Day 3 - Text (Advanced)

UMN CSS Workshop 2025

Instructor: Alvin Zhou

Group

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  - Shreepriya Dogra
  - Jialu Fan
- Group 2
  - Jiacheng Huang
  - Paulina Vergara Buitrago
  - Jong Won Lee
  - Eun Sun Kyoung
- Group 3
  - Sijin Chen
  - Michael Ofori
  - Jinny Zhang
  - Dongwook Kim
- Group 4
  - Raj Wahlquist
  - Nicole Marie Klevanskaya
  - Wenhui Cheng
  - Rita Rongwei Tang

- Mixed background and coding skills
- Group members who are confident in their coding skills, please help other members during the afternoon coding labs

Learning Goals

- Learn word embedding
- Understand topic modeling and its use in social science
- Explore creative uses of computational text methods
- Practice using external text APIs and topic modeling

Last Class

- Dictionary-Based Methods
- Traditional Classifier (pre-2020)
  - Create features (independent variables) from text: n-grams (bag of words), metadata (emoji, length), TF-IDF, dictionaries (LIWC, MFD)
    - For example, the text "I love data science! 🧪" can have these features
      - "I": 1, "love": 1, "data": 1, "science": 1, "🧪": 1
      - No. of Characters: 22
      - Punctuation Count: 1
      - "PRP (personal pronoun)": 1, "VBP (verb)": 1, "NN (noun)": 2, "SYM (symbol)": 1
    - The Y (dependent variable) is binary (uncivil/civil; relevant/irrelevant, etc.)
    - Fit different models (e.g., logistic regression with regularization) with training data
    - Evaluate how the model performs
    - Apply the model to the remaining dataset

Limitations of Traditional Features

- Bag of Words and TF-IDF are sparse and high-dimensional
- Vocabulary is rigid: struggles with new/rare words
- Ignores word meaning and semantic similarity
  - “happy” and “joyful” are treated as unrelated
- Doesn’t capture context: “good” ≠ “not good”
- Performance plateaus in many classification tasks

Word Embedding

- Each word is represented by a vector
- Words with similar meanings are close in vector space
- Captures semantic and syntactic similarity
  - “king” – “man” + “woman” ≈ “queen”
  - “love” and “like” have similar embeddings
- The “GloVe 6B 300-dimensional” model from Stanford
  - trained on Wikipedia + Gigaword, in which:
  - "man" → [0.20217, 0.12963, -0.17952, -0.00857, 0.05105, -0.32036, 0.18403, 0.39143, 0.46551, -0.22903, …]
  - cosine_similarity("man", "woman") ≈ high

Why Use Word Embeddings? (post-2020)

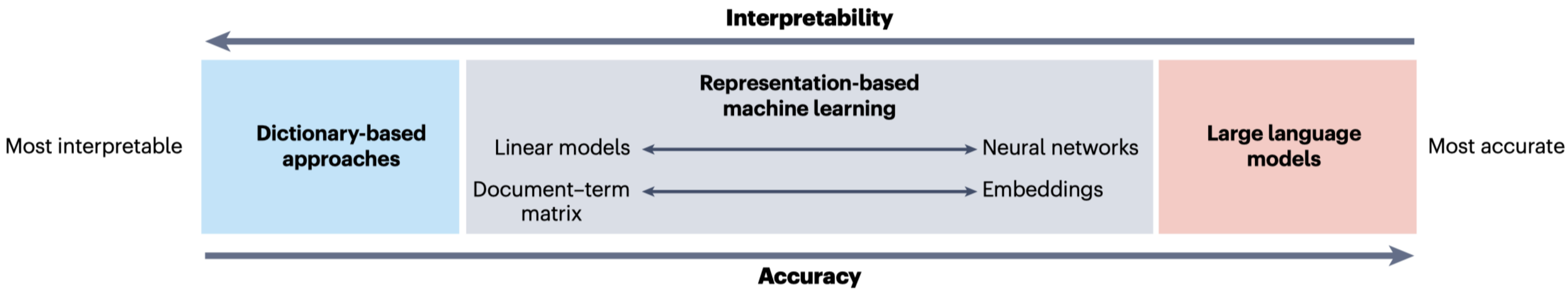
- Low-dimensional: ~100–300 dimensions vs. 10,000s for BoW
- Generalizes across similar terms (e.g., “happy”, “joyful”)
- Pretrained models available (Word2Vec, GloVe, BERT) – simply download to your computer and you are good to go
- Reduces need for manual feature engineering (e.g., L1/L2 regularization)
- Improved performance in many areas of NLP

