

Conditional Models

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Workspace

Packages

```
library(psych)
library(sjPlot)
library(broom)
library(lme4)
library(MuMIn)
library(merTools)
library(egghelper)
library(stargazer)
library(lsmmeans)
library(multcompView)
library(plyr)
library(tidyverse)
```

Background

Basic Syntax

From last week:

- **Level 1:** $Y_{ij} = \beta_{0j} + \varepsilon_{ij}$
- **Level 2:** $\beta_{0j} = \gamma_{00} + U_{0j}$

Sample Data

The National Longitudinal Study of Youths 1979 Child and Young Adult Sample (NLSYCYA) is a longitudinal study conducted by the National Bureau of Labor Statistics. The sample includes the children of the original 1979 sample. Here, we are going to use a subset of the more than 11,000 variables available that include the following.

Item Name	Description	Time-Varying?
PROC_CID	Participant ID	No
Dem_DOB	Year of Date of Birth	No
groups	Jail, Community Service, None	No
DemPWeight	Weight Percentile at age 10	No
age	Age of participant	Yes
Year	Year of Survey	Yes
age0	Age of participant (centered)	Yes
SensSeek	Sensation-Seeking Composite	Yes

Item Name	Description	Time-Varying?
CESD	CESD Depression Composite	Yes

```
data_path <- "https://github.com/longitudinal-data/1-descriptives-and-graphs-emoryiebeck/raw/master/Cond
load(url(paste(data_path, "sample.RData", sep = "/")))

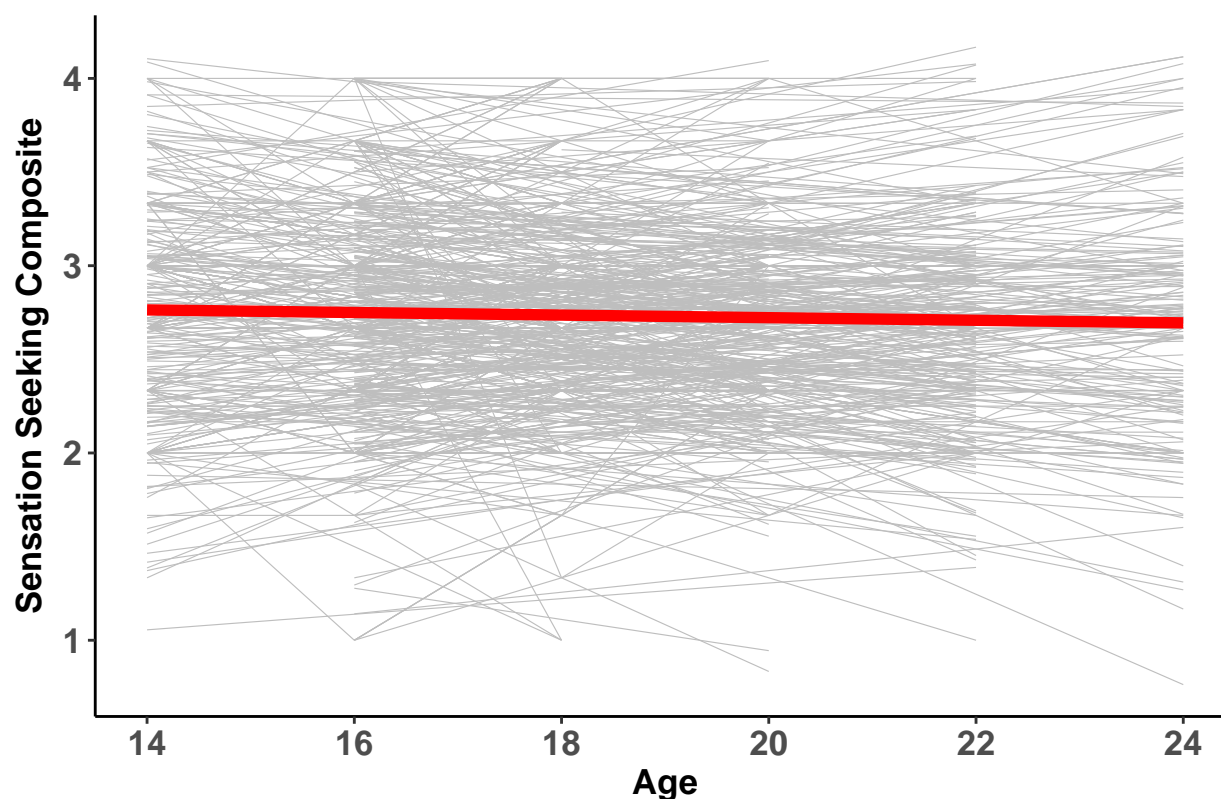
head(sample_dat)
```

```
## # A tibble: 6 x 8
##   PROC_CID age year age0 groups CESD SensSeek DemPweight
##   <dbl> <dbl> <dbl> <dbl> <fctr> <dbl> <dbl> <dbl>
## 1 1601 16 2006 2 CommServ 0.4285714 3.666667 0.8159399
## 2 1601 18 2008 4 CommServ 2.0000000 3.000000 0.8159399
## 3 9102 16 2012 2 None 0.1818182 3.333333 0.6712397
## 4 9501 14 2000 0 Jail 0.5000000 3.000000 0.5477584
## 5 9501 18 2004 4 Jail 0.4285714 3.000000 0.5477584
## 6 9501 22 2008 8 Jail 0.4285714 3.000000 0.5477584
```

Simple Growth Curve Model

- **Level 1:** $Y_{ij} = \beta_{0j} + \beta_{1j} * time_{ij} + \varepsilon_{ij}$
- **Level 2:**
 - $\beta_{0j} = \gamma_{00} + U_{0j}$
 - $\beta_{1j} = \gamma_{10} + U_{1j}$

Simple Growth Curve



In R

```
mod0 <- lmer(SensSeek ~ age0 + (1|PROC_CID), data = sample_dat)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: SensSeek ~ age0 + (1 | PROC_CID)
## Data: sample_dat
##
## REML criterion at convergence: 3404.2
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -3.6782 -0.5396  0.0276  0.4739  3.2174
##
## Random effects:
## Groups Name Variance Std.Dev.
## PROC_CID (Intercept) 0.1349  0.3673
## Residual 0.2003  0.4475
## Number of obs: 2084, groups: PROC_CID, 924
##
## Fixed effects:
##              Estimate Std. Error t value
## (Intercept)  2.765851  0.020067 137.83
## age0        -0.005879  0.003407  -1.73
##
## Correlation of Fixed Effects:
##      (Intr)
## age0 -0.611
```

Conditional Models: Adding Predictors

Let's see if we can better predict participants' change in sensation seeking over time by adding covariates.

Predictor	Continuous	Categorical
Time Invariant	Weight for Age	Group
Time Varying	CESD Scores	Depression

Time Invariant Predictors

Time Invariant Predictors: Continuous

The basic equation, specifying a random intercept and slope:

- **Level 1:** $Y_{ij} = \beta_{0j} + \beta_{1j} * time_{1j} + \varepsilon_{ij}$
- **Level 2:**
 - $\beta_{0j} = \gamma_{00} + \gamma_{01} * X_{2j} + U_{0j}$
 - $\beta_{1j} = \gamma_{10} + \gamma_{11} * X_{2j} + U_{1j}$

But we need to break this down to see that adding additional predictors results in interaction terms:

$$Y_{ij} = \gamma_{00} + \gamma_{01} * X_{2j} + U_{0j} + (\gamma_{10} + \gamma_{11} * X_{2j} + U_{1j}) * X_{1j} + \varepsilon_{ij}$$

$$Y_{ij} = \gamma_{00} + \gamma_{01} * X_{2j} + \gamma_{10} * X_{1j} + \gamma_{11} * X_{2j} * X_{1j} + U_{0j} + U_{1j} * X_{1j} + \varepsilon_{ij}$$

