Week 2 Homework

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September 7, 2017

1. Run linear models on all of your subjects (a basic regression). What is the average intercept, the average slope?

```
model.1p <- lm(Utterances.with.Letters ~ Session, data=parents)
summary(model.1p)
```

```
##
## Call:
## lm(formula = Utterances.with.Letters ~ Session, data = parents)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -11.510  -7.849  -4.817  -1.329 197.490
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   2.5854     1.5239   1.697 0.090257 .
## Session       0.7437     0.2077   3.580 0.000369 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 18.22 on 646 degrees of freedom
## Multiple R-squared:  0.01945,    Adjusted R-squared:  0.01794
## F-statistic: 12.82 on 1 and 646 DF,  p-value: 0.0003694
```

```
(summary(model.1p)$sigma)**2
```

```
## [1] 332.1347
```

```
model.1c <- lm(Utterances.with.Letters ~ Session, data=children)
summary(model.1c)
```

```
##
## Call:
## lm(formula = Utterances.with.Letters ~ Session, data = children)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -10.634  -6.752  -3.343  -0.933 165.129
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.05067    1.33293   0.038     0.97
## Session      0.88198    0.18118   4.868 1.42e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 15.96 on 650 degrees of freedom
```

```
## Multiple R-squared:  0.03518,    Adjusted R-squared:  0.03369
## F-statistic:  23.7 on 1 and 650 DF,  p-value: 1.417e-06
```

```r
(summary(model.1c)$sigma)**2
```

```
## [1] 254.5669
```

For Parents:

Average intercept = 2.29 utterances with letters at Session 0 (around child age 10 months)

Average slope = .74 utterances with letters every 4 months

Residual variance = 332.2693

For Children:

Average intercept = 0.05 utterances with letters at Session 0 (around child age 10 months)

Average slope = .88 utterances with letters every 4 months

Residual variance = 254.5669

2. Now run a mlm/lmer model with only a random intercept. What is the ICC?

```r
model.2p <- lmer(Utterances.with.Letters ~ 1 + (1|Subject), data = parents)
summary(model.2p)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: Utterances.with.Letters ~ 1 + (1 | Subject)
##    Data: parents
##
## REML criterion at convergence: 5575.3
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.1017 -0.3594 -0.2152 -0.0640 10.0856
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  Subject  (Intercept)  44.5     6.671
##  Residual             294.1    17.149
## Number of obs: 648, groups:  Subject, 55
##
## Fixed effects:
##             Estimate Std. Error t value
## (Intercept)    7.368      1.124   6.555
```

```r
44.5/(44.5+294.1)
```

```
## [1] 0.1314235
```

```r
model.2c <- lmer(Utterances.with.Letters ~ 1 + (1|Subject), data = children)
summary(model.2c)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: Utterances.with.Letters ~ 1 + (1 | Subject)
##    Data: children
##
```

```
## REML criterion at convergence: 5465.6
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -1.1005 -0.3171 -0.2153 -0.0986 10.3950
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  Subject  (Intercept)  22.43    4.736
##  Residual             241.36   15.536
## Number of obs: 652, groups:  Subject, 55
##
## Fixed effects:
##             Estimate Std. Error t value
## (Intercept)   5.7741     0.8822   6.545
```

```
22.43/(22.43+241.36)
```

```
## [1] 0.08502976
```

For Parents:

Average intercept = 7.37 utterances with letters

Slope = we set it at 0

Residual variance = 294.1

ICC = 0.1314235

For Children:

Average intercept = 0.05 utterances with letters

Slope = we set it at 0

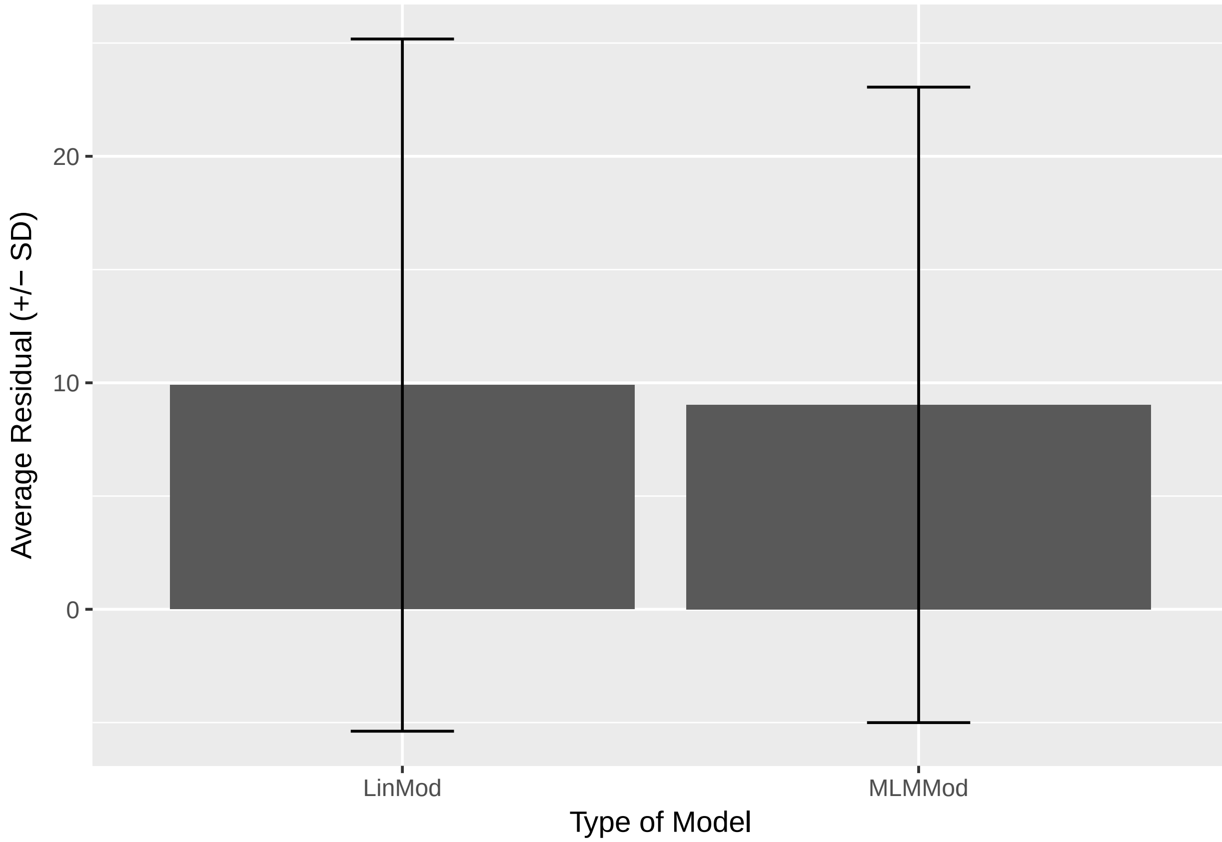
Residual variance = 241.36

ICC = 0.08502976

What does residual variance look like compared to linear model? Create a graph to show this effect.

```
#plotting residuals
library(broom)
lin.resid <- abs(augment(model.1p)[,c(5)])
mean.lin.resid <- mean(lin.resid)
sd.lin.resid <- sd(lin.resid)

mlm.resid <- abs(augment(model.2p)[,c(4)])
mean.mlm.resid  <- mean(mlm.resid)
sd.mlm.resid <- sd(mlm.resid)


dataframe <- data.frame("Type" = c("LinMod", "MLMMod"),
                        "Mean" = c(mean.lin.resid, mean.mlm.resid), "SD"= c(sd.lin.resid, sd.mlm.resid)

ResidPlot <- ggplot(dataframe, aes(Type, Mean)) +
```

```
                   geom_col() +
                   geom_errorbar(aes(ymin = Mean - SD, ymax = Mean + SD), width=0.2)
ResidPlot + labs(y="Average Residual (+/- SD)", x = "Type of Model")
```



Residual variance (the variance not accounted for by the model) is smaller in the in the mixed-effect model compared to the linear model, even though the linear model uses age as a predictor whereas the MLM model does not.

3. Introduce a fixed slope term. What is the difference in terms of the fixed effects estimates between this estimate and the previous? Of the residual standard error?

```
model.3p <- lmer(Utterances.with.Letters ~ 1 + Session + (1|Subject), data = parents)
summary(model.3p)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: Utterances.with.Letters ~ 1 + Session + (1 | Subject)
##    Data: parents
##
## REML criterion at convergence: 5562.1
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.2139 -0.4125 -0.1893  0.0343  9.9391
##
```

```
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  Subject  (Intercept)  45.08    6.714
##  Residual             287.38   16.952
## Number of obs: 648, groups:  Subject, 55
##
## Fixed effects:
##             Estimate Std. Error t value
## (Intercept)   2.5448     1.6824   1.513
## Session       0.7449     0.1933   3.852
##
## Correlation of Fixed Effects:
##         (Intr)
## Session -0.744
```

```r
model.3c <- lmer(Utterances.with.Letters  ~ 1 + Session + (1|Subject), data = children)
summary(model.3c)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: Utterances.with.Letters ~ 1 + Session + (1 | Subject)
##    Data: children
##
## REML criterion at convergence: 5441.5
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -1.1762 -0.4023 -0.1680  0.0331 10.3798
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  Subject  (Intercept)  23.47    4.844
##  Residual             231.43   15.213
## Number of obs: 652, groups:  Subject, 55
##
## Fixed effects:
##             Estimate Std. Error t value
## (Intercept) 0.008465   1.429321   0.006
## Session     0.887184   0.172811   5.134
##
## Correlation of Fixed Effects:
##         (Intr)
## Session -0.786
```

For Parents:

Average intercept = 2.55 utterances with letters at Session 0 (around child age 10 months) *(7.37 in model without age)*

Average slope = .75 utterances with letters every 4 months *(.74 in linear model)*

Residual variance = 287.38 *(294.1 in model without age)*

For Children:

Average intercept = 0.001 utterances with letters at Session 0 (around child age 10 months) *(0.05 in model without age)*

Average slope = .89 utterances with letters every 4 months *(.88 in linear model)*

Residual variance = 231.43 *(241.36 in model without age)*

The fixed effect estimates of the intercept have decreased. The estimates of the slopes are about equal to those of the linear model. The residual error has decreased.

Create a graph to show both fixed effects estimates and the CIs around them.

```
##FOR PARENTS
# Get fixed effect confidence intervals
confint(model.3p, level = .95)
```

```
## Computing profile confidence intervals ...
```

```
##                  2.5 %    97.5 %
## .sig01       4.8464579  8.787091
## .sigma      16.0180269 17.948930
## (Intercept) -0.7510901  5.840187
## Session      0.3656021  1.124076
```

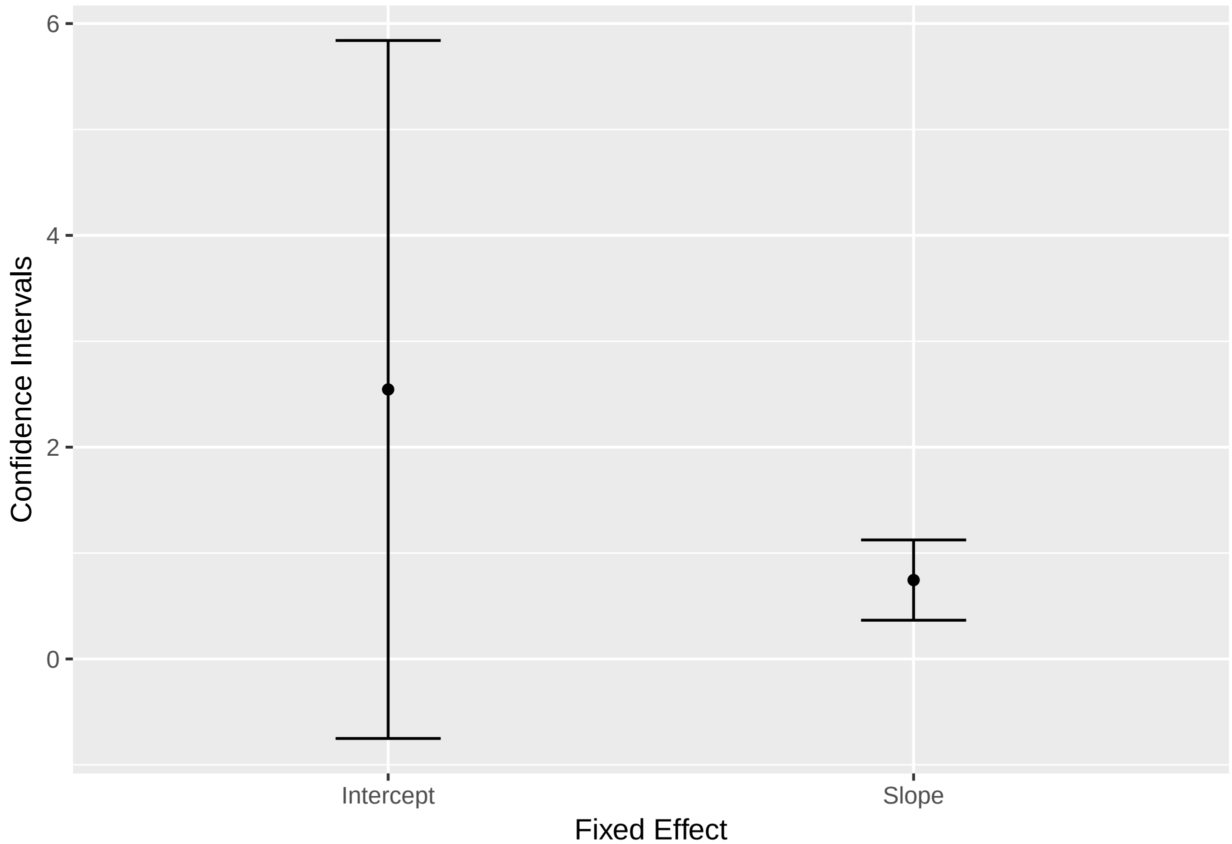
```
CIs <- data.frame(confint(model.3p, level = .95)[3:4,])
```

```
## Computing profile confidence intervals ...
```

```
CIs$fixef <- fixef(model.3p)

summary1 <- tidy(model.3p)
summary1
```

```
##                       term   estimate std.error statistic    group
## 1             (Intercept)  2.5448102 1.6824034  1.512604    fixed
## 2                 Session  0.7448542 0.1933443  3.852475    fixed
## 3  sd_(Intercept).Subject  6.7143301        NA        NA  Subject
## 4 sd_Observation.Residual 16.9521541        NA        NA Residual
```

```
# graph fixed effect CIs
dataframe <- data.frame("Fixed Effect" = c("Intercept", "Slope"),
                        "Mean" = c(CIs[1,3], CIs[2,3]), "LowerCI" = c(CIs[1,1], CIs[2,1]), "UpperCI" = c

CIPlot <- ggplot(dataframe, aes(Fixed.Effect, Mean)) +
                   geom_point() +
                   geom_errorbar(aes(ymin = LowerCI, ymax = UpperCI), width=0.2)
CIPlot + labs(y="Confidence Intervals", x = "Fixed Effect")
```




```
##FOR CHILDREN
# Get fixed effect confidence intervals
confint(model.3c, level = .95)
```

