

So, like the previous one we will again set working data to source file location, put my Recommender lab library. The data in this case is inbuilt called MovieLens. So, data is equal to MovieLens and the MovieLens data has basically again the various movies, their years, and etcetera and the genres, remember this is something that we have created in the last video and MovieLens is the matrix which is like looks like this so, this is something that is there in MovieLens dataset already available with us.

Now, I have in the previous video have manually created all of these things so here our focus is not to manually create, is already there in the dataset. So, we will directly jump into the picture. So, what I am doing here is that the pre processing first so, MovieLens, I am changing it to a sparse datasets, sparse is a specific form of dataset. So, movie as that means it changes it to sparse dataset it looks like this, the user, the item and the rating that you are getting, the user ID that item ID and the rating ID. Now, I am changing user to numeric and item to numeric data so both are numeric, fair enough.

The screenshot shows the RStudio interface. The main window displays a data table with columns 'user', 'item', and 'rating'. The table shows a few rows of data, including user 1 rating item 1 as 5, user 453 rating item 1 as 3, and so on. The console shows the following R code:

```
(movies$item)),
+
dimnames = list(paste("u", 1:length(unique(movies$u
ser)), sep = ""),
+
paste("m", 1:length(unique(movies$
item)), sep = "")))
> view(sparse_ratings)
> 943*1664
[1] 1569152
> view(movies)
>
```

The screenshot shows the RStudio interface with the 'Attributes' of the 'sparse_ratings' object displayed. The attributes are listed in a table:

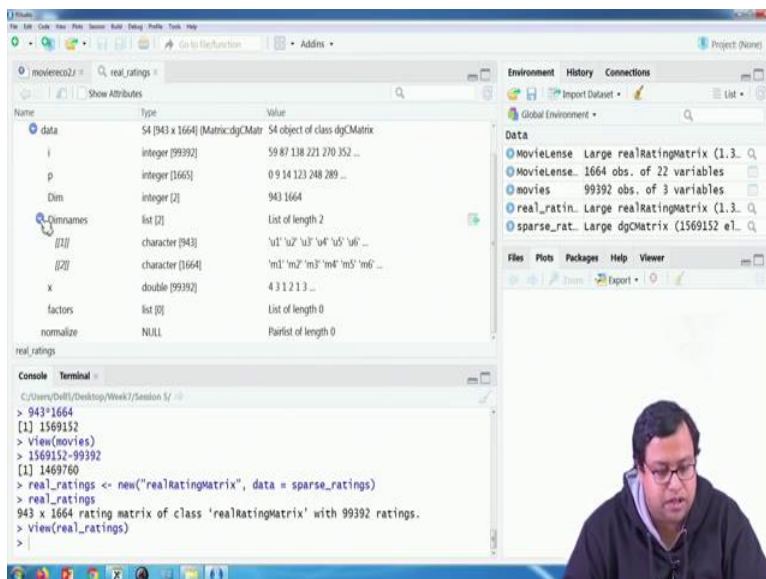
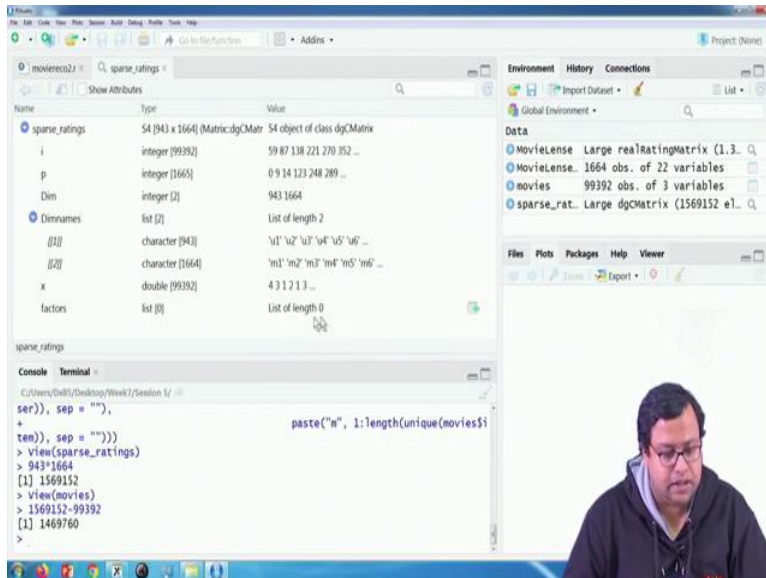
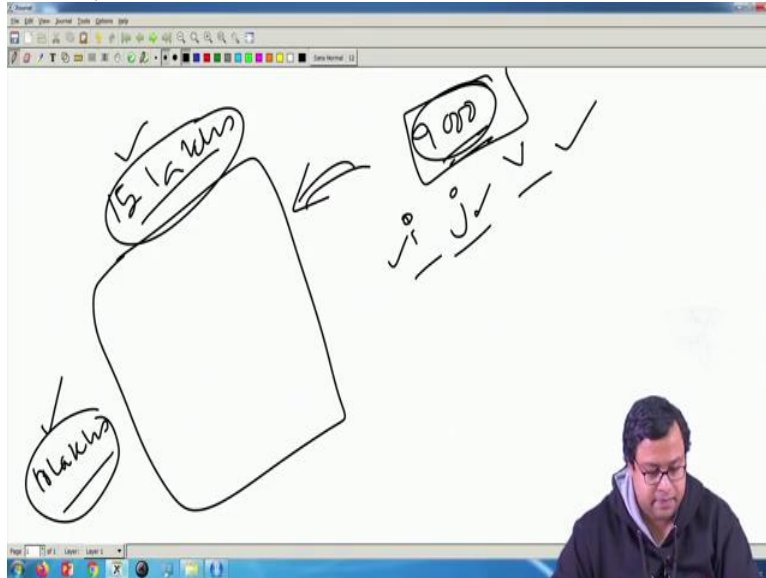
Name	Type	Value
sparse_ratings	54 [943 x 1664] (Matrix:dgCMatr	54 object of class dgCMat
i	integer [99392]	59 87 138 221 270 352 ...
p	integer [1665]	0 9 14 123 248 289 ...
Dim	integer [2]	943 1664
Dimnames	list [2]	List of length 2
[[1]]	character [943]	"u1" "u2" "u3" "u4" "u5" "u6" ...
[[2]]	character [1664]	"m1" "m2" "m3" "m4" "m5" "m6" ...
x	double [99392]	4 3 1 2 1 3 ...
factors	list [0]	List of length 0

