Predicting book ratings: can a simple model outperform singular value decomposition?

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Summary

This report describes my work on the project of my choice, within the Capstone course of Harvardx's Data Science Professional Certificate.

The question that I investigate is: can a simple model that predicts book ratings perform better than more advanced ones, that apply singular value decomposition?

The question is interesting and may lead to useful learnings, since the simple models have important advantages in a real recommendation system: 1. They could easily be applied to new users and new books, thus providing a good way to deal with the 'cold start' problem. 2. If a user rates an item and we are interested in recommending a new item immediately, we do not need to train the algorithm on the whole matrix again. We can immediately apply a model that requires a simple calculation, thus saving both time and processing power.

The analysis was structured as follows:

Section 1 - Downloading the data

In order to address this question, I downloaded the "Book-Crossing" dataset that contains book ratings provided by users of the Book-Crossing website. The data is available online here (http://www2.informatik.uni-freiburg.de/~cziegler/BX/) and on Kaggle (https://www.kaggle.com/somnambwl/bookcrossing-dataset). The website's url is: https://www.bookcrossing.com/.

Section 2 - Preparing the data

Next, I prepared the data for analysis.

Section 3 - Exploratory data analysis

Afterwards I explored the data through some calculations and visualizations.

Section 4 - Evaluating simple models (validation part 1)

Afterwards I evaluated some simple models, similar to those that we learned in the machine learning course. However, I introduced a bit more information to the models. While in the course we only included unique user effects and unique item effects, I included 'side information' as well. That is, I included information on users, such as age and country, and information on the items (books), such as author and publisher.

Section 5 - Introducing regularization (validation part 2)

I then added regularization to the simple models, to account for the difference between average ratings provided by a few users and average ratings provided by many users.

Section 6 - Evaluating more advanced models (validation part 3)

I proceeded to evaluate some more advanced ones, through validation. First I evaluated the 'Popular' model because of its' simplicity. Then I evaluated the 'Singular Value Decomposition' (SVD) and 'Funk Singular Value Decomposition' models (SVDF), since the matrix was very sparse. I discovered that the simple models produced a much lower Root Mean Squared Error (RMSE) than the advanced ones!

Section 7 - Applying the chosen model to the test set

Finally, I applied the model that produced the lowest RMSE to the test dataset. It produced an RMSE that was very similar to the one that it produced in the validation stage, indicating that the model was probably not over-fitted in the validation stage. This was expected, given the low number of features in the model and its' simplicity.

Section 8 - Conclusion and discussion

My conclusion is that under certain conditions, simple models can outperform more advanced ones. There could be several reasons for this, in this case. First, the dataset was rather small. Second, there was a small number of ratings per book. This could be problematic for algorithms that rely on the associations between ratings given to items (e.g. two books tend to receive similar ratings). Third, the matrix was extremely sparse, and that might be too difficult to handle, even for the SVD and SVDF algorithms. Finally, I may have made a mistake in the analysis (although I tried pretty hard not to do that :)). Further analyses would be required in order to find out what combination of these possibilities is indeed the cause of the very poor performance of the advanced models in comparison to the simple ones.

In sum, I feel like I learned an important lesson - in machine learning, sometimes there is no trade-off between simplicity and accuracy. Under certain conditions, simple models could also be more accurate!

Table of contents

1. Downloading the data

Let us begin by downloading the data.

```
################################
### 1. Downloading the data ###
################################

### Installing packages
suppressWarnings(suppressMessages(if(!require(downloader)) install.packages("downloader", repos = "http
suppressWarnings(suppressMessages(if(!require(dplyr)) install.packages("dplyr", repos = "http://cran.us
suppressWarnings(suppressMessages(if(!require(tidyverse)) install.packages("tidyverse", repos = "http:/
suppressWarnings(suppressMessages(if(!require(caret)) install.packages("caret", repos = "http://cran.us
suppressWarnings(suppressMessages(if(!require(data.table)) install.packages("data.table", repos = "http
suppressWarnings(suppressMessages(if(!require(ggplot2)) install.packages("ggplot2", repos = "http://cra
suppressWarnings(suppressMessages(if(!require(recommenderlab)) install.packages("recommenderlab", repos
suppressWarnings(suppressMessages(if(!require(stringr)) install.packages("stringr", repos = "http://cra

### loading libraries
suppressWarnings(suppressMessages(library(downloader)))
suppressWarnings(suppressMessages(library(dplyr)))
suppressWarnings(suppressMessages(library(tidyverse)))
suppressWarnings(suppressMessages(library(caret)))
suppressWarnings(suppressMessages(library(data.table)))
suppressWarnings(suppressMessages(library(ggplot2)))
suppressWarnings(suppressMessages(library(recommenderlab)))
suppressWarnings(suppressMessages(library(stringr)))

### description of the data set
### by publisher: "http://www2.informatik.uni-freiburg.de/~cziegler/BX/"
### in Kaggle: "https://www.kaggle.com/somnambwl/bookcrossing-dataset"
### (the website: "https://www.bookcrossing.com/")

### downloading the dataset
download("http://www2.informatik.uni-freiburg.de/~cziegler/BX/BX-CSV-Dump.zip", dest="dataset.zip", mode
unzip ("dataset.zip")

### converting the files to data frame format
books<-read.csv(file = 'BX-Books.csv', sep=";")
users<-read.csv(file = 'BX-Users.csv', sep=";")
ratings<-read.csv(file = 'BX-Book-Ratings.csv', sep=";")

### saving the data frames
saveRDS(books, "books")
saveRDS(users, "users")
saveRDS(ratings, "ratings")
```

2. Preparing the data

Let us now prepare the data for the analysis. Our preparation includes creating an additional variable that will enable us to include interaction effects between users and authors (it seems reasonable that a users' rating of a book by a certain author would be rather similar to their rating of other books by the same author). We also create another variable, 'age bracket', in order to account for non-linear effects of age on our outcome in the models that we will apply. We also perform 'sanity checks' by examining some key distributions.

```r
##############################
### 2. Preparing the data ###
##############################

### cleaning the working space
rm(list=ls())

### loading the data
books<-readRDS("books")
users<-readRDS("users")
ratings<-readRDS("ratings")

### exploring the three data files
dim(books)
```

```
## [1] 115253      8
```

```r
names(books)
```

```
## [1] "ISBN"                "Book.Title"          "Book.Author"
## [4] "Year.Of.Publication" "Publisher"           "Image.URL.S"
## [7] "Image.URL.M"         "Image.URL.L"
```

```r
dim(users)
```

```
## [1] 140291      3
```

```r
names(users)
```

```
## [1] "User.ID"  "Location" "Age"
```

```r
head(users)
```

```
##   User.ID                           Location  Age
## 1       1                 nyc, new york, usa NULL
## 2       2          stockton, california, usa   18
## 3       3    moscow, yukon territory, russia NULL
## 4       4          porto, v.n.gaia, portugal   17
## 5       5 farnborough, hants, united kingdom NULL
## 6       6      santa monica, california, usa   61
```

```r
dim(ratings)
```

```
## [1] 493813      3
```

```r
names(ratings)
```

```
## [1] "User.ID"     "ISBN"        "Book.Rating"
```

```r
head(ratings)
```

```
##   User.ID       ISBN Book.Rating
## 1  276725 034545104X           0
## 2  276726 0155061224           5
## 3  276727 0446520802           0
## 4  276729 052165615X           3
## 5  276729 0521795028           6
## 6  276733 2080674722           0
```

```r
### extracting country names from the 'users' data frame
users_processed<-users # duplicating the raw 'users' dataset

### examining the first 10 values in the users$Location column
users$Location[1:10]
```

```
##  [1] "nyc, new york, usa"                 "stockton, california, usa"
##  [3] "moscow, yukon territory, russia"    "porto, v.n.gaia, portugal"
##  [5] "farnborough, hants, united kingdom" "santa monica, california, usa"
##  [7] "washington, dc, usa"                "timmins, ontario, canada"
##  [9] "germantown, tennessee, usa"         "albacete, wisconsin, spain"
```

```r
### The users$Location column contains three entries, separated by commas.
### In our model we will only use the country

### Extracting the country names
### extracting country names
users_processed$country<-sub(".*, ", "", users_processed$Location)

### making sure that it worked
### first 10 rows
users_processed$country[1:10]
```

```
##  [1] "usa"            "usa"            "russia"         "portugal"
##  [5] "united kingdom" "usa"            "usa"            "canada"
##  [9] "usa"            "spain"
```

```r
users_processed$Location[1:10]
```

```
##  [1] "nyc, new york, usa"                 "stockton, california, usa"
##  [3] "moscow, yukon territory, russia"    "porto, v.n.gaia, portugal"
##  [5] "farnborough, hants, united kingdom" "santa monica, california, usa"
##  [7] "washington, dc, usa"                "timmins, ontario, canada"
##  [9] "germantown, tennessee, usa"         "albacete, wisconsin, spain"
```

```r
### an arbitrary sample of rows
users_processed$country[647:658]
```

```
##  [1] "australia"      "canada"         "usa"            "usa"
##  [5] "usa"            "usa"            "united kingdom" "canada"
##  [9] "usa"            "new zealand"    "usa"            "usa"
```

```r
users_processed$Location[647:658]
```

```
##  [1] "perth, western australia, australia" "kamloops, british columbia, canada"
##  [3] "san diego, california, usa"          "santa cruz, california, usa"
##  [5] "interlachen, florida, usa"           "slippery rock, pennsylvania, usa"
##  [7] "bristol, wales, united kingdom"      "ottawa, ontario, canada"
##  [9] "monroe, north carolina, usa"         "feilding, manawatu, new zealand"
## [11] "chattanooga, tennessee, usa"         "jasper, georgia, usa"
```

```r
names(users_processed)
```

```
## [1] "User.ID"  "Location" "Age"      "country"
```

```r
### merging all three datasets to one file, on the rating level
### i.e. each row will contain a rating, and information
### about both the user and the book that were involved

### adding user information
names(users_processed)
```

```
## [1] "User.ID"  "Location" "Age"      "country"
```

```r
class(users_processed$User.ID)
```

```
## [1] "character"
```

```r
class(users_processed$User.ID)
```

```
## [1] "character"
```

```r
### converting the users$User.ID column to numeric form, since that is its' form in the ratings dataset
suppressWarnings(users_processed$User.ID<-as.numeric(users_processed$User.ID))

### merging the files
all_together <- left_join(ratings, users_processed, by = "User.ID")

### making sure that the merged file is fine
head(all_together)
```

```
##   User.ID       ISBN Book.Rating                     Location  Age   country
## 1  276725 034545104X           0            tyler, texas, usa NULL       usa
## 2  276726 0155061224           5      seattle, washington, usa NULL       usa
## 3  276727 0446520802           0 h, new south wales, australia   16 australia
## 4  276729 052165615X           3          rijeka, n/a, croatia   16   croatia
## 5  276729 0521795028           6          rijeka, n/a, croatia   16   croatia
## 6  276733 2080674722           0            paris, n/a, france   37    france
```

```r
dim(all_together)
```

```
## [1] 493813      6
```

```r
### adding books information
names(books)
```

```
## [1] "ISBN"                "Book.Title"          "Book.Author"
## [4] "Year.Of.Publication" "Publisher"           "Image.URL.S"
## [7] "Image.URL.M"         "Image.URL.L"
```

```r
class(books$ISBN)
```

```
## [1] "character"
```

```r
class(ratings$ISBN)
```

```
## [1] "character"
```

```r
### merging the files
all_together <- left_join(all_together, books, by = "ISBN")

### making sure that the merged file is fine
names(all_together)
```

```
##  [1] "User.ID"             "ISBN"                "Book.Rating"
##  [4] "Location"            "Age"                 "country"
##  [7] "Book.Title"          "Book.Author"         "Year.Of.Publication"
## [10] "Publisher"           "Image.URL.S"         "Image.URL.M"
## [13] "Image.URL.L"
```

```r
dim(all_together)
```

```
## [1] 493813     13
```

```r
### keeping the relevant columns only
colnames<-names(all_together)
colnames
```

```
##  [1] "User.ID"             "ISBN"                "Book.Rating"
##  [4] "Location"            "Age"                 "country"
##  [7] "Book.Title"          "Book.Author"         "Year.Of.Publication"
## [10] "Publisher"           "Image.URL.S"         "Image.URL.M"
## [13] "Image.URL.L"
```

```r
keep<-c(colnames[1], colnames[2], colnames[3], colnames[5], colnames[6], colnames[8], colnames[9], colna
dat<-all_together[keep]
head(dat)
```

```
##   User.ID       ISBN Book.Rating  Age   country        Book.Author
## 1  276725 034545104X           0 NULL       usa         M. J. Rose
## 2  276726 0155061224           5 NULL       usa               <NA>
## 3  276727 0446520802           0   16 australia               <NA>
## 4  276729 052165615X           3   16   croatia               <NA>
## 5  276729 0521795028           6   16   croatia               <NA>
## 6  276733 2080674722           0   37    france Michel Houellebecq
##   Year.Of.Publication        Publisher
## 1                2002 Ballantine Books
## 2                <NA>             <NA>
## 3                <NA>             <NA>
## 4                <NA>             <NA>
## 5                <NA>             <NA>
## 6                1998       Flammarion
```

```
### simplifying the names
names(dat)<- c("userid", "bookid", "rating", "age", "country", "author", "year", "publisher")
names(dat) # making sure that the renaming worked properly
```

```
## [1] "userid"    "bookid"    "rating"    "age"       "country"   "author"
## [7] "year"      "publisher"
```

```
### checking the classes of the columns that are supposed to be numeric
class(dat$userid)
```

```
## [1] "numeric"
```

```
class(dat$bookid)
```

```
## [1] "character"
```

```
class(dat$rating)
```

```
## [1] "integer"
```

```
class(dat$age)
```

```
## [1] "character"
```

```
class(dat$year)
```

```
## [1] "character"
```

```
### converting columns that should be numeric to numeric class
dat_backup<-dat # creating a backup
saveRDS(dat_backup, "dat_backup") # saving it

### converting to numeric
suppressWarnings(dat$bookid<-as.numeric(dat$bookid))
```

```r
suppressWarnings(dat$age<-as.numeric(dat$age))
suppressWarnings(dat$year<-as.numeric(dat$year))

### making sure that it worked
class(dat$userid)
```

```
## [1] "numeric"
```

```r
class(dat$bookid)
```

```
## [1] "numeric"
```

```r
class(dat$rating)
```

```
## [1] "integer"
```

```r
class(dat$age)
```

```
## [1] "numeric"
```

```r
class(dat$year)
```

```
## [1] "numeric"
```

```r
### preparing a column with the concatenation of userid and author
### (see the rationale in the beginning of this section)

### first, let's check for missing values
n_missing_userid<-sum(is.na(dat$userid)) # the number of missing values in the userid column
n_missing_userid
```

```
## [1] 0
```

```r
n_missing_author<-sum(is.na(dat$author)) # the number of missing values in the author column
n_missing_author
```

```
## [1] 294664
```

```r
nrow(dat)
```

```
## [1] 493813
```

```r
### the author columns contains missing values
### indexing the rows that do not have a missing value in the author column
index<-which(!is.na(dat$author))

### making sure that the indexing worked properly
head(index)
```

```
## [1]  1  6 11 12 13 14
```

```r
length(index)+n_missing_author-nrow(dat) # this should be zero
```

```
## [1] 0
```

```r
### concatenating userid and author in rows that contain both
dat$userid_author<-"missing" # creating default value
dat$userid_author[index]<-paste(dat$userid[index], dat$author[index]) # concatenating
head(dat$userid_author)
```

```
## [1] "276725 M. J. Rose"         "missing"
## [3] "missing"                   "missing"
## [5] "missing"                   "276733 Michel Houellebecq"
```

```r
dat$userid_author[dat$userid_author=="missing"]<-NA # replacing "missing" with NAs

### making sure that it worked properly
dat$userid_author[4300:4400] # examining
```

```
##   [1] NA                             NA
##   [3] NA                             NA
##   [5] "278390 Patricia Cornwell"     NA
##   [7] NA                             "278390 Kate White"
##   [9] "278390 Margaret Atwood"       NA
##  [11] "278390 Dan Brown"             "278390 Alice Walker"
##  [13] "278390 Alice Walker"          NA
##  [15] NA                             NA
##  [17] "278390 Amy Tan"               "278390 Amy Tan"
##  [19] NA                             NA
##  [21] NA                             "278400 Terry C. Johnston"
##  [23] NA                             NA
##  [25] "278409 Amy Ephron"            NA
##  [27] NA                             NA
##  [29] NA                             NA
##  [31] NA                             NA
##  [33] NA                             NA
##  [35] NA                             NA
##  [37] NA                             "278418 Virginia Hamilton"
##  [39] NA                             "278418 C. S. Lewis"
##  [41] NA                             "278418 Alan Paton"
##  [43] NA                             NA
##  [45] NA                             NA
##  [47] NA                             NA
##  [49] NA                             NA
##  [51] "278418 Ellen Weiss"           NA
##  [53] "278418 Richard Hefter"        "278418 Richard Hefter"
##  [55] NA                             NA
##  [57] NA                             NA
##  [59] "278418 Roseanne"              NA
##  [61] NA                             "278418 Olivia Goldsmith"
##  [63] NA                             NA
##  [65] NA                             "278418 Tony Hillerman"
##  [67] NA                             NA
```

```
##  [69] NA                            NA
##  [71] NA                            "278418 Margaret Wise Brown"
##  [73] NA                            NA
##  [75] NA                            NA
##  [77] NA                            "278418 Thacher Hurd"
##  [79] NA                            NA
##  [81] NA                            "278418 Michael Johnson"
##  [83] NA                            "278418 John Gunther"
##  [85] "278418 John F. Kennedy"      NA
##  [87] NA                            "278418 Bryan Burrough"
##  [89] "278418 Oscar Hijuelos"       NA
##  [91] NA                            NA
##  [93] NA                            NA
##  [95] NA                            "278418 Bill Dugan"
##  [97] NA                            "278418 Barbara Delinsky"
##  [99] "278418 Chri Carter"          NA
## [101] NA
```

```r
nonmissing1<-sum(!is.na(dat$userid_author)) # counting non-missing values
nonmissing2<-nrow(dat)-n_missing_author
nonmissing1-nonmissing2 # this should be zero
```

```
## [1] 0
```

```r
### creating age brackets for the analysis
### (see rationale in the beginning of this section)
dat$age<-round(dat$age,0) # rounding the values of the age variable, in case they aren't rounded yet
dat$age_bracket[dat$age<=10]<-"0-10"
dat$age_bracket[dat$age>=11 & dat$age<=20]<-"11-20"
dat$age_bracket[dat$age>=21 & dat$age<=30]<-"21-30"
dat$age_bracket[dat$age>=31 & dat$age<=40]<-"31-40"
dat$age_bracket[dat$age>=41 & dat$age<=50]<-"41-50"
dat$age_bracket[dat$age>=51 & dat$age<=60]<-"51-60"
dat$age_bracket[dat$age>=61 & dat$age<=70]<-"61-70"
dat$age_bracket[dat$age>=71 & dat$age<=80]<-"71-80"
dat$age_bracket[dat$age>=81 & dat$age<=90]<-"81-90"
dat$age_bracket[dat$age>=91 & dat$age<=100]<-"91-100"

### examining the distribution of ratings
table(dat$rating)
```

```
## 
##      0      1      2      3      4      5      6      7      8      9     10 
## 317794    658   1184   2622   3802  21546  15222  31300  42046  26549  31090
```

```r
### there seem to be many rows with rating = 0
### in the book crossing website, books are rated from 1 to 10
### with an option to mark "haven't read" as well
### (see the website: "https://www.bookcrossing.com/")
### so we need to remove the rows with ratings of zero

### removing the rows with ratings of zero
dim(dat)
```

```
## [1] 493813     10
```

```r
dat<-dat[dat$rating!=0,]
dim(dat)
```

```
## [1] 176019     10
```

