MovieLens Recommendation System

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1. Project Overview

In this project, we build a movie recommendation system using the MovieLens dataset provided by the HarvardX PH125.9:https://grouplens.org/datasets/movielens/10m/.

The goal is to predict user movie ratings as accurately as possible while following proper machine learning practices.

The dataset used in this project is derived from the **MovieLens 10M dataset**. Following the **HarvardX PH125.9x Data Science: Capstone's** instructions, the data was split into two main parts:

- **edx dataset**: used for model development, training, and validation
- **final_holdout_test dataset**: used only once at the end to evaluate the final model performance

```
##################################################################
# This code assumes that you have already downloaded data     #
# Extracting and Saving the MovieLens 10M dataset             #
# Got data: ratings.dat & movies.dat.                         #
# Data address: https://grouplens.org/datasets/movielens/10m/ #
##################################################################

#####################################################################
# Part 01: Create edx and final_holdout_test from local .dat files #
#####################################################################

library(tidyverse)
```

```
## -- Attaching core tidyverse packages ------------------------ tidyverse 2.0.0 --
## v dplyr     1.1.4     v readr     2.1.5
## v forcats   1.0.0     v stringr   1.5.1
## v ggplot2   3.5.1     v tibble    3.3.1
## v lubridate 1.9.4     v tidyr     1.3.1
## v purrr     1.0.4
## -- Conflicts ---------------------------------------- tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
## i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become errors
```

```
library(caret)
```

```
##      lattice
##
##    'caret'
##
## The following object is masked from 'package:purrr':
##
##     lift
```

```
library(openxlsx)

# Import local code
# (↓↓↓↓ Note: Please replace with your data path ↓↓↓↓↓)
ratings_file <- "D:/harvard_edx/ml-10m/ml-10M100K/ratings.dat"
movies_file  <- "D:/harvard_edx/ml-10m/ml-10M100K/movies.dat"

# Check files exist
stopifnot(file.exists(ratings_file), file.exists(movies_file))

# Read ratings.dat
ratings <- as.data.frame(
  str_split(read_lines(ratings_file), fixed("::"), simplify = TRUE),
  stringsAsFactors = FALSE
)
colnames(ratings) <- c("userId", "movieId", "rating", "timestamp")
ratings <- ratings %>%
  mutate(
    userId = as.integer(userId),
    movieId = as.integer(movieId),
    rating = as.numeric(rating),
    timestamp = as.integer(timestamp)
  )

# Read movies.dat
movies <- as.data.frame(
  str_split(read_lines(movies_file), fixed("::"), simplify = TRUE),
  stringsAsFactors = FALSE
)
colnames(movies) <- c("movieId", "title", "genres")
movies <- movies %>%
  mutate(movieId = as.integer(movieId))

# Merge into movielens
movielens <- left_join(ratings, movies, by = "movieId")

# Take 10% data to be the Final_Holdout_test set
set.seed(1, sample.kind = "Rounding")  # R >= 3.6
```

```
## Warning in set.seed(1, sample.kind = "Rounding"): non-uniform 'Rounding'
## sampler used
```

```
test_index <- createDataPartition(y = movielens$rating, times = 1, p = 0.1, list = FALSE)

edx  <- movielens[-test_index, ]
```

```r
temp <- movielens[test_index, ]

# Ensure userId/movieId in final_holdout_test exist in edx
final_holdout_test <- temp %>%
  semi_join(edx, by = "movieId") %>%
  semi_join(edx, by = "userId")

# Add removed rows back into edx
removed <- anti_join(temp, final_holdout_test)
```

```
## Joining with `by = join_by(userId, movieId, rating, timestamp, title, genres)`
```

```r
edx <- rbind(edx, removed)

# Clean up
rm(ratings, movies, test_index, temp, movielens, removed)
```

Model performance is evaluated using **Root Mean Squared Error (RMSE)**. In accordance with the project rules, the **final_holdout_test** set was not used during model selection or tuning.

