Gender differences in emotion cues in *Oblivion*

Abstract

The emotional content of lines of dialogue from *Elder Scrolls IV: Oblivion* were analysed, testing various hypotheses about how their distribution might be biased by the gender of the speaking NPC. Support was found for the hypothesis that female NPCs are "backgrounded" (given a smaller range of emotional dialogue) and that emotions which are seen as more masculine were more likely to be given to male NPCs, and conversely emotions seen as more feminine were more likely to be given to female NPCs.

Introduction

The data source for dialogue from *Elder Scrolls IV: Oblivion* (Bethesda Softworks, 2006) includes emotion and intensity cues for about 62,000 lines of dialogue. These were used by the game engine to dynamically animate the faces of the NPCs speaking the lines. They provide a window into the content of the dialogue and an opportunity to test how this content differs between genders.

The emotions are: Anger, Disgust, Fear, Happiness, Sadness, Surprise and 'Neutral'. The emotion intensity scores range from 0 to 100, though there are only 20 unique values. *Oblivion* contains dialogue for named NPCs (with a backstory, quests, etc.) and generic NPCs (e.g. guards). The main analysis only considers unique characters' lines of dialogue, since generic characters tended to have duplicated lines of dialogue for male and female NPCs.

We propose three hypotheses for how the distribution of emotions might be influenced by gender biases.

The first hypothesis derives from the observation that female characters are often "backgrounded" in video games. Carillo Masso (2011) studied imagery and dialogue from *Diablo* and *World of Warcraft*. It was found that masculine pronouns were used three times as frequently as feminine pronouns and there are no significant female characters in the main storyline of the game as portrayed in the game cinematics. Carillo Masso explains this using Fairclough (2003)'s notion of "backgrounding": the presence of female characters needs to be assumed and implied by the game player. Similarly, Miller and Summers (2007, p. 739), find that female characters were more often "supplemental" in video games.

For this study, gender-biased "backgrounding" would predict that female NPCs would play a smaller range of roles and less important roles. This suggests that their dialogue would be more likely to be "neutral" than male dialogue and less likely to have any of the other emotions than male dialogue. By having a higher proportion of neutral utterances compared to other emotions, female characters would be more frequently excluded from the main 'drama' and emotional narrative of the game, thus instead fading into the background.

The second hypothesis is that the game will reflect the tendency (or the belief) in the real world for females to publicly express more emotions than males (Kring & Gordon, 1998; Jansz, 2000; Timmers et al., 2003). This would predict the opposite of the first hypothesis: that male NPCs would be more likely to express neutral emotions and less likely to express other emotions compared to females (except perhaps anger, see e.g. Fischer & Evers, 2011).

The third hypothesis is based on the idea of gendered emotions: the distribution will reflect stereotypes and cultural beliefs about which emotions are more 'feminine' or 'masculine'. Stereotypically feminine emotions would include happiness, surprise, sadness, fear, and disgust, while sterotypically masculine emotions would include anger (see Brody & Hall, 2008). This would predict that female NPCs would be more likely to express all emotions except neutral and anger, compared to male NPCs. We note that this third hypothesis is independent of the first two: female dialogue might show less emotional diversity than male dialogue while at the same time males are more likely to display anger.

For the intensity scores, the "backgrounding" hypothesis would predict that female NPCs more "neutral" or "default" intensity. Alternatively, various studies (e.g. Robinson & Johnson, 1997) show that women are believed to express more intense emotions than men, which would predict that intensity scores for female NPCs would be higher than for male NPCs.

Examples of facial emotion, from https://www.youtube.com/watch?v=chalWNAUjp8

```r
knitr::include_graphics("Emotions.png")
```

Anger

Disgust

Fear

Happy

Sad

Surprise

Load libraries

```
library(rjson)
library(ggplot2)
library(lmtest)
library(sjPlot)
library(pander)
library(knitr)
library(quanteda)
library(quanteda.textstats)
library(entropy)
library(brms)
```

Load data

Load data and select only lines of dialogue:

```
d = fromJSON(file="../../data/ElderScrolls/Oblivion/data.json")
d = d[[1]]

m = fromJSON(file="../../data/ElderScrolls/Oblivion/meta.json")
charGroups = m$characterGroups

emotions = data.frame(
  name = sapply(d,function(X){names(X)[1]}),
  cue = sapply(d,function(X){X[["_Emotion"]]}),
  gender = "Female",
  charType = "Unique",
  stringsAsFactors = F
)
dialogue = sapply(d,function(X){as.character(X[[1]])})
```

Assign gender, generic/unique and dialogue text to each observation from metadata:

```
emotions[emotions$name %in% charGroups$male,]$gender = "Male"
emotions[emotions$name %in%
           c(charGroups$GenericMale,
             charGroups$GenericFemale),]$charType = "Generic"
emotions[grepl("Generic",emotions$name),]$charType = "Generic"
```

`emotions` is now a data frame where each row is a line of dialogue and CharType is whether the character is a generic character or a named, unique character.

Parse emotion and intensity into separate columns:

```
emotions$emotion = sapply(strsplit(emotions$cue," "),head,n=1)
emotions$intensity = sapply(strsplit(emotions$cue," "),tail,n=1)
emotions$intensity = as.numeric(emotions$intensity)
```

Select only unique characters (remove generic characters):

```
dialogue.generic = dialogue[emotions$charType=="Generic"]
emotions.generic = emotions[emotions$charType=="Generic",]

dialogue = dialogue[emotions$charType=="Unique"]
emotions = emotions[emotions$charType=="Unique",]
```

Some example sentences:

```
set.seed(106)
med = tapply(which(emotions$intensity==50),
```

```
            emotions[emotions$intensity==50,]$emotion,
            sample, size=1)

high = tapply(which(emotions$intensity==100),
            emotions[emotions$intensity==100,]$emotion,
            sample, size=1)
examp = data.frame(
  Emotion = rep(sort(unique(emotions$emotion)),each=2),
  Intensity = rep(c(50,100),times=length(sort(unique(emotions$emotion)))),
  dialogue = c(rbind(dialogue[med],dialogue[high])))
pander(examp)
```

Emotion	Intensity	dialogue
Anger	50	Order has always proved the stronger.
Anger	100	Ugh! Darkness, give me strength!
Disgust	50	I'm Krognak gro-Brok, landsman, and I don't much care who you are.
Disgust	100	Excuse me, the Empire doesn't run itself, you know. Submit a complaint to the usual department and I'm sure someone will take care of it.
Fear	50	Get to the Sigil Keep!
Fear	100	Bringer of Light, bless these wretches that they may see the path to your glory.
Happy	50	Don't worry, pal, you'll get used to losing after a while.
Happy	100	Capital! This may be the last piece of the puzzle. I need to spend more time with Savilla's Stone first.
Neutral	50	He's an odd one. I'm sure someone will take care of him soon.
Neutral	100	Now go, and may Sithis guide you in this new stage of your life's dark journey.
Sad	50	I can't make that deal. Even for you.
Sad	100	Armies can only mean one thing... more sorrow and more death.
Surprise	50	Yes, honored Listener? Do you have orders for me?
Surprise	100	They're using Hist Sap? And they claim to have brought a tree into Cyrodiil? Amazing. I can't imagine what the sap might do to non-Argonians.

