English Nominal Recursion Study, Part 5:
Item nested within Condition

```
> #   5. Trying to do better with Item nested within Condition
> # Limit the analysis to just kids and no Item e6.
> # Item e1 is also out for children.
> # Eliminate the 6 rows with NA for AllTargets and StrictTarget.
>
> rm(list=ls()); options(scipen=999) # To avoid scientific notation
> # Install packages if necessary. Only need to do this once.
> # install.packages("lme4")
> # install.packages("car")
> # Load packages -- do this every time
> library(lme4) # For lmer function
Loading required package: Matrix
> library(car)  # For F-tests with p-values, Wald chi-squared tests
>
> # Read data into a data frame
> rdata =
read.table("http://www.utstat.toronto.edu/~brunner/workshops/mixed/Recursion.data.txt",
header=T)
> dim(rdata)
[1] 2100   18
> # Eliminate adults and Item e6
> rdata = subset(rdata,Item != 'e6'); rdata = subset(rdata,Item != 'e1')
> rdata = subset(rdata,Group == 'Child'); dim(rdata)
[1] 1633   18
> # Also eliminate 6 rows with NA for AllTargets and StrictTarget. This reduces headaches later.
> rdata = subset(rdata, !is.na(AllTargets))
> dim(rdata)
[1] 1627   18
>
> head(rdata); attach(rdata)
  Participant AgeinMonths Group Agegroup Condition Item StrictTarget AllTargets Years Months
1           1        48.5 Child     4yos         A  a1a            1          1     4      0
2           1        48.5 Child     4yos         A  a1b            0          0     4      0
3           1        48.5 Child     4yos         A   a2            0          0     4      0
4           1        48.5 Child     4yos         A   a3            0          0     4      0
5           1        48.5 Child     4yos         A   a4            0          0     4      0
7           1        48.5 Child     4yos         A   a6            0          0     4      0
  Days KABC_Hand CELF_SS CELF_WS CELF_EV CELF_Sent PPVT KBIT
1   14         4      16      13      22        21   92   NA
2   14         4      16      13      22        21   92   NA
3   14         4      16      13      22        21   92   NA
4   14         4      16      13      22        21   92   NA
5   14         4      16      13      22        21   92   NA
7   14         4      16      13      22        21   92   NA
> Item = factor(Item); Agegroup = factor(Agegroup) # To eliminate empty levels
>
> # Effect coding
> # contrasts(Agegroup) = contr.sum; contrasts(Condition) = contr.sum
> # contrasts(Item) = contr.sum
>
> # Quick look
> table(AllTargets,Condition)
          Condition
AllTargets   A   B   C   E
         0 362 299 376 254
         1 130 127  50  29
```

```
> itemtable = table(AllTargets,Item)
> round( prop.table( itemtable, 2 ), 3)
          Item
AllTargets   a1a   a1b    a2    a3    a4    a5    a6    b1    b2    b3    b4    b5    b6
         0 0.380 0.648 0.873 0.871 0.944 0.667 0.768 0.521 0.887 0.662 0.845 0.521 0.775
         1 0.620 0.352 0.127 0.129 0.056 0.333 0.232 0.479 0.113 0.338 0.155 0.479 0.225
          Item
AllTargets    c1    c2    c3    c4    c5    c6    e2    e3    e4    e5
         0 0.944 0.831 0.930 0.901 0.775 0.915 0.887 0.800 0.930 0.972
         1 0.056 0.169 0.070 0.099 0.225 0.085 0.113 0.200 0.070 0.028
>
> # model8b = glmer(AllTargets ~ Item + (1 | Participant), family=binomial, nAGQ=1) # Failed
> # model8b = glmer(AllTargets ~ Item + (1 | Participant), family=binomial, nAGQ=1,
> #                 contrasts = list(Item="contr.sum")  ) # Failed
> model8b = glmer(AllTargets ~ 0 + Item + (1 | Participant), family=binomial, nAGQ=1) # No
intercept
Warning message:
In checkConv(attr(opt, "derivs"), opt$par, ctrl = control$checkConv,  :
  Model failed to converge with max|grad| = 0.0020057 (tol = 0.001, component 1)
> # This version of 8b failed but not too badly: maxgrad = 0.0020057  tol = 0.001
> # Go with it.
>
> # Compose contrast matrices for Item nested within Condition. Note these are fixed effects.
