Lesson 9 - Topics Models

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Language Topics Discussed

- Expansion of semantic vector models into Topics Models
- Types of relations
- How to differentiate topics and other models

Topics Background

- What does it take to understand a sentence?
  - Retrieving concepts from memory
  - Dynamic process based on incoming information
  - Use the semantic context to create a “gist” representation

Topics Background

- Pulling the right information from memory can be improved by predicting what concepts are going to be relevant (expectancy generation)
  - For example, *bank* might prime *federal* and *reserve*
  - However, multiple senses can sometimes make this difficult
  - Gist representation allows us to create an overarching topic to disambiguate sense

Topics Background

- Four types of ways to think about relation:
  - Word-concept: knowledge that a word refers to some concept (physical letters dog refer to dog)
  - Concept-concept: knowledge that a concept is related to some other concept (dog is a type of animal)
  - Concept-precept/action: knowledge about what a concept looks like or does (dogs are furry and bark)
  - Word-word: knowledge that the word co-occurs with another word (dog-cat)

Topics Background

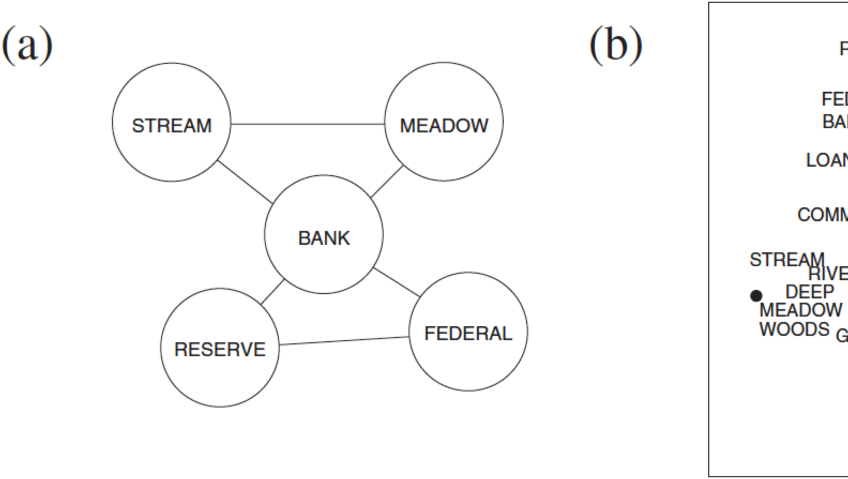


Figure 1. Approaches to semantic represen

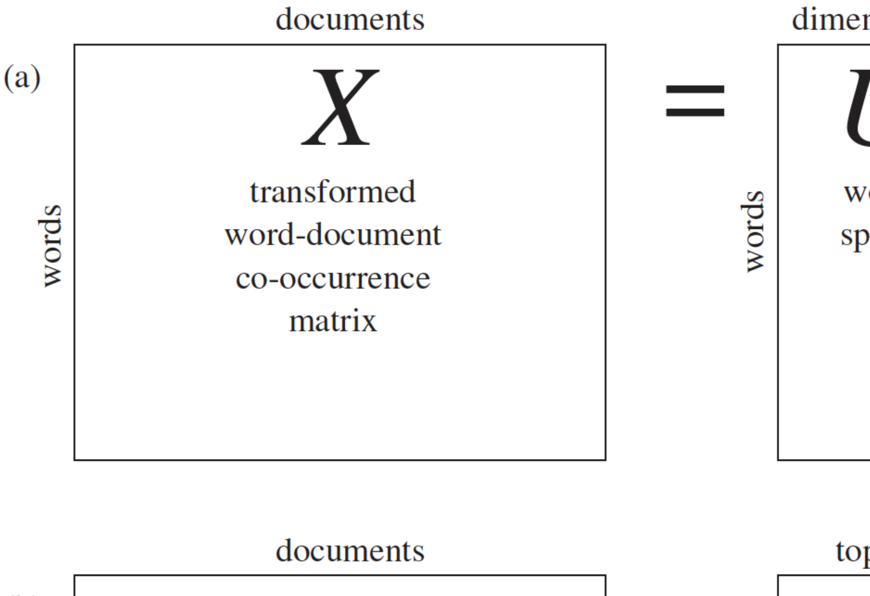
Topics Background

- These are useful to understand, because they predict different ways to think about semantic memory.
- What are people doing when they read a sentence and how can we represent that?
  - Translating words to concepts and using background knowledge to pull in other related concepts
  - Using word co-occurrence to predict the next words