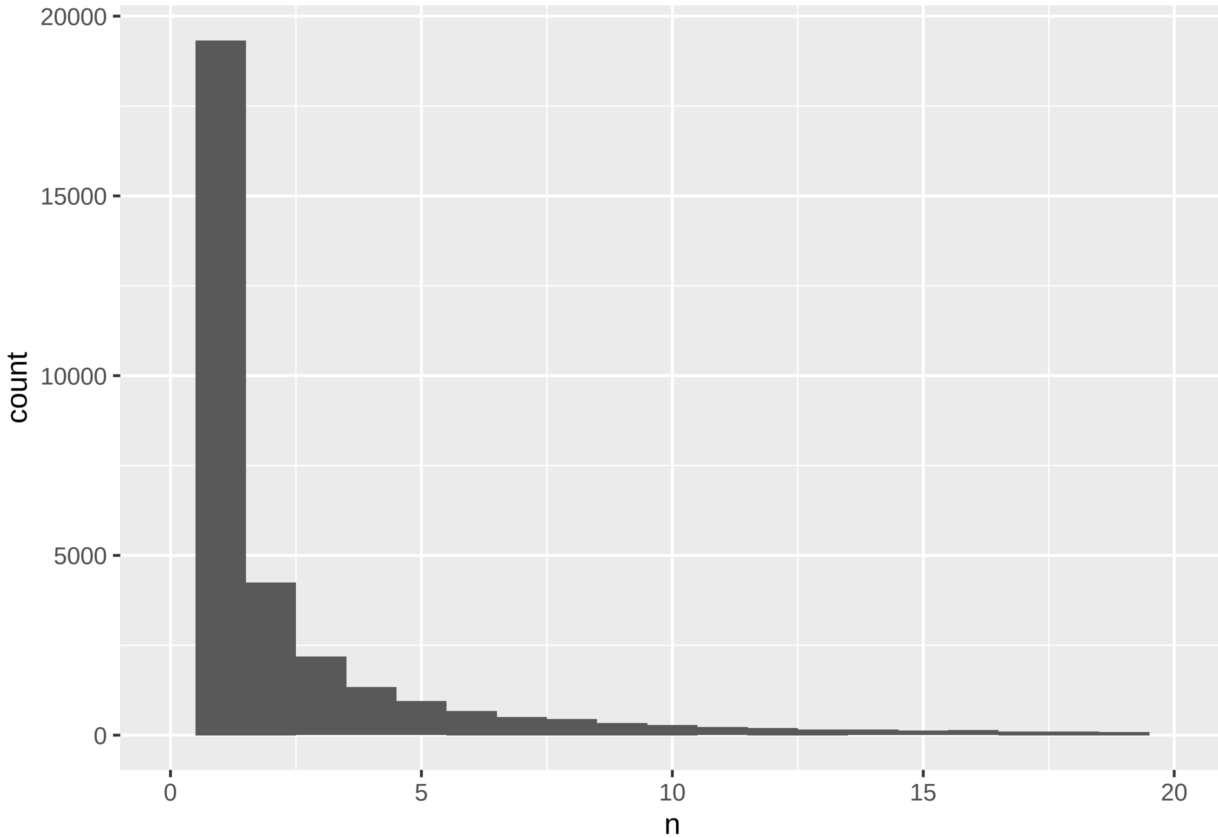
```r
### saving
saveRDS(dat, file="dat")

### cleaning up the working space
rm(list=ls())

### reloading the dataset
dat<-readRDS("dat")

### cleaning memory
invisible(gc())

### checking the percentage of missing values in each variable

# creating a function that computes the percentage of missing values in a vector
percent_missing<-function(x){
  n_missing<-sum(is.na(x)) # calculate the number of missing values
  p_missing<-n_missing/length(x) # calculate the percentage of missing values
  p_missing # print the percentage
}

# applying the function to each of the columns
apply(dat, MARGIN = 2, percent_missing)
```

```
##        userid        bookid        rating           age       country
##     0.0000000     0.0828206     0.0000000     0.6116896     0.4580926
##        author          year     publisher userid_author   age_bracket
##     0.5797726     0.5798124     0.5797726     0.5797726     0.6136269
```

```r
# examining the distribution of the number of ratings per user
ratings_per_user<-dat %>%
  filter(!is.na(rating))  %>%
  count(userid)

ggplot(ratings_per_user, aes(x=n)) +
        geom_histogram(binwidth=1) +
        xlim(0,20)
```

```
## Warning: Removed 1474 rows containing non-finite values (stat_bin).
```

```
## Warning: Removed 2 rows containing missing values (geom_bar).
```




```
### splitting the data into training and test sets
### since the number of ratings per user is fairly low
### and some variables have a high percentage of missing values,
### I choose a 50-50 initial split to make sure that the test set is large enough.
### In the final split, the percentage of users in the training set will be larger than 50
### (and less than 50 in the test set) since we are going to remove users who appear only in the test s
### from the test set and add them to the training set.

# creating index of 50%
suppressWarnings(set.seed(1, sample.kind="Rounding")) # setting the seed
test_index <- createDataPartition(y = dat$rating, times = 1, p = 0.5, list = FALSE) # defining a 50% sp
train <- dat[-test_index,]
temp <- dat[test_index,]

# making sure that the temporary split is 50-50
length(test_index)/nrow(dat)
```

```
## [1] 0.5000028
```

```
# creating a test set that includes only userids and bookids that are also in the training set
test <- temp %>%
  semi_join(train, by = "bookid") %>%
  semi_join(train, by = "userid")

# adding rows that were included in the index, but not in the test set, to the training set
removed <- anti_join(temp, test)
```

```
## Joining, by = c("userid", "bookid", "rating", "age", "country", "author", "year", "publisher", "user
```

```
train <- rbind(train, removed)

### making sure that the number of rows in the training and test sets is equal to
### the number of rows in the full dataset
nrow(dat)-(nrow(train)+nrow(test)) # this should be zero
```

```
## [1] 0
```

```
### checking the final relative sizes of the training and test sets
nrow(train)/nrow(dat) # the train set is ~70% of the full data
```

```
## [1] 0.7740471
```

```
nrow(test)/nrow(dat) # the test set is ~30% of the full data
```

```
## [1] 0.2259529
```

```
### saving the files
saveRDS(train, file="train")
saveRDS(test, file="test")

### cleaning the working space
rm(list=ls())

### cleaning memory
invisible(gc())

### reloading the training set
train<-readRDS("train")
```

3. Exploring the data

Now we explore the data. We also 'clean' it where it seems to make sense, by removing age values that are above 100.

```
#############################
### 3. Exploring the data ###
#############################

### we already examined the percentage of missing values in each column
### and the distribution of the number of users above, in the full data set,
### in order to determine the split between the training and test sets.
### from this point until the final validation, we will proceed with the train data only.
### let us examine some properties of the train data.

### examining the number of unique values in each column
dim(train)
```

```
## [1] 136247     10
```

```r
names(train)
```

```
##  [1] "userid"        "bookid"        "rating"        "age"
##  [5] "country"       "author"        "year"          "publisher"
##  [9] "userid_author" "age_bracket"
```

```r
### examining the number of unique users
n_distinct(train$userid)
```

```
## [1] 33095
```

```r
nrow(train)
```

```
## [1] 136247
```

```r
### examining the number of unique books
n_distinct(train$bookid)
```

```
## [1] 87817
```

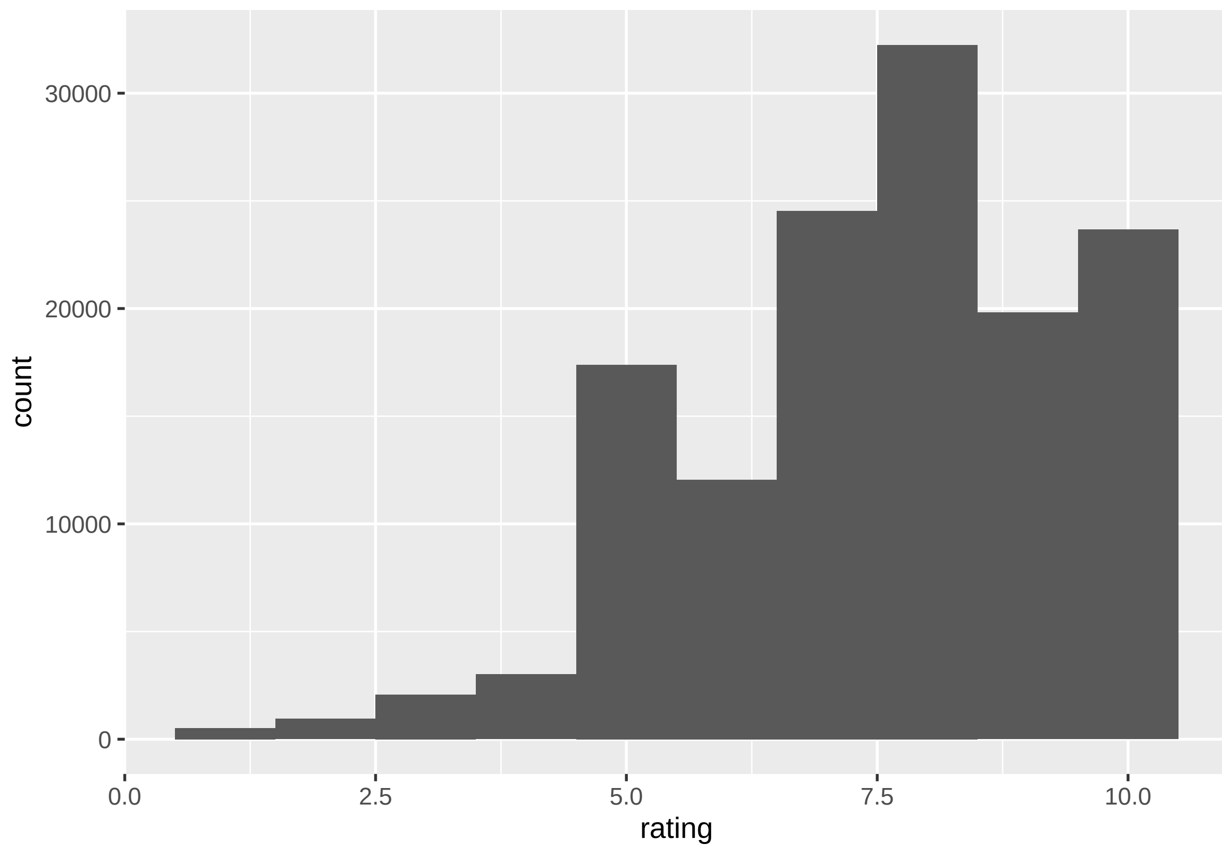
```r
nrow(train)
```

```
## [1] 136247
```

```r
### examining the distribution of ratings
table(train$rating)
```

```
##
##     1     2     3     4     5     6     7     8     9    10
##   517   943  2078  3008 17385 12058 24537 32246 19809 23666
```

```r
train %>% ggplot(aes(x=rating)) +
  geom_histogram(binwidth=1)
```




```r
### the distribution is skewed to the right.

### counting the countries
n_distinct(train$country)
```

```
## [1] 218
```

```r
### counting the authors
n_distinct(train$author)
```

```
## [1] 18472
```

```r
### counting the years
n_distinct(train$year)
```

```
## [1] 82
```

```r
### counting the publishers
n_distinct(train$publisher)
```

```
## [1] 4391
```

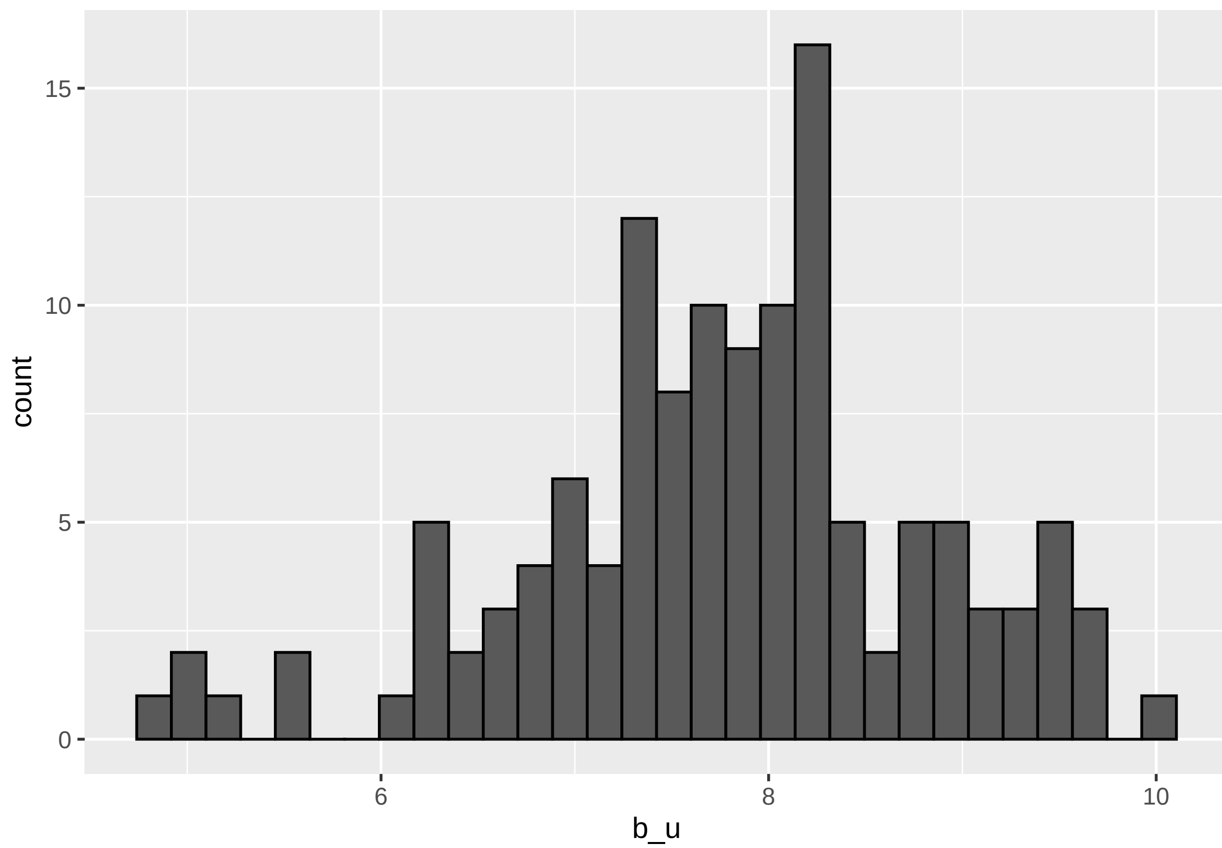
```r
### counting the usierid-author combinations
n_distinct(train$userid_author)
```

```
## [1] 50612
```

```r
### checking the average number of times each value appears in each column
### creating the function
avpu_func<-function(x){
  x<-x[!is.na(x)] # removing missing values
  n_unique_units<-n_distinct(x) # counting distinct values
  n_values<-length(x) # counting the overall number of values
  avpu<-round(n_values/n_unique_units,1) # calculating the number of times each distinct value appears
  avpu
}

### applying the function to each of the columns
apply(train, MARGIN = 2, avpu_func)
```

```
##        userid        bookid        rating           age       country
##           4.1           2.2       13624.7         491.7         339.4
##        author          year     publisher userid_author   age_bracket
##           3.0         678.2          12.5           1.1        5236.7
```

```r
### examining the distribution of the average rating per user
train %>%
  group_by(userid) %>%
  filter(n()>=100) %>%
  summarize(b_u = mean(rating)) %>%
  ggplot(aes(b_u)) +
  geom_histogram(bins = 30, color = "black")
```

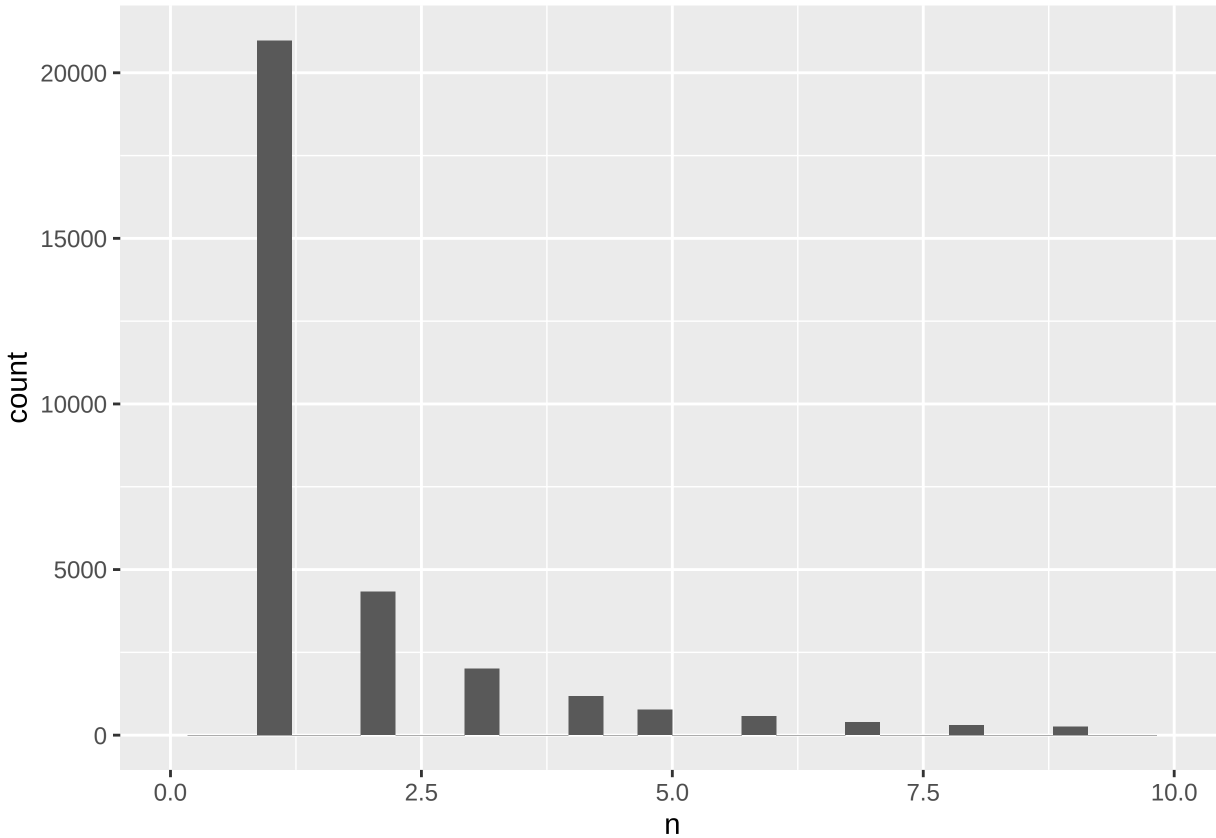



```
### examining the distribution of the number of ratings per user
ratings_per_user<-train %>%
  filter(!is.na(rating) & !is.na(userid)) %>%
  count(userid)

ratings_per_user %>% ggplot(aes(x=n)) +
  geom_histogram() +
  xlim(0,10)
```

