ECS189G Term Project Report Problem B

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1 Introduction

This dataset contains the following information: the drug's name and condition, the patient's review and rating, the review's date and the number of users who found the review useful. 75% of the data are in the training set and 25% are in the test set. The goal of the project is to investigate how reliable the verbal reviews are in establishing a numeric rating and predict the numeric rating using the verbal reviews and other useful variable information. We want to apply our model to predict ratings for other datasets that do not have numeric evaluation. We have 161297 number of observations in the training set and 53766 number of observations in the test set. Due to the limited computing power, we decide to randomly select 12000 number of observations from the training set and 4000 from the test set to preserve the original train-test split ratio and minimize the dataset's size while ensuring it is representative.

2 Obstacles

In the general recommender system, we have user ID, item ID and rating. However, since this dataset was obtained by crawling online review sites, we do not know which individual rates the drug. In this case, the userID is unique for each review and it will affect the result from the Latent Factor Model because it takes user i's effect on rating into consideration. Therefore, in order to provide a more accurate model, we decide to use the condition (disease that the drug cures) as userID because each condition/disease corresponds to multiple drug names. This modification can help us to create a more suitable data structure for the recommender system model.

3 Data Pre-Processing

- Check whether there are missing values in the data
- Check the rating score distribution to see whether there is bias in the dataset
- Check whether the training set and test set have similar rating distribution

Training Set									
1	2	3	4	5	6	7	8	9	10
0.134	0.043	0.040	0.031	0.050	0.039	0.059	0.117	0.171	0.316

Test Set									
1	2	3	4	5	6	7	8	9	10
0.136	0.043	0.041	0.031	0.050	0.039	0.057	0.114	0.171	0.316

From the table above, we see that the training set and test set have very similar distribution. Both of them have relatively high number of ratings in score 10.

4 Review Data Pre-Processing for R Sentiment Analysis

- Tokenize the words, remove numbers, punctuations, symbols and hyphen
- Filter out the stop words (common words that provides very little meaning, such as 'the', 'a' and etc.)
- Perform stemming, in which takes similar words and collapse them into one on the tokens
- Save the processed tokens in a list

5 Methods and Discussion

We use R sentiment library (sentimentr) to analyze the feelings of the review response and get a numeric value (the average of the all the tokens' sentiment score in a review) to indicate how positive or negative the review is. With the R sentiment analysis score, we find that some of the review scores tend to be negative even though the rating is relatively high.

	rating	mean	sd
1:	10	0.0095008294474	0.08418113816
2:	9	0.0025290761294	0.06877517517
3:	8	-0.0009447431966	0.07063739058
4:	7	-0.0035860472025	0.07027751384
5:	6	-0.0123387156969	0.05772298979
6:	5	-0.0180928833763	0.05684068549
7:	4	-0.0187657405613	0.06313352298
8:	3	-0.0210377905691	0.05526532302
9:	2	-0.0237766412720	0.06700426201
10:	1	-0.0408442785238	0.07101458952

After further investigation, we discover that the patients would discuss their pains and describe their disease in the review, in which leads to the negative review sentiment score even though the drug's rating is high. Therefore, we need to filter out the negativity brought by the condition/disease in order to provide a more accurate result when we predict the rating using the review sentiment score.

In addition, we notice that some of the ratings get more useful counts while others do not. In order to increase our model's accuracy, we create an additional component called useful count ratio, which equals to the number of useful count for each individual review/the total number of useful counts in the same condition/disease. We believe the reviews with more useful counts deserve more weights and modify the getUINN function provided by matloff/rectools API to calculate the weighted mean sentiment score instead of a simple mean.

6 Hypothesis

6.1 Linear Model

Hypothesis: There is a linear relationship between review sentiment score and rating, in other words, the verbal reviews are reliable in establishing a numeric rating. We assume there is a linear relationship because both of these metrics reflect users' preferences on drugs and measure the same effect.

