Supplement

1 Read data

The following chunk reads the data and processes it for analysis.

```
gestures <- read_csv("./data/gestures.csv")

gestures_tot <- gestures %>%
  group_by(dyad, background, months, gesture) %>%
  summarise(
    count = sum(count),
    ct = sum(ct)
  ) %>%
  ungroup() %>%
  mutate(
    gesture = factor(gesture, levels = c("reach", "point", "ho_gv"))
  ) %>%
  mutate_if(is.character, as.factor) %>%
  mutate(
    back_o = ordered(background, levels = c("English", "Bengali", "Chinese"))
  )

contrasts(gestures_tot$back_o) <- "contr.treatment"

utterances <- read_csv("./data/utterances.csv")

utterances_tot <- utterances %>%
  group_by(dyad, background, months) %>%
  summarise(
    utterances = sum(utterances) # there are NAs that must be kept
  ) %>%
  ungroup() %>%
  mutate_if(is.character, as.factor) %>%
  mutate(
    back_o = ordered(background, levels = c("English", "Bengali", "Chinese"))
  )

contrasts(utterances_tot$back_o) <- "contr.treatment"

hg_tot <- filter(gestures_tot, gesture == "ho_gv")
reach_tot <- filter(gestures_tot, gesture == "reach")
point_tot <- filter(gestures_tot, gesture == "point")
all_tot <- gestures_tot %>%
  group_by(dyad, back_o, months) %>%
  summarise(count = sum(count), ct = sum(ct))

hg_point_lead <- gestures_tot %>%
  dplyr::select(-ct) %>%
  spread(gesture, count) %>%
  dplyr::select(-reach) %>%
  group_by(dyad) %>%
```

```
  mutate(
    lead_point = lead(point)
  ) %>%
  filter(months != 12)

reach_point_lead <- gestures_tot %>%
  dplyr::select(-ct) %>%
  spread(gesture, count) %>%
  dplyr::select(-ho_gv) %>%
  group_by(dyad) %>%
  mutate(
    lead_point = lead(point)
  ) %>%
  filter(months != 12)

reach_point_lead <- gestures_tot %>%
  dplyr::select(-ct) %>%
  spread(gesture, count) %>%
  dplyr::select(-ho_gv) %>%
  group_by(dyad) %>%
  mutate(
    lead_point = lead(point)
  ) %>%
  filter(months != 12)

ct_point_lead <- gestures_tot %>%
  filter(gesture == "point") %>%
  dplyr::select(-gesture) %>%
  rename(point = count) %>%
  group_by(dyad) %>%
  mutate(
    lead_point = lead(point)
  ) %>%
  filter(months != 12)

utter_point_lead <- gestures_tot %>%
  filter(gesture == "point") %>%
  right_join(y = utterances_tot) %>%
  group_by(dyad) %>%
  mutate(
    lead_point = lead(count)
  ) %>%
  filter(months != 12)

pointing <- gestures_tot %>%
  dplyr::select(-ct) %>%
  spread(gesture, count)

gestures <- read_csv("./data/gestures.csv")

gestures_tot_2 <- gestures %>%
  group_by(dyad, background, months, gesture) %>%
  summarise(
```

```
    count = sum(count),
    ct = sum(ct)
  ) %>%
  ungroup() %>%
  mutate(
    gesture = factor(gesture, levels = c("reach", "point", "ho_gv"))
  ) %>%
  mutate_if(is.character, as.factor)

point <- gestures %>%
  filter(gesture == "point") %>%
  group_by(dyad, background, months) %>%
  summarise(
    count = sum(count)
  ) %>%
  ungroup() %>%
  mutate_if(is.character, as.factor)

utter_point <- left_join(utterances_tot, point) %>%
  rename(point = count)

utterances_compl <- utterances %>% na.omit()
utterances_tcompl <- utterances_tot %>% na.omit()

hgp_tot <- gestures_tot_2 %>%
  filter(gesture != "reach") %>%
  group_by(dyad, background) %>%
  summarise(hgp_tot = sum(count))

reach_tot_2 <- gestures_tot_2 %>%
  filter(gesture == "reach") %>%
  group_by(dyad, background) %>%
  summarise(reach_tot = sum(count))

vocab_gest <- gestures_tot_2 %>%
  group_by(dyad, background) %>%
  summarise(count_tot = sum(count), ct_tot = sum(ct)) %>%
  full_join(y = hgp_tot) %>%
  full_join(y = reach_tot_2)

vocab_utt <- utterances_tot %>%
  group_by(dyad, background) %>%
  summarise(utt_tot = sum(utterances))

vocab <- read_csv("./data/vocab.csv") %>%
  full_join(y = vocab_gest) %>%
  full_join(y = vocab_utt) %>%
  arrange(dyad, months) %>%
  mutate_if(is.character, as.factor)
```

2 Analysis 1a. The development of reaches, hold out and gives (HoGs), and points from 10-12 months.

For analysis 1a, we fitted a series of GAMMs using the negative binomial function. The choice of using the negative binomial rather than the Poisson distribution is justified by the overdispersion of the data (and the very long tail in the distribution). The negative binomial distribution requires the specification of the theta parameter. The parameter has been estimated from the data by fitting a generalised linear model with the negative binomial distribution using `MASS::glm.nb`.

2.1 Reaches development

The following models test cultural group.

```
reach_nb <- glm.nb(count ~ months, data = reach_tot)

reach_gam <- gam(
  count ~
    back_o +
    s(months, k = 3) +
    s(months, k = 3, by = back_o) +
    s(months, dyad, k = 2, bs = "fs", m = 1),
  data = reach_tot,
  method = "ML",
  family = negbin(0.986)
)
```

```
## Warning in gam.side(sm, X, tol = .Machine$double.eps^0.5): model has
## repeated 1-d smooths of same variable.
```

```
summary(reach_gam)
```

```
##
## Family: Negative Binomial(0.986)
## Link function: log
##
## Formula:
## count ~ back_o + s(months, k = 3) + s(months, k = 3, by = back_o) +
##     s(months, dyad, k = 2, bs = "fs", m = 1)
##
## Parametric coefficients:
##                     Estimate Std. Error z value Pr(>|z|)
## (Intercept)           0.6377     0.1920   3.322 0.000895 ***
## back_oBangladeshi     0.5873     0.2601   2.258 0.023930 *
## back_oChinese         0.2402     0.2650   0.906 0.364737
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Approximate significance of smooth terms:
##                                edf  Ref.df Chi.sq p-value
## s(months)                    1.155   1.286  1.181  0.2854
## s(months):back_oBangladeshi  1.000   1.000  0.437  0.5086
## s(months):back_oChinese      1.000   1.000  0.125  0.7237
## s(months,dyad)              14.509 112.000 20.040  0.0316 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## R-sq.(adj) =  0.165   Deviance explained = 21.4%
## -ML = 378.53  Scale est. = 1         n = 173
```

```
reach_gam_null <- gam(
  count ~
    # back_o +
    s(months, k = 3) +
    # s(months, k = 3, by = back_o) +
    s(months, dyad, k = 2, bs = "fs", m = 1),
  data = reach_tot,
  method = "ML",
  family = negbin(0.986)
)
```

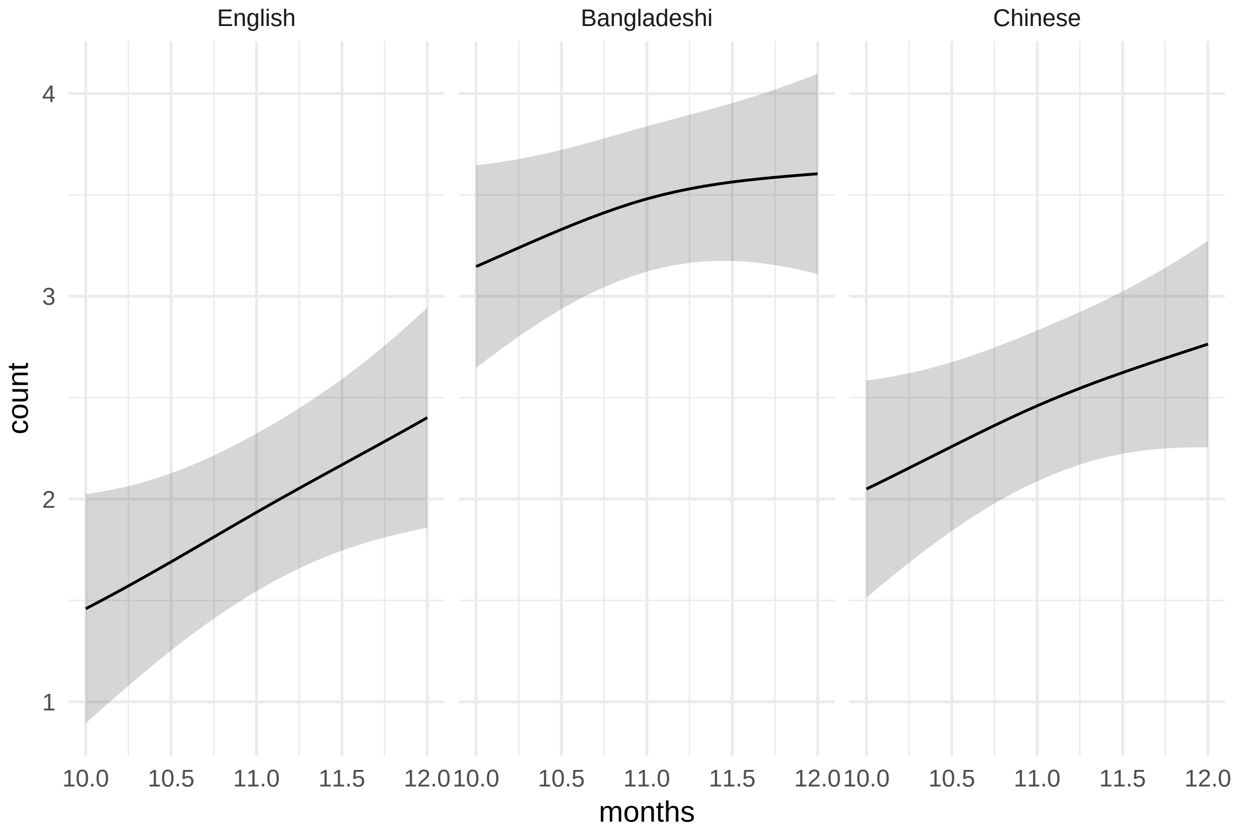
```
## Warning in gam.side(sm, X, tol = .Machine$double.eps^0.5): model has
## repeated 1-d smooths of same variable.
```

```
compareML(reach_gam_null, reach_gam)
```

```
## reach_gam_null: count ~ s(months, k = 3) + s(months, dyad, k = 2, bs = "fs",
##     m = 1)
##
## reach_gam: count ~ back_o + s(months, k = 3) + s(months, k = 3, by = back_o) +
##     s(months, dyad, k = 2, bs = "fs", m = 1)
##
## Chi-square test of ML scores
## -----
##            Model    Score Edf Difference    Df p.value Sig.
## 1 reach_gam_null 381.3264   5
## 2      reach_gam 378.5345  11      2.792 6.000   0.471
##
## AIC difference: -1.91, model reach_gam_null has lower AIC.
```

```
## Warning in compareML(reach_gam_null, reach_gam): Only small difference in ML...
```

```
plot_smooths(reach_gam, months, facet_terms = back_o, series_length = 25, transform = exp)
```



The following models test time sample.

```
reach_gam_2 <- gam(
  count ~
    s(months, k = 3) +
    s(months, dyad, k = 2, bs = "fs", m = 1),
  data = reach_tot,
  method = "ML",
  family = negbin(0.986)
)
```

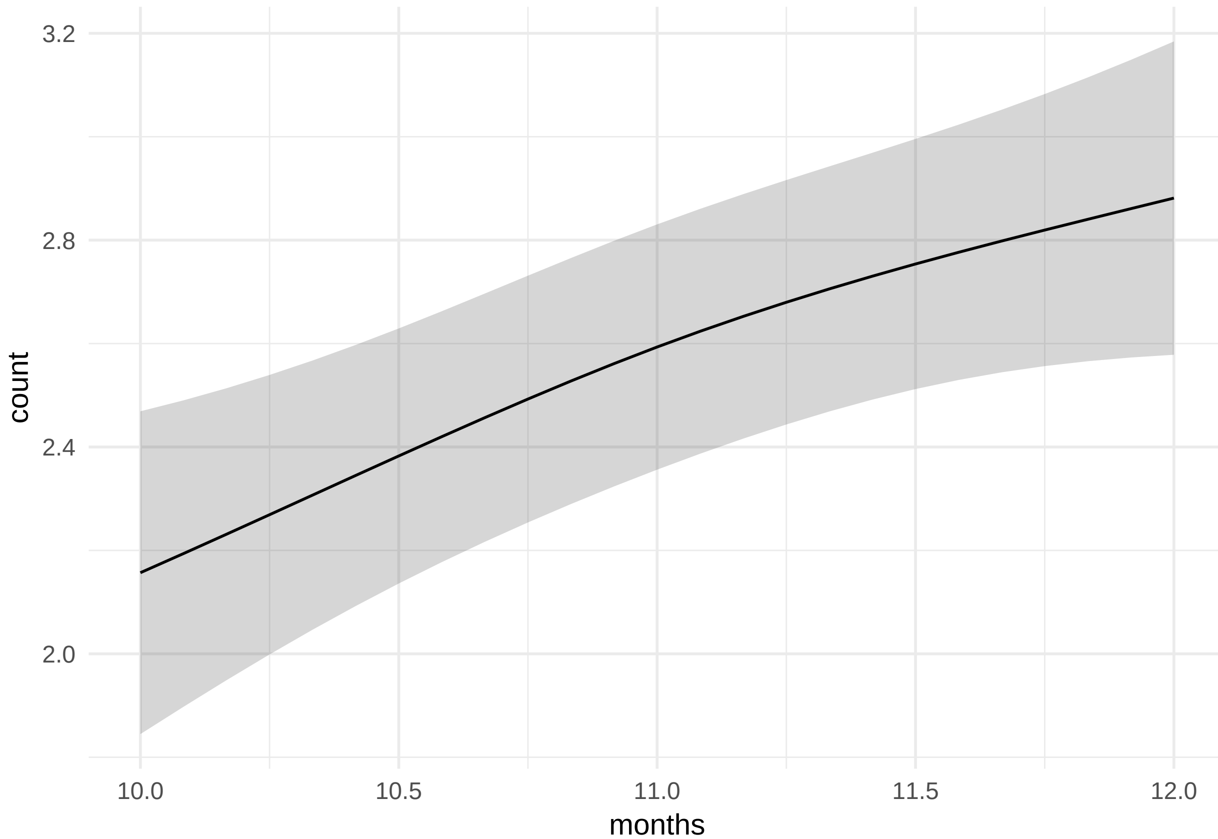
```
## Warning in gam.side(sm, X, tol = .Machine$double.eps^0.5): model has
## repeated 1-d smooths of same variable.
```

```
reach_gam_2_null <- gam(
  count ~
    # s(months, k = 3) +
    s(months, dyad, k = 2, bs = "fs", m = 1),
  data = reach_tot,
  method = "ML",
  family = negbin(0.986)
)
compareML(reach_gam_2_null, reach_gam_2)
```

```
## reach_gam_2_null: count ~ s(months, dyad, k = 2, bs = "fs", m = 1)
##
## reach_gam_2: count ~ s(months, k = 3) + s(months, dyad, k = 2, bs = "fs",
##     m = 1)
##
```

```
## Chi-square test of ML scores
## -----
##              Model    Score Edf Difference    Df p.value Sig.
## 1 reach_gam_2_null 382.1555   3
## 2      reach_gam_2 381.3264   5      0.829 2.000   0.436
##
## AIC difference: -3.95, model reach_gam_2_null has lower AIC.

## Warning in compareML(reach_gam_2_null, reach_gam_2): Only small difference in ML...
```

```r
plot_smooths(reach_gam_2, months, series_length = 25, transform = exp)
```



2.2 HGs development

The following models test cultural group.

```r
hg_nb <- glm.nb(count ~ months, data = hg_tot)

hg_gam <- gam(
  count ~
    back_o +
    s(months, k = 3) +
    s(months, k = 3, by = back_o) +
    s(months, dyad, k = 2, bs = "fs", m = 1),
  data = hg_tot,
  method = "ML",
  family = negbin(0.6434)
)
```

```
## Warning in gam.side(sm, X, tol = .Machine$double.eps^0.5): model has
## repeated 1-d smooths of same variable.
```

```r
summary(hg_gam)
```

```
##
## Family: Negative Binomial(0.643)
## Link function: log
##
## Formula:
## count ~ back_o + s(months, k = 3) + s(months, k = 3, by = back_o) +
##     s(months, dyad, k = 2, bs = "fs", m = 1)
##
## Parametric coefficients:
##                     Estimate Std. Error z value Pr(>|z|)
## (Intercept)           0.7491     0.2316   3.234  0.00122 **
## back_oBangladeshi     0.9117     0.3143   2.901  0.00372 **
## back_oChinese         0.7257     0.3163   2.295  0.02176 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Approximate significance of smooth terms:
##                                 edf Ref.df Chi.sq p-value
## s(months)                       1.0      1  9.707 0.00184 **
## s(months):back_oBangladeshi  1.0      1  0.025 0.87559
## s(months):back_oChinese      1.0      1  0.426 0.51391
## s(months,dyad)             17.7    112 26.330 0.01075 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## R-sq.(adj) =  0.335   Deviance explained = 38.5%
## -ML = 451.06  Scale est. = 1         n = 173
```

```r
hg_gam_null <- gam(
  count ~
    # back_o +
    s(months, k = 3) +
    # s(months, k = 3, by = back_o) +
    s(months, dyad, k = 2, bs = "fs", m = 1),
  data = hg_tot,
  method = "ML",
  family = negbin(0.6434)
)
```

```
## Warning in gam.side(sm, X, tol = .Machine$double.eps^0.5): model has
## repeated 1-d smooths of same variable.
```

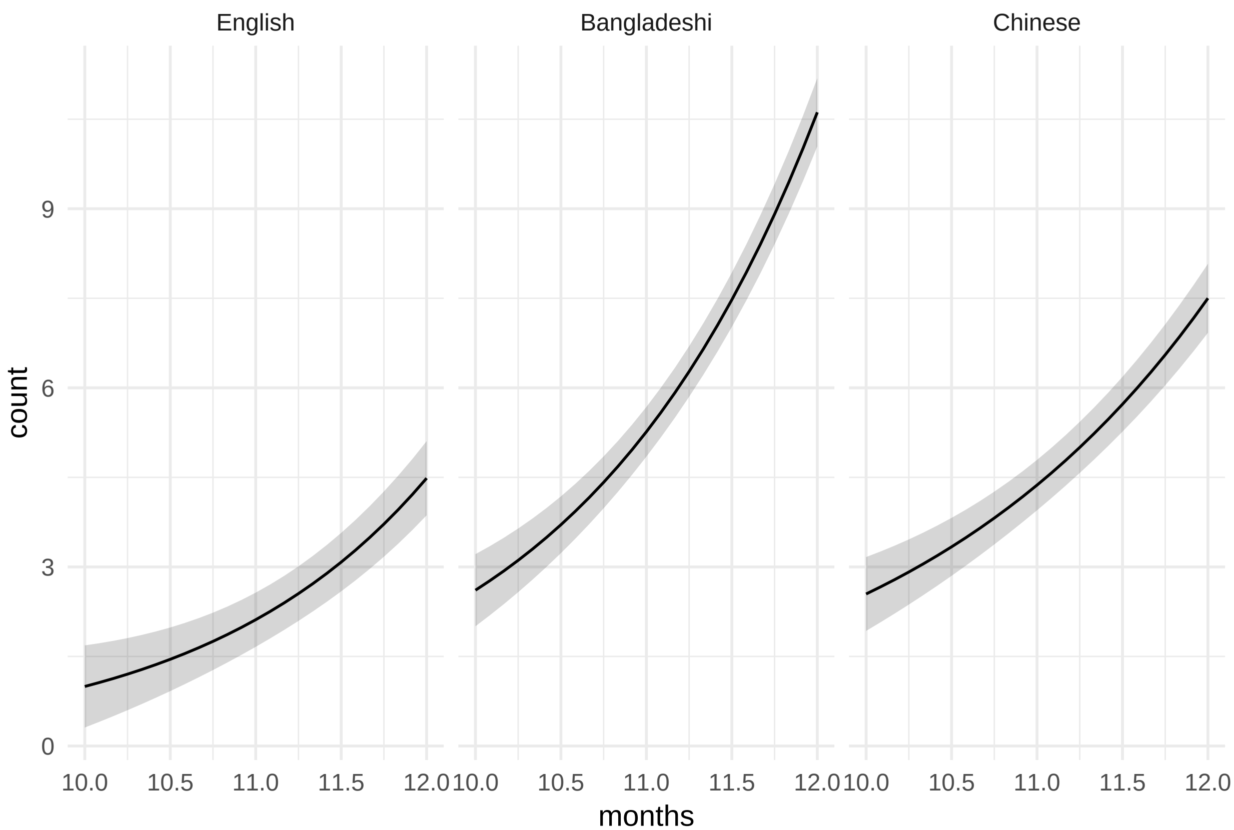
```r
compareML(hg_gam_null, hg_gam)
```

```
## hg_gam_null: count ~ s(months, k = 3) + s(months, dyad, k = 2, bs = "fs",
##     m = 1)
##
## hg_gam: count ~ back_o + s(months, k = 3) + s(months, k = 3, by = back_o) +
##     s(months, dyad, k = 2, bs = "fs", m = 1)
##
## Chi-square test of ML scores
```

```
## -----
##         Model    Score Edf Difference    Df p.value Sig.
## 1 hg_gam_null 455.3697   5
## 2      hg_gam 451.0601  11      4.310 6.000   0.196
##
## AIC difference: -2.20, model hg_gam_null has lower AIC.
```

```
## Warning in compareML(hg_gam_null, hg_gam): Only small difference in ML...
```

```
plot_smooths(hg_gam, months, facet_terms = back_o, series_length = 25, transform = exp)
```



