

# Cog Control

## Replication Analysis Questions

1. Do monolinguals and bilinguals show the same pattern of learning to anticipate the response in the pre-switch phase of the trial?
2. Do bilinguals perform better in the post-switch phase than monolinguals, and if so, at both ages?

## Data

### Number of Keepers in each group

These are the number of infants who contributed at least 500 milliseconds of data for at least 5/9 trials in each condition (both pre-switch and post-switch).

```
## # A tibble: 4 x 3
## # Groups:   age_group [2]
##   age_group language   num_participants
##   <fct>     <fct>           <int>
## 1 7 months  Monolinguals      21
## 2 7 months  Bilinguals       22
## 3 20 months Monolinguals     20
## 4 20 months Bilinguals      19
```

### Block means by group and trial type (for replication analysis)

We will use these means for the block analysis to follow the Kovács & Mehler 2009 analysis as closely as possible. These means are the average number of infants for each block who looked more at the target than at the distractor.

```
## # A tibble: 24 x 6
## # Groups:   language, age_group, trial_type [8]
##   language age_group trial_type block_num correct_anticip~
##   <fct>    <fct>    <fct>    <fct>           <dbl>
## 1 Monolin~ 7 months  pre-switch 1        0.556
## 2 Monolin~ 7 months  pre-switch 2        0.627
## 3 Monolin~ 7 months  pre-switch 3        0.6
## 4 Monolin~ 7 months  post-swit~ 1       0.183
## 5 Monolin~ 7 months  post-swit~ 2       0.119
## 6 Monolin~ 7 months  post-swit~ 3       0.294
## 7 Monolin~ 20 months pre-switch 1       0.667
## 8 Monolin~ 20 months pre-switch 2       0.85
## 9 Monolin~ 20 months pre-switch 3       0.658
## 10 Monolin~ 20 months post-swit~ 1      0.380
## # ... with 14 more rows, and 1 more variable: num_trials_contributed <dbl>
```

## Explore data visually

### Histograms by age, language group, and trial type for trials 1 and 9

```

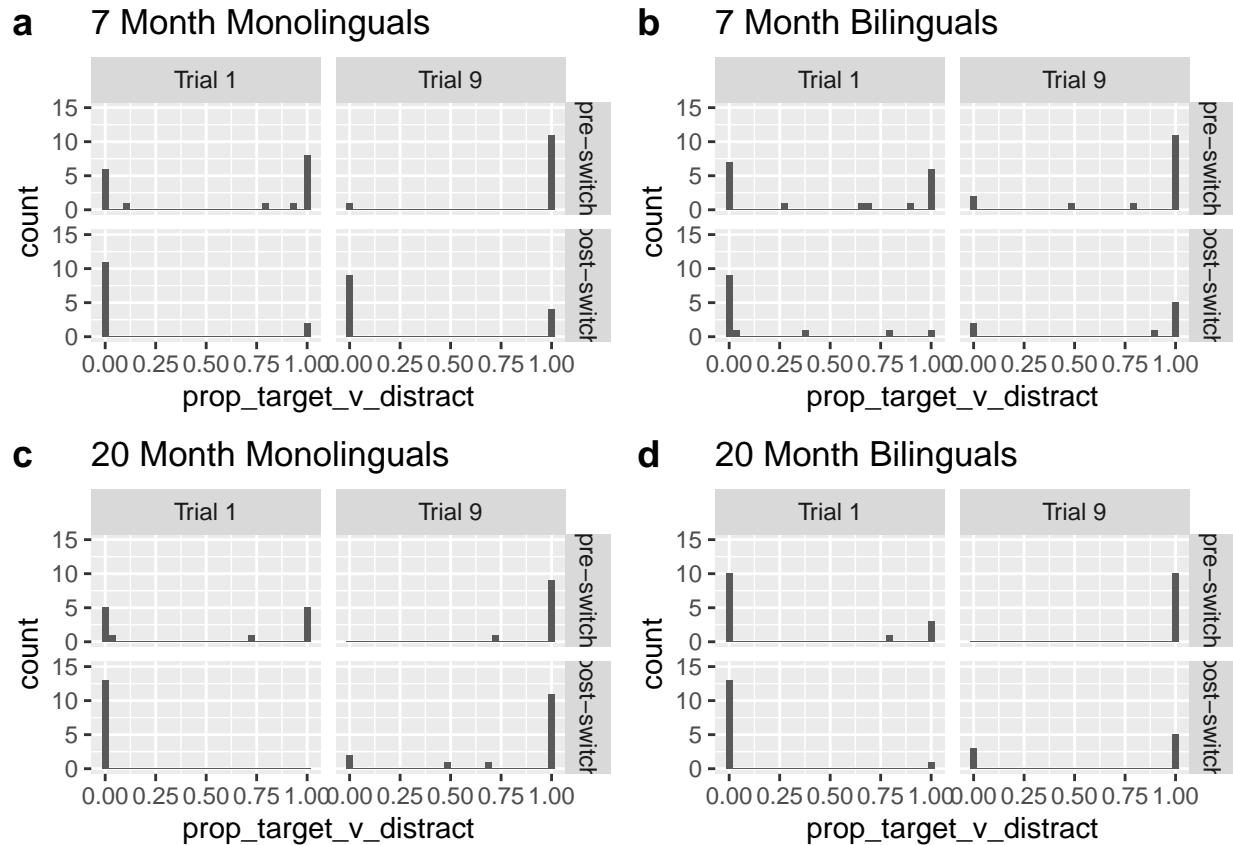
## Warning: Removed 13 rows containing non-finite values (stat_bin).

## Warning: Removed 19 rows containing non-finite values (stat_bin).

## Warning: Removed 10 rows containing non-finite values (stat_bin).

## Warning: Removed 14 rows containing non-finite values (stat_bin).

```



A histogram of the proportion data shows that we have a lot of 0s and 1s, and not much in between. Since this data is not normally distributed, we will have to use a nonparametric test (generalized linear mixed effects model) for our own analyses.

These histograms suggest that by the 9th trial, 7-month-old bilinguals may indeed outperform 7-month-old monolinguals in the post-switch condition, but the pre-switch condition looks pretty similar for both groups.

At 20 months, it looks like the bilinguals may not have the same advantage in the post-switch condition, although the count of data points post-switch appears to be low. Some infants' data points don't have a valid proportion number for some trials because Target/(Target + Distractor) includes NaNs due to dividing by 0. Let's check how many 'proportion of looking time to target vs distractor' data points we have for each trial.

```

## # A tibble: 72 x 5
## # Groups:   language, age_group, trial_type [8]
##   language    age_group trial_type  trial_number num_data_points
##   <fct>        <fct>     <fct>          <dbl>            <int>
## 1 Monolinguals 20 months pre-switch      8                 7

```

```

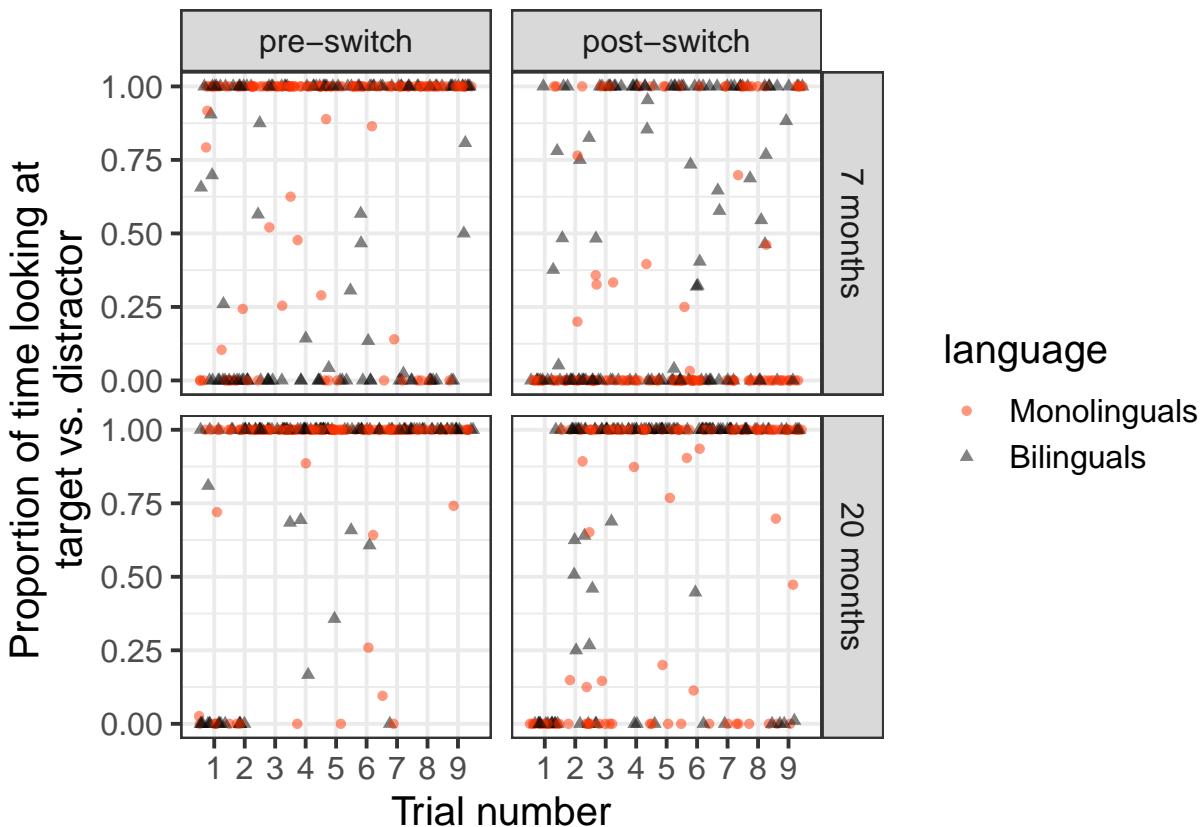
## 2 Bilinguals 7 months post-switch 9 8
## 3 Bilinguals 20 months post-switch 9 8
## 4 Monolinguals 20 months post-switch 6 9
## 5 Monolinguals 7 months post-switch 7 10
## 6 Monolinguals 20 months pre-switch 9 10
## 7 Monolinguals 20 months post-switch 7 10
## 8 Bilinguals 20 months pre-switch 9 10
## 9 Bilinguals 20 months post-switch 8 10
## 10 Monolinguals 7 months post-switch 4 11
## # ... with 62 more rows

```

There are some trials for certain groups that are missing quite a bit of data. The range is 7 data points to 18 data points. The trials with the lowest number of data points tend to be higher number trials and tend to be in the post-switch condition, suggesting loss of data due to boredom as the study goes on.