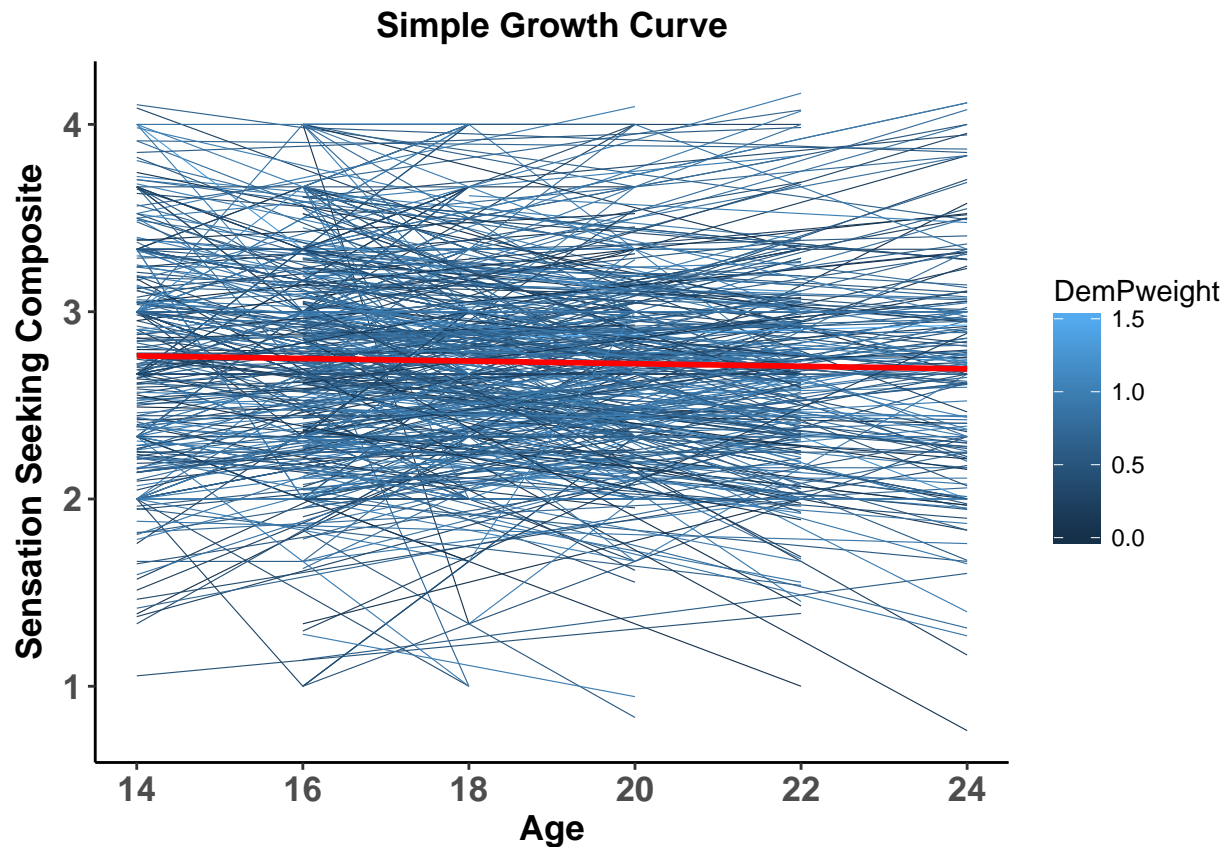
We can also fit this with intercepts depending on weight, but without the change (slope) dependent on weight:

$$Y_{ij} = \gamma_{00} + \gamma_{01} * X_{2j} + U_{0j} + (\gamma_{10} + U_{1j}) * X_{1j} + \varepsilon_{ij} \quad Y_{ij} = \gamma_{00} + \gamma_{01} * X_{2j} + \gamma_{10} * X_{1j} + U_{0j} + U_{1j} * X_{1j} + \varepsilon_{ij}$$

Continuous Example - Weight for Age Percentile

```
describe(sample_dat$DemPweight)
```

```
##      vars      n mean  sd median trimmed  mad   min  max range  skew kurtosis
## X1      1 2084 0.66 0.31   0.69    0.67 0.36 -0.06 1.62  1.68 -0.29   -0.56
##          se
## X1 0.01
```



```
# time invariant covariate with random intecept (with weight as covariate)
# and slope (without weight as a covariate)
mod1a <- lmer(SensSeek ~ age0 + DemPweight + (age0|PROC_CID),
              data = sample_dat)

summary(mod1a)

# time invariant predictor with random slope and intercept
mod1b <- lmer(SensSeek ~ age0 + DemPweight + age0*DemPweight +
              (age0|PROC_CID), data = sample_dat)

summary(mod1b)
```

Time Invariant Predictors: Categorical

Categorical Example - 2 level group

Let's start with the basic syntax:

- **Level 1:** $Y_{ij} = \beta_{0j} + \beta_{1j} * time_{1j} + \varepsilon_{ij}$
- **Level 2:**
 - $\beta_{0j} = \gamma_{00} + \gamma_{01} * X_{2j} + U_{0j}$
 - $\beta_{1j} = \gamma_{10} + \gamma_{11} * X_{2j} + U_{1j}$

Now let's swap that out for a 2 group sample from the present data:

- **Level 1:** $Y_{ij} = \beta_{0j} + \beta_{1j} * age0_{ij} + \varepsilon_{ij}$

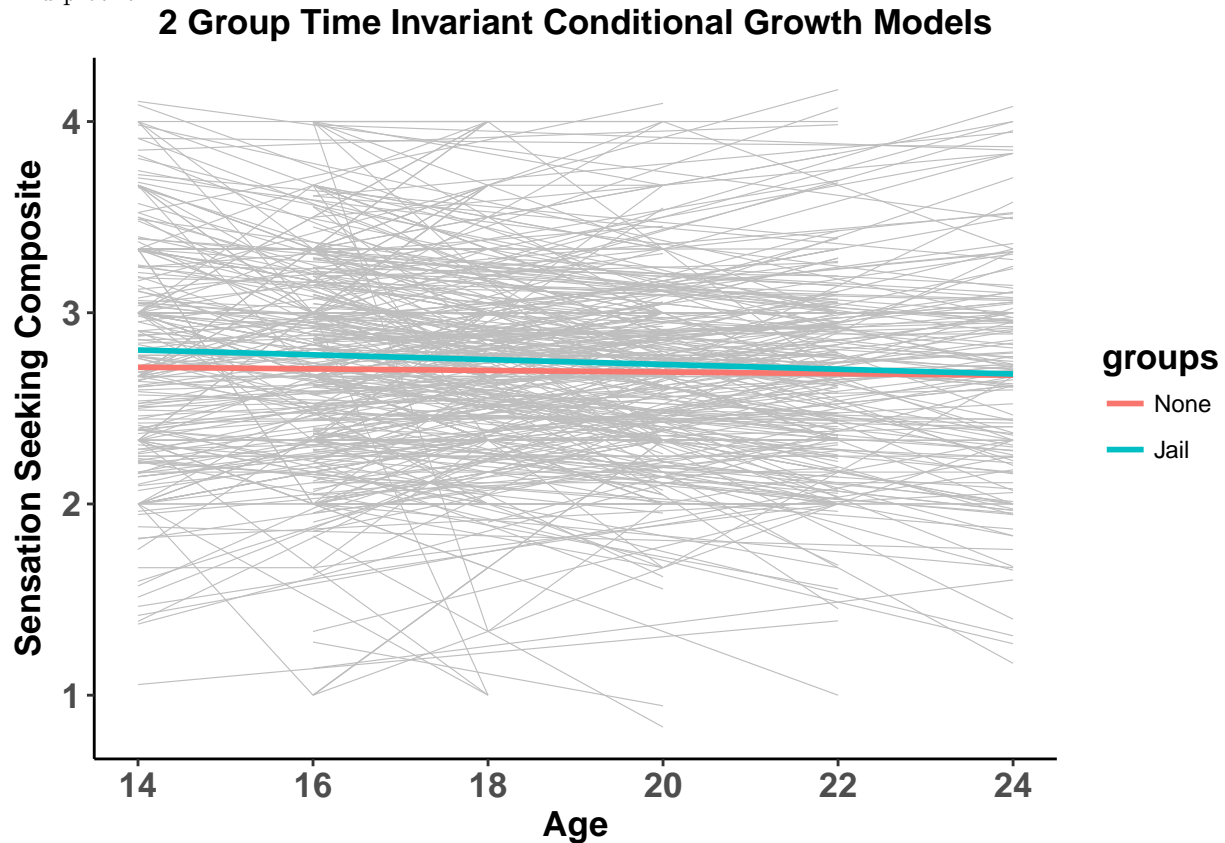
- **Level 2:**

- $\beta_{0j} = \gamma_{00} + \gamma_{01} * groupsNone + U_{0j}$

- $\beta_{1j} = \gamma_{10} + \gamma_{11} * groupsNone + U_{1j}$

Variable	D1
Jail	0
None	1

And plot it.



