Newsflow: An R package for analyzing content homogeneity and news diffusion using computational text analysis

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Abstract

Given the sheer amount of news sources in the digital age (e.g., newspapers, blogs, social media) it has become difficult to determine where news is first introduced and how it diffuses across sources. We introduce Newsflow: an R package for analyzing content homogeneity and diffusion patterns using computational text analysis. The content of news messages is compared using techniques from the field of information retrieval, similar to plagiarism detection. By using a sliding window approach to only compare messages within a given time distance, many sources can be compared over long periods of time. Furthermore, the package introduces an approach for analyzing the news similarity data as a network, and includes various functions to analyze and visualize this network.

Introduction

The news diffusion process in the digital age involves many interdependent sources, ranging from news agencies and traditional newspapers to blogs and people on social media [Meraz, 2011, Paterson, 2005, Pew Research Center, 2010]. We offer the `Newsflow` R package[1] as a toolkit to analyze the homogeneity and diffusion of news content using computational text analysis. This analysis consists of two steps. First, techniques from the field of information retrieval are used to measure the similarity of news messages (e.g., addressing the same event, containing identical phrases). Second, the temporal order in which messages are published is used to analyze consistent patterns in who follows whom.

The main contribution of this package lies in the specialized application of document similarity measures for the purpose of analyzing the homogeneity and diffusion of news. News is a special type of information in the sense that it has a time dimension—it quickly loses its relevance. Therefore, we are often only interested in the similarity of news documents that occured within a short time distance. By restricting document comparisons to a given time distance, it becomes possible to compare many documents over a long period of time, but available document comparison software generally does not have this feature. We therefore offer the `documents.window.compare` function which compares documents using a sliding window over time. In addition, this package offers tools to aggregate, analyze and visualize the document similarity data. By proposing a standardized network format, using the `igraph` package, to organize the document similarity data, it lays the foundation for developing standardized procedures to analyze this type of data.

The primary intended audience of this package is scholars and professionals in fields where the impact of news on society is a prime factor, such as journalism, political communication and public relations [Baum and Groeling, 2008, Boczkowski and De Santos, 2007, Ragas, 2014]. To what extent the content of certain sources is homogeneous or diverse has implications for central theories of media effects, such as agenda-setting and the spiral of silence [Bennett and Iyengar, 2008, Blumler and Kavanagh, 1999] Identifying patterns in how news travels from the initial source to the eventual audience is important for understanding who the most influential "gatekeepers" are [Shoemaker and Vos, 2009]. Furthermore, the document similarity data enables one to study news values [Galtung and Ruge, 1965] by analyzing what elements of news predict their diffusion rate and patterns.

The package is designed to appeal to scholars and professionals without prior experience in computational text analysis. This vignette covers the entire chain from processing raw data—written text with source and date information—to analyzing and visualizing the output. It points to relevant software within and

[1] R is an open-source statistical software package (https://www.r-project.org/).

outside of R for pre-processing written texts, and demonstrates how to use the core functions of this package. For more advanced users there are additional functions and parameters to support versatility. `Newsflow` is completely open-source to promote active involvement in developing and evaluating the methodology. The source code is available on Github—https://github.com/masked (repository hidden for review). All data used in this vignette is included in the package for easy replication.

The structure of this vignette is as follows. The first part discusses the data preparation. There are several choices to be made here that determine on what grounds the content of documents is compared. The second part shows how the core function of this packages, `documents.window.compare`, is used to calculate document similarities for many documents over time. The third part demonstrates functions for exploring, aggregating and visualizing the document similarity data. Finally, conclusions regarding the current version of the package and future directions are discussed.

Preparing the data

To analyse content homogeneity and news diffusion using computational text analysis, we need to know *who* said *what* at *what time*. Thus, our data consists of messages in text form, including meta information for the source and publication date of each message. The texts furthermore need to be pre-processed and represented as a *document-term matrix* (DTM). This section first discusses techniques and refers to existing software to pre-process texts and create the DTM, and reflects on how certain choices influence the analysis. Second, it shows how the source and date information should be organized. Third, it discusses several ways to filter and weight the DTM based on word statistics.

Pre-processing texts and creating the DTM

A DTM is a matrix in which rows represent documents, columns represent terms, and cells indicate how often each term occurred in each document. This is referred to as a *bag of words* respresentation of texts, since we ignore the order of words. This simplified representation makes analysis much easier and less computationally demanding, and as much research has shown: "a simple list of words, which we call unigrams, is often sufficient to convey the general meaning of a text" [Grimmer and Stewart, 2013, 6].