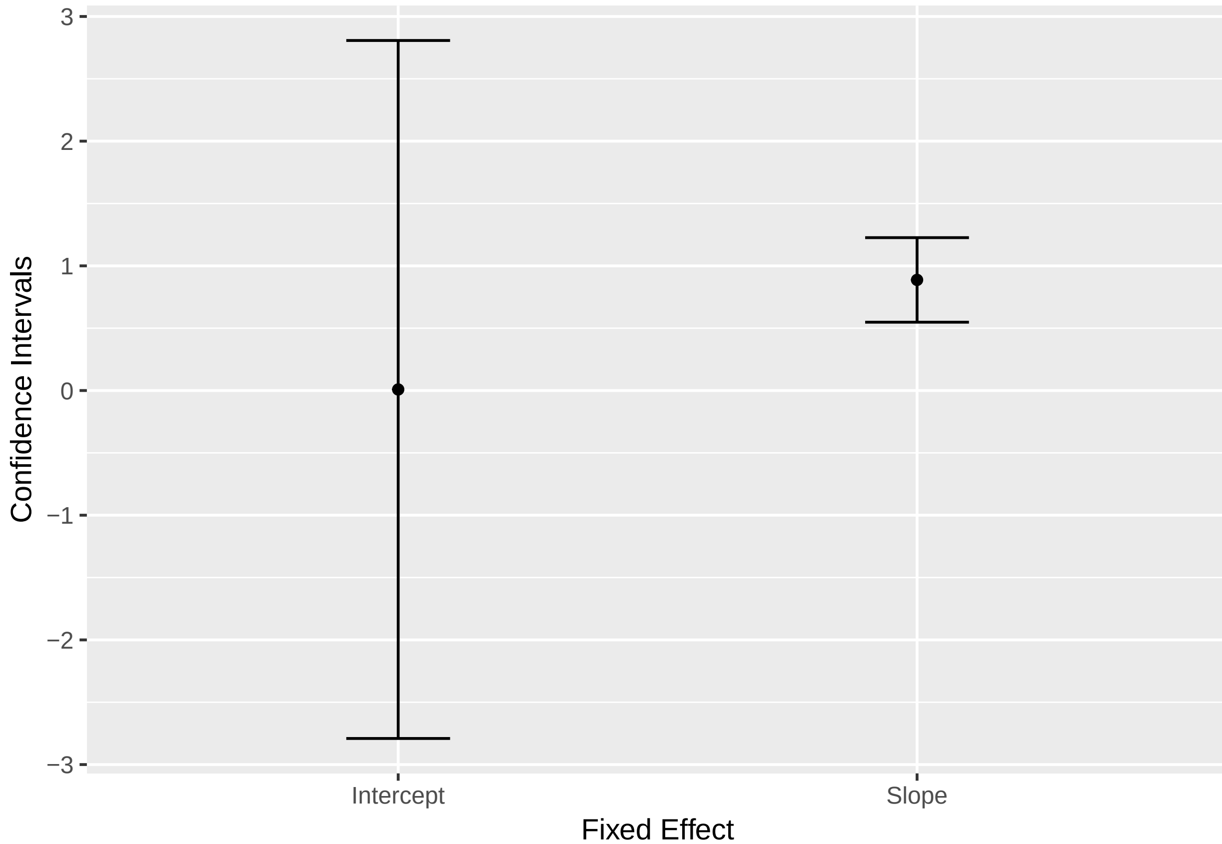
```
## Computing profile confidence intervals ...
```

```
##                  2.5 %    97.5 %
## .sig01       3.1555429  6.592970
## .sigma      14.3772293 16.104843
## (Intercept) -2.7908665  2.807329
## Session      0.5481127  1.226046
```

```
CIs <- data.frame(confint(model.3c, level = .95)[3:4,])
```

```
## Computing profile confidence intervals ...
```

```
CIs$fixef <- fixef(model.3c)

# graph fixed effect CIs
dataframe <- data.frame("Fixed Effect" = c("Intercept", "Slope"),
                        "Mean" = c(CIs[1,3], CIs[2,3]), "LowerCI" = c(CIs[1,1], CIs[2,1]), "UpperCI" = c

CIPlot <- ggplot(dataframe, aes(Fixed.Effect, Mean)) +
                   geom_point() +
                   geom_errorbar(aes(ymin = LowerCI, ymax = UpperCI), width=0.2)
CIPlot + labs(y="Confidence Intervals", x = "Fixed Effect")
```



