group project 2

Group 05

2022/3/15

Contents

Introduction of dataset

Question to be explored

Imagine you have been asked by a film producer to investigate the following question of interest:

- Which properties of films influence whether they are rated by IMDB as greater than 7 or not?

You should conduct an analysis to answer your question using a Generalised Linear Model (GLM). Following your analyses, you should then summarise your results in the form of a presentation.

Explain each variables

- film.id – The unique identifier for the film
- year – Year of release of the film in cinemas
- length – Duration (in minutes)
- budget – Budget for the films production (in $1000000s)
- votes – Number of positive votes received by viewers
- genre – Genre of the film
- rating – IMDB rating from 0-10

Data processing

```
film <- read.csv("dataset5.csv")
```

Create a column to separate the rating: >7(1), <=7(0)

```
film <- film %>%
  mutate(rating.large7 = cut(rating, breaks = c(0,7,Inf), labels=c(0,1))) %>%
  dplyr::select(-film_id, -rating)%>%
  na.omit()
```

Exploratory data analysis

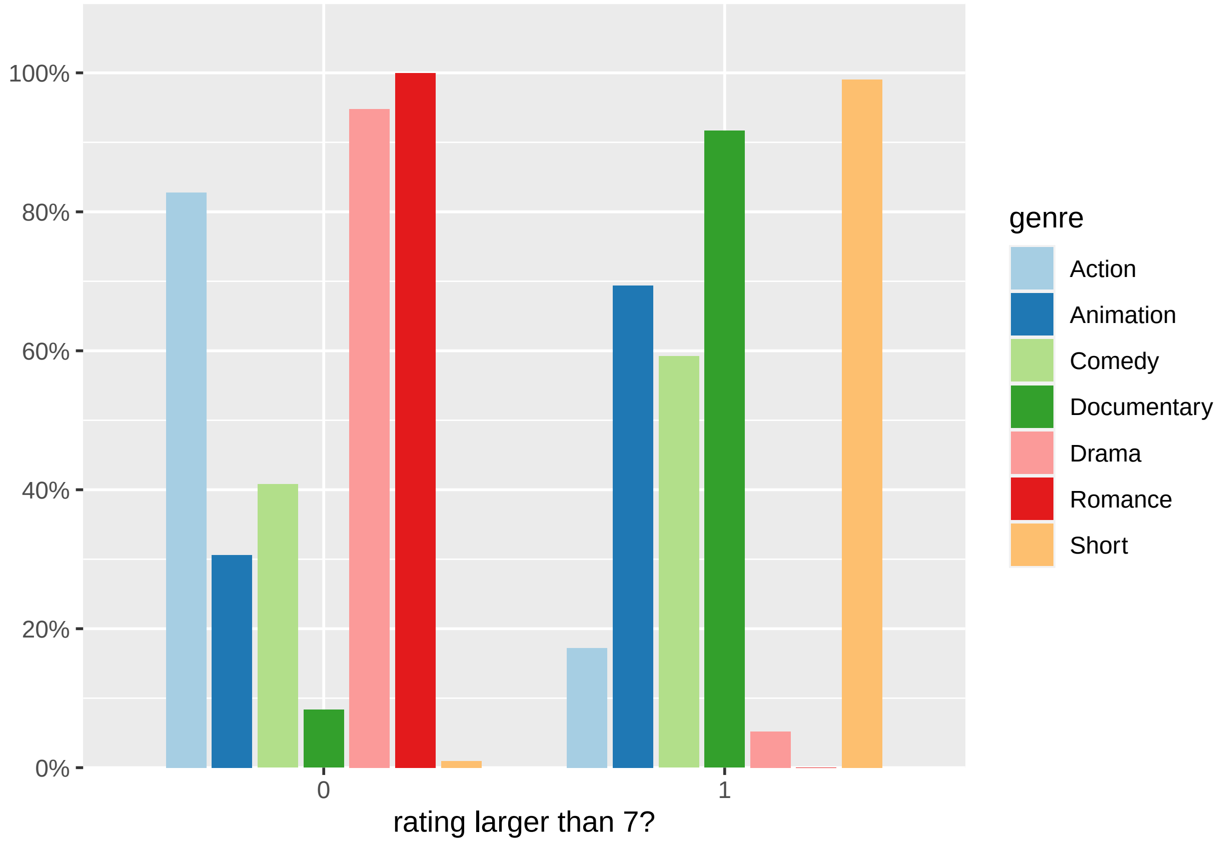
The distribution of rating.large7 by genre

```
film %>%
  group_by(genre, rating.large7)%>%
  summarise(n = n())
```

```
## `summarise()` has grouped output by 'genre'. You can override using the `.groups` argument.
```

```
## # A tibble: 13 x 3
## # Groups:   genre [7]
##    genre       rating.large7     n
##    <chr>       <fct>         <int>
##  1 Action      0               563
##  2 Action      1               117
##  3 Animation   0                49
##  4 Animation   1               111
##  5 Comedy      0               224
##  6 Comedy      1               325
##   7 Documentary 0                11
##   8 Documentary 1               121
##   9 Drama       0               620
##  10 Drama       1                34
##  11 Romance     0                15
##  12 Short       0                 1
##  13 Short       1               104
```

```
plot_xtab(film$rating.large7,film$genre,show.values =FALSE,show.total =FALSE,
axis.labels =c("0","1"),
axis.titles=c("rating larger than 7?"))
```