As input for this package, the DTM has to be in the `DocumentTermMarix` class of the `tm` package. This is a popular R package for text mining, or computational text analysis, which also contains functions to create a DTM based on raw text in various formats. We also recommend the `RTextTools` package, which has the `create_matrix` function that wraps various `tm` functions for creating a DTM into a single convenient function. For example, see the following DTM, created with the `create_matrix` function.

```r
document1 = 'Socrates is human'
document2 = 'Humans are mortal'
document3 = 'Therefore, Socrates is mortal'
dtm = RTextTools::create_matrix(textColumns = c(document1,document2,document3),
                                minWordLength = 1, removeStopwords = F)

rownames(dtm) = paste('Document', 1:nrow(dtm))
as.matrix(dtm)
```

	are	human	humans	is	mortal	socrates	therefore
Document 1	0	1	0	1	0	1	0
Document 2	1	0	1	0	1	0	0
Document 3	0	0	0	1	1	1	1

Based on the representation of texts in the DTM, the similarity of documents can be calculated as the similarity of row vectors. However, as seen in the example, this approach has certain pitfalls if we simply look at all words in their literal form. For instance, the words "human" and "humans" are given separate columns, despite having largely the same meaning. As a result, this similarity of the first two texts is not recognized. Also, the words "are", and "is" do not have any substantial meaning, so they are not informative and can be misleading for the calculation of document similarity. There are various techniques to filter and transform words that can be used to mend these issues. In addition, we can use these techniques to steer on what grounds documents are compared.

- First of all, it is advisable to make all terms lowercase, and reduce terms to their root using stemming or lemmatizing[2]. Thus, "Hope", "hoped", "hoping", etc. all become "hope". This is because we are interested in the meaning of these terms, and not the specific form in which they are used.
- Second, one should filter out irrelevant words. Very common words, stopwords and boilerplate words contain little or no relevant information about news items. Very rare terms, while ignored in many computational text analysis approaches, are particularly informative for our current purpose, and should be kept.
- Third, It is also possible to specifically select or filter out only certain types of words by using part-of-speech tagging[3]. For instance, to compare whether documents address the same event one can focus on nouns and proper names.
- Finally, an alternative approach is to combine words into N-grams (i.e. sets of N consecutive words). This way the comparison of documents focuses more on similarity in specific segments of text, which is useful if the goal is to trace whether sources literally copy each other (in which case most other pre-processing steps can be skipped).

All mentioned techniques except for lemmatization and part-of-speech tagging are available in the `tm` package and in the `create_matrix` function of the `RTextTools` package. To use lemmatization or part-of-speech tagging there are several free to use grammar parsers, such as *CoreNLP* for English [Manning et al., 2014] and *Frog* for Dutch [Van den Bosch et al., 2007]. To create a DTM based on externally pre-processed documents, one can use the base function `xtabs` to create a sparse matrix and the `as.DocumentTermMatrix` function from the `tm` package to transform this matrix to the `DocumentTermMatrix` class.

For this vignette, data is used that has been preprocessed with the Dutch grammar parser Frog. The data is based on a recent study on the influence of a Dutch news agency on the print and online editions of Dutch newspapers in political news coverage (Author citation, forthcoming). The terms have been lemmatized, and only the nouns and proper names of the headline and first five sentences (that generally contain the essential who, what and where of news) are used. By focusing on these elements, the analysis in this study focused on whether documents address the same events. This data is also made available in the package as demo data, in which the actual nouns and proper names have been substituded with indexed part-of-speech tags.

```
data(dtm)
as.matrix(dtm[1:3,1:5])
```

	person.688	noun.1516	location.119	organization.323	person.493
35573532	0	0	0	0	0
35573536	0	0	0	0	0
35573539	0	0	0	0	0

[2]Stemming and lemmatization are both techniques for reducing words to their root, or more specifically their stem and lemma. This is used to group different forms of the same word together. Without going into specifics, lemmatization is a much more computationally demanding approach, but generally gives better results. Especially for richly inflicted languages such as German or Dutch it is highly recommended to use lemmatization instead of stemming.

[3]Part-of-speech tagging is a technique that identifies types of words, such as verbs, nouns and adjectives.

Organizing document meta information

In addition to the DTM, we need meta information for each document. This should be structured as a data frame with at least two columns. The first column contains the document names, and should match with the rownames (i.e. document names) of the DTM. The second column contains the publication date of the document, which should be in the `Date` or `POSIXct` class. For easy compatibility with the functions offered in this package, it is recommended to label these columns "document_id" and "date". Any additional columns in the meta data.frame can be used in the analysis to aggregate and visualize results. Here it is recommended to have at least a column containing the source of the document, labeled "source".[4]

```
data(meta)
head(meta,3)
```

document_id	date	source	sourcetype
35573532	2013-06-01 06:00:00	Print NP 2	Print NP
35573536	2013-06-01 06:00:00	Print NP 2	Print NP
35573539	2013-06-01 06:00:00	Print NP 2	Print NP

