textNet: Directed, Multiplex, Multimodal Event Network Extraction from Textual Data

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Introduction

Network measurement in social science typically relies on data collected through surveys and interviews. Document-based measurement is automatable and scalable, providing opportunities for large scale or longitudinal research that are not possible through traditional methods. A number of tools exist to generate networks based on co-occurrence of words within documents (such as the Nocodefunctions app (Levallois et al. 2012), the "textnets" package (Bail 2024), InfraNodus (Paranyushkin 2018), and many more). But there is, to our knowledge, no open-source tool that generates network data based on the syntactic relationships between entities within a sentence. *textNet* allows a user to input one or more PDF documents and create arbitrarily complex directed, multiplex, and multimodal network graphs. *textNet* also works on arbitrarily long documents, making it well suited for research applications using long texts such as government planning documents, court proceedings, regulatory impact analyses, and environmental impact assessments.

Statement of Need

Network extraction from documents has typically required manual coding. Furthermore, existing network extraction methods that use co-occurrence leave a vast amount of data on the table, namely, the rich edge attribute data and directionality of each verb phrase defining the particular relationship between two entities, and the respective roles of the entity nodes involved in that verb phrase. We present an R package, *textNet*, designed to enable directed, multiplex, multimodal network extraction from text documents through syntactic dependency parsing, in a replicable, automated fashion for collections of arbitrarily long documents. The *textNet* package facilitates the automated analysis and comparison of many documents, based on their respective network characteristics. Its flexibility allows for any desired entity categories, such as organizations, geopolitical entities, dates, or custom-defined categories, to be preserved.

Directed Graph Production

As a syntax-based network extractor, *textNet* identifies source and target nodes. This produces directed graphs that contain information about network flow. Methods based on identifying co-occurring nodes in a document, by contrast, produce undirected graphs. textNet also allows the user to code ties based on co-occurrence in a designated piece of text if desired.

Multiplex Graph Output

Syntax-based measurement encodes edges based on subject-verb-object relationships. *textNet* stores verb information as edge attributes, which allows the user to preserve arbitrarily complex topological layers (of different types of relationships) or customize groupings of edge types to simplify representation.

Multimodal Graph Output

Multimodal networks, or networks where there are multiple categories of nodes, have common use cases such as social-ecological network analysis of configurations of actors and environmental features. Existing packages such as the manynet package (Hollway 2024) provide analytical functions for multimodal network statistics. *textNet* provides a structure for tagging and organizing arbitrarily complex node labeling schemes that can then be fed into packages for multi-node network statistical analysis. Node labels can be automated (e.g., the default entity type tags for an NLP engine such as *spaCy* (Honnibal et al. 2021)), customized using a dictionary, or based on a hybrid scheme of default and custom labels. Any node type is possible (e.g., species, places, people, concepts, etc.) so this can be adapted to domain specific research applications by applying dictionaries or using a custom NER model.

Avoids Saturation

Co-occurrence graphs have the tendency to generate saturated subgraphs, since every co-occurring collection of entities has every possible edge drawn amongst them. By contrast, *textNet* draws connections not between every entity in the document or even the sentence, but specifically between pairs of entities that are mediated by an event relationship. This leads to sparser graphs that preserve the ability for greater structural variance, and correspondingly, network analysis of structural attributes of the graphs.

Installation

The stable version of this package can be installed from Github, using the *devtools* package (Wickham et al. 2022):

```
devtools::install_github("ucd-cepb/textnet")
```

The *textNet* package suggests several convenience wrappers of packages such as *spacyr* (Benoit et al. 2023), *pdftools* (Ooms 2024), *igraph* (Csárdi et al. 2024), and *network* (Butts et al. 2023). To use the full functionality of *textNet*, such as pre-processing tools and post-processing analysis tools, we recommend installing these packages, which for *spacyr* requires integration with Python. However, the user may wish to preprocess and parse data using their own NLP engine, and skip directly to the textnet_extract() function, which does not depend on any of the aforementioned packages. The textnet_extract() function does, however, use functions from *pbapply* (Solymos et al. 2023), *data_table* (Barrett et al. 2024), *dplyr* (Wickham et al. 2023), and *tidyr* (Wickham et al. 2024).

Overview and Main Functions

The package architecture relies on four sets of functions around core tasks:

- [OPTIONAL] Pre-processing: pdf_clean(), a wrapper for the pdftools::pdf_text() function which includes a custom header/footer text removal feature; and parse_text(), which is a wrapper for the *spacyr* package and uses the *spaCy* natural language processing engine (Honnibal et al. 2021) to parse text and perform part of speech tagging, dependency parsing, and named entity recognition (NER). Alternatively, as described below, the user can skip this step and load parsed text directly into the package.
- Network extraction: textnet_extract(), which generates a graph database from parsed text based upon tags and dependency relations
- Disambiguation: tools for cleaning, recoding, and aggregating node and edge attributes, such as the find_acronyms() function, which can be paired with the disambiguation() function to identify acronyms in the text and replace them with the full entity name.

- Exploration: the export_to_network() function for exporting the graph database to igraph and network objects, top_features() for viewing node and edge attributes, and combine_networks() for aggregating multiple document-based graphs based on common nodes.

The figure below summarizes the functionality of *textNet* and the flow of function outputs. Optional data cleaning features are shown with dotted arrows.

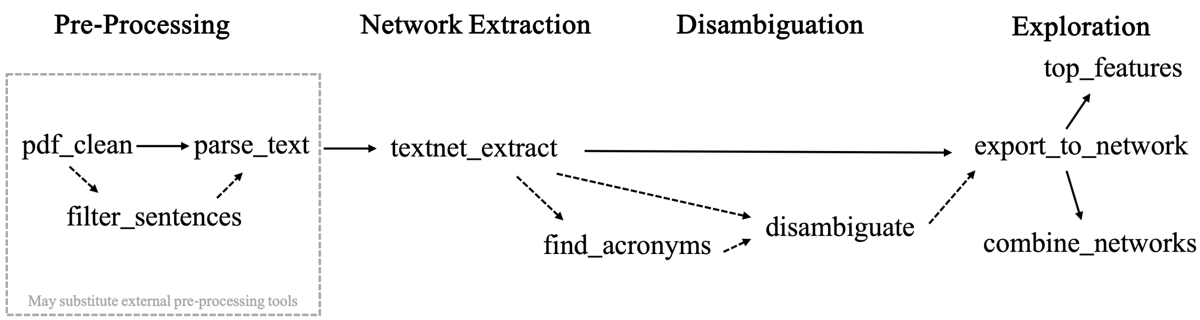


Figure 1: Workflow of textNet Functions

Applications

textNet has applications in governance network scholarship, as demonstrated by Zufall and Scott (2024) and by ongoing work on groundwater governance at the UC Davis Center for Environmental Policy and Behavior. Additional potential applications include legal scholarship, social-ecological network analysis, government planning documents, court proceedings, archival research, communication and media research, and other fields interested in exploring events and entity relationships in textual data.