Analysis

Emotion categories

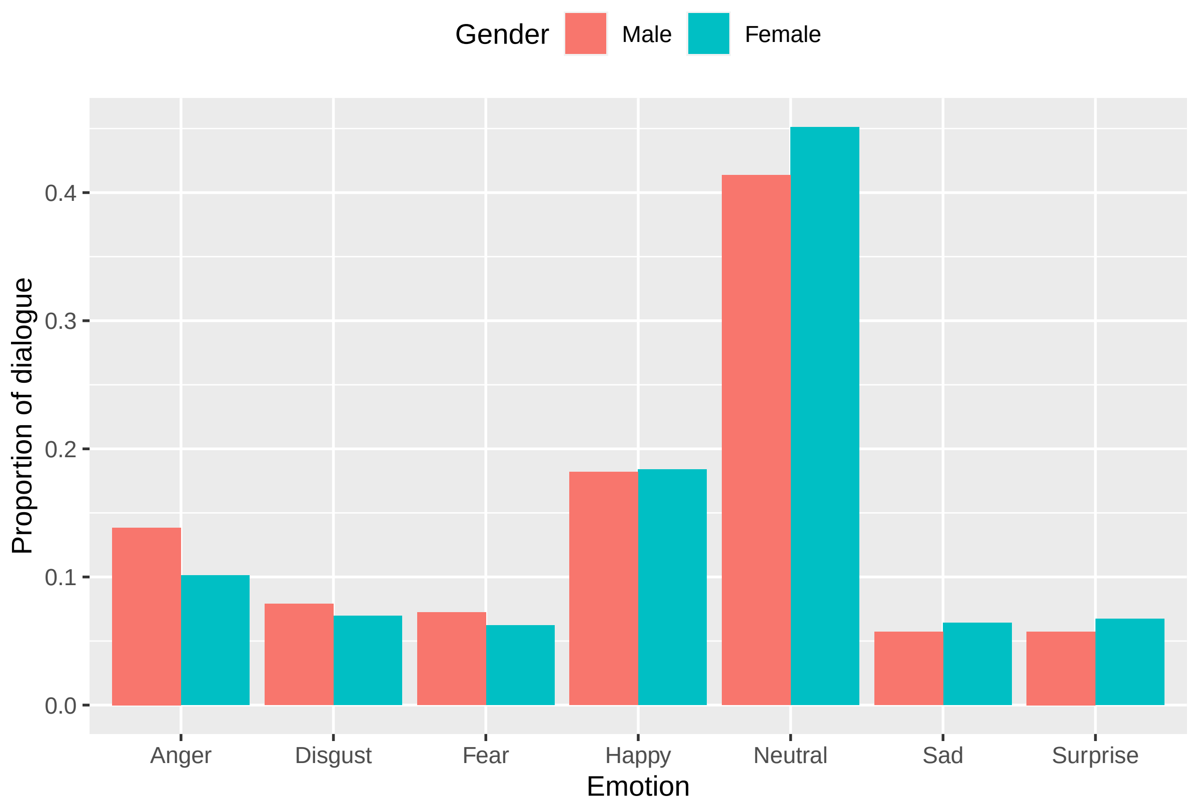
The tables below show the emotion cues assigned to male and female characters (raw numbers and proportionally by gender):

```
tab = table(emotions$emotion,emotions$gender)
colnames(tab) = paste(colnames(tab)," (N)")
propTab = prop.table(tab,margin=2)
colnames(propTab) = gsub("\\(N\\)","\\(%\\)",colnames(propTab))
kable(tab,"latex")
```

	Female (N)	Male (N)
Anger	978	2234
Disgust	674	1276
Fear	602	1166
Happy	1779	2936
Neutral	4362	6674
Sad	622	921
Surprise	650	925

```
kable(round(propTab*100,1),"latex")
```

	Female (%)	Male (%)
Anger	10.1	13.8
Disgust	7.0	7.9
Fear	6.2	7.2
Happy	18.4	18.2
Neutral	45.1	41.4
Sad	6.4	5.7
Surprise	6.7	5.7



Basic chi square test of proportion of emotion types by gender:

```
chiSqEmotion = chisq.test(tab)
chiSqEmotion
```

```
##
##  Pearson's Chi-squared test
##
## data:  tab
## X-squared = 118.5, df = 6, p-value < 2.2e-16
```

The distribution of emotions by gender is significantly different from what would be expected in a random distribution ($\chi^2(6) = 118.5$, $p = 0.0001$). Male NPCs have a higher proportion of anger, disgust, and fear dialogue compared to female NPCs. Female NPCs have a higher proportion of neutral, sad and surprise dialogue compared to male NPCs. The proportion of happy dialogue is roughly the same.

We can formally test the “backgrounding” hypothesis by comparing neutral and non-neutral dialogue:

```
emotions$neutral = factor(emotions$emotion=="Neutral",
                          levels=c(T,F),labels = c("Neutral","Non-neutral"))
tabN = table(emotions$neutral,emotions$gender)
kable(tabN,"latex")
```

	Female	Male
Neutral	4362	6674
Non-neutral	5305	9458

```
pt = round(prop.table(tabN,2)*100,1)
colnames(pt) = paste(colnames(pt),"(%)")
kable(pt,"latex")
```

	Female (%)	Male (%)
Neutral	45.1	41.4
Non-neutral	54.9	58.6

```
chiSqN = chisq.test(table(emotions$neutral,emotions$gender))
chiSqN
```

```
##
##  Pearson's Chi-squared test with Yates' continuity correction
##
## data:  table(emotions$neutral, emotions$gender)
## X-squared = 34.599, df = 1, p-value = 4.051e-09
```

Female NPCs have a significantly more likely to have neutral emotion dialogue than male NPCs ($\chi^2(1) = 34.6$, $p < 0.0001$).

We can also formally test the gendered emotions hypothesis by creating a variable ‘emotionGender’ that is either masculine (for Anger) or feminine (for other non-neutral emotions). (this test is run on Non-neutral emotions only):

```
emotions$emotionGender = "feminine"
emotions$emotionGender[emotions$emotion=="Anger"] = "masculine"

tabEG = table(emotions[emotions$emotion!="Neutral",]$emotionGender,
          emotions[emotions$emotion!="Neutral",]$gender)
kable(tabEG,"latex")
```

	Female	Male
feminine	4327	7224
masculine	978	2234

```
ptEG = prop.table(tabEG,2)
colnames(ptEG) = paste(colnames(ptEG),"(%)")
kable(round(ptEG*100,1),"latex")
```

	Female (%)	Male (%)
feminine	81.6	76.4
masculine	18.4	23.6

```
chisqEG = chisq.test(tabEG)
chisqEG
```

```
##
##  Pearson's Chi-squared test with Yates' continuity correction
##
## data:  tabEG
## X-squared = 53.365, df = 1, p-value = 2.77e-13
```

There is a significant association between the gender of the NPC and masculinity/femininity of the emotion ($\chi^2(1) = 53.36$, $p < 0.0001$). Male NPCs are more likely to use masculine emotions (anger) than female NPCs, and female NPCs are more likely to use feminine emotions (happiness, sadness, surprise, fear and disgust).

Testing the difference between the "backgrounding" and gendered emotions hypotheses is hard. The "neutral" emotions aren't masculine or feminine, and the analysis above removes them from the data. But this is the key distinction for the backgrounding hypothesis. So the two variables can't be put together in a regression, and the two analyses above were based on different data, so can't be compared directly.

