# Homework 5

Psych 5068

### Emorie Beck

March 17, 2018

## Contents

Workspace           Packages			
Question 1	2	2	
Question 2	•	2	
Question 3		3	
Part A	;	3	
Part B		3	
Question 4	;	3	
Part A		3	
Part B		4	
Part C		4	
Part D		4	
Part E		5	
Question 5	(	6	
Part A		6	
Part B		6	
Part C	(	6	
Question 6	,	7	
Part A	8	8	
Part B		8	
For this assignment, you will extend our analyses of the Curran reading data (Curran_New_	Trimmed.csv	).	

# Workspace

# Packages

```
library(psych)
library(lme4)
library(knitr)
library(qqplotr)
library(influence.ME)
library(HLMdiag)
library(multcomp)
library(kableExtra)
```

```
library(plyr)
library(tidyverse)
```

#### Data

```
data_url <- "https://raw.githubusercontent.com/emoriebeck/homeworks/master/homework6/Curran_New_Trimmed
dat <- data_url %>% read.csv %>% tbl_df
```

# Question 1

Create dummy codes for each of the four time periods. Call these new variables TD1, TD2, TD3, and TD4.

```
dat <- dat %>%
  mutate(
    TD1 = ifelse(time == 1, 1, 0),
    TD2 = ifelse(time == 2, 1, 0),
    TD3 = ifelse(time == 3, 1, 0),
    TD4 = ifelse(time == 4, 1, 0)
)
```

# Question 2

Fit a no-intercept model:

Level 1:

$$read_{ti} = \pi_{0i}TD1_{ti} + \pi_{1i}TD2_{ti} + \pi_{2i}TD3_{ti} + \pi_{3i}TD4_{ti} + e_{ij}$$

$$\pi_{0i} = \beta_{00} + r_{0i}$$

$$\pi_{1i} = \beta_{10}$$

$$\pi_{2i} = \beta_{20}$$

$$\pi_{3i} = \beta_{30}$$

	Model 2			
	b	CI		
Fixed				
TD1	2.55	[2.42, 2.62]		
TD2	4.09	[4.01, 4.21]		
TD3	5.09	[5.02, 5.17]		
TD4	5.80	[5.64, 5.92]		
Rando	m			
$ au_{00}$	0.00	[0.00, 0.15]		
$R_m^2$	0.55	-		
$R_c^2$	0.55			

# Question 3

Perform follow-up tests on the model.

#### Part A

Create a matrix of contrasts that will test the linear, quadratic, and cubic trends in the data.

```
contr <- t(contr.poly(4))</pre>
```

## Part B

Test this matrix using glht() in the multcomp package. Which trends are significant?

```
ghlt_fit2 <- multcomp::glht(fit2, linfct = contr)
res_fit2 <- confint(ghlt_fit2, calpha = univariate_calpha())
res_fit2_df <- res_fit2$confint %>% data.frame()
```

# Question 4

Test each of the following models (use ML not REML):

#### Part A

```
Model 1:
```

Level 1:

$$read_{ti} = \pi_{0i} + e_{ti}$$

$$\pi_{0i} = \beta_{00} + r_{0i}$$

```
fit4a <- lmer(read ~ 1 + (1 | id), data = dat)
tab4a <- table_fun(fit4a)</pre>
```

### Part B

Model 2:

Level 1:

$$read_{ti} = \pi_{0i} + \pi_{1i}(age - 10)_{ti} + e_{ti}$$

Level 2:

$$\pi_{0i} = \beta_{00} + r_{0i}$$

$$\pi_{1i} = \beta_{10} + r_{1i}$$

```
dat <- dat %>% mutate(age_10 = kidagetv - 10)
fit4b <- lmer(read ~ age_10 + (age_10 | id), data = dat)
tab4b <- table_fun(fit4b)</pre>
```

## Part C

Model 3: Level 1:

$$read_{ti} = \pi_{0i} + \pi_{1i}(age - 10)_{ti} + \pi_{2i}(age - 10)_{ti}^{2} + e_{ti}$$

Level 2:

$$\pi_{0i} = \beta_{00} + r_{0i}$$

$$\pi_{1i} = \beta_{10} + r_{1i}$$

$$\pi_{2i} = \beta_{20} + r_{2i}$$

```
dat <- dat %>% mutate(age_10_2 = age_10^2)
fit4c <- lmer(read ~ age_10 + age_10_2 + (age_10 + age_10_2 | id), data = dat)
tab4c <- table_fun(fit4c)</pre>
```

### Part D

Model 4:

Level 1:

$$read_{ti} = \pi_{0i} + \pi_{1i}(age - 10)_{ti} + \pi_{2i}(age - 10)_{ti}^{2} + \pi_{3i}(age - 10)_{ti}^{3} + e_{ti}$$

$$\pi_{0i} = \beta_{00} + r_{0i}$$

$$\pi_{1i} = \beta_{10} + r_{1i}$$

$$\pi_{2i} = \beta_{20} + r_{2i}$$

$$\pi_{3i} = \beta_{30} + r_{3i}$$

```
dat <- dat %>% mutate(age_10_3 = age_10^3)
fit4d <- lmer(read ~ age_10 + age_10_2 + age_10_3 + (age_10 + age_10_2 + age_10_2 | id), data = dat)
tab4d <- table_fun(fit4d)</pre>
tab4a %>% mutate(model = "4a") %>%
  full_join(tab4b %>% mutate(model = "4b")) %>%
  full_join(tab4c %>% mutate(model = "4c")) %>%
  full_join(tab4d %>% mutate(model = "4d")) %>%
  # mutate(est = ifelse(type != "Fit",
      sprintf("\\makecell{%s \\\\ {\%s}}\", b, CI), b)) \%>\%
  # select(-b, -CI) %>%
  gather(key = est, value = value, b, CI) %>%
  unite(tmp, model, est, sep = ".") %>%
  spread(key = tmp, value = value) %>%
  select(-type) %>%
  kable(., "latex", escape = F, digits = 2, booktabs = T,
        col.names = c("", rep(c("b", "CI"), times = 4))) %>%
  kable_styling(full_width = F) %>%
  group_rows("Fixed", 1,4) %>%
  group_rows("Fit", 5, 6) %>%
  group_rows("Random", 7, 9) %>%
  add_header_above(c(" " = 1, "Model 4a" = 2, "Model 4b" = 2,
                     "Model 4c" = 2, "Model 4b" = 2))
```

	N	Model 4a	Ν	Iodel 4b	1	Model 4c	1	Model 4b
	b	CI	b	CI	b	CI	b	CI
Fixed								
$age\_10$			0.56	[0.55, 0.58]	0.53	[0.50, 0.55]	0.50	[0.48, 0.53]
$age\_10\_2$					-0.05	[-0.05, -0.04]	-0.05	[-0.05, -0.04]
$age\_10\_3$							0.00	[0.00, 0.01]
Intercept	4.15	[4.02, 4.30]	4.43	[4.35, 4.57]	4.67	[4.52, 4.77]	4.66	[4.63, 4.71]
$R_c^2$	0.11		0.87		0.91		0.91	
$R_c^2 \ R_m^2$	0.00		0.58		0.60		0.60	
Random								
$ au_{00}$	0.29	[0.15,  0.37]	0.85	[0.77, 1.00]	1.12	[0.99, 1.30]	1.12	[1.07, 1.28]
$ au_{11}$		-	0.02	[0.01, 0.02]	0.02	[0.01, 0.02]	0.02	[0.01, 0.02]
$ au_{22}$					0.00	[0.00, 0.00]	0.00	[0.00, 0.00]

### Part E

Using likelihood ratio tests, compare the fit of these models. Which fits the data the best?

```
anova(fit4a, fit4b, fit4c, fit4d)
```

```
## Data: dat
## Models:
## fit4a: read ~ 1 + (1 | id)
## fit4b: read ~ age_10 + (age_10 | id)
## fit4c: read ~ age_10 + age_10_2 + (age_10 + age_10_2 | id)
## fit4d: read ~ age_10 + age_10_2 + age_10_3 + (age_10 + age_10_2 + age_10_2 |
## fit4d: id)
## Df AIC BIC logLik deviance Chisq Chi Df Pr(>Chisq)
```

```
## fit4a 3 4428.1 4443.3 -2211.1 4422.1
## fit4b 6 2855.3 2885.6 -1421.6 2843.3 1578.8036 3 < 2e-16 ***
## fit4c 10 2641.1 2691.7 -1310.6 2621.1 222.1635 4 < 2e-16 ***
## fit4d 11 2636.8 2692.4 -1307.4 2614.8 6.3072 1 0.01203 *
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1</pre>
```

## Question 5

Compare what you found in the two approaches (discrete time and continuous age).

#### Part A

Are there any important differences in the inferences you would draw?

