Post-hoc analysis of the sets

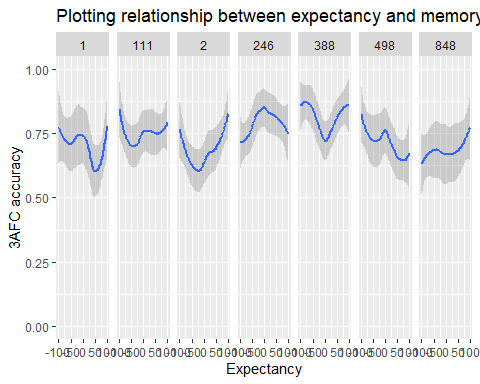
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# Aim of this document

In this document I try to see if there is anything that could explain the variability between the sets with respect to the U-shape. A full analysis is provided with set as a random as well as with set as a fixed effect.

**Important point**: As predicted, there were some issues with convergenves and singularity. I therefore had to sometimes drop terms or just give up.



Especially ‘problematic’ is the set 246 which shows an inverted U-shape, which in some models with which I played around is even significant.

# Checking accuracy on the object level

A Table with all object at all the different locations is provided in case you want to look something up.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| objNum | objNam | setNum | targetLocation | acc | n | exp |
| 1 | microwave | 1 | 14 | 0.2000000 | 15 | -8.773073 |
| 1 | microwave | 111 | 13 | 0.8000000 | 20 | -63.767050 |
| 1 | microwave | 2 | 19 | 0.8333333 | 24 | 77.578719 |
| 1 | microwave | 246 | 13 | 0.8181818 | 22 | -77.401625 |
| 1 | microwave | 388 | 11 | 0.8888889 | 18 | -34.865154 |
| 1 | microwave | 498 | 10 | 0.7894737 | 19 | -88.206893 |
| 1 | microwave | 848 | 19 | 0.6000000 | 15 | 52.647117 |
| 2 | kitchen roll | 1 | 8 | 0.5000000 | 14 | 62.622150 |
| 2 | kitchen roll | 111 | 11 | 0.7777778 | 18 | 14.882511 |
| 2 | kitchen roll | 2 | 17 | 0.8095238 | 21 | 68.093687 |
| 2 | kitchen roll | 246 | 15 | 0.9473684 | 19 | 20.691249 |
| 2 | kitchen roll | 388 | 4 | 0.9500000 | 20 | -45.862111 |
| 2 | kitchen roll | 498 | 19 | 0.6875000 | 16 | 65.589399 |
| 2 | kitchen roll | 848 | 2 | 0.6666667 | 12 | 44.790112 |
| 3 | saucepan | 1 | 3 | 0.6000000 | 15 | 62.595005 |
| 3 | saucepan | 111 | 15 | 0.7000000 | 20 | 36.351410 |
| 3 | saucepan | 2 | 2 | 0.6086957 | 23 | 64.884577 |
| 3 | saucepan | 246 | 18 | 0.7142857 | 21 | 15.702353 |
| 3 | saucepan | 388 | 15 | 0.7222222 | 18 | 29.432762 |
| 3 | saucepan | 498 | 12 | 0.8750000 | 16 | -51.464579 |
| 3 | saucepan | 848 | 13 | 0.9285714 | 14 | 99.395461 |
| 4 | toaster | 1 | 12 | 0.7692308 | 13 | -75.043849 |
| 4 | toaster | 111 | 20 | 0.7000000 | 20 | 26.695974 |
| 4 | toaster | 2 | 4 | 0.8333333 | 24 | -51.296146 |
| 4 | toaster | 246 | 1 | 0.6818182 | 22 | -13.084279 |
| 4 | toaster | 388 | 8 | 0.7500000 | 20 | -17.955432 |
| 4 | toaster | 498 | 1 | 0.7222222 | 18 | -6.624296 |
| 4 | toaster | 848 | 9 | 0.5333333 | 15 | -8.836014 |
| 5 | bowl of fruits | 1 | 13 | 0.8000000 | 15 | -62.388708 |
| 5 | bowl of fruits | 111 | 6 | 0.7058824 | 17 | -68.386420 |
| 5 | bowl of fruits | 2 | 11 | 0.6400000 | 25 | -26.219259 |
| 5 | bowl of fruits | 246 | 16 | 0.6818182 | 22 | -80.073132 |
| 5 | bowl of fruits | 388 | 18 | 0.9000000 | 20 | 94.477258 |
| 5 | bowl of fruits | 498 | 16 | 0.7500000 | 16 | -83.634652 |
| 5 | bowl of fruits | 848 | 1 | 0.4666667 | 15 | 57.812444 |
| 6 | tea pot | 1 | 18 | 0.5714286 | 14 | 76.989297 |
| 6 | tea pot | 111 | 5 | 0.6470588 | 17 | 25.922785 |
| 6 | tea pot | 2 | 5 | 0.5833333 | 24 | 5.941109 |
| 6 | tea pot | 246 | 7 | 0.6500000 | 20 | 38.834232 |
| 6 | tea pot | 388 | 2 | 0.8125000 | 16 | 65.381893 |
| 6 | tea pot | 498 | 15 | 0.6666667 | 18 | 38.225359 |
| 6 | tea pot | 848 | 4 | 0.6000000 | 15 | -90.346402 |
| 7 | knife | 1 | 20 | 0.6250000 | 8 | 56.921824 |
| 7 | knife | 111 | 10 | 0.8333333 | 18 | -77.702824 |
| 7 | knife | 2 | 13 | 0.6521739 | 23 | -45.796157 |
| 7 | knife | 246 | 14 | 0.6153846 | 13 | 76.214810 |
| 7 | knife | 388 | 6 | 0.9333333 | 15 | -74.957304 |
| 7 | knife | 498 | 13 | 0.8235294 | 17 | -42.172506 |
| 7 | knife | 848 | 14 | 0.7142857 | 14 | 79.996116 |
| 8 | mixer | 1 | 9 | 0.7857143 | 14 | 63.669148 |
| 8 | mixer | 111 | 12 | 1.0000000 | 16 | -65.579671 |
| 8 | mixer | 2 | 18 | 0.7619048 | 21 | 25.650092 |
| 8 | mixer | 246 | 3 | 0.7500000 | 20 | 74.755276 |
| 8 | mixer | 388 | 14 | 0.6000000 | 20 | 46.478268 |
| 8 | mixer | 498 | 14 | 0.2500000 | 16 | 39.296753 |
| 8 | mixer | 848 | 17 | 0.7142857 | 14 | 28.621446 |
| 9 | bread | 1 | 4 | 0.7857143 | 14 | -73.859935 |
| 9 | bread | 111 | 19 | 0.4500000 | 20 | 70.535614 |
| 9 | bread | 2 | 15 | 0.8400000 | 25 | -14.342054 |
| 9 | bread | 246 | 11 | 0.8636364 | 22 | -56.170591 |
| 9 | bread | 388 | 16 | 0.8500000 | 20 | -77.832031 |
| 9 | bread | 498 | 4 | 0.9411765 | 17 | -85.654954 |
| 9 | bread | 848 | 16 | 0.7692308 | 13 | -87.820513 |
| 10 | glass jug | 1 | 15 | 0.7692308 | 13 | 42.821348 |
| 10 | glass jug | 111 | 8 | 0.8000000 | 20 | 83.298343 |
| 10 | glass jug | 2 | 7 | 0.7222222 | 18 | 48.548340 |
| 10 | glass jug | 246 | 4 | 0.8125000 | 16 | -68.305219 |
| 10 | glass jug | 388 | 7 | 0.7647059 | 17 | 38.315630 |
| 10 | glass jug | 498 | 8 | 0.8000000 | 15 | 71.258992 |
| 10 | glass jug | 848 | 6 | 0.5833333 | 12 | -80.951836 |
| 11 | mug | 1 | 17 | 0.4615385 | 13 | 81.032323 |
| 11 | mug | 111 | 3 | 0.4375000 | 16 | 91.011675 |
| 11 | mug | 2 | 3 | 0.1904762 | 21 | 72.116331 |
| 11 | mug | 246 | 19 | 0.7222222 | 18 | 80.600773 |
| 11 | mug | 388 | 20 | 0.6250000 | 16 | 41.246459 |
| 11 | mug | 498 | 3 | 0.3333333 | 15 | 81.215589 |
| 11 | mug | 848 | 11 | 0.7333333 | 15 | -31.815678 |
| 12 | dishes | 1 | 6 | 0.8333333 | 12 | -63.409338 |
| 12 | dishes | 111 | 9 | 0.9500000 | 20 | 92.302906 |
| 12 | dishes | 2 | 10 | 0.9565217 | 23 | -51.982722 |
| 12 | dishes | 246 | 12 | 0.6666667 | 21 | -63.912277 |
| 12 | dishes | 388 | 10 | 0.9411765 | 17 | -72.929515 |
| 12 | dishes | 498 | 20 | 0.8125000 | 16 | 49.672226 |
| 12 | dishes | 848 | 10 | 0.7857143 | 14 | -79.167818 |
| 13 | towels | 1 | 7 | 0.5384615 | 13 | 60.285643 |
| 13 | towels | 111 | 17 | 0.8947368 | 19 | 35.363717 |
| 13 | towels | 2 | 14 | 0.5217391 | 23 | 17.865741 |
| 13 | towels | 246 | 10 | 0.8095238 | 21 | -49.211116 |
| 13 | towels | 388 | 5 | 0.7894737 | 19 | 15.768624 |
| 13 | towels | 498 | 18 | 0.7777778 | 18 | 15.522525 |
| 13 | towels | 848 | 5 | 0.6923077 | 13 | 18.928005 |
| 14 | toy | 1 | 11 | 1.0000000 | 14 | 48.150302 |
| 14 | toy | 111 | 2 | 0.9000000 | 20 | -42.435786 |
| 14 | toy | 2 | 12 | 0.8750000 | 24 | 36.773834 |
| 14 | toy | 246 | 6 | 0.9523810 | 21 | 40.649479 |
| 14 | toy | 388 | 1 | 0.9473684 | 19 | -28.824750 |
| 14 | toy | 498 | 9 | 0.7777778 | 18 | -26.824189 |
| 14 | toy | 848 | 15 | 1.0000000 | 14 | 63.075152 |
| 15 | pile of books | 1 | 2 | 0.7333333 | 15 | -23.702497 |
| 15 | pile of books | 111 | 4 | 0.8888889 | 18 | -32.339876 |
| 15 | pile of books | 2 | 1 | 0.7727273 | 22 | 11.206303 |
| 15 | pile of books | 246 | 8 | 0.7619048 | 21 | -26.567549 |
| 15 | pile of books | 388 | 19 | 0.8235294 | 17 | 31.334751 |
| 15 | pile of books | 498 | 7 | 0.5789474 | 19 | -59.149050 |
| 15 | pile of books | 848 | 7 | 0.4285714 | 14 | -79.739577 |
| 16 | umbrella | 1 | 1 | 1.0000000 | 11 | -15.265028 |
| 16 | umbrella | 111 | 18 | 0.8333333 | 18 | 34.155653 |
| 16 | umbrella | 2 | 8 | 0.8750000 | 16 | -10.311482 |
| 16 | umbrella | 246 | 17 | 0.8181818 | 22 | 25.086080 |
| 16 | umbrella | 388 | 12 | 1.0000000 | 18 | 18.010998 |
| 16 | umbrella | 498 | 5 | 0.7142857 | 14 | 44.984010 |
| 16 | umbrella | 848 | 8 | 0.8181818 | 11 | -37.251613 |
| 17 | hat | 1 | 16 | 0.8000000 | 15 | -35.135722 |
| 17 | hat | 111 | 1 | 0.7000000 | 20 | -51.220247 |
| 17 | hat | 2 | 6 | 0.8400000 | 25 | -17.920925 |
| 17 | hat | 246 | 2 | 0.8235294 | 17 | -28.446666 |
| 17 | hat | 388 | 17 | 0.8947368 | 19 | 30.969872 |
| 17 | hat | 498 | 11 | 0.7647059 | 17 | 11.128185 |
| 17 | hat | 848 | 20 | 0.7333333 | 15 | -58.205019 |
| 18 | helmet | 1 | 5 | 0.8000000 | 15 | 21.943540 |
| 18 | helmet | 111 | 16 | 0.8421053 | 19 | -43.392301 |
| 18 | helmet | 2 | 9 | 0.4285714 | 21 | -26.523965 |
| 18 | helmet | 246 | 20 | 0.8181818 | 22 | -45.790650 |
| 18 | helmet | 388 | 3 | 0.8235294 | 17 | -24.446234 |
| 18 | helmet | 498 | 6 | 0.8421053 | 19 | -42.806397 |
| 18 | helmet | 848 | 12 | 0.8666667 | 15 | -29.905277 |
| 19 | calendar | 1 | 10 | 0.9230769 | 13 | -63.580556 |
| 19 | calendar | 111 | 14 | 0.5555556 | 18 | -26.229604 |
| 19 | calendar | 2 | 20 | 0.8260870 | 23 | 18.772700 |
| 19 | calendar | 246 | 5 | 0.9473684 | 19 | 50.355221 |
| 19 | calendar | 388 | 13 | 0.8421053 | 19 | -72.491776 |
| 19 | calendar | 498 | 17 | 1.0000000 | 17 | 70.672113 |
| 19 | calendar | 848 | 3 | 0.5384615 | 13 | 47.255250 |
| 20 | fan | 1 | 19 | 0.6250000 | 16 | 25.142508 |
| 20 | fan | 111 | 7 | 0.7058824 | 17 | -40.422315 |
| 20 | fan | 2 | 16 | 0.5238095 | 21 | -12.028083 |
| 20 | fan | 246 | 9 | 0.7619048 | 21 | 30.016262 |
| 20 | fan | 388 | 9 | 0.5789474 | 19 | 16.219431 |
| 20 | fan | 498 | 2 | 0.4117647 | 17 | 3.096982 |
| 20 | fan | 848 | 18 | 0.6428571 | 14 | 47.028112 |

