

Mixed models in R using the lme4 package

Part 3: Longitudinal data

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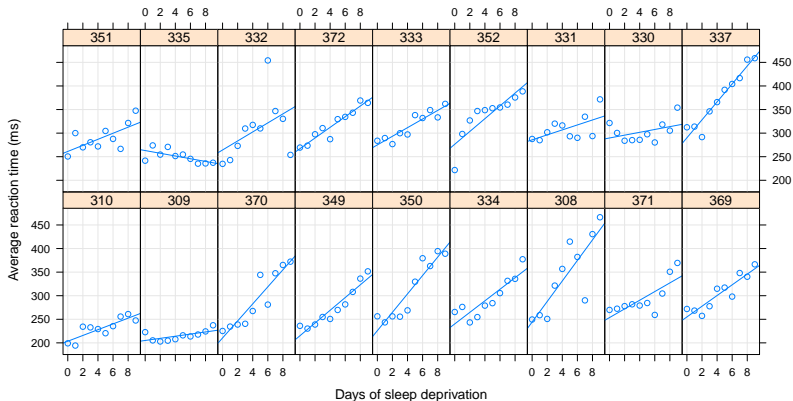
Simple longitudinal data

- *Repeated measures* data consist of measurements of a response (and, perhaps, some covariates) on several *experimental* (or observational) *units*.
- Frequently the experimental (observational) unit is **Subject** and we will refer to these units as “subjects”. However, the methods described here are not restricted to data on human subjects.
- *Longitudinal* data are repeated measures data in which the observations are taken over time.
- We wish to characterize the response over time within subjects and the variation in the time trends between subjects.
- Frequently we are not as interested in comparing the particular subjects in the study as much as we are interested in modeling the variability in the population from which the subjects were chosen.

Sleep deprivation data

- This laboratory experiment measured the effect of sleep deprivation on cognitive performance.
- There were 18 subjects, chosen from the population of interest (long-distance truck drivers), in the 10 day trial. These subjects were restricted to 3 hours sleep per night during the trial.
- On each day of the trial each subject's reaction time was measured. The reaction time shown here is the average of several measurements.
- These data are *balanced* in that each subject is measured the same number of times and on the same occasions.

Reaction time versus days by subject



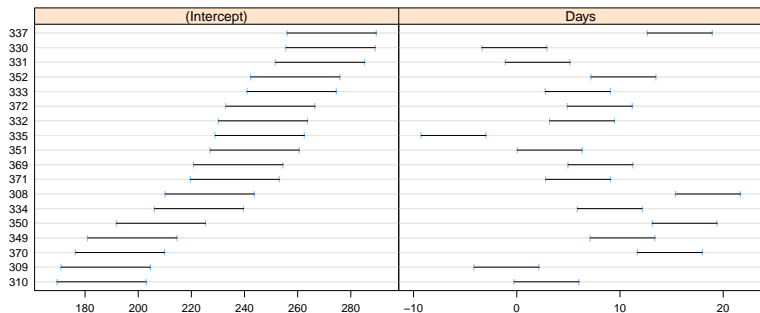
Comments on the sleep data plot

- The plot is a “trellis” or “lattice” plot where the data for each subject are presented in a separate panel. The axes are consistent across panels so we may compare patterns across subjects.
- A reference line fit by simple linear regression to the panel's data has been added to each panel.
- The aspect ratio of the panels has been adjusted so that a typical reference line lies about 45° on the page. We have the greatest sensitivity in checking for differences in slopes when the lines are near $\pm 45^\circ$ on the page.
- The panels have been ordered not by subject number (which is essentially a random order) but according to increasing intercept for the simple linear regression. If the slopes and the intercepts are highly correlated we should see a pattern across the panels in the slopes.

Assessing the linear fits

- In most cases a simple linear regression provides an adequate fit to the within-subject data.
- Patterns for some subjects (e.g. 350, 352 and 371) deviate from linearity but the deviations are neither widespread nor consistent in form.
- There is considerable variation in the intercept (estimated reaction time without sleep deprivation) across subjects – 200 ms. up to 300 ms. – and in the slope (increase in reaction time per day of sleep deprivation) – 0 ms./day up to 20 ms./day.
- We can examine this variation further by plotting confidence intervals for these intercepts and slopes. Because we use a pooled variance estimate and have balanced data, the intervals have identical widths.
- We again order the subjects by increasing intercept so we can check for relationships between slopes and intercepts.