The console shows the same R code as the previous screenshot, but with the output of 'view(sparse_ratings)' showing the dimensions of the matrix:

```
> view(sparse_ratings)
> 943*1664
[1] 1569152
> view(movies)
> 1569152-99392
[1] 1469760
>
```

If you check this particular dataset, each column is one unique review, each row is one unique review. So, there are 99,392 reviews but I have 1569152 this much is the value so $1569152 - 99,392$ gives me so, most of the places of blank. Now, if I put zeros there and etcetera that will create a huge matrix, that much matrix, the large matrix I might not need because so, all I would rather know that okay, this is a matrix, I can create those the same thing.

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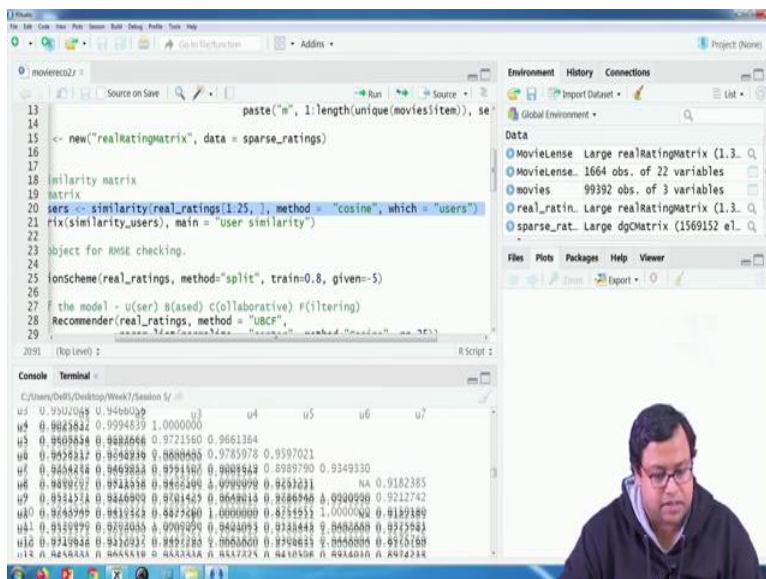
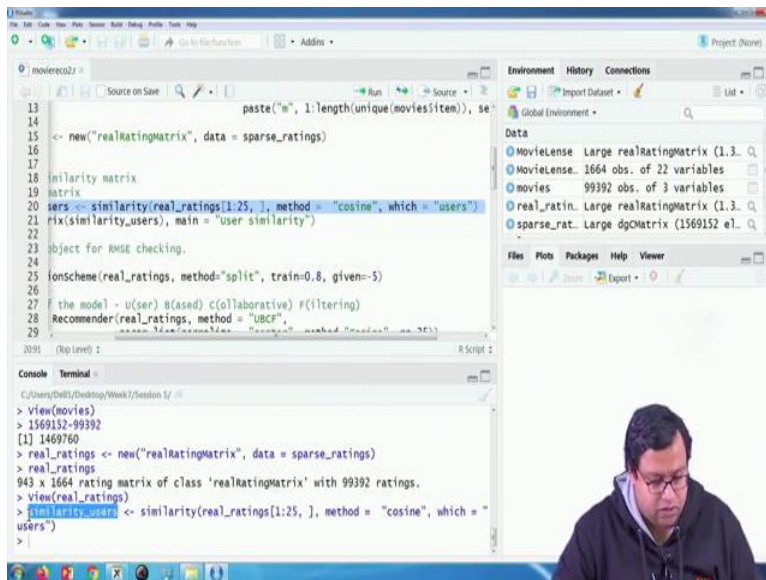
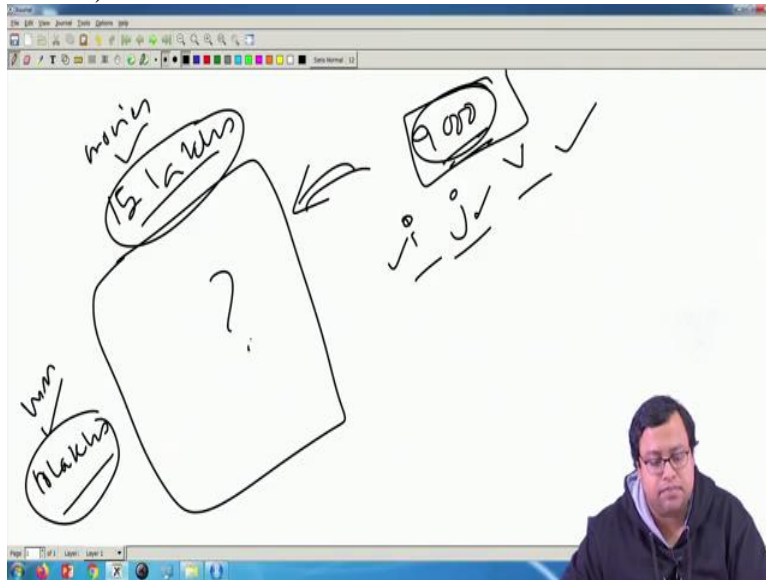
The same information I am create like this, that this is a matrix which has let us say 10 lakh rows here, I do not know and 15 lakh columns here, I do not know. And I will tell that in this 10 lakhs, 15 lakhs, there are only let us say 9,000 elements which are actually positive elements or valid elements, all other elements are zero. So, if I just tell you that there are 10 lakhs and 15 lakhs and there are 9,000 elements, for each element I am giving you i, j and value, that means the row number, column number and the value of that, then you can create this matrix. You can create, it will be very big, but you can create on your own.

