Project3 - evaluating recommender systems

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This project uses the recommenderlab package to create recommendations using the Beer Advocate data set used in previous projects. The recommendations are created using the SVD function, and the model is evaluated for accuracy and predictive power.

Data Source: https://data.world/socialmediadata/beer (https://data.world/socialmediadata/beer) advocate

Data Exploration

The total number of distinct beers in the data is 42719 and the beers cover a wide range of number of ratings, from as few as 1 to 3000. The beer data is sparse, as there are 41564 beers that have received less than 200 ratings. This accounts for0.9729629 of the total number of items.

The number of ratings per user shows a fairly uniform distribution across the 28762 distinct users, with the number of ratings ranging from 1 to 3763. There are 26411 users that have rated less than 100 items. This accounts for 0.9182602 of the total number of users.

Our raw data contains 1048575 data points, and a ratings matrix for this data would be 28762 X 42719. By removing beers that have received less than 200 ratings and users that have rated less than 100 of the remaining beers we can reduce the size significantly.

We still retain valuable information for beers that have frequent ratings and can create predictions for users with longer history of ratings, but this method is also limited. It lends itself to reinforcing existing options, without offering opportunity for new items to be recommended. It also does not allow for an intelligent way to recommend for new users. One way this can be addressed in a full model is to randomly recommend to well-known users a sample of beers excluded from the original model but that have been rated positively or neutrally. This creates an opportunity to gain new information on both the beers and the users. For newer users excluded from our model due to lack of ratings, we can recommend a random selection of positively rated beers to develop enough history to be included in the model.

```
#keep only items with more than than 200 ratings, and of those only users ratin
g more than 100.
v <- sparseratings%>% filter(count > 200)

dfbeerrm <- beerdata%>%
  filter(beer_beerid %in% v$beer_beerid)

w <- dfbeerrm%>%select(beer_beerid, review_profilename)%>%
  group_by(review_profilename)%>%
  summarise(count=n())%>% filter(count > 100)

dfbeerrm <- dfbeerrm%>%
  filter(review_profilename %in% w$review_profilename)

items <- dfbeerrm%>%select(beer_name, review_overall)%>%
  group_by(beer_name)%>%
  summarise(count=n())%>%arrange(-count)
items_n <- nrow(items)

users<- dfbeerrm%>%select(review_profilename, review_overall)%>%
  group_by(review_profilename)%>%
  summarise(count=n())%>%arrange(-count)


users_n <- nrow(users)


df <- dfbeerrm%>%select(user = review_profilename,beer =beer_name,rate =review_
overall)
df[is.na(df)] <- 0

#Head of data

(head(df))
```

```
##             user          beer rate
## 1         jdhilt Amstel Light  2.5
## 2          Brent Amstel Light  3.0
## 3       Mora2000  Caldera IPA  4.0
## 4        Rutager  Caldera IPA  4.0
## 5 CHILLINDYLAN  Caldera IPA  4.5
## 6    beerman207  Caldera IPA  4.5
```

The new data set containing only users that have rated more than 100beers, and only beers with more than 200 ratings has been reduced to 375314 rows, with 1137 items and 1633 users. By removing these items we have reduced the ratings matrix to a more manageable size.

Now that we have a reduced data set we will set up a training and testing scheme using the recommenderlab package function evaluation scheme. In this scheme I chose to split the data into 80% training and 20% testing, a positive rating is considered 3 and above, with all but 10 ratings given for the testing set, to evaluate how the model predicts the unknown items in the testing set.

```
# create ratings matrix
ratemat <- as(df,"realRatingMatrix")
#norm_ratemat <- normalize(ratemat)


#number to take as given in testing
numgiven <- -10 # min number of ratings is 20
splitsville <- .2
posthreshold <- 3
evals <- 4



#split data into train and test

evalsplit <- evaluationScheme(data=ratemat, method = "split", train = splitsvil
le,
                              given =numgiven, goodRating = posthreshold, k = e
vals)
(evalsplit)
```

```
## Evaluation scheme using all-but-10 items
## Method: 'split' with 4 run(s).
## Training set proportion: 0.200
## Good ratings: >=3.000000
## Data set: 1633 x 1137 rating matrix of class 'realRatingMatrix' with 368766
ratings.
```

