

Repeated
Measures
ANOVA, RIP

Mariel

Goals

Review

Random
Intercepts
Random
Intercepts
and Slopes

Multiple
groups

Let's do it!

PS

Nonlinear
time effects
Bayesian
p-values

Conclusions

Advanced Mixed Effects Modelling

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Gladstone Bioinformatics Core
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Goals

- ① How to use *indicator variables* to describe a mixed effects model with multiple groups?
 - (a) Write down the regression equation
 - (b) Fit and plot the regression in R.
 - (c) Interpret the regression output.
- ② What to do when time trends are not linear?
- ③ What to do if your reviewer doesn't like the default method of calculating p-values?

Mixed = fixed + random

- Fixed effects (α, β)
 - Population characteristics
 - Shared by all individuals
 - Describe the mean response trajectory in the population
 - Useful to epidemiologists
- Random effects (a, b)
 - Subject-specific effects
 - Vary from one individual to another
 - Describe individuals' response trajectories
 - Useful to clinicians

The simplest case: a random intercept model

$$\begin{aligned}y &= \alpha + \beta x + a + \varepsilon \\ &= (\alpha + a) + \beta x + \varepsilon\end{aligned}$$

- α is the fixed, population-level intercept
- β is the fixed, population-level time slope
- a is the random, subject-specific intercept:
By how much does each individual deviate from the population average?
- ε is the error term

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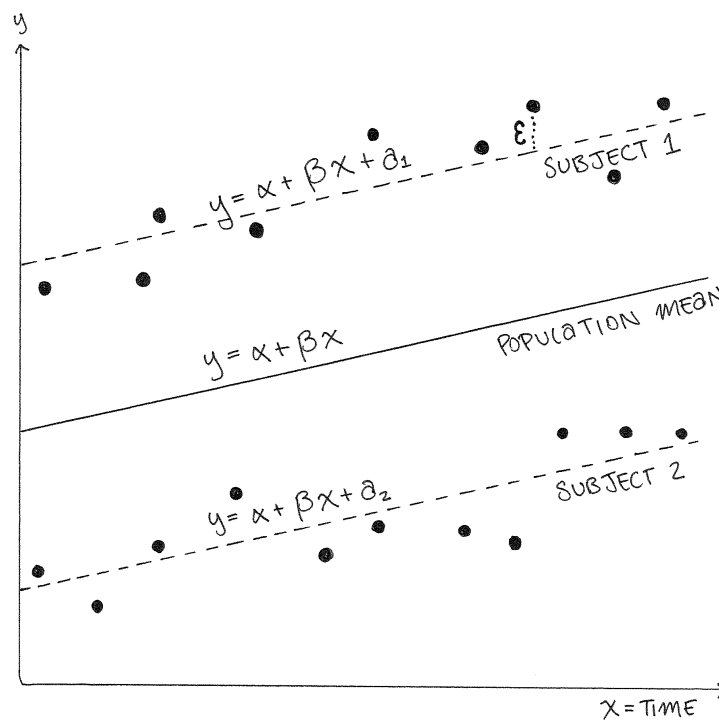
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Random intercept model

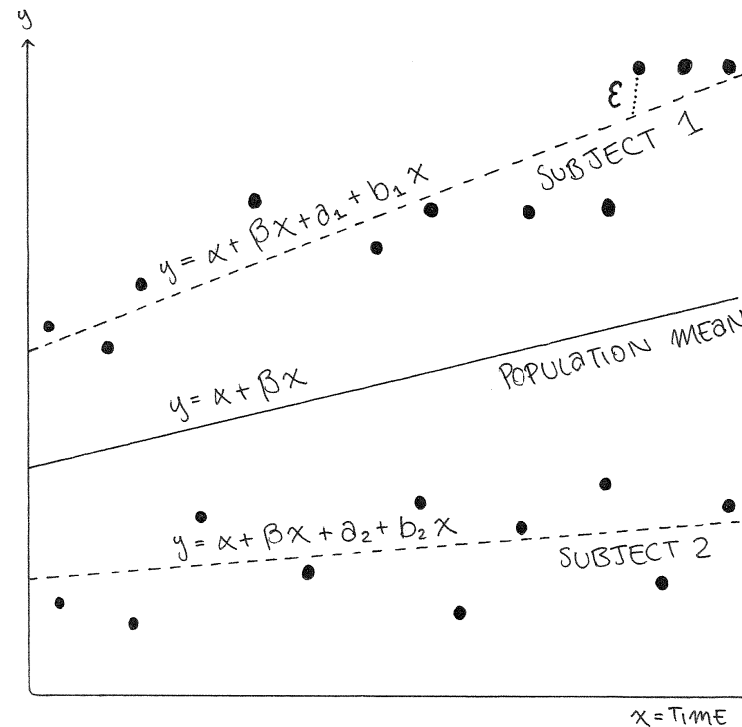


The more common scenario: a random intercept and slope model

$$\begin{aligned}y &= \alpha + \beta x + a + b x + \varepsilon \\ &= (\alpha + a) + (\beta + b)x + \varepsilon\end{aligned}$$

