**Supplementary Materials**

The below are the R codes and the detailed analysis procedures for the present experiments.

**Supplementary Materials 1.**

**R code for the analysis of sentence completion task**

**SCT Poisson Log-linear**

Authors

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**Possion Log-linear**

**Package preparation**

If you haven't installed the packages yet, please first install the packages.

**install.packages**("stats")  
**install.packages**("tidyr")  
**install.packages**("dplyr")  
**install.packages**("car")  
**install.packages**("sjPlot")  
**install.packages**("lsmeans")  
**install.packages**("MASS")

Then read the necessary packages

**library**(stats)  
**library**(tidyr)  
**library**(dplyr)  
**library**(car)  
**library**(sjPlot)  
**library**(lsmeans)  
**library**(MASS)

**Reading the data**

sct.all<-**read.table**("SCT-table.csv",header=T,sep=",")  
**print**(sct.all)

## Verb Noun Category Freq  
## 1 Recip conj Intr 20  
## 2 Recip conj Trans 13  
## 3 Recip conj Recip 126  
## 4 Recip conj Error 1  
## 5 Recip PDD Intr 34  
## 6 Recip PDD Trans 38  
## 7 Recip PDD Recip 83  
## 8 Recip PDD Error 5  
## 9 OT conj Intr 77  
## 10 OT conj Trans 83  
## 11 OT conj Recip 0  
## 12 OT conj Error 0  
## 13 OT PDD Intr 82  
## 14 OT PDD Trans 76  
## 15 OT PDD Recip 0  
## 16 OT PDD Error 2

**Analysis for reciprocal verbs**

**Preparing data sets**

Exctracting the data for reciprocal verbs

sct.all%>%  
 **filter**(Verb=="Recip")->dat.recip  
**print**(dat.recip)

## Verb Noun Category Freq  
## 1 Recip conj Intr 20  
## 2 Recip conj Trans 13  
## 3 Recip conj Recip 126  
## 4 Recip conj Error 1  
## 5 Recip PDD Intr 34  
## 6 Recip PDD Trans 38  
## 7 Recip PDD Recip 83  
## 8 Recip PDD Error 5

We are not going to use error data. However, it will inevitablly have an impact on the sum frequency of the observation. That is, the more the error data is, the less the sum frequency is. To control a different number of the sum frequency, we are going to use the number of observation as an offset term in the poisson loglinear analysis.

*#Exclude the error data*  
dat.recip%>%  
 **filter**(Category != "Error")->recip.NoError

You can see that there is one error observation in [Recip-conj] condition and 5 error observations in [Recip-PDD] condition among each 160 obvervations. Therefore, the sum frequency for the [Recip-conj] condition is 160-1 = 159, and for the [Recip-PDD] condition is 160-5 = 155. We add the sum frequency into Obs variable

recip.NoError$Obs<-**c**(**rep**(159,3),**rep**(155,3))  
**print**(recip.NoError)

## Verb Noun Category Freq Obs  
## 1 Recip conj Intr 20 159  
## 2 Recip conj Trans 13 159  
## 3 Recip conj Recip 126 159  
## 4 Recip PDD Intr 34 155  
## 5 Recip PDD Trans 38 155  
## 6 Recip PDD Recip 83 155

**Change coding**

Since it is very likely that we face multicolinearlity issue with dummy coding of the categorical variable, we are going to change it to contrast coding.

*#For two levels*  
c2<-**contr.treatment**(2)  
my.coding2<-**matrix**(**rep**(1/2,2),ncol=1)  
my.simple2<-c2-my.coding2  
**contrasts**(recip.NoError$Noun)<-my.simple2  
  
*#For three levels*  
*#We first need to drop the empty level (Error) from the Category variable*  
recip.NoError$Category<-**droplevels**(recip.NoError$Category)  
c3<-**contr.treatment**(3)  
c3

## 2 3  
## 1 0 0  
## 2 1 0  
## 3 0 1

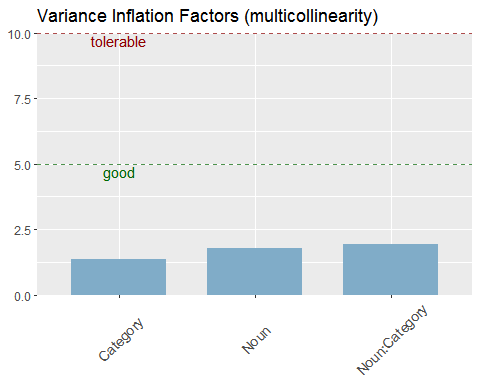
my.coding3<-**matrix**(**rep**(1/3,6),ncol=2)  
my.simple3<-c3-my.coding3  
**contrasts**(recip.NoError$Category)<-my.simple3

**Log-linear regreggion by glm**

model1<-**glm**(Freq~Noun+Category+Noun:Category, offset = **log**(Obs), family = poisson, data = recip.NoError)  
**vif**(model1)

## GVIF Df GVIF^(1/(2\*Df))  
## Noun 1.767144 1 1.329340  
## Category 1.357462 2 1.079399  
## Noun:Category 1.916803 2 1.176642

**sjp.glm**(model1,type = "vif") *#check VIF visually*



Seek the best model by step wise procedure.

**stepAIC**(model1)

## Start: AIC=45.04  
## Freq ~ Noun + Category + Noun:Category  
##   
## Df Deviance AIC  
## <none> 0.000 45.041  
## - Noun:Category 2 25.331 66.372

##   
## Call: glm(formula = Freq ~ Noun + Category + Noun:Category, family = poisson,   
## data = recip.NoError, offset = log(Obs))  
##   
## Coefficients:  
## (Intercept) Noun2 Category2 Category3   
## -1.3929 0.4208 1.3665 -0.1598   
## Noun2:Category2 Noun2:Category3   
## -0.9481 0.5420   
##   
## Degrees of Freedom: 5 Total (i.e. Null); 0 Residual  
## Null Deviance: 169.6   
## Residual Deviance: 5.995e-15 AIC: 45.04

The full model with interaction term was chosen as the best model, so let us now see the results of poisson loglinear analysis

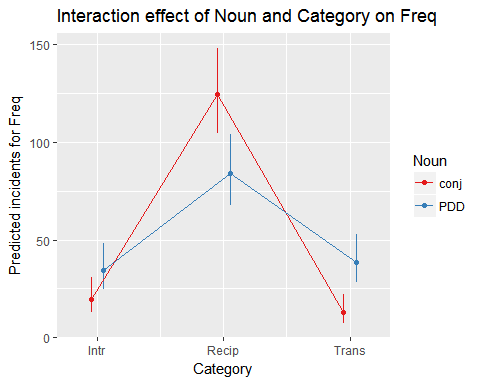
**summary**(model1)

##   
## Call:  
## glm(formula = Freq ~ Noun + Category + Noun:Category, family = poisson,   
## data = recip.NoError, offset = log(Obs))  
##   
## Deviance Residuals:   
## [1] 0 0 0 0 0 0  
##   
## Coefficients:  
## Estimate Std. Error z value Pr(>|z|)   
## (Intercept) -1.39287 0.07503 -18.565 < 2e-16 \*\*\*  
## Noun2 0.42075 0.15005 2.804 0.00505 \*\*   
## Category2 1.36651 0.15764 8.669 < 2e-16 \*\*\*  
## Category3 -0.15978 0.21369 -0.748 0.45463   
## Noun2:Category2 -0.94807 0.31527 -3.007 0.00264 \*\*   
## Noun2:Category3 0.54201 0.42738 1.268 0.20472   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## (Dispersion parameter for poisson family taken to be 1)  
##   
## Null deviance: 1.6959e+02 on 5 degrees of freedom  
## Residual deviance: 5.9952e-15 on 0 degrees of freedom  
## AIC: 45.041  
##   
## Number of Fisher Scoring iterations: 3

We found there is a significant interaction between the Noun type and the Category. We visualize the interaction by sjp.int function.

**Visualization**

**sjp.int**(model1,show.ci = T,plevel = .05,jitter.ci = T)



It seems that the frequency of reciprocal verbs and transitive verbs differs between conjoined NP and plural definite nouns.To look at the freqnecy differences, we carry out multiple comparison using least square means.