>
> ItemWithinConditionA = rbind(
+ # a1a a1b a2  a3  a4  a5  a6  b1  b2  b3  b4  b5  b6  c1  c2  c3  c4  c5  c6  e2  e3  e4  e5
+ c( 1, -1, 0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0),
+ c( 1,  0,-1,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0),
+ c( 1,  0, 0, -1,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0),
+ c( 1,  0, 0,  0, -1,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0),
+ c( 1,  0, 0,  0,  0, -1,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0),
+ c( 1,  0, 0,  0,  0,  0, -1,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0))
> ItemWithinConditionB = rbind(
+ c( 0,  0, 0,  0,  0,  0,  0,  1, -1,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0),
+ c( 0,  0, 0,  0,  0,  0,  0,  1,  0, -1,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0),
+ c( 0,  0, 0,  0,  0,  0,  0,  1,  0,  0, -1,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0),
+ c( 0,  0, 0,  0,  0,  0,  0,  1,  0,  0,  0, -1,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0),
+ c( 0,  0, 0,  0,  0,  0,  0,  1,  0,  0,  0,  0, -1,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0))
> ItemWithinConditionC = rbind(
+ c( 0,  0, 0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  1, -1,  0,  0,  0,  0,  0,  0,  0,  0),
+ c( 0,  0, 0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  1,  0, -1,  0,  0,  0,  0,  0,  0,  0),
+ c( 0,  0, 0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  1,  0,  0, -1,  0,  0,  0,  0,  0,  0),
+ c( 0,  0, 0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  1,  0,  0,  0, -1,  0,  0,  0,  0,  0),
+ c( 0,  0, 0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  1,  0,  0,  0,  0, -1,  0,  0,  0,  0))
> ItemWithinConditionE = rbind(
+ c( 0,  0, 0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  1, -1,  0,  0),
+ c( 0,  0, 0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  1,  0, -1,  0),
+ c( 0,  0, 0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  1,  0,  0, -1))
> ItemWithinCondition = rbind(ItemWithinConditionA,
+                             ItemWithinConditionB,
+                             ItemWithinConditionC,
+                             ItemWithinConditionE)
>
```

```
> # Test Item within Condition overall
> linearHypothesis(model8b,ItemWithinCondition)
Linear hypothesis test

Hypothesis:
Itema1a - Itema1b = 0
Itema1a - Itema2 = 0
Itema1a - Itema3 = 0
Itema1a - Itema4 = 0
Itema1a - Itema5 = 0
Itema1a - Itema6 = 0
Itemb1 - Itemb2 = 0
Itemb1 - Itemb3 = 0
Itemb1 - Itemb4 = 0
Itemb1 - Itemb5 = 0
Itemb1 - Itemb6 = 0
Itemc1 - Itemc2 = 0
Itemc1 - Itemc3 = 0
Itemc1 - Itemc4 = 0
Itemc1 - Itemc5 = 0
Itemc1 - Itemc6 = 0
Iteme2 - Iteme3 = 0
Iteme2 - Iteme4 = 0
Iteme2 - Iteme5 = 0

Model 1: restricted model
Model 2: AllTargets ~ 0 + Item + (1 | Participant)

  Df  Chisq            Pr(>Chisq)
1
2 19 153.88 < 0.00000000000000022 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
> # Now within each condition
> linearHypothesis(model8b,ItemWithinConditionA)
Linear hypothesis test

Hypothesis:
Itema1a - Itema1b = 0
Itema1a - Itema2 = 0
Itema1a - Itema3 = 0
Itema1a - Itema4 = 0
Itema1a - Itema5 = 0
Itema1a - Itema6 = 0

Model 1: restricted model
Model 2: AllTargets ~ 0 + Item + (1 | Participant)

  Df  Chisq            Pr(>Chisq)
1
2  6 84.235 0.000000000000004755 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
> linearHypothesis(model8b,ItemWithinConditionB)
Linear hypothesis test

Hypothesis:
Itemb1 - Itemb2 = 0
Itemb1 - Itemb3 = 0
Itemb1 - Itemb4 = 0
Itemb1 - Itemb5 = 0
Itemb1 - Itemb6 = 0

Model 1: restricted model
Model 2: AllTargets ~ 0 + Item + (1 | Participant)

  Df Chisq     Pr(>Chisq)
1
2  5 52.72 0.000000000384 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
> linearHypothesis(model8b,ItemWithinConditionC)
Linear hypothesis test

Hypothesis:
Itemc1 - Itemc2 = 0
Itemc1 - Itemc3 = 0
Itemc1 - Itemc4 = 0
Itemc1 - Itemc5 = 0
Itemc1 - Itemc6 = 0

Model 1: restricted model
Model 2: AllTargets ~ 0 + Item + (1 | Participant)

  Df  Chisq Pr(>Chisq)
1
2  5 17.076   0.004358 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
> linearHypothesis(model8b,ItemWithinConditionE)
Linear hypothesis test

Hypothesis:
Iteme2 - Iteme3 = 0
Iteme2 - Iteme4 = 0
Iteme2 - Iteme5 = 0

Model 1: restricted model
Model 2: AllTargets ~ 0 + Item + (1 | Participant)

  Df  Chisq Pr(>Chisq)
1
2  3 12.767   0.005169 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
> # Pairwise comparisons of items within conditions are easy and probably a good idea.
