The interactive origin of iconiciy: Mixed effects models

This file contains an analysis of the spikiness ratings of the final output languages and the accuracy of guessing during the experiments. The spikiness ratings are not bimodally disributed, so the analysis of spikiness ratings is done using both the continuous spikiness rating values and a binarised version of the ratings.

Load libraries

```
library(gplots)
library(lattice)
library(ggplot2)
library(lme4)
library(party)
library(sjPlot)
```

Load data

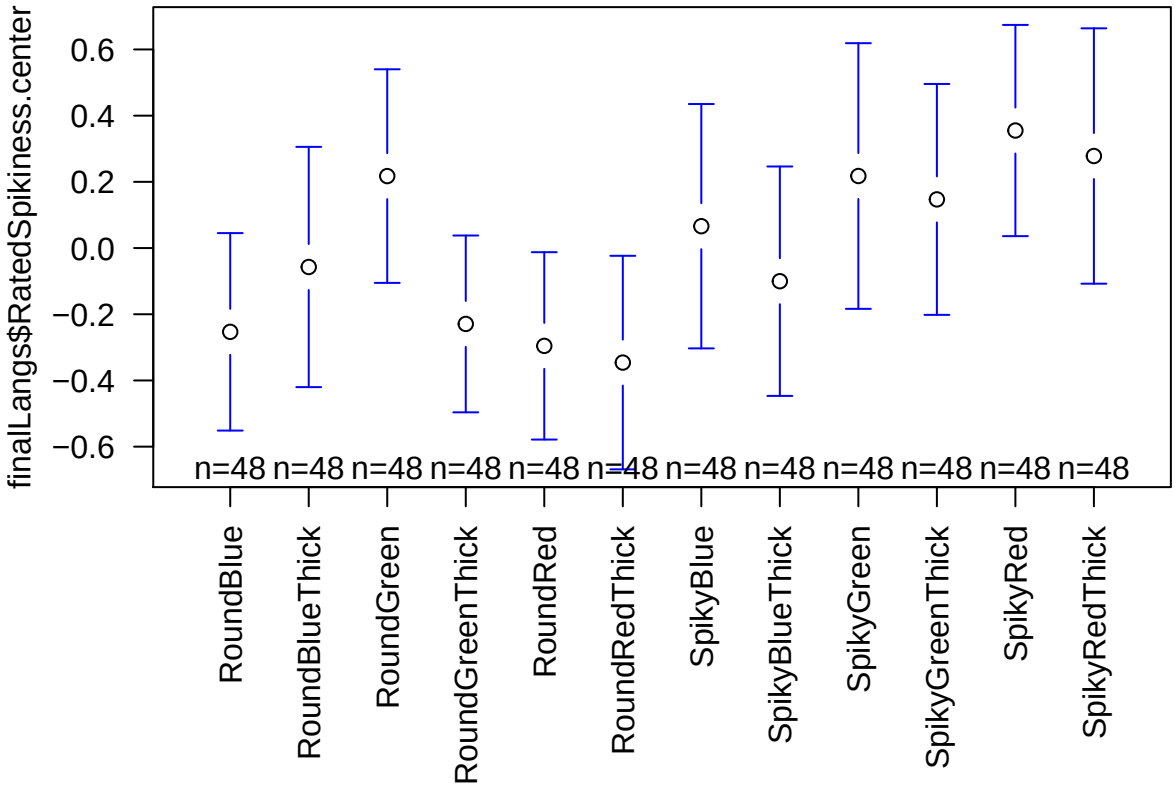
```
finalLangs = read.csv("../data/finalLanguages/FinalLanguages.csv", stringsAsFactors = F)
# convert labels to English
finalLangs$Shape[finalLangs$Shape=="Picudo"] = "Spiky"
finalLangs$Shape[finalLangs$Shape=="Redondo"] = "Round"
```

Center spikiness ratings and re-level factors.

```
finalLangs$RatedSpikiness.center =
  finalLangs$RatedSpikiness- mean(finalLangs$RatedSpikiness)

finalLangs$Cond = factor(finalLangs$Cond, levels=c("Learn","Communication"))
finalLangs$Shape = factor(finalLangs$Shape, levels=c("Round","Spiky"))
```

Plot the data by item (all conditions, all generations)

```
par(mar=c(8,4,2,2))
plotmeans(finalLangs$RatedSpikiness.center~finalLangs$Item, las=2, xlab="", connect=F)
```



There are differences between items

Mixed effects model

Build a series of models with random effects for Chain and Item.

```
# null model
m0 = lmer(RatedSpikiness.center ~ 1 + (1 |Chain)  + (1|Item), data=finalLangs)
# + condition
m1 = lmer(RatedSpikiness.center ~ Cond + (1 |Chain)  + (1|Item), data=finalLangs)
# + generation
m2 = lmer(RatedSpikiness.center ~ Cond + Gen + (1 |Chain) + (1|Item), data=finalLangs)
# + shape
m3 = lmer(RatedSpikiness.center ~ Cond + Gen + Shape + (1 |Chain)
          + (1|Item), data=finalLangs)
# + interaction between shape and generation
m4 = lmer(RatedSpikiness.center ~ Cond + (Gen * Shape) + (1 |Chain)
          + (1|Item), data=finalLangs)
# + interaction between condition and generation
m5 = lmer(RatedSpikiness.center ~ (Cond*Gen) + (Gen * Shape) + (1 |Chain)
          + (1|Item), data=finalLangs)
# + interaction between shape and condition
m6 = lmer(RatedSpikiness.center ~ (Cond*Gen) + (Gen * Shape) + (Shape:Cond)
          + (1 |Chain)  + (1|Item), data=finalLangs)
# + 3-way interaction
m7 = lmer(RatedSpikiness.center ~ Cond * Gen * Shape + (1 |Chain)
          + (1|Item), data=finalLangs)
```

Results

Look inside main model

```
summary(m7)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: RatedSpikiness.center ~ Cond * Gen * Shape + (1 | Chain) + (1 |
##     Item)
##    Data: finalLangs
##
## REML criterion at convergence: 1767.9
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -1.8411 -0.8370 -0.1665  0.7906  2.3066
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  Item     (Intercept) 0.01058  0.1029
##  Chain    (Intercept) 0.18043  0.4248
##  Residual             1.17881  1.0857
## Number of obs: 576, groups:  Item, 12; Chain, 8
##
## Fixed effects:
##                                  Estimate Std. Error t value
## (Intercept)                      0.022530   0.299064   0.075
## CondCommunication                0.096751   0.418750   0.231
## Gen                             -0.033860   0.052978  -0.639
## ShapeSpiky                      -0.003530   0.297764  -0.012
## CondCommunication:Gen           -0.064573   0.074923  -0.862
## CondCommunication:ShapeSpiky    -0.032181   0.412642  -0.078
## Gen:ShapeSpiky                   0.002764   0.074923   0.037
## CondCommunication:Gen:ShapeSpiky  0.189234   0.105957   1.786
##
## Correlation of Fixed Effects:
##             (Intr) CndCmm Gen    ShpSpk CndC:G CnC:SS Gn:ShS
## CondCmmnctn -0.700
## Gen         -0.620  0.443
## ShapeSpiky  -0.498  0.341  0.623
## CndCmmnct:G  0.438 -0.626 -0.707 -0.440
## CndCmmnc:SS  0.345 -0.493 -0.449 -0.693  0.635
## Gen:ShpSpky  0.438 -0.313 -0.707 -0.881  0.500  0.635
## CndCmm:G:SS -0.310  0.443  0.500  0.623 -0.707 -0.899 -0.707
```

Test the differences between model fits.