**Multiple Comparison**

*#library(lsmeans)*  
**lsmeans**(model1,pairwise~Category|Noun)$contrasts

## Noun = conj:  
## contrast estimate SE df z.ratio p.value  
## Intr - Recip -1.8405496 0.2407000 NA -7.647 <.0001  
## Intr - Trans 0.4307829 0.3562627 NA 1.209 0.4477  
## Recip - Trans 2.2713325 0.2913067 NA 7.797 <.0001  
##   
## Noun = PDD:  
## contrast estimate SE df z.ratio p.value  
## Intr - Recip -0.8924801 0.2036172 NA -4.383 <.0001  
## Intr - Trans -0.1112256 0.2360668 NA -0.471 0.8849  
## Recip - Trans 0.7812544 0.1958673 NA 3.989 0.0002  
##   
## Results are given in the log (not the response) scale.   
## P value adjustment: tukey method for comparing a family of 3 estimates

**lsmeans**(model1,pairwise~Noun|Category)$contrasts

## Category = Intr:  
## contrast estimate SE df z.ratio p.value  
## conj - PDD -0.5561073 0.2818009 NA -1.973 0.0484  
##   
## Category = Recip:  
## contrast estimate SE df z.ratio p.value  
## conj - PDD 0.3919622 0.1413673 NA 2.773 0.0056  
##   
## Category = Trans:  
## contrast estimate SE df z.ratio p.value  
## conj - PDD -1.0981159 0.3213081 NA -3.418 0.0006  
##   
## Results are given in the log (not the response) scale.

In summary, we found:

* Intransitive verbs: PDD > conj
* Reciprocal verbs: conj > PDD
* Transitive verbs: PDD > conj

and

* conjoined NP
  + Intransitive < Reciprocal
  + Intransitive = Transitive
  + Reciprocal > Transitive
* Plural definite nouns (PDD)
  + Intransitive < Reciprocal
  + Intransitive = Transitive
  + Reciprocal > Transitive

**Analysis for Optionally Transitive Verbs**

Now, let us analyze the case of optionally transitive (OT) verbs

sct.all%>%  
 **filter**(Verb=="OT")->dat.ot  
**print**(dat.ot)

## Verb Noun Category Freq  
## 1 OT conj Intr 77  
## 2 OT conj Trans 83  
## 3 OT conj Recip 0  
## 4 OT conj Error 0  
## 5 OT PDD Intr 82  
## 6 OT PDD Trans 76  
## 7 OT PDD Recip 0  
## 8 OT PDD Error 2

As we did above, we exclude the error data. Also, there are strctural zeros of reciprocal verbs, so we also delete those rows.

*#Exclude the error data*  
dat.ot%>%  
 **filter**(Category != "Error" & Category != "Recip")->ot.NoError  
**print**(ot.NoError)

## Verb Noun Category Freq  
## 1 OT conj Intr 77  
## 2 OT conj Trans 83  
## 3 OT PDD Intr 82  
## 4 OT PDD Trans 76

You can see that there is no error observation in [OT-conj] condition but 2 error observations are found in [OT-PDD] condition among each 160 obvervations. Therefore, the sum frequency for the [OT-conj] condition is 160, and for the [OT-PDD] condition is 160-2 = 158. We add the sum frequency into Obs variable

ot.NoError$Obs<-**c**(**rep**(160,2),**rep**(158,2))  
**print**(ot.NoError)

## Verb Noun Category Freq Obs  
## 1 OT conj Intr 77 160  
## 2 OT conj Trans 83 160  
## 3 OT PDD Intr 82 158  
## 4 OT PDD Trans 76 158

**Change coding**

Since it is very likely that we face multicolinearlity issue with dummy coding of the categorical variable, we are going to change it to contrast coding.

*#For two levels*  
**contrasts**(ot.NoError$Noun)<-my.simple2  
**contrasts**(ot.NoError$Noun)<-my.simple2

**Log-linear regression by glm**

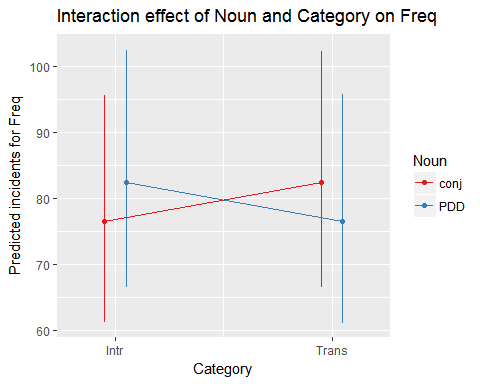
model2<-**glm**(Freq~Noun\*Category,offset = **log**(Obs),data=ot.NoError,family = poisson)  
**summary**(model2)

##   
## Call:  
## glm(formula = Freq ~ Noun \* Category, family = poisson, data = ot.NoError,   
## offset = log(Obs))  
##   
## Deviance Residuals:   
## [1] 0 0 0 0  
##   
## Coefficients:  
## Estimate Std. Error z value Pr(>|z|)   
## (Intercept) -0.6936221 0.0793444 -8.742 <2e-16 \*\*\*  
## Noun2 0.0754926 0.1586887 0.476 0.634   
## CategoryTrans -0.0004754 0.1122366 -0.004 0.997   
## Noun2:CategoryTrans -0.1510211 0.2244731 -0.673 0.501   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## (Dispersion parameter for poisson family taken to be 1)  
##   
## Null deviance: 4.5296e-01 on 3 degrees of freedom  
## Residual deviance: -8.8818e-16 on 0 degrees of freedom  
## AIC: 32.86  
##   
## Number of Fisher Scoring iterations: 2

**vif**(model2)

## Noun Category Noun:Category   
## 2.001901 1.001466 2.000991

**sjp.int**(model2,show.ci=T,jitter.ci = T)



We can see that there is no interaction between the noun type and the category. Now, we reduce the terms by backward procedure.

**stepAIC**(model2,direction = "backward")

## Start: AIC=32.86  
## Freq ~ Noun \* Category  
##   
## Df Deviance AIC  
## - Noun:Category 1 0.45296 31.313  
## <none> 0.00000 32.860  
##   
## Step: AIC=31.31  
## Freq ~ Noun + Category  
##   
## Df Deviance AIC  
## - Noun 1 0.45296 29.313  
## - Category 1 0.45296 29.313  
## <none> 0.45296 31.313  
##   
## Step: AIC=29.31  
## Freq ~ Category  
##   
## Df Deviance AIC  
## - Category 1 0.45296 27.313  
## <none> 0.45296 29.313  
##   
## Step: AIC=27.31  
## Freq ~ 1

##   
## Call: glm(formula = Freq ~ 1, family = poisson, data = ot.NoError,   
## offset = log(Obs))  
##   
## Coefficients:  
## (Intercept)   
## -0.6931   
##   
## Degrees of Freedom: 3 Total (i.e. Null); 3 Residual  
## Null Deviance: 0.453   
## Residual Deviance: 0.453 AIC: 27.31

The result of model selection shows that neither factor explains the frequency differences, suggesting that the frequency is evenly distributed.

model3<-**stepAIC**(model2,direction = "backward")

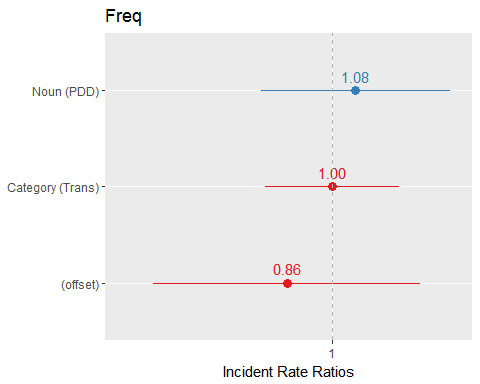
## Start: AIC=32.86  
## Freq ~ Noun \* Category  
##   
## Df Deviance AIC  
## - Noun:Category 1 0.45296 31.313  
## <none> 0.00000 32.860  
##   
## Step: AIC=31.31  
## Freq ~ Noun + Category  
##   
## Df Deviance AIC  
## - Noun 1 0.45296 29.313  
## - Category 1 0.45296 29.313  
## <none> 0.45296 31.313  
##   
## Step: AIC=29.31  
## Freq ~ Category  
##   
## Df Deviance AIC  
## - Category 1 0.45296 27.313  
## <none> 0.45296 29.313  
##   
## Step: AIC=27.31  
## Freq ~ 1