To address this, we create two regression models. The first model predicts the NPC's gender only based on neutral vs. non-neutral emotions. The second model uses a three-category variable that distinguishes "neutral" from "feminine" and "masculine". We then compare the fit of these models against each other. This effectively tests whether the prediction from the gendered emotions hypothesis helps predict the NPCs gender *over and above* the backgrounding hypothesis.

```
emotions$emotionGender[emotions$emotion=="Neutral"] = "neutral"
mNeutral = glm(gender=="Female" ~ neutral,
                data = emotions,family="binomial")
mEmGen = glm(gender=="Female" ~ emotionGender,
                data = emotions,family="binomial")
lrtest(mNeutral,mEmGen)
```

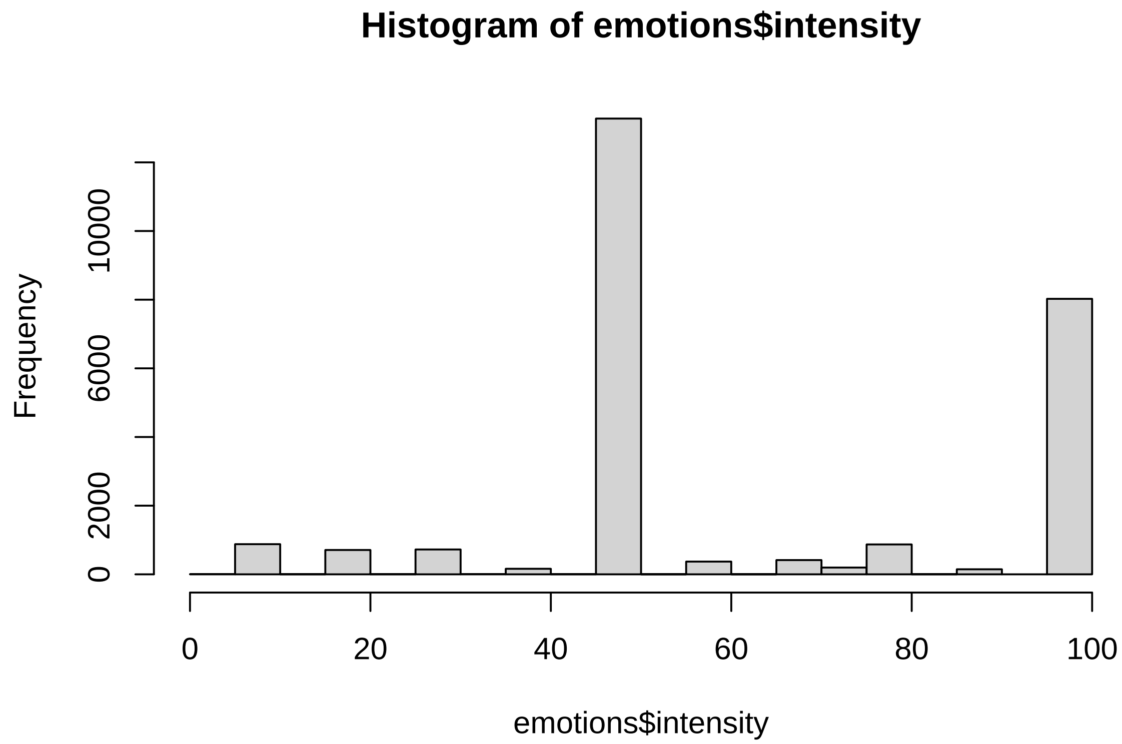
```
## Likelihood ratio test
##
## Model 1: gender == "Female" ~ neutral
## Model 2: gender == "Female" ~ emotionGender
##   #Df LogLik Df Chisq Pr(>Chisq)
## 1   2 -17046
## 2   3 -17019  1 54.67  1.425e-13 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The improvement in the model fit for the second model is significant. This suggests that we should prefer the second model: the distribution of emotions is best explained by considering both neutral and gendered emotions (hypothesis 1 and 3).

Emotion intensity

The intensity of emotion cues in the Oblivion script is represented by a score from 0 – 100. However, there are only 20 unique values, and only 7 are used more than 1% of the time (see the histogram below).

```
emotions$intensityCategory =
  cut(emotions$intensity,
     breaks=c(-1,49,51,99,101),
     labels=c("Low","Medium","High","Max"))
hist(emotions$intensity,breaks=seq(0,100,by=5))
```



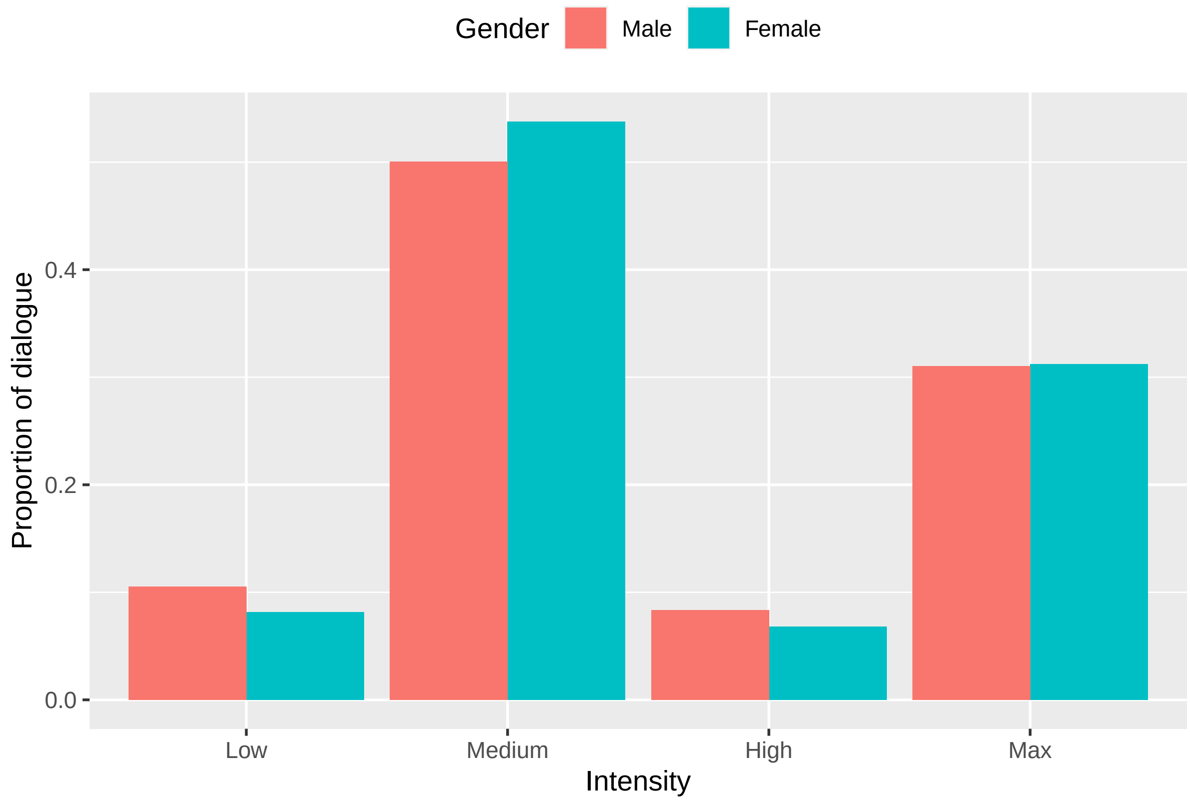
These scores were split into categories in order to facilitate analysis. Scores from 0 to 49 were classed as 'low', from 49 to 51 as 'medium', from 51-99 as 'high' and 100 as 'max'. The tables below show how lines of dialogue are distributed across intensity categories and genders.

