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Topic Models: A Novel Method for Modeling Couple and Family Text Data

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Couple and family researchers often collect open-ended linguistic data—either through free-response questionnaire items, or transcripts of interviews or therapy sessions. Because participants' responses are not forced into a set number of categories, text-based data can be very rich and revealing of psychological processes. At the same time, it is highly unstructured and challenging to analyze. Within family psychology, analyzing text data typically means applying a coding system, which can quantify text data but also has several limitations, including the time needed for coding, difficulties with interrater reliability, and defining a priori what should be coded. The current article presents an alternative method for analyzing text data called topic models (Steyvers & Griffiths, 2006), which has not yet been applied within couple and family psychology. Topic models have similarities to factor analysis and cluster analysis in that they identify underlying clusters of words with semantic similarities (i.e., the "topics"). In the present article, a nontechnical introduction to topic models is provided, highlighting how these models can be used for text exploration and indexing (e.g., quickly locating text passages that share semantic meaning) and how output from topic models can be used to predict behavioral codes or other types of outcomes. Throughout the article, a collection of transcripts from a large couple-therapy trial (Christensen et al., 2004) is used as example data to highlight potential applications. Practical resources for learning more about topic models and how to apply them are discussed.

Keywords: text, linguistic analyses, topic models, couple therapy

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Some of the most interesting data that we collect as couple and family researchers is linguistic data, whether spoken language (e.g., psychotherapy sessions and clinical interviews) or open-ended responses to questionnaires. The nature of linguistic data is unstructured, which imparts both strength and weakness. For example, the Oral History Interview (Gottman & Krokoff, 1989) provides a rich description of a couple's current and past functioning, which is highly specific to the couple. The semistructured format lends broad parameters to the interview's content, but the majority of the data (i.e., the narrative) is generated by the couple. This type of data stands in sharp contrast to forced-choice, questionnaire data, in which item content and response categories are defined by the researcher in advance. As a result, self-report questionnaires limit responses a priori, though analyses of such

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data are much more straightforward. Conversely, the highly unstructured nature of text data affords a richer source of information, in that participants have more opportunity to reveal information about themselves, but such data are challenging to analyze. Typically, the analysis of linguistic data is done by applying a behavioral coding system, in either an exploratory, inductive fashion (e.g., qualitative content-analysis coding), or through a predefined, deductive coding system (Kerig & Baucom, 2004).

Although the use of behavioral coding data has yielded many important findings within couple and family research, it also brings its own challenges: (a) training raters to use coding systems is time consuming; (b) interrater reliability can be difficult; (c) the actual coding process is typically time-consuming; (d) deductive coding systems allow only for what is specified in their manuals; and (e) the portability of a given coding system across research labs can be problematic due to variation in interpretations of coding manuals. In addition to these methodological issues, observational coding methods have been criticized for unintentionally disguising potentially rich and meaningful distinctions in related interaction behaviors by applying labels that are too broad or sweeping (e.g., Heyman, 2001). Thus, an alternative method for analyzing unstructured text that is highly reliable, portable, and flexible, and that quantifies specific aspects of interaction behavior without losing the nuances of families' and couples' private communication systems (i.e., Hopper, Knapp, & Scott, 1981) could be a welcome addition to the family researcher's analytic toolbox.

The current paper presents a novel method (within family psychology) for analyzing text data in the form of topic models (Blei, Ng, & Jordan, 2003; Steyvers & Griffiths, 2006). Topic models provide an alternative, data-driven quantitative method for analyzing text data such as transcripts, journal entries, or other open-ended response questions. Topic models share some similarities with other dimensionality-reduction techniques, such as cluster analysis or principle components analysis (Tabachnick & Fidell, 2007), but are designed specifically for use with text. Similar to these other methods, topic models search for semantic structure without input from the data analyst and hence provide a broad summary of the semantic content, as opposed to finding semantic content in prespecified areas. An advantage of this method is that, in addition to greatly reducing the dimensionality of text, the topics (i.e., word clusters) are typically quite interpretable, which makes them useful for situations in which the goal is not only data reduction, but also interpreting and understanding the basic, underlying dimensions of the linguistic data.

In the remainder of the article, we provide an overview of topic models using several illustrative applications to a corpus of linguistic data from a couple-therapy trial, comprising transcripts of therapy sessions and semistructured communication assessments (Christensen et al., 2004). The present article is not intended to be a tutorial in fitting topic models, though online, supplementary material provides additional technical details and practical information on fitting topic models. Instead, the intent of the present article is to familiarize the reader with this approach and illustrate its potential uses in family psychology. The illustrative applications focus on two broad areas:

1. *Summarization and exploration of transcripts*. By summarizing a therapy session using topics, the model provides a concise overview of the themes in the linguistic data of each therapy session. Topic models assign individual words to specific topics, allowing a researcher to browse through transcripts according to a topic, or locate portions of transcripts that are highly related to specific topics. In addition, a researcher can investigate temporal changes in topics, which can reveal general changes in positive or negative language, or sessions with specific content (e.g., particular interventions or important topics, such as infidelity or divorce).

2. *Prediction of behavioral codes*. Topic models can also be used in prediction models of behavioral codes or other external outcomes (i.e., external to the text). Topic models summarize semantic information quantitatively and could provide a method for assigning behavioral codes that are semantic in nature. More generally, topic models provide a reduced dimensional description of the semantic content of a corpus that could be useful for predicting outcomes.

To be clear, we do not see topic models as a replacement for existing coding methods but rather as an additional, supplementary tool for analyzing text data—but a tool that overlaps behavioral coding with a strong semantic basis. Topic models can be used to efficiently and reliably find dimensions of the data that lie beyond the scope of a coding system, but they can also be trained to locate topics that are associated with existing codes. Thus, they provide an alternative, and in some cases complementary, set of tools for text data relative to behavioral coding.

Topic Models

Overview

Perhaps the easiest way to intuitively understand what a topic model does is to examine the types of output it provides. Figure 1 presents 18 (out of a total of 100) topics that were derived by applying a topic model to the corpus of transcripts from Christensen et al. (2004). Further detail on the corpus is provided below. For each topic, the 15 most probable words are presented in descending order. Reviewing the topics and words in Figure 1, it is clear that the high-probability words within each topic capture semantically related content. Similar to factor analysis, the model provides estimates of how closely each word is associated with a given topic, but it is up to the researcher to discern what this content might be (i.e., how to name the factor or topic). Thus, the first group of topics in the top row of Figure 1 was labeled "content-based topics," as they tap language that might be discussed during couple therapy, such as family, work, money, and sex.

The second group of topics in Figure 1, labeled "emotion-based topics," captures features related to specific emotional content, whereas the third set of topics in Figure 1 (i.e., "therapy-related topics") captures features of therapist-intervention language specific to the two approaches in the Christensen et al. (2004) study: traditional behavioral couple therapy (TBCT; Jacobson & Margolin, 1979) and integrative behavioral couple therapy (IBCT; Jacobson & Christensen, 1998). TBCT is a skills-based therapy that focuses on communication training and problem solving, which is

CONTENT-BASED TOPICS

Family		*Finances*		*Relationships*		*Sex*		*Transportation*		*Work*	
Topic 64	.011	Topic 23	.011	Topic 50	.014	Topic 63	.010	Topic 1	.008	Topic 91	.010
mom	.096	money	.104	married	.080	sex	.131	car	.167	job	.197
mother	.060	dollars	.054	together	.053	sexual	.068	drive	.118	work	.139
dad	.056	buy	.050	relationship	.045	love	.026	park	.026	career	.027
sister	.040	hundred	.043	date	.044	part	.021	down	.018	money	.024
brother	.030	card	.031	live	.036	interesting	.018	street	.017	day	.022
call	.028	thousand	.021	met	.034	initially	.017	turn	.016	company	.019
day	.027	bought	.018	move	.028	touch	.016	traffic	.013	support	.019
father	.023	credit	.017	attracted	.024	back	.016	accident	.013	people	.018
deal	.018	pay	.015	remember	.023	desire	.016	home	.013	situation	.014
live	.014	fifty	.015	marriage	.022	physical	.015	bus	.012	hours	.013
parents	.014	cost	.014	thought	.018	intimacy	.014	drove	.010	week	.013
down	.014	give	.014	months	.017	life	.013	hours	.010	positive	.012
care	.013	car	.012	two	.016	talk	.013	direction	.010	happy	.011
stuff	.013	expensive	.012	decided	.015	relationship	.011	freeway	.009	business	.011
house	.012	five	.012	pretty	.015	pleasure	.010	walk	.008	interview	.010