>
> # There is an easier but less straightforward way to test for Item within Condition.
> # Fit a no-intercept model (model8a) for just Condition. Then 8b is a more refined version
> # of 8a and the difference is Item nested within Condition.
> # Compare this likelihood ratio test to the Wald test with Chi-squared = 153.88, df = 19.
> model8a = glmer(AllTargets ~ 0 + Condition + (1 | Participant), family=binomial, nAGQ=1)
> anova(model8a,model8b)
Data: NULL
Models:
model8a: AllTargets ~ 0 + Condition + (1 | Participant)
model8b: AllTargets ~ 0 + Item + (1 | Participant)
        Df    AIC    BIC  logLik deviance Chisq Chi Df            Pr(>Chisq)
model8a  5 1438.9 1465.9 -714.46   1428.9
model8b 24 1283.9 1413.4 -617.96   1235.9   193     19 < 0.00000000000000022 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
> # Chisq = 193,  df = 19, p = 0.00000000000000022
> # Note the df is 19 = 6 + 5 + 5 + 3, exactly right for Item within Condition.
>
> ###################
> # Now try Item as a random effect. Items are naturally nested within Condition by
> # the way they are named. If Item = 1, 2, etc. meant different things within each
> # condition, this would have to be indicated in the glmer syntax.
>
> model8c = glmer(AllTargets ~ Condition + (1 | Participant) + (1 | Item),
+                 family=binomial, nAGQ=1)
> summary(model8c) # Note variance estimates.
Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']
 Family: binomial  ( logit )
Formula: AllTargets ~ Condition + (1 | Participant) + (1 | Item)

     AIC      BIC   logLik deviance df.resid
  1316.7   1349.1   -652.4   1304.7     1621

Scaled residuals:
    Min      1Q  Median      3Q     Max
-3.0788 -0.4232 -0.2354 -0.0896  9.6590

Random effects:
 Groups      Name        Variance Std.Dev.
 Participant (Intercept) 2.200    1.4832
 Item        (Intercept) 0.928    0.9634
Number of obs: 1627, groups:  Participant, 71; Item, 23

Fixed effects:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  -1.6308     0.4291  -3.800 0.000145 ***
ConditionB    0.3002     0.5666   0.530 0.596288
ConditionC   -1.2063     0.5782  -2.086 0.036973 *
ConditionE   -1.4517     0.6599  -2.200 0.027806 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:
           (Intr) CndtnB CndtnC
ConditionB -0.617
ConditionC -0.597  0.456
ConditionE -0.522  0.399  0.395
```

```
> # Let's add Agegroup and the interaction. Use effect coding
> contrasts(Agegroup) = contr.sum; contrasts(Condition) = contr.sum
>
> model8d = glmer(AllTargets ~ Agegroup*Condition + (1 | Participant) + (1 | Item),
+                 family=binomial)
> summary(model8d)
Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']
 Family: binomial  ( logit )
Formula: AllTargets ~ Agegroup * Condition + (1 | Participant) + (1 |      Item)

     AIC      BIC   logLik deviance df.resid
  1302.8   1378.3   -637.4   1274.8     1613

Scaled residuals:
    Min      1Q  Median      3Q     Max
-2.9291 -0.4168 -0.2287 -0.0886  6.8836

Random effects:
 Groups      Name        Variance Std.Dev.