Example

The following example uses parsed text from the Gravelly Ford Water District Groundwater Sustainability Plan in the state of California, before and after the plan underwent revisions required by the California Department of Water Resources. Both versions of the plan were pre-processed using the optional pdf_clean() and parse_text() functions, as shown in the appendix below and package repository. *textNet* is designed for modularity with respect to pdf-to-text conversion and NLP engine. The user can derive plain text by any approach, and likewise perform event extraction with any NLP engine or large language model (LLM) (more on LLM extensions below) and bring these data to *textNet*. The textnet_extract() function expects the parsed table to follow specific conventions for column names and speech tagging, so externally produced data must be converted to standards outlined in the package manual.

Extract Networks

First, we read in the pre-processed data and call textnet_extract() to produce the network object:

```
library(textNet)
old_new_parsed <- textNet::old_new_parsed
```

```
extracts <- vector(mode="list",length=length(old_new_parsed))
   for(m in 1:length(old_new_parsed)){
      extracts[[m]] <- textnet_extract(old_new_parsed[[m]],concatenator="_",cl=4,
```

```
                  keep_entities = c('ORG','GPE','PERSON','WATER'),
                  return_to_memory=T, keep_incomplete_edges=T)
}
```

```
## [1] "crawling 856 sentences"
## [1] "crawling 1150 sentences"
```

The textnet_extract() function extracts the entity network. It reads in the result of parse_text() as described in the appendix, or another parsing tool with appropriate column names and tagging conventions. The resulting object consists of a nodelist, an edgelist, a verblist, and a list of appositives. The nodelist variables are entity_name, the concatenated name of the entity; entity_type, which is a preservation from the entity_type attribute from the output of textNet::parse_text(); and num_appearances, which is the number of times the entity appears in the PDF text. (This is not the same as node degree, since there may be multiple edges, or if keep_incomplete_edges is set to false, no edges resulting from a single appearance of the entity in the document.) The entity_type attribute represents *spaCy*'s determination of entity type using its NER recognition, or if a custom parser or NER tool is used, the textnet_extract() function will preserve these entity type designations.

The file is saved to the provided filename, if provided. It is returned to memory if return_to_memory is set to T. At least one of these return pathways must be established to avoid an error. In this example, we only keep entity types in the nodelist, edgelist, and appositivelist that are listed under keep_entities; namely, "ORG", "GPE", "PERSON", and "WATER".

The resulting object consists of a nodelist, an edgelist, a verblist, and a list of appositives. The nodelist variables are entity_name, the concatenated name of the entity; entity_type, which is a preservation from the entity_type attribute from the output of textNet::parse_text(); and num_appearances, which is the number of times the entity appears in the PDF text. The default entity types are based on *spaCy*'s NER tags, but entity types can be customized as desired. In this example, we only keep entity types in the nodelist, edgelist, and appositivelist that are listed under keep_entities; namely, "ORG", "GPE", "PERSON", and "WATER".

Consolidate Entity Synonyms

In a document, the same real-world entity may be referenced in multiple ways. For instance, the document may introduce an organization using its full name, then use an acronym for the remainder of the document. To have more reliable network results, it is important to consolidate nodes that represent different naming conventions into a single node. The *textNet* package comes with a built-in tool for finding acronyms defined parenthetically within the text. This can be run on the result of pdf_clean() to generate a table with one column for acronyms and another for the corresponding full names, such that each row is a different instance of a phrase for which an acronym was detected. The use of find_acronyms() is demonstrated below.

```
old_new_text <- textNet::old_new_text
old_acronyms <- find_acronyms(old_new_text[[1]])
new_acronyms <- find_acronyms(old_new_text[[2]])

print(head(old_acronyms))
```

```
##                               name acronym
##                             <char>  <char>
## 1:                  Central_Valley      CV
## 2:          Total_Dissolved_Solids     TDS
## 3: California_Code_of_Regulations     CCR
## 4:  Department_of_Water_Resources     DWR
```

```
## 5:       Best_Management_Practice     BMP
## 6:   Gravelly_Ford_Water_District    GFWD
```

The resulting table of acronyms can then be fed into a disambiguation tool, the *textNet* function disambiguate(). This tool is very flexible, allowing a user-defined custom vector or list of strings representing the original entity name to search for in the textnet_extract object, and another user-defined custom vector or list of strings representing the entity name to which to convert those instances. Additional inputs that may be useful here are names and abbreviations of known federal and state or regional agencies, or other entities that are likely to be discussed in the particular type of document being analyzed. There may also be topic-specific words or phrases that are likely to be discussed in the document. For instance, in Groundwater Sustainability Plans, it is common to discuss entities that involve the term "subbasin," but the spelling of this is not always consistent.

In the example below, we define a "from" vector that includes the acronyms found through the previous step, as well as non-standard spellings of "subbasin." This function is case sensitive, so we have included two alternate cases that are likely to appear in the dataset. The "to" vector includes the full names from the find_acronyms result, along with the standard spelling of "subbasin".

There are a few rules about defining the "from" and "to" columns. First, the length of "from" and "to" must be identical, since from[[i]] is replaced with to[[i]]. Second, there may not be any duplicated terms in the "from" list, since each string must be matched to a single replacement without ambiguity. It is acceptable to have duplicated terms in the "to" list.

The "from" argument may be formatted as either a vector or a list. However, if it is a list, no element may contain more than one string. The "match_partial_entity" argument defaults to F for each element of "from" and "to." However, it can be set to T or F for each individual element. (Replacing an acronym with its full name may only be wise if the entire name of the node is that acronym. Otherwise "EPA" could accidentally match on "NEPAL" and create a nonsense entity called "NEnvironmental_Protection_AgencyL". The risk of this for modern, sentence-case documents is decreased, as disambiguate() is intentionally a case-sensitive function.) For the example below, we set match_partial_entity to F for each of the acronyms, but to T for the word "Sub_basin," since "Sub_basin" may very well be a portion of a longer entity, for which we would want to standardize the spelling.

Each element in the "from" object must be a single character vector. This is not the case for the "to" argument; a user may define elements of "to" to contain multiple character vectors in order to convert a single node into multiple nodes. Specifically, there may be some cases in which one would want to convert a single node into multiple nodes, each preserving the original node's edges to other nodes. For instance, suppose a legal document refers to "The_Defendants" as a shorthand for referring to three individuals involved in the case. In the network, it may be desirable for these individuals to be represented as their own separate nodes, especially if the network is to be merged with those resulting from other documents, where the three defendants may be named separately. To convert this single node into multiple nodes that preserve all of their original edges to other entities, from[[j]] should be set to "The_Defendants", and to[[j]] should be set to a string vector including the individuals' names, such as c("John_Doe", "Jane_Doe", "Emily_Doe").

