Topic Modeling

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```
library(lexicon)
library(tidyverse)
## -- Attaching core tidyverse packages ----- tidyverse 2.0.0 --
## v dplyr 1.1.4 v readr
                                    2.1.4
## v forcats 1.0.0 v stringr 1.5.0
## v ggplot2 3.5.1
                       v tibble
                                    3.2.1
## v lubridate 1.9.2
                        v tidyr
                                    1.3.1
## 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(factoextra)
## Welcome! Want to learn more? See two factoextra-related books at https://goo.gl/ve3WBa
library(dplyr)
library(ggplot2)
library(wordcloud)
## Loading required package: RColorBrewer
library(RColorBrewer)
movies <- read.csv("movie_plots.csv")</pre>
Group by Genre, summarize common words, and find genre frequency
# Extract genres based on common keywords found in the plot descriptions
movies <- movies %>%
  mutate(Genre = case_when(
   str_detect(Plot, "(?i)science|space|experiment|future|alien|
              robot|technology|planet|human|new world|earth") ~ "Sci-Fi",
    str_detect(Plot, "(?i)love|romance|relationship|affair|
```

```
wedding|couple|meets|girl") ~ "Romance",
    str_detect(Plot, "(?i)war|battle|army|soldier|conflict|
               military|enemy|tank|battlefield|dead") ~ "War",
    str_detect(Plot, "(?i)ghost|haunt|horror|fear|terror|
               scary|supernatural|creepy") ~ "Horror",
    str_detect(Plot, "(?i)crime|detective|murder|investigate|
               thriller | mafia | heist | mystery") ~ "Crime",
    str detect(Plot, "(?i)action|fight|fighting|adventure|hero|explosion|
               battle|rescue") ~ "Action",
    str_detect(Plot, "(?i)comedy|funny|humor|laugh|joke|
               satire|parody") ~ "Comedy",
    str_detect(Plot, "(?i)history|historical|biography|true story|
               period drama|century|ancient") ~ "History",
    str_detect(Plot, "(?i)fantasy|magic|myth|legend|superhero|
               kingdom|evil") ~ "Fantasy",
    str_detect(Plot, "(?i)western|cowboy|wild west|sheriff|ranch|
               town|outlaw") ~ "Western",
    str_detect(Plot, "(?i)documentary|docu|true events|reality|
               biopic") ~ "Documentary",
    str_detect(Plot, "(?i)sport|game|team|match|championship|
               wrestling") ~ "Sport",
    str_detect(Plot, "(?i)home|people|brother|daughter|brothers|
               friend|wife|son|father|mother") ~ "Family",
   TRUE ~ "Other"
  ))
# Calculate the frequency of each genre
genre_frequency <- movies %>%
  count(Genre, name = "Frequency")
# Tokenize the plots and remove stop words
plot_words <- movies %>%
  unnest_tokens(word, Plot) %>%
  anti_join(get_stopwords()) %>%
  count(Genre, word, sort = TRUE)
## Joining with 'by = join_by(word)'
# Group by Genre, summarize common words, and find genre frequency
nested_data <- plot_words %>%
  group_by(Genre) %>%
  summarize(
   Words = paste(unique(word), collapse = ", ")
  left_join(genre_frequency, by = "Genre")
view(nested_data)
```

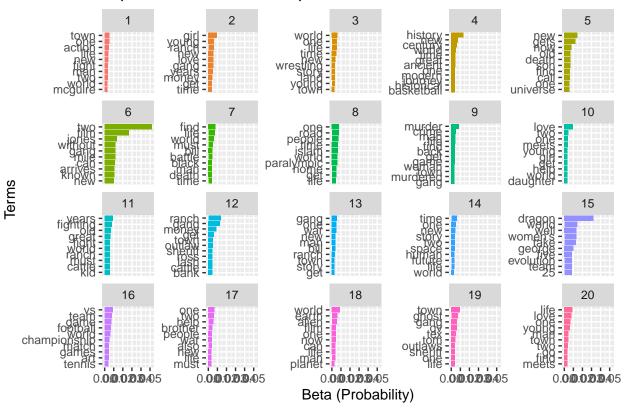
Create a Document Term Matrix