 Participant (Intercept) 1.3271   1.1520
 Item        (Intercept) 0.9278   0.9632
Number of obs: 1627, groups:  Participant, 71; Item, 23

Fixed effects:
                     Estimate Std. Error z value           Pr(>|z|)
(Intercept)          -2.17144    0.27222  -7.977 0.0000000000000015 ***
Agegroup1            -0.75868    0.24154  -3.141            0.00168 **
Agegroup2            -0.56451    0.23941  -2.358            0.01838 *
Condition1            0.63492    0.35544   1.786            0.07405 .
Condition2            0.93663    0.37062   2.527            0.01150 *
Condition3           -0.55403    0.38070  -1.455            0.14559
Agegroup1:Condition1  0.06970    0.18700   0.373            0.70937
Agegroup2:Condition1  0.02820    0.18417   0.153            0.87829
Agegroup1:Condition2 -0.07506    0.18857  -0.398            0.69057
Agegroup2:Condition2  0.24722    0.18340   1.348            0.17766
Agegroup1:Condition3  0.10638    0.22623   0.470            0.63817
Agegroup2:Condition3  0.03258    0.22223   0.147            0.88346
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:
            (Intr) Aggrp1 Aggrp2 Cndtn1 Cndtn2 Cndtn3 Ag1:C1 Ag2:C1 Ag1:C2 Ag2:C2 Ag1:C3
Agegroup1    0.046
Agegroup2    0.029 -0.519
Condition1  -0.149 -0.023 -0.019
Condition2  -0.094 -0.021 -0.026 -0.220
Condition3  -0.035  0.000 -0.003 -0.247 -0.275
Aggrp1:Cnd1 -0.034 -0.231  0.168  0.052  0.013 -0.005
Aggrp2:Cnd1 -0.029  0.169 -0.231  0.037  0.022  0.002 -0.597
Aggrp1:Cnd2 -0.028 -0.221  0.170  0.013  0.050 -0.006  0.036 -0.079
Aggrp2:Cnd2 -0.046  0.169 -0.243  0.025  0.025  0.008 -0.080  0.057 -0.589
Aggrp1:Cnd3 -0.005 -0.015  0.012 -0.004 -0.004  0.070 -0.170  0.083 -0.175  0.081
Aggrp2:Cnd3 -0.007  0.013 -0.019  0.002  0.007  0.050  0.083 -0.162  0.080 -0.159 -0.635
> Anova(model8d, type="III")
Analysis of Deviance Table (Type III Wald chisquare tests)

Response: AllTargets
                     Chisq Df           Pr(>Chisq)
(Intercept)        63.6298  1 0.000000000000001501 ***
Agegroup           31.6554  2 0.000000133693299449 ***
Condition          12.1541  3             0.006873 **
Agegroup:Condition  3.9003  6             0.690166
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
>
```

```
> # To see what's happening, earlier code may be copied almost exactly.
>
> # Make a table of estimated population mean log odds
> X = model.matrix(model8d) # The X matrix
> summary8 = summary(model8d)
> betahat = cbind(summary8$coef[,1]) # Estimated fixed effects as a column vector.
> estlogodds = X %*% betahat # Estimated pop mean log odds for each observation.
>
> # Just look at marginal estimated population mean log odds
> aggregate(estlogodds, by = list(Agegroup), FUN = mean)
  Group.1         V1
1    4yos -2.8030692
2    5yos -2.5936661
3    6yos -0.7719827
> aggregate(estlogodds, by = list(Condition), FUN = mean)
  Group.1        V1
1       A -1.599870
2       B -1.299659
3       C -2.792190
4       E -3.283842
>
> # Test pairwise differences between marginal means with a Bonferroni correction
> # First make a combination variable.
>
> # The combination variable AgeCond will have 12 values.
> n = length(AllTargets); n
[1] 1627
> AgeCond = character(n) # A character-valued variable of length n
> for(j in 1:n) AgeCond[j] = paste(Agegroup[j],Condition[j],sep='')
> freq = table(AgeCond); freq
AgeCond
4yosA 4yosB 4yosC 4yosE 5yosA 5yosB 5yosC 5yosE 6yosA 6yosB 6yosC 6yosE
  172   150   150    99   173   150   150   100   147   126   126    84
>
> # Fit a no-intercept model on the combination variable.
> noint = glmer(AllTargets ~ 0+ AgeCond + (1 | Participant), family=binomial)
Warning message:
In checkConv(attr(opt, "derivs"), opt$par, ctrl = control$checkConv,  :
  Model failed to converge with max|grad| = 0.00251889 (tol = 0.001, component 1)
> nointsum = summary(noint); nointsum
Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']
 Family: binomial  ( logit )
Formula: AllTargets ~ 0 + AgeCond + (1 | Participant)

     AIC      BIC   logLik deviance df.resid
  1424.4   1494.5   -699.2   1398.4     1614

Scaled residuals:
    Min      1Q  Median      3Q     Max
-2.1596 -0.4796 -0.2731 -0.1325  4.8617

Random effects:
 Groups      Name        Variance Std.Dev.