Using word statistics to filter and weight the DTM

As a final step in the data preparation, we can filter and weight words based on word statistics, such as how often a word occured. Since we are analyzing news diffusion, a particularly interesting characteristic of words is the distribution of their use over time. To focus the comparison of documents on words that indicate new events, we can filter out words that are evenly used over time. To calculate this, we offer the `term.day.dist` function.

```
tdd = term.day.dist(dtm, meta)
head(tdd)
```

term	freq	doc.freq	days.n	days.pct	days.entropy	days.entropy.norm
person.688	1	1	1	0.033	1	0.033
noun.1516	4	3	1	0.033	1	0.033
location.119	1	1	1	0.033	1	0.033
organization.323	2	2	1	0.033	1	0.033
person.493	3	2	1	0.033	1	0.033
noun.1415	2	2	1	0.033	1	0.033

Of particular interest is the `days.entropy` score, which is the entropy of the distribution of words over days. This tells us whether the occurrence of a word over time is evenly distributed (high entropy) or concentrated (low entropy).[5] The maximum value for entropy is the total number of days (in case of a uniform distribution). The `days.entropy.norm` score normalizes the entropy by dividing by the number of days. By selecting the terms with low entropy scores, the DTM can be filtered by using the selected terms as column values.

[4] "document_id", "date" and "source" are the default labels used in several functions to interpret the meta information. Note that these defaults can always be changed using the function parameters. Using the default labels only serves as a convenience.

[5] Note that this is also a good automatic approach for filtering out stopwords, boilerplate words, and word forms such as articles and common verbs.

```
select_terms = tdd$term[tdd$days.entropy.norm <= 0.3]
dtm = dtm[,select_terms]
```

Instead of deleting terms, we can also weight terms. Turney explains that `The idea of weighting is to give more weight to surprising events and less weight to expected events'', which is important because`surprising events, if shared by two vectors, are more discriminative of the similarity between the vectors than less surprising events" [?, 156]. Thus, we want to give more weight to rare words than common words. A classic weighting scheme and recommended standard in information retrieval is the term-frequency inverse document frequency (tf.idf) [?, ?]. This and other weighting schemes can easily be applied using the `tm` pacakge, for instance using the `weightTfIdf` function.

```
dtm = weightTfIdf(dtm)
```

Calculating document similarities

Given a DTM and corresponding document meta data, the document similarities over time can be calculated with the `documents.window.compare` function. The calculation of document similarities is performed using a vector space model [Salton et al., 1975, Salton and Harman, 2003] approach, but with a sliding window over time to only compare document that occur within a given time distance. The function has two main data inputs: the DTM and a data.frame with meta information. The meta data.frame should have a column containing document id's that match the rownames of the DTM (i.e. documents) and should have a column indicating the publication time. By default these columns should be labeled "document_id" and "date", but the column labels can also be set using the `id.var` and `date.var` parameters. Any other columns will automatically be included as document meta information in the output.

Furthermore, three parameters are of particular importance. The `hour.window` parameter determines the time window in hours within which each document is compared to other documents. The argument is a vector of length 2, in which the first and second value determine the left and right side of the window, respectively. For example, c(-36, 0) will compare each document to all documents within the previous 36 hours. The `measure` parameter, which determines what measure for similarity is used, defaults to *cosine similarity*. This is a commonly used measure, which indicates similarity as a score between 0 (no similarity) and 1 (identical)[6]. The `min.similarity` parameter is used to ignore all document pairs below a certain similarity score. In the current example we use a minimum similarity of 0.4, because a validity test in the vignette on which this data is based found this to be a good threshold for finding documents that address the same events. Whether or not a threshold should be used and what the value should be depends on the goal of the analysis and the data.

```
g = documents.window.compare(dtm, meta,
                             hour.window = c(-36,0),
                             min.similarity = 0.4)
```

The output `g` is a network, or graph, in the format of the `igraph` package. The vertices (or nodes) of this network represent documents, and the date and source of each document are stored as vertex attributes. The edges (or ties) represent the similarity of documents, and the similarity score and time difference are stored as edge attributes. To avoid confusion, keep in mind that from hereon when we talk about vertices or a vertex we are talking about documents, and that edges are essentially document pairs. An advantage of using a network format is that it combines this data in an efficient way, without copying the document meta information for each edge. This network forms the basis for all the analysis functions offered in this package[7].

[6] If the DTM contains negative values, the cosine similarity score can range from -1 to 1.

[7] If data about document similarities is imported, then the `document.network` function can be used to create this network. This way the functions of this package for aggregating and visualizing the network can still be used.

