Final Project

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For my Final project I will build a recommendation system that will look at recommendation from Item Based Collaborative Filtering, User Based Collaborative Filtering and recommendations by genre with Hierarchal clustering. I will create models to get Movies from similar Genres based on the distance of the clusters.Hierarchal Clustering is an unsupervised learning method where the goal is to segment data into similar groups.The dataset used is from the MovieLens dataset avaliable in the Recommenderlab package or from their website http://grouplens.org/datasets/movielens.

Data Exploration

```r
#Visualization of the data
str(MovieLense)
```

```
## Formal class 'realRatingMatrix' [package "recommenderlab"] with 2 slots
##   ..@ data     :Formal class 'dgCMatrix' [package "Matrix"] with 6 slots
##   .. .. ..@ i       : int [1:99392] 0 1 4 5 9 12 14 15 16 17 ...
##   .. .. ..@ p       : int [1:1665] 0 452 583 673 882 968 994 1386 1605 1904 ...
##   .. .. ..@ Dim     : int [1:2] 943 1664
##   .. .. ..@ Dimnames:List of 2
##   .. .. .. ..$ : chr [1:943] "1" "2" "3" "4" ...
##   .. .. .. ..$ : chr [1:1664] "Toy Story (1995)" "GoldenEye (1995)" "Four Rooms (1995)" "Get Shorty
##   .. .. ..@ x       : num [1:99392] 5 4 4 4 4 3 1 5 4 5 ...
##   .. .. ..@ factors : list()
##   ..@ normalize: NULL
```

```r
class(MovieLense)
```

```
## [1] "realRatingMatrix"
## attr(,"package")
## [1] "recommenderlab"
```

```r
head(MovieLense)
```

```
## 1 x 1664 rating matrix of class 'realRatingMatrix' with 271 ratings.
```

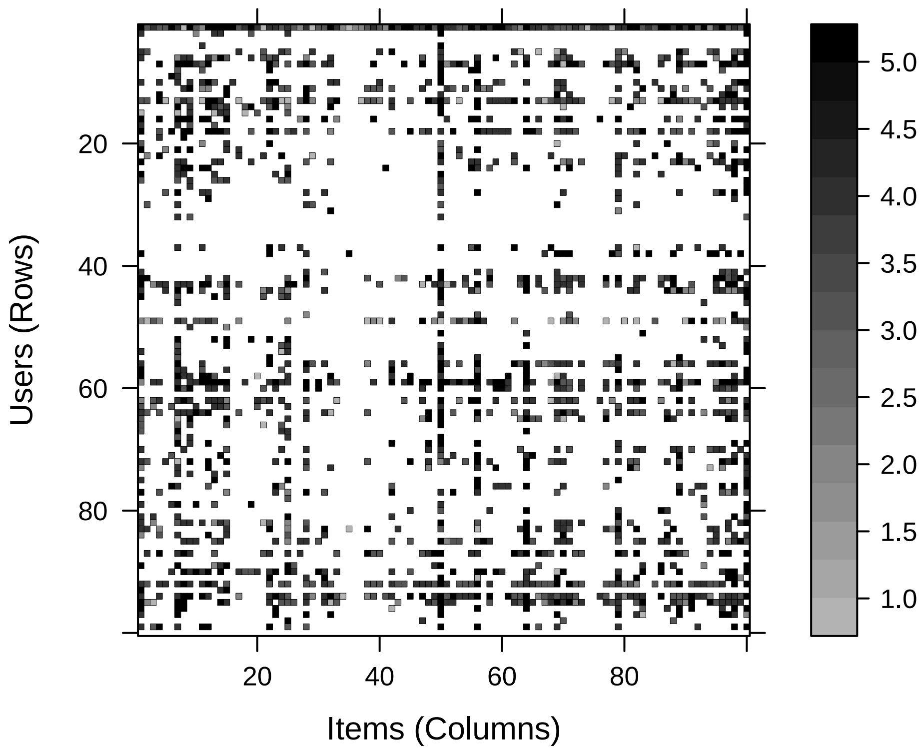
```r
dim(MovieLense)
```

```
## [1]  943 1664
```

```r
summary(MovieLense)
```

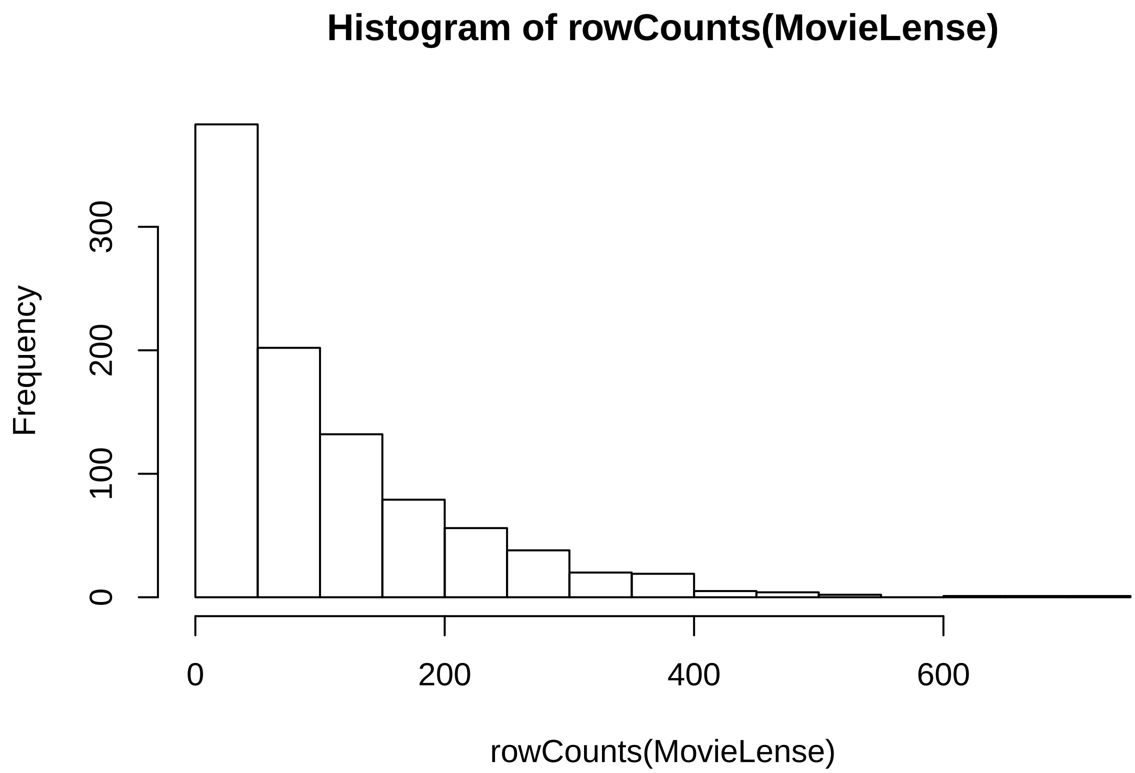
```
##          Length            Class              Mode 
##               1 realRatingMatrix                S4
```

```r
## visualize part of the matrix
image(MovieLense[1:100,1:100])
```