How Embeddings Are Used in Practice

- Average word vectors for each document, so that one document is represented by a vector. If
  - “man” is [1, 0, 1]
  - “and” is [1, 0, 0]
  - “woman” is [1, 1, 1]
  - A document with “man and woman” is represented as [1, 0.333, 0.666]
- TF-IDF–weighted average
  - If “man” appears too many times in the document, its influence on “averaging word vectors for each document” decreases
- Sentence or document embeddings (e.g., Sentence-BERT)

- **Feed into any classifier (logistic, SVM, NN)**

TF-IDF vs. Word Embedding

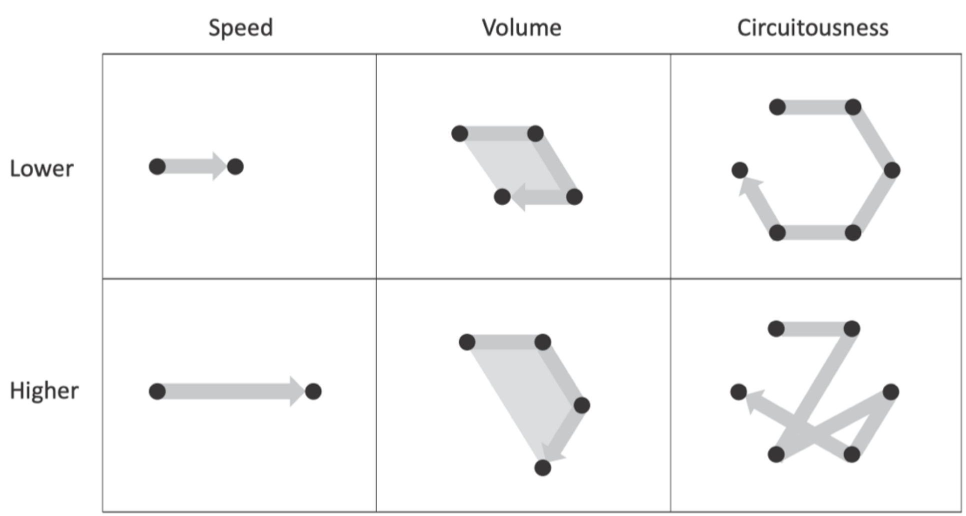


Feature Type	TF-IDF	Word Embedding
Sparse/Dense	Sparse	Dense
Dimensionality	High	Low
Handles Synonyms?	No	Yes
Context-Aware?	No	Sometimes (if BERT)
Pretrained?	Not really	Yes (Word2Vec, GloVe, BERT)
Model Input	Classic ML	ML + DL

Presentation: Toubia et al. (2021)

Presentation: Toubia et al. (2021)

- How quantifying the shape of stories predicts success
- Track emotional arc over time using NLP
- Shape features predict box office revenue
- Social science application: narrative structure & diffusion



You can fine-tune embeddings for your study

- TF-IDF studies usually “start from scratch”
- But studies using embeddings usually grab an existing model and fine-tune it with new data
- “Fine-tuning” means continuing to train a pretrained model on a new, domain-specific corpus, so it adapts to the language and meaning specific to your data.

For Example

- Fine-Tuning GloVe on Social Media
  - Let’s say you’re studying vaccine discourse on Twitter. You start with GloVe (trained on news/Wikipedia), but you want to adapt it to Twitter slang + COVID-specific terms.
  - In Python (conceptually):

```
from gensim.models import Word2Vec
from gensim.models.keyedvectors import KeyedVectors

# Load pretrained word vectors (e.g., from GloVe)
pretrained_model = KeyedVectors.load_word2vec_format("glove.6B.300d.txt", binary=False)

# Load your own corpus (e.g., tokenized tweets)
custom_corpus = [["get", "vaccinated", "bro"], ["vax", "saves", "lives"]]

# Initialize a Word2Vec model with pretrained weights
model = Word2Vec(vector_size=300, window=5, min_count=1)
model.build_vocab(custom_corpus)
model.build_vocab([list(pretrained_model.key_to_index.keys())], update=True)
model.wv.vectors_lockf = np.ones(len(model.wv), dtype=np.float32)  # allows updating
model.wv.intersect_word2vec_format("glove.6B.300d.txt", binary=False, lockf=1.0)

# Fine-tune on your corpus
model.train(custom_corpus, total_examples=len(custom_corpus), epochs=5)
```