A full understanding of the `igraph` package is not required to use the current package, but one does need some basic understanding of the functions for viewing and extracting the document/vertex and edge attributes. First, vertex and edge attributes cannot be directly selected, but require the functions `V()` and `E()` to be used, for vertex and edge attributes, respectively. These can be used as follows.

```
vertex.sourcetype = V(g)$sourcetype
edge.hourdiff = E(g)$hourdiff

head(vertex.sourcetype)
```

```
## [1] "Newsagency" "Online NP"  "Newsagency" "Newsagency" "Online NP"
## [6] "Online NP"
```

```
head(edge.hourdiff)
```

```
## [1]  -1.32  -1.12  -2.08  -1.40 -10.50  -4.50
```

Alternatively, all vertex and edge attributes can be viewed or extracted with the `get.data.frame` function of the `igraph` package.

```
v = get.data.frame(g, 'vertices')
e = get.data.frame(g, 'edges')

head(v,3)
```

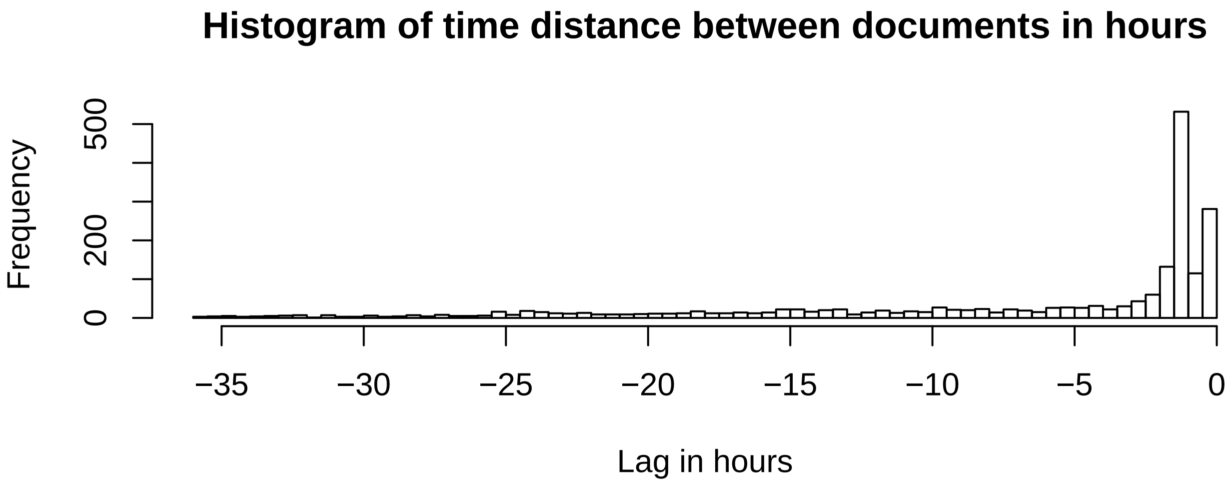
	name	date	source	sourcetype
97360803	97360803	2013-06-03 16:54:00	Newsagency	Newsagency
35734376	35734376	2013-06-03 18:13:00	Online NP 1	Online NP
97361657	97361657	2013-06-05 09:21:00	Newsagency	Newsagency

```
head(e,3)
```

from	to	weight	hourdiff
35734376	97360803	1	-1.32
36022422	97361657	1	-1.12
36043529	97361740	1	-2.08

The `weight` attribute of the edges represents the similarity score. The `hourdiff` attribute represents the time difference in hours between two documents, where a negative score indicates that the `to` article was published before the `from` article. A histogram can provide a good first indication of this data.

```
hist(E(g)$hourdiff, main='Histogram of time distance between documents in hours',
     xlab = 'Lag in hours', breaks = 100)
```



In the histogram we see that most document pairs with a similarity score above the threshold are about an hour apart (-1 on the x-axis). This is mainly because the online newspapers often follow the news agency within a very short amount of time. As time distance increases, the number of document pairs decreases, which makes sense because news gets old fast, so news diffusion should occur within a limited time after publication.

Tailoring the document comparison window

If news diffuses from one source to another, then the time difference cannot be zero, since the source that follows needs time to edit and publish the news. This delay period can also differ between sources. Websites can adopt news within minutes, but newspapers have a long time between pressing and publishing the newspaper, meaning that there is a period of several hours before publication during which influence is not possible. Thus, we have to adjust the window for document pairs. To make it more convenient to adjust and inspect the window settings for different sources, we offer the `filter.window` and `show.window` functions.

The `filter.window` function can be used to filter the document pairs (i.e. edges) using the `hour.window` parameter, which works identical to the `hour.window` parameter in the `documents.window.compare` function. In addition, the `select.vertices` parameter can be used to select the vertices (i.e. documents) for which this filter is applied. This makes it easy to tailor the window for different sources, especially if the sourcetype is included in the vertex information.

```
# set window for all vertices
g = filter.window(g, hour.window = c(-36, -0.1))

# set window for print newspapers
is.print = V(g)$sourcetype == 'Print NP'
g = filter.window(g, hour.window = c(-36, -6), select.vertices=is.print)
```

For all sources the window has now been adjusted so that a document can only match a document that occured at least 0.1 hours earlier. But for print newspapers, this is more specifically set to 6 hours. With the `show.window` function we can view the actual window in the data. A vertex.attribute can also be given to view the window separately for the unique values of this attribute.

```
show.window(g, vertex.attribute = 'source')
```

vertex.attribute	window.left	window.right
Newsagency	-35.4	-0.150

vertex.attribute	window.left	window.right
Online NP 1	-35.8	-0.100
Online NP 2	-36.0	-0.117
Print NP 1	-36.0	-7.017
Print NP 2	-35.1	-7.350

