CIS4930 Group Project

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Introduction

The following report details the procedures and research done to carry out data mining tasks on a sample(s) of the Internet Movie Database (IMDb) and its collection of movies. These procedures were broken into the following major categories:

- Dataset Creation
- Genre prediction (classification)
- *The usual* casts (association rule mining)
- Finding similar movies (clustering)

Literature Review

Overview of Data

The data overview is divided into the following steps, as significant decisions or observations worth explaining were made at each point.

- Building the dataset
- Preprocessing
- Datset Statistics

The packages and required workspace prepartion steps are listed below for reproducibility purposes.

```r
#Dynamically load/install required packages
ready <- FALSE
loadPackages1 <- function() {
  if( require(R.utils) == FALSE) { install.packages("R.utils") }
  if( require(stringr) == FALSE) { install.packages("stringr") }
  if( require(data.table) == FALSE) { install.packages("data.table") }
  if( require(jsonlite) == FALSE) { install.packages("jsonlite") }
  if( require(ggplot2) == FALSE) { install.packages("ggplot2") }
  ready <- TRUE
}
while(ready == FALSE) { ready <- loadPackages1() }

#Set seed
set.seed(7131)
```

Building the Dataset

Our working dataset was created using a python script making calls to the OMDb API. While this method was slow, completing approximately 3-5 http requests per second on an average wifi connection, it saved an enormous amount of time in preprocessing and fine-tuning as it loads all the available, useful information as JSON objects which can be read into R efficiently and cheaply.

As seen below, the *imdbscraper.py* script was set to a sample size of 30 thousand values (for reasons explained later) and made a unique http request for each randomly generated seven-digit id up to the approximate maximum of 5262000. Each request return a json object which was stored in an array of sample size.

Once the specified number of requests were made, the json array was dumped and written to a file.

Note that although the dataset is created from OMBb's 3rd-party API, each request contains an IMDb ID corresponding to the same values in the IMDb database.

```
## Title: IMDB sample database creator
## Author: Dax Gerts
## Date: 14 December 2016
## Description: use OMDb API to rapidly build a clean JSON IMDb data sample

import requests
import numpy as np
import json
import urllib2
import csv
import codecs

sample_size = 30000

random_ids = np.random.choice(5262000,size=sample_size,replace=False)

data = [None] * sample_size

for i in range(sample_size):
    temp_id = "%07d" % random_ids[i]
    data[i] = json.load(urllib2.urlopen('http://www.omdbapi.com/?i=tt' +
                                        temp_id + '&plot=short&r=json'))
    print("QUERY#"+str(i))

with codecs.open('imdb_re_30k_sample.txt','w','utf8') as f:
    json.dump(data, f)
```

Preprocessing

Each variable was examined to make sure that it had a

Load Dataset Into R

Having created a working dataset, the following function, *jsonToCsv*, was written to speed up the process of formatting the data for use in R. *jsonToCsv* first reads the json object from the given file (defaulting to *imdb_30K_sample.json*) using the R package *jsonlite*. While the function returns a data frame, it also backs up the data to a local csv file.

```r
# Reformat OMDB JSON queries as csv
jsonToCsv <- function(filename = "imdb_30K_sample.json",write=TRUE,csvfile = "imdb_30K_sample.csv") {
  data <- fromJSON(txt=as.character(filename))
  if(write==TRUE) {
    write.csv(data,file=csvfile,row.names = FALSE)
  }
  data
}
data <- jsonToCsv()
```

Variables

The OMDb query returned the following attributes for each movie.

```r
names(data)
```

```
##  [1] "Plot"       "Rated"      "Title"      "Writer"     "Actors"
##  [6] "Type"       "imdbVotes"  "seriesID"   "Season"     "Director"
## [11] "Released"   "Awards"     "Genre"      "imdbRating" "Poster"
## [16] "Episode"    "Language"   "Country"    "Runtime"    "imdbID"
## [21] "Metascore"  "Response"   "Year"       "Error"
```

Not all of these attributes were for use in any data mining task, however they were retained for archiveal purposes. In particular, *seriesID*, *Episode*, and *Season* were largely useless because non-movie elements were dropped from the sample set. Also, the values for *Poster*, *imdbID*, *Response*, and *Error* were more for archival purposes.