And model it:

```
mod2g <- lmer(SensSeek ~ age0 + groups + age0*groups + (age0|PROC_CID),
              data = sample_dat %>% filter(groups != "CommServ"))
summary(mod2g)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: SensSeek ~ age0 + groups + age0 * groups + (age0 | PROC_CID)
## Data: sample_dat %>% filter(groups != "CommServ")
##
## REML criterion at convergence: 2607.6
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -3.2324 -0.4860  0.0463  0.4643  3.0578
##
## Random effects:
```

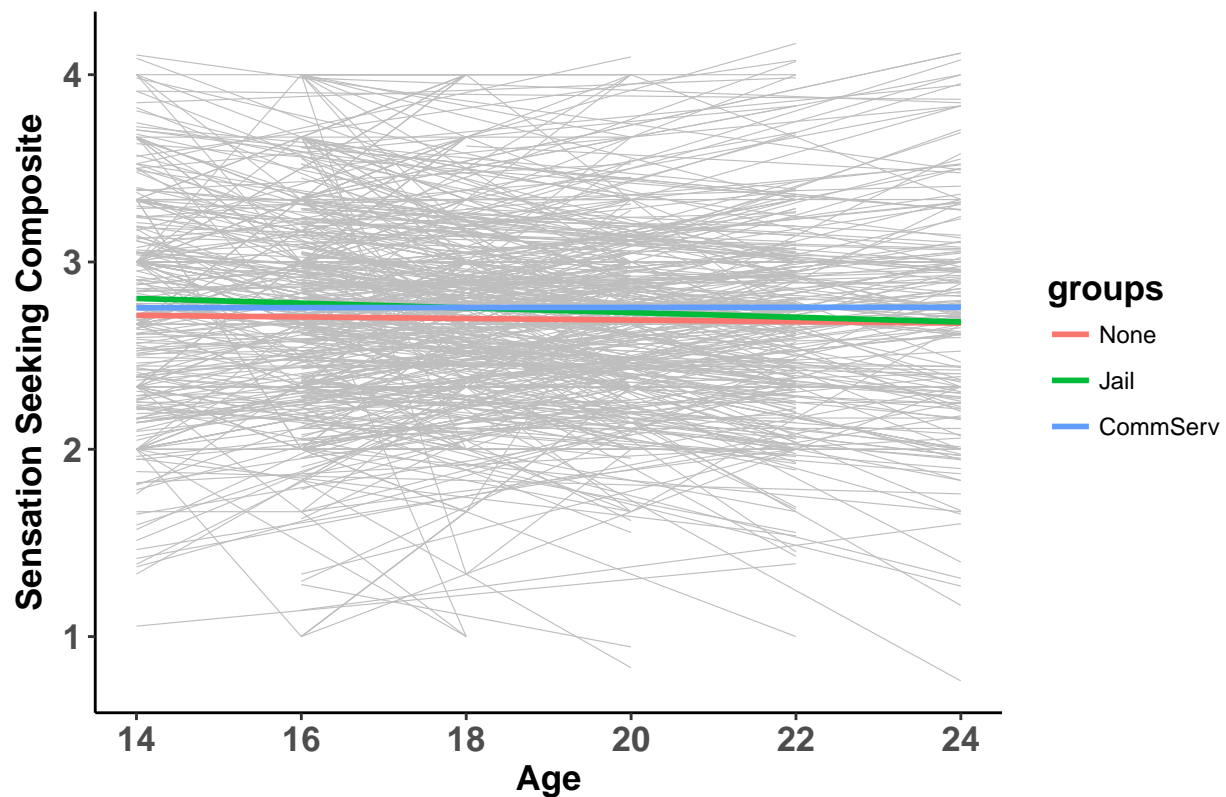
```

## Groups      Name      Variance Std.Dev. Corr
## PROC_CID (Intercept) 0.1613721 0.40171
##      age0      0.0008963 0.02994 -0.31
## Residual      0.1897644 0.43562
## Number of obs: 1573, groups:  PROC_CID, 689
##
## Fixed effects:
##              Estimate Std. Error t value
## (Intercept)    2.717417   0.036423   74.61
## age0          -0.003998   0.006382   -0.63
## groupsJail      0.093497   0.048257    1.94
## age0:groupsJail -0.007432   0.008272   -0.90
##
## Correlation of Fixed Effects:
##              (Intr) age0  grpsJl
## age0          -0.624
## groupsJail    -0.755  0.471
## age0:grpsJl   0.481 -0.772 -0.623

```

Categorical Example - 3 level group

2 Group Time Invariant Conditional Growth Models



- Level 1: $Y_{ij} = \beta_{0j} + \beta_{1j} * age0_{ij} + \varepsilon_{ij}$
- Level 2:
 - $\beta_{0j} = \gamma_{00} + \gamma_{01} * D1 + \gamma_{02} * D2 + U_{0j}$
 - $\beta_{1j} = \gamma_{10} + \gamma_{11} * D1 + \gamma_{12} * D2 + U_{1j}$

Variable	D1	D2
Jail	0	0
None	1	0
CommServ	0	1

```
mod3g <- lmer(SensSeek ~ age0 + groups + age0*groups +
              (age0|PROC_CID), data = sample_dat)
summary(mod3g)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: SensSeek ~ age0 + groups + age0 * groups + (age0 | PROC_CID)
## Data: sample_dat
##
## REML criterion at convergence: 3418.7
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -3.2994 -0.5006  0.0368  0.4533  3.0815
##
## Random effects:
## Groups Name Variance Std.Dev. Corr
## PROC_CID (Intercept) 0.1446194 0.38029
##      age0      0.0008903 0.02984 -0.23
## Residual      0.1888364 0.43455
## Number of obs: 2084, groups: PROC_CID, 924
##
## Fixed effects:
##              Estimate Std. Error t value
## (Intercept)    2.717703   0.035554   76.44
## age0          -0.004101   0.006376   -0.64
## groupsJail      0.092594   0.047097    1.97
## groupsCommServ  0.035192   0.053386    0.66
## age0:groupsJail -0.007181   0.008265   -0.87
## age0:groupsCommServ 0.005939   0.009871    0.60
##
## Correlation of Fixed Effects:
##      (Intr) age0   grpsJl  grpsCS  ag0:gJ
## age0      -0.619
## groupsJail -0.755  0.467
## groupsCmmSrv -0.666  0.412  0.503
## age0:grpsJl  0.478 -0.772 -0.618 -0.318
## ag0:grpsCmS  0.400 -0.646 -0.302 -0.612  0.498
```

Side Notes: Practical Applications

Side Note: lme4 helper functions

```
vcov(mod2g)
VarCorr(mod2g)
fixef(mod2g)
head(ranef(mod2g)[[1]])
head(coef(mod2g)[[1]])
confint.merMod(mod2g, method = "boot")
```



```
reghelper::ICC(mod2g)
MuMIn::r.squaredGLMM(mod2g)
```

```
vcov(mod2g)
```

```
## 4 x 4 Matrix of class "dpoMatrix"
##              (Intercept)          age0      groupsJail age0:groupsJail
## (Intercept)    0.0013266680 -1.449788e-04 -0.0013266680    1.449788e-04
## age0          -0.0001449788  4.072833e-05  0.0001449788   -4.072833e-05
## groupsJail    -0.0013266680  1.449788e-04  0.0023287011   -2.486054e-04
## age0:groupsJail 0.0001449788 -4.072833e-05 -0.0002486054    6.842322e-05
```

```
VarCorr(mod2g)
```

```
## Groups   Name          Std.Dev. Corr
## PROC_CID (Intercept) 0.401711
##          age0        0.029938 -0.313
## Residual              0.435620
```

```
fixef(mod2g)
```

```
##      (Intercept)          age0      groupsJail age0:groupsJail
##      2.717416961  -0.003997618    0.093496648   -0.007431764
```

```
head(ranef(mod2g)[[1]])
```

```
##      (Intercept)          age0
## 9102    0.2825889 -0.0036110312
## 9501    0.1582912  0.0013310875
## 9502    0.1542974 -0.0003923893
## 9503    0.1411350  0.0002529397
## 10001   0.1814453 -0.0008900323
## 12802   0.2999653 -0.0027624589
```

```
head(coef(mod2g)[[1]])
```

```
##      (Intercept)          age0 groupsJail age0:groupsJail
## 9102    3.000006 -0.007608649 0.09349665   -0.007431764
## 9501    2.875708 -0.002666530 0.09349665   -0.007431764
## 9502    2.871714 -0.004390007 0.09349665   -0.007431764
## 9503    2.858552 -0.003744678 0.09349665   -0.007431764
## 10001   2.898862 -0.004887650 0.09349665   -0.007431764
## 12802   3.017382 -0.006760077 0.09349665   -0.007431764
```

```
confint.merMod(mod2g, method = "boot", nsim = 10)
```

```
##              2.5 %      97.5 %
## .sig01        0.37825912  0.442446652
## .sig02       -0.59786608 -0.087752901
## .sig03        0.02074286  0.050678276
## .sigma        0.41349474  0.459740673
## (Intercept)    2.61954063  2.822716922
## age0          -0.01474274  0.004169720
## groupsJail     0.02965519  0.221246440
## age0:groupsJail -0.02043541  0.001165393
```

