Chapter 4

Lin 205C
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Chapter Precap

- Discuss the analysis of data made up of multiple observations from members of a ‘single group’.

- Introduce and explain the following concepts:
  - ‘multilevel’ models.
  - ‘repeated measures’ data.
  - No pooling, complete pooling, and adaptive partial pooling.
  - ‘Random’ and ‘fixed’ effects.

- Fit a multilevel model with a structure that is appropriate for our repeated measures data than the models presented in the previous chapter.

- Simulate some repeated-measures data based on the parameters estimated by our model and see how the exclusion of different components affects our simulated data.

Repeated Measures Data

- Multiple observations from a given ‘source’ or ‘experimental unit’.
- Observations may not all be independent, which causes a problem if we act like it is.
- For example, our listening experiment featured 139 observations from 15 different listeners (and 15 observations for each speaker).

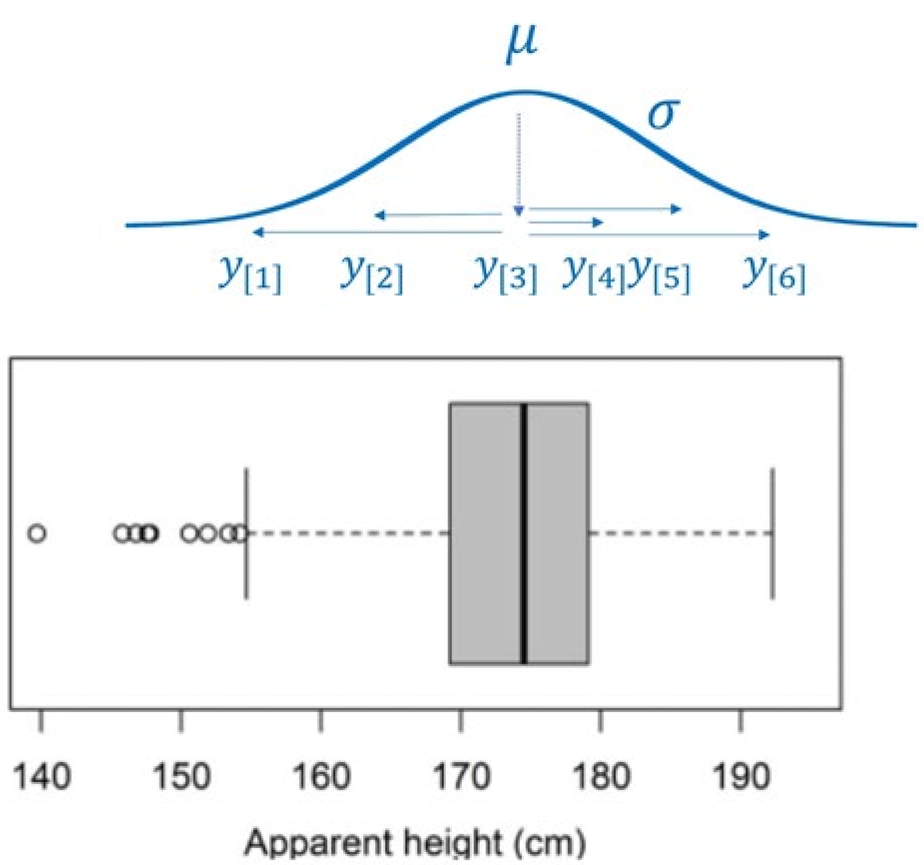
Last Chapter: One Big Pile of Data

$$\text{height}_{[i]} \sim \text{N}\left(\mu_{[i]}, \sigma\right)$$
$$\mu_{[i]} = \text{Intercept}$$

Priors:

$$\text{Intercept} \sim \text{N}(176, 15)$$
$$\sigma \sim \text{N}(0, 15)$$

“Unilevel” Model



Repeated Measures Data

$$\text{height}_{[i]} \sim \text{N}\left(\mu_{[i]}, \sigma\right)$$

$$\mu_{[i]} = \text{Intercept}$$

?

Priors:

$$\text{Intercept} \sim \text{N}(176, 15)$$

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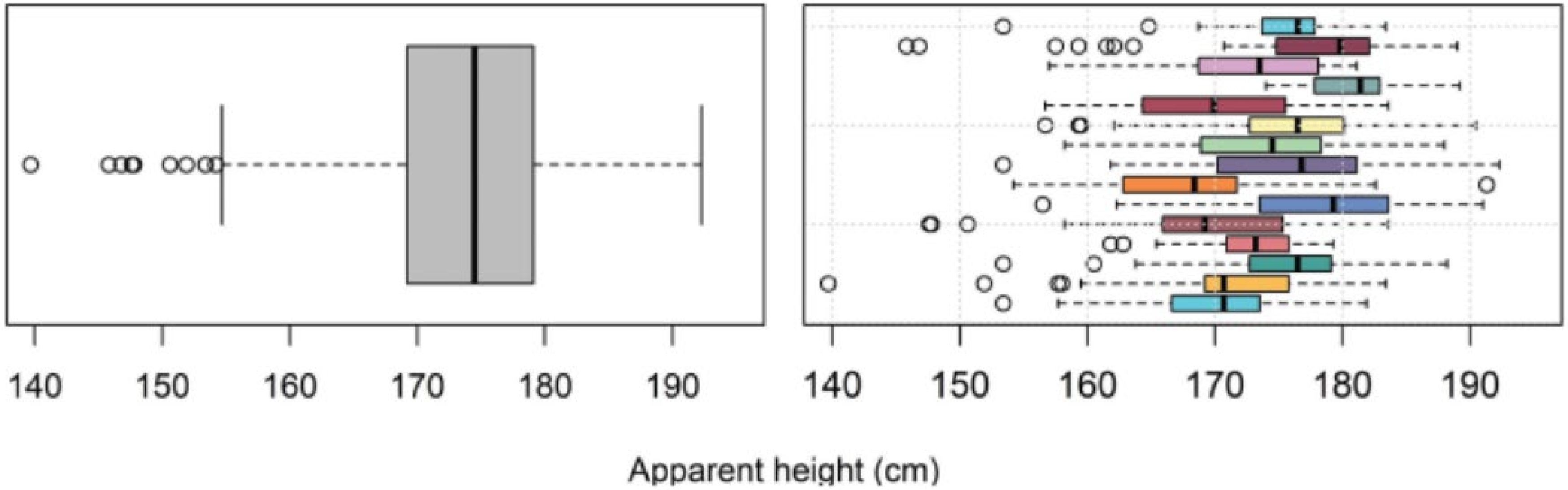
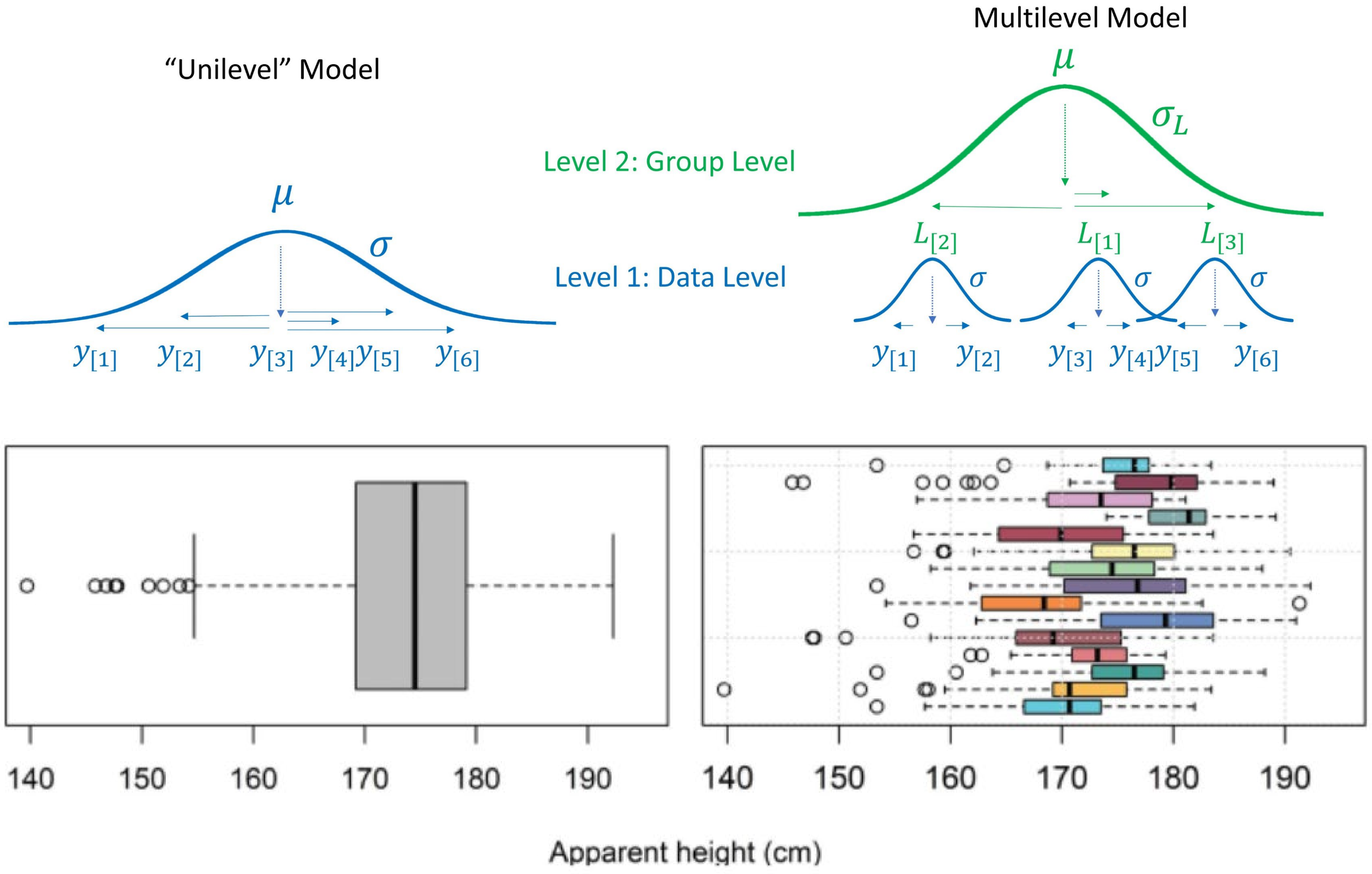
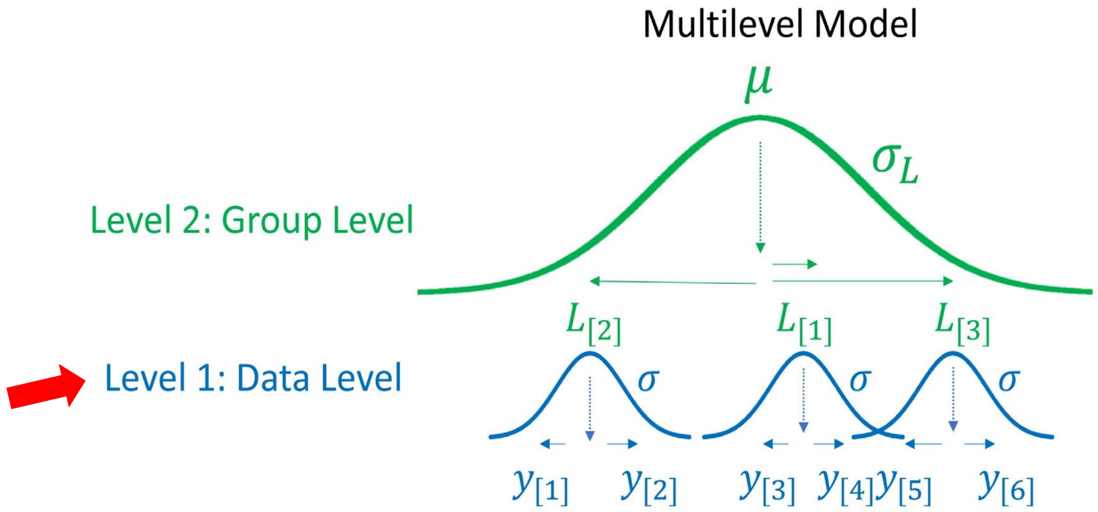


