

# Digital Humanities Across Borders

**Class 8: Topic Modeling**

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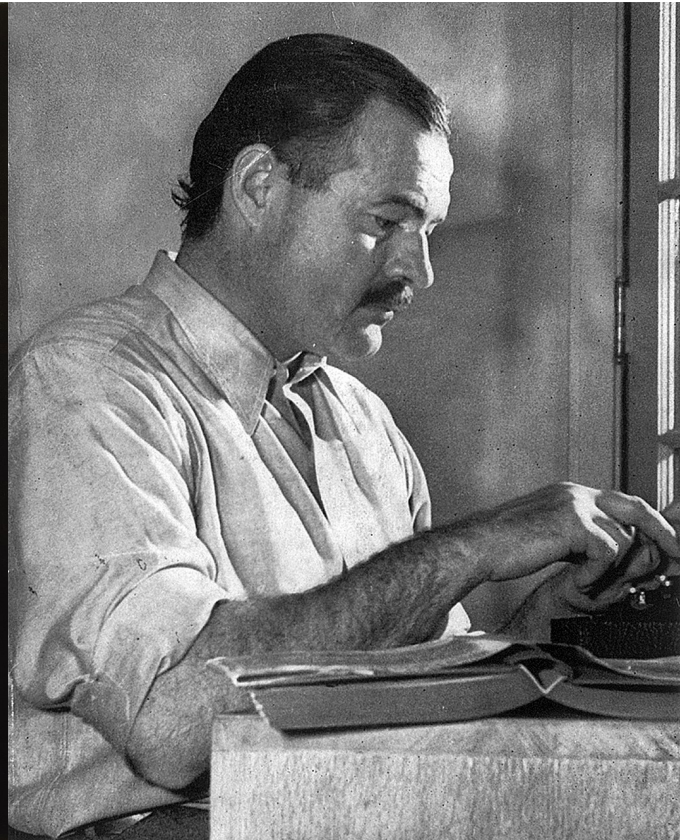
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Topic modeling uncovers the structure of these "topics" by identifying the probability that every word in the text is in a given topic.

# The LDA Buffet

## A parable by Matt Jockers



# How does LDA work?

1. First choose the topics, each one from a distribution over distributions.
2. Then, for each document, choose topic weights to describe which topics that document is about.
3. Finally, for each word in each document, choose a topic assignment — a pointer to one of the topics — from those topic weights and then choose an observed word from the corresponding topic.
4. Each time the model generates a new document it chooses new topic weights, but the topics themselves are chosen once for the whole collection

# tf-idf

## term frequency - inverse document frequency

*"Simply put, a tf-idf score is the frequency of a word multiplied by the total number of documents and divided by the number of documents containing the word"*

- David Hoover



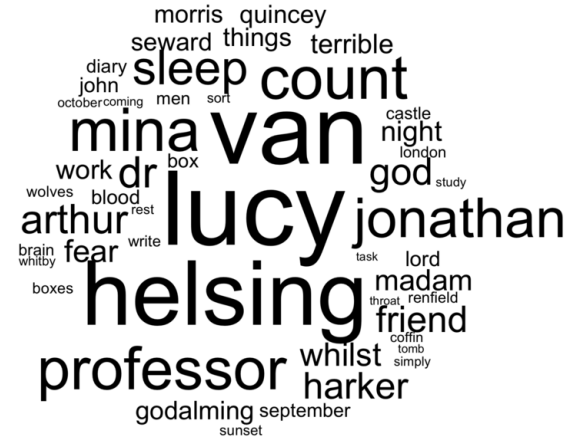
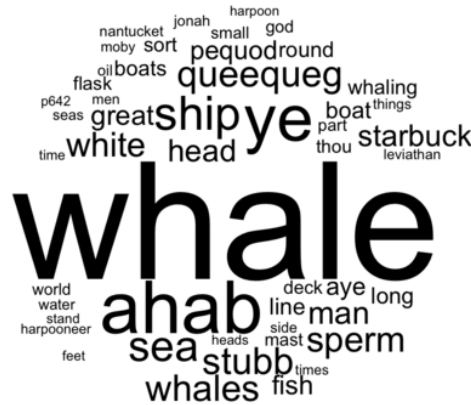
# "It's all text and no subtext"