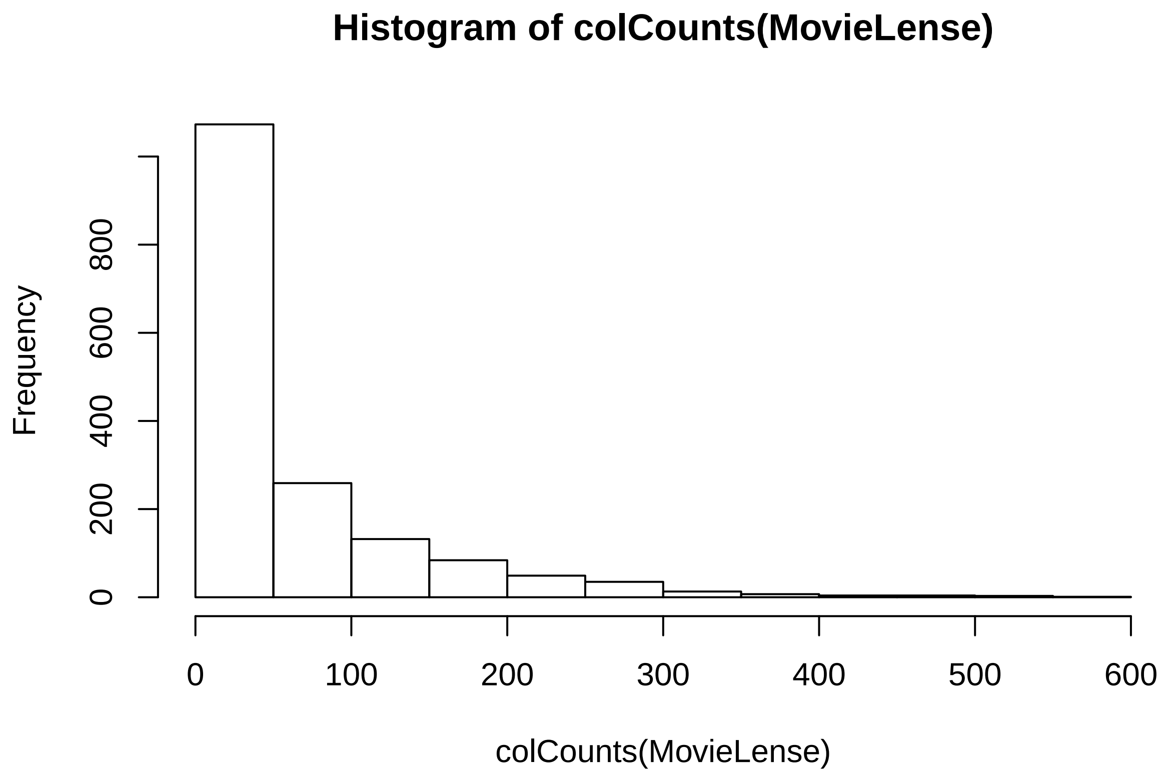


Dimensions: 100 x 100

```r
## number of ratings per user
hist(rowCounts(MovieLense))
```




```
## number of ratings per movie
hist(colCounts(MovieLense))
```




```
## mean rating (averaged over users)
mean(rowMeans(MovieLense))
```

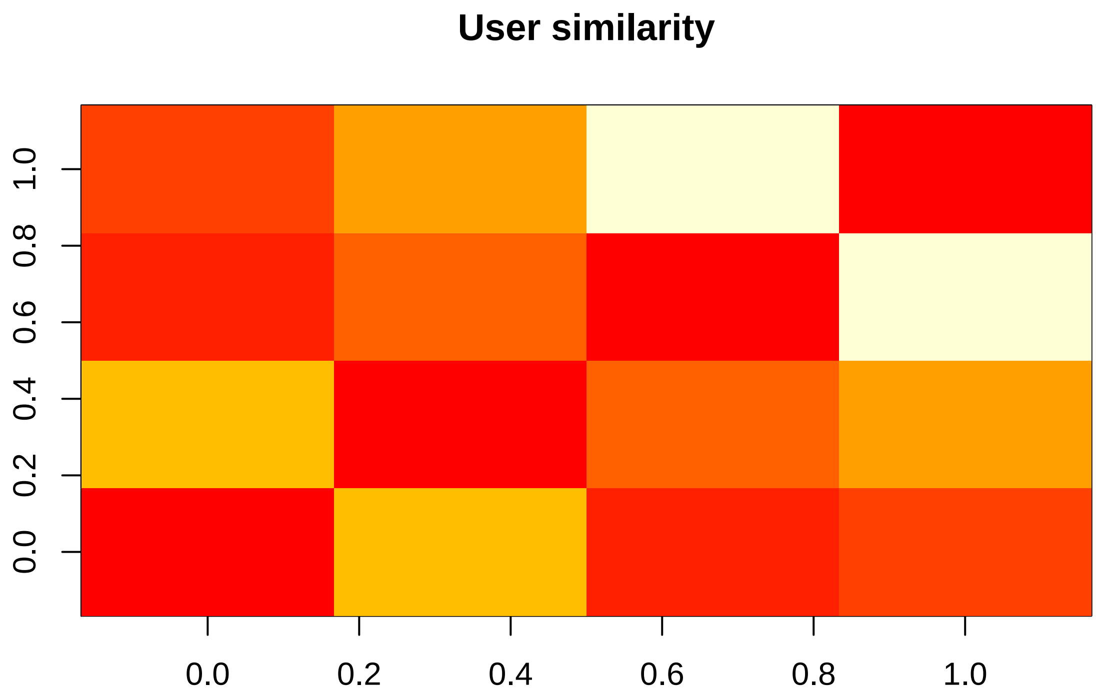
```
## [1] 3.587565
```

calculate similarity between user ratings and item ratings

```
#calculate Similarity matrix
similarity_users <- similarity(MovieLense[1:4,], method = "cosine", which = "users")
as.matrix( similarity_users)
```

```
##            1          2          3          4
## 1 0.00000000 0.16893670 0.03827203 0.06634975
## 2 0.16893670 0.00000000 0.09706862 0.15310468
## 3 0.03827203 0.09706862 0.00000000 0.33343036
## 4 0.06634975 0.15310468 0.33343036 0.00000000
```