The first conclusion is that there is huge variation in the mean accuracy ranging from to -.

I went through the table of object/location accuracy and identified the following suspicious values (These are mostly values that very low (eyeballed)):

* microwave at 14,
* bowl of fruits at 1,
* mixer at 14,
* bread at 19,
* mug at 3,
* helmet at 9,
* fan at 2

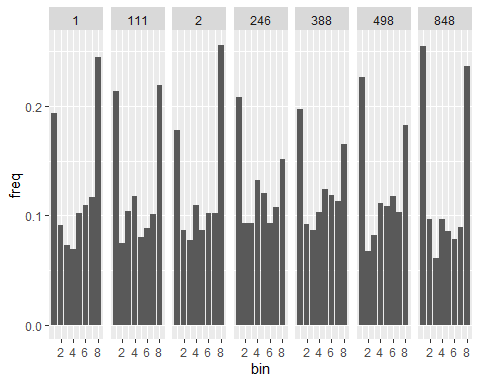
None of these are included in 246.

Interestingly, really visible but expected combinations like the mixer at 3 (8\_3) has only an accuracy of 0.75. ]

Furthermore, I’ve checked all screenshots from 246 and cannot really see anything that sticks out.

# How to sets differ from each other in terms of the expectancy distribution.

# Get sets  
sets <- unique(combinedData\_AFC$setNum)  
  
# Parameters for the analysis  
numBins <- 8   
bins <- seq(from = -100, to = 100, length.out = numBins + 1)  
  
# Create empty DF  
binDF <- data.frame(bin = integer(0),  
 length = integer(0),  
 set = character(0))  
# Empty vector for difference values  
summed\_absolute\_diff <- c()  
  
# Loop through all sets  
for(i in 1:length(sets)){  
 # Get set data only  
 temp <- combinedData\_AFC[combinedData\_AFC$setNum == sets[i], 'objLocTargetRating']  
   
 # Create empty var  
 binned <- c()  
   
 # Loop through the bins  
 for(j in 1:(numBins)){  
 binned[j] <- length(temp[temp >= bins[j] & temp <= bins[j + 1]])  
 }  
   
 # Calculate this value  
 summed\_absolute\_diff[i] <- sum(abs(mean(binned) - binned))  
   
 # Add to DF  
 binDF <- rbind(binDF,  
 data.frame(bin = 1:numBins, freq = binned/sum(binned), set = rep(sets[i], numBins)))  
  
}  
  
diffDF <- data.frame(set = sets,  
 difference = summed\_absolute\_diff)



|  |  |
| --- | --- |
| set | difference |
| 1 | 103.0 |
| 2 | 165.5 |
| 111 | 137.0 |
| 246 | 96.0 |
| 388 | 83.0 |
| 498 | 108.0 |
| 848 | 134.5 |

Examining the binned frequency values and the summed absolute difference from the mean that there is nothing apparently wrong with set 246.

# Analysing set as random effect

In the following, the data of Experiment 3 and 4 is analysed with regard to the question whether the quadratic component significantly varies across sets. For this I **tried** to compare a model where the quadratic component varies as a function of set versus a model where only the intercept and the linear component varies as a function of the set.

Note the model comparison is **attempted** between these two models

m1: Y ~ sExp + I(sExp\*sExp) + (sExp | setNum) + (1 | subNum) + (1 | objNum)

m2: Y ~ sExp + I(sExpz\*sExp) + (sExp + I(sExp\*sExp) | setNum) + (1 | subNum) + (1 | objNum)

These models had issues to converge so that sometimes they either didn’t converge at all or I had to remove some components (e.g. the random intercept for set or the random slope for the linear component) because of singularity issues.

**Please check the code chunks for the exact models!** To be clear -1 or -sExp means a particular effect is *not* included. This was always done because otherwise a model could not be estimated without issues.

## Experiment 3

|  |  |
| --- | --- |
| Var1 | Freq |
| 111 | 5 |
| 246 | 5 |
| 388 | 5 |
| 498 | 5 |
| 848 | 4 |

The Table above contains the distribution of sets for Experiment 3, which shows that all sets occur five times apart from set 846, which was used four times because one participant had to be removed.

### Recogntion

# Scale  
dataSchemaVR3\_AFC$sExp <- dataSchemaVR3\_AFC$objLocTargetRating/(sd(dataSchemaVR3\_AFC$objLocTargetRating)\*2)  
  
m1 <- glmer(accAFC ~ sExp + I(sExp\*sExp) +   
 (-1 + sExp | setNum) +   
 (1 | subNum) +   
 (1 | objNum),   
 data = dataSchemaVR3\_AFC, family = 'binomial')  
  
m2 <- glmer(accAFC ~ sExp + I(sExp\*sExp) +   
 (-1 + sExp + I(sExp\*sExp) | setNum)+   
 (1 | subNum) +   
 (1 | objNum),   
 data = dataSchemaVR3\_AFC, family = 'binomial', control = glmerControl(optimizer ='optimx', optCtrl=list(method='L-BFGS-B')))  
  
  
kable(anova(m1, m2))

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | npar | AIC | BIC | logLik | deviance | Chisq | Df | Pr(>Chisq) |
| m1 | 6 | 506.2187 | 530.8475 | -247.1094 | 494.2187 | NA | NA | NA |
| m2 | 8 | 509.1589 | 541.9973 | -246.5795 | 493.1589 | 1.059802 | 2 | 0.5886632 |

Model comparison shows that m2 did not significantly fit the data better than m1.

M2 has singular fit that arises from the correlation between setNum sExp and I(sExp \* sExp) being 1.

This can be seen in this table.

|  |  |  |
| --- | --- | --- |
|  | sExp | I(sExp \* sExp) |
| 111 | -0.1928462 | -0.1805289 |
| 246 | 0.4169780 | 0.3903452 |
| 388 | 0.0013137 | 0.0012298 |
| 498 | -0.7598011 | -0.7112718 |
| 848 | 0.3696599 | 0.3460493 |

I don’t think we can estimate the model they way we want. Here are nevertheless the results:

## Generalized linear mixed model fit by maximum likelihood (Laplace  
## Approximation) [glmerMod]  
## Family: binomial ( logit )  
## Formula: accAFC ~ sExp + I(sExp \* sExp) + (-1 + sExp + I(sExp \* sExp) |   
## setNum) + (1 | subNum) + (1 | objNum)  
## Data: dataSchemaVR3\_AFC  
## Control:   
## glmerControl(optimizer = "optimx", optCtrl = list(method = "L-BFGS-B"))  
##   
## AIC BIC logLik deviance df.resid   
## 509.2 542.0 -246.6 493.2 440   
##   
## Scaled residuals:   
## Min 1Q Median 3Q Max   
## -3.9701 -0.8989 0.4307 0.5795 1.1983   
##   
## Random effects:  
## Groups Name Variance Std.Dev. Corr  
## subNum (Intercept) 0.3892 0.6238   
## objNum (Intercept) 0.2943 0.5425   
## setNum sExp 0.3493 0.5910   
## I(sExp \* sExp) 0.3061 0.5533 1.00  
## Number of obs: 448, groups: subNum, 24; objNum, 20; setNum, 5  
##   
## Fixed effects:  
## Estimate Std. Error z value Pr(>|z|)   
## (Intercept) 0.9642 0.2570 3.752 0.000175 \*\*\*  
## sExp 0.4461 0.3673 1.215 0.224551   
## I(sExp \* sExp) 1.0083 0.6748 1.494 0.135117   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Correlation of Fixed Effects:  
## (Intr) sExp   
## sExp -0.006   
## I(sEx\*sExp) -0.503 0.337  
## optimizer (optimx) convergence code: 0 (OK)  
## boundary (singular) fit: see ?isSingular

In m2, neither the linear nor the quadratic effect were significant.

### Remember rates

# Calculate remember rates  
remembered <- rep(0, dim(dataSchemaVR3)[1])  
remembered[dataSchemaVR3$resCon == 1] <- 1  
dataSchemaVR3$remembered <- remembered  
  
# Exclude no-memory (i.e. hasn't seen object)   
dataSchemaVR3 <- dataSchemaVR3[dataSchemaVR3$resCon != 0, ]  
  
# Scale  
dataSchemaVR3$sExp <- dataSchemaVR3$objLocTargetRating/(sd(dataSchemaVR3$objLocTargetRating)\*2)  
  
m1 <- glmer(remembered ~ sExp + I(sExp\*sExp) +   
 (1 | subNum) +   
 (1 | objNum),   
 data = dataSchemaVR3, family = 'binomial')  
  
m2 <- glmer(remembered ~ sExp + I(sExp\*sExp) +   
 (1 + -sExp + I(sExp\*sExp) | setNum)+   
 (1 | subNum) +   
 (1 | objNum),   
 data = dataSchemaVR3, family = 'binomial')  
  
kable(anova(m1, m2))

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | npar | AIC | BIC | logLik | deviance | Chisq | Df | Pr(>Chisq) |
| m1 | 5 | 598.5989 | 619.1229 | -294.2995 | 588.5989 | NA | NA | NA |
| m2 | 8 | 603.8211 | 636.6594 | -293.9105 | 587.8211 | 0.7778847 | 3 | 0.8547491 |

For remember I also did not find that adding a random effect for the quadratic effects significantly improve the model fit.