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

```
## refitting model(s) with ML (instead of REML)
```

```
## Data: finalLangs
```

```
## Models:
## m0: RatedSpikiness.center ~ 1 + (1 | Chain) + (1 | Item)
## m1: RatedSpikiness.center ~ Cond + (1 | Chain) + (1 | Item)
## m2: RatedSpikiness.center ~ Cond + Gen + (1 | Chain) + (1 | Item)
## m3: RatedSpikiness.center ~ Cond + Gen + Shape + (1 | Chain) + (1 |
## m3:     Item)
## m4: RatedSpikiness.center ~ Cond + (Gen * Shape) + (1 | Chain) +
## m4:     (1 | Item)
## m5: RatedSpikiness.center ~ (Cond * Gen) + (Gen * Shape) + (1 | Chain) +
## m5:     (1 | Item)
## m6: RatedSpikiness.center ~ (Cond * Gen) + (Gen * Shape) + (Shape:Cond) +
## m6:     (1 | Chain) + (1 | Item)
## m7: RatedSpikiness.center ~ Cond * Gen * Shape + (1 | Chain) + (1 |
## m7:     Item)
##    Df    AIC    BIC  logLik deviance   Chisq Chi Df Pr(>Chisq)
## m0  4 1779.7 1797.1 -885.83   1771.7
## m1  5 1781.2 1803.0 -885.61   1771.2  0.4475      1  0.5035471
## m2  6 1782.8 1808.9 -885.40   1770.8  0.4234      1  0.5152634
## m3  7 1777.7 1808.2 -881.87   1763.7  7.0627      1  0.0078704 **
## m4  8 1776.4 1811.3 -880.21   1760.4  3.3049      1  0.0690737 .
## m5  9 1778.1 1817.3 -880.05   1760.1  0.3156      1  0.5742584
## m6 10 1768.1 1811.6 -874.04   1748.1 12.0326      1  0.0005228 ***
## m7 11 1766.9 1814.8 -872.43   1744.9  3.2087      1  0.0732495 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

There was a significant main effect of shape (beta = -0.0035 , std.err = 0.3 , Wald t = -0.012 ; log likelihood difference = 3.5 , df = 1 , Chi Squared = 7.06 , p = 0.0079).

There was a significant interaction between shape and condition (beta = -0.032 , std.err = 0.41 , Wald t = -0.078 ; log likelihood difference = 6 , df = 1 , Chi Squared = 12.03 , p = 0.00052).

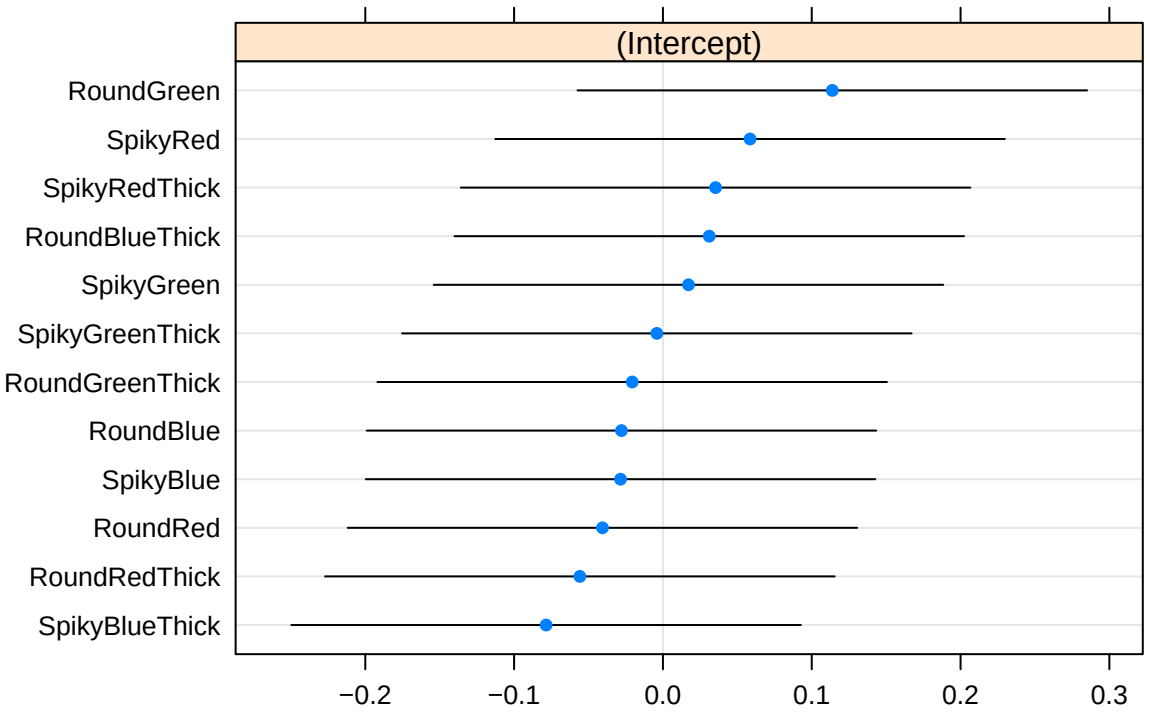
There was a marginal interaction between shape and generation (beta = 0.0028 , std.err = 0.075 , Wald t = 0.037 ; log likelihood difference = 1.7 , df = 1 , Chi Squared = 3.3 , p = 0.069).

There was a marginal three-way interaction between shape, condition and generation (beta = 0.19 , std.err = 0.11 , Wald t = 1.8 ; log likelihood difference = 1.6 , df = 1 , Chi Squared = 3.21 , p = 0.073).

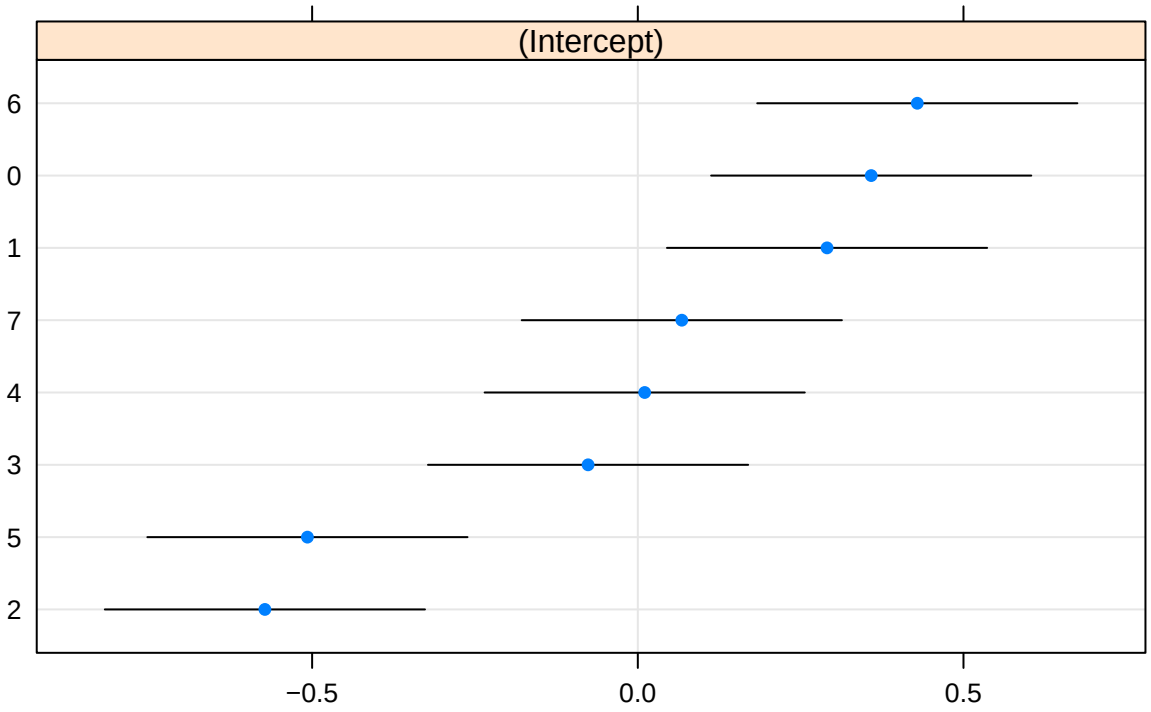
Plot the random effects.