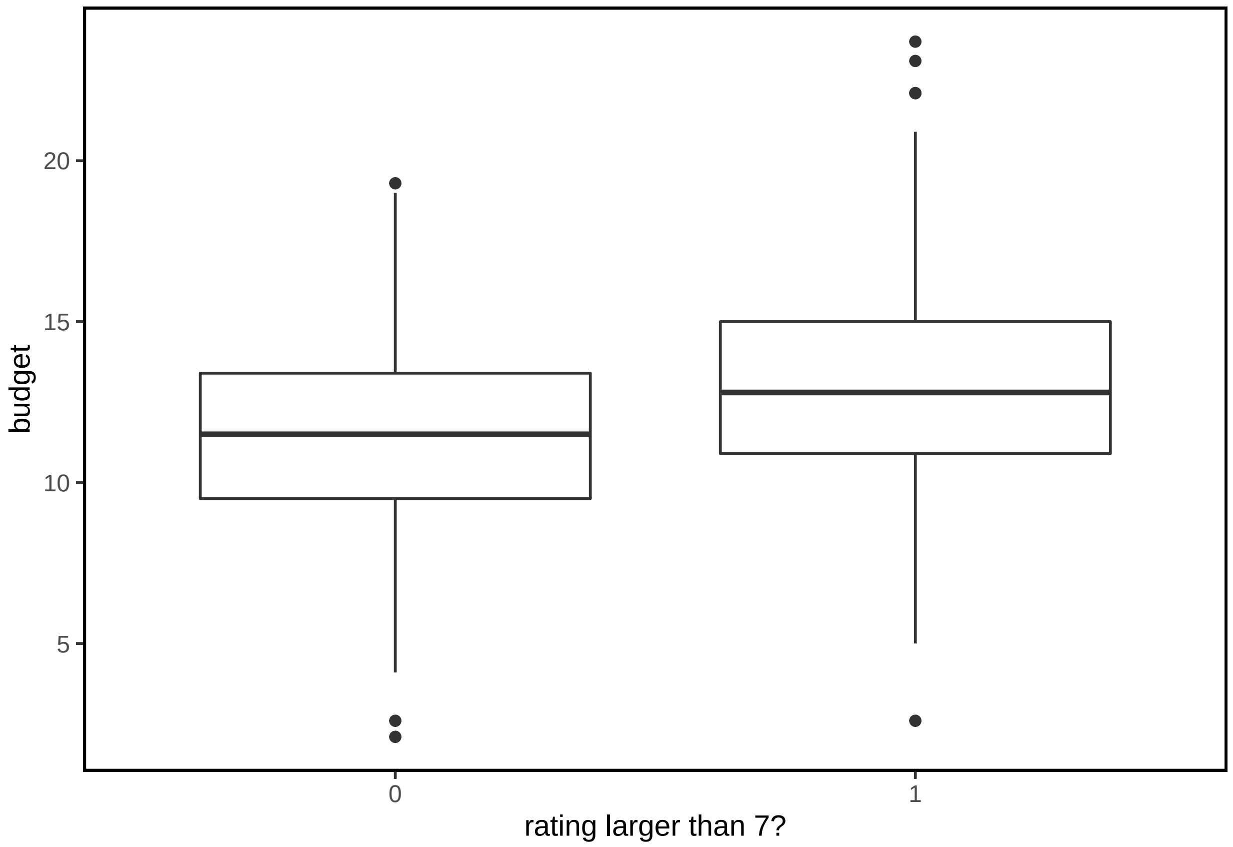
```
film %>%
  tabyl(rating.large7, genre) %>%
  adorn_percentages() %>%
  adorn_pct_formatting() %>%
  adorn_ns()
```

```
##   rating.large7      Action    Animation       Comedy Documentary        Drama
##               0 38.0% (563)  3.3%  (49) 15.1% (224)  0.7%  (11) 41.8% (620)
##               1 14.4% (117) 13.7% (111) 40.0% (325) 14.9% (121)  4.2%  (34)
##     Romance       Short
##   1.0% (15)  0.1%   (1)
##   0.0%  (0) 12.8% (104)
```

The distribution of rating.large7 by other numerical variables

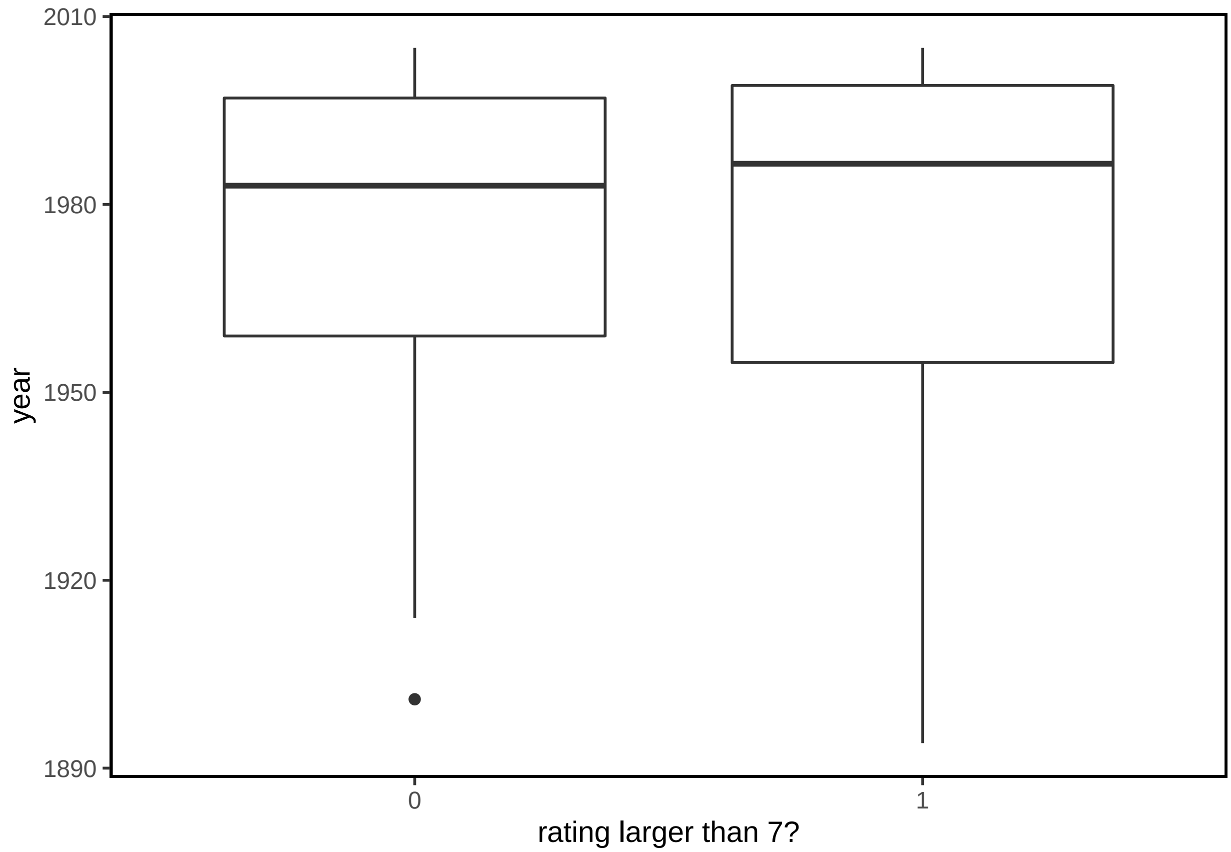
```
## budget
film.plot1<-ggplot(film, aes(y=budget,x=rating.large7))

film.plot1+geom_boxplot()+xlab("rating larger than 7?")+
theme(panel.background =element_rect(fill ="transparent",colour =NA),
plot.background =element_rect(fill ="transparent",colour =NA),
panel.border =element_rect(fill =NA,colour ="black",size =1))
```