#### All data points - plot for proportion of looking time

```
## Warning: Removed 272 rows containing missing values (geom_point).
```

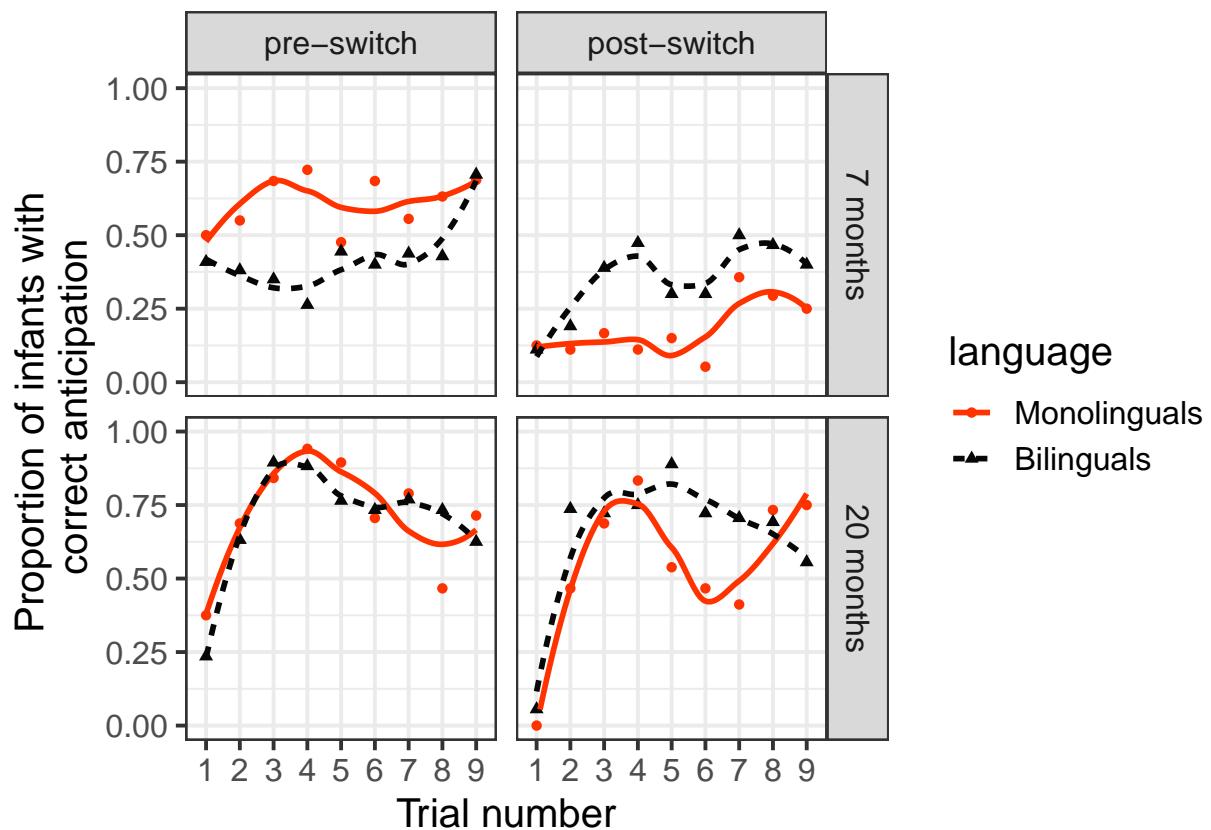


Again, these plots show a lot of 0 and 1 values, and not a lot in between. In general, it looks like there are fewer 0 values in later trials for both conditions, though this is more pronounced in the pre-switch condition.

#### Means plot - for proportion of infants with correct anticipation per trial

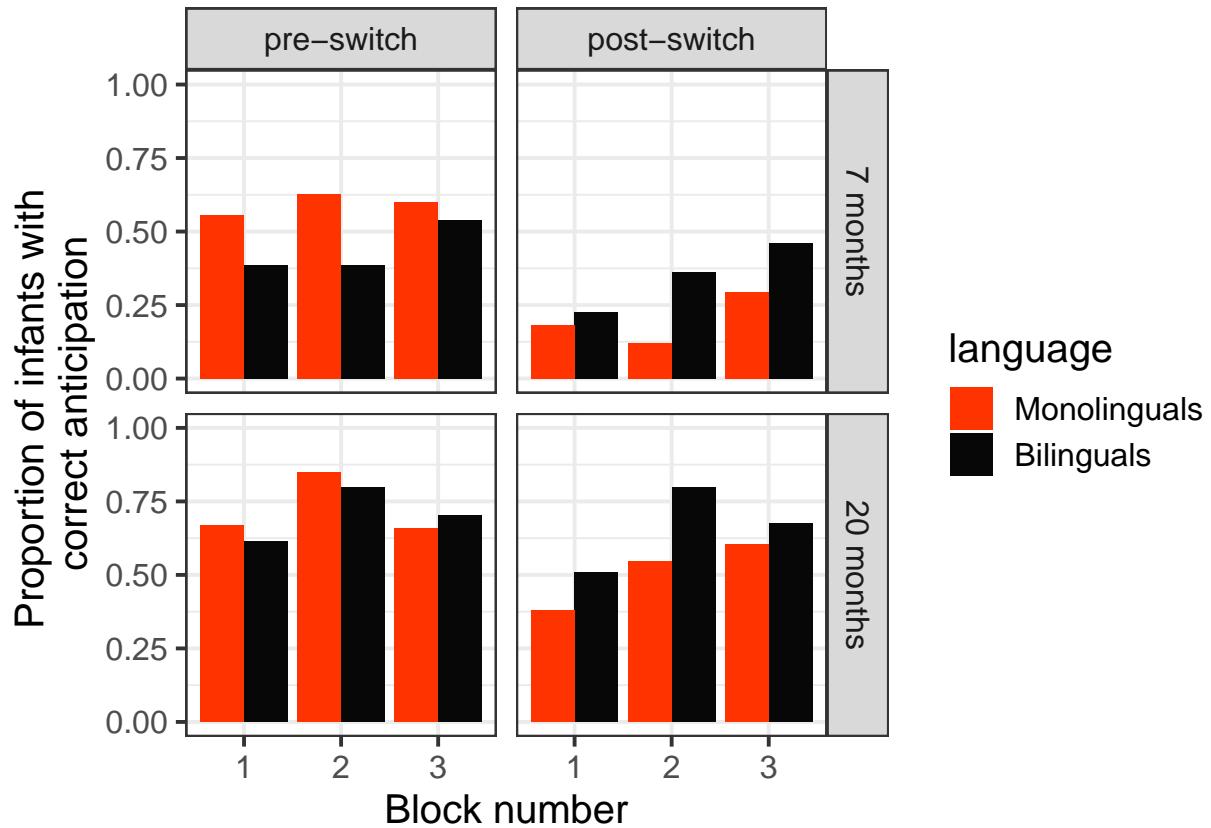
```
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```

```
## Warning: Removed 1 rows containing missing values (geom_smooth).
```



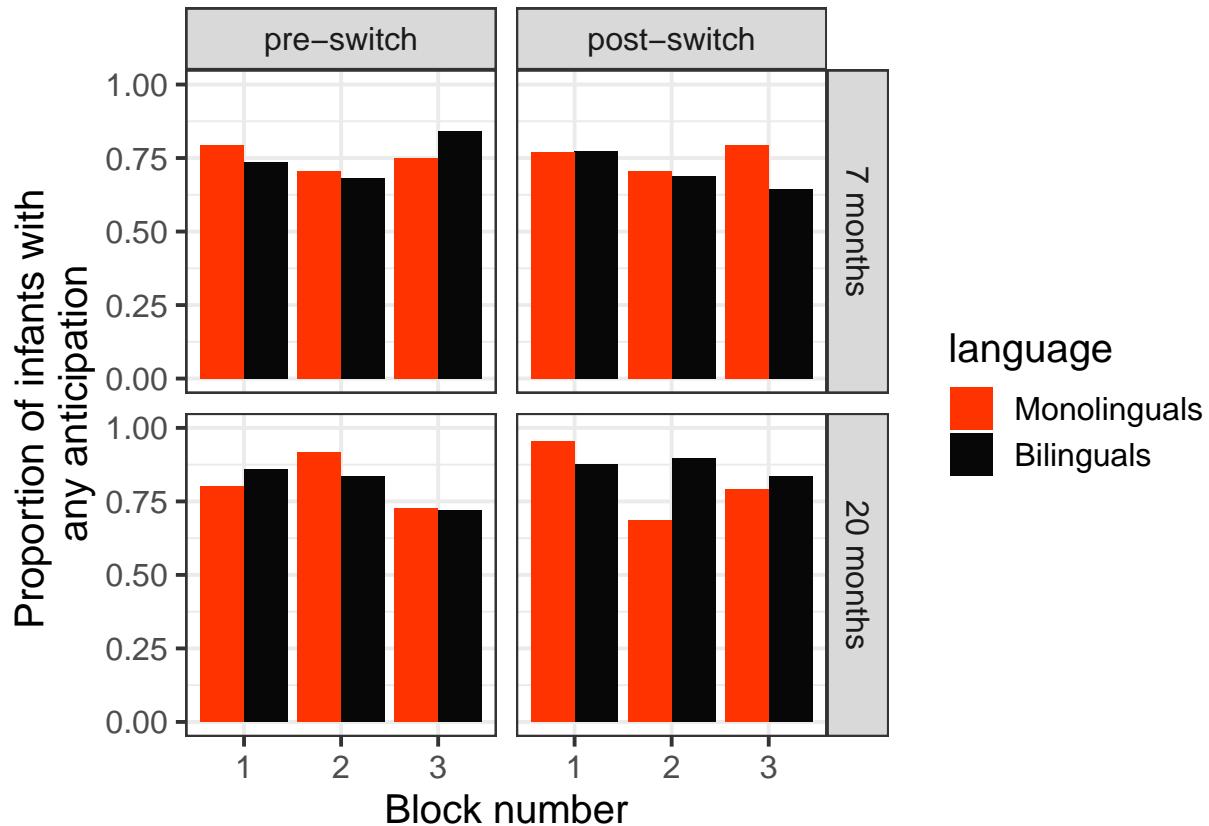
From this plot it looks like 20-month-olds are more accurate than 7-month-olds, and that at both ages, the post-switch condition reduces correct anticipation.

#### Blocks figure



Splitting the 9 trials into 3 blocks, we see again that 20-month-olds seem to be more accurate and that the post-switch condition appears to hinder correct anticipation.

#### Any anticipation figure



This figure suggests that there aren't great differences between monolinguals and bilinguals in total anticipation (looks to both the correct and incorrect side), except for perhaps block 3 post-switch for 7-month-olds and block 2 post-switch for 20-month-olds.

