A2 Soln

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Question 1

```
school_data = read_csv("school.csv")
```

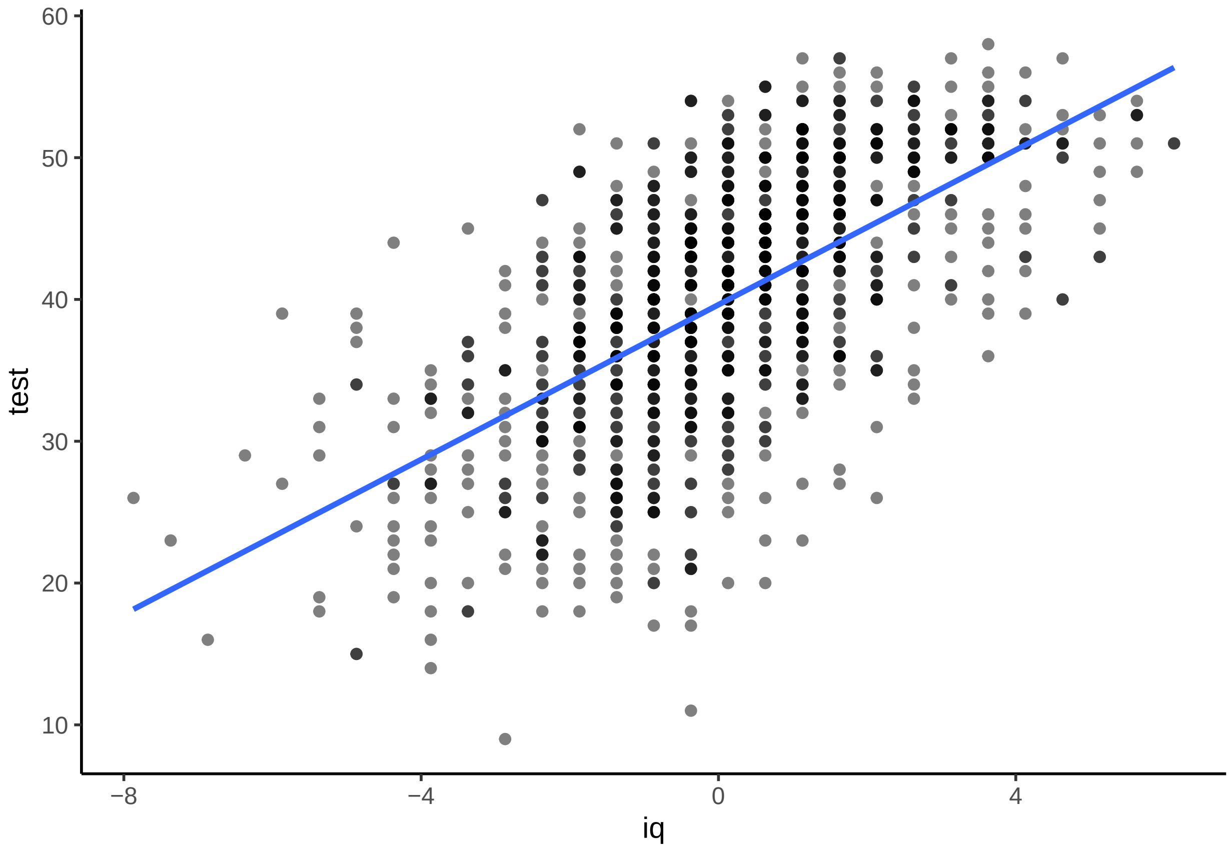
```
## Warning: Missing column names filled in: 'X1' [1]
```

Question 1.a

The independence assumption may be violated. A school with better teaching resources or better environment may be more likely to have students with better end-of-year language scores. Since there will be multiple observations taken from the same school, they may be dependent and correlated.

Question 1.b

```
ggplot(school_data, aes(x = iq, y = test)) +
  geom_point(alpha = 0.5) +
  geom_smooth(method = "lm", se = FALSE) +
  theme_classic()
```



Students' iqs and end-of-year language scores are positively related. Students with higher iq tend to achieve a better score in the end-of-year language test.

Question 1.c

```
school_data = school_data %>%
  group_by(school) %>%
  mutate(mean_ses = mean(ses),
         mean_iq = mean(iq))
```

Question 1.d

```r
school_lm = lm(test ~ iq + sex + ses + minority_status + mean_ses + mean_iq,
               data = school_data)

summary(school_lm)
```

```
##
## Call:
## lm(formula = test ~ iq + sex + ses + minority_status + mean_ses +
##     mean_iq, data = school_data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -26.4126  -4.5967   0.5543   4.9639  18.6042
##
## Coefficients:
##                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)     38.45808    0.31251 123.061  < 2e-16 ***
## iq               2.28556    0.11979  19.079  < 2e-16 ***
## sex              2.34325    0.43385   5.401 8.30e-08 ***
## ses              0.19332    0.02641   7.319 5.19e-13 ***
## minority_status -0.17083    0.97592  -0.175    0.861
## mean_ses        -0.21555    0.04641  -4.644 3.88e-06 ***
## mean_iq          1.42674    0.30264   4.714 2.77e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6.818 on 985 degrees of freedom
## Multiple R-squared:  0.4511, Adjusted R-squared:  0.4477
## F-statistic: 134.9 on 6 and 985 DF,  p-value: < 2.2e-16
```

```r
knitr::kable(confint(school_lm), digits = 4)
```

