

ECON 424 - Final Project (Winter 2023)

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Questions

For this project, these are the questions that we will be answering:

1. Without any interactions, which covariate(s) affect revenue the most?
2. Are there any certain genres, actors, or keywords that affect revenue the most?
3. If we do interactions between genres, actors, and keywords, are there any particular combination(s) that affect revenue the most?
4. Do people's preferences on movie genres and actors change over the years/decades?

Data

In this project, we will be using the Movies dataset from Kaggle: <https://www.kaggle.com/datasets/akshaypawar7/millions-of-movies?resource=download>. We downloaded this dataset on April 2, 2023 on 2pm EST and continue to work with it locally. This dataset consists of around 723 thousand rows of movies, with their descriptions and details separated into columns. The response variable that we are focusing on from this dataset is the "revenue" column, which shows us the revenue of the movie. The covariates that might be useful from this dataset includes: date published, budget, genres, casts, keywords, and runtime.

Here is the first few rows of the data:

```
data <- read.csv("./movies.csv")
head(data)
```

```
##      id                title                genres
## 1  76600  Avatar: The Way of Water Science Fiction-Adventure-Action
## 2 631842      Knock at the Cabin      Horror-Mystery-Thriller
## 3 646389      Plane      Action-Adventure-Thriller
## 4 505642 Black Panther: Wakanda Forever Action-Adventure-Science Fiction
## 5 956101      The Eighth Clause      Thriller
## 6 603692      John Wick: Chapter 4      Action-Thriller-Crime
## original_language
## 1      en
## 2      en
## 3      en
## 4      en
## 5      la
## 6      en
##
## 1      Set more than a decade after the
```

```

## 2 While vacationing at a remote cabin a young girl and her
## 3
## 4 Queen Ramonda Shuri M'Baku Okoye and the Dora Milaje fight to protect their nation from intervening
## 5
## 6 With the price on his head
## popularity
## 1 10255.685
## 2 3422.537
## 3 2618.646
## 4 2525.408
## 5 2259.303
## 6 2252.114
##
## production_companies
## 1 20th Century Studios-Lightstorm Entertainment
## 2 Blinding Edge Pictures-Universal Pictures-FilmNation Entertainment-Wishmore-Perfect World Pictures
## 3 MadRiver Pictures-Di Bonaventura Pictures-G-BASE-Olive Hill Media-Riverstone Pictures
## 4 Marvel Studios
## 5 SDB Films-El Hombre Orquesta
## 6 Thunder Road-87Eleven-Lionsgate-Summit Entertainment-El-Torky Art Production
## release_date budget revenue runtime status
## 1 2022-12-14 4.6e+08 2309660236 192 Released
## 2 2023-02-01 2.0e+07 52000000 100 Released
## 3 2023-01-12 2.5e+07 51000000 107 Released
## 4 2022-11-09 2.5e+08 858535561 162 Released
## 5 2022-04-29 0.0e+00 0 0 Released
## 6 2023-03-22 9.0e+07 0 169 Released
## tagline vote_average vote_count
## 1 Return to Pandora. 7.739 6227
## 2 Save your family or save humanity. Make the choice. 6.457 888
## 3 Survive together or die alone. 6.901 785
## 4 Forever. 7.338 3922
## 5 4.600 10
## 6 No way back. One way out. 8.319 202
##
## 1
## 2
## 3
## 4 Letitia Wright-Lupita Nyong'o-Danai Gurira-Winston Duke-Dominique Thorne-Tenoch Huerta Mejía-Angel
## 5
## 6
##
## 1 loss of loved one-dying and death-alien life-form-resurrection-sequel-dysfunctional family
## 2 based on novel or book-sacrifice-cabin-faith-end of the world-apocalypse-home invasion-lgbt-afterc
## 3
## 4 loss of loved one-hero-sequel-superhero-based on comic-mourning-c
## 5
## 6 new york city-martial arts-hit
## poster_path backdrop_path
## 1 /t6HIqrRAclMCA60NsSmeqe9RmNV.jpg /ovM06PdF3M8wvKb06i4sjW3xoww.jpg
## 2 /dm06L9pxDOL9jNSK4Cb6y139rrG.jpg /zWDMQX0sPaW2u0N2pJaYA8bVVAJ.jpg
## 3 /qi9r5xBgcc9KTxl0LjssEbDg00J.jpg /9Rq14Eyrf7Tu1xk0P17VcNbNh1n.jpg
## 4 /sv1xJUazXeYqALzczSZ306nkH75.jpg /xDmI184Qo5Tsu62c9DGWhmPI67A.jpg
## 5 /8tc8eMFAX2SDC1TRu987qFQy8Cl.jpg /kLnqNE9Af5QHyyUxw8cDGhF1ilv.jpg
## 6 /vZloFAK7NmvmGKE7Vkf5UHaz0I.jpg /i8dshLvq4LE3s0v8PrkDdUyb1ae.jpg

```

```
##
## 1      183392-111332-702432-505642-1064215-436270-874764-613200-315162-965839-1013870-100287-758009-10
## 2 1058949-646389-772515-505642-143970-667216-1048522-785084-1058617-986054-640146-937278-1001500-717
## 3                                     505642-758769-864692-631842-1058949-925943-758009-315162-6157
## 4                               436270-829280-76600-56969-312634-1037858-238-551271-22023-736526-899112-468073-63285
## 5
## 6
```

Before we do some analysis, we will clean the data. First, we will remove unnecessary columns and also data with zero revenues. We are only keeping released movies above 40 minutes as we are not including short movies in the data. This is based on the definition from the Academy of Motion Picture Arts and Sciences, where they define a short film as “an original motion picture that has a running time of 40 minutes or less, including all credits”. We also do not include the movies with runtime of value 999. There might also be duplicates in the data, so we need to remove duplicates as well. Since people can add random movies into this database, we try as best as we can to filter those out. To make sure that a movie is legitimate, we filter the movies that do not have any genres, production companies, and credits (all three are empty values).

```
# Only movies that has revenue, is released, and more than
# 40 minutes long Also remove if runtime = 999 and remove
# the movies with missing genres, production companies, and
# credits
clean_data <- data[data$revenue > 0 & data$status == "Released" &
  data$runtime > 40 & data$runtime != 999 & !(data$genres ==
  "" & data$production_companies == "" & data$credits == ""),
  !names(data) %in% c("overview", "popularity", "status", "tagline",
    "vote_average", "vote_count", "poster_path", "backdrop_path",
    "recommendations")]

# removing empty ID rows
clean_data <- clean_data[!is.na(clean_data$id), ]

# resetting row.names
row.names(clean_data) <- NULL

# remove duplicate data
clean_data <- clean_data[!duplicated(clean_data[, 1]), ]

write.csv(clean_data, file = "./movies_filtered.csv", row.names = FALSE)

n <- length(clean_data[, 1])
```

We took this data and use a Python API to calculate the adjusted revenues by adding inflation factors. Here are the Python code below.

```
# import libraries
import pandas as pd
import matplotlib.pyplot as plt
import requests
import json
from tqdm import tqdm
from pathlib import Path
```

```

# get movies from movies_filtered.csv
movies = pd.read_csv(r'movies_filtered.csv')
n = len(movies)

# Function to get the inflation rate from the API
# Input: start_time (based on release_date)
# Output: inflation rate (inflated to April 3, 2023)
def get_dollar(start_time):
    api_url = "https://www.statbureau.org/calculate-inflation-price-jsonp?jsoncallback=?"

    headers = {'Content-type': 'application/json'}

    payload = {
        "country": "united-states",
        "start": str(start_time),
        "end": "2023/04/03",
        "amount": "1",
        "format": True
    }
    response = requests.post(api_url, data=json.dumps(payload), headers=headers)
    my_bytes = response.content

    amount_s = my_bytes.decode('utf8').replace("'", '')
    amount_s = amount_s[4:-2]
    return float(amount_s)

# getting the inflation rate of each movie
inflation = [0] * n
failed = []
for i in tqdm(range(n)):
    try:
        inflation[i] = get_dollar(movies.iloc[i]['release_date'])
    except:
        failed.append(i)

# data with no release_date will be given inflation = 1 (no inflation)
for fail in failed:
    inflation[fail] = 1

# getting the adjusted revenue for each movie
revenue_adjusted_c = movies['revenue'] * np.array(inflation)
df2 = movies.assign(revenue_adjusted=revenue_adjusted_c)

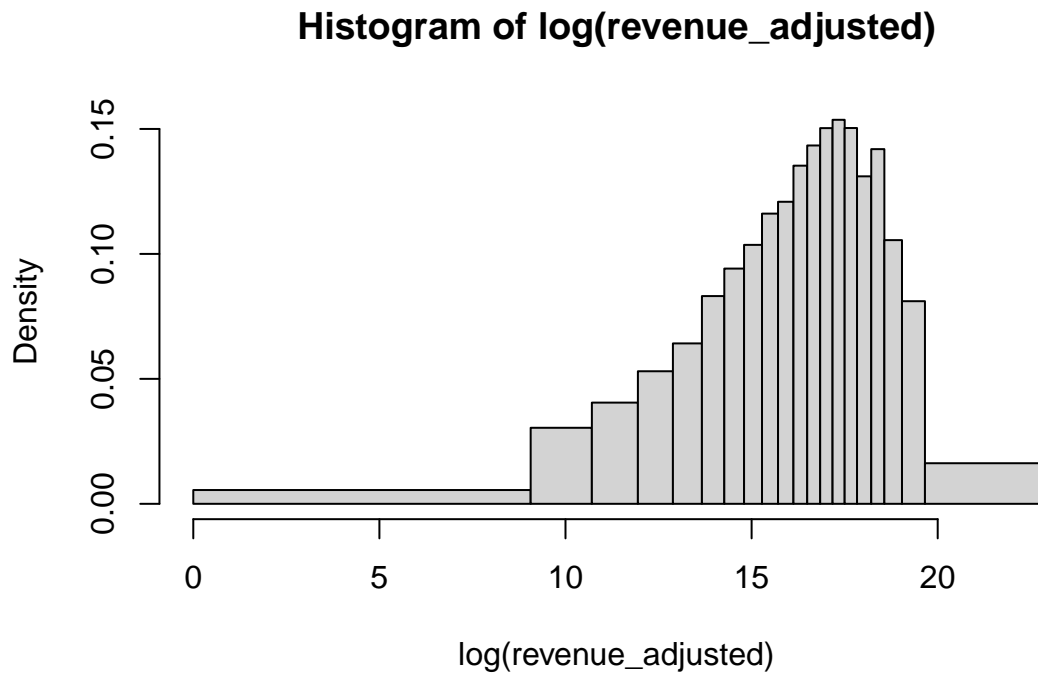
# exporting the file movies_adjusted.csv
filepath = Path('movies_adjusted.csv')
filepath.parent.mkdir(parents=True, exist_ok=True)
df2.to_csv(filepath)

```

We calculated all the revenues inflated to April 3, 2023 and include them in the data as a new column called “revenue_adjusted”. The data that do not have release_date will have their adjusted revenue be the same as their revenue.

```
clean_data <- read.csv("./movies_adjusted.csv")
n <- length(clean_data[, 1])

hist(log(clean_data$revenue_adjusted), breaks = quantile(log(clean_data$revenue_adjusted),
  p = seq(0, 1, length.out = 21)), freq = FALSE, xlab = "log(revenue_adjusted)",
  main = "Histogram of log(revenue_adjusted)")
```



From the histogram above, we can see that when we split the dataset into 20 bins of 5% quantiles each, most of them have high values on revenues after being adjusted to inflation.

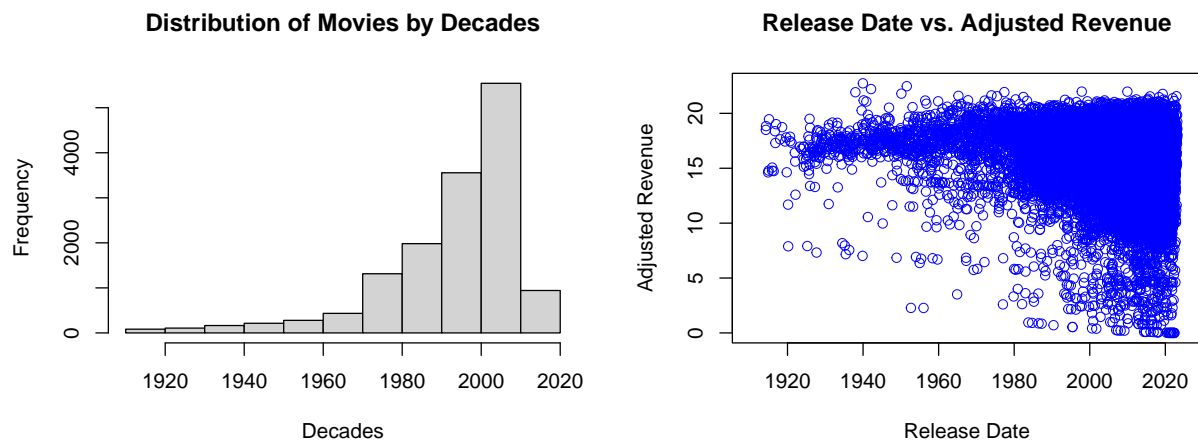
After cleaning the data, we have a total of 14,678 rows of movies.

Limitations

Before we start with our methods, we would like to address the limitation of the methods that we are using here.

```
clean_data$year <- format(as.Date(clean_data$release_date), format = "%Y")
clean_data$decades <- floor(as.numeric(clean_data$year)/10) *
  10
df_list <- split(clean_data, clean_data$decades)
```

```
par(mfrow = c(1, 2))
hist(clean_data$decades, xlab = "Decades", main = "Distribution of Movies by Decades")
plot(as.Date(clean_data$release_date), log(clean_data$revenue_adjusted),
  xlim = c(as.Date("1910-01-01"), as.Date("2025-01-01")), col = "blue",
  lwd = 0.5, xlab = "Release Date", ylab = "Adjusted Revenue",
  main = "Release Date vs. Adjusted Revenue")
```



Based on the histogram above, we can see that the distribution of the movies are not equal across time. There are more recent movies in the dataset than the older movies. Also, from the scatterplot above, it is visible that the variance of the data changes over time. This shows that our data is non-stationary. In addition, we do not see a lot of data points in the early decades, and not a lot of them have low revenues. Since this is a problem, we do not use time as a variable in our model. We do not change the distribution of the data since it is better to have more data on recent decades. This gives us a notion of weights on the data, with having more movies closer to the present.

Other than that, note that the data cleaning process is not perfect. Since the data source is publicly available to be added, there are some made-up data points in the raw data. We cleaned it as best as we could, but there is no guarantee on whether there are still some made-up data in this dataset.