```
## # A tibble: 8 x 4
## # Groups:   language, trial_type [4]
##   language   trial_type age_group mean_total_ant
##   <fct>     <fct>    <fct>           <dbl>
## 1 Monolinguals pre-switch 7 months      0.759
## 2 Monolinguals pre-switch 20 months     0.809
## 3 Monolinguals post-switch 7 months     0.75
## 4 Monolinguals post-switch 20 months     0.842
## 5 Bilinguals   pre-switch 7 months      0.725
## 6 Bilinguals   pre-switch 20 months     0.811
## 7 Bilinguals   post-switch 7 months     0.713
## 8 Bilinguals   post-switch 20 months     0.856
```

Do monolinguals and bilinguals differ in total anticipation across blocks?

Pre-Switch 7-month-olds

```
## Warning: You have removed one or more Ss from the analysis. Refactoring
## "recording_name" for ANOVA.

## Warning: Data is unbalanced (unequal N per group). Make sure you specified
## a well-considered value for the type argument to ezANOVA().
```

```

##  

##  

## ANOVA results  

##  

##  

## Predictor df_num df_den Epsilon SS_num SS_den      F      p ges
## (Intercept) 1.00 39.00          69.97   9.65 282.88 .000 .83
## language    1.00 39.00          0.02   9.65   0.08 .777 .00
## block_num   1.92 74.82       0.96   0.25   4.36   2.27 .112 .02
## language x block_num 1.92 74.82       0.96   0.07   4.36   0.60 .544 .00
##  

## Note. df_num indicates degrees of freedom numerator. df_den indicates degrees of freedom denominator  

## Epsilon indicates Greenhouse-Geisser multiplier for degrees of freedom,  

## p-values and degrees of freedom in the table incorporate this correction.  

## SS_num indicates sum of squares numerator. SS_den indicates sum of squares denominator.  

## ges indicates generalized eta-squared.  

##

```

Post-Switch 7-month-olds

```

## Warning: You have removed one or more Ss from the analysis. Refactoring
## "recording_name" for ANOVA.

```

```

## Warning: Data is unbalanced (unequal N per group). Make sure you specified
## a well-considered value for the type argument to ezANOVA().

```

```

##  

##  

## ANOVA results  

##  

##  

## Predictor df_num df_den Epsilon SS_num SS_den      F      p ges
## (Intercept) 1.00 41.00          68.58  10.48 268.25 .000 .81
## language    1.00 41.00          0.10  10.48   0.38 .543 .01
## block_num   1.96 80.47       0.98   0.12   5.60   0.90 .409 .01
## language x block_num 1.96 80.47       0.98   0.15   5.60   1.08 .342 .01
##  

## Note. df_num indicates degrees of freedom numerator. df_den indicates degrees of freedom denominator  

## Epsilon indicates Greenhouse-Geisser multiplier for degrees of freedom,  

## p-values and degrees of freedom in the table incorporate this correction.  

## SS_num indicates sum of squares numerator. SS_den indicates sum of squares denominator.  

## ges indicates generalized eta-squared.  

##

```

Pre-Switch 20-month-olds

```

## Warning: You have removed one or more Ss from the analysis. Refactoring
## "recording_name" for ANOVA.

```

```

## Warning: Data is unbalanced (unequal N per group). Make sure you specified
## a well-considered value for the type argument to ezANOVA().

```

```

##  

##  

## ANOVA results  

##  

##  

## Predictor df_num df_den Epsilon SS_num SS_den      F      p ges
## (Intercept) 1.00 37.00          76.52   3.90 725.83 .000 .90
## language    1.00 37.00          0.00   3.90   0.03 .871 .00
## block_num   1.94 71.82       0.97   0.48   4.53  3.93 .025 .05
## language x block_num 1.94 71.82       0.97   0.10   4.53   0.82 .443 .01
##  

## Note. df_num indicates degrees of freedom numerator. df_den indicates degrees of freedom denominator  

## Epsilon indicates Greenhouse-Geisser multiplier for degrees of freedom,  

## p-values and degrees of freedom in the table incorporate this correction.  

## SS_num indicates sum of squares numerator. SS_den indicates sum of squares denominator.  

## ges indicates generalized eta-squared.  

##

```

Post-Switch 20-month-olds

```

## Warning: You have removed one or more Ss from the analysis. Refactoring
## "recording_name" for ANOVA.

## Warning: Data is unbalanced (unequal N per group). Make sure you specified
## a well-considered value for the type argument to ezANOVA().

##  

##  

## ANOVA results  

##  

##  

## Predictor df_num df_den Epsilon SS_num SS_den      F      p ges
## (Intercept) 1.00 32.00          71.25   2.55 892.95 .000 .92
## language    1.00 32.00          0.07   2.55   0.91 .348 .01
## block_num   1.67 53.35       0.83   0.41   3.74  3.49 .046 .06
## language x block_num 1.67 53.35       0.83   0.50   3.74   4.25 .025 .07
##  

## Note. df_num indicates degrees of freedom numerator. df_den indicates degrees of freedom denominator  

## Epsilon indicates Greenhouse-Geisser multiplier for degrees of freedom,  

## p-values and degrees of freedom in the table incorporate this correction.  

## SS_num indicates sum of squares numerator. SS_den indicates sum of squares denominator.  

## ges indicates generalized eta-squared.  

##

```

## Analyses

### Replication analyses

```

## Warning: You have removed one or more Ss from the analysis. Refactoring
## "recording_name" for ANOVA.

## Warning: Data is unbalanced (unequal N per group). Make sure you specified
## a well-considered value for the type argument to ezANOVA().

```

```

## Warning: You have removed one or more Ss from the analysis. Refactoring
## "recording_name" for ANOVA.

## Warning: You have removed one or more Ss from the analysis. Refactoring
## "recording_name" for ANOVA.

## Warning: You have removed one or more Ss from the analysis. Refactoring
## "recording_name" for ANOVA.

## Warning: Data is unbalanced (unequal N per group). Make sure you specified
## a well-considered value for the type argument to ezANOVA().

## Warning: You have removed one or more Ss from the analysis. Refactoring
## "recording_name" for ANOVA.

## Warning: You have removed one or more Ss from the analysis. Refactoring
## "recording_name" for ANOVA.

## Warning: You have removed one or more Ss from the analysis. Refactoring
## "recording_name" for ANOVA.

## Warning: Data is unbalanced (unequal N per group). Make sure you specified
## a well-considered value for the type argument to ezANOVA().

## Warning: You have removed one or more Ss from the analysis. Refactoring
## "recording_name" for ANOVA.

## Warning: You have removed one or more Ss from the analysis. Refactoring
## "recording_name" for ANOVA.

## Warning: You have removed one or more Ss from the analysis. Refactoring
## "recording_name" for ANOVA.

## Warning: Data is unbalanced (unequal N per group). Make sure you specified
## a well-considered value for the type argument to ezANOVA().

## Warning: You have removed one or more Ss from the analysis. Refactoring
## "recording_name" for ANOVA.

## Warning: You have removed one or more Ss from the analysis. Refactoring
## "recording_name" for ANOVA.

## Warning: You have removed one or more Ss from the analysis. Refactoring
## "recording_name" for ANOVA.

## Warning: Data is unbalanced (unequal N per group). Make sure you specified
## a well-considered value for the type argument to ezANOVA().