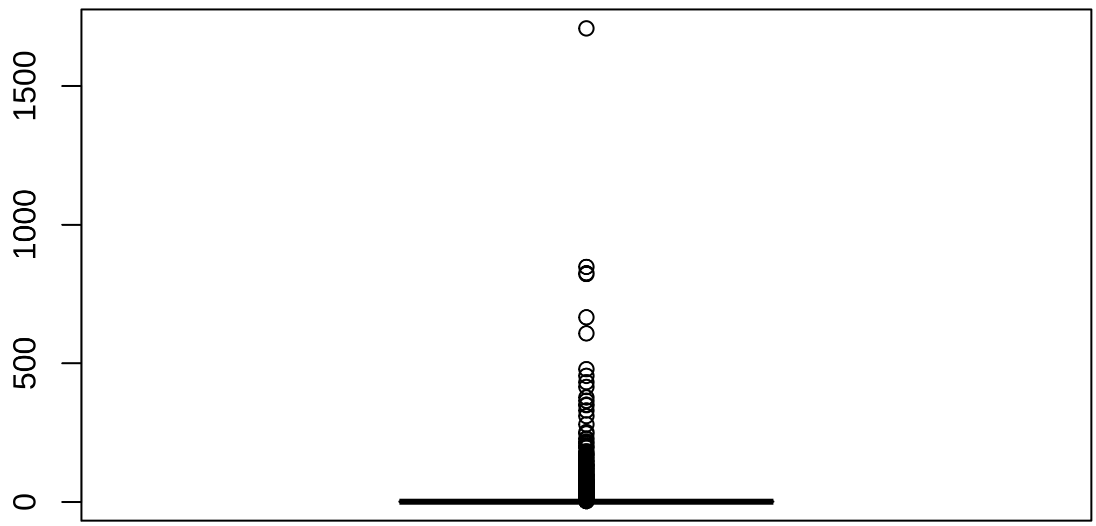
```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

```
## Warning: Removed 2078 rows containing non-finite values (stat_bin).
```

```
## Warning: Removed 2 rows containing missing values (geom_bar).
```




```
boxplot(ratings_per_user$n)
```

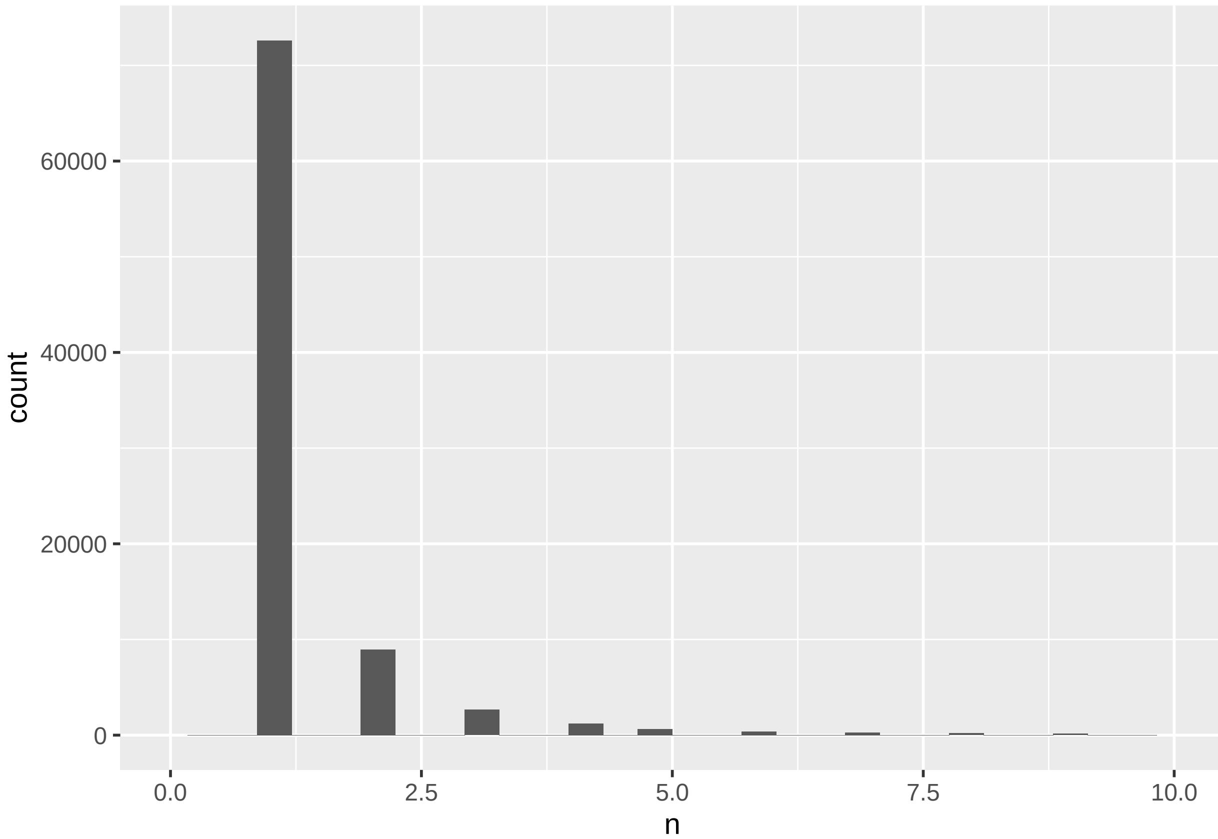



```r
### examining the distribution of the number of ratings per book
ratings_per_book<-train %>%
  filter(!is.na(rating) & !is.na(bookid)) %>%
  count(bookid)

ratings_per_book %>% ggplot(aes(x=n)) +
  geom_histogram() +
  xlim(0,10)
```

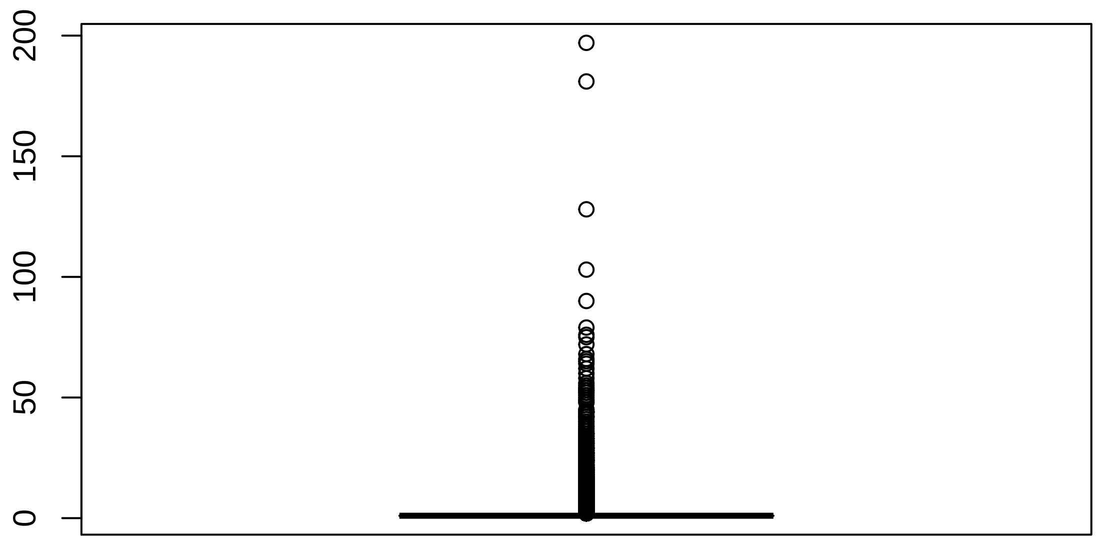
```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

```
## Warning: Removed 640 rows containing non-finite values (stat_bin).
```

```
## Warning: Removed 2 rows containing missing values (geom_bar).
```




```
boxplot(ratings_per_book$n)
```

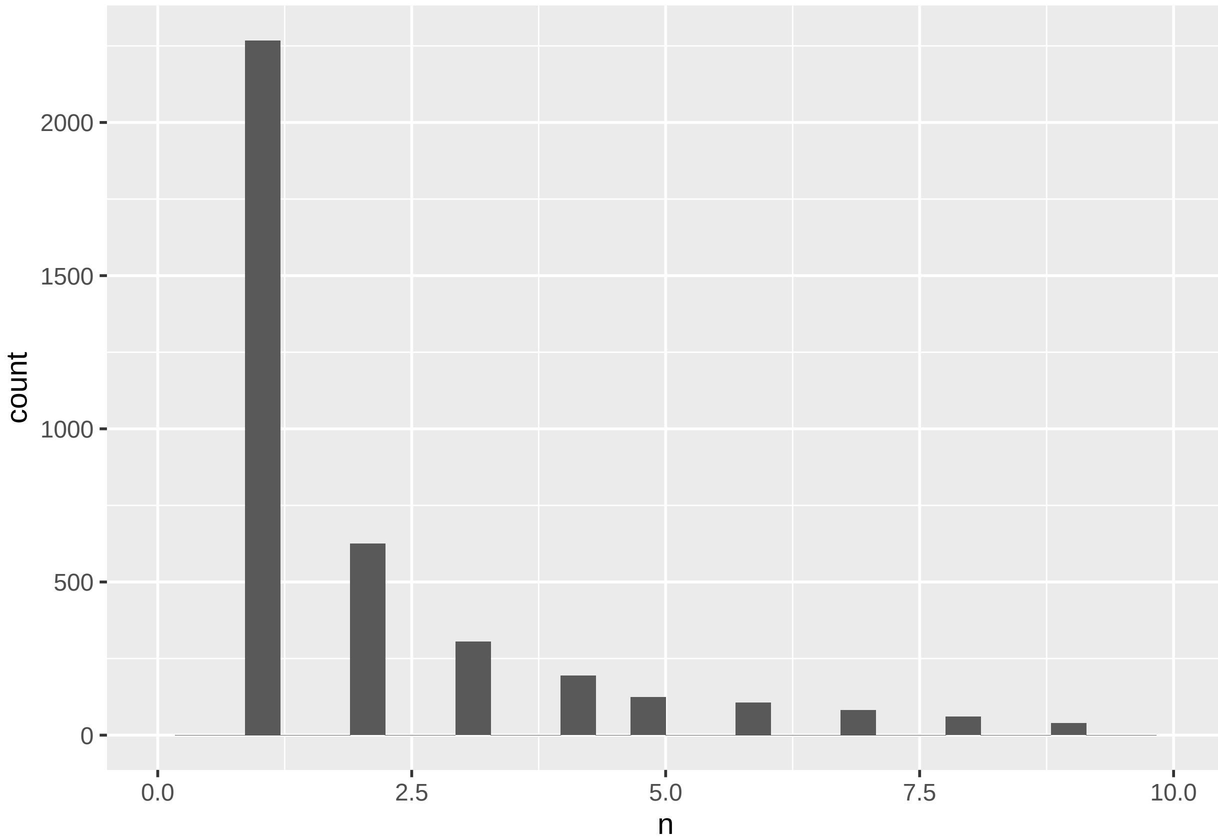



```
### examining the distribution of the number of ratings per publisher
ratings_per_publisher<-train %>%
  filter(!is.na(rating) & !is.na(publisher)) %>%
  count(publisher)

ratings_per_publisher %>% ggplot(aes(x=n)) +
  geom_histogram() +
  xlim(0,10)
```

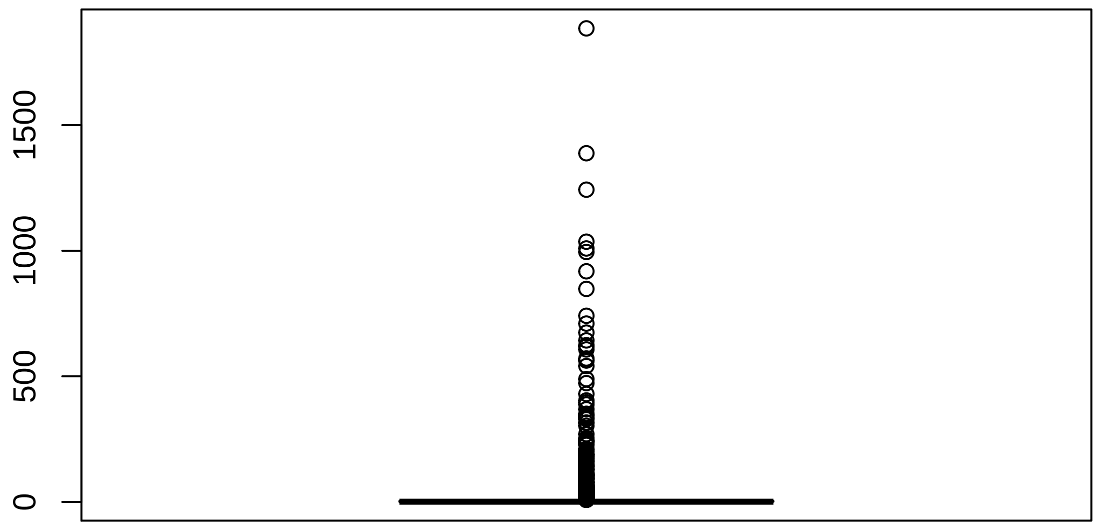
```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

```
## Warning: Removed 548 rows containing non-finite values (stat_bin).
```

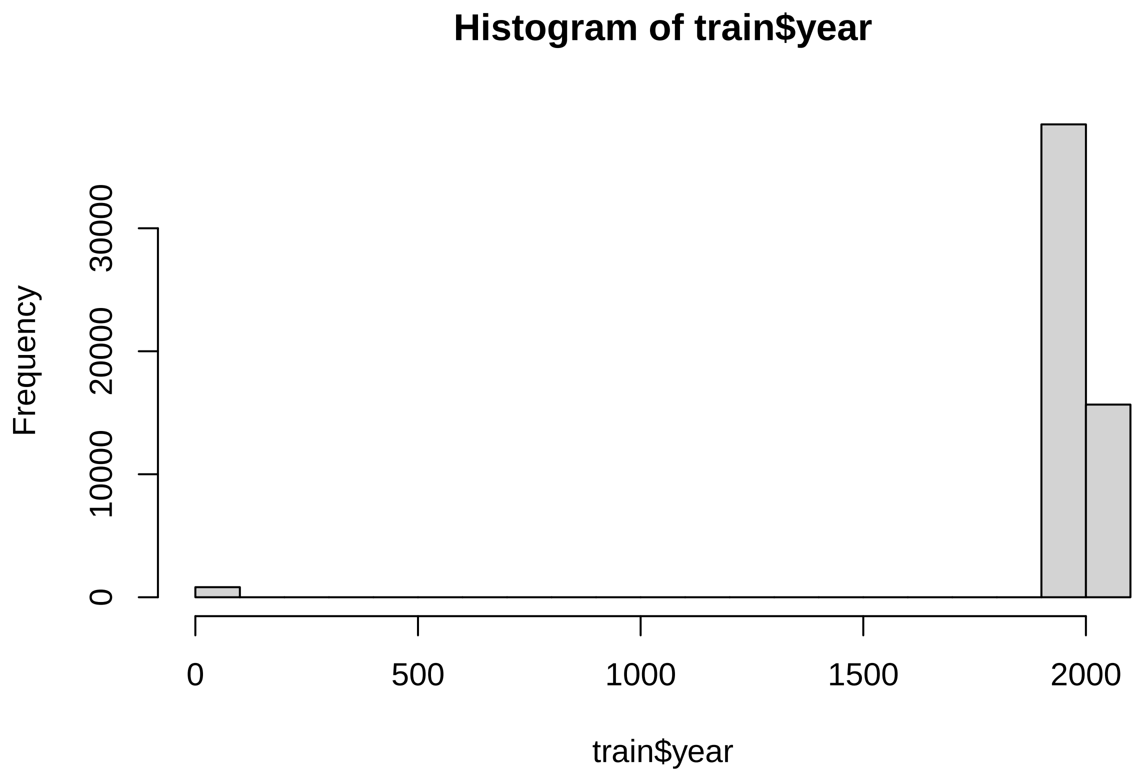
```
## Warning: Removed 2 rows containing missing values (geom_bar).
```