Repeated Measures Data: Levels of Variation



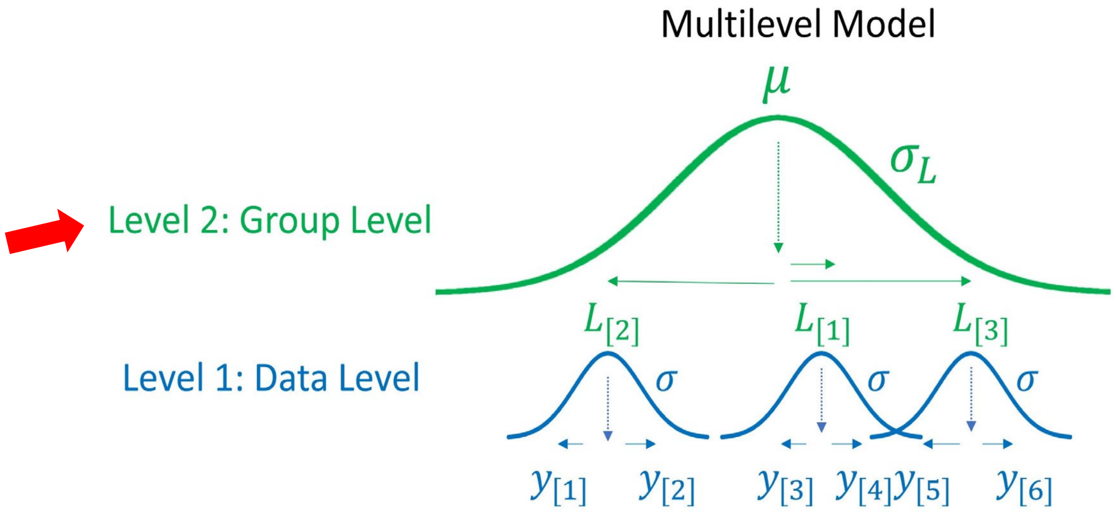
‘Levels’ of Variation: The ‘Lower’ level

- The ‘data level’ distribution of data *within* a given cluster/unit/listener.
- The conditional distribution of data *given* a specific source of data.
- Example: A single person will have a distribution of reaction times for a given experimental task.



‘Levels’ of Variation: The ‘Upper’ level

- The ‘group level’ distribution of parameters *across* different clusters/units/listeners.
- The marginal distribution of parameters *across* all sources of data.
- Example: There will be a distribution of average reaction times for a given experimental task, across participants.



Multilevel Models

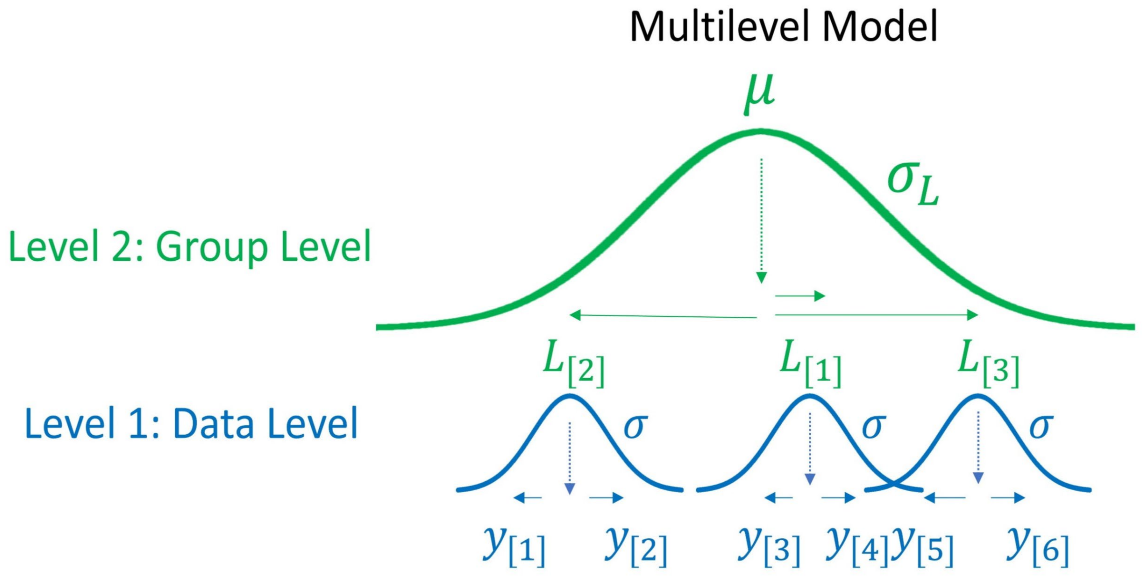
- Multilevel models can estimate parameters from 'multiple levels' simultaneously.

- For example, we can model:

  - Within listener variation (σ).

  - Listener averages ($L_{[i]}$).

  - Between-listener variation (σ_{L}).



