A thematic study of the business-strategy literature, 1980 - 2020

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Abstract

A *big-data* text-mining analysis detects prominent themes in the business-strategy literature. A *Latent Dirichlet Allocation* (LDA) model is applied to a corpus comprised of journal-article titles and abstracts from eight journals spanning the period 1980 – 2020. This corpus consists of around 5,500 documents containing an aggregate of 1.25 million words. Five prominent business-strategy themes are identified *a priori*. The LDA model based on the aforementioned corpus is applied to eight articles known to coincide with the dominant themes. These known-theme documents are found to correspond to distinct topics inferred by the model. Substantial overlap exists, making thematic discrimination challenging.

Subsequent work for the INFORMS Annual Meeting will seek to improve the thematic-discriminant power of the approach. This includes expanding the corpus size to include full-text articles. More-sophisticated modeling will attempt to pull in additional grammatical information. Also, the LDA approach will extended in order to expressly bridge between LDA-inferred topics and *a-priori-specified* themes. The intended result seeks to demonstrate a concept of operations for literature research potentially useful for academic researchers and business consultants.

Introduction.

Advances in statistical methods for text-mining — variously referred to as "big" data, text analytics, natural-language processing, *etc* — offer new ways to perform literature search. Statistical algorithms sift through expansive collections of text in document or message format. The applications include topic detection, document classification, and trending [Srivastava2009].

Such methods have in recent years assumed an increasingly prominent role in academic research. Blei and Lafferty provided an early demonstration of their potential to group scientific texts by topic [Blei2009]. [Antons2019] extended this work, attempting to infer scientific impact. [Schmiedel2019] performed a methodological demonstration of big-data tools for research in organizational culture. [Tay2018] studied visualization approaches to interpreting topic-analysis results. [Liu2019] conducted a thematic survey of the business-ethics literature. [Torabi2019] tried to discriminate between "fake" news and factual reporting. [Brooks2018] performed a critical comparison of topic analysis with more-conventional methods for discourse studies using UK National Health System content.

We describe here a *topic-analysis* study of the business-strategy literature. Detecting specific major themes in the literature is our goal. This intent coincides closely with that of [Blei2009] and [Liu2019]. We look for five distinct themes that appear prominently in business-strategy research during the last half-century.

We employ a method called *Latent Dirichlet Allocation* (LDA), commonly used for topic analysis. LDA attempts to group documents by *topic*. It is an *unsupervised-learning* method in that it does not depend on exogenous, *a-priori* assignment of documents to topic classes. Such algorithms probabilistically estimates the strength of association between each document and each topic based on statistical similarities in their texts. LDA was first described by [Blei2003].

After training our LDA model, we examine its handling of documents known to preponderantly address our *a-priori*-identified themes. Subsequent work extends the approach in an attempt to produce a more-robust thematic classifier. These extensions are inspired by [Xie2013], but do not explicitly reproduce its approach.

Target audience.

At least three constituencies may find this work particularly interesting. Academic researchers represent the first. [Schmiedel2019] explicitly seeks to demonstrate the utility of topic analysis as a *strategy for inquiry*. Topic analysis bins documents from a corpus into topically coherent latent topic groups. This aides in the localization of research content associated with a theme of interest.

Business consultants are the second potential beneficiaries of topic analysis. Automation of text classification can reduce their barrier to accessing the breadth and depth of academic research related to their practice. Innovative ideas with potential to advance consulting practices become more-easily discoverable.

Thirdly, text-mining practitioners may take note of an apparently-novel approach to processing. Inspired by [Xie2013], this work extends the original method of [Blei2003]. We focus here on the distinction between *Latent Topics* inferred by LDA modeling and *Themes*, in which researchers and consultants actually take interest. This work moves towards an *adaptive*, Bayesian-Learning approach [Jihan2018] to document classification according to research themes. This might support a use case for interactive literature search, in which a model "learns" thematic associations based on LDA topic allocations and other machine-learning outputs.