EMOTION-BASED TOPICS

Negative Emotional Content						*Positive Emotional Content*					
Topic 3	.009	Topic 46	.008	Topic 79	.010	Topic 14	.010	Topic 95	.007	Topic 10	.011
angry	.170	give	.023	upset	.113	good	.039	[laugh]	.383	good	.101
anger	.072	shit	.021	back	.030	thought	.036	guess	.031	nice	.078
hurt	.047	pissed	.021	mad	.030	[laughing]	.031	good	.017	thought	.070
frustrated	.037	point	.019	temper	.024	pretty	.029	work	.017	felt	.048
trying	.032	whatever	.019	talk	.021	people	.025	thank	.012	appreciate	.033
upset	.027	man	.018	crying	.020	talk	.020	give	.012	week	.031
mad	.020	fuck	.017	angry	.018	part	.019	wow	.012	remember	.026
point	.018	care	.016	sorry	.018	summer	.017	definitely	.012	day	.026
sad	.016	god	.016	understand	.017	enjoy	.017	[laughing]	.010	couple	.020
emotional	.016	black	.015	fact	.015	remember	.016	back	.010	notice	.019
part	.016	problem	.015	late	.015	fun	.016	obviously	.010	work	.019
felt	.014	fine	.015	apologize	.013	u	.016	you'll	.010	great	.019
whatever	.014	walk	.014	fine	.012	nice	.014	hard	.009	pretty	.017
express	.014	white	.013	ready	.012	great	.014	relax	.009	thank	.016
respond	.014	cannot	.013	reason	.012	vacation	.014	[all laugh]	.009	realize	.015

THERAPY-RELATED TOPICS

TBCT						*IBCT*					
Topic 60	.016	Topic 49	.013	Topic 83	.014	Topic 90	.010	Topic 53	.012	Topic 34	.010
problem	.262	solution	.088	listen	.072	pattern	.036	felt	.107	talk	.047
solving	.092	down	.067	communicatio	.053	point	.034	love	.056	control	.041
issue	.049	write	.062	paraphrase	.030	two	.032	hurt	.052	emotional	.040
solution	.035	idea	.051	give	.029	down	.027	care	.052	fear	.029
work	.025	pros	.038	person	.027	become	.023	talk	.049	anxiety	.028
talk	.022	cons	.037	talk	.027	part	.023	bad	.035	afraid	.026
two	.022	brainstorming	.034	trying	.026	conflict	.019	connection	.024	express	.021
define	.020	good	.025	level	.023	response	.019	close	.018	wondering	.021
part	.019	two	.024	speaker	.022	process	.016	heart	.017	two	.021
definitely	.018	problem	.023	practice	.019	recognize	.016	pain	.014	back	.020
brainstorming	.015	possible	.021	point	.018	situation	.016	hard	.013	anxious	.020
trying	.014	trying	.018	editing	.017	deal	.015	wish	.012	guess	.019
communicatio	.014	discuss	.017	x	.017	withdraw	.015	share	.012	part	.019
process	.013	talk	.017	floor	.016	style	.014	words	.011	hard	.019
discuss	.012	agree	.016	summarize	.015	change	.013	acknowledge	.010	scared	.018

Figure 1. Examples of topics from a topic model applied to couple-therapy transcripts. The fifteen most likely words for each topic are shown. Topics have been organized into groups and labeled to aid interpretation. Note that the labels (i.e., in bold typeface) are interpretations of the topics provided by the authors and are not automatically learned by the model.

apparent in the topics presented in the bottom row of Figure 1. In contrast, IBCT focuses on identifying couple's relational patterns and underlying emotions. One of the strengths of topic models is that they derive the linguistic structure inductively, without any specific guidance about what type of linguistic content it should find. Thus, a topic model of the couple-therapy corpus can identify a number of semantic clusters that are directly relevant to the content and process of couple therapy.

After fitting the model, researchers can then use these topics to summarize and explore the semantic content of a set of therapy sessions, or to make predictions about other aspects of therapy (e.g., behavioral codes or therapy outcomes). Before presenting potential applications of topic models, we first describe the couple-therapy corpus in greater detail, provide details about text processing prior to model fitting, and then describe some of the statistical underpinnings of topic models.

Couple-Therapy Corpus

The present text data came from a randomized trial of two couple therapies for chronically and stably distressed couples seeking treatment (Christensen et al., 2004). Couples (N = 134) were randomly assigned to one of two treatments: TBCT or IBCT. TBCT is a skills-based couple therapy that has a didactic style, where the primary focus of the therapist is helping the couple to learn new skills to ameliorate their relationship problems. IBCT is strongly rooted in a behavioral case-conceptualization approach, in which the therapist helps the couple to identify core patterns or themes in their relationship, and also helps spouses express and respond to vulnerable emotions that are often underlying intense conflict. Couples received up to 26 sessions of therapy and completed self-report assessment batteries prior to therapy, at 13 and 26 weeks after the start of therapy, at the final session of therapy, and several times over five years of posttherapy follow-up. In addition, couples completed structured communication assessments prior to therapy, at the 26-week assessment, and at two years posttherapy. Finally, there was also a small, nondistressed couple-comparison group (n = 48). These couples were selected for having satisfying and functional relationships and completed a single assessment battery, mirroring the pretherapy assessment of the treatment-seeking couples. Primary treatment outcomes at posttherapy, two years posttherapy, and five years posttherapy are reported elsewhere (Christensen et al., 2004; Christensen, Atkins, Baucom, & George, 2006; Christensen, Atkins, Baucom, & Yi, 2010), as well as outcomes from observational coding of the communication assessments (Sevier, Eldridge, Jones, Doss, & Christensen, 2008) and therapy sessions (Sevier, 2005).

As described above, topic models work with text data, and a supplemental grant from the United States Department of Health and Human Services, National Institutes of Health, National Institute of Mental Health provided support for significant transcription of therapy sessions and communication assessments, which comprise the couple-therapy corpus of text used in the present analyses. For therapy sessions, couples were randomly selected for transcription, stratified by treatment condition and initial distress. For the 91 couples selected for therapy-session transcription, four sessions were transcribed in their entirety: the first session, the next to last session, and then two sessions closest to standardized assessments at 13 and 26 weeks after the start of therapy. For remaining sessions, a randomly selected quarter of each session was transcribed (approximately 13 min each). This design allowed a greater number of sessions to have some transcription from each couple, albeit incomplete transcription. Finally, communication assessments at pretherapy, posttherapy, and two years following therapy were transcribed for all 134 treatment-seeking couples and 48 nondistressed comparison couples. Communication assessments included two, 10-min problem-solving interactions, in which each partner selected a topic for one of the interactions. In total, the couple-therapy corpus contains approximately 6.5 million words (and bracketed expressions, e.g., [laugh]), across 1,486 unique therapy sessions and 765 communication assessments.

Text Processing and Topic Models/Latent Dirichlet Allocation

As noted earlier, relative to most other data with which family and couple researchers work, linguistic data is highly unstructured and has high dimensionality.[1] To better understand the dimensionality problem of raw text, a comparison with behavioral-coding data may be useful. The communication assessments in the present data were coded using the Couple Interaction Rating System (CIRS; Heavey, Gill, & Christensen, 2002). The CIRS has 13 codes that were rated for each partner during a communication task. Thus, a 10-min conversation between spouses is reduced to 26 numeric values through coding with the CIRS, and the overall behavioral-coding data could be summarized by a matrix of 26 (items) by 134 (couples) for each communication assessment. On the other hand, the linguistic content of an equivalent corpus of communication assessments will be vastly more complex. Considering each of the individual words spoken as single items, the problem here becomes obvious: The dimensionality of such a model would be enormous, as the representation of a corpus would be a matrix where there could be hundreds to thousands of sessions (e.g., the couple-therapy corpus has 2,251 unique sessions or assessments). Unique word tokens (i.e., a specific instance of a specific word) can often be in the millions. Let's examine how text processing and topic models make this seemingly intractable problem manageable.

