FIT3152 Data analytics

Assignment 3

Name: Rhyme Bulbul

Student ID: 31865224

AI statement: No content generated by AI technologies has been used in this assessment.

Task 1

I gathered a collection of 20 text documents from different sources that covered a range of themes for this task. Primarily these focus on either `linux`, or movie reviews. `fast`, `pirates` and `impossible` are the movie reviews included in these publications. These refer to the movie sequels "The Fast and The Furious", "The Pirates of the Caribbean" and "Mission Impossible" respectively.

Text files were created by copying and pasting the document contents, and references can be found in the appendix.

Task 2

The document's contents pasted into text files in Task 1. The text files were assembled into the `text` folder within the working directory in order to generate the corpus. Next, the code that follows is executed. It installs and imports the necessary libraries, sets the seed and uses the `Corpus()` function from the `tm` package to construct the corpus.

```r
rm(list = ls())
set.seed(31865224)

library(tm)
library(cluster)
library(igraph)

cname <- file.path(".", "text")
docs <- Corpus(DirSource((cname)))
list.files("text")
```

```
##  [1] "fast01.txt"       "fast02.txt"       "fast03.txt"       "fast04.txt"
##  [5] "fast05.txt"       "impossible01.txt" "impossible02.txt" "impossible03.txt"
##  [9] "impossible04.txt" "impossible05.txt" "linux01.txt"      "linux02.txt"
## [13] "linux03.txt"      "linux04.txt"      "linux05.txt"      "pirates01.txt"
## [17] "pirates02.txt"    "pirates03.txt"    "pirates04.txt"    "pirates05.txt"
```

Documents are named based on the topic, suffixed by a number. Such as, `linux01.txt` is the first text document on linux systems, followed by `linux02.txt` the second text document on the same topic, and so fourth.

Task 3

We start by text transforming the corpus, meanwhile replacing dashes and line breaks with spaces for consistency, removing numbers, punctuation, converting all characters to lowercase, and removing any extra white spaces. In addition, we also remove English stop words before finally stemming all words for consistency. This is required as we don't want these characters creating an unwanted bias in our data, as it would be harder to work with, as well as inaccurate.

```r
to_space <- content_transformer(function(x, pattern) gsub(pattern, " ", x))
docs <- tm_map(docs, to_space, "-")
docs <- tm_map(docs, to_space, "\n")
docs <- tm_map(docs, removeNumbers)
docs <- tm_map(docs, removePunctuation)
docs <- tm_map(docs, content_transformer(tolower))
docs <- tm_map(docs, stripWhitespace)
docs <- tm_map(docs, removeWords, stopwords("english"))
docs <- tm_map(docs, stemDocument, language = "english")
```

With our unwanted terms removed, and desired keywords preserverd, the corpus is now ready to create a document term matrix from.

```r
dtm <- DocumentTermMatrix(docs)
```

Let's analyse the attributes of the document term matrix by inspecting a sample of 20 from it's head and tail of most and least frequent terms in alphabetical order.

```r
inspect(dtm)
```

```
## <<DocumentTermMatrix (documents: 20, terms: 5539)>>
## Non-/sparse entries: 13346/97434
## Sparsity           : 88%
## Maximal term length: 58
## Weighting          : term frequency (tf)
## Sample             :
##               Terms
## Docs            android devic fast furious googl kernel linux pirat use version
##   fast01.txt          0     0   70       68     0      0     0     4   0       3
##   fast04.txt          0     0   85       57     0      0     0     6   1       1
##   fast05.txt          0     0   76       68     0      0     0     4   2       6
##   linux01.txt        14    37    5        0     8    283   244     0  69      76
##   linux02.txt         0     4    0        0     3      8    42     0  52      27
##   linux03.txt       468   178    1        0   262     36    42     3 104      77
##   linux04.txt        17    41    0        0    10      2     3     0  17      38
##   linux05.txt        96    39    0        0    28      1     3     0  19      29
##   pirates01.txt       0     0    2        2     0      0     0    38   4       2
##   pirates05.txt       0     0    2        2     0      0     0    53   1       1
```

```r
freq <- colSums(as.matrix(dtm))
freq[head(order(freq), 20)]
```

```
##             actress                 apr            assassin           bandolero
##                   1                   1                   1                   1
##               blast              bloodi                 blu               campo
##                   1                   1                   1                   1
##                cara           chemistri claudiocarvalhodec               clown
##                   1                   1                   1                   1
##              conner              convoy               crawl         distributor
##                   1                   1                   1                   1
##             drivera              dwight               enemi              entwin
##                   1                   1                   1                   1
```

```r
freq[tail(order(freq), 20)]
```

```
##      user       man    imposs   mission    ubuntu    system   support caribbean
##       187       188       194       203       204       218       219       235
##   develop     pirat    releas   version       use     devic   furious     googl
##       249       264       264       273       278       301       307       311
##    kernel     linux      fast   android
##       330       334       356       595
```

With 6062 terms, or as we call it, tokens; the DTM is highly sparse at 88%. Interestingly, the least occurring tokens seem to only appear once, while the most frequent token is `android`, occurring almost 500 times, although it is only expected to be used in 3 documents, pointing to it's sparsity.

This leads us to the removal of sparse tokens from the document term matrix. This time we set the sparsity to 9% as it gives us the best mix of efficiency, reliability, and observability. This figure was chosen as it allows the DTM to have around 20 tokens after removing sparse terms without sacrificing on other attributes, due to the nature of the corpus chosen.

```r
dtms <- removeSparseTerms(dtm, 0.09)
inspect(dtms)
```

```
## <<DocumentTermMatrix (documents: 20, terms: 30)>>
## Non-/sparse entries: 582/18
## Sparsity           : 3%
## Maximal term length: 7
## Weighting          : term frequency (tf)
## Sample             :
##                  Terms
## Docs               also compani featur offici one open play releas see user
##   fast04.txt          1       2      2      2   7    1    1      1   5    2
##   fast05.txt          2       2      2      2   3    2    4      1   5    2
##   impossible01.txt    2       2      1      3   4    2    1      2   4    2
##   linux01.txt        39       6     18      7  17    8    1     62   8   36
##   linux02.txt        24       2     10     12  11   13    1     57   5   20
##   linux03.txt        48      25     29     15  22   51   50     45  11   73
##   linux04.txt        15       2     16     20   4   11    7     18   1   15
##   linux05.txt        11      11     15      8   9   19    3     61   3   13
##   pirates01.txt       2       2      3      1   6    2    1      1   5    2
##   pirates05.txt       1       2      2      4   2    3    1      3   7    2
```

```r
freqs <- colSums(as.matrix(dtms))
freqs[head(order(freqs), 20)]
```

```
##    sign connect  critic technic    date languag    help   color countri popular
##      22      23      28      29      31      34      35      36      36      44
##    unit   video     box  origin   known   offic     top  review product    like
##      50      50      52      52      58      60      66      71      73      76
```

```r
freqs[tail(order(freqs), 20)]
```

```
##    unit   video     box  origin   known   offic     top  review product    like
##      50      50      52      52      58      60      66      71      73      76
## compani    play  offici     see     one  featur    open    also    user  releas
##      78      83      87      93     112     119     134     165     187     264
```

This time round, the least frequent tokens are `exact`, `speed`, `pass` and `care` while the most frequent is `use` with 259 uses. The Document term matrix in it's full length can be found attached in the appendix.