At its present state of maturity, topic analysis by no means obviates the need for traditional research. It could be used to compile a preliminary bibliography for a research project. Human "touch labor" remains to ascertain which documents in a topical class are useful and which are not. Identification of potentially-related work that might not have otherwise occurred to a researcher is the primary benefit.

Branded as *artificial intelligence*, the abilities text-mining methods such as topic analysis are sometimes overestimated. [Vladawsky-Berger2020] emphasizes that these methods fundamentally are specialized applications of statistics. [Waters2016] and [Davenport2018] contain cautionary tales about over-estimating their capabilities.

Summary of thematic study.

Business-strategy corpus.

We assemble a textual *corpus* of business-strategy articles published in the period 1980 – 2020. Preliminary results illustrated here are based on titles and abstracts. The corpus for the annual-meeting presentation will be based on full-text articles.

Fourteen academic journals, most of which are focused primarily on business strategy, were considered. Details are listed in [Hamlett2020]. Of these, eight were determined to be useful and practical. The summary table in [Hamlett2020] provides the rationale for and document count for each.

The resulting corpus contains approximately 5,500 documents — article titles and abstracts — in all. Each document is processed through a text-manipulation process called *annotation* [Weiss2010, Chapter 2], [JSLabs]. This involves cleaning up the text and discarding non-information-bearing words like prepositions, conjunctions, and articles. Consecutive words are also combined so that key phrases remain intact. When all of this is done, this corpus contains more than 1.275 million distinct terms, or *tokens*.

Dominant themes in business strategy.

We seek to detect five dominant themes in our corpus. Figure 1 summarizes these themes. Four of these themes have occupied central positions in the business-strategy conversation during the last 50 years. The fifth theme — information as a differentiating asset — is still emerging.

Business strategy focused on operational efficiency beginning in the late-nineteenth century. Frederick Winslow Taylor pioneered the field of *Scientific Management*. Relentless pursuit of industrial efficiency was his focus. Although much of Taylor's actual work fell into disrepute, its underlying hypothesis retained credibility. A *Management-Science* discipline focused on industrial efficiency became the staple of graduate schools of business throughout the academy

Figure 1: We seek to detect five dominant themes in the our document corpus.

Theme	Key Ideas	Early Originators	Period of Prevalance
Operations Research and Management Science	⊳ Operational efficiency is the key. ⊳ Leads to narrow focus on cost, price.	⊳ Fredrick Taylor ⊳ Patrick Blackett	Late 1800s to 1980s
Competitive Advantage	⊳ Factors other than price can provide bases for differentiation. ⊳ Emphasizes industry structure, resources, positioning. ⊳ Explains industries in "steady state".	⊳ Michael Porter	1980s to early 2000s
Disruptive Innovation	⊳ Recognizes that industry structures can be fragile. ⊳ Describes specific mode in which low-cost firms "eat" incumbents markets from the bottom. ⊳ Originator complained that the term "disruption" is overused, misused.	⊳ Clayton Christensen	Late 1990s to present
Dynamic Capabilities	⊳ Adaptability, resilience, agility are keys in industries subject to periodic change. ⊳ Describes three key classes of capabilities: Sensing, siezing, managing competitive landscape.	⊳ David Teece	Early 2000s to present
Information as Differentiating Asset	⊳ Information, Knowledge began to provide greater return than traditional asset classes as early as 1960s. ⊳ Explains power of platform operating models.	⊳ Michael Porter ⊳ Peter Drucker ⊳ Martin Reeve ⊳ N. Hamlett	Emerging

[Stewart2009]. [Kiechel2012] describes a *Management Century*, during which these ideas dominated.

In the late 1970s, Harvard Business-School professor Michael Porter observed that price alone does not unequivocally explain marketplace success [Porter1979, Porter1990, Porter1996]. He asserted to the effect that "The race is not to the swift, nor the battle to the strong", necessarily. Were price the dominant determinant, the *Bertrand Model* of competition would prevail, and many markets would tend to states of unprofitability [Pindyck2017, Chap 12].

