

Module 6: Random Effects & Linear Mixed Models

Linear Mixed Models

Example 6.3: Knee Brace

Researchers study 4 knee braces: Control, Air Armor 2, Breg, Don Joy

10 high school running backs with previous ACL injury participate. Each player: Wears all 4 braces, Order randomized

Time to complete 40-yard agility course recorded

Run										
1	Control	Air	Control	Control	Air	Breg	Air	Breg	Air	Control
2	Breg	Don	Don	Air	Breg	Control	Control	Air	Don	Don
3	Air	Control	Air	Breg	Don	Air	Don	Control	Control	Air
4	Don	Breg	Breg	Don	Control	Don	Breg	Don	Breg	Breg

Example 6.3: Skeleton ANOVA

Do we care only about these 10 running backs?

Source of Variation	DF
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When one factor is fixed and one is random

Linear Mixed Models (LMM)

Mixed models come about when one factor is fixed and one factor is random. A mixed model should be used to study the effects of one factor on the population mean and the effects of another factor on the population variance.

Statistical Effects Model

$$y_{ij} = \mu + \tau_i + p_j + \epsilon_{ij} \text{ with } p_j \sim \text{iid } N(0, \sigma_{blk}^2) \text{ and } \epsilon_{ij} \sim \text{iid } N(0, \sigma_\epsilon^2)$$

for $i = 1, 2, 3; j = 1, 2, \dots, 10$

where:

- y_{ij} is the time to complete a 40-yard agility course for the j^{th} running back wearing the i^{th} knee brace
- μ is the overall mean time to complete the agility course
- τ_i is the fixed effect of the i^{th} knee brace
- p_j is the random effect of the j^{th} running back (block)
- ϵ_{ij} is the random error term associated with the j^{th} running back wearing the i^{th} knee brace

Scope of Inference

Note

- If blocks were fixed: Inference limited to these 10 running backs
- If blocks are random: Inference extends to *all* similar running backs

The Data

```
1 library(tidyverse)
2 kneebrace_data <- read_csv("data/06-kneebrace-data.csv") |>
3   mutate(across(RunningBack:KneeBrace, as.factor))
4 head(kneebrace_data, n = 12)
```

```
# A tibble: 12 × 3
  RunningBack KneeBrace AgilityTime
  <fct>      <fct>     <dbl>
1 1           Control    19.1
2 1           AirArmor   18
3 1           Breg       18.0
4 1           DonJoy     17.9
5 2           Control    19
6 2           AirArmor   18.4
7 2           Breg       18.2
8 2           DonJoy     17.7
9 3           Control    19.9
10 3          AirArmor   18.7
11 3          Breg       18.6
12 3          DonJoy     18.7
```

R: Fitting a LMM

```
1 library(lme4)
2 kneebrace_mod <- lmer(AgilityTime ~ KneeBrace + (1 | RunningBack), data = kneebrace_data)
3 summary(kneebrace_mod)
```

```
Linear mixed model fit by REML ['lmerMod']
Formula: AgilityTime ~ KneeBrace + (1 | RunningBack)
Data: kneebrace_data
```

```
REML criterion at convergence: 1.2
```

```
Scaled residuals:
```

Min	1Q	Median	3Q	Max
-1.72607	-0.47036	-0.03709	0.53329	1.71255

```
Random effects:
```

Groups	Name	Variance	Std.Dev.
RunningBack	(Intercept)	0.15453	0.3931
Residual		0.01965	0.1402