```
boxplot(ratings_per_publisher$n)
```

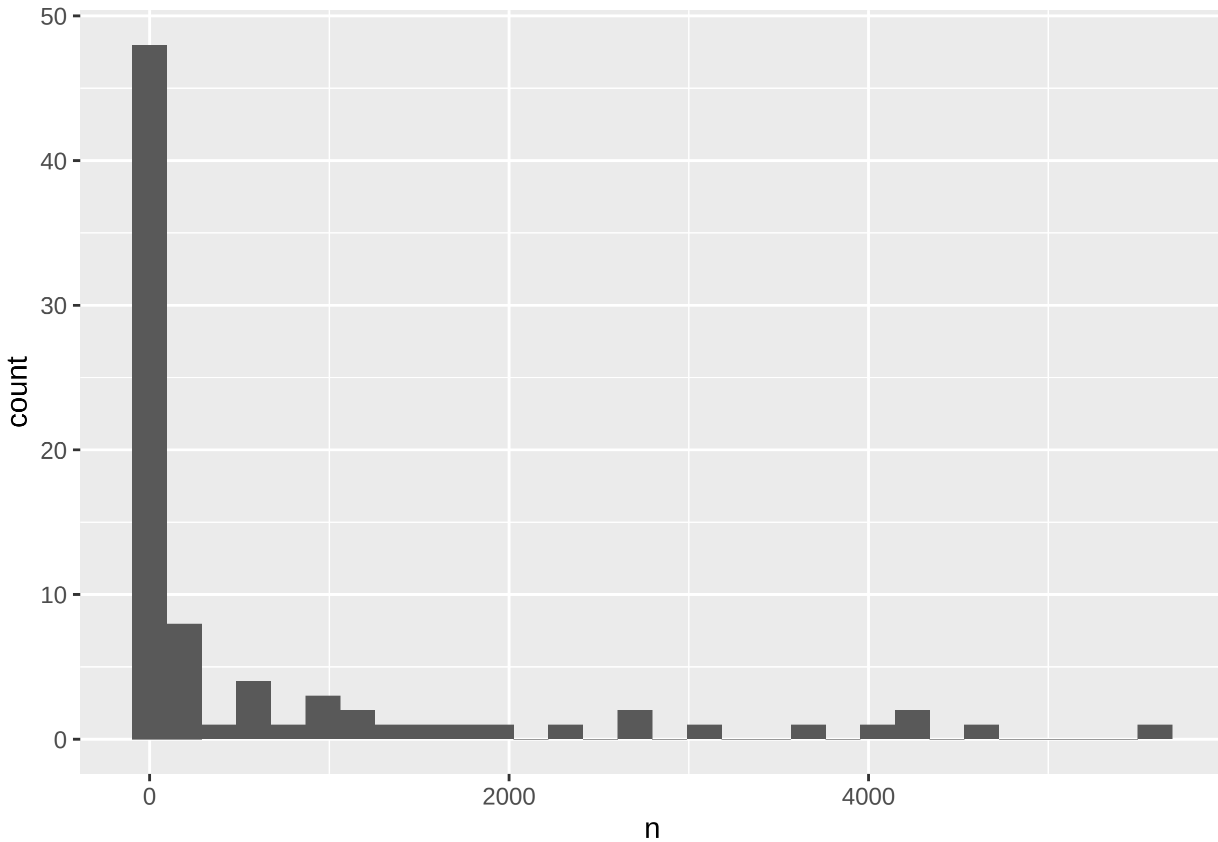



```r
### examining the distribution of the number of ratings per year
hist(train$year)
```

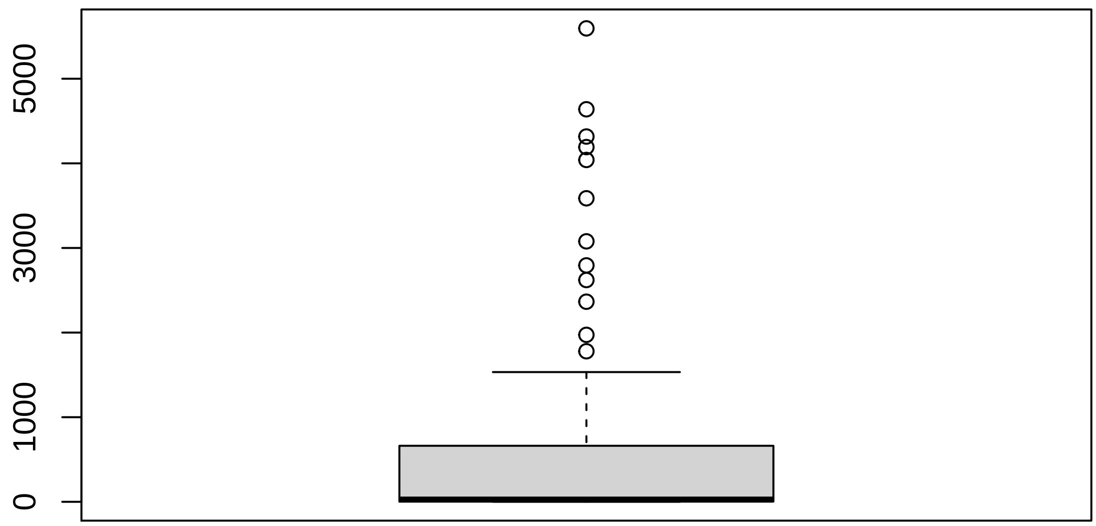



```
ratings_per_year<-train %>%
  filter(!is.na(rating) & !is.na(year)) %>%
  count(year)

ratings_per_year %>% ggplot(aes(x=n)) +
  geom_histogram()
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```




```
boxplot(ratings_per_year$n)
```

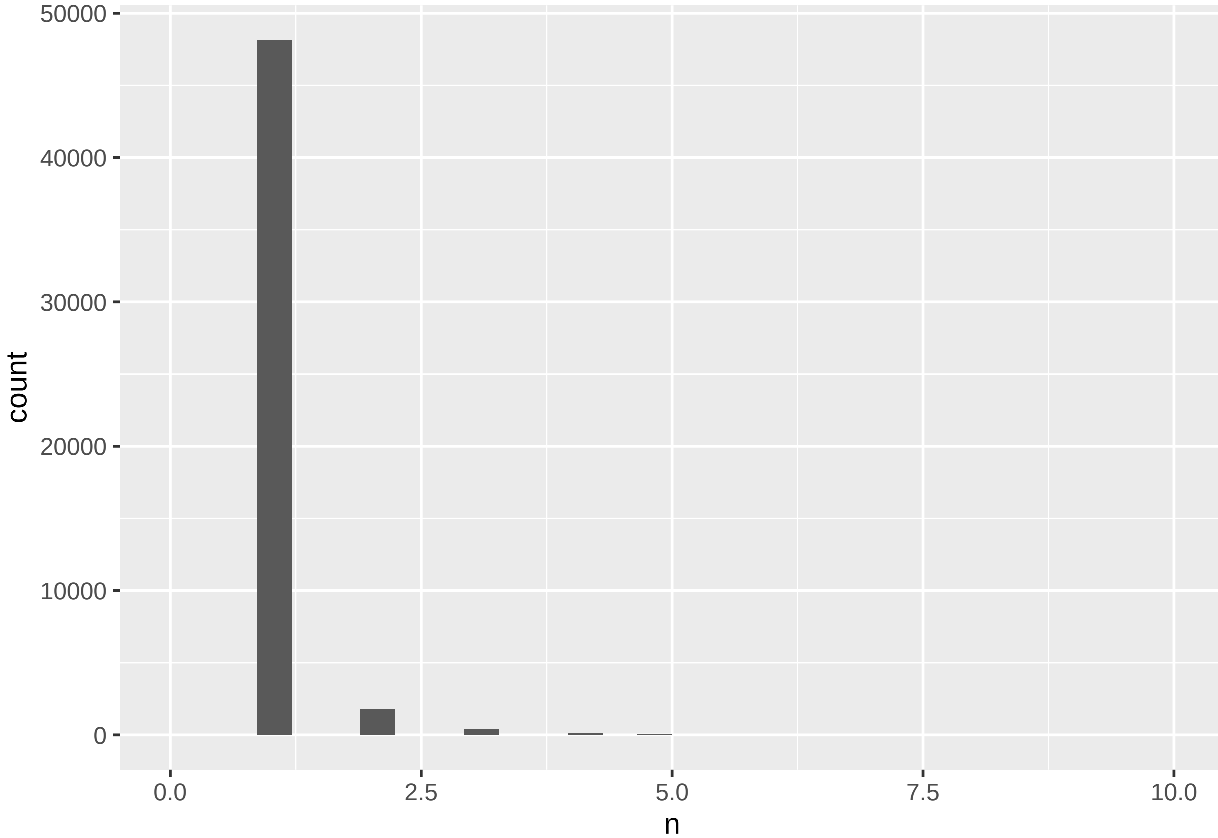



```
### examining the distribution of the number of ratings per user_author pair
ratings_per_userid_author<-train %>%
  filter(!is.na(rating) & !is.na(userid_author)) %>%
  count(userid_author)

ratings_per_userid_author %>% ggplot(aes(x=n)) +
  geom_histogram() +
  xlim(0,10)
```

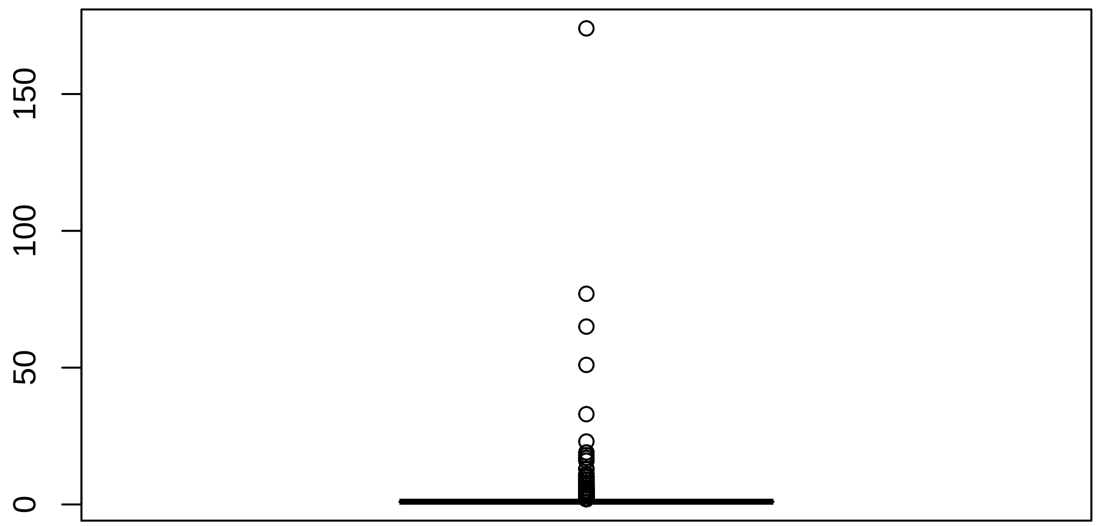
```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

```
## Warning: Removed 21 rows containing non-finite values (stat_bin).
```

```
## Warning: Removed 2 rows containing missing values (geom_bar).
```




```
boxplot(ratings_per_userid_author$n)
```




```r
### examining the distribution of age
age_without_nas<-train$age[!is.na(train$age) & train$age!="NULL"]
length(age_without_nas)
```

```
## [1] 52607
```

```r
length(train$age)
```

```
## [1] 136247
```

```r
n_distinct(age_without_nas)
```

```
## [1] 107
```

```r
n_distinct(train$age)
```

```
## [1] 108
```

```r
head(age_without_nas)
```

```
## [1] 16 16 25 25 25 19
```

```r
class(age_without_nas)
```

```
## [1] "numeric"
```

```r
length(age_without_nas)
```

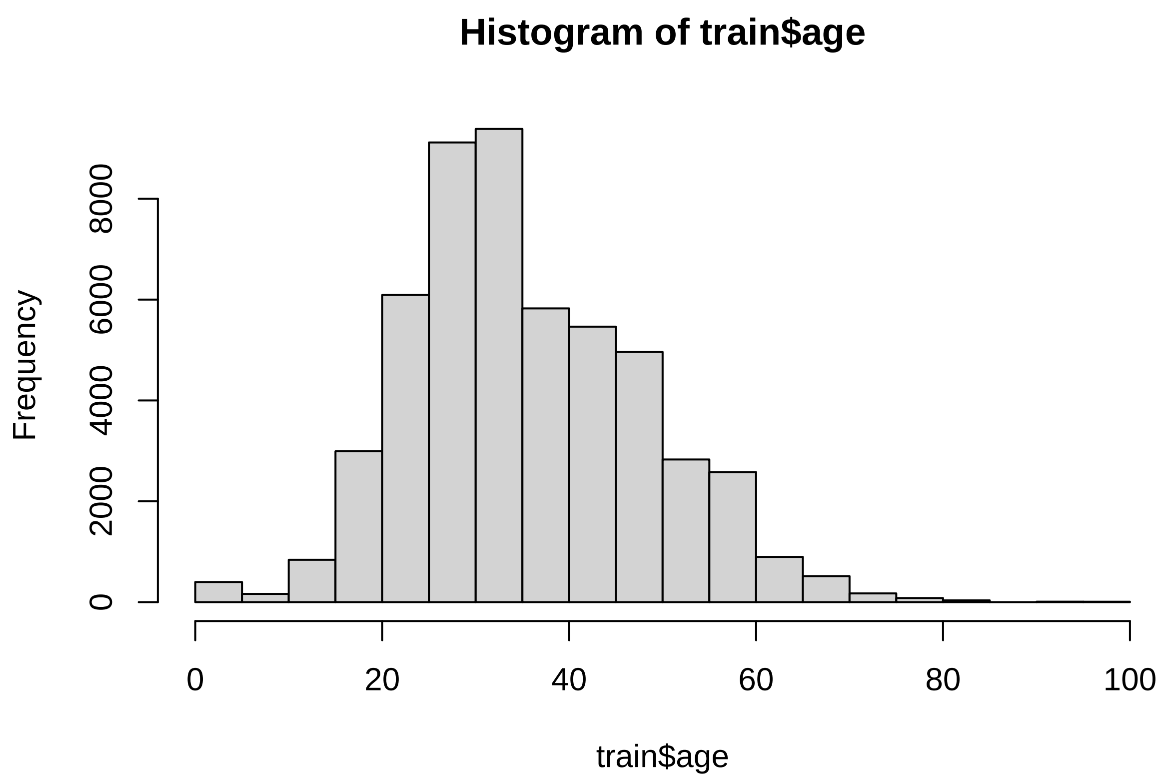
```
## [1] 52607
```

```r
hist(age_without_nas)
```


```r
sum(age_without_nas>100, na.rm=T)
```

```
## [1] 240
```

```r
### removing rows with age>100 since that is probably false
train$age[train$age>100]<-NA

### examining the age distribution
hist(train$age)
```

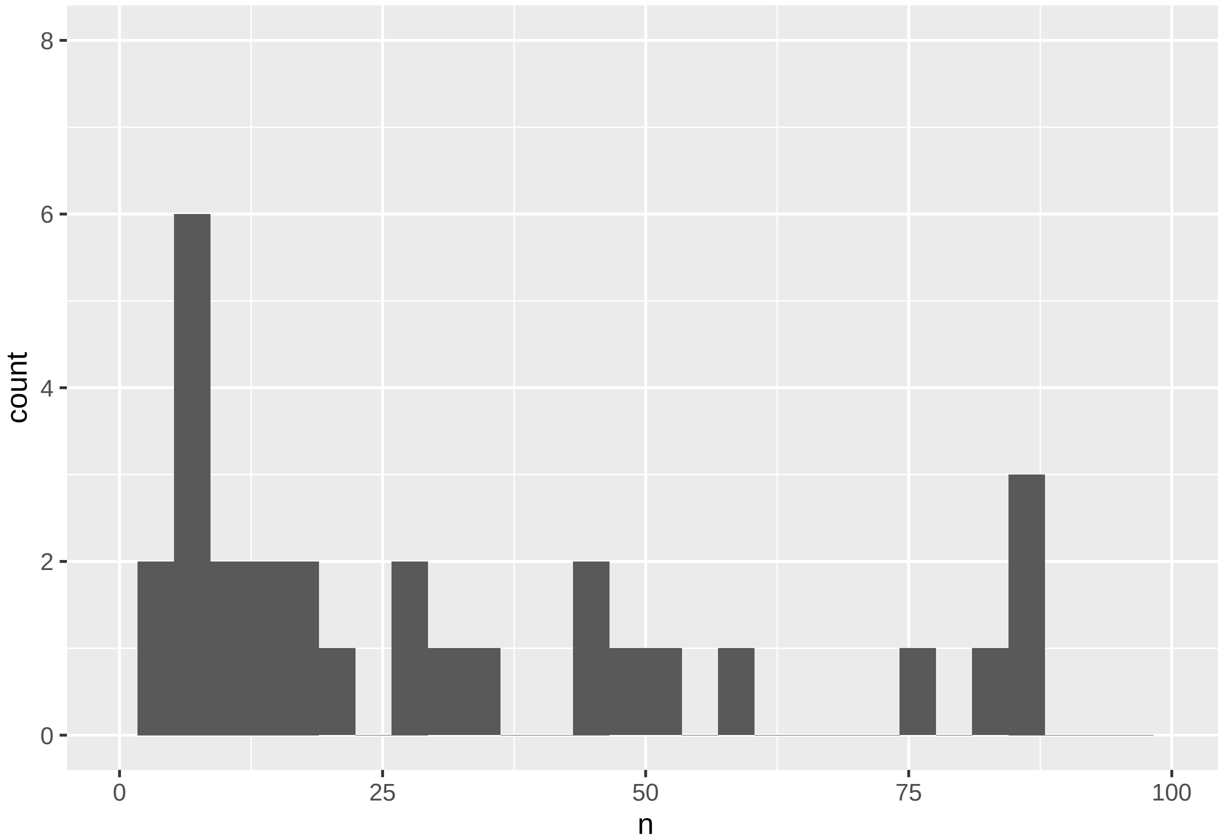



```
ratings_per_age<-train %>%
  filter(!is.na(rating) & !is.na(age) & train$age!="NULL") %>%
  count(age)

ratings_per_age %>% ggplot(aes(x=n)) +
  geom_histogram() +
  xlim(0,100)
```

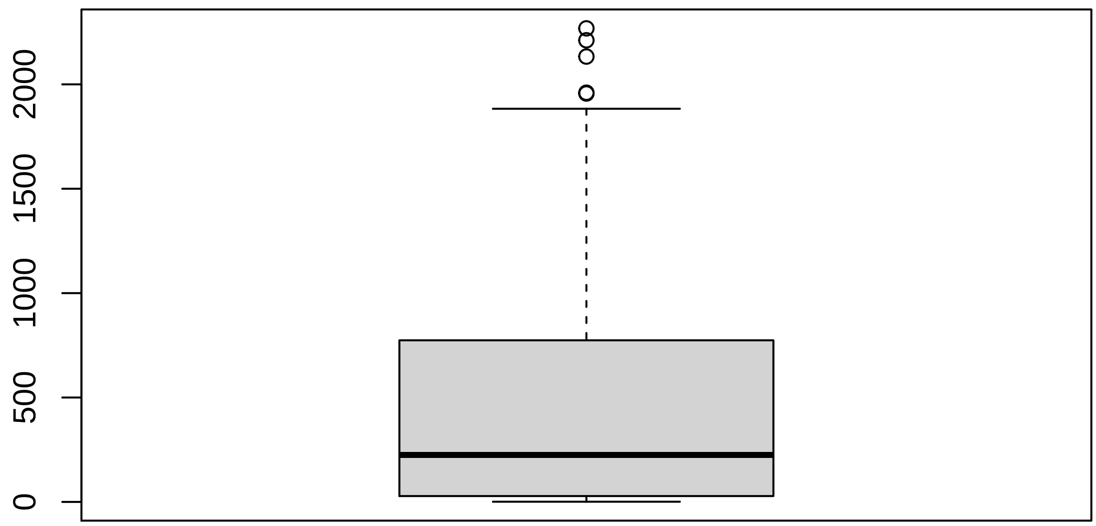
```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

```
## Warning: Removed 56 rows containing non-finite values (stat_bin).
```

```
## Warning: Removed 2 rows containing missing values (geom_bar).
```



