

Movie recommendation results

Loading packages and data

```
# Load required packages
library(tidyverse)

## -- Attaching packages ----- tidyverse 1.2.1 --

## v ggplot2 3.1.1      v purrr  0.3.2
## v tibble  2.1.1      v dplyr  0.8.0.1
## v tidyr   0.8.3      v stringr 1.4.0
## v readr   1.3.1      v forcats 0.4.0

## Warning: package 'ggplot2' was built under R version 3.5.3

## Warning: package 'tibble' was built under R version 3.5.3

## Warning: package 'tidyr' was built under R version 3.5.3

## Warning: package 'readr' was built under R version 3.5.3

## Warning: package 'purrr' was built under R version 3.5.3

## Warning: package 'dplyr' was built under R version 3.5.3

## Warning: package 'stringr' was built under R version 3.5.3

## Warning: package 'forcats' was built under R version 3.5.3

## -- Conflicts ----- tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()

library(lubridate)

##
## Attaching package: 'lubridate'

## The following object is masked from 'package:base':
##
##     date

# Load locally stored data
edx_original <- readRDS("edx.RData")
validation_original <- readRDS("validation.RData")
```

Preparing data

```
# Separating user characteristics, ratings and movie features
user_data <- edx_original %>% select(userId) %>%
  mutate(userId = as.factor(userId)) %>% unique()

rating_data <- edx_original %>% select(userId, movieId, rating, timestamp) %>%
  mutate(userId = as.factor(userId),
         movieId = as.factor(movieId),
         date = as.POSIXct(timestamp, origin = "1970-01-01")) %>% # Turn
  mutate(rating_year = year(date)) %>%
  select(-timestamp, -date)

# MOVIE DATA
movie_data <- edx_original %>% select(movieId, title, genres) %>%
  unique() %>%
  mutate(movieId = as.factor(movieId),
         movie_year = as.factor(str_sub(title, -5, -2)),
         title = str_sub(title, 0, -8))

# Let's determine which genres we have
unique_genres <- unique(str_extract(movie_data$genres, "[^\\|]+"))
# Now lets add them as columns
movie_data[, unique_genres] <- NA
# For each of the ratings we detect present genres
for(g in 1:length(unique_genres)) {
  #print(paste("Detecting: ", unique_genres[g]))
  movie_data[, unique_genres[g]] <- str_detect(movie_data$genres, unique_genres[g])
}
# Drop old columns
movie_data <- movie_data %>% select(-genres)

# Let's explore our new data sets
head(user_data)
```

```
##      userId
## 1         1
## 20        2
## 37        3
## 68        4
## 103       5
## 177       6
```

```
head(rating_data)
```

```
##      userId movieId rating rating_year
## 1         1     122      5      1996
## 2         1     185      5      1996
## 3         1     292      5      1996
## 4         1     316      5      1996
## 5         1     329      5      1996
## 6         1     355      5      1996
```

```
head(movie_data)
```

```
##      movieId      title movie_year Comedy Action Children
## 1      122      Boomerang      1992   TRUE  FALSE   FALSE
## 2      185      Net, The      1995  FALSE   TRUE   FALSE
## 3      292      Outbreak      1995  FALSE   TRUE   FALSE
## 4      316      Stargate      1994  FALSE   TRUE   FALSE
## 5      329 Star Trek: Generations      1994  FALSE   TRUE   FALSE
## 6      355      Flintstones, The      1994   TRUE  FALSE   TRUE
##      Adventure Animation Drama Crime Sci-Fi Horror Thriller Film-Noir Mystery
## 1      FALSE      FALSE FALSE FALSE  FALSE  FALSE   FALSE   FALSE  FALSE
## 2      FALSE      FALSE FALSE  TRUE  FALSE  FALSE   TRUE   FALSE  FALSE
## 3      FALSE      FALSE  TRUE FALSE  TRUE  FALSE   TRUE   FALSE  FALSE
## 4      TRUE      FALSE FALSE FALSE  TRUE  FALSE   FALSE   FALSE  FALSE
## 5      TRUE      FALSE  TRUE FALSE  TRUE  FALSE   FALSE   FALSE  FALSE
## 6      FALSE      FALSE FALSE FALSE  FALSE  FALSE   FALSE   FALSE  FALSE
##      Western Documentary Romance Fantasy Musical  War  IMAX
## 1      FALSE      FALSE   TRUE  FALSE  FALSE FALSE FALSE
## 2      FALSE      FALSE  FALSE  FALSE  FALSE FALSE FALSE
## 3      FALSE      FALSE  FALSE  FALSE  FALSE FALSE FALSE
## 4      FALSE      FALSE  FALSE  FALSE  FALSE FALSE FALSE
## 5      FALSE      FALSE  FALSE  FALSE  FALSE FALSE FALSE
## 6      FALSE      FALSE  FALSE   TRUE  FALSE FALSE FALSE
##      (no genres listed)
## 1      FALSE
## 2      FALSE
## 3      FALSE
## 4      FALSE
## 5      FALSE
## 6      FALSE
```