The default behavior is to loop through the disambiguation recursively, though by setting recursive to F, this can be overridden. The difference can be seen in the following example. Suppose that the following from list and to list are defined: from = c("MA","Mass"); to = c("Mass","Massachusetts"). If recursive = F, all instances of MA in the original textnet_extract object would be set to Mass, and all instances of Mass in the original textnet_extract object would be set to Massachusetts. If recursive = T, all instances of MA and Mass in the original textnet_extract object would be set to Massachusetts. The ability to toggle this behavior can be useful when concatenating a large from and to list based on multiple sources.

The disambiguate() function is designed to be usable even for very large graphs; when disambiguating thousands of nodes, a user may choose to use web scraping or another automated tool to help generate a long list of "from" and "to" elements by which to merge or separate the nodes of the graph. Use of an automated tool to generate "to" and "from" columns with hundreds or thousands of elements can lead to uncertainty about the behavior of the "to" and "from" columns. Such problems are anticipated and resolved automatically by the function. For instance, the function resolves loops such as from = c("hello","world"); to = c("world","hello") automatically, with a warning summarizing the rows that were removed. It also resolves loops resulting from poorly specified partial matching rules on the part of the user. This is the only tool we are aware of that can help users troubleshoot user-defined rules governing node merging and separation.

The textnet_extract argument of disambiguate() accepts the result of the textnet_extract() function. The object returned by disambiguate() updates the edgelist$source column, edgelist$target column, and nodelist$entity_name column to reflect the new node names.

Information about the optional argument try_drop can be found in the package documentation. When specified, the function merges nodes that differ only by the regex phrase specified by try_drop, and which become identical upon removal of the regular expression encoded in try_drop.

```
tofrom <- data.table::data.table(
   from = c(as.list(old_acronyms$acronym),
            list("Sub_basin",
                 "Sub_Basin",
                 "upper_and_lower_aquifers",
                 "Upper_and_lower_aquifers",
                 "Lower_and_upper_aquifers",
                 "lower_and_upper_aquifers")),
   to = c(as.list(old_acronyms$name),
            list("Subbasin",
                 "Subbasin",
                 c("upper_aquifer","lower_aquifer"),
                 c("upper_aquifer","lower_aquifer"),
                 c("upper_aquifer","lower_aquifer"),
                 c("upper_aquifer","lower_aquifer"))))

   old_extract_clean <- disambiguate(
      textnet_extract = extracts[[1]],
      from = tofrom$from,
      to = tofrom$to,
      match_partial_entity = c(rep(F,nrow(old_acronyms)),T,T,F,F,F,F))

   tofrom <- data.table::data.table(
   from = c(as.list(new_acronyms$acronym),
            list("Sub_basin",
                 "Sub_Basin",
                 "upper_and_lower_aquifers",
                 "Upper_and_lower_aquifers",
                 "Lower_and_upper_aquifers",
                 "lower_and_upper_aquifers")),
   to = c(as.list(new_acronyms$name),
            list("Subbasin",
                 "Subbasin",
                 c("upper_aquifer","lower_aquifer"),
                 c("upper_aquifer","lower_aquifer"),
                 c("upper_aquifer","lower_aquifer"),
                 c("upper_aquifer","lower_aquifer"))))

   new_extract_clean <- disambiguate(
      textnet_extract = extracts[[2]],
      from = tofrom$from,
```

```
    to = tofrom$to,
    match_partial_entity = c(rep(F,nrow(new_acronyms)),T,T,F,F,F,F))
```

Get Network Attributes

A tool that generates an igraph or network object from the textnet_extract output is included in the package as the function export_to_network(). It returns a list that contains the igraph or network itself as the first element, and an attribute table as the second element. Functions from the *sna* (Butts 2024), *igraph* (Csárdi et al. 2024), and *network* packages (Butts et al. 2023) are invoked to create a network attribute table of common network-level attributes; see package documentation for details.

```
old_extract_net <- export_to_network(old_extract_clean, "igraph", keep_isolates = F,
                                     collapse_edges = F, self_loops = T)
new_extract_net <- export_to_network(new_extract_clean, "igraph", keep_isolates = F,
                                     collapse_edges = F, self_loops = T)

table <- t(format(rbind(old_extract_net[[2]], new_extract_net[[2]]), digits = 3,
                  scientific = F))
colnames(table) <- c("old","new")
print(table)
```

```
##                         old      new
## num_nodes               " 92"    "123"
## num_edges               "172"    "260"
## connectedness           "0.721"  "0.689"
## centralization          "0.220"  "0.332"
## transitivity            "0.111"  "0.152"
## pct_entitytype_homophily "0.506"  "0.581"
## reciprocity             "0.250"  "0.304"
## mean_in_degree          "1.87"   "2.11"
## mean_out_degree         "1.87"   "2.11"
## median_in_degree        "1"      "1"
## median_out_degree       "1"      "1"
## modularity              "0.523"  "0.520"
## num_communities         "11"     "17"
## percent_vbn             "0.355"  "0.404"
## percent_vbg             "0.0698" "0.0500"
## percent_vbp             "0.1337" "0.0846"
## percent_vbd             "0.0698" "0.0692"
## percent_vb              "0.128"  "0.131"
## percent_vbz             "0.244"  "0.262"
```