Firstly, we use linear regression model to find the review sentiment score's effect on rating:

$$Y_{ij} \sim sentiment\_score + e_{ij}$$

The coefficient for sentiment score equals to 9.88, which indicates the linear model considers the review sentiment score has comparatively significant effect on the rating. But the Mean Absolute Prediction Error (the average of the absolute difference between the prediction value and the actual value) is high.

7 Latent Factor Model

Secondly, we use the Latent Factor Model to further investigate the linear relationship between the review sentiment score and rating; check whether the error rate would decrease. Based on the hypothesis above, we can use the review sentiment score to predict rating in the Latent Factor Model. If we find the model gives a low Mean Absolute Prediction Error, our hypothesis is correct and the linearity between the review sentiment score and rating exists. We examine three cases here:

- We only include drug's effect on the mean sentiment score and assume there's no user IDs.
- We include condition/disease and drug's effect on the mean sentiment score and assume conditionID as userID.
- 3) We include condition/disease and drug's effect on the mean sentiment score and assume conditionID as userID. In addition, we add more weights to the mean sentiment score that has more useful count.

Suppose α_i = condition i's effect on the mean sentiment score and β_j = drug j's effect on the mean sentiment score. For all the models below, we have review_length as covariate.

7.1 Model 1: Includes drug's effect on the mean sentiment score

$$E(Y_{ij}|i,j) = u + \beta_j + \epsilon_{ij}$$

The expected numeric rating = Prediction from respective overall mean sentiment score of drug j

7.2 Model 2: Includes condition and drug's effect on the mean sentiment score

$$E(Y_{ij}|i,j) = u + \alpha_i + \beta_j + \epsilon_{ij}$$

The expected numeric rating = Prediction from respective overall mean sentiment score of condition i and drug j

7.3 Model 3: Includes condition and drug's effect on the mean sentiment score, taking into consideration of the useful count ratio

$$E(Y_{ij}|i,j) = u + \alpha_i + \beta_j + \epsilon_{ij}$$

with α_i, β_j calculated using weighted mean instead of normal mean

7.4 Mean Absolute Prediction Error

We discover that the error rate is the lowest when we add the useful_count_ ratio/weights to the Latent Factor Model with drug and condition/disease effect, followed by the Latent Factor Model with only drug's effect, linear regression model with sentiment score and Latent Factor Model with drug and condition effect but without useful_count_ratio. However, all the error rates are relatively close and large since the rating scale is from 1 to 10. Therefore, we reject our hypothesis based on the results. The review sentiment score is not reliable in establishing the rating, even with the covariates.

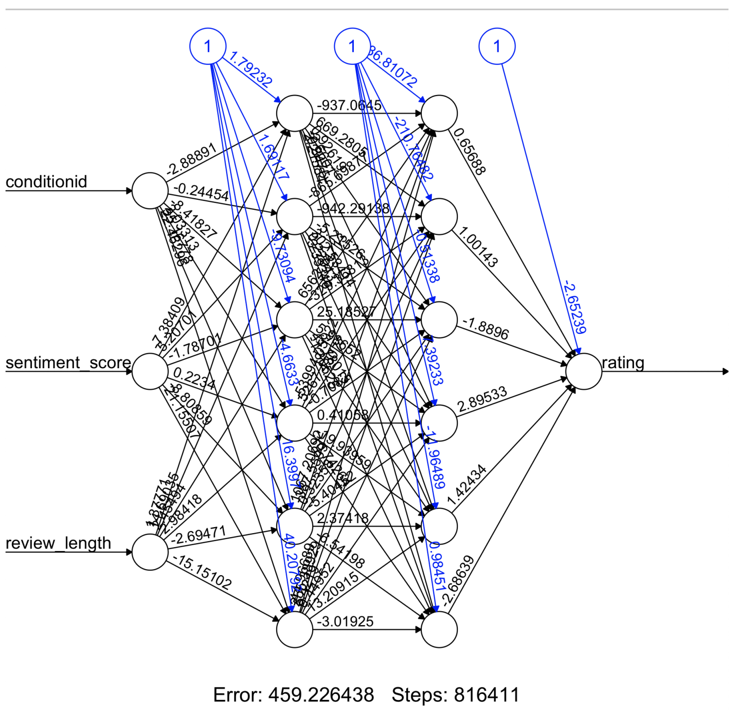
Mean Absolute Prediction Error			
Linear Regression Model with review sentiment score	**Latent Factor Model with drug effect**	**Latent Factor Model with condition/disease & drug effect**	**Latent Factor Model with condition/disease & drug effect (Weighted)**
2.76734	**2.76714**	**2.76738**	**2.76583**

