Untitled

Load libraries

```r
library(gplots)
library(lattice)
library(lme4)
library(party)
```

Load data

```r
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"
```

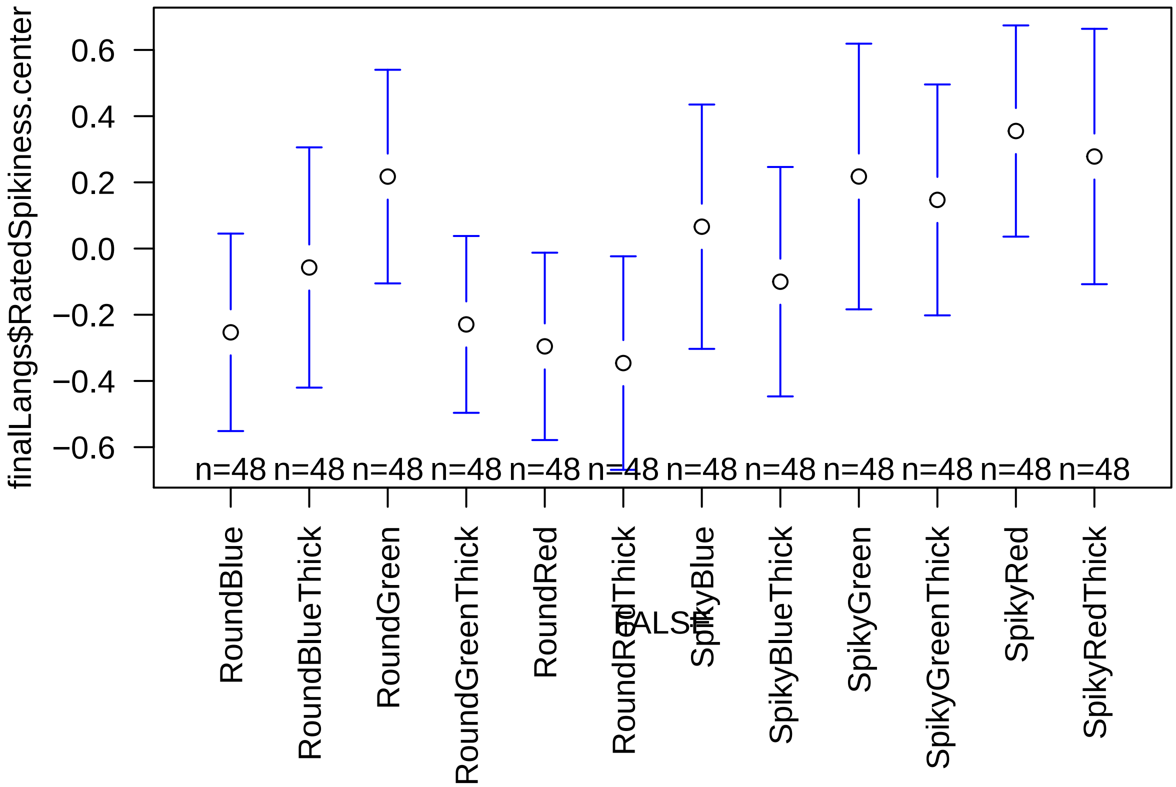
Center spikiness ratings and re-level factors.

```r
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)

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



There are differences between items

Anova

```
summary(aov(RatedSpikiness ~ Cond * Gen * Shape , data=finalLangs))
```

```
##                  Df Sum Sq Mean Sq F value   Pr(>F)
## Cond              1    5.0   4.972   3.752 0.053225 .
## Gen               1    0.5   0.512   0.386 0.534473
## Shape             1   14.9  14.857  11.213 0.000866 ***
## Cond:Gen          1    0.4   0.379   0.286 0.592921
## Cond:Shape        1   14.3  14.295  10.789 0.001084 **
## Gen:Shape         1    4.0   3.983   3.006 0.083501 .
## Cond:Gen:Shape    1    3.8   3.760   2.838 0.092621 .
## Residuals       568  752.6   1.325
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Effects of shape (spiky things rated more spiky), Condition:Shape (communication condition are rated more spiky)

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.

