CHAPTER 8

Case Study: Mining NASA Metadata

There are over 32,000 datasets hosted and/or maintained by NASA; these datasets cover topics from Earth science to aerospace engineering to management of NASA itself. We can use the metadata for these datasets to understand the connections between them.

What is metadata? Metadata is a term that refers to data that gives information about other data; in this case, the metadata informs users about what is in these numerous NASA datasets but does not include the content of the datasets themselves.

eg, you can use XML tags to define metadata in a transcript of a medieval text (Look at Medieval Mary Magdelene project)

The metadata includes information like the title of the dataset, a description field, what organization(s) within NASA is responsible for the dataset, keywords for the dataset that have been assigned by a human being, and so forth. NASA places a high priority on making its data open and accessible, even requiring all NASA-funded research to be openly accessible online. The metadata for all its datasets is publicly available online in JSON format. JavaScript Object Notation (like we learned in Computational Thinking)

In this chapter, we will treat the NASA metadata as a text dataset and show how to implement several tidy text approaches with this real-life text. We will use word co-occurrences and correlations, tf-idf, and topic modeling to explore the connections between the datasets. Can we find datasets that are related to each other? Can we find clusters of similar datasets? Since we have several text fields in the NASA metadata, most importantly the title, description, and keyword fields, we can explore the connections between the fields to better understand the complex world of data at NASA. This type of approach can be extended to any domain that deals with text, so let's take a look at this metadata and get started.

This is NOT a Research Question; rather, it is a question you ask to support your RQ and arguments.

How Data Is Organized at NASA

First, let's download the JSON file and take a look at the names of what is stored in the metadata.

```
library(jsonlite)
metadata <- fromJSON("https://data.nasa.gov/data.json")
names(metadata$dataset)
```

```
##  [1] "_id"                "@type"              "accessLevel"
##  [4] "accrualPeriodicity" "bureauCode"         "contactPoint"
##  [7] "description"        "distribution"       "identifier"
## [10] "issued"             "keyword"            "landingPage"
## [13] "language"           "modified"           "programCode"
## [16] "publisher"          "spatial"            "temporal"
## [19] "theme"              "title"              "license"
## [22] "isPartOf"           "references"         "rights"
## [25] "describedBy"
```

i.e. these are all of the categories of metadata that we can sort it by.

We see here that we could extract information from who publishes each dataset to what license each dataset is released under.

It seems likely that the title, description, and keywords for each dataset may be most fruitful for drawing connections between datasets. Let's check them out.

I like this case study's methodology. How can I find other metadata JSON files on my own?

```
class(metadata$dataset$title)
## [1] "character"
class(metadata$dataset$description)
## [1] "character"
class(metadata$dataset$keyword)
## [1] "list"
```

→ variable types

These 3 functions on the left take a few mins to run, so I must be patient & let them finish before going on.

The title and description fields are stored as character vectors, but the keywords are stored as a list of character vectors.

Wrangling and Tidying the Data

Let's set up separate tidy data frames for title, description, and keyword, keeping the dataset IDs for each so that we can connect them later in the analysis if necessary.

use "tibble" because the previous command ("data_frame()") is deprecated.

```
library(dplyr)
nasa_title <- ~~data_frame~~tibble(id = metadata$
                                   title = metada
nasa_title
## # A tibble: 32,089 × 2
##                          id
##                       <chr>
## 1  55942a57c63a7fe59b495a77
```

I am missing an "ID #" column: I only have the "title" column. I suspect that the regex we used to import the "ID" column isn't right anymore, so I tried to check the JSON to see how I could adjust the regex. But the JSON took too long to load... how can I figure out what went wrong when loading in IDs?

Wait, JSON did load... I looked for the ID # "55942a..." and it didn't exist. What?!

```
## 2  55942a57c63a7fe59b495a78                15 Minute Stream Flow Data: USGS (FIFE
## 3  55942a58c63a7fe59b495a79                15 Minute Stream Flow Data: USGS (FIFE
## 4  55942a58c63a7fe59b495a7a 2000 Pilot Environmental Sustainability Index (ESI
## 5  55942a58c63a7fe59b495a7b 2000 Pilot Environmental Sustainability Index (ESI
## 6  55942a58c63a7fe59b495a7c 2000 Pilot Environmental Sustainability Index (ESI
## 7  55942a58c63a7fe59b495a7d       2001 Environmental Sustainability Index (ESI
## 8  55942a58c63a7fe59b495a7e       2001 Environmental Sustainability Index (ESI
## 9  55942a58c63a7fe59b495a7f       2001 Environmental Sustainability Index (ESI
## 10 55942a58c63a7fe59b495a80       2001 Environmental Sustainability Index (ESI
## # ... with 32,079 more rows
```

These are just a few example titles from the datasets we will be exploring. Notice that we have the NASA-assigned IDs here, and also that there are duplicate titles on separate datasets.

```
nasa_desc <- data_frame(id = metadata$dataset$`_id`$`$oid`,
                        desc = metadata$dataset$description)

nasa_desc %>%
  select(desc) %>%
  sample_n(5)
```

```
## # A tibble: 5 × 1
##
##
## 1 MODIS (or Moderate Resolution Imaging Spectroradiometer) is a key instrument
## 2                                  Fatigue Countermeasures: A Meta-Ana
## 3  Mobile communications systems require programmable embedded platforms that
## 4  The Doppler Aerosol WiNd (DAWN), a pulsed lidar, operated aboard a NASA DC-
## 5 MODIS (or Moderate Resolution Imaging Spectroradiometer) is a key instrument
```

Here we see the first part of several selected description fields from the metadata.

Now we can build the tidy data frame for the keywords. For this one, we need to use `unnest()` from tidyr, because they are in a list-column.

```
library(tidyr)

nasa_keyword <- data_frame(id = metadata$dataset$`_id`$`$oid`,
                           keyword = metadata$dataset$keyword) %>%
  unnest(keyword)

nasa_keyword
```

```
## # A tibble: 126,814 × 2
##                         id       keyword
##                      <chr>         <chr>
## 1  55942a57c63a7fe59b495a77 EARTH SCIENCE
## 2  55942a57c63a7fe59b495a77   HYDROSPHERE
## 3  55942a57c63a7fe59b495a77 SURFACE WATER
## 4  55942a57c63a7fe59b495a78 EARTH SCIENCE
## 5  55942a57c63a7fe59b495a78   HYDROSPHERE
## 6  55942a57c63a7fe59b495a78 SURFACE WATER
## 7  55942a58c63a7fe59b495a79 EARTH SCIENCE
```

```
## 8  55942a58c63a7fe59b495a79   HYDROSPHERE
## 9  55942a58c63a7fe59b495a79 SURFACE WATER
## 10 55942a58c63a7fe59b495a7a EARTH SCIENCE
## # ... with 126,804 more rows
```

This is a tidy data frame because we have one row for each keyword; this means we will have multiple rows for each dataset because a dataset can have more than one keyword.

Now it is time to use tidytext's `unnest_tokens()` for the title and description fields so we can do the text analysis. Let's also remove stop words from the titles and descriptions. We will not remove stop words from the keywords, because those are short, human-assigned keywords like "RADIATION" or "CLIMATE INDICATORS."

```
library(tidytext)

nasa_title <- nasa_title %>%
  unnest_tokens(word, title) %>%
  anti_join(stop_words)

nasa_desc <- nasa_desc %>%
  unnest_tokens(word, desc) %>%
  anti_join(stop_words)
```

These are now in the tidy text format that we have been working with throughout this book, with one token (word, in this case) per row; let's take a look before we move on in our analysis.

```
nasa_title
```

```
## # A tibble: 210,914 × 2
##                          id         word
##                       <chr>        <chr>
## 1  56d07ee5a759fdadc44e5923       marble
## 2  56d07ee5a759fdadc44e5923         epic
## 3  56d07c16a759fdadc44e5922       fitara
## 4  56d07c16a759fdadc44e5922         ocio
## 5  56cf5b00a759fdadc44e5849 implementing
## 6  56cf5b00a759fdadc44e5846     receding
## 7  56cf5b00a759fdadc44e5846    recursive
## 8  56cf5b00a759fdadc44e5840   complaints
## 9  56cf5b00a759fdadc44e583b        score
## 10 56cf5b00a759fdadc44e583a          fix
## # ... with 210,904 more rows
```

```
nasa_desc
```

```
## # A tibble: 2,677,811 × 2
##                          id           word
##                       <chr>          <chr>
## 1  56d07c16a759fdadc44e5922         fitara
## 2  56d07c16a759fdadc44e5922           ocio
## 3  56cf5b00a759fdadc44e584a   degradation's
```

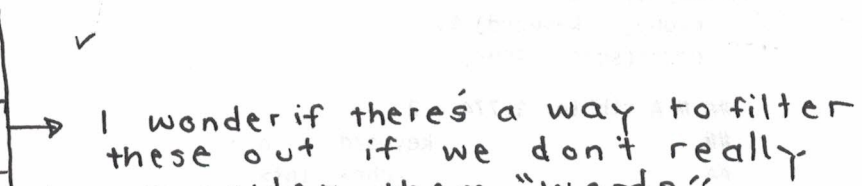
```
## 4  56cf5b00a759fdadc44e5847          dchwp1s
## 5  56cf5b00a759fdadc44e5847         dchwp1sp
## 6  56cf5b00a759fdadc44e5847           dchwdp
## 7  56cf5b00a759fdadc44e5847          dchwsnf
## 8  56cf5b00a759fdadc44e5847          dchwssf
## 9  56cf5b00a759fdadc44e5847         bursting
## 10 56cf5b00a759fdadc44e5847 consequentially
## # ... with 2,677,801 more rows
```

