MovieLens Report

Dylon Hussain

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Introduction

Machine learning is a ubiquitous tool used in industry today that enables people to make informed decisions from massive amounts of data that would not otherwise be feasible. This report describes a supervised machine learning algorithm that predicts user ratings for movies, trained with the MovieLens dataset. Each observation in this dataset contains the movie, user, rating, and time of rating. This dataset was split into a training set (0.9 of the original observations) and a validation set that was only used to evaluate the performance of the algorithm. The following packages are used in this report.

```
library(ggplot2)
library(tidyverse)
```

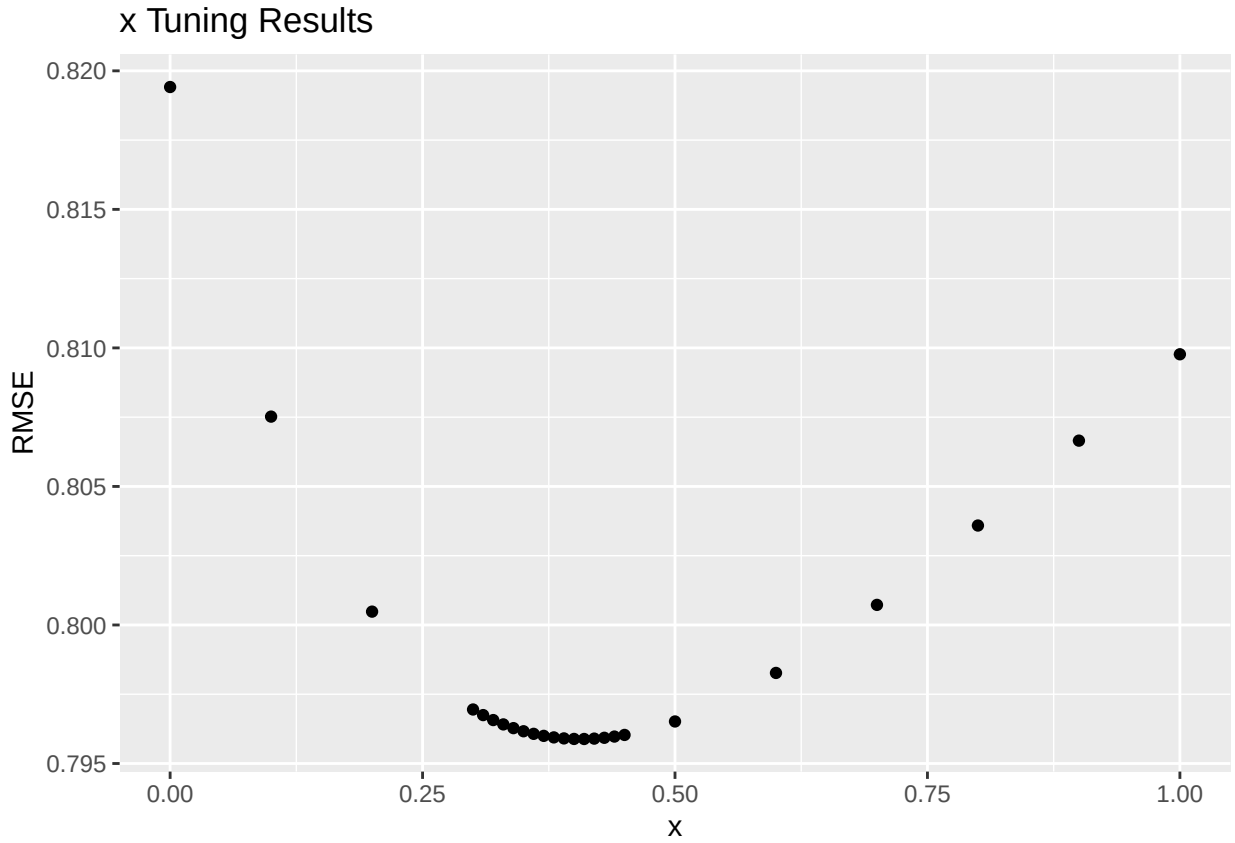
Methods

This prediction algorithm uses matrix factorization (described in Introduction to Data Science R. Irizarry) where it is assumed that $Y_{m,u,t} = \mu + b_m + b_u + bg_{u,m} + b_t + \epsilon$ where $Y_{m,u,t}$ is the rating user u will give movie m at time t, μ is the mean movie rating, b_m is the effect of movie m, b_u is the effect of user u, b_t is the effect of time t, $bg_{u,m}$ is the genre effect for user u and the genres associated with movie m, and ϵ is the independent sampling error. To estimate μ the mean of all ratings in the training set was taken, $\hat{\mu} = \bar{Y}$. b_m was similarly calculated to be the mean of ratings that movie received minus μ, $\hat{b}_m = \overline{Y_m - \hat{\mu}}$. $\hat{b}_u$ was similarly calculated with the following formula $\hat{b}_u = \overline{Y_m - \hat{\mu} - \hat{b_m}}$, this was done to minimize movie biases on the