Topics Background

- What do topics models propose people do?
  - Predict: people predict the next word or concept because it helps with retrieval
  - Disambiguation: of senses or meanings of words
  - Gist: creating a coherent representation of the text (mental model not individual words)

Topics Background



Other thoughts

- Topics modeling could allow us to reveal topics present in text
- OR find ways to sort various texts into different groups
- Similar to clustering, classification, finds the natural groups in the corpus

A little bit of math

- Latent Dirichlet allocation (LDA) is the most popular math
- Estimates topics based on the idea that every document includes a mix of topics, and every topic includes a mix of words
- That specification allows topics to overlap, such that they might have some of the same words/content
- LDA is the middle group that finds both the words for each topic and the topics for each document

Getting started with raw data

- First, you would need to load the libraries for the Topic Modeling packages:

```
library(tm)
library(topicmodels)
library(tidyverse)
library(tidytext)
library(slam)
```

Load a dataset or corpus

- Then, you could load a dataset you are interested in working with:

```
importdf = read.csv('exam_answers.csv', header = F, strings
```

Convert to a Corpus

- From these documents, we will create a corpus (a set of text documents).
- Because our data is in one column in our dataset, we will use `VectorSource()` to create the corpus:

```
import_corpus = Corpus(VectorSource(importdf$V1))
```

Clean up the text

- When you perform these analyses, you usually have to edit the text.
- Therefore, we are going to lower case the words, take out the punctuation, and remove English stop words (like *the, an, a*).
- This step will also transform the documents in a term (words) by document matrix.

Clean up the text

```
import_mat =
  DocumentTermMatrix(import_corpus,
           control = list(stemming = TRUE, #create root wo
                          stopwords = TRUE, #remove stop wo
                          minWordLength = 3, #cut out smal
                          removeNumbers = TRUE, #take out t
                          removePunctuation = TRUE)) #take
```

Weight the matrix

- Then you would want to weight that matrix to help control for the sparsity of the matrix.
- That means you are controlling for the fact that not all words are in each document, as well as the fact that some words are very frequent.
- Then you usually ignore very frequent words and words with zero frequency.

Weight the matrix

```
#weight the space
import_weight = tapply(import_mat$v/row_sums(import_mat)[in
                       import_mat$j,
                       mean) *
  log2(nDocs(import_mat)/col_sums(import_mat > 0))

#ignore very frequent and 0 terms
import_mat = import_mat[ , import_weight >= .1]
import_mat = import_mat[ row_sums(import_mat) > 0, ]
```

Parameters and terms

- Alpha: a measure of the number of topics; low scores indicate a few dominant topics per document, high scores indicate more
- Beta: a measure of the number of words, low scores indicate each topic only composes of a few words
- Gamma: probability of that topic in that document
- Entropy: a measure of randomness

A bit more math

- There are several model types:
  - The LDA Fit model is an analysis with VEM (variational expectation-maximization) algorithm and estimating an alpha.
    - The LDA Fixed model using the VEM algorithm with a fixed alpha value.
    - Last, the LDA Gibbs option uses a Gibbs (Bayesian) algorithm to fit the data.
    - CTM stands for correlated topics models, which allows the correlation between topics, and this method uses a VEM algorithm.