All units of the random effects are in standard deviation units (which means you need to square them to get the variance!!)

- .sig01 = sd of random intercept = $\sqrt{\tau_{00}}$
- .sig02 = correlation between slope and intercept = $\sqrt{\tau_{10}}$
- .sig03 = sd of random slope = $\sqrt{\tau_{11}}$

- σ^2 = residual variance = $\hat{\sigma}^2$

```
reghelper::ICC(mod2g)
```

```
## [1] 0.4609468
```

Conditional R^2 : How much variance fixed + random effects explain

Marginal R^2 : how much variance the fixed effects explain

explained here

```
MuMIn::r.squaredGLMM(mod2g)
```

```
##           R2m           R2c
## 0.005234242 0.452019164
```

Side Note: Creating MLM Tables

There are lots of helpful packages for this, including **stargazer** and **sjPlot**, which are demonstrated below.

```
stargazer::stargazer(mod2g)
```

```
sjPlot::sjt.lmer(mod2g)
```

The problem is that **stargazer()** doesn't include all the terms we want, and **sjt.lmer()** only renders html. Embedded in the .Rmd version of these slides is some code that should help you to extract the terms you need and create a table using **dplyr** and **tidyr** that you can render in L^AT_EX using **stargazer**.

But let's understand where those variables came from. To do so, we'll use the **broom** package in R to grab the terms we need.

Description	Math Notation
Fixed Effect Intercept	γ_{00}
Fixed Effect Group Intercept	γ_{01}
Fixed Effect Age Slope	γ_{10}
Fixed Effect Group Slope	γ_{11}
Individual Random Intercepts	U_{0j}
Variance of Random Intercepts	τ_{00}
Random Age Slopes	U_{10}
Variance of Random Age Slopes	τ_{11}
Correlation b/w Random Slopes and Intercepts	τ_{10}
Residual Variance	$\hat{\sigma}^2$
Intraclass Correlation	ICC
Conditional R^2	R_c^2
Marginal R^2	R_m^2

```
broom::tidy(mod2g)
```

```
broom::glance(mod2g)
```

```
##           term      estimate std.error statistic
## 1 (Intercept)  2.717416961 0.036423454  74.6062393
## 2      age0 -0.003997618 0.006381875  -0.6264017
## 3  groupsJail 0.093496648 0.048256617   1.9374887
## 4 age0:groupsJail -0.007431764 0.008271833  -0.8984423
## 5 sd_(Intercept).PROC_CID 0.401711448      NA      NA
## 6 sd_age0.PROC_CID 0.029938129      NA      NA
## 7 cor_(Intercept).age0.PROC_CID -0.312526843      NA      NA
```

```
## 8      sd_Observation.Residual  0.435619527      NA      NA
##      group
## 1      fixed
## 2      fixed
## 3      fixed
## 4      fixed
## 5 PROC_CID
## 6 PROC_CID
## 7 PROC_CID
## 8 Residual

##      sigma      logLik      AIC      BIC deviance df.residual
## 1 0.4356195 -1303.786 2623.571 2666.457 2579.802      1565
```

Below is code that *should* work for all models. Just run the function and save it as an R object. You can use this with `papaja` and the `apa_table()` function pretty easily. The trick is that if you are not using the `papaja` template, the proper LaTeX packages may not be loaded. You can get around this by attaching a `.tex` file calling the packages under “in_header: header.tex” in your YAML header. The YAML header of this `.Rmd` file contains the necessary syntax and the `header.tex` file with the proper packages.

```
## here's some code to make a table. You shouldn't need to modify anything here
# unless you add additional random effects terms
## fixed effects first ##
table_fun <- function(model){
  fixed <- broom::tidy(mod2g) %>% filter(group == "fixed") %>%
    select(term, estimate)
  ## add random effects ##
  rand <- broom::tidy(mod2g) %>% filter(group != "fixed") %>%
    select(term, estimate)
  ## get confidence intervals ##
  CI <- data.frame(confint.merMod(mod2g, method = "boot", nsim = 10)) %>%
    mutate(term = rownames(.)) %>% setNames(c("lower", "upper", "term"))

  ## Get ICC & R2 values ##
  ICC <- reghelper::ICC(mod2g)
  R2 <- MuMIn::r.squaredGLMM(mod2g)

  ## format the fixed effects
  fixed <- fixed %>% left_join(CI %>% filter(!grepl(".sig", term))) %>%
    mutate(type = "Fixed Parts")

  rand <- rand %>%
    mutate(term = mapvalues(term, unique(term),
      c("$\\tau_{00}$", "$\\tau_{11}$", "$\\tau_{10}$", "$\\hat{\\sigma}^2$"),
      estimate = estimate^2) %>%
    left_join(
      CI %>% filter(grepl(".sig", term)) %>%
        mutate(term = mapvalues(term, unique(term),
          c("$\\tau_{00}$", "$\\tau_{10}$", "$\\tau_{11}$", "$\\hat{\\sigma}^2$"),
          lower = lower^2, upper = upper^2) %>%
        mutate(type = "Random Parts")

  mod_terms <- tribble(
    ~term, ~estimate, ~type,
    "ICC", ICC, "Model Terms",
    "$R^2_m$", R2[1], "Model Terms",
    "$R^2_c$", R2[2], "Model Terms"
  )

  tab <- fixed %>%
```

```

full_join(rand) %>%
mutate(CI = sprintf("%.2f, %.2f", lower, upper)) %>%
select(-lower, -upper) %>%
full_join(mod_terms) %>%
mutate(estimate = sprintf("%.2f", estimate)) %>%
select(type, everything())
}

# you can use this with papaja and the apa_table function pretty easily
# the trick is that if you are not using the papaja template, the proper
# LaTeX packages may not be loaded. You can get around this by attaching
# a .tex file calling the packages under "in_header: header.tex" in your YAML
# header the YAML header of this .Rmd file contains the necessary syntax and
# the header.tex file with the proper packages

tab <- table_fun(mod2g)

```

Basic: kable()

```

options(knitr.kable.NA = '')
knitr::kable(tab, caption = "Ugly MLM Table Example")

```

Table 6: Ugly MLM Table Example

type	term	estimate	CI
Fixed Parts	(Intercept)	2.72	(2.65, 2.74)
Fixed Parts	age0	-0.00	(-0.01, 0.01)
Fixed Parts	groupsJail	0.09	(0.04, 0.18)
Fixed Parts	age0:groupsJail	-0.01	(-0.03, -0.00)
Random Parts	τ_{00}	0.16	(0.14, 0.19)
Random Parts	τ_{11}	0.00	(0.00, 0.00)
Random Parts	τ_{10}	0.10	(1.00, 0.00)
Random Parts	σ^2	0.19	(0.17, 0.20)
Model Terms	ICC	0.46	
Model Terms	R_m^2	0.01	
Model Terms	R_c^2	0.45	