Task 4

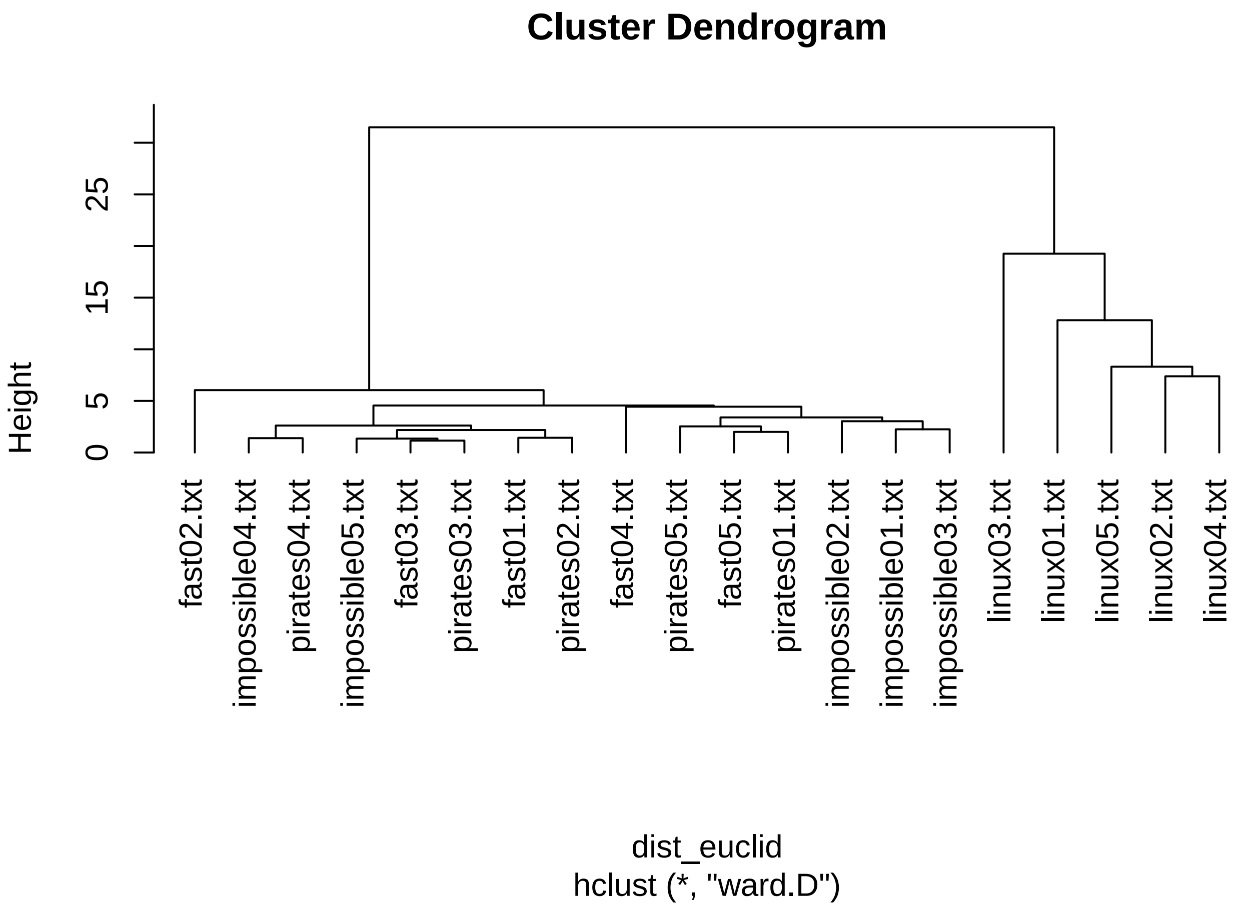
To determine which performs better, a hierarchical clustering of the corpus is carried out using two metrics: Euclidean distance and cosine distance. First, the DTM is transformed into a regular matrix format.

```r
dtms_matrix <- as.matrix(dtms)
```

Each document in document clustering is represented as a vector with numerous dimensions that match the terms it contains. Euclidean distance classifies these vectors according to proximity by measuring the straight-line distance between them. Greater similarity is indicated by a shorter distance. The angle between vectors is measured by cosine distance; smaller angles indicate closer distances and more similarity. By pre-weighting the DTM with the term frequency-inverse document frequency (TF-IDF) statistic, which gives higher weights to terms that appear frequently within a document (implying importance) but infrequently across all documents (implying significance), clustering with cosine distance can be further enhanced.

This code is an adaptation of Lecture 10's clustering using Euclidean distance algorithm. After scaling and converting `dtms_matrix` to a Euclidean distance matrix, a dendrogram is shown.

```r
dist_euclid <- dist(scale(dtms_matrix))
fit_euclid <- hclust(dist_euclid, method = "ward.D")
plot(fit_euclid, hang = -1)
```

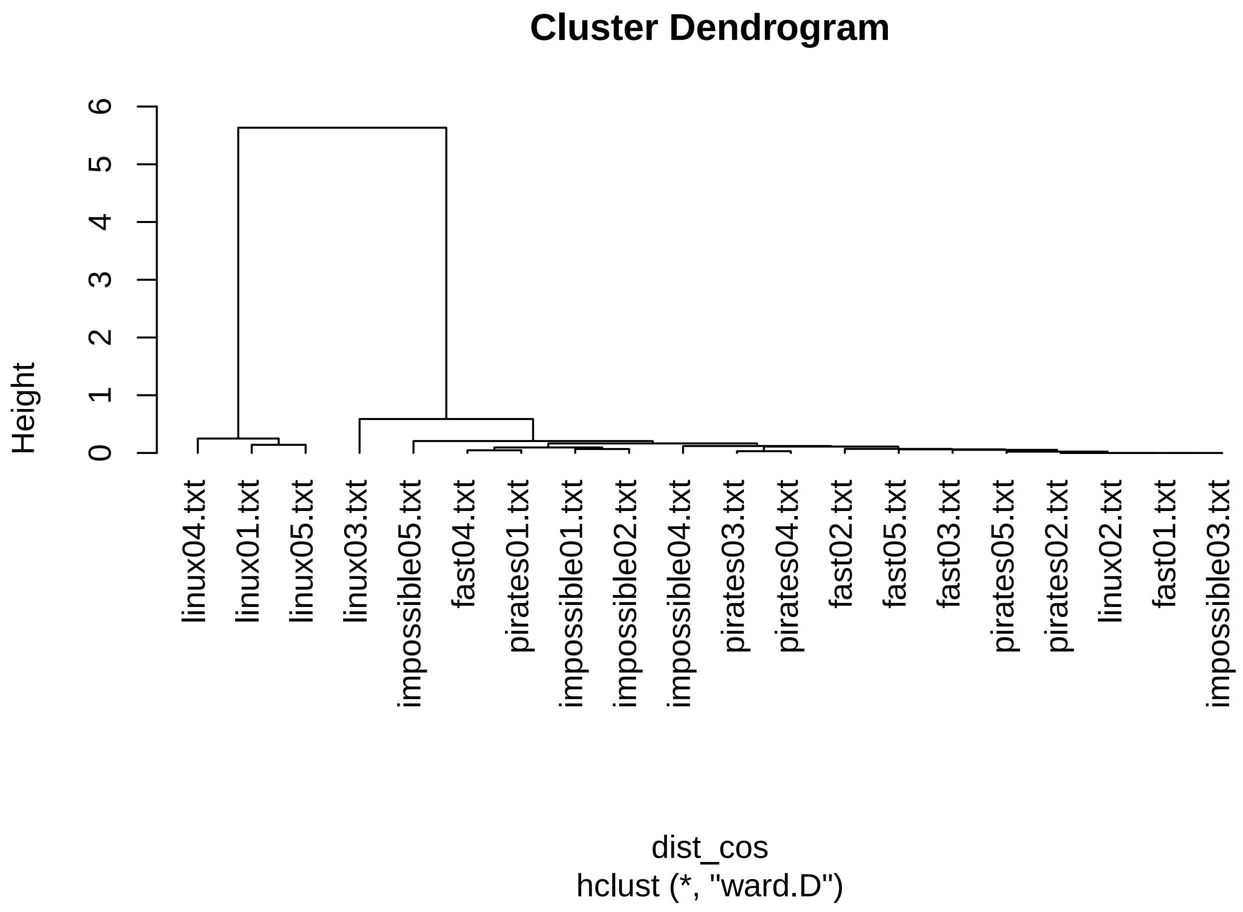


The IDF for each term is first calculated, and a TF-IDF weighted matrix is generated by applying the cross product of the TFs and IDFs in order to cluster with TF-IDF weighting and cosine distance. Next, the matrix is subjected to the cosine distance formula to obtain a cosine distance matrix. After that, the dendrogram is plotted.

```r
idf <- log(ncol(dtms_matrix) / (1 + rowSums(dtms_matrix != 0)))
idf <- diag(idf)
dtms_matrix_tfidf <- crossprod(dtms_matrix, idf)
colnames(dtms_matrix_tfidf) <- rownames(dtms_matrix)
```

```r
dist_cos <- 1 - crossprod(dtms_matrix_tfidf) / (sqrt(colSums(dtms_matrix_tfidf ** 2) %*%
            t(colSums(dtms_matrix_tfidf ** 2))))
dist_cos[is.na(dist_cos)] <- 0
dist_cos <- as.dist(dist_cos)

fit_cos <- hclust(dist_cos, method = "ward.D")
plot(fit_cos, hang = -1)
```



In terms of Euclidean distance clustering, the first divide is between two clusters, one of movie reviews including `fast`, `pirates` and `impossible`, and another of purely `linux`. This is pretty accurate, with the `linux` cluster branching off with a new document in each cluster. The movies reviews cluster is further branched off with `fast02` seperated from all others. While unexpected, this points the document to be an outlier. The next two clusters branched do a worse job, with all movies reviews being split accross the clusters, it also noted that with heights much lower than 20, we expect lower accuracy compared to the `linux` cluster.