## Warning: You have removed one or more Ss from the analysis. Refactoring
## "recording_name" for ANOVA.

## Warning: You have removed one or more Ss from the analysis. Refactoring
## "recording_name" for ANOVA.

```

## Anovas

### Pre-switch 7 (compare language groups by block)

```

library(apaTables)
apa.ezANOVA.table(pre_7)

```

```

##
##
```

```

## ANOVA results
##
##
## Predictor df_num df_den Epsilon SS_num SS_den      F      p ges
## (Intercept) 1.00 39.00          32.62 11.32 112.37 .000 .65
## language    1.00 39.00          0.53 11.32  1.81 .186 .03
## block_num   1.93 75.39          0.97  0.21  6.47  1.28 .283 .01
## language x block_num 1.93 75.39          0.97  0.11  6.47  0.63 .528 .01
##
## Note. df_num indicates degrees of freedom numerator. df_den indicates degrees of freedom denominator
## Epsilon indicates Greenhouse-Geisser multiplier for degrees of freedom,
## p-values and degrees of freedom in the table incorporate this correction.
## SS_num indicates sum of squares numerator. SS_den indicates sum of squares denominator.
## ges indicates generalized eta-squared.
##

```

### Pre-switch 7 monolinguals (compare blocks)

```
apa.ezANOVA.table(pre_7_mono)
```

```

##
##
## ANOVA results
##
##
## Predictor df_num df_den Epsilon SS_num SS_den      F      p ges
## (Intercept) 1.00 19.00          20.22  5.25 73.19 .000 .70
## block_num   1.95 37.02          0.97  0.07  3.43  0.37 .685 .01
##
## Note. df_num indicates degrees of freedom numerator. df_den indicates degrees of freedom denominator
## Epsilon indicates Greenhouse-Geisser multiplier for degrees of freedom,
## p-values and degrees of freedom in the table incorporate this correction.
## SS_num indicates sum of squares numerator. SS_den indicates sum of squares denominator.
## ges indicates generalized eta-squared.
##
```

### Pre-switch 7 bilinguals (compare blocks)

```
apa.ezANOVA.table(pre_7_bi)
```

```

##
##
## ANOVA results
##
##
## Predictor df_num df_den Epsilon SS_num SS_den      F      p ges
## (Intercept) 1.00 20.00          12.74  6.07 41.97 .000 .58
## block_num   1.83 36.57          0.91  0.25  3.04  1.68 .203 .03
##
## Note. df_num indicates degrees of freedom numerator. df_den indicates degrees of freedom denominator
## Epsilon indicates Greenhouse-Geisser multiplier for degrees of freedom,
## p-values and degrees of freedom in the table incorporate this correction.
```

```

## SS_num indicates sum of squares numerator. SS_den indicates sum of squares denominator.
## ges indicates generalized eta-squared.
##

```

### Post-switch 7 (compare language groups by block)

```
apa.ezANOVA.table(post_7)
```

```

##
##
## ANOVA results
##
##
## Predictor df_num df_den Epsilon SS_num SS_den      F      p ges
## (Intercept) 1.00 41.00          9.73 11.59 34.41 .000 .37
## language    1.00 41.00          0.75 11.59  2.65 .111 .04
## block_num   1.94 79.55          0.97  0.71  5.30  5.53 .006 .04
## language x block_num 1.94 79.55          0.97  0.22  5.30  1.69 .192 .01
##
## Note. df_num indicates degrees of freedom numerator. df_den indicates degrees of freedom denominator
## Epsilon indicates Greenhouse-Geisser multiplier for degrees of freedom,
## p-values and degrees of freedom in the table incorporate this correction.
## SS_num indicates sum of squares numerator. SS_den indicates sum of squares denominator.
## ges indicates generalized eta-squared.
##

```

### Post-switch 7 monolinguals (compare blocks)

```
apa.ezANOVA.table(post_7_mono)
```

```

##
##
## ANOVA results
##
##
## Predictor df_num df_den Epsilon SS_num SS_den      F      p ges
## (Intercept) 1.00 20.00          2.48  4.73 10.48 .004 .25
## block_num   1.96 39.13          0.98  0.33  2.60  2.53 .094 .04
##
## Note. df_num indicates degrees of freedom numerator. df_den indicates degrees of freedom denominator
## Epsilon indicates Greenhouse-Geisser multiplier for degrees of freedom,
## p-values and degrees of freedom in the table incorporate this correction.
## SS_num indicates sum of squares numerator. SS_den indicates sum of squares denominator.
## ges indicates generalized eta-squared.
##
```

### Post-switch 7 bilinguals (compare blocks)

```
apa.ezANOVA.table(post_7_bi)
```

```

##  

##  

## ANOVA results  

##  

##  

##      Predictor df_num df_den Epsilon SS_num SS_den      F      p ges  

## (Intercept)   1.00  21.00        8.13   6.86 24.90 .000 .46  

## block_num    1.91  40.21       0.96   0.61   2.70  4.75 .015 .06  

##  

## Note. df_num indicates degrees of freedom numerator. df_den indicates degrees of freedom denominator  

## Epsilon indicates Greenhouse-Geisser multiplier for degrees of freedom,  

## p-values and degrees of freedom in the table incorporate this correction.  

## SS_num indicates sum of squares numerator. SS_den indicates sum of squares denominator.  

## ges indicates generalized eta-squared.  

##

```

### Pre-switch 20 (compare language groups by block)

```
apa.ezANOVA.table(pre_20)
```

```

##  

##  

## ANOVA results  

##  

##  

##      Predictor df_num df_den Epsilon SS_num SS_den      F      p ges  

## (Intercept)   1.00  37.00        59.75   5.01 441.27 .000 .84  

## language     1.00  37.00        0.01   5.01   0.09 .767 .00  

## block_num    1.77  65.65       0.89   0.73   6.47  4.17 .024 .06  

## language x block_num  1.77  65.65       0.89   0.06   6.47  0.34 .687 .01  

##  

## Note. df_num indicates degrees of freedom numerator. df_den indicates degrees of freedom denominator  

## Epsilon indicates Greenhouse-Geisser multiplier for degrees of freedom,  

## p-values and degrees of freedom in the table incorporate this correction.  

## SS_num indicates sum of squares numerator. SS_den indicates sum of squares denominator.  

## ges indicates generalized eta-squared.  

##

```

### Pre-switch 20 monolinguals (compare blocks)

```
apa.ezANOVA.table(pre_20_mono)
```

```

##  

##  

## ANOVA results  

##  

##  

##      Predictor df_num df_den Epsilon SS_num SS_den      F      p ges  

## (Intercept)   1.00  19.00        31.54   3.34 179.29 .000 .83  

## block_num    1.45  27.49       0.72   0.47   3.12  2.86 .089 .07  

##  

## Note. df_num indicates degrees of freedom numerator. df_den indicates degrees of freedom denominator

```

```

## Epsilon indicates Greenhouse-Geisser multiplier for degrees of freedom,
## p-values and degrees of freedom in the table incorporate this correction.
## SS_num indicates sum of squares numerator. SS_den indicates sum of squares denominator.
## ges indicates generalized eta-squared.
##

```

### Pre-switch 20 bilinguals (compare blocks)

```
apa.ezANOVA.table(pre_20_bi)
```

```

##
##
## ANOVA results
##
##
## Predictor df_num df_den Epsilon SS_num SS_den      F      p ges
## (Intercept) 1.00 18.00          28.30  1.67 305.51 .000 .85
## block_num   1.96 35.33          0.98   0.32   3.34   1.74 .191 .06
##
## Note. df_num indicates degrees of freedom numerator. df_den indicates degrees of freedom denominator
## Epsilon indicates Greenhouse-Geisser multiplier for degrees of freedom,
## p-values and degrees of freedom in the table incorporate this correction.
## SS_num indicates sum of squares numerator. SS_den indicates sum of squares denominator.
## ges indicates generalized eta-squared.
##

```

### Post-switch 20 (compare language groups by block)

```
apa.ezANOVA.table(post_20)
```

```

##
##
## ANOVA results
##
##
## Predictor df_num df_den Epsilon SS_num SS_den      F      p ges
## (Intercept) 1.00 32.00          33.24  4.96 214.25 .000 .73
## language    1.00 32.00          0.74   4.96   4.79 .036 .06
## block_num   1.91 61.15          0.96   0.73   7.35   3.20 .050 .06
## language x block_num 1.91 61.15          0.96   0.24   7.35   1.04 .358 .02
##
## Note. df_num indicates degrees of freedom numerator. df_den indicates degrees of freedom denominator
## Epsilon indicates Greenhouse-Geisser multiplier for degrees of freedom,
## p-values and degrees of freedom in the table incorporate this correction.
## SS_num indicates sum of squares numerator. SS_den indicates sum of squares denominator.
## ges indicates generalized eta-squared.
##

```

### Post-switch 20 monolinguals (compare blocks)

```
apa.ezANOVA.table(post_20_mono)
```

```
##  
##  
## ANOVA results  
##  
##  
## Predictor df_num df_den Epsilon SS_num SS_den      F      p ges  
## (Intercept) 1.00 14.00          10.76  2.45 61.51 .000 .60  
## block_num   1.80 25.17          0.90   0.24  4.73  0.70 .490 .03  
##  
## Note. df_num indicates degrees of freedom numerator. df_den indicates degrees of freedom denominator  
## Epsilon indicates Greenhouse-Geisser multiplier for degrees of freedom,  
## p-values and degrees of freedom in the table incorporate this correction.  
## SS_num indicates sum of squares numerator. SS_den indicates sum of squares denominator.  
## ges indicates generalized eta-squared.  
##
```

### Post-switch 20 bilinguals (compare blocks)

```
apa.ezANOVA.table(post_20_bi)
```

```
##  
##  
## ANOVA results  
##  
##  
## Predictor df_num df_den Epsilon SS_num SS_den      F      p ges  
## (Intercept) 1.00 18.00          24.89  2.52 178.03 .000 .83  
## block_num   1.77 31.78          0.88   0.80  2.62   5.50 .011 .13  
##  
## Note. df_num indicates degrees of freedom numerator. df_den indicates degrees of freedom denominator  
## Epsilon indicates Greenhouse-Geisser multiplier for degrees of freedom,  
## p-values and degrees of freedom in the table incorporate this correction.  
## SS_num indicates sum of squares numerator. SS_den indicates sum of squares denominator.  
## ges indicates generalized eta-squared.  
##
```

The anovas show:

7-month-olds of either language group do not show a difference between block one and block 3 pre-switch, but they do post-switch Post-switch, 7-month-old bilingual babies have a significant difference between performance in block 1 and block 3 20-month olds of either language group show an improvement between block 1 and block 3 pre-switch and post-switch Post-switch, 20-month-old monolinguals perform differently than bilinguals - only bilinguals do significantly better in block 3 than block 1

### T-tests comparing correct anticipation for Blocks 1 and 3, by trial type, language group, age group

```
## `mutate_if()` ignored the following grouping variables:  
## Columns `age_group`, `language`, `trial_type`
```

```

## Warning: funs() is soft deprecated as of dplyr 0.8.0
## Please use a list of either functions or lambdas:
##
## # Simple named list:
## list(mean = mean, median = median)
##
## # Auto named with `tibble::lst()`:
## tibble::lst(mean, median)
##
## # Using lambdas
## list(~ mean(., trim = .2), ~ median(., na.rm = TRUE))
## This warning is displayed once per session.