For m2, there is still singularity issue that arises because the correlation between the intercept and the quadratic term is -1.

|  |  |  |
| --- | --- | --- |
|  | (Intercept) | I(sExp \* sExp) |
| 111 | -0.2727079 | 0.7295108 |
| 246 | 0.0363777 | -0.0973126 |
| 388 | -0.1852066 | 0.4954394 |
| 498 | 0.2328185 | -0.6228042 |
| 848 | 0.2377979 | -0.6361244 |

I again think we can’t really estimate this model. However, m2 shows that there is a U-shape for remember ratings.

## Generalized linear mixed model fit by maximum likelihood (Laplace  
## Approximation) [glmerMod]  
## Family: binomial ( logit )  
## Formula: remembered ~ sExp + I(sExp \* sExp) + (1 + -sExp + I(sExp \* sExp) |   
## setNum) + (1 | subNum) + (1 | objNum)  
## Data: dataSchemaVR3  
##   
## AIC BIC logLik deviance df.resid   
## 603.8 636.7 -293.9 587.8 440   
##   
## Scaled residuals:   
## Min 1Q Median 3Q Max   
## -1.8625 -0.8622 0.4710 0.7912 2.4797   
##   
## Random effects:  
## Groups Name Variance Std.Dev. Corr   
## subNum (Intercept) 0.5381 0.7335   
## objNum (Intercept) 0.1441 0.3796   
## setNum (Intercept) 0.1161 0.3408   
## I(sExp \* sExp) 0.8310 0.9116 -1.00  
## Number of obs: 448, groups: subNum, 24; objNum, 20; setNum, 5  
##   
## Fixed effects:  
## Estimate Std. Error z value Pr(>|z|)   
## (Intercept) -0.2885 0.2880 -1.002 0.3165   
## sExp -0.1711 0.2194 -0.780 0.4356   
## I(sExp \* sExp) 1.3993 0.6899 2.028 0.0425 \*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Correlation of Fixed Effects:  
## (Intr) sExp   
## sExp -0.003   
## I(sEx\*sExp) -0.702 -0.014  
## optimizer (Nelder\_Mead) convergence code: 0 (OK)  
## boundary (singular) fit: see ?isSingular

### Recall

# Scale  
dataSchemaVR3\_recall$sExp <- dataSchemaVR3\_recall$objLocTargetRating/(sd(dataSchemaVR3\_recall$objLocTargetRating)\*2)  
  
m1 <- glmer(accRecall ~ sExp + I(sExp\*sExp) +   
 (1 | setNum) +   
 (1 | subNum) +   
 (1 | objNum),   
 data = dataSchemaVR3\_recall, family = 'binomial')  
  
m2 <- glmer(accRecall ~ sExp + I(sExp\*sExp) +   
 (1 + -sExp + I(sExp\*sExp) | setNum) +   
 (1 | subNum) +   
 (1 | objNum),   
 data = dataSchemaVR3\_recall, family = 'binomial')  
  
kable(anova(m1, m2))

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | npar | AIC | BIC | logLik | deviance | Chisq | Df | Pr(>Chisq) |
| m1 | 6 | 558.3841 | 582.4811 | -273.1921 | 546.3841 | NA | NA | NA |
| m2 | 8 | 562.0498 | 594.1791 | -273.0249 | 546.0498 | 0.3343012 | 2 | 0.8460722 |

Again m2 (with random quadratic component) did not fit better than m1.

For m2, there is still singularity issue that arises because the correlation between the intercept and the quadratic term is -1.

|  |  |  |
| --- | --- | --- |
|  | (Intercept) | I(sExp \* sExp) |
| 111 | -0.3519947 | 0.5444076 |
| 246 | 0.1476882 | -0.2284198 |
| 388 | 0.0575547 | -0.0890161 |
| 498 | 0.0529282 | -0.0818606 |
| 848 | 0.1039048 | -0.1607029 |

If I also removed the random intercept, it doesn’t help as the random slope for the quadratic terms because essentially zero. In contrast to remember ratings, there was not U-shape.

## Generalized linear mixed model fit by maximum likelihood (Laplace  
## Approximation) [glmerMod]  
## Family: binomial ( logit )  
## Formula: accRecall ~ sExp + I(sExp \* sExp) + (1 + -sExp + I(sExp \* sExp) |   
## setNum) + (1 | subNum) + (1 | objNum)  
## Data: dataSchemaVR3\_recall  
##   
## AIC BIC logLik deviance df.resid   
## 562.0 594.2 -273.0 546.0 402   
##   
## Scaled residuals:   
## Min 1Q Median 3Q Max   
## -1.7524 -0.8532 0.4316 0.8323 1.8965   
##   
## Random effects:  
## Groups Name Variance Std.Dev. Corr   
## subNum (Intercept) 0.4411 0.6641   
## objNum (Intercept) 0.2465 0.4965   
## setNum (Intercept) 0.1137 0.3372   
## I(sExp \* sExp) 0.2720 0.5215 -1.00  
## Number of obs: 410, groups: subNum, 24; objNum, 20; setNum, 5  
##   
## Fixed effects:  
## Estimate Std. Error z value Pr(>|z|)  
## (Intercept) -0.112535 0.295903 -0.380 0.704  
## sExp -0.001027 0.225843 -0.005 0.996  
## I(sExp \* sExp) 0.674937 0.643821 1.048 0.294  
##   
## Correlation of Fixed Effects:  
## (Intr) sExp   
## sExp -0.008   
## I(sEx\*sExp) -0.657 0.011  
## optimizer (Nelder\_Mead) convergence code: 0 (OK)  
## boundary (singular) fit: see ?isSingular

## Experiment 4

|  |  |
| --- | --- |
| Var1 | Freq |
| 111 | 15 |
| 246 | 17 |
| 388 | 15 |
| 498 | 14 |
| 848 | 11 |

The Table above contains the distribution of sets for Experiment 4, which the distribution of sets is pretty unbalanced.

### Recogntion

# Scale  
dataSchemaVR4\_AFC$sExp <- dataSchemaVR4\_AFC$objLocTargetRating/(sd(dataSchemaVR4\_AFC$objLocTargetRating)\*2)  
  
m1 <- glmer(accAFC ~ sExp + I(sExp\*sExp) +   
 (1 + -sExp | setNum) +   
 (1 | subNum) +   
 (1 | objNum), data = dataSchemaVR4\_AFC, family = 'binomial')  
  
m2 <- glmer(accAFC ~ sExp + I(sExp\*sExp) +   
 (1 + sExp + I(sExp\*sExp) | setNum)+   
 (1 | subNum) +   
 (1 | objNum),   
 data = dataSchemaVR4\_AFC, family = 'binomial', control = glmerControl(optimizer ='optimx', optCtrl=list(method='L-BFGS-B')))  
  
kable(anova(m1, m2))

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | npar | AIC | BIC | logLik | deviance | Chisq | Df | Pr(>Chisq) |
| m1 | 6 | 1365.999 | 1397.029 | -676.9994 | 1353.999 | NA | NA | NA |
| m2 | 11 | 1374.619 | 1431.507 | -676.3094 | 1352.619 | 1.380057 | 5 | 0.9264824 |

Model comparison shows that m2 did not significantly fit the data better than m1.

In m2, neither the linear nor the quadratic effect were significant.

## Generalized linear mixed model fit by maximum likelihood (Laplace  
## Approximation) [glmerMod]  
## Family: binomial ( logit )  
## Formula: accAFC ~ sExp + I(sExp \* sExp) + (1 + sExp + I(sExp \* sExp) |   
## setNum) + (1 | subNum) + (1 | objNum)  
## Data: dataSchemaVR4\_AFC  
## Control:   
## glmerControl(optimizer = "optimx", optCtrl = list(method = "L-BFGS-B"))  
##   
## AIC BIC logLik deviance df.resid   
## 1374.6 1431.5 -676.3 1352.6 1291   
##   
## Scaled residuals:   
## Min 1Q Median 3Q Max   
## -3.3341 0.2526 0.4088 0.5505 1.2960   
##   
## Random effects:  
## Groups Name Variance Std.Dev. Corr   
## subNum (Intercept) 0.625644 0.79098   
## objNum (Intercept) 0.148760 0.38569   
## setNum (Intercept) 0.013443 0.11595   
## sExp 0.005306 0.07284 -0.22   
## I(sExp \* sExp) 0.348446 0.59029 0.75 -0.81  
## Number of obs: 1302, groups: subNum, 72; objNum, 20; setNum, 5  
##   
## Fixed effects:  
## Estimate Std. Error z value Pr(>|z|)   
## (Intercept) 1.2659 0.1826 6.931 4.19e-12 \*\*\*  
## sExp -0.1575 0.1557 -1.012 0.312   
## I(sExp \* sExp) 0.3962 0.4654 0.851 0.395   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Correlation of Fixed Effects:  
## (Intr) sExp   
## sExp -0.048   
## I(sEx\*sExp) -0.290 -0.057  
## optimizer (optimx) convergence code: 0 (OK)  
## boundary (singular) fit: see ?isSingular

As you can see, the fit is still singular but I have no idea why.

### Remember rates

# Calculate remember rates  
remembered <- rep(0, dim(dataSchemaVR4)[1])  
remembered[dataSchemaVR4$resCon == 1] <- 1  
dataSchemaVR4$remembered <- remembered  
  
# Exclude no-memory (i.e. hasn't seen object)   
dataSchemaVR4 <- dataSchemaVR4[dataSchemaVR4$resCon != 0, ]  
  
# Scale  
dataSchemaVR4$sExp <- dataSchemaVR4$objLocTargetRating/(sd(dataSchemaVR4$objLocTargetRating)\*2)  
  
m1 <- glmer(remembered ~ sExp + I(sExp\*sExp) +   
 (sExp | setNum) +   
 (1 | subNum) +   
 (1 | objNum),   
 data = dataSchemaVR4, family = 'binomial')  
  
m2 <- glmer(remembered ~ sExp + I(sExp\*sExp) +   
 (-1 + -sExp + I(sExp\*sExp) | setNum) +   
 (1 | subNum) +   
 (1 | objNum),   
 data = dataSchemaVR4, family = 'binomial', control = glmerControl(optimizer ='optimx', optCtrl=list(method='L-BFGS-B')))  
  
kable(anova(m1, m2))

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | npar | AIC | BIC | logLik | deviance | Chisq | Df | Pr(>Chisq) |
| m2 | 6 | 1694.249 | 1725.278 | -841.1243 | 1682.249 | NA | NA | NA |
| m1 | 8 | 1698.425 | 1739.799 | -841.2127 | 1682.425 | 0 | 2 | 1 |

For remember I also did not find that adding a random effect for the quadratic effects significantly improves the model fit. Using m2, shows that there is a only a significant negative linear component.

