Measure of Text Deviation between Two Editions of Peony Pavilion

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0. Introduction

Kunqu Opera is a genre of Chinese opera, which is both poetry and performing arts. As for the literature side, a Kunqu Opera is mainly consists of rhyming poems which conforms to strict music theories and phonetic rules. But since it's also performing arts, during actual performance the artists often modify its scripts, to different degrees.

Peony Pavilion is a masterpiece in the genre of Kunqu Opera. It's written in seventeenth centuries and contains 55 acts in its original text. But only a small subset of it is often performed.

In this project, we would try to measure the text deviation of the actual scripts from the original text for the subset of Peony Pavilion which is often played.

1. Initialisation

Before actual analysis, we first needs to install and load the packages needed. And the usage of those packages are given below:

```
# Load required packages, and try to install them if not yet installed
source('./bin/initPackage.R')
# rvest                 : HTML-scrapping
# glue, stringr, stringi: String manipulation
# stringdis             : Calculating string distance
# purrr                 : Mapper and Reducer
# ggplot2               : Visualisation
# data.table            : Enhanced data.frame
initPackage(c('rvest', 'purrr', 'glue', 'stringr', 'stringi', 'stringdist',
              'ggplot2', 'data.table'))
```

Except from R packages, we would also use an external tool, PhantomJS to scrap the web pages. The 'rvest' package works great for static web pages, but cannot render dynamic contents well. PhantomJS has a built-in render for JavaScript and we would use it to obtain the raw HTML files, and then use

'rvest' package to navigate through the nodes of the the HTML. We will use the scripts below to download PhantomJS according to the operating system.

```
# Download PhantomJS to current working directory if it's not downloaded yet,
# which is required to scrap the text corpus  of Peony Pavillion
# This scripts need not to be sourced here because the downloading script will
# source it when PhantomJS is needed.
source('./bin/initPhantomJS.R')
initPhantomJS()
```

PhantomJS alone only provides a interface for web scraping, and we wrote a JavaScript program, i.e. 'scrape.js', for actual scraping. It takes two arguments, which specify the URL to target web page and the destination where we'd like to store the downloaded raw HTML files.

2. Data Preparation

With the environment set up properly, we'd be able to obtain the data.

First we need to acquire the URLS to the text corpus we need, which are acquired from the two data sources introduced below. The first one is gongchepu.net, where volunteers have manually input a subset of Peony Pavilion that is frequently played. Aside from the text corpus, there's also music notation available. But in the scope of this project, the text corpus is all we need. Our second data source is wikisource.org. It belongs to the same organisation behind Wikipedia, and provides a huge set of text corpus freely to the public. In this project, we would obtain the original script of all 55 acts of Peony Pavilion from Wikisource.

```
# The following two scripts would acquire the URLs to the actual text corpus
# from the two aforementioned data scource. They don't need to be sourced here,
# since the downloading script will source them to acquire the URLs.
#source('./bin/dlGongchepuMenu.R')
#source('./bin/dlWikisourceMenu.R')
```

As the next step, we would download the HTML files given the URLs we just extracted, and store them locally. Storing the raw HTML files locally serves two purposes:

1. If there were structural changes in the web pages, or if the relevant text web pages were not accessible due to certain reasons, then we would still be able to obtain the text corpus based on the cached HTML files.
2. Processing cached HTML files would reduce the traffic to the target websites, and in many real world scenarios, this may help to circumvent rate limits imposed by web service providers.

```
# The following two scripts would download the target HTML filesand store them
# locally under ./data/gongchepu and ./data/wikisource directories respectively.
source('./bin/dlGongchepu.R')
```

```
source('./bin/dlWikisource.R')
dlGongchepu()
```

```
## All files are downloaded under "data/gongchepu" dir
```

```
dlWikisource()
```

```
## All files are downloaded under "data/wikisource" dir
```

Based on the raw HTML files we downloaded, we will use the HTML and CSS tags to pin down the HTML elements containing the text corpus, and extract relevant information with the help of regular expression, and generate a data frames with the text and name of each verses.

```
source('./bin/processGongchepu.R')
DTGongchepu <- processGongchepu()
source('./bin/processWikisource.R')
DTWikisource <- processWikisource()
```

