Colour experiment

Contents

Introduction

This analysis looks at the sign variants used in a colour naming game between signers of different sign languages meeting after 1 week of interaction and after 3 weeks of interaction. The data was collected by Kang Suk Byun (Kang-Suk.Byun@mpi.nl).

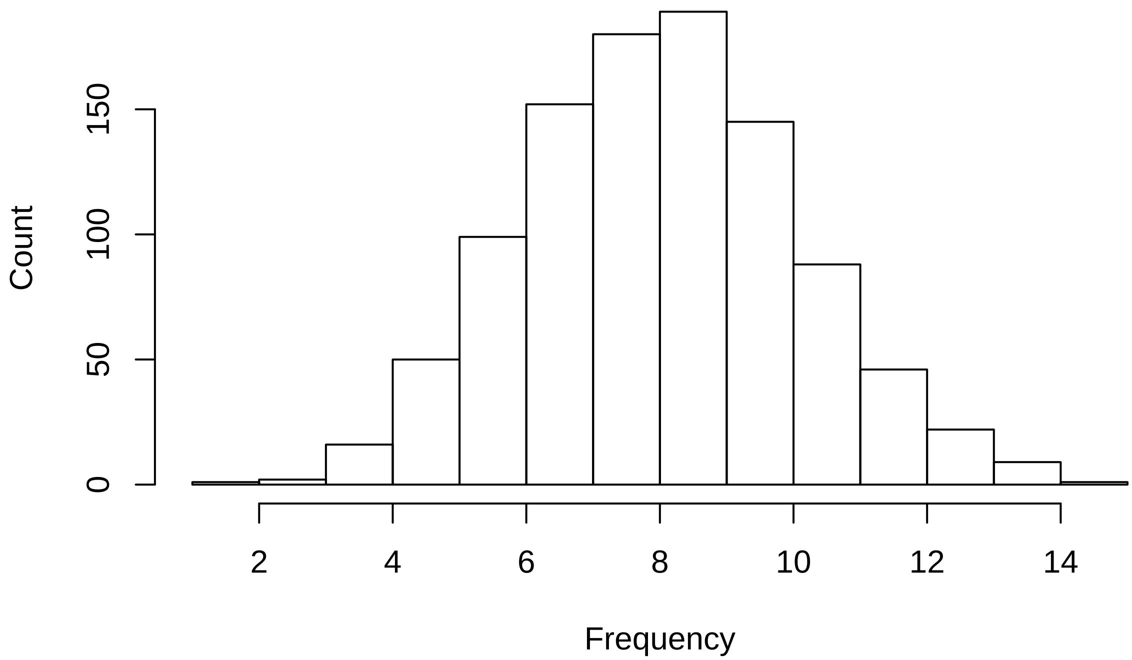
The analysis tries to predict the relative frequency of each variant within a colour category in week 3, based on measures from week 1.

Data

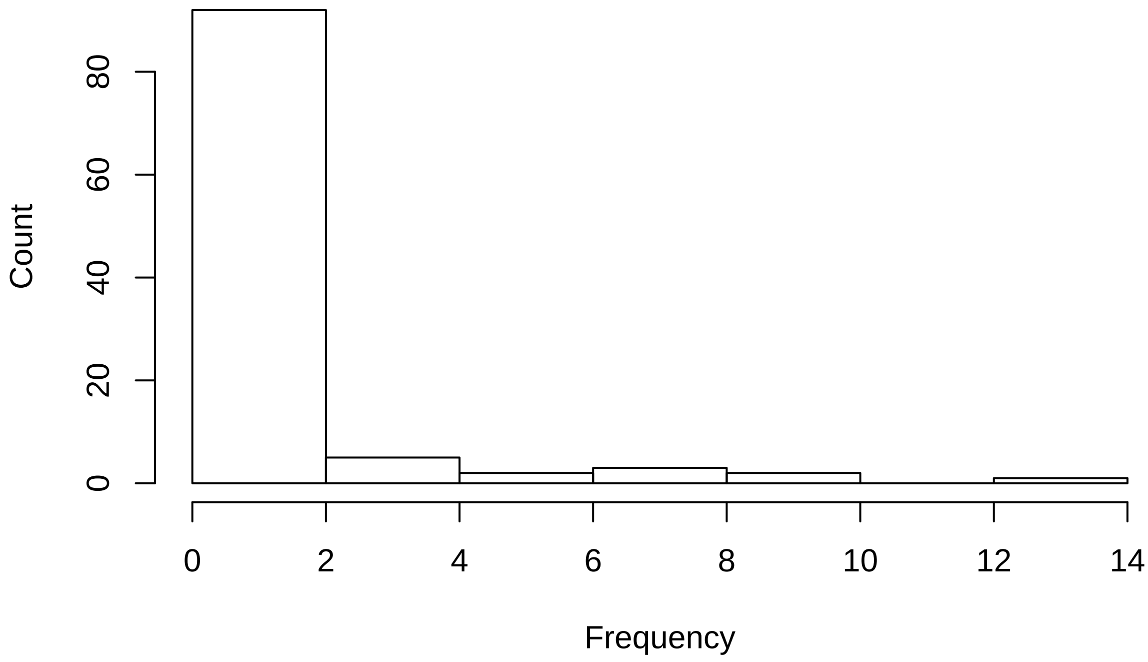
- colour: Code of the target colour
- colourName: English name of the target colour
- sign: label for the variant produced
- freq_week_1_total: Total number of occurances of the variant in the first week, across all colour contexts.
- freq_week_4_total: Total number of occurances of the variant in the final week, across all colour contexts.
- freq_week_1: Number of occurances of the variant used during the given target colour context in week 1.
- freq_week_4: Number of occurances of the variant used during the given target colour context in the final week.
- prop_week_1: Same as freq_week_1, but as a proportion of all variants used in the given colour context.
- prop_week_4: Same as freq_week_4, but as a proportion of all variants used in the given colour context.
- origin: The origin language of the sign. For many, identifying an origin is not possible, so is labelled "None"
- iconic: Old variable
- check: The number of times this variable was used in a checking turn.
- indexical: Is the variant non-indexical, indexical or indexical of the body?
- inventedBy: The name of the first signer to use this variant in the experiment.
- TryMarked: The number of times this sign was used in try-marking.
- Teach: The number of times this sign was explicitly taught.
- averageLength_week_1: Average time to produce the variant in milliseconds
- averageTrialLength_week_1: Average time for completing the trial for the given target colour.
- BodyAnchor: Is the variant body-anchored (redundant with 'indexical')

Poisson regression

This study uses a mixed effects regression model with poisson distributions. Most standard regression analyses assume that the values they are trying to model come from a normal distribution, like this:



However, the main variable for this study is the frequency of sign variants, with a strong skew and many zero values:



Instead of using a normal distribution as the basis for the statistical model or transforming the data (which is difficult anyway because of the large number of zero counts), we can use a poisson distribution. This also has the advantage of only predicting whole, non-negative numbers, which makes sense for this data because a variant can't be used half a time or a negative number of times.