- α is the fixed, population-level intercept
- β is the fixed, population-level time slope
- a is the random, subject-specific intercept:
By how much does each individual deviate from the population average?
- b is the random, subject-specific time slope:
By how much does the effect of time on each individual deviate from the population-average effect?
- ε is the error term

Random intercept and slope model



To include multiple groups,
we need indicator variables

Consider an experiment with **two groups** of interest:

- Some subjects receive a **placebo**,
- Others receive a **drug**.

To describe this experiment statistically, we use an **indicator**
(a.k.a. **dummy**) variable:

$$z = \begin{cases} 0 & \text{if the subject received the placebo} \\ 1 & \text{if the subject received the drug} \end{cases}$$

An extension: two groups

Model	$y = \alpha + \beta x + \delta z + \gamma xz + a + bx + \varepsilon$ $= (\alpha + \delta z + a) + (\beta + \gamma z + b)x + \varepsilon$
Placebo	$y = (\alpha + \delta 0 + a) + (\beta + \gamma 0 + b)x + \varepsilon$ $= (\alpha + a) + (\beta + b)x + \varepsilon$
Drug	$y = (\alpha + \delta 1 + a) + (\beta + \gamma 1 + b)x + \varepsilon$ $= (\alpha + \delta + a) + (\beta + \gamma + b)x + \varepsilon$

- α is the fixed, population-level intercept
- β is the fixed, population-level time slope
- δ is the fixed, population-level effect of the drug
- γ is the fixed, population-level effect of the drug *on the time slope*
- a is the random, subject-specific intercept
- b is the random, subject-specific time slope effect?
- ε is the error term

A further extension: 3+ groups

Consider an experiment with **four groups** of interest (e.g. diets 1, 2, 3, and 4). To describe this experiment statistically, we use **3** indicator variables:

$$z_2 = \begin{cases} 1 & \text{if the subject received diet 2} \\ 0 & \text{otherwise} \end{cases}$$

$$z_3 = \begin{cases} 1 & \text{if the subject received diet 3} \\ 0 & \text{otherwise} \end{cases}$$

$$z_4 = \begin{cases} 1 & \text{if the subject received diet 4} \\ 0 & \text{otherwise} \end{cases}$$

Let's look at some data

```
> # install.packages('arm')  
> library(arm)  
> head(ChickWeight)
```

INSTALL AND LOAD A PACKAGE CALLED
"arm" THAT CONTAINS SOME OF THE
FUNCTIONS WE'LL BE USING.

Grouped Data: weight ~ Time | Chick

	weight	Time	Chick	Diet
1	42	0	1	1
2	51	2	1	1
3	59	4	1	1
4	64	6	1	1
5	76	8	1	1
6	93	10	1	1

SHOW ME THE "head" OF
THE DATASET CALLED
"ChickWeight".

```
> attach(ChickWeight)
```

GIVE ME ACCESS TO THE
VARIABLES IN THE
DATASET "ChickWeight".