Analyzing the document similarity network

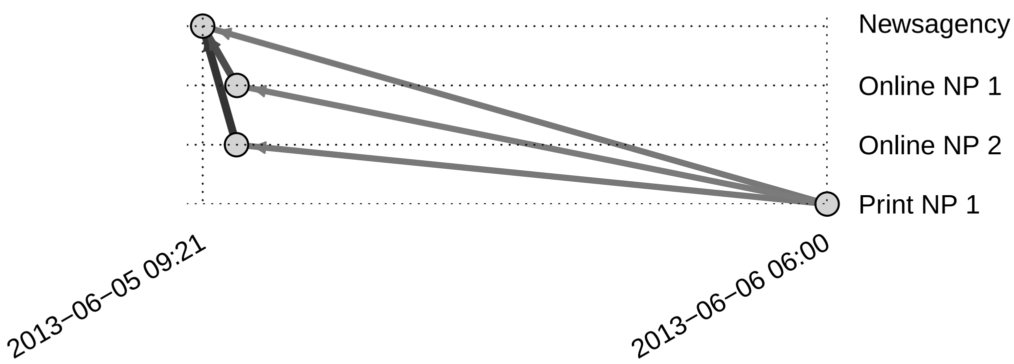
Before we aggregate the network, it can be informative to look at the individual sub-components. If a threshold for document similarity is used, then there should be multiple disconnected components of documents that are only similar to each other. With the current data, these components tend to reflect documents that address the same or related events. Decomposing the network can be done with the `decompose.graph()` function from the `igraph` package.

```
g_subcomps = decompose.graph(g)
length(g_subcomps)
```

```
## [1] 658
```

The current data has 658 sub-components. To visualize these components, we offer the `plot.document.network` function. This function draws a network where nodes (i.e. documents) are positioned based on their date (x-axis) and source (y-axis).

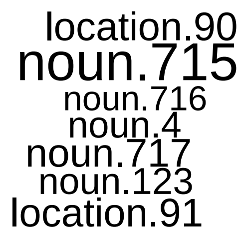
```
gs = g_subcomps[[2]] # select the second sub-component
plot.document.network(gs)
```

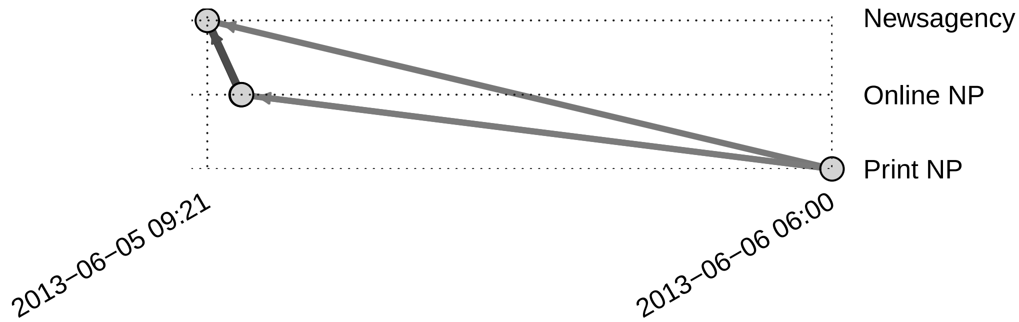


The visualization shows that a news message was first published by the news agency on June 5th around 9 AM. Soon after this messages was adopted by two online newspapers, and later on also by a print newspaper. The grayscale and width of the edges also show that the online newspaper messages were very similar (i.e. thick and black) to the news agency message.

By default, the "source" attribute is used for the y-axis, but this can be changed to other document attributes using the `source.attribute` parameters. If a DTM is also provided, the visualization will also include a word cloud with the most frequent words of these documents.

```
plot.document.network(gs, source.attribute = 'sourcetype', dtm=dtm)
```