The following models test time sample.

```
hg_gam_2 <- gam(
  count ~
    s(months, k = 3) +
    s(months, dyad, k = 2, bs = "fs", m = 1),
  data = hg_tot,
  method = "ML",
  family = negbin(0.6434)
)
```

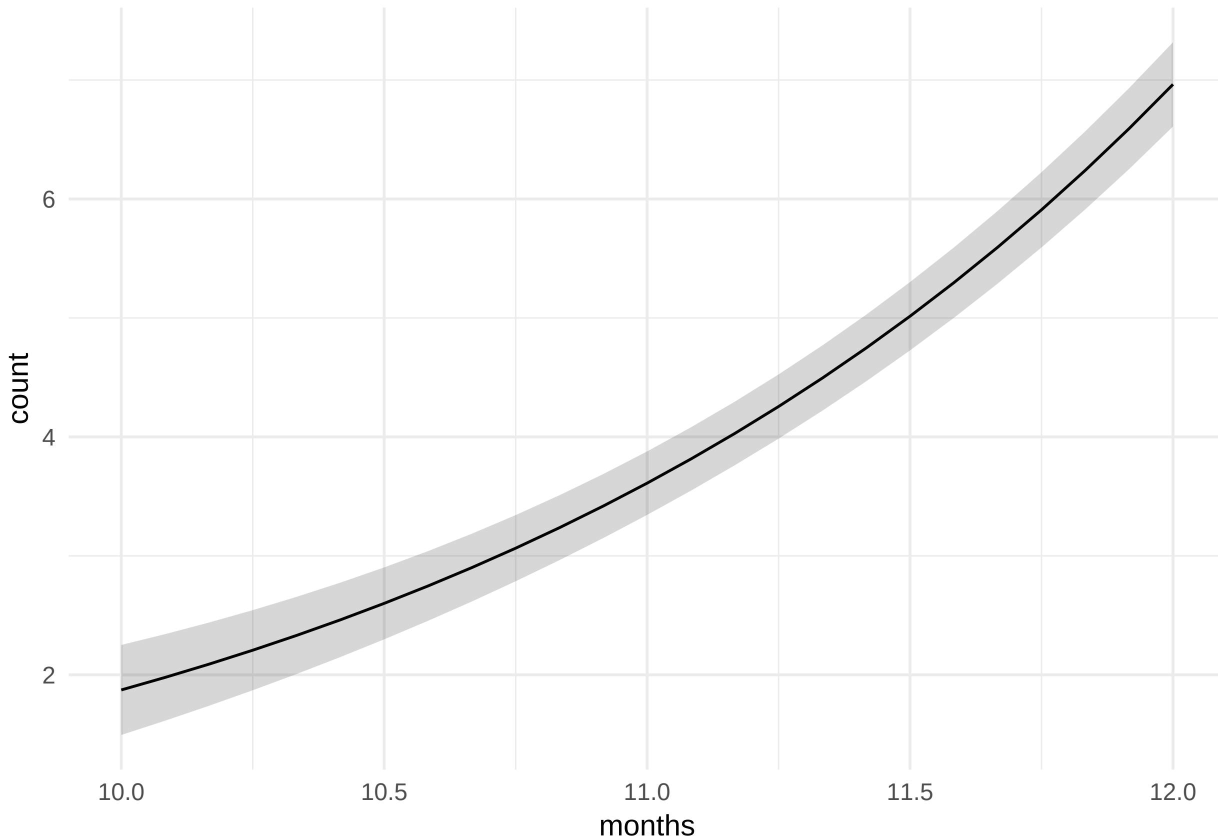
```
## Warning in gam.side(sm, X, tol = .Machine$double.eps^0.5): model has
## repeated 1-d smooths of same variable.
```

```
hg_gam_2_null <- gam(
  count ~
    # s(months, k = 3) +
    s(months, dyad, k = 2, bs = "fs", m = 1),
  data = hg_tot,
```

```
  method = "ML",
  family = negbin(0.6434)
)
compareML(hg_gam_2_null, hg_gam_2)
```

```
## hg_gam_2_null: count ~ s(months, dyad, k = 2, bs = "fs", m = 1)
##
## hg_gam_2: count ~ s(months, k = 3) + s(months, dyad, k = 2, bs = "fs",
##     m = 1)
##
## Chi-square test of ML scores
## -----
##           Model    Score Edf Difference    Df   p.value Sig.
## 1 hg_gam_2_null 467.6973   3
## 2      hg_gam_2 455.3697   5     12.328 2.000 4.428e-06  ***
##
## AIC difference: 29.26, model hg_gam_2 has lower AIC.
```

```
plot_smooths(hg_gam_2, months, series_length = 25, transform = exp)
```



2.3 Points development

The following models test cultural group.

```
point_nb <- glm.nb(count ~ months, data = point_tot)

point_gam <- gam(
  count ~
```

```r
    back_o +
    s(months, k = 3) +
    s(months, k = 3, by = back_o) +
    s(months, dyad, k = 2, bs = "fs", m = 1),
  data = point_tot,
  method = "ML",
  family = negbin(0.1946)
)
```

```
## Warning in gam.side(sm, X, tol = .Machine$double.eps^0.5): model has
## repeated 1-d smooths of same variable.
```

```r
summary(point_gam)
```

```
##
## Family: Negative Binomial(0.195)
## Link function: log
##
## Formula:
## count ~ back_o + s(months, k = 3) + s(months, k = 3, by = back_o) +
##     s(months, dyad, k = 2, bs = "fs", m = 1)
##
## Parametric coefficients:
##                    Estimate Std. Error z value Pr(>|z|)
## (Intercept)          0.6917     0.3953   1.750   0.0802 .
## back_oBangladeshi  -0.4993     0.5588  -0.894   0.3716
## back_oChinese      -0.5735     0.5675  -1.011   0.3122
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Approximate significance of smooth terms:
##                              edf  Ref.df Chi.sq p-value
## s(months)                  1.000   1.000  1.068  0.3014
## s(months):back_oBangladeshi  1.538   1.786  0.726  0.5736
## s(months):back_oChinese      1.000   1.000  2.118  0.1456
## s(months,dyad)            18.373 112.000 26.009  0.0224 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## R-sq.(adj) =  0.332   Deviance explained =   41%
## -ML = 326.23  Scale est. = 1         n = 173
```

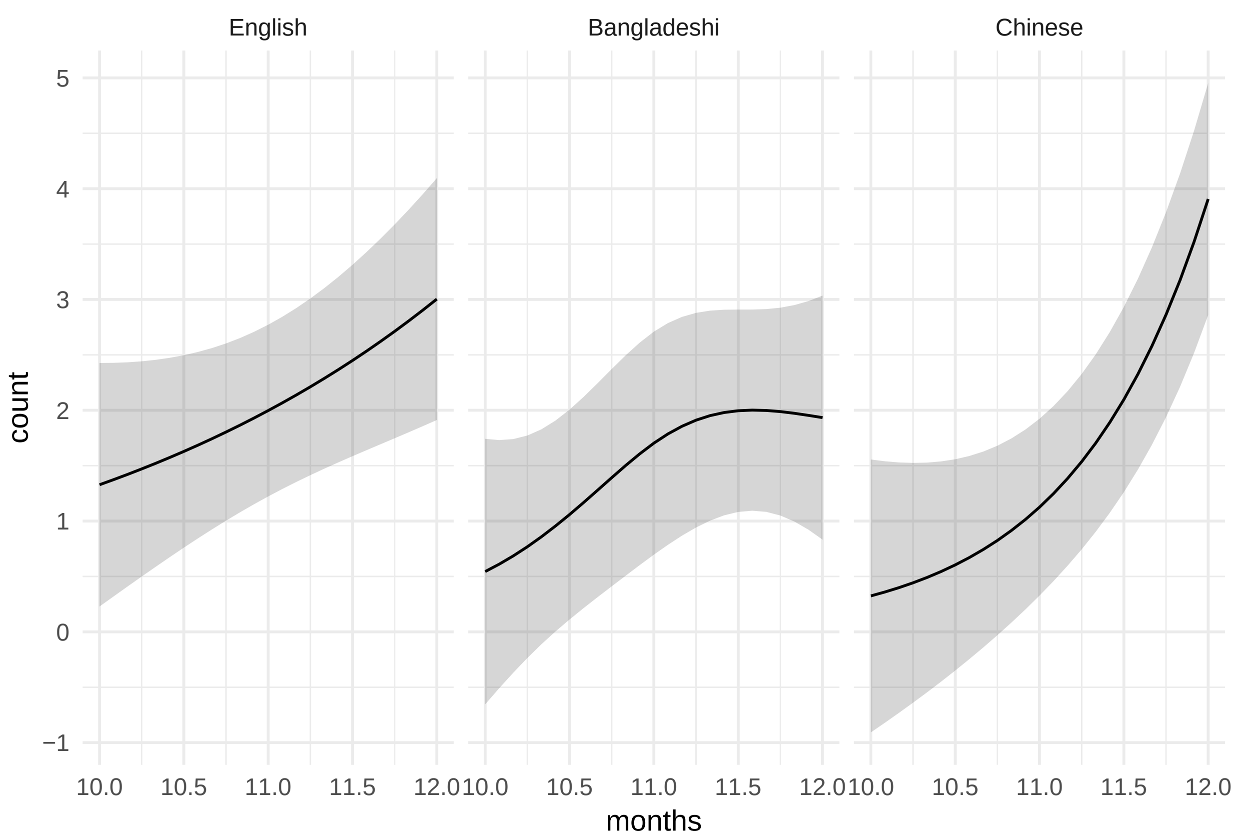
```r
point_gam_null <- gam(
  count ~
    # back_o +
    s(months, k = 3) +
    # s(months, k = 3, by = back_o) +
    s(months, dyad, k = 2, bs = "fs", m = 1),
  data = point_tot,
  method = "ML",
  family = negbin(0.1946)
)
```

```
## Warning in gam.side(sm, X, tol = .Machine$double.eps^0.5): model has
## repeated 1-d smooths of same variable.
```

```r
compareML(point_gam_null, point_gam)
```

```
## point_gam_null: count ~ s(months, k = 3) + s(months, dyad, k = 2, bs = "fs",
##     m = 1)
##
## point_gam: count ~ back_o + s(months, k = 3) + s(months, k = 3, by = back_o) +
##     s(months, dyad, k = 2, bs = "fs", m = 1)
##
## Chi-square test of ML scores
## -----
##            Model    Score Edf Difference    Df p.value Sig.
## 1 point_gam_null 327.9346   5
## 2      point_gam 326.2345  11      1.700 6.000   0.757
##
## AIC difference: -7.40, model point_gam_null has lower AIC.

## Warning in compareML(point_gam_null, point_gam): Only small difference in ML...
```

```r
plot_smooths(point_gam, months, facet_terms = back_o, series_length = 25, transform = exp)
```



The following models test time sample.

```r
point_gam_2 <- gam(
  count ~
    s(months, k = 3) +
    s(months, dyad, k = 2, bs = "fs", m = 1),
  data = point_tot,
  method = "ML",
  family = negbin(0.1946)
```

```r
)
```

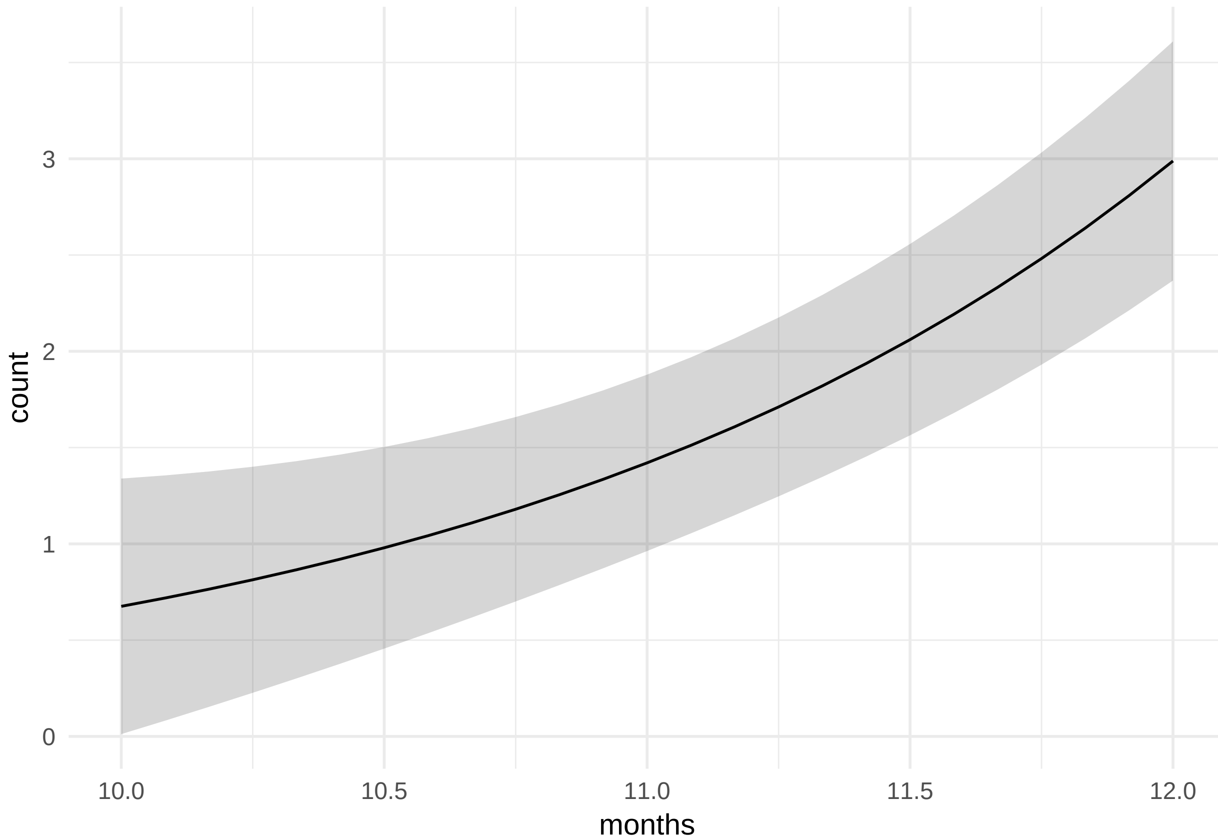
```
## Warning in gam.side(sm, X, tol = .Machine$double.eps^0.5): model has
## repeated 1-d smooths of same variable.
```

```r
point_gam_2_null <- gam(
  count ~
    # s(months, k = 3) +
    s(months, dyad, k = 2, bs = "fs", m = 1),
  data = point_tot,
  method = "ML",
  family = negbin(0.1946)
)
compareML(point_gam_2_null, point_gam_2)
```

```
## point_gam_2_null: count ~ s(months, dyad, k = 2, bs = "fs", m = 1)
##
## point_gam_2: count ~ s(months, k = 3) + s(months, dyad, k = 2, bs = "fs",
##     m = 1)
##
## Chi-square test of ML scores
## -----
##              Model    Score Edf Difference    Df p.value Sig.
## 1 point_gam_2_null 332.5507   3
## 2      point_gam_2 327.9346   5      4.616 2.000   0.010  **
##
## AIC difference: 10.13, model point_gam_2 has lower AIC.
```

```
## Warning in compareML(point_gam_2_null, point_gam_2): Only small difference in ML...
```

```r
plot_smooths(point_gam_2, months, series_length = 25, transform = exp)
```



3 Analysis 1b. Frequency of maternal utterances and contingent talk to infants aged 10-12 months.

For maternal utterances we used a normal distribution, since the distribution of the data was almost normal. For maternal contingent talks instead we used again the negative binomial distribution for the same reasons as above.