**summary**(model3)

##   
## Call:  
## glm(formula = Freq ~ 1, family = poisson, data = ot.NoError,   
## offset = log(Obs))  
##   
## Deviance Residuals:   
## 1 2 3 4   
## -0.3375 0.3333 0.3354 -0.3397   
##   
## Coefficients:  
## Estimate Std. Error z value Pr(>|z|)   
## (Intercept) -0.69315 0.05608 -12.36 <2e-16 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## (Dispersion parameter for poisson family taken to be 1)  
##   
## Null deviance: 0.45296 on 3 degrees of freedom  
## Residual deviance: 0.45296 on 3 degrees of freedom  
## AIC: 27.313  
##   
## Number of Fisher Scoring iterations: 3

**Visualization of Odds Ratio**

**sjp.glm**(model2)



**Supplementary Materials 2.**

**R code for the analysis of self-paced reading task.**

**Japanese EFL Learners' Online Sentence Processing**

Authors

January 5, 2018

This document explains the GLMM analysis of Authors (2018) submitted to Applied Psycholinguistics.

**Reading Time Analysis**

**Preparing required packages**

*#install.packages("lmer4")*  
*#install.packages("effects")*  
*#install.packages("dplyr")*  
*#install.packages("sjplot")*  
**library**(lme4)  
**library**(effects)  
**library**(dplyr)  
**library**(sjPlot)  
**library**(lsmeans)  
*#useful code by Jaeger to calculate vif in glmer*  
**source**("https://raw.githubusercontent.com/aufrank/R-hacks/master/mer-utils.R")

**Preparing data sets**

first.noun<-**read.csv**("first-noun-28\_20170109.csv",header=T) *#the head noun before the target verb (the subject noun of hte main clause)*  
target.verb<-**read.csv**("target-verb-28\_20170109.csv",header=T) *#the target verb (the verb of the main clause)*   
aft.verb1<-**read.csv**("one-word-aft-verb-28\_20170109.csv",header=T) *#The following region of the target verb (One word after the target verb, which is either definite or indefinite article)*  
aft.verb2<-**read.csv**("two-words-aft-verb-28\_20170109.csv",header=T) *#The following region of the target verb (Two words after the target verb, which is the head noun of the object NP of the main verb)*

**Checking the data sets**

**head**(first.noun)

## condition item region stimuli participant rt recip conj  
## 1 a 3 8 chef 1 397 reciprocal conjoinedNP  
## 2 a 5 8 student 1 1493 reciprocal conjoinedNP  
## 3 a 13 8 editor 1 406 reciprocal conjoinedNP  
## 4 a 18 8 man 1 438 reciprocal conjoinedNP  
## 5 a 20 8 employer 1 270 reciprocal conjoinedNP  
## 6 b 8 5 girl 1 1345 reciprocal PDD  
## TOEIC c.TOEIC  
## 1 805 45.89286  
## 2 805 45.89286  
## 3 805 45.89286  
## 4 805 45.89286  
## 5 805 45.89286  
## 6 805 45.89286

**str**(first.noun)

## 'data.frame': 560 obs. of 10 variables:  
## $ condition : Factor w/ 4 levels "a","b","c","d": 1 1 1 1 1 2 2 2 2 2 ...  
## $ item : int 3 5 13 18 20 8 9 10 11 16 ...  
## $ region : int 8 8 8 8 8 5 5 5 5 5 ...  
## $ stimuli : Factor w/ 18 levels "actor","baby",..: 4 16 6 11 8 9 12 17 10 2 ...  
## $ participant: int 1 1 1 1 1 1 1 1 1 1 ...  
## $ rt : int 397 1493 406 438 270 1345 1459 382 1200 566 ...  
## $ recip : Factor w/ 2 levels "OT","reciprocal": 2 2 2 2 2 2 2 2 2 2 ...  
## $ conj : Factor w/ 2 levels "conjoinedNP",..: 1 1 1 1 1 2 2 2 2 2 ...  
## $ TOEIC : int 805 805 805 805 805 805 805 805 805 805 ...  
## $ c.TOEIC : num 45.9 45.9 45.9 45.9 45.9 ...

**summary**(first.noun)

## condition item region stimuli participant   
## a:140 Min. : 1.00 Min. :5.0 man : 56 Min. : 1.00   
## b:140 1st Qu.: 5.75 1st Qu.:5.0 manager: 56 1st Qu.: 9.75   
## c:140 Median :10.50 Median :6.5 woman : 56 Median :16.50   
## d:140 Mean :10.53 Mean :6.5 actor : 28 Mean :16.75   
## 3rd Qu.:15.25 3rd Qu.:8.0 baby : 28 3rd Qu.:24.25   
## Max. :20.00 Max. :8.0 boy : 28 Max. :32.00   
## (Other):308   
## rt recip conj TOEIC   
## Min. : 202.0 OT :280 conjoinedNP:280 Min. :600.0   
## 1st Qu.: 374.8 reciprocal:280 PDD :280 1st Qu.:800.0   
## Median : 521.5 Median :860.0   
## Mean : 576.5 Mean :850.9   
## 3rd Qu.: 693.8 3rd Qu.:911.2   
## Max. :2071.0 Max. :990.0   
## NA's :24   
## c.TOEIC   
## Min. :-139.107   
## 1st Qu.: -60.357   
## Median : -9.107   
## Mean : 0.000   
## 3rd Qu.: 50.893   
## Max. : 250.893   
##

**head**(target.verb)

## condition item region stimuli participant rt recip conj  
## 1 a 3 9 cooked 1 NA reciprocal conjoinedNP  
## 2 a 5 9 sang 1 851 reciprocal conjoinedNP  
## 3 a 13 9 heard 1 754 reciprocal conjoinedNP  
## 4 a 18 9 took 1 396 reciprocal conjoinedNP  
## 5 a 20 9 called 1 NA reciprocal conjoinedNP  
## 6 c 1 9 cancelled 1 2497 OT conjoinedNP  
## TOEIC c.TOEIC  
## 1 805 45.89286  
## 2 805 45.89286  
## 3 805 45.89286  
## 4 805 45.89286  
## 5 805 45.89286  
## 6 805 45.89286

**str**(target.verb)

## 'data.frame': 560 obs. of 10 variables:  
## $ condition : Factor w/ 4 levels "a","b","c","d": 1 1 1 1 1 3 3 3 3 3 ...  
## $ item : int 3 5 13 18 20 1 4 7 14 17 ...  
## $ region : int 9 9 9 9 9 9 9 9 9 9 ...  
## $ stimuli : Factor w/ 16 levels "called","canceled",..: 4 13 7 15 1 3 5 15 1 14 ...  
## $ participant: int 1 1 1 1 1 1 1 1 1 1 ...  
## $ rt : int NA 851 754 396 NA 2497 368 2318 600 329 ...  
## $ recip : Factor w/ 2 levels "OT","reciprocal": 2 2 2 2 2 1 1 1 1 1 ...  
## $ conj : Factor w/ 2 levels "conjoinedNP",..: 1 1 1 1 1 1 1 1 1 1 ...  
## $ TOEIC : int 805 805 805 805 805 805 805 805 805 805 ...  
## $ c.TOEIC : num 45.9 45.9 45.9 45.9 45.9 ...

