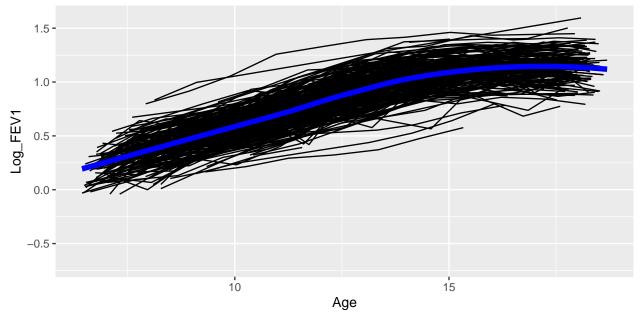
Fixed Effects Models

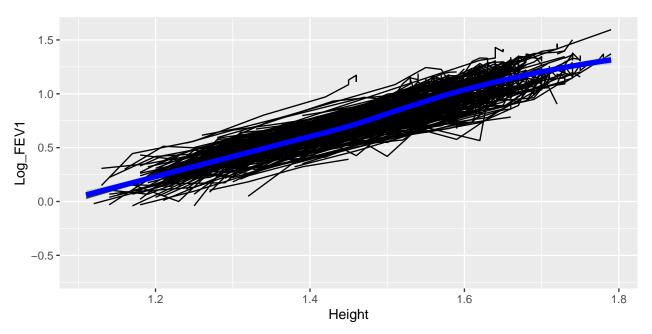
Alexander McLain

Contents

The Six Cities Study of Air Pollution and Health example (see the first R notes for details).

	ID	Height	Age	INI_Height	INI_Age	Log_FEV1
1987	299	1.64	17.9904	1.57	12.9555	1.09527
1988	300	1.44	11.9617	1.44	11.9617	0.68310
1989	300	1.50	12.9993	1.44	11.9617	0.85015
1990	300	1.57	13.9055	1.44	11.9617	0.81536
1991	300	1.61	14.9596	1.44	11.9617	1.11841
1992	300	1.62	15.9398	1.44	11.9617	1.08181
1993	300	1.62	17.0075	1.44	11.9617	1.12817
1994	300	1.63	17.8645	1.44	11.9617	1.16938