 Participant (Intercept) 0.8895   0.9431
Number of obs: 1627, groups:  Participant, 71

Fixed effects:
             Estimate Std. Error z value           Pr(>|z|)
AgeCond4yosA -1.79096    0.28970  -6.182 0.0000000006323229 ***
AgeCond4yosB -1.74933    0.29831  -5.864 0.0000000045157394 ***
AgeCond4yosC -3.02881    0.39289  -7.709 0.0000000000000127 ***
AgeCond4yosE -3.58580    0.55346  -6.479 0.0000000000923854 ***
AgeCond5yosA -1.66621    0.28376  -5.872 0.0000000043084812 ***
AgeCond5yosB -1.30435    0.28097  -4.642 0.0000034442719780 ***
AgeCond5yosC -2.91566    0.38038  -7.665 0.0000000000000179 ***
```

```
AgeCond5yosE -3.58566    0.55218  -6.494 0.0000000000837954 ***
AgeCond6yosA -0.26245    0.27232  -0.964           0.335165    
AgeCond6yosB -0.06752    0.28104  -0.240           0.810132    
AgeCond6yosC -1.37449    0.30578  -4.495 0.0000069576380643 ***
AgeCond6yosE -1.25218    0.33821  -3.702           0.000214 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:
             AgCn4A AgCn4B AgCn4C AgCn4E AgCn5A AgCn5B AgCn5C AgCn5E AgCn6A AgCn6B AgCn6C
AgeCond4ysB 0.473                                                                       
AgeCond4ysC 0.375  0.364                                                                
AgeCond4ysE 0.269  0.261  0.213                                                         
AgeCond5ysA 0.025  0.024  0.025  0.019                                                  
AgeCond5ysB 0.022  0.021  0.022  0.016  0.496                                           
AgeCond5ysC 0.026  0.025  0.025  0.019  0.387  0.383                                    
AgeCond5ysE 0.019  0.018  0.019  0.014  0.269  0.266  0.215                             
AgeCond6ysA 0.002  0.002  0.002  0.001  0.002  0.001  0.002  0.001                      
AgeCond6ysB 0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.556               
AgeCond6ysC 0.009  0.009  0.009  0.007  0.008  0.007  0.008  0.006  0.512  0.494        
AgeCond6ysE 0.007  0.007  0.007  0.005  0.007  0.006  0.007  0.005  0.463  0.447  0.422 
convergence code: 0
Model failed to converge with max|grad| = 0.00251889 (tol = 0.001, component 1)

> # In spite of the no convergence warning, go with it.
> 
> # Rows of Condmat are contrasts for pairwise comparisons of marginal
> # Condition means
> freq
AgeCond
4yosA 4yosB 4yosC 4yosE 5yosA 5yosB 5yosC 5yosE 6yosA 6yosB 6yosC 6yosE 
  172   150   150    99   173   150   150   100   147   126   126    84 
> Condmat = rbind(
+ # 4yosA 4yosB 4yosC 4yosE 5yosA 5yosB 5yosC 5yosE 6yosA 6yosB 6yosC 6yosE
+ c(  1,    -1,   0,    0,    1,    -1,   0,    0,    1,    -1,   0,   0),
+ c(  1,     0,  -1,    0,    1,     0,  -1,    0,    1,     0,  -1,   0),
+ c(  1,     0,   0,   -1,    1,     0,   0,   -1,    1,     0,   0,  -1),
+ c(  0,     1,  -1,    0,    0,     1,  -1,    0,    0,     1,  -1,   0),
+ c(  0,     1,   0,   -1,    0,     1,   0,   -1,    0,     1,   0,  -1),
+ c(  0,     0,   1,   -1,    0,     0,   1,   -1,    0,     0,   1,  -1))
> colnames(Condmat) = names(freq)
> rownames(Condmat) = c("AvsB","AvsC","AvsE","BvsC","BvsE","CvsE")
> Condmat
     4yosA 4yosB 4yosC 4yosE 5yosA 5yosB 5yosC 5yosE 6yosA 6yosB 6yosC 6yosE
AvsB     1    -1     0     0     1    -1     0     0     1    -1     0     0
AvsC     1     0    -1     0     1     0    -1     0     1     0    -1     0
AvsE     1     0     0    -1     1     0     0    -1     1     0     0    -1