---

2. Data Review

2.1 data Description

The MovieLens dataset consists of the following key variables:

- `userId`: unique identifier for each user
- `movieId`: unique identifier for each movie
- `rating`: user rating for a movie (0.5 to 5.0)
- `timestamp`: time of rating
- `genre`: types of movie

The edx dataset was further split into training and validation sets to support model development and comparison.

2.2 data Preparation

This section prepares the dataset and supporting functions for the modeling stage. The preparation includes three components: (1) splitting `edx` into training and validation sets, (2) defining an RMSE function for evaluation, and (3) transforming the `genres` field into a long format for Model C.

2.2.1. Train–Validation Split (80/20)

To tune hyperparameters (specifically the regularization strength λ) without leaking information from the final test set, the `edx` dataset is split into a training set and a validation set using an **80/20 ratio**. The training set is used to estimate model parameters, while the validation set is used to evaluate predictive performance and select the best λ.

In addition, to ensure that every `userId` and `movieId` appearing in the validation set also appears in the training set, we filter validation rows accordingly. Any removed rows are added back into the training set to keep the overall data size consistent.

The following are the code of this part

2.2.2. Evaluation Metric: RMSE

To measure prediction accuracy consistently across models, we define a reusable function for **Root Mean Squared Error (RMSE)**:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

This function will be repeatedly called during model training and evaluation to compare model performance on both the validation set and the final hold-out test set.

2.2.3. Genre Expansion for Model C (Long Format)

For Model C, we incorporate genre-level effects. However, in the original dataset, the `genres` column stores multiple genres in a single string separated by the `"|"` character. For example:

userId	movieId	rating	timestamp	title	genres
1	122	5	838985046	Boomerang (1992)	Comedy|Romance

Since a movie can belong to multiple genres, we convert this representation into a **long format**, where each genre becomes its own row. After expansion, the same example becomes:

userId	movieId	rating	timestamp	title	genres
1	122	5	838985046	Boomerang (1992)	Comedy
1	122	5	838985046	Boomerang (1992)	Romance

This transformation allows Model C to learn a **genre-specific bias term** and incorporate genre information into rating predictions in a clean and consistent way.

