

Linear Regression Models

P8111

Lecture 22

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April 14, 2016



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Today's Lecture

- Random intercept models ✓

- Random slope ✓

- Example (pig data!) ✓

- Example (CD4 data!) ✓

Recall the setting

- We observe data y_{ij}, x_{ij} for subjects $i = 1, \dots, I$ at visits $j = 1, \dots, J_i$
- Overall, we pose the model

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon}$$

where $\text{Var}(\boldsymbol{\epsilon}) = \sigma^2 V$ and

$$V = \begin{bmatrix} V_1 & 0 & \dots & 0 \\ 0 & V_2 & \dots & 0 \\ \vdots & \vdots & \ddots & \\ 0 & 0 & & V_I \end{bmatrix}$$

Recall the setting

- We've focused on random intercept models and (equivalently) uniform correlation marginal models
- Today we'll review random intercept approaches and introduce random slope models

Random intercept model

A random intercept model with one covariate is given by

$$y_{ij} = \beta_0 + b_i + \beta_1 x_{ij} + \epsilon_{ij}$$

where

- $b_i \sim N [0, \tau^2]$
- $\epsilon_{ij} \sim N [0, \nu^2]$

Random intercept model

More compactly, we write

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{Z}\mathbf{b} + \boldsymbol{\epsilon}$$

where

- $\mathbf{b} \sim \text{N} [0, \tau^2 I_I]$
- $\boldsymbol{\epsilon} \sim \text{N} [0, \nu^2 I_n]$

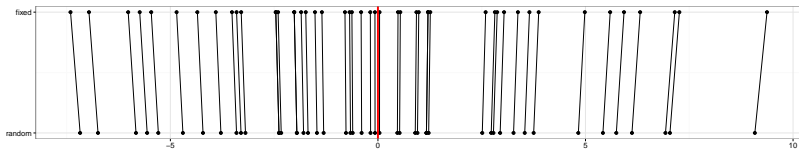
Random intercept model

In the model

$$y = X\beta + Zb + \epsilon$$

we've discussed why we use random effects rather than fixed effects:

- Random effects induce correlation; fixed effects don't
- This reduces the number of parameters we estimate
- Random effect modeling is similar mathematically to introducing penalization



Estimation – random intercept model

Estimation is done using MLE with model and distributional assumptions

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{Z}\mathbf{b} + \boldsymbol{\epsilon}$$

where

- $\mathbf{b} \sim \text{N} [0, \tau^2 I_I]$
- $\boldsymbol{\epsilon} \sim \text{N} [0, \nu^2 I_n]$

Remember that BLUPs from this model can be derived without distributional assumptions (similarly to OLS and BLUEs).

Estimation – BLUPs

Our estimate for fixed and random effects are

$$\begin{bmatrix} \hat{\boldsymbol{\beta}} \\ \hat{\mathbf{b}} \end{bmatrix} = \left(\mathbf{C}^T \mathbf{C} + \frac{\nu^2}{\tau^2} \mathbf{R} \right)^{-1} \mathbf{C}^T \mathbf{y}$$

where $\mathbf{C} = [\mathbf{X} \ \mathbf{Z}]$ and

$$\mathbf{R} = \begin{bmatrix} 0 & \dots & 0 & 0 & \dots & 0 \\ \vdots & \ddots & \vdots & \vdots & & \vdots \\ 0 & \dots & 0 & 0 & \dots & 0 \\ 0 & \dots & 0 & 1 & & 0 \\ \vdots & & \vdots & & \ddots & \\ 0 & \dots & 0 & 0 & & 1 \end{bmatrix}$$

Random slope model

A random slope model with one covariate is given by

$$y_{ij} = \beta_0 + b_{i,0} + \beta_1 x_{ij} + b_{i,1} x_{ij} + \epsilon_{ij}$$

where

$$\begin{bmatrix} b_{i,0} \\ b_{i,1} \end{bmatrix} \sim \text{N} \left[\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \tau_0^2 & \tau_{01} \\ \tau_{10} & \tau_1^2 \end{bmatrix} \right]$$

and

$$\epsilon_{ij} \sim \text{N} [0, \nu^2]$$

Random slope model

Using vectors, we can write

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{Z}_0\mathbf{b}_0 + \mathbf{Z}_1\mathbf{b}_1 + \boldsymbol{\epsilon}$$

Estimation – random slope model

Omitting the details –

- Again use MLE to set up approach and derive BLUPs (which don't depend on distributional assumptions)
- This is easier if one assumes $\tau_{01} = 0$, and usually the results aren't affected much
- The estimates look similar to the BLUPs for one random intercept, although there are more “ R ”s to deal with
- Results again resemble ridge regression estimates, although with more than one penalty