Run the models

- First, you will pick a number of expected topics - which is the k option.
- The SEED should be a random number to start the analysis on.

```
k = 3 #set the number of topics

SEED = 2010 #set a random number

LDA_fit = LDA(import_mat, k = k,
              control = list(seed = SEED))

LDA_fixed = LDA(import_mat, k = k,
                control = list(estimate.alpha = FALSE, seed
```

Run the models

```
LDA_gibbs = LDA(import_mat, k = k, method = "Gibbs",
                control = list(seed = SEED, burnin = 1000,
                               thin = 100, iter = 1000))

CTM_fit = CTM(import_mat, k = k,
              control = list(seed = SEED,
                             var = list(tol = 10^-4),
                             em = list(tol = 10^-3)))
```

Get the alpha values

- You can then get the alpha values, and smaller alpha values indicate higher percentages of documents that were classified to one single topic.

```
LDA_fit@alpha
```

```
## [1] 0.05846617
```

```
LDA_fixed@alpha
```

```
## [1] 16.66667
```

```
LDA_gibbs@alpha
```

```
## [1] 16.66667
```

Get the entropy values

- You can also get entropy values where higher values indicate that topics are evenly spread.

```
sapply(list(LDA_fit, LDA_fixed, LDA_gibbs, CTM_fit),
       function (x)
         mean(apply(posterior(x)$topics, 1, function(z) - s
```

```
## [1] 0.2402260 1.0920326 1.0946644 0.5894953
```

The actual topics

- The topic matrix indicates the rank of the number of topics for each document.
- For instance, if you select to estimate 5 topics, you will see see which topic is covered most in each document, with less covered topics ranked lower.
- Therefore, a score set of 5, 3, 1, 2, 4 indicates that the 5th topic was covered most in that document, and the 4th topic was covered least.

The actual topics

```
topics(LDA_fit, k)
```

```
##      1 2 3 4 5 6 7 8 9 10 11 14 15 16 17 18 19 20 21 22
## [1,] 3 3 1 3 3 1 1 1 2  1  1  2  3  2  3  1  3  3  1  2
## [2,] 2 1 3 1 1 2 3 2 1  3  2  1  1  1  2  2  1  1  2  1
## [3,] 1 2 2 2 2 3 2 3 3  2  3  3  2  3  1  3  2  2  3  3
##      30 31 32 33 34 35 36 37 38 39 40 41 42
## [1,]  1  1  1  3  2  2  3  2  2  1  2  2  2
## [2,]  2  3  3  1  3  1  1  1  1  2  1  1  3
## [3,]  3  2  2  2  1  3  2  3  3  3  3  3  1
```

The actual topics

```r
topics(LDA_gibbs, k)
```

```
##       1 2 3 4 5 6 7 8 9 10 11 14 15 16 17 18 19 20 21 22
## [1,] 2 3 1 2 3 1 1 2 2  2  2  2  2  1  1  1  3  1  2  2
## [2,] 1 1 2 1 1 2 2 1 1  1  3  1  1  2  2  2  1  2  3  1
## [3,] 3 2 3 3 2 3 3 3 3  3  1  3  3  3  3  3  2  3  1  3
##      30 31 32 33 34 35 36 37 38 39 40 41 42
## [1,]  1  3  1  1  2  3  2  2  2  3  3  1  2
## [2,]  2  1  2  3  1  1  1  1  3  1  1  2  1
## [3,]  3  2  3  2  3  2  3  3  1  2  2  3  3
```

```r
##you can do all of them saving space
#topics(LDA_fixed, k)
#topics(CTM_fit, k)
```

The terms for topics

- You can get the most frequent terms for each of the topics that were estimated.

```r
terms(LDA_fit,10)
```

```
##       Topic 1    Topic 2    Topic 3
##  [1,] "top"      "element"  "bike"
##  [2,] "actual"   "observ"   "mean"
##  [3,] "previous" "gorilla"  "success"
##  [4,] "surround" "black"    "ride"
##  [5,] "environ"  "line"     "gorilla"
##  [6,] "dont"     "screen"   "red"
##  [7,] "discuss"  "demonstr" "dont"
##  [8,] "therefor" "flash"    "your"
##  [9,] "hand"     "lead"     "environ"
## [10,] "rememb"   "monitor"  "effici"
```