```r
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 , 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 , t = -0.078 log likelihood difference = 6 , df = 1 Chi Squared = 12.03 p = 0.00052).

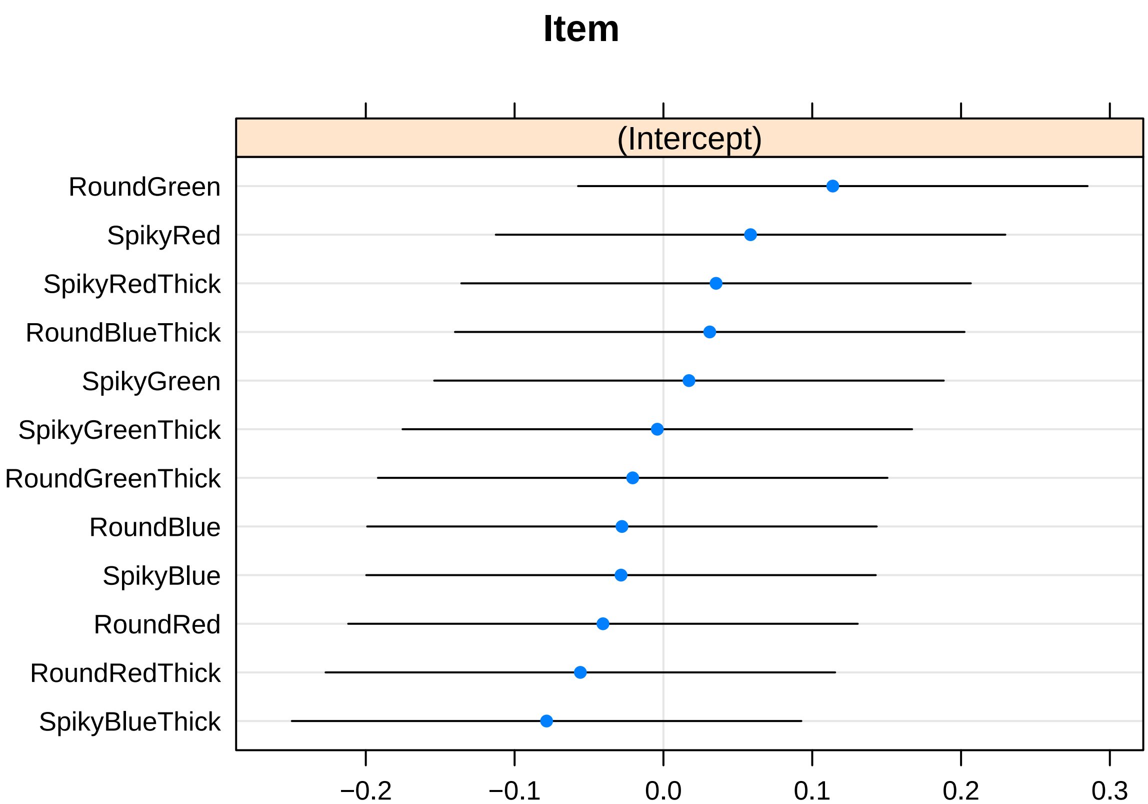
There was a marginal interaction between shape and generation (beta = 0.0028 , std.err = 0.075 , t = 0.037 log likelihood difference = 1.7 , df = 1 Chi Squared = 3.3 p = 0.069).

