


Week 9: *Uncertainty*

 EMSE 6035: Marketing Analytics for Design Decisions

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 October 27, 2021

Quick correction from last week

Observations - Height of students (inches):

```
#> [1] 65 69 66 67 68 72 68 69 63 70
```

a) Let's say we know that the height of students, \tilde{x} , in a classroom follows a normal distribution. A professor obtains the above height measurements students in her classroom. What is the log-likelihood that $\tilde{x} \sim \mathcal{N}(68, 4)$? In other words, compute $\ln \mathcal{L}(\mu = 68, \sigma = 4)$.

b) Compute the log-likelihood function using the same standard deviation ($\sigma = 4$) but with the following different values for the mean, μ : 66, 67, 68, 69, 70. How do the results compare? Which value for μ produces the highest log-likelihood?

Computing the *likelihood*

Load the data

```
x <- c(65, 69, 66, 67, 68, 72, 68, 69, 63, 70)
```

Compute the value of $f(x)$ for each x

```
f_x <- dnorm(x, 68, 4)
```

Likelihood is the product of values in f_x

```
prod(f_x)
```

```
#> [1] 1.447528e-11
```

Computing the *log-likelihood*

Take the log of the likelihood

```
log(prod(f_x))
```

```
#> [1] -24.95858
```

The way we typically compute the log-likelihood is by summing up the log of the values in f_x

```
sum(log(f_x))
```

```
#> [1] -24.95858
```

```
library(tidyverse)
```

```
# Create a vectors of values for the mean
```

```
means <- c(66, 67, 68, 69, 70)
```

```
# Compute the likelihood using different  
values for the mean:
```

```
L1 <- sum(log(dnorm(x, means[1], 4)))
```

```
L2 <- sum(log(dnorm(x, means[2], 4)))
```

```
L3 <- sum(log(dnorm(x, means[3], 4)))
```

```
L4 <- sum(log(dnorm(x, means[4], 4)))
```

```
L5 <- sum(log(dnorm(x, means[5], 4)))
```

```
logLiks <- c(L1, L2, L3, L4, L5)
```

```
# Plot the result:
```

```
df <- data.frame(means, logLiks)
```

```
df %>%
```

```
  ggplot(aes(x = means, y = logLiks)) +
```

```
  geom_line() +
```

```
  geom_point() +
```

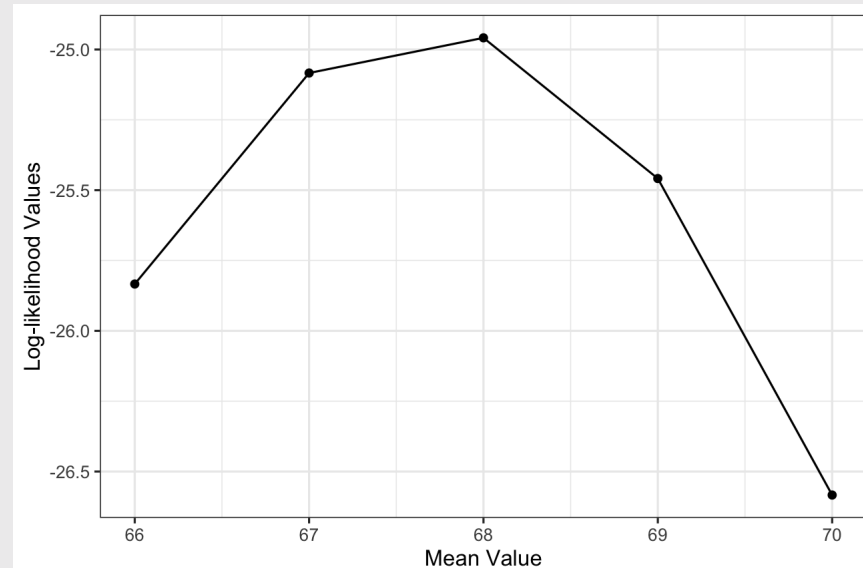
```
  theme_bw() +
```

```
  labs(
```

```
    x = "Mean Value",
```

```
    y = "Log-likelihood Values"
```

```
)
```



Week 9: *Uncertainty*

1. Computing uncertainty

2. Reshaping data

BREAK

3. Cleaning pilot data

4. Estimating pilot data models

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Maximum likelihood estimation

$$\begin{aligned}\tilde{u}_j &= \boldsymbol{\beta}' \mathbf{x}_j + \tilde{\varepsilon}_j \\ &= \boxed{\beta_1} x_{j1} + \boxed{\beta_2} x_{j2} + \dots + \tilde{\varepsilon}_j\end{aligned}$$