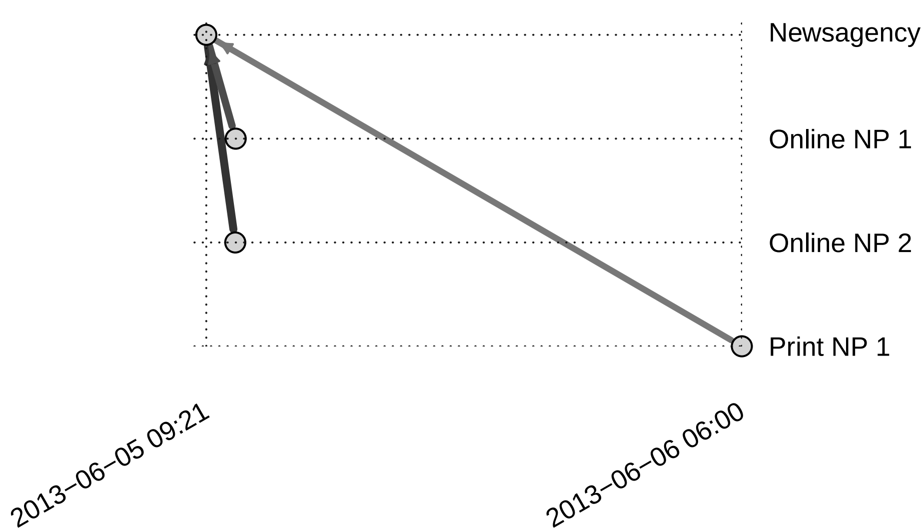




These visualizations and the corresponding subcomponents help us to qualitatively investigate specific cases. This also helps to evaluate how well the document similarity measures are valid given the goal of the analysis. Furthermore, they illustrate how we can analyze homogeneity and news diffusion patterns. For each source we can count what proportion of its publications is similar to earlier publications by specific other sources. We can also analyze the average time between publications.

Another usefull application is that we can use them to see whether certain transformation of the network might be required. Depending on the purpose of the analysis it can be relevant to add or delete certain edges. For instance, in the previous visualizations we see that a print newspaper message matched both a recent newsagency message and two online newspaper messages. If we are specifically interested in who the original source of the message is, then it makes sense to only count the edge to the newsagency. Thus, we can develop functions to transform the network to enable such alternative types of analysis. here we demonstrate the `only.first.match` function, which transforms the network so that a document only has an edge to the earliest dated document it matches within the specified time window.

```
gs_onlyfirst = only.first.match(gs)
plot.document.network(gs_onlyfirst)
```



Aggregating the document similarity network

This package offers the `aggregate.network` function as a versatile way to aggregate the edges of the document similarity network based on the vertex attributes (i.e. the document meta information). The first argument is the network (in the `igraph` class). The second argument, for the `by` parameter, is a character vector to indicate one or more vertex attributes based on which the edges are aggregated. Optionally, the `by` characteristics can also be specified separately for `by.from` and `by.to`. This gives flexible control over the data, for instance to look at source and sourcetypes, or to aggregate scores per month.

By default, the function returns the number of edges, as well as the number of nodes that is connected for both the `from` and `to` group. These values are relevant if a threshold for similarity (edge weight) is used, so that whether or not an edge exists indicates whether or not two documents are similar. In addition, if an `edge.attribute` is given, this attribute will be aggregated using the function specified in `agg.FUN`. For the following example we include this to analyze the median of the `hourdiff` attribute.

```
g.agg = aggregate.network(g, by='source', edge.attribute='hourdiff', agg.FUN=median)

e = get.data.frame(g.agg, 'edges')
head(e)
```

from	to	edges	agg.hourdiff	from.V	from.V_prop	to.V	to.V_prop
Newsagency	Newsagency	124	-8.08	95	0.159	112	0.188
Online NP 1	Newsagency	451	-1.27	384	0.831	425	0.712
Online NP 2	Newsagency	379	-1.33	330	0.791	374	0.626
Print NP 2	Newsagency	60	-15.92	45	0.344	60	0.101
Print NP 1	Newsagency	38	-16.55	34	0.231	38	0.064
Newsagency	Online NP 1	107	-4.82	91	0.152	90	0.195

In the edges of the aggregated network there are six scores for each edge. The `edges` attribute counts the number of edges from the `from` group to the `to` group. For example, we see that *online NP 1* documents have 451 edges to *newsagency* documents. The `agg.hourdiff` attribute shows that the median of the hourdiff attribute of these 451 edges is -1.27 (1 hour and 16 minutes). In addition to the edges, we can look at the number of vertices (i.e. documents) in the `from` group that matched with at least one vertex in the `to` group. This is given by the `from.V` attribute, which shows here that 384 *online NP 1* documents matched with a *newsagency* document. [8]. This is also given as the proportion of all vertices/documents in the `from` group, as the `from.V_prop` attribute. Substantially, the `from.V_prop` score thus indicates that 83.12% of political news messages in *online NP 1* is similar or identical to recent *newsagency* messages. For the analysis of content homogeneity and news diffusion, the `from.V_prop` attribute is often most relevant.

The `V' and 'V_prop` scores are also reported for the `to` group. This gives an inversed perspective on the relation between the `from` and `to` groups. Based on the `to.V` score, we see that 71.12% of documents published by the *newsagency* is similar or identical to future documents in *online NP 1*. In other words, of all the political news messages published by the *newsagency*, 71.12% was afterwards also published by *online NP 1*. Thus, `from.V_prop` and `to.v_prop` are related but different scores, and can be used to answer different research questions.

Inspecting and visualizing results

We already saw that the network data can be transformed to a common data.frame with the `get.data.frame` function. Alternatively, `igraph` has the `get.adjacency` function to return the values for one edge attribute

[8] Note that the `edges` score is always equal to or higher than the `from.matched` score, since one document can match with multiple other documents.