Some Initial Simple Exploration

What are the most common words in the NASA dataset titles? We can use `count()` from dplyr to check this out.

```
nasa_title %>%
  count(word, sort = TRUE)
```

```
## # A tibble: 11,614 × 2
##       word     n
##      <chr> <int>
## 1  project  7735
## 2     data  3354
## 3        1  2841
## 4    level  2400
## 5   global  1809
## 6       v1  1478
## 7    daily  1397
## 8        3  1364
## 9     aura  1363
## 10       2  1311
## # ... with 11,604 more rows
```



What about the descriptions?

```
nasa_desc %>%
  count(word, sort = TRUE)
```

```
## # A tibble: 35,940 × 2
##          word     n
##         <chr> <int>
## 1        data 68871
## 2       modis 24420
## 3      global 23028
## 4           2 16599
## 5           1 15770
## 6      system 15480
## 7     product 14780
## 8        aqua 14738
## 9       earth 14373
## 10 resolution 13879
## # ... with 35,930 more rows
```

Words like "data" and "global" are used very often in NASA titles and descriptions. We may want to remove digits and some "words" like "v1" from these data frames for many types of analyses; they are not too meaningful for most audiences.

We can do this by making a list of custom stop words and using `anti_join()` to remove them from the data frame, just like we removed the default stop words that are in the tidytext package. This approach can be used in many instances and is a great tool to bear in mind.

```
my_stopwords <- data_frame(word = c(as.character(1:10),
                                    "v1", "v03", "l2", "l3", "l4", "v5.2.0",
                                    "v003", "v004", "v005", "v006", "v7"))

nasa_title <- nasa_title %>%
  anti_join(my_stopwords)
nasa_desc <- nasa_desc %>%
  anti_join(my_stopwords)
```

What are the most common keywords?

```
nasa_keyword %>%
  group_by(keyword) %>%
  count(sort = TRUE)
```

```
## # A tibble: 1,774 × 2
##                    keyword     n
##                      <chr> <int>
## 1            EARTH SCIENCE 14362
## 2                  Project  7452
## 3               ATMOSPHERE  7321
## 4              Ocean Color  7268
## 5             Ocean Optics  7268
## 6                  Oceans  7268
## 7                completed  6452
## 8  ATMOSPHERIC WATER VAPOR  3142
## 9                   OCEANS  2765
## 10           LAND SURFACE  2720
## # ... with 1,764 more rows
```

I wonder why these words (plural) count as one keyword; is it like a comma seperated value?

We likely want to change all of the keywords to either lower- or uppercase to get rid of duplicates like "OCEANS" and "Oceans." Let's do that here.

```
nasa_keyword <- nasa_keyword %>%
  mutate(keyword = toupper(keyword))
```

Word Co-ocurrences and Correlations

As a next step, let's examine which words commonly occur together in the titles, descriptions, and keywords of NASA datasets, as described in Chapter 4. We can then

examine word networks for these fields; this may help us see, for example, which datasets are related to each other.

Networks of Description and Title Words

We can use `pairwise_count()` from the widyr package to count how many times each pair of words occurs together in a title or description field.

```
library(widyr)

title_word_pairs <- nasa_title %>%
  pairwise_count(word, id, sort = TRUE, upper = FALSE)

title_word_pairs
```

```
## # A tibble: 156,689 × 3
##    item1   item2     n
##    <chr>   <chr> <dbl>
## 1  system project   796
## 2     lba     eco   683
## 3    airs    aqua   641
## 4   level    aqua   623
## 5   level    airs   612
## 6    aura     omi   607
## 7  global    grid   597
## 8  global   daily   574
## 9    data  boreas   551
## 10 ground     gpm   550
## # ... with 156,679 more rows
```

These are the pairs of words that occur together most often in title fields. Some of these words are obviously acronyms used within NASA, and we see how often words like "project" and "system" are used.

```
desc_word_pairs <- nasa_desc %>%
  pairwise_count(word, id, sort = TRUE, upper = FALSE)

desc_word_pairs
```

```
## # A tibble: 10,889,084 × 3
##         item1      item2     n
##         <chr>      <chr> <dbl>
## 1        data     global  9864
## 2        data resolution  9302
## 3  instrument resolution  8189
## 4        data    surface  8180
## 5      global resolution  8139
## 6        data instrument  7994
## 7        data     system  7870
## 8  resolution      bands  7584
## 9        data      earth  7576
```

```
## 10      orbit resolution  7462
## # ... with 10,889,074 more rows
```

These are the pairs of words that occur together most often in descripton fields. "Data" is a very common word in description fields; there is no shortage of data in the datasets at NASA!

Let's plot networks of these co-occurring words so we can see these relationships better in Figure 8-1. We will again use the ggraph package for visualizing our networks.

```
library(ggplot2)
library(igraph)
library(ggraph)

set.seed(1234)
title_word_pairs %>%
  filter(n >= 250) %>%
  graph_from_data_frame() %>%
  ggraph(layout = "fr") +
  geom_edge_link(aes(edge_alpha = n, edge_width = n), edge_colour = "cyan4") +
  geom_node_point(size = 5) +
  geom_node_text(aes(label = name), repel = TRUE,
                 point.padding = unit(0.2, "lines")) +
  theme_void()
```

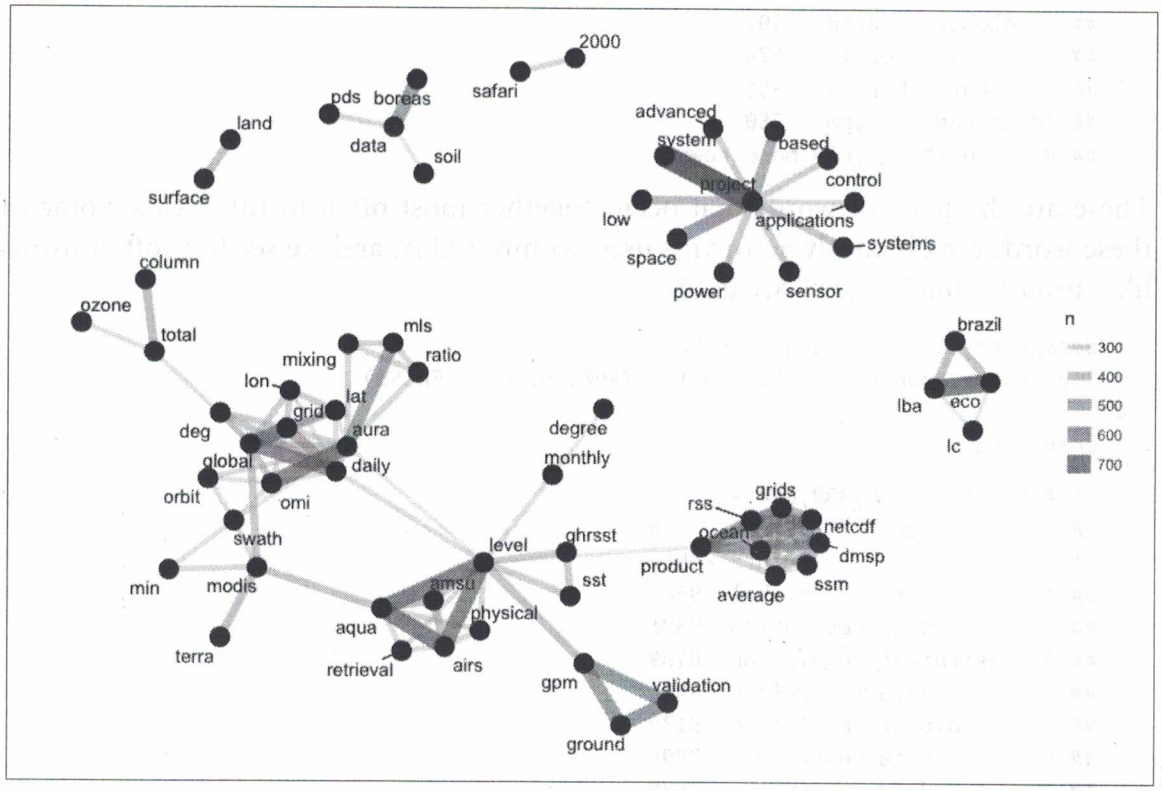


Figure 8-1. Word network in NASA dataset titles

```
## 10      orbit resolution  7462
## # ... with 10,889,074 more rows
```

These are the pairs of words that occur together most often in descripton fields. "Data" is a very common word in description fields; there is no shortage of data in the datasets at NASA!