Representing Factors with Many Levels

- Each level of a factor needs a predictor.
- Mathematically this is a matrix of 1s and 0s.
- We have (about) 15 predictors for our 15 levels of listener.

$$\mu_{[i]} = \text{Intercept} + L_{[1]} \cdot 0 + L_{[2]} \cdot 1 + L_{[3]} \cdot 0 + \ldots + L_{[15]} \cdot 0$$

$$\mu_{[i]} = \text{Intercept} + L_{[2]}$$

Representing Factors with Many Levels

- We'll represent parameters representing levels of a factor as vectors.
- These will be selected by our predictors of the same name.
- This means: "Our predicted value for trial i, $\mu_{[i]}$, is the sum of the model intercept and the L coefficient indexed by the value of the L predictor for trial i ($\mathsf{L}_{[i]}$)."

$$\mu_{[i]} = \text{Intercept} + L_{\left[\mathsf{L}_{[i]}\right]}$$

$$\mathsf{L}_{[1]} = 2, \mathsf{L}_{[2]} = 4, \mathsf{L}_{[3]} = 1, \ldots$$

$$\mu_{[i=1]} = \text{Intercept} + L_{\left[\mathsf{L}_{[i=1]}\right]} = \text{Intercept} + L_{[2]}$$

$$\mu_{[i=2]} = \text{Intercept} + L_{\left[\mathsf{L}_{[i=2]}\right]} = \text{Intercept} + L_{[4]}$$

$$\mu_{[i=3]} = \text{Intercept} + L_{\left[\mathsf{L}_{[i=3]}\right]} = \text{Intercept} + L_{[1]}$$

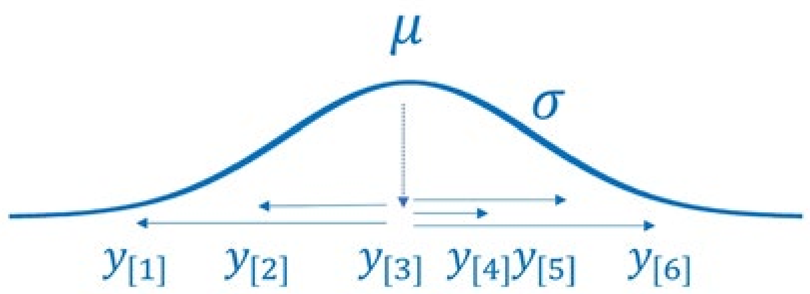
$$\ldots$$

Strategies for Estimating Factors with Many Levels

- Your factors may have >10 (or greater than >100!) levels.
- This can lead to a large number of model parameters.
- There are three general approaches to dealing with factors with many levels:
    - Complete pooling
    - No pooling.
    - (Adaptive) partial pooling.

Complete Pooling

- Throw everything in a big pile and act like you don't have individual data clusters.



- You miss some useful information (e.g., σ_{L}).

$$\text{height}_{[i]} \sim \mathrm{N}\left(\mu_{[i]}, \sigma\right)$$
$$\mu_{[i]} = \text{Intercept}$$

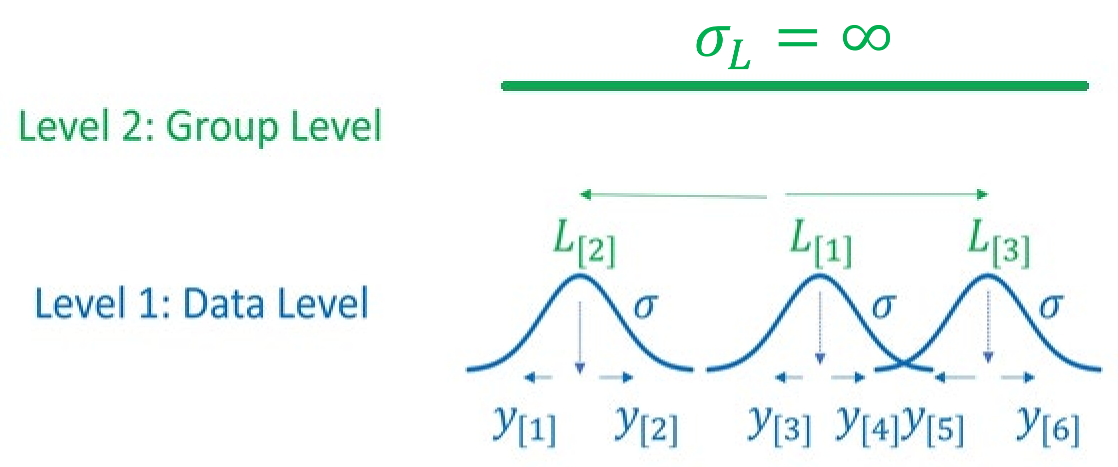
- Big problem: Data is probably not independent, CIs will be unreliable.

Priors:

$$\text{Intercept} \sim \mathrm{N}(176, 15)$$
$$\sigma \sim \mathrm{N}(0, 15)$$

No Pooling

- Acknowledge the clusters but impose no/weak constraints on their values.
- You miss some useful information (e.g., σ_{L}).
- Medium problem: Parameter values across clusters (i.e. L) are usually not totally unrelated to each other.



$$\text{height}_{[i]} \sim \mathrm{N}\left(\mu_{[i]}, \sigma\right)$$

$$\mu_{[i]} = \text{Intercept} + L_{[\mathrm{L}[i]]}$$

Priors:

$$L_{[\bullet]} \sim \text{uniform}(-\infty, \infty)$$

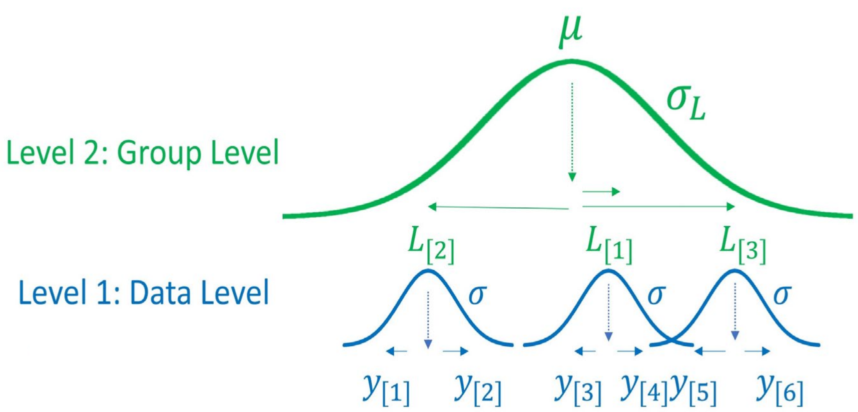
$$\text{Intercept} \sim \mathrm{N}(176, 15)$$

Partial Pooling

- Acknowledge the clusters and impose probabilistic constraints on their values.

- Use the information in the 'second' level (e.g, σ_{L}) for modelling.

- Big benefit: More information and better behaving/performing models.



$$\text{height}_{[i]} \sim \mathrm{N}\left(\mu_{[i]}, \sigma\right)$$

$$\mu_{[i]} = \text{Intercept} + L_{\left[\mathrm{L}[i]\right]}$$

Priors :

$$L_{[\bullet]} \sim \mathrm{N}(0, \sigma_L)$$

$$\text{Intercept} \sim \mathrm{N}(176, 15)$$

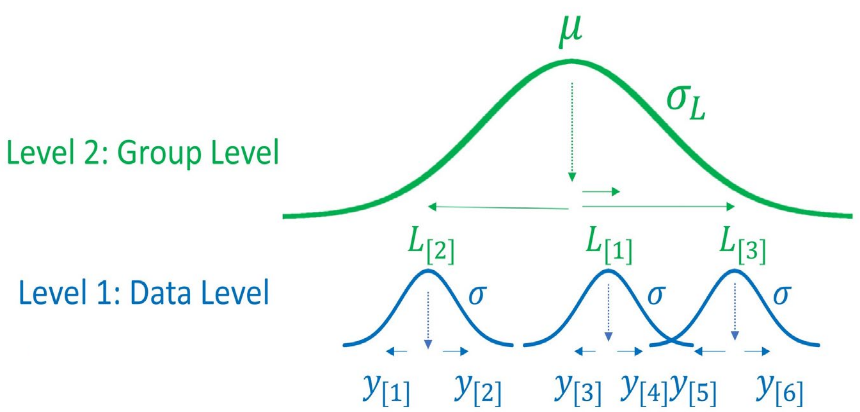
$$\sigma \sim \mathrm{N}(0, 15)$$

$$\sigma_L \sim \mathrm{N}(0, 15)$$

Adaptive Partial Pooling

- Partial pooling is any model that uses the same information (e,g, σ_{L}) for different parameters.