## Generalized linear mixed model fit by maximum likelihood (Laplace  
## Approximation) [glmerMod]  
## Family: binomial ( logit )  
## Formula: remembered ~ sExp + I(sExp \* sExp) + (-1 + -sExp + I(sExp \* sExp) |   
## setNum) + (1 | subNum) + (1 | objNum)  
## Data: dataSchemaVR4  
## Control:   
## glmerControl(optimizer = "optimx", optCtrl = list(method = "L-BFGS-B"))  
##   
## AIC BIC logLik deviance df.resid   
## 1694.2 1725.3 -841.1 1682.2 1296   
##   
## Scaled residuals:   
## Min 1Q Median 3Q Max   
## -2.6242 -0.8480 0.3822 0.8319 2.1906   
##   
## Random effects:  
## Groups Name Variance Std.Dev.  
## subNum (Intercept) 0.3239 0.5691   
## objNum (Intercept) 0.3890 0.6237   
## setNum I(sExp \* sExp) 0.1001 0.3163   
## Number of obs: 1302, groups: subNum, 72; objNum, 20; setNum, 5  
##   
## Fixed effects:  
## Estimate Std. Error z value Pr(>|z|)   
## (Intercept) -0.04551 0.18538 -0.245 0.806   
## sExp -0.58979 0.13365 -4.413 1.02e-05 \*\*\*  
## I(sExp \* sExp) 0.50093 0.36366 1.377 0.168   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Correlation of Fixed Effects:  
## (Intr) sExp   
## sExp -0.022   
## I(sEx\*sExp) -0.407 0.056

### Recall

# Scale  
dataSchemaVR4\_recall$sExp <- dataSchemaVR4\_recall$objLocTargetRating/(sd(dataSchemaVR4\_recall$objLocTargetRating)\*2)  
  
m1 <- glmer(accRecall ~ sExp + I(sExp\*sExp) +   
 (sExp | setNum) +   
 (1 | subNum) +   
 (1 | objNum),   
 data = dataSchemaVR4\_recall, family = 'binomial')  
  
m2 <- glmer(accRecall ~ sExp +   
 I(sExp\*sExp) +   
 (-1 + -sExp +   
 I(sExp\*sExp) | setNum) +   
 (1 | subNum) +   
 (1 | objNum),   
 data = dataSchemaVR4\_recall, family = 'binomial')  
  
kable(anova(m1, m2))

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | npar | AIC | BIC | logLik | deviance | Chisq | Df | Pr(>Chisq) |
| m2 | 6 | 1549.588 | 1580.335 | -768.7942 | 1537.588 | NA | NA | NA |
| m1 | 8 | 1552.685 | 1593.680 | -768.3423 | 1536.685 | 0.9038321 | 2 | 0.6364076 |

Again m2 (with random quadratic component) did not fit better than m1. In contrast to remember ratings, there the U-shape reached significance but the model also had issues with singular fit.

## Generalized linear mixed model fit by maximum likelihood (Laplace  
## Approximation) [glmerMod]  
## Family: binomial ( logit )  
## Formula: accRecall ~ sExp + I(sExp \* sExp) + (-1 + -sExp + I(sExp \* sExp) |   
## setNum) + (1 | subNum) + (1 | objNum)  
## Data: dataSchemaVR4\_recall  
##   
## AIC BIC logLik deviance df.resid   
## 1549.6 1580.3 -768.8 1537.6 1236   
##   
## Scaled residuals:   
## Min 1Q Median 3Q Max   
## -1.6210 -0.7178 -0.4279 0.8799 3.2363   
##   
## Random effects:  
## Groups Name Variance Std.Dev.   
## subNum (Intercept) 9.343e-01 9.666e-01  
## objNum (Intercept) 1.531e-01 3.913e-01  
## setNum I(sExp \* sExp) 1.328e-10 1.152e-05  
## Number of obs: 1242, groups: subNum, 72; objNum, 20; setNum, 5  
##   
## Fixed effects:  
## Estimate Std. Error z value Pr(>|z|)   
## (Intercept) -0.81851 0.18343 -4.462 8.11e-06 \*\*\*  
## sExp -0.09922 0.13978 -0.710 0.4778   
## I(sExp \* sExp) 0.82678 0.35388 2.336 0.0195 \*   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Correlation of Fixed Effects:  
## (Intr) sExp   
## sExp -0.029   
## I(sEx\*sExp) -0.498 0.108  
## optimizer (Nelder\_Mead) convergence code: 0 (OK)  
## boundary (singular) fit: see ?isSingular

## Combinded data

### Recognition

# Scale  
dataSchemaVR3\_4\_AFC$sExp <- dataSchemaVR3\_4\_AFC$objLocTargetRating/(sd(dataSchemaVR3\_4\_AFC$objLocTargetRating)\*2)  
  
m1 <- glmer(accAFC ~ sExp + I(sExp\*sExp) +   
 (sExp | setNum) +   
 (1 | subNum) +   
 (1 | objNum),   
 data = dataSchemaVR3\_4\_AFC, family = 'binomial')  
  
m2 <- glmer(accAFC ~ sExp + I(sExp\*sExp) +   
 (sExp + I(sExp\*sExp) | setNum) +   
 (1 | subNum) +   
 (1 | objNum),   
 data = dataSchemaVR3\_4\_AFC, family = 'binomial', control = glmerControl(optimizer ='optimx', optCtrl=list(method='L-BFGS-B')))  
  
kable(anova(m1, m2))

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | npar | AIC | BIC | logLik | deviance | Chisq | Df | Pr(>Chisq) |
| m1 | 8 | 1860.987 | 1904.726 | -922.4936 | 1844.987 | NA | NA | NA |
| m2 | 11 | 1866.259 | 1926.401 | -922.1297 | 1844.259 | 0.7277958 | 3 | 0.8666474 |

The model m2 does not fit the data better than m1 and there is no significant quadratic relationship. M2 converged but gave me a warning: Parameters or bounds appear to have different scalings. This can cause poor performance in optimization. No idea if that is a cause for concern. In any case, no effects are significant.

## Generalized linear mixed model fit by maximum likelihood (Laplace  
## Approximation) [glmerMod]  
## Family: binomial ( logit )  
## Formula: accAFC ~ sExp + I(sExp \* sExp) + (sExp + I(sExp \* sExp) | setNum) +   
## (1 | subNum) + (1 | objNum)  
## Data: dataSchemaVR3\_4\_AFC  
## Control:   
## glmerControl(optimizer = "optimx", optCtrl = list(method = "L-BFGS-B"))  
##   
## AIC BIC logLik deviance df.resid   
## 1866.3 1926.4 -922.1 1844.3 1739   
##   
## Scaled residuals:   
## Min 1Q Median 3Q Max   
## -3.6288 0.2439 0.4171 0.5549 1.3733   
##   
## Random effects:  
## Groups Name Variance Std.Dev. Corr   
## subNum (Intercept) 0.57333 0.7572   
## objNum (Intercept) 0.19334 0.4397   
## setNum (Intercept) 0.04057 0.2014   
## sExp 0.06379 0.2526 0.87   
## I(sExp \* sExp) 0.12769 0.3573 -0.27 -0.71  
## Number of obs: 1750, groups: subNum, 96; objNum, 20; setNum, 5  
##   
## Fixed effects:  
## Estimate Std. Error z value Pr(>|z|)   
## (Intercept) 1.18273 0.18477 6.401 1.54e-10 \*\*\*  
## sExp 0.04689 0.17217 0.272 0.785   
## I(sExp \* sExp) 0.54523 0.36211 1.506 0.132   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Correlation of Fixed Effects:  
## (Intr) sExp   
## sExp 0.264   
## I(sEx\*sExp) -0.435 -0.167  
## optimizer (optimx) convergence code: 0 (OK)  
## Parameters or bounds appear to have different scalings.  
## This can cause poor performance in optimization.   
## It is important for derivative free methods like BOBYQA, UOBYQA, NEWUOA.

### Recall

# Scale  
dataSchemaVR3\_4\_recall$sExp <- dataSchemaVR3\_4\_recall$objLocTargetRating/(sd(dataSchemaVR3\_4\_recall$objLocTargetRating)\*2)  
  
m1 <- glmer(accRecall ~ sExp + I(sExp\*sExp) +   
 (-1 + sExp | setNum) +   
 (1 | subNum) +   
 (1 | objNum),   
 data = dataSchemaVR3\_4\_recall, family = 'binomial')  
  
m2 <- glmer(accRecall ~ sExp + I(sExp\*sExp) +   
 (-1 + -sExp + I(sExp\*sExp) | setNum) +   
 (1 | subNum) +   
 (1 | objNum),   
 data = dataSchemaVR3\_4\_recall, family = 'binomial', control = glmerControl(optimizer ='optimx', optCtrl=list(method='L-BFGS-B')))  
  
kable(anova(m1, m2))

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | npar | AIC | BIC | logLik | deviance | Chisq | Df | Pr(>Chisq) |
| m1 | 6 | 2089.957 | 2122.416 | -1038.979 | 2077.957 | NA | NA | NA |
| m2 | 6 | 2091.075 | 2123.533 | -1039.537 | 2079.075 | 0 | 0 | NA |

M2 does not fit better than m1 but there is a U-shape that is significant. The singular fit in m2 does not go away when adding the random slope for the quadratic effect. When I remove everything but the random slope for the quadratic effect, it is estimated to be zero.

## Generalized linear mixed model fit by maximum likelihood (Laplace  
## Approximation) [glmerMod]  
## Family: binomial ( logit )  
## Formula: accRecall ~ sExp + I(sExp \* sExp) + (-1 + -sExp + I(sExp \* sExp) |   
## setNum) + (1 | subNum) + (1 | objNum)  
## Data: dataSchemaVR3\_4\_recall  
## Control:   
## glmerControl(optimizer = "optimx", optCtrl = list(method = "L-BFGS-B"))  
##   
## AIC BIC logLik deviance df.resid   
## 2091.1 2123.5 -1039.5 2079.1 1646   
##   
## Scaled residuals:   
## Min 1Q Median 3Q Max   
## -2.0173 -0.7512 -0.4215 0.8590 3.1889   
##   
## Random effects:  
## Groups Name Variance Std.Dev.  
## subNum (Intercept) 0.8911 0.9440   
## objNum (Intercept) 0.2021 0.4496   
## setNum I(sExp \* sExp) 0.0000 0.0000   
## Number of obs: 1652, groups: subNum, 96; objNum, 20; setNum, 5  
##   
## Fixed effects:  
## Estimate Std. Error z value Pr(>|z|)   
## (Intercept) -0.64962 0.16997 -3.822 0.000132 \*\*\*  
## sExp -0.05333 0.12018 -0.444 0.657223   
## I(sExp \* sExp) 0.84598 0.30851 2.742 0.006103 \*\*   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Correlation of Fixed Effects:  
## (Intr) sExp   
## sExp -0.021   
## I(sEx\*sExp) -0.463 0.077  
## optimizer (optimx) convergence code: 0 (OK)  
## boundary (singular) fit: see ?isSingular

### Remember

# Scale  
dataSchemaVR3\_4$sExp <- dataSchemaVR3\_4$objLocTargetRating/(sd(dataSchemaVR3\_4$objLocTargetRating)\*2)  
  
m1 <- glmer(remembered ~ sExp + I(sExp\*sExp) +   
 (1 + -sExp | setNum) +   
 (1 | subNum) +   
 (1 | objNum),   
 data = dataSchemaVR3\_4, family = 'binomial')  
  
m2 <- glmer(remembered ~ sExp + I(sExp\*sExp) +   
 (-1 + -sExp + I(sExp\*sExp) | setNum) +   
 (1 | subNum) +   
 (1 | objNum),   
 data = dataSchemaVR3\_4, family = 'binomial', control = glmerControl(optimizer ='optimx', optCtrl=list(method='L-BFGS-B')))  
  
kable(anova(m1, m2))

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | npar | AIC | BIC | logLik | deviance | Chisq | Df | Pr(>Chisq) |
| m1 | 6 | 2283.846 | 2316.650 | -1135.923 | 2271.846 | NA | NA | NA |
| m2 | 6 | 2282.713 | 2315.517 | -1135.357 | 2270.713 | 1.132937 | 0 | NA |

M2 does not fit better than m1 but there is a U-shape that is significant. There is significant negative relationship and a U-shape. Here, the model actually didn’t produce an issue.

