

Models

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```
library(tidyverse)
```

```
## -- Attaching packages -----
```

```
## v ggplot2 3.2.1    v purrr  0.3.2
## v tibble  2.1.3    v dplyr  0.8.3
## v tidyr   1.0.0    v stringr 1.4.0
## v readr   1.3.1    v forcats 0.4.0
```

```
## -- Conflicts -----
```

```
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
```

```
library(geepack)
```

```
library(MASS)
```

```
##
```

```
## Attaching package: 'MASS'
```

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

```
##
```

```
##      select
```

Read data

```
alc_dat <- readxl::read_xls("./data/ALCDEP.xls")
```

```
alc_dat <- janitor::clean_names(alc_dat) %>%
  mutate(treatment = factor(treatment)) %>%
  mutate(gender = factor(gender, levels = c(0,1), labels = c("Male", "Female")))
```

```
alc_dat_long <- alc_dat %>%
  pivot_longer(nd0:nd60, names_to = "days", values_to = "drinks", names_prefix = "nd")
```

Fit GEE models

```
alc_dat_long <- alc_dat_long %>%
  mutate(exposure = 30)
```

```
pois_gee <- geeglm(drinks ~ treatment*days + gender,
  family = poisson,
  data = alc_dat_long,
  id = sid,
  corstr = "ar1")
```

```
summary(pois_gee)
```

```
##
## Call:
## geeglm(formula = drinks ~ treatment * days + gender, family = poisson,
##       data = alc_dat_long, id = sid, corstr = "ar1")
##
## Coefficients:
##              Estimate Std.err      Wald Pr(>|W|)
## (Intercept)      5.22610  0.01571 1.106e+05  <2e-16 ***
## treatment2      -0.01593  0.01907  6.980e-01    0.403
## treatment3      -0.02585  0.02040  1.606e+00    0.205
## days30          -0.39386  0.01425  7.642e+02  <2e-16 ***
## days60          -0.41353  0.01253  1.089e+03  <2e-16 ***
## genderFemale    -1.01273  0.01493  4.602e+03  <2e-16 ***
## treatment2:days30 -0.01293  0.01901  4.620e-01    0.497
## treatment3:days30 -0.39227  0.02087  3.534e+02  <2e-16 ***
## treatment2:days60 -0.38624  0.01892  4.165e+02  <2e-16 ***
## treatment3:days60 -0.38748  0.01928  4.038e+02  <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Estimated Scale Parameters:
##              Estimate Std.err
## (Intercept)      1.901  0.1119
##
## Correlation: Structure = ar1 Link = identity
##
## Estimated Correlation Parameters:
##              Estimate Std.err
## alpha          0.5486  0.03297
## Number of clusters: 314 Maximum cluster size: 3
```

```
pois_gee_unst <- geeglm(drinks ~ treatment*days + gender,
  family = poisson,
  data = alc_dat_long,
  id = sid,
  corstr = "unstructured")
```

```
summary(pois_gee_unst)
```

```
##
## Call:
## geeglm(formula = drinks ~ treatment * days + gender, family = poisson,
##       data = alc_dat_long, id = sid, corstr = "unstructured")
##
## Coefficients:
##              Estimate Std.err      Wald Pr(>|W|)
## (Intercept)      5.2252  0.0157 1.11e+05  <2e-16 ***
## treatment2      -0.0157  0.0191  6.80e-01    0.41
## treatment3      -0.0257  0.0204  1.58e+00    0.21
## days30          -0.3939  0.0142  7.64e+02  <2e-16 ***
## days60          -0.4135  0.0125  1.09e+03  <2e-16 ***
## genderFemale    -1.0095  0.0144  4.89e+03  <2e-16 ***
```

```

## treatment2:days30 -0.0129 0.0190 4.60e-01 0.50
## treatment3:days30 -0.3923 0.0209 3.53e+02 <2e-16 ***
## treatment2:days60 -0.3862 0.0189 4.17e+02 <2e-16 ***
## treatment3:days60 -0.3875 0.0193 4.04e+02 <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Estimated Scale Parameters:
##           Estimate Std.err
## (Intercept)      1.9    0.112
##
## Correlation: Structure = unstructured Link = identity
##
## Estimated Correlation Parameters:
##           Estimate Std.err
## alpha.1:2      0.529 0.0453
## alpha.1:3      0.500 0.0485
## alpha.2:3      0.352 0.0455
## Number of clusters: 314 Maximum cluster size: 3

```