Cosine Distance clustering is similar story, however only correctly identifying three `linux` documents into a cluster, and all the others into another. With an even lower height, less than one, for this cluster this time, even for the `linux` cluster, it is no surprise that the movies reviews cluster is highly inaccurate, with no real correlation between clustered documents.

By marking each document with its topic, creating a confusion matrix of the clustering, and calculating the accuracy, it is able to obtain a quantitative assessment of each clustering because each document's true topic is known. Owing to their length, the Appendix displays the confusion matrices and the cluster-topic assignments, and in order to reduce topic-cluster ambiguity for Euclidean distance, 15 clusters are produced.

```r
short_name <- function(doc) {
    return(substr(doc, 1, nchar(doc) - 6))
}

doc_names <- list.files("text")
doc_names_short <- unlist(lapply(doc_names, short_name))

table(Topic = doc_names_short, Cluster = cutree(fit_euclid, k = 15))
table(Topic = doc_names_short, Cluster = cutree(fit_cos, k = 10))
```

The matrix accuracy is determined by hand. This is provided for clustering using Euclidean distance by

```r
4 / 20
```

```
## [1] 0.2
```

And for Cosine distance is provided by

```r
9 / 20
```

```
## [1] 0.45
```

Clustering with cosine distance has a considerably higher accuracy than clustering with Euclidean distance, which is consistent with the data.

Hierarchical clustering can be said to be the quicker and easier way to get an understanding of the relationships between documents and tokens in the corpus. It neatly groups documents into clusters at different heights, so groupings can be interpreted based on the desired cluster size. The accuracies of the clusterings performed in Task 4 are not very high, but an accuracy of around 45% for clustering with cosine distance can be considered strong for a small corpus (only 20 documents) and the genericness of the tokens in contrast to Euclidean Distance clustering, which did extremely poorly at 20%, but is justified given the sparisty, topic overlap, and small smaple size.

Euclidean distance clustering has an accuracy of 20%, low homogeneity, poor cluster purity, and weak cohesion. On the other hand, cosine distance clustering has an accuracy of 45%, moderate homogeneity, better cluster purity, and improved cohesion. Both methods have their strengths and weaknesses, with cosine distance clustering demonstrating better accuracy, homogeneity, cluster purity, and cohesion compared to Euclidean distance clustering.

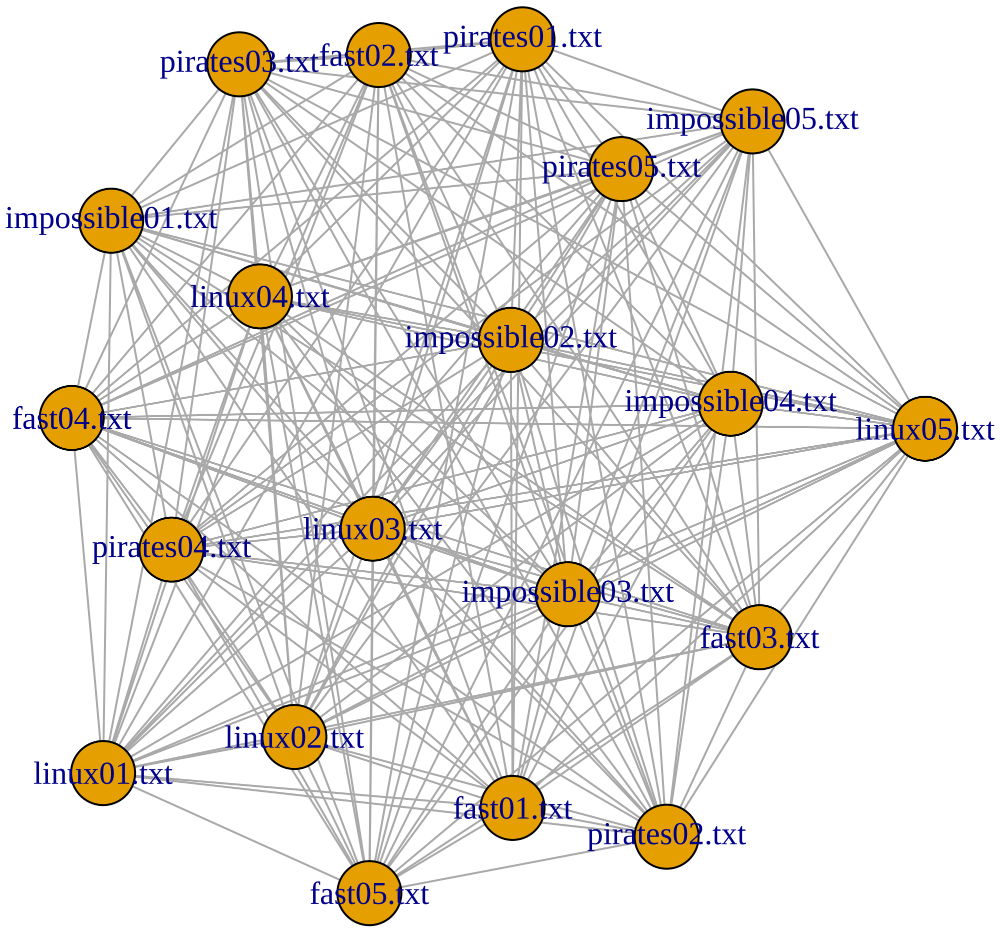
Clustering, however, is unable to recognise significant documents, tokens, or groupings. Social network analysis helps users quickly understand the relationships within the corpus by visualising the relationships between documents, tokens, and document-token pairs. Viewers can use computed metrics (such as proximity, betweenness, transitivity, etc.) to determine the significance of each document or token or the network's overall connectivity if necessary. Because of this, social networks provide a versatile means of locating significant clusters and connections within the data that may be leveraged by a larger number of users, whether they be technical or public viewers.

Task 5

The DTM is first transformed into a binary matrix and then multiplied by its transpose in order to construct a single-mode network that visualises the connections between documents based on the quantity of shared phrases. Following the first phase, a matrix is created that has a record of 1 for each token that appears in the document of that row. Following multiplication, the number of shared tokens in every pair of documents is displayed in the resulting matrix.

```r
dtms_mat_bin <- as.matrix((dtms_matrix > 0) + 0)
abs_mat <- dtms_mat_bin %*% t(dtms_mat_bin)
diag(abs_mat) <- 0
```

```r
abs_net <- graph_from_adjacency_matrix(abs_mat, mode = "undirected", weighted = TRUE)
plot(abs_net)
```



The graph depicted is quite dense; practically every pair of vertices that might exist has an edge. This is demonstrated by computing the graph's density.

```r
graph.density(abs_net)
```

```
## Warning: `graph.density()` was deprecated in igraph 2.0.0.
## i Please use `edge_density()` instead.
## This warning is displayed once every 8 hours.
## Call `lifecycle::last_lifecycle_warnings()` to see where this warning was
## generated.
```

```
## [1] 1
```

This demonstrates how each document is connected to nearly every other document to some degree based on common phrases. In comparison to other vertex pairings, `pirates03`, and `pirates01` are extremely close to `fast02`, suggesting a strong association, whereas `linux05` appears to have comparatively weaker ties to the other documents.

Finding the graph's transitivity is an excellent place to start when trying to find distinct groups in the data.

```r
transitivity(abs_net)
```

```
## [1] 1
```

The ratio of triangles to linked triples is known as transitivity, or clustering coefficient; a larger value of this ratio denotes more closely spaced groups. This graph has an extremely high transitivity of 1. There are numerous ways to divide the documents into groups, such as hierarchical clustering, but the `linux`, `pirates` and `fast` may be the most influential groups.