Load libraries

```
library(ggplot2)
library(lme4)
library(party)
library(Rmisc)
library(dplyr)
```

Load data

```
variants = read.csv('../data/processedData/variants_summary.csv', stringsAsFactors = F)
```

There is only 1 variant for 'white'. Therefore, we remove it from this statistical analysis.

```
variants = variants[variants$colourName!='white',]
```

Transform some variables.

```
# The range of values for 'Teach' is very small:
table(variants$Teach)
```

```
##
##  0  1  2  3
## 86 12  3  3
```

```
# So we'll turn it into a binary category:
#  variants that were never taught and variants that were
variants$Teach = variants$Teach >0

# Similar for checking
variants$check.any = variants$check>0

# Transform total frequency
variants$freq_week_1_total.logcenter =
  log(variants$freq_week_1_total + 1)
variants$freq_week_1_total.logcenter =
  variants$freq_week_1_total.logcenter - mean(variants$freq_week_1_total.logcenter)

# cut TryMarking into two categories
variants$TryMarked.cat = cut(variants$TryMarked,
                             c(-Inf,3,Inf),
                             labels = c("Low",'High'))

# transform length
variants$averageLength_week_1.logcenter = log(variants$averageLength_week_1)
variants$averageLength_week_1.logcenter =
  variants$averageLength_week_1.logcenter -
    mean(variants$averageLength_week_1.logcenter)
```

LMER models

Each model predicts the frequency of a variant in week 4, with a random intercept by colourName. The random intercept allows some colours to have higher variant frequencies than others. This is useful because we know that signs for some colours are converged on quickly, making their frequencies within those colours potentially higher. In other words, the use of a particular variant to refer to a given colour is not entierly independent of the use of another variant to refer to the same colour.

We begin with a null model and gradually add predictor variables, using model comparison to judge the significance of each variable.

```
# Null model
m0 = glmer(freq_week_4 ~
             1
           + (1 | colourName) ,
           data=variants, family=poisson)

# add indexicality
m1 = glmer(freq_week_4 ~
             1 +
             indexical +
            (1 | colourName) ,
           data=variants, family=poisson)

# add whether the variant is explicitly taught
m2 = glmer(freq_week_4 ~
             1 +
             indexical +
             Teach +
            (1 | colourName) ,
           data=variants, family=poisson)

m3 = glmer(freq_week_4 ~
             1 +
             indexical +
             Teach +
             TryMarked +
            (1 | colourName) ,
           data=variants, family=poisson)

m4 = glmer(freq_week_4 ~
             1 +
             indexical +
             Teach +
             TryMarked +
             check.any +
            (1 | colourName) ,
           data=variants, family=poisson)

m5 = glmer(freq_week_4 ~
             1 +
             indexical +
             Teach +
             TryMarked +
             check.any +
```

```r
            freq_week_1_total +
           (1 | colourName) ,
          data=variants, family=poisson)

m6 = glmer(freq_week_4 ~
            1 +
            indexical +
            Teach +
            TryMarked +
            check.any +
            freq_week_1_total +
            averageLength_week_1.logcenter +
           (1 | colourName) ,
          data=variants, family=poisson)

m7 = glmer(freq_week_4 ~
            1 +
            indexical +
            Teach +
            TryMarked +
            check.any +
            freq_week_1_total +
            averageLength_week_1.logcenter +
            inventedBy +
           (1 | colourName) ,
          data=variants, family=poisson)

m8 = glmer(freq_week_4 ~
            1 +
            indexical +
            Teach +
            TryMarked +
            check.any +
            freq_week_1_total +
            averageLength_week_1.logcenter +
            inventedBy +
            Teach : TryMarked +
           (1 | colourName) ,
          data=variants, family=poisson)

m9 = glmer(freq_week_4 ~
            1 +
            indexical +
            Teach +
            TryMarked +
            check.any +
            freq_week_1_total +
            averageLength_week_1.logcenter +
            inventedBy +
            Teach : TryMarked +
            Teach : check.any +
           (1 | colourName) ,
          data=variants, family=poisson)
```

```r
m10 = glmer(freq_week_4 ~
             1 +
             indexical +
             Teach +
             TryMarked +
             check.any +
             freq_week_1_total +
             averageLength_week_1.logcenter +
             inventedBy +
             Teach : TryMarked +
             Teach : check.any +
             TryMarked : check.any +
            (1 | colourName) ,
           data=variants, family=poisson)

anova(m0,m1,m2,m3,m4,m5,m6,m7,m8,m9,m10)
```

```
## Data: variants
## Models:
## m0: freq_week_4 ~ 1 + (1 | colourName)
## m1: freq_week_4 ~ 1 + indexical + (1 | colourName)
## m2: freq_week_4 ~ 1 + indexical + Teach + (1 | colourName)
## m3: freq_week_4 ~ 1 + indexical + Teach + TryMarked + (1 | colourName)
## m4: freq_week_4 ~ 1 + indexical + Teach + TryMarked + check.any +
## m4:     (1 | colourName)
## m5: freq_week_4 ~ 1 + indexical + Teach + TryMarked + check.any +
## m5:     freq_week_1_total + (1 | colourName)
## m6: freq_week_4 ~ 1 + indexical + Teach + TryMarked + check.any +
## m6:     freq_week_1_total + averageLength_week_1.logcenter + (1 |
## m6:     colourName)
## m7: freq_week_4 ~ 1 + indexical + Teach + TryMarked + check.any +
## m7:     freq_week_1_total + averageLength_week_1.logcenter + inventedBy +
## m7:     (1 | colourName)
## m8: freq_week_4 ~ 1 + indexical + Teach + TryMarked + check.any +
## m8:     freq_week_1_total + averageLength_week_1.logcenter + inventedBy +
## m8:     Teach:TryMarked + (1 | colourName)
## m9: freq_week_4 ~ 1 + indexical + Teach + TryMarked + check.any +
## m9:     freq_week_1_total + averageLength_week_1.logcenter + inventedBy +
## m9:     Teach:TryMarked + Teach:check.any + (1 | colourName)
## m10: freq_week_4 ~ 1 + indexical + Teach + TryMarked + check.any +
## m10:     freq_week_1_total + averageLength_week_1.logcenter + inventedBy +
## m10:     Teach:TryMarked + Teach:check.any + TryMarked:check.any +
## m10:     (1 | colourName)
##     Df    AIC    BIC   logLik deviance   Chisq Chi Df Pr(>Chisq)
## m0   2 374.62 379.91 -185.309   370.62
## m1   4 335.93 346.51 -163.966   327.93 42.6860      2  5.381e-10 ***
## m2   5 314.99 328.22 -152.497   304.99 22.9388      1  1.672e-06 ***
## m3   6 247.69 263.55 -117.843   235.69 69.3069      1  < 2.2e-16 ***
## m4   7 238.17 256.68 -112.086   224.17 11.5155      1  0.0006902 ***
## m5   8 237.78 258.94 -110.891   221.78  2.3890      1  0.1221921
## m6   9 233.97 257.77 -107.985   215.97  5.8122      1  0.0159158 *
## m7  12 230.17 261.90 -103.084   206.17  9.8012      3  0.0203338 *
## m8  13 219.75 254.13  -96.877   193.75 12.4149      1  0.0004259 ***
```

```
## m9  14 216.91 253.93  -94.457   188.91  4.8405      1  0.0277992 *
## m10 15 217.82 257.49  -93.912   187.82  1.0897      1  0.2965421
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Results

Model comparison test:

```r
anova(m0,m1,m2,m3,m4,m5, m6,m7,m8, m9, m10)
```

```
## Data: variants
## Models:
## m0: freq_week_4 ~ 1 + (1 | colourName)
## m1: freq_week_4 ~ 1 + indexical + (1 | colourName)
## m2: freq_week_4 ~ 1 + indexical + Teach + (1 | colourName)
## m3: freq_week_4 ~ 1 + indexical + Teach + TryMarked + (1 | colourName)
## m4: freq_week_4 ~ 1 + indexical + Teach + TryMarked + check.any +
## m4:     (1 | colourName)
## m5: freq_week_4 ~ 1 + indexical + Teach + TryMarked + check.any +
## m5:     freq_week_1_total + (1 | colourName)
## m6: freq_week_4 ~ 1 + indexical + Teach + TryMarked + check.any +
## m6:     freq_week_1_total + averageLength_week_1.logcenter + (1 |
## m6:     colourName)
## m7: freq_week_4 ~ 1 + indexical + Teach + TryMarked + check.any +
## m7:     freq_week_1_total + averageLength_week_1.logcenter + inventedBy +
## m7:     (1 | colourName)
## m8: freq_week_4 ~ 1 + indexical + Teach + TryMarked + check.any +
## m8:     freq_week_1_total + averageLength_week_1.logcenter + inventedBy +
## m8:     Teach:TryMarked + (1 | colourName)
## m9: freq_week_4 ~ 1 + indexical + Teach + TryMarked + check.any +
## m9:     freq_week_1_total + averageLength_week_1.logcenter + inventedBy +
## m9:     Teach:TryMarked + Teach:check.any + (1 | colourName)
## m10: freq_week_4 ~ 1 + indexical + Teach + TryMarked + check.any +
## m10:     freq_week_1_total + averageLength_week_1.logcenter + inventedBy +
## m10:     Teach:TryMarked + Teach:check.any + TryMarked:check.any +
## m10:     (1 | colourName)
##     Df    AIC    BIC   logLik deviance   Chisq Chi Df Pr(>Chisq)
## m0   2 374.62 379.91 -185.309   370.62
## m1   4 335.93 346.51 -163.966   327.93 42.6860      2  5.381e-10 ***
## m2   5 314.99 328.22 -152.497   304.99 22.9388      1  1.672e-06 ***
## m3   6 247.69 263.55 -117.843   235.69 69.3069      1  < 2.2e-16 ***
## m4   7 238.17 256.68 -112.086   224.17 11.5155      1  0.0006902 ***
## m5   8 237.78 258.94 -110.891   221.78  2.3890      1  0.1221921
## m6   9 233.97 257.77 -107.985   215.97  5.8122      1  0.0159158 *
## m7  12 230.17 261.90 -103.084   206.17  9.8012      3  0.0203338 *
## m8  13 219.75 254.13  -96.877   193.75 12.4149      1  0.0004259 ***
## m9  14 216.91 253.93  -94.457   188.91  4.8405      1  0.0277992 *
## m10 15 217.82 257.49  -93.912   187.82  1.0897      1  0.2965421
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Choose a final model for the beta values.

```r
finalModel = glmer(freq_week_4 ~
            1 +
             indexical +
             Teach +
             TryMarked +
             check.any +
             freq_week_1_total +
             averageLength_week_1.logcenter +
             inventedBy +
             Teach : TryMarked +
             Teach : check.any +
            (1  | colourName),
          data=variants, family=poisson)
```

Fixed effects:

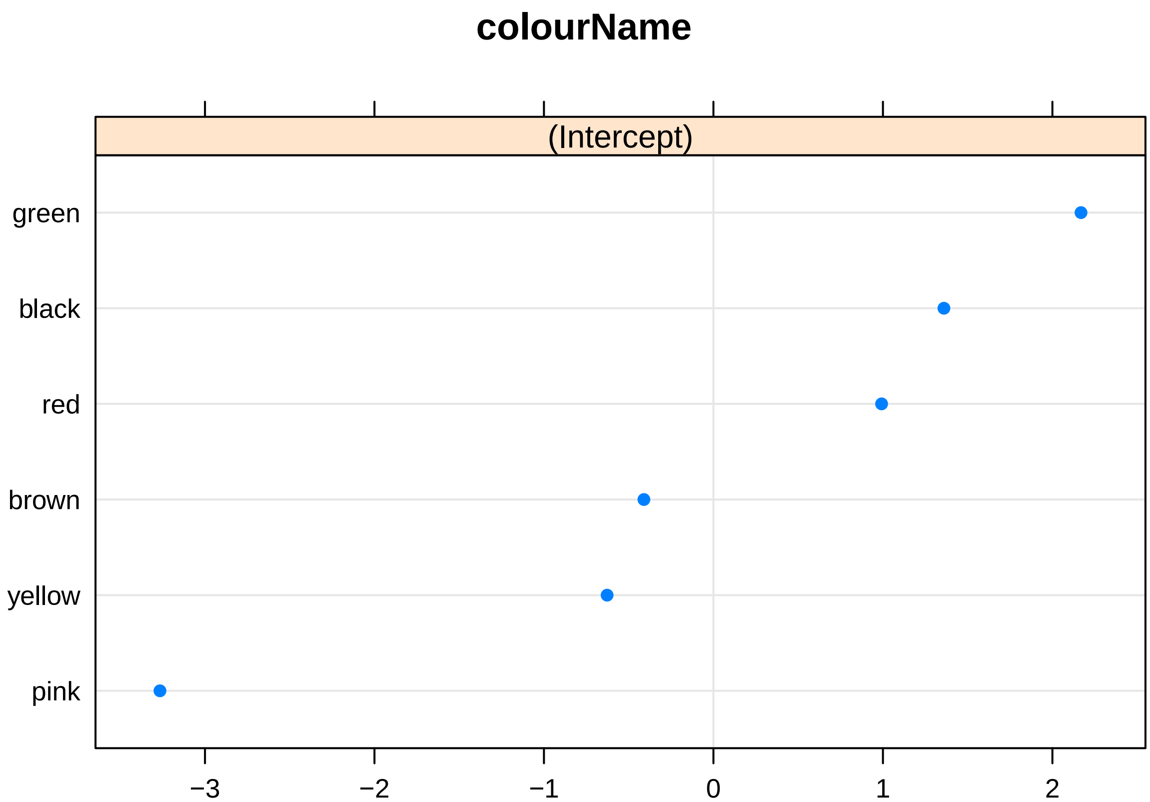
```r
coef(summary(finalModel))[,1:3]
```

```
##                                   Estimate Std. Error     z value
## (Intercept)                    -3.54877182 0.90420433 -3.92474545
## indexicalYes                    1.34307671 0.68878087  1.94993324
## indexicalYes-body               1.04190909 0.32792092  3.17731820
## TeachTRUE                       2.52779425 0.92964707  2.71909023
## TryMarked                       0.96935153 0.13895508  6.97600636
## check.anyTRUE                   1.11633836 0.38408155  2.90651391
## freq_week_1_total              -0.01241724 0.02245822 -0.55290385
## averageLength_week_1.logcenter -0.01336033 0.19039901 -0.07017018
## inventedByIndonesia             0.25398881 0.48605145  0.52255539
## inventedByJordan                1.45727444 0.55910638  2.60643500
## inventedByNepal                -0.32470114 0.47785322 -0.67949975
## TeachTRUE:TryMarked            -0.58263336 0.14612713 -3.98716769
## TeachTRUE:check.anyTRUE        -1.75425992 0.81900972 -2.14192810
```

Random effects:

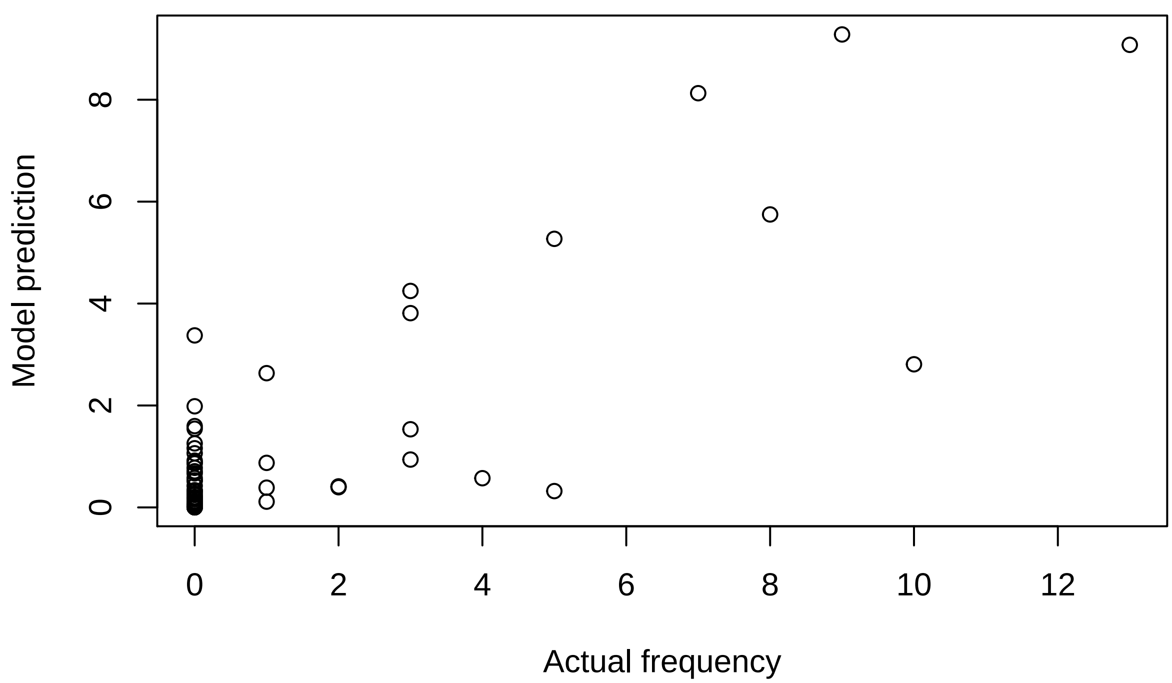
```r
dotplot(ranef(finalModel))
```

```
## $colourName
```



Check the predictions:

```
plot(variants$freq_week_4, exp(predict(finalModel)),
     xlab="Actual frequency",
     ylab="Model prediction")
```