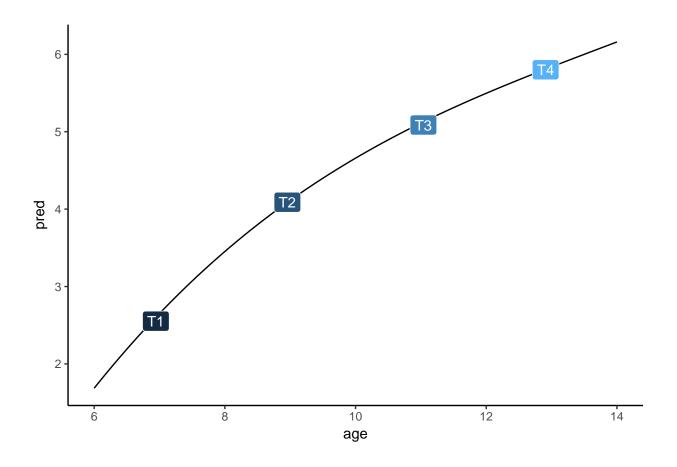
#### Part B

What might account for the different findings?

## Part C

Plot the results of Model 4. Use Age on the abscissa, ranging from 6 to 14. On the same figure, add the mean reading scores for TD1, TD2, TD3, and TD4 (the intercepts from Question 2). Locate these means along the abscissa according to the average age of the kids at each time period. Does this plot offer any further insights relevant to (b)?

```
pred_dat <- tibble(</pre>
  age = seq(6, 14, .01),
  age_{10} = age_{10},
  age_10_2 = age_10^2,
  age_{10_3} = age_{10_3}
  ) %>%
  mutate(pred = predict(fit4d, newdata = ., re.form = NA))
mean_dat <- dat %>%
  group_by(time) %>%
  summarize_at(vars(read, kidagetv), funs(mean(., na.rm = T)))
pred_dat %>%
  ggplot(aes(x = age, y = pred)) +
    geom_line() +
    geom_label(data = mean_dat, color = "white",
               aes(x = kidagetv, y = read, label = paste0('T',time), fill = time)) +
    theme_classic() +
    theme(legend.position = "none")
```



# Question 6

Using Model 3, add the age of the mother (momage) as a moderator:

Level 1:

$$read_{ti} = \pi_{0i} + \pi_{1i}(age - 10)_{ti} + \pi_{2i}(age - 10)_{ti}^2 + e_{ti}$$

$$\pi_{0i} = \beta_{00} + \beta_{01} momage_i + r_{0i}$$

$$\pi_{1i} = \beta_{10} + \beta_{11} momage_i + r_{1i}$$

$$\pi_{2i} = \beta_{20} + \beta_{21} momage_i + r_{2i}$$

```
group_rows("Random", 7, 9) %>%
add_header_above(c(" " = 1, "Model 6" = 2))
```

	Model 6		
	b	CI	
Fixed			
Intercept	1.41	[-0.01, 2.78]	
$age\_10$	0.03	[-0.25, 0.17]	
momage	0.13	[0.07, 0.18]	
$age\_10\_2$	0.01	[-0.05, 0.07]	
$age\_10:momage$	0.02	[0.01, 0.03]	
$momage:age\_10\_2$	-0.00	[-0.00, 0.00]	
Random			
$ au_{00}$	1.07	[0.94, 1.31]	
$ au_{11}$	0.02	[0.01, 0.02]	
$ au_{22}$	0.00	[0.00, 0.00]	
$R_m^2$	0.61		
$R_c^2$	0.91		

#### Part A

Are any of the interactions involving momage significant? If so, explain what they mean. The interaction between the linear age term and age of the mother is significant. In other words, reading ability varies as a function of both the age of the child and the age of the mother at baseline. Students who are farther above the age 10 with older mothers show steeper increases in reading age than those below age 10.

#### Part B

Illustrate this new model by plotting the age-reading relationship separately for mothers 1 standard deviation below the mean for momage and 1 standard deviation above the mean for momage.

```
means <- dat %>% summarize_at(vars(momage), funs(mean = mean(., na.rm = T), sd = sd(., na.rm = T)))
crossing(
  age_{10} = seq(-4,4,.5),
  momage = c(means$mean, means$mean - means$sd, means$mean + means$sd)
) %>% mutate(age_10_2 = age_10^2) %>%
  mutate(pred = predict(fit4c, newdata = ., re.form = NA),
         momage = mapvalues(momage, unique(momage), c("-1 SD", "0 SD", "+1 SD"))) %>%
  ggplot(aes(x = age_10, y = pred, color = momage)) +
    geom_line(size = 1) +
   labs(x = "Age Centered at 10", y = "Model Estimated Reading Score", color = "Mother Age at Baseline
   theme classic() +
    theme(legend.position = "bottom",
          axis.text = element_text(face = "bold"),
          axis.title = element_text(face = "bold", size = rel(1.2)),
          legend.text = element_text(face = "bold"),
          legend.title = element_text(face = "bold", size = rel(1.2)))
```