```

pois_gee_int <- geeglm(drinks ~ treatment*days + treatment*gender,
  family = poisson,
  data = alc_dat_long,
  id = sid,
  corstr = "ar1")

summary(pois_gee_int) #ns

```

```

##
## Call:
## geeglm(formula = drinks ~ treatment * days + treatment * gender,
##   family = poisson, data = alc_dat_long, id = sid, corstr = "ar1")
##
## Coefficients:
##              Estimate Std.err      Wald Pr(>|W|)
## (Intercept)      5.2287 0.0178 85835.74 <2e-16 ***
## treatment2      -0.0197 0.0225   0.76   0.38
## treatment3      -0.0298 0.0247   1.47   0.23
## days30          -0.3939 0.0142  764.23 <2e-16 ***
## days60          -0.4135 0.0125 1089.27 <2e-16 ***
## genderFemale    -1.0222 0.0235 1884.16 <2e-16 ***
## treatment2:days30 -0.0129 0.0190   0.46   0.50
## treatment3:days30 -0.3923 0.0209  353.36 <2e-16 ***
## treatment2:days60 -0.3862 0.0189  416.54 <2e-16 ***
## treatment3:days60 -0.3875 0.0193  403.80 <2e-16 ***
## treatment2:genderFemale 0.0150 0.0351   0.18   0.67
## treatment3:genderFemale 0.0159 0.0370   0.18   0.67
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Estimated Scale Parameters:
##           Estimate Std.err
## (Intercept)      1.9    0.112
##
## Correlation: Structure = ar1 Link = identity

```

```
##
## Estimated Correlation Parameters:
##      Estimate Std.err
## alpha    0.549    0.033
## Number of clusters: 314    Maximum cluster size: 3

pois_gee_intd <- geeglm(drinks ~ treatment*days + days*gender,
  family = poisson,
  data = alc_dat_long,
  id = sid,
  corstr = "ar1")

broom::tidy(pois_gee_intd, exponentiate = TRUE, conf.int = TRUE) #significant effect for day 60 but ver

## # A tibble: 12 x 7
##   term                estimate std.error statistic p.value conf.low conf.high
##   <chr>              <dbl>     <dbl>    <dbl>   <dbl>   <dbl>   <dbl>
## 1 (Intercept)        185.        0.0158  1.09e+5    0       180.    191.
## 2 treatment2          0.985      0.0191  6.17e-1  0.432    0.949    1.02
## 3 treatment3          0.975      0.0204  1.51e+0  0.219    0.937    1.02
## 4 days30             0.677      0.0150  6.72e+2    0       0.658    0.698
## 5 days60             0.670      0.0136  8.62e+2    0       0.652    0.688
## 6 genderFemale       0.368      0.0172  3.38e+3    0       0.356    0.381
## 7 treatment2:days~   0.986      0.0190  5.39e-1  0.463    0.950    1.02
## 8 treatment3:days~   0.675      0.0209  3.53e+2    0       0.648    0.703
## 9 treatment2:days~   0.677      0.0189  4.24e+2    0       0.653    0.703
## 10 treatment3:days~  0.677      0.0193  4.08e+2    0       0.652    0.703
## 11 days30:genderFe~  0.984      0.0199  6.55e-1  0.418    0.947    1.02
## 12 days60:genderFe~  0.953      0.0197  5.84e+0  0.0156   0.917    0.991

anova(pois_gee, pois_gee_int)

## Analysis of 'Wald statistic' Table
##
## Model 1 drinks ~ treatment * days + treatment * gender
## Model 2 drinks ~ treatment * days + gender
##   Df    X2 P(>|Chi|)
## 1  2 0.257    0.88

anova(pois_gee, pois_gee_intd)

## Analysis of 'Wald statistic' Table
##
## Model 1 drinks ~ treatment * days + days * gender
## Model 2 drinks ~ treatment * days + gender
##   Df    X2 P(>|Chi|)
## 1  2 5.86    0.053 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