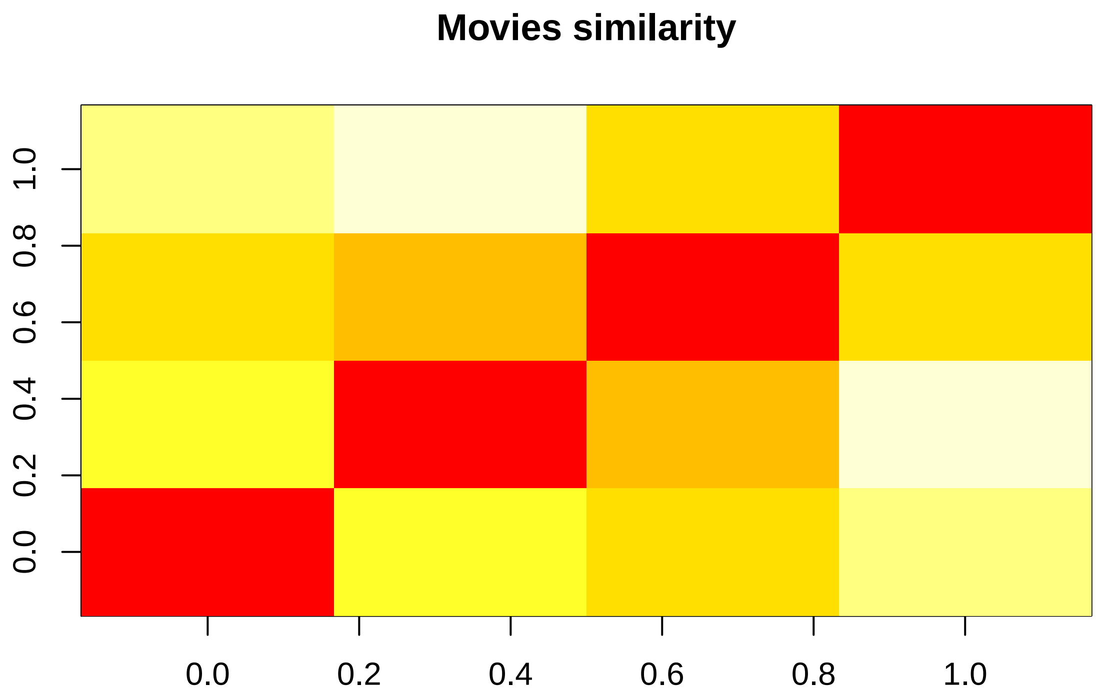
```
image(as.matrix(similarity_users), main = "User similarity")
```




```
  similarity_items <- similarity(MovieLense[,1:4], method = "cosine", which = "items")
as.matrix(similarity_items)
```

```
##                    Toy Story (1995) GoldenEye (1995) Four Rooms (1995)
## Toy Story (1995)          0.0000000        0.4023822         0.3302448
## GoldenEye (1995)          0.4023822        0.0000000         0.2730692
## Four Rooms (1995)         0.3302448        0.2730692         0.0000000
## Get Shorty (1995)         0.4549379        0.5025708         0.3248664
##                    Get Shorty (1995)
## Toy Story (1995)           0.4549379
## GoldenEye (1995)           0.5025708
## Four Rooms (1995)          0.3248664
## Get Shorty (1995)          0.0000000
```

```
image(as.matrix(similarity_items), main = "Movies similarity")
```



splitting the data set into training and test where i will use the traing to traing the data and use the test data set to predict the movies by IBCF and UBCF

```
#=========================================================================================================
#Splitting the dataset into Train and test
#=========================================================================================================
#Subsetting the dataset
ratings_movies <- MovieLense[ rowCounts( MovieLense) > 50, colCounts( MovieLense) > 100]
ratings_norm<-(ratings_movies)

which_train<-sample(x=c(TRUE,FALSE),size = nrow(ratings_norm),replace = TRUE,prob = c(.8,.2))
rec_data_train<-ratings_movies[which_train,]
rec_data_test<-ratings_movies[!which_train,]
```

```
#Prediction for Item Based Collaborative Filtering

#build recommender Model
rec_modelI<-Recommender(data=rec_data_train,method='IBCF')

#predict 5 movies for specific users
n_rec<-5
recom2<-predict(rec_modelI,newdata=rec_data_test[1],n=n_rec)
#convert recommenderlab object to readable list
recom_list <- as(recom2, "list")
recom_list
```

```
## $`1`
## [1] "Schindler's List (1993)"  "Secrets & Lies (1996)"
## [3] "Casablanca (1942)"        "L.A. Confidential (1997)"
## [5] "Boot, Das (1981)"
```

```r
#predict 10 movies for N users
rec_predictI<-predict(rec_modelI,newdata=rec_data_test,n=n_rec)
rec_predictI
```

```
## Recommendations as 'topNList' with n = 5 for 104 users.
```

```r
rec_matrix<-sapply (rec_predictI@items,
function(x)
  {
  colnames(rec_data_test)[x]
  }
)
rec_matrix[,1:5]
```

```
##      1                          7
## [1,] "Schindler's List (1993)"  "Bound (1996)"
## [2,] "Secrets & Lies (1996)"    "Good Will Hunting (1997)"
## [3,] "Casablanca (1942)"        "Searching for Bobby Fischer (1993)"
## [4,] "L.A. Confidential (1997)" "Wag the Dog (1997)"
## [5,] "Boot, Das (1981)"         "Wrong Trousers, The (1993)"
##      12                                   77
## [1,] "Ed Wood (1994)"                     "Kiss the Girls (1997)"
## [2,] "Quiz Show (1994)"                   "Spawn (1997)"
## [3,] "What's Eating Gilbert Grape (1993)" "Seven Years in Tibet (1997)"
## [4,] "Mask, The (1994)"                   "Professional, The (1994)"
## [5,] "Ghost and the Darkness, The (1996)" "Birds, The (1963)"
##      121
## [1,] "Searching for Bobby Fischer (1993)"
## [2,] "Nightmare on Elm Street, A (1984)"
## [3,] "Star Trek VI: The Undiscovered Country (1991)"
## [4,] "Monty Python and the Holy Grail (1974)"
## [5,] "Arsenic and Old Lace (1944)"
```

```r
#==========================================================================================
#Prediction for User Based Collaborative Filtering
#==========================================================================================
#build recommender Model
rec_modelU<-Recommender(data=rec_data_train,method='UBCF')
model_details <- getModel(rec_modelU)

#predict 5 movies for specific users
n_rec<-10

#Obtain top 10 recommendations for 1st user in dataset
recom <- predict(object=rec_modelU, newdata=rec_data_test[1], n=n_rec)

#convert recommenderlab object to readable list
```

```r
recom_list <- as(recom, "list")
recom_list
```

```
## $`1`
##  [1] "L.A. Confidential (1997)"
##  [2] "Casablanca (1942)"
##  [3] "Glory (1989)"
##  [4] "Butch Cassidy and the Sundance Kid (1969)"
##  [5] "Lawrence of Arabia (1962)"
##  [6] "Close Shave, A (1995)"
##  [7] "Schindler's List (1993)"
##  [8] "Dr. Strangelove or: How I Learned to Stop Worrying and Love the Bomb (1963)"
##  [9] "Magnificent Seven, The (1954)"
## [10] "Heathers (1989)"
```

```r
#predict 10 movies for N users
rec_predictU<-predict(rec_modelU,newdata=rec_data_test,n=n_rec)
rec_predictU
```

```
## Recommendations as 'topNList' with n = 10 for 104 users.
```

```r
rec_matrixU<-sapply(rec_predictU@items,function(x){colnames(rec_data_test)[x]})
rec_matrixU[,1:5]
```

```
##       1
##  [1,] "L.A. Confidential (1997)"
##  [2,] "Casablanca (1942)"
##  [3,] "Glory (1989)"
##  [4,] "Butch Cassidy and the Sundance Kid (1969)"
##  [5,] "Lawrence of Arabia (1962)"
##  [6,] "Close Shave, A (1995)"
##  [7,] "Schindler's List (1993)"
##  [8,] "Dr. Strangelove or: How I Learned to Stop Worrying and Love the Bomb (1963)"
##  [9,] "Magnificent Seven, The (1954)"
## [10,] "Heathers (1989)"
##       7
##  [1,] "Lone Star (1996)"
##  [2,] "Leaving Las Vegas (1995)"
##  [3,] "Wrong Trousers, The (1993)"
##  [4,] "Hoop Dreams (1994)"
##  [5,] "Mighty Aphrodite (1995)"
##  [6,] "Close Shave, A (1995)"
##  [7,] "This Is Spinal Tap (1984)"
##  [8,] "Trainspotting (1996)"
##  [9,] "L.A. Confidential (1997)"
## [10,] "Amistad (1997)"
##       12
##  [1,] "To Kill a Mockingbird (1962)"
##  [2,] "Shawshank Redemption, The (1994)"
##  [3,] "Braveheart (1995)"
##  [4,] "One Flew Over the Cuckoo's Nest (1975)"
##  [5,] "Pulp Fiction (1994)"
```

```
##  [6,] "Glory (1989)"
##  [7,] "Indiana Jones and the Last Crusade (1989)"
##  [8,] "Casablanca (1942)"
##  [9,] "Usual Suspects, The (1995)"
## [10,] "E.T. the Extra-Terrestrial (1982)"
##       77
##  [1,] "2001: A Space Odyssey (1968)"
##  [2,] "Twelve Monkeys (1995)"
##  [3,] "Usual Suspects, The (1995)"
##  [4,] "Shawshank Redemption, The (1994)"
##  [5,] "Apocalypse Now (1979)"
##  [6,] "Unforgiven (1992)"
##  [7,] "Rear Window (1954)"
##  [8,] "Wrong Trousers, The (1993)"
##  [9,] "Henry V (1989)"
## [10,] "Babe (1995)"
##       121
##  [1,] "Shawshank Redemption, The (1994)"
##  [2,] "Amadeus (1984)"
##  [3,] "L.A. Confidential (1997)"
##  [4,] "Lawrence of Arabia (1962)"
##  [5,] "Princess Bride, The (1987)"
##  [6,] "Twelve Monkeys (1995)"
##  [7,] "Godfather: Part II, The (1974)"
##  [8,] "Secrets & Lies (1996)"
##  [9,] "Chasing Amy (1997)"
## [10,] "Bound (1996)"
```