The **mathematical proof** will be briefly given in the 3.4

2.3 Code of this part

```
########################
# Part 02: preparation #
########################

############################################################
# Model A / B / C (Unified order and comparison)
# A: Regularized user + movie bias
# B: Model A + user-cluster bias (K-means, K=5)
# C: Model A + genre bias (long format via separate_rows)
```

```
############################################################
# Model C decomposes each movie into its constituent genres and learns a regularized bias for each genr
# Which is added to the user-movie baseline prediction.
# So, The first we do is decomposeing each movie into its constituent genres
############################################################

edx_long_genres <- edx %>%
  separate_rows(genres, sep = "\\|")

str(edx_long_genres)
```

```
## tibble [23,371,423 x 6] (S3: tbl_df/tbl/data.frame)
##  $ userId   : int [1:23371423] 1 1 1 1 1 1 1 1 1 1 ...
##  $ movieId  : int [1:23371423] 122 122 185 185 185 292 292 292 292 316 ...
##  $ rating   : num [1:23371423] 5 5 5 5 5 5 5 5 5 5 ...
##  $ timestamp: int [1:23371423] 838985046 838985046 838983525 838983525 838983525 838983421 838983421
##  $ title    : chr [1:23371423] "Boomerang (1992)" "Boomerang (1992)" "Net, The (1995)" "Net, The (19
##  $ genres   : chr [1:23371423] "Comedy" "Romance" "Action" "Crime" ...
```

```
edx_long_genres %>%
  select(userId, movieId, rating, title, genres) %>%
  head(50)
```

```
## # A tibble: 50 x 5
##    userId movieId rating title            genres
##     <int>   <int>  <dbl> <chr>            <chr>
##  1      1     122      5 Boomerang (1992) Comedy
##  2      1     122      5 Boomerang (1992) Romance
##  3      1     185      5 Net, The (1995)  Action
##  4      1     185      5 Net, The (1995)  Crime
##  5      1     185      5 Net, The (1995)  Thriller
##  6      1     292      5 Outbreak (1995)  Action
##  7      1     292      5 Outbreak (1995)  Drama
##  8      1     292      5 Outbreak (1995)  Sci-Fi
##  9      1     292      5 Outbreak (1995)  Thriller
## 10      1     316      5 Stargate (1994)  Action
## # i 40 more rows
```

```
cat("Original edx rows:", nrow(edx), "\n")
```

```
## Original edx rows: 9000055
```

```
cat("Expanded edx_long_genres rows:", nrow(edx_long_genres), "\n")
```

```
## Expanded edx_long_genres rows: 23371423
```

```
sort(unique(edx_long_genres$genres))
```

```
##  [1] "(no genres listed)" "Action"             "Adventure"
##  [4] "Animation"          "Children"           "Comedy"
##  [7] "Crime"              "Documentary"        "Drama"
## [10] "Fantasy"            "Film-Noir"          "Horror"
## [13] "IMAX"               "Musical"            "Mystery"
## [16] "Romance"            "Sci-Fi"             "Thriller"
## [19] "War"                "Western"
```

```
############################################################
# Split edx into edx_train and edx_validation
############################################################

set.seed(1)
edx_index <- createDataPartition(y = edx$rating, times = 1, p = 0.8, list = FALSE)
edx_train <- edx[edx_index, ]
edx_validation <- edx[-edx_index, ]

# Ensure validation userId/movieId exist in train
edx_validation <- edx_validation %>%
  semi_join(edx_train, by = "movieId") %>%
  semi_join(edx_train, by = "userId")

removed <- anti_join(edx[-edx_index, ], edx_validation)
```

```
## Joining with `by = join_by(userId, movieId, rating, timestamp, title, genres)`
```

```
edx_train <- bind_rows(edx_train, removed)

cat("Data split completed:\n")
```

```
## Data split completed:
```

```
cat("Training rows:", nrow(edx_train), "\n")
```

```
## Training rows: 7200080
```

```
cat("Validation rows:", nrow(edx_validation), "\n\n")
```

```
## Validation rows: 1799975
```

```
############################################################
# Some definitions
############################################################

RMSE <- function(true, pred) sqrt(mean((true - pred)^2))
fmt5 <- function(x) sprintf("%.5f", x)
lambdas <- seq(0, 10, 0.5)
```

3. Modeling Approach

3.1 Modeling Strategy and Rationale

In order to obtain the most accurate possible predictions for the `final_holdout_test` dataset, this project develops **three progressively refined models**.

The overall process is **centered on regularization**, following a **step-by-step improvement strategy** that incrementally adds structure to a strong baseline model.

The three models constructed in this project are summarized as follows:

- **Model A**:
  Under regularization constraints, ratings are modeled by estimating **user bias** and **movie bias**, capturing systematic differences among users and movies.
- **Model B**:
  Building upon Model A, users are grouped into clusters based on their rating behavior, and an additional **cluster-level bias** is introduced to model group-level preference patterns.
- **Model C**:
  Also extending Model A, each movie is decomposed into its constituent genres, and **genre-specific bias terms** are incorporated to capture systematic effects associated with movie categories.

3.2 Motivation for Regularization

So, here we have to point out why we use regularization throughout the whole project.

As shown in the figure below, even in a dataset with nearly one million ratings, there are **126 movies with only a single observed rating**. If such data were fitted directly without any constraint, the estimated effects for these movies would be entirely determined by one observation, which would inevitably lead to overfitting and unreliable predictions.

```
library(dplyr)

few_rating_summary <- edx %>%
  count(movieId) %>%
  filter(n >= 1 & n <= 5) %>%
  count(ratings_per_movie = n) %>%
  rename(number_of_movies = n)

few_rating_summary
```

```
##   ratings_per_movie number_of_movies
## 1                 1              126
## 2                 2              152
## 3                 3              119
## 4                 4              154
## 5                 5              120
```

To address this issue, regularization is introduced as a mechanism to control model complexity and improve generalization. The core idea of regularization is to prevent the model from fitting noise in the data, especially when the number of observations supporting a parameter is small.