Random slopes

For each of the predictors, we see if random slopes help improve the model. Random slopes allow the strenght of the effect of a factor to be different for each colour concept. There were some convergence issues with some of the models (hence chancing the optimiser and maximum iterations below), which indicates that the random slopes may not be suitable with this amount of data. However, the tests below can serve as indicators about whether there is variation within colours.

```
rsControl = glmerControl(
            optimizer = "bobyqa",
            optCtrl = list(maxfun=500000))

m8R = glmer(freq_week_4 ~
            1 +
             indexical +
             Teach +
             TryMarked +
             check.any +
             freq_week_1_total +
             averageLength_week_1.logcenter +
             inventedBy +
             Teach : TryMarked +
             Teach : check.any +
           (1 | colourName) ,
          data=variants, family=poisson,
          control = rsControl)

m8R.indexical = glmer(freq_week_4 ~
            1 +
             indexical +
             Teach +
             TryMarked +
             check.any +
             freq_week_1_total +
             averageLength_week_1.logcenter +
             inventedBy +
             Teach : TryMarked +
             Teach : check.any +
           (1 + indexical| colourName),
          data=variants, family=poisson,
          control = rsControl)

anova(m8R,m8R.indexical)
```

```
## Data: variants
## Models:
## m8R: freq_week_4 ~ 1 + indexical + Teach + TryMarked + check.any +
## m8R:     freq_week_1_total + averageLength_week_1.logcenter + inventedBy +
## m8R:     Teach:TryMarked + Teach:check.any + (1 | colourName)
## m8R.indexical: freq_week_4 ~ 1 + indexical + Teach + TryMarked + check.any +
## m8R.indexical:     freq_week_1_total + averageLength_week_1.logcenter + inventedBy +
## m8R.indexical:     Teach:TryMarked + Teach:check.any + (1 + indexical | colourName)
##               Df    AIC    BIC  logLik deviance Chisq Chi Df Pr(>Chisq)
## m8R           14 216.91 253.94 -94.457   188.91
```

```
## m8R.indexical 19 208.28 258.53 -85.142   170.28 18.63      5   0.002252 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
m8R.Teach = glmer(freq_week_4 ~
            1 +
             indexical +
             Teach +
             TryMarked +
             check.any +
             freq_week_1_total +
             averageLength_week_1.logcenter +
             inventedBy +
             Teach : TryMarked +
             Teach : check.any +
          (1 + Teach| colourName),
          data=variants, family=poisson,
          control=rsControl)
anova(m8R,m8R.Teach)
```

```
## Data: variants
## Models:
## m8R: freq_week_4 ~ 1 + indexical + Teach + TryMarked + check.any +
## m8R:     freq_week_1_total + averageLength_week_1.logcenter + inventedBy +
## m8R:     Teach:TryMarked + Teach:check.any + (1 | colourName)
## m8R.Teach: freq_week_4 ~ 1 + indexical + Teach + TryMarked + check.any +
## m8R.Teach:     freq_week_1_total + averageLength_week_1.logcenter + inventedBy +
## m8R.Teach:     Teach:TryMarked + Teach:check.any + (1 + Teach | colourName)
##           Df    AIC    BIC  logLik deviance Chisq Chi Df Pr(>Chisq)
## m8R       14 216.91 253.94 -94.457   188.91
## m8R.Teach 16 209.06 251.37 -88.532   177.06 11.85      2   0.002671 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
m8R.TryMark = glmer(freq_week_4 ~
          1 +
             indexical +
             Teach +
             TryMarked +
             check.any +
             freq_week_1_total +
             averageLength_week_1.logcenter +
             inventedBy +
             Teach : TryMarked +
             Teach : check.any +
          (1 | colourName) +
          (0 + TryMarked| colourName),
          data=variants, family=poisson,
          control = rsControl)
anova(m8R,m8R.TryMark)
```

```
## Data: variants
## Models:
## m8R: freq_week_4 ~ 1 + indexical + Teach + TryMarked + check.any +
## m8R:     freq_week_1_total + averageLength_week_1.logcenter + inventedBy +
```

```
## m8R:     Teach:TryMarked + Teach:check.any + (1 | colourName)
## m8R.TryMark: freq_week_4 ~ 1 + indexical + Teach + TryMarked + check.any +
## m8R.TryMark:     freq_week_1_total + averageLength_week_1.logcenter + inventedBy +
## m8R.TryMark:     Teach:TryMarked + Teach:check.any + (1 | colourName) + (0 +
## m8R.TryMark:     TryMarked | colourName)
##             Df    AIC    BIC  logLik deviance Chisq Chi Df Pr(>Chisq)
## m8R         14 216.91 253.94 -94.457   188.91
## m8R.TryMark 15 214.54 254.20 -92.268   184.54 4.378      1    0.03641 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
m8R.Check = glmer(freq_week_4 ~
           1 +
             indexical +
             Teach +
             TryMarked +
             check.any +
             freq_week_1_total +
             averageLength_week_1.logcenter +
             inventedBy +
             Teach : TryMarked +
             Teach : check.any +
          (1 | colourName) +
          (0 + check.any| colourName),
          data=variants, family=poisson,
          control = rsControl)
```

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

```r
anova(m8R,m8R.Check)
```

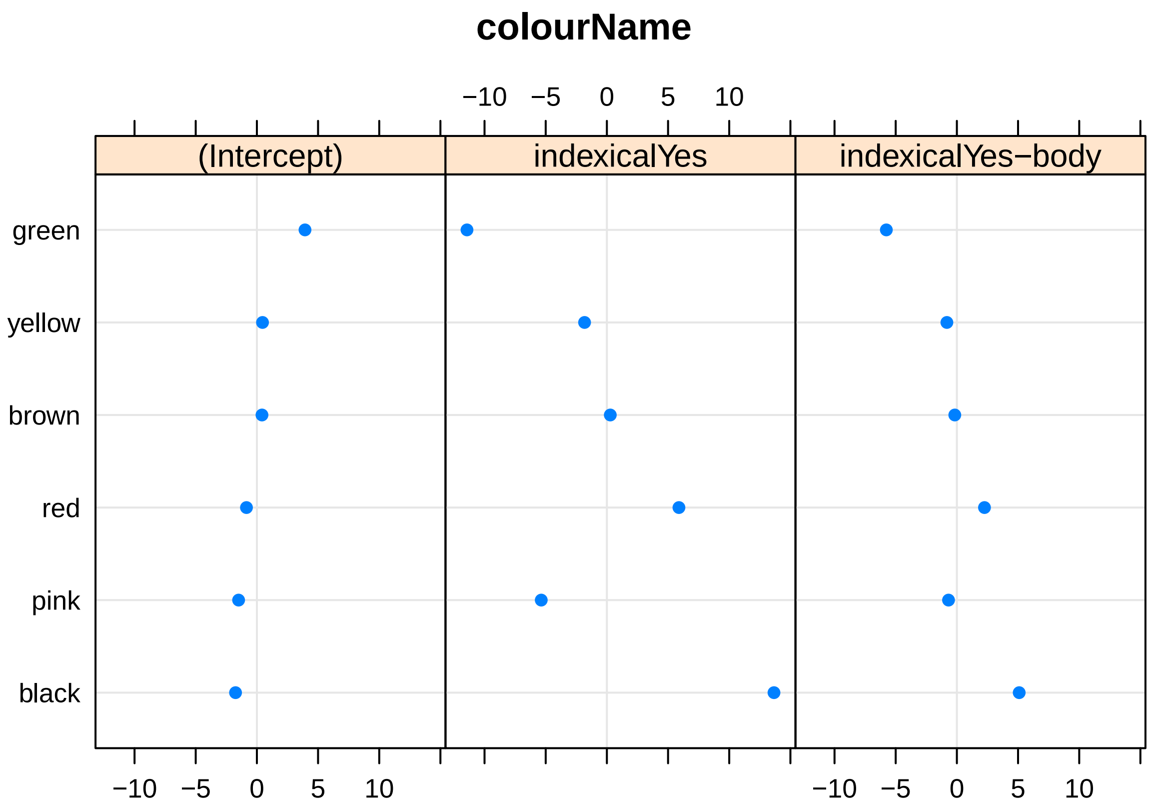
```
## Data: variants
## Models:
## m8R: freq_week_4 ~ 1 + indexical + Teach + TryMarked + check.any +
## m8R:     freq_week_1_total + averageLength_week_1.logcenter + inventedBy +
## m8R:     Teach:TryMarked + Teach:check.any + (1 | colourName)
## m8R.Check: freq_week_4 ~ 1 + indexical + Teach + TryMarked + check.any +
## m8R.Check:     freq_week_1_total + averageLength_week_1.logcenter + inventedBy +
## m8R.Check:     Teach:TryMarked + Teach:check.any + (1 | colourName) + (0 +
## m8R.Check:     check.any | colourName)
##           Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
## m8R       14 216.91 253.94 -94.457   188.91
## m8R.Check 17 215.15 260.10 -90.574   181.15 7.7647      3    0.05113 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

We see that indexicality, try marking and teaching. We can plot the random slopes below:

- Indexicality