95% conf int on within-subject intercept and slope



These intervals reinforce our earlier impressions of considerable variability between subjects in both intercept and slope but little evidence of a relationship between intercept and slope.

Outline

Longitudinal data: sleepstudy

A model with random effects for intercept and slope

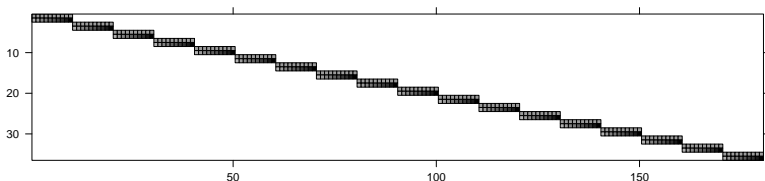
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A preliminary mixed-effects model

- We begin with a linear mixed model in which the fixed effects $[\beta_1, \beta_2]'$ are the representative intercept and slope for the population and the random effects $\mathbf{b}_i = [b_{i1}, b_{i2}]', i = 1, \dots, 18$ are the deviations in intercept and slope associated with subject i .
- The random effects vector, \mathbf{b} , consists of the 18 intercept effects followed by the 18 slope effects.



Fitting the model

```
> (fm1 <- lmer(Reaction ~ Days + (Days | Subject),  
+             sleepstudy))
```

Linear mixed model fit by REML ['merMod']

Formula: Reaction ~ Days + (Days | Subject)

Data: sleepstudy

REML criterion at convergence: 1743.628

Random effects:

Groups	Name	Variance	Std.Dev.	Corr
Subject	(Intercept)	612.09	24.740	
	Days	35.07	5.922	0.066
Residual		654.94	25.592	

Number of obs: 180, groups: Subject, 18

Fixed effects:

	Estimate	Std. Error	t value
(Intercept)	251.405	6.825	36.84
Days	10.467	1.546	6.77

Correlation of Fixed Effects:

(Intr)

Days -0.138

Terms and matrices

- The term `Days` in the formula generates a model matrix \mathbf{X} with two columns, the intercept column and the numeric `Days` column. (The intercept is included unless suppressed.)
- The term `(Days|Subject)` generates a vector-valued random effect (intercept and slope) for each of the 18 levels of the `Subject` factor.

A model with uncorrelated random effects

- The data plots gave little indication of a systematic relationship between a subject's random effect for slope and his/her random effect for the intercept. Also, the estimated correlation is quite small.
- We should consider a model with uncorrelated random effects. To express this we use two random-effects terms with the same grouping factor and different left-hand sides. In the formula for an `lmer` model, distinct random effects terms are modeled as being independent. Thus we specify the model with two distinct random effects terms, each of which has `Subject` as the grouping factor. The model matrix for one term is intercept only (`1`) and for the other term is the column for `Days` only, which can be written `0+Days`. (The expression `Days` generates a column for `Days` and an intercept. To suppress the intercept we add `0+` to the expression; `-1` also works.)

A mixed-effects model with independent random effects

Linear mixed model fit by REML ['merMod']

Formula: Reaction ~ Days + (1 | Subject) + (0 + Days | Subject)

Data: sleepstudy

REML criterion at convergence: 1743.669

Random effects:

Groups	Name	Variance	Std.Dev.
Subject	(Intercept)	627.57	25.051
Subject	Days	35.86	5.988
Residual		653.58	25.565

Number of obs: 180, groups: Subject, 18

Fixed effects:

	Estimate	Std. Error	t value
(Intercept)	251.405	6.885	36.51
Days	10.467	1.560	6.71

Correlation of Fixed Effects:

	(Intr)
Days	-0.184

Comparing the models

- Model `fm1` contains model `fm2` in the sense that if the parameter values for model `fm1` were constrained so as to force the correlation, and hence the covariance, to be zero, and the model were re-fit, we would get model `fm2`.
- The value 0, to which the correlation is constrained, is not on the boundary of the allowable parameter values.
- In these circumstances a likelihood ratio test and a reference distribution of a χ^2 on 1 degree of freedom is suitable.

```
> anova(fm2, fm1)
```