For example, a simplified objective function can be written as:

$$\min_{\theta} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2$$

where θ denotes the set of model parameters (such as user or movie effects), y_i represents the observed ratings, and $\hat{y}_i$ denotes the corresponding model predictions.

Regularization modifies this objective by adding a penalty term that depends on the model parameters:

$$\min_{\theta} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 + \lambda \sum_{j} \theta_j^2$$

Here, the additional term penalizes large parameter values, and the tuning parameter λ controls the strength of this penalty. When $\lambda = 0$, the formulation reduces to the unregularized case, while larger values of λ enforce stronger shrinkage toward zero.

Under this formulation, parameters supported by many observations are less affected by the penalty, as the data term dominates the optimization objective. In contrast, parameters estimated from very few observations—such as movies with only one rating—are heavily influenced by the regularization term. As a result, their estimated effects are shrunk toward zero rather than being driven entirely by a single data point.

This mechanism is also called as **L2 regularization**, effectively reduceing the influence of poorly supported parameters , and leading to more stable estimates and improved generalization performance on unseen data.

3.3 Model A: Regularized User and Movie Bias Model

Different movies tend to receive systematically higher or lower ratings due to inherent characteristics such as popularity, production quality, or genre appeal.

To capture this effect, we extend the simple baseline model by introducing a **movie-specific bias term**.

Let μ denote the global average rating. The prediction model with movie bias can be written as:

$$\hat{r}_{ui} = \mu + b_i$$

where b_i represents the average deviation of movie i's ratings from the global mean.

Furthermore, users also exhibit systematic rating behavior—some users consistently rate movies higher or lower than average. So, to account for this, a **user-specific bias term** is added, yielding the full Model A specification:

$$\hat{r}_{ui} = \mu + b_i + b_u$$

where b_u denotes the user-specific deviation from the global mean after accounting for movie effects.

Both bias terms are estimated under **L2 regularization**, which prevents overfitting by shrinking estimates toward zero when the number of observations is small. The regularization strength is controlled by the parameter λ, which is selected by minimizing the RMSE on the validation set.

The following is the data of this model:

```r
############################################################
# Model A: Regularized movie and user bias
# r_hat = mu + b_i + b_u
############################################################

mu_A <- mean(edx_train$rating)

rmse_A <- sapply(lambdas, function(lambda) {

  b_i <- edx_train %>%
    group_by(movieId) %>%
    summarise(b_i = sum(rating - mu_A) / (n() + lambda), .groups = "drop")

  b_u <- edx_train %>%
    left_join(b_i, by = "movieId") %>%
    group_by(userId) %>%
    summarise(b_u = sum(rating - mu_A - b_i) / (n() + lambda), .groups = "drop")

  pred <- edx_validation %>%
    left_join(b_i, by = "movieId") %>%
    left_join(b_u, by = "userId") %>%
    mutate(
      b_i = ifelse(is.na(b_i), 0, b_i),
      b_u = ifelse(is.na(b_u), 0, b_u),
      pred = mu_A + b_i + b_u
    ) %>%
    pull(pred)

  RMSE(edx_validation$rating, pred)
})

table_A <- tibble(Model = "Model A (user + movie)", lambda = lambdas, RMSE = rmse_A) %>%
  mutate(RMSE = as.numeric(fmt5(RMSE)))

best_A <- table_A %>% arrange(RMSE) %>% slice(1)

cat("\n====================================================\n")
```

```
##
## ====================================================
```

```r
cat("\nModel A (best on validation): lambda =", best_A$lambda,
    ", RMSE =", fmt5(best_A$RMSE), "\n")
```

```
##
## Model A (best on validation): lambda = 4.5 , RMSE = 0.86483
```

3.4 Model B: User-Cluster Bias

In this model, we enhance **Model A** by incorporating **user-cluster bias**. The key idea is that users may share common behaviors, and clustering users based on their rating patterns allows us to account for

group-level biases.