Porter's *Competitive-Advantage* framework recognized that firms can differentiate on factors other than price. His framework also explains industry structure and balances of power between buyers and sellers. It views combinations of positioning and resources as the key [Martin2015]. Porter's framework is fundamentally grounded in bedrock concepts from microeconomics.

Clayton Christensen, one of Porter's students, noticed in the 1990s that industry structures can shift surprisingly and quickly. Dominant firms' positions based on product distinction can suddenly be upended by lower-price substitutes. This phenomenon is referred to as *Disruptive Innovation* [Christensen2015]. Christensen's framework shares with Porter's an emphasis on positioning and resources.

Beginning in the late 1990s, Professor David Teece of the University of California at Berkeley studied competitive differentiation from an organizational-behavior perspective. He established that organizational competencies can trump resource- and positioning-based advantages emphasized by Porter and Christensen. Teece called his framework *Dynamic Capabilities* [Teece1998, Teece2009]. Organizations possessing this characteristic adaptively reconfigure themselves in response to emergent opportunities or threats.

Martin Reeves, leader of Boston Consulting Group's Henderson Research Institute, formulated a similar *Adaptivity-Advantage* concept into a consulting framework [Reeves2012]. Adaptivity Advantage appears influenced by technology-based concepts such as *Enterprise Architecture* [Ross2006]. Reeves apparently views technology as an essential enabler for organizational-behavior-based dynamic capabilities Teece describes [Bessen2018].

Finally, Porter first noticed "the information revolution sweeping through our economy" in the mid-1980s [Porter1985]. Peter Drucker, father of modern business consulting, observed a few years later that information and knowledge contribute more to corporate returns than traditional real and financial assets [Drucker1993]. Reeves bridges this concept to his adaptivity-advantage framework by "Competing on the Rate of Learning" [Reeves2018]. [Hamlett2019] describes three distinct distinct modes that produce competitive differentiation based on information.

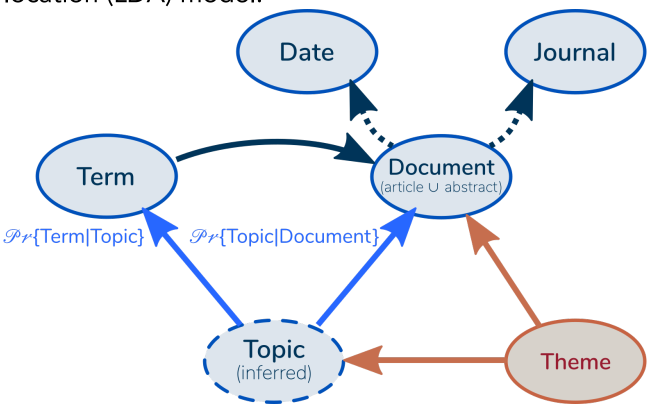
The notion that *information is a strategic asset* remains an emerging theme in business strategy. Platform operating models comprise one important manifestation of information-centric business models [Evans2016, VanAlstyne2016, Iansiti2017]. An information-centric strategic framework might also blend concepts from disruptive innovation and dynamic capabilities.

Topic-analysis modeling approach.

Figure 2 depicts the fundamental concept underlying topic analysis using Latent Dirichlet Allocation (LDA). It is aptly named. LDA attempts to infer membership in *Latent* topic classes for each document. It belongs to a more-general family of methods called *Latent Variable Models* (*e.g.*, [Loehlin2003]). *Dirichlet* refers to a key probability distribution on which the model is based [Evans1993, chapter 10]. *Allocation* pertains to the use of *soft* logic to associate documents with topic classes. Rather than trying to definitively link a given document to a distinct class, LDA estimates the probability that the document belongs to each class.

To reiterate, LDA is an *unsupervised*-learning approach. Its topic-to-document associations do not require a priori, exogenous assignment of documents to

Figure 2: Conceptual depiction of Latent-Dirichlet Allocation (LDA) model.