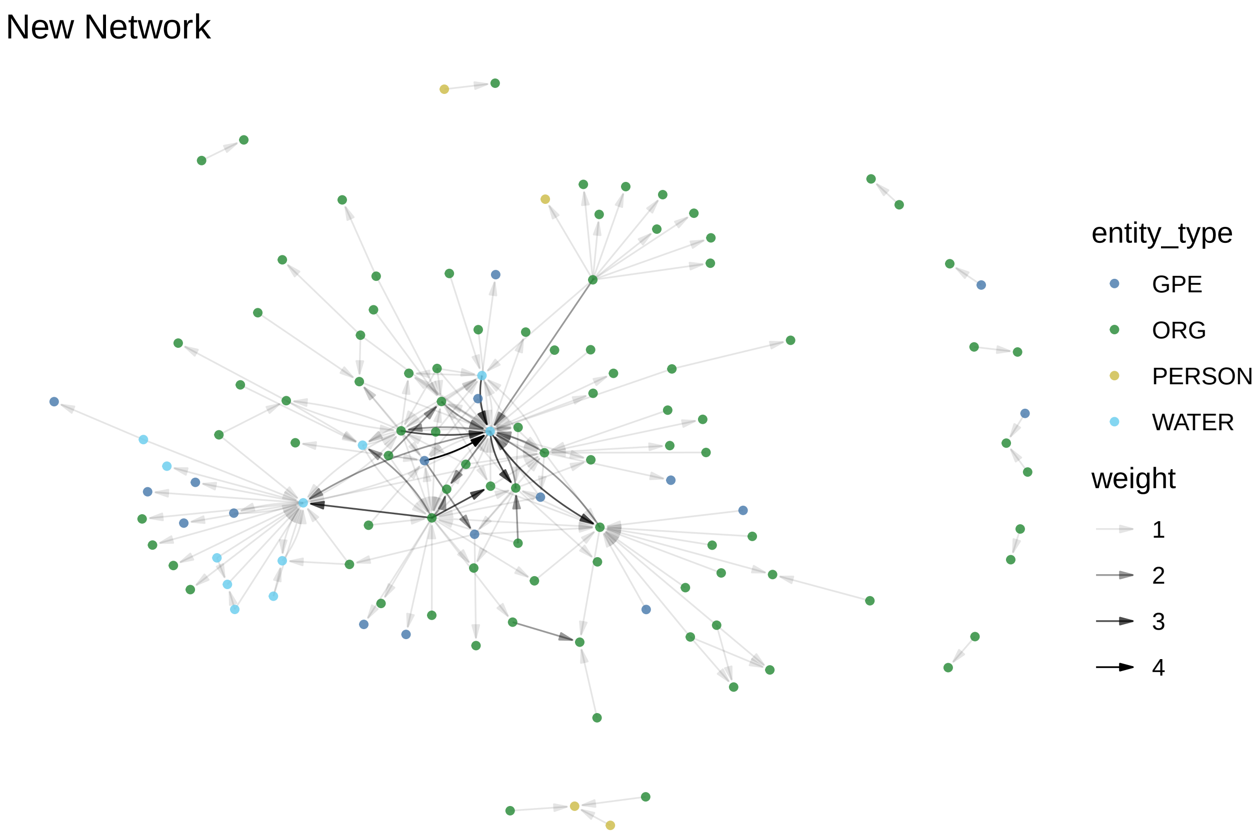
The *ggraph* package (Pedersen and RStudio 2024) has been used to create the two network visualizations seen here, using a weighted version of the igraphs constructed below. We set collapse_edges = T to convert the multiplex graph into its weighted equivalent.

```
library(ggraph)
old_extract_plot <- export_to_network(old_extract_clean, "igraph", keep_isolates = F,
                                      collapse_edges = T, self_loops = T)[[1]]
new_extract_plot <- export_to_network(new_extract_clean, "igraph", keep_isolates = F,
                                      collapse_edges = T, self_loops = T)[[1]]
#order of these layers matters
```

```r
ggraph(old_extract_plot, layout = 'fr')+
  geom_edge_fan(aes(alpha = weight),
                end_cap = circle(1,"mm"),
                color = "#000000",
                width = 0.3,
                arrow = arrow(angle=15,length=unit(0.07,"inches"),ends = "last",
                              type = "closed"))+
  #from Paul Tol's bright color scheme
  scale_color_manual(values = c("#4477AA","#228833","#CCBB44","#66CCEE"))+
  geom_node_point(aes(color = entity_type), size = 1,
                  alpha = 0.8)+
  labs(title= "Old Network")+
  theme_void()
```


```r
#order of these layers matters
ggraph(new_extract_plot, layout = 'fr')+
  geom_edge_fan(aes(alpha = weight),
                end_cap = circle(1,"mm"),
                color = "#000000",
                width = 0.3,
                arrow = arrow(angle=15,length=unit(0.07,"inches"),ends = "last",
                              type = "closed"))+
  #from Paul Tol's bright color scheme
  scale_color_manual(values = c("#4477AA","#228833","#CCBB44","#66CCEE"))+
  geom_node_point(aes(color = entity_type), size = 1,
```

```
                        alpha = 0.8)+
    labs(title= "New Network")+
    theme_void()
```



Explore Edge Attributes

The top_features() tool calculates the most common verbs across the entire corpus of documents, as shown below.

```
top_feats <- top_features(list(old_extract_net[[1]], new_extract_net[[1]]))
head(top_feats[[2]],10)
```

```
## # A tibble: 10 x 2
##    names   avg_fract_of_a_doc
##    <chr>                <dbl>
##  1 be                  0.149
##  2 include             0.0802
##  3 provide             0.0628
##  4 locate              0.0493
##  5 result              0.0386
##  6 base                0.0261
##  7 receive             0.0242
##  8 show                0.0212
##  9 develop             0.0202
## 10 make                0.0193
```

Using a syntax-based extraction technique enables the preservation of a rich set of edge attributes giving insight into the nature of the relationship between each pair of nodes. The edge attributes "head_verb_name" and "head_verb_lemma," respectively, indicate the verb and infinitive form of the verb mediating the relationship between the source and target nodes. The edge attributes "helper_token" and "helper_lemma" indicate the presence of a helping verb in the verb phrase, while the edge attributes "xcomp_helper_lemma" and "xcomp_helper_token" indicate the presence of an open causal complement in the verb phrase. Open causal complements, such as "monitor" in the sentence "The agency is expected to monitor the results," can provide key supplemental information about the relationship between the source and target nodes. Additional edge attributes include indicators for verb tense and the presence of uncertain "hedging" language in the sentence. Other edge attributes travel with the edge to document where in the document, and in which document, the edge occurs. For instance, we can summarize the verb tense of edges in the original plan in a table. The abbreviations follow Penn Treebank classifications (Marcus et al. 1999), such that VB = base form, VBD = past tense, VBG = gerund or present participle, VBN = past participle, VBP = non-3rd person singular present, and VBZ = 3rd person singular present. The most common verb tense used in the plan was VBN, or past participle.

```r
table(igraph::E(old_extract_net[[1]])$head_verb_tense)
```

```
##
##  VB VBD VBG VBN VBP VBZ
##  22  12  12  61  23  42
```