User characteristics

```
## Ratings statistics
user_stats <- rating_data %>% group_by(userId) %>%
  summarise(user_ratings = n(),
            user_median = median(rating),
            user_mean = mean(rating),
            user_sd = sd(rating)) %>%
  select(userId, user_median, user_mean, user_sd) %>%
  unique()

user_data <- user_data %>% inner_join(user_stats, by = "userId")

## TO DO: ADD GENRE AVERAGES
```

Movie characteristics

```
# Movie rating statistics
movie_stats <- rating_data %>% group_by(movieId) %>%
  summarise(movie_ratings = n(),
            movie_median = median(rating),
            movie_mean = mean(rating),
            movie_sd = sd(rating)) %>%
  select(movieId, movie_median, movie_mean, movie_sd) %>%
  unique()

movie_data <- movie_data %>% inner_join(movie_stats, by = "movieId")
```

Rating characteristics

```
## Rating characteristics
rating_mean <- mean(rating_data$rating)

rating_data <- rating_data %>% mutate(rating_mean_diff = rating - rating_mean) %>%
  inner_join(movie_data[, c("movieId", "movie_mean")], by = "movieId") %>%
  mutate(movie_mean_diff = rating - movie_mean) %>%
  inner_join(user_data[, c("userId", "user_mean")], by = "userId") %>%
  mutate(user_mean_diff = rating - user_mean)
```

Model training preparation

```
library(caret)
```

```
## Warning: package 'caret' was built under R version 3.5.3
```

```
## Loading required package: lattice
```

```
##
```

```
## Attaching package: 'caret'
```

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

```
##
```

```
## lift
```

```
# RMSE loss function function to evaluate models
RMSE <- function(true_ratings, predicted_ratings){
  sqrt(mean((true_ratings - predicted_ratings)^2))
}
```

```
# Create train and test sets
```

```

test_index <- createDataPartition(y = rating_data$rating, times = 1,
                                p = 0.2, list = FALSE)
train_set <- rating_data[-test_index,]
test_set <- rating_data[test_index,]

# To make sure movies and users are in both train and test sets
test_set <- test_set %>%
  semi_join(train_set, by = "movieId") %>%
  semi_join(train_set, by = "userId")

```

Manual model building

```

### Building the Recommendation System

```

```

# Naive model using average rating
rating_mean <- mean(train_set$rating)
rating_mean

```

```

## [1] 3.51242

```

```

naive_rmse <- RMSE(test_set$rating, rating_mean)

rmse_results <- data_frame(method = "Average rating", RMSE = naive_rmse)

```

```

## Warning: `data_frame()` is deprecated, use `tibble()`.
## This warning is displayed once per session.

```

```

# Model using fixed number
fixed_number <- rep(2.5, nrow(test_set))

fixed_rmse <- RMSE(test_set$rating, fixed_number)

rmse_results <- bind_rows(rmse_results,
                        data_frame(method = "Fixed number 2.5",
                                  RMSE = fixed_rmse ))

rmse_results

```

```

## # A tibble: 2 x 2
##   method      RMSE
##   <chr>      <dbl>
## 1 Average rating  1.06
## 2 Fixed number 2.5  1.47