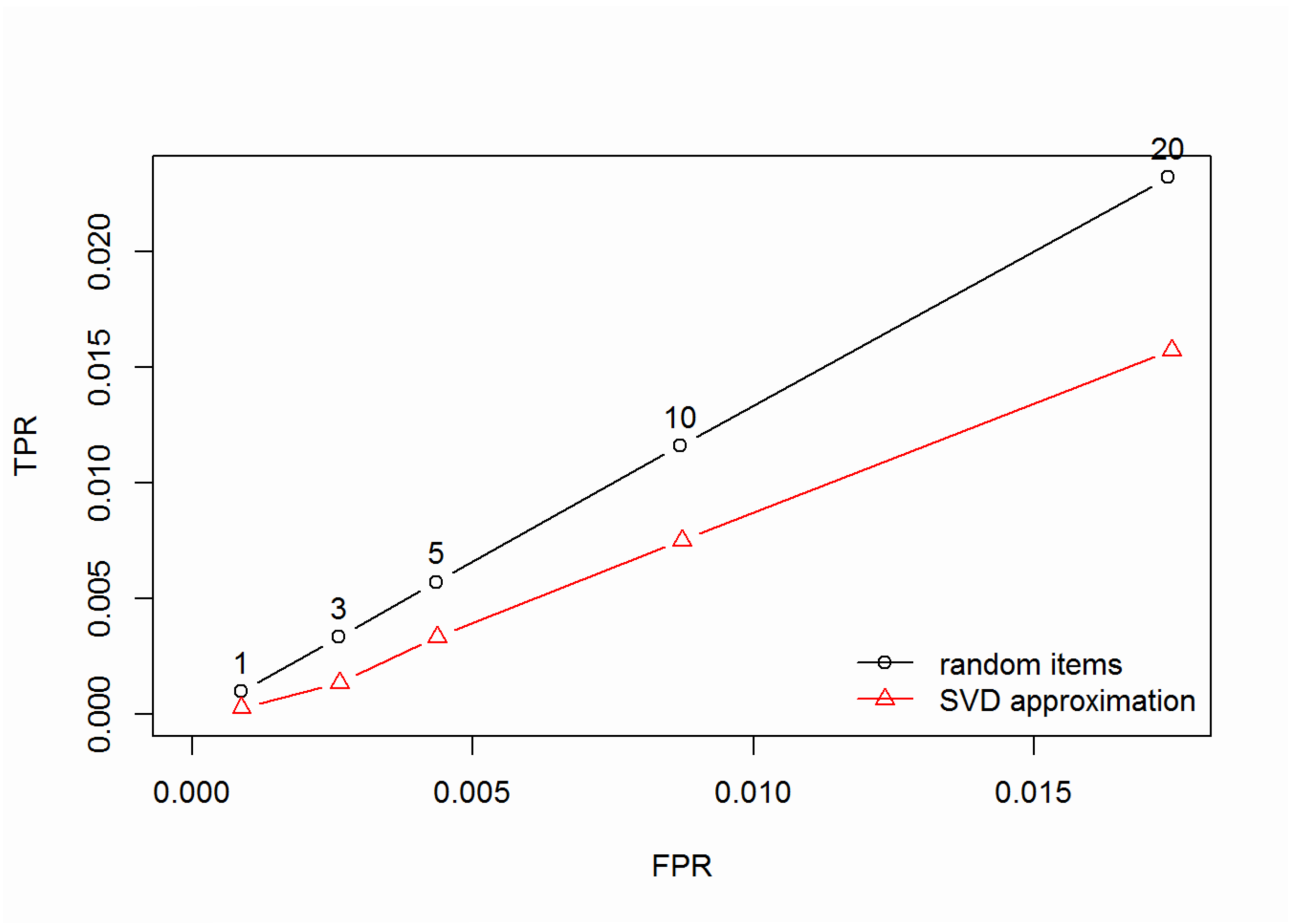
I am using the SVD and random methods in the recommenderlab package to create two models using default parameters, in order to determine if the SVD method is actually better than a random recommendation. The evaluate function can evaluate the efficiency of the algorithm for different levels of results.