```
dotplot(ranef(m7, condVar=T))
```

```
## $Item
```

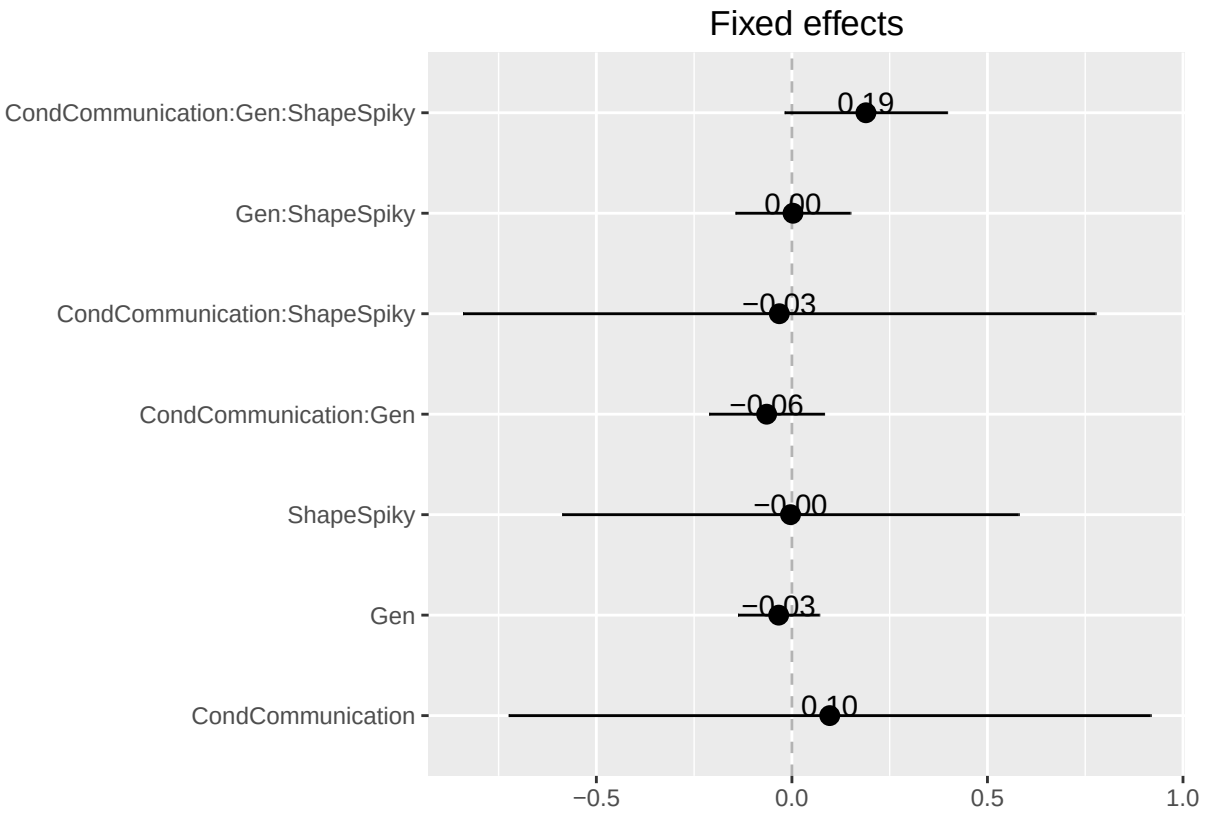

Item
(Intercept)
RoundGreen
SpikyRed
SpikyRedThick
RoundBlueThick
SpikyGreen
SpikyGreenThick
RoundGreenThick
RoundBlue
SpikyBlue
RoundRed
RoundRedThick
SpikyBlueThick
−0.2
−0.1
0.0
0.1
0.2
0.3

```
##
## $Chain
```


Chain
(Intercept)
6
0
1
7
4
3
5
2
−0.5
0.0
0.5

Plot the fixed effects with error estiamtes from the final model. The 3-way interaction between condition, generation and shape is marginaly significant:

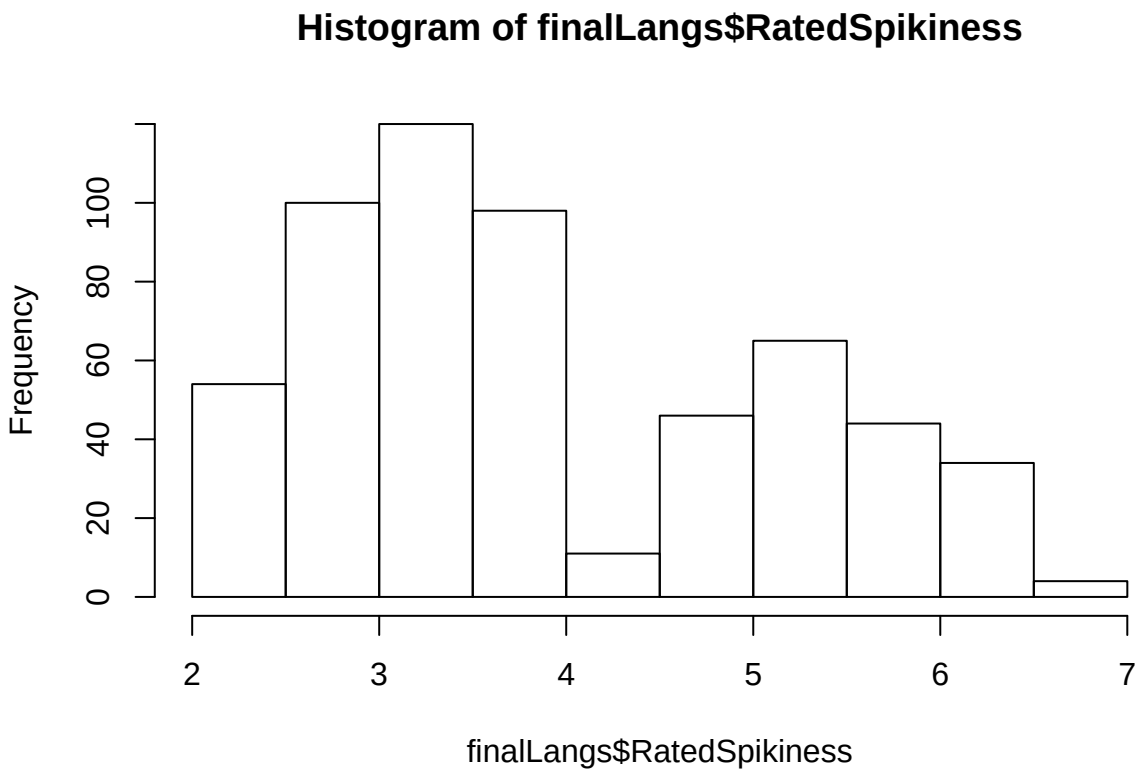
```
sjp.lmer(m7, type='fe', geom.colors=c(1,1))
```



Mixed effects model with binarised spikiness ratings

The spikiness ratings are not normally distributed:

```
hist(finalLangs$RatedSpikiness)
```



So we binarise the variable into spiky/not spiky:

```
finalLangs$RatedSpikiness.bin = finalLangs$RatedSpikiness >4
```

Run a series of models. Note that intermediate models 5 and 6 do not converge, but the final model 7 does.