For Example

- You get an embedding model that understands “vax,” “jabbed,” “anti-vaxxer” as used in your data, but still retains core semantic structure from GloVe.
- https://pmc.ncbi.nlm.nih.gov/articles/PMC9578521/
  - Our study investigated and compared public sentiment related to COVID-19 vaccines expressed on 2 popular social media platforms—Reddit and Twitter—harvested from January 1, 2020, to March 1, 2022.
  - To accomplish this task, we created a fine-tuned DistilRoBERTa model to predict the sentiments of approximately 9.5 million tweets and 70 thousand Reddit comments. To fine-tune our model, our team manually labeled the sentiment of 3600 tweets and then augmented our data set through back-translation. Text sentiment for each social media platform was then classified with our fine-tuned model using Python programming language and the Hugging Face sentiment analysis pipeline.

You can definitely train it from scratch

- Presentation: Kozlowski et al. (2019)

Presentation: Kozlowski et al. (2019)

- Trained custom Word2Vec embeddings on Google Books Ngram data from each decade (1900–1999)
  - Downloaded the Google Books Ngram corpus, stratified by decade (1900–1999).
  - Trained separate Word2Vec models for each decade.
  - Used these decade-specific embeddings to:
    - Measure how meanings of cultural terms shifted across time.
    - Project words into latent dimensions (e.g., class, gender, affluence) defined by antonym word pairs (e.g., rich vs. poor).

Other Text-Based Methods

- **Choose methods to answer your questions!**
  - Named entity recognition
  - PoS Tagging
  - Topic models

Presentation: Knight (2022)

Presentation: Knight (2022)

- The New York Times (1890–1934) and Wall Street Journal (1905–1934)
  - OCR, 400,000+ articles
- Analyzed “agentic talk” — linguistic indicators that describe corporations as intentional actors (e.g., “decided,” “believed”)
- Named entity recognition (NER) to identify organizations
  - Standard Named Entity Recognizer
  - Authors’ own + manual cleaning
- Parsing
  - “nsubj” - the active subject in a sentence
  - Stanford Tagger + manual cleaning
- Dictionary for Verbs
  - Harvard General Inquirer database
  - “cognitive orientation” and “communicating”
- STM

Topic Models

- An unsupervised method to discover hidden thematic structure
  - “what do these documents/text talk about?”
- Useful for exploratory analysis when labels aren't available
- Widely popular in social sciences

Basic Logic of Topic Modeling

- Three Levels:
  - Documents
  - Topics
  - Words

- Documents are composed of multiple topics, with weights
- Each topic is described by a set of words, with weights