Depending on the size of the corpus, the total vocabulary could be quite large, and it is common to take one or two steps to reduce the overall size of the vocabulary. One method of reducing the size of the vocabulary is to stem all of the words. Many different words share the same root. For example, walk, walks, walking, and walked all share the common root "walk." Stemming is an automated method for reducing similar words to their common stem (Porter, 1980). The unstemmed (or raw) couple-therapy corpus contained 33,216 unique words, whereas after stemming, the corpus had 22,409 unique words. (Software options for text preprocessing and topic models are considered later.) A second common strategy in preprocessing text data is to remove highly frequent functional words—often referred to as stop words. For example, the words "a," "of," and "the" are extremely common, but convey relatively little meaning. In our corpus, removal of approximately 600 stop words[2] reduced the total number of word tokens from approximately 6.5 to 1.1 million. It is beyond the scope of the present article to give a complete overview of preprocessing, but a book-length introduction can be found in Manning and Schutze (1999), or a briefer applied overview using the R statistical software can be found in Feinerer, Hornik, and Meyer (2008). Stemming and stop-word removal serve two key functions: a) They help to reduce the computational burden of fitting topic models (or other text-mining procedures), and b) these procedures enhance the

[1] In the present article, we use linguistic data synonymously with text data. More generally, spoken language encompasses both what is said (i.e., semantic content in text) and how it is said (i.e., prosody and tone of spoken language). Although outside the scope of the present article, speech signal-processing analyses have examined pitch and other acoustic features of the spoken language in this couple-therapy corpus (Black et al., in press).

[2] The list of stop words can be obtained from the authors.

interpretability of topics by removing redundancy (stemming) and words with little content (stop words).

A final step before topic modeling is to define a "document" in the corpus. In original applications of topic models, documents were quite clear in that the model was often applied to articles or scientific abstracts. Each article or abstract defined a unique document, which is simply a unit of text with some semantic similarity. In spoken language there are a couple of possibilities for defining a document. For example, a document could be defined as the full set of words spoken during a therapy session, or could be defined as the set of words spoken by a specific person (e.g., the husband) within a therapy session. In the present analyses, documents were defined as all words spoken by a single individual (i.e., husband, wife, therapist) in a single therapy session or communication assessment; further discussion of defining documents is found below. Once we have defined our set of documents, we can apply a topic model to the corpus. The basic steps are outlined in Figure 2.

A standard method for representing a corpus of documents is using a word-document matrix (WDM). A WDM is simply a frequency (or crosstabs) table in which each of the W unique words in the corpus corresponds to a row, and each of the D unique documents corresponds to a column. The actual values of each cell in this table are simply counts of the number of times each word occurs in each document. So, if word w shows up five times in document d, the value of the cell $M_{w,d}$ would equal five.[3] Note that the WDM representation does not capture word-order information, and thus models that use only the WDM as input make what is known as a "bag-of-words" assumption (where the ordering of the words is assumed to be unimportant). Despite the fact that we know that word order is very important for the particulars of human communication, word order is less critical for deriving the basic semantic dimensions of text. This assumption is extremely common, since it greatly simplifies model complexity (Harris, 1954). Nonetheless, it is important to realize that this is an assumption of the basic topic model, which could affect certain applications. Extensions to the basic topic model presented in the current paper have examined incorporating word order, though model and computational complexity increase enormously (see, e.g., Griffiths, Steyvers, Blei, & Tenenbaum, 2005).

Once we have constructed our word-document matrix from the set of documents in the corpus (Figure 2, Step 2), we can then apply the topic model to this dataset (Figure 2, Step 3). As previously indicated, topic modeling is an unsupervised[4] machine-learning method for finding a set of topics that can be used to summarize a collection of documents. In the technical literature, topic models are often referred to as latent Dirichlet allocations (LDA; Blei et al., 2003), which characterize the statistical model that is the basis for topic modeling. Given the input of the WDM, the model derives: (a) a set of topics that captures underlying semantic themes in the corpus, (b) a representation of each document in terms of the set of topics, and (c) the assignment of each individual word within the corpus to a specific topic (Figure 2, Step 4). Specifically, each topic is modeled as a probability distribution (i.e., a mixture) over words, and each document is modeled as a probability distribution of these topics, where the topics with high probability for a given document capture the semantic themes that are most prevalent within the document. Here in the main text, we avoid technical details underlying the model; additional details about the model, its estimation, and model settings can be found in the supplementary technical appendix.

The matrix of topic–word probabilities can be used to visualize the semantic themes in the corpus (as illustrated in Figure 1). The document–topic matrix can be used to summarize the semantic themes in a specific document (e.g., a transcript from a single therapy session or assessment); for example, one can quickly get a sense of what themes a document contains by looking at the top few topics in that document. Additionally, the document–topic matrix can be used to create topic-model-based regression covariates for additional modeling of outcomes or codes. That is, just as principal component analysis can be used as a preprocessing step for extracting a lower dimensional representation to be used in regression modeling, the output of LDA similarly provides a lower dimensional representation, where the number of features (e.g., covariates in a regression) is equal to the number of topics. The remainder of this paper will focus on the ideas described in this paragraph, using the couple-therapy corpus.

We first provide several illustrations of how LDA can be used for data exploration and summarization, and then discuss using topic-model output for discovering associations of topics with behavioral codes, including details on appropriate methods for regression models with topic-model data as covariates. Finally, we discuss some simple extensions of the standard LDA procedure, which can be useful for between-group comparisons and ways that behavioral codes can be used directly in the topic model (i.e., the topic-generation process is informed by behavioral coding data).

Using Topic Models to Summarize and Explore Text

Following the preprocessing of the text data described earlier (i.e., stemming and stop-word removal), a series of topic models were fit to the couple-therapy corpus, varying the number of topics (25, 50, 100, and 200). The number of topics is set by the data analyst when estimating the model, and different numbers of topics may be useful for different tasks (i.e., description and summary vs. predicting outcomes). The supplementary material provides additional details on determining the number of topics. In the current section, we use the 100-topic model to explore the text and examine the semantic themes found by the model, and models with additional topic numbers are used later in the prediction of behavioral codes. Figures 3 and 4 show brief sections of a transcript in which the topic-model assignment of given words to specific topics is indicated by shading and numeric superscript. Note that words not assigned to a topic were either stop words that were removed, or did not cross a threshold for assignment by the model (i.e., each word has a posterior probability from the model of being assigned to a specific topic, and in some cases, the model cannot

[3] We note in passing that WDM are typically very sparse matrices in that many entries are zero. Because of this, WDM are stored using a sparse matrix representation in which only nonzero entries are recorded in triplet format (i.e., a three number encoding of word, document, and frequency). This vastly reduces the overall size of the matrix and greatly reduces computing time.

[4] In machine-learning parlance, unsupervised methods are those that find structure without additional input, such as cluster analysis, whereas supervised methods are comprised of learning associations to a particular outcome, such as regression models.