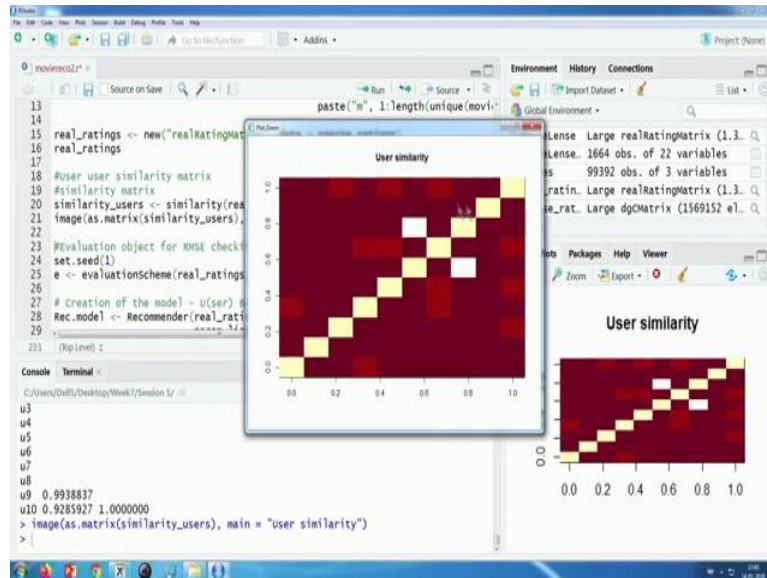
So, all the information that you need to create such a matrix is how many rows, how many columns, this number, and then how many elements and the element position and the element value. So, if you get that the matrix is created, you do not have to create the matrix. So, that is what is here. In sparse matrix, it is giving you the i, the p that means the integer, this is I think the position if I am not wrong, this is the cell number 1665, there are 1665 movies. So, the movies numbers I would say and this is a dimension, just one minute.

So, currently, it is absolutely zero, everything is zero and then I will populate it slowly so, real ratings is equal to new real rating matrix, data is equal to sparse ratings. So, if I just populate it, real ratings, this will give me the same thing whether ratings figures are given, see the rating figures are given here 4, 3, 1, 2 etcetera, etcetera, that is the rating figure that is given and correspondingly the u1, u2, u3 and the character names, the dimension names are given and the position will also be given.

So, these are the positions, this 993 is the position and this is basically the corresponding values at that position. So, that has been given to you in this sparse matrix. Now, based on this sparse matrix what I am getting?

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Basically I am getting something like this, where there are, these are my users and these are my movies and these are my ratings. So now from there, I can create a similarity matrix either user user or item item. So here I am creating a similarity ratings method is equal to cosine and which is equal to user so, I am taking each users at a time and creating a similarity matrix.

So, if I just run this, the similarity of users, first 25 I have taken, this is the similarity of the first 25 users corresponding matrix. So, this looks a little bit bad, let us do it for first 10 or first 10, and you will be able to understand this. This is the similarity matrix for first 10 guys, and if I just find out the image, that is the image, so, the more red it is, the more red it is the stronger is the similarity between two people.

(Refer Slide Time: 7:15)

```
13
14
15 real_ratings <- new("realRatingMatrix")
16 real_ratings
17
18 #user user similarity matrix
19 #similarity matrix
20 similarity_users <- similarity(real_ratings, method="cosine", which="users")
21 image(as.matrix(similarity_users), main="User similarity")
22
23 #Evaluation object for RMSE checking
24 set.seed(1)
25 e <- evaluationScheme(real_ratings, method="split", train=0.8, given=5)
26
27 # Creation of the model - u(user) c(collaborative) #(filtering)
28 Rec.model <- Recommender(real_ratings, method="UBCF",
29                           param=list(normalize="center", method="cosine", nn=25))
30
31 #Making predictions
32 prediction <- predict(Rec.model, real_ratings[1:25, ], type="ratings")
33 as(prediction, "matrix")[,1:5]
34
35 #Estimating RMSE
36 set.seed(1)
37
38 RMSE.model <- Recommender(getdata(e, "train"), method="UBCF",
39                           param=list(normalize="center", method="cosine", nn=25))
40
41 prediction <- predict(RMSE.model, getdata(e, "known"), type="ratings")
42
43 rmse_ubcf <- calcPredictionAccuracy(prediction, getdata(e, "unknown"))[1]
44 rmse_ubcf
45
```

Environment

- real_ratings Large realRatingMatrix (1.3 Mb)
- similarity_users Large realRatingMatrix (1.3 Mb)
- e Large evaluationScheme (2.8 Mb)
- Rec.model Large Recommender (1.5 Mb)