	2.5 %	97.5 %
(Intercept)	37.8448	39.0714
iq	2.0505	2.5206
sex	1.4919	3.1946
ses	0.1415	0.2452
minority_status	-2.0860	1.7443
mean_ses	-0.3066	-0.1245
mean_iq	0.8329	2.0206

Estimates:

- The intercept shows that the average end-of-year language scores for the baseline subgroup is 38.46. This baseline subgroup consists of male, white (non-minority ethnics) students with a verbal IQ score of 0, who live in a family with socioeconomic status of 0, and study in a school with students' mean socioeconomic status of 0 and mean verbal IQ score of 0.
- An increase in student's iq level by 1 tends to make a student's end-of-year language score increase by 2.29.
- A female student tend to have an end-of-year language score 2.34 higher than a male student.
- An increase in student's ses level by 1 tends to make a student's end-of-year language score increase by 0.19.
- A minority student tend to have an end-of-year language score 0.17 lower than a non-minority student.
- An increase in the school's mean ses level by 1 tends to make a student's end of year language score decrease by 0.22.
- An increase in the school's mean iq level by 1 tends to make a student's end of year language score increase by 1.43.

Confidence Intervals:

- The 95% confidence interval for the model's intercept is between 37.84 and 39.07.
- For `iq`, `sex`, `ses` and `mean_iq`, the 95% confidence intervals are positive. This indicates that they are likely to have a positive relationship with the student's end-of-year language scores.
- For `mean_ses`, the 95% confidence interval is negative. This means that there is likely to be a negative relationship between `mean_ses` the students' end-of-year language scores.
- The confidence interval for `minority_status` includes 0. It is possible that it does not have a strong effect on the students' test scores.

Question 1.e

```r
school_lmm <-
  lme4::lmer(test ~ iq + sex + ses + minority_status + mean_ses +
               mean_iq + (1 | school),
             data = school_data)

summary(school_lmm)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: test ~ iq + sex + ses + minority_status + mean_ses + mean_iq +
##     (1 | school)
##    Data: school_data
##
## REML criterion at convergence: 6518.1
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.9926 -0.6304  0.0757  0.6945  2.6361
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  school   (Intercept)  8.177   2.859
##  Residual             38.240   6.184
## Number of obs: 992, groups:  school, 58
##
## Fixed effects:
##                 Estimate Std. Error t value
## (Intercept)     38.37951    0.48384  79.323
## iq               2.27784    0.10881  20.935
## sex              2.29199    0.40260   5.693
## ses              0.19283    0.02396   8.047
## minority_status -0.65259    0.96943  -0.673
## mean_ses        -0.20131    0.08000  -2.517
## mean_iq          1.62512    0.52017   3.124
##
## Correlation of Fixed Effects:
##             (Intr) iq     sex    ses    mnrty_ men_ss
## iq          -0.035
## sex         -0.408  0.045
## ses          0.013 -0.284 -0.048
## minrty_stts -0.129  0.131  0.001  0.053
## mean_ses    -0.140  0.092  0.003 -0.296  0.039
## mean_iq      0.089 -0.199 -0.007  0.064  0.052 -0.494
```

```r
knitr::kable(confint(school_lmm), digits = 4)
```

	2.5 %	97.5 %
.sig01	2.1819	3.5182
.sigma	5.9011	6.4604
(Intercept)	37.4412	39.3176
iq	2.0649	2.4909
sex	1.5045	3.0801
ses	0.1459	0.2398
minority_status	-2.5424	1.2493
mean_ses	-0.3564	-0.0461
mean_iq	0.6166	2.6352

Random Effects:

- By looking at the Random effects section in the summary, we can see that `school` effects explain about $\frac{8.177}{8.177+38.240} \times 100 = 17.62\%$ of the residual variance in the model.

Estimates:

- The intercept shows that the average end-of-year language scores for the baseline subgroup is 38.38. This baseline subgroup consists of male, white (non-minority ethnics) students with a verbal IQ score of 0, who live in a family with socioeconomic status of 0, and study in a school with students' mean socioeconomic status of 0 and mean verbal IQ score of 0.
- An increase in student's iq level by 1 tends to make a student's end-of-year language score increase by 2.28.
- A female student tend to have an end-of-year language score 2.29 higher than a male student.
- An increase in student's ses level by 1 tends to make a student's end-of-year language score increase by 0.19.
- A minority student tend to have an end-of-year language score 0.65 lower than a non-minority student.
- An increase in the school's mean ses level by 1 tends to make a student's end of year language score decrease by 0.20.
- An increase in the school's mean iq level by 1 tends to make a student's end of year language score increase by 1.64.

Confidence Intervals: - The first line in the linear mixed model's confidence interval is `.sig01`. This is the confidence interval for the standard deviation for the random effect for school. The standard deviation for random effect for school is not small, so this means that individual schools will have an impact on their students' end-of-year language scores. - The second line in the linear mixed model's confidence interval is `.sigma`. This is the confidence interval for the residuals' standard deviation. This represents the variability of students' end-of-year verbal test scores that is not caused by being in different schools. - The 95% confidence interval for the model's intercept is between 37.44 and 39.32. - For `iq`, `sex`, `ses` and `mean_iq`, the 95% confidence intervals are positive. This indicates that they are likely to have a positive relationship with the student's end-of-year language scores. - For `mean_ses`, the 95% confidence interval is negative. This means that there is likely to be a negative relationship between `mean_ses` the students' end-of-year language scores. - The confidence interval for `minority_status` includes 0. It is possible that it does not have a strong effect on the students' test scores.