Each attribute were individually examined and set to the right type. An example of some of the variable preprocessing can be seen below with the *timeSet* function which was used on *Runtime*. The original *Runtime* data had three cases: **"N/A"**, **"# hours # min"**, or **"# min"**. These were reduced down to as single numeric for the number of minutes, with "N/A" values being 0 minutes.

```r
# Runtime reformat, string -> minutes (integer)
timeSet <- function(x) {
  if(length(x == 2)) {
    x = as.numeric(x)
  } else if (length(x == 4))  {
    x = (as.numeric(substr(x,1,1))*60)+as.numeric(substr(x,2,3))
  } else {
    x = as.numeric("0")
  }
  x
}
```

The full preprocessing script is shown below. Note that the script ends with two significant steps:

1. Subset data to retain only movies (30K rows ==> ~12K rows)
2. Save dataset to R data object (for coherent use across all project members)

```r
# Clean data set, set proper types, drop invalid rows,
preprocessing <- function(data) {
  # Step 1: Variable type checking

  # 1.1 Plot - char (fine as is)
  # 1.2 Rated - factor (49 levels) (sparse)
  data$Rated <- as.factor(data$Rated)
  summary(data$Rated)

  # 1.3 Title - char (fine as is)

  # 1.4 Writer - factor (>10000 levels)
  data$Writer <- as.factor(data$Writer)
  summary(data$Writer)

  # 1.5 Actors - list (will require more processing later)
  data$Actors <- strsplit(data$Actors,", ")
  data$Actors <- sapply(data$Actors,'[',seq(max(sapply(data$Actors,length))),simplify=FALSE)
  data$Actors[1:5]

  # 1.6 Type - factor
  data$Type <- as.factor(data$Type)
  summary(data$Type)

  # 1.7 imdbVotes - numeric
  data$imdbVotes <- as.numeric(data$imdbVotes)
  summary(data$imdbVotes)

  # 1.8 seriesID - char (fine as is)

  # 1.9 Season
  data$Season <- as.numeric(data$Season)
  summary(data$Season)

  # 1.10 Director - factor (> 10000 levels)
  data$Director <- as.factor(data$Director)
  levels(data$Director)

  # 1.11 Released - date
  data$Released <- as.Date(data$Released,"%d %b %Y")

  # 1.12 Awards - to finicky to do anything with now (parse for numeric values later, maybe)

  # 1.13 Genre - fact list
  data$Genre <- strsplit(data$Genre,", ")
  data$Genre <- sapply(data$Genre,'[',seq(max(sapply(data$Genre,length))),simplify=FALSE)
  data$Genre[1:5]

  # 1.14 imdbRating - numeric
  data$imdbRating <- as.numeric(data$imdbRating)

  # 1.15 Poster - char (fine as is)
  # 1.16 Episode - numeric
  data$Episode <- as.numeric(data$Episode)

  # 1.17 Language - factor list
  data$Language <- strsplit(data$Language,", ")
  data$Language <- sapply(data$Language,'[',seq(max(sapply(data$Language,length))),simplify=FALSE)
  data$Language[1:5]

  # 1.18 Country
  data$Country <- strsplit(data$Country,", ")
  data$Country <- sapply(data$Country,'[',seq(max(sapply(data$Country,length))),simplify=FALSE)
  data$Country[1:5]

  # 1.19 Runtime (unfinished)
  data$Runtime <- gsub("[^0-9]"," ",data$Runtime)
  for(i in 1:length(data$Runtime)) {
    data$Runtime[i] = timeSet(data$Runtime[i])
  }
  data$Runtime <- as.numeric(data$Runtime)
  summary(data$Runtime)

  # 1.20 imdbID (fine as is)

  # 1.21 Metascore
  data$Metascore <- as.factor(data$Metascore)
  levels(data$Metascore)

  # 1.22 Response (irrelevant)

  # 1.23 Year - as numeric (only takes first year in range)
  data$Year <- as.numeric(gsub("\\-.*","",data$Year))
  summary(data$Year)

  # 1.24 Error (fine as is, meaningless)

  # 2 Prepare valid data

  # 2.1 Drop non-movie entries
  data <- data[data$Type == "movie",]

  # 2.2 Drop bad/"N/A" entries
  data <- data[!(is.na(as.factor(data$Title))),]

  # 2.3 Save table as R object
  saveRDS(data,"clean10Kdataset.rds")

  # 2.4 Return output table
  data
}
```

Dataset Statistics

The following are some of the observations made in determining statistical validity for our sample set, as well grounds for determing how to subset the original 30K row rough samples set.