*The algorithm is constrained by the words used in the text; if Freudian psychoanalysis is your thing, and you feed the algorithm a transcription of your dream of bear-fights and big caves, the algorithm will tell you nothing about your father and your mother; it'll only tell you things about bears and caves.*

-Scott Weingart, <http://www.scottbot.net/HIAL/index.html@p=19113.html>

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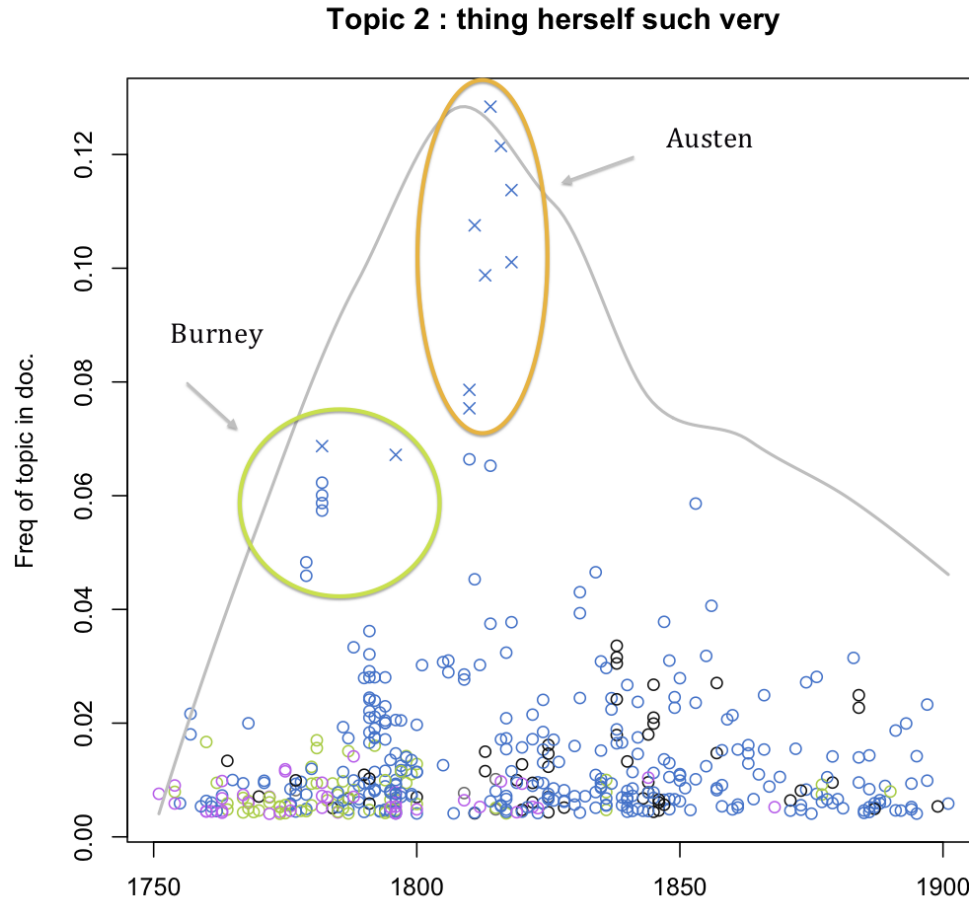
A word cloud shaped like a whale, with the word 'whale' as the largest and most central term. Other prominent words include 'ahab', 'ship', 'ye', 'great', 'white', 'head', 'boat', 'starbuck', 'pequod', 'round', 'queequeg', 'whaling', 'boat', 'part', 'thou', 'leviathan', 'jonah', 'small', 'god', 'nantucket', 'moby', 'sort', 'flask', 'men', 'p642', 'seas', 'time', 'world', 'water', 'stand', 'harpoon', 'feet', 'deck', 'aye', 'long', 'line', 'man', 'side', 'mast', 'sperm', 'stubb', 'times', 'fish', 'whales', 'sea', 'heads', 'world', 'water', 'stand', 'harpoon', 'feet'.