Number of obs: 40, groups: RunningBack, 10

```
Fixed effects:
```

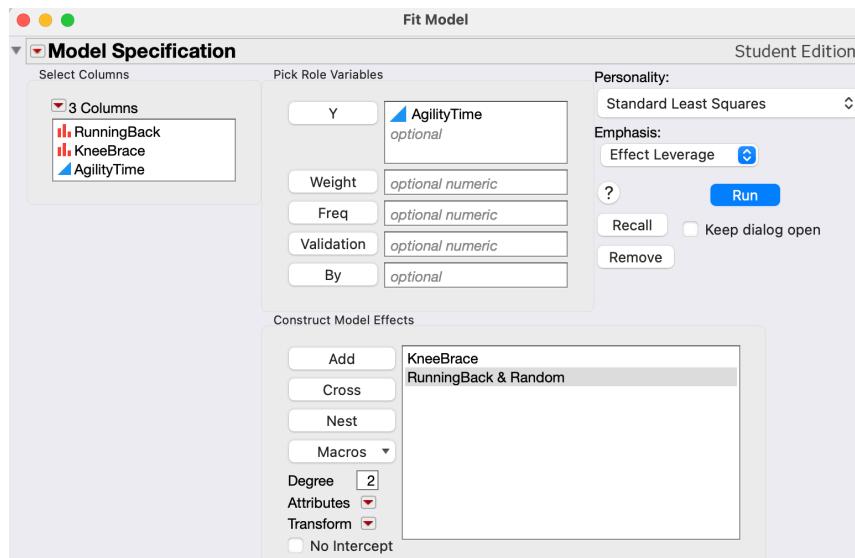
	Estimate	Std. Error	t value
(Intercept)	18.24200	0.13198	138.22
KneeBraceBreg	-0.01000	0.06269	-0.16
KneeBraceControl	0.97500	0.06269	15.55
KneeBraceDonJoy	-0.16800	0.06269	-2.68

```
Correlation of Fixed Effects:
```

(Intr)	KnBrcB	KnBrcC
KneeBracBrg	-0.237	...

JMP: Fitting a LMM

Analyze > Fit Model



Parameter Estimates						
Term	Estimate	Std Error	DFDen	t Ratio	Prob> t	
Intercept	18.44125	0.126272	9	146.04	<.0001*	
KneeBrace[AirArmor]	-0.19925	0.038388	27	-5.19	<.0001*	
KneeBrace[Breg]	-0.20925	0.038388	27	-5.45	<.0001*	
KneeBrace[Control]	0.77575	0.038388	27	20.21	<.0001*	

REML Variance Component Estimates							
Random Effect	Var Ratio	Component	Std Error	95% Lower	95% Upper	Wald p-Value	Pct of Total
RunningBack	7.8649595	0.1545341	0.0751755	0.0071927	0.3018754	0.0398*	88.720
Residual		0.0196484	0.0053476	0.0122818	0.0364025		11.280
Total		0.1741825	0.0752706	0.0867447	0.5112768		100.000

Testing Hypotheses About the Treatment Means

$H_0 : \tau_1 = \tau_2 = \tau_3 = \tau_4$ vs $H_A : \text{at least one } \tau_i \text{ differs}$

```
1 library(lmerTest)
2 anova(kneebrace_mod)
```

```
Analysis of Variance Table
  npar Sum Sq Mean Sq F value
KneeBrace   3 8.2015  2.7338 139.14
```

Fixed Effect Tests

Source	Nparm	DF	DDF	F Ratio	Prob > F
KneeBrace		3	3	27	139.1370 <.0001*

Estimating Treatment Means (balanced design)

Recall $y_{ij} = \mu + \tau_i + p_j + \epsilon_{ij}$

In the mixed model:

- $E[y_{ij}] = \hat{\mu} + \hat{\tau}_i$
- $Var(y_{ij}) = \hat{\sigma}_{blk}^2 + \hat{\sigma}_{\epsilon}^2.$

Thus, the estimated mean and variance are given by:

- Mean: $\hat{\mu}_i = \hat{\mu} + \hat{\tau}_i$
- SE of Mean: $SE(\hat{\mu}_i) = \sqrt{\frac{\hat{\sigma}_{blk}^2 + \hat{\sigma}_{\epsilon}^2}{r}}$
- SE of Diff in Means: $SE(\hat{\mu}_i - \hat{\mu}_{i'}) = \sqrt{\frac{2}{r}\hat{\sigma}_{\epsilon}^2}$

Estimating Treatment Means

```

1 library(emmeans)
2 library(multcomp)
3 # emmip(kneebrace_mod, ~ KneeBrace, CI = T)
4 emmeans(kneebrace_mod, specs = ~KneeBrace) |>
5   cld(Letters = LETTERS, decreasing = T, adjust = "tukey")

```

KneeBrace	emmean	SE	df	lower.CL	upper.CL	group
Control	19.2	0.132	10.7	18.8	19.6	A
AirArmor	18.2	0.132	10.7	17.8	18.6	B
Breg	18.2	0.132	10.7	17.8	18.6	B
DonJoy	18.1	0.132	10.7	17.7	18.5	B