The terms for topics

```
terms(LDA_gibbs,10)
```

```
##       Topic 1    Topic 2            Topic 3
##  [1,] "mean"     "gorilla"          "bike"
##  [2,] "dont"     "observ"           "success"
##  [3,] "environ"  "surround"         "ride"
##  [4,] "element"  "hand"             "actual"
##  [5,] "top"      "therefor"         "previous"
##  [6,] "rememb"   "your"             "red"
##  [7,] "screen"   "attentioncontrol" "black"
##  [8,] "act"      "demonstr"         "discuss"
##  [9,] "although" "lead"             "line"
## [10,] "close"    "neutral"          "monitor"
```

```
##again you can do all of them
#terms(LDA_fixed, 10)
#terms(CTM_fit,10)
```

Make some pretty plots

```r
#use tidyverse to clean up the the fit
LDA_fit_topics = tidy(LDA_fit, matrix = "beta")

#create a top terms
top_terms = LDA_fit_topics %>%
  group_by(topic) %>%
  top_n(10, beta) %>%
  ungroup() %>%
  arrange(topic, -beta)
```

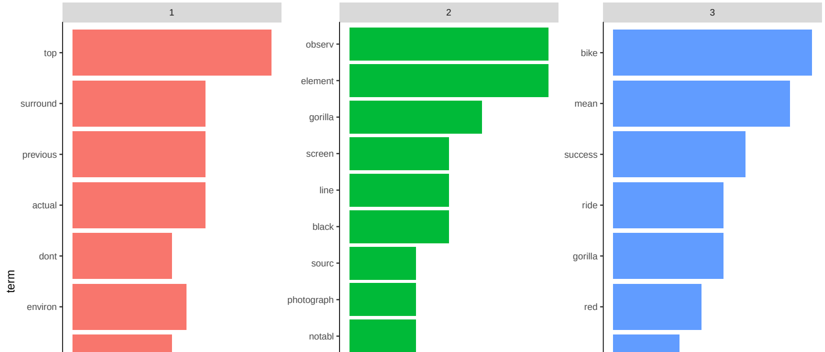
Make some pretty plots

- Some code to clean up the ggplot2 defaults

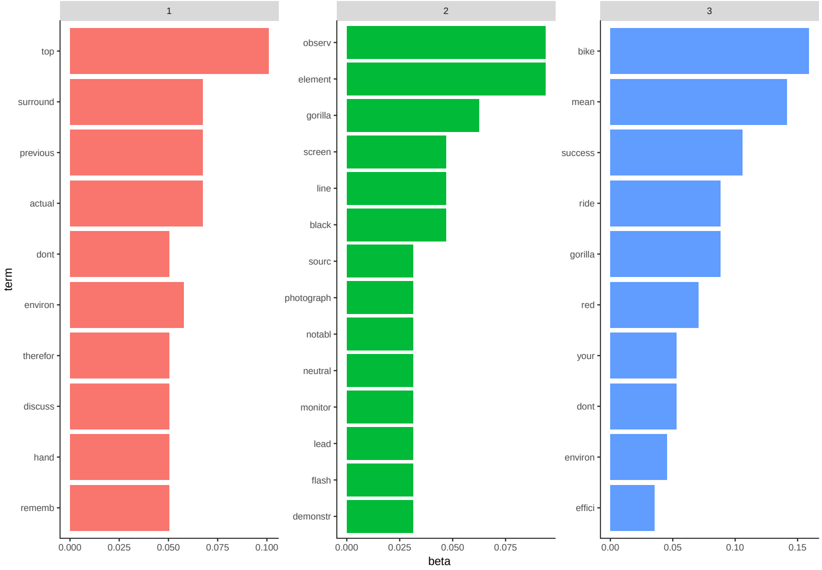
```
cleanup = theme(panel.grid.major = element_blank(),
                panel.grid.minor = element_blank(),
                panel.background = element_blank(),
                axis.line.x = element_line(color = "black"),
                axis.line.y = element_line(color = "black"),
                legend.key = element_rect(fill = "white"),
                text = element_text(size = 10))
```