Because of their prominent locations, `impossible02`, `impossible03` and `linux03` initially appear to be the most significant documents. To obtain numerical measurements, execute the code provided. The outcomes are displayed in the Appendix due of their length.

```r
sort(-closeness(abs_net))
sort(-betweenness(abs_net))
sort(evcent(abs_net)$vector)
```

```
## Warning: `evcent()` was deprecated in igraph 2.0.0.
## i Please use `eigen_centrality()` instead.
## This warning is displayed once every 8 hours.
## Call `lifecycle::last_lifecycle_warnings()` to see where this warning was
## generated.
```

```r
sort(degree(abs_net))
```

Eigenvector centrality evaluates a document's quality of connections, degree counts the number of connections made by a vertex, closeness assesses a document's connectivity to others, betweenness evaluates a document's ability to act as an intermediary and thus have more influence over the network flow. The results for closeness and betweenness are negative because the weights of the vertices match the amount of common phrases. This means that when two documents are tightly related, there is a high distance (weight of the edge) between them.

Documents with values of 0 for betweenness have the most potential to be the "hubs" of the network. Just `linux`, `impossible03` and `pirates02` are disconnected from all other documents in terms of degree. Their degrees are all still at the maximum of 19, meaning that they are quite significant. Others, however, do not give us meaningful insights in contrast to each document.

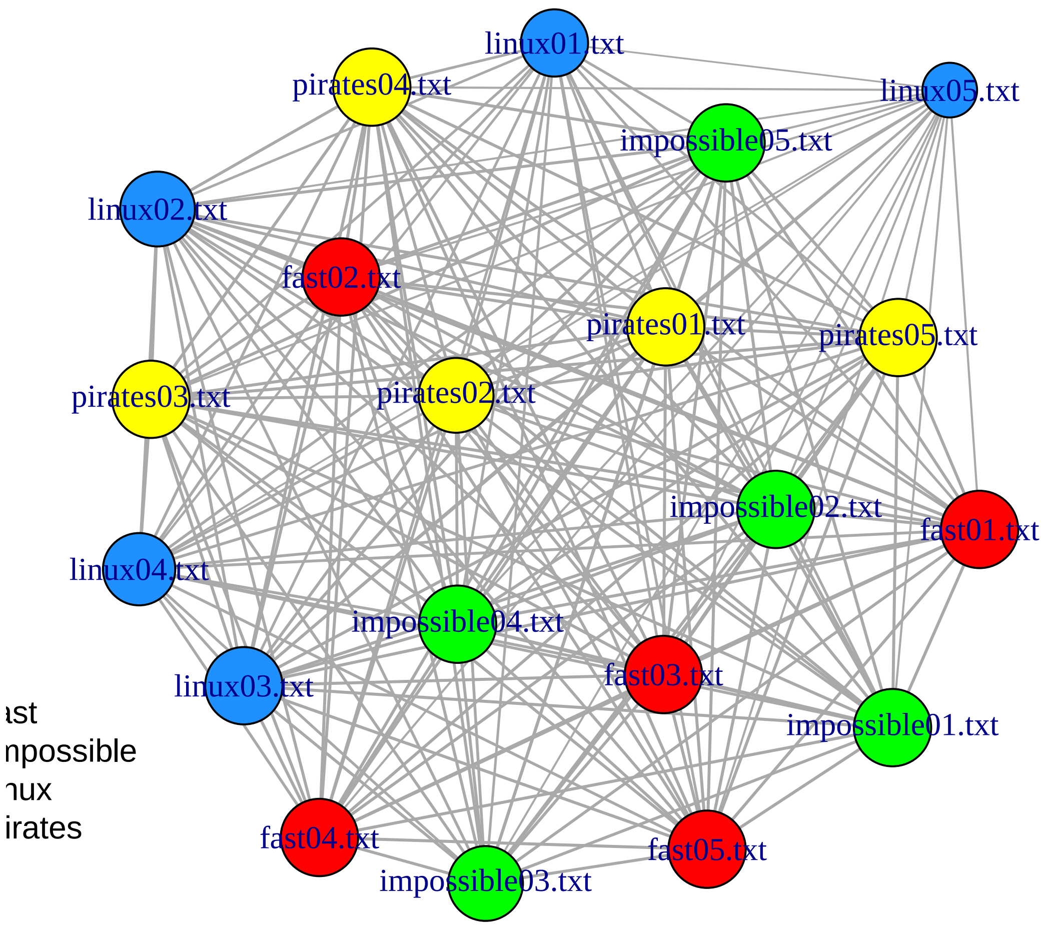
The graph is enhanced by colouring the vertices according to subject, scaling the edge widths according to inter-document strength (number of common terms), and scaling the vertex sizes according to the closeness centrality of the document in order to visually represent the noteworthy aspects of the data. This code can be used to accomplish this.

```r
doc_colr <- c("red", "green", "dodgerblue", "yellow", "orange", "magenta", "pink",
              "chocolate", "gray", "cyan")
topics <- unique(doc_names_short)

for (doc in doc_names) {
    V(abs_net)[doc]$color <- doc_colr[match(short_name(doc), topics)]
}

V(abs_net)$size <- 1 / closeness(abs_net, mode = "all") / 30
E(abs_net)$width <- E(abs_net)$weight / 20

plot(abs_net)
legend(x = -1.5, y = -0.5, legend = topics, pch = 21, cex = 1,
       pt.bg = doc_colr, bty = "n", ncol = 1)
```



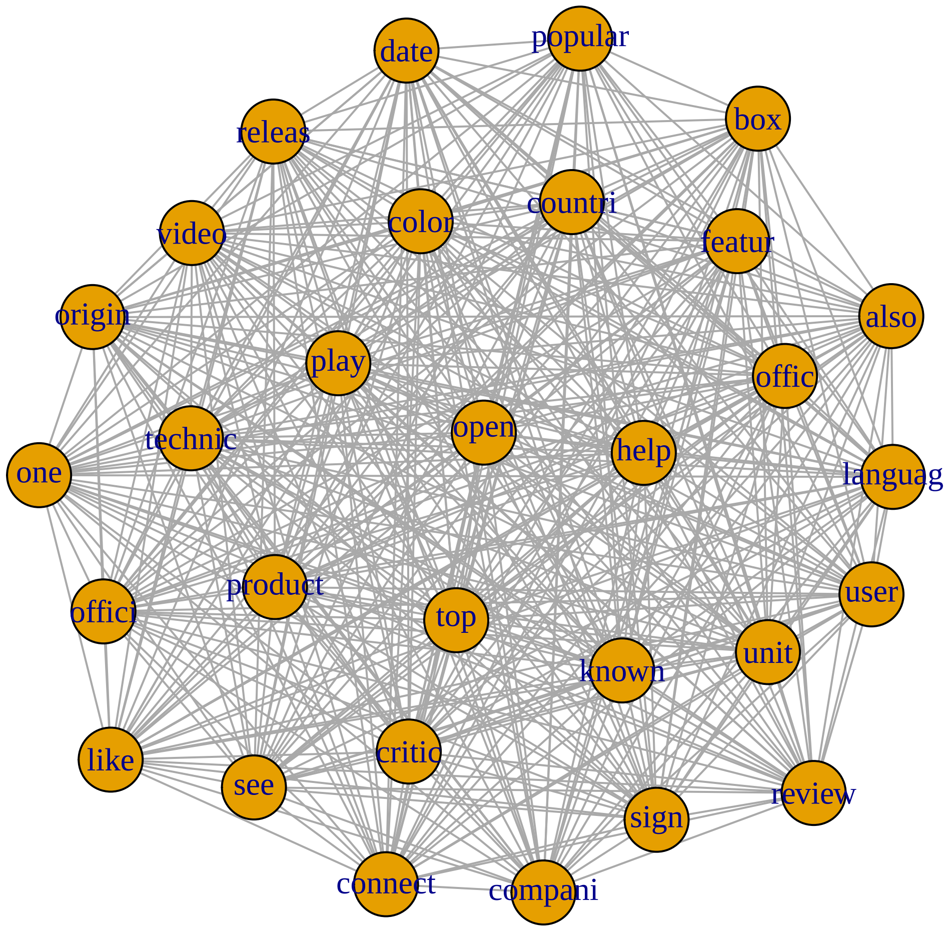
We can see how far apart the `fast` docs are from the others with greater clarity thanks to this graph. It is also simpler to see that some topics like `pirates` contain all of the papers closely together, whereas other topics have the reverse.