## Generalized linear mixed model fit by maximum likelihood (Laplace  
## Approximation) [glmerMod]  
## Family: binomial ( logit )  
## Formula: remembered ~ sExp + I(sExp \* sExp) + (-1 + -sExp + I(sExp \* sExp) |   
## setNum) + (1 | subNum) + (1 | objNum)  
## Data: dataSchemaVR3\_4  
## Control:   
## glmerControl(optimizer = "optimx", optCtrl = list(method = "L-BFGS-B"))  
##   
## AIC BIC logLik deviance df.resid   
## 2282.7 2315.5 -1135.4 2270.7 1744   
##   
## Scaled residuals:   
## Min 1Q Median 3Q Max   
## -2.6532 -0.8629 0.4093 0.8331 2.1525   
##   
## Random effects:  
## Groups Name Variance Std.Dev.  
## subNum (Intercept) 0.3720 0.6099   
## objNum (Intercept) 0.3167 0.5628   
## setNum I(sExp \* sExp) 0.2013 0.4487   
## Number of obs: 1750, groups: subNum, 96; objNum, 20; setNum, 5  
##   
## Fixed effects:  
## Estimate Std. Error z value Pr(>|z|)   
## (Intercept) -0.1014 0.1657 -0.612 0.540491   
## sExp -0.4366 0.1142 -3.823 0.000132 \*\*\*  
## I(sExp \* sExp) 0.7073 0.3508 2.016 0.043756 \*   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Correlation of Fixed Effects:  
## (Intr) sExp   
## sExp -0.016   
## I(sEx\*sExp) -0.350 0.030

# Analysing set as fixed effect

Here the models that I try to use:

m1: Y ~ sExp\*setNum + I(sExp\*sExp) + (1 | subNum) + (1 | objNum)

m2: Y ~ sExp\*setNum + I(sExp\*sExp)\*setNum + (1 | subNum) + (1 | objNum)

## Experiment 3

### Recognition

# Scale  
dataSchemaVR3\_4\_AFC$sExp <- dataSchemaVR3\_4\_AFC$objLocTargetRating/(sd(dataSchemaVR3\_4\_AFC$objLocTargetRating)\*2)  
  
m1 <- glmer(accAFC ~ sExp\*setNum +   
 I(sExp\*sExp) +   
 (1 | subNum) +   
 (1 | objNum),   
 data = dataSchemaVR3\_4\_AFC, family = 'binomial')  
  
m2 <- glmer(accAFC ~ sExp\*setNum +   
 I(sExp\*sExp)\*setNum +   
 (1 | subNum) +   
 (1 | objNum),   
 data = dataSchemaVR3\_4\_AFC, family = 'binomial')  
  
kable(anova(m1, m2, test = "Chisq"))

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | npar | AIC | BIC | logLik | deviance | Chisq | Df | Pr(>Chisq) |
| m1 | 13 | 1856.564 | 1927.639 | -915.2818 | 1830.564 | NA | NA | NA |
| m2 | 17 | 1860.586 | 1953.531 | -913.2930 | 1826.586 | 3.977437 | 4 | 0.4090681 |

Even though adding the interaction between set and the quadratic effect didn’t improve the fit significantly, there seems to be significant effects.

## Generalized linear mixed model fit by maximum likelihood (Laplace  
## Approximation) [glmerMod]  
## Family: binomial ( logit )  
## Formula: accAFC ~ sExp \* setNum + I(sExp \* sExp) \* setNum + (1 | subNum) +   
## (1 | objNum)  
## Data: dataSchemaVR3\_4\_AFC  
##   
## AIC BIC logLik deviance df.resid   
## 1860.6 1953.5 -913.3 1826.6 1733   
##   
## Scaled residuals:   
## Min 1Q Median 3Q Max   
## -3.7029 0.2337 0.4081 0.5558 1.4494   
##   
## Random effects:  
## Groups Name Variance Std.Dev.  
## subNum (Intercept) 0.5189 0.7204   
## objNum (Intercept) 0.1868 0.4322   
## Number of obs: 1750, groups: subNum, 96; objNum, 20  
##   
## Fixed effects:  
## Estimate Std. Error z value Pr(>|z|)   
## (Intercept) 1.00890 0.27968 3.607 0.000309 \*\*\*  
## sExp -0.22215 0.28648 -0.775 0.438069   
## setNum246 0.56960 0.36932 1.542 0.122996   
## setNum388 0.40941 0.37547 1.090 0.275543   
## setNum498 -0.08137 0.37183 -0.219 0.826766   
## setNum848 -0.12544 0.40660 -0.309 0.757694   
## I(sExp \* sExp) 1.21878 0.67484 1.806 0.070915 .   
## sExp:setNum246 0.63564 0.40105 1.585 0.112985   
## sExp:setNum388 0.43028 0.44017 0.978 0.328309   
## sExp:setNum498 -0.30748 0.39289 -0.783 0.433854   
## sExp:setNum848 0.51461 0.40764 1.262 0.206804   
## setNum246:I(sExp \* sExp) -1.55578 0.94682 -1.643 0.100350   
## setNum388:I(sExp \* sExp) 0.07946 1.00772 0.079 0.937155   
## setNum498:I(sExp \* sExp) -0.64185 0.94751 -0.677 0.498148   
## setNum848:I(sExp \* sExp) -1.07185 0.98416 -1.089 0.276109   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

### Recall

# Scale  
dataSchemaVR3\_recall$sExp <- dataSchemaVR3\_recall$objLocTargetRating/(sd(dataSchemaVR3\_recall$objLocTargetRating)\*2)  
  
m1 <- glmer(accRecall ~ sExp\*setNum +   
 I(sExp\*sExp) +   
 (1 | subNum) +   
 (1 | objNum),   
 data = dataSchemaVR3\_recall, family = 'binomial')  
  
m2 <- glmer(accRecall ~ sExp\*setNum +   
 I(sExp\*sExp)\*setNum +   
 (1 | subNum) +   
 (1 | objNum),   
 data = dataSchemaVR3\_recall, family = 'binomial', control = glmerControl(optimizer ='optimx', optCtrl=list(method='L-BFGS-B')))  
  
  
kable(anova(m1, m2, test = "Chisq"))

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | npar | AIC | BIC | logLik | deviance | Chisq | Df | Pr(>Chisq) |
| m1 | 13 | 564.2363 | 616.4464 | -269.1182 | 538.2363 | NA | NA | NA |
| m2 | 17 | 568.2473 | 636.5220 | -267.1237 | 534.2473 | 3.989013 | 4 | 0.4074948 |

Again m2 did not fit better than m1 but there is a U-shape and ‘only’ indications that there is an interactions (as trends).

## Generalized linear mixed model fit by maximum likelihood (Laplace  
## Approximation) [glmerMod]  
## Family: binomial ( logit )  
## Formula: accRecall ~ sExp \* setNum + I(sExp \* sExp) \* setNum + (1 | subNum) +   
## (1 | objNum)  
## Data: dataSchemaVR3\_recall  
## Control:   
## glmerControl(optimizer = "optimx", optCtrl = list(method = "L-BFGS-B"))  
##   
## AIC BIC logLik deviance df.resid   
## 568.2 636.5 -267.1 534.2 393   
##   
## Scaled residuals:   
## Min 1Q Median 3Q Max   
## -2.0782 -0.8807 0.4294 0.8168 2.1098   
##   
## Random effects:  
## Groups Name Variance Std.Dev.  
## subNum (Intercept) 0.3392 0.5824   
## objNum (Intercept) 0.2553 0.5053   
## Number of obs: 410, groups: subNum, 24; objNum, 20  
##   
## Fixed effects:  
## Estimate Std. Error z value Pr(>|z|)   
## (Intercept) -1.3498 0.5297 -2.548 0.0108 \*  
## sExp 0.1016 0.4846 0.210 0.8340   
## setNum246 1.6637 0.6972 2.386 0.0170 \*  
## setNum388 1.4210 0.7000 2.030 0.0424 \*  
## setNum498 1.4376 0.6862 2.095 0.0362 \*  
## setNum848 1.5694 0.7463 2.103 0.0355 \*  
## I(sExp \* sExp) 2.7599 1.3472 2.049 0.0405 \*  
## sExp:setNum246 0.3739 0.7152 0.523 0.6011   
## sExp:setNum388 0.1601 0.6940 0.231 0.8175   
## sExp:setNum498 -0.6407 0.7305 -0.877 0.3804   
## sExp:setNum848 -0.5503 0.7263 -0.758 0.4486   
## setNum246:I(sExp \* sExp) -2.3430 1.9671 -1.191 0.2336   
## setNum388:I(sExp \* sExp) -1.6667 1.7797 -0.937 0.3490   
## setNum498:I(sExp \* sExp) -3.1972 1.9145 -1.670 0.0949 .  
## setNum848:I(sExp \* sExp) -3.1786 1.8718 -1.698 0.0895 .  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

### Remember rates

# Calculate remember rates  
remembered <- rep(0, dim(dataSchemaVR3)[1])  
remembered[dataSchemaVR3$resCon == 1] <- 1  
dataSchemaVR3$remembered <- remembered  
  
# Exclude no-memory (i.e. hasn't seen object)   
dataSchemaVR3 <- dataSchemaVR3[dataSchemaVR3$resCon != 0, ]  
  
# Scale  
dataSchemaVR3$sExp <- dataSchemaVR3$objLocTargetRating/(sd(dataSchemaVR3$objLocTargetRating)\*2)  
  
m1 <- glmer(remembered ~ sExp\*setNum +   
 I(sExp\*sExp) +   
 (1 | subNum) +   
 (1 | objNum),   
 data = dataSchemaVR3, family = 'binomial')  
  
m2 <- glmer(remembered ~ sExp\*setNum +   
 I(sExp\*sExp)\*setNum +   
 (1 | subNum) +   
 (1 | objNum),   
 data = dataSchemaVR3, family = 'binomial')  
  
kable(anova(m1, m2, test = "Chisq"))

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | npar | AIC | BIC | logLik | deviance | Chisq | Df | Pr(>Chisq) |
| m1 | 13 | 609.2464 | 662.6087 | -291.6232 | 583.2464 | NA | NA | NA |
| m2 | 17 | 609.8701 | 679.6516 | -287.9350 | 575.8701 | 7.376311 | 4 | 0.1172888 |

Here m2 *nearly* fits better than m1. In this case, there is a U-shape and an interaction for 848.