**summary**(target.verb)

## condition item region stimuli participant   
## a:140 Min. : 1.00 Min. :6.0 played : 84 Min. : 1.00   
## b:140 1st Qu.: 5.75 1st Qu.:6.0 called : 56 1st Qu.: 9.75   
## c:140 Median :10.50 Median :7.5 took : 56 Median :16.50   
## d:140 Mean :10.53 Mean :7.5 heard : 36 Mean :16.75   
## 3rd Qu.:15.25 3rd Qu.:9.0 canceled : 28 3rd Qu.:24.25   
## Max. :20.00 Max. :9.0 cancelled: 28 Max. :32.00   
## (Other) :272   
## rt recip conj TOEIC   
## Min. : 202.0 OT :280 conjoinedNP:280 Min. :600.0   
## 1st Qu.: 406.0 reciprocal:280 PDD :280 1st Qu.:800.0   
## Median : 564.0 Median :860.0   
## Mean : 667.1 Mean :850.9   
## 3rd Qu.: 786.0 3rd Qu.:911.2   
## Max. :2829.0 Max. :990.0   
## NA's :59   
## c.TOEIC   
## Min. :-139.107   
## 1st Qu.: -60.357   
## Median : -9.107   
## Mean : 0.000   
## 3rd Qu.: 50.893   
## Max. : 250.893   
##

**head**(aft.verb1)

## condition item region stimuli participant rt recip conj  
## 1 a 3 10 the 1 381 reciprocal conjoinedNP  
## 2 a 5 10 the 1 459 reciprocal conjoinedNP  
## 3 a 13 10 the 1 440 reciprocal conjoinedNP  
## 4 a 18 10 his 1 756 reciprocal conjoinedNP  
## 5 a 20 10 the 1 322 reciprocal conjoinedNP  
## 6 c 1 10 the 1 968 OT conjoinedNP  
## TOEIC c.TOEIC  
## 1 805 45.89286  
## 2 805 45.89286  
## 3 805 45.89286  
## 4 805 45.89286  
## 5 805 45.89286  
## 6 805 45.89286

**str**(aft.verb1)

## 'data.frame': 560 obs. of 10 variables:  
## $ condition : Factor w/ 4 levels "a","b","c","d": 1 1 1 1 1 3 3 3 3 3 ...  
## $ item : int 3 5 13 18 20 1 4 7 14 17 ...  
## $ region : int 10 10 10 10 10 10 10 10 10 10 ...  
## $ stimuli : Factor w/ 2 levels "his","the": 2 2 2 1 2 2 2 2 2 2 ...  
## $ participant: int 1 1 1 1 1 1 1 1 1 1 ...  
## $ rt : int 381 459 440 756 322 968 775 1413 394 760 ...  
## $ recip : Factor w/ 2 levels "OT","reciprocal": 2 2 2 2 2 1 1 1 1 1 ...  
## $ conj : Factor w/ 2 levels "conjoinedNP",..: 1 1 1 1 1 1 1 1 1 1 ...  
## $ TOEIC : int 805 805 805 805 805 805 805 805 805 805 ...  
## $ c.TOEIC : num 45.9 45.9 45.9 45.9 45.9 ...

**summary**(aft.verb1)

## condition item region stimuli participant   
## a:140 Min. : 1.00 Min. : 7.0 his: 28 Min. : 1.00   
## b:140 1st Qu.: 5.75 1st Qu.: 7.0 the:532 1st Qu.: 9.75   
## c:140 Median :10.50 Median : 8.5 Median :16.50   
## d:140 Mean :10.53 Mean : 8.5 Mean :16.75   
## 3rd Qu.:15.25 3rd Qu.:10.0 3rd Qu.:24.25   
## Max. :20.00 Max. :10.0 Max. :32.00   
##   
## rt recip conj TOEIC   
## Min. : 233.0 OT :280 conjoinedNP:280 Min. :600.0   
## 1st Qu.: 382.0 reciprocal:280 PDD :280 1st Qu.:800.0   
## Median : 448.0 Median :860.0   
## Mean : 541.3 Mean :850.9   
## 3rd Qu.: 585.0 3rd Qu.:911.2   
## Max. :2520.0 Max. :990.0   
## NA's :13   
## c.TOEIC   
## Min. :-139.107   
## 1st Qu.: -60.357   
## Median : -9.107   
## Mean : 0.000   
## 3rd Qu.: 50.893   
## Max. : 250.893   
##

**head**(aft.verb2)

## condition item region stimuli participant rt recip conj  
## 1 a 3 11 dish 1 393 reciprocal conjoinedNP  
## 2 a 5 11 song 1 376 reciprocal conjoinedNP  
## 3 a 13 11 news 1 315 reciprocal conjoinedNP  
## 4 a 18 11 phone 1 467 reciprocal conjoinedNP  
## 5 a 20 11 chief 1 360 reciprocal conjoinedNP  
## 6 c 1 11 offer 1 809 OT conjoinedNP  
## TOEIC c.TOEIC  
## 1 805 45.89286  
## 2 805 45.89286  
## 3 805 45.89286  
## 4 805 45.89286  
## 5 805 45.89286  
## 6 805 45.89286

**str**(aft.verb2)

## 'data.frame': 560 obs. of 10 variables:  
## $ condition : Factor w/ 4 levels "a","b","c","d": 1 1 1 1 1 3 3 3 3 3 ...  
## $ item : int 3 5 13 18 20 1 4 7 14 17 ...  
## $ region : int 11 11 11 11 11 11 11 11 11 11 ...  
## $ stimuli : Factor w/ 20 levels "argument","article",..: 5 19 12 14 4 13 18 15 11 10 ...  
## $ participant: int 1 1 1 1 1 1 1 1 1 1 ...  
## $ rt : int 393 376 315 467 360 809 508 1083 2780 500 ...  
## $ recip : Factor w/ 2 levels "OT","reciprocal": 2 2 2 2 2 1 1 1 1 1 ...  
## $ conj : Factor w/ 2 levels "conjoinedNP",..: 1 1 1 1 1 1 1 1 1 1 ...  
## $ TOEIC : int 805 805 805 805 805 805 805 805 805 805 ...  
## $ c.TOEIC : num 45.9 45.9 45.9 45.9 45.9 ...

**summary**(aft.verb2)

## condition item region stimuli participant   
## a:140 Min. : 1.00 Min. : 8.0 argument: 28 Min. : 1.00   
## b:140 1st Qu.: 5.75 1st Qu.: 8.0 article : 28 1st Qu.: 9.75   
## c:140 Median :10.50 Median : 9.5 book : 28 Median :16.50   
## d:140 Mean :10.53 Mean : 9.5 chief : 28 Mean :16.75   
## 3rd Qu.:15.25 3rd Qu.:11.0 dish : 28 3rd Qu.:24.25   
## Max. :20.00 Max. :11.0 dog : 28 Max. :32.00   
## (Other) :392   
## rt recip conj TOEIC   
## Min. : 200.0 OT :280 conjoinedNP:280 Min. :600.0   
## 1st Qu.: 381.0 reciprocal:280 PDD :280 1st Qu.:800.0   
## Median : 502.5 Median :860.0   
## Mean : 572.8 Mean :850.9   
## 3rd Qu.: 672.0 3rd Qu.:911.2   
## Max. :2780.0 Max. :990.0   
## NA's :28   
## c.TOEIC   
## Min. :-139.107   
## 1st Qu.: -60.357   
## Median : -9.107   
## Mean : 0.000   
## 3rd Qu.: 50.893   
## Max. : 250.893   
##

**Adding the word length**

first.noun$Wlength<-**nchar**(**as.character**(first.noun$stimuli), type="chars")  
target.verb$Wlength<-**nchar**(**as.character**(target.verb$stimuli), type="chars")  
aft.verb1$Wlength<-**nchar**(**as.character**(aft.verb1$stimuli), type="chars")  
aft.verb2$Wlength<-**nchar**(**as.character**(aft.verb2$stimuli), type="chars")

**Scaling TOEIC score and centering word length**

*#TOEIC score*  
first.noun$s.TOEIC<-**scale**(first.noun$TOEIC)  
target.verb$s.TOEIC<-**scale**(target.verb$TOEIC)  
aft.verb1$s.TOEIC<-**scale**(aft.verb1$TOEIC)  
aft.verb2$s.TOEIC<-**scale**(aft.verb2$TOEIC)  
  
*#Word length*  
first.noun$c.Wlength<-**mean**(first.noun$Wlength)-first.noun$Wlength  
target.verb$c.Wlength<-**mean**(target.verb$Wlength)-target.verb$Wlength  
aft.verb1$c.Wlength<-**mean**(aft.verb1$Wlength)-aft.verb1$Wlength  
aft.verb2$c.Wlength<-**mean**(aft.verb2$Wlength)-aft.verb2$Wlength