3.1 Maternal utterances development

The following models test cultural group.

```
utter_gam <- gam(
  utterances ~
    back_o +
    s(months, k = 3) +
    s(months, k = 3, by = back_o) +
    s(months, dyad, k = 2, bs = "fs", m = 1),
  data = utterances_tot,
  method = "ML"
)
```

```
## Warning in gam.side(sm, X, tol = .Machine$double.eps^0.5): model has
## repeated 1-d smooths of same variable.
```

```
summary(utter_gam)
```

```
##
```

```
## Family: gaussian
## Link function: identity
##
## Formula:
## utterances ~ back_o + s(months, k = 3) + s(months, k = 3, by = back_o) +
##     s(months, dyad, k = 2, bs = "fs", m = 1)
##
## Parametric coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)          284.44      27.10  10.494   <2e-16 ***
## back_oBangladeshi    -65.59      37.82  -1.734   0.0865 .
## back_oChinese        -37.80      37.74  -1.002   0.3193
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Approximate significance of smooth terms:
##                                 edf  Ref.df     F p-value
## s(months)                     1.693   1.880 0.966   0.333
## s(months):back_oBangladeshi  1.001   1.001 1.065   0.305
## s(months):back_oChinese      1.334   1.533 1.924   0.107
## s(months,dyad)              73.930 111.000 7.087  <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## R-sq.(adj) =  0.837   Deviance explained = 91.6%
## -ML = 991.97  Scale est. = 2827.4    n = 167
```

```
utter_gam_null <- gam(
  utterances ~
    # back_o +
    s(months, k = 3) +
    # s(months, k = 3, by = back_o) +
    s(months, dyad, k = 2, bs = "fs", m = 1),
  data = utterances_tot,
  method = "ML"
)
```

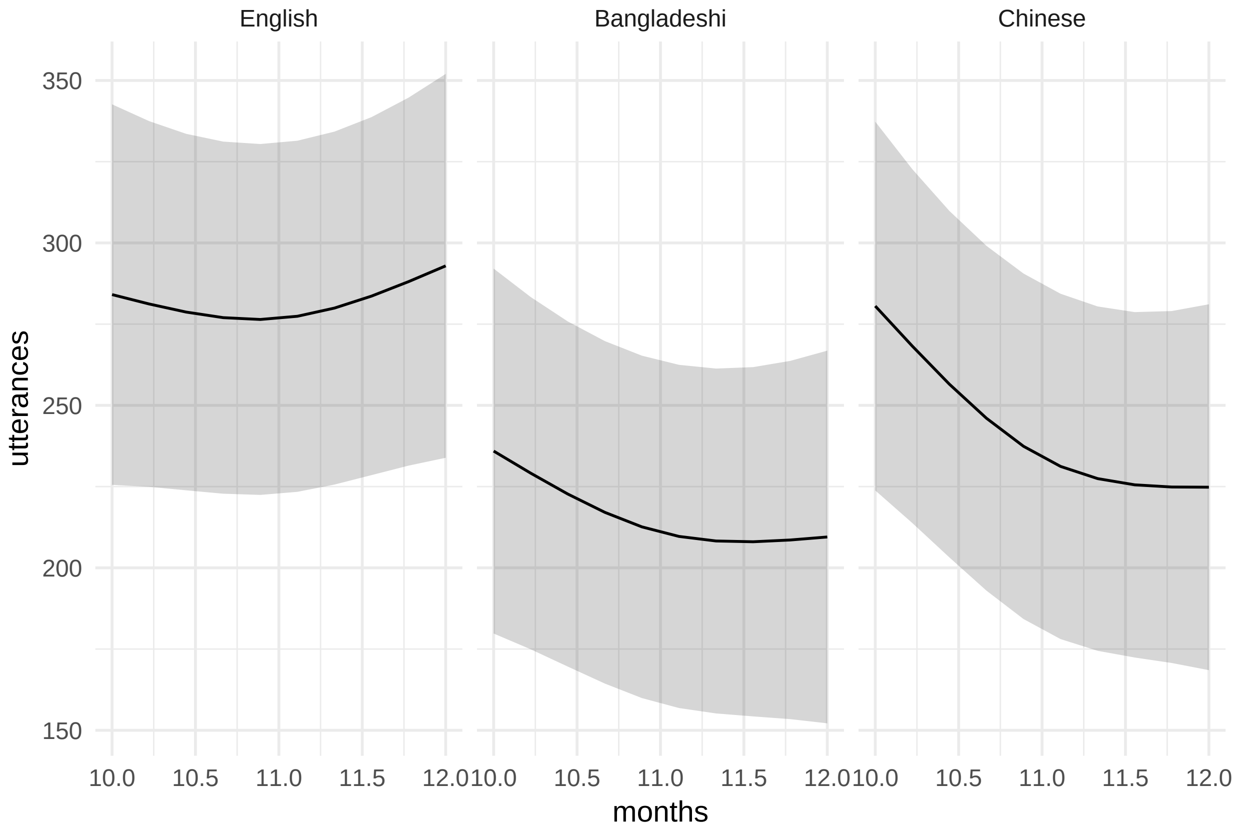
```
## Warning in gam.side(sm, X, tol = .Machine$double.eps^0.5): model has
## repeated 1-d smooths of same variable.
```

```
compareML(utter_gam_null, utter_gam)
```

```
## utter_gam_null: utterances ~ s(months, k = 3) + s(months, dyad, k = 2, bs = "fs",
##     m = 1)
##
## utter_gam: utterances ~ back_o + s(months, k = 3) + s(months, k = 3, by = back_o) +
##     s(months, dyad, k = 2, bs = "fs", m = 1)
##
## Chi-square test of ML scores
## -----
##            Model    Score Edf Difference    Df p.value Sig.
## 1 utter_gam_null 995.3291   5
## 2      utter_gam 991.9724  11      3.357 6.000   0.348
##
## AIC difference: -3.68, model utter_gam_null has lower AIC.
```

```
## Warning in compareML(utter_gam_null, utter_gam): Only small difference in ML...
```

```r
plot_smooths(utter_gam, months, facet_terms = back_o, series_length = 10)
```



The following models test time sample.

```r
utter_gam_2 <- gam(
  utterances ~
    s(months, k = 3) +
    s(months, dyad, k = 2, bs = "fs", m = 1),
  data = utterances_tot,
  method = "ML"
)
```

```
## Warning in gam.side(sm, X, tol = .Machine$double.eps^0.5): model has
## repeated 1-d smooths of same variable.
```

```r
utter_gam_2_null <- gam(
  utterances ~
    # s(months, k = 3) +
    s(months, dyad, k = 2, bs = "fs", m = 1),
  data = utterances_tot,
  method = "ML"
)

compareML(utter_gam_2_null, utter_gam_2)
```

```
## utter_gam_2_null: utterances ~ s(months, dyad, k = 2, bs = "fs", m = 1)
##
## utter_gam_2: utterances ~ s(months, k = 3) + s(months, dyad, k = 2, bs = "fs",
```

```
##     m = 1)
##
## Chi-square test of ML scores
## -----
##                Model     Score Edf Difference    Df p.value Sig.
## 1 utter_gam_2_null 997.9664   3
## 2      utter_gam_2 995.3291   5      2.637 2.000   0.072
##
## AIC difference: 6.07, model utter_gam_2 has lower AIC.

## Warning in compareML(utter_gam_2_null, utter_gam_2): Only small difference in ML...
```

3.2 Contingent talks development

The following models test cultural group.

```
ct_nb <- glm.nb(ct ~ months, data = all_tot)

ct_gam <- gam(
  ct ~
    back_o +
    s(months, k = 3) +
    s(months, k = 3, by = back_o) +
    s(months, dyad, k = 2, bs = "fs", m = 1),
  data = all_tot,
  method = "ML",
  family = negbin(0.3845)
)
```

```
## Warning in gam.side(sm, X, tol = .Machine$double.eps^0.5): model has
## repeated 1-d smooths of same variable.
```

```
summary(ct_gam)
```

```
##
## Family: Negative Binomial(0.384)
## Link function: log
##
## Formula:
## ct ~ back_o + s(months, k = 3) + s(months, k = 3, by = back_o) +
##     s(months, dyad, k = 2, bs = "fs", m = 1)
##
## Parametric coefficients:
##                    Estimate Std. Error z value Pr(>|z|)
## (Intercept)          0.6528     0.2977   2.193   0.0283 *
## back_oBangladeshi  -0.9863     0.4347  -2.269   0.0233 *
## back_oChinese      -0.2083     0.4226  -0.493   0.6221
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Approximate significance of smooth terms:
##                                edf  Ref.df Chi.sq p-value
## s(months)                     1.00   1.000  3.039 0.08130 .
## s(months):back_oBangladeshi  1.75   1.937  3.064 0.24025
## s(months):back_oChinese      1.00   1.000  0.391 0.53191
## s(months,dyad)              18.38 112.000 27.596 0.00938 **
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## R-sq.(adj) =  0.394   Deviance explained = 43.7%
## -ML = 315.49  Scale est. = 1         n = 172
```

```
ct_gam_null <- gam(
  ct ~
    # back_o +
    s(months, k = 3) +
    # s(months, k = 3, by = back_o) +
    s(months, dyad, k = 2, bs = "fs", m = 1),
  data = all_tot,
  method = "ML",
  family = negbin(0.3845)
)
```

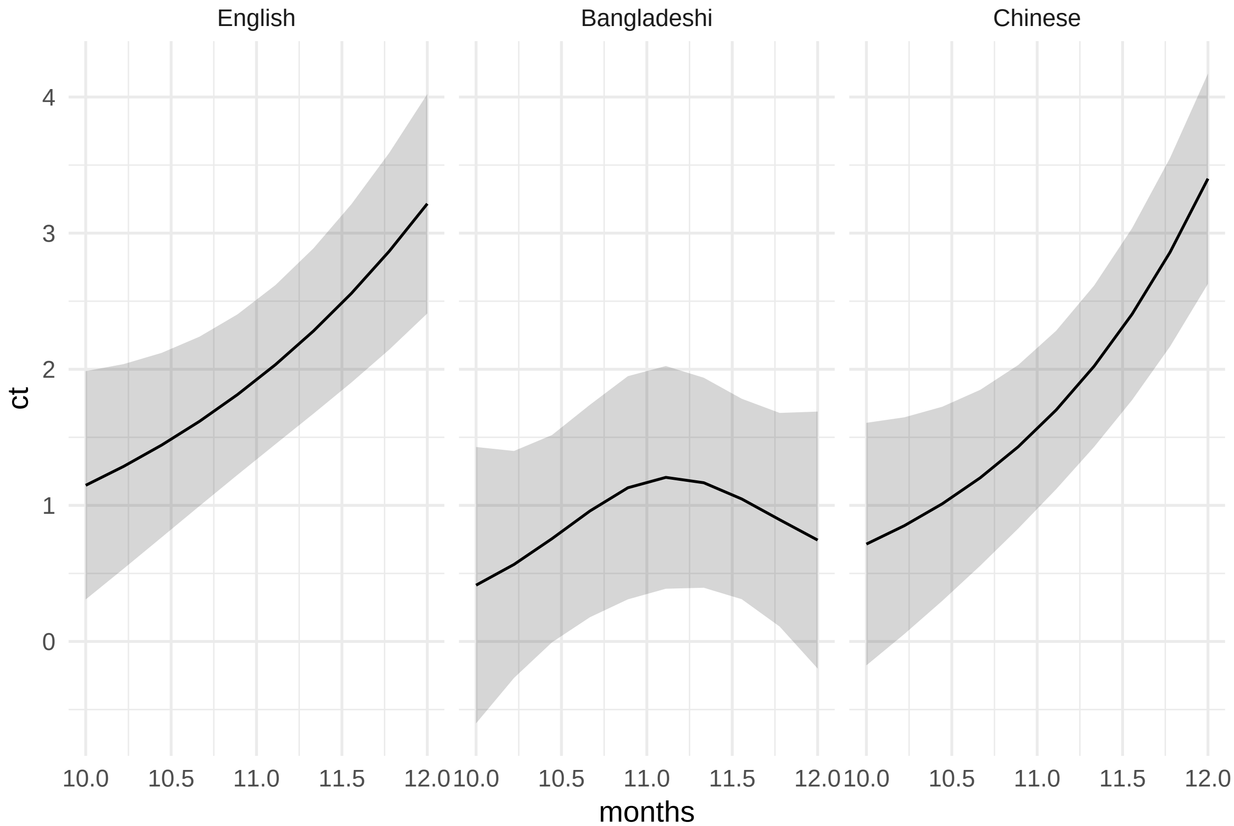
```
## Warning in gam.side(sm, X, tol = .Machine$double.eps^0.5): model has
## repeated 1-d smooths of same variable.
```

```
compareML(ct_gam_null, ct_gam)
```

```
## ct_gam_null: ct ~ s(months, k = 3) + s(months, dyad, k = 2, bs = "fs", m = 1)
##
## ct_gam: ct ~ back_o + s(months, k = 3) + s(months, k = 3, by = back_o) +
##     s(months, dyad, k = 2, bs = "fs", m = 1)
##
## Chi-square test of ML scores
## -----
##         Model    Score Edf Difference    Df p.value Sig.
## 1 ct_gam_null 318.9151   5
## 2      ct_gam 315.4869  11      3.428 6.000   0.334
##
## AIC difference: 0.60, model ct_gam has lower AIC.
```

```
## Warning in compareML(ct_gam_null, ct_gam): Only small difference in ML...
```

```
plot_smooths(ct_gam, months, facet_terms = back_o, series_length = 10, transform = exp)
```



The following models test time sample.

```
ct_gam_2 <- gam(
  count ~
    s(months, k = 3) +
    s(months, dyad, k = 2, bs = "fs", m = 1),
  data = all_tot,
  method = "ML",
  family = negbin(0.3845)
)
```

```
## Warning in gam.side(sm, X, tol = .Machine$double.eps^0.5): model has
## repeated 1-d smooths of same variable.
```

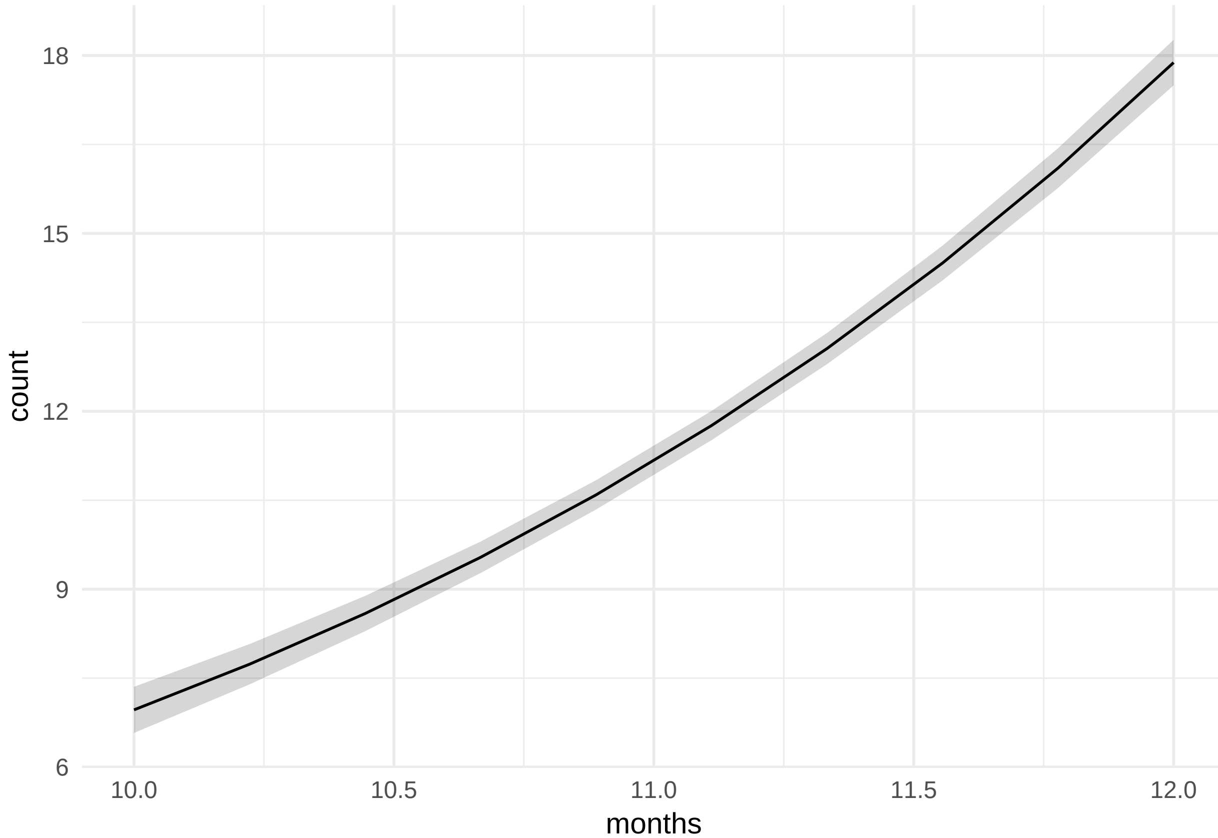
```
ct_gam_2_null <- gam(
  count ~
    # s(months, k = 3) +
    s(months, dyad, k = 2, bs = "fs", m = 1),
  data = all_tot,
  method = "ML",
  family = negbin(0.3845)
)

compareML(ct_gam_2_null, ct_gam_2)
```

```
## ct_gam_2_null: count ~ s(months, dyad, k = 2, bs = "fs", m = 1)
##
## ct_gam_2: count ~ s(months, k = 3) + s(months, dyad, k = 2, bs = "fs",
##     m = 1)
```

```
##
## Chi-square test of ML scores
## -----
##            Model    Score Edf Difference    Df p.value Sig.
## 1 ct_gam_2_null 641.7191   3
## 2      ct_gam_2 637.2383   5      4.481 2.000   0.011  *
##
## AIC difference: 6.96, model ct_gam_2 has lower AIC.
```

```
## Warning in compareML(ct_gam_2_null, ct_gam_2): Only small difference in ML...
```

```
plot_smooths(ct_gam_2, months, series_length = 10, transform = exp)
```



4 Analysis 1c. Predictors of pointing at 12 months

The following GLMMs test the relation between pointing as the outcome variable and reaches/HoGs.

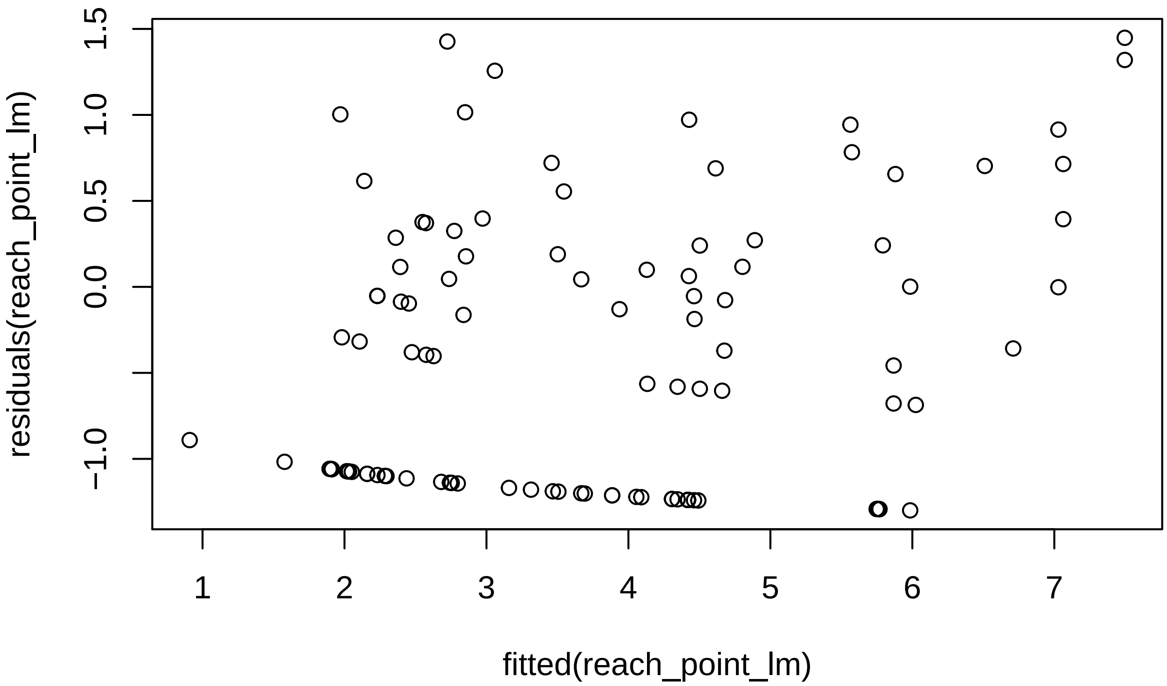
4.1 Reaches

```
reach_point_lead_nb <- glm.nb(lead_point ~ reach, data = reach_point_lead)

reach_point_lm <- glmer(
  lead_point ~
    reach *
    background +
    (1|dyad),
  data = reach_point_lead,
```