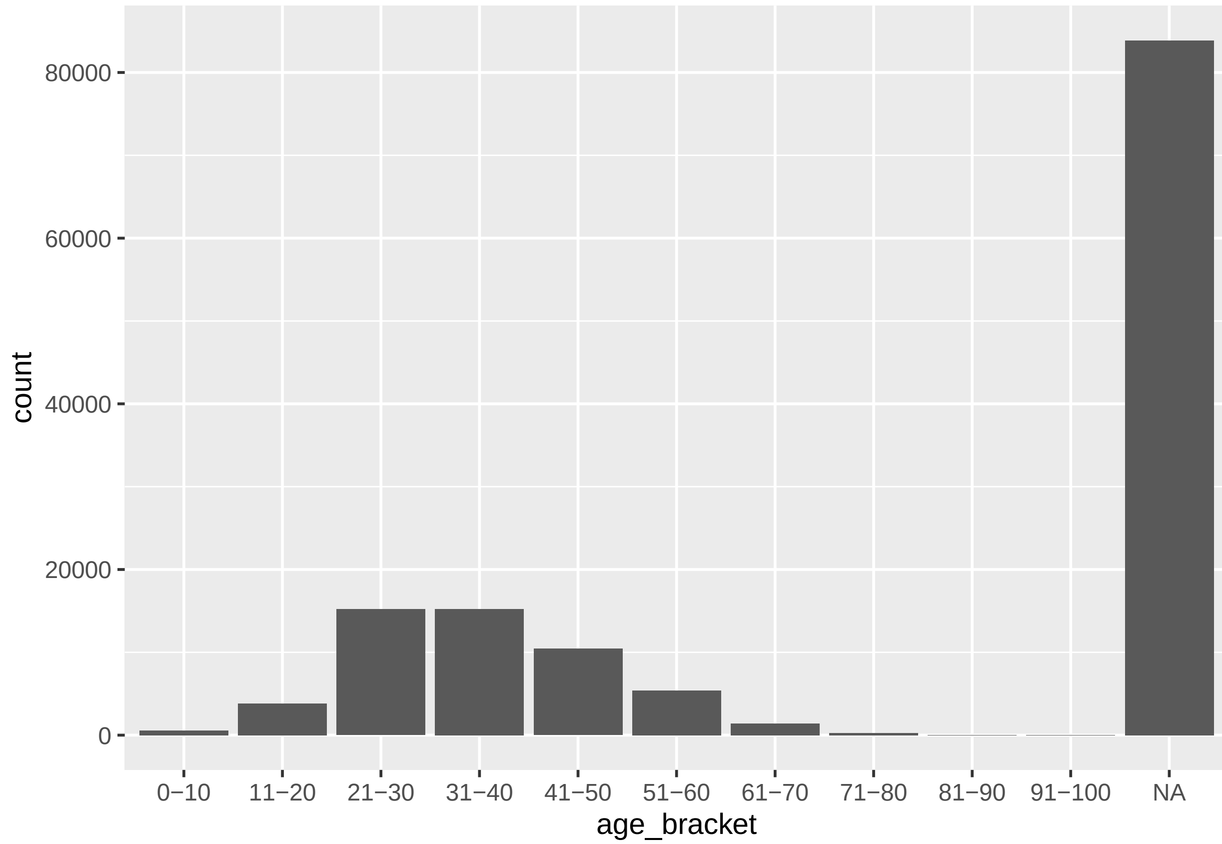

```
boxplot(ratings_per_age$n)
```




```r
### examining the distribution of the age brackets
table(train$age_bracket)
```

```
##
##   0-10  11-20  21-30  31-40  41-50  51-60  61-70  71-80  81-90 91-100
##    562   3832  15209  15211  10427   5407   1413    254     35     17
```

```r
train %>% ggplot(aes(x=age_bracket)) +
  geom_bar()
```




```r
### saving the train set
saveRDS(train, "train")

### cleaning the working space
rm(list=ls())

### cleaning memory
invisible(gc())

### reloading the train set
train<-readRDS("train")
```

4. Evaluating simple models

```r
#########################
### 4. A simple model ###
#########################

### To keep things simple, we will use the method of "Leave One Out Cross Validation" (LOOCV)

### creating a subset of the training set, for evaluating the model ###
### creating index of 20%
suppressWarnings(set.seed(1, sample.kind="Rounding")) # setting the seed
test_index <- createDataPartition(y = train$rating, times = 1, p = 0.2, list = FALSE) # defining a 50% 
```

```
core <- train[-test_index,]
temp <- train[test_index,]

# making sure that the temporary split is 80-20
length(test_index)/nrow(train)
```

```
## [1] 0.2000117
```

```
# creating a 'sub' set that includes only userids and bookids that are also in the training set
sub <- temp %>%
  semi_join(train, by = "bookid") %>%
  semi_join(train, by = "userid")

# adding rows that were included in the index, but not in the test set, to the training set
removed <- anti_join(temp, sub)
```

```
## Joining, by = c("userid", "bookid", "rating", "age", "country", "author", "year", "publisher", "user
```

```
core <- rbind(core, removed)

### making sure that the number of rows in the training and test sets is equal to
### the number of rows in the full dataset
nrow(train)-(nrow(core)+nrow(sub)) # this should be zero
```

```
## [1] 0
```

```
### checking the final relative sizes of the training and test sets
nrow(core)/nrow(train) # the core set is ~80% of the training data
```

```
## [1] 0.7999883
```

```
nrow(sub)/nrow(train) # the sub set is ~20% of the training data
```

```
## [1] 0.2000117
```

```
### The first model ###
# Predicting only according to the average rating in the core dataset ###
mu <- mean(core$rating)
mu
```

```
## [1] 7.519716
```

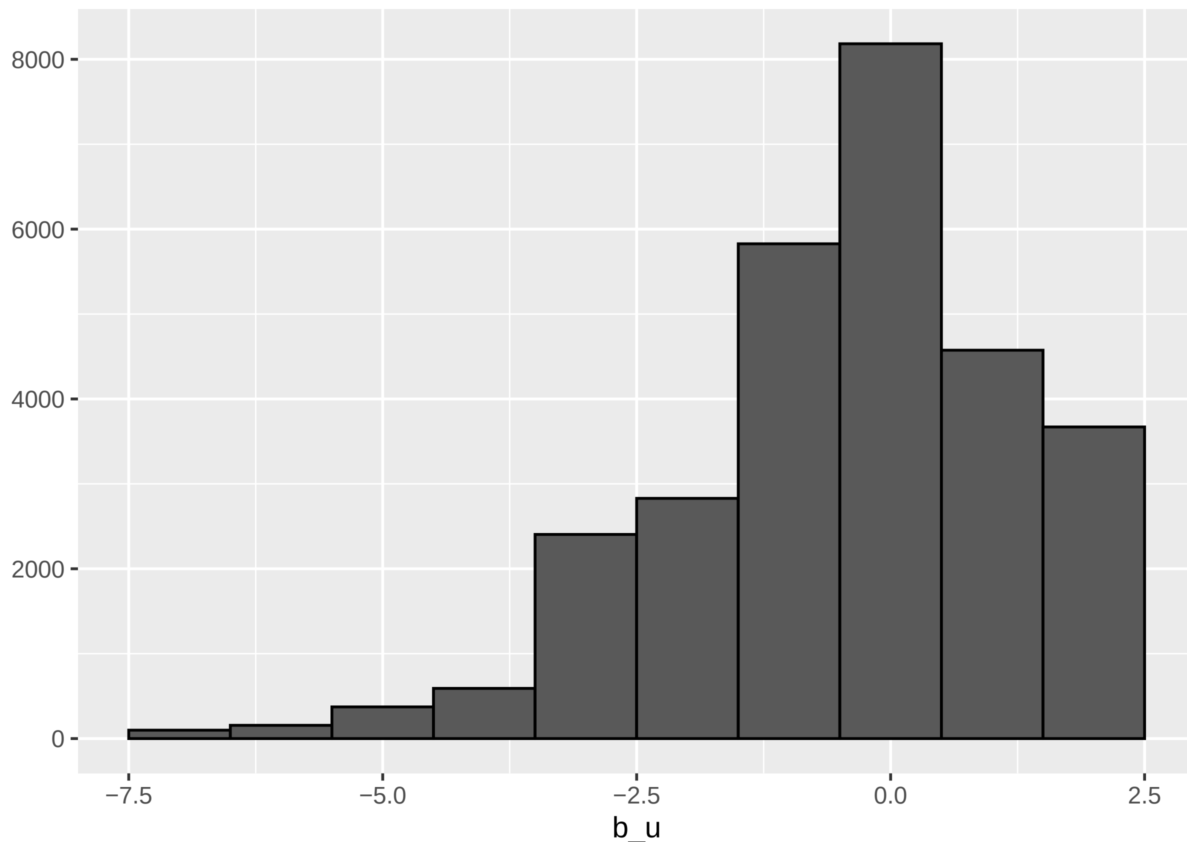
```
# checking the root mean squared error
core$mean<-mu
naive_rmse <- RMSE(core$rating, core$mean)
naive_rmse
```

```
## [1] 1.861179
```

```r
# creating a results table
rmse_results <- c("Just the average", round(naive_rmse,5))
names(rmse_results)<-c("method", "RMSE")
rmse_results
```

```
##             method               RMSE
## "Just the average"          "1.86118"
```

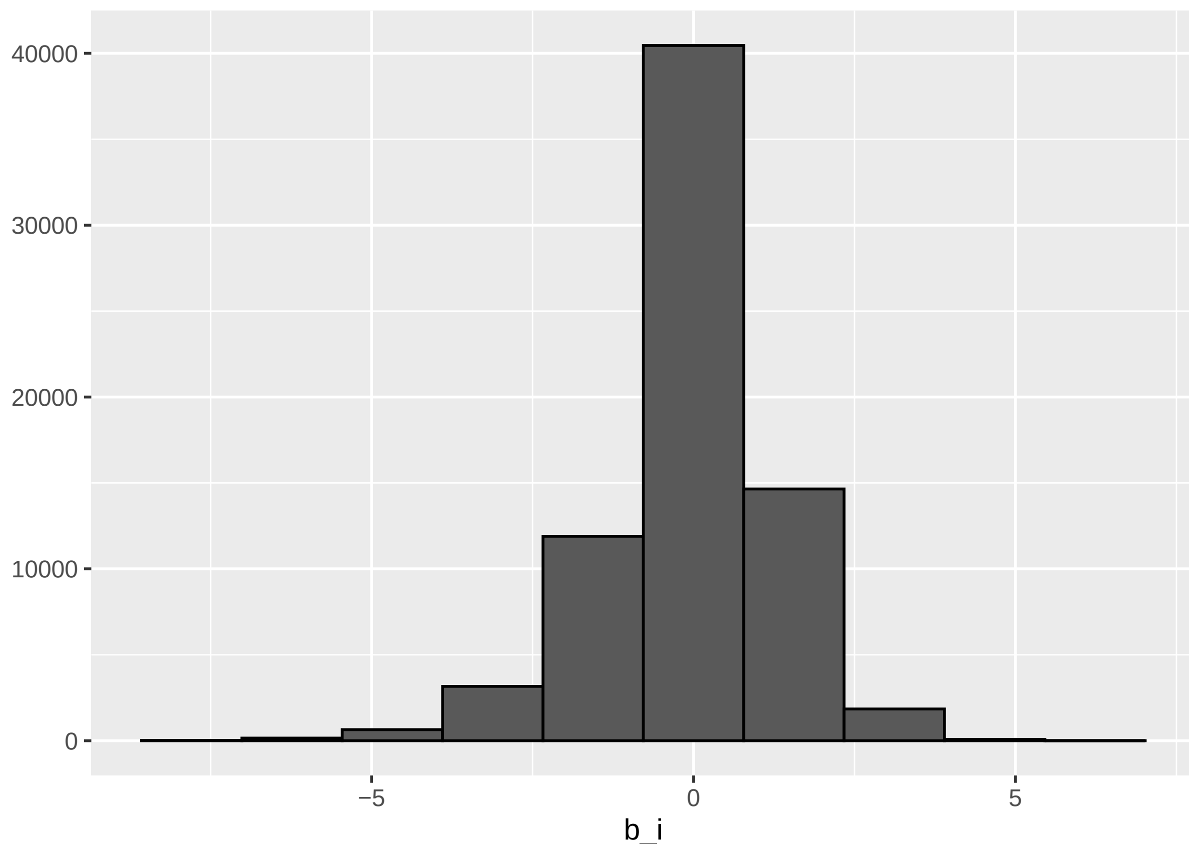
```r
### adding user effects ###
user_avgs <- core %>%
  group_by(userid) %>%
  summarize(b_u = mean(rating - mu))

# examining the distributions of user effects
qplot(b_u, data = user_avgs, bins = 10, color = I("black"))
```




```r
# checking the rmse
predicted_ratings <- mu + sub %>%
  left_join(user_avgs, by='userid') %>%
  pull(b_u)
user_effects_rmse<-RMSE(predicted_ratings, sub$rating, na.rm = T)

rmse_results <- rbind.data.frame(rmse_results, c("User effects", round(user_effects_rmse,5)))
names(rmse_results)<-c("method", "RMSE")
rmse_results
```

```
##             method    RMSE
## 1 Just the average 1.86118
## 2     User effects 1.69647
```

```
### examining book effects ###
# estimating the book effects, by computing
# the overall average and the user effect, and then
# the book effect is the average of the remainder, after they
# are substracted from the rating (book effect= average of (rating - overall average - user effect)
book_avgs <- core %>%
  left_join(user_avgs, by='userid') %>%
  group_by(bookid) %>%
  summarize(b_i = mean(rating - mu - b_u))

# examining the distributions of book effects
qplot(b_i, data = book_avgs, bins = 10, color = I("black"))
```

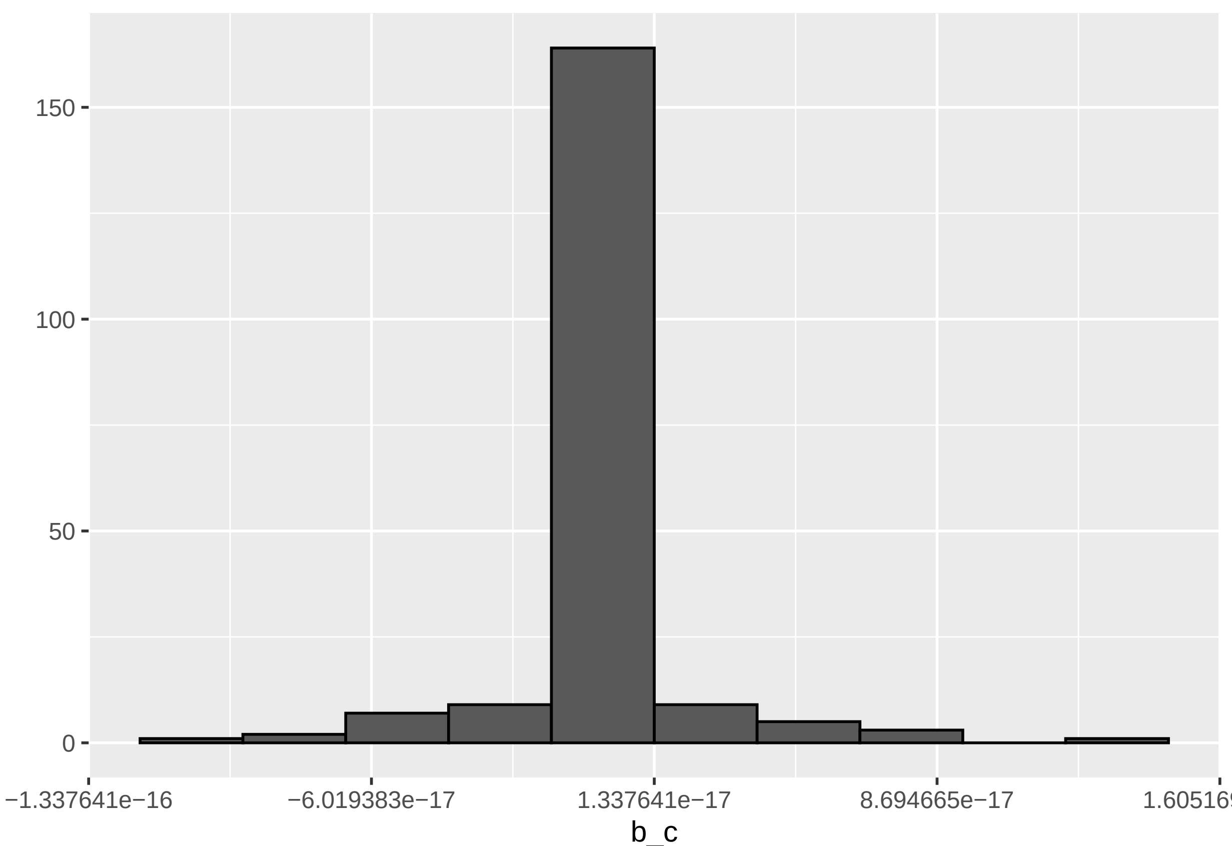



```
# checking the rmse
predicted_ratings <- sub %>%
  left_join(user_avgs, by='userid') %>%
  left_join(book_avgs, by='bookid') %>%
  mutate(pred = mu + b_u + b_i) %>%
  pull(pred)
user_and_book_effects_rmse<-RMSE(predicted_ratings, sub$rating, na.rm = T)
```

```
rmse_results <- rbind.data.frame(rmse_results, c("User and book effects", round(user_and_book_effects_rm
names(rmse_results)<-c("method", "RMSE")
rmse_results
```

```
##                  method    RMSE
## 1      Just the average 1.86118
## 2          User effects 1.69647
## 3 User and book effects 1.87867
```

```
### Adding book effects does not improve the RMSE
### Let us try to add other 'side information'

### adding country effects ###
country_avgs <- core %>%
  left_join(user_avgs, by='userid') %>%
  group_by(country) %>%
  summarize(b_c = mean(rating - mu - b_u))

# examining the distributions of country effects
qplot(b_c, data = country_avgs, bins = 10, color = I("black"))
```