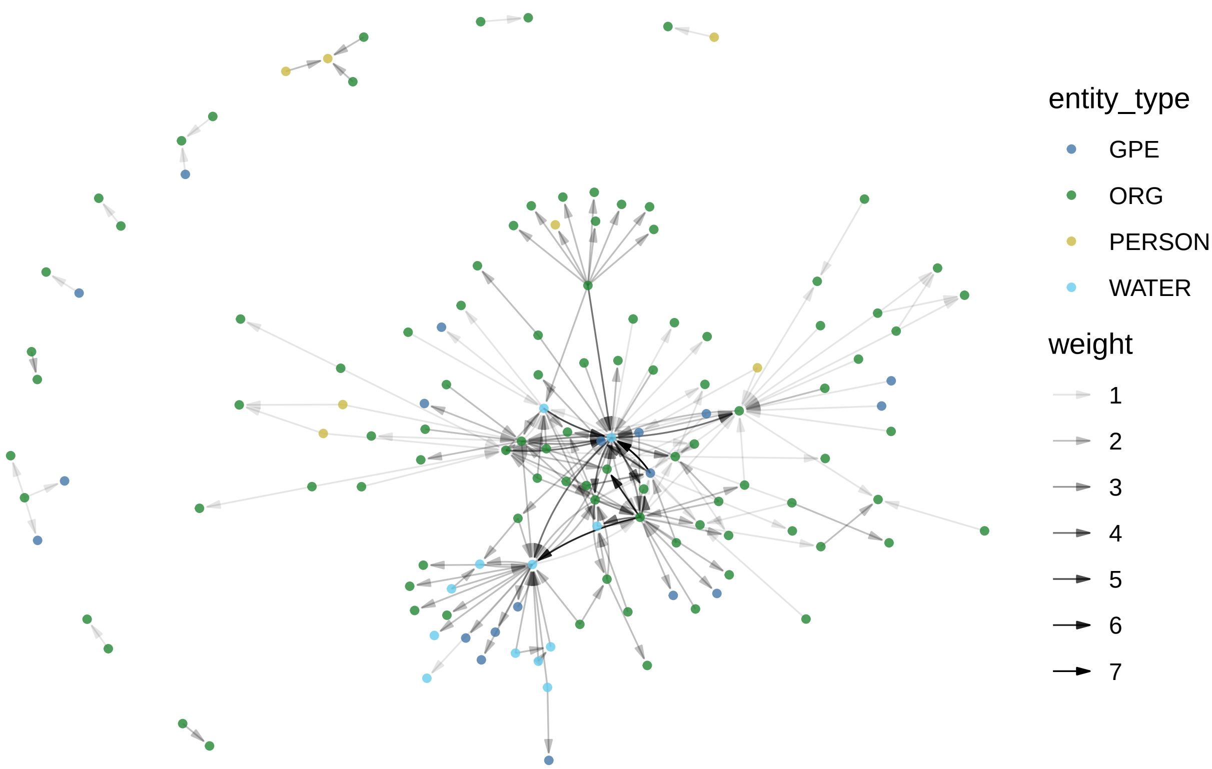
Generate Composite Network

The combine_networks function allows a composite network to be generated from multiple export_to_network() outputs. This function is useful for understanding and analyzing the overlaps between the network of multiple documents. In this example, a composite network is not as useful, since these documents are not from two different regions being discussed but rather are two versions of the same document. However, for illustration purposes, the composite network is generated below.

For best results, composite network generation should not be done without an adequate disambiguation in Step 4. A function is included that merges the edgelists and nodelists of all documents. If the same node name is mentioned in multiple documents, the node attributes associated with the highest total number of edges for that node name are preserved.

```r
composite_net <- combine_networks(list(old_extract_net[[1]], new_extract_net[[1]]),
                                  mode = "weighted")
ggraph(composite_net, layout = 'fr')+
   geom_edge_fan(aes(alpha = weight),
                 end_cap = circle(1,"mm"),
                 color = "#000000",
                 width = 0.3,
                 arrow = arrow(angle=15,length=unit(0.07,"inches"),ends = "last",
                               type = "closed"))+
   #from Paul Tol's bright color scheme
   scale_color_manual(values = c("#4477AA","#228833","#CCBB44","#66CCEE"))+
   geom_node_point(aes(color = entity_type), size = 1,
                   alpha = 0.8)+
   labs(title= "Composite Network")+
   theme_void()
```

Composite Network



Explore Node Attributes

The network objects generated from export_to_network can be used to analyze the node attributes of the graphs. Below we demonstrate several node attribute exploration tools. First, we use the the top_features() function to calculate the most common entities across the entire corpus of documents.

```
library(network)
library(igraph)

   top_feats <- top_features(list(old_extract_net[[1]], new_extract_net[[1]]))
   print(head(top_feats[[1]],10))
```

```
## # A tibble: 10 x 2
##    names                                        avg_fract_of_a_doc
##    <chr>                                                     <dbl>
##  1 groundwater                                              0.185
##  2 gsa                                                      0.0835
##  3 san_joaquin_river                                        0.0705
##  4 gfwd_gsa                                                 0.0430
##  5 surface_water                                            0.0405
##  6 gravelly_ford_water_district                             0.0367
##  7 subbasin                                                 0.0362
##  8 north_kings_groundwater_sustainability_agency            0.0290
##  9 madera_subbasin                                          0.0280
## 10 gsp                                                      0.0279
```

Next, we calculate node-level attributes on a weighted version of the networks. First we prepare the data frames for both the old and new networks. We can include the variable num_graphs_in from our composite network to investigate what kinds of nodes are found in both plans.

```
composite_tbl <- igraph::as_data_frame(composite_net, what = "vertices")
composite_tbl <- composite_tbl[,c("name","num_graphs_in")]

#prepare data frame version of old network, to add composite_tbl variables
old_tbl <- igraph::as_data_frame(old_extract_net[[1]], what = "both")
#this adds the num_graphs_in variable from composite_tbl
old_tbl$vertices <- dplyr::left_join(old_tbl$vertices, composite_tbl)
```

```
## Joining with `by = join_by(name)`
```

```
#turn back into a network
old_net <- network::network(x=old_tbl$edges[,1:2], directed = T,
                      hyper = F, loops = T, multiple = T,
                      bipartite = F, vertices = old_tbl$vertices,
                      matrix.type = "edgelist")
#we need a matrix version for some node statistics
old_mat <- as.matrix(as.matrix(export_to_network(old_extract_clean, "igraph",
                      keep_isolates = F, collapse_edges = T, self_loops = F)[[1]]))

#prepare data frame version of new network, to add composite_tbl variables
new_tbl <- igraph::as_data_frame(new_extract_net[[1]], what = "both")
#this adds the num_graphs_in variable from composite_tbl
new_tbl$vertices <- dplyr::left_join(new_tbl$vertices, composite_tbl)
```

```
## Joining with `by = join_by(name)`
```

```
#turn back into a network
new_net <- network::network(x=new_tbl$edges[,1:2], directed = T,
                      hyper = F, loops = T, multiple = T,
                      bipartite = F, vertices = new_tbl$vertices,
                      matrix.type = "edgelist")
#we need a matrix version for some node statistics
new_mat <- as.matrix(as.matrix(export_to_network(new_extract_clean, "igraph",
                      keep_isolates = F, collapse_edges = T, self_loops = F)[[1]]))
```