```
mcontrol = glmerControl(optCtrl = list(maxfun = 500000))

mb0 = glmer(RatedSpikiness.bin ~ 1 + (1 |Chain)  + (1|Item),
            data=finalLangs, family=binomial, control = mcontrol)
mb1 = glmer(RatedSpikiness.bin ~ Cond + (1 |Chain)  + (1|Item),
            data=finalLangs, family=binomial, control = mcontrol)
mb2 = glmer(RatedSpikiness.bin ~ Cond + Gen + (1 |Chain) + (1|Item),
            data=finalLangs, family=binomial, control = mcontrol)
mb3 = glmer(RatedSpikiness.bin ~ Cond + Gen + Shape + (1 |Chain)  + (1|Item),
            data=finalLangs, family=binomial, control = mcontrol)
mb4 = glmer(RatedSpikiness.bin ~ Cond + (Gen * Shape) + (1 |Chain)  + (1|Item),
            data=finalLangs, family=binomial, control = mcontrol)
mb5 = glmer(RatedSpikiness.bin ~ (Cond*Gen) + (Gen * Shape) + (1 |Chain)  + (1|Item),
            data=finalLangs, family=binomial, control = mcontrol)
```

```
## Warning in checkConv(attr(opt, "derivs"), opt$par, ctrl = control
## $checkConv, : Model failed to converge with max|grad| = 0.00112016 (tol =
## 0.001, component 1)
```

```
mb6 = glmer(RatedSpikiness.bin ~ (Cond*Gen) + (Gen * Shape) + (Shape:Cond) + (1 |Chain)  + (1|Item),
            data=finalLangs, family=binomial, control = mcontrol)
```

```
## Warning in checkConv(attr(opt, "derivs"), opt$par, ctrl = control
## $checkConv, : Model failed to converge with max|grad| = 0.00254262 (tol =
## 0.001, component 1)
```

```
mb7 = glmer(RatedSpikiness.bin ~ Cond * Gen * Shape + (1 |Chain)  + (1|Item),
            data=finalLangs, family=binomial, control = mcontrol)
```

Results

Look inside main model

```
summary(mb7)
```

```
## Generalized linear mixed model fit by maximum likelihood (Laplace
##   Approximation) [glmerMod]
##  Family: binomial  ( logit )
## Formula: RatedSpikiness.bin ~ Cond * Gen * Shape + (1 | Chain) + (1 |
##     Item)
##    Data: finalLangs
## Control: mcontrol
##
##      AIC      BIC   logLik deviance df.resid
##    722.9    766.4   -351.4    702.9      566
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -1.4001 -0.7152 -0.4951  0.9714  2.5752
##
## Random effects:
##  Groups Name        Variance Std.Dev.
##  Item   (Intercept) 0.06298  0.2510
##  Chain  (Intercept) 0.30153  0.5491
## Number of obs: 576, groups:  Item, 12; Chain, 8
##
## Fixed effects:
##                                 Estimate Std. Error z value Pr(>|z|)
## (Intercept)                     -0.80967    0.50900  -1.591    0.112
## CondCommunication                0.11711    0.72308   0.162    0.871
## Gen                              0.06152    0.10567   0.582    0.560
## ShapeSpiky                       0.52479    0.60063   0.874    0.382
## CondCommunication:Gen           -0.25227    0.16195  -1.558    0.119
## CondCommunication:ShapeSpiky    -0.06135    0.83301  -0.074    0.941
## Gen:ShapeSpiky                  -0.16967    0.15042  -1.128    0.259
## CondCommunication:Gen:ShapeSpiky  0.39112    0.21894   1.786    0.074 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) CndCmm Gen    ShpSpk CndC:G CnC:SS Gn:ShS
## CondCmmnctn -0.675
## Gen         -0.736  0.518
## ShapeSpiky  -0.600  0.398  0.623
```

```
## CndCmmnct:G  0.480 -0.751 -0.653 -0.407
## CndCmmnc:SS  0.407 -0.617 -0.449 -0.679  0.652
## Gen:ShpSpky  0.518 -0.364 -0.703 -0.871  0.459  0.628
## CndCmm:G:SS -0.356  0.556  0.483  0.599 -0.740 -0.893 -0.687
```

Test model comparison:

```
anova(mb0,mb1,mb2,mb3,mb4,mb5,mb6,mb7)
```

```
## Data: finalLangs
## Models:
## mb0: RatedSpikiness.bin ~ 1 + (1 | Chain) + (1 | Item)
## mb1: RatedSpikiness.bin ~ Cond + (1 | Chain) + (1 | Item)
## mb2: RatedSpikiness.bin ~ Cond + Gen + (1 | Chain) + (1 | Item)
## mb3: RatedSpikiness.bin ~ Cond + Gen + Shape + (1 | Chain) + (1 |
## mb3:     Item)
## mb4: RatedSpikiness.bin ~ Cond + (Gen * Shape) + (1 | Chain) + (1 |
## mb4:     Item)
## mb5: RatedSpikiness.bin ~ (Cond * Gen) + (Gen * Shape) + (1 | Chain) +
## mb5:     (1 | Item)
## mb6: RatedSpikiness.bin ~ (Cond * Gen) + (Gen * Shape) + (Shape:Cond) +
## mb6:     (1 | Chain) + (1 | Item)
## mb7: RatedSpikiness.bin ~ Cond * Gen * Shape + (1 | Chain) + (1 |
## mb7:     Item)
##     Df    AIC    BIC  logLik deviance   Chisq Chi Df Pr(>Chisq)
## mb0  3 729.66 742.72 -361.83   723.66
## mb1  4 731.64 749.07 -361.82   723.64  0.0130      1  0.9092167
## mb2  5 733.09 754.87 -361.54   723.09  0.5560      1  0.4558874
## mb3  6 730.23 756.37 -359.12   718.23  4.8538      1  0.0275855 *
## mb4  7 732.22 762.71 -359.11   718.22  0.0115      1  0.9147795
## mb5  8 734.12 768.97 -359.06   718.12  0.1001      1  0.7517608
## mb6  9 724.09 763.29 -353.04   706.09 12.0352      1  0.0005221 ***
## mb7 10 722.88 766.44 -351.44   702.88  3.2044      1  0.0734423 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

There was a significant main effect of shape (beta = 0.52 , std.err = 0.6 , Wald t = 0.87 , Wald p = 0.38 ; log likelihood difference = 2.4 , df = 1 , Chi Squared = 4.85 , p = 0.028).

There was a significant interaction between shape and condition (beta = -0.061 , std.err = 0.83 , Wald t = -0.074 , Wald p = 0.94 ; log likelihood difference = 6 , df = 1 , Chi Squared = 12.04 , p = 0.00052).

