FIT3152 Data analytics

Assignment 3

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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 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.

```
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.

```
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
```

```
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
```

```
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 10%, as it allows the DTM to have around 20 tokens after removing sparse terms. The choice of setting such a low value significantly impacts other attributes, such as accuracy and clustering, due to the nature and length of the corpus chosen. While it is possible to achieve much better accuracy and clustering with 65% sparsity, the number of tokens would be several fold more (Zong, Xia and Zhang, 2021).

```
sparse_dtm <- removeSparseTerms(dtm, 0.1)
inspect(sparse_dtm)
```

```
## <<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
```

```
freqs <- colSums(as.matrix(sparse_dtm))
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
```

```
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

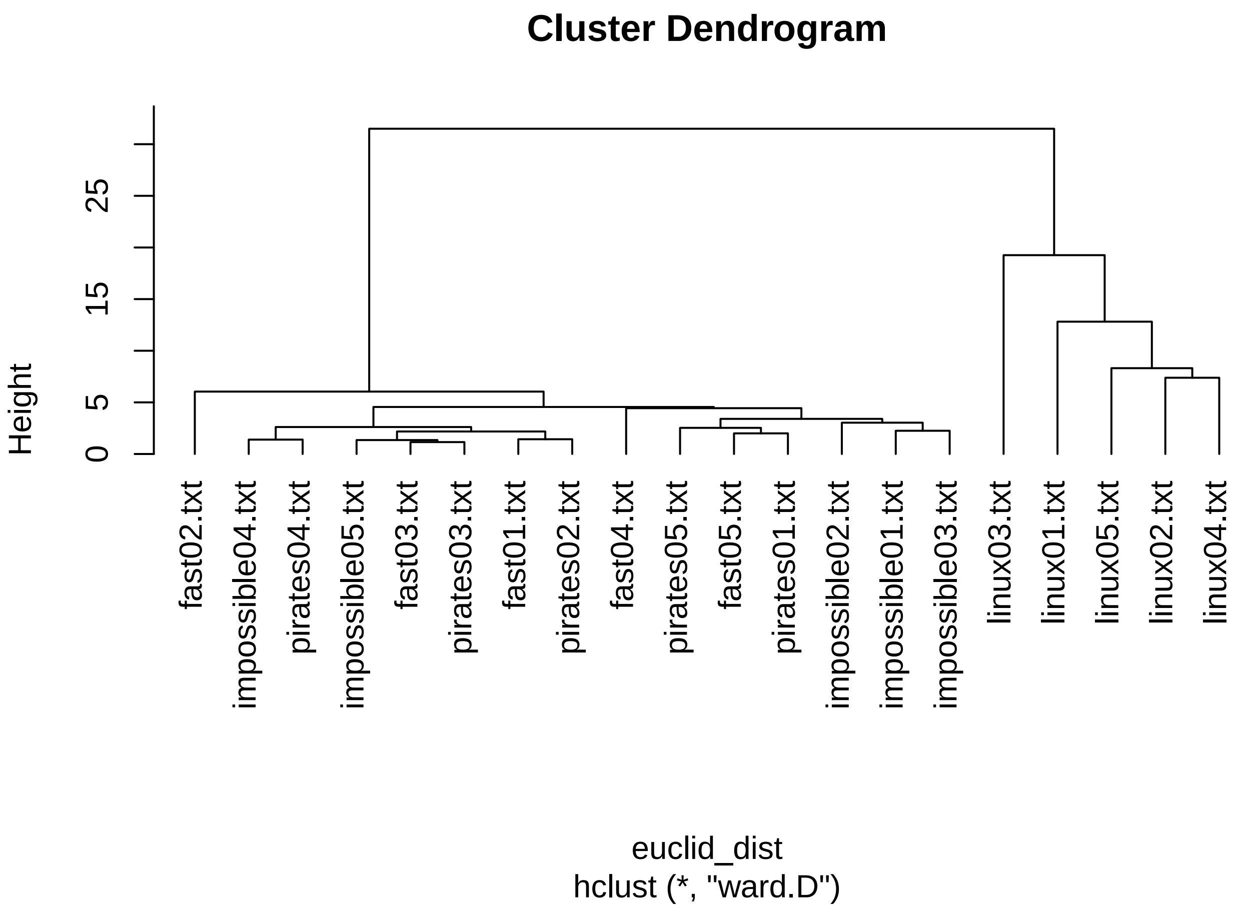
To determine which performs better, a hierarchical clustering of the corpus is carried out using two metrics: Euclidean distance and cosine distance. First, the DTM is transformed into a regular matrix format.