Let's plot networks of these co-occurring words so we can see these relationships better in Figure 8-1. We will again use the ggraph package for visualizing our networks.

```
library(ggplot2)
library(igraph)
library(ggraph)

set.seed(1234)
title_word_pairs %>%
  filter(n >= 250) %>%
  graph_from_data_frame() %>%
  ggraph(layout = "fr") +
  geom_edge_link(aes(edge_alpha = n, edge_width = n), edge_colour = "cyan4") +
  geom_node_point(size = 5) +
  geom_node_text(aes(label = name), repel = TRUE,
                 point.padding = unit(0.2, "lines")) +
  theme_void()
```

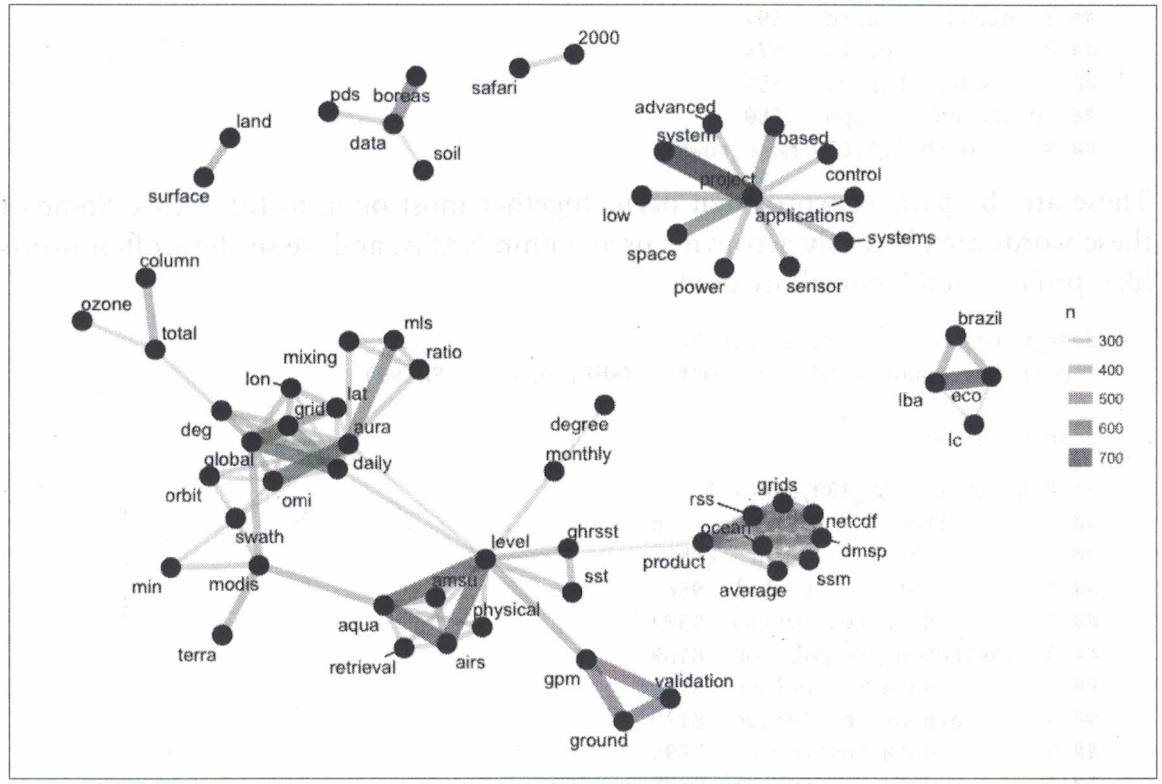


Figure 8-1. Word network in NASA dataset titles

We see some clear clustering in this network of title words; words in NASA dataset titles are largely organized into several families of words that tend to go together.

What about the words from the description fields (Figure 8-2)?

```
set.seed(1234)
desc_word_pairs %>%
  filter(n >= 5000) %>%
  graph_from_data_frame() %>%
  ggraph(layout = "fr") +
  geom_edge_link(aes(edge_alpha = n, edge_width = n), edge_colour = "darkred") +
  geom_node_point(size = 5) +
  geom_node_text(aes(label = name), repel = TRUE,
                 point.padding = unit(0.2, "lines")) +
  theme_void()
```

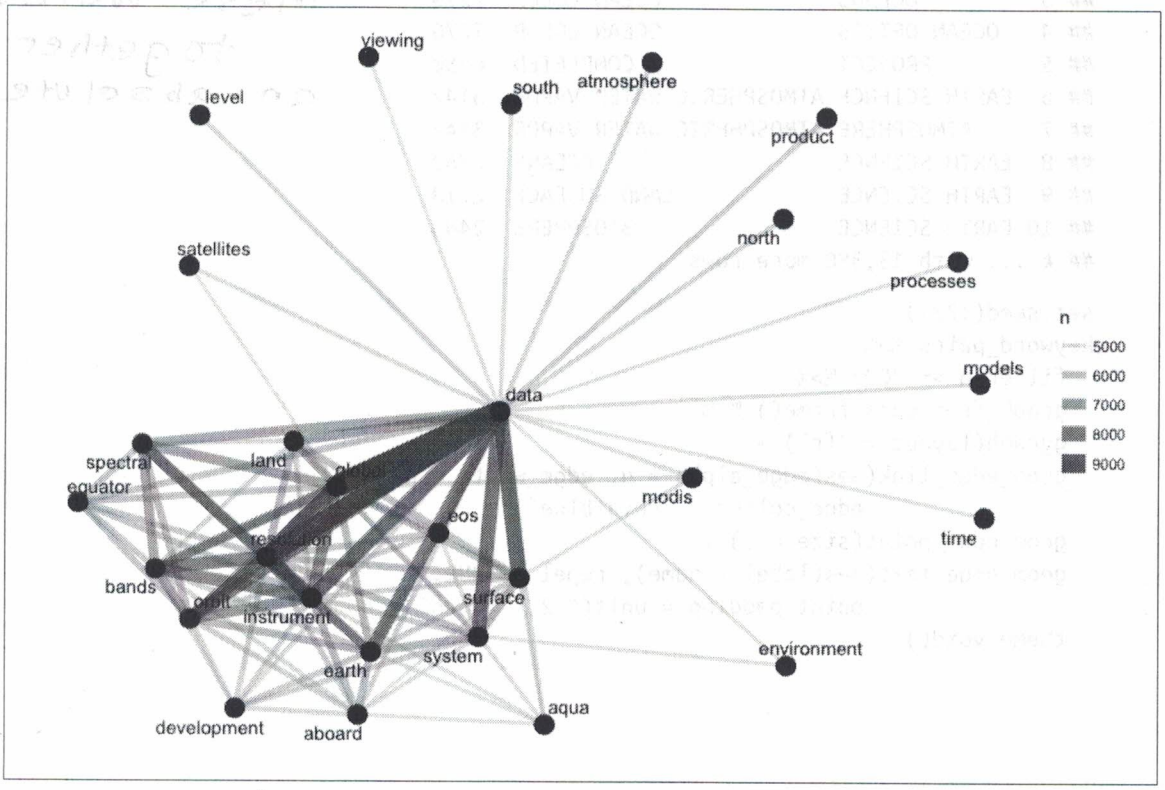


Figure 8-2. Word network in NASA dataset descriptions

Figure 8-2 shows such *strong* connections between the top dozen or so words (words like "data," "global," "resolution," and "instrument") that we do not see a clear clustering structure in the network. We may want to use tf-idf (as described in detail in Chapter 3) as a metric to find characteristic words for each description field, instead of looking at counts of words.

I don't understand this explanation. Since there is a strong connection, isn't there a clear clustering network?

Networks of Keywords

Next, let's make a network of the keywords in Figure 8-3 to see which keywords commonly occur together in the same datasets.

```
keyword_pairs <- nasa_keyword %>%
  pairwise_count(keyword, id, sort = TRUE, upper = FALSE)

keyword_pairs
```

```
## # A tibble: 13,390 × 3
##            item1                    item2     n
##            <chr>                    <chr> <dbl>
## 1         OCEANS            OCEAN OPTICS  7324
## 2  EARTH SCIENCE              ATMOSPHERE  7318
## 3         OCEANS             OCEAN COLOR  7270
## 4   OCEAN OPTICS             OCEAN COLOR  7270
## 5        PROJECT               COMPLETED  6450
## 6  EARTH SCIENCE ATMOSPHERIC WATER VAPOR  3142
## 7     ATMOSPHERE ATMOSPHERIC WATER VAPOR  3142
## 8  EARTH SCIENCE                  OCEANS  2762
## 9  EARTH SCIENCE            LAND SURFACE  2718
## 10 EARTH SCIENCE              BIOSPHERE  2448
## # ... with 13,380 more rows
```

```
set.seed(1234)
keyword_pairs %>%
  filter(n >= 700) %>%
  graph_from_data_frame() %>%
  ggraph(layout = "fr") +
  geom_edge_link(aes(edge_alpha = n, edge_width = n),
                 edge_colour = "royalblue") +
  geom_node_point(size = 5) +
  geom_node_text(aes(label = name), repel = TRUE,
                 point.padding = unit(0.2, "lines")) +
  theme_void()
```