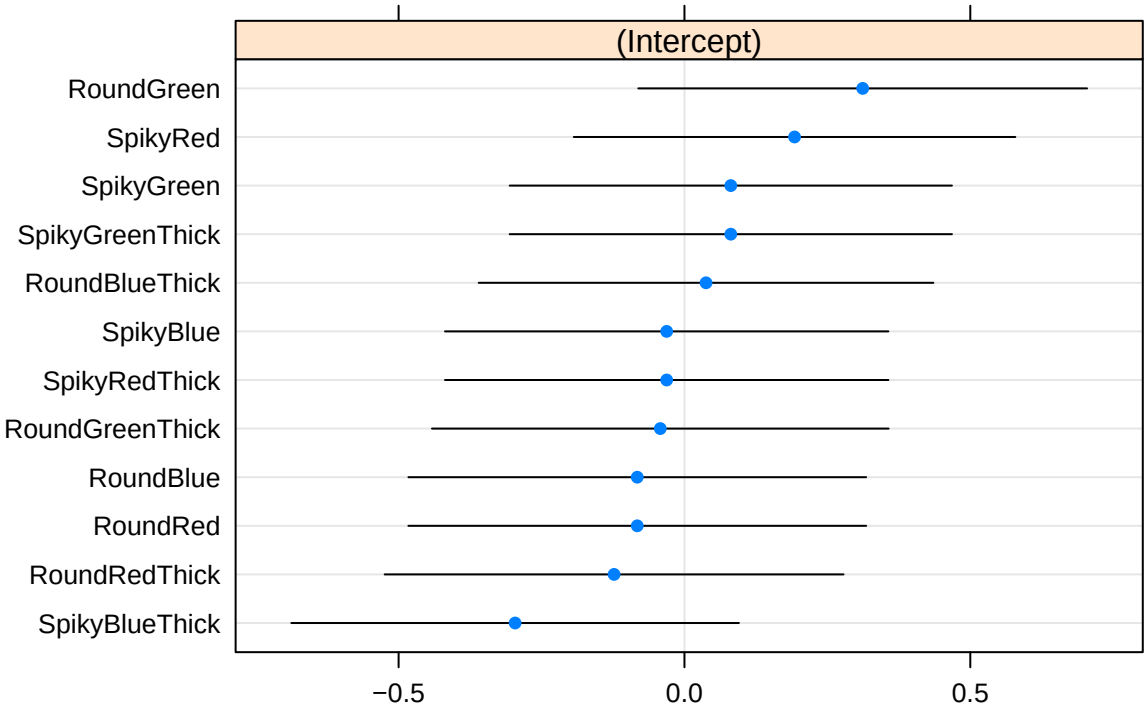
There was no significant interaction between shape and generation (beta = -0.17 , std.err = 0.15 , Wald t = -1.1 , Wald p = 0.26 ; log likelihood difference = 0.0057 , df = 1 , Chi Squared = 0.01 , p = 0.91).

There was a marginal three-way interaction between shape, condition and generation (beta = 0.39 , std.err = 0.22 , Wald t = 1.8 , Wald p = 0.074 ; log likelihood difference = 1.6 , df = 1 , Chi Squared = 3.2 , p = 0.073).

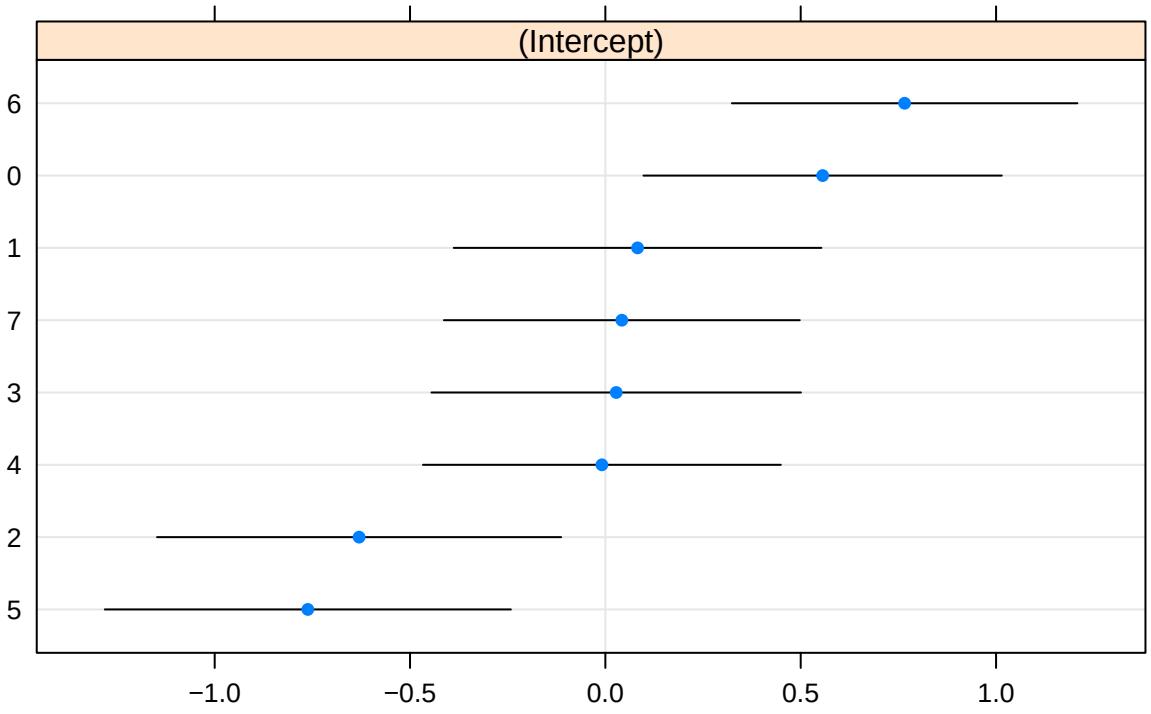
Plot random effects of final model

```
dotplot(ranef(mb7,  condVar=T))
```

```
## $Item
```

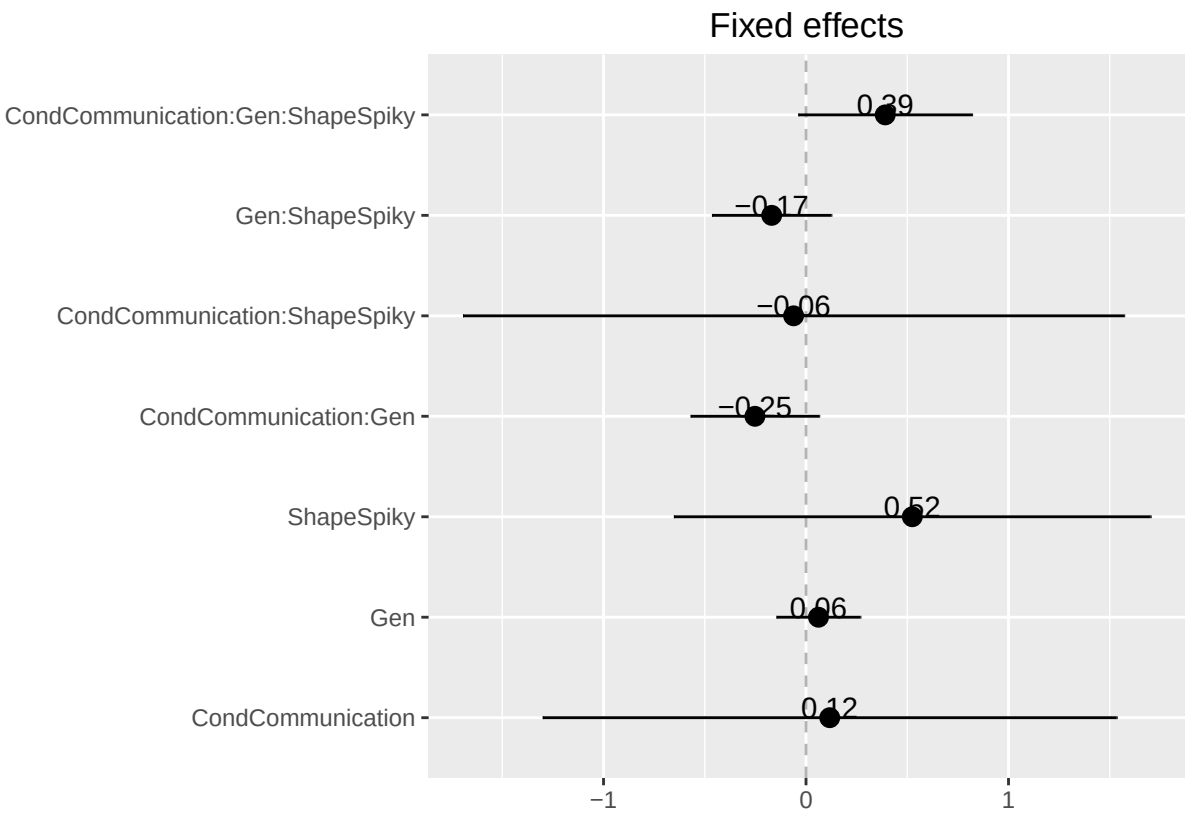

Item
(Intercept)
RoundGreen
SpikyRed
SpikyGreen
SpikyGreenThick
RoundBlueThick
SpikyBlue
SpikyRedThick
RoundGreenThick
RoundBlue
RoundRed
RoundRedThick
SpikyBlueThick
−0.5
0.0
0.5

```
##
## $Chain
```