## Generalized linear mixed model fit by maximum likelihood (Laplace  
## Approximation) [glmerMod]  
## Family: binomial ( logit )  
## Formula: remembered ~ sExp \* setNum + I(sExp \* sExp) \* setNum + (1 | subNum) +   
## (1 | objNum)  
## Data: dataSchemaVR3  
##   
## AIC BIC logLik deviance df.resid   
## 609.9 679.7 -287.9 575.9 431   
##   
## Scaled residuals:   
## Min 1Q Median 3Q Max   
## -2.1337 -0.8460 0.3778 0.7941 2.9589   
##   
## Random effects:  
## Groups Name Variance Std.Dev.  
## subNum (Intercept) 0.4252 0.6520   
## objNum (Intercept) 0.1395 0.3735   
## Number of obs: 448, groups: subNum, 24; objNum, 20  
##   
## Fixed effects:  
## Estimate Std. Error z value Pr(>|z|)   
## (Intercept) -1.32202 0.50944 -2.595 0.00946 \*\*  
## sExp 0.08104 0.46080 0.176 0.86039   
## setNum246 1.28086 0.69251 1.850 0.06437 .   
## setNum388 0.83603 0.69299 1.206 0.22766   
## setNum498 1.63642 0.67391 2.428 0.01517 \*   
## setNum848 1.30508 0.73168 1.784 0.07448 .   
## I(sExp \* sExp) 3.00730 1.21256 2.480 0.01313 \*   
## sExp:setNum246 -0.29728 0.68790 -0.432 0.66563   
## sExp:setNum388 -0.50148 0.69667 -0.720 0.47163   
## sExp:setNum498 -0.19274 0.67327 -0.286 0.77467   
## sExp:setNum848 -0.29915 0.67380 -0.444 0.65707   
## setNum246:I(sExp \* sExp) -1.20520 1.85141 -0.651 0.51507   
## setNum388:I(sExp \* sExp) -0.01318 1.67960 -0.008 0.99374   
## setNum498:I(sExp \* sExp) -2.93838 1.70250 -1.726 0.08436 .   
## setNum848:I(sExp \* sExp) -3.43275 1.69837 -2.021 0.04326 \*   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

## Experiment 4

### Recognition

# Scale  
dataSchemaVR4\_AFC$sExp <- dataSchemaVR4\_AFC$objLocTargetRating/(sd(dataSchemaVR4\_AFC$objLocTargetRating)\*2)  
  
m1 <- glmer(accAFC ~ sExp\*setNum +   
 I(sExp\*sExp) +   
 (1 | subNum) +   
 (1 | objNum),   
 data = dataSchemaVR4\_AFC, family = 'binomial')  
  
m2 <- glmer(accAFC ~ sExp\*setNum +   
 I(sExp\*sExp)\*setNum +   
 (1 | subNum) +   
 (1 | objNum),   
 data = dataSchemaVR4\_AFC, family = 'binomial', control = glmerControl(optimizer ='optimx', optCtrl=list(method='L-BFGS-B')))  
  
  
kable(anova(m1, m2, test = "Chisq"))

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | npar | AIC | BIC | logLik | deviance | Chisq | Df | Pr(>Chisq) |
| m1 | 13 | 1368.977 | 1436.209 | -671.4885 | 1342.977 | NA | NA | NA |
| m2 | 17 | 1371.246 | 1459.164 | -668.6230 | 1337.246 | 5.730987 | 4 | 0.2201592 |

Here, m2 *does not* fit the data better than m1. In this model there are no significant effects. The problem here was that I can’t get m2 to converge.

## Generalized linear mixed model fit by maximum likelihood (Laplace  
## Approximation) [glmerMod]  
## Family: binomial ( logit )  
## Formula: accAFC ~ sExp \* setNum + I(sExp \* sExp) \* setNum + (1 | subNum) +   
## (1 | objNum)  
## Data: dataSchemaVR4\_AFC  
## Control:   
## glmerControl(optimizer = "optimx", optCtrl = list(method = "L-BFGS-B"))  
##   
## AIC BIC logLik deviance df.resid   
## 1371.2 1459.2 -668.6 1337.2 1285   
##   
## Scaled residuals:   
## Min 1Q Median 3Q Max   
## -3.6153 0.2305 0.4030 0.5494 1.2655   
##   
## Random effects:  
## Groups Name Variance Std.Dev.  
## subNum (Intercept) 0.5581 0.7470   
## objNum (Intercept) 0.1435 0.3788   
## Number of obs: 1302, groups: subNum, 72; objNum, 20  
##   
## Fixed effects:  
## Estimate Std. Error z value Pr(>|z|)   
## (Intercept) 1.45504 0.33609 4.329 1.5e-05 \*\*\*  
## sExp -0.38527 0.34790 -1.107 0.268   
## setNum246 0.07454 0.43918 0.170 0.865   
## setNum388 -0.07064 0.45152 -0.156 0.876   
## setNum498 -0.57334 0.45401 -1.263 0.207   
## setNum848 -0.55993 0.49252 -1.137 0.256   
## I(sExp \* sExp) 0.59328 0.82682 0.718 0.473   
## sExp:setNum246 0.51542 0.46283 1.114 0.265   
## sExp:setNum388 0.39498 0.54560 0.724 0.469   
## sExp:setNum498 -0.09217 0.46776 -0.197 0.844   
## sExp:setNum848 0.33009 0.47664 0.693 0.489   
## setNum246:I(sExp \* sExp) -1.13962 1.09712 -1.039 0.299   
## setNum388:I(sExp \* sExp) 1.35729 1.26812 1.070 0.284   
## setNum498:I(sExp \* sExp) 0.39322 1.14057 0.345 0.730   
## setNum848:I(sExp \* sExp) -1.01363 1.19037 -0.852 0.394   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
## optimizer (optimx) convergence code: 0 (OK)  
## Model failed to converge with max|grad| = 0.00404667 (tol = 0.002, component 1)

### Recall

# Scale  
dataSchemaVR4\_recall$sExp <- dataSchemaVR4\_recall$objLocTargetRating/(sd(dataSchemaVR4\_recall$objLocTargetRating)\*2)  
  
m1 <- glmer(accRecall ~ sExp\*setNum +   
 I(sExp\*sExp) +   
 (1 | subNum) +   
 (1 | objNum),   
 data = dataSchemaVR4\_recall, family = 'binomial')  
  
m2 <- glmer(accRecall ~ sExp\*setNum +   
 I(sExp\*sExp)\*setNum +   
 (1 | subNum) +   
 (1 | objNum),   
 data = dataSchemaVR4\_recall, family = 'binomial')  
  
  
kable(anova(m1, m2, test = "Chisq"))

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | npar | AIC | BIC | logLik | deviance | Chisq | Df | Pr(>Chisq) |
| m1 | 13 | 1551.698 | 1618.316 | -762.8490 | 1525.698 | NA | NA | NA |
| m2 | 17 | 1556.671 | 1643.787 | -761.3354 | 1522.671 | 3.027181 | 4 | 0.5532871 |

M2 does not fit the data better than m1 and there are not significant effects of interest.

## Generalized linear mixed model fit by maximum likelihood (Laplace  
## Approximation) [glmerMod]  
## Family: binomial ( logit )  
## Formula: accRecall ~ sExp \* setNum + I(sExp \* sExp) \* setNum + (1 | subNum) +   
## (1 | objNum)  
## Data: dataSchemaVR4\_recall  
##   
## AIC BIC logLik deviance df.resid   
## 1556.7 1643.8 -761.3 1522.7 1225   
##   
## Scaled residuals:   
## Min 1Q Median 3Q Max   
## -1.6428 -0.7169 -0.4116 0.8520 3.0842   
##   
## Random effects:  
## Groups Name Variance Std.Dev.  
## subNum (Intercept) 0.8820 0.9391   
## objNum (Intercept) 0.1897 0.4356   
## Number of obs: 1242, groups: subNum, 72; objNum, 20  
##   
## Fixed effects:  
## Estimate Std. Error z value Pr(>|z|)   
## (Intercept) -1.10727 0.36333 -3.048 0.00231 \*\*  
## sExp -0.61829 0.32533 -1.900 0.05737 .   
## setNum246 0.19793 0.46763 0.423 0.67210   
## setNum388 0.32274 0.47579 0.678 0.49757   
## setNum498 0.81443 0.49368 1.650 0.09900 .   
## setNum848 0.06442 0.54897 0.117 0.90659   
## I(sExp \* sExp) 0.14903 0.75670 0.197 0.84387   
## sExp:setNum246 1.15513 0.44918 2.572 0.01012 \*   
## sExp:setNum388 0.72773 0.45834 1.588 0.11234   
## sExp:setNum498 0.41304 0.43380 0.952 0.34103   
## sExp:setNum848 0.38055 0.47328 0.804 0.42136   
## setNum246:I(sExp \* sExp) 1.16669 1.02529 1.138 0.25516   
## setNum388:I(sExp \* sExp) 1.45117 1.03958 1.396 0.16274   
## setNum498:I(sExp \* sExp) 0.11519 1.05769 0.109 0.91327   
## setNum848:I(sExp \* sExp) 0.85754 1.19569 0.717 0.47326   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

### Remember rates

# Calculate remember rates  
remembered <- rep(0, dim(dataSchemaVR4)[1])  
remembered[dataSchemaVR4$resCon == 1] <- 1  
dataSchemaVR4$remembered <- remembered  
  
# Exclude no-memory (i.e. hasn't seen object)   
dataSchemaVR4 <- dataSchemaVR4[dataSchemaVR4$resCon != 0, ]  
  
# Scale  
dataSchemaVR4$sExp <- dataSchemaVR4$objLocTargetRating/(sd(dataSchemaVR4$objLocTargetRating)\*2)  
  
m1 <- glmer(remembered ~ sExp\*setNum +   
 I(sExp\*sExp) +   
 (1 | subNum) +   
 (1 | objNum),   
 data = dataSchemaVR4, family = 'binomial')  
  
m2 <- glmer(remembered ~ sExp\*setNum +   
 I(sExp\*sExp)\*setNum +   
 (1 | subNum) +   
 (1 | objNum),   
 data = dataSchemaVR4, family = 'binomial', control = glmerControl(optimizer ='optimx', optCtrl=list(method='L-BFGS-B')))  
  
  
kable(anova(m1, m2, test = "Chisq"))

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | npar | AIC | BIC | logLik | deviance | Chisq | Df | Pr(>Chisq) |
| m1 | 13 | 1701.636 | 1768.867 | -837.8178 | 1675.636 | NA | NA | NA |
| m2 | 17 | 1705.355 | 1793.273 | -835.6777 | 1671.355 | 4.280227 | 4 | 0.3694076 |

M2 did not fir the data better than m1 and there are no significant effects of interest.

## Generalized linear mixed model fit by maximum likelihood (Laplace  
## Approximation) [glmerMod]  
## Family: binomial ( logit )  
## Formula: remembered ~ sExp \* setNum + I(sExp \* sExp) \* setNum + (1 | subNum) +   
## (1 | objNum)  
## Data: dataSchemaVR4  
## Control:   
## glmerControl(optimizer = "optimx", optCtrl = list(method = "L-BFGS-B"))  
##   
## AIC BIC logLik deviance df.resid   
## 1705.4 1793.3 -835.7 1671.4 1285   
##   
## Scaled residuals:   
## Min 1Q Median 3Q Max   
## -3.0176 -0.8388 0.3594 0.8334 2.2095   
##   
## Random effects:  
## Groups Name Variance Std.Dev.  
## subNum (Intercept) 0.3026 0.5501   
## objNum (Intercept) 0.3925 0.6265   
## Number of obs: 1302, groups: subNum, 72; objNum, 20  
##   
## Fixed effects:  
## Estimate Std. Error z value Pr(>|z|)   
## (Intercept) 0.05605 0.29179 0.192 0.8477   
## sExp -0.70076 0.28555 -2.454 0.0141 \*  
## setNum246 -0.20562 0.34477 -0.596 0.5509   
## setNum388 0.07967 0.35771 0.223 0.8237   
## setNum498 -0.41856 0.37351 -1.121 0.2624   
## setNum848 0.06275 0.41515 0.151 0.8799   
## I(sExp \* sExp) 0.13052 0.66881 0.195 0.8453   
## sExp:setNum246 0.35788 0.40517 0.883 0.3771   
## sExp:setNum388 0.20823 0.43196 0.482 0.6298   
## sExp:setNum498 -0.12436 0.39999 -0.311 0.7559   
## sExp:setNum848 0.09804 0.43356 0.226 0.8211   
## setNum246:I(sExp \* sExp) 0.17578 0.91742 0.192 0.8481   
## setNum388:I(sExp \* sExp) 1.24507 0.99454 1.252 0.2106   
## setNum498:I(sExp \* sExp) 1.15373 0.98373 1.173 0.2409   
## setNum848:I(sExp \* sExp) -0.60150 1.06907 -0.563 0.5737   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

## Combined data

### Recognition

# Scale  
dataSchemaVR3\_4\_AFC$sExp <- dataSchemaVR3\_4\_AFC$objLocTargetRating/(sd(dataSchemaVR3\_4\_AFC$objLocTargetRating)\*2)  
  
m1 <- glmer(accAFC ~ sExp\*setNum +   
 I(sExp\*sExp) +   
 (1 | subNum) +   
 (1 | objNum),   
 data = dataSchemaVR3\_4\_AFC, family = 'binomial')  
  
m2 <- glmer(accAFC ~ sExp\*setNum +   
 I(sExp\*sExp)\*setNum +   
 (1 | subNum) +   
 (1 | objNum),   
 data = dataSchemaVR3\_4\_AFC, family = 'binomial')  
  
kable(anova(m1, m2, test = "Chisq"))

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | npar | AIC | BIC | logLik | deviance | Chisq | Df | Pr(>Chisq) |
| m1 | 13 | 1856.564 | 1927.639 | -915.2818 | 1830.564 | NA | NA | NA |
| m2 | 17 | 1860.586 | 1953.531 | -913.2930 | 1826.586 | 3.977437 | 4 | 0.4090681 |

The model m2 does not fit the data better than m1 and there is no significant quadratic relationship.