Using the built in functions from RecommenderLab to evaluate the models,Using K fold validation it can be seen that UBCF performs better than IBCF

```
#Model Evaluation
#k=5 meaning a 5-fold cross validation. given=3 meaning a Given-3 protocol
n_fold=5
evaluation_scheme <- evaluationScheme(ratings_movies, method="cross-validation", n_fold, given=3, goodRa
evaluation_results <- evaluate(evaluation_scheme, method="UBCF")
```

```
## UBCF run fold/sample [model time/prediction time]
##   1  [0sec/0.17sec]
##   2  [0sec/0.36sec]
##   3  [0.02sec/0.15sec]
##   4  [0sec/0.18sec]
##   5  [0.01sec/0.17sec]
##   6  [0sec/0.17sec]
##   7  [0.02sec/0.17sec]
##   8  [0sec/0.17sec]
##   9  [0sec/0.17sec]
##   10  [0sec/0.19sec]
```

```
eval_results <- getConfusionMatrix(evaluation_results)[[1]]
eval_results#The evaluation results of the top-N recommender
```

```
##            TP        FP        FN        TN precision     recall         TPR
```

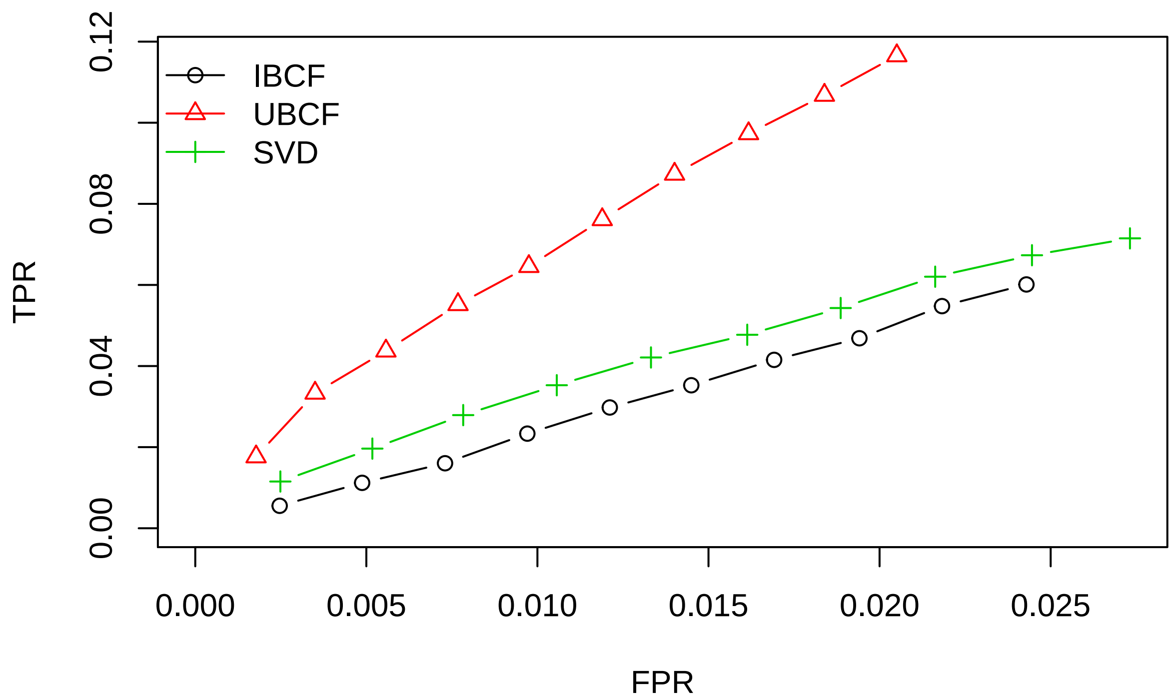
```
## 1  0.4285714 0.3928571 25.19643 302.9821 0.5217391 0.02069579 0.02069579
## 2  0.7500000 0.8928571 24.87500 302.4821 0.4565217 0.03192758 0.03192758
## 3  1.0178571 1.4464286 24.60714 301.9286 0.4130435 0.04232663 0.04232663
## 4  1.2678571 2.0178571 24.35714 301.3571 0.3858696 0.05398871 0.05398871
## 5  1.5000000 2.6071429 24.12500 300.7679 0.3652174 0.06113478 0.06113478
## 6  1.7678571 3.1607143 23.85714 300.2143 0.3586957 0.07305189 0.07305189
## 7  1.9107143 3.8392857 23.71429 299.5357 0.3322981 0.07744686 0.07744686
## 8  2.1250000 4.4464286 23.50000 298.9286 0.3233696 0.08694115 0.08694115
## 9  2.3392857 5.0535714 23.28571 298.3214 0.3164251 0.09638930 0.09638930
## 10 2.6250000 5.5892857 23.00000 297.7857 0.3195652 0.10736091 0.10736091
##            FPR
## 1  0.001261601
## 2  0.002869570
## 3  0.004662199
## 4  0.006523131
## 5  0.008432455
## 6  0.010241898
## 7  0.012453662
## 8  0.014436392
## 9  0.016419979
## 10 0.018161584
```

```r
algorithms <- list(
  IBCF = list(name = "IBCF", param = NULL),
  UBCF = list(name = "UBCF", param = NULL),
  SVD = list(name = "SVD", param = NULL)
)
evlist <- evaluate(evaluation_scheme, algorithms)
```