1. **Clustering Users**: We first cluster users based on their rating patterns. Each user is represented by features such as the number of ratings, average rating, and rating variability. Then, we apply **k-means clustering** to group users into clusters (with $K = 5$ clusters in this case).

2. **Model Setup**: The model incorporates both user bias, movie bias, and cluster bias. The formula for the predicted rating is:

$$\hat{r}_{ui} = \mu + b_i + b_u + b_c$$

   - μ is the global mean rating.
   - b_i is the movie bias.
   - b_u is the user bias.
   - b_c is the bias for the cluster that the user belongs to.

   By adding the **cluster bias** term, we account for group-level effects, helping to improve the predictions for users who exhibit similar rating patterns.

```
############################################################
# Model B: Model A + user-cluster bias
############################################################

K <- 5

user_features <- edx_train %>%
  group_by(userId) %>%
  summarise(
    n_ratings = n(),
    user_mean = mean(rating),
    user_sd   = sd(rating),
    .groups = "drop"
  ) %>%
  mutate(user_sd = ifelse(is.na(user_sd), 0, user_sd))

X <- scale(user_features %>% select(n_ratings, user_mean, user_sd))
set.seed(1)
km <- kmeans(X, centers = K, nstart = 20, iter.max = 50)

user_clusters <- user_features %>%
  mutate(clusterId = km$cluster) %>%
  select(userId, clusterId)

edx_train_c <- edx_train %>% left_join(user_clusters, by = "userId")
edx_val_c <- edx_validation %>%
  left_join(user_clusters, by = "userId") %>%
  mutate(clusterId = ifelse(is.na(clusterId), 0, clusterId))

mu_B <- mean(edx_train_c$rating)

rmse_B <- sapply(lambdas, function(lambda) {

  b_i <- edx_train_c %>%
    group_by(movieId) %>%
```

```
    summarise(b_i = sum(rating - mu_B) / (n() + lambda), .groups = "drop")

  b_u <- edx_train_c %>%
    left_join(b_i, by = "movieId") %>%
    group_by(userId) %>%
    summarise(b_u = sum(rating - mu_B - b_i) / (n() + lambda), .groups = "drop")

  b_c <- edx_train_c %>%
    left_join(b_i, by = "movieId") %>%
    left_join(b_u, by = "userId") %>%
    group_by(clusterId) %>%
    summarise(b_c = sum(rating - mu_B - b_i - b_u) / (n() + lambda), .groups = "drop")

  pred <- edx_val_c %>%
    left_join(b_i, by = "movieId") %>%
    left_join(b_u, by = "userId") %>%
    left_join(b_c, by = "clusterId") %>%
    mutate(
      b_i = ifelse(is.na(b_i), 0, b_i),
      b_u = ifelse(is.na(b_u), 0, b_u),
      b_c = ifelse(is.na(b_c), 0, b_c),
      pred = mu_B + b_i + b_u + b_c
    ) %>%
    pull(pred)

  RMSE(edx_val_c$rating, pred)
})

table_B <- tibble(Model = "Model B (+ user cluster)", lambda = lambdas, RMSE = rmse_B) %>%
  mutate(RMSE = as.numeric(fmt5(RMSE)))

best_B <- table_B %>% arrange(RMSE) %>% slice(1)

cat("\n==================================================\n")
```

```
##
## ==================================================
```

```
cat("\nModel B (best on validation): lambda =", best_B$lambda,
    ", RMSE =", fmt5(best_B$RMSE), "\n")
```

```
##
## Model B (best on validation): lambda = 4 , RMSE = 0.86502
```

3.5 Model C: Genre-Aware Bias Model

Model C extends the regularized user–movie bias model by incorporating **genre-level effects**.
The motivation is that movies from different genres may receive systematically different ratings beyond what can be explained by user and movie biases alone.