```

Derived models

```
# Derived predictions
```

```
predictions <- test_set %>% group_by(movieId) %>%  
  # Rating effect (effect of rating scale used; looking at differences from rating mean)  
  summarise(rating_mean_diff_avg = rating_mean + mean(rating_mean_diff),  
  # Movie effect (effect of general movie popularity; looking at differences between user  
    movie_mean_diff_avg = rating_mean + mean(movie_mean_diff),  
  # User effect (effect of user rating behaviour; looking at differences between rating and  
    user_mean_diff_avg = rating_mean + mean(user_mean_diff),  
  # User-movie effect (effect of user rating behaviour; looking at differences between user  
    user_movie_mean_diff_avg = mean(movie_mean) + mean(user_mean_diff))
```

```
# Calculate RMSEs
```

```
rating_effect_rmse <- RMSE(test_set$rating,  
  predictions$rating_mean_diff_avg)
```

```
## Warning in true_ratings - predicted_ratings: longer object length is not a  
## multiple of shorter object length
```

```
movie_effect_rmse <- RMSE(test_set$rating,  
  predictions$movie_mean_diff_avg)
```

```
## Warning in true_ratings - predicted_ratings: longer object length is not a  
## multiple of shorter object length
```

```
user_effect_rmse <- RMSE(test_set$rating,  
  predictions$user_mean_diff_avg)
```

```
## Warning in true_ratings - predicted_ratings: longer object length is not a  
## multiple of shorter object length
```

```
user_movie_effect_rmse <- RMSE(test_set$rating,  
  predictions$user_movie_mean_diff_avg)
```

```
## Warning in true_ratings - predicted_ratings: longer object length is not a  
## multiple of shorter object length
```

```
# Print RMSEs
```

```
rmse_results <- bind_rows(rmse_results,  
  data_frame(method = "Rating effect",  
    RMSE = rating_effect_rmse))  
rmse_results <- bind_rows(rmse_results,  
  data_frame(method = "Movie effect",  
    RMSE = movie_effect_rmse))  
rmse_results <- bind_rows(rmse_results,  
  data_frame(method = "User effect",  
    RMSE = user_effect_rmse))  
rmse_results <- bind_rows(rmse_results,
```

```
data_frame(method = "User-movie effect",
            RMSE = user_movie_effect_rmse))

rmse_results
```

```
## # A tibble: 6 x 2
##   method      RMSE
##   <chr>      <dbl>
## 1 Average rating 1.06
## 2 Fixed number 2.5 1.47
## 3 Rating effect 1.27
## 4 Movie effect 1.11
## 5 User effect 1.21
## 6 User-movie effect 1.59
```

Merge all data for calculating models

```
# Let's merged derived data
train_set_plus <- train_set %>% select(-user_mean) %>%
  left_join(user_data, by = "userId") %>%
  select(-movie_mean) %>%
  left_join(movie_data, by = "movieId")

test_set_plus <- test_set %>% select(-user_mean) %>%
  left_join(user_data, by = "userId") %>%
  select(-movie_mean) %>%
  left_join(movie_data, by = "movieId")
```