Methods & Results

To answer the questions above, we will create some models using LASSO method via `cv.glmnet` function. We use LASSO since we will have a lot of variables coming from the text columns. Thus, we use LASSO to do variable reduction to obtain a balanced model. To build the model, we will have to do text analysis on the texts first. There are five columns which has text variables: `production_companies`, `genres`, `credits`, `keywords`, and `original_language`. The terms that we are using from these columns are separated by dashes (“-”). Using this information, we will separate these text columns into a sparse matrix full of terms. For each document, the term will be equal to 1 if it appears on that document, and 0 if it does not appear. After getting each term separated, we added single letter prefixes with “\$” on the terms to be able to tell which column the terms come from. Then, we filter the sparse matrix so that only terms that appear in at least 50 movies is included to be in the model.

```
library(pdftools)
```

```
## Using poppler version 22.04.0
```

```
library(tm)
```

```
## Loading required package: NLP
```

```
library(SnowballC)
```

```
to_another <- content_transformer(function(x, y, z) gsub(y, z,
```

```

x))

add_pre <- function(x, pre) {
  ifelse(!is.na(x) & x != "" & nchar(x) > 0 & x != " ", return(paste(pre,
    x, sep = " ")), return(x))
}

add_prefix <- content_transformer(add_pre)

```

For terms coming from production_companies column, we have to change “Metro-Goldwyn-Mayer” to “Metro_Goldwyn_Mayer” due to the name having dashes in it. This is the only company that appears in at least 50 movies that contains “-” in its name. We added “p\$” to indicate production_companies terms. From here, we got a result of 71 production companies.

```

#### PRODUCTION COMPANIES
prod_comp <- clean_data$production_companies
docs <- Corpus(VectorSource(prod_comp))
# Remove '-' from the name since it is the separator of the
# data
docs <- tm_map(docs, to_another, "Metro-Goldwyn-Mayer", "Metro_Goldwyn_Mayer")
docs <- tm_map(docs, to_another, "no_production_companies", "")
docs <- tm_map(docs, to_another, " ", "_")
docs <- tm_map(docs, to_another, "-", " ")
docs <- tm_map(docs, stripWhitespace)
# adding prefix p$ for production_companies
docs <- tm_map(docs, add_prefix, "p$")
docs <- tm_map(docs, to_another, " ", " p$")
dtm <- DocumentTermMatrix(docs)

# get production companies in at least 50 movies
key_pc <- sort(findFreqTerms(dtm, 50))
key_pc

```

```

## [1] "p$20th_century_fox"           "p$amblin_entertainment"
## [3] "p$arte_france_cinéma"        "p$atresmedia"
## [5] "p$bbc_film"                  "p$blumhouse_productions"
## [7] "p$canal+"                   "p$canal+_españa"
## [9] "p$cannon_group"             "p$castle_rock_entertainment"
## [11] "p$ciné+"                    "p$cj_entertainment"
## [13] "p$cnc"                      "p$columbia_pictures"
## [15] "p$constantin_film"          "p$dentsu"
## [17] "p$dimension_films"          "p$dreamworks_pictures"
## [19] "p$dune_entertainment"        "p$europacorp"
## [21] "p$film_i_väst"              "p$film4_productions"
## [23] "p$filmnation_entertainment"  "p$focus_features"
## [25] "p$fox_2000_pictures"         "p$fox_searchlight_pictures"
## [27] "p$france_2_cinéma"          "p$france_3_cinéma"
## [29] "p$gaumont"                  "p$hollywood_pictures"
## [31] "p$imagine_entertainment"     "p$ingenious_media"
## [33] "p$lakeshore_entertainment"   "p$lionsgate"
## [35] "p$malpaso_productions"       "p$metro_goldwyn_mayer"
## [37] "p$millennium_films"          "p$miramax"
## [39] "p$morgan_creek_productions"  "p$new_line_cinema"

```

```
## [41] "p$new_regency_pictures"      "p$orion_pictures"
## [43] "p$paramount"                "p$participant"
## [45] "p$pathé"                    "p$polygram_film_entertainment"
## [47] "p$regency_enterprises"      "p$relativity_media"
## [49] "p$scott_free_productions"    "p$scott_rudin_productions"
## [51] "p$screen_gems"              "p$silver_pictures"
## [53] "p$sony_pictures"            "p$studiocanal"
## [55] "p$summit_entertainment"      "p$téléfilm_canada"
## [57] "p$tf1_films_production"     "p$the_weinstein_company"
## [59] "p$toei_company"             "p$toho"
## [61] "p$touchstone_pictures"      "p$tristar_pictures"
## [63] "p$tsg_entertainment"        "p$united_artists"
## [65] "p$universal_pictures"       "p$village_roadshow_pictures"
## [67] "p$walt_disney_pictures"     "p$warner_bros._pictures"
## [69] "p$wild_bunch"               "p$working_title_films"
## [71] "p$zdf"
```

For terms coming from genres column, we added “g\$” to indicate genre terms. We decided to use all genres since there are only 19 of them. The only genre with less than 50 movies is “tv_movie”, but we decided to include it as a term.

```
#### GENRES
genres <- clean_data$genres
docs2 <- Corpus(VectorSource(genres))
docs2 <- tm_map(docs2, to_another, " ", "_")
docs2 <- tm_map(docs2, to_another, "-", " ")
docs2 <- tm_map(docs2, stripWhitespace)
# adding prefix g$ for genres
docs2 <- tm_map(docs2, add_prefix, "g$")
docs2 <- tm_map(docs2, to_another, " ", " g$")
dtm2 <- DocumentTermMatrix(docs2)

# get all genres
key_gen <- sort(findFreqTerms(dtm2, 0))
key_gen
```

```
## [1] "g$action"      "g$adventure"    "g$animation"
## [4] "g$comedy"      "g$crime"        "g$documentary"
## [7] "g$drama"       "g$family"       "g$fantasy"
## [10] "g$history"     "g$horror"       "g$music"
## [13] "g$mystery"     "g$romance"      "g$science_fiction"
## [16] "g$thriller"    "g$tv_movie"     "g$war"
## [19] "g$western"
```

For terms coming from credits column, there are a lot of names that contains a dash symbol. The names of Korean casts can be dealt with since they follow a regex pattern, as seen in the code. However, this does not cover all names. It is hard to clean this, so we decided to remove one-word names from the results. We added “c\$” to indicate cast terms. From this column, we managed to get 67 terms.

```
#### CREDITS
casts <- clean_data$credits
docs3 <- Corpus(VectorSource(casts))
docs3 <- tm_map(docs3, to_another, " ", "_")
```



```

# deal with Korean names
docs3 <- tm_map(docs3, to_another, "_(\\[:alpha:]+)-(\\[:lower:]+)$",
  "\\1_\\2")
docs3 <- tm_map(docs3, to_another, "_(\\[:alpha:]+)-(\\[:lower:]+)-",
  "\\1_\\2-")
docs3 <- tm_map(docs3, to_another, "-", " ")
docs3 <- tm_map(docs3, stripWhitespace)
# adding prefix c$ for casts
docs3 <- tm_map(docs3, add_prefix, "c$")
docs3 <- tm_map(docs3, to_another, " ", " c$")
dtm3 <- DocumentTermMatrix(docs3)

# get all casts in at least 50 movies
key_cast <- sort(findFreqTerms(dtm3, 50))

# hard to remove '-' from two-worded names separated by '-'
# so we remove single-word names that comes from them
key_cast <- key_cast[grep("_", key_cast)]
key_cast

```

```

## [1] "c$alec_baldwin"      "c$alfred_molina"      "c$anthony_hopkins"
## [4] "c$antonio_banderas" "c$ben_kingsley"       "c$ben_stiller"
## [7] "c$bess_flowers"     "c$bill_murray"        "c$brad_pitt"
## [10] "c$brian_cox"        "c$bruce_willis"       "c$cate_blanchett"
## [13] "c$christopher_plummer" "c$christopher_walken" "c$clint_eastwood"
## [16] "c$danny_glover"     "c$danny_trejo"        "c$dennis_quaid"
## [19] "c$donald_sutherland" "c$ethan_hawke"        "c$forest_whitaker"
## [22] "c$frank_welker"     "c$gene_hackman"       "c$harrison_ford"
## [25] "c$harvey_dean_stanton" "c$harvey_keitel"      "c$j.k._simmons"
## [28] "c$james_franco"     "c$joe_chrest"         "c$john_cusack"
## [31] "c$john_goodman"     "c$john_hurt"          "c$john_leguizamo"
## [34] "c$john_turturro"    "c$johanny_depp"       "c$julianne_moore"
## [37] "c$keanu_reeves"     "c$keith_david"        "c$kevin_bacon"
## [40] "c$liam_neeson"      "c$m._emmet_walsh"     "c$matt_damon"
## [43] "c$meryl_streep"     "c$michael_caine"      "c$michael_papajohn"
## [46] "c$morgan_freeman"   "c$nicolas_cage"       "c$nicole_kidman"
## [49] "c$owen_wilson"      "c$paul_giamatti"      "c$richard_jenkins"
## [52] "c$robert_de_niro"   "c$robert_downey_jr."  "c$robert_duvall"
## [55] "c$robin_williams"   "c$samuel_l._jackson"  "c$sigourney_weaver"
## [58] "c$stanley_tucci"    "c$stephen_root"       "c$stephen_tobolowsky"
## [61] "c$steve_buscemi"    "c$susan_sarandon"     "c$sylvester_stallone"
## [64] "c$thomas_rosales_jr." "c$tom_hanks"          "c$willem_dafoe"
## [67] "c$woody_harrelson"

```

For terms coming from keywords column, we added “k\$” to indicate keyword terms. From this column, we managed to get 312 terms.

```

#### KEYWORDS
keywords <- clean_data$keywords
docs4 <- Corpus(VectorSource(keywords))
docs4 <- tm_map(docs4, to_another, " ", "_")
docs4 <- tm_map(docs4, to_another, "-", " ")
docs4 <- tm_map(docs4, stripWhitespace)

```

```
# adding prefix k$ for keywords
docs4 <- tm_map(docs4, add_prefix, "k$")
docs4 <- tm_map(docs4, to_another, " ", " k$")
dtm4 <- DocumentTermMatrix(docs4)
```

```
# get all keywords in at least 50 movies
key_keys <- sort(findFreqTerms(dtm4, 50))
key_keys
```

```
## [1] "k$1920s" "k$1930s"
## [3] "k$1940s" "k$1950s"
## [5] "k$1960s" "k$1970s"
## [7] "k$1980s" "k$1990s"
## [9] "k$19th_century" "k$action_hero"
## [11] "k$adultery" "k$africa"
## [13] "k$aftercreditsstinger" "k$airplane"
## [15] "k$alcohol" "k$alcoholic"
## [17] "k$alcoholism" "k$alien"
## [19] "k$alien_invasion" "k$amnesia"
## [21] "k$animal" "k$anime"
## [23] "k$anthropomorphism" "k$anti_hero"
## [25] "k$apocalyptic_future" "k$army"
## [27] "k$artificial_intelligence" "k$assassin"
## [29] "k$assassination" "k$australia"
## [31] "k$author" "k$baby"
## [33] "k$bank_robbery" "k$baseball"
## [35] "k$based_on_children's_book" "k$based_on_comic"
## [37] "k$based_on_manga" "k$based_on_novel_or_book"
## [39] "k$based_on_play_or_musical" "k$based_on_short_story"
## [41] "k$based_on_true_story" "k$based_on_video_game"
## [43] "k$based_on_young_adult_novel" "k$battle"
## [45] "k$beach" "k$best_friend"
## [47] "k$betrayal" "k$biography"
## [49] "k$black_and_white" "k$blackmail"
## [51] "k$bomb" "k$brother"
## [53] "k$brutality" "k$buddy_cop"
## [55] "k$bullying" "k$california"
## [57] "k$cancer" "k$car_crash"
## [59] "k$castle" "k$cat"
## [61] "k$chase" "k$chicago_illinois"
## [63] "k$child_abuse" "k$china"
## [65] "k$christmas" "k$church"
## [67] "k$cia" "k$code"
## [69] "k$college" "k$coming_of_age"
## [71] "k$competition" "k$concert"
## [73] "k$conspiracy" "k$cop"
## [75] "k$corruption" "k$creature"
## [77] "k$criminal" "k$cult_film"
## [79] "k$dance" "k$dark_comedy"
## [81] "k$daughter" "k$death"
## [83] "k$demon" "k$depression"
## [85] "k$desert" "k$detective"
## [87] "k$disaster" "k$divorce"
```

## [89]	"k\$doctor"	"k\$dog"
## [91]	"k\$dragon"	"k\$dream"
## [93]	"k\$drug_addiction"	"k\$drug_dealer"
## [95]	"k\$drugs"	"k\$duringcreditsstinger"
## [97]	"k\$dying_and_death"	"k\$dysfunctional_family"
## [99]	"k\$dystopia"	"k\$england"
## [101]	"k\$epic"	"k\$escape"
## [103]	"k\$ex"	"k\$experiment"
## [105]	"k\$explosion"	"k\$extramarital_affair"
## [107]	"k\$fairy_tale"	"k\$faith"
## [109]	"k\$falling_in_love"	"k\$family"
## [111]	"k\$family_relationships"	"k\$father"
## [113]	"k\$father_daughter_relationship"	"k\$father_son_relationship"
## [115]	"k\$fbi"	"k\$female_friendship"
## [117]	"k\$female_protagonist"	"k\$female_wrestler"
## [119]	"k\$fight"	"k\$film_noir"
## [121]	"k\$fire"	"k\$flashback"
## [123]	"k\$florida"	"k\$forest"
## [125]	"k\$found_footage"	"k\$france"
## [127]	"k\$friends"	"k\$friendship"
## [129]	"k\$funeral"	"k\$future"
## [131]	"k\$gambling"	"k\$gang"
## [133]	"k\$gangster"	"k\$gay"
## [135]	"k\$gay_interest"	"k\$ghost"
## [137]	"k\$giant_monster"	"k\$good_versus_evil"
## [139]	"k\$gore"	"k\$grief"
## [141]	"k\$gun"	"k\$gunfight"
## [143]	"k\$hallucination"	"k\$haunted_house"
## [145]	"k\$heist"	"k\$helicopter"
## [147]	"k\$hero"	"k\$high_school"
## [149]	"k\$hitman"	"k\$holiday"
## [151]	"k\$hollywood"	"k\$horror"
## [153]	"k\$horse"	"k\$hospital"
## [155]	"k\$hostage"	"k\$hotel"
## [157]	"k\$husband_wife_relationship"	"k\$in"
## [159]	"k\$infidelity"	"k\$investigation"
## [161]	"k\$island"	"k\$japan"
## [163]	"k\$jealousy"	"k\$journalist"
## [165]	"k\$jungle"	"k\$kidnapping"
## [167]	"k\$killer"	"k\$kung_fu"
## [169]	"k\$las_vegas"	"k\$lawyer"
## [171]	"k\$lgbt"	"k\$lgbt_interest"
## [173]	"k\$live_action_and_animation"	"k\$london_england"
## [175]	"k\$los_angeles_california"	"k\$loss_of_loved_one"
## [177]	"k\$love"	"k\$love_of_one's_life"
## [179]	"k\$love_triangle"	"k\$mafia"
## [181]	"k\$magic"	"k\$male_friendship"
## [183]	"k\$male_homosexuality"	"k\$manhattan_new_york_city"
## [185]	"k\$marijuana"	"k\$marriage"
## [187]	"k\$martial_arts"	"k\$mental_illness"
## [189]	"k\$mexico"	"k\$military"
## [191]	"k\$money"	"k\$monster"
## [193]	"k\$mother_daughter_relationship"	"k\$mother_son_relationship"
## [195]	"k\$motorcycle"	"k\$movie_business"