Chain
(Intercept)
6
0
1
7
3
4
2
5
−1.0
−0.5
0.0
0.5
1.0

Plot fixed effects with standard error from final model.

```
sjp.lmer(mb7, type='fe', geom.colors=c(1,1))
```

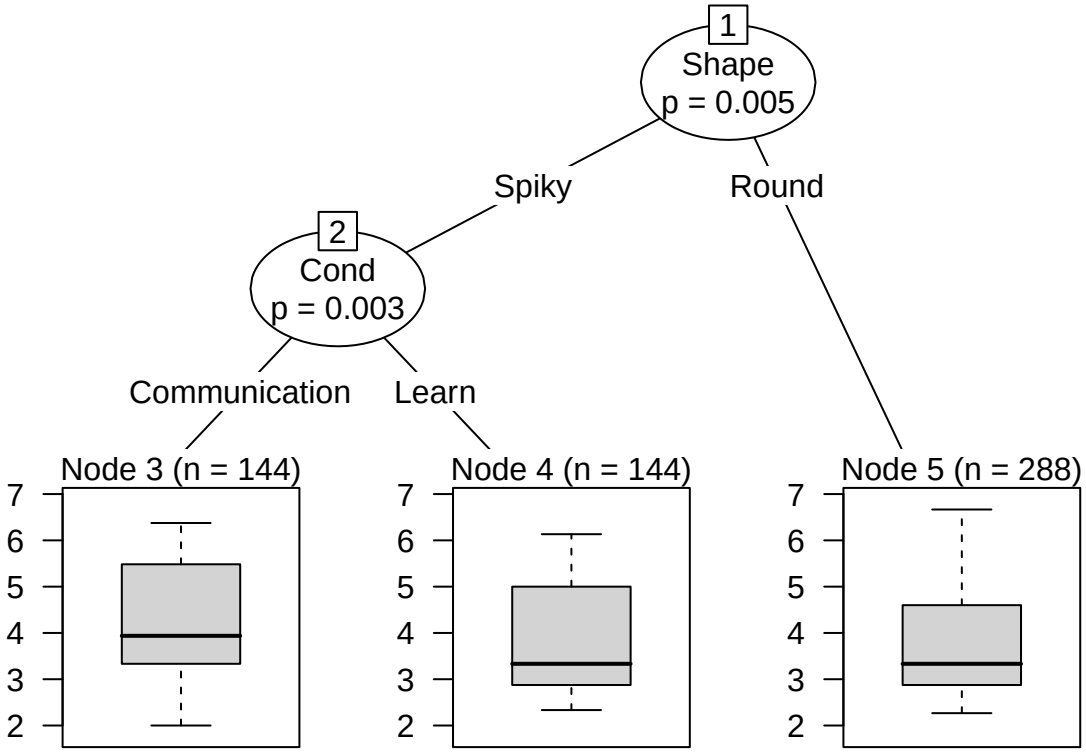


Binary tree analysis

We use a binary decision tree to predict spikiness ratings by condition, generation, item shape, item colour and item border type.

The results agree with those above, namely that the main effects are for shape, but spiky meanings are rated as more spiky in the communication condition

```
finalLangs2 = finalLangs
finalLangs2$Shape = factor(finalLangs2$Shape)
finalLangs2$Colour = factor(finalLangs2$Colour)
finalLangs2$Border = factor(finalLangs2$Border)
finalLangs2$Cond = factor(finalLangs2$Cond)

cx = ctree(RatedSpikiness~Cond+Gen+Shape+Colour+Border, data=finalLangs2)
plot(cx)
```



Accuracy

Note that the column *Human* in the data indicates whether the signal was sent by a human. This is always the case in the communication condition, but only true for half of the trials in the learning condition. In the learning condition, when *Human* is `FALSE`, the human participant is guessing meaning from the signal sent by the program.

Load data

```
datax = read.csv("../results/IncreaseInIconicity.csv", stringsAsFactors = F)
alldatx = read.csv("../results/AllTrialData.csv", stringsAsFactors = F)
```

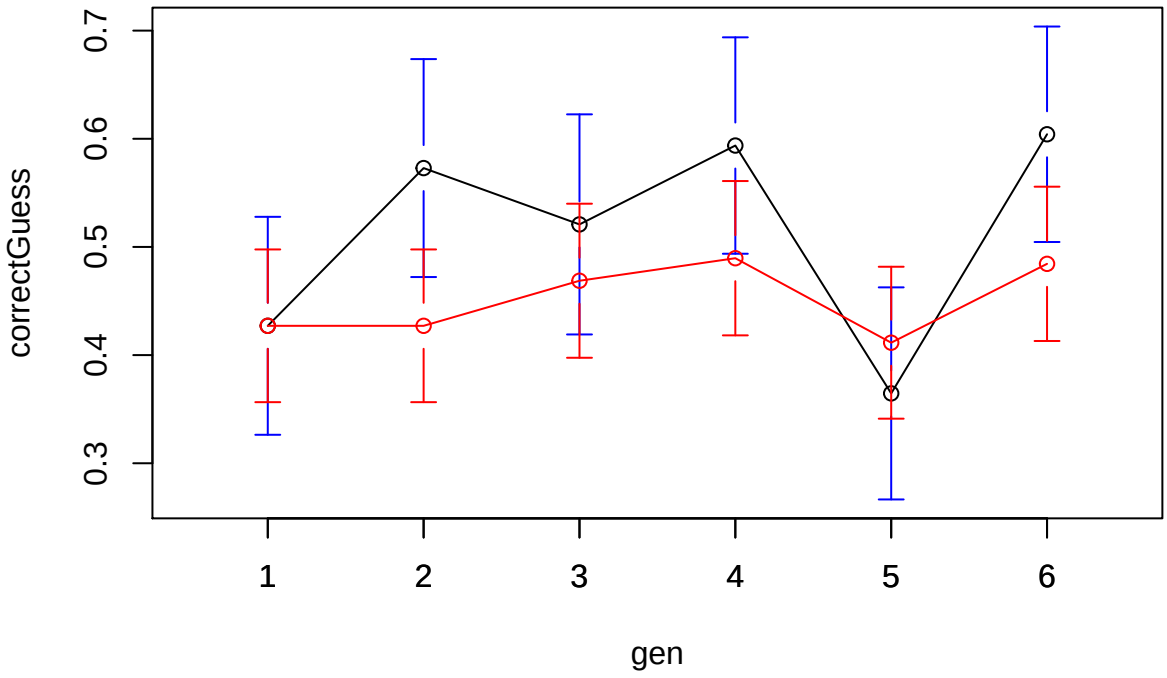
The mean proportion of correct guesses in the communication condition was 45.14%. The mean proportion of correct guesses by the human participant in the learning condition was 51.39

Plot the correct guesses by generation:

```
plotmeans(correctGuess~gen,alldatx[alldatx$condition=='Learn' & !alldatx$Human,], n.label = F)
plotmeans(correctGuess~gen,alldatx[alldatx$condition=='Comm',],add=T,col=2,barcol=2, n.label = F)
```

```
## Warning in axis(1, at = 1:length(means), labels = legends, ...): "add" is
## not a graphical parameter
```

```
## Warning in plot.xy(xy.coords(x, y), type = type, ...): "add" is not a
## graphical parameter
```



Mixed effects model

Binomial mixed effects model, with random effects for chain, target item. Test whether there are differences between conditions.