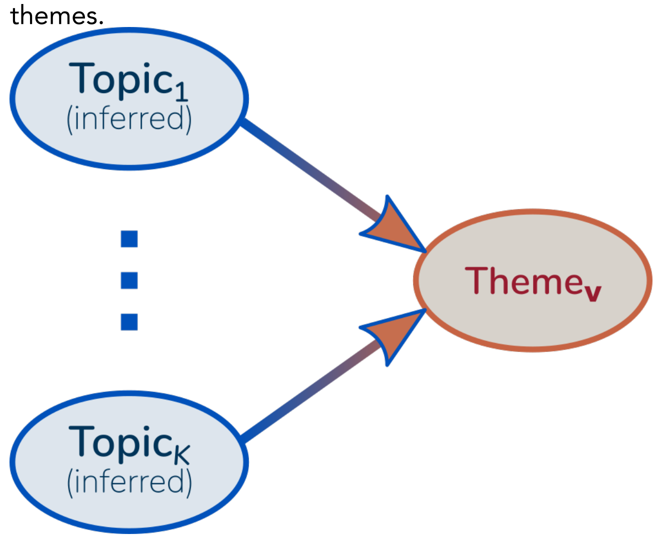
topics. Such associations are expensive, usually manually produced by subject-matter experts (SMEs) for a subset of a corpus. Unsupervised-learning methods give us a path to minimize the use of expensive SME labor to make topic associations.

Figure 2 represents the LDA's informational structure using a *graph*. Belonging to the family of *Probabilistic Graphical Models* (PGMs) (e.g., [Koller2009]), LDA is also a *generative* model. It assumes that authors intend to compose documents addressing specific topics. *Topics* generate *Terms*, of which *Documents* are comprised. Topics are latent variables, here, in that they are not explicitly observable in the corpus. The LDA model infers each document's association with topics.

In Figure 2 the light-blue-colored *graph edges* — arrows — are labeled with the *conditional-probability estimates* produced by the LDA model. Such quantities are typical of PGM approaches. Specifically, $Pr\,\{\text{Term} \mid \text{Topic}\}$ is the probability that a given topic produces the corresponding term. Also, $Pr\,\{\text{Topic} \mid \text{Document}\}$ is the probability that a given document is associated with a particular topic. We can alternatively get $Pr\,\{\text{Document} \mid \text{Topic}\}$ via Bayesian-inversion techniques [Koller2009, §9.3.1]. This latter probability would be of particular use for researchers.

Figure 2 also shows *Themes* in a distinct color from topics and documents. Themes are what interest us. An LDA model infers topics, which may be distinct from themes. The LDA literature (*e.g.,* [Blei2003]) makes no mention whatsoever of themes. Keeping this in mind is important when interpreting model's results.

Figure 3: Concept for extending LDA to associate model-induced topics with researcher-identified themes.



As with many unsupervised-learning methods, we must specify the quantity of topics to which the LDA model allocates probabilities. This occurs through a combination of analysts' judgment and trial and error. We train a large number of LDA models with different topic counts and score them statistically. We pick the model with the best statistical scores.

Figure 3 depicts the concept — not demonstrated presently — for extending our LDA topic allocations to themes. Candidate approaches remain under consideration. Our LDA model gives us document-to-topic associations. *We seek document-to-theme associations.* This requires a second stage of probability allocation. The desired approach minimizes use of SME touch labor.

This second stage of allocation might be accomplished through a combination of supervised- and unsupervised-learning modeling techniques. A second unsupervised-learning stage — accomplished via a simpler technique than LDA — might give us clusters in LDA-topic space. A combination of topic-space dimensionality and non-lantent cluster analyses might also inform our decision regarding the number of LDA clusters to fit the model.

Operationally, a thematic-assignment model might adaptively learn as SMEs provide additional documents with known-theme assignments. Following a Bayesian-inspired methodology, topic-to-theme prob-

Figure 4: Known-theme documents used to illustrate document-to-topic association via LDA modeling.