## [197]	"k\$murder"	"k\$musical"
## [199]	"k\$musician"	"k\$nazi"
## [201]	"k\$neighbor"	"k\$neo"
## [203]	"k\$new_love"	"k\$new_york_city"
## [205]	"k\$nightclub"	"k\$nightmare"
## [207]	"k\$noir"	"k\$obsession"
## [209]	"k\$organized_crime"	"k\$orphan"
## [211]	"k\$paranoia"	"k\$parent_child_relationship"
## [213]	"k\$paris_france"	"k\$parody"
## [215]	"k\$period_drama"	"k\$pets"
## [217]	"k\$police"	"k\$police_officer"
## [219]	"k\$politics"	"k\$post"
## [221]	"k\$pregnancy"	"k\$priest"
## [223]	"k\$princess"	"k\$prison"
## [225]	"k\$pro_wrestling"	"k\$prostitute"
## [227]	"k\$psychological_thriller"	"k\$psychopath"
## [229]	"k\$racism"	"k\$rape"
## [231]	"k\$relationship"	"k\$religion"
## [233]	"k\$remake"	"k\$rescue"
## [235]	"k\$restaurant"	"k\$revenge"
## [237]	"k\$rivalry"	"k\$road_trip"
## [239]	"k\$robbery"	"k\$robot"
## [241]	"k\$romance"	"k\$romantic_comedy"
## [243]	"k\$rural_area"	"k\$sadism"
## [245]	"k\$san_francisco_california"	"k\$satire"
## [247]	"k\$school"	"k\$scientist"
## [249]	"k\$secret_agent"	"k\$secret_identity"
## [251]	"k\$seduction"	"k\$self"
## [253]	"k\$sequel"	"k\$serial_killer"
## [255]	"k\$sheriff"	"k\$ship"
## [257]	"k\$shootout"	"k\$showdown"
## [259]	"k\$sibling_relationship"	"k\$silent_film"
## [261]	"k\$singer"	"k\$single_mother"
## [263]	"k\$slasher"	"k\$small_town"
## [265]	"k\$snow"	"k\$soldier"
## [267]	"k\$space"	"k\$space_travel"
## [269]	"k\$spacecraft"	"k\$spoof"
## [271]	"k\$sports"	"k\$spy"
## [273]	"k\$street_gang"	"k\$suicide"
## [275]	"k\$suicide_attempt"	"k\$summer"
## [277]	"k\$super_power"	"k\$superhero"
## [279]	"k\$supernatural"	"k\$surrealism"
## [281]	"k\$survival"	"k\$sword_fight"
## [283]	"k\$teacher"	"k\$teen_movie"
## [285]	"k\$teenage_girl"	"k\$teenager"
## [287]	"k\$terrorism"	"k\$terrorist"
## [289]	"k\$texas"	"k\$thief"
## [291]	"k\$time_travel"	"k\$torture"
## [293]	"k\$train"	"k\$transformation"
## [295]	"k\$travel"	"k\$undercover"
## [297]	"k\$up"	"k\$usa_president"
## [299]	"k\$vampire"	"k\$vigilante"
## [301]	"k\$village"	"k\$villain"
## [303]	"k\$wedding"	"k\$whodunit"

```
## [305] "k$widow"           "k$winter"
## [307] "k$witch"            "k$woman_director"
## [309] "k$world_war_ii"     "k$wrestling"
## [311] "k$writer"           "k$zombie"
```

For terms coming from original_language column, we added “l\$” to indicate language terms. From this column, we managed to get 20 terms.

```
#### ORIGINAL LANGUAGE
og_lng <- clean_data$original_language
docs5 <- Corpus(VectorSource(og_lng))
# adding prefix l$ for language
docs5 <- tm_map(docs5, add_prefix, "l$")
docs5 <- tm_map(docs5, to_another, " ", " l$")
dtm5 <- DocumentTermMatrix(docs5)

# get all languages in at least 50 movies
key_lang <- sort(findFreqTerms(dtm5, 50))
key_lang
```

```
## [1] "l$ar" "l$cn" "l$de" "l$en" "l$es" "l$fa" "l$fr" "l$hi" "l$it" "l$ja"
## [11] "l$ko" "l$ml" "l$pt" "l$ru" "l$sv" "l$ta" "l$te" "l$tr" "l$ur" "l$zh"
```

With all of the terms above combined, we managed to get a total of 489 terms. We used these terms as variables in our model, and include the budget_adjusted as a variable as well. Due to large values of budgets and revenues, we decided to use log transformation on both of these variables and do modelling with them.

```
X <- cbind(dtm[, key_pc], dtm2[, key_gen], dtm3[, key_cast],
           dtm4[, key_keys], dtm5[, key_lang])
y_adj <- log(clean_data$revenue_adjusted)
```

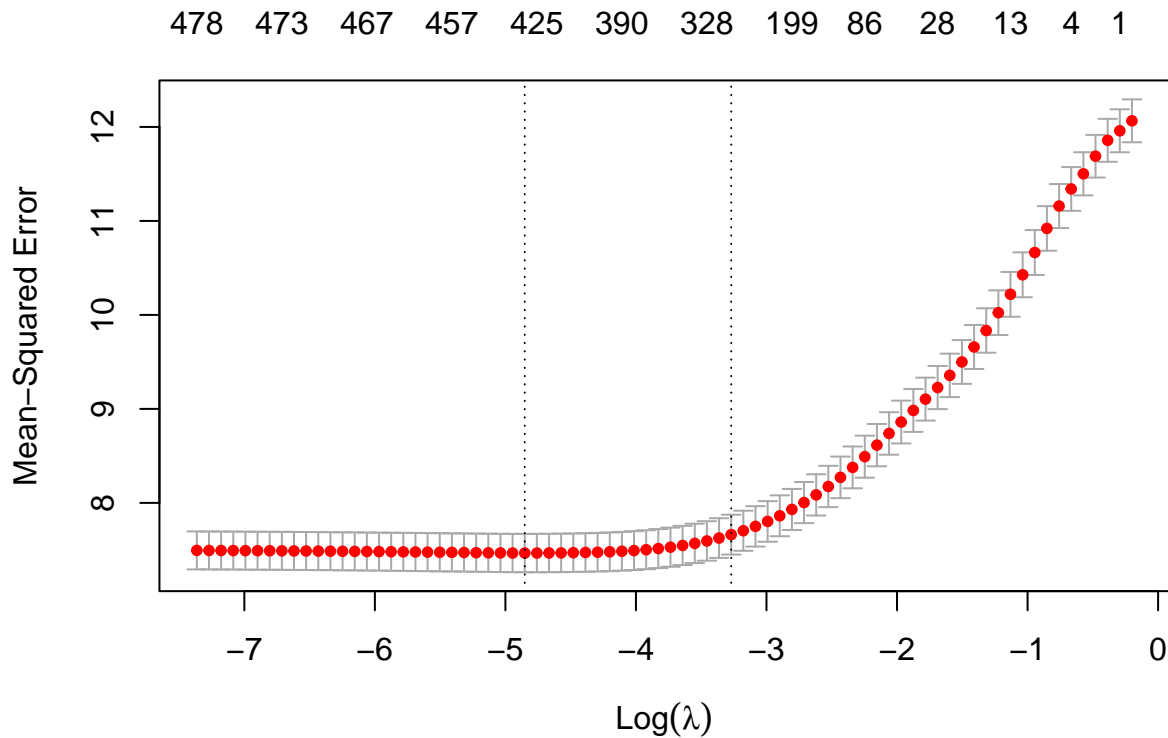
At first, we would like to include the budget column into the model. However, it turns out that 5,178 rows have either zero budget or unspecified amount. So, we decided to not include this column to the model.

```
library(glmnet)
```

```
## Loading required package: Matrix
```

```
## Loaded glmnet 4.1-6
```

```
set.seed(424)
model1 <- cv.glmnet(as.matrix(X), y_adj)
plot(model1, xvar = "lambda")
```



```
coef1 <- coef(model1, s = "lambda.min")
length(coef1[which(coef1 != 0), ][-1]) # -1 to exclude intercept
```

```
## [1] 429
```

```
sort(coef1[which(coef1 != 0), 1], decreasing = TRUE)
```

```
##                (Intercept)                p$screen_gems
##          12.612435319                2.691182943
##          p$paramount                p$columbia_pictures
##          2.568606204                2.443533753
##          p$walt_disney_pictures      p$20th_century_fox
##          2.411202846                2.385320720
##          p$touchstone_pictures      p$universal_pictures
##          2.285197787                2.222275215
##          p$new_line_cinema          p$warner_bros._pictures
##          2.183598777                2.139672383
##          p$united_artists            p$tristar_pictures
##          2.124228780                2.053181355
##          p$hollywood_pictures      p$metro_goldwyn_mayer
##          2.044048905                1.900867954
##          l$ta                        p$orion_pictures
##          1.767718471                1.609278386
##          p$fox_2000_pictures        l$hi
```

##	1.512771358	1.509731902
##	p\$lionsgate	p\$cj_entertainment
##	1.477667013	1.467142319
##	p\$summit_entertainment	k\$haunted_house
##	1.461621725	1.423593144
##	p\$the_weinstein_company	p\$fox_searchlight_pictures
##	1.414129347	1.357834505
##	p\$focus_features	k\$giant_monster
##	1.339756615	1.311197780
##	p\$miramax	k\$single_mother
##	1.238019098	1.227285480
##	k\$slasher	k\$duringcreditsstinger
##	1.222694671	1.171117731
##	l\$ja	c\$sylvester_stallone
##	1.149753390	1.148462561
##	c\$harrison_ford	p\$constantin_film
##	1.148393558	1.146232666
##	l\$ko	p\$dreamworks_pictures
##	1.129634686	1.109828006
##	k\$code	l\$zh
##	1.105787694	1.078517569
##	l\$it	k\$spacecraft
##	1.072918529	1.071859756
##	k\$dying_and_death	p\$blumhouse_productions
##	1.067982777	1.049773647
##	p\$tf1_films_production	k\$florida
##	1.037376939	1.033666301
##	k\$silent_film	p\$castle_rock_entertainment
##	1.032217861	1.029050154
##	c\$bess_flowers	k\$based_on_play_or_musical
##	1.017065439	0.989306179
##	k\$pets	k\$anthropomorphism
##	0.981832191	0.979077775
##	k\$love_of_one's_life	c\$samuel_l._jackson
##	0.951116709	0.941334724
##	p\$relativity_media	p\$canal+_españa
##	0.936022730	0.930793976
##	l\$cn	p\$participant
##	0.921700596	0.916153272
##	k\$based_on_young_adult_novel	k\$space
##	0.915551064	0.914312165
##	k\$epic	k\$villain
##	0.909096291	0.891713258
##	p\$cannon_group	c\$tom_hanks
##	0.890193712	0.886693133
##	p\$europacorp	p\$dimension_films
##	0.881080099	0.872209925
##	p\$village_roadshow_pictures	c\$brad_pitt
##	0.864188666	0.859829314
##	c\$ben_stiller	k\$father_daughter_relationship
##	0.857228878	0.851363777
##	p\$film_i_väst	k\$based_on_comic
##	0.837571688	0.828496289
##	k\$cult_film	c\$liam_neeson

##	0.823800102	0.823743063
##	k\$sequel	p\$new_regency_pictures
##	0.822446566	0.814488034
##	k\$creature	k\$aftercreditsstinger
##	0.810802471	0.805296881
##	p\$tsg_entertainment	c\$gene_hackman
##	0.805281425	0.798126670
##	c\$robert_downey_jr.	k\$airplane
##	0.794558511	0.759823990
##	p\$atresmedia	k\$buddy_cop
##	0.752174260	0.747914568
##	k\$biography	k\$divorce
##	0.743077567	0.742053662
##	c\$ben_kingsley	k\$romantic_comedy
##	0.738715773	0.728139844
##	k\$demon	k\$usa_president
##	0.723220144	0.723048407
##	k\$widow	c\$m._emmet_walsh
##	0.707083437	0.700591322
##	k\$loss_of_loved_one	c\$morgan_freeman
##	0.694099810	0.690978711
##	k\$kung_fu	k\$remake
##	0.690430362	0.689538921
##	c\$matt_damon	k\$concert
##	0.686122540	0.675649458
##	k\$suicide_attempt	k\$super_power
##	0.673597824	0.672771245
##	c\$nicole_kidman	k\$california
##	0.661613779	0.654948310
##	k\$film_noir	p\$dentsu
##	0.654199611	0.649467457
##	c\$meryl_streep	k\$sports
##	0.648053300	0.640966285
##	p\$pathé	k\$psychological_thriller
##	0.639636399	0.639279800
##	p\$filmnation_entertainment	k\$army
##	0.639267314	0.632039765
##	k\$school	c\$richard_jenkins
##	0.626544585	0.624750611
##	k\$secret_agent	c\$donald_sutherland
##	0.616739250	0.616332900
##	c\$robert_de_niro	g\$adventure
##	0.613826260	0.613652777
##	k\$orphan	k\$1980s
##	0.606425428	0.603262776
##	k\$falling_in_love	l\$fr
##	0.596041718	0.594918561
##	k\$new_york_city	c\$joe_chrest
##	0.589327598	0.584186598
##	k\$extramarital_affair	k\$based_on_novel_or_book
##	0.583446919	0.580541253
##	p\$imagine_entertainment	k\$parent_child_relationship
##	0.580480990	0.580080372
##	c\$clint_eastwood	k\$faith

##	0.578775382	0.577760225
##	k\$san_francisco_california	p\$france_2_cinéma
##	0.574673970	0.572257877
##	k\$cat	g\$war
##	0.561578398	0.560689396
##	k\$village	l\$en
##	0.560103899	0.558772790
##	k\$musical	c\$alec_baldwin
##	0.553659059	0.551340738
##	l\$te	p\$dune_entertainment
##	0.550571694	0.549662919
##	k\$princess	k\$neighbor
##	0.545020921	0.534125917
##	k\$lawyer	k\$lgbt_interest
##	0.529143632	0.527023265
##	k\$politics	k\$husband_wife_relationship
##	0.514859553	0.513289805
##	k\$magic	c\$julianne_moore
##	0.512329539	0.512214757
##	g\$history	k\$spoof
##	0.504838574	0.503307045
##	c\$robert_duvall	k\$live_action_and_animation
##	0.502597098	0.501821393
##	k\$supernatural	c\$thomas_rosales_jr.
##	0.500223282	0.499773389
##	k\$london_england	k\$1930s
##	0.496354031	0.493747146
##	k\$doctor	c\$stanley_tucci
##	0.486703058	0.480722674
##	g\$action	g\$animation
##	0.480213975	0.477838597
##	k\$artificial_intelligence	k\$disaster
##	0.476570718	0.471325215
##	c\$anthony_hopkins	k\$castle
##	0.470647030	0.469857803
##	k\$whodunit	c\$harry_dean_stanton
##	0.469573728	0.469380431
##	p\$france_3_cinéma	k\$male_friendship
##	0.467894806	0.465546707
##	k\$bank_robbery	p\$scott_rudin_productions
##	0.461693051	0.461153215
##	k\$travel	p\$malpaso_productions
##	0.459449057	0.455616245
##	k\$restaurant	c\$forest_whitaker
##	0.454805005	0.453943923
##	k\$baseball	k\$drug_addiction
##	0.453054961	0.452543902
##	k\$journalist	k\$author
##	0.448052346	0.446966362
##	k\$based_on_true_story	c\$keanu_reeves
##	0.442602980	0.442024564
##	p\$toho	k\$hospital
##	0.439125826	0.439081715
##	k\$space_travel	g\$comedy