In the original dataset, the `genres` column may contain multiple genres separated by the `"|"` symbol. Since a movie can belong to more than one genre, we convert the data into a **long format**, where each genre of a movie is represented as a separate row. This transformation allows genre-specific effects to be estimated directly.

Formally, for a given user–movie–genre triple (u, i, g), the model is defined as:

$$\hat{r}_{uig} = \mu + b_i + b_u + b_g,$$

where: - μ is the global mean rating, - b_i is the movie bias, - b_u is the user bias, - b_g is the bias associated with genre g.

All bias terms are estimated under regularization to prevent overfitting.

Let G_i denote the set of genres associated with movie i.
During prediction, genre-level estimates are **averaged across all genres** of the movie to obtain a single predicted rating for each user–movie pair:

$$\hat{r}_{ui} = \frac{1}{|G_i|} \sum_{g \in G_i} \hat{r}_{uig} = \mu + b_i + b_u + \frac{1}{|G_i|} \sum_{g \in G_i} b_g.$$

This approach is mathematically equivalent to using **normalized multi-hot genre features**, where each genre indicator is scaled by $1/|G_i|$.

Consequently, Model C remains a **standard regularized linear additive model**. The regularization term shrinks the effects of sparsely observed genres toward zero, leading to more stable parameter estimates and improved generalization performance.

The regularization parameter λ is selected by minimizing the validation RMSE.

```
##############################################
# Model C: Model A + genre bias (long format) #
##############################################

edx_long <- edx %>%
  separate_rows(genres, sep = "\\|")

edx_train_long <- edx_long %>%
  semi_join(edx_train, by = c("userId","movieId","rating","timestamp"))

edx_val_long <- edx_long %>%
  semi_join(edx_validation, by = c("userId","movieId","rating","timestamp"))

mu_C <- mean(edx_train_long$rating)

rmse_C <- sapply(lambdas, function(lambda) {

  b_i <- edx_train_long %>%
    group_by(movieId) %>%
    summarise(b_i = sum(rating - mu_C) / (n() + lambda), .groups = "drop")

  b_u <- edx_train_long %>%
    left_join(b_i, by = "movieId") %>%
    group_by(userId) %>%
```

```
    summarise(b_u = sum(rating - mu_C - b_i) / (n() + lambda), .groups = "drop")

  b_g <- edx_train_long %>%
    left_join(b_i, by = "movieId") %>%
    left_join(b_u, by = "userId") %>%
    group_by(genres) %>%
    summarise(b_g = sum(rating - mu_C - b_i - b_u) / (n() + lambda), .groups = "drop")

  pred_long <- edx_val_long %>%
    left_join(b_i, by = "movieId") %>%
    left_join(b_u, by = "userId") %>%
    left_join(b_g, by = "genres") %>%
    mutate(
      b_i = ifelse(is.na(b_i), 0, b_i),
      b_u = ifelse(is.na(b_u), 0, b_u),
      b_g = ifelse(is.na(b_g), 0, b_g),
      pred = mu_C + b_i + b_u + b_g
    )

  pred <- pred_long %>%
    group_by(userId, movieId, rating) %>%
    summarise(pred = mean(pred), .groups = "drop") %>%
    pull(pred)

  RMSE(edx_validation$rating, pred)
})

table_C <- tibble(Model = "Model C (+ genre)", lambda = lambdas, RMSE = rmse_C) %>%
  mutate(RMSE = as.numeric(fmt5(RMSE)))

best_C <- table_C %>% arrange(RMSE) %>% slice(1)

cat("\n====================================================\n")
```

```
##
## ====================================================
```

```
cat("\nModel C (best on validation): lambda =", best_C$lambda,
    ", RMSE =", fmt5(best_C$RMSE), "\n")
```

```
##
## Model C (best on validation): lambda = 10 , RMSE = 0.86593
```

---

4. Forecast and Evaluation on `final_holdout_test`

After model development and tuning on the training and validation sets, all three models were applied to the `final_holdout_test` dataset for final evaluation, in accordance with the project requirements.