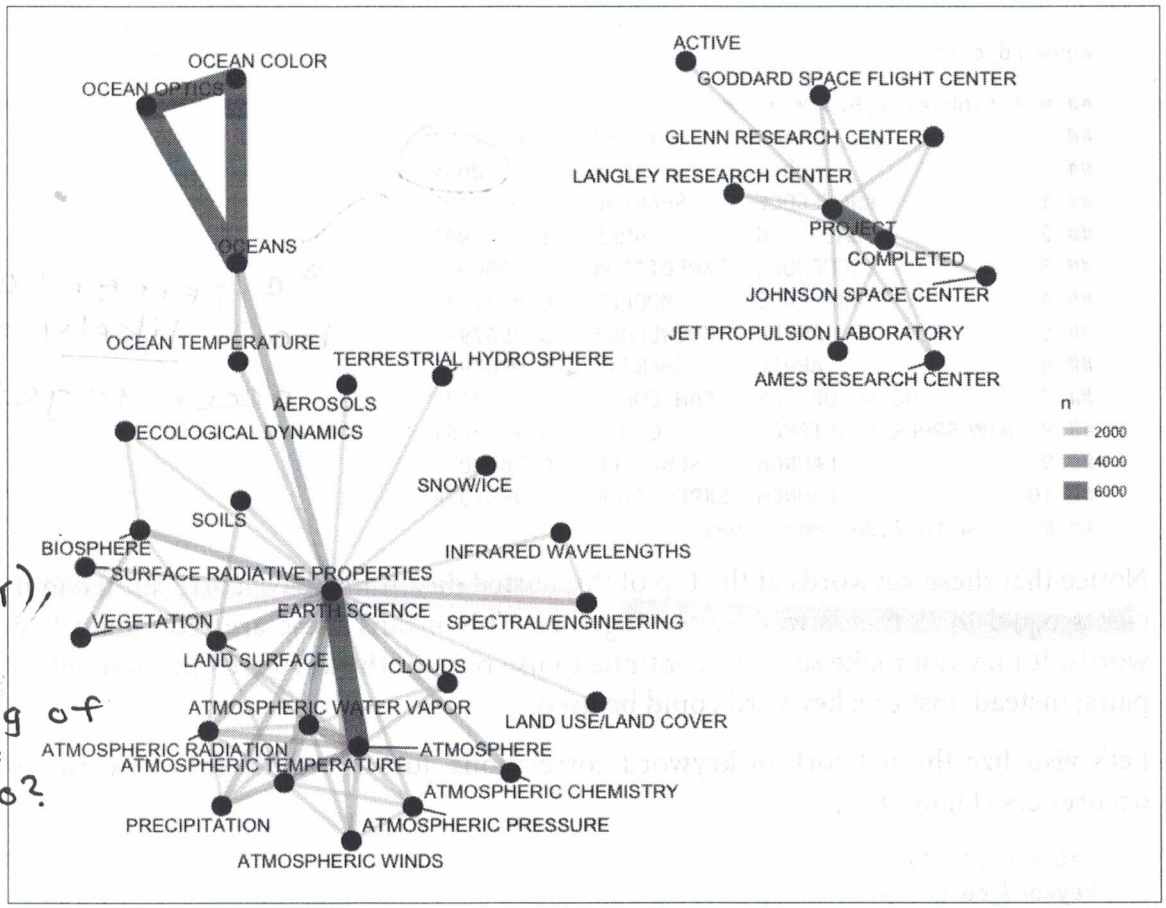
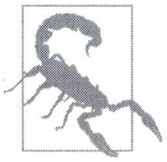


Figure 8-3. Co-occurrence network in NASA dataset keywords

We definitely see clustering here, and strong connections between keywords like "OCEANS," "OCEAN OPTICS," and "OCEAN COLOR," or "PROJECT" and "COMPLETED."



These are the most commonly co-occurring words, but also just the most common keywords in general.

To examine the relationships among keywords in a different way, we can find the correlation among the keywords as described in Chapter 4. This looks for those keywords that are more likely to occur together than with other keywords in a description field.

```
keyword_cors <- nasa_keyword %>%
  group_by(keyword) %>%
  filter(n() >= 50) %>%
  pairwise_cor(keyword, id, sort = TRUE, upper = FALSE)
```

```
keyword_cors
```

```
## # A tibble: 7,875 × 3
##                 item1          item2 correlation
##                 <chr>          <chr>       <dbl>
## 1           KNOWLEDGE        SHARING   1.0000000
## 2            DASHLINK           AMES   1.0000000
## 3            SCHEDULE     EXPEDITION   1.0000000
## 4          TURBULENCE         MODELS   0.9971871
## 5              APPEL      KNOWLEDGE   0.9967945
## 6              APPEL        SHARING   0.9967945
## 7       OCEAN OPTICS   OCEAN COLOR   0.9952123
## 8  ATMOSPHERIC SCIENCE         CLOUD   0.9938681
## 9             LAUNCH       SCHEDULE   0.9837078
## 10            LAUNCH     EXPEDITION   0.9837078
## # ... with 7,865 more rows
```

"a percentage of how likely these occur together"

Notice that these keywords at the top of this sorted data frame have correlation coefficients equal to 1; they always occur together. This means these are redundant keywords. It may not make sense to continue to use both of the keywords in these sets of pairs; instead, just one keyword could be used.

Let's visualize the network of keyword correlations, just as we did for keyword co-occurences (Figure 8-4).

```
set.seed(1234)
keyword_cors %>%
  filter(correlation > .6) %>%
  graph_from_data_frame() %>%
  ggraph(layout = "fr") +
  geom_edge_link(aes(edge_alpha = correlation, edge_width = correlation),
                 edge_colour = "royalblue") +
  geom_node_point(size = 5) +
  geom_node_text(aes(label = name), repel = TRUE,
                 point.padding = unit(0.2, "lines")) +
  theme_void()
```

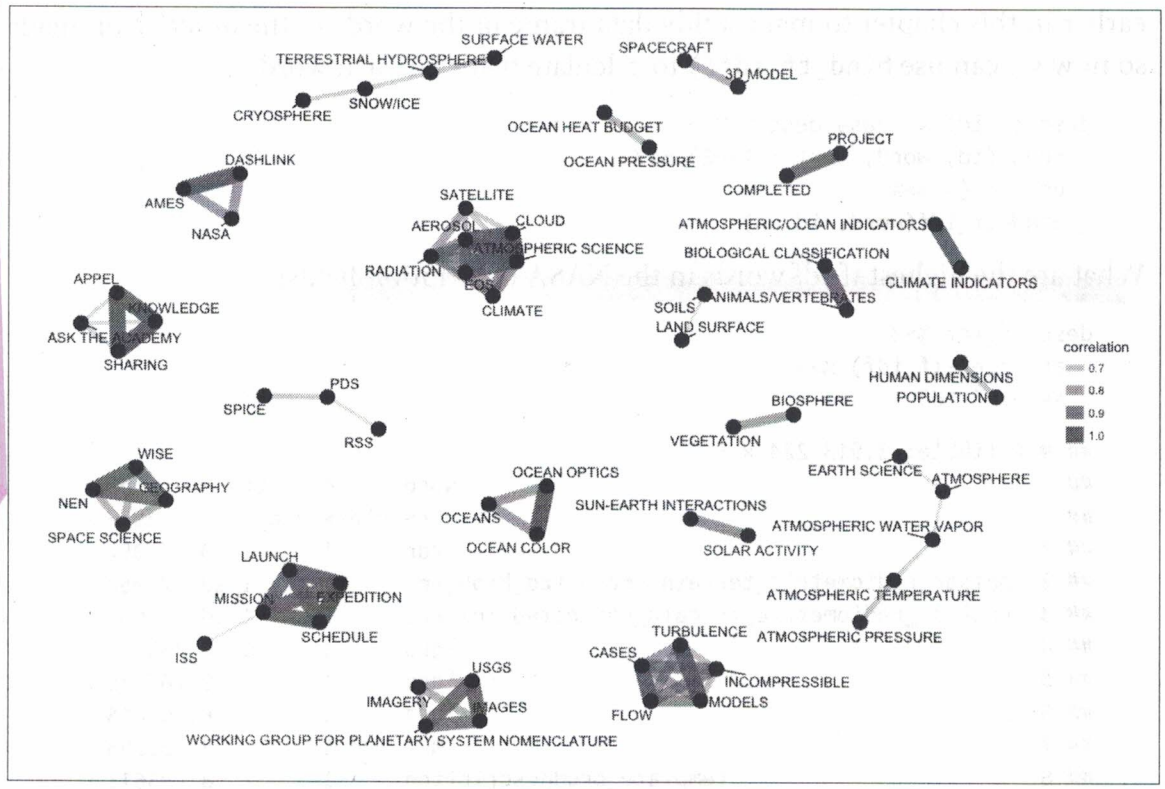


Figure 8-4. Correlation network in NASA dataset keywords

This network in Figure 8-4 appears much different than the co-occurence network. The difference is that the co-occurrence network asks a question about which keyword pairs occur most often, and the correlation network asks a question about which keywords occur more often together than with other keywords. Notice here the high number of small clusters of keywords; the network structure can be extracted (for further analysis) from the `graph_from_data_frame()` function above.

Calculating tf-idf for the Description Fields

The network graph in Figure 8-2 showed us that the description fields are dominated by a few common words like "data," "global," and "resolution"; this would be an excellent opportunity to use tf-idf as a statistic to find characteristic words for individual description fields. As discussed in Chapter 3, we can use tf-idf, the term frequency times inverse document frequency, to identify words that are especially important to a document within a collection of documents. Let's apply that approach to the description fields of these NASA datasets.