## # A tibble: 8 x 12
## # Groups:   age_group, language, trial_type [8]
##   age_group language trial_type estimate statistic p.value parameter
##   <fct>     <fct>    <fct>      <dbl>     <dbl>    <dbl>    <dbl>
## 1 7 months Monolin~ pre-switch -0.067    -0.653    0.522     19
## 2 7 months Monolin~ post-swit~ -0.111    -1.32     0.201     20
## 3 7 months Bilingu~ pre-switch -0.135    -1.47     0.157     20
## 4 7 months Bilingu~ post-swit~ -0.235    -2.87     0.009     21
## 5 20 months Monolin~ pre-switch  0.008     0.074    0.942     19
## 6 20 months Monolin~ post-swit~ -0.225    -1.86     0.081     16
## 7 20 months Bilingu~ pre-switch -0.088    -0.832    0.416     18
## 8 20 months Bilingu~ post-swit~ -0.167    -1.69     0.109     18
## # ... with 5 more variables: conf.low <dbl>, conf.high <dbl>,
## #   method <chr>, alternative <chr>, cohen_d <dbl>

```

These T-tests indicate that only 7-month-old bilingual infants showed a significant difference between block 1 and block 3, in the post-switch condition. However, some nuance is lost with these tests because within block 1, in most groups, there is a steep increase in correct anticipation over the 3 trials that gets averaged out when using block means.

## Generalized Linear Mixed Effects Model

Since our data is not normal and has a lot of 0 and 1 values, we can use a binomial logit link with glmer to build a model.

### Analysis questions

1. When analyzing proportion of looking time to target (instead of proportion of babies who looked more at target), do we see the same patterns as above?
2. Does vocabulary size have any effect on 20-month-olds' accuracy?

### Outcome variable

- Proportion of time spent looking at target vs. distractor ( $\text{Target}/(\text{Target} + \text{Distractor})$ ) – this means we are only including trials with anticipation, unlike in the replication analyses above.

## Fixed effects

- Language group
- Vocab group
- Age
- trial type (pre- or post-switch)
- trial number (we expect later trials to have better scores than earlier trials)

## Random effects

- Participant

We want participants to have their own intercepts (and potentially their own slopes?). Best to try the maximal model first and reduce if it doesn't converge. Do we expect any interactions? Trial type and language group could interact (since we've seen that bilinguals might have different response patterns in the post-switch condition).

Not sure that vocab group would interact with age or language group—we would expect, say, high vocabulary to have the same effect on monolinguals' and bilinguals' performance.

## Maximum model... do all these variables make sense?

Rachel didn't think I need anything other than recording\_name in the random effects side

`prop_target_v_distract ~ language x age_group x trial_type X trial_number + (1 + trial_type | recording_name)` *this model is too complex—we will break it down so each age group has its own model for each trial type*

So let's try:

`prop_target_v_distract ~ langauge x trial_number + (1 | recording_name)` and for the 20-month-olds `prop_target_v_distract ~ langauge x trial_number + vocab_group + (1 | recording_name)`

```
#make proportion data milliseconds instead of seconds so the binomial function will work properly (doesnt work with seconds)
model_data <- trial_data_all %>%
  mutate(Target = Target * 1000) %>%
  mutate(Distractor = Distractor * 1000) %>%
  mutate(Target_plus_Distractor = Target + Distractor) %>%
  mutate(prop_for_model = Target/Target_plus_Distractor) %>%
  #mutate(trial_number = as.factor(trial_number)) %>% don't do this!
  filter(total_anticipation == 1)

model_data_figure <- model_data %>%
  mutate(trial_number = as.numeric(trial_number)) %>%
  group_by(age_group, language, trial_type, trial_number) %>%
  summarise(prop_for_model = mean(prop_for_model, na.rm = T)) %>%
  ggplot(aes(x = trial_number, y = prop_for_model, color = language, shape = language, linetype = language)) +
  stat_summary(fun.y = "mean", geom = "point") +
  stat_smooth(se = FALSE) +
  facet_grid(age_group ~ trial_type) +
  scale_x_discrete(limits = c(1:9)) +
  scale_y_continuous(limits = c(0:1)) +
```

```

theme_bw(base_size=15) +
scale_color_manual(values = c("#ff3300", # bilingual colour
                            "#070707")) + # mono colour
ggtitle("Data used for glmer model \n(proportion of looking time)") +
xlab("Trial number") +
ylab("Proportion of time spent looking at \ntarget v distractor")

prop_infants_figure <- prop_infants_figure + ggtitle("Data used for replication analysis \n(proportion of time spent looking at target v distractor)")

plot_grid(model_data_figure, prop_infants_figure, labels = "auto", nrow = 2)

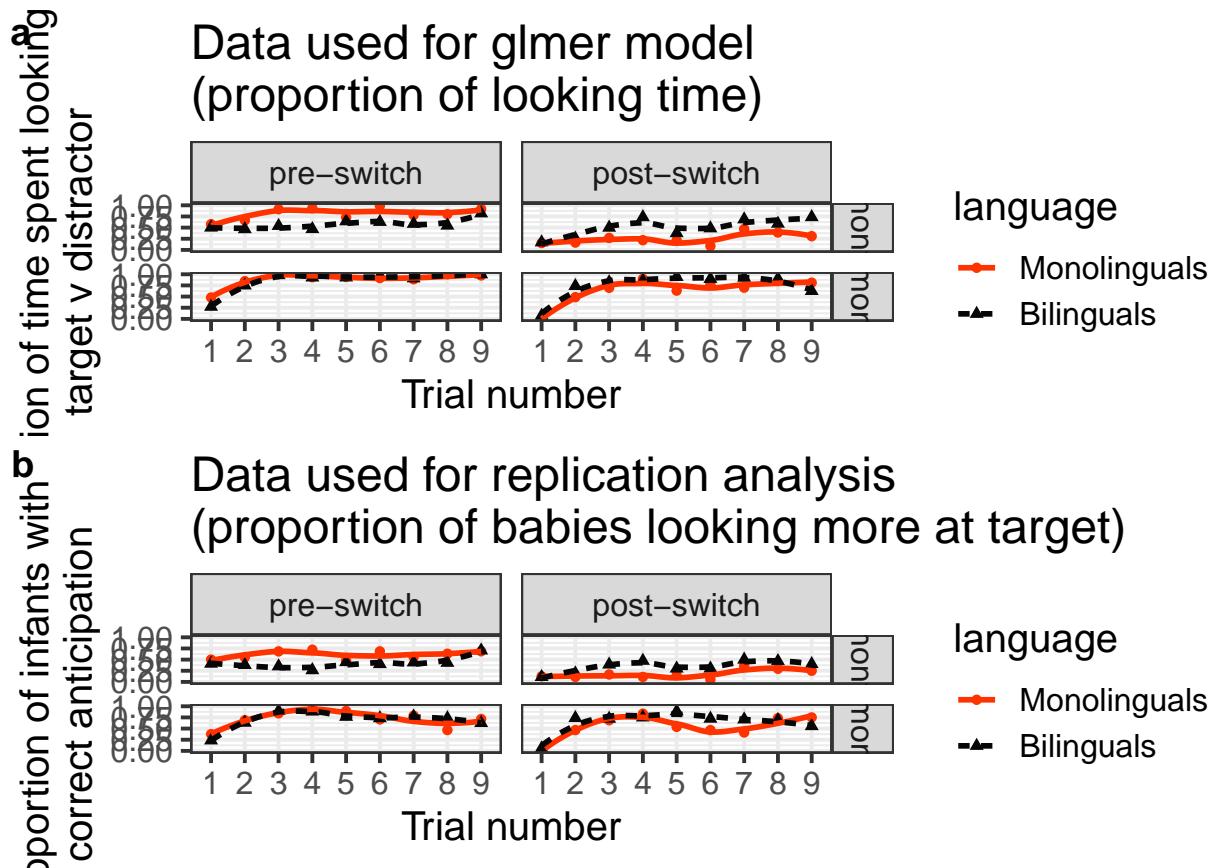
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'

## Warning: Removed 3 rows containing missing values (geom_smooth).

## `geom_smooth()` using method = 'loess' and formula 'y ~ x'

## Warning: Removed 1 rows containing missing values (geom_smooth).

```



This was the first model we ran:

```

model1 <- glmer(prop_for_model ~ language * age_group * trial_type + (1 | recording_name), data = model1)
summary(model1)

```

