

Topic Modeling

EDP 618 Week 12

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Setting Up

1. You can retrieve the *exercising with dogs* data set and both installation and walkthrough  scripts by clicking on the icon below



2. Open up RStudio
3. Open and run Week 12 install.R
4. Open Week 12 script.R



Take a look at the various types of files that can be imported in the tidyverse

[PDF](#)



Getting Prepped

Run the following commands which can be found in the file Week 12 script.R

1. Setting the working directory as source

```
setwd(dirname(rstudioapi:::getActiveDocumentContext()$path))
```

2. Loading the needed packages for this walkthrough

```
library(tidyverse)
library(tidytext)
library(tm)
library(textclean)
library(topicmodels)
library(ldatuning)
library(stopwords)
library(textstem)
library(broom)
```

Alternatively if you have the **pacman** package, run `pacman::p_install("tidyverse", "tidytext", "tm", "textclean", "topicmodels", "ldatuning", "stopwords", "textstem", "broom")`

3. Bringing in the PDF data

```
exwdogs <-  
  pdfTools::pdf_text("exercising_with_dogs.pdf")
```



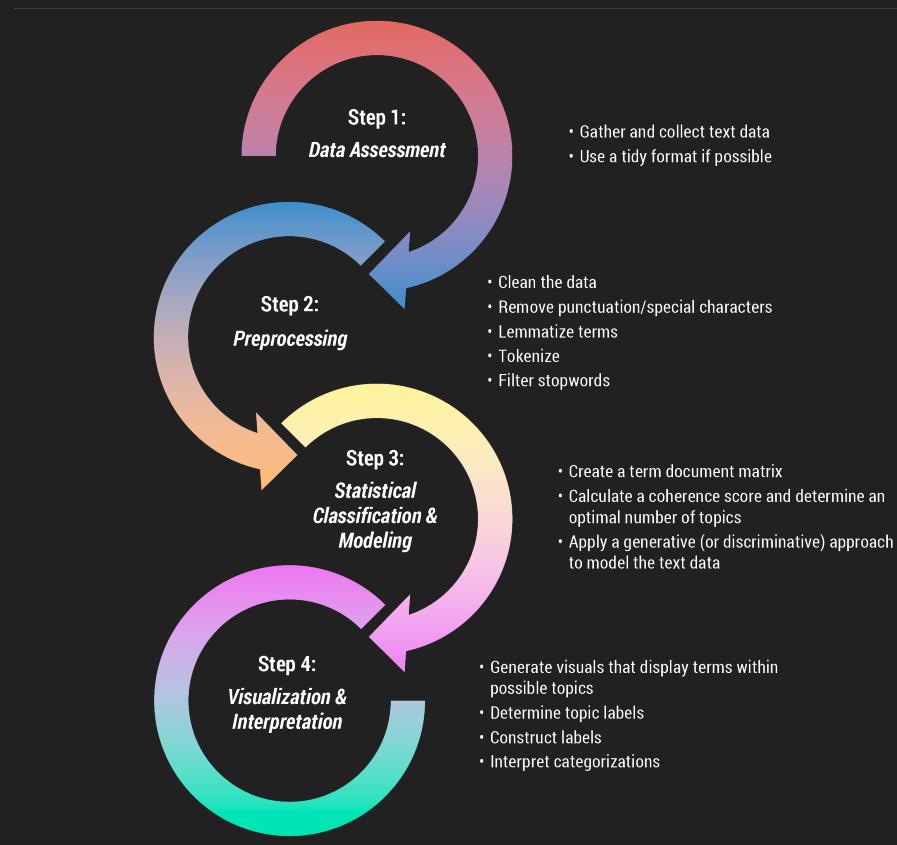
4. Retrieving stopwords

```
data("stop_words")
```

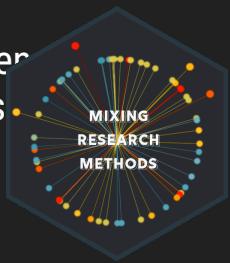


Before We Begin

This is the process we'll cover lightly. There is a lot more going on under the hood and you may not be able to recognize all of the terms, but if you can get a basic understanding of the process, the rest can be filled in by conducting a topic model!