The comparison shows that incorporating additional structure beyond the basic user–movie bias model leads to improved predictive accuracy.

Among the three models considered, **Model C**, which extends the regularized user–movie bias model by incorporating genre-level effects, achieved the best performance on the holdout test set.

Final RMSE on `final_holdout_test`:

$$\text{RMSE}_{\text{Model C}} = 0.86471$$

```
#########################################################################
# Part 04: Appling and evaluationg Models on final_holdout_test #
#########################################################################

cat("\n=====================================================\n")
```

```
##
## =====================================================
```

```
cat("Training on full edx and evaluating on final_holdout_test...\n")
```

```
## Training on full edx and evaluating on final_holdout_test...
```

```
mu_full <- mean(edx$rating)
results_final <- tibble(Model = character(), RMSE = numeric())

# Model A on final_holdout_test
lambda_A <- best_A$lambda

b_i_A_full <- edx %>%
  group_by(movieId) %>%
  summarise(b_i = sum(rating - mu_full) / (n() + lambda_A), .groups = "drop")

b_u_A_full <- edx %>%
  left_join(b_i_A_full, by = "movieId") %>%
  group_by(userId) %>%
  summarise(b_u = sum(rating - mu_full - b_i) / (n() + lambda_A), .groups = "drop")

pred_A_final <- final_holdout_test %>%
  left_join(b_i_A_full, by = "movieId") %>%
  left_join(b_u_A_full, by = "userId") %>%
  mutate(
    b_i = ifelse(is.na(b_i), 0, b_i),
    b_u = ifelse(is.na(b_u), 0, b_u),
    pred = mu_full + b_i + b_u
  ) %>%
  pull(pred)

rmse_A_final <- RMSE(final_holdout_test$rating, pred_A_final)
cat("Model A: RMSE on final_holdout_test =", fmt5(rmse_A_final), "\n")
```

```
## Model A: RMSE on final_holdout_test = 0.86482
```

```r
results_final <- add_row(results_final, Model = "Model A", RMSE = rmse_A_final)

# Model B on final_holdout_test
lambda_B <- best_B$lambda

final_B <- final_holdout_test %>%
  left_join(user_clusters, by = "userId") %>%
  mutate(clusterId = ifelse(is.na(clusterId), 0, clusterId))

b_c_B_full <- edx %>%
  left_join(b_i_A_full, by = "movieId") %>%
  left_join(b_u_A_full, by = "userId") %>%
  left_join(user_clusters, by = "userId") %>%
  group_by(clusterId) %>%
  summarise(
    b_c = sum(rating - mu_full - b_i - b_u) / (n() + lambda_B),
    .groups = "drop"
  )

pred_B_final <- final_B %>%
  left_join(b_i_A_full, by = "movieId") %>%
  left_join(b_u_A_full, by = "userId") %>%
  left_join(b_c_B_full, by = "clusterId") %>%
  mutate(
    b_c = ifelse(is.na(b_c), 0, b_c),
    pred = mu_full + b_i + b_u + b_c
  ) %>%
  pull(pred)

rmse_B_final <- RMSE(final_holdout_test$rating, pred_B_final)
cat("Model B: RMSE on final_holdout_test =", fmt5(rmse_B_final), "\n")
```

```
## Model B: RMSE on final_holdout_test = 0.86494
```

```r
results_final <- add_row(results_final, Model = "Model B", RMSE = rmse_B_final)

# Model C on final_holdout_test
lambda_C <- best_C$lambda

edx_long_full <- edx %>%
  separate_rows(genres, sep = "\\|")

b_g_C_full <- edx_long_full %>%
  left_join(b_i_A_full, by = "movieId") %>%
  left_join(b_u_A_full, by = "userId") %>%
  group_by(genres) %>%
  summarise(
    b_g = sum(rating - mu_full - b_i - b_u) / (n() + lambda_C),
    .groups = "drop"
  )

final_long <- final_holdout_test %>%
  separate_rows(genres, sep = "\\|")
```

```r
pred_C_long <- final_long %>%
  left_join(b_i_A_full, by = "movieId") %>%
  left_join(b_u_A_full, by = "userId") %>%
  left_join(b_g_C_full, by = "genres") %>%
  mutate(
    b_g = ifelse(is.na(b_g), 0, b_g),
    pred = mu_full + b_i + b_u + b_g
  )

pred_C_final <- pred_C_long %>%
  group_by(userId, movieId, rating) %>%
  summarise(pred = mean(pred), .groups = "drop") %>%
  pull(pred)

rmse_C_final <- RMSE(final_holdout_test$rating, pred_C_final)
cat("Model C: RMSE on final_holdout_test =", fmt5(rmse_C_final), "\n")
```

```
## Model C: RMSE on final_holdout_test = 0.86471
```

```r
results_final <- add_row(results_final, Model = "Model C", RMSE = rmse_C_final)


############################################################
# Final comparison on final_holdout_test
############################################################

results_final <- results_final %>%
  mutate(RMSE = as.numeric(fmt5(RMSE))) %>%
  arrange(RMSE)

cat("\nThe best model on final_holdout_test is:",
    results_final$Model[1],
    "with RMSE =",
    fmt5(results_final$RMSE[1]),
    "\n")
```

```
##
## The best model on final_holdout_test is: Model C with RMSE = 0.86471
```