- *Adaptive* partial pooling is when a model estimates these constraints (e,g, σ_{L}) from the data.



$$\text{height}_{[i]} \sim \mathrm{N}\left(\mu_{[i]}, \sigma\right)$$

$$\mu_{[i]} = \text{Intercept} + L_{\left[\mathrm{L}_{[i]}\right]}$$

Priors :

$$L_{[\bullet]} \sim \mathrm{N}(0, \sigma_L)$$

$$\text{Intercept} \sim \mathrm{N}(176, 15)$$

$$\sigma \sim \mathrm{N}(0, 15)$$

$$\sigma_L \sim \mathrm{N}(0, 15)$$

Comparison of Approaches

Complete pooling

$$\text{height}_{[i]} \sim \mathrm{N}\left(\mu_{[i]}, \sigma\right)$$
$$\mu_{[i]} = \text{Intercept}$$

Priors:

$$\text{Intercept} \sim \mathrm{N}(176, 15)$$
$$\sigma \sim \mathrm{N}(0, 15)$$

No pooling

$$\text{height}_{[i]} \sim \mathrm{N}\left(\mu_{[i]}, \sigma\right)$$
$$\mu_{[i]} = \text{Intercept} + L_{\left[\mathsf{L}[i]\right]}$$

Priors:

$$L_{[\cdot]} \sim \text{uniform}(-\infty, \infty)$$

$$\text{Intercept} \sim \mathrm{N}(176, 15)$$

Partial pooling

$$\text{height}_{[i]} \sim \mathrm{N}\left(\mu_{[i]}, \sigma\right)$$
$$\mu_{[i]} = \text{Intercept} + L_{\left[\mathsf{L}[i]\right]}$$

Priors :

$$L_{[\cdot]} \sim \mathrm{N}(0, \sigma_L)$$

$$\text{Intercept} \sim \mathrm{N}(176, 15)$$
$$\sigma \sim \mathrm{N}(0, 15)$$
$$\sigma_L \sim \mathrm{N}(0, 15)$$

Hyperpriors

- The priors for your priors.

$$\text{height}_{[i]} \sim \mathrm{N}\left(\mu_{[i]}, \sigma\right)$$

$$\mu_{[i]} = \text{Intercept} + L_{[\mathrm{L}[i]]}$$

$$\text{Priors}:$$

$$L_{[\bullet]} \sim \mathrm{N}(0, \sigma_L)$$

$$\text{Intercept} \sim \mathrm{N}(176, 15)$$

$$\sigma \sim \mathrm{N}(0, 15)$$

$$\sigma_L \sim \mathrm{N}(0, 15)$$

$$P\left(L_{[\bullet]} \mid y\right) = \frac{P\left(y \mid L_{[\bullet]}\right) \cdot P\left(L_{[\bullet]}\right)}{P\left(y\right)}$$

$$P\left(L_{[\bullet]}, \sigma_L \mid y\right) = \frac{P\left(y \mid L_{[\bullet]}, \sigma_L\right) \cdot P\left(L_{[\bullet]}, \sigma_L\right)}{P\left(y\right)}$$

$$P\left(L_{[\bullet]}, \sigma_L \mid y\right) = \frac{P\left(y \mid L_{[\bullet]}\right) \cdot P\left(L_{[\bullet]} \mid \sigma_L\right) \cdot P(\sigma_L)}{P\left(y\right)}$$

What Gets a Prior?

- All estimated parameters get a prior.

- For example:

    - L and σ_L get priors because they are estimated.

    - The standard deviation of σ_L is 15. It is not estimated.

$$\text{height}_{[i]} \sim \mathrm{N}\left(\mu_{[i]}, \sigma\right)$$

$$\mu_{[i]} = \text{Intercept} + L_{\left[\mathsf{L}[i]\right]}$$

$$\text{Priors}:$$

$$L_{[\bullet]} \sim \mathrm{N}(0, \sigma_L)$$

$$\text{Intercept} \sim \mathrm{N}(176, 15)$$

$$\sigma \sim \mathrm{N}(0, 15)$$

$$\sigma_L \sim \mathrm{N}(0, 15)$$

Data and Research Questions

```
# load book package and brms
library (bmmb)
library (brms)

# load and subset experimental data
data (exp_data)
men = exp_data[exp_data$C_v=='m',]
```

- `L`: An integer from 1 to 15 indicating which *listener* responded to the trial.
- `height`: A floating-point number representing the *height* (in centimeters) reported for the speaker on each trial.

```
head (men)
##     L C height R  S C_v  vtl  f0 dur G A G_v A_v
## 93  1 m  169.9 a 47   m 14.8 172 339 m a   m   a
## 95  1 m  173.5 a 48   m 15.6 108 236 m a   m   a
## 97  1 m  172.0 a 49   m 15.5  96 315 m a   m   a
```

Data and Research Questions

We are going to answer the questions below again, this time with a legitimate multilevel model:

(Q1) How tall does the average adult male sound?

(Q2) Can we set limits on credible average apparent heights based on the data we collected?

The Model Formula

- Our previous model said: “predict height using a single overall intercept”.

```
height ~ 1
```

- We want to model not one intercept, but an intercept for each listener.

- We want to understand the distribution of the intercept <u>given</u> the value of listener.

```
P(Intercept|Listener)
```

The Model Formula

- To model listener-dependent intercepts using adaptive partial pooling, we use this formula:

```
height ~ 1 + ( 1 | L)
```

- Anything you put in parentheses is fit using partial pooling.

```
(Predictor|Grouping factor)
```

Description of the Model

$$\text{height}_{[i]} \sim \mathrm{N}\left(\mu_{[i]}, \sigma\right)$$

$$\mu_{[i]} = \text{Intercept} + L_{\left[\mathsf{L}_{[i]}\right]}$$

We expect height judgments to be normally distributed around the expected value for any given trial, $\mu_{[i]}$, with some unknown standard deviation σ. The expected value for a trial is equal to a fixed overall average (Intercept) and some value associated with the individual listener who made a perceptual judgment on the trial $\left(L_{\left[\mathsf{L}_{[i]}\right]}\right)$. The listener coefficients $\left(L_{[\bullet]}\right)$ were modeled as coming from a normal distribution with a mean of zero and a standard deviation (σ_L) that was estimated from the data.

Priors :

$$L_{[\bullet]} \sim \mathrm{N}(0, \sigma_L)$$

$$\text{Intercept} \sim \mathrm{N}(176, 15)$$

$$\sigma \sim \mathrm{N}(0, 15)$$

$$\sigma_L \sim \mathrm{N}(0, 15)$$

Decomposing Variation

'Unilevel' model → $\sigma^2_{\text{total}} = \sigma^2$

Multilevel model → $\sigma^2_{\text{total}} = \sigma^2_L + \sigma^2$

Specifying Priors

- `Intercept`: This is a unique class, only for intercepts.
- `sd`: This is for standard deviation parameters related to 'batches' of parameters, e.g. `sd(Intercept)` for `L` (σ_L).
- `sigma`: The data-level error term.

```
bmmb::get_prior (height ~ 1 + (1|L), data = men)[,-c(7:9)]
##                  prior     class      coef group resp dpar  source
##  student_t(3, 174.5, 7.1) Intercept                        default
##      student_t(3, 0, 7.1)    sd                            default
##      student_t(3, 0, 7.1)    sd                  L         default
##      student_t(3, 0, 7.1)    sd  Intercept       L         default
##      student_t(3, 0, 7.1)    sigma                         default
```

Fitting the Model

```
# Fit the model yourself
model_multilevel =  brms::brm (
  height ~ 1 + (1|L), data = men, chains = 4, cores = 4,
  warmup = 1000, iter = 3500, thin = 2,
  prior = c(brms::set_prior("normal(176, 15)", class = "Intercept"),
          brms::set_prior("normal(0, 15)", class = "sd"),
          brms::set_prior("normal(0, 15)", class = "sigma")))

# Or download it from the GitHub page:
model_multilevel = bmmb::get_model ('4_model_multilevel.RDS')
```

Interpreting the Model

```
# inspect model
bmmb::short_summary (model_multilevel)
## Formula:  height ~ 1 + (1 | L)
##
## Group-Level Effects:
## ~L (Number of levels: 15)
##               Estimate Est.Error l-95% CI u-95% CI
## sd(Intercept)     3.78      0.87     2.47     5.84
##
## Population-Level Effects:
##           Estimate Est.Error l-95% CI u-95% CI
## Intercept    173.8      1.02    171.8    175.8
##
## Family Specific Parameters:
##       Estimate Est.Error l-95% CI u-95% CI
## sigma     7.03      0.19     6.67     7.41
```

$$\text{height}_{[i]} \sim \mathrm{N}\left(\mu_{[i]}, \sigma\right)$$

$$\mu_{[i]} = \text{Intercept} + L_{\left[\mathsf{L}_{[i]}\right]}$$

Priors :

$$L_{[\bullet]} \sim \mathrm{N}\left(0, \sigma_L\right)$$

$$\text{Intercept} \sim \mathrm{N}(176, 15)$$

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$$\sigma_L \sim \mathrm{N}(0, 15)$$

Interpreting the Model

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# inspect model
bmmb::short_summary (model_multil
## Formula:  height ~ 1 + (1 | L)
##
## Group-Level Effects:
## ~L (Number of levels: 15)
##                Estimate Est.Er
## sd(Intercept)      3.78       0.
##
## Population-Level Effects:
##           Estimate Est.Error l
## Intercept     173.8      1.02
##
## Family Specific Parameters:
##       Estimate Est.Error l-95%
## sigma     7.03      0.19      6
```

```
# find mean height for each listener
listener_means = aggregate (height ~ L, data = men, FUN = mean)

# find the within listener standard deviation
# This is the within-talker 'error'.
listener_sigmas = aggregate (height ~ L, data = men, FUN = sd)