What Is tf-idf for the Description Field Words?

We will consider each description field a document, and the whole set of description fields the collection or corpus of documents. We have already used `unnest_tokens()`

earlier in this chapter to make a tidy data frame of the words in the description fields, so now we can use `bind_tf_idf()` to calculate tf-idf for each word.

```
desc_tf_idf <- nasa_desc %>%
  count(id, word, sort = TRUE) %>%
  ungroup() %>%
  bind_tf_idf(word, id, n)
```

What are the highest tf-idf words in the NASA description fields?

```
desc_tf_idf %>%
  arrange(-tf_idf) %>%
  select(-id)
```

```
## # A tibble: 1,913,224 × 6
##                                          word     n    tf       idf
##                                         <chr> <int> <dbl>     <dbl>
## 1                                         rdr     1     1 10.375052
## 2  palsar_radiometric_terrain_corrected_high_res     1     1 10.375052
## 3  cpalsar_radiometric_terrain_corrected_low_res     1     1 10.375052
## 4                                        lgrs     1     1  8.765615
## 5                                        lgrs     1     1  8.765615
## 6                                        lgrs     1     1  8.765615
## 7                                         mri     1     1  8.583293
## 8                       template_proddescription     1     1  8.295611
## 9                       template_proddescription     1     1  8.295611
## 10                      template_proddescription     1     1  8.295611
## # ... with 1,913,214 more rows, and 1 more variables: tf_idf <dbl>
```

These are the most important words in the description fields as measured by tf-idf, meaning they are common but not too common.

Notice we have run into an issue here; both n and term frequency are equal to 1 for these terms, meaning that these were description fields that only had a single word in them. If a description field only contains one word, the tf-idf algorithm will think that is a very important word.

Depending on our analytic goals, it might be a good idea to throw out all description fields that have very few words.

Connecting Description Fields to Keywords

We now know which words in the descriptions have high tf-idf, and we also have labels for these descriptions in the keywords. Let's do a full join of the keyword data frame and the data frame of description words with tf-idf, and then find the highest tf-idf words for a given keyword.

```
desc_tf_idf <- full_join(desc_tf_idf, nasa_keyword, by = "id")
```

Let's plot some of the most important words, as measured by tf-idf, for a few example keywords used on NASA datasets. First, let's use dplyr operations to filter for the keywords we want to examine and take just the top 15 words for each keyword. Then, let's plot those words in Figure 8-5.

```
desc_tf_idf %>%
  filter(!near(tf, 1)) %>%
  filter(keyword %in% c("SOLAR ACTIVITY", "CLOUDS",
                        "SEISMOLOGY", "ASTROPHYSICS",
                        "HUMAN HEALTH", "BUDGET")) %>%
  arrange(desc(tf_idf)) %>%
  group_by(keyword) %>%
  distinct(word, keyword, .keep_all = TRUE) %>%
  top_n(15, tf_idf) %>%
  ungroup() %>%
  mutate(word = factor(word, levels = rev(unique(word)))) %>%
  ggplot(aes(word, tf_idf, fill = keyword)) +
  geom_col(show.legend = FALSE) +
  facet_wrap(~keyword, ncol = 3, scales = "free") +
  coord_flip() +
  labs(title = "Highest tf-idf words in NASA metadata description fields",
       caption = "NASA metadata from https://data.nasa.gov/data.json",
       x = NULL, y = "tf-idf")
```

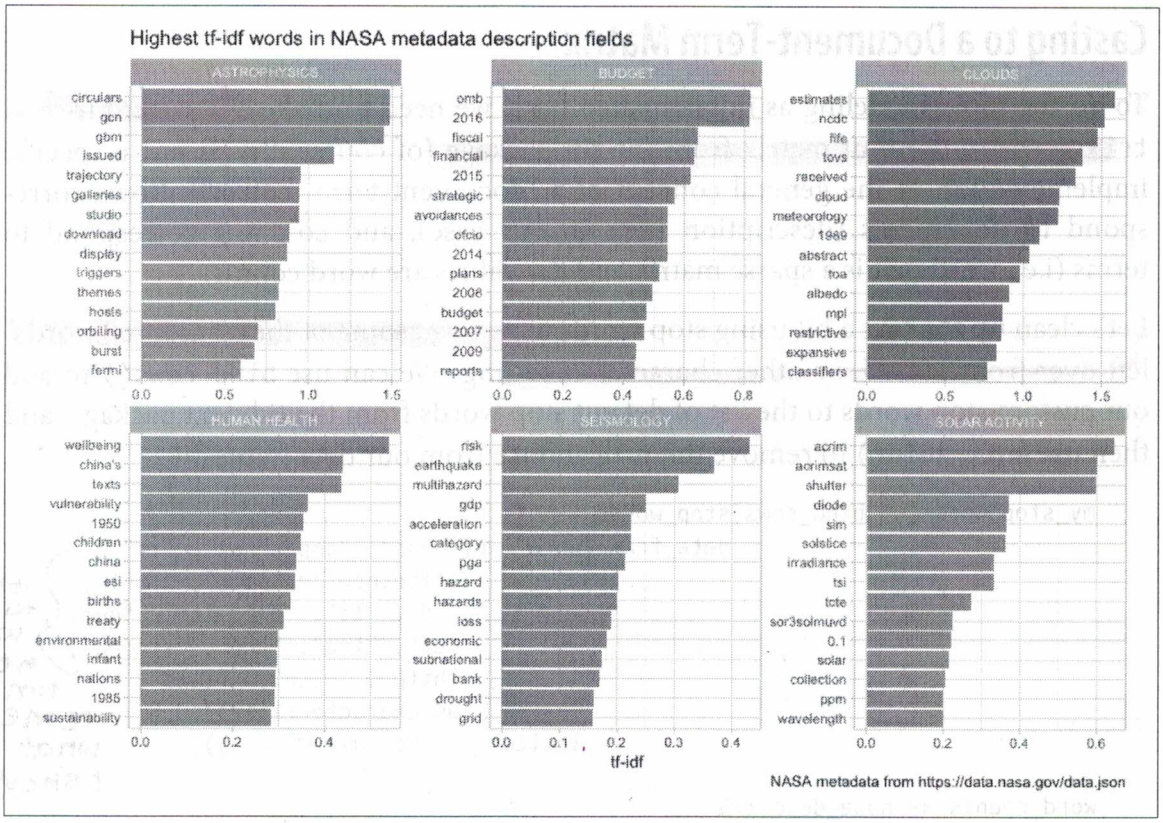


Figure 8-5. Distribution of tf-idf for words from datasets labeled with select keywords

Using tf-idf has allowed us to identify important description words for each of these keywords. Datasets labeled with the keyword "SEISMOLOGY" have words like "earthquake," "risk," and "hazard" in their description, while those labeled with "HUMAN HEALTH" have descriptions characterized by words like "wellbeing," "vulnerability," and "children." Most of the combinations of letters that are not English words are certainly acronyms (like OMB for the Office of Management and Budget), and the examples of years and numbers are important for these topics. The tf-idf statistic has identified the kinds of words it is intended to—important words for individual documents within a collection of documents.

Topic Modeling

Using tf-idf as a statistic has already given us insight into the content of NASA description fields, but let's try an additional approach to the question of what the NASA descriptions fields are about. We can use topic modeling, as described in Chapter 6, to model each document (description field) as a mixture of topics, and each topic as a mixture of words. As in earlier chapters, we will use latent Dirichlet allocation (LDA) for our topic modeling; there are other possible approaches for topic modeling.

Casting to a Document-Term Matrix

To do the topic modeling as implemented here, we need to make a `DocumentTermMatrix`, a special kind of matrix from the tm package (of course, this is just a specific implementation of the general concept of a "document-term matrix"). Rows correspond to documents (description texts in our case), and columns correspond to terms (i.e., words); it is a sparse matrix and the values are word counts.

Let's clean up the text a bit using stop words to remove some of the nonsense "words" left over from HTML or other character encoding. We can use `bind_rows()` to add our custom stop words to the list of default stop words from the tidytext package, and then use `anti_join()` to remove them all at once from our data frame.

```
my_stop_words <- bind_rows(stop_words,
                           data_frame(word = c("nbsp", "amp", "gt", "lt",
                                               "timesnewromanpsmt", "font",
                                               "td", "li", "br", "tr", "quot",
                                               "st", "img", "src", "strong",
                                               "http", "file", "files",
                                               as.character(1:12)),
                                      lexicon = rep("custom", 30)))

word_counts <- nasa_desc %>%
  anti_join(my_stop_words) %>%
  count(id, word, sort = TRUE) %>%
  ungroup()
```

it'd be nice to know what these mean so next time I can remember what stop words I should include.

```
word_counts
```

```
## # A tibble: 1,895,310 × 3
##                          id     word     n
##                       <chr>    <chr> <int>
## 1  55942a8ec63a7fe59b4986ef     suit    82
## 2  55942a8ec63a7fe59b4986ef    space    69
## 3  56cf5b00a759fdadc44e564a     data    41
## 4  56cf5b00a759fdadc44e564a     leak    40
## 5  56cf5b00a759fdadc44e564a     tree    39
## 6  55942a8ec63a7fe59b4986ef pressure    34
## 7  55942a8ec63a7fe59b4986ef   system    34
## 8  55942a89c63a7fe59b4982d9       em    32
## 9  55942a8ec63a7fe59b4986ef       al    32
## 10 55942a8ec63a7fe59b4986ef    human    31
## # ... with 1,895,300 more rows
```

This is the information we need, the number of times each word is used in each document, to make a `DocumentTermMatrix`. We can `cast()` from our tidy text format to this nontidy format, as described in detail in Chapter 5.

```
desc_dtm <- word_counts %>%
  cast_dtm(id, word, n)

desc_dtm
```

```
## <<DocumentTermMatrix (documents: 32003, terms: 35901)>>
## Non-/sparse entries: 1895310/1147044393
## Sparsity           : 100%
## Maximal term length: 166
## Weighting          : term frequency (tf)
```

We see that this dataset contains documents (each of them a NASA description field) and terms (words). Notice that this example document-term matrix is (very close to) 100% sparse, meaning that almost all of the entries in this matrix are zero. Each nonzero entry corresponds to a certain word appearing in a certain document.

