interval for an exponential median

```r
# Number of simulations
k <- 100000

# Simulate 10 exponentials with the 'right' mean k times
sim_samples <- replicate(k, rexp(10, 1/26.08))

# Compute the median of the 10 simulated observations k times
sim_medians <- apply(sim_samples, 2, median)

# Find relevant quantiles of the k simulated medians
quantile(sim_medians, c(0.025, 0.975))

##  2.5% 97.5%
##     7    38
```


Example: Confidence interval for an exponential median

```r
# Make histogram of simulated medians
hist(sim_medians, col = "blue", nclass = 30, main = "", prob = TRUE, xlab = "Simulated medians")
```



Confidence interval for any feature (including μ)

Method 4.7: Confidence interval for any feature θ by parametric bootstrap

Assume we have actual observations $x_1, \ldots, x_n$, and that they come from some probability distribution with density f.

1. Simulate k samples of n observations from the assumed distribution f where the mean[a] is set to $\bar{x}$.
2. Calculate the statistic $\hat{\theta}$ in each of the k samples to obtain $\hat{\theta}_1^*, \ldots, \hat{\theta}_k^*$.
3. Find the $100(\alpha/2)\%$ and $100(1-\alpha/2)\%$ quantiles of $\hat{\theta}_1^*, \ldots, \hat{\theta}_k^*$, $q_{\alpha/2}^*$ and $q_{1-\alpha/2}^*$, to obtain the $100(1-\alpha)\%$ confidence interval: $\left[q_{\alpha/2}^*,\ q_{1-\alpha/2}^*\right]$

[a] And otherwise chosen to match the data as well as possible: Some distributions have more than one mean related parameter, e.g. the normal or the log-normal. For these one should use a distribution with a variance that matches the sample variance of the data. Even more generally, the approach would be to match the chosen distribution to the data using the so-called *maximum likelihood* approach.

Example: 99% CI for Q_3 assuming a normal distribution

```
# Heights data
x <- c(168, 161, 167, 179, 184, 166, 198, 187, 191, 179)
n <- length(x)

# Define a Q3-function
Q3 <- function(x){ quantile(x, 0.75)}

# Set number of simulations
k <- 100000

# Simulate k samples of n = 10 normals with the 'right' mean and variance
sim_samples <- replicate(k, rnorm(n, mean(x), sd(x)))

# Compute the Q3 of the n = 10 simulated observations k times
simQ3s <- apply(sim_samples, 2, Q3)

# Find the two relevant quantiles of the k simulated Q3s
quantile(simQ3s, c(0.005, 0.995))

##  0.5% 99.5%
##   173   198
```


Two-sample confidence interval for any feature comparison $\theta_1 - \theta_2$ (including $\mu_1 - \mu_2$)

Method 4.10: Two-sample confidence interval for any feature comparison $\theta_1 - \theta_2$ by parametric bootstrap

Assume we have actual observations $x_1, \ldots, x_n$ and $y_1, \ldots, y_n$, and that they stem from probability distributions with densities f_1 and f_2.

1. Simulate k sets of 2 samples of n_1 and n_2 observations from the assumed distributions, setting the means[a] to $\hat{\mu}_1 = \bar{x}$ and $\hat{\mu}_2 = \bar{y}$, respectively.
2. Calculate the difference between the features in each of the k samples: $\hat{\theta}_{x1}^* - \hat{\theta}_{y1}^*, \ldots, \hat{\theta}_{xk}^* - \hat{\theta}_{yk}^*$.
3. Find the $100(\alpha/2)\%$ and $100(1-\alpha/2)\%$ quantiles for these, $q_{\alpha/2}^*$ and $q_{1-\alpha/2}^*$, to obtain the $100(1-\alpha)\%$ confidence interval: $\left[q_{\alpha/2}^*,\ q_{1-\alpha/2}^*\right]$

[a] As before

Example: Confidence interval for the difference of exponential means

```
# Day 1 data
x <- c(32.6, 1.6, 42.1, 29.2, 53.4, 79.3,  2.3 , 4.7, 13.6, 2.0)
n1 <- length(x)

# Day 2 data
y <- c(9.6, 22.2, 52.5, 12.6, 33.0, 15.2, 76.6, 36.3, 110.2,
       18.0, 62.4, 10.3)
n2 <- length(y)
```

Example: Confidence interval for the difference of exponential means

```r
# Set number of simulations:
k <- 100000

# Simulate k samples of each n1 = 10 and n2 = 12 exponentials
# with the 'right' means

simX_samples <- replicate(k, rexp(n1, 1/mean(x)))
simY_samples <- replicate(k, rexp(n2, 1/mean(y)))

# Compute the difference between the simulated means k times
sim_dif_means <- apply(simX_samples, 2, mean) -
  apply(simY_samples, 2, mean)

# Find the relevant quantiles of the k simulated differences of means:
quantile(sim_dif_means, c(0.025, 0.975))

##  2.5% 97.5%
##   -41    14
```


Parametric bootstrap - an overview

We assume *some* distribution!

Two confidence interval method boxes were given:

	One-sample	Two-sample
For any feature	Method 4.7	Method 4.10

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Non-parametric bootstrap - an overview

We do *not* assume *any* distribution!

Two confidence interval method boxes will be given:

	One-sample	Two-sample
For any feature	Method 4.15	Method 4.17

Example: Womens' cigarette consumption

In a study, womens' cigarette consumption before and after giving birth is explored. The following observations of the number of smoked cigarettes per day were obtained:

before	after	before	after
8	5	13	15
24	11	15	19
7	0	11	12
20	15	22	0
6	0	15	6
20	20		

Compare the before and after means! (Are they different?)