```

## Generalized linear mixed model fit by maximum likelihood (Laplace
## Approximation) [glmerMod]
## Family: binomial  ( logit )
## Formula:
## prop_for_model ~ language * age_group * trial_type + (1 | recording_name)
## Data: model_data
## Weights: Target_plus_Distractor
##
##          AIC      BIC  logLik deviance df.resid
## 372559.6 372603.4 -186270.8 372541.6      955
##
## Scaled residuals:
##    Min     1Q Median     3Q    Max
## -124.43 -10.65   5.28  11.32  77.12
##
## Random effects:
## Groups           Name        Variance Std.Dev.
## recording_name (Intercept) 2.791     1.671
## Number of obs: 964, groups: recording_name, 82
##
## Fixed effects:
##                               Estimate
## (Intercept)                  2.17552
## languageBilinguals            -1.89554
## age_group20 months             0.85710
## trial_typepost-switch         -2.97056
## languageBilinguals:age_group20 months       1.00112
## languageBilinguals:trial_typepost-switch      2.63047
## age_group20 months:trial_typepost-switch      0.95462
## languageBilinguals:age_group20 months:trial_typepost-switch -1.39148
##                               Std. Error
## (Intercept)                  0.36479
## languageBilinguals            0.50919
## age_group20 months             0.52290
## trial_typepost-switch          0.01729
## languageBilinguals:age_group20 months       0.73815
## languageBilinguals:trial_typepost-switch      0.02244
## age_group20 months:trial_typepost-switch      0.02542
## languageBilinguals:age_group20 months:trial_typepost-switch  0.03315
##                               z value
## (Intercept)                  5.964
## languageBilinguals            -3.723
## age_group20 months              1.639
## trial_typepost-switch         -171.811
## languageBilinguals:age_group20 months       1.356
## languageBilinguals:trial_typepost-switch      117.219
## age_group20 months:trial_typepost-switch      37.550
## languageBilinguals:age_group20 months:trial_typepost-switch -41.976
##                               Pr(>|z|)
## (Intercept)          0.000000000247
## languageBilinguals          0.000197
## age_group20 months          0.101184
## trial_typepost-switch < 0.0000000000000002
## languageBilinguals:age_group20 months      0.175019

```

```

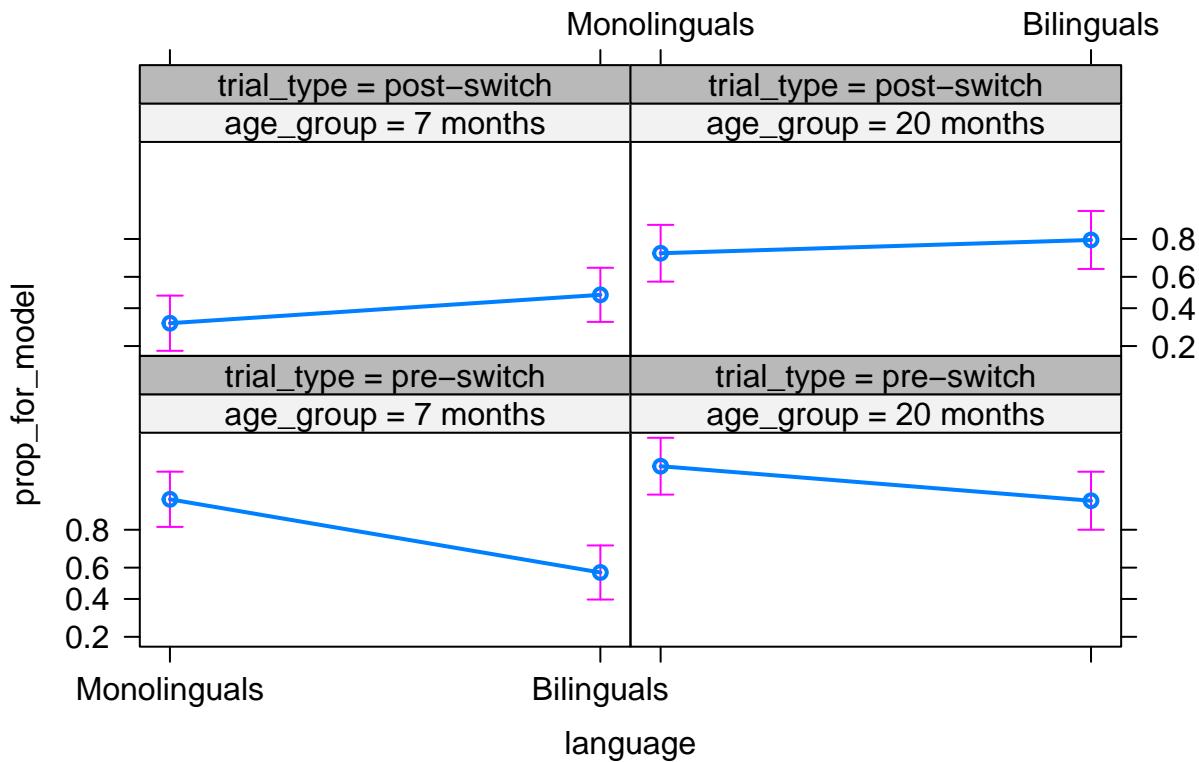
## languageBilinguals:trial_typepost-switch < 0.0000000000000002
## age_group20 months:trial_typepost-switch < 0.0000000000000002
## languageBilinguals:age_group20 months:trial_typepost-switch < 0.0000000000000002
##
## (Intercept) ***
## languageBilinguals ***
## age_group20 months
## trial_typepost-switch ***
## languageBilinguals:age_group20 months
## languageBilinguals:trial_typepost-switch ***
## age_group20 months:trial_typepost-switch ***
## languageBilinguals:age_group20 months:trial_typepost-switch ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
## (Intr) lnggBl ag_20m trl_t- lnB:_20m lnB:_- a_20m:
## langgBlngls -0.712
## ag_grp20mnt -0.696  0.495
## trl_ttyppst- -0.027  0.019  0.019
## lnggBl:_20m  0.490 -0.688 -0.705 -0.013
## lnggBlng:_-  0.020 -0.023 -0.014 -0.770  0.016
## ag_gr20m:_-  0.018 -0.013 -0.032 -0.680  0.022    0.524
## lnB:_20m:_- -0.014  0.015  0.024  0.522 -0.028   -0.677 -0.767

plot(allEffects(model1))

## Warning in eval(family$initialize): non-integer #successes in a binomial
## glm!

```

### language\*age\_group\*trial\_type effect plot



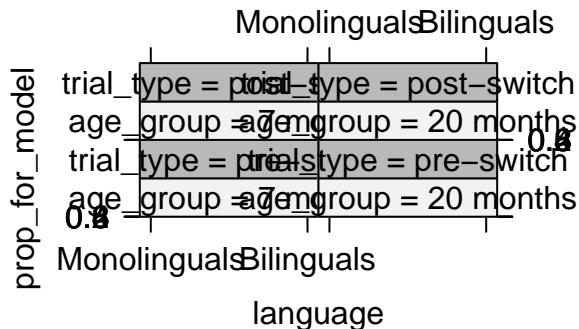
```
plot(predictorEffects(model1))
```

```
## Warning in eval(family$initialize): non-integer #successes in a binomial
## glm!

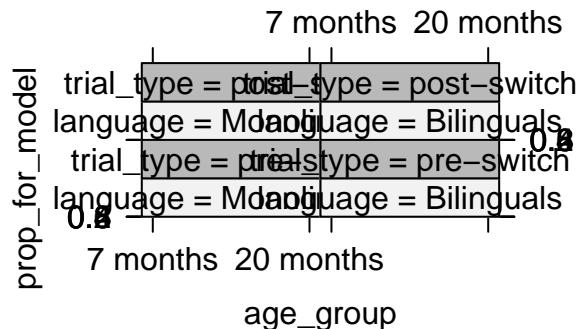
## Warning in eval(family$initialize): non-integer #successes in a binomial
## glm!

## Warning in eval(family$initialize): non-integer #successes in a binomial
## glm!
```

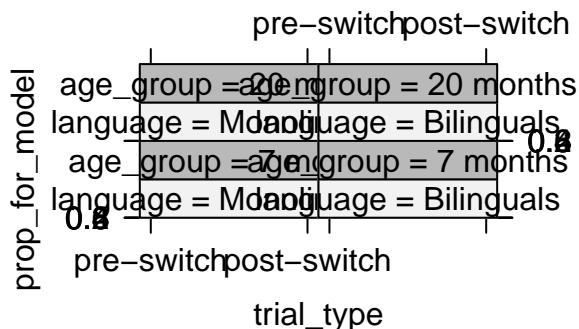
## language predictor effect plot



## age\_group predictor effect plot



## trial\_type predictor effect plot



```
emmeans(model1, pairwise ~ age_group)
```

```
## NOTE: Results may be misleading due to involvement in interactions
```

```
## $emmeans
##   age_group    emmean     SE  df  asymp.LCL  asymp.UCL
##   7 months     0.40  0.256 Inf   -0.102     0.902
##   20 months    1.89  0.268 Inf    1.361     2.413
##
## Results are averaged over the levels of: language, trial_type
## Results are given on the logit (not the response) scale.
## Confidence level used: 0.95
##
## $contrasts
##   contrast      estimate     SE  df z.ratio p.value
##   7 months - 20 months   -1.49 0.371 Inf -4.011  0.0001
##
## Results are averaged over the levels of: language, trial_type
## Results are given on the log odds ratio (not the response) scale.
```