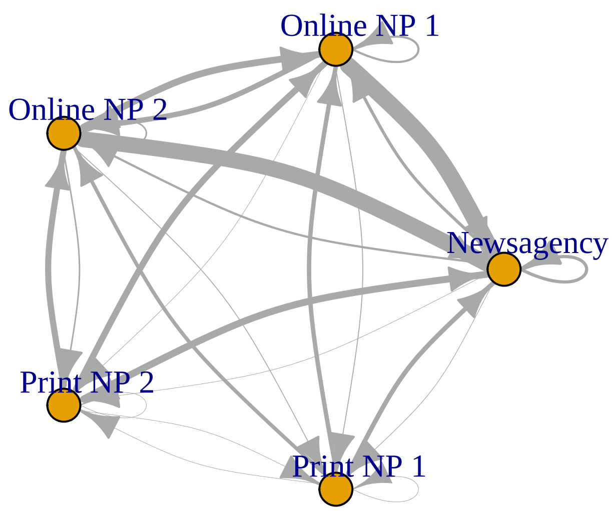
as a matrix with the vertices in the rows and columns.

```
get.adjacency(g.agg, attr= 'from.V_prop', sparse = F)
```

	Newsagency	Online NP 1	Online NP 2	Print NP 2	Print NP 1
Newsagency	0.159	0.152	0.109	0.017	0.030
Online NP 1	0.831	0.106	0.264	0.026	0.045
Online NP 2	0.791	0.336	0.077	0.074	0.041
Print NP 2	0.344	0.313	0.305	0.008	0.015
Print NP 1	0.231	0.218	0.184	0.007	0.027

Furthermore, we can use the network visualization features.

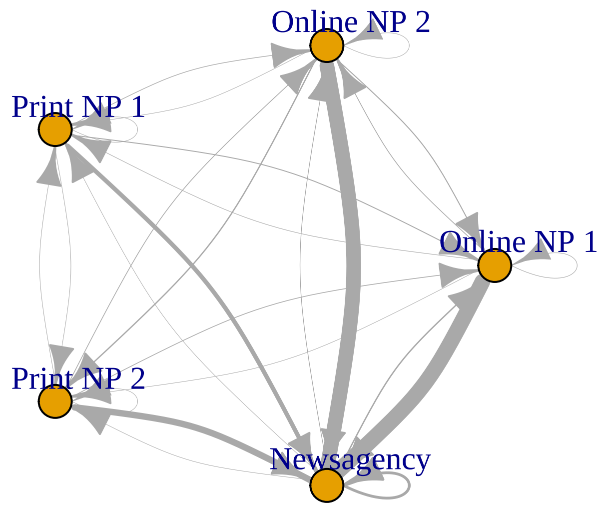
```
plot(g.agg, layout=layout.circle, edge.width = E(g.agg)$from.V_prop*10,
             edge.curved=0.2, vertex.label.dist=0.6)
```



For illustration, we can now see how the results change if we transform the network with the `only.first.match` function, as discussed above.

```
g2 = only.first.match(g)
g2.agg = aggregate.network(g2, by='source', edge.attribute='hourdiff', agg.FUN=median)

plot(g2.agg, layout=layout.circle, edge.width = E(g2.agg)$from.V_prop*10,
             edge.curved=0.2, vertex.label.dist=0.6)
```



The first network is much more dense compared to the second. In particular, we see stronger edges between the print and online editions of the newspapers. In the second network almost only the ties to the news agency remain. This implies that many of the edges between newspapers in the first network resulted from cases where both newspapers adopt the same news agency articles.

Note, however, that the second network is not better per se. It is possible that the initial source of a message is not the direct source. For example, a blog might not have acces to the news agency feed, and therefore only receive news agency messages if they are published by another source. Thus, the most suitable approach depends on the purpose of the analysis. One of the goals of this package is to develop best practises for different occasions.

Alternative applications of this package

There are several alternative applications of the functions offered in this package that are not covered in this vignette. Here we briefly point out some of the more usefull alternatives.

In the aggregate.network function it is possible to use different vertex attributes to aggregate the edges for `from` and `to` nodes. A particularlly interesting application of this feature is to use the publication date in the aggregation. For instance, with the following settings, we can get the proportion of matched documents per day. Here we also use the `return.df` parameter in the `aggregate.network` function, to directly return the results as a data.frame[^returndf].

```
V(g)$day = format(as.Date(V(g)$date), '%Y-%m-%d')
agg.perday = aggregate.network(g, by.from=c('source', 'day'), by.to='source',
                               edge.attribute='hourdiff', agg.FUN=median,
                               return.df=T)

head(agg.perday)
```

to.source	from.source	from.day	edges	agg.hourdiff	from.V	to.V	from.V_prop	to.V_prop
Newsagency	Newsagency	2013-06-01	1	-9.70	1	1	0.100	0.002
Newsagency	Print NP 2	2013-06-06	2	-26.10	1	2	0.333	0.003
Newsagency	Online NP 1	2013-06-09	9	-1.25	7	9	0.875	0.015
Newsagency	Print NP 2	2013-06-22	2	-20.27	2	2	0.333	0.003
Newsagency	Newsagency	2013-06-02	1	-28.72	1	1	0.200	0.002
Newsagency	Newsagency	2013-06-03	2	-3.53	2	1	0.091	0.002

This way the aggregated document similarity data can be analyzed as a time-series. For instance, to analyze whether certain developments affect content homogeneity or intermedia dynamics. Also, it enables us to analyze the mean of the aggregated results over time. The `return.df` feature is convenient for this purpose, because it directly matches all the vertex and edge attributes (as opposed to the `get.data.frame` function).