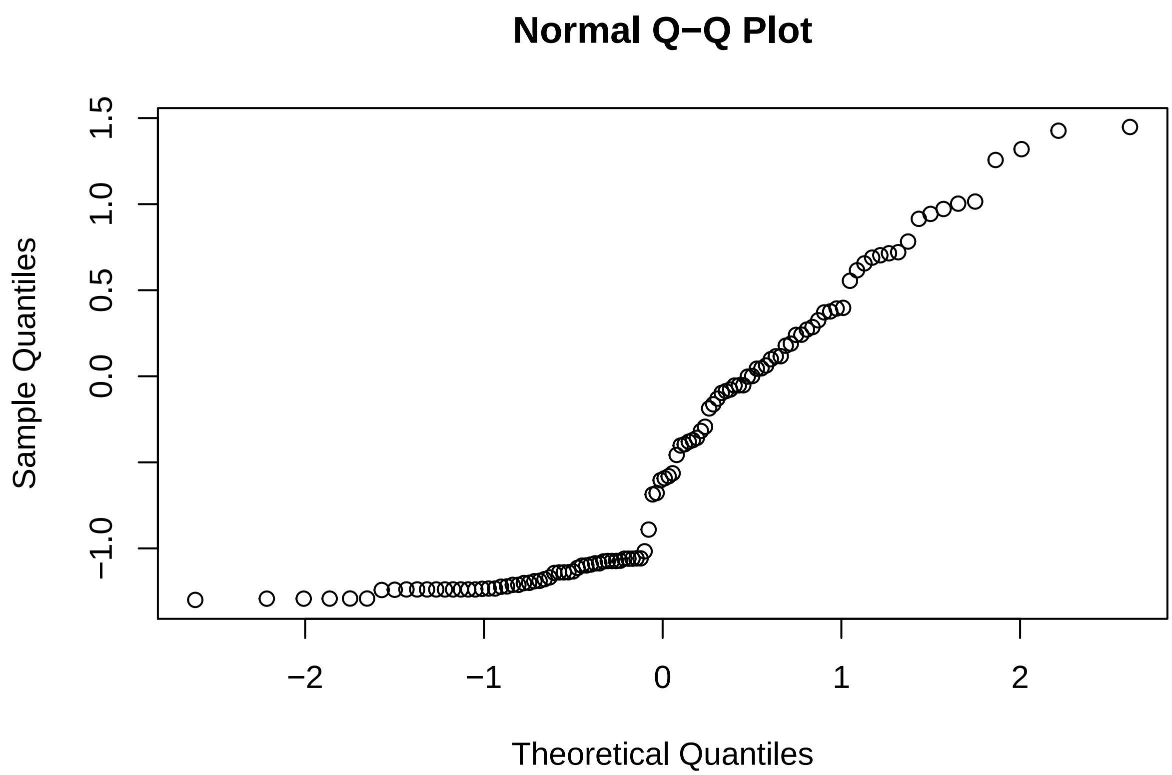
```r
  family = negbin(0.2681)
)
summary(reach_point_lm)
```

```
## Generalized linear mixed model fit by maximum likelihood (Laplace
##   Approximation) [glmerMod]
##  Family: Negative Binomial(0.268)  ( log )
## Formula: lead_point ~ reach * background + (1 | dyad)
##    Data: reach_point_lead
##
##      AIC      BIC   logLik deviance df.resid
##    523.3    545.1   -253.7    507.3      104
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -0.5066 -0.4982 -0.3934  0.1437  3.0203
##
## Random effects:
##  Groups Name        Variance Std.Dev.
##  dyad   (Intercept) 0.1569   0.396
## Number of obs: 112, groups:  dyad, 57
##
## Fixed effects:
##                         Estimate Std. Error z value Pr(>|z|)
## (Intercept)              0.72163    0.60141   1.200    0.230
## reach                    0.06136    0.09716   0.632    0.528
## backgroundChinese        1.10777    0.72841   1.521    0.128
## backgroundEnglish        0.84357    0.68166   1.238    0.216
## reach:backgroundChinese -0.24686    0.16105  -1.533    0.125
## reach:backgroundEnglish -0.08716    0.13746  -0.634    0.526
##
## Correlation of Fixed Effects:
##             (Intr) reach  bckgrC bckgrE rch:bC
## reach       -0.724
## bckgrndChns -0.709  0.550
## bckgrndEngl -0.557  0.506  0.508
## rch:bckgrnC  0.453 -0.610 -0.710 -0.298
## rch:bckgrnE  0.449 -0.681 -0.366 -0.599  0.412
```

```r
plot(fitted(reach_point_lm), residuals(reach_point_lm))
```

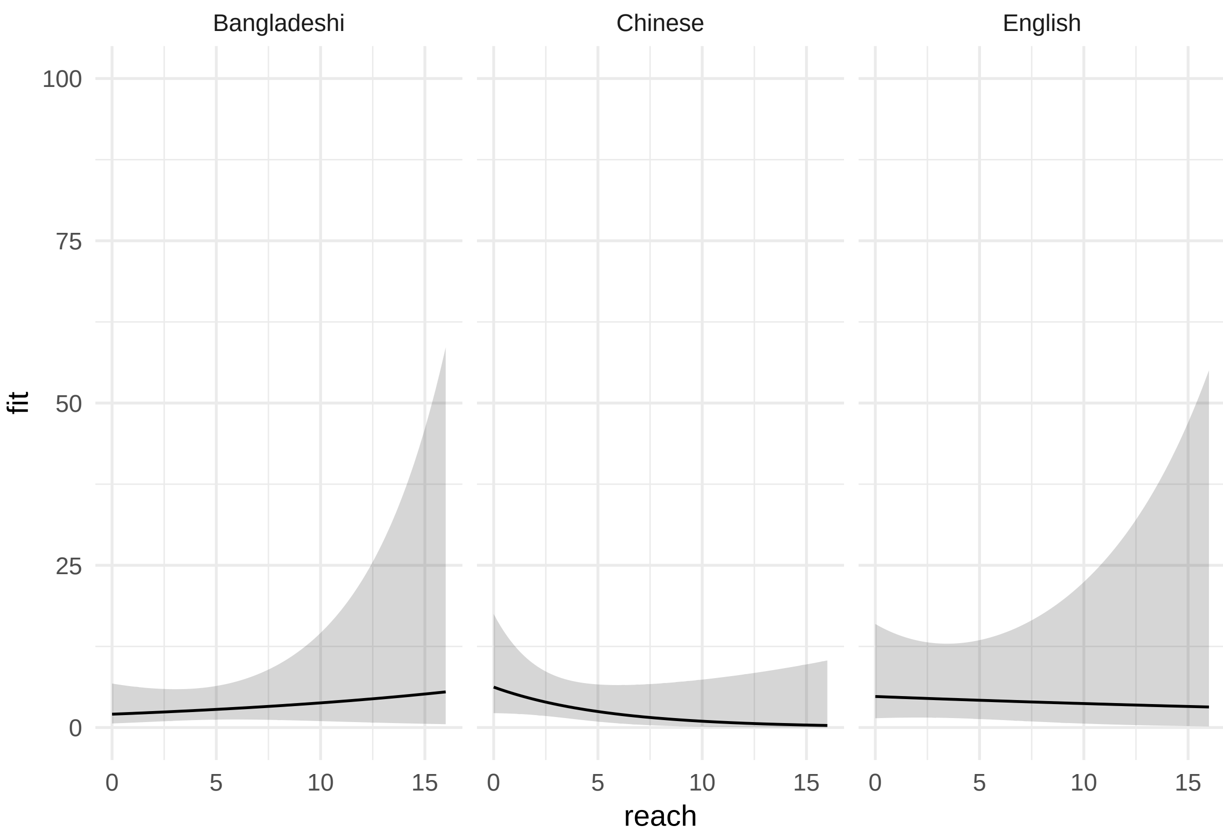



```
qqnorm(residuals(reach_point_lm))
```

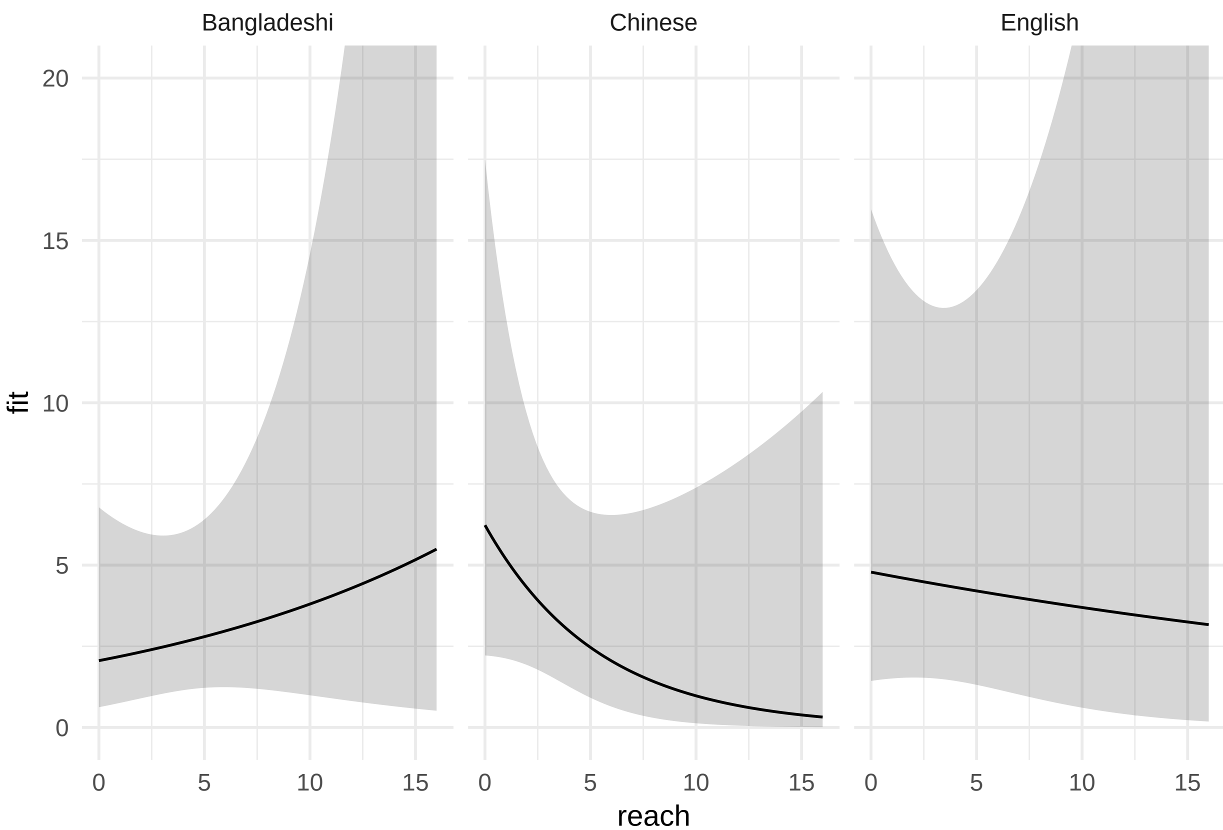



```
reach_eff <- as_tibble(effect("reach:background", reach_point_lm, xlevels = 100))

ggplot(reach_eff, aes(reach, fit)) +
  geom_ribbon(aes(ymax = upper, ymin = lower), alpha = 0.2) +
  geom_line() +
  facet_grid(~ background) +
```

```
  coord_cartesian(ylim = c(0, 100))
```




```
ggplot(reach_eff, aes(reach, fit)) +
  geom_ribbon(aes(ymax = upper, ymin = lower), alpha = 0.2) +
  geom_line() +
  facet_grid(~ background) +
  coord_cartesian(ylim = c(0, 20))
```



4.2 HoGs

```
hg_point_lead_nb <- glm.nb(lead_point ~ ho_gv, data = filter(hg_point_lead, ho_gv < 20))

hg_point_lm <- glmer(
  lead_point ~
    ho_gv *
    background +
    (1|dyad),
  data = filter(hg_point_lead, ho_gv < 20),
  family = negbin(0.2606)
)
```

```
## singular fit
```

```
summary(hg_point_lm)
```

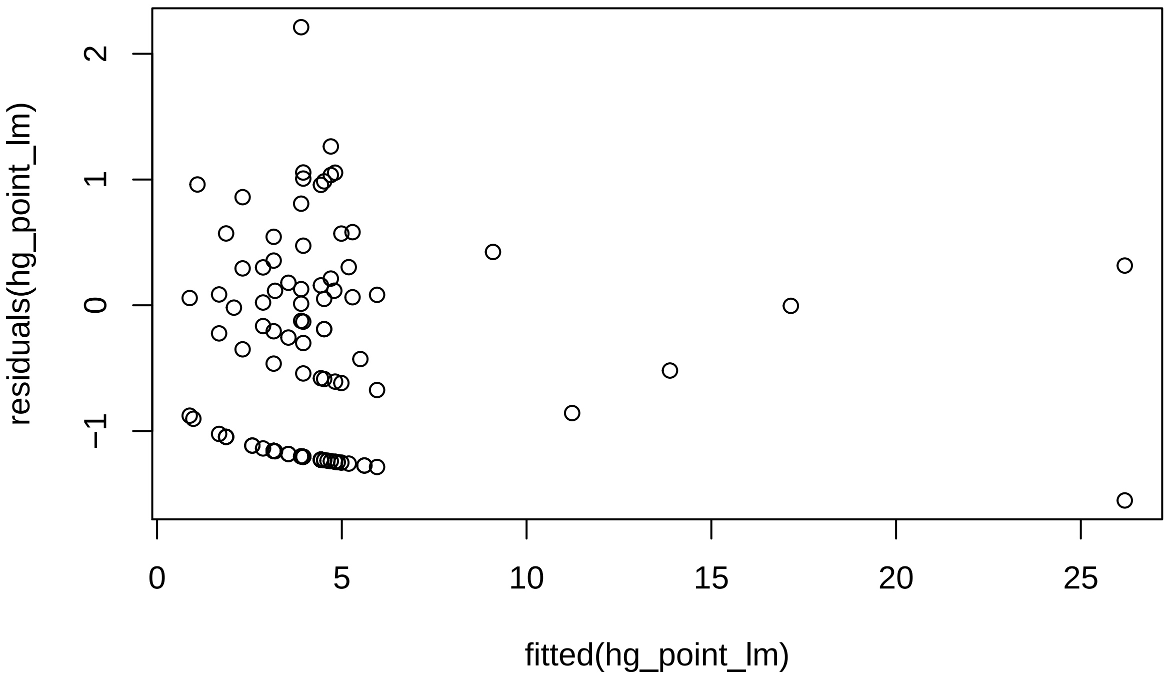
```
## Generalized linear mixed model fit by maximum likelihood (Laplace
##   Approximation) [glmerMod]
##  Family: Negative Binomial(0.261)  ( log )
## Formula: lead_point ~ ho_gv * background + (1 | dyad)
##    Data: filter(hg_point_lead, ho_gv < 20)
##
##      AIC      BIC   logLik deviance df.resid
##    503.8    525.3   -243.9    487.8      101
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
```

```
## -0.5080 -0.4942 -0.3979  0.1241  6.0969
##
## Random effects:
##  Groups Name        Variance Std.Dev.
##  dyad   (Intercept) 1.41e-10 1.187e-05
## Number of obs: 109, groups:  dyad, 57
##
## Fixed effects:
##                            Estimate Std. Error z value Pr(>|z|)
## (Intercept)                 1.37529    0.46393   2.964  0.00303 **
## ho_gv                      -0.10718    0.08031  -1.335  0.18200
## backgroundChinese           0.11400    0.68904   0.165  0.86859
## backgroundEnglish          -0.22613    0.62893  -0.360  0.71919
## ho_gv:backgroundChinese     0.12680    0.13875   0.914  0.36081
## ho_gv:backgroundEnglish     0.31880    0.15566   2.048  0.04056 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##              (Intr) ho_gv  bckgrC bckgrE h_gv:C
## ho_gv        -0.681
## bckgrndChns -0.673  0.459
## bckgrndEngl -0.738  0.502  0.497
## h_gv:bckgrC  0.394 -0.579 -0.714 -0.291
## h_gv:bckgrE  0.351 -0.516 -0.237 -0.621  0.299
## convergence code: 0
## singular fit
```

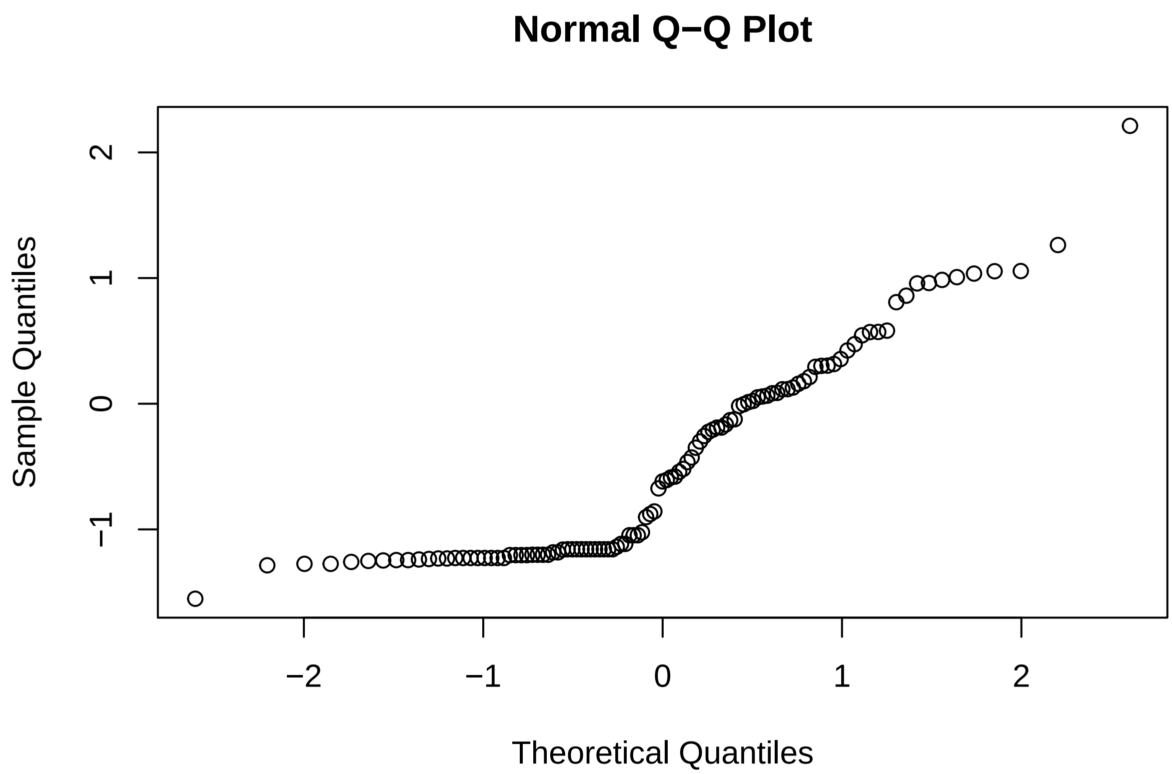
```r
hg_point_lm_null <- glmer(
  lead_point ~
    ho_gv +
    background +
    (1|dyad),
  data = filter(hg_point_lead, ho_gv < 20),
  family = negbin(0.2606)
)
anova(hg_point_lm_null, hg_point_lm)
```

```
## Data: filter(hg_point_lead, ho_gv < 20)
## Models:
## hg_point_lm_null: lead_point ~ ho_gv + background + (1 | dyad)
## hg_point_lm: lead_point ~ ho_gv * background + (1 | dyad)
##                  Df    AIC    BIC  logLik deviance  Chisq Chi Df
## hg_point_lm_null  6 504.69 520.84 -246.35   492.69
## hg_point_lm       8 503.79 525.32 -243.89   487.79 4.9055      2
##                  Pr(>Chisq)
## hg_point_lm_null
## hg_point_lm         0.08606 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
plot(fitted(hg_point_lm), residuals(hg_point_lm))
```