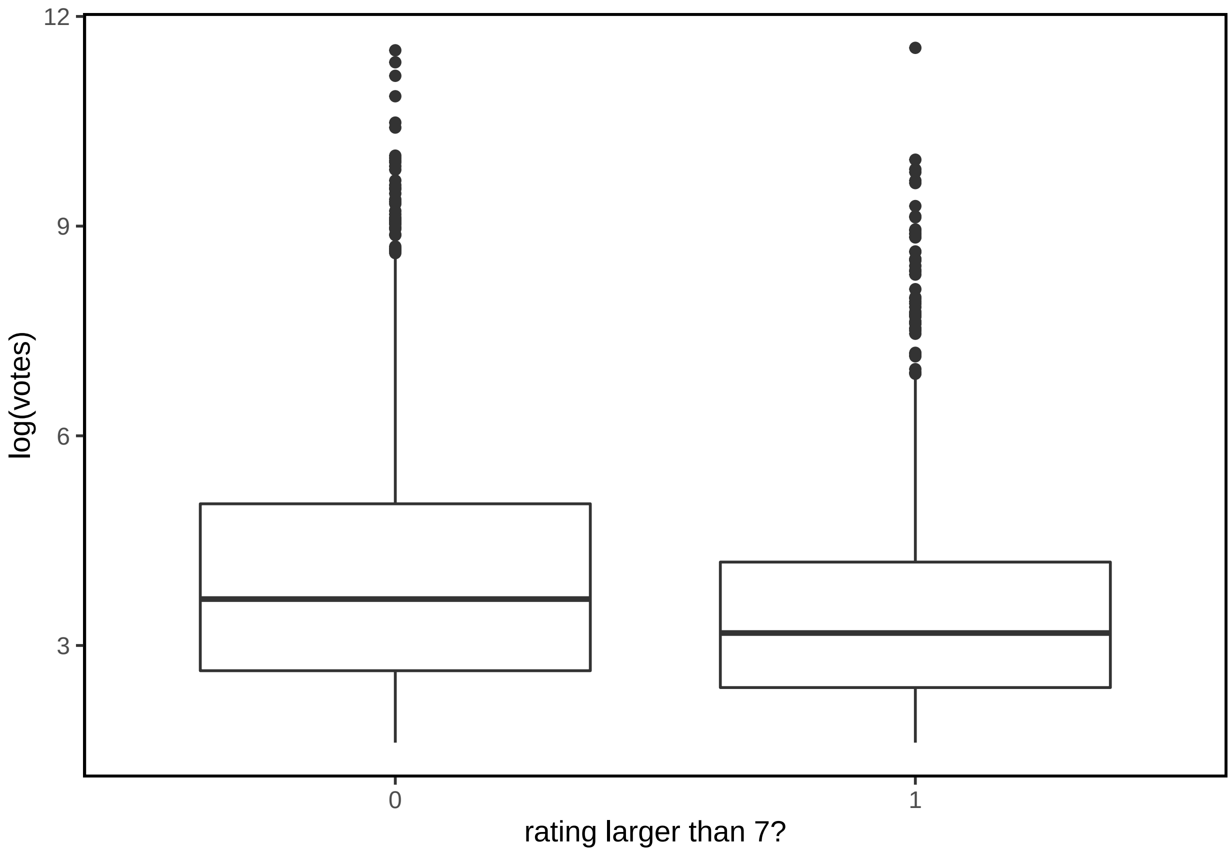
```
## year
film.plot2<-ggplot(film, aes(y=year,x=rating.large7))

film.plot2+geom_boxplot()+xlab("rating larger than 7?")+
theme(panel.background =element_rect(fill ="transparent",colour =NA),
plot.background =element_rect(fill ="transparent",colour =NA),
panel.border =element_rect(fill =NA,colour ="black",size =1))
```



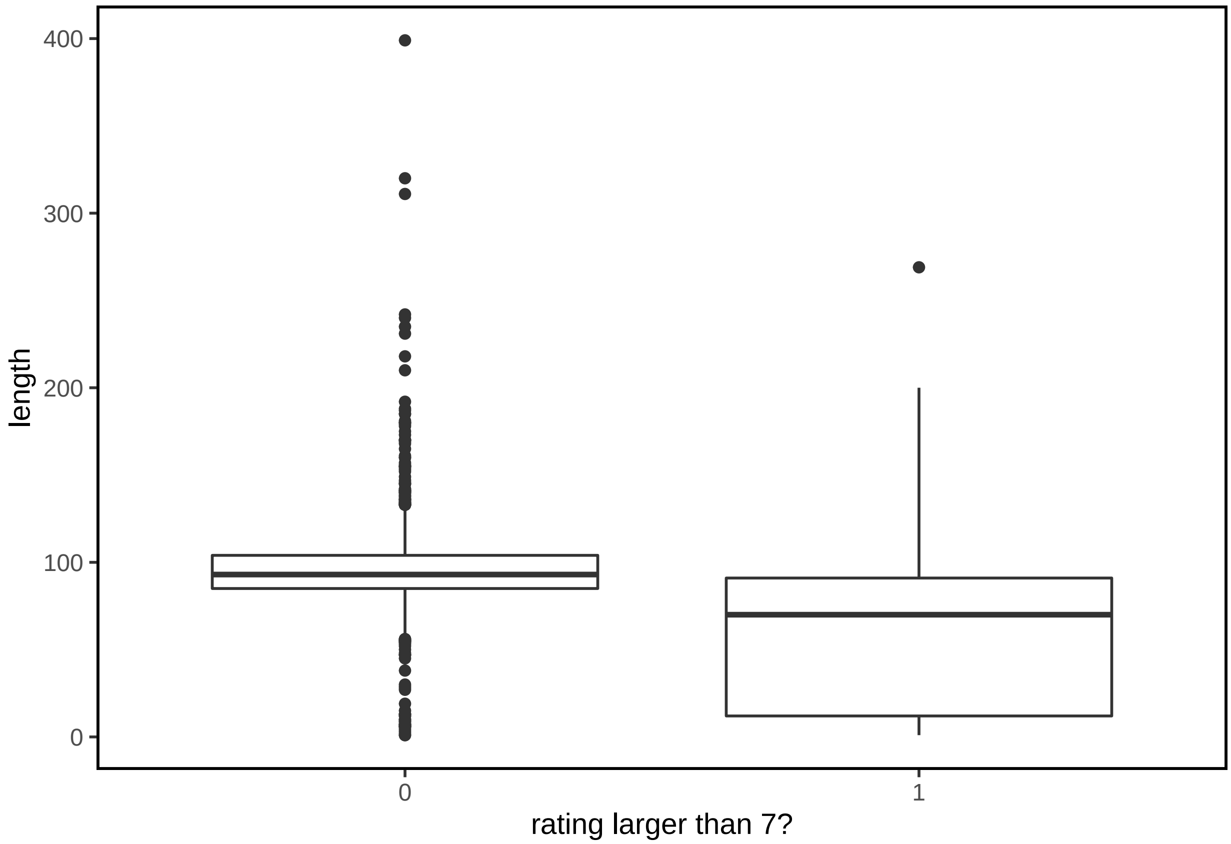
```
## votes
film.plot3<-ggplot(film, aes(y=log(votes),x=rating.large7))

film.plot3+geom_boxplot()+xlab("rating larger than 7?")+
theme(panel.background =element_rect(fill ="transparent",colour =NA),
plot.background =element_rect(fill ="transparent",colour =NA),
panel.border =element_rect(fill =NA,colour ="black",size =1))
```



```
## length
film.plot4<-ggplot(film, aes(y=length,x=rating.large7))

film.plot4+geom_boxplot()+xlab("rating larger than 7?")+
theme(panel.background =element_rect(fill ="transparent",colour =NA),
plot.background =element_rect(fill ="transparent",colour =NA),
panel.border =element_rect(fill =NA,colour ="black",size =1))
```



Formal data analysis

Take log transformation of variable “vote” because the scale is not linear.

```
film <- film %>%
  mutate(log.votes = log(votes))
```

Stepwise Slection: choosing which variables need to be removed.