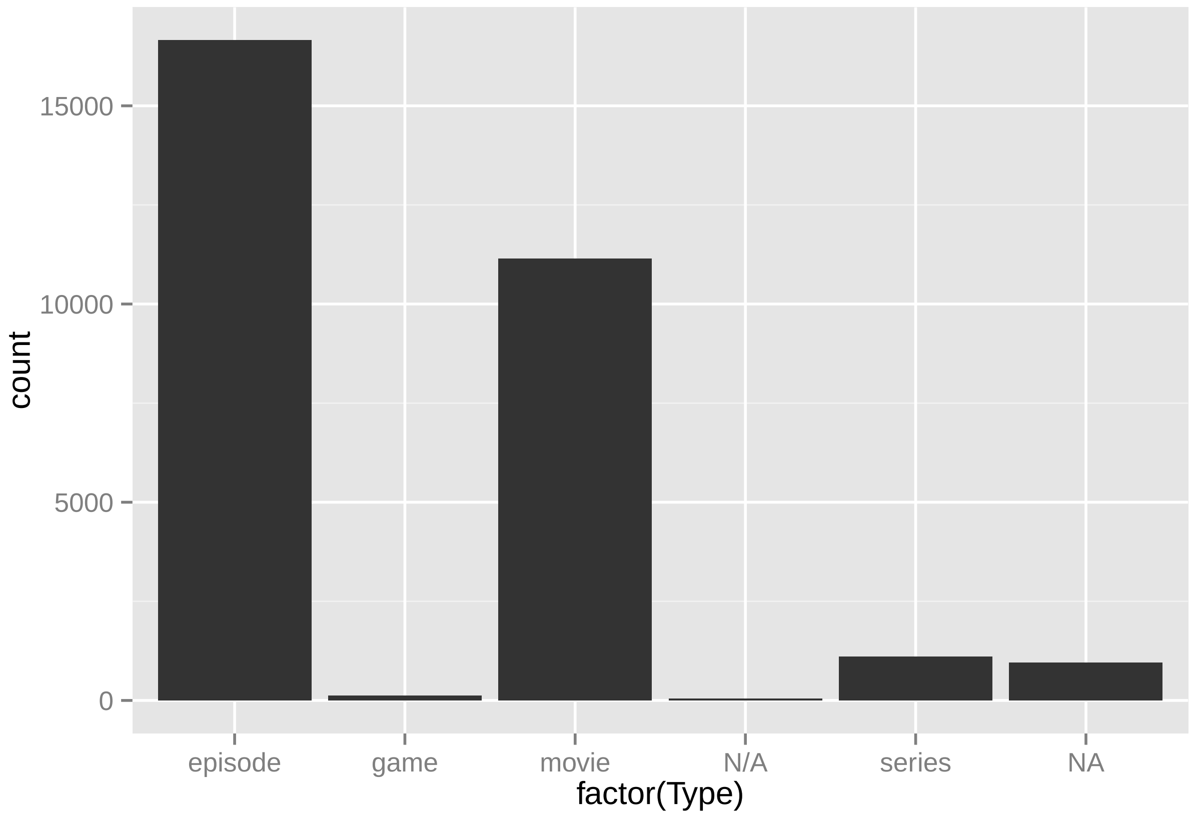
Before Preprocessing

```
# Prepare example set
stats <- jsonToCsv()

# Null rows in original query set (dropped in preprocessing)
sum(is.na(as.factor(stats$Type)))
```

```
## [1] 950
```

```
# Entry-type information by level
ggplot(stats, aes(x = factor(Type))) + geom_bar(stat = "bin")
```



After Preprocessing

```r
# Run preprocessing procedures
stats <- preprocessing(stats)

# Null rows in original query set (dropped in preprocessing)
sum(is.na(as.factor(stats$Type)))
```

```
## [1] 0
```

```r
# Entry-type information by level
summary(as.factor(stats$Type))
```

```
## episode    game   movie     N/A  series
##       0       0   11138       0       0
```

Method and Materials

Results

Discussion

Conclusion

References & Resources

The Internet Movie Database http://www.imdb.com

IMDbPY - Python API and Materials for IMDB searches http://www.imdbpy.sourceforge.net

The Open Movie Database http://www.omdbapi.com/