##	0.438965684	0.435660952
##	k\$fairy_tale	k\$drug_dealer
##	0.433408344	0.431063127
##	k\$self	k\$heist
##	0.428132959	0.427673156
##	c\$michael_papajohn	c\$danny_glover
##	0.427027751	0.424232355
##	k\$transformation	k\$1960s
##	0.419793434	0.419698676
##	g\$romance	k\$brother
##	0.416884244	0.415435401
##	k\$england	k\$in
##	0.415432268	0.414620787
##	p\$canal+	k\$racism
##	0.413370048	0.405786353
##	c\$robin_williams	c\$johnny_depp
##	0.404256316	0.401181785
##	k\$torture	k\$christmas
##	0.400646837	0.399926862
##	k\$terrorist	c\$frank_welker
##	0.397029099	0.389777218
##	k\$black_and_white	k\$teacher
##	0.389279358	0.386160604
##	k\$fbi	k\$scientist
##	0.385634453	0.385535339
##	k\$friends	k\$marijuana
##	0.382391292	0.375200131
##	g\$western	k\$teenager
##	0.372853794	0.370816486
##	k\$movie_business	k\$19th_century
##	0.367527600	0.367476836
##	k\$marriage	p\$morgan_creek_productions
##	0.367068551	0.367049911
##	k\$wedding	k\$china
##	0.366383368	0.363280079
##	k\$holiday	c\$paul_giamatti
##	0.363253287	0.362066838
##	k\$forest	k\$monster
##	0.360105686	0.355083387
##	p\$scott_free_productions	k\$mexico
##	0.353637278	0.350716875
##	k\$animal	k\$rescue
##	0.350016273	0.349892854
##	g\$family	k\$period_drama
##	0.348288297	0.347177859
##	k\$paris_france	k\$pregnancy
##	0.345079155	0.339241781
##	g\$fantasy	k\$martial_arts
##	0.338076474	0.338001199
##	k\$switch	k\$competition
##	0.337812746	0.336307965
##	k\$mafia	p\$amblin_entertainment
##	0.331400758	0.330995848
##	k\$sibling_relationship	k\$sheriff

##	0.330583750	0.322438618
##	g\$mystery	k\$horror
##	0.322238070	0.321881060
##	k\$summer	k\$based_on_children's_book
##	0.320991857	0.319568145
##	c\$susan_sarandon	k\$family
##	0.318627014	0.316478061
##	p\$studiocanal	c\$dennis_quaid
##	0.316100862	0.315875917
##	k\$time_travel	p\$lakeshore_entertainment
##	0.314597268	0.313661719
##	k\$ rivalry	k\$alcohol
##	0.313540442	0.311142331
##	k\$beach	c\$bruce_willis
##	0.309013896	0.308395077
##	k\$los_angeles_california	k\$corruption
##	0.308142247	0.308134587
##	k\$adultery	k\$vampire
##	0.307549664	0.306121941
##	k\$baby	k\$gun
##	0.305779225	0.305449797
##	c\$bill_murray	p\$wild_bunch
##	0.301284457	0.301067487
##	c\$sigourney_weaver	k\$based_on_video_game
##	0.298999000	0.298277983
##	k\$priest	k\$money
##	0.297611246	0.296141200
##	k\$psychopath	c\$john_goodman
##	0.294703680	0.294166812
##	k\$obsession	k\$friendship
##	0.292914200	0.287960874
##	l\$ar	p\$regency_enterprises
##	0.287300825	0.284142255
##	k\$love_triangle	k\$showdown
##	0.280839436	0.280634714
##	k\$female_friendship	k\$helicopter
##	0.279547156	0.278944485
##	k\$funeral	k\$brutality
##	0.278816765	0.278725458
##	p\$polygram_filmed_entertainment	k\$japan
##	0.273875483	0.270839492
##	k\$anti_hero	k\$teenage_girl
##	0.270535178	0.269096436
##	k\$cop	k\$island
##	0.266059127	0.265409138
##	k\$jungle	k\$undercover
##	0.265177066	0.264990747
##	k\$organized_crime	k\$romance
##	0.263631073	0.261991202
##	k\$police_officer	k\$desert
##	0.261073527	0.260371604
##	k\$soldier	k\$1920s
##	0.256549209	0.250049228
##	k\$alien_invasion	c\$willem_dafoe

##	0.246961040	0.244126131
##	k\$bomb	p\$working_title_films
##	0.243591007	0.242630257
##	k\$1950s	k\$prison
##	0.240121370	0.237806528
##	k\$thief	k\$investigation
##	0.235344643	0.233058982
##	k\$action_hero	k\$spy
##	0.231999295	0.229456904
##	k\$flashback	k\$survival
##	0.228602152	0.227799143
##	c\$alfred_molina	p\$gaumont
##	0.222651872	0.221014976
##	k\$hotel	c\$antonio_banderas
##	0.217478947	0.216989570
##	k\$road_trip	k\$alcoholic
##	0.211676635	0.209232923
##	k\$ship	k\$anime
##	0.201443279	0.201190506
##	k\$best_friend	g\$thriller
##	0.200489478	0.200393047
##	c\$john_cusack	k\$1940s
##	0.198673300	0.198400518
##	k\$revenge	k\$street_gang
##	0.198009957	0.195663316
##	k\$jealousy	k\$seduction
##	0.194688004	0.194045077
##	k\$child_abuse	k\$gunfight
##	0.190649595	0.189773697
##	k\$escape	g\$science_fiction
##	0.189215093	0.188353126
##	c\$woody_harrelson	k\$daughter
##	0.187740302	0.186469768
##	c\$john_leguizamo	k\$parody
##	0.183608636	0.182319953
##	k\$dystopia	k\$vigilante
##	0.176868862	0.176747241
##	k\$death	k\$car_crash
##	0.176171208	0.174918239
##	c\$michael_caine	k\$dragon
##	0.173863259	0.173039679
##	k\$satire	k\$nazi
##	0.171947445	0.168826552
##	l\$de	k\$college
##	0.167765965	0.158877431
##	k\$amnesia	p\$film4_productions
##	0.155205162	0.152284394
##	k\$high_school	k\$male_homosexuality
##	0.152282550	0.151425822
##	g\$crime	c\$ethan_hawke
##	0.150079519	0.146952885
##	l\$ru	k\$small_town
##	0.146874022	0.144087124
##	k\$police	k\$texas

##	0.142535546	0.139874712
##	p\$sony_pictures	c\$stephen_root
##	0.138766798	0.135392554
##	k\$train	k\$father
##	0.134358956	0.129813455
##	k\$dream	k\$robot
##	0.127545804	0.124318723
##	c\$kevin_bacon	k\$chicago_illinois
##	0.119968754	0.119875893
##	k\$musician	k\$sadism
##	0.119107945	0.117611725
##	p\$silver_pictures	c\$cate_blanchett
##	0.115535446	0.114361095
##	k\$gangster	c\$j.k._simmons
##	0.107959088	0.106524815
##	k\$1990s	k\$mother_son_relationship
##	0.103342366	0.100960017
##	k\$zombie	k\$fight
##	0.097795960	0.092483853
##	g\$music	k\$hitman
##	0.088342979	0.079902514
##	k\$experiment	k\$killer
##	0.077983741	0.076847967
##	k\$world_war_ii	k\$noir
##	0.076570302	0.073943418
##	k\$shootout	k\$manhattan_new_york_city
##	0.063839576	0.055945807
##	k\$love	c\$christopher_plummer
##	0.054833314	0.048787932
##	k\$father_son_relationship	k\$religion
##	0.048633572	0.046873197
##	k\$ex	k\$gambling
##	0.046560887	0.040331584
##	l\$sv	k\$nightmare
##	0.035055297	0.034031908
##	k\$new_love	k\$assassin
##	0.031665605	0.030872350
##	k\$kidnapping	p\$bbc_film
##	0.029945822	0.026975868
##	k\$hero	k\$explosion
##	0.024050573	0.018593473
##	c\$brian_cox	k\$1970s
##	0.018313188	0.016290446
##	k\$conspiracy	k\$church
##	0.013827079	0.011352618
##	k\$family_relationships	c\$john_hurt
##	0.008652759	0.007953874
##	k\$prostitute	k\$up
##	0.006196392	-0.001942926
##	c\$nicolas_cage	k\$serial_killer
##	-0.010852775	-0.023050012
##	k\$gay	k\$coming_of_age
##	-0.036488339	-0.039189843
##	k\$dance	p\$ingenious_media

##	-0.043309880	-0.046699749
##	k\$hollywood	g\$drama
##	-0.069784634	-0.088935468
##	k\$woman_director	k\$surrealism
##	-0.093459917	-0.129488168
##	k\$teen_movie	k\$gay_interest
##	-0.131351962	-0.132369104
##	k\$detective	p\$millennium_films
##	-0.141238641	-0.142542877
##	c\$james_franco	c\$danny_trejo
##	-0.143946212	-0.146672570
##	c\$owen_wilson	k\$robbery
##	-0.148928681	-0.159102189
##	k\$rural_area	k\$found_footage
##	-0.189195873	-0.229293838
##	k\$depression	p\$ciné+
##	-0.241362479	-0.241719553
##	c\$christopher_walken	k\$gore
##	-0.244824995	-0.256591641
##	p\$cnc	k\$writer
##	-0.263609364	-0.269504383
##	g\$horror	k\$female_wrestler
##	-0.280295919	-0.315658525
##	k\$assassination	p\$téléfilm_canada
##	-0.355630692	-0.356301807
##	k\$dark_comedy	k\$pro_wrestling
##	-0.395777237	-0.524640742
##	l\$ur	k\$grief
##	-0.582455642	-0.599084443
##	k\$lgbt	l\$pt
##	-0.780566881	-1.028575719
##	l\$fa	g\$documentary
##	-1.153459063	-1.552939934
##	k\$wrestling	g\$tv_movie
##	-2.692157715	-2.971512671

From 489 variables, we have 429 variables in our model. Below are the intercept of the model, the top 10 variables that positively affect revenue, and top 10 variables that negatively affect revenue.

```
ic1 <- coef1[c("(Intercept)"), 1]
paste("The intercept is ", ic1)
```

```
## [1] "The intercept is 12.6124353194507"
```

```
paste("Top 10 variables that positively affect the revenue:")
```

```
## [1] "Top 10 variables that positively affect the revenue:"
```

```
coef1_sort <- sort(coef1[, 1], decreasing = TRUE)[-1]
head(coef1_sort, 10)
```

##	p\$screen_gems	p\$paramount	p\$columbia_pictures
----	----------------	--------------	----------------------

```
##          2.691183          2.568606          2.443534
## p$walt_disney_pictures    p$20th_century_fox    p$touchstone_pictures
##          2.411203          2.385321          2.285198
##    p$universal_pictures    p$new_line_cinema    p$warner_bros._pictures
##          2.222275          2.183599          2.139672
##          p$united_artists
##          2.124229
```

```
paste("Top 10 variables that negatively affects the revenue:")
```

```
## [1] "Top 10 variables that negatively affects the revenue:"
```

```
tail(coef1_sort, 10)
```

```
##    k$dark_comedy k$pro_wrestling    l$ur    k$grief    k$lgbt
##    -0.3957772    -0.5246407    -0.5824556    -0.5990844    -0.7805669
##          l$pt          l$fa    g$documentary    k$wrestling    g$tv_movie
##    -1.0285757    -1.1534591    -1.5529399    -2.6921577    -2.9715127
```

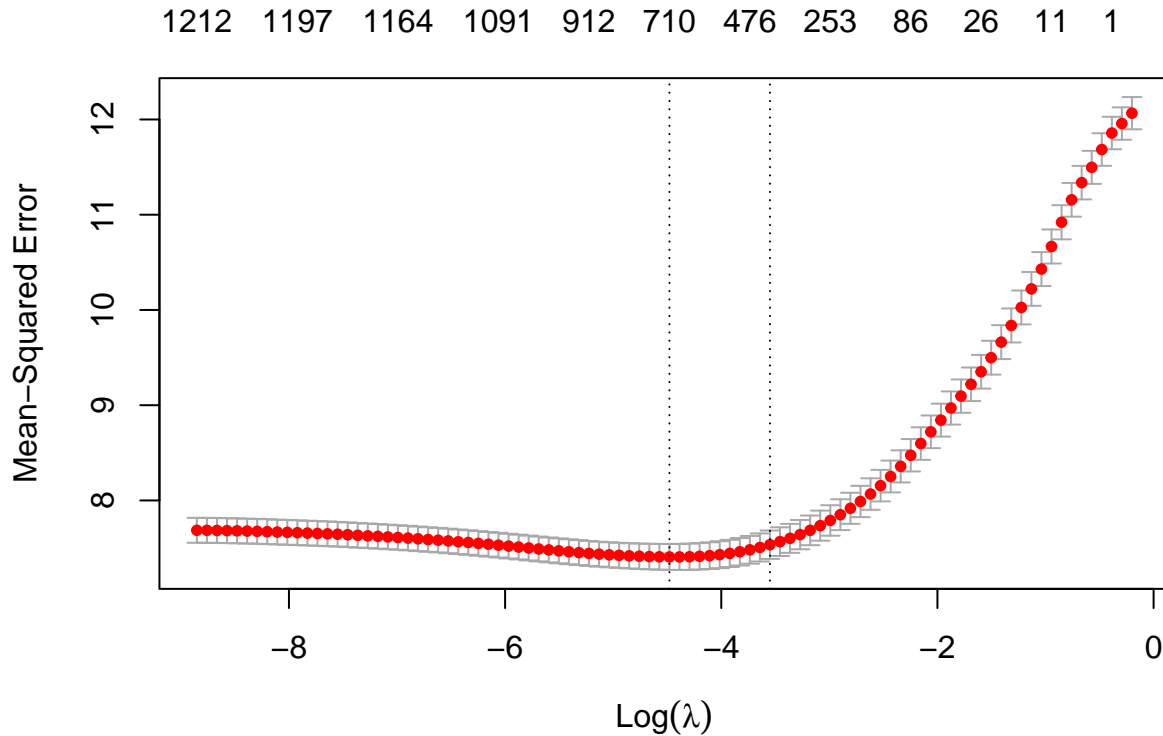
To improve the model more, we want to include interactions between terms in the model. Since it is too much to interact all of the terms that we have, we will get top 10 terms from each column and interact them with each other to make a pair of terms. We do not include the original `_language` column in the interaction since most of the movies' original language is English. So, we have 40 terms to be paired with each other, giving us 780 interaction variables.

```
# top 10 of each
key_pc2 <- names(findMostFreqTerms(dtm, 10, INDEX = rep(1, each = n))[[1]])
key_gen2 <- names(findMostFreqTerms(dtm2, 10, INDEX = rep(1,
  each = n))[[1]])
key_cast2 <- names(findMostFreqTerms(dtm3, 14, INDEX = rep(1,
  each = n))[[1]])
key_cast2 <- key_cast2[grepl("_", key_cast2)] # 4 of them are single names
key_keys2 <- names(findMostFreqTerms(dtm4, 10, INDEX = rep(1,
  each = n))[[1]])
int_vars <- c(key_pc2, key_gen2, key_cast2, key_keys2)
inact <- c()
inact_name <- c()
for (i in 1:(length(int_vars) - 1)) {
  for (j in (i + 1):length(int_vars)) {
    a = as.matrix(X[, int_vars[i]])
    b = as.matrix(X[, int_vars[j]])
    var_name = paste(int_vars[i], ".", int_vars[j])
    v = a * b
    inact <- cbind(inact, v)
    inact_name <- c(inact_name, var_name)
  }
}

df_inact = data.frame(inact)
colnames(df_inact) <- inact_name
```