Since Model with “year” removed has lowest AIC=1303.21 and deviance D=1283.2 we will go ahead and compared the three link function in our model

```
model_sat <-  glm(rating.large7 ~ length + budget + genre + log.votes + year, family = binomial(link =

logit.step <- step(model_sat,direction='both')
```

```
## Start:  AIC=1304.73
## rating.large7 ~ length + budget + genre + log.votes + year
##
##             Df Deviance    AIC
## - year       1   1283.2 1303.2
## <none>           1282.7 1304.7
## - log.votes  1   1293.0 1313.0
## - length     1   1595.2 1615.2
## - budget     1   1658.2 1678.2
## - genre      6   2101.0 2111.0
##
## Step:  AIC=1303.21
## rating.large7 ~ length + budget + genre + log.votes
##
##             Df Deviance    AIC
## <none>           1283.2 1303.2
## + year       1   1282.7 1304.7
## - log.votes  1   1294.3 1312.3
## - length     1   1602.0 1620.0
## - budget     1   1659.2 1677.2
## - genre      6   2118.6 2126.6
```

```
summary(logit.step)
```

```
##
## Call:
## glm(formula = rating.large7 ~ length + budget + genre + log.votes,
##     family = binomial(link = "logit"), data = film)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -3.7981  -0.3973  -0.1132   0.2672   4.3137
##
## Coefficients:
##                    Estimate Std. Error z value Pr(>|z|)
## (Intercept)       -3.902725   0.454750  -8.582  < 2e-16 ***
## length            -0.054295   0.003818 -14.220  < 2e-16 ***
## budget             0.499131   0.031641  15.775  < 2e-16 ***
## genreAnimation    -0.335711   0.346575  -0.969 0.332719
## genreComedy        2.677837   0.184023  14.552  < 2e-16 ***
## genreDocumentary   4.908172   0.414732  11.835  < 2e-16 ***
## genreDrama        -2.081558   0.259941  -8.008 1.17e-15 ***
## genreRomance     -14.705910 513.365991  -0.029 0.977147
## genreShort         4.192245   1.051548   3.987 6.70e-05 ***
## log.votes          0.139433   0.041932   3.325 0.000884 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 2982.5  on 2294  degrees of freedom
## Residual deviance: 1283.2  on 2285  degrees of freedom
## AIC: 1303.2
##
## Number of Fisher Scoring iterations: 15
```

Comparing different link functions

The AIC and BIC in model1 is the smallest, and the Pseudo-R^2 is the largest. Hence we choose 'logit' link function to fit our model

Model 1: logit link

```
model1 <- glm(rating.large7 ~ length + budget + log.votes + genre, family = binomial(link = "logit"), da
summary(model1)
```

```
##
## Call:
## glm(formula = rating.large7 ~ length + budget + log.votes + genre,
##     family = binomial(link = "logit"), data = film)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -3.7981  -0.3973  -0.1132   0.2672   4.3137
##
## Coefficients:
##                    Estimate Std. Error z value Pr(>|z|)
## (Intercept)       -3.902725   0.454750  -8.582  < 2e-16 ***
## length            -0.054295   0.003818 -14.220  < 2e-16 ***
## budget             0.499131   0.031641  15.775  < 2e-16 ***
## log.votes          0.139433   0.041932   3.325 0.000884 ***
## genreAnimation    -0.335711   0.346575  -0.969 0.332719
## genreComedy        2.677837   0.184023  14.552  < 2e-16 ***
## genreDocumentary   4.908172   0.414732  11.835  < 2e-16 ***
## genreDrama        -2.081558   0.259941  -8.008 1.17e-15 ***
## genreRomance     -14.705910 513.365991  -0.029 0.977147
## genreShort         4.192245   1.051548   3.987 6.70e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 2982.5  on 2294  degrees of freedom
## Residual deviance: 1283.2  on 2285  degrees of freedom
## AIC: 1303.2
##
## Number of Fisher Scoring iterations: 15
```

Model 2: probit link

```
model2 <- glm(rating.large7 ~ length + budget + log.votes + genre, family = binomial(link = "probit"), d
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```
summary(model2)
```

```
##
## Call:
## glm(formula = rating.large7 ~ length + budget + log.votes + genre,
##     family = binomial(link = "probit"), data = film)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -4.2418  -0.4281  -0.0836   0.2941   5.1505
##
## Coefficients:
##                  Estimate Std. Error z value Pr(>|z|)
## (Intercept)      -2.25801    0.24005  -9.407  < 2e-16 ***
## length           -0.02704    0.00190 -14.227  < 2e-16 ***
## budget            0.26517    0.01612  16.452  < 2e-16 ***
## log.votes         0.07415    0.02294   3.233  0.00123 **
## genreAnimation    0.01144    0.18502   0.062  0.95071
## genreComedy       1.43664    0.09722  14.776  < 2e-16 ***
## genreDocumentary  2.67883    0.20897  12.819  < 2e-16 ***
## genreDrama       -1.12547    0.13240  -8.501  < 2e-16 ***
## genreRomance     -4.79462   76.38417  -0.063  0.94995
## genreShort        2.30958    0.44871   5.147 2.64e-07 ***
## ---
## Signif. codes:  0 ’***’ 0.001 ’**’ 0.01 ’*’ 0.05 ’.’ 0.1 ’ ’ 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 2982.5  on 2294  degrees of freedom
## Residual deviance: 1308.2  on 2285  degrees of freedom
## AIC: 1328.2
##
## Number of Fisher Scoring iterations: 14
```