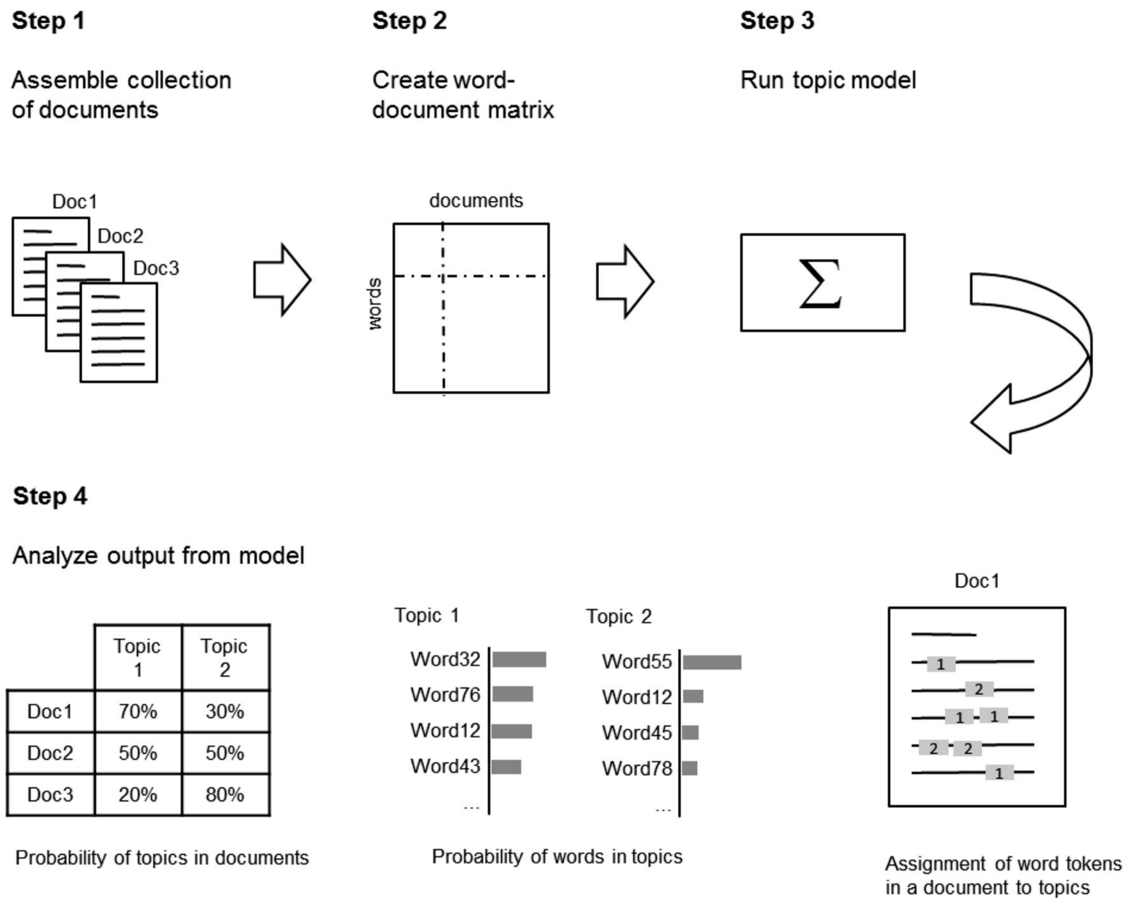

Figure 2. Overview flowchart of how topic models are applied to a corpus of documents (or, in the present example, therapy transcripts).

make a clear decision). In Figure 3, a therapist is describing some of the basic elements of problem solving.

This brief section shows that the topic model has located several semantic clusters related to "problem-solving language," specifically, Topics 49, 60, and 77. Moreover, each of these three topics is describing specific elements of problem solving, including defining the problem (Topic 60), generating problem solutions (Topic 49), and weighing the options (Topic 77). At the same time, this section also shows the challenges of similar (or exact) words used to convey slightly different meanings. The final statement from the therapist is asking whether the wife is having "problems" with the problem-solving model, which also gets assigned to Topic 60. Although topic models were developed in part to deal with polysemy (i.e., words with different meanings such as "play" or "bank;" see, e.g., Griffiths, Steyvers, & Tenenbaum, 2007), nuanced word usage such as the just-noted example can be challenging for the model to discriminate.

Figure 4 shows a section of a transcript from a different couple with a notably different focus. This portion of the transcript from a couple that is not doing well in therapy shows how the model is locating negative-affect words and topics. The topic model is clearly identifying this portion of transcript as negative, with topics on hatred (Topic 36), anger/disgust (Topic 3), arguments/screaming (Topic 16), and divorce (Topic 44). Readers will also notice that some word assignments to topics are not readily obvious. For example, "truly" and "guess" are assigned to Topic 3, as are "anger" and "disgusted." Topic models fit a distribution of topics over documents, meaning that some topics are prevalent in a given document, whereas others are not. Because of this feature of topic models, the base rate of a topic within a document influences the assignment of more ambiguous words in that document. With the present example, the session had strongly negative content, which raises the general probability that words get assigned to negative topics, assuming that the model does not have a clear indication to assign it to an alternative topic. However, by looking at the most prevalent words in Topic 3, which include "anger," "angry," and "hurt," it is clear that the topic is largely reflecting conflict and negative affect.

The previous two illustrations focused on specific portions of transcripts, which is helpful for understanding how the model handles text at the word level. It is also possible to use topic models to explore broader semantic themes by summarizing topic-model output over entire therapy sessions. For example, the relative prevalence of topics for a single therapy session portrays which semantic themes were prevalent for that particular session. Moreover, we can use topic-model output to examine which topics are prevalent for a particular couple across all sessions. To illustrate this, Figure 5 presents an image plot that shows specific topic

THERAPIST: ...and the model[77] is one in which you define[60] the problem[60], you brainstorm[49] ideas[49], you talk[77] about the pros[49] and cons[49] of the options[77], and then the last part[60] of it , or the next to last part[60] of it is to integrate[77] the ideas[49] that you decided[77] were good[49] ideas[49] into a strategy[77] that you're going to um ... that doesn't mean that we know for sure it is going to work[18]. In fact[19] that is the reason[77] why the last stage[60] of the model[77] is to set specified[49] times that we should reevaluate[77] and see how your solution[49] is working[18] or not working[18] and you adjust[18] it accordingly[4]. Right? That was the model[77], so um, are you um, contemplating[97] some problems[60] with the model[77] or are you um, suggesting[77] some problems[60] with the items[49] that we went through with that, that hasn't[88] been articulated[77] yet?

WIFE: Well, I mean I'm, I'm looking at the problem[60] and the potential[60] solutions[60] and, short[12] of me doing something, then nothing will change[22].

Figure 3. Transcript focusing on therapist problem-solving language showing topic assignment for individual words via highlighting and superscripting. Words not assigned to a topic are either stop words that were removed prior to topic modeling, or words which had a lower than .5 posterior probability of being assigned to a single topic (i.e., words for which the model was uncertain about the appropriate topic assignment).

distributions over time (i.e., therapy sessions) for a single couple. Each row in this figure corresponds to a single topic, and each column corresponds to a single therapy session. The relative proportion of words assigned to each topic within a given session is represented by the brightness of the corresponding cell; brighter cells indicate that a higher proportion of words were assigned to the topic for that session. The topics have been divided into three groups, relating to: (a) intervention language (the top block of topics), (b) therapy content/problems (middle block), and (c) affective topics (bottom block).[5]

Figure 5 is a representation of how the semantic content in therapy evolved over time for this couple. In examining the top blocks of topics, Topic 83 relates to communication-training language, and it is most prevalent in Sessions 4–8, at which point there is a shift toward problem solving (Topics 6, 46, and 60). The middle block of topics illustrates the particular content that were most central for this couple. As we might predict, given that this couple received TBCT, these content topics were discussed in the first few, assessment-oriented sessions and then appear again around the time that the problem-solving intervention is introduced (Sessions 9–12). For this particular couple, the wife was a flight attendant and traveled frequently with erratic schedules. Work and finances were notable concerns for them (Topics 23, 91, 92). In addition, her schedule plus their young children also meant the spouses were frequently exhausted with limited energy for each other (e.g., Topic 100). After effective use of problem solving on these topics, the final portion of therapy shifted to helping the couple find time for doing enjoyable activities, including planning for a vacation and exercising more (Topics 4 and 81). The final set of topics show how the affective content of sessions shifted over time for this couple. Initially, there was notable “frustration” language as they described their relationship (e.g., Topic 85). Over time, this topic largely drops out of the couple’s transcripts, whereas positive affect as seen in Topic 69 becomes relatively more prevalent.

