Bios 611 HW5

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Q1: Explain functions

```
'md5_hash': return a MD5 hash from the given URL
```

'fetch_raw': retrieve the raw HTML content from the given URL without caching and adding a random delay (6 to 12 sec) to avoid excessive requests. Also, logs the time of each request.

'fetch': First, check if there's local cache file for the given URL, if not, it fetches it and saves it to the cache and returns a parsed HTML object.

'episode lists urls': get each episode's url from the webpage

'tokenize_and_count': Process the input text by removing punctuation, converting to lowercase, tokenizing, filtering out stopwords and count the frequency of each word

'get_text_of_episodes': extract text content from the episode URL

'get_word_counts_for_episodes': calculate the word frequency for the text of each episode

'get_total_word_count': sum word counts frequency from all episodes

'convert_to_word_count_vectors': convert the word counts into vector

'write_word_counts_to_csv': write the vector for each url into a csv file

Q2: Visualization

Part a

```
d <- read_csv("episode_word_counts.csv")
```

```
## Rows: 176 Columns: 3149
## -- Column specification ------
## Delimiter: ","
## chr (1): Episode URL
## dbl (3148): captains, log, stardate, destination, planet, four, beyond, lies...
##
## i Use 'spec()' to retrieve the full column specification for this data.
## i Specify the column types or set 'show_col_types = FALSE' to quiet this message.
```

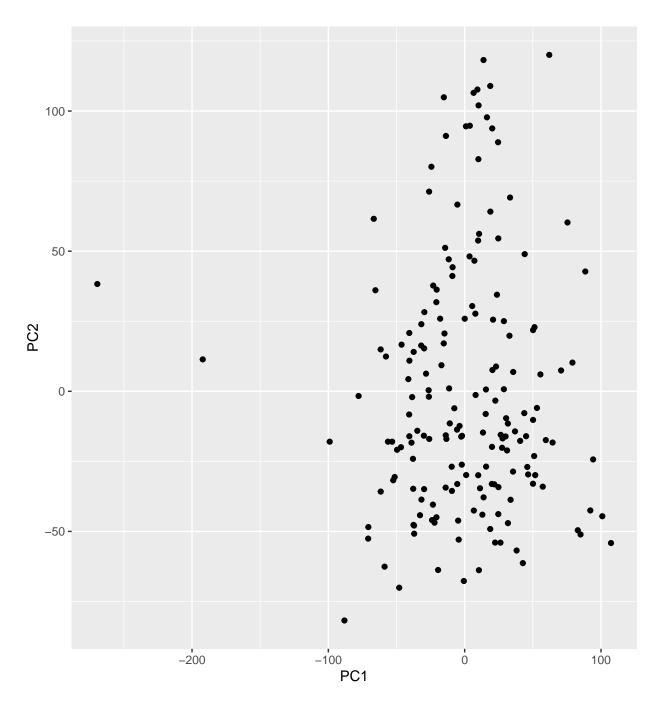
^{&#}x27;cache_path': return the cache path from the given URL

```
m <- d %>% select(-`Episode URL`) %>% colSums() %>% as_tibble()
d <- d %>% select(-`Episode URL`) %>% mutate(`Episode URL` = d %>% pull(`Episode URL`))
1 <- d %>% pivot_longer(cols=captains:devron) %>%
    group_by(name) %>%
    summarise(total=sum(value))
1 <- 1 %>% mutate(name = factor(name, 1 %>% arrange(desc(total)) %>% pull(name)))
ggplot(1 %>% filter(total > 1000), aes(name, total)) + geom_col() + theme(axis.text.x = element_text(an)
   15000 -
   10000 -
    5000 -
```

name

Part b

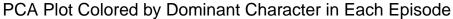
```
pca <- prcomp(d %>% select(-`Episode URL`) %>% as.matrix())
pcs <- pca$x %>% as_tibble()
pcs1 <- pcs[,1:2] %>% as.data.frame()
pcs %>% ggplot(aes(PC1,PC2))+geom_point()
```