```r
sparse_dtm_matrix <- as.matrix(sparse_dtm)
```

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. Clustering with cosine distance can be further improved by pre-weighting the DTM with the term frequency-inverse document frequency statistic, which assigns higher weights to terms that appear frequently within a document, implying importance, but infrequently across all documents, implying significance.

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

```r
euclid_dist <- dist(scale(sparse_dtm_matrix))
euclid_fitted <- hclust(euclid_dist, method = "ward.D")
plot(euclid_fitted, hang = -1)
```

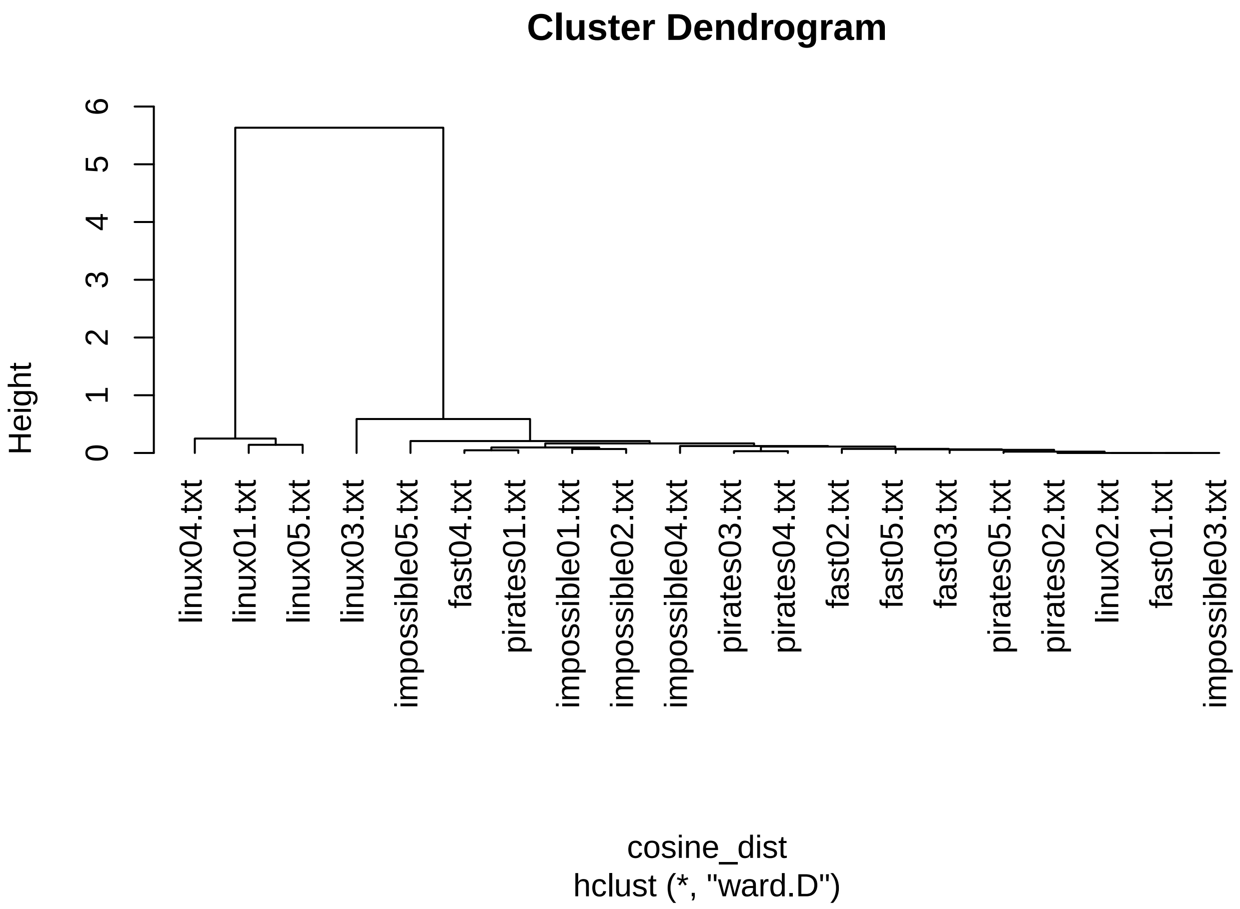


The IDF for each term is first calculated, and a TF-IDF weighted matrix is generated by applying the cross product of the TFs and IDFs in order to cluster with TF-IDF weighting and cosine distance. Next, the matrix is subjected to the cosine distance formula to obtain a cosine distance matrix. After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

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

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

cosine_fitted <- hclust(cosine_dist, method = "ward.D")
plot(cosine_fitted, 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
remove_suffix <- function(doc) {
    return(substr(doc, 1, nchar(doc) - 6))
}

document_names <- list.files("text")
short_document_names <- unlist(lapply(document_names, remove_suffix))

table(Topic = short_document_names, Cluster = cutree(euclid_fitted, k = 15))