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

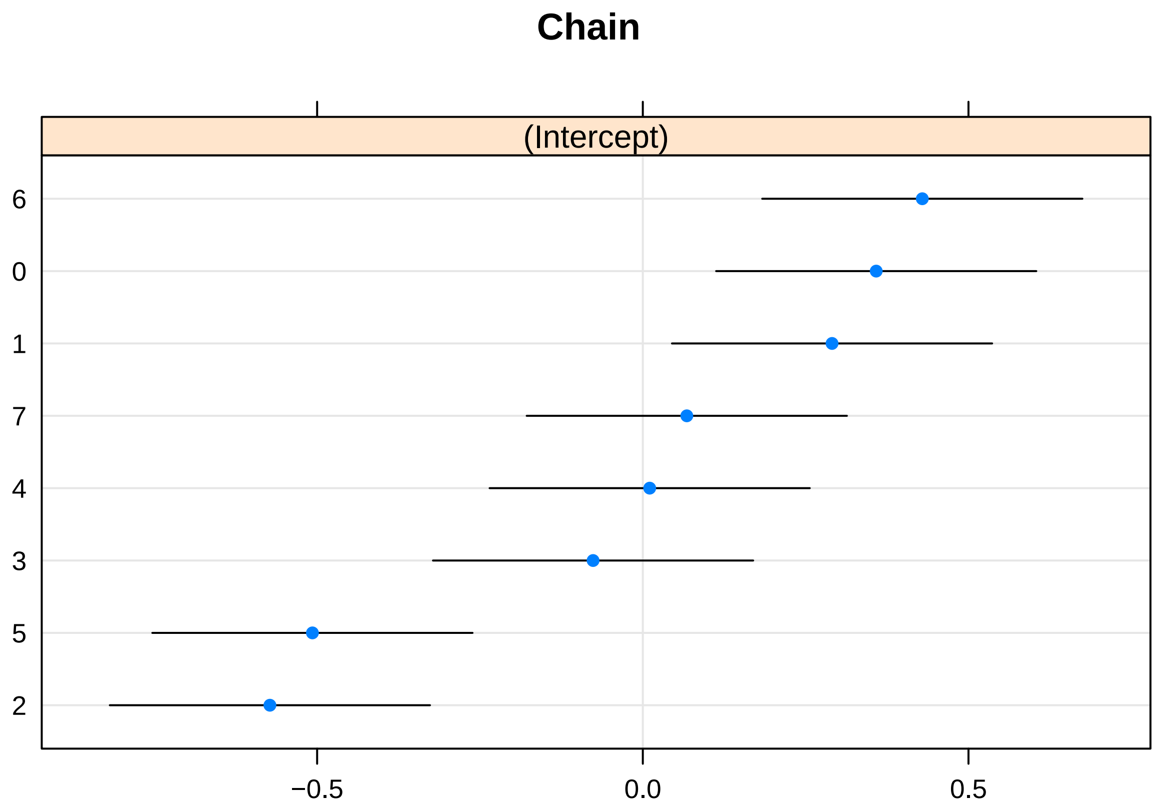
Plot the random effects.

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

```
## $Item
```

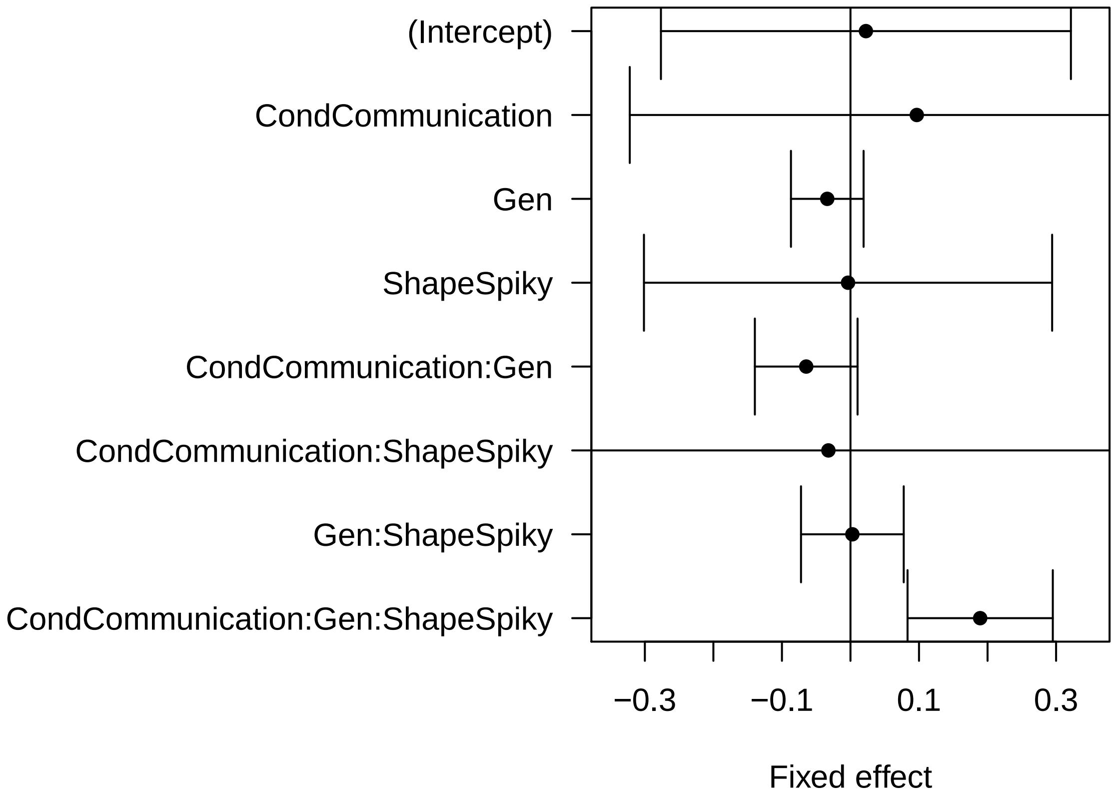



```
##
## $Chain
```



Plot the fixed effects with standard errors from the final model.

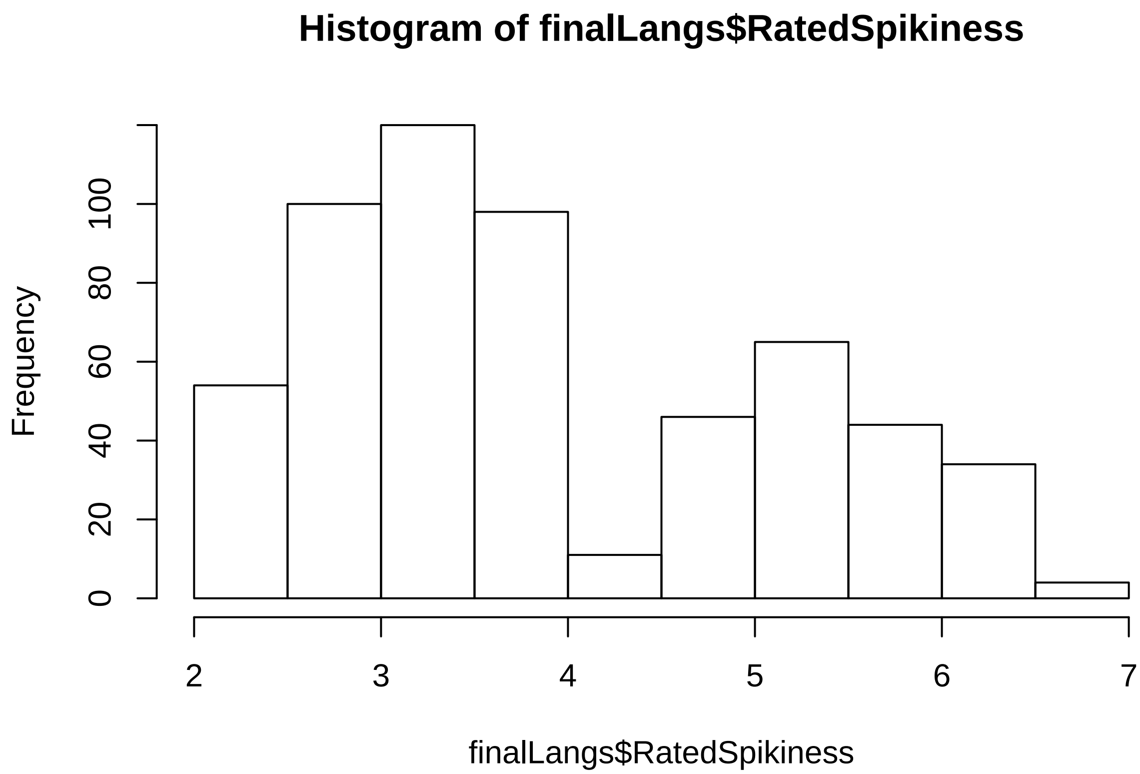
```