Data: sleepstudy

Models:

```
fm2: Reaction ~ Days + (1 | Subject) + (0 + Days | Subject)
```

```
fm1: Reaction ~ Days + (Days | Subject)
```

	Df	AIC	BIC	logLik	deviance	Chisq	Chi	Df	Pr(>Chisq)
fm2	5	1762.0	1778.0	-876.00	1752.0				
fm1	6	1763.9	1783.1	-875.97	1751.9	0.0639		1	0.8004

Conclusions from the likelihood ratio test

- Because the large p-value indicates that we would not reject `fm2` in favor of `fm1`, we prefer the more parsimonious `fm2`.
- This conclusion is consistent with the AIC (Akaike's Information Criterion) and the BIC (Bayesian Information Criterion) values for which “smaller is better”.
- We can also use a Bayesian approach, where we regard the parameters as themselves being random variables, is assessing the values of such parameters. A currently popular Bayesian method is to use sequential sampling from the conditional distribution of subsets of the parameters, given the data and the values of the other parameters. The general technique is called *Markov chain Monte Carlo* sampling.
- We will expand on the use of likelihood-ratio tests in the next section.

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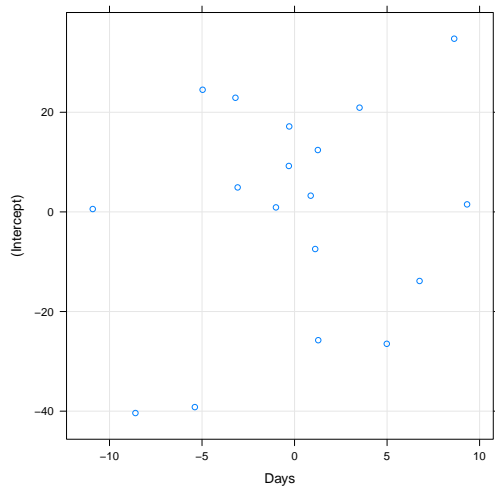
Conditional means of the random effects

```
> (rr2 <- ranef(fm2))
```

\$Subject

	(Intercept)	Days
308	1.5126966	9.3234892
309	-40.3738980	-8.5991691
310	-39.1810421	-5.3877905
330	24.5189047	-4.9686457
331	22.9144336	-3.1939347
332	9.2219738	-0.3084935
333	17.1561215	-0.2872073
334	-7.4517336	1.1159900
335	0.5787248	-10.9059662
337	34.7679289	8.6276161
349	-25.7543240	1.2806877
350	-13.8650351	6.7564004
351	4.9159801	-3.0751329
352	20.9290430	3.5122097
369	3.2586474	0.8730507
370	-26.4758268	4.9837864
371	0.9056475	-1.0052929
372	12.4217577	1.2584028