table(Topic = short_document_names, Cluster = cutree(cosine_fitted, 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 is a quick and easy method for understanding document-token relationships in a corpus. It groups documents into clusters at different heights, allowing interpretation based on desired cluster size. Task 4's accuracy is not high, but around 45% for cosine distance clustering is strong for a small corpus and generic tokens. Euclidean Distance clustering performs poorly at 20%, but is justified due to sparsity, topic overlap, and small sample 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.

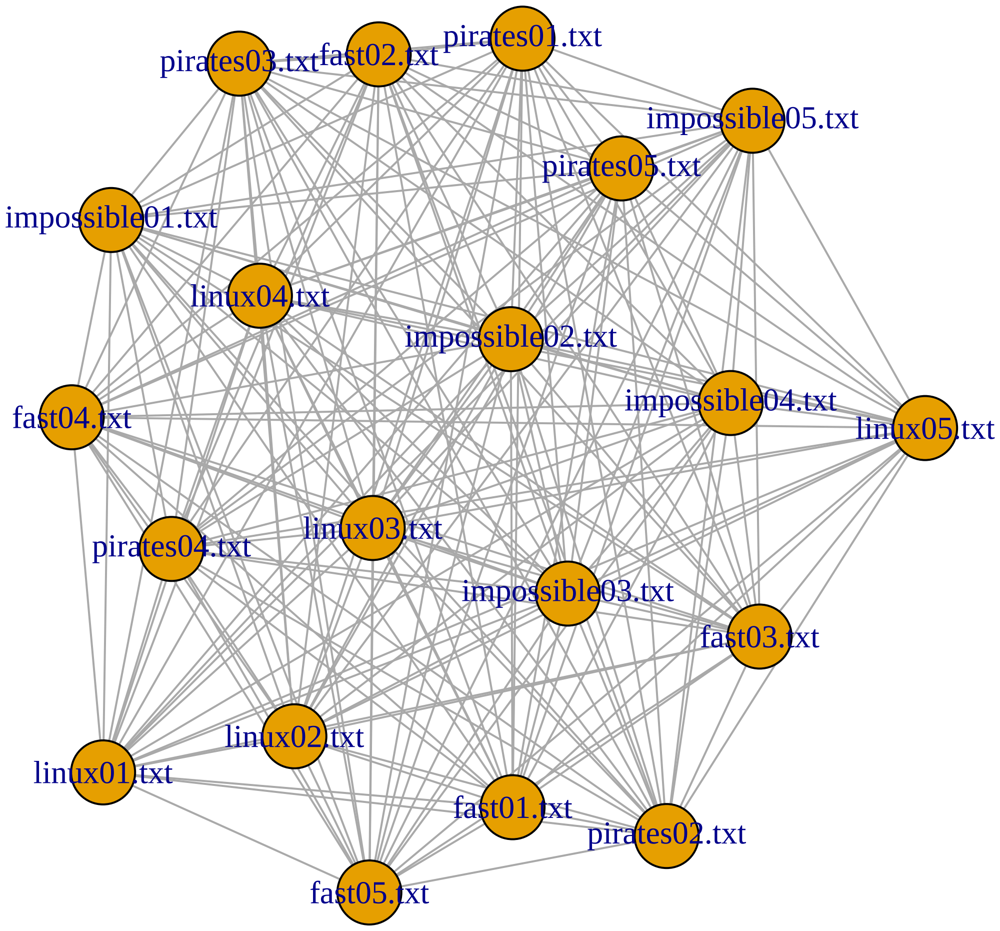
Clustering, however, is unable to recognise significant documents, tokens, or groupings. Social network analysis helps users quickly understand the relationships within the corpus by visualising the relationships between documents, tokens, and document-token pairs. Viewers can use computed metrics (such 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

To create a single-mode network that shows the relationships between documents based on the number of shared phrases, the DTM is first converted into a binary matrix and then multiplied by its transpose. After the initial stage, a matrix is made with a record of 1 for every token that appears in that row's document. The resulting matrix shows the number of shared tokens in each pair of documents after multiplication.