fe = fixef(m7)
stderr = summary(m7)$coefficients[,2]
par(mar=c(4,17,2,2))
plot(1:length(fixef(m7))~fixef(m7), pch=16, xlim=c(-0.35,0.35),ylim=c(length(fe),1), xlab='Fixed effect
axis(2,at=1:8, labels=names(fe), las=2)
abline(v=0)
for(i in 1:length(fe)){
  arrows(fe[i]-stderr[i],i,fe[i]+stderr[i],i,code=3, angle=90)
}
```



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 , t = 0.87 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 , t = -0.074 log likelihood difference = 6 , df = 1 Chi Squared = 12.04 p = 0.00052).

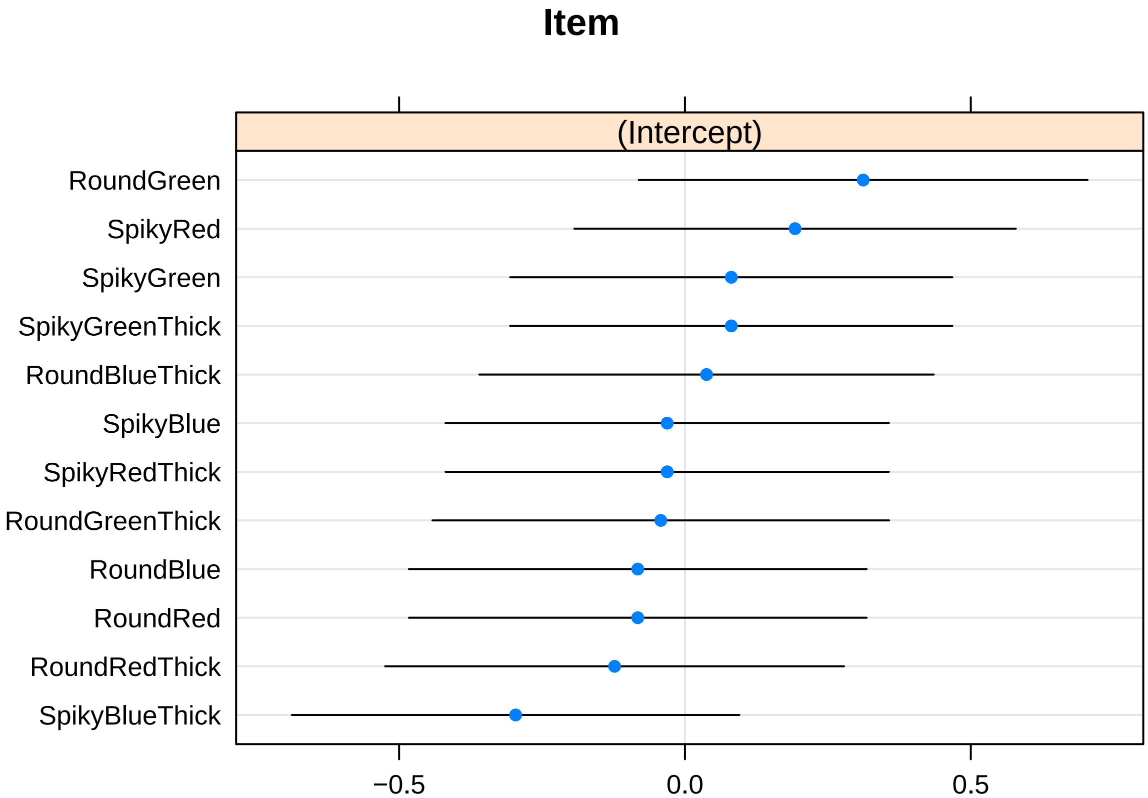
There was no significant interaction between shape and generation (beta = -0.17 , std.err = 0.15 , t = -1.1 log likelihood difference = 0.0057 , df = 1 Chi Squared = 0.01 p = 0.91).