4. Run an additional model with a random slope. How does this change compare to the previous model? Should you keep the random slope or not?

```
model.4p <- lmer(Utterances.with.Letters  ~ 1 + Session + (1 + Session|Subject), data = parents)
summary(model.4p)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: Utterances.with.Letters ~ 1 + Session + (1 + Session | Subject)
##    Data: parents
##
## REML criterion at convergence: 5487.8
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.7444 -0.3140 -0.2232 -0.0046  7.1589
##
## Random effects:
##  Groups   Name        Variance Std.Dev. Corr
##  Subject  (Intercept)  19.041   4.364
##           Session       3.163   1.778   -1.00
##  Residual             243.260  15.597
## Number of obs: 648, groups:  Subject, 55
##
## Fixed effects:
```

```
##             Estimate Std. Error t value
## (Intercept)   2.5858     1.4313   1.807
## Session       0.7398     0.2987   2.477
##
## Correlation of Fixed Effects:
##         (Intr)
## Session -0.810
```

```
model.4c <- lmer(Utterances.with.Letters  ~ 1 + Session + (1 + Session|Subject), data = children)
summary(model.4c)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: Utterances.with.Letters ~ 1 + Session + (1 + Session | Subject)
##    Data: children
##
## REML criterion at convergence: 5397.9
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.6942 -0.2634 -0.1600 -0.0619  9.9342
##
## Random effects:
##  Groups   Name        Variance Std.Dev. Corr
##  Subject  (Intercept)   9.170   3.028
##           Session       1.682   1.297   -1.00
##  Residual             206.758  14.379
## Number of obs: 652, groups:  Subject, 55
##
## Fixed effects:
##             Estimate Std. Error t value
## (Intercept) 0.001973   1.269116   0.002
## Session     0.892108   0.239371   3.727
##
## Correlation of Fixed Effects:
##         (Intr)
## Session -0.806
```

For Parents:

Average intercept = 2.55 utterances with letters at Session 0 (around child age 10 months) *(2.55 in model without random slope)*

Average slope = .74 utterances with letters every 4 months *(.75 in model without random slope)*

Residual variance = 243.260 *(287.38 in model without random slope)*

For Children:

Average intercept = 0.002 utterances with letters at Session 0 (around child age 10 months) *(0.001 in model without random slope)*

Average slope = .89 utterances with letters every 4 months *(.89 in model without random slope)*

Residual variance = 206.76 *(231.43 in model without random slope)*

The residual error has decreased in both models, suggesting I should keep the random slope.

5. Interpret the correlation between the slope and the intercept.

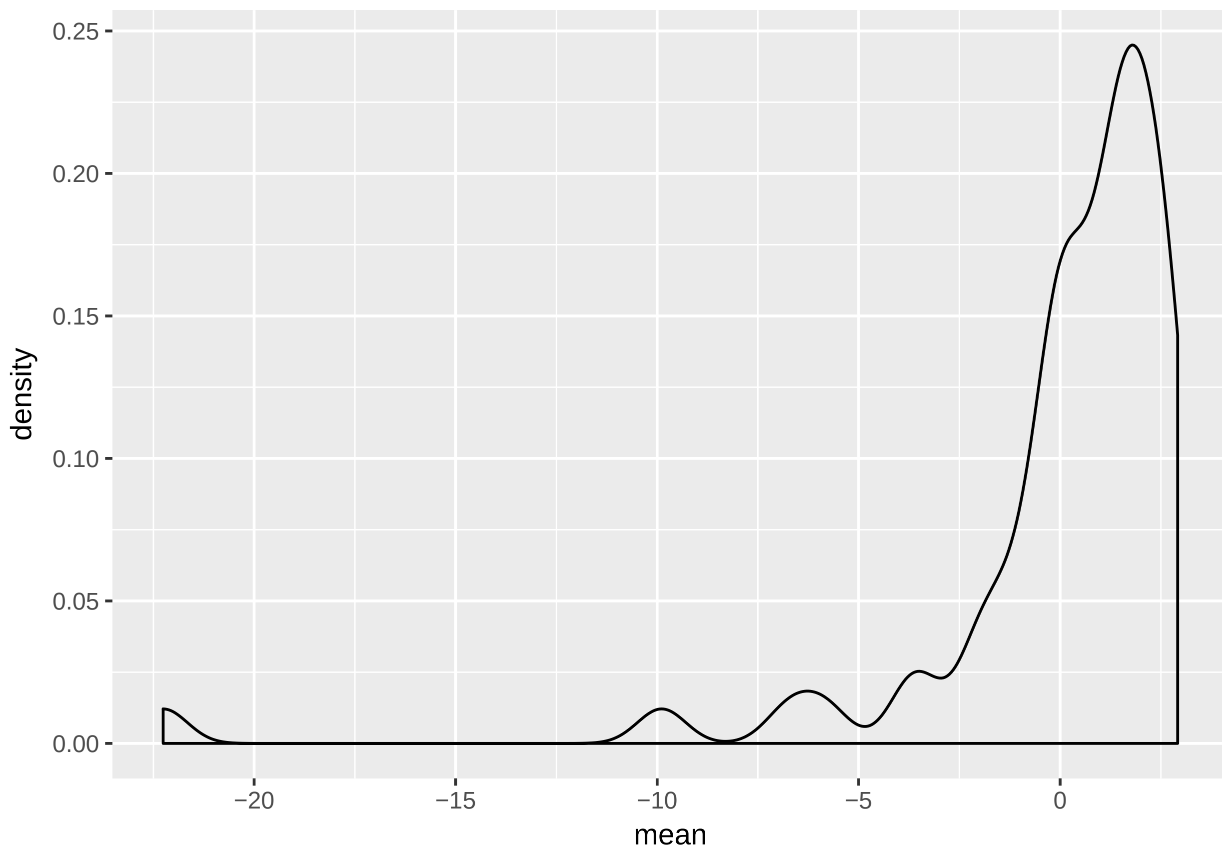
The fixed effects correlation is -0.81. The lower the intercept the greater the slope. There is a very strong relationship between the average intercept and the average slope.