Weights that denote the
relative value of attributes

x_{j1}, x_{j2}, \dots

Estimate β_1, β_2, \dots , by minimizing
the negative log-likelihood function:

$$\text{minimize } -\ln(\mathcal{L}) = -\sum_{j=1}^J y_j \ln[P_j(\boldsymbol{\beta}|\mathbf{x})]$$

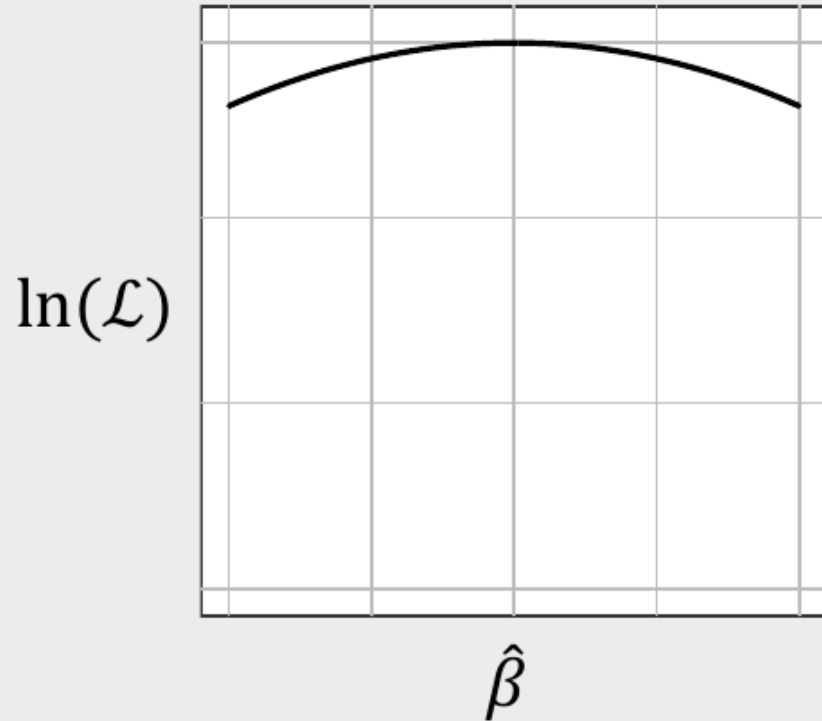
with respect to $\boldsymbol{\beta}$

$y_j = 1$ if alternative j was chosen

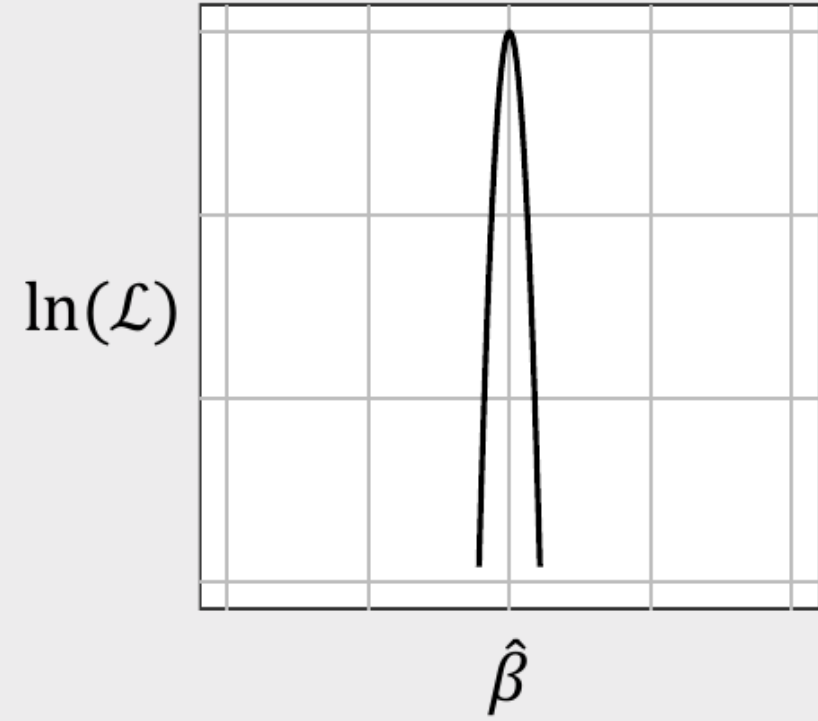
$y_j = 0$ if alternative j was not chosen