```
tabI = table(emotions$intensityCategory,emotions$gender)
tabIprop = prop.table(tabI,2)
colnames(tabIprop) = paste(colnames(tabIprop),"(%)")
kable(tabI,"latex")
```

	Female	Male
Low	791	1701
Medium	5200	8076
High	658	1348
Max	3018	5007

```
kable(round(100*tabIprop,1),"latex")
```

	Female (%)	Male (%)
Low	8.2	10.5
Medium	53.8	50.1
High	6.8	8.4
Max	31.2	31.0




```
chiSqIntensity = chisq.test(tabI)
chiSqIntensity
```

```
##
##  Pearson's Chi-squared test
##
## data:  tabI
## X-squared = 69.971, df = 3, p-value = 4.331e-15
```

The distribution of intensity categories by gender is significantly different from what would be expected in a random distribution ($\chi^2(6) = 118.5$, p = 0.0001). Female NPCs are more likely to be given "Medium" intensity lines than male NPCs, and less likely to be given Low or High intensities. The proportion of "Max" intensities is roughly equal.

Treating the intensity scores as continuous, we find that the average intensity is about half a point lower for male NPCs than female NPCs. Below we test whether this is statistically significant using a permutation test (a t-test is not appropriate, since the distribution is not normal).

```
trueDiff = diff(tapply(emotions$intensity,emotions$gender,mean))
trueDiff
```

```
##       Male
## -0.4994472
```

```
permuteI = function(){
  diff(tapply(emotions$intensity,sample(emotions$gender),mean))
}
n = 10000
permutedDiff = replicate(n,permuteI())
p.value = sum(permutedDiff < trueDiff) / n
if(p.value==0){
  p.value = 1/n
}
z.score = (trueDiff- mean(permutedDiff)) / sd(permutedDiff)
```

```r
paste("Permutation z =",round(z.score,2), ", p = ",p.value)
```

```
## [1] "Permutation z = -1.43 , p =  0.0758"
```

The result is not significant and the effect size for the continuous data is very small. The patterns may be better captured by the categorical analysis above.

Exploratory analyses

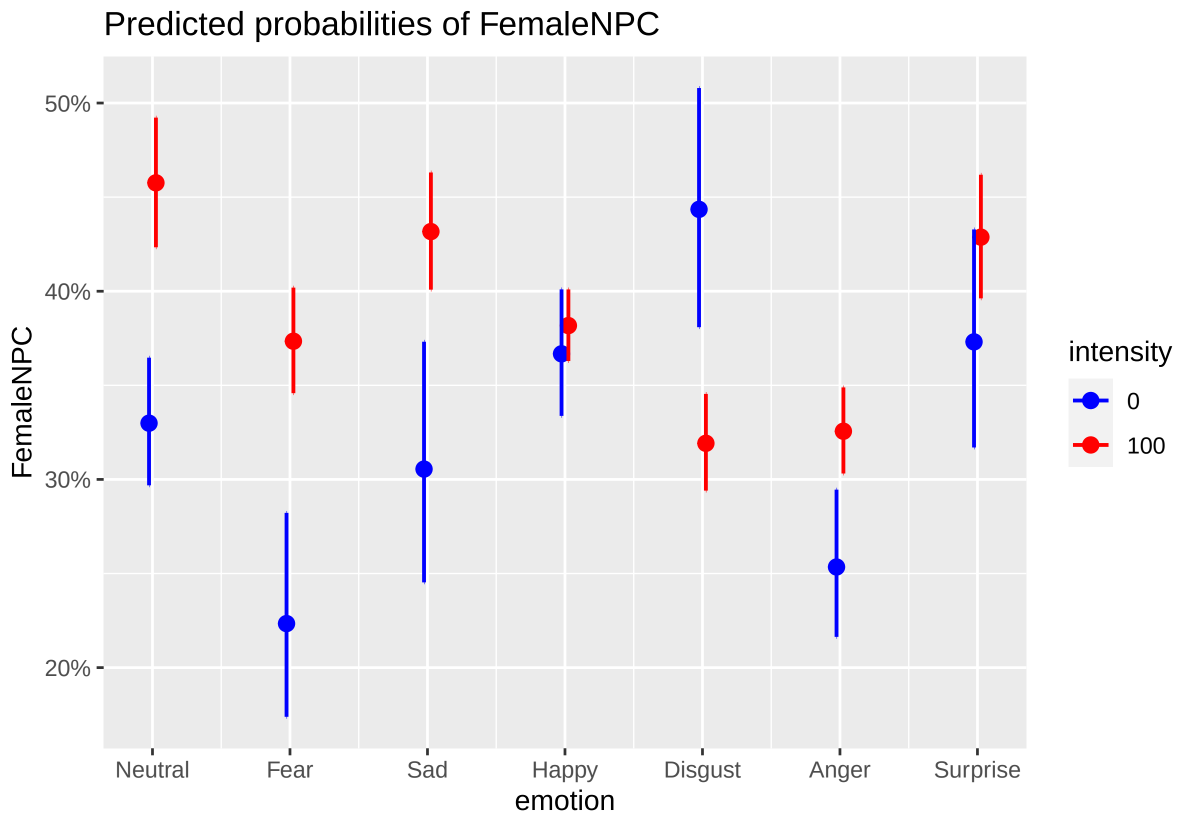
Interactions between emotion and intensity

We explored the interaction between emotion type and intensity. For simplicity, we use the continuous measure of intensity in a binomial regression predicting the gender of the NPC:

```
table(emotions$emotion,emotions$intensityCategory,emotions$gender)
```

```
## , ,  = Female
##
##
##             Low Medium High  Max
##   Anger     135    245  121  477
##   Disgust    96    145   68  365
##   Fear       45    104   66  387
##   Happy     296    442  250  791
##   Neutral    47   4006   29  280
##   Sad        65    105   69  383
##   Surprise  107    153   55  335
##
## , ,  = Male
##
##
##             Low Medium High  Max
##   Anger     298    566  480  890
##   Disgust   123    265  113  775
##   Fear      158    222  123  663
##   Happy     585    627  366 1358
##   Neutral   263   5941   74  396
##   Sad       117    198  123  483
##   Surprise  157    257   69  442
```

```
emotions$FemaleNPC = factor(emotions$gender=="Female")
mCombo = glm(FemaleNPC ~ emotion* intensity,
            data = emotions,family="binomial")
plot_model(mCombo,"int",colors = c("blue","red"))
```



For anger, fear and sadness, increasing intensity is associated with a higher likelihood of being from a female NPC. For disgust, the opposite was true: higher intensity was associated with a higher likelihood of being from a male NPC.

Emotions per character

We looked at the range of emotions per character. It's possible that, while females may be more likely to exhibit neutral emotions, an individual female may be more likely to exhibit a greater range of emotions than an individual man. Or put it another way, a female may exhibit a range of emotions while a man may specialise in one emotion.

```
LinesPerChar = as.vector(table(emotions$name))
emotionEntropy = tapply(factor(emotions$emotion), emotions$name, function(X){
  entropy(table(X))
})
emotionNum = tapply(factor(emotions$emotion),emotions$name,function(X){length(unique(X))})

ent = data.frame(name = names(emotionEntropy),
                 entropy= emotionEntropy,
                 emotionNum = emotionNum,
                 lines=LinesPerChar)
ent$lines.log = log(ent$lines)
ent$gender = emotions[match(ent$name,emotions$name),]$gender
ent$gender = factor(ent$gender,levels=c("Male","Female"))
contrasts(ent$gender) = contr.sum(2)/2
```

The table below shows the proportion of characters displaying only 1 emotion, 2 emotions, 3 emotions etc.