Train calculated models

```
# Let's prepare parallel processing
library(doParallel)
```

```
## Warning: package 'doParallel' was built under R version 3.5.3
```

```
## Loading required package: foreach
```

```
##
```

```
## Attaching package: 'foreach'
```

```
## The following objects are masked from 'package:purrr':
```

```
##
```

```
##   accumulate, when
```

```
## Loading required package: iterators
```

```
## Warning: package 'iterators' was built under R version 3.5.1
```

```
## Loading required package: parallel
```

```
cl <- makePSOCKcluster(5)
registerDoParallel(cl)

## Model training in parallel

tc <- trainControl(number = 3)
training_data <- train_set_plus[1:100000,]

system.time({
  model_1 <- train(rating ~ movie_median,
                  data = training_data, method = "lm",
                  na.action = na.omit, metric = "RMSE",
                  trainControl = tc)
})
```

```
## Warning: In lm.fit(x, y, offset = offset, singular.ok = singular.ok, ...) :
## extra argument 'trainControl' will be disregarded
```

```
##      user system elapsed
##      1.53    0.05    9.18
```

```
model_1$finalModel
```

```
##
## Call:
## lm(formula = .outcome ~ ., data = dat, trainControl = ..1)
##
## Coefficients:
## (Intercept) movie_median
##      0.6499      0.8104
```

```
system.time({
  model_2 <- train(rating ~ movie_median + movie_mean,
                  data = training_data, method = "lm",
                  na.action = na.omit, metric = "RMSE",
                  trainControl = tc)
})
```

```
## Warning: In lm.fit(x, y, offset = offset, singular.ok = singular.ok, ...) :
## extra argument 'trainControl' will be disregarded
```

```
##      user system elapsed
##      1.56    0.11    3.20
```

```
model_2$finalModel
```

```
##
## Call:
## lm(formula = .outcome ~ ., data = dat, trainControl = ..1)
```



```
##
## Coefficients:
## (Intercept) movie_median movie_mean
## -0.01194 -0.01049 1.02753
```

```
system.time({
  model_3 <- train(rating ~ movie_median + movie_mean + movie_sd,
    data = training_data, method = "lm",
    na.action = na.omit, metric = "RMSE",
    trainControl = tc)
})
```

```
## Warning: In lm.fit(x, y, offset = offset, singular.ok = singular.ok, ...) :
## extra argument 'trainControl' will be disregarded
```

```
## user system elapsed
## 1.60 0.09 2.93
```

```
model_3$finalModel
```

```
##
## Call:
## lm(formula = .outcome ~ ., data = dat, trainControl = ..1)
##
## Coefficients:
## (Intercept) movie_median movie_mean movie_sd
## -0.09988 -0.01362 1.03891 0.06294
```

```
## Does it matter what the movies are? Maybe focus on the ratings
```

```
system.time({
  model_4 <- train(rating ~ user_median,
    data = training_data, method = "lm",
    na.action = na.omit, metric = "RMSE",
    trainControl = tc)
})
```

```
## Warning: In lm.fit(x, y, offset = offset, singular.ok = singular.ok, ...) :
## extra argument 'trainControl' will be disregarded
```

```
## user system elapsed
## 1.55 0.08 2.87
```

```
model_4$finalModel
```

```
##
## Call:
## lm(formula = .outcome ~ ., data = dat, trainControl = ..1)
##
## Coefficients:
## (Intercept) user_median
## 1.0848 0.6759
```

```
system.time({
  model_5 <- train(rating ~ user_median + user_mean,
                  data = training_data, method = "lm",
                  na.action = na.omit, metric = "RMSE",
                  trainControl = tc)
})
```

```
## Warning: In lm.fit(x, y, offset = offset, singular.ok = singular.ok, ...) :
## extra argument 'trainControl' will be disregarded
```

```
## user system elapsed
## 1.56 0.11 2.70
```

```
model_5$finalModel
```

```
##
## Call:
## lm(formula = .outcome ~ ., data = dat, trainControl = ..1)
##
## Coefficients:
## (Intercept) user_median user_mean
## 0.0007519 -0.0054273 1.0053696
```

```
system.time({
  model_6 <- train(rating ~ user_median + user_mean + user_sd,
                  data = training_data, method = "lm",
                  na.action = na.omit, metric = "RMSE",
                  trainControl = tc)
})
```

```
## Warning: In lm.fit(x, y, offset = offset, singular.ok = singular.ok, ...) :
## extra argument 'trainControl' will be disregarded
```

```
## user system elapsed
## 1.50 0.14 2.83
```

```
model_6$finalModel
```

```
##
## Call:
## lm(formula = .outcome ~ ., data = dat, trainControl = ..1)
##
## Coefficients:
## (Intercept) user_median user_mean user_sd
## 0.021604 -0.002668 1.000265 -0.013519
```

```
# User and movie effects combined
```

```
system.time({
  model_7 <- train(rating ~ movie_median + user_median,
```

```

        data = training_data, method = "lm",
        na.action = na.omit, metric = "RMSE",
        trainControl = tc)
})

```

```

## Warning: In lm.fit(x, y, offset = offset, singular.ok = singular.ok, ...) :
## extra argument 'trainControl' will be disregarded

```

```

## user system elapsed
## 1.58 0.05 2.77

```

```

model_7$finalModel

```

```

##
## Call:
## lm(formula = .outcome ~ ., data = dat, trainControl = ..1)
##
## Coefficients:
## (Intercept) movie_median user_median
## -1.2895 0.7458 0.5889

```

```

system.time({
  model_8 <- train(rating ~ movie_median + movie_mean + user_median + user_mean,
    data = training_data, method = "lm",
    na.action = na.omit, metric = "RMSE",
    trainControl = tc)
})

```

```

## Warning: In lm.fit(x, y, offset = offset, singular.ok = singular.ok, ...) :
## extra argument 'trainControl' will be disregarded