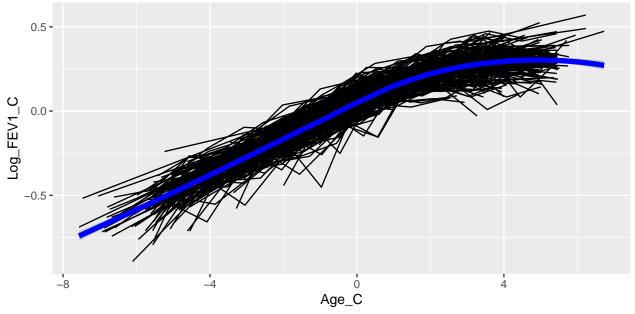




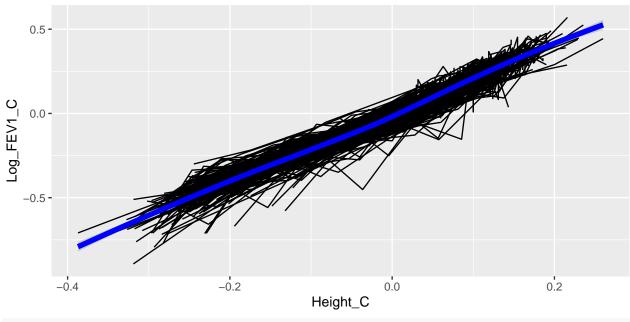
Let's look at fitting this model with a fixed effects model. First, we'll center Log_FEV1, Height, and Age by the subjects mean. Then we'll plot again.

```
## # A tibble: 10 x 9
## # Groups:
              ID [2]
                    Age INI_Height INI_Age Log_FEV1 Log_FEV1_C Height_C Age_C
           Height
                                                                   <dbl> <dbl>
##
      <fct> <dbl> <dbl>
                              <dbl>
                                      <dbl>
                                               <dbl>
                                                         <dbl>
##
   1 1
             1.2
                   9.34
                               1.2
                                       9.34
                                               0.215
                                                       -0.417
                                                                 -0.190 -3.36
##
   2 1
             1.28 10.4
                               1.2
                                       9.34
                                              0.372
                                                       -0.260
                                                                 -0.110 -2.31
   3 1
             1.33 11.5
                                       9.34
                                              0.489
                                                       -0.143
                                                                 -0.0600 -1.25
                               1.2
             1.42 12.5
                                                                  0.03
                                                                         -0.242
##
  4 1
                               1.2
                                       9.34
                                              0.751
                                                        0.120
## 5 1
             1.48 13.4
                              1.2
                                       9.34
                                              0.833
                                                        0.201
                                                                  0.09
                                                                          0.717
##
  6 1
             1.5 15.5
                               1.2
                                       9.34
                                              0.892
                                                        0.260
                                                                  0.11
                                                                          2.77
##
  7 1
             1.52 16.4
                               1.2
                                       9.34
                                              0.871
                                                        0.239
                                                                  0.13
                                                                          3.67
## 8 2
             1.13 6.59
                               1.13
                                       6.59
                                              0.307
                                                       -0.510
                                                                 -0.319 -6.61
             1.19 7.65
## 9 2
                               1.13
                                       6.59
                                              0.351
                                                       -0.467
                                                                 -0.259 -5.55
## 10 2
             1.49 12.7
                               1.13
                                       6.59
                                              0.756
                                                        -0.0615
                                                                0.0413 -0.457
## Check ##
Six_cities$Height[Six_cities$ID==1] - mean(Six_cities$Height[Six_cities$ID==1])
## [1] -0.19 -0.11 -0.06 0.03 0.09 0.11 0.13
Six_cities$Height[Six_cities$ID==2] - mean(Six_cities$Height[Six_cities$ID==2])
## [1] -0.31875 -0.25875 0.04125 0.08125 0.10125 0.11125 0.12125 0.12125
par(mfrow = c(1,2))
p <- ggplot(Six_cities, aes(x = Age_C, y = Log_FEV1_C, group = ID))</pre>
p + geom_line() +
 geom_smooth(aes(group = 1), method = "loess",
                              color = "blue", size = 2)
```

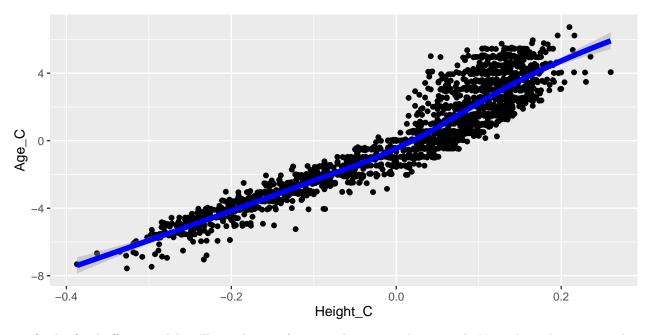
`geom_smooth()` using formula 'y ~ x'



`geom_smooth()` using formula 'y ~ x'



$geom_smooth()$ using formula 'y ~ x'



To fit the fixed effects model we'll use the gls function that we used previously Note that when we use this model we do not include an intercept. First, i'm going to fit the data by height and look at the residuals by age (all using the centered variables).

```
library(nlme)
Model_form <- Log_FEV1_C ~ 0 + Height_C + Age_C
cor_fun <- corIdent(form = ~ 1|ID)</pre>
lm_indep <- gls(model = Model_form, data = Six_cities, correlation = cor_fun)</pre>
summary(lm indep)
## Generalized least squares fit by REML
##
    Model: Model_form
##
    Data: Six_cities
##
           AIC
                     BIC
                           logLik
##
     -5638.943 -5622.152 2822.471
##
## Correlation Structure: Independent
## Formula: ~1 | ID
## Parameter estimate(s):
## numeric(0)
##
## Coefficients:
                Value Std.Error t-value p-value
## Height_C 1.6135411 0.02874199 56.13882
## Age_C
          0.0199618 0.00124361 16.05151
##
##
   Correlation:
##
        Hght C
## Age_C -0.937
## Standardized residuals:
                        Q1
                                   Med
                                                 QЗ
                                                            Max
## -6.38698429 -0.54781812 0.03431464 0.62763430 3.19497703
##
## Residual standard error: 0.05850395
## Degrees of freedom: 1994 total; 1992 residual
```