```
dtm <- plot_words %>%
  cast_dtm(Genre, word, n)
```

```
dtm
```

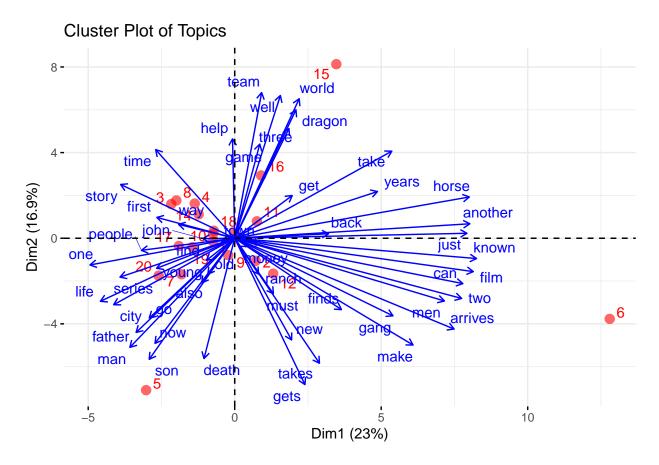
```
## <<DocumentTermMatrix (documents: 14, terms: 14842)>>
## Non-/sparse entries: 30812/176976
## Sparsity
                     : 85%
## Maximal term length: 17
## Weighting
                : term frequency (tf)
Fir the LDA Model
# Since we have 14 genres, we try to set k close to the number of genres.
k <- 20
# Fit the LDA model with k = 14
lda_model <- LDA(dtm, k = k, control = list(seed = 999))</pre>
# Extract the topic-term matrix
topics <- tidy(lda_model, matrix = "beta")</pre>
# View the top 10 terms for each topic
top_terms <- topics %>%
  group_by(topic) %>%
  slice_max(beta, n = 10) %>%
  ungroup() %>%
  arrange(topic, -beta)
print(top_terms)
## # A tibble: 205 x 3
##
      topic term
                      beta
##
      <int> <chr>
                     <dbl>
##
                   0.00552
  1
         1 town
                   0.00545
## 2
         1 one
         1 action 0.00474
## 3
## 4
        1 life 0.00427
## 5
        1 new
                   0.00387
## 6
        1 fight
                   0.00378
## 7
         1 man
                   0.00347
## 8
        1 two
                   0.00339
## 9
         1 world 0.00300
## 10
         1 mcguire 0.00296
## # i 195 more rows
# Plot the top terms for visualization
ggplot(top_terms, aes(x = reorder_within(term, beta, topic), y = beta,
                     fill = factor(topic))) +
  geom_col(show.legend = FALSE) +
  facet_wrap(~ topic, scales = "free_y") +
  coord_flip() +
  scale_x_reordered() +
  labs(title = "Top 10 Terms for Each Topic", x = "Terms",
       y = "Beta (Probability)")
```

Top 10 Terms for Each Topic



Cluster Plot and Gamma Plot

```
# Filter the topic-term matrix to include only the top 50 most frequent terms
filtered_topics <- topics %>%
  group_by(term) %>%
  summarize(total_beta = sum(beta)) %>%
  top_n(50, total_beta)
topic_term_matrix <- topics %>%
  filter(term %in% filtered_topics$term) %>%
  spread(term, beta) %>%
  column_to_rownames(var = "topic")
# Perform PCA on the filtered topic-term matrix
pca_result <- prcomp(topic_term_matrix, scale. = TRUE)</pre>
# Plot the PCA result
fviz_pca_biplot(pca_result,
                repel = TRUE,
                col.var = "blue",
                col.ind = "red",
                pointsize = 3,
                alpha.ind = 0.6,
                title = "Cluster Plot of Topics")
```



```
# Extract the document-topic distribution (gamma values)
doc_topic_matrix <- tidy(lda_model, matrix = "gamma")

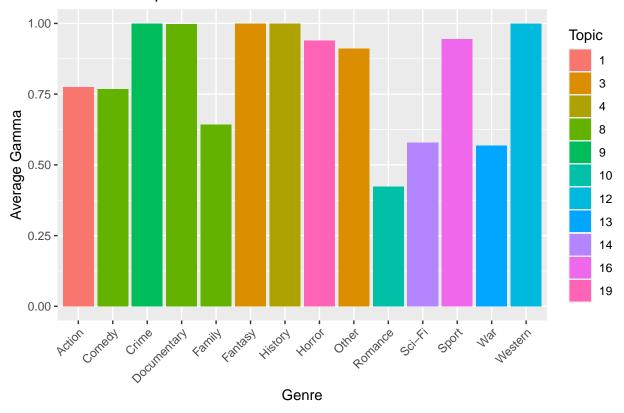
# Aggregate by genre and calculate the average gamma per topic
genre_topic_distribution <- doc_topic_matrix %>%
    rename(Genre = document) %>%
    group_by(Genre, topic) %>%
    summarize(avg_gamma = mean(gamma, na.rm = TRUE), .groups = "drop")

# Identify the dominant topic for each genre
dominant_topics <- genre_topic_distribution %>%
    group_by(Genre) %>%
    slice_max(avg_gamma, n = 1) %>%
    ungroup()
```

```
## # A tibble: 14 x 3
##
      Genre
                  topic avg_gamma
##
      <chr>
                   <int>
                             <dbl>
                             0.775
##
    1 Action
    2 Comedy
                       8
                             0.769
##
                       9
                             1.00
   3 Crime
##
  4 Documentary
                       8
                             0.998
    5 Family
                             0.643
```

```
1.00
##
    6 Fantasy
                      3
##
   7 History
                      4
                             1.00
                      19
                             0.939
##
    8 Horror
   9 Other
                      3
                             0.910
##
## 10 Romance
                      10
                             0.423
## 11 Sci-Fi
                      14
                             0.579
## 12 Sport
                      16
                             0.945
## 13 War
                             0.567
                      13
## 14 Western
                      12
                             1.00
```

Dominant Topics for Each Genre



Create a Word Clound for each genre

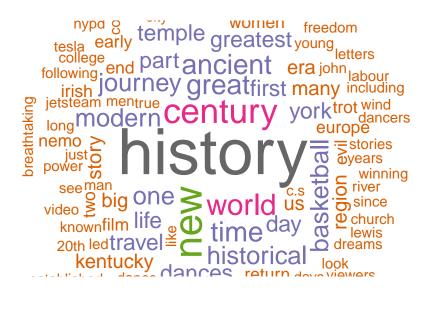
```
# Set up color palette
palette <- brewer.pal(8, "Dark2")

# Create word clouds for each topic in a loop
k <- 14
for (i in 1:k) {</pre>
```

order monster series jones away set day adventure martial find family son also can las find family son also can las ringo twofight law young life one get would gang blaine action world fighting new man otake rescue mcguire go three local people horse marshal must freedom

become of protner uauginer of york dead redlife money of knows enever take three son old ove must even city sisteralso ranch back family men make of time soon man years latertry billy goes young of falls arrives secret land young of falls sheriff takes town gold tow

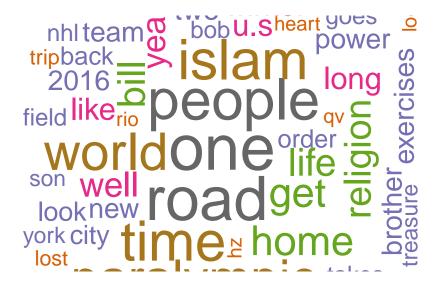
west find town New along west find town New al

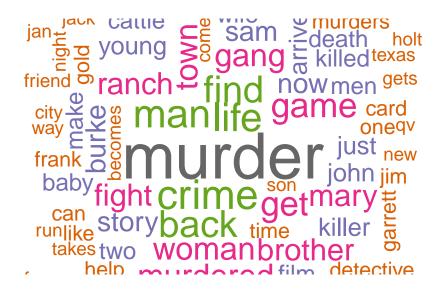


grouppeople machinebrothers
grouppeople machinebrothers
go mission
go mission
sides
treasure
treasure
storm year
slavestime
wife jack map
players self
ctim of self
grouppeople machinebrothers
go mission
treasure
treasure
storm year
slavestime
grather men
way young
one man lies united
universebrings of light
universebrings of lies
grouppeople machinebrothers
grouppeople machinebrothers
grouppeople machinebrothers
sides
treasure
treasure
slavestime
men
wife jack map
players self
universebrings of lies



indians daughter behind waydan takes death must behind waydan takes death must behind son substance blackworld son story deadtime indians daughter behind waydan takes death must behind son story son story deadtime indians daughter behind waydan takes death must behind son story son story deadtime indians daughter behind waydan takes death must behind son story dan deadtime indians daughter behind waydan takes death must be hind son story deadtime indians daughter behind waydan takes death must behind son story death must be hind waydan takes death must be hind son story death must be hind





friend last another time help get film meet falls gold meets one takes girls must be john love father movie daughter two girl now go wants outlaw can young life man love comesoon line begins story wife land friends





```
streets way land men killed of participations of the learn ranch bill world wo
```

fight go make live make live three Space takes team back bestbattle Story love town movie planet time war also first earth one life save will be life save w