**Change coding**

*#First make all the variable factor*   
first.noun$recip<-**as.factor**(first.noun$recip)  
target.verb$recip<-**as.factor**(target.verb$recip)  
aft.verb1$recip<-**as.factor**(aft.verb1$recip)  
aft.verb2$recip<-**as.factor**(aft.verb2$recip)  
first.noun$conj<-**as.factor**(first.noun$conj)  
target.verb$conj<-**as.factor**(target.verb$conj)  
aft.verb1$conj<-**as.factor**(aft.verb1$conj)  
aft.verb2$conj<-**as.factor**(aft.verb2$conj)  
  
c<-**contr.treatment**(2)  
my.coding<-**matrix**(**rep**(1/2,2),ncol=1)  
my.simple<-c-my.coding  
my.simple

## 2  
## 1 -0.5  
## 2 0.5

**contrasts**(first.noun$recip)<-my.simple  
**contrasts**(first.noun$conj)<-my.simple  
**contrasts**(target.verb$recip)<-my.simple  
**contrasts**(target.verb$conj)<-my.simple  
**contrasts**(aft.verb1$recip)<-my.simple  
**contrasts**(aft.verb1$conj)<-my.simple  
**contrasts**(aft.verb2$recip)<-my.simple  
**contrasts**(aft.verb2$conj)<-my.simple

**GLMM**

**Analysis 1 (The first noun)**

Note that only converged models are presented here.

analysis1 <-**list**()  
analysis1[[1]]<-**glmer**(rt ~ recip\*conj+s.TOEIC+Wlength+(1+conj+recip+Wlength|participant)+(1+conj+s.TOEIC|item),data = first.noun,family = **Gamma**(link = "identity"),**glmerControl**(optimizer = "bobyqa",optCtrl = **list**(maxfun=2e5)))  
*#summary(analysis1[[1]])*  
*#vif.mer(analysis1[[1]])*  
*#sjp.int(analysis1[[1]],show.ci = T)*  
  
analysis1[[2]]<-**glmer**(rt ~ recip\*conj+s.TOEIC+Wlength+(1+conj+Wlength|participant)+(1+recip+conj|item),data = first.noun,family = **Gamma**(link = "identity"),**glmerControl**(optimizer = "bobyqa",optCtrl = **list**(maxfun=2e5)))  
*#summary(analysis1[[2]])*  
*#vif.mer(analysis1[[2]])*  
*#sjp.int(analysis1[[2]],show.ci = T)*  
  
analysis1[[3]]<-**glmer**(rt ~ recip\*conj+s.TOEIC+Wlength+(1+conj+recip|participant)+(1+conj|item),data = first.noun,family = **Gamma**(link = "identity"),**glmerControl**(optimizer = "bobyqa",optCtrl = **list**(maxfun=2e5)))  
*#summary(analysis1[[3]])*  
*#vif.mer(analysis1[[3]])*  
*#sjp.int(analysis1[[3]],show.ci = T)*  
  
analysis1[[4]]<-**glmer**(rt ~ recip\*conj+s.TOEIC+Wlength+(1+conj|participant)+(1|item),data = first.noun,family = **Gamma**(link = "identity"),**glmerControl**(optimizer = "bobyqa",optCtrl = **list**(maxfun=2e5)))  
*#summary(analysis1[[4]])*  
*#vif.mer(analysis1[[4]])*  
*#sjp.int(analysis1[[4]],show.ci = T)*  
  
analysis1[[5]]<-**glmer**(rt ~ recip\*conj+s.TOEIC+Wlength+(1+recip|participant)+(1|item),data = first.noun,family = **Gamma**(link = "identity"),**glmerControl**(optimizer = "bobyqa",optCtrl = **list**(maxfun=2e5)))  
*#summary(analysis1[[5]])*  
*#vif.mer(analysis1[[4]])*  
*#sjp.int(analysis1[[4]],show.ci = T)*  
  
analysis1[[6]]<-**glmer**(rt ~ recip\*conj+s.TOEIC+Wlength+(1|participant)+(1|item),data = first.noun,family = **Gamma**(link = "identity"),**glmerControl**(optimizer = "bobyqa",optCtrl = **list**(maxfun=2e5)))  
*#summary(analysis1[[5]])*  
*#vif.mer(analysis1[[5]])*  
*#sjp.int(fit1.first.noun,show.ci = T)*

**Model Comparison of the random effects**

**sapply**(analysis1,AIC)%>% data.frame

## .  
## 1 7229.137  
## 2 7225.682  
## 3 7229.027  
## 4 7230.229  
## 5 7244.121  
## 6 7242.728

**sapply**(analysis1,AIC)%>% which.min

## [1] 2

The model2 showed the lowest AIC. Thus, let us look at the results of the model4

**Checking the results of analysis1**

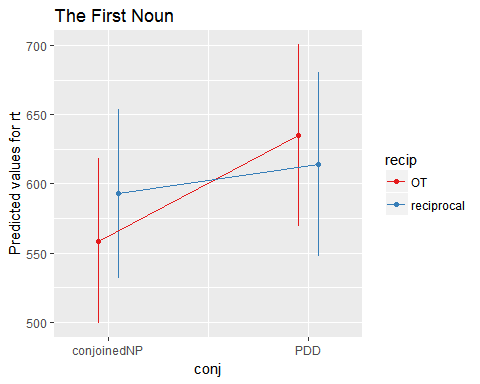
**summary**(analysis1[[4]])

## Generalized linear mixed model fit by maximum likelihood (Laplace  
## Approximation) [glmerMod]  
## Family: Gamma ( identity )  
## Formula:   
## rt ~ recip \* conj + s.TOEIC + Wlength + (1 + conj | participant) +   
## (1 | item)  
## Data: first.noun  
## Control:   
## glmerControl(optimizer = "bobyqa", optCtrl = list(maxfun = 2e+05))  
##   
## AIC BIC logLik deviance df.resid   
## 7230.2 7277.4 -3604.1 7208.2 525   
##   
## Scaled residuals:   
## Min 1Q Median 3Q Max   
## -1.7284 -0.6127 -0.1735 0.3581 5.6057   
##   
## Random effects:  
## Groups Name Variance Std.Dev. Corr  
## participant (Intercept) 9859.4974 99.2950   
## conj2 9244.9698 96.1508 0.22  
## item (Intercept) 1448.3427 38.0571   
## Residual 0.1639 0.4048   
## Number of obs: 536, groups: participant, 28; item, 20  
##   
## Fixed effects:  
## Estimate Std. Error t value Pr(>|z|)   
## (Intercept) 498.888 24.834 20.089 < 2e-16 \*\*\*  
## recip2 6.609 14.714 0.449 0.653333   
## conj2 48.775 21.749 2.243 0.024922 \*   
## s.TOEIC -15.372 25.980 -0.592 0.554055   
## Wlength 18.445 5.437 3.393 0.000693 \*\*\*  
## recip2:conj2 -54.808 23.131 -2.369 0.017813 \*   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Correlation of Fixed Effects:  
## (Intr) recip2 conj2 s.TOEI Wlngth  
## recip2 0.019   
## conj2 0.139 0.001   
## s.TOEIC -0.060 0.088 0.061   
## Wlength -0.458 0.021 0.027 0.048   
## recip2:cnj2 -0.005 0.040 0.022 -0.007 -0.001

**vif.mer**(analysis1[[4]]) *#Checking vif for multicolinearity*

## recip2 conj2 s.TOEIC Wlength recip2:conj2   
## 1.009863 1.004917 1.013816 1.003116 1.002283

**sjp.int**(analysis1[[4]],show.ci = T,jitter.ci = T, title = "The First Noun")

 We can see that there is an interaction between the type of noun and the type of verb; therefore, we move on to the test of simple main effects to see the RT differences in more detail.