Model 3: complementary log-log link

```
model3 <- glm(rating.large7 ~ length + budget + log.votes + genre, family = binomial(link = "cloglog"),
```

```
## Warning: glm.fit: algorithm did not converge
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```
summary(model3)
```

```
##
## Call:
## glm(formula = rating.large7 ~ length + budget + log.votes + genre,
##     family = binomial(link = "cloglog"), data = film)
##
## Deviance Residuals:
```

```
##     Min       1Q   Median       3Q      Max
## -6.7671  -0.4993  -0.2349   0.2710   3.1957
##
## Coefficients:
##                   Estimate Std. Error z value Pr(>|z|)
## (Intercept)      -3.060e+00  2.770e-01 -11.048  < 2e-16 ***
## length           -2.613e-02  2.018e-03 -12.948  < 2e-16 ***
## budget            2.727e-01  1.770e-02  15.407  < 2e-16 ***
## log.votes         6.313e-02  2.702e-02   2.336   0.0195 *
## genreAnimation    2.914e-01  2.000e-01   1.457   0.1452
## genreComedy       1.618e+00  1.181e-01  13.702  < 2e-16 ***
## genreDocumentary  2.821e+00  1.889e-01  14.929  < 2e-16 ***
## genreDrama       -1.423e+00  1.921e-01  -7.411 1.25e-13 ***
## genreRomance     -2.446e+01  7.992e+04   0.000   0.9998
## genreShort        2.352e+00  3.408e-01   6.902 5.11e-12 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 2982.5  on 2294  degrees of freedom
## Residual deviance: 1382.1  on 2285  degrees of freedom
## AIC: 1402.1
##
## Number of Fisher Scoring iterations: 25
```

Model	link function	AIC	BIC
model1	$g(p_i) = log(\frac{p_i}{1-p_i})$	1303.21	1360.6
model2	$g(p_i) = \phi^{-1}(pi), p_i = \phi(\frac{x_i-\mu}{\sigma})$	1328.18	1385.57
model3	$g(p_i) = log[-log(1-p_i)]$	1402.13	1459.51

final model

$$log(\frac{p_{(rating.large7=1)}}{1-p_{(rating.large7=1)}}) = -3.9 + -0.05 length_i + 0.5 * budget_i + 0.14 * log(votes_i) + -0.34 * I_(genre = Animation) + 2.68 * I_(genr$$

$$I_{(genre=Animation)} = \begin{cases} 1, genre = Animation \\ 0, otherwise \end{cases} \quad ,$$

$$I_{(genre=Comedy)} = \begin{cases} 1, genre = Comedy \\ 0, otherwise \end{cases} \quad ,$$

$$I_{(genre=Documentary)} = \begin{cases} 1, genre = Documentary \\ 0, otherwise \end{cases} \quad ,$$

$$I_{(genre=Drama)} = \begin{cases} 1, genre = Drama \\ 0, otherwise \end{cases} \quad ,$$

$$I_{(genre=Romance)} = \begin{cases} 1, genre = Romance \\ 0, otherwise \end{cases} \quad ,$$

$$I_{(genre=Short)} = \begin{cases} 1, genre = Short \\ 0, otherwise \end{cases} \quad .$$

Residual Deviance

$$D_0 - D_1 = 2982.47 - 1283.21 = 1699.26 > \chi^2(0.95, 9) = 16.9189776$$

We reject H0, and we can say that the model1 fits the data better than Null model.

```
model1$null.deviance - model1$deviance
```

```
## [1] 1699.256
```

```
df = model1$df.null - model1$df.residual
qchisq(p=0.95, df = df)
```

```
## [1] 16.91898
```

Deviance

To assess the adequacy of the model1 compared to the full/saturated model

The deviance of model1 is $D = 1283.21 > \chi^2(0.95, 2) = 5.9914645$

So we can conclude that there is no evidence of lack of fit for the model1.

```
qchisq(p=0.95,df=(length(model_sat$coefficients)-length(model1$coefficients)))
```

```
## [1] 3.841459
```

Odds ratios of model1

We interpret the odds ratios as follows: for the increase in the film's length, the odds of rating bigger than 7 decrease; for the increase in the film's budget, the odds of rating bigger than 7 increase; for the increase in the film's votes, the odds of rating bigger than 7 increase; Animation's odds of survival were 0.71 times those of Action, Comedy's odds of survival were 14.55 times those of Action, Documentary's odds of survival were 135.39 times those of Action, Drama's odds of survival were 0.12 times those of Action, Short's odds of survival were 66.17 times those of Action.

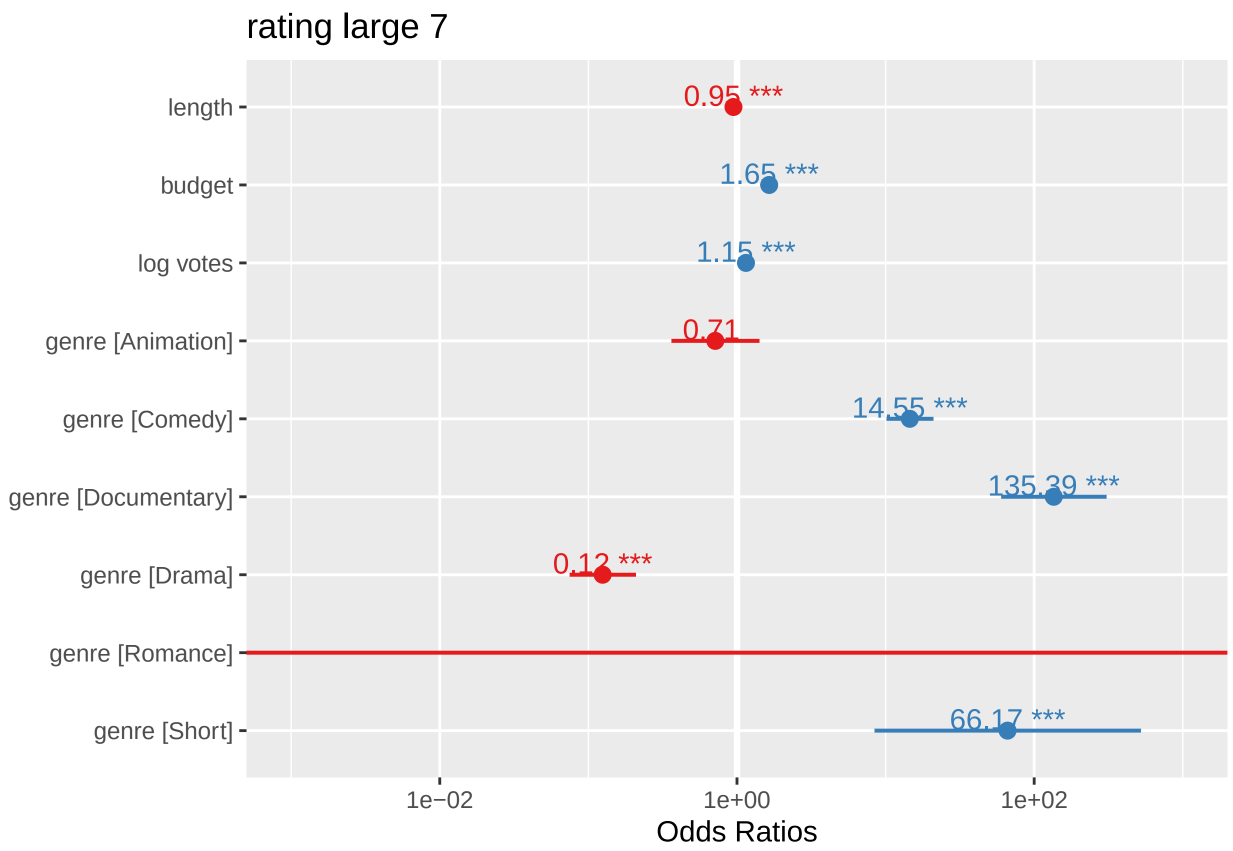
```
plot_model(model1,show.values=TRUE)+
  scale_y_log10(limits = c(0.001, 1000))
```

```
## Scale for 'y' is already present. Adding another scale for 'y', which will
## replace the existing scale.
```

```
## Warning: Transformation introduced infinite values in continuous y-axis
```

```
## Warning: Removed 1 rows containing missing values (geom_point).
```

