Social Science Methods for Lawyers: Text Analysis

A Survey of Text Analysis Methods

Joshua C. Fjelstul, Ph.D.

Post-Doctoral Research Fellow, University of Geneva

Researcher, ARENA Centre for European Studies, University of Oslo

What are we going to cover in this workshop?

- What is text analysis? What methods does it include?
- How does text analysis relate to statistics, machine learning (ML), and natural language processing (NLP)?
- How can we use text analysis to study international legal texts?
- How can we implement some basic text analysis tools in R?

What is quantitative text analysis?

- Quantitative text analysis is the use of quantitative methods to analyze the content of documents

Levels of analysis

- Corpus
- Documents
  - Books, documents, judgments, speeches, tweets
- Paragraphs
- Sentences
- Words

Assumptions

- The content of text reveals something meaningful and interesting about the author that we can use to answer research questions
- Text can be represented by features (words, lemmas, *n*-grams)
- The relative distribution of words in documents captures meaningful variation in topics and substantively important latent dimensions
  - We make a matrix called a document feature matrix (DFM) with words in columns, documents in rows, and frequencies in cells that describe these distributions
  - This might seem unsatisfactory
  - Some kinds of neural networks can take into account word order
  - Taking into account word order adds a lot of complexity but doesn't usually change things much

Types of quantitative text analysis

- Frequency analysis
  - What words/tokens are important?
  - Descriptive
- Similarity
  - How similar are documents/paragraphs/sentences?
  - Descriptive
- Scaling
  - How do documents/paragraphs/sentences compare on a continuous latent dimension?
  - Inferential (statistical models, machine learning models)
- Classification
  - How do documents/paragraphs/sentences cluster into discrete groups?
  - Inferential (statistical models, machine learning models)

Natural language processing (NLP)

- Text analysis overlaps with NLP — using computers to process and analyze language
  - Language processing
    - Optical character recognition (OCR)
    - Speech recognition
  - Morphology
    - Lemmatization
    - Stemming
    - Part-of-speech (POS) tagging
  - Semantics
    - Sentiment analysis
    - Named entity recognition
    - Word-sense disambiguation
  - High-level tasks
    - Machine translation
    - Natural language generation
    - Question answering

Machine learning (ML)

- Machine learning is the use of algorithms to predict outcomes based on data
- Algorithms learn the relationship between input data and labels based on training data and then make predictions for unseen data
- Quantitative text analysis is an application of ML to text data

Learning

- Supervised learning
  - Train a scaling/classification model on a pre-defined dimension using pre-coded training data
- Unsupervised learning
  - Train a scaling/classification model to endogenously learn an underlying dimension or categories using training data

Learning

- Supervised learning
  - Advantages
    - You already know the topics/dimensions so you know how to interpret your estimates
  - Disadvantages
    - It requires labeled training data (a lot of work)
    - You have to know ahead of time what the relevant topics/dimensions are
- Unsupervised learning
  - Advantages
    - You can explore naturally occurring topics and primary latent dimensions
    - You don't have to create labeled training data
  - Disadvantages
    - You have to validate that the topics/dimensions you uncover are meaningful and you have to figure out how to interpret them
    - You might not find meaningful topics/dimensions (or the ones you expect)
    - Unsupervised methods are harder to learn

Parametric vs non-parametric models

- Scaling and classification models can be parametric or non-parametric
- Parametric models overlap with statistics and involve estimating the values of parameters that you can interpret to learn about the content of documents
- Non-parametric methods overlap with machine learning and depend on complex algorithms to learn the relationship between text data and labels

Classification

- Supervised methods for text
  - Naive Bayes classifier (non-parametric)
  - Regression classifiers (parametric)
  - Random forests (non-parametric)
  - Neural networks (non-parametric)
  - Support vector machines (SVM) (non-parametric)
- Unsupervised methods for text
  - Latent Dirichlet allocation (LDA) (parametric)
  - Seeded LDA (parametric)
  - Structural topic models (STM) (parametric)

Scaling

- Supervised
  - Wordscores
- Unsupervised
  - Correspondence analysis (non-parametric) (dimensionality reduction)
  - Latent semantic analysis (non-parametric) (dimensionality reduction)
  - Wordfish (parametric)

Topic models

- Topics models are unsupervised methods for identifying naturally occurring topics in documents
- The most common type of topic model is latent Dirichlet allocation (LDA)
- It assumes that documents are mixtures of topics and that topics are mixtures of words
- Documents are not sorted into discrete categories
- A topic is a distribution of words
- The goal is to figure out which words are associated with which topics and which topics make up each document

Topic models

- You have to tell the model how many topics to find
- You can look at the words that are most strongly associated with each topic
- Based on that list of words, we can label each topic
- Some topics will be more distinct that others
- If topics overlap too much, we may need fewer topics
- It topics are not distinct, we may need more topics
- The model estimates the probability that each topic applies to each document

Word scores

- Supervised scaling method
- You start with a set of reference texts
- These need to represent the two poles of your latent dimension
- The reference texts are like a training set
- You calculate word scores based on the reference text and then use them to score the rest of the texts
- Each document will have a single score that represents its position on the latent dimension