##Trajectories##
#get contrast of treatment 3 days 60 to treatment 3 days 30
#get contrast of treatment 1 days 60 to treatment 1 days 30
#get contrast of treatment 3 days 60 to treatment 3 days 30

## Treatment effect ##
```

```

#get contrast of treatment 3 days 60 to treatment 2 days 60
#get contrast of treatment 3 days 60 to treatment 2 days 20

colnames(pois_gee$geese$vbeta) = names(coef(pois_gee))
rownames(pois_gee$geese$vbeta) = names(coef(pois_gee))
var_b0 = pois_gee$geese$vbeta["(Intercept)","(Intercept)"]
var_b1 = pois_gee$geese$vbeta["treatment2","treatment2"]
var_b2 = pois_gee$geese$vbeta["(Intercept)","(Intercept)"]
var_b3 = pois_gee$geese$vbeta["(Intercept)","(Intercept)"]
var_b4 = pois_gee$geese$vbeta["(Intercept)","(Intercept)"]

var_b6 = pois_gee$geese$vbeta["genderFemale","genderFemale"]
cov_b0b6 = pois_gee$geese$vbeta["genderFemale","(Intercept)"]
women_count_baseline = exp(coef(pois_gee)["(Intercept)"] + coef(pois_gee)["genderFemale"])
women_var_baseline = var_b0 + var_b6 + 2*cov_b0b6
women_ci_baseline = c(exp(coef(pois_gee)["(Intercept)"] + coef(pois_gee)["genderFemale"] - qchisq(0.975, 1)*sqrt(women_var_baseline),
exp(coef(pois_gee)["(Intercept)"] + coef(pois_gee)["genderFemale"] + qchisq(0.975, 1)*sqrt(women_var_baseline)))

var_b4 = pois_gee$geese$vbeta["days30","days30"]
var_b5 = pois_gee$geese$vbeta["days60","days60"]
cov_b4b5 = pois_gee$geese$vbeta["days30","days60"]
d30_to_d60_rr = exp(coef(pois_gee)["days60"] - coef(pois_gee)["days30"])
d30_d60_var = var_b4 + var_b5 - 2*cov_b4b5
d30_to_d60_ci = c(exp(coef(pois_gee)["days60"] - coef(pois_gee)["days30"] - qchisq(0.975, 1)*sqrt(d30_d60_var),
exp(coef(pois_gee)["days60"] - coef(pois_gee)["days30"] + qchisq(0.975, 1)*sqrt(d30_d60_var)))

#treatment 2 to treatment 1
var_trt2 = pois_gee$geese$vbeta["treatment2","treatment2"]
var_trt2d30 = pois_gee$geese$vbeta["treatment2:days30","treatment2:days30"]
cov_day30trt2 = pois_gee$geese$vbeta["treatment2:days30","treatment2"]
trt2day30totrt1day30_rr = exp(coef(pois_gee)["treatment2"] + coef(pois_gee)["treatment2:days30"])
trt2day30totrt1day30_var = var_trt2 + var_trt2d30 - 2*cov_day30trt2
trt2day30totrt1day30_ci = c(exp(log(trt2day30totrt1day30_rr) - qchisq(0.975, 1)*sqrt(trt2day30totrt1day30_var),
exp(log(trt2day30totrt1day30_rr) + qchisq(0.975, 1)*sqrt(trt2day30totrt1day30_var))))

var_trt2d60 = pois_gee$geese$vbeta["treatment2:days60","treatment2:days60"]
cov_day60trt2 = pois_gee$geese$vbeta["treatment2:days60","treatment2"]
trt2day60totrt1day60_rr = exp(coef(pois_gee)["treatment2"] + coef(pois_gee)["treatment2:days60"])
trt2day60totrt1day60_var = var_trt2 + var_trt2d60 + 2*cov_day60trt2
trt2day60totrt1day60_ci = c(exp(log(trt2day60totrt1day60_rr) - qchisq(0.975, 1)*sqrt(trt2day60totrt1day60_var),
exp(log(trt2day60totrt1day60_rr) + qchisq(0.975, 1)*sqrt(trt2day60totrt1day60_var))))

cov_day60day30trt2 = pois_gee$geese$vbeta["treatment2:days60","treatment2:days30"]
trt2trt1_day60today30_r_rr = exp(coef(pois_gee)["treatment2:days60"] - coef(pois_gee)["treatment2:days30"])
trt2trt1_day60today30_r_var = var_trt2d30 + var_trt2d60 - 2*cov_day60day30trt2
trt2trt1_day60today30_r_ci = c(exp(log(trt2trt1_day60today30_r_rr) - qchisq(0.975, 1)*sqrt(trt2trt1_day60today30_r_var),
exp(log(trt2trt1_day60today30_r_rr) + qchisq(0.975, 1)*sqrt(trt2trt1_day60today30_r_var))))