This example shows how the output from topic models can provide an overview of significant themes in a couple’s course of therapy. Moreover, these examples focused on specific couples, whereas a similar process could be used with the entire sample, which might highlight particular problems that were prevalent in couples overall and general patterns of intervention language over time for the sample as a whole.

Using Topic-Model Output to Predict Behavioral Codes

As noted earlier, the most common method for analyzing linguistic data is behavioral coding, in which coding systems define a priori linguistic content that is thought to be important. As an example of how topic models can encode semantic information to be used in predictive models (e.g., regression models), we examine how topic models from the couple-therapy corpus can predict behavioral codes. At the outset, we note that this is a specific application of a much more general process of using topic models to quantify semantic information, which is then used to predict external outcomes (i.e., external to the text).

Due to the high-dimensional nature of linguistic data, dimensionality reduction and feature selection are common practices in the area of text-based regression modeling. The reason for this is directly tied to our earlier discussion of dimensionality: Suppose that we wanted to use our corpus of therapy transcripts to predict whether a couple will get divorced or not. Even after stemming and stop-word removal, the corpus contains over 20,000 unique words. Using logistic regression or a variant thereof, this would require estimating coefficients for each of the over 20,000 unique terms in our corpus. Given that we have data for only 91 couples (i.e., couples with transcripts and outcomes), this model would be greatly overparameterized, which presents a problem for developing a reasonable regression model.[6] A common solution to this issue of overparameterization is to use dimensionality reduction, such as principal-components analysis, to reduce the number of coefficients in the model. In a similar vein, topic models provide

[5] As noted earlier, the model was fit using 100 topics, and thus those presented in Figure 5 are a small subset. Not surprisingly, out of 100 different semantic themes, many are not relevant for any single couple. In generating Figure 5, we began by displaying only topics that were prevalent in this couple’s language above a certain threshold, which then led to an interpretable subset.

[6] Some readers may wonder whether such a model would even be possible to estimate. Although not currently common in family science, machine-learning methods have been developed to deal with situations in which the number of potential predictors is larger (and sometimes far larger) than the number of individuals or samples, which is common in some genetic studies, for example. See Hastie, Tibshirani, and Friedman (2009) for an overview.

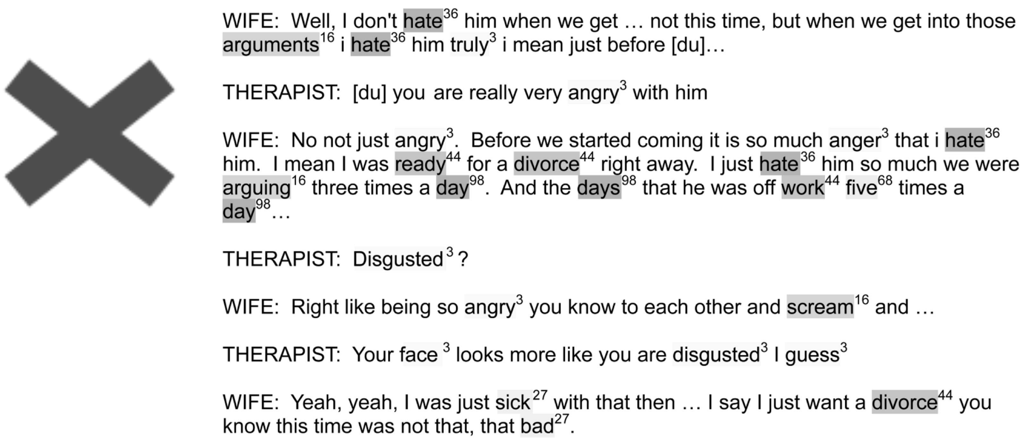

Figure 4. Transcript focusing on negative-affect language showing topic assignment for individual words via highlighting and superscripting. Words not assigned to a topic were either stop words that were removed prior to topic modeling, or did not cross a threshold for posterior probability of assignment (i.e., the model is uncertain about assigning to a specific topic).

a lower dimensional representation of the data; each document (i.e., session or assessment) can be summarized by the T topics, rather than by counts for each unique term in the corpus, which both simplifies the regression modeling and increases interpretability by using topics as predictors.

A subset of therapy sessions in the Christensen et al. (2004) study was coded using the Couple-Therapy in-Session Behavior-Rating System (Sevier & Christensen, 2002). This coding system rates each partner separately on 17 behavioral items, using a 1–9 ordinal scale. The codes comprise four subscales: constructive change behaviors, acceptance-promotion behaviors, positive behaviors, and negative behaviors. The models described below were fit to each of the 17 items, though for parsimony, we focus on four items, one each from the four subscales: constructive problem-solving skills (CPS), descriptive/nonblaming discussion (DIS), positive emotion (PEM), and blame (BLA). There were a total of 1,470 sets of ratings for individuals with matching transcription data available for analysis. The original, ordinal scaling was converted to a binary outcome, taking the top and bottom 20% of the ratings associated with each behavioral code. The rationale for this procedure is that the ratings in the tails of the distributions are most informative for distinguishing between the high and low end of the rating scale, and allows for a balanced binary outcome (i.e., 50% accuracy represents chance). Furthermore, as noted by Georgiou, Black, Lammert, Baucom, and Narayanan (2011), the distributions of most of the behavioral codes in this dataset tend to be unimodal, with the majority of coded sessions taking on intermediate values for most codes. The distributions of these code values—as well as

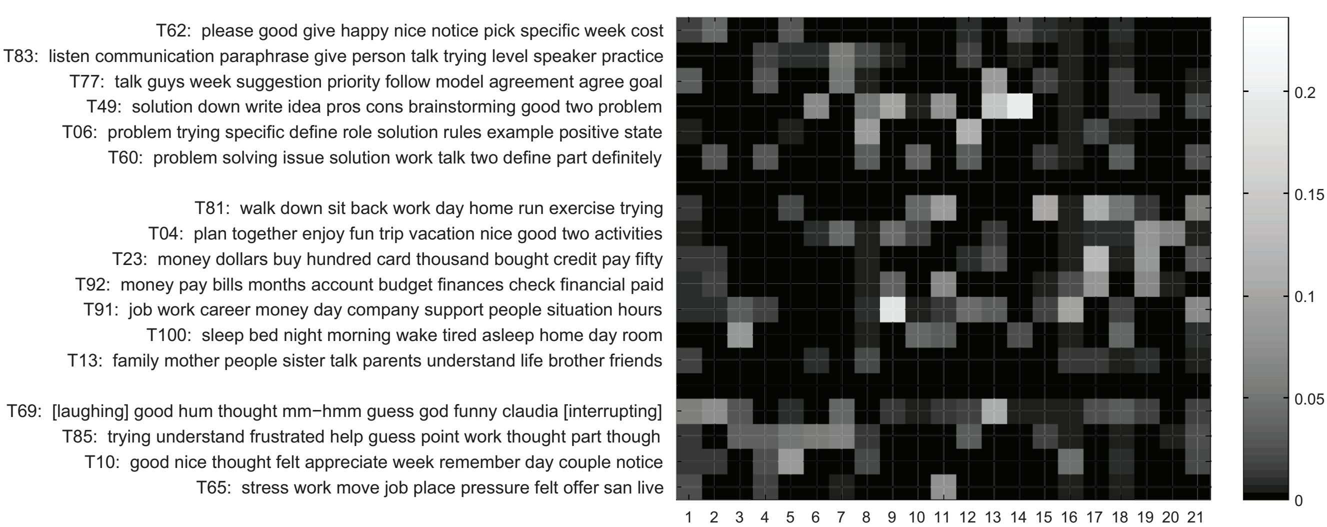

Figure 5. Image plot of the proportion of words from couple-therapy transcripts assigned to 17 topics for a particular couple. Rows of the plot are defined by topics, and columns are defined by session number. Topic proportions are presented in grayscale, and lighter shades indicate higher topic proportions. The color mapping has been scaled for easier interpretation.

the variance across individual coders—indicates that for the majority of codes, only sessions for which codes take on extreme scores (e.g., the top and bottom 20% of sessions), are reliably discriminated by human coders. Therefore, our focus is on an approach of utilizing only the extreme scores in our classification task, which has been employed in previous studies involving modeling behavioral codes (Georgiou et al., 2011; Black et al., in press). Based on this procedure, 588 therapy sessions (40% of the 1,470 therapy sessions total) were used for model estimation and testing. For comparison purposes, we also investigated the approach where no data were removed, that is, in which the ratings were converted to a binary outcome by taking the top and bottom 50% of ratings.