```r
dotplot(ranef(m8R.indexical))
```

```
## $colourName
```

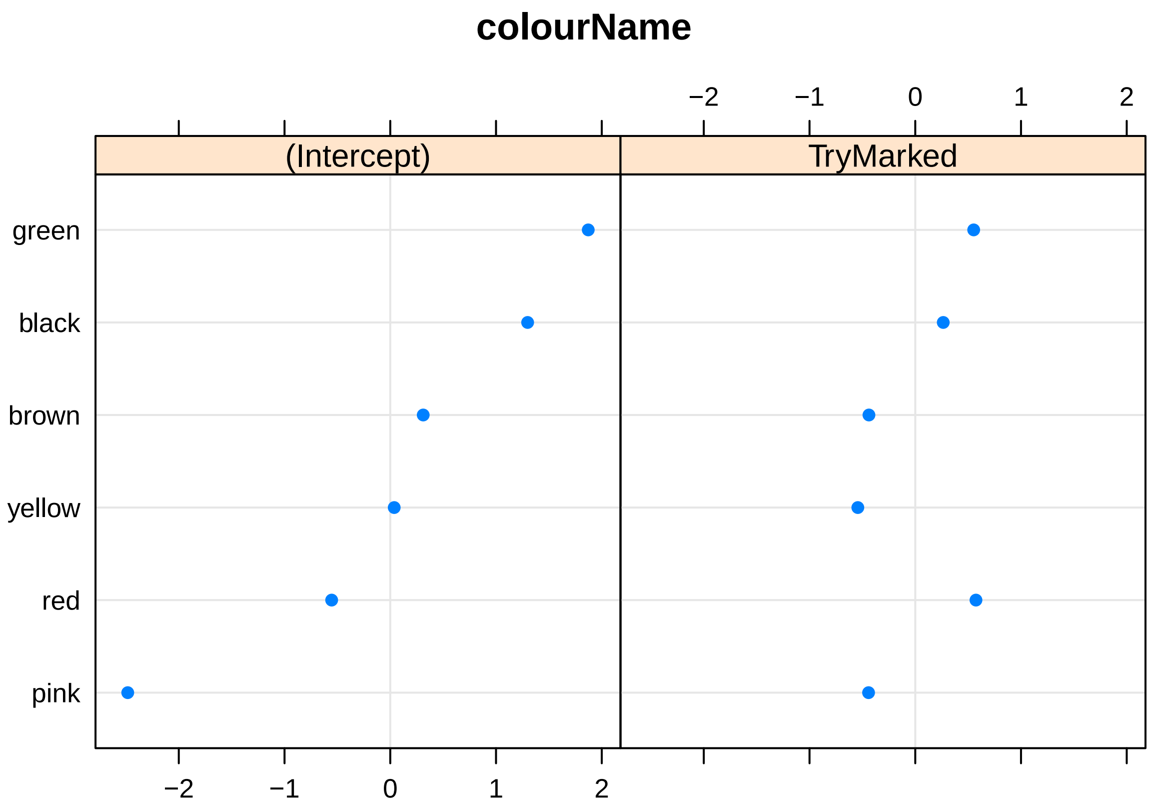


Indexicality improves the chance of selection of variants for black and red, but reduces the chance of selection for green and pink.

- Try Marking

```
dotplot(ranef(m8R.TryMark))
```

```
## $colourName
```

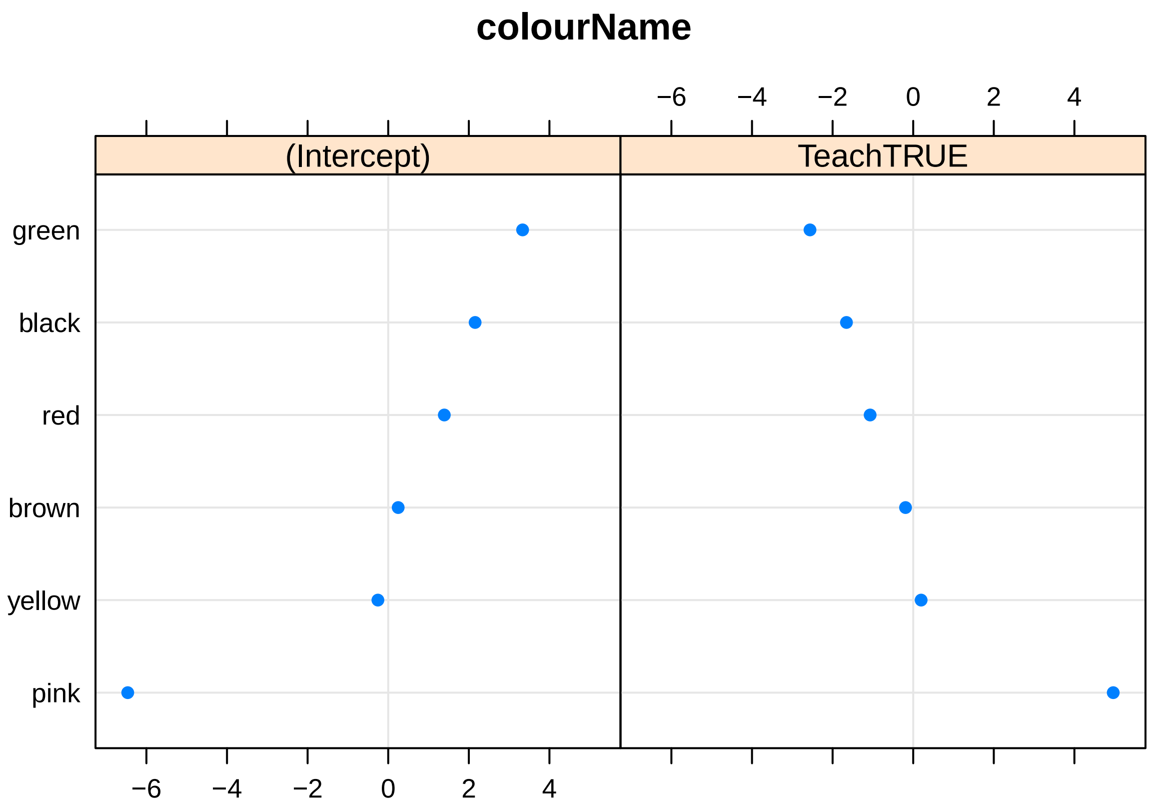


Try marking improves the probability of selection for red, green and black, but decreases the probability of selection for brown, yellow an pink.

- Teaching