```
emmeans(model1, pairwise ~ age_group:language|trial_type)
```

```
## $emmeans
## trial_type = pre-switch:
```

```

## age_group language      emmean     SE  df asymp.LCL asymp.UCL
## 7 months Monolinguals  2.1755  0.365 Inf    1.461    2.8905
## 20 months Monolinguals 3.0326  0.375 Inf    2.297    3.7681
## 7 months Bilinguals   0.2800  0.357 Inf   -0.421    0.9805
## 20 months Bilinguals   2.1382  0.383 Inf    1.387    2.8892
##
## trial_type = post-switch:
## age_group language      emmean     SE  df asymp.LCL asymp.UCL
## 7 months Monolinguals -0.7950  0.365 Inf   -1.510   -0.0802
## 20 months Monolinguals 1.0167  0.375 Inf    0.282    1.7517
## 7 months Bilinguals   -0.0601  0.357 Inf   -0.761    0.6405
## 20 months Bilinguals   1.3613  0.383 Inf    0.610    2.1120
##
## Results are given on the logit (not the response) scale.
## Confidence level used: 0.95
##
## $contrasts
## trial_type = pre-switch:
## contrast                               estimate     SE  df z.ratio
## 7 months,Monolinguals - 20 months,Monolinguals -0.8571 0.523 Inf -1.639
## 7 months,Monolinguals - 7 months,Bilinguals      1.8955 0.509 Inf  3.723
## 7 months,Monolinguals - 20 months,Bilinguals      0.0373 0.529 Inf  0.070
## 20 months,Monolinguals - 7 months,Bilinguals      2.7526 0.519 Inf  5.308
## 20 months,Monolinguals - 20 months,Bilinguals      0.8944 0.536 Inf  1.669
## 7 months,Bilinguals - 20 months,Bilinguals      -1.8582 0.524 Inf -3.549
## p.value
## 0.3565
## 0.0011
## 0.9999
## <.0001
## 0.3401
## 0.0022
##
## trial_type = post-switch:
## contrast                               estimate     SE  df z.ratio
## 7 months Monolinguals - 20 months Monolinguals -1.8117 0.523 Inf -3.466
## 7 months Monolinguals - 7 months Bilinguals      -0.7349 0.509 Inf -1.443
## 7 months Monolinguals - 20 months Bilinguals      -2.1563 0.529 Inf -4.074
## 20 months Monolinguals - 7 months Bilinguals      1.0768 0.518 Inf  2.077
## 20 months Monolinguals - 20 months Bilinguals      -0.3446 0.536 Inf -0.643
## 7 months Bilinguals - 20 months Bilinguals      -1.4214 0.524 Inf -2.715
## p.value
## 0.0030
## 0.4722
## 0.0003
## 0.1606
## 0.9179
## 0.0335
##
## Results are given on the log odds ratio (not the response) scale.
## P value adjustment: tukey method for comparing a family of 4 estimates

```

```
emmeans(model1, pairwise ~ age_group:trial_type|language)
```

```

## $emmeans
## language = Monolinguals:
##   age_group trial_type    emmean     SE  df asymp.LCL asymp.UCL
##   7 months  pre-switch   2.1755  0.365 Inf    1.461    2.8905
##   20 months pre-switch  3.0326  0.375 Inf    2.297    3.7681
##   7 months  post-switch -0.7950  0.365 Inf   -1.510   -0.0802
##  20 months post-switch  1.0167  0.375 Inf    0.282    1.7517
##
## language = Bilinguals:
##   age_group trial_type    emmean     SE  df asymp.LCL asymp.UCL
##   7 months  pre-switch   0.2800  0.357 Inf   -0.421    0.9805
##   20 months pre-switch  2.1382  0.383 Inf    1.387    2.8892
##   7 months  post-switch -0.0601  0.357 Inf   -0.761    0.6405
##  20 months post-switch  1.3613  0.383 Inf    0.610    2.1120
##
## Results are given on the logit (not the response) scale.
## Confidence level used: 0.95
##
## $contrasts
## language = Monolinguals:
##   contrast                               estimate     SE  df z.ratio
##   7 months,pre-switch - 20 months,pre-switch -0.857  0.5229 Inf  -1.639
##   7 months,pre-switch - 7 months,post-switch   2.971  0.0173 Inf 171.811
##   7 months,pre-switch - 20 months,post-switch   1.159  0.5227 Inf  2.217
##   20 months,pre-switch - 7 months,post-switch   3.828  0.5229 Inf  7.321
##   20 months,pre-switch - 20 months,post-switch   2.016  0.0186 Inf 108.161
##   7 months,post-switch - 20 months,post-switch -1.812  0.5227 Inf  -3.466
##
## p.value
## 0.3565
## <.0001
## 0.1186
## <.0001
## <.0001
## 0.0030
##
## language = Bilinguals:
##   contrast                               estimate     SE  df z.ratio
##   7 months pre-switch - 20 months pre-switch -1.858  0.5236 Inf  -3.549
##   7 months pre-switch - 7 months post-switch   0.340  0.0143 Inf  23.774
##   7 months pre-switch - 20 months post-switch  -1.081  0.5235 Inf  -2.065
##   20 months pre-switch - 7 months post-switch   2.198  0.5236 Inf   4.198
##   20 months pre-switch - 20 months post-switch   0.777  0.0157 Inf  49.346
##   7 months post-switch - 20 months post-switch -1.421  0.5236 Inf  -2.715
##
## p.value
## 0.0022
## <.0001
## 0.1646
## 0.0002
## <.0001
## 0.0335
##
## Results are given on the log odds ratio (not the response) scale.
## P value adjustment: tukey method for comparing a family of 4 estimates

```

The emmeans plots indicate that bilinguals do worse than monolinguals pre-switch at both ages and better than monolinguals post-switch at both ages. Monolinguals have a much steeper drop between pre- and post-switch trial types than do bilinguals, where the slope is fairly flat between trial types. Age appears to have a similar effect across the board (performance increases about the same for monolinguals/bilinguals).

Next we tried another model for only 7-month-olds that included trial number, but this one has problems:

```
model_data_7 <- model_data %>% filter(age_group == "7 months")

model2 <- glmer(prop_for_model ~ language * trial_type * trial_number + (1 | recording_name), data = model_data_7,
                 optCtrl=list(maxfun=100000))

## Warning in checkConv(attr(opt, "derivs"), opt$par, ctrl = control$checkConv, : Model is nearly uniden
## - Rescale variables?

summary(model2)

## Generalized linear mixed model fit by maximum likelihood (Laplace
## Approximation) [glmerMod]
## Family: binomial ( logit )
## Formula: prop_for_model ~ language * trial_type * trial_number + (1 |
##           recording_name)
## Data: model_data_7
## Weights: Target_plus_Distractor
## Control:
## glmerControl(optimizer = "bobyqa", optCtrl = list(maxfun = 100000))
##
##      AIC      BIC  logLik deviance df.resid
## 1777734.6 177772.2 -88858.3 177716.6      475
##
## Scaled residuals:
##    Min     1Q   Median     3Q    Max
## -157.690 -11.542    1.816   11.222  77.664
##
## Random effects:
## Groups      Name        Variance Std.Dev.
## recording_name (Intercept) 3.739     1.934
## Number of obs: 484, groups: recording_name, 43
##
## Fixed effects:
##                                         Estimate Std. Error
## (Intercept)                         1.437958  0.423836
## languageBilinguals                  -1.719091  0.592799
## trial_typepost-switch                -2.913846  0.035382
## trial_number                          0.159308  0.004545
## languageBilinguals:trial_typepost-switch 1.916235  0.047614
## languageBilinguals:trial_number       -0.042502  0.005914
## trial_typepost-switch:trial_number    -0.015334  0.006464
## languageBilinguals:trial_typepost-switch:trial_number 0.149820  0.008792
##
## z value
## (Intercept)          3.393
## languageBilinguals   -2.900
## trial_typepost-switch -82.354
```

```

## trial_number                      35.055
## languageBilinguals:trial_typepost-switch      40.245
## languageBilinguals:trial_number                  -7.187
## trial_typepost-switch:trial_number                 -2.372
## languageBilinguals:trial_typepost-switch:trial_number 17.041
##                                         Pr(>|z|)
## (Intercept)                           0.000692
## languageBilinguals                    0.003732
## trial_typepost-switch < 0.0000000000000002
## trial_number                         < 0.0000000000000002
## languageBilinguals:trial_typepost-switch < 0.0000000000000002
## languageBilinguals:trial_number          0.000000000000664
## trial_typepost-switch:trial_number           0.017682
## languageBilinguals:trial_typepost-switch:trial_number < 0.0000000000000002
##
## (Intercept)                          ***
## languageBilinguals                   **
## trial_typepost-switch                ***
## trial_number                         ***
## languageBilinguals:trial_typepost-switch *** 
## languageBilinguals:trial_number       ***
## trial_typepost-switch:trial_number    *
## languageBilinguals:trial_typepost-switch:trial_number ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) lnggBl trl_t- trl_nm lnB:_- lngB:_ tr_-:_
## langgBlngls -0.714
## trl_typpst- -0.037  0.027
## trial_numbr -0.046  0.033  0.568
## lnggBlng:_-  0.028 -0.034 -0.743 -0.422
## lnggBlngl:_  0.035 -0.044 -0.437 -0.768  0.561
## trl_typp:_-  0.032 -0.023 -0.868 -0.705  0.645  0.542
## lnggBl:_-:_ -0.024  0.030  0.638  0.518 -0.878 -0.675 -0.735
## convergence code: 0
## Model is nearly unidentifiable: very large eigenvalue
## - Rescale variables?

emmeans(model2, pairwise ~ trial_number)

## NOTE: Results may be misleading due to involvement in interactions

## Note: Use 'contrast(regrid(object), ...)' to obtain contrasts of back-transformed estimates

## $emmeans
##   trial_number emmean     SE  df asymp.LCL asymp.UCL
##        4.81  0.408 0.296 Inf    -0.173     0.989
## 
## Results are averaged over the levels of: language, trial_type
## Results are given on the logit (not the response) scale.
## Confidence level used: 0.95
##
```

```

## $contrasts
## contrast estimate SE df z.ratio p.value
## (nothing) nonEst NA NA NA NA
##
## Results are averaged over the levels of: language, trial_type
## Note: contrasts are still on the logit scale

emmeans(model2, pairwise ~ language:trial_type)