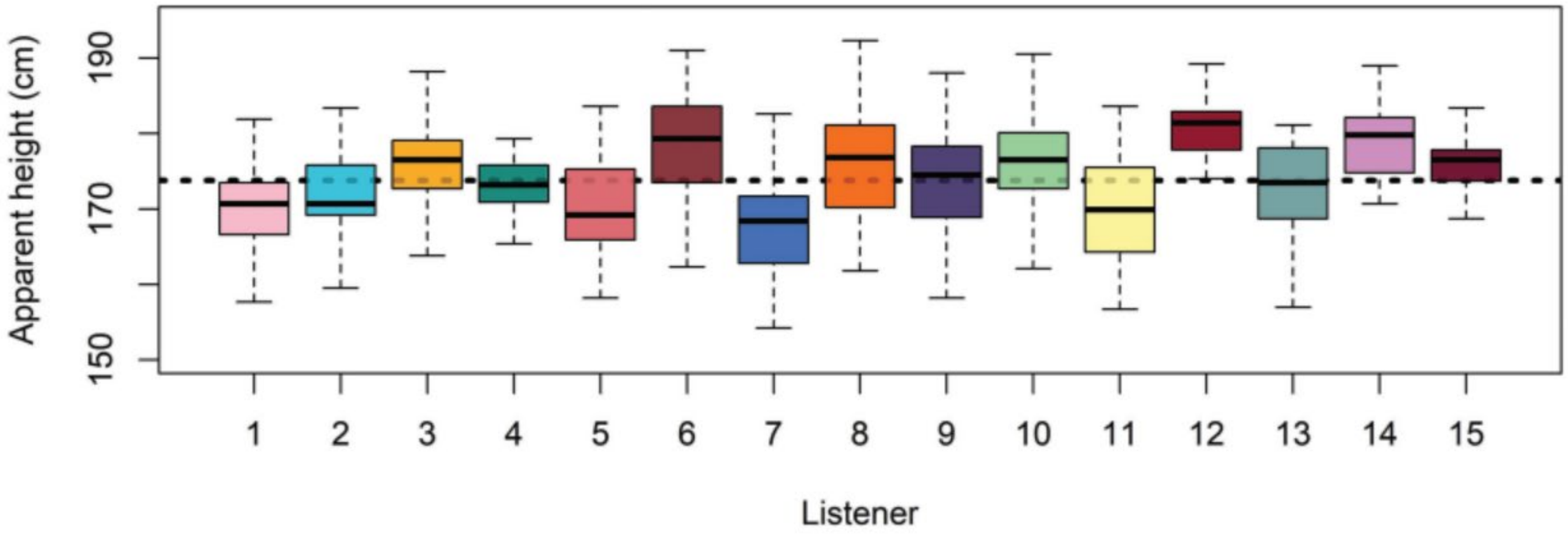
# the mean of the listener means corresponds to our Intercept
mean (listener_means$height)
## [1] 173.8

# the standard deviation of the listener means corresponds
# to 'sd(Intercept)', the estimate of the standard deviation
# of listener intercepts
sd (listener_means$height)
## [1] 3.594

# the average within-listener standard deviation corresponds
# to sigma, the estimated error
mean (listener_sigmas$height)
## [1] 6.822
```

Interpreting the Model

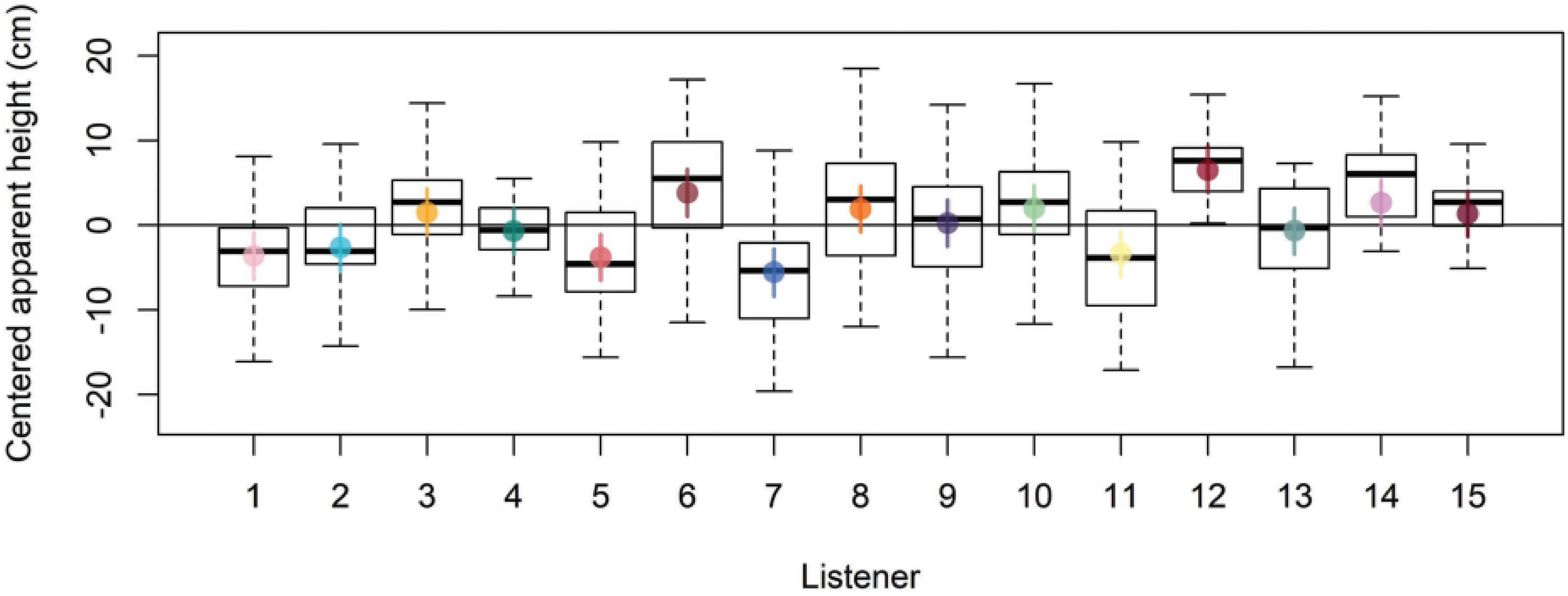
```
## Group-Level Effects:
## ~L (Number of levels: 15)
##                 Estimate Est.Error l-95% CI u-95% CI
## sd(Intercept)       3.78      0.87     2.47     5.84
##
## Population-Level Effects:
##             Estimate Est.Error l-95% CI u-95% CI
## Intercept      173.8      1.02    171.8    175.8
##
## Family Specific Parameters:
##         Estimate Est.Error l-95% CI u-95% CI
## sigma       7.03      0.19     6.67     7.41
```



‘Random’ and ‘Fixed’ Effects

- Many inconsistent definitions of these terms.
- In practice:
  - ‘Fixed’ effects are estimated using no pooling, or minimal pooling.
  - Random effects are usually fit with adaptive partial pooling.

Inspecting the 'Random' Effects



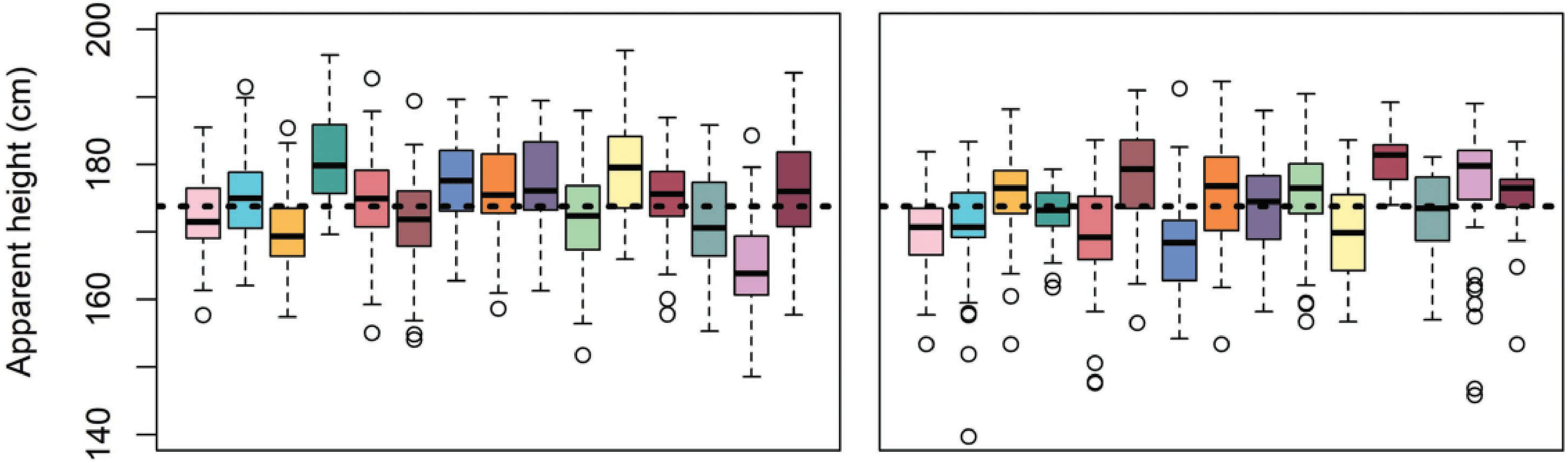
Simulating Data