Coding outcomes were predicted from topic-model output using topic models with 25, 50, 100, or 200 topics. For each of these topic models, sessions were summarized by the proportion of words assigned to each of the topics. For example, each session from the 25-topic model will have a vector of 25 numbers describing how prevalent each of the 25 topics was in that particular session. Thus, the number of topics defines the number of covariates in each of the predictive models. Regression models with 100 or more covariates are not that common in couple and family research, and blindly fitting a standard logistic regression could very well lead to poor-fitting models. Thus, we provide details on how the current models guarded against overfitting, an issue that is standard to address in the machine-learning literature.

For each behavioral coding item, a sparse logistic regression model was fit (Krishnapuram, Figueiredo, Carin, & Hartemink, 2005). The sparse logistic regression model is based on logistic regression, but adds a penalty term for the regression coefficients such that the regression ends up with only a subset of the covariates associated with nonzero coefficients. This procedure is useful in situations where a large number of covariates is used and improves generalization performance (Hastie, Tibshirani, & Friedman, 2009). The performance of the sparse logistic regression model was assessed by a simple accuracy measure of percentage of codes correctly classified. Because the base rates of the two binary outcomes were equal, chance performance for this model is 50%. Cross-validation was used to assess performance, a standard approach to evaluate the predictive ability of regression models and other supervised learning procedures (Hastie et al., 2009). With the couple-therapy corpus, a "leave-one-couple-out" cross-validation was used. All of the data from a single couple were removed (or withheld), and the sparse logistic regression was fit to the remaining couples; this is often called the training set. The fitted regression model was then used to predict the behavioral code for the one couple that was withheld. This procedure was then iteratively applied, leaving out each couple in the sample, and the overall prediction accuracy was averaged across all the individual predictions. Using this type of cross-validation provides strong evidence for generalizability of the model to predict new couples' behaviors, treatments, and outcomes.[7] The difference in prediction between cross-validated and noncross-validated data results is an estimate of the degree of overfitting, somewhat similar to the difference between R^2 and adjusted R^2. For example, a model with a large number of regressors is expected to perform well on the sample data, but can potentially show poor generalization performance as assessed through cross-validation.

Figure 6 shows the prediction results from using sparse logistic regression to predict behavioral codes based on topic-modeling covariates. The results are shown for the four selected behavioral codes, as well as aggregated across the four codes (ALL). Different lines show the results for leave-one-couple-out cross-validation (gray line) and results with no cross-validation (black line). Within an individual code, each line shows from left to right the prediction accuracy based on regression covariates from topic models with 25, 50, 100, and 200 topics. Overall, results show that the topic models predict the binarized codes with between 65% and 70% accuracy, and that results vary by the number of topics extracted. There is some consistency across codes that covariates yield, based on 200 topics, inferior predictions to those with 25, 50, or 100 topics. This makes some substantive sense in that the codes are characterizing broad content that would be applicable to many couples (e.g., positive emotion). A topic model with 200 topics would have many idiosyncratic topics that would be highly specific to individual couples or small subsets of couples. As discussed in the technical appendix, this general procedure of iteratively fitting cross-validated regression models to an external criterion while varying the number of topics is one route to determining an appropriate number of topics to extract. At least with respect to predicting the current behavioral codes, these results would suggest that 25–50 underlying semantic dimensions are optimal. In addition, the results show that models without cross-validation are too optimistic, and such prediction models would likely not generalize.

We also investigated whether it makes any difference to use only the top and bottom 20% of ratings when constructing binary outcomes, or to use the full dataset. In the latter case, we created binary outcomes based on the top and bottom 50% of ratings. Performance remained fairly consistent, independent of how much data was included: In the 20%-tails procedure, average prediction accuracy across all 17 codes was 58.9%, with performance significantly better than chance on 13 out of 17 of the total codes, as measured using a binomial exact test. In the full-data condition (50% tails), average prediction accuracy across all codes was 56.3%, with performance significantly better than chance on 15 out of 17 codes. Therefore, our prediction results did not change much by focusing on the extremes of the ratings.

Finally, we investigated whether the resulting coefficients from the sparse logistic regression make substantive sense. Figure 7 presents a summary of the results of these models. For each code, the six topics with the largest regression coefficients are shown in rank order, and the top 10 words for each topic are provided. The bar plot for each code shows the relative strength of the regression coefficient. Across the four outcomes, the most predictive topics provide an interpretable set of features that make intuitive sense in terms of the codes with which they are associated. For example, the top three

[7] We also examined an alternative cross-validation approach. In this second approach, 10-fold cross-validation was applied at the session level by leaving out a random 10% of the sessions in the model-estimation procedure and measuring prediction accuracy on the held-out sessions (this process of leaving out 10% of the sessions was repeated 10 times on nonoverlapping sets of held-out sessions). In this approach, we test the model's ability to predict codes in novel sessions, but from the same couples. As might be expected, prediction accuracy was somewhat better using this approach than the "leave one couple out" approach, as the model has information about the couples it is trying to predict.

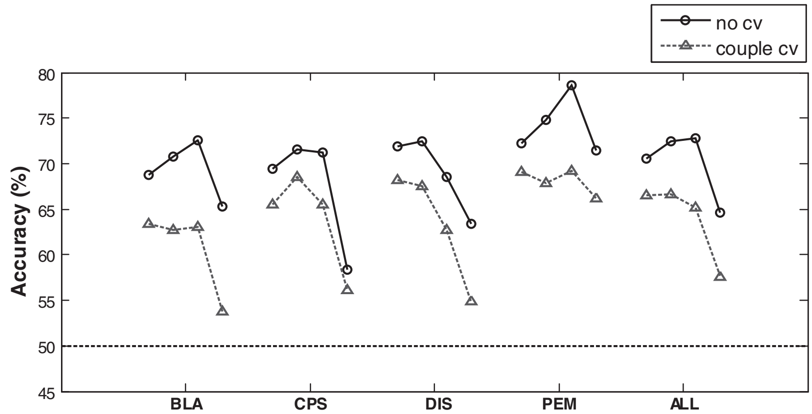

Figure 6. Accuracy in predicting four behavioral codes (CPS = constructive problem solving; DIS = descriptive nonblaming discussions; PEM = positive emotion; BLA = blame), as well as average prediction of four codes (ALL), based on sparse logistic regression models. Results are presented by the number of topics, type of cross-validation analysis, and behavioral code. For each line, the four points from left to right indicate the results for a topic model with 25, 50, 100, and 200 topics. Accuracy is based on percentage of sessions where the model correctly predicts that the behavioral code is associated with a rating in the bottom or top 20% of ratings.

topics that are most predictive of high scores on CPS all clearly relate directly to the issue of problem solving. The first three topics have certain high-probability words such as “pros,” “cons,” and “brainstorming” that capture specific language associated with problem-solving interventions, whereas the remaining three topics appear to capture linguistic content that may be a focus on problem-solving interventions (or communication strategies to use in the course of problem solving). These final three topics also demonstrate the utility of topic models for preserving the nuances of couples’ language within a quantitative framework. From these results, it is clear that sex and communication were two of the topics most frequently addressed within a problem-solving framework. Though it may not be surprising to anyone who has worked with couples clinically that sex and communication were common topics of discussion, topic models identify the presence of these themes in a manner that allows themes to be linked with other behaviors of interest. Because topic models are not confined to predetermined codes, we could use the present finding to ask more inductive research questions such as, “What are the most common themes addressed using problem-solving training in successful and unsuccessful couple-therapy cases?” Moreover, we could do so in a quantitatively rigorous manner.