8 Neural Network

We use the neuralnet R package to construct a neural network to predict the drug's rating. The predictive variables are conditionid, sentiment_score, and review_length. Generally speaking, two layers are sufficient to build an effective neural network framework. We then use cross validation to find out the optimal number of nodes in the two layers. In order for neuralnet to converge, we scale the data and increase the stepmax (the maximum steps for the training of the neural network) to 1e8. Below is the cross-validation result that we get, and we see that the neural network with 5 nodes in layer 1 and 4 nodes in layer 2 has the lowest mean absolute prediction error. However, it still performs worse than the Latent Factor model.

Number of nodes in each layer		
Layer 1	Layer 2	Mean Absolute Prediction Error
4	2	6.6235
5	4	3.8429
6	6	6.0558

Below is the neural network graph that shows the weights of the best neural network.



In order to increase the reliability of review sentiment score on the numeric rating, we suggest the future researchers to create a function/model that separates the review into two parts, one that describes the condition/disease and one describes the drug. We believe the sentiment score calculated from the drug description would be more reliable in getting the actual numeric rating.

9 Author Contributions

All group members contributed equally in this project.

10 Appendix

```
# Problem 2
# 1. drugName (categorical): name of drug
# 2. condition (categorical): name of condition
# 3. review (text): patient review
# 4. rating (numerical): 10 star patient rating
# 5. date (date): date of review entry
# 6. usefulCount (numerical): number of users who found review useful
#
# train_set(75%), test_set(25%)

# Use Reference in the Youtube Series created by Data Science Dojo
# setwd('/Users/jieyichen/Desktop/R Final Project/')
# linear model and neural networks

require(data.table)
drug_test = as.data.frame(fread('drugsComTest_raw.tsv'))
drug_train = as.data.frame(fread('drugsComTrain_raw.tsv'))

library(ggplot2)

data_preprocess = function(dataframe){
  # check whether there are missing values in the data
  if (length(which(!complete.cases(dataframe))) == 0) {
    print('Dataset has no missing values.')
  } else{
    print('Dataset has missing values.')
  }
  print('The table below shows the rating score distribution:')
  # see the rating score distribution
  print(prop.table(table(dataframe$rating)))
  # get the review length
  dataframe$review_length = nchar(dataframe$review)
  return(dataframe)
```

```
}

ggplot_draw = function(dataframe){
  # visualize the review lengths with class labels
  ggplot(dataframe, aes(x = rating, fill = review_length)) +
    geom_histogram(bins = 20) +
    labs(y = 'Review Text Count', x = 'Length of Text',
    title = 'Distribution of Review Text Lengths with Rating Score') +
    theme(plot.title = element_text(hjust = 0.5))
}

drug_train_output = data_preprocess(drug_train)
ggplot_draw(drug_train_output)
drug_test_output = data_preprocess(drug_test)
ggplot_draw(drug_test_output)