Files Plots Packages Help Viewer

User similarity

```
21 image(as.matrix(similarity_users), main="user similarity")
22
23 #Evaluation object for RMSE checking.
24 set.seed(1)
25 e <- evaluationScheme(real_ratings, method="split", train=0.8, given=5)
26
27 # Creation of the model - u(user) c(collaborative) #(filtering)
28 Rec.model <- Recommender(real_ratings, method="UBCF",
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33 as(prediction, "matrix")[,1:5]
34
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36 set.seed(1)
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38 RMSE.model <- Recommender(getdata(e, "train"), method="UBCF",
39                           param=list(normalize="center", method="cosine", nn=25))
40
41 prediction <- predict(RMSE.model, getdata(e, "known"), type="ratings")
42
43 rmse_ubcf <- calcPredictionAccuracy(prediction, getdata(e, "unknown"))[1]
44 rmse_ubcf
45
```

Environment

- e Large evaluationScheme (2.8 Mb)
- Movielense Large realRatingMatrix (1.3 Mb)
- Movielense.1664 obs. of 22 variables
- movies 99392 obs. of 3 variables
- real_ratin Large realRatingMatrix (1.3 Mb)
- Rec.model Large Recommender (1.5 Mb)

Files Plots Packages Help Viewer

User similarity

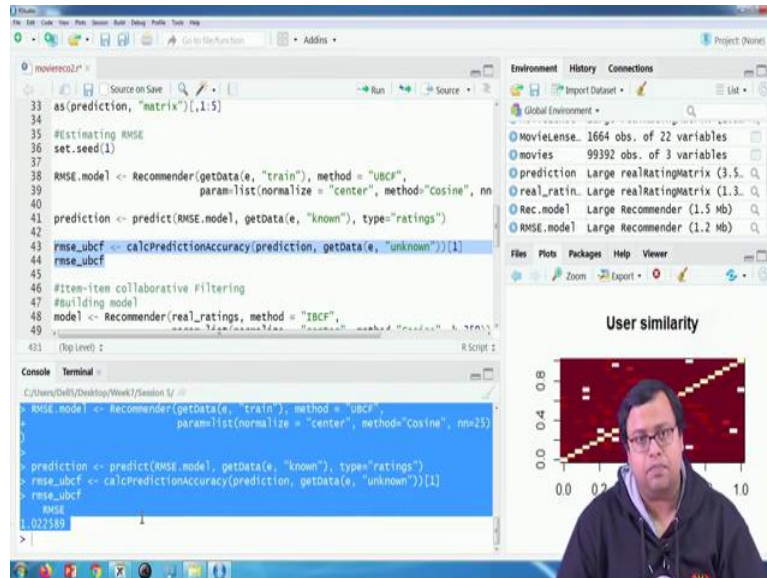
```
29
30 param=list(normalize="center", method="cosine", nn=25)
31
32 #Making predictions
33 prediction <- predict(Rec.model, real_ratings[1:25, ], type="ratings")
34 as(prediction, "matrix")[,1:5]
35
36 #Estimating RMSE
37 set.seed(1)
38 RMSE.model <- Recommender(getdata(e, "train"), method="UBCF",
39                           param=list(normalize="center", method="cosine", nn=25))
40
41 prediction <- predict(RMSE.model, getdata(e, "known"), type="ratings")
42
43 rmse_ubcf <- calcPredictionAccuracy(prediction, getdata(e, "unknown"))[1]
44 rmse_ubcf
45
```

Environment

- e Large evaluationScheme (2.8 Mb)
- Movielense Large realRatingMatrix (1.3 Mb)
- Movielense.1664 obs. of 22 variables
- movies 99392 obs. of 3 variables
- prediction Large realRatingMatrix (573 B)
- real_ratin Large realRatingMatrix (1.3 Mb)

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User similarity



So, 1 to 25 I have taken, initially I will come back to that 1 to 25 and then I will just run this once more. So, image of similarity comes up to be this, you see there are certain guys which are absolutely zero, the red ones are very similar and there are some small less red ones which are in between, so, something like that is there.

Now, I will find out with this similarity matrix how I can create a user based collaborative filtering. So, e is the evaluation where I am saying the evaluation parameter is the split method with training data 80 % rest data with 20 % and given $n=5$. So, I run that and then the recommender model is UBCF that means user based collaborative filtering and the parameter is normalized towards the center.