Degrees-of-freedom method: kenward-roger

Confidence level used: 0.95

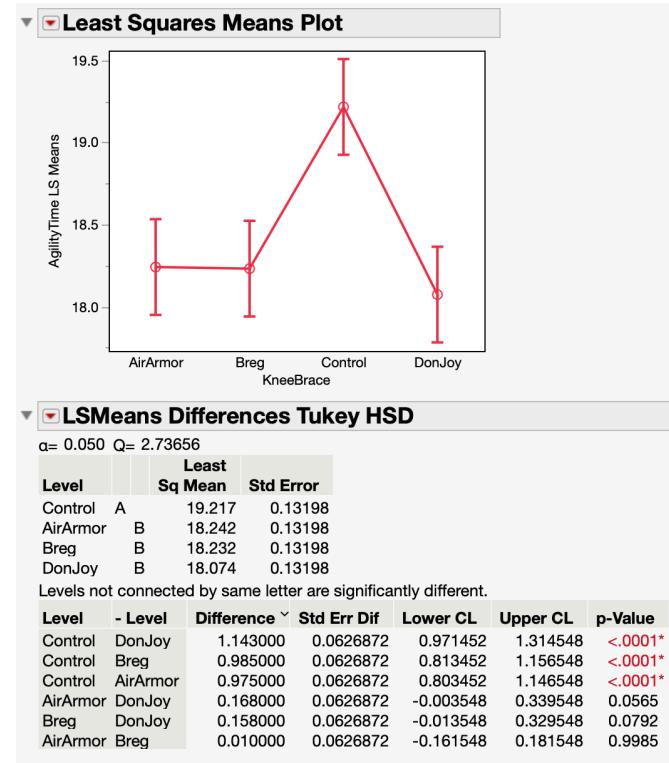
Conf-level adjustment: sidak method for 4 estimates

P value adjustment: tukey method for comparing a family of 4 estimates

significance level used: alpha = 0.05

NOTE: If two or more means share the same grouping symbol,
then we cannot show them to be different.

But we also did not show them to be the same.



Effect on Standard Errors

Treating blocks as random (instead of fixed) (1) Increases SE of treatment means (2) Does NOT change SE of treatment differences

Running back Fixed (LM)

```
1 kneebrace_lm <- lm(AgilityTime ~ KneeBrace + RunningBack,  
2                      data = kneebrace_data)  
3 emmeans(kneebrace_lm, specs = ~KneeBrace)
```

```
KneeBrace emmean    SE df lower.CL upper.CL  
AirArmor   18.24 0.0443 27   18.15   18.33  
Breg       18.23 0.0443 27   18.14   18.32  
Control    19.22 0.0443 27   19.13   19.31  
DonJoy     18.07 0.0443 27   17.98   18.16
```

Results are averaged over the levels of: RunningBack
Confidence level used: 0.95

```
1 emmeans(kneebrace_lm, specs = ~KneeBrace) |> pairs()
```

```
contrast      estimate    SE df t.ratio p.value  
AirArmor - Breg      0.010 0.0627 27   0.160  0.9985  
AirArmor - Control   -0.975 0.0627 27  -15.553 <0.0001  
AirArmor - DonJoy     0.168 0.0627 27   2.680  0.0565  
Breg - Control      -0.985 0.0627 27  -15.713 <0.0001  
Breg - DonJoy        0.158 0.0627 27   2.520  0.0792  
Control - DonJoy     1.143 0.0627 27   18.233 <0.0001
```

Results are averaged over the levels of: RunningBack
P value adjustment: tukey method for comparing a family of 4 estimates

Running back Random (LMM)

```
1 kneebrace_lmer <- lmer(AgilityTime ~ KneeBrace + (1 | RunningBack),  
2                           data = kneebrace_data)  
3 emmeans(kneebrace_lmer, specs = ~KneeBrace)
```

```
KneeBrace emmean    SE df lower.CL upper.CL  
AirArmor   18.2 0.132 10.7   18.0   18.5  
Breg       18.2 0.132 10.7   17.9   18.5  
Control    19.2 0.132 10.7   18.9   19.5  
DonJoy     18.1 0.132 10.7   17.8   18.4
```

Degrees-of-freedom method: kenward-roger
Confidence level used: 0.95

```
1 emmeans(kneebrace_lmer, specs = ~KneeBrace) |> pairs()
```

```
contrast      estimate    SE df t.ratio p.value  
AirArmor - Breg      0.010 0.0627 27   0.160  0.9985  
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```

Degrees-of-freedom method: kenward-roger
P value adjustment: tukey method for comparing a family of 4 estimates