# We have checked that the data distribution is
# relatively similar between the train set and test set.


# Data Pre-Processing Steps:
# 1) Tokenize the words, remove numbers, punctuations,
# symbols and hyphens
# 2) Covert the case of tokens so that we do not have repetitive words
# 3) Filter out the stop words (common words that
# provides very little meaning, such as 'the', 'a' and etc)
# 4) Perform stemming (take similar words and
# collapse them into one) on the tokens,
# 5) Create a matrix using the pre-processed tokens


#install.packages('quanteda')
library(quanteda)

word_tokenize = function(dataframe) {
  # tokenize the words
  # remove numbers, punctuations, symbols and hyphens
  # because we only want to analyze the feelings that the
  # text tries to convey
  dataframe_tokens = tokens(dataframe$review, what =
  'word', remove_numbers = TRUE, remove_punct = TRUE,
  remove_symbols = TRUE, remove_hyphens = TRUE)
  # lower case the tokens
  dataframe_tokens = tokens_tolower(dataframe_tokens)
  # remove stop words
  dataframe_tokens = tokens_select(dataframe_tokens,
```

```
  stopwords(), selection = 'remove')
  # stem the tokens
  dataframe_tokens = tokens_wordstem(dataframe_tokens,
  language = 'english')
  list_text = sapply(dataframe_tokens, as.character)
  return(list_text)
}

test_text = word_tokenize(drug_test)
train_text = word_tokenize(drug_train)

#install.packages('sentimentr')
library(sentimentr)

sentiment_avg = function(text_analyze) {
  # gives a score that indicates the positiveness or
  # negativeness of the words
  text_sentiment = sentiment(text_analyze)
  # take the average of the sentiment score
  return (mean(text_sentiment$sentiment))
}

# We found that the review messages generally converys
negative feelings because the patient describes
# their pains caused by the disease in the review as well.

create_feature_df = function(sentiment_score, orig_df) {
  # create sentiment_df with its score
  final_df = data.frame(sentiment_score)
  # select certain columns from df
  orig_df_select = orig_df[, c('drugName', 'condition',
  'rating', 'usefulCount', 'review_length')]
  # combine sentiment_df with selected_column_df
  drug_df = cbind(final_df, orig_df_select)
  drug_df$drugName = as.numeric(as.factor(drug_df$drugName))
  drug_df$conditionid = as.numeric(as.factor(drug_df$condition))
  drug_df = drug_df[,c('conditionid', 'drugName', 'rating',
  'sentiment_score', 'usefulCount', 'review_length')]
  return(drug_df)
}

mean_rating = function(train_list, drug_train_output){
  train_df = create_feature_df(train_list, drug_train_output)
  # get the mean and sd value
  dt = data.table(train_df)
  dt_table = dt[, list(mean = mean(sentiment_score), sd =
```

```
  sd(sentiment_score)), by = rating]

  return (dt_table[with(dt_table, order(-mean))])
}

set.seed(9999)
trainidxs <- sample(1:nrow(drug_train),1200)
testidxs <- sample(1:nrow(drug_test),400)
trainset <- drug_train[trainidxs, ]
testset <- drug_test[testidxs, ]

train_list = sapply(train_text[trainidxs], sentiment_avg)
test_list = sapply(test_text[testidxs], sentiment_avg)
mean_rating(train_list, drug_train_output[trainidxs, ])
mean_rating(test_list, drug_test_output[testidxs, ])


library(caret)

convert_df = function(df_list, drug_train){
  df = create_feature_df(df_list, drug_train)
  # the range of the variable is relatively large,
  therefore, we need to normalize the data
  # normalize the data in interval [0, 1]
  df$usefulCount = df$usefulCount + 0.1

  aggre_sum_condition = aggregate(.~conditionid, df, sum)
  aggre_sum_condition = aggre_sum_condition[,
  c('conditionid', 'usefulCount')]