So, it is a center normalization, method is cosine and nearest neighbor is 25. So, take top first 25 similarity so, if I just run that, and based on that if I mark the predictions, I get these are my predictions for the first 5 m_1, m_2, m_3, m_4, m_5 these are my corresponding user 1 to user 25 the predictions are given.

Now, based on that I will estimate the RMSE of this particular model so, the RMSE of this particular model is, see it is a training testing model. So, 80 % data has been taken so, rest of the 20 % we are checking that whatever recommendations I am giving and whatever this guy has actually seen are same or not. So, to do that I am creating the prediction here based on the same UBCF same model that I have created. And then I am calculating the RMSE which is

the calculating the prediction accuracy, RMSE is coming 1.02. So, I will have used UBCF the same thing I will use by item based IBCF and then I will see that what is RMSE score.

So, whatever was there before UBCF, I have changed to IBCF, that is all and $k = 350$ means, nearest 350 movies you will be taken into account. So, instead of 25, because there are more number of movies and very less number of users so, user to user similarity 25 users is okay. But movie to movie similarity you have to take more movies.

So, that is what I am doing here and then predicting it so, it will take some time to do it 350 by 350, you might want to probably run it in the background because it might take some time, because I have taken 350 by 350 rather I will stop it probably.

(Refer Slide Time: 10:17)

The screenshot displays the RStudio environment with the following components:

- Source Editor:** Contains R code for building a recommender model using IBCF with $k=350$ and making predictions. The code includes comments and function calls like `Recommender`, `predict`, and `as`.
- Environment:** Lists objects in the workspace, including `model` (Large Recommender), `Movielense` (Large realRatingMatrix), `Movielense_1664` (obs. of 22 variables), `movies` (99392 obs. of 3 variables), `prediction` (Formal class realRatingMatr.), and `real_ratin` (Large realRatingMatrix).
- Console:** Shows the execution of the prediction code, resulting in a matrix of predicted ratings for users u1 through u7 across movies m1 through m5.
- Plots:** A heatmap titled "User similarity" is visible, showing a diagonal pattern of high similarity (red) and low similarity (black) between users.

```

53 as(prediction, "matrix")[1:5]
54
55 #Estimating RMSE
56 set.seed(1)
57
58 model <- Recommender(getData(e, "train"), method = "IBCF",
59                       param=list(normalize = "center", method="cosine",k=35))
60
61 prediction <- predict(model, getData(e, "know"), type="ratings")
62
63 rmse_ubcf <- calcPredictionAccuracy(prediction, getData(e, "unknown"))[1]
64 rmse_ubcf
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68 #MODEL APPLICATION
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```

Environment History Connections

- Global Environment
- model Large Recommender (975 kb)
- Movielense Large realRatingMatrix (1.3...)
- Movielense_1664 obs. of 22 variables
- movies 99392 obs. of 3 variables
- prediction Formal class realRatingMatr...
- real_ratin Large realRatingMatrix (1.3...)

Files Plots Packages Help Viewer

Zoom Export

User similarity

Console Terminal

```

C:/Users/Dell/Desktop/Week7/Session 1/ >
u21 NA NA NA NA NA NA
u22 4.500000 4.500000 NA NA
u23 3.000000 4.000000 3 5 NA
u24 NA NA NA NA NA NA
u25 NA 4.000000 NA NA NA
> set.seed(1)
>
> model <- Recommender(getData(e, "train"), method = "IBCF",
+ param=list(normalize = "center", method="cosine",k=35))

```

```

58 model <- Recommender(getData(e, "train"), method = "IBCF",
59                       param=list(normalize = "center", method="cosine",k=35))
60
61 prediction <- predict(model, getData(e, "know"), type="ratings")
62
63 rmse_ubcf <- calcPredictionAccuracy(prediction, getData(e, "unknown"))[1]
64 rmse_ubcf
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68 #MODEL APPLICATION
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```

Environment History Connections

- prediction Large realRatingMatrix (1.6...)
- real_ratin Large realRatingMatrix (1.3...)
- Rec.model Large Recommender (1.5 Mb)
- recommende_ Formal class topNList
- RMSE.model Large Recommender (1.2 Mb)
- sparse_rat_ Large dgMatrix (1569152 el...)