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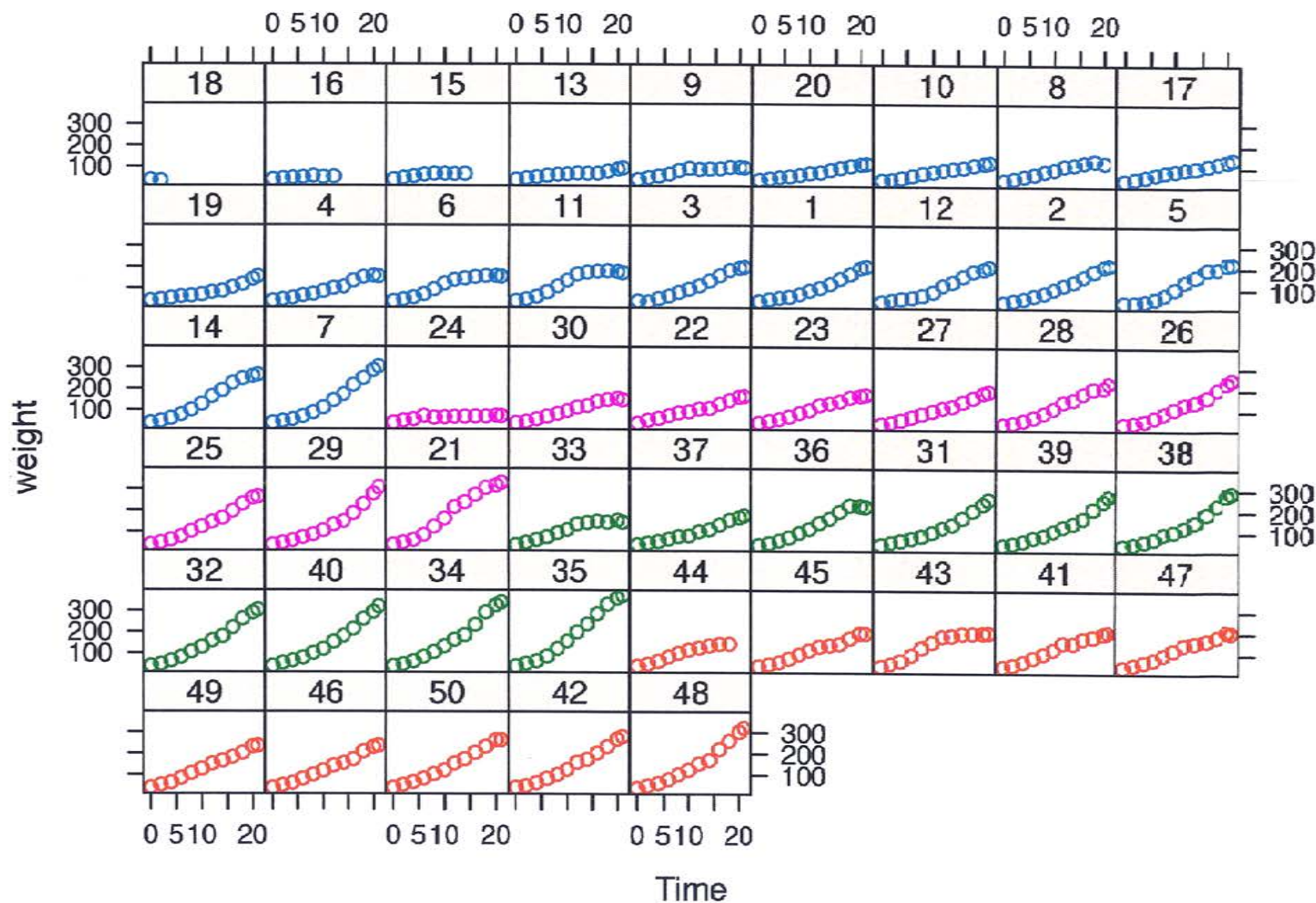
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```
> xyplot(weight ~ Time | Chick, group = Diet, as.table = T)
```

["FOR EACH"]
["VS."]
[DRAW A "LATTICE" PLOT OF y VS x FOR EACH CHICK]



Fitting a mixed effects model

[CREATE AN OBJECT CALLED "model".]
> model <- lmer(weight ~ Time + Diet + Time*Diet + (1+Time|Chick))

$$y = \alpha + \beta x + \delta z + \gamma xz + a + bx + \varepsilon$$

[AND PUT INTO IT]

[A "LINEAR MIXED EFFECTS REGRESSION".]

SHOW ME THE
"FIXED" EFFECTS
FROM "model".

Extracting fixed/random effects

> **fixef**(model)

(Intercept)	Time	Diet2	Diet3	Diet4