Below we printed out the first three rows of each data frame as an example.

```
head(DTGongchepu, 3)
```

```
##     Qupai
## 1: 夜行船
## 2: 香遍🄵
## 3: 懶畫眉
##
## 1: 瞥下天仙何處也？影空🄵、似月籠紗。有恨徘徊，無言窘約，早是夕陽西下。一片紅雲下太清，如花巧🄵
## 2:
## 3:
```

```
head(DTWikisource, 3)
```

```
##     Qupai
## 1: 孤飛🄵
## 2: 金錢花
## 3: 尾犯序
##
## 1:
## 2: 自小疙辣郎當，郎當。官司🄵俺🄵姑娘，姑娘。盡了法，腦皮撞。得了命，賣了房。充小🄵，串街坊。「
## 3:
```

3. Measure of Text Deviation

With the data prepared, we will compute the text deviation now. But before that, there's one extra step needed.

In the end of last section where we output the first three rows of both data frames, there appear to be some characters that are not displayed, even if the operating system is able to display Chinese characters. The reason is that, only a small subset of Chinese characters are often used, and there's no operating system now that is able to print the whole set of Chinese characters.

Although we would still be able to match unprintable characters since we can match them by their Unicode representation, but the real problem is, people may use substitute a rare characters with a more common one. This means that we may not be able to match the texts from the two data sources just by the name of each verses. And not even to mention that the names of verses are highly duplicated.

The solution is, we will first calculate the text distance of all combinations of verses from the two data sets, and for each one in the often-performed subset, we will choose the one with smallest text distance as its 'fuzzy match'. And then we would only keep those 'matched' one, and explore the distribution of the text deviation.-

Below are the available measures of text distance of 'stringdist' package: - osa Optimal string alignment, (restricted Damerau-Levenshtein distance). - lv Levenshtein distance (as in R's native adist). - dl Full Damerau-Levenshtein distance. - lcs Longest common sub-string distance. - hamming Hamming distance (a and b must have same number of characters). - qgram q-gram distance. - cosine cosine distance between q-gram profiles - jaccard Jaccard distance between q-gram profiles - jw Jaro-Winkler distance.

```
# Applying different string matching methods
# https://www.r-bloggers.com/fuzzy-string-matching-a-survival-skill-to-tackle
# -unstructured-information/
# We've stored the text distances in a csv file and we will use that instead of
# calculating agian.
source('./bin/getTextDistance.R')
DTDistance <-
  getTextDistance(DTGongchepu[,Lyrics],
                  DTWikisource[,Lyrics],
                  c( 'osa', 'lv', 'dl', 'lcs'))
```

The q-gram based methods won't generate meaningful result because phrases of Chinese language is not separated by white spaces as in most languages. We tried the OSA, LV distance, DL distance and LCS. It turns out that LCS distance hardly gives any meaningful result while the other three measures suggests similar matches. Thus we will use the matches measured by OSA in the next step.