BvsC     0     1    -1     0     0     1    -1     0     0     1    -1     0
BvsE     0     1     0    -1     0     1     0    -1     0     1     0    -1
CvsE     0     0     1    -1     0     0     1    -1     0     0     1    -1
> # Rows of Agemat are contrasts for pairwise comparisons of marginal
> # Agegroup means
> Agemat = rbind(
+ # 4yosA 4yosB 4yosC 4yosE 5yosA 5yosB 5yosC 5yosE 6yosA 6yosB 6yosC 6yosE
+ c(  1,     1,   1,    1,   -1,    -1,  -1,   -1,    0,     0,   0,   0),
+ c(  1,     1,   1,    1,    0,     0,   0,    0,   -1,    -1,  -1,  -1),
+ c(  0,     0,   0,    0,    1,     1,   1,    1,   -1,    -1,  -1,  -1))
> colnames(Agemat) = names(freq)
> rownames(Agemat) = c("4vs5","4vs6","5vs6")
```

```
> Agemat
     4yosA 4yosB 4yosC 4yosE 5yosA 5yosB 5yosC 5yosE 6yosA 6yosB 6yosC 6yosE
4vs5     1     1     1     1    -1    -1    -1    -1     0     0     0     0
4vs6     1     1     1     1     0     0     0     0    -1    -1    -1    -1
5vs6     0     0     0     0     1     1     1     1    -1    -1    -1    -1
>
> # Make pairwise comparison matrices. Chi-squared test statistics will be in the
> # upper triangle, and unadjusted p-values in the lower triangle.
> ConditionPairwise = diag(4)
> rownames(ConditionPairwise) = colnames(ConditionPairwise) = c("A","B","C","E")
>
> # Fill the ConditionPairwise matrix
> rowno = 0
> for(i in 1:3)
+     {
+     for(j in (i+1):4)
+         {
+         rowno=rowno+1
+         L = Condmat[rowno,]
+         Ltest = linearHypothesis(noint,L) # Testing H0: L beta = 0
+         ConditionPairwise[i,j] = Ltest[2,2] # Test statistic
+         ConditionPairwise[j,i] = Ltest[2,3] # p-value
+         } # Next j
+     } # Next i
> AgePairwise = diag(3)
> rownames(AgePairwise) = colnames(AgePairwise) = c("4yos","5yos","6yos")
> rowno = 0
> for(i in 1:2)
+     {
+     for(j in (i+1):3)
+         {
+         rowno=rowno+1
+         L = Agemat[rowno,]
+         Ltest = linearHypothesis(noint,L) # Testing H0: L beta = 0
+         AgePairwise[i,j] = Ltest[2,2] # Test statistic
+         AgePairwise[j,i] = Ltest[2,3] # p-value
+         } # Next j
+     } # Next i
>
> # Here are the marginal means again.
> aggregate(estlogodds, by = list(Agegroup), FUN = mean)
  Group.1         V1
1    4yos -2.8030692
2    5yos -2.5936661
3    6yos -0.7719827
> aggregate(estlogodds, by = list(Condition), FUN = mean)
  Group.1        V1
1       A -1.599870
2       B -1.299659
3       C -2.792190
4       E -3.283842
>
> # Pairwise comparisons between Condition means A, B, C, E
> ConditionPairwise
                 A                   B          C         E
A 1.000000000000000 1.49427865008775673 34.2397307 31.159399
B 0.221553788003150 1.00000000000000000 45.2413706 38.967502
C 0.000000004872398 0.00000000001741864  1.0000000  1.439196
E 0.000000023768574 0.00000000043091968  0.2302695  1.000000
```

```
> # Pairwise comparisons between Agegroup means 4,5,6 yrs old
> AgePairwise
               4yos           5yos     6yos
4yos 1.0000000000000 0.215093680964 25.79351
5yos 0.6428039891223 1.000000000000 21.54594
6yos 0.0000003799642 0.000003454529  1.00000
> # To protect all 9 tests with a Bonferroni correction, compare p-values to
> 0.05/9
[1] 0.005555556
>
> # Same conclusions: 6year olds use more recursion than 4 and 5, and AB elicits more
> # recursion than CE. Could start adding covariates ...
>
```