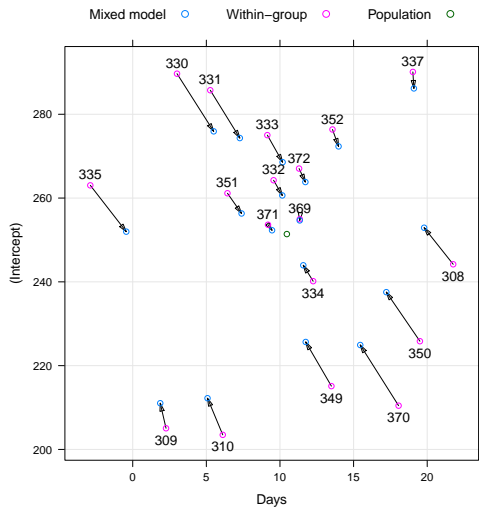
Scatterplot of the conditional means



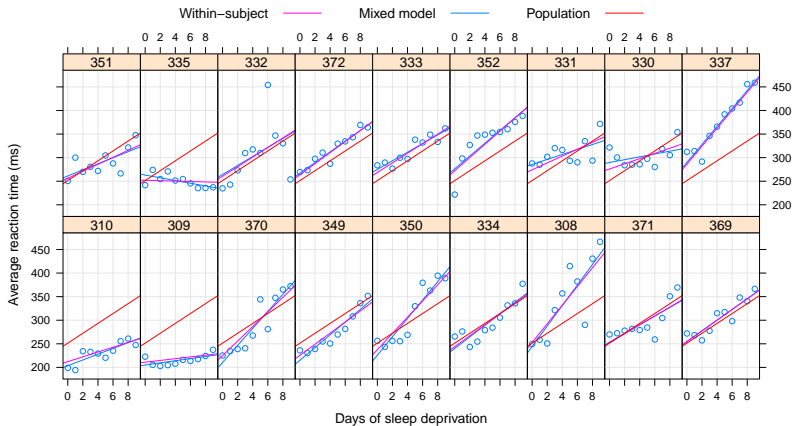
Comparing within-subject coefficients

- For this model we can combine the conditional means of the random effects and the estimates of the fixed effects to get conditional means of the within-subject coefficients.
- These conditional means will be “shrunk” towards the fixed-effects estimates relative to the estimated coefficients from each subject’s data. John Tukey called this “borrowing strength” between subjects.
- Plotting the shrinkage of the within-subject coefficients shows that some of the coefficients are considerably shrunk toward the fixed-effects estimates.
- However, comparing the within-group and mixed model fitted lines shows that large changes in coefficients occur in the noisy data. Precisely estimated within-group coefficients are not changed substantially.

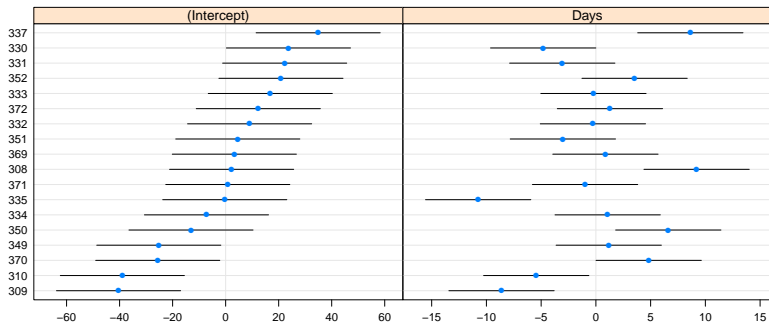
Estimated within-group coefficients and BLUPs



Observed and fitted



Plot of prediction intervals for the random effects



Each set of prediction intervals have constant width because of the balance in the experiment.

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Conclusions from the example

- Carefully plotting the data is enormously helpful in formulating the model.
- It is relatively easy to fit and evaluate models to data like these, from a balanced designed experiment.
- We consider two models with random effects for the slope and the intercept of the response w.r.t. time by subject. The models differ in whether the (marginal) correlation of the vector of random effects per subject is allowed to be nonzero.
- The “estimates” (actually, the conditional means) of the random effects can be considered as penalized estimates of these parameters in that they are shrunk towards the origin.
- Most of the prediction intervals for the random effects overlap zero.

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Random slopes and interactions

- In the `sleepstudy` model fits we allowed for random effects for `Days` by `Subject`.
- These random effects can be considered as an interaction between the fixed-effects covariate `Days` and the random-effects factor `Subject`.
- When we have both fixed-levels categorical covariates and random-levels categorical covariates we have many different ways in which interactions can be expressed.
- Often the wide range of options provides “enough rope to hang yourself” in the sense that it is very easy to create an overly-complex model.