```r
sparse_dtm_matrix_binary <- as.matrix((sparse_dtm_matrix > 0) + 0)
abs_matrix <- sparse_dtm_matrix_binary %*% t(sparse_dtm_matrix_binary)
diag(abs_matrix) <- 0

abs_network <- graph_from_adjacency_matrix(abs_matrix, mode = "undirected", weighted = TRUE)
plot(abs_network)
```



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.

```
graph.density(abs_network)
```

```
## [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.

```
transitivity(abs_network)
```

```
## [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_network))
sort(-betweenness(abs_network))
sort(evcent(abs_network)$vector)
sort(degree(abs_network))
```

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. The low betweeness of zero amongst tokens indicates that the graph is fully connected, or if there are alternative paths between nodes that don't necessarily involve that particular node As such we look into other centrality measures such as closeness and Eignevector. 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.

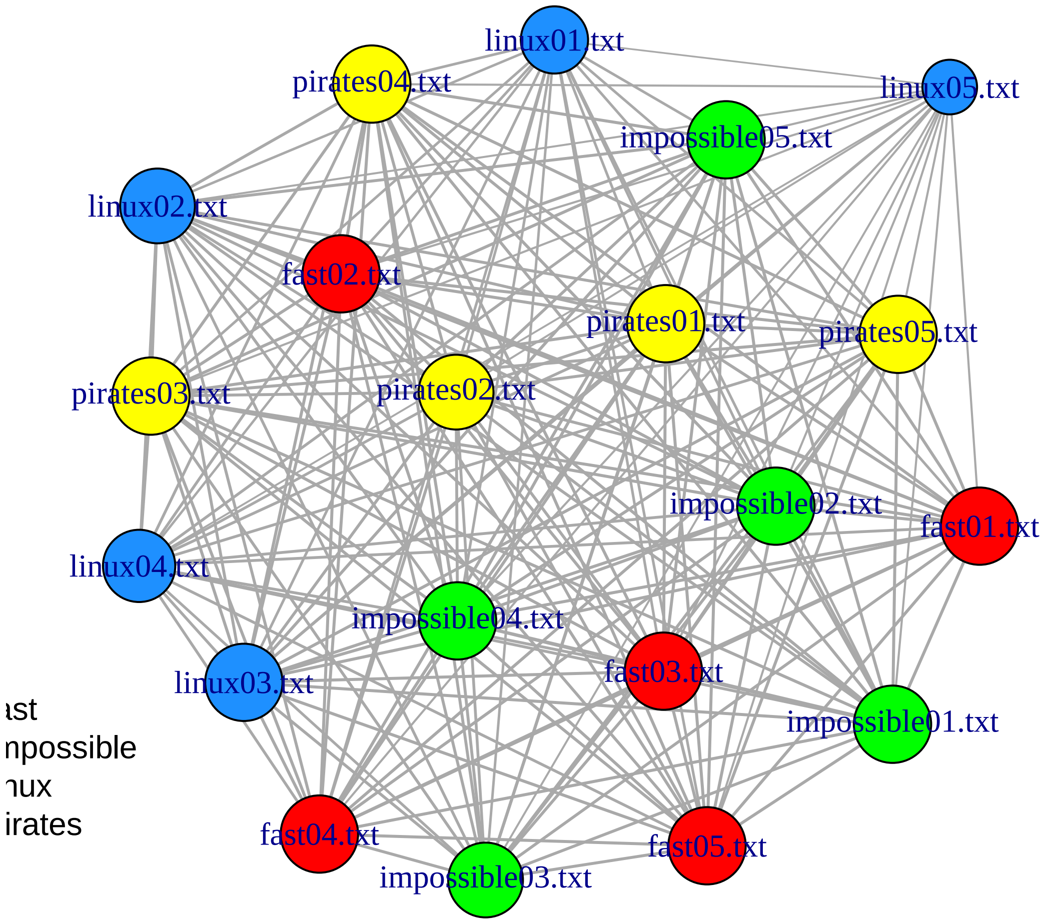
The graph is enhanced by colouring the vertices according to subject, scaling the edge widths according to inter-document strength (number of common terms), and scaling the vertex sizes according to the closeness centrality of the document in order to visually represent the noteworthy aspects of the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

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

for (doc in document_names) {
    V(abs_network)[doc]$color <- document_coloured[match(remove_suffix(doc), topics)]
}