Another usefull application of this feature is to only aggregate the `by.to` nodes, by using the vertex name in the `by.from` argument. This way, the data can easily be matched to data on content characteristics of individual documents. For instance, to analyze whether certain elements of documents predict whether or not the message is also covered by other sources. In addition, we set the `edge.attribute` to "weight" and `agg.FUN` to max, so that for each document we can see how strong the strongest match with each source was.

```
agg.perdoc = aggregate.network(g, by.from='name', by.to='sourcetype',
                               edge.attribute='weight', agg.FUN=max,
                               return.df=T)

docXsource = xtabs(agg.weight ~ from.name + to.sourcetype, agg.perdoc, sparse = F)
head(docXsource)
```

	Newsagency	Online NP	Print NP
147908495	0.000	0.000	0.520
150454037	0.000	0.000	0.429
150454094	0.000	0.415	0.000
150454110	0.403	0.000	0.000
150454132	0.542	0.542	0.000
150454155	0.000	0.000	0.415

Finally, note that we have now only compared documents to prior documents. We thereby focus the analysis on whether each document is potentially influenced by certain other documents. By changing the window setting, it is also possible to compare each document to both prior and future documents, to focus on content homogeneity. Or to compare only to future documents, to shift the focus to influence (what messages become adopted) instead of dependence (what messages were adopted from others).

Conclusion and future improvements

We have demonstrated how the *newsflow* package can be used to perform a many-to-many comparison of documents. The primary focus and most important feature of this package is the `documents.window.compare` function. This function compares all documents that occur within a given time distance, which makes it computationally feasible for longitudinal data. Using this data, we can analyze to what extent different sources publish the same content and whether there are consistent patterns in who follows whom. The secondary focus of this package is to provide functions to conduct this analysis, and to provide a platform for scholars to share additional or alternative approaches.

The data input required for this analysis consists solely of textual documents and their corresponding publication date and source. If the texts are imported as natural language, the `tm` package or `RTextTools` package can be used to preprocess them and to create a DTM. If the texts are imported as preprocessed tokens, the `create.dtm` function can be used to create a DTM. Since no human coding is required, the package enables large scale comparative and longitudinal studies. Although the demonstration in this vignette used a moderate sized dataset, the functions can handle much larger data [9].

[9] A test showed that on a laptop with 8Gb RAM and a 1.80GHz processor (no multi-threading used) the analysis performed well with a DTM containing 315.000 documents and 120.000 unique terms. This data covered 1 year in 14 sources, and a window of 3 days and threshold of 0.4 was used.

The goal is to continue developing this package as a specialized toolkit for analyzing the homogeneity and diffusion of news content. First of all, additional approaches for measuring whether documents are related will be added. Currently only a vector space model approach for calculating document similarity is implemented. For future versions alternative approaches such as language modeling will also be explored. In particular, we want to add alternative measures to express the relation of documents over time in terms of probability and information gain. This would also allow us to define a more formal way to determine whether or not a relation exists, other than using a similarity threshold. Secondly, new methods for analyzing and visualizing the network data will be explored. In particular, methods will be implemented for analyzing patterns beyond dyadic ties between news outlets, building on techniques from the field of network analysis. To promote the involvement of other scholars and professionals in this development, the package is entirely open-source. The source code is hosted on GitHub–*https://github.com/kasperwelbers/newsflow*.

Practical code example

```
# Prepare DTM and meta data
data(dtm)
data(meta)

tdd = term.day.dist(dtm, meta)
dtm = dtm[,tdd$term[tdd$days.entropy.norm <= 0.3]]

dtm = weightTfIdf(dtm)

# Prepare document similarity network
g = documents.window.compare(dtm, meta, hour.window = c(-36,-0.1), min.similarity = 0.4)
g = filter.window(g, hour.window = c(-36, -6), V(g)$sourcetype == 'Print NP')

# Aggregate and visualize network
g.agg = aggregate.network(g, by='source', edge.attribute='hourdiff', agg.FUN=median)

get.adjacency(g.agg, attr='from.V_prop')
plot(g.agg, layout=layout.circle, edge.width = E(g.agg)$from.V_prop*10,
             edge.curved=0.2, vertex.label.dist=0.6)
```

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