The Multilocation data set

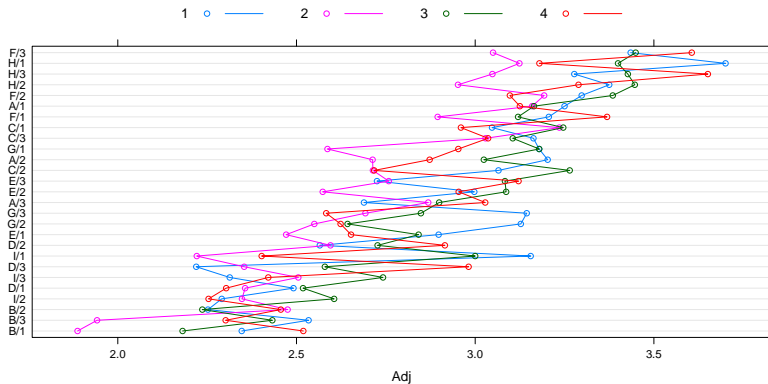
- Data from a multi-location trial of several treatments are described in section 2.8 of Littell, Milliken, Stroup and Wolfinger (1996) **SAS System for Mixed Models** and are available as `Multilocation` in package `SASmixed`.
- Littell et al. don't cite the source of the data. Apparently `Adj` is an adjusted response of some sort for 4 different treatments applied at each of 3 blocks in each of 9 locations. Because `Block` is implicitly nested in `Location`, the `Grp` interaction variable was created.

```
> str(Multilocation)
```

```
'data.frame': 108 obs. of 7 variables:
```

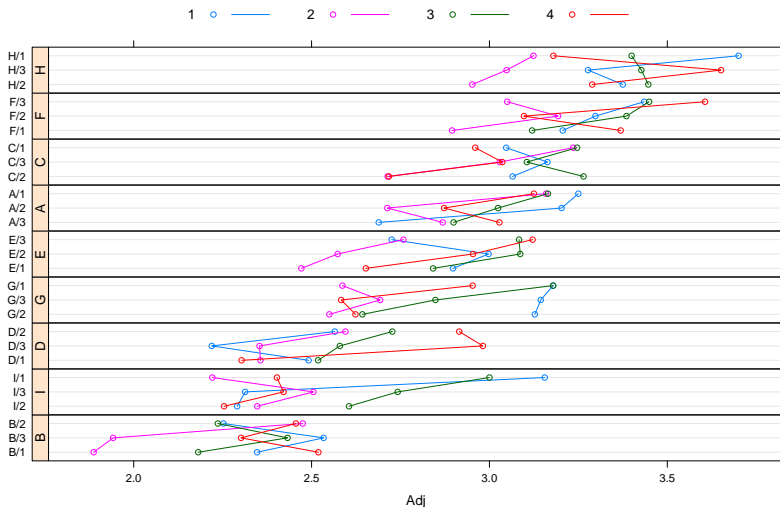
```
$ obs      : num  3 4 6 7 9 10 12 16 19 20 ...
$ Location: Factor w/ 9 levels "A","B","C","D",...: 1 1 1 1 1 1..
$ Block    : Factor w/ 3 levels "1","2","3": 1 1 1 1 2 2 2 2 3 ..
$ Trt      : Factor w/ 4 levels "1","2","3","4": 3 4 2 1 2 1 3 ..
$ Adj      : num  3.16 3.12 3.16 3.25 2.71 ...
$ Fe       : num  7.1 6.68 6.83 6.53 8.25 ...
$ Grp      : Factor w/ 27 levels "A/1","A/2","A/3",...: 1 1 1 1 1 ..
```

Response by Grp and Trt



- From this one plot (Littell et al. do not provide any plots but instead immediately jump into fitting several “cookie-cutter” models) we see that there are differences between locations, not as much between blocks within location, and that treatment 2 is providing a lower adjusted response.

Response by Block and Trt within Location



Fixed-levels categorical covariates and “contrasts”

- In this experiment we are interested in comparing the effectiveness of these four levels of `Trt`.
- That is, the levels of `Trt` are fixed levels and we should incorporate them in the fixed-effects part of the model.
- Unlike the situation with random effects, we cannot separately estimate “effects” for each level of a categorical covariate in the fixed-effects and an overall intercept term.
- Even if we suppress the intercept term we still encounter redundancies in trying to estimate effects for each level when we have more than one categorical covariate in the fixed-effects terms.
- Because of this we estimate coefficients for “contrasts” associated with the levels of a factor. If we have k levels we generate $k - 1$ contrasts.
- The default contrasts (called `contr.treatment`) measure changes relative to a reference level which is the first level of the factor. Other contrasts can be used when particular

A simple model for Trt controlling for Grp

```
> print(fm3 <- lmer(Adj ~ Trt + (1 | Grp), Multilocation),  
+       corr = FALSE)
```