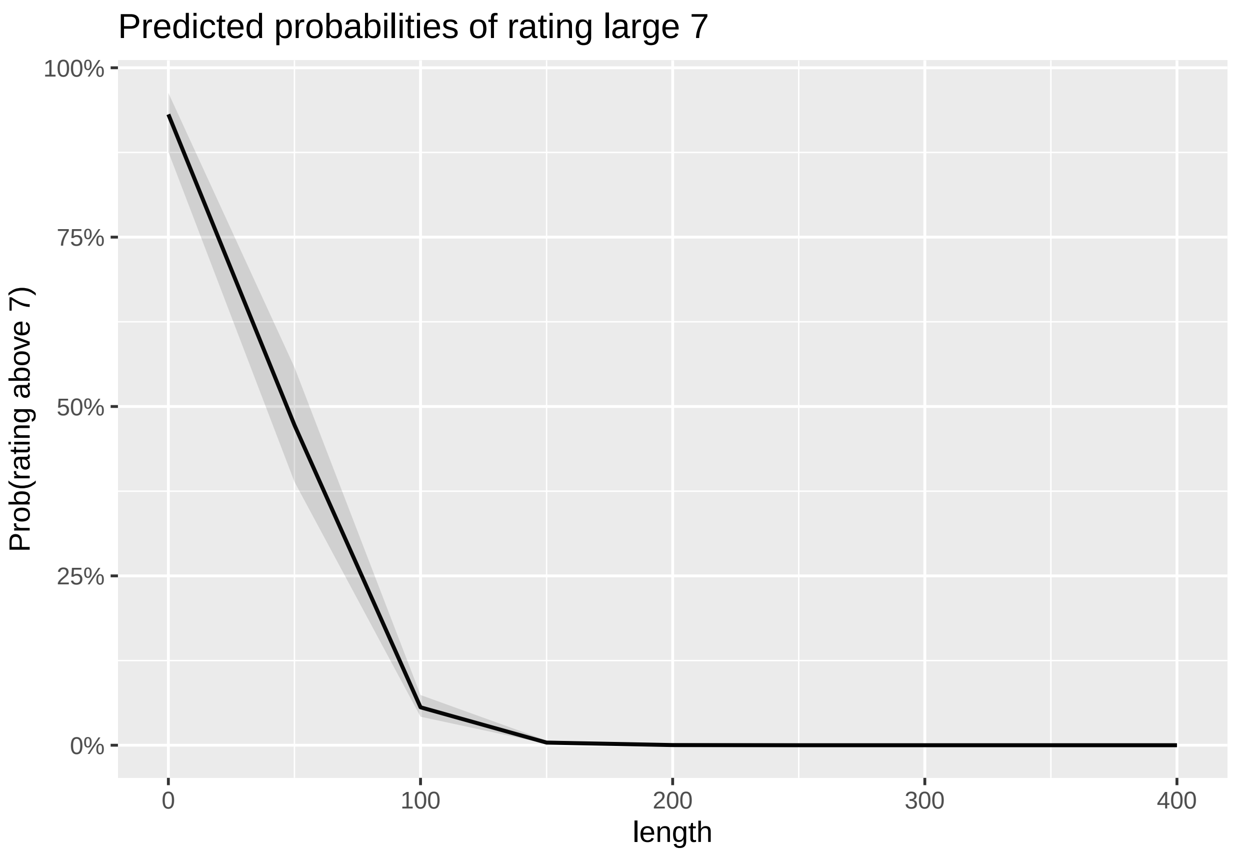
```
## Warning: Removed 1 rows containing missing values (geom_text).
```



Prediction

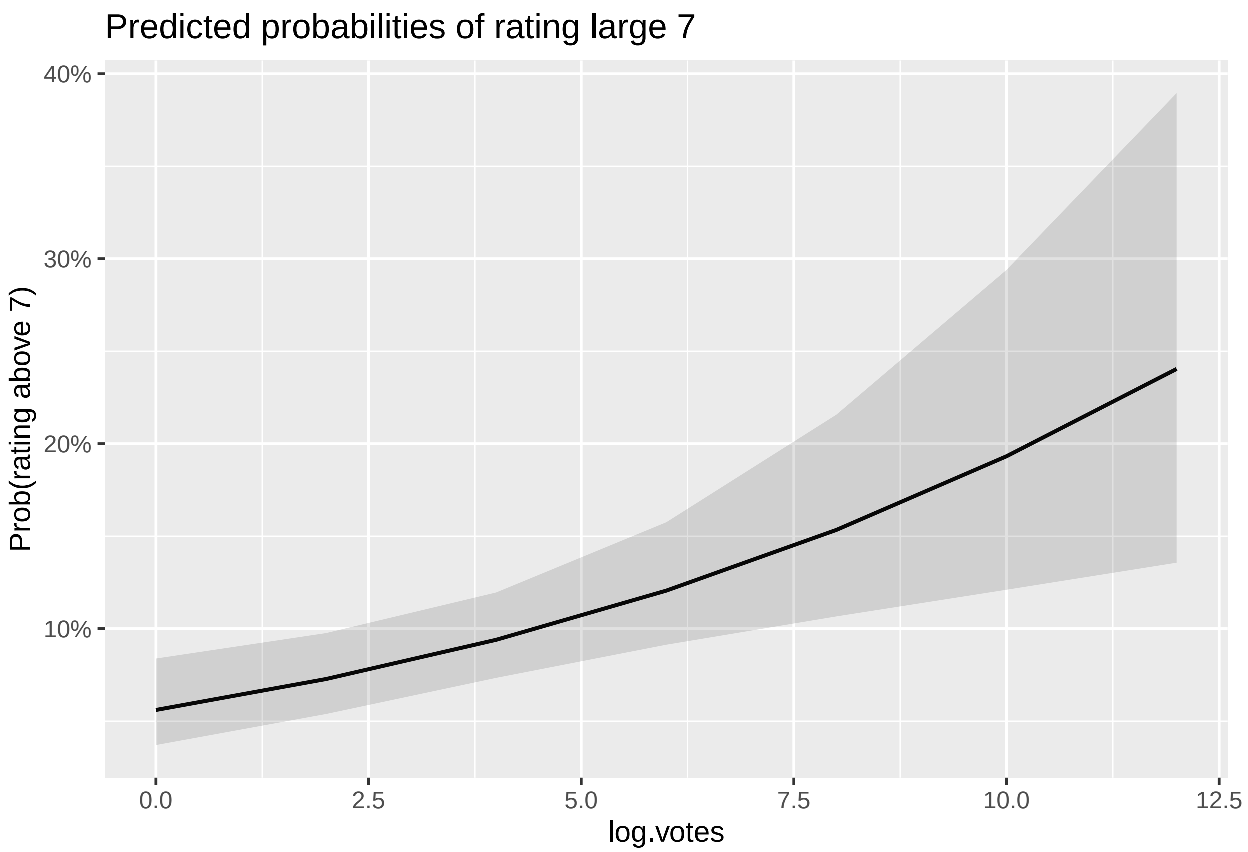
```
plot_model(model1,type="pred",terms=c("length"),axis.title=c("length","Prob(rating above 7)"))
```

```
## Data were 'prettified'. Consider using `terms="length [all]"` to get smooth plots.
```