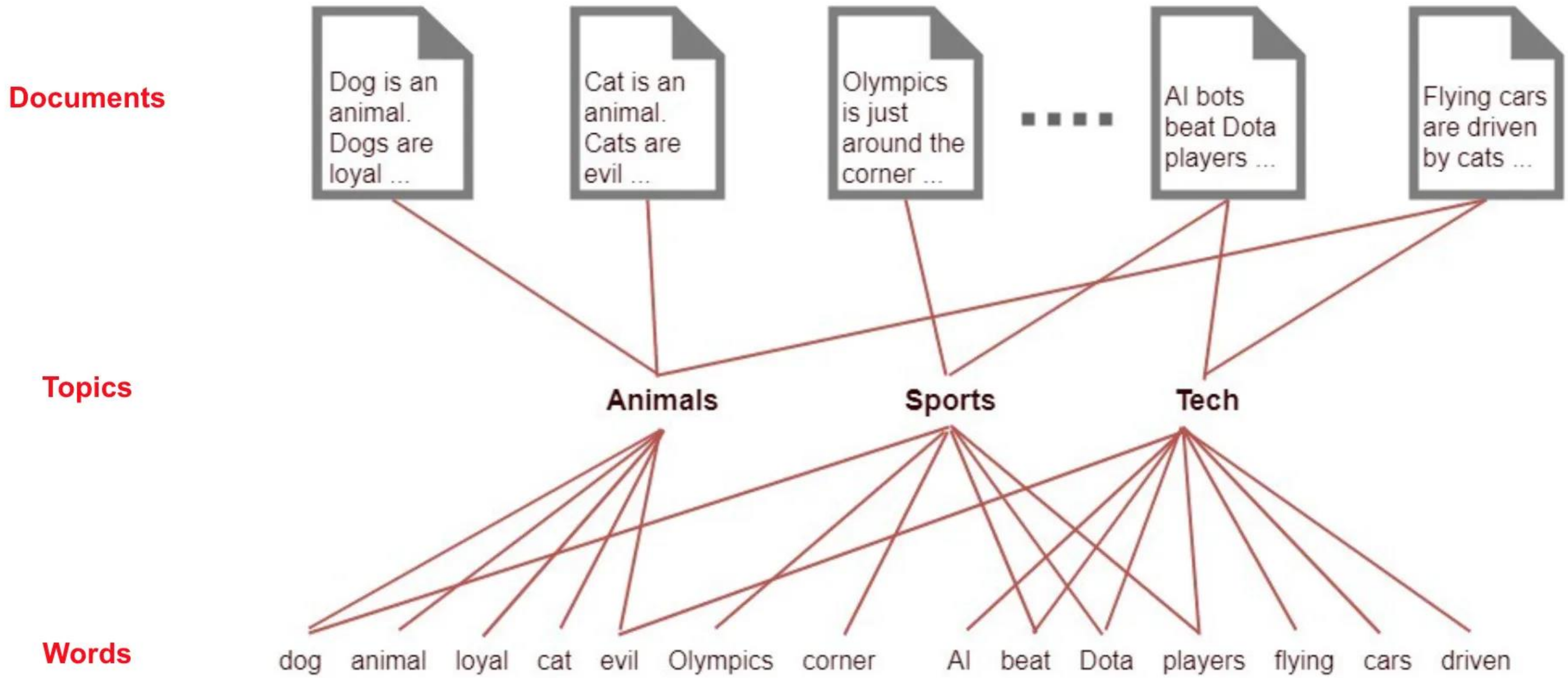
Basic Logic of Topic Modeling

- Early/Most topic models based on TF-IDF
- Newer models based on word embedding

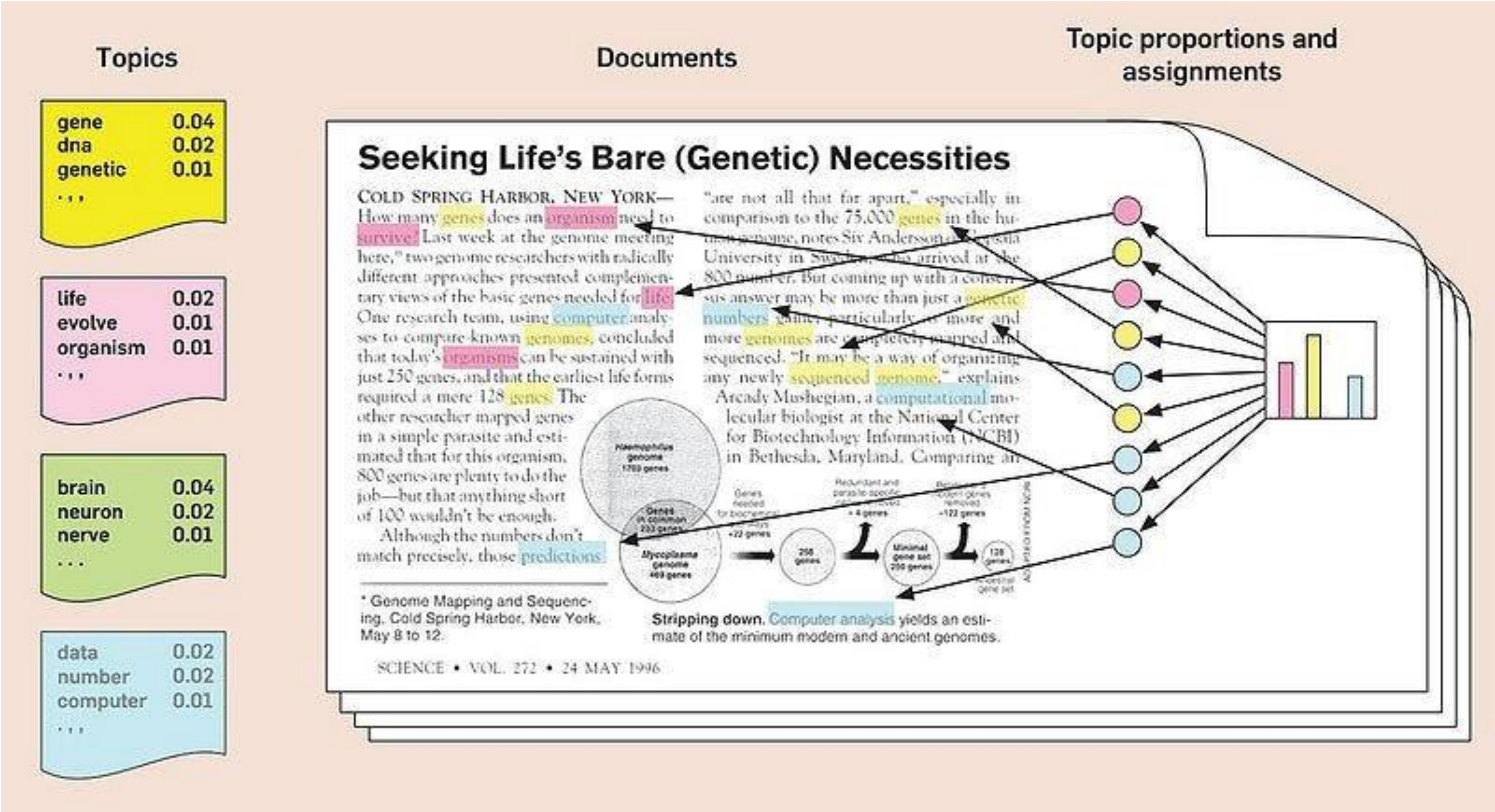
- If two words (word 1 and word 2) always co-occur, the computer understands that they might belong to the same topic

	words1	words2	words3	words4	words5
doc1	0	0	1	0	0
doc2	2	0	1	1	0
doc3	0	0	1	1	0
doc4	0	0	1	1	1

Basic Logic of Topic Modeling



Basic Logic of Topic Modeling



Latent Dirichlet Allocation (LDA)

- Introduced by Blei, Ng, and Jordan (2003)
- Assumption
  - Each document is a mixture of topics
  - Each topic is a mixture of words
  - **Both mixtures are drawn from Dirichlet distributions**
- Widely used, but with limitations:
  - Cannot integrating metadata
  - Doesn’t work well with short text

Structural Topic Modeling (STM)

- Extends LDA by incorporating document-level metadata/covariate
  - Year
  - Political Party
  - Before/After Treatment
- Instead of assuming Dirichlet distributions, it uses logistic-normal prior (has a normal distribution in log-space)
  - Don’t ask me what they mean ☺
- Allows topic prevalence and content to vary by covariates
- Excellent for theory-testing in social science
- Implemented in R using stm package

LDA/STM Output Example

- You get:
  - A list of topics (top words per topic)
    - Topic 1's top words: animal, cat, dog, cow, farm, …
    - Topic 2's top words: work, employ, farm, rice…
    - …
  - Document-topic proportions
    - This document consists of 50% Topic 1, 25% Topic 2, 15% Topic 3, and 10% Topic 4
- Specific to STM:
  - Topic correlations across all documents
    - How likely Topic 1 and Topic 2 can co-occur (i.e., a network)
  - Covariate effect (e.g., topic prevalence by party/time/treatment)