## Generalized linear mixed model fit by maximum likelihood (Laplace  
## Approximation) [glmerMod]  
## Family: binomial ( logit )  
## Formula: accAFC ~ sExp \* setNum + I(sExp \* sExp) \* setNum + (1 | subNum) +   
## (1 | objNum)  
## Data: dataSchemaVR3\_4\_AFC  
##   
## AIC BIC logLik deviance df.resid   
## 1860.6 1953.5 -913.3 1826.6 1733   
##   
## Scaled residuals:   
## Min 1Q Median 3Q Max   
## -3.7029 0.2337 0.4081 0.5558 1.4494   
##   
## Random effects:  
## Groups Name Variance Std.Dev.  
## subNum (Intercept) 0.5189 0.7204   
## objNum (Intercept) 0.1868 0.4322   
## Number of obs: 1750, groups: subNum, 96; objNum, 20  
##   
## Fixed effects:  
## Estimate Std. Error z value Pr(>|z|)   
## (Intercept) 1.00890 0.27968 3.607 0.000309 \*\*\*  
## sExp -0.22215 0.28648 -0.775 0.438069   
## setNum246 0.56960 0.36932 1.542 0.122996   
## setNum388 0.40941 0.37547 1.090 0.275543   
## setNum498 -0.08137 0.37183 -0.219 0.826766   
## setNum848 -0.12544 0.40660 -0.309 0.757694   
## I(sExp \* sExp) 1.21878 0.67484 1.806 0.070915 .   
## sExp:setNum246 0.63564 0.40105 1.585 0.112985   
## sExp:setNum388 0.43028 0.44017 0.978 0.328309   
## sExp:setNum498 -0.30748 0.39289 -0.783 0.433854   
## sExp:setNum848 0.51461 0.40764 1.262 0.206804   
## setNum246:I(sExp \* sExp) -1.55578 0.94682 -1.643 0.100350   
## setNum388:I(sExp \* sExp) 0.07946 1.00772 0.079 0.937155   
## setNum498:I(sExp \* sExp) -0.64185 0.94751 -0.677 0.498148   
## setNum848:I(sExp \* sExp) -1.07185 0.98416 -1.089 0.276109   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

### Recall

# Scale  
dataSchemaVR3\_4\_recall$sExp <- dataSchemaVR3\_4\_recall$objLocTargetRating/(sd(dataSchemaVR3\_4\_recall$objLocTargetRating)\*2)  
  
m1 <- glmer(accRecall ~ sExp\*setNum +   
 I(sExp\*sExp) +   
 (1 | subNum) +   
 (1 | objNum),   
 data = dataSchemaVR3\_4\_recall, family = 'binomial', control = glmerControl(optimizer ='optimx', optCtrl=list(method='L-BFGS-B')))  
  
m2 <- glmer(accRecall ~ sExp\*setNum +   
 I(sExp\*sExp)\*setNum +   
 (1 | subNum) +   
 (1 | objNum),   
 data = dataSchemaVR3\_4\_recall, family = 'binomial', control = glmerControl(optimizer ='optimx', optCtrl=list(method='L-BFGS-B', maxfun=2e4\*10)))  
  
kable(anova(m1, m2, test = "Chisq"))

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | npar | AIC | BIC | logLik | deviance | Chisq | Df | Pr(>Chisq) |
| m1 | 13 | 2088.524 | 2158.850 | -1031.262 | 2062.524 | NA | NA | NA |
| m2 | 17 | 2093.552 | 2185.517 | -1029.776 | 2059.552 | 2.972211 | 4 | 0.5624866 |

M2 does not fit better than m1 but there is no a U-shape that is significant. More importantly, I can’t get m2 to converge.

## Generalized linear mixed model fit by maximum likelihood (Laplace  
## Approximation) [glmerMod]  
## Family: binomial ( logit )  
## Formula: accRecall ~ sExp \* setNum + I(sExp \* sExp) \* setNum + (1 | subNum) +   
## (1 | objNum)  
## Data: dataSchemaVR3\_4\_recall  
## Control:   
## glmerControl(optimizer = "optimx", optCtrl = list(method = "L-BFGS-B",   
## maxfun = 20000 \* 10))  
##   
## AIC BIC logLik deviance df.resid   
## 2093.6 2185.5 -1029.8 2059.6 1635   
##   
## Scaled residuals:   
## Min 1Q Median 3Q Max   
## -2.3274 -0.7594 -0.4115 0.8404 3.3088   
##   
## Random effects:  
## Groups Name Variance Std.Dev.  
## subNum (Intercept) 0.8220 0.9066   
## objNum (Intercept) 0.2372 0.4870   
## Number of obs: 1652, groups: subNum, 96; objNum, 20  
##   
## Fixed effects:  
## Estimate Std. Error z value Pr(>|z|)   
## (Intercept) -1.1836 0.3186 -3.715 0.000203 \*\*\*  
## sExp -0.4476 0.2715 -1.649 0.099225 .   
## setNum246 0.5663 0.4006 1.414 0.157495   
## setNum388 0.5843 0.4079 1.432 0.152043   
## setNum498 0.9777 0.4168 2.346 0.018997 \*   
## setNum848 0.5300 0.4561 1.162 0.245154   
## I(sExp \* sExp) 0.8494 0.6602 1.287 0.198223   
## sExp:setNum246 0.9983 0.3826 2.609 0.009074 \*\*   
## sExp:setNum388 0.6969 0.3842 1.814 0.069724 .   
## sExp:setNum498 0.1605 0.3724 0.431 0.666560   
## sExp:setNum848 0.1373 0.4004 0.343 0.731615   
## setNum246:I(sExp \* sExp) 0.2917 0.9072 0.322 0.747826   
## setNum388:I(sExp \* sExp) 0.7641 0.8978 0.851 0.394756   
## setNum498:I(sExp \* sExp) -0.6616 0.9265 -0.714 0.475198   
## setNum848:I(sExp \* sExp) -0.3576 0.9885 -0.362 0.717519   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
## optimizer (optimx) convergence code: 0 (OK)  
## Model failed to converge with max|grad| = 0.00217231 (tol = 0.002, component 1)  
## unknown names in control: maxfun

### Remember

# Scale  
dataSchemaVR3\_4$sExp <- dataSchemaVR3\_4$objLocTargetRating/(sd(dataSchemaVR3\_4$objLocTargetRating)\*2)  
  
m1 <- glmer(remembered ~ sExp\*setNum +   
 I(sExp\*sExp) +   
 (1 | subNum) +   
 (1 | objNum),   
 data = dataSchemaVR3\_4, family = 'binomial')  
  
m2 <- glmer(remembered ~ sExp\*setNum +   
 I(sExp\*sExp)\*setNum +   
 (1 | subNum) +   
 (1 | objNum),   
 data = dataSchemaVR3\_4, family = 'binomial', control = glmerControl(optimizer ='optimx', optCtrl=list(method='L-BFGS-B', maxfun=2e4\*10)))  
  
kable(anova(m1, m2, test = "Chisq"))

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | npar | AIC | BIC | logLik | deviance | Chisq | Df | Pr(>Chisq) |
| m1 | 13 | 2291.782 | 2362.858 | -1132.891 | 2265.782 | NA | NA | NA |
| m2 | 17 | 2294.408 | 2387.354 | -1130.204 | 2260.408 | 5.37348 | 4 | 0.2510765 |

M2 does not fit better than m1, there is no U-shape that is significant. I can’t get m2 to converge.

## Generalized linear mixed model fit by maximum likelihood (Laplace  
## Approximation) [glmerMod]  
## Family: binomial ( logit )  
## Formula: remembered ~ sExp \* setNum + I(sExp \* sExp) \* setNum + (1 | subNum) +   
## (1 | objNum)  
## Data: dataSchemaVR3\_4  
## Control:   
## glmerControl(optimizer = "optimx", optCtrl = list(method = "L-BFGS-B",   
## maxfun = 20000 \* 10))  
##   
## AIC BIC logLik deviance df.resid   
## 2294.4 2387.4 -1130.2 2260.4 1733   
##   
## Scaled residuals:   
## Min 1Q Median 3Q Max   
## -2.8700 -0.8580 0.3849 0.8312 2.1501   
##   
## Random effects:  
## Groups Name Variance Std.Dev.  
## subNum (Intercept) 0.3590 0.5992   
## objNum (Intercept) 0.3169 0.5629   
## Number of obs: 1750, groups: subNum, 96; objNum, 20  
##   
## Fixed effects:  
## Estimate Std. Error z value Pr(>|z|)   
## (Intercept) -0.25939 0.26042 -0.996 0.3192   
## sExp -0.45591 0.24434 -1.866 0.0621 .  
## setNum246 0.17195 0.31037 0.554 0.5796   
## setNum388 0.25984 0.31966 0.813 0.4163   
## setNum498 0.09522 0.32637 0.292 0.7705   
## setNum848 0.30982 0.36140 0.857 0.3913   
## I(sExp \* sExp) 0.70267 0.57986 1.212 0.2256   
## sExp:setNum246 0.18454 0.35087 0.526 0.5989   
## sExp:setNum388 0.06550 0.36797 0.178 0.8587   
## sExp:setNum498 -0.15374 0.34524 -0.445 0.6561   
## sExp:setNum848 -0.02520 0.36863 -0.068 0.9455   
## setNum246:I(sExp \* sExp) -0.23608 0.81287 -0.290 0.7715   
## setNum388:I(sExp \* sExp) 1.02286 0.84614 1.209 0.2267   
## setNum498:I(sExp \* sExp) 0.23928 0.84655 0.283 0.7774   
## setNum848:I(sExp \* sExp) -1.04703 0.89266 -1.173 0.2408   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
## optimizer (optimx) convergence code: 0 (OK)  
## Model failed to converge with max|grad| = 0.00574528 (tol = 0.002, component 1)  
## unknown names in control: maxfun

# Use Experiment as between factor

### Recognition

# Scale  
dataSchemaVR3\_4\_AFC$sExp <- dataSchemaVR3\_4\_AFC$objLocTargetRating/(sd(dataSchemaVR3\_4\_AFC$objLocTargetRating)\*2)  
  
m1 <- glmer(accAFC ~ sExp\*Experiment +   
 I(sExp\*sExp)\*Experiment +   
 (1 | subNum) +   
 (1 | objNum), data = dataSchemaVR3\_4\_AFC, family = 'binomial')

There is no significant effect.