33.661	6.277	-5.028	-15.411	-1.750
Time:Diet2	Time:Diet3	Time:Diet4		
2.332	5.146	3.255		

> **head**(ranef(model)\$Chick)

SHOW ME THE "head" OF THE
"CHICK-SPECIFIC" RANDOM
"EFFECTS FROM MODEL."

	(Intercept)	Time
18	0.3389	-0.175
16	15.9678	-5.405
15	13.1031	-4.207
13	12.6833	-4.173
9	10.9972	-3.142
20	8.0702	-2.759

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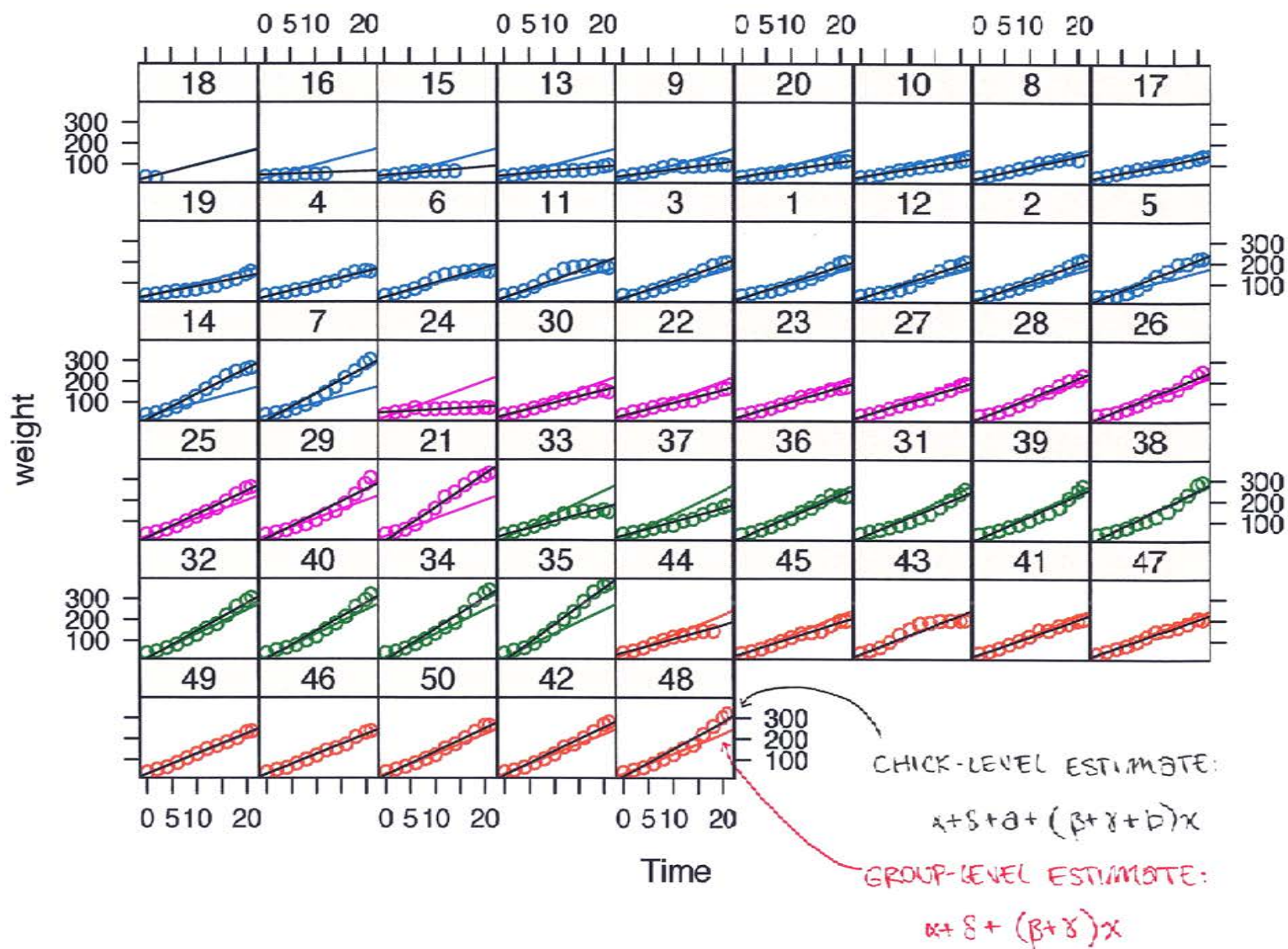
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Summarizing the fitted model

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```
> display(model)
```

```
lmer(formula = weight ~ Time + Diet + Time * Diet + (1 + Time |  
      Chick))
```