Additionally here are a few things we won't be covering in this session so please read over the areas you lack familiarity with. Given it is absolutely fine if you cannot fully understand all of these ideas right now - they will hopefully become apparent as we progress.



BAG OF WORDS

Converts text to a matrix where every row is an observation and every feature is a unique word. The value of each element in the matrix is either a binary indicator marking the presence of that word or an integer of the number of times that word appears.

ChrisAlbon

STANDARDIZATION

$$\hat{x}_i = \frac{x_i - \bar{x}}{\sigma}$$

Standardized feature value
Value of the i th observation
Mean of the feature vector
Standard deviation of the feature vector

Standardization is a common scaling method. \hat{x}_i represents the number of standard deviations each value is from the mean value. It rescales a feature to have a mean of 0 and unit variance.

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CLASSIFICATION

Classification problems are when we are training a model to predict qualitative targets. For example: gender or a type of fruit.



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TOKENIZING TEXT

Splitting up text into individual units like paragraphs, sentences, or words.

Example:

"I like birds" → "I", "like", "birds"

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Topic Modeling

A type of probabilistic statistical model for

- (a) discovering the abstract "topics"
 - or hidden semantic structures -
 - that occur in a collection of documents
- (b) dimensionality reduction



The Most Annoying Thing About Data

The 80/20 Rule¹: *Most data scientists spend only 20 percent of their time on actual data analysis and 80 percent of their time finding, cleaning, and reorganizing huge amounts of data*

¹ Loosely based on an idea called **Pareto's Principle** which states that *roughly 80% of outcomes come from 20% of causes*



Step 1: Assessing Data

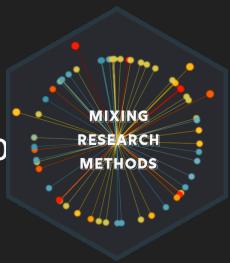
1. Take a look at the data set and think about categorizing terms that may skew how terms are assessed

the names of the dogs are not important so we could replace all of them simply with the word **dog**

canines are prevalent in the data so we could Remove word **dog** altogether

2. Open up an empty text document and try going through on your own to consider terms that could be collapsed

3. Open up Week 12 script.R





Step 2: Preprocessing



```
exwdogs %>%  
read_lines() %>% # Parse text into individual lines  
as_tibble_col("text") %>% # Create a single tidy column  
slice(24:n()) %>% # Remove unnecessary text  
mutate(text = textclean::replace_non_ascii(text)) %>% # Convert to a standard format  
mutate(text = str_to_lower(text)) %>% # Convert all words to lower case  
mutate(text = str_remove_all(text, "[[:digit:]]")) %>% # Remove all numbers  
mutate(text = str_remove_all(text, "[[:punct:]]")) %>% # Remove all punctuation  
mutate(text = str_remove_all(text, "stage")) %>% # Remove term  
mutate(text = str_replace_all(text, "sri ranganatha temple", "temple")) %>% # Replace term  
mutate(text = str_replace_all(text, "shakti", "dog")) %>% # Replace term  
mutate(text = str_replace_all(text, "foxhounds", "dog")) %>% # Replace term  
mutate(text = str_replace_all(text, "swami", "dog")) %>% # Replace term  
mutate(text = str_replace_all(text, "max", "dog")) %>% # Replace term  
mutate(text = lemmatize_strings(text)) %>% # Lemmatize term  
mutate(text = str_remove_all(text, c("dog"))) %>% # Remove term  
mutate(text = str_remove_all(text, c("human"))) %>% # Remove term  
mutate(text = str_squish(text)) %>% # Remove whitespace  
mutate(text = na_if(text, "")) %>% # Replace blanks with NA  
drop_na() # Drop all columns with NA
```

```
## # A tibble: 167 × 1  
##   text  
##   <chr>  
## 1 crazy pave day temple unbearably hot join by thirsty drink my  
## 2 cement mix water then come over for scratch overwhelm by how much i miss first  
## 3 time i have touch another since his death strong mnemonic smell touch do bernese  
## 4 mountain have double coat too feel like it she seem to recognise something be up  
## 5 very much a person like cry and make her fur damp she stay with me til i stop  
## 6 cry then go to entrance and lie down so hot how do she cope in here why do she
```