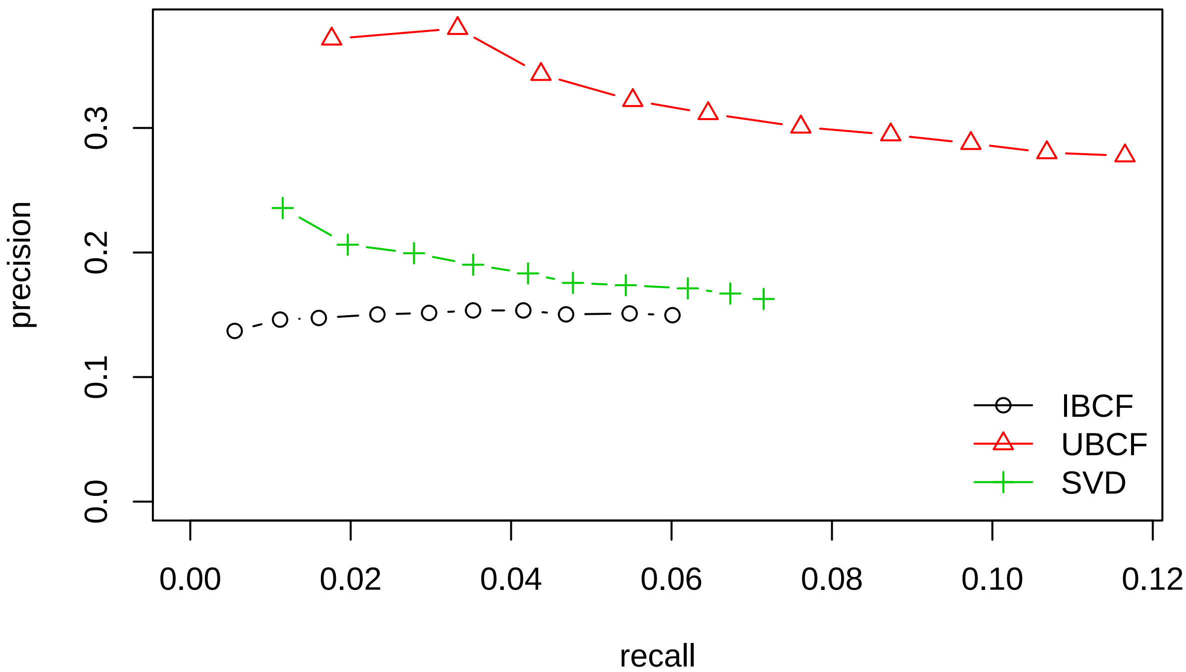
```
## IBCF run fold/sample [model time/prediction time]
##   1  [0.79sec/0.03sec]
##   2  [0.79sec/0.01sec]
##   3  [0.77sec/0.03sec]
##   4  [0.8sec/0.03sec]
##   5  [0.8sec/0.03sec]
##   6  [0.73sec/0.03sec]
##   7  [0.73sec/0.03sec]
##   8  [0.82sec/0.01sec]
##   9  [0.73sec/0.02sec]
##   10  [0.75sec/0.04sec]
## UBCF run fold/sample [model time/prediction time]
##   1  [0sec/0.18sec]
##   2  [0sec/0.19sec]
##   3  [0sec/0.17sec]
##   4  [0sec/0.18sec]
##   5  [0sec/0.35sec]
##   6  [0sec/0.17sec]
##   7  [0.02sec/0.17sec]
##   8  [0sec/0.17sec]
##   9  [0sec/0.18sec]
##   10  [0.02sec/0.17sec]
## SVD run fold/sample [model time/prediction time]
##   1  [0.53sec/0.04sec]
##   2  [0.19sec/0.06sec]
```

```
##    3  [0.38sec/0.05sec]
##    4  [0.22sec/0.05sec]
##    5  [0.17sec/0.06sec]
##    6  [0.31sec/0.04sec]
##    7  [0.14sec/0.04sec]
##    8  [0.16sec/0.06sec]
##    9  [0.35sec/0.05sec]
##    10  [0.16sec/0.06sec]
```

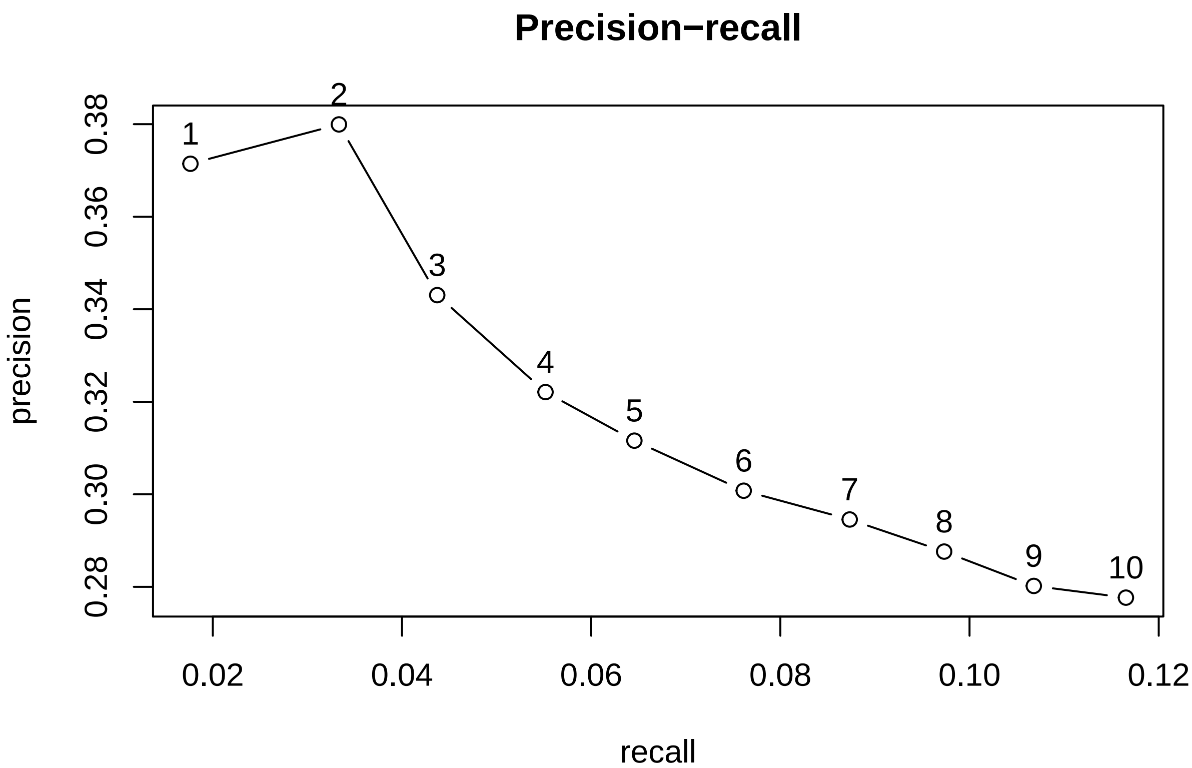
```r
plot(evlist, legend="topleft")
```




```r
plot(evlist,"prec", legend="bottomright")
```




```
plot(evaluation_results,"prec/rec", annotate = TRUE, main = "Precision-recall")
```



Recommendation by Genres

to begin the data has to be re-organize in such a way that allows for the movies to be displayed by specific genres. From the design perspective, this is much easier for the user compared to selecting a movie from a single list of all the available movies

Take a subset from the data and calculate the distance matrix,using the Euclidean method which is the distance between each pairs of points per cluster .After calculating the distance I used a dendogram to display the data with average,complete and ward methods.The distance matrix shows the distance between clusters e.g. the distance between cluster 3 and 20 is 1.73 so this indicates that there are possible good similarity of movoes between these two clusters.