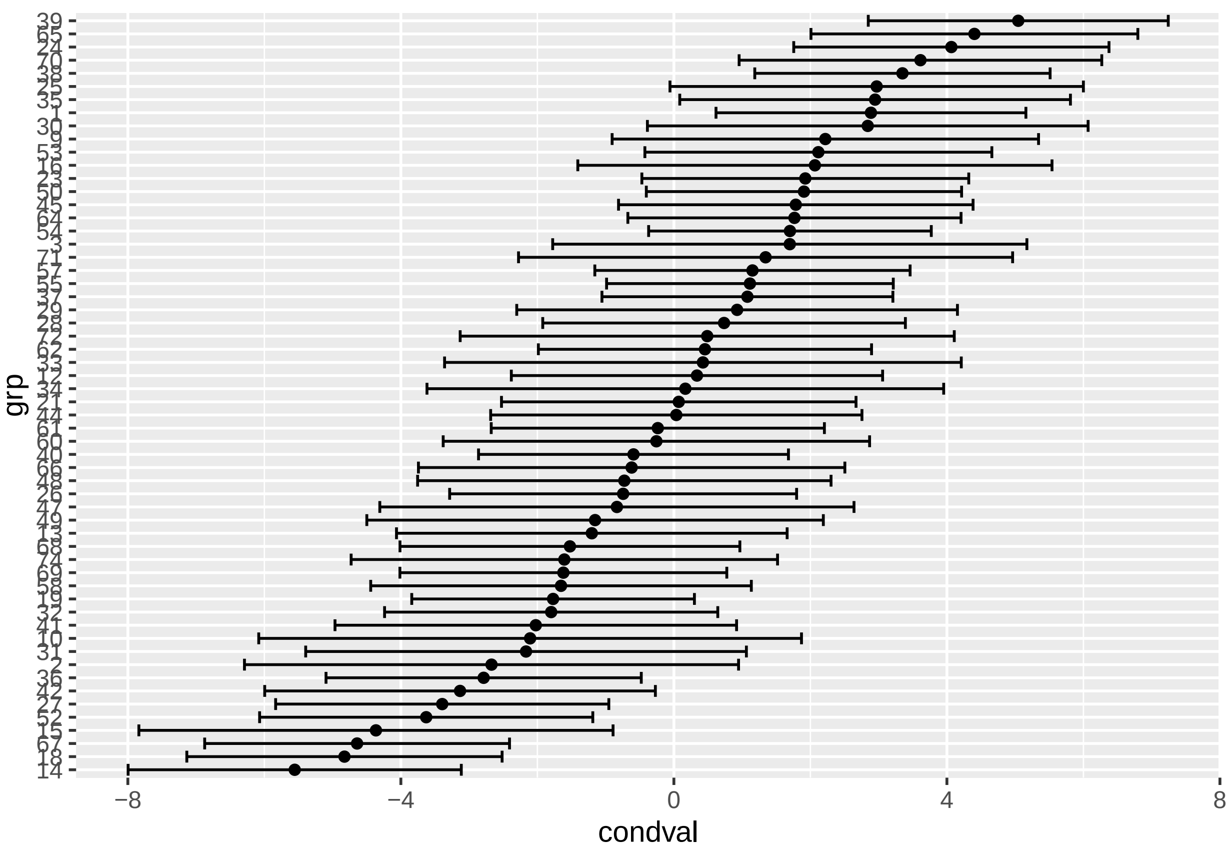
Question 1.f

The estimated fixed effects in the mixed linear model are very similar to the estimates given by the simple linear regression model. Most estimated values are slightly decreased, meaning they have a weaker effect when considering `school` as a random effect. `minority_status` and `mean_iq` have slightly higher absolute values comparing to the linear regression model, meaning when considering `school` as a random effect, they have more impact on the students' end-of-year language scores.

Question 1.g

```r
set.seed(1234)

rand_effects <- lme4::ranef(school_lmm, condVar = TRUE)
ranef_df <- as.data.frame(rand_effects)
ranef_df %>%
  ggplot(aes(
    x = grp,
    y = condval,
    ymin = condval - 2 * condsd,
    ymax = condval + 2 * condsd
  )) +
  geom_point() +
  geom_errorbar() +
  coord_flip()
```



The plot shows that for different schools, there conditional mean values differ from the grand. The confidence interval does not completely overlap with each other. The plot forms a visible trend, and this indicates that adding the random effect is appropriate in this case because it explains the variation in mean to a certain degree.

Question 1.h

It is inappropriate to directly compare students' iq with their end-of-year language score. This is because the schools that the students are studying in also affects the student's language score. This can be visually shown in the conditional mean and confidence interval plot above, and can also be statistically shown after fitting a linear mixed model with `school` as the random effect. The `school` effects explain about $\frac{8.177}{8.177+38.240} \times 100 = 17.62\%$ of the residual variance in the model.