**Simple main effects**

lsmeans::**lsmeans**(analysis1[[4]],pairwise~conj|recip) *#simple main effect of noun type*

## $lsmeans  
## recip = OT:  
## conj lsmean SE df asymp.LCL asymp.UCL  
## conjoinedNP 558.7840 30.30428 NA 499.3887 618.1793  
## PDD 634.9631 33.36675 NA 569.5655 700.3607  
##   
## recip = reciprocal:  
## conj lsmean SE df asymp.LCL asymp.UCL  
## conjoinedNP 592.7966 30.97375 NA 532.0892 653.5040  
## PDD 614.1680 33.88136 NA 547.7618 680.5743  
##   
## Results are given on the identity (not the response) scale.   
## Confidence level used: 0.95   
##   
## $contrasts  
## recip = OT:  
## contrast estimate SE df z.ratio p.value  
## conjoinedNP - PDD -76.17908 24.40314 NA -3.122 0.0018  
##   
## recip = reciprocal:  
## contrast estimate SE df z.ratio p.value  
## conjoinedNP - PDD -21.37141 24.86104 NA -0.860 0.3900

lsmeans::**lsmeans**(analysis1[[4]],pairwise~recip|conj) *#simple main effect of verb type*

## $lsmeans  
## conj = conjoinedNP:  
## recip lsmean SE df asymp.LCL asymp.UCL  
## OT 558.7840 30.30428 NA 499.3887 618.1793  
## reciprocal 592.7966 30.97375 NA 532.0892 653.5040  
##   
## conj = PDD:  
## recip lsmean SE df asymp.LCL asymp.UCL  
## OT 634.9631 33.36675 NA 569.5655 700.3607  
## reciprocal 614.1680 33.88136 NA 547.7618 680.5743  
##   
## Results are given on the identity (not the response) scale.   
## Confidence level used: 0.95   
##   
## $contrasts  
## conj = conjoinedNP:  
## contrast estimate SE df z.ratio p.value  
## OT - reciprocal -34.01257 18.34401 NA -1.854 0.0637  
##   
## conj = PDD:  
## contrast estimate SE df z.ratio p.value  
## OT - reciprocal 20.79510 19.07959 NA 1.090 0.2758

**Analysis 2 (The target verb)**

Note that only converged models are presented here.

analysis2 <-**list**()  
analysis2[[1]]<-**glmer**(rt ~ recip\*conj+s.TOEIC+Wlength+(1+conj+Wlength+s.TOEIC|participant)+(1+conj|item),data = target.verb,family = **Gamma**(link = "identity"),**glmerControl**(optimizer = "bobyqa",optCtrl = **list**(maxfun=2e5)))   
*#summary(analysis2[[1]])*  
*#vif.mer(analysis2[[1]])*  
*#sjp.int(analysis2[[1]],show.ci = T)*  
  
analysis2[[2]]<-**glmer**(rt ~ recip\*conj+s.TOEIC+Wlength+(1+recip+conj+s.TOEIC|participant)+(1+s.TOEIC|item),data = target.verb,family = **Gamma**(link = "identity"),**glmerControl**(optimizer = "bobyqa",optCtrl = **list**(maxfun=2e5)))  
*#summary(analysis2[[2]])*  
*#vif.mer(analysis2[[2]])*  
*#sjp.int(analysis2[[2]],show.ci = T)*  
  
analysis2[[3]]<-**glmer**(rt ~ recip\*conj+s.TOEIC+Wlength+(1+recip+conj|participant)+(1+recip+conj|item),data = target.verb,family = **Gamma**(link = "identity"),**glmerControl**(optimizer = "bobyqa",optCtrl = **list**(maxfun=2e5)))  
*#summary(analysis2[[3]])*  
*#vif.mer(analysis2[[3]])*  
*#sjp.int(analysis2[[3]],show.ci = T)*  
  
analysis2[[4]]<-**glmer**(rt ~ recip\*conj+s.TOEIC+Wlength+(1+conj|participant)+(1+conj|item),data = target.verb,family = **Gamma**(link = "identity"),**glmerControl**(optimizer = "bobyqa",optCtrl = **list**(maxfun=2e5)))  
*#summary(analysis2[[4]])*  
*#vif.mer(analysis2[[4]])*  
*#sjp.int(analysis2[[4]],show.ci = T)*  
  
analysis2[[5]]<-**glmer**(rt ~ recip\*conj+s.TOEIC+Wlength+(1+conj|participant)+(1|item),data = target.verb,family = **Gamma**(link = "identity"),**glmerControl**(optimizer = "bobyqa",optCtrl = **list**(maxfun=2e5)))  
*#summary(analysis2[[5]])*  
*#vif.mer(analysis2[[5]])*  
*#sjp.int(analysis2[[5]],show.ci = T)*  
  
analysis2[[6]]<-**glmer**(rt ~ recip\*conj+s.TOEIC+Wlength+(1|participant)+(1|item),data = target.verb,family = **Gamma**(link = "identity"),**glmerControl**(optimizer = "bobyqa",optCtrl = **list**(maxfun=2e5)))  
*#summary(analysis2[[6]])*  
*#vif.mer(analysis2[[5]])*  
*#sjp.int(analysis2[[5]],show.ci = T)*

**Model Comparison of the random effects**

**sapply**(analysis2,AIC)%>% data.frame

## .  
## 1 6935.350  
## 2 6945.613  
## 3 6947.110  
## 4 6938.030  
## 5 6934.074  
## 6 6934.137

**sapply**(analysis2,AIC)%>% which.min

## [1] 5

Model5 and Model6 showed similar AIC; therefore, let us check BIC.

**sapply**(analysis2,BIC)%>% data.frame

## .  
## 1 7019.682  
## 2 7029.945  
## 3 7027.226  
## 4 6992.846  
## 5 6980.456  
## 6 6972.086

**sapply**(analysis2,BIC)%>% which.min

## [1] 6

The model6 shows the lowest BIC. Thus, let us look at the results of the model6

**Checking the results of analysis2**

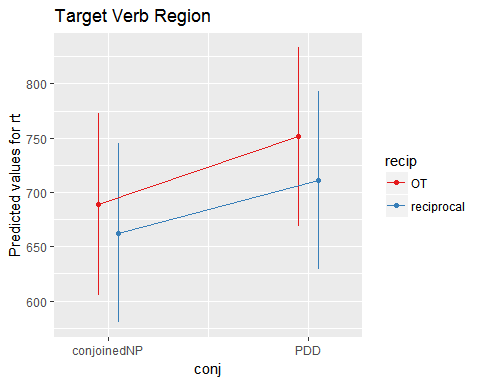
**summary**(analysis2[[6]])

## Generalized linear mixed model fit by maximum likelihood (Laplace  
## Approximation) [glmerMod]  
## Family: Gamma ( identity )  
## Formula: rt ~ recip \* conj + s.TOEIC + Wlength + (1 | participant) + (1 |   
## item)  
## Data: target.verb  
## Control:   
## glmerControl(optimizer = "bobyqa", optCtrl = list(maxfun = 2e+05))  
##   
## AIC BIC logLik deviance df.resid   
## 6934.1 6972.1 -3458.1 6916.1 492   
##   
## Scaled residuals:   
## Min 1Q Median 3Q Max   
## -1.6299 -0.6105 -0.1609 0.3911 5.0803   
##   
## Random effects:  
## Groups Name Variance Std.Dev.  
## participant (Intercept) 2.026e+04 142.3501  
## item (Intercept) 1.165e+03 34.1282  
## Residual 1.837e-01 0.4286  
## Number of obs: 501, groups: participant, 28; item, 20  
##   
## Fixed effects:  
## Estimate Std. Error t value Pr(>|z|)   
## (Intercept) 482.378 36.029 13.389 < 2e-16 \*\*\*  
## recip2 -33.173 16.187 -2.049 0.04042 \*   
## conj2 55.359 17.170 3.224 0.00126 \*\*   
## s.TOEIC -35.876 24.417 -1.469 0.14175   
## Wlength 37.785 6.775 5.577 2.44e-08 \*\*\*  
## recip2:conj2 -14.170 27.809 -0.510 0.61036   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Correlation of Fixed Effects:  
## (Intr) recip2 conj2 s.TOEI Wlngth  
## recip2 -0.040   
## conj2 -0.051 -0.013   
## s.TOEIC 0.020 0.018 -0.002   
## Wlength -0.447 0.017 0.010 0.010   
## recip2:cnj2 0.125 0.028 -0.040 -0.085 -0.099

**vif.mer**(analysis2[[6]]) *#Checking vif for multicolinearity*

## recip2 conj2 s.TOEIC Wlength recip2:conj2   
## 1.001770 1.001794 1.007725 1.010396 1.019776

**sjp.int**(analysis2[[6]],show.ci = T,jitter.ci = T, title = "Target Verb Region")



We can see that there are main effects of the type of noun and the type of verb.