We add this 780 variables on top of the initial 489 variables in the first model, giving us 1269 variables for the second model.

```
X2 <- cbind(dtm[, key_pc], dtm2[, key_gen], dtm3[, key_cast],
            dtm4[, key_keys], dtm5[, key_lang], df_inact)
model2 <- cv.glmnet(as.matrix(X2), y_adj)
plot(model2, xvar = "lambda")
```



```
coef2 <- coef(model2, s = "lambda.min")
length(coef2[which(coef2 != 0), ][-1]) # -1 to exclude intercept
```

```
## [1] 710
```

```
sort(coef2[which(coef2 != 0), 1], decreasing = TRUE)
```

```
##                (Intercept)
##                1.249912e+01
##      c$robert_de_niro . k$woman_director
##                3.121845e+00
##      p$columbia_pictures
##                2.643334e+00
##      p$screen_gems
##                2.615547e+00
##      p$paramount
##                2.595986e+00
##      p$touchstone_pictures
##                2.561390e+00
```



```

##                p$20th_century_fox
##                2.514055e+00
##                p$walt_disney_pictures
##                2.420880e+00
##                p$warner_bros._pictures
##                2.343409e+00
##                p$universal_pictures
##                2.313728e+00
##                g$science_fiction . c$robert_de_niro
##                2.312593e+00
##                p$new_line_cinema
##                2.277045e+00
##                p$united_artists
##                2.156397e+00
##                p$metro_goldwyn_mayer
##                2.145121e+00
##                c$j.k._simmons . k$love
##                2.095606e+00
##                p$hollywood_pictures
##                2.076517e+00
##                p$tristar_pictures
##                2.003320e+00
##                c$samuel_l._jackson . c$liam_neeson
##                1.697209e+00
##                c$nicolas_cage . k$biography
##                1.676166e+00
##                l$ta
##                1.653243e+00
##                p$orion_pictures
##                1.576818e+00
##                p$fox_2000_pictures
##                1.560967e+00
##                p$the_weinstein_company
##                1.487038e+00
##                p$summit_entertainment
##                1.473376e+00
##                p$lionsgate
##                1.473322e+00
##                k$duringcreditsstinger
##                1.412087e+00
##                l$hi
##                1.394998e+00
##                p$focus_features
##                1.361757e+00
##                p$canal+ . c$frank_welker
##                1.357823e+00
##                p$fox_searchlight_pictures
##                1.343146e+00
##                p$cj_entertainment
##                1.339942e+00
##                k$haunted_house
##                1.293407e+00
##                g$romance . c$willem_dafoe
##                1.241388e+00

```

```

##                p$miramax
##                1.212257e+00
##                k$single_mother
##                1.201212e+00
##    g$science_fiction . c$samuel_l._jackson
##                1.159302e+00
##                p$dreamworks_pictures
##                1.143496e+00
##                k$giant_monster
##                1.060618e+00
##                l$ko
##                1.055847e+00
##                k$buddy_cop
##                1.052702e+00
##                p$constantin_film
##                1.052543e+00
##                c$brad_pitt
##                1.047456e+00
##                c$sylvester_stallone
##                1.045275e+00
##                k$dying_and_death
##                1.036354e+00
##                k$silent_film
##                1.019610e+00
##                l$ja
##                1.012502e+00
##                k$slasher
##                1.008986e+00
##    c$j.k._simmons . k$based_on_novel_or_book
##                1.004464e+00
##                k$code
##                1.002505e+00
##                g$family . c$steve_buscemi
##                9.961378e-01
##                g$family . c$bruce_willis
##                9.874252e-01
##    c$robert_de_niro . c$morgan_freeman
##                9.709606e-01
##                l$zh
##                9.375226e-01
##                p$tf1_films_production
##                9.324411e-01
##                k$florida
##                9.282380e-01
##                c$harrison_ford
##                9.281722e-01
##                k$based_on_play_or_musical
##                9.273600e-01
##                g$adventure
##                9.185655e-01
##    p$castle_rock_entertainment
##                9.172846e-01
##                k$pets
##                9.150230e-01

```

```

##          g$science_fiction . k$love
##          9.130249e-01
##          k$epic
##          9.074391e-01
##          c$ben_stiller
##          9.069395e-01
##          l$it
##          8.949374e-01
##          k$creature
##          8.861610e-01
##          c$bess_flowers
##          8.828913e-01
##          p$relativity_media
##          8.794182e-01
##          k$father_daughter_relationship
##          8.755584e-01
##          k$anthropomorphism
##          8.743774e-01
##          p$columbia_pictures . c$robert_de_niro
##          8.739832e-01
##          k$love_of_one's_life
##          8.715907e-01
##          g$romance . c$nicolas_cage
##          8.709968e-01
##          p$canal+_españa
##          8.595089e-01
##          g$horror . c$morgan_freeman
##          8.569961e-01
##          p$canal+ . c$morgan_freeman
##          8.523741e-01
##          p$participant
##          8.504760e-01
##          l$cn
##          8.448109e-01
##          g$comedy
##          8.320128e-01
##          k$spacecraft
##          8.241830e-01
##          p$blumhouse_productions
##          8.192420e-01
##          p$village_roadshow_pictures
##          8.137941e-01
##          c$tom_hanks
##          8.123906e-01
##          p$dimension_films
##          8.032815e-01
##          k$space
##          7.992673e-01
##          k$villain
##          7.865623e-01
##          p$cannon_group
##          7.853691e-01
##          k$based_on_young_adult_novel
##          7.782826e-01

```

```

##                p$film_i_väst
##                7.756398e-01
##                c$samuel_l._jackson
##                7.748496e-01
##                k$based_on_novel_or_book
##                7.642640e-01
##                c$matt_damon
##                7.413751e-01
##                c$j.k._simmons . k$new_york_city
##                7.410187e-01
##                k$cult_film
##                7.318618e-01
##                k$sequel
##                7.235152e-01
##                p$new_regency_pictures
##                7.205081e-01
##                p$europacorp
##                7.193952e-01
##                k$usa_president
##                7.000752e-01
##                g$drama . c$frank_welker
##                6.974909e-01
##                c$liam_neeson
##                6.945593e-01
##                k$demon
##                6.892090e-01
##                k$based_on_comic
##                6.870760e-01
##                p$tsg_entertainment
##                6.836161e-01
##                g$action
##                6.793915e-01
##                k$concert
##                6.792923e-01
##                k$aftercreditsstinger
##                6.791355e-01
##                k$airplane
##                6.761271e-01
##                k$secret_agent
##                6.714371e-01
##                k$remake
##                6.629631e-01
##                k$divorce
##                6.592426e-01
##                c$ben_kingsley
##                6.532820e-01
##                c$willem_dafoe . k$woman_director
##                6.513428e-01
##                k$kung_fu
##                6.483162e-01
##                k$widow
##                6.463279e-01
##                k$psychological_thriller
##                6.411760e-01

```

```

##                g$horror . c$liam_neeson
##                6.405494e-01
##                k$super_power
##                6.346303e-01
##                p$20th_century_fox . c$bruce_willis
##                6.340520e-01
##                c$m._emmet_walsh
##                6.325546e-01
##                k$california
##                6.322016e-01
##                p$filmmation_entertainment
##                6.225361e-01
##                k$sports
##                6.211511e-01
##                p$dentsu
##                6.209699e-01
##                k$orphan
##                6.198137e-01
##                k$romantic_comedy
##                6.161792e-01
##                c$gene_hackman
##                6.133935e-01
##                k$loss_of_loved_one
##                6.132478e-01
##                c$joe_chrest
##                6.122899e-01
##                k$school
##                6.050066e-01
##                k$san_francisco_california
##                5.982607e-01
##                c$clint_eastwood
##                5.973423e-01
##                g$family . c$morgan_freeman
##                5.939863e-01
##                k$suicide_attempt
##                5.929272e-01
##                k$faith
##                5.909168e-01
##                c$meryl_streep
##                5.877919e-01
##                c$nicole_kidman
##                5.857945e-01
##                p$pathé
##                5.841771e-01
##                p$atresmedia
##                5.836289e-01
##                c$liam_neeson . k$murder
##                5.803617e-01
##                k$parent_child_relationship
##                5.765675e-01
##                c$robert_downey_jr.
##                5.692035e-01
##                k$spoof
##                5.689656e-01

```

```

##          k$based_on_true_story
##          5.669564e-01
##      c$bruce_willis . c$willem_dafoe
##          5.618420e-01
##      p$walt_disney_pictures . k$murder
##          5.490955e-01
##          k$film_noir
##          5.451954e-01
##          g$war
##          5.436421e-01
##          k$1980s
##          5.415277e-01
##      k$extramarital_affair
##          5.394664e-01
##      c$nicolas_cage . k$love
##          5.385782e-01
##      c$donald_sutherland
##          5.357480e-01
##      g$horror . c$frank_welker
##          5.321484e-01
##      c$richard_jenkins
##          5.320359e-01
##          k$musical
##          5.306410e-01
##      k$duringcreditsstinger . k$love
##          5.299613e-01
##          k$cat
##          5.264879e-01
##          g$history
##          5.231505e-01
##          k$magic
##          5.221871e-01
##      k$falling_in_love
##          5.211684e-01
##          k$lawyer
##          5.170851e-01
##      c$morgan_freeman
##          5.167982e-01
##      k$husband_wife_relationship
##          5.158077e-01
##          k$neighbor
##          5.150038e-01
##      p$imagine_entertainment
##          5.048504e-01
##      c$willem_dafoe . c$j.k._simmons
##          5.007863e-01
##          k$whodunit
##          4.973902e-01
##          g$family
##          4.940985e-01
##          k$village
##          4.927393e-01
##          k$1930s
##          4.913076e-01

```

```

##          k$new_york_city
##          4.897370e-01
##      p$france_2_cinéma
##          4.876889e-01
##      c$julianne_moore
##          4.855361e-01
##          p$canal+
##          4.831596e-01
##          l$fr
##          4.807756e-01
##      c$thomas_rosales_jr.
##          4.783023e-01
##          k$princess
##          4.743269e-01
##          k$army
##          4.692439e-01
##          k$vampire
##          4.663048e-01
##          k$torture
##          4.662805e-01
##      c$alec_baldwin
##          4.629514e-01
##          k$biography
##          4.628030e-01
##      g$horror . c$j.k._simmons
##          4.609908e-01
##      k$based_on_novel_or_book . k$love
##          4.608640e-01
##          k$politics
##          4.603056e-01
##      p$dune_entertainment
##          4.593629e-01
##          k$london_england
##          4.579641e-01
##          l$en
##          4.577728e-01
##          k$transformation
##          4.575241e-01
##          k$drug_addiction
##          4.567764e-01
##          l$te
##          4.539333e-01
##      g$drama . k$biography
##          4.511028e-01
##      p$scott_rudin_productions
##          4.473477e-01
##      g$action . c$willem_dafoe
##          4.470800e-01
##          k$bank_robbery
##          4.469806e-01
##      c$harry_dean_stanton
##          4.458753e-01
##          k$lgbt_interest
##          4.449351e-01

```

```

##          k$black_and_white
##          4.439426e-01
##      g$horror . c$willem_dafoe
##          4.435949e-01
##          k$self
##          4.371899e-01
##          p$toho
##          4.326404e-01
##      c$paul_giamatti
##          4.301743e-01
##          k$1960s
##          4.300113e-01
##          g$animation
##          4.274920e-01
##      c$robin_williams
##          4.263073e-01
##          k$drug_dealer
##          4.251101e-01
##          g$romance
##          4.229601e-01
##          g$western
##          4.224298e-01
##      c$johnny_depp
##          4.217258e-01
##          k$hospital
##          4.208732e-01
##          k$supernatural
##          4.200345e-01
##      k$male_friendship
##          4.193118e-01
##      c$stanley_tucci
##          4.175308e-01
##          k$journalist
##          4.154961e-01
##      k$artificial_intelligence
##          4.149688e-01
##          k$teacher
##          4.124518e-01
##      k$live_action_and_animation
##          4.111310e-01
##          c$keanu_reeves
##          4.078841e-01
##          k$author
##          4.071627e-01
##          c$robert_duvall
##          4.057867e-01
##          c$forest_whitaker
##          4.021262e-01
##          c$anthony_hopkins
##          3.992732e-01
##          p$france_3_cinéma
##          3.974556e-01
##      k$sibling_relationship
##          3.954100e-01

```



```

##                                k$racism
##                                3.947433e-01
##                                k$fbi
##                                3.926466e-01
##                                k$restaurant
##                                3.885058e-01
##                                k$doctor
##                                3.869933e-01
##                                p$canal+ . k$based_on_true_story
##                                3.850616e-01
##                                k$fairy_tale
##                                3.838866e-01
##                                k$travel
##                                3.829529e-01
##                                g$crime . c$j.k._simmons
##                                3.813524e-01
##                                k$martial_arts
##                                3.808840e-01
##                                k$space_travel
##                                3.808256e-01
##                                g$fantasy
##                                3.804865e-01
##                                p$touchstone_pictures . c$bruce_willis
##                                3.802644e-01
##                                k$movie_business
##                                3.801359e-01
##                                p$lakeshore_entertainment
##                                3.776525e-01
##                                c$danny_glover
##                                3.722250e-01
##                                k$in
##                                3.680238e-01
##                                c$john_goodman
##                                3.672527e-01
##                                g$comedy . c$bruce_willis
##                                3.670100e-01
##                                k$paris_france
##                                3.644581e-01
##                                k$switch
##                                3.641642e-01
##                                k$castle
##                                3.641384e-01
##                                p$walt_disney_pictures . c$samuel_l._jackson
##                                3.619544e-01
##                                k$disaster
##                                3.605719e-01
##                                p$malpaso_productions
##                                3.604743e-01
##                                k$gun
##                                3.541545e-01
##                                k$brother
##                                3.540774e-01
##                                k$china
##                                3.513248e-01

```

```

##          k$adultery
##          3.498358e-01
##          k$19th_century
##          3.463795e-01
##          k$period_drama
##          3.443949e-01
##          g$mystery
##          3.443562e-01
##          k$baseball
##          3.428503e-01
##          k$marijuana
##          3.418812e-01
##          p$morgan_creek_productions
##          3.415326e-01
##          p$wild_bunch
##          3.401405e-01
##          k$zombie
##          3.361284e-01
##          k$showdown
##          3.339270e-01
##          k$england
##          3.338296e-01
##          k$marriage
##          3.315388e-01
##          k$monster
##          3.306447e-01
##          k$money
##          3.298129e-01
##          k$rescue
##          3.268109e-01
##          c$j.k._simmons . k$revenge
##          3.267302e-01
##          k$anti_hero
##          3.225618e-01
##          k$helicopter
##          3.194652e-01
##          k$psychopath
##          3.171130e-01
##          k$horror
##          3.120754e-01
##          k$mafia
##          3.112135e-01
##          k$based_on_children's_book
##          3.100598e-01
##          k$family
##          3.095019e-01
##          g$thriller . c$robert_de_niro
##          3.084982e-01
##          k$beach
##          3.051926e-01
##          k$spy
##          3.041940e-01
##          k$based_on_novel_or_book . k$revenge
##          3.026899e-01

```

```

##                c$bill_murray
##                2.994364e-01
##      g$drama . c$morgan_freeman
##                2.993421e-01
##      g$family . c$willem_dafoe
##                2.992950e-01
##      c$steve_buscemi . k$murder
##                2.986310e-01
##                c$susan_sarandon
##                2.983545e-01
##      g$science_fiction
##                2.977668e-01
##      c$michael_papajohn
##                2.963695e-01
##      p$scott_free_productions
##                2.961675e-01
##                k$rivalry
##                2.958666e-01
##                k$summer
##                2.957218e-01
##                k$sheriff
##                2.935239e-01
##                k$scientist
##                2.934839e-01
##      g$science_fiction . k$new_york_city
##                2.932682e-01
##                k$time_travel
##                2.925804e-01
##      p$new_line_cinema . g$horror
##                2.879041e-01
##                k$funeral
##                2.863133e-01
##                k$heist
##                2.858946e-01
##      g$thriller . g$horror
##                2.848327e-01
##                k$christmas
##                2.834205e-01
##      p$amblin_entertainment
##                2.806535e-01
##      p$studiocanal
##                2.787488e-01
##                k$pregnancy
##                2.750117e-01
##      p$polygram_filmed_entertainment
##                2.732096e-01
##                k$corruption
##                2.708941e-01
##                k$friends
##                2.708625e-01
##                k$teenager
##                2.706081e-01
##                g$crime
##                2.696396e-01