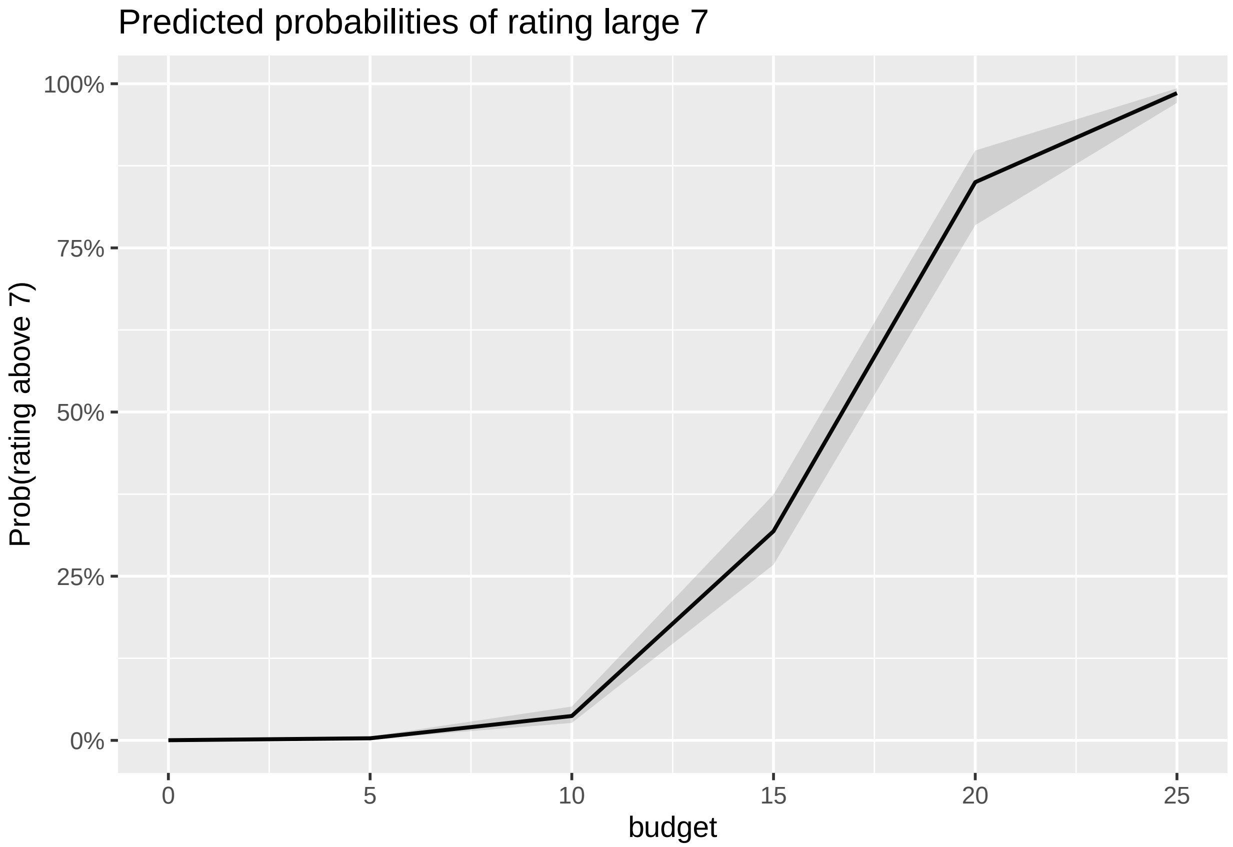
```
plot_model(model1,type="pred",terms=c("log.votes"),axis.title=c("log.votes","Prob(rating above 7)"))
```

```
## Data were 'prettified'. Consider using `terms="log.votes [all]"` to get smooth plots.
```