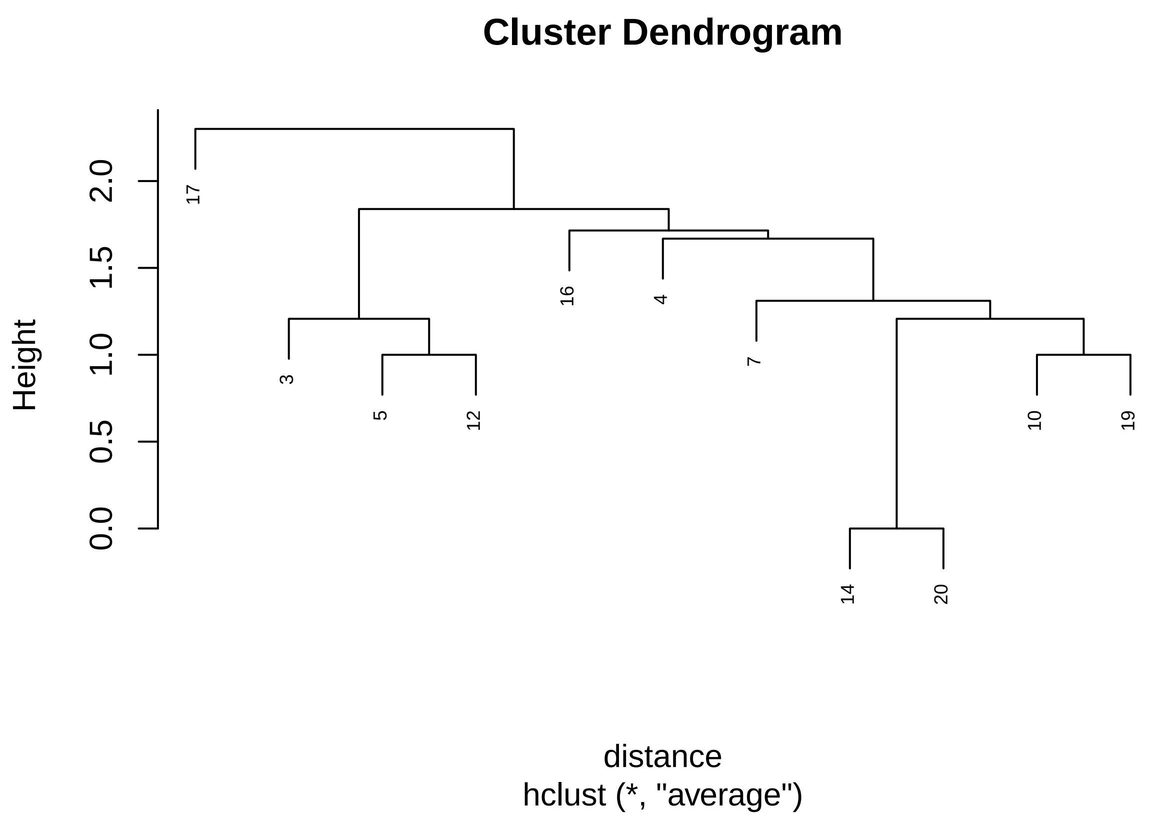
Initially each genre is trated as a single cluster and then the algorithm tries to find the closest in distance until all the genres form one large cluster

```
set.seed(1306)
sammovies <- movies[sample(2:20, 11),] # sample from the data set

distance<- dist(sammovies[2:20], method="euclidean") #The distance between two points in space
print(distance,digits=3)#euclidean distance between each variable
```

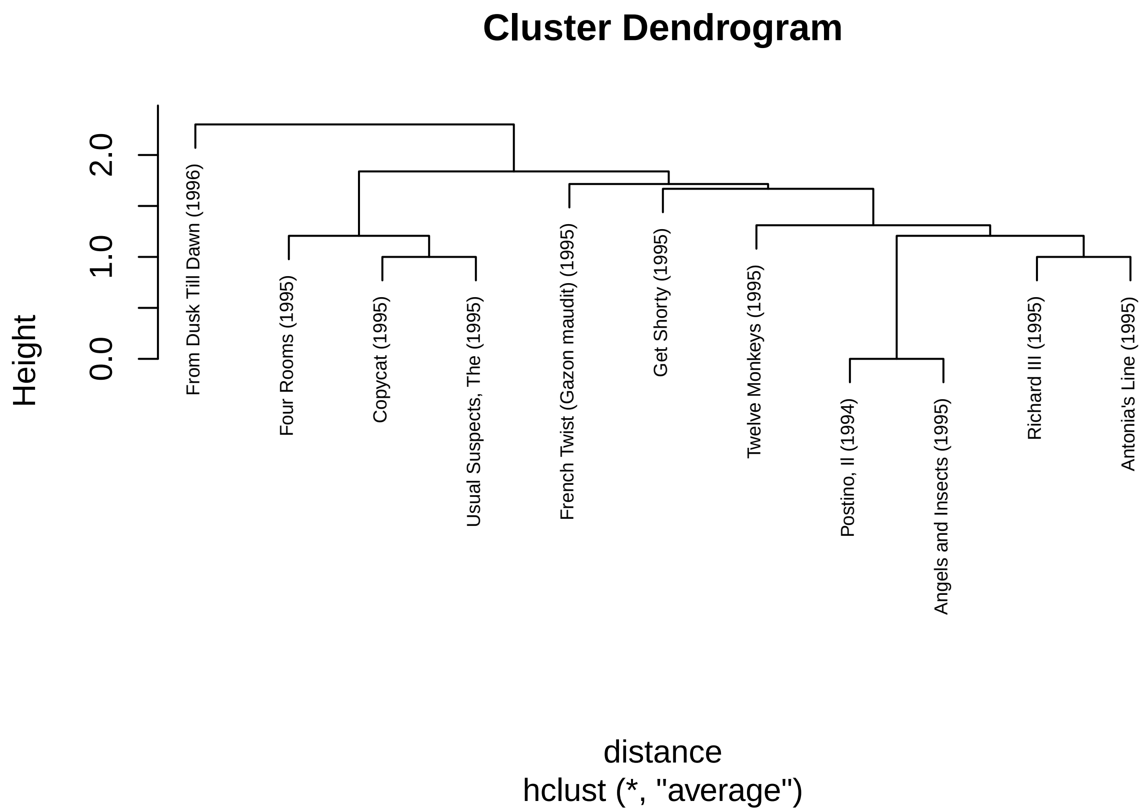
```
##      16    5   10    3   12   14    7   20   17    4
## 5  2.24
## 10 2.00 1.73
## 3  1.73 1.41 1.73
## 12 2.00 1.00 2.00 1.00
```

```
## 14 1.41 1.73 1.41 1.73 2.00
## 7  2.00 1.73 1.41 1.73 2.00 1.41
## 20 1.41 1.73 1.41 1.73 2.00 0.00 1.41
## 17 2.24 2.00 2.65 2.00 1.73 2.65 2.65 2.65
## 4  1.73 2.00 1.73 2.00 2.24 1.73 1.73 1.73 2.00
## 19 1.73 1.41 1.00 1.41 1.73 1.00 1.00 1.00 2.45 1.41
```

```r
cluster<- hclust(distance)#dendogram with complete linkage

cluster<- hclust(distance, method="average")#dendogram with average linkage
#The vertical lines represents the distance
plot(cluster, cex = 0.6)
```