```
dotplot(ranef(m8R.Teach))
```

```
## $colourName
```



Explicit teaching improves the likelihood of selection for pink, but not for other colours.

Summary

Here is a summary of the main results:

There was a significant main effect of indexicality (beta = 1.3 , log likelihood difference = 21 , df = 2 , Chi Squared = 42.69 , p = 5.4e-10). (beta for body-indexical = 0.853). Indexical variants were more likely to be selected.

There was a significant main effect of teaching (beta = 2.5 , log likelihood difference = 11 , df = 1 , Chi Squared = 22.94 , p = 1.7e-06). Teaching increased the likelyhood of selection.

There was a significant main effect of try marking (beta = 0.97 , log likelihood difference = 35 , df = 1 , Chi Squared = 69.31 , p = 8.4e-17). Variants that were try marked more often were more likely to be selected.

There was a significant main effect of checking (beta = 1.1 , log likelihood difference = 5.8 , df = 1 , Chi Squared = 11.52 , p = 0.00069). A variant was more likely to be selected if it had been used in a checking context.

There was no significant main effect of frequency in week 1 (beta = -0.012 , log likelihood difference = 1.2 , df = 1 , Chi Squared = 2.39 , p = 0.12). On its own, more frequent variants in week 1 are also more frequent in the final week (r = 0.2748784). However, when considering this variable with the other variables the relationship dissappears. An explanation may be the following: A poor variant may be repeated many times before it is understood, while a good variant only needs to be used once. That is, frequent use in the first week may be an indication of communication problems. The sequential measures (teaching, try marking, checking) and indexicality are better measures of whether a variant is problematic, so the predictive power of frequency is small in comparison.

There was a significant main effect of sign length (beta = -0.013 , log likelihood difference = 2.9 , df = 1 , Chi Squared = 5.81 , p = 0.016). Shorter signs were more likely to be selected. However the effect size is very small.

There was a significant main effect of first user (inventedBy) (log likelihood difference = 4.9 , df = 3 , Chi Squared = 9.8 , p = 0.02). Sign variants first used by the Jordanian signer were more likely to be selected than variants first used by other signers.

There was a significant interaction between try marking and teaching (beta = -0.58 , log likelihood difference = 6.2 , df = 1 , Chi Squared = 12.41 , p = 0.00043). The effect of teaching was bigger when the variant was also often try marked (see graphs below).

There was a significant interaction between teaching and checking (beta = -1.8 , log likelihood difference = 2.4 , df = 1 , Chi Squared = 4.84 , p = 0.028). (see graphs below).

We also found some evidence that certain factors are more important for particular colours:

- Try marking predicts increased selection particularly for red, green and black.
- Indexicality predicts increased selection particularly for black and red, but decreased selection (relatively) for green and pink.
- Explicit teaching predicts increased selection particularly for pink.

Graphs

Teaching and Try marking

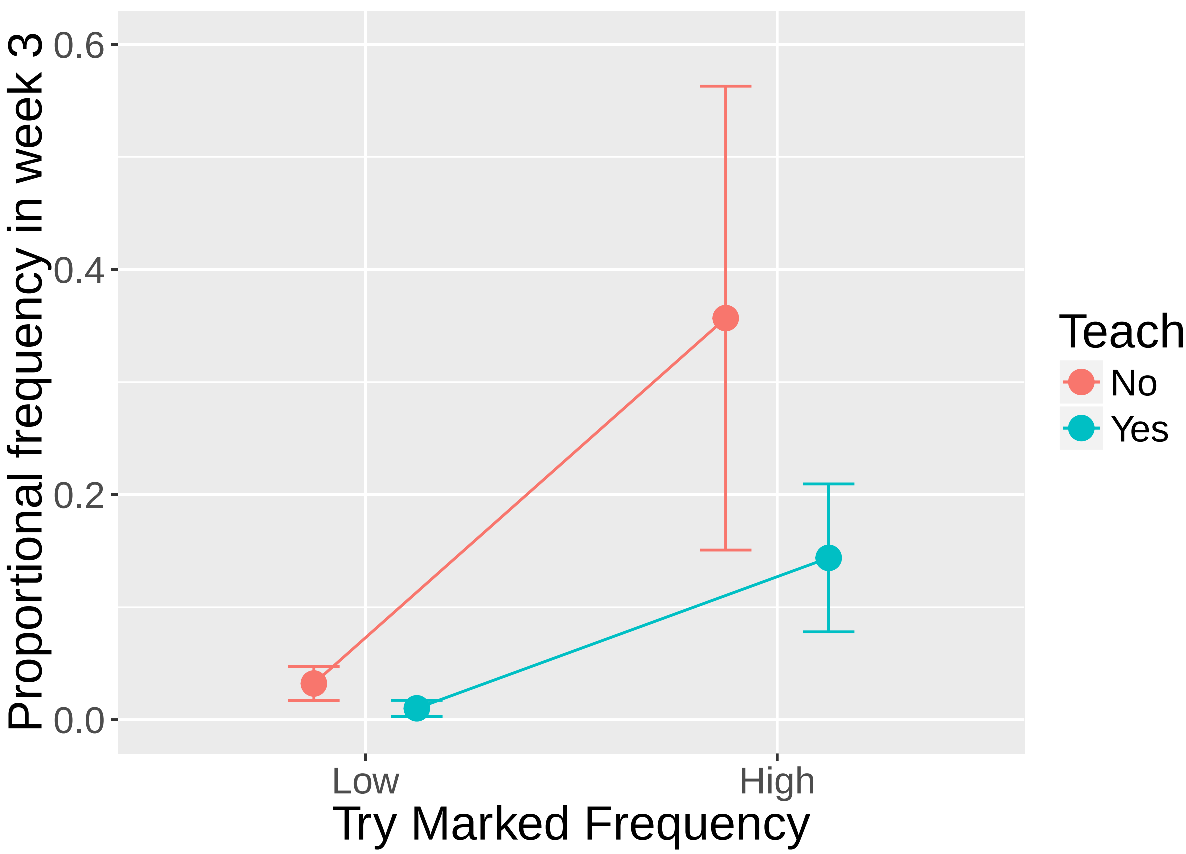
Plot the interaction between teaching and try marking.

Overall, the model suggests that teaching a variant improves its chances of being selected. However, this effect is mainly due to the interaction between teaching and try marking.