**Analysis 3 (One word after the target verb)**

Note that only converged models are presented here. Here, we don't need to include word length as a covariate because all the word lengths are equal.

analysis3 <-**list**()  
analysis3[[1]]<-**glmer**(rt ~ recip\*conj+s.TOEIC+(1+recip+conj+s.TOEIC|participant)+(1+recip+conj+s.TOEIC|item),data = aft.verb1,family = **Gamma**(link = "identity"),**glmerControl**(optimizer = "bobyqa",optCtrl = **list**(maxfun=2e5)))   
*#summary(analysis3[[1]])*  
*#vif.mer(analysis3[[1]])*  
*#sjp.int(analysis3[[1]],show.ci = T)*  
  
analysis3[[2]]<-**glmer**(rt ~ recip\*conj+s.TOEIC+(1+recip+conj+s.TOEIC|participant)+(1+recip+conj|item),data = aft.verb1,family = **Gamma**(link = "identity"),**glmerControl**(optimizer = "bobyqa",optCtrl = **list**(maxfun=2e5)))  
*#summary(analysis3[[2]])*  
*#vif.mer(analysis3[[2]])*  
*#sjp.int(analysis3[[2]],show.ci = T)*  
  
analysis3[[3]]<-**glmer**(rt ~ recip\*conj+s.TOEIC+(1+recip+conj|participant)+(1+recip+conj|item),data = aft.verb1,family = **Gamma**(link = "identity"),**glmerControl**(optimizer = "bobyqa",optCtrl = **list**(maxfun=2e5)))  
*#summary(analysis3[[3]])*  
*#vif.mer(analysis3[[3]])*  
*#sjp.int(analysis3[[3]],show.ci = T)*  
  
analysis3[[4]]<-**glmer**(rt ~ recip\*conj+s.TOEIC+(1+recip+conj|participant)+(1|item),data = aft.verb1,family = **Gamma**(link = "identity"),**glmerControl**(optimizer = "bobyqa",optCtrl = **list**(maxfun=2e5)))  
*#summary(analysis3[[4]])*  
*#vif.mer(analysis3[[4]])*  
*#sjp.int(analysis3[[4]],show.ci = T)*  
  
analysis3[[5]]<-**glmer**(rt ~ recip\*conj+s.TOEIC+(1+recip|participant)+(1|item),data = aft.verb1,family = **Gamma**(link = "identity"),**glmerControl**(optimizer = "bobyqa",optCtrl = **list**(maxfun=2e5)))  
*#summary(analysis3[[5]])*  
*#vif.mer(analysis3[[5]])*  
*#sjp.int(analysis3[[5]],show.ci = T)*  
  
analysis3[[6]]<-**glmer**(rt ~ recip\*conj+s.TOEIC+(1|participant)+(1|item),data = aft.verb1,family = **Gamma**(link = "identity"),**glmerControl**(optimizer = "bobyqa",optCtrl = **list**(maxfun=2e5)))  
*#summary(analysis3[[6]])*  
*#vif.mer(analysis3[[6]])*  
*#sjp.int(analysis3[[6]],show.ci = T)*

**Model Comparison of the random effects**

**sapply**(analysis3,AIC)%>% data.frame

## .  
## 1 7259.965  
## 2 7255.048  
## 3 7248.273  
## 4 7245.063  
## 5 7252.035  
## 6 7263.054

**sapply**(analysis3,AIC)%>% which.min

## [1] 4

The model4 shows the lowest AIC. Thus, let us look at the results of the model4

**Checking the results of analysis3**

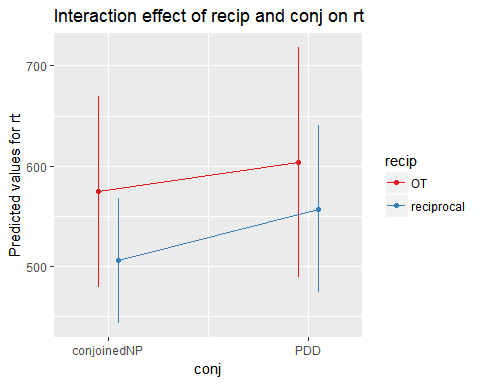
**summary**(analysis3[[4]])

## Generalized linear mixed model fit by maximum likelihood (Laplace  
## Approximation) [glmerMod]  
## Family: Gamma ( identity )  
## Formula: rt ~ recip \* conj + s.TOEIC + (1 + recip + conj | participant) +   
## (1 | item)  
## Data: aft.verb1  
## Control:   
## glmerControl(optimizer = "bobyqa", optCtrl = list(maxfun = 2e+05))  
##   
## AIC BIC logLik deviance df.resid   
## 7245.1 7301.0 -3609.5 7219.1 534   
##   
## Scaled residuals:   
## Min 1Q Median 3Q Max   
## -1.4703 -0.5621 -0.2297 0.2429 5.2294   
##   
## Random effects:  
## Groups Name Variance Std.Dev. Corr   
## participant (Intercept) 9455.7327 97.2406   
## recip2 6523.6131 80.7689 -0.53   
## conj2 7884.6199 88.7954 0.28 0.10  
## item (Intercept) 373.1694 19.3176   
## Residual 0.1539 0.3923   
## Number of obs: 547, groups: participant, 28; item, 20  
##   
## Fixed effects:  
## Estimate Std. Error t value Pr(>|z|)   
## (Intercept) 560.512 40.600 13.806 <2e-16 \*\*\*  
## recip2 -57.874 26.830 -2.157 0.031 \*   
## conj2 40.381 32.719 1.234 0.217   
## s.TOEIC -1.629 20.387 -0.080 0.936   
## recip2:conj2 21.785 26.528 0.821 0.412   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Correlation of Fixed Effects:  
## (Intr) recip2 conj2 s.TOEI  
## recip2 -0.631   
## conj2 0.340 -0.130   
## s.TOEIC 0.030 -0.052 -0.068   
## recip2:cnj2 -0.018 0.044 -0.237 -0.050

**vif.mer**(analysis3[[4]]) *#Checking vif for multicolinearity*

## recip2 conj2 s.TOEIC recip2:conj2   
## 1.021007 1.084435 1.012960 1.064667

**sjp.int**(analysis3[[4]],show.ci = T,jitter.ci = T)

 We can see that there is a main effect of the type of verb.

**Analysis 4 (Two words after the target verb)**

Note that only converged models are presented here.

analysis4 <-**list**()  
analysis4[[1]]<-**glmer**(rt ~ recip\*conj+s.TOEIC+Wlength+(1+conj+recip+s.TOEIC|participant)+(1+s.TOEIC+recip|item),data = aft.verb2,family = **Gamma**(link = "identity"),**glmerControl**(optimizer = "bobyqa",optCtrl = **list**(maxfun=2e5)))   
*#summary(analysis4[[1]])*  
*#vif.mer(analysis4[[1]])*  
*#sjp.int(analysis4[[1]],show.ci = T)*  
  
analysis4[[2]]<-**glmer**(rt ~ recip\*conj+s.TOEIC+Wlength+(1+recip+s.TOEIC+Wlength|participant)+(1+recip|item),data = aft.verb2,family = **Gamma**(link = "identity"),**glmerControl**(optimizer = "bobyqa",optCtrl = **list**(maxfun=2e5)))  
*#summary(analysis4[[2]])*  
*#vif.mer(analysis4[[2]])*  
*#sjp.int(analysis4[[2]],show.ci = T)*  
  