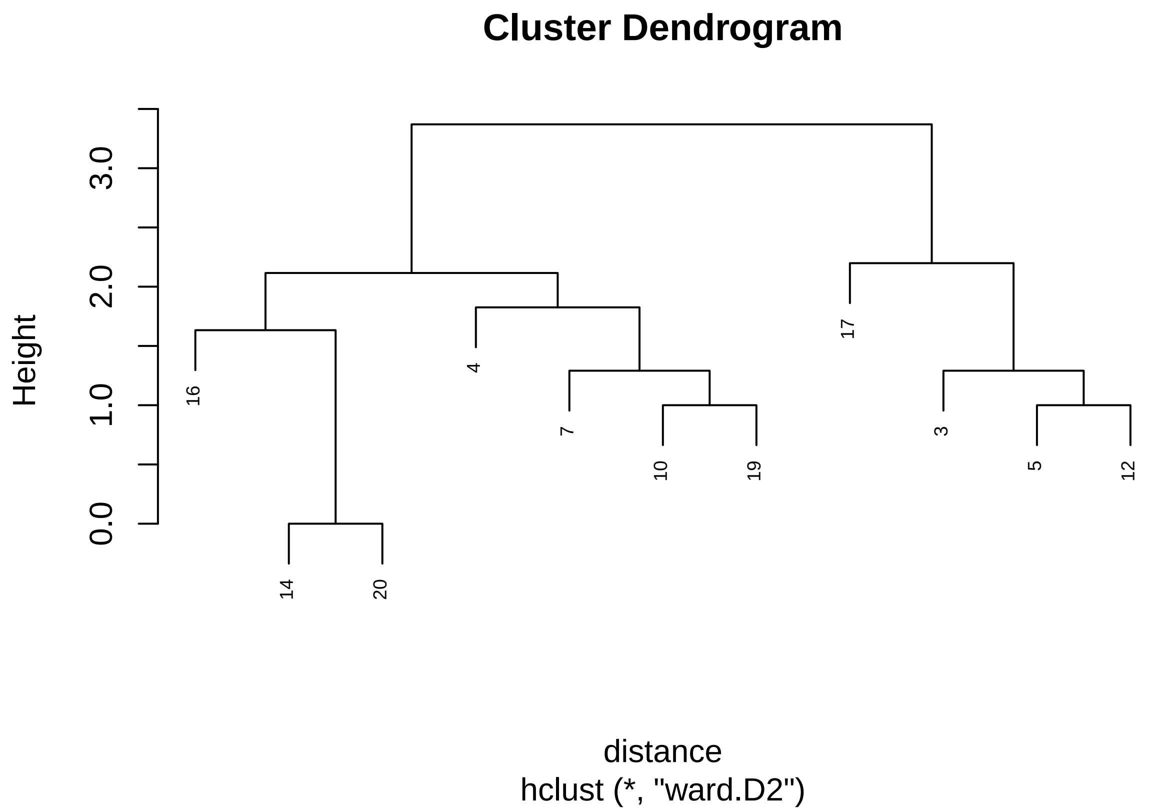



```r
plot(cluster, labels=sammovies$Title,cex = 0.6)
```