estimate of the user effect. $bg_{u,m}$ was more complicated to estimate: first the estimate of the effect a particular genre would have on a particular users rating was calculated by $\hat{b}_{u,g(m)} = \overline{Y_g - \hat{\mu} - \hat{b_m} - \hat{b_u}}$ then it was assumed that $bg_{u,m} = f_{x,y}(b_{u,g_1}, b_{u,g_2}, ..., b_{u,g_N}, N) = y\frac{\sum b_{u,g_i(m)}}{N^x}$ where y and x are tuning parameters and N is the number of genres associated with the movie. This function was chosen because it includes both the sum ($x = 0$) and the mean ($x = 1$) of b_{u,g_i} and is versatile in the effect of N on $bg_{u,m}$. To tune the parameters of f, 10-fold cross validation was used on the training set to estimate the root mean squared error (RMSE) for a set of tuning parameters and the parameters that minimized the root mean squared error were chosen. 10-fold cross validation was chosen because the training set was large (~9 million observations) so computational efficiency was important; 10-fold cross validation produced an estimate by applying the algorithm to the number of elements in the training set whereas bootstrapping would have required the algorithm to have been applied to more observations or far more calculations after it had been applied. It was then assumed that $b_t \approx \overline{Y_g - \hat{\mu} - \hat{b_m} - \hat{b_u} - \hat{b}_{u,g}}$ and a loess algorithm was applied to $b(t)$.

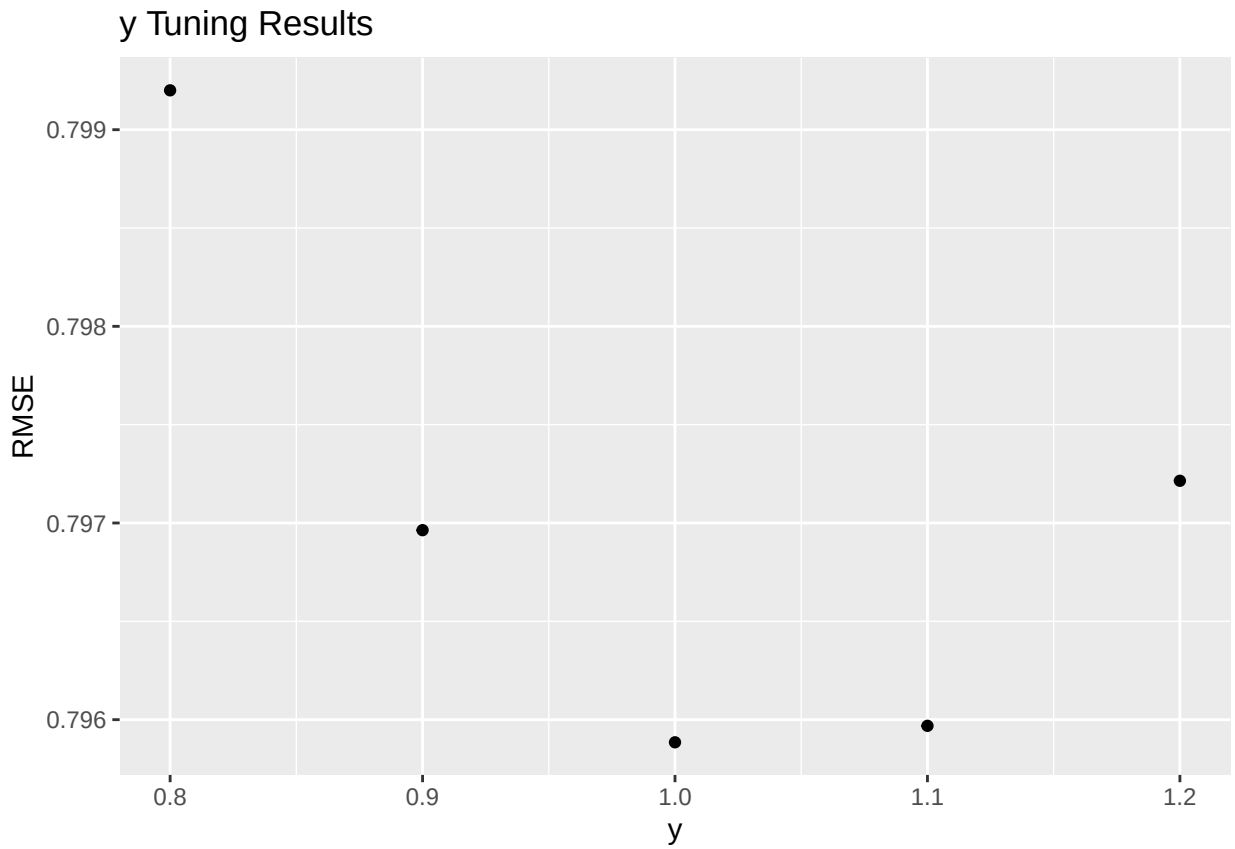
Results

As shown in the graph below, the optimal value for x (for y = 1) was found to be .41. This is consistent with intuition because it was less than 1 (implying that a movie with multiple genres, that a user dislikes,