Ready for Topic Modeling

Now let's use the topicmodels package to create an LDA model. How many topics will we tell the algorithm to make? This is a question much like in k-means clustering; we don't really know ahead of time. We tried the following modeling procedure using 8, 16, 24, 32, and 64 topics; we found that at 24 topics, documents are still getting sorted into topics cleanly, but going much beyond that caused the distributions of γ, the probability that each document belongs in each topic, to look worrisome. We will show more details on this later.

```
library(topicmodels)

# be aware that running this model is time intensive
desc_lda <- LDA(desc_dtm, k = 24, control = list(seed = 1234))
desc_lda

## A LDA_VEM topic model with 24 topics.
```

This is a stochastic algorithm that could have different results depending on where the algorithm starts, so we need to specify a seed for reproducibility as shown here.

Interpreting the Topic Model

Now that we have built the model, let's `tidy()` the results of the model, i.e., construct a tidy data frame that summarizes the results of the model. The tidytext package includes a tidying method for LDA models from the topicmodels package.

```
tidy_lda <- tidy(desc_lda)

tidy_lda

## # A tibble: 861,624 × 3
##    topic  term          beta
##    <int> <chr>        <dbl>
## 1      1  suit 1.003981e-121
## 2      2  suit 2.630614e-145
## 3      3  suit  1.916240e-79
## 4      4  suit  6.715725e-45
## 5      5  suit  1.738334e-85
## 6      6  suit  7.692116e-84
## 7      7  suit  3.283851e-04
## 8      8  suit  3.738586e-20
## 9      9  suit  4.846953e-15
## 10    10  suit  4.765471e-10
## # ... with 861,614 more rows
```

The column β tells us the probability of that term being generated from that topic for that document. It is the probability of that term (word) belonging to that topic. Notice that some of the values for β are very, very low, and some are not so low.

What is each topic about? Let's examine the top 10 terms for each topic.

```
top_terms <- tidy_lda %>%
  group_by(topic) %>%
  top_n(10, beta) %>%
  ungroup() %>%
  arrange(topic, -beta)

top_terms

## # A tibble: 240 × 3
##    topic      term      beta
##    <int>     <chr>     <dbl>
```

```
## 1      1        data 0.04488960
## 2      1        soil 0.03676198
## 3      1    moisture 0.02954555
## 4      1        amsr 0.02437751
## 5      1         sst 0.01684001
## 6      1  validation 0.01322457
## 7      1 temperature 0.01317075
## 8      1     surface 0.01290046
## 9      1    accuracy 0.01225131
## 10     1         set 0.01155372
## # ... with 230 more rows
```

It is not very easy to interpret what the topics are about from a data frame like this, so let's look at this information visually in Figures 8-6 and 8-7.

super helpful! Looking @ #s isn't great...

```
top_terms %>%
  mutate(term = reorder(term, beta)) %>%
  group_by(topic, term) %>%
  arrange(desc(beta)) %>%
  ungroup() %>%
  mutate(term = factor(paste(term, topic, sep = "__"),
                       levels = rev(paste(term, topic, sep = "__")))) %>%
  ggplot(aes(term, beta, fill = as.factor(topic))) +
  geom_col(show.legend = FALSE) +
  coord_flip() +
  scale_x_discrete(labels = function(x) gsub("__.+$", "", x)) +
  labs(title = "Top 10 terms in each LDA topic",
       x = NULL, y = expression(beta)) +
  facet_wrap(~ topic, ncol = 3, scales = "free")
```

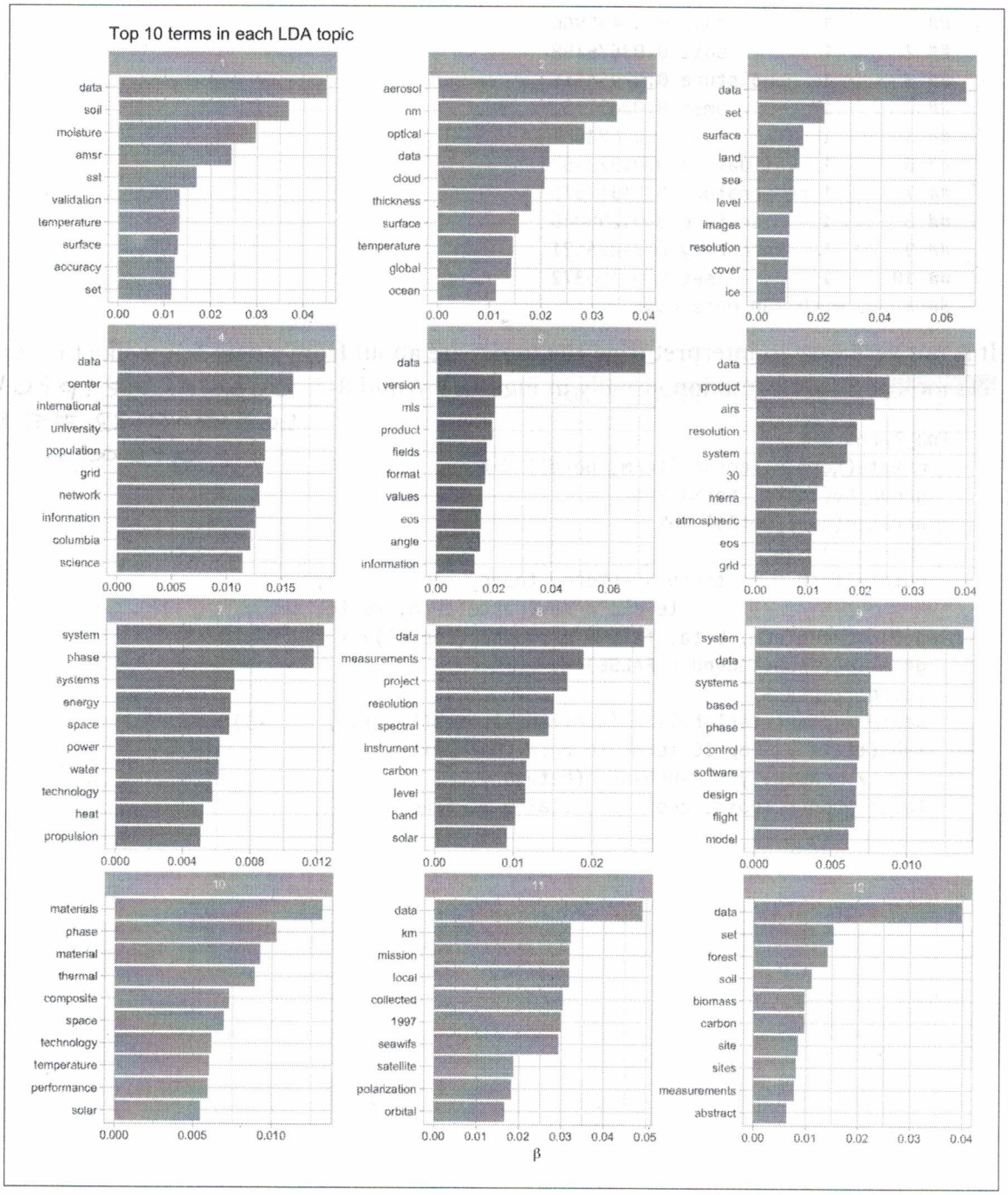


Figure 8-6. Top terms in topic modeling of NASA metadata description field texts

Figure 8-7. Top terms in topic modeling of NASA metadata description field texts

We can see what a dominant word "data" is in these description texts. In addition, there are meaningful differences between these collections of terms, from terms about soil, forests, and biomass in topic 12 to terms about design, systems, and technology in topic 21. The topic modeling process has identified groupings of terms that we can understand as human readers of these description fields.