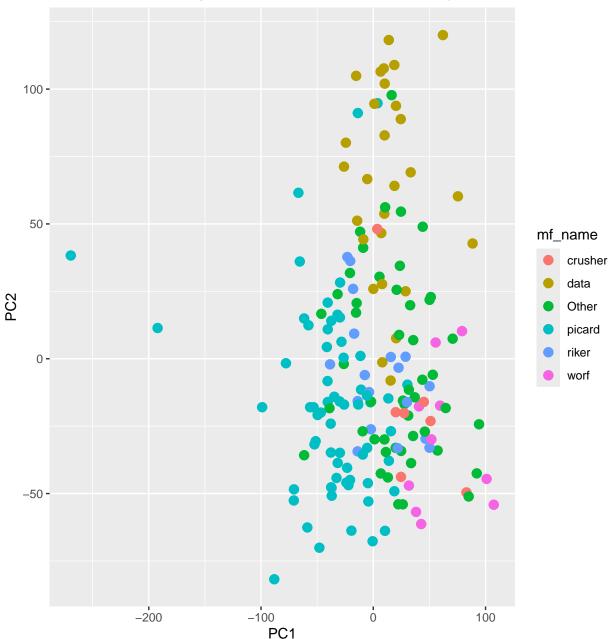


Part c

```
mf_chr <- d %>%
    pivot_longer(captains:devron) %>%
    group_by(`Episode URL`) %>%
    arrange(desc(value)) %>%
    slice_head(n = 1) %>%
    mutate(rank = row_number()) %>%
    select(mf_name = name, mf_value = value)
```

Adding missing grouping variables: 'Episode URL'

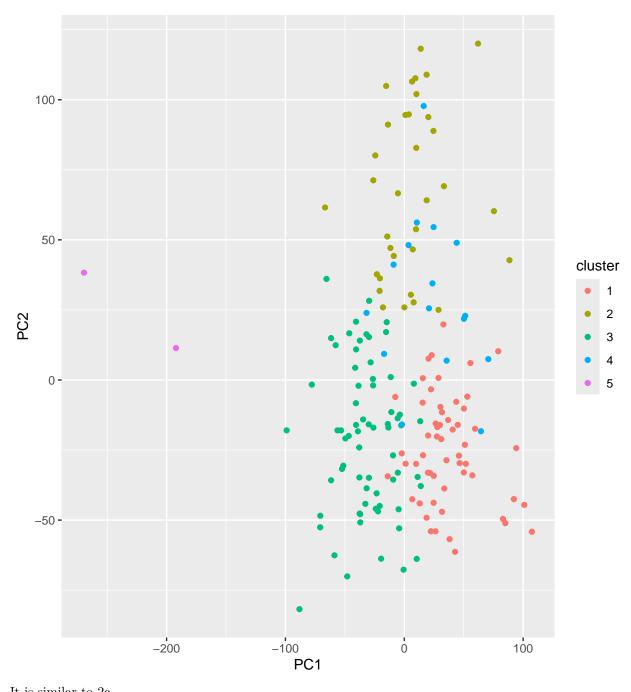




The top 5 most often names are picard, data, riker, worf, crusher. Picard-dominated episodes appear across PC1, indicating his consistent presence across various themes and episode types. And data-dominated episodes appear in specific area.

Q3: Clustering

```
pca_mf$cluster <- factor(kmeans(d %>% select(-`Episode URL`), centers = 5)$cluster)
pca_mf %>% ggplot(aes(PC1,PC2,color=cluster)) + geom_point()
```



It is similar to 2c.

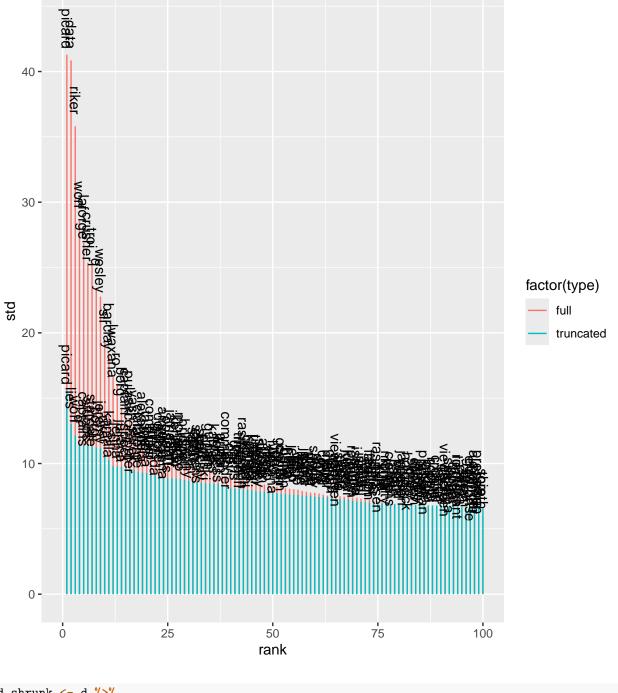
Q4: Classifier

```
stds <- d %>%
    summarise(across(captains:devron, sd)) %>%
    pivot_longer(captains:devron) %>%
   rename(std=value) %>%
    arrange(desc(std)) %>%
```

```
mutate(name = factor(name, name)) %>%
    mutate(rank=1:nrow(.))
pcs <- pca$x %>% as_tibble() %>% mutate(across(PC71:PC176, ~ 0)) %>% as.matrix()
truncated_stds <- pca$rotation %*% pcs %>% t() %>% as_tibble() %>%
    summarise(across(captains:devron, sd)) %>%
    pivot longer(captains:devron) %>%
    rename(std=value) %>%
    arrange(desc(std)) %>%
    mutate(name = factor(name, name)) %>%
    mutate(rank=1:nrow(.))
std_df <- bind_rows(stds %>% mutate(type="full"),
                    truncated_stds %>% mutate(type="truncated"))
ggplot(std_df, aes(rank, std)) +
    geom_segment(aes(x=rank, xend=rank, y=0, yend=std, color=factor(type))) + xlim(0, 100) +
    geom_text(aes(label=name, y=std+2), angle=-90)
## Warning: Removed 6096 rows containing missing values or values outside the scale range
## ('geom_segment()').
```

Warning: Removed 6096 rows containing missing values or values outside the scale range

('geom_text()').



```
d_shrunk <- d %>%
    select(all_of(std_df %>% filter(type=="truncated" & rank <= 70) %>% pull(name))) %>%
    mutate(first_half=(row_number() < max(row_number())/2)*1)

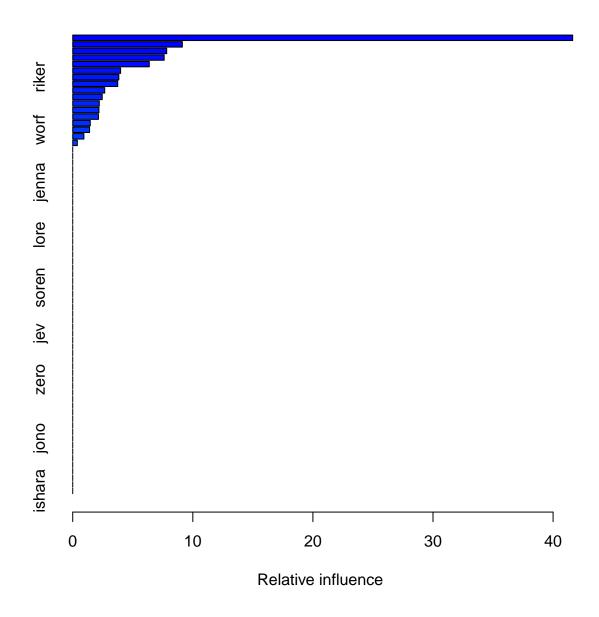
library(gbm)</pre>
```

Loaded gbm 2.2.2

This version of gbm is no longer under development. Consider transitioning to gbm3, https://github.c

```
## Type 'citation("pROC")' for a citation.
##
## Attaching package: 'pROC'
## The following objects are masked from 'package:stats':
##
##
       cov, smooth, var
train_i <- runif(nrow(d_shrunk)) < 0.75;</pre>
train <- d_shrunk %>% filter(train_i);
test <- d_shrunk %>% filter(!train_i);
model <- gbm(first_half ~ ., data=train)</pre>
## Distribution not specified, assuming bernoulli ...
## Warning in gbm.fit(x = x, y = y, offset = offset, distribution = distribution,
## : variable 9: jeremy has no variation.
## Warning in gbm.fit(x = x, y = y, offset = offset, distribution = distribution,
## : variable 24: susanna has no variation.
## Warning in gbm.fit(x = x, y = y, offset = offset, distribution = distribution,
## : variable 26: marr has no variation.
## Warning in gbm.fit(x = x, y = y, offset = offset, distribution = distribution,
## : variable 35: tam has no variation.
## Warning in gbm.fit(x = x, y = y, offset = offset, distribution = distribution,
## : variable 40: jev has no variation.
## Warning in gbm.fit(x = x, y = y, offset = offset, distribution = distribution,
## : variable 54: liko has no variation.
## Warning in gbm.fit(x = x, y = y, offset = offset, distribution = distribution,
## : variable 58: nuria has no variation.
summary(model)
```

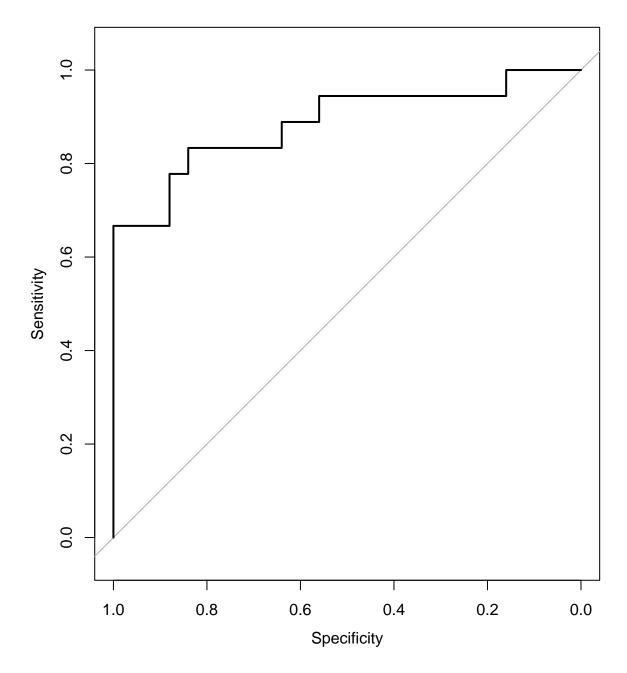
library(pROC)



```
##
                 var
                        rel.inf
## wesley
              wesley 41.6312337
## captain
             captain 9.1300516
## picard
              picard 7.8255167
## obrien
              obrien 7.6153515
## tasha
               tasha
                      6.3745707
## sir
                      3.9865261
                 sir
                      3.8412927
## riker
               riker
## stardate stardate
                     3.7471870
## doctor
              doctor
                      2.6644346
## laforge
             laforge
                      2.4579258
```

```
## computer computer
                       2.2140904
## captains captains
                       2.1842807
## pulaski
             pulaski
                       2.1444385
## oc
                       1.4636689
                   οс
## worf
                 worf
                       1.4031468
## four
                 four
                       0.9317518
## lies
                       0.3845324
                 lies
## q
                       0.0000000
                    q
## stubbs
              stubbs
                       0.0000000
## borg
                 borg
                       0.0000000
   jeremy
               jeremy
                       0.0000000
  kamala
                       0.0000000
##
              kamala
   jenna
                jenna
                       0.0000000
   juliana
             juliana
                       0.0000000
  spock
                       0.0000000
               spock
## sarek
               sarek
                       0.0000000
## nella
               nella
                       0.0000000
## okona
               okona
                       0.0000000
                       0.0000000
## fajo
                fajo
## amanda
              amanda
                       0.0000000
## lore
                 lore
                       0.0000000
## susanna
             susanna
                       0.000000
## armus
                       0.0000000
               armus
## marr
                marr
                       0.0000000
## alkar
               alkar
                       0.0000000
                       0.0000000
## jellico
             jellico
##
  scott
                scott
                       0.0000000
                       0.0000000
## timothy
             timothy
## soren
                       0.0000000
                soren
## clemens
             clemens
                       0.0000000
## barclay
             barclay
                       0.0000000
## tam
                  tam
                       0.000000
##
   jr
                   jr
                       0.000000
                       0.0000000
## kahless
             kahless
## john
                 john
                       0.000000
## jev
                  jev
                       0.0000000
## korris
              korris
                       0.000000
## macduff
             {\tt macduff}
                       0.000000
## russell
             russell
                       0.000000
                       0.0000000
## kolrami
             kolrami
## ardra
               ardra
                       0.0000000
## jason
                jason
                       0.0000000
                       0.0000000
##
  zero
                 zero
## lwaxana
             lwaxana
                       0.0000000
## odan
                       0.0000000
                 odan
## liko
                 liko
                       0.0000000
## leah
                leah
                       0.0000000
## dirgo
                dirgo
                       0.0000000
## satie
               satie
                       0.0000000
## nuria
               nuria
                       0.0000000
## wyatt
               wyatt
                       0.0000000
## jono
                 jono
                       0.0000000
## kyle
                kyle
                       0.0000000
## riva
                riva
                       0.0000000
```

```
## finn finn 0.0000000
## guinan guinan 0.0000000
            soong 0.0000000
## soong
               vash 0.0000000
## vash
## kehleyr kehleyr 0.0000000
## ishara
            ishara 0.0000000
predict_part <- predict(model, newdata = test, type = "response")</pre>
## Using 100 trees...
predict_part
## [1] 0.60170070 0.99573002 0.82005315 0.43216239 0.95104593 0.66202207
## [7] 0.97852929 0.14890888 0.98249392 0.91134607 0.09735571 0.42808708
## [13] 0.98550141 0.79692446 0.84102386 0.91637967 0.35422121 0.03560656
## [19] 0.47726716 0.04638075 0.26657591 0.45037571 0.09976602 0.07372857
## [25] 0.05532362 0.06995522 0.07770646 0.25106809 0.17453177 0.02450838
## [31] 0.15287921 0.07648308 0.59330870 0.38122921 0.05957594 0.03344363
## [37] 0.06462630 0.05342155 0.10371848 0.23464450 0.01354863 0.02686260
## [43] 0.03581457
roc <- roc(test$first_half,predict_part)</pre>
## Setting levels: control = 0, case = 1
## Setting direction: controls < cases
plot(roc)
```



The AUC is

roc\$auc

Area under the curve: 0.8867

Q5: load into python

```
import pandas as pd
df = pd.read_csv("episode_word_counts.csv")
print(f"the data contains {len(df)} rows")

## the data contains 176 rows

df_cleaned = df[df.iloc[:, 1:].select_dtypes(include='number').sum(axis=1) >= 100]
df_cleaned.to_csv("episode_word_counts_cleaned.csv", index=False)
```