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

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



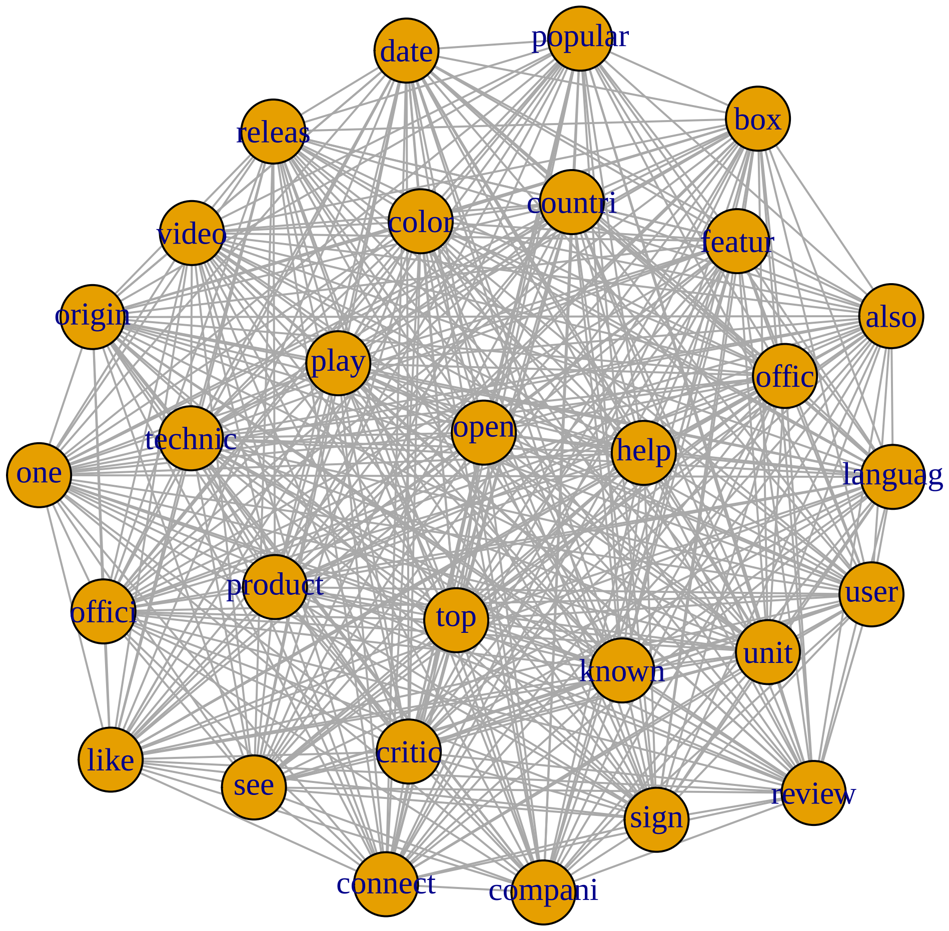
We can see how far apart the `fast` docs are from the others with greater clarity thanks to this graph, as documents from the same topic are marked in the same colour. It is also simpler to see that some topics like `pirates` contain all of the papers closely together, whereas other topics have the reverse. Likewise, as nodes of the same colour seem to cluster nearby, the relative importance is denoted a by a community of similar documents.

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.

```
token_matrix <- t(sparse_dtm_matrix_binary) %*% sparse_dtm_matrix_binary
diag(token_matrix) <- 0

token_network <- graph_from_adjacency_matrix(token_matrix, mode = "undirected", weighted = TRUE)
plot(token_network)
```