```
table(ent$emotionNum,ent$gender)
```

```
##
##     Male Female
##   1  147     61
##   2  143     71
##   3   93     63
##   4   90     49
##   5   72     54
##   6   83     50
##   7   52     38
```

```
prop.table(table(ent$emotionNum,ent$gender),2)
```

```
##
##           Male     Female
##   1 0.21617647 0.15803109
##   2 0.21029412 0.18393782
##   3 0.13676471 0.16321244
##   4 0.13235294 0.12694301
##   5 0.10588235 0.13989637
##   6 0.12205882 0.12953368
##   7 0.07647059 0.09844560
```

```
barplot(t(prop.table(table(ent$emotionNum,ent$gender),2)),
        beside = T,
        xlab="Number of emotions",
        ylab = "Proportion of characters (within gender)",
        legend.text = c("Male","Female"),col=c("blue","pink"))
```

It looks like the distribution for males is more biased towards low ranges of emotions, while the distribution for females is slightly higher.

However, this effect might be confounded by the amount of dialogue. There is no significant effect of gender on the number of emotions displayed when the (log) number of lines is considered:

```
mx = glm(emotionNum ~ lines.log+gender, data = ent, family="poisson")
summary(mx)
```

```
##
## Call:
## glm(formula = emotionNum ~ lines.log + gender, family = "poisson",
##     data = ent)
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -2.13764  -0.46977  -0.05695   0.38011   1.60908
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  0.38192    0.03842   9.942   <2e-16 ***
## lines.log    0.33809    0.01183  28.579   <2e-16 ***
## gender1     -0.04042    0.03376  -1.197    0.231
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for poisson family taken to be 1)
##
##     Null deviance: 1212.99  on 1065  degrees of freedom
## Residual deviance:  394.72  on 1063  degrees of freedom
## AIC: 3564.4
##
```

```
## Number of Fisher Scoring iterations: 4
```

Similarly, looking at the entropy of emotions displayed per-character shows that females have higher entropy than males:

```
t.test(ent$entropy~ent$gender)
```

```
##
##  Welch Two Sample t-test
##
## data:  ent$entropy by ent$gender
## t = -2.7609, df = 828.08, p-value = 0.005892
## alternative hypothesis: true difference in means between group Male and group Female is not equal
## 95 percent confidence interval:
##  -0.16129027 -0.02724875
## sample estimates:
##   mean in group Male mean in group Female
##            0.8223120            0.9165815
```

However, this is also confounded by the number of lines of dialogue for each character. Below we show that there is no significant effect of gender when taking into account the (log) number of lines each character speaks.

```
# The entropy measure has a normal distribution,
# but also lots of characters who only display one emotion.
#  (entropy of zero)
# So we use a zero-inflated beta distribution.

# First, scale entropy to be between zero and 1
ent$entropy2 = ent$entropy / (max(ent$entropy)+0.00001)
bmx = brm(entropy2 ~ lines.log + gender,data=ent, family = "zero_inflated_beta")
```

```
## Running /Library/Frameworks/R.framework/Resources/bin/R CMD SHLIB foo.c
## clang -arch arm64 -I"/Library/Frameworks/R.framework/Resources/include" -DNDEBUG   -I"/Library/Fr
## In file included from <built-in>:1:
## In file included from /Library/Frameworks/R.framework/Versions/4.1-arm64/Resources/library/StanHe
## In file included from /Library/Frameworks/R.framework/Versions/4.1-arm64/Resources/library/RcppEi
## In file included from /Library/Frameworks/R.framework/Versions/4.1-arm64/Resources/library/RcppEi
## /Library/Frameworks/R.framework/Versions/4.1-arm64/Resources/library/RcppEigen/include/Eigen/src/
## namespace Eigen {
## ^
## /Library/Frameworks/R.framework/Versions/4.1-arm64/Resources/library/RcppEigen/include/Eigen/src/
## namespace Eigen {
##                ^
##                ;
## In file included from <built-in>:1:
## In file included from /Library/Frameworks/R.framework/Versions/4.1-arm64/Resources/library/StanHe
## In file included from /Library/Frameworks/R.framework/Versions/4.1-arm64/Resources/library/RcppEi
## /Library/Frameworks/R.framework/Versions/4.1-arm64/Resources/library/RcppEigen/include/Eigen/Core
## #include <complex>
##          ^~~~~~~~~
## 3 errors generated.
## make: *** [foo.o] Error 1
##
## SAMPLING FOR MODEL 'dea086090905fb2839955020334863e6' NOW (CHAIN 1).
## Chain 1:
## Chain 1: Gradient evaluation took 0.000592 seconds
## Chain 1: 1000 transitions using 10 leapfrog steps per transition would take 5.92 seconds.
## Chain 1: Adjust your expectations accordingly!
## Chain 1:
## Chain 1:
```