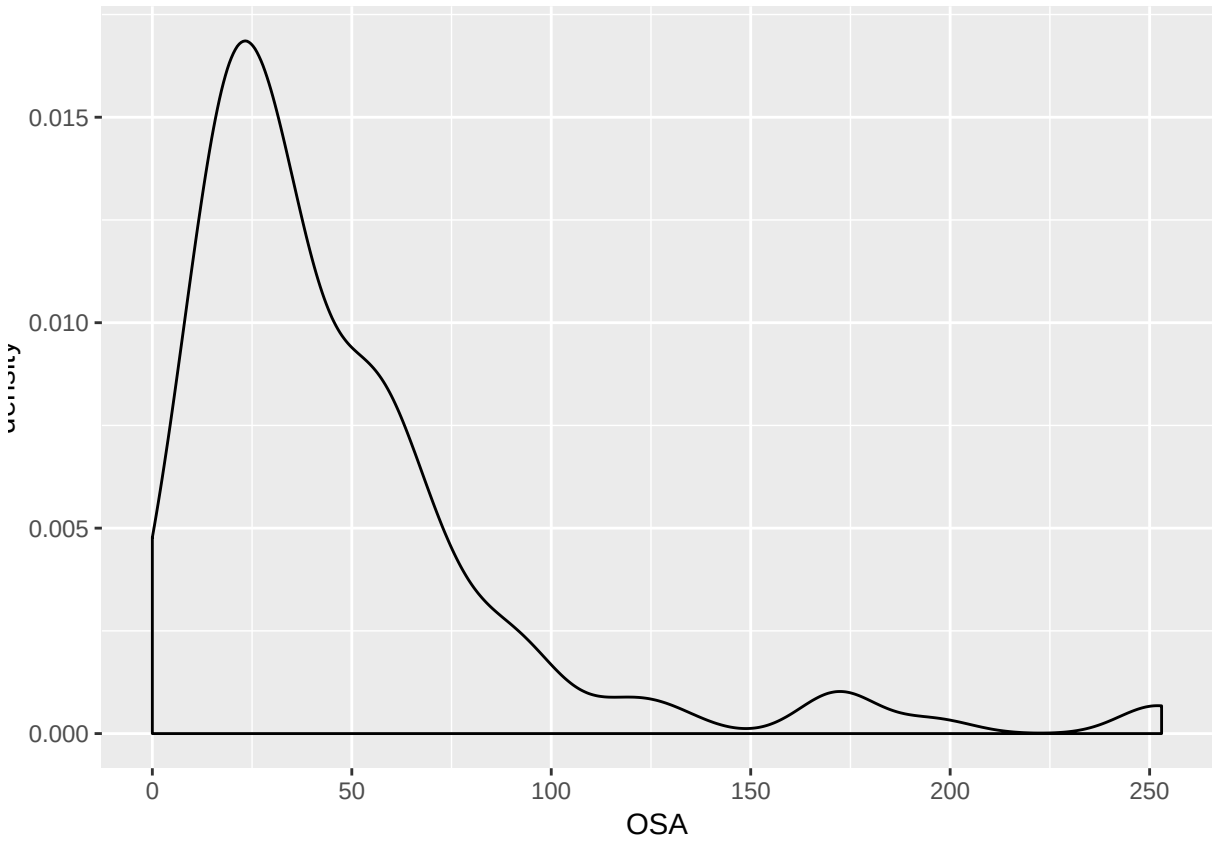
```
# Take 5 random samples
set.seed(222)
idx = sample(1:nrow(DTGongchepu), 5)
DTMatchOSA <-
  data.table(gongchepu = DTGongchepu[idx, Lyrics],
             wikisource = DTWikisource[unlist(DTDistance[1, ])]$Lyrics[idx])
DTMatchLV <-
  data.table(gongchepu = DTGongchepu[idx, Lyrics],
             wikisource = DTWikisource[unlist(DTDistance[2, ])]$Lyrics[idx])
DTMatchDL <-
  data.table(gongchepu = DTGongchepu[idx, Lyrics],
             wikisource = DTWikisource[unlist(DTDistance[3, ])]$Lyrics[idx])
DTMatchLCS <-
  data.table(gongchepu = DTGongchepu[idx, Lyrics],
             wikisource = DTWikisource[unlist(DTDistance[4, ])]$Lyrics[idx])
```

We will store the matched pairs in a CSV files, so that readers can check it visually.

```
# Only keep the distance measured by osa
DT <-
  data.table(gongchepu = DTGongchepu[, Lyrics],
             wikisource = DTWikisource[unlist(DTDistance[1, ])]$Lyrics[])
fwrite(DT, './data/matchedOSA.csv')
```

And after matching these text, now we will visualise the distribution of the text deviation now.

```
OSADistance <-
  data.table(i = 1: nrow(DTGongchepu),
             OSA = apply(stringdistmatrix(DTGongchepu[,Lyrics],
                                          DTWikisource[,Lyrics],
                                          c('osa')),
                         1, min))
ggplot(OSADistance, aes(OSA)) + geom_density()
```



4. Summary

In this project, we acquired two text corpus from two sources, Gongchepu.net and Wikisource, and matched them by Optimal String Alignment. The density plot is given and it turns out that, the mean OSA measure is around 25. In the future, we could apply this framework to compare text corpus from other sources.