```
sumStats2 = summarySE(variants, measurevar="prop_week_4",
                      groupvars=c("TryMarked.cat","Teach"))

dodge <- position_dodge(width=0.5)

main.plot <- ggplot(sumStats2,
    aes(x = TryMarked.cat, y = prop_week_4, colour=Teach)) +
  geom_point(position=dodge, size=4) + geom_line(aes(group=Teach),position=dodge) +
  geom_errorbar(aes(ymax=prop_week_4+se, ymin=prop_week_4-se), width=0.25,position=dodge) +
  xlab("Try Marked Frequency") +
  ylab("Proportional frequency in week 3") +
  coord_cartesian(ylim=c(0,0.6)) +
  scale_color_discrete(breaks=c(FALSE,TRUE),
                       labels=c("No","Yes"),
                       name="Teach") +
  theme(text=element_text(size=18))
main.plot
```




```
## pdf
```

```
## 	2
```

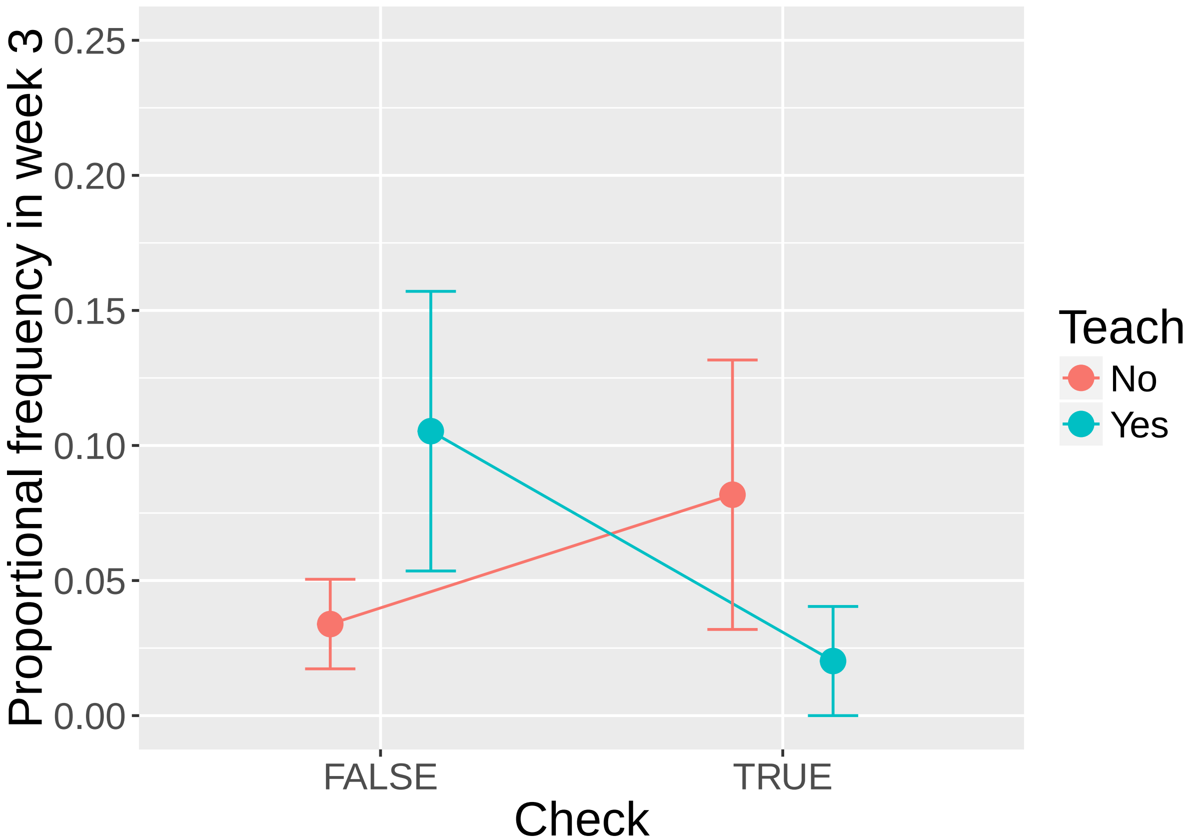
Teaching and checking

Plot the interaction between teaching and checking.

```
sumStats2 = summarySE(variants, measurevar="prop_week_4",
                      groupvars=c("Teach","check.any"))

dodge <- position_dodge(width=0.5)

main.plot2 <- ggplot(sumStats2,
    aes(x = check.any, y = prop_week_4, colour=Teach)) +
  geom_point(position=dodge, size=4) + geom_line(aes(group=Teach),position=dodge) +
  geom_errorbar(aes(ymax=prop_week_4+se, ymin=prop_week_4-se), width=0.25,position=dodge) +
  xlab("Check") +
  ylab("Proportional frequency in week 3") +
  coord_cartesian(ylim=c(0,0.25)) +
  scale_color_discrete(breaks=c(FALSE,TRUE),
                       labels=c("No","Yes"),
                       name="Teach") +
  theme(text=element_text(size=18))
main.plot2
```




```
FALSE pdf
FALSE   2
```

```
## pdf
```

2