#treatment 3 to treatment 1
var_trt3 = pois_gee$geese$vbeta["treatment3","treatment3"]
var_trt3d30 = pois_gee$geese$vbeta["treatment3:days30","treatment3:days30"]
cov_day30trt3 = pois_gee$geese$vbeta["treatment3:days30","treatment3"]
trt3day30totrt1day30_rr = exp(coef(pois_gee)["treatment3"] + coef(pois_gee)["treatment3:days30"])
trt3day30totrt1day30_var = var_trt3 + var_trt3d30 - 2*cov_day30trt3
trt3day30totrt1day30_ci = c(exp(log(trt3day30totrt1day30_rr) - qchisq(0.975, 1)*sqrt(trt3day30totrt1day30_var),
exp(log(trt3day30totrt1day30_rr) + qchisq(0.975, 1)*sqrt(trt3day30totrt1day30_var))))

var_trt3d60 = pois_gee$geese$vbeta["treatment3:days60","treatment3:days60"]
cov_day60trt3 = pois_gee$geese$vbeta["treatment3:days60","treatment3"]

```

```

trt3day60totrt1day60_rr = exp(coef(pois_gee)["treatment3"] + coef(pois_gee)["treatment3:days60"])
trt3day60totrt1day60_var = var_trt3 + var_trt3d60 + 2*cov_day60trt3
trt3day60totrt1day60_ci = c(exp(log(trt3day60totrt1day60_rr) - qchisq(0.975, 1)*sqrt(trt3day60totrt1day60_var))
                             , exp(log(trt3day60totrt1day60_rr) + qchisq(0.975, 1)*sqrt(trt3day60totrt1day60_var)))

cov_day60day30trt3 = pois_gee$geese$vbeta["treatment3:days60", "treatment3:days30"]
trt3trt1_day60today30_r_rr = exp(coef(pois_gee)["treatment3:days60"] - coef(pois_gee)["treatment3:days30"])
trt3trt1_day60today30_r_var = var_trt3d30 + var_trt3d60 - 2*cov_day60day30trt3
trt3trt1_day60today30_r_ci = c(exp(log(trt3trt1_day60today30_r_rr) - qchisq(0.975, 1)*sqrt(trt3trt1_day60today30_r_var))
                              , exp(log(trt3trt1_day60today30_r_rr) + qchisq(0.975, 1)*sqrt(trt3trt1_day60today30_r_var)))

#treatment 3 to treatment 2
cov_day30trt3trt2 = pois_gee$geese$vbeta["treatment3:days30", "treatment2"]
cov_day30trt3day30trt2 = pois_gee$geese$vbeta["treatment3:days30", "treatment2:days30"]
cov_trt3day30trt2 = pois_gee$geese$vbeta["treatment3", "treatment2:days30"]
cov_trt3trt2 = pois_gee$geese$vbeta["treatment3", "treatment2"]
trt3day30totrt2day30_rr = exp(coef(pois_gee)["treatment3"] + coef(pois_gee)["treatment3:days30"] -
                              coef(pois_gee)["treatment2"] - coef(pois_gee)["treatment2:days30"])
trt3day30totrt2day30_var = var_trt3 + var_trt3d30 + var_trt2 + var_trt2d30 + 2*cov_day30trt3 + 2*cov_day30trt2
trt3day30totrt2day30_ci = c(exp(log(trt3day30totrt2day30_rr) - qchisq(0.975, 1)*sqrt(trt3day30totrt2day30_var))
                             , exp(log(trt3day30totrt2day30_rr) + qchisq(0.975, 1)*sqrt(trt3day30totrt2day30_var)))