6. Create a density plot of the random effects from your final model.

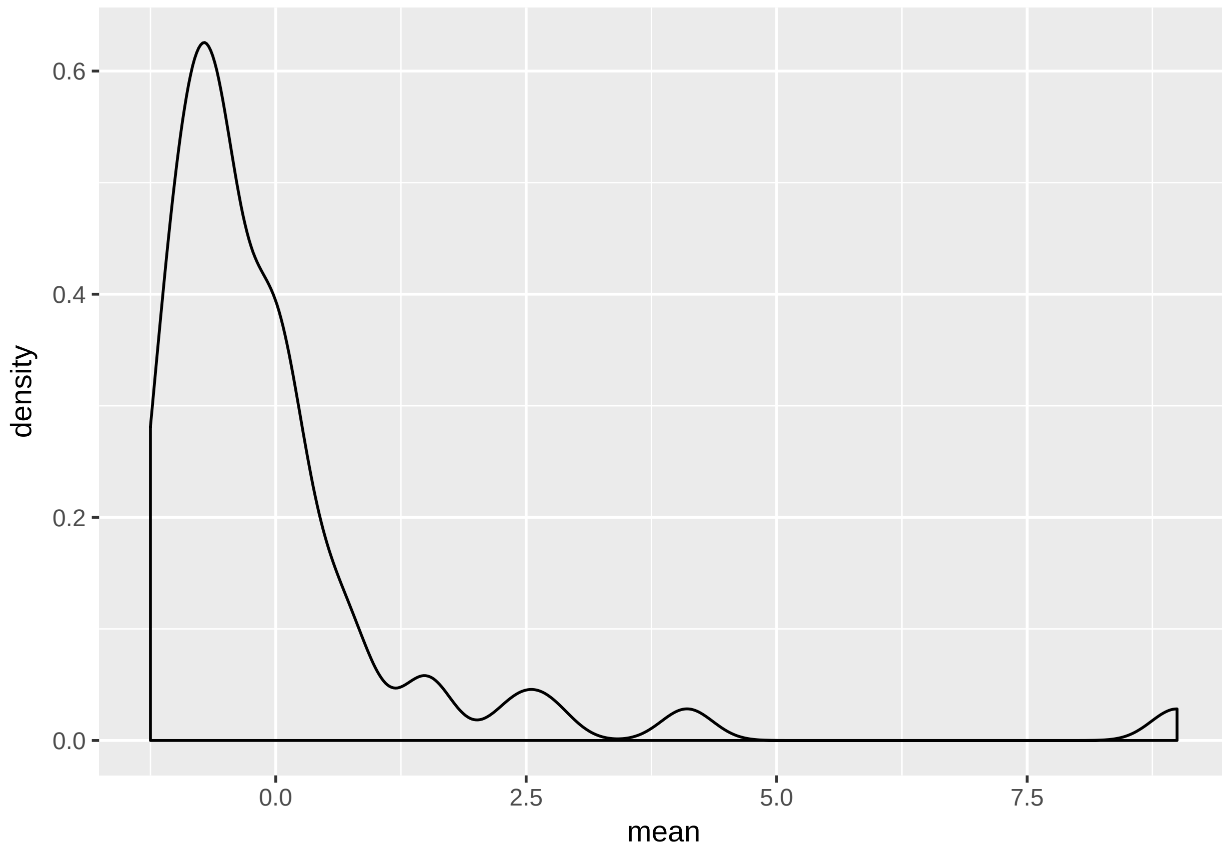
```r
library(merTools)
```

```
## Loading required package: arm

## Loading required package: MASS

##
## Attaching package: 'MASS'

## The following object is masked from 'package:dplyr':
##
##     select

##
## arm (Version 1.9-3, built: 2016-11-21)

## Working directory is C:/Users/Molly/Documents/1-descriptives-and-graphs-mfarrythorn

##
## Attaching package: 'arm'

## The following objects are masked from 'package:psych':
##
##     logit, rescale, sim

##
## Attaching package: 'merTools'

## The following object is masked from 'package:psych':
##
##     ICC
```

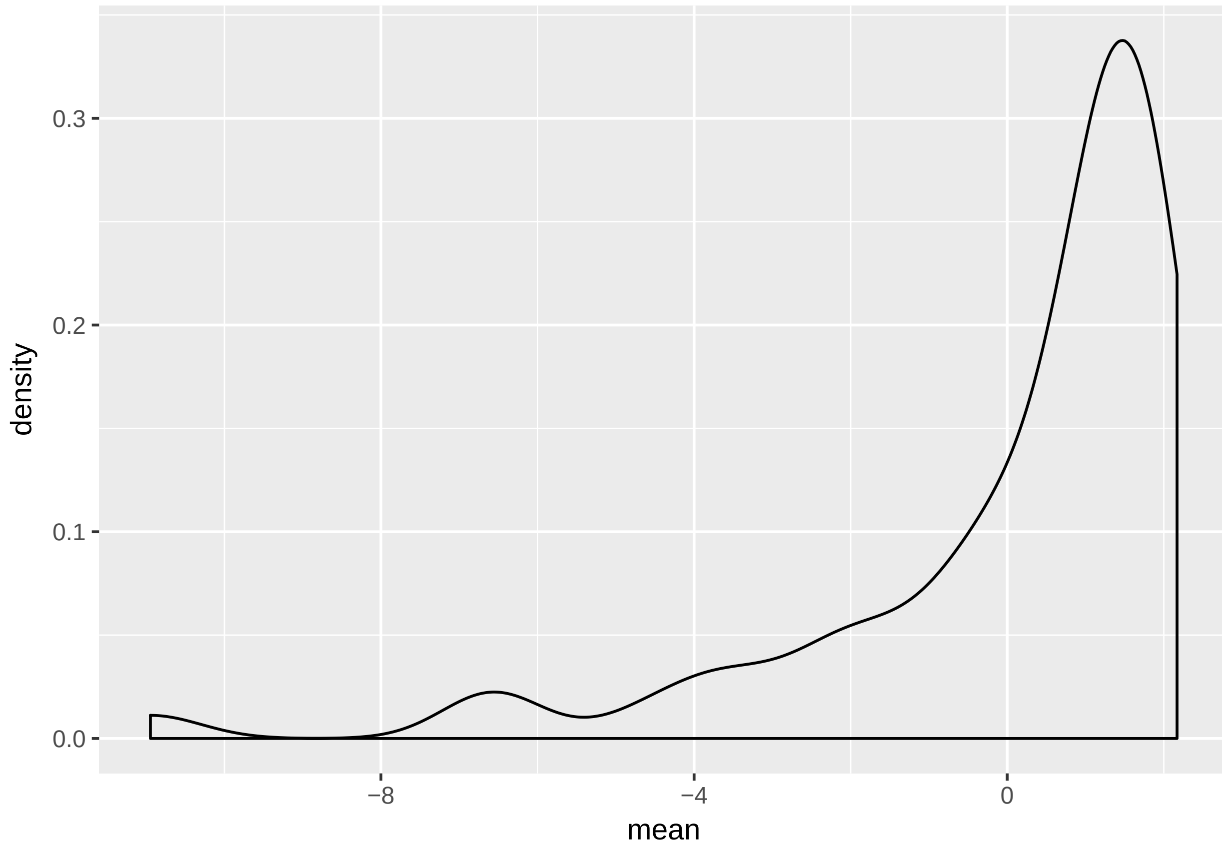
```r
## FOR PARENTS
re.sim.p <- REsim(model.4p)

# Intercept random effects
p1.gg1 <- re.sim.p %>%
  filter(term == "(Intercept)")

ggplot(p1.gg1, aes(mean)) +
  geom_density()
```