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

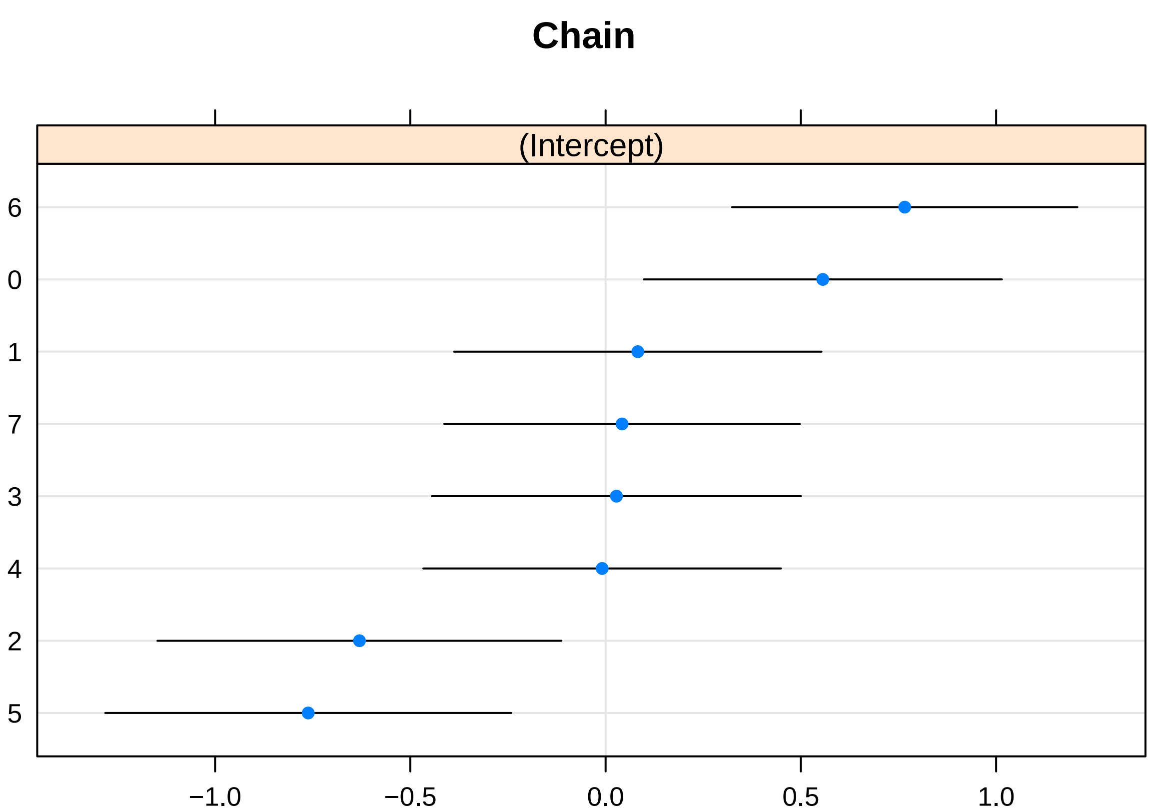
Plot random effects of final model

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

```
## $Item
```

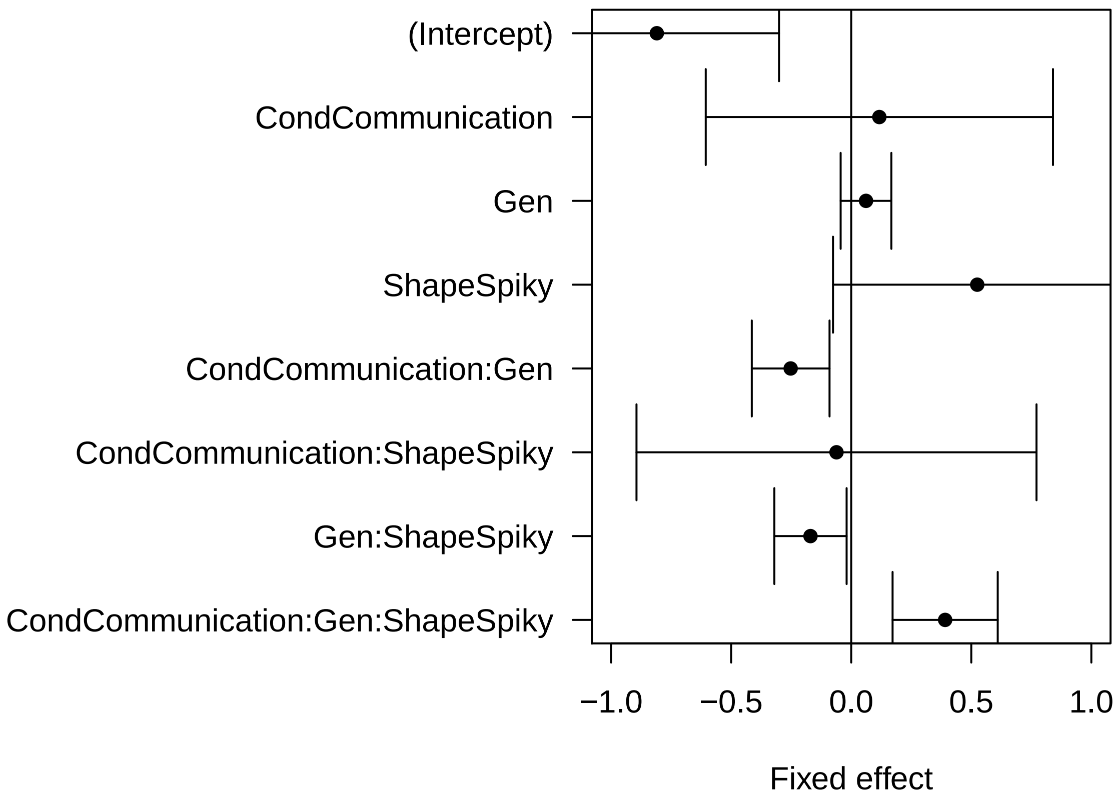

Item
(Intercept)
RoundGreen
SpikyRed
SpikyGreen
SpikyGreenThick
RoundBlueThick
SpikyBlue
SpikyRedThick
RoundGreenThick
RoundBlue
RoundRed
RoundRedThick
SpikyBlueThick
−0.5
0.0
0.5

```
##
## $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.

```
fe = fixef(mb7)
stderr = summary(mb7)$coefficients[,2]
par(mar=c(4,17,2,2))
plot(1:length(fixef(mb7))~fixef(mb7), pch=16, xlim=c(-1,1),ylim=c(length(fe),1),
     xlab='Fixed effect', ylab='', yaxt='n')
axis(2,at=1:8, labels=names(fe), las=2)
abline(v=0)
for(i in 1:length(fe)){
  arrows(fe[i]-stderr[i],i,fe[i]+stderr[i],i,code=3, angle=90)
}
```



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

```
cx = ctree(RatedSpikiness~as.factor(Cond)+as.factor(Gen) + as.factor(Shape) +
                as.factor(Colour) + as.factor(Border), data=finalLangs)
plot(cx)
```