Theme	Period of Prevalance	Noteworthy Publications (known-theme documents)
Operations Research and Management Science	Late 1800s to 1980s	[Wikipedia] Scientific Management.
Competitive Advantage	1980s to early 2000s	[Porter1979] M. Porter, "Five forces...", Harvard Business Review, March 1979. [Porter1996] M. Porter, "What is strategy?" *Harvard Business Review*, Nov 1996.
Disruptive Innovation	Late 1990s to present	[Christensen2015] C. Christensen, "What is disruptive innovation?" *Harvard Business Review*, Dec 2015.
Dynamic Capabilities	Early 2000s to present	[Teece1997] D. Teece, "Dynamic capabilities and strategic management," *Strategic Management Journal*, Aug 1997.
Information as Strategic Asset	Emerging	[Porter1985] M. Porter, "How information gives competitive advantage," *Harvard Business Review*, July 1985. [Drucker1993] P. Drucker, Post-Capitalist Society, Harper-Collins, 1993. [Reeves2018] M. Reeves, "Competing on the rate of learning", BCG Henderson Institute, Jul 2018. [Hamlett2019] N. Hamlett, "Competitive advantage based on information", working paper, April 2019.

ability allocations are progressively updated as researchers identify new known-theme documents.

Preliminary, illustrative results.

A small number of *known-theme* documents are used to for a preliminary illustration of LDA topic modeling. These are listed in Figure 4. Samples were cursorily selected to get at least one example for each of the five themes. Many of these were referenced above in the *Dominant-themes* subsection.

The LDA model was first trained using the 5,000-document, 1.25×10^6-term corpus described above. The known-theme documents in Figure 4 were then applied to the trained model. We focus specifically on the resulting document-to-topic probability allocations.

The demonstration using these documents preliminarily illustrates LDA functionality. This by no means satisfies the criteria of a formally-designed statistical experiment (*e.g.*, [Lawson2015]). At this instance, we simply seek to "exercise the machinery". More-rigorous characterization awaits the sequel.

Figure 5 contains illustrative results from applying the known-theme documents from Figure 4 to an LDA model. This model assumes $K = 10$ latent-topic classes and uses a dictionary size of $L = 450$ terms. A heat-map depiction is used because LDA does not unequivocally assign each document to a distinct topic. For each Document$_n$ it produces a set of conditional probabilities $\left\{ Pr(\text{Topic}_\kappa \mid \text{Document}_n), \quad \kappa = 1, \cdots, K \right\}$. These are conditional probabilities, so as usual,

$$\sum_{\kappa=1}^{K} Pr(\text{Topic}_\kappa \mid \text{Document}_n) = 1.$$

One might naïvely consider assigning a Document$_n$ to the category

$$\hat{\kappa}_n = \arg\max_{\kappa} Pr(\text{Topic}_\kappa \mid \text{Document}_n).$$

But, this would not produce high-confidence assignments. The highest conditional probability in Figure 5 is

$$\max_{\kappa,n} Pr(\text{Topic}_\kappa \mid \text{Document}_n) \approx 0.17.$$

To summarize Figure 5, LDA-inferred topics by themselves do not appear to sharply discriminate between themes attributed to the known-theme documents. We see considerable overlap, for example, between *Dynamic Capabilities* and *Information as an Asset* themes. Similarly, the $Pr(\text{Topic}_\kappa \mid \text{Document}_n)$s for the *Competitive Advantage* and *Disruptive Innovation* themes also substantially coincide.

What do we believe is going on here?