```
## Chain 1: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 1: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 1: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 1: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 1: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 1: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 1: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 1: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 1: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 1: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 1: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 1: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 1:
## Chain 1:  Elapsed Time: 2.52281 seconds (Warm-up)
## Chain 1:                2.54467 seconds (Sampling)
## Chain 1:                5.06748 seconds (Total)
## Chain 1:
##
## SAMPLING FOR MODEL 'dea086090905fb2839955020334863e6' NOW (CHAIN 2).
## Chain 2:
## Chain 2: Gradient evaluation took 0.000393 seconds
## Chain 2: 1000 transitions using 10 leapfrog steps per transition would take 3.93 seconds.
## Chain 2: Adjust your expectations accordingly!
## Chain 2:
## Chain 2:
## Chain 2: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 2: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 2: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 2: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 2: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 2: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 2: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 2: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 2: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 2: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 2: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 2: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 2:
## Chain 2:  Elapsed Time: 2.50907 seconds (Warm-up)
## Chain 2:                2.48588 seconds (Sampling)
## Chain 2:                4.99494 seconds (Total)
## Chain 2:
##
## SAMPLING FOR MODEL 'dea086090905fb2839955020334863e6' NOW (CHAIN 3).
## Chain 3:
## Chain 3: Gradient evaluation took 0.000396 seconds
## Chain 3: 1000 transitions using 10 leapfrog steps per transition would take 3.96 seconds.
## Chain 3: Adjust your expectations accordingly!
## Chain 3:
## Chain 3:
## Chain 3: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 3: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 3: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 3: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 3: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 3: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 3: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 3: Iteration: 1200 / 2000 [ 60%]  (Sampling)
```

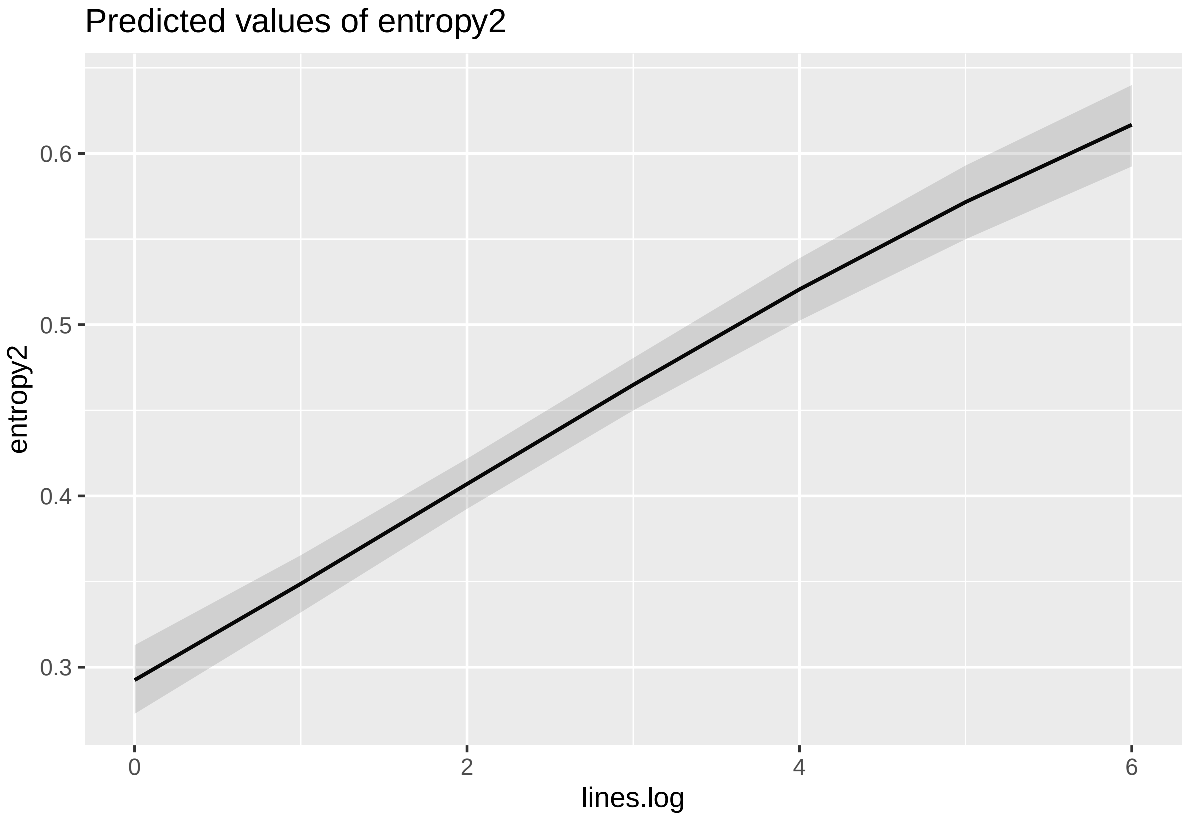
```
## Chain 3: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 3: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 3: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 3: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 3:
## Chain 3:  Elapsed Time: 2.59876 seconds (Warm-up)
## Chain 3:                2.31574 seconds (Sampling)
## Chain 3:                4.91451 seconds (Total)
## Chain 3:
##
## SAMPLING FOR MODEL 'dea086090905fb2839955020334863e6' NOW (CHAIN 4).
## Chain 4:
## Chain 4: Gradient evaluation took 0.000393 seconds
## Chain 4: 1000 transitions using 10 leapfrog steps per transition would take 3.93 seconds.
## Chain 4: Adjust your expectations accordingly!
## Chain 4:
## Chain 4:
## Chain 4: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 4: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 4: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 4: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 4: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 4: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 4: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 4: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 4: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 4: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 4: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 4: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 4:
## Chain 4:  Elapsed Time: 2.52473 seconds (Warm-up)
## Chain 4:                2.72139 seconds (Sampling)
## Chain 4:                5.24611 seconds (Total)
## Chain 4:
```

```
summary(bmx)
```

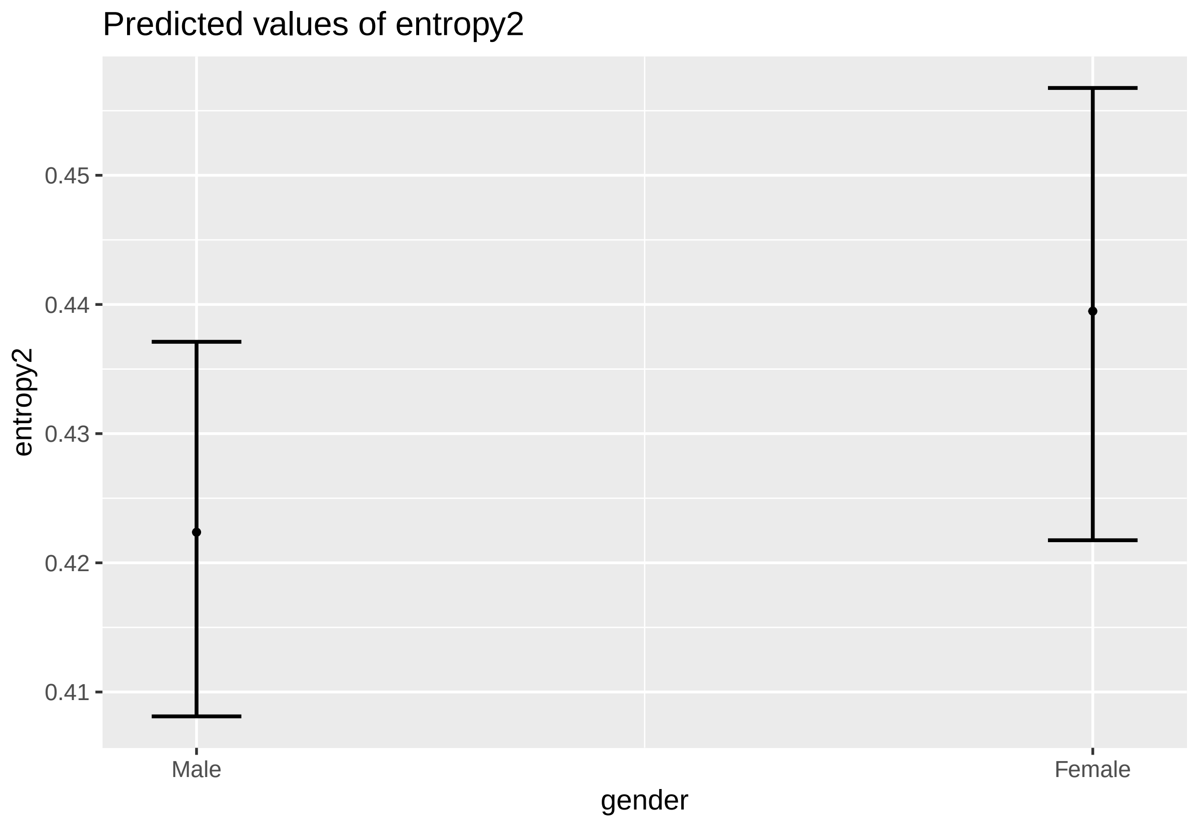
```
##  Family: zero_inflated_beta
##   Links: mu = logit; phi = identity; zi = identity
## Formula: entropy2 ~ lines.log + gender
##    Data: ent (Number of observations: 1066)
##   Draws: 4 chains, each with iter = 2000; warmup = 1000; thin = 1;
##          total post-warmup draws = 4000
##
## Population-Level Effects:
##           Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## Intercept    -0.52      0.06    -0.64    -0.40 1.00     4228     3044
## lines.log     0.29      0.02     0.25     0.33 1.00     4819     3345
## gender1      -0.09      0.05    -0.19     0.02 1.00     4499     2883
##
## Family Specific Parameters:
##     Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## phi     6.21      0.29     5.67     6.78 1.00     4891     3269
## zi      0.20      0.01     0.17     0.22 1.00     4231     2347
##
## Draws were sampled using sampling(NUTS). For each parameter, Bulk_ESS
## and Tail_ESS are effective sample size measures, and Rhat is the potential
## scale reduction factor on split chains (at convergence, Rhat = 1).
```

```r
plot_model(bmx,"pred")
```

```
## $lines.log
```




```
##
## $gender
```


Predicted values of entropy2
0.45
0.44
0.43
0.42
0.41
entropy2
Male
Female
gender

Cues in angry dialogue

There was a difference between genders in the emotion and intensity. One of the biggest differences was for lines marked with the "anger" emotion. However, is there a difference between genders in the linguistic expression of these emotions? That is, do male and female characters express anger differently?

Below, we extract frequencies of profanities in male and female dialogue for lines tagged with the "anger" emotion.