analysis4[[3]]<-**glmer**(rt ~ recip\*conj+s.TOEIC+Wlength+(1+recip+conj|participant)+(1+conj|item),data = aft.verb2,family = **Gamma**(link = "identity"),**glmerControl**(optimizer = "bobyqa",optCtrl = **list**(maxfun=2e5)))  
*#summary(analysis4[[3]])*  
*#vif.mer(analysis4[[3]])*  
*#sjp.int(analysis4[[3]],show.ci = T)*  
  
analysis4[[4]]<-**glmer**(rt ~ recip\*conj+s.TOEIC+c.Wlength+(1+recip+conj|participant)+(1+recip|item),data = aft.verb2,family = **Gamma**(link = "identity"),**glmerControl**(optimizer = "bobyqa",optCtrl = **list**(maxfun=2e5)))  
*#summary(analysis4[[4]])*  
*#vif.mer(analysis4[[4]])*  
*#sjp.int(analysis4[[4]],show.ci = T)*  
  
analysis4[[5]]<-**glmer**(rt ~ recip\*conj+s.TOEIC+c.Wlength+(1+conj|participant)+(1|item),data = aft.verb2,family = **Gamma**(link = "identity"),**glmerControl**(optimizer = "bobyqa",optCtrl = **list**(maxfun=2e5)))  
*#summary(analysis4[[5]])*  
*#vif.mer(analysis4[[5]])*  
*#sjp.int(analysis4[[5]],show.ci = T)*  
  
analysis4[[6]]<-**glmer**(rt ~ recip\*conj+s.TOEIC+c.Wlength+(1+recip|participant)+(1|item),data = aft.verb2,family = **Gamma**(link = "identity"),**glmerControl**(optimizer = "bobyqa",optCtrl = **list**(maxfun=2e5)))  
*#summary(analysis4[[5]])*  
*#vif.mer(analysis4[[5]])*  
*#sjp.int(analysis4[[5]],show.ci = T)*  
  
analysis4[[7]]<-**glmer**(rt ~ recip\*conj+s.TOEIC+c.Wlength+(1|participant)+(1|item),data = aft.verb2,family = **Gamma**(link = "identity"),**glmerControl**(optimizer = "bobyqa",optCtrl = **list**(maxfun=2e5)))  
*#summary(analysis4[[6]])*  
*#vif.mer(analysis4[[6]])*  
*#sjp.int(analysis4[[6]],show.ci = T)*

**Model Comparison of the random effects**

**sapply**(analysis4,AIC)%>% data.frame

## .  
## 1 7083.393  
## 2 7068.016  
## 3 7076.139  
## 4 7076.632  
## 5 7080.466  
## 6 7078.103  
## 7 7079.770

**sapply**(analysis4,AIC)%>% which.min

## [1] 2

The model2 shows the lowest AIC. Thus, let us look at the results of the model4

**Checking the results of analysis4**

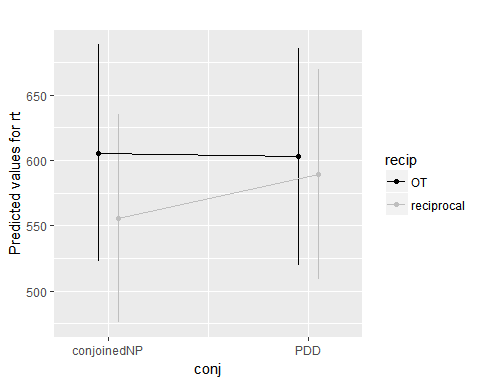
**summary**(analysis4[[2]])

## Generalized linear mixed model fit by maximum likelihood (Laplace  
## Approximation) [glmerMod]  
## Family: Gamma ( identity )  
## Formula: rt ~ recip \* conj + s.TOEIC + Wlength + (1 + recip + s.TOEIC +   
## Wlength | participant) + (1 + recip | item)  
## Data: aft.verb2  
## Control:   
## glmerControl(optimizer = "bobyqa", optCtrl = list(maxfun = 2e+05))  
##   
## AIC BIC logLik deviance df.resid   
## 7068.0 7153.5 -3514.0 7028.0 512   
##   
## Scaled residuals:   
## Min 1Q Median 3Q Max   
## -1.5961 -0.5359 -0.1274 0.3361 7.9537   
##   
## Random effects:  
## Groups Name Variance Std.Dev. Corr   
## participant (Intercept) 5236.3565 72.3627   
## recip2 5972.3391 77.2809 0.54   
## s.TOEIC 339.0369 18.4130 -0.27 -0.68   
## Wlength 428.3996 20.6978 -0.45 -0.41 -0.38  
## item (Intercept) 718.4374 26.8037   
## recip2 1576.1839 39.7012 0.10   
## Residual 0.1405 0.3748   
## Number of obs: 532, groups: participant, 28; item, 20  
##   
## Fixed effects:  
## Estimate Std. Error t value Pr(>|z|)   
## (Intercept) 308.076 25.564 12.051 < 2e-16 \*\*\*  
## recip2 -31.740 21.941 -1.447 0.1480   
## conj2 15.511 12.949 1.198 0.2310   
## s.TOEIC 7.704 19.633 0.392 0.6948   
## Wlength 49.483 7.456 6.637 3.2e-11 \*\*\*  
## recip2:conj2 36.398 19.286 1.887 0.0591 .   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Correlation of Fixed Effects:  
## (Intr) recip2 conj2 s.TOEI Wlngth  
## recip2 0.144   
## conj2 0.025 0.003   
## s.TOEIC -0.047 -0.068 0.009   
## Wlength -0.419 -0.161 -0.014 -0.065   
## recip2:cnj2 0.075 0.022 0.034 0.017 -0.031

**vif.mer**(analysis4[[2]]) *#Checking vif for multicolinearity*

## recip2 conj2 s.TOEIC Wlength recip2:conj2   
## 1.033407 1.001400 1.010943 1.033453 1.002709

**sjp.int**(analysis4[[2]],show.ci = T,jitter.ci = T,geom.colors = **c**("black","grey"),title = "")

 We can see that there is a tendency toward an interaction between the type of noun and the type of verb; therefore, we move on to the test of simple main effects to see the RT differences in more detail.

**Simple main effects**

lsmeans::**lsmeans**(analysis4[[2]],pairwise~conj|recip) *#simple main effect of noun type*

## $lsmeans  
## recip = OT:  
## conj lsmean SE df asymp.LCL asymp.UCL  
## conjoinedNP 605.5126 42.27044 NA 522.6640 688.3611  
## PDD 602.8246 42.19938 NA 520.1153 685.5338  
##   
## recip = reciprocal:  
## conj lsmean SE df asymp.LCL asymp.UCL  
## conjoinedNP 555.5736 40.52824 NA 476.1398 635.0075  
## PDD 589.2837 40.76163 NA 509.3924 669.1751  
##   
## Results are given on the identity (not the response) scale.   
## Confidence level used: 0.95   
##   
## $contrasts  
## recip = OT:  
## contrast estimate SE df z.ratio p.value  
## conjoinedNP - PDD 2.6880 15.87654 NA 0.169 0.8656  
##   
## recip = reciprocal:  
## contrast estimate SE df z.ratio p.value  
## conjoinedNP - PDD -33.7101 16.40888 NA -2.054 0.0399

lsmeans::**lsmeans**(analysis4[[2]],pairwise~recip|conj) *#simple main effect of verb type*

## $lsmeans  
## conj = conjoinedNP:  
## recip lsmean SE df asymp.LCL asymp.UCL  
## OT 605.5126 42.27044 NA 522.6640 688.3611  
## reciprocal 555.5736 40.52824 NA 476.1398 635.0075  
##   
## conj = PDD:  
## recip lsmean SE df asymp.LCL asymp.UCL  
## OT 602.8246 42.19938 NA 520.1153 685.5338  
## reciprocal 589.2837 40.76163 NA 509.3924 669.1751  
##   
## Results are given on the identity (not the response) scale.   
## Confidence level used: 0.95   
##   
## $contrasts  
## conj = conjoinedNP:  
## contrast estimate SE df z.ratio p.value  
## OT - reciprocal 49.93891 23.76805 NA 2.101 0.0356  
##   
## conj = PDD:  
## contrast estimate SE df z.ratio p.value  
## OT - reciprocal 13.54081 24.16358 NA 0.560 0.5752