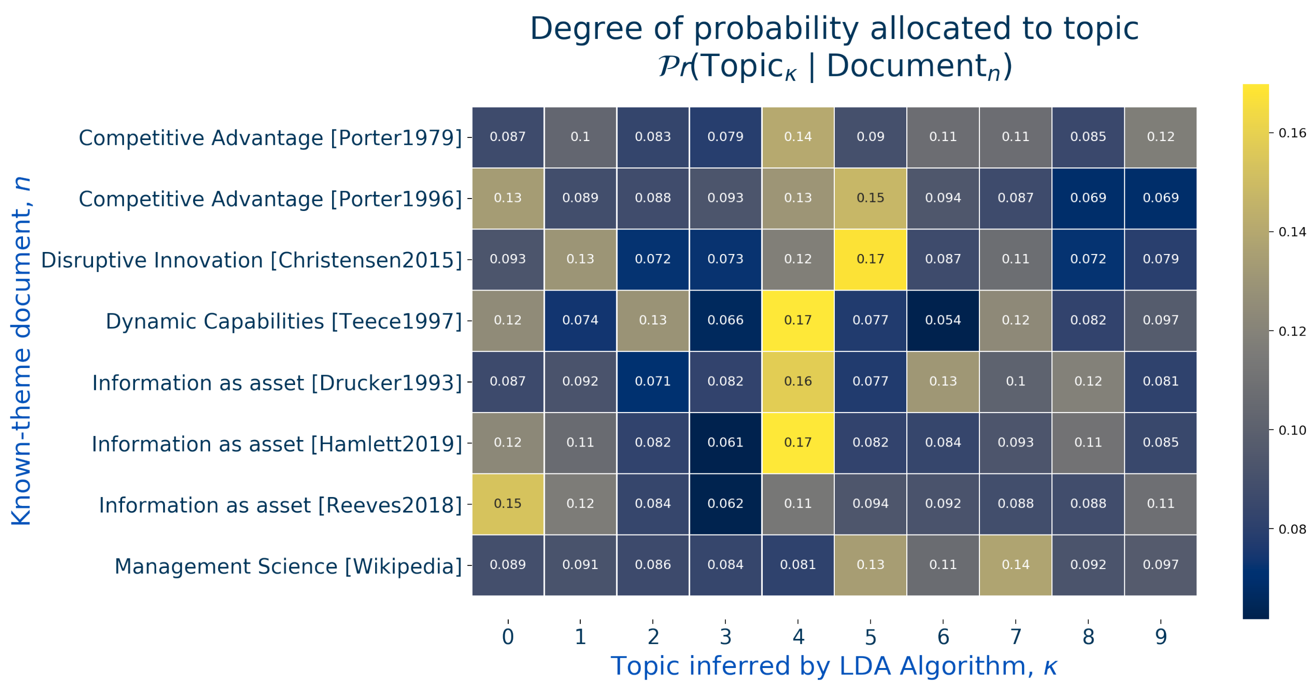
That our model appears not to resolve themes well seems disconcerting at first blush. Thinking more-deeply, we hypothesize explanations. This is the first step in improving our thematic-discriminant power.

What you say versus what you mean.

We must think carefully about what LDA text-mining is actually doing. Figure 2 calls deliberate attention to the distinction between **Topics** and **Themes**. What's the difference? [Blei2003] distinguishes between *syntax* and *semantics*. Syntax pertains to the vocabulary and grammar of language. Semantics addresses the implicit meaning.

Now, [Blei2003] makes clear that LDA makes no inferences about documents' semantics: The meaning intended by the author. *Topics* inferred by LDA are derived from the syntax. LDA operates on documents' syntax: Vocabulary and, to a lesser extent, grammar. In fact, LDA's derivation makes use *exchangeability*, a prominent result from [deFinetti1970, §11.4]. Exchangeabilty makes no assumptions about ordering of the terms in documents. The resulting groupings may

Figure 5: Illustrative topic-to-document conditional-probability allocations from LDA modeling for known-theme documents from Figure 4.



be more informationally-rich than those from other machine-learning methods. They remain nonetheless syntactic derivatives.

Themes, in contrast, reside in the realm of *semantics*. When distinct themes' lexicons overlap significantly, bridging between semantics and syntax requires inductive logic, at which statistical algorithms tend to struggle [Stove1986, Briggs2016]. Human cognition's advantage over machine-calculated statistical deduction persists for this type of reasoning.

Figure 6 presents a qualitative summary of the quantitative results in Figure 5. We use Porter's *Competitive Advantage* framework as a baseline. The analysis in Figure 6 notes that many of the themes use similar vernaculars. Recalling that LDA operates largely on syntax — vocabulary and grammar — coincidence between themes with overlapping vocabularies is unsurprising.