Random effect models

Our random slope model with one covariate given by

$$y_{ij} = \beta_0 + b_{i,0} + \beta_1 x_{ij} + b_{i,1} x_{ij} + \epsilon_{ij}$$

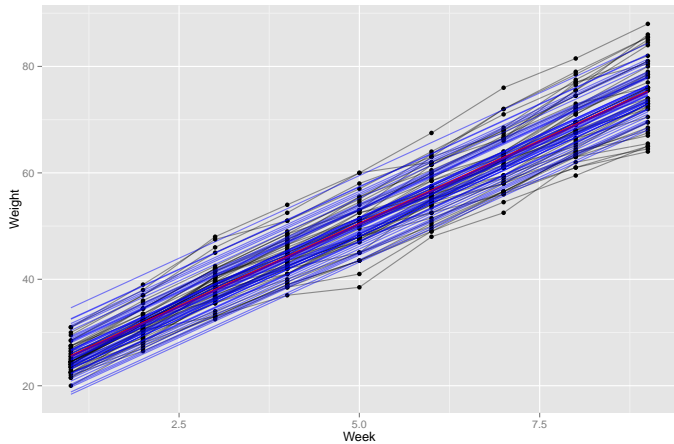
has the following properties

- $E(\mathbf{y}) = \beta_0 + \beta_1 x_{ij}$
- $E(\mathbf{y} | b_{i,0}, b_{i,1}) = (\beta_0 + b_{i,0}) + (\beta_1 + b_{i,1}) x_{ij}$

So main effect parameters are interpreted as the effect for *an average* subject; the interpretation for *a particular* subject is conditional on the random effects.

Pig data

Random intercept model fit for pig data



Pig data

Random intercept model code

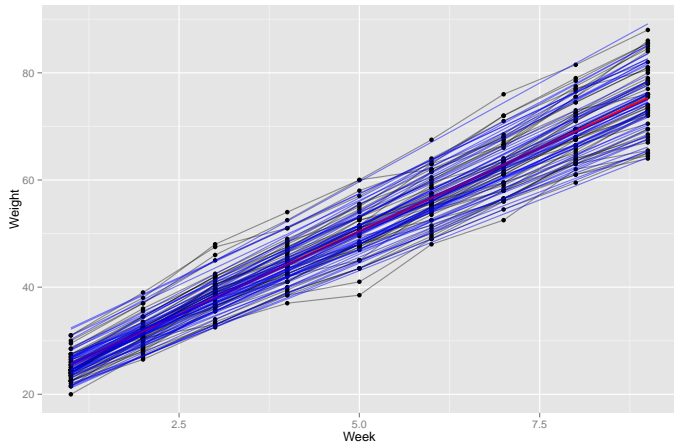
```
> library(lme4)
> ranef.mod = lmer(weight ~ (1 | id.num) + num.weeks, data = pig.weights)
> summary(ranef.mod)
Linear mixed model fit by REML
Formula: weight ~ (1 | id.num) + num.weeks
Data: pig.weights
   AIC   BIC logLik deviance REMLdev
2042 2058 -1017   2030    2034
Random effects:
   Groups   Name      Variance Std.Dev.
id.num  (Intercept) 15.1418  3.8913
Residual                    4.3947  2.0964
Number of obs: 432, groups: id.num, 48

Fixed effects:
              Estimate Std. Error t value
(Intercept) 19.35561    0.60311   32.09
num.weeks   6.20990    0.03906  158.97

> (15.1418) / (15.1418 + 4.3947)
[1] 0.7750518
```

Pig data

Random slope model fit for pig data



Pig data

Random slope model code

```
> ranef.mod = lmer(weight ~ (1 + num.weeks | id.num) + num.weeks, data = pig.weights)
```

```
> summary(ranef.mod)
```

Linear mixed model fit by REML

Formula: weight ~ (1 + num.weeks | id.num) + num.weeks

Data: pig.weights

AIC	BIC	logLik	deviance	REMLdev
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1753	1777	-870.4	1738	1741
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Random effects:

Groups	Name	Variance	Std.Dev.	Corr
id.num	(Intercept)	6.9865	2.64319	
	num.weeks	0.3800	0.61644	-0.063
Residual		1.5968	1.26366	