Assigning a Variable

Let's save the entire cleaning process

```
exwdogs_cleaned <-  
  exwdogs %>%  
  read_lines() %>%  
  as_tibble_col("text") %>%  
  slice(24:n()) %>%  
  mutate(text = textclean::replace_non_ascii(text)) %>%  
  mutate(text = str_to_lower(text)) %>%  
  mutate(text = str_remove_all(text, "[[:digit:]]")) %>%  
  mutate(text = str_remove_all(text, "[[:punct:]]")) %>%  
  mutate(text = str_remove_all(text, "stage")) %>%  
  mutate(text = str_replace_all(text, "sri ranganatha temple", "temple")) %>%  
  mutate(text = str_replace_all(text, "shakti", "dog")) %>%  
  mutate(text = str_replace_all(text, "foxhounds", "dog")) %>%  
  mutate(text = str_replace_all(text, "swami", "dog")) %>%  
  mutate(text = str_replace_all(text, "max", "dog")) %>%  
  mutate(text = lemmatize_strings(text)) %>%  
  mutate(text = str_remove_all(text, c("dog")))) %>%  
  mutate(text = str_remove_all(text, c("human")))) %>%  
  mutate(text = str_squish(text)) %>%  
  mutate(text = na_if(text, "")) %>%  
  drop_na()
```



What Just Happened?

Let's try doing something similar but with shorter and simpler text taken from the very funny skit Sharknado Pitch Meeting

```
example_text <-
  c("Excerpt from Sharknado Pitch Meeting.
  Creator: Ryan George.

  (1) It's peer reviewed.
  (2) Multiple scientists looked over that and approved of it?
  (3) No some drunk guy on the pier checked it out. He loved it!
  (4) That is technically peer reviewed. I think we're good.

  --The End--
  ")
```

```

example_text %>%
  read_lines() %>% # Parse text into individual lines
  as_tibble_col("text") %>% # Create a single tidy column
  slice(4:n()) %>% # Remove unnecessary text
  mutate(text = textclean::replace_non_ascii(text)) %>% # Convert to a standard format
  mutate(text = str_to_lower(text)) %>% # Convert all words to lower case
  mutate(text = str_remove_all(text, "[[:digit:]]")) %>% # Remove all numbers
  mutate(text = str_remove_all(text, "[[:punct:]]")) %>% # Remove all punctuation
  mutate(text = str_remove_all(text, "the end")) %>% # Remove term
  mutate(text = str_replace_all(text, "multiple scientists", "scientists")) %>% # Replace term
  mutate(text = str_replace_all(text, "its", "paper")) %>% # Replace term
  mutate(text = str_replace_all(text, "it", "paper")) %>% # Replace term
  mutate(text = str_replace_all(text, "that", "paper")) %>% # Replace term
  mutate(text = lemmatize_strings(text)) %>% # Lemmatize term
  mutate(text = str_remove_all(text, c("paper")))) %>% # Remove term
  mutate(text = str_squish(text)) %>% # Remove whitespace
  mutate(text = na_if(text, "")) %>% # Replace blanks with NA
  drop_na() # Drop all columns with NA

## # A tibble: 4 × 1
##   text
##   <chr>
## 1 peer review
## 2 scientist look over and approve of
## 3 no some drink guy on the pier check out he love
## 4 be technically peer review i think be good

```





Normalization of Remaining Wording

is used to reduce word randomness which allows some level of standardization to help to reduce the amount of different information that a computer has to process therefore improving efficiency

the overall goal is to reduce inflectional forms and sometimes derivationally related forms of a word to a common base form

two popular normalization techniques are ***lemmatization*** and ***stemming***



Lemmatization vs. Stemming

Lemmatization

the process of reducing words to their base word
(takes more time)

Stemming

the process of reducing words to their word stem or root form
by removing word endings or other affixes
(takes less time)