Files Plots Packages Help Viewer

Zoom Export

User similarity

Console Terminal

```

C:/Users/Dell/Desktop/Week7/Session 1/ >
RMSE
1.35408
> real_ratings[610,]
1 x 1664 rating matrix of class 'realRatingMatrix' with 295 ratings.
> recommended.items.u610<- predict(Rec.model, real_ratings[610,], n=5)
> as(recommended.items.u610, "list")
$u610
[1] "m831" "m100" "m574" "m623" "m1502"
>

```

```

58 model <- Recommender(getData(e, "train"), method = "IBCF",
59                       param=list(normalize = "center", method="cosine",k=35))
60
61 prediction <- predict(model, getData(e, "know"), type="ratings")
62
63 rmse_ubcf <- calcPredictionAccuracy(prediction, getData(e, "unknown"))[1]
64 rmse_ubcf
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68 #MODEL APPLICATION
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```

Environment History Connections

- prediction Large realRatingMatrix (1.6...)
- real_ratin Large realRatingMatrix (1.3...)
- Rec.model Large Recommender (1.5 Mb)
- recommende_ Formal class topNList
- RMSE.model Large Recommender (1.2 Mb)
- sparse_rat_ Large dgMatrix (1569152 el...)

Files Plots Packages Help Viewer

Zoom Export

User similarity

Console Terminal

```

C:/Users/Dell/Desktop/Week7/Session 1/ >
RMSE
1.35408
> real_ratings[610,]
1 x 1664 rating matrix of class 'realRatingMatrix' with 295 ratings.
> recommended.items.u610<- predict(Rec.model, real_ratings[610,], n=5)
> as(recommended.items.u610, "list")
$u610
[1] "m831" "m100" "m574" "m623" "m1502"
>

```

Let us do it for 35 then we can actually see the result so, 35 by 35 so, it has to be actually 350. It has to be big, but I am doing it because the time otherwise will be very high. So, 35 let us check the result. Still taking quite a bit of time. So, let it, I will give it one minute if it does not stop in one minute then we will see, we will probably reduce it. So, the real ratings, then what we will do is we will actually change it to probably a little bit so I have got 35 for m1, m2, m3, m4, m5. And that has been, that is something that has been plotted for the 25 observations and then if I do it for set seed1, the same thing $k = 35$ when I try to make the prediction, I will get a prediction something like this.

So it might take one minute again, because now it will be creating the model for the testing data and with the testing data, it will create the prediction and then match the prediction with the actual value. And it will give me RMSE score. So, it might take another one minute probably to give the RMSE score, if you remember the previous RMSE score was 1.02. So, I have to check the whether this RMSE code is similar to that or not.

So, you can do a...so, here it is 1.35 which is higher so, user to user is something that matches better than item to item so, this is a trial and error procedure. And the moral obligation is what? So, let us see for 6, item number 610 I will be creating that whether somebody should see it or not. So, 164 ratings of class and this class has been used for user 610 the best movies are m831, m100, m574, m623 and m1502.

So, again, the reference is this particular link you can go and read about from this link the details that the code has been taken from there. But the idea is that you can create a user if even if you have a huge rating matrix, you can change it to your sparse matrix and then use the recommender lab, recommender lab I am suggesting because recommender lab is fast, much faster than you running your loop. If you do not want to use recommender lab you can run your own loops also, it might take a little bit more time if you do column operations, you might be able to do a bit more faster.

But that is something that you can do. So, we have discussed quite a lot about recommendation engine for the last six videos. Please carefully see them, the code is sometimes are difficult, please listen to it carefully and try to do it on your hand, try to do it in a new dataset. Best practice is create a new dataset from some other sources from let us say a source that is available in Kaggle or you get your own dataset from somewhere or create a

small matrix on your own, and then try to replicate whatever work, whatever data that we have done because these codes were readymade for that particular data.

That is why is coming very simple and smooth but if the data is bad then the code has to be changed and you have to actually fight a little bit to find out those codes. So I will strongly suggest try to do that and in the next week, we will meet with newer topics. Thank you very much for listening to me and following me up and I will see you in the next week. Thank you.