	coef.est	coef.se
(Intercept)	33.66 α	2.92
Time	6.28 β	0.76
Diet2	-5.03 δ_2	5.01
Diet3	-15.41 δ_3	5.01
Diet4	-1.75 δ_4	5.02
Time:Diet2	2.33 γ_2	1.30
Time:Diet3	5.15 γ_3	1.30
Time:Diet4	3.25 γ_4	1.31

Error terms:

Groups	Name	Std.Dev.	Corr
Chick	(Intercept)	10.81	
	Time	3.30	-0.97
	Residual	12.78	

[STANDARD DEVIATION OF δ 's]

[STANDARD DEVIATION OF δ 's]

```
---  
number of obs: 578, groups: Chick, 50  
AIC = 4805.5, DIC = 4820  
deviance = 4800.5
```


Summarizing the fitted model

```
> # install.packages('car')
> library(car)
> Anova(model)
```

Analysis of Deviance Table (Type II tests)

Response: weight

	Chisq	Df	Pr(>Chisq)
Time	314.1	1	< 2e-16 ***
Diet	15.6	3	0.00136 **
Time:Diet	17.1	3	0.00068 ***

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

CALCULATED ACCORDING TO THE
PRINCIPLE OF MARGINALITY,
TESTING EACH TERM AFTER
ALL OTHERS, EXCEPT IGNORING
THE TERM'S HIGHER-ORDER
RELATIVES

Interpreting the R output

- For your Methods section:
 - *"We fit a linear mixed effects model of chick weight on time, including fixed intercepts and slopes for each of the four diets, and random intercepts and slopes for each chick."*
 - *"We assessed differences in the time effect across diets using a Wald chi-square test."*
- For your Results section:
 - *"We found a significant difference in the rates of weight gain across diets ($p < 0.001$), with chicks on diets 1, 2, 3, and 4 gaining 6.3, 8.6, 11.4, and 9.5 g/day, respectively."*
 - *"Chicks varied in their baseline weight ($SD=10.8$) and in their rates of weight gain over time ($SD=3.3$)."*

Postscript 1 – Nonlinear time effects

[CREATE AN OBJECT
CALLED model2.]

```
> model2 <- lmer(weight ~ Time + I(Time^2) + Diet + Time*Diet +  
+ I(Time^2)*Diet + (1+Time+I(Time^2)|Chick))
```

$$y = \alpha + \beta x + \varphi x^2 + \delta z + \gamma xz + \zeta x^2 z + a + bx + cx^2 + \varepsilon$$

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```
> fixef(model2)
```

	(Intercept)	Time	I(Time^2)
	37.519476	5.123906	0.046931 φ
	Diet2	Diet3	Diet4
	0.160646	1.304480	-1.700774
	Time:Diet2	Time:Diet3	Time:Diet4
	0.686292	-0.066387	3.262591
	I(Time^2):Diet2	I(Time^2):Diet3	I(Time^2):Diet4
	0.083358 ξ_2	0.249372 ξ_3	0.003115 ξ_4