The certainty of $\hat{\beta}$ is inversely related to the curvature of the log-likelihood function

Greater variance in $\ln(\mathcal{L})$,
Less certainty in $\hat{\beta}$



Less variance in $\ln(\mathcal{L})$,
Greater certainty in $\hat{\beta}$



The *curvature* of the log-likelihood function is related to the hessian

$$\sum_{\beta} = - \overbrace{[\nabla_{\beta}^2 \ln(\mathcal{L})]^{-1}}^{\text{Hessian}}$$

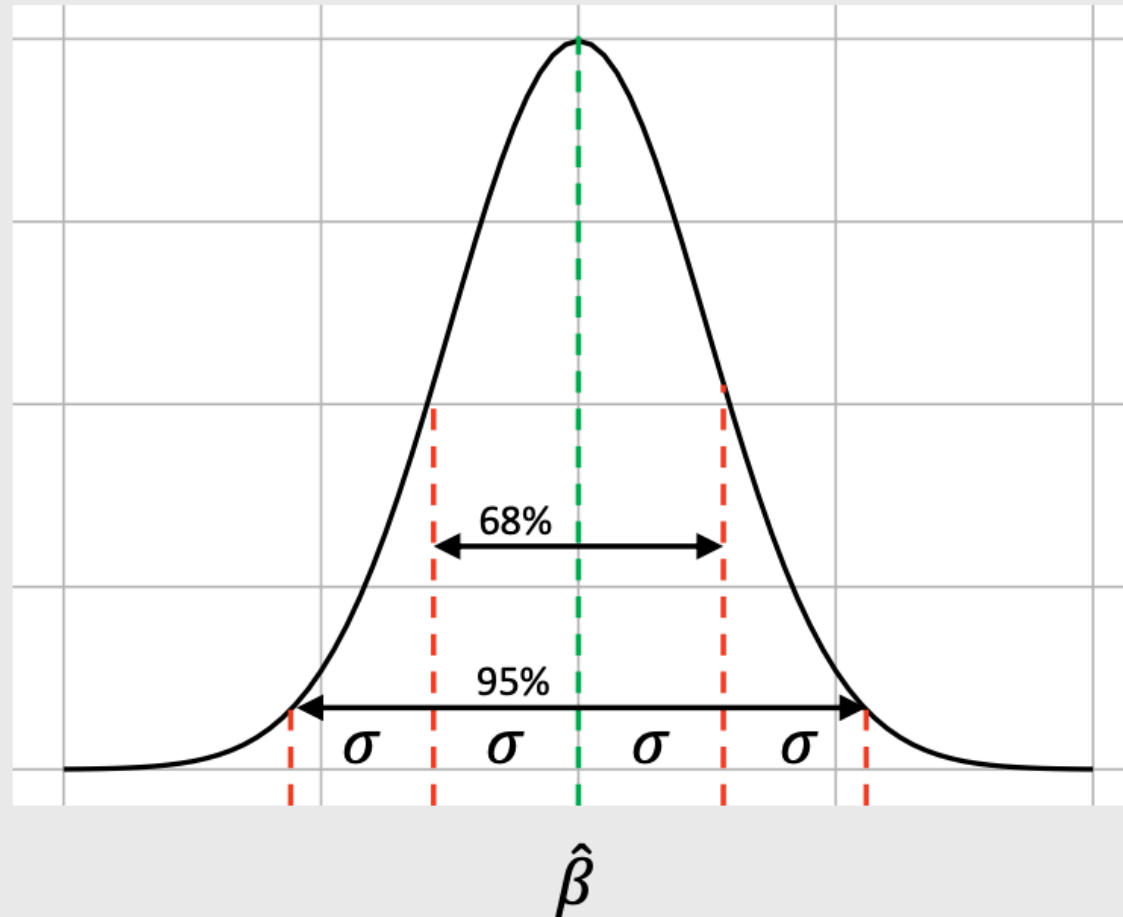
↑
Covariance of $\hat{\beta}$

The *curvature* of the log-likelihood function is related to the hessian

$$\begin{array}{c} \text{Covariance of } \hat{\boldsymbol{\beta}} \\ \uparrow \\ \sum_{\boldsymbol{\beta}} = - \overbrace{[\nabla_{\boldsymbol{\beta}}^2 \ln(\mathcal{L})]}^{\text{Hessian}}^{-1} = \end{array} \begin{bmatrix} \sigma_{11}^2 & \cdots & \sigma_{m1}^2 \\ \vdots & \ddots & \vdots \\ \sigma_{1n}^2 & \cdots & \sigma_{mn}^2 \end{bmatrix}$$