More Advanced: kable() + kableExtra

```

library(kableExtra)
options(knitr.kable.NA = '')
knitr::kable(tab %>% select(-type) %>%
  mutate(term = gsub("[()]", "", term)),
  caption = "Ugly MLM Table Example", format = "latex",
  longtable = T, booktabs = T, escape = F) %>%
group_rows("Fixed", 1,4) %>%
group_rows("Random", 5,9) %>%
group_rows("Model", 9,11) %>%
#kable_styling(latex_options = c("striped", "repeat_header"), full_width = F)
add_header_above(c(" ", "Model 1" = 2))

```

Table 7: Ugly MLM Table Example

term	Model 1	
	estimate	CI

Table 8: MLM Table Example

term	estimate	CI
Fixed		
(Intercept)	2.72	(2.65, 2.74)
age0	-0.00	(-0.01, 0.01)
groupsJail	0.09	(0.04, 0.18)
age0:groupsJail	-0.01	(-0.03, -0.00)
Random		
τ_{00}	0.16	(0.14, 0.19)
τ_{11}	0.00	(0.00, 0.00)
τ_{10}	0.10	(1.00, 0.00)
$\hat{\sigma}^2$	0.19	(0.17, 0.20)
ICC	0.46	
R_m^2	0.01	
R_c^2	0.45	

Fixed		
Intercept	2.72	(2.65, 2.74)
age0	-0.00	(-0.01, 0.01)
groupsJail	0.09	(0.04, 0.18)
age0:groupsJail	-0.01	(-0.03, -0.00)
Random		
τ_{00}	0.16	(0.14, 0.19)
τ_{11}	0.00	(0.00, 0.00)
τ_{10}	0.10	(1.00, 0.00)
$\hat{\sigma}^2$	0.19	(0.17, 0.20)
Model		
ICC	0.46	
R_m^2	0.01	
R_c^2	0.45	

Alternative: `papaja + apa_table()`

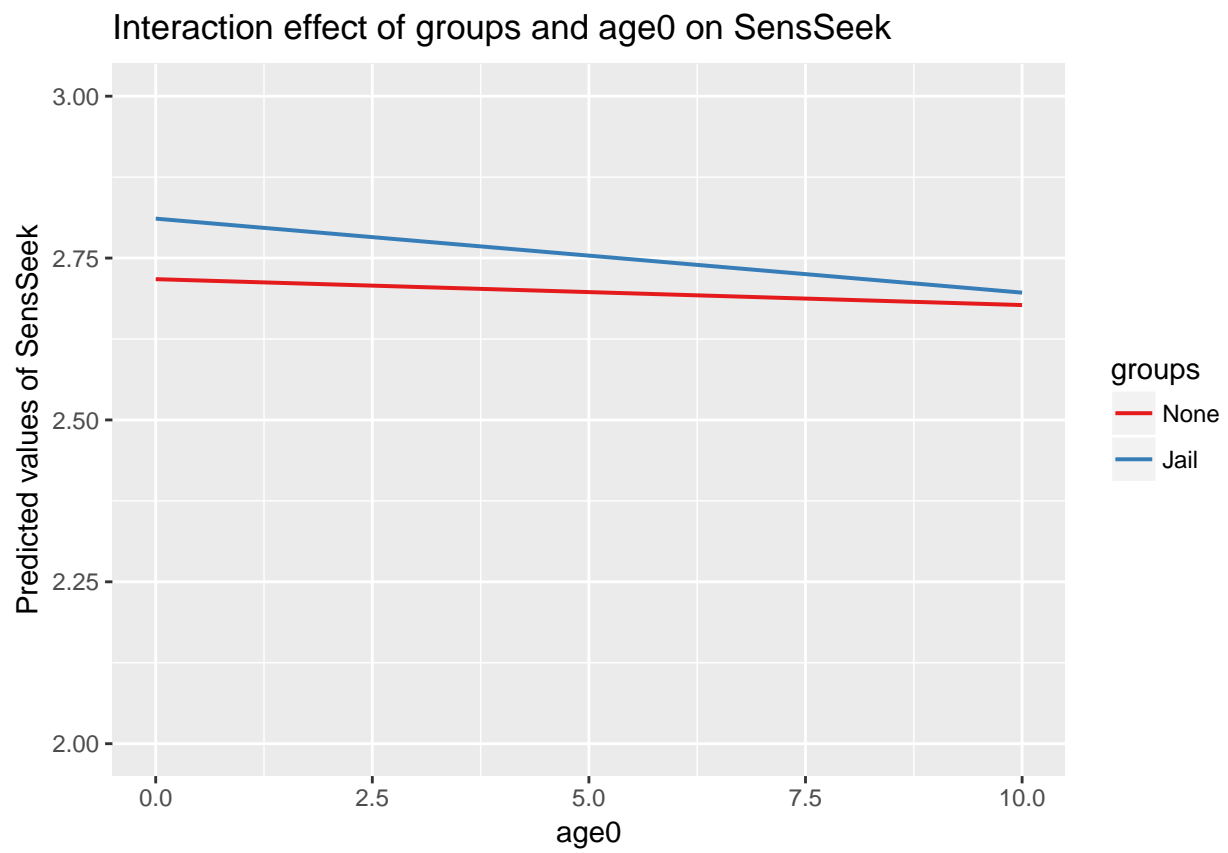
```
papaja::apa_table(tab %>% select(-type), caption = "MLM Table Example",
  na_string = "", stub_indents = list(Fixed = c(1:4), Random = c(5:11)))
```

Side Note: Plotting

Lazy Method: `sjPlot + sjt.int()`

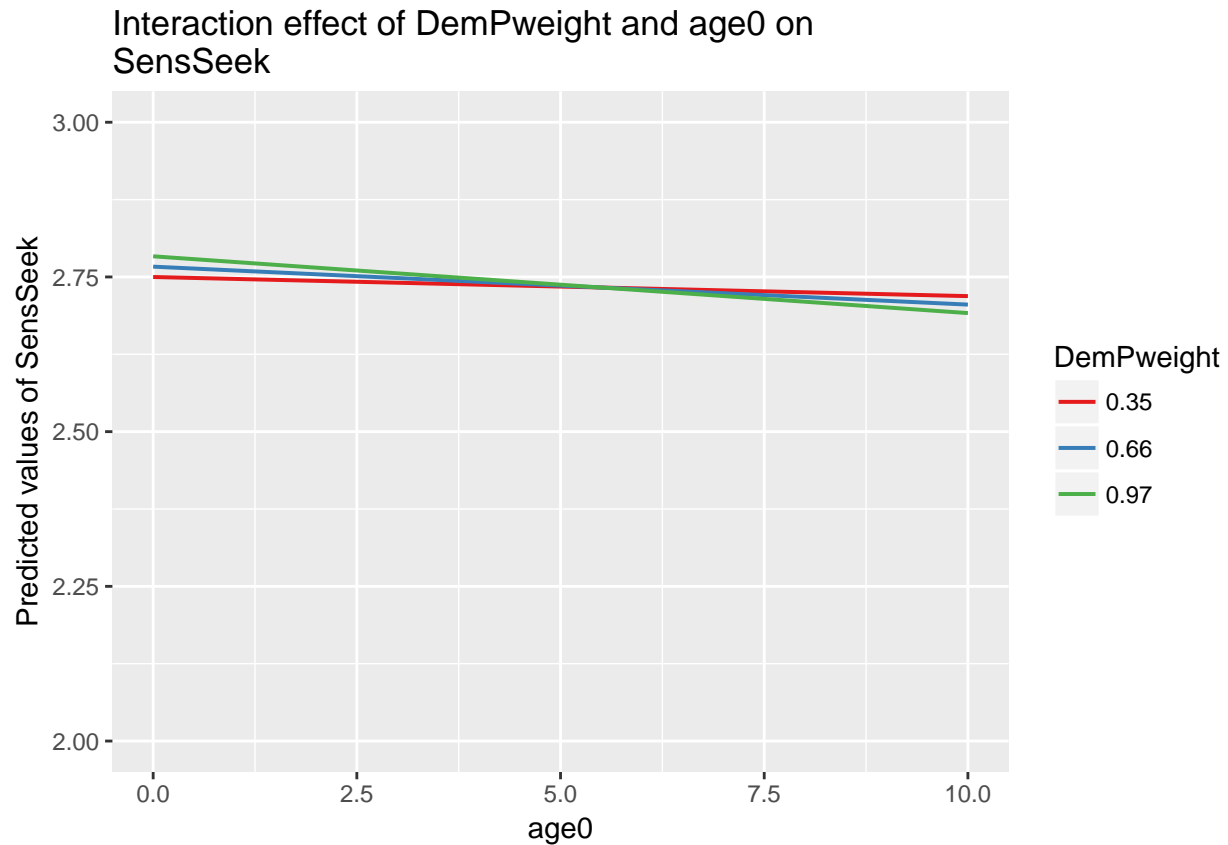
Categorical

```
sjp.int(mod2g, type = "eff", p.kr = F, swap.pred = T)
```