Word scores

- Advantages
  - After you choose the reference text, it's fully automated
  - It scales all documents between the references texts at each end of the dimension
- Disadvantages
  - It really matters which documents you use as the reference texts
  - The dimension you define by choosing the reference texts may not be the dimension that explains the most variation in the content of your documents
  - It's hard to choose the most extreme documents without a lot of knowledge about the content of documents (hard when there are a lot)

Wordfish (intuition)

- Unsupervised scaling method
- The input data is a DFM
- We don't have to know the underlying dimension ahead of time
- So we have to show that our estimates capture a meaningful latent dimension
- Based on a poison distribution
  - The poisson distribution models counts of discrete events — like the occurrence of words in a document
  - Wordfish is a type of poisson scaling model

Wordfish (equation)

- The model equation is:

  $$log\lambda_{ij} = \alpha_i + \theta_i\beta_j + \phi_j$$

- Parameters:
  - λ_{ij} is the expected frequency of a word *i* in document *j*
  - *i* indexes documents
  - *j* indexes words
  - θ_i is the latent position of document *i* that we want to estimate
  - β_j is the latent position of word *j* (the strong of the relationship between the latent dimension and the frequency)
  - α_i is a document fixed effect (controls for how long each document is)
  - ϕ_j is a word fixed effect (controls for how common/rare each word is)
- We can estimate standard errors and construct confidence intervals for each parameter to express uncertainty, just like with a regression model

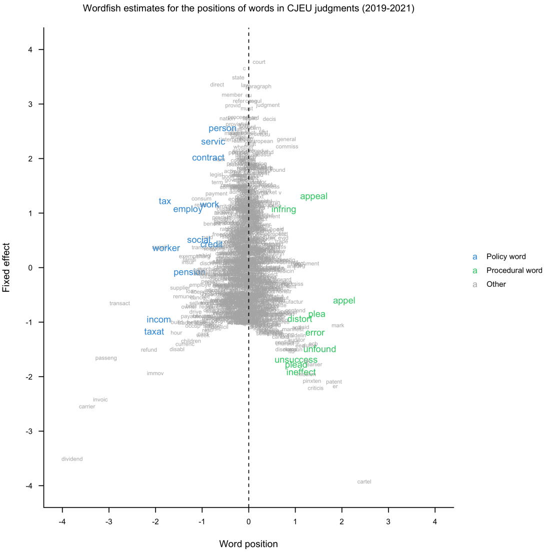
Wordfish (estimation)

- On the right-hand side of a regression equation, we have data and parameters
- The data is constant and we estimate the parameters
- But here, there's no data on the right-hand side, so what do we do?
  - We start with random values for all of the parameters
  - We hold ϕ and β (the word parameters) constant and estimate α and θ (the document parameters)
  - Then we hold α and θ (the document parameters) constant and estimate ϕ and β (the word parameters)
  - And we iterate back and forth
  - This is called expectation-maximization
  - Eventually, we'll converge to good estimates of all parameters

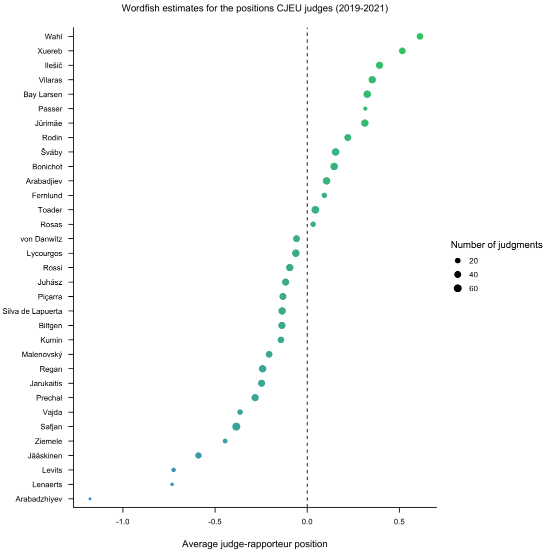
Wordfish (interpretation)

- We can interpret the θ estimates as the position of each document on our latent dimension. This is the main thing we're interested in
- But this is an unsupervised model, so how do we know what the latent dimension is?
  - We can plot the word fixed effects (y-axis) against the word positions (x-axis) to get an idea of what the dimension is
  - Rarer words (lower fixed effect) will be more discriminatory (will provide more information about how documents differ)
  - Words with more extreme positions (x-axis) will define the substantive content of each pole of the latent dimension
  - You have to convince your audience that your latent dimension is meaningful and interesting

Wordfish (word positions)



Wordfish (document positions)



Research questions

- We'll answer two research questions about the content of judgments delivered by the Court of Justice of the European Union (CJEU)
  - To what extent do judges specialize in certain areas of law?
  - What is the primary latent dimension in CJEU judgments? Is it a left/right dimension? Is it a pro-/anti-European integration dimension? Or is it something else, like a policy/procedure dimension?
- We'll use unsupervised and semi-supervised topic models to address the first question and an unsupervised scaling model to address the second question