Usually report parameter uncertainty ("standard errors") with σ values

Est.	Std. Err.
$\hat{\beta}_1$	σ_1
$\hat{\beta}_2$	σ_2
\vdots	\vdots
$\hat{\beta}_m$	σ_m



A 95% confidence interval is approximately $[\hat{\beta} - 2\sigma, \hat{\beta} + 2\sigma]$

Practice Question 1

Suppose we estimate a model and get the following results:

$$\hat{\beta} = \begin{bmatrix} -0.4 \\ 0.5 \end{bmatrix}$$

$$\nabla_{\beta}^2 \ln(\mathcal{L}) = \begin{bmatrix} -6000 & 60 \\ 60 & -700 \end{bmatrix}$$

- a) Use the hessian to compute the standard errors for $\hat{\beta}$
- b) Use the standard errors to compute a 95% confidence interval around $\hat{\beta}$

Simulating uncertainty

We can use the coefficients and hessian from a model to obtain draws that reflect parameter uncertainty

```
beta <- c(-0.7, 0.1, -4.0)

hessian <- matrix(c(
  -6000, 50, 60,
    50, -700, 50,
    60, 50, -300),
  ncol = 3, byrow = TRUE)
```

```
covariance <- -1*solve(hessian)
draws <- MASS::mvrnorm(10^5, beta,
  covariance)

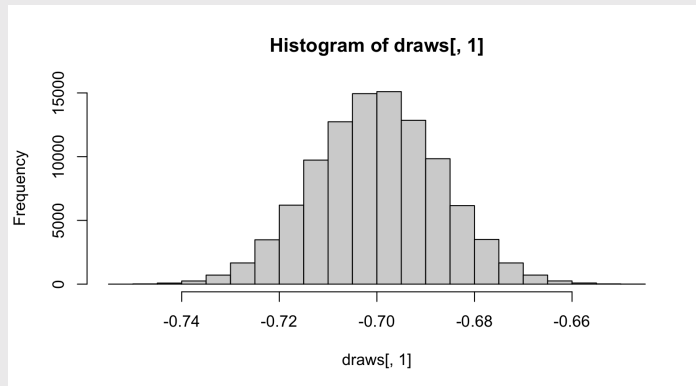
head(draws)
```

```
#>           [,1]      [,2]      [,3]
#> [1,] -0.6946433  0.1206494 -3.973694
#> [2,] -0.7128098  0.1381762 -3.975379
#> [3,] -0.6941685  0.1334979 -4.002586
#> [4,] -0.7166425  0.1122484 -4.079662
#> [5,] -0.6983785  0.1447645 -4.033314
#> [6,] -0.7060643  0.1088229 -3.999648
```

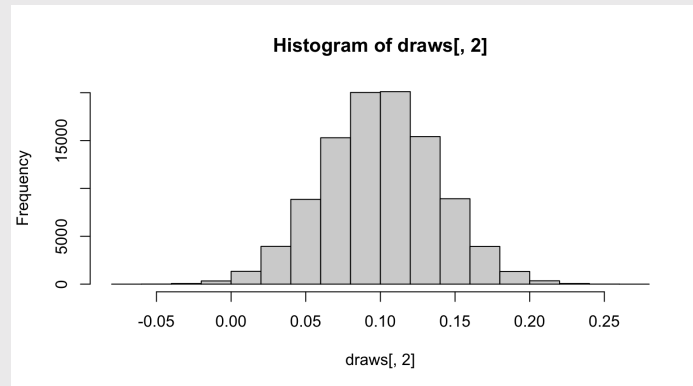
Simulating uncertainty

We can use the coefficients and hessian from a model to obtain draws that reflect parameter uncertainty