A word cloud shaped like a ship, with the words 'ship', 'boat', 'captain', 'sea', 'deck', 'vessel', and 'board' as the most prominent terms. Other words include 'cabin', 'silver', 'sail', 'sir', 'sailed', 'hands', 'mate', 'water', 'sailors', 'voyage', 'round', 'north', 'land', 'ice', 'shore', 'islands', 'hold', 'boats', 'sailor', 'breeze', 'doctor', 'crew', 'rum', 'coast', 'peters', 'south', 'schooner', 'port', 'men', 'sails', 'began', 'cap', 'shore', 'weather', 'livesey', 'aboard', 'cook', 'lay', 'brig', 'round', 'north', 'land', 'ice', 'shore'.

A word cloud shaped like a person, with the words 'mina van', 'lucy', 'helsing', and 'professor' as the most prominent terms. Other words include 'morris', 'quincey', 'seward', 'things', 'terrible', 'sleep', 'count', 'diary', 'john', 'october', 'coming', 'men', 'sort', 'castle', 'night', 'london', 'god', 'study', 'work', 'dr', 'box', 'wolves', 'blood', 'rest', 'arthur', 'fear', 'write', 'brain', 'whitby', 'boxes', 'task', 'lord', 'madam', 'thrust', 'renfield', 'coffin', 'tomb', 'simply', 'whilst', 'harker', 'god', 'alming', 'september', 'sunset'.

A word cloud shaped like a person, with the words 'heyward', 'scout', 'indian', 'eye', and 'hawk' as the most prominent terms. Other words include 'munro', 'warrior', 'countenance', 'returned', 'dark', 'trail', 'hurons', 'enemy', 'rifle', 'uncas', 'continued', 'delaware', 'indians', 'men', 'chief', 'woods', 'red', 'friends', 'deer', 'tribe', 'sounds', 'language', 'white', 'air', 'eyes', 'arms', 'warriors', 'huron', 'magua', 'head', 'blood', 'enemies', 'delawares', 'party', 'companions', 'manner', 'exclaimed', 'prisoners', 'demanded', 'nation', 'montcalm', 'chingachgook'.

# Author signal



Blue/fic, purple/poe, green/drama, black/bio, brown/nonfic, triangle/letters or orations.

Graph from Ted Underwood

# Assumptions

*To make topic models present new raw material for humanists to read, analysts generally assume that an individual topic produced by the algorithm has two properties. First, it is coherent: a topic is a set of words that all tend to appear together, and will therefore have a number of things in common. Second, it is stable: if a topic appears at the same rate in two different types of documents, it means essentially the same thing in both. Together, these let humanists assume that the co-occurrence patterns described by topics are meaningful; topics are useful because they describe things that resemble “concepts,” “discourses,” or “fields.”*

- Benjamin Schmidt

# Information retrieval vs. literary analysis

*A poorly supervised machine learning algorithm is like a bad research assistant. It might produce some unexpected constellations that show flickers of deeper truths; but it will also produce tedious, inexplicable, or misleading results. If it is not doing the desired task, it is time to give it some clearer instructions, or to find a new one.*

- Benjamin Schmidt

# Trying out the Topic Modeling Tool

Tutorials by Miriam Posner:

[https://github.com/miriamposner/tmt\\_get\\_started](https://github.com/miriamposner/tmt_get_started)

<http://miriamposner.com/blog/very-basic-strategies-for-interpreting-results-from-the-topic-modeling-tool/>