```

```

## user system elapsed
## 1.68 0.08 3.33

```

```

model_8$finalModel

```

```

##
## Call:
## lm(formula = .outcome ~ ., data = dat, trainControl = ..1)
##
## Coefficients:
## (Intercept) movie_median movie_mean user_median user_mean
## -2.6614750 0.0159165 0.8877218 0.0001111 0.8514821

```

```

system.time({
  model_9 <- train(rating ~ movie_median + movie_mean + movie_sd + user_median + user_mean + user_sd,
    data = training_data, method = "lm",
    na.action = na.omit, metric = "RMSE",
    trainControl = tc)
})

```

```
## Warning: In lm.fit(x, y, offset = offset, singular.ok = singular.ok, ...) :
## extra argument 'trainControl' will be disregarded
```

```
## user system elapsed
## 1.76 0.04 3.42
```

```
model_9$finalModel
```

```
##
## Call:
## lm(formula = .outcome ~ ., data = dat, trainControl = ..1)
##
## Coefficients:
## (Intercept) movie_median movie_mean movie_sd user_median
## -2.665190 0.014477 0.892506 0.025176 0.004373
## user_mean user_sd
## 0.843633 -0.020355
```

```
# Basic movie_mean and user_mean seem most influential
final_model_data <- train_set_plus %>% select(movieId, rating, movie_mean, user_mean) %>% unique()
system.time({
  model_10 <- train(rating ~ movie_mean + user_mean,
                    data = final_model_data, method = "lm",
                    na.action = na.omit, metric = "RMSE",
                    trainControl = tc)
})
```

```
## Warning: In lm.fit(x, y, offset = offset, singular.ok = singular.ok, ...) :
## extra argument 'trainControl' will be disregarded
```

```
## user system elapsed
## 48.75 5.78 170.15
```

```
model_10$finalModel
```

```
##
## Call:
## lm(formula = .outcome ~ ., data = dat, trainControl = ..1)
##
## Coefficients:
## (Intercept) movie_mean user_mean
## -2.5280 0.8791 0.8390
```

```
## Stopping clusters
stopCluster(cl)
```

Prediction and results

```

# Predict on test_set
model_1_predictions <- predict(model_1, newdata = test_set_plus)
model_2_predictions <- predict(model_2, newdata = test_set_plus)
model_3_predictions <- predict(model_3, newdata = test_set_plus)
model_4_predictions <- predict(model_4, newdata = test_set_plus)
model_5_predictions <- predict(model_5, newdata = test_set_plus)
model_6_predictions <- predict(model_6, newdata = test_set_plus)
model_7_predictions <- predict(model_7, newdata = test_set_plus)
model_8_predictions <- predict(model_8, newdata = test_set_plus)
model_9_predictions <- predict(model_9, newdata = test_set_plus)
model_10_predictions <- predict(model_10, newdata = test_set_plus)

# Print results on test set

print(paste("Model 1 RMSE in test set: ", RMSE(test_set_plus$rating, model_1_predictions)))

## [1] "Model 1 RMSE in test set:  0.961856858351706"

print(paste("Model 2 RMSE in test set: ", RMSE(test_set_plus$rating, model_2_predictions)))

## [1] "Model 2 RMSE in test set:  0.943715761622832"

print(paste("Model 3 RMSE in test set: ", RMSE(test_set_plus$rating, model_3_predictions)))

## [1] "Model 3 RMSE in test set:  0.943720720931866"

print(paste("Model 4 RMSE in test set: ", RMSE(test_set_plus$rating, model_4_predictions)))

## [1] "Model 4 RMSE in test set:  0.992816763316907"

print(paste("Model 5 RMSE in test set: ", RMSE(test_set_plus$rating, model_5_predictions)))

## [1] "Model 5 RMSE in test set:  0.970130044036678"

print(paste("Model 6 RMSE in test set: ", RMSE(test_set_plus$rating, model_6_predictions)))

## [1] "Model 6 RMSE in test set:  0.97013451409216"

print(paste("Model 7 RMSE in test set: ", RMSE(test_set_plus$rating, model_7_predictions)))

## [1] "Model 7 RMSE in test set:  0.9072658857676"

print(paste("Model 8 RMSE in test set: ", RMSE(test_set_plus$rating, model_8_predictions)))

## [1] "Model 8 RMSE in test set:  0.8725047933572"