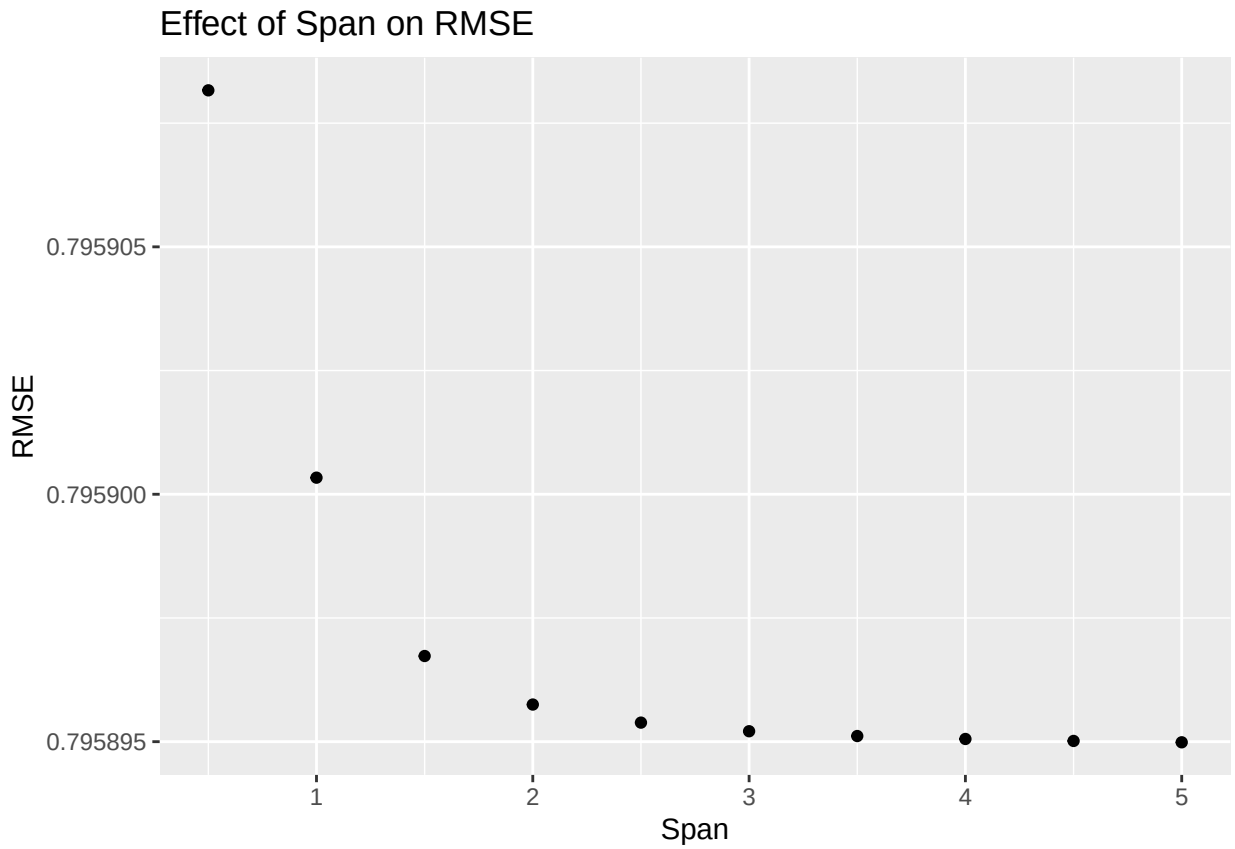
would be rated lower than a movie with just one genre that the user dislikes) and greater than 0 (this would likely cause a run-away effect on movies with many genres).