```
dialogueAnger= dialogue[emotions$emotion=="Anger"]
anger = corpus(dialogueAnger,
               docvars = data.frame(
                 gender = emotions[emotions$emotion=="Anger",]$gender))
toks_nopunct <- tokens(anger, remove_punct = TRUE)
totalWords = table(toks_nopunct$gender)

dfmat <- dfm(toks_nopunct)
tstat_freq <- textstat_frequency(dfmat, n = 40)

swears = read.csv("https://gist.githubusercontent.com/tjrobinson/2366772/raw/97329ead3d5ab06160c3c7a
                  stringsAsFactors = F,header = F)
swears = swears[,1]
swears = swears[!swears %in% c("snatch")]
nx = c("hell","dago","ass")
swears[!swears %in% nx]= paste0(swears[!swears %in% nx],"*")
swears = c(swears,"vermin","scum")
swears = dictionary(list(swears=swears))
toks_swears = tokens_keep(toks_nopunct,swears)
dfmat_swears <- dfm(toks_swears)
tstat_freq_swears <- textstat_frequency(dfmat_swears, groups = gender)

tots = sapply(unique(tstat_freq_swears$feature),function(X){
  z = tstat_freq_swears[tstat_freq_swears$feature==X,]
  f = z[z$group=="Female",]$frequency
  m = z[z$group=="Male",]$frequency
  c(Female = ifelse(length(f)==0,0,f),
    Male = ifelse(length(m)==0,1,m))
  })
tots = t(tots)
swearSums = colSums(tots)
tots = rbind(tots,TOTAL = swearSums)
tots = rbind(tots,TOTAL.PerThousand = 1000 * (swearSums/totalWords))
tots
```

```
##                      Female    Male
## damned              7.00000 12.0000
## damn                5.00000 28.0000
## bloody              3.00000  1.0000
## bastard             3.00000  6.0000
## hell                2.00000  6.0000
## bastards            1.00000 15.0000
## arse                1.00000  1.0000
## scum                0.00000 10.0000
## ass                 0.00000  5.0000
## pisses              0.00000  4.0000
## vermin              0.00000  3.0000
## damnable            0.00000  1.0000
## asses               0.00000  1.0000
## crap                0.00000  1.0000
## goddam              0.00000  1.0000
```

```
## cocky               0.00000  1.0000
## goddamn             0.00000  1.0000
## mongrel             0.00000  1.0000
## TOTAL              22.00000 98.0000
## TOTAL.PerThousand 22.49489 43.8675
```

```
chisqSwear = chisq.test(rbind(swearSums,totalWords - swearSums))
chiSqString = paste0("female frequency per thousand words = ",
                     round(tots[nrow(tots),1],1),
                     ", male frequency per thousand words = ",
                     round(tots[nrow(tots),2],1),", ",
        "$\\chi^2$(",chisqSwear$parameter,
        ") = ",round(chisqSwear$statistic,2),
        ", p = ",signif(chisqSwear$p.value,2))
cat(chiSqString,file="../../results/latexStats/OblivionSwearingChiSq.tex")
```

Male characters use profanities twice as often as female characters in angry dialogue (female frequency per thousand words = 22.5, male frequency per thousand words = 43.9, $\chi^2(1) = 8.06$, p = 0.0045).

Dialogue by generic NPCs

Oblivion also includes spoken dialogue by "generic" NPCs, for example guards. These lines are usually duplicated for each gender. For example, the phrase "It's time for you to go" is recorded for both generic Imperial male NPC and a generic Imperial female NPC (also for all other races in the game).

However, not all lines are duplicated. There are some unique lines of dialogue for generic characters.

```
# Find unique dialogue
tab = table(dialogue.generic)
uniqueGenericDialogue = which(dialogue.generic %in% names(tab[tab==1]))
```

There are 942 unique lines of dialogue for generic characters. We can identify how these are distributed by gender:

```
uniqueGenericDialogueByGender = rbind(
  Unique = table(emotions.generic[uniqueGenericDialogue,]$gender),
  Duplicated = table(emotions.generic[-uniqueGenericDialogue,]$gender))
kable(uniqueGenericDialogueByGender,"latex")
```

	Female	Male
Unique	140	802
Duplicated	16573	19174

```
ugpt= prop.table(uniqueGenericDialogueByGender,2)
colnames(ugpt) = paste(colnames(ugpt),"(%)")
kable(round(ugpt*100,1),"latex")
```

	Female (%)	Male (%)
Unique	0.8	4
Duplicated	99.2	96

```
chiSqUniqueGenericDialogue = chisq.test(uniqueGenericDialogueByGender)
chiSqUniqueGenericDialogue
```

```
##
##  Pearson's Chi-squared test with Yates' continuity correction
##
## data:  uniqueGenericDialogueByGender
## X-squared = 365.91, df = 1, p-value < 2.2e-16
```

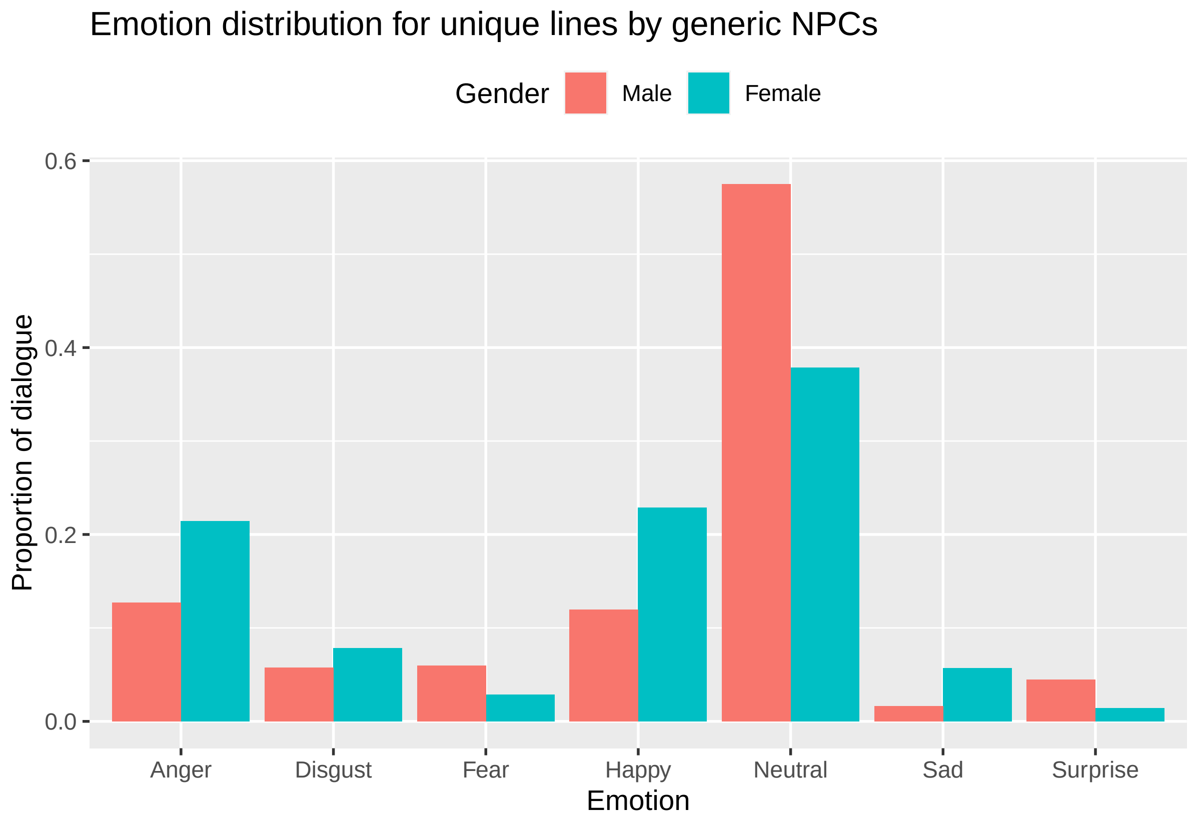
There is a significant imbalance: generic male NPCs are more than four times more likely to be given unique lines of dialogue than generic female NPCs.