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

```r
graph.density(token_network)
```

```
## [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(token_network)
```

```
## [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.Manually eliminating a few generic terms during DTM creation had been attempted, 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.

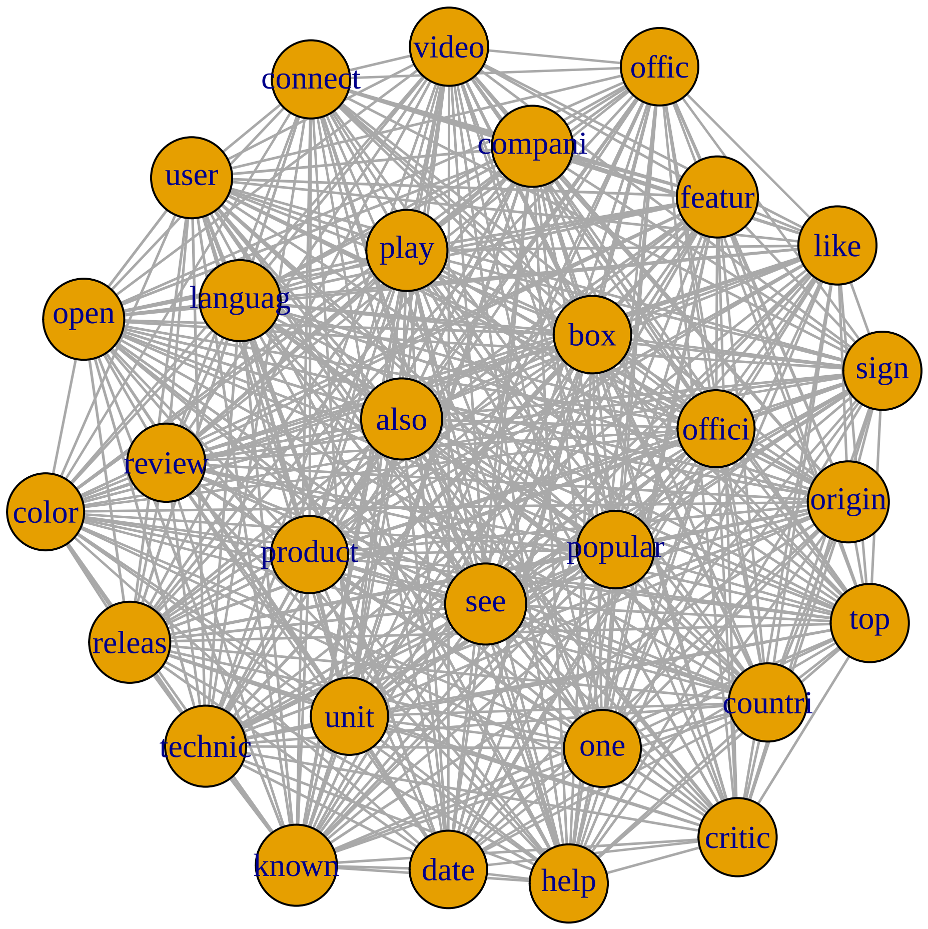
```
sort(-closeness(token_network))
sort(-betweenness(token_network))
sort(evcent(token_network)$vector)
sort(degree(token_network))
```

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.

```
V(token_network)$size <- 1 / closeness(token_network, mode = "all") / 29
E(token_network)$width <- E(token_network)$weight / 15