```

```

##                k$japan
##                2.691719e-01
##                k$friendship
##                2.681208e-01
##                c$dennis_quaid
##                2.666808e-01
##                k$mexico
##                2.629952e-01
##                p$20th_century_fox . g$drama
##                2.612212e-01
##                c$sigourney_weaver
##                2.598305e-01
##                g$action . g$science_fiction
##                2.591819e-01
##                k$based_on_video_game
##                2.586369e-01
##                k$terrorist
##                2.585999e-01
##                k$wedding
##                2.583441e-01
##                c$stephen_root
##                2.556472e-01
##                g$family . k$biography
##                2.495337e-01
##                k$police_officer
##                2.472347e-01
##                k$desert
##                2.453373e-01
##                k$parody
##                2.452577e-01
##                k$bomb
##                2.449883e-01
##                k$forest
##                2.442312e-01
##                k$competition
##                2.435827e-01
##                k$1950s
##                2.433793e-01
##                c$cate_blanchett
##                2.424496e-01
##                k$ship
##                2.412486e-01
##                p$working_title_films
##                2.405223e-01
##                c$alfred_molina
##                2.399806e-01
##                k$holiday
##                2.384905e-01
##                k$baby
##                2.381922e-01
##                k$los_angeles_california
##                2.374074e-01
##                k$prison
##                2.362325e-01

```

```

##                g$thriller . k$sequel
##                2.354943e-01
##                p$regency_enterprises
##                2.322330e-01
##                p$touchstone_pictures . g$thriller
##                2.318840e-01
##                k$romance
##                2.292965e-01
##                k$road_trip
##                2.291921e-01
##                p$touchstone_pictures . g$comedy
##                2.287123e-01
##                g$romance . c$frank_welker
##                2.279426e-01
##                p$walt_disney_pictures . g$crime
##                2.267159e-01
##                k$priest
##                2.250638e-01
##                p$paramount . g$drama
##                2.239650e-01
##                p$new_line_cinema . c$steve_buscemi
##                2.226642e-01
##                k$jungle
##                2.196225e-01
##                k$action_hero
##                2.186515e-01
##                k$undercover
##                2.178181e-01
##                k$investigation
##                2.162052e-01
##                k$female_friendship
##                2.157926e-01
##                g$comedy . k$revenge
##                2.146488e-01
##                k$love_triangle
##                2.137629e-01
##                g$science_fiction . k$murder
##                2.132116e-01
##                k$hotel
##                2.108632e-01
##                k$anime
##                2.108277e-01
##                k$teenage_girl
##                2.099500e-01
##                k$organized_crime
##                2.086745e-01
##                k$cop
##                2.066143e-01
##                k$texas
##                2.052944e-01
##                k$obsession
##                2.050783e-01
##                c$bruce_willis . k$woman_director
##                1.988474e-01

```

```

##          g$crime . c$robert_de_niro
##          1.958690e-01
##          g$thriller
##          1.937492e-01
##          k$soldier
##          1.926180e-01
## k$murder . k$based_on_true_story
##          1.912208e-01
##          c$robert_de_niro
##          1.910289e-01
##          k$flashback
##          1.873762e-01
##          k$animal
##          1.867742e-01
##          g$romance . k$sequel
##          1.852605e-01
##          g$comedy . c$frank_welker
##          1.837197e-01
##          k$father
##          1.832356e-01
##          k$alcohol
##          1.819160e-01
##          k$dragon
##          1.815044e-01
##          k$thief
##          1.809829e-01
##          k$survival
##          1.807732e-01
##          k$street_gang
##          1.782187e-01
##          g$comedy . c$nicolas_cage
##          1.772172e-01
##          g$horror . k$duringcreditsstinger
##          1.737471e-01
##          k$best_friend
##          1.734493e-01
##          g$thriller . k$new_york_city
##          1.722169e-01
##          g$horror . k$murder
##          1.720703e-01
##          p$universal_pictures . g$thriller
##          1.672134e-01
##          p$sony_pictures
##          1.671064e-01
##          k$nazi
##          1.668462e-01
##          k$police
##          1.616242e-01
##          k$jealousy
##          1.607593e-01
##          k$1940s
##          1.603090e-01
##          k$robot
##          1.598364e-01

```

```

##                p$film4_productions
##                1.597078e-01
##                k$brutality
##                1.584958e-01
##                p$silver_pictures
##                1.564908e-01
##                g$comedy . k$sequel
##                1.563442e-01
##                k$shootout
##                1.534936e-01
##                g$drama . c$robert_de_niro
##                1.525313e-01
##                k$small_town
##                1.512312e-01
##                g$action . k$new_york_city
##                1.505046e-01
##                p$canal+ . g$drama
##                1.501847e-01
##                g$romance . k$woman_director
##                1.488301e-01
##                l$ar
##                1.484047e-01
##                c$john_cusack
##                1.476543e-01
##                g$adventure . c$frank_welker
##                1.464234e-01
##                k$high_school
##                1.449714e-01
##                k$car_crash
##                1.421652e-01
##                g$comedy . g$family
##                1.402765e-01
##                c$antonio_banderas
##                1.391933e-01
##                p$gaumont
##                1.384699e-01
##                k$daughter
##                1.370441e-01
##                c$ethan_hawke
##                1.331477e-01
##                k$seduction
##                1.318896e-01
##                k$dream
##                1.311723e-01
##                k$island
##                1.310028e-01
##                g$adventure . c$nicolas_cage
##                1.304604e-01
##                p$paramount . c$frank_welker
##                1.300107e-01
##                k$death
##                1.263953e-01
##                c$bruce_willis . k$duringcreditsstinger
##                1.262757e-01

```

```

##          k$child_abuse
##          1.250211e-01
##          k$gunfight
##          1.238922e-01
##          k$hitman
##          1.235698e-01
##          k$noir
##          1.205952e-01
##          g$action . g$thriller
##          1.178112e-01
##          k$college
##          1.161136e-01
##          k$1920s
##          1.156834e-01
##          k$mother_son_relationship
##          1.152139e-01
##          g$drama . g$romance
##          1.149837e-01
##          g$science_fiction . k$biography
##          1.135925e-01
##          g$thriller . k$love
##          1.132899e-01
##          c$michael_caine
##          1.116359e-01
##          k$vigilante
##          1.101592e-01
##          k$1990s
##          1.098731e-01
##          k$escape
##          1.074891e-01
##          c$samuel_l._jackson . c$steve_buscemi
##          1.059085e-01
##          g$crime . c$bruce_willis
##          1.051504e-01
##          g$family . c$frank_welker
##          1.047269e-01
##          k$satire
##          1.042641e-01
##          c$woody_harrelson
##          1.020701e-01
##          p$paramount . g$horror
##          1.000907e-01
##          g$music
##          9.739743e-02
##          k$amnesia
##          9.325223e-02
##          p$universal_pictures . g$comedy
##          9.317007e-02
##          k$dystopia
##          9.199477e-02
##          k$sadism
##          8.973561e-02
##          k$gangster
##          8.928485e-02

```



```

##           g$crime . k$new_york_city
##           8.912839e-02
##           g$comedy . c$liam_neeson
##           8.811772e-02
##           k$revenge
##           8.460841e-02
##           k$fight
##           7.888086e-02
## c$frank_welker . k$duringcreditsstinger
##           7.670475e-02
## p$warner_bros._pictures . g$horror
##           7.660251e-02
##           k$male_homosexuality
##           7.651768e-02
## p$touchstone_pictures . k$love
##           7.630614e-02
##           k$alien_invasion
##           7.567982e-02
## c$willem_dafoe . k$murder
##           7.424101e-02
## p$walt_disney_pictures . g$family
##           7.286288e-02
## g$science_fiction . k$duringcreditsstinger
##           7.281725e-02
##           k$train
##           7.245885e-02
## g$thriller . c$steve_buscemi
##           7.055254e-02
## g$drama . k$based_on_true_story
##           6.987822e-02
##           g$drama . k$revenge
##           6.745485e-02
##           k$killer
##           6.739238e-02
## g$action . c$morgan_freeman
##           6.690972e-02
##           p$paramount . g$comedy
##           6.585300e-02
## p$warner_bros._pictures . g$thriller
##           6.504889e-02
##           g$drama . k$love
##           6.457807e-02
##           k$ex
##           6.447615e-02
##           l$de
##           6.433475e-02
## p$touchstone_pictures . g$romance
##           6.067561e-02
##           k$world_war_ii
##           5.654676e-02
## g$romance . k$based_on_novel_or_book
##           5.654305e-02
## p$columbia_pictures . c$bruce_willis
##           5.592149e-02

```

```

##                                c$john_leguizamo
##                                5.565507e-02
##                                k$alcoholic
##                                5.501019e-02
##    k$woman_director . k$based_on_true_story
##                                5.027553e-02
##                                g$horror . k$sequel
##                                4.962329e-02
##                                k$paranoia
##                                4.769801e-02
##                                g$romance . c$bruce_willis
##                                4.614198e-02
##                                k$cia
##                                4.504530e-02
##                                k$father_son_relationship
##                                4.194841e-02
##                                g$adventure . g$family
##                                4.180987e-02
##                                g$romance . k$new_york_city
##                                4.111290e-02
##    k$woman_director . k$duringcreditsstinger
##                                4.105966e-02
##                                k$experiment
##                                4.002148e-02
##                                k$new_love
##                                3.968769e-02
##                                k$musician
##                                3.914901e-02
##                                g$crime . k$revenge
##                                3.833517e-02
##                                g$thriller . g$romance
##                                3.594109e-02
##                                k$chicago_illinois
##                                3.369790e-02
##    c$willem_dafoe . k$based_on_novel_or_book
##                                3.247067e-02
##                                g$crime . k$sequel
##                                2.899846e-02
##                                k$religion
##                                2.742391e-02
##                                c$bruce_willis
##                                2.664769e-02
##                                g$crime . k$woman_director
##                                2.472756e-02
##                                k$conspiracy
##                                1.953909e-02
##                                g$action . c$j.k._simmons
##                                1.631259e-02
##                                p$walt_disney_pictures . g$action
##                                1.009559e-02
##                                g$action . k$love
##                                8.846260e-03
##                                k$rape
##                                8.429605e-03

```

```

##          k$manhattan_new_york_city
##          7.512869e-03
##      g$thriller . c$morgan_freeman
##          4.900464e-03
##          k$family_relationships
##          4.865821e-03
##      g$crime . c$steve_buscemi
##          4.087352e-03
##          k$criminal
##          3.423561e-03
##      g$drama . k$woman_director
##          3.283772e-03
##          g$drama . k$sequel
##          7.337859e-04
##      c$robert_de_niro . c$steve_buscemi
##          -5.584550e-07
##          k$hollywood
##          -7.394166e-03
##      p$warner_bros._pictures . c$bruce_willis
##          -8.180840e-03
##          k$terrorism
##          -1.044466e-02
##      g$crime . c$morgan_freeman
##          -1.048818e-02
##      p$warner_bros._pictures . k$woman_director
##          -1.052512e-02
##          g$comedy . c$j.k._simmons
##          -1.144162e-02
##          g$drama . g$science_fiction
##          -1.356548e-02
##      p$columbia_pictures . k$new_york_city
##          -1.557886e-02
##          k$dance
##          -1.605197e-02
##      g$thriller . g$science_fiction
##          -1.861654e-02
##      p$new_line_cinema . g$crime
##          -2.047067e-02
##      p$new_line_cinema . g$drama
##          -2.118589e-02
##          c$danny_trejo
##          -2.144765e-02
##      c$willem_dafoe . c$steve_buscemi
##          -2.386744e-02
##          k$detective
##          -2.713474e-02
##          l$tr
##          -2.886830e-02
##      p$touchstone_pictures . g$family
##          -3.436195e-02
##          l$es
##          -3.583714e-02
##      p$paramount . c$j.k._simmons
##          -3.659021e-02

```

```

##      p$walt_disney_pictures . c$frank_welker
##                                -3.700049e-02
##      p$universal_pictures . c$robert_de_niro
##                                -4.113969e-02
##                                k$gay_interest
##                                -4.268127e-02
##                                k$gay
##                                -4.488758e-02
##                                k$murder . k$revenge
##                                -4.510949e-02
##                                c$christopher_walken
##                                -4.763619e-02
##                                k$new_york_city . k$love
##                                -5.066212e-02
##                                g$family . c$nicolas_cage
##                                -5.699956e-02
##                                g$thriller . c$samuel_l._jackson
##                                -5.771274e-02
##                                k$teen_movie
##                                -5.826037e-02
##      p$walt_disney_pictures . k$new_york_city
##                                -5.952199e-02
##                                g$adventure . c$morgan_freeman
##                                -5.969365e-02
##      p$metro_goldwyn_mayer . k$revenge
##                                -6.027484e-02
##                                g$thriller . k$murder
##                                -6.029324e-02
##                                p$canal+ . g$horror
##                                -6.365880e-02
##                                p$20th_century_fox . k$revenge
##                                -6.452527e-02
##      g$science_fiction . k$based_on_novel_or_book
##                                -6.603250e-02
##                                p$warner_bros._pictures . g$adventure
##                                -6.734768e-02
##                                c$samuel_l._jackson . c$willem_dafoe
##                                -7.067994e-02
##                                g$romance . k$biography
##                                -7.191612e-02
##                                p$canal+ . k$based_on_novel_or_book
##                                -7.402640e-02
##      p$columbia_pictures . k$based_on_true_story
##                                -7.693511e-02
##                                p$columbia_pictures . g$crime
##                                -7.807017e-02
##      p$warner_bros._pictures . k$based_on_novel_or_book
##                                -7.869858e-02
##                                c$nicolas_cage . k$based_on_novel_or_book
##                                -7.990310e-02
##                                p$millennium_films
##                                -8.251056e-02
##                                g$adventure . c$robert_de_niro
##                                -8.703973e-02

```

```

##                g$drama . g$adventure
##                -8.832354e-02
##                p$20th_century_fox . g$adventure
##                -9.694978e-02
##                p$canal+ . g$thriller
##                -9.805932e-02
##                k$duringcreditsstinger . k$sequel
##                -1.016061e-01
##                g$action . k$based_on_novel_or_book
##                -1.016965e-01
##                k$murder . k$sequel
##                -1.026894e-01
##                p$toei_company
##                -1.086450e-01
##                g$action . k$biography
##                -1.098864e-01
##                p$warner_bros._pictures . k$new_york_city
##                -1.109589e-01
##                p$universal_pictures . k$based_on_true_story
##                -1.110706e-01
##                p$cnc
##                -1.142615e-01
##                k$based_on_novel_or_book . k$new_york_city
##                -1.203583e-01
##                p$universal_pictures . g$adventure
##                -1.216796e-01
##                p$universal_pictures . k$duringcreditsstinger
##                -1.261041e-01
##                g$comedy . g$romance
##                -1.264724e-01
##                p$touchstone_pictures . k$sequel
##                -1.283028e-01
##                g$adventure . k$love
##                -1.289082e-01
##                g$action . g$romance
##                -1.319857e-01
##                p$warner_bros._pictures . k$sequel
##                -1.326224e-01
##                k$murder . k$new_york_city
##                -1.359525e-01
##                k$rural_area
##                -1.452035e-01
##                p$ciné+
##                -1.473203e-01
##                k$robbery
##                -1.485616e-01
##                g$family . k$based_on_true_story
##                -1.485994e-01
##                k$gore
##                -1.503455e-01
##                g$romance . c$j.k._simmons
##                -1.505677e-01
##                k$depression
##                -1.543192e-01