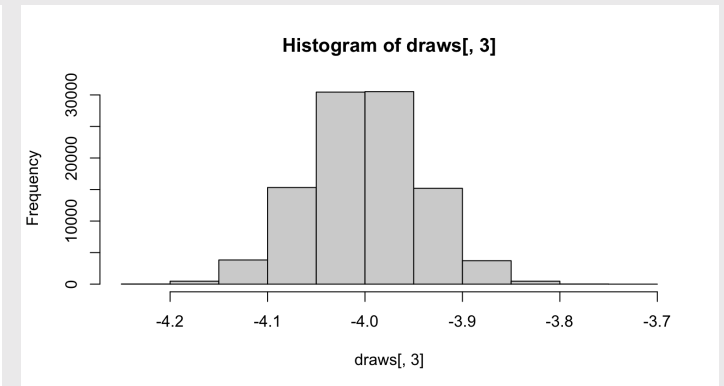
```
hist(draws[, 1])
```



```
hist(draws[, 2])
```



```
hist(draws[, 3])
```



Practice Question 2

Suppose we estimate the following utility model describing preferences for cars:

$$u_j = \alpha p_j + \beta_1 x_j^{mpg} + \beta_2 x_j^{elec} + \varepsilon_j$$

a) Generate 10,000 draws of the model coefficients using the estimated coefficients and hessian. Use the `mvrnorm()` function from the **MASS** library.

b) Use the draws to compute the mean and 95% confidence intervals of each parameter estimate.

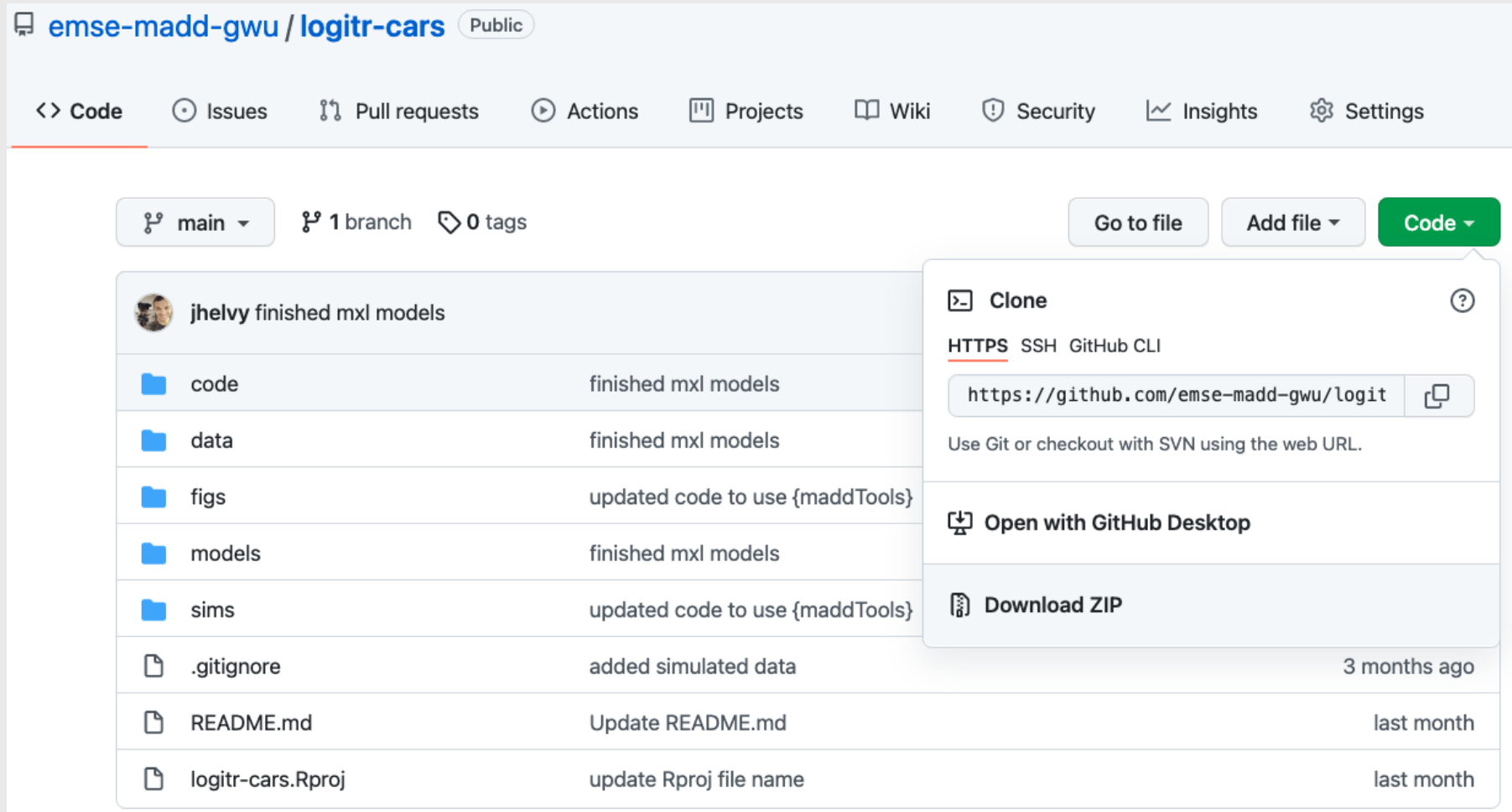
The estimated model produces the following results:

Parameter Coefficient	
α	-0.7
β_1	0.1
β_2	-0.4

Hessian:

$$\begin{bmatrix} -6000 & 50 & 60 \\ 50 & -700 & 50 \\ 60 & 50 & -300 \end{bmatrix}$$

Download the **logitr-cars** repo from GitHub



emse-madd-gwu / **logitr-cars** Public

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Go to file Add file Code

jhelvy finished mxl models

code	finished mxl models
data	finished mxl models
figs	updated code to use {maddTools}
models	finished mxl models
sims	updated code to use {maddTools}
.gitignore	added simulated data
README.md	Update README.md
logitr-cars.Rproj	update Rproj file name

Clone ?

HTTPS SSH GitHub CLI

<https://github.com/emse-madd-gwu/logitr-cars>

Use Git or checkout with SVN using the web URL.

Open with GitHub Desktop

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Computing and visualizing uncertainty

1. Open `logitr-cars`
2. Open `code/5.1-uncertainty.R`

Week 9: *Uncertainty*

1. Computing uncertainty

2. Reshaping data

BREAK

3. Cleaning pilot data

4. Estimating pilot data models

Names, Values, and Observations

- Variable **Name**: The name of something you can measure
- Variable **Value**: One instance of a measured variable
- **Observation**: A set of associated measurements across multiple variables

```
head(fed_spend_long)
```

```
#> # A tibble: 6 × 3
#>   department year rd_budget_mil
#>   <chr>      <dbl>      <dbl>
#> 1 DOD        1976        35696
#> 2 NASA        1976        12513
#> 3 DOE         1976        10882
#> 4 HHS         1976         9226
#> 5 NIH         1976         8025
#> 6 NSF         1976         2372
```

"Long" format data

- Each **variable** has its own **column**
- Each **observation** has its own **row**

country	year	cases	population
Afghanistan	1999	745	19987071
Afghanistan	2000	9666	20593360
Brazil	1999	37737	17206362
Brazil	2000	80488	174504898
China	1999	212258	127291272
China	2000	216766	128042583

variables

country	year	cases	population
Afghanistan	1999	745	19987071
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China	1999	212258	127291272
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observations

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#> # A tibble: 6 × 3
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#>   <chr>      <dbl>      <dbl>
#> 1 DOD        1976      35696
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#> 3 DOE         1976      10882
#> 4 HHS         1976       9226
#> 5 NIH         1976       8025
#> 6 NSF         1976       2372
```

country	year	cases	population
Afghanistan	1999	1745	19987071
Afghanistan	2000	1666	20595360
Brazil	1999	37737	17206362
Brazil	2000	80488	174504898
China	1999	211258	1272915272
China	2000	216766	128042583

variables

country	year	cases	population
Afghanistan	1999	1745	19987071
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observations

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Afghanistan	1999	1745	19987071
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Brazil	1999	37737	17206362
Brazil	2000	80488	174504898
China	1999	211258	1272915272
China	2000	216766	128042583

values

"Long" format

```
#> # A tibble: 6 × 3
#>   department year rd_budget_mil
#>   <chr>      <dbl>      <dbl>
#> 1 DOD      1976      35696
#> 2 NASA     1976      12513
#> 3 DOE      1976      10882
#> 4 HHS      1976       9226
#> 5 NIH      1976       8025
#> 6 NSF      1976       2372
```

"Wide" format

```
#> # A tibble: 6 × 8
#>   year DHS   DOC   DOD   DOE   DOT   EPA   HHS
#>   <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
#> 1 1976     0   819 35696 10882 1142   968  9226
#> 2 1977     0   837 37967 13741 1095   966  9507
#> 3 1978     0   871 37022 15663 1156  1175 10533
#> 4 1979     0   952 37174 15612 1004  1102 10127
#> 5 1980     0   945 37005 15226 1048   903 10045
#> 6 1981     0   829 41737 14798   978   901  9644
```

"Long" format: variable names describe the values below them

"Long" format