Topic Modeling Does Not Give You Labels

- You get:
  - A list of topics (top words per topic)
    - Topic 1’s top words: animal, cat, dog, cow, farm, …
    - Topic 2’s top words: work, employ, farm, rice…
    - …
- But they never tell you what the topics are, the computer only knows that these words seem to co-occur here
  - No labels like “animal,” “farming,” or “climate change” / “terrorism” etc
  - Labels are interpretive, researcher-assigned summaries
  - Needs researchers’ substantial expertise to cover research areas
- You must:
  - Inspect top words
  - Read exemplar documents for each topic
  - Assign a topic label and discuss with co-authors

Topic Modeling Does Not Give You Labels

- Topic modeling is a discovery tool, not a labeling machine.
- It helps uncover patterns — you provide the meaning.

- A topic with top words like “children,” “school,” “teacher,” “lunch,” “bus” might sound like it’s about “Education”
- But since I am aware that the documents I have are all NY Times articles mentioning “gun,” I should know that it’s mostly about “school shootings.”
- If I did the search about “poverty,” then I should label it “childhood hunger.”
- Reading top representative documents is also helpful.

Specify the No. of Topics (*K*) (LDA/STM)

- There is no “correct” K, as much art as science
  - It’s a modeling choice, not a ground truth
  - Too few topics → overgeneralized, mixed themes
  - Too many topics → fragmented, redundant, hard to interpret
  - Need to find a balanced *K* with human interpretation
- Model diagnosis does help
  - Held-out likelihood (predictive performance)
  - Semantic coherence (do top words make sense together?)
  - Exclusivity (are top words unique to topics?)
  - But most important: <u>**Interpretability**</u> (read top documents, qualitative)
- Tip
  - Plot “Exclusivity vs. Semantic Coherence” to find a sweet spot
  - Favor interpretability over statistical fit for most social science audiences
  - Be transparent and communicate the transparency (in appendix)

Limitations of LDA/STM

- Bag-of-words assumption: no word order
- Topics can be hard to interpret
- Sensitive to preprocessing choices
- STM assumes linear effects of covariates

What Comes After STM?

- BERTopic: combines transformer embeddings with clustering
  - **No need to specify topic count in advance**
  - More coherent topics via sentence-level context
  - Better for short texts (e.g., tweets)

- Not always good
  - You might get 15 topics, but your theory posits 6 dimensions
  - So when social scientists use BERTopic (which typically returns more topics than they want), they have to do *post-hoc merging*
    - Merge topics 3, 8, and 14 because they all relate to “government surveillance.”
  - This is defensible but might come off weird in eyes of reviewers
- Instead, use STM, run various *K* models, and pick the consensus

Topic Modeling Summary

- Use LDA to explore topics of long documents
- Use STM when you have metadata and theory-driven questions
- Use BERTopic for modern, contextual embeddings + better clustering
- All topic models are tools — interpret with care

Case: Zhou et al. (2023)

- Exploring PR research topics via topic modeling
- Use STM to identify topics and clusters
- Compare topic distributions across journals and time
- Network simulation to test inter-cluster dynamics

RQ & Findings

- What topics do public relations scholars study?
- What clusters/themes emerge?
- Do these clusters/themes intersect with each other?

RQ & Findings

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- Do these clusters/themes intersect with each other?

- Identify 65 topics
- These 65 topics cluster into 9 subfields
- These subfields do not talk to each other

Data and Methods

- Web Scraping Data
  - Time: from 2010 to 2020
  - Journals:
    - Public Relations Review (PRR)
    - Journal of Public Relations Research (JPRR)
  - 1093 papers from PRR and 200 from JPRR
  - 7,400,685 words

Data and Methods

- Method 1: Structural Topic Modeling
  - We identified 65 topics, such as
    - “Twitter” “Facebook”
    - “Relationship management” “Nonprofit Management”
    - “Image Repair” “Situational Crisis Communication Theory”

Data and Methods

- Method 1: Structural Topic Modeling
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    - "Relationship management" "Nonprofit Management" --- "Strategic Management"
    - "Image Repair" "Situational Crisis Communication Theory" --- "Crisis Comm"

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    - “Image Repair” “Situational Crisis Communication Theory” --- “Crisis Comm”