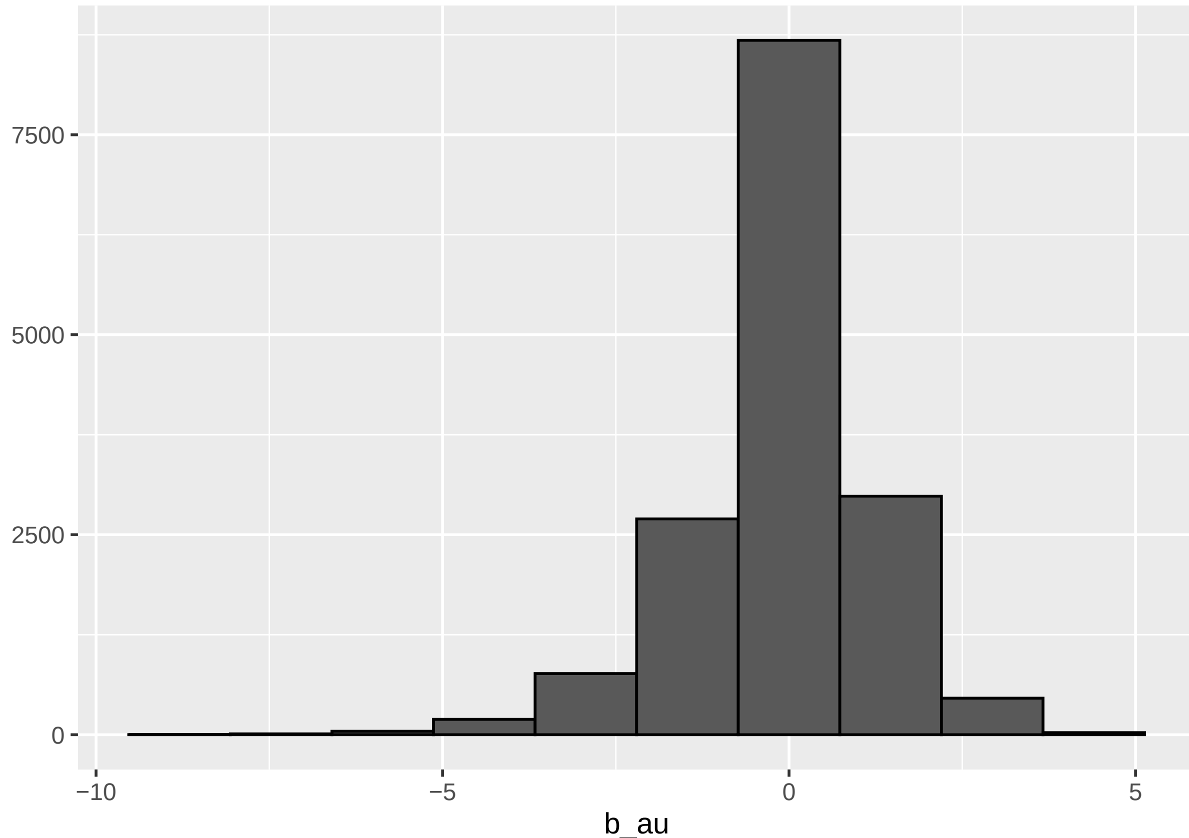



```
# checking the rmse
predicted_ratings <- sub %>%
  left_join(user_avgs, by='userid') %>%
```

```
  left_join(country_avgs, by='country') %>%
  mutate(pred = mu + b_u + b_c) %>%
  pull(pred)
user_and_country_effects_rmse<-RMSE(predicted_ratings, sub$rating, na.rm = T)

rmse_results <- rbind.data.frame(rmse_results, c("User and country effects", round(user_and_country_effe
names(rmse_results)<-c("method", "RMSE")
rmse_results
```

```
##                     method    RMSE
## 1         Just the average 1.86118
## 2             User effects 1.69647
## 3    User and book effects 1.87867
## 4 User and country effects 1.69647
```

```
### Adding country effects does not improve the RMSE
### Let us try to add other 'side information'

### adding author effects ###
author_avgs <- core %>%
  left_join(user_avgs, by='userid') %>%
  group_by(author) %>%
  summarize(b_au = mean(rating - mu - b_u))

# examining the distributions of author effects
qplot(b_au, data = author_avgs, bins = 10, color = I("black"))
```

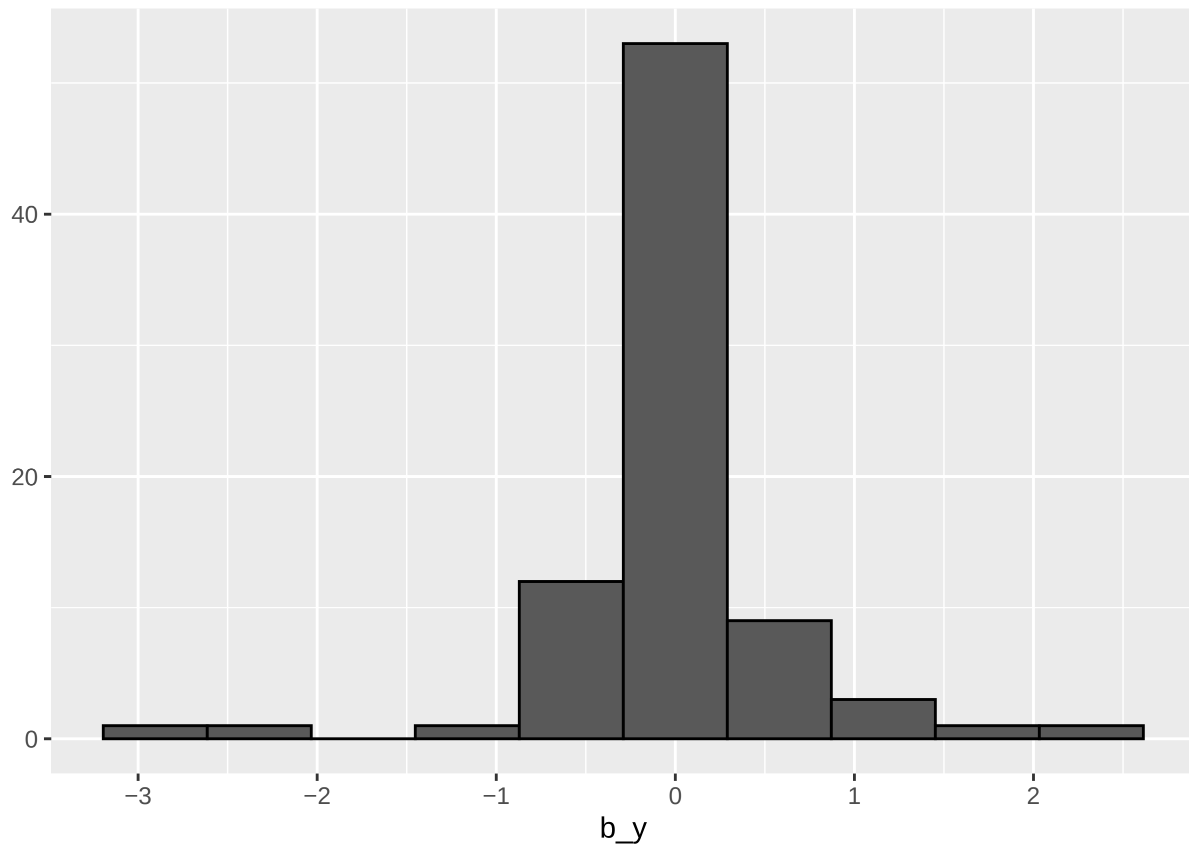



```
# checking the rmse
predicted_ratings <- sub %>%
  left_join(user_avgs, by='userid') %>%
  left_join(author_avgs, by='author') %>%
  mutate(pred = mu + b_u + b_au) %>%
  pull(pred)
user_and_author_effects_rmse<-RMSE(predicted_ratings, sub$rating, na.rm = T)

rmse_results <- rbind.data.frame(rmse_results, c("User and author effects", round(user_and_author_effec
names(rmse_results)<-c("method", "RMSE")
rmse_results
```

```
##                       method    RMSE
## 1          Just the average 1.86118
## 2              User effects 1.69647
## 3     User and book effects 1.87867
## 4 User and country effects 1.69647
## 5  User and author effects 1.71147
```

```
### Adding author effects does not improve the RMSE
### Let us try to add other 'side information'

### adding year effects ###
year_avgs <- core %>%
  left_join(user_avgs, by='userid') %>%
```

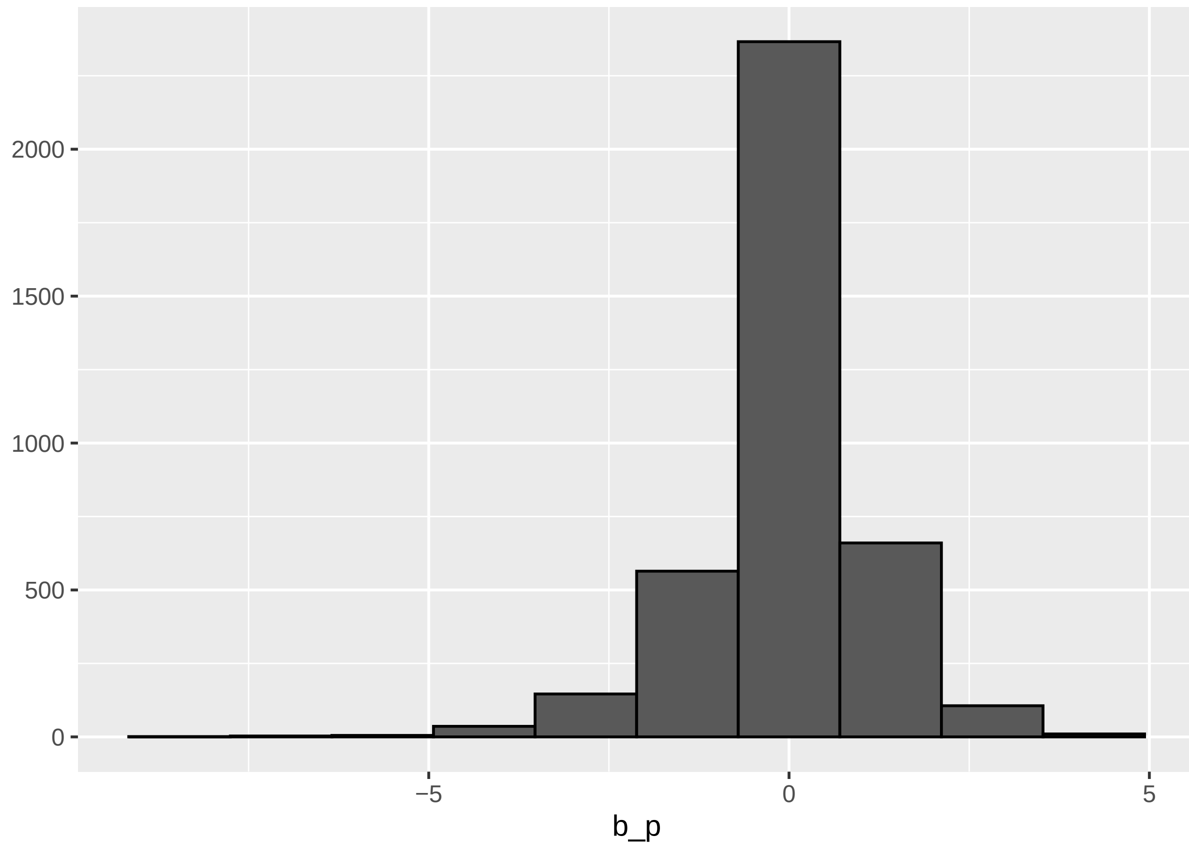
```
  group_by(year) %>%
  summarize(b_y = mean(rating - mu - b_u))

# examining the distributions of year effects
qplot(b_y, data = year_avgs, bins = 10, color = I("black"))
```




```
# checking the rmse
predicted_ratings <- sub %>%
  left_join(user_avgs, by='userid') %>%
  left_join(year_avgs, by='year') %>%
  mutate(pred = mu + b_u + b_y) %>%
  pull(pred)
user_and_year_effects_rmse<-RMSE(predicted_ratings, sub$rating, na.rm = T)

rmse_results <- rbind.data.frame(rmse_results, c("User and year effects", round(user_and_year_effects_rm
names(rmse_results)<-c("method", "RMSE")
rmse_results
```

```
##                     method    RMSE
## 1         Just the average 1.86118
## 2             User effects 1.69647
## 3    User and book effects 1.87867
## 4 User and country effects 1.69647
## 5  User and author effects 1.71147
## 6    User and year effects 1.69625
```

```r
### Adding year effects does not improve the RMSE
### Let us try to add other 'side information'

### adding publisher effects ###
publisher_avgs <- core %>%
  left_join(user_avgs, by='userid') %>%
  group_by(publisher) %>%
  summarize(b_p = mean(rating - mu - b_u))

# examining the distributions of publisher effects
qplot(b_p, data = publisher_avgs, bins = 10, color = I("black"))
```

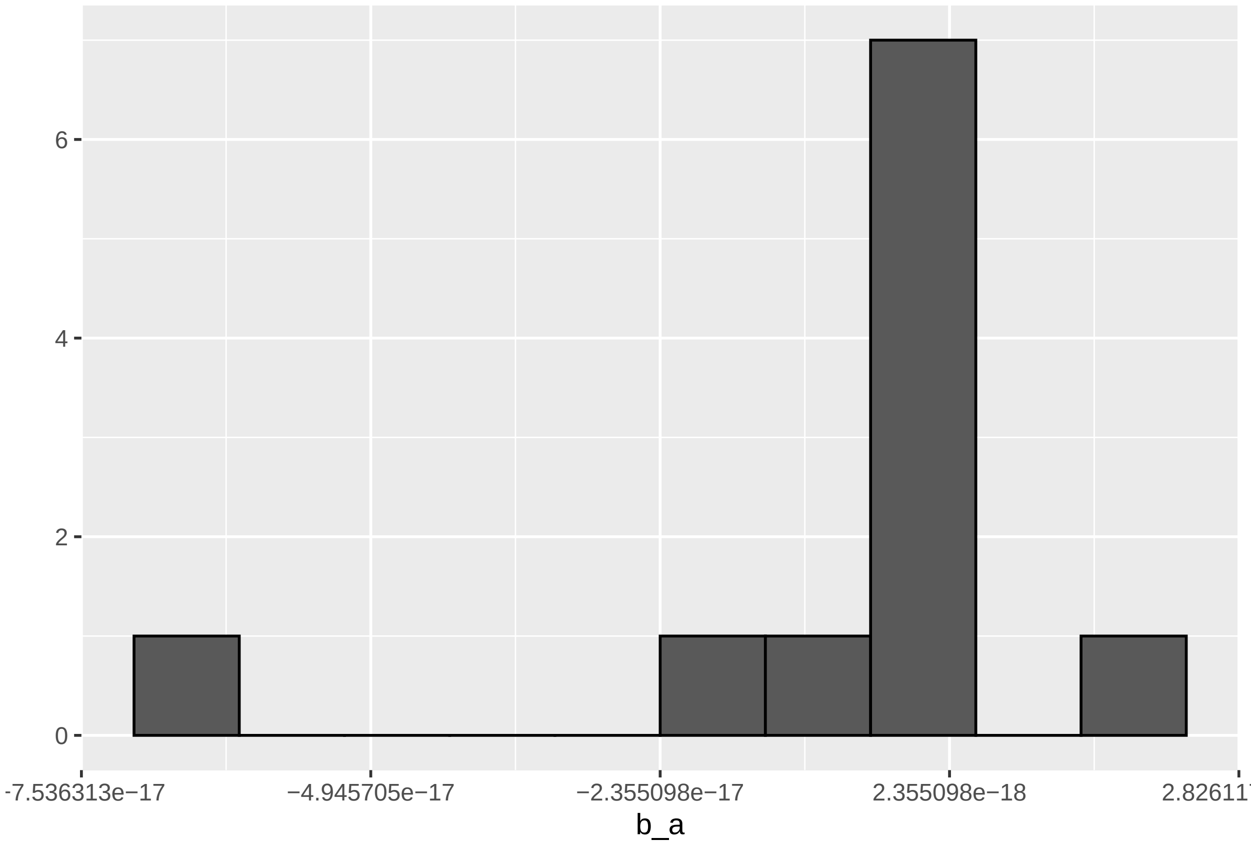



```r
# checking the rmse
predicted_ratings <- sub %>%
  left_join(user_avgs, by='userid') %>%
  left_join(publisher_avgs, by='publisher') %>%
  mutate(pred = mu + b_u + b_p) %>%
  pull(pred)
user_and_publisher_effects_rmse<-RMSE(predicted_ratings, sub$rating, na.rm = T)

rmse_results <- rbind.data.frame(rmse_results, c("User and publisher effects", round(user_and_publisher_
names(rmse_results)<-c("method", "RMSE")
rmse_results
```

```
##                          method     RMSE
```

```
## 1           Just the average 1.86118
## 2                User effects 1.69647
## 3       User and book effects 1.87867
## 4    User and country effects 1.69647
## 5     User and author effects 1.71147
## 6       User and year effects 1.69625
## 7 User and publisher effects 1.69914
```

```r
### Adding publisher effects does not improve the RMSE
### Let us try to add other 'side information'

### adding age bracket effects ###
age_bracket_avgs <- core %>%
  left_join(user_avgs, by='userid') %>%
  group_by(age_bracket) %>%
  summarize(b_a = mean(rating - mu - b_u))

# examining the distributions of age_bracket effects
qplot(b_a, data = age_bracket_avgs, bins = 10, color = I("black"))
```