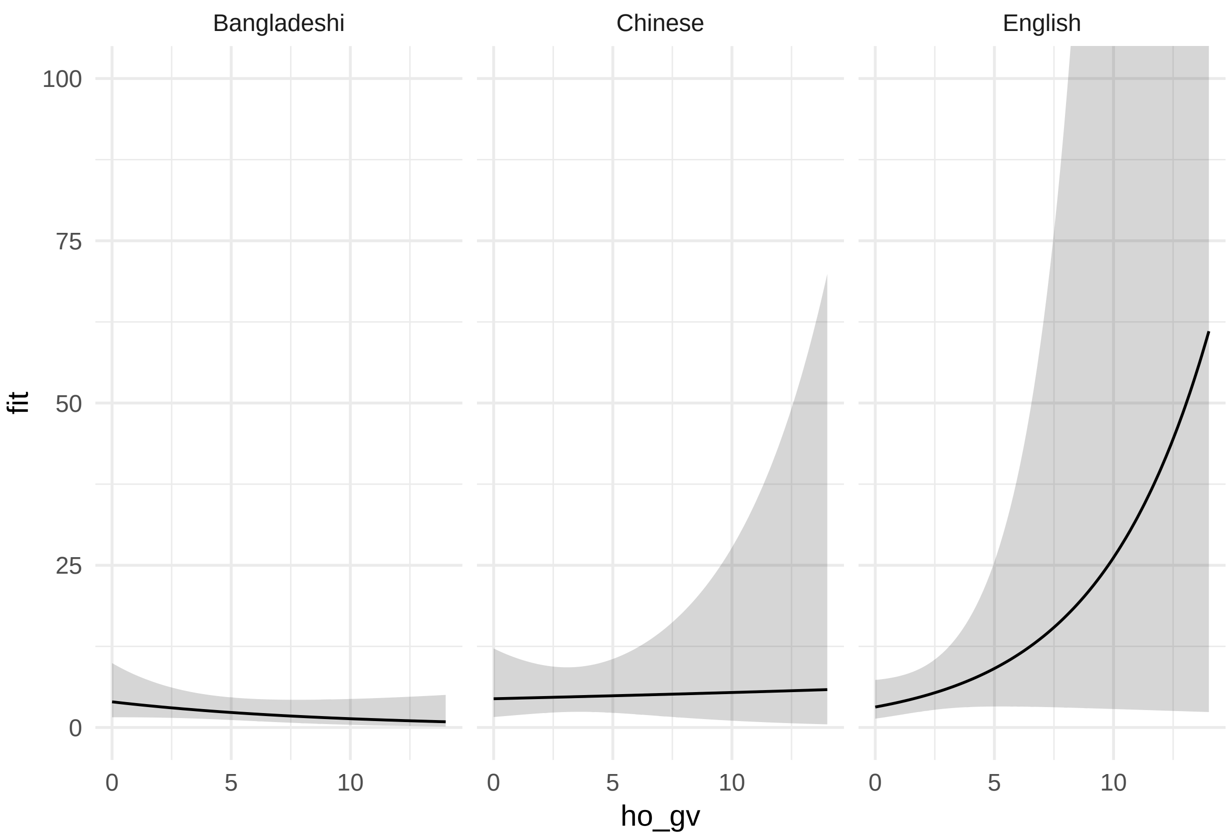



```r
qqnorm(residuals(hg_point_lm))
```

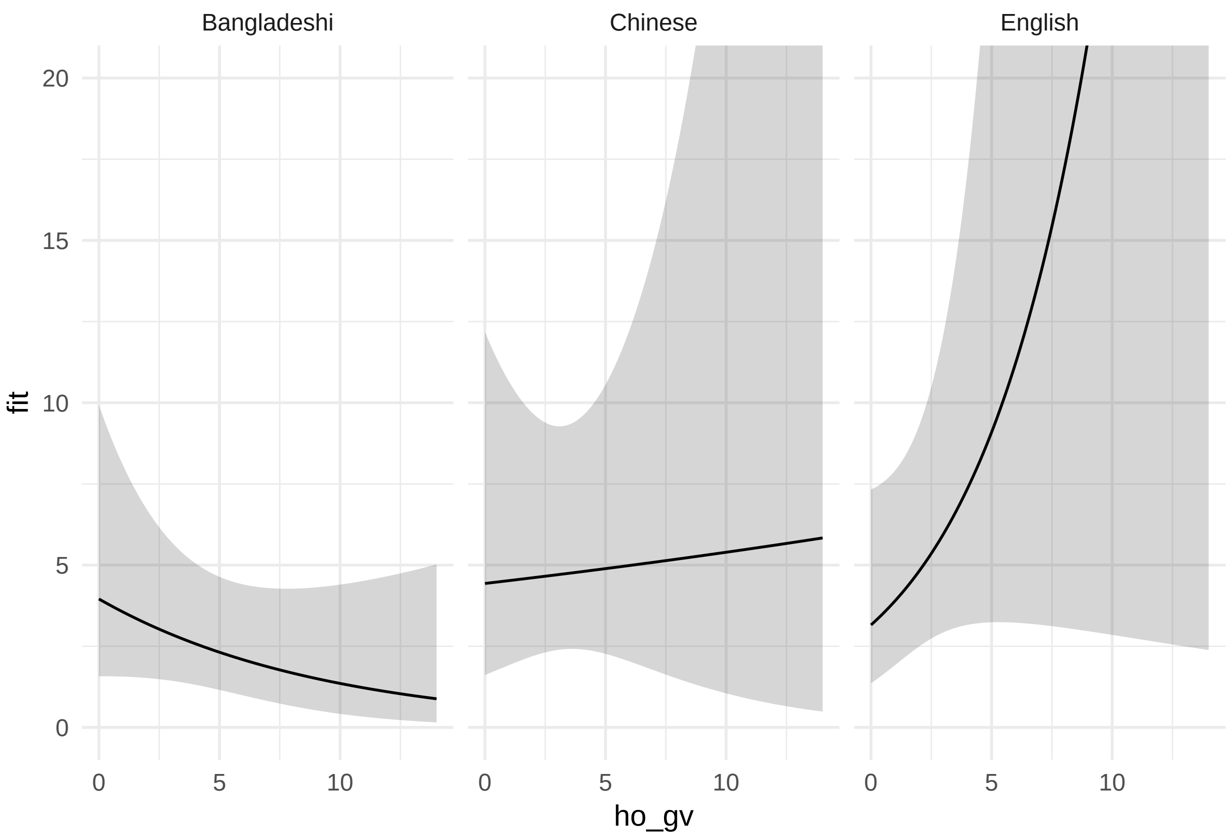



```r
hg_eff <- as_tibble(effect("ho_gv:background", hg_point_lm, xlevels = 100))

ggplot(hg_eff, aes(ho_gv, fit)) +
  geom_ribbon(aes(ymax = upper, ymin = lower), alpha = 0.2) +
  geom_line() +
  facet_grid(~ background) +
```

```
  coord_cartesian(ylim = c(0, 100))
```




```
ggplot(hg_eff, aes(ho_gv, fit)) +
  geom_ribbon(aes(ymax = upper, ymin = lower), alpha = 0.2) +
  geom_line() +
  facet_grid(~ background) +
  coord_cartesian(ylim = c(0, 20))
```



5 Analysis 2. Predictors of vocabulary scores at 12 and 18 months

5.1 Comprehension at 12 and 18 months

5.1.1 All gestures combined

```
all_gest_lm <- lmer(
  understand ~
    count_tot *
    months *
    background +
    (1|dyad),
  data = vocab
)
summary(all_gest_lm)
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: understand ~ count_tot * months * background + (1 | dyad)
##    Data: vocab
##
## REML criterion at convergence: 1180.8
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -1.74717 -0.54694  0.01362  0.40251  1.85188
##
```

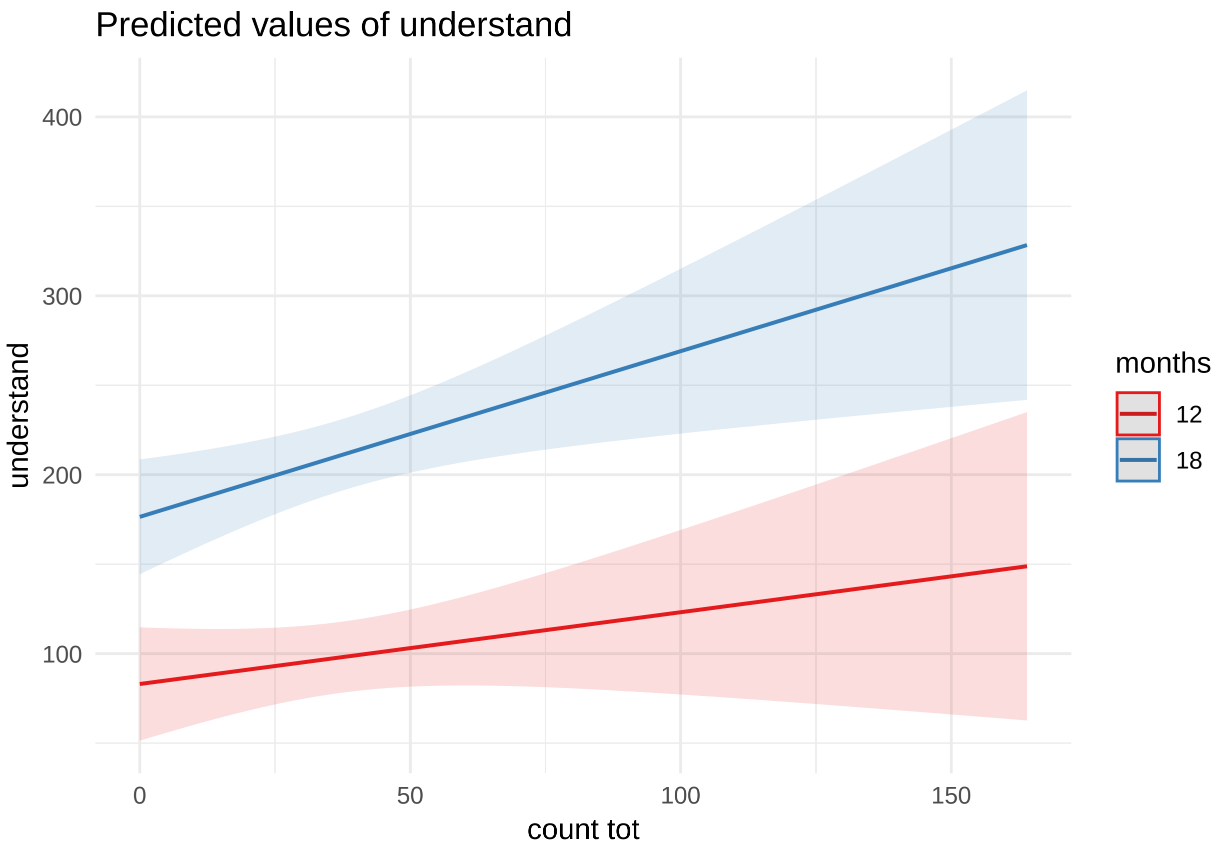
```
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  dyad     (Intercept) 2671     51.68
##  Residual             2299     47.95
## Number of obs: 109, groups:  dyad, 55
##
## Fixed effects:
##                                    Estimate Std. Error         df
## (Intercept)                       -11.53326   90.20899   60.50470
## count_tot                          -1.71945    2.03317   60.50470
## months                             10.30257    5.65012   47.87064
## backgroundChinese                -215.33019  116.59958   60.50470
## backgroundEnglish                 -90.30873  106.47214   60.64043
## count_tot:months                    0.11738    0.12734   47.87064
## count_tot:backgroundChinese         3.78521    2.52892   60.50470
## count_tot:backgroundEnglish        -0.24189    2.31867   60.53955
## months:backgroundChinese            9.90219    7.30306   47.87064
## months:backgroundEnglish            6.81052    6.69456   48.26704
## count_tot:months:backgroundChinese -0.10980    0.15840   47.87064
## count_tot:months:backgroundEnglish  0.01585    0.14537   47.97274
##                                    t value Pr(>|t|)
## (Intercept)                         -0.128   0.8987
## count_tot                           -0.846   0.4011
## months                               1.823   0.0745 .
## backgroundChinese                   -1.847   0.0697 .
## backgroundEnglish                   -0.848   0.3997
## count_tot:months                     0.922   0.3613
## count_tot:backgroundChinese          1.497   0.1397
## count_tot:backgroundEnglish         -0.104   0.9173
## months:backgroundChinese             1.356   0.1815
## months:backgroundEnglish             1.017   0.3141
## count_tot:months:backgroundChinese  -0.693   0.4915
## count_tot:months:backgroundEnglish   0.109   0.9136
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) cnt_tt months bckgrC bckgrE cnt_t: cnt_:C cnt_:E mnth:C
## count_tot   -0.888
## months      -0.940  0.835
## bckgrndChns -0.774  0.687  0.727
## bckgrndEngl -0.847  0.753  0.796  0.655
## cnt_tt:mnth  0.835 -0.940 -0.888 -0.646 -0.707
## cnt_tt:bckC  0.714 -0.804 -0.671 -0.861 -0.605  0.755
## cnt_tt:bckE  0.779 -0.877 -0.732 -0.603 -0.826  0.824  0.705
## mnths:bckgC  0.727 -0.646 -0.774 -0.940 -0.616  0.687  0.809  0.566
## mnths:bckgE  0.793 -0.705 -0.844 -0.613 -0.940  0.750  0.566  0.775  0.653
## cnt_tt:mn:C -0.671  0.755  0.714  0.809  0.569 -0.804 -0.940 -0.662 -0.861
## cnt_tt:mn:E -0.731  0.823  0.778  0.566  0.777 -0.876 -0.662 -0.940 -0.602
##             mnth:E cn_::C
## count_tot
## months
## bckgrndChns
## bckgrndEngl
```

```
## cnt_tt:mnth
## cnt_tt:bckC
## cnt_tt:bckE
## mnths:bckgC
## mnths:bckgE
## cnt_tt:mn:C -0.603
## cnt_tt:mn:E -0.825  0.704
```

```r
all_gest_lm_2 <- lmer(
  understand ~
    count_tot *
    months +
    (1|dyad),
  data = vocab
)
summary(all_gest_lm_2)
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: understand ~ count_tot * months + (1 | dyad)
##    Data: vocab
##
## REML criterion at convergence: 1220.4
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -1.53820 -0.47681 -0.09134  0.45523  1.97984
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  dyad     (Intercept) 3279     57.26
##  Residual             2365     48.63
## Number of obs: 109, groups:  dyad, 55
##
## Fixed effects:
##                    Estimate Std. Error        df t value Pr(>|t|)
## (Intercept)      -103.79077   40.02556  67.41098  -2.593   0.0117 *
## count_tot          -0.64884    0.83279  67.33012  -0.779   0.4386
## months             15.56858    2.50342  52.42242   6.219 8.42e-08 ***
## count_tot:months    0.08750    0.05192  52.11407   1.685   0.0979 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) cnt_tt months
## count_tot   -0.781
## months      -0.933  0.728
## cnt_tt:mnth  0.731 -0.932 -0.783
```

```r
plot_model(all_gest_lm_2, type = "pred", terms = c("count_tot", "months"))
```



5.1.2 HoGs + points

```
hgp_lm <- lmer(
  understand ~
    hgp_tot *
    months *
    background +
    (1|dyad),
  data = vocab
)
summary(hgp_lm)
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: understand ~ hgp_tot * months * background + (1 | dyad)
##    Data: vocab
##
## REML criterion at convergence: 1183.1
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -1.64675 -0.51967 -0.00448  0.42619  1.76485
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  dyad     (Intercept) 2890     53.75
```

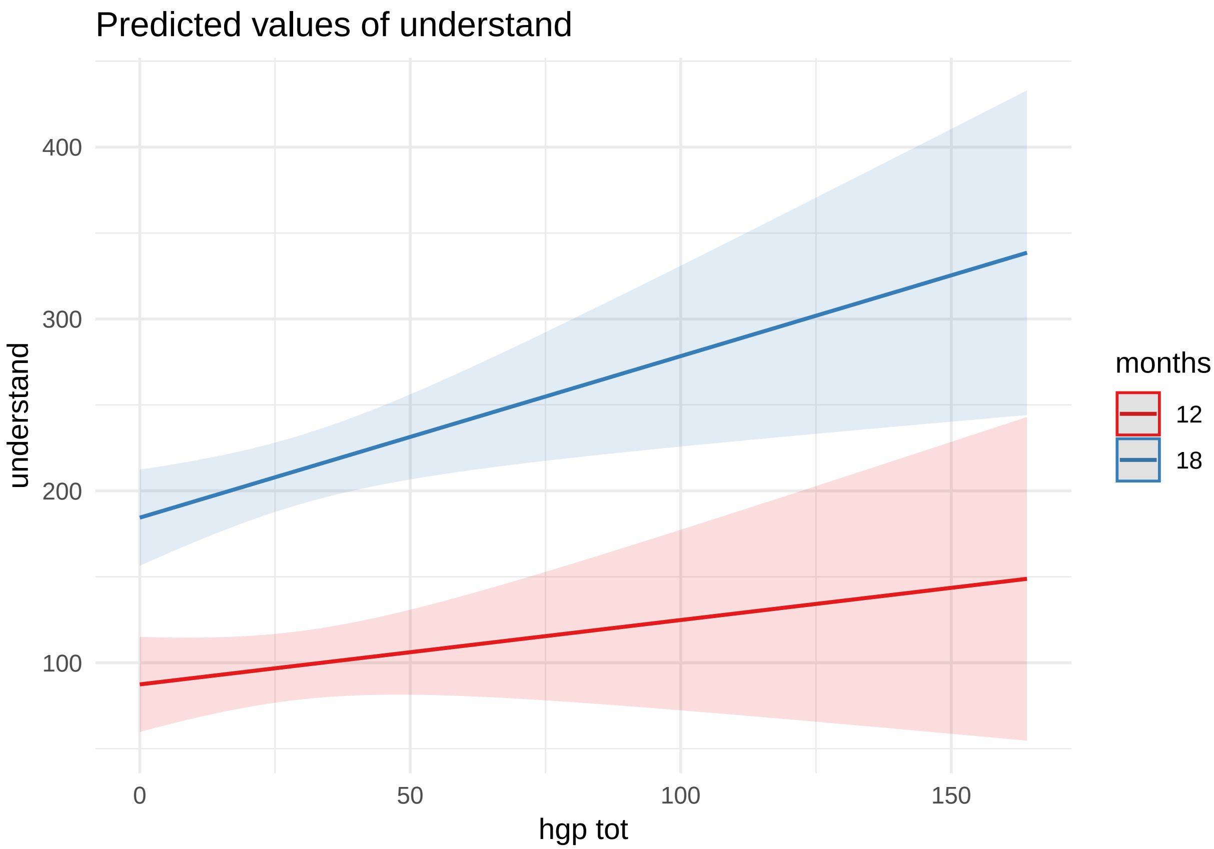
```
##  Residual             2304     48.00
## Number of obs: 109, groups:  dyad, 55
##
## Fixed effects:
##                                    Estimate Std. Error         df t value
## (Intercept)                      -3.025e+01  7.880e+01  6.121e+01  -0.384
## hgp_tot                          -1.743e+00  2.377e+00  6.121e+01  -0.733
## months                            1.113e+01  4.919e+00  4.790e+01   2.262
## backgroundChinese                -1.724e+02  1.018e+02  6.121e+01  -1.694
## backgroundEnglish                -8.627e+01  9.437e+01  6.133e+01  -0.914
## hgp_tot:months                    1.350e-01  1.484e-01  4.790e+01   0.910
## hgp_tot:backgroundChinese         3.597e+00  2.822e+00  6.121e+01   1.275
## hgp_tot:backgroundEnglish        -1.949e-01  2.624e+00  6.123e+01  -0.074
## months:backgroundChinese          9.052e+00  6.353e+00  4.790e+01   1.425
## months:backgroundEnglish          7.037e+00  5.916e+00  4.830e+01   1.189
## hgp_tot:months:backgroundChinese -1.246e-01  1.762e-01  4.790e+01  -0.707
## hgp_tot:months:backgroundEnglish -5.375e-03  1.639e-01  4.797e+01  -0.033
##                                  Pr(>|t|)
## (Intercept)                        0.7024
## hgp_tot                            0.4664
## months                             0.0283 *
## backgroundChinese                  0.0954 .
## backgroundEnglish                  0.3642
## hgp_tot:months                     0.3676
## hgp_tot:backgroundChinese          0.2073
## hgp_tot:backgroundEnglish          0.9410
## months:backgroundChinese           0.1607
## months:backgroundEnglish           0.2401
## hgp_tot:months:backgroundChinese   0.4829
## hgp_tot:months:backgroundEnglish   0.9740
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) hgp_tt months bckgrC bckgrE hgp_t: hgp_:C hgp_:E mnth:C
## hgp_tot     -0.850
## months      -0.936  0.796
## bckgrndChns -0.774  0.658  0.725
## bckgrndEngl -0.835  0.709  0.782  0.647
## hgp_tt:mnth  0.796 -0.936 -0.850 -0.616 -0.664
## hgp_tt:bckC  0.716 -0.842 -0.670 -0.809 -0.597  0.789
## hgp_tt:bckE  0.770 -0.906 -0.721 -0.596 -0.771  0.848  0.763
## mnths:bckgC  0.725 -0.616 -0.774 -0.936 -0.605  0.658  0.758  0.558
## mnths:bckgE  0.779 -0.661 -0.831 -0.603 -0.937  0.706  0.557  0.721  0.644
## hgp_tt:mn:C -0.670  0.789  0.716  0.758  0.559 -0.842 -0.936 -0.715 -0.809
## hgp_tt:mn:E -0.720  0.848  0.769  0.558  0.724 -0.905 -0.714 -0.937 -0.596
##             mnth:E hg_::C
## hgp_tot
## months
## bckgrndChns
## bckgrndEngl
## hgp_tt:mnth
## hgp_tt:bckC
## hgp_tt:bckE
```

```
## mnths:bckgC
## mnths:bckgE
## hgp_tt:mn:C -0.595
## hgp_tt:mn:E -0.771  0.763
```

```
hgp_lm_2 <- lmer(
  understand ~
    hgp_tot *
    months +
    (1|dyad),
  data = vocab
)
summary(hgp_lm_2)
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: understand ~ hgp_tot * months + (1 | dyad)
##    Data: vocab
##
## REML criterion at convergence: 1220.2
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -1.48779 -0.47461 -0.06162  0.46424  1.92329
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  dyad     (Intercept) 3315     57.58
##  Residual             2349     48.47
## Number of obs: 109, groups:  dyad, 55
##
## Fixed effects:
##                   Estimate Std. Error         df t value Pr(>|t|)
## (Intercept)     -106.62133   34.78108   67.61030  -3.065  0.00312 **
## hgp_tot           -0.75634    0.84955   67.53140  -0.890  0.37648
## months            16.16696    2.17268   52.40323   7.441 9.39e-10 ***
## hgp_tot:months     0.09424    0.05290   52.09060   1.782  0.08065 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##              (Intr) hgp_tt months
## hgp_tot      -0.698
## months       -0.932  0.650
## hgp_tt:mnth   0.652 -0.932 -0.700
```

```
plot_model(hgp_lm_2, type = "pred", terms = c("hgp_tot", "months"))
```