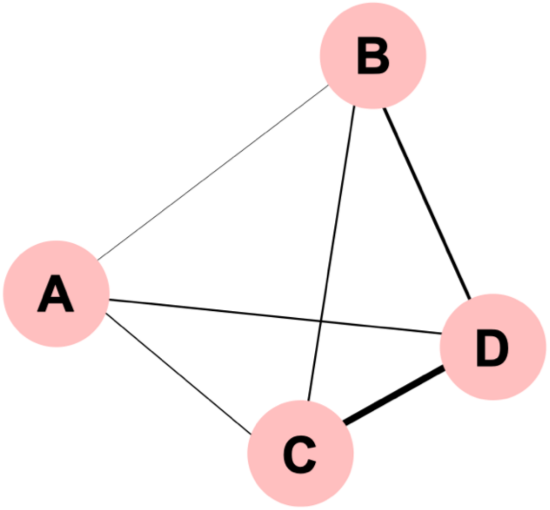
  - <Like, comment, and share on Facebook: How each behavior differs from the other> is detected to have:
    - Digital Media (73.7%)
    - Strategic Management (18.7%)
    - Public Relations Professionalism (0.1%), Crisis Communication (2.3%), Internal Communication (0.8%), Global Public Relations (0.0%), Rhetoric and Philosophy (0.1%), Media Relations (0.2%), Critical Studies (0.0%)

Data and Methods

- Method 2: Inter-Cluster Network Analysis

	Cluster A	Cluster B	Cluster C	Cluster D
Article 1	0.1	0.2	0.3	0.4

Article 1's Contribution to the Tie Strength in the Inter-Cluster Network				
	Cluster A	Cluster B	Cluster C	Cluster D
Cluster A	-	0.1*0.2	0.1*0.3	0.1*0.4
Cluster B	-	-	0.2*0.3	0.2*0.4
Cluster C	-	-	-	0.3*0.4
Cluster D	-	-	-	-



Data and Methods

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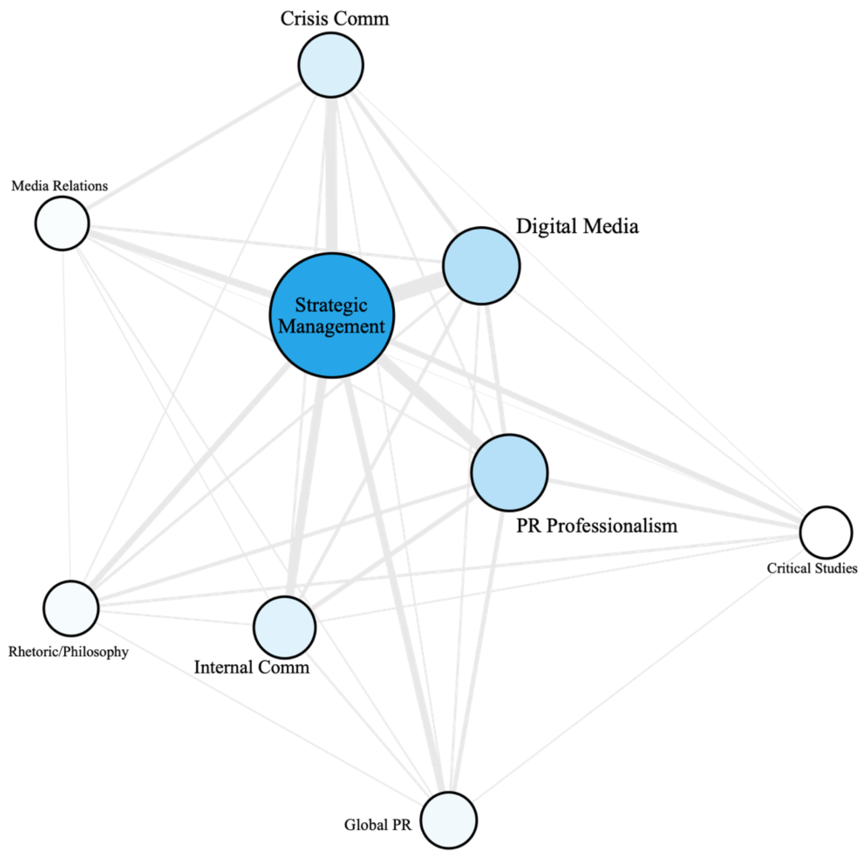