Another model we might want to try is log transformed age. To do this, we'll first create the log transformed variable and then mean center it.

```
Six_cities <- Six_cities %>% group_by(ID) %>%
  mutate( log_Age = log(Age))%>%
  mutate( log_Age_C = log_Age - mean(log_Age))

Model_form <- Log_FEV1_C ~ 0 + Height_C + log_Age_C
cor_fun <- corIdent(form = ~ 1|ID)

lm_indep_log <- gls(model = Model_form, data = Six_cities, correlation = cor_fun)
anova(lm_indep, lm_indep_log)</pre>
```

call	Model	df	AIC	BIC	logLik
lm_indep gls(model = Model_form, data = Six_cition	es, 1	3	-	-	2822.471
$correlation = cor_fun$			5638.943	5622.152	
$lm_indep_logs(model = Model_form, data = Six_citie)$	es, 2	3	-	-	2822.987
$correlation = cor_fun$			5639.973	5623.183	

```
summary(lm_indep_log)
## Generalized least squares fit by REML
     Model: Model_form
##
##
     Data: Six_cities
##
           AIC
                     BIC
                           logLik
##
     -5639.973 -5623.183 2822.987
##
## Correlation Structure: Independent
## Formula: ~1 | ID
## Parameter estimate(s):
## numeric(0)
##
## Coefficients:
##
                 Value Std.Error t-value p-value
## Height_C 1.4677786 0.03773612 38.89585
## log_Age_C 0.3112462 0.01958350 15.89329
##
  Correlation:
             Hght_C
##
## log_Age_C -0.964
##
## Standardized residuals:
           Min
                        Q1
                                   Med
                                                 0.3
## -6.55804835 -0.57183519 0.03678813 0.63210271 3.00530086
## Residual standard error: 0.05856978
## Degrees of freedom: 1994 total; 1992 residual
Let's compare this to one of the mixed effects models we considered.
Six_cities <- Six_cities %>% mutate( INI_log_Age = log( INI_Age ) )
library(lme4)
library(lmerTest)
LMM_formula <- Log_FEV1 ~ INI_Height + Height + INI_log_Age + log_Age + (1 + Height | ID)
LMM_int_slp <- lmer( formula = LMM_formula , data = Six_cities)</pre>
summary(LMM_int_slp)
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: LMM_formula
##
      Data: Six_cities
##
## REML criterion at convergence: -4582
##
## Scaled residuals:
##
       Min
                1Q Median
                                30
                                        Max
## -6.6258 -0.4939 0.0856 0.5685 2.9134
##
## Random effects:
                         Variance Std.Dev. Corr
## Groups
             Name
## ID
             (Intercept) 0.079370 0.28173
##
             Height
                         0.036043 0.18985 -0.93
## Residual
                         0.003428 0.05855
```

```
## Number of obs: 1994, groups: ID, 300
##
## Fixed effects:
##
            Estimate Std. Error df t value Pr(>|t|)
## (Intercept) -2.09856 0.09273 304.79008 -22.630 < 2e-16 ***
## INI_Height 0.39140 0.12102 336.11240 3.234 0.00134 **
             ## Height
                      0.07211 306.96596 -3.919 0.00011 ***
## INI_log_Age -0.28257
            0.29914
## log_Age
                      0.02059 1684.12517 14.526 < 2e-16 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## Correlation of Fixed Effects:
            (Intr) INI_Hg Height INI__A
## INI_Height -0.301
## Height
         -0.030 -0.312
## INI_log_Age -0.281 -0.817 0.238
## log_Age -0.024 0.301 -0.918 -0.252
```