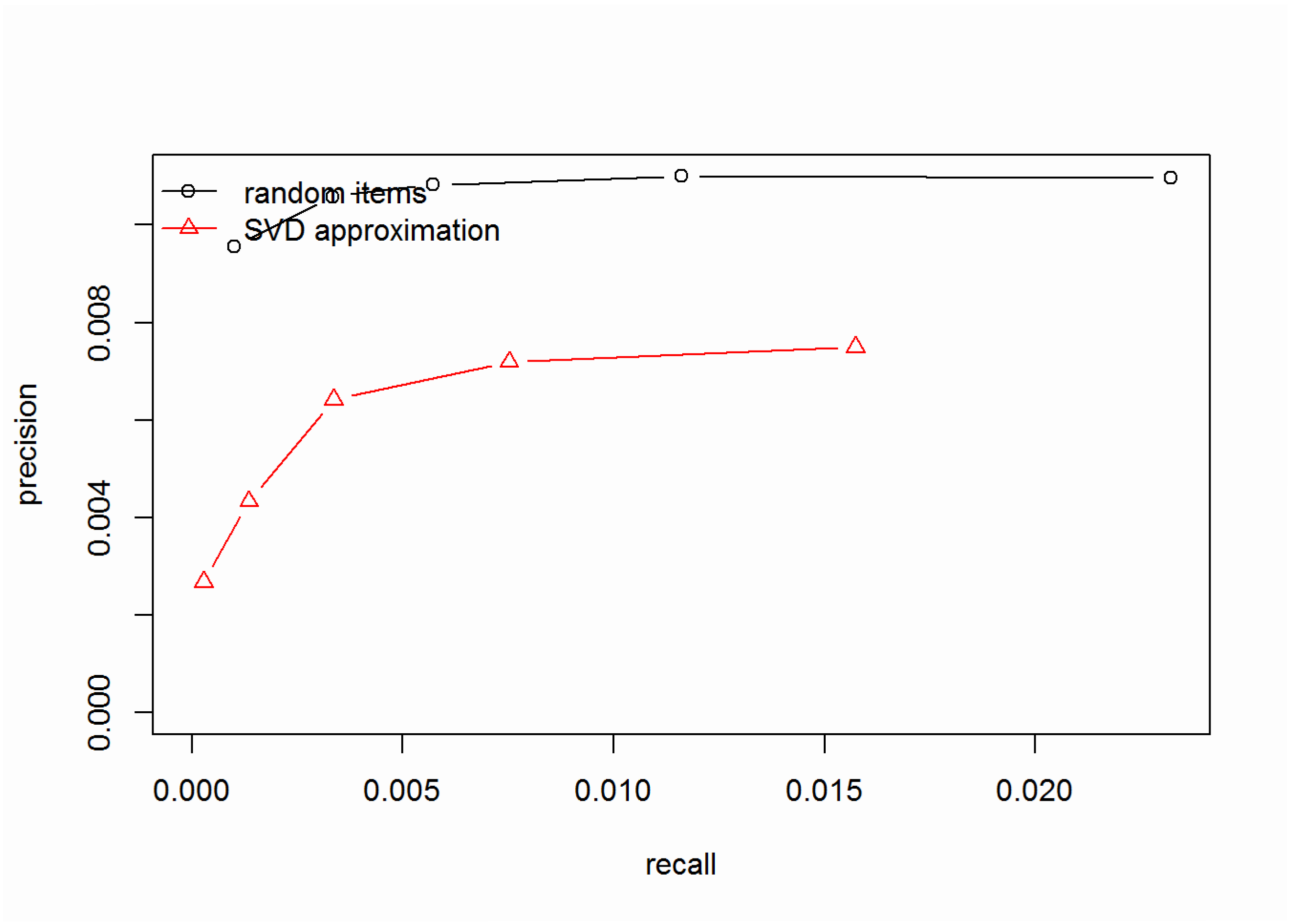
```
#train models

systems <-  list("random items" = list(name="RANDOM", param=NULL),
                 "SVD approximation" = list(name="SVD", param=NULL))

sysresults <- evaluate(evalsplit, systems, type = "topNList", n=c(1, 3, 5, 10,
20))
```

```
## RANDOM run fold sample [model time prediction time]
##   1  [0.01sec 13. 4sec]
##   2  [0sec 13.51sec]
##   3  [0sec 14.83sec]
##   4  [0.02sec 12.8sec]
## SVD run fold sample [model time prediction time]
##   1  [0.03sec 78.71sec]
##   2  [0.03sec 64.78sec]
##   3  [0.03sec 87.12sec]
##   4  [0.03sec 82.57sec]
```

The run time for a random model was much faster than that of the SVD method. If this was calculated once per day it may not be a large problem, but if it was needed to reevaluate real-time this resource-intensive method may not be scaleable.