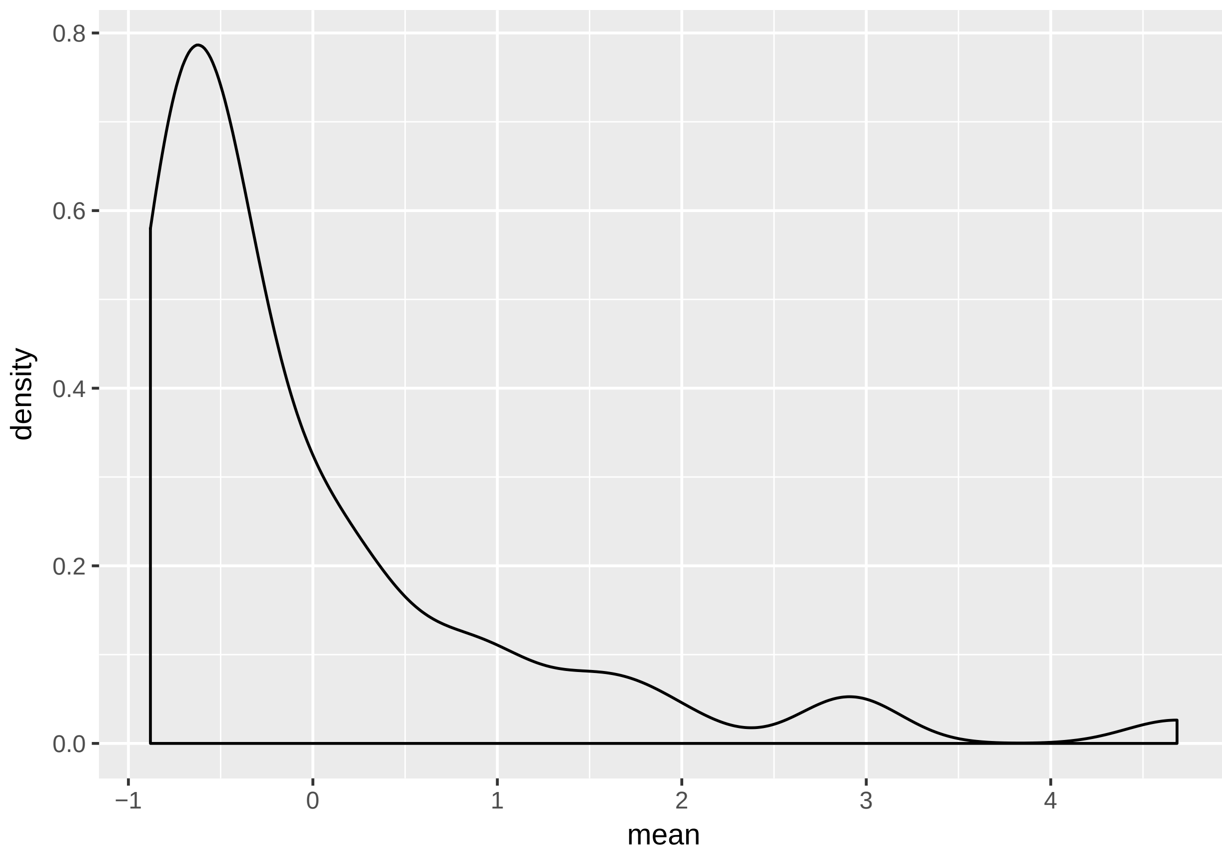

```
# Slope random effects
p1.gg2 <- re.sim.p %>%
  filter(term == "Session")

ggplot(p1.gg2, aes(mean)) +
  geom_density()
```




```
## FOR CHILDREN
re.sim.c <- REsim(model.4c)

# Intercept random effects
p1.gg3 <- re.sim.c %>%
  filter(term == "(Intercept)")

ggplot(p1.gg3, aes(mean)) +
  geom_density()
```

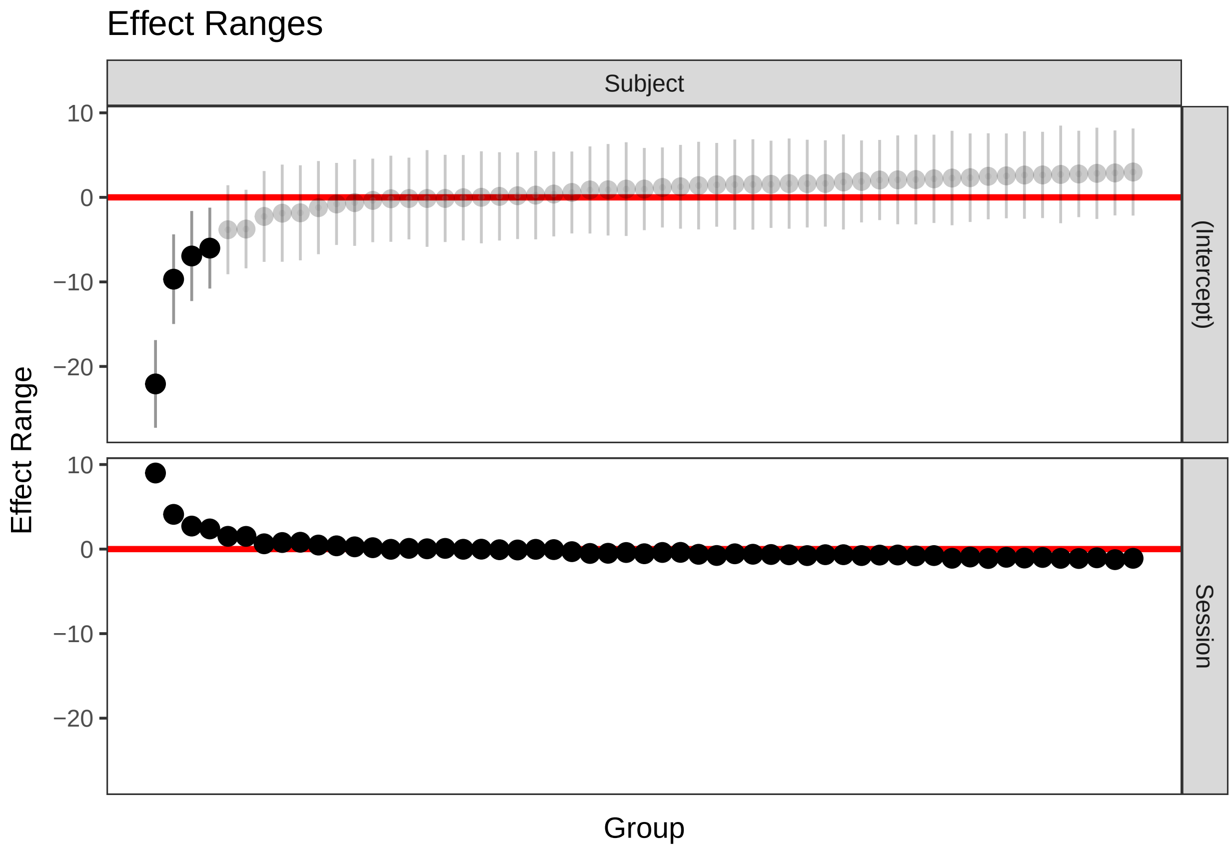



```r
# Slope random effects
p1.gg4 <- re.sim.c %>%
  filter(term == "Session")

ggplot(p1.gg4, aes(mean)) +
  geom_density()
```