Example

the term *better* has the lemma *good*

Example

the term *flooding* has the stem *flood*

For a great rundown of this topic, avoid the syntax and read over Text Normalization for Natural Language Processing (NLP)



Sentence

My friend had a beautiful singing voice

Lemmatization

my friend have a beautiful singing voice

Stemming

my friend had a beauti sing voic



Tokenizing Handled Data

A process of distinguishing and classifying sections of a string of input characters

What you should take from this is that **unnesting** data successfully is a requirement to be able to **tokenize**. While the next set of commands should look familiar, please consider taking a bit of time to really see what occurs in each step

```
exwdogs_cleaned %>%
  unnest_tokens(word, text) %>%
  anti_join(stop_words) %>%
  count(word, sort = TRUE) %>%
  add_column(document = 1)                                ## Joining, by = "word"
#> # A tibble: 690 × 3
#>   word      n document
#>   <chr>     <int>    <dbl>
#> 1 temple     16        1
#> 2 feel       11        1
#> 3 eye        10        1
#> 4 care        9        1
#> 5 animal      8        1
#> 6 tail        8        1
#> 7 sense       7        1
#> 8 canine       6        1
#> 9 emotional    6        1
#> 10 hear       6        1
#> # ... with 680 more rows
```





Assign a Variable

Let's save the tokenized data frame

```
exwdogs_tokens <-  
  exwdogs_cleaned %>%  
  unnest_tokens(word, text) %>%  
  anti_join(stop_words) %>%  
  count(word, sort = TRUE) %>%  
  add_column(document = 1)  
  
## Joining, by = "word"
```



Step 3: Statistical Classification and Modeling

```
exwdogs_tokens %>%
  cast_dtm(document, word, n) ## <<DocumentTermMatrix (documents: 1, terms:
## Non-/sparse entries: 690/0
## Sparsity           : 0%
## Maximal term length: 19
## Weighting          : term frequency (tf)
```





Assigning a Variable

```
exwdogs_dtm <-  
  exwdogs_tokens %>%  
  cast_dtm(document, word, n)
```

```

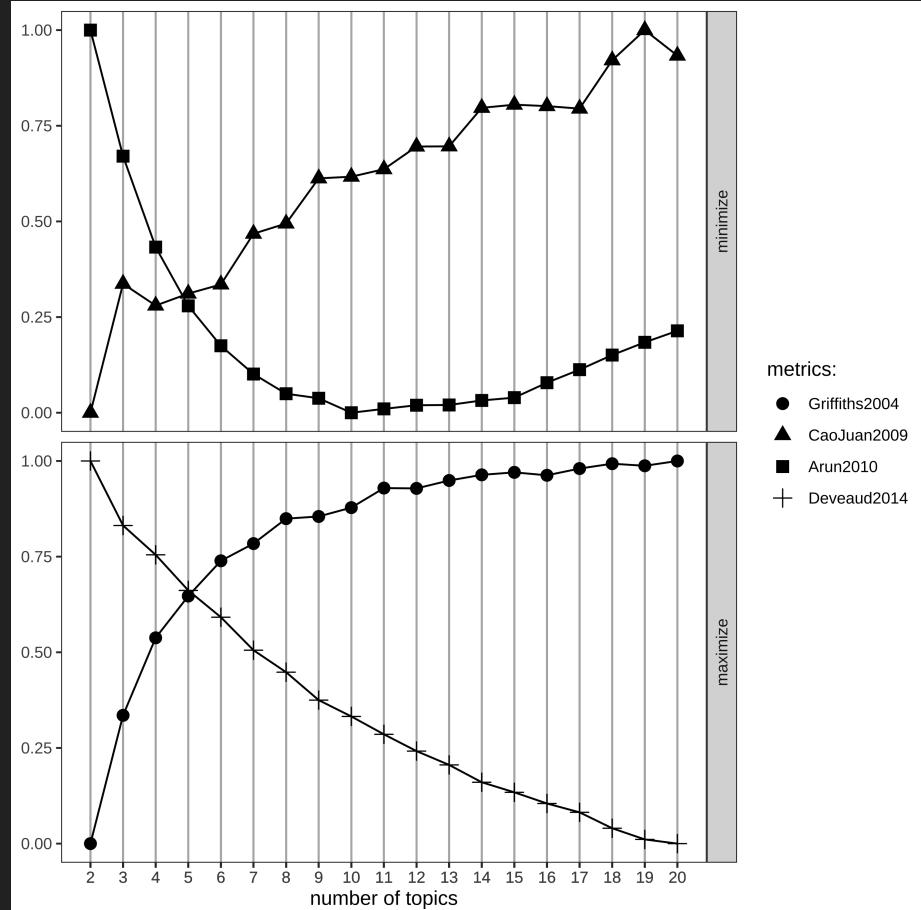
FindTopicsNumber(
  exwdogs_dtm,
  topics = seq(from = 2, to = 20, by = 1),
  metrics = c("Griffiths2004",
             "CaoJuan2009",
             "Arun2010",
             "Deveaud2014"),
  method = "Gibbs",
  control = list(seed = 77),
  mc.cores = 2L,
  verbose = TRUE
) %>%
  FindTopicsNumber_plot()