Continuous

```
sjp.int(mod1b, type = "eff", p.kr = F, swap.pred = T, mdrt.values = "meansd")
```



More advanced: `expand.grid()` + `fixef()` + `ggplot2()`

Categorical

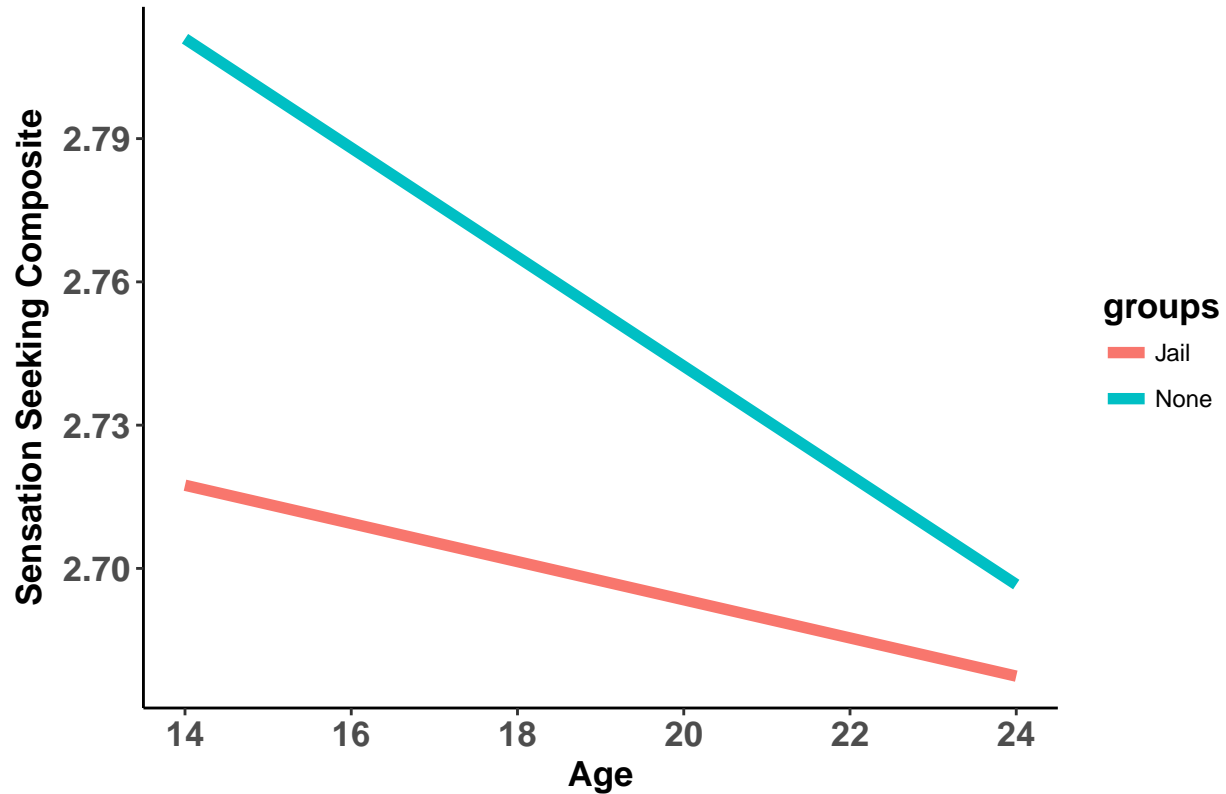
```
# example for categorical
fixed.frame <-
  data.frame(
    expand.grid(
      # here, you add values for your time variable and predictors
      age0 = seq(0,10,2),
      groupsNone = c(0,1)) %>%
    # now take care of interactions and add an intercept
    mutate(`age0:groupsNone` = age0*groupsNone,
      Intercept = 1) %>%
    # reordering everything
    select(Intercept, everything())

# multiplying to get values for model frame
fixed.frame$value <- as.vector(as.matrix(fixed.frame) %*% fixef(mod2g))

fixed.frame %>%
  mutate(groups = factor(groupsNone, levels = c(0,1), labels = c("Jail", "None")),
    age = age0 + 14) %>%
  ggplot(aes(x = age, y = value, color = groups)) +
    geom_line(size = 2) +
    labs(x = "Age", y = "Sensation Seeking Composite",
      title = "2 Group Time Invariant Conditional Growth Models") +
    theme_classic() +
    theme(axis.text = element_text(face = "bold", size = rel(1.2)),
```

```
axis.title = element_text(face = "bold", size = rel(1.2)),
legend.title = element_text(face = "bold", size = rel(1.2)),
plot.title = element_text(face = "bold", size = rel(1.2), hjust = .5))
```

2 Group Time Invariant Conditional Growth Models



Continuous

```
# example for continuous
fixed.frame <- sample_dat %>%
  summarise(mean = mean(DemPweight, na.rm = T),
            sd = sd(DemPweight, na.rm = T))

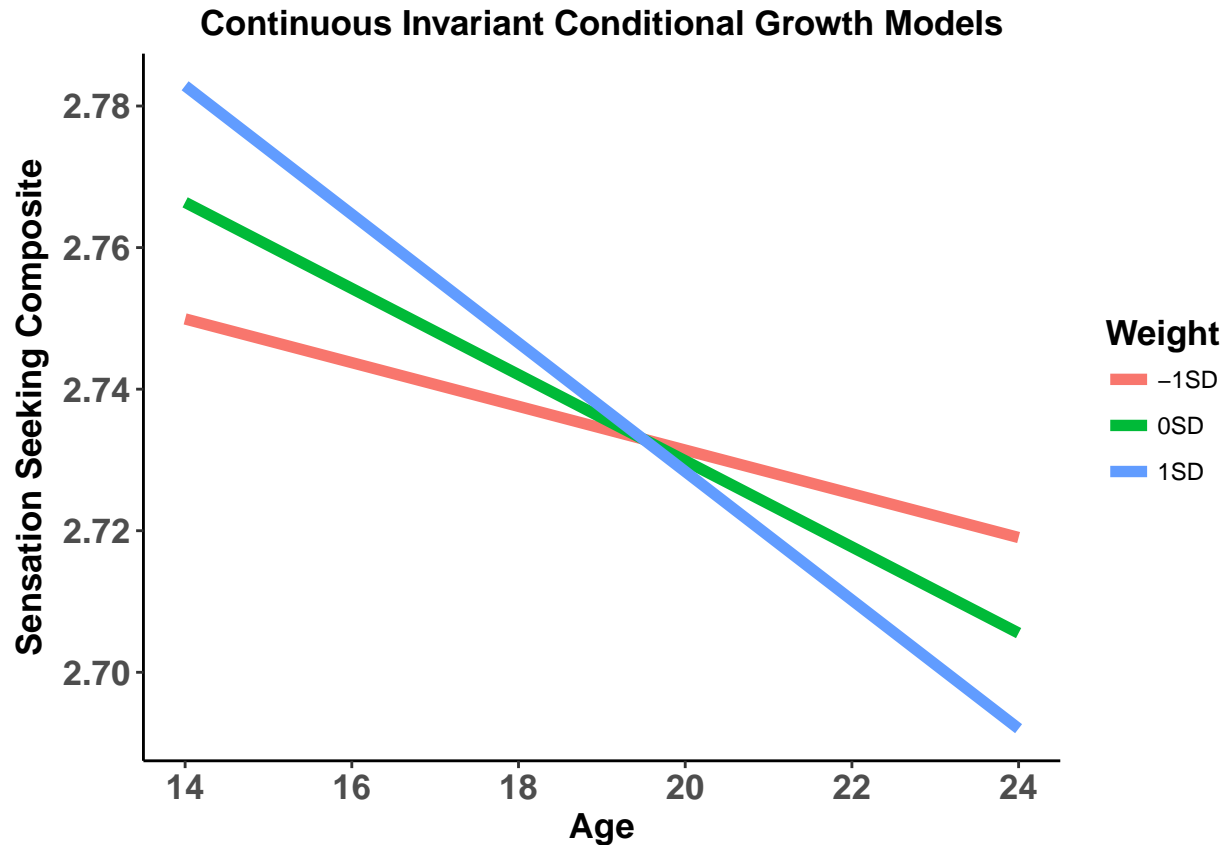
fixed.frame <-
  data.frame(
    expand.grid(
      # here, you add values for your time variable and predictors
      age0 = seq(0,10,2),
      DemPweight = c(fixed.frame$mean-fixed.frame$sd,
                    fixed.frame$mean,
                    fixed.frame$mean+fixed.frame$sd)) %>%
    # now take care of interactions and add an intercept
    mutate(`age0:DemPweight` = age0*DemPweight,
           Intercept = 1) %>%
    # reordering everything
    select(Intercept, everything())

# multiplying to get values for model frame
fixed.frame$value <- as.vector(as.matrix(fixed.frame) %*% fixef(mod1b))

fixed.frame %>%
```



```
mutate(Weight = factor(DemPweight, levels = unique(DemPweight), labels = c("-1SD", "0SD", "1SD")),
       age = age0 + 14) %>%
ggplot(aes(x = age, y = value, color = Weight)) +
  geom_line(size = 2) +
  labs(x = "Age", y = "Sensation Seeking Composite",
       title = "Continuous Invariant Conditional Growth Models") +
  theme_classic() +
  theme(axis.text = element_text(face = "bold", size = rel(1.2)),
        axis.title = element_text(face = "bold", size = rel(1.2)),
        legend.title = element_text(face = "bold", size = rel(1.2)),
        plot.title = element_text(face = "bold", size = rel(1.2), hjust = .5))
```