plot(token_network)
```



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. While some nodes are now larger than others, in contrast, it is hard to differentiate, given the dependent factors do not differ very much between tokens. For example, `see` is larger than `one`, indicating higher relative importance.

Task 7

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

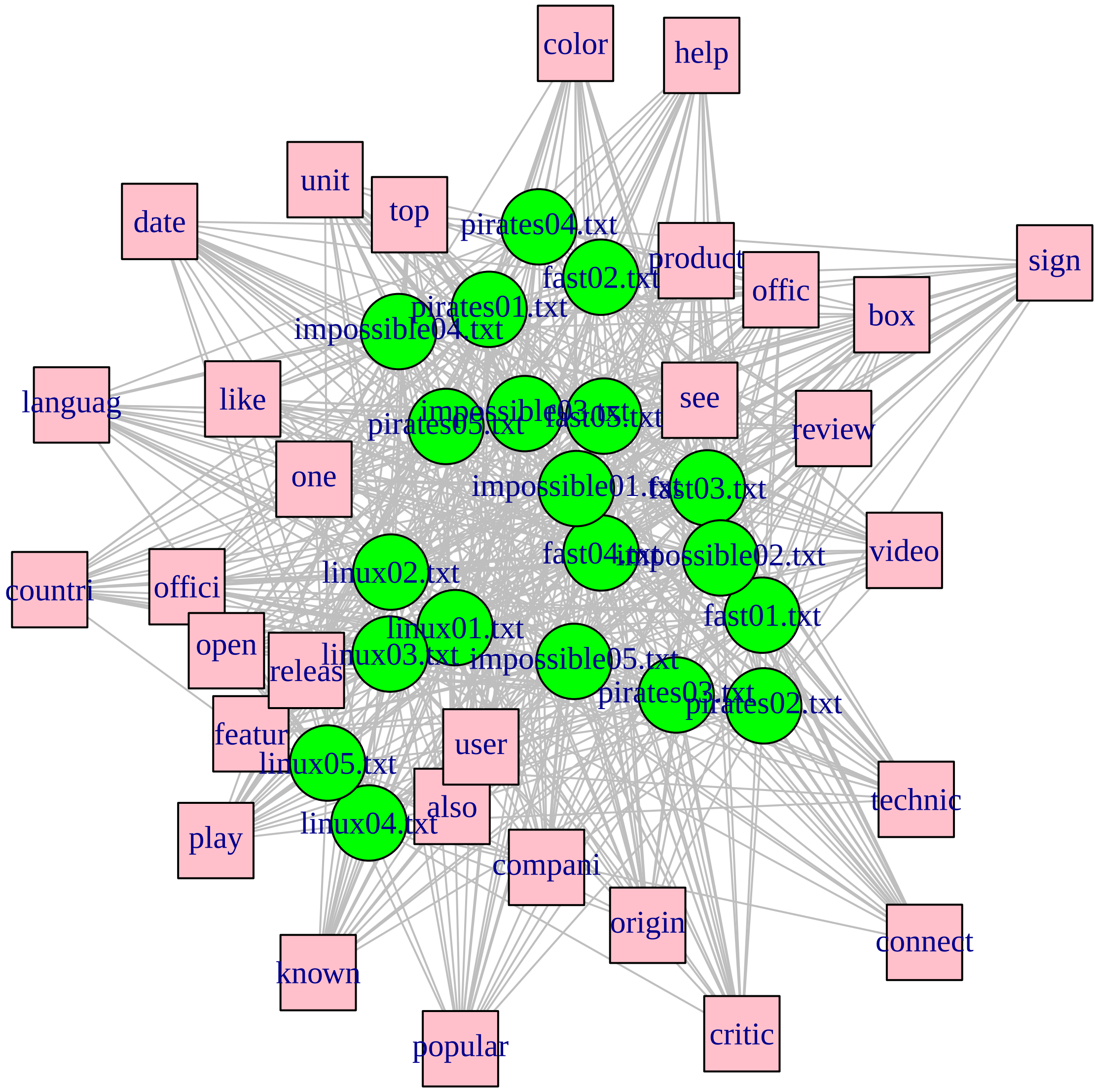
```r
sparse_dtm_df_one <- as.data.frame(sparse_dtm_matrix)
sparse_dtm_df_one$abstract <- rownames(sparse_dtm_df_one)
sparse_dtm_df_two <- data.frame()
for (i in seq_len(nrow(sparse_dtm_df_one))) {
    for (j in seq_len(ncol(sparse_dtm_df_one) - 1)) {
        to_use <- cbind(sparse_dtm_df_one[i, j], sparse_dtm_df_one[i,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

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

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

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

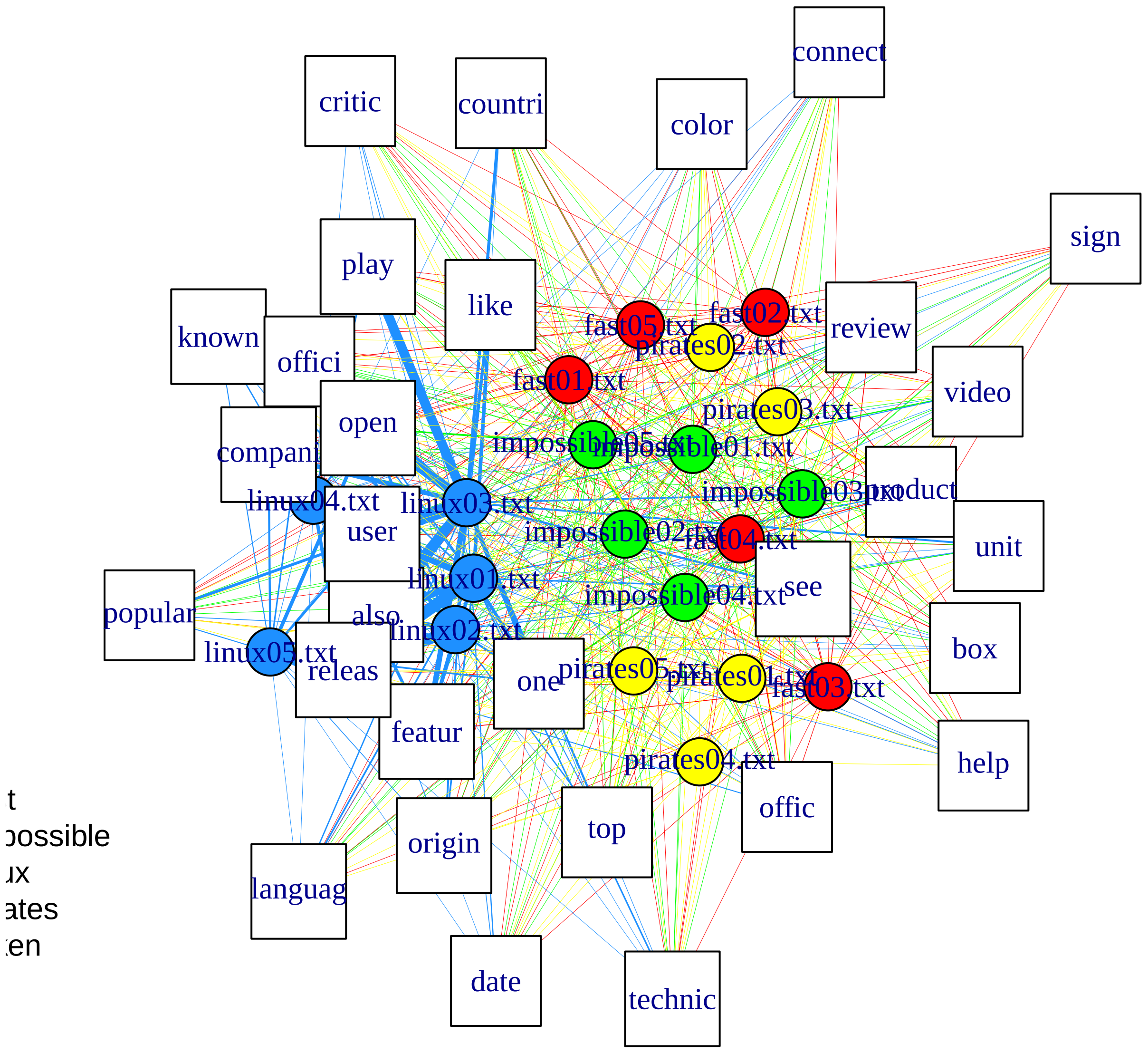
Most movie reviews, such as `pirates`, `fast` and `impossible` have the highest degrees of 30, while `box`, `color`, `connect` and several others jointly have the least.