```
# skip this line if you want a new simulated data set.
set.seed(1)
# this is the value of our intercept
Intercept = 174
# this is a vector of 15 listener effects
L_ = rnorm (15, 0, 3.8 )
# vector indicating which listener produced which utterance
L = rep (1:15, each = 45)
# this vector contains the error
error = rnorm (45 * 15, 0, 7)
```

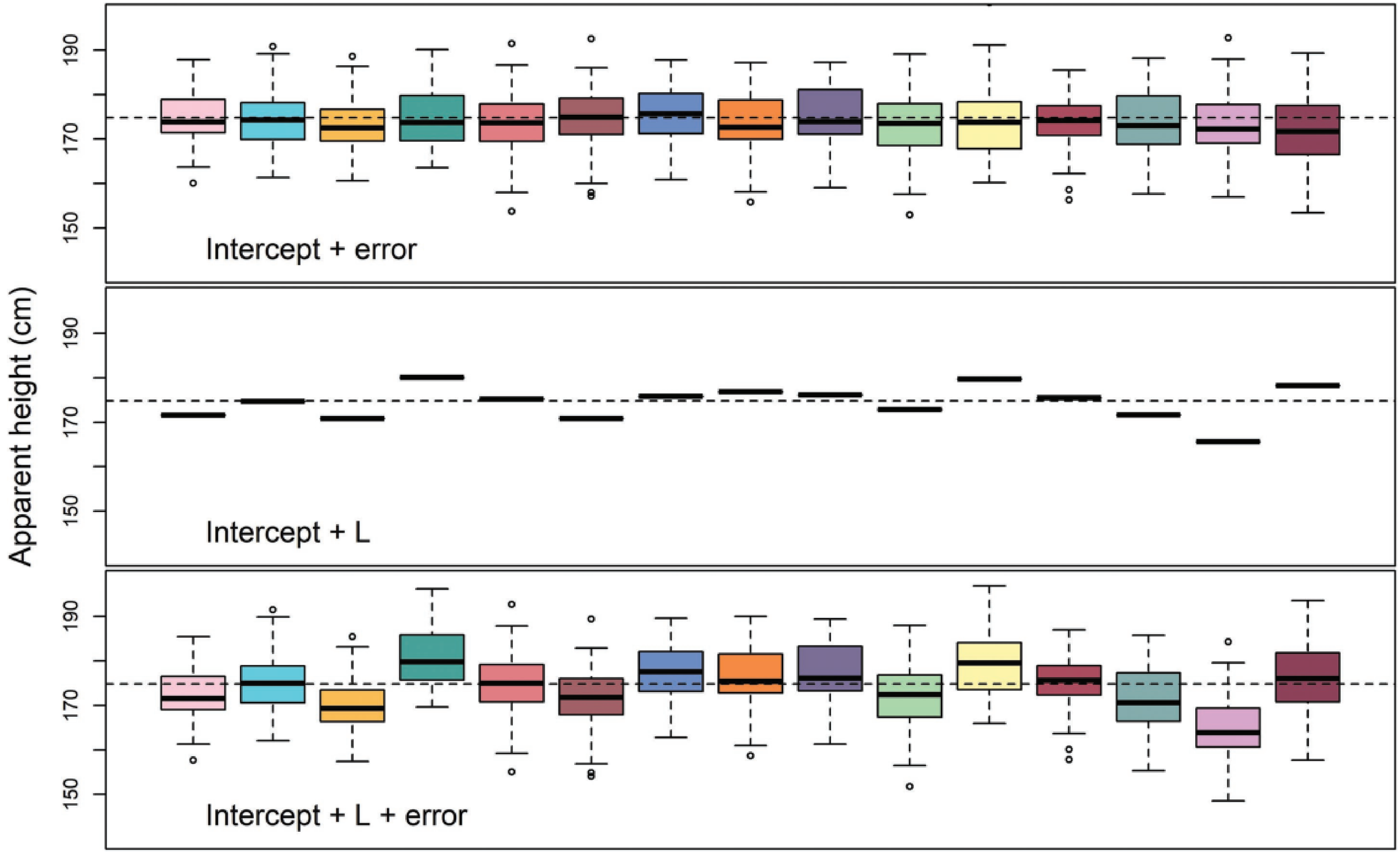
```
# the sum of an intercept, listener effects and random error
height_rep = Intercept + L_[L] + error
```

```
# this fake data is missing between listener variation
height_rep_1 = Intercept + error
# this fake data is missing within listener variation
height_rep_2 = Intercept +  L_[L]
```

Simulating Data



Simulating Data



Simulating Data

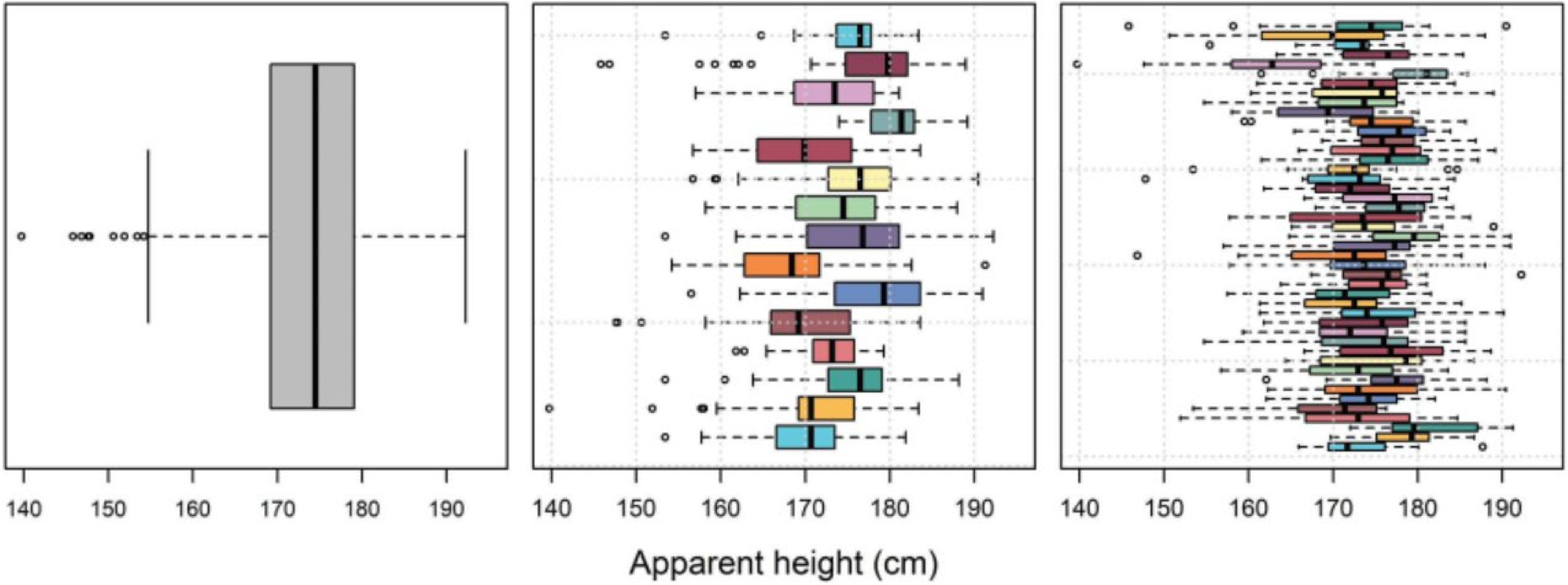
```r
set.seed(1)
# do 10,000 replications
reps = 10000

# hold the replicated values of sigma_L
sigma_L_rep = rep(0,reps)
for ( i in 1:reps){
  Intercept = 173.8 # set the intercept
  L_L = rnorm (15, 0, 0)   # zero between-listener variance
  L = rep (1:15, each = 45) # 45 responses from each of 15 listeners
  epsilon = rnorm (45 * 15, 0, 7.78) # generate random noise
  height_rep = Intercept + L_L[L] + epsilon # add up to components

# get replicated listener means
  L_rep_means = tapply(height_rep, L, mean)
  sigma_L_rep[i] = sd (L_rep_means) # find sigma of listener effects
}
```

```r
quantile(sigma_L_rep)
##      0%    25%    50%    75%   100%
## 0.4429 0.9862 1.1337 1.2810 2.0813
```

Adding a Second Random Effect



Updating our Model Description

$$\text{height}_{[i]} \sim \text{N}\left(\mu_{[i]}, \sigma\right)$$

$$\mu_{[i]} = \text{Intercept} + L_{\left[\mathsf{L}_{[i]}\right]} + S_{\left[\mathsf{S}_{[i]}\right]}$$

Priors :

$$L_{[\cdot]} \sim \text{N}(0, \sigma_L)$$

$$S_{[\cdot]} \sim \text{N}(0, \sigma_S)$$

$$\text{Intercept} \sim \text{N}(176, 15)$$

$$\sigma \sim \text{N}(0, 15)$$

$$\sigma_L \sim \text{N}(0, 15)$$

$$\sigma_S \sim \text{N}(0, 15)$$

Fitting our Model