We can now use these data structures to calculate node statistics, as printed below.

```
paths2 <- diag(old_mat %*% old_mat)
recip <- 2*paths2 / sna::degree(old_net)
totalCC <- as.vector(unname(DirectedClustering::ClustF(old_mat,
        type = "directed", isolates="zero")$totalCC))
closens <- sna::closeness(old_net, gmode = "graph", cmode="suminvundir")
between <- sna::betweenness(old_net,gmode = "graph",cmode="undirected")
deg <- sna::degree(old_net, gmode = "graph", cmode = "undirected")
old_node_df <- dplyr::tibble(name = network::get.vertex.attribute(old_net,
        "vertex.names"),
        closens,
        between,
```

```r
        deg,
        recip,
        totalCC,
        entity_type = network::get.vertex.attribute(old_net,"entity_type"),
        num_graphs_in = network::get.vertex.attribute(old_net, "num_graphs_in"))


paths2 <- diag(new_mat %*% new_mat)
recip <- 2*paths2 / sna::degree(new_net)
totalCC <- as.vector(unname(DirectedClustering::ClustF(new_mat,
             type = "directed", isolates="zero")$totalCC))
closens <- sna::closeness(new_net, gmode = "graph", cmode="suminvundir")
between <- sna::betweenness(new_net,gmode = "graph",cmode="undirected")
deg <- sna::degree(new_net, gmode = "graph", cmode = "undirected")
new_node_df <- dplyr::tibble(name = network::get.vertex.attribute(new_net,
        "vertex.names"),
        closens,
        between,
        deg,
        recip,
        totalCC,
        entity_type = network::get.vertex.attribute(new_net,"entity_type"),
        num_graphs_in = network::get.vertex.attribute(new_net, "num_graphs_in"))

summary(old_node_df)
```

```
##      name              closens            between             deg        
##  Length:92          Min.   :0.01099   Min.   :   0.0   Min.   : 0.000  
##  Class :character   1st Qu.:0.26282   1st Qu.:   0.0   1st Qu.: 0.000  
##  Mode  :character   Median :0.29597   Median :   0.0   Median : 1.000  
##                     Mean   :0.26742   Mean   :  67.1   Mean   : 1.685  
##                     3rd Qu.:0.32042   3rd Qu.:  20.7   3rd Qu.: 1.000  
##                     Max.   :0.51648   Max.   :1271.4   Max.   :20.000  
##      recip            totalCC          entity_type        num_graphs_in 
##  Min.   :0.00000   Min.   :0.000000   Length:92          Min.   :1.00  
##  1st Qu.:0.00000   1st Qu.:0.000000   Class :character   1st Qu.:2.00  
##  Median :0.00000   Median :0.000000   Mode  :character   Median :2.00  
##  Mean   :0.05151   Mean   :0.083182                      Mean   :1.87  
##  3rd Qu.:0.00000   3rd Qu.:0.002273                      3rd Qu.:2.00  
##  Max.   :1.00000   Max.   :1.000000                      Max.   :2.00
```

```r
summary(new_node_df)
```

```
##      name              closens             between              deg        
##  Length:123         Min.   :0.008197   Min.   :   0.000   Min.   : 0.000  
##  Class :character   1st Qu.:0.239413   1st Qu.:   0.000   1st Qu.: 0.000  
##  Mode  :character   Median :0.282104   Median :   0.000   Median : 1.000  
##                     Mean   :0.248514   Mean   :  88.480   Mean   : 1.797  
##                     3rd Qu.:0.312159   3rd Qu.:   5.404   3rd Qu.: 1.000  
##                     Max.   :0.516393   Max.   :2279.689   Max.   :33.000  
##      recip            totalCC        entity_type        num_graphs_in 
##  Min.   :0.00000   Min.   :0.0000   Length:123         Min.   :1.00  
##  1st Qu.:0.00000   1st Qu.:0.0000   Class :character   1st Qu.:1.00
```

```
##  Median :0.00000   Median :0.0000   Mode  :character   Median :2.00
##  Mean   :0.04079   Mean   :0.1209                      Mean   :1.65
##  3rd Qu.:0.00000   3rd Qu.:0.1110                      3rd Qu.:2.00
##  Max.   :1.00000   Max.   :1.0000                      Max.   :2.00
```

The 2x2 table below summarizes the rate at which each entity type is found in both plans. Very few nodes in the old version (12 out of 88) are absent from the new version. Conversely, a substantial minority of nodes in the new version (42 out of 118) are absent from the old version.

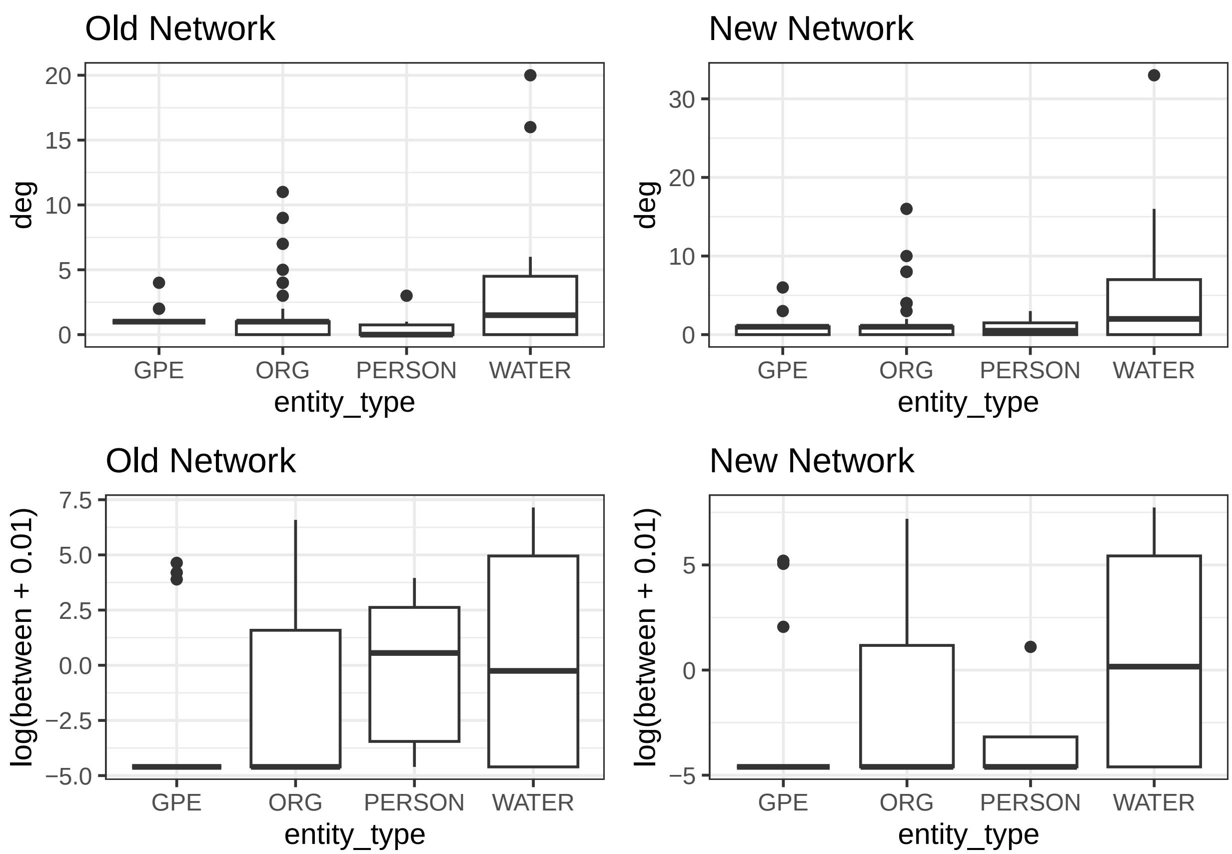
```r
old_node_df$plan_version <- "old"
new_node_df$plan_version <- "new"
combineddf <- rbind(old_node_df, new_node_df)
with(combineddf,table(plan_version,num_graphs_in))
```

```
##             num_graphs_in
## plan_version  1  2
##          new 43 80
##          old 12 80
```