```

```

## fit models... done.
## calculate metrics:
## Griffiths2004... done.
## CaoJuan2009... done.
## Arun2010... done.
## Deveaud2014... done.

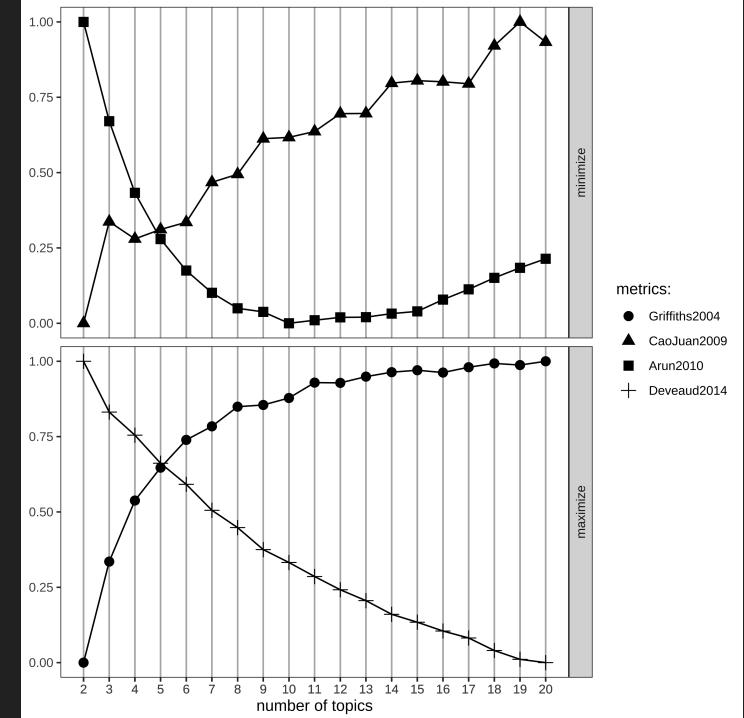
```