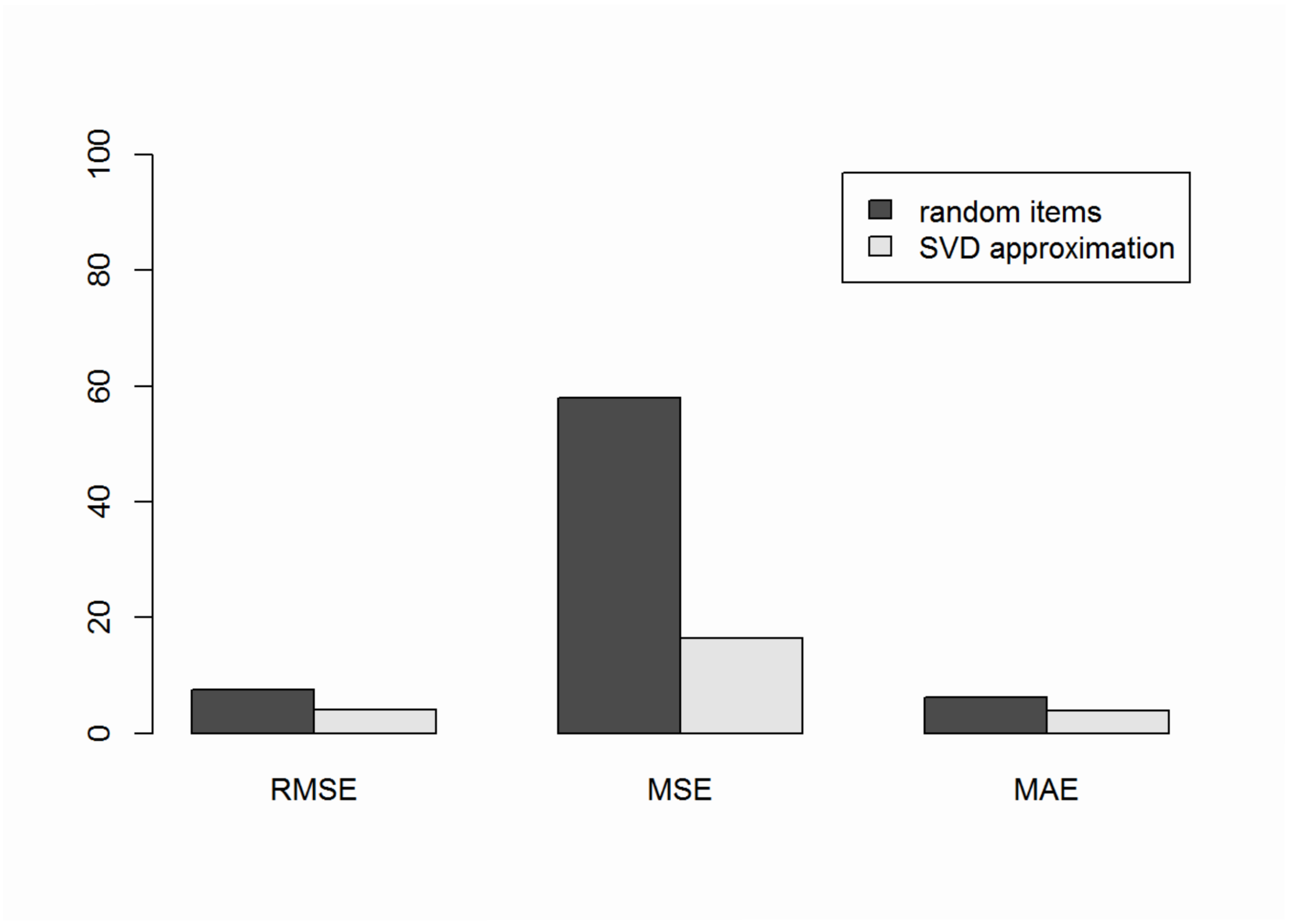
Comparing the two model s evaluation schemes using a ROC curve shows that for a lower number of recommendations the random model actually seems to be a better approach than the SVD model.





Further evaluating the models, we can look at how each actually predicts the rating. Comparing the errors form each model, it is interesting to note that the random method, although appearing to predict better for a group of recommendations, actually has a significantly higher error when evaluating individual predictions.

```
## RANDOM run fold sample [model time prediction time]
##   1  [0.02sec 2.36sec]
##   2  [0sec 2.35sec]
##   3  [0.02sec 2.36sec]
##   4  [0sec 2.35sec]
## SVD run fold sample [model time prediction time]
##   1  [0.03sec 64.12sec]
##   2  [0.03sec 63.22sec]
##   3  [0.03sec 64. 6sec]
##   4  [0.03sec 64.4sec]
```



This is an indication that although a random selection of items offers a better chance of positively rated items, it doesn't predict the user's rating for individual items as well.

This may be a result of how the data was selected, reducing a very sparse matrix down to much denser data for the purpose of this evaluation. We may just have a densely packed matrix full of positively rated items, in which case a random selection of several would be the simplest and best model. It is certainly faster and uses less resources.
This result is surprising however, because it appears that no information is gained by having user and item history, and would need to be examined carefully before deciding that this data is not an appropriate candidate for the SVD method. The reduction of the data may have changed the true shape of the data and the large dimension problem may need to be approached in another fashion, by partitioning the data into subsets instead of only selecting for the dense elements.