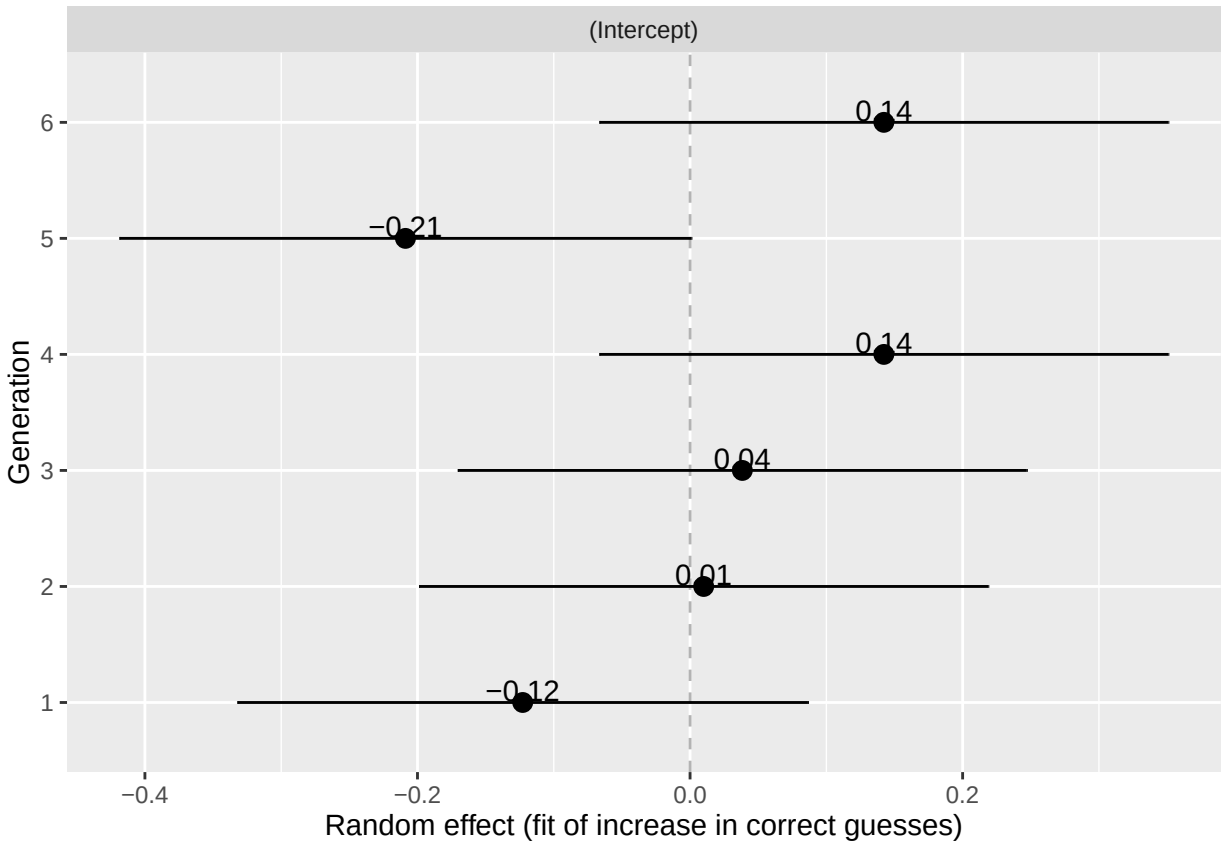
```
ctrl = glmerControl(optCtrl = list(maxfun=50000))
# we want to exclude trials where the computer is guessing meanings
# from the participant's signals in the learning condition
m0 = glmer(correctGuess ~ 1 + (1|chain) + (1|target.meaning) ,
    data=alldatx[alldatx$condition=='Comm' | (!alldatx$Human),],
    family = binomial, control= ctrl)

m1 = glmer(correctGuess ~ 1 + (1|chain) + (1|target.meaning) + (1|gen),
    data=alldatx[alldatx$condition=='Comm' | (!alldatx$Human),],
    family = binomial, control= ctrl)
m2 = glmer(correctGuess ~ condition + (1|chain) + (1|target.meaning)+ (1|gen),
    data=alldatx[alldatx$condition=='Comm' | (!alldatx$Human),],
    family = binomial, control= ctrl)
anova(m0,m1,m2)
```

```
## Data: alldatx[alldatx$condition == "Comm" | (!alldatx$Human), ]
## Models:
## m0: correctGuess ~ 1 + (1 | chain) + (1 | target.meaning)
## m1: correctGuess ~ 1 + (1 | chain) + (1 | target.meaning) + (1 |
## m1:     gen)
## m2: correctGuess ~ condition + (1 | chain) + (1 | target.meaning) +
## m2:     (1 | gen)
##    Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
## m0  3 2375.7 2392.0 -1184.8   2369.7
## m1  4 2372.8 2394.6 -1182.4   2364.8 4.9062      1    0.02676 *
## m2  5 2373.1 2400.4 -1181.5   2363.1 1.6748      1    0.19562
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

There was no significant main effect of condition (beta = 0.26 , std.err = 0.19 , Wald t = 1.4 , Wald p = 0.17 ; log likelihood difference = 0.84 , df = 1 , Chi Squared = 1.67 , p = 0.2).

There was a significant difference between generations (log likelihood difference = 2.5 , df = 1 , Chi Squared = 4.91 , p = 0.027). There is a weak trend for the proportion of correct guesses to increase by generation, as shown by the estimates for the random effects for generation:

```
x = sjp.lmer(m2, sort.est='sort.all', prnt.plot=F,
             axis.labels=c("Chain",'Item','Generation'),
             geom.colors=c(1,1))
x$plot.list[[3]] +
  xlab("Generation") +
  ylab("Random effect (fit of increase in correct guesses)")
```

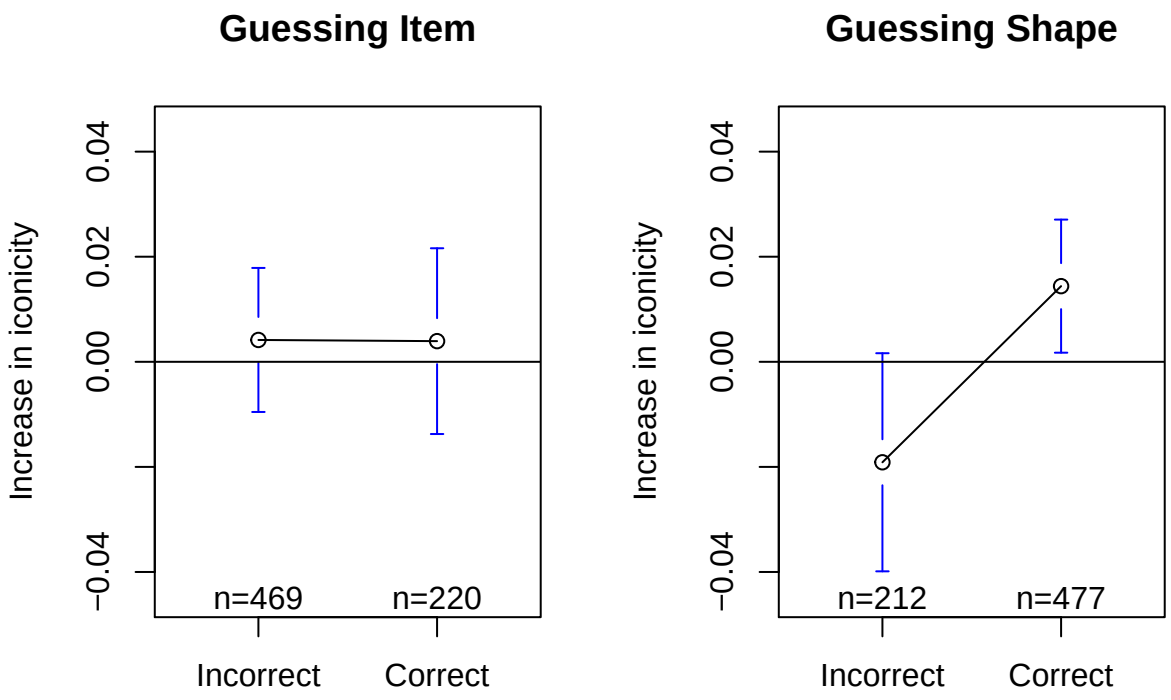


Iconicity and accuracy

Innovations are either more or less iconic than the words they replace. There is no difference in how accurate the guesses are in terms of choosing the right item (see below, left), but the innovation tends to be more iconic when the shape of a meaning is guessed correctly (spiky or round). That is, the iconicity is helping participants guess the shape of a target meaning correctly.

Note that this analysis only makes sense for the communication condition.