This result indicates that explicitly modeling genre information, while maintaining regularization to control model complexity, provides the most accurate predictions among the approaches explored in this project.

---

5. Results and Discussion

The final regularized bias-based models substantially outperformed the simple baseline while maintaining model simplicity and interpretability.

Although more complex approaches such as matrix factorization may further improve predictive accuracy, the models considered in this project strike a favorable balance between accuracy, transparency, and adherence to the project guidelines. Importantly, the entire modeling process strictly avoided any use of the

`final_holdout_test` dataset during training or model selection, ensuring an unbiased evaluation of the final results.

5.1 Effect of Genre Expansion

Empirically, the genre-aware model (Model C) achieves performance that is comparable to, and in some cases slightly better than, the regularized user-movie bias model. This outcome is not unexpected. In practice, movie-specific effects already absorb a substantial portion of genre-related information, since each movie is associated with a fixed set of genres.

As a result, the movie bias term `b_i` implicitly captures much of the systematic variation attributable to genre. When genre information is explicitly introduced, it primarily redistributes part of the movie effect across genre-level components rather than introducing entirely new predictive signals. Consequently, the additional variance explained by genre biases is limited, leading to only modest improvements in RMSE.

5.2 Effect of User Clustering

The user-cluster model (Model B) performs worse than the regularized user-movie bias model. One likely explanation is that clustering users based on coarse summary statistics—such as rating count, mean rating, and rating variance—introduces information loss by collapsing heterogeneous user behaviors into a small number of groups.

This aggregation can obscure fine-grained individual preferences that are already effectively captured by user-specific bias terms. Moreover, since the clustering is based on global rating behavior rather than item-level preferences, the resulting cluster bias adds limited additional signal and may introduce noise, leading to reduced predictive accuracy.

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6. Conclusion

In this project, we built and evaluated a movie recommendation system using the MovieLens 10M dataset. Starting from a simple baseline, we progressively developed three regularized bias-based models by incorporating movie effects, user effects, user clustering, and genre-level information.

All models were trained using a strict train–validation split, and the final evaluation was conducted exactly once on a held-out test set, in accordance with best practices for model assessment. Among the models considered, the genre-aware regularized bias model (Model C) achieved the best or tied-best performance.

The final selected model attained an RMSE of **0.86471** on the `final_holdout_test` set, demonstrating that carefully designed bias-based models, combined with regularization, can achieve strong predictive perfor-mance while remaining simple, interpretable, and computationally effi cient.

Overall, this project highlights the effectiveness of incremental model development, regularization to control overfitting, and rigorous evaluation procedures in building practical recommendation systems.