5.1.3 Reaches

```
reach_lm <- lmer(
  understand ~
    reach_tot *
    months *
    background +
    (1|dyad),
  data = vocab
)
summary(reach_lm)
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: understand ~ reach_tot * months * background + (1 | dyad)
##    Data: vocab
##
## REML criterion at convergence: 1178.6
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -1.77264 -0.51430  0.02511  0.54580  1.62157
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  dyad     (Intercept) 3654     60.45
```

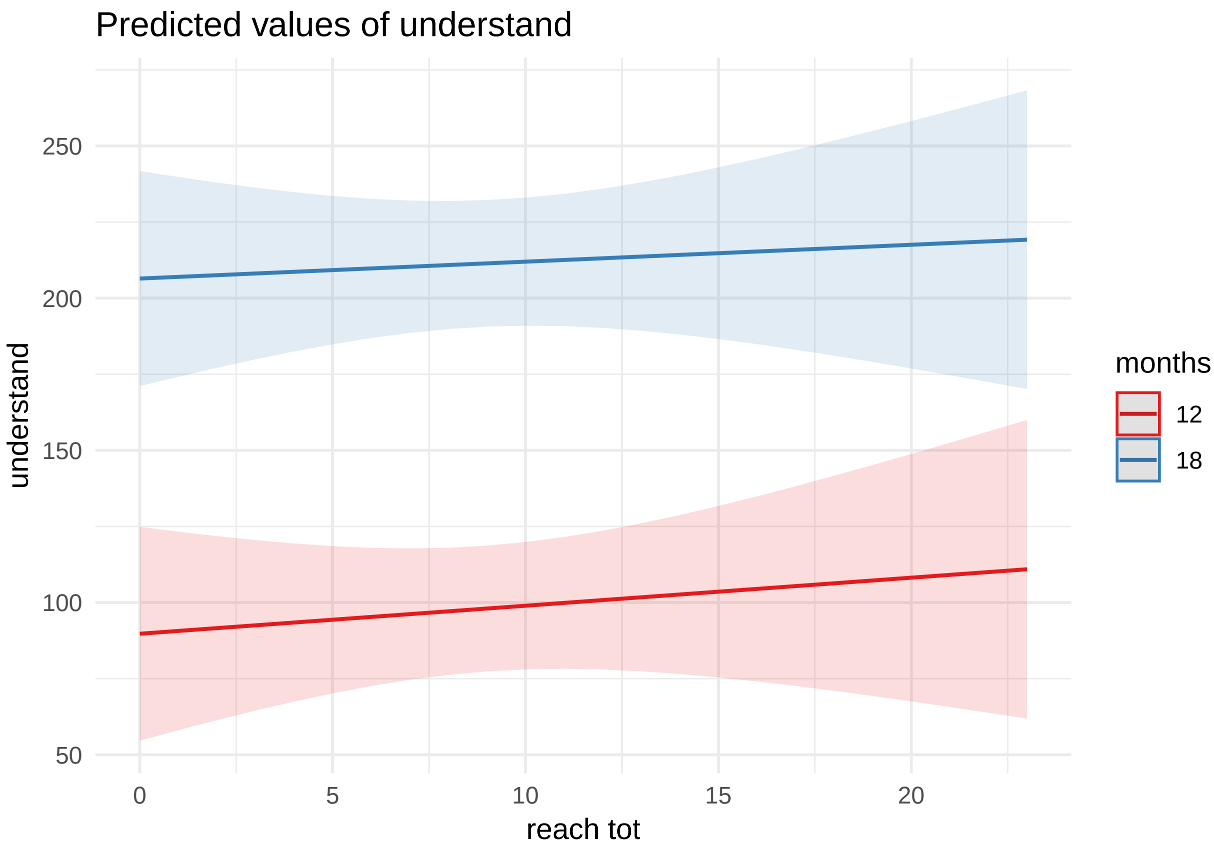
```
##  Residual             2485     49.85
## Number of obs: 109, groups:  dyad, 55
##
## Fixed effects:
##                                    Estimate Std. Error       df t value
## (Intercept)                        -31.8808    86.6703  62.7555  -0.368
## reach_tot                           -4.2115     6.6556  62.7555  -0.633
## months                              12.9846     5.3702  47.8794   2.418
## backgroundChinese                 -163.7787   118.8588  62.7555  -1.378
## backgroundEnglish                 -138.0321   108.6959  62.8027  -1.270
## reach_tot:months                     0.1727     0.4124  47.8794   0.419
## reach_tot:backgroundChinese         10.3022    10.4027  62.7555   0.990
## reach_tot:backgroundEnglish          4.5599     9.4843  62.7579   0.481
## months:backgroundChinese             8.1027     7.3647  47.8794   1.100
## months:backgroundEnglish             8.3412     6.7510  48.0873   1.236
## reach_tot:months:backgroundChinese  -0.2407     0.6446  47.8794  -0.373
## reach_tot:months:backgroundEnglish  -0.1323     0.5877  47.8900  -0.225
##                                   Pr(>|t|)
## (Intercept)                         0.7142
## reach_tot                           0.5292
## months                              0.0195 *
## backgroundChinese                   0.1731
## backgroundEnglish                   0.2088
## reach_tot:months                    0.6772
## reach_tot:backgroundChinese         0.3258
## reach_tot:backgroundEnglish         0.6323
## months:backgroundChinese            0.2767
## months:backgroundEnglish            0.2226
## reach_tot:months:backgroundChinese  0.7105
## reach_tot:months:backgroundEnglish  0.8229
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) rch_tt months bckgrC bckgrE rch_t: rch_:C rch_:E mnth:C
## reach_tot   -0.865
## months      -0.929  0.804
## bckgrndChns -0.729  0.631  0.678
## bckgrndEngl -0.797  0.690  0.741  0.581
## rch_tt:mnth  0.804 -0.929 -0.865 -0.586 -0.641
## rch_tt:bckC  0.553 -0.640 -0.514 -0.843 -0.441  0.595
## rch_tt:bckE  0.607 -0.702 -0.564 -0.443 -0.795  0.652  0.449
## mnths:bckgC  0.678 -0.586 -0.729 -0.929 -0.540  0.631  0.783  0.411
## mnths:bckgE  0.739 -0.639 -0.795 -0.539 -0.930  0.688  0.409  0.738  0.580
## rch_tt:mn:C -0.514  0.595  0.553  0.783  0.410 -0.640 -0.929 -0.417 -0.843
## rch_tt:mn:E -0.564  0.652  0.607  0.411  0.739 -0.702 -0.417 -0.929 -0.443
##             mnth:E rc_::C
## reach_tot
## months
## bckgrndChns
## bckgrndEngl
## rch_tt:mnth
## rch_tt:bckC
## rch_tt:bckE
```

```
## mnths:bckgC
## mnths:bckgE
## rch_tt:mn:C -0.440
## rch_tt:mn:E -0.794  0.449
```

```r
reach_lm_2 <- lmer(
  understand ~
    reach_tot *
    months +
    (1|dyad),
  data = vocab
)
summary(reach_lm_2)
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: understand ~ reach_tot * months + (1 | dyad)
##    Data: vocab
##
## REML criterion at convergence: 1221.3
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -1.5140 -0.5941 -0.0561  0.5158  1.7552
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  dyad     (Intercept) 3640     60.34
##  Residual             2473     49.73
## Number of obs: 109, groups:  dyad, 55
##
## Fixed effects:
##                    Estimate Std. Error        df t value Pr(>|t|)
## (Intercept)      -143.62983   43.54107  68.11489  -3.299  0.00155 **
## reach_tot           1.65200    3.91756  68.06536   0.422  0.67458
## months             19.44798    2.70583  52.22044   7.187 2.43e-09 ***
## reach_tot:months   -0.06093    0.24289  52.00199  -0.251  0.80291
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) rch_tt months
## reach_tot   -0.809
## months      -0.930  0.751
## rch_tt:mnth  0.753 -0.929 -0.809
```

```r
plot_model(reach_lm_2, type = "pred", terms = c("reach_tot", "months"))
```



5.1.4 Maternal utterances

```r
utt_lm <- lmer(
  understand ~
    utt_tot *
    months *
    background +
    (1|dyad),
  data = vocab
)
```

```
## Warning: Some predictor variables are on very different scales: consider
## rescaling

## Warning: Some predictor variables are on very different scales: consider
## rescaling
```

```r
summary(utt_lm)
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: understand ~ utt_tot * months * background + (1 | dyad)
##    Data: vocab
##
## REML criterion at convergence: 1111.2
##
## Scaled residuals:
```

```
##      Min       1Q   Median       3Q      Max
## -1.51565 -0.49198  0.00639  0.48531  1.73592
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  dyad     (Intercept) 3872     62.23
##  Residual             2410     49.09
## Number of obs: 99, groups:  dyad, 50
##
## Fixed effects:
##                                    Estimate Std. Error         df t value
## (Intercept)                      -8.473e+01  7.748e+01  5.740e+01  -1.094
## utt_tot                           6.841e-03  1.028e-01  5.740e+01   0.067
## months                            1.444e+01  4.778e+00  4.322e+01   3.021
## backgroundChinese                -1.069e+02  1.257e+02  5.740e+01  -0.851
## backgroundEnglish                 1.413e+02  2.405e+02  5.764e+01   0.587
## utt_tot:months                    1.704e-03  6.341e-03  4.322e+01   0.269
## utt_tot:backgroundChinese         5.678e-02  1.572e-01  5.740e+01   0.361
## utt_tot:backgroundEnglish        -2.117e-01  2.786e-01  5.756e+01  -0.760
## months:backgroundChinese          6.038e+00  7.750e+00  4.322e+01   0.779
## months:backgroundEnglish          1.574e+00  1.511e+01  4.459e+01   0.104
## utt_tot:months:backgroundChinese -1.938e-03  9.693e-03  4.322e+01  -0.200
## utt_tot:months:backgroundEnglish  1.116e-03  1.740e-02  4.414e+01   0.064
##                                  Pr(>|t|)
## (Intercept)                       0.27869
## utt_tot                           0.94718
## months                            0.00422 **
## backgroundChinese                 0.39851
## backgroundEnglish                 0.55921
## utt_tot:months                    0.78945
## utt_tot:backgroundChinese         0.71923
## utt_tot:backgroundEnglish         0.45037
## months:backgroundChinese          0.44021
## months:backgroundEnglish          0.91753
## utt_tot:months:backgroundChinese  0.84243
## utt_tot:months:backgroundEnglish  0.94916
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) utt_tt months bckgrC bckgrE utt_t: utt_:C utt_:E mnth:C
## utt_tot     -0.821
## months      -0.925  0.760
## bckgrndChns -0.617  0.506  0.570
## bckgrndEngl -0.322  0.265  0.298  0.199
## utt_tt:mnth  0.760 -0.925 -0.821 -0.468 -0.245
## utt_tt:bckC  0.537 -0.654 -0.497 -0.867 -0.173  0.605
## utt_tt:bckE  0.303 -0.369 -0.280 -0.187 -0.953  0.341  0.241
## mnths:bckgC  0.570 -0.468 -0.617 -0.925 -0.184  0.506  0.802  0.173
## mnths:bckgE  0.293 -0.240 -0.316 -0.180 -0.927  0.260  0.157  0.881  0.195
## utt_tt:mn:C -0.497  0.605  0.537  0.802  0.160 -0.654 -0.925 -0.223 -0.867
## utt_tt:mn:E -0.277  0.337  0.299  0.171  0.887 -0.364 -0.221 -0.926 -0.185
##             mnth:E ut_::C
## utt_tot
```

```
## months
## bckgrndChns
## bckgrndEngl
## utt_tt:mnth
## utt_tt:bckC
## utt_tt:bckE
## mnths:bckgC
## mnths:bckgE
## utt_tt:mn:C -0.170
## utt_tt:mn:E -0.954  0.238
## fit warnings:
## Some predictor variables are on very different scales: consider rescaling
```

```r
utt_lm_2 <- lmer(
  understand ~
    utt_tot *
    months +
    (1|dyad),
  data = vocab
)
```

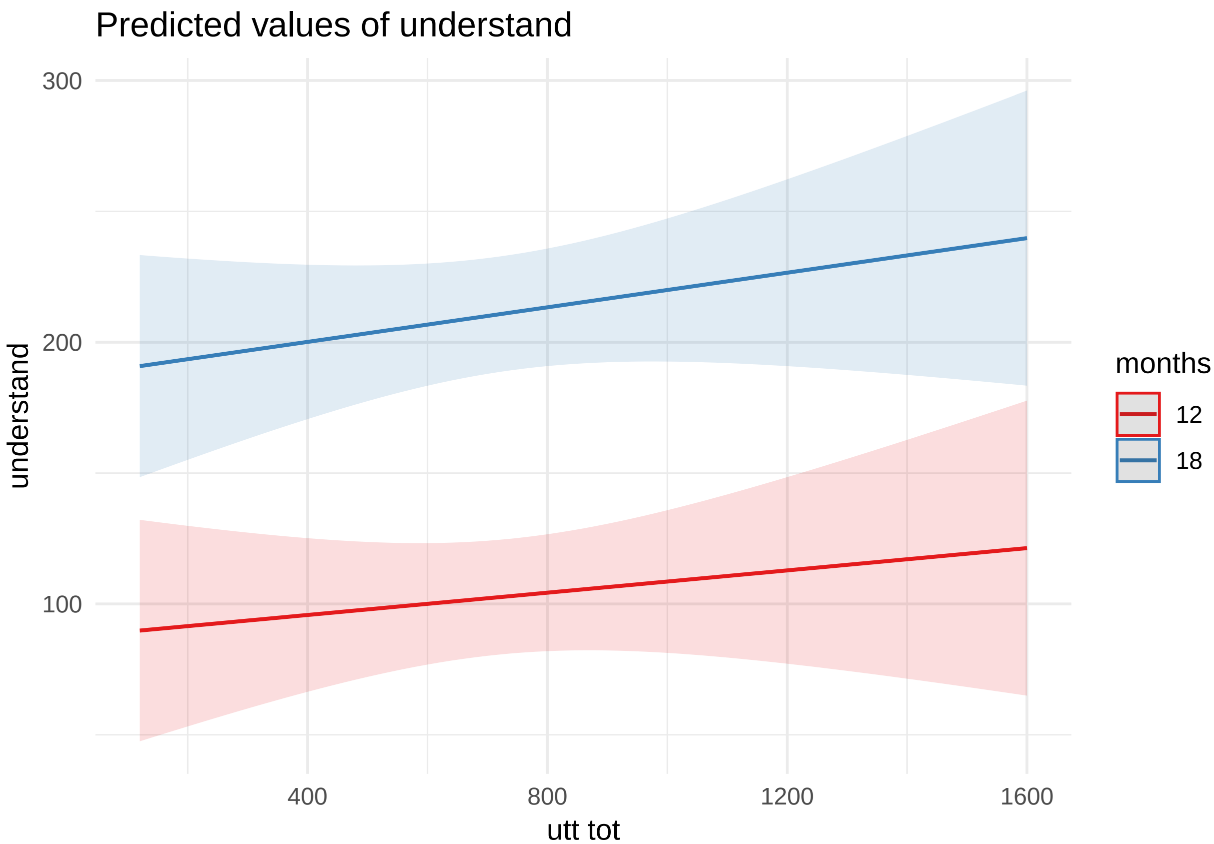
```
## Warning: Some predictor variables are on very different scales: consider
## rescaling

## Warning: Some predictor variables are on very different scales: consider
## rescaling
```

```r
summary(utt_lm_2)
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: understand ~ utt_tot * months + (1 | dyad)
##    Data: vocab
##
## REML criterion at convergence: 1122.3
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -1.50968 -0.52981  0.00072  0.46811  1.80340
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  dyad     (Intercept) 3963     62.95
##  Residual             2290     47.86
## Number of obs: 99, groups:  dyad, 50
##
## Fixed effects:
##                  Estimate Std. Error         df t value Pr(>|t|)
## (Intercept)    -1.120e+02  5.767e+01  6.337e+01  -1.943   0.0565 .
## utt_tot        -2.221e-03  7.058e-02  6.336e+01  -0.031   0.9750
## months          1.661e+01  3.547e+00  4.711e+01   4.682 2.43e-05 ***
## utt_tot:months  1.959e-03  4.336e-03  4.701e+01   0.452   0.6534
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

```
## Correlation of Fixed Effects:
##              (Intr) utt_tt months
## utt_tot      -0.892
## months       -0.921  0.821
## utt_tt:mnth   0.822 -0.921 -0.891
## fit warnings:
## Some predictor variables are on very different scales: consider rescaling
```

```
plot_model(utt_lm_2, type = "pred", terms = c("utt_tot", "months"))
```



5.1.5 Contingent talks