Task 6

Most of the code is repurposed from Task 5 with minor modifications to create a single-mode network that shows the relationships between the tokens depending on the number of common documents they appear in. The binary matrix's transpose is multiplied by the original to get the tokens matrix. Next, the graph is plotted using the identical function.

```
tok_mat <- t(dtms_mat_bin) %*% dtms_mat_bin
diag(tok_mat) <- 0

tok_net <- graph_from_adjacency_matrix(tok_mat, mode = "undirected", weighted = TRUE)
plot(tok_net)
```



The graph depicted appears to be much denser than the one for documents, with many more connections between nodes.

```r
graph.density(tok_net)
```

```
## [1] 1
```

According to the observation, the network has a density of 1, indicating that every vertex is connected, making it denser. This indicates that the tokens are quite general terms that show up in all publications on different subjects.

The vertices of the graph appear to be rather uniformly distributed, making it challenging to discern distinct groups. `date`, `popular` and `box` at the top of the graph, which form a prominent triangle, are suspected clusters.

```r
transitivity(tok_net)
```

```
## [1] 1
```

The graph's transitivity is 1. This measure shows us that every three tokens can form a triangle, indicating a very large number of potential clusters, even though it is difficult to distinguish clusters by observation. The generic nature of the tokens may also be to blame for this.*During DTM pre-processing, I tried manually eliminating a few generic terms, but it resulted in worse clustering performance. This is most likely due to the fact that, despite being widely used, generic phrases offer crucial contextual information that ties papers together.

`open`, `play`, `help` and `top` are the tokens that appear to be the most central, suggesting that they may hold some significance. To look into this, execute the code below. The Appendix displays the results.

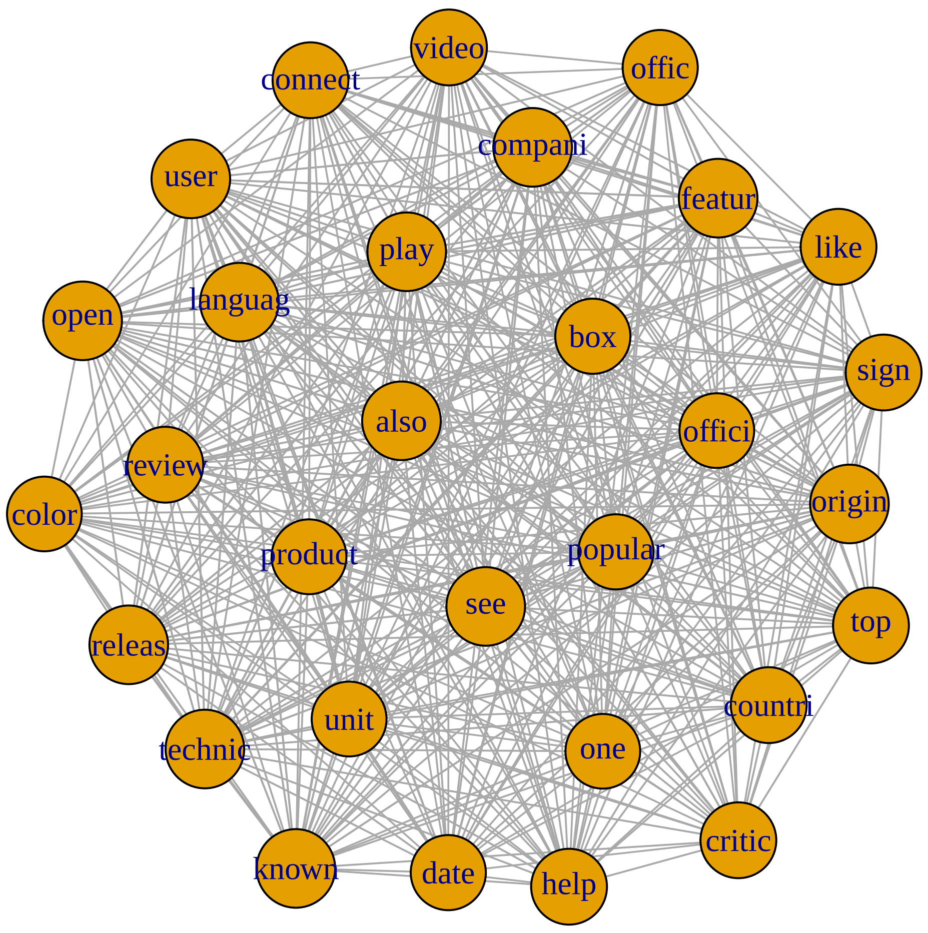
```r
sort(-closeness(tok_net))
sort(-betweenness(tok_net))
sort(evcent(tok_net)$vector)
sort(degree(tok_net))
```

Overall, quite a few tokens including `languag`, `see`, `releas`, `open` and many more have the highest eigenvector centrality, while tokens such as `video`, `user`, `unit` and many others have the highest degree, suggesting the edges surrounding these vertices are layered and denser.

In order to make this graph better, the weights of the number of shared documents between tokens and the vertex sizes are scaled to their closest centralities.

```r
V(tok_net)$size <- 1 / closeness(tok_net, mode = "all") / 30
E(tok_net)$width <- E(tok_net)$weight / 20

plot(tok_net)
```



Using this graph, it is evident that `play` and `product` are two significant central tokens, whereas `top` is significantly less significant and is situated further away from the others, as supported by the previously calculated metrics.

Task 7

Using code taken from Lecture 12, the data is first prepared to produce a bipartite (two-mode) network graph.

```
dtms_dfa <- as.data.frame(dtms_matrix)
dtms_dfa$abstract <- rownames(dtms_dfa)
dtms_dfb <- data.frame()
for (i in seq_len(nrow(dtms_dfa))) {
    for (j in seq_len(ncol(dtms_dfa) - 1)) {
        to_use <- cbind(dtms_dfa[i, j], dtms_dfa[i, ncol(dtms_dfa)],
                        colnames(dtms_dfa[j]))
        dtms_dfb <- rbind(dtms_dfb, to_use)
    }
}
colnames(dtms_dfb) <- c("weight", "abstract", "token")

dtms_dfc <- dtms_dfb[dtms_dfb$weight != 0, ]
dtms_dfc <- dtms_dfc[, c("abstract", "token", "weight")]
```