We can also investigate differences in network statistics between the two plans. For instance, the distribution of degree does not change much between plan versions. The distribution of betweenness, likewise, is relatively stable except for person nodes, which are the least common nodes in the graph.

```r
library(gridExtra)
library(ggplot2)
b1 <- ggplot(old_node_df, aes(x = entity_type, y = deg)) + geom_boxplot() +
  theme_bw() + labs(title="Old Network")
b2 <- ggplot(new_node_df, aes(x = entity_type, y = deg)) + geom_boxplot() +
  theme_bw() + labs(title="New Network")
    b3 <- ggplot(old_node_df, aes(x = entity_type, y = log(between+0.01))) +
      geom_boxplot() + theme_bw() + labs(title="Old Network")
b4 <- ggplot(new_node_df, aes(x = entity_type, y = log(between+0.01))) +
  geom_boxplot() + theme_bw() + labs(title="New Network")

grid.arrange(b1, b2, b3, b4, ncol=2)
```



Potential Further Analyses

The network-level attributes output from export_to_network can also be analyzed against exogenous metadata that has been collected separately by the researcher regarding the different documents and their real-world context. The extracted networks, with their collections of verb attributes, node attributes, edge incidences, and edge attributes, can also be analyzed through a variety of tools, such as an Exponential Random Graph Model, to determine the probability of edge formation under certain conditions. A Temporal Exponential Random Graph Model could also shed light on the changes of a document over time, such as the multiple versions of the groundwater sustainability plan in this example.

Entity Network Extraction Algorithm

The directed network generated by *textNet* represents the collection of all identified entities in the document, joined by edges signifying the verbs that connect them. The user can specify which entity categories should be preserved. The output format is a list containing four data.tables: an edgelist, a nodelist, a verblist, and an appositive list.

The edgelist includes edge attributes such as verb tense, any auxiliary verbs in the verb phrase, whether an open clausal complement (Universal Dependencies code “xcomp”) is associated with the primary verb, whether any hedging words were detected in the sentence, and whether any negations were detected in the sentence.

The returned edgelist by default contains both complete and incomplete edges. A complete edge includes a source, verb, and target. An incomplete edge includes either a source or a target, but not both, along with its associated verb. Incomplete edges convey information about which entities are commonly associated with different verbs, even though they do not reveal information about which other entities they are linked to in the network. These incomplete edges can be filtered out when converting the output into a network object, such as through the *network* package or the *igraph* package. The nodelist returns all entities of the desired types found in the document, regardless of whether they were found in the edgelist. Thus, the nodelist allows the presence of isolates to be documented, as well as preserving node attributes. The verblist includes all of the verbs found in the document, along with verb attributes imported from *VerbNet* (Kipper-Schuler 2006). This can be used to conduct analyses of certain verb classifications of interest. Finally, the appositive list is a table of entities that may be synonyms. This list is generated from entities whose universal dependency parsing labels as appositives, and whose head token points to another entity. These pairs are included in the table as potential synonyms. If this feature is used, cleaning and filtering by hand is recommended, as appositives can at times be misidentified by existing NLP tools. An automated alternative we recommend is our find_acronym tool, which scans the entire document for acronyms defined parenthetically in-text and compiles them in a table.

This network is directed such that the entities that form the subject of the sentence are denoted as the "source" nodes, and the remaining entities are denoted as the "target" nodes. To identify whether each entity is a "source" or a "target", we use dependency parsing in the Universal Dependencies format, in which each token in a given sentence has an associated "syntactic head" token from which it is derived. Starting with each entity in the sentence, the chain of syntactic head tokens is traced back until either a subject or a verb is reached. If it reaches a subject first, the entity is considered a "source." If it reaches a verb first, it is considered a "target."

To identify the subject, we search for the presence of at least one of the following subject tags: "nsubj" (nominal subject), "nsubjpass" (nominal subject – passive), "csubj" (clausal subject), "csubjpass" (clausal subject – passive), "agent", and "expl" (expletive). To identify the object, we search for the presence of at least one of the following: "pobj" (object of preposition), "iobj" (indirect object), "dative", "attr" (attribute), "dobj" (direct object), "oprd" (object predicate), "ccomp" (clausal complement), "xcomp" (open clausal complement), "acomp" (adjectival complement), or "pcomp" (complement of preposition).

If a subject token is reached first ("nsubj," "nsubjpass," "csubj," "csubjpass," "agent," or "expl"), this indicates that the original token is doing the verb action. That is, it serves some function related to the subject of the sentence. We designate this by tagging it "source," since these types of relationships will be used to designate the "from" or "source" nodes in our directed network. If a verb token is reached first ("VERB" or "AUX"), this indicates that the verb action is occurring for or towards the original token, which we denote with the tag "target." These tokens are potential "to" or "target" nodes in our directed network. Linking the two nodes is an edge representing the verb that connects them in the sentence.

Due to the presence of tables, lists, or other anomalies in the original document, it is possible that a supposed "sentence" has a head token trail that does not lead to a verb as is normatively the case. In these instances, the tokens whose trails terminate with a non-subject, non-verb token are assigned neither "source" nor "target" tags. Finally, an exception is made if an appositive token is reached first, since this indicates that the token in question is merely a synonym or restatement of an entity that is already described elsewhere in the sentence and, accordingly, should not be treated as a separate node. Tokens that lead to appositives are assigned neither "source" nor "target" tags, but are preserved as a separate appositive list.

If a verb phrase in the edgelist does not have any sources, the sources associated with the head token of the verb phrase's main verb (that is, the verb phrase's parent verb) are adopted as sources of that verb phrase. As of Version 1.0, *textNet* does not do this recursively, to preserve performance optimization.

The textNet::textnet_extract() function returns the full list of open clausal complement lemmas associated with the main verb as an edge attribute: "xcomp_verb". The list of auxiliary verbs and their corresponding lemmas associated with the main verb, as well as the list of auxiliary verbs and corresponding lemmas associated with the open clausal complements linked to the main verb, are also included as edge attributes: "helper_token", "helper_lemma", "xcomp_helper_token", and "xcomp_helper_lemma", respectively.