Figure 6: Interpretation of $Pr(\text{Topic}_\kappa \mid \text{Document}_n)$ estimates in Figure 5.

Theme	Known-Theme Documents	LDA-Algorithm Associations of Known-Theme Documents to Topics.
Operations Research and Management Science	[Wikipedia]	⊳ Significant association with two distinct topics. ⊳ Some overlap with competitive advantage. ▹ *Unsurprising* since both grounded in microeconomic concepts.
Competitive Advantage	[Porter1979] [Porter 1996]	⊳ Significant association with three topics. ▹ *Unsrurpising* given that framework spans at least four distinct concepts.
Disruptive Innovation	[Christensen2015]	⊳ Significant association with two topics. ⊳ Shared association with one competitive-advantage topic. ▹ *Unsurprising* given close assocation between respective themes: Disruptive Innovation elaborates on Competitive Advantage.
Dynamic Capabilities	[Teece1997]	⊳ Significant association with two topics. ⊳ Shared association with one competitive-advantage topic. ▹ *Somewhat surprising* given emphasis with which some adherents distance themselves from Porter framework.
Information as Strategic Asset	[Drucker1993] [Reeves2018] [Hamlett2019]	⊳ Significant association with two topics. ⊳ Close alignment of [Drucker1993], [Hamlett2019] to dynamic capabilities. ⊳ [Reeves2018] less thematically-aligned than expected.

More to it than that.

Our cursory demonstration here focuses on five distinct themes. The last 40 years of business-strategy discourse has covered many more topics than these. Our cursory model employed ten latent-topic classes to look for five themes. The 5,500-document, 1.25×10^6-word corpus spans a diverse set of concepts.

Beyond that, many documents will span multiple topics. This will become particulary pronounced as we move from only titles and abstracts to full-text articles. Figure 5 provides a preliminary hint of this. *Text Segmentation* is a method to deal with this [Memmon2020]. This involves trying to break documents into topic-distinct segments. One thereby obtains topically-distinct sub-documents.

Remaining work.

The preceding sets the stage for subsequent work in preparation for the final presentation to the Annual Meeting.

Extend the corpus.

The preceding analysis is based on only titles and abstracts. Orthodoxy in the applied-statistics community holds that greater quantities of data produce better results. (See [Wilson2019] for a contrarian view.) Titles and abstracts provide an easy starting point. Most publishers make them generally available. They suffice to exercise the end-to-end topic-modeling machinery.

Expanding the corpus to full-text articles will be the next step. This represents a tradeoff. Full-text articles will not be accessible for all journals. In terms of Figure 2, we definitely will end up with more *Terms* for modeling. We may have fewer *Documents*.

Whether to mix in documents, for which only title and abstract are available with full-text documents will be weighed. Fortunately, the journals for which full-text articles are accessible account for a majority of the documents. This will provide a corpus whose dimensions roughly coincide with that used by [Liu2019].

Expand the use of grammatical information.

The preceding work is largely vocabulary-based, and only makes minimal use of grammatical content. Getting LDA-inferred topics that more-closely coincide with themes may be enhanced by making more-extensive use of the grammatical structure of the corpus. More-advanced annotation allows us to pull in more grammatical information into the model [Weiss2010, JSLabs].

Additional model optimization.

Tuning — looking for the best model parameters — is part of any statistical-modeling activity. The preceding work tuned the LDA model using a rather textbook, pedestrian approach. Opportunities remain to improve the amount of information that the LDA model extracts from the corpus. For example, [Hamlett2020] illustrates a dimensional analysis of the vocabulary space. This could help find the optimum vocabulary size, limited only to the *Terms* that convey the greatest amount of information about the corpus.

Extend the LDA model.

LDA-inferred *Topics* may not suffice to discriminate between topics of different themes. The results from Figures 5 and 6 appear to indicate this. [Xie2013] illustrated the combination of LDA with other text-mining methods. This in of itself does not appear to give the theme-discriminating power we seek. Extensions to the LDA model suggested by Figure 3 potentially get us to greater theme-discriminant power.

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