After considering the `school` effect, by looking at the confidence interval for iq, we can see that the 95% confidence interval is greater than 0. This shows that considering the effect explained by students studying in different schools, in general, students with higher iq will achieve a better end-of-year language score.

As for the other factors, by looking at their confidence intervals, female students are more likely to achieve a higher score than male students. Students in families with higher socioeconomic status is more likely to achieve a higher score. Students' minority statuses may have less of an impact because the p-value for the estimate is insignificant, and the confidence intervals include 0. Students in a school with higher mean iq are also likely to achieve a higher score, but students in a school with higher average socioeconomic status is likely to achieve a lower score.

Question 2

```
smokeFile = "smokeDownload.RData"
if (!file.exists(smokeFile)) {
  download.file("http://pbrown.ca/teaching/303/data/smoke.RData",
                smokeFile)
}
(load(smokeFile))
```

```
## [1] "smoke"        "smokeFormats"
```

```
smokeFormats[smokeFormats[, "colName"] == "chewing_tobacco_snuff_or",
             c("colName", "label")]
```

```
##                       colName
## 151 chewing_tobacco_snuff_or
##                                                                              label
## 151 RECODE: Used chewing tobacco, snuff, or dip on 1 or more days in the past 30 days
```

```
# get rid of 9, 10 year olds and missing age and race
smokeSub = smoke[which(smoke$Age > 10 & !is.na(smoke$Race)),]
smokeSub$ageC = smokeSub$Age - 16
```

```
library("glmmTMB")

smokeModelT = glmmTMB(
  chewing_tobacco_snuff_or ~ ageC * Sex +
    RuralUrban + Race + (1 | state / school),
  data = smokeSub,
  family = binomial(link = "logit")
)

summary(smokeModelT)
```

```
##  Family: binomial  ( logit )
## Formula:
## chewing_tobacco_snuff_or ~ ageC * Sex + RuralUrban + Race + (1 |
##     state/school)
## Data: smokeSub
##
##      AIC      BIC   logLik deviance df.resid
##   4973.4   5068.5  -2474.7   4949.4    20382
##
## Random effects:
##
## Conditional model:
##  Groups       Name        Variance Std.Dev.
##  school:state (Intercept) 0.56307  0.7504
##  state        (Intercept) 0.09916  0.3149
## Number of obs: 20394, groups:  school:state, 207; state, 35
```

```
##
## Conditional model:
##                 Estimate Std. Error z value Pr(>|z|)
## (Intercept)     -3.07507    0.17166 -17.914  < 2e-16 ***
## ageC             0.35857    0.02994  11.975  < 2e-16 ***
## SexF            -2.03923    0.12579 -16.211  < 2e-16 ***
## RuralUrbanRural  1.00216    0.18995   5.276 1.32e-07 ***
## Raceblack       -1.52599    0.18678  -8.170 3.09e-16 ***
## Racehispanic    -0.51145    0.11932  -4.286 1.82e-05 ***
## Raceasian       -1.11633    0.35328  -3.160  0.00158 **
## Racenative       0.02942    0.29077   0.101  0.91941
## Racepacific      1.12190    0.39077   2.871  0.00409 **
## ageC:SexF       -0.32855    0.05556  -5.914 3.35e-09 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
knitr::kable(summary(smokeModelT)$coef$cond, digits = 2)
```