We just explored which words are associated with which topics. Next, let's examine which topics are associated with which description fields (i.e., documents). We will look at a different probability for this, γ, the probability that each document belongs in each topic, again using the `tidy` verb.

```
lda_gamma <- tidy(desc_lda, matrix = "gamma")

lda_gamma
```

```
## # A tibble: 768,072 × 3
##                      document topic        gamma
##                         <chr> <int>        <dbl>
## 1  55942a8ec63a7fe59b4986ef     1 6.453820e-06
## 2  56cf5b00a759fdadc44e564a     1 1.158393e-05
## 3  55942a89c63a7fe59b4982d9     1 4.917441e-02
## 4  56cf5b00a759fdadc44e55cd     1 2.249043e-05
## 5  55942a89c63a7fe59b4982c6     1 6.609442e-05
## 6  55942a86c63a7fe59b498077     1 5.666520e-05
## 7  56cf5b00a759fdadc44e56f8     1 4.752082e-05
## 8  55942a8bc63a7fe59b4984b5     1 4.308534e-05
## 9  55942a6ec63a7fe59b496bf7     1 4.408626e-05
## 10 55942a8ec63a7fe59b4986f6     1 2.878188e-05
## # ... with 768,062 more rows
```

Notice that some of the probabilities visible at the top of the data frame are low and some are higher. Our model has assigned a probability to each description belonging to each of the topics we constructed from the sets of words. How are the probabilities distributed? Let's visualize them (Figure 8-8).

```
ggplot(lda_gamma, aes(gamma)) +
  geom_histogram() +
  scale_y_log10() +
  labs(title = "Distribution of probabilities for all topics",
       y = "Number of documents", x = expression(gamma))
```

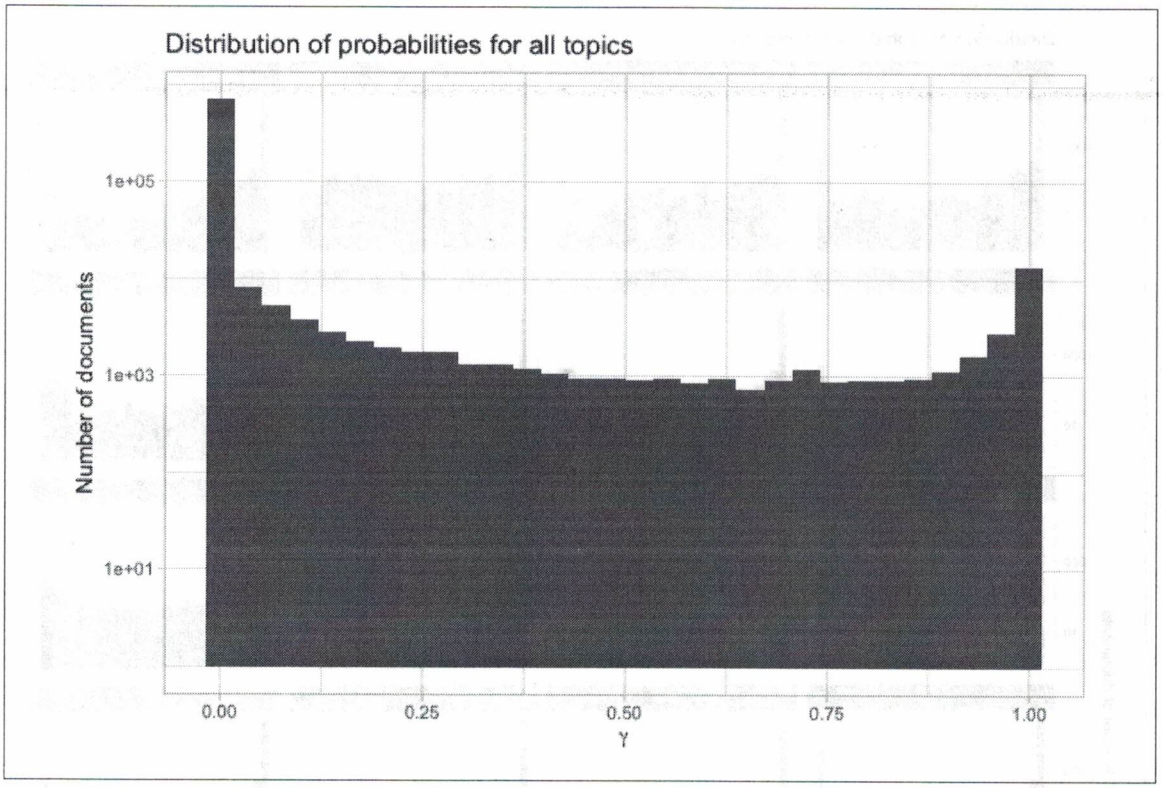


Figure 8-8. Probability distribution in topic modeling of NASA metadata description field texts

First notice that the y-axis is plotted on a log scale; otherwise it is difficult to make out any detail in the plot. Next, notice that γ runs from 0 to 1; remember that this is the probability that a given document belongs in a given topic. There are many values near zero, which means there are many documents that do not belong in each topic. Also, there are many values near $\gamma = 1$; these are the documents that *do* belong in those topics. This distribution shows that documents are being well discriminated as belonging to a topic or not. We can also look at how the probabilities are distributed within each topic, as shown in Figure 8-9.

→ ie topics are sometime super specifica related only to one document in the set of documents

```
ggplot(lda_gamma, aes(gamma, fill = as.factor(topic))) +
  geom_histogram(show.legend = FALSE) +
  facet_wrap(~ topic, ncol = 4) +
  scale_y_log10() +
  labs(title = "Distribution of probability for each topic",
       y = "Number of documents", x = expression(gamma))
```

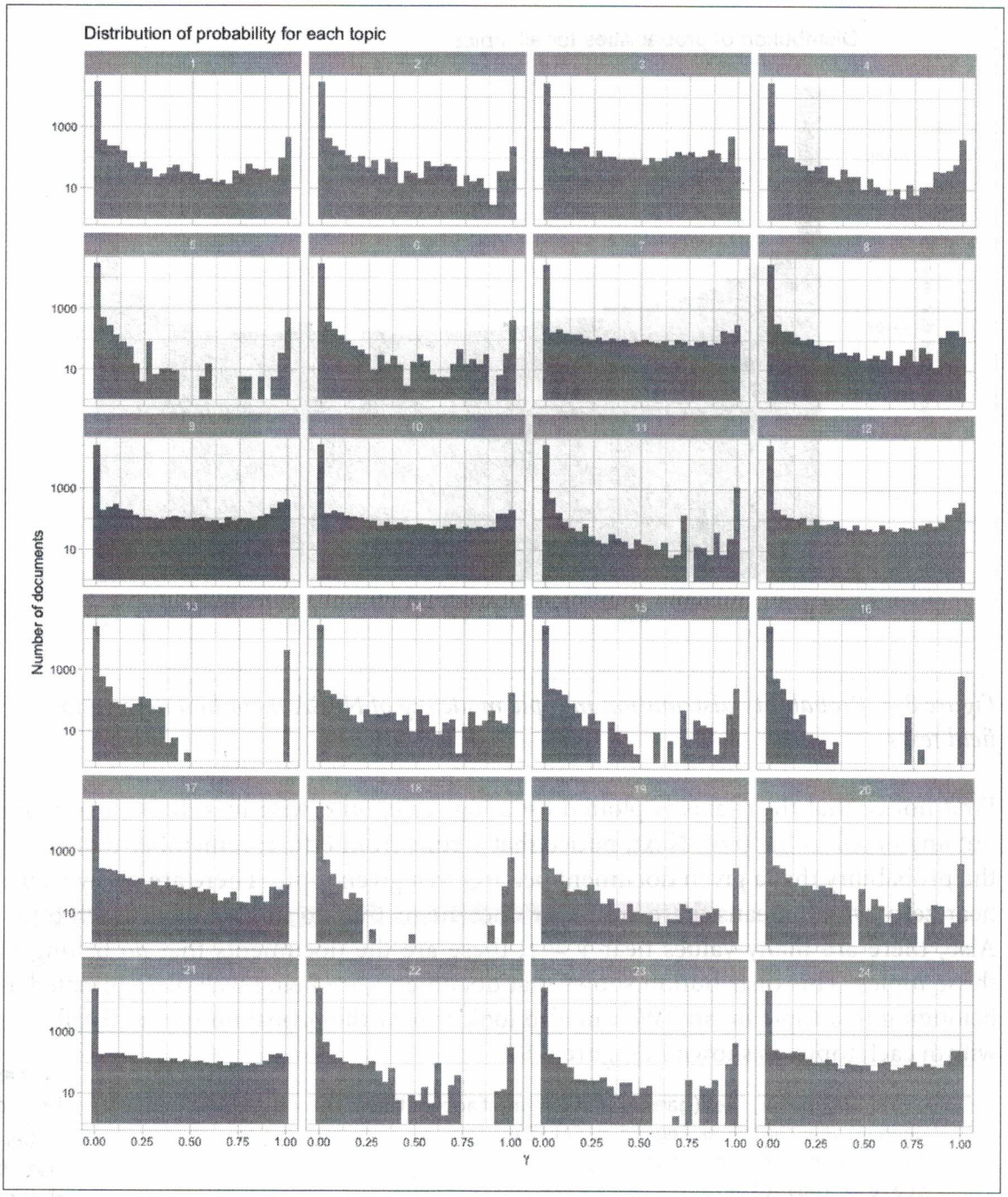


Figure 8-9. Probability distribution for each topic in topic modeling of NASA metadata description field texts

Let's look specifically at topic 18 in Figure 8-9, a topic that had documents cleanly sorted in and out of it. There are many documents with γ close to 1; these are the documents that *do* belong to topic 18 according to the model. There are also many documents with γ close to 0; these are the documents that do *not* belong to topic 18.