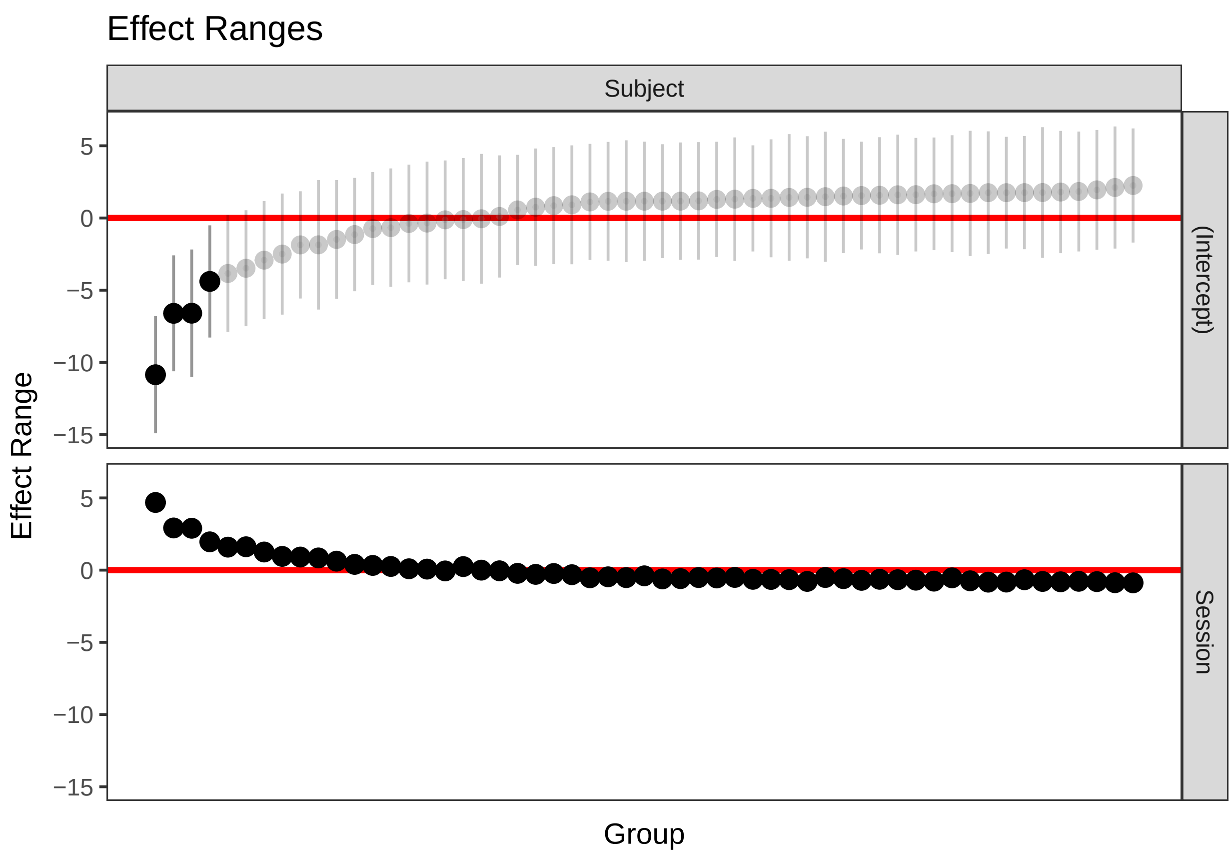


7. Create a catepilar plot of the random effects. Is there any person that seems odd in terms of a large standard errors around intercept and slope estimates?

```
p1 <- plotREsim(re.sim.p)
p1
```




```
# 75, 27, 85, 25

p2 <- plotREsim(re.sim.c)
p2
```