```

```

##                                c$james_franco
##                                -1.556562e-01
##                                p$warner_bros._pictures . p$canal+
##                                -1.557284e-01
##                                p$warner_bros._pictures . c$samuel_l._jackson
##                                -1.566902e-01
##                                p$canal+ . g$romance
##                                -1.570256e-01
##                                g$crime . k$love
##                                -1.581539e-01
##                                k$based_on_novel_or_book . k$woman_director
##                                -1.712857e-01
##                                g$comedy . k$based_on_novel_or_book
##                                -1.735542e-01
##                                g$thriller . k$woman_director
##                                -1.759075e-01
##                                c$samuel_l._jackson . c$nicolas_cage
##                                -1.993621e-01
##                                g$adventure . k$biography
##                                -2.013313e-01
##                                c$frank_welker . k$new_york_city
##                                -2.147097e-01
##                                p$columbia_pictures . k$based_on_novel_or_book
##                                -2.180465e-01
##                                c$steve_buscemi . k$duringcreditsstinger
##                                -2.201407e-01
##                                p$warner_bros._pictures . k$duringcreditsstinger
##                                -2.267263e-01
##                                g$romance . g$adventure
##                                -2.275380e-01
##                                p$columbia_pictures . k$sequel
##                                -2.352130e-01
##                                g$drama . g$comedy
##                                -2.363450e-01
##                                k$woman_director . k$biography
##                                -2.376975e-01
##                                p$warner_bros._pictures . k$based_on_true_story
##                                -2.405659e-01
##                                p$walt_disney_pictures . k$based_on_novel_or_book
##                                -2.438654e-01
##                                g$thriller . k$duringcreditsstinger
##                                -2.473534e-01
##                                p$warner_bros._pictures . k$murder
##                                -2.566732e-01
##                                g$drama . g$horror
##                                -2.613771e-01
##                                k$writer
##                                -2.642950e-01
##                                k$found_footage
##                                -2.644666e-01
##                                p$metro_goldwyn_mayer . g$action
##                                -2.687279e-01
##                                k$biography . k$love
##                                -2.779844e-01

```

```

##                k$dark_comedy
##                -2.785039e-01
##                g$romance . c$robert_de_niro
##                -2.853557e-01
##                p$paramount . g$family
##                -2.921894e-01
##                g$drama . g$family
##                -2.959880e-01
##                p$20th_century_fox . c$steve_buscemi
##                -2.984458e-01
##                k$female_wrestler
##                -3.036067e-01
##                k$assassination
##                -3.153630e-01
##                p$columbia_pictures . p$canal+
##                -3.213863e-01
##                p$téléfilm_canada
##                -3.323517e-01
##                p$paramount . p$metro_goldwyn_mayer
##                -3.330974e-01
##                p$universal_pictures . p$canal+
##                -3.619353e-01
##                g$science_fiction . c$willem_dafoe
##                -3.753879e-01
##                k$grief
##                -3.762781e-01
##                p$walt_disney_pictures . k$duringcreditsstinger
##                -3.786336e-01
##                p$new_line_cinema . c$samuel_l._jackson
##                -3.826168e-01
##                k$duringcreditsstinger . k$biography
##                -3.842253e-01
##                g$crime . k$biography
##                -3.937721e-01
##                c$samuel_l._jackson . k$based_on_novel_or_book
##                -3.947800e-01
##                p$touchstone_pictures . g$crime
##                -4.110381e-01
##                p$warner_bros._pictures . p$columbia_pictures
##                -4.136583e-01
##                p$new_line_cinema . k$murder
##                -4.193294e-01
##                g$crime . g$horror
##                -4.243871e-01
##                g$romance . g$science_fiction
##                -4.273132e-01
##                g$comedy . g$adventure
##                -4.298255e-01
##                g$family . c$j.k._simmons
##                -4.356424e-01
##                p$paramount . k$based_on_novel_or_book
##                -4.677210e-01
##                g$crime . g$family
##                -4.710831e-01

```

```

##          g$crime . g$science_fiction
##          -4.976461e-01
##      p$warner_bros._pictures . g$family
##          -5.099082e-01
##      p$columbia_pictures . k$duringcreditsstinger
##          -5.233493e-01
##      p$metro_goldwyn_mayer . k$sequel
##          -5.408620e-01
##      g$horror . k$based_on_true_story
##          -5.597206e-01
##      p$paramount . k$biography
##          -5.607216e-01
##      g$comedy . g$action
##          -5.617953e-01
##      k$pro_wrestling
##          -5.648268e-01
##      g$comedy . g$thriller
##          -5.660489e-01
##      g$adventure . g$crime
##          -5.803667e-01
##      p$metro_goldwyn_mayer . k$love
##          -5.866391e-01
##      p$walt_disney_pictures . k$sequel
##          -5.896217e-01
##      g$thriller . k$based_on_true_story
##          -5.903012e-01
##      l$ur
##          -5.913147e-01
##      g$action . g$family
##          -6.114573e-01
##      c$steve_buscemi . k$love
##          -6.127544e-01
##      g$romance . c$steve_buscemi
##          -6.168900e-01
##      p$columbia_pictures . c$j.k._simmons
##          -6.215784e-01
##      g$science_fiction . c$bruce_willis
##          -6.254616e-01
##      g$science_fiction . k$woman_director
##          -6.308524e-01
##      g$romance . g$horror
##          -6.437923e-01
##      g$action . g$horror
##          -6.852733e-01
##      g$horror . c$steve_buscemi
##          -6.860559e-01
##      p$walt_disney_pictures . c$morgan_freeman
##          -6.936592e-01
##      g$comedy . g$horror
##          -7.093510e-01
##      c$robert_de_niro . k$biography
##          -7.201388e-01
##      g$family . k$love
##          -7.450912e-01

```



```

##                                k$lgbt
##                                -7.475970e-01
##                                p$metro_goldwyn_mayer . p$canal+
##                                -7.508359e-01
##                                p$walt_disney_pictures . p$touchstone_pictures
##                                -7.528190e-01
##                                g$adventure . g$horror
##                                -7.532253e-01
##                                g$comedy . g$science_fiction
##                                -7.561218e-01
##                                p$20th_century_fox . k$duringcreditsstinger
##                                -7.564058e-01
##                                p$warner_bros._pictures . k$love
##                                -7.624349e-01
##                                p$20th_century_fox . k$based_on_novel_or_book
##                                -7.887702e-01
##                                c$samuel_l._jackson . k$revenge
##                                -8.133199e-01
##                                p$universal_pictures . k$based_on_novel_or_book
##                                -8.251867e-01
##                                c$frank_welker . k$sequel
##                                -8.375187e-01
##                                p$touchstone_pictures . k$based_on_novel_or_book
##                                -8.528736e-01
##                                p$touchstone_pictures . k$murder
##                                -8.545799e-01
##                                p$columbia_pictures . c$willem_dafoe
##                                -8.591651e-01
##                                p$touchstone_pictures . k$biography
##                                -9.052055e-01
##                                p$metro_goldwyn_mayer . c$samuel_l._jackson
##                                -9.251117e-01
##                                p$touchstone_pictures . k$duringcreditsstinger
##                                -9.341935e-01
##                                p$columbia_pictures . p$metro_goldwyn_mayer
##                                -9.383670e-01
##                                p$universal_pictures . p$touchstone_pictures
##                                -9.658964e-01
##                                p$warner_bros._pictures . p$metro_goldwyn_mayer
##                                -9.870168e-01
##                                l$pt
##                                -9.992032e-01
##                                c$steve_buscemi . k$revenge
##                                -1.001325e+00
##                                p$universal_pictures . p$columbia_pictures
##                                -1.042375e+00
##                                p$canal+ . k$woman_director
##                                -1.061219e+00
##                                g$horror . g$family
##                                -1.068087e+00
##                                p$walt_disney_pictures . c$liam_neeson
##                                -1.076769e+00
##                                p$paramount . p$canal+
##                                -1.085632e+00

```

```

##      p$warner_bros._pictures . p$new_line_cinema
##                                -1.143456e+00
##                                l$fa
##                                -1.160576e+00
##      p$universal_pictures . p$20th_century_fox
##                                -1.228540e+00
##      p$warner_bros._pictures . c$steve_buscemi
##                                -1.235897e+00
##                                g$horror . k$woman_director
##                                -1.253977e+00
##      p$paramount . p$touchstone_pictures
##                                -1.338622e+00
##                                g$documentary
##                                -1.344474e+00
##      p$warner_bros._pictures . p$20th_century_fox
##                                -1.356099e+00
##                                p$canal+ . c$willem_dafoe
##                                -1.401906e+00
##      p$paramount . p$columbia_pictures
##                                -1.510158e+00
##                                c$bruce_willis . k$biography
##                                -1.523262e+00
##                                c$nicolas_cage . k$murder
##                                -1.654725e+00
##      p$warner_bros._pictures . p$touchstone_pictures
##                                -1.824671e+00
##      p$warner_bros._pictures . p$paramount
##                                -1.862702e+00
##      p$columbia_pictures . c$liam_neeson
##                                -1.921133e+00
##      p$20th_century_fox . p$columbia_pictures
##                                -2.029013e+00
##      p$universal_pictures . p$paramount
##                                -2.045971e+00
##      p$universal_pictures . p$new_line_cinema
##                                -2.049035e+00
##      c$morgan_freeman . k$duringcreditsstinger
##                                -2.144882e+00
##      p$canal+ . p$walt_disney_pictures
##                                -2.162287e+00
##      p$metro_goldwyn_mayer . c$morgan_freeman
##                                -2.266051e+00
##      p$metro_goldwyn_mayer . k$duringcreditsstinger
##                                -2.316966e+00
##                                c$steve_buscemi . k$sequel
##                                -2.371802e+00
##                                g$horror . k$biography
##                                -2.507689e+00
##                                k$wrestling
##                                -2.681321e+00
##      p$paramount . p$20th_century_fox
##                                -2.687947e+00
##                                c$nicolas_cage . c$willem_dafoe
##                                -2.692918e+00

```

```
##          c$bruce_willis . k$based_on_true_story
##                                -2.817947e+00
##                                g$tv_movie
##                                -2.837188e+00
##          p$20th_century_fox . p$metro_goldwyn_mayer
##                                -3.132617e+00
```

From 1269 variables, we have 674 variables in our model with interactions. Below are the intercept of the model, the top 10 variables that positively affect revenue, and top 10 variables that negatively affect revenue.

```
ic2 <- coef2[c("(Intercept)"), 1]
paste("The intercept is ", ic2)
```

```
## [1] "The intercept is 12.4991157439431"
```

```
paste("Top 10 variables that positively affect the revenue:")
```

```
## [1] "Top 10 variables that positively affect the revenue:"
```

```
coef2_sort <- sort(coef2[, 1], decreasing = TRUE)[-1]
head(coef2_sort, 10)
```

```
## c$robert_de_niro . k$woman_director          p$columbia_pictures
##                3.121845                    2.643334
##                p$screen_gems                  p$paramount
##                2.615547                    2.595986
##                p$touchstone_pictures          p$20th_century_fox
##                2.561390                    2.514055
##                p$walt_disney_pictures          p$warner_bros._pictures
##                2.420880                    2.343409
##                p$universal_pictures g$science_fiction . c$robert_de_niro
##                2.313728                    2.312593
```

```
paste("Top 10 variables that negatively affects the revenue:")
```

```
## [1] "Top 10 variables that negatively affects the revenue:"
```

```
tail(coef2_sort, 10)
```

```
##          p$metro_goldwyn_mayer . c$morgan_freeman
##                                -2.266051
##          p$metro_goldwyn_mayer . k$duringcreditsstinger
##                                -2.316966
##                                c$steve_buscemi . k$sequel
##                                -2.371802
##                                g$horror . k$biography
##                                -2.507689
##                                k$wrestling
##                                -2.681321
##          p$paramount . p$20th_century_fox
```

```
##                                -2.687947
##          c$nicolas_cage . c$willem_dafoe
##                                -2.692918
##          c$bruce_willis . k$based_on_true_story
##                                -2.817947
##                                g$tv_movie
##                                -2.837188
##          p$20th_century_fox . p$metro_goldwyn_mayer
##                                -3.132617
```

Next, we will try to see which terms are included in the model (without interactions) when we split the data set into decades.

```
coefs <- c()

for (df in df_list) {
  #### PRODUCTION COMPANIES
  sub_prod_comp <- df$production_companies
  sub_docs <- Corpus(VectorSource(sub_prod_comp))
  # Remove '-' from the name since it is the splitter
  # symbol of the data
  sub_docs <- tm_map(sub_docs, to_another, "Metro-Goldwyn-Mayer",
    "Metro_Goldwyn_Mayer")
  sub_docs <- tm_map(sub_docs, to_another, "no_production_companies",
    "")
  sub_docs <- tm_map(sub_docs, to_another, " ", "_")
  sub_docs <- tm_map(sub_docs, to_another, "-", " ")
  sub_docs <- tm_map(sub_docs, stripWhitespace)
  # adding prefix p$ for production_companies
  sub_docs <- tm_map(sub_docs, add_prefix, "p$")
  sub_docs <- tm_map(sub_docs, to_another, " ", " p$")
  sub_dtm <- DocumentTermMatrix(sub_docs)

  # get top 10 production companies
  sub_key_pc <- findMostFreqTerms(sub_dtm, 10, INDEX = rep(1,
    each = length(df[, 1])))
  # print(sub_key_pc)

  #### GENRES
  sub_genres <- df$genres
  sub_docs2 <- Corpus(VectorSource(sub_genres))
  sub_docs2 <- tm_map(sub_docs2, to_another, " ", "_")
  sub_docs2 <- tm_map(sub_docs2, to_another, "-", " ")
  sub_docs2 <- tm_map(sub_docs2, stripWhitespace)
  # adding prefix g$ for genres
  sub_docs2 <- tm_map(sub_docs2, add_prefix, "g$")
  sub_docs2 <- tm_map(sub_docs2, to_another, " ", " g$")
  sub_dtm2 <- DocumentTermMatrix(sub_docs2)

  # get top 10 genres
  sub_key_gen <- findMostFreqTerms(sub_dtm2, 10, INDEX = rep(1,
    each = length(df[, 1])))
  # sub_key_gen
```

```

#### CREDITS
sub_casts <- df$credits
sub_docs3 <- Corpus(VectorSource(sub_casts))
sub_docs3 <- tm_map(sub_docs3, to_another, " ", "_")
# deal with Korean names
sub_docs3 <- tm_map(sub_docs3, to_another, "_([[:alpha:]]+)-([[:lower:]]+)$",
  "_\\1\\2")
sub_docs3 <- tm_map(sub_docs3, to_another, "_([[:alpha:]]+)-([[:lower:]]+)-",
  "_\\1\\2-")
sub_docs3 <- tm_map(sub_docs3, to_another, "-", " ")
sub_docs3 <- tm_map(sub_docs3, stripWhitespace)
# adding prefix c$ for casts
sub_docs3 <- tm_map(sub_docs3, add_prefix, "c$")
sub_docs3 <- tm_map(sub_docs3, to_another, " ", " c$")
sub_dtm3 <- DocumentTermMatrix(sub_docs3)

# get top 10 casts
sub_key_cast <- findMostFreqTerms(sub_dtm3, 10, INDEX = rep(1,
  each = length(df[, 1])))

#### KEYWORDS
sub_keywords <- df$keywords
sub_docs4 <- Corpus(VectorSource(sub_keywords))
sub_docs4 <- tm_map(sub_docs4, to_another, " ", "_")
sub_docs4 <- tm_map(sub_docs4, to_another, "-", " ")
sub_docs4 <- tm_map(sub_docs4, stripWhitespace)
# adding prefix k$ for keywords
sub_docs4 <- tm_map(sub_docs4, add_prefix, "k$")
sub_docs4 <- tm_map(sub_docs4, to_another, " ", " k$")
sub_dtm4 <- DocumentTermMatrix(sub_docs4)

# get top 10 keywords
sub_key_keys <- findMostFreqTerms(sub_dtm4, 10, INDEX = rep(1,
  each = length(df[, 1])))
# sub_key_keys

#### ORIGINAL LANGUAGE
sub_og_lng <- df$original_language
sub_docs5 <- Corpus(VectorSource(sub_og_lng))
# adding prefix l$ for language
sub_docs5 <- tm_map(sub_docs5, add_prefix, "l$")
sub_docs5 <- tm_map(sub_docs5, to_another, " ", " l$")
sub_dtm5 <- DocumentTermMatrix(sub_docs5)

# get all languages in at least 50 movies
sub_key_lang <- findMostFreqTerms(sub_dtm5, 10, INDEX = rep(1,
  each = length(df[, 1])))
# sub_key_lang

sub_X <- cbind(sub_dtm[, names(sub_key_pc[[1]])], sub_dtm2[,
  names(sub_key_gen[[1]])], sub_dtm3[, names(sub_key_cast[[1]])],
  sub_dtm4[, names(sub_key_keys[[1]])], sub_dtm5[, names(sub_key_lang[[1]])])
sub_y <- log(df$revenue_adjusted)