## NOTE: Results may be misleading due to involvement in interactions

## $emmeans
##   language     trial_type    emmean      SE   df asympp.LCL asympp.UCL
##   Monolinguals pre-switch  2.2045 0.423 Inf    1.375    3.0344
##   Bilinguals   pre-switch  0.2809 0.415 Inf   -0.532    1.0936
##   Monolinguals post-switch -0.7831 0.423 Inf   -1.613    0.0467
##   Bilinguals   post-switch -0.0695 0.415 Inf   -0.882    0.7432
##
## Results are given on the logit (not the response) scale.
## Confidence level used: 0.95
##
## $contrasts
##   contrast                               estimate      SE   df
##   Monolinguals,pre-switch - Bilinguals,pre-switch    1.924 0.5922 Inf
##   Monolinguals,pre-switch - Monolinguals,post-switch  2.988 0.0176 Inf
##   Monolinguals,pre-switch - Bilinguals,post-switch    2.274 0.5922 Inf
##   Bilinguals,pre-switch - Monolinguals,post-switch    1.064 0.5922 Inf
##   Bilinguals,pre-switch - Bilinguals,post-switch     0.350 0.0146 Inf
##   Monolinguals,post-switch - Bilinguals,post-switch   -0.714 0.5922 Inf
##   z.ratio p.value
##   3.248 0.0064
##   170.001 <.0001
##   3.840 0.0007
##   1.797 0.2748
##   24.026 <.0001
##   -1.205 0.6237
##
## Results are given on the log odds ratio (not the response) scale.
## P value adjustment: tukey method for comparing a family of 4 estimates

```

The above are my first attempts at building suitable models. Model 1 includes both age groups, but cannot converge with the effect of trial number included. We can split the data into 2 sets (one for each age group) and then include trial number as an effect, but the model kind of breaks.

After discussing with Krista, we decided to break it down by age group and trial type, so that we can include trial number as a predictor (since we expect that higher trial numbers will have higher scores overall).

Here is an attempt to run a model for just the 7-month-olds in the pre-switch condition, and again we run into some problems. I noticed that when I run this model using milliseconds as the “weights”, everything is significant. But when I run the same model using seconds as “weights”, the model is “singular” and nothing is significant.

After reading up on this, it appears that telling the model that the proportions come from milliseconds instead of seconds increases the ‘trustworthiness’ of the proportions, and completely changes the results of

the model—I am not sure which is the correct measurement to use. This issue makes me wonder whether the glmm is actually correct to use in this case, since the calculated proportion of time spent looking at a target over a distractor doesn't come from a true binomial success/failure situation, where each “trial” is meant to be independent. It also doesn't account for the correlation of datapoints that are close together in time – see <https://link.springer.com/article/10.1007%2Fs11336-018-9604-2>

```
#model using milliseconds

model_data_7pre <- model_data %>%
  filter(age_group == "7 months") %>%
  filter(trial_type == "pre-switch")

model_7pre <- glmer((Target / Target_plus_Distractor) ~ language * trial_number + (1 | recording_name),
summary(model_7pre)

## Generalized linear mixed model fit by maximum likelihood (Laplace
## Approximation) [glmerMod]
## Family: binomial ( logit )
## Formula: (Target/Target_plus_Distractor) ~ language * trial_number + (1 |
##   recording_name)
## Data: model_data_7pre
## Weights: Target_plus_Distractor
##
##      AIC      BIC  logLik deviance df.resid
## 47626.4 47644.0 -23808.2 47616.4     245
## 
## Scaled residuals:
##    Min     1Q Median     3Q    Max
## -64.196 -2.651  0.311  6.850 57.803
## 
## Random effects:
##   Groups      Name        Variance Std.Dev.
##   recording_name (Intercept) 25.82     5.081
##   Number of obs: 250, groups: recording_name, 42
## 
## Fixed effects:
##                               Estimate Std. Error z value
## (Intercept)                3.920463  1.173285  3.341
## languageBilinguals         -4.261070  1.609972 -2.647
## trial_number                 0.292129  0.006437 45.381
## languageBilinguals:trial_number -0.158954  0.008385 -18.958
##                               Pr(>|z|)
## (Intercept)                0.000833 ***
## languageBilinguals          0.008129 **
## trial_number                  < 0.0000000000000002 ***
## languageBilinguals:trial_number < 0.0000000000000002 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 
## Correlation of Fixed Effects:
##           (Intr) lnggBl trl_nm
## langgBlnlgs -0.731
## trial_numbr -0.021  0.015
```

```

## lnnBlnl:_ 0.016 -0.021 -0.768

#model using seconds
model_data_7pre_s <- model_data %>%
  filter(age_group == "7 months") %>%
  filter(trial_type == "pre-switch") %>%
  mutate(Target = Target / 1000) %>%
  mutate(Distractor = Distractor / 1000) %>%
  mutate(Target_plus_Distractor = Target + Distractor)

model_7pre_s <- glmer((Target / Target_plus_Distractor) ~ language * trial_number + (1 | recording_name)

## Warning in eval(family$initialize, rho): non-integer #successes in a
## binomial glm!

## boundary (singular) fit: see ?isSingular

summary(model_7pre_s)

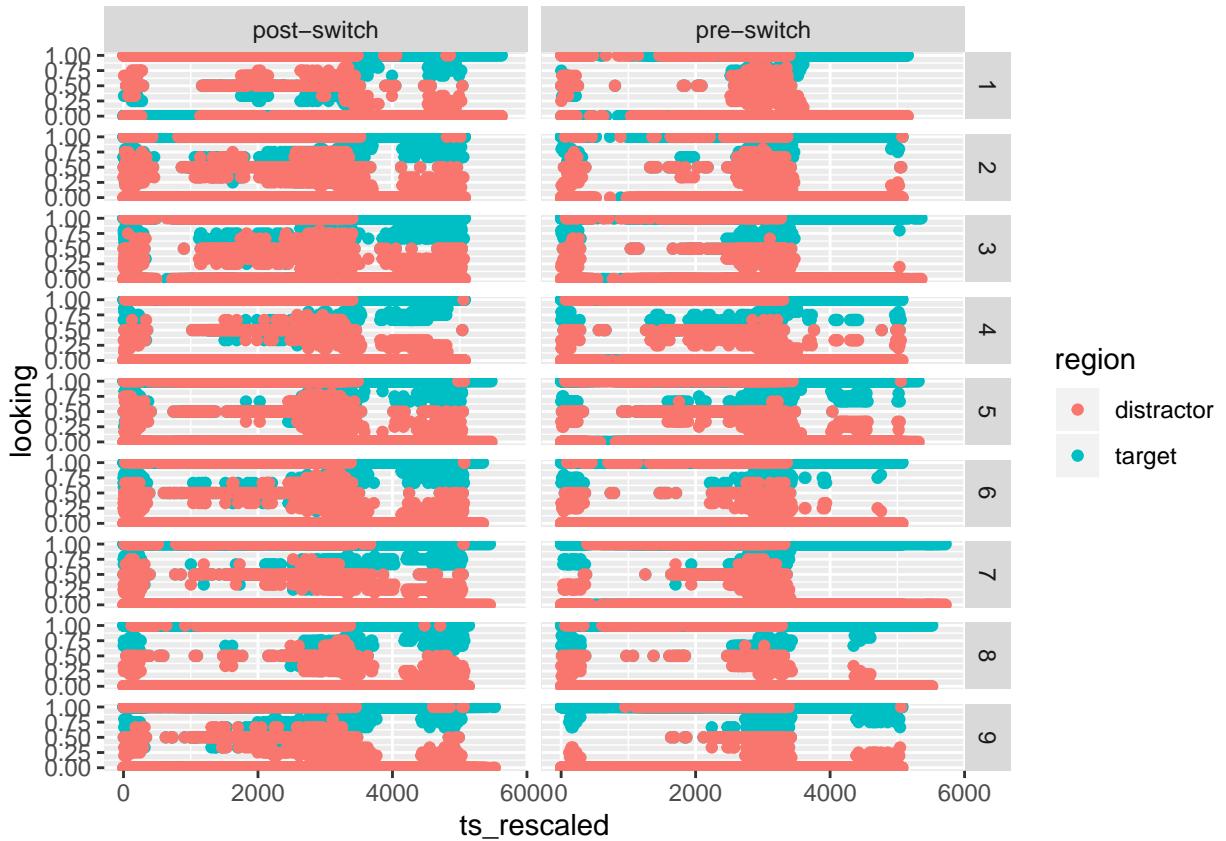
## Generalized linear mixed model fit by maximum likelihood (Laplace
## Approximation) [glmerMod]
## Family: binomial ( logit )
## Formula: (Target/Target_plus_Distractor) ~ language * trial_number + (1 |
##   recording_name)
## Data: model_data_7pre_s
## Weights: Target_plus_Distractor
##
##       AIC      BIC  logLik deviance df.resid
##     73.0    90.6   -31.5     63.0     245
##
## Scaled residuals:
##       Min     1Q Median     3Q    Max
## -2.6144 -0.4652  0.2520  0.4192  0.8944
##
## Random effects:
##   Groups      Name        Variance Std.Dev.
##   recording_name (Intercept) 0         0
##   Number of obs: 250, groups: recording_name, 42
##
## Fixed effects:
##                   Estimate Std. Error z value Pr(>|z|)
##   (Intercept)      0.8158    1.0136   0.805   0.421
##   languageBilinguals -0.8753    1.2670  -0.691   0.490
##   trial_number      0.1586    0.1927   0.823   0.410
##   languageBilinguals:trial_number -0.1272    0.2404  -0.529   0.597
##
## Correlation of Fixed Effects:
##           (Intr) lnnBlnl trl_nm
## langgBlnl -0.800
## trial_numbr -0.872  0.698
## lnnBlnl:_  0.699 -0.867 -0.802
## convergence code: 0
## boundary (singular) fit: see ?isSingular

```

## Full Time Series Data - trying to make figures like in <http://rpubs.com/mcfrank/mb2-pilot>

(this takes ages to run from scratch, so I've commented it out and saved the final dataset as a .Rda object to load in)

```
## Warning: Column `recording_name` joining factors with different levels,  
## coercing to character vector
```



Well, that did not work well. The output from Tobii doesn't have a consistent frame rate (sometimes it's 16 ms between each row, sometimes it's 17 or 18), and the timestamps are also not always the same time difference from the beginning of each trial.