  colnames(aggre_sum_condition) = c('conditionid',
  'usefulCount_condition_sum')
  df = merge(df, aggre_sum_condition, by = 'conditionid', all = T)

  aggre_sum_drug = aggregate(.~drugName, df, sum)
  aggre_sum_drug = aggre_sum_drug[, c('drugName', 'usefulCount')]

  colnames(aggre_sum_drug) = c('drugName', 'usefulCount_drug_sum')

  df = merge(df, aggre_sum_drug, by = 'drugName', all = T)

  df$uWeight_condition = df$usefulCount / df$usefulCount_condition_sum
  df$uWeight_drug = df$usefulCount / df$usefulCount_drug_sum

  df = df[, c('conditionid',  'drugName',  'rating',
  'sentiment_score', 'uWeight_condition', 'uWeight_drug',
  'review_length')]
```

```
  return(df)
}


train_final_df = convert_df(train_list, drug_train_output[trainidxs, ])
test_final_df = convert_df(test_list, drug_test_output[testidxs, ])


RStoReg <- function (ratingsIn, useNij = FALSE, weighted = FALSE)
{
  UINN <- getUINN(ratingsIn, weighted)
  if (ncol(ratingsIn) > 3) {
    covs <- as.matrix(ratingsIn[, -(1:3)])
    dimnames(covs)[[2]] <- names(ratingsIn[, -(1:3)])
  }
  usrsInput <- as.character(ratingsIn[, 1])
  itmsInput <- as.character(ratingsIn[, 2])
  userMeans <- UINN$uMeans[usrsInput]
  itemMeans <- UINN$iMeans[itmsInput]
  means <- data.frame(uMeans = userMeans, iMeans = itemMeans)
  if (useNij) {
    userN <- UINN$uN[usrsInput]
    itemN <- UINN$iN[itmsInput]
    means <- cbind(means, userN, itemN)
    names(means)[3:4] <- c("uN", "iN")
  }
  if (ncol(ratingsIn) > 3) {
    xy <- cbind(means, covs)
  }
  else xy <- means
  xy <- cbind(xy, ratingsIn[, 3])
  names(xy)[ncol(xy)] <- names(ratingsIn)[3]
  rownames(xy) <- rownames(ratingsIn)
  xy
}

getUINN <- function (ratingsIn, weighted = FALSE)
{
  users <- as.character(ratingsIn[, 1])
  items <- as.character(ratingsIn[, 2])

  if(weighted) {
    ratings1 <- ratingsIn$sentiment_score * ratingsIn$uWeight_condition
    ratings2 <- ratingsIn$sentiment_score * ratingsIn$uWeight_drug
    umean <- function(x) {
```

```
      sum(x)
    }
    Ni. <- tapply(ratings1, users, length)
    N.j <- tapply(ratings2, items, length)
    usrMeans <- tapply(ratings1, users, umean)
    itmMeans <- tapply(ratings2, items, umean)
    final <- list(uMeans = usrMeans, iMeans =
    itmMeans, uN = Ni., iN = N.j)
    return (final)
  } else {
    ratings1 <- ratingsIn$sentiment_score
    ratings2 <- ratingsIn$sentiment_score
    umean <- function(x) {
      mean(x)
    }
    Ni. <- tapply(ratings1, users, length)
    N.j <- tapply(ratings2, items, length)
    usrMeans <- tapply(ratings1, users, umean)
    itmMeans <- tapply(ratings2, items, umean)
    final <- list(uMeans = usrMeans, iMeans =
    itmMeans, uN = Ni., iN = N.j)
    return (final)
  }
}


model_list = list()
# Linear Model
# 1) Yij ~ rev_score + eij
library(rectools)
udconv_train = RStoReg(train_final_df, weighted = FALSE)
# run the linear model
delete = c('uWeight_condition', 'uWeight_drug')
udconv_train = udconv_train[, !(colnames(udconv_train)
%in% delete), drop=FALSE]
udconvout = lm(rating ~ ., data = udconv_train[-c(1:2)])
udconvout$coefficients
# predict the test_df using the linear model
udconv_test = RStoReg(test_final_df,weighted = FALSE)
preds_cov = predict(udconvout, udconv_test)
model_list[['linear_on_segment_score']] = mean(abs(
  preds_cov - udconv_test[, 'rating']), na.rm = T)