```
par(mfrow=c(1,2))
ylimx = c(-0.045,0.045)
plotmeans(increaseIconicity ~ paste(condition, correctGuess),
          data = datax[datax$Human & datax$condition=="Comm",],
          ylim=ylimx, legends = c("Incorrect","Correct"),
          xlab='',
          ylab="Increase in iconicity")
title("Guessing Item")
abline(h=0)
plotmeans(increaseIconicity ~ paste(condition, correctSpikiness),
          data = datax[datax$Human& datax$condition=="Comm",],
          ylim=ylimx,legends = c("Incorrect","Correct"),
          xlab='',
          ylab="Increase in iconicity")
title("Guessing Shape")
abline(h=0)
```



Mixed effects model for accuracy and iconicity

A mixed effects model predicting the increase in iconicity by whether the reciever selected the correct target item, and by whether the reciever selected an item which matched the target in the shape dimension, with random effects for chain, generation and item. Note that it would make more intuitive sense to predict accuracy by increase in iconicity, but this way we can compare the effects of item accuracy versus shape accuracy.

```
m0 = lmer(increaseIconicity ~ 1 + (1|chain) + (1|gen) ,
          data=datax[datax$condition=="Comm",])

m1 = lmer(increaseIconicity ~ correctGuess + (1|chain) + (1|gen)+ (1|meaning),
          data=datax[datax$condition=="Comm",])

m2 = lmer(increaseIconicity ~ correctGuess + correctSpikiness + (1|chain) + (1|gen)+ (1|meaning),
          data=datax[datax$condition=="Comm",])

anova(m0,m1,m2)
```

```
## refitting model(s) with ML (instead of REML)

## Data: datax[datax$condition == "Comm", ]
## Models:
## m0: increaseIconicity ~ 1 + (1 | chain) + (1 | gen)
## m1: increaseIconicity ~ correctGuess + (1 | chain) + (1 | gen) +
## m1:     (1 | meaning)
## m2: increaseIconicity ~ correctGuess + correctSpikiness + (1 | chain) +
## m2:     (1 | gen) + (1 | meaning)
##    Df     AIC     BIC logLik deviance  Chisq Chi Df Pr(>Chisq)
## m0  4 -694.34 -676.20 351.17  -702.34
```

```
## m1  6 -690.34 -663.13 351.17  -702.34 0.0004      2   0.999820
## m2  7 -698.34 -666.59 356.17  -712.34 9.9963      1   0.001569 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

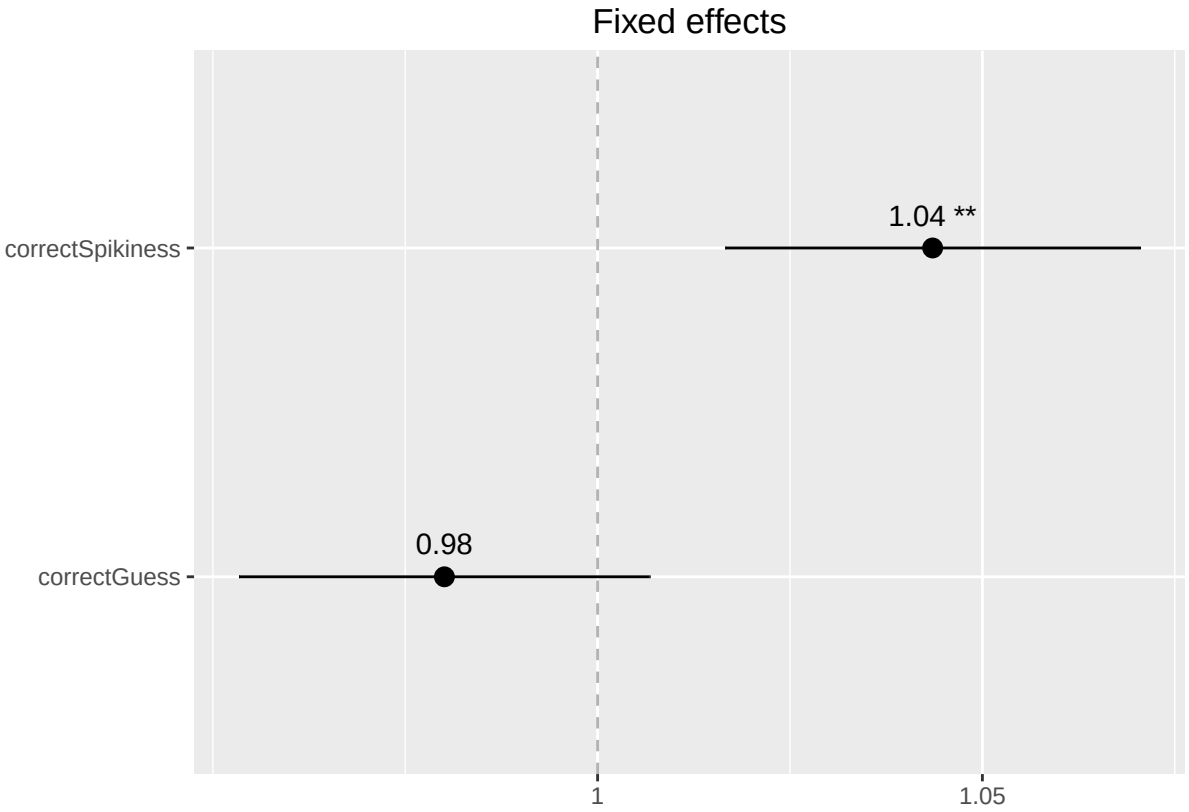
```
summary(m2)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula:
## increaseIconicity ~ correctGuess + correctSpikiness + (1 | chain) +
##     (1 | gen) + (1 | meaning)
##    Data: datax[datax$condition == "Comm", ]
##
## REML criterion at convergence: -689.9
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.3006 -0.3909 -0.0257  0.4642  3.2271
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  meaning  (Intercept) 0.00000  0.0000
##  gen      (Intercept) 0.00000  0.0000
##  chain    (Intercept) 0.00000  0.0000
##  Residual             0.02091  0.1446
## Number of obs: 689, groups:  meaning, 12; gen, 6; chain, 4
##
## Fixed effects:
##                       Estimate Std. Error t value
## (Intercept)          -0.019121   0.009932  -1.925
## correctGuessTRUE     -0.019429   0.013283  -1.463
## correctSpikinessTRUE  0.042482   0.013417   3.166
##
## Correlation of Fixed Effects:
##             (Intr) cGTRUE
## crrctGsTRUE  0.000
## crrctSpTRUE -0.740 -0.457
```

There was a significant main effect of guessing the shape correctly (beta = 0.042 , std.err = 0.013 , Wald t = 3.2 ; log likelihood difference = 5 , df = 1 , Chi Squared = 10 , p = 0.0016).

Plot the fixed effects:

```
sjp.glmer(m2, type='fe', geom.colors=c(1,1) )
```



Note that the model is probably overfitted, since the random effects are singulative. But the effect is clear from the plot of the raw data.