For the two codes relating to emotional content, PEM and BLA, the regression coefficients are clearly picking up on topics that specifically capture affective content in the language. For PEM, there are high-probability words with positive emotional content (e.g., “good,” “nice”), but also bracketed terms that capture posi-

Awesome!!!😄

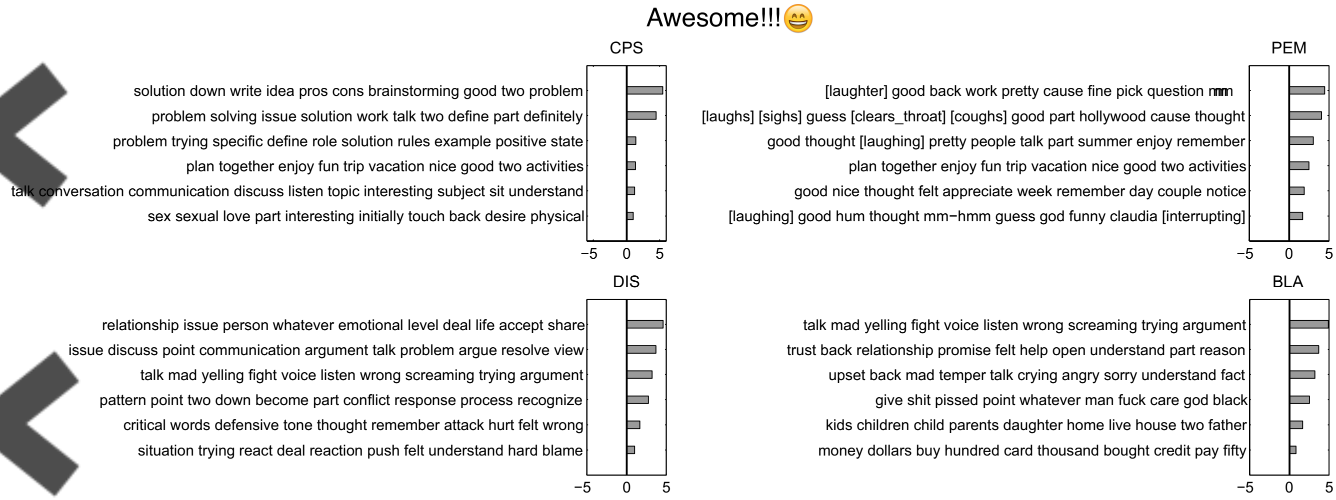

Figure 7. The six topics that are most predictive for high scores on four behavioral codes of couple-therapy transcripts based on logistic regression models (CPS = constructive problem solving; DIS = descriptive nonblaming discussions; PEM = positive emotion; BLA = blame). For each topic, the ten most likely words are shown alongside the β weights from the logistic regression.

tive emotional expressions ([laugh], [laughter]). For the BLA code, the topics capture words at the other end of the emotional spectrum. The most highly weighted topic seems to capture language that would arise during heated conflicts, and other topics include swearing, trust, children, and money, presumably therapy topics around which blame can arise. As with the associations between sex, communication, and CPS, these results help to contextualize blame language in a manner that is very difficult to achieve with observational coding. For example, many of the words in the swearing topic are dismissive statements that are not overtly critical, but that function to create emotional distance from a spouse in much the same way as the overtly angry and critical words in the first topic. Note that, although BLA contrasts strongly with PEM, these two codes are not exact opposites; although we would expect that blame would tend to co-occur with negative emotions, the notion of blame is more subtle than simply "negative emotions." Although it is difficult to be certain whether the topic model-based regression is picking up on this distinction, there is some evidence that it is. Specifically, whereas the topics with large coefficients for PEM all seem to capture topics with positive emotional content, the most predictive topics for BLA are not all directly related to negative emotional content, but also include substantive topics such as children and money.

This example was intended to illustrate how topic models might be used in predictive models of external outcomes. In the present case, the external outcomes were behavioral codes, and the results show that topic models have strong concordance with some behavioral codes. The ability of topic models to predict behavioral codes will be directly related to how strongly semantic a given code is. For example, another code in the current coding data is "withdraw." This code captures a range of behaviors that are primarily nonverbal (i.e., not engaging nor responding to partner), and the prediction accuracy of the regression model reflects this, as it is no better than chance. Thus, for behavioral codes with strong semantic content, topic models and regression procedures just described could be one route to developing a model-based coding procedure. That is, given the availability of some coding data to train the model, procedures such as those described above could be used to estimate codes for uncoded transcripts. In addition, the general process described above could be used with other criterion variables, such as therapy outcomes. These types of models could be used to characterize linguistic content prior to or during therapy that is associated with good (or poor) outcomes.

Limitations, Additional Resources, and Future Directions

Topic models have a notable, practical limitation: They require transcripts. There was significant cost and effort required to generate the couple-therapy corpus. However, it seems likely that this limitation will lessen over time. More and more data are being collected electronically, and the days of "paper and pencil" measures are quickly fading. Thus, open-ended response data is often collected electronically, without requiring additional transcription. For spoken language, recording quality is consistently improving, as is speech recognition software. Thus, we are guardedly optimistic that the transcription barrier to using topic models is lowering. A different limitation is that topic models are fundamentally lexical and semantic models, and they do not capture linguistic tone for transcripts of spoken language. nor do they capture nonverbal behavior that might be evident in a video recording (see, e.g., Black et al., in press; Ramseyer & Tschacher, 2011).

Our goal in this article was to provide an applied introduction to topic models, which provide the basis for a quantitative method for analyzing new text in the field of couple and family research. As with any introduction paper, it is impossible to go into detail on all of the relevant issues relating to the topic models. In the supplementary appendix of this paper, we provide further technical details and references for those interested in understanding the underlying mathematical details of the topic model. Here, we provide some additional comments relating to variants of the topic model that may be useful for future directions of research, as well as resources for those interested in learning more about the model or in using the model themselves.

The model employed in this paper is the standard LDA, or topic model (Blei et al., 2003). However, the flexible nature of this model has lead to the development of numerous variants and extensions of the model (e.g., see: Blei, 2011; Griffiths et al., 2007), and topic modeling now comprises a large and diverse field of research. Many of the more recent extensions of topic models could be extremely useful in the context of family psychology. For example, several topic models have incorporated both text and additional data, such as labels or annotations applied to documents (e.g., Blei & McAuliffe, 2008; Mimno & McCallum, 2008). Similar approaches could be beneficial in the context of clinical psychology, and could be used for exploring joint models of both textual data and the wide array of additional data collected in clinical work (e.g., behavioral codes, questionnaire data, etc.). Furthermore, whereas the results presented in this paper used topics derived without any knowledge of the behavioral codes, variants of topic models could incorporate this supplementary clinical data directly into the generative process for topics. Not only is this useful in that it can be used to associate linguistic content with specific codes (Ramage, Hall, Nallapati, & Manning, 2009), but this class of topic models is capable of achieving highly competitive prediction performance (Rubin, Chambers, Smyth, & Steyvers, 2012). This specific variant of topic models may serve as an excellent model for exploring areas such as automated behavioral coding.

Resources on working with text and preprocessing text prior to running topic models can be found in Manning and Schutze (1999) and Feinerer et al. (2008). At the present time, topic models are easily accessible in MATLAB via the topic-modeling toolbox (Steyvers & Griffiths, 2011), in R via the tm (for text mining; Feinerer et al., 2008) and topicmodels packages (Gruen & Hornik, 2011), and in a variety of other languages.[8]

Concluding Remarks

Albert Einstein famously said: "If atoms could talk, I would surely listen." Couple and family researchers have tried to listen to the talk that constitutes so much within close relationships. However, they have not always known how to make sense of that talk,

[8] David Blei's topic-modeling webpage (http://www.cs.princeton.edu/~blei/topicmodeling.html) is also an excellent resource, and contains a number of introductory/review papers on topic models, links to web-based topic-modeling applications and browsers, as well as a number of implementations of various topic models in R, C, and Python.

and have often resorted to the constraints of forced-choice questionnaires or predetermined coding categories as a method of studying relationships. Topic models represent ways to avoid these constraints and allow couple and family researchers to use open-ended text data in their full richness. They are one way in which qualitative data can be used in quantitative modeling and offer added flexibility over coding systems. Moreover, the initial applications described here show that they can detect important linguistic processes in interaction data, both at the level of what is discussed (i.e., content) and in what way (i.e., emotionally). We hope that these methods might enable couple and family researchers to more directly model linguistic hypotheses and therapy mechanisms.