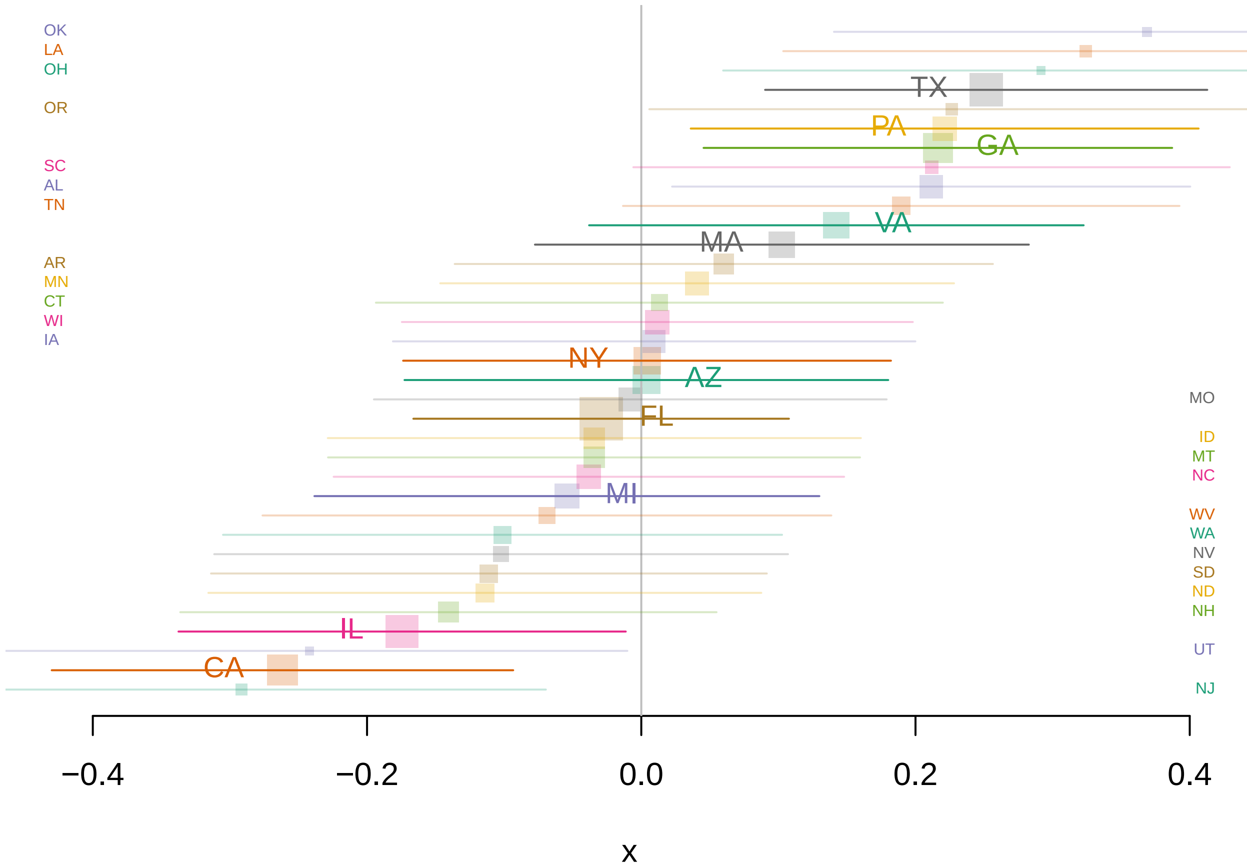
	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-3.08	0.17	-17.91	0.00
ageC	0.36	0.03	11.97	0.00
SexF	-2.04	0.13	-16.21	0.00
RuralUrbanRural	1.00	0.19	5.28	0.00
Raceblack	-1.53	0.19	-8.17	0.00
Racehispanic	-0.51	0.12	-4.29	0.00
Raceasian	-1.12	0.35	-3.16	0.00
Racenative	0.03	0.29	0.10	0.92
Racepacific	1.12	0.39	2.87	0.00
ageC:SexF	-0.33	0.06	-5.91	0.00

```
Pmisc::coefTable(smokeModelT)
```