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(document_names))) {
    V(bipart)[j]$color <- document_coloured[match(remove_suffix(document_names[j]), topics)]
}
for (k in c(21:length(V(bipart)))) V(bipart)[k]$color <- "white"
E(bipart)$width <- as.numeric(sparse_dtm_df_three$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(document_coloured, "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.

Task 8

Clustering and Social Network Analysis are powerful tools for identifying groups of data points with similar characteristics, segmenting customers, or classifying documents. SNA is designed to analyze connections and relationships within a network, revealing influential nodes, tightly knit communities, and information flow patterns. Combining both techniques can identify potential communities within a network.

Techniques such as Topic Modeling, Named Entity Recognition (NER), Sentiment Analysis, Part-of-Speech (POS) Tagging, and Syntactic Analysis can help improve document discrimination by identifying latent topics within a document corpus. NER identifies and classifies named entities based on their focus, while Sentiment Analysis determines the emotional tone of the text, helping distinguish between documents with similar factual content but different emotional stances. POS tagging assigns grammatical labels to each word, revealing the writing style and purpose of documents. Understanding sentence structure and grammar can differentiate between documents with similar vocabulary but different writing styles.

To improve text processing and discrimination between documents, N-gram Analysis, Term Frequency-Inverse Document Frequency (TF-IDF), Word Embedding, Topic Modeling, Named Entity Recognition (NER), Part-of-Speech Tagging, Dependency Parsing, and Document Structure Analysis are recommended. These methods extract different aspects of text data and represent it in a way that facilitates document discrimination.

N-gram Analysis focuses on analyzing sequences of words to capture nuanced relationships between words and improve understanding of document context. TF-IDF weights terms based on their frequency in a document relative to their frequency across all documents, prioritizing terms that are more discriminating for a particular document. Word Embedding capture semantic relationships between words, while Topic Modeling techniques like Latent Dirichlet Allocation or Non-negative Matrix Factorization help identify latent topics in documents (Song and Nie, 2006).

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Appendix

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

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

```
##                   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.

```r
table(Topic = short_document_names, Cluster = cutree(euclid_fitted, 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 = short_document_names, Cluster = cutree(cosine_fitted, 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_network))
```

```
##      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
```

```
sort(-betweenness(abs_network))
```

```
##       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
```

```
sort(evcent(abs_network)$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
```

```
sort(degree(abs_network))
```

```
##       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.

```
sort(-closeness(token_network))
```

```
##        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(token_network))
```

```
##    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(token_network)$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
```

```r
sort(degree(token_network))
```

```
##    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.

```r
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
```