Each document appears in each panel in this plot, and its γ for that topic tells us that document's probability of belonging in that topic.

This plot displays the type of information we used to choose the number of topics for our topic modeling procedure. When we tried options higher than 24 (such as 32 or 64), the distributions for γ started to look very flat toward $\gamma = 1$; documents were not getting sorted into topics very well.

Connecting Topic Modeling with Keywords

Let's connect these topic models with the keywords and see what relationships we can find. We can `full_join()` this to the human-tagged keywords and discover which keywords are associated with which topic.

```
lda_gamma <- full_join(lda_gamma, nasa_keyword, by = c("document" = "id"))

lda_gamma
```

```
## # A tibble: 3,037,671 × 4
##                    document topic        gamma                    keyword
##                       <chr> <int>        <dbl>                      <chr>
## 1  55942a8ec63a7fe59b4986ef     1 6.453820e-06       JOHNSON SPACE CENTER
## 2  55942a8ec63a7fe59b4986ef     1 6.453820e-06                    PROJECT
## 3  55942a8ec63a7fe59b4986ef     1 6.453820e-06                  COMPLETED
## 4  56cf5b00a759fdadc44e564a     1 1.158393e-05                   DASHLINK
## 5  56cf5b00a759fdadc44e564a     1 1.158393e-05                       AMES
## 6  56cf5b00a759fdadc44e564a     1 1.158393e-05                       NASA
## 7  55942a89c63a7fe59b4982d9     1 4.917441e-02 GODDARD SPACE FLIGHT CENTER
## 8  55942a89c63a7fe59b4982d9     1 4.917441e-02                    PROJECT
## 9  55942a89c63a7fe59b4982d9     1 4.917441e-02                  COMPLETED
## 10 56cf5b00a759fdadc44e55cd     1 2.249043e-05                   DASHLINK
## # ... with 3,037,661 more rows
```

Now we can use `filter()` to keep only the document-topic entries that have probabilities (γ) greater than some cutoff value; let's use 0.9. → so 90% likely or higher

```
top_keywords <- lda_gamma %>%
  filter(gamma > 0.9) %>%
  count(topic, keyword, sort = TRUE)

top_keywords
```

```
## Source: local data frame [1,022 x 3]
## Groups: topic [24]
##
##    topic       keyword     n
##    <int>         <chr> <int>
## 1     13   OCEAN COLOR  4480
## 2     13  OCEAN OPTICS  4480
## 3     13        OCEANS  4480
## 4     11   OCEAN COLOR  1216
## 5     11  OCEAN OPTICS  1216
```

```
## 6     11         OCEANS  1216
## 7      9        PROJECT   926
## 8     12 EARTH SCIENCE   909
## 9      9      COMPLETED   834
## 10    16    OCEAN COLOR   768
## # ... with 1,012 more rows
```

What are the top keywords for each topic (Figure 8-10)?

```
top_keywords %>%
  group_by(topic) %>%
  top_n(5, n) %>%
  group_by(topic, keyword) %>%
  arrange(desc(n)) %>%
  ungroup() %>%
  mutate(keyword = factor(paste(keyword, topic, sep = "__"),
                          levels = rev(paste(keyword, topic, sep = "__")))) %>%
  ggplot(aes(keyword, n, fill = as.factor(topic))) +
  geom_col(show.legend = FALSE) +
  labs(title = "Top keywords for each LDA topic",
       x = NULL, y = "Number of documents") +
  coord_flip() +
  scale_x_discrete(labels = function(x) gsub("__.+$", "", x)) +
  facet_wrap(~ topic, ncol = 3, scales = "free")
```

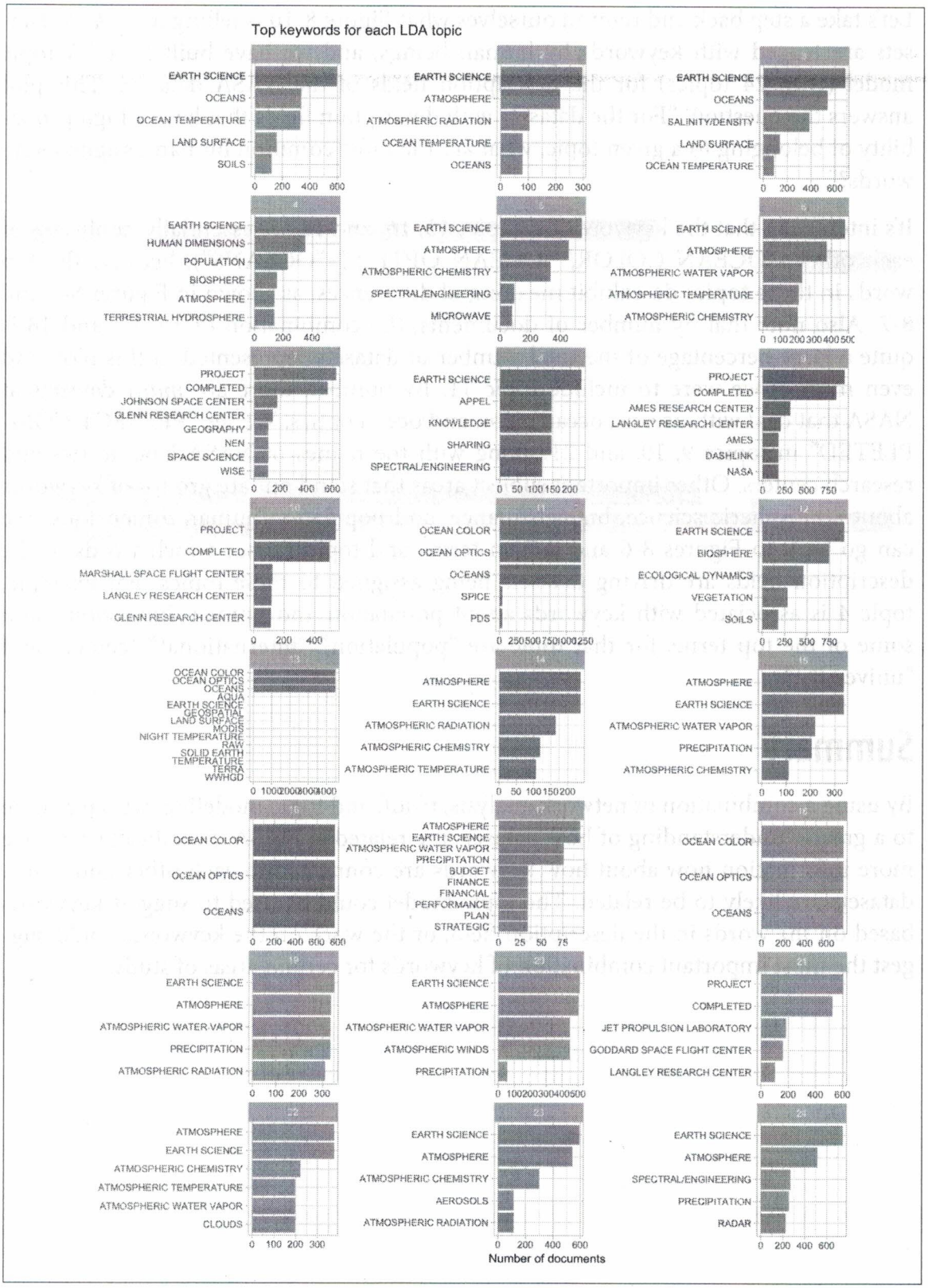


Figure 8-10. Top keywords in topic modeling of NASA metadata description field texts

Let's take a step back and remind ourselves what Figure 8-10 is telling us. NASA datasets are tagged with keywords by human beings, and we have built an LDA topic model (with 24 topics) for the description fields of the NASA datasets. This plot answers the question, "For the datasets with description fields that have a high probability of belonging to a given topic, what are the most common human-assigned keywords?"

It's interesting that the keywords for topics 13, 16, and 18 are essentially duplicates of each other ("OCEAN COLOR," "OCEAN OPTICS," "OCEANS"), because the top words in those topics do exhibit meaningful differences, as shown in Figures 8-6 and 8-7. Also note that by number of documents, the combination of 13, 16, and 18 is quite a large percentage of the total number of datasets represented in this plot, and even more if we were to include topic 11. By number, there are *many* datasets at NASA that deal with oceans, ocean color, and ocean optics. We see "PROJECT COMPLETED" in topics 9, 10, and 21, along with the names of NASA laboratories and research centers. Other important subject areas that stand out are groups of keywords about atmospheric science, budget/finance, and population/human dimensions. We can go back to Figures 8-6 and 8-7 on terms and topics to see which words in the description fields are driving datasets being assigned to these topics. For example, topic 4 is associated with keywords about population and human dimensions, and some of the top terms for that topic are "population," "international," "center," and "university."

Summary

By using a combination of network analysis, tf-idf, and topic modeling, we have come to a greater understanding of how datasets are related at NASA. Specifically, we have more information now about how keywords are connected to each other and which datasets are likely to be related. The topic model could be used to suggest keywords based on the words in the description field, or the work on the keywords could suggest the most important combination of keywords for certain areas of study.