```
ct_lm <- lmer(
  understand ~
    ct_tot *
    months *
    background +
    (1|dyad),
  data = vocab
)
summary(ct_lm)
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: understand ~ ct_tot * months * background + (1 | dyad)
##    Data: vocab
##
```

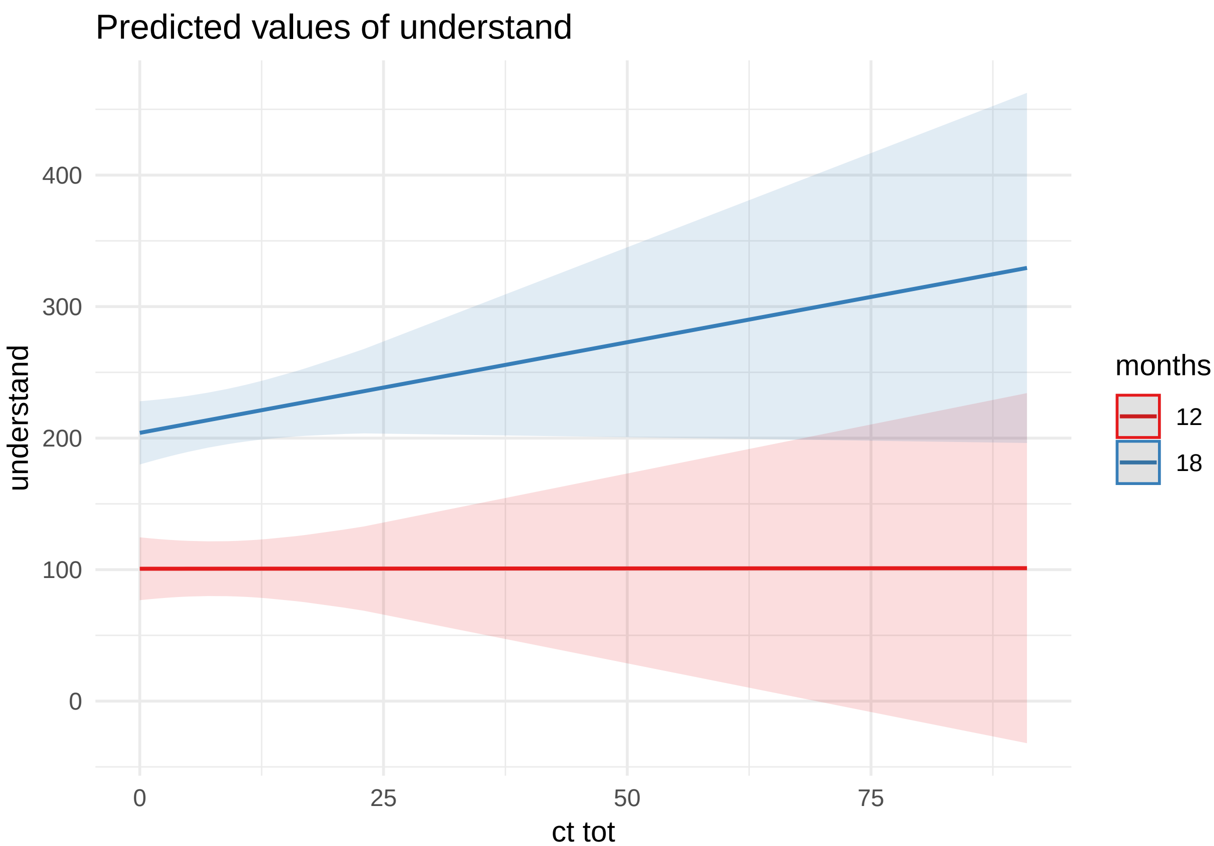
```
## REML criterion at convergence: 1158.5
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -1.5331 -0.5368  0.0162  0.4602  1.6119
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  dyad     (Intercept) 3625     60.21
##  Residual             2446     49.46
## Number of obs: 107, groups:  dyad, 54
##
## Fixed effects:
##                                  Estimate Std. Error        df t value
## (Intercept)                     -110.6215    53.7851   61.5684  -2.057
## ct_tot                             9.8165     9.9876   61.5684   0.983
## months                            16.6784     3.3313   46.9256   5.007
## backgroundChinese                -47.4939    87.2923   61.5684  -0.544
## backgroundEnglish                -18.8444    74.4312   61.6706  -0.253
## ct_tot:months                     -0.4354     0.6186   46.9256  -0.704
## ct_tot:backgroundChinese          -7.3882    11.7782   61.5684  -0.627
## ct_tot:backgroundEnglish         -13.0948    10.2215   61.5696  -1.281
## months:backgroundChinese           2.4688     5.4067   46.9256   0.457
## months:backgroundEnglish           2.3351     4.6350   47.3826   0.504
## ct_tot:months:backgroundChinese    0.5818     0.7295   46.9256   0.797
## ct_tot:months:backgroundEnglish    0.6581     0.6331   46.9308   1.039
##                                 Pr(>|t|)
## (Intercept)                        0.044 *
## ct_tot                             0.330
## months                          8.25e-06 ***
## backgroundChinese                  0.588
## backgroundEnglish                  0.801
## ct_tot:months                      0.485
## ct_tot:backgroundChinese           0.533
## ct_tot:backgroundEnglish           0.205
## months:backgroundChinese           0.650
## months:backgroundEnglish           0.617
## ct_tot:months:backgroundChinese    0.429
## ct_tot:months:backgroundEnglish    0.304
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) ct_tot months bckgrC bckgrE ct_tt: ct_t:C ct_t:E mnth:C
## ct_tot      -0.596
## months      -0.929  0.554
## bckgrndChns -0.616  0.367  0.572
## bckgrndEngl -0.723  0.431  0.671  0.445
## ct_tt:mnths  0.554 -0.929 -0.596 -0.341 -0.400
## ct_tt:bckgC  0.506 -0.848 -0.470 -0.624 -0.365  0.788
## ct_tt:bckgE  0.583 -0.977 -0.541 -0.359 -0.493  0.908  0.829
## mnths:bckgC  0.572 -0.341 -0.616 -0.929 -0.414  0.367  0.579  0.333
## mnths:bckgE  0.668 -0.398 -0.719 -0.411 -0.930  0.428  0.338  0.456  0.443
## ct_tt:mnt:C -0.470  0.788  0.506  0.579  0.339 -0.848 -0.929 -0.770 -0.624
```

```
## ct_tt:mnt:E -0.541  0.908  0.583  0.333  0.458 -0.977 -0.770 -0.929 -0.359
##             mnth:E ct_::C
## ct_tot
## months
## bckgrndChns
## bckgrndEngl
## ct_tt:mnths
## ct_tt:bckgC
## ct_tt:bckgE
## mnths:bckgC
## mnths:bckgE
## ct_tt:mnt:C -0.363
## ct_tt:mnt:E -0.491  0.829
```

```
ct_lm_2 <- lmer(
  understand ~
    ct_tot *
    months +
    (1|dyad),
  data = vocab
)
summary(ct_lm_2)
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: understand ~ ct_tot * months + (1 | dyad)
##    Data: vocab
##
## REML criterion at convergence: 1199.7
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -1.50281 -0.53484 -0.06465  0.45958  1.71123
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  dyad     (Intercept) 3680     60.67
##  Residual             2393     48.92
## Number of obs: 107, groups:  dyad, 54
##
## Fixed effects:
##                Estimate Std. Error        df t value Pr(>|t|)
## (Intercept)   -105.9926    29.3160   67.3472  -3.616 0.000574 ***
## ct_tot          -2.7417     1.9235   67.2909  -1.425 0.158670
## months          17.2216     1.8184   51.2881   9.471 7.53e-13 ***
## ct_tot:months    0.2289     0.1189   51.0070   1.924 0.059887 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) ct_tot months
## ct_tot      -0.494
## months      -0.928  0.457
## ct_tt:mnths  0.459 -0.927 -0.494
```

```r
plot_model(ct_lm_2, type = "pred", terms = c("ct_tot", "months"))
```



5.2 Production at 12 and 18 months

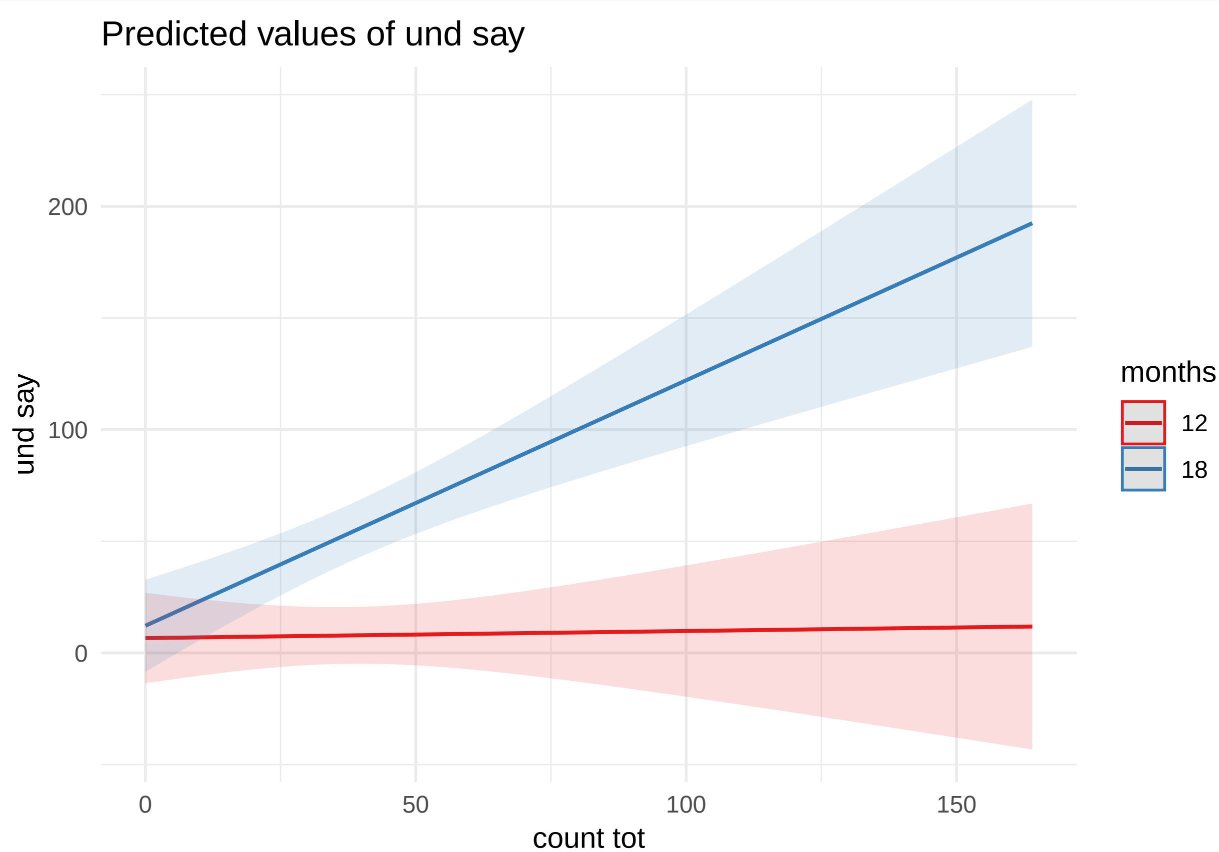
5.2.1 All gestures combined

```r
all_gest_lm_2_undsay <- lmer(
  und_say ~
    count_tot *
    months +
    (1|dyad),
  data = vocab
)
summary(all_gest_lm_2_undsay)
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: und_say ~ count_tot * months + (1 | dyad)
##    Data: vocab
##
## REML criterion at convergence: 1147.1
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -1.6451 -0.2949 -0.0400  0.1150  5.1936
##
## Random effects:
```

```
##  Groups   Name        Variance Std.Dev.
##  dyad     (Intercept)  281     16.76
##  Residual             2026     45.01
## Number of obs: 109, groups:  dyad, 55
##
## Fixed effects:
##                  Estimate Std. Error       df t value Pr(>|t|)
## (Intercept)      -4.40898   35.33834 58.60030  -0.125 0.901137
## count_tot        -2.10393    0.73592 58.32093  -2.859 0.005887 **
## months            0.92064    2.30729 53.64769   0.399 0.691468
## count_tot:months  0.17796    0.04795 53.17912   3.711 0.000495 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) cnt_tt months
## count_tot   -0.781
## months      -0.975  0.761
## cnt_tt:mnth  0.763 -0.975 -0.782
```

```
plot_model(all_gest_lm_2_undsay, type = "pred", terms = c("count_tot", "months"))
```



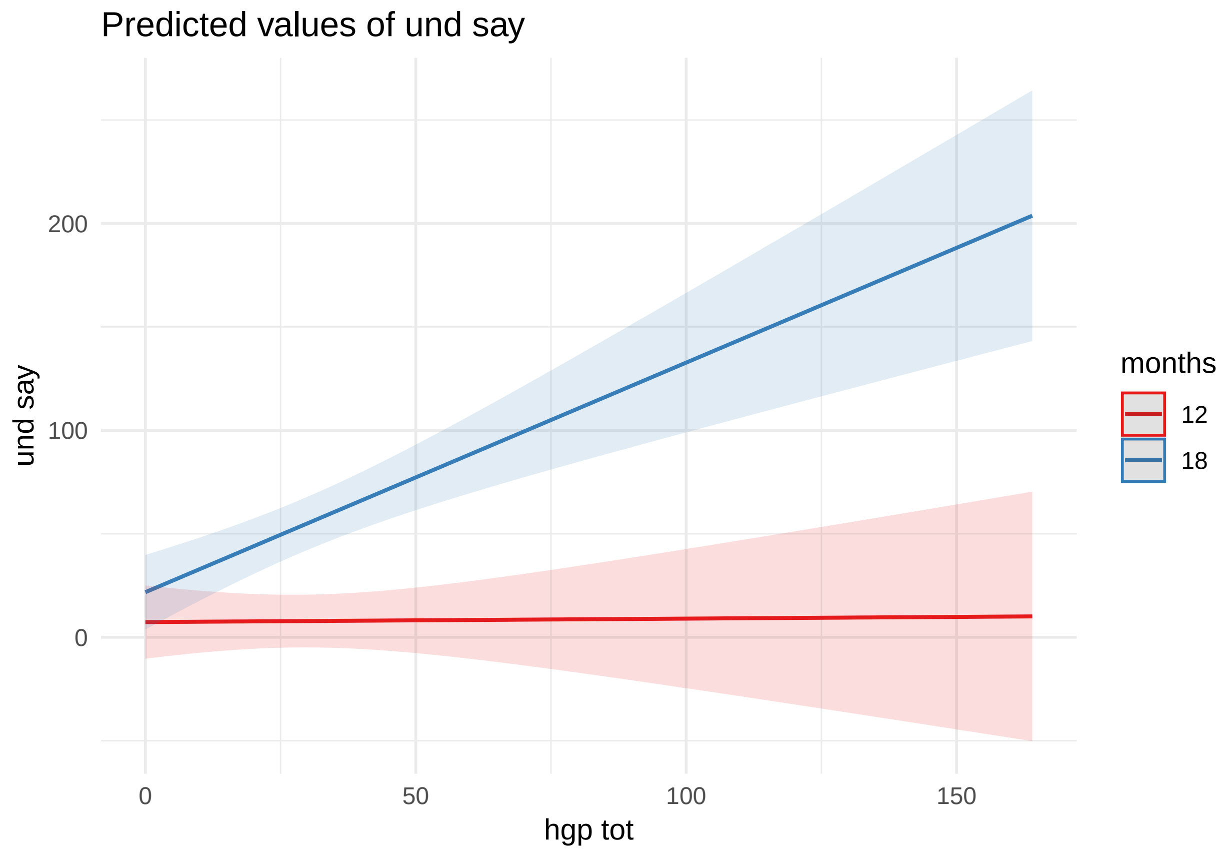
5.2.2 HoGs + point

```
hgp_lm_2_undsay <- lmer(
  und_say ~
    hgp_tot *
```

```r
    months +
    (1|dyad),
  data = vocab
)
summary(hgp_lm_2_undsay)
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: und_say ~ hgp_tot * months + (1 | dyad)
##    Data: vocab
##
## REML criterion at convergence: 1147.5
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -1.6473 -0.2989 -0.0408  0.1149  5.2699
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  dyad     (Intercept)  296.9   17.23
##  Residual             2024.2   44.99
## Number of obs: 109, groups:  dyad, 55
##
## Fixed effects:
##                   Estimate Std. Error        df t value Pr(>|t|)
## (Intercept)    -21.53337   30.78529  58.62260  -0.699 0.487025
## hgp_tot         -2.16893    0.75263  58.33881  -2.882 0.005525 **
## months           2.40664    2.00891  53.57824   1.198 0.236195
## hgp_tot:months   0.18213    0.04901  53.10111   3.716 0.000488 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) hgp_tt months
## hgp_tot     -0.697
## months      -0.975  0.680
## hgp_tt:mnth  0.681 -0.975 -0.699
```

```r
plot_model(hgp_lm_2_undsay, type = "pred", terms = c("hgp_tot", "months"))
```



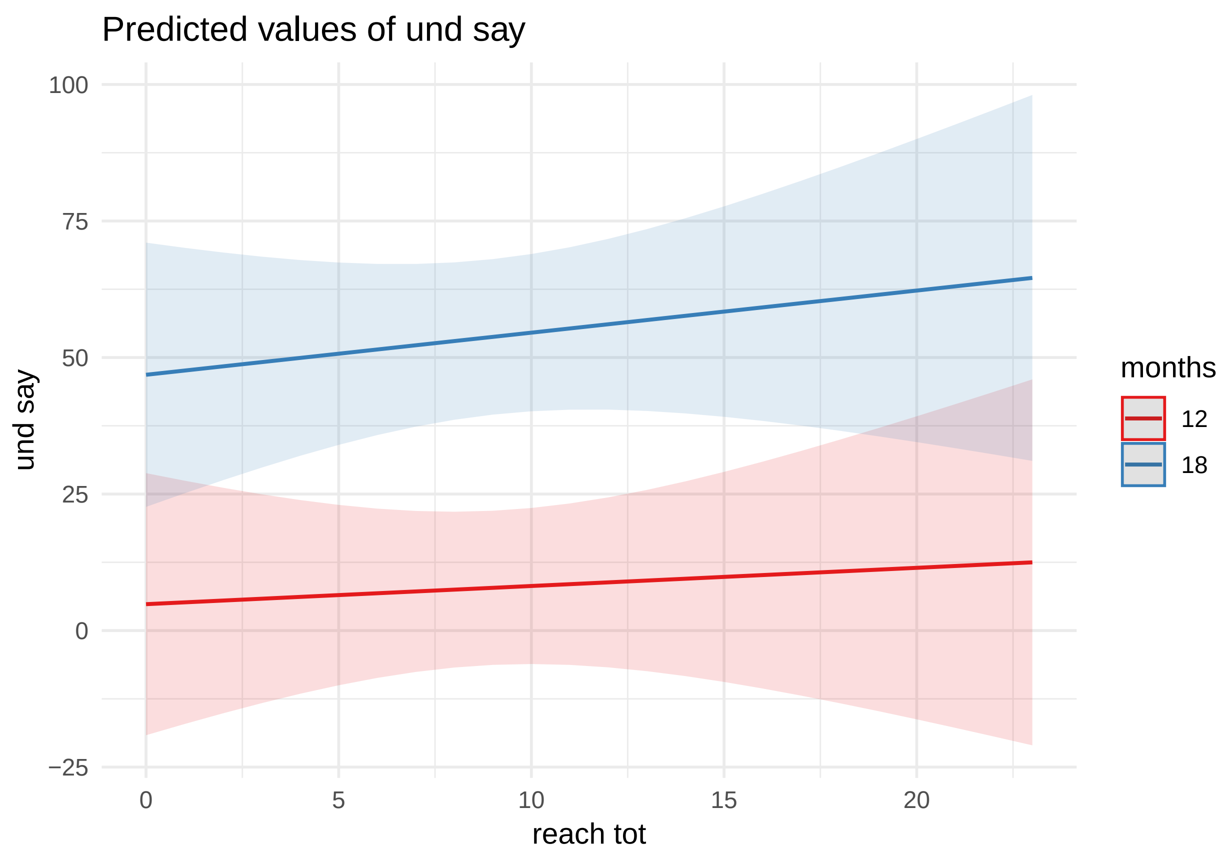
5.2.3 Reaches

```
reach_lm_2_undsay <- lmer(
  und_say ~
    reach_tot *
    months +
    (1|dyad),
  data = vocab
)
summary(reach_lm_2_undsay)
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: und_say ~ reach_tot * months + (1 | dyad)
##    Data: vocab
##
## REML criterion at convergence: 1163.4
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -1.0021 -0.5942 -0.0473  0.0622  4.8782
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  dyad     (Intercept)  301.7   17.37
##  Residual             2548.9   50.49
```

```
## Number of obs: 109, groups:  dyad, 55
##
## Fixed effects:
##                    Estimate Std. Error       df t value Pr(>|t|)
## (Intercept)       -79.18384   42.04927 58.12865  -1.883   0.0647 .
## reach_tot          -0.54333    3.78589 57.92651  -0.144   0.8864
## months              7.00150    2.74140 53.13124   2.554   0.0136 *
## reach_tot:months    0.07302    0.24647 52.79269   0.296   0.7682
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##              (Intr) rch_tt months
## reach_tot   -0.809
## months      -0.976  0.789
## rch_tt:mnth  0.790 -0.976 -0.809
```