cov_day60trt3trt2 = pois_gee$geese$vbeta["treatment3:days60", "treatment2"]
cov_day60trt3day60trt2 = pois_gee$geese$vbeta["treatment3:days60", "treatment2:days60"]
cov_trt3day60trt2 = pois_gee$geese$vbeta["treatment3", "treatment2:days60"]
cov_trt3trt2 = pois_gee$geese$vbeta["treatment3", "treatment2"]
trt3day60totrt2day60_rr = exp(coef(pois_gee)["treatment3"] + coef(pois_gee)["treatment3:days60"] -
                              coef(pois_gee)["treatment2"] - coef(pois_gee)["treatment2:days60"])
trt3day60totrt2day60_var = var_trt3 + var_trt3d30 + var_trt2 + var_trt2d30 + 2*cov_day30trt3 + 2*cov_day60trt3
trt3day60totrt2day60_ci = c(exp(log(trt3day60totrt2day60_rr) - qchisq(0.975, 1)*sqrt(trt3day60totrt2day60_var))
                             , exp(log(trt3day60totrt2day60_rr) + qchisq(0.975, 1)*sqrt(trt3day60totrt2day60_var)))

broom::tidy(pois_gee, exponentiate = TRUE, conf.int = TRUE)

```

```

## # A tibble: 10 x 7
##   term                estimate std.error statistic p.value conf.low conf.high
##   <chr>                <dbl>    <dbl>    <dbl>    <dbl>    <dbl>    <dbl>
## 1 (Intercept)         186.      0.0157  1.11e+5     0        180.     192.
## 2 treatment2           0.984     0.0191  6.98e-1   0.403     0.948     1.02
## 3 treatment3           0.974     0.0204  1.61e+0   0.205     0.936     1.01
## 4 days30              0.674     0.0142  7.64e+2     0        0.656     0.694
## 5 days60              0.661     0.0125  1.09e+3     0        0.645     0.678
## 6 genderFemale        0.363     0.0149  4.60e+3     0        0.353     0.374
## 7 treatment2:days~    0.987     0.0190  4.62e-1   0.497     0.951     1.02
## 8 treatment3:days~    0.676     0.0209  3.53e+2     0        0.648     0.704
## 9 treatment2:days~    0.680     0.0189  4.17e+2     0        0.655     0.705
## 10 treatment3:days~   0.679     0.0193  4.04e+2     0        0.654     0.705

```

1. Treatment effect question

At baseline, the expected count of past-30 day alcoholic drinks for men is 186 (95% Wald CI (180, 192)), and for women the expected count is 67.584 (95% Wald CI 62.576 , 72.993), in treatment 1. These estimates of the baseline count by gender is not significantly different between treatments, indicating that randomization was successful.

A treatment by gender interaction term was considered, but it was not significant, which is unsurprising

examining the plot trajectory.

The ratio of the expected count of past-30 day alcoholic drinks for those in treatment 1 30 days after baseline compared to baseline is 0.674 (95% CI 0.656 - 0.694), adjusted for gender. The ratio of the expected count of past-30 day alcoholic drinks for those in treatment 1 60 days after baseline compared to baseline is 0.661 (95% CI 0.645 - 0.678). From day 30 to day 60, the ratio of the expected count of past-30 day alcoholic drinks for those in treatment 1 is 0.981 and the 95% CI is (0.906, 1.062). This means that the expected count of past-30 day alcoholic drinks is not significantly different from day 30 to day 60 for the population of patients in treatment 1.

The ratio of the expected count of past-30 day alcoholic drinks for those in treatment 2 at 30 days compared to those in treatment 1 at 30 days is 0.972 (95% CI 0.83, 1.137), adjusted for gender. The ratio of the expected count of past-30 day alcoholic drinks for those in treatment 2 at 60 days compared to those in treatment 1 at 60 days is 0.669 (95% CI 0.599, 0.747). And the difference-in-difference, that is, the ratio of the ratio of expected count of past-30 day alcoholic drinks for those in treatment 2 at 60 days compared to at 30 days to the ratio of expected count of past-30 day alcoholic drinks for those in treatment 1 at 60 days compared to at 30 days is 0.688 (95% CI 0.613, 0.773). This means that while treatment 1 and 2 do not differ at days 30 in terms of the expected counts of alcoholic drinks, they do differ from the days 30 to days 60 period, where those in treatment 2 have a ratio of expected drinks from days 30 to days 60 that is 0.688 times that of treatment 1 (which is not significantly different from 1, as shown above). These patterns apply to both gender subpopulations.