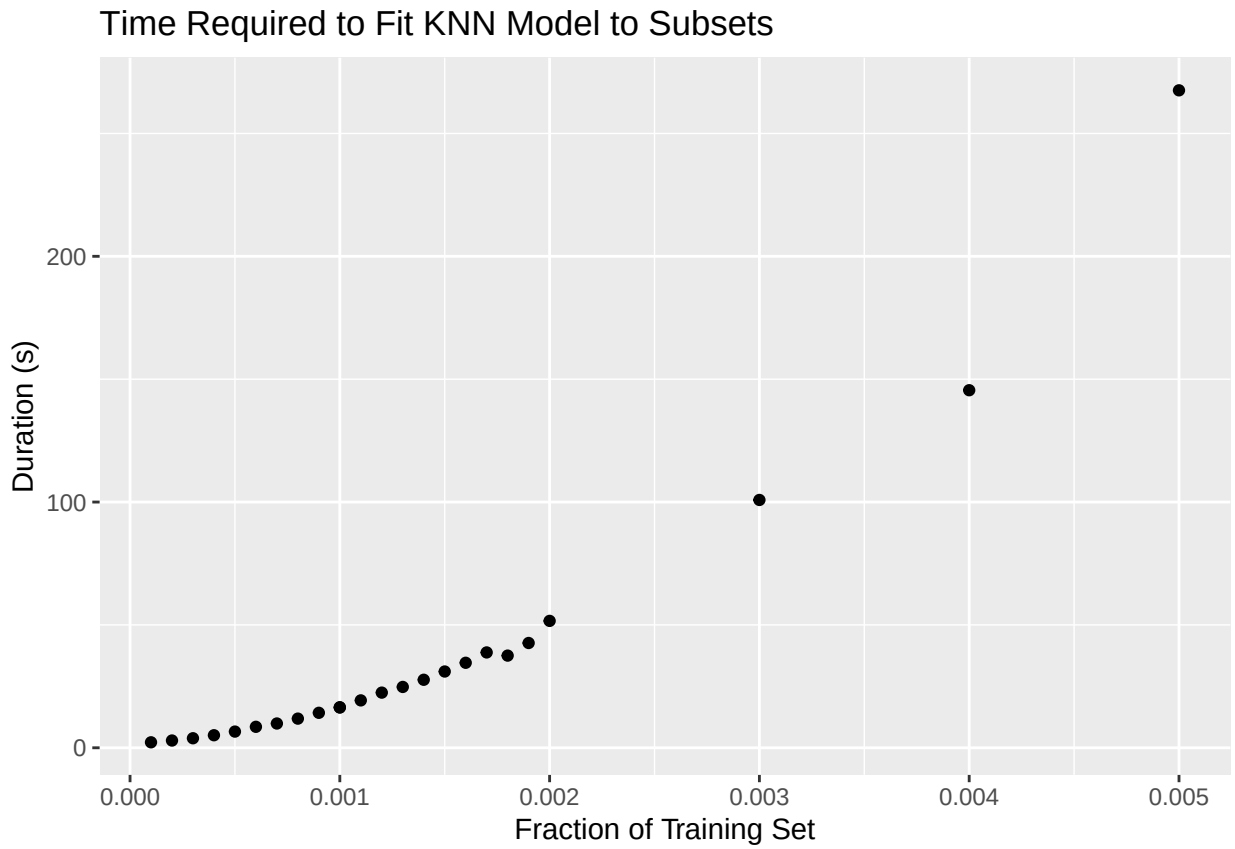
The program was structured to allow for easy minimum searching on the x-y plane but, auspiciously, the minimum y happened to be 1 as shown below. This is not surprising because it indicates that the genre effect has the same weight as the other effects.



When the loess smoothing algorithm was applied to time in an attempt to improve the prediction, the estimated root mean squared error asymptotically approached a value greater than that which was achieved without smoothing, shown in the graph below. For this reason it was assumed that, for this model, $b_t = 0$.



A KNN model was initially implemented to explore potential means to improve the root mean squared error. As shown below, this algorithm scales exponentially with the number of observations making it prohibitively expensive to run on the entire training set. Also the root mean squared error estimation actually increased after applying the KNN algorithm. For these reasons no KNN model was used in the the final code.



The final model using $\hat{Y}_{m,u} = \hat{\mu} + \hat{b}_m + \hat{b}_u + \hat{bg}_{u,m}$ predicted a significant number of impossible ratings so it was corrected so that any $\hat{Y}_{m,u} = 0.5 \forall \hat{Y}_{m,u} < 0.5$ and $\hat{Y}_{m,u} = 5 \forall \hat{Y}_{m,u} > 5$ to keep the predicted rating in the bounds of possible ratings. When this algorithm was applied to the validation set, a root mean squared error of 0.85852 was achieved.

Conclusion

A satisfactory prediction algorithm was produced using matrix decomposition with the model $Y_{m,u} = \mu + b_m + b_u + bg_{u,m} + \epsilon_{u,i}$. Future work on this algorithm would likely benefit from an implementation of a KNN algorithm that uses the entire training set. Due to computational limitations, only a small subset of the training set was used to train the KNN algorithm. Also, exploration of other smoothing algorithms might improve the root mean squared error. These changes would increase the computational cost of running the algorithm so the benefits, in relation to the cost, must be assessed before implementing them. In conclusion, a satisfactory prediction algorithm was achieved using only the user, movie, genre effects, and mean.