```
plot_model(reach_lm_2_undsay, type = "pred", terms = c("reach_tot", "months"))
```



5.2.4 Maternal utterances

```
utt_lm_2_undsay <- lmer(
  und_say ~
    utt_tot *
    months +
    (1|dyad),
  data = vocab
```

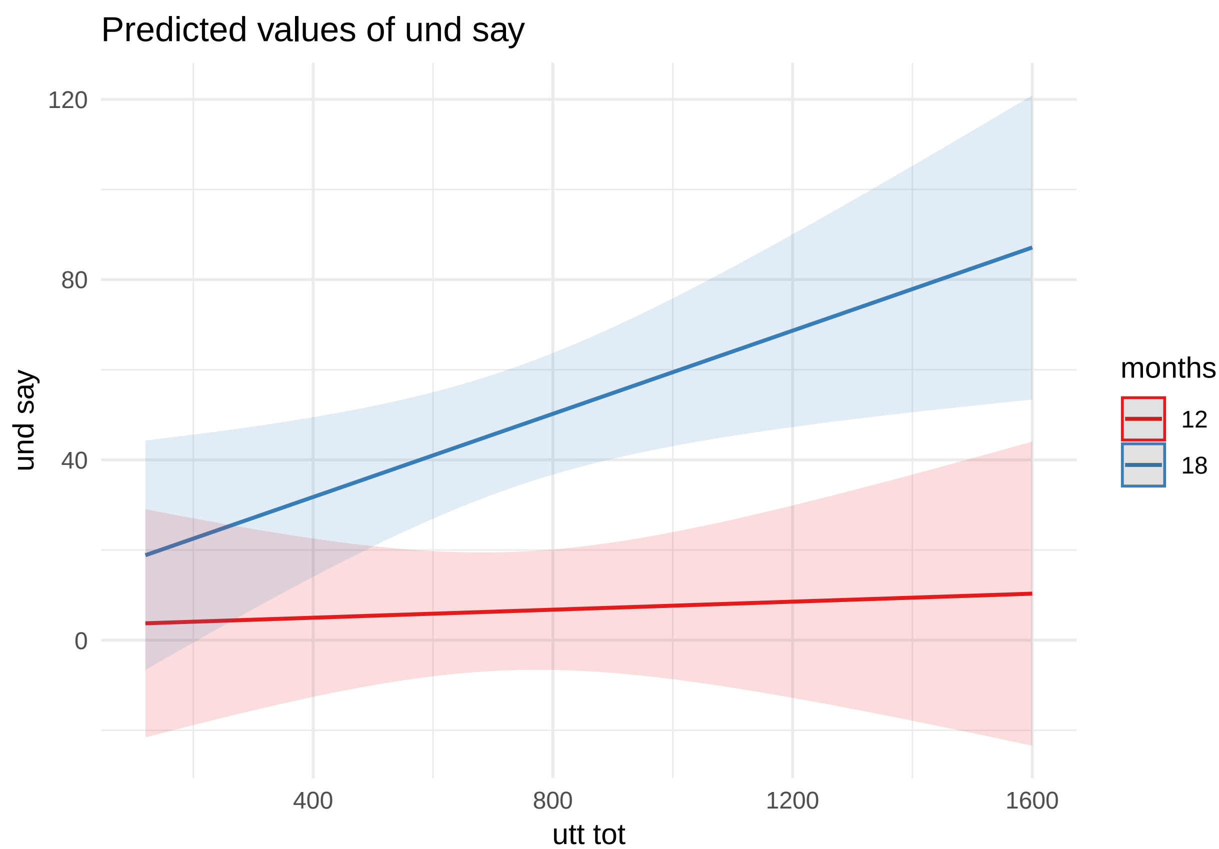
```r
)
```

```
## Warning: Some predictor variables are on very different scales: consider
## rescaling

## Warning: Some predictor variables are on very different scales: consider
## rescaling
```

```r
summary(utt_lm_2_undsay)
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: und_say ~ utt_tot * months + (1 | dyad)
##    Data: vocab
##
## REML criterion at convergence: 1048.3
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -1.5455 -0.3786 -0.0439  0.0721  4.9551
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  dyad     (Intercept)  252.7   15.90
##  Residual             1988.0   44.59
## Number of obs: 99, groups:  dyad, 50
##
## Fixed effects:
##                  Estimate Std. Error         df t value Pr(>|t|)
## (Intercept)    -17.010657  50.696871  52.550812  -0.336   0.7386
## utt_tot         -0.078926   0.062078  52.447768  -1.271   0.2092
## months           1.684411   3.301037  47.882950   0.510   0.6122
## utt_tot:months   0.006948   0.004039  47.709819   1.720   0.0919 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) utt_tt months
## utt_tot     -0.892
## months      -0.976  0.870
## utt_tt:mnth  0.871 -0.976 -0.892
## fit warnings:
## Some predictor variables are on very different scales: consider rescaling
```

```r
plot_model(utt_lm_2_undsay, type = "pred", terms = c("utt_tot", "months"))
```



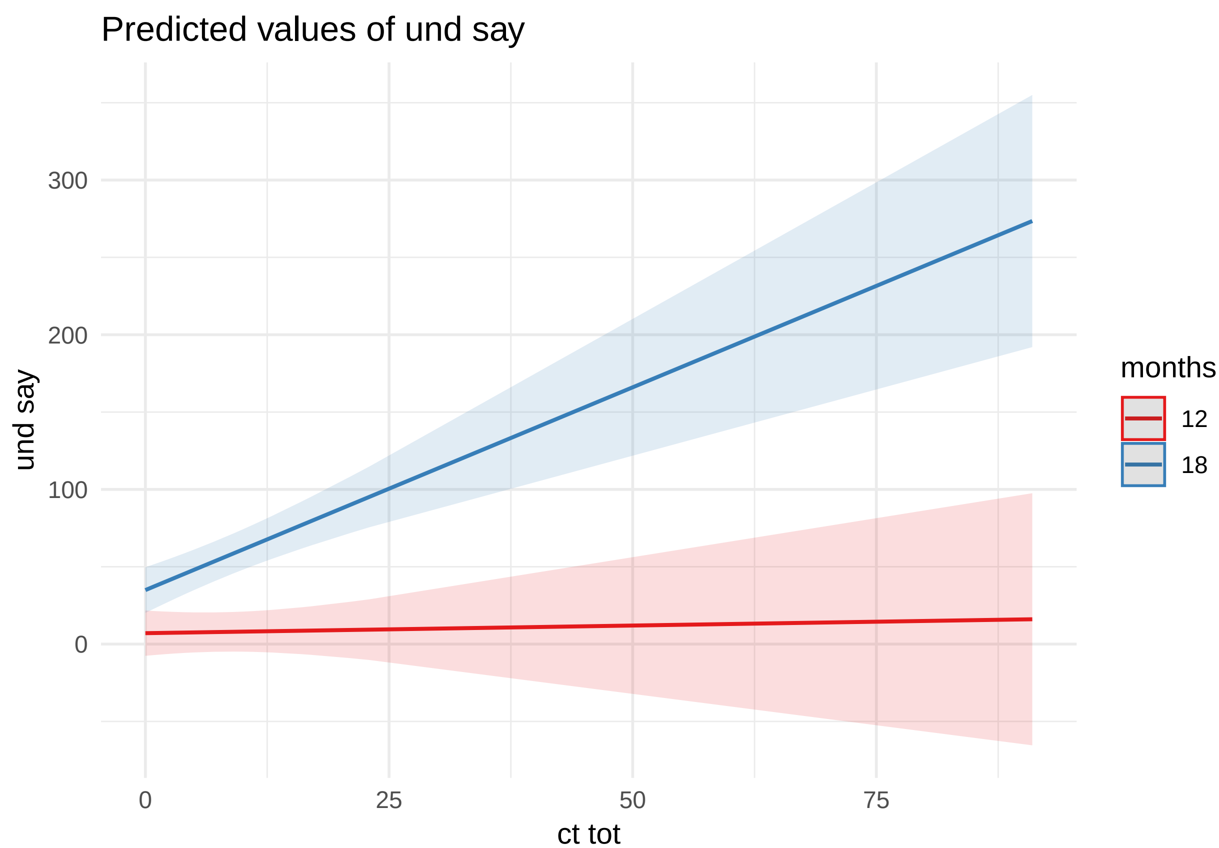
5.2.5 Contingent talks

```
ct_lm_2_undsay <- lmer(
  und_say ~
    ct_tot *
    months +
    (1|dyad),
  data = vocab
)
summary(ct_lm_2_undsay)
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: und_say ~ ct_tot * months + (1 | dyad)
##    Data: vocab
##
## REML criterion at convergence: 1121.2
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -1.4538 -0.4998 -0.0264  0.0844  5.0390
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  dyad     (Intercept)  272.8   16.52
##  Residual             2004.2   44.77
```

```
## Number of obs: 107, groups:  dyad, 54
##
## Fixed effects:
##                Estimate Std. Error       df t value Pr(>|t|)
## (Intercept)    -48.6655    25.4770  57.1883  -1.910 0.061130 .
## ct_tot          -4.9476     1.6731  56.9250  -2.957 0.004514 **
## months           4.6434     1.6602  52.1618   2.797 0.007210 **
## ct_tot:months    0.4205     0.1088  51.7189   3.864 0.000312 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##              (Intr) ct_tot months
## ct_tot       -0.494
## months       -0.975  0.481
## ct_tt:mnths   0.482 -0.975 -0.494
```

```
plot_model(ct_lm_2_undsay, type = "pred", terms = c("ct_tot", "months"))
```



6 R session

```
devtools::session_info()
```

```
## - Session info ----------------------------------------------------------
##  setting  value
##  version  R version 3.5.2 (2018-12-20)
```

```
##  os       macOS Mojave 10.14.2
##  system   x86_64, darwin15.6.0
##  ui       X11
##  language (EN)
##  collate  en_GB.UTF-8
##  ctype    en_GB.UTF-8
##  tz       Europe/London
##  date     2019-01-21
##
## - Packages --------------------------------------------------------------
##  package       * version  date       lib
##  abind           1.4-5    2016-07-21 [1]
##  assertthat      0.2.0    2017-04-11 [1]
##  backports       1.1.3    2018-12-14 [1]
##  bayesplot       1.6.0    2018-08-02 [1]
##  bindr           0.1.1    2018-03-13 [1]
##  bindrcpp      * 0.2.2    2018-03-29 [1]
##  binom           1.1-1    2014-01-02 [1]
##  broom           0.5.1    2018-12-05 [1]
##  callr           3.1.1    2018-12-21 [1]
##  car             3.0-2    2018-08-23 [1]
##  carData       * 3.0-2    2018-09-30 [1]
##  cellranger      1.1.0    2016-07-27 [1]
##  cli             1.0.1    2018-09-25 [1]
##  coda            0.19-2   2018-10-08 [1]
##  codetools       0.2-16   2018-12-24 [1]
##  coin            1.2-2    2017-11-28 [1]
##  colorspace      1.4-0    2019-01-13 [1]
##  crayon          1.3.4    2017-09-16 [1]
##  curl            3.3      2019-01-10 [1]
##  data.table      1.12.0   2019-01-13 [1]
##  desc            1.2.0    2018-05-01 [1]
##  devtools        2.0.1    2018-10-26 [1]
##  digest          0.6.18   2018-10-10 [1]
##  dplyr         * 0.7.8    2018-11-10 [1]
##  effects       * 4.1-0    2018-11-30 [1]
##  emmeans         1.3.1    2018-12-13 [1]
##  estimability    1.3      2018-02-11 [1]
##  evaluate        0.12     2018-10-09 [1]
##  forcats       * 0.3.0    2018-02-19 [1]
##  foreign         0.8-71   2018-07-20 [1]
##  fs              1.2.6    2018-08-23 [1]
##  generics        0.0.2    2018-11-29 [1]
##  ggeffects       0.8.0    2019-01-09 [1]
##  ggplot2       * 3.1.0    2018-10-25 [1]
##  ggridges        0.5.1    2018-09-27 [1]
##  glmmTMB         0.2.3    2019-01-11 [1]
##  glue            1.3.0    2018-07-17 [1]
##  gtable          0.2.0    2016-02-26 [1]
##  haven           2.0.0    2018-11-22 [1]
##  hms             0.4.2    2018-03-10 [1]
##  htmltools       0.3.6    2017-04-28 [1]
##  httr            1.4.0    2018-12-11 [1]
##  iterators       1.0.10   2018-07-13 [1]
```

```
##  itsadug       * 2.3      2017-08-31 [1]
##  jsonlite        1.6      2018-12-07 [1]
##  knitr           1.21     2018-12-10 [1]
##  labeling        0.3      2014-08-23 [1]
##  lattice         0.20-38  2018-11-04 [1]
##  lazyeval        0.2.1    2017-10-29 [1]
##  lme4          * 1.1-19   2018-11-10 [1]
##  lmerTest      * 3.0-1    2018-04-23 [1]
##  lubridate       1.7.4    2018-04-11 [1]
##  magrittr        1.5      2014-11-22 [1]
##  MASS          * 7.3-51.1 2018-11-01 [1]
##  Matrix        * 1.2-15   2018-11-01 [1]
##  memoise         1.1.0    2017-04-21 [1]
##  mgcv          * 1.8-26   2018-11-21 [1]
##  minqa           1.2.4    2014-10-09 [1]
##  mnormt          1.5-5    2016-10-15 [1]
##  modelr          0.1.2    2018-05-11 [1]
##  modeltools      0.2-22   2018-07-16 [1]
##  multcomp        1.4-8    2017-11-08 [1]
##  munsell         0.5.0    2018-06-12 [1]
##  mvtnorm         1.0-8    2018-05-31 [1]
##  nlme          * 3.1-137  2018-04-07 [1]
##  nloptr          1.2.1    2018-10-03 [1]
##  nnet            7.3-12   2016-02-02 [1]
##  numDeriv        2016.8-1 2016-08-27 [1]
##  openxlsx        4.1.0    2018-05-26 [1]
##  pbkrtest        0.4-7    2017-03-15 [1]
##  pillar          1.3.1    2018-12-15 [1]
##  pkgbuild        1.0.2    2018-10-16 [1]
##  pkgconfig       2.0.2    2018-08-16 [1]
##  pkgload         1.0.2    2018-10-29 [1]
##  plotfunctions * 1.3      2017-08-30 [1]
##  plotrix         3.7-4    2018-10-03 [1]
##  plyr            1.8.4    2016-06-08 [1]
##  prediction      0.3.6.1  2018-12-04 [1]
##  prettyunits     1.0.2    2015-07-13 [1]
##  processx        3.2.1    2018-12-05 [1]
##  ps              1.3.0    2018-12-21 [1]
##  psych           1.8.12   2019-01-12 [1]
##  purrr         * 0.2.5    2018-05-29 [1]
##  pwr             1.2-2    2018-03-03 [1]
##  R6              2.3.0    2018-10-04 [1]
##  Rcpp            1.0.0    2018-11-07 [1]
##  readr         * 1.3.1    2018-12-21 [1]
##  readxl          1.2.0    2018-12-19 [1]
##  remotes         2.0.2    2018-10-30 [1]
##  reshape2        1.4.3    2017-12-11 [1]
##  rio             0.5.16   2018-11-26 [1]
##  rlang           0.3.1    2019-01-08 [1]
##  RLRsim          3.1-3    2016-11-04 [1]
##  rmarkdown       1.11     2018-12-08 [1]
##  rprojroot       1.3-2    2018-01-03 [1]
##  rstudioapi      0.9.0    2019-01-09 [1]
##  rvest           0.3.2    2016-06-17 [1]
```

```
##   sandwich          2.5-0    2018-08-17 [1]
##   scales            1.0.0    2018-08-09 [1]
##   sessioninfo       1.1.1    2018-11-05 [1]
##   simr            * 1.0.4    2018-04-30 [1]
##   sjlabelled        1.0.16   2019-01-10 [1]
##   sjmisc            2.7.7    2019-01-02 [1]
##   sjPlot          * 2.6.2    2018-12-18 [1]
##   sjstats           0.17.3   2019-01-07 [1]
##   snakecase         0.9.2    2018-08-14 [1]
##   stringdist        0.9.5.1  2018-06-08 [1]
##   stringi           1.2.4    2018-07-20 [1]
##   stringr         * 1.3.1    2018-05-10 [1]
##   survey            3.35     2018-12-17 [1]
##   survival          2.43-3   2018-11-26 [1]
##   testthat          2.0.1    2018-10-13 [1]
##   TH.data           1.0-9    2018-07-10 [1]
##   tibble          * 2.0.1    2019-01-12 [1]
##   tidymv          * 2.0.0    2019-01-15 [1]
##   tidyr           * 0.8.2    2018-10-28 [1]
##   tidyselect        0.2.5    2018-10-11 [1]
##   tidyverse       * 1.2.1    2017-11-14 [1]
##   TMB               1.7.15   2018-11-09 [1]
##   usethis           1.4.0    2018-08-14 [1]
##   withr             2.1.2    2018-03-15 [1]
##   xfun              0.4      2018-10-23 [1]
##   xml2              1.2.0    2018-01-24 [1]
##   xtable            1.8-3    2018-08-29 [1]
##   yaml              2.2.0    2018-07-25 [1]
##   zip               1.0.0    2017-04-25 [1]
##   zoo               1.8-4    2018-09-19 [1]
##   source
##   CRAN (R 3.5.0)
##   CRAN (R 3.5.0)
##   CRAN (R 3.5.0)
##   CRAN (R 3.5.0)
##   CRAN (R 3.5.0)
##   CRAN (R 3.5.0)
##   CRAN (R 3.5.0)
##   CRAN (R 3.5.0)
##   CRAN (R 3.5.0)
##   CRAN (R 3.5.0)
##   CRAN (R 3.5.0)
##   CRAN (R 3.5.0)
##   CRAN (R 3.5.0)
##   CRAN (R 3.5.0)
##   CRAN (R 3.5.2)
##   CRAN (R 3.5.0)
##   CRAN (R 3.5.2)
##   CRAN (R 3.5.0)
##   CRAN (R 3.5.2)
##   CRAN (R 3.5.2)
##   CRAN (R 3.5.0)
##   CRAN (R 3.5.2)
##   CRAN (R 3.5.0)
```

```
##   CRAN (R 3.5.0)
##   CRAN (R 3.5.0)
##   CRAN (R 3.5.0)
##   CRAN (R 3.5.0)
##   CRAN (R 3.5.0)
##   CRAN (R 3.5.0)
##   CRAN (R 3.5.2)
##   CRAN (R 3.5.0)
##   CRAN (R 3.5.0)
##   CRAN (R 3.5.2)
##   CRAN (R 3.5.0)
##   CRAN (R 3.5.0)
##   CRAN (R 3.5.2)
##   CRAN (R 3.5.0)
##   CRAN (R 3.5.0)
##   CRAN (R 3.5.0)
##   CRAN (R 3.5.0)
##   CRAN (R 3.5.0)
##   CRAN (R 3.5.0)
##   CRAN (R 3.5.0)
##   CRAN (R 3.5.0)
##   CRAN (R 3.5.0)
##   CRAN (R 3.5.2)
##   CRAN (R 3.5.0)
##   CRAN (R 3.5.2)
##   CRAN (R 3.5.0)
##   CRAN (R 3.5.0)
##   CRAN (R 3.5.0)
##   CRAN (R 3.5.0)
##   CRAN (R 3.5.0)
##   CRAN (R 3.5.2)
##   CRAN (R 3.5.2)
##   CRAN (R 3.5.0)
##   CRAN (R 3.5.2)
##   CRAN (R 3.5.0)
##   CRAN (R 3.5.0)
##   CRAN (R 3.5.0)
##   CRAN (R 3.5.0)
##   CRAN (R 3.5.0)
##   CRAN (R 3.5.0)
##   CRAN (R 3.5.0)
##   CRAN (R 3.5.2)
##   CRAN (R 3.5.0)
##   CRAN (R 3.5.2)
##   CRAN (R 3.5.0)
##   CRAN (R 3.5.0)
##   CRAN (R 3.5.0)
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## [1] /Library/Frameworks/R.framework/Versions/3.5/Resources/library
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