Topic Modelling

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```
library(tidyverse)
## -- Attaching core tidyverse packages ----- tidyverse 2.0.0 --
## v dplyr 1.1.4 v readr
                                   2.1.5
## v forcats 1.0.0 v stringr 1.5.1
## v ggplot2 3.5.1 v tibble 3.2.1
                     v tidyr
                                   1.3.1
## v lubridate 1.9.3
## v purrr
              1.0.2
## -- Conflicts ----- tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()
                    masks stats::lag()
## i Use the conflicted package (<a href="http://conflicted.r-lib.org/">http://conflicted.r-lib.org/</a>) to force all conflicts to become error
library(topicmodels)
library(tidytext)
library(lexicon)
library(factoextra)
## Welcome! Want to learn more? See two factoextra-related books at https://goo.gl/ve3WBa
library(wordcloud)
## Loading required package: RColorBrewer
set.seed(100)
knitr::opts_chunk$set(echo = TRUE)
movies <- read.csv("movie_plots_with_genres.csv")</pre>
plots_by_word <- movies |> unnest_tokens(word,Plot)
plot_word_counts <- plots_by_word |>
 anti_join(stop_words) |>
 count(Movie.Name, word, sort=TRUE)
## Joining with 'by = join_by(word)'
```

```
data("freq_first_names")
first_names <- tolower(freq_first_names$Name)

plot_word_counts <- plot_word_counts |>
   filter(!(word %in% first_names))

dtm <- plot_word_counts |>
   cast_dtm(Movie.Name, word, n)

lda <- LDA(dtm, k = 20, control = list(seed=100))

top_terms <- terms(lda, 10)</pre>
```

Extract greeks

```
betas <- tidy(lda, matrix = "beta")

gamma_df <- tidy(lda, matrix = "gamma")

gamma_df <- gamma_df |>
    pivot_wider(names_from = topic, values_from = gamma)

cluster <- kmeans(gamma_df |>
    select(-document),10)
```

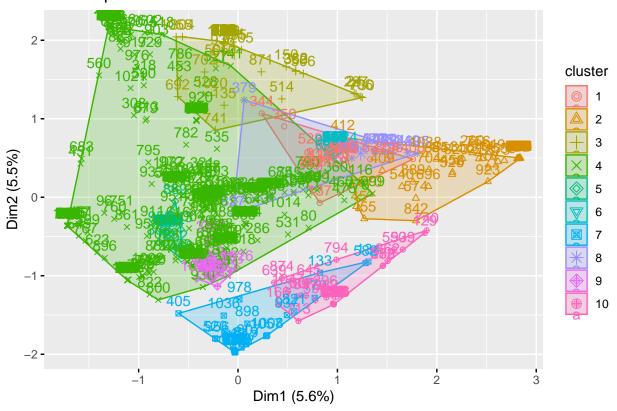
Take highest gamma for each movie

```
top_movies_by_topic <- gamma_df |>
  pivot_longer(cols = `1`:`20`, names_to = "topic", values_to = "gamma") |>
  group_by(document) |>
  slice_max(gamma, n = 1) |>
  ungroup() |>
  select(document, topic, gamma)
```

But do get a more detailed look, we need to cluster the movies into 10 clusters by topic

```
cluster <- kmeans(gamma_df |> select(-document),10)
fviz_cluster(cluster, data = gamma_df |> select(-document))
```

Cluster plot



```
movies <- movies |>
  distinct(Movie.Name, .keep_all = TRUE)

clusters <- cluster[["cluster"]]
cluster$cluster <- clusters
movies$cluster <- clusters</pre>
```

Create clusters

```
gamma_df <- gamma_df |>
  left_join(movies |> select(Movie.Name, cluster), by = c("document" = "Movie.Name"))

cluster_1 <- gamma_df |> filter(cluster == 1)

cluster_2 <- gamma_df |> filter(cluster == 2)

cluster_3 <- gamma_df |> filter(cluster == 3)

cluster_4 <- gamma_df |> filter(cluster == 4)

cluster_5 <- gamma_df |> filter(cluster == 5)

cluster_6 <- gamma_df |> filter(cluster == 6)

cluster_7 <- gamma_df |> filter(cluster == 7)
```

```
cluster_8 <- gamma_df |> filter(cluster == 8)

cluster_9 <- gamma_df |> filter(cluster == 9)

cluster_10 <- gamma_df |> filter(cluster == 10)
```

Find which topic is most associated with each cluster

```
col_avg <- function(df) {
    selected_columns <- df |>
        select(`1`:`20`)

    column_averages <- colMeans(selected_columns, na.rm = TRUE)

    return(column_averages)
}

averages_cluster_1 <- col_avg(cluster_1)

print(averages_cluster_1)</pre>
```

```
3
##
## 0.0222333661 0.0527353347 0.0144461738 0.0402533374 0.0213391882 0.0924116503
              7
                           8
                                        9
                                                     10
                                                                  11
## 0.0554159975 0.1244689656 0.0046185883 0.0385350630 0.0966434180 0.0332871895
                          14
                                       15
                                                     16
                                                                  17
##
             13
## 0.0596147530 0.0002856475 0.1095327048 0.0367526515 0.0302752900 0.0575822571
             19
## 0.0765102692 0.0330581547
```

We can see that these probailites are pretty small, however a few of them stick out, particuarily topics 4 and 14. This indicates that cluster 1 is most assiciates with topics 4 and 14.

Make word clouds

1 2 3 4 5 6

```
## 0.038518157 0.052704407 0.049074038 0.002578612 0.076848261 0.026983826
##
             7
                         8
                                     9
                                                 10
                                                             11
                                                                          12
## 0.051280390 0.045101622 0.009226373 0.036245027 0.051364319 0.040780356
                                                             17
                        14
                                    15
                                                 16
                                                                          18
            13
## 0.025769782 0.094288860 0.033810315 0.025751320 0.092990747 0.057026639
##
            19
                        20
## 0.122000641 0.067656309
```

Lets make some fun word clouds

wordcloud(1)

```
california business movie people western wyoming lives fall time family local land riff world town u.s sky o'hara alen girl sold planet story paralympic to matthews relationship
```

wordcloud(2)

```
forces people
indian family brother
train
white wagon
civil
time and
home father
union
indians brothers
black killed army
josey soldiers
outlaws
```

wordcloud(3)

```
maverick championships
british day pame
free set history war
world filmfuture
morrell captain farm
french space
bullitt ife oneygirl
wars in dian law return
freedom women
basketball indians
```

Jon helped me with the word cloud code