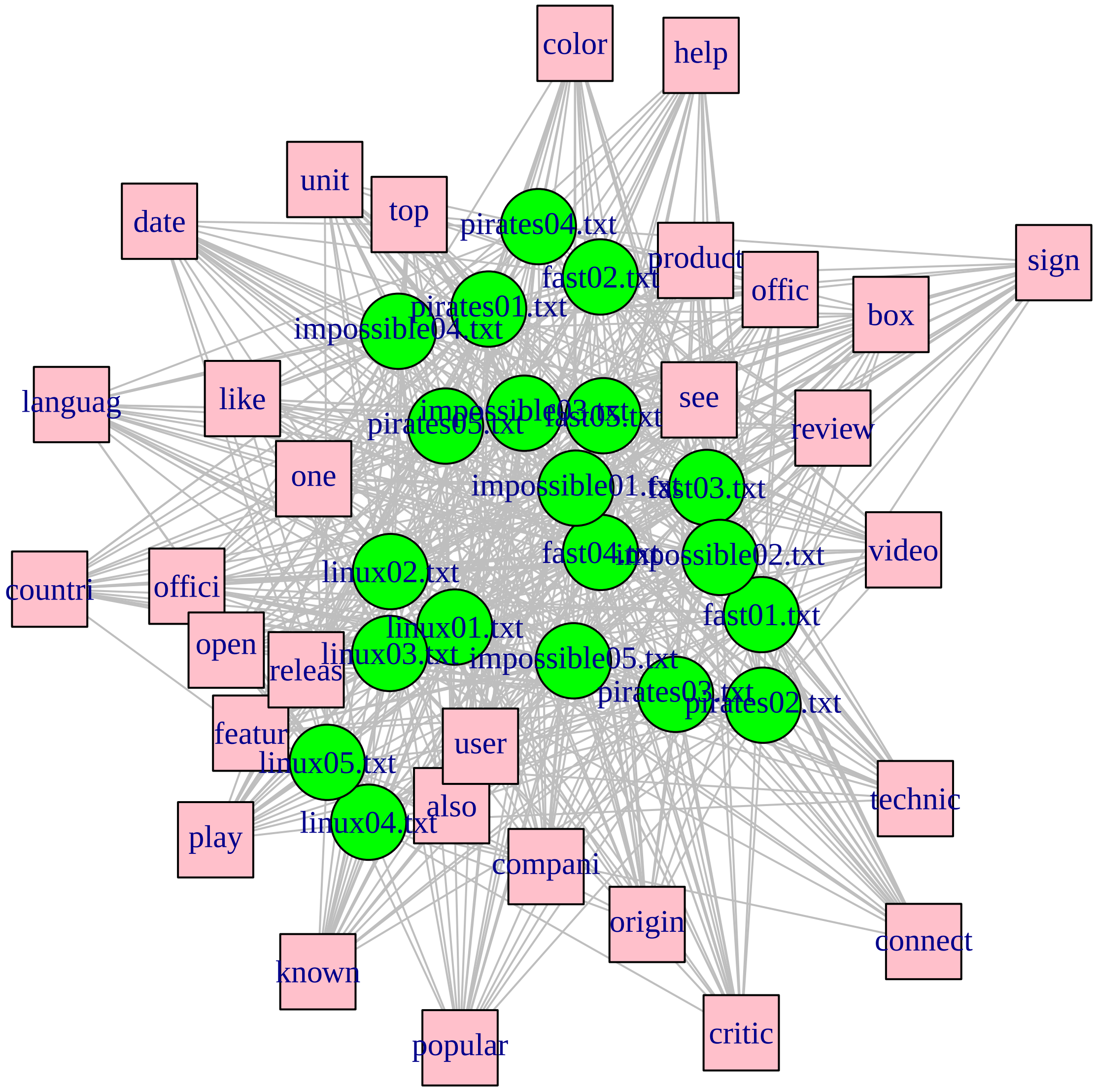
The code mentioned above creates a data frame called `dtms_dfb` that displays the weight of each token in each document. The bipartite graph is plotted using a fresh data frame `dtms_dfc` that has had all of its rows with weights of 0 removed.

```
bipart <- graph.data.frame(dtms_dfc, directed = FALSE)
```

```
## Warning: `graph.data.frame()` was deprecated in igraph 2.0.0.
## i Please use `graph_from_data_frame()` instead.
## This warning is displayed once every 8 hours.
## Call `lifecycle::last_lifecycle_warnings()` to see where this warning was
## generated.
```

```
V(bipart)$type <- bipartite_mapping(bipart)$type
V(bipart)$color <- ifelse(V(bipart)$type, "pink", "green")
V(bipart)$shape <- ifelse(V(bipart)$type, "square", "circle")
E(bipart)$color <- "grey"

plot(bipart)
```



Given that this graph is bipartite, extremely low transitivity and density are anticipated. Since the relationship between tokens and documents has previously been examined in Tasks 5 and 6, the proximity, betweenness, and eigenvector centralities do not provide any new information. This graph is therefore examined through observation.

This graph's general structure is similar to a "cluster" of documents in the centre encircled by tokens arranged in a circle, which are then encircled by the remaining documents. The majority of the tokens are connected to the central cluster of papers because of their placement. `pirates`, and `impossible` are among the papers in this cluster that Task 5's metrics assessed to be comparatively more essential. Similar to Task 5, `linux` has linkages to fewer tokens and is comparatively farther from the other vertices. This is demonstrated by the vertex degrees (output displayed in Appendix).

```
sort(degree(bipart))
```

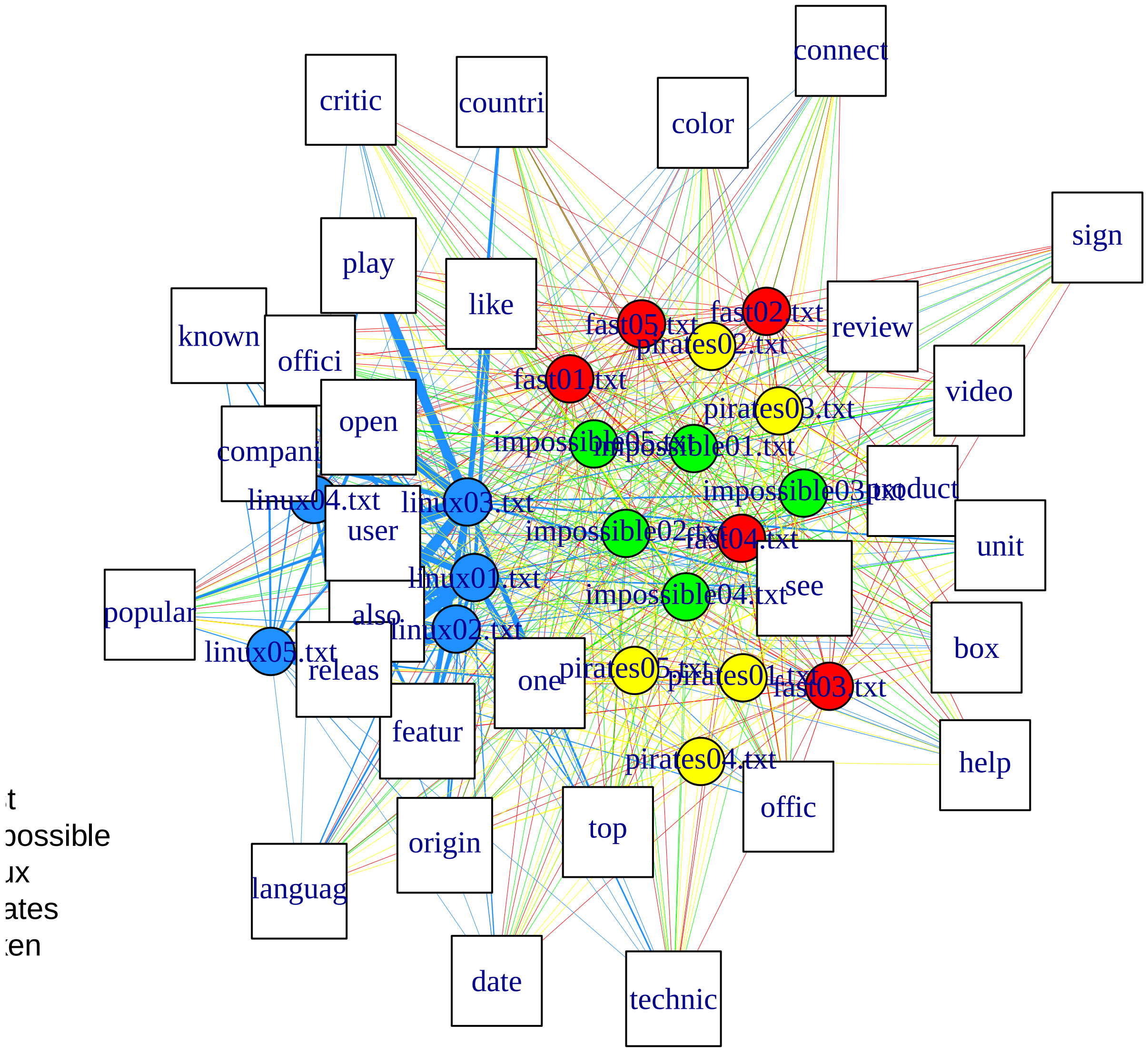
Most movie reviews, such as `pirates`, `fast` and `impossible` have the highest degrees of 30, while `box`, `color`, `connect` and several others jointly have the least.

It also noteworthy, while `linux` documents are situated away from the other documents which are movie reviews, `linux05` and `linux04` in particular are even further out, almost divided by a wall of tokens. Similarly, all `pirates` documents seem to be on either outer side of the movies reviews cluster.