```
> head(ranef(model2)$Chick)
```

	(Intercept)	Time	I(Time^2)
18	1.4061	-0.8994	0.0113795
16	4.8281	-3.0882	-0.1241312
15	0.3046	-0.1948	-0.2359140
13	4.2501	-2.7185	-0.0498864
9	-3.1273	2.0003	-0.2422971
20	3.7762	-2.4154	0.0001437

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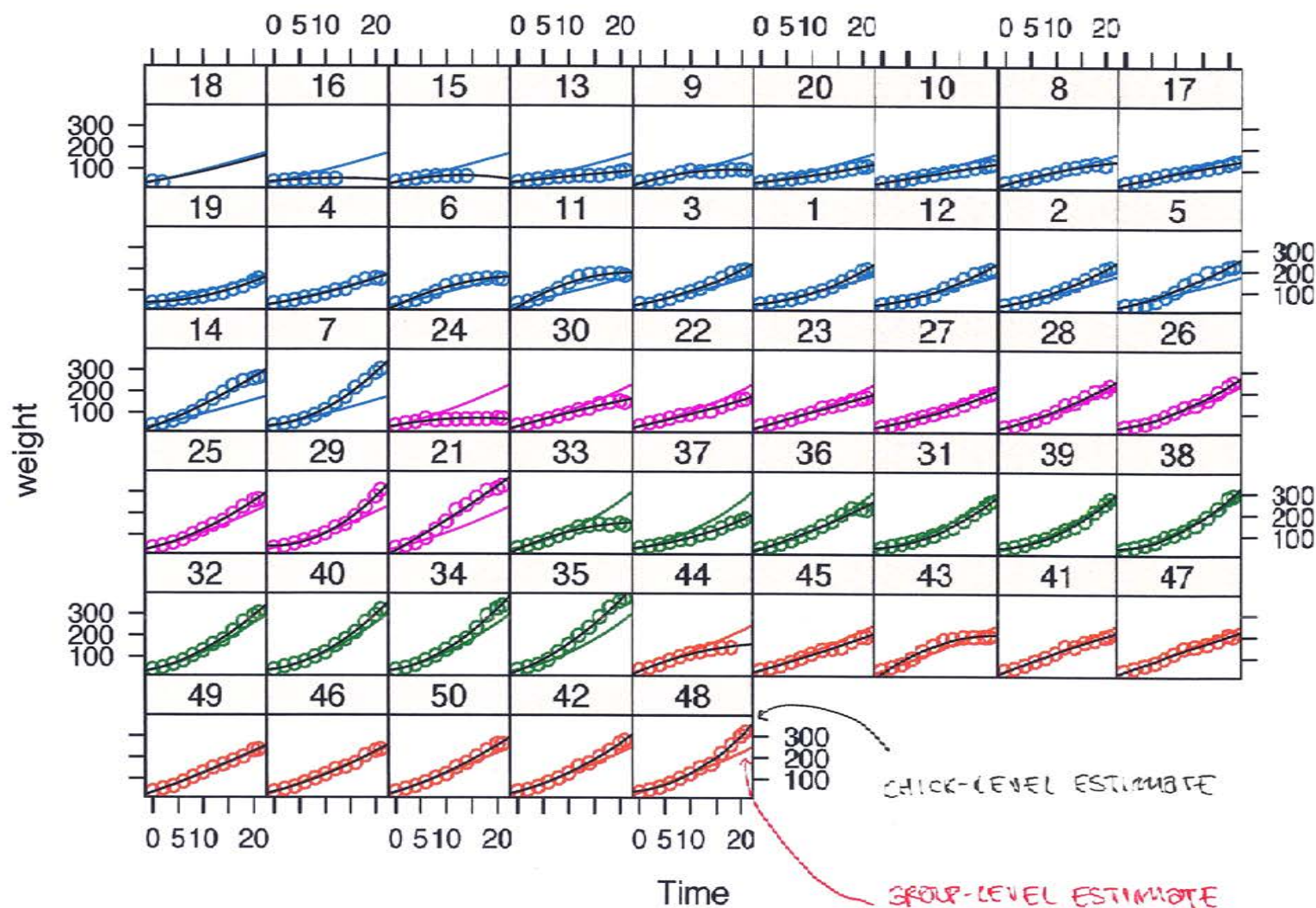
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Postscript 2 – Bayesian Inference

- Most reviewers would be fine with the Wald chi-square test given here, but a small minority (myself included, to be honest) would argue that the Wald tests may be anti-conservative, especially for small datasets. (*Dempster, Rubin, & Tsutakawa (1981). Estimation in covariance components models. JASA, 76(374), 341-353.*)
- An alternative, which requires some extra statistical programming, is Bayesian inference.

Postscript 2 – Bayesian Inference

For example: “*Do chicks on diet 2 gain weight significantly faster than chicks on diet 1?*”

- For your Methods Section:
 - “*We obtained 5000 draws of the difference in time effects between diets 1 and 2, and we estimated a 95% confidence interval (CI) as the 2.5th and 97.5th quantiles of these draws. We calculated a p-value for this difference by inverting the simulated confidence interval.*”
- For your Results Section:
 - “*Mice on diet 2 gain 2.3 more g/day than mice on diet 1 (95% CI -0.1, 4.9, $p=0.07$).*”

Postscript 2 – Bayesian Inference

```
> sims <- sim(model, 5000)
> fixefs <- fixef(sims)
> m <- fixef(model)['Time:Diet2']
> quantile(fixefs[, 'Time:Diet2'], c(.025, .975))
```

[OBTAIN 5000 DRAWS,
OR "SIMULATIONS".]

[ESTIMATE THE 95% CI.]

```
      2.5%   97.5%
-0.1475  4.9553
```

```
> se <- sd(fixefs[, 'Time:Diet2'])
> z <- abs(m/se)
> p <- (1-pnorm(z))*2
> p
```

[INVERT THE CI TO
OBTAIN A P-VALUE.]

```
Time:Diet2
0.07363
```


Conclusions

If your outcome is continuous, but your observations are not independent:

- ① Don't use repeated measures ANOVA!
- ② Linear mixed effects models offer a flexible, powerful alternative.
- ③ You should now feel comfortable fitting a simple mixed effects model in R.
- ④ If your data are complex (e.g. multi-level hierarchy, extra-quadratic non-linearity) or your hypotheses are complex (e.g. comparisons at time x , predictions), please don't hesitate to drop me a line.