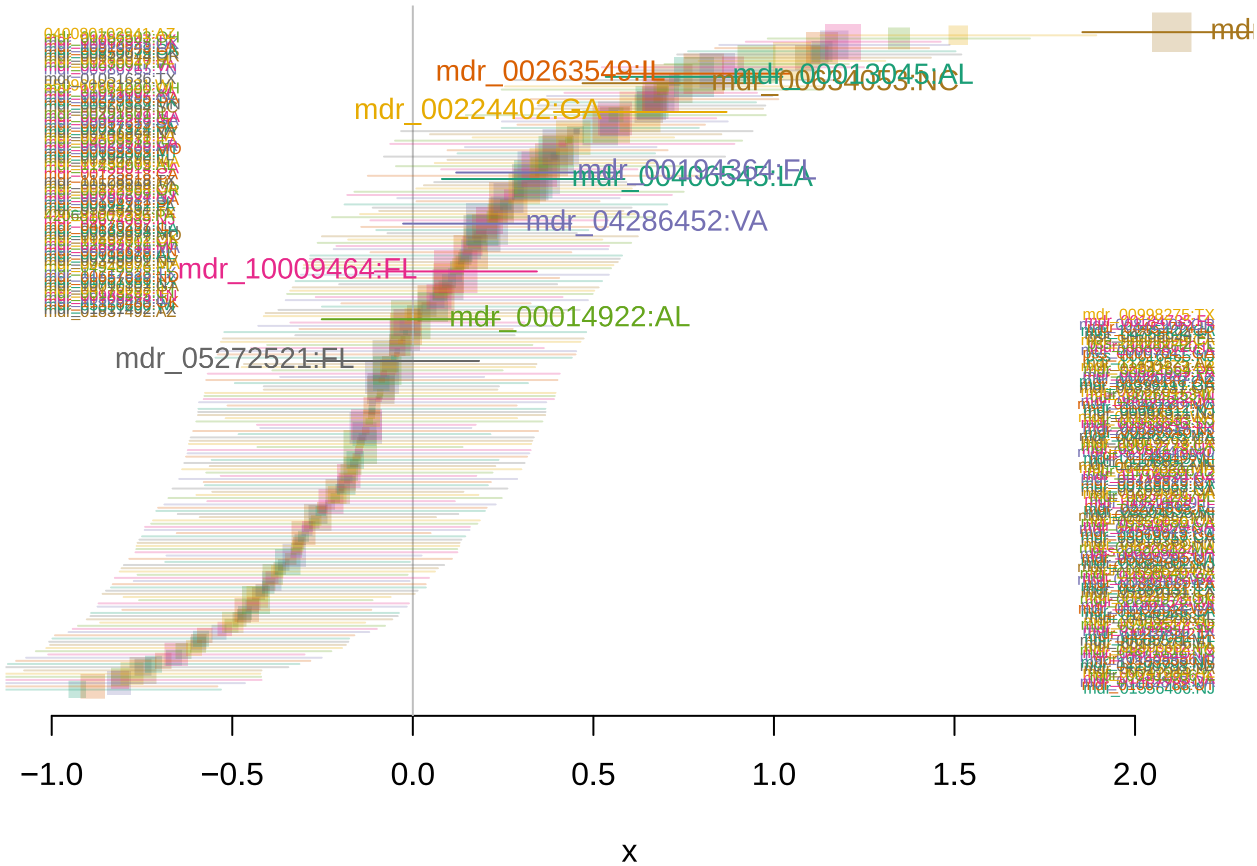
```
## $confint
##                                         2.5 %     97.5 %   Estimate
## cond.(Intercept)                   -3.4115164 -2.7386150 -3.0750657
## cond.ageC                           0.2998825  0.4172636  0.3585731
## cond.SexF                          -2.2857722 -1.7926850 -2.0392286
## cond.RuralUrbanRural                0.6298634  1.3744609  1.0021622
## cond.Raceblack                     -1.8920774 -1.1598957 -1.5259866
## cond.Racehispanic                  -0.7453189 -0.2775739 -0.5114464
## cond.Raceasian                     -1.8087463 -0.4239125 -1.1163294
## cond.Racenative                    -0.5404718  0.5993118  0.0294200
## cond.Racepacific                    0.3559952  1.8877982  1.1218967
## cond.ageC:SexF                     -0.4374384 -0.2196560 -0.3285472
## school:state.cond.Std.Dev.(Intercept)  0.5935253  0.9486883  0.7503802
## state.cond.Std.Dev.(Intercept)      0.1338326  0.7409208  0.3148958
##
## $tableRaw
## $tableRaw$cond
##                   Estimate Std. Error     z value     Pr(>|z|)
## (Intercept)     -3.0750657 0.17166167 -17.9135249 9.248859e-72
```

```
## ageC             0.3585731 0.02994471  11.9745053 4.833118e-33
## SexF            -2.0392286 0.12578986 -16.2113909 4.189782e-59
## RuralUrbanRural  1.0021622 0.18995183   5.2758754 1.321238e-07
## Raceblack       -1.5259866 0.18678449  -8.1697712 3.089750e-16
## Racehispanic    -0.5114464 0.11932490  -4.2861665 1.817828e-05
## Raceasian       -1.1163294 0.35328043  -3.1598959 1.578255e-03
## Racenative       0.0294200 0.29076645   0.1011809 9.194069e-01
## Racepacific      1.1218967 0.39077323   2.8709661 4.092194e-03
## ageC:SexF       -0.3285472 0.05555774  -5.9136166 3.346763e-09
##
## $tableRaw$zi
## NULL
##
## $tableRaw$disp
## NULL
##
##
## $table
##                   variable         level        est      2.5 %     97.5 %
## (Intercept)       ref prob M:Urban:white 0.04414757 0.03193748 0.06073286
## ageC                  ageC               1.43128563 1.34970025 1.51780261
## SexF                   Sex             F 0.13012905 0.10169550 0.16651248
## RuralUrbanRural RuralUrban         Rural 2.72416560 1.87735419 3.95294520
## Raceblack             Race         black 0.21740647 0.15075829 0.31351889
## Racehispanic          Race      hispanic 0.59962765 0.47458292 0.75761958
## Raceasian             Race         asian 0.32747964 0.16385944 0.65448117
## Racenative            Race        native 1.02985704 0.58247340 1.82086518
## Racepacific           Race       pacific 3.07067281 1.42760074 6.60480990
## ageC:SexF         ageC:Sex             F 0.71996894 0.64568831 0.80279489
## school:state.SD         sd  school:state 0.75038024 0.59352531 0.94868828
## state.SD                sd         state 0.31489584 0.13383264 0.74092084
```

```r
Pmisc::ranefPlot(smokeModelT,
                 grpvar = "state",
                 level = 0.5,
                 maxNames = 12)
```


OK
LA
OH
OR
SC
AL
TN
AR
MN
CT
WI
IA
TX
PA
GA
VA
MA
NY
AZ
FL
MI
IL
CA
MO
ID
MT
NC
WV
WA
NV
SD
ND
NH
UT
NJ
−0.4
−0.2
0.0
0.2
0.4
x

```r
Pmisc::ranefPlot(
  smokeModelT,
  grpvar = "school:state",
  level = 0.5,
  maxNames = 12,
  xlim = c(-1, 2.2)
)
```



Question 2.a

The model can be represented by

$$\begin{aligned} Y_{ij} \mid A, B &\sim Binomial(N_{ij}, \mu_{ij}) \\ h(\mu_{ij}) = logit(\mu_{ij}) = \frac{\mu_{ij}}{1-\mu_{ij}} &= X_{ij}\beta + A_i + B_{ij} \\ A_i &\sim N(0, \sigma_A^2) \\ B_{ij} &\sim N(0, \sigma_B^2) \end{aligned}$$

where

- Y_{ij} is the number of people who have used chewing tobacco, snuff, or dip on 1 or more days in the past 30 days, from the jth school of the ith state.
- N_{ij} is the number of people in the jth school of the ith state.
- μ_{ij} is the proportion of the people who have used chewing tobacco, snuff, or dip on 1 or more days in the past 30 days, from the jth school of the ith state.
- A_i is the state i's deviation from the population average
- B_{ij} is the ith state's j's school's deviation from the population average.
- X_{ij} is the covariate matrix for the jth school of the ith state.
- $h(\mu_{ij})$ is the logit function.