Side Note: Comparisons with lsmeans

The `lsmeans` package has a lot of useful functions. They are listed below. Then I'll demonstrate them in turn.

```
# create a reference grid
ref.grid2g <- ref.grid(mod2g)
# create the lsmeans object
lsgroups <- lsmeans(ref.grid2g, "groups")
# compact letter display
cld(lsgroups, alpha = .10)
# plot
plot(lsgroups)
# contrasts of the ref.grid object
contrast(ref.grid2g, method = "eff")
# comparisons
```

```
groups.sum <- summary(lsgroups, infer = c(TRUE,TRUE),
                      level = .90, adjust = "bon", by = "groups")
```

```
# create a reference grid
(ref.grid2g <- ref.grid(mod2g))
```

```
## 'ref.grid' object with variables:
##   age0 = 3.9123
##   groups = None, Jail
```

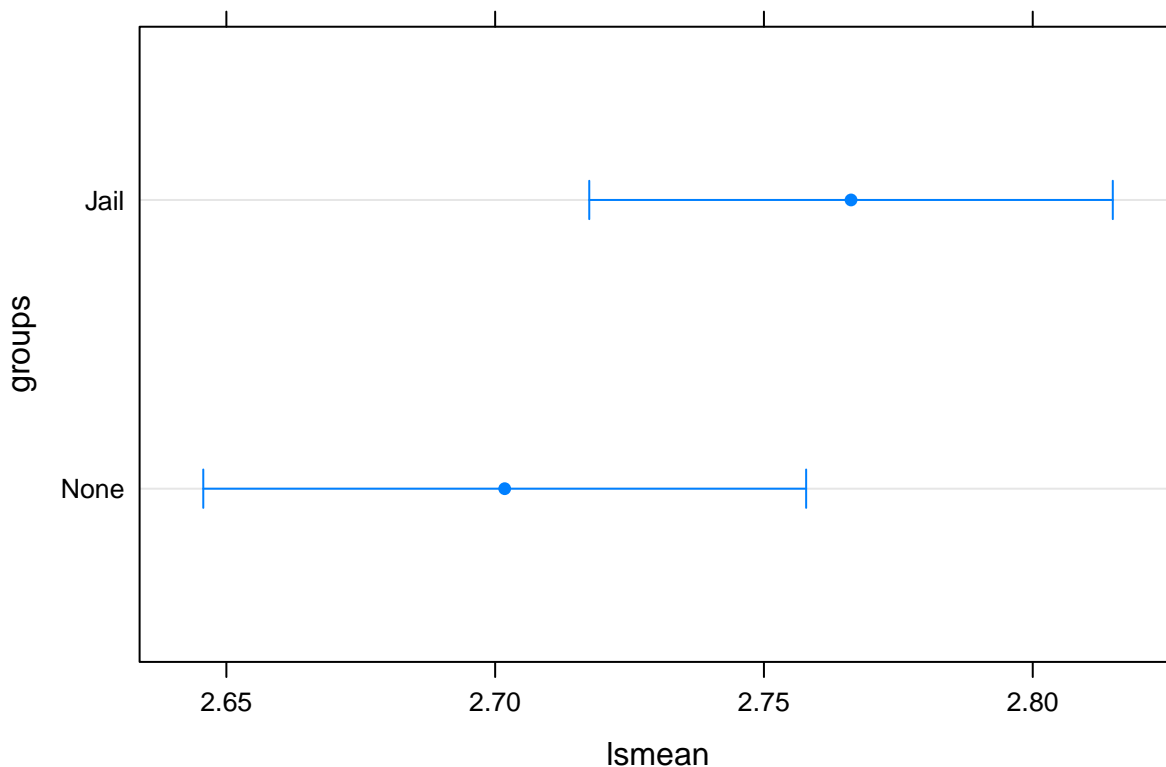
```
# create the lsmeans object
(lsgroups <- lsmeans(ref.grid2g, "groups"))
```

```
## groups  lsmean      SE      df lower.CL upper.CL
## None    2.701777 0.02855972 701.42 2.645704 2.757850
## Jail    2.766199 0.02480113 676.80 2.717505 2.814892
##
## Degrees-of-freedom method: satterthwaite
## Confidence level used: 0.95
```

```
# compact letter display
cld(lsgroups, alpha = .10)
```

```
## groups  lsmean      SE      df lower.CL upper.CL .group
## None    2.701777 0.02855972 701.42 2.645704 2.757850 1
## Jail    2.766199 0.02480113 676.80 2.717505 2.814892 2
##
## Degrees-of-freedom method: satterthwaite
## Confidence level used: 0.95
## significance level used: alpha = 0.1
```

```
# plot
plot(lsgroups)
```



```
# contrasts of the ref.grid object
contrast(ref.grid2g, method = "eff")

## contrast                estimate      SE    df t.ratio
## 3.91226954863318,None effect -0.03221079 0.01891265 690.74  -1.703
## 3.91226954863318,Jail effect  0.03221079 0.01891265 690.74   1.703
## p.value
## 0.0890
## 0.0890
##
## P value adjustment: fdr method for 2 tests

# comparisons
(groups.sum <- summary(lsgroups, infer = c(TRUE,TRUE),
                        level = .90, adjust = "bon", by = "groups"))

## groups = None:
##   lsmean      SE    df lower.CL upper.CL t.ratio p.value
## 2.701777 0.02855972 701.42 2.654739 2.748816  94.601  <.0001
##
## groups = Jail:
##   lsmean      SE    df lower.CL upper.CL t.ratio p.value
## 2.766199 0.02480113 676.80 2.725351 2.807047 111.535  <.0001
##
## Degrees-of-freedom method: satterthwaite
## Confidence level used: 0.9
```

Time Varying Predictors

Time Varying Predictors: Continuous

Next, we'll add in a time-varying predictor. Maybe it's not that our participants sensation seeking is moderated by early life experiences of jail or court-ordered community service. Instead, their sensation seeking is moderated by depression.

How does this look?