```
#> # A tibble: 6 × 3
#>   department year rd_budget_mil
#>   <chr>      <dbl>      <dbl>
#> 1 DOD        1976      35696
#> 2 NASA        1976      12513
#> 3 DOE         1976      10882
#> 4 HHS         1976       9226
#> 5 NIH         1976       8025
#> 6 NSF         1976       2372
```

"Wide" format

```
#> # A tibble: 6 × 8
#>   year DHS   DOC   DOD   DOE   DOT   EPA   HHS
#>   <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
#> 1  1976     0   819 35696 10882  1142   968  9226
#> 2  1977     0   837 37967 13741  1095   966  9507
#> 3  1978     0   871 37022 15663  1156  1175 10533
#> 4  1979     0   952 37174 15612  1004  1102 10127
#> 5  1980     0   945 37005 15226  1048   903 10045
#> 6  1981     0   829 41737 14798   978   901  9644
```

Quick practice 1: "long" or "wide" format?

Description: Tuberculosis cases in various countries

```
#> # A tibble: 6 × 4
#>   country      year  cases population
#>   <chr>      <dbl>  <dbl>      <dbl>
#> 1 Afghanistan 1999     745    19987071
#> 2 Afghanistan 2000    2666    20595360
#> 3 Brazil      1999   37737   172006362
#> 4 Brazil      2000   80488   174504898
#> 5 China       1999  212258  1272915272
#> 6 China       2000  213766  1280428583
```


Quick practice 2: "long" or "wide" format?

Description: Word counts by character type in "Lord of the Rings" trilogy

```
#> # A tibble: 9 × 4
#>   Film                                Race    Female    Male
#>   <chr>                                <chr>    <dbl>  <dbl>
#> 1 The Fellowship Of The Ring      Elf        1229    971
#> 2 The Fellowship Of The Ring    Hobbit         14   3644
#> 3 The Fellowship Of The Ring      Man          0   1995
#> 4 The Return Of The King          Elf        183    510
#> 5 The Return Of The King          Hobbit         2   2673
#> 6 The Return Of The King          Man        268   2459
#> 7 The Two Towers                  Elf        331    513
#> 8 The Two Towers                  Hobbit         0   2463
#> 9 The Two Towers                  Man       401   3589
```

Quick practice 3: "long" or "wide" format?

Description: Word counts by character type in "Lord of the Rings" trilogy

```
#> # A tibble: 18 × 4
#>   Film      Race Gender Word_Count
#>   <chr>    <chr> <chr>      <dbl>
#> 1 The Fellowship Of The Ring Elf      Female      1229
#> 2 The Fellowship Of The Ring Elf      Male        971
#> 3 The Fellowship Of The Ring Hobbit    Female        14
#> 4 The Fellowship Of The Ring Hobbit    Male      3644
#> 5 The Fellowship Of The Ring Man      Female         0
#> 6 The Fellowship Of The Ring Man      Male     1995
#> 7 The Return Of The King    Elf      Female      183
#> 8 The Return Of The King    Elf      Male       510
#> 9 The Return Of The King    Hobbit    Female         2
#> 10 The Return Of The King    Hobbit    Male     2673
#> 11 The Return Of The King    Man      Female      268
#> 12 The Return Of The King    Man      Male     2459
#> 13 The Two Towers          Elf      Female      331
#> 14 The Two Towers          Elf      Male       513
#> 15 The Two Towers          Hobbit    Female         0
#> 16 The Two Towers          Hobbit    Male     2463
#> 17 The Two Towers          Man      Female      401
#> 18 The Two Towers          Man      Male     3589
```

Reshaping data with `pivot_longer()` and `pivot_wider()`

From "long" to "wide" with `pivot_wider()`

long			wide			
id	name	value	id	name		
1	x	a	1	x	y	z
2	x	b	1	a	c	e
1	y	c	2	b	d	f
2	y	d				
1	z	e				
2	z	f				

From "long" to "wide" with `pivot_wider()`

```
head(fed_spend_long)
```

```
#> # A tibble: 6 × 3  
#>   department year rd_budget_mil  
#>   <chr>      <dbl>      <dbl>  
#> 1 DOD        1976      35696  
#> 2 NASA        1976      12513  
#> 3 DOE         1976      10882  
#> 4 HHS         1976       9226  
#> 5 NIH         1976       8025  
#> 6 NSF         1976       2372
```