The ratio of the expected count of past-30 day alcoholic drinks for those in treatment 3 at 30 days compared to those in treatment 1 at 30 days is 0.678 (95% CI 0.555, 0.781), adjusted for gender. The ratio of the expected count of past-30 day alcoholic drinks for those in treatment 3 at 60 days compared to those in treatment 1 at 60 days is 0.661 (95% CI 0.589, 0.743). And the difference-in-difference, that is, the ratio of the ratio of expected count of past-30 day alcoholic drinks for those in treatment 2 at 60 days compared to at 30 days to the ratio of expected count of past-30 day alcoholic drinks for those in treatment 1 at 60 days compared to at 30 days is 1.005 (95% CI 0.896, 1.127). This means treatment 1 and 3 differ at days 30 and at days 60 in terms of the expected counts of alcoholic drinks, with treatment 3 being more efficacious at reducing counts of alcoholic drinks. But they do not differ in terms of their respective change in expected count of alcoholic drinks from the days 30 to days 60 period, indicating that treatment 3, similar to treatment 1, has most of its reduction effects in the first block of time between day 0 and day 30. These patterns apply to both gender subpopulations.

The ratio of the expected count of past-30 day alcoholic drinks for those in treatment 3 at 30 days compared to those in treatment 2 at 30 days is 0.658 (95% CI 0.606, 0.758), adjusted for gender. The ratio of the expected count of past-30 day alcoholic drinks for those in treatment 3 at 60 days compared to those in treatment 2 at 60 days is 0.989 (95% CI 0.89, 1.098). This means treatment 2 and 3 differ at days 30 in terms of the expected counts of alcoholic drinks, with treatment 3 being more efficacious, but they do not differ at days 60.

Given the information above, we can conclude the following:

- Patients in treatments 1 and 3 have similar trajectories of alcoholic drink consumption, with the reduction occurring between day 0 and day 30 and no significant reduction (or increase) between day 30 and day 60.
- But patients in treatment 3 have a steeper reduction from day 0 to 30 than those in treatment 1 (the 30-day count being 0.678 times that of treatment 1, or about an average of 85 drinks for men and 31 drinks for women in treatment 3 compared to an average of 125 drinks for men and 46 drinks for women in treatment 1).
- Patients in treatment 2 have a different trajectory: reduction occurs in both the day 0-30 blocks and day 30-60 blocks. Patients in treatment 2 do not have a significant difference in reduction compared to treatment 1 at 30 days, but at 60 days, the ratio of the expected count of past 30-day alcoholic drinks for treatment 2 versus treatment 1 is estimated as 0.669. And while they differ at 30 days, treatment 2

is not significantly different from treatment 3 in terms of the expected past-30 day count of alcoholic drinks at 60 days, (ratio estimated as 0.989).

- These trajectories and treatment effects are not significantly heterogenous in the gender subgroups; men and women differ in that women have a baseline expected count of alcoholic drinks about 0.363x that of men in this study. A treatment by gender term was tested and was nonsignificant by a Wald test at $\alpha = 0.05$), $\chi^2_2 = 0.251$, and similarly treatment by gender term was tested and was nonsignificant at $\alpha = 0.05$), $\chi^2_2 = 5.86$. Additional visual information supporting a lack of heterogeneity of treatment effects by gender is shown in Plot (XX).

fit mixed effect model to use negative binomial? nope - overdispersion is not important

```
pois_glmml <- lme4::lmer(drinks ~ treatment*days + gender + (1|sid),
  family = poisson,
  data = alc_dat_long)

## Warning in lme4::lmer(drinks ~ treatment * days + gender + (1 | sid),
## family = poisson, : calling lmer with 'family' is deprecated; please use
## glmer() instead

summary(pois_glmml)