```

```

sub_model1 <- cv.glmnet(cbind(as.matrix(sub_X), budget = log(df$budget)),
  sub_y)
sub_coef1 <- coef(sub_model1, s = "lambda.min")
sub_coef_sort <- sort(sub_coef1[which(sub_coef1 != 0), 1],
  decreasing = TRUE)
coefs <- c(coefs, sub_coef_sort)

print(df$decades[1])
print(sub_coef_sort)
}

```

```

## [1] 1910
##               (Intercept) p$jesse_l._lasky_feature_play_company
##               17.619188                                -2.037566
## [1] 1920
##               (Intercept)                                l$en
##               12.872678334                                2.515355239
##               g$music                                k$world_war_i
##               1.572596046                                1.560638871
##               k$based_on_novel_or_book p$charles_chaplin_productions
##               0.822351799                                0.700643326
##               c$harold_lloyd                                k$silent_film
##               0.698528915                                0.544411996
##               p$united_artists                                g$romance
##               0.428811161                                0.391860588
##               k$code p$the_vitaphone_corporation
##               0.347126199                                0.281911891
##               g$action                                c$john_gilbert
##               0.242734866                                0.219200601
##               g$adventure                                g$drama
##               0.212686060                                0.070313929
##               c$noble_johnson p$warner_bros._pictures
##               0.057078012                                0.051760059
##               c$nigel_de_brulier                                k$pre
##               0.047115097                                0.008536016
##               l$zh
##               -5.169422687
## [1] 1930
##               (Intercept)                                l$en                                g$adventure
##               13.35492875                                3.82657050                                0.39509310
##               c$irving_bacon k$based_on_novel_or_book                                k$musical
##               0.39501978                                0.27075923                                0.23081056
##               k$black_and_white c$clark_gable                                c$ward_bond
##               0.04833436                                0.03865860                                0.01243344
##               p$warner_bros._pictures g$drama p$rho_radio_pictures
##               -0.02852272                                -0.05415548                                -0.66325381
##               p$first_national_pictures l$zh l$sv
##               -1.80483687                                -3.43722103                                -4.02346834
## [1] 1940
##               (Intercept)                                l$en                                g$family
##               15.5739766                                1.7904567                                0.6221444
##               p$walt_disney_productions c$bert_moorhouse k$black_and_white

```

```

##          0.3285450          0.3108720          0.2751412
##          g$drama          l$fr
##          0.0116140          -3.1339220
## [1] 1950
##          (Intercept)          l$en p$walt_disney_productions
##          14.01406765          2.73212189          1.83971429
##          k$epic          c$bess_flowern          g$romance
##          0.74312169          0.47505151          0.32310133
##          g$thriller          k$musical k$based_on_novel_or_book
##          0.23444109          0.22173996          0.19897367
##          c$franklyn_farnum          l$it          l$zh
##          0.09930969          -0.30331202          -4.32828693
## [1] 1960
##          (Intercept)          l$el
##          13.79014960          2.93332389
##          l$en          l$ja
##          2.91435762          2.12048806
## k$based_on_play_or_musical          l$it
##          1.36996240          1.25700882
##          c$frank_baker          k$epic
##          1.06703617          0.83283244
##          p$united_artists          g$adventure
##          0.79462128          0.78341680
##          c$paul_newman p$warner_bros._pictures
##          0.68694503          0.66826751
##          k$musical          c$john_wayne
##          0.63191755          0.60100324
##          k$new_york_city          g$action
##          0.49003242          0.48393764
##          p$20th_century_fox k$based_on_novel_or_book
##          0.39508430          0.38180402
##          p$metro_goldwyn_mayer p$columbia_pictures
##          0.36525624          0.30889991
##          g$thriller          g$war
##          0.26071218          0.24500781
##          c$al_bain          c$arthur_tovey
##          0.20794112          0.18202296
##          g$drama          g$crime
##          0.14596997          0.12853139
##          c$bert_stevens          g$western
##          0.08529632          0.07598935
##          l$tr          l$es
##          -0.06728581          -0.08449426
##          c$jean          k$cult_film
##          -0.18116967          -0.30000364
##          l$fa          l$sv
##          -2.03212288          -2.15777742
## [1] 1970
##          (Intercept)          l$en          l$fr
##          13.87015674          3.00268601          2.26708756
##          l$it          l$ja          l$sv
##          2.18202972          1.94060889          1.55480931
##          p$paramount p$warner_bros._pictures p$walt_disney_productions
##          1.27936799          1.07138399          1.04815586

```

##	c\$arthur_tovey	p\$columbia_pictures	p\$20th_century_fox
##	0.92969578	0.87519520	0.75186122
##	p\$universal_pictures	p\$united_artists	k\$new_york_city
##	0.54677529	0.53072478	0.48793989
##	k\$musical	g\$science_fiction	g\$thriller
##	0.43787811	0.39385770	0.38601106
##	g\$action	g\$comedy	k\$police
##	0.34800193	0.32897615	0.31015823
##	c\$burt_reynolds	p\$metro_goldwyn_mayer	p\$malpaso_productions
##	0.21870918	0.18933499	0.08099298
##	g\$crime	c\$robert_duvall	g\$adventure
##	0.05604740	0.04842614	0.04752269
##	g\$romance	c\$ned_beatty	l\$tr
##	0.02824088	0.02440882	-0.21166567
##	k\$sports	c\$m._emmet_walsh	g\$mystery
##	-0.35207672	-0.44310853	-0.48344011
##	[1] 1980		
##	(Intercept)	l\$en	p\$paramount
##	13.89905010	1.82778249	1.81906516
##	c\$sylvester_stallone	p\$20th_century_fox	l\$sv
##	1.48692788	1.46321868	1.44100156
##	p\$universal_pictures	l\$ja	c\$frank_welker
##	1.32452977	1.24234903	1.23232011
##	p\$warner_bros._pictures	p\$metro_goldwyn_mayer	k\$sequel
##	1.15589328	1.06691026	0.91995750
##	p\$tristar_pictures	c\$dan_aykroyd	p\$columbia_pictures
##	0.85515911	0.81154316	0.77466050
##	k\$new_york_city	p\$orion_pictures	c\$m._emmet_walsh
##	0.71814985	0.71626304	0.70287922
##	l\$it	g\$adventure	k\$based_on_novel_or_book
##	0.61340999	0.58225244	0.52375062
##	k\$martial_arts	k\$revenge	c\$john_candy
##	0.50697243	0.50348480	0.44735945
##	c\$jean	c\$peter_jason	k\$los_angeles_california
##	0.44558948	0.34885817	0.30536553
##	g\$comedy	k\$police	c\$robert_loggia
##	0.28300566	0.20666617	0.15690247
##	l\$cn	g\$thriller	g\$fantasy
##	0.14726297	0.13083631	0.10518175
##	g\$romance	g\$science_fiction	g\$crime
##	0.10202353	0.09583170	0.06829004
##	p\$cannon_group	l\$es	g\$horror
##	-0.04652501	-0.16066176	-0.21423347
##	g\$drama	c\$dick_miller	k\$woman_director
##	-0.31123069	-0.49666933	-0.53212941
##	l\$tr	l\$zh	
##	-0.81733132	-1.18439981	
##	[1] 1990		
##	(Intercept)	p\$20th_century_fox	p\$paramount
##	13.720757127	2.206850882	2.087479002
##	p\$columbia_pictures	p\$universal_pictures	p\$touchstone_pictures
##	1.886018123	1.881050193	1.738760563
##	p\$tristar_pictures	p\$warner_bros._pictures	l\$ja
##	1.644264077	1.613253595	1.610805786

##	c\$frank_welker	c\$robin_williams	p\$hollywood_pictures
##	1.560736571	1.511392863	1.474940512
##	p\$new_line_cinema	c\$bruce_willis	c\$robert_de_niro
##	1.382403003	0.987984202	0.955454456
##	k\$based_on_novel_or_book	k\$martial_arts	l\$en
##	0.889702102	0.836977454	0.828841150
##	c\$samuel_l._jackson	g\$adventure	p\$miramax
##	0.823513621	0.785618621	0.692722691
##	g\$thriller	k\$new_york_city	l\$it
##	0.685003161	0.621321141	0.591272377
##	k\$los_angeles_california	c\$thomas_rosales_jr.	c\$dan_hedaya
##	0.553431907	0.489165535	0.471287020
##	l\$hi	g\$family	g\$comedy
##	0.435066306	0.398755244	0.367024631
##	g\$romance	g\$action	c\$jones
##	0.345123882	0.314035654	0.157788389
##	k\$revenge	k\$police	g\$horror
##	0.140494122	0.136421170	0.133583726
##	l\$ta	g\$science_fiction	c\$jean
##	0.132756870	0.125371487	0.088701763
##	k\$murder	l\$de	g\$drama
##	0.027585913	-0.004287399	-0.057595978
##	k\$woman_director	l\$zh	
##	-0.279046763	-1.837899989	
##	[1] 2000		
##	(Intercept)	p\$columbia_pictures	
##	12.61244355	2.74771847	
##	p\$warner_bros._pictures	p\$universal_pictures	
##	2.66962573	2.60278671	
##	p\$new_line_cinema	p\$walt_disney_pictures	
##	2.57037434	2.33777122	
##	p\$dreamworks_pictures	p\$20th_century_fox	
##	2.31671042	2.29660207	
##	p\$paramount	l\$ja	
##	2.23948373	1.99134851	
##	l\$hi	l\$ko	
##	1.93195968	1.92529145	
##	l\$de	l\$it	
##	1.82036494	1.78232946	
##	p\$miramax	k\$duringcreditsstinger	
##	1.69680067	1.52386840	
##	c\$samuel_l._jackson	l\$en	
##	1.38103387	1.36010170	
##	c\$jones	c\$bruce_willis	
##	1.34930001	1.34829750	
##	p\$canal+	c\$keith_david	
##	1.20485638	1.15624653	
##	k\$parent_child_relationship	k\$loss_of_loved_one	
##	1.02933395	0.96657352	
##	l\$fr	l\$zh	
##	0.95346062	0.94644874	
##	l\$es	k\$based_on_novel_or_book	
##	0.92159115	0.88467866	
##	k\$friendship	g\$fantasy	

##	0.86685655	0.77882279
##	c\$willem_dafoe	g\$action
##	0.76114084	0.74616265
##	k\$new_york_city	g\$adventure
##	0.71088120	0.67138589
##	c\$morgan_freeman	g\$family
##	0.55706324	0.53629208
##	g\$thriller	g\$romance
##	0.52535440	0.49146181
##	l\$ru	g\$comedy
##	0.48953322	0.41782800
##	c\$jean	c\$david_koechner
##	0.39149510	0.34113609
##	c\$marie	k\$murder
##	0.33485901	0.33380671
##	k\$sports	g\$crime
##	0.32726149	0.19847428
##	g\$horror	k\$woman_director
##	0.19144594	0.05502081
##	g\$drama	k\$revenge
##	-0.09068283	-0.09601916
##	c\$justin_long	
##	-0.10545322	
##	[1] 2010	
##	(Intercept)	p\$warner_bros._pictures
##	12.322133772	3.401782560
##	p\$20th_century_fox	p\$paramount
##	3.131444226	3.100950661
##	p\$universal_pictures	p\$lionsgate
##	2.881218723	2.275124953
##	c\$samuel_l._jackson	c\$liam_neeson
##	1.756017270	1.669748150
##	l\$ja	p\$relativity_media
##	1.480024703	1.474050135
##	k\$based_on_novel_or_book	l\$hi
##	1.397301271	1.377900301
##	k\$based_on_true_story	l\$zh
##	1.236522516	1.201010232
##	k\$friendship	c\$joe_chrest
##	0.932092714	0.924104306
##	p\$canal+	p\$studiocanal
##	0.780160044	0.776022433
##	g\$thriller	c\$bill_hader
##	0.724151839	0.663429052
##	g\$family	g\$romance
##	0.647299240	0.625278838
##	c\$jean	k\$revenge
##	0.519376715	0.492722602
##	c\$jones	l\$en
##	0.398056765	0.384382114
##	l\$fr	g\$crime
##	0.330218603	0.289608133
##	c\$j.k._simmons	k\$murder
##	0.139690495	0.129353692
		p\$columbia_pictures
		3.216685469
		p\$walt_disney_pictures
		3.029579880
		k\$duringcreditsstinger
		2.134907953
		k\$sequel
		1.666026750
		l\$ko
		1.403209998
		k\$biography
		1.293368335
		g\$adventure
		1.167805572
		g\$fantasy
		0.876887070
		g\$comedy
		0.767181449
		g\$action
		0.661057856
		k\$love
		0.529420113
		c\$smith
		0.487087961
		c\$marie
		0.337754379
		l\$m1
		0.288904415
		g\$drama
		0.113813158

```
##          l$ru          g$horror          k$woman_director
##          0.008290509          -0.036884321          -0.087694833
##          l$de          c$james_franco          l$es
##          -0.139944734          -0.217332030          -0.363613470
## [1] 2020
##          (Intercept)          l$zh          p$paramount
##          12.087304591          3.921624687          3.180876603
##          p$universal_pictures p$warner_bros._pictures p$columbia_pictures
##          2.738808140          2.673959836          2.294189751
##          k$sequel          p$focus_features k$duringcreditsstinger
##          2.110304894          1.797544324          1.697885299
##          l$ko          c$joy          p$bron_studios
##          1.693729477          1.524905682          1.523702809
##          k$based_on_comic          c$anthony_molinari          k$murder
##          1.422460670          1.363106498          1.306277112
##          g$action          p$lionsgate          l$ja
##          1.289708784          1.192233090          1.143895503
##          l$fr          g$adventure          k$based_on_true_story
##          1.068539163          1.047272717          0.991453298
##          k$anime k$based_on_novel_or_book          k$aftercreditsstinger
##          0.953351926          0.844944935          0.831584008
##          p$canal+          g$drama          g$fantasy
##          0.803874310          0.517732182          0.454619018
##          g$comedy          k$superhero          c$jean
##          0.384640959          0.338885732          0.333984681
##          g$thriller          g$family          c$michelle_yeoh
##          0.288610630          0.265129662          0.249500713
##          p$blumhouse_productions          g$animation          p$ingenious_media
##          0.221367373          0.198826393          0.118964231
##          g$romance          c$jones          k$woman_director
##          0.118189999          0.116224343          0.027057797
##          g$horror          l$de          l$ru
##          -0.006439627          -0.092382844          -0.193508780
##          l$es
##          -0.542501300
```

```
# coefs
```