- **Level 1:** $Y_{ij} = \beta_{0j} + \beta_{1j} * time + \beta_{2j} * CESD + \varepsilon_{ij}$
- **Level 2:**
 - $\beta_{0j} = \gamma_{00} + \gamma_{01} + U_{0j}$
 - $\beta_{1j} = \gamma_{10} + U_{1j}$
 - $\beta_{2j} = \gamma_{20}$

To Interaction or Not - That Is the Question

- **Level 1:** $Y_{ij} = \beta_{0j} + \beta_{1j} * age0 + \beta_{2j} * CESD + \varepsilon_{ij}$
- **Level 2:**
 - $\beta_{0j} = \gamma_{00} + \gamma_{01} + U_{0j}$
 - $\beta_{1j} = \gamma_{10} + U_{1j}$
 - $\beta_{2j} = \gamma_{20}$

$$Y_{ij} = \gamma_{00} + \gamma_{01} + U_{0j} + (\gamma_{10} + U_{1j}) * age0 + \gamma_{20} * CESD$$

Example: Does depression influence changes in sensation seeking over time?

```
modTV1 <- lmer(SensSeek ~ age0 + CESD + (age0|PROC_CID), data = sample_dat)

summary(modTV1)

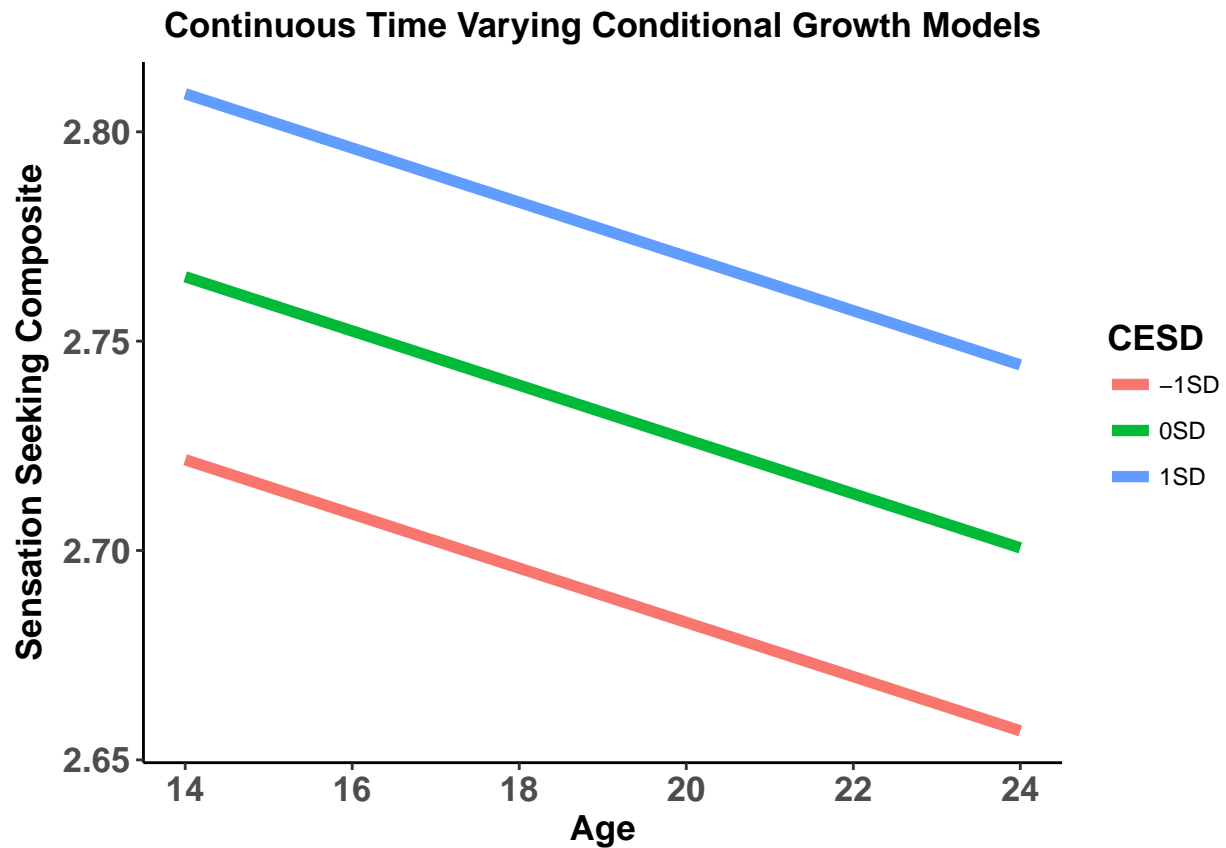
## Linear mixed model fit by REML ['lmerMod']
## Formula: SensSeek ~ age0 + CESD + (age0 | PROC_CID)
## Data: sample_dat
##
## REML criterion at convergence: 3391.9
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -3.4390 -0.5035  0.0363  0.4423  3.1508
##
## Random effects:
## Groups Name Variance Std.Dev. Corr
## PROC_CID (Intercept) 0.1412389 0.37582
## age0 0.0008117 0.02849 -0.21
## Residual 0.1892164 0.43499
## Number of obs: 2084, groups: PROC_CID, 924
##
## Fixed effects:
## Estimate Std. Error t value
## (Intercept) 2.710845 0.025121 107.91
## age0 -0.006475 0.003553 -1.82
## CESD 0.078617 0.021519 3.65
##
## Correlation of Fixed Effects:
## (Intr) age0
## age0 -0.467
## CESD -0.604 -0.036

# example for continuous
# note MEANS ARE AT AGE0 = 0
fixed.frame <- sample_dat %>%
  filter(age0 == 0) %>%
  summarise(mean = mean(CESD, na.rm = T),
            sd = sd(CESD, na.rm = T))

fixed.frame <-
  data.frame(
    expand.grid(
      # here, you add values for your time variable and predictors
      age0 = seq(0,10,2),
      CESD = c(fixed.frame$mean-fixed.frame$sd,
                fixed.frame$mean,
                fixed.frame$mean+fixed.frame$sd))) %>%
  # now take care of interactions and add an intercept
  mutate(Intercept = 1) %>%
  # reordering everything
  select(Intercept, everything())

# multiplying to get values for model frame
fixed.frame$value <- as.matrix(fixed.frame) %*% as.vector(fixef(modTV1))
```

```
fixed.frame %>%
  mutate(CESD = factor(CESD, levels = unique(CESD), labels = c("-1SD", "0SD", "1SD")),
         age = age0 + 14) %>%
  ggplot(aes(x = age, y = value, color = CESD)) +
  geom_line(size = 2) +
  labs(x = "Age", y = "Sensation Seeking Composite",
       title = "Continuous Time Varying Conditional Growth Models") +
  theme_classic() +
  theme(axis.text = element_text(face = "bold", size = rel(1.2)),
        axis.title = element_text(face = "bold", size = rel(1.2)),
        legend.title = element_text(face = "bold", size = rel(1.2)),
        plot.title = element_text(face = "bold", size = rel(1.2), hjust = .5))
```



Time Varying Predictors: Categorical

Next, we'll add in a time-varying predictor. Maybe it's not that our participants sensation seeking is moderated by early life experiences of jail or court-ordered community service. Instead, their sensation seeking is moderated by depression.

How does this look?

- **Level 1:** $Y_{ij} = \beta_{0j} + \beta_{1j} * time + \beta_{2j} * depressed + \varepsilon_{ij}$
- **Level 2:**
 - $\beta_{0j} = \gamma_{00} + \gamma_{01} + U_{0j}$
 - $\beta_{1j} = \gamma_{10} + U_{1j}$

$$- \beta_{2j} = \gamma_{20}$$

```
# creating a dummy variable for time varying categorical depression
sample_dat <- sample_dat %>%
  mutate(depressed =
    factor(ifelse(CESD <= 1.5, 0, 1), levels = c(0,1),
           labels = c("Depressed", "Not Depressed")))
modTV2 <- lmer(SensSeek ~ age0 + depressed + (age0|PROC_CID),
               data = sample_dat)
summary(modTV2)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: SensSeek ~ age0 + depressed + (age0 | PROC_CID)
## Data: sample_dat
##
## REML criterion at convergence: 3401
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -3.3686 -0.5094  0.0363  0.4522  3.1406
##
## Random effects:
## Groups Name Variance Std.Dev. Corr
## PROC_CID (Intercept) 0.1427349 0.37780
## age0 0.0008415 0.02901 -0.21
## Residual 0.1895332 0.43535
## Number of obs: 2084, groups: PROC_CID, 924
##
## Fixed effects:
## Estimate Std. Error t value
## (Intercept) 2.760189 0.020388 135.38
## age0 -0.006154 0.003564 -1.73
## depressedNot Depressed 0.068617 0.039992 1.72
##
## Correlation of Fixed Effects:
## (Intr) age0
## age0 -0.599
## dprssdNtDpr -0.174 -0.024
```