`smokeModelT` is a Generalized Linear Mixed Model. The difference between `smokeModelT` and the Generalized Linear Model is that `smokeModelT` contains nested random effects from `state` and `school`. It assumes that the state and the school that the students are from affects the number of people who have used chewing tobacco, snuff, or dip on 1 or more days in the past 30 days.

Question 2.b

The generalized linear mixed model with a logit link is more appropriate for this dataset than a linear mixed model because the responses are binary, and we are interested in the number of success (number of people who have used chewing tobacco, snuff, or dip on 1 or more days in the past 30 days) out of a fixed number of trials (the total number of people within the specific subgroup).

Question 2.c

From the table output using `Pmisc::coefTable(smokeModelT)`, the last two lines of the table represents the standard deviation explained by schools nested within states and states. We can see that one standard deviation difference in school nested in state level variation increases weight by $100 \times [\exp(0.75) - 1] = 111.70\%$, where as one standard deviation difference in state level variation increases weight by $100 \times [\exp(0.31) - 1] = 36.34\%$. This means that the difference between schools within a state is much greater than the state-level differences.

Also, according to the plot generated using `state` as the group variable, there is a trend and very little overlap between the confidence intervals, meaning that using `state` as a random variable is appropriate. However, the plot generated using `school:state` indicates that there is a greater trend than the plot generated using just `state`. The plot is right skewed (there are more schools with value greater than 0), and the confidence intervals also do not overlap.

The two evidence above indicate that differences between schools within a state in chewing tobacco usage amongst high school students are much larger than state-level differences, contradicting to the hypothesis. This suggests that if one was interested in identifying locations with many tobacco chewers, it would be more important to find individual schools with high chewing rates, rather than just targeting those states where chewing is most common.

Question 3

```r
pedestrainFile = Pmisc::downloadIfOld('http://pbrown.ca/teaching/303/data/pedestrians.rds')
pedestrians = readRDS(pedestrainFile)
pedestrians = pedestrians[!is.na(pedestrians$time), ]
pedestrians$y = pedestrians$Casualty_Severity == 'Fatal'
```

```r
theGlm = glm(
  y ~ sex + age + Light_Conditions + Weather_Conditions,
  data = pedestrians,
  family = binomial(link = "logit")
)
knitr::kable(summary(theGlm)$coef, digits = 3)
```

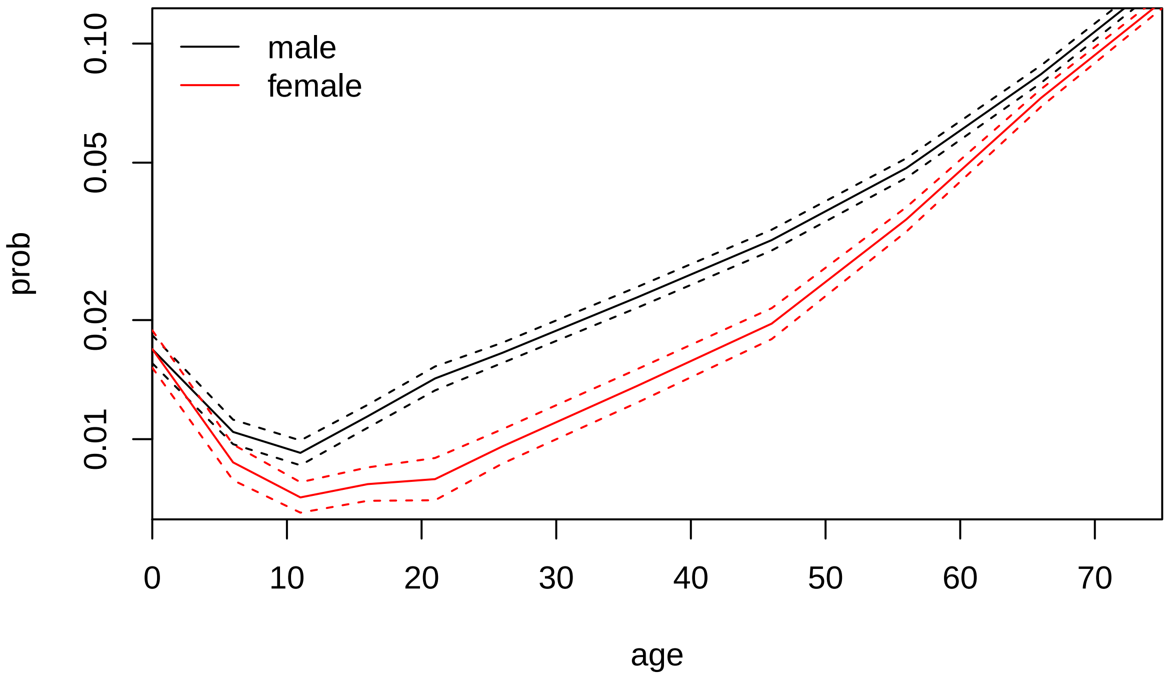
	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-4.177	0.020	-203.929	0.000
sexFemale	-0.275	0.011	-24.665	0.000
age0 - 5	0.186	0.032	5.831	0.000
age6 - 10	-0.357	0.030	-12.030	0.000
age11 - 15	-0.504	0.029	-17.668	0.000
age16 - 20	-0.338	0.027	-12.298	0.000
age21 - 25	-0.159	0.029	-5.457	0.000
age36 - 45	0.324	0.027	12.213	0.000
age46 - 55	0.660	0.026	25.030	0.000
age56 - 65	1.138	0.025	45.355	0.000
age66 - 75	1.760	0.023	75.234	0.000
ageOver 75	2.328	0.022	104.302	0.000
Light_ConditionsDarkness - lights lit	0.995	0.012	81.220	0.000
Light_ConditionsDarkness - lights unlit	1.176	0.052	22.415	0.000
Light_ConditionsDarkness - no lighting	2.765	0.021	131.303	0.000
Light_ConditionsDarkness - lighting unknown	0.259	0.068	3.788	0.000
Weather_ConditionsRaining no high winds	-0.214	0.017	-12.957	0.000
Weather_ConditionsSnowing no high winds	-0.751	0.092	-8.136	0.000
Weather_ConditionsFine + high winds	0.175	0.037	4.774	0.000
Weather_ConditionsRaining + high winds	-0.066	0.040	-1.648	0.099
Weather_ConditionsSnowing + high winds	-0.550	0.172	-3.193	0.001
Weather_ConditionsFog or mist	0.069	0.069	0.989	0.323

```r
theGlmInt = glm(
  y ~ sex * age + Light_Conditions + Weather_Conditions,
  data = pedestrians,
  family = binomial(link = "logit")
)
knitr::kable(summary(theGlmInt)$coef, digits = 3)
```