References

Black, M., Katsamanis, A., Baucom, B. R., Lee, C. C., Lammert, A. C., Christensen, A., . . . Narayanan, S. S. (in press). Toward automating a human behavioral coding system for married couples' interactions using speech acoustic features. *Speech Communication*.

Blei, D. (2011). *Introduction to probabilistic topic models. Communications of the ACM*. Retrieved from http://www.cs.princeton.edu/~blei/papers/blei2011.pdf

Blei, D., & McAuliffe, J. (2008). Supervised topic models. In J. C. Platt, D. Koller, Y. Singer, & S. Roweis (Eds.), *Advances in Neural Information Processing Systems* (Vol. 20, pp. 121–128). Red Hook, NY: Curran.

Blei, D., Ng, A. Y., & Jordan, M. I. (2003). Latent Dirichlet allocation. *Journal of Machine Learning Research, 3,* 993–1022.

Christensen, A., Atkins, D. C., Baucom, B., & Yi, J. (2010). Couple and individual adjustment for 5 years following a randomized clinical trial comparing traditional versus integrative behavioral couple therapy. *Journal of Consulting and Clinical Psychology, 78,* 225–235. doi:10.1037/a0018132

Christensen, A., Atkins, D. C., Berns, S., Wheeler, J., Baucom, D. H., & Simpson, L. E. (2004). Traditional versus integrative behavioral couple therapy for significantly and chronically distressed married couples. *Journal of Consulting and Clinical Psychology, 72,* 176–191. doi:10.1037/0022-006X.72.2.176

Christensen, A., Atkins, D. C., Yi, J., Baucom, D. H., & George, W. H. (2006). Couple and individual adjustment for two years following a randomized clinical trial comparing traditional versus integrative behavioral couple therapy. *Journal of Consulting and Clinical Psychology, 74,* 1180–1191. doi:10.1037/0022-006X.74.6.1180

Feinerer, I., Hornik, K., & Meyer, D. (2008). Text mining infrastructure in R. *Journal of Statistical Software, 25,* 1–54.

Georgiou, P. G., Black, M. P., Lammert, A., Baucom, B., & Narayanan, S. S. (2011). "That's aggravating, very aggravating": Is it possible to classify behaviors in couple interactions using automatically derived lexical features? In S. D'Mello, A. Graesser, B. Schuller, & J.-C. Martin (Eds.), *Proceedings of affective computing and intelligent interaction: Part I. Lecture Notes in Computer Science, 6974,* 87–96. doi:10.1007/978-3-642-24600-5

Gottman, J. M., & Krokoff, L. J. (1989). The relationship between marital interaction and marital satisfaction: A longitudinal view. *Journal of Consulting and Clinical Psychology, 57,* 47–52. doi:10.1037/0022-006X.57.1.47

Griffiths, T. L., & Steyvers, M., Blei, D. M., & Tenenbaum, J. B. (2005). Integrating topics and syntax. In L. K. Saul, Y. Weiss, & L. Bottou (Eds.), *Advances in Neural Information Processing Systems* (Vol. 17, pp. 537–544). Boston, MA: MIT Press.

Griffiths, T. L., Steyvers, M., & Tenenbaum, J. B. T. (2007). Topics in semantic representation. *Psychological Review, 114,* 211–244. doi:10.1037/0033-295X.114.2.211

Gruen, B., & Hornik, K. (2011). Topicmodels: An R package for fitting topic models. *Journal of Statistical Software, 40,* 1–30.

Harris, Z. S. (1954). Distributional structure. *Word, 10,* 146–162.

Hastie, T., Tibshirani, R., & Friedman, J. (2009). *Elements of statistical learning: Data mining, inference, and prediction* (2nd ed.). New York, NY: Springer.

Heavey, C., Gill, D., & Christensen, A. (2002). *Couples Interaction Rating System* (2nd ed.). Unpublished manuscript, University of California, Los Angeles, CA.

Heyman, R. E. (2001). Observation of couple conflicts: Clinical assessment applications, stubborn truths, and shaky foundations. *Psychological Assessment, 13,* 5–35. doi:10.1037/1040-3590.13.1.5

Hopper, R., Knapp, M. L., & Scott, L. (1981). Couples' personal idioms: Exploring intimate talk. *Journal of Communication, 31,* 23–33. doi:10.1111/j.1460-2466.1981.tb01201.x

Jacobson, N. S., & Christensen, A. (1998). *Acceptance and change in couple therapy: A therapist's guide to transforming relationships*. New York, NY: Norton.

Jacobson, N. S., & Margolin, G. (1979). *Marital therapy: Strategies based on social learning and behavior exchange principles*. New York, NY: Brunner/Mazel.

Kerig, P. K., & Baucom, D. H. (Eds.). (2004). *Couple observational coding systems*. Mahwah, NJ: Erlbaum.

Krishnapuram, B., Figueiredo, M., Carin, L., & Hartemink, A. (2005). Sparse multinomial logistic regression: Fast algorithms and generalization bounds. *IEEE Transactions on Pattern Analysis and Machine Intelligence, 27,* 957–968. doi:10.1109/TPAMI.2005.127

Manning, C., & Schutze, H. (1999). *Foundations of statistical natural language processing*. Cambridge, MA: MIT Press.

Mimno, D., & McCallum, A. (2008, July). *Topic models conditioned on arbitrary features with Dirichlet-multinomial regression*. Paper presented at the 24th Conference on Uncertainty in Artificial Intelligence, Helsinki, Finland.

Porter, M. F. (1980). An algorithm for suffix stripping. *Program: Electronic library and information systems, 14,* 130–137. doi:10.1108/eb046814

Ramage, D., Hall, D., Nallapati, R., & Manning, C. D. (2009, August). *Labeled LDA: A supervised topic model for credit attribution in multi-labeled corpora*. Paper presented at the Conference on Empirical Methods in Natural Language Processing (EMNLP 2009), Singapore.

Ramseyer, F., & Tschacher, W. (2011). Nonverbal synchrony in psychotherapy: Coordinated body movement reflects relationship quality and outcome. *Journal of Consulting and Clinical Psychology, 79,* 284–295. doi:10.1037/a0023419

Rubin, T. N., Chambers, A., Smyth, P., & Steyvers, M. (2012). Statistical topic models for multi-label document classification. *Machine Learning, 88,* 157–208. doi:10.1007/s10994-011-5272-5

Sevier, M. (2005). *Client change processes in traditional behavioral couple therapy and integrative behavioral couple therapy: An observational study of in-session spousal behavior* (Unpublished doctoral dissertation). University of California, Los Angeles, Los Angeles, CA.

Sevier, M., & Christensen, A. (2002). *Couple therapy in-session behavior rating system*. Unpublished manuscript, University of California, Los Angeles.

Sevier, M., Eldridge, K., Jones, J., Doss, B., & Christensen, A. (2008). Observed changes in communication during traditional and integrative behavioral couple therapy. *Behavior Therapy, 39,* 137–150. doi:10.1016/j.beth.2007.06.001

Steyvers, M., & Griffiths, T. (2006). Probabilistic topic models. In T. Landauer, D. McNamara, S. Dennis, & W. Kintsch (Eds.), *Latent semantic analysis: A road to meaning*. (pp. 427–448). Mahwah, NJ: Erlbaum.

Steyvers, M., & Griffiths, T. (2011). Matlab topic modeling toolbox, Version 1.4 [Software]. Retrieved from http://psiexp.ss.uci.edu/research/programs_data/toolbox.htm

Tabachnick, B. G., & Fidell, L. S. (2007). *Using Multivariate Statistics* (5th ed.). Boston, MA: Allyn and Bacon.

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These are super weak, by and large.