## Generalized linear mixed model fit by maximum likelihood (Laplace  
## Approximation) [glmerMod]  
## Family: binomial ( logit )  
## Formula: accAFC ~ sExp \* Experiment + I(sExp \* sExp) \* Experiment + (1 |   
## subNum) + (1 | objNum)  
## Data: dataSchemaVR3\_4\_AFC  
##   
## AIC BIC logLik deviance df.resid   
## 1859.2 1903.0 -921.6 1843.2 1742   
##   
## Scaled residuals:   
## Min 1Q Median 3Q Max   
## -3.3207 0.2461 0.4193 0.5555 1.2889   
##   
## Random effects:  
## Groups Name Variance Std.Dev.  
## subNum (Intercept) 0.6162 0.7850   
## objNum (Intercept) 0.1823 0.4269   
## Number of obs: 1750, groups: subNum, 96; objNum, 20  
##   
## Fixed effects:  
## Estimate Std. Error z value Pr(>|z|)   
## (Intercept) 0.9593 0.2617 3.666 0.000246 \*\*\*  
## sExp 0.3830 0.2386 1.605 0.108414   
## Experiment4 0.3166 0.2833 1.118 0.263753   
## I(sExp \* sExp) 0.9501 0.5873 1.618 0.105708   
## sExp:Experiment4 -0.4644 0.2747 -1.690 0.090943 .   
## Experiment4:I(sExp \* sExp) -0.6003 0.6806 -0.882 0.377791   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Correlation of Fixed Effects:  
## (Intr) sExp Exprm4 I(E\*sE sEx:E4  
## sExp -0.015   
## Experiment4 -0.790 0.014   
## I(sEx\*sExp) -0.537 0.065 0.486   
## sExp:Exprm4 0.016 -0.842 -0.025 -0.060   
## Ex4:I(E\*sE) 0.450 -0.053 -0.584 -0.834 0.068

### Recall

# Scale  
dataSchemaVR3\_4\_recall$sExp <- dataSchemaVR3\_4\_recall$objLocTargetRating/(sd(dataSchemaVR3\_4\_recall$objLocTargetRating)\*2)  
  
m1 <- glmer(accRecall ~ sExp\*Experiment +   
 I(sExp\*sExp)\*Experiment +   
 (1 | subNum) +   
 (1 | objNum),   
 data = dataSchemaVR3\_4\_recall, family = 'binomial', control = glmerControl(optimizer ='optimx', optCtrl=list(method='L-BFGS-B')))

I can’t get the model to converge to converge.

## Generalized linear mixed model fit by maximum likelihood (Laplace  
## Approximation) [glmerMod]  
## Family: binomial ( logit )  
## Formula: accRecall ~ sExp \* Experiment + I(sExp \* sExp) \* Experiment +   
## (1 | subNum) + (1 | objNum)  
## Data: dataSchemaVR3\_4\_recall  
## Control:   
## glmerControl(optimizer = "optimx", optCtrl = list(method = "L-BFGS-B"))  
##   
## AIC BIC logLik deviance df.resid   
## 2087.9 2131.2 -1036.0 2071.9 1644   
##   
## Scaled residuals:   
## Min 1Q Median 3Q Max   
## -2.0861 -0.7558 -0.4163 0.8585 3.2391   
##   
## Random effects:  
## Groups Name Variance Std.Dev.  
## subNum (Intercept) 0.8149 0.9027   
## objNum (Intercept) 0.2027 0.4502   
## Number of obs: 1652, groups: subNum, 96; objNum, 20  
##   
## Fixed effects:  
## Estimate Std. Error z value Pr(>|z|)   
## (Intercept) -0.087619 0.277736 -0.315 0.7524   
## sExp -0.001484 0.218098 -0.007 0.9946   
## Experiment4 -0.744682 0.299072 -2.490 0.0128 \*  
## I(sExp \* sExp) 0.571522 0.561150 1.018 0.3084   
## sExp:Experiment4 -0.072428 0.252746 -0.287 0.7744   
## Experiment4:I(sExp \* sExp) 0.352348 0.647211 0.544 0.5862   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Correlation of Fixed Effects:  
## (Intr) sExp Exprm4 I(E\*sE sEx:E4  
## sExp -0.010   
## Experiment4 -0.797 0.008   
## I(sEx\*sExp) -0.525 0.013 0.469   
## sExp:Exprm4 0.010 -0.834 -0.018 -0.015   
## Ex4:I(E\*sE) 0.438 -0.010 -0.557 -0.836 0.045  
## optimizer (optimx) convergence code: 0 (OK)  
## Model failed to converge with max|grad| = 0.00211601 (tol = 0.002, component 1)

### Remember

# Scale  
dataSchemaVR3\_4$sExp <- dataSchemaVR3\_4$objLocTargetRating/(sd(dataSchemaVR3\_4$objLocTargetRating)\*2)  
  
m1 <- glmer(remembered ~ sExp\*Experiment + I(sExp\*sExp)\*Experiment + (1 | subNum) + (1 | objNum), data = dataSchemaVR3\_4, family = 'binomial')

No interaction between Experiment and anything but a U-shape.

## Generalized linear mixed model fit by maximum likelihood (Laplace  
## Approximation) [glmerMod]  
## Family: binomial ( logit )  
## Formula: remembered ~ sExp \* Experiment + I(sExp \* sExp) \* Experiment +   
## (1 | subNum) + (1 | objNum)  
## Data: dataSchemaVR3\_4  
##   
## AIC BIC logLik deviance df.resid   
## 2283.8 2327.5 -1133.9 2267.8 1742   
##   
## Scaled residuals:   
## Min 1Q Median 3Q Max   
## -2.5717 -0.8618 0.4076 0.8268 2.2478   
##   
## Random effects:  
## Groups Name Variance Std.Dev.  
## subNum (Intercept) 0.3839 0.6196   
## objNum (Intercept) 0.3172 0.5632   
## Number of obs: 1750, groups: subNum, 96; objNum, 20  
##   
## Fixed effects:  
## Estimate Std. Error z value Pr(>|z|)   
## (Intercept) -0.2411 0.2458 -0.981 0.3266   
## sExp -0.1497 0.2137 -0.701 0.4836   
## Experiment4 0.1908 0.2421 0.788 0.4307   
## I(sExp \* sExp) 1.2483 0.5371 2.324 0.0201 \*  
## sExp:Experiment4 -0.3948 0.2447 -1.614 0.1066   
## Experiment4:I(sExp \* sExp) -0.7660 0.6141 -1.247 0.2123   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Correlation of Fixed Effects:  
## (Intr) sExp Exprm4 I(E\*sE sEx:E4  
## sExp -0.004   
## Experiment4 -0.737 0.002   
## I(sEx\*sExp) -0.544 -0.022 0.533   
## sExp:Exprm4 0.007 -0.845 -0.015 0.012   
## Ex4:I(E\*sE) 0.458 0.019 -0.627 -0.844 0.009

# Additional analysis as reminder

accAFC ~ I(sExp\*sExp) + (1 | subNum) + (1 | objNum), data = Exp3

m1 <- glmer(accAFC ~ sExp + I(sExp\*sExp)+ (1 | subNum) + (1 | objNum), data = dataSchemaVR3\_AFC, family = 'binomial')  
  
summary(m1)

## Generalized linear mixed model fit by maximum likelihood (Laplace  
## Approximation) [glmerMod]  
## Family: binomial ( logit )  
## Formula: accAFC ~ sExp + I(sExp \* sExp) + (1 | subNum) + (1 | objNum)  
## Data: dataSchemaVR3\_AFC  
##   
## AIC BIC logLik deviance df.resid   
## 505.0 525.5 -247.5 495.0 443   
##   
## Scaled residuals:   
## Min 1Q Median 3Q Max   
## -3.3331 -0.9041 0.4405 0.5720 1.1869   
##   
## Random effects:  
## Groups Name Variance Std.Dev.  
## subNum (Intercept) 0.4435 0.6659   
## objNum (Intercept) 0.2766 0.5259   
## Number of obs: 448, groups: subNum, 24; objNum, 20  
##   
## Fixed effects:  
## Estimate Std. Error z value Pr(>|z|)   
## (Intercept) 0.9611 0.2597 3.701 0.000215 \*\*\*  
## sExp 0.4049 0.2476 1.635 0.102007   
## I(sExp \* sExp) 0.9586 0.6172 1.553 0.120405   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Correlation of Fixed Effects:  
## (Intr) sExp   
## sExp -0.007   
## I(sEx\*sExp) -0.542 0.079

accAFC ~ I(sExp\*sExp) + (1 | subNum) + (1 | objNum), data = Exp3+half-Exp4 (ie results in preprint)

sub\_dat <- dataSchemaVR3\_4\_AFC[!(dataSchemaVR3\_4\_AFC$subNum %in% exclude), ]  
  
m1 <- glmer(accAFC ~ sExp + I(sExp\*sExp)+ (1 | subNum) + (1 | objNum), data = sub\_dat, family = 'binomial')  
  
summary(m1)

## Generalized linear mixed model fit by maximum likelihood (Laplace  
## Approximation) [glmerMod]  
## Family: binomial ( logit )  
## Formula: accAFC ~ sExp + I(sExp \* sExp) + (1 | subNum) + (1 | objNum)  
## Data: sub\_dat  
##   
## AIC BIC logLik deviance df.resid   
## 1459.2 1485.3 -724.6 1449.2 1367   
##   
## Scaled residuals:   
## Min 1Q Median 3Q Max   
## -3.3428 0.2659 0.4221 0.5533 1.2397   
##   
## Random effects:  
## Groups Name Variance Std.Dev.  
## subNum (Intercept) 0.5557 0.7455   
## objNum (Intercept) 0.1665 0.4080   
## Number of obs: 1372, groups: subNum, 75; objNum, 20  
##   
## Fixed effects:  
## Estimate Std. Error z value Pr(>|z|)   
## (Intercept) 1.14114 0.16982 6.72 1.82e-11 \*\*\*  
## sExp -0.04131 0.14254 -0.29 0.7719   
## I(sExp \* sExp) 0.69895 0.36404 1.92 0.0549 .   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Correlation of Fixed Effects:  
## (Intr) sExp   
## sExp -0.025   
## I(sEx\*sExp) -0.518 0.064

accAFC ~ I(sExp\*sExp) + (1 | subNum) + (1 | objNum), data = Exp3+all-Exp4

m1 <- glmer(accAFC ~ sExp + I(sExp\*sExp)+ (1 | subNum) + (1 | objNum), data = dataSchemaVR3\_4\_AFC, family = 'binomial')  
  
summary(m1)

## Generalized linear mixed model fit by maximum likelihood (Laplace  
## Approximation) [glmerMod]  
## Family: binomial ( logit )  
## Formula: accAFC ~ sExp + I(sExp \* sExp) + (1 | subNum) + (1 | objNum)  
## Data: dataSchemaVR3\_4\_AFC  
##   
## AIC BIC logLik deviance df.resid   
## 1857.2 1884.5 -923.6 1847.2 1745   
##   
## Scaled residuals:   
## Min 1Q Median 3Q Max   
## -3.4137 0.2506 0.4178 0.5571 1.3403   
##   
## Random effects:  
## Groups Name Variance Std.Dev.  
## subNum (Intercept) 0.6140 0.7836   
## objNum (Intercept) 0.1838 0.4287   
## Number of obs: 1750, groups: subNum, 96; objNum, 20  
##   
## Fixed effects:  
## Estimate Std. Error z value Pr(>|z|)   
## (Intercept) 1.18990 0.16048 7.415 1.22e-13 \*\*\*  
## sExp 0.04743 0.12845 0.369 0.712   
## I(sExp \* sExp) 0.52522 0.32395 1.621 0.105   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Correlation of Fixed Effects:  
## (Intr) sExp   
## sExp -0.020   
## I(sEx\*sExp) -0.479 0.062

accAFC ~ Exp34 \* I(sExp\*sExp) + (1 | subNum) + (1 | objNum), data = Exp3+all-Exp4#

????