Linear mixed model fit by REML ['merMod']

Formula: Adj ~ Trt + (1 | Grp)

Data: Multilocation

REML criterion at convergence: 31.5057

Random effects:

Groups	Name	Variance	Std.Dev.
Grp	(Intercept)	0.11092	0.3331
Residual		0.03672	0.1916

Number of obs: 108, groups: Grp, 27

Fixed effects:

	Estimate	Std. Error	t value
(Intercept)	2.92401	0.07395	39.54
Trt2	-0.24637	0.05215	-4.72
Trt3	0.02544	0.05215	0.49
Trt4	-0.05834	0.05215	-1.12

Interpretation of the results

- We see that the variability between the Location/Block combinations (levels of `Grp`) is greater than the residual variability, indicating the importance of controlling for it.
- The contrast between levels 2 and 1 of `Trt`, labeled `Trt2` is the greatest difference and apparently significant.
- If we wish to evaluate the “significance” of the levels of `Trt` as a group, however, we should fit the trivial model and perform a LRT.

```
> fm4 <- lmer(Adj ~ 1 + (1 | Grp), Multilocation)
> anova(fm4, fm3)
```

Data: Multilocation

Models:

fm4: Adj ~ 1 + (1 | Grp)

fm3: Adj ~ Trt + (1 | Grp)

	Df	AIC	BIC	logLik	deviance	Chisq	Chi	Df	Pr(>Chisq)
fm4	3	49.731	57.777	-21.8654	43.731				
fm3	6	26.951	43.044	-7.4756	14.951	28.78		3	2.491e-06

Location as a fixed-effect

- We have seen that `Location` has a substantial effect on `Adj`. If we are interested in these specific 9 locations we could incorporate them as fixed-effects parameters.
- Instead of examining 8 coefficients separately we will consider their cumulative effect using the single-argument form of `anova`.

```
> anova(fm5 <- lmer(Adj ~ Location + Trt + (1 | Grp),  
+   Multilocation))
```

Analysis of Variance Table

	Df	Sum Sq	Mean Sq	F value
Location	8	7.3768	0.92210	25.115
Trt	3	1.2217	0.40725	11.092

An interaction between fixed-effects factors

- We could ask if there is an interaction between the levels of `Trt` and those of `Location` considered as fixed effects.

```
> anova(fm6 <- lmer(Adj ~ Location * Trt + (1 | Grp),
+   Multilocation))
```

Analysis of Variance Table

	Df	Sum Sq	Mean Sq	F value
Location	8	6.9475	0.86843	25.1147
Trt	3	1.2217	0.40725	11.7774
Location:Trt	24	0.9966	0.04152	1.2008

```
> anova(fm5, fm6)
```

Data: Multilocation

Models:

fm5: Adj ~ Location + Trt + (1 | Grp)

fm6: Adj ~ Location * Trt + (1 | Grp)

	Df	AIC	BIC	logLik	deviance	Chisq	Chi	Df	Pr(>Chisq)
fm5	14	-24.504	13.046	26.252	-52.504				
fm6	38	-11.146	90.775	43.573	-87.146	34.642		24	0.07388

Considering levels of Location as random effects

```
> print(fm7 <- lmer(Adj ~ Trt + (1 | Location) + (1 |  
+   Grp), Multilocation), corr = FALSE)
```

Linear mixed model fit by REML ['merMod']

Formula: Adj ~ Trt + (1 | Location) + (1 | Grp)

Data: Multilocation

REML criterion at convergence: 1.8978

Random effects:

Groups	Name	Variance	Std.Dev.
Grp	(Intercept)	0.005085	0.07131
Location	(Intercept)	0.114657	0.33861
Residual		0.036715	0.19161

Number of obs: 108, groups: Grp, 27; Location, 9

Fixed effects:

	Estimate	Std. Error	t value
(Intercept)	2.92401	0.11953	24.462
Trt2	-0.24637	0.05215	-4.724
Trt3	0.02544	0.05215	0.488
Trt4	-0.05834	0.05215	-1.119

Is Grp needed in addition to Location?