Assigning a Variable



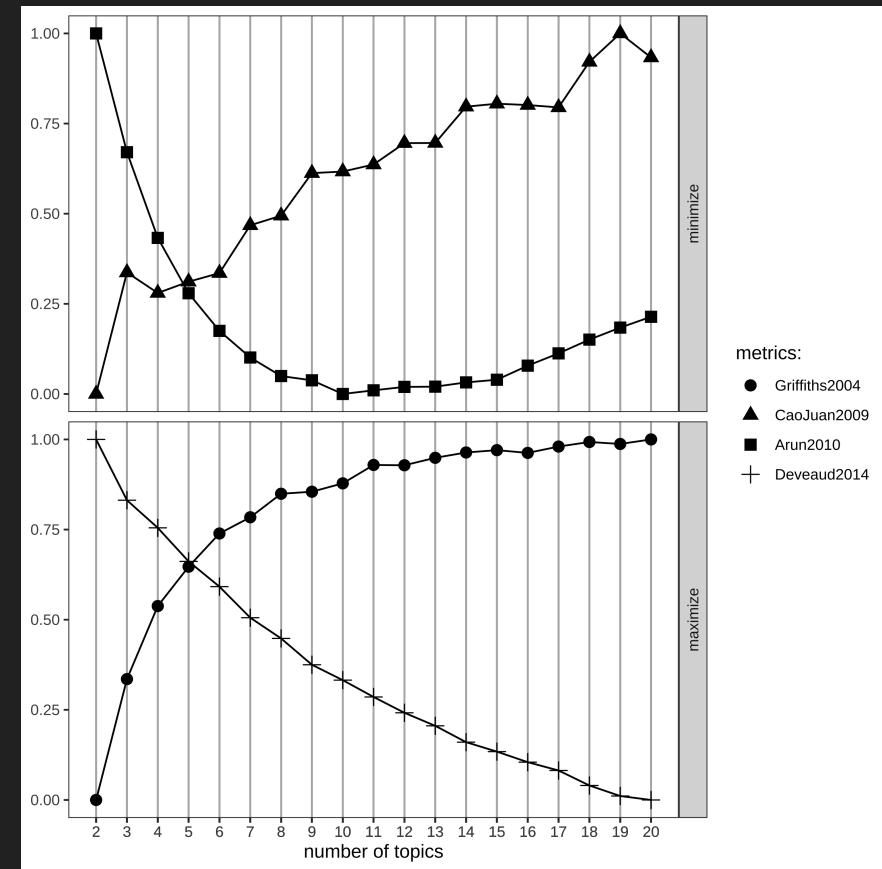
```
exwdogs_topic_est <-
  FindTopicsNumber(
    exwdogs_dtm,
    topics = seq(from = 2, to = 20, by = 1), # amend these
    metrics = c("Griffiths2004",
               "CaoJuan2009",
               "Arun2010",
               "Deveaud2014"),
    method = "Gibbs",
    control = list(seed = 77),
    mc.cores = 2L,
    verbose = TRUE
  ) %>%
  FindTopicsNumber_plot()
```



The estimate for a total number of topics can be a lowest single value or range of values. We do this by observing where the metric curves tend to plateau and get as close to each other as possible along the horizontal axis. This is known as a limit

From the plot, the metrics symbolized by Δ and $+$ are already diverging from each other. While they may head back towards the horizontal axis in the future, the metrics symbolized by \square and \circ look to be the closest between 11 and 15

So let's start by modeling 11 topics!



```
LDA(exwdogs_dtm,  
    k = 11, # Number of topics  
    control = list(seed = 1234)) %>%  
tidy(matrix = "beta")
```

```
## # A tibble: 7,590 × 3  
##   topic term      beta  
##   <int> <chr>     <dbl>  
## 1     1 temple 0.0165  
## 2     2 temple 0.0221  
## 3     3 temple 0.0191  
## 4     4 temple 0.00465  
## 5     5 temple 0.0204  
## 6     6 temple 0.0173  
## 7     7 temple 0.00208  
## 8     8 temple 0.0247  
## 9     9 temple 0.0198  
## 10    10 temple 0.00473  
## # ... with 7,580 more rows
```





Assigning a Variable

Let's save the topics list

```
exwdogs_topics <-  
  LDA(exwdogs_dtm,  
    k = 11, # Amend this to test a certain number of topics  
    control = list(seed = 1234)) %>%  
  tidy(matrix = "beta")
```