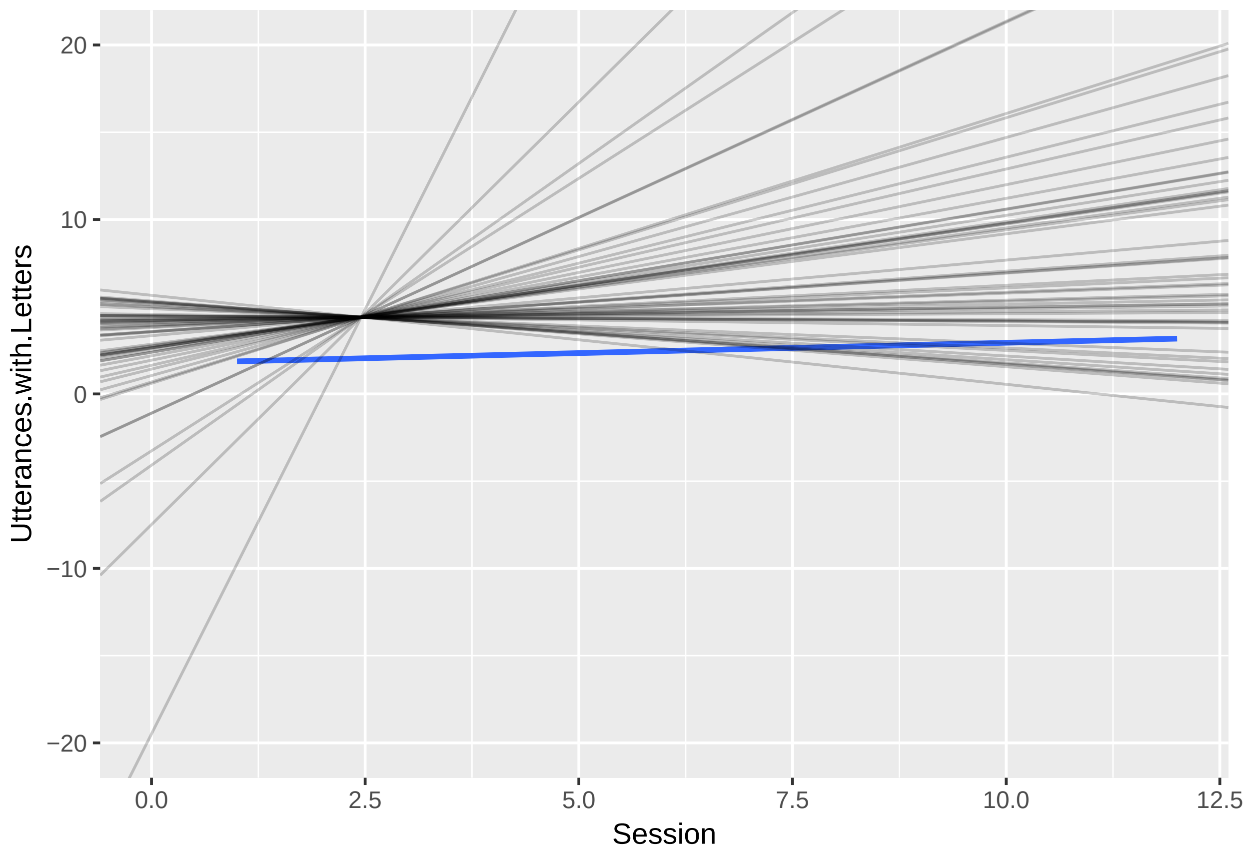

```
#75, 25, 89, 51
```

The listed participant numbers aboce have effect ranges for the intercept differ significantly from 0. However, by and large, standard errors around the intercept and slope values all seem to be within normal limits.

8. Create a plot of the trajectory, along with a spaghetti plot of each person's individual slope. Set the alpha level (transparency) on the individual slopes to make them easier to see.

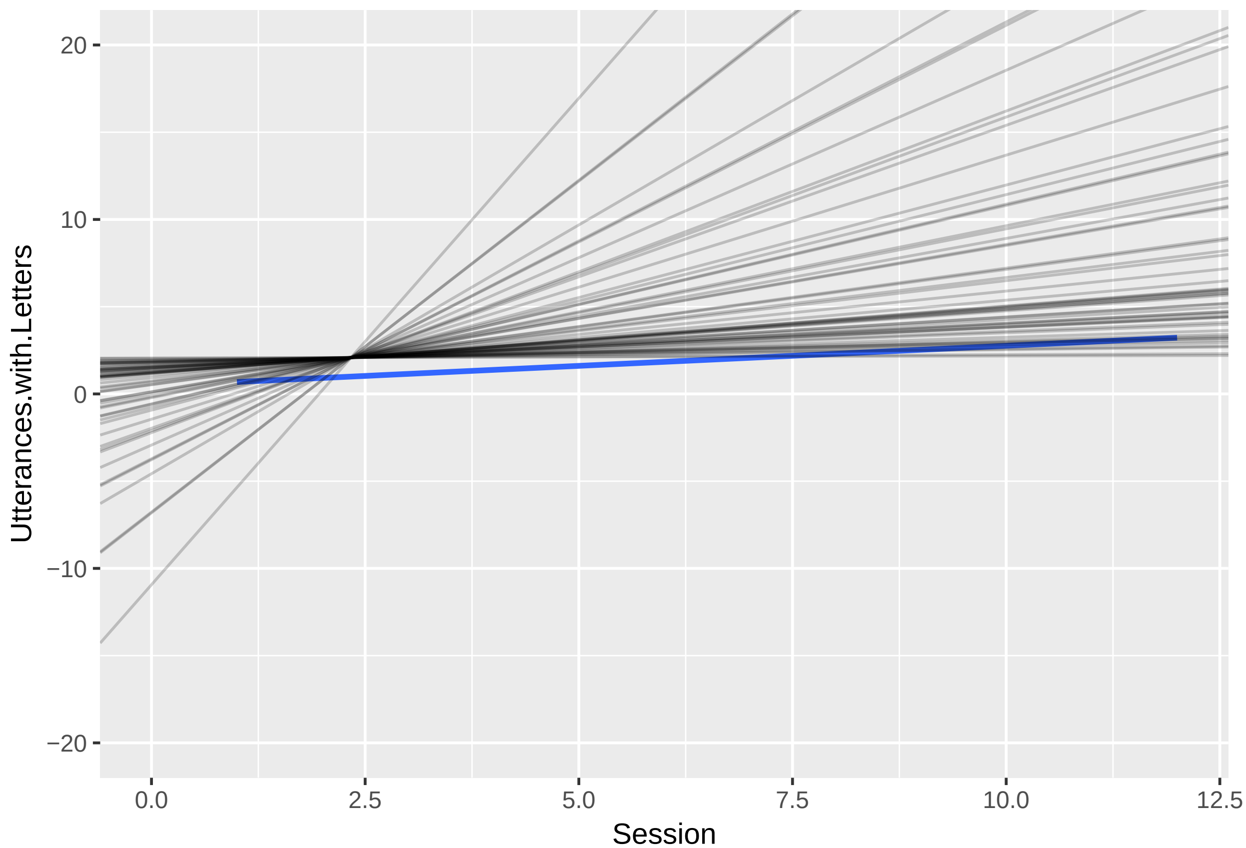
```
coefs <- data.frame(coef(model.4p)[[1]])

ggplot(data = parents, aes(Session, Utterances.with.Letters)) +
   stat_smooth(aes(Session, Utterances.with.Letters), method = lm, se = F) +
   xlim(0,12) + ylim (-20,20) +
  geom_abline(data = coefs, aes(slope = Session, intercept = X.Intercept.), alpha = 0.2)
```

```
## Warning: Removed 69 rows containing non-finite values (stat_smooth).
```




```
coefs <- data.frame(coef(model.4c)[[1]])

ggplot(data = children, aes(Session, Utterances.with.Letters)) +
   stat_smooth(aes(Session, Utterances.with.Letters), method = lm, se = F) +
   xlim(0,12) + ylim (-20,20) +
  geom_abline(data = coefs, aes(slope = Session, intercept = X.Intercept.), alpha = 0.2)
```

```
## Warning: Removed 54 rows containing non-finite values (stat_smooth).
```



20
10
0
−10
−20
Utterances.with.Letters
0.0
2.5
5.0
7.5
10.0
12.5
Session