- At this point we may want to check whether the random effect for **Block** within **Location** is needed in addition to the random effect for **Location**.

```
> fm8 <- lmer(Adj ~ Trt + (1 | Location), Multilocation)
> anova(fm8, fm7)
```

Data: Multilocation

Models:

fm8: Adj ~ Trt + (1 | Location)

fm7: Adj ~ Trt + (1 | Location) + (1 | Grp)

	Df	AIC	BIC	logLik	deviance	Chisq	Chi	Df	Pr(>Chisq)
fm8	6	0.25442	16.347	5.8728	-11.746				
fm7	7	0.39496	19.170	6.8025	-13.605	1.8595		1	0.1727

- Apparently not, but we may want to revisit this issue after checking for interactions.

Ways of modeling random/fixed interactions

- There are two ways we can model the interaction between a fixed-levels factor (**Trt**) and a random-levels factor (**Location**, as we are currently viewing this factor).
- The first, and generally preferable, way is to incorporate a simple scalar random-effects term with the interaction as the grouping factor.
- The second, more complex, way is to use vector-valued random effects for the random-levels factor. We must be careful when using this approach because it often produces a degenerate model, but not always obviously degenerate.

Scalar random effects for interaction

```
> (fm9 <- lmer(Adj ~ Trt + (1 | Trt:Location) + (1 |
+      Location), Multilocation, REML = FALSE))
```

Linear mixed model fit by maximum likelihood ['merMod']

Formula: Adj ~ Trt + (1 | Trt:Location) + (1 | Location)

Data: Multilocation

	AIC	BIC	logLik	deviance
	2.2544	21.0293	5.8728	-11.7456

Random effects:

Groups	Name	Variance	Std.Dev.
Trt:Location	(Intercept)	0.0000	0.0000
Location	(Intercept)	0.1029	0.3207
Residual		0.0393	0.1982

Number of obs: 108, groups: Trt:Location, 36; Location, 9

Fixed effects:

	Estimate	Std. Error	t value
(Intercept)	2.92401	0.11351	25.759
Trt2	-0.24637	0.05396	-4.566
Trt3	0.02544	0.05396	0.472
Trt4	-0.05834	0.05396	-1.081

Both interaction and Block-level random effects

```
> (fm10 <- update(fm9, . ~ . + (1 | Grp)))
```

Linear mixed model fit by maximum likelihood [`'merMod'`]

Formula: `Adj ~ Trt + (1 | Trt:Location) + (1 | Location) + (1 | Grp)`

Data: Multilocation

AIC	BIC	logLik	deviance
2.3564	23.8134	6.8218	-13.6436

Random effects:

Groups	Name	Variance	Std.Dev.
Trt:Location	(Intercept)	0.0007769	0.02787
Grp	(Intercept)	0.0056193	0.07496
Location	(Intercept)	0.1011949	0.31811
Residual		0.0345787	0.18595

Number of obs: 108, groups: Trt:Location, 36; Grp, 27; Location, 9

Fixed effects:

	Estimate	Std. Error	t value
(Intercept)	2.92401	0.11322	25.826
Trt2	-0.24637	0.05229	-4.712
Trt3	0.02544	0.05229	0.487
Trt4	-0.05834	0.05229	-1.116

Scalar interaction random effects are still not significant

```
> anova(fm10, fm8)
```

```
Data: Multilocation
```

```
Models:
```

```
fm8: Adj ~ Trt + (1 | Location)
```

```
fm10: Adj ~ Trt + (1 | Trt:Location) + (1 | Location) + (1 | Grp)
```

	Df	AIC	BIC	logLik	deviance	Chisq	Chi	Df	Pr(>Chisq)
fm8	6	0.25442	16.347	5.8728	-11.746				
fm10	8	2.35640	23.813	6.8218	-13.644	1.898		2	0.3871

- We have switched to ML fits because we are comparing models using `anova`. In a comparative `anova` any REML fits are refit as ML before comparison so we start with the ML fits.
- In model `fm9` the estimated variance for the scalar interaction random effects was exactly zero in the ML fit. In `fm10` the estimate is positive but still not significant.