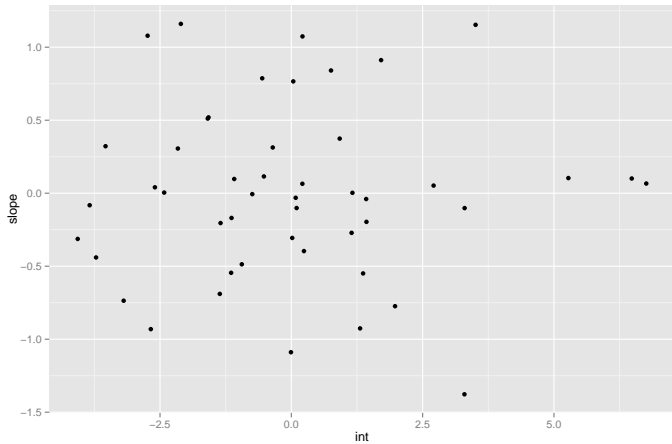
Number of obs: 432, groups: id.num, 48

Fixed effects:

	Estimate	Std. Error	t value
(Intercept)	19.35561	0.40387	47.93
num.weeks	6.20990	0.09204	67.47

Pig data

Random intercept against random slope



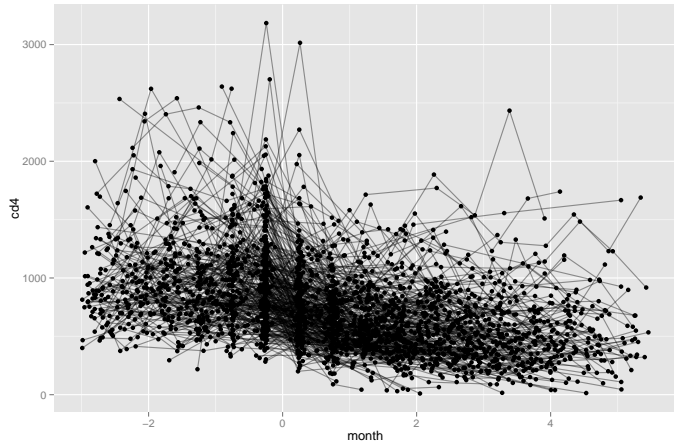
Quick questions

What data would lead to the random intercept and random slope having high positive correlation? High negative correlation?

Pig data summary

- Overall, the random slope model provides a pretty good fit
- Lowest AIC of all models considered (linear model not shown, but trust me)
- Visual inspection of data indicates a good fit
- Easy to interpret

CD4 data



CD4 data

SLR model code

```
> lin.mod = lm(cd4 ~ month, data = cd4)
> summary(lin.mod)
```

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	839.398	8.147	103.03	<2e-16 ***
month	-89.027	3.965	-22.45	<2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 362.9 on 2369 degrees of freedom

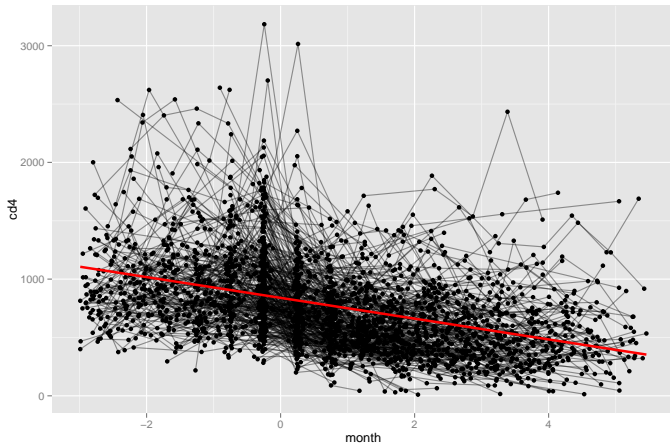
Multiple R-squared: 0.1754, Adjusted R-squared: 0.1751

```
> AIC(lin.mod)
```

```
[1] 34682.64
```

CD4 data

SLR model fit for CD4 data



CD4 data

B spline model code

```
> bs.mod = lm(cd4 ~ bs(month, 5), data = cd4)
> summary(bs.mod)
```

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	898.19	57.65	15.580	< 2e-16	***
bs(month, 5)1	181.75	101.47	1.791	0.07340	.
bs(month, 5)2	154.21	57.27	2.693	0.00713	**
bs(month, 5)3	-544.31	84.28	-6.459	1.28e-10	***
bs(month, 5)4	-230.25	80.16	-2.873	0.00411	**
bs(month, 5)5	-400.92	98.69	-4.063	5.01e-05	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 356.2 on 2365 degrees of freedom