```
model_multilevel_L_S =  brms::brm (
  height ~ 1 + (1|L) + (1|S), data = men, chains = 4, cores = 4,
  warmup = 1000, iter = 3500, thin = 2,
  prior = c(brms::set_prior("normal(176, 15)", class = "Intercept"),
            brms::set_prior("normal(0, 15)", class = "sd"),
            brms::set_prior("normal(0, 15)", class = "sigma")))
```

Interpreting the New Information

```
bmmb::short_summary (model_multilevel_L_S)
## Formula:  height ~ 1 + (1 | L) + (1 | S)
##
## Group-Level Effects:
## ~L (Number of levels: 15)
##                Estimate Est.Error l-95% CI u-95% CI
## sd(Intercept)      3.81      0.86     2.51     5.87
##
## ~S (Number of levels: 45)
##                Estimate Est.Error l-95% CI u-95% CI
## sd(Intercept)      2.83      0.42      2.1     3.72
##
## Population-Level Effects:
##            Estimate Est.Error l-95% CI u-95% CI
## Intercept     173.8      1.12    171.6    176.1
##
## Family Specific Parameters:
##        Estimate Est.Error l-95% CI u-95% CI
## sigma      6.47      0.19     6.11     6.85
```

$$\text{height}_{[i]} \sim \mathrm{N}\left(\mu_{[i]}, \sigma\right)$$

$$\mu_{[i]} = \text{Intercept} + L_{\left[\mathsf{L}_{[i]}\right]} + S_{\left[\mathsf{S}_{[i]}\right]}$$

Priors :

$$L_{[\bullet]} \sim \mathrm{N}(0, \sigma_L)$$

$$S_{[\bullet]} \sim \mathrm{N}(0, \sigma_S)$$

$$\text{Intercept} \sim \mathrm{N}(176, 15)$$

$$\sigma \sim \mathrm{N}(0, 15)$$

$$\sigma_L \sim \mathrm{N}(0, 15)$$

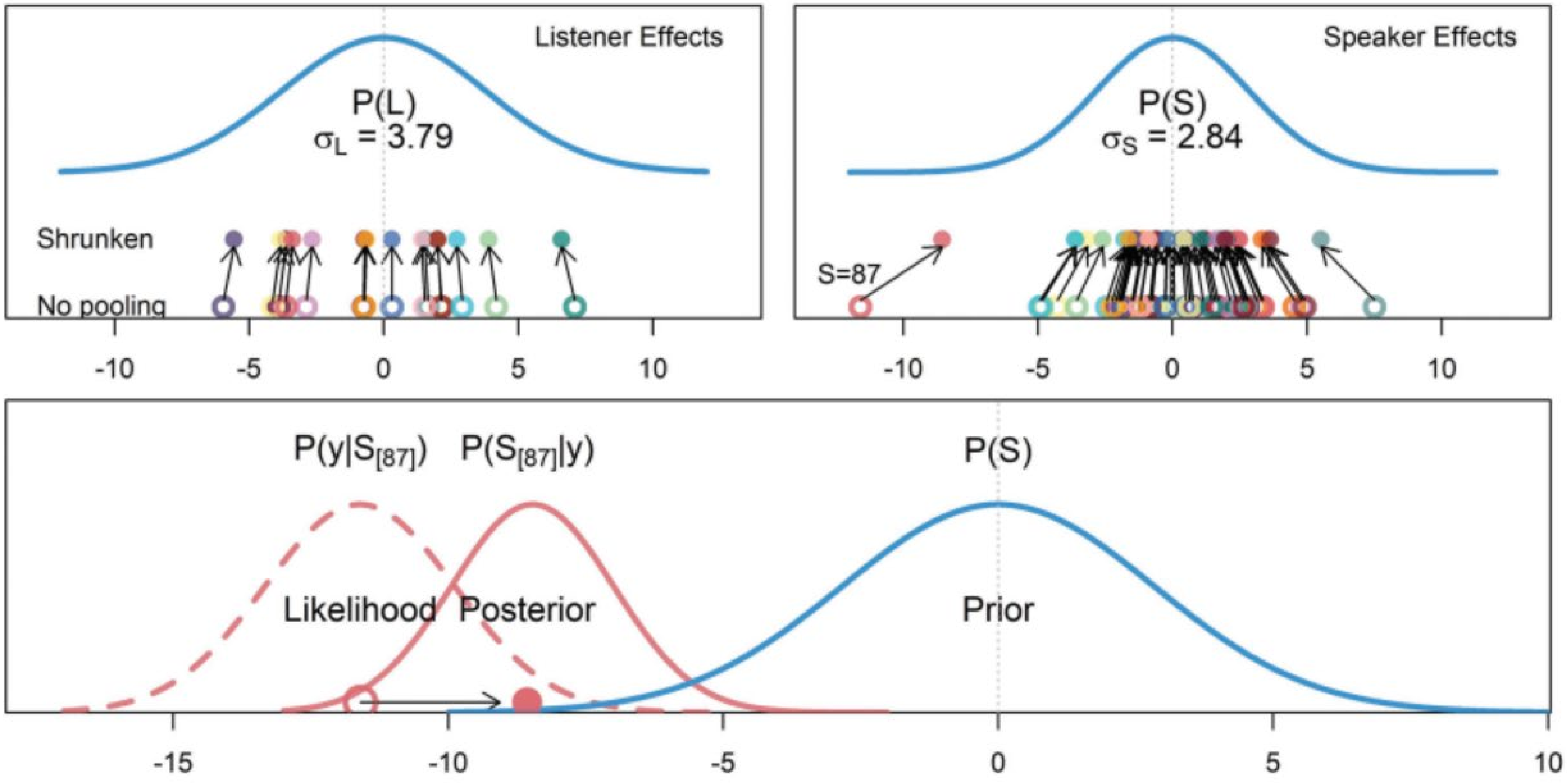
$$\sigma_S \sim \mathrm{N}(0, 15)$$

Comparing Models

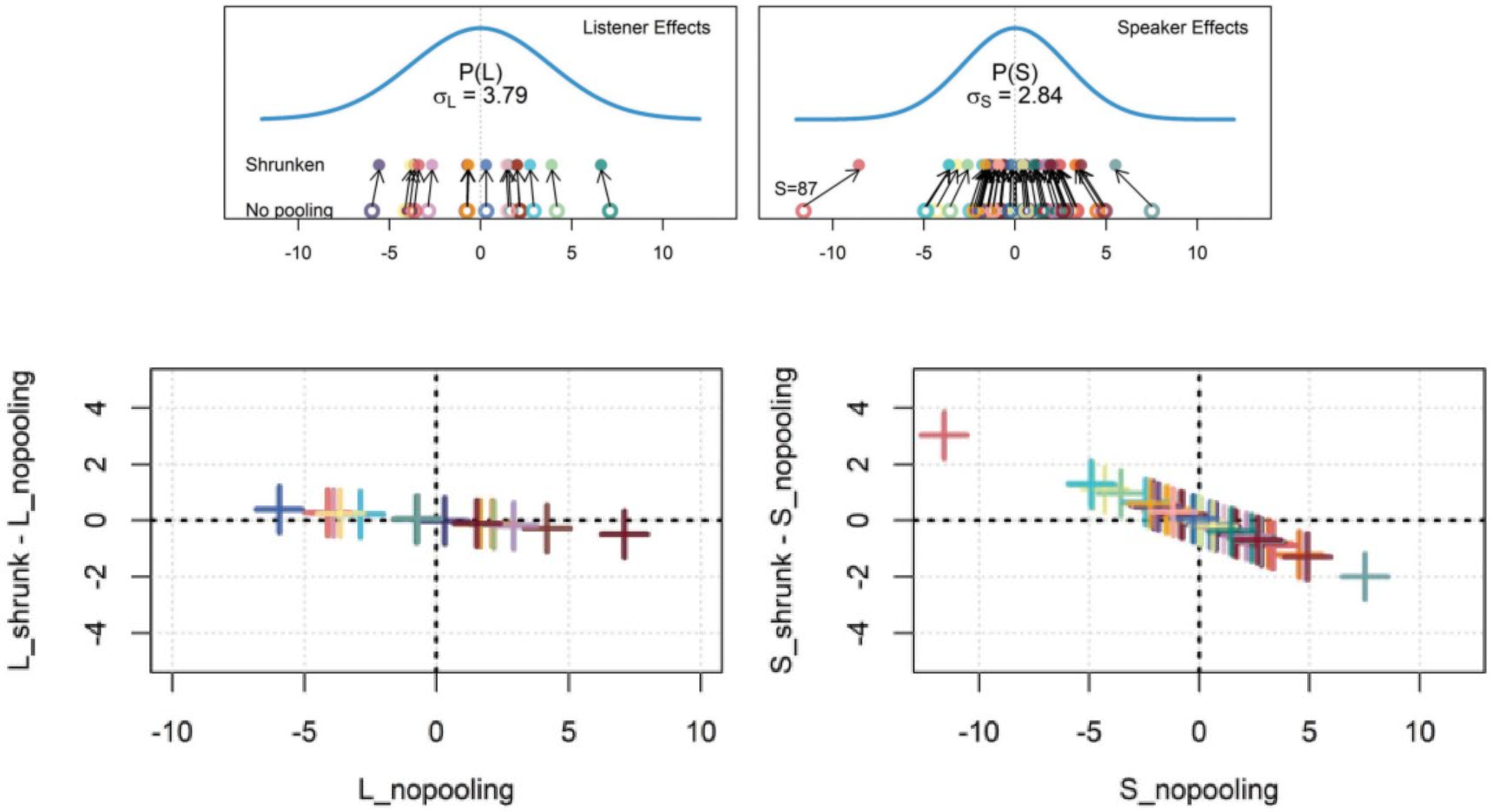
```
bmmb::short_summary (model_priors)
## Formula:  height ~ 1
## Population-Level Effects:
##             Estimate Est.Error l-95% CI u-95% CI
## Intercept      173.8      0.31    173.2    174.4
##
## Family Specific Parameters:
##         Estimate Est.Error l-95% CI u-95% CI
## sigma       7.77      0.21     7.37     8.19
```