Vector-valued random effects

- An alternative formulation for an interaction between `Trt` and `Location` (viewed as a random-levels factor) is to use vector-valued random effects.
- We have used a similar construct in model `fm1` with vector-valued random effects (intercept and slope) for each level of `Subject`.
- One way to fit such a model is

```
> fm11 <- lmer(Adj ~ Trt + (Trt | Location) + (1 |
+      Grp), Multilocation, REML = FALSE)
```

but interpretation is easier when fit as

```
> fm11 <- lmer(Adj ~ Trt + (0 + Trt | Location) + (1 |
+      Grp), Multilocation, REML = FALSE)
```

Examining correlation of random effects

- The random effects summary for `fm11`

```

      AIC      BIC    logLik deviance
15.8244  58.7385    8.0878 -16.1756

```

Random effects:

```

Groups   Name             Variance Std.Dev. Corr
Grp      (Intercept) 0.006352 0.0797
Location Trt1        0.119330 0.3454
          Trt2        0.093347 0.3055    0.984
          Trt3        0.104075 0.3226    0.994 0.996
          Trt4        0.099934 0.3161    0.921 0.967 0.941
Residual              0.031647 0.1779

```

Number of obs: 108, groups: Grp, 27; Location, 9

shows very high correlations between the random effects for the levels of `Trt` within each level of `Location`.

- Such a situation pass by unnoticed if estimates of variances and covariances are all that is reported.
- In this case (and many other similar cases) the variance-covariance matrix of the vector-valued random effects is effectively singular.

Singular variance-covariance for random effects

- When we incorporate too many fixed-effects terms in a model we often find out about it because the standard errors of coefficients become very large.
- For random effects terms, especially those that are vector-valued, overparameterization is sometimes more difficult to detect.
- The REML and ML criteria for mixed-effects models seek to balance the complexity of the model versus the fidelity of the fitted values to the observed responses.
- The way “complexity” is measured in this case, a model with a singular variance-covariance matrix for the random effects is considered a good thing - it is optimally simple.
- When we have only scalar random-effects terms singularity means that one of the variance components must be exactly zero (and “near singularity” means very close to zero).

Detecting singular random effects

- The `Lambda` slot in a `merMod` object is the triangular factor of the variance-covariance matrix.
- We can directly assess its condition number using the `kappa` (condition number) or `rcond` (reciprocal condition number) functions. Large condition numbers are bad.
- We do need to be cautious when we have a large number of levels for the grouping factors because `Lambda` will be **very** large (but also very sparse). At present the `kappa` and `rcond` functions transform the sparse matrix to a dense matrix, which could take a very long time.

```
> kappa(fm11@re@Lambda)
```

```
[1] 79889009
```

```
> rcond(fm11@re@Lambda)
```

```
[1] 8.711617e-09
```

Using verbose model fits

- An alternative, which is recommended whenever you have doubts about a model fit, is to use `verbose=TRUE` (the lines don't wrap and we miss the interesting part here).

```
npt = 17 , n = 11
rhobeg = 0.2 , rhoend = 2e-07
  0.020: 41:      -9.00509;0.533967  1.75302 0.993757  1.29209  1.1159
  0.0020: 124:    -16.1175;0.447975  1.92583  1.66682  1.78453  1.6196
  0.00020: 249:    -16.1600;0.443888  1.93046  1.68903  1.80077  1.6293
  2.0e-05: 312:    -16.1601;0.443985  1.93147  1.68963  1.80133  1.6303
  2.0e-06: 348:    -16.1601;0.443994  1.93151  1.68967  1.80139  1.6303
  2.0e-07: 625:    -16.1756;0.447997  1.94182  1.69047  1.80284  1.6360
At return
654:      -16.175574: 0.447997  1.94182  1.69047  1.80284  1.63601 0.3032
> fm11@re@theta

[1] 4.479973e-01 1.941823e+00 1.690473e+00 1.802841e+00
[5] 1.636013e+00 3.032622e-01 1.790633e-01 6.128860e-01
[9] 7.972121e-02 -3.249879e-01 2.727706e-07

> fm11@re@theta[is.finite(fm11@re@lower)]

[1] 4.479973e-01 1.941823e+00 3.032622e-01 7.972121e-02
```