Example: Womens' cigarette consumption

A paired t-test setting, *but* with clearly non-normal data!

```
# Data
x1 <-  c(8, 24, 7, 20, 6, 20, 13, 15, 11, 22, 15)
x2 <-  c(5, 11, 0, 15, 0, 20, 15, 19, 12, 0, 6)

# Compute differences
dif <- x1-x2
dif

##  [1]  3 13  7  5  6  0 -2 -4 -1 22  9

# Compute average difference
mean(dif)

## [1] 5.3
```


Example: Women's cigarette consumption - bootstrapping

```
t(replicate(5, sample(dif, replace = TRUE)))

##      [,1] [,2] [,3] [,4] [,5] [,6] [,7] [,8] [,9] [,10] [,11]
## [1,]   -2    0    9   22    0   -1    0   -2    0     3     0
## [2,]   13    3   -2   -1   -2    7   13   -4   -2    -1     5
## [3,]    9   -4    5   -4    5    3   -4   13    3     0    22
## [4,]   -1   22   -2   -1   13    6   -4    0    0    -1    22
## [5,]    9   -2   13    6    9   22    0   -1    7     7    -1
```


Example: Womens' cigarette consumption - the non-parametric results

Let us find the 95% confidence interval for the *mean* change in cigarette consumption.

```
k = 100000
sim_samples = replicate(k, sample(dif, replace = TRUE))
sim_means = apply(sim_samples, 2, mean)
quantile(sim_means, c(0.025,0.975))

##  2.5% 97.5%
##   1.4   9.8
```

One-sample confidence interval for any feature θ (including μ)

Method 4.15: Confidence interval for any feature θ by non-parametric bootstrap

Assume we have actual observations $x_1, \ldots, x_n$.

1. Simulate k samples of size n by randomly sampling from the available data (with replacement).
2. Calculate the statistic $\hat{\theta}$ for each of the k samples: $\hat{\theta}_1^*, \ldots, \hat{\theta}_k^*$.
3. Find the $100(\alpha/2)\%$ and $100(1-\alpha/2)\%$ quantiles for these, $q^*_{\alpha/2}$ and $q^*_{1-\alpha/2}$, as the $100(1-\alpha)\%$ confidence interval: $\left[q^*_{\alpha/2},\, q^*_{1-\alpha/2}\right]$

Example: Womens' cigarette consumption

Let us find the 95% confidence interval for the *median* change in cigarette consumption in the example from above.

```
k = 100000
sim_samples = replicate(k, sample(dif, replace = TRUE))
sim_medians = apply(sim_samples, 2, median)
quantile(sim_medians, c(0.025,0.975))

##  2.5% 97.5%
##    -1     9
```


Example: Tooth health and infant bottle use

In a study, it was explored whether children who had received milk from a bottle had worse or better tooth health than those who had *not* received milk from a bottle. For 19 randomly selected children, is was recorded when they had had their first incident of caries:

bottle	age	bottle	age	bottle	age
no	9	no	10	yes	16
yes	14	no	8	yes	14
yes	15	no	6	yes	9
no	10	yes	12	no	12
no	12	yes	13	yes	12
no	6	no	20		
yes	19	yes	13		

Example: Tooth health and infant bottle use - a 95% confidence interval for $\mu_1 - \mu_2$

```
# Reading in data
x <- c(9, 10, 12, 6, 10, 8, 6, 20, 12)
y <- c(14,15,19,12,13,13,16,14,9,12)

# 95% CI for mean difference by non-parametric bootstrap
k <- 100000
simx_samples <- replicate(k, sample(x, replace = TRUE))
simy_samples <- replicate(k, sample(y, replace = TRUE))
sim_mean_difs <- apply(simx_samples, 2, mean)-
                         apply(simy_samples, 2, mean)
quantile(sim_mean_difs, c(0.025,0.975))

##  2.5% 97.5%
## -6.21 -0.11
```

Two-sample confidence interval for $\theta_1 - \theta_2$ (including $\mu_1 - \mu_2$) by non-parametric bootstrap

Method 4.17: Two-sample confidence interval for $\theta_1 - \theta_2$ by non-parametric bootstrap

Assume we have actual observations $x_1, \ldots, x_n$ and $y_1, \ldots, y_n$.

1. Randomly draw k sets of 2 samples of n_1 and n_2 observations from the respective groups of data (with replacement).
2. Calculate the difference between the features in each of the k samples: $\hat{\theta}^*_{x1} - \hat{\theta}^*_{y1}, \ldots, \hat{\theta}^*_{xk} - \hat{\theta}^*_{yk}$.
3. Find the $100(\alpha/2)\%$ and $100(1-\alpha/2)\%$ quantiles for these, $q^*_{\alpha/2}$ and $q^*_{1-\alpha/2}$, to obtain the $100(1-\alpha)\%$ confidence interval: $\left[q^*_{\alpha/2},\, q^*_{1-\alpha/2}\right]$

Example: Tooth health and infant bottle use - a 99% confidence interval for the difference of medians

```
k <- 100000
simx_samples <- replicate(k, sample(x, replace = TRUE))
simy_samples <- replicate(k, sample(y, replace = TRUE))
sim_median_difs <- apply(simx_samples, 2, median)-
                   apply(simy_samples, 2, median)
quantile(sim_median_difs, c(0.005,0.995))

##  0.5% 99.5%
##    -8     0
```


Bootstrapping - an overview

We were given 4 similar method boxes

1. With distribution assumptions or not (parametric or non-parametric).
2. For one- or two-sample analysis.

Note:

Means also included in *other features*. Or: These methods may be used *not only* for means!

Hypothesis testing also possible

We can do hypothesis testing by looking at the confidence intervals!

Overview