Data and Methods

- Method 3: Network Simulation

Article	Crisis	Digital	Global	…	Management	Critical	Media
1	0.000	0.003	0.001	…	0.749	0.001	0.000
2	0.006	0.002	0.070	…	0.420	0.005	0.003
3	0.204	0.010	0.004	…	0.226	0.025	0.370
4	0.167	0.028	0.031	…	0.124	0.000	0.012
…	…	…	…	…	…	…	…
1291	0.008	0.061	0.012	…	0.076	0.063	0.007
1292	0.786	0.001	0.002	…	0.102	0.001	0.001
1293	0.003	0.233	0.001	…	0.142	0.082	0.006

Data and Methods

- Method 3: Network Simulation
  - For each article, cluster proportions add up to 100%
  - For each cluster, its proportion across all articles remains the same

	Cluster 1	Cluster 2	Cluster 3	Cluster 4	...	Cluster 7	Cluster 8	Cluster 9
Paper 1								
Paper 2								
Paper 3								
...								
Paper 1292								
Paper 1293								

Data and Methods

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Paper 1								
Paper 2								
Paper 3			$[i_1, j_1]$			$[i_1, j_2]$		
...								
Paper 1292			$[i_2, j_1]$			$[i_2, j_2]$		
Paper 1293								

Data and Methods

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Paper 1								
Paper 2								
Paper 3			$[i_1, j_1] - \Delta$			$[i_1, j_2] + \Delta$		
...								
Paper 1292			$[i_2, j_1] + \Delta$			$[i_2, j_2] - \Delta$		
Paper 1293								

Data and Methods

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- 1000 Simulated Networks / Alternative Universes/Timelines
- 95%/5% upper/lower bound as the confidence interval for tie strengths
- We simulated “what the field’s interconnection could have been”.

Data and Methods

- Method 3: Network Simulation

	Public Relations Professionalism	Digital Media	Crisis Communication	Internal Communication	Global Public Relations	Rhetoric and Philosophy	Media Relations	Critical Studies
Strategic Management	*20.549 [26.535, 26.615]*	**28.031 [25.162, 25.240]**	*20.493 [23.409, 23.483]*	*16.518 [18.079, 18.139]*	*12.960 [14.895, 14.946]*	*11.071 [14.593, 14.644]*	*12.801 [14.059, 14.110]*	*10.528 [13.308, 13.355]*
Public Relations Professionalism		*8.494 [13.193, 13.244]*	*4.114 [12.235, 12.286]*	*8.630 [9.337, 9.377]*	**7.934 [7.661, 7.696]**	*6.890 [7.490, 7.523]*	*3.735 [7.185, 7.218]*	**7.889 [6.823, 6.855]**
Digital Media			*7.872 [11.559, 11.607]*	*6.484 [8.755, 8.793]*	*4.181 [7.168, 7.200]*	*5.363 [7.036, 7.068]*	*5.337 [6.742, 6.774]*	*2.900 [6.377, 6.406]*
Crisis Communication				*4.440 [8.144, 8.180]*	*3.236 [6.648, 6.680]*	*3.048 [6.521, 6.552]*	**7.374 [6.293, 6.323]**	*1.411 [5.910, 5.938]*
Internal Communication					*4.044 [4.997, 5.022]*	*3.107 [4.890, 4.915]*	*2.110 [4.698, 4.723]*	*3.210 [4.441, 4.464]*
Global Public Relations						*2.664 [3.981, 4.002]*	*3.071 [3.832, 3.853]*	*2.714 [3.612, 3.632]*
Rhetoric and Philosophy							*1.579 [3.751, 3.772]*	**5.239 [3.558, 3.579]**
Media Relations								*1.035 [3.402, 3.421]*

Lab Preview

- Explore semantic similarity using word embedding

- Practice Google Perspective API

- Run STM with presidential speech corpus and metadata
- Pick *K*, generate the model, label topics
- Explore covariates' effects on topical proportion
- Visualize topic correlations

- Tomorrow's Presentation
  - Eunsun Kyoung
  - Dongwook Kim
  - Rita Tang