The extraction function also detects hedging words and negations. The function textNet::textnet_extract() produces an edge attribute "has_hedge", which is T if there is a hedging auxiliary verb ("may","might", "can","could") or main verb ("seem","appear","suggest","tend","assume","indicate","estimate","doubt","believe") in the verb phrase.

Tense is also detected. The six tenses tagged by *spaCy* in textNet::parse_text() are preserved by textNet::textnet_extract() as an edge attribute "head_verb_tense". This attribute can take on one of six values: "VB" (verb, base form), "VBD" (verb, past tense), "VBG" (verb, gerund or present participle), "VBN" (verb, past participle), "VBP" (verb, non-3rd person singular present), or "VBZ" (verb, 3rd person singular present). Additionally, an edge attribute "is_future" is generated by textNet::textnet_extract(), which is T if the verb phrase contains an xcomp, has the token "going" as a head verb, and a being verb token as an auxiliary verb (i.e. is of the form "going to ") or contains one of the following auxiliary verbs: "shall","will","wo", or "'ll" (i.e. is of the form "will ").

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Appendix

This appendix describes the pre-processing tools available through the *textNet* package, which enable the user to generate the data frame expected by the textnet_extract() function.

Pre-Processing Step I: Process PDFs

This is a wrapper for pdftools, which has the option of using pdf_text or OCR. We have also added an optional header/footer removal tool. This optional tool is solely based on carriage returns in the first or last few lines of the document, so may inadvertently remove portions of paragraphs. However, not removing headers or footers can lead to improper inclusion of header and footer material in sentences, artificially inflating the presence of nodes whose entity names are included in the header and footer. Because of the risk of headers and footers to preferentially inflate the presence of a few nodes, the header/footer remover is included by default. It can be turned off if the user has a preferred header/footer removal tool to use instead, or if the input documents lack headers and footers.

```r
library(textNet)
library(stringr)
URL <- "https://sgma.water.ca.gov/portal/service/gspdocument/download/2840"
download.file(URL, destfile = "vignettes/old.pdf", method="curl")

URL <- "https://sgma.water.ca.gov/portal/service/gspdocument/download/9625"
download.file(URL, destfile = "vignettes/new.pdf", method="curl")

pdfs <- c("vignettes/old.pdf",
       "vignettes/new.pdf")

old_new_text <- textNet::pdf_clean(pdfs, ocr=F, maxchar=10000,
                   export_paths=NULL, return_to_memory=T, suppressWarn = F,
                   auto_headfoot_remove = T)
names(old_new_text) <- c("old","new")
```

Pre-Processing Step II: Parse Text

This is a wrapper for the pre-trained multipurpose NLP model *spaCy* (Honnibal et al. 2021), which we access through the R package *spacyr* (Benoit et al. 2023). It produces a table that can be fed into the textnet_extract function in the following step. To initialize the session, the user must define the "RETICULATE_PYTHON" path, abbreviated as "ret_path" in *textNet*, as demonstrated in the example below. The page contents processed in the Step 1 must now be specified in vector form in the "pages" argument. To determine which file each page belongs to, the user must specify the file_ids of each page. We have demonstrated how to do this below. The package by default does not preserve hyphenated terms, but rather treats them as separate tokens. This can be adjusted.

The user may also specify "phrases_to_concatenate", an argument representing a set of phrases for spaCy to keep together during its parsing. The example below demonstrates how to use this feature to supplement the NER capabilities of spaCy with a custom list of entities. This supplementation could be used to ensure that specific known entities are recognized; for instance, spaCy might not detect that a consulting firm such as "Schmidt and Associates" is one entity rather than two. Conversely, this capability could be leveraged to create a new category of entities to detect, that a pretrained model is not designed to specifically recognize. For instance, to create a public health network, one might include a known list of contaminants and diseases and designate custom entity type tags for them, such as "CONTAM" and "DISEASE"). In this example, we investigate the connections between the organizations, people, and geopolitical entities discussed in the plan with the flow of water in the basin. To assist with this, we have input a custom list of known water bodies in the region governed by our test document and have given it the entity designation "WATER". This is carried out by setting the variable "phrases_to_concatenate" to a character vector, including all of the custom entities. Then, the entity type can be set to the desired category. Note that this function is case-sensitive.

```r
library(findpython)
ret_path <- find_python_cmd(required_modules = c('spacy', 'en_core_web_lg'))


water_bodies <- c("surface water", "Surface water", "groundwater", "Groundwater",
                  "San Joaquin River", "Cottonwood Creek", "Chowchilla Canal Bypass",
                  "Friant Dam", "Sack Dam", "Friant Canal", "Chowchilla Bypass",
                  "Fresno River", "Sacramento River", "Merced River","Chowchilla River",
                  "Bass Lake", "Crane Valley Dam", "Willow Creek", "Millerton Lake",
                  "Mammoth Pool", "Dam 6 Lake", "Delta","Tulare Lake",
                  "Madera-Chowchilla canal", "lower aquifer", "upper aquifer",
                  "upper and lower aquifers", "lower and upper aquifers",
                  "Lower aquifer", "Upper aquifer", "Upper and lower aquifers",
                  "Lower and upper aquifers")

old_new_parsed <- textNet::parse_text(ret_path,
                        keep_hyph_together = F,
                        phrases_to_concatenate = water_bodies,
                        concatenator = "_",
                        text_list = old_new_text,
                               parsed_filenames=c("old_parsed","new_parsed"),
                               overwrite = T,
                        custom_entities = list(WATER = water_bodies))
```

Another NLP tool may be used instead of the built-in *textNet* function at this phase, as long as the output conforms to spaCy tagging standards: Universal Dependencies tags for the "pos" part-of-speech column (Nivre 2017), and Penn Treebank tags for the "tags" column (Marcus et al. 1999). The textnet_extract function expects the parsed table to follow specific conventions. First, a row must be included for each token. The column names expected by textnet_extract are:

- doc_id, a unique ID for each page
- sentence_id, a unique ID for each sentence
- token_id, a unique ID for each token
- token, the token, generally a word, represented as a string
- lemma, the canonical or dictionary form of the token
- pos, a code referring to the token's part of speech, defined according to Universal Dependencies (Nivre 2017).
- tag, a code referring to the token's part of speech, according to Penn Treebank (Marcus et al. 1999).
- head_token_id, a numeric ID referring to the token_id of the head token of the current row's token
- dep_rel, the dependency label according to ClearNLP Dependency labels (Choi 2024)
- entity, the entity type category defined by OntoNotes 5.0 (Weischedel et al. 2012). This is represented as as string, ending in "_B" if it is the first token in the entity or "_I" otherwise).

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