```

```

print(paste("Model 9 RMSE in test set: ", RMSE(test_set_plus$rating, model_9_predictions)))

## [1] "Model 9 RMSE in test set: 0.872542123139385"

print(paste("Model 10 RMSE in test set: ", RMSE(test_set_plus$rating, model_10_predictions)))

## [1] "Model 10 RMSE in test set: 0.8724270826599"

# Verify results on validation set

# Shall we explore auto ML?

library(h2o)

## Warning: package 'h2o' was built under R version 3.5.3

##
## -----
##
## Your next step is to start H2O:
##   > h2o.init()
##
## For H2O package documentation, ask for help:
##   > ??h2o
##
## After starting H2O, you can use the Web UI at http://localhost:54321
## For more information visit http://docs.h2o.ai
##
## -----

##
## Attaching package: 'h2o'

## The following objects are masked from 'package:lubridate':
##
##   day, hour, month, week, year

## The following objects are masked from 'package:stats':
##
##   cor, sd, var

## The following objects are masked from 'package:base':
##
##   %*%, %in%, &&, ||, apply, as.factor, as.numeric, colnames,
##   colnames<-, ifelse, is.character, is.factor, is.numeric, log,
##   log10, log1p, log2, round, signif, trunc

h2o.init()

```

```
## Connection successful!
##
## R is connected to the H2O cluster:
##   H2O cluster uptime:      3 hours 25 minutes
##   H2O cluster timezone:    Europe/Berlin
##   H2O data parsing timezone: UTC
##   H2O cluster version:     3.22.1.1
##   H2O cluster version age:  4 months and 22 days !!!
##   H2O cluster name:        H2O_started_from_R_Codrin_wgs510
##   H2O cluster total nodes:  1
##   H2O cluster total memory: 13.18 GB
##   H2O cluster total cores:  12
##   H2O cluster allowed cores: 12
##   H2O cluster healthy:      TRUE
##   H2O Connection ip:        localhost
##   H2O Connection port:      54321
##   H2O Connection proxy:     NA
##   H2O Internal Security:    FALSE
##   H2O API Extensions:       Algos, AutoML, Core V3, Core V4
##   R Version:                 R version 3.5.0 (2018-04-23)

## Warning in h2o.clusterInfo():
## Your H2O cluster version is too old (4 months and 22 days)!
## Please download and install the latest version from http://h2o.ai/download/
```

```
# Import a sample binary outcome train/test set into H2O
train <- as.h2o(train_set_plus)
```

```
##
|
|                                     | 0%
|
|=====| 100%
```

```
test <- as.h2o(test_set_plus)
```

```
##
|
|                                     | 0%
|
|=====| 100%
```

```
# Identify predictors and response
y <- "rating"
x <- setdiff(names(train_set_plus), y)

# Run AutoML for 10 base models (limited to 1 hour max runtime by default)
aml <- h2o.automl(x = x, y = y,
                  training_frame = train,
                  max_models = 10,
                  seed = 1)
```

##		
		0%
=		1%
=		2%
==		2%
==		3%
==		4%
===		4%
===		5%
====		6%
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=====		18%


```

|=====| 19%
|
|=====| 20%
|
|=====| 88%
|
|=====| 94%
|
|=====| 100%

```

View the AutoML Leaderboard

```

lb <- aml@leaderboard
print(lb, n = nrow(lb))

```

```

##                                model_id
## 1                DRF_1_AutoML_20190520_180116
## 2                XRT_1_AutoML_20190520_180116
## 3  StackedEnsemble_AllModels_AutoML_20190520_180116
## 4  StackedEnsemble_BestOfFamily_AutoML_20190520_180116
## 5          GLM_grid_1_AutoML_20190520_180116_model_1
##  mean_residual_deviance      rmse      mse      mae
## 1          1.133491e-07 0.0003366736 1.133491e-07 8.194040e-06
## 2          5.458101e-07 0.0007387896 5.458101e-07 1.646689e-04
## 3          5.483918e-06 0.0023417767 5.483918e-06 1.858332e-03
## 4          5.483918e-06 0.0023417767 5.483918e-06 1.858332e-03
## 5          2.873683e-04 0.0169519415 2.873683e-04 1.359361e-02
##          rmsle
## 1 0.0001312058
## 2 0.0001985072
## 3 0.0007049445
## 4 0.0007049445
## 5 0.0044671316
##
## [5 rows x 6 columns]

```