## Generalized linear mixed model fit by maximum likelihood (Laplace
## Approximation) [glmerMod]
## Family: poisson ( log )
## Formula: drinks ~ treatment * days + gender + (1 | sid)
## Data: alc_dat_long
## Control:
## structure(list(optimizer = c("bobyqa", "Nelder_Mead"), calc.derivs = TRUE,
## use.last.params = FALSE, restart_edge = FALSE, boundary.tol = 1e-05,
## tolPwrss = 1e-07, compDev = TRUE, nAGQ0initStep = TRUE, checkControl = list(
## check.nobs.vs.rankZ = "ignore", check.nobs.vs.nlev = "stop",
## check.nlev.gtreq.5 = "ignore", check.nlev.gtr.1 = "stop",
## check.nobs.vs.nRE = "stop", check.rankX = "message+drop.cols",
## check.scaleX = "warning", check.formula.LHS = "stop",
## check.response.not.const = "stop"), checkConv = list(
## check.conv.grad = list(action = "warning", tol = 0.001,
## relTol = NULL), check.conv.singular = list(action = "message",
## tol = 1e-04), check.conv.hess = list(action = "warning",
## tol = 1e-06)), optCtrl = list()), class = c("glmerControl",
## "merControl"))
##
##      AIC      BIC   logLik deviance df.resid
##    7154    7207   -3566    7132     931
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -2.644 -0.581 -0.062  0.558  2.674
##
## Random effects:
## Groups Name          Variance Std.Dev.
## sid      (Intercept) 0.00978  0.0989
```



```
## Number of obs: 942, groups:  sid, 314
##
## Fixed effects:
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept)      5.2208    0.0145  359.82  <2e-16 ***
## treatment2       -0.0158    0.0185   -0.85    0.39
## treatment3       -0.0241    0.0188   -1.28    0.20
## days30           -0.3939    0.0136  -28.87  <2e-16 ***
## days60           -0.4135    0.0137  -30.13  <2e-16 ***
## genderFemale     -1.0142    0.0139  -73.22  <2e-16 ***
## treatment2:days30 -0.0129    0.0190   -0.68    0.50
## treatment3:days30 -0.3923    0.0207  -18.97  <2e-16 ***
## treatment2:days60 -0.3862    0.0203  -19.01  <2e-16 ***
## treatment3:days60 -0.3875    0.0208  -18.64  <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##               (Intr) trtmn2 trtmn3 days30 days60 gndrFm tr2:30 tr3:30 tr2:60
## treatment2   -0.676
## treatment3   -0.661  0.503
## days30       -0.379  0.297  0.292
## days60       -0.377  0.295  0.290  0.400
## genderFemal -0.417  0.068  0.060  0.000  0.000
## trtmnt2:d30  0.272 -0.412 -0.210 -0.719 -0.288  0.000
## trtmnt3:d30  0.250 -0.196 -0.387 -0.660 -0.264  0.000  0.474
## trtmnt2:d60  0.254 -0.385 -0.196 -0.270 -0.675  0.000  0.375  0.178
## trtmnt3:d60  0.249 -0.195 -0.385 -0.264 -0.660  0.000  0.190  0.350  0.446
```

```
library(glmTMB)
nb_glmm <- glmTMB(drinks ~ treatment*days + gender + (1|sid),
  family = nbinom1,
  data = alc_dat_long)
summary(nb_glmm)
```

```
## Family: nbinom1 ( log )
## Formula:      drinks ~ treatment * days + gender + (1 | sid)
## Data: alc_dat_long
##
##      AIC      BIC    logLik deviance df.resid
##    7156    7214    -3566    7132    930
##
## Random effects:
##
## Conditional model:
## Groups Name      Variance Std.Dev.
## sid (Intercept) 0.00978  0.0989
## Number of obs: 942, groups:  sid, 314
##
## Overdispersion parameter for nbinom1 family (): 7.82e-07
##
## Conditional model:
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept)      5.2208    0.0145    360  <2e-16 ***
## treatment2       -0.0158    0.0185    -1    0.39
```

```

## treatment3      -0.0241    0.0188     -1     0.20
## days30          -0.3939    0.0136    -29    <2e-16 ***
## days60          -0.4135    0.0137    -30    <2e-16 ***
## genderFemale    -1.0142    0.0139    -73    <2e-16 ***
## treatment2:days30 -0.0129    0.0190     -1     0.50
## treatment3:days30 -0.3923    0.0207    -19    <2e-16 ***
## treatment2:days60 -0.3862    0.0203    -19    <2e-16 ***
## treatment3:days60 -0.3875    0.0208    -19    <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```