```
fed_spend_wide <- fed_spend_long %>%  
  pivot_wider(  
    names_from = department,  
    values_from = rd_budget_mil)
```

```
head(fed_spend_wide)
```

```
#> # A tibble: 6 × 7  
#>   year  DHS  DOC  DOD  DOE  DOT  EPA  
#>   <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>  
#> 1  1976     0   819 35696 10882  1142   968  
#> 2  1977     0   837 37967 13741  1095   966  
#> 3  1978     0   871 37022 15663  1156  1175  
#> 4  1979     0   952 37174 15612  1004  1102  
#> 5  1980     0   945 37005 15226  1048   903  
#> 6  1981     0   829 41737 14798   978   901
```

From "wide" to "long" with `pivot_longer()`

wide					long		
id	x	y	z	name	id	name	value
1	a	c	e	value	1	x	a
2	b	d	f		2	x	b
					1	y	c
					2	y	d
					1	z	e
					2	z	f

From "wide" to "long" with `pivot_longer()`

```
names(fed_spend_wide)
```

```
#> [1] "year"      "DHS"      "DOC"
"DOD"      "DOE"      "DOT"      "EPA"
"HHS"      "Interior" "NASA"     "NIH"
"NSF"      "Other"    "USDA"     "VA"
```

```
fed_spend_long <- fed_spend_wide %>%
  pivot_longer(
    cols = DHS:VA,
    names_to = "department",
    values_to = "rd_budget_mil")
```

```
head(fed_spend_long)
```

```
#> # A tibble: 6 × 3
#>   year department rd_budget_mil
#>   <dbl> <chr>         <dbl>
#> 1  1976 DHS             0
#> 2  1976 DOC           819
#> 3  1976 DOD          35696
#> 4  1976 DOE          10882
#> 5  1976 DOT           1142
#> 6  1976 EPA            968
```

Can also set `cols` by selecting which columns *not* to use

```
names(fed_spend_wide)
```

```
#> [1] "year"      "DHS"      "DOC"
"DOD"      "DOE"      "DOT"      "EPA"
"HHS"      "Interior" "NASA"     "NIH"
"NSF"      "Other"    "USDA"     "VA"
```

```
fed_spend_long <- fed_spend_wide %>%
  pivot_longer(
    cols = -year,
    names_to = "department",
    values_to = "rd_budget_mil")

head(fed_spend_long)
```

```
#> # A tibble: 6 × 3
#>   year department rd_budget_mil
#>   <dbl> <chr>         <dbl>
#> 1  1976 DHS             0
#> 2  1976 DOC           819
#> 3  1976 DOD          35696
#> 4  1976 DOE          10882
#> 5  1976 DOT           1142
#> 6  1976 EPA           968
```


Your turn: Long <--> Wide

Open the `practice.Rmd` file.

Under "In Class Question 1", write code to read in the following two files:

- `pv_cells.csv`: Data on solar photovoltaic cell production by country
- `milk_production.csv`: Data on milk production by state

Now modify the format of each:

- If the data are in "wide" format, convert it to "long" with `pivot_longer()`
- If the data are in "long" format, convert it to "wide" with `pivot_wider()`

Break

05 : 00

Week 9: *Uncertainty*

1. Computing uncertainty

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BREAK

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Download the **formr4conjoint** repo from GitHub

jhelvy / **formr4conjoint** Public

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jhelvy added package installs to readme

figs	added package installs to readme
survey	added consent form content in p1
.gitignore	Update .gitignore
LICENSE.md	Create LICENSE.md
README.Rmd	added package installs to readme
README.md	added package installs to readme 20 minutes ago
formr4conjoint.Rproj	Init 2 years ago

Clone ?

HTTPS SSH GitHub CLI

<https://github.com/jhelvy/formr4conjoint>

Use Git or checkout with SVN using the web URL.

Open with GitHub Desktop

Download ZIP

Cleaning formr survey data

1. Open `formr4conjoint.Rproj`
2. Open `code/data_cleaning.R`

Your Turn

20:00

As a team, pick up where you left off last week and create a **choiceData** data frame in a "long" format

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Estimating pilot data models

1. Open `formr4conjoint.Rproj`
2. Open `code/modeling.R`

Your Turn

As a team:

1. Use your `choiceData` data frame to estimate preliminary choice models.
2. Interpret your model coefficients with uncertainty.