# 2) E(Yij|i,j) = u + Bj + eij
udconvout_1 = lm(rating ~ ., data = udconv_train[-1])
```

```
udconvout_1$coefficients
# predict the test_df using the linear model
udconv_test_1 = RStoReg(test_final_df,weighted = FALSE)
preds_cov_1 = predict(udconvout_1, udconv_test_1)
model_list[['linear_on_imeans']] = mean(abs(preds_cov_1
- udconv_test_1[, 'rating']), na.rm = T)

# 3) E(Yij|i,j) = u + ai + Bj + eij
udconvout_2 = lm(rating ~ ., data = udconv_train)
udconvout_2$coefficients
# predict the test_df using the linear model
udconv_test_2 = RStoReg(test_final_df,weighted = FALSE)
preds_cov_2 = predict(udconvout_2, udconv_test_2)
model_list[['linear_on_umeans_imeans']] = mean(abs(preds_cov_2
- udconv_test_2[, 'rating']), na.rm = T)

# 4) E(Yij|i,j) = u + ai + Bj + eij (Weighted)
udconv_train_3 = RStoReg(train_final_df, weighted = TRUE)
# run the linear model
delete = c('uWeight_condition', 'uWeight_drug')
udconv_train_3 = udconv_train_3[, !(colnames(udconv_train_3)
%in% delete), drop=FALSE]
udconvout_3 = lm(rating ~ ., data = udconv_train_3)
udconvout_3$coefficients
# predict the test_df using the linear model
udconv_test_3 = RStoReg(test_final_df,weighted = TRUE)
preds_cov_3 = predict(udconvout_3, udconv_test_3)
model_list[['linear_on_umeans_imeans_weighted']] =
mean(abs(preds_cov_3 - udconv_test_3[, 'rating']), na.rm = T)

model_list


# Neural Network
library(neuralnet)

# scale the data
scaledData <- scale(train_final_df)

# get all the column name of the dataframe
allVars = colnames(train_final_df)
# remove the "rating", "condition_id", "drugName"
# from all vars and the rest are predictor variables
predictorVars = allVars[!allVars%in% c("rating",
"condition_id", "drugName", "uWeight_condition", "uWeight_drug")]
```

```
predictorVars = paste(predictorVars, collapse = "+")
form = as.formula(paste("rating~", predictorVars, collapse = "+"))

# 4 hidden nodes in the second layer and 2 hidden nodes
# in the third layer

neuralnet_cv = function(node_layer_1, node_layer_2){
  neuralModel = neuralnet(formula = form, hidden =
  c(node_layer_1, node_layer_2), linear.output = TRUE,
  data = scaledData, stepmax=1e8)
  plot(neuralModel)
  # Neural network produces continuous variable
  # because our last layer uses linear output.
  predictions = compute(neuralModel, test_final_df[,
  allVars[!allVars%in%c("rating", "condition_id",
  "drugName", "uWeight_condition", "uWeight_drug")]])
  scaledResults = predictions$net.result * attr(scaledData,
  "scaled:scale")["rating"]  + attr(scaledData,
  "scaled:center")["rating"]
  return(mean(abs(scaledResults - udconv_test[, 'rating'])))
}

# do cross validation to find the optimal hidden nodes
# for the neural network
hidden_node_df = data.frame(c(4, 2), c(5, 4), c(6, 6))
hidden_node_df = data.frame(t(hidden_node_df))
names(hidden_node_df) = c('nodes_layer_1', 'nodes_layer_2')

for (num_row in seq(1, nrow(hidden_node_df))) {
  node_layer_1 = hidden_node_df$nodes_layer_1[num_row]
  node_layer_2 = hidden_node_df$nodes_layer_2[num_row]
  hidden_node_df$error_rate[num_row] =
  c(neuralnet_cv(node_layer_1, node_layer_2))
}

rownames(hidden_node_df) = NULL
hidden_node_df
```

References

[1] Norman Matloff *A Tour of Recommender Systems* 2018.

[2] Data Science Dojo (Youtube) *Introduction to Text Analytics with R: Data Pipelines* 2017.

[3] Data Science by Arpan Gupta IIT, Roorkee (Youtube) *Neural Networks in R* 2017.