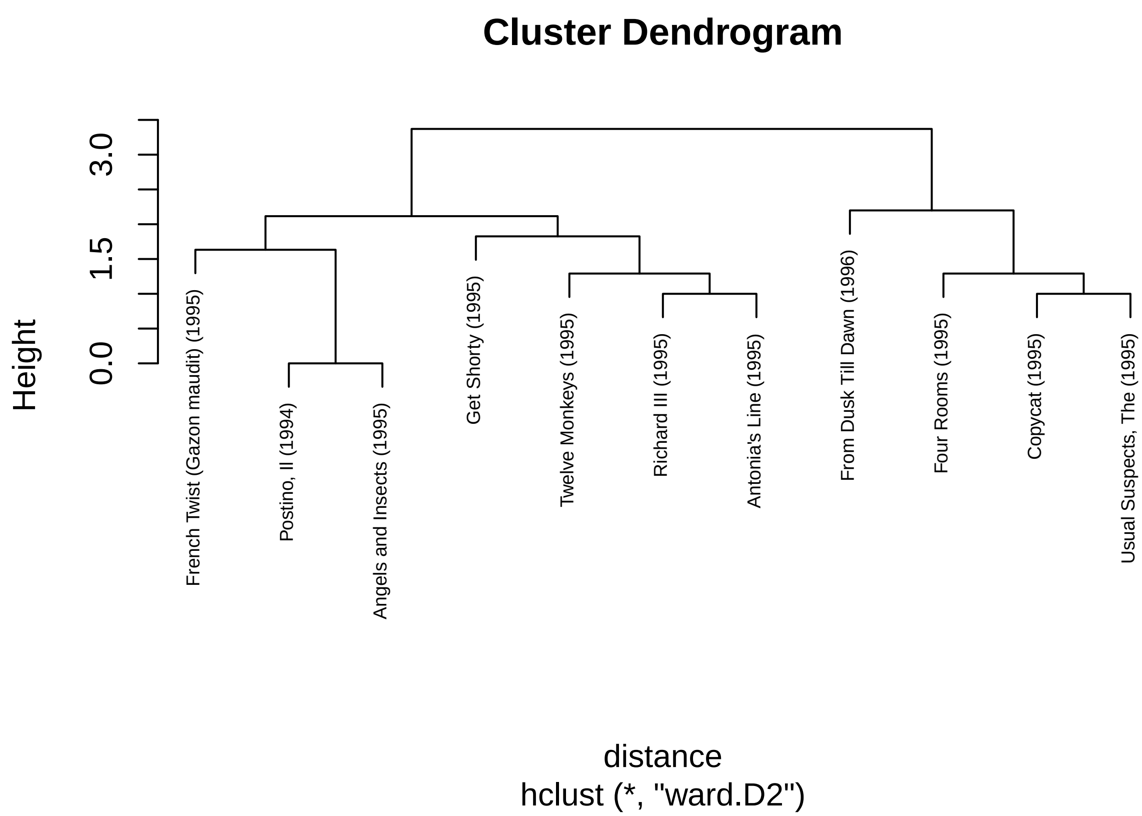


Displaying cluster with Ward.D2 method taking a look at the movies Toy Story and Psycho to see which movies would be similar to those and the genres that they belong to

```
clustMovies = hclust(distance, method = "ward.D2")
cm=hclust(distance, method = "ward.D2")
plot(cm, cex = 0.6)
plot(clustMovies,cex = 0.6)
```




```
plot(clustMovies, labels=sammovies$Title,cex = 0.6)
```




```
#cuts the tree in to groups of 10
clustGrps1=cutree(clustMovies, k=10)

# Calculate distances between genre features:
distances = dist(movies[2:20], method = "euclidean")

clustMovies = hclust(distances, method = "ward.D2")

#plot(clustMovies, hang=-1,cex = 0.6)

#Label each movie in clusters with k=10 clusters
clustGrps = cutree(clustMovies, k=10)

tapply(movies$Comedy, clustGrps, mean)
```

```
##          1          2          3          4          5          6
## 0.34645669 0.12790698 0.11111111 0.12195122 0.00000000 0.22033898
##          7          8          9         10
## 1.00000000 0.09166667 0.83809524 0.10280374
```

```
tapply(movies$Horror, clustGrps, mean)
```

```
##          1          2          3          4          5          6
## 0.00000000 0.06201550 0.07407407 0.02439024 0.00000000 0.00000000
##          7          8          9         10
```

```
## 0.00000000 0.01666667 0.00000000 0.54205607
```

```r
subset(movies, Title=="Toy Story (1995)")
```

```
##              Title Unknown Action Adventure Animation Childrens Comedy
## 1 Toy Story (1995)       0      0         0         1         1      1
##   Crime Documentary Drama Fantasy FilmNoir Horror Musical Mystery Romance
## 1     0           0     0       0        0      0       0       0       0
##   SciFi Thriller War Western
## 1     0        0   0       0
```

```r
cluster2 = subset(movies, clustGrps==1)
cluster2$Title[1:10]
```

```
##  [1] Toy Story (1995)
##  [2] Babe (1995)
##  [3] Free Willy 2: The Adventure Home (1995)
##  [4] Santa Clause, The (1994)
##  [5] Lion King, The (1994)
##  [6] Mask, The (1994)
##  [7] Free Willy (1993)
##  [8] Home Alone (1990)
##  [9] Aladdin (1992)
## [10] Snow White and the Seven Dwarfs (1937)
## 1664 Levels: 'Til There Was You (1997) ... Zeus and Roxanne (1997)
```

```r
subset(movies, Title=="Psycho (1960)")
```

```
##             Title Unknown Action Adventure Animation Childrens Comedy
## 185 Psycho (1960)       0      0         0         0         0      0
##     Crime Documentary Drama Fantasy FilmNoir Horror Musical Mystery
## 185     0           0     0       0        0      1       0       0
##     Romance SciFi Thriller War Western
## 185       1     0        1   0       0
```

```r
cluster3 = subset(movies, clustGrps==3)
cluster3$Title[1:10]
```

```
##  [1] Four Rooms (1995)
##  [2] Taxi Driver (1976)
##  [3] Disclosure (1994)
##  [4] Dolores Claiborne (1994)
##  [5] Firm, The (1993)
##  [6] Blade Runner (1982)
##  [7] So I Married an Axe Murderer (1993)
##  [8] Silence of the Lambs, The (1991)
##  [9] Diabolique (1996)
## [10] Lone Star (1996)
## 1664 Levels: 'Til There Was You (1997) ... Zeus and Roxanne (1997)
```

```r
#calculate the cluster means
binsp = split(movies[2:20], clustGrps)
lapply(binsp, colMeans)
```

```
## $`1`
##     Unknown      Action   Adventure   Animation   Childrens      Comedy
## 0.000000000 0.070866142 0.338582677 0.307086614 0.889763780 0.346456693
##       Crime Documentary       Drama     Fantasy    FilmNoir      Horror
## 0.007874016 0.000000000 0.157480315 0.165354331 0.000000000 0.000000000
##     Musical     Mystery     Romance       SciFi    Thriller         War
## 0.149606299 0.000000000 0.031496063 0.062992126 0.007874016 0.000000000
##     Western
## 0.000000000
##
## $`2`
##     Unknown      Action   Adventure   Animation   Childrens      Comedy
## 0.000000000 0.732558140 0.333333333 0.011627907 0.011627907 0.127906977
##       Crime Documentary       Drama     Fantasy    FilmNoir      Horror
## 0.031007752 0.000000000 0.147286822 0.000000000 0.000000000 0.062015504
##     Musical     Mystery     Romance       SciFi    Thriller         War
## 0.000000000 0.007751938 0.046511628 0.317829457 0.298449612 0.038759690
##     Western
## 0.100775194
##
## $`3`
##     Unknown      Action   Adventure   Animation   Childrens      Comedy
##  0.01234568  0.03703704  0.00000000  0.00000000  0.01234568  0.11111111
##       Crime Documentary       Drama     Fantasy    FilmNoir      Horror
##  0.09876543  0.00000000  0.31481481  0.00617284  0.14197531  0.07407407
##     Musical     Mystery     Romance       SciFi    Thriller         War
##  0.00000000  0.35185185  0.06790123  0.03703704  0.79012346  0.00000000
##     Western
##  0.00000000
##
## $`4`
##     Unknown      Action   Adventure   Animation   Childrens      Comedy
##  0.00000000  0.17073171  0.01219512  0.00000000  0.00000000  0.12195122
##       Crime Documentary       Drama     Fantasy    FilmNoir      Horror
##  0.97560976  0.00000000  0.48780488  0.00000000  0.00000000  0.02439024
##     Musical     Mystery     Romance       SciFi    Thriller         War
##  0.00000000  0.01219512  0.07317073  0.01219512  0.32926829  0.00000000
##     Western
##  0.00000000
##
## $`5`
##     Unknown      Action   Adventure   Animation   Childrens      Comedy
##           0           0           0           0           0           0
##       Crime Documentary       Drama     Fantasy    FilmNoir      Horror
##           0           0           1           0           0           0
##     Musical     Mystery     Romance       SciFi    Thriller         War
##           0           0           0           0           0           0
##     Western
##           0
```

```
##
## $`6`
##     Unknown      Action   Adventure   Animation   Childrens      Comedy
##  0.00000000  0.22033898  0.03389831  0.00000000  0.00000000  0.22033898
##       Crime Documentary       Drama     Fantasy    FilmNoir      Horror
##  0.00000000  0.01694915  0.59322034  0.00000000  0.00000000  0.00000000
##     Musical     Mystery     Romance       SciFi    Thriller         War
##  0.00000000  0.00000000  0.20338983  0.03389831  0.05084746  1.00000000
##     Western
##  0.01694915
##
## $`7`
##     Unknown      Action   Adventure   Animation   Childrens      Comedy
##   0.0000000   0.0000000   0.0000000   0.0000000   0.0000000   1.0000000
##       Crime Documentary       Drama     Fantasy    FilmNoir      Horror
##   0.0000000   0.0000000   0.2372263   0.0000000   0.0000000   0.0000000
##     Musical     Mystery     Romance       SciFi    Thriller         War
##   0.0000000   0.0000000   0.0000000   0.0000000   0.0000000   0.0000000
##     Western
##   0.0000000
##
## $`8`
##     Unknown      Action   Adventure   Animation   Childrens      Comedy
## 0.000000000 0.116666667 0.000000000 0.000000000 0.000000000 0.091666667
##       Crime Documentary       Drama     Fantasy    FilmNoir      Horror
## 0.016666667 0.000000000 0.666666667 0.000000000 0.008333333 0.016666667
##     Musical     Mystery     Romance       SciFi    Thriller         War
## 0.000000000 0.000000000 1.000000000 0.000000000 0.091666667 0.008333333
##     Western
## 0.000000000
##
## $`9`
##     Unknown      Action   Adventure   Animation   Childrens      Comedy
##  0.00000000  0.03809524  0.00952381  0.00000000  0.01904762  0.83809524
##       Crime Documentary       Drama     Fantasy    FilmNoir      Horror
##  0.00000000  0.00000000  0.08571429  0.00000000  0.00000000  0.00000000
##     Musical     Mystery     Romance       SciFi    Thriller         War
##  0.35238095  0.00000000  0.75238095  0.00952381  0.00952381  0.00952381
##     Western
##  0.00000000
##
## $`10`
##     Unknown      Action   Adventure   Animation   Childrens      Comedy
##  0.00000000  0.00000000  0.00000000  0.00000000  0.00000000  0.10280374
##       Crime Documentary       Drama     Fantasy    FilmNoir      Horror
##  0.00000000  0.45794393  0.07476636  0.00000000  0.00000000  0.54205607
##     Musical     Mystery     Romance       SciFi    Thriller         War
##  0.00000000  0.00000000  0.00000000  0.00000000  0.00000000  0.00000000
##     Western
##  0.00000000
```