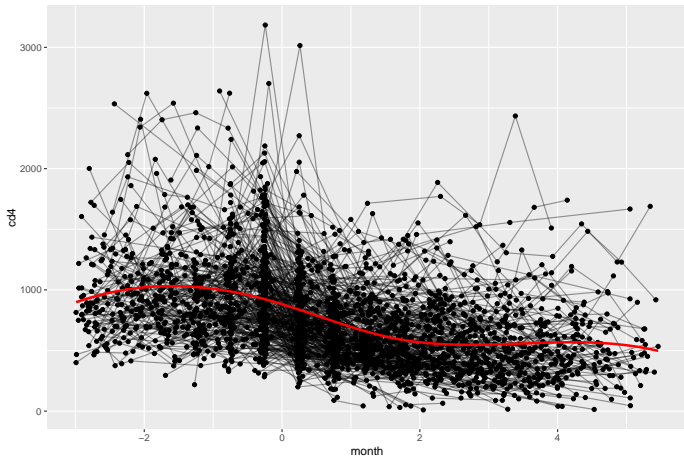
Multiple R-squared: 0.2068, Adjusted R-squared: 0.2051

```
> AIC(bs.mod)
```

```
[1] 34598.69
```


CD4 data

Polynomial model fit for CD4 data



CD4 data

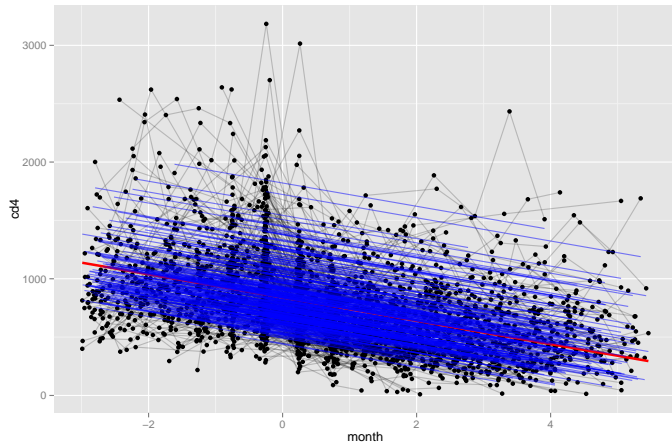
Random intercept model code

```
> ranint.mod = lmer(cd4 ~ (1 | ID) + month, data = cd4)
> summary(ranint.mod)
Random effects:
  Groups   Name      Variance Std.Dev.
  ID      (Intercept) 64982    254.92
  Residual                66532    257.94
Number of obs: 2371, groups: ID, 364

Fixed effects:
              Estimate Std. Error t value
(Intercept)  838.925    14.724   56.98
month        -99.703     3.449  -28.91
> AIC(ranint.mod)
[1] 33755.67
```

CD4 data

Random intercept fit for CD4 data



CD4 data

Random intercept, slope + B spline model code

```
> ranbs.mod = lmer(cd4 ~ (1 + month | ID) + bs(month, 5), data = cd4)
> summary(ranbs.mod)
```

Random effects:

Groups	Name	Variance	Std.Dev.	Corr
ID	(Intercept)	71333	267.08	
	month	4851	69.65	-0.43
Residual		50484	224.69	

Number of obs: 2371, groups: ID, 364

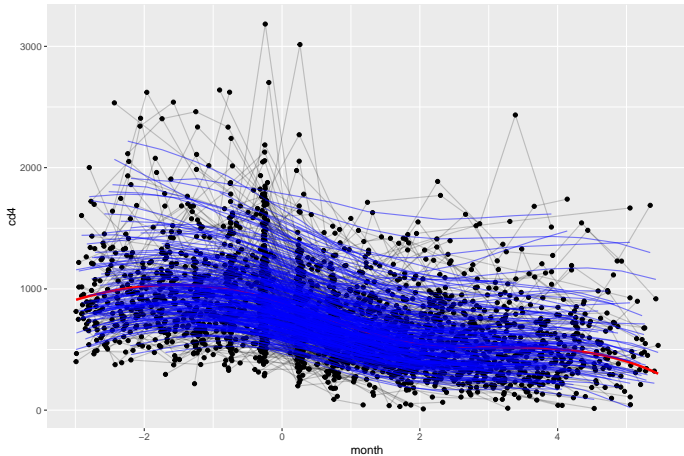
Fixed effects:

	Estimate	Std. Error	t value
(Intercept)	910.11	50.09	18.169
bs(month, 5)1	157.54	73.43	2.145
bs(month, 5)2	164.87	47.42	3.477
bs(month, 5)3	-588.42	64.43	-9.133
bs(month, 5)4	-264.07	65.57	-4.027
bs(month, 5)5	-609.54	82.14	-7.421

```
> AIC(ranbs.mod)
[1] 33428.49
```

CD4 data

Random intercept, slope + B spline fit for CD4 data



CD4 data summary

Which model do you prefer?

Today's big ideas

- Random slope models
 - Pig data analysis
 - CD4 data analysis
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