```
bmmb::short_summary (model_multilevel_L_S)
## Formula:  height ~ 1 + (1 | L) + (1 | S)
##
## Group-Level Effects:
## ~L (Number of levels: 15)
##               Estimate Est.Error l-95% CI u-95% CI
## sd(Intercept)     3.81      0.86     2.51     5.87
##
## ~S (Number of levels: 45)
##               Estimate Est.Error l-95% CI u-95% CI
## sd(Intercept)     2.83      0.42      2.1     3.72
##
## Population-Level Effects:
##           Estimate Est.Error l-95% CI u-95% CI
## Intercept    173.8      1.12    171.6    176.1
##
## Family Specific Parameters:
##       Estimate Est.Error l-95% CI u-95% CI
## sigma     6.47      0.19     6.11     6.85
```

Investigating 'Shrinkage'



Investigating ‘Shrinkage’



Answering our Research Questions

```
bmmb::short_summary (model_multilevel_L_S)
## Formula:  height ~ 1 + (1 | L) + (1 | S)
##
## Group-Level Effects:
## ~L (Number of levels: 15)
##               Estimate Est.Error l-95% CI u-95% CI
## sd(Intercept)     3.81      0.86     2.51     5.87
##
## ~S (Number of levels: 45)
##               Estimate Est.Error l-95% CI u-95% CI
## sd(Intercept)     2.83      0.42      2.1     3.72
##
## Population-Level Effects:
##           Estimate Est.Error l-95% CI u-95% CI
## Intercept    173.8      1.12    171.6    176.1
##
## Family Specific Parameters:
##       Estimate Est.Error l-95% CI u-95% CI
## sigma     6.47      0.19     6.11     6.85
```

Based on our model the average apparent height of adult males is likely to be 173.8 cm (s.d. = 1.1, 95% CI = [171.6, 176.1]). The estimated magnitude of the random error was 6.5 cm (s.d. = 0.2, 95% CI = [6.1, 6.9]). Systematic between-listener variation averages about 3.8 cm (s.d. = 0.9, 95% CI = [2.5, 5.8]), while systematic between-speaker variation averages about 2.8 cm (s.d. = 0.4, 95% CI = [2.1, 3.8]).

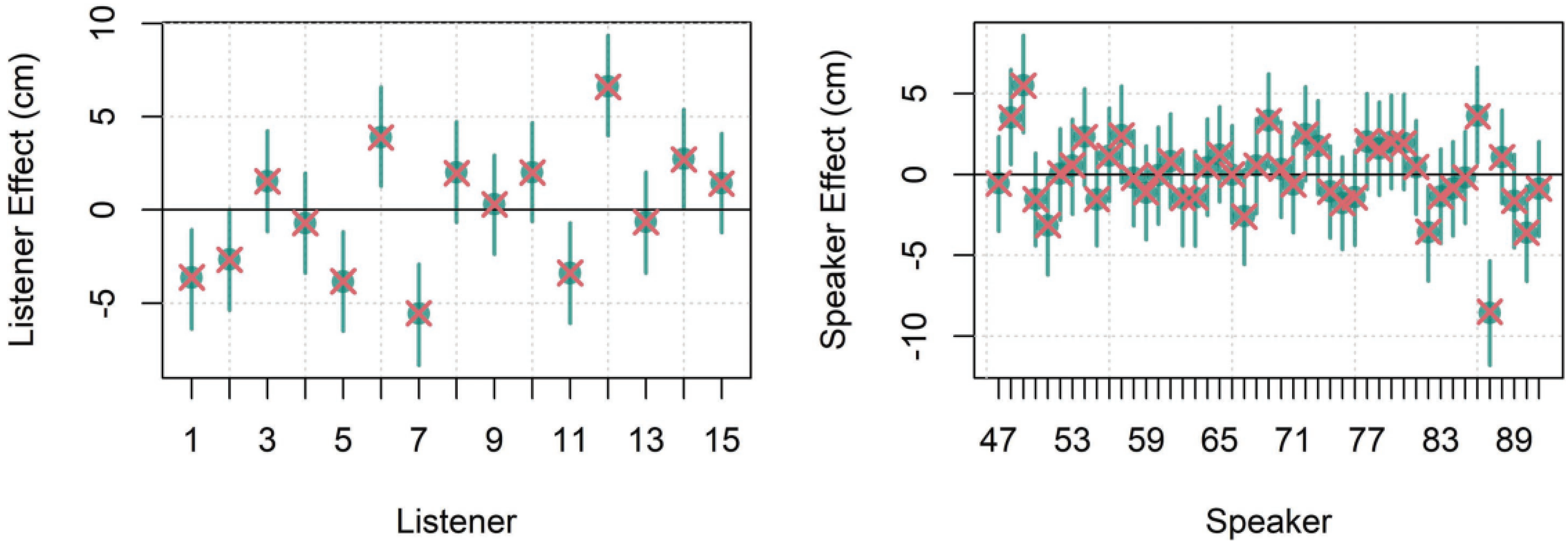
Traditionalists Corner: lmer

```
lmer_model = lme4::lmer (height ~ 1 + (1|L) + (1|S), data = men)
```

```
bmmb::short_summary(model_multilevel_L_S)
## (1) Formula:  height ~ 1 + (1 | L) + (1 | S)
##
## (2) Group-Level Effects:
##     ~L (Number of levels: 15)
##                   Estimate Est.Error l-95% CI u-95% CI
## (3) sd(Intercept)      3.81      0.86     2.51     5.87
##
##     ~S (Number of levels: 45)
##                   Estimate Est.Error l-95% CI u-95% CI
## (4) sd(Intercept)      2.83      0.42      2.1     3.72
##
##     Population-Level Effects:
##               Estimate Est.Error l-95% CI u-95% CI
## (5) Intercept    173.8      1.12    171.6   176.05
##
##     Family Specific Parameters:
##           Estimate Est.Error l-95% CI u-95% CI
## (6) sigma     6.47      0.19     6.11     6.85
```

```
summary (lmer_model)
##     Linear mixed model fit by REML ['lmerMod']
## (1) Formula: height ~ 1 + (1 | L) + (1 | S)
##        Data: men
##
##     REML criterion at convergence: 4527.4
##
##     Scaled residuals:
##         Min      1Q  Median      3Q     Max
##     -4.6205 -0.4868  0.0722  0.5700  2.7179
##
## (2) Random effects:
##      Groups   Name        Variance Std.Dev.
## (3)  S        (Intercept)  7.593   2.756
## (4)  L        (Intercept) 11.990   3.463
## (6)  Residual             41.630   6.452
##     Number of obs: 675, groups:  S, 45; L, 15
##
##     Fixed effects:
##                 Estimate Std. Error t value
## (5) (Intercept)  173.788      1.015   171.3
```

Traditionalists Corner: lmer



Exercises

Use the data in ‘exp_ex’ to do one of the following. You may also use your own data to answer a related question. In any case, describe the model, present and explain the results, and include at least two figures.

1. Easy: Analyze the (pre-ft) model that’s exactly like model_multilevel_L_S, except using the data in exp_ex (bmmb::get_model("model_multilevel_L_S_ex.RDS")).

2. Medium: Fit a model just like model_multilevel_L_S, but for the data from some other group, for either the original or big resonance levels.

3. Hard: Fit two models like model_multilevel_L_S for two groups, or for one group across resonance levels, and compare results across models.