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-4.103	0.023	-179.887	0.000
sexFemale	-0.545	0.044	-12.425	0.000
age0 - 5	0.021	0.039	0.544	0.587
age6 - 10	-0.460	0.035	-13.105	0.000
age11 - 15	-0.582	0.035	-16.625	0.000
age16 - 20	-0.369	0.032	-11.461	0.000
age21 - 25	-0.149	0.033	-4.501	0.000
age36 - 45	0.322	0.031	10.508	0.000
age46 - 55	0.656	0.031	21.281	0.000
age56 - 65	1.075	0.030	35.727	0.000
age66 - 75	1.622	0.029	56.315	0.000
ageOver 75	2.180	0.027	79.597	0.000
Light_ConditionsDarkness - lights lit	0.990	0.012	80.676	0.000
Light_ConditionsDarkness - lights unlit	1.174	0.052	22.399	0.000
Light_ConditionsDarkness - no lighting	2.746	0.021	130.165	0.000
Light_ConditionsDarkness - lighting unknown	0.257	0.068	3.759	0.000
Weather_ConditionsRaining no high winds	-0.211	0.017	-12.764	0.000
Weather_ConditionsSnowing no high winds	-0.746	0.092	-8.075	0.000
Weather_ConditionsFine + high winds	0.176	0.037	4.803	0.000
Weather_ConditionsRaining + high winds	-0.062	0.040	-1.545	0.122
Weather_ConditionsSnowing + high winds	-0.548	0.172	-3.189	0.001
Weather_ConditionsFog or mist	0.065	0.069	0.943	0.346
sexFemale:age0 - 5	0.546	0.068	7.970	0.000
sexFemale:age6 - 10	0.367	0.066	5.606	0.000
sexFemale:age11 - 15	0.285	0.062	4.603	0.000
sexFemale:age16 - 20	0.150	0.062	2.408	0.016
sexFemale:age21 - 25	-0.041	0.069	-0.596	0.551
sexFemale:age36 - 45	0.029	0.062	0.475	0.635
sexFemale:age46 - 55	0.059	0.060	0.976	0.329
sexFemale:age56 - 65	0.246	0.056	4.417	0.000
sexFemale:age66 - 75	0.406	0.052	7.877	0.000
sexFemale:ageOver 75	0.411	0.049	8.348	0.000

```r
newData = expand.grid(
  age = levels(pedestrians$age),
  sex = c('Male', 'Female'),
  Light_Conditions = levels(pedestrians$Light_Conditions)[1],
  Weather_Conditions = levels(pedestrians$Weather_Conditions)[1]
)
thePred = as.matrix(as.data.frame(
  predict(theGlmInt, newData, se.fit = TRUE)[1:2])) %*% Pmisc::ciMat(0.99)
thePred = as.data.frame(thePred)
thePred$sex = newData$sex
thePred$age = as.numeric(gsub("[[:punct:]].*|[[:alpha:]]", "", newData$age))
toPlot2 = reshape2::melt(thePred, id.vars = c('age', 'sex'))
toPlot3 = reshape2::dcast(toPlot2, age ~ sex + variable)

matplot(
  toPlot3$age,
  exp(toPlot3[, -1]),
  type = 'l',
  log = 'y',
  col = rep(c('black', 'red'), each = 3),
  lty = rep(c(1, 2, 2), 2),
  ylim = c(0.007, 0.11),
  xaxs = 'i',
  xlab = 'age',
  ylab = 'prob'
)
legend(
  'topleft',
  lty = 1,
  col = c('black', 'red'),
  legend = c('male', 'female'),
  bty = 'n'
)
```



male
female
prob
0.10
0.05
0.02
0.01
0
10
20
30
40
50
60
70
age

Question 3.a

Question 3.b

Question 3.c