

PANEL DATA ANALYSIS: LINEAR MIXED-EFFECT MODELS

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Introduction and Motivation

Random Intercept vs. Random Slope:

- Note that each scenario and each subject is assigned a different intercept. That's what we would expect, given that we've told the model with "(1|subject)" and "(1|scenario)" to take by-subject and by-item variability into account.
- On the other hand, the fixed effects (attitude and gender) are all the same for all subjects and items. This model is called a **random intercept model**.
- In this model, we account for baseline-differences in pitch, but we assume that whatever the effect of politeness is, it's going to be the same for all subjects and items.

```
> coef(politeness.lmm2)
$scenario
(Intercept) attitudepol genderM
1 243.3398 -19.72111 -108.5163
2 263.4292 -19.72111 -108.5163
3 268.2541 -19.72111 -108.5163
4 277.4757 -19.72111 -108.5163
5 254.9102 -19.72111 -108.5163
6 244.6724 -19.72111 -108.5163
7 245.8426 -19.72111 -108.5163

$subject
(Intercept) attitudepol genderM
F1 242.9386 -19.72111 -108.5163
F2 267.2654 -19.72111 -108.5163
F3 260.3348 -19.72111 -108.5163
M3 285.2283 -19.72111 -108.5163
M4 262.2248 -19.72111 -108.5163
M7 223.0857 -19.72111 -108.5163

attr(,"class")
[1] "coef.mer"
```

- However, it may not be a valid assumption. For instance, it is possible that some items would elicit more or less politeness. That is, the effect of politeness might be different for different items. Likewise, the effect of politeness might be different for different subjects.
- In this case, we need a **random slope mode** where subjects and items are not only allowed to have differing intercepts, but different slopes for the effect of politeness.

```
Linear mixed model fit by maximum likelihood ['lmerMod']
Formula: frequency ~ attitude + gender + (1 + attitude | subject) + (1 +
  attitude | scenario)
Data: politeness
```

AIC	BIC	logLik	deviance	df.resid
814.9	839.1	-397.4	794.9	73

Scaled residuals:

Min	1Q	Median	3Q	Max
-2.1947	-0.6691	-0.0789	0.5256	3.4252

Random effects:

Groups	Name	Variance	Std.Dev.	Corr
scenario	(Intercept)	182.082	13.494	
	attitudopol	31.262	5.591	0.22
subject	(Intercept)	392.474	19.811	
	attitudopol	1.707	1.307	1.00
Residual		627.880	25.058	

Number of obs: 83, groups: scenario, 7; subject, 6

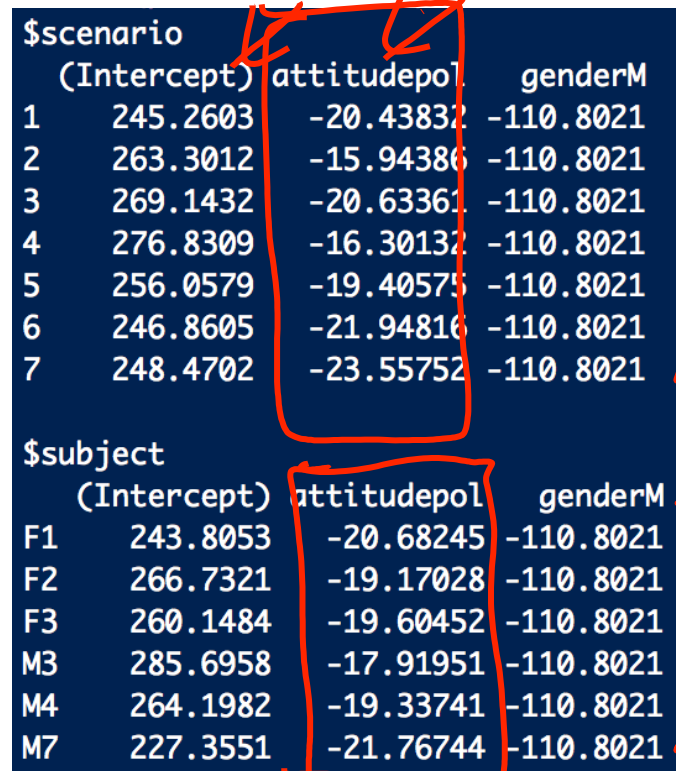
Fixed effects:

	Estimate	Std. Error	t value
(Intercept)	257.989	13.529	19.069
attitudopol	-19.747	5.922	-3.334
genderM	-110.802	17.512	-6.327

Correlation of Fixed Effects:

	(Intr)	atttdp
attitudopol	-0.105	
genderM	-0.647	0.003

- Note that the only thing being changed is the random effects:
 “(1 + *attitude*|*subject*)” means that you inform the model to expect differing baseline-levels of frequency (the intercept, represented by 1) as well as differing responses to the main factor in question, which is “attitude” in this case.
- Let's look at the coefficients of this updated model:



	\$scenario		
	(Intercept)	attitudepol	genderM
1	245.2603	-20.43832	-110.8021
2	263.3012	-15.94386	-110.8021
3	269.1432	-20.63361	-110.8021
4	276.8309	-16.30132	-110.8021
5	256.0579	-19.40575	-110.8021
6	246.8605	-21.94816	-110.8021
7	248.4702	-23.55752	-110.8021

	\$subject		
	(Intercept)	attitudepol	genderM
F1	243.8053	-20.68245	-110.8021
F2	266.7321	-19.17028	-110.8021
F3	260.1484	-19.60452	-110.8021
M3	285.6958	-17.91951	-110.8021
M4	264.1982	-19.33741	-110.8021
M7	227.3551	-21.76744	-110.8021

- Now, with the by-subject and by-item coefficients, the effect of politeness (“attitudepol”) is different for each subject and item.
- **Interpretation:** Note the coefficients are always negative and quite similar to each other, meaning that despite individual variation, there is also consistency in how politeness affects the voice: for all of our speakers, the voice tends to go down when speaking politely, but for some people it goes down slightly more so than for others.
- The coefficients for gender have not changed, as we did not specify random slopes for the by-subject or by-item effect of gender.
- Let’s obtain the *p-value* using likelihood ratio test:
- Note that the null model needs to have the same random effects structure. If the full model is a random slope model, then the null model also needs to be a random slope model.

```
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subject	(Intercept)	392.474	19.811	
	attitudepol	1.707	1.307	1.00
Residual		627.880	25.058	

Number of obs: 83, groups: scenario, 7; subject, 6

Fixed effects:

	Estimate	Std. Error	t value
(Intercept)	257.989	13.529	19.069
attitudepol	-19.747	5.922	-3.334
genderM	-110.802	17.512	-6.327

Correlation of Fixed Effects:

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attitudepol	-0.105	
genderM	-0.647	0.003

```
Linear mixed model fit by maximum likelihood ['lmerMod']
Formula: frequency ~ gender + (1 + attitude | subject) + (1 + attitude | scenario)
Data: politeness
```

AIC	BIC	logLik	deviance	df.resid
819.6	841.4	-400.8	801.6	74

Scaled residuals:

Min	1Q	Median	3Q	Max
-2.09488	-0.64641	-0.08678	0.60655	3.00533

Random effects:

Groups	Name	Variance	Std.Dev.	Corr
scenario	(Intercept)	231.845	15.226	
	attitudepol	410.122	20.251	-0.40
subject	(Intercept)	378.499	19.455	
	attitudepol	5.439	2.332	1.00
Residual		628.654	25.073	

Number of obs: 83, groups: scenario, 7; subject, 6

Fixed effects:

	Estimate	Std. Error	t value
(Intercept)	253.37	13.44	18.856
genderM	-112.49	17.47	-6.439

Correlation of Fixed Effects:

	(Intr)
genderM	-0.650

```
> anova(politeness.null, politeness.lmm3)
Data: politeness
Models:
politeness.null: frequency ~ gender + (1 + attitude | subject) + (1 + attitude |
politeness.null: scenario)
politeness.lmm3: frequency ~ attitude + gender + (1 + attitude | subject) + (1 +
politeness.lmm3: attitude | scenario)
              Df    AIC    BIC logLik deviance Chisq Chi Df Pr(>Chisq)
politeness.null  9 819.61 841.37 -400.80  801.61    6.7082  1 0.009597 **
politeness.lmm3 10 814.90 839.09 -397.45  794.90
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```


- What kind of random slope structure, if at all, should be imposed?
- It turns out that random slopes are very useful in practice. In experimental settings, experimental subjects often differ with how they react to an experimental manipulation, and the effect of an experimental manipulation differs for different items.
- **Assumptions:** We will study them in details in the next section. For now, we just want to highlight the importance of the independence assumption.
- Mixed models can still violate independence if important fixed or random effects are excluded in the model.
- In fact, missing some of the important variables may also lead to omitted variable bias, if these variables are correlated with the explanatory variables included in the model.
- For example, if we analyzed our data with a model that excluded the “subject-specific” random effect, then the model would not “know” that there are multiple responses per subject. This leads to a violation of the independence assumption. The punchline is that choose fixed effects and random effects carefully, and always try to resolve non-independencies when using data with repeated measurements.

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