```
p.val = round(chiSqUniqueGenericDialogue$p.value,3)
if(p.val < 0.0001){ p.val = "0.0001"}else{p.val = paste("=",p.val)}
chiSqString = paste0("$\\chi^2$(",chiSqUniqueGenericDialogue$parameter,
                     ") = ",round(chiSqUniqueGenericDialogue$statistic,2),
                     ", p = ",p.val)
cat(chiSqString, file="../../results/latexStats/OblivionUniqueGenericDialogueChiSq.tex")
```

We can also look at how the emotions are distributed:

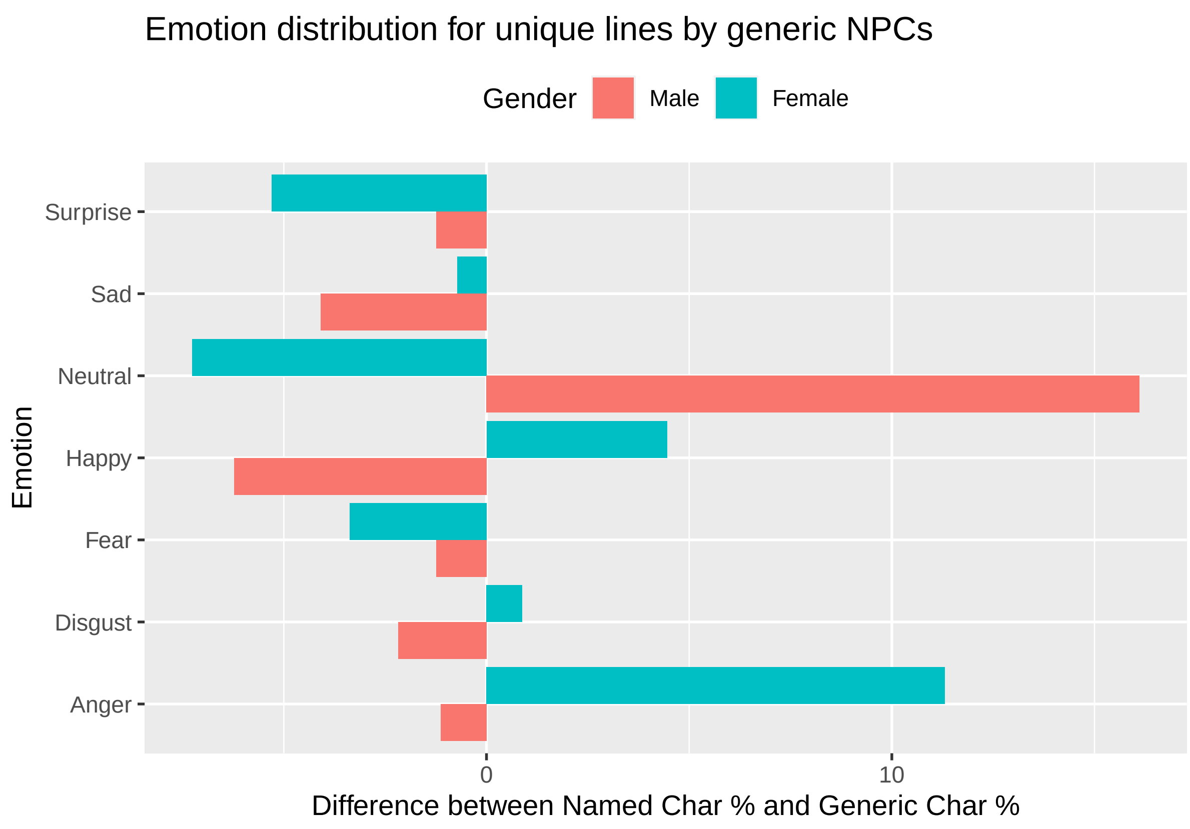
```
ugdByGenderAndEmotion = table(
  emotions.generic[uniqueGenericDialogue,]$emotion,
  emotions.generic[uniqueGenericDialogue,]$gender)

ugdByGenderAndEmotionProp = prop.table(ugdByGenderAndEmotion,2)

dxG = data.frame(
  n = as.vector(ugdByGenderAndEmotionProp),
  Gender = rep(c("Female","Male"),each=nrow(ugdByGenderAndEmotionProp)),
  Emotion = rep(rownames(ugdByGenderAndEmotionProp),2)
)
```

```
dxG$Gender = factor(dxG$Gender,levels = c("Male","Female"))
ggplot(dxG, aes(fill=Gender,y=n, x=Emotion)) +
    geom_bar(position="dodge", stat="identity") +
  ylab("Proportion of dialogue") +
  ggtitle("Emotion distribution for unique lines by generic NPCs") +
  theme(legend.position = "top")
```



The biggest differences between the named and generic characters are for females: they are less likely to have neutral emotions, are more likely to have happy and angry emotions. The differences between the two types of character are visualised below:

```
dx$diff = 100*(dxG$n - dx$n)
ggplot(dx,aes(y=diff,fill=Gender,x=Emotion)) +
  geom_bar(position="dodge", stat="identity") +
  theme(legend.position = "top") +
  coord_flip() +
  ggtitle("Emotion distribution for unique lines by generic NPCs") +
  ylab("Difference between Named Char % and Generic Char %")
```


Emotion distribution for unique lines by generic NPCs
Gender
Male
Female
Surprise
Sad
Neutral
Happy
Fear
Disgust
Anger
Emotion
0
10
Difference between Named Char % and Generic Char %

Conclusion

Compared to Male NPCs, Female NPCs are statistically more likely to be given ‘neutral’ emotion cues with ‘medium’ intensity. This supports the hypothesis that female characters are “backgrounded”. This may be because they have a narrower range of roles or are less relevant at the most ‘emotional’ or dramatic moments in the game. However, this hypothesis did not predict the finding that female NPCs would express more sadness and surprise.

We also found support for the gendered emotions hypothesis: female NPCs were more likely to express feminine emotions and male NPCs were more likely to express masculine emotions. However, this is mainly a test of anger versus the other (non-neutral) emotions. This hypothesis also does not predict the difference in neutral emotion lines.

We found no support for the hypothesis based on the belief that women express more emotion than men. However, there are some hints that emotion is expressed differently. For example, male NPCs were more likely to use curse words when expressing anger than female NPCs. Although it is often believed that, in the real world, men use curse words more frequently than women, some studies show no difference between genders (e.g. McEnery 2006, p. 29).

The patterns in the generic character dialogue require more analysis. Tellingly, there is less unique dialogue for female generic NPCs, fitting with the “backgrounding” hypothesis.

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