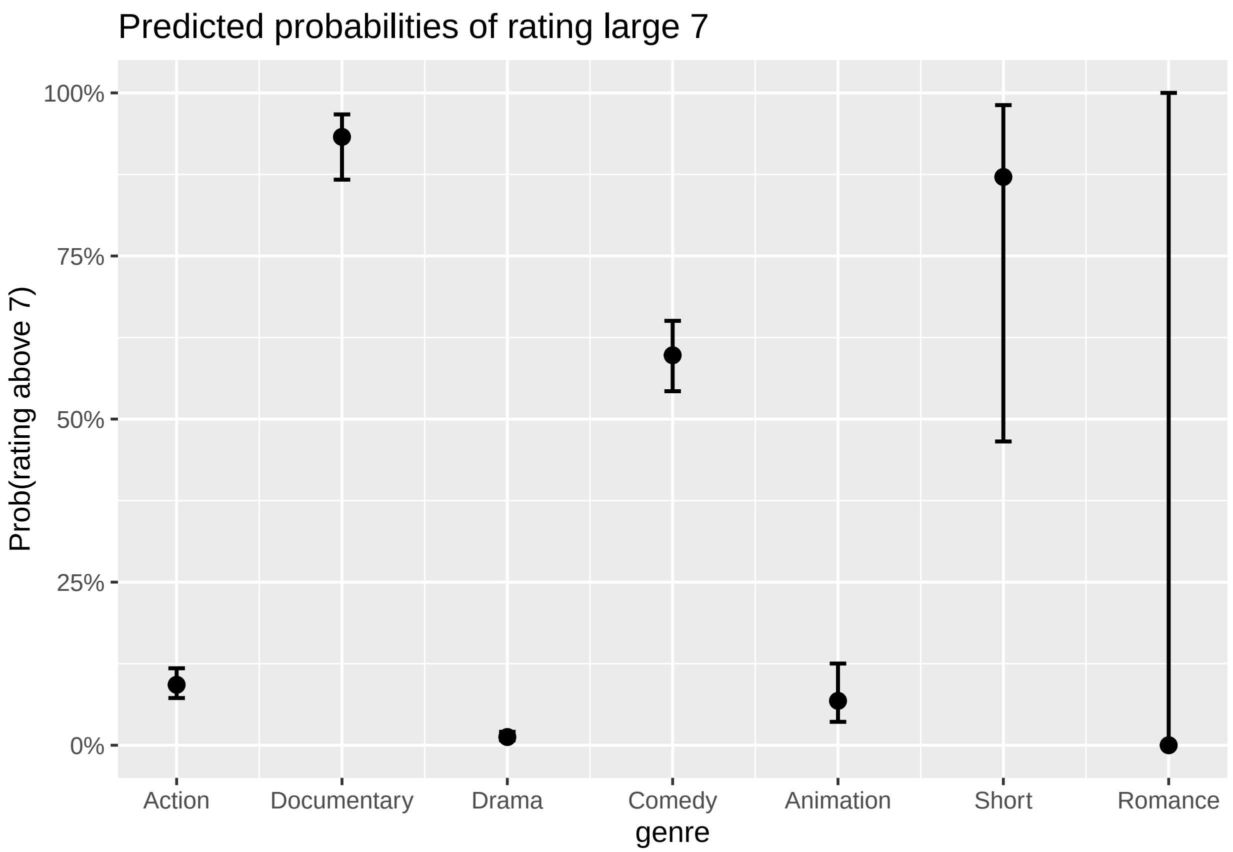


```
plot_model(model1,type="pred",terms=c("budget"),axis.title=c("budget","Prob(rating above 7)"))
```

```
## Data were 'prettified'. Consider using `terms="budget [all]"` to get smooth plots.
```



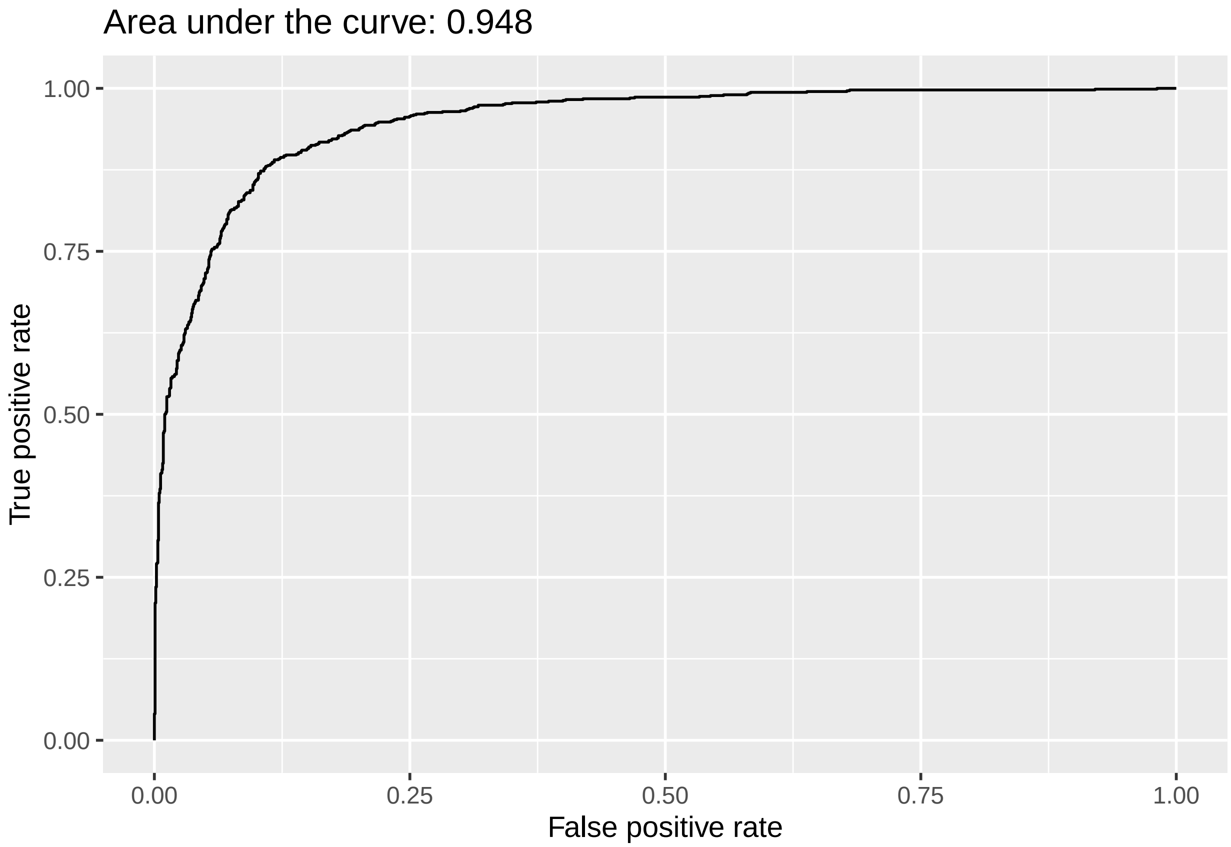
```
plot_model(model1,type="pred",terms=c("genre"),axis.title=c("genre","Prob(rating above 7)"))
```



Model checking and diagnostics

ROC curve and AUC

```
film$Prid <- predict(model1, film, type="response")
score <- prediction(film$Prid,film$rating.large7)
perf <- performance(score,"tpr","fpr")
auc <- performance(score,"auc")
perfd <- data.frame(x= perf@x.values[1][[1]], y=perf@y.values[1][[1]])
p4<- ggplot(perfd, aes(x= x, y=y)) + geom_line() +
xlab("False positive rate") + ylab("True positive rate") +
ggtitle(paste("Area under the curve:", round(auc@y.values[[1]], 3)))
p4
```



The area under Curve (AUC) = 0.948 indicated that model 1 is very good at predicting the films rating greater than 7 given all predictor variables.

Hosmer-Lemeshow goodness of fit test

H_0 : Model1 fits the data well

H_1 : Model1 is not a good fit for the data

```
source(url("http://www.chrisbilder.com/categorical/Chapter5/AllGOFTests.R"))
HLTest(model1,g=6)
```

```
## Warning in HLTest(model1, g = 6): Some expected counts are less than 5. Use
## smaller number of groups
```

```
##
##  Hosmer and Lemeshow goodness-of-fit test with 6 bins
##
## data:  model1
## X2 = 5.4773, df = 4, p-value = 0.2417
```

The large p-value = 0.2417 indicates no lack of fit for the model1 and we fail to reject H_0.