Make some pretty plots

```
#make the plot
top_terms %>%
  mutate(term = reorder(term, beta)) %>%
  ggplot(aes(term, beta, fill = factor(topic))) +
  geom_bar(stat = "identity", show.legend = FALSE) +
  facet_wrap(~ topic, scales = "free") +
  cleanup +
  coord_flip()
```



The plot



1
2
3
term
beta
top
surround
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actual
dont
environ
therefor
discuss
hand
rememb
observ
element
gorilla
screen
line
black
sourc
photograph
notabl
neutral
monitor
lead
flash
demonstr
bike
mean
success
ride
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0.000
0.025
0.050
0.075
0.100
0.000
0.025
0.050
0.075
0.00
0.05
0.10
0.15

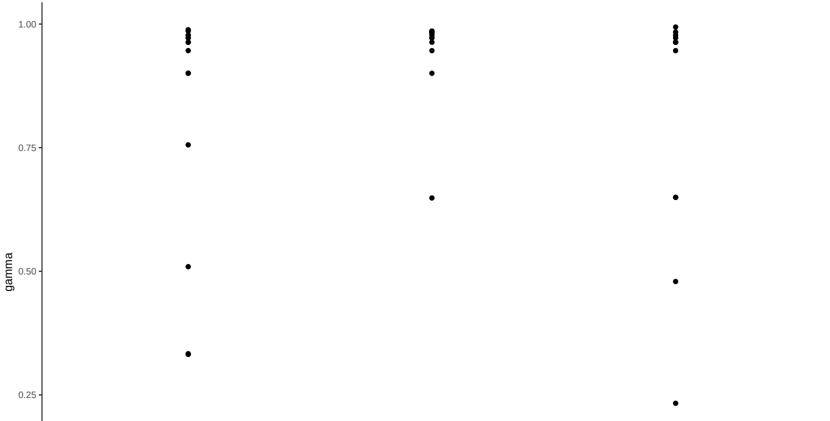
Document classification

- We saw earlier with the `topics()` function, we could figure out the most to least likely topics.
- This matrix is organized by gamma, which is the probability of that topic in for each document.
- Let's visualize those numbers.

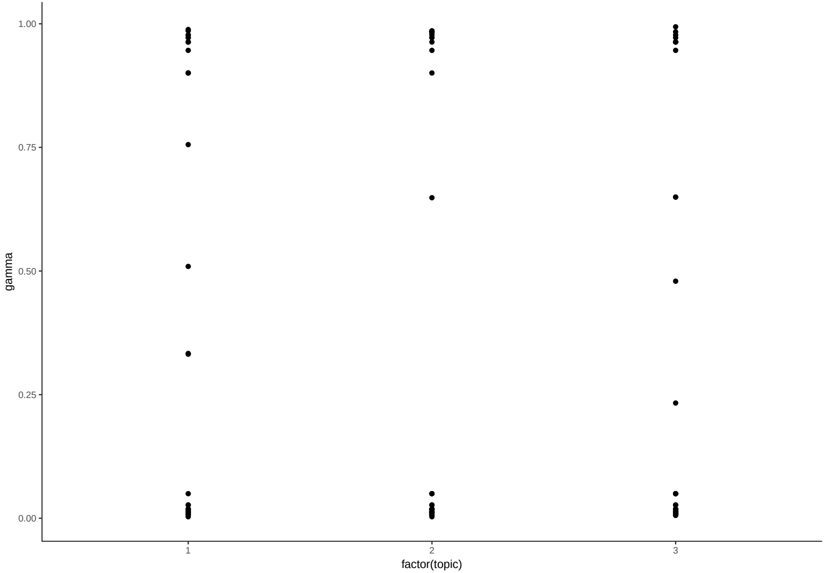
Document classification

```
LDA_gamma = tidy(LDA_fit, matrix = "gamma")

LDA_gamma %>%
  ggplot(aes(factor(topic), gamma)) +
  geom_point() +
  cleanup
```



Document classification



Summary

- We explored how the theoretical background for topics models is different than other semantic vector space models.
- We talked about how to build topics models with various settings.
- We talked about the output you can pull from a topic model.
- Extensions can be made to unsupervised classification and clustering.