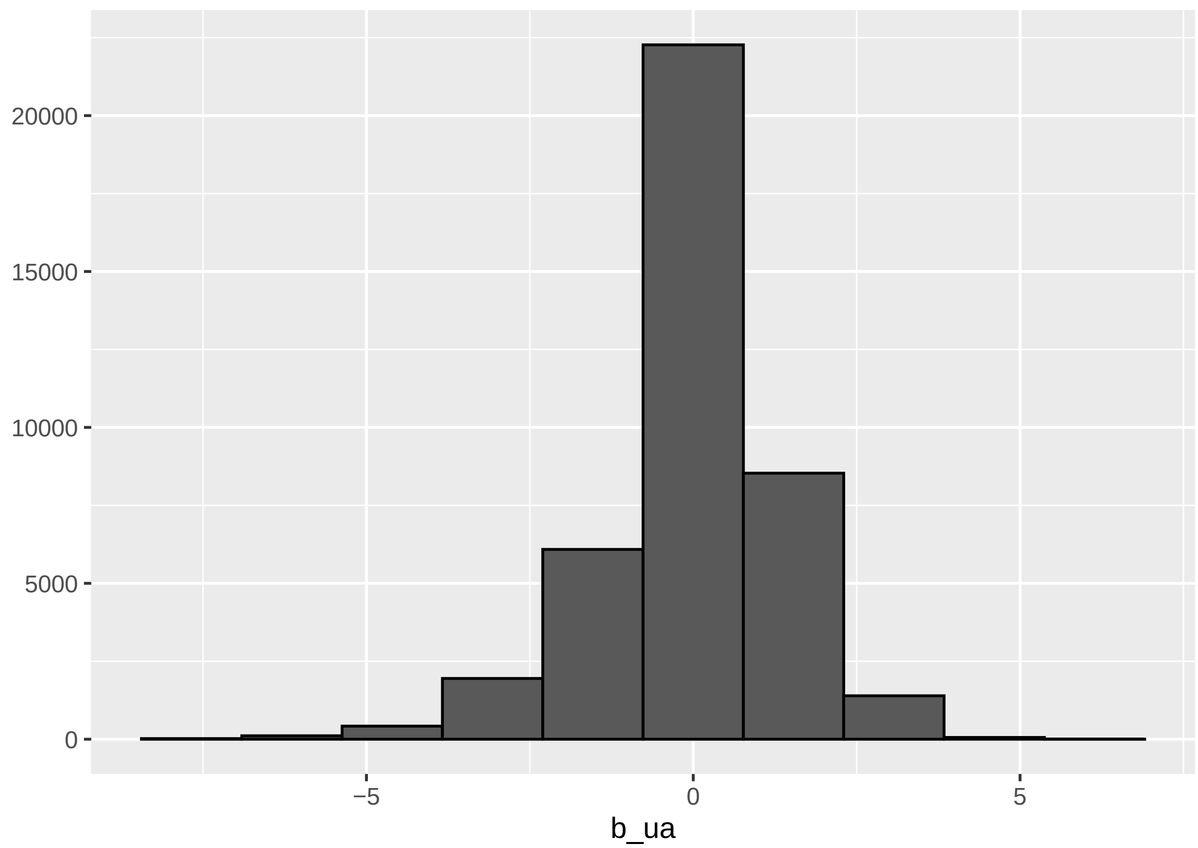



```r
# checking the rmse
predicted_ratings <- sub %>%
  left_join(user_avgs, by='userid') %>%
  left_join(age_bracket_avgs, by='age_bracket') %>%
  mutate(pred = mu + b_u + b_a) %>%
```

```r
  pull(pred)
user_and_age_bracket_effects_rmse<-RMSE(predicted_ratings, sub$rating, na.rm = T)

rmse_results <- rbind.data.frame(rmse_results, c("User and age_bracket effects", round(user_and_age_bra
names(rmse_results)<-c("method", "RMSE")
rmse_results
```

```
##                         method    RMSE
## 1             Just the average 1.86118
## 2                 User effects 1.69647
## 3        User and book effects 1.87867
## 4     User and country effects 1.69647
## 5      User and author effects 1.71147
## 6        User and year effects 1.69625
## 7   User and publisher effects 1.69914
## 8 User and age_bracket effects 1.69647
```

```r
### Adding country effects does not improve the RMSE.
### Let us try to add an interaction between users and authors.
### it seems reasonable that a users' rating of a book by a certain author
### would be rather similar to their rating of other books by the same author,
### and different than the mean rating of all books by a certain user

### adding userid_author effects ###
userid_author_avgs <- core %>%
  left_join(user_avgs, by='userid') %>%
  group_by(userid_author) %>%
  summarize(b_ua = mean(rating - mu - b_u))

# examining the distributions of userid_author effects
qplot(b_ua, data = userid_author_avgs, bins = 10, color = I("black"))
```

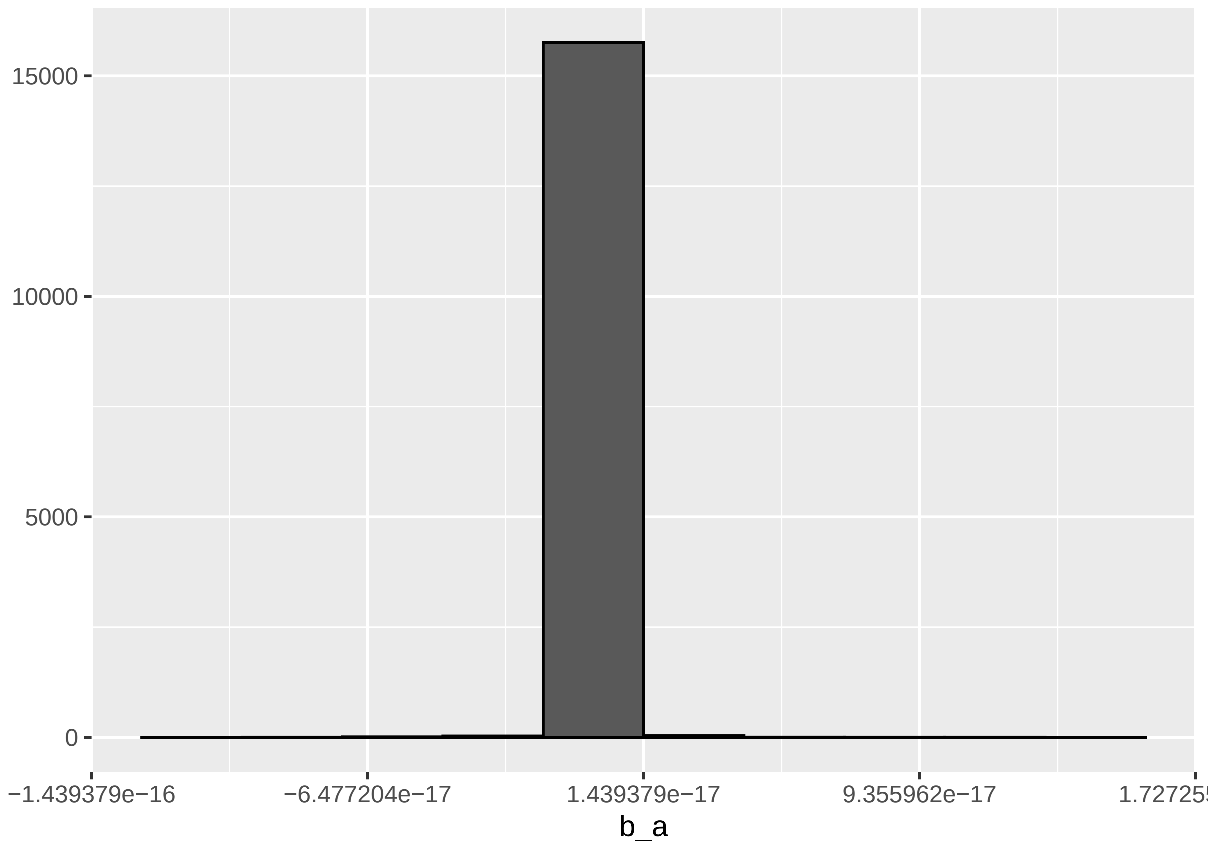



```
# checking the rmse
predicted_ratings <- sub %>%
  left_join(user_avgs, by='userid') %>%
  left_join(userid_author_avgs, by='userid_author') %>%
  mutate(pred = mu + b_u + b_ua) %>%
  pull(pred)
user_and_userid_author_effects_rmse<-RMSE(predicted_ratings, sub$rating, na.rm = T)

rmse_results <- rbind.data.frame(rmse_results, c("User and User*Author effects", round(user_and_userid_a
names(rmse_results)<-c("method", "RMSE")
rmse_results
```

```
##                          method    RMSE
## 1              Just the average 1.86118
## 2                  User effects 1.69647
## 3         User and book effects 1.87867
## 4      User and country effects 1.69647
## 5       User and author effects 1.71147
## 6         User and year effects 1.69625
## 7    User and publisher effects 1.69914
## 8 User and age_bracket effects 1.69647
## 9 User and User*Author effects 1.64854
```

```
### Adding country effects somewhat improves the RMSE.
### Now let us add author effects
```

```r
### Are there authors who receive higher ratings, or lower
### ratings, on average?

### adding author effects ###
author_avgs <- core %>%
  left_join(user_avgs, by='userid') %>%
  left_join(userid_author_avgs, by='userid_author') %>%
  group_by(author) %>%
  summarize(b_a = mean(rating - mu - b_u - b_ua))

# examining the distributions of userid_author effects
qplot(b_a, data = author_avgs, bins = 10, color = I("black"))
```




```r
# checking the rmse
predicted_ratings <- sub %>%
  left_join(user_avgs, by='userid') %>%
  left_join(userid_author_avgs, by='userid_author') %>%
  left_join(author_avgs, by='author') %>%
  mutate(pred = mu + b_u + b_ua +b_a) %>%
  pull(pred)
user_and_userid_author_and_author_effects_rmse<-RMSE(predicted_ratings, sub$rating, na.rm = T)

rmse_results <- rbind.data.frame(rmse_results, c("User and userid_author and author effects", round(use
names(rmse_results)<-c("method", "RMSE")
rmse_results
```

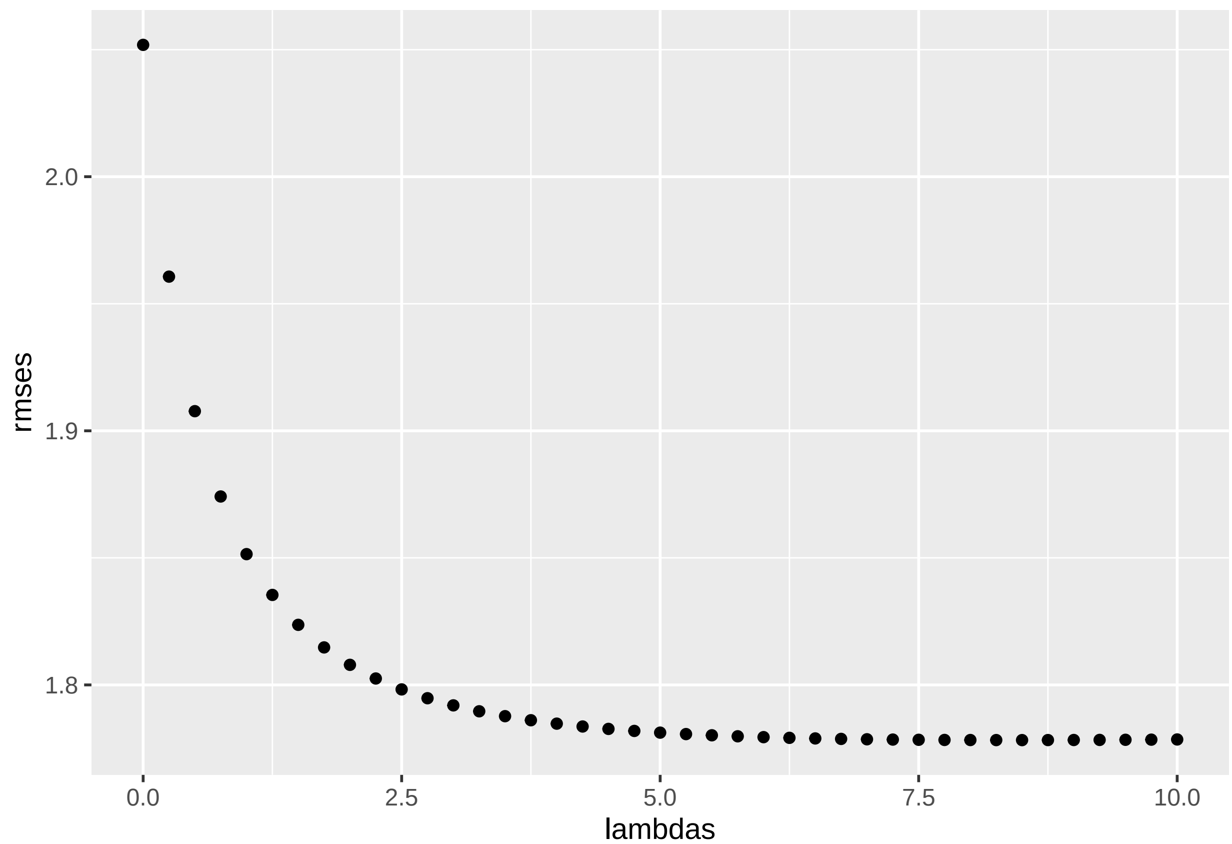
```
##                                      method    RMSE
## 1                          Just the average 1.86118
## 2                              User effects 1.69647
## 3                     User and book effects 1.87867
## 4                  User and country effects 1.69647
## 5                   User and author effects 1.71147
## 6                     User and year effects 1.69625
## 7                User and publisher effects 1.69914
## 8              User and age_bracket effects 1.69647
## 9              User and User*Author effects 1.64854
## 10 User and userid_author and author effects 1.64854
```

Adding country effects does not improve the RMSE. This could perhaps be explained by the fact that people choose which books to read. We may think of it this way: people implicitly 'predict' the rating they are going to give the book before they buy it, and their errors are centered around the average ratings that they give to books. To me that seems to be a plausible explanation

5. Adding regularization

Adding regularization, to account for the difference between average ratings provided by a few users and average ratings provided by many users. We will add regularization only to the model with the lowest RMSE so far, which is the one with user effects and interactive effects of users and authors.

```
################################
### 5. Adding regularization ###
################################

### We will use the model with user and userid_author effects,
### since it produced the lowest RMSE (and adding author effects did not make any difference)

### Choosing lambda
lambdas <- seq(0, 10, 0.25)

mu <- mean(core$rating)
just_the_sum <- core %>%
  group_by(bookid) %>%
  summarize(s = sum(rating - mu), n_i = n())

rmses <- sapply(lambdas, function(l){
  predicted_ratings <- sub %>%
    left_join(just_the_sum, by='bookid') %>%
    mutate(b_i = s/(n_i+l)) %>%
    mutate(pred = mu + b_i) %>%
    pull(pred)
  return(RMSE(predicted_ratings, sub$rating))
})
qplot(lambdas, rmses)
```




```r
lambdas[which.min(rmses)]
```

```
## [1] 8.5
```

```r
### Regularizing with lambda = 3
lambda <- 8.5
mu <- mean(core$rating)
mu
```

```
## [1] 7.519716
```

```r
### user effects are calculated in the same way as without regularization
user_avgs <- core %>%
  group_by(userid) %>%
  summarize(b_u = mean(rating - mu))

### userid_author effects are calculated differently
userid_author_avgs_reg <- core %>%
  left_join(user_avgs, by='userid') %>%
  group_by(userid_author) %>%
  summarize(b_ua = sum(rating - mu - b_u)/(n()+lambda), n_ua = n())

### Calculating RMSE ###
predicted_ratings <- sub %>%
  left_join(user_avgs, by='userid') %>%
```

```r
  left_join(userid_author_avgs_reg, by='userid_author') %>%
    mutate(pred = mu + b_u + b_ua) %>%
  pull(pred)
user_and_userid_author_effects_with_regularization_rmse<-RMSE(predicted_ratings, sub$rating, na.rm = T)

# checking the RMSE
rmse_results <- rbind.data.frame(rmse_results, c("User and User*Author effects with regularization", rou
names(rmse_results)<-c("method", "RMSE")
rmse_results
```

```
##                                              method    RMSE
## 1                                  Just the average 1.86118
## 2                                      User effects 1.69647
## 3                             User and book effects 1.87867
## 4                          User and country effects 1.69647
## 5                           User and author effects 1.71147
## 6                             User and year effects 1.69625
## 7                        User and publisher effects 1.69914
## 8                      User and age_bracket effects 1.69647
## 9                      User and User*Author effects 1.64854
## 10       User and userid_author and author effects 1.64854
## 11 User and User*Author effects with regularization  1.6516
```

```r
### saving files
saveRDS(core, "core")
saveRDS(sub, "sub")
saveRDS(train, "train")
saveRDS(rmse_results, "rmse_results")
```

Adding regularization did not improve the RMSE, perhaps since many books were only rated by a small number of people. ### 6. Evaluating other algorithms: Popular, SVD, SVDF Now let us evaluate more advanced prediction models, namely: 1. 'Popular' 2. Singular Value Decomposition (SVD) 3. Funk Singular Value Decomposition (SVDF) (I tried to evaluate both Item and User Based Collaborative Filtering as well, but it took too much time.)

```r
###########################
### 6. Other algorithms ###
###########################

### cleaning the working space
rm(list=ls())

### cleaning memory
invisible(gc())

### reloading the train set
train<-readRDS("train")
test<-readRDS("test")
rmse_results<-readRDS("rmse_results")

### Preparing the data ###
### removing books in the training set that do not appear in the test set
trainmat_final <- train %>%
```

```r
  semi_join(test, by = "bookid")

### exploring the datasets
dim(train)
```

```
## [1] 136247     10
```

```r
dim(trainmat_final)
```

```
## [1] 51498    10
```

```r
### saving
saveRDS(trainmat_final, file="trainmat_final")

### converting the training set into a matrix
users_and_ratings_train_set<-cbind.data.frame(trainmat_final$userid, trainmat_final$bookid, trainmat_fi
names(users_and_ratings_train_set)<-c("userid", "bookid", "rating")

### exploring
dim(users_and_ratings_train_set)
```

```
## [1] 51498     3
```

```r
head(users_and_ratings_train_set)
```

```
##   userid    bookid rating
## 1 276729        NA      3
## 2 276744        NA      7
## 3 276747 679776818      8
## 4 276754 684867621      8
## 5 276755 451166892      5
## 6 276762 380711524      5
```

```r
### counting missing values
n_missing<-sum(is.na(users_and_ratings_train_set))

### removing rows with missing bookids
### (that is the only column that contains missing values)
index<-which(is.na(users_and_ratings_train_set$bookid))
head(index)
```

```
## [1]  1  2  9 15 18 32
```

```r
length(index)
```

```
## [1] 8359
```

```r
users_and_ratings_train_set<-users_and_ratings_train_set[-index,]

### making sure that it worked
dim(users_and_ratings_train_set)
```

```
## [1] 43139     3
```

```r
### making sure that there are no missing values left
sum(is.na(users_and_ratings_train_set)) # this should be zero
```

```
## [1] 0
```

```r
### converting the matrix into a "realRatingMatrix")
trainmat_final <- as(users_and_ratings_train_set, "realRatingMatrix")
dim(trainmat_final)
```

```
## [1] 17652 13443
```

```r
### saving
saveRDS(trainmat_final, file="trainmat_final")

### creating a regular matrix
trainmat_final_reg<-as(trainmat_final, "matrix")

### saving
saveRDS(trainmat_final_reg, file="trainmat_final_reg")

### exploring the matrix
class(trainmat_final_reg)
```

```
## [1] "matrix" "array"
```

```r
n_missing<-sum(is.na(trainmat_final_reg)) # counting missing values
n_missing
```

```
## [1] 237252697
```

```r
n_non_missing<-sum(!is.na(trainmat_final_reg)) # counting non-missing values
n_non_missing
```

```
## [1] 43139
```

```r
all<-nrow(trainmat_final_reg)*ncol(trainmat_final_reg) # counting all values
all
```

```
## [1] 237295836
```

```r
p_missing<-n_missing/all # calculating the percentage of missing values
p_missing
```

```
## [1] 0.9998182
```

```r
p_non_missing<-1-p_missing
p_non_missing
```

```
## [1] 0.0001817942
```

```r
rm(trainmat_final_reg, n_missing, all) # removing the matrix and other unnecessary objects

### Increasing memory size
memory.limit(size = 10^10)
```

```
## [1] 1e+10
```

```r
### cleaning memory
invisible(gc())

### checking number of ratings per item
number_of_ratings<-colCounts(trainmat_final)
min(number_of_ratings)
```