This graph is improved by making the document vertices smaller for easier reading and colouring them as in Task 5, scaling the token vertices based on their degree and recoloring them white, colouring the edges based on the document vertex they connect to, and scaling the edge widths based on the weight of the edge (frequency of token in document). Since the visible number of coloured outgoing edges provides a good indication of their degrees, document vertex sizes are not scaled.

```r
for (i in seq_len(20)) V(bipart)$size[i] <- 10
V(bipart)$size[21:50] <- degree(bipart)[21:50]
for (j in seq_len(length(doc_names))) {
    V(bipart)[j]$color <- doc_colr[match(short_name(doc_names[j]), topics)]
}
for (k in c(21:length(V(bipart)))) V(bipart)[k]$color <- "white"
E(bipart)$width <- as.numeric(dtms_dfc$weight) / 10
E(bipart)$color <- tail_of(bipart, E(bipart))$color

plot(bipart)
legend(x = -1.5, y = -0.5, legend = c(topics, "token"), pch = 21, cex = 1,
       pt.bg = c(doc_colr, "white"), bty = "n", ncol = 1)
```



The revised graph depicts all `linux` documents with higher relative importance than others. It is hard to find a token that appears in all documents, however `open`, `release`, `user` and `feature` seem to be shared in all `linux` documents, which comes as no surprise given the documents describe software releases and features for users. The only token that seems to be common among the movie reviews cluster is `see`, appearing related to `fast` movies the most, as well as some `pirates` movies. However movie reviews in general have relatively thinner edges, denoting fewer shared tokens between them as well.

Appendix

References

Wikimedia Foundation. (2024, May 14). Ubuntu. Wikipedia. https://en.wikipedia.org/wiki/Ubuntu

Wikimedia Foundation. (2024c, May 18). Linux kernel. Wikipedia. https://en.wikipedia.org/wiki/Linux_kernel

Wikimedia Foundation. (2024a, April 5). Lineageos. Wikipedia. https://en.wikipedia.org/wiki/LineageOS

Wikimedia Foundation. (2024b, May 7). Android (Operating System). Wikipedia. https://en.wikipedia.org/wiki/Android_(operating_system)

Wikimedia Foundation. (2024b, May 7). Android (Operating System). Wikipedia. https://en.wikipedia.org/wiki/CyanogenMod

IMDb.com. (2003, June 6). 2 fast 2 furious. IMDb. https://www.imdb.com/title/tt0322259/?ref_=nv_sr_srsg_0_tt_7_nm_1_q_2%2520fast

IMDb.com. (2009, April 3). Fast & Furious. IMDb. https://www.imdb.com/title/tt1013752/?ref_=nv_sr_srsg_1_tt_7_nm_0_q_fast%2520and%2520fur

IMDb.com. (2006, June 16). The Fast and the Furious: Tokyo Drift. IMDb. https://www.imdb.com/title/tt0463985/?ref_=nv_sr_srsg_1_tt_7_nm_0_q_tokyo%2520d

IMDb.com. (2011, April 29). Fast five. IMDb. https://www.imdb.com/title/tt1596343/?ref_=fn_al_tt_6

IMDb.com. (2013). Fast & Furious 6. IMDb. https://www.imdb.com/title/tt1905041/?ref_=nv_sr_srsg_0_tt_8_nm_0_q_fast%25206

IMDb.com. (2003b, July 9). Pirates of the Caribbean: The curse of the black pearl. IMDb. https://www.imdb.com/title/tt0325980/?ref_=nv_sr_srsg_0_tt_8_nm_0_q_pirates

IMDb.com. (2006). Pirates of the Caribbean: Dead Man's Chest. IMdb. https://www.imdb.com/title/tt0383574/?ref_=nv_sr_srsg_6_tt_5_nm_3_q_pirates%2520of%2520the%2520carribean

IMDb.com. (2003b, July 9). Pirates of the Caribbean: At World's End. IMdb. https://www.imdb.com/title/tt0449088/?ref_=nv_sr_srsg_7_tt_5_nm_3_q_pirates%2520of%2520the%2520carribean

IMDb.com. (2003b, July 9). Pirates of the Caribbean: On Stranger Tides. IMdb. https://www.imdb.com/title/tt1298650/?ref_=nv_sr_srsg_9_tt_5_nm_3_q_pirates%2520of%2520the%2520carribean

IMDb.com. (2017, May 26). Pirates of the caribbean: Dead men tell no tales. IMDb. https://www.imdb.com/title/tt1790809/?ref_=nv_sr_srsg_3_tt_8_nm_0_q_pirates

IMDb.com. (1996, May 22). Mission: Impossible. IMDb. https://www.imdb.com/title/tt0117060/?ref_=nv_sr_srsg_0_tt_8_nm_0_q_mission

IMDb.com. (2000). Mission: Impossible II. IMDb. https://www.imdb.com/title/tt0120755/?ref_=tt_sims_tt_t_1

IMDb.com. (2006). Mission: Impossible III. IMDb. https://www.imdb.com/title/tt0317919/?ref_=tt_sims_tt_t_2

IMDb.com. (2011). Mission: Impossible - Ghost Protocol. IMDb. https://www.imdb.com/title/tt1229238/?ref_=tt_sims_tt_t_3

IMDb.com. (2015). Mission: Impossible - Rogue Nation. IMDb. https://www.imdb.com/title/tt2381249/?ref_=tt_sims_tt_t_4

At the conclusion of Task 3, the document-term matrix is printed as a data frame.

```r
as.data.frame(as.matrix(dtms))
```

```
##                  also box color compani connect countri critic date featur help
## fast01.txt          1   3     2       2       1       1      1    2      1    1
## fast02.txt          2   3     2       2       1       1      1    1      3    3
## fast03.txt          1   3     2       2       1       1      1    1      4    1
## fast04.txt          1   4     2       2       2       1      1    1      2    1
## fast05.txt          2   3     2       2       1       2      2    1      2    3
## impossible01.txt    2   3     2       2       1       1      1    1      1    2
## impossible02.txt    1   3     2       3       1       1      1    1      1    1
## impossible03.txt    2   3     2       2       1       1      1    1      2    1
## impossible04.txt    3   3     2       2       1       1      1    2      2    2
## impossible05.txt    2   3     2       2       1       1      1    1      2    1
## linux01.txt        39   0     1       6       1       1      4    0     18    4
## linux02.txt        24   2     0       2       1       2      2    4     10    3
## linux03.txt        48   1     1      25       3      16      3    6     29    4
## linux04.txt        15   1     2       2       2       1      3    2     16    1
## linux05.txt        11   2     2      11       0       0      0    1     15    0
## pirates01.txt       2   3     2       2       1       1      1    1      3    2
## pirates02.txt       1   3     2       2       1       1      1    1      2    1
## pirates03.txt       3   3     2       2       1       1      1    1      2    1
## pirates04.txt       4   3     2       3       1       1      1    1      2    2
## pirates05.txt       1   3     2       2       1       1      1    2      2    1
##                  known languag like offic offici one open origin play popular
## fast01.txt           1       1    1     3      2   3    1      3    1       1
## fast02.txt           1       1    3     3      2   2    1      1    1       1
## fast03.txt           1       1    2     3      2   1    1      2    1       1
## fast04.txt           1       1    3     5      2   7    1      2    1       1
## fast05.txt           1       1    2     3      2   3    2      3    4       1
## impossible01.txt     1       1    3     3      3   4    2      1    1       1
## impossible02.txt     1       1    2     3      1   4    3      3    1       2
## impossible03.txt     2       1    1     3      0   6    1      1    2       1
## impossible04.txt     1       1    5     3      1   3    4      1    1       1
## impossible05.txt     2       1    1     3      2   4    8      1    3       1
## linux01.txt          8       9   19     0      7  17    8      9    1       0
## linux02.txt          4       1    6     3     12  11   13      2    1       4
## linux03.txt         17       7   16     4     15  22   51      9   50      15
## linux04.txt          7       1    2     1     20   4   11      1    7       3
## linux05.txt          5       1    0     5      8   9   19      4    3       5
## pirates01.txt        1       1    4     3      1   6    2      1    1       1
## pirates02.txt        1       1    2     3      1   0    1      3    1       1
## pirates03.txt        1       1    1     3      1   2    1      1    1       2
## pirates04.txt        1       1    1     3      1   2    1      1    1       1
## pirates05.txt        1       1    2     3      4   2    3      3    1       1
##                  product releas review see sign technic top unit user video
## fast01.txt             3      3      4   5    1       1   2    2    2     1
## fast02.txt             4      1      4   5    3       1   2    2    2     1
## fast03.txt             3      1      4   4    1       1   2    2    2     3
## fast04.txt             5      1      4   5    1       1   3    3    2     2
## fast05.txt             3      1      4   5    1       1   2    2    2     3
## impossible01.txt       4      2      4   4    1       1   4    2    2     6
## impossible02.txt       4      1      4   3    2       1   4    2    2     3
## impossible03.txt       4      1      4   3    1       1   3    4    2     4
## impossible04.txt       4      1      4   3    1       1   2    4    2     2
## impossible05.txt       3      1      4   3    1       1   3    2    2     2
## linux01.txt            6     62      3   8    1       8   5    2   36     2
## linux02.txt            3     57      1   5    1       1   7    1   20     2
## linux03.txt            9     45      4  11    1       3  11   10   73     5
## linux04.txt            0     18      3   1    1       1   1    0   15     2
## linux05.txt            1     61      0   3    0       1   0    1   13     0
## pirates01.txt          3      1      4   5    1       1   4    2    2     3
## pirates02.txt          4      1      4   6    1       1   2    2    2     2
## pirates03.txt          4      2      4   4    1       1   2    2    2     2
## pirates04.txt          3      1      4   3    1       1   2    3    2     2
## pirates05.txt          3      3      4   7    1       1   5    2    2     3
```