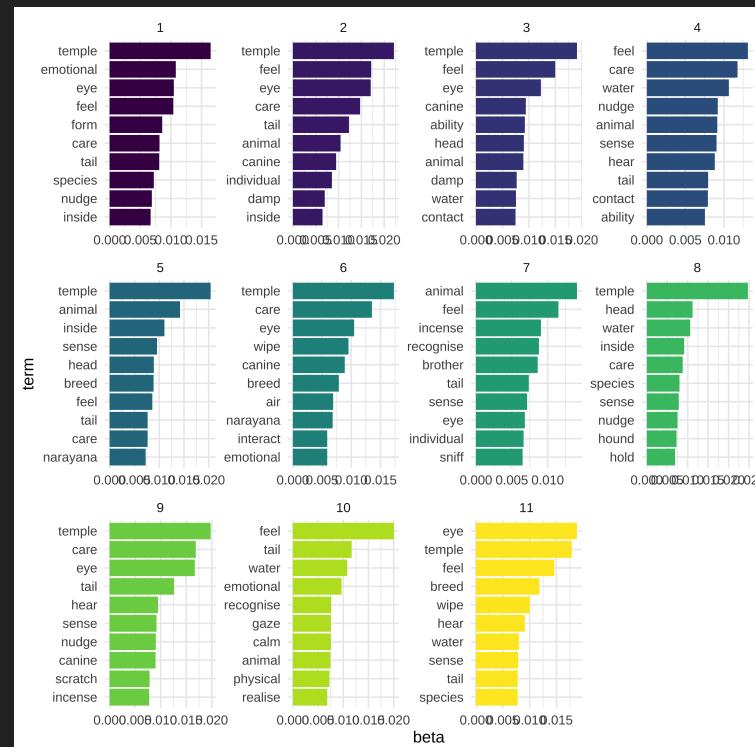


Step 4: Visualization and Interpretation

```

exwdogs_topics %>%
group_by(topic) %>%
slice_max(beta, n = 10) %>%
ungroup() %>%
arrange(topic, -beta) %>%
mutate(term = reorder_within(term, beta, topic)) %>%
ggplot(aes(beta, term, fill = factor(topic))) +
geom_col(show.legend = FALSE) +
scale_fill_viridis_d() +
facet_wrap(~ topic, scales = "free") +
scale_y_reordered() +
theme_minimal()

```





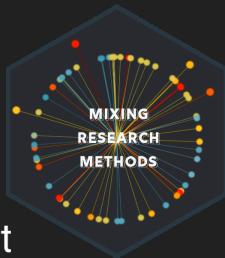
Assigning a Variable

Let's save the plot

```
exwdogs_top_terms <-
  exwdogs_topics %>%
  group_by(topic) %>%
  slice_max(beta, n = 10) %>%
  ungroup() %>%
  arrange(topic, -beta) %>%
  mutate(term = reorder_within(term, beta, topic)) %>%
  ggplot(aes(beta, term, fill = factor(topic))) +
  geom_col(show.legend = FALSE) +
  scale_fill_viridis_d() +
  facet_wrap(~ topic, scales = "free") +
  scale_y_reordered() +
  theme_minimal()
```



You can save high (or really any) resolution visuals easily using `ggsave`



What Just Happened?

LDA is a form of (unsupervised) learning that views documents as bags-of-words (BoW) where order does not matter. Not having to track the placement of every term saves a lot of time and computational energy

LDA works by first making a key assumption: the way a document was generated was by picking a set of topics and then for each topic picking a set of words



Steps to Finding Topics

In a nutshell for each document m

1. Assume there are k topics across all of the documents
2. Create a distribution α where the k topics are symmetric or asymmetrically spread across each document m by assigning each word a topic
3. For each word w in every document m , assume its topic is associated incorrectly but every other word is assigned the correct topic
4. Probabilistically assign word w a topic based on two things:
 - what topics are in document m
 - Create a distribution β to assess how many times word w has been assigned a particular topic across all of the documents
5. Repeat this process a number of times for each document until saturation



Interpret

Much like you would assess a factor or component, the topics are unlabeled and it is up to you to figure out what they could mean. Not every topic may be directly applicable, but should still be interpreted and reported. Discarding topics means that you are removing potentially relevant information

Here is a brief assessment of some possible topics that are represented in the topic model with reference to *dogs*



Topic	Label
1	assessing humans' emotional states
2	adressing the needs of crying people
3	eye contact between humans and dogs
4	ability to care for humans
5	aptitude to sense others emotional states without being physically present
6	physically removing emotional artifacts
7	ability to read the world through smell
8	skill in refocusing attention on them
9	need for physical touch
10	focusing attention via the use of staring
11	senses and responses affect on emotional states

Your assessment would likely differ to varying degrees and that is the point - in that qualitative concepts such as triangulation and saturation still play a large and impactful role in the interpretation phase. Note with a much larger text data set, this task could be significantly easier



That's It!

Any questions?



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