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

```r
max(number_of_ratings)
```

```
## [1] 197
```

```r
### exploring a sample of the matrix
trainmat_final@data[1500:1510, 2001:2009]
```

```
## 11 x 9 sparse Matrix of class "dgCMatrix"
##        312966091 312966210 312966393 312966555 312966806 312966970 312967004
## 166778         .         .         .         .         .         .         .
## 166793         .         .         .         .         .         .         .
## 166795         .         .         .         .         .         .         .
## 166799         .         .         .         .         .         .         .
## 166809         .         .         .         .         .         .         .
## 166812         .         .         .         .         .         .         .
## 166813         .         .         .         .         .         .         .
## 166815         .         .         .         .         .         .         .
## 166824         .         .         .         .         .         .         .
## 166825         .         .         .         .         .         .         .
## 166828         .         .         .         .         .         .         .
##        312968191 312968302
## 166778         .         .
## 166793         .         .
```

```
## 166795         .         .
## 166799         .         .
## 166809         .         .
## 166812         .         .
## 166813         .         .
## 166815         .         .
## 166824         .         .
## 166825         .         .
## 166828         .         .
```

```r
### normalizing the values
normalize(trainmat_final, method = "Z-score")
```

```
## 17652 x 13443 rating matrix of class 'realRatingMatrix' with 43139 ratings.
## Normalized using z-score on rows.
```

```r
### saving
saveRDS(trainmat_final, file="trainmat_final")

### Setting up the evaluation scheme.
### We will use cross-validation

### calculating the mean of all ratings again, in order to determine
### the value of a "good" rating for the evaluation function
train<-readRDS("train")
mean(train$rating)
```

```
## [1] 7.520239
```

```r
rm(train) # removing the dataset from the workspace to save memory

Sys.time() # recording the time in order to see how long each step takes
```

```
## [1] "2022-01-14 22:25:15 CET"
```

```r
scheme <- trainmat_final %>%
  evaluationScheme(method = "cross-validation",
                   k=2, # 2-fold cross validation
                   given  = 1,
                   goodRating = 8
  )

Sys.time() # recording the time in order to see how long each step takes
```

```
## [1] "2022-01-14 22:25:18 CET"
```

```r
### saving
saveRDS(scheme, file="scheme")

Sys.time()
```

```
## [1] "2022-01-14 22:25:18 CET"
```

```r
#################### Evaluating the models ################################

### cleaning the working space
rm(list=ls())

### cleaning memory
invisible(gc())

### loading the scheme and the rmse_results
scheme<-readRDS("scheme")
rmse_results<-readRDS("rmse_results")

### Popular ###
### evaluating the "Popular" model
Sys.time() # recording the time in order to see how long each step takes
```

```
## [1] "2022-01-14 22:25:19 CET"
```

```r
result_rating_popular <- evaluate(scheme,
                                  method = "popular",
                                  parameter = list(normalize = "Z-score"),
                                  type  = "ratings"
)
```

```
## popular run fold/sample [model time/prediction time]
##   1  [0.16sec/38.22sec]
##   2  [0.13sec/40.64sec]
```

```r
### examining the results
results_pop<-result_rating_popular@results %>%
  map(function(x) x@cm) %>%
  unlist() %>%
  matrix(ncol = 3, byrow = T) %>%
  as.data.frame() %>%
  summarise_all(mean) %>%
  setNames(c("RMSE", "MSE", "MAE"))

results_pop
```

```
##       RMSE      MSE      MAE
## 1 4.864844 23.66689 3.212177
```

```r
### adding the results to the list
rmse_results <- rbind.data.frame(rmse_results, c("Popular model", round(results_pop$RMSE,5)))
rmse_results
```

```
##                                         method    RMSE
## 1                             Just the average 1.86118
## 2                                 User effects 1.69647
```

```
## 3                              User and book effects 1.87867
## 4                           User and country effects 1.69647
## 5                            User and author effects 1.71147
## 6                              User and year effects 1.69625
## 7                         User and publisher effects 1.69914
## 8                       User and age_bracket effects 1.69647
## 9                       User and User*Author effects 1.64854
## 10        User and userid_author and author effects 1.64854
## 11 User and User*Author effects with regularization  1.6516
## 12                                    Popular model 4.86484
```

```
Sys.time() # recording the time in order to see how long each step takes
```

```
## [1] "2022-01-14 22:27:11 CET"
```

```
### saving
saveRDS(result_rating_popular, file="result_rating_popular")

Sys.time() # recording the time in order to see how long each step takes
```

```
## [1] "2022-01-14 22:27:11 CET"
```

```
### saving
### saveRDS(result_rating_ubcf, file="result_rating_ubcf")

### svd ###
### evaluating the svd model
result_rating_svd <- evaluate(scheme,
                              method = "svd",
                              parameter = list(normalize = "Z-score", k = 5),
                              type  = "ratings"
)
```

```
## svd run fold/sample [model time/prediction time]
##   1  [11.44sec/160.65sec]
##   2  [10.82sec/152.65sec]
```

```
### examining the results
results_svd<-result_rating_svd@results %>%
  map(function(x) x@cm) %>%
  unlist() %>%
  matrix(ncol = 3, byrow = T) %>%
  as.data.frame() %>%
  summarise_all(mean) %>%
  setNames(c("RMSE", "MSE", "MAE"))

results_svd
```

```
##       RMSE      MSE     MAE
## 1 4.256153 18.11662 2.84132
```

```r
### adding the results to the list
rmse_results <- rbind.data.frame(rmse_results, c("Singular Value Decomposition", round(results_svd$RMSE
rmse_results
```

```
##                                              method    RMSE
## 1                                  Just the average 1.86118
## 2                                      User effects 1.69647
## 3                             User and book effects 1.87867
## 4                          User and country effects 1.69647
## 5                           User and author effects 1.71147
## 6                             User and year effects 1.69625
## 7                        User and publisher effects 1.69914
## 8                      User and age_bracket effects 1.69647
## 9                      User and User*Author effects 1.64854
## 10        User and userid_author and author effects 1.64854
## 11 User and User*Author effects with regularization  1.6516
## 12                                    Popular model 4.86484
## 13                     Singular Value Decomposition 4.25615
```

```r
### saving
saveRDS(result_rating_svd, file="result_rating_svd")

Sys.time() # recording the time in order to see how long each step takes
```

```
## [1] "2022-01-14 22:33:21 CET"
```

```r
### svdf ###

### evaluating
result_rating_svdf <- evaluate(scheme,
                               method = "svdf",
                               parameter = list(normalize = "Z-score", k = 5),
                               type  = "ratings"
)
```

```
## svdf run fold/sample [model time/prediction time]
##   1  [587.21sec/676.25sec]
##   2  [497.48sec/582.5sec]
```

```r
Sys.time() # recording the time in order to see how long each step takes
```

```
## [1] "2022-01-14 23:12:59 CET"
```

```r
### examining the results
results_svdf<-result_rating_svdf@results %>%
  map(function(x) x@cm) %>%
  unlist() %>%
  matrix(ncol = 3, byrow = T) %>%
  as.data.frame() %>%
  summarise_all(mean) %>%
  setNames(c("RMSE", "MSE", "MAE"))

results_svdf
```

```
##       RMSE      MSE      MAE
## 1 4.384726 19.22768 2.959894
```

```
### adding the results to the list
rmse_results <- rbind.data.frame(rmse_results, c("Funk Singular Value Decomposition", round(results_svdf
rmse_results
```

```
##                                            method    RMSE
## 1                               Just the average 1.86118
## 2                                   User effects 1.69647
## 3                          User and book effects 1.87867
## 4                       User and country effects 1.69647
## 5                        User and author effects 1.71147
## 6                          User and year effects 1.69625
## 7                     User and publisher effects 1.69914
## 8                   User and age_bracket effects 1.69647
## 9                   User and User*Author effects 1.64854
## 10        User and userid_author and author effects 1.64854
## 11 User and User*Author effects with regularization  1.6516
## 12                                 Popular model 4.86484
## 13                  Singular Value Decomposition 4.25615
## 14             Funk Singular Value Decomposition 4.38473
```

```
Sys.time() # recording the time in order to see how long each step takes
```

```
## [1] "2022-01-14 23:12:59 CET"
```

```
### Identifying the model with the lowest RMSE
### finding the row numbers
rows<-which(rmse_results$RMSE==min(rmse_results$RMSE))
rows
```

```
## [1]  9 10
```

```
### finding the models
rmse_results$method[c(rows)]
```

```
## [1] "User and User*Author effects"
## [2] "User and userid_author and author effects"
```

```
### both models produce the same RMSE (when rounded), so we will choose the simpler one:
chosen_model<-rmse_results$method[c(rows)[1]]
chosen_model
```

```
## [1] "User and User*Author effects"
```

```
### saving
saveRDS(result_rating_svdf, file="result_rating_svdf")
saveRDS(rmse_results, file="rmse_results")
```

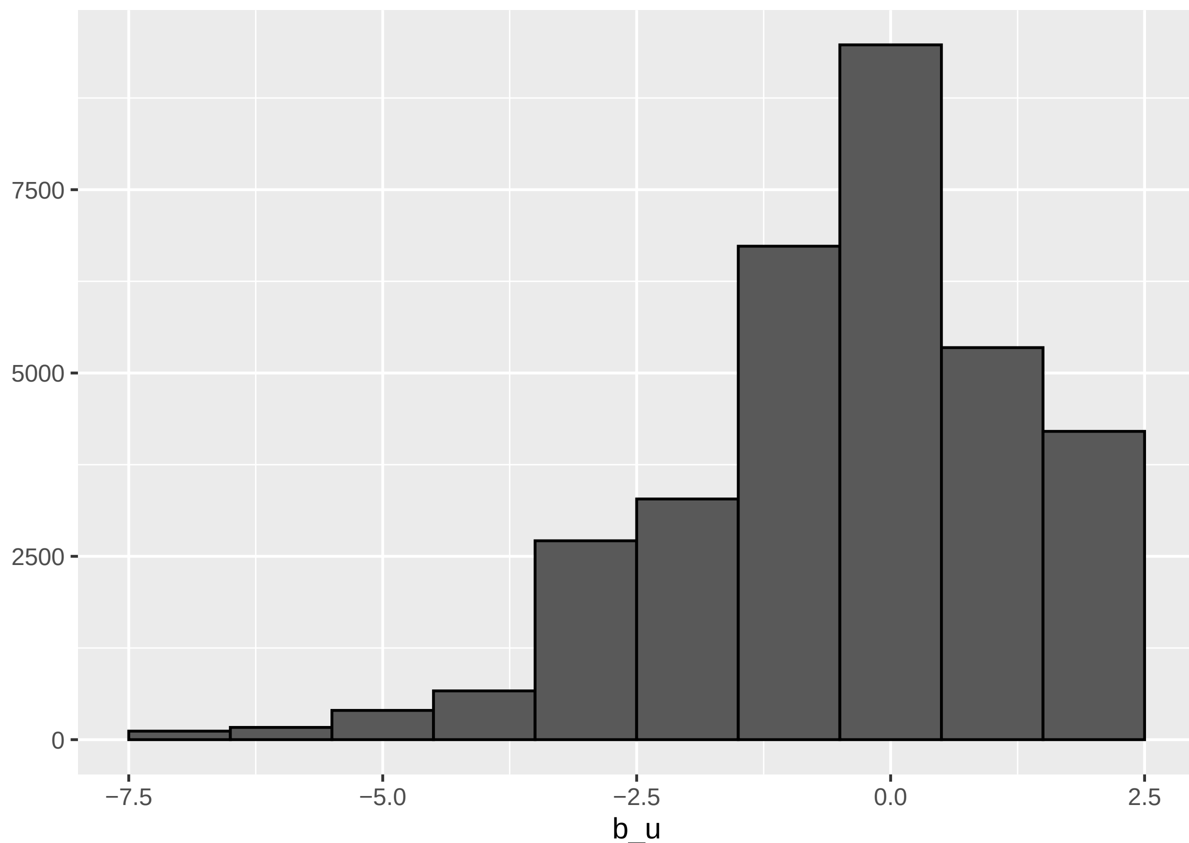
Since over 98% percent of the values are missing, we try to apply SVD and SVDF. These model are supposed to deal with sparse matrices well.

7. Applying the chosen model to the test set

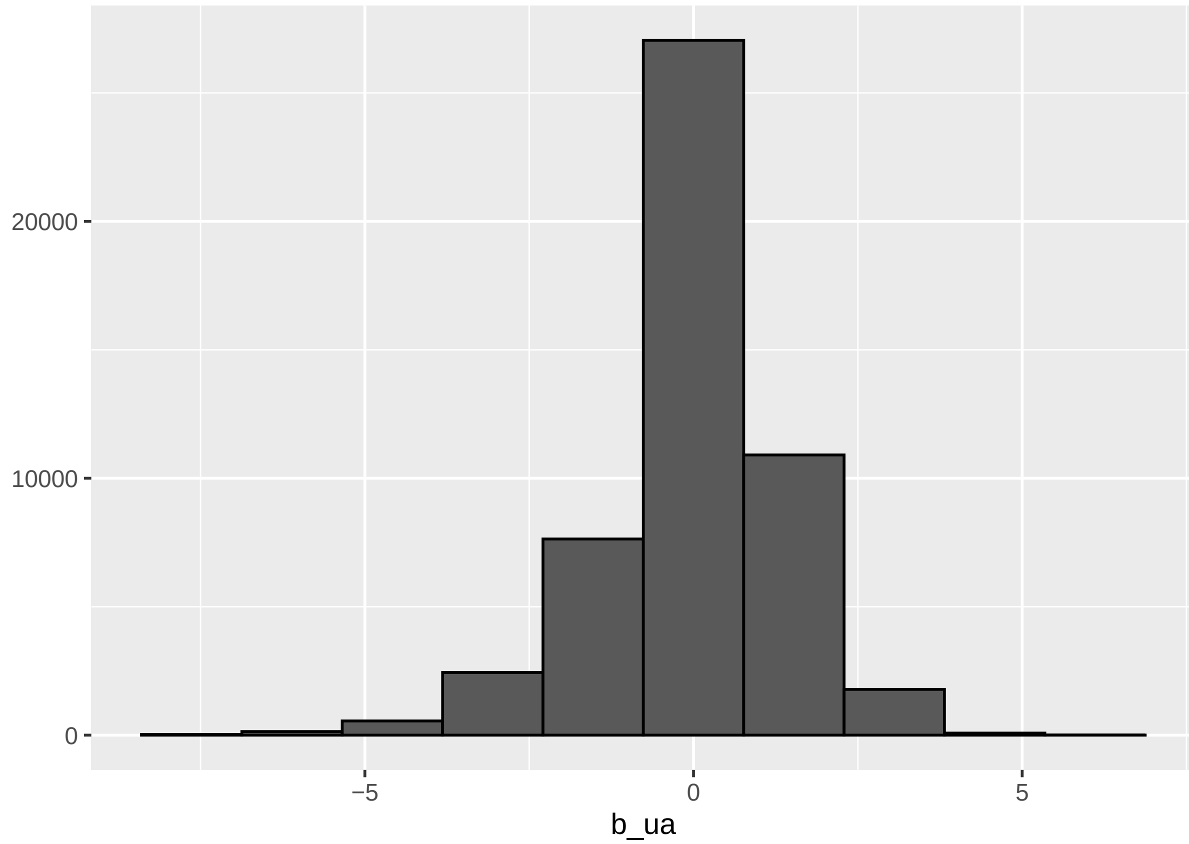
```
########################################################
### 7. Applying the chosen algorithm to the test set ###
########################################################

### cleaning the working space
rm(list=ls())

### cleaning memory
invisible(gc())

### loading the datasets
train<-readRDS("train")
test<-readRDS("test")
rmse_results<-readRDS("rmse_results")

### calculating the mean rating
mu <- mean(train$rating)
mu
```

```
## [1] 7.520239
```

```
### adding user effects ###
user_avgs <- train %>%
  group_by(userid) %>%
  summarize(b_u = mean(rating - mu))

# examining the distributions of user effects
qplot(b_u, data = user_avgs, bins = 10, color = I("black"))
```




```r
### adding userid_author effects ###
userid_author_avgs <- train %>%
  left_join(user_avgs, by='userid') %>%
  group_by(userid_author) %>%
  summarize(b_ua = mean(rating - mu - b_u))

# examining the distributions of userid_author effects
qplot(b_ua, data = userid_author_avgs, bins = 10, color = I("black"))
```




```r
# checking the rmse
predicted_ratings <- test %>%
  left_join(user_avgs, by='userid') %>%
  left_join(userid_author_avgs, by='userid_author') %>%
  mutate(pred = mu + b_u + b_ua) %>%
  pull(pred)
user_and_userid_author_effects_rmse<-RMSE(predicted_ratings, test$rating, na.rm = T)

rmse_results <- rbind.data.frame(rmse_results, c("Test set: user and User*Author effects", round(user_a
names(rmse_results)<-c("method", "RMSE")
rmse_results
```

```
##                                          method    RMSE
## 1                              Just the average 1.86118
## 2                                  User effects 1.69647
## 3                         User and book effects 1.87867
## 4                      User and country effects 1.69647
## 5                       User and author effects 1.71147
## 6                         User and year effects 1.69625
## 7                    User and publisher effects 1.69914
## 8                  User and age_bracket effects 1.69647
## 9                  User and User*Author effects 1.64854
## 10        User and userid_author and author effects 1.64854
## 11 User and User*Author effects with regularization  1.6516
## 12                                Popular model 4.86484
## 13                  Singular Value Decomposition 4.25615
```

```
## 14                 Funk Singular Value Decomposition 4.38473
## 15           Test set: user and User*Author effects 1.63248
```

8. Conclusion and discussion

My conclusion is that under certain conditions, simple models can outperform more advanced ones. There could be several reasons for this, in this case. First, the dataset was rather small. Second, there was a small number of ratings per book. This could be problematic for algorithms that rely on the associations between ratings given to items (e.g. two books tend to receive similar ratings). Third, the matrix was extremely sparse, and that might be too difficult to handle, even for the SVD and SVDF algorithms. Finally, I may have made a mistake in the analysis (although I tried pretty hard not to do that :)). Further analyses would be required in order to find out what combination of these possibilities is indeed the cause of the very poor performance of the advanced models in comparison to the simple ones.

Interestingly, the simple model produced about the same RMSE as it produced in the first exercise of this course, in which I applied it to the MovieLens data! The RMSE in that exercise was about 0.86, and the rating scale ranged between 1 and 5 (see my results here). On a scale that is twice of 1 to 5, i.e. 1 to 10, we would expect the RMSE to also be twice as large if the method performs the same, i.e. around 1.72. That is approximately the RMSE of the simple model in this exercise! My interim learning is that it seems that the simple model performs quite well under different conditions. But we would need to see the results of additional analyses in order to become more confident about that, it could also be just a coincidence.

In sum, I feel like I learned an important lesson - in machine learning, sometimes there is no trade-off between simplicity and accuracy. Under certain conditions, simple models could also be more accurate!