Confusion matrices utilised in Task 4 to quantify clustering.

```
table(Topic = doc_names_short, Cluster = cutree(fit_euclid, k = 10))
```

```
##             Cluster
## Topic         1 2 3 4 5 6 7 8 9 10
##   fast        2 1 1 1 0 0 0 0 0  0
##   impossible  2 0 0 0 3 0 0 0 0  0
##   linux       0 0 0 0 0 1 1 1 1  1
##   pirates     3 0 0 2 0 0 0 0 0  0
```

```
table(Topic = doc_names_short, Cluster = cutree(fit_cos, k = 10))
```

```
##             Cluster
## Topic         1 2 3 4 5 6 7 8 9 10
##   fast        4 1 0 0 0 0 0 0 0  0
##   impossible  1 0 2 1 1 0 0 0 0  0
##   linux       1 0 0 0 0 1 1 1 1  0
##   pirates     2 1 0 0 0 0 0 0 0  2
```

Cluster assignment based on Euclidean distance for every topic, as of Task 4.

- **1** `fast`
- **2** `impossible`
- **3** `linux`
- **4** `pirates`

Task 4 assigns a cosine distance cluster to each topic.

- **1** `fast`
- **2** `impossible`
- **3** `linux`
- **4** `pirates`

Results for the abstractions network for Task 5 in terms of proximity, betweeness, eigenvector centralities, and degree measures.

```
sort(-closeness(abs_net))
```

```
##      linux05.txt      linux01.txt      linux04.txt impossible03.txt
##     -0.002564103     -0.002083333     -0.001937984     -0.001872659
##      linux02.txt    pirates02.txt       fast01.txt       fast02.txt
##     -0.001872659     -0.001872659     -0.001811594     -0.001811594
##       fast03.txt       fast04.txt       fast05.txt impossible01.txt
##     -0.001811594     -0.001811594     -0.001811594     -0.001811594
## impossible02.txt impossible04.txt impossible05.txt       linux03.txt
##     -0.001811594     -0.001811594     -0.001811594     -0.001811594
##      pirates01.txt    pirates03.txt    pirates04.txt    pirates05.txt
##     -0.001811594     -0.001811594     -0.001811594     -0.001811594
```

```r
sort(-betweenness(abs_net))
```

```
##       fast01.txt       fast02.txt       fast03.txt       fast04.txt
##                0                0                0                0
##       fast05.txt impossible01.txt impossible02.txt impossible03.txt
##                0                0                0                0
## impossible04.txt impossible05.txt      linux01.txt      linux02.txt
##                0                0                0                0
##      linux03.txt      linux04.txt      linux05.txt    pirates01.txt
##                0                0                0                0
##    pirates02.txt    pirates03.txt    pirates04.txt    pirates05.txt
##                0                0                0                0
```

```r
sort(evcent(abs_net)$vector)
```

```
##      linux05.txt      linux01.txt      linux04.txt impossible03.txt
##        0.7148700        0.8755370        0.9382096        0.9692139
##    pirates02.txt      linux02.txt      linux03.txt       fast05.txt
##        0.9692139        0.9692139        1.0000000        1.0000000
## impossible04.txt    pirates04.txt       fast02.txt       fast03.txt
##        1.0000000        1.0000000        1.0000000        1.0000000
##       fast04.txt impossible02.txt impossible05.txt    pirates01.txt
##        1.0000000        1.0000000        1.0000000        1.0000000
##    pirates03.txt    pirates05.txt       fast01.txt impossible01.txt
##        1.0000000        1.0000000        1.0000000        1.0000000
```

```r
sort(degree(abs_net))
```

```
##       fast01.txt       fast02.txt       fast03.txt       fast04.txt
##               19               19               19               19
##       fast05.txt impossible01.txt impossible02.txt impossible03.txt
##               19               19               19               19
## impossible04.txt impossible05.txt      linux01.txt      linux02.txt
##               19               19               19               19
##      linux03.txt      linux04.txt      linux05.txt    pirates01.txt
##               19               19               19               19
##    pirates02.txt    pirates03.txt    pirates04.txt    pirates05.txt
##               19               19               19               19
```

Results for the tokens matrix for Task 6 in terms of proximity, betweeness, eigenvector centralities, and degree measures.

```r
sort(-closeness(tok_net))
```

```
##        color        offici          one      product         unit          box
## -0.001872659 -0.001872659 -0.001872659 -0.001869159 -0.001869159 -0.001862197
##         date        offic      popular      connect      countri       critic
## -0.001862197 -0.001862197 -0.001862197 -0.001845018 -0.001845018 -0.001845018
##         help         like       review         sign          top        video
## -0.001845018 -0.001845018 -0.001845018 -0.001845018 -0.001845018 -0.001845018
##         also      compani       featur        known      languag         open 
## -0.001779359 -0.001779359 -0.001779359 -0.001779359 -0.001779359 -0.001779359 
##       origin         play       releas          see      technic         user 
## -0.001779359 -0.001779359 -0.001779359 -0.001779359 -0.001779359 -0.001779359
```

```
sort(-betweenness(tok_net))
```

```
##    also     box   color compani connect countri  critic    date  featur    help 
##       0       0       0       0       0       0       0       0       0       0 
##   known languag    like   offic  offici     one    open  origin    play popular 
##       0       0       0       0       0       0       0       0       0       0 
## product  releas  review     see    sign technic     top    unit    user   video 
##       0       0       0       0       0       0       0       0       0       0
```

```
sort(evcent(tok_net)$vector)
```

```
##       one     color    offici   product      unit       box   popular     offic 
## 0.9518295 0.9518295 0.9518295 0.9535132 0.9535132 0.9568986 0.9568986 0.9568986 
##      date    critic      like      sign     video      help   connect   countri 
## 0.9568986 0.9654682 0.9654682 0.9654682 0.9654682 0.9654682 0.9654682 0.9654682 
##    review       top   technic   compani      user      also    origin      play 
## 0.9654682 0.9654682 1.0000000 1.0000000 1.0000000 1.0000000 1.0000000 1.0000000 
##       see    featur     known   languag      open    releas 
## 1.0000000 1.0000000 1.0000000 1.0000000 1.0000000 1.0000000
```

```
sort(degree(tok_net))
```

```
##    also     box   color compani connect countri  critic    date  featur    help 
##      29      29      29      29      29      29      29      29      29      29 
##   known languag    like   offic  offici     one    open  origin    play popular 
##      29      29      29      29      29      29      29      29      29      29 
## product  releas  review     see    sign technic     top    unit    user   video 
##      29      29      29      29      29      29      29      29      29      29
```

Vertex degrees of Task 7's bipartite graph.

```
sort(degree(bipart))
```

```
##              box           color         connect         countri 
##               19              19              19              19 
##           critic            date            help            like 
##               19              19              19              19 
##            offic          offici             one         popular 
##               19              19              19              19 
##          product          review            sign             top 
##               19              19              19              19 
##             unit           video            also         compani 
##               19              19              20              20 
##           featur           known         languag            open 
##               20              20              20              20 
##           origin            play          releas             see 
##               20              20              20              20 
##          technic            user     linux05.txt     linux01.txt 
##               20              20              21              26 
##      linux04.txt impossible03.txt     linux02.txt    pirates02.txt 
##               28              29              29              29 
##       fast01.txt      fast02.txt      fast03.txt      fast04.txt
##                30                30                30                30
##        fast05.txt impossible01.txt impossible02.txt impossible04.txt
##                30                30                30                30
## impossible05.txt       linux03.txt    pirates01